A Case Study on Forehand Footwork Mistake Detection in Table Tennis

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Abstract

This work proposes a detection method for detecting the footwork mistake during a table tennis forehand shot. When hitting the ball far from the body with the forehand, players should usually move their feet before hitting the ball, rather than hitting the ball with the arm outstretched. This work proposes two methods, RFRW and LFRW+LFRF to detect this mistake of hitting the ball without foot movement. In addition, to improve the processing speed, we adopt the method of saving only the frames of interest to the HDD. The results show that the average correct response rate, true positive rate, true negative rate, and accuracy are 91.8%, 98.6%, 78.6%, and 90.0%, respectively, when footwork mistakes are detected using LFRW+LFRF. The frame rate is successfully improved by 75% compared to the method which alternates between capturing images and storing them on HDD.

Keywords

table tennis, forehand, footwork, mistake detection, frame rate

1. Introduction

Table tennis has become one of the most popular sports for decades since it was adopted as an Olympic sport in 1988. However, it is difficult for many beginners and amateur players to improve their table tennis skills without scientific instruction. For this reason, development of systems to support table tennis training is actively pursued[1]. For example, in addition to player motion analysis, research on stroke detection and classification[2][3][4], ball tracking[5][6], and ball spin estimation[7][8] is conducted. Image processing[9] or sensors[10] are used to develop training systems.

Although footwork is important in table tennis, few AI-based assisted training systems focus on this issue. In particular, when hitting the ball far from the body with the forehand, players should usually move their feet before hitting the ball, rather than hitting the ball with the arm outstretched. This study addresses this issue. We propose two methods for detecting footwork mistakes: Right Foot Right Wrist (RFRW), and Left Foot Right Wrist + Left Foot Right Foot (LFRW+LFRF). In addition, to improve the processing speed, we adopt the method of saving only the frames of interest to the HDD.

The paper is organized as follows: Related works are introduced in Section 2. Section 3 describes the foot position analysis, Section 4 describes the frame rate improvement, and Section 5 summarizes the paper and discusses future issues.

2. Related Work

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In recent years, various motion analyses are conducted in table tennis. In study [11], a national-level table tennis player is compared the difference between hitting the ball diagonally from the right end of his own court to the right end of the opponent's court (cross court) and hitting the ball from the right end of his own court to the left end of the opponent's court (long line). By using eight cameras and attaching sensors to the entire body and to the table tennis racket, this work calculates 21 characteristics such as racket speed and elbow angle. The results of the experiment show that there are significant differences in the movements when hitting the ball between the long line and the cross court, such as a larger elbow deflection angle, greater distance to the ball, greater racket tilt, and greater lower body rotation angle when hitting the ball with the long line. In study [12], an experiment is conducted to determine if player level and ball spin affect the arm and racket motion when hitting the ball with a topspin forehand. All subjects are university students. Players are classified into two levels: advanced and intermediate. Players who competed in national tournaments are classified as advanced players, and those who do not have the right to compete in national tournaments are classified as intermediate players. All subjects hit a topspin forehand against low and high backspin, respectively. The experiment is recorded at 200 fps using five high-speed cameras. During the experiment, the subjects wear only a swimsuit and table tennis shoes, and a total of 16 sensors are attached to their shoulders, elbows, and rackets. The results of the experiment showed that there is no significant difference in the speed and tilt of the racket at the moment of hitting the ball, but there is a significant difference in the rotation speed of the hips between the advanced and intermediate players. There is also a correlation between hip rotation speed and the time required to increase racket speed. In study[13], five features are designed: normalized path, joint angle, phase duration, RMS, speed, and entropy. The five features are designed as follows: normalized path is the stability of the stroke, joint angle is the elbow angle, phase duration is the time spent in the four phases of backswing phase, hitting phase, follow-through phase, and reduction phase, RMS is the magnitude of impact when the ball is hit, and speed entropy is an indicator of the stability of the swing speed. This work examines whether there are significant differences in the five designed features between advanced players and beginners. University students who belong to a table tennis association are classified as advanced players, and those who have never taken a table tennis course are classified as beginners. Beginners are taught how to hit the backhand block, and after a short practice session, the data on the backhand block movement are collected. During the experiment, a total of 10 sensors are attached to the upper arm, forearm, hand, and waist. The results of the experiment show that there are significant differences between the novice and advanced players in the four features except for phase duration.

3. Analysis of Foot Position

This section describes the foot position analysis method.

