ScienceDirect

00 (2019) 000–000

Procedia
Computer Science

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The 11th International Conference on Ambient Systems, Networks and Technologies (ANT)
April 6 - 9, 2020, Warsaw, Poland

# Online detection and classification of in-corrected played strokes in table tennis using IR depth camera

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**Abstract**

Table tennis is a complex sport with a distinctive style of play. Due to the rising interest in this sport the past years, attempts have been targeted towards enhancing the training experience and quality through various techniques. Technology has been used to support training sessions for table tennis players before, with a focus on players' performance measures rather than technique. In this paper, we propose a methodology based on IR depth camera for detecting and classifying the efficiency of strokes performed by players in order to enhance the training experience. Our system is to based on analyzing depth data collected from IR depth camera and recognized using fastDTW algorithm. The results show an average accuracy of 88% - 100%. This is the first paper to address the usage of IR depth camera on the table tennis player to detect and classify the strokes played.



*Keywords:* Table tennis; stroke detection; stroke classification; hand gestures; IR depth camera

## 1. Introduction

Competitive sports have been the main focus of various spectators all over the world. One of the most popular competitive internationally is table tennis or ping pong [12, 19]. It is being viewed and enjoyed by more than 291 million viewers [5]. To increase competitiveness, it's very important to focus on the training period for the trainees. In table tennis, it is very difficult to monitor the accuracy of the stroke in the training phase consistently.

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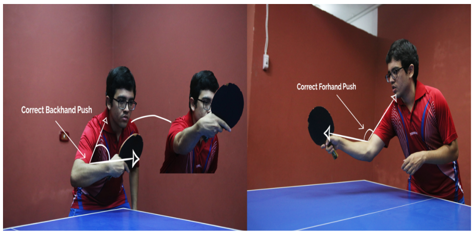


Fig. 1. Correct Movement a) Backhand push b) forehand push

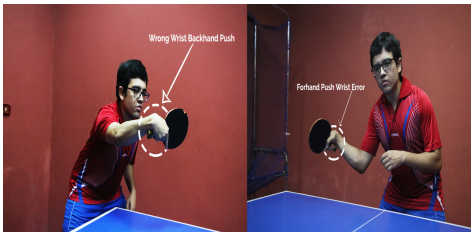


Fig. 2. Wrong wrist Movement a) Backhand push b) forehand push

Table tennis strokes are divided into basic and advance levels. Basic strokes are push and drive swings movements [15]. Moreover, each stroke can be played with the back called backhand or front side of the racket called forehand, and this is based on the player if he is right or left-handed. Also, the accuracy of the stroke is based on different joints of the body such as wrist, waist, elbows, legs, and shoulders. Therefore, any mistake in the movement of any joint will Produce a wrong swing. Performing the strokes swings differs from one stroke to another. The most common strokes that the players got to be trained at the beginning are the backhand push and the forehand push.

Starting with performing a backhand push needs the player's elbow to make an angle of 90-110 degrees with the forearm as in Figure 1)a. The elbow moves forward and back closing the angle with the forearm. Therefore, we can say that the angle starts between 90-110 degrees and ends at less than 180 degrees. While executing the stroke the wrist to move parallel with the elbow. Finally, the racket ends parallel to the table making an angle of 35-65 degrees. According to [20, 9, 11] Mistakes in backhand push performance could include:

1. Ball lifted, which means that the racket moves from down to up and this also includes the movement of the wrist. In other words, moving the wrist from down to up. Figure 2)a shows the wrong movement.
2. The elbow extends completely while performing the stroke creating a 180 degree angle such as in figure 3.

Then there is the forehand push requires the player to start the stroke with the racket with an angle between 90-140 degrees with the table as in Figure 1b. The stroke was performed by moving the hands slightly behind from the shoulder followed by a foreword and backward trajectory. As in backhand push, the racket must end parallel with the table producing angle between 35-65 degrees. According to[20, 9, 11] Mistakes in forehand push performance could include:

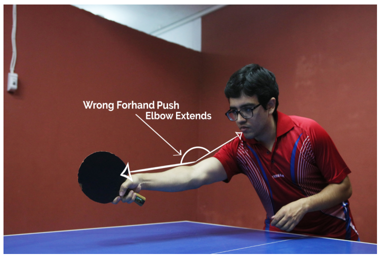


Fig. 3. Forehand push, elbow extends

1. The continuous movement of the hand after the ball even when hitting it. Follow-through the ball will result that the stroke ends in a wrong position, and that's the ball speed and movement are not based on hitting it.
2. Excessive backlift, where the shoulder and the elbow move toward the back more than needed. In other words, the stroke starts from the back of the body and not parallel to the waist.

