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DETERMINATION OF EXTERNAL LOAD IN MEN’S ELITE OLYMPIC TRIATHLON AND ITS CORRELATION WITH OVERALL PERFORMANCE RESULTS

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Abstract

The Olympic Triathlon is a combined endurance sport, which includes back-to-back swimming, cycling and running, always in that order, with total time measurements including the transition between events. The goal of the current study was to analyse transition time in nine international, top-level, competitive events (6 World Championships and 3 Olympic Games men’s events), in particular Lost Time in T1 and T2 and its correlation with final race scores. The results showed that the percentages of total time corresponding to each segment of the race and the transition times from segment to segment were: 16.2\% for the swimming, 0.74\% for the swimming-cycling transition (T1), 53.07\% for the cycling, 0.47\% of the time for the cycling-running transition (T2) and, finally, 29.5\% for the running. The correlation coefficients between time durations of segments and transitions, and the final overall classifications were $r=0.36$ for the swimming, $r=0.25$ for T1, $r=0.34$ for Lost Time T1, $r=0.62$ for the cycling, $r=0.33$ for T2, $r=0.43$ for Lost Time T2, $r=0.83$ for the running. In conclusion, determining Lost Time T2 may provide significant information about performance in the Elite Olympic Triathlon. The running segment seems to be strongly related to performance success.

KEY WORDS, TRIATHLON, PERFORMANCE, TRANSITION, CORRELATION, LOST TIME

Introduction

The triathlon is a combined endurance sport, which includes back-to-back swimming, cycling and running events, always in that order, with total time measurements that include the transition between events. Transition time refers to the changeover from swimming to cycling (T1) and from cycling to running (T2).

Thirty years have passed since the triathlon was first conceived as a sport and it has been recognised officially by the International Olympic Committee and included as an
Olympic sport since the Sydney 2000 Games. It was a resounding success, with numerous countries taking part in the inaugural event.

The distance of each of the phases in Triathlon (swimming, cycling and running) depends on the level of competition. However, the most common race is the Olympic Distance Triathlon (1.5 km swim, 40 km ride, and 10 km run). In order to study performance in triathlon, we have taken into account that one of the most difficult (strategically and physically) parts of the triathlon is the transition from cycling to running.

Transitions are a fundamental part of the triathlon and have a large impact on the final result in many high-level competitive events. Some authors have assessed the duration of the transition phases (Sleivert et al., 1996; Hue et al., 1998) and reported times for elite tri-athletes at national or international levels that can be as short as >8 seconds per phase while considering the transition phase as only the actions carried out within the box. The first transition period T1 (swimming-to-cycling) includes removing the neoprene suit, taking off the swimming cap and goggles, and then putting on the cycle helmet while getting the bike. The second transition period T2 (cycling-to-running) includes parking the bike, removing the helmet and putting on running shoes.

Speed and precision in executing the transitions is a major factor affecting performance in a triathlon. The smaller the competition distance, the greater the importance of the transitions. The percentage of time represented by transitions has been previously reported to represent 0.8-1.5% of the time measured in the short triathlon Sprint competition (750 m swimming, 20 km ride and 5 km run; Cejuela et al., 2007).

In the current study, we analyse the time of each segment (swim, ride and run) and transition (T1 and T2) during nine top-level competitive international events, where we consider the importance of transition times as regards final competition scores. Specifically, we hypothesize about the possible relationship between the time lapse T1 and T2 (lost time for the swim-ride and ride-run transitions) for each competitor compared with the triathlete that started the run first and the final competition ranking.

**Methods**

We studied 9 top-level international male triathlon competitions held from 2000 to 2008. The total number of participants was 537 (n=537), with an average of 59.67±11.08 participants per competition, corresponding to 6 World Championship (2000, 2001, 2004, 2006, 2007 and 2008) and 3 Olympic Games events (2000, 2004 and 2008) for men. The participants analysed were all those who finished the competitions. We discarded the partial results of competitors who were disqualified or retired.

In collaboration with the International Triathlon Union (ITU), we gathered the data for all events. In order to gather the times for all competitions we used the “Champion-Chip®” microchip timing system. All athletes wore the chip on their left ankles and when they crossed the reading mats located at the start, entrance and exit from the transition area and finish line, the partial times for each segment, transition and total competition time were recorded. The data for the 2002, 2003 and 2005 world championships were not analysed, due to the fact that the timing system did not record the time taken to carry out the transitions separately (T1: swimming-cycling, T2: cycling-running) but included them in the time of the cycling segment.
Determination of lost time in T1 and T2

Lost time in transitions T1 and T2 is the time lag between the first triathlete to start cycling, for T1, or running, for T2, leaving the transition area, and the rest of the triathletes who arrived at the transition area in the same swimming or cycling pack. This time depends on two factors:

The first is the position of the triathlete in the swimming or cycling pack on entering the transition area; the lower the position, the more time is lost during transition and vice versa, the higher the position less time is lost during transition.

The second is the time taken by the triathlete to carry out the specific actions required in the transition area to change equipment and cross the area designated for this.

This time is only valid for reference for the swimming or cycling pack in which each triathlete reaches the transition area. It cannot be compared between groups.

The time lost in the transitions can be calculated by filming and analysing the videos of each entrance and exit from the transition area (Cejuela et al, 2008) or by mathematical calculations based on the partial times recorded.

Lost time in T1 is calculated by the difference in time with the best partial accumulated time of the event at the end of T1 belonging to the same swimming pack when entering T1. The criteria for deciding whether two triathletes belong to the same swimming pack is that the difference in time between the partial time at the end of the swimming segment of the triathlete preceding the triathlete to be analysed should not exceed 5 seconds.

\[ \text{Lost Time T1} = \text{Best partial accumulated time} - \text{accumulated time of each triathlete in the same swimming pack} \]

\[ \text{Accumulated Time} = \text{Time for the swimming segment} + \text{time for the swimming-cycling transition (T1)} \]

Lost time in T2 is calculated by the difference in time with the best partial accumulated time of the event at the end of T2 belonging to the same cycling pack when entering T2. The criteria for deciding whether two triathletes belong to the same cycling pack is that the difference in time between the partial time at the end of the cycling segment of the triathlete preceding the triathlete to be analysed should not exceed 5 seconds.

\[ \text{Lost Time T2} = \text{Best partial accumulated time} - \text{accumulated time of each triathlete in the same cycling pack} \]

\[ \text{Accumulated Time} = \text{Time for the swimming segment} + \text{Time for transition T1} + \text{Time for the cycling segment} + \text{Time for transition T2} \]

The reason for choosing 5 seconds as the time to decide that a triathlete belongs to the same swimming or cycling pack is based on hydrodynamic resistance calculations that show the ideal distance to draft behind another triathlete. This has not been determined exactly, but it has been shown to benefit the drafting triathlete (Chatard et al, 1998;
Bentley et al, 2007), while swimming more than 5 seconds behind the preceding triathlete has been shown to offer no advantage over swimming alone.

The same concept is used to decide whether a triathlete belongs to a particular cycling pack. In the pack the separation between riders provides a greater or lesser aerodynamic resistance to forward movement. With practically inexistent separations between wheels, we can achieve up to 44% reduction in aerodynamic resistance to forward movement, 27% with a separation of 2 metres (McCole et al 1990; Lucía et al. 2001; Faria et al, 2005).

This is why it is considered that swimming or cycling at over 5 seconds from the preceding triathlete is similar to the effort made doing so alone, meaning that the triathlete in question does not belong to the preceding group or pack of triathletes.

Statistical procedure

The descriptive statistical procedure involved calculating mean values, typical deviations, frequencies and percentages. To compare the mean values of the times for each segment and transition, we used the single-factor ANOVA parametric statistical test. The level of significance was set at p<0.05 (significant) and p<0.001 (highly significant).

We established the relationships between variables with bivariate correlation technique design, using Pearson’s correlation coefficient (r) analysis technique. The level of statistical significance was set at p<0.05. To carry out the statistical procedure, we used the SPSS statistical programme version 15.0 for Windows and the Microsoft Excel 2008 spreadsheet.

Results

The average time spent in the competitions analysed was 1 hour, 52 minutes and 5 seconds. Table 1 shows the average time spent for each segment, transition and the total time for each competition analysed. The segment taking the longest time was cycling, followed by running and swimming. T1 lasts longer than T2. The time showing greatest variability was for the cycling segment.

Table 2 compares the average time of all participants as an average of all the competitions analysed with the average time of the winners of the competitions. We found significant differences (p<0.05) for the total time and very significant differences (p<0.001) in the time spent for the running section.
Table 1. Average time in hours:minutes:seconds for each of the segments, transitions and total time for all male competitors in each competition.

<table>
<thead>
<tr>
<th>Competition</th>
<th>Swim</th>
<th>SD</th>
<th>T1</th>
<th>SD</th>
<th>Bike</th>
<th>SD</th>
<th>T2</th>
<th>SD</th>
<th>Run</th>
<th>SD</th>
<th>Total Time</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sydney 2000 Olympic Games</td>
<td>0:17:59</td>
<td>0:00:24</td>
<td>0:00:23</td>
<td>0:00:03</td>
<td>0:59:14</td>
<td>0:01:27</td>
<td>0:00:19</td>
<td>0:00:02</td>
<td>0:33:31</td>
<td>0:01:57</td>
<td>1:51:30</td>
<td>0:02:41</td>
</tr>
<tr>
<td>W.Camp. 2000</td>
<td>0:18:28</td>
<td>0:00:20</td>
<td>0:00:46</td>
<td>0:00:03</td>
<td>1:01:19</td>
<td>0:00:54</td>
<td>0:00:34</td>
<td>0:00:16</td>
<td>0:32:57</td>
<td>0:01:30</td>
<td>1:54:06</td>
<td>0:01:57</td>
</tr>
<tr>
<td>W.Camp. 2001</td>
<td>0:18:36</td>
<td>0:00:32</td>
<td>0:00:54</td>
<td>0:00:03</td>
<td>0:58:02</td>
<td>0:01:56</td>
<td>0:00:30</td>
<td>0:00:04</td>
<td>0:34:13</td>
<td>0:01:57</td>
<td>1:52:16</td>
<td>0:03:46</td>
</tr>
<tr>
<td>World Cup 2004</td>
<td>0:18:30</td>
<td>0:00:21</td>
<td>0:01:07</td>
<td>0:00:04</td>
<td>0:52:19</td>
<td>0:01:08</td>
<td>0:00:37</td>
<td>0:00:03</td>
<td>0:32:35</td>
<td>0:01:50</td>
<td>1:45:06</td>
<td>0:02:37</td>
</tr>
<tr>
<td>Athens 2004 Olympic Games</td>
<td>0:18:19</td>
<td>0:00:20</td>
<td>0:00:18</td>
<td>0:00:01</td>
<td>1:03:24</td>
<td>0:02:21</td>
<td>0:00:20</td>
<td>0:00:02</td>
<td>0:34:18</td>
<td>0:01:52</td>
<td>1:56:20</td>
<td>0:03:42</td>
</tr>
<tr>
<td>W.Camp. 2006</td>
<td>0:17:51</td>
<td>0:00:25</td>
<td>0:00:51</td>
<td>0:00:03</td>
<td>1:04:13</td>
<td>0:02:12</td>
<td>0:00:35</td>
<td>0:00:03</td>
<td>0:33:32</td>
<td>0:01:38</td>
<td>1:57:00</td>
<td>0:03:33</td>
</tr>
<tr>
<td>W.Camp. 2007</td>
<td>0:17:39</td>
<td>0:00:14</td>
<td>0:00:41</td>
<td>0:00:04</td>
<td>0:55:38</td>
<td>0:01:11</td>
<td>0:00:21</td>
<td>0:00:03</td>
<td>0:32:19</td>
<td>0:01:36</td>
<td>1:46:39</td>
<td>0:02:22</td>
</tr>
<tr>
<td>W.Camp. 2008</td>
<td>0:19:01</td>
<td>0:00:13</td>
<td>0:00:46</td>
<td>0:00:04</td>
<td>0:59:19</td>
<td>0:01:49</td>
<td>0:00:24</td>
<td>0:00:03</td>
<td>0:34:13</td>
<td>0:01:35</td>
<td>1:53:43</td>
<td>0:02:59</td>
</tr>
<tr>
<td>Beijing 2008 Olympic Games</td>
<td>0:18:23</td>
<td>0:00:15</td>
<td>0:00:28</td>
<td>0:00:02</td>
<td>0:58:52</td>
<td>0:00:21</td>
<td>0:00:30</td>
<td>0:00:02</td>
<td>0:33:49</td>
<td>0:02:05</td>
<td>1:52:01</td>
<td>0:02:08</td>
</tr>
<tr>
<td>Average Time</td>
<td>0:18:19</td>
<td>0:00:25</td>
<td>0:00:42</td>
<td>0:00:16</td>
<td>0:59:09</td>
<td>0:03:41</td>
<td>0:00:28</td>
<td>0:00:07</td>
<td>0:33:30</td>
<td>0:00:44</td>
<td>1:52:05</td>
<td>0:04:00</td>
</tr>
</tbody>
</table>

Table 2. Comparison of the time in hours:minutes:seconds each of the segments, transitions and total time for all male competitors in each competition (World Championships 2000, 2001, 2004, 2006, 2007 and 2008, Olympic Games 2000, 2004 and 2008). *World Championships 1997, with a total of 116 triathletes (Landers, 2002) #Highly significant difference (p<0.001). *Significant difference (p<0.05).

<table>
<thead>
<tr>
<th>Time</th>
<th>Swim</th>
<th>T1</th>
<th>Bike</th>
<th>T2</th>
<th>Run</th>
<th>Total Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Men</td>
<td>18:19±00:25</td>
<td>00:42±00:16</td>
<td>59:09±3:41</td>
<td>00:19±00:07</td>
<td>33:30±00:44#</td>
<td>1:52:05±04:00*</td>
</tr>
<tr>
<td></td>
<td>18:09±00:25</td>
<td>00:39±00:15</td>
<td>57:56±03:20</td>
<td>00:26±00:09</td>
<td>31:03±00:51#</td>
<td>1:48:13±03:44*</td>
</tr>
<tr>
<td></td>
<td>19:18±00:26#</td>
<td></td>
<td>59:15±00:59</td>
<td></td>
<td>32:02±01:36</td>
<td>1:52:26±02:25</td>
</tr>
</tbody>
</table>

Table 3 shows the relative distribution (%) of the time of the different segments and transitions of the event. The cycling segment lasts for over half the total time of the event. Nearly 30% corresponds to the running segment, 16.3% to the swimming segment, while the transitions only account for 1% of the total duration of the competition.

The time distribution percentages of the competition winners are very similar to the average of all competitors and only show significant differences (p<0.05) for the running segment. They show a lower percentage of time for the running segment, lower than the average of all participants (28.7% versus 29.9%), with a higher percentage for the cycling segment (53.5% versus 52.8%).

In order to see whether this distribution of time had any relationship with the final classification obtained, we calculated the correlation of the time used for each segment, transition and the time lost in the transitions with the final classification. The results are shown in Figure 1.

<table>
<thead>
<tr>
<th></th>
<th>Swim</th>
<th>T1</th>
<th>Bike</th>
<th>T2</th>
<th>Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Men</td>
<td>16.35±0.62</td>
<td>0.62±0.23</td>
<td>52.73±1.47</td>
<td>0.41±0.10</td>
<td>29.90±0.72*</td>
</tr>
<tr>
<td>Average Winners</td>
<td>16.79±0.70</td>
<td>0.60±0.23</td>
<td>53.50±1.38</td>
<td>0.40±0.13</td>
<td>28.70±0.58*</td>
</tr>
<tr>
<td>Sprint Triathlon</td>
<td>16.5±1.5</td>
<td>0.8±0.3</td>
<td>51.1±3.1</td>
<td>0.65±0.2</td>
<td>28.4±3.4</td>
</tr>
<tr>
<td>Olympic Triathlon</td>
<td>16.5</td>
<td>52.4</td>
<td>31.3*</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


Discussion

The average time spent for the men’s Elite Olympic Triathlon competition is similar to the figures published in scientific literature, Table 2. There are highly significant differences (p<0.001) for the swimming segment, with less time being used in the competitions we studied, something that indicates that current performance is higher in this segment. The time for the cycling segment is similar, but bearing in mind the fact that the references in the literature relate to events that took place with no drafting allowed for the cycling segment, prior to the debut of the sport at the Olympic Games (Sydney, 2000), this segment would cause greater preceding fatigue for the running segment (Patton and Hopkins, 2005). The times for the running segment do not show significant differences, although the average time is lower for the 1997 world championships analysed by Landers (2002).

The total length of the race, each segment and transition is conditioned in full by the particular circumstances of each competition and the organisation of each specific event. Weather conditions have been shown to be a source of variability with regard to
the event time in the Olympic Triathlon by Paton & Hopkins (2005), it being greater in warm conditions. Due to these variables, the absolute times obtained for each competition cannot be compared in absolute and objective terms with the times of other competitions of a similar level or with the times obtained separately for the sports that make up the triathlon.

If we compare the average duration of the competition between the male winners and all participants, we find highly significant differences (p<0.001) for the running segment time (31:03±00:51 versus 33:30±00:44), and significant differences (p<0.05) for the total duration (1:48:13±03:44 versus 1:52:05±04:00) (Table 2).

If we analyse the relative distribution (%) of event time (Table 3), as with the absolute times, these figures show that the segment showing the greatest difference between the winners and the mean time for all participants is the running segment, indicating that performance in this segment has a greater importance for the final result. If we take into account the fact that the swimming and cycling segments offer the possibility of swimming or riding in a pack, and that the participants are of international elite level, performance in all segments is very high but the time differences largely appear in the last segment, where running in a group has less biomechanical and physiological effects than in the other two segments, and the preceding fatigue has a very significant influence.

These figures represent an important difference with the triathlon format where drafting is not allowed in the cycling segment (e.g. the Ironman), meaning that the analysis of the competition and final performance factors are different from the Olympic Triathlon competition (Paton & Hopkins, 2005; Bentley et al, 2007).

Several studies have analysed the triathlon competition, differentiating the competition solely by the three sports it consists of (Landers, 2002; Millet et al, 2002). These studies included transition times (T1 and T2) in the cycling segment. With the development of the Olympic Triathlon, several authors have realised the importance of the transitions for final performance (Paton & Hopkins, 2005; Vleck et al, 2006; Vleck et al, 2008).

The Olympic Triathlon is a complex sport, not only because three sports are performed back-to-back without stopping the clock, but also because of the speed and precision required during the transitions that allow competitors to pass from one segment to the next (Millet & Vleck, 2000). Transitions are a fundamental part of the Olympic Triathlon. They are a determining factor in the final results of many competitions. This study takes another step forwards in analysing Olympic Triathlon performance and we have divided the competition into: swimming segment, transition swimming-cycling (T1), time lost in T1, cycling segment, cycling-running transition (T2), time lost in T2, and the running segment.

We have correlated the average time spent by all competitors in each of the competitions and the final result obtained in each of these stages - Figure 1.

The time spent in the swimming segment has a low value correlation (0.36) with the final position obtained. This figure is significantly different (p<0.05) to that found by Landers (2002) in his analysis of 10 international ITU competitions in 1999. The correlation of the swimming segment was significantly higher (p<0.05) (0.49 versus 0.36) in the 1999 competitions. This may be due to the increase in the level of the male swim-
ming segment, with differences in the segment being greater and more decisive in the past than in current competitions.

In this segment, it is very important to obtain a good position at the end, in order to be able to join the most advanced group possible in the cycling segment (Millet & Veck, 2000). Drafting is very important when competing in this segment, in order to save as much energy as possible for the rest of the competition (Chatard et al, 1998; Millet, et al, 2002).

Despite the fact that the correlation between the time taken for the swimming segment and the final classification is low or medium, this does not mean that taking more time in the swimming section than the main pack allows you to compete at the front of the race, but that the level in the swimming segment is very high in the international elite Olympic Triathlon. A very numerous main pack is formed in the lead whose members swim in more or less similar time ranges. This means that the triathletes who do not form part of the pack find it very difficult to try to win later.

There is a low correlation (0.25) between the time of the first transition (T1) and the final classification obtained. This may be due to that fact that, during the cycling segment, it is possible to make up the time lost in T1 by catching up with the pack, as the profiles of most championship routes do not have difficult mountainous sections (steep hills or mountain passes), except for the 2004 Olympic Games, although they do have certain technical difficulties (sharp bends, narrow sections, etc.). This means, as stated by Bentley et al, 2007, that drafting may be a beneficial tactic in swimming and cycling to increase elite Olympic triathlon performance.

Vleck et al, 2007, analysed the 2002 Lausanne World Cup using a GPS device for each athlete and several video cameras. They split the swimming segment into two parts and the cycling section into six, the same as the running segment. They did this to try to identify the importance of changes in rhythm at decisive points in the competition and the best tactics to adopt, but the problem with this analysis is that the format of the Olympic Triathlon competition is open and the environment in which the event is contested conditions the tactical actions of those taking part.

High correlations were found associating speed of movement with position at the start of the swimming segment (r = -0.88 for men, r = -0.97 for women), the cycling segment (r = 0.81 for men, r = 0.93 for women) and the running segment (r = -0.94 for men, r = -0.71 for women). The changes of rhythm at the beginnings and ends of the segments, together with the transitions, are the decisive moments in the competition. These changes in rhythm at the start and end of the transitions can be the cause of the time lost in the same.

In T1, the time lost is different for each swimming pack. We identified two packs in our analysis; 1st and 2nd swimming packs when exiting to the cycling segment. The mean correlation of the 1st swimming pack with its final position was medium-low (r=0.34), the same as for the 2nd pack (r=0.4) in the male category.

The reason why this time does not show high correlation with final performance may be due to the fact that most competitions programme a flat cycling segment (except for the 2004 Olympic Games). In competitions where the cycling section has difficult mountainous sections that lead to the creation of smaller packs and reduce the importance of
drafting, this fact would be more important, for example in the 2004 Olympic Games in Athens. This was the only competition where the correlation of the time taken for the cycling segment with the final classification obtained has a higher value (r=0.86) than the correlation of the time used in the running segment with the final classification obtained (r=0.76).

Normally, during the cycling segment of elite competitions with flat profiles, 1 or two, or at the most 3, packs are formed. Those who do not form part of the first pack cannot normally hope to win. This is shown by the medium-high correlation (0.62) between the time taken for the cycling segment and the final classification obtained, reinforcing the hypothesis of Bentley et al, 2007, with regard to the importance of tactics during this segment.

There are significant differences (p<0.05) in the correlations between the time taken for the cycling segment and the final classifications in the different competitions analysed. These differences may be due to two reasons: Firstly, the individual or group tactics adopted by the triathletes during the segment; aggressive or conservative, trying to break away from the main pack to reach the running segment with a time advantage, or trying to save as much energy as possible to reach the running segment in the best condition possible. Secondly, the orography of the segment: if the profile has mountainous difficulties, the correlation is higher than if the profile is flat. With flat profiles, it is easier and more beneficial to draft in a pack than when riders have to climb mountains, passes or steep slopes (Faria et al, 2005).

The second transition (cycling-running or T2) has been described as the most important with regard to the final result of the competition (Millet & Veck, 2000). When a large pack arrives at the transition area, a clean, fast transition normally becomes a major performance factor for the final result of the competition. We found a low correlation (r=0.33 men, r=0.36 women) between the time taken for T2 and the final classification obtained, and carrying out a good T2 determines the time lost in T2.

The correlation for the main pack in the cycling segment has an average of (r=0.43) for the time lost in T2 with regard to the final classification obtained in the competition. Losing less time is related to obtaining a better final classification. Determining this parameter provides information that, although known by trainers, had not had its importance regarding final performance in the competition identified. It is a performance factor that should be taken into account when analysing high-level Olympic Triathlon competitions. We should point out that this time varies from 1 to 15 seconds and represents an average correlation with final performance in competitions that last slightly less than 2 hours, when the leading positions are often decided by final sprints with differences of very few seconds. Therefore, this time may be a decisive factor as regards the final classification of these competitions.

The time lost in T2 is valid for determining the final performance of triathletes arriving at T2 in the same cycling pack or group. Losing as little time as possible in T2 depends on two factors; firstly, arriving at T2 in the most advanced position possible within the pack, and secondly, carrying out the necessary actions in T2 as quickly as possible.

The final running segment has been described as the most decisive segment with regard to performance in the triathlon (Slelvert & Rowlands, 1996; Hue et al, 2002; Bentley et al, 2007). Our mean correlation figures for the time taken for the running segment and
the final classification obtained reaffirm the data described in the literature, obtaining the highest correlation of all the segments and transitions (0.83). The tactics adopted in the cycling segment will mark the greater or lesser correlation of the time taken for the running segment with the final classification.

Two race scenarios that could cause differences have been identified:

*Scenario One, when the profile of the cycling segment has major orographic difficulties.* Of the competitions analysed, only the 2004 Olympic Games showed a higher correlation for the cycling segment \( (r=0.86) \) than the running segment \( (r=0.76) \). This is due to the fact that cycling segment was contested over a mountainous profile.

*Scenario Two, when aggressive tactics leading to breakaways are adopted during the cycling segment.* Of the competitions analysed, this only happened in the 2006 World Championships, when the correlation of the time of the cycling segment was similar to that of the running segment \( (r=0.82 \text{ versus } r=0.83) \).

These figures may show that the tactics generally adopted for the men’s cycling segment are more conservative, or that it is more difficult to create the circumstances where breakaways reach the running segment with a clear advantage. In addition, the performance level in the cycling segment may be very high and similar for all participants, and the fact that there is little collaboration or teamwork may be the reason why breakaways rarely happen. We need more studies that analyse trends in the current format of the World Championship Trial Series competition.

**Conclusions**

The current overall trend in the male Elite Olympic Triathlon is that the result is decided in the final running segment, with performance in the two previous segments (swimming and cycling) being very high and similar for all competitors.

Competitors need to leave the water in the leading pack if they are to have better chances of winning. The time lost in T1 can be made up in the initial kilometres of the cycling segment, with a medium-low \( (p<0.05) \) significance regarding the final classification in the men’s category, but it is important for competitors not to drop out of the leading pack in the cycling segment if they are to have better chances of winning.

The time taken for the cycling segment has different significance \( (p<0.05) \) for each competition, depending on the orography of the segment and events that take place during the race (weather, breakaways, etc.), being high for all of them with regard to the final performance achieved.

Determining the time lost in T2 provides medium significance information \( (p<0.05) \), depending on the competition, for performance in the international elite Olympic Triathlon. It is a performance factor for training, determined by the position in the cycling pack on entering the transition area and the time taken to carry out the necessary actions in T2.

The orography of the cycling section and any breakaways can lead to differences in the importance of the time lost in T2. In competitions with a flatter profile and more competitors in the main pack, there is usually a higher correlation with final performance.
However, in circuits with a more complicated orography (steep slopes and mountain passes), it may be less important; as there are fewer packs and they reach T2 in more widely spaced groups.

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OPTIMAL GUIDANCE IN THE DEVELOPMENT OF SPEED IN YOUNG SWIMMERS

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Abstract

Scientists are searching continuously for tools that will allow for non intuitive steering of the training process. Despite many attempts, a direct algorithm has not been developed, upon which a precise determination of training loads would be possible. The main objective of this work was to verify the usefulness of a mathematical model for determining optimal steering. The mathematical model was created from data obtained during an experiment conducted on 45 young swimmers. The average body height and body mass of the tested subjects equaled respectively 163.1±6.25 cm and 49.68±6.5 kg. All of the examined subjects performed 3 swimming (45min) sessions per week and 2 on land (90min) training sessions carried out in the gym. The training loads were changed each month, considering both, the volume and intensity of exercises. The experiment lasted for 9 month and was preceded by a 2 year initial general fitness training program. The dependent variable included the freestyle swim time at 25m. The created model was used to determine optimal training loads directed at maximal improvement of the 25m time for particular athletes for 8 week time periods. Comparing the obtained results, was concluded that the development of a mathematical model is a helpful tool in non intuitive directing of the training process. This allows for the calculation of optimal strategy for athletes preparing for competition. It was concluded that mathematical models are a significant tool in planning training loads, at the same time indicating the necessity of further research that would include a higher amount of variables that would increase the precision of the model.

KEY WORDS, OPTIMAL TRAINING LOADS, MATHEMATICAL MODEL, SPEED, SWIMMING
Introduction

The continuous progress of results in sport compels competitors to look for better and better training methods in order to be able to compete with the best in world athletes. This phenomenon can be seen at almost every stage of sports training. The existing pressure in international, national, regional and even local sport is so big that when faced between a rational and gradual increase of training loads or an increase following the rule “the more, the better”, the latter usually prevails. Therefore, it seems very important to work out a method that would allow both to optimize the tendency of increasing the volume and intensity in training and take advantage of wide cognitive knowledge concerning sports training [Bulgakowa, Sachnowski 2000, Edelmann-Nusser et al. 2006, McGarry, Perl 2004, Perl et al. 2002].

The problem of relation between training stimulus and reaction of the individual to this stimulus is one of the most significant problems of sport training. Excessive training loads may lead to overtraining or injury, while insufficient ones do not stimulate adaptive changes [Kelly 2006, Winnick 2005]. Scientists are continuously searching for tools that will allow for non-intuitive steering of the training process. Despite many attempts, a direct algorithm has not been developed, upon which a precise determination of training loads would be possible [Perl et al. 2002].

When optimizing a training process, one should try to answer the question whether it is possible to build a mathematical model that would include different sports phenomena in training and accompanying it physiological reactions. Such models could be later used in steering sports trainings.


Scientists use models in development and testing research hypothesis as well as to identify parameters and variables for measurements. The main objective of this work was to evaluate the application of the mathematical model in evaluation of effectiveness of chosen training means in developing speed in youth swimmers. The following, specific research questions were created:

1. Does the mathematical model created upon experimental data allow to estimate the influence of particular training means on the level of speed in youth swimmers?
2. Which of the applied training means have the greatest effect on improvement of speed in swimming?

Materials and methods

The mathematical model was created from data obtained during an experiment conducted on 45 young swimmers. The average body height and body mass of the tested subjects equaled respectively 163.1±6.25cm and 49.68±6.5kg. All of the examined subjects performed 3 swimming (45min) sessions per week and 2 on land (90min) training sessions carried out in the gym.
The training loads were changed each month, considering both, the volume and intensity of exercises. The experiment lasted for 9 months and was preceded by a 2-year initial general fitness training program. A simplified catalogue of training means was developed. Quantitative and qualitative variables of the training load were registered.

There were 5 levels of intensity in this scale, which were based mainly on heart rate and time of the exercise. These levels are presented below:
Level 1. Aerobic, low intensity (HR ≤ 140 bts/min),
Level 2. Aerobic, moderate to high intensity (HR = 150-165 bts/min),
Level 3. Above AT, high intensity (HR = 165-175 bts/min),
Level 4. Anaerobic glycolytic, submax intensity (HR = 180-200 bts/min),
Level 5. Anaerobic phosphagen, max intensity.

The quantity was expressed by time of exercise.

During the experiment, the following training means were used, playing the role of decision variables (control variables):

The means used on land:
1. General fitness exercises: athletics, strength exercises, agility, flexibility (int.4),
2. Continuous distance runs, team sports (int.3),
3. Speed training: distances up to 25 m., starts, turns, (full recovery rest periods) (int.5),
4. Speed endurance, lactate tolerance: distances between 25 and 50 m., swimming exercises with the use of only upper or lower limbs or in combination. (full recovery rest periods) (int.4),
5. Exercises above AT: distances between 100 - 200 m., swimming exercises with the use of only upper or lower limbs or in combination. Incomplete recovery during rest periods (int.3),
6. Aerobic endurance exercises, distances between 400 and 800 m., Incomplete recovery during rest periods (int.2),
7. Slow pace continuous swimming. (int.1),
8. Exercises directed at the improvement of swimming technique (int.2),
9. Exercises directed at teaching swimming technique (int.1),
10. Competition.

For development of a model, the quality indices were results at 25 m distance. The measurements were made under competitive conditions.

During the experiment, the following features (variables) were measured:
1. State variables: X1 - body height [cm], X2 - body mass [kg], X3 - the length of lower limbs [cm], X4 - the length of upper limbs [cm], X5 - aerobic capacity (VO\textsubscript{2max}) [l/kg*min], X6 - anaerobic power, evaluated by the Wingate test [W/kg], X7 - vital capacity [cm³], X8 - stand legs jump [cm], X9 - score in 10 m run [s], X10 - swimmer step [number of full cycles at distance of 25 m].
2. Decision variables: summary time of exercise in separate training cycles in 10 training cycles described above.
Table 1. Static characteristics of state variables of the swimmers.

<table>
<thead>
<tr>
<th>State variables</th>
<th>$\overline{x}$</th>
<th>S</th>
<th>$A_s$</th>
<th>Ku-3</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heigth [cm]</td>
<td>163.1</td>
<td>6.25</td>
<td>1.57</td>
<td>2.65</td>
<td>4.34</td>
</tr>
<tr>
<td>Body mass [kg]</td>
<td>49.68</td>
<td>6.50</td>
<td>-1.32</td>
<td>2.45</td>
<td>13.20</td>
</tr>
<tr>
<td>Length of upper limbs [cm]</td>
<td>72.98</td>
<td>3.72</td>
<td>0.52</td>
<td>2.11</td>
<td>4.54</td>
</tr>
<tr>
<td>Length of lower limbs [cm]</td>
<td>78.43</td>
<td>4.76</td>
<td>1.29</td>
<td>2.51</td>
<td>4.31</td>
</tr>
<tr>
<td>$V_{o2\text{max}}$ [L/min]</td>
<td>3.32</td>
<td>0.52</td>
<td>-1.87</td>
<td>2.21</td>
<td>16.60</td>
</tr>
<tr>
<td>Maximum power [W/kg]</td>
<td>8.99</td>
<td>1.56</td>
<td>1.11</td>
<td>2.34</td>
<td>15.10</td>
</tr>
<tr>
<td>Breathing capacity [cm³]</td>
<td>3121.5</td>
<td>254.79</td>
<td>2.09</td>
<td>-1.52</td>
<td>6.03</td>
</tr>
<tr>
<td>Stand legs jump [cm]</td>
<td>198.33</td>
<td>22.45</td>
<td>1.12</td>
<td>2.76</td>
<td>11.79</td>
</tr>
<tr>
<td>10 m run [s]</td>
<td>1.54</td>
<td>0.32</td>
<td>-1.43</td>
<td>-2.78</td>
<td>31.00</td>
</tr>
<tr>
<td>Swimmer step [number of full cycles]</td>
<td>13.78</td>
<td>2.56</td>
<td>1.12</td>
<td>2.12</td>
<td>15.20</td>
</tr>
</tbody>
</table>

$\overline{x}$ - mean,
S - standard deviation,
$A_s$ - asymmetry index,
Ku - kurtosis,
V - variability index

In accordance with the methodology of optimization tasks a mathematical model was created with a system of differentiation equations [Rygula, Wyderka 1993]. In order to apply the possibilities of optimal steering according to Pontriagin, the model was continues with the increments converted to derivatives.

The value of each state variable (physical condition, scores) at the end of certain unit of time is a function of general condition of the athlete, his scores, described by the state variables at the beginning of this unit and adapted training, that is implemented intensity of separate training means (control variables) in the analyzed unit of time. This may be written in symbolic notation:

$$X^{(l+1)} = X^{(l)} + \Delta X^{(l)}$$

where

$$\Delta X^{(l)} = \Phi(X^{(l)}, U^{(l)})$$

$l$ denotes the number of training periods, $l=0, \ldots, N-1$.

The aim of the optimization of swimmers training is to determine such a set of controls $U^{(0)}, \ldots, U^{(N-1)}$, to obtain the extreme value of certain state variable (the score, physical fitness).

$X^{(N)}$ = max (min)

In a general case determination of the $\Phi$ is not possible. Its approximation may be implemented for certain group of athletes, for which we know the measurement results of both state variables and control variables. To be able to use optimization methods and automatic the construction of a model, the $\Phi$ function should be expressed with possibly simple formula. The following formula is suggested:

$$\Phi(X,U) = aX + cU + bUX + d$$
This is a part of Taylor series for the $\Phi$ function. In the above formula, the first term at the right hand side ($aX$) may be interpreted as a description of the influence of the condition of the athlete on his scores, the second term ($cU$) - as the influence of training, and the third ($bUX$) - the influence of condition and training together.

To be able to use the methods of determination of optimum control according to Pontryagin principle, the model should be transformed into continuous model and replace finite increments in the training periods with derivatives.

For further analysis, we have assumed to have at our disposal the measurement of $n$ state variables and $m$ training means. Henceforth, the state variable vector is denoted as $X(t)=(x_1(t),...,x_n(t))^T$, vector of control variables as $U(t)=(u_1(t),...,u_m(t))^T$. The upper index $^T$ denotes transposition.

In accordance with earlier considerations, as a model of sport training has been adapted a set of differential equations of the form:

\[
\frac{dx_i}{dt} = \sum_{j=1}^{n} a_{ij}x_j + \sum_{j=1}^{m} \sum_{k=1}^{n} b_{jk}x_ju_k + \sum_{j=1}^{m} c_{ij}u_j + d_i + h_i(t, U) \quad i=1,...,n
\]

where:
- $x_i$ is the $i$-th state variable, $i=1,...,n$,
- $u_j$ is the utilization of the $j$-th training means, $j=1,...,m$,
- $u_j \in [0,1]$, 0 - none, 1 - maximum possible use of the $j$-th training means.

This equation was considered in the interval $[0,T]$, where 0 is the conventional beginning and $T$ - the end of the training period. It is also possible to use in the model the absolute values of the training means, such as the time of doing a certain exercise during the training. In this case, defining the upper and lower limit for such control is also required.

The quality of the adaptation of the model to the measured data was determined from the formula:

\[
\delta_i = \frac{H_i}{\sum_{l=1}^{N-1} \sum_{s=0}^{z} (\xi_i^l(s+1) - \xi_i^l(s))} \quad i=1,...,n
\]

$\xi_i^l(s)$ - value of $i$-th state variable for $l$-th athlete in $s$-th time unit,
- $H_i$ - partial derivatives Hamilton function.

The quantity $\delta_i$ will be henceforth called coefficient of fitting. The values of fit coefficients were very small, what suggested high precision of the model.

Due to the space limitations at this paper, the description of method of model solving and determination of its parameters have been omitted. These results may be checked by the authors.
Results

It was decided to use the first seven state variables and all control variables for the construction of the model. The smaller number of variables will facilitate the interpretation of results. The simplification of the model brings material shortening of computation, which enabled to make a greater number of different optimizations. To confirm the correctness of this approach, in maximizing the score on 25. The computations were made for the full and abridged model. The optimum controls and values for best score were almost identical.

Using the formula (2) the coefficients of fitting model to data were calculated; they form multidimensional equivalent of the relative error (ratio of difference between the exact value and approximated to the exact value). The results are shown in table below.

Table 2. The coefficients of fitting for separate equations

<table>
<thead>
<tr>
<th>Equation for variable</th>
<th>δᵢ [%]</th>
<th>Equation for variable</th>
<th>δᵢ [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>5.5</td>
<td>X5</td>
<td>4.9</td>
</tr>
<tr>
<td>X2</td>
<td>4.0</td>
<td>X6</td>
<td>1.2</td>
</tr>
<tr>
<td>X3</td>
<td>6.8</td>
<td>X7</td>
<td>4.4</td>
</tr>
<tr>
<td>X4</td>
<td>5.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The values of the coefficients of fitting are very small, which indicates a great accuracy of the model. It was therefore assumed that the model sufficiently approximates the experimental data.

After construction of the model, one athlete was chosen and his initial conditions were introduced to the model. The optimal controls was determined, for maximization of point score at the distance of 25 m. Table 3 shows the results theoretically possible to obtain in case of using the optimal training. The graphs 1,2 illustrates the course of controls for optimization of 25 m score.

Table 3. Comparison of the scores: real and calculated from the model at different optimizations for the athlete Xₑ.

<table>
<thead>
<tr>
<th>Maximum score</th>
<th>State variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>X1</td>
</tr>
<tr>
<td>25 m</td>
<td>368</td>
</tr>
<tr>
<td>Real</td>
<td>191</td>
</tr>
</tbody>
</table>

Because in the numerical calculation of the model equations, the step equal to half of the observation period was assumed, the optimal control was determined with the frequency of two weeks. The values of the separate control variables therefore define the total time of doing given exercise during two weeks.
Table 4. Steering leading to maximum point result at the distance of 25m for competitor X_E

<table>
<thead>
<tr>
<th>Week</th>
<th>Training means</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>U1</td>
<td>U2</td>
</tr>
<tr>
<td>1-2</td>
<td>25</td>
<td>135</td>
</tr>
<tr>
<td>3-4</td>
<td>10</td>
<td>98</td>
</tr>
<tr>
<td>5-6</td>
<td>25</td>
<td>45</td>
</tr>
<tr>
<td>7-8</td>
<td>25</td>
<td>45</td>
</tr>
<tr>
<td>9-10</td>
<td>25</td>
<td>45</td>
</tr>
<tr>
<td>11-12</td>
<td>25</td>
<td>45</td>
</tr>
<tr>
<td>13-14</td>
<td>60</td>
<td>135</td>
</tr>
<tr>
<td>15-16</td>
<td>60</td>
<td>135</td>
</tr>
<tr>
<td>17-18</td>
<td>60</td>
<td>135</td>
</tr>
<tr>
<td>19-20</td>
<td>60</td>
<td>135</td>
</tr>
<tr>
<td>21-22</td>
<td>60</td>
<td>135</td>
</tr>
<tr>
<td>23-24</td>
<td>60</td>
<td>135</td>
</tr>
<tr>
<td>25-26</td>
<td>60</td>
<td>135</td>
</tr>
<tr>
<td>27-28</td>
<td>60</td>
<td>135</td>
</tr>
</tbody>
</table>

Figure 1. Optimum controls of 10 training means.
Discussion

The analysis of optimal steering functions change in time. The range of variability was very high as well as the proportions between a particular steering, especially with regards to different training periods. The application of the steering models allowed for an improvement in results, yet they were smaller than those estimated by the model. Comparing the obtained results on optimal steering to those of Gordon et al. [1973] it was concluded that the development of a mathematical model is a helpful tool in non intuitive directing of the training process. This allows for the calculation of optimal strategy for athletes preparing for competition. It was concluded that mathematical models are a significant tool in planning training loads, at the same time indicating the necessity of further research that could include a higher amount of variables that in turn would increase the precision of the model [Mester, Perl 2000, Perl et al. 2002].

Carried out research also confirmed theoretical considerations performed by Banister and Calvert [1975] and the practical application of models by Calvert et al. [1976]. They invented a mathematical of sports training, which was next used to calculate training parameters aimed at improving results. The research was performed on American university swimmers, whose initial training levels were first estimated, and later individual training parameters were calculated to improve sports results. In most cases the foreseen results were comparable with those in fact achieved, however, they often differed. The authors stated that those differences were not due to simplification of the model but rather resulted from different lifestyles of examined swimmers, which was not evaluated [Calvert and others 1976, Taha, Thomas 2003].

Highly differentiated results were obtained by Mujika et al. [1996] who carried out research on highly advanced swimmers, where training loads were estimated by the use of

![Figure 2. Value of the quality coefficient (25 m score) of chosen swimmer, applying optimum controls.](image-url)
calculated models. The actual improvement of results after training periods compared to those calculated in models varied between 45% to 85%. Such big differences were attributed by the authors to not accurate described training loads and changes of parameters during the long training periods. However, they confirmed the high usefulness of applied model in the description of influence of sports training on obtained results.

In the analysis of most effective training means aimed at improving results at the distance of 25 meters, swimming technique exercises were found to play the most important role, which confirms the findings of many researchers stressing the importance of focusing on teaching swimming techniques and improving overall coordination fitness, especially at the first training stages [Bompa 2000, Colwin 2003]. It allows to draw the conclusion that the examined competitors should already be after the comprehensive training before proceeding to consecutive oriented training improving general development. The overall sports training at this stage should be directed at obtaining the best possible fitness efficiency and technique adapted to abilities of athletes. The increased amount of special exercises, including those developing technique is a stronger impulse on the developing the human body. Counsilman 1994, Maglischo 2003].

Conclusions

The empirical data and the conducted analysis allow for the following conclusions, which can have practical implications for coaches:

• The construction of a mathematical model of sport training allows to determine the effectiveness of particular training means.

• The greatest influence on speed in youth swimmers are achieved by exercising swimming techniques.

• On the basis of calculated fit coefficients, which are a multidimensional appropriate of the relative error it can be stated that the constructed model has a significant practical application.

References


CORRELATION OF NOVEL TRAINING LOAD AND PERFORMANCE METRICS IN ELITE CYCLISTS

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Abstract

The aim of this study was to develop a model which enables the accurate prediction of cycling performance using field derived training and racing data. A novel training load quantification technique (PTRIMP) was developed to overcome limitations with Training Stress Score (TSS), an existing load quantification technique popularised for cycling (Coggan, 2006). A performance quantification technique allowing performance to be calculated from power data obtained from any race / training session where the athlete makes a 100% effort was developed. Heart Rate Variability (HRV) indices were calculated from daily orthostatic tests. The fit of the model developed was good ($R^2 = 0.40$). Although additional work with a larger sample size is required, these data indicate that a correlation between training load, HRV indices and performance exists when calculated using the methods described. This data allows a model to be created which can assist an athlete in manipulating training load and fatigue levels, such that they arrive at a competition in a state from which a high performance is likely, and a low performance is unlikely. The use of field-derived model inputs makes this model a practical tool for the planning of a taper to maximise competition performance.

KEY WORDS, TRAINING LOAD, PERFORMANCE, HEART RATE VARIABILITY, MODELLING

Introduction

Athletes and coaches seek to optimise athletic performance for key competitions by maximising fitness and minimising fatigue. An understanding of the relationship between training and performance is required to achieve this. From the 1970’s onwards, numerous studies have focused on modelling physiological responses to training input using linear mathematical concepts in an attempt to better understand the training - performance relationship (Banister et. al, 1975; Banister, Carter, & Zarkadas, 1999; Busso, 2003; Busso, Carasso, & Lacour, 1991).

These “Banister” derived models, require frequent performance testing to enable estimation of model parameters. Such frequent testing, however, is generally not feasible due to the pressures of competition, travel and training placed on elite cyclists.

A technique to simulate the interaction between training load and performance using a state – event model with adaptive delays has been developed (referred to as the PerPot model) by Perl (2001). Pfeiffer and Schrot (2009) obtained an excellent model fit for performance using a PerPot model. As with the linear mathematical models, however,
this type of model requires frequent performance testing to enable estimation of parameters. Other nonlinear methods to model training response relationships have encountered practical limitations. Neural networks can model training and performance effectively (Hohmann, Edelmann-Nusses, and Hennerberg 2001) but similar to other artificial intelligence techniques require large volumes of data in order to converge on an accurate model.

A limited volume of data is inevitable in this domain. Training data accumulate with one data point per day, per athlete. Performances occur at most every week. Hellard et al. (2006) suggests that greater than 60 observations would be required for estimation of a four parameter Banister model.

We propose using multiple linear regression to create a model for the relationship between training and performance. It is suggested that realistic number of observations (20) would be required for such a model (Soper, 2009). This type of model also makes it possible to take into account possible interactions between input variables (Sen & Shrivastava, 1990).

In order to model training load and performance techniques to quantify these variables must be utilised. There has been great difficulty in finding a way to quantify training load effectively using a single term (Foster et al., 2001). Banister (1991) proposed quantifying training load using a unit of training termed a TRIMP (TRaining IMPulse). A TRIMP is derived from multiplying the duration of training by the relative training intensity (measured by heart rate). A multiplying factor is applied in order to weight higher heart rate (HR) ratios proportionally higher. Heart rate is affected by many factors, which impacts its validity and reliability as a measure of load (Skiba, 2008) particularly at very high exercise intensities (Foster et al., 2001).

Power - which in cycling is the amount of energy transferred to the pedals (in watts) per second - is a direct reflection of exercise intensity (Jeukendrup, 2002). Power is recorded commonly at frequencies of 1Hz, producing a large amount of raw data. Some sort of transformation of the raw data is required before it can be used as the basis for load quantification. Training Stress Score (TSS) is one load quantification method which uses power output (Coggan, 2003, 2006).

The relationship between exercise intensity and physiological load is curvilinear (McArdle, Katch & Katch, 2006). We argue that, along with TRIMPS, TSS places too much emphasis on the duration of a session, while not weighting high intensity training enough. The load quantification technique we have named PTRIMP was developed to accurately reflect the curvilinear relationship between exercise intensity and physiological load.

Tracking training load is one method of estimating fatigue levels of an athlete. Generally, previous models have used training load as the sole input to the model (e.g. Banister et. al, 1975; Busso, 2003; Ganter, 2006; Thomas, Majika & Busso, 2008). Training load does not provide the complete picture, however, as other factors such as sleep will affect the fatigue levels of an athlete. HRV has been proposed as a tool for monitoring training-related fatigue in athletes (Earnest et. al., 2004; Atlaoui et al., 2007).

Heart rate (HR) is not constant – rather it fluctuates from beat to beat. HRV refers to the variation of the beat-to-beat interval, measured as the time between beats. Electrocardiographs (ECGs) and some types of heart rate monitors are capable of measuring the time points in milliseconds between beats.
HRV is a function of the synergistic action between the two branches of the autonomic nervous system (the parasympathetic nervous system (PNS) and the sympathetic nervous system (SNS)), which act in balance to maintain cardiovascular variables in an optimal range during changing external or internal conditions (Earnest et al., 2004). Activity in the SNS elevates heart rate while the PNS has the opposite effect (Atlaoui et al., 2007). Measuring the beat-to-beat interval during an orthostatic test is a reliable method of assessing HRV in athletes (Wisbey & Montgomery n.d.).

Fatigue alters the balance between the PNS and SNS. Theoretically, the autonomic imbalances observed in fatigued or overtrained athletes should be discernable from HRV indices, and there is some evidence to suggest this is the case (Baumert et al., 2006; Earnest et al., 2004). We propose that adding HRV indices of fatigue, which reflect other stressors such as illness and lack of sleep, will increase the fit of the model. The final input needed to build up the model we propose is performance – and a technique for quantifying performance is required. Numerous studies (Thomas, Majika & Busso, 2008; Majika et al., 1996; Avalos et al., 2005) have used a method where performances are converted into a percentage of personal best performances. A similar approach in cycling would require the athlete to complete a regular performance test. As discussed, this is generally not practical.

An athlete’s best performances are likely to occur during an actual competition where training induced fatigue was minimised by tapering prior to the event. Ignoring this data eliminates a particularly important component of the training – performance relationship. One study which quantified performance from actual competition data was done by Millet et al. (2002), who used a subjective rating technique to measure performance in triathlon competitions. The validity of this method is questioned by Taha and Thomas (2003), however, due to its subjective nature.

A technique which enables performance data to be collected from training and racing data greatly increases the volume of usable data available to a researcher. We propose such a technique, which identifies the shape of an athlete’s Maximal Mean Power (MMP) curve of personal bests over a range of durations; and compares the area under the curve to that of the MMP curve from a performance.

The aims of the present study were to use a novel training load quantification method (PTRIMP) and HRV indices (Recovery Index or RI) as predictors in a multiple regression model to predict cycling performance using field derived training and racing data.

**Methods**

A professional female cyclist provided data for the study over a 250 day period. This period included the European racing season, as well as a break from training over the Christmas period, and subsequent early season training.

**Training Load**

An SRM power monitor (professional model, SRM, Julich, Welldorf, Germany) was fitted to the subject’s road and time trial bikes over the data collection period. Power data from all rides (training and racing) was captured at 1Hz. In accordance with operator instructions, the SRM was zeroed prior to the start of each session. Data was imported into MATLAB 2007b (Mathworks Inc., Boston, MA, USA) for the calculation of PTRIMP.

The following steps were taken to calculate PTRIMP. The power data was first smoothed by taking 3 rolling averages, of durations of 5s, 30s, and 4mins. Each of the smoothed points was then given a weight, which is calculated by determining the percentage the point represents of the athlete’s Maximal Mean Power (MMP) for that duration. The percentage is then multiplied by an exponential formula (refer to equation (1)).
The weight of each point, for each of the 3 smoothed datasets is then added together to determine PTRIMP (refer to equation (2)).

\[ \text{PTRIMP}(s) = \sum_{i=1}^{n-1} p_i \times c. \]  

(1)

where \( c \) = exponential curve based on MMP.

\[ \text{PTRIMP} = \frac{\text{PTRIMP}(5s) + \text{PTRIMP}(30s) + \text{PTRIMP}(240s)}{1000}. \]  

(2)

A record of MMPs for 5s, 30s, and 4mins achieved by the athlete was kept, and updated when a new personal best was achieved. TSS was calculated using MATLAB, according to the method presented by Coggan (n.d).

Quantifying Performance

The athlete kept a training diary where a subjective rating of the percentage of effort expended for each session was recorded. This was used to identify races and training sessions where a 100% effort (‘I gave everything I had’) was made.

The durations for which MMP were recorded were at regular intervals from 5s to 20min. These durations are chosen to represent a spectrum of energy system contributions. For durations of up to approximately 10 seconds, energy is predominantly supplied by the anaerobic alactic system. From around 10 seconds to approximately 60 seconds, energy is predominantly supplied by the anaerobic lactic system. Beyond this, the contribution of the aerobic energy system increasingly becomes the major contributor (Gore et al, 2000; 45). The range in durations thus theoretically balanced out the effects of different types of races.

A curve was created from the MMPs for time durations from 5s to 20min for the power file from which performance is to be measured. The area under the curve was then compared to that of the athlete’s maximum MMP profile at the time of the performance (Figure 1). The definite integral was calculated using the trapezium rule.

Orthostatic Test

The subject completed an orthostatic test each morning upon first arising (Wisbey & Montgomery, n.d). Wearing a Polar CS600 heart rate monitor (Polar Electro Oy), set to
record R-R intervals, the subject lay down in a quiet place for 3 minutes. Recording started after the HR settled. At the three minute mark, the subject raised themselves into a standing position, and recording continued for a further 2 minutes. The HR data was then downloaded, and transmitted for analysis.

**HRV Analysis**

Custom-built software (HRV Athlete, FitSense Australia) was used to analyse the HR file. The software uses a fast Fourier transform and a power spectral density analysis to decompose the signal into its sinusoidal components, allowing plotting of the power of each component as a function of its frequency. Power is broken down into two frequency bands – low frequency (LF) and high frequency (HF) (Wisbey & Montgomery, n.d). Parasympathetic activity is considered responsible for HF, and both parasympathetic and sympathetic outflows are considered to determine LF (Aubert et al, 2003). The LF/HF ratio thus gives an indication of the status of the autonomic nervous system on that morning. The LF/HF data is smoothed, and then standardised using a z-score to give a RI for that day.

**Data Pre-processing**

PTRIMP data was smoothed over 3, 7, 14 and 30 days using a rolling average. Missing values for PTRIMP and RI (caused by equipment failure etc.) were interpolated. A linear interpolation was used for RI. Missing PTRIMP values were interpolated by using HR data captured on the same day. A HR TRIMP was calculated using the equation:

\[
TRIMP = T (\text{min}) \times \frac{HR_{ex}}{HR_{max}}
\]

where \(T\) = time in minutes, \(HR_{ex}\) = average HR for the session and \(HR_{max}\) = the athlete’s maximum HR. Z-scores were then calculated for HR TRIMP values. The following equation was then solved for PTRIMP:

\[
t = \frac{PTRIMP - \mu}{\sigma}
\]

where \(t\) = HR TRIMP z-score, \(\mu\) = mean of PTRIMP sample and \(\sigma\) = SD of PTRIMP sample.

Scatterplots indicated that the relationship between PTRIMP smoothed over 3 days (PTRIMP(3)) and performance is non-linear (U-shaped). The data was transformed using the natural log of Performance to improve the linear relationship. A constant was added to Performance so that all values were positive prior to transformation. As performance is measured in arbitrary values (a.u), it was judged no information was lost in this process.

The dataset contained outliers. Trials showed that one outlier with very poor performance was artificially inflating the fit of the model. This worst performance was capped at -155000(a.u).

Successive data points were treated as independent, as in most cases the performance measurements are separated in time.

**Modelling**

Mean and standard deviation (SD) were calculated for all variables. For log transformed data the mean is back-transformed (\(e^{\text{mean}}\)) and SD is presented as a coefficient of variation (100(\(e^{\text{SD}}\) - 1)). The Shapiro-Wilk normality test was performed to verify the normality of the distribution. Pearson’s product-moment correlation coefficient was used to determine the association between variables. The Breusch-Pagan test was used to test for heteroskedasticity of residuals. A Durbin-Watson test was used to test for autocorrelation in the residuals.

Correlation analysis was performed to give an initial indication of whether PTRIMP data smoothed over 3, 7, 14 or 30 days was likely to have the strongest influence on
performance. From this analysis, PTRIMP(3) and RI were selected as the variables showing the highest correlation with performance. PTRIMP(3) and RI were not significantly correlated.

A multiple linear regression model was created using linear least squares to minimise the residual sum of squares. The adjusted coefficient of determination ($R^2$) was calculated. A process of data exploration was followed to find the best model. The outcome of this process was the inclusion of interaction terms between RI and PTRIMP(3) and a quadratic term for PTRIMP(3) increased the fit of the model.

