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ScienceDirect

Procedia Computer Science 00 (2019) 000–000

Procedia Computer Science

www.elsevier.com/locate/procedia

The 17th International Conference on Mobile Systems and Pervasive Computing (MobiSPC)
August 9-12, 2020, Leuven, Belgium

IPingPong: A Real-time Performance Analyzer System for Table Tennis Stroke's Movements

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Abstract

Assisting table tennis coaching using modern technologies is one of the most trending researches in the sports field. In this paper, we present a methodology to identify and recognize the wrong strokes executed by players to improve the training experience by the usage of an IR depth camera. The proposed system focuses mainly on the errors in table tennis player's strokes and evaluating them efficiently and based on the analysis and classification of the data obtained from an IR depth camera using multiple algorithms. This paper is a continuation of our previous work [10], focusing more on identifying common wrong strokes in table tennis by utilizing IR depth camera classification algorithms. The classification of the mistakes that took place while playing can be classified based on each player dependently or independently for all players.

Keywords: Table Tennis; Stroke Detection; Stroke Classification; Hand Gestures; IR Depth Camera;

1. Introduction

Technology is now used to provide training sessions for table tennis athletes, with a concentration on the output of players as compared to an automated player. Specifically, IoT acts as a part of this technology. Sensors are devices that people use daily, everywhere in everything, and have been used in several partitions of life. According to the National Science Foundation, IoT is on track to connect 50 billion "smart" things by 2020 and 1 trillion sensors soon [14]. Accelerometer, Gyroscope, and IR depth cameras are used to detect and respond to some type of input from the physical environment and provide a certain output. With the presence of these types of sensors in everyday devices used, such as mobile devices, smartwatches, and cameras. IoT has been used in training and competitive sports as table tennis is

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one of the most common sports in the world and the main reason behind this popularity is that people of all ages can play it. Statistics currently reveal that the number of players in table tennis in the United States has grown from 2006 to 2017. In 2017, the number of players that have been aged between six years and above was estimated at 16.04 million. [18]. Since a lot of teenagers are joining the sport, that leads to a huge number of beginners and people who are new to the game. But the majority of them don't know the right way to play and a lot of wrong plays occur when they practice.

Strokes in table tennis rely on multiple joints like a wrist, elbow, shoulder, and waist and any simple joint mistake can affect a whole movement. A stroke can be converted from an attacking stroke to a defending stroke due to a wrist angle or elbow being extendable more than needed. Practicing movement rather than incorrect movement quickly will result in better performance. Firstly, the elbow of a player can be backward and "tucked in" against their sides [15]. Also, one of the most common mistakes using the elbow is overextending it [19], where the player lunges their arm directly at the ball and finishes with a straight elbow as shown in (1b). The elbow should be relatively bent around 70-90 degrees while playing the stroke, and the player needs to leave a small gap between the elbow and the body. Secondly, waist and shoulder joints are considered to be connected in the movements. In other words, a wrong move in the waist will be considered a wrong movement in the shoulder and vice versa. The waist joint is considered to be the main joint in the motion of other joints, a wrong waist movement will affect the angle and movements of other joints. Players sometimes twist their shoulders and not moving their waist, the shoulder along with the waist need to rotate forward together to meet the ball. The player needs to bend at the waist at an angle of 40-60 degrees and the shoulder needs to be free from the body alignment as shown in the figure (1c). This gives the player a free movement in playing the strokes. Finally, the wrist is the most critical joint in the table tennis sport in which it controls the trajectory of the bounced ball. To keep the starting position ready, the wrist should be an extension of the arms, not turned up or down as shown in the figure (1a). Also, you need to keep your hand upright, but let the weight of the racket slip down [15].

(a) Wrist angle error (b) Elbow extension error (c) Waist angle error

Fig. 1: Most common mistakes in table tennis techniques

Our main contribution in this paper which relies mainly on comparing to the most accurate stroke segmentation in table tennis is divided into analyzing wrong strokes within both user-dependent and independent environments and classifying these strokes on different joints through various algorithms. The paper is partitioned into four parts. Firstly, the related work where we present other researches in different domains related to the techniques used in the proposed system. Secondly, the methodology where we mainly explain the proposed approach and the techniques used. Thirdly, experiment where we show the proposed system contribution and results. Fourthly, a discussion where we explore the underlying of the proposed system. Finally, summary and future studies where the results and outcomes of the research are presented.