One of the Common Mistakes between both forehand push and backhand push is that the hands move from left to right while performing which produces that the ball brushes sideways. The results in rising the elbow and shoulder which ends the stroke nonparallel to the table.

With the use of IR depth camera, the swing movement of the player can be analyzed for enhancing and improving the player's strokes. Also,In the field of table tennis, there are few number of papers that concentrate on the use of cameras . Previous research [31] proposed a system for analyzing the performance of the player while receiving balls using camera and different algorithms.

The rest of the paper is divided into five different sections. Section 2 which talks about the background, related work, and other approaches. Section 3 mainly explains our proposed approach. Section 4 states the experiment that took place. Section 5 discusses the results of the system has reached. Finally, Section 6 we conclude our work and show our future work.

## 2. Related Work

This section is divided into several parts. Every part is mandatory to mention as it is used in our system.

### *2.1. Table tennis systems*

Table tennis has different types of strokes divided into basics and advance levels. The main basics strokes are drive, push and topspin. By recording the movement of the hand it will be enough to detect and distinguish tennis strokes. Attaching a hardware device to the racket to record player movements was an approach of search and study [4] and by this methodology, some researches reached to an accuracy of 95.7% [3]. By the time wearable devices had an approach to be used. Researches started by using Wearable IMU device and using some simple calculations [13] reached to a good accuracy in general strokes of table tennis serves, forehand strokes and backhand strokes. Research [32] proposed an online android application for analysis of the player strokes played using a decision tree and attaching the mobile to the player wrist resulting in an average accuracy of 77.21% and 69.63%.

Another research was about the classification of ball spins. There are many strokes types which resulting in several ball speeds and spins. [2] provided a system to evaluate the ball speed and spin with a single IMU which is inserted inside a table tennis racket. The system results in an accuracy of 79.4%. In another research, authors did manufactured a robot device that can have the ability to compete with a human player [30]. As Table Tennis sport based on hands movements, therefore classification and detection of a table tennis stroke are considered to be a hand gesture issue.

### *2.2. Hand gestures*

Hand gesture recognition is a serious field in human computer interfaces. It provides different methods that are considered to be similar to human nature [24]. Gestures are highly important and efficient approach in augmented reality and virtual environments, especially in sports training applications. Authors in [34] proposed an AR system that provide guidance and feedback mainly in the sports field. The main problems in the hand gestures field would be the time taken to get the best accuracy in classification, because the major variety in which how people execute gestures with different speed levels while performing it. Research [21] proposed a very successful online system of classification and detection of hand gestures with zero or negative lateness. [7] provides a likable real-time alternative to ponderous interface devices for HCI by using Kinect and SVM algorithm resulting in 95.42% accuracy. Authors in [1] presented a solution to decrease the time needed by presenting a multi-core DTW algorithm, which indicates a time needed of 0.28 seconds. Hand gestures to be obtained needed to be captured by any means. Sensors plays an important roll in capturing hand gestures and movements of the body [7, 34]. One of those sensors is IR Depth camera.

### *2.3. IR Depth camera sensor background*

The concept of smart technology is about using technology in various applications and fields. One of these fields is sports. Therefore, people try to use technology effectively in order to enhance competitiveness in sports. The main focus from the technology aspect in competitive sports is the detection and classification of the player's movements. Detection of movements mainly done with the usage of a camera especially IR depth camera or sensor motion wearable devices. In [16] authors targeted the human posture recognition using depth camera and SVM as an algorithm to achieve high accuracy of multiple interesting postures. Their results show that using low-cost device Kinect which can detect different postures with high accuracy. In addition to that, research [28] pointed on how

Kinect SDK can achieve high accuracy in detecting the joints, and they proposed an AR trainer system for judo. Therefore, the usage of IR depth camera such as Kinect acts as leading function in future of the sports field.

