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Editorial

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Dear readers:

Welcome to the winter 2010 issue of the **International Journal of Computer Science in Sport (IJCSS).**

Three research papers and two scientific reports have been included within this issue.

The investigations made by **Kazumoto Tanaka**, **Makoto Hasegawa**, **Takayuki Kataoka** and **Larry Katz** illustrate the effect of self-position and posture information based on measured reaction times of karate athletes against a video representation of a virtual opponent's punch.

Peter G. O'Donoghue discusses modelling techniques involving statistical procedures for the prediction of match outcomes (win, draw or lose) or goal difference on the example of predicting the FIFA Wold Cup 2010.

The paper by **Thorsten Stein, Christian Simonidis, Andreas Fischer, Wolfgang Seemann** and **Hermann Schwameder** presents a kinematic analysis of multi-joint goal-directed movements in 3D space in a natural environment using an IR-tracking system.

Takeshige Nishiyama and **Masaki Suwa** have developed a software tool for the visualization of the changes of an athlete's body posture based on motion data (e.g. swing practice of a baseball player). The main purpose thereby is to encourage an athlete's meta-cognitive exploration for embodied skill.

Lastly, **Zhang Hui**, **Yu Lijuan** and **Hu Jinju** demonstrate applied systematic, non-systematic and intelligent game analysis methods of net sports including data mining and artificial neural network techniques for the preparation of Chinese teams for the 2008 Beijing Olympics.

If you have any questions, comments, suggestions and points of criticism, please send them to me.

Best wishes for 2011!

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The Effect of Self-Position and Posture Information on Reaction Time

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Abstract

In competitive sport, a player's ability to immediately perceive and react to offensive and defensive situations impacts on success. While skilled performers demonstrate a superior ability to pick up crucial cues from the visual information of an opponent's or teammate's position and posture, perception of one's own position and posture may also be important for advanced performance. This study focused on self-position recognition by comparing reaction times (RTs) of karate athletes performing against a virtual opponent's attacks under two test situations; one where visual information about self-position and posture was provided and one where it was not. Differences were examined between karate experts and novices. A virtual karate system using Mixed Reality technology was developed to allow for interaction with a virtual opponent during real-time observation of images of an opponent and oneself. Results showed that novices given self-information had significantly shorter RTs. Experts did not show any change in RTs, with or without the information and consistently produced fast RTs. The results show that inputting self-position and posture information can improve the accuracy of tactical decision making for novice karate athletes but not for expert practitioners.

KEYWORDS: SELF-POSITION AND POSTURE PERCEPTION, OFFENSIVE AND DEFENSIVE SITUATION, REACTION TIME, FORWARD MODEL, KARATE EXPERT

Introduction

In competitive sport, it is required that players perceive and react to offensive and defensive situations immediately. Information processing for the reaction comprises the following four stages: stimulus detection, differentiation, recognition, and identification (Proctor & Dutta, 1995). Over the past two decades, perceptual skills on the first two stages have been discussed especially on visual perception, and studies have revealed that an expert player's superiority is characterized in terms of visual search strategies using fewer fixations of longer duration (e.g., Mann et al., 2007; Takeuchi & Inomata, 2009), quiet eye (Vickers, 1996), and peripheral vision with visual pivot (e.g., Ripoll et al., 1995; Nagano et al., 2004).

While skilled athletes demonstrate a superior ability to pick up crucial cues from the visual information of an opponent's or teammate's position and posture (e.g., Savelsbergh et al., 2002), the skill that perceives self-position and posture is also important for advanced performance. In combat sports such as a karate match, self-perception is necessary in order to select an appropriate technique for the spatial relationship between oneself and the opponent. A study that analyzed karate matches indicated that a causal relationship existed among players' positions, postures, and scored technique (Tanaka & Kurose, 2008). Furthermore, a study that investigated successful punch conditions in boxing indicated that the relationship among target distance, the forward body lean length, and the effective arm length was important in punch decision making (Hristovski et al., 2006). These results suggest that superior performance in combat sports not only needs skillful visual perception of the opponent but also immediate and accurate perception of a player's own position and posture.

Most of the studies on perceprual skills of combat sport athletes have focused on expert's visual perceptual superiority in terms of reaction time (RT) (e.g., Mori et al., 2002; Fontani, 2006) or visual search strategies (e.g., Ripoll et al., 1995; Williams & Elliott, 1999; Kato & Fukuda, 2003). In this study, we focused on the self-position and posture perception skill of karate athletes in offensive and defensive situation. However, evaluating the perception directly is challenging as it is difficult to measure proprioceptual data in the moment. Thus, we examined the differences in RTs to a karate attack on video (stimulus video) between two situations: one showing the image of the athlete in both an offensive and defensive situation with the karate attack image (virtual opponent); the other showing only the virtual opponent. The experiment was conducted on both karate novices and experts. By evaluating the effect of the visual information of self-position and posture on RT, we investigated whether this additional visual information would facilitate or distract the self-position and posture perception skill and considered the robustness of the skill which experts should have well acquired already.

For this experiment, we developed a virtual karate system using Mixed Reality (MR). MR refers to the computer systems which combine images of the real world with rendered images of virtual worlds (Freeman et al., 2005). Our system can identify the location in the real world where a virtual object should be superimposed on a marker (Kato & Billinghurst, 1999) and create a virtual opponent image as a video stimulus. Furthermore, to provide a subject with the position and posture information visually, the MR system allows the subject to watch the offensive and defensive situation from the third person point of view by adding the subject's image to the virtual opponent video.

The system determines the virtual opponent's action such as a punch or footwork according to the user's head motion using interactive game technology with real-time motion capturing (e.g., Pronost et al., 2008; Tanaka 2009). The interactive function implements a measurement of RT on the situation of stimulus change according to subject's motion, thereby creating the possibility to evaluate self-position and posture perception.

Method

Virtual Karate System

The configuration of the virtual karate system is shown in Figure 1. Figure 2 shows the layout of the experiment. The hardware of the system was comprised of a personal computer (2.00 GHz CPU, 3.00 GB memory), two video cameras (frame rate: 110 Hz, 320×240 pixels), a wireless 3-dimensional accelerometer (sampling rate: 1 kHz, measurement range: ±3.3 G, acceleration resolution: 10 bit, weight: 35 g) and a video projector (refresh rate: 60 Hz, 1024×768 pixels). The external inputs for the system were the images of the subject taken from a horizontally installed video camera, video camera images of the subject and the marker used for MR, and the acceleration data from the wireless accelerometer held by the subject. The video camera used for MR was installed above the subject, slanted downward toward the subject at an approximate 40° angle. Those items in Figure 1 within the dotted line were responsible for MR processing.

The Head Motion Detector (see Figure 1) calculated the time-series coordinates of the head region (two-dimensional: front–back and up–down) and passed that information to the Action Selector for the virtual opponent. The Action Selector determined the next action based upon the movements of the subject and the virtual opponent and passed this on to the Computer Graphics (CG) Renderer.

The Marker Detector identified the marker on the floor from input images and passed feature point information of the marker to the Transformation Matrix Calculator. This, along with the input marker size information was used to calculate the transformation matrix needed to convert the marker coordinate system to the video camera coordinate system. This matrix was then passed to the CG Renderer. Since the position of the marker was fixed on an appropriate place during the experiment, the transformation matrix that was calculated at the beginning of the experiment was able to be utilized throughout the study. Thus, the calculations for MR were executed simply and quickly, and the system demonstrated real-time processing. As a result, the visual feedback delay depended solely upon the refresh rate of the video and was considered negligible.

The CG Renderer used the matrix to portray the virtual opponent from the point of view of the video camera. However, in the case where self-position and posture information was provided to the subject, the CG Renderer rendered on top of the input image including subject image. When self-position information was not provided to the subject, it rendered on top of the image after the Subject Image Eraser removed the subject from the image.

The RT represented the time that took the subject to block the virtual opponent's punch with his hand. For this purpose, the Reaction Detector used an appropriate threshold for detecting the rapid build-up time from the acceleration data of the subject’s hand and relayed this to the Recorder. In addition, the Recorder received start times for attack action rendering from the CG Renderer and saved this data. The RT was calculated from this data and additional timestamps from the Recorder were attached and saved to the subject images. It was then possible to refer to these images and to remove acceleration detection noise from the reaction time calculations. The precision of the RT was determined from the refresh rate of the projector with the sampling rate of the wireless accelerometer and was estimated at approximately 18 msec.

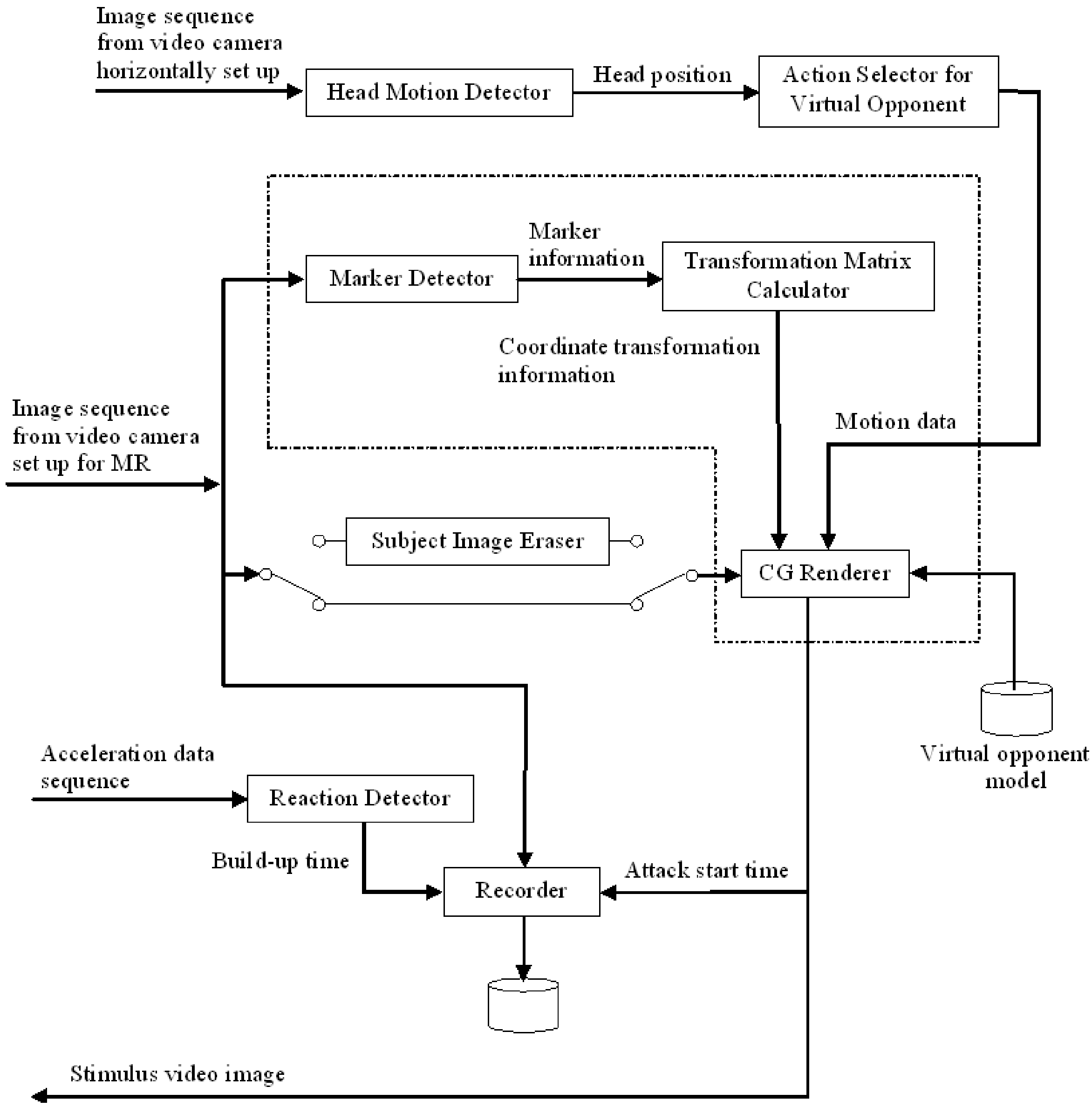

Figure 1. Mixed Reality system configuration.

There were eight types of actions that could be performed by the virtual opponent: jumping in place, advancing (slow and small steps, fast and small steps, fast and large steps), retreating (slow and small steps, fast and small steps, fast and large steps), and punching to the face. These actions were replayed from motion data extracted from the motion capture of a right handed karate expert, however, the movements of the virtual opponent could be replayed with the left and right hands switched.

In consultation with a karate expert, the following rules for actions of the virtual opponent were applied:

Rule 1: If the distance between the leading fist (the punching fist) and the player's head region (an appropriately determined distance, D) changed, advance or retreat to maintain D. Adjust the speed and step width according to the size of the distance change.

Rule 2: If there was no change in distance, randomly select between jumping in place and combining short advances and retreats at the same speed.

Rule 3: If the four conditions below were met, the punch action was chosen by a pseudo-randomly generated number with odds set to 50%. This rule was given priority over Rule 1.

Condition 1: The distance between the head region and the fist was less than D.

Condition 2: The player's head region was in the predetermined height range.

Condition 3: It is the end of player's head advancing whose average speed was above a predetermined appropriate value.

Condition 4: The virtual opponent had finished an action and was in the time-frame to select the next action.

Rule 4: When the punch action ended, the virtual opponent's action was completed (measurement completed).

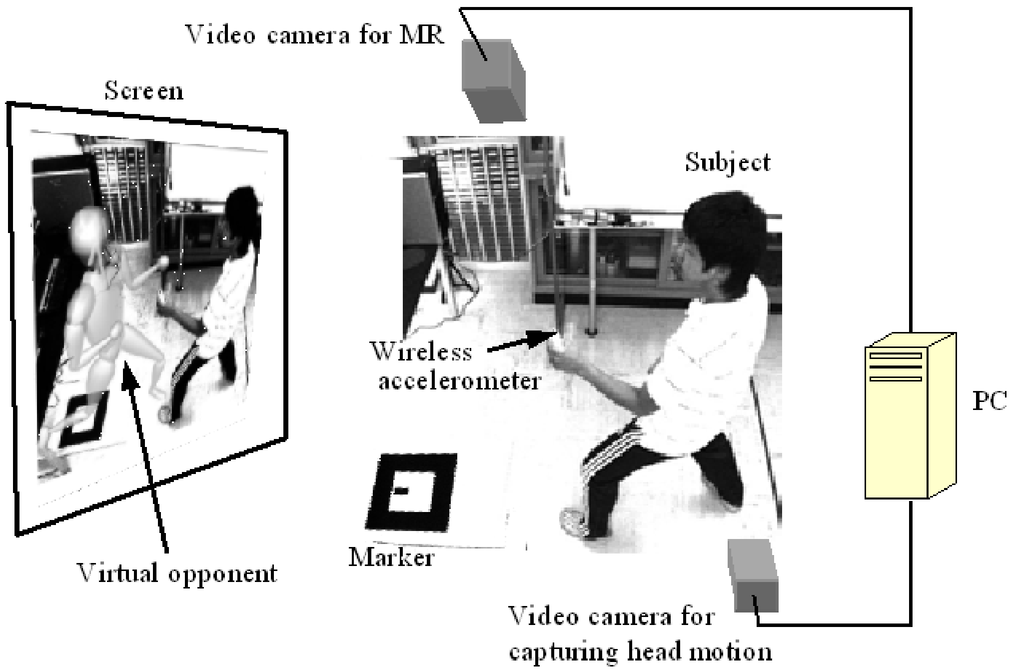

Figure 2. Layout of reaction time measurement using the virtual karate system. Note: In cases where the self-position and posture information was not provided to the subject, the subject was erased from the screen.

Participants

Test subjects consisted of six karate novices (average age of 19 years) and five karate experts (average age of 21 years), all of whom were right-handed, male, college students. The karate experts were members of their universities' karate clubs and had at least nine years of experience as well as members of the Japan National Athletic Meet. Video and live demonstrations were used to explain the basic techniques of karate to the novices.

Before the experiment, the purpose and methods of the study were explained and consent was received. Subjects were taught the action rules of the virtual opponent and ensured that they were understood prior to continuing the experiment. Subjects were given the opportunity to experience the spatial relationship which would cause the virtual opponent's punch through a rehearsal (described below). This was important, as the purpose of this experiment was to evaluate self-position and posture control, not the skill for finding the position and posture.

Procedure

The video was projected onto a 90 inch, 4:3 ratio screen. This image aimed to maximize the size of the subject and the virtual opponent. For consistency, in trials when only the virtual opponent was projected, the opponent image was in the same screen position and magnification as when both the subject and virtual opponent were shown.

The marker for MR was set up on the floor one meter in front of the screen. The screen image of the virtual opponent was rendered on the marker (see Figure 2). The subject was instructed to stand in a left-side front stance (a neutral stance in karate match, see Figure 2) with the hands placed between the abdomen and chest virtually facing to the opponent portrayed on the marker. The subject held the wireless accelerometer in his forward hand. Subjects were asked to remain in this position and use their upper body to move back and forth (ignoring the natural movements of both hands), while watching the stimulus video on the screen and use their forward hand to block the opponent's punch as nimbly as possible.

Measurements were taken during two sessions; once when both the virtual opponent and the subject were shown, and once when only the virtual opponent was shown. In each case, measurements were taken five times, and the two sessions were repeated four times thereby yielding 40 data points for each subject. Subjects rested for 90 seconds between the two sessions. If the reaction time exceeded 1000 ms, the reaction was determined to be invalid, and the data was discarded and replaced with new trial data. The RT for the subject was an average of the 20 trials.

Prior to the first session, each subject underwent 20 rehearsals in the order of his choosing; 10 with a virtual opponent and self-image and 10 without self-image. In each rehearsal trial, subjects practiced the action that would cause the virtual opponent's punch based on the Rule 3 (see Virtual Karate System in Method section), and the block action.

Results

The average RT values by experts (n = 5) and novices (n = 6) for each case are shown in Figure 3. Results showed that regardless of the protocol, experts were quicker to react than novices. Additionally, the type of stimulus image did not have a significant effect on the RT of the experts. On the other hand, a difference was seen in the RT for novices.

RTs were analyzed using a two-way repeated measures analysis of variance (ANOVA) with Group (Novice, Expert) as a between-subject factor and Stimulus (SI: self-information provided to subject, N: no self-information provided to subject) as a within-subject factor. Statistical significance was set at $p < 0.05$. The Group factor was $F(1, 9) = 71.39$, $p < 0.01$, $\eta^2 p = 0.89$, the Stimulus factor was $F(1, 9) = 19.35$, $p < 0.01$, $\eta^2 p = 0.68$, and the Group × Stimulus interaction was $F(1, 18) = 7.72$, $p = 0.02$, $\eta^2 p = 0.30$, where $\eta^2 p$ represents partial eta-squared value, which is an index of effect size when using a two-way or multi-way ANOVA. All of these results were significant.

As the interaction was significant, the simple main effect test of Group at SI or N using a one-way ANOVA and the test of Stimulus at Novice or Expert using a one-way repeated ANOVA were executed with significance level of $p < 0.05$. The effect sizes for the Group and Stimulus were obtained by computing Cohen's d and dz respectively. These results (SI Group factor of result F = 57.85, $p < 0.01$, $d = 4.69$; N Group factor result of F = 78.47, $p < 0.01$, $d = 6.55$; Novice Stimulus factor result of F = 25.76, $p < 0.01$, $dz = 2.01$; all significant) were in contrast to the Expert Stimulus factor result of F = 1.31, $p = 0.28$, $dz = 0.78$ which was not significant.