3.1. Importance of Footwork

The following is an explanation of the technical aspects of table tennis positional movement. In table tennis, footwork is the rapid movement with the feet to a position where it is easier to hit the ball. When hitting the ball with the forehand, the opponent's return ball is not often in your ideal position. However, if you fail to move into position for a return ball from an opponent and reach out to hit the ball, you are unlikely to hit a good shot because it is not your ideal shape for hitting the ball. Also, hitting the ball with the elbow extended increases the likelihood of hitting an errant shot because it is difficult to hit the ball with power and control. In other words, when hitting the ball, it is important to move the feet to a position where it is easy for the player to hit the ball[14].

Figure 1(a) shows a case in which a player hits the ball without moving his feet.

(a) How to hit when the foot is not moving

(b) How to hit when the foot is moving

(c) When hitting a ball close to the body

Figure 1. Example of how to hit the ball

There are several basic ways to move the footwork, and the way you move depends on the position of the ball hit by the opponent. If the ball is far from the player's body on the dominant player's side, the player should move the dominant foot first, move the body closer to the ball, and strike the ball after the foot has landed[15]. Figure 1(b) shows a case in which the player hits the ball by moving his feet.

3.2. Prerequisites

Figure *2* shows the flow of this research. This study uses images of a player hitting the ball. Based on the images, we aim to detect images in which the player neglects footwork and to indicate the possibility that the player has neglected footwork. In this research, a ball hit far from the body is called a ball hit far from the body if it comes to the right side of the body and is clearly distant from the body. When a player hits a ball far from the body without moving his feet and with only his hands extended, the player is judged to have neglected his footwork and the image is stored.

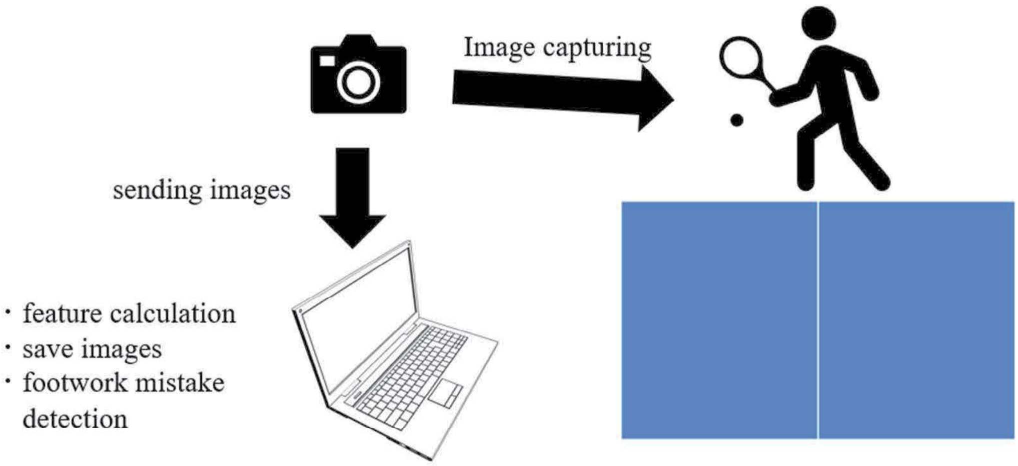


Figure 2. Flow of this study

3.3. System Overview

Figure 3 shows the overall image of the proposed system. First, start the camera. After the camera is activated, an image is captured and stored in RAM. Then, the joint coordinates are extracted, and the feature values are calculated. If the condition is not satisfied, the camera returns to capturing the image. If the condition is satisfied, the system captures up to (N+10) frames, where N is the number of frames in the image when the condition is satisfied, and stores the images in RAM. Then, it saves the images from (N-10) to (N+10) frames to HDD and releases the images in RAM. The camera then returns to capturing images. The camera used in this study is Azure Kinect, which can obtain the position and orientation of the coordinates of 32 joints of the person captured by the camera.