2. Related Work

Table tennis sport is built on different movements using different joints of the body. A movement is categorized to be either an attack or defense as any other sport, however, a movement could be as simple as the movement of the wrist or advanced as the movement of the waist, elbow, shoulder, and wrist at a very specific angle and distance [20, 9]. A game of table tennis is based on movements as it's considered being hand gestures issue. Recognition of hand gestures is a genuine area of computer-interfaces. Hand gestures provide various methods and strategies deemed similar to human nature [26]. Although, proposing a human gesture system with zero lateness helps to increase the accuracy of a system and decrease the required time needed in real-time systems [21].

Movement detection is quite important in the augmented reality field and real-time technologies, however, time is a major issue in getting the highest accuracy possible. This is due to a significant variety of individuals motions with different levels of speed while performing it. According to Kos et al. [12], which suggests that you can obtain a rather strong precision in general table tennis strokes using some easy calculations. Chen et al. authors of [5] offer a real-time solution to serious HCI control systems utilizing an IR depth camera and support vector machine algorithm that leads to 95.42% accuracy. Yeo et al. [36] proposed an augmented reality framework that essentially provides guidance in the field of sports, suggesting that the angle and speed of table tennis stroke can be determined sensor such as IR depth camera.

On the other hand, technology was introduced into sports especially competitive sports as a tool for analyzing and reporting training and matches. The main sensors introduced to the sports field or mainly table tennis was IR depth camera or mobile inner sensors. According to [3, 2] the attachment of an equipment gadget to the racket is one of the strategies utilizing accelerometer and gyroscope for recording player's movements. Viyanon et al. [33] attached the mobile phone into the player's wrist which acts like a handheld accelerometer and gyroscope sensors. Researchers obtained an overall precision of 69.63% and 77.21% by using a decision tree as a classification method by using a handheld accelerometer and gyroscope. They created an online software program to evaluate the match strokes that they performed. Moreover, The usage of depth camera along with any classification algorithm such as SVM to recognition human postures provide high precision of accuracy [16]. Moreover, the usage of Kinect software that can sense and recognize different postures with high precision especially sports [30]. [32] proposed a strategy for assessing player yield utilizing a minimal effort camera and various calculations.

The usage of IR depth cameras and external sensors results in a large amount of noise impacting data captures and device detection [4], therefore filtering is the key pre-processing needed for sensors. Light-based systems are the main reason for data noise in IR depth camera, therefore the noise needed to be reduced well as it affects the classification [7]. According to Li et al. [17], they used a joint bilateral filter to denote the images that were collected thus increasing the image quality. The idea of using a Gabor filter with the SVM algorithm has been addressed by [11], this technique will dispense with the impediment of light conditions and improve recognition precision. Butterworth filter smoothes the time series by removing signals above cutoff frequency while leaving the signals in the passband undistorted [35]. The Kalman filter used to track the joints of the body by reducing noise from excessive vibrations and eliminates the disparity in the central location of the joint. [6]. Moreover, according to [13] The Kalman filter was given to have a strong impact on the development of real-time applications using devices of sensor motion.

After the intake of signals and association of the sensors, the part which is left is to arrange the movements and strokes. lots of data mining and machine learning algorithm was used to classify hand gesture motions. SVM algorithm was used in lots of offline hand gesture applications [2, 29], where accuracy can reach over 85%. on the other hand, k-NN algorithm usage proved to reach an accuracy of 80.77% into investigating hand gesture recognition [23]. Another research implemented a methodology that differentiates different fixed hand gestures in a complex context by using the Naïve Bayes classifier and Gabor filter reaching an accuracy of 90% [1]. For classifying real-time applications, a dynamic time wrapping (DTW) algorithm is considered being a key classifier. DTW is a method that processes a perfect match between two given sequences with various limitations. With the recognition of human conduct, dynamic time warping and IR depth cameras have been utilized for human advancement because of their impact on appearing different to concern speed or style while directing exercises [28, 25]. Also, this algorithm is utilized with a mobile sensor that accomplishes a high precision rate. [24]. By the proximity of FastDTW, it affected the frameworks that rely on speed and precision [27]. Outcomes indicate that the FastDTW algorithm has outperformed several arrangement strategies and may be linked to a high exactness for subject client motions which can be approximately 98%. Authors of both [8, 34] used FastDTW to make ongoing applications that show a remarkable improvement in exactness rather than the usage of DTW.