The statistical power was calculated for the analysis of SI Group factor, N Group factor, Novice Stimulus factor and Expert Stimulus factor using G* Power (Faul et al., 2007) and showed 0.99, 0.99, 0.99 and 0.74 respectively.

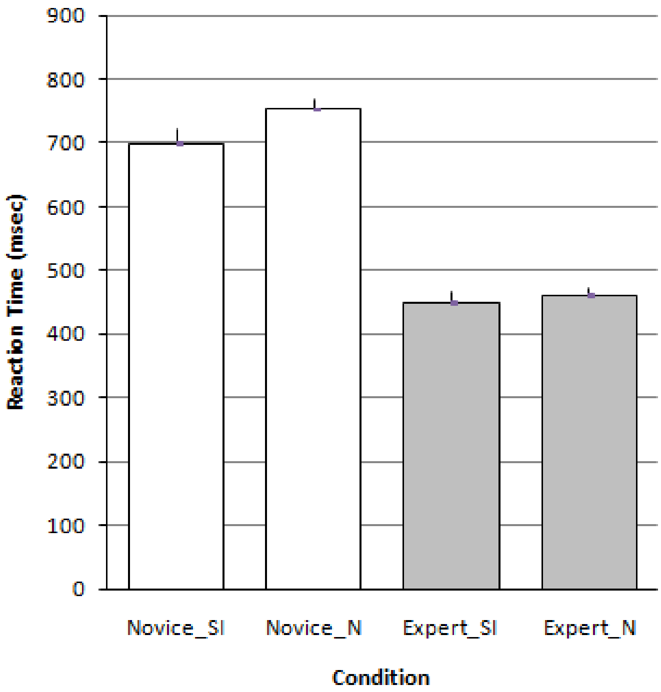

Figure 3. Mean Reaction Times. Note: Error bars indicate standard errors of mean. SI = self-information provided to subject. N = no self-information provided to subject.

Discussion

The simple main effect test shows that expert athletes demonstrate consistently fast RTs regardless of whether they were provided with the self-position and posture information. This suggests that the experts seem to be able to identify their relative position and posture without looking at video images of themselves. Thus, it would appear that they have superior internal mechanisms for perceiving self-position and posture and can utilize it in offensive and defensive situations. Prior studies on motor control have proposed a computational motor control framework called optimal feedback control (e.g., Todorov, 2004). This framework supports that the brain is able to predict the sensory consequence of motor commands accurately utilizing an internal model (forward model) and combine the predictions with actual sensory feedback to estimate the state of the body. Furthermore, recent physiological studies have shown experimental evidence of the forward model and the body-state estimation in the brain (Miall et al., 2007; Shadmehr & Krakauer, 2008). The forward model can be improved through learning (Wagner & Smith, 2008), demonstrated in the skilled athlete (Yarrow et al., 2009). Thus, karate experts in this study seem to have their own trained forward model for perceiving their position and posture. In this experiment, since the position and posture that were related to the opponent's punch condition were common karate actions, the experts seem to have learnt the proprioceptive information of the position and posture through the rehearsal trials. As a result, it can be hypothesized that they were able to perceive the proprioceptive information accurately and were thereby able to direct their visual attention to the opponent’s motion, thus demonstrating consistently fast RTs. This result suggests that experts utilize the forward model effectively in the offensive and defensive situations.

This study also found that when the self-position and posture information is provided to novice karate athletes, RTs become significantly shorter. Since visual information provides useful information for dynamic control (e.g., Patla, 1997), novices may have recognized the spatial relationship between the virtual opponent and themselves from visual information and reacted successfully by anticipating the opponent's punch. However, the result that novice RTs worsen when the self-images were not provided suggests that the rehearsal trials did not improve their forward models for the self-position and posture perception. It can be said that the visual feedback seems to improve the reaction performance temporarily but does not appear to enhance proprioceptive learning (e.g., Krakauer, 1999; Franklin, 2007).

Regardless of the stimulus image there is a significant difference between the RTs of experts and novices. This difference exceeded 200 ms which is extreme when compared with other studies showing a difference of approximately 100 ms (e.g., Mori et al., 2002). Based on the forward model theory, the experts consistently executed decision making of self-position and posture estimations based on their internal models and the visual search of opponent's motion. On the other hand, from the result of the simple main effect test on the Novice Stimulus factor, it is reasonable to conclude that the novices' information processing was different between the trials in which self-information was provided and when it was not. In the case of no visual self-information, information processing seems to have required more time due to un-trained internal models. As for the case of providing the self-information, the novices appear to have done both opponent's motion detection and recognition of their position and posture from the visual information. We can consider that the large RT difference between the experts and the novices was caused by the information processing time difference between the self-position and posture estimation based on the experts’ use of internal models and the novices' use of position and posture recognition from the visual information.

Finally, the training in the MR environment needs to be considered. The MR provided the subjects with the third person point of view of the opponent and themselves. Therefore, athletes might have been compelled to do additional processing such as a coordinate transformation to the first person point of view when picking up position and posture information from the images. Table 1 shows the information processing required in each scenario. Based on the discussion and assuming that additional processing is necessary with MR, expert athletes' consistently fast RTs suggest that they utilize the same manner for perceiving self-position and posture in each case, since both RTs include equally the additional processing time for perceiving opponent's motion. Therefore, the assumption would not affect the argument that expert athletes utilize their internal models in each case. As for the consideration that self-position and posture information improved novice RTs in the SI case, the argument would not be modified as the RT of the SI case was faster than that of the N case even though the RT of the SI case included the extra processing time for perceiving opponent's motion.

However, when considering the additional information processing, it could be a significant factor in the RT difference between the experts and novices. An investigation into the effects of processing is future work.

Table 1. Information processing in each case for expert and novice karate athletes.

		SI	N
Novice	Self- position and posture perception	Visual search + Additional processing caused by MR	Estimation using internal model (un-trained internal model)
	Opponent’s motion perception	Visual search + Additional processing caused by MR	Visual search + Additional processing caused by MR
Expert	Self- position and posture perception	Estimation using internal model (trained internal model)	Estimation using internal model (trained internal model)
	Opponent’s motion perception	Visual search + Additional processing caused by MR	Visual search + Additional processing caused by MR

Conclusion

In this study we investigated the reaction times (RT) of karate athletes against a video representation of a virtual opponent’s punch. There were two test situations; one where visual information about athletes’ self-position and posture was given and one where it was not via Mixed Reality technology. The subjects were divided into two groups, karate experts and novices and the difference between these groups was also investigated. Results found that when novices were given self-information, the outcome was significantly shorter RTs. However, while the given self information effects to self-position and posture perception, it does not appear to enhance proprioceptive learning.

On the other hand, experts did not show any change, demonstrating consistently fast RTs. This result is consistent with the former researcher's conclusion that expert athletes have superior forward models and suggests that they utilize the models in the offensive and defensive situation.

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The Effectiveness of Satisfying the Assumptions of Predictive Modelling Techniques: An Exercise in Predicting the FIFA World Cup 2010

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Abstract

The assumptions of statistical procedures are enforced more rigorously in some disciplines than in others. Previous research into the accuracy of predictive modelling techniques has provided examples where models based on data that violate the relevant assumptions is greater than that of models where the assumptions were satisfied. The purpose of this investigation was to develop two sets of 4 models; one set being based on untransformed data that violated the assumptions of the modelling techniques and a second set where the data were transformed in order to satisfy the assumptions of the modelling techniques. Data from 153 pool matches and 54 knock out matches from international soccer tournaments from July 2006 to February 2010 were used to produce predictive models of match outcomes (win, draw or lose) or goal difference with respect to the higher ranked teams within matches according to the FIFA World rankings. The independent variables used were difference between the teams FIFA World ranking points, difference between distance from capital city to capital city of the host nation and difference in recovery days from previous match within the tournament. The two sets of models were used to predict the 2010 FIFA World Cup, 119 human predictions and 20 weighted random predictions were also produced. An evaluation process marked the predictions with respect to the actual outcomes of matches in the 2010 FIFA World Cup out of a total possible score of 64 points. The mean accuracy of the models where the assumptions were satisfied was 33.50 points which was similar to the 35.13 points for those where the assumptions were violated. The accuracy score of the 8 model based predictions was 34.31$\pm$2.70 compared to 33.75$\pm$3.86 for the human predictions and 35.55$\pm$2.50 for the weighted random predictions. There was no significant difference in the accuracy of the three types of prediction ($p = 0.116$). These results provide evidence that challenges the value of satisfying the assumptions of discriminant function analysis, binary logistic regression and multiple linear regression.

KEYWORDS: PREDICTIVE, MODELLING, SIMULATION, STATISTICAL ASSUMPTIONS

Introduction

The quality of predictive models depends on several factors including whether the assumptions of modelling techniques have be satisfied by the data used (Manly, 1994; Tabachnick and Fidell, 1996; Ntoumanis, 2001). However, a series of prediction studies in sport has shown that satisfying the assumptions of the modelling techniques does not always produce the most accurate forecasts of the actual outcomes of matches. In previous prediction studies of the 2003 Rugby World Cup (O'Donoghue & Williams, 2004), the Euro 2004 soccer tournament (O'Donoghue, 2005) and the 2006 FIFA World Cup (O'Donoghue, 2006), predictions based on models where the relevant assumptions were satisfied were not as accurate as predictions where those assumptions were violated. One study of Euro 2008 did find that the models where the assumptions were satisfied to be more accurate than those where the assumptions were violated (O'Donoghue, 2009). However, the difference was so small that it was difficult to justify the effort of satisfying the assumptions. The purpose of the current investigation was to predict the pool and knock out stages of the 2010 FIFA World Cup before the competition commenced using pairs of models based on multiple linear regression, discriminant function analysis and binary logistic regression. Each pair of models included one where the data used to create the model were not transformed in any way and one where the data were transformed so that the assumptions of the modelling techniques were satisfied. The pairs of models used the following techniques where the superior team within a match refers to the team ranked highest by FIFA and the inferior team referring to their opponents:

(a) Discriminant function analysis to predict the outcomes of pool matches (win, draw or loss for the superior team) and binary logistic regression to predict the outcome of knockout matches (superior team progressing or being eliminated).
(b) Multiple linear regression to predict the goal difference between the superior and inferior teams within matches. During the pool stages, values of between -0.5 and +0.5 were interpreted as draws. During the knockout stages, values of 0.0 and above indicated that the superior team progresses.
(c) Multiple linear regression with -0.5 and +0.5 (and 0.0 during the knockout stages) being replaced by cut-off values intended to produce a proportionate number of wins, draws and losses for the superior team within pool matches (and proportionate number of matches where the superior team progresses during the knock out stages).
(d) A simulation based on multiple linear regression to determine expected results and representing variability in performance evidenced by residuals between predicted and actual goal difference.

Unlike the study of the 2006 FIFA World Cup (O'Donoghue, 2006), the current investigation did not attempt to correct for regional biases in FIFA World rankings or to represent the consistency or erraticness of individual teams. The reason for this was that the FIFA World ranking system changed after the 2006 World Cup and, therefore, there are insufficient historical data under the new system to incorporate these factors. In particular there has only been one inter-confederation tournament since the 2006 World Cup (the 2009 Confederations Cup) which only included 12 pool matches and 4 knock out matches. This makes the incorporation of regional effects impossible in the current investigation. A secondary aim of the study was to compare the accuracy of these quantitative predictions with a set of weighted random predictions and predictions made by humans using qualitative methods.

Data Sources

All of the models used the same data set of international tournament soccer matches. The data set consisted of 7 variables for 207 Confederations Cup and intra-confederation championship matches from 2006 to 2010. Only matches played since the 2006 World Cup were used to produce the predictive models for the 2010 World Cup. There were 153 pool matches and 54 knock out matches within the data set. Each match was contested between two sides; the superior side (the higher ranked side according to FIFA) and the inferior side (the lower ranked side according to FIFA). The outcome variable was the difference in goals between the two sides (superior team's goals – inferior team's goals) after 90 minutes plus any injury time. A categorical version of this variable was also included classifying matches as wins, draws or losses for the superior team. All knock out stage matches were classified as wins or losses depending on the actual outcome including any extra time and penalty shoot outs. There were 3 independent variables which were differences between the superior and inferior sides contesting the match. These were:

- Rankδ: Difference between the FIFA world rankings of the superior and inferior teams involved in a match. It was decided to use FIFA World ranking rather than FIFA World ranking points due to changes in the scale of measurement for FIFA World ranking points that have occurred between 1994 and 2006.
- Distδ: Difference in distance traveled to the tournament by the superior and inferior sides. For each team involved in a match, the distance traveled was estimated by the giant circle distance between the capital city of the country and the capital city of the host nation. This was obtained from an internet based distance calculator (Indonesia, 2006).
- Recδ: The difference in the recovery days from the previous matches within the tournament played by the two teams (+1 meant the superior team had an extra recovery day, -1 meant that the inferior team had an extra recovery day and 0 meant the two teams had the same number of recovery days from their previous matches).

Some of the modelling techniques being used had assumptions that could be satisfied if normally distributed independent variables were used. Kolmogorov Smirnov tests revealed that none of these three independent variables were normally distributed ($p < 0.05$). Therefore, the variables were mapped onto a standard normal distribution with a mean of 0 and a standard deviation of 1 using the techniques described by O'Donoghue (2006). These mapping functions allowed three new independent variables ZRankδ, ZDistδ and ZRecδ to be included in the data set. Kolmogorov Smirnov tests revealed that ZRankδ and ZDistδ were normally distributed ($p > 0.05$) but that ZRecδ was not ($p < 0.001$).

Prediction Techniques

Discriminant Function Analysis and Binary Logistic Regression (Violating Assumptions)

Discriminant function analysis was performed on the 153 cases of pool matches from previous international soccer tournaments to predict group membership according to match outcome (wins, draws and losses for the superior team) using Rankδ, Distδ and Recδ as predictor variables. This was done in SPSS Version 17.0 (SPSS Inc., Chicago Il) with a territorial map and the two canonical discriminant functions being recorded. SPSS Version 17.0 (SPSS Inc, Chicago, Il) was also used to perform the binary logistic regression on the 53 knockout matches from previous international tournaments.

Discriminant Function Analysis and Binary Logistic Regression (Satisfying Assumptions)

SPSS Version 17.0 was also used to do the discriminant function analysis and binary logistic regression with data that satisfied the assumptions of these techniques. The discriminant function analysis in this model used ZRankδ and ZDistδ and resulted in 2 canonical discriminant functions and a territorial map being produced. These were used to predict the outcomes of pool matches in the 2010 World Cup. There were two outliers for zPP_Diff; the 2009 Confederations Cup matches Spain v New Zealand and between Italy v Brazil. There were also two outliers in the zDist_Diff variable; South Africa v New Zealand and Spain v South Africa from the 2009 Confederations Cup. These were removed from the data to ensure that the data used to produce the model satisfied all of the assumptions of discriminant function analysis.

Binary logistic regression does not have any assumptions relating to the distribution of predictor variables and so the untransformed Rankδ, Distδ and Recδ variables were used in the binary logistic regression. Furthermore, no outliers were found when the residual values of the binary logistic regression were examined and all other assumptions of the method were satisfied without any need to transform the variables. This meant that the only difference was that the knockout matches to be forecast were different as a result of different discriminant function analyses being done within the predictions of the pool matches.

Multiple Linear Regression (Violating Assumptions)

SPSS Version 17.0 was used to perform the multiple linear regression to predict goal difference between the superior and inferior teams within the pool matches and knockout matches respectively. When the regression equation was applied to the new cases from the pool matches of the 2010 FIFA World Cup, goal difference values between -0.5 and +0.5 were interpreted as draws. When using the regression equation to forecast the outcomes of knockout matches, goal difference values of 0.0 and above were interpreted as wins for the superior side within matches.

Multiple Linear Regression (Satisfying Assumptions)

Although multiple linear regression does not require each independent variable to be normally distributed, there were other assumptions of the technique that were violated when ZRecδ was included. This was the case with the model of pool matches and the model of knock out matches. The models based on ZRankδ and ZDistδ achieved normality in the residual values produced for goal difference.

Multiple Linear Regression with Proportionate Outcomes (Violating Assumptions)

When inspecting the actual and predicted goal differences within matches, it was clear that there was much greater variability in the actual goal differences than the predicted goal differences for both pool and knock out matches. Wins (n=77), draws (n=36) and losses (n=40) were predicted more proportionately by replacing the cut-off values of -0.5 and +0.5 for draws in pool matches by 0.2228 and 0.5307 respectively. The cut-off value of 0.0 and above for wins in knockout matches was replaced by 0.5271 and above to predict wins for the superior team more proportionately. These cut off values were derived using the sorted predicted goal difference values produced for the previous data when the linear regression was carried out in SPSS.

Multiple Linear Regression with Proportionate Outcomes (Satisfying Assumptions)

A similar process was carried out for the multiple linear regression model where the assumptions were satisfied by the independent variables used. Predicted goal difference values of between 0.2029 and 0.6191 were forecasted as draws for the pool matches and predicted goal difference values of 0.5792 and above were predicted as wins for the superior team within the knockout stages.

Multiple Linear Regression Based Simulation (Violating Assumptions)

The simulation system was implemented in Microsoft Excel. The system stored the FIFA World rankings and the distances between capital city and Pretoria for each of the 32 countries in the 2010 World Cup. The system simulated the 2010 FIFA World Cup 1000 times accumulating results and progression statistics. The simulation used an underlying model of expected results based on multiple linear regression. The mean and standard deviation of residual values had been determined in SPSS and these values were used to produce random match effects to add to the expected result. The fact that this random variation was based on the distribution of residual values found in the linear regression meant that proportionate outcomes were achieved using cut off values of -0.5 to +0.5 for draws in the pool matches and 0.0 for the knock out matches. The backtracking process developed by O'Donoghue *et al.* (2004) was used to determine a single modal prediction made by the simulator.

Multiple Linear Regression Based Simulation (Satisfying Assumptions)

A second simulator was produced using the underlying regression equations derived from data that had satisfied the assumptions of the technique. The system stored the same variables as the previous simulator but also included the necessary mapping functions to allow ZRankδ and ZDistδ to be determined. The system was implemented in Microsoft Excel, used random numbers based on the residual distribution for the underlying regression model and iterated the tournament 1000 times accumulating results. Progression statistics were accumulated allowing a single modal prediction to be determined.

Human Predictions

A prediction form for the 2010 FIFA World Cup was distributed to colleagues and friends of the author. The form allowed the respondents to predict a win, draw or loss for the superior team in each of the 48 pool matches as well as predicting the teams reaching different positions in the knock out stages. There were 119 human predictions provided before the World Cup commenced and these were included in the study.

Weighted Random Assignment of Results

The 153 pool matches and 54 knockout matches from previous international tournaments were divided into four and three partitions respectively based on gap in FIFA World ranking between the two teams in the matches. The number of wins, draws and losses for the superior teams in each partition allowed the proportion of matches resulting in each outcome type to be determined as shown in Table 1. These proportions allowed cut off probabilities to be determined so that random numbers between 0 and 1 could be used to predict wins, draws and losses. This process allowed the randomised results to be weighted so that a proportionate number of wins, draws and losses would be predicted for matches between teams separated by different numbers of places in the FIFA World rankings.

Table 1. Outcomes of previous matches and cut off probabilities used to produce weighted random results.

