Reaction Time Estimation Based on Recursive Short-Term Principal Component Analysis for Skeletal Information of Badminton Players

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Abstract: The aim of this paper is to measure the shot-reaction intervals of badminton players based on time-series 3D skeletal information. In competitions where game dominance changes, effective plays and tactics in situations can be investigated by analyzing the measured reaction intervals. In our proposed method, we estimated shot-reaction intervals using a badminton player's motion information and applied a short-term principal component analysis to the sequential 3D skeletal information of athletes to extract features useful for motion analysis. Hit and reaction times were detected by identifying the extrema in the first and second principal component scores. We estimated a shot's reaction interval from the hit time to the reaction time at which the player starts moving in response. We applied the proposed method to the 3D skeletal information of a badminton player and confirmed that reaction intervals can be estimated. By using the results of this study to provide feedback to badminton players on the analysis of reaction intervals, players can learn and improve their effective and ineffective tactics and plays.

1 INTRODUCTION

Data analysis is becoming more important in competitive sports (Bhatnagar & Babbar, 2019). Both performance and tactical analysis have investigated effective plays and the tactics of situations where game dominance changes, such as soccer (Rein & Memmert, 2019; Mackenzie & Christopher, 2012). For the purposes of this paper, we use the term "game dominance" as a degree of team dominance that changes from moment to moment in a game. For such strategic games as *go* and *shogi*, TV programs that stream AI-based game analysis have emerged since grasping game situations are difficult for average viewers. Thus, interests in information provision and data analysis techniques to help diverse users to better understand the game situation have been rising.

Competitive badminton is characterized by the fastest shuttle speed (ball speed for other sports) (Bańkosz et al. 2013). In a rally, a shuttle is returned in approximately one second (Cabello & González, 2003), requiring that badminton players have the ability to move and react quickly. Reaction speed, return position, footwork position, and connection to the next move significantly impact performance (Kuo et al. 2020). For example, if the reaction speed is slow because the opponent's strokes are deceptive, the game will be at a disadvantage. Therefore, knowing the length of the reaction interval makes it possible to know which plays affected the match. Furthermore, the interval between the changes in a game situation is very short, less than a second. Therefore, based on the game situations in *go* and *shogi*, the application of AI decision-making to badminton is impractical because such situations can change within one second for each shot. On the other hand, we hypothesize that information about effective plays and tactics may be concentrated at specific times when game dominance changes because these crucial points are related to shot-reaction intervals. Therefore, the purpose of this research is to measure the shot-reaction intervals of badminton players and statistically analyze the intervals to identify effective plays and tactics at the timing

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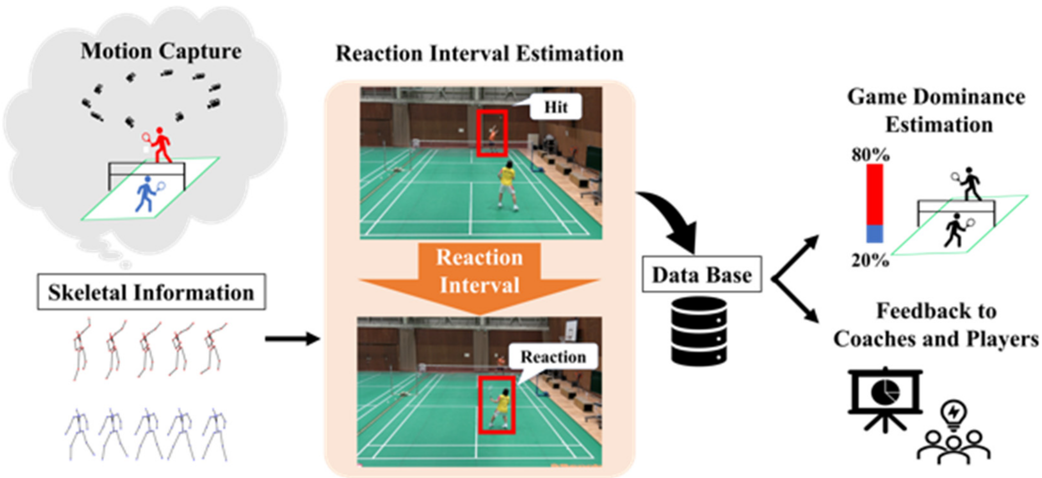

Figure 1: Reaction interval estimation using skeletal information of a badminton player obtained by motion capture: Reaction intervals are estimated as time from opponent's hit time to reaction time where player starts moving in response. By analyzing reaction interval data, feedback is provided to coaches and players for estimating game dominance.

of changes in game dominance. We believe that the visualization of such information can provide feedback to players and augment their performance.