A K-Means cluster analysis was performed on the performance data to derive three clusters (interpreted as low, moderate and high performance).

Models were fitted using the R Statistical Package Version 2.6.1 (The R Development Core) and the package Rcmdr (version 1.3-15).

**Results**

Table 1 outlines the general characteristics of the data. The test for normality indicated that PTRIMP(3) and RI were not normally distributed ($W = 0.884$, $P = 0.0084$ and $W = 0.8946$, $P = 0.014$ respectively). As these values are near-normal however, for the purposes of this study a transformation was not applied.

<table>
<thead>
<tr>
<th>Performance(log)</th>
<th>PTRIMP(3)</th>
<th>RI</th>
</tr>
</thead>
<tbody>
<tr>
<td>99681.96± 46.26</td>
<td>13.75 ± 7.58</td>
<td>75.76 ± 25.53</td>
</tr>
</tbody>
</table>

Table 1. Characteristics of PTRIMP(3) and RI for records paired with a performance. $N = 25$. All parameters are recorded in arbitrary units (a.u)

The model providing the best fit included a term for interaction between PTRIMP3 and RI (Performance $\sim$ PTRIMP(3) + PTRIMP(3)$^2$ * RI) (Adjusted $R^2 = 0.40$, $P = 0.006$).

PTRIMP and TSS are highly correlated over the entire dataset of rides collected ($N = 163$). The correlation was 0.98, and 95% confidence intervals were 0.98 to 0.99.

**Discussion**

The results indicate that PTRIMP(3) and RI can be used as variables in a multiple regression model to predict performance ranges. The model obtained explained 40% of the variation in the performance measured. Statistics of the goodness of the fit obtained in modelling training and performance in the literature are quite variable, but help to establish a comparison for the fit obtained by this model. Ranges between 45% - 85% and 67% - 68% for model explained variances in performance have been reported for Banister type models (Mujika et al, 1996; Busso et al., 1997). One study reported a fit for the PerPot model as between 13% and 92% (Ganter, Witte and Edelmann-Nusser, 2006). These models require large numbers of performances in order to estimate model parameters (Hellard, et al, 2006; Ganter, Witte and Edelmann-Nusser, 2006), however, limiting their practicality.

Limited work has investigated the relationship between training and performance outside of the laboratory setting. Performance testing in the laboratory attempts to control for as many performance impacting factors as possible. Factors such as nutrition, hydration, temperature, and pacing strategies have not been controlled for in this research using real-world performances. As such, the fit of this model using real world performances is not expected to be as good as those reported for studies using performances measured by frequent laboratory testing. The aim of this study, however, is to use field-derived data to develop a model which can be used as a practical tool by athletes and coaches.

The significant explanatory power of the model suggests that the methodology used to calculate performance has potential for allowing modelling in the real world. The non-
linear relationship between PTRIMP and RI (Figure 2) indicates that for peak performance, an athlete should be fresh, but not too fresh. This is in accordance with common tapering strategies.

Although the fit of the present model is not sufficient to enable prediction of absolute levels of performance, the analysis of predicted performance against actual performance (organised into clusters of low, moderate and high performance) shows that the model is able to predict the optimum range where a peak performance is likely. It also identifies the levels of PTRIMP and RI where a low performance is likely (Figure 3). The fit of the model was improved significantly by adding RI as an explanatory variable. HRV indices capture more information about an athlete’s state of fatigue than training load alone. HRV is affected by other factors such as sleep, life stress and illness (Fletcher, 2007; Wisbey & Montgomery, n.d.).

Two findings of this study were not in accordance with the literature. We found that PTRIMP smoothed with rolling average over 3 days showed the highest correlation with performance. The values for the time course of fatigue parameter (an input into the Banister model) have been reported as 15 days (Morton et al., 1990) and 12.4 days (Mujika et al., 1996). Coggan (n.d) suggests using a time constant of 7 days to model the time course of training induced fatigue. The findings in the present study suggests a shorter time frame for the time course of fatigue than has been generally reported in the literature.

Banister (1991) proposed that the relationship between training and performance could be conceptualised by the formula Performance = Fitness – Fatigue. A variant of this concept was tested for significance in the model, by introducing a variable obtained by subtracting PTRIMP(7) (representing fatigue) from PTRIMP(30) (representing fitness). The resultant fit was poor.

These findings appear to be interrelated. The correlation between performance and training load decreased as the number of days PTRIMP was averaged over increased. We speculate that this is related to the algorithm used for quantifying performance. Performance was calculated relative to the athlete’s best performance at that time. As the athlete became fitter, the level required to achieve a ‘good’ performance also rose, thus decreasing the impact of ‘fitness’ (dependent on long term training) and increasing the impact of ‘fatigue’ (induced by short term training).

It is suggested that further work be conducted in a number of areas. The hypothesis that the algorithm used to quantify performance reduced the impact of long term training on the model can be tested by constructing another model. By adjusting the performance algorithm to be relative to the best performance achieved by the athlete over the entire course of the study, the correlation between long term training and performance can be examined.

It is important to note that the relationship between training and performance is expected to change over time. This variation was not captured in the present model. Use of this data in a time varying model (PerPot for example) may provide a better fit.

PTRIMP is highly correlated with TSS. Further analysis needs to be completed to determine if PTRIMP provides any advantage over TSS in achieving a more physiologically accurate relationship between the relative weighting of duration and intensity.
Conclusion

This paper describes a model which enables the prediction of performance from an athlete’s training and HRV indices. The model provides athletes with target ranges for training load and fatigue levels to increase the likelihood of a high performance. This research is an initial case study, and additional work with a larger sample size is required. It is suggested that a dynamic system model created using these data may increase the explanatory power of the model. The use of field-derived model inputs makes this model a practical tool for the planning of a taper to maximise competition performance.
Acknowledgements

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MODELING, SIMULATION, AND VALIDATION OF CYCLING TIME TRIALS ON REAL TRACKS

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Abstract

We develop methods for data acquisition, analysis, modeling and visualization of performance parameters in endurance sports with emphasis on competitive cycling. For this purpose, we designed a simulator to facilitate the measurement of training parameters in a laboratory environment, to familiarize cyclists with unknown tracks, and to develop models for training control and performance prediction. The simulation includes real height profiles and a video playback that is synchronized with the cyclist’s current virtual position on the track and online visualization of various course and performance parameters. We compared our field data with a the state-of-the art mathematical model for road cycling power, established by Martin et al in 1998, which accounts for the gradient force, air resistance, rolling resistance, frictional losses in wheel bearings, and inertia. We found that the model is able to describe the performance parameters accurately. In both cases the correlation coefficients were between 0.87–0.95 with signal-to-noise ratios of 18–19 dB. We showed that the mathematical model can be implemented on an ergometer for simulating rides on real courses. Comparing field and simulator measurements we obtained correlation coefficients between 0.66–0.81 with signal-to-noise ratios of 13–16 dB. The major challenge remains to determine the model parameters more precisely. Additionally, high quality GPS data would improve the results.

Keywords: road cycling, performance parameters, mathematical model, simulation, model validation, height profiles.
Introduction

Computer science in sports is an emerging interdisciplinary field, which has evolved in the last 20 to 30 years focusing on the following areas of research: data acquisition, processing and analysis, modeling and simulation, data bases and expert systems, multimedia and presentation, and IT networks/communication. Recording devices for a host of physical and physiological parameters have become available both to the professional athlete as well as to hobby and amateur sportsmen. These parameters are used for monitoring and measuring sports activities in the lab, during training and even in competitions. However, after the data has become available, it still remains difficult to efficiently extract the relevant information. In our work we contribute to the research aimed at the entire cycle of data acquisition, filtering, analysis, visualization, modeling, and prediction of such complex data. We selected endurance sports as a particularly suitable application since it allows for long-term data series that are expected to be more homogeneous, and that depend to a lesser degree on chance events than, e.g., in game sports. Currently our work focuses on road cycling, that may later be extended to include, e.g., running and rowing.

For road cycling we develop methods for data acquisition, analysis, modeling and visualization of performance parameters. We designed a simulator to facilitate the measurement of training parameters in a laboratory environment in addition to measuring performance parameters in the field [10]. Several mathematical models have been introduced to model road cycling performance, e.g., [4, 7, 8, 9]. These models were derived from the equilibrium of energy demands and supplies. The state-of-the-art mathematical model for road cycling power, established by Martin et al in 1998 [7], accounts for the gradient force, air resistance, rolling resistance, frictional losses in wheel bearings and inertia. The models were used to predict time trial performance [9] and required power output during cycling [7]. Mathematical performance models were also used to derive optimal pacing strategies in variable synthetic terrain and wind conditions [1, 2, 5, 6].

This paper focusses on a comparison of performance parameters in the field, on our lab simulator, and in the mathematical model. Previously, validations of mathematical models for cycling performance were performed by comparing predictions of the models to measurements on a flat course. For this study we chose two uphill tracks with varying steepness. Specifically, the cyclist’s climbing progress on real outdoor rides on these tracks together with measurements of a power meter is compared to predictions of the mathematical model for these tracks.

Another contribution of this paper is the comparison between performance parameters measured by the simulator and calculated by the mathematical model. The main purpose of this task is to provide a means to evaluate the extent to which a lab ergometer ride can accurately simulate an outdoor ride on real-world tracks. Such simulations may then be used by athletes to prepare for competitions on unknown courses.

In the following subsection we outline the mathematical model for cycling power that we used for our comparison with field and lab tests. In the section Methods we discuss the cycling courses, the equipment, the test setup, the data preprocessing, and the means of comparison of measurements and model prediction. The following three sections include the results, their discussion, and conclusions.
The mathematical model

Beginning in the 1980s, mathematical models have been developed to describe the relation between pedaling power and velocity with cycling time trials. Although these models comprise a multitude of physical phenomena, their accuracy could not be determined before the SRM Training system [11] became available commercially in 1994. Then, in 1998 Martin et al summarized the significant components to form a mathematical model for road cycling power and successfully validated it, [7]. They compared outdoor measurements of the SRM system on a flat road with different constant velocities to power predictions derived from the model, which accounted for over 97% of the variation of cycling power.

The model is based on Newtonian mechanics, as an equilibrium of resistance power and pedaling power $P_{\text{ped}}$ provided by the cyclist to propel his bicycle. The resistance power is composed of power due to gain in potential energy $P_{\text{pot}}$, aerodynamic drag $P_{\text{air}}$, frictional losses in wheel bearings $P_{\text{bear}}$, rolling friction $P_{\text{roll}}$, and gain in kinetic energy $P_{\text{kin}}$,

$$P_{\text{pot}} + P_{\text{air}} + P_{\text{bear}} + P_{\text{roll}} + P_{\text{kin}} = \eta P_{\text{ped}} . \quad (1)$$

The efficiency factor $\eta < 1$ accounts for frictional loss in the drive chain.

Dividing this equation by the angular velocity of the wheels yields the corresponding equilibrium of torques where we have to consider the lever principle using the transmission ratio $\gamma = \frac{n_{\text{front}}}{n_{\text{rear}}}$, i.e., the ratio of the number of teeth on the front sprocket to the number of teeth on the rear sprocket:

$$T_{\text{pot}} + T_{\text{air}} + T_{\text{bear}} + T_{\text{roll}} + T_{\text{kin}} = \frac{\eta}{\gamma} T_{\text{ped}} . \quad (2)$$

The pedal torque is equal to the product of the pedal force and the length of the crank: $T_{\text{ped}} = F_{\text{ped}}l_c$. Moreover, we divide Equation (2) by the radius of the wheels, $r_w$, in order to obtain the decomposition of resistance forces on the left hand side, (3). These forces act at the contact area between the rear wheel and the road.

$$F_{\text{pot}} + F_{\text{air}} + F_{\text{bear}} + F_{\text{roll}} + F_{\text{kin}} = \frac{\eta}{\gamma} \frac{l_c}{r_w} F_{\text{ped}} . \quad (3)$$

Eventually, we substitute the specific mechanical models into each component:

$$mg \sin(\arctan(s(x))) + \frac{1}{2} \frac{c_d \rho A \dot{x}^2}{F_{\text{air}}} + (\beta_0 + \beta_1 \dot{x}) + \mu mg + \left( m + \frac{I_w}{r_w^2} \right) \ddot{x} = \frac{\eta}{\gamma} \frac{l_c}{r_w} F_{\text{ped}} . \quad (4)$$

Here, $x = x(t)$ is the distance traveled as a function of time $t$, $\dot{x} = v(t)$ is the velocity, and $\ddot{x} = \ddot{v}(t)$ is the acceleration. The other physical parameters are listed in Table 1. For our purposes, we neglect ambient wind and aerodynamic drag by rotation of spokes.

Thus, the sought relation can be rewritten as a nonlinear differential equation of the form

$$\gamma \frac{r_w}{l_c} f(x(t), \dot{x}(t), \ddot{x}(t)) = \eta F_{\text{ped}}(t) , \quad (5)$$
<table>
<thead>
<tr>
<th>Cyclist/bicycle/simulator</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>mass cyclist $m_c$</td>
<td>Tab. 3</td>
</tr>
<tr>
<td>mass bicycle $m_b$</td>
<td>10.6 kg</td>
</tr>
<tr>
<td>total mass $m$</td>
<td>$m_b + m_c$</td>
</tr>
<tr>
<td>simulator inertia $I'$</td>
<td>0.543 kgm$^2$</td>
</tr>
<tr>
<td>wheel circumference $c_w$</td>
<td>2100 mm</td>
</tr>
<tr>
<td>wheel radius $r_w$</td>
<td>$(2\pi)^{-1} c_w$</td>
</tr>
<tr>
<td>wheel inertia $I_w$</td>
<td>0.14 kgm$^2$</td>
</tr>
<tr>
<td>cross-sectional area $A$</td>
<td>0.4 m$^2$</td>
</tr>
<tr>
<td>length of crank $l_c$</td>
<td>175 mm</td>
</tr>
<tr>
<td>bearing coefficient $\beta_0$</td>
<td>0.091 N</td>
</tr>
<tr>
<td>bearing coefficient $\beta_1$</td>
<td>0.0087 Ns/m</td>
</tr>
<tr>
<td>mechanical gear ratio, bicycle $\gamma$</td>
<td>39/26, ..., 53/12</td>
</tr>
<tr>
<td>fixed gear ratio, simulator $\gamma'$</td>
<td>53/13</td>
</tr>
<tr>
<td>simulated gear ratio $\gamma_{sim}'$</td>
<td>39/26, ..., 53/12</td>
</tr>
</tbody>
</table>

Table 1: Physical parameters of the mathematical model. These parameters originate from our own measurements or were taken from the literature as follows: $m_c, m_b$ weighted with scales; $l_c, I'$ manufacturer information; $c_w, L, s(x)$ measured using GPS functionality of Garmin Edge 705 device; $I_w, \beta_0, \beta_1, \eta$ from [7]; $c_d, A$ average value from [12], $\mu$ standard value from Cyclus2 for asphalt road.

respectively,

$$f(x(t), \dot{x}(t), \ddot{x}(t)) \cdot \dot{x}(t) = \eta P_{ped}(t),$$

where the discounted pedaling force $\eta F_{ped}(t)$, respectively the discounted pedaling power $\eta P_{ped}(t)$, occurs as the driving term for the covered distance $x(t)$, as the independent variable, and $f(x, \dot{x}, \ddot{x})$ denotes the left hand side of Equation (4).

With the mathematical model on hand we used it in two ways.

1. Given the distance measurements $x(t)$ for the duration of a ride, we computed the corresponding pedaling forces $F_{ped}(t)$, respectively pedaling power $P_{ped}$, by evaluating $f(x(t), \dot{x}(t), \ddot{x}(t))$ in Equation (5). These values were then compared with the actual power measurements provided by the SRM.

2. Given measured or prescribed pedaling power $P_{ped}(t)$ for the duration of a ride, we solved Equation (6) for $x(t)$ numerically (using MATLAB’s ode45 function). The derived values for the velocity $v(t) = \dot{x}(t)$ were then compared with the actual velocity measurements provided by the SRM.

For the model with the simulator, we agree on using primed quantities in the following. Here, the cyclist pedals against the power of the eddy current brake $P'_{brake}$. 

4
the power due frictional losses in the bearings \( P'_{\text{bear}} \), to changes of kinetic energy of the flywheel \( P'_{\text{kin}} \), and frictional losses in the chain (factor \( \eta \)):

\[
P'_{\text{brake}} + P'_{\text{bear}} + P'_{\text{kin}} = \eta P'_{\text{ped}} .
\]

(7)

In analogy to Equations (2) and (3), we write the equilibrium in terms of torques

\[
T'_{\text{brake}} + T'_{\text{bear}} + T'_{\text{kin}} = \frac{\eta}{\gamma'} T'_{\text{ped}} ,
\]

(8)

and in terms of forces

\[
F'_{\text{brake}} + F'_{\text{bear}} + F'_{\text{kin}} = \frac{\eta}{\gamma'} l_c F'_{\text{ped}} .
\]

(9)

Again, we can plug in the specific mechanical models:

\[
F'_{\text{brake}} + (\beta_0 + \beta_1 x) + \frac{I'}{r_w^2} \dot{x} = \frac{\eta}{\gamma'} l_c F'_{\text{ped}} .
\]

(10)

Here, we assume that the frictional losses, represented by \( \beta_0 \) and \( \beta_1 \), are the same as with the bicycle. In fact, their contribution is so small that we could neglect them. The moment of inertia of the ergometer’s flywheel \( I' \) corresponds to a combined inertial mass of cyclist and bicycle of \( m'_i = \frac{I'}{r_w} \approx 4.86 \text{ kg} \), which is – as with most ergometers – by far too low.

The ergometer enables us to impose an arbitrary brake torque \( T'_{\text{brake}} \) with our own control software. In order to simulate real courses, we use the physical models to compute a simulated brake torque \( T'_{\text{sim,brake}} \) as the sum of simulated torques due to gain in potential energy \( T'_{\text{sim,pot}} \), aerodynamic drag \( T'_{\text{sim,air}} \), and rolling resistance \( T'_{\text{sim,roll}} \). Furthermore, we want to simulate arbitrary gears without any mechanical changes. Therefore, we introduce a factor \( \gamma'_{\text{sim}} \) that represents virtual gears and incorporate it together with the simulated brake torque into the controlled brake torque \( T'_{\text{brake}} \) of the ergometer. The mechanical gear ratio remains fixed (\( \gamma' = \frac{53}{13} \)) at all times.

\[
T'_{\text{brake}} = \gamma'_{\text{sim}} T'_{\text{sim,brake}} = \gamma'_{\text{sim}} \left( T'_{\text{sim,pot}} + T'_{\text{sim,air}} + T'_{\text{sim,roll}} \right) .
\]

(11)

However, we want to enforce that the power that is absorbed by the brake matches the simulated power for gain in potential energy, aerodynamic drag and rolling resistance.

\[
P'_{\text{brake}} = P'_{\text{sim,pot}} + P'_{\text{sim,air}} + P'_{\text{sim,roll}} .
\]

(12)

Therefore, we recalculate the angular velocity in the simulation \( \omega'_{\text{sim}} \) which then differs from the angular velocity of the ergometer’s flywheel \( \omega' \):

\[
\omega'_{\text{sim}} = \frac{P'_{\text{brake}}}{T'_{\text{brake}}} = \frac{\gamma'_{\text{sim}}}{\gamma'} \omega' .
\]

(13)

This clearly affects the simulated torques due to kinetic energy \( T'_{\text{sim,kin}} \) and frictional losses in the wheel bearing \( T'_{\text{sim,bear}} \) in Equation (8). These aspects will be
subject of a future publication. In the following experiments and computations they play only a minor role. With constant velocity, power due to changes in kinetic energy vanishes and in all other model computations for the simulator we accounted for these effects using Newtonian mechanics. Frictional losses in the wheel bearings are much smaller than all other components, so we can expect a negligible error if we assume that they are the same for the bicycle, the ergometer and in our simulation.

Methods

Courses

We selected two uphill courses of about 3 km length, with an ascent of about 250 m each and varying steepness, namely the Schiener Berg and Ottenberg, located near Radolphzell, Germany, and Weinfelden, Switzerland, respectively. See Table 2 and Figures 1–3 for details and picture overviews of the courses. The tracks were recorded by a video camera simultaneously together with the corresponding altitude and GPS tracks with a sampling rate of 1 per second. This allowed us to geo-reference each individual video frame. From this alignment we calculated for each frame the distance traveled from the starting point of the course, the altitude above sea level, and the road gradient. Likewise, for an arbitrary position on the track with a given distance from the starting point one may calculate a corresponding (fractional) video frame number for display in the simulation setting [10].

<table>
<thead>
<tr>
<th></th>
<th>Schiener Berg</th>
<th>Ottenberg</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance</td>
<td>3630 m</td>
<td>2820 m</td>
</tr>
<tr>
<td>Start height</td>
<td>429 m</td>
<td>441 m</td>
</tr>
<tr>
<td>End height</td>
<td>674 m</td>
<td>664 m</td>
</tr>
<tr>
<td>Average gradient</td>
<td>6.7%</td>
<td>7.9%</td>
</tr>
<tr>
<td>Maximum gradient</td>
<td>9.7%</td>
<td>13.5%</td>
</tr>
<tr>
<td>Standard deviation of gradient</td>
<td>1.7%</td>
<td>2.5%</td>
</tr>
</tbody>
</table>

Table 2: Two courses, called Schiener Berg and Ottenberg were chosen for the tests.

Equipment

The riders used the same standard road race bicycle (Radon RPS 9.0 with a 60 cm frame), both in the field and on the simulator. The bicycle has a 10-speed cassette (13–19 and 21, 23, 26 teeth) and is equipped with an SRM power meter with four strain gauge strips (Schoberer Rad Messtechnik, Jülich, Germany) attached to the chain wheel (53, 39 teeth). Such devices for measuring power are considered state-of-the-art and have been validated in [7]. In our studies, the SRM measurements for distance travelled, velocity, and power were recorded and used. In addition, other parameters (heart rate, pedaling frequency) were also recorded but not used here.

Our simulator is based on a Cyclus2 ergometer (RBM Elektronik-Automation GmbH, Leipzig, Germany). It allows to mount the user’s personal bicycle and has a flexible front axle attachment, thus, providing a realistic cycling experience, also when riding out of the saddle. The ergometer is governed by an eddy current brake.
Figure 1: Gradient versus distance of the courses Schiener Berg (left) and Ottenberg (right). The gradient is smoothed with a Gaussian filter ($\sigma = 30$ m).

Figure 2: 3D view of the courses: Schiener Berg (left), Ottenberg (right).

Figure 3: Screenshot of simulation program window. Scene from the Schiener Berg course.
which can be directly controlled by an external PC-based software at a 2 Hz rate. In the so-called slave mode we can have the ergometer simulated an appropriate braking action. Our system makes use of this control in order to fully implement the effects of the actual real-world gradient induced forces, and forces due to aerial drag, and rolling resistance. Inertial forces and frictional losses in the wheel bearings are accounted for by the erometer mechanics.

In addition we implemented an option that lets the system set virtual gears exactly as given by the 20-speed road bicycle even though the ergometer is designed to accommodate the mechanical gears like those that come with the user’s bicycle. These “soft gears” were necessary because the ergometer is not capable to generate large braking forces at low (simulated) velocities, i.e., in low mechanical gears and with a low back wheel angular velocity, as it would be realistic at the very steep sections of the courses. Instead, a (constant) higher mechanical gear is used throughout leading to a high angular velocity requiring a prescribed lower than the real brake force.

The simulation includes a video playback that is synchronized with the cyclist’s current position on the track and online visualization of various course and performance parameters, namely the time since the start of the ride, the distance travelled, the current velocity, road gradient, pedaling frequency, heart rate, gear ratio, power output, and average power output. Moreover, the height profile for the whole course and a plot of the gradient near the current position of the rider is shown. This visual feedback was displayed during the simulated rides in the lab using an LCD projection unit onto a screen of size of about 1 m². See Figure 3. The details of our simulation system have been presented at [3] and will be published elsewhere. As for the outdoor rides the same parameters were recorded using the mounted SRM chain wheel. Moreover, the Cyclus 2 also provided the measurements of the same parameters.

Field and simulation tests

The two selected courses were ridden by several riders of differing age, weight and training level, including hobby, amateur and competitive cyclists. Each ride was performed on the real course as well as with the simulator in the lab. Since the objective of the experiments was to compare the model predictions for power respectively for velocity with the performance on the road and in the lab, the riders were instructed to try to maintain either a prescribed constant velocity or constant power for each run.

<table>
<thead>
<tr>
<th>Age (yrs.)</th>
<th>Weight (kg)</th>
<th>Sex</th>
<th>Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>24</td>
<td>78.6</td>
<td>male</td>
</tr>
<tr>
<td>B</td>
<td>29</td>
<td>73.8</td>
<td>male</td>
</tr>
<tr>
<td>C</td>
<td>27</td>
<td>91.0</td>
<td>male</td>
</tr>
<tr>
<td>D</td>
<td>55</td>
<td>73.2</td>
<td>male</td>
</tr>
<tr>
<td>E</td>
<td>31</td>
<td>60.5</td>
<td>male</td>
</tr>
</tbody>
</table>

Table 3: Cyclists in the study.
Data preprocessing of outdoor measurements

In order to compare the measured power or velocity during an uphill ride with the corresponding model prediction we needed for each such data the corresponding road gradient, which was taken from height profiles generated separately. The height profiles were measured with a GPS device mounted on a bicycle (a Garmin Edge 705) slowly pushing the bicycle up the hills. The elevation measurement were noisy and, thus, filtered by a Gauss Filter with $\sigma = 30$ m. Finally, each elevation was associated with the corresponding measured distance from the defined starting point of the ride.

To look up the road gradient for a given point of an actual ride one has to take the distance traveled from the start, look up the corresponding altitudes in the preprocessed height profiles and estimate a gradient. There are two practical problems to carry out this task.

- The distances measured on the rides by the SRM differed slightly from those in the height profiles. There are several reasons for that. The riders did not ride along the exact same path on the road, and, moreover, the distances measured for the height profile had been obtained with a device partly based on (noisy) GPS data while on the actual rides only wheel revolutions were automatically counted and multiplied by the wheel circumference to obtain the traveled distance.

- The points for the start and end of the tracks were difficult to locate in the measurement log files because they cannot be exactly marked by the riders when passing them.

To solve both problems jointly, we propose to scale and translate the height profile to match the measured distances. We did this manually with a computer program as follows. Two parameters, namely the start and end position in the log data, had to be searched for. We identified them by the best match of the measured power curves with the corresponding predicted power curve of the mathematical model, which was obtained by visual comparison together with computed correlation coefficients. This worked for both types of rides, i.e., with constant velocity and with constant power. In the second case we could compare the measured velocity with the velocity that the model predicts using the measured power. This semi-automatic procedure provided good results. We thus refrained from an automated correlation analysis to determine optimal start and end positions.

Comparison of measurements with model prediction

As result of the preprocessing of the data measured in the field we achieved time series of vectors with the components: time $t$, distance $x(t)$, velocity $\dot{x}(t)$, power $P_{\text{ped}}(t)$, and gradient $s(x(t))$. For evaluating the rides with constant velocity, these values (except $P_{\text{ped}}(t)$), inserted in the left side of the model equation (6), yield the predicted power for comparison with the measured power. In the Results section below we provide corresponding graphs and give correlation coefficients and signal-to-noise ratios (SNR). The latter are defined as

\[
\text{SNR} = 10 \log_{10} \frac{\text{MSP}_{\text{ped}}}{\text{MSE}} \text{dB} \quad (14)
\]
where MSP and MSE denote the mean square power amplitude and the mean square error between the prediction and the actual power, respectively, measured in decibel. From the SNR we compute the percentage $p$ of the variation of the data that is accounted for by the model as follows,

$$
p = 100 \left( 1 - \frac{\text{MSE}}{\text{MSP}_{\text{ped}}} \right) \%.
$$

For evaluating the rides with approximately constant power we simply reversed the roles of velocity and power in the above and define the SNR and percentage $p$ accordingly.

For the analysis for the data obtained with the simulator we proceeded similarly. Since the measured velocity and power data was automatically linked to the used height profiles no preprocessing to align gradients to the measurements was required. The modified model equation (9) was used in place of Equation (3) as the basis of the computations.

**Comparison of simulated rides with outdoor rides**

Let us consider a comparison of the field rides with constant velocity with corresponding simulations in the lab. Two steps are required as a preprocessing.

1. Since distances in the field and in the simulations are not exactly identical as discussed further above, we scaled the distances in the field to match those used in the simulator. Care had to be taken so that the velocities are modified accordingly.

2. For comparison of power output the velocities in the field and in the simulator should be identical, but naturally they differed. We propose to use the model to estimate the power output assuming the preset constant velocities, e.g., $v^* = 10$ km/h.

The compensation for variable velocity proceeds as follows. At each point in time the model for the field resp. the simulator predicts a pedaling power $P_{\text{ped}}^m = P_{\text{ped}}^m(x(t), \dot{x}(t), \ddot{x}(t))$. For constant prescribed velocity $v^*$, however, the model would predict at that same location of the course a value of $P_{\text{ped}}^* = P_{\text{ped}}^m(x(t), v^*, 0)$. Then we can compensate the measured power for the mismatch of the velocity simply by multiplying with the factor $P_{\text{ped}}^*/P_{\text{ped}}^m$. The compensation must be applied to the measured data from both the field and the simulation. We call the resulting time series the *normalized* power sequences. For rides with attempted constant power we proceeded likewise, normalizing the velocity to exactly constant power. The resulting normalized power resp. velocity was then compared using the same methods as described in the last subsection.

**Results**

To gain a view of the contributions of the components of the overall work required to perform a ride on one of the courses we calculated the average powers, $\overline{P}_\epsilon$, and the
corresponding fractions that account for gain in potential energy $\bar{P}_{pot}$, aerodynamic drag $\bar{P}_{air}$, frictional losses in wheel bearings $\bar{P}_{bear}$, rolling friction $\bar{P}_{roll}$, and gain in kinetic energy $\bar{P}_{kin}$. For our lightest rider (rider E) at the highest approximately constant velocity ($v^* = 17 \text{ km/h}$) on the Schiener Berg the average power was 253.8 W, which was distributed as given in Table 4. The total work was 54.2 Wh. It is clear that the fraction due to overcoming the potential energy $\bar{P}_{pot}$ is dominant while the others are small or even neglectable ($\bar{P}_{bear}$). The average power due to changes of kinetic energy vanishes perfectly. For other (heavier) riders and for lower velocity the fraction for overcoming potential energy on this course was even higher.

<table>
<thead>
<tr>
<th>Power</th>
<th>Average power</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{P}_{pot}$</td>
<td>222.3 W</td>
<td>87.6%</td>
</tr>
<tr>
<td>$\bar{P}_{air}$</td>
<td>17.7 W</td>
<td>7.0%</td>
</tr>
<tr>
<td>$\bar{P}_{bear}$</td>
<td>0.6 W</td>
<td>0.2%</td>
</tr>
<tr>
<td>$\bar{P}_{roll}$</td>
<td>13.2 W</td>
<td>5.2%</td>
</tr>
<tr>
<td>$\bar{P}_{kin}$</td>
<td>0.0 W</td>
<td>0.0%</td>
</tr>
<tr>
<td>total</td>
<td>253.8 W</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Table 4: Distribution of power for a ride up Schiener Berg (3.63 km, 245 m altitude) at $17 \text{ km/h}$ requiring a total time of 12 min 49 s and a total energy of 52.4 Wh.

In order to present the main results we chose four bicycle rides that are representative and cover different subjects, courses and pacing strategies out of the 17 that were obtained both outdoors on a real course and indoors on the simulator using the same course and pacing. Three of these selected rides were performed with approximately constant velocity $v^*$ and power was computed using the model. For the fourth one, having approximately constant power $P^*$, the velocity was computed. In each case we plotted the computed quantity against the measurement data. Figures 4, 5, and 6 show field measurements and model prediction, simulator measurements and model prediction, and normalized field and simulator measurements, respectively. The Tables 5–7 characterize the deviations of the model predictions from the measurements by giving the correlation coefficient $\rho$, the mean error $m_e$, the standard deviation of the error $\sigma_e$, the SNR as defined in (14), and the percentage $p$ as defined in (15).

**Discussion**

We organize the discussion in three parts: the comparison of the model predictions with the measurements in the field, with those in the lab, and the comparison of the performance in the field with that in the lab.

**Comparison of measurements in the field with model predictions**

The results in Figure 4 and Table 5 show that the mathematical model describes the dynamics of power output on an uphill course with good precision. The signal-to-noise ratio was 18–19 dB, which means that 98 to 99% of the variation of the
Figure 4: Field rides versus model predictions. The solid line in each plot gives the power resp. velocity prediction of the model. The prediction errors are analyzed in Table 5.
Figure 5: Simulated rides versus model. The solid line in each plot gives the power resp. velocity prediction of the model. The prediction errors are analyzed in Table 6.
Figure 6: Field versus simulator rides (for normalized measurements). The differences between real-world and simulator rides are analyzed in Table 7.
Table 5: Comparison of measured power resp. velocity versus model prediction. In Tables 5–7: $\rho$ is the correlation coefficient, $\sigma_e$ is the standard deviation of the prediction error, SNR is the signal-to-noise ratio, and $p$ the percentage of variation explained by the model. In this table the mean error $m_e$ is the predicted average power resp. velocity minus the average measured power resp. velocity. Note that in the first three lines power is compared, while in the last line velocity is compared.

<table>
<thead>
<tr>
<th>Biker</th>
<th>Condition</th>
<th>Course</th>
<th>$\rho$</th>
<th>$m_e$</th>
<th>$\sigma_e$</th>
<th>SNR</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$v^* = 10\text{ km/h}$</td>
<td>Schienen Berg</td>
<td>0.87</td>
<td>-9.3 W</td>
<td>24.2 W</td>
<td>18.0 dB</td>
<td>98.8%</td>
</tr>
<tr>
<td>E</td>
<td>$v^* = 17\text{ km/h}$</td>
<td>Schienen Berg</td>
<td>0.88</td>
<td>-10.9 W</td>
<td>28.9 W</td>
<td>19.3 dB</td>
<td>98.8%</td>
</tr>
<tr>
<td>B</td>
<td>$v^* = 10\text{ km/h}$</td>
<td>Ottenberg</td>
<td>0.92</td>
<td>-14.0 W</td>
<td>17.9 W</td>
<td>18.2 dB</td>
<td>98.4%</td>
</tr>
<tr>
<td>D</td>
<td>$P^* = 250\text{ W}$</td>
<td>Ottenberg</td>
<td>0.95</td>
<td>0.23 km/h</td>
<td>0.28 km/h</td>
<td>19.2 dB</td>
<td>98.5%</td>
</tr>
</tbody>
</table>

Table 6: Comparison of the measured power resp. velocity in the simulation with the model predictions. The mean error $m_e$ is the predicted average power resp. velocity minus the average measured power resp. velocity.

<table>
<thead>
<tr>
<th>Biker</th>
<th>Condition</th>
<th>Course</th>
<th>$\rho$</th>
<th>$m_e$</th>
<th>$\sigma_e$</th>
<th>SNR</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$v^* = 10\text{ km/h}$</td>
<td>Schienen Berg</td>
<td>0.90</td>
<td>-8.4 W</td>
<td>18.7 W</td>
<td>19.7 dB</td>
<td>98.9%</td>
</tr>
<tr>
<td>E</td>
<td>$v^* = 17\text{ km/h}$</td>
<td>Schienen Berg</td>
<td>0.93</td>
<td>-4.2 W</td>
<td>22.0 W</td>
<td>21.7 dB</td>
<td>99.3%</td>
</tr>
<tr>
<td>B</td>
<td>$v^* = 10\text{ km/h}$</td>
<td>Ottenberg</td>
<td>0.88</td>
<td>-5.2 W</td>
<td>29.0 W</td>
<td>17.7 dB</td>
<td>98.3%</td>
</tr>
<tr>
<td>D</td>
<td>$P^* = 250\text{ W}$</td>
<td>Ottenberg</td>
<td>0.80</td>
<td>-0.005 km/h</td>
<td>0.52 km/h</td>
<td>16.7 dB</td>
<td>97.9%</td>
</tr>
</tbody>
</table>

Table 7: Comparison of the measured power resp. velocity in the simulation with those measured in the field. Mean error is the average measured power resp. velocity in the field minus that on the simulator. The mean error $m_e$ is the average power resp. velocity in the field minus the average measured power resp. velocity with the simulator.

<table>
<thead>
<tr>
<th>Biker</th>
<th>Condition</th>
<th>Course</th>
<th>$\rho$</th>
<th>$m_e$</th>
<th>$\sigma_e$</th>
<th>SNR</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$v^* = 10\text{ km/h}$</td>
<td>Schienen Berg</td>
<td>0.70</td>
<td>8.4 W</td>
<td>39.1 W</td>
<td>14.3 dB</td>
<td>96.3%</td>
</tr>
<tr>
<td>E</td>
<td>$v^* = 17\text{ km/h}$</td>
<td>Schienen Berg</td>
<td>0.66</td>
<td>19.2 W</td>
<td>58.6 W</td>
<td>13.6 dB</td>
<td>95.6%</td>
</tr>
<tr>
<td>B</td>
<td>$v^* = 10\text{ km/h}$</td>
<td>Ottenberg</td>
<td>0.78</td>
<td>7.4 W</td>
<td>40.0 W</td>
<td>14.7 dB</td>
<td>96.6%</td>
</tr>
<tr>
<td>D</td>
<td>$P^* = 250\text{ W}$</td>
<td>Ottenberg</td>
<td>0.81</td>
<td>-0.02 km/h</td>
<td>0.52 km/h</td>
<td>15.6 dB</td>
<td>97.2%</td>
</tr>
</tbody>
</table>

measured power over the course was accounted for by the model. This finding is even better than the 97% reported in the previous study [7] of Martin et al. We think that this may be due to fact that in the previous study the model was evaluated only for the constant prescribed velocity (on a flat course) while in our study we evaluated the model equations for all of the time steps, thus, also accounting for variations in velocity.

Even though overall the agreement between measurements and model was good there were two types of notable deviations. The first one concerned minima and maxima of power output. At these peaks the model prescribed more moderate values, i.e., the measurements exceeded the prediction. This defect can be attributed to the way the road gradients were computed, namely by Gaussian filtering of a sequence of noisy GPS elevation measurements ($\sigma = 30 \text{ m}$) followed by finite difference approximation of the slope. The filtering – required to eliminate spurious gradient peaks – also smoothed the natural peaks of the road gradient. This lead to
the observed smaller model predictions of power at real gradient maxima and larger predictions at minima.

The other notable deviation of the measurements from the model predictions was the large mean error of the predictions, negative for power predictions, and positive for velocity predictions. We believe that this defect may be due to several factors: the physical model parameters may not be sufficiently precise. Some were taken from the literature and should be adapted for our bicycle, the courses, and the riders. Others were measured with errors. Moreover, the model may be incomplete, e.g., we ignored wind effects.

Comparison of simulator measurements with model predictions

As above for field measurements we have that also the measurements of power and velocity on the simulator agreed well with the mathematical model predictions with a signal-to-noise-ratio ranging from about 17 to 22 dB, see Figure 5 and Table 6. As before, we clearly note differences near peaks and a significant negative mean error of predicted power output. However, in contrast to the above the causes for these artifacts should be explained differently. This is because we cannot blame insufficiencies of the mathematical model for imprecise model predictions since it is the model itself which was implemented in the simulator.

Firstly, unlike above, here we note that the predicted power peaks were more pronounced than the measured ones and not the other way around. We believe that this artifact is due to an insufficiency of the eddy current brake of the ergometer to rapidly react to changing demand in order to produce the required highly variable braking power.

Secondly, the mean error was smaller in magnitude than the error for power predictions in the field, but not equal to zero as expected. This led us to the conjecture of a systematic positive bias in the power as given by the simulator. In order to test this hypothesis, we compared the power measurements of the Cyclus 2 ergometer with those obtained by the SRM system by mounting our bicycle equipped with the SRM system on the ergometer. For example with rider B on the Ottenberg with \( v^* = 10 \text{ km/h} \) we obtained a mean power of 195.2 W as measured by the simulator, which was on average 6.5 W larger than that simultaneously measured by the SRM (standard deviation was 10.7 W). This clearly confirms our conjecture, as, in fact, the outcome should have been reverse, because the power measured by the SRM at the chain wheel should be larger than that applied to the rear wheel accounting for the losses in the chain and drive system of the bicycle corresponding to the chain efficiency factor \( \eta = 0.975 \), see Table 1.

Comparison of simulated rides with outdoor rides

Overall, the performance parameters in the simulations were very similar to those in the field, with a deviation of still 13–15 dB in SNR. See the curves in Figure 6 and Table 7. However, since the SRM power measurements in the field had stronger peaks than the modeled power, which in turn had stronger peaks than the power measurements of the simulator, peaks of field and simulator power measurements
differed more strongly. Thus, the variation in power on the simulator was less pronounced than in the field.

Conclusions and future work

In this study we confirmed that a mathematical model for performance parameters in road cycling is capable of accurately predicting required power output also on uphill courses with variable road gradients given the location and velocity along with physical, mechanical, and geographical parameters. Alternatively, the model can accurately predict velocity of the cyclist given the power applied at the chain wheel.

We showed that the mathematical model can be implemented on an ergometer for simulated rides on real courses. To a good extent but with certain restrictions the simulation was accurate in modeling the performance parameters on the real courses.

Our study has some limitations; it incorporated (also steep) slopes, but not high velocities, which would test for accuracy of the model regarding higher order terms of the velocity. It did not consider hilly terrain including downhill sections. Furthermore, our results were limited by the accuracy of the required gradients of the courses, which were obtained from noisy GPS elevation data, and by the quality of the other physical and physiological parameters of the mathematical model such as, e.g., the cross-sectional area of a rider.

We conclude the paper with suggested future work. To obtain more accurate road gradients we will consider better estimation methods from noisy elevation data such as Kalman filtering. Also the quality of the elevation data can be improved by more accurate measurements using differential GPS or, beginning in 2010, by the new European satellite navigation system Galileo. Alternatively, commercially available airborne laser scanned elevation data may be used.

To derive improved parameters for the mathematical model we will consider an indirect method. Based on measurements of location, power, and velocity during longer rides over variable terrain we propose to fit the parameters of a generalized model to that data. As a result, we will obtain parameters that act, e.g., as factors for the linear and quadratic terms in the model rather than a complete list of physical parameters. Moreover, in this way we may be able to improve the model by incorporating higher order terms that are not accounted for in the current model.

To improve the operation of our simulator we may redesign its computer control such that the power given by the mathematical model as required at the chain wheel must actually be provided by the rider. This may be achieved by a training procedure to be developed using a feedback loop that includes the SRM measurements at the chain wheel as a control mechanism.

Future work includes measuring also wind direction and velocity both on ground and on the bicycle, simulator rides on terrain with mild hills, so that the downhill parts do not violate the simulator design, i.e., the simulator must still generate a braking force (due to air drag).

We also strive to use the model to find the optimum pacing strategy as Maronski, 1994 [6], Gordon, 2005 [5], and Atkinson, 2007 [2], recently discussed for simple hy-
pothetic height profiles. Together with an extension of physiological measurements and their modeling the whole system shall indicate and train effective tactics using sophisticated biofeedback visualization and enable cyclists to optimally prepare themselves even for unfamiliar tracks.

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References


Classification Of Changes In Speed And Inclination During Running

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³adidas innovation team, adidas AG, Portland OR, USA

Abstract

This paper presents methods for classifying speed and inclination changes during recreational runs using sensor data from the “adidas_1” shoe. Running speed, altitude and shoe heel compression were recorded continuously while athletes ran freely outdoors. 84 one-hour-runs were collected in order to have sufficient ground truth as well as sensor data for classification.

The data was analyzed using features computed for each step of the athlete to distinguish three speed and three surface inclination classes, respectively. The speed and inclination classes were established using the collected ground truth data. While surface inclination classification was only possible with an accuracy of 67.2% due to measurement restrictions, we could show that speed classification is feasible with up to 89.2% accuracy.

This classification system can be used to support sportsmen, for example by adapting their equipment to the specific running speed.

KEY WORDS, EMBEDDED CLASSIFICATION, ADIDAS_1, INCLINATION CLASSIFICATION, SPEED CLASSIFICATION, DIGITAL SPORTS

Introduction

Smart sensors embedded in clothes and equipment for sports afford novel opportunities to support and guide athletes. A prominent example is the “adidas_1” running shoe, which is the first shoe that features an embedded system (see Figure 1). This shoe is built to adapt to various running conditions like the prevailing surface situation, the runner’s fatigue state and speed by changing the cushioning of the sole. A precise classification of the mentioned conditions is mandatory for the adaptation, which is conducted by a motor driven cable system inside the shoe. To facilitate the classification, the heel compression signal of the runner is continually measured and processed by the embedded microcontroller. A description of the “adidas_1”, its functionality and embedded system hardware can be found below and in more detail in [1].

In this paper, we consider the important task of classifying the current surface inclination and running speed of a runner. Based on the heel strike compression signal, we designed a set of 88 features that are suited ideally for the task at hand. They have proven to represent the information that is present in the original signal reliably [4].
Even more importantly, they are computationally inexpensive and can be calculated using the embedded microcontroller of the “adidas_1”. We will then show how we apply pattern recognition techniques to identify a subset of our features that are most important for classifying the current surface inclination and running speed of sportsmen during free outdoor runs. Athletes can benefit a lot from that information. In the particular case of running with the “adidas_1”, the shoe can be adapted accordingly, setting itself to an ideal cushioning state. However, the “adidas_1” shoe is just one example of smart sensors embedded in clothes. Similar actions could be taken in other endurance sports, where it is equally important to actively support an athlete by adapting the equipment to the prevailing situation. Our methods are general in nature, and can be used for a lot of similar problems.

This paper is organized as follows. We will first give an overview of the collected data in Section 2 in order to motivate which methods we used. Those will be described in Section 3 before we show our analysis results in Section 4. We will then conclude the paper in Section 5.

**Data Collection**

A total of 84 runners (30 female, 54 male) participated in the one-hour outdoor data collection. The age of the subjects was 32.9 ± 7.9 years (average, standard deviation). The subjects were not chosen specifically according to running experience; instead, the group contained runners of all activity levels. The measurement system consisted of three separate devices. Firstly, we used a “Polar RS800 Running Computer” [7], which included an “S3 stride sensor” and chest strap. This system is capable of measuring running speed, stride frequency and barometric height. We set the sampling interval for the collected signals to 5 s.

We measured continuously the heel compression signal f[t] of the runners using the “adidas_1” shoe also. Figure 1 shows the measurement principle. A hall sensor mounted at the top of the cushioning element detects the magnetic field strength induced by a small magnet. The sensor was sampled with a rate \( f_s \) of 342Hz. The sensor-magnet distance \( d_m \) can then be computed from the field strength with an accuracy of ±0.1mm. See Figure 3 for a depiction of the sensor output signal.

![Figure 1. The “adidas_1” shoe, its cushioning element, magnet and motor unit.](image-url)

We used a specially programmed mobile phone [3] to store the GPS position of the runner in 1 s intervals. After completion of the run, each participant was asked to fill in a
questionnaire. Only two out of the 84 runners perceived a notable impediment by the equipment while running. An example run is visualized in Figure 2 using the Google Earth software. In this illustration, running speed is displayed as the height of the band along the running track. The software that we used to generate this figure is available for download from http://www5.informatik.uni-erlangen.de/research/areas/digital-sports-and-sportronics.

Figure 2. Visualization of an example run.

Data Processing Methods

Out of the 84 study participants, 28 had to be excluded from further processing for various reasons. More specifically, five runners had incomplete data from the Polar RS800 system, the remaining 23 participants had to be excluded because of unusable data from the “adidas_1” shoe. In eight of these cases, data collection was not possible because the “adidas_1” was not present in all shoe sizes at the beginning of the study, and therefore the runners had to use other shoe models. In the remaining 15 cases, the runners were mid- or forefoot strikers. The measurement system of the “adidas_1” is located at the heel of the shoe and can therefore only capture significant data for rearfoot strikers which account for more than 80% of the population [5]. To circumvent further problems with data collection, we made sure that the Polar devices were working properly before the run. We did not want to ask runners specifically whether they are fore- or midfoot strikers before the run to prevent a change in running style. Following this procedure, we had to cope with data loss for these runners. However, no additional bias was introduced thereby.
**Step Identification**

Prior to feature extraction, we had to separate the single steps by finding the deflection of the compression phase. We used a linear filter with the convolution vector

\[ v_{\text{con}} = (-1, -1, -1, -1, -1, -1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1) \]  \hspace{1cm} (1)

It yields high values for step events and avoids misdetecting noise as compression. The beginnings of each compression phase are defining the boundaries of a stride \( t_{s,i} \) and \( t_{e,i} \), where \( s \) and \( e \) indicate the start and the end of stride \( i \), respectively. Within these boundaries we were able to find easily the point of maximum compression \( t_{m,i} \) and the end of the compression phase \( t_{c,i} \), which we defined as the first sample value after maximum compression that is greater than the mean value before the actual compression phase minus two.

**Feature Extraction**

Once the single steps were established, we calculated hand-selected features that are listed in Table 1 and are furthermore displayed in Figure 3. To add context information we also calculated the means \( \mu_N \) and standard deviations \( \sigma_N \) for \( N = \{4, 8, 16\} \) steps, as well as the gradients of all features using \( N = 16 \) steps. For standard deviation calculation we used the unbiased version given in Equation 2, where \( c_m \) denotes a single calculated feature value and \( \bar{c} \) is the mean value of the regarded feature values.

\[ \sigma_N = \left( \frac{1}{N-1} \sum_{m=1}^{N} (c_m - \bar{c}) \right)^{\frac{1}{2}} \]  \hspace{1cm} (2)

Consequently, we have a total of \( N_f = 88 \) features, which are denoted by \( F_1 \ldots F_{88} \). For feature extraction, the first five minutes of each run were not considered to ensure that the runners were warmed up and accustomed to data collection.

Table 1. Definitions of the main features.

<table>
<thead>
<tr>
<th>( F_1 )</th>
<th>Inter step time</th>
<th>( t_{s,i+1} - t_{s,i} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( F_2 )</td>
<td>Time to peak</td>
<td>( t_{m,i} - t_{s,i} )</td>
</tr>
<tr>
<td>( F_3 )</td>
<td>Maximum compression</td>
<td>( f[t_{m,i}] ) (Func. value at ( t_{m,i} ))</td>
</tr>
<tr>
<td>( F_4 )</td>
<td>Compression time</td>
<td>( t_{c,i} - t_{s,i} )</td>
</tr>
<tr>
<td>( F_5 )</td>
<td>Mean compression</td>
<td>( 1/F_{f,i} \sum_{m=t_{s,i}}^{t_{c,i}} f[m] )</td>
</tr>
<tr>
<td>( F_6 )</td>
<td>Step energy</td>
<td>( \sum_{m=t_{s,i}}^{t_{c,i}} f[m] )</td>
</tr>
<tr>
<td>( F_7 )</td>
<td>Step mass center</td>
<td>( 1/F_{6,i} \sum_{m=t_{s,i}}^{t_{c,i}} (m - t_{s,i}) f[m] )</td>
</tr>
<tr>
<td>( F_8 )</td>
<td>Relation ( F_4 / F_1 )</td>
<td>( F_4 / F_1 )</td>
</tr>
<tr>
<td>( F_9 )</td>
<td>Relation ( F_2 / F_4 )</td>
<td>( F_2 / F_4 )</td>
</tr>
<tr>
<td>( F_{10} )</td>
<td>Compression gradient</td>
<td>( (f[t_{m,i}] - f[t_{s,i}]) / F_{2,i} )</td>
</tr>
<tr>
<td>( F_{11} )</td>
<td>Decompression gradient</td>
<td>( (f[t_{c,i}] - f[t_{m,i}]) / (t_{c,i} - t_{m,i}) )</td>
</tr>
</tbody>
</table>
After consulting sports experts, we define three classes according to running speed $v$ and surface inclination, respectively. See Table 2 for the speed classes $\omega_{k,v}$ and Table 3 for the inclination classes $\omega_{k,\alpha}$ where $k = 1 \ldots 3$ indicates the class number. Each detected step was labeled according to these classes using the measured speed and elevation signals for the subsequent experiments.

Table 2. Definition of the three classes according to running speed $v$.

<table>
<thead>
<tr>
<th>Class $\omega_{k,v}$</th>
<th>Class Definition in m/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\omega_{1,v}$</td>
<td>$0 \leq v &lt; 2.5$</td>
</tr>
<tr>
<td>$\omega_{2,v}$</td>
<td>$2.5 \leq v &lt; 3.6$</td>
</tr>
<tr>
<td>$\omega_{3,v}$</td>
<td>$3.6 \leq v$</td>
</tr>
</tbody>
</table>

Table 3. Definition of the three classes according to surface inclination $\alpha$. A negative value indicates downhill running.

<table>
<thead>
<tr>
<th>Class $\omega_{k,\alpha}$</th>
<th>Class Definition in deg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\omega_{1,\alpha}$</td>
<td>$\alpha &lt; -3^\circ$</td>
</tr>
<tr>
<td>$\omega_{2,\alpha}$</td>
<td>$-3^\circ \leq \alpha \leq 3^\circ$</td>
</tr>
<tr>
<td>$\omega_{3,\alpha}$</td>
<td>$3^\circ &lt; \alpha$</td>
</tr>
</tbody>
</table>
Analysis Methods

For the classification experiments, we compared five different classifiers in order to compare their performance on our data. More specifically, we used the

- Bayes Classifier (BC, [6])
- Polynomial Classifier (PC, [6])
- Linear Discriminant Analysis (LDA, [6])
- Support Vector Machine (SVM, [8])
- Multilayer Perceptron Classifier (MLP, [2])

for our evaluation. Details about each of these classifiers have to be omitted here but can be found in the given literature. With these classifiers, each vector of observed features \( x = (F_1 \ldots F_{88}) \) is assigned to the class \( \omega_k \) for that the discriminant function \( g_k \) of the respective classifier is maximal. In our experiments, we performed five-fold cross-validation, where in each of the iterations the classifier was trained using all but the feature vectors from one specific fold, then classifying that fold’s feature vectors according to maximum \( g_k \) and calculating the mean classification accuracy. To ensure that feature vectors were equally distributed over all classes, we randomly picked 10000 vectors from each class. This allows us to use equal priors for example for the Bayes Classifier.

Because it is impossible to implement a classifier based on the complete set of 88 features on the embedded microcontroller of the “adidas_1”, we implemented an additional feature selection algorithm. We used the dynamic programming algorithm [6]. It requires that the initial feature set is rather small, and that the scoring metric is monotone and separable. This is true for the Mahalanobis distance

\[
G_{k,l} = (\mu_k - \mu_l) \Sigma^{-1} (\mu_k - \mu_l)
\]

between two classes \( \omega_k \) and \( \omega_l \). In Equation 3, \( \mu_k \) and \( \mu_l \) denote the class means and \( \Sigma \) a common covariance matrix. In every step of the dynamic programming algorithm we add the feature that gives the most improvement for the worst class pair. The results for the inclination classification with feature selection are given in Table 4. The most important features for this task are \( \mu_{16} (F_2) \), \( \mu_{16} (F_3) \) and \( \mu_{16} (F_{11}) \). It can be seen that by using more features, better classification results can be achieved. The best accuracy is reached by calculating six features and then using the MLP classifier.

<table>
<thead>
<tr>
<th>Nr. of features used</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>BC</td>
<td>46.5</td>
<td>48.7</td>
<td>50.9</td>
<td>54.2</td>
<td>56.1</td>
<td>56.4</td>
</tr>
<tr>
<td>PC</td>
<td>42.6</td>
<td>44.2</td>
<td>46.1</td>
<td>46.2</td>
<td>45.6</td>
<td>49.2</td>
</tr>
<tr>
<td>LDA</td>
<td>42.7</td>
<td>44.1</td>
<td>46.6</td>
<td>46.7</td>
<td>45.9</td>
<td>49.6</td>
</tr>
<tr>
<td>SVM</td>
<td>42.6</td>
<td>46.2</td>
<td>48.2</td>
<td>48.8</td>
<td>47.0</td>
<td>50.7</td>
</tr>
<tr>
<td>MLP</td>
<td>49.5</td>
<td>53.9</td>
<td>59.5</td>
<td>64.7</td>
<td>65.3</td>
<td>67.2</td>
</tr>
</tbody>
</table>

However, the rates shown in Table 4 indicate that classification of inclination is not doable with high accuracy. A major problem is imposed by the fact that the quality of the signal that is measurable with the “adidas_1” is decreasing with increasing inclination (both up- and downhill). As the sensor is located in the heel part of the shoe, and even a lot of rearfoot runners tend to run more on the forefoot in case of higher inclinations. In consequence, less overall compression is sensed. This results in a worse signal to noise ratio.
When conducting the speed classification, we noticed that a runner dependent feature rescaling significantly improved our result. We therefore decided to implement a \([0, 1]\) scaling for each feature \(F_{nf}\) of a runner, where \(nf = 1 \ldots Nf\), according to

\[
\hat{F}_{nf} = \frac{F_{nf, old} - \min(F_{nf, old})}{\max(F_{nf, old}) - \min(F_{nf, old})}
\]  

This approach can be performed easily on the embedded microcontroller by keeping the current extreme values for the features selected for implementation. Those have to be updated regularly. This way the shoe adapts to the runner after some amount of time. The results for the inclination classification with feature selection are given in Table 5.