Difference in FIFA World rankings between superior and inferior teams within matches	Wins	Draws	Losses	Total	Cut off for Lose (below)	Cut off for Win (above)
Pool matches						
Less than 125 ranking points	10	13	14	37	0.378	0.730
125 to269 ranking points	17	9	12	38	0.316	0.553
270 to 412 ranking points	22	8	8	38	0.211	0.421
More than 412 ranking points	26	6	6	38	0.158	0.316
Knockout matches						
Less than 125 ranking points	8		10	18	0.556	N/A
125 to 300 ranking points	10		8	18	0.444	N/A
300 or more ranking points	17		1	18	0.056	N/A

Evaluation Procedure

The predictions for each pool match were given 1 mark where the outcome was correctly predicted. Where the prediction was a draw but the actual match was won by one of the teams, 0.5 marks were awarded. Similarly, 0.5 marks were awarded where a win was predicted for one of the teams but the actual match resulted in a draw. The second part of the evaluation related to the predictions of knockout matches. The prediction models were awarded 1 mark for each of the quarter finalists successfully predicted, 1 mark for each semi-finalist and finalist successfully predicted, 1 mark if the winner of the third place play off was correctly predicted and 1 mark if the tournament winner was successfully predicted. This gave a maximum of 64 marks for each prediction.

The number of points awarded to each prediction at the various stages of the tournament was compared between quantitative, human and random predictions using a Kruskal Wallis H test. A p value of less than 0.05 was taken as being significant. Where a significant difference was found, Bonferroni adjusted Mann Whitney U tests were used to compare pairs of prediction types with a p value of less than 0.017 indicating a significant difference.

Results

Despite the 8 quantitative predictions being made using subsets and derivatives of the same data, there were no two pairs of predictions that were the same for the 48 pool matches. Table 2 shows that the accuracy of those models created with data that satisfied the assumptions of the methods was lower than that of models created with data that violated the assumptions in 3 of the 4 cases. The most successful quantitative technique was multiple linear regression without proportionate outcomes.

Table 2. Accuracy scores for the quantitative predictions.

Method	Data used violate assumptions	Data used satisfy assumptions	Mean
Discriminant Function Analysis / Binary Logistic Regression	33.00	34.50	33.75
Multiple Linear Regression (MLR)	38.50	36.00	37.25
MLR with proportionate outcomes	32.00	30.50	31.25
MLR based simulation	37.00	33.00	35.00
Mean	35.13	33.50	34.31

Table 3 shows that the accuracy of the quantitative methods was lower than that of the weighted random predictions and the human predictions for the pool matches but greater than the accuracy of the human predictions for the knock out stages. The accuracy of the human predictions ranged from 25.0 to 43.0 while that of the random predictions ranged from 31.0 to 40.0. There were 2 of the weighted random predictions that performed better than the best quantitative prediction. The only significant differences between the three types of predictions were between the human predictions and the weighted random predictions with the weighted random predictions being significantly more accurate for predicting the knock out stages, semi-finalists, finalists and the tournament winner.

Table 3. Mean accuracy score of different types of predictions at different stages of the tournament.

Stage / Total points allocated	Quantitative (n=8)	Human (n=119)	Random (n=20)	H_2	p
Pool matches /48	27.31±1.77	28.15±2.49	28.20±2.27	1.56	0.459
Quarter-finalists /8	4.00±1.07	3.52±1.15	3.85±0.81	2.74	0.254
Semi-finalists /4	1.38±0.52	1.09±0.76	1.65±0.75 &	9.82	0.007
Finalists / 2	1.00±0.00	0.64±0.62	0.95±0.22 &	9.64	0.008
Third place /1	0.25±0.46	0.13±0.33	0.15±0.37	1.01	0.603
Winners /1	0.38±0.52	0.22±0.41	0.75±0.44 &	23.14	<0.001
Knockout stages /16	7.00±1.69	5.60±2.29	7.35±1.60 &	13.81	0.001
Total /64	34.31±2.70	33.75±3.86	35.55±2.50	4.31	0.116

Key: & Mann Whitney U test revealed significantly different to human predictions ($p < 0.017$).

Tables 4(a) to 4(b) show that the multiple linear regression models that used cut off values of -0.5 to +0.5 for pool matches only predicted one upset between them. Tables 4(c) and 4(d) show that when proportionate outcomes were forced by adjusting the cut off values for predicting draws, 14 and 13 upsets were predicted by the models where the data violated and satisfied the assumptions respectively. Although this resulted in a similar breakdown of wins, draws and losses being predicted to the 23, 14 and 11 that occurred in the actual 2010 World Cup, the number of correct outcomes did not exceed that of the models where cut off values of

-0.5 and +0.5 were used. Furthermore, Tables 4(a) to 4(d) show that the models where cut off values of -0.5 to +0.5 were used earned more half points using the evaluation scheme than the methods that forced proportionate outcomes. Tables 4(e) and 4(f) show that the discriminant function analysis based predictions forecasted fewer draws than the other techniques which cost these techniques a lot of half points during the evaluation.

Table 4. Correctness of predictions of pool matches (MLR = multiple linear regression, 0.5 = cut off values of -0.5 to +0.5 used, P = proportionate outcomes forced, DFA = discriminant function analysis, V = violating assumptions, S = satisfying assumptions).

(a) MLR-0.5-V

Predicted	Actual			
	L	D	W	All
L	0	0	0	0
D	5	7	13	25
W	6	7	10	23
All	11	14	23	48

(b) MLR-0.5-S

Predicted	Actual			
	L	D	W	All
L	0	0	1	1
D	5	6	9	20
W	6	8	13	27
All	11	14	23	48

(c) MLR-P-V

Predicted	Actual			
	L	D	W	All
L	3	3	8	14
D	3	4	5	12
W	5	7	10	22
All	11	14	23	48

(d) MLR-P-S

Predicted	Actual			
	L	D	W	All
L	3	3	7	13
D	3	3	5	11
W	5	8	11	24
All	11	14	23	48

(e) DFA-V

Predicted	Actual			
	L	D	W	All
L	2	2	6	10
D	0	1	1	2
W	9	11	16	36
All	11	14	23	48

(f) DFA-S

Predicted	Actual			
	L	D	W	All
L	1	2	6	9
D	5	2	2	9
W	5	10	15	30
All	11	14	23	48

The modal predictions derived though backtracking within the output of the simulation packages produced a modal prediction for each simulator. However, each simulator did produce 1000 predictions that should be considered. Table 5 summarises the 1000 predictions made by each of the two simulation packages. The performance of these packages was very similar throughout the tournament with the simulator based on an underlying model where the data violated its assumptions being slightly more accurate overall.

Table 5. Predictions made by the simulation packages.

Metric	Violates	Satisfies
%Loses during pool matches	26.529	26.135
%Draws during pool matches	19.488	18.915
%Wins during pool matches	53.983	54.950
Correct pool results /48	18.806	18.870
Pool matches where half points awarded /48	17.751	17.448
Quarter-finalists correctly predicted / 8	3.211	3.187
Semi-finalists correctly predicted / 4	0.999	0.967
Finalists correctly predicted /2	0.424	0.440
Third place winner correctly predicted /1	0.072	0.062
Tournament winner correctly predicted /1	0.175	0.185
Total points awarded for the prediction /64	32.563	32.435

Discussion

The forecasting performance of the models where the assumptions were satisfied was marginally lower than that of the models where the assumptions were violated. This agrees with 3 previous investigations that deliberately compared the accuracy of these two types of model (O'Donoghue and Williams, 2004; O'Donoghue, 2005; O'Donoghue, 2006). There was a prediction study of the Euro 2008 soccer where the models that satisfied the assumptions performed better than those that did not (O'Donoghue, 2009). The modelling data available to predict Euro 2008 was the most limited of all of the prediction studies done by this author. This was because FIFA changed its ranking system after the 2006 World Cup. Furthermore, the accuracy of the Euro 2008 predictions where the models satisfied the assumptions was only marginally greater than of the models that did not. The balance of evidence from the current study and the three previous studies is that the effort required to transform the data to satisfy the assumptions cannot be justified for this type of application.

There is some evidence that satisfying certain types of assumption in certain models can be beneficial. In order to satisfy the assumptions, it was necessary to remove 4 matches that were statistical outliers in the historical data when forming the discriminant function model. This resulted in 3 pool matches of the 2010 World Cup being predicted as draws rather than wins for the superior teams. In all three cases (France v Mexico, Cameroon v Japan and Chile v Honduras) lower ranked teams who travelled further than their higher ranked opponents were predicted to do better by holding their opponents to a draw. The removal of outliers from the historical data, therefore, earned 0.5 points more in the evaluation scheme than if the outliers remained (2 x 0.5 points extra for Mexico and Japan predicted to draw matches they actually won but 1 x 0.5 points less for Honduras predicted to draw a match they actually lost. Irrespective of whether outliers were removed or not, the predicted winners and runners up of the three pools involved remained the same. Therefore, the prediction excluding the outliers was awarded 0.5 marks more than it would have been if the 3 outliers remained in the historical data.

Despite the extra 0.5 points achieved by removing the four outliers from the historical data, there are issues to be raised by removing the outliers. Two matches were removed because they were outliers for the ZRankδ variable (Italy v Brazil and Spain v New Zealand from the 2009 Confederations Cup). Italy and Brazil were ranked 4th and 5th in the World at the time there were only 4 ranking points between them. Spain was ranked 1st with 1761 ranking points while New Zealand was ranked 82nd with 431 ranking points. It is possible for teams to have the same number of ranking points without there being any measurement error. This would suggest that removing the Italy v Brazil match could be challenged. There were teams ranked lower than 82nd in the 2010 World Cup; South Africa were 83rd and North Korea were 105th. Indeed, the top ranked team (Brazil) played against North Korea in a pool match in 2010. Therefore the exclusion of the Spain v New Zealand match could be challenged.

The current study attempted to predict the outcome of matches of the 2010 World Cup which is a tournament involving teams from different confederations (FIFA's continental zones). Because FIFA changed its World ranking system in 2006, the only matches included in the previous case data that involve teams from different confederations were 2009 Confederations Cup matches. These matches involve the greatest amount of travel in the data set and similar distances would have to be travelled to South Africa or the 2010 World Cup. Excluding Confederations Cup matches risked a danger of extrapolating the effect of distance travelled within intra-confederation tournaments (like Copa America and Euro 2008) beyond the distances used to create the predictive model. Therefore, the exclusion of the South Africa v New Zealand and Spain v South Africa Confederations Cup matches from the historical data could be challenged. Indeed, there was a match in the 2010 world cup (Mexico v South Africa) where the Distδ of 14,588km exceeded that of the two statistical outliers in the historical data for this variable. Interestingly, the effect that was extrapolated was for teams travelling further to do better rather than worse. This might be explained by the relatively poor performance of host nations in the tournaments included in the historical data (for example Switzerland and Austria in Euro 2008).

The quantitative predictions relied on 3 variables which can be considered by reflecting on the actual results of the 2010 World cup matches. FIFA World ranking points have a good association with match outcome with 23 pool matches being won by the higher ranked team in the 2010 World Cup, 14 being drawn and 11 being lost. Similarly, 14 of the 16 knock out matches played in the 2010 World Cup were won by the higher ranked team. To predict soccer matches successfully, the task becomes one of predicting the upsets and draws. Table 1 shows that upsets do occur in matches where the two teams involved are close or far apart in the World rankings. Future work needs to determine the factors that can be used to indicate upsets and how such factors can be quantified. This may be an impossible task as the volume of data required multiplies as new factors are added. Further difficulty is caused by changes in the rules of soccer and advances in the way players and teams prepare for competition.

Home advantage has been demonstrated in many sports (Courneya and Carron, 1992). The African teams in the 2010 World Cup had mixed fortunes with 2 finishing in better pool positions than their World rankings would have suggested (Ghana and South Africa), two finishing where their rankings would have suggested (Ivory Coast and Algeria) and two finishing in lower pool positions than their World rankings would suggest (Cameroon and Nigeria). This does not provide any evidence for or against the concept of home advantage in World Cup soccer. However, the tournament winners have come from the same continent as the host nation in 16 out of 18 World Cups from 1930 to 2006 if North and South America are considered as a single continent. The host nation has won 6 of these 18 World cups. Until the 2010 World Cup, no European team had won the tournament outside Europe and Brazil were the only South American team to win the World cup outside the Americas. The top 3 placed sides in the 2010 World Cup were all European leading to speculation that distance travelled might not be related to performance as much as time-zone difference. Future research should consider the relative accuracy of forecasts that use time-zone, distance between capital cities and other indicators of home advantage.

There were 12 matches of the 2010 World Cup where one team had more recovery days from their previous match than their opponents. The team with an extra recovery day won 5 of these matches, drew 3 of these matches and lost 4 of these matches. This is weak evidence supporting a recovery effect because other factors such as team strength (ranking) need to be considered.

The most accurate quantitative predictions were the regression models where predicted goal differences of between -0.5 and +0.5 were counted as draws. This is in contrast to previous research where simulation has been the most successful (O'Donoghue *et al.*, 2004; O'Donoghue and Williams, 2005; O'Donoghue, 2005; O'Donoghue, 2006). The evaluation scheme has used a single modal prediction for each simulator which may be a weakness of the evaluation technique. However, the mean evaluation score of the simulated World cups is actually lower than that of the modal value for each of the two simulators. The win:draw:loss breakdown in pool matches forecast by the simulators was 26%:19%:54% which was close to the 48%:29%:23% breakdown that actually occurred in the 2010 World cup. However, the simulators lost marks in the evaluation as the forecasted draws and upsets were not always the draws and upsets that occurred in reality. There is an interesting contrast between the current investigation and O'Donoghue *et al.*'s (2004) study of the 2002 World Cup. In the 2002 World Cup, France were the highest ranked team and they started the tournament on the first day of matches meaning their schedule would include more recovery days than that of other teams. The simulator gave Brazil a greater chance of winning the 2002 World Cup than France because France's pool was harder than Brazil's and France would have to play stronger opponents in round 2 than Brazil would if they qualified from their pool. The simulators in the current investigation of the 2010 World Cup recognised that Spain had a difficult schedule of matches because if they qualified from their pool, they would have to meet a team from Pool G which include Brazil and Portugal, the 1st and 3rd ranked teams in the World. The potential for Spain to meet Brazil or Portugal in the second round actually reduced the probability of all three teams winning the tournament. The simulator that satisfied the modelling assumptions still determined that Brazil (.196) and Spain (.185) had the highest probabilities of winning the tournament, but Portugal's chance (.072) was lower than Holland's (.093). The simulator that violated the modelling assumptions also determined that Brazil (.209) and Spain (.175) had the highest chances of winning the tournament, with Portugal's chance (.062) being lower than that of Holland (.080). The gap in world ranking points between the World's top 2 teams (Brazil and Spain) and the following pack of teams meant that these two teams were still determined to have the best chance of winning the tournament despite the difficult draws they faced.

The weighted random predictions were more accurate than human or quantitative predictions. This is largely explained by the ranking and performance of Spain in 2010. There was a large gap in the ranking points that Brazil (1611) and Spain (1565) had and the third ranked team, Portugal (1249). Table 1 shows that only 1 out of 18 knock out matches in the historical data where there was a gap of 300 ranking points between the two teams resulted in an upset. There were 19 of the 20 random predictions where Spain were predicted to reach the final with Spain predicted to win 15 of these. The weighted random predictions did not favour Brazil as much due to their tougher group leading to 4 of these forecasting that Brazil would fail to qualify from their pool. Table 1 also shows that in the 18 historical knock out matches where there were fewer than 125 ranking points between the two teams there were 10 upsets. This favoured Spain if they were predicted to play Brazil in round 2 or in the final.

There was a greater variability in the forecasting accuracy of the human predictions than that of the quantitative predictions with the 119 human predictors forecasting 15 different teams to win the World Cup. The greater variety of predictions is explained by the subjective methods used in the human predictions being able to draw on a wider range of information than the 3 variables used by the quantitative predictions. These may have included squad selections, players missing the World Cup through injury, performance during qualifying campaigns, the quality of individual players and coaching staff, team cohesion, squad cohesion, the level of support the team might have in the World Cup, altitude at some of the matches, climate and time-zone effects. Even where two people are considering the same factors, they may come up with different predictions due to the different levels of importance they attach to different factors and how the available data is judged. The mean human prediction was more accurate than some quantitative predictions and less accurate than others. This supports the view expressed by O'Donoghue *et al*. (2004) that both quantitative and qualitative methods have strengths and weaknesses.

Conclusion

The current investigation has revealed no benefit arising from the effort of ensuring that data satisfy the assumptions of the modelling techniques used. More evidence is needed to support these assumptions if they are to be addressed by researchers into performance prediction in sport. The quantitative predictions were not as successful as human or weighted random predictions when evaluated using the actual results of the 2010 World Cup.

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Kinematic Analysis of Human Goal Directed Movements

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Abstract

One of the major goals of robotics research is the construction of humanoid robots that enter human-centred environments. To promote man-machine interaction in daily life robots should have a roughly humanoid shape and use human-like movements. It is therefore crucial to understand how humans coordinate their upper-body movements during daily motor tasks. One of the key assumptions in motor control research is that information about the process of movement planning and control can be deduced from behavioural regularities. The purpose of the following study was to analyse multi-joint goal-directed movements in 3D space in a natural environment with respect to the identification of such regularities. This paper presents a study in which 20 subjects had to point to different targets in a kitchen. All pointing movements were tracked using an IR-tracking system and joint angles were calculated using a kinematic model. The limb movements were analyzed in extrinsic and intrinsic kinematic coordinates and the results were discussed against the background of theoretical assumptions of biological motor control and the generation of human-like movements on humanoid robots.

KEYWORDS: COORDINATION, KINEMATIC MODELLING, HUMANOID ROBOTS

Introduction

The technological progress during the last 20 years is reflected in the development of robotics research and its focus on humanoid robot development. One of the goals of robotics research is to create a team of humanoid robots that is able to defeat the current FIFA Football World Champion by 2050 (Ferrein, 2005). Other possible future applications of humanoid robots are residential service, personal robots for elderly or playmate robots in child education. To promote man-machine interaction the robot should have a roughly humanoid shape and use human-like movements (Schaal, 2007). This study was conducted in the Collaborative Research Center (CRC) 588 "Humanoid Robots" at the KIT. The goal of CRC 588 is to construct a humanoid service robot, which will be able to share its activity space with human partners. For the development of such a robot that is supposed to interact with humans in a human environment and use objects and tools of human daily life, it is essential to understand how humans coordinate their upper-body movements during daily motor tasks.

The diverse manipulations humans are able to perform are the result of the numerous degrees of freedom (DOFs) on a skeletal, muscular and neural level (Bernstein, 1996). This redundancy is advantageous because it enables humans to avoid obstacles and joint limits. However, this flexibility leads to a control problem. Which particular movement of the large number of possible movements should be chosen? The process of coordinating upper-extremity movements like reaching or pointing toward an object is ill-posed in the sense that the task requirements can theoretically be met by an infinite number of different movements. Bernstein (1996, p. 41) defined the coordination of a movement as the process of "overcoming excessive degrees of freedom of our movement organs, that is, turning the movement organs into controllable systems." Given the complexity of the human body, the question arises as to which principles humans use for the coordination of their movements. In this context, one of the key assumptions in motor control is that information about the process of movement planning and control can be deduced from behavioral regularities (Bernstein, 1996). Thereby, an important assumption is that represented movement features differ from non-represented features in the *criterion of simplicity* and the *criterion of invariance* (Heuer & Konczak, 2003).