As shown in Fig. 1, this paper estimates the reaction intervals and reaction movements of badminton players. Faster reaction speed is a key characteristic in the reaction intervals of badminton players (Cabello Manrique & González-Badillo, 2003), a theory that has been confirmed with experiments using force plates (De et al. 2023). However, it is unrealistic to measure footwork movements during badminton competitions with a force plate, because the size of the equipment limits the movements that can be measured. Therefore, in our previous work, we analyzed reaction motions using deep learning, which estimated the 3D skeletal poses of players from video to determine their reaction intervals during badminton games. We used the acceleration information of their waists to estimate a shot's reaction interval. Three types of movements occur during a game: stroke movement, reaction movement, and translation. Separating the reaction movements and the translation features was difficult using a classification method based on waist acceleration. In addition, we confirmed that the difference in the angle of the view of the camera used in the training dataset and the target images distorted the estimated human poses. We also confirmed that the estimation error lowered the waist acceleration.

As shown in Fig. 1, this paper estimates the reaction intervals and reaction movements of badminton players utilizing a motion-capture system that acquires more accurate skeletal position information. The following are the main contributions of this paper:

- a method that automatically measures the reaction intervals of badminton players during games;
- a motion-extraction technique tailored for competitions with different time intervals of motion, such as badminton games;
- a method that identifies hit and reaction motions by detecting the hit and reaction times.

2 RELATED WORKS

Deep learning has been used extensively in the field of sports and biomechanics (Halilaj et al. 2018). It has made skeletal pose estimation from images both robust and reliable (Badiola & Mendez, 2021). OpenPose (Cao et al. 2021), which is a representative method for acquiring skeletal pose information by applying deep learning, can estimate 25 points of a person's skeleton from input video in real-time. HRNet (Sun et al. 2019), which maintains high-resolution representation by connecting high-resolution and low-resolution subnetworks in parallel, addresses the problems of OpenPose, including frequent false positives when occlusion occurs and the low detection rate of small objects. In both Cao's and Sun's studies, the output is 2D skeletal coordinates on the input video.

This research field has been extended by a study in which a person's 3D skeletal coordinates are output from input video (Liu et al. 2021). Although estimation methods for 2D and 3D skeletal positions using deep learning have made remarkable progress, a problem remains: the estimation accuracy drops significantly during self-occlusion, which frequently happens when the arms and legs are hidden by the subject's body. Therefore, 3D motion-capture systems are the most commonly used method of acquiring 3D skeletal information in the field of sports biomechanics research (Zhao & Li, 2019).

In this paper, we propose a method that measures the reaction intervals of players based on highly accurate skeletal information obtained from a motion-capture measurement taken during games. In the field of motion analysis using time-series skeletal data, another research (Xu et al. 2010) detected walking and running rhythms by applying short-term principal component analysis (ST-PCA) to motion-capture data. In addition, another work (Federolf et al. 2014) detected the motion characteristics of skiers by applying principal component analysis to motion-capture data. When the entire body rotates while the foot motion represents the ground timing, we clarified that the features representing whole-body motion can be extracted from the first principal component and features representing partial motion can be extracted from the second principal component. In badminton games as well, whole-body translation occurs when players hit a shuttle and such partial body movements as extension and flexion of the hip and knee joints, abduction and adduction of the hip joint and jumping occur during footwork. We extract features that represent the whole-body translation during a hit using the first principal component and features that represent partial body movements using the second principal component and estimate the reaction intervals based on these features.

3 REACTION INTERVAL ESTIMATION METHOD USING RECURSIVE SHORT-TERM PRINCIPAL COMPONENT ANALYSIS

A reaction interval is estimated by observing the player’s movements comprised of whole-body translation and partial movements. A whole-body translation is a movement with which a player advances toward a hit point; partial movements include jumping and swinging while moving toward a hit point. In section 3.1 we explain how and why we define a reaction interval as the pause between two types of keyframes: hit times and reaction times. In section 3.2 we apply ST-PCA to our time-series data. In section 3.3 we employ a preliminary experiment to demonstrate how to use ST-PCA to detect both types of keyframes and determine the reaction intervals.