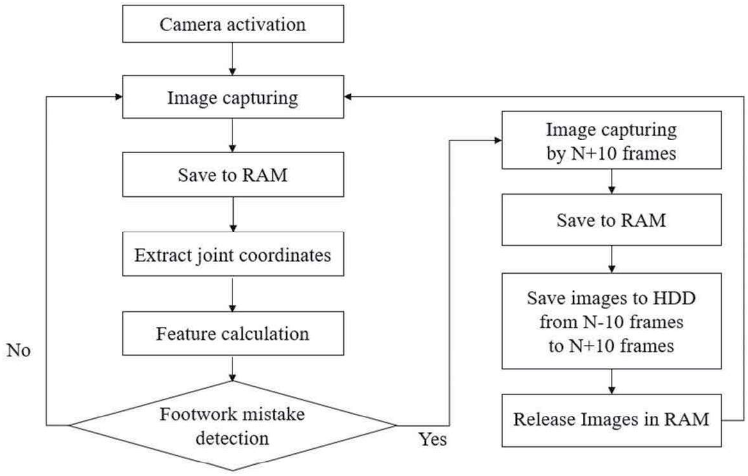


Figure 3. System overview

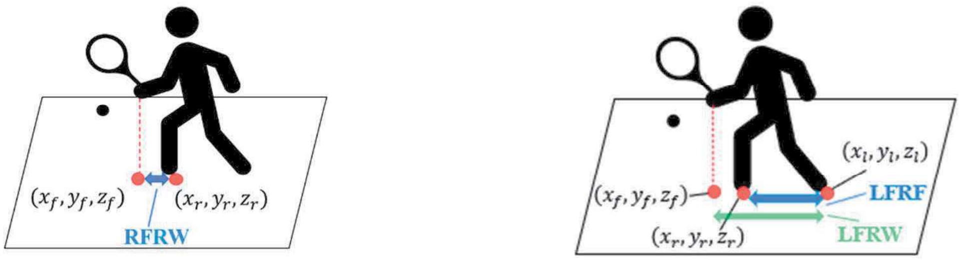
3.4. Proposed Method

Our proposed method is based on the case of a right-hand shot.

3.4.1. RFRW

If a player hits the ball far from her/his body using forehand without foot movement, usually the right wrist is farther from the right foot than in a shot with foot movement. To quantitatively describe this distance, we propose a feature called RFRW to detect footwork mistakes. To reduce the influence of the height of the wrist, we project the wrist to the ground plane and calculate the distance from the right wrist to the right foot. The distances indicated by RFRW are shown in Figure 4(a). Let (x_f, y_f, z_f) be the point where the coordinates of the right wrist are projected onto the floor, and the coordinates of the right foot are (x_r, y_r, z_r). RFRW can be expressed as in equation (1).

$$RFRW = \sqrt{(x_f - x_r)^2 + (y_f - y_r)^2 + (z_f - z_r)^2} \tag{1}$$



(a) Proposed feature RFRW (b) Proposed feature LFRF and LFRW

Figure 4. Proposed features

3.4.2. LFRW+LFRF

Considering the situation that the right wrist quickly moves to the left after hitting the ball, which leads to the false detection of RFRW, we propose another method, which includes two feature quantities: LFRW+LFRF. Figure 4(b) shows the distance indicated by LFRW. The coordinates of the right wrist projected onto the floor are (x_f, y_f, z_f) and those of the left foot (x_l, y_l, z_l), LERW can be expressed as in equation (2).

$$LFRW = \sqrt{(x_f - x_l)^2 + (y_f - y_l)^2 + (z_f - z_l)^2} \tag{2}$$

Next, we will explain how to find LFRF. Let the coordinates of the right foot be (x_r, y_r, z_r) and the coordinates of the left foot be (x_l, y_l, z_l), we can express LFRF as in equation (3).

$$LFRF = \sqrt{(x_r - x_l)^2 + (y_r - y_l)^2 + (z_r - z_l)^2} \tag{3}$$

3.4.3. Method of Determining the Threshold

To prepare for this, each feature is manually classified as either having a footwork mistake or not having a footwork mistake. A footwork mistake is defined as hitting a ball far from the body without moving the feet. Conversely, the cases with no footwork mistake consist of two groups: cases in which the player hits the ball close to the body and cases in which the player hits the ball far from the body by moving the feet. Table 1 shows the classification of hitting styles when there are footwork mistakes and when there are no footwork mistakes.