Morasso (1981) showed that in multi-joint arm movements, the hand trajectories between pairs of targets in the horizontal plane are roughly straight-line paths in external Cartesian coordinates with single-peaked, bell-shaped velocity profiles regardless of the initial and final location of the hand. In contrast, when the trajectories of the hand were expressed in joint coordinates, the profiles were more complex and variable. These results were subsequently reproduced in a number of studies (e.g. Gordon et al., 1994; Haggard et al., 1995) and led to the hypothesis that goal-directed movements like pointing or reaching toward an object, are planned in external coordinates of the hand and not in joint coordinates. In contrast, Soechting and Lacquaniti (1981) showed in an experiment where subjects had to perform a goal-directed two-joint movement in the sagittal plane that both joints reached their peak angular velocities at the same time and that the ratio of the peak velocity at the elbow to the peak velocity at the shoulder is equal to the ratio of the angular excursions of the two joints. These couplings were interpreted by the authors as evidence that movements are planned in intrinsic joint coordinates. Additionally, several other researchers have suggested that goal directed movements are planned on joint level (e.g. Flanagan & Ostry, 1990; Desmurget & Prablanc, 1997). It seems that both planning spaces are supported by a large number of experimental results. However, kinematic regularities may also result from planning movements in dynamic coordinates (Nakano et al., 1999). Currently, there is no consensus on this issue.

In summary, behavioral research has discovered various regularities in human goal-directed movements. These invariants have become central in understanding the coordination of human movements, as they appear to indicate some fundamental organizational principles within the central nervous system (CNS). Although the previously mentioned studies address different research questions and highlight key principles underlying the coordination of goal-directed movements, they overlook important features of natural movements due to somewhat artificial experimental protocols and partial restriction to certain movement planes. In contrast, only little research has been performed on unconstrained multi-joint daily movements in 3D space, even though these types of movements are more common in daily life. Accordingly, the purpose of the following study is the analysis of multi-joint goal-directed movements in 3D space in a natural environment. The results will be discussed against the background of theoretical assumptions of biological motor control and the generation of human-like movements on humanoid robots.

Methods

Subjects

Twenty healthy students of the KIT (16 male; 4 female) between 20 and 25 years of age (mean: 22.2 years; SD: 1.3 years) participated voluntarily in the study (Table 1). Their height ranged from 1.60 to 1.89 m (mean: 1.77 m; SD: 0.09 m), and their mass ranged from 49 to 100 kg (mean: 70.6 kg; SD: 12.5 kg).

Table 1: Subject data.

Subjects	Sex	Age	Height (m)	Mass (kg)	Subjects	Sex	Age	Height (m)	Mass (kg)
1	male	22	1.72	65	11	male	22	1.85	75
2	female	24	1.60	49	12	male	20	1.89	81
3	female	21	1.70	59	13	male	22	1.75	75
4	male	24	1.82	79	14	male	21	1.83	64
5	male	23	1.72	60	15	male	23	1.80	75
6	male	22	1.79	80	16	female	21	1.60	49
7	male	21	1.76	100	17	male	22	1.85	87
8	male	21	1.73	65	18	male	22	1.80	66
9	male	25	1.87	75	19	male	21	1.85	70
10	male	23	1.84	78	20	female	24	1.63	60

Procedures

Human pointing gestures were captured in a kitchen at the Institute for Anthropomatics (KIT) that serves as a test center for the development of humanoid robots. All subjects stood in a neutral upright posture at the same starting position in the capture volume (Figure. 1). Four plates with numbers were attached in the kitchen representing objects which the robot would have to bring to its human user after the user pointed toward the object.

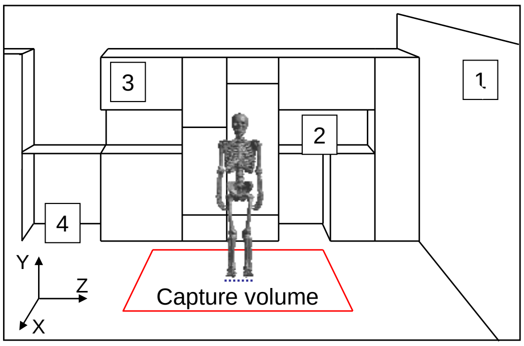

Figure 1. Starting position of the subjects in the kitchen. Numbers indicate pointing targets.

Subjects were instructed to perform the pointing gestures with their left or right arm like they would in their daily life. Instructions concerning speed, accuracy or choice of arm were not provided. Moreover, the subjects should not touch or grasp at the numbers. Besides the starting position, the order of number announcement was standardized. However, subjects were not informed about the order of number announcement before the trial. Each number was called five times resulting in 20 pointing gestures. For instance, when the researcher called “Number 1”, the subject pointed into the direction of the corresponding number. Prior to data collection, one test trial was performed for each target.

Data acquisition and processing

All pointing movements were tracked at 120 Hz using an IR-tracking system. In order to capture human movements, reflective markers were attached to the subjects. We developed a marker set based on the Vicon "PlugInGait" marker set (Figure 2). Ten cameras were installed around the subject, making up the capture volume. It was ensured that each marker was recognized by at least two cameras, which was necessary to enable the transformation of coordinates of frame markers into 3D space. Recording and data processing was done using the Vicon Workstation software.

Biomechanical Modelling

In order to compute the joint angles and hand trajectories from marker position data a kinematic multibody model of the upper body and a procedure to transfer the recorded data on the kinematic model were required.

The multibody model of the upper body was combined from the kinematics of the Stanford upper extremity model (Holzbaur et al., 2005) and a torso model (Simonidis, 2010). The model consists of 32 DOFs (Figure 2, right). Body reference frame and segment length definition fulfil the standards in biomechanics (Wu et al., 1995; 2005) and segment length parameters were selected based on regression equations (de Leva, 1996). The joint axes corresponding to the DOFs and the local body reference frames are visualized in figure 2 (right).

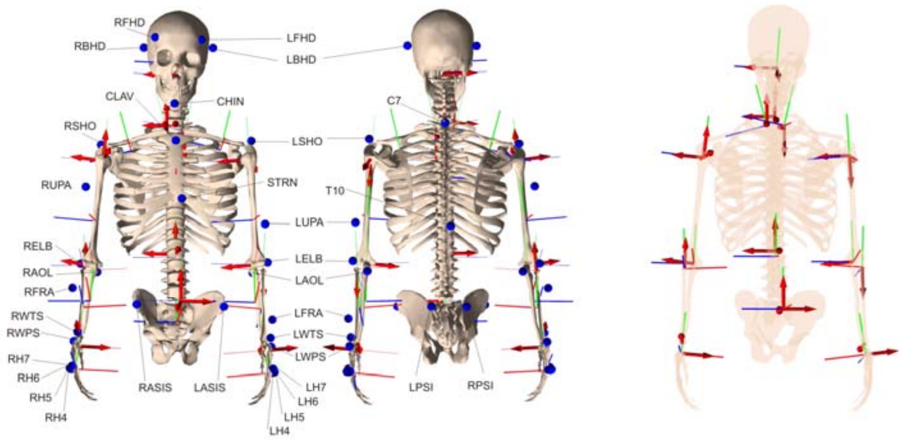

Figure 2. The marker set (left and middle) and the skeletal body model (right).

A recursive multibody algorithm (Simonidis, 2010) was used to generate the kinematic equations of motion. The DOFs of the model form a minimal set of coordinates, which describe the relative position and orientation of two adjacent bodies associated with the joint kinematics. The model is determined on position and velocity level if all coordinates and its first derivatives are known. Adaptation of the segment lengths to the individual dimensions of the subject is achieved by a scaling algorithm (Simonidis, 2010) using the position information of markers on anatomical landmarks (markers: rfhd, lfhd, rbhd, lbhd, chin, rsho, lsho, relb, lelb, rwts, rwps, lwts, lwps, rh5, lh5, rasis, lasis, rpsi, lpsi in Figure 2) and an inverse kinematics optimization procedure to automatically determine a scaling factor per body segment. Inverse kinematics is applied to compute the time trajectories of the coordinates of DOFs from the recorded marker position trajectories using a nonlinear constrained optimization approach (Lu & Connor, 1999).

At the recorded discrete time instances $t_n = [t_0 + n\Delta t], n = 0,1,2,...,n_t$, the measured smoothed coordinates $\hat{M}_m, m = 1,2,...,n_m$, are available in absolute space $\hat{\mathbf{R}}_m(t_n) = [\hat{R}_m^x(t_n), \hat{R}_m^y(t_n), \hat{R}_m^z(t_n)]^T$. A corresponding marker M_m is defined in the model and its absolute coordinates $\mathbf{R}_m(\mathbf{q}) = [R_m^x(\mathbf{q}), R_m^y(\mathbf{q}), R_m^z(\mathbf{q})]^T$ depend on the coordinates of DOFs $\mathbf{q} = [q_1, q_2, ..., q_{32}]^T$ as well as on the kinematics of the model. $\mathbf{R}_m(\mathbf{q})$ does not explicitly depend on time. The coordinates $\mathbf{q}_n$ at time instance t_n are obtained by minimizing the difference of the corresponding markers $\mathbf{f}_m^r(\mathbf{q}_n) = \hat{\mathbf{R}}_m(t_n) - \mathbf{R}_m(\mathbf{q}_n)$ (Figure 3, left) forming the global objective vector function $\mathbf{f}^r(\mathbf{q}_n) = [\mathbf{f}_1^r(\mathbf{q}_n), ..., \mathbf{f}_{n_m}^r(\mathbf{q}_n)]^T$ and optimizing for each time instance t_n in a least-squares sense. The results in sequence make up the time trajectories of $\mathbf{q}$. Figure 3 (right) visualizes the error globally distributed over the model and its minimization.

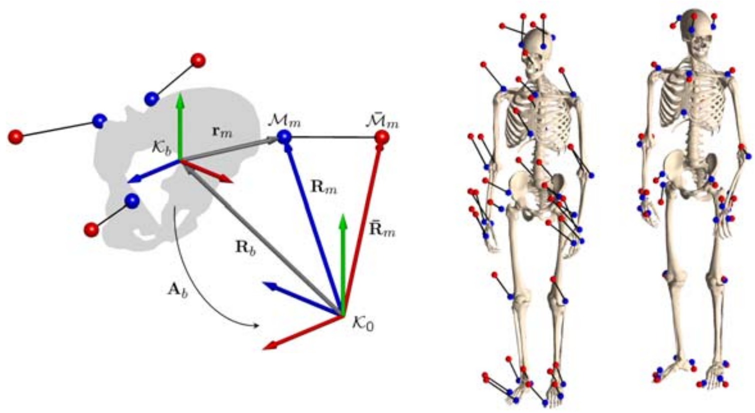

Figure 3. The pelvis segment, its model markers (blue) and measured markers (red) and coordinate relations (left); distribution of markers over the global model in an initial pose (middle) and the associated residuals, which become optimal (right).

The velocities $\dot{\mathbf{q}}$, i.e. the first derivatives of the coordinates, are computed by minimizing the difference between the marker velocities $\mathbf{f}_m^v(\dot{\mathbf{q}}_n) = \dot{\hat{\mathbf{R}}}_m(t_n) - \dot{\mathbf{R}}_m(\mathbf{q}_n, \dot{\mathbf{q}}_n)$, where $\dot{\hat{\mathbf{R}}}_m(t_n)$ is the velocity computed by derivation of the quintic smoothing spline of measured marker coordinates evaluated at t_n and $\dot{\mathbf{R}}_m(\mathbf{q}_n, \dot{\mathbf{q}}_n)$ is the velocity of a model marker depending on coordinate position $\mathbf{q}_n$ and velocity $\dot{\mathbf{q}}_n$. To improve the compensation of skin artefacts the known value of $\mathbf{q}_n$ from the previous optimization on position level is taken and only $\dot{\mathbf{q}}_n$ has to be computed. Again, optimization was carried out in a least-squares sense.

Data Analysis

Data analysis was carried out using Matlab (V. 7.7) and SPSS (V. 17). The beginning of the movement was defined as the point where the origin of the local reference frame of the hand segment surpassed 5% of its peak velocity. Time normalization was conducted using a cubic spline interpolation (101 data points). Averages over five trials were calculated for each subject for each of the four movement tasks.

The hand paths were determined based on the local reference frame of the hand and the tangential velocity profiles of the hand were calculated based on the velocity of the local reference frame of the hand.

On an intrinsic kinematic level the head and thorax rotation toward the target were of particular interest. Moreover, depending on which arm was used for the pointing gesture the clavicle abduction/adduction, shoulder abduction/adduction, shoulder rotation, shoulder anteversion/retroversion, elbow flexion/extension, forearm supination/pronation, wrist flexion/extension and wrist abduction/adduction of the right or left side of the upper body were included in the analysis. However, to be able to reduce these high-dimensional data sets to smaller numbers of modes or structures Principal Component Analysis (PCA) was carried out (Daffertshofer et al., 2004). For each averaged trial of a subject a 101×10 matrix was constructed. Each data set was standardized to a mean of 0.0 and a standard deviation of 1.0. The standardized data sets were transformed into principal components using an eigenvector analysis of the covariance matrices. Thereby, each eigenvector represented a principal component and the associated eigenvalue the amount of variability captured. Based on the Kaiser criterion, Principal Components (PCs) with eigenvalues greater than one were retained. In addition, the percent of the total variability explained by each principal component was calculated and Scree plots were created. Finally, Varimax rotation was applied to facilitate the interpretation of PCs and loading plots were created.

Results

The coordination strategies used by the subjects in this study could be assigned to one of four groups, as follows.

- Ten subjects (Table 1, subjects 1-10), comprising group 1, did not leave the starting position and pointed with their left hand to targets 1 and 2 and with their right hand to targets 3 and 4.
- In group 2, four subjects (Table 1, subjects 11-14) again did not leave the starting position but pointed with their right hand to all four targets.
- Two subjects (Table 1, subjects 15-16), group 3, left the starting position and turned toward the targets, subsequently pointing with their left hand to the targets 1 and 2 and with their right hand to the targets 3 and 4.
- The fourth group, consisting of four subjects (Table 1, subjects 17-20), did not use consistent coordination strategies for each target. For example, in five separate tasks, one subject pointed to target 1 twice with the left hand and three times with the right hand. In other words, the subjects of the fourth group used the same strategies as the subjects of groups 1 and 2, but changed coordination strategies from trial to trial for each target.

The results indicated that 16 subjects preferred recurring coordination strategies for each target, while four subjects preferred alternating coordination strategies for each target. The four subjects implementing alternating coordination strategies used the available DOFs to a far greater extent. In the following sections, typical results of groups 1 and 2 for the targets 1 and 3 are presented.

Hand Kinematics

A visual inspection of the subject trials in groups 1 and 2 revealed that the hand paths appear to always be curved, not straight (Figure 4).

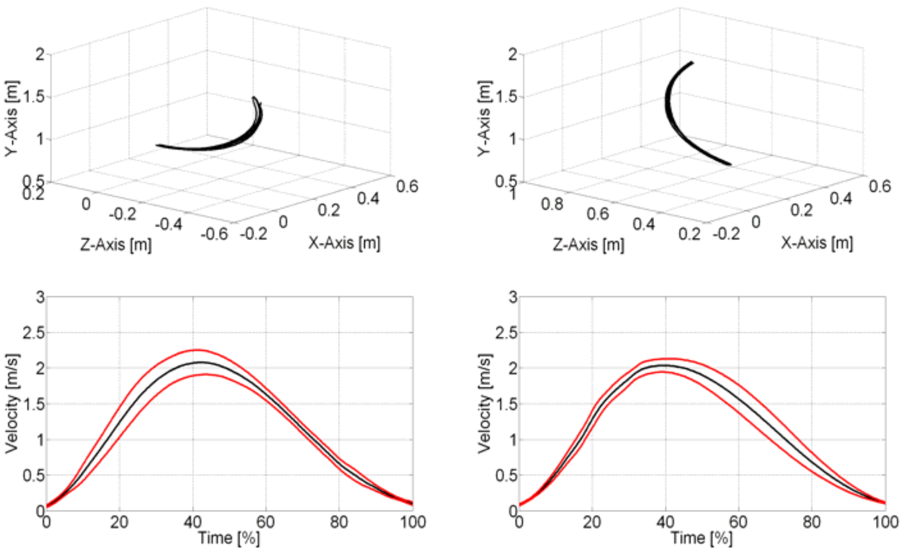

Figure 4. Five typical hand paths for target 1 (left column) and target 3 (right column) and corresponding tangential velocity profiles of the hand (mean=black, SD=red) for subject 5 (group 1).

Although there were some unsystematic differences concerning the trial to trial variability between and within the subjects, these results indicate that movements of the hand in space show a topological invariance concerning the shape of the hand path despite the different pointing tasks and different coordination strategies (e.g. left hand or right hand). Moreover, subjects of group 1 and 2 showed smooth and single-peak tangential velocity profiles for both targets (Figure 4). The velocity profiles do not appear to be precisely bell-shaped. In most cases, the peak velocity was reached slightly before 50 % of the movement time had passed indicating a slightly longer deceleration than acceleration phase. In some cases the tangential velocity profiles showed some distortions at the end.

Joint Kinematics

Target 1 & Group 1

For each averaged movement pattern of the ten subjects of group 1 a PCA was conducted. The results of the ten PCAs show that two or three PCs are necessary to explain most of the variance in the data sets. In figure 5 the Scree plots of the eigenvalues of two representative PCAs are shown.

The first PC of the PCA for subject 5 accounted for 71.3% of the variance in the data set and the second PC accounted for 19.7% of the variance (Figure 5, left). Together, these two PCs explained 91% of the variance. The first PC of PCA for subject 9 accounted for 76.7% of the variance and the second PC accounted for 13.3% of the variance (Figure 5, right). Together these two PCs accounted for 90% of the variance in the data set of subject 9. The third PC showed an eigenvalue of 0.95 and was thus not included.

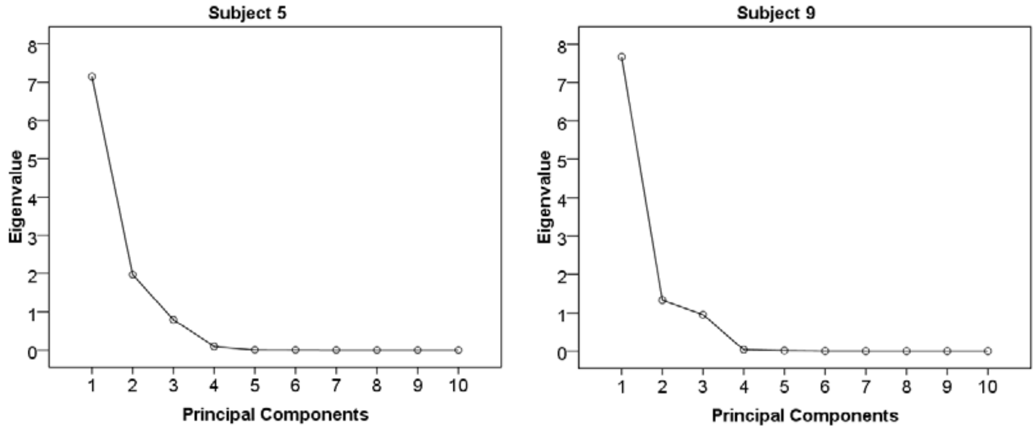

Figure 5. Scree plots of the two PCAs for the subjects 5 and 9 (group 1 & target 1). In both cases two PCs were retained.

To be able to interpret the results of the conducted PCAs the corresponding loading plots were created after the Varimax rotation to visualize the component loadings (Figure 6). These represent the correlation coefficients between the variables and the principal components.