We used an optical motion-capture system to get the skeletal information of the players. 20 motion-capture cameras were installed at 8 m to surround the court. Skeletal information was obtained by a motion-capture system, comprised of an OptiTrack Prime 41, which captured images at 120 fps. “Motive: Body” software was used as the motion capture system. We attached 37 reflective markers to specified points on the body of each player. The positions of 37 reflective markers follow baseline (37) of Entertainment Marksets. A skeleton model of 19 joint points was tracked based on the marker positions. Fig. 2 shows the skeletal information obtained by the motion-capture system.

Due to the limitation of its temporal resolution, the skeletal model lacks data during high-speed arm swings. In such cases, linear interpolation compensated for the missing data.

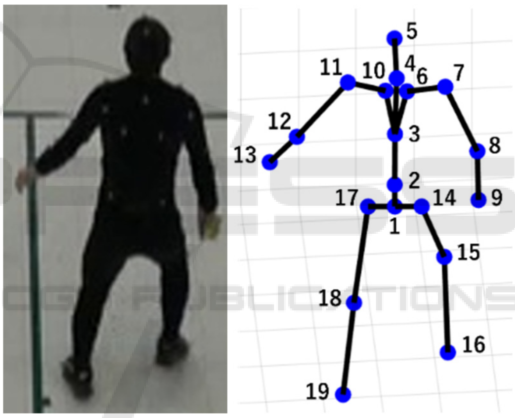

Figure 2: Skeletal information acquired by motion-capture system.

3.1 Definition of Reaction Intervals

In badminton, when moving around the court, the following actions are repeated to respond to an opponent's shot: 1) pushing off from the playing center, 2) decelerating toward the hitting point, and 3) pushing off toward the playing center after stroke. Therefore, in this research, the *time of the opponent's hit* is defined as the beginning of the reaction interval, and *the reaction time* (i.e., the time of pushing off at the playing center to respond to the opponent's shot) is defined as its end (Fig. 3).

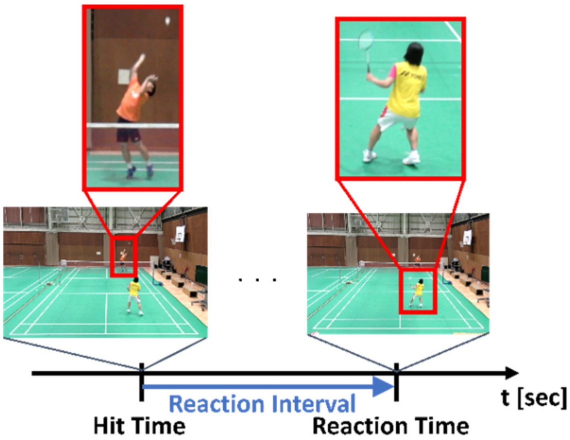

Figure 3: Definition of reaction interval: Time of opponent's hit is defined as beginning of reaction interval, and reaction time (i.e., time of pushing off at playing center to respond to opponent's shot) is defined as end of reaction interval.

3.2 Short-Term Principal Component Analysis

Short-term principal component analysis (ST-PCA) is applied to the movements of joints (time-series skeletal data) acquired by motion capture (Fig. 4). The skeletal information is $J \times 3 \times T$ dimensional data, where J is the number of skeletal joints and T is the total number of frames included in the analysis section. The skeletal coordinates are converted to one-dimensional data for each frame to create $3J \times T$ dimensional data (middle, Fig. 4). The skeletal data for k-th frame $\boldsymbol{p}_k$ are expressed as

$$\boldsymbol{p}_k = [\boldsymbol{x}_{1k}, \boldsymbol{y}_{1k}, \boldsymbol{z}_{1k}, \dots, \boldsymbol{x}_{Jk}, \boldsymbol{y}_{Jk}, \boldsymbol{z}_{Jk}]^t \quad (k = 1, \dots, T). \tag{1}$$