Table 1. Classification of hitting with and without footwork mistakes

when there are no footwork mistakes	when there are footwork mistakes
1. hitting a ball close to the body (Figure 1(a)) 2. hitting a ball far from the body by moving the feet (Figure 1(b))	hitting a ball far from the body without moving the feet (Figure 1(c))

Hereafter, the feature values classified for hitting the ball close to the body and for hitting the ball far from the body by moving the feet are called the true group, while the feature values classified for hitting the ball far from the body without moving the feet are called the false group. For each feature value, we derive the value obtained by averaging the feature values in the true group.

$$\forall i \in Set_{true} \tag{4}$$

$$MeanTrue_{RFRW} = \frac{\sum_i RFRW_i}{\sum_i i} \tag{5}$$

$$MeanTrue_{LFRW} = \frac{\sum_i LFRW_i}{\sum_i i} \tag{6}$$

$$MeanTrue_{LFRF} = \frac{\sum_i LFRF_i}{\sum_i i} \tag{7}$$

Next, we derive an additive average of the features in each of the false groups.

$$\forall j \in Set_{false} \tag{8}$$

$$MeanFalse_{RFRW} = \frac{\sum_j RFRW_j}{\sum_j j} \tag{9}$$

$$MeanFalse_{LFRW} = \frac{\sum_j LFRW_j}{\sum_j j} \tag{10}$$

$$MeanFalse_{LFRF} = \frac{\sum_j LFRF_j}{\sum_j j} \tag{11}$$

Finally, the obtained averages of the true and false groups are again averaged for each feature and are given as thresholds in this study.

$$threashold_{RFRW} = \frac{MeanTrue_{RFRW} + MeanFalse_{RFRW}}{2} \tag{12}$$

$$threashold_{LFRW} = \frac{MeanTrue_{LFRW} + MeanFalse_{LFRW}}{2} \tag{13}$$

$$threashold_{LFRF} = \frac{MeanTrue_{LFRF} + MeanFalse_{LFRF}}{2} \tag{14}$$

3.5. Footwork Mistake Detection

The application scenario is assumed to be that, under the guidance of the coach, the coach points out the correct footwork and the incorrect footwork. Through the image data of these footwork, the system calculates the feature quantity according to the method proposed in sub-section 3.4.1-3.4.2 and calculates the threshold for classifying correct footwork and incorrect footwork according to the method in sub-section 3.4.3. After that, in the absence of a coach and the user is practicing by herself/himself, the system calculates the feature amount through the user's image data and classifies whether the action is correct or not according to the previously calculated threshold, prompting the user that the footwork may or may not be correct.

When using method RFRW, in case RFRW is smaller than $threashold_{RFRW}$, determine that the user may not make a footwork mistake. On the other hand, in case RFRW is larger than $threashold_{RFRW}$, determine that the user may make a footwork mistake.

When using method LFRW+LFRF, in case LFRW is smaller than $threashold_{LFR}$ and LFRF is smaller than $threashold_{LFRF}$, determine that the user may not make a footwork mistake. If it is otherwise, it determines that the user may make a footwork mistake.

3.6. Experimental Method

For this experiment, we take two groups of images, one for obvious wrong hits and one for normal hits. First, images of three patterns of forehand motion are taken and the values of the joint coordinates are stored: hitting a ball close to the body, hitting a ball far from the body after moving the feet, and hitting a ball far from the body without moving the feet. After the images are taken, the values of the feature values are calculated, and the feature value with the highest value for each forehand motion is extracted. The number of times the ball is hit is 315 times in total, and the k-fold method (k=3) is used to calculate the feature classification thresholds. A confusion matrix is used to measure the accuracy of the feature thresholds. The Accuracy, Precision, Recall, and True Negative Rate are used to measure performance.

3.7. Experimental Results

Table 2 shows the experimental results of footwork mistake detection using RFRW. The mean values of Accuracy, Recall, True Negative Rate, and Precision are 73.0%, 85.3%, 58.6%, and 77.1%, respectively.

Table 2. Experimental method of footwork mistake detection using RFRW

Accuracy	Recall	True Negative Rate	Precision
73.0%	85.3%	58.6%	77.1%

Table 3 shows the experimental results of footwork mistake detection using LFRW+LFRF.

Table 3. Experimental method of footwork mistake detection using LFRW+LFRF

Accuracy	Recall	True Negative Rate	Precision
91.8%	98.6%	78.1%	90.0%

The mean values of Accuracy, Recall, True Negative Rate, and Precision are 91.8%, 98.6%, 78.1%, and 90.0%, respectively.

From Table 2 and Table 3, all indices of correctness, Accuracy, Recall, True Negative Rate and Precision have been improved. These results indicate that higher results are obtained when the features LFRW+LFRF are used.

4. Improvement of Frame Rate

We propose an algorithm to increase the frame rate. Because table tennis swings are very fast, a higher frame rate allows for more accurate analysis. However, when images are captured and color images with large data volume are stored on HDD at the same time, the frame rate decreases because it takes time to store the color images. To improve the frame rate, we propose a method in which the captured images are once stored in RAM, and the images are stored after the capturing process is completed.