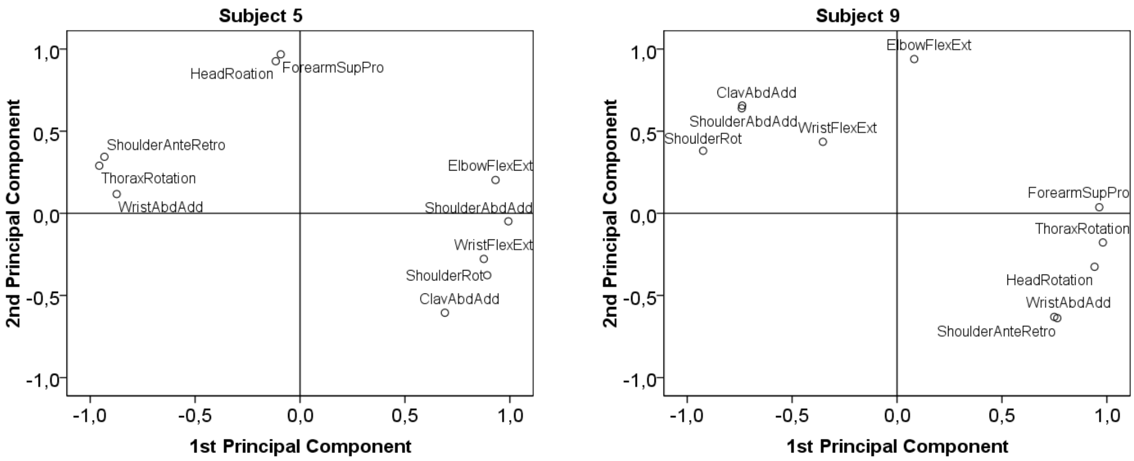

Figure 6. Loading plots of the two PCAs for the subjects 5 and 9 (group 1 & target 1) after Varimax rotation.

The DOFs of the shoulder abduction/adduction, elbow flexion/extension, shoulder rotation, wrist flexion/extension and clavicle abduction/adduction exhibited loadings ≥ 0.7 for the first PC (Figure 6, left). The DOFs of forearm supination/pronation and the head rotation showed loadings > 0.9 and the shoulder anteversion/retroversion, thorax rotation and wrist abduction/adduction exhibited loadings < 0.4 for the second PC.

The DOFs of the thorax rotation, forearm supination/pronation, head rotation, shoulder anteversion/retroversion and wrist abduction/adduction had loadings > 0.7 for the first PC (Figure 6, right). In contrast the DOFs of the elbow flexion/extension, shoulder abduction/adduction, clavicle abduction/adduction, wrist flexion/extension and shoulder rotation exhibited loadings ≥ 0.4 for the second PC.

The two loading plots illustrated that the relation between the original DOFs and the extracted PCs were different between the movement patterns of subject 5 and 9. This was a representative result for the ten movement patterns of the first group. Therefore, it has to be stated that across the movement patterns of the subjects no consistent relation could be found between the joint angle sequences of the ten degrees of freedom and the calculated PCs. In other words, based on a PCA no invariant mode across the different movement patterns could be identified in joint space.

Target 1 & Group 2

For each averaged movement pattern of the four subjects of group 2 a PCA was conducted. The results of the four PCAs showed that two PCs were necessary to explain most of the variance in the data sets. In figure 7 the Scree plots of the eigenvalues of two representative PCAs were shown.

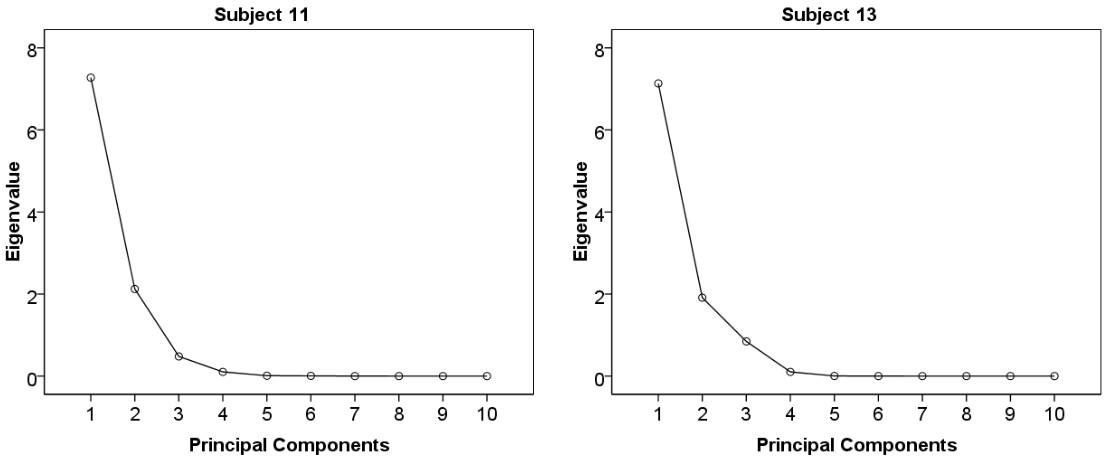

Figure 7. Scree plots of the two PCAs for the subjects 11 and 13 (group 2 & target 1). In both cases two PCs were retained.

The first PC of the PCA for subject 11 accounted for 72.8% of the variance in the data set and the second PC accounted for 21.3% of the variance (Figure 7, left). Together, these two PCs explained 94.1% of the variance. The first PC of PCA for subject 13 accounted for 71.3% of the variance and the second PC accounted for 19.1% of the variance (Figure 7, right). These two PCs accounted for 90.4% of the variance in the data set of subject 13.

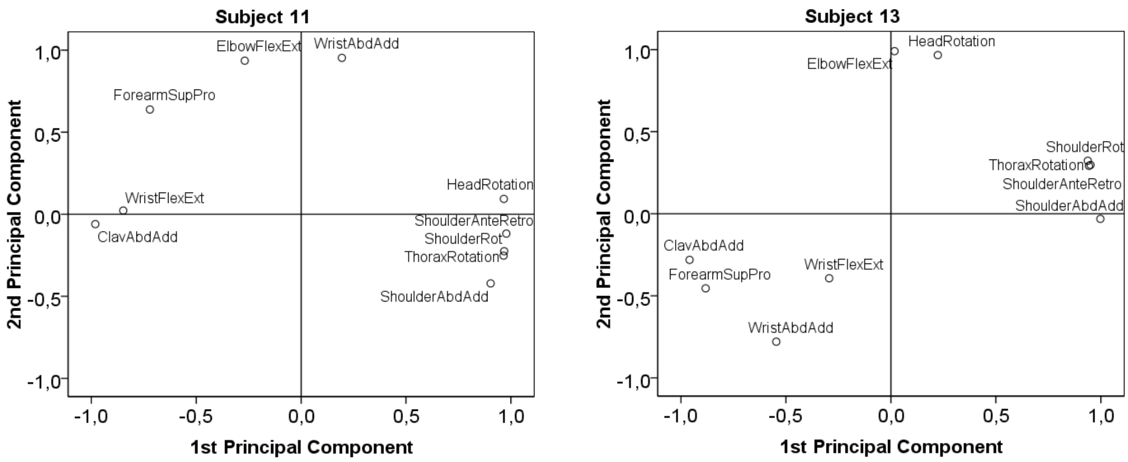

Figure 8. Loading plots of the two PCAs for the subjects 11 and 13 (group 2 & target 1) after Varimax rotation.

The loading plot exhibited for subject 11 (Figure 8, left) loadings ≥ 0.9 for the shoulder anteversion/retroversion, shoulder rotation, head rotation, thorax rotation and shoulder abduction/adduction on the first PC. The DOFs of the wrist abduction/adduction, elbow flexion/extension and forearm supination/pronation showed loadings > 0.6 for the second PC. The wrist flexion/extension and clavicle abduction/adduction revealed negative loadings <-0.8 on the first PC. For the second PC the wrist flexion/extension exhibited a loading of 0.0 and the clavicle abduction/adduction showed a loading of -0.1.

The DOFs of the shoulder abduction/adduction, thorax rotation, shoulder anteversion/retroversion and shoulder rotation revealed loadings > 0.9 (Figure 8, right). In contrast the elbow flexion/extension and the head rotation exhibited loadings > 0.9 for the second PC. The remaining four DOFs showed loadings < -0.3 for both PCs.

The two described PCAs represented typical results for the four subjects of group 2. Across the four conducted PCAs the three DOFs of the shoulder and the thorax rotation showed high loadings on the first PC and the elbow flexion/extension always exhibited high loadings for the second PC. The results for the other DOFs are inhomogeneous. However, it seems that across the four movement patterns the DOFs of the shoulder and the thorax rotation were associated. Moreover, the movements of these four DOFs were not associated with the elbow flexion/extension.

Target 3 & Group 1 and 2

Because the subjects of groups 1 and 2 pointed with their right arm toward target 3, the PCAs of the 14 subjects were analyzed in one step.

For each averaged movement pattern of the 14 subjects a PCA was conducted. The results of the 14 PCAs showed that with one exception two PCs were necessary to explain most of the variance in the data sets. In figure 9 the Scree plots of the eigenvalues of two representative PCAs were shown.

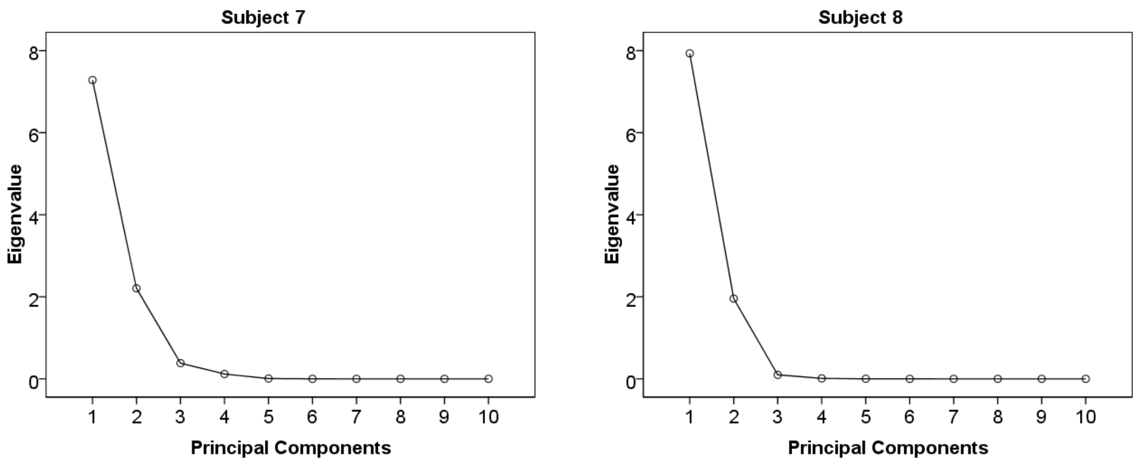

Figure 9. Scree plots of the two PCAs for the subjects 7 and 8 (group 1 & target 3). In both cases two PCs were retained.

The first PC of the PCA for subject 7 accounted for 72.8% of the variance in the data set and the second PC accounted for 22.1% of the variance (Figure 9, left). Together, these two PCs explained 94.9% of the variance. The first PC of PCA for subject 8 accounted for 79.3% of the variance and the second PC accounted for 19.6% of the variance (Figure 9, right). These two PCs accounted for 98.9% of the variance in the data set of subject 8.

The DOFs of the wrist flexion/extension, clavicle abduction/adduction, shoulder rotation and shoulder abduction/adduction revealed loadings > 0.7 for the first PC, whereas the elbow flexion/extension showed a loading of 0.3 and the wrist abduction/adduction a loading of -0.9 (Figure 10, left). The thorax rotation, shoulder anteversion/retroversion and head rotation exhibited loadings > 0.8 for the second PC and the forearm supination/pronation revealed a loading of -0.8.

The loading plot exhibited for subject 8 (Figure 10, right) loadings > 0.7 for the shoulder abduction/adduction, clavicle abduction/adduction, forearm supination/pronation, shoulder rotation, wrist flexion/extension and thorax rotation on the first PC. In contrast, the DOFs of the shoulder anteversion/retroversion, head rotation and wrist abduction/adduction showed loadings > 0.8 and the elbow flexion/extension exhibited a loading of -0.9 for the second PC.

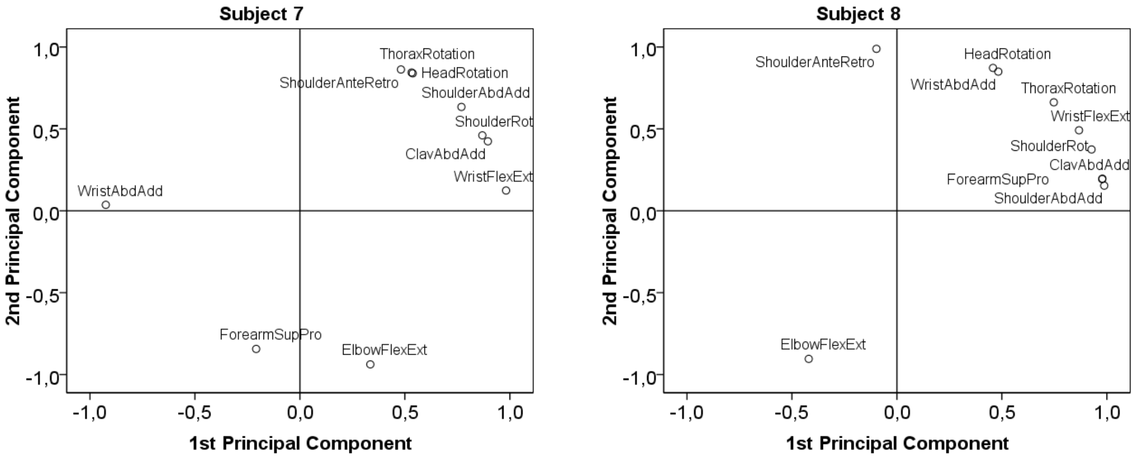

Figure 10. Loading plots of the two PCAs for the subjects 7 and 8 after Varimax rotation (group 1 & target 3).

Again, the two loading plots represented typical results for the PCAs of the fourteen subjects. For most of the fourteen PCAs the thorax rotation, clavicle abduction/adduction, shoulder abduction/adduction, shoulder rotation and wrist flexion/extension revealed high loadings on the first PC, indicating that in pointing task 3 these DOFs seemed to be associated. In contrast, the results for the other DOFs were rather inhomogeneous, indicating no driving principle behind these DOFs or subgroups of these DOFs.

Discussion

The purpose of this study was the examination of different multi-joint upper-extremity movements in 3D space, and this was accomplished using different pointing gestures. An important assumption of motor control research is that represented movement features differ from non-represented features in the *criterion of simplicity* and/or the *criterion of invariance* (Heuer & Konczak, 2003). The analysis of the trajectories of the hand of the subjects from groups 1 and 2 showed that the hand paths are curved with smooth, single-peaked and almost bell shaped velocity profiles. In other words, the subjects produced movements across the two tasks that shared the same invariant movement features no matter if the right or the left arm was used during the task (criterion of invariance). Furthermore, the courses of the hand paths and tangential hand velocities are rather simple (criterion of simplicity). Based on these findings a motor planning in extrinsic coordinates of the hand appears to be plausible. Since these movement features were found across different unconstrained movement tasks, they are most likely not a result of the experimental protocol. Therefore, the question arises as to why the subjects produced movements with these features. If the observed human behavior is seen in a larger evolutionary context, the human brain may have learned during evolution to optimize behaviour with respect to biologically relevant task goals. This implies that some movements will lead to reward (e.g. food) and some to punishment (e.g. hunger), which establishes a link to the field of optimal control (Todorov, 2004). In other words, some movements are optimal since they assure a reward while others are not. Optimal control models incorporate a cost (e.g. minimum jerk), defined as some function of the movement, and the movement with the lowest cost is chosen and executed. However, the human brain did not evolve to optimize movements to produce certain invariant features, but it evolved to promote the transmission of genes to future generations. It is possible that some movements with certain features are more likely to pass on genes and the human CNS may have learned to indirectly represent this through cost functions (Wolpert & Ghahramani, 2004).

Because of the anatomical design of the human arm, joint rotations are required to be able to translate the hand from one position to another. If movements are planned in extrinsic coordinates, a transformation from external space into joint space is needed. This computation is called inverse kinematics and is ill-posed (Kawato, 1996). The CNS may have adopted a strategy during evolution that avoids the problem. One possibility is that motor planning takes place in joint space. Based on the above outlined assumptions, invariant movement features and/or simple couplings should be found in joint space. The dimensionality of joint space is higher than the dimensionality of extrinsic space. On the basis of the movement tasks under consideration ten DOFs were selected resulting in a ten-dimensional space. To be able to detect simple relationships or couplings between different DOFs in this high dimensional space PCA was used. The results of the PCAs for the pointing tasks 1 and 3 of the groups 1 and 2 revealed that there are no invariant coordination modes across all subjects and across the two pointing tasks in joint space. However, the PCAs exhibited for the subjects of group 2 for the first pointing task that the DOFs of the shoulder and the thorax rotation are associated. Moreover, the PCAs showed for most of the subjects of group 1 and 2 for the pointing task 3 that thorax rotation, clavicle abduction/adduction, shoulder abduction/adduction, shoulder rotation and wrist flexion/extension are associated. These associations can be interpreted as functional units of coordination that form synergies to reduce the available DOFs of the human body. In our view the results of the PCAs indicate that even for similar movement tasks the coordination of joint movements seem to be task-specific. Moreover, in highly practiced movement tasks like pointing gestures humans seem to use the available DOFs to a great extend resulting in different forms of coordinating the individual DOFs. This assumption is consistent with Bernstein’s (1967) stage-theory of motor learning. This could be an explanation for the partly inhomogeneous results of the PCA. However, given the stereotypical movement features in extrinsic coordinates of the hand across different subjects and different tasks the CNS might use different compensational strategy on joint level to assure these invariant features in extrinsic coordinates.

Modern humanoid robots should use human-like movements to promote man-machine interaction (Schaal, 2007). The stereotypical features of human pointing gestures identified in this paper denote a first step in this direction. In the CRC 588 two types of models are currently investigated to generate human-like movements on a humanoid robot. Simonidis et al. (2009) used different optimal control models to reproduce the pointing movements analyzed in this paper. Their simulations revealed that a minimum angle jerk principle can reproduce most of the properties of the described human pointing movements. The application of a minimum angle jerk principle in robotics has the advantage of solving the inverse kinematics problem because trajectory planning takes place in intrinsic kinematic coordinates. Some scientists in robotics believe that the “reverse engineering” problem of finding the correct optimal control model to reproduce human movements cannot be solved. Thus, in robotics research the problem of trajectory planning is addressed with alternative methods like motor primitives (Schaal, 2007). The basic idea is to create a library of elementary movements (motor primitives), which can be repeatedly reorganized to create a sufficiently large spectrum of human movements. Based on the analysis presented in this paper, Schulz and Wörner (2010) developed an automatic motion segmentation algorithm that splits motion capture data into motor primitives that can be used to generate new motion sequences. Current research focuses on the development of an algorithm that combines given motor primitives to new movements to be able to cope with new movement tasks. However, based on the current state of research it is impossible to objectively favour one approach over the other.