To apply ST-PCA to the skeletal information, we divided it into small analysis windows along the time dimension. Similar to a previous work (Xu et al. 2010), the width of the analysis window is set to N and the sliding width is set to the same value as the analysis window width (lower part, Fig. 4). The divided $3J \times N$ dimensional time-series coordinate vectors are analyzed in each analysis window. For example, when applying ST-PCA to the 3D skeletal information of a badminton player, the T frames from the service to the end of the rally are used as the analysis section, and each bit of skeletal information is divided into N frames. Time-series coordinate vector $\mathbf{P}_\mathrm{i}$ in the i-th analysis window can be expressed as

$$\boldsymbol{P}_i = [\boldsymbol{p}_{(i-1)N+1}, \dots, \boldsymbol{p}_{iN}] \left(i = 1, \dots, \left[\frac{T}{N}\right]\right). \tag{2}$$

In the last analysis window where the total number of frames in the analysis segment is not divisible by N, $\boldsymbol{P}_i$ is expressed by

$$\boldsymbol{P}_{\left[\frac{T}{N}\right]+1} = \left[\boldsymbol{p}_{\left[\frac{T}{N}\right]N+1}, \dots, \boldsymbol{p}_T\right]. \tag{3}$$

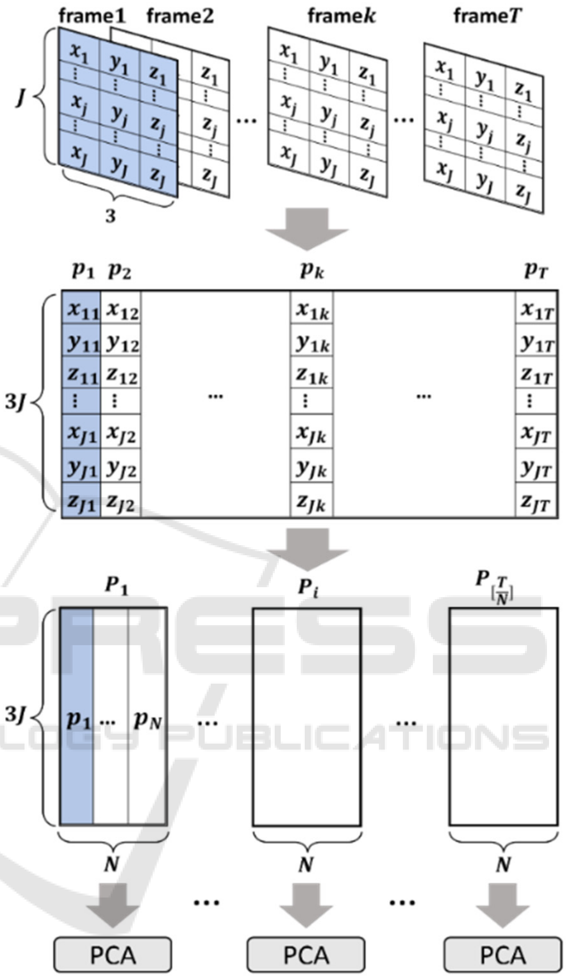

Figure 4: Application of short-term principal component analysis to skeletal information: Skeletal information is converted into 1D data frame by frame, and PCA is applied to skeletal information for all N frames.

In ST-PCA, we applied ordinary principal component analysis (PCA) to the standardized coordinate vector $\boldsymbol{P}_i{}'$ of each analysis window. $\boldsymbol{P}_i{}'$ is calculated by $\boldsymbol{P}_i{}' = \boldsymbol{P}_i - \overline{\boldsymbol{P}_i}$, where $\overline{\boldsymbol{P}_i}$ is the average posture of the i-th analysis window. In PCA, the eigenvectors of each principal component (PC) are calculated by the singular value decomposition of the covariance matrix of the input matrix. Each PC score is calculated by projecting skeletal coordinate vector $\boldsymbol{P}_i{}'$ onto the partial space on which each eigenvector is based. By independently applying PCA to each analysis window, a discontinuity is created in the time-series of the PC scores between two neighboring analysis windows. A previous work (Xu et al. 2010) showed that the coordinates can be smoothly combined by applying inversion and translation since the bases of the adjacent analysis windows are temporally consistent. Examples of the first PC scores before and after merging are shown in Fig. 5. Its top and bottom rows respectively show the PC scores before and after merging. The time-series data, which have discontinuity before merging, can be converted to continuous data. According to a previous work (Federolf, 2016), the PC scores represent the amplitude of the posture changes in each principal component space.