For our best knowledge, none of the past researches pointed to the usage of IR depth camera in table tennis domain that focusing on the player movements. Rather than that IR depth camera in table tennis had included in analyzing the performance of the player while receiving balls, the paper showed accuracy average of 96.29% [31]. Still the usage of IR depth camera results in a huge amount of noise that does affect the data captures and therefore affects the classification of the system [6]. Therefore, a main pre-processing needed with sensors is filtering.

### *2.4. Pre-processing (Filters)*

Devices like IR depth cameras and other sensor motion devices detect data with a huge amount of noise [6]. This is where the need for noise removal is very important, the data is surrounded by noise due to the kind of the light-based systems. Joint bilateral filter was used to denoise the images collected so that it improves the quality of the image [17]. [10] used Gabor filter with SVM to approach a hand gesture recognition method which eliminated the limitation of illumination conditions. Additionally, they included that Gabor filter improved the recognition accuracy. Kalman filter was used for the body joints to be tracked with removing the noise of the undesirable vibrations also reduces the difference in the joint center position [8]. Moreover, Kalman filter helped in building a real-time application using sensor motion devices by denoising the signals that affect the signal reliability of the moving object position and orientation [14]. After capturing Table Tennis hand gestures using IR depth camera, the main part left is to classify the movements. One of the main classifiers for real-time systems in the Dynamic Time Warping Algorithm.

### *2.5. Dynamic Time Warping Algorithm*

Dynamic Time Warping (DTW) is a technique that calculates an ideal match with specific constraints between two given sequences. Any information which can be changed into a linear sequence can be investigated utilizing DTW. In human activity acknowledgment, they used dynamic time warping and IR profundity camera to Take on human development on account of its solidness against contrast in speed or style while performing activities [27, 23]. In the other case of using DTW algorithm with a smartwatch (accelerometer and gyroscope)[22]. Authors of [29] proposed a system for training data for different tennis shots, this approach was built on the idea of using DTW and QDTW at the two levels of a hierarchical classifier for classification. Researchers of [25] used Microsoft Kinect to construct hand gesture recognition using 2 algorithms DTW and HMM. Researchers they concluded that DTW is a better choice than HMM at the point when time is a requirement to be considered.

By the appearance of FastDTW, it did made a difference in systems speed and accuracy [26]. This helped a lot of real-time systems to achieve accuracy approximated to be 100%. authors in [33] Propose a system to simplify the concept of athlete coaching by using an IR camera to track the athlete's misplaced joints and notify the athlete before an injury occurs.Their results show that The FastDTW approach has exceeded other classification approaches and can obtain recognition for dependent user gestures with 100% percent accuracy.

## 3. Methodology

### *3.1. System phases*

#### *3.1.1. Pre-processing*

This phase is where the data is obtained from the sensor and filtered before the classification/processing phase. The very first part needed is the automatic detection of the strokes. Automatic detection is done using IR depth camera's SDK to detect various joints from the player body, graph at figure 4 shows an example of data obtained. The collected data is sent through a socket to the Inner room server. Then by using Kalman filter which shows an acceptable pre-processing in [8, 14]. It consists of a collection of mathematical equations which infer the state of a linear process of discrete time from indirect, imprecise and unsure assumptions. It is considered optimal if only the white Gaussian noise is affected (usually distributed with mean zero and standard deviation), the KF reduces the mean square error of the predicted parameters. The state of a discrete-time process is modeled with a measure by the linear stochastic differential equation as in table 1 equation[1].

Figure 4 indicates the data corresponding to the action of table tennis strokes of the skeleton joint frames and the inertial sensor data, and shows the the acceleration throw the x,y,z dimensions.

We utilized the euclidean distance in order to separate every stroke from the series obtained from the sensor. Euclidean distance measures the Segment length which connects the two points as in table 1 equation[2].

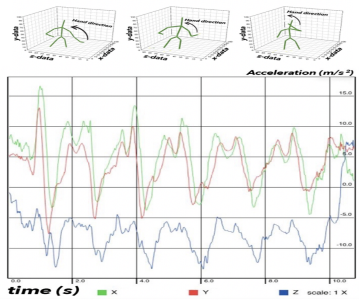


Fig. 4. Stroke detection for the forehand push

As known in table tennis a stroke moves through three main phases to be called fully done stroke as shown in figure 5. It starts with a 1) preparation where the hand of the play is slightly back to his body or beside his body, then 2) contact where the racket contacts the ball and finally 3) follow-through where the player ends his through by moving the racket in a certain direction to move the ball. Through these phases the system calculates the Euclidean distance between the first start point in the 1) preparation and the next point that the player moves to, if the distance is increasing that means that we still going forward throw these phases and the stroke is not yet finished until the system find that the distance is starting to decrease, that means that we reached the end of the 3) follow-through and the stroke is finished. The opposite goes with the backward movement from 3) follow-through phase to 1) preparation phase, if the distance is decreasing that means that we still going backward to start a new stroke and the data is neglected until we find that the distance is starting to increase, that means that we reached the start of the 1) preparation and so a new stroke begins.