<table>
<thead>
<tr>
<th>Nr. of features used</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>BC</td>
<td>68.1</td>
<td>74.2</td>
<td>76.0</td>
<td>81.3</td>
<td>81.1</td>
<td>81.0</td>
</tr>
<tr>
<td>PC</td>
<td>59.1</td>
<td>73.3</td>
<td>73.4</td>
<td>73.3</td>
<td>73.2</td>
<td>73.1</td>
</tr>
<tr>
<td>LDA</td>
<td>67.2</td>
<td>74.0</td>
<td>74.5</td>
<td>73.2</td>
<td>73.2</td>
<td>73.1</td>
</tr>
<tr>
<td>SVM</td>
<td>67.2</td>
<td>74.6</td>
<td>75.1</td>
<td>80.8</td>
<td>80.9</td>
<td>81.3</td>
</tr>
<tr>
<td>MLP</td>
<td>68.1</td>
<td>72.3</td>
<td>75.0</td>
<td>82.8</td>
<td>85.9</td>
<td>89.2</td>
</tr>
</tbody>
</table>

The classification accuracies show a significant rise when using two features for all classification approaches. For some approaches (BC, SVM, MLP), another significant rise when using four features can be noticed. This suggests using either two or four features for the final implementation on the microcontroller. For computational reasons, we chose the two feature approach. The selected features were \(\mu_{16}(F_3)\), \(\mu_{16}(F_1)\). Because the SVM delivered the best results in the two feature case, we decided for using it in the final implementation. The confusion matrix for the SVM case is given in Table 6. It can be seen that the SVM yields nearly equally good results for all classes.

<table>
<thead>
<tr>
<th>Classified as</th>
<th>(\omega_{1,v})</th>
<th>(\omega_{2,v})</th>
<th>(\omega_{3,v})</th>
</tr>
</thead>
<tbody>
<tr>
<td>labeled (\omega_{1,v})</td>
<td>73.7</td>
<td>11.7</td>
<td>14.7</td>
</tr>
<tr>
<td>labeled (\omega_{2,v})</td>
<td>4.0</td>
<td>74.9</td>
<td>21.1</td>
</tr>
<tr>
<td>labeled (\omega_{3,v})</td>
<td>7.7</td>
<td>17.0</td>
<td>75.2</td>
</tr>
</tbody>
</table>

**Microcontroller Evaluation**

Based on the results of our analysis above, we implemented the speed classifier on the embedded microcontroller of the “adidas_1” in order to validate our results. The framework requirements for this implementation were the limited size of internal memory. This meant that our program had to be as short as possible to save ROM and that we had to economize on variables. Moreover the classification has to be done in real-time with the available computing power. Finally we were lacking a floating point unit and therefore had to work with integer operations only. We used the SVM approach with two features (\(\mu_{16}(F_3)\) and \(\mu_{16}(F_1)\)) for the implementation, because of its classifi-
cation rates and the fact that we can easily include the runner dependent normalization in the classifier’s parameters.

For the multi-class system we used a one-against-one approach, calculating the decision for every class against each other. The one who wins the most decisions is the selected class. If two classes win exactly the same number of comparisons, the selection depends on the iteration sequence. In the case of a three class problem this is equal to a decision tree, so we only have to calculate two decision functions per step. Our tests showed a concordance of over 99% with the results using the freely available libsvm library for SVM classification. Thus, we could show that our approach to do all the evaluations that require high computational effort on powerful PCs while only evaluating the final product solution on the embedded microcontroller delivers very good results.

Conclusions

This research demonstrates the application of pattern recognition methods to detect running surface inclination and speed using features from heel compression measured with the “adidas_1” running shoe. We showed that in the three-class inclination case, we can significantly improve the recognition rate by using multiple features from 49.5% in the best one-feature case to 67.2% using six features and a MLP classifier. Perfect performance was not expected due to the fact that only the heel compression is measured, and some inclinations settings require more information. However, we showed that if we have a continuously good heel compression signal as in the three-class speed classification case, we achieve quite good rates of 74.6% using only two and even 89.2% using six features. This suggests that a trained automatic system can support very precisely the athlete, for example by providing more shoe stiffness and thus more stability by the “adidas_1” running shoe when the sportsman is running faster.

Acknowledgments

The authors would like to thank the adidas innovation team ait. for the financial and technical support of this research. We are indebted to Pascal Kühner for data collection, and also thank the participants of the running study. Special thanks go to our colleagues that were proofreading this manuscript for their time and support.

References

DATA VISUALISATION IN ROWING: CONVEYING THE MESSAGE TO COACHES

Margy Galloway¹, Conny Draper¹
Australian Institute of Sport

Abstract

Information regarding boat and crew performance during training and racing in rowing is generally confined to split times and stroke rates collected by the observing coach. This paper illustrates the various methods available to acquire more comprehensive information in regard to boat and crew performance. It traces the early methods of determining boat velocity and stroke rate information through to the more comprehensive information now available using GPS, accelerometer and gyroscope data. Measuring multidimensional boat-related aspects of rowing performance during training and racing is seen as an area of opportunity to extend our knowledge of the 3D boat motion characteristics in all boat categories. However, the data presentation is vital to succinctly convey the message and meaning of the data to coaches and athletes. Various ways of utilising the average and stroke by stroke information post training and racing, and in real time will be discussed.

KEY WORDS: ROWING, BIOMECHANICS, DATA VISUALISATION, RACE STRATEGIES

Introduction

Rowing coaches are continually striving to accurately assess exactly how their crews are performing in racing and training. Information regarding rowing race performance is generally difficult to collect due to the geography of rowing training venues and regatta courses, and the number of boats requiring monitoring at any one time. The aim of this paper is to describe the various methods that have been utilised to collect and display boat performance characteristics. The goal was to develop a method of collecting as much information as possible and displaying it in the most meaningful way in the least possible time.

Methods

Split Time Method

Split times can be collected where there is suitable real-time access to the side of the rowing course. Coaches cycle the length of the course and activate their stopwatches in real time, or alternatively view the rowing through binoculars from a fixed vantage point. There are a number of stopwatches available (e.g. NK Interval 2000 Split/rate
watch, Fastime 9, Fastime 8) that allow average stroke rate (SR) to be determined manually by pressing the appropriate button at the beginning and end of three consecutive strokes. The SR data cannot be stored and must be manually transferred to paper or computer. Split times can be stored and retrieved at a later time in order to gain an overall picture of the race performance by deriving average velocity and distance per stroke (dps). Only one or two crews can be monitored by each coach with this method.

**Video–based Method**

On rowing courses where there is appropriate access to the side of the course it is possible to video the race and derive post race the split times and SRs. The accuracy of this method has previously been determined to be affected by the clarity of filming and the accuracy of the marker buoys being used to determine each split distance. Split times and SRs are normally averaged over 50m or 100m. This method has been used for many years in rowing, sprint kayaking and athletics. Video software such as Swinger (Webbsoft) can be used to capture, view the video and measure split times using the clock function, which measures to 0.02s. Segment velocities and SRs can be calculated manually, or in a spreadsheet. Proprietary software (AIS Sprint Kayaking Competition Video Analysis V6.6) has been written to semi-automate this process. The main limitation of this method is the time taken to analyse each boat post-race. Immediate feedback is not possible.

**Accelerometer, Gyroscope and GPS method**

During the past three years Australian boats were equipped with minimaxX tracking devices (Catapult Innovations) during training, and domestic and international racing. They are attached to the stern of the boat and contain three accelerometers, gyroscopes and magnetometers. Data from the minimaxX can be downloaded immediately post race. The SR and boat velocity of multiple boats can also be monitored in real time by simultaneously transmitting selected data to a receiving unit on the coach’s boat. Data transmission is used extensively in training. Data can be displayed on an Ipaq using proprietary software (MaxTrack, 2008). Velocity is calculated by integrating the forward acceleration, adjusted for drift using the GPS (1 or 5Hz) derived velocity each second. 3D boat acceleration, 3D boat orientation, which is derived from the gyroscopes, and the GPS data were collected continuously at 100Hz.

**Results**

**Data Visualisation**

Data collected by stopwatch or derived from video based data can be tabulated and displayed graphically (Figure 1). Stroke rate and distance per stroke are averaged over the smallest measured distance (e.g. 50m splits, or 100m splits) and historical information utilised to evaluate race strategies, crew strengths and weaknesses, and the efficiency of effort throughout a race. The greater the number of splits the more information can be derived.
As per the stopwatch or video derived data, the SR and velocity data derived from the minimaxX can also be graphed and displayed continuously using proprietary software (Logan V33.1) (Figure 2). Data can be exported and manipulated as text. The minimaxX also measures other features of the boat movement including 3D acceleration and 3D boat orientation (roll, pitch and yaw). Displaying any or all of this information in a timely, succinct manner has been a challenge. Rowing is a cyclical motion, and as such it is possible to display information on a stroke by stroke (sbs) basis, so long as an identifiable start and finish of each stroke is detectable. Boat acceleration is characterised by a sharp deceleration immediately after the oar is placed in the water. The minimum acceleration is used to consistently detect the start of each stroke. Data can be displayed as a series of 2D or 3D images (Figures 3 and 4) and highlights stroke consistency patterns and performance-related events during the rowing stroke. The software and reports are used to assess the boat run and crew performance in relation to boat velocity.

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Computer animation (AIS-Row VIS) is also driven by the boat movement parameters collected by the minimaxX device (Figure 4) and offers coaches a way to interactively view the continuous rowing performance and boat orientation data. In order for coaches to get an immediate snapshot of the entire race 3D time scatter plots with a defined colour scheme have been developed. They can reveal the sbs consistency of boat-related intra-stroke patterns in regards to technique, performance and race progress (Figure 5). Boat acceleration data from each stroke is displayed horizontally, with the start of the race at the bottom of the graph. The data is displayed by colour according to the scale on the right hand side. Similarly, boat velocity and SR are displayed using a band of colours selected and adjusted according to expected race velocities and SR. The sbs data is assessed in context of the overall race performance and corresponding boat velocity and SR (Draper et al, 2008, 2009).
Figure 2. Continuous display of SR (pink), forward acceleration (g) (light blue) and boat velocity (m/s) (dark blue) of a 2000m race.

Figure 3. 2D representation of the sbs forward boat acceleration.

Figure 4. Screen shot of the 3D representation of sbs boat movement and performance (AIS Row VIS computer animation software).
Conclusions

Evaluation of race performance over 200m from a spectator or coach’s point of view has notoriously been difficult and reliant on minimal split times and/or athletes’ and coaches’ subjective memory of the performance. The development of new unobtrusive devices has enabled a far more accurate and reliable method of gaining information on boat and crew performance. Simple displays of the complex and vast amount of information now collected on a routine basis during racing and training have been developed in order for coaches to obtain accurate, reliable and succinct views of performance. Long term monitoring and data basing of results will lead to improved understanding of race performance, variability between crews and boat categories and will aid in fine-tuning racing strategies.

References


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STRUCTURAL EQUATION MODELLING AND AMOS: FACTOR ANALYSIS OF TORQUE, WORK AND POWER

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ACU National, Sydney, Australia

Abstract

The software AMOS, a second generation statistical method based on structural equation modelling (SEM), can address complex problems and interactions in sport and exercise science, and especially factor analytic research relevant to measurement theory in biomechanics, exercise physiology and motor skill learning. Sixty healthy and active participants (32 males; 28 females) were involved in the study located in an exercise laboratory. AMOS was applied as a method of confirmatory factor analysis (CFA) to confirm a measurement model for torque-work and power based on isokinetic leg extension at isokinetic speeds of 60°s⁻¹ (5 reps), 180°s⁻¹ (15 reps) and 300°s⁻¹ (15 reps) using leg extension/flexion with CYBEX technology and measures of power using vertical jump concepts of height, flight time, contact time and 10m sprint acceleration. The hypothesis was that many dependent variables are only measuring a small set of underlying factors or latent constructs. The results indicated that the two factor model was partially supported using SEM goodness of fit indices, however more substantively by arguments based on construct, convergent and discriminant validity. The discussion promotes CFA-SEM as methods to understand more completely sports specific fitness tests based on multiple measurements and measurement parsimony.

KEY WORDS, FACTOR ANALYSIS, AMOS SOFTWARE, STATISTICAL MODELS, GOODNESS OF FIT

Introduction

A second generation statistical method is structural equation modelling (SEM), which is a generic multivariate analysis technique that includes specialized versions of a number of other analysis methods. These are regression models, path analysis, factor analysis, second order factor analysis, an alternative to analysis of covariance and simultaneous analysis of several groups. Software has been developed, such as LISREL and AMOS (Arbuckle, 1997; Arbuckle & Wothke, 1999; Hair et al., 2006) based on structural equation modelling that can address complex problems and interactions in sport and exercise science (Hair et al., 2006; Yamada & Nishijima, 2003; Nakano & Nishijima, 2004). It is considered a confirmatory approach in model analysis, where model development and alternative models can be analysed and tested statistically.

Factor analytic approaches are applied to understand the relationships among variables in terms of sports training and competition implications (Heazlewood, 2006; Heazlewood, 2008a; 2008b), to identify redundancy in measurement, explore relationships among variables not previously evaluated and to confirm or refute theoretical models, usually based on conceptual modelling, using statistical evidence based approaches. Within biomechanics and exercise physiology many measurements of different depen-
dent variable are often undertaken on conceptual arguments not statistical argument, which mask measurement redundancy and measurement parsimony. That is researchers are measuring the same constructs in the belief they are different constructs based on conceptual or operational definitions.

Confirmatory factor analysis using structural equation modeling as the statistical approach enables the researcher to assess how well the measured variables represent the experimental constructs. This is defined as construct validity (Hair, et al., 2006) as is the extent to which a set of measured items or variables actually reflects the theoretical latent constructs the items are designed to measure. “The key advantage is that the researcher can analytically test a conceptually grounded theory explaining how different measured items represent psychological, sociological, or business measures,” (Hair et al., 2006, p. 770). This quotation is just as relevant to the exercise and sports science disciplines of biomechanics, exercise physiology and motor skill learning. The importance of thoroughly assessing the quality of selected measures in exercise and sport science cannot be overstated as no valid conclusions or inferences can exist without valid measurement.

The purpose of this study was to build upon earlier research based on the factor structure of isokinetic, isotonic and isometric torque production in humans (Heazlewood, 1996, 1998) by including measures of power and print acceleration to confirm that these additional constructs in fact represent specific factors or constructs. The theoretical relevance of the additional constructs were examined by applying AMOS structural equation modeling (SEM) solving software to understand and evaluate the interrelationship between multiple measures of torque, work, power and sprint acceleration. This is a direct application of confirmatory factor analysis (CFA) and the advantage of this approach is that CFA and SEM provide a confirmatory test of the measurement theory.

The measurement model hypothesised the CYBEX 340 isokinetic measures of peak torque and total work were measuring almost identical constructs across the three isokinetic speeds, whereas the vertical jump measures of jump height, flight time and contact time as well as 10m sprint acceleration world measure constructs of human power production. In the model two factors or latent variables (unobserved exogenous variables) were defined. The first factor was torque-work based on the three isokinetic speeds for peak torque and total work output and the second factor as power using three measures associated with vertical jump and time for 10m acceleration sprint. In terms of measurement theory can we reduce the set of variables to a meaningful set of inferred factors, which can result in measurement parsimony, that is only measure those variables that best reflect the constructs and not many variables that in reality measure the same construct.

**Methods**
Research ethics’ approval for undertaking research for humans was sought from and approved by the ACU National Research Ethics’ Committee. A screening process was applied to include only physically fit and active participants as the participants were expected to perform all tests at maximal effort. The final sample was composed of sixty healthy, physically fit, active males (n=32; age=23.87yrs, s.d.=+/−8.00; height=181.65cm, s.d.=8.04; weight=79.62kg, s.d.=+/−10.27) and females (n=28; age=21.10yrs, s.d.=+/−6.35; height=167.82cm, s.d.=+/−4.99; weight=58.93kg, s.d.=+/−6.41) participated in the study.
The endogenous variables in the model were isokinetic peak torque (N.m) and total work output (J), vertical jump performance as measured by flight time (s), peak vertical height (m) and jump contact time (s) and 10m (s) acceleration sprint performance. Peak torque and total work output (dependent variable set), were measured on the CYBEX 340 isokinetic muscle evaluation system with HUMAC software at isokinetic speeds of 60°s⁻¹ (5 reps), 180°s⁻¹ (15 reps) and 300°s⁻¹ (15 reps) using leg extension/flexion. However, only the leg extension scores were used in the analysis. All participants were instructed to perform the tests to the best of their ability (maximal effort) Leg power using the indices of contact time, flight time and height from were assessed with Speed Light Sports Timing System using the jump mode and the participants were instructed to perform maximal effort vertical jumps. Sprint acceleration was tested by a 10m sprint time using the Speed Light Sports Timing System to the nearest 0.01s. Once again, participants were instructed to perform the sprint test with maximum effort.

The testing environment was in a laboratory environment with climate control, specifically the Exercise Science Laboratory, ACU National, Strathfield Campus, Sydney.

Statistical analysis consisted of analysis of normal distributions for each variable using SPSS version 17 software (SPSS, 2009) to tests underlining statistical assumptions; means, standard deviation, range, minimum scores, maximum scores, variance and standard error data were derived based on the polled data from male and female participants to understand the spread of performances across variables; and finally a factor analysis based on structural equation modelling utilising AMOS (analysis of moment structures) software version 17.0 (AMOS, 2009) was completed to test the measurement model with the data set. The usual model fit indices to assess the quality of the model were generated from AMOS using the maximum likelihood estimates where the maximum-likelihood method produces parameter estimates that are the most likely to have produced the observed correlation matrix if the sample is from a multivariate normal distribution and the correlations are weighted by the inverse of the uniqueness of the variable (Norusis, 1985).

**Results**

The pooled data for each variable were explored for normality using SPSS Version 17 Software graphical and tabular approaches such as histograms with normal plot, stem and leaf plots, box plots, normal Q-Q plots, detrended normal Q-Q plots, tests of skewness and kurtosis, Kolmogorov-Smirnov and Shapiro-Wilk tests to the distribution assumptions for data using factor analysis approaches.

The means and standard deviations have been displayed in table 1 based on the pooled data from both male and female participants and indicate a broad range of abilities on the different experimental tasks.
Table 1 Means and Standard Deviations of Measured Variable Based on Pooled Data from Males and Female Participants

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak Torque (N.m) 60°s⁻¹</td>
<td>149.13</td>
<td>48.45</td>
</tr>
<tr>
<td>Total Work (J) 60°s⁻¹</td>
<td>171.03</td>
<td>53.75</td>
</tr>
<tr>
<td>Peak Torque (N.m) 180°s⁻¹</td>
<td>97.02</td>
<td>32.18</td>
</tr>
<tr>
<td>Total Work (J) 180°s⁻¹</td>
<td>1397.48</td>
<td>475.32</td>
</tr>
<tr>
<td>Peak Torque (N.m) 300°s⁻¹</td>
<td>64.26</td>
<td>25.84</td>
</tr>
<tr>
<td>Total Work (J) 300°s⁻¹</td>
<td>810.72</td>
<td>376.96</td>
</tr>
<tr>
<td>10m Sprint (s)</td>
<td>1.98</td>
<td>.18</td>
</tr>
<tr>
<td>Vertical Height (m)</td>
<td>.42</td>
<td>.14</td>
</tr>
<tr>
<td>Flight Time (s)</td>
<td>.53</td>
<td>.11</td>
</tr>
<tr>
<td>Contact Time (s)</td>
<td>.29</td>
<td>.07</td>
</tr>
</tbody>
</table>

The CFA-SEM solution using the two factor measurement model indicated significant standardised coefficients of .67 to .96 for the torque work factor and .01 to .87 (absolute magnitude) for the power factor. The standardised covariation between the two derived variables was -0.49. The model is displayed in figure 1.

Figure 1 The two factor model for torque-work and power based on standardised coefficients. The variables to the right such as ep60 are the error or disturbance exogenous variables and each error term arrow links to a measured variable.

All coefficients were significant based on CR values except contact time in the model. The model fit was significant for (Chi-square=149.8, df=34, p<.01), which means a discrepancy between hypothesised model and goodness of fit. The comparative fit index
(CFI) was .792 and is usually expected to exceed .90 for a good fit between the measurement model and the data. The Tucker Lewis index (TLI) was .724 and index should approach 1 if the fit is good. However, the fit measures were lower than expected, once again indicating the fit discrepancy. The coefficient (loading) for the factor of power with contact (jump contact time) in the model is non significant. As consequence of this finding, the jump contact time variable was removed due to the poor factor loading and non-significant CR value and then model was retested. The goal is to find the most parsimonious model (fewer variables in model which have theoretical and statistical significance) and which is well-fitting as indicated by goodness of fit tests.

The new trimmed model indicated in Figure 2 shows a slight improvement in model fit (Chi-square=137, df=26, p<.01), however all the standardised coefficients in the model were now significant. For the torque work factor values were .674 to .961 and for the power factor values were .610 to .868 (absolute values). Although it is important to note that assessing the measurement model validity (Hair, et al., 2006) these factor loadings, as illustrated in figure 2, are considered reasonably good. Other fit indices can be applied as well as Chi-square to evaluate the model. Once again, goodness of fit measures as identified by CFI (.798) and TLI (.721) fit measures were lower than expected, once again indicating the fit discrepancy, although CFI did increase marginally. With this sample size and number of measured variables used in this analysis (Hair, et al., 2006) the values for CFI and TLI should exceed 0.95, as well as root mean square error of approximation (RMSEA) should be less than .08, whereas in this second analysis is was .269 and somewhat high.

Figure 2 The trimmed two factor model for torque-work and power based on standardised coefficients with the observed/endogenous variable of contact time removed.

The CFI and TLI values although not ideal were approaching values that suggest some simple factor structure. Factor loadings for the hypothesized Torque-Work factor were .674 to .961 and all except total work at 300°s⁻¹ (loading .674) were greater than .85, which is considered good. In relation to the hypothesized Power factor loadings were...
.610 to .868 (absolute values) and once again above the critical .5 loading value. In this context construct validity to a degree has been established where the measured variables actually reflect the hypothesized theoretical relationships of peak torque and total work being one factor and the performances on the jump indices and sprint acceleration as measures of power the second factor. Variance extracted for each factor indicates the 76.9% of the variance displayed by the measures of peak torque and total work across the three isokinetic speeds is common to the factor of Torque-Power and 53% is common to the factor of Power based on the latent factor structure imposed in the measurement model. These findings suggest convergent validity where the hypothesized factor structure was supported by the factor loadings or convergence of the measured variables/items on the theorized factors of Torque-Work and Power, especially when contact was trimmed from the original model.

Discriminant validity is supported where the variance extracted (VE) percentages are compared with the square of the correlation estimates, where the variance extracted percentages should significantly greater than the square of the correlation estimates. The results indicate the VE for Torque-Work factor is 79.9% and 53% for Power factor, whereas the square of the correlation estimate between factors was 24% (=.49^2 x100). This suggests that each measured variable is represents only one latent construct or factor.

Discussion
In biomechanics and exercise physiology, measurements of peak torque and total work using different isokinetic speeds, power via vertical jump power tests and sprint acceleration are undertaken routinely for general motor fitness, specific motor fitness and assessing adaptations to physical training. In these assessment situations the current research indicates that these variables are not discrete constructs or factors and researchers are testing isolated concepts, in fact they are just variants of the underlying latent constructs (factors) of isokinetic ‘Torque-Work’ ability and ‘Power’ ability. This interpretation is supported by CFA-SEM analysis, which supported construct, convergent and discriminant validity for the proposed revised theoretical model based on two latent constructs or factors as displayed in the trimmed model in Figure 2. This is the revised model where contact time as a measure of power was deleted, as the factor loading for this variable was non significant.

The implications based on the outcome of this research are that CFA-SEM can be applied to other forms of multiple variable testing in biomechanics, exercise physiology and motor skill learning to develop measurement or testing parsimony. That is reduce the dependent variable set to the essential constructs using the most indicative variable of the construct and supported by evidenced based practice.

Researchers now have the software, theoretical approaches, statistical approaches and computer functionality to evaluate more complete theories and models of measurement in exercise and sport science. For example, evaluating the interrelationships between many of dependent variables used in general motor fitness assessment, sports specific motor fitness assessment and talent identification and across many different sports to understand the more complex relationships among variables and hypothesized factors that they are measuring.

Explore in more detail how the derivation of factor scores from factor analysis, although not analysed in this research, can be applied to general motor fitness assessment, sports
specific motor fitness assessment and talent identification. This represents a more global approach to answering research questions in the areas of talent identification and performance prediction.

Conclusions
The current literature indicated that second generation multivariate statistics combined with new and revised software based on structural equation modeling is probably an under utilised strategy and resource for solving problems in exercise and sport science in biomechanics, exercise physiology and motor skill learning. The same criticism cannot be applied the exercise and sport psychology where these methods have been applied for some time.

References


AN EXAMPLE OF GAME THEORETIC ANALYSIS IN THE PHASE OF RECEPTION ATTACK IN VOLLEYBALL

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Abstract

In the phase of reception attack in volleyball, tactical conflicts between attacking formations and blocking formations appear. In order to analyze the conflicts, we have been developing software to identify equilibrium points under a zero-sum game model. In our model, we categorize the attacking formations into 9 patterns which consist of 3 moving patterns of forward players and 3 positions (right, center and left) from which the ball can be spiked. We also categorize the blocking formations into 3 formations: “spread”, “bunch” and “dedicate”. The conflicts are formulated as a zero-sum game by tabulating these formations, and analyzed by calculating the equilibrium points together with the value of the game. Using this model, we tried an application of game theoretic analysis, using the empirical data taken from an intercollegiate women’s league in 2004. We estimate the values of the game in the matches, and illustrate a possible improvement in terms of the allocation of attacking and blocking formations used in the matches from the macro-view of game theoretic analysis. This approach could hopefully provide a new standpoint of the analysis of real volleyball matches.

KEY WORDS, GAME THEORY, TACTICS, RECEPTION ATTACK, VOLLEYBALL

Introduction

Together with the recent enhancements in information technology, a variety of computer systems have been developed to analyze the performance in sporting activities. In terms of volleyball, some game analysis systems have been used for recording game data and providing statistical information to coaches and players for tactical support. For example, a well-known program, “Data Volley”, is widely used by national teams and club teams to feed back the result of the analysis to coaches and players. Another program, “Touch Volley”, (Shigenaga, Ezaki, Yamamoto, & Yamada, 2001; Shigenaga, Ezaki, Hirotsu, & Miyaji, 2004) has been developed for users to input data easily using laptop computers with a touch sensor.
On the other hand, volleyball will be a possible sport which game theory can be applied in practical analysis. Game theory is a theory of decision-making in conciliation (e.g. Davis, 1983), and this theory can be useful for formulating and solving the problem in volleyball. Game theory has been applied mainly to economic issues rather than to sports, although some applications to sports such as soccer (Sadovskii & Sadovskii, 1993) and tennis (Winston, 1993) have been used in textbooks to illustrate the concepts of game theory. In terms of academic research, Hirotsu and Wright (2006) and Hirotsu et al. (2009) applied game theory to modeling the tactical changes in formation of field players in a soccer game, and for volleyball, Yoshida, Noro, Sato and Wen (1994) applied game theory in order to identify the optimal strategy for use of the four blocking formations, conducting an experiment using intercollegiate players by repeating the attacking-blocking situation. However, until now there does not appear to have been any research published applying game theory to volleyball using real match data.

In this paper, we propose a method for analyzing tactics in volleyball using game theory. Here, we focus on the phase of reception attack, because the tactical conflicts between attacking formations and blocking formations appear in this phase. Firstly, we categorize the patterns of the attacking formations and blocking formations. For the purpose of application of game theory, we separated the attacking formations into 9 patterns of 3 moving patterns of forward players and 3 positions (right, center and left) from which the ball can be spiked. In terms of blocking formations, we separated them into 3 formations: “spread”, “bunch” and “dedicate”. Then we formulated the conflict between attack and block as a zero-sum game by tabulating these patterns and analyzed the tactics by calculating the value of the game.

In this paper, we try an application of game theoretic analysis, using the empirical data taken from an intercollegiate women’s league in 2004. We estimate the game values in the matches and illustrate a possible improvement of the allocation of tactics from this macro-view of game theoretic analysis. Although there can be a lot of subtle conflict which is too complicated to be analysed in each phase of real matches, this approach has an advantage of quantifying the confliction as a game value and we can discuss the tactics based on the empirical data.

This research will be a first step to provide a practical application of game theory to real volleyball matches. We hope that this method may help coaches or players to analyse tactics quantitatively in volleyball matches.

Methods

Modeling the confliction in the phase of reception attack

Here we describe how to model a tactical conflict in volleyball, which consists of a series of plays starting off with a service. Here, the phase of reception attack (i.e. the first attack after a serve-receive) can be considered as one tactical conflict between attacking formations and blocking formations. To model this conflict, we tried to categorize the patterns of the attacking formations and blocking formations.

We separated the attacking formations into 9 patterns which consist of 3 moving patterns of forward players and 3 positions (right, center and left) from which the ball can be spiked. Figure 1 shows the 3 moving patterns of forward players for attacking. The patterns are named using the similarly shaped Roman numeral. In terms of Pattern III shown in Figure 1(a), three forward players move without crossing toward the net for attacking. In terms of Pattern XI and IX, two of three forward players cross toward the
net for attacking as shown in Figure 1(b) and (c), respectively. By taking into account 3 positions (right, center and left) from which the ball can be spiked with the above 3 moving patterns, we separate the attacking formations into 9 patterns (\(= 3 \text{ moving patterns} \times 3 \text{ positions}\)).

![Patterns III, XI, IX](image)

Figure 1. Three moving patterns of forward players for attacking

In terms of blocking formations, we also separated them into 3 formations: “spread”, “bunch” and “dedicate” (Figure 2).

![Blockings Spread, Bunch, Dedicate](image)

Figure 2. Three blocking formations

We look at the situations which are categorized in the above patterns, and analyse the ratio of successful blocks. Regarding to the judgment of success or fail of blocks, we define the successful blocks as the case that blocking team gets the blocking point, touch the ball to help the dig or return the ball by blocking. We note that we do not include the number of the mistake of attacks or feint as the number of attacks.

Although this analysis may not reflect the real intention of tactics because we estimate the tactics by watching the players’ movement or even players can move without being aware of it, we would like to propose a way of modeling the tactical confliction in volleyball, especially a method for analysis of attacking-blocking situation in this paper. Application of this proposed method will become more practical and informative for coaches and players if the tactics or patterns considered into this macro-view of game theoretic analysis are set based on teams’ needs or aims.
The mathematical formulation

We now briefly explain how we formulated the conflicts between the attacking formations and the blocking formations in the phase of reception attack using the above patterns. Here, we formulated it as a so called (two-person) zero-sum game, in which two teams play a game and both teams cannot get any points at the same time— if one team gets a point, then the other team loses and the gain of the ratio of successful blocks of one team should be equal to the loss of the ratio of successful attacks of the other team. Actually, this situation can be formulated by tabulating those patterns which can be represented in Table 1. In this table, each entry is a ratio of successful blocks in the combination of the attacking and blocking in the phase of reception attack. Let $a_{ij}$ be the ratio, for example, $a_{IIIRS}$ be the ratio of successful blocks in the case of attacking pattern III with a spike from the right position and blocking formation “spread”. That is, we formulate this problem by defining matrix $A= (a_{ij}, i \in \{III \ R, \ III \ C, \ III \ L, \ XI \ R, \ XI \ C, \ XI \ L, \ IX \ R, \ IX \ C, \ IX \ L\}, j \in \{S,B,D\})$, following the notation in Table 1.

Table 1. Payoff matrix for the phase of the reception attack in the formulation of zero-sum game

<table>
<thead>
<tr>
<th>Attacks</th>
<th>Blocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pattern III</td>
<td></td>
</tr>
<tr>
<td>Right (R)</td>
<td>$a_{IIIRS}$</td>
</tr>
<tr>
<td>Center (C)</td>
<td>$a_{IIICS}$</td>
</tr>
<tr>
<td>Left (L)</td>
<td>$a_{IIILS}$</td>
</tr>
<tr>
<td>Pattern XI</td>
<td></td>
</tr>
<tr>
<td>Right (R)</td>
<td>$a_{XIRS}$</td>
</tr>
<tr>
<td>Center (C)</td>
<td>$a_{XICS}$</td>
</tr>
<tr>
<td>Left (L)</td>
<td>$a_{XILS}$</td>
</tr>
<tr>
<td>Pattern IX</td>
<td></td>
</tr>
<tr>
<td>Right (R)</td>
<td>$a_{IXRS}$</td>
</tr>
<tr>
<td>Center (C)</td>
<td>$a_{IXCS}$</td>
</tr>
<tr>
<td>Left (L)</td>
<td>$a_{IXLS}$</td>
</tr>
</tbody>
</table>

In a zero-sum game, each team chooses a tactic that enables the team to do the best it can. That is, if both teams play rationally, the attacking team chooses a tactic that provides the smallest ratio of successful blocks in row of the matrix. On the other hand, the blocking team will choose its tactic that provides the largest ratio of successful blocks in column of the matrix. Following this type of inference, if this matrix satisfies the condition that the largest minimum of the rows equals to the smallest maximum of these columns (i.e. $\max (\text{row minimum}) = \min (\text{column maximum})$). That is, if

$$\max \min a_{ij} = \min \max a_{ij} \quad i \in \{III \ R, III \ C, III \ L, XI \ R, XI \ C, XI \ L, IX \ R, IX \ C, IX \ L\}, j \in \{S, B, D\}$$

(1)

holds, it is said to have a saddle point and this value is called the value of the game. A saddle point can also be thought of as an equilibrium point, in the sense that even if one team were to change from this tactic, it will not increase their gain (here, the ratio of successful attacks or blocks).

If there are not any saddle points, then the game is solved as mixed strategies, in which each team selects its tactics with a probability. Let the attacking team choose tactic $i$ among $m$ tactics with a probability $p_i$ ($i=1, \ldots, m$). In the same manner, the blocking team choose tactic $j$ among $n$ tactics with a probability $p_j$ ($j=1, \ldots, n$). Here, by defining probability vector $p = (p_1, p_2, \ldots, p_m)$ and $q = (q_1, q_2, \ldots, q_n)$, let $E(\ , \ )$ be the expected payoff taken by blocking team, this is expressed by
Now in terms of the expected payoff there will be an equilibrium point. That is, \[ \min_p \max_q E(p, q) \] for the attacking team is equal to \[ \max_p \min_q E(p, q) \] for the blocking team,

\[ \max_p \min_q E(p, q) = \min_p \max_q E(p, q) \]  \hspace{1cm} (3)

holds. In this way, if mixed strategies are allowed, it can be shown that this type of zero sum game has an equilibrium point, the value of the game can be obtained. In practice, for example, by solving the following linear programming problem, the value of the game \( v \) with tactic \( i \) and probability \( p_i \) can be calculated.

\[
\begin{align*}
\min \quad & v \\
\text{subject to} \quad & a_{1j} p_1 + a_{2j} p_2 + \cdots + a_{mj} p_m \leq v \quad (j = 1, 2, \ldots, n) \\
& p_1 + p_2 + \cdots + p_m = 1 \\
& p_1, p_2, \ldots, p_m \geq 0
\end{align*}
\]

The Data

In this analysis we use the data taken from 32 matches of Division 1 of the Kanto inter-collegiate women’s league in the fall of the 2004 season. There were 8 teams in the league and we here name the teams as A, B, ..., H in order of final standings of the season. We took the data by watching recorded scenes after the matches and observed each play. We analyzed the 1830 cases of the successful service-receive i.e. the setter gets the received ball without moving his position in the phase of reception attack. We finally selected 1753 cases for this analysis by excluding the mistakes of an attack or a feint, and count the number of successful blocks with regard to the situations of attacking formations and blocking formation.

Numerical Result

Overall result

We firstly describe the explanatory statistics for this analysis. Table 2 represents the frequency and the ratio of the situations which have occurred in the 9 attacking patterns (3 moving patterns of forward players and 3 positions from which the ball can be spiked). We separate the case of the attacking teams’ setter being in backward position from the case of the setter being in forward position, and in this paper we focus on the former case i.e. attacking teams’ setter being in backward position. As shown in table 2, III and XI were used 63% and 27%, respectively, but IX was used just around 10% in total. With regard to the positions from which the ball was spiked, C is used more (41%) than L (26%) but there looks not so much difference in distribution.
Table 2. Frequency of the attacks with regard to moving patterns and positions.

<table>
<thead>
<tr>
<th></th>
<th>R</th>
<th>C</th>
<th>L</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>III</td>
<td>225 (22%)</td>
<td>246 (24%)</td>
<td>179 (17%)</td>
<td>650 (63%)</td>
</tr>
<tr>
<td>X I</td>
<td>95 (9%)</td>
<td>121 (12%)</td>
<td>62 (6%)</td>
<td>278 (27%)</td>
</tr>
<tr>
<td>I X</td>
<td>28 (3%)</td>
<td>51 (5%)</td>
<td>25 (2%)</td>
<td>104 (10%)</td>
</tr>
<tr>
<td>Total</td>
<td>348 (34%)</td>
<td>418 (41%)</td>
<td>266 (26%)</td>
<td>1032 (100%)</td>
</tr>
</tbody>
</table>

Table 3 represents the relationship between attacking patterns and blocking formations. According to this table, 99.3% of all blocking formations are categorized into the 3 blocking formations (S, B and C), and mostly into S and B.

Table 3. Relationship between attacking patterns and blocking formations.

<table>
<thead>
<tr>
<th>Frequency of Attacks</th>
<th>Frequency of Blocks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S</td>
</tr>
<tr>
<td>III,R</td>
<td>91</td>
</tr>
<tr>
<td>III,C</td>
<td>71</td>
</tr>
<tr>
<td>III,L</td>
<td>71</td>
</tr>
<tr>
<td>X I, R</td>
<td>27</td>
</tr>
<tr>
<td>X I, C</td>
<td>21</td>
</tr>
<tr>
<td>X I, L</td>
<td>11</td>
</tr>
<tr>
<td>I X, R</td>
<td>10</td>
</tr>
<tr>
<td>I X, C</td>
<td>19</td>
</tr>
<tr>
<td>I X, L</td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td>330</td>
</tr>
</tbody>
</table>

Table 4 shows the detail of Table 3 by adding the information of the success ratio of blocks. In Table 3, we exclude the combination of attacking patterns and blocking formations which occurred less than 10 times and make it as a blank in Table 4.

Table 4. Success ratio of blocks

<table>
<thead>
<tr>
<th>Attacking Pattern</th>
<th>Success ratio of blocks</th>
<th>Breakdown</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>S</td>
</tr>
<tr>
<td>III,R</td>
<td>0.418</td>
<td>0.330</td>
</tr>
<tr>
<td>III,C</td>
<td>0.290</td>
<td>0.254</td>
</tr>
<tr>
<td>III,L</td>
<td>0.386</td>
<td>0.338</td>
</tr>
<tr>
<td>X I, R</td>
<td>0.295</td>
<td>0.296</td>
</tr>
<tr>
<td>X I, C</td>
<td>0.298</td>
<td>0.429</td>
</tr>
<tr>
<td>X I, L</td>
<td>0.492</td>
<td>0.273</td>
</tr>
<tr>
<td>I X, R</td>
<td>0.464</td>
<td>0.500</td>
</tr>
<tr>
<td>I X, C</td>
<td>0.412</td>
<td>0.211</td>
</tr>
<tr>
<td>I X, L</td>
<td>0.400</td>
<td>0.500</td>
</tr>
<tr>
<td>Total</td>
<td>0.361</td>
<td>0.312</td>
</tr>
</tbody>
</table>

As shown in Table 4, pattern “III,C” was used most frequently (23.8%) and its success ratio of blocking is small (0.290). That is, the attacking is not bad because the attacking was done at the least average success ratio of blocks. However, “III,R” was also used
frequently (21.8%) although its average success ratio of blocking is quite high (0.418). So, in general the allocation of the attacking patterns seems not to be efficient.

We can obtain the value of the game based on Table 4. The smallest maximum of these rows is 0.299 and the largest minimum of these columns is 0.273. We calculated the value of the game as 0.297, which is realized by the combination of “Pattern III C” in 0.75 and “Pattern XI C in 0.25 for the attacking teams. This implies that if the attacking teams had used the tactics of “III C” in 0.75 and “III C” in 0.25 as a mixed strategy, it could have reduce the success ratio of blocks to 0.297.

**Result for each team**

In the previous section we represented overall result of the league. Now in this section we describe the result for each team separately as shown in Table 5. Note that in Table 5 each team’s data is summarized such that each team is considered as a blocking team, and other 7 teams are aggregated as an attacking team against team A. We also exclude the combination of attacking patterns and blocking formations which occurred few times and make it as a blank in Table 5.

Here, for example, team A have the minimum average success ratio of blocks 0.268 against the attacking pattern “III,C”, which was highly used 26.8%. That is, team A was frequently attacked by the patterns which has relatively low success ratio of blocks, although “III,R” of the average success ratio of blocks 0.472 was used 22.9%.

We can also obtain the value of the game based on Table 5. For example, as the smallest maximum of these rows is 0.417 and the largest minimum of these columns is 0.214. We obtained the value of the game as 0.315, which is realized by the combination of “III, C” in 0.58 and “III, L in 0.42 for the attacking teams. This implies that if the attacking teams had used the tactics of “III C” in 0.58 and “III L” in 0.42 as a mixed strategy, it could have reduced the success ratio of blocks to 0.315. We also represent the other 7 teams in Table 5 and each team can be analyzed in the same manner.

**Discussion**

**Overall evaluation of the league**

We now discuss the result of overall tendency of the plays by looking over the whole league data. As shown in Table 4, in general, “III,C” which realized small average success ratio of blocks was used most frequently by attacking teams, but “III,R” which realized high average success ratio of blocks was also used frequently. Thus, the attacking patterns seem not to be used efficiently. From the game theoretic point of view, as the value of the game is 0.297 which is smaller than the average success ratio of blocks, the attacking teams could decrease the average success ratio of blocks by changing the allocation of the attacking patterns.
Table 5. The data from the standpoint of each team’s blocking formations

<table>
<thead>
<tr>
<th>Team</th>
<th>Team A</th>
<th>Team B</th>
<th>Team C</th>
<th>Team D</th>
<th>Team E</th>
<th>Team F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Freq. of Attacks</td>
<td>125</td>
<td>107</td>
<td>110</td>
<td>108</td>
<td>120</td>
<td>112</td>
</tr>
<tr>
<td>Freq. of Blocks</td>
<td>120</td>
<td>105</td>
<td>110</td>
<td>108</td>
<td>120</td>
<td>112</td>
</tr>
<tr>
<td>Success ratio of blocks</td>
<td>0.96</td>
<td>0.95</td>
<td>0.97</td>
<td>0.96</td>
<td>0.98</td>
<td>0.97</td>
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<table>
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<tr>
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<tbody>
<tr>
<td>Total</td>
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<td>107</td>
<td>110</td>
<td>108</td>
<td>120</td>
<td>112</td>
</tr>
<tr>
<td>Others</td>
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<td>107</td>
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<td>108</td>
<td>120</td>
<td>112</td>
</tr>
<tr>
<td>Game Max</td>
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<td>0.95</td>
<td>0.97</td>
<td>0.96</td>
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<table>
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<td>Total</td>
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<td>107</td>
<td>110</td>
<td>108</td>
<td>120</td>
<td>112</td>
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<td>0.95</td>
<td>0.97</td>
<td>0.96</td>
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<table>
<thead>
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<tbody>
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<td>107</td>
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<td>120</td>
<td>112</td>
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<td>0.95</td>
<td>0.97</td>
<td>0.96</td>
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<td>0.97</td>
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<table>
<thead>
<tr>
<th>Team D</th>
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<td>120</td>
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<table>
<thead>
<tr>
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</tr>
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<tbody>
<tr>
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<table>
<thead>
<tr>
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<tbody>
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<td>107</td>
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<td>0.97</td>
<td>0.96</td>
<td>0.98</td>
<td>0.97</td>
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Table 6. The data from the standpoint of each team' attacking patterns

<table>
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<tr>
<th>Team</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>Others</th>
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<th>D</th>
<th>O</th>
<th>Total</th>
<th>S</th>
<th>D</th>
<th>O</th>
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<td>-</td>
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</tr>
</tbody>
</table>

The data from the standpoint of each team' attacking patterns.
Result for each team

Similar to the overall result in the league as discussed in the previous section, the attacking teams could decrease the average success ratio of blocks by changing the allocation of the attacking patterns. For example, team A has the value of the game as 0.315 and it could be realized by the combination of “III, C” in 0.58 and “III, C in 0.42 for the opponent attacking teams as a mixed strategy.

Until now, we have analyzed the data from the standpoint of the blocking team, i.e. the team we focused is a blocking team. But, we can look at the situation from the standpoint of the attacking team by changing the aspect of the data. In Table 6, we considered team A, for example, as an attacking team and other 7 teams are aggregated as a opposing team against team A. From this aspect, team A have the minimum average success ratio of opponent blocks 0.24 against team A’s attacking pattern “XI,C”, which was used 23.1% as shown in Table 6. On the other hand, “XI, L” against the success ratio of opponent blocks 0.65 was used 12.5%. That is, team A frequently attacked with the patterns which has low average success ratio of opponent blocks. The value of the game as 0.295 is realized by the combination of “III, L” in 0.92 and “XI, C in 0.08. This implies that team A could still have reduced the success ratio of opponent blocks to 0.295. That is, by changing the allocation of attacking pattern of team A, it could decrease the success ratio of blocking by 0.346 - 0.295 = 0.051. We also represent the other 7 teams in Table 6 and each team can be analyzed in the same manner.

Here, we summarize the difference between the average success ratio of blocks and the value of the game in Table 7.

<table>
<thead>
<tr>
<th>Team</th>
<th>Success ratio</th>
<th>Success ratio</th>
<th>1−2</th>
<th>Game Value</th>
<th>3−4</th>
<th>Game Value</th>
<th>5−6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Team A</td>
<td>0.404</td>
<td>0.346</td>
<td>0.058</td>
<td>0.315</td>
<td>0.088</td>
<td>0.295</td>
<td>0.051</td>
</tr>
<tr>
<td>2 Team B</td>
<td>0.418</td>
<td>0.298</td>
<td>0.120</td>
<td>0.280</td>
<td>0.138</td>
<td>0.167</td>
<td>0.131</td>
</tr>
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<td>3 Team C</td>
<td>0.404</td>
<td>0.351</td>
<td>0.053</td>
<td>0.222</td>
<td>0.182</td>
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<td>0.077</td>
</tr>
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<td>0.315</td>
<td>0.368</td>
<td>-0.053</td>
<td>0.067</td>
<td>0.248</td>
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<td>0.368</td>
<td>0.002</td>
<td>0.250</td>
<td>0.120</td>
<td>0.284</td>
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</tr>
<tr>
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<td>0.314</td>
<td>0.047</td>
<td>0.278</td>
<td>0.083</td>
<td>0.228</td>
<td>0.086</td>
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<tr>
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<td>0.076</td>
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<td>0.123</td>
</tr>
<tr>
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<td>0.210</td>
<td>0.045</td>
<td>0.250</td>
<td>0.170</td>
</tr>
<tr>
<td>Total</td>
<td>0.361</td>
<td>0.361</td>
<td>0.297</td>
<td>0.064</td>
<td>0.297</td>
<td>0.064</td>
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</tbody>
</table>

In Table 7, firstly we look at the difference of the success ratio of blocks between the standpoint of blocking and attacking. For example, as shown Table 7 team A has the average success ratio of blocks 0.404 as the blocking team. This value corresponds to the value in Table 5. As an attacking team, team A faces the opponent blocks as the average success ratio of 0.346, which corresponds to the value in Table 6. Here the difference 0.404 - 0.346 = 0.058 is considered to be a superiority of average blocking ability by team A to average ability being blocked by other 7 teams.

On the other hand, team A has the difference between the average success ratio of blocks and the value of the game in blocking such that 0.404 - 0.315 = 0.088. This is considered to be a potential gain comes from the tendency that other 7 teams do not use suitable allocation of attacking patterns. In other words, if other 7 teams change the
allocation of attacking patterns, team A could decrease the success ratio of blocks by 0.088. (i.e. Team A seems to get benefit 0.088 from other 7 teams’ inefficiencies.)

Team A also has the difference between the average success ratio of opponent blocks and the value of the game in terms of attacking such that $0.346 - 0.295 = 0.051$. This is considered to be a potential loss of team A which does not use suitable allocation of attacking patterns. In other words, if team A change the allocation of attacking patterns, team A could decrease the average success ratio of opponent blocks by 0.051. (i.e. Team A seems to lose benefit 0.051 from other 7 teams by team A’s inefficiencies.)

In total, team A gets benefit of 0.088 and lose 0.051, so it gets $0.088 - 0.051 = 0.037$ as shown in the right column of Table 7. The other 7 teams are analyzed in the same manner.

We plot these values shown in Table 7 on Figure 3. As illustrated in Figure 3, this macro-view of the game theoretic analysis shed the light on the characteristics of teams. In this figure, x-axis represents the difference of success ratio of blocking between the standpoint of blocking and attacking, which is observed just by the statistical data represented by the heading “” in Table 7. Y-axis represents the difference of potential benefit, which is estimated by this game theoretical analysis represented by “” in Table 7. Therefore, the teams plotted in the upper right area are considered that they are relatively not only superior in average success ratio of blocks but also get potential benefit from other teams’ poor allocation of attacking patterns. On the other hand the team located in the lower left area are relatively inferior in average success ratio of blocks but also lose potential benefit by its own poor allocation of patterns.

Not surprisingly, the top 3 teams of the league (teams A, B and C) locate in the upper right area. Here, team C get the highest potential benefit by the allocation of attacking patterns from the standpoint of this game theoretic analysis. The bottom 2 teams (teams G and H) locate in the lower left area. Team D is not good in the sense of its relative success ratio of blocks but it seems to get quite large benefit by allocation of attacking patterns. These results are of particular interest since they give insights which could in no way be ascertained without help of game theory.

![Figure 3. Characteristics of teams](image-url)
Conclusions

We have presented a method for analyzing tactics in volleyball using game theory, focusing on the phase of reception attack. We have formulated the conflict between attacking formations and blocking formations as a zero-sum game by tabulating these patterns of formations, and have analyzed the tactics by calculating the value of the game. We have also shown an example of a macro-view of game theoretic analysis, using the data taken from the intercollegiate women’s league in 2004. Here, we have estimated the game values for the league and showed a possible improvement of the allocation of attacking patterns. We have tried also to illustrate the characteristics of teams from the point of success ratio of blocks and allocation of attacking patterns.

Although we have used the empirical data of the intercollegiate women’s league in the situation that the setter’s position in backward, we will analyze the situation that the setter’s position in forward which will be more complicated to model the tactics. We can also state that we should extend our analysis from the women’s league to other level and modifying the mathematical model of the pattern of attacking and blocking suitable for the level of play in practice.

This research is just a first step to provide a practical application of game theory to real volleyball matches, but this approach could hopefully provide a new standpoint of the macro-view of the volleyball match analysis.

Acknowledgments

We thank Dr. K. Nemoto, in Faculty of Sport Science at Nippon Sport Science University, for allowing us to refer to the video tapes and giving us practical advice. This research is supported by Grant-in-aid for Scientific Research (C), #17510144.

References


MEASUREMENT OF TRUNK MOTION IN FRONT CRAWL SWIMMING USING INERTIAL SENSORS

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Abstract

The purpose of this study was to quantify the acceleration and the angular velocity of the swimmer's trunk in front crawl swimming using inertial sensors, and to estimate the attitude angle of the trunk and swimming acceleration. The subject was a well-trained male swimmer. The acceleration sensor and gyroscope were waterproofed and attached on the swimmer's 4th lumbar. The trials were front crawl swimming with and without kicking. In the trial without kicking, the swimmer attached the buoy to his legs in order to support his legs. It was easier to quantify the acceleration and angular velocity of swimmer's trunk using sensors than by videography. It was suggested that the sensor measurements would provide useful information and have advantages to be applied to the training and coaching in swimming.

KEY WORDS: INERTIAL SENSOR, TRUNK MOTION, QUANTIFICATION, FRONT CRAWL SWIMMING

Introduction

Inertial sensors, such as acceleration sensor and gyroscope, have been developed recently to be very small and applied to the measurement in sports scene. The use of sensor technology in athletic performance monitoring has been validated by research covering a range of disciplines (Callaway et al. 2009). The technology has also been applied to the quantification of swimming motion (Ichikawa et al. 2006, Ohgi 2004). The measurement by sensors has advantages because of the high sampling rate and accuracy. The online measurement by the sensors has possibility to feedback information about swimming motion easily and quickly, which is important to apply to the training and coaching of swimming.

The purpose of this study was to quantify the acceleration and the angular velocity of the swimmer's trunk in front crawl swimming using inertial sensors, and to estimate the attitude angle of the trunk and swimming velocity.
Methods

Experiments

The subject was a well-trained male swimmer (age: 22.7yrs, height: 1.74m, weight: 67.0kg, best record of 100m freestyle: 50.7sec). The trial was front crawl swimming with and without kicking. In the trial with kicking, the subject performed front crawl swimming with six-beat kicking per one arm stroke. In the trial without kicking, the subject attached the buoy to his legs in order to support his legs.

The sensor module (Figure 1), which included a tri-axial acceleration sensor (LIS3L06AL, STMicroelectronics.) and two dual-axial gyroscopes (IDG-300, Inven-sense Inc.), were waterproofed and attached on the subject’s 4th lumber. The output signals from the sensors were recorded on a laptop computer at a sampling frequency of 200Hz during each trial. The swimming pool for the experiments had the underwater window for the swimmer’s side view. A video camera (TK-C1381, Victor Inc.) was set up to take the swimming motion through the window of the swimming pool. Each image from the camera was superimposed the sequential field number using the field counter (PH-1540, DKH Inc.) to be synchronized for the sensor data, and recorded by the digital video recorder. From the recorded images, the displacements of the subject’s 4th lumber were digitized and transformed into two-dimensional coordinates with DLT-method using the software for motion analysis (Frame-DIAS IV, DKH Inc.). The displacements were smoothed by IIR digital filter with the cutting-off frequency 2Hz.

Figure 1 A waterproofed sensor module included a tri-axial acceleration sensor and two dual-axial gyroscopes. The small scale of a ruler as reference indicates a millimeter.
Calculation

The acceleration and the angular velocity measured by the sensors are based on the moving coordinate system with the sensor module, which is fixed to the swimmer’s trunk. The direction of the axes to be measured by the sensors varies momentarily. The attitude of the swimmer’s trunk is needed and described by the inertia coordinate system in order to obtain the acceleration and velocity along with the swimming direction from sensor data. The attitude of the trunk was calculated by the integral of the measured angular velocity. The measured acceleration was converted from the moving coordinate to the inertia coordinate, which had the axis along with the swimming direction. The velocity of the trunk was also estimated by the integral of the estimated acceleration.

Results

Figure 3 shows the measured acceleration and angular velocity of the 4th lumber in front crawl swimming with and without kicking. All output signals were the characteristic that was cyclic corresponding with the arm stroke. The acceleration along with the transverse axis of the trunk and the angular velocity about the longitudinal axis of the trunk were major component of the motion in front crawl swimming. The data were separated by the time when the trunk’s transverse component of the measured acceleration was zero. It was treat as the time when the transverse axis of the trunk would be horizontal. From the video in lateral view, it was observed that the swimmer’s arm was stretching forward after arm entry when the trunk’s horizontal time.

The attitude of the trunk was calculated by the integral of the measured angular velocity with the attitude of the trunk in the trunk’s horizontal time as the initial condition. The trunk’s rotational angles about the longitudinal axis of the trunk are illustrated in Figure 4.
The trial with kicking

The trial without kicking

Figure 3 Acceleration and angular velocity of the trunk in front crawl swimming, measured by the sensors. Upper graphics are shown in the trial with six-beat kicking, and lowers are in without kicking. The vertical dashed lines in the graphics mean the time when the transverse axis of swimmer’s trunk is horizontal.

Figure 4 Body rolling angle estimated from the sensor data in the trial with kicking (Left graphic) and without kicking (Right graphic). The vertical dashed lines in the graphics mean the time when the transverse axis of swimmer’s trunk is horizontal.
The acceleration along with the swimming direction was estimated from the measured acceleration and angular velocity. To validate the estimation of the acceleration, the estimated acceleration was compared with the acceleration obtained by the videography (Figure 5). The estimated acceleration from sensor data corresponded with that by the videography regardless of trials with / without kicking.