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Visualization of Posture Changes for Encouraging Meta-cognitive Exploration of Sports 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 his or her own body. It is important for an athlete to explore his or her own body movements in order to construct an internal skill model. Meta-cognitive verbalization about one's own body movements is one of the methods for accelerating the exploration process. The literature indicates that meta-cognitive verbalization is effective for acquisition of embodied skills, and suggests 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 color. The procedure consists of motion measurement by using an optical motion-capture system, segmentation of body movements by a K-means algorithm, and visualization by color. The visualization of body movements by color gives an athlete an opportunity for meta-cognitive exploration. In the case study of baseball swing practice, using the visualization software helped a baseball player discover an important aspect of his form and facilitated a remarkable improvement of his batting average.

KEYWORDS: 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 the body is the proper or suitable way. In the exploration processes, an athlete keeps constructing an internal skill model by trial and error. The internal skill model consists of some variables in his or her own body or the surrounding environment and of their relationships, and thus is specific to the athlete (Suwa, 2008). The exploration process consists of discovering new variables and incorporating them to the existing skill model.

We believe that the methodology of embodied meta-cognition is suitable for driving the athlete's exploration process. Meta-cognition is a powerful means for internal observation (Nakashima, 2006). It is an act of reflecting on one's own thoughts, perception and movements. In the methodology of embodied meta-cognition, the "reflections" consists of two components:

(1) self-awareness of what we think, what we perceive, and how we move our body, and (2) verbalization of them (Suwa, 2009). What should be verbalized in meta-cognition is:

- what one thinks/thought,
- how one moves/moved body parts and operates on the surrounding environment,
- what one perceives from the environment through five senses, and
- what one senses thought the proprioceptive system (as a result of moving body parts).

Suwa (2008) suggests that meta-cognition promotes the acquisition of embodied skills. Meta-cognitive verbalization enables the detection of variables in one's own body and the surrounding environment, and thereby findings new relations between these variables. This detection changes the ways in which to think, perceive, and act. This is the reason why meta-cognitive verbalization promotes acquisition of embodied skills. Since perception and body movements are performed usually without self-awareness, it is almost impossible to verbalize perfectly the whole cognition. It is important, however, to make efforts to verbalize as much as possible because verbalization is a means to promote changes of one's cognition, rather than one to know what is going on in cognition.

Literature suggests that a support of some kind is necessary in order to encourage athletes to do meta-cognitive verbalization, because verbalization of embodied cognition, i.e. reflections on one's own body movement and perception, is not an easy task (Suwa, 2005). However, there is few literature that shows the specific idea of the environment to support meta-cognitive verbalization. This study explores ways to encourage meta-cognitive verbalization based on motion data. The present paper presents a software tool to represent and visualize an athlete's changes of body posture using a color-bar. We have used this tool with an amateur baseball player's acquisition of skills of bat swing. And through this case study, have found, revised and accumulated ways to use it for encouraging his meta-cognition.

Visualization of Body Posture Changes

This section of the paper shows our visualization tool for encouraging embodied meta-cognition and a procedure of visualization in the tool. The interface of our visualization tool consists of video file(s) of an athlete's performance and symbolic data, what we call color-bar(s) (Nishiyama and Suwa, 2008), that is generated based on the measurement of his or her body movements. Figure 1 shows a user interface of our software tool, and the marked parts in the figure are the color-bar. The color-bar shows segmented body movements in discrete phases according to similarity, and represents each phase by one color. Use of symbolic data of this sort is unprecedented as a research that utilizes the technique of motion capturing. Most of past researches have utilized motion capturing for the purpose of grasping a detailed understanding of body movements by attaching as many makers as enough to obtain desirable spatial resolution of body movements. Our approach provides data on body movements with an athlete by reducing its time-resolution on purpose, i.e. rough segmentation of the whole sequence of body movements. We believe that it is rough segmentation that provides important cues for an athlete to reflect on the way he or she moves body.

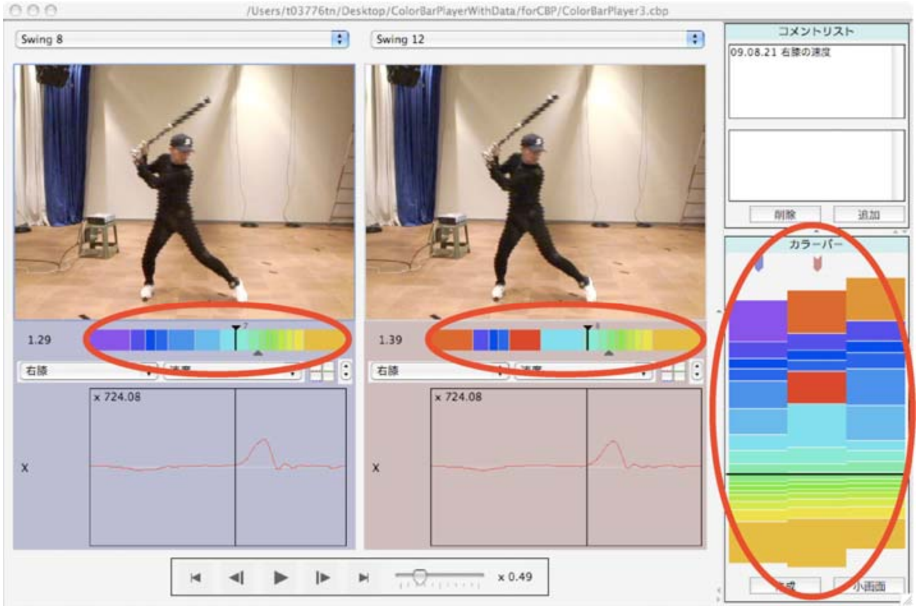


Figure 1. A user interface of software tool for encouraging athlete's meta-cognition.

How does this tool support user's meta-cognitions? The user will be able to:

- check really has been realized in body movements,
- see the stability of performances through different trials in a day and throughout different days,
- compare color-bars among trials, and if any difference, be encouraged to meta-cognitively explore "why".

The following is the procedure of generating a color-bar as shown in Figure 2 that is based on data on 4 trials of performance.

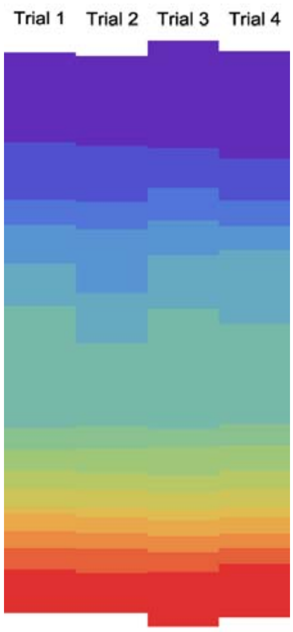


Figure 2. An example of several color-bars generated from 4 trials.

The procedure consists of motion measurement by using an optical motion-capture system, segmentation of body movements by a K-means algorithm, and visualization by color.

We employed a motion-capture system (Motion Analysis, MAC3D system) to measure bat swings of a baseball player, using twelve cameras. The frame rate was 240 Hz. Figure 3 shows the positions to attach makers.

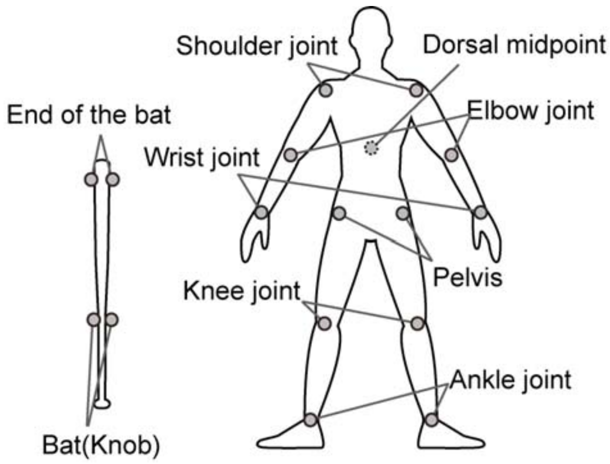


Figure 3. Marker position in measurement by an optical motion-capture system.

A simple set of thirteen positions (twelve markers as shown in Figure3 and Midpoint of pelvis) for the body is sufficient for the purpose of our visualization tool. We attached four markers to bat.

Based on the marker positions, we represent a player's body posture by several triangles, five in the case as shown in Figure 4.

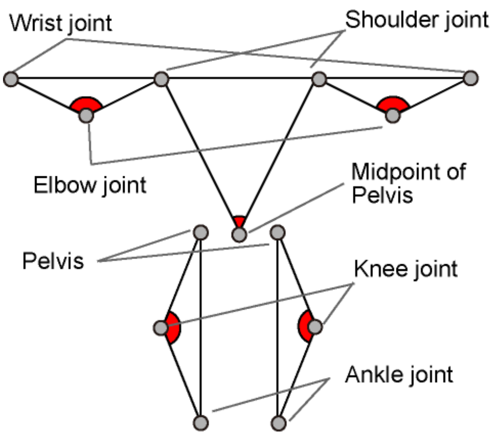


Figure 4. Representation of an athlete's body postures.

If the spatial resolution of an athlete's meta-cognition is very precise, he or she is allowed to select more precise representation. A more precise model our tool currently provides is, for example, to represent the whole body by eight triangles by dividing the upper body to two triangles using the data of the dorsal midpoint marker, and by using two triangles formed by the bat and each of the both lower arms.

The body posture of each time frame, 1/240 seconds, can be plotted in a 15-dimensional space in the simpler model consisting of 5 triangles, comprising of five for the primaly angle (the angle marked in red in Figure4) of each triangle and ten, i.e.${}_5C_2$, 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 a K-means algorithm in order to segment the whole posture changes into different groups. The larger the number of plots is, the better the K-means algorithm works. Therefore, all the data from the set of trials of performance that an athlete wants to compare are input to the K-means clustering. 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. The cluster number K is decided by a user of the tool. If a user’s request is a detailed and precise time-resolution of posture changes, the value of K is to be large. When a rough visualization is requested, K is reduced in the case of bat swing. In the present paper, K was 20. After the clustering, the body posture for each time frame is labelled with the name of the allocated cluster. Figure 5 shows the concept of segmentation of body movements by a K-means algorithm.

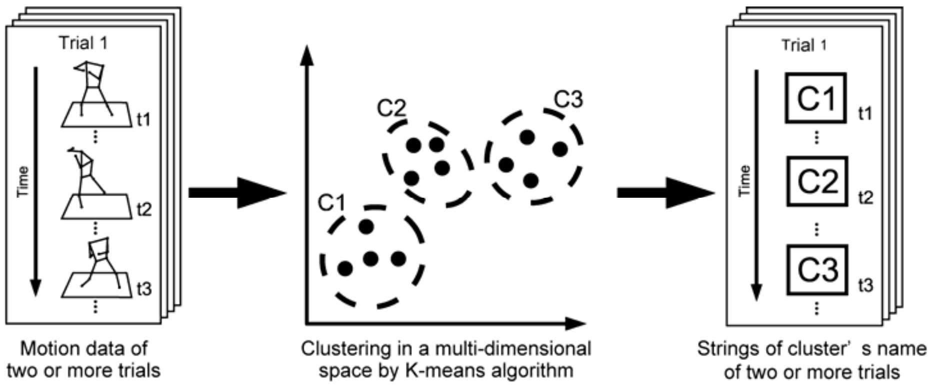


Figure 5. A concept of a segmentation of body movements of two or more trials by K-means algorithm.

One color 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 colors. We call the sequence of colors generated for each trial a “color-bar” . The colors used for a "color-bar" depend upon a cluster number K, and it is selected between blue and red on a hue circle. Figure 6 shows the examples of the colors when cluster number K adopts 10,15, and 20 numbers respectively.

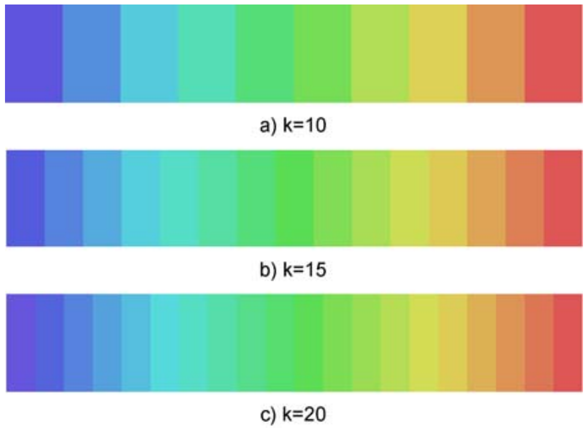


Figure 6. Examples of the colors when cluster number K is 10,15,and 20.

Upon making several color-bars, colors are allocated from the first frame of the left side of the trial. When K-means clustering is executed, each cluster contains the data from the set of trials of performance that an athlete wants to compare, and a same cluster is included in several trials. Therefore, the comparison between trials becomes possible by a same color allocated in several trials. As shown in Figure 7, when posture changes in the second and fourth trial are the same as in the case of the first trial, the color sequence is same as the first trial as a cluster C1 to C6. However, the color sequence changes when the pattern of new posture (cluster C7) appears from the third trial. The appearance of a new cluster C7 in the color sequence is shown, and let users recognize clearly the difference trial 3 and other trials.

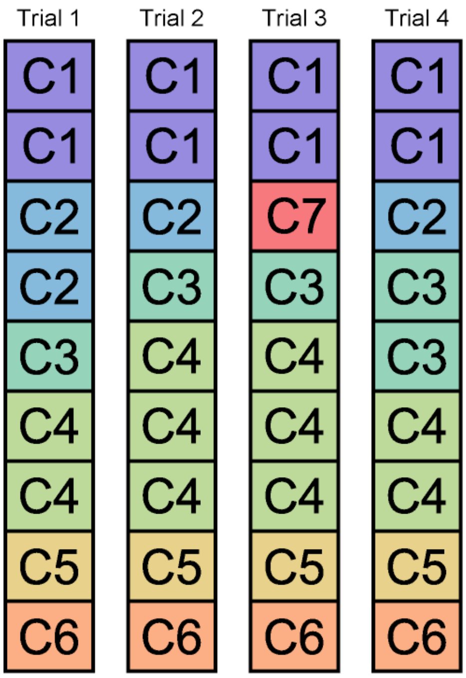


Figure 7. An example of a cluster not included in the first trial appears in the sequence of other trials.

Findings About How the Tool Encourages Meta-cognition

This part of the paper describes the findings we have accumulated about how to use this tool for encouraging a athlete's meta-cognition. Just looking at a single color-bar generated from one trial of bat swing does not encourage interpretation at all. Rather, comparing several color-bars promotes interpretation and discovery, and thereby seems to encourage meta-cognition. Figure 8 shows a series of 16 color-bars arranged in parallel, each corresponding to 16 trials of a bat swing on June 18, 2008. We call a series of aligned color-bars an "aggregated color-bar". In order to make comparison easy, all the color-bars are arranged so that the time frames for the landing of the left foot are horizontally aligned. As shown in the stick picture in Figure 8, the baseball 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.

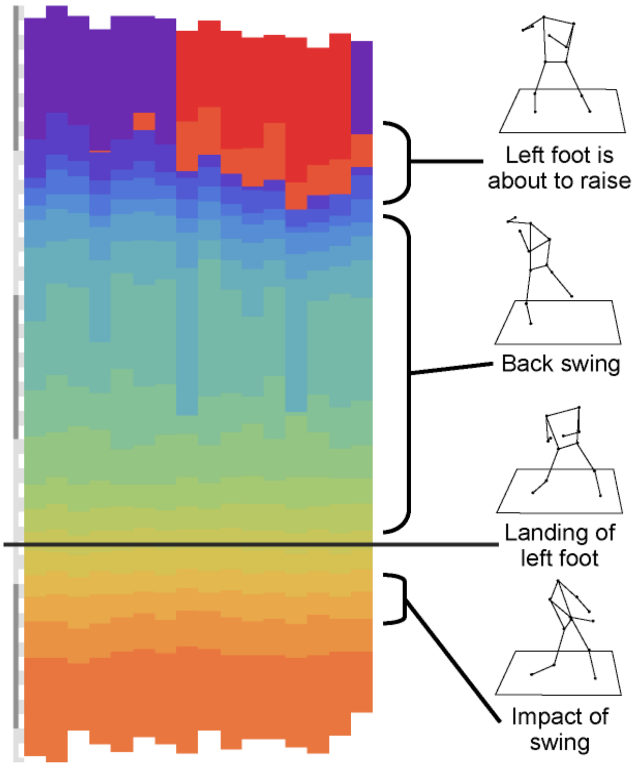
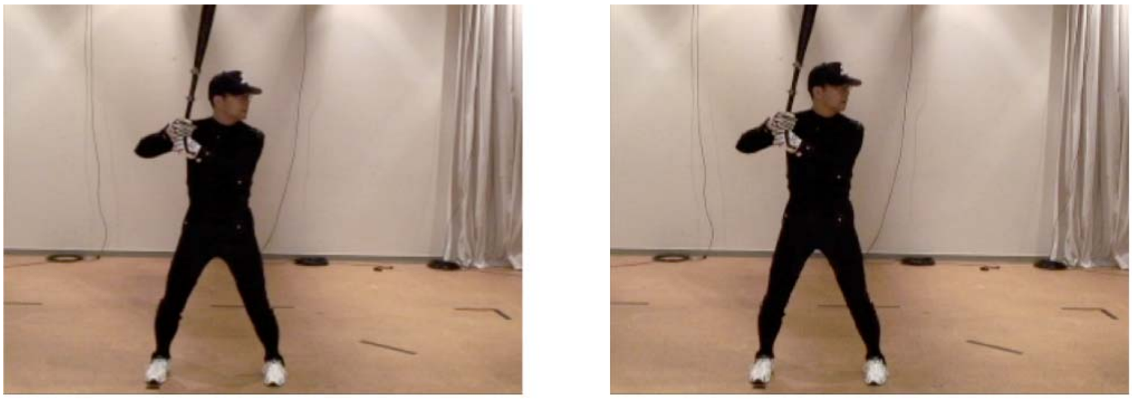


Figure 8. Color-bars generated from data of June 18, 2008.

If the baseball player swings, in every trial, exactly the same way in terms of the timings and the body postures, rigid horizontal color layers, in which the borderlines between adjacent colors are horizontal appear in an aggregated color-bar. Normally, however, the timings of the shift from one color to another differ for all the trials, and thus the borderlines between adjacent colors in several color-bars vary. In the aggregated color-bars for June 18, 2008, the variation is not so large and something like horizontal layers are observed, especially after the raise of the left foot. For all the 16 trials, the colors 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 18.

The only salient difference in the aggregated color-bars for June 18 lies before the raise of the left foot. That corresponds to the first stance, i.e. standing still waiting for the beginning of the pitcher's motion. The color used for the 8 color-bars, ranging from the 8th from the left to the

15th, is different from that used for the other color-bars. For every swing, the baseball 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 swing. Although the change of the baseball 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. Figure 9 shows the initial stance of the 7th and the 8th swings.



a) 7th swing b) 8th swing

Figure 9. The initial stances of the 7th and the 8th swings.

Our color-bar identified the difference. The baseball player was satisfied in two respects. First, even a tiny difference of body movement are identified by the tool and successfully visualized. This is significant because the power of visualization with a resolution to this degree augmented the player's feeling of trust in 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.

Figure 10 shows the change of his batting average (three games moving average) throughout June to October in 2008. In the beginning of the season, the player's performance was quite poor, the average being 0.083, 1hit for 12 at bats, for the beginning 4 games.