4.1. Proposed Method

The flow chart is shown in Figure 5. First, the camera is started, images are captured, and all images are stored in RAM. If the number of images captured is less than 500 frames, the camera returns to capturing images. 500 frame images are captured, and then an arbitrary number of images are stored.

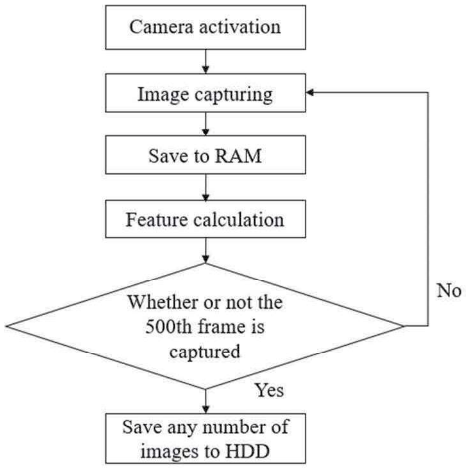


Figure 5. Flowchart of the proposed method

4.2. Experimental Method

First, 500 frame images are captured using the method shown in Figure 16, and 10%, 25%, 50%, or 75% of all images are stored on HDD. When capturing the images, the time taken to finish capturing 500 frames and the time taken to save the images to the HDD are each measured. The flowchart of the compared method is shown in Figure 6.

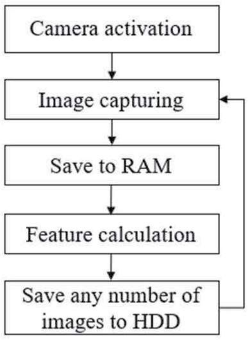


Figure 6. Flowchart of the compared method

The compared method alternates between capturing images and storing them on HDD for 500 frames, and measures the time required.

The experimental setup is as follows: CPU processing speed is 2.4GHz, RAM speed is 3200MHz, HDD read/write speed is 145MB/s and 150MB/s respectively.

4.3. Experimental Results

Figure 7 shows the experimental results. Compared to the method which alternates between capturing images and storing them on HDD, the processing time of proposed method is reduced by 39% when 10% of the images are saved, by 33% when 25% of the images are saved, by 22% when 50% of the images are saved, and by 14% when 75% of the images are saved. The frame rate increased 75% over compared method, regardless of the number of images saved.

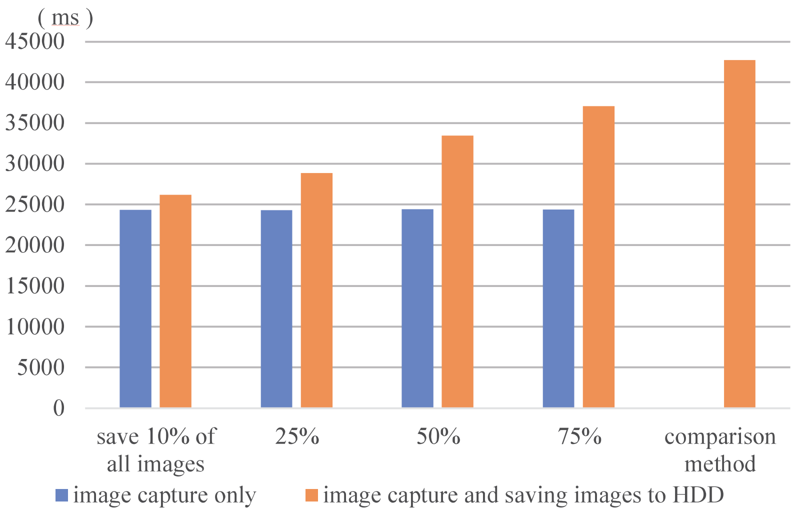


Figure 7. Comparison of processing times

5. Conclusion

This work proposed two methods, RFRW and LFRW+LFRF to detect some kind of mistakes of hitting the ball without foot movement in table tennis. In addition, to improve the processing speed, we adopted the method of saving only the frames of interest to the HDD. The results show that the average correct response rate, true positive rate, true negative rate, and accuracy are 91.8%, 98.6%, 78.6%, and 90.0%, respectively, when footwork mistakes are detected using LFRW+LFRF. The frame rate is improved by 75% compared to the method which alternates between capturing images and storing them on HDD. Increasing the number of trials, analyzing other batting situations, and importing AI-based analytics will be for future work.

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