The velocity of the trunk along with the swimming direction was estimated by the integral of the estimated acceleration. Our methodology by the sensor cannot estimate the initial velocity. The calculation was carried out with the initial velocity 0 m/s. The mean velocity calculated from the videography was added to the estimated velocity to compare with the results of the videography (Figure 6).
The trial with kicking

The trial without kicking

Figure 6 Comparisons of the velocity of the swimmer’s trunk along with swimming direction between the estimation from the sensor data and the calculation from videography. The vertical dashed lines in the graphics mean the time when the transverse axis of swimmer’s trunk is horizontal. The horizontal dashed-dotted line is the mean velocity calculated from videography.

Discussion

It is easier to quantify the acceleration and angular velocity of swimmer's trunk using sensors than by videography. In this research, the output signals from the sensor module were obtained through the cable. It is hoped that the developments of the measurement device, such as MEMS technology and wireless transmission, will make it simple and easy to apply the measurement to the training and coaching of swimming.

The measured acceleration along with transverse axis of the trunk oscillated from -9.8m/s to +9.8m/s, which equals the amplitude of the gravitational acceleration. The output signal of the acceleration sensor used in this research includes the effect of the gravity, which depends on the direction of the measuring axes. The transverse component of the acceleration would result from the rotation of the trunk and the gravity, and the translational motion of the trunk would have little effect on the acceleration output along transverse axis.

In the trial without kicking, the measured angular velocity repeated the quite symmetric pattern about time when the transverse line of the trunk was horizontal. In the trial with 6-beat kicking, it was not symmetric in the component about the longitudinal axis of the angular velocity in particular. The difference of angular velocities with / without kicking means the effect of the kicking on the body roll. It seems to be difficult to recognize the effect from the angle data of the body roll, such as Figure 4. It was suggested that the angular velocity data would be available to obtain the behaviour of the trunk motion on detail, and so the gyroscope had advantages to measure and evaluate the body roll quantitatively.

The acceleration along with the swimming direction was estimated and compared with the acceleration obtained by videography (Figure 5). The promising results demonstrated that the estimation by the inertial sensors would be available as a methodology to
quantify swimming motion. It is believed that the point on 4th Lumber would be treated as the alternative to the centre of gravity of whole body. The propulsive force is larger than the drag force, when the acceleration of the point is positive. The propulsive force is smaller than drag, when acceleration is negative. The estimation of the acceleration along with swimming direction would make it possible to discuss swimming propulsion and dynamics. The videography can also obtain the acceleration, which is the second order differential of the displacement. The range of measurement of the videography was limited by the angle of view of camera. Actually the duration of the measurements was 2 to 3 seconds in our experiments used one camera (Figure 5). The usage of the sensors has advantage in long measurement.

The velocity along with the swimming direction was estimated (Figure 6). The estimation had two problems, which were the accuracy of the estimation and the boundary condition for the integral computation. It would be necessary to improve the measurement and the algorithm to calculate the velocity in order to be more accurate of the estimation. The additional measurements might be needed, such as measuring the swimming time to calculate mean velocity, to obtain the appropriate boundary conditions.

**Conclusion**

The acceleration and the angular velocity of the trunk in front crawl swimming were measured by the inertia sensors, such as the acceleration sensor and the gyroscope. It was easy to quantify the acceleration and the angular velocity of swimmer’s trunk during swimming. The estimated acceleration along with swimming direction would be available to evaluate the swimming technique. It was suggested that the sensor measurement would provide useful information and have advantages to be applied to the training and coaching in swimming.

**References**


USE OF ON-BODY SENSORS TO SUPPORT ELITE SPRINT COACHING

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Abstract

The purpose of this project was to evaluate a custom built foot pressure sensor system (StrideSense) for elite sprinting. StrideSense is an extremely lightweight, wireless sensor system capable of kHz sampling and automated data processing, meeting the specific requirements for use in running spikes, coaching support and scientific analysis. Sprint coach interviews revealed the need for the development of such a pressure sensing system to monitor non-intrusively athletic performance throughout a sprint run. Foot contact data contains essential information on a number of parameters including velocity, step frequency and limb asymmetries. The aim of the project was to obtain user-specific system and data feedback from sprint coaches and athletes to evaluate the ease of use and usefulness of StrideSense as well as the perceived relevance of the data provided to coaching and performance monitoring.

KEY WORDS, WIRELESS, ATHLETICS, FSR, INSOLES

Introduction

Lightweight, wireless sensor systems offer novel possibilities for the investigation of athletic performance. Traditional motion analysis methods quickly reach their limits of practicality when applied to a dynamic sporting setting. They can be disruptive to the sporting activity and data processing and interpretation can be cumbersome and difficult for the coach. Efforts have been made to resolve this problem through the use of on-body sensors. Examples include the work by Michahelles and Schiele (2005) for skiing, Aylward and Paradiso (2006 and 2007) for dancers and Purcell et al. (2006) for running. However, due to the high sampling rates required, the application of this technology to the analysis of sporting technique has not yet been exploited to its full potential.

Track and field athletics and the sprinting events in particular present a challenging environment for the investigation of technique using on-body sensors. Sprinting is a highly technical discipline involving a clearly defined goal, repeated strength, conditioning and technical training exercises and close athlete / coach interaction to optimize movement routines. While coaches currently use a variety of basic tools to track performance (e.g. light-gates, stop watches and video cameras), it is thought that the use of wearable, non-intrusive sensors, augmented by video-footage, may have the potential to provide domain-specific data that will assist the coach and athlete in preparation for competition.
In order to investigate the potential benefits of the use of wireless technology to assist coaches in the sprint disciplines, a series of semi-structured interviews with a set of leading coaches were performed (Thomson et al. 2009). These interviews revealed a number of parameters that are of particular interest to the sprints’ coach, including the action of the arms, contact of the foot with the ground, hip height and the athletes running posture. Particularly the contact of the foot with the ground was thought to be of interest as coaches believed that there may be a strong relationship to running velocity and is information that is currently not available. Furthermore, the interviews revealed the need for accurate and meaningful performance data to create a reliable reference point to track athlete development over time and to enhance coach / athlete communication. It is therefore not only a real-time but also a long-term activity requiring a definitive sensor data record.

As part of the SESAME (SEnsing for Sport and Managed Exercise) project a wireless and extremely lightweight foot pressure sensing system was developed (StrideSense). This paper will summarize the developmental steps of the StrideSense systems that were taken to extract and visualize domain-specific performance data for sprinting. This will be followed by an outline of the current system implementation and validation to ensure capture of accurate, automated and meaningful data for the coach and researcher. Finally, the plans for future work and further system developments will be covered.

Technology Demands

Further to addressing the specific knowledge of elite coaches on ideal sprinting technique and the methods for acquiring this knowledge, the coaching interviews provided essential guidance on the technological prerequisites of the use of wireless sensors in athletic monitoring. While current biomechanical measurement technologies (e.g. force-plates and motion capture) are highly accurate they are also generally too large and heavy for on-body use and require considerable resources for purchase, maintenance and use. Measurement within the dynamic sporting setting therefore requires on-body sensors to be extremely small and lightweight to ensure minimal interference with the athlete and the sporting task. Moreover, effective use of sensor data for active coaching support requires that data are derived and visualized with minimal delay between the end of the run and the athlete returning for coach feedback. This means that ideally the measurement system records and transmits data wirelessly, automatically processes raw data (using specific algorithms) to extrapolate meaningful performance data and visualize these data in a comprehensible fashion to meet the sprint coach user demands.

System Design and Validation

The StrideSense system was developed with the aim of addressing the domain-specific requirements described above. Foot pressure data is registered using force sensing resistor (FSR) sensors mounted to a standard insole (see Figure 1c). FSR technology, compared to alternatives such as piezo-electric sensors, was found to be the ideal option for obtaining high frequency data from a highly robust and flexible sensor, essential for use in hard-soled, formed, sprinting spikes. FSR sensors are attached to a central sensor node responsible for data logging and wireless communication with a trackside laptop. The node consisted of a Crossbow Imote2 sensor board (Crossbow 2009) and Marvell 8686 WiFi chip (Marvell 2009) (total weight 32 g, see Figure 1 a) and b), worn at pelvis height by the athlete. Data is off-loaded from the athlete via a WiFi network both during and immediately after each repetition.
Figure 1 a) and b) show the sensor node consisting of the Imote2 sensor board and the Marvell 8686 WiFi chip. Power is supplied using a Li-Ion battery and connectors for the left and right insole are shown at below the node. Figure c) shows the underside of the insoles used, with FSR sensors attached to the anterior aspects of the insoles, on the lateral side of the ball of the foot (midfoot) and the area of the great toe (toe).

Data analysis and visualization is performed on the trackside laptop using custom software (see Figure 2). The visualizer has the ability to display video clips synchronized with the sensor data.

Figure 2 Custom web-based visualizer software for the display of raw and derived sensor data as well as video footage collected during a repetition. Visual options for data magnification and scrolling are provided. Raw sensor data plots are displayed with derived contact and flight times displayed below. Furthermore, data export functions are available, controlled by start and end cursors visible at the start and end points of the data streams (vertical lines).
In order to provide instant data on contact times in sprinting, a fully automated custom-made detection algorithm was developed. Data from the toe and midfoot sensors (see Figure 1c) was used for accurate contact identification. As sprinting uses a front and midfoot contact only, it was not necessary to include a heel sensor for this application. The accuracy of the system and algorithm for the identification of contact times was validated using StrideSense (2 kHz) and a force plate (1 kHz). Data for the start, the acceleration and maximum velocity phases were analyzed to verify accuracy during these distinct phases. Currently available data (38 contact events) indicate an RMS error of <1ms which provides a very favorable accuracy metric.

**Current Application and Future Application**

In order to enhance our understanding of the performance characteristics of sprinting, the StrideSense system has been used for the investigation of the relationship of contact time and velocity in 60m maximal sprinting (Kuntze et al. 2009) (see Figure 3). While these investigations are currently on-going, initial data indicate a usable, individual athlete based relationship between contact time and velocity that may provide useful coaching information for the tracking of sprint performance.

![Figure 3 Current application of StrideSense for the investigation of contact time and velocity in sprinting, with CODA scanners being used to provide foot contact time validation data (Bezodis et al. 2007).](image)

To allow for a truly wireless application, current work is focused on removing the wired connection between the FSR sensor and the Imote. To achieve this aim a sensor cluster system is proposed with a central Imote and peripheral Ions located at the ankle of the athlete and connected to the FSR sensors. This will provide a truly wireless sensor system, opening up new application settings and research opportunities. New research areas of immediate interest are both the short (100m and 110m) and long (400m) hurdle events. Preliminary coach interviews revealed that hurdles coaches may assess hurdling performance and competence based on a variety of split time measures as well as visual assessment of hurdling form. Since hurdle locations on the track are specified it appears eminently possible to extend the recording capabilities of the StrideSense system to the automated recording of split times between hurdles, step frequencies and flight times over hurdles. Foot pressure data from a hurdling pilot study identified a number of key...
parameters that show the potential for automated hurdle event identification. These initial data will be further assessed to verify the automation opportunities and the potential for a reliable, hurdling-specific analysis system.

Conclusions

The current StrideSense system achieved the aim of providing a reliable, lightweight and non-intrusive method for sprint performance investigation. Domain specific information is relayed to the coach in an understandable manner and work is being undertaken to extract further sprint performance data. There are further opportunities for system enhancement which are the focus of current development efforts. These developments will aid in providing a robust and usable system for regular use in sprint training as well as expanding the investigation of performance for further sporting disciplines.

References


SELF-ORGANISING MAPS: AN OBJECTIVE METHOD FOR CLUSTERING COMPLEX HUMAN MOVEMENT

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Abstract
In this study Self-Organising Maps (SOM) were used to classify the coordination patterns of four participants performing three different types of basketball shots from different distances. The shots were the free throw, the three-point and the hook shot. The coordination required to execute the free throw and three-point shot were hypothesised to show lower variability between them, than when compared to the hook shot. The first analysis involved an analysis of trial trajectories visualised on a U-matrix. Two of the participants, unexpectedly, showed lower variability between the coordination of the three-point shot and the hook shot, instead of the free throw. Where the first analysis was useful in showing aspects of the movement that were not obvious from viewing the computer animation of the original movement, a second SOM was trained on the appearance of the original trajectories and used to produce an output that shows the variability, or similarity, in coordination between all trials in the study. The second SOM showed distinctions between the three shooting conditions which were against the natural inclination of the movement analyst. The second SOM technique may provide a more objective method for, explaining movement patterning and structuring practice routines.

KEY WORDS, NEURAL NETWORKS, KOHONEN, SOM, COORDINATION, BASKETBALL.

Introduction
The data used for this study were generated from four players performing three different types of basketball shots from different distances. The shots selected were the free throw shot, the three-point shot, and the hook shot. The free throw is awarded commonly when an offensive player is fouled during shooting. Each foul usually results in the offended player being awarded two free throw shots, which makes the free throw shot an important skill. The three-point shot is a more strategic type of shot; the probability of making the shot is much less but the reward is higher. The three-point shot is taken from further away than the free throw shot and is often performed in the presence of defenders. For these two reasons the three-point shot is almost always performed as a jump shot, both to afford more power for the shot and to release the ball higher thus reducing the chance of being blocked. During the study, the hook shot is performed starting with the player’s back to the net then turning and shooting with a one handed release. The hook shot is a lower percentage shot but, because of the release point, it is a
difficult shot to defend. A good hook shot involves the position of ball release between the shooter’s body and the defender. Typically the hook shot is used as a last resort and, therefore, occurs less frequently than the other two shots.

A likely practice routine would reflect the hook shot’s infrequent use. This intuition is reinforced by an assumption that the hook shot is a separate movement pattern compared to the similarity between the free throw and the three-point shot—which are often thought of as modifications of the ‘set shot’ movement pattern. Consider why these assumptions exist. The observational learning literature suggests the motion of distal segments as one of the most influential factors when learning new skills (Hodges et al., 2007). The typical one-handed release of the hook shot makes the kinematics of the distal segments a plausible explanation for its distinction as a unique shot. If such visual information actually acts as a crutch and a threat to functionality, the opportunity exists for a new method of structuring practice and thinking about movement patterning to come to light. The purpose of this paper is to show that SOMs are an objective tool for movement analysis. The implications may be that, as a result of an objective understanding of how movements are patterned, coaches may structure practice to facilitate skill acquisition in their athletes.

Methods

Data Collection and Processing

A 12-camera, three-dimensional motion capture system (Motion Analysis Corporation Inc, Santa Rosa, CA, USA) was used to collect the data for this study. Using post-processing software (Visual3D, C-Motion), a 12-segment body model was established. Based on the Euler convention, motion in the primary plane for the right and left ankles, knees, hips and shoulders were processed for the SOM analysis.

Trials were time normalised to 101 data points. Within each trial, each variable was range normalised to maximum and minimum values of +1 and -1, respectively. The trials were appended one after the other to create one block of data used for training the neural network.

SOM Outline

The SOM can be thought of as a layer of nodes with associated weight vectors, fed forward by a layer of inputs. Weight vectors of the map nodes are adjusted based on an unsupervised learning strategy to represent relevant information in the input. The output node whose weight vector has the smallest Euclidean distance to a given input is declared that input’s best matching node. Convergence to the input is achieved by iteratively updating the weights of the best matching node and its neighbours, within a specified radius, according to the neighbourhood function and learning rate (Kohonen, 2001). Because of such non-linear properties, the SOM is able to remove redundancies in high-dimensional input data and produce a low-dimensional mapping of the output while preserving topological relationships in the data. The neighbourhood function effectively allows local interactions between map nodes to coalesce into states of global order and achieve self-organisation.
Network Architecture

The SOM toolbox for MATLAB was integrated into the software tool (Vesanto, Himberg, Alhoniemi, & Parkankangas, 2000) for the analysis. A PCA-based initialisation process was used to create a 2-D hexagonal lattice output map (Table 2). The neighbourhood sizes were selected according to the principal components of the data (Barton, Lees, Lisboa, & Attfield, 2006).

A second SOM, inspired by Barton (1999), was trained on the trajectories from the original SOM. Inputs for the second SOM were created from projecting the weight vectors into weight space using Sammon’s mapping (Sammon, 1969). The 2-D coordinates of each consecutive best matching node were used to create an input vector representative of an individual trial. This process was repeated for the best matching nodes of all trials in the study. The result of the second map is a SOM in which each trial can be represented by one node on the output map and, therefore, a clustering of all the trials in the dataset can be visualised more easily. In what follows we will refer to the original SOM as the phase SOM and the second SOM as the trial SOM.

Table 2: SOM training parameters and quality measures

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<th>trial SOM</th>
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Analysis

We chose to use the U-matrix (see Figure 2.a) to visualise the output of the phase SOM. Trajectories connecting nodes on the U-matrix that best represent the input were used to visualise the multi-segment coordination performed by the participants. The nodes in Region A of the U-matrix represent the preparation phase of the shot. Region B represents the extension phase where the player generates power for the release. Region C represents the final release phase of the movement. Typical movement patterns activate nodes in Region A, ascend up the map through Region B and end at the release phase in Region C. Movements that were patterned uniquely activated nodes in Region D. Clusters of data can be identified on the U-matrix with blue ‘distance cells’ which are evidence of similar data among neighbouring nodes. Orange and red distance cells represent larger Euclidean distances between neighbouring nodes and therefore outline borders between clusters.
The phase SOM analysis uses the trajectory of the best matching nodes through the time series of each trial to compare various trials simulated on the same U-matrix visualisation (Lamb, Bartlett, Robins, & Kennedy, 2008). The orange trajectories shown on the U-matrix (Figure 3.a, c and e) give a representation of the order of the best matching nodes with respect to time. However, the trajectory can potentially be misleading as it gives the impression that the best matching nodes move fluidly through the U-matrix. Visualising trials with just the best matching nodes highlighted in white on black shows the discontinuity on the U-matrix for this dataset. Figure 3 (b, d and f) shows these hit histograms with best matching nodes shown as white patches with their size increasing and the frequency of hits increases. For these nodes to stand out the rest of the U-matrix is blacked out.

Sammon’s mapping was used to visualise the trial SOM because the map size was small with an accordingly small topographical error (Table 2). Each trial in the dataset was assigned a best matching node which was shown on the output map (Figure 7). The text at each node represents the type of shot, the colour of the text identifies the player and the size of the text increases as the hit frequency increases. The lateral connections between nodes represent the Euclidean distance between them.

**Results**

**Phase SOM analysis**

The trajectories for the three-point shot and free throw are visually similar in Regions A and C of the U-matrix, suggesting that the coordination patterns in the preparation and release phases were similar. The trajectories differ in the middle area of the map, in Region B, in which the three-point shot moves closer to the right edge of the map (Figure 2.a) than the trajectories for the free throw (Figure 2.c). The trajectory for the hook shot (Figures 2.e, f) is qualitatively different from the other two shots for Player 1. The main visual difference in the trajectories was seen as the trajectory moves diagonally up and across the U-matrix in Region C.
Figure 3: Player 1, a) Three-point shot trajectory, b) Three-point shot hits, c) Free throw trajectory, d) Free throw hits, e) Hook shot trajectory, f) Hook shot hits, g) U-matrix with movement phases.

For Player 2 (Figure 4), the preparation phase for the three-point shot and the free throw are almost identical, occupying many of the same nodes and clustering similarly. During the release phase, the three-point shot moves diagonally up and to the left from the right edge of the map in Region C (Figure 4.a, b), similarly to the three-point shot and free throw of Player 1. The diagonal movement on the U-matrix of the free throw is not as long or as consistent as the three-point shot (compare Figure 4.a with Figure 4.c). The hook shot (Figure 4.e, f) is, again, qualitatively different from the other two shots. Unlike all other shooting conditions for all other players, the best matching node trajectory for the hook shot for Player 2 does not always progress upwards on the U-matrix. The hit histogram in Figure 4.f shows the best matching nodes for most of the movement are within two brightly coloured borders in Region D of the U-matrix. This is different from any other shots in the dataset.

Figure 4: Player 2, a) Three-point shot trajectory, b) Three-point shot hits, c) Free throw trajectory, d) Free throw hits, e) Hook shot trajectory, f) Hook shot hits, g) U-matrix with movement phases.

The best matching node trajectories for Player 3 are similar for the three-point shot and the free throw (Figure 5.a, c). The hit histograms show a large discontinuity as the movement transitions from preparation to release (see Figure 5.b, d). The trajectory jumps from Region A to a series of about three different nodes in Region D before jumping into Region C for the release phase of the shot. The jump into Region D is dif-
different from any of the other shots in the dataset. The hook shot is visually much different from the three-point shot and the free throw; it stays within Region D, without jumping across any borders, and along a very consistent trajectory of nodes (Figure 5.e).

Figure 5: Player 3, a) Three-point shot trajectory, b) Three-point shot hits, c) Free throw trajectory, d) free throw hits, e) hook shot trajectory, f) hook shot hits, g) U-matrix with movement phases.

For Player 4, the trajectories for the preparation phase of each shot are different. The three-point (Figure 6.a, b) and hook shot (Figure 6.e, f) best matching nodes were in Region A, as expected, whereas the free throw (Figure 6.c, d) began in Region D. In Region B, the three-point shot and hook shot trajectories travel to the left of the bright blue border near the right edge of the U-matrix whereas the free throw travels to the right of the border. The release, shown in Region C, of the three-point shot and the free throw are quite similar, as shown in Figure 6.a, c. The release of all three shots of Player 4 resemble the release of Player 1. The trajectories for the three-point shot and the free throw move above the bright blue border in the middle of Region C, while the trajectory for the hook shot moves below the border.

Figure 6: Player 4, a) Three-point shot trajectory, b) Three-point shot hits, c) Free throw trajectory, d) free throw hits, e) hook shot trajectory, f) hook shot hits, g) U-matrix with movement phases.
**Trial SOM analysis**

Starting with Player 1 (blue text in Figure 7), the three-point shot and hook shot occupy nodes at the left edge of the map which makes the two shots second nearest neighbours. The free throw hits a region toward the bottom of the map, located more closely to different shot types of different players than to other shots by Player 1. As was shown in the previous section in Figure 3 and 3, the coordination patterns for each respective shot for Player 1 and Player 4 (red) are similar. Also the three-point shots and free throws of Player 2 (green) were clustered near the three-point shot of Player 1 (compare Figure 7 with Figure 3 and Figure 4).

The three-point shot and free throw for Players 2 and 3, respectively, are second nearest neighbours with a noticeably short Euclidean distance between them (compare trajectories in Figure 4.a and c and Figure 5.a and c). Most of the hook shots for Player 2 were isolated toward the top right corner of the map. Higher variability within this shooting condition is evident by the distribution of hits across six nodes. Three other shooting conditions occupy more than one node (Player 2 three-point and free throw and Player 3 free throw); however, the Euclidean distance spanned by the hook shots of Player 2 show this to be the most variable shooting condition in the dataset.

![Figure 7: Sammon's mapping of trial SOM. Player 1 is shown in blue, Player 2 in green, Player 3 in red and Player 4 in cyan.](image)

Figure 5 showed the three-point shot and free throw shot of Player 3 (red) to appear similar to, although, distinct from, other shots in the dataset. The hook shot occupied a small area in Region D in Figure 5, which was also distinct from other shots in the dataset. Both of these observations are apparent in Figure 7 (in red). The three-point
shot and free throw are separated by only one node and the hook shot is isolated in the top right corner of the map.

The free throw of Player 4 (cyan) is another shot that is clustered away from the rest of the data, in this case the bottom right corner of the map. The three-point and hook shot are shown to be more similar to each other than to the free throw; these shots are also more similar to the three-point and hook shot of Player 1 that they are to the free throw of Player 4. Finally, notice that the three-point shot appears to be the most similar shooting condition among the players, and the hook the least similar.

Discussion

The Jump Hook

Qualitatively, Player 1 supported the hypothesis that the three-point shot (Figure 3.a) and the free throw (Figure 3.b) would be most similar only for the preparation and release phases. Although all time frames of the movement were weighted equally, the trial SOM classified the data for the three-point shot and hook shot in the extension phase to be a larger contributor to overall similarity, partly because of a slight delay at mid-flight between lower and upper body extension in these shots. Overall, the trial SOM showed the lowest variability for the three-point versus the hook shot; during the late extension phase and the beginning of the release of the shot, the three-point shot showed more similarity with the hook shot than with the free throw.

For the three-point (Figure 6.a) and hook (Figure 6.e) shots, many similar nodes were activated in the extension phase (region B, Figure 6.g) for Player 4, adding further evidence to the idea that the kinematics involved in the jump in these two shots contribute to the data for each of these shooting conditions being more similar to each other than to the free throw, which does not involve a jump. The release phase of the three-point shot (Figure 6.a) and free throw (Figure 6.c) showed more similarity on the U-matrix. This was expected since the three-point shot and the free throw are two-handed shots, whereas the hook shot is a one-handed shot. Viewing the computer animation, the noticeable difference between the three-point shot and the free throw for Player 4 was the in-phase extension of the upper and lower body, while for the free throw the knees and hips reached maximum extension while the upper arms continued to flex and the elbows and ankles continued to extend. The upper arms then stopped, leaving both the ankles and elbows still extending—a somewhat atypical sequence. This sequence is shown on the U-matrix by nodes between the edge of the map and the rightmost brightly coloured border in Region B (Figure 6.c). Player 4's free throw was the only shot for any of the players to activate these nodes. The overall similarity of these shots is verified in Figure 7.

The best matching nodes for the release phase of the hook shot for Players 1 and 4 were very close; this was supported by the short Euclidean distance for the hook shots between Players 1 and 4 on the trial SOM (Figure 7). The high dimensionality of the time series data for these throws makes an in-depth, visual analysis of coordination difficult using conventional methods. Research into the information attended to in visual demonstrations has shown that the kinematics of distal segments (arms) has a greater impact than the kinematics of more proximal segments (legs) in skill acquisition (Hodges et al., 2007). This may be used as evidence suggesting that certain information biases the movement analyst. Since the major difference associated with the hook shot compared to the other two shots is the one handed release, one could speculate that the movement
of the distal segments over-influence the analyst into classifying the hook shot as a completely different movement. If this is the case, the SOM might provide an objective method for analysing human movement for movement analysts and coaches.

The standing hook

Only the shots of Players 2 and 3 were clustered on the trial SOM in support of the hypothesis that the three-point shot and free throw would show lower variability between them than when compared to the hook shot. Qualitatively, the three-point shot and free throw, for both Player 2 (Figure 4.a, c) and Player 3 (Figure 5.a, c), were similar to each other for not only the preparation and release phases of the movement, as for Player 1, but also the extension phase of the movement. The hook shots were qualitatively different for each phase and occupied Region D on the U-matrix (Figure 4.e; Player 2: Figure 5.e; Player 3). Unique to Players 2 and 3 were that their hook shots lacked a significant jump along with an early release of their three-point shot. The jumping kinematics that separated the three-point shot and the free throw for Players 1 and 4 were much less pronounced for Players 2 and 3, reflected in the short Euclidean distance between the three-point shot and free throw on the trial SOM (Figure 7, Participant 2, Participant 3).

Conclusions

The phase SOM drew our attention to aspects of the movement that were not obvious from more traditional approaches—such as visual analysis of the original movement, or from multiple time series data. Characteristics of the movements found by analysis of the phase SOM were summarised on a single output map using the trial SOM. In several cases, the SOM output and our natural inclinations as movement analysts did not agree; SOMs thus proved to be a useful tool in our analysis of coordination. The movement analyst might be distracted by visual information in the movement; the SOM might provide a more objective method for explaining movement coordination. In particular, the trial SOM approach may be useful for gaining a more global representation of the dataset and thus neatly summarise the relationships between a set of coordination patterns.

References

A RECONCEPTUALISATION OF TRADITIONAL VOLLEYBALL STATISTICS TO PROVIDE A COACHING TOOL FOR SETTING

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Abstract

Systematic statistical analysis of volleyball and beach volleyball matches has been done by coaches for decades. Complex computerised systems have replaced hand collected data and enable greater ease of collection as well as more complex analysis. However most systems do not take into account the skill of setting (approximately 30% of a team’s ball contacts), as it doesn’t fit into the same objective categorisations as all other volleyball skills.

The fundamental purpose of the set is for the subsequent spike to win the point. Location, selection and tempo are simply aspects of the set which can assist in achieving the fundamental purpose. As a consequence, this paper suggests that by using existing systems and data, the set can be rated as a combination of the pass before it and the spike after it. It is important to note that this is not a subjective rating of the quality of the set, but an objective rating based on the preceding and following actions.

Analysis of over 150 beach volleyball matches from the FIVB World Tour between 2006 and 2008 suggests that the Set Rate can be a useful tool to assist coaches and players in evaluation, goal-setting and feedback.

Introduction

Due to the predictable nature of game flow in volleyball, it is relatively easy to collect comprehensive statistics in real time during matches. While a sport like football (soccer) may have an unlimited number of ‘passes’ before a score is made, volleyball’s nature is that it has a strict flow of skills in each discrete rally. Going back to the early 80s there has been literature (Baacke, 1981) discussing the collection and analysis of volleyball statistics. Computer systems have been used to capture detailed real-time data in indoor volleyball since the mid 80s (Penner (1985), Byra and Scott (1983)) and, though the lack of published data may suggest the contrary (Laios, 2009), in Beach Volleyball since the late 90s. Though McGarry (2009) comments that “the generation of scientific knowledge must precede its application” (pp128), these data collection and analysis systems are pervasively used by coaches even when there may be no recorded literature noting it.

There is certainly variation but generally systems follow the principles defined by Baacke in 1981 (pp46), specifically, that there are “four basic principles (describing) how a rally continues after a playing action”:

- Action results in a direct success,
- Action gains or preserves the initiative of a play,
- Action leads to the loss of the initiative of the play and
- Action results in a lost point.

These four outcomes can be associated with rating numbers (3, 2, 1, 0) in order to further analyse them.

This system of analysis was developed because it was determined the above mentioned skills can be objectively rated. Although Baacke (1981) originally included setting in his analysis, setting data is rarely systematically collected along with all other skills in coaching tools, though coaches may use other structures to do this. It is deemed too hard to rate the outcome objectively as the set very rarely ends the rally itself (except in error in which case it is obvious). Laios (2009) goes so far as to state that “The analysis included all the technical characteristics of the game (service, reception, attack, block and defense)”, omitting to count the set as a technical characteristic of the game. While there have been papers discussing setting (Barzouka et al (2006), Eom and Schutz (1992), Hughes and Daniel (2003)) the data analysed has always been collected in addition to usual data collected by teams.

Because of the relative ease to objectively assess skill execution for 2 of the 3 hits each side, the 3rd (set) has been ignored, even though it accounts for 30% of a team’s contacts (based on the data analysed in this paper). This is not a criticism, merely an observation, and it is common with other teams sports as well. For example the quality of a basketball pass or a football (soccer) pass is not rated in any standard, real time, statistics collected. However, unlike most other team sports, in volleyball it is not possible to have a variable string of sets before a spike (eg: basketball can have a variable number of passes before a scoring shot). Volleyball can have only one set on each side’s play, and almost always does.

As has been stated, it is possible to objectively state that a Serve is a 3, 2, 1 or 0 based on the outcome. However this doesn’t take into account whether an ‘easy’ serve was an ace due to an error by the receiving team. A player can get a kill (Spike rated 3) from a ‘bad’ spike. This is not a rating of the ‘quality’ of the spike but the outcome (though there is of course an inference that the quality of the spike has a positive impact on the outcome). Similarly, a pass that bounces off the passer’s head directly to the setter is considered a 3 because of the outcome, and a dig which was an error due to the player being in the wrong position is an error, even if the ball would have come directly to the player if he/she was in the correct position. Many sports battle with these issues, for example in Baseball there is generally considered to be a fielding error when the fielder fumbles the ball, but a great fielder is likely to be able to get to balls (and consequently fumble them at times) that a mediocre fielder cannot, and consequently ‘earns’ more errors. Another example is that an ‘assist’ in basketball is only given if the player’s team mate scores, regardless of whether they miss a easy shot or make a difficult one.

It must be clearly stated again that the aim of this paper is not to cast doubt on existing systems, nor to attempt to ‘fix’ them. Having said that, it is important to recognise that existing analysis systems used in volleyball and beach volleyball have flaws which are sometimes glossed over due to the historical nature of the systems used. Just as in basketball young players learn that points, rebounds and assists are how their performance will be judged, then grow up to understand the limitations of only using these, volleyball players learn what a Service Ace (Serve rated 3), a Spike Kill, and a Stuff Block (Block rated 3) from an early age. They will, from time to time, get...
annoyed that their 0 pass was due to a great serve, or their team-mate’s calling error. They will get annoyed that their opponent blocked them on a ball that was a bad set that they were lucky to reach. They will get frustrated when a great block bounces off the spiker’s head and back over the net into their empty court. But they know that these are the definitions.

The aim of this paper is simply to look at existing and future data which has and will be collected regardless, in a slightly different way, in order to provide coaches and players with more context within which to evaluate performance. It is to address the fact that the second touch of the ball on each side of the net is not currently evaluated consistently and therefore objective evaluation and feedback is rarely given to what many perceive to be the most important position on the court. It is to suggest that a flawed and derivative way of evaluating the set is no more nor less accurate and reliable than existing evaluations, and therefore has merit as a coaching tool.

The aim of this paper is to suggest that the set can be objectively rated as a derivative of the Pass before it and the Spike after it.

**Method**

This data used for this analysis was collected on World Tour, Grand Slam, World Championships and Olympic Games matches over an 3 year period (2006-2008). By most definitions all these matches would be described as elite, however there is still a large variation in ability even at this level.

The basis behind the rating lies in the most fundamental purpose of the set. It can be argued that this is to put the ball in a good location for the hitter, and (in indoor Volleyball) to choose the best option to set to, however at a deeper level the premise of this paper is that the purpose of the set is for the spiker to kill the ball. This premise is supported by international Olympic Medal winning coaches of both indoor and beach volleyball.

Once this principle is established it logically follows that if the outcome of the set is that if the spiker kills the ball, this is better than any other outcome, and that if the spike is rated as a 2, this is better than a 1, and so on. thus we can rank the ‘Spike’ in column 2 of Table 1.

The Rating column links the pass to the Spike. Within each of the possible outcomes of the spike there is a rating based on the difficulty created by the quality of the pass. For a kill, if it is from a 3 pass it can be argued that the set is relatively easy, but from a 1 pass it must have been more difficult. So the combination of a 3 spike and a 1 pass has the top Rating (1) within the ‘Excellent’ outcome. The same logic is used for other outcomes. These twelve variations are then rated from 12-1 (with 0 being added setting error, which is clearly the worst possible outcome for a set). One could argue that the Error Rate of the set could be broken further to factor in a difference for an error on a 3 pass compared to other passes, however this is a setting statistic and an error is an error. Deeper analysis is always possible and coaches do this as a matter of course. The Set Rate is intended only as a starting point.

Again, the key to this Set Rate is that, at its most fundamental level, the objective of the set is that the subsequent spike is a kill. There are situations where a great set will lead
to a hitting error, just as where a great hit is not a kill, but the objective remains constant.

One important point here is that the Set Rate is not limited by the scales used to rate the pass and spike (the example used here just happens to have 4 point scales for both these skills). By creating a Table using the same principles, any scales can be used, as long as there is a Ranking at the end. Coaches who use a 3 point scale for hitting will end up with a 9 point scale on the Set Rate, and coaches who use a 5 point scale for passing will end up with a 16 point Set Rate on the set.

Table 1. Establishing the relationship between the pass and the spike.

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Spike</th>
<th>Pass</th>
<th>Rating</th>
<th>Set Rate</th>
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<tr>
<td>Excellent</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>Excellent</td>
<td>3</td>
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</table>

Once the rank has been determined it is a simple matter for the computer program to calculate the Set Rate for any given set. If a computer is not used it can still be done by hand, but it may require some adjustments in the data collection phase to ensure that it is possible to link any given pass/spike combination. With a little more effort the software can also determine the player who set the ball. This is relatively easy in beach volleyball as you can assume the player who did not hit must have set the ball, but can also be done with indoor volleyball on the top systems used today.

In the data being analysed the block and dig are rated on a 4 point scale in the same way as the pass. Therefore the extrapolation of the set has been extended to spikes which did not follow a pass, but followed a dig or block (ie: Sideout Spikes as opposed to Transition Spikes). It is important to note that the definitions of the dig and block differ from that of the pass in that a 2 block/dig is one where the team executing it has an advantage and a 1 where there opponent does. A 3 block ends the rally so there is no set and a 3 dig is the equivalent of a 3 pass. Therefore there will be differences in the Set Rate depending on whether a spike was for Sideout (after a Pass) or in Transition (any other spike) but, just as with spiking, they can be looked at in combination and also separately, depending on the coach’s needs.
Validation

There were a number of steps in the Validation process based on the existing data. It should be noted at this point that the data was only collected on one of the two teams competing in each match.

1 - An application was written to process the raw data and ‘Add In’ the set to the raw data. This was validated by importing into SportsCode software and cross-referencing the data recorded against the footage of the game. The logic behind is was to identify every spike, then associate the ‘non-spiker’, the rating of the spike, and the rating of the preceding skill to the Set.

2 - This application was found to be 100% accurate when the data was accurately entered. However there were two possible ways to miss sets based on the data collected. If the ball was accidentally set directly over the net (in which case there was no spike) no set was calculated. This happened twice in the 349 rallies validated. The second possibility was if there was a data collection error and the action prior to the spike was not entered which happened 9 times. So a total of 11 sets were missed and 196 were recognised in the 349 rallies.

Results

Data from 159 matches from between 2006 and 2008 were processed.

In order to determine if the Set Rate demonstrated a distinction in the quality of setting the results were initially separated into those where the set was won and those where it was lost (note, in this context the set is used as the section of the match, not the skill). 8190 records were analysed in this way.

Figure 1 displays histograms which were generated using JMP software. Looking at these charts it is clear that in sets won there is a different, with the distribution ranging higher. More importantly there seems to be a point (about 8) above which you are likely to win the set. As a coaching tool this clearly indicates an opportunity for goal setting and player feedback.

![Histograms of Set Rate distribution in winning and losing sets for entire dataset.](image)

The histograms indicate a Set Rate of 8 being the point above which the team is likely to win and below which it is likely to lose. The target of 8 also resonates in that in 383 sets analysed, only on 2 occasions did a player achieve a Set Rank of 10 or more, which
is an improbable target that the setter averages a kill for every set. Having said this, the
distribution clearly demonstrates that it is still possible to lose with good setting, as you
would expect.

Further investigation of this target was done by determining the percentage of sets Won
depending on the Set Rate. As can be seen in Figure 2, if the Set Rate is 7.5 or more,
just over 70% of sets are won, 8 or more indicates a winning rate of greater than 80%.
This confirms the visual assessment from the histograms that for this cohort of
international beach volleyball players a Set Rating of 8 would be a good target, but also
suggests 7.5 may be a sufficient one also.

![Figure 2. Percentage of sets won related to Set Rates.](image)

As the Set Rate is a derivative of spiking and ranks higher for kills (ie: points won from
the spike) the fact that there is a relationship is not surprising, but the Set Rate also
takes into account other outcomes and rates the set based on the quality of the pass, dig
or block preceding it, so there is clearly a difference between the Set Rate and Spiking
statistics.

Much of the data came from one team, so their results were removed from the dataset to
ensure that they weren’t affecting the range of other teams analysed. Figure 3 displays
the same data with this team’s sets removed.

![Figure 3. Histograms of Set Rate distribution in winning and losing sets excluding one team.](image)
As can be seen, the same trend can be identified from the remaining 3131 records as from the dataset in its entirety. That is, a relatively normal distribution, with winning sets (left) indicating a Set Rate of 8 is a point after which the chances of winning are high, conversely with losing sets (right) most sets are lost when the Set Rank is below 8.

The final analysis (Figure 4) is distinguishing between from Service Reception (Sideout) and all other sets (sets from Transition) or, as Eom (1992) defines it, the Attack Process (AP) and the Counterattack Process (CP).

![Histograms of Set Rate distribution in sideout and transition setting.](image)

Figure 4. Histograms of Set Rate distribution in sideout and transition setting.

The results show a skew to the right for sideout setting. Transition Setting shows a wider spread of Set Rates, as well as a greater portion of the distribution towards lower ratings. This is consistent with both the fact that setting in Sideout phase is generally a more controlled situation, and also the fact that the Block and Dig (precursor to the Spike in Transition) are rated slightly differently to that of the Pass and so you would expect lower Set Rates.

**Conclusion**

The data suggests that the Set Rate represents an indication of the success of a team. Based on the data of elite beach volleyball players it seems that a target Set Rate of 8 is a good starting point for coaches to use in goal setting and feedback.

The key to this way of assessing Sets is that, rather than inventing a new method which will require more resources, it can be extrapolated from existing data and systems. The Set Rate does not replace anything, and therefore require an analysis of comparative value, it fills a void which has existed for so long that there is a tendency not to notice it anymore (Laios, 2009), and provides objective feedback to a key skill in volleyball which had previously been ignored. It has positives and negatives, just like other more traditional ratings, but the analysis demonstrates that there is a logical distribution of the results.

Ultimately it will be up to coaches to decide whether or not the Set Rate is used as a tool.
Reference


CURRENT DEVELOPMENTS AND CHALLENGES IN COMPUTER-BASED SPORTS GAME ANALYSIS

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Abstract

Fully automated analysis of competitions in the field of sports game observation will certainly be one of the greatest challenges in computer science in sports over the coming years. Looking at the traditional three stages of the sport game analysis process, namely, data collection, data evaluation and data analysis, we find that in the past computers were often used for the first two stages. The analysis itself was predominantly performed in a qualitative, expert-oriented way. This paper deals with "computer based" sport game analysis, where all three phases of the process are performed fully automatically by a computer. In the context of the three stages mentioned above, current developments and future challenges in computer science in sports are discussed for soccer as an example of a field sport and table tennis as an example of a racket sport.

In soccer, position data of the players and the ball at any time during a match provide the basis for comprehensive game analyses. Position data allows conditional parameters (distances, running speeds, etc.) to be calculated, tactical behaviour (e.g., zone marking) to be judged, and some technical capabilities and skills (e.g. the precision of passes) to be assessed. A number of commercial suppliers and some scientific research groups already use systems of this kind.

The primary purpose of data evaluation is to identify game scenes and situations in order to make them usable for statistical evaluation and further analysis. This can be achieved by using the position data of the objects involved, their mutual relationships and their variations over time. Beetz et al. (2006) already developed a first approach to this technique.

At the data analysis stage, the data collected is to be used for interpreting the game action and evaluating playing performance. Artificial intelligence methods appear to be promising tools for this purpose. Approaches to solutions for partial tasks are mainly provided by multi agent systems (e.g., Atkinson & Rojas, 2008), although it may take many years yet before a computer could actually replace a human expert.

A fully automated analysis of a table tennis game requires the time of each shot and its point of impact on the table, the position data of the players and the technique used for each shot. The first type of data, for instance, can be collected using the system for automatic detection of ball impact points presented by Baca and Kornfeind (2004). For identifying the players' positions, see above. To identify shot types, the author feels that additional cameras and image processing algorithms should be used. While development efforts in this area are still few and far between, some pilot projects are under way already (e.g. Han, Farin & With, 2008).
In table tennis, data evaluation is not an extremely complex task. The structure of this sport game being simple and clear, a simple descriptive/statistical evaluation of collected data is usually good enough for further analysis. This can be done automatically by standard software. When it comes to data analysis itself, we are faced with the same problem as in soccer. Although the complexity of this sports game is low enough for partial evaluations of playing performance to be more directly derived from raw data, qualitative, expert-oriented analyses include a quality that computers are as yet unable to provide.

To summarize, hardware for automated data collection in game observation is rather advanced by now and used in many instances. Also, promising software solutions are available for automating data evaluation, while equipment for data analysis is still almost inexistent. It is necessary to call for intensified research for the development of systems that are capable of imitating complex human thinking and pattern identification processes.

KEY WORDS, GAME ANALYSIS; SYSTEM DEVELOPMENT; RESEARCH DEMAND

References
INTERDISCIPLINARITY IN SPORT INFORMATICS: A VIEW FROM PHILOSOPHY OF SCIENCE

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Abstract

Computer science has become an important partner for sport science. Although many cases for the successful application of computers in sport exist, only a few meta-theoretical mediations on this research field can be found. To fill this gap, this paper examines the quality of interdisciplinary cooperation between computer science and sport science. Using existing models of interdisciplinarity it classifies research activities into four types of cooperation. Because knowledge is often only transferred “one-way” from computer science to sport science, it emphasizes the importance of “genuine” interdisciplinary research. Finally, the paper gives a compact definition of the discipline sport informatics and proposes a graphical model, which illustrates its subject matter and the structural relations between sport science, computer science and their fields of application.

KEY WORDS, COMPUTER SCIENCE IN SPORTS, INTERDISCIPLINARITY, SELF DEFINITION, STRUCTURE

Introduction

Over the past three decades, the discipline “sport informatics” - also called “computer science in sports” - has become an important part in the spectrum of sport scientific research. The term covers all activities at the interface of computer science and sport science, ranging from simple tools for handling data and controlling sensors on to the modelling and simulation of complex sport-related phenomena. Whereas first applications in the 1970s used computers for information and documentation purposes only, current approaches describe virtual environments in the training of perception tasks specific to sport (Bideau et al., 2004), the scope of computer technologies for coaching (Lames, 2008) or the automatic analysis of sport games using pattern recognition (Hoyningen-Huene & Beetz, 2009).

Today, computer science in sport is a well-established research field. An International Association on Computer Science in Sport (IACSS) has existed since 2002 and promotes research in this area. The IACSS organizes a biennial international symposium, publishes a peer reviewed e-Journal and disseminates information via a newsletter (details of the historical development and the organization of IACSS are described by Baca, 2006). In many countries such as Australia, Austria, Germany, Croatia and India national workgroups have been established, which represent sport informatics in the...
national scientific community and contribute new technological innovations to sport. The IACSS also maintain good relations with various other sport scientific organisations like the International Association for Sports Information (IASI), the International Council of Sport Science and Physical Education (ICSSPE) or the International Sports Engineering Association (ISEA).

Although there is no lack in research activities and scientific institutionalization, only a few meta-theoretical studies on sport informatics can be found. Most publications report on applications of computer technology, software tools and informatic methods and paradigms in sport, but they do not deal with epistemological questions about the discipline. While some authors (Perl & Lames, 1995; Baca, 2006) suggest a rough internal structure of the discipline, others (Fischer, 1998) allude to the characteristics of interdisciplinary cooperation, but forgo a detailed discussion.

To fill this gap, this paper takes the philosophy of science perspective in order to discuss interdisciplinarity in sport informatics. With this end in view, the second section outlines the conceptual structure and conception the individual disciplines have of themselves. (What do computer science and sport science think about themselves?). This part focuses on the epistemological discussion in the German scientific community and intends to make the German perspective available to readers outside of this country.

The third section deals with cooperation interests between computer science and sport science in common projects (Why do computer science and sport science work together?). While the motive of sport science is quite obvious, that of computer science needs more elaborate discussion. The fourth section poses the question, which quality of interdisciplinarity between sport science and computer science exists today and which quality would be desirable and realistic (How do computer science and sport science work (or should work) together?). This is done by discussing existing models of interdisciplinarity and proposing a classification for research activities in computer science in sport. Based on this discussion, the final section suggests a compact self definition of sport informatics and proposes a graphical model, which describes the structural relations between sport science, computer science and their application fields (What is the self concept of sport informatics?).

Self conceptions - What do computer science and sport science think about themselves?

In the sixties and the seventies of the last century, the German term “Informatik” was mainly associated with questions of technology. A popular German encyclopaedia described “Informatik” as “the science of the systematic processing of information, in particular the automatic processing using digital computers” (Engesser, 1986). In terms of this definition, the discipline includes mathematical activities, which deal with algorithmic processes for the description and transformation of information and also engineering activities, concerning aspects of the development and application of computers. This technological perspective conforms to the common understanding of the discipline “computer science” in the United States or Great Britain (National Research Council, 2004).

In the beginning of the eighties, the importance of computer systems increased in almost every part of society. It became more and more clear, that the use of computer systems leads to interactions between system processes and the processes in the real world. To study these interactions, many computer scientists adopted approaches and methods from social and behavioural sciences. After all, these research fields were accepted as a
part of the discipline “Informatik”. Today, many countries use the English term “informatics” - derived from the German “Informatik” - for the science of information. Nygaard (1986) for example defines “informatics” as the “science that has as its domain information processes and related phenomena in artifacts, society and nature”. This perspective separates the mathematical/logical part from the technical one and refers to the concepts of cybernetics and system theory.

![Diagram](image_url)

Fig. 1. Commonly used structural model of informatics. Informatics emerges by separation from mathematics and engineering science - later approaches from human sciences were integrated. The discipline is divided into the subdisciplines theoretical, technical and practical informatics, which are called “core”-informatics (Claus, 1975). The application and question related to the use of computers are studied by applied informatics. Also some autonomous research fields like bio-informatics or neuro-informatics exists, but they are not treated as a part of the discipline.

One characteristic of computer science is its ambition to support others scientific disciplines. In many cases the combination of technical expertise from computer science and specific domain knowledge leads to autonomous research fields like bio-informatics, neuro-informatics, business informatics or sport informatics. In Germany there was a dispute, if these research fields should be accepted as a part of the discipline. Luft (1992) for example, claims a strict distinction between the cooperation fields and the core area of “Informatik”. Today, the discipline in Germany (also “Informatique” in France) is a kind of mixture between computer sciences and Nygaards concept of informatics (see Fig. 1), but nevertheless the question about its boundaries is still a topic of discussion.

In the same way “Informatik” has done, German sport science has run through a process of defining themselves. One common definition, published in a German Encyclopaedia, describes sport science as the “collectivity of knowledge, scientific argumentation and research methods that deal with problems and phenomena related to sport” (Röthig & Prohl, 2003). While this definition is obvious, it provides no sight into the epistemological characteristics of the discipline. For example, it is quite difficult to define, what the term “sport” exactly means. One approach was the formulation of criteria, which are common to all instances of sport (e.g. motor activity, principle of organisation, non-productiveness, fair-play, performance). It is easy to see, that these criteria - however they are selected – do not apply every type of sport. To call an activity sport, it is neither necessary that all criteria are present, nor is it possible to say, which of the possible combinations can be regarded as being sport.

Another important point in the theoretical discussion is the relationship between the subdisciplines of sport science. In the late 1960s, the existence of German sport science was a “bone” of political contention. The proponents needed a good reason as to why a
new discipline with its own structures and resources should be established in the academic landscape. Therefore the argument was put forward that the complexity of sport could not be investigated by existing research fields (Grupe, 1971). The exigency of one unified discipline, with a high degree of interdisciplinarity between its subdisciplines, was the central argument for the foundation of sport science. To support this position, Ries and Kriesi (1974) proposed a model, which shows the development of sport science in three phases, (1) detaching from base disciplines, (2) aggregation of subdisciplines within a multidisciplinary science and (3) integration of sub disciplines into a consistent and integrative science (fig. 2).

![Idealized model of sport science development](image)

Fig. 2. Idealized model of sport science development (Ries & Kriesi, 1974). Detaching of sport related research fields from bases sciences, additive aggregation into a multidisciplinary science and integration of sub disciplines into a unified science.

The scientific reality showed, that - in contrast to this idealized model - the subject sport was mostly studied through the eyes of each subdiscipline (e.g. sport sociology, sport psychology, exercise science). Today, German sport science has accepted that the idea of an integrative science was not a very realistic one. Sport science does not describe itself as a “unified science of sport”, but as a collection of overlapping research programs, in which interdisciplinarity exists only in a sporadic and theme centred way (Höhner, 2001).

**Common fields of interests – Why do computer science and sport science cooperate?**

Here it is useful to differentiate between political, scientific and personal motivations behind cooperation. From a political perspective we must bear in mind that interdisciplinarity is considered an important research paradigm in most countries. The German Research Foundation (DFG), which is the central research funding organisation in Germany, holds the view that “scientific progress arises more and more at the borders and intersections of disciplines” (DFG, 2008). The national promoter for sport science in Germany (German Federal Institute of Sport Science) terms interdisciplinarity a “key element” of their foundation policy. In announcements made on funding initiatives, refer to an “inter- and multidisciplinary approach […], integrated construction of theories, highly specialised choice of research methods and [… ] integrative presentation of results” (BISp, 2008). While the precise meaning of such catch-phrases is somewhat clouded in jargon, a scientist, whose career depends on the positive evaluation (and funding) of his research projects, is ill-advised to refuse the commitment to interdisciplinarity.
Sweeping aside this consideration, sound scientific justification for cooperation does exist (see fig. 3). First of all - from sports science perspectives - computer science serves as an appreciated partner in those areas in which sports scientists do not themselves excel. This applies to the handling of data and the development of software, e.g. for the purpose of documenting training, controlling sensors or visualizing data. Secondly, information technology is an important source of innovations for training and competition. Collaborations with computer science help sport scientists to become aware of new technology and have the advantage of facilitating their availability in good time. Thirdly, sport science expects that the approaches and perspectives of computer science should be transferable to the field of sport. The concept of soft computing can assist the understanding of complex systems in sport. The analysis of tactical structures in handball using artificial neuronal networks (Pfeiffer & Perl, 2006), the optimization of a bow riser with genetic algorithms (Vajna, et al., 2007) or the modelling of game dynamics in tennis using dynamic system theory (Walter et al., 2007) serve as examples of this.

Fig. 3. Cooperation interests of computer science and sport science.

Less immediate are the benefits of cooperation with sport science from computer science perspective. While traditionally computer science has supported other sciences, extending its own area of influence would not provide sufficient argument in favour of supporting projects in the field of sports. Of greater interests is the complexity of sport, which is well suited for testing and validation of methods and techniques of computer sciences.

The existing structures in sports are neither too simple to be interesting, nor to complex to be described using mathematical models. One example of a problem is that of reconstructing human intention, e.g. as in the case of computer-aided crime detecting based on video recordings of surveillance systems (see Boghossian & Black, 2005). In fact sport science deals with sport games analyses in which similar computational requirements exists (automatic recognition of players, moves and strategies) albeit with reduced complexity (limited degrees of freedom, common rules, tactical invariants) is a similar problem. Computer science expects the development and validation of solutions for sports, to lead to knowledge, which then can be transferred to the initial problem. More generally speaking, sport could act as an attractive testing field for computer science, in which human behaviour can be observed and studied in a simplified, yet authentic field.

Additional motives for computer scientists are the societal relevance of sport and its close contact to the mass media. This gives them the chance to present research programs of their own to those sections of society, which do not have a high affinity to science. The “exotic” application field can also help them to build a reputation in the scien-
tific community. Last but not least, many computer scientists, working with sport science, a personally involved in sport. Even if collaboration cannot be fully justified on the basis of individual involvement, political considerations and increasing publicity, these factors do seem to have importance as secondary motives.

Quality of Interdisciplinarity – How do computer science and sport science work (or should work) together?

There are many ways in which the concept of “interdisciplinarity” has been classified by philosophy of science. One milestone in nomenclature was a congress in the year 1972, where the OECD proposed a classification of interactions between disciplines (OECD, 1972). In terms of this definition, multidisciplinarity is a juxtaposition of various disciplines without a connection between them. Interdisciplinarity describes any interaction between disciplines, which can range from simple communication of ideas to the integration of concepts, methodologies and epistemologies. Transdisciplinarity is the highest degree of cooperation and stands for a common set of theories and axioms for a set of disciplines (fig, 4). On this basis, enhanced models, focusing on different aspects of interaction were developed: Heckhausen (1972) for example identifies six types of interdisciplinarity research, Boisot (1972) advises three categories of interdisciplinarity, Karlquist (1999) lists five modes of interdisciplinarity (an overview is provided by Chettiparamb, 2007).

Fig. 4. Commonly used classification of types of interdisciplinarity (OECD, 1972).

When looking into the practice of sport informatics, it emerges that not any of these models is adequate to describe the existing interaction. The “borrowing” of computer scientific methods (type a, b, c) matches to Heckhausens concept of auxiliary-interdisciplinarity. The simple usage of pre-defined tools (type a) corresponds to the OECD-term multidisciplinarity. The corporate development of tolls/methods (type b) can be called pseudo-interdisciplinarity (Heckhausen) or restrictive interdisciplinarity (Boisot). The use of sport scientific knowledge in computer science (type d) accords with the idea of structural interdisciplinarity (Boisot). In this regard, this paper proposes an own classification, using four types of cooperation (see fig. 5):

- Type a: Sport science applies existing approaches and tools from computer science. In this case, sports science does not take part in conceptualization and development. Computer science (or commercial software developing companies) only act as an anonymous service provider, without contact with sport science.
• Type b: Sport science integrates knowledge from computer science. This happens, when its own area of studies needs technical solutions, which do not exist on the market. Knowledge is assimilated either by acquiring the skills necessary or by entering into partnerships with computer science e.g. by means of student or third party funded projects. One aspect of this cooperation is that computer science provides nothing but skills in software development. There is no collaboration on a scientific level.

• Type c: Computer and sport science cooperate in research programs, which are in accordance with the research interest of both disciplines. Examples are the use of artificial neuronal networks for analyzing movement patterns in squash (see Perl & Dauscher, 2006) or the application of pattern matching algorithms in soccer game analysis (Beetz, Kirchlechner & Lames, 2005). In this cases, computer science gets new insights by validating concepts and methods which have relevance for additional - perhaps more complex - problems. Sports science benefits from an improved and faster data acquisition and by getting a different perspective on the structures of sport.