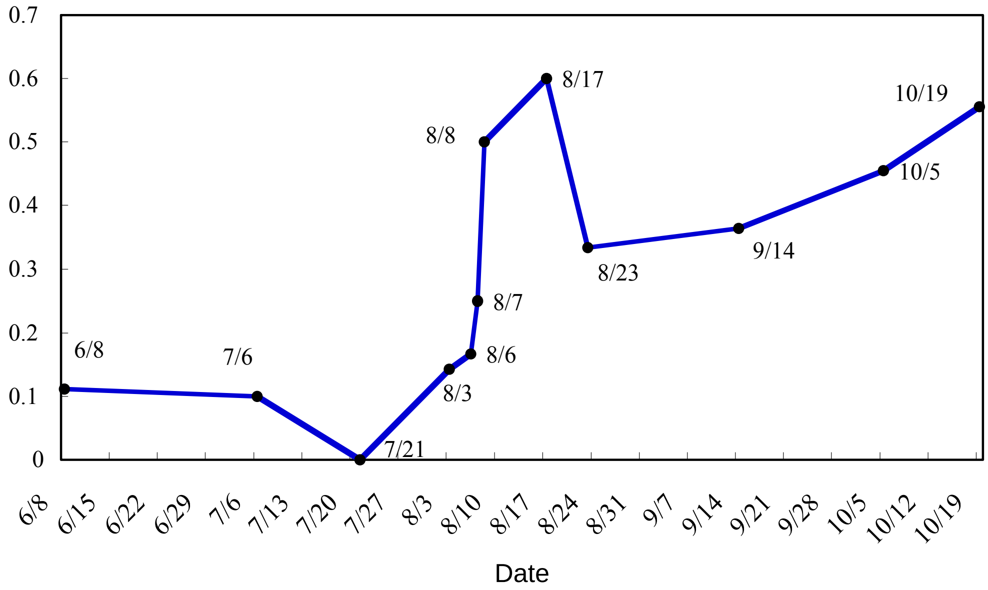


Figure 10. Batting average (three games moving average) 2008 season.

Thus he determined to change his batting form radically at the beginning of July; he began to explore a new form that does not raise the left foot too much as shown in Figure 11.

Figure 11. The changes of the user's batting form.

Figure 12 shows an aggregated color-bar on July 2, 2008. 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 the swing. In the beginning of August, his performance suddenly reached a breakthrough as shown in Figure10. He reported that his meta-cognition reached an 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 stabilized.

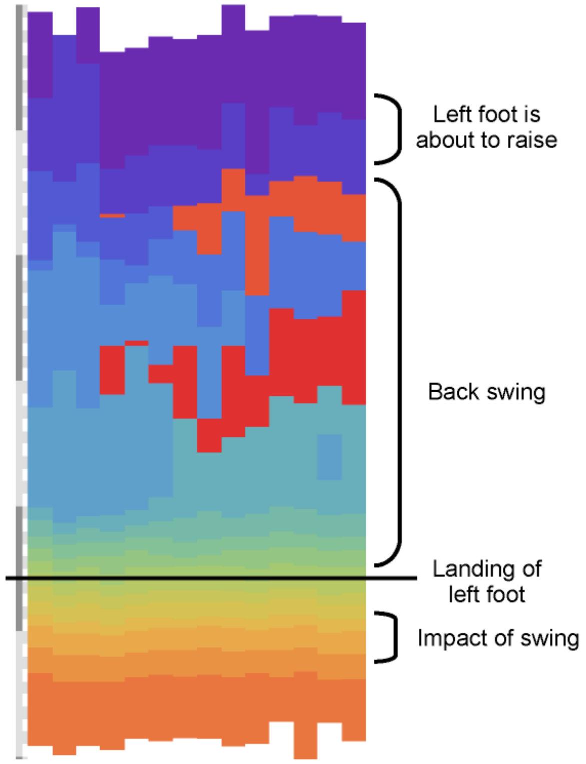


Figure 12. Color-bars generated from data of July 2, 2008.

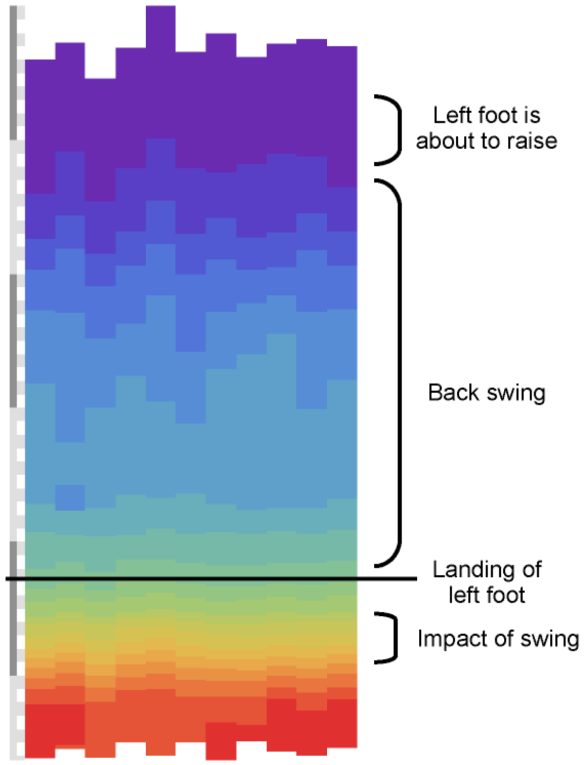


Figure 13. Color-bars generated from data of August 21, 2008.

Figure 13 shows an aggregated color-bar on August 21. The aggregated color-bar 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 baseball 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 really has been realized in body movements,
- see the stability of swings through different trials in a day and throughout different days, and
- compare color-bars among trials, and if any difference, obtain a driving-force to meta-cognitively explore why.

Conclusion

We have developed a visualisation tool to encourage an athlete's meta-cognitive exploration for embodied skill. In a case study of swing practice of a baseball player, its use helped him discover an important aspect of his form in a meta-cognitive way, and as a result, became a driving force of a remarkable improvement of batting average. This provides evidence that rough segmentation of the sequence of body movements and its visualization serve as a cue to encourage meta-cognitive reflection. Although this evidence is from a single case study, we believe that this is one significant insight concerning how to design support environment for encouraging embodied meta-cognition. The universality of the insight is to be further examined by accumulation of case studies in future.

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Computer-aided Game Analysis of Net Sports in Preparation of Chinese Teams for Beijing Olympics

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Abstract

In the preparation of the 2008 Beijing Olympics, the Technique and Tactic Research Center of Shanghai University of Sport developed a series of softwares and conducted a large number of game analyses for national teams of table tennis, badminton, tennis and volleyball, and the results proved to be quite effective.

Based on the methods of data collection and computation, the present paper classifies the computer-aided game analysis into non-systematic analysis, systematic analysis and intelligent analysis. The non-systematic analysis is mainly conducted by collecting the technique and tactic attributes of the last stroke in every rally (such as the technique, position, striking sequence, scoring and losing). The strength of non-systematic analysis lies in its quick feedback of the results to the coaches and players, but this method may fail to obtain the technical and tactical attributes of other strokes. The systematic analysis is done according to the strictly defined technical and tactical observation system by collecting all the technical and tactical attributes of every stroke of the player in the competition (match, set, score, player, striking technique, striking position, striking placement, technical state, effect, scoring and losing). It can provide complete information of the techniques and tactics and conduct different types of detailed analysis, but due to the heavy workload of data collection for systematic analysis, it may need longer time to provide feedback to coaches and players.

Intelligent analysis is the method based on data mining and artificial neural network techniques. Data mining (association analysis) could reveal the association characteristics between several consecutive strokes or stroke positions or placements and scoring or losing. It could help coaches understand better the characteristics of the techniques and tactics and thus is likely to become one of the major methods in future ball game analysis. Through automatic training with only the input data (such as technique and tactic indexes) and output data (such as winning probability), the artificial neural network can construct models with very high precision. Therefore, further investigation in this field is necessary and worthwhile.

KEYWORDS: NET SPORTS, BEIJING OLYMPICS, NON-SYSTEMATIC ANALYSIS, SYSTEMATIC ANALYSIS, INTELLIGENT ANALYSIS

Introduction

Game observation and analysis originated from the American scouting, which was used to examine the technical levels and capabilities of the players. In Europe, game observation was first systemized by Stiehler and gradually evolved into a traditional method for game analysis (Stiehler, 1962). In his book "*Systematic Observation of Ball Games*", Czwalina (1988) explained the fundamental theories and methods of ball game observation and analysis and their specific applications to the analyses of basketball, handball, volleyball, tennis and table tennis matches (Czwalina, 1988). In his book "*Systematic Competition Observation*", Lames (1994) discussed in details the principles, functions and methods for competition observation and analysis (Lames, 1994). Based on their long accumulated experience as team followers, expert consultation and investigations into world events, Wu Huanqun and Zhang Xiaopeng proposed in the early 1990s the "phased index evaluation method", which proved quite to be effective in the diagnosis as well as technical and tactical analysis of Chinese table tennis players in preparing for the Olympic Games and World Championships (Wu et al., 1989; Zhang, 2004).

With the development of computer science and technology, some international sports software companies and research institutes have developed all kinds of softwares for the technical and tactical analysis of sports competitions, such as SIMI Scout, Dartfish, Utilius® VS, Digital Scout and so on. The common features of these game analysis softwares consist in their heightened speed in data collection, their statistical analysis of data, their presentation of analysis results with video and charts, and their quick feedback to coaches and players.

Drawing on the ideas of experimental study from natural science, Lames proposed the theory and method for computer simulation diagnosis and put them into analysis of tennis and volleyball competitions (Lames, 1991; Lames & Hohmann, 1997).

The application of modern scientific computation method to the technical and tactical analysis, such as artificial neural network and data mining technology, brings the technical and tactical analysis out of the traditional research methods (Perl, 2002; Yu et al., 2008; Zhang et al., 2008; Xiao & Zhang, 2008; Zhao et al., 2008; Wang et al. 2009). Data mining based on technical and tactical analysis, with its quality of sequence in time and continuity in space, fits better the demands of technical and tactical analysis of sports, and is more likely to become the major method in future technical and tactical analysis.

During the 2005-2008 preparations for the Beijing Olympic Games, Chinese table tennis teams, badminton teams, tennis teams and volleyball teams, working together with researchers, developed a series of game analysis software and achieved favorable results in the practical training and competitions.

Based on the methods of data collection and computation, the present paper classifies the computer-aided game analysis into non-systematic analysis, systematic analysis and intelligent analysis, which will be discussed in the following sections.

Non-Systematic Game Analysis

A common feature in table tennis, badminton, tennis and volleyball competitions is that the last behavior in each rally of these sports is most decisive for scoring or losing. Therefore, non-systematic analysis is done by recording the technique and tactic attributes of the last striking behavior in each rally.

Development of a "Real-Time Video Analysis" Software

In order to analyze the technique and tactic features of each player in the real time of competition, a real-time video analysis software was developed. It can record the technique and tactic attributes of the last striking behavior of the player in each rally, including the technique, tactic, line, position and effect of the stroke. Another advantage of the software is that it can also record the relevant video while recording the major technique and tactic attributes of each rally, as shown in Figure 1.

Figure 1. Data collection interface of real-time video analysis systems of table tennis, badminton, tennis.

The real-time video analysis software consists of three modules: game information, technical and tactical video editing and statistical analysis. The software 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, providing quick video feedback about the opponents' technique and tactic features right after the matches.

Examples of Non-Systematic Game Analysis Application

Non-systematic game analysis could provide multimedia technique and tactic analysis reports for coaches and players right after the competition. For example, on the evening of Jan. 28, 2008, in the second stage of the men's team competition during the 49th World Table Tennis Championship, the winner of Czech and Singapore would be the China's competitor in the 8th round. The competition lasted for more than three hours, and the players fought for five matches with 3:2 in favor of Czech. Thirty minutes after the competition, the researchers accomplished five reports of the technique and tactic analysis for the Chinese men's team, ready for the use of the coaches and players in preparing for the next day's competition with Czech.

For another instance, using this software, 44 reports on the technique and tactic multimedia analysis of the opponents were accomplished for the Chinese men's table tennis team during the Beijing Olympics, providing very useful information in the preparatory conferences.

The major contents of the non-systematic analysis of table tennis techniques and tactics are listed in Table 1.

Table 1. Major contents for non-systematic analysis of table tennis techniques and tactics.

Technique and tactic analysis for singles	**Technique and tactic analysis for doubles**	**Technique and tactic analysis for chopping**
Statistical data of games	Statistical data of games	Statistical data of games
Points scored and lost in service	Points scored and lost in round of Player A service/Player B the third stroke	Points scored and lost in service
Points scored and lost in receiving	Points scored and lost in round of Player A receives/Player B the forth stroke	Points scored and lost in attack after service
Points scored and lost in the third stroke	Points scored and lost in round of Player B service/Player A the third stroke	Points scored and lost in chopping and attack
Points scored and lost in the fourth stroke	Points scored and lost in round of Player B receive/Player A the fourth stroke	Points scored and lost in forehand chop
Points scored and lost in rally		Points scored and lost in backhand chop

Systematic Game Analysis

The systematic analysis refers to the analysis according to the strictly defined technical and tactical observation system by collecting all the technical and tactical attributes of every stroke of the player in the competition.

Development of the "Data Collection and Intellectual Analysis" Software

In order to have a more detailed analysis of the matches, the data collection and intellectual analysis software was also developed, which uses the C/S mode and consists of the client application, the server manager and middleware (Figure 2). The technique and tactic data collection interface of the sofeware mainly consists of three parts: video monitoring window, simulation competition field (or table) and technique and tactic index button. The striking placements are accomplished through clicking the correspondent area in the simulation competition field (or table), and other technique and tactic information is recorded by pressing buttons.

Figure 2. The data collection and intellectual analysis systems of table tennis, badminton, tennis and volleyball competitions.

The software has the following characteristics: (1) it can collect all the base data of a player's game behaviour, such as the position, route, direction, techniques, tactic, effect, score and striking sequence (Table 2), providing sufficient data for the intelligent game analysis; (2) each game behaviour of each player is connected to the video clips; (3) the present system can analyze one or more matches based on data mining technology.

Table 2. Technique and tactic data collection indexes in table tennis, badminton, tennis and volleyball competitions.

	Table tennis	Badminton	Tennis	Volleyball
Striking technique	service, loop, flick, half volley, smash, chop, chop short, block, cut, drop short, lob	service, lob, drop shot, smash, cut smash, chop, drive, cross court flight, flick, rush shot, even drive, even block	service, drive, volley drive, intercept flick, smash, chop, drop shot, tackle, passing shot, bounce	service, dig, pass, smash, block
Striking placement	forehand short, forehand half long, forehand long, mid-short, mid half long, midlong, backhand short, backhand half long, backhand long	forehand/backhand/mid-way near net, forhand/backhand forecourt, forehand/ backhand/midway/ bodyhit midcourt, forehand/backhand/ midway/overhead backcourt	right/right mid forecourt, right mid/right backcourt, mid right/mid right mid forecourt, mid right mid/mid right backcourt, mid left/mid left mid forecourt, mid left mid/mid left backcourt, left/left mid forecourt, left mid/left backcourt	forefield (left, middle, right), midfield (left, middle, right), backfield (left, middle, right)
Striking position	forehand, backhand, sideways, counter sideways	forehand, backhand, overhead, midway, backcourt, midcourt, forecourt, near net	right zone, mid right zone, mid left zone, left zone, sideways, counter sideways	the first/the sixth/ the fifth/the fourth/ the third/the second position
Tactics behavior	attack, rally, defence, control	attack, rally, defence, control, chance, passive	attack, rally, defence, control, chance, passive	block, defence, organize, attack

This software can conduct an individual analysis of one player in one match or a combined analysis of one player in several matches. For example, the game analysis softwares of table tennis, badminton and tennis can conduct separated or combined analysis of the technique and tactic status of each stroke, its placement, sequence and position of each player. Moreover, it can also analyze the winning or losing games of a player, or analyze a particular phase of a game. As there are more strokes in badminton matches, the system may also to help analyze the technique and tactic state of a certain stroke according to the specific demand of the coaches and players.

The volleyball analysis software can also, as required 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.

Examples of Systematic Game Analysis Application

The following sections illustrate the technique and tactic analyses of the competitions between the Korean player Ryu Seung-min and the Chinese player Ma Lin (the 2008 World Table Tennis Championship), Wang Hao (the 2008 Korea Open) and Wang Li-qin (the 2007 World Championship Single) using the data collection and intellectual analysis software. Ryu Seung-min was the champion of men's singles in the 2004 Athens Olympics.

Analysis of the Technique and Tactic Features of Ryu Seung-min's Serve

From the competition videos, it can be seen that Ryu Seung-min mainly serves midway, accompanied with forehand short or backhand (midway) fast long and his midway short spins strongly. But Chinese players need to pay more attention to his sudden backhand long balls. Table 3 shows the statistics of his scoring and losing in the serves in the three selected games.

Table 3. The scoring and losing of Ryu Seung-min in his serves.

Competitors	Point scored	Point lost
Ma Lin	2	1
Wang Hao	7	2
Wang Li-qin	9	1
Total	18	4

Analysis of Technique and Tactic Features in Ryu Seung-min's Receiving

Ryu Seung-min is very fast in flicks and much diversified in his lines (five direct scores and five misses). His forehand swats are short and spinning (eight direct scores and eight misses) and his long striking placement is rather long. Ryu Seung-min is the weakest in receiving the big angled forehand and backhand short. Table 4 illustrates the statistics of the scoring and losing of Ryu Seung-min in receiving.

Table 4. The scoring and losing in Ryu Seung-min's receiving.

Competitors	Point scored				Point lost			
	Flick	Loop	Chop	Chop short	Flick	Loop	Chop	Chop short
Ma Lin	2	-	-	1	-	-	1	2
Wang Hao	2	-	2	2	1	4	1	2
Wang Li-qin	1	1	1	5	4	1	1	2
Total	5	1	3	8	5	5	3	6

Analysis of the Technique and Tactic Features of Ryu Seung-min's Third Stroke

Ryu Seung-min is very strong in the forehand and backhand half-out attacking in the third stroke (scored 24 points in forehand attack, missed 17), and especially powerful in his sideway attacks: fast, multi-lined and posing greater threat (Table 5). In addition, Ryu Seung-min often uses striking techniques, so Chinese players need to be aware of his striking when they bat to his midway and backhand way.

Table 5. The scoring and losing of Ryu Seung-min in the third stroke.

Competitors	Point scored			Point lost		
	Forehand attack	Backhand attack	Control	Forehand attack	Backhand attack	Control
Ma Lin	6	1	2	4	1	3
Wang Hao	7	2	6	5	4	1
Wang Liqin	11	2	-	8	3	-
Total	24	5	8	17	8	4

In view of Ryu Seung-min's weakness in his third bat attack, using the forehand and backhand big angled short balls could very effectively curb his third bat attack. Wang Hao and Wang Li-qin could effectively ruin his attack after serve by serving two lines in backhand pull (oblique and straight). Table 5 shows the statistics of Ryu Seung-min's scoring and losing in his third stroke.

Analysis of the Technique and Tactic Features of Ryu Seung-min's Fourth Stroke

Ryu Seung-min poses great threat in his fourth counter loop striking, especially in his sideway and forehand way. Besides, he is quite powerful in his stress drives. Table 6 shows that he is weakest in the fourth stroke. After Chinese players serve short balls and keep control, the forehand and backhand positions of Ryu Seung-min are both the major breaking points of Chinese players, for example, in the fourth stroke in forehand position, he lost 25 points, in backhand position he lost 16 points (Table 6).

Table 6. The scoring and losing of Ryu Seung-min in the fourth stroke.