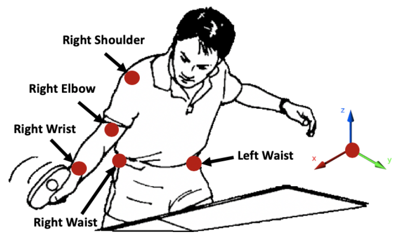
Our proposed methodology, is an extension for our previous work [10]. The system shows the usage of IR depth camera on a real-time system in the field of table tennis. Moreover, both experiments presented in this paper was not mentioned to be done under any paper titled with table tennis.

3. Methodology

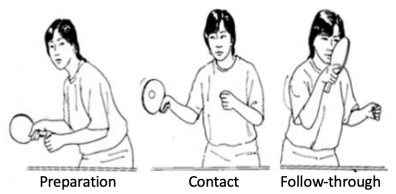
The system is categorized into multiple phases. Firstly, data acquisition where data is obtained for several joints using different sensors. Secondly, the pre-processing step, consisting of segmentation of strokes and filtering of data. Finally, the processing phase in which the classification is made to identify strokes.

3.1. Data Acquisition

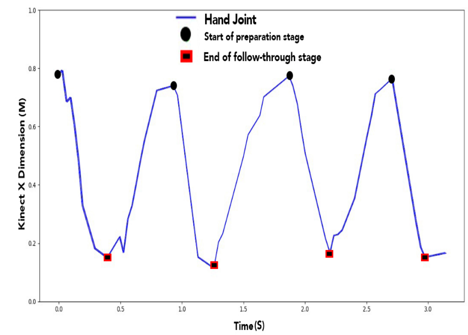
Data Acquisition is performed using the IR depth camera to identify the various joints (elbow, shoulder, waist, and wrist) from the body of the player. The data obtained from the IR depth camera sensor are three-dimensional points (X, Y, Z) for each joint as shown in the figure(2a). The collected data were sent to the inner room server.



(a) Joints captured by the system while player while playing the stroke



(b) Table tennis phases



(c) Stroke detection graph for the beginning and ending of stroke

Fig. 2: Stroke Segmentation

3.2. Pre-Processing

As stroke in table tennis is considered to be a forward gesture that moves through three main phases as in the figure (2b) stroke segmentation was a necessary phase in the project. Moreover, as data of the stroke are collected by the usage of an IR depth camera, filtration is needed to remove all the noise that might exist with the stream of data collected.

3.2.1. Stroke Segmentation

Following data acquisition, the stroke must be segmented from the data stream that is collected. It starts with the phase of preparation, where the player's hand is directly behind or parallel to the waist. Following the contact phase where the stroke is done until the racket is in contact with the ball. Eventually, the follow-through phase is where the player closes his stroke by pushing the racket in a precise way to push the ball. In table tennis phases, the method estimates the euclidean interval between the primary starting point at the preparation phase until it reaches the follow-through phase. When the euclidean interval between the original point and the next point is increasing, this implies that the movement is going forward and the stroke is not yet finished. The backward movement of the stroke is where the interval is decreasing, and the motion is from the follow-through phase to the preparation phase is neglected as its not a part of the stroke. Figure (2c) shows a full stream of movement over 5 seconds, where the points decreased over the graph shows the start and the end of each stroke. Stroke start is calculated by getting the equidistance distance between two successive points using equation[1] table (1).

3.2.2. Data filtration

Kalman filter was used to eliminate IR depth camera noise. Kalman filter used a noise reduction and motion detection filter. It is used to raise the accuracy of the depth camera's joint position estimation and to present an appropriate pre-processing and precision enhancement as indicated in [31, 22]. Two forms of noise influence the time-series data of the IR depth camera due to high-frequency variations and the detection of the joint position from the skeleton. Our collected data were passed through the Kalman filter to boost the joint location estimate of the IR depth camera and to eliminate the noise that affects data such as temperature shift, momentum, vibration, etc. It shows an appropriate pre-processing and precision enhancement as specified in [6, 13].