• Type d: This type is comparable with type c, with the difference that paradigms and knowledge of sport science are used in computer science. An example would be the use of kinesiological models in controlling the motion of humanoid robots.

A review of the research activities in the last 20 years reveal that many projects of type a and b, but only a very few projects of type c and d can be found. One reason, why the popularity of sport informatics in the computer scientific community is not very high (there are computer scientists, who never heard about it or do not show interest in cooperation with sport science) might be, that there is often no genuine interdisciplinary research. A deeper concentration on those fields where computer science can profit from sport scientific paradigms and knowledge (types c and d), could improve the situation. This would require better communication of sport scientific expertise and recognition of sport as a fruitful application field for computer scientists (see Fischer, 1998).

![Fig. 5. Types of cooperation in sport informatics.](image-url)
(like biology and chemistry, astronomy and physics or sociology and psychology), there is no common borderline, where one discipline changes into another and no shared knowledge. Consequently sport informatics cannot be an autonomous inter-discipline like astrophysics or biochemistry. One-way-transfer is also a natural problem, because the processing of information is fundamental for all sciences, whereas the applications fields of computer sciences usually cannot provide any knowledge for the core area of computer science (apart from mathematics and electrical engineering). Even sport science and computer science have problems in creating real interdisciplinarity between their sub disciplines. They are both heterogeneous sciences without consistency in level of theoretical integration, axioms, methods and terminology (see discussion in section two). For this reason, while it is advisable to postulate and advance interdisciplinarity, it does well not to overcharge the idea of integration.

Mission statement – The self concept of sport informatics

With regard to the discussion in the last sections, this paper suggests differentiating between sport informatics and computer science in sport. Computer science in sport stands exclusively for the use of computer technology in sport and sport science. Sport informatics also includes the application of methods and paradigms from computer/information science as well as from research programs, which try to transfer sport scientific knowledge to computer sciences. The following definition shows this enhanced self concept:

Sport informatics is a set of multi- and interdisciplinary research programs at the interface of sport science and computer science. The material field is the application of tools, methods and paradigms from computer science on questions of sport science as well as the integration of sport scientific knowledge in computer science.

Figure 6. Basic structure of sport informatics. The discipline can be described as a set of multi- and interdisciplinary research programs. Most of these programs apply technological and methodological knowledge of computer science to study questions of sport science, but there are also some sport scientific findings, which can be useful for computer science.

We can see in figure 6 a structure diagram which visualizes this standpoint: In both disciplines there is knowledge, which is potentially useful for the other discipline. Con-
versely there is a second area, which might be an application field for the findings of the other discipline. The research programs include parts of sports science and computer science and can be dedicated to one of the four types, identified in the last section.

Figure 7 shows a refinement of this rough structure by using a matrix with four areas: the first area (top, left) shows themes of computer science, which may be useful for sport science. Following a paper published by Perl and Lames (1995), these subject matters are divided into two dimensions. The first dimension includes four main research areas of computer science, which are important to sport: (1) handling (e.g., the recording, processing and management) of data, (2) modelling, analysis and simulation, (3) presentation and visualization and (4) communication. The second dimension illustrates the opinion, that sport informatics is (and must be) more than just the simple application of tools for recording, managing and presenting data. In addition to the “tool-level”, there are methods, theories and paradigms of computer science which are able to make a contribution to sport scientific theories (see section 3).

Figure 7. Subjects of sport informatics. The matrix shows examples for research and application fields mentioned in figure 6.

The second part of the matrix (top, right) shows examples for application fields in sport and sport science. These fields are structured with “theory building” (getting new theoretical insights into phenomena of sports), “intervention” (improving training and competition) and “organisation” (managing activities related to sport). The third and forth part (bottom left and right) show examples for sport scientific knowledge fields, which are potentially useful for research in computer science. Here, no internal differentiation seems to be expedient. It should be mentioned, that categories are open lists and items only examples. A concrete and more detailed outline of research activities is available in meta-studies (Baca, 2006, Perl, 2006).
Conclusion

The paper has shown options for reasonable and fruitful liaisons between sport science and computer science. They hold a set of advantages for both disciplines, if projects are designed and performed with the view on genuine interdisciplinary research. As scientific progress in this area is closely connected to technological progress, sport sciences is well advised to monitor developments and to integrate partners from computer science into own research activities. Important technological improvements in the future will be increased computing power and network capacity, networks concepts such as ubiquitous or pervasive computing, small and cheap one way electronics, thin and flexible displays as well as better speech recognition and geo-spatial positioning technologies (Oertzen, Cuhls & Kimpeler, 2006). These technologies have a potential impact e.g. on the measurement and reporting of physiological and positional data, on computerized performance analysis, sport clothing and the quality of computer simulations in the fields of sports engineering, motor behavior and physiological adaptation. The development and implementation of innovative prototypes in these areas, will comprise the central area of work for the sport informatics community in the years to come.

References


EXPERIENCES USING SMART-SYSTEM

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Abstract
The SMART-system is a sport competition-based video database developed at JISS. It has been made available to all national sports federations (NF) in Japan from the year 2007. Since then more than 12 NFs are using the system; 726 users are registered, and 39,601 video files are archived as of Aug. 2009. Provision of this software system demonstrates various factors for training athletes and coaches: (1) if good instruction is given to the users, this kind of software will become a good tool for top athlete support, (2) each NF has shown a different purpose for using this software according to each NF’s training strategies, (3) videos are archived and categorized into two categories: competitions videos and daily training videos, (4) meta-data gathering and its uploading are one of the tedious tasks of the system that should be simplified.

KEY WORDS, VIDEO, MULTIMEDIA, DATABASE, META-DATA

What is SMART-system
SMART-system is a video database, designed and developed at JISS to assist in the training activities of athletes and coaches. The purposes of the system are,

- Ability to manipulate thousands of videos with simple searching methods
- Capacity to share videos with coaches and athletes
- Provision of suitable video browsing to many different sports

The system is based on server/client architecture. Meta-data is archived on the server for searching, and videos are accessible using streaming technology. Meta-data searching uses simple searching methods, with streaming on the Internet that enables the sharing of video with coaches and athletes. To browse the video, client software was built, named SMART-viewer. This makes possible step-by-step, slow motion, simultaneous two videos playback, plus ability to add textual or pictorial comments on the videos. This client software provides sports oriented browsing.

Fig.1 shows system’s overview. Meta-data servers on JISS, distributed streaming servers, and SMART-viewer are illustrated. The streaming server is placed on JISS or NF’s training center because of the accessibility for uploading video files.

Windows 2003 server or 2008 server are used for video streaming. Because of 1 Mbps bit-rate encoding for all files, 39,601 files only need 1.05 TB disk spaces.

The system is operated under 4 system engineers in JISS who work daily on system maintenance, and support for users and managers. Managers for each NF work for video uploading, meta-data uploading, and user registration.
The history of SMART-system

JISS first experimented with video support at competition sites with a synchronized swimming team in 2002. We noticed the limitation of the commercial software that was used for the support. The need for creating a new system was recognized, and after several surveys and tests, the project for developing a video database was started in 2005.

It was four-year project, and the author lead the project with several researchers from sports information department, engineers from information technology, and two external programmers (server programming and client programming). In this project, the present system was designed and programs were developed. After a one year alpha test with several NFs, the system was opened to all NFs in the year 2007. The project has then moved to operation phase from development phase. The project was finished year 2009, and new projects for developing SMART 2.0 and operating SMART-system were started form year 2009.

Its chronological history is summarized as below,

2002: Commercial software was used for synchronized swimming video support
2003: Survey and design for new movie database
2004: Trial development for the new system
2005: Project started and complete alpha version
2006: Start trial use with several national sport foundations
2007: Open the system to NFs
2008: Improve the system and engineer's team start daily operation
2009: Project was finished and new SMART 2.0 project is started

The first public announcement of the system was IASI World Congress 2005; the author gave a presentation with the title "Content-based Movie Database for Sports" (MIYAJI 2005). Although the system does not have the name at the first announcement, (ISEA conference 2006), the author used the name SMART-system for the presentation (MIYAJI et al. 2006). At the IACSS Conference in Calgary 2006, searching methods of the system was presented (MIYAJI et al. 2007). At the IASI World Congress 2009, the author explained the system for the panel discussion of "Video and Digital Asset Repositories in Sports" (MIYAJI et al. 2009).

**Statistics of the system**

The size of the system can be captured from the number of files registered on the system for streaming. Although the records are incomplete, monthly changes are plotted as below,

![Figure 2. Transition of the number of files archived on SMART-system](image)

From the figure, it shows that the system has grown constantly (an increase of 1000 files every month) just after the public announcement in the year 2007.

The item details of the 39,601 files on Aug. 2009 are summarized below,
Table 1. Item details of archived files on Aug. 2009

<table>
<thead>
<tr>
<th>Discipline</th>
<th>Files</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerials</td>
<td>43</td>
</tr>
<tr>
<td>Figure Skating</td>
<td>660</td>
</tr>
<tr>
<td>Judo</td>
<td>11678</td>
</tr>
<tr>
<td>Moguls</td>
<td>6509</td>
</tr>
<tr>
<td>Sailing</td>
<td>61</td>
</tr>
<tr>
<td>Ski Alpine</td>
<td>105</td>
</tr>
<tr>
<td>Ski Cross</td>
<td>1525</td>
</tr>
<tr>
<td>Snowboard Half-pipe</td>
<td>15</td>
</tr>
<tr>
<td>Speed Skating</td>
<td>6628</td>
</tr>
<tr>
<td>Swimming</td>
<td>4190</td>
</tr>
<tr>
<td>Synchronized Swimming</td>
<td>4804</td>
</tr>
<tr>
<td>Table Tennis</td>
<td>1110</td>
</tr>
<tr>
<td>Tennis</td>
<td>1113</td>
</tr>
<tr>
<td>Volleyball</td>
<td>750</td>
</tr>
<tr>
<td>Other</td>
<td>410</td>
</tr>
</tbody>
</table>

We do not have the monthly record for the meta-data registration, 380,129 records are on the database, and it tells that each file has 10 meta-data on average.

Total number of the users are 726, and larger groups are summarized below,

Table 2. Top 7 groups of larger members.

<table>
<thead>
<tr>
<th>Discipline</th>
<th>Members</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed Skating</td>
<td>142</td>
</tr>
<tr>
<td>Synchronized Swimming</td>
<td>78</td>
</tr>
<tr>
<td>Judo</td>
<td>63</td>
</tr>
<tr>
<td>Volleyball</td>
<td>51</td>
</tr>
<tr>
<td>Freestyle</td>
<td>39</td>
</tr>
<tr>
<td>Table Tennis</td>
<td>33</td>
</tr>
<tr>
<td>Figure Skating</td>
<td>29</td>
</tr>
</tbody>
</table>

To understand the users activities, the system logs client use activity. SMART-viewer collects users’ actions during running, and sends the information to the log server at JISS. The information is summarized on a web page, and is sent to managers every month. Below is a sample output of the page.
SMART-system is used mainly to archive world-class competition videos, and share them with coaches and athletes. Although they share the videos, the purposes of use are different. For example, speed skating shares their videos to improve the education level of domestic coaches, but figure skating shares videos for quick and accurate junior talent identification. Because of these different purposes, the number of the users of speed skating is large. The system should have flexible authentication and restriction mechanisms in order to fit various purposes of the NFs.

SMART-system has flexible authentication for browsing the video, but it needs more restriction on meta-data display. One NF complains that the meta-data they attached gives too much information for the athlete when they use the system. This is because we thought that video restriction would cover everything even meta-data was opened to all. But it was not enough.

**Volleyball**

Japan Volleyball Association (JVA) has their own streaming server on their office. They archive not only world-class competitions, but also take video during training attaching meta-data for athletes to browse after training. For example, when they train at National Training Center (NTC), a fixed camera takes all training sessions. This video is saved to files on a computer. JVA technical staff attaches meta-data and upload them 1 hour after training.

We expect this type of application will increase, and the system should be simpler and quicker for gathering meta-data and uploading the data.
Judo

The Judo federation is the best customer for SMART-system. They archived 11,678 files on the system. The federation sent their staff to take videos for all world class competitions. They then shared these videos with athletes, coaches, and staff using SMART-system. For example, the Olympic women 70 kg gold medalist Ms. Ueno stated that she checked all her opponents' matches using SMART-system at her training site, and then practiced how to respond to them. Her coach commented that video is very useful only when athletes watch the videos with a positive attitude. Below is a snapshot of Ms. Ueno using the SMART-system.

SMART-system will be useful for any combat sports which needs to practice correspondent moves to their opponent.

![Figure 4. Olympic gold medalist Ms. Ueno uses SMART-system](image)

Synchronized Swimming

From 2002 to date, JISS worked with Synchronized Swimming, providing athletes and coaches with under and above water video at competition sites. This NF was very cooperative, and many trials for the system were started at this event. Below is the history of this immediate video feedback,

- 2002 Japan Open (using a commercial software)
- 2003 Japan Open (using a commercial software)
- 2004 Japan Open (using a commercial software)
- 2004 World Grandprix (modify a commercial software)
- 2005 Japan Open (modify a commercial software)
- 2006 Japan Open (using SMART-system)
- 2006 FINA World Cup (using SMART-system)
- 2007 Japan Open (using SMART-system with uploading through the Internet)
2008 Japan Open (using SMART-system with local file server)
2009 Japan Open (using SMART-system with High Definition Video)

Below is a snapshot at feedback site. The Japan Open is open to overseas teams, and the system is open to these foreign athletes. To watch how they use the system provided good information for improving the system. Top athletes especially are very enthusiastic about using the system with their team mates or coaches. All videos of competitions are archived on the system and provided to the athletes and coaches.

![Figure 5. Spanish duet uses SMART-system at Japan Open.](image)

**The future of SMART-system**

During working with several NFs, we learn how to improve the system. Here is the concept to design SMART 2.0,

**Improve scalability**

In order to archive from world class competitions to video during training, the system should have more scalability with a more distributed system suitable for these needs.

**Good cooperation with web system**

To improve meta-data uploading, editing, analyzing, the system should work smoothly with web system.

**High definition video ready system**

High definition (HD) video is suitable for sport in various aspects. The system should be compatible to HD video from the viewpoint of camera capturing and video file format.
References


VISUALIZATION OF POSTURE CHANGES FOR ENCOURAGING META-COGNITIVE EXPLORATION OF SPORT SKILL

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Abstract
Acquisition of embodied skills in sports can be regarded as a process in which an athlete explores how to move their body. It is important for an athlete to explore their own body movements for constructing an internal skill model. Meta-cognitive verbalization about own body movements is one of the methods for accelerating the exploration process. Research has indicated that meta-cognitive verbalization is effective for acquisition of embodied skills, and in addition, has suggested that such support based on motion measurement that encourages this verbalization is necessary. This study explores ways to encourage meta-cognitive verbalization based on motion data. This paper presents a software tool to simply represent and visualize changes of an athlete’s body posture. The software segments an athlete’s body movements into discrete phases according to similarity, and represents each phase by one colour. The procedure consists of motion measurement by using an optical motion-capture system, segmentation of body movements by K-means algorithm, and visualization by colour. The visualization of body movements by colour gives an athlete an opportunity of meta-cognitive exploration. In the case study of swing practice of a baseball, using the visualization software helped a baseball player discover an important aspect of his form in a meta-cognitive custom, and as a result, became a driving force of a remarkable improvement of batting average.

KEY WORDS, EMBODIED SKILL, VISUALIZATION, META COGNITION

Introduction
Acquisition of embodied skills in sports can be regarded as a process in which an athlete explores how to move his or her own body. In sports, a proper way for an athlete to move body depends on his or her physical characteristics, and it is not necessarily common among all athletes. Therefore, it is important for an athlete to explore what way of moving body is the proper or suitable way. In the exploration processes, an athlete keeps constructing an internal skill model by trials and errors. The internal skill model consists of some key features in his or her own body or the surrounding environment and of their relationships, and thus is original to the athlete. The exploration process consists of discovering new features and incorporating them to the existing skill model.

Meta-cognitive verbalization about own body movements is one of methods for accelerating the process. Past literature has indicated that meta-cognitive verbalization is effective for acquisition of embodied skills, and in addition, has suggested that such support
based on motion measurement that encourages meta-cognitive verbalization is necessary (Suwa, 2008). Visualization of body movements and its quick feedback to an athlete seem to be significant for that support. This study is to explore ways to encourage meta-cognitive verbalization based on motion data. The present paper presents an idea of a software tool to simply represent and visualize changes of body posture of an athlete using a colour bar. We have used this tool for a process of an amateur baseball player’s acquisition of skills of bat swing, and through that case study, have found, revised and accumulated ways to use it for encouraging his meta-cognition.

**Visualization of body movements**

This chapter describes a procedure of visualization of body movements in this study. Our visualization tool segments an athlete’s body movements into discrete phases according to similarity, and represents each phase by one colour. The procedure consists of motion measurement by using an optical motion-capture system, segmentation of body movements by K-means algorithm, and visualization by colour.

We employed a motion-capture system (Motion Analysis, MAC3D system) to measure bat swings of a baseball player, using 12 cameras. The frame rate is 240 Hz. Figure 1 shows the positions to attach markers.

![Figure 1. Marker position in measurement by an optical motion-capture system](image)

A simple set of 13 positions for the body is sufficient for the purpose of our visualization tool. For a bat we attached 4 markers. Based on the marker positions, we simply represent a player’s body posture by several triangles, 5 in the simpler case as shown in Figure 2.
Figure 2. A simplest several triangles of representing an athlete’s body postures

The more complex model consisting of 8 triangles is the following. First, the upper body is divided into two triangles using the data of dorsal midpoint. Further, in order to consider the angle formed by the bat and the lower arm, we add two triangles, one for the angle between the right arm and the bat and the other for the angle between the left arm and the bat.

The body posture of each time frame is converted into a plot in a multi-dimensional space. In the simpler case, for example, we suppose 15 dimensional space, comprising of 5 dimensions for the area of each triangle and 10, i.e., $\binom{5}{2}$, for the angle formed by each pair of two triangles out of five (the inner product of normal vectors of the two triangles). Since the frame rate is 240 Hz, 480 points are plotted in the 15-dimensional space for the body movements during 2 seconds, for example. One trial of bat swing lasts approximately 2 seconds.

These plots in the multi-dimensional space are, then, clustered by K-means algorithm in order to segment the whole posture changes into different groups. The larger the number of plots is, the better K-means algorithm works. Therefore, all the data from two or more trials is plotted into the multi-dimensional space. This is advantageous for the purpose of comparing the “colour bars” generated from two or more trials of bat swing, too. By the K-means clustering, neighbour plots are classified in one cluster, which means that the body postures corresponding to those plots are judged to be similar. After the clustering, the body posture for each time frame is labelled with the name of the allocated cluster. Figure 3 shows the concept of segmentation of body movements by K-means algorithm.

Figure 3. A concept of a segmentation of body movements of two or more trials by K-means algorithm

Then, one colour is allocated to each cluster, and thus the entire posture changes for each trial of body movements, e.g. bat swing in the present paper, is represented by the sequence of colours. We call the sequence of colours generated for each trial a “colour bar” (Nishiyama and Suwa, 2008).

Findings about how the tool encourages meta-cognition

This chapter describes the findings we have accumulated about how to use this tool for encouraging a player’s meta-cognition. Just looking at a single colour bar generated from one trial of bat swing does not encourage interpretation at all. Rather, comparing
several colour bars promotes interpretation and discovery, and thereby seems to encourage meta-cognition. Figure 4 shows a series of 16 colour bars arranged parallel, each corresponding to 16 trials of bat swing in June 18th, 2008. We call a series of aligned colour bars “aggregated colour bars”. In order to make comparison easy, all the colour bars are arranged so that the time frames for the landing of the left foot are horizontally aligned. As shown in the video frames in Figure. 4, the player raises the left foot high for backswing. We identified the time frames for the raise and the landing of the left foot based on the data on the marker of the left ankle joint.

If the player swings, in every trial, exactly the same way in terms of the timings and the body postures, rigid horizontal colour layers, in which the borderlines between adjacent colours are horizontal, are to appear in an aggregated colour bars. Normally, however, the timings of the shift from one colour to another differ for all the trials, and thus the borderlines between adjacent colours in several colour bars are disarranged more or less. In the aggregated colour bars for June 18th, 2008, the disarrangement is not so large and something like horizontal layers is observed, especially after the raise of the left foot. For all the 16 trials, the colours used are exactly the same and the timings of shift are similar. That is to say, we can say that bat swings were relatively stable on June 18th.

The only salient difference in the aggregated colour bars for June 18th lies before the raise of the left foot. That corresponds to the first stance, i.e. standing still waiting for the beginning of (supposed) pitcher’s motion. The colour used for the 8 colour bars, ranging from the 8th from the left to the 15th, is different from that used for the other colour bars. For every swing, the player meta-cognitively wrote down what he perceived and thought concerning the ways to use body parts and the swing as a result. Actually he noticed after the 7th swing that he had not attended to a checkpoint of not bending angles of knee too much, and revised the initial stance a little for the subsequent trials. This checkpoint was what he thought during those months he should attend to. He had just forgotten it before the 8th trial. Although the change of the player’s intention was clear, the revision was physically just tiny to such a degree that it is hard to identify the difference for a mere video observation. Our colour bar identified the dif-
ference. The player was satisfied in two respects. First, the change of his intention is reflected and visualized even if it is a tiny difference physically. This is significant because the power of visualization with a resolution to this degree augmented the player’s feeling of trust to this tool and motivated the use of this tool in his swing practice. Secondly, he was satisfied to recognize that he was able to keep attention to this checkpoint, and actually made it stable for all the subsequent trials of swing except the last one.

During the spring to summer months, the player’s performance in actual games was terrible; the batting average was 0.083, 1 hit for 12 at bats for 4 games. Thus he determined to change his batting form radically at the beginning of July; he explored a new form that does not raise the left foot too much. Figure 5 shows an aggregated colour bars on July 2nd, exactly during the exploration.

![Figure 5. Colour bars generated from data of July 2th](image)

Figure 5. Colour bars generated from data of July 2th
There is no clear horizontal layer around the timing of backswing, which means that the swing was very unstable. Ways to keep posture during backswing seemed to differ for almost every trial of swing. In the beginning of August, his performance suddenly reached a breakthrough. He reported that his meta-cognition reached understanding of how the body parts function and relate to one another in the new form, and also that he sensed that the new form turned stable. Figure 6 shows an aggregated color-bars on August 21th. The aggregated colour bars showed clear horizontal layers.

The batting average after August turned to remarkable improvement, i.e. 0.409 (9 hits for 22 at bats) for 11 games. The player reported that the use of this tool was one cause for the success.

We have so far found the following three roles of this visualization tools. An athlete is able to

- check if his or her meta-cognitive intention really reflects the body movements,
- see the stability of swings through different trials in a day and throughout different days, and
- compare colour bars among trials, and if any difference, obtain a driving-force to meta-cognitively explore why.
Conclusion

In this study, we developed a visualization tool for encouraging an athlete’s meta-cognitive exploration for own embodied skill. Simply representing the whole body by several triangles and representing the posture by the relations of those triangles provide rough segmentation of posture changes. The tool was applied to a feasibility study of swing practice of a baseball player. Its use helped him discover an important aspect of his form in a meta-cognitive custom, and as a result, became a driving force of a remarkable improvement of batting average.

References


MOBILE COACHING

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The field of Mobile Coaching has its main goal in providing mobile and handy training support to sport-related people like athletes and coaches. This mobilization is achieved, amongst others, by the integration of modern handheld computers such as PDAs or MIDs into the training process. Meanwhile, most of these mobile devices have the ability to connect wirelessly to the Internet and different other computer networks, allowing in this way the usage of online services, e.g. for data transmission, also at the place of training. A mobile coaching system that makes use of mobile technology to provide sports performance tracking and feedback methods in a generic manner is proposed.

The system is built up according to a client-server model, where primary data is gathered at level of the athlete-clients (A-clients). Modern wireless sensors are attached to the sportsmen for the time of their training, thereby allowing a constant generation and registration of sport-related parameters. Consequently, completely cable-free measurements of training data can be carried out and later on used for analysis purposes. The measured signals are transmitted through a wireless network and thereupon received onto a mobile device, which is primarily responsible for the temporary storage and synchronization of the parameters. If the handheld computer is also connected to the Internet (for example through a WiFi or UMTS connection) the data is forwarded to the server component, where the information is stored permanently. Consequently, the server part is responsible, amongst others, for the administration, organization, management control and storage of the obtained data.

In addition, coaches and other experts should be able to monitor the athletes' performance simultaneously from remote locations. Therefore, further client applications - the so-called E-clients - have to establish the necessary bidirectional web connection between athletes and experts via the server component. In this way, the E-clients provide means to analyze the training data and return feedback to the A-clients from a distant place. Athletes could then benefit from feedback given by trainers and experts who are currently not at the same location. Furthermore, sportsmen are able to get important information about their performance outcome just after their workout or even concurrently.

Our current research is a work-in-progress: While a simplified prototype including an A-client implementation as well as a web-based visualization tool for basic feedback purposes is at a final development stage, first steps on the integration of the E-client applications has already been started. Their integration into the framework would then allow an efficient mobile feedback support between remotely located athletes and experts and complete the ultimate aim of the coaching system.

KEYWORDS: MOBILE COMPUTING, SENSOR TECHNOLOGIES, FEEDBACK, COACHING
MUSCULAR ACTIVATION STRATEGIES DURING COUNTERMOVEMENT JUMP IN FEMALE VOLLEYBALL


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ABSTRACT

Volleyball is a game in which success depends largely on athletic abilities of participants. Understanding the biomechanics of jumping is therefore a prerequisite for designing effective training program (Reeser & Bahr, 2003). The purpose of this study is to define the muscular activation strategies during countermovement jump among female volleyball players. Twenty-one healthy female volleyball players and fifteen sedentary participated into this study. Surface electromyographic (EMG) activity of biceps femoris (BF), gastrocnemius (GAS), gluteus maximus (GM), vastus lateralis (VL), vastus medialis (VM) were recorded on countermovement jump. To define the muscular activation strategies during countermovement jump, which was analyzed in propulsion, flight and landing phases, independent two samples t-test was used. Besides, activations of muscles were more in high level volleyball players than that of the control group subjects during propulsion phase (p<0.05). Volleyball players had more BF muscular activation during propulsion phase (P<0.05). As being VM and VL agonists and BF antagonist during propulsion phase, the results showed that volleyball players had higher agonist-antagonist contraction ratio than control group. The highest EMG activation during landing phase was recorded in GAS. GAS muscular activation was higher in control group than that of volleyball players (p<0.05).

KEY WORDS, COUNTERMOVEMENT JUMP, EMG, MUSCULAR ACTIVATION, VOLLEYBALL PLAYERS, PLYOMETRICS, MVC

INTRODUCTION

Volleyball is a game in which success depends largely on athletic abilities of participants. In particular, the ability to jump high, quickly and explosively is essential to most of the volleyball skills, including spiking, blocking, jump serving and even setting. Each one of the volleyball players jump 22 times on each game (Tillman et al, 2004a).

Thus, it is common to include plyometric trainings in volleyball players training programs. Countermovement jump start from an upright standing position and make a downward movement before starting to move upward and countermoved until the knee
was flexed to 90° (Kubo et al, 1999; Bobbert et al, 2005). Understanding the biomechanics of jumping is therefore a prerequisite for designing effective training program. Muscles, acting about a joint, function naturally through a combination of eccentric (lengthening) and concentric (shortening) activations (Reeser & Bahr, 2003). The stretch-shortening cycle (SSC) is a natural component of muscle function in many daily activities, such as running, jumping, and throwing. Normal locomotion involves use of stretch shortening cycle (SSC) muscle action in which the active muscle is first stretch and subsequently shortened. The SSC is defined as a sequence of an eccentric muscle action immediately followed by a concentric muscle action. It is well known that if an activated muscle is stretched before shortening, its performance is enhanced during the concentric phase (Hoffren et al, 2007; Kubo et al, 1999).

In human movement studies standing jumps with or without countermovement have been widely explored both kinetic and kinematic (Hoffren et al, 2007; Kubo et al, 1999; Chappell et al, 2006; Viitasalo, 1998). Previous studies show also that knee and hip motion patterns and quadriiceps and hamstring activation patterns exhibited significant gender differences. Lower extremity motion patterns during landing of the stop-jump task are preprogrammed before landing. Myoelectrical activity (EMG) before and during the eccentric phase of contact has been found to be highly correlated with the contact time, contact force and angular parameters in trained athletes (Chappell et al, 2007). Such a knowledge can be helpful for building up the more specific training programs for volleyball players.

The purpose of this study is to define the muscular activation strategies during countermovement jump among female volleyball players and control group.

METHODS

Subjects

Twenty-one healthy female volleyball players (age=18.2 ± 4.1, training age=8±3, weight= 61.86 ± 7.93, height=175 ± 6.4, age=18.2 ± 4.1) and fifteen sedentary (age=21.2 ± 3.1, weight= 56.9 ± 6.5, height=170 ± 4.2, age=21.2 ± 3.1) with no severe previous lower leg injury participated into this study. During the experiment period, volleyball players were on 2. division.

Design of Research

Subjects were informed about the countermovement jumping technique. Fallowing instructions were given to the subjects for measuring the true technique.

Stand in a neutral position, trunk flex and knee flex then forward slightly with back neutral position.

Explode vertically and drive arms up.

Land on both feet and repeat. Prior to takeoff extend the ankles to their maximum range (full plantar flexion) to ensure proper mechanics (Price, 2005).

Players have performed 3 maximum countermovement jump. Average of the three trials used for the EMG and statistical analyzes.
Special jumping mat from copper cables was designed for this research. Also copper plate was fixed under the shoes of subjects. When the subject contact the floor copper plate and jumping mat also contact each other and send +/- 5 mV signal to the system. We could determine the contact time of foot with this method. Also we could calculate the time when the subjects take off time duration. With this data jumping height was calculate from jumping height formula.
Bipolar surface electromyographic (EMG) activity of biceps femoris (BF), gastrocnemius (GAS), gluteus maximus (GM), vastus lateralis (VL), vastus medialis (VM) were recorded on countermovement jump. All EMG data that were measured on the dominant leg of the subjects were recorded using bipolar surface electrodes. Electrode sites were prepared by shaving, abrading and cleansing the area. Skin tack F55 circular Ag/AgCl surface electrodes, filled with conductive electrolyte. The distance between two electrodes was approximately 2 cm and they were positioned longitudinally along each muscle. The reference electrode was placed on the knee joint. Maximum voluntary contraction (MVC) tests were done when the subject fastened to isokinetic dynamometer. Isometric MVC of the VL and VM were calculated at 65° in sitting position. MVC of BF were calculated at 30° in prone position (Kellis and Baltzopoulos, 1988). For MVC of GAS muscle of subjects were asked to do planter flexion against a certain resistance when they are supine position. Raw EMG data were epoched starting from 800 msec prior to and ending after the ground contact, full wave rectified, normalized with respect to maximum voluntary contractions (MVC) and integrated. During the 800 msc prior and 800 msec after the ground contact were analyzed. Analog signals were digitized by a 12-bit A/D converter. Pass band of the EMG amplifier, sampling rate, maximum intra-electrode impedance and CMMR were 8–500 Hz, 1000 Hz and 95 dB, respectively.

Statistical analysis

Descriptive statistics were applied to identify the characteristics of the subjects and groups. All data are expressed as means±SD. To define the muscular activation strategies during countermovement jump, which was analyzed in propulsion, flight and landing phases, independent two samples t-test was used for the comparison of groups. The level of significance was set at p<0.05. VL, VM, GAS and BF muscles analysed for takeoff time and landing time respectively.

RESULTS

Statistical information of take off times of volleyball players and control group is shown in Table 1. Jumping height was calculated with \( h = \frac{(g.t^2)}{8} \) formula (Urabe et al., 2005). The longest takeoff time was used for calculating jumping height.

Jumping height of control group was 22 cm and jumping height of volleyball group was 34 cm. Take of time of volleyball players for three trials were more than the control group (p<0.001).
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Table 1. Statistical Information of Take off Time

All phases (jumping and landing phases) of countermovement jump belong to volleyball players and control group are showed in Figure 1 and figure 2. In figure 1 time ‘0’ means when the foots leave from the ground (take off time). In figure 2 time ‘0’ means when the foots touch the ground (landing time). Take off and landing time of countermovement jump of volleyball players are different. Because of this reason take off and landing times couldn’t be shown in one graph.

Stars over the bar graphs represents statistical significant differences (p<0.05) between groups. Strips over the bar graphs show the standard errors. Axis of x shows the time as a msc, axis of y shows the isometric MVC values of four muscles. Name of the muscles was shown the right corner of the graphs.
Jumping phase consist of propulsion and flight phases and when the time ‘0’ it means feet leave from ground. Between -1000 msec and 0 msec shows the propulsion phase, 0-500 msec shows flight phase and 500-600 msec shows landing phase.

Muscular activation differences of VM in volleyball players and control group

The first peak activation occurred at -300msec in propulsion phase with 29% of MVC of volleyball players and control group. Statistical significant differences (p<0.05) occurred in 400 msec and control group have showed higher activation than volleyball players. Statistical significant differences (p<0.05) occurred in 600 msec and volleyball players have showed higher activation than control group.
**Muscular activation differences of VL in volleyball players and control group**

The first peak activation occurred at -300 msec in propulsion phase with 28% of MVC of volleyball players and control group. As in VM muscle statistical significant differences (p<0.05) occurred in 400 msec and control group have showed higher activation than volleyball players. Statistical significant differences (p<0.05) occurred in 600 msec and volleyball players have showed higher activation than control group.

**Muscular activation differences of GAS in volleyball players and control group**

The first peak activation occurred at -200 msec in propulsion phase with 32% of MVC of volleyball players and control group. Statistical significant differences (p<0.05) occurred in -100 and 600 msec and volleyball players have showed higher activation than control group.

**Muscular activation differences of BF in volleyball players and control group**

The first peak activation occurred at -200 msec in propulsion phase with 32% of MVC of volleyball players and control group. As in GAS muscle statistical significant differences (p<0.05) occurred in -100 and 600 msec and volleyball players have showed higher activation than control group.
Landing phase consist of flight and landing phases and when the time ‘0’ it means foots touch the ground. Between -200 msc and 0 msc shows the flight phase, 0-800 msc shows landing phase.

Muscular activation differences of VM in volleyball players and control group

Statistical significant differences (p<0.05) occurred in 400 msc and control group have showed higher activation than control group.
Muscular activation differences of VL in volleyball players and control group

As in VM muscle statistical significant differences (p<0.05) occurred in 400 msc and control group have showed higher activation than control group.

Muscular activation differences of GAS in volleyball players and control group

Statistical significant differences (p<0.05) occurred in 600 msc and volleyball players have showed higher activation than control group.

Muscular activation differences of BF in volleyball players and control group

As in GAS muscle statistical significant differences (p<0.05) occurred in 600 msc and volleyball players have showed higher activation than control group.

Besides, activations of VM, VL, GM, GAS and BF muscles were more in high level volleyball players than that of the control group subjects during propulsion phase (p<0.05). BF and VL, VM contraction values were almost similar to each other in high-level volleyball players when compared with control group. Volleyball players had more BF muscular activation during propulsion phase (p<0.05). As being VM and VL agonists and BF antagonist during propulsion phase, the results showed that volleyball players had higher agonist-antagonist contraction ratio than control group. The highest EMG activation during landing phase was recorded in GAS. GAS muscular activation was higher in control group than that of volleyball players (p<0.05).

DISCUSSION

Results of the current study showed that agonist-antagonist contraction ratios and coordination, landing technique and intramuscular coordination are the important factors for countermovement jump. Having high GAS activation values during landing may be explained by landing technique as Coh et al. (2008) did.

Long compliant tendons in the plantar flexors are an elegant solution to the problem of maximizing jumping performance (Bobbert, 2001). This study also supported our study. VM, VL, GAS, GM and BF muscles are activated before ground contact in order to stiffen the joint in preparation for touch down. It can be said that pre-activation is important for the jumping performance.

It can be concluded that high level volleyball players showed higher muscular activation during propulsion phase, but lower during landing and post landing phases compared with control group.

It appears that strategic planning and training of jumps in volleyball and other jumping sports is critical (Tillman et al, 2004a, 2004b).

Mediana et al (2008), compared the pre-activation of rektus femoris, VM, medial hamstring and lateral hamstring between athletes and control group in landing. They find that muscular activation of rectus femoris and VM were more in athletes than control group. It has been seen that the results of these study are similar.
The centrally pre-programmed activity and the associated elastic behavior of the series elastic component in the knee extensor muscle in conjunction with the muscle contractile property play a major role in regulating the performance in drop jump (Horita et al, 2002). The same results were found for countermovement jump.

In this study electromyogram activity of the muscles in flight phase (stretching phase) of countermovement jump were less than other phases. Taija (2000) found that the stretching phase in CMJ was characterised by little or no electromyogram activity. The results of studies are parallel.

Having high GAS activation values during landing may be explained by landing technique as Coh et al. (2008) did. VM, VL, GAS, GM and BF muscles are activated before ground contact in order to stiffen the joint in preparation for touch down. It can be said that pre-activation is important for the jumping performance.

Conclusion

It can be concluded that high level volleyball players showed higher muscular activation during propulsion phase, but lower during landing and post landing phases compared with control group.

Pre-activation of lower extremity muscles in jumping has an important role for jumping performance and jumping height. Muscles and joints in the body are exposed to stress in landing and post landing phases.

Results of the current study showed that motor learning has an important for neuromuscular function of muscles. Agonist-antagonist contraction ratios and coordination, landing technique and intramuscular coordination are the important factors for countermovement jump.

References


TESTING DIFFERENT DEGREES OF INTERACTIVITY – AN EXPERIMENTAL STUDY

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Abstract

Interactive features play an important role within e-learning courses. In this paper we report an experimental pilot study which tested different degrees of interactivity of e-learning units. A specific experimental design adapted to a blended-learning scenario was developed. Participants learned with e-learning units, dealing with different movement analysis concepts (MACs), which only differ in interactive features (different degrees of interactivity). Pretest, posttest and immediate knowledge tests measured participants’ basic and transfer knowledge of the concepts at a given time. A comparison of pretest and posttest first results shows that students could improve their performance. The results did not show significant differences between the groups who learned with different degrees of interactivity.

KEY WORDS, E-LEARNING, DEGREES OF INTERACTIVITY, EXPERIMENTAL STUDY

Introduction

Interactive features are important for designing e-learning environments (Roblyer & Ekhaml, 2000). According to Wiemeyer (2008) within an e-learning system complex interactions can be distinguished (interactions between learners, teachers, learning content and learning system). But what makes an e-learning course interactive? In the literature different classifications, concepts and categories how to design an interactive e-learning course exist (Chou, 2003; Roblyer & Ekhaml, 2000; Sims, 1997; Wagner, 1997). Different technologies like synchronous communication tools (online-chats, video-conferencing) or asynchronous communication tools (discussion forum, e-mailing, mailing-lists, wikis) as well as specifically designed learning objects (tasks/questions with feedback, simulations, animations and interactive videos) are required to make interactions possible. These interactive features can increase the efficacy of e-learning courses. In the subproject “Functional movement analysis” of the HeLPS project, a cooperative project of the five Hessian Institutes of Sport Science, interactive e-learning units were designed. The aim was to teach knowledge of three different movement analysis concepts (Göhner, 1979; Kassat, 1995; Meinel & Schnabel, 1998) in an interactive way and moreover to practice the application of these concepts. First formative evaluations of the developed e-learning units in the winter term 2007/08 and in
the summer term 2008 showed, that students liked and appreciated the interactive features and wished more interactive support (Roznawski & Wiemeyer, 2008). To analyze the effects of interactive features in more detail, especially the differences between different degrees of interactivity, knowledge assessment and students’ motivation, a specific experimental design was developed and tested in a pilot study in the winter term 2008/09.

**Methods**

The pilot study was performed in the course “How do movements work?”. A sample of 12 students (9 males, 3 females, mean age of 24.4 years) participated and completed the course. This course was organized based on a blended-learning concept with alternating online working phases and phases of physical presence. The online working phases were supported by ILIAS, a web-based open-source learning management system. We used ILIAS for providing the online learning units, communication with the students (chat and discussion forum) and online-tests. Altogether three online phases took place. During these phases participants worked on e-learning units for one week, dealing with the movement analysis concepts (MACs) of Meinel and Schnabel (1998; MAC-MS), Göhner (1979; MAC-G) and Kassat (1995; MAC-K). In the following two phases of physical presence students applied these concepts to selected sport movements. In the first lesson students discussed in teamwork with a movement expert how to apply the concepts supported by checklists which illustrate the procedure of the MACs. In the second lesson the results of the teamwork were presented and discussed.

*The experimental design and tests*

The experimental design was adapted to the course structure. For testing the differences between varying levels of interactivity we used an experimental control design with two experimental groups (group 1/ group 2). The participants’ knowledge was assessed by five tests: a pretest, three immediate tests and a posttest. At the beginning and at the end of the experiment the participants had to answer a questionnaire to assess their motivation and attitude towards e-learning. Furthermore the participants completed a short online survey after each immediate test to evaluate their attitude towards the e-learning units (the results will not be reported here).

*Experimental design*

Based on pretest performance participants were assigned to the experimental groups (matching method). In each online working phase the experimental groups worked on an e-learning unit with identical content. The e-learning units only differ in interactive features. Interactive units (I) consist of tasks and questions with system feedback, whereas non-interactive units (NI) do not deliver any system feedback. Figure 1 shows an example for an interactive and non interactive task in the Meinel and Schnabel (1998) e-learning unit. Active units (A) required active engagement with tasks and questions and non-active units (NA) did not contain tasks and questions. Figure 2 shows an example for an active task (drag and drop) which assists active engagement with the learning content and the same learning content which is represented as tabular form and assists no active engagement.
Figure 1. Interactive Task (I) concept of Meinel and Schnabel (1998) with system feedback and Non Interactive Task (NI) without system feedback.

Figure 2. Active Unit (A) concept of Göhner (1979) task with active engagement and Non Active Unit (NA) learning content which assists no active engagement.
Figure 3 illustrates the treatment for the experimental groups: group 1 – interactive unit ‘MAC-MS’ (I), non-active unit ‘MAC-G’ (NA), active unit ‘MAC-K’ (A) – and group 2 – non-interactive unit ‘MAC-MS’ (NI), active unit ‘MAC-G’ (A), non-active unit ‘MAC-K’ (NA). Each online-working phase was followed by an immediate knowledge test performed online. One week after the last session of the course a posttest about all MACs followed. Whereas the results of the knowledge pretest and the three specific knowledge tests did not count for the course grade the results of the final knowledge test contributed 50% to the final course grade.

Tests

Pretests and posttests covered each of three MACs and were structured identically; one part assessed basic knowledge and the other part tested transfer knowledge. Altogether both tests consist of 30 basic knowledge questions (10 for each MAC) and 12 transfer knowledge questions for all MACs. In order to avoid recognition effects questions at pretest and posttest were different. The basic knowledge questions were chosen randomly from a question pool which consists of 145 questions. Students were asked if these short statements dealing with the different MACs were correct or wrong and how confident (5 stages: from ‘very sure’ to ‘very unsure’) they were with their answers. The design of the transfer knowledge questions was geared to the procedure of the different MACs and the developed checklists. Students were asked to apply the three MACs to sport movements (i.e., butterfly stroke, high jump and kip on the high bar).

Each of the three immediate knowledge tests addressed basic knowledge about one of the studied movement analysis concepts. These questions (short statements) were also taken from the question pool and the answering options were identical with the options at pretest and posttest. The immediate knowledge tests were performed using the ILIAS survey tool and have been carried out after each online-working phase.
Procedure

Pretest

In the second lesson of the course students performed the pretest to measure students’ existing basic and transfer knowledge about the three MACs. The test was carried out as a paper-and-pencil test in the classroom and took 45 minutes. Students were informed that pretest results did not count for the course grade. Furthermore they were instructed to answer the test to the best of their knowledge. Based on pretest performance students were assigned to the experimental groups.

Online phase concept of Meinel and Schnabel (1998)

After a further lesson held by the teacher the first online learning unit followed addressing the concept of Meinel and Schnabel (1998). Group 1 learned with the interactive unit (I) and group 2 with the non interactive unit (NI) for one week. The phase of online self-study ended with an online session where all students met to perform the first immediate online knowledge test dealing with the MAC of Meinel and Schnabel (1998). Additionally students answered a questionnaire about the learning units. Altogether they got 20 minutes time to pass test and questionnaire. Students were instructed to answer the test to the best of their knowledge and without any help (consult a book, look up at the learning units) in order to measure the learning performance. Furthermore the students got the information that the results did not count for the final grade. Immediately after passing the test and questionnaire an online chat lesson followed. In the chat lesson students applied the concept of Meinel and Schnabel (1998) to a selected sport movement with the assistance of the lecturer.

Phase of physical presence concept of Meinel and Schnabel (1998)

One week later a phase of physical presence with two lessons followed. In the first lesson students applied the concept in teamwork to a selected sport movement and in the following lesson their results were discussed; students were supported by a checklist.

For the MACs of Göhner (1979) and Kassat (1995) the procedure was structured and performed identically, starting with one week of online learning which closed with an immediate knowledge test about the concept. Then the two-week phase of physical presence with teamwork and whole-group discussions followed.

Posttest

One week after finishing the last MAC the posttest was performed as a paper-and-pencil test in the classroom. Like the pretest students got 45 minutes to answer the test. This time the results counted for the final grade.
Results

The total scores of the pretest and posttest were analyzed using a 2 (groups) x 2 (knowledge test) ANOVA with repeated measures on the factor knowledge test. There was a significant main effect of knowledge test (F (1, 10) = 124.14, p<.001) indicating a gain from pretest to posttest (see Figure 4). The analysis yielded no significant main effect of experimental groups (F (1, 10) = .001, p= .975) and no group x knowledge test interaction (F (1,10) =.002, p=.965).

![Figure 4. Means of total knowledge score (%) of the two experimental groups in different tests](image)

Furthermore participants’ basic knowledge for each MAC at pretest, immediate test and posttest was analyzed. The 2 (groups) x 3 (knowledge tests) ANOVA with repeated measures on the factor knowledge test yielded significant effects for the knowledge tests of MAC-MS (F (2, 20) = 80.11, p<.001), MAC-G (F (2, 18) = 42.72, p<.001) and MAC-K (F (2, 20) = 36.50, p<.001). The groups x knowledge test interaction of MAC-MS (F (2, 20) = 1.91, p=.175), MAC-G (F (2, 18) =.950, p=.405) and of MAC-K (F (2, 20) = 1.52, p=.243) were not significant. Furthermore no group effect was found for MAC-MS (F (1, 10) = .008, p=.932), MAC-G (F (1, 9) =1.51, p=.251) and MAC-K (F (1, 10) = .223, p=.647). Figure 5 shows the percentage basic knowledge scores of the two experimental groups in the different tests. Wilcoxon tests revealed that participants continuously increased performance at each test for each MAC.
Figure 5. Basic knowledge scores (%) of the two experimental groups at different tests

The participants’ transfer knowledge of each MAC at pretest and posttest was analyzed with a 2 (groups) x 2 (knowledge tests) ANOVA with repeated measures on the factor knowledge test. We found a significant main effect of knowledge test for MAC-MS (F (1, 10) = 7.49, p<.05) and MAC-K (F (1, 10) = 5.25, p<.05) but not for MAC-G (F (1,10)=2.22, p=.167) indicating knowledge gain concerning the MACs of Meinel and Schnabel (1998) and Kassat (1995). No significant group effects for MAC-MS (F (1, 10) = .123, p=.733), MAC-G (F (1, 10) =.009, p=.926) and MAC-K (F (1, 10) = 1.368, p=.269) were found. The groups x knowledge test interactions were also not significant for MAC-MS (F (1, 10) = .320, p=.584), MAC-G (F (1, 10) =.251, p=.627 and MAC-K (F (1, 10) =.000, p=.983). Figure 6 shows the transfer knowledge scores of each MAC at pretest and posttest.
Discussion and Conclusions

The reported pilot study served to test an experimental design for examining different degrees of interactivity and to measure knowledge, motivation, and attitude towards e-learning.

The results reveal various learning effects. A total effect refers to the whole course and a specific effect to the e-learning units. Both experimental groups could improve their knowledge of the three different MACs during the course. Compared to pretest results the results of the immediate tests showed that both experimental groups improved their basic knowledge of each concept after learning with the e-learning units. Altogether they could improve their knowledge continuously until the posttest (no ceiling effect).

Comparing the immediate test knowledge scores of all MACs, these scores showed, that both groups scored best at MAC-MS, second best at MAC-G and they achieved the lowest scores at MC-K. This is possibly caused by the degree of difficulty of the three concepts, because difficulty and complexity of the concepts are increasing from MC-MS to MC-K. Furthermore it is noticeable that group 2 received lower scores than group 1 at all immediate tests and that they only performed comparably well at posttest.

A detailed analyze of the immediate knowledge test scores of group 2 showed, that motivation to score well at the immediate tests (especially at test MAC-G and MAC-K) presumably was not high enough for group 2 participants (zero scores) because test scores had no effects on the final grade.

The students also improved their transfer knowledge of (MAC-MS and MAC-K) from pretest to posttest but there was no effect for MAC-G. A reason for this could be, that transfer knowledge questions of MAC-G possibly had a higher level of difficulty at posttest than the transfer knowledge questions of MAC-MS and MAC-K.

Contrary to our expectations we did not find any significant differences between the groups who learned with different degrees of interactivity. This could be due to the fact that we only tested small groups (6 participants per group). Moreover we could not eliminate or control the impact of potential external factors like using additional support during the online tests.

As a consequence the following improvements are planned for the next term: The immediate knowledge tests will be organized as paper-and-pencil tests demanding physical presence during a course session. Furthermore all test results will contribute to the final grade. In addition this experiment will be repeated with a larger number of participants in the summer term 2009.

References


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AN AUTOMATED APPROACH TO COMPARE IN-THE-RUN MARKETS WITH SCORE IN EVALUATION OF TEAM PERFORMANCE

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Abstract

Often in sporting events, the real-time betting odds (or “in-the-run” odds) and the score are misaligned; that is, there is a clear difference in market opinion of victory and the current score. This difference can be attributed to the in-the-run odds being based on expectations, incorporating: past results, home ground advantage and any perceived momentum. A graphical representation of these in-the-run odds is of particular importance to coaches as they can determine whether their team exceeds or falls short of expectations during the match. This research focuses on the automation process involved in recording in-the-run odds by utilizing Betfair’s Application Programming Interface (API) using a Perl script. These recordings are updated in a MySQL database which can then be exported directly as a CSV file for manipulation. This paper will focus on this application to Australian Rules Football (AFL), and investigates the dissonance between expectations (odds) and observed (score). Notably, this program can be easily modified for other games sports, leading to a plethora of opportunities for sports scientists.

KEY WORDS: APPLICATION PROGRAMMING INTERFACE, PERL, MYSQL, EXPECTATION, AFL

Introduction

Using in-the-run betting odds as a statistical benchmark of the expectations of the two competing teams is becoming extremely popular in game sports. More recently at AFL games the in-the-run odds are displayed at the conclusion of each quarter. This gives spectators and players an inclination of whether there team is expected to win taking into consideration factors other than score including but not limited to: past results, home ground advantage, any perceived momentum, injuries or the lack thereof and time remaining. A graphical representation of these expectations over time is of great interest to coaches. At what point(s) during the match did their team exceed or fall short of these expectations and why? This paper focuses on the automation process involved in recording in-the-run odds by utilizing Betfair’s Application Programming Interface (API); and transforming this data into a measure of expectation and then graphically comparing it with score.

This paper is divided into four stages: (1) a literature review is conducted on real-time sports predictions; (2) we describe the betting exchange Betfair; (3) details and the requirements of the automation process of recording in-the-run odds; (4) transforming the betting data into a single probability measure; (5) the final product including a couple of case studies. To begin we review past research on real-time sports predictions.
Literature Review

Graphically displaying game sports relative to time is nothing new. Westfall (1990) showed how much information could be extracted from a real-time plot of the score difference against elapsed time for a basketball (NCAA) game. In game sports such as basketball, the scoreboard is typically summarized by displaying quarter by quarter or half by half scores. A simple real-time plot allows the general public to easily see several interesting features including: the percentage of time for which a team held the lead, the maximum point surplus (or deficit), number of lead changes, rapid scoring or the lack thereof, critical periods in the game (time-outs, injuries, etc) and the effect they have on margin and finally the winner and winning margin. However, this method of judging a team’s performance based solely on current score fails to take into account:

- Any perceived home ground advantage
- Past results of the two competing teams
- Dominant passage(s) of play by a particular team without scoring
- A score by either team which might be considered lucky (e.g. a fortunate umpiring decision)

Authors such as Stern (1994) and Glasson (2006) calculated the probability of either team winning in real-time for basketball and AFL respectively via a Brownian motion model. These incorporate a pre-game point estimate, time remaining and current score. However, these models assume that future scoring behaviour is independent of current score.

Ryall and Bedford (2008) transformed a mass of performance variables into a single probability assessment of the home team winning relative to the opposition in AFL. They found early on in the match the probability measure outperformed score but as the match progressed score had more and more influence since ultimately the team ahead at the final siren wins the match. Therefore, this statistical measure was more indicative of the “better team” rather than the team which is expected to win at any point in time. The overlay of all these measures would provide great interest to coaches and fans alike.

Betfair

Betfair is the world’s largest betting exchange. They match up users worldwide to arrive at a matched bet; which comprises someone that “backs” the event (That is betting on team A to win) and someone that “lays” the event (That is betting on team A to not win) for a specified amount of money known as “volume”. If team A wins the person who backed team A to win receives volume bet multiplied by the betting odds. For example, if team A is paying $1.40 (for every $1 bet $1.40 is returned) they would receive (volume bet × 1.40) from whoever laid the bet. However, if team A loses the person who laid team A to lose receives the volume bet from whoever backed bet. Betfair takes a 5% commission on all winning bets thus removing the need for a bookies markup or “over-round”. In a typical betting market the bid price (back) does not match the ask price (lay), this differential is usually smaller for the favourite than the underdog. The more volume which is bet on a particular event the closer the bid and ask price become. This
type of betting exchange is somewhat akin to the share market, for every buyer there is a seller. If the number of buyers outweighs the number of sellers the price increases; similarly if the number of sellers outweighs the number of buyers the price decreases.

Methods

According to Wikipedia an Application Programming Interface (API) “is a set of routines, data structures, object classes and/or protocols provided by libraries and/or operating system services in order to support the building of applications”. The Betfair API’s are language independent which means they can be called by several programming languages, these API’s are accessed via a Simple Object Access Protocol (SOAP) interface over a secure web connection. For the purpose of this research Perl will be the programming language used to access the API’s.

There are three connection end-point URL’s that access the Betfair sports betting API services, they are given as follows:

The global services are used to log in and out, administer your Betfair account and funds and navigate though the events hierarchy until you reach a particular market. The exchange services are used to view and bet on sports events.

The requirements for this research are the global services Login, GetActiveEventTypes and GetEvents and the exchange (AUS) services GetMarket and GetMarketPricesCompressed. The Login service requires three input parameters a username, password and productId (82 is Betfair’s free access API). This service logs into the users Betfair account and, if logged in successfully, returns a parameter called sessionToken which is a unique code which is required for all other services. The GetActiveEventTypes service requires the input parameter sessionToken. This service retrieves a list of all different sports (AFL, Soccer, Cricket etc) provided there is at least one active event, it returns a unique id which identifies each sport and the name of the sport is also returned. The GetEvents service requires the input parameters sessionToken and eventParentId where eventParentId is the id value returned by GetActiveEventTypes (or GetAllEventTypes) or an earlier GetEvents request. This service returns event items (such as eventId and eventName) and/or marketItems (such as marketId and marketName)

For example a GetEvents request (on 28/05/09) using the eventParentId for AFL (61420) returned by GetActiveEventTypes would return the event names Coupons and AFL 2009 and their corresponding eventId. Figure 1 shows the equivalent if “Australian Rules” was selected from the Betfair web interface.

![Figure 1. Betfair web interface - “Australian Rules”](image-url)
If another GetEvents request (on 27/02/09) using the eventId for AFL 2009 would return the event names **Coupons, Accumulators, Brownlow Medal 2009, Ladder Position, Number of Wins, Round 10 – 29 May, Round 10 – 30 May, Round 10 – 31 May, Round 14 – 15 July and Season Match Bets** and their corresponding eventId and the market names: **2009 Minor Premiers, Cats Perfect Season, Coleman Medal, Grand Final Quinella, Last Team Standing, Premiers 2009, To Reach Top 4, To Reach Top 8, Winning State and Wooden Spoon** and their corresponding marketId. Figure 2 shows the equivalent if “AFL 2009” was selected from the Betfair web interface. This process of cycling through the event hierarchy can continue until no event names are returned (i.e. only market names).

**Figure 2. Betfair web interface - “AFL 2009”**

The **GetMarket** exchange service requires the input parameters sessionToken and marketId. It returns all the static market data associated with that market such as the names of the two competing teams.