Competitors	Point scored		Point lost	
	Forehand attack	Backhand attack	Forehand attack	Backhand attack
Ma Lin	1	-	3	10
Wang Hao	3	2	10	5
Wang Li-qin	4	5	12	1
Tatol	8	7	25	16

Analysis of the Technique and Tactic Features of Ryu Seung-min's Fifth Stroke and Subsequent Strokes

In the competition with Wang Hao and Wang Li-qin, Ryu Seung-min is in obvious disadvantages in his fifth and subsequent bats. As indicated in Table 7, in the competition with Wang Hao, he scored 11 points, lost 24 points; in the competition with Wang Liqin, he scored 19 points and lost 34 points.

Ryu Seung-min is also very powerful in his forehand attack, but his backhand position is his weak point. Therefore, after attacking his backhand position, then whether attacking his forehand or mid road, the competitor could achieve effective results.

Table 7. Analysis of the scoring and losing of Ryu Seung-min's fifth and subsequent bats.

Competitors	Point scored		Point lost	
	Forehand attack	Backhand attack	Forehand attack	Backhand attack
Ma Lin	2	5	3	4
Wang Hao	6	5	9	15
Wang Li-qin	14	5	25	9
Tatol	22	15	37	28

Intelligent Game Analysis

In the present paper, intelligent analysis is referred as the analysis method using data mining or artificial neural network computations. The following section will take the table tennis technique and tactic analysis as an example using the technique and tactic analysis method based on data mining (association rules) and artificial neural network.

Application of Data Mining (Association Rule) Technology in Game Analysis

Based on the characteristics of competitions in table tennis, badminton, tennis and volleyball, the association rule is selected as the major computation method for technical and tactical data mining analysis.

Association Rule Mining Technology

An association rule (Hu et al., 2008) is an implication of the following logical entailment: $A \Rightarrow B$, where A, B are itemsets. To the transaction set D, $A \in D$, $B \in D$, $A \cap B = \phi$. Two parameters are generally used to describe the attribute of association rules.

Support: Support ($A \Rightarrow B$) is the sum of tuples containing A and B ($A \cup B$). Support describes the appearance probability of A and B tuples in all the transactions, P ($A \cup B$).

Confidence: Confidence（$A \Rightarrow B$） refers to “reliability”. The confidence of （$A \Rightarrow B$） can be defined as: Confidence ($A \Rightarrow B$) equals the sum of tuples containing A and B/containing the tuples of A; Confidence describes the probability of itemset B in D when itemset A is in D, $P(B \mid A)$.

The main issue of association rule mining is to find out in a mass database association rules between the given min_sup and min_conf.

The computation of the association rule mining is largely a two-step process:

(1) Find out all the frequent itemsets in a large database. If $Support(X) \geq min\ sup$, then X is a frequent itemset. By definition, each of these itemsets will occur at least as frequently as a pre-determined minimum support count.
(2) Generate association rules from the frequent itemsets: For each frequent itemset X, if $Y \subset X$ and $Y \neq \phi$ and Confidence$\{Y \Rightarrow (X - Y)\} \geq min\ conf$, then there is a association rule $Y \Rightarrow (X - Y)$.

The second step is relatively easy. Currently, the majority of researches focus on the first step, of which the Apriori computation is the most classical one.

Algorithm **1** *Apriori*

Input: DB, min sup.

Output: Result = all frequent itemsets and their supports

Method:

Result : = {}

k : = 1;

C_1: = all 1-itemsets

while (C_k) *do*

begin

Make a counter for each itemset of C_k

for$(i = 1; i \leq |DB|; i{+}{+})$

begin // To record T of all DB

To each itemset of C_k, the counter will add one if record T(i) support it.

end

L_k: = C_k (L_K :=all itemsets which support frequency > min sup)

L_k save the support frequency of L_k

Result : = *Result* $\cup L_k$

C_{k+1} : = those (k+1)-itemsets whose all k-subsets are in L_k

$k = k + 1$;

enddo

Methods of Game Analysis Based on Association Rules

The general game analysis usually is to study scoring and losing, the scoring rate and losing rate or the using rate of technical and tactical indexes. Since the indexes are relatively independent, the coaches and players could only make very limited use of the analysis results in game planning. However, data mining can be 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 8 shows the main contents of association analysis of table tennis, badminton, tennis and volleyball matches.

Table 8. The main contents of association analysis of table tennis, tennis, badminton and volleyball matches.

Event	Main contents of association analysis
Table tennis	The association characteristics of the placements/techniques/positions of the first three strokes and the scoring/losing in the service/receiving round
Badminton	The association characteristics between the scoring/chance ball/passive ball/losing and its previous three/six strokes
Tennis	The association characteristics between the first three/four stroke placements/techniques/positions and the scoring/losing in the service/receiving round
Volleyball	The mining of the technique characteristics of the individual player/the team of the first/second attack

Cases of Table Tennis Game Analysis Based on Association Rules

Through the association analysis of the semi-finals of the 15th Asian Games between Wang Hao (Chinese) and Ryu Seung-min (Korean), the obvious technical and tactical characteristics of Wang were obtained, as shown in Table 9.

Table 9. The results of Wang's technical and tactical analysis based on data mining technology.

Serial number	Stroke placements	Sup (%)	Conf (%)
1	Wang's service → Ryu's short middle zone	91.83	68.89
2	Wang's service → Ryu's short middle zone → Wang's long backhand zone	42.86	61.90
3	Wang's service → Ryu's short middle zone → Wang's short middle zone	10.20	80.00
4	Wang's receiving in the long backhand zone → Ryu's long backhand zone	8.70	75.00
5	Wang's receiving in the short middle zone → Ryu's halflong backhand zone → Wang's long backhand zone	6.52	33.33
6	Wang's receiving in the short middle zone → Ryu's short backhand zone → Wang's long backhand zone	6.52	33.33

(1) Most placements of Wang's service are to the short middle zone and quite effective, with the winning support of 91.83 % and the confidence of 68.89 %.

(2) If Wang serves to the short middle zone, and Ru receives to the long backhand zone, then Wang's winning support is 42.86 % and the confidence is 61.90 %; but if Ryu receives the ball to the short middle zone, then Wang's winning support decreases to 10.20 % and the confidence reaches to the highest: 80.00 %.

(3) When Ryu serves the ball to the long backhand zone and Wang receives to the long backhand zone, then Wang's winning support is 8.70 % with the confidence of 75.00 %.

(4) But when Ryu serves the ball to the middle short zone, if Wang receives the ball to the halflong backhand zone or to the short backhand zone, and Ryu strokes 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 was not in a good shape in the semi-final of men's single, so he lost to Wang with 1:4. In the following the association analysis of Ryu's main tactics leading to his failure (Table 10) is illustrated:

Table 10. The results of Ryu's technical and tactical analysis based on data mining technology.

Serial number	Stroke placements	Sup (%)	Conf (%)
1	Ryu's service → Wang's long backhand zone → Ryu's long backhand zone	8.69	25.00
2	Ryu's receiving in the short middle zone → Wang's long backhand zone	42.86	38.10
3	Ryu's receiving in the short middle zone → Wang's short middle zone	6.67	33.33
4	Ryu's receiving in the short middle zone → Wang's long backhand zone → Ryu's long backhand zone	24.49	25.00

(1) If Ryu serves the ball to the long backhand zone, and Wang receives the ball to the long backhand zone, then Ryu's winning support is 8.69 % with the confidence of 25.00 %.

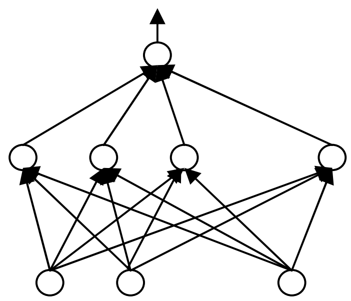
(2) When Wang serves the ball to the short middle zone, and Ryu receives the ball to the long backhand zone, then Ryu's winning support is 42.86 % and the confidence is 38.10 %. It is one of the main reasons of Ryu's losing. If Ryu receives the ball to the short middle zone, then

Ryu's winning support is 6.67 % with the confidence of 33.33 %.

(3) When Wang serves the ball to the short middle zone, if Ryu receives the ball to the long backhand zone, and Wang strikes the third bat to the long backhand zone, then Ryu's winning support is 24.49 % and the confidence is 25.00 %. It is another major reason leading to Ryu's losing of the game.

Application of Artificial Neural Network in Game Analysis

An Artificial Neural Network (ANN) is a machine designed to imitate human brain and an information processing system characterized by distributional memory, parallel processing and auto-adapted study. Multi-layered feed-forward networks may approach any continuous function. That is to say, any kind of functional relations between the result and the indexes of the competition can be fitted by the table tennis match diagnostic model established with the multi-layered feed-forward networks, thus the network has overcome the inadequacy of the multiple regression model and gray model. Take the structure of multi-layered feed-forward network as an example, shown in Figure 3.



Outputs

Hidden Layer

Inputs

Figure 3. Three-Layer Feed-forward Network Model (Wang & Zhang, 2007).

Features of the Game Ananlysis Model Based on Artificial Neural Network

(1) Without any preliminary mathematic models, the artificial neural network can construct models based only on input, output and the statistical information of network stores in the great weighting matrix.

(2) The network can retain the mapping relationship between technical indexes and the previous competition results. When the technique and tactic level of the player changes, only by putting in the latest data on the previous basis and retraining the current neural network, the connection weight of the neural network reflecting the current level of the player can be obtained as well as also the modified model of the player's technical diagnosis. This model reflects the functional relationship between the latest technical index and competition performance and stored the past competition performance of the player.

Methods of Game Analysis Based on Back Propagation (BP)

The basic idea of the technique and tactic analysis based on artificial neural network is to determine the influence of each index on the winning of the match through calculating the competitive effectiveness value (CEV) of the technique and tactic index. Its basic principles are to increase (or reduce) a certain observed index value while keeping other values of the index unchanged, to put it into neural network training model, and to recalculate the D-value between the simulation value of the competition results and simulation value of the winning probability when unchanged. The bigger the absolute difference value, the greater the technique value influences on the winning of the competition. The calculation method is shown as follows:

(1) According to the formula, increase or decrease the value of a certain observed index while keeping other values unchanged.

(2) Substitute it into the neural network-training model and recalculate the simulation value of the winning probability.

(3) CEV = SWP - OWP

In the equation, CEV refers to the competitive effectiveness value; SWP, the simulation value of competition winning probability and OWP, the original calculation value of winning probability. The greater the absolute value, the greater the technique value influences over the winning of the competition.

Cases of Table Tennis Game Analysis Based on Artificial Neural Network

40 international competitions of elite players from the Chinese women team (Zhang Yining, Wang Nan, Guo Yue, Niu Jianfeng and Guo Yan) were chosen for analysis, among which 30 of them were used for the establishment of the technical and tactical analysis model for table tennis matches and 10 of them were used for the validity check of the model.

The Model of Table Tennis Game Analysis for Women's Singles

Based on the technique and tactic analysis method in table tennis matches, choose 10 table tennis technique indexes as input data, that is, set 10 neurons in the input layer, the input data correspond with 10 index values respectively: x1: the scoring rate in service; x2: the using rate of attack after service; x3: the scoring rate of attack after service; x4: the error probability of the third bat; x5: the using rate of attacking on service; x6: the using rate of the fourth attack; x7: the scoring rate of the fourth attack; x8: the error probability of the fourth bat; x9: the scoring rate of the rally balls; x10: the error probability of the rally balls.

The number of the neuron in the output layer is one. The output data is the winning probability of the table tennis match. According to the neural network theory, select one hidden layer. A great number of experiments indicate that the model is most stable and desirable if it is set up using Levenberg-Marquardt training function, the number of neuron in hidden layer is taken as 30 and the transferring function between each neuron is taken as linear function purelin(n). Levenberg-Marquardt regulation training is fast and precise in training forward neural network, whose structure is shown in Figure 4.

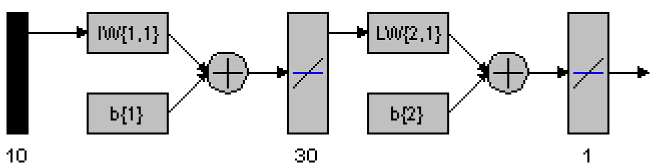


Figure 4. The model of table tennis game analysis for women's singles (Wang & Zhang, 2007).

The Training Times and Errors of Model Training

The number of training times and errors of the technique and tactic decision analysis model are shown in Figure 5. The horizontal axis indicates the training times, the vertical axis shows the training error, and the anticipated error precision is set at 10^{-4} . In the second training, the error is already steady, with the error value about $10^{-3.134}$. If it is close to the anticipated precision, it shows that the established model has good stability and high precision.

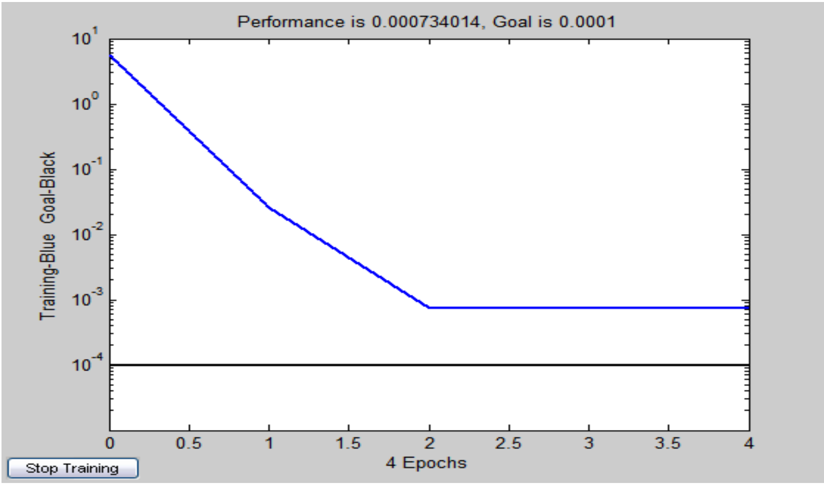


Figure 5. The number of times of training and error curve (Wang & Zhang, 2007).

The following steps are: Input the data of the 10 indexes about the 10 matches into the established neural network, and use the data to check again the precision of the model. Obtain the simulataion value of the winning probability of the 10 matches. The errors between the real value and simulation value are shown in Table 11.

Table 11. The error between the real value and simulation value (Wang & Zhang, 2007).

	No.1	**No.2**	**No.3**	**No.4**	**No.5**	**No.6**	**No.7**	**No.8**	**No.9**	**No.10**
Actual value	0.5276	0.4688	0.5439	0.5673	0.6250	0.5091	0.6119	0.5495	0.3818	0.6389
Simulated value	0.5462	0.5255	0.5593	0.5887	0.6289	0.4828	0.5910	0.5049	0.3638	0.6342
Tolerance	-0.0187	-0.0567	-0.0154	-0.0214	-0.0039	0.0263	0.0210	0.0446	0.0180	0.0047

It can be seen from Table 11 that the maximum absolute value of error of the 10 matches is 0.0446, the minimum value is 0.0039. The mean error is 0.00231, the precision of the model is up to 97.69 %. As revealed in Table 11 and from the technique and tactic diagnostic model established using methods above, the obtained simulation winning probability is very close to the actual winning probability, showing that the technique and tactic diagnostic model established by BP network has reached a rather high precision.

Sample Analysis with Artificial Neural Network Model

In the following the game analysis of Chinese elite female players Zhang Yining and Wang Nan based on the artificial neural network model is illustrated.

Figure 6 shows the analyses of 10 randomly selected matches of Wang Nan and those of Zhang Yining. It can be seen that the 9^{th} index (scoring rate of the rally) and the 10^{th} index (losing probability of the rally) have far greater impact over winning than the other 8 indexes. It can also be seen that promoting rallying ability is more significant to Wang Nan than to Zhang Yining.

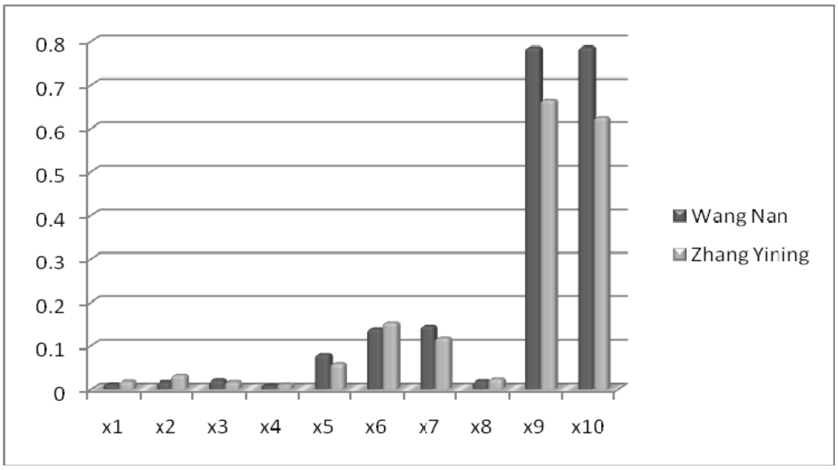


Figure 6. The technical and tactical analysis of Wang Nan and Zhang Yi-ning (Wang & Zhang, 2007).

Figure 6 also indicates that the 6th index (the using rate of the attack in the fourth stroke) and the 7th index (the scoring rate of the attack in the fourth stroke) are in the second highest position in the present research, showing that the fourth stroke technique plays an increasingly important role in modern high-level table tennis matches.

Game analysis in preparation of Chinese teams for the Beijing Olympics

Game analysis in preparation of Chinese teams for the Beijing Olympics can be divided into three stages: the stage of data collection, the stage of the preparing trainings and the stage of the competitions.

The first stage is fundamental to the analysis and involves huge workload, strong expertise and high accuracy.

The second stage 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, about 300 analyses were conducted 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 third stage, the analysis was conducted about 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 the winning of 10 golds, 6 silvers and 8 bronzes in total.

Summary

The present paper, based on the methods of technical data collection and computation, classifies computer aided game analysis into non-systematic analysis, systematic analysis and intelligent analysis.

In net sports competitions such as table tennis, badminton, tennis and volleyball, non-systematic analysis is conducted by collecting the technique and tactic attributes of the last stroke in every rally with the advantage of quick feedback and the disadvantage of losing the technical and tactical attributes of other strokes.

The systematic analysis analyzes the game by collecting all the technical and tactical attributes of every stroke of the player in the competition. It could provide complete information of the techniques and tactics and conduct different detailed analysis. But due to its huge work of data collection, it needs longer time to provide feedback to coaches and players

Data mining (association analysis) can reveal the association characteristics between several consecutive strokes or stroke positions or stroke placements and scoring or losing. It can help coaches understand better the technique and tactic characteristics and therefore is likely to become one of the major methods in future ball game analysis.

Artificial neural network can construct models with very high precision through automatic training with only input (such as technique and tactic indexes) and output (such as winning probability). Therefore, further investigation in this field is quite worth the effort.

In the preparation of Chinese table tennis teams, badminton teams, Chinese women tennis teams and Chinese women volleyball teams for the 2008 Beijing Olympics, various game analysis methods were used quite successfully. Currently, they have become an essential part in the preparation of Chinese table tennis teams and badminton teams for world competitions.

During the practical process of technical and tactical analysis, the quantity of technical and tactical indexes was found to be the most significant factor influencing the effectiveness of competition analysis. If the technical and tactical indexes are too many and too meticulous, the statistical data will become over scattering, failing to reflect the technical and tactical features of the players. But if the technical and tactical indexes are too few or too abstract, it will be difficult for players and coaches to implement the results in actual trainings and competitions.

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