Kalman filter is an active filter which includes a group of mathematical formulas that calculate the inner state of a sequential complicated system from a sequence of uncertain observations and generates an estimation of unknown factors that tend to be more reliable than those related to a particular calculation only, by calculating the combined distributions of possibilities over parameters through each period. The condition of a discrete-time cycle is designed with a calculation by the linear stochastic differential equation[2] table (1).

3.3. Processing - Dynamic Time Wrapping

In this stage, the proposed platform has utilized various algorithms to identify and recognize the consequence of the player's stroke movement. The main focus is on the player's different wrong movements such as elbow overextending, wrist bend, and the wrong rotation of the waist and shoulder. However, FastDTW was utilized to group the stroke movements as correct or wrong.

The dynamic time wrapping algorithm can find the optimal balance between the two-time series. It is also used to evaluate the similarities between time series, to distinguish and to locate matching regions between two-time series. FastDTW is a DTW approximation that has a continuous-time and space complexity. It uses a multi-level approach that iterative constructs a solution based on rough resolution and modifies the projected solution.

Firstly, FastDTW starts constructing a cost matrix between each stroke of the dataset and the stroke of the player. It proceeds to establish each point in the matrix among the test stroke points and the stroke points found in the dataset by extracting the least value between the two positions and the neighbors defined by the equation[3] table (1). Secondly, FastDTW utilizes the cost matrix backtracking and greedy search to obtain the distance among the two strokes. In general, the interval between the two strokes begins by adding a point from the top left of the cost matrix cell defined by equation[4] table (1). The proposed algorithm aims to achieve the correct distance among each stroke throughout the dataset and the stroke being tested. This always tends to look for the correct balance distance. The stroke mark will then be omitted from the dataset when it is known.

Table 1: Equations

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

4. Experiments

This section presents the implementation and assessment of cutting strokes techniques and FastDTW, k-NN, SVM, and Naive Bayes algorithms for user-dependent and user-independent detection and classification of table tennis strokes.

4.1. Equipment Setup

Motion capturing was achieved with the original IR depth camera in the proposed system. The IR depth camera was used to monitor the X, Y, Z directions of four skeleton joints along with its timestamps. The IR depth camera has been placed on the tennis table, 78 cm from the beginning, the player is set to be 152 cm apart as seen in the figure(3).

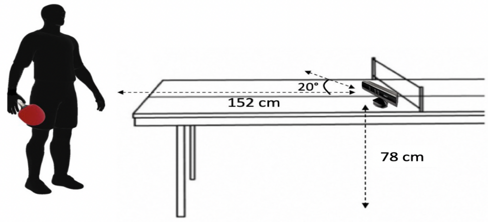


Fig. 3: Practical experimental control environment lab

4.2. Data Collection

In general, the data acquired consists of 960 strokes gathered from four professional players (three males and one female) divided into two parts. First part each player repeated each correct stroke 40 times with a total of 80 for 2 correct strokes per user. Second part each player repeated each wrong stroke 20 times with a total of 160 for 2 wrong strokes in each of the joints (waist, elbow, shoulder, wrist) per user. The data is acquired by our own constructed programming and joints position transmitted to the inner room server for order through attachment programming to reduce time utilization, keep away from loss of information and keep up information uprightness.

4.3. Experiment (1) - Segmenting Strokes

In this experiment, our system evaluates different techniques in stroke segmentation. Firstly, the timestamp approach was used, but the difference in the time range of each stroke from one player to another timestamp wasn't successful. Therefore, the proposed system used Euclidean distance and it solved the problem by measuring by the distance between the player's hand and the IR depth camera, and from that, we could measure if the stroke direction of the stroke and accordingly we get more accurate results. Using Euclidean distance we could specify the initial starting point and the end-point for each stroke, neglecting the unwanted backward hand movement and achieved more accuracy than timestamp by 20% as shown in the graph at the figure (4).