Again **GetMarketPricesCompressed** exchange service requires the input parameters sessionToken and marketId. This service returns dynamic market data in a compressed format volume for all runners (or in our case two teams). The back price, back volume, lay price and lay volume can then be extracted from the compressed format. Another important return parameter for this service is ‘delay’ which returns a value greater than zero once the match has started. This is because there is a delay in matching bets for in-the-run markets to allow punters the chance to cancel their current back or
lay bet (which is unmatched) after a significant event has occurred (i.e. a goal is scored). The return parameter ‘marketStatus’ is also of importance, it can return a status of active, suspended or inactive. Therefore for the purpose of our program (collecting in-the-run prices) we want to collect prices when the match has started (‘delay’>0) and stop collecting prices when the match has finished (‘marketStatus’ equals suspended or inactive). This can be achieved by implementing a simple IF statement. A loop is required for a specified time interval (i.e. 12 seconds) for the GetMarketPricesCompressed service to collect prices.

This information also needs to be exported to a MySQL database. A table(s) needs to be created in MySQL (within a specified database) which will print the team, timestamp, back price, back volume, lay price and lay volume. Then code is written within the loop of the Perl script that exports the GetMarketPricesCompressed information after every iteration in the table in MySQL. Once the match has concluded the program exits the perl environment at which point the data can be exported as a CSV file, which can in turn be manipulated in Excel.

The only requirement for this program is the marketId. Since this program is required for multiple games each week (eight games of AFL per round) for multiple rounds (22 rounds per home and away season in AFL) the program is modified to reduce the amount of person time. This program is set to run prior to the start of each round, automatically exits once the final match has concluded, and writes each games betting data to a separate MySQL table. This program is also equipped to handle games which may overlap with other game(s). The only inputs required is the round number and the dates which the games are played (see Figure 2).

**Probability Measure**

To calculate the probability of either team winning at any point in time the betting data needs to be transformed into a single probability measure. Firstly the bid price and the ask price for each team needs to be reduced to a unique value for example taking the midpoint of the two values. That is:

\[
\text{Odds}_t^i = \frac{A_t^i + B_t^i}{2}
\]  

[1]

where \( A_t^i \) is the ask price of team \( t \) at time \( i \) and \( B_t^i \) is the bid prices of team \( t \) at time \( i \). However since we have the volume associated with each price (which can be interpreted as the level of confidence a punter has with a given price, the higher the volume the higher the level of confidence) we can weight the bid price and ask price with their respective volumes. So now the odds can be written as:

\[
\text{Odds}_t^i = \frac{A_t^i V_a(t) + B_t^i V_b(t)}{V_a(t) + V_b(t)}
\]  

[2]

Where \( V_a(t) \) is the volume associated with the ask price for team \( t \) at time \( i \), similarly \( V_b(t) \) is the volume associated with the bid price for team \( t \) at time \( i \). Now the unique values in [2] need to be transformed into a single probability assessment for each team \( t \).
at time $i$. Taking the inverse of $Odds_i(t)$ will produce a probability for each team $i$, however the sum of these two probabilities should always be greater than one (otherwise an arbitrage opportunity exists). Therefore we calculate probability of the home team winning relative to the opposition. That is:

$$\text{Relative}_{i}(\text{home}) = \frac{1/\text{odds}_{i}(\text{home})}{[1/\text{odds}_{i}(\text{home}) + 1/\text{odds}_{i}(\text{away})]}$$  \[3\]

Results

Prowess Sports provide comprehensive statistics to media outlets, AFL clubs, and subscribers via both their website (www.pro-stats.com.au) and associated dedicated software. Their software package ProEdge generates transaction data (time-stamped data) which can be easily exported to Excel. Therefore at the conclusion of each round the betting data for each game are exported as a CSV file and married up the time-stamped margin from the transaction data. A simple macro is written in EXCEL which extracts the relative probability from the betting data and margin from the transaction data and generates the real-time probability plot. A problem was that the length of time between each quarter in AFL was not always equal. There is a maximum allocation of 6 minutes allowed between the first and second, and third and fourth quarters; and 20 minutes between the second and third quarters. Therefore for each game the length of these intervals needs to be estimated. A couple of case studies were investigated:

Round 1 2009: Collingwood (Home) vs. Adelaide (away)

It is important to note pre-game factors which may influence the final result, such as recent form and home ground advantage. Although this was the opening round of the season Collingwood went into the game the form team having made the Pre-season final (knock out competition) and Adelaide were knocked out in the opening round albeit to the eventual winner Geelong. Collingwood have a significant home ground advantage (Clarke 2005) since Adelaide have to travel well over 800kms to the required destination. This meant Collingwood went into the game with a 73% chance of victory (according to market). Figure 3 shows the probability of Collingwood relative to Adelaide.
At the end of the first quarter Collingwood were behind by 23 points, yet they were deemed almost an even chance of winning the match. In this instance this expectation was later justified as Collingwood were defeated by a measly four points. Midway through the third quarter Adelaide were behind by almost 20 points and were deemed only a roughly 25% chance of victory therefore from this point in time they far exceeded their expectations.

**Round 1 2009: Hawthorn vs. Geelong (neutral ground)**

This opening round match for 2009 was a replay of the 2008 AFL grand final. Although Hawthorn won the grand final in 2008; Geelong were a 75% chance of winning according to the market after losing only one match in the previous season and winning the Pre-season competition. Although Hawthorn lost only five games in the previous season they were knocked out in the 2nd round (out of a possible four rounds) of the Pre-season competition and they also had several key players missing due to injury. The first half was relatively close in terms of the score however the Geelong were always clearly expected to win the game albeit a late scare in the last quarter.

The power of the relative probability in [3] based on the in-running markets can be tested against score at specific intervals in the match by determining the number of games each approach correctly classifies. Based upon the games recorded in 2009 to date (73 games) Table 1 displays the accuracy of each approach.

<table>
<thead>
<tr>
<th>Quarter</th>
<th>Score</th>
<th>Relative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>68.49%</td>
<td>75.34%</td>
</tr>
<tr>
<td>2</td>
<td>81.51%</td>
<td>83.56%</td>
</tr>
<tr>
<td>3</td>
<td>95.89%</td>
<td>95.21%</td>
</tr>
</tbody>
</table>

Table 1. Percentage of games correctly classified

There is an overwhelming increase in the power of the relative probability when compared to score particularly early on the match. It is interesting to note the score actually
outperforms the relative probability in the 3rd quarter by just over 0.5%, this is likely to be attributed to the small sample size used.

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Conclusion

The authors acknowledge that the probability of two competing teams derived from market odds does not represent the true probability of either team winning; since the true probability will always be unknown. However we do know that over time the in-running markets will always correct itself towards the true probability. That is, although there are likely to be some inefficiencies in the in-the-run market, the market as a whole is relatively efficient. The results suggest that the relative probability derived from the “in-the-run” betting odds is a better indication of the expected result than current score. The usefulness of such odds may actually indicate player perceptions given that price reflects consensus, what a great motivation to align difference in price to result!

References


ADVERGAMING: A CASE STUDY ON POLO CUP

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Abstract

Nowadays, nearly all the brands tend to use all the new methods one can imagine in order to sustain. One of these new inclinations is “advergaming”. Advergaming is derived from the words advertisement and game. This term is explained as use of interactive game technology to distribute the hidden advertisement messages to the consumers. This advergaming application puts the message of the advertisement in the game by including the marking in the frame of game. The aim of this study is to present detecting the advergaming application used in Polo Cup arranged in Turkey. Different brands used in this scope, enables users to be aware. In our country, a lot of automobile brands developed a strategy by creating their own games in 2006. Volkswagen Polo Cup prepared a game with the same sense and both the billboards on the path and different-colored Volkswagen automobiles provided them with experience and enabled the endurance of the awareness of brand difference. CNBC-e is used as a brand on the race path and the cars. Bonus was another brand used on the cars. The race consisted of paths with different names. In the game, there were paths the names of which was made up of different brands such as; Castrol, Garanti, Dunlop, DMS, Bonus, NTV and CNBC-e. While the number of the subscribers of the Volkswagen Polo Cup was over 60,000 during the first week, the average number of players was nearly 100,000, which proves the immense interest of the consumers. One car that it’s brand is Polo was given to the person who won the racing as a gift. In addition to, a player who do best time win Toshiba L10–205 Satellite laptop computer every month. After Polo Cup final play, organized at Turkish national channel NTV, people who win the gift became definite.

Introduction

The magnificent improvements in technology affect sport area as the others and it causes new developments in this area. One of these developments in relation with sport area is “electronic sport”. Although electronic sport is called electronic game, cyber game, computer game and online game etc. in literature, actually the main subject is electronic sport. Electronic sport is a sport which can bring people together from one side of the world to the other side via internet or the people from everywhere in the world can meet via big electronic sport organizations; also it consists more physical and mental requirements than other sports. Nowadays a lot of official and private tournaments are organized internationally, federations in relation with electronic sport are trying to complete the process of constitution. Million dollars supports of the sponsors to the international organizations can be evaluated as a proof of the potential development of electronic sport. Participation in e-sport international organizations in Turkey was provided as an individually and a team and it continues to provide (Argan, M., Özer, A., Akın, E., 2006).
The place of the improvements of computer games and electronic sport is the salons which is called arcade. Internet became widespread, LAN cafes and competition atmosphere appears, then these results made progress in mentality of arcade saloons (Yavru, 2006). Local web connections used in bigger organizations and internet cafes carry limited rivalry atmosphere to the global size. The first tournament with award of electronic sport called “red annihilation” was organized in England 1997 (www.computergames.com). Also in 1997 an entrepreneur called Angel Munoz set up a company called Cyber athlete Professional League and provide to take attention into the electronic sports in the world (Ersoy, 2002). Therefore, the subject called electronic sport started to take part in industry revolution and it continues to take part (Ayhan, 2000).

Nowadays, a lot of company brands in industry revolution attempt to use new methods to maintain their existence. Companies emplace their productions with brand to the cinema film, television show or music video of package, signal or other commercial production (Argan, 2007). Once the product placement is being used to cinema and television, producers of the games start to use product placement effectively (Kline, 2003). Advergaming include the brands in the games, so it provides that the message of advertisement becomes the center of the game (Argan, 2007).

The aim of this study is to point out advergaming study which was held in Polo Cup arranged on behalf of Volkswagen automotive company in Turkey. The brands used in this extent provide awareness of the users.

**Literature Review**

**Product Placement**

Product placement refers to the practice of including a brand name product, package, signage or other trademark merchandise within a motion picture, television show or music video. This placement is done to influence the audience (Argan; Velioglu; T. Argan; 2007). The placement could be done within a movie scene to add realism to movie scenes, but from the product placement practitioners’ point of view, the desired influence is in the form of increased awareness of and intention to purchase the placed brand. Product placement dates back to the 1930s when “soap operas” were produced to advertise washing powder. However, the true potential of the method was not fully explored until the marketer of Gordon’s Gin paid to have the product placed in the movie “The African Queen”, which was shown for the first time in 1951. From there, product placement rapidly developed, partly to cover the increasing budgets of movies, and partly to make them appear more realistic by the placing of real consumer brands. During the 1980s the first product placement occurred in games, when Sega placed a Marlboro banner in some of its arcade games. In the early period of product placement in games it was common practice for the game publisher to have to pay companies to get permission to place real brands in their games. Nowadays, however, game publishers get paid to include a real brand in their productions and marketers are more than willing to pay the price (Argan; Suher; Özer; Akin; T. Argan, 2007). Before the launch of Electronic Arts’ Need for Speed: Under Ground 2, for instance, several advertisers were bidding against each other to be placed in the game (Jasper, 2006).

Product placement strategies can be categorized into three modes: (1) visual only, (2) audio only, and (3) combined audio-visual (Gupta and Lord, 1998). The first strategy of product placement involves demonstration of a product, logo, billboard or other visual
brand identifiers without any accompanying message or sound (Smith, 1985). The second strategy refers to audio placement whereby the brand is not shown but is mentioned in the film dialogues (Russell, 2002). The third strategy of product placement refers to a combination of the first two strategies i.e. to a hybrid strategy. The reason why product placement is so important and why it has increasing share is that the advantageous of the cinema films and games (Karrh, 1998).

**Advergaming**

Computer game sector is not only interacting with entertainment and the sector of hardware software. Last years, computer games and virtual world created in the game start to use for introduction and advertisement. The auto which you play in the game, the city you travel, the advertisement bulletins and shop windows in the race path can be used as advertisement object. The advertisement used in the computer games can be divided into two categories: Advergaming (the games aiming introduction and advertisement), In Game Advertisement (Placing the Advertisement messages into the games). Advergaming is to constitute an interactive advertisement channel for production or institution. Thanks to this method, consumers find an opportunity to interact with the advertisement. (www.iletsem.anadolu.edu.tr/2006) in relation with advergaming there are different approaches.

**Table 1: Different Advergaming approaches and Brand integration**

<table>
<thead>
<tr>
<th>Connection</th>
<th>Descriptive</th>
<th>Indicative</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Law</strong></td>
<td><strong>Brand Integration</strong></td>
<td><strong>High</strong></td>
</tr>
</tbody>
</table>

1- *Descriptive game- advertisement*: It increases awareness in connection with the activity feature in the game and lifestyle. Example: Jack Daniel 3D Billiard supports as a sponsor to the 3D Billiard game aiming 21–34 aged boys on shockwave.com. The aim is to increase awareness and to be clicked on the promotion website of Jack Daniel.

2- *Indicative game- Advertisement*: It shows the production in the game clearly. Example: When player plays Super Monkey Ball Game, he has to lead the game cube through the monkey, at the same time player tries to get bonus while gathering bananas. And every banana has the label of Dole Food Company.

3- *Indicative game- advertisement*: It permits to try the production in the game area, and thanks to this it provides to the interaction and increase interaction. Example: Volkswagen company constitutes a game under the name of Polo Cup, and the gamers compete with the cars whose brands are Polo for winning the award.

With these approaches, the brands used in the games increase the recalling the production.

In Game Advertisement is a method which is applied at first. In Game Advertisement is a method emplacing the brand or the advertisement itself in a game (Argan, 2007).
Table 2: 2003–2009 The Incomes of Advertisement of Computer Games

<table>
<thead>
<tr>
<th>Year</th>
<th>In-Game Advertisement</th>
<th>Advertisers</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>100</td>
<td>200</td>
</tr>
<tr>
<td>2004</td>
<td>200</td>
<td>300</td>
</tr>
<tr>
<td>2005</td>
<td>300</td>
<td>400</td>
</tr>
<tr>
<td>2006</td>
<td>400</td>
<td>500</td>
</tr>
<tr>
<td>2007</td>
<td>500</td>
<td>600</td>
</tr>
<tr>
<td>2008</td>
<td>600</td>
<td>700</td>
</tr>
<tr>
<td>2009</td>
<td>700</td>
<td>800</td>
</tr>
</tbody>
</table>


Advertisers predict that by the end of the 2006, 350 million dollars will be spent for “The brands in the game” and “the games aiming Advertisement and Introduction”, moreover they think that this number will be more than 700 million dollars by 2010(www.iletsem.anadolu.edu.tr/2006).

The placement of production or brand is not directly communication, on the contrary; it is indirect communication. The aim is audiences not to realize the commercial effect of the brand or the aim is to evaluate the given message differently than the other commercial messages (Sarýyer, 2005).

**Case Study: Polocup**

VW Polo Cup Tournament which is auto race and can be played on internet [www.ntvmsnbc.com](http://www.ntvmsnbc.com), 3D was organized in Turkey. Participants take points according to their level which they took from the race. At the end of the season, everybody above 18 years old can attend the game which will be raced at big final. If competitors want, they can do training at first or they can start with ordering tour. They take part in the main teams classifying according to their success in the ordering tour. All details which are in the real race area were thought in the game. Tribunes, safety fences, billboards, competitor autos are thought and also for the purpose of watching the way in different views, a lot of camera are placed in the game. There are three main parts in every race: training, ordering and race. In training part; drivers learn the race, in ordering part; drivers are competing with the other 7 competitors to start the race advantageously. In the race part; drivers are competing with 7 competitors virtually and at the end of the 5 tours degrees are determined.


The race consists of paths having different names. There are parks consisting of brands of sponsors in the game. In the race different track will be used in every month. The competition was organized in these tracks respectively: CNBC-e White Park, VDF Jet Ring, Castrol Edge Speed Track, garanti.com.tr Park, Dunlop passion of driver Track, DMS Speed Circuit, Bonus Fast Track, NTV Park Track.

[http://polocup.ntvmsnbc.com](http://polocup.ntvmsnbc.com)
Table 3: The sponsor brands in the table were used in race track and on autos as a billboard.

<table>
<thead>
<tr>
<th>CNBC</th>
<th>Garanti</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>Bonus card</td>
</tr>
<tr>
<td>DUNLOP</td>
<td>NTV</td>
</tr>
</tbody>
</table>

The competition was organized in 8 months. In 8 months; more than 350 thousand registered player are registered, and VW Polo Cup game was played more than 10 million, the winner of every month was given Toshiba L10–205 Satellite Notebook as an award. Final was arranged among 10 players who gain more points at the result of the virtual competition. Finally, the winner who had the best point was given Volkswagen Polo 1.4 as an award. (http://www.vw.com.tr/basin/basinda_vw_index.htm)

Both the billboards and the different colored Volkswagen Polo cars, which were used in the Polo Cup Tournament, provide to the players to gain an experience and also provide to continue the brand awareness (Argan, 2007).
Discussion And Conclusion

Computer game sector is not only interacting with entertainment and the sector of hardware software. Last years, computer games and virtual world created in the game start to use for introduction and advertisement. Polo Cup Tournament which was arranged by The Brand of Polo Automotive used the advergaming advertisement in its game. They placed their own brand Volkswagen and also brands of 7 sponsors both on the autos and the edges of the tracks. They placed sponsor brands on the different 8 tracks and this cause different commercial view for the players.

In this system which everybody perceived like a potential consumer, all needs of the people are determined and the difference between virtual life and the real life are lessening. Advertisement gives an endless opportunity for unlimited creation in the virtual games.

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DIFFERENCES BETWEEN LAST THREE SOCCER
WORLD CUPS IN FIELD AREAS AND ACTIONS
DURING ATTACK

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Abstract
The aim of the study was to establish differences between the teams at three soccer World Cups by using a computerized system Focus X3 to gather and analyse data on field areas and attacks. There were a total of 3880 entities (attacks) that consisted of 5778 actions in different sub-areas of the field (during World Cup '98, World Cup '02 and World Cup '06). The analysed actions in Back field, Midfield and Front field area were described by twelve variables: RBTM, TNADA, PBLP25, PBSP5-6, PBMLP25, GPB, RP25, RP5_6, RP25, DB25, D5-6 and D25. The results show that there are quantitatively bigger changes in actions which occurred in the observed field areas during World Cups '02 and 06' compared to the World Cup '98. This change, which was expected, can be attributed to more complex and sophisticated forms of a training process that improves each year. By analysing the discriminative function, it can be seen that the biggest differences occur with the variables: passing of the ball to a team-mate (PBSP-5-6) and dribbling the ball over long distances (DB25).

KEY WORDS, ANALYSIS, FOOTBALL, FIELD AREAS, ACTIONS DURING ATTACK
Introduction

The analysis of the play of individual players, or the whole team, as well as the play of the players from the opposing team, or the teams that could be possible rivals, is becoming the central problem of the modern football. All coaches and other football experts are concerned with the question of how to ‘guess’ the play of the opposing team in order to choose the right tactics for their teams and to ensure the winning. Besides decoding the opponent, there is always a question how to play and how to outsmart the opponent in order to win. These demands exist at all levels of competition in football, especially at big competitions, i.e. World Cups. Game analyses are therefore used by experts to dissect the opponent’s play, and to improve the play of their own team. This scientific approach towards football might seem too complicated for some average spectator who has a more romantic approach towards football. Game analyses based on the use of modern and highly sophisticated technical and electronic devices that enable scientific observation of all relevant factors in football were published. It is important to mention Bishovets et al. (1993) who deal with computer analysis of technical and tactical moves of the football players during the games at the Olympic Games and World Cup. The sample of variables was comprised of number of attacks, areas of the field during the attack, number of passes, number of shots at goal and the positions. The authors conclude that these data should be a basis for the preparation of players. Based on the video recording, Gerish and Reichelt (1993) evaluate all situations where the player is in duel with the player from the opposing team. They use the following categories: time, player, action, area of the field, winner (at duel), fouls, ball possession, intention-success and opponent. The authors point out the complexity of the gathered material which should not be used to burden the coaches and the players but rather to make diagrams that point out the important aspects of play. Jinshan and co-authors (1993) analyse scoring of goals at the 14th World Cup. These authors set up, for the purpose of game analysis, three sub-areas of the field. With regard to these areas and situations during the game, they establish evaluation of the situation for scoring a goal depending on the type of action and sub-areas of the field. In the research paper published by Hughes, Cooper and Nevill (2003), the authors point out that the reliability of a data gathering system must be demonstrated clearly and in a way that is compatible with certain types of data analysis. According to the authors, the most common form of data analysis in notation
studies is to record frequencies of actions and their respective positions in the
performance area. Argilaga and co-authors (2003) point out in their paper on match and
player analysis in football by computer coding and analytic possibilities that in the team
sports there is a certain complexity of the interaction (substitutes, lacks that will enable
regulation of interruptions, throws, ball losses, ball recoveries, passes, duration of at-
tack, etc.). The authors suggest an instrument that combines a structure of field formats
with system of categories in order to achieve a systematized game analysis. The ap-
proaches of the instrument are: time of the play, lateral spaces, area of ball reception,
player and pass area. Miljković, Jerković and Šimenc (2002) used video recording for
the collection of data. The analyses applied to the following variables (action, body,
space, ball, player, phase of attack, type of attack, area according to the type of player
and phase of game) give a vital contribution to the game analysis because differences in
play between two teams can be observed. Miljković and Barišić (2002) used in their
paper the pieces of data collected by using a video recording of the football game Brazil
– Scotland, played at the 1998 FIFA World Cup in France. The goal of that analysis was
to find out whether the applied variables will produce any significant differences be-
tween two teams, thus hypothesizing the possibility to differentiate between two types
of football schools. The Brazilian team, as the representative of the so-called ‘South-
American football school’, more frequently applied the so-called ‘pass-play’ that is
characterized by short passes. The Scottish team, as the representative of the so-called
‘Island football’, executed their attacks more frequently across outside position by kick-
ing long through parabolic shots. Main purpose of this article was to establish differ-
ences between the teams at three World Cups by using a computerized system Focus X3
to gather and analyse data on field areas and attacks

Methods

The Sample of Variables
The action variables during attack used in this paper are a part of the model for acquisi-
tion and analysis of data that were also used in papers by Miljković, Jerković & Šimenc
There are 12 attack action variables:

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>RBTM</td>
<td>receiving the ball from a team-mate</td>
</tr>
<tr>
<td>(2)</td>
<td>TNADA</td>
<td>total number of actions during one attack</td>
</tr>
<tr>
<td>(3)</td>
<td>PBLP25</td>
<td>passing the ball to a team-mate (a long pass – more than 25 m)</td>
</tr>
<tr>
<td>(4)</td>
<td>PBSP5-6</td>
<td>passing the ball to a team-mate (a short 5-6 m pass)</td>
</tr>
<tr>
<td>(5)</td>
<td>PBMLP25</td>
<td>passing the ball to a team-mate (a medium-long pass up to 25 m)</td>
</tr>
<tr>
<td>(6)</td>
<td>GPB</td>
<td>gaining the possession of the ball (by taking it away from the opponent, by interception, or gaining possession due to the incorrect pass by an opponent)</td>
</tr>
<tr>
<td>(7)</td>
<td>RP25</td>
<td>receiving and passing the ball to a team-mate (over 25 m)</td>
</tr>
<tr>
<td>(8)</td>
<td>RP5-6</td>
<td>receiving and passing the ball to a team-mate (a short 5-6 m pass)</td>
</tr>
<tr>
<td>(9)</td>
<td>RP25</td>
<td>receiving and passing the ball to a team-mate (a medium-long pass up to 25 m)</td>
</tr>
<tr>
<td>(10)</td>
<td>DB25</td>
<td>dribbling the ball over long distances (over 25 m)</td>
</tr>
<tr>
<td>(11)</td>
<td>D5-6</td>
<td>dribbling the ball over short distances (5-6 m)</td>
</tr>
<tr>
<td>(12)</td>
<td>D25</td>
<td>dribbling the ball over medium long distances (up to 25 m)</td>
</tr>
</tbody>
</table>

The following areas of the field were analysed: a) BACK FIELD, b) MIDFIELD, and c) FRONT FIELD

a) Back field is the sub-area in front of the goal (approximately 1/3 of the field).
b) Midfield is the sub-area at the centre (approximately 1/3 of the field).
c) Front field is the sub-area in front of the opponent’s goal (approximately 1/3 of the field).

*The Sample of Entities*

The sample of entities was taken from the football games played at the 1998 FIFA World Cup in France, the 2002 FIFA World Cup in Japan and South Korea and the 2006 FIFA World Cup in Germany. In each World Cup games played in the quarter-final, semi-final and final were analyzed. The sample of entities is represented by at-
attacks executed by the teams monitored. At least two contacts with the ball by players from the team now in possession of the ball are necessary for commencement of an attack. The total number of attacks was 3880. The first part of the sample of entities is from the World Cup in France (WORLD CUP ’98; N=808), the second part is from the World Cup held in Japan and South Korea (WORLD CUP ’02; N=1221) and the third World Cup held in Deutschland (WORLD CUP ’06; N=1850). Each attack, as an entity, can be identified by the summation of actions executed during its duration from the moment at which a team gains possession of the ball until the moment at which the team loses possession of the ball. The term ACTION represents the basic unit of attack. It represents the activity of the player from the moment he gets the ball until he passes the ball to another player from his team or towards the goal, i.e. until this action is interrupted by the player from the other team or by the referee.

The total number of actions of the analysed attacks (Table 1) was 3226.

Table 1: Number of actions

<table>
<thead>
<tr>
<th></th>
<th>Back field</th>
<th>Midfield</th>
<th>Front field</th>
</tr>
</thead>
<tbody>
<tr>
<td>N ’98</td>
<td>415</td>
<td>530</td>
<td>312</td>
</tr>
<tr>
<td>N ’02</td>
<td>641</td>
<td>859</td>
<td>469</td>
</tr>
<tr>
<td>N ’06</td>
<td>834</td>
<td>1134</td>
<td>578</td>
</tr>
<tr>
<td>T</td>
<td>1890</td>
<td>2523</td>
<td>1359</td>
</tr>
</tbody>
</table>

N – number of actions, Z – back field area, S – midfield area, P – front field area, T – total

Data Processing Methods

Mean (AS) and Standard Deviation (SD) were calculated for each group (Cup) and for each field. The differences between these three World Cups (WORLD CUP ’98; WORLD CUP ’02 and WORLD CUP ’06) were established by the analysis of variance.

Results

From the given data (Table 1) it can be seen that the total number of actions has increased, as well as for certain field areas (zones) in favour of the World Cup ’02. Table 2 shows that a total number of actions for Back field area have increased for the follow-
ing variables: RBTM, TNADA, PBLP25, PBSP5-6, RP25, DB25, D5-6 (for World Cup '98, '02 and '06).

Table 2: Back field area

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean 98</th>
<th>Mean 02</th>
<th>Mean 06</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBTM</td>
<td>2.725‡§</td>
<td>3.356</td>
<td>4.435</td>
</tr>
<tr>
<td>TNADA</td>
<td>10.014</td>
<td>11.399</td>
<td>12.345</td>
</tr>
<tr>
<td>PBLP25</td>
<td>.634‡§</td>
<td>.889</td>
<td>1.645</td>
</tr>
<tr>
<td>PBSP5-6</td>
<td>.545</td>
<td>.679</td>
<td>0.945</td>
</tr>
<tr>
<td>PBMLP25</td>
<td>2.137</td>
<td>2.268</td>
<td>2.356</td>
</tr>
<tr>
<td>GPB</td>
<td>.393</td>
<td>.427</td>
<td>.564</td>
</tr>
<tr>
<td>RP25</td>
<td>.140</td>
<td>.193</td>
<td>.231</td>
</tr>
<tr>
<td>RP5-6</td>
<td>.451</td>
<td>.446</td>
<td>.476</td>
</tr>
<tr>
<td>RP25</td>
<td>1.024</td>
<td>.947</td>
<td>1.234</td>
</tr>
<tr>
<td>DB25</td>
<td>.087</td>
<td>.151</td>
<td>.235</td>
</tr>
<tr>
<td>D5-6</td>
<td>.880</td>
<td>1.070</td>
<td>1.876‡§</td>
</tr>
<tr>
<td>D25</td>
<td>.805</td>
<td>.782</td>
<td>.987</td>
</tr>
</tbody>
</table>

‡ Statistically significant at p < 0.01 for World Cup '98 vs. World Cup '02
§ Statistically significant at p < 0.01 for World Cup '02 vs. World Cup '06
† Statistically significant at p < 0.01 for World Cup '98 vs. World Cup '06

There is also a slight increase for the variables PBMLP25 (2.268), GPB (.472), while the variables RP5-6 (.451), RP25 (1.024), D25 (805) were higher for World Cup '98. Discriminative function shows that variables: PBLP25 (.580), RBTM (.404), DB25 (.338) should be used to display differences. The analysis of results for the Midfield area (Table 3) shows that there is an increase of actions in favour of World Cup '02 and World Cup '06.
Table 3: Midfield area

<table>
<thead>
<tr>
<th></th>
<th>Mean 98</th>
<th>Mean 02</th>
<th>Mean 06</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBTM</td>
<td>3.377</td>
<td>3.738</td>
<td>4.213†</td>
</tr>
<tr>
<td>TNADA</td>
<td>11.738</td>
<td>12.375</td>
<td>13.432</td>
</tr>
<tr>
<td>PBLP25</td>
<td>.589</td>
<td>.842</td>
<td>1.023†</td>
</tr>
<tr>
<td>PBSP5-6</td>
<td>.775</td>
<td>.837</td>
<td>1.023</td>
</tr>
<tr>
<td>PBMLP25</td>
<td>2.555</td>
<td>2.496</td>
<td>2.543</td>
</tr>
<tr>
<td>GPB</td>
<td>.326</td>
<td>.389</td>
<td>.413</td>
</tr>
<tr>
<td>RP25</td>
<td>.102</td>
<td>.154</td>
<td>.231</td>
</tr>
<tr>
<td>RP5-6</td>
<td>.534</td>
<td>.482</td>
<td>.465</td>
</tr>
<tr>
<td>RP25</td>
<td>1.117</td>
<td>1.006</td>
<td>1.023</td>
</tr>
<tr>
<td>DB25</td>
<td>.081</td>
<td>.168</td>
<td>.234†</td>
</tr>
<tr>
<td>D5-6</td>
<td>1.117</td>
<td>1.171</td>
<td>1.235</td>
</tr>
<tr>
<td>D25</td>
<td>.925</td>
<td>.852</td>
<td>1.023</td>
</tr>
</tbody>
</table>

† Statistically significant at $p < 0.01$ for World Cup '98 vs. World Cup '06
‡ Statistically significant at $p < 0.01$ for World Cup '98 vs. World Cup '02
§ Statistically significant at $p < 0.01$ for World Cup '02 vs. World Cup '06

There is a significant increase for the following variables: RBTM (3.738), PBLP25 (.842), GPB (.389), RP25 (.154), DB25 (.168). There is also a slight increase for: TNADA, PBSP5-6, D5-6. The following variables: PBMLP25, RP5-6, RP25, DB25 are in favour of the World Cup '98.

Discriminative function shows that the biggest differences are for the variable PBLP25 (.534), and then DB25 (.433) and then the variable RP25 (.255). In the Front field (Table 4) there are some differences in favour of the World Cup '06 and only for 3 variables: PBLP25 (1.049), RP25 (.160) and DB25 (.220).
Table 4: Front field area

<table>
<thead>
<tr>
<th></th>
<th>Mean 98</th>
<th>Mean 02</th>
<th>Mean 06</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBTM</td>
<td>4.179</td>
<td>4.424</td>
<td>4.813</td>
</tr>
<tr>
<td>TNADA</td>
<td>14.295</td>
<td>14.635</td>
<td>14.632</td>
</tr>
<tr>
<td>PBLP25</td>
<td>.686</td>
<td>1.049</td>
<td>1.073†</td>
</tr>
<tr>
<td>PBSP5-6</td>
<td>1.000</td>
<td>.964</td>
<td>1.023</td>
</tr>
<tr>
<td>PBMLP25</td>
<td>3.016</td>
<td>2.883</td>
<td>2.543</td>
</tr>
<tr>
<td>GPB</td>
<td>.346</td>
<td>.399</td>
<td>.413</td>
</tr>
<tr>
<td>RP25</td>
<td>.064</td>
<td>.160</td>
<td>.231†</td>
</tr>
<tr>
<td>RP5-6</td>
<td>.631</td>
<td>.537</td>
<td>.665</td>
</tr>
<tr>
<td>RP25</td>
<td>1.212</td>
<td>1.098</td>
<td>1.023</td>
</tr>
<tr>
<td>DB25</td>
<td>.087</td>
<td>.220</td>
<td>.234†</td>
</tr>
<tr>
<td>D5-6</td>
<td>1.410</td>
<td>1.407</td>
<td>1.635</td>
</tr>
<tr>
<td>D25</td>
<td>1.247</td>
<td>1.055</td>
<td>1.023</td>
</tr>
</tbody>
</table>

† Statistically significant at p < 0.01 for World Cup '98 vs. World Cup '06
§ Statistically significant at p < 0.01 for World Cup '02 vs. World Cup '06
‡ Statistically significant at p < 0.01 for World Cup '98 vs. World Cup '02

There is a slight increase for the variables: RBTM, TNADA, GPB. There is a significant increase for the variable D25 (1.247) in favour of World Cup '98, while the variables: PBSP5-6, PBMLP25, RP5-6, RP25 and D5-6 show only a slight increase.

Discussion

A general conclusion is that there is an increase in all the variables in favour of the World Cup '02 and World Cup '06, and the reason for these positive changes is a good training process that improves each year. By observing certain sub-areas of the field and frequency of individual actions, it can be concluded that the acquired results show what is characteristic for certain field area. The results for the front field (World Cup '02 and World Cup '06) show that there were some tactical changes in favour of greater control.
of the ball and the play in the back field area with the emphasis on the so-called 'safe' play and goal defence. In the midfield area there is an increase for the majority of observed variables in favour of World Cup '02 and World Cup '06. This proves that most of the actions concerning the attack are concentrated in the midfield area. All these activities are possible because of the better fitness condition of the players. The results for the front field show that there is a slight increase in the total number of actions in favour of World Cup '02. This is because of the characteristic type of play during the attack in the front field. The possibilities of improving the activities in that area are very limited because the destruction of the play by the opponent is great. It will be interesting to analyse the play in that area (in the future), although some drastic changes are not to be expected. This paper deals with the analysis of differences between the teams at three World Cups concerning the field areas and actions during attack, by using the computerised system for gathering and analysis of data. 2030 entities (attacks) were analysed, i.e. 3226 actions that occurred during these attacks at three World Cups (1998, 2002 and 2006). By using the analysis of variance, canonical discriminative analysis and by discriminative function it can be concluded that there is an increase in the total number of actions in all field areas in favour of the World Cup '02 and World Cup '06 which was expected. The differences in the back field area are because of the tactical ideas in the play during defence with the main goal to control the ball and so called 'safe play'. In the midfield area the changes occur because the team wants to ensure the best possible position for the final phase of the attack. The main precondition for this is better fitness condition of the players. The differences are not so obvious in the front field area because of the characteristic type of play in this area where the activities are limited. Discriminative function shows that the biggest differences are for the variable: passing the ball to a team-mate (a long pass) (PBLP25) and dribbling the ball over long distances (DB25).
References


PERFORMANCE ANALYSIS OF FEMALE PROFESSIONAL TENNIS PLAYERS

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Abstract
The purpose of current study was to analyse the performance of female professional tennis players. This analysis was conducted to determine the characteristics of elite female tennis tactics and training methods. The computerised scorebook for tennis was used to collect data from 36 matches in Grand Slam events held in 2005 and 2006. The ratio of last shot of rally showed significant differences on the outcome of rally. When the server won a point, the ratio of return showed significantly high. On the other hand, when the server lost a point, the ratio of the ground stroke showed significantly high. Those results indicated that the serve had an effect on winning a point for female professional tennis players. The time duration of 1st serve was 0.79±0.11 s and the time duration of 2nd serve was 0.91±0.13 s. The time duration of serve on female professional players nowadays became closed with male professional players. It was suggested that the importance of serve for female professional players have been increased. It is considered that a training method to receive the serve of male professional players has an effect to adjust a timing of serve return for female professional players.

KEY WORDS, TENNIS, PERFORMANCE ANALYSIS, TIME DURATION OF SHOT, LAST SHOT OF RALLY, FEMALE PROFESSIONAL PLAYERS

Introduction
The purpose of current study was to analyse the performance of female professional tennis players. This analysis was conducted to determine the characteristics of elite female tennis tactics and training methods.
Methods

A computerised scorebook for tennis was used to collect data from 36 matches in Grand Slam events held in 2005 and 2006. The computerised scorebook for tennis was developed by the authors (Takahashi et al. 2006). We recorded the following data from the scorebook; the outcome of the rally, type of stroke at the last shot of each rally, the score and time factors in playing shots. The time is recorded from the computer's internal clock time when the operator clicks the button at the same time on the player's impact.

Takahashi et al. (2007a) verified the accuracy of the time duration of shot. They defined the time duration of shot as the time difference between one player's impact and the opponent's. The error of the time duration of shot was calculated as the difference between each data from three operators recruited for this experiment and the data from one of the developers on the same match data collection. As a result, the error from all three operators did not show significant differences. The 95% limits of agreement between one operator and the developer was 0.001±0.135 s. It was, therefore, verified that the computerised scorebook records the time duration of shots accurately.

The operators recruited for the current study were well trained for operating the scorebook before collecting the data in accordance with the training guidelines of Takahashi et al. (2006).

Total number of points of all matches in the current study was 4,991. The variables of current study were the ratio of last shot of rally and the time duration of serve. The ratio of last shot of rally was compared by the outcome of rally. The time duration of serve was defined as the time difference between the server's impact and the receiver's impact.

Results

The ratio of last shot of rally showed significant differences on the outcome of rally. When the server won a point, the ratio of return showed significantly high. On the other hand, when the server lost a point, the ratio of the ground stroke showed significantly high. Those results indicated that the serve had an effect on winning a point for female professional tennis players.
The time duration of 1st serve was 0.79±0.11 s and the time duration of 2nd serve was 0.91±0.13 s.
Discussions

The last shot of rally insisted the tendency of the rally and the concept of the player in the rally. In current study, the ratio of the serve and the return showed over 30%. The results such highly percentage suggested that the importance of the serve in female professional tennis became high nowadays. Especially, in current results, the ratio of the return became higher when the server won the point. It showed that the rally was finished by the error of the return. The serve leaded those errors. The importance of the serve in male professional tennis was reported in the past study (Haake et al., 2007; Takahashi et al., 2007b). These results also suggested the importance in female professional tennis.

The ratio of ground strokes became high when the server lost the point. It suggested the importance of the return for the receiver. When the receiver had success on the return, the rally continued to the ground strokes. Those rally leaded highly percentage for receiver to win the point. The return was considered as the most important technique for the receiver.

Takahashi et al. (2009) reported that the time duration of 1st serve was 0.70±0.09 s and the time duration of 2nd serve was 0.86±0.12 s on male professional tennis matches. The time duration of serve on female professional players nowadays became closed with male professional players.

In other words, time duration of serve is a timing of the serve. Those results suggested the training for serve and return for female professional players. It was suggested that the importance of serve for female professional players have been improved than past.

Female professional players need to realize the effectiveness of the serve to win a point. It is considered that a training method to receive the serve of male professional players has an effect to adjust a timing of serve return for female professional players.

Conclusions

The ratio of the return became high when the server won the point. The serve lead the error of the return.

The ratio of ground strokes became high when the server lost the point. It suggested the importance of the return for the receiver.

The time duration of the 1st serve was 0.79±0.11 s and the time duration of 2nd serve was 0.91±0.13 s. The time duration of serve on female professional players nowadays became closed with male professional players.

These results suggest that the serve is very important in female professional tennis nowadays.

Acknowledgement

The part of this study was supported by the Grant-in-Aid for Scientific Research from the Ministry of Education, Science, Sports and Culture of Japan (No:21700620).
References


A WI-FI BASED EMBEDDED SYSTEM FOR
BIOMECHANICAL DATA TELEMETRY

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Abstract

By using a commercially available low cost embedded microcontroller Wi-Fi module, a highly adaptable platform is now available for biomechanical performance data telemetry. A prototype application of the technology for the real-time acquisition, display and analysis of “on the water” rowing performance data from up to 32 channels is presented.

KEY WORDS, WI-FI EMBEDDED MULTI-CHANNEL

Introduction

The ability to acquire accurate telemetered data from a large number of sensors simultaneously is a common requirement of biomechanical performance research. For example, an ideal telemetered data acquisition system for the research we are currently undertaking involving on-the-water rowing performance assessment requires the following features...

- At least 32 data channels at 100 samples per second per channel.
- At least 100 meters outdoor range.
- Easily and quickly adaptable to a wide range of sensor types.
- Very accurate.
- Compact and lightweight with a battery life of at least 5 hours.
- Reasonable cost.

Previously it has proven difficult to source a commercial system which fully meets all these requirements, however, with the recent development of microcontroller modules with inbuilt Wi-Fi wireless connectivity the opportunity has presented itself to develop a low cost multichannel system specifically designed for our rowing research, which can also be readily adapted to other research projects as needed.

Embedded Wi-Fi microcontrollers

Using the 802.11b/g Wi-Fi standard for biomechanics data telemetry has many advantages when compared to other wireless technologies. The Wi-Fi standard has ample bandwidth (up to 54Mbps for 802.11g) and range (>500 meters with suitable high gain directional antennas) and its ubiquity means that 802.11b/g compatible hardware tends to be low cost and easy to obtain [1]. As well, nearly all notebook and desktop computers either have built in Wi-Fi connectivity or have it as a low cost addition.
Easily programmed low cost embedded microcontrollers with built-in Wi-Fi connectivity have only recently become commercially available. Previously if Wi-Fi functionality was required in a design the developer had to incorporate the Wi-Fi circuitry, greatly adding to design complexity and development time.

The microcontroller module selected for the on-the-water system is the RabbitCore RCM5400W by Digi International Inc (figure 1). The RCM5400W is one of the first low cost microcontroller designs to incorporate 802.11b/g Wi-Fi functionality. The RCM5400W is a small (47mm x 72mm x 14mm) unit based on the Rabbit 5000 microprocessor, it provides up to 35 general purpose I/O lines as well as 6 serial ports. It is readily programmed with a no cost ‘extended’ C development environment (Dynamic C) which includes an extensive library of Wi-Fi and I/O control routines [2].

Multi-channel Rowing Performance Wi-Fi System Overview

The RCM5400W is incorporated into the on-the-water component of the prototype multi-channel Wi-Fi telemetry system. It acts as the data processor and Wi-Fi communication module connecting to the on-shore data receiver and ‘command station’.

Sensor data is acquired on-the-water by up to four 8 channel analogue to digital converter (ADC) modules. The ADC modules are connected to the Wi-Fi module by channel select and serial data cables, as well as a DC power cable.

Sensor data from the ADC modules passes through to the Wi-Fi module where it is transmitted to the shore based command station. On shore the received data is scaled and displayed in real time, as well as stored for later review (Figure 2).
The ADC Module

Each ADC module (figure 3) contains an advanced LTC1859 integrated circuit by Linear Technology [3]. The LTC1859 is a complete 8 channel, 16 bit, 100k sample per second analogue to digital converter with SPI interface. It also incorporates software selectable ranges of ±5V, ±10V, 0-5V and 0-10V which, combined with its high resolution, permits accurate data readings from most sensors without any additional signal conditioning.

Three LVDS lines are used to sequentially select a single ADC module via a 74HC138 decoder IC. While the selected module is active the converted analogue channel results are clocked out of the LTC1859 via the SPI interface back to the Wi-Fi module.

The Wi-Fi Module

The Wi-Fi module (figure 4) contains the RabbitCore RCM5400W mounted on a support board which supplies power regulation and ADC module interface circuitry.

Connection to the ADC modules is via the RCM5400W serial port C in Serial Peripheral Interface (SPI) mode. The SPI communication standard is normally limited to approximately 20 cm [4] so to achieve reliable connection to the ADC modules (which may be up to 10 meters away) the SPI signals are buffered by Low Voltage Differential Signalling (LVDS) transceivers. LVDS buffering also allows low noise high speed data communication over standard twisted pair Ethernet cabling, greatly reducing cabling cost.

One cable is used to select the active module and control a sensor reset function. The other cable transfers the SPI signals.

The RCM5400W Software

The software for the RCM5400W is developed using Dynamic C and compiled directly into flash memory via a simple serial link. The program makes extensive use of the included SPI and Wi-Fi library functions.

The code utilizes the ‘Finite State Machine’ model to determine program flow, that is, the program is composed of a finite number of states. The current program state is determined by the connection mode, as the connection mode changes so does the ‘state’ (figure 5).
void StateHandler(MyStateType* current_state) {
    switch(current_state->state) {
        case MY_INIT:
            Initialize Wi-Fi hardware, set current_state to MY_LISTEN when hardware ready...
            break;
        case MY_LISTEN:
            Passively open and listen on TCP port for a connection, when connected set current_state to MY_CONFIG...
            break;
        case MY_CONFIG:
            Accept commands from Command Station including configuration settings. Set current_state to MY_SENDDATA when 'start' command received...
            break;
        case MY_SENDDATA:
            Start buffered data acquisition and stream data to Command Station until 'stop' command received. Once 'stop' received set current_state to MY_CONFIG...
            break;
    }
}

void main() {
    Start state machine in an endless loop
    for(;;) {
        StateHandler(&my_state);
    }
}

Figure 5.
Pseudo-code for Wi-Fi module RCM5400W.

Essentially, after a reset the RCM5400W initializes the Wi-Fi hardware then transition to the 'listen' state, awaiting a valid Wi-Fi connection. Once connected the program switches to the 'configuration' state where it processes system configuration information as well as listens for the 'start' command.

On receipt of the 'start' command the program transitions to the 'send data' state. In this state a background interrupt routine scans all active channels at 10 millisecond intervals, buffering the resultant conversions. The buffer ensures that no data is lost as the Wi-Fi routines streams data to the command station.

Data transmission continues until the command station program issues the 'stop' command causing a return to the 'configuration' state.
The Command Station

The command station program issues commands to (and receives sensor data back from) the Wi-Fi module. In use the operator sets up a configuration for a test, detailing active modules and channels, input ranges, names, units and scaling factors. Once prepared the configuration is uploaded to the Wi-Fi module making the system ready for sensor data transfer.

When the operator issues the ‘start’ command raw data is streamed from the Wi-Fi module. The received data is scaled and presented in real time in graphical, as well as tabular, format (figure 6). Scaled data is also saved to disk for later analysis and review.

![Command station display showing telemetered data.](image)

Results and Discussion

The prototype has been tested successfully with two ADC modules for a total of 16 channels of 100 Hz 16 bit resolution data over 100 meters using a +5dBi omni-directional antenna on the Wi-Fi module and a +8dBi omni-directional antenna at the command station.

The technology has been tested successfully also with a data stream equal to a full 32 channel setup over water to a distance of over 500 meters using a +8dBi omni-directional antenna on the Wi-Fi module with a +15dBi omni-directional antenna at the command station.

Even greater distance is likely to be obtained using a high gain (+18dBi or greater) directional antenna combined with a Wi-Fi signal booster at the command station.

Current consumption was measured at ~450mA for the Wi-Fi module (when transmitting) and ~100mA for each of the ADC modules. Thus a full 4 ADC module 32 channel system would consume approximately 850mA. Thus with the present design it is estimated that a 9V/44Wh Lithium Ion battery pack will last for between 5 and 6 hours.
It should be possible to lower dramatically the current consumption of the system by putting much of the circuitry into a low power ‘sleep’ mode between test runs. It is planned to implement this feature in the next version of the system.

Conclusion

The prototype on-the-water design presented has shown the potential of using embedded microcontroller Wi-Fi technology as the basis for very cost effective systems for the telemetry of biomechanical sensor data.

References


Note: Wi-Fi is a registered trademark of the Wi-Fi Alliance.
LabVIEW is a registered trademark of National Instruments Corporation.
Rabbit, Rabbit 5000, RabbitCore and Dynamic C are registered trademarks of Digi International Inc.
DEVELOPMENT OF GENERAL AND
SOCCER-SPECIFIC PERCEPTUAL MOTOR
SKILLS IN EARLY PUBERTY – A TWO-YEAR
FOLLOW-UP STUDY IN A REGIONAL SOCCER
TEAM

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Abstract
The aim of the present study was to examine how general and soccer-specific perceptual motor skills develop during early puberty. The players of the regional soccer club (n = 10) were measured at the age of 10 years in general and soccer-specific perceptual motor skills and same measurements were repeated two years later at the age of 12 years. General perceptual motor skills were measured using a Wayne saccadic fixator (simple reaction time and eye-hand-foot coordination) and a peripheral awareness trainer (reaction time to peripheral stimulus). A test track was constructed in order to examine soccer-specific perceptual motor skills. In the test track, the subjects performed a series of typical on-the-ball soccer actions: anticipating, receiving, dribbling, feinting and passing. From the result of this study it can be concluded that general and soccer-specific perceptual motor skills improved similarly from 10y to 12y but were not related to each other. It seemed also that in successful on-the-ball soccer performance the soccer-specific perceptual skills were more important at the age of 12y compared to 10y.

KEY WORDS, SOCCER, CHILDREN, PERCEPTUAL SKILLS, MOTOR SKILLS

Introduction
In general, the ability to process information becomes more efficient with increasing age [1]. The actual visual system develops throughout childhood and reaches the adult functional level at the age of 10-15 years [2, 3, 4]. At the same age children are able to select relevant information from various sources in the environment [5]. On the other hand, expert-novice comparisons have indicated that perceptual motor skills are taskspecific [6]. This task-specificity has been shown to appear among soccer juniors already at the age of 9 years [7]. In other words, the level of expertise attained by extensive task-specific practice is considered to be more important than age itself in the development of task-specific cognitive skills in sports [8]. It is also important to remember that in top level sports where the differences between the players’ physical performance characteristics are minimal, it is more likely that cognitive skills act as the limiting factors of successful sport performance [9]. As most of the studies examining general and
task-specific perceptual motor skills are carried out with adults, the aim of the present study was to examine how general and soccer-specific perceptual motor skills develop during early puberty.

**Methods**

**Subjects**

Subjects (n = 10) of the present study were male soccer players recruited from a local club of the area around 160,000 inhabitants. Players were tested twice at the age of 10.7 ± 0.3y (1.44 ± 0.06m, 33.0 ± 4.0kg, 9.2 ± 3.4%) and 12.7 ± 0.3y (1.54 ± 0.08m, 40.2 ± 5.9kg, 10.0 ± 4.1%) in terms of general and soccer-specific perceptual motor skills.

**General perceptual motor skill tests**

General perceptual motor skills were measured with a Wayne saccadic fixator [WSF] and a Wayne peripheral awareness trainer [WPAT]. Analyzed variables in general perceptual motor skill tests were simple reaction time [SR], eye-hand-foot coordination [EHF] and reaction time to peripheral stimulus [PAT]. In the SR test, the subject was instructed to extinguish red signal light switched into a WSF board as fast as possible with the right index finger. From total of 5 trials, the average of three responses (without best and worst reaction time) was calculated as a result. In the EHF test, the subjects tried to extinguish as many randomly illuminating lights on the WSF board as possible in 30 seconds using hands (29 positions) and feet (4 positions) in pre-ordered manner. The number of extinguished lights was counted as a final score and the best out of three trials was selected. PAT was measured with WPAT which is a compact wall-mounted instrument with eight peripheral target lights mounted on plastic rods extend at 45-degree angles from a cylinder that contains a 4-digit LED display and a central fixation light. The peripheral target lights lighted up at random and the subject responded by a joystick while fixating on the central light. WPAT displayed reaction time in hundredths of a second for each target light. Average reaction time for eight directions was used as a result and the best out of three trials was selected for further analysis.

**Soccer-specific test**

A test track (Figure 1.) was constructed in order to examine soccer-specific perceptual motor skills. In test track, the subject performed a series of actions typically performed in soccer: anticipating the pass, receiving the ball, dribbling, feinting and passing. First, the subject reacted (1) as fast as possible to near life size video sequence of a soccer player receiving the ball - running shortly towards the subject - and giving a pass either to the right or left side, after which the subject turned and took the ball (2) located either left or right of him. Next, the subject dribbled the ball between two cones (3) and through a photocell-gate (4) which illuminated a signal light (5) giving a direction (left or right) from which side of the signal light pole the pass (6) should be given. Then, the subject directed the pass between two switched lights in a running light track (7) proceeding at speed of 4.17 m/s (~15 km/h). The subjects were instructed to perform the entire track as fast and accurately as possible. The subjects performed 4 practice and 16 test trials with a resting period of around 45 s between the trials. All trials were filmed with three camcorders (50 Hz = 0.02 s) and analyzed with APAS motion analysis software. The results of the soccer-specific test track were expressed as an average of 16 test trials.
Analyzed variables in soccer-specific test were:

- anticipation/reaction time to a pass illustrated on a full-sized video screen [SANT] = time from the moment of ball impact on the video screen to initiation of the first movement towards the selected ball
- dribbling time [SDRB] = time from the first ball touch to the moment when player entered the photocell gate
- reaction time to light signal evoked during dribbling [SREAC] = time from entering the photocell gate (gaze to signal light) to directing gaze from signal light back to the ball
- aiming time [SAIM] = time from directing gaze to the ball to the moment of the pass impact
- passing time [SVEL] = time from the moment of pass impact to the moment when ball entered the line of the running light track
- total performance time [STIME] = time from the moment of ball impact on the video screen to the moment when ball entered the line of the running light track
- passing accuracy [SACC] = points of faults = position from the target light-pair when ball entered the line of the running light track (0 point = between target lights, 1 point = missed one light-pair, 2 points = missed two light-pairs, …).

**Statistics**

Paired samples T-test was applied to detect differences between the tests. Pearson’s correlation coefficient and linear regression analysis was applied to evaluate the relationships between general and soccer-specific tests. The level of significance was set at \( p<0.05 \).
Results

As shown in Tables 1 and 2, the players were significantly better at the age of 12y compared to 10y in all other measured variables except in PAT and in SREAC. At the age of 10y STIME was associated with PAT (r = 0.70; p<0.05) and at the age of 12y with PAT (r = 0.68; p<0.05), SDRB (r = 0.76; p<0.05) and SREAC (r = 0.68; p<0.05). At the age of 12y association between STIME and SANT was almost significant (r = 0.60; p<0.06) (Figure 1). There was no significant relationship between SACC and any measured variable at either age. No associations were found between general and soccer-specific perceptual motor skills at either age or between relative developments of these skills during follow-up. As presented in Figure 2, the durations in different phases of soccer performance test remained proportionally constant during follow-up.

Table 1. The results of general perceptual skill tests at the age of 10y and 12y.

<table>
<thead>
<tr>
<th></th>
<th>SR (s)</th>
<th>PAT (s)</th>
<th>EHF (times/30s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 years</td>
<td>0.25 ± 0.03</td>
<td>0.35 ± 0.06</td>
<td>28.3 ± 3.0</td>
</tr>
<tr>
<td>12 years</td>
<td>0.23 ± 0.03</td>
<td>0.33 ± 0.06</td>
<td>35.9 ± 3.7</td>
</tr>
<tr>
<td>Sig.</td>
<td>P&lt;0.05</td>
<td>ns.</td>
<td>P&lt;0.001</td>
</tr>
<tr>
<td>Dev. %</td>
<td>7.1± 7.4</td>
<td>6.3 ± 15.6</td>
<td>27.7 ± 16.3</td>
</tr>
</tbody>
</table>

(SR = simple reaction time; EHF = eye-hand-foot coordination; PAT = peripheral awareness; Dev. % = relative development)

Table 2. The results of soccer-specific skill test at the age of 10y and 12y.