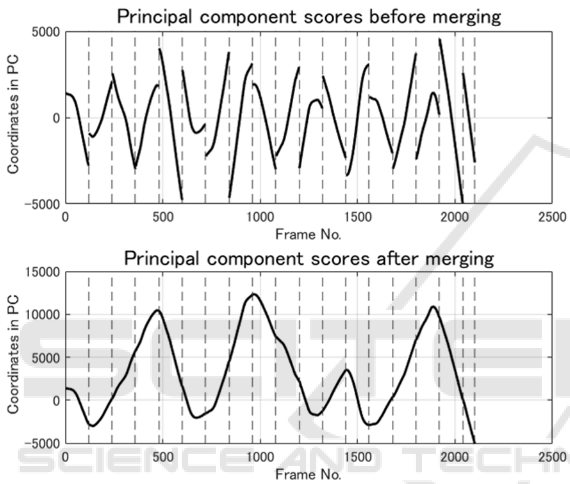

Figure 5: (Top) First principal component scores before merging: (Bottom) First principal component scores after merging: Data that were discontinuous before merging are converted to continuous data by inversion and translation. ST-PCA is applied with N= 120, and dashed lines represent analysis window width.

3.3 Reaction Interval Estimation by Recursive Short-Term Principal Component Analysis

As described in section 3.1, the reaction interval of a player is defined as the interval between the opponent's *hit time* and the player's corresponding *reaction time*. The procedures to determine the hit and reaction times are summarized below: 1) Perform ST-PCA for Player 1 and find frame f_1 where the extreme value of the PC1 score appears. 2) Perform ST-PCA for Player 1 again but on an analysis window around f_1. 3) From the result of step 2, find frame f_2 where the extreme value of the PC2 score appears and label it the *hit time* of Player 1. 4) Perform ST-PCA for Player 2 on an analysis window around f_2. 5) From the result of step 4, find the frame where the extreme value of the PC2 score appears and label it the *reaction time* of Player 2.

We conducted a preliminary experiment by applying ST-PCA to the skeletal information of badminton players. In a badminton singles match, since the players hit the shuttle in turn about every second [5], $N=120$ was set as the width of the analysis window for the data captured at 120 fps. The ST-PCA results of the two players are shown in Figs. 6 and 7. The former shows the PC1 and PC2 scores and the hit times of Player 1, and the latter shows the PC2 scores and reaction times of Player 2. The blue lines in Fig. 6 and the orange lines in Fig. 7 respectively show the actual hit and reaction times. They were judged visually by an experienced badminton player. The top and middle rows of Fig. 6 and the top row of Fig. 7 show the time series of the PC scores obtained from the ST-PCA result of a fixed analysis window described in section 3.2. The bottom row of Fig. 6 shows the time series of the recalculated PC2 score of Player 1, obtained by conducting a PCA on the 120-frame window around the time where the extrema of the PC1 scores appear. The bottom row of Fig. 7 shows the time series of the recalculated PC2 score of Player 2, obtained by conducting another PCA on the 120-frame window around the detected hit time of Player 1.

Since the PC1 of the skeletal data represents the translational and rotational movements of the whole body within the analysis window, extreme values were observed during the player's braking movements. PC2 represents the player's postural changes, and thus extreme values are observed during arm swinging, footwork, and at starting/ending of jumping.

The local extrema of the PC1 scores, calculated in a fixed analysis window, were located around the real hit time but with a rather significant error (top row, Fig. 6). The local extreme times of the PC2 scores are closer to the real hit times compared to those of the PC1 (middle row, Fig. 6). The error between the local extremum of the recalculated PC2 scores and the real hit time is even smaller, indicating a higher estimation accuracy (bottom row, Fig. 6). Therefore, the time of the extremum found in the recalculated PC2 score is defined as the player's hit time.

The PC2 score of Player 2, calculated in a fixed window in the neighbourhood of the hit time of Player 1, has a local extremum around the real reaction time but with a large error (top row, Fig. 7). Since the local extreme values of the recalculated PC2 scores of Player 2 appear very close to the real reaction time (lower row, Fig. 7), it is defined as Player 2's reaction time.

In the process of calculating the local extrema, prominence p, which represents the degree of prominence of each peak, were calculated to reduce the false positives caused by small changes (Cox et al. 2020). For the hit time detection, local extreme values are considered when $p \geq k$, and if multiple local extrema are detected in the th s, the local extreme value is adopted with the largest prominence p. For reaction time detection, the local extreme value with the largest prominence in the PC2 score recalculated in the neighborhood of the hit time is adopted. Recursive principal component analysis was performed with a window of analysis from frame b before the reference time to frame a after it.