The obtained value of a single result might differ in range to our dataset. Therefore, the technique of signal interpolation or extrapolation was very important. Extrapolation is often used to expand the range of values obtained so that it does not have empty slots while processing. The opposite of extrapolation will be an interpolation, where the range of data is minimized.

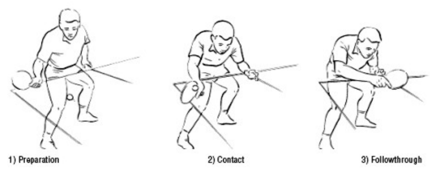


Fig. 5. Table tennis phases

### 3.1.2. Processing

After pre-processing, the obtained data is then classified with the dataset using FastDTW [26]. FastDTW is a Time series analysis and used algorithms to measure the similarity of two temporal sequences differing in time and speed. FastDTW offers almost-optimal alignments over DTW with O(N) time and memory complexity which takes O($N^2$).

Based on Stan Salvador and Philip Chan [26] FastDTW was made on a very useful approach which is the usage of a multilevel method that involves three main operations. Firstly,the Coarsening in which the data points are decreasing to shrink the time series. Secondly, is the Projection which is mainly finding the minimum-distance warp path at the lower part of the stroke stream. Finally, Refinement, which is to refine the warp path projected from a lower part of the stroke stream through local warp path modifications. By this approach FastDTW decreases the time-series taken in DTW.

Firstly, the FastDTW starts creating a cost matrix between the played stroke by the player and each stroke in the dataset as in table 1 equation[3]. FastDTW starts to establish each point in the matrix between the test stroke points and each stroke point in the dataset by obtaining the minimum value between the two points and their neighbors.

Secondly, The FastDTW utilizes cost matrix backtracking and greedy search to just get the distance between the two strokes as in table 1 equation[4]. Moreover, FastDTW usually starts to get the distance between the two strokes, by adding the point from the top left of the cost matrix cell. The FastDTW works to get all the balanced distance between each stroke in the dataset and the tested stroke. In the end, FastDTW starts searching for the minimum equilibrium distance. Therefore, It can get the label of the stroke from the dataset as it is the classified one.

Table 1. Equations

| | Equation | Description ($t$) |
|---|---|---|
| 1 | $d(p,q) = d(q,p) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2}$ | p: points of played stroke (test), q: points of each stroke from dataset. |
| 2 | $d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$ | x: first coordinate, y: second coordinate, of the first point in stroke stream. |
| 3 | $d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$ | I:points of played stroke (test), J: one stroke points from data set |
| 4 | $Dist(W) = \sum_{K=1}^{K=L} Dist(W_{KI} - W_{KJ})$ | W: the cost matrix, K:each cell in the matrix, L: Last left point in the cost matrix. |

## 4. Experiments

In this section, we specify the equipment setup and the dataset of our system for the detection and classification of wrong strokes in table tennis.

### 4.1. Equipment setup

In our trainer system, Motion capture was achieved with the first-generation Kinect camera, and software was created using Microsoft libraries.

The Kinect, along with the time-stamp, had been used to record X, Y, Z coordinates of four skeleton joints. The IR depth camera has been positioned on a table tennis table 65 cm from the ground and the player is 152 cm away, as shown in the figure. (6). The player was requested to perform multiple strokes multiple times (forehand push, backhand push).

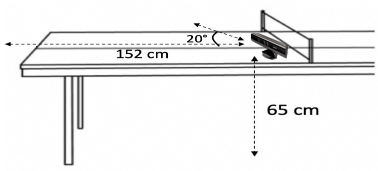

Fig. 6. Experiment setup

### 4.2. Data acquisition

Since there are no public benchmarking datasets that provide the depth map sequences that contain the different movement of joints needed in our system, we collected our own dataset the tennis stroke dataset (TSD) from the data provided by the IR depth camera from the spatial-temporal variation of the position of the skeletal joints in direction X, Y, Z from four different joints Left / Right (Wrist, Elbow, Shoulder, Waist). Figure 7 clearly shows the skeleton joints that we obtained the data by using the IR depth camera sensor. We started to collect the strokes data forehand and backhand push.