<table>
<thead>
<tr>
<th></th>
<th>SANT (s)</th>
<th>SDRB (s)</th>
<th>SREAC (s)</th>
<th>SAIM (s)</th>
<th>SVEL (s)</th>
<th>STIME (s)</th>
<th>SACC (“faults”)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 years</td>
<td>0.18±0.04</td>
<td>1.89±0.17</td>
<td>0.34±0.02</td>
<td>1.41±0.20</td>
<td>0.83±0.13</td>
<td>5.62±0.24</td>
<td>1.87±0.56</td>
</tr>
<tr>
<td>12 years</td>
<td>0.16±0.03</td>
<td>1.66±0.11</td>
<td>0.32±0.02</td>
<td>1.25±0.13</td>
<td>0.67±0.09</td>
<td>4.95±0.25</td>
<td>1.38±0.44</td>
</tr>
<tr>
<td>Sig.</td>
<td>P&lt;0.05</td>
<td>P&lt;0.01</td>
<td>ns.</td>
<td>P&lt;0.05</td>
<td>P&lt;0.01</td>
<td>P&lt;0.001</td>
<td>P&lt;0.05</td>
</tr>
<tr>
<td>Dev. %</td>
<td>10.7±12.2</td>
<td>12.3±6.2</td>
<td>3.3±11.6</td>
<td>9.8±13.1</td>
<td>17.5±12.8</td>
<td>12.0±3.2</td>
<td>21.2±30.8</td>
</tr>
</tbody>
</table>

(SANT = anticipation time; SDRB = dribbling time; SREAC = reaction time during ball-handling; SAIM = aiming time; SVEL = passing “velocity”; STIME = total performance time; SACC = passing accuracy; Dev. % = relative development)
Figure 1. Relationship between reaction time to general peripheral stimulus (PAT; circles) and total performance time in soccer-specific test (STIME) and between soccer-specific anticipation time (SAIM; squares) and total performance time in soccer-specific test (STIME) in soccer players aged 10 (black) and 12 years (white).

Figure 2. Relative durations (in proportion to total performance time) in different phases of soccer-specific test.

**Discussion**

There is a consensus in cognitive sport psychology research that superior sport performance is not linked to differences in visual or sensory abilities [10] even though controversial results from sport vision research has also been presented [11]. Expert-novice comparisons have indicated that perceptual motor skills are task-specific [6] and this specificity is shown to appear as early as 8-9 years of age [7]. It has been documented also that sport-specific perceptual and cognitive skills improve, in general, with increasing age and experience but are likely to be partly determined by genetics [12, 13, 14].

In earlier cross-sectional study comparing 10y and 14y old soccer juniors with the same testing procedure used in the present study, the current authors [15] found that soccer-specific anticipation time in the 14y group (0.09s) was half of that found in the 10y group (0.18s). It was also found that the 14y group was faster than the 10y group in every other phase of the soccer-specific test except that the 14y players took relatively more time to direct the pass towards the running target. As the 14y players were also more accurate compared to the 10y players, it was suggested that there might be a difference in cognitive strategy between the age groups. Furthermore, the 14y players were better than the 10y players in all general perceptual motor skill tests although the difference in peripheral awareness test (PAT) was not significant. The results suggested also that general perceptual motor skills were more important variables to explain successful...
soccer performance in the 10y group and soccer-specific perceptual motor skills in the 14y group.

In the present study, during a two year follow-up from 10 to 12 years the players developed in general and in soccer-specific perceptual motor skills but these skills or their relative development were not associated with each other. In other words, the players with better general perceptual motor skills did not possessed better soccer-specific perceptual motor skills. It was also noteworthy to realize that general and soccer-specific perceptual skills improved remarkably in a same scale. Simple and peripheral reaction time (general skills) as well as anticipation time (soccer-specific skill) improved 0.02s from 10y to 12y. At the same time it was observed also that the tasks requiring motor skills (eye-hand-foot coordination and dribbling) developed more than the tasks requiring mostly perceptual skills (reaction times and anticipation time). For example dribbling time in soccer test improved more than 0.2s compared to 0.02s improvement in anticipation time. This might be one explanation why the players’ motor skills, which are closely related to players’ maturity status, are in overemphasized role at early puberty when players’ future potentiality is evaluated and when they are selected to talent camps. However, it is important to keep in mind that a multidisciplinary approach is needed in talent identification process [16]. It has even been proposed that in top level sports where the differences between the players’ physical performance characteristics are minimal, it is more likely that the cognitive skills act as the limiting factors of successful sport performance [9].

From the results of the present and earlier cross-sectional study it can be suggested that the progression in general perceptual motor skills during puberty is linear in nature. In all three measures of general perceptual motor skills, the 12y players results settled in the middle of the 10y and the 14y players. In earlier cross-sectional study, the relationship between reaction time to peripheral stimulus (PAT) and total performance time in soccer-specific test (STIME) correlated in the 10y group (r=0.72, p<0.01) but not in the 14y group (r=0.34, ns.) which suggested that the general perceptual motor skills may have more important role in soccer at the younger age groups. The results of the present follow-up study did not support this assumption. In the present study, the ability to react quickly to general peripheral stimulus (PAT) demonstrated the strongest relationship with soccer test time (STIME) at both ages without any changes during follow-up. Therefore, even though there is still possibility that general perceptual motor skills have more important role in soccer during pre- and early puberty than later, it is more likely that the significant relationship (or lack of it) between PAT and STIME was age-independent and related to research group participating in the present study.

Contrary to findings between general perceptual motor skills and soccer performance, it seemed that soccer-specific perceptual motor skills became more important with age. At least soccer-specific anticipation time (SANT) explained 36% of the variance in soccer test time (STIME) at the age of 12y compared to 1% at the age of 10y. According to the results of the present follow-up study and earlier cross-sectional set-up it seems also that the development of soccer-specific anticipation time was faster during puberty (~44% from 12 to 14y) compared to pre- or early puberty (~11% from 10 to 12y). These results confirm the suggestion that accumulated training leads to the acquisition and development of soccer-specific perceptual skills to a level required to reach domain expertise [9].
The difference found in aiming strategy (14y group aimed longer than 10y) in earlier cross-sectional study was not fully supported by the data of the present follow-up study. Even though the relative aiming time remained same during follow-up, the actual aiming time decreased almost 10% from 10y to 12y without compromising the passing accuracy. Actually the passing accuracy at the age of 12y (1.38 pts) in the present study was similar that was found in the 14y group (1.36 pts) in the earlier study. Thus, it is likely that the difference found in aiming strategy in earlier study was due to cross-sectional sampling and was not related to age. Nevertheless, further research is needed in order to develop realistic and economical ways (compared to very simple test procedure used in the present study) to examine soccer-specific cognitive skills more deeply.

Conclusion

The aim of the present study was to examine soccer juniors’ development in general and soccer-specific perceptual motor skills during early puberty. The results of the present study suggested that general and soccer-specific perceptual motor skills improved with age but these skills were not related to each other. That is, it is likely that specific types of activities in soccer training lead to the acquisition and development of soccer-specific perceptual motor skills which are not directly related to general perceptual motor skills. In addition, it seemed that with age the soccer-specific perceptual motor skills became more important part of successful on-the-ball soccer performance and therefore further research is needed in order to develop realistic and economical ways to measure soccer-specific perceptual and game reading skills.

References


PRACTICAL USE OF ICT FOR SPORTS INTERNSHIPS: E-LEARNING SYSTEM, GROUPWARE AND IPOD TOUCH

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Abstract

Our university has introduced academic sports internships for undergraduate physical education students to develop their instruction skills about fitness and sports. It is important to make prior preparation and establish a post reviewing process to improve the effectiveness of the internships. We have tried to utilize information and communication technology (ICT) to support internships. A general e-Learning system was employed for processes relate to internships, for example, providing information to students, receiving requests and various documents from students, and presenting e-Learning contents for self-study. For students who find it difficult to arrange a PC or an internet connection, we prepared iPod Touches that containing full complement e-Learning contents. Students can study anytime and anywhere with these iPods. A groupware system was deployed to contribute to the collaboration between students’ and interns’ on-site supervisors. The groupware provides an easy way to share documents that relate to internships. These trials contribute to carrying out sports internships more smoothly and effectively.

KEY WORDS: INTERNSHIP, E-LEARNING, GROUPWARE

Introduction

Internships provide valuable opportunities to convert classroom theory into practical skills, especially for students who are developing fitness and sports instruction skills. The National Institute of Fitness and Sports has provided academic sports internships as a part of curriculum for undergraduate physical education students since its establishment to develop their instruction skills about fitness and sports (Hagi, 2007). Internships are carried out at sports clubs, sports facilities or sports related companies that run sports, fitness or recreation programs. During the past twenty years, nearly 3000 students have received academic credits through the internships.

To participate in an internship, students need to process several procedures with faculty in advance. It is also important to make prior preparation and establish a post reviewing process to improve the effectiveness of the internship. However these procedures and processes can be a long term and demanding work for both students and faculty. Also it is hard to increase readiness for internships by students themselves.
Thus, we have tried to utilize information and communication technology (ICT) to support these internships. This paper introduces our trial to support activities related to internships for both students and faculty.

**ICT support for sports internships**

*Utilization of e-Learning system*

Numerous procedures and consultations must take place between students and faculty to take an internship. In our university, these procedures and consultations begin in October of the second-year. Then internships are held in next summer and reviewing process and follow-up education will continue until the end of October of the third-year.

To support these long term process between students and faculty, we have opened an “Internship Course” on our university’s e-Learning system. All intern candidates are registered to this course as members, and professors in charge of internships are registered as teachers. This course is used for several purposes including consultations, process management and communications. In Table 1 selected purposes of this course, and employed functions of the e-Learning system are listed.

<table>
<thead>
<tr>
<th>Purposes</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>To provide information to students</td>
<td>Textbook</td>
</tr>
<tr>
<td>To receive internship requests and record communication logs while coordinating internship sites</td>
<td>Study chart</td>
</tr>
<tr>
<td>To collect and counsel students in making documents</td>
<td>Study chart/Assignments</td>
</tr>
<tr>
<td>To provide self-study contents for internship</td>
<td>Textbook</td>
</tr>
<tr>
<td>To grasp the progress status of students</td>
<td>Quizzes</td>
</tr>
<tr>
<td>To receive repots and provide follow-ups</td>
<td>Assignments</td>
</tr>
</tbody>
</table>

General functions of the e-Learning system such as textbook, quizzes, assignments and study chart are used for communication and sharing information between students and teachers. Figure 1 shows screen captures of this course. With study chart function, teachers can make personal records like medical records in hospital. We use this function for individual counselling e.g. selecting internship facility. With quiz function, we make simple questions to grasp the progress status of students. Teachers can overlook student’s status by score of this quiz.
(a) Personal counseling with study chart function
   (personal record function)

   "You must pass all listed below before you leave for internship."

   "Did you submit a report for preparation?"
   "Did you have a preliminary discussions with instructor?"
   "Did you investigate your internship site?"
   "Did you check your dress?" ...

(b) Check list for interns with by quizzes function
We also developed several e-Learning contents for preparation and for reference during the internship. Figure 2 shows the titles of the contents. It consists of theoretical subjects, practical subjects and internship related subjects. Most subjects are selected from undergraduate classes, and some subjects such as machine training, business manner and safety management are specially edited for preparation of internship.

An on-line logbook service by groupware system

Interns are required to record and comment on all their activities in their logbook during internships. They need also to get comments from their local instructor every day. These logbooks were handwriting and exchanged between instructor and student. To simplify these processes and to be freed from the constraints of paper, we employ a groupware to share a logbook and other information on-line. Logbooks are official documents to award an academic credit, so it is important to guarantee their appropriateness. To fulfil this condition, we selected a groupware that provides documents versioning functions.

This time, the Microsoft Windows SharePoint Services 3.0 (WSS3.0) is selected, and it used to share MS-Word documents as logbooks. WSS 3.0 is provided as a free download from Microsoft for Windows Server 2003, so the system can be constructed with relatively low cost. WSS 3.0 provides intuitive operations with Microsoft Office, i.e. Microsoft Word. Students and instructors can edit documents with their familiar MS Word.
Figure 3 shows a sample of a “Document Library” page. We use a “Document Library” function to store and share logbooks. To record a log and a comment, users simply access to this page with their web browser, and click a title of a document. Then MS-Word starts up with the document, and then user edits it. The edited document is automatically saved to the server with new version number, thus document are shared by both interns and instructors.

![Image of Document Library on WSS 3.0 as e-logbook](image)

**Utilization of iPod Touch**

Students can use internship related e-Learning contents for multiple purposes, for their prior preparation, for reference during internships and for a post reviewing process. However to access these e-Learning contents, a PC and an internet connection are required. Not all students have their own PC or internet connection, and it will be more difficult to find a PC and internet connection on the internship site.

On the other hand, portable digital devices that can display images and videos are getting popular. These devices are equipped with a LCD monitor, large memories and a battery. There are several reports that providing educational materials with these devices (Majima, 2009). We have compared several portable devices such as Walkman, PSP (PlayStation Portable), and other PDAs. As a result, we selected the iPod Touch. The main reason was iPod Touch has a large and high resolution LCD and provides an intuitive operation to display/playback images and videos.

We tried to install all our e-learning contents with standard functions of iPod Touch. Video contents were installed as “Videos”, and HTML contents were converted to JPEG images and installed as “Photo” (Figure 4). Figure 4 (a) shows a sample of textbook style content displayed with “Photo” function. These pages can contain about 400 Japanese characters. Figure 4 (b) is a turned and zoom upped image of (a). Figure 4 (c) is a sample of an illustration content. Figure 4 (d) is a chapter guide of a video content. Each video content is chaptered for easy playback. Chapters are added using QuickTime Pro. Figure 4 (e) is a sample of a video.
To make clear text images for “Photos Viewer” of iPod, HTML documents are first adjusted with CSS, and printed to PDF files, and then converted again to high resolution JPEG images.

We lend iPods to intern candidates about 2-3 months before their internships, and collect those 2-3 months after internships.

![Figure 4. Displaying e-Learning Contents with iPod touch](image)

**Results**

We have been running these systems since 2007. More than 60 students use this support program every year. We had a questionnaire for students who used those systems. We received 55 and 56 answers in 2007 and 2008.

To use e-Learning system for procedures and consultations are accepted by most students. 64% students satisfied with the system, 25% were neutral, and 11% were dissatisfied in 2007. In 2008, 53% were satisfied, 33% were neutral, and 14% were dissatisfied. The representative reason for a positive answer was that they can process from everywhere and whenever. We are considering that dissatisfied students might have poor environment about PCs or internet connection, and with less computer literacy.

Our on-line logbook service ran a trial in 2007 with 2 internship sites, and made available for all internship sites in 2008. However, only 5 of 47 sites used this service. Users of this service were almost satisfied. They feel much easier to make records and to share documents. Some internship sites started to use several groupware functions which we did not introduced, such as calendars, BBS or information. These functions could be powerful collaboration tools even for internship.

The iPod Touch succeeds to increase student’s usage rate of e-Learning contents from 30-40% to 70-80%. Most students were satisfied with usability of the device, but 13% of students were dissatisfied for providing text contents with Photo Viewer, and 6% of students were dissatisfied for Video Viewer with usability.
**Conclusion**

To support our internship, we have tried to utilize computer systems and mobile devices. These systems and devices contribute to the smooth running and effectiveness of our sports internships program. This supporting model can be adapted to other activities such as a practicum, a teaching practice or other career development processes in a university environment.

**Acknowledgement**

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SERIOUS GAMES –
A NEW CHALLENGE FOR COMPUTER SCIENCE
IN SPORT?

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Abstract

Digital games can be used not only for fun and entertainment. The term ‘ seri-
ous games’ denotes digital games serving serious purposes like education,
training, advertising, research, and health. In the contribution the chances
and challenges of serious games for computer science in sport will be dis-
cussed.

Serious games, particularly adventure and shooter games, already play an
important role in health education and rehabilitation, e.g., to enhance health-
related physical activity, prevent asthma, change nutrition behavior and al-
leviate diabetes, prevent smoking or HIV.

Serious games also offer new options for training in sport. In our laboratory,
we developed a prototype for application in volleyball training.

Education in sport and sport science is another promising application field
of serious games. Particularly the natural sciences offer the opportunity to
combine simulations and gaming in order to learn about the basics of
movement.

The effects of Serious Games depend on the specific game genre. They can
be described and explained by different mechanisms including social, psy-
chological, and motor processes.

Despite first promising results the sustainability is a critical factor. In this
regard, computer science in sport can help to develop and implement serious
games and test appropriate settings that ensure sustainable use of serious
games.

KEY WORDS, SERIOUS GAMES, REHABILITATION, PREVENTION, HEALTH,
EDUCATION

Introduction

Playing games is a fundamental human activity. Engaging in playing means to pursue a
purposeless activity (i.e., driven by intrinsic motivation) that is free of external re-
straints, experiencing inner infinity (e.g., flow), and acting within an illusionary (sym-
bolic) ‘quasi-reality’. Games are ambivalent and open concerning both process and out-
come. On the other hand, games are subject to closed rules defining goals, allowed and
forbidden actions etc. Games normally have simple goal structures. Because of immedi-
ate feedback, players experience presence and directness. Games can be repeated over
and over like rituals. Because of all these features games in general have a positive con-
notation, particularly concerning human development. Particularly children and young adults can act in fictional or ‘virtual’ contexts, test different roles and experience different behaviour without the danger of causing ‘real’ consequences.

Concerning digital games, i.e., games that are played on electronic devices working with microprocessors, this positive connotation seems to be not valid. On the one hand, digital games (i.e., video games, computer games, and mobile games) are considered appropriate options to enhance cognitive, perceptual-motor, emotional, personal and social competencies (see figure 1; e.g., Gebel, Gurt, & Wagner, 2005; Wiemeyer, 2009). On the other hand, digital gaming is considered to cause addiction, obesity and other social, psychological or physical hazards (e.g. Griffiths, 2005; Mitchell & Savill-Smith, 2004, p.25).

![Figure 1. Competencies that can be enhanced by playing digital games (adopted with modifications from Gebel, Gurt, & Wagner, 2005, p.262)](image)

Recently an area of digital games emerged termed ‘serious games’. The idea of ‘serious games’ is to integrate playing games, simulation, and learning or training for serious purposes like education, exercising, health, prevention, rehabilitation, and advertisement (for a review cf. Smith & Sawyer, 2008). This combination of gaming and serious application purposes on the one hand offers new fascinating options and on the other hand raises critical questions. The purpose of this contribution is to address this ambivalence of ‘serious games’ and to discuss the specific chances and challenges for computer sci-
ence in sport. Three application areas will be discussed: prevention, rehabilitation, and learning.

**Serious games for prevention – exergames and games for health**

Physical inactivity and its consequences (e.g., obesity, hypertony, and metabolic syndrome) are among the most serious threats to health and well-being. Preventing accidents and falling is another important area of prevention, particularly for elder people. Besides control of nutrition and drug consumption, performing an adequate, continuous, and enduring physical activity or sport program is an important issue.

One goal of these activities is to raise the energy expenditure above a minimum 600 to 800 kcal per week, with an optimum of about 3,000 kcal per week (Sygusch et al., 2005). There have been many attempts to motivate and encourage people to engage in health-enhancing physical activities (HEPA). One key issue is to establish a sustainable modification of behaviour. In this regard, psychological aspects like motivation, volition, and self-efficacy play an important role (e.g., Godin & Kok, 1996, Hagger et al., 2002, Hausenblass, Carron & Mack, 1997, Sheeran, Conner & Norman, 2001, Theodorakis, 1992, Theodorakis et al., 1991). Furthermore, the structure of factors contributing to engagement in HEPA may change over time (e.g., Wagner, 2000). According to the proposed theory of planned behaviour and its extensions, digital games may offer a good option for HEPA because of their positive effects on attitude, emotions, motivation, intention, and self-efficacy.

The new generation of digital games, especially video games, works on interfaces that demand whole-body movements to control the game, like Sony eye-toy kinetics and Nintendo Wii sport. Specific sensors like cameras, motion sensors and force sensors register the movements of the players and integrate this information into the control of the respective game.

Numerous studies have been published showing great differences concerning the applied research methods (see Baranowski et al., 2008; Lager & Bremberg, 2005; Lieberman, 2005 for recent reviews). Concerning the rise of energy expenditure, figure 2 shows the results of the studies available. The impact of playing games on energy expenditure is highly depending on gaming device, game and intensity of gaming. Energy expenditure in ‘virtual’ sport games is always below the respective ‘real’ sports activity. At best an energy expenditure of above 400 kcal per hour can be achieved. This means that in order to meet the minimum requirements for HEPA, one has to play at least two hours per week; for the optimum at least 7.5 hours are required. From long-term studies we know that this demand has never been met by the subjects.

Other application fields are perception, motor control, asthma prevention, prevention of drug abuse, smoking prevention, HIV prevention, prevention of violence, and nutrition. Most of the studies find positive short-term effects of serious gaming on attitude, knowledge, motivation, volition, and behaviour. Almost nothing is known about long-term effects.

Summing up the existing evidence, the following effects can be expected from health games:

- Improvement of simple reactions
- Improvement of simple perceptual skills (e.g., spatial resolution)
- Improvement of basic motor control (e.g., balance)
- Improvement of knowledge concerning HEPA
- Improvement of self-efficacy and other motivational, emotional, and volitional components
Which are the particular challenges for computer science in sport?
Computer Science in Sport as an interdisciplinary scientific area has to deal with the following questions:
- Development of appropriate sensor systems being able to measure sport performance
- Development of appropriate algorithms for recognition of sport activities and action parameters
- Development of appropriate game concepts for effective and enduring enhancement of all components of health behaviour
- Evaluation of health games in order to identify the appropriate learning and training settings.

**Serious games for rehabilitation – Rehagames**

In rehabilitation numerous applications have been reported (see Wiemeyer, under review). Many of them are just case reports or qualitative studies based on small samples of patients. The following applications fields of therapy and rehabilitation are covered:
- Asthma
- Diabetes
- Cancer
• Respiratory diseases
• Neurological therapy after stroke and other brain injuries
• Burns

The first applications date back to the 1980s, where specific interfaces were developed and the motivational impact of games was exploited. In modern medical therapy, analogous to prevention, the effect models comprise all relevant aspects of human action and perception, ranging from knowledge to actual behaviour. One important result of these studies is that therapy has to employ meaningful movements, i.e. movement embedded into a context that makes sense to the patients. Using movements to control a game instead of rote movements had a significant positive effect on therapeutic results.

Again, in the area of rehabilitation some specific challenges exist for computer science in sport:
• Selection of appropriate sport or sport-like movements in order to offer meaningful contexts
• Construction of appropriate training devices (including sensors and interfaces) to enhance motor control
• Development and evaluation of adequate training settings.

**Serious games for learning – Edugames**

A third application field of serious games is education. According to Mitchell and Savill-Smith (2004) there are many reasons to apply digital games to education and learning:
• Digital games enhance individual engagement and active involvement in learning by increased motivation.
• Digital games deliver fast, individualized and immediate feedback.
• Digital games increase learning efficiency.
• Digital games individualize learning by means of numerous options for interaction, adaptation and communication.
• Particularly simulation games offer unique opportunity to learn without having to face real consequences like injuries (e.g., Lee, 1999). Particularly the natural sciences like maths, physics, and chemistry offer good options for simulation games because a high level of formalization exists that can easily be transformed into game scenarios with clearly defined tasks and feedback options.

In general digital games have been used predominantly in the following application fields:
• Clinics – diagnostics, training, and therapy
• Language and maths education
• Physics
• Psychology
• Basic perceptual and sensory-motor skills and abilities
• Problem solving

In sport and sport science only few reports have been published so far using digital games for learning motor skills or enhancing motor abilities. The results show that digital games have a great potential for learning.

Fery and Ponserre (2001) showed that using a golf video game could enhance putting accuracy. The players had to control a virtual player’s putt. However, only the game group who could watch a symbolic representation of the putting force (gauge on a scale) showed enhanced learning.
Hebbel-Seeger (2008) adopted a simulative sailing game to enhance sailing skills. In a preliminary study, he found positive transfer effects to real sailing. He assumes that cognitive transfer was supported by the training environment. In three consecutive experiments on learning table tennis skills, Sohnsmeyer (2009) found effects on both knowledge and reaction in table tennis.

Brumels et al. (2008) applied the video games ‘Dance Dance Revolution’ and ‘Wii fit’ to the training of balance skills. They found differential effects of video gaming compared to a traditional balance program: Whereas the traditional group performed better at the Star Excursion Balance Test, the two game groups outperformed the traditional group at the postural sway task. Furthermore, the game groups reported that the training program was less strenuous and more enjoyable compared to the traditional group.

In general, applying digital games to education in sport seems to support at least two components: knowledge about movements and basic perceptual-motor skills. There is some evidence that sports-specific motor control may also be improved.

In our lab a volleyball prototype was developed (in cooperation with the research group of Dr. Stefan Göbel) in order to improve tactical knowledge and behaviour (see figure 3). The player has to solve typical tactic tasks of increasing difficulty. She has to proceed in different steps:

1. She has to choose three options from a menu of suggested actions: ideal, sub-optimal, and emergency option. Depending on the quality of reception one of these options are chosen by the program.
2. She has to control the receiving player. First, she has to place the player at the correct location to receive the ball and second she has to initiate the receiving action at the correct time.
3. She has to control the attacking player. She has to decide on attacking technique, direction and speed of the attacking action.
4. Finally the quality of the three steps is recorded and a final score is displayed. Then the sequence starts again with the first step.
Which are the challenges for computer science in sport?

- First of all, appropriate application to learning needs to establish a perfect fit of didactics, learning theory, and the respective digital game system.
- Appropriate interfaces and sensors have to be developed which allow a realistic transformation of players’ actions to sensor signals.
- To identify action types and parameters in real-time appropriate and fast algorithms have to be developed.
- One important challenge is to determine the adequate level of transfer. The transfer problem is one of the crucial issues for learning (e.g., Hossner, 2003; Smyth, 2003).
- The key issue is to establish an appropriate balance of gaming and learning (e.g., Ang & Rao, 2008). This is not at all trivial. In this regard, Ang and Rao (2008) have identified three main reasons why educational games may not be as attractive as commercial digital games: lack of a narration that addresses phantasy and curiosity, lack of semantic rules that address education and learning, and lack of explicit ludus rules that demand solving challenging tasks of adequate difficulty.

**How do Serious Games work?**

This issue has already been addressed in the previous sections. Applying digital games to serious purposes like prevention, rehabilitation, and education is far away from a naive expectation of just enhancing fun and activation. Most of the studies are based on a
detailed model of effects. To sum it up, the following levels can be distinguished (see also figure 1):

- **Motivation, emotion, and volition**
  Positive effects on intrinsic motivation, attitude, self-concept, perceived control, and self-efficacy are expected and have been confirmed by research.

- **Cognitive learning**
  Serious games support a specific way of cognitive learning. By solving attractive tasks, repeating the attempts to solve the problems, getting immediate feedback and background information, a deeper information processing becomes possible. Transfer may be enhanced by more authentic contexts or the appropriate symbolic representation of transfer-relevant information.

- **Perceptual-motor learning**
  Depending on the quality of the (wo)man-game interface, basic or specific perceptual-motor skills and abilities can be acquired and transferred.

- **Social interaction and communication**
  Constructivist approaches emphasize the importance of social interaction and communication for learning. This component can be addressed by a specific genre of digital games: massively multi-player online games (MMOG). Mobile devices like cell phones and PDAs (personal digital assistants) can also be used to support interaction and communication.

As a result, the surplus value of serious games must not be reduced to the simple formula ‘serious purpose + motivation’. Rather, serious games offer options for a new kind of prevention, rehabilitation, and education.

**Conclusion – Chances and challenges**

In this contribution, three application fields of serious games have been discussed. Existing studies clearly show that serious games have much to offer to the fields of prevention, rehabilitation, and education. On the other hand, to avoid a new ‘hype’ overestimating the potentials of serious games, the new options of serious games can only take effect if serious games are developed and designed based on an interdisciplinary understanding of the respective application field. The requirements of the field have to match the options of digital games. Successful applications show that this synthesis is possible and can produce substantial benefits of serious games.

One key problem to be solved is sustainability. Serious games have been proved to produce short-term effects. This effect may be due to initial increase of motivation. But prevention, rehabilitation, and education aim at enduring effects. Few studies investigating long-term effects are much less promising. In order to ensure sustainability, research has to evaluate which settings support long-term motivation and engagement in serious games.

Furthermore, there are great challenges for computer science in sport concerning development of appropriate sensor and interface technology, real-time activity recognition, and establishing a balance of narration, rules, and application purposes. To achieve high quality of serious games, there is a strong demand for truly interdisciplinary cooperation. The future will show whether computer science in sport is willing and ready to meet these ambitious demands.
References


THE DESIGN OF EFFECTIVE FEEDBACK IN COMPUTER BASED SPORT TRAINING

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Abstract
This paper presents the design of effective feedback in the motor skill domain via Computer-based Sport Training (CBST) in order to support athletes’ achievement of their intended training outcomes. With increasingly rapid development in Computer-based Sport Training (CBST), feedback plays an important role in both coaching and learning. A good CBST system includes not only good training strategies but also effective feedback design. Feedback in the motor skill domain via CBST may be synthetically designed to allow athletes to practise in a more effective way, and enhance their skill acquisition. Existing designs lack pedagogical elements. To bridge the gap, we propose a framework for the design of pedagogically-informed feedback based on; learning transactions, competence, cybernetics, and behaviourism. We present the design of effective feedback in the motor skill domain which focuses on the requirements and analysis stage.

KEY WORDS, COMPUTER ASSISTED INSTRUCTION, FEEDBACK, PEDAGOGY, COMPETENCE, INSTRUCTIONAL DESIGN

1.0 Introduction
In traditional sports training, the coach directs and improves the performance of athletes by giving information on techniques, tactics, and physiological demands whilst observing them. The volume of data generated means it is often not possible for a coach to track all the variables and information. Furthermore, the environment of training in large fields out of doors and the consequent scattering of athletes, make the coaches’ exact observation of the action of athletes difficult. To overcome these drawbacks, Computer-based technology (e.g., virtual reality, motion training systems, and ergometer machines) has been introduced into the sport domain and is used to record athletes’ performance (Beetz, Kirchlechner, & Lames, 2005; Guang-zhong, 2008; Liebermann, et al., 2002). Thus, CBST serves as both a stimulus towards and a method for the study of choices that athletes make during athlete-controlled training opportunities.

The development of CBST has made it possible to augment and improve the feedback that athletes receive during training. Hardware-based feedback systems incorporate embedded sensors and devices into the sports equipment and use sensors attached to the athlete to acquire information about learning processes and the achievement of intended
training and learning outcomes (Baca & Kornfeind, 2006). Through feedback, athletes recognize areas of deficiency in their knowledge and skills which they seek to remedy.

Feedback can be intrinsic or extrinsic, the latter consisting of knowledge of results or knowledge of performance (Newell, Quinn, Sparrow, & Walter, 1983; Partridge, 1967; Schmidt, Lange, & Young, 1990). Knowledge of results allows performers to examine their efforts in relation to an externally defined goal (Goldstein & Rittenhouse, 1954; Locke, Cartledge, & Koeppel, 1968; Salmoni, Ross, Dill, & Zoeller, 1983; Stockbridge & Chambers, 1958). However, such information feedback provides only goal-related information and ignores knowledge of performance, which is information about how the action was completed. We suggest that pedagogically designed feedback in the motor skill domain would allow athletes to know both their performance goals and the performance changes needed to achieve some expected or learning training outcome. Such pedagogically designed feedback would allow adaptive training experiences that are tailored to the different needs and characteristics of athletes, especially in terms of their current competence.

Thus, the main research question that this paper seeks to address is the design of effective feedback to the athletes when using CBST.

In this paper we present the key components of feedback in the motor skill domain, propose a framework for pedagogical feedback, and construct a more detailed blueprint for its pedagogically informed design and provision.

### 2.0 Motivation of this paper

Effective feedback to athletes has been identified as a key strategy in motor skill learning. Effective feedback supports athletes in developing their motivation, awareness about their learning process, and selection of the competences they wish to develop. This type of feedback provides some of the events of instruction described by Gagné and Driscoll (1988).

Effective feedback is specific, immediate, and contingent (Gilbert & Gale, 2008): appropriate and timely, suited to the needs of the situation, and sufficient. Feedback in CBST contributes to learning by allowing athletes to verify their movements, evaluate their progress, and determine the cause of errors. It also motivates them to remain involved in the training tasks, given that they perceive the feedback as helpful. This requires the active processing of feedback which is specific as well as feedback which addresses general metacognitive knowledge and strategies.

Hence, there exists a large variety of information that might be provided as feedback. The challenge for educational researchers and designers of CBST environments is to determine what constitutes effective and appropriate feedback for athletes in their training trajectory.

Currently, issues of feedback in the motor skill domain via CBST concern:

1. delivery of the feedback contents such as speed, accuracy, movement, time, and reaction time (Baudouin & Hawkins, 2004; Cheng & Hailes, 2008; Walls, Bertrand, Gale, & Saunders, 1998),

2. providing athletes with access to their feedback via an appropriate user interface (Cyboran, 1995), and

3. modality of feedback, such as visual, audio, tactile, and haptic feedback (Kwon & Gross, 2005; Philo Tan, et al., 2003).
Currently, feedback design is typically led by technology and fails to properly consider pedagogical issues. Feedback in CBST does not usually derive from the goals, actions, performances, outcomes, and contexts of a learning process.

Thus, for pedagogical reasons, this paper proposes the design of effective feedback that can:

1. support athletes in their achievement of the underlying intended training and learning outcomes,
2. assist athletes in identifying the gaps in their performance, and
3. help athletes to determine performance expectations, identify what they have already learned and what they need to learn next, and judge their personal learning progress.

3.0 Pedagogically designed feedback

The inputs to the pedagogically designed feedback in the motor skill domain are illustrated in summary in Figure 1.

![Figure 1: Inputs to the development of pedagogically designed feedback in the motor skill domain](image)

The four inputs are the learning transaction, competency, cybernetics and behaviourism. These components were chosen as they repetitively surfaced in research as the keys to effective teaching and learning.

3.1 Learning transaction

The learning transaction is a model (see Figure 2) of “what goes on” at the coach-athlete interface (Gilbert & Gale, 2008), providing an overview of what is needed to analyze, design and implement pedagogically designed. It is a simplified version of the ‘learning conversation’ (Laurillard, 2001), based on active learning tasks, goal setting, reflection and adaptation. Interaction between the athlete and coach is central to the skill acquisition. A key of the learning transaction is that it is a dynamic and dependent dialogue: each iteration occurs as a sequence of coach-athlete interaction involving description, performance, and interpretation of their impact in the world of action.

During a training session, effective instruction would be crucial to the pursuit of optimal sporting performance, as the more effective the instruction, the more the coach’s role
will benefit athlete performance. Such instruction requires the application of skills that range from the planning and organization of learning experiences to the presentation of instructional and feedback information. Hence, the primary role of coach and athlete is to stimulate the performance of training activities that will progressively result in the attainment of the intended training and learning objectives. The coach defines the tasks, provides the contexts and resources to perform the tasks, supports the athlete during task performance, and provides feedback about the results. This may involve providing instruction about optimal movement patterns or feedback on errors relating to specific task goals.

It is anticipated that pedagogical feedback in this context can be straightforwardly designed and engineered, given an appropriate specification of the intended objectives as they are required to be learned in a CBST.

![Learning transaction diagram](image)

**Figure 2: Learning transaction diagram (Gilbert & Gale, 2008)**

### 3.2 Competence

![Competence conceptual model](image)

**Figure 3: Competence conceptual model (Sitthisak, 2009)**

A competence may be defined as any form of knowledge, skill, attitude, ability or educational objective that can be described in a context of learning, education or training (Sampson, Karampiperis, & Fytros, 2007). The notion of competence is important for optimizing skill acquisition, since the term ‘competence’ can be considered as a subject matter component, based upon knowledge representation models, an action component (capability) which describes how the knowledge or subject matter is used (Figure 3), and a context in which the competency is evidenced.
There are taxonomies which classify the action components, such as Dave’s taxonomy (Kennedy, Hyland, & Ryan, 2007). The classified action components describe different motor skill processing modes and can be characterised with specific action verbs.

Dave’s taxonomy provides a qualitative way of organizing skills consisting of five levels of skills, in increasing order of competency:

1. **Imitation**: Observing the behaviour of another person and copying this behaviour. This is the first stage in learning a complex skill.
2. **Manipulation**: Ability to perform certain actions by following instructions and practicing skills.
3. **Precision**: At this level, the athlete has the ability to carry out a task with fewer errors and become more precise without the presence of the original source. The skill has been attained and proficiency is indicated by smooth and accurate performance.
4. **Articulation**: Ability to co-ordinate a series of actions by combining two or more skills. Patterns can be modified to fit special requirements or solve a problem.
5. **Naturalisation**: Displays a high level of performance naturally (“without thinking”). Skills are combined, sequenced and performed consistently with ease.

### 3.3 Cybernetics

![Figure 4: Basic cybernetics model (Pratt, 1978)](image)

It is well-known that the development of cybernetics as a modern discipline with a distinctive influence on almost all branches of science and technology follows from Norbert Wiener's publication on the subject in 1948 (cited by Roos & Hamilton, 2005). In this paper, the cybernetic orientation views the athlete as an element in a larger human-machine or a human-computer system. The athlete is not merely reacting to external stimuli and not merely processing perceptions internally; the athlete reacts to information and processes that information in cooperation with the instructional media. This orientation to learning is most applicable to designers of computer-based instruction.

Cybernetics provides a model where discrepancies in performance capabilities can be identified and corrective action taken (Figure 4). If there are discrepancies, the behaviour of the controlled system is changed according to differences in actual output and required standard. Ultimately, feedback governs the changes in communication, which changes behaviour, which changes the communication, and so on in a circular feedback loop that enables a system to maintain a desired state. Cybernetics may provide a different and interesting explanation for why a particular approach seems to work while another does not.

In accordance with such engineering models, closed loop systems were designed to keep homeostasis or equilibrium around a reference value, which, in turn, would allow
the work of a main actuator (Scott, Shurville, Maclean, & Cong, 2007). Deviations from
the steady-state reference were coded as error, which would then drive the system to
compensate or correct. That is, in movement science, feedback information about
movement was generally expected to allow systematic corrections in the performance.
However, feedback will be relevant to the human learner if, and only if, the individual
knows the performance goal and perceives the need to carry out corrections relative to
some expected outcome. Under such assumptions, a coach should strive to provide an
environment that is conducive to optimum learning by augmenting the feedback that
athletes receive. Feedback should thus enable athletes to modify their movements and
produce optimum performance.

The analysis of pedagogic feedback in the motor skill domain from a cybernetic point of
view has four major components;

1. measurement of the current competency of the athlete,
2. statement of the required standard of the competency,
3. comparison of the current competency to the required competency, and
4. corrective feedback and information.

3.4 Behaviourism

The question of how people acquire novel motor skills has long been a topic of interest.
This dates back to the early work of the behaviourists (e.g. Thorndike, 1927; Skinner,
1953) (cited by Mergel, 1998), when the outcome of the movement and the determina-
tion environmental contingencies were of primary significance.

The term reinforcement, which refers in general to the effects made upon learning by its
consequences, continues to play a prominent role in the explanation of learning phe-
nomena. Once learners have exhibited the new performance made possible by learning,
they at once perceive that they have achieved the anticipated goal. This informational
feedback is what many learning theories consider essential to the process called rein-
forcement. This process is of widespread significance to human behaviour, particularly
to human learning. According to this conception, reinforcement works in human learn-
ing because the expectancy established at the beginning of learning is now confirmed
during the feedback phase. The process of reinforcement operates in the human being
not because a reward is actually provided, but because an anticipation of reinforcer is
confirmed.

From a behaviourist perspective, pedagogical feedback should be designed as a result of
the task analysis. A task analysis is a step-by-step description of the performance that
the task represents, and results in the identification of (1) the executive subroutine that
must be learned in order for the athlete to carry out the task, and (2) the links between
the individual task procedures, each of which must be recalled from previous learning or
newly learned (Gagné & Driscoll, 1988). Task analysis is done for performance support
tools since it elicits knowledge for design purposes, provides a reference for evaluation
and ensures the efficiency and accuracy of the resulting system. The aim of task analy-
ses is to identify domain-specific subject matter content (e.g. facts, concepts, procedures
and, principles).

Pedagogically designed feedback, therefore determines whether the athlete has acquired
all the links of the chains in all the specific R-S units. Since every link is the response
for the succeeding link, the absence of one link means that the skill cannot be performed. The feedback also determines if the athlete has learned all the components.

A skill is a series or chain of movements, with each link and individual Response-Stimulus (R-S) unit acting as a stimulus for the next link. The term “contingency” is used to refer to the “if-then” relation, which connects behaviour with its consequences. In a contingency, then, a response is an operant, and its effect is upon the environment. The connection between them is the contingency.

Chains of motor responses become the components of motor skills, often as part-skills. These latter are combined into organized motor performances which continued practice invest with smoothness and precise timing. Each link of the chain to be acquired must have been previously learned as an R-S association.

The contingencies of reinforcement must be suitably arranged so that the reinforcement is made contingent upon the occurrence of the behavior to be learned. This means that feedback must be arranged so that some reinforcing activity follows closely the occurrence of the desired receptive behavior.

### 5.0 Framework for design feedback based on pedagogy

The framework of pedagogical feedback in the motor skill domain (see Figure 5) draws a picture of how the principles from learning transaction, competency, cybernetics, and behaviourism work together to build sound pedagogical feedback for the implementation of a CBST system. The objective of the framework is to identify and represent the athlete’s current knowledge and the competence level s/he wants to achieve, and using those to formulate their personal competence development plan.

![Figure 5: Framework of pedagogical feedback in the motor skill domain](image-url)
The framework shows how the iterative cycles required for learning work together. The essential steps are active learning, feedback, and reflection. In particular, the framework offers a more complex appreciation of the nature of a coach athlete interaction and the nature of feedback to facilitate learning. The learning experience explicitly builds on the learning transaction theory.

The framework can be seen as a lifecycle which aims at the continuous enhancement and development of an athlete’s competence. Additionally, it might assist in increasing consciousness and focus on personal competence development. The main steps of this lifecycle can be identified as follows:

1. The creation of a competence model from the coach.

Competence models are used to inform the design of appropriate learning activities so as to minimize the gap between the required competences of a given curriculum and the ones owned by an individual athlete.

The required competence will influence what behaviours are exhibited by the learner and thus influence the selection of an initial response. A certain strategy may be adopted as a result of this information, such as avoidance or adoption of a particular movement behaviour.

An athlete typically engages in a series of training activities to acquire a certain competence. The athlete determines which competences s/he wants to develop. Once this decision has been made, the athlete has a choice. One very quick route is to go directly to the competence development activities, based on the learner’s interests and proceed by collecting evidence, which shows the athlete’s current proficiency level. After the athlete has collected this evidence, they can again choose: either they can have their proficiency level officially recognized by others, or they can go directly to the training activities.

2. The gap analysis between required competences and current competence of the athletes

Whenever an athlete with a particular learning goal that can be interpreted in terms of a set of competences with particular proficiency levels, the competence comparator measures the performance of the athlete and compares it with the required competence as defined by the coach. The result is a gap analysis, which yields the required feedback and information output. The feedback generated is based on the results from the assessment that reflect the attainment of the intended learning outcome. During learning, personalised learning activities are continuously monitored and the data corrected used for feedback generation. For athletes this implies that they should be advised on the learning possibilities that match their current competence level and that work toward their desired competence level (learning goals), taking into account their restrictions and preferences.

3. The continuous performance monitoring and assessment to confirm improvement.

A ‘portfolio’ serves several roles in competence development. A portfolio is a dynamic collection of authentic and diverse evidence that represent which competencies a person has developed over time. It provides (a) profiles of competencies, and (b) opportunities for athletes to document their competencies in different contexts. Athletes define these evidences through a self-reflection process through which they attribute their competences to learning outcomes, and reflect on how they acquired such competences. From
the pedagogical point of view, this process helps athletes better to understand themselves (knowledge-self) and become self-directed learners.

6.0 How to design effective feedback to the athletes when using CBST?

The data flow diagram of Figure 6 presents the feedback system functionality, illustrating the data that is exchanged between the system and the environment, and the main data flows within the system. The purpose of the feedback system is the collection of traces of athlete actions and to present feedback based upon these traces to the athlete.

6.1 Manage athlete competence profile

In order to take any practical steps towards achieving intended learning outcomes of their training, the athlete needs to find or create an appropriate target competence profile which will provide the basis for defining a path for reaching it. In order to offer the right training activities to athletes at the right time, the system will have complete, accurate, and reliable information about athletes and training activities. Concretely speaking, the system need to know athletes’ competence profiles (a set of competences at a particular level of proficiency) and the required competence profiles and objective competence profiles of courses and training programs. Athlete personal competence result from his/her personal portfolio, personal information available, formal, accredited learning as well as from experience gained in informal learning situations.

![Figure 6: Feedback system data flow diagram](image)

6.2 Clustering performance

Having determined the required competence, the system will cluster the athlete performance onto the set of acquired competence. Sensors are responsible for capturing appropriate measures of the athlete’s interactions.
6.3 Compare competence

The system will map both athlete and coach competences in generating a gap analysis of the athlete's performances. This involves assessment of current competences and a comparison of competences.

6.4 Addressing the gap

Feedback relies on the athlete’s previous actions as well as on the interaction context in which an action occurs. This feedback is critical for learning. Important questions to consider are how often should feedback be provided, how precise this should be and when it should be provided. Without the knowledge that an error has been made, the athlete will not be motivated to change their response on the next trial and thus improve performance. Feedback relating to the movement should be as simple as possible and convey important information about their intended learning outcome. This feedback should be compatible with the required competence, such that error information is easily attainable to determine the intended learning outcome.

Whenever an athlete has performed a training activity, the relevant proficiency level of the athlete will be automatically updated if previous level was lower than the required proficiency level. This automatic mechanism can timely trace the competence development without adding human users’ burden to do assessment work. The fusion process of this method takes only the newest competence record into account. Using this method implies that the associated competences of all learning activities and assessment activities in the learning network are appropriately described and they are equally credible and trustworthy. If the objective proficiency level of one activity is described higher than the actual associated competence, after an athlete successfully performs this activity, the competence estimate of the athlete will be updated to a level that may be higher than the level of potential competence.

Once the system decides how much feedback to give, it must determine the content of the advice. The feedback should contain enough information so that the athlete can proceed to the next step. Furthermore, the advice given to the athlete should be appropriate for their ability level. By using this technique, athlete will not be required to wade through many levels of hints before receiving useful help. However, the athlete is usually not interested in the details; they rather want to know about higher level information such as “progress” or “achievements”. Therefore it is not useful to show each event or cue separately.

6.5 Generate competence achievement

Competences can be acquired at different levels. These levels are modeled via proficiency levels, each representing a discrete ordinal measure to which a competence has been acquired. There may be a number of evidence records relevant to the same competence of an athlete, which originated from the same or/and different performances. A set of evidence records can be integrated into a competence record, which explicitly shows that an athlete has a known proficiency in a particular competence. The feedback relies on the athletes’ previous actions as well as on the interaction context in which the training occurs.
7.0 Conclusion

The paper argues for the design of feedback based on pedagogy, and what is now needed is empirical evidence. The core deliverables of the research will be a simulator demonstrating effective feedback: engineering and pedagogic processes for motor skill competence development. We provide a machine-processable representation of competences, relationships among them and competence profiles. Such a design will be specially designed for reusability and allows advanced algorithms for competence gap analysis and profile matching.

Potential benefits for effective feedback in the motor skill domain include:

1. athletes can focus more specifically and more exactly where improvements are needed,
2. athletes need not focus so much time on their training for what they have already learned, and can instead concentrate on areas of required improvement,
3. athletes can focus on personal competence development of the athlete by eliminating the gap between acquired and required competences,
4. athletes avoid information overload since the system deliver personalised feedback, and
5. athletes will find training that better matches their competences and preferences.

On-going research is being planned for experiments to validate pedagogically designed feedback in the motor skill domain. We believe that a pedagogical feedback in the motor skill domain is critical to successfully ensuring a pedagogic focus on coaching and learning activities. To do this, this paper has suggested that we must start from “what it takes to learn,” using all we know from learning theory, and construct a pedagogical framework with which to provide a strong challenge to the technology.

References


PROVIDING AUTOMATED DECISION SUPPORT
FOR ELITE ATHLETES

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Abstract
The Victorian Institute of Sport routinely collects vast amounts of data. To utilise the use of this data and develop decision support systems to help improve elite athletes’ performances, we describe how knowledge discovery from databases, feature subset selection and recommender systems can be gainfully employed.

KEY WORDS, DECISION SUPPORT SYSTEMS, ELITE ATHLETES, RECOMMENDER SYSTEMS, FEATURE SELECTION

1. Introduction
Each year, a vast amount of competition, psychological and physiological data is collected about elite athletes. However, these data are rarely appropriately analysed to provide advice for coaches and athletes decision-making. To better utilise the available data and knowledge, we are developing decision support systems that analyse the information and provide useful advice with regard to advanced training and performance.

Once decision models of success in individual sports have been developed, we are developing data mining techniques for finding the smallest feature set having the most beneficial impact on performance and constructing recommender systems, tailored for individual athletes.

Following testing against design specifications and user acceptance, a generic framework for the construction of decision support systems to support elite sports performance will be developed.

To construct such a framework we are using

a) Decision models – we are developing decision models for defining and understanding success in specific sporting domains;

b) Knowledge Discovery from Databases – given a model of successful athletic performance, we can attempt to learn the patterns that led to the attainment of excellence and which variables can lead to negative repercussions, such as loss or injury. For example, what strategies are most significant for successful performance and which variables can be used to predict the development of injuries during training or competition;

c) Feature subset selection - finding the smallest feature set having the most beneficial impact on performance;
d) **Developing recommender systems** - once we have evaluated and agreed upon the results of the learning used in b) and c), we can then build systems to advise upon training, performance and strategies. These systems are being tailored for individual athletes, and use data and knowledge to enhance training, reduce injuries and improve performance. When completed, they will be tested against design specifications and emphasize user acceptance.

Our goal is to use the vast amount of physiological and competition data available to us to integrate these approaches, where possible. We recognise both the importance and the difficulty of providing semi-automated psychological advice and hence do not address this task in the current project.

### 2. Modeling Sports Performance

The German Research Center for Peak Performance Cologne at German Sport University Cologne annually tests about 600 young and national level athletes on about 3000 variables\(^2\). So they have an electronic internet based data-set that also can be visually/textual printed for different athletes and coaches. Currently, a one-page information sheet is selected in a profile-manner for individual athletes and compared to some means of talent groups to see if specific athletes are far above/beyond the mean. There are also already decision meetings implemented between the diagnostic centre, coaches and other people. However, currently, they do not have an electronic decision support system: instead all the information is shown to the coach without any help or comparisons. Our goal in this project is to meet this need by providing both the Victorian Institute of Sport and the German Research Center for Peak Performance Cologne with electronic decision support.

Johnson (2006) provides an introduction to the theoretical, practical, and methodological advantages of applying cognitive models to sports decisions. The use of sequential sampling models, in particular, is motivated by their correspondence with the dynamic, variable processes that characterize decision-making in sports. He offers a brief yet detailed description of these process models, and encourages their use in research on decision-making in sports. Although the formulation focuses primarily on deliberation among a set of options, incorporating other critical task components (e.g. option generation, learning) is contemplated. A criticism of Johnson’s modelling is that it may not be appropriate in application to athlete option choice which is time-constrained {limiting the ability to generate options, for example, see also Zsambok and Klein (1997)}. The use of the cognitive models of (Johnson 2006) will prove highly useful for developing process models. Recent mathematical modelling of choices can be used as a framework to set up choice rules for talents description (Johnson and Raab, submitted), talent prediction and a decision tool for coaching decisions as individuals or groups (Farrow & Raab, 2008).

#### 2.1 Decision Analysis and Sport:

There are numerous approaches for developing decision analysis techniques for the sporting domain. A well known use of statistics in baseball is sabermatics - a statistically-based approach for developing and applying objective knowledge to baseball. James (2004) coined the term “Sabermetrics” which stems from the group SABR (Society for American Baseball Research). Lewis (2003) in his book Moneyball details how

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Oakland Athletics general manager Billy Beane and his staff used statistical analysis to design a low-budget team that could compete with teams in bigger markets with larger payrolls. He did this by isolating the important factors in winning baseball games. Under Beane’s leadership, the A’s managed to reach the playoffs for four consecutive years. Over that period their salary cost per victory was less than half of the next highest spending team and less than a quarter of teams like the New York Yankees. Whilst the Yankees are relatively successful, this success has occurred at a great price.

Gröschner and Raab (2005) have used a theoretical approach that is called simple heuristics (e.g. less information can lead to better decisions) and compared them to Bayesian strategies\(^3\). For instance, according to the take-the-best heuristic, when making a judgment based on multiple criteria, the criteria are tried one at a time according to their cue validity, and a decision is made based on the first criterion which discriminates between the alternatives (Gigerenzer and Goldstein 1996). Decision support systems and algorithms that use regression or Bayes, versus simple heuristics are natural comparison candidates for further testing the benefits of decision support systems. Given our experience in modelling sporting comparisons, we wish to develop support systems based on the Decision Field theory \{see Raab & Johnson, (2004)\}, T-ECHO \{Explanatory Coherence for Harmonic Optimization\} computational approach on choices (Johnson & Raab, submitted), simple heuristics versus regression and Bayesian networks. (Gröschner & Raab, 2005) and compare these to the artificial intelligent approaches such as neural networks, optimization procedures and KDD (see below).

For a variety of sports chosen by the Victorian Institute of Sport (beginning with swimming, but including cycling, rowing, track and field and golf) we will develop criteria to define ‘success’. Depending on the individual athlete, this might mean winning a gold medal, winning any medal, reaching the final or semi-finals, or achieving a personal best. Different success criteria will also be developed for athletes at different stages of their careers.

Strategy and risk is also a component of performance in sport. In many human endeavours such as business, government, law and medicine, decision-makers wish to minimise risk. Hence, they do not attempt to find optimal solutions to problems (Zeleznikow 2002). Unique to sport, however, it is generally the participant’s goal to achieve an optimal result\(^4\), where often the margin for losing may matter less than the loss itself, hence strategic risk-taking in both training and performance is standard. Contrary to optimizing strategies are satisfying strategies as described above in form of simple heuristics or rules of thumb or thresholds in a decision field theory that allows coping with limited time, limited resources and limited capacity of humans making fast and frugal decisions.

2.2 KDD and Sport:

According to Frawley et al (1991) knowledge discovery from databases (KDD) is the ‘non trivial extraction of implicit, previously unknown and potentially useful information from data’. Data mining is a problem-solving methodology that finds a logical or

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\(^3\) Bayesian methods provide formalism for reasoning about partial beliefs under conditions of uncertainty. In this formalism, propositions are given numerical values, signifying the degree of belief accorded to them. Bayes’ theorem is an important result in probability theory, which deals with conditional probability.

\(^4\) In the 1960s, the great American (Green Bay Packers) football coach Vince Lombardi is quoted as saying “Winning isn’t everything, it is the only thing”. However, the quote is first attributed to UCLA Bruins football coach Henry Russell (“Red”) Sanders, who in 1950, at a California Polytechnical University at San Luis Obispo physical education workshop developed the notion (Rosenbaum 1950).
mathematical description, eventually of a complex nature, of patterns and regularities in a set of data (Fayyad et al 1996).

Recent reviews of expertise in sport have indicated that many coaching practices are based on “anecdotal evidence and historical precedence” developed from “intuition, tradition and emulation” (Williams and Ericsson, 2005), rather than from empirical research. This highlights the need for empirical evidence to rationalize evaluation and skill testing practices in order to guide training, selection and decision making practices with regard to maximizing performance.

The KDD process begins with the analysis of data stored in a database or data warehouse and ends with the production of new knowledge. Fayyad et al (1996) describe knowledge discovery as a process with five distinct stages:

a) Data selection;
b) Data pre-processing;
c) Data transformation;
d) Data mining and
e) Evaluation/Deployment.

Fayyad et al (1996) claim that data mining techniques derive from four different sources:

1) artificial intelligence;
2) database theory;
3) inferential statistics, and
4) mathematical programming.

Artificial intelligence research has contributed data mining techniques such as neural networks, rule induction and association rules. Linear logistic and multiple regression in addition to algorithms such as K-means and K-medians have been developed by statisticians. Mathematical programming has contributed techniques such as the min-max method from optimisation theory.

Recent developments in KDD, data mining and statistics have allowed analysts to develop significant models of how decisions are made. In sport, competition and physiological data is precise, each team and individual has their own capabilities and needs. It is desirable to provide athletes with specific realistic training regimes and performance targets.

Whilst Knowledge Discovery has been used in individual sports (for example the Advanced Scout system for basketball in USA, described in Bhandari et al (1997)), there is no generally accepted framework for using KDD in sport. In this project we shall examine the use of artificial intelligence, inferential statistics and mathematical programming in modeling elite sports performance.

Bhandari et al. (1997) claim that the Advanced Scout software seeks out and discovers interesting patterns in game data. They argue that with this information, a coach can assess the effectiveness of certain coaching decisions and formulate game strategies for subsequent games.
Smith et al. (2007) used a form of data mining, Bayesian classifiers, to predict Cy Young Award winners (best pitchers) in American baseball. The model was compared against two statistical models designed to perform the same task {James (2004) and Sparks and Abrahamson (2005)}. Over the years from 1967 through 2006, the accuracy of the Bayesian classifier was similar to that of the other two models. When all three models were used with starting pitchers, accuracy was greater than 80%.

Performance evaluation falls under the domain of skill acquisition, sports biomechanics, and sports physiology. Typical applications have included structuring training sessions (Shea and Morgan, 1979) and monitoring training loads (Halson and Leukendrup 2004), examining technique and coordination patterns, developing instructional material, and managing administrative tasks.