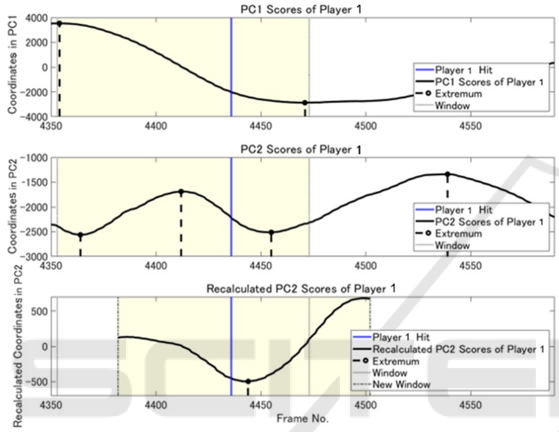

Figure 6: First two principal component scores and hit time: Yellow areas represent analysis window. Blue line represents actual hit time specified visually.

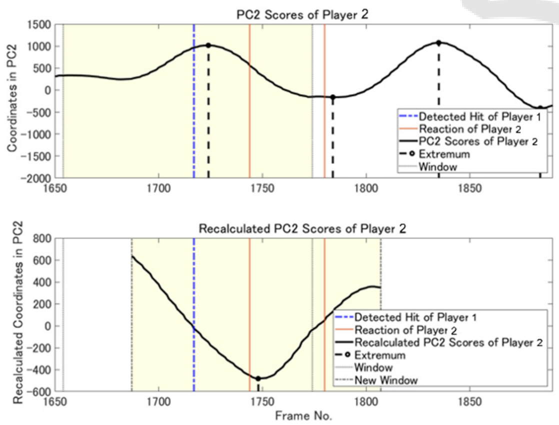

Figure 7: Second Principal Component Scores and Reaction times: Yellow Areas Represent Analysis Window. Orange Lines Represent Actual Reaction Time Tolerance Specified Visually.

We applied the above algorithm to both players to estimate their reaction intervals. For example, when estimating the reaction interval of Player 2, we detected the hit time of Player 1 and the reaction time of Player 2 and output the interval between them as the reaction interval. An example of the calculated reaction interval is shown in Fig. 8.

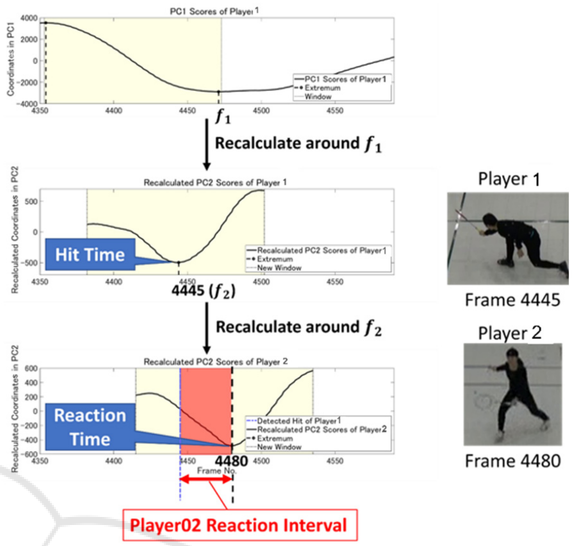

Figure 8: Reaction interval estimation using recursive short-term principal component analysis.

4 EXPERIMENTS

We verified the effectiveness of our proposed method through empirical experiments. The data used in the verification were single matches of 10 innings played by one female and one male member of the University of Tsukuba badminton club. A badminton court was set up in a 25-m-wide, 15-m-deep, 8-m-high space. The subjects wore motion-capture suits to which 37 reflective markers were attached, and 20 motion-capture cameras and one fixed RGB camera were installed at 8 m to surround the court. Skeletal information was obtained by a motion-capture system, comprised of an OptiTrack Prime 41, which captured images at 120 fps. The fixed camera was a Sony FDR AX-55, which captured 1440 × 720 pixel frames at 30 fps. The fixed camera shot the video from the rear of the court with the net in front of it so that both players can be seen in the video. “Motive: Body” software was used as the motion capture system.