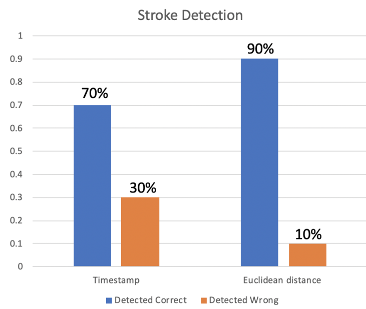


Fig. 4: Comparison graph for stroke segmentation techniques

4.4. Experiment (2) - Stroke Classification Accuracy

In this experiment, our system evaluated FastDTW, k-NN, SVM, and Naive Bayes algorithms for user dependent and independent detection and classification of two table tennis strokes performed correctly and incorrectly. For User-dependent Classification, we used 28 samples for training and 12 samples for testing for each correct stroke. In the case of the incorrect strokes, we used 14 samples for training and 6 samples for testing for each incorrect type of stroke (waist, elbow, shoulder, wrist). Algorithms user-dependent results are shown in the table (2). And for User-independent Classification, we used 224 samples for training and 96 samples for testing for each correct stroke from all users. In the case of the incorrect strokes, we used 440 samples for training and 200 samples for testing for each incorrect type of stroke (waist, elbow, shoulder, wrist). Algorithms user-dependent results are shown in the table (2).

5. Discussion

According to the results shown in table (2) FastDTW has shown the highest accuracy average. Since the FastDTW algorithm works better with our type of time series data as it measure the similarity between two temporal sequences. Naive Bayes shows the lowest accuracy average, it is simple, fast, accurate, and reliable algorithm, however time series data is not its power because Naive Bayes learner invalidly supposes independence from stroke attributes. However, there is a slight difference between the accuracy averages of the algorithms, so we cannot decide upon the average only. We conducted an Analysis of variance (ANOVA) tests on the algorithms results to analyze the differences among

Table 2: Different classification algorithm comparison on user-dependent and user-independent.

	FastDTW		KNN		SVM		Naive Bayes	
	dep.	indep.	dep.	indep.	dep.	indep.	dep.	indep.
Correct BP	100%	100%	91.67%	95.83%	91.67%	87.50%	83.33%	72.92%
Correct FP	100%	97.92%	91.67%	93.75%	100%	83.34%	91.67%	79.17%
Wrong BP (Elbow joint)	100%	100%	100%	100%	83.33%	76%	66.66%	72%
Wrong BP (Wrist joint)	83.33%	84%	83.33%	84%	66.66%	76%	66.66%	72%
Wrong BP (Shoulder joint)	100%	96%	100%	96%	100%	92%	83.33%	84%
Wrong BP (Waist joint)	83.33%	84%	66.66%	68%	66.66%	60%	50.00%	52%
Wrong FP (Elbow joint)	100%	96%	100%	96%	83.33%	84%	83.33%	72%
Wrong FP (Wrist joint)	83.33%	80%	83.33%	84%	83.33%	72%	66.66%	60%
Wrong FP (Shoulder joint)	100%	92%	83.33%	84%	83.33%	76%	83.33%	72%
Wrong FP (Waist joint)	66.66%	64%	66.66%	68%	66.66%	56%	50%	52%
Precision	0.8276	0.7851	0.7586	0.7521	0.6970	0.6357	0.5833	0.5252
Recall	1.0000	0.989	0.9167	0.9479	0.9583	0.8542	0.8750	0.7604
F-Measure	0.9057	0.8756	0.8302	0.8387	0.8070	0.7289	0.7000	0.6213
Accuracy	93.06%	90.88%	87.50%	88.18%	84.72%	79.39%	75.00%	69.93%

them. In the case of user-dependent classification P-value was 0.015984569 which means that there is a significant difference between the accuracy of the algorithms. In the case of the user-independent classification, there was a statistically significant difference between groups was determined by one-way ANOVA ($F(3,36) = 6.808490236$, $p = 0.000942206$). The results shows that there is a difference in the algorithm accuracy, depending on the user style of playing and if there is a similar data exists in our data set or not. Despite these limitations, FastDTW achieved high and the best classification accuracy for user-dependent and user-independent data-set.

6. Conclusion and Future Work

In this paper, we proposed a system that uses an IR depth camera to distinguish between the wrong table tennis strokes on each joint. The system's recognition and classification algorithm were evaluated on different algorithms: Dynamic time warping (DTW), K-nearest neighbor (k-NN) and, Support Vector Machine (SVM) algorithms based on accuracy. Our evaluation based on our Table Tennis Dataset (TSD), gathered with a high level of experience and expertise from several players. The dataset consists of 960 strokes for four players. User dependent and independent classification experiment's results showed that the FastDTW algorithm achieved the best accuracy. In future work, we look forward to adding more different advanced strokes to the system dataset, standardize, and increase it. Also, we aim to evaluate the algorithms of wearable devices to develop other sports like swimming.

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