Owusu (2007) claims there is enormous potential for Artificial Intelligence technologies to make a significant contribution in the analysis phase. Indeed AI technologies have been applied to performance evaluation in recent years, though their applicability has been limited for a variety of reasons. The main factor has been a lack of characterisation of the domain of performance evaluation. Owusu (2007) reviews selected research and applications of computational models and Artificial Intelligence technologies in particular in performance evaluation of sporting feats for individual based events.

Liao (2008) performed a tactics analysis on female swimmers in the 800m freestyle race using speed coefficient theory. Chen et al (2007) use cluster analysis to identify elite swimmers’ race patterns. They claim that the identification of elite swimmers’ race patterns is of fundamental importance for coaches in training promising elite swimmers. To address this problem, a system of cluster analysis for studying group structures on the basis of elite swimmers’ race results and various available race components, such as lengths, speeds and times, is described that uses standard statistical algorithms to arrange elite swimmers according to similarity of tactics in their race patterns.

Puterman and Wittman (2009) used statistical methods to categorise PGA tour players’ careers. They used K-means cluster analysis and multinomial mixture models to categorize professional golfer performance for the period between 1980 and 2006. Correlation patterns between other measures suggested that career performance was well described by the proportion of years a player finished in specific meaningful money list categories such as the Top 10 or outside the Top 125. Using both clustering methods, they found that players divide into five natural and interpretable groupings, one being a small ‘Elite’ group and four others which the authors refer to as ‘Distinguished,’ ‘Established,’ ‘Journeymen’ and ‘Grinders.’ They used analysis of variance to compare groups on the basis of other career performance measures including consistency, streakiness, longevity, and others as well as to investigate differences in the clusters produced by the two methods. This methodology extends to any sport or endeavour in which performance is measured in terms of end of year rankings or money lists.

3. Decision Support Techniques for Enhancing Elite Sports Performance

3.1 The Victoria Institute of Sport

The Victorian Institute of Sport (VIS) (http://www.vis.org.au/about.asp) was established in 1990, by the Victorian Government, to assist the development of Victoria’s best athletes. The VIS is a non-residential institute, which utilises Melbourne’s sporting facilities, to allow high performance athletes to live and train in Melbourne. VIS programs are conducted in partnership with State Sporting Organisations. Over 400 athletes from
a wide range of sports participate in VIS programs. Both able-bodied athletes and athletes with a disability have scholarships. Support Services include advanced and specialised coaching, sport science and sports medicine services, career and education advice, and training and competition support are provided to VIS athletes.

The VIS provides scholarship holders with the best possible integration of the key athlete services of sports medicine, sport science, sports psychology, physical preparation, physiotherapy, nutrition, massage, athlete career and education advice, and an information resource centre. VIS Sport Science has achieved a total focus on improving performance through the integration of internal and external scientists and consultants into VIS programs. The key discipline areas of VIS Sport Science are Physiology, Biomechanics, Psychology, Human Perception and Performance, Sports Engineering and Computer Science. VIS Sport Science has a diverse staff with qualifications and experience in the traditional areas of sport science and new areas such as aerospace engineering, industrial design and computer hardware and software design. This has led to a large array of in-house skills to draw upon and the emergence of some exciting projects within VIS Sport Science.

In its goal to provide enhanced sports science advice to its coaches and athletes, VIS is keen to enhance the computer supported analysis and advice it offers. It has a huge repository of data: such as split-times and event times in races, currents in ocean swimming, blood analysis, VO2 max, BMI, body fat, time taken underwater in swimming turns and numerous golf data inputted to the TRACKMAN system.

VIS approached Professor Zeleznikow in the hope that his research group could help analyse and interpret their vast data repositories with the goal of developing decision support systems to enhance elite sports performance. Examples of questions they would like answered include:

a) How can biomechanics and the TRACKMAN system be best used to enhance how golfers should best use swing, angle and trajectory to improve their performances?

b) What are the key variables to examine whether an amateur golfer should turn professional?

c) How can we best provide feedback and training and race plans for coaches and athletes?

d) In analysis swimming performances, what variables are important (heart rate, stroke rate, break out time, distance turn time, physiological data, blood analysis, hydration)?

e) In triathlons, what sort of 10 km times should athletes be completing? And where should they be positioned at the end of the swim leg?

To meet VIS needs, we are conducting research on feature selection and recommender systems.

3.2 Feature Selection

Feature selection or relevance analysis attempts to identify features that contribute to the knowledge discovery task (Stranieri & Zeleznikow 2005). Feature subset selection aims at finding the smallest feature set having the most beneficial impact on machine learning algorithms, i.e. its prime goal is to identify a subset of features to focus on. By removing the most irrelevant and redundant features from the data, feature selection
helps improve the performance of learning models by speeding up the learning process and improving model interpretability.

Skabar et al. (1997) used genetic algorithms to determine which features Australian Family Court judges consider the most important in deciding the distribution of marital property. Stranieri et al (1994) had previously used 94 variables in their neural network model that examined marital property distribution. Skabar et al. (1997) however, were able to make more accurate predictions using only 16 variables.

Our research is using feature selection techniques to help decide what competition and physiological factors (e.g. PH, hydration, heart rate, split-times and event times in races, currents in ocean swimming, blood analysis, VO2 max, BMI, body fat, time taken underwater in swimming turns) are important in predicting future results and improving training. By using feature selection algorithms, we expect to maximise training techniques by focusing upon the small number of vital factors that significantly help and/or hinder success.

3.3 Recommender Systems

Maes et al. (1999) claim that recommender systems provide advice to users about items they might wish to purchase or examine. Typically, a recommender system compares the user's profile to some reference characteristics, and seeks to predict the 'rating' that a user would give to an item they had not yet considered. Bridge et al. (2005) describe case-based recommender systems, and further, define a framework in which such systems can be understood.

Whilst recommender systems have been heavily used in providing tourism advice (Ricci et al 2002), they have not been used in providing advice for athletes. However, we argue that they can prove very valuable in providing training and performance advice. Developing specific training schedules for each individual athlete based on this greater analysis of the data will enable the VIS and associated sport scientists to enhance athlete performance and minimize injury. Moreover, the publication of our results on the use of KDD, feature selection and recommender systems will enhance global training and performance.

We can also use Information Technology to support Decision Making during an event. Many decisions need to be made by athletes and coaches during an event in progress. For example, an athlete in a high jump or pole vault has decisions to determine at what height on the bar should the athlete enter or resume in the competition. It is common for athletes to raise the height of the bar, rather than clearing it at a lower height. If successful then the athlete gains a significant advantage over the other competitors by requiring fewer jumps and less effort. However, if unsuccessful then the athlete runs the risk of finishing in a lower position than if they attempted to jump at the lower height, or even worse, being eliminated. These decisions are usually subjectively based and do not involve the use of information technology.

Bedford et al. (2009) developed methods to determine how much risk a badminton player should be taking on serve during a match in progress, where coaching intervention and the use of computers are allowed. Pollard et al. (2008) developed methods to determine how much risk a tennis player should be taking on serve during a match in progress, where coaching intervention may or may not be allowed. In the latter case, the model incorporated players viewing real-time statistics from the scoreboard.

We are developing quantitative models to assist athletes during an event in progress on the height of the bar in high jump or pole vault; the level of difficulty in gymnastics,
dive or aerial skiing; the amount of weight in weightlifting; and the club selection in
golf. The analyses for all these sports depend on the scoreboard, i.e., the current posi-
tioning of the athlete relative to the other competitors at a particular time in the event.
With the use of coaching intervention and computer technology, the decision making
process around strategy could help improve performance.

Acknowledgements

We greatly value the advice and support of Professor Markus Raab, head of the De-
partment of Performance, Institute of Psychology at the German Sport University Co-
logne, Germany who provided direct research input on decision support and testing and
evaluating decision tools in athletic and coaches diagnostics.

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COMPUTER-AIDED ANALYSIS OF ANTAGONISTIC EVENTS IN THE PREPARATION OF CHINESE TEAMS FOR BEIJING OLYMPICS

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Abstract

The paper introduces in details various methods of computer-aided analysis including on-line analysis, systematic analysis and scientific computation analysis of the techniques and tactics in antagonistic events such as table tennis, badminton, tennis, volleyball and so on. It also introduces the actual applications of these analysis methods to the preparation of Chinese teams for Beijing Olympics.

KEY WORDS, TECHNICAL AND TACTICAL ANALYSIS, ANTAGONISTIC EVENTS, BEIJING OLYMPICS, CHINESE TEAMS

1 Introduction

Techniques and tactics are key winning factors in antagonistic events, and they are paid great attention to by all the Chinese national teams in the preparation of Beijing Olympics. For this reason, various kinds of game analysis software are developed during 2005-2008 and put into the analysis of the technique and tactic characteristics of the major opponents of the Chinese teams of table tennis, badminton, boxing, fencing, women’s tennis and women’s volleyball, which have proved quite effective and produced very successful results.

According to the ways of data collection and treatment, and the particular demands of the coaches and players, modern game analysis can be classified into three kinds: scout-online analysis, systematic game analysis and scientific computing analysis, which will be discussed in the following several parts.

2 Scout-online analysis

A common feature in table tennis, badminton, tennis, volleyball, fencing, etc. lies in that the last behavior in each rally in these events is most decisive for scoring or losing. Therefore, timely recordings between rallies of the technique attributes of the player’s last behavior, such as the technique, tactic, line, position and effect of the stroke, play a crucial role in the analysis of the games.

Accordingly, the real-time technical and tactical statistic system and the real-time video analysis system are developed. The former helps record the real time score differences of each technique and tactic, as shown in Figure 1, and the real time statistical system of table tennis and fencing competitions. The latter records the score differences and helps collect the corresponding video clips, as shown in Figure 2.
The real-time video analysis system consists of three modules: game information, technical and tactical video editing and statistical analysis. It can choose camera or television as video signal sources. The technical and tactical video editing module can edit video clips and demarcate techniques and tactics words. The statistical analysis module can search, preview, compound and retrieve information according to the terms to be searched. The system can provide quick video feedback about the opponents’ technique and tactic features right after the matches. For example, this system has been applied to the technical and tactical analysis of a large number of multimedia reports for the Chinese table tennis team in Beijing Olympic Games.

3 Systematic game analysis

In order to have a more detailed analysis of the matches, the multi-media interactive data collection and analysis system are also developed, which uses C/S mode, and consists of the client application, the server manager and middleware (Figure 3). It has the following characteristics: (1) The system can collect all the base data of a player game behaviour, such as the position, route, direction, techniques, tactics, effects, scores, striking sequence, providing sufficient data for the intelligent game analysis; (2) Each game behaviour of each player is connected to the video clips; (3) Compared with other game analysis software (e.g. Dartfish), the present system can analyze one or more matches based on data mining technology.
This system could conduct an individual analysis of one player in one match or a combined analysis of one player in several matches. For example, the table tennis match analysis system could conduct separated or combined analysis of the technique and tactic status of each stroke, its placement, sequence and position of each player. Moreover, it could also analyze the winning or losing games of a player, or analyze a particular phase of a game, such as the beginning, middle or the ending phase.

The badminton match analysis system could conduct separated or comprehensive analysis of the posture of the striking, the area, action, line and number of the strokes, the scoring or losing of the player. As there are more strokes in badminton matches, the system could also help analyze the technique and tactic state of a certain stroke according to the specific demand of the coaches and players.

The tennis match analysis system could conduct separated or comprehensive analysis of the numbers of the games, sets and bats, the technique, position and effect of the stroke, the state of the match, and the formation of the players.

The volleyball match analysis system could, according to the requirement of the coaches and players, conduct separated or comprehensive analysis of the tactic, technique, area, turns, placement, line and effect of a stroke of a certain team or player. However, since there are different turns for players in different volleyball matches, it is not possible to have combined analysis of several matches.

Figure 3. The multimedia interactive data collection and analysis systems of table tennis, bedminton, tennis and volleyball

4 Scientific computing analysis

4.1 Application of data mining Association Rule technology in game analysis

The general game analysis usually is to study scoring and losing, the scoring rate and losing rate or the usage rate of technical and tactical indexes. Since the indexes are relatively independent, the coaches and players could only play a limited role in using the analysis results for game planning. But data mining is used to analyze the association relationship characteristics between the combination of technical or tactical factors and scoring or losing. Therefore it is a very good supplement for general game analysis. Table 1 shows the main contents of association analysis in table tennis, badminton, tennis and volleyball.
Table 1: The main contents of association analysis of table tennis, tennis, badminton, and volleyball

<table>
<thead>
<tr>
<th>Event</th>
<th>Main content of association analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table Tennis</td>
<td>The association characteristics of the placements/techniques of the first three strokes and the scoring/losing in the service/receiving round</td>
</tr>
<tr>
<td>Badminton</td>
<td>The association characteristics between the scoring/chance ball/passive ball/losing and its previous three/six strokes</td>
</tr>
<tr>
<td>Tennis</td>
<td>The association characteristics between the first three/four stroke placements/techniques and the scoring/losing in the service/receiving round</td>
</tr>
<tr>
<td>Volleyball</td>
<td>The mining of the technique characteristics of the individual player/the team of the first/second attack</td>
</tr>
</tbody>
</table>

Through the association analysis of the semi-finals of 15th Asian Games between Wang Hao and Ryu Seung Min (Korean), the obvious technical and tactical characteristics of Wang (Chinese) are obtained, shown as follows in Table 2:

Table 2: The results of Wang’s technical and tactical analysis based on data mining technology

<table>
<thead>
<tr>
<th>Serial number</th>
<th>Stroke placements</th>
<th>Sup (%)</th>
<th>Conf (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Wang’s service → Ryu’s short middle zone</td>
<td>91.83</td>
<td>68.89</td>
</tr>
<tr>
<td>2</td>
<td>Wang’s service → Ryu’s short middle zone → Wang’s long backhand zone</td>
<td>42.86</td>
<td>61.90</td>
</tr>
<tr>
<td>3</td>
<td>Wang’s service → Ryu’s short middle zone → Wang’s short middle zone</td>
<td>10.20</td>
<td>80.00</td>
</tr>
<tr>
<td>4</td>
<td>Wang’s receiving in long backhand zone → Ryu’s long backhand zone</td>
<td>8.70</td>
<td>75.00</td>
</tr>
<tr>
<td>5</td>
<td>Wang’s receiving in short middle zone → Ryu’s half-long backhand zone → Wang’s long backhand zone</td>
<td>6.52</td>
<td>33.33</td>
</tr>
<tr>
<td>6</td>
<td>Wang’s receiving in short middle zone → Ryu’s short backhand zone → Wang’s long backhand zone</td>
<td>6.52</td>
<td>33.33</td>
</tr>
</tbody>
</table>

(1) Most placements of Wang’s service are to short middle zone and quite effective, with the winning support of 91.83 %, and the confidence of 68.89%.
(2) If Wang serves the ball to short middle zone, and Ryu receives the ball to long backhand zone, then Wang’s winning support is 42.86% and the confidence is 61.90 %; But if Ryu receives the ball to short middle zone, then Wang’s winning support is only 10.20 % and the confidence reaches the highest: 80.00 %.
(3) When Ryu serves the ball to long backhand zone and Wang receives to long backhand zone, then Wang’s winning support is 8.70 % and the confidence is 75.00 %.
(4) But when Ryu serves the ball to middle short zone, if Wang receives the ball to half-long backhand zone or to short backhand zone, and Ryu strikes the third stroke to Wang’s long backhand zone, then Wang’s winning support is 6.52 % and the confidence is only 33.33 %.

Ryu is not in good form in the semi-finals of men’s singles, so he lost to Wang at 1:4. The following is the association analysis of Ryu’s main tactics that led to his failure (Table 3):

Table 3: The results of Ryu’s technical and tactical analysis based on data mining technology

<table>
<thead>
<tr>
<th>Serial number</th>
<th>Stroke placements</th>
<th>Sup (%)</th>
<th>Conf (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Ryu’s service → WANG’s long backhand zone → Ryu’s long backhand zone</td>
<td>8.69</td>
<td>25.00</td>
</tr>
<tr>
<td>2</td>
<td>Ryu’s receiving in short middle zone → Wang’s long backhand zone</td>
<td>42.86</td>
<td>38.10</td>
</tr>
<tr>
<td>3</td>
<td>Ryu’s receiving in short middle zone → Wang’s short middle zone</td>
<td>6.67</td>
<td>33.33</td>
</tr>
<tr>
<td>4</td>
<td>Ryu’s receiving in short middle zone → Wang’s long backhand zone → Ryu’s long backhand zone</td>
<td>24.49</td>
<td>25.00</td>
</tr>
</tbody>
</table>
(1) If Ryu serves the ball to long backhand zone, and Wang receives the ball to long backhand zone, then Ryu’s winning support is 8.69%, the confidence is 25.00%.
(2) When Wang serves the ball to short middle zone, and Ryu receives the ball to long backhand zone, then Ryu’s winning support is 42.86%, the confidence is 38.10%. It is one of the main reasons of Ryu’s losing. If Ryu receives the ball to short middle zone, then Ryu’s winning support is 6.67%, the confidence is 33.33%.
(3) When Wang serves the ball to short middle zone, if Ryu receives the ball to long backhand zone, and Wang strikes the third stroke to long backhand zone, then Ryu’s winning support is 24.49%, the confidence is 25.00%. It is another major reasons that led to Ryu’s losing of the game.

4.2 Appilation of artificial neural network in game analysis

A universal problem with the various mathematical models of technical and tactical analysis is that the observation indexes are too abstract. Though the mathematical models can be actualized in theory, they are difficult to be applied in actual training and game analysis. This paper attempts to construct a model respectively for technique and tactic analysis of table tennis by the combination of striking techniques and striking placements, technique situations and striking sequence based on artificial neural network (as shown in Table 4 and 5)

<table>
<thead>
<tr>
<th>Input data (Observation index)</th>
<th>number of neuron in hidden layer</th>
<th>output layer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scoring / using rate of service-in short zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of service-in half long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of service-in long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of forehand topspin-in forehand long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of forehand topspin-in middle long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of forehand topspin-in backhand long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of backhand topspin-in forehand long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of backhand topspin-in middle long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of backhand topspin-in backhand long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of flip-in forehand long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of flip-in middle long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of flip-in backhand long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of puch (block)-in forehand long zone</td>
<td>31</td>
<td>winning probability</td>
</tr>
<tr>
<td>Scoring / using rate of puch (block)-in middle long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of puch (block)-in backhand long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of chop-in forehand long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of chop-in middle long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of chop-in backhand long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of chopping short-in forehand short zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of chopping short-in middle short zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of chopping short-in backhand short zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of chopping short-in forehand half long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of chopping short-in middle half long zone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of chopping short-in backhand half long zone</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 5  Tactics analysis model of table tennis based on artificial neural network

<table>
<thead>
<tr>
<th>Scoring / using rate of service and the third stroke attack</th>
<th>number of neuron in hidden layer</th>
<th>output layer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scoring / using rate of service and the third stroke control</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of service and the third stroke defense</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of receiving and the fourth stroke attack</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of receiving and the fourth stroke stalemate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of receiving and the fourth stroke control</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of receiving and the fourth stroke defense</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of the last attack after the fifth stroke</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of last stroke stalemate after the fifth stroke</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of last stroke control after the fifth stroke</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scoring / using rate of last stroke defense after the fifth stroke</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

From the analysis of Zhang’s techniques, it can be seen that Zhang’s scoring rate is very high when he attacks by forehand looping to the opponent’s middle zone, backhand looping to the opponent’s backhand and forehand looping to the opponent’s backhand. These techniques have very high winning probabilities (Figure 4). Besides, it can also be found that Zhang’s techniques prove quite effective when she does long chopping (often used in receiving) to the opponent’s backhand long short, which indicates her effectiveness in active long shot or rally.

Figure 4. The results of ZHANG’s technique analysis based on ANN technical model

Figure 5 shows the analysis result of Zhang’s tactics. It can be seen that the scoring rate of service and the third stroke is very critical to the winning of the game and equally critical is the scoring rate of receiving and the fourth attack, the scoring rate of receiving and the fourth stroke control, the attacking rally after the fifth stroke.
5 Game analysis in preparation of Chinese teams for Beijing Olympics

Game analysis is very important in the preparation for the Olympic Games in antagonistic events and therefore highly recognized in every national team.

5.1 Contents of game analysis

Game analysis is usually classified into systematic analysis, brief analysis and special analysis. Systematic analysis is used in the preparatory training session for the important events; brief analysis is often used during the process of competition, and special analysis is mainly used to solve problems like winning play, scoring or individualized features of techniques and tactics of the players (Figure 6).

Figure 6. The framework of game analysis of China's teams preparation for Beijing Olympic Games

The main contents of the systematic analysis include the opponent’s performance analysis in the recent international competitions and the competitions between Chinese players and their opponents, the analysis of the opponent’s technical and tactical characteristics, statistical data, summary and suggestions. For example, the major contents of the table tennis systematic game analysis are shown in Table 6.
Table 6  The main contents of table tennis game systematic analysis

<table>
<thead>
<tr>
<th>Analysis of the singles</th>
<th>Analysis of the doubles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance analysis of</td>
<td>Performance analysis of international</td>
</tr>
<tr>
<td>international competitions</td>
<td>competitions</td>
</tr>
<tr>
<td>Performance analysis of</td>
<td>Performance analysis of the competitions</td>
</tr>
<tr>
<td>the competitions between</td>
<td>between Chinese players and their</td>
</tr>
<tr>
<td>Chinese players and their</td>
<td>opponents</td>
</tr>
<tr>
<td>opponents</td>
<td>Characteristic analysis of the round of</td>
</tr>
<tr>
<td>Analysis of service characteristics</td>
<td>opponent A’s service / opponent B’s</td>
</tr>
<tr>
<td>Analysis of receiving</td>
<td>third stroke</td>
</tr>
<tr>
<td>characteristics</td>
<td>Characteristic analysis of the round of</td>
</tr>
<tr>
<td>Analysis of the third stroke</td>
<td>opponent A’s receiving / opponent B’s</td>
</tr>
<tr>
<td>characteristics</td>
<td>fourth stroke</td>
</tr>
<tr>
<td>Analysis of the fourth stroke</td>
<td>Characteristics analysis of the round of</td>
</tr>
<tr>
<td>characteristics</td>
<td>opponent B’s service / opponent A’s third stroke</td>
</tr>
<tr>
<td>Analysis of the stroke</td>
<td>Characteristics analysis of the round of</td>
</tr>
<tr>
<td>characteristics after the</td>
<td>opponent B’s receiving / opponent A’s</td>
</tr>
<tr>
<td>fifth stroke</td>
<td>fourth stroke</td>
</tr>
<tr>
<td>Analysis of statistical data</td>
<td>Analysis of statistical data</td>
</tr>
<tr>
<td>Summary and suggestions</td>
<td>Summary and suggestions</td>
</tr>
</tbody>
</table>

The brief analysis includes two parts: (1) statistic data analysis of the opponents; (2) the analysis of the scoring or losing of the technical and tactical indexes. The main contents of the brief analysis of table tennis matches are shown as follows (Table 7).

Table 7  The main contents of table tennis game brief analysis

<table>
<thead>
<tr>
<th>Analysis of the singles</th>
<th>Analysis of the doubles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Analysis of statistic data</td>
<td>Analysis of statistic data</td>
</tr>
<tr>
<td>Scoring and losing analysis of</td>
<td>Scoring and losing analysis of the round</td>
</tr>
<tr>
<td>opponent’s service</td>
<td>of opponent A’s service / opponent B’s</td>
</tr>
<tr>
<td>Scoring and losing analysis of</td>
<td>third stroke</td>
</tr>
<tr>
<td>opponent’s receiving</td>
<td>Scoring and losing analysis of the round</td>
</tr>
<tr>
<td>Scoring and losing analysis of</td>
<td>of opponent A’s receiving / opponent B’s</td>
</tr>
<tr>
<td>the opponent’s third stroke</td>
<td>fourth stroke</td>
</tr>
<tr>
<td>Scoring and losing analysis of</td>
<td>Scoring and losing analysis of the round</td>
</tr>
<tr>
<td>the opponent’s fourth stroke</td>
<td>of opponent B’s service / opponent B’s</td>
</tr>
<tr>
<td>Scoring and losing analysis of</td>
<td>third stroke</td>
</tr>
<tr>
<td>the opponent’s last stroke</td>
<td>Scoring and losing analysis of the round</td>
</tr>
<tr>
<td>after the fifth stroke</td>
<td>of opponent B’s receiving / opponent A’s</td>
</tr>
<tr>
<td></td>
<td>fourth stroke</td>
</tr>
</tbody>
</table>

5.2 Methods of game analysis
Each elite player has his individualized technical and tactical features and employs different tactics when competing with different opponents. Therefore, the most commonly used method in antagonistic events is the comparative and contrastive method.

5.2.1 “Many-to-one” analysis
Due to the strong individualization of the player (or team), the player (or team) will use different techniques and tactics when playing with different players (teams). Therefore, the “many-to-one” method is often used to analyze various matches between many Chinese major players and one foreign player or the matches between many teams with one opponent. This method has the following features: (1) The changes of techniques can be observed when the opponent plays with different Chinese players; (2) The real strengths and weakness of the opponent’s techniques and tactics could also be perceived; (3) The problems and effective tactics of each Chinese player could be understood.
The “many-to-one” comparative and contrastive method can also be used to analyze the matches between a Chinese player and his opponent, or the opponent and his team member. Through analyzing the matches between the opponent and his team members, we could more easily find his problems in techniques.

5.2.2 “Right-hand to left-hand” analysis
The combination and change of the striking placements (or striking route) are the key factors in table tennis, badminton or tennis technique and tactics. When the opponent plays with left-handed or right-handed players, the placements (or route) tend to change a lot. Therefore, the analysis of the matches between right-handed and left-handed players could reveal more clearly the opponent’s technique and tactic features.

5.2.3 “Different-staged” analysis
In antagonistic events, the player’s psychology changes with the scores, which may affect the use and effect of the techniques and tactics. Therefore, game analysis is often conducted according to different bases so as to observe the techniques the opponent uses in different stages of competition.

5.2.4 “Good-Poor performance” analysis
Generally, close matches are often chosen for multi-media technical and tactic analysis. If the match has a wide score gap, it’s difficult to reveal the actual features and levels of the opponent’s techniques and tactics. However, sometimes, the matches when the opponent plays quite poorly are also chosen for analysis for the purpose of observing the opponent’s technique and tactic uses.

5.3 Multimedia Game analysis in the training of Chinese teams for Beijing Olympics
Multimedia game Analysis can be divided into three stages: the stage of data collection, the stage of analysis and discussion and the stage of technical and tactical analysis during the competitions.

The stage of data collection is fundamental to the analysis and involves huge workload, strong expertise and high accuracy.

The stage of discussion and analysis involves two ways of work: collective and individual. The collective way of work generally consists of multi-media based lectures, observations of the technical and tactical characteristics of the major opponents and afterward discussions, while the individual way of learning gives prominence to individuality. During the preparation for the Olympic Games, we conducted about 300 analyses for the Chinese teams of table tennis and badminton respectively, about 200 analyses for the Chinese fencing and boxing teams, nearly 100 analyses for the Chinese female teams of tennis team and volleyball, and 300 analyses for the Chinese Badminton team.

In the stage of technique and tactic analysis during the competitions, we conducted analysis of the techniques and tactics of the major opponents (after the opponents are made known) for the reference of the coaches and players in their preparatory meetings. The above research work contributed a lot to the victory of the relevant Chinese teams in Beijing Olympic Games, including 10 gold medals, 6 silver medals and 8 bronze medals in total.
References


Computer Simulation Of Table Tennis Ball’s Flying Curve On Service

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Abstract

Table tennis service can be divided into four processes: the tossing of the ball, the striking of the ball, the flying of the ball and the colliding of the ball with the playing surface of the table. A movement equation is established for each of the four processes. The displacements of the X-direction and Y-direction are calculated by a computer system and the trajectory is reproduced of the entire flying movement. The simulation experiment reveals: (1) When other conditions are the same, the higher the ball is tossed, the nearer the first placement is to the endline of the playing surface of the table on the home side, the farther the second placement is to the net and the farther the third placement is with the endline of the playing surface on the opponent’s side. (2) In backspin service, the closer the striking point is to the bottom of the ball, and the farther the first placement is to the endline of the playing surface on the opponent’s side, the nearer the second placement is to the net, and the lower is the flying curve of the ball. But in topspin service, the opposite is true. (3) When a ball is tossed to a higher point (for example, 1.36 m), the striking height does not have much influence over the height of the flying curve.

KEY WORDS, TABLE TENNIS SERVICE, FLYING CURVE, COMPUTER SIMULATION

1 Introduction

Because the table tennis ball is small and light, many factors including spin, speed and power greatly influence the flying curve of the ball, among which service is one of the most complicated techniques in table tennis game. In normal cases, researchers find experimental methods are not desirable to obtain the features of the flying curve of the ball.

The present paper uses several physical models to describe the basic features of the table tennis service and researches through computer solutions into the influences of the height of ball tossing, the striking point of ball-racket collision and the striking height over the flying curve on service.

2 Methods

2.1 System modeling

2.1.1 Tossing Process
In the ball tossing process, the influence that air friction has on ball tossing and falling is ignored. Suppose the ball were only influenced by gravity. The tossing height is set as H, then the starting velocity of the ball on service in the vertical direction is 
\[ v_{1y} = \sqrt{2Hg / \cos \theta} \]
the velocity in horizontal direction is 
\[ v_{1x} = \sqrt{2Hg / \cos \theta \times \tan \theta} \]
in which \( \theta \) is the backward angle when the ball is tossed up. The velocity of the ball when it is struck and falling to a certain height (h) is 
\[ v_{0y} = \sqrt{2hg} \]
\[ v_{0x} = v_{1x} \]
the horizontal distance of the ball from the starting point is 
\[ x = v_{0x} \left( \sqrt{2H/g} + \sqrt{2h/g} \right) \]

2.1.2 Racket-ball striking process

When striking the ball, the player leans the racket forward and exerts himself forward, hence the action line of the force passes through the top of the ball. Therefore in addition to the pressure from the front impact of the racket \( N \) (Normal direction), the ball also gets the friction force from the surface of the racket \( f \) (tangential direction). The ball rotates forward after being stricken, as shown in figure 1, hence resulting in the topspin.

![Figure 1](image1.png)

**Figure 1 Force analysis of the topspin service**

When striking the ball, the player leans the racket backward and exerts himself forward and downward, hence the action line of the force passes through the bottom the ball. Therefore in addition to the pressure from the front impact of the racket \( N \) (Normal direction), the ball also gets the friction force from the facedown of the racket \( f \) (tangential direction). The ball backspins from the racket, as shown in figure 2, resulting in the backspin.

![Figure 2](image2.png)

**Figure 2 Force analysis of the backspin service**

In service, whether it is a topspin or backspin, the contact of the racket and the ball is in fact a face contact, and the acting force on the ball is also a variable force. In the simulation analysis, to simply the process, suppose the racket within a very short period of
time acts a certain constant force on a certain point of the ball. Therefore, in service, the effect of the racket on the ball is simply the matter of collision. It can be solved by the theorem of impulse and the theorem impulse of moment.

Suppose the ball is tossed to a certain height and falls to the point of striking, and the speed of the ball during this period is $V$, according to the theorem of impulse, the following can be obtained:

The impulse on the tangential line is

$$F_t t = m(u_{0t} - v_{0t}),$$

The impulse on the normal line is

$$F_n t = m(u_{0n} - v_{0n})$$

According to the theorem of impulse, we can find:

$$F_t R = I \omega$$

in which $I$ is the moment of inertia of the ball \( I = \frac{2}{3}mR^2 \); $R$, the radius of the ball; $m$, the mass of the ball; and $\omega$, the rotating angular velocity. $T$ refers to the acting time and $u_{0t}, u_{0n}$ refers to the speed of the ball along the tangential line and normal line respectively after the striking.

For the convenience of analysis, we suppose $F_t, F_n$ and $t$ are already known, and then analyze the effect of the tossing height of the ball on the flying curve.
2.1.3 The ball flying process

The ball flies after being struck by the racket. At this moment, the ball is an object rotating around its own axis and moving forward, influenced not only by air obstruction but also by Magnus force.

The flying trajectory of the topspin

The ball moves leftward at the speed \( v \), and rotates around its own axis at angular velocity \( \omega \), with the counter-clockwise rotation. Besides the head airflow, the air around the ball also forms a layer of circulating current resulted from the friction with the ball surface. Therefore, a topspin ball confronts with both the head airflow and circulating flow when flying. The combination of the two flows enhances the linear density of the airflow in the lower part of the ball, speeds up the flowing and releases the pressure. But the case of the upper part of the ball is quite the contrary. Therefore, the airflow brings to a topspin not only head resistance \( F_D \) but also the downward pressure \( F_L \) (as indicated in Fig. 3)

![Fig. 3 The Magnus effect in a topspin flying process](image)

Whether in the rising or falling process of topspin service, the power \( F_L \) direction always coincides with the normal line of the flying curve, and is perpendicular to the velocity direction, downward.

In the backspin movement, due to the Magnus effect, the resulting \( F_L \) is upward, and also coincides with the normal line of the flying curve, and is perpendicular to the velocity direction, upward.

According to the lift formula put forward by Zhou Yuqing and Ye Zhaoning (2002):

\[
F_L = C_L \rho D^3 f v
\]

in which \( C_L \) is the coefficient of the lift, \( \rho \), the air density; \( D \), the diameter of the ball, \( f \), the rotational frequency and \( v \) the ball velocity.

However, the head resistance formula (Zhou Yuqing, Ye Zhaoning 2002) is

\[
F_D = \frac{1}{2} C_D \rho A v^2
\]

\( A \) is the sectional area of the ball, \( C_D \) is the resistance coefficient.

Therefore, according to Newton’s second law, we can obtain:

In the rising process of a topspin:

Along the horizontal direction:

\[
m \frac{dv_x}{dt} = -F_{Dx} + F_{Lx}
\]

Along the vertical direction

\[
m \frac{dv_y}{dt} = -F_{Dy} - F_{Ly} - mg
\]
In the falling process of a topspin:

Along the horizontal direction

$$m \frac{dv_x}{dt} = -F_{Dx} - F_{Lx}$$

Along the vertical direction

$$m \frac{dv_y}{dt} = F_{Dy} - F_{Ly} - mg$$

In the rising process of a backspin

Along the horizontal direction

$$m \frac{dv_x}{dt} = -F_{Dx} + F_{Lx}$$

Along the vertical direction:

$$m \frac{dv_y}{dt} = -F_{Dy} + F_{Ly} - mg$$

To obtain the flying trajectory of the ball, the horizontal distance and the vertical height

$$\frac{dx}{dt} = v_x$$
$$\frac{dy}{dt} = v_y$$

must be obtained, hence, the following two equations are listed:

Use Runge-Kutte method to solve the above-mentioned partial differential equation, and we can find out the displacements of the ball in direction $x$ and direction $y$ at any time $t$, hence obtain the flying trajectory of the ball.

### 2.1.4 Ball-table collision process

The collision of the ball and the table is a matter of collision, according to the formula (Guo Dongsheng and Li Jianshe, 1996), we can obtain the after-collision velocity along the horizontal direction:

$$V_{2x} = \frac{(3 + 2k)v_x + (2k - 1)\omega R}{5}$$

The velocity along the vertical direction is

$$V_{2y} = ev_y$$

upward, in which $e$ is the normal restitution coefficient, $k$ is the tangential restitution coefficient.

The rotation angular velocity is

$$\omega_{2x} = \frac{3(k - 1)v_x + (3k + 2)\omega R}{5R}$$

The ball continues to rise and fall after colliding with the playing surface of the table, therefore the flying process formula is still used to find out the trajectory of the second curve.

### 2.2 The table tennis high toss service technique simulation system
Visual C++ is used to design dynamic simulation software of table tennis service. The system model is made up of the ball, racket and table. The essential parameters of the ball are set as follows: weight 2.7g, diameter 40mm, thin-shelled. The parameters of the ball is set according to the parameters of the standard table. In order to analyze the influence of service on the ball’s flying trajectory, we divide the movement of the ball from being tossed to the second placement into four processes: tossing of the ball, striking of the ball, flying of the ball, and colliding of the ball with the table, establish the movement equation for each of the four processes, find out the displacement in direction \(x\) and direction \(y\) and then reveal the entire flying path.

### 2.3 Table Tennis service simulation experiment

#### 2.3.1 Defining the major features of the flying curve on service

The major features of the flying curve on service are defined as follows, shown in figure 4.

1. The first placement distance: the distance between the first placement on the playing surface and the endline of the table on home side after the ball hits the racket on service.
2. The first curve height: the height between the highest point on the first curve and the playing surface.
3. The second placement distance: the distance between the second placement (on the opposite side) and the net.
4. The second curve height: the height between the highest point on the second curve and the playing surface on the opposite side.
5. The third placement distance: when the third placement is not out of the playing surface, it refers to the distance between the ball and the endline of the table (on the opposite side), represented in negative number. When the third placement is out of the playing surface, it refers to the distance between the ball and the endline of the table (on the opposite side) when the ball falls to the same height as the playing surface, represented in positive number.
6. Cross-net height: the height of the first curve when the ball crosses the net.

![Figure 4 Flying curve of high toss service](image)

#### 2.3.2 Simulation experiment of flying curve on service

##### 2.3.2.1 The influence of the tossing height on flying curve on service

Set the racket-ball striking time as 0.01s, the normal line stress 1.1N; the tangential stress 0.9N; the rotation 40c/s; the striking point of the racket on the ball 4 to 5 point (shown in fig. 5); the striking height 0.16 m; the distance of the ball from the endline of the playing surface 0.05m. The ball is tossed vertically upward to the height of 0.46-2.86 m, and simulated once in 0.3 m. The features are observed of the flying curve on service of different spins (topspin, backspin) and striking routes (horizontal, mid-way and cross line).
2.3.2.2 The influence of the striking point of the ball over the flying curve

The racket-ball striking time is 0.01 s; the normal-line stress, 1.1 N; the tangential-line stress, 0.9 N; the rotation, 40 c/s; the striking height, 0.16 m; the distance of the ball from the endline of the playing surface, 0.05 m; Toss the ball vertically upward to the height of 1 m in the mid-way striking route. Observe the different features of the flying curves on service with different striking points on the ball (Figure 5).

![Fig. 5 Ball-Racket striking points](image)

2.3.2.3 The influence of the striking height on the flying curve on service

The racket-ball striking time is 0.01 s; the normal-line stress, 1.1 N; the tangential-line stress, 0.9 N; the rotation, 40 c/s; the distance of the ball from the endline of the playing surface, 0.05 m; Toss the ball vertically upward, the striking point are 4-5 point; the tossing height is 1.36 m, in the mid-way striking route. Observe the different features of topspin and backspin services on different striking heights.

3 Results and Analysis

3.1 The influence of tossing height on the flying curves on service

3.1.1 The influence of tossing height on backspin service flying curve

Table 1 reveals the characteristics of the influence of tossing height over the flying curve on backspin service:

<table>
<thead>
<tr>
<th>Pitching height</th>
<th>0.46</th>
<th>0.70</th>
<th>1.06</th>
<th>1.32</th>
<th>1.58</th>
<th>1.85</th>
<th>2.12</th>
<th>2.38</th>
</tr>
</thead>
<tbody>
<tr>
<td>The first placement distance</td>
<td>Straight-line</td>
<td>0.304</td>
<td>0.210</td>
<td>0.154</td>
<td>0.151</td>
<td>0.101</td>
<td>0.030</td>
<td>0.073</td>
</tr>
<tr>
<td></td>
<td>Middle-line</td>
<td>0.300</td>
<td>0.206</td>
<td>0.161</td>
<td>0.132</td>
<td>0.099</td>
<td>0.032</td>
<td>0.073</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.274</td>
<td>0.189</td>
<td>0.148</td>
<td>0.122</td>
<td>0.091</td>
<td>0.030</td>
<td>0.072</td>
</tr>
<tr>
<td>The first curve height</td>
<td>Straight-line</td>
<td>0.145</td>
<td>0.239</td>
<td>0.314</td>
<td>0.399</td>
<td>0.403</td>
<td>0.435</td>
<td>0.424</td>
</tr>
<tr>
<td></td>
<td>Middle-line</td>
<td>0.145</td>
<td>0.239</td>
<td>0.314</td>
<td>0.399</td>
<td>0.403</td>
<td>0.456</td>
<td>0.424</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.145</td>
<td>0.239</td>
<td>0.314</td>
<td>0.399</td>
<td>0.403</td>
<td>0.456</td>
<td>0.424</td>
</tr>
<tr>
<td>The second placement distance</td>
<td>Straight-line</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.202</td>
<td>0.236</td>
<td>0.352</td>
<td>0.437</td>
</tr>
<tr>
<td></td>
<td>Middle-line</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.192</td>
<td>0.280</td>
<td>0.351</td>
<td>0.467</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.228</td>
<td>0.323</td>
<td>0.376</td>
<td>0.462</td>
</tr>
<tr>
<td>The second curve height</td>
<td>Straight-line</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.268</td>
<td>0.247</td>
<td>0.284</td>
<td>0.319</td>
</tr>
<tr>
<td></td>
<td>Middle-line</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.268</td>
<td>0.247</td>
<td>0.284</td>
<td>0.319</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.267</td>
<td>0.284</td>
<td>0.319</td>
<td>0.352</td>
</tr>
<tr>
<td>The third placement distance</td>
<td>Straight-line</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.264</td>
<td>0.348</td>
<td>0.383</td>
</tr>
<tr>
<td></td>
<td>Middle-line</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.630</td>
<td>0.520</td>
<td>0.440</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.487</td>
<td>0.413</td>
<td>0.355</td>
</tr>
</tbody>
</table>

(1) As the tossing height increases, the first placement distance decreases. That is, the first placement becomes nearer to the endline of the table on home side. At the same time, the simulation experiment also indicates that, when the tossing height exceeds 1.66m, the first placement distance begins to decrease at a lower rate.
(2) As the tossing height increases, the vertical velocity along the playing surface of the ball also increases after ball-table collision. Therefore, the first curve height increases too. At the same time, the fist curve distance also increases.

(3) As the tossing height increases, the second curve height also increases. At the same time, the second curve distance also increases, which is shown by the shorter (when the third placement is not out of the playing surface) or longer (when the third placement is out of the playing surface) distance between the third placement and the endline of the table at the opposite side.

(4) As the tossing height increases, the cross-net height also increases. The simulation experiment also reveals that the major difference among the straight-line, mid-line and cross-line striking lies in the net height. Under the same condition, the straight-line service has the highest cross-net flying curve, then the mid-line service, and the cross-line service has the lowest cross-net height.

3.1.2 The influence of the tossing height over topspin service flying curve

The influence of tossing height over topspin service flying curve demonstrates the following characteristics (Table 5):

Table 2 The influences of the tossing height over the flying curve (topspin) unitm

<table>
<thead>
<tr>
<th>Tossing height</th>
<th>0.46</th>
<th>0.76</th>
<th>1.06</th>
<th>1.36</th>
<th>1.66</th>
<th>1.96</th>
<th>2.26</th>
<th>2.56</th>
<th>2.86</th>
</tr>
</thead>
<tbody>
<tr>
<td>The first placement distance</td>
<td>Straight-line</td>
<td>0.190</td>
<td>0.141</td>
<td>0.114</td>
<td>0.096</td>
<td>0.083</td>
<td>0.074</td>
<td>0.068</td>
<td>0.059</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.186</td>
<td>0.138</td>
<td>0.112</td>
<td>0.094</td>
<td>0.081</td>
<td>0.072</td>
<td>0.065</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.171</td>
<td>0.127</td>
<td>0.103</td>
<td>0.087</td>
<td>0.075</td>
<td>0.067</td>
<td>0.060</td>
<td>0.053</td>
</tr>
<tr>
<td>The first curve height</td>
<td>Straight-line</td>
<td>0.195</td>
<td>0.277</td>
<td>0.354</td>
<td>0.428</td>
<td>0.496</td>
<td>0.568</td>
<td>0.640</td>
<td>0.712</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.195</td>
<td>0.277</td>
<td>0.354</td>
<td>0.428</td>
<td>0.496</td>
<td>0.568</td>
<td>0.640</td>
<td>0.712</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.195</td>
<td>0.277</td>
<td>0.354</td>
<td>0.428</td>
<td>0.496</td>
<td>0.568</td>
<td>0.640</td>
<td>0.712</td>
</tr>
<tr>
<td>The second placement distance</td>
<td>Straight-line</td>
<td>-</td>
<td>0.414</td>
<td>0.594</td>
<td>0.720</td>
<td>0.854</td>
<td>0.960</td>
<td>1.061</td>
<td>1.152</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>-</td>
<td>0.406</td>
<td>0.564</td>
<td>0.707</td>
<td>0.830</td>
<td>0.940</td>
<td>1.039</td>
<td>1.128</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>-</td>
<td>0.373</td>
<td>0.523</td>
<td>0.651</td>
<td>0.762</td>
<td>0.866</td>
<td>0.953</td>
<td>1.039</td>
</tr>
<tr>
<td>The second curve height</td>
<td>Straight-line</td>
<td>-</td>
<td>0.151</td>
<td>0.189</td>
<td>0.224</td>
<td>0.257</td>
<td>0.288</td>
<td>0.317</td>
<td>0.345</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>-</td>
<td>0.151</td>
<td>0.189</td>
<td>0.224</td>
<td>0.257</td>
<td>0.288</td>
<td>0.317</td>
<td>0.345</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>-</td>
<td>0.151</td>
<td>0.189</td>
<td>0.224</td>
<td>0.257</td>
<td>0.288</td>
<td>0.317</td>
<td>0.345</td>
</tr>
<tr>
<td>The third placement distance</td>
<td>Straight-line</td>
<td>-</td>
<td>0.169</td>
<td>0.222</td>
<td>0.282</td>
<td>0.342</td>
<td>0.401</td>
<td>0.459</td>
<td>0.507</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>-</td>
<td>0.166</td>
<td>0.210</td>
<td>0.257</td>
<td>0.304</td>
<td>0.351</td>
<td>0.399</td>
<td>0.446</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>-</td>
<td>0.152</td>
<td>0.201</td>
<td>0.248</td>
<td>0.295</td>
<td>0.342</td>
<td>0.389</td>
<td>0.437</td>
</tr>
<tr>
<td>Cross-net height</td>
<td>Straight-line</td>
<td>-</td>
<td>0.057</td>
<td>0.138</td>
<td>0.249</td>
<td>0.373</td>
<td>0.490</td>
<td>0.607</td>
<td>0.724</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>-</td>
<td>0.057</td>
<td>0.138</td>
<td>0.249</td>
<td>0.373</td>
<td>0.490</td>
<td>0.607</td>
<td>0.724</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>-</td>
<td>0.158</td>
<td>0.260</td>
<td>0.367</td>
<td>0.473</td>
<td>0.546</td>
<td>0.617</td>
<td>0.680</td>
</tr>
</tbody>
</table>

(1) Under the same condition, the first placement of the cross-line is nearest to the endline of the table at home side, and that of the straight-line is the farthest. But the third placement of the cross-line is nearest to the endline of the table at the opposite side, and that of the straight-line is the farthest. As the tossing height increases, the first placement distance also decreases, and all are shorter than the first placement distances of a backspin when under the same condition. The general trend of the first curve height is the same as that of a backspin.

(2) As the tossing height increases, the second placement distance increases (that is, the distance to the net is farther), the second curve height also increases, which is shown by the longer distance between the third placement and the endline of the table at the opposite side.

(3) As the tossing height increases, the cross-net height also increases. The simulation experiment also reveals that the major difference among the straight-way, mid-way and cross-way also lies in the cross-net height, just like the case with the backspin service: the straight-line service has the highest cross-net flying curve, then the mid-line service, and finally the cross-line service.

3.2 The influence of ball-racket striking point over the flying curve on service
3.2.1 The influence of ball-racket striking point over the flying curve on backspin service

Table 3 shows the characteristics of the flying curve on backspin service in different striking points.

Table 3 The influence of the striking point over the flying curve (Tossing height 1.3m, backspin) (unit. m)

<table>
<thead>
<tr>
<th>Ball-racket striking point</th>
<th>4 point</th>
<th>4-5 point</th>
<th>5 point</th>
<th>5-6 point</th>
<th>6 point</th>
</tr>
</thead>
<tbody>
<tr>
<td>The first placement distance</td>
<td>Straight-line</td>
<td>0.145</td>
<td>0.190</td>
<td>0.247</td>
<td>0.315</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.145</td>
<td>0.190</td>
<td>0.247</td>
<td>0.315</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.145</td>
<td>0.190</td>
<td>0.247</td>
<td>0.315</td>
</tr>
<tr>
<td>The first curve height</td>
<td>Straight-line</td>
<td>0.792</td>
<td>0.382</td>
<td>0.225</td>
<td>0.132</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.792</td>
<td>0.382</td>
<td>0.225</td>
<td>0.132</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.792</td>
<td>0.382</td>
<td>0.225</td>
<td>0.132</td>
</tr>
<tr>
<td>The second placement distance</td>
<td>Straight-line</td>
<td>0.410</td>
<td>0.233</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.410</td>
<td>0.233</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.410</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>The second curve height</td>
<td>Straight-line</td>
<td>0.256</td>
<td>0.200</td>
<td>-</td>
<td>0.075</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.256</td>
<td>0.200</td>
<td>-</td>
<td>0.075</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.256</td>
<td>-</td>
<td>-</td>
<td>0.075</td>
</tr>
<tr>
<td>The third placement distance</td>
<td>Straight-line</td>
<td>-0.412</td>
<td>-0.614</td>
<td>-</td>
<td>-1.472</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>-0.412</td>
<td>-0.614</td>
<td>-</td>
<td>-1.472</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>-0.412</td>
<td>-</td>
<td>-</td>
<td>-1.472</td>
</tr>
<tr>
<td>Cross-net height</td>
<td>Straight-line</td>
<td>0.2655</td>
<td>0.0255</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.2395</td>
<td>0.0905</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.1145</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

(1) As the backward angle of the racket increases, or the striking point becomes nearer to the bottom of the ball (point 6, see figure 5), the vertical velocity decreases along the playing surface of the ball after being struck, so it needs longer time to fall down the same height. Therefore, the ball flies longer distance along the horizontal direction. That’s why the first placement distance of the flying curve becomes larger and larger (that is, the first bounce of the ball becomes nearer to the net). But the second placement distance decreases.

(2) As the backward angle of the racket increases, or the striking point becomes nearer to the bottom of the ball, the vertical velocity of the playing service decreases, the heights of the first curve, the second curve and the cross-net also decrease. Therefore, if the tossing height is the same, the player needs to serve short-curved, near-to-the net and fast-spun balls, lean the racket moderately backward and try to rub the bottom of the ball.

3.2.2 The influence of the racket-ball striking point over the flying curve of topspin service

Table 4 demonstrates the characteristics of the flying curve on topspin service with different striking points when the ball is tossed to 1.3 m height.
Table 4 The influence of the striking point over the flying curve (tossing height 1.3m, topspin) (unit: m)

<table>
<thead>
<tr>
<th>Ball-racket striking point</th>
<th>2 point</th>
<th>2-1 point</th>
<th>1 point</th>
<th>1-0 point</th>
</tr>
</thead>
<tbody>
<tr>
<td>The first placement distance</td>
<td>Straight-line</td>
<td>0.192</td>
<td>0.146</td>
<td>0.114</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.192</td>
<td>0.146</td>
<td>0.114</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.192</td>
<td>0.146</td>
<td>0.114</td>
</tr>
<tr>
<td>The first curve height</td>
<td>Straight-line</td>
<td>0.270</td>
<td>0.231</td>
<td>0.192</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.270</td>
<td>0.231</td>
<td>0.192</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.270</td>
<td>0.231</td>
<td>0.192</td>
</tr>
<tr>
<td>The second placement distance</td>
<td>Straight-line</td>
<td>0.427</td>
<td>0.375</td>
<td>0.311</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.427</td>
<td>0.375</td>
<td>0.311</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.427</td>
<td>0.375</td>
<td>0.311</td>
</tr>
<tr>
<td>The second curve height</td>
<td>Straight-line</td>
<td>0.147</td>
<td>0.217</td>
<td>0.289</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.147</td>
<td>0.217</td>
<td>0.289</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.147</td>
<td>0.217</td>
<td>0.289</td>
</tr>
<tr>
<td>The third placement distance</td>
<td>Straight-line</td>
<td>0.179</td>
<td>0.641</td>
<td>0.934</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.179</td>
<td>0.641</td>
<td>0.934</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.179</td>
<td>0.641</td>
<td>0.934</td>
</tr>
<tr>
<td>Cross-net height</td>
<td>Straight-line</td>
<td>0.0545</td>
<td>0.2375</td>
<td>0.4915</td>
</tr>
<tr>
<td></td>
<td>Mid-line</td>
<td>0.0442</td>
<td>0.2303</td>
<td>0.4263</td>
</tr>
<tr>
<td></td>
<td>Cross-line</td>
<td>0.0355</td>
<td>0.4055</td>
<td>0.5975</td>
</tr>
</tbody>
</table>

(1) As the racket face leans forward, the striking point becomes nearer to the top of the ball, the horizontal speed and the vertical speed increases after the striking. Therefore, the first placement distance decreases (that is, the distance becomes shorter between the first placement and the endline of the playing surface at home side). The increase of the first curve also increases the distance between the second placement and net.

(2) As the racket face leans forward, the heights of the first curve, the second curve and the over-net also increase.

3.3 The influence of the striking height over the flying curve on service

3.3.1 The influence of the striking height over the flying curve on backspin service

Table 5 shows, in the 1.36m tossing height, the major characteristics of the influences of the striking height over the flying curve on backspin service.

Table 5 When the ball is tossed to 1.36m, the influence of the striking height over flying curve on service (backspin mid-line) (unit: m)

<table>
<thead>
<tr>
<th>The striking height of the ball racket</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
<th>21</th>
<th>22</th>
<th>23</th>
<th>24</th>
<th>25</th>
</tr>
</thead>
<tbody>
<tr>
<td>The first placement distance</td>
<td>0.126</td>
<td>0.138</td>
<td>0.150</td>
<td>0.162</td>
<td>0.173</td>
<td>0.185</td>
<td>0.197</td>
<td>0.209</td>
<td>0.221</td>
<td>0.233</td>
<td>0.245</td>
<td>0.257</td>
<td>0.269</td>
<td>0.281</td>
<td>0.293</td>
</tr>
<tr>
<td>The first curve height</td>
<td>0.399</td>
<td>0.399</td>
<td>0.399</td>
<td>0.399</td>
<td>0.399</td>
<td>0.399</td>
<td>0.399</td>
<td>0.399</td>
<td>0.399</td>
<td>0.399</td>
<td>0.399</td>
<td>0.399</td>
<td>0.400</td>
<td>0.400</td>
<td>0.400</td>
</tr>
<tr>
<td>The second placement distance</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>The second curve height</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>The third placement distance</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Cross-net height</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.0835</td>
<td>0.1023</td>
<td>0.1213</td>
<td>0.1393</td>
<td>0.1523</td>
<td>0.1663</td>
<td>0.1823</td>
<td>0.1983</td>
<td>0.2143</td>
<td>0.2303</td>
<td>0.2463</td>
<td>0.2623</td>
</tr>
</tbody>
</table>

(1) If a backspin is served when the ball is tossed to a certain height, for example, 1.36m, as the striking height increases, the height of the first, second and third distance of the flying curve increases too, but only to a small extent.

(2) If a backspin is served when the ball is tossed to a certain height, for example, 1.36m, as the striking height increases, the height of the first and second curve remains roughly the same, but the cross-net height increases quite significantly.

3.3.2 The influence of the striking height over the flying curve on topspin service

Table 6 shows the major characteristics of the influence of striking height over the flying curve on topspin service:

Table 6 The influence of striking height (when the ball is tossed to 1.36m) over the flying curve (topspin mid-line) (unit: m)
If a topspin is served when the ball is tossed to a certain height, for example, 1.36m, as the striking height increases, the first, second and third placement distance of the flying curve does not change much. This indicates that in high tossing, the striking height does not have much influence over the flying curve, no matter on topspin and backspin service.

(2) If a topspin is served when the ball is tossed to a certain height, for example, 1.36m, as the striking height increases, the height of the first, second and third curve and the height of cross-net remain roughly the same. The experiment findings show that the striking height has even smaller influence over the height of flying curve.

4 Conclusions

4.1 If other conditions were the same, the higher the tossing of the ball, the nearer the first placement is to the endline of the playing surface at the home side, the farther the second placement to the net and the third placement to the endline of the table at the opposite side (if not out of the playing surface, the nearer to the endline of the playing surface at the opposite side) and the higher the flying curve. This is roughly the same case with topspin and backspin service.

4.2 The striking point is also an important factor influencing the flying curve on service. If other conditions were the same, the nearer the striking point in backspin service is to the bottom of the ball, the farther the first placement is to the endline of the table at the home side (that is, the first jump of the ball becomes nearer to the net), the second placement becomes nearer to the second placement, and the flying curves becomes lower. Contrary to this, in topspin service, the nearer the striking point is to the top of the ball, the first placement distance becomes nearer to the endline of the playing surface of at the home side, and the second placement becomes farther to the net, and the flying curve becomes higher.

4.3 When a ball is tossed to a higher point (for example, 1.36 m), the striking height does not have much influence over the height of the flying curve.
References