Our proposed reaction interval estimation algorithm assumes that the hit times are correctly detected. Therefore, in our experimental demonstration of the proposed method, after an experiment that verified the hit time’s detection accuracy, we verified the accuracy of the reaction time detection for the reaction times to the correctly detected hit times. In addition, to verify the recursive principal component analysis's effectiveness in the proposed method, we evaluated the method using only PC scores in a fixed analysis window and the proposed method using recursive principal component analysis.

In experiments that evaluated the accuracy of the hit time detection, we compared the following three results: 1) the visual annotation results of the hit times, 2) the detection results using only PC scores in a fixed analysis window, and 3) the detection results using the proposed method. The detection using only the PC scores in a fixed analysis window is a method that searches for the extreme times of the PC1 scores and uses the extreme times of the PC2 scores (calculated in a fixed analysis window) immediately before them as hit times. The results are correct if the absolute error is within a threshold value; otherwise, they are erroneous. Since the stroke times of badminton players are approximately 0.3 to 0.4 s, the absolute error threshold is set to 0.3 s.

We evaluated the accuracy of the reaction time detection for the correctly detected hit times by comparing the following three results. We compared the reaction time detection results using the proposed method with the reaction time detection results using only PC scores in a fixed analysis window and visually annotated the reaction time ranges by experienced badminton players. The annotated tolerance range was set from the time when the players pushed off their feet to when they started moving toward the next hit. For the specified tolerance range, the output by the proposed method was labeled correct if it was within the tolerance range and incorrect if it was outside of it. If a shot in the hit time is an error and the opponent does not react, no reaction time was output. In this experiment, $N = 120$, $p = 100$, and $th = 0.5$, where th was set to 0.5, assuming that in badminton competitions, two hits by one player are never made within 0.5 s (Cabello & González, 2003).

Table 1: Results of hit time detection accuracy evaluation.

Method		Recall (%)	Precision (%)	F-score (%)
Simple ST-PCA	Player 1	77.8	51.2	61.8
	Player 2	73.1	52.8	61.3
	Total	75.4	52.0	61.5
Recursive ST-PCA (a=90, b=30)	Player 1	88.9	68.6	77.4
	Player 2	80.8	60.0	68.9
	Total	84.8	64.3	73.1

Table 2: Results of reaction time detection accuracy evaluation.

Method		Recall (%)
Simple ST-PCA	Player 1	34.8
	Player 2	42.9
	Total	38.8
Recursive ST-PCA (a=30, b=90)	Player 1	38.1
	Player 2	47.8
	Total	43.0

5 RESULTS

Table 1 shows the results of the hit time detection's accuracy evaluation and Table 2 shows the results of the reaction time detection accuracy evaluation. Accuracy evaluation showed that recursive ST-PCA outperformed the simple ST-PCA in all the hit time detection accuracy measures: Recall, Precision, and F-score. Recursive ST-PCA also outperformed simple ST-PCA in the precision evaluation of the reaction interval detection. This result seems to be due to the fact that simple ST-PCA does not allow for an analysis window for a specific movement, whereas recursive ST-PCA allows for an analysis window for the time the hit or reaction movement occurred. In the hit time detection, the hit times were undetected when the player hit while jumping and when serving. False positives were observed at the start and end of a jump and at the reaction time in the case of hits while jumping. In the reaction time detection, a detection was made when the highest point of a hop was reached immediately before a reaction, resulting in many cases of undetected times. When receiving a service, there were cases where the first step after a push-off was not detected at the time of the push-off, although it was detected when the first foot touched the ground, resulting in undetected results.

6 LIMITATIONS

The system proposed in this study has the following limitations, which still make it difficult to implement an automatic analysis solution for actual badminton matches.

- Skeletal information is captured using motion capture with reflective markers on the athlete;
- Skeletal information is analyzed offline after acquisition.

7 CONCLUSIONS

We proposed a method for estimating reaction intervals using recursive short-term principal component analysis for the 3D skeletal information of players in badminton games. Our proposed method detected the extreme times of the second principal component score near the time of the opponent's first principal component score as the hit time of a reaction interval. The extreme times of the other player's second principal component scores near the opponent's hit times were detected as the end of the reaction interval, and the shot-reaction intervals were estimated. The results of the detection accuracy evaluation showed that recall was 84.8% for the hit time detection and 43.0% for the reaction time detection. The effectiveness of recursive short-term principal component analysis was confirmed in both detection accuracy evaluations. The next step is to examine the relationship between reaction time and game dominance, and to use reaction time and other factors as inputs to predict and visualize game dominance.

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