The collected data overall was 500 trials from five professional different players on two main strokes which are forehand push and backhand push. 50% of the trials are correct strokes and the rest is wrong played strokes. The wrong strokes differentiate between different movements like wrong movement angles, raised elbow and wrong wrist movements. The data collected by our own developed software, and the coordinates of the joints sent to the inner room server for classification through socket programming to reduce time consumption, prevent data loss and provide data integrity. Then other

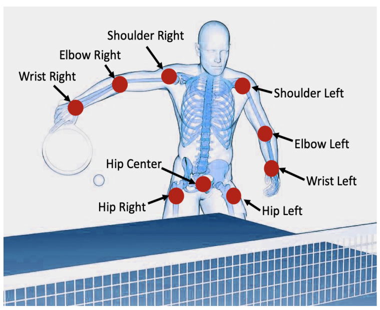

Fig. 7. System captures the player while playing the stroke and which joints that it captures

five players performed the stroke more than one time to test the system in real-time feedback. Table 2 is a confusion matrix made on the testing data (40% of overall collected data) which shows how successfully the system was able to detect the strokes and classify either they are correct or wrong according to our dataset. By using overall 10 player 5 for training and other 5 for testing the system provide to accept movements of different new players.

### 4.3. Experiment - Algorithm comparison

In the following table 3, shows the results for which was performed to evaluate the performance of the different key points classification algorithms using four main algorithms that were discussed in previous work [3, 16, 22]. In these algorithms, the most important point that we are looking for in an algorithm is that it has the highest average percentage in classifying the movement of the player correctly. The comparison was done and passed on the dataset we collected and created. Each algorithm computed on the dataset and tested three times to get the average percentage.

Our results show that FastDTW had the highest accuracy average from all classifiers followed by KNN, SVM, and Naive Bayes respectively. We obtain this result because the FastDTW algorithm analyzes different time series to calculate the correlation between two temporal sequences with the same behavior where time and speed vary.. Depending on Lindsay et al. [18], The Naive Bayes showed the leastest accuracy in time series analysis this is because Naive Bayes learner invalidly supposes independence from stroke attributes.

Table 2. Confusion Matrix Testing Data.

| | correct BP | correct FP | wrong BP | wrong FP |
|---|---|---|---|---|
| correct BP | 50 | 2 | 0 | 0 |
| correct FP | 0 | 48 | 0 | 3 |
| wrong BP | 0 | 0 | 50 | 3 |
| wrong FP | 0 | 0 | 0 | 44 |

Table 3. Different classification algorithm comparison.

| | FastDTW | KNN | SVM | Naive Bayes |
|---|---|---|---|---|
| correct Backhand Push | 100% | 96% | 92% | 88% |
| correct Forehand Push | 96% | 90% | 86% | 80% |
| wrong Backhand Push | 100% | 92% | 88% | 84% |
| wrong Forehand Push | 88% | 82% | 82% | 78% |

## 5. Discussion and Results

The main material of our proposed system was the tennis stroke database (TSD), Overall 500 strokes was captured with various players in different level of experience and knowledge. The recorded dataset was mainly focusing on two main basic strokes forehand and backhand push. Dataset contains joints position in X, Y, Z directions from 4 different joints (wrist, elbow, Shoulder, waist). The results of our proposed system presented a very good classification accuracy. Also, Quality of stroke detection is also very strong for a real-time system. All the strokes obtained have been successfully and correctly detected in the database. The overall average classification accuracy of tennis strokes was achieved between 88% and 100%.

## 6. Conclusion and Future Work

To sum up in this work, we introduce a system that uses of IR depth camera on the table tennis player to detect and classify the strokes that have been played. Forehand and backhand pushes are the primary strokes for playing table tennis. We considered these two strokes. The system helps the player in training and increasing his performance by acknowledging him the mistakes presented in his/her technique of playing. Our future work, we aim to add more different movements of strokes and serves. Also, to normalize the dataset and increase it.

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