TennisMaster: An IMU-based Online Serve Performance Evaluation System

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ABSTRACT

Tennis sport has become more popular all over the world in recent years. While tennis lovers wish to improve their tennis skill set for better performance, unfortunately only few of them could be guided under professional training. Especially, serve is probably the most important skill in tennis skill set. In this paper, we present TennisMaster, an online diagnosis and feedback system, that aims at performing online assessment of tennis serve during the training process using IMU sensors. In particular, we propose a hierarchical evaluation approach based on the fusion of two IMU sensors mounted on the racket and shank of the player. In order to achieve online serve assessment, we first develop an online serve extraction algorithm to identify the serve segments and filter the non-serve events. Then we use Hidden Markov Model (HMM) to segment the serve process into eight stages. By extracting unique features on the basis of the serve segmentation, we build a regression model which outputs the score of a serve. We conduct experiments to collect 1,030 serves involving 12 subjects at various professional levels. Evaluation results show that our system achieves high accuracy of performance assessment for tennis serves.

CCS Concepts

•**Human-centered computing** → Human computer interaction (HCI);

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Figure 1: An application scenario of TennisMaster through the IMU sensors mounted on the bottom of racket and the shank of user with smartphone controlling.

Keywords

Skill assessment, Activity recognition, Wearable device, Tennis

1. INTRODUCTION

With the advance of mobile computing, cyber physical systems, as well as communication with almost every physical and virtual object for fine grained automatic control, wearable devices are becoming more and more popular nowadays. The development and popularity of wearable devices make the interaction between human and computers not limited to the PCs or mobile phones. The applications of wearable devices widely span the fields of health [6], fitness [19] and sports [7]. The shape of wearable devices includes wristbands, watches, or even sensing device embedded in clothes or sports equipment like tennis rackets [1].

Figure 2: The eight stages of tennis serve process.

More and more wearable devices have been used in the field of sports. In [15], Hao et al. propose a running rhythm monitoring system based on capturing breath sound through smartphone embedded sensors. In [19], Kranz et al. propose an automated assessment system for balance board training called Gymskill, which provides training quality and feedback to the user based on smartphone integrated sensors. Additionally, there are several research papers in other sports like running [4], skiing [11], climbing [18], swimming [8], football [22], dressage [21], and table tennis [10].

There are also applications of wearable devices in tennis training. Several commercial tennis assistant systems [1, 2, 3] are available on the market that aim to improve players performance. For example, Zepp Inc.[1] places a special type of sensor at the bottom of the racket, in order to record the frequency of fore-hands, back-hands, and serve. The information of speed and type (e.g., flat, topspin, slice) when hitting the ball is also collected. The Smart Tennis Sensor for Tennis Rackets project from Sony[2] adopts similar technology. There have also been existing works in the research on analyzing tennis performance, for instance, Yuri et al.[16] use a wrist mounted gyroscope to analyze the tennis stroke and serve between novice and expert players.

However, existing systems are only capable of collecting statistics of performance, but cannot provide diagnosis and evaluation of the motion performance. Motivated by the unique characteristics of tennis skill set, in this paper we propose TennisMaster - an online diagnosis and feedback system for tennis players using multiple wearable IMU sensors. TennisMaster is designed to provide online assessment of the serve performance to the user based on smartphone and IMU sensors. Specifically, TennisMaster assesses the serve performance on the basis of the theory of 8-stage tennis serve evaluation model proposed by Mark et al.[17]. In this model, a serve can be divided into eight stages thus providing a more in-depth analysis of the serve. Figure 1 shows the application scenario of our system.

To implement the proposed system, we address several challenges in practice. First, while a standard and high quality serve always correctly follows the 8-stage serve model, there are also many serves, especially the serves of the low-level players, in these serves the boundary of different stages are not as clear as the good serves. This situation request the robustness of serve assessment algorithm for adapting among different levels of player. Moreover, since the process of a tennis training always involves other unconcerned activities such as bouncing the ball, running in the court, we need precisely identify and locate the serve segment and filter the data of other motions. Lastly, in order to provide real-time feedback, the serve evaluation algorithm must be low time complexity while achieving good accuracy.

The main technical contribution of our work lies in an online assessment system. In order to achieve accurate online evaluation, we propose a novel online serve extracting approach which precisely identifies and locates the serve segments and filters the non-serve events such as forehand and backhand strokes. In order to provide in-depth assessment of the serve performance, we propose a novel hierarchical evaluation method based on serve segmentation. After extracting the serve segment, we use hidden Markov model(HMM) to segment the serve into eight stages on the basis of the 8-stage serve model. By extracting the features from each of the stage, we propose a regression model to make score on the performance of the serve. The evaluation result is based on the analysis of the sub-stages of a serve, not directly based on the simple domain knowledge.

To evaluate the performance of our system, we conduct experiments to collect 1,030 serves involving 12 subjects at various professional levels. Evaluation results demonstrate that our TennisMaster system achieves 96.0% serve detection precision and 94.9% phase dividing precision of the system. In addition, we achieve an average mean absolute error (MAE) of 0.398 for the serve assessment accuracy, which is quite a promising result.

The remainder of this paper is organized as follows. We introduce the related work in Section 2 and present the system design in Section 3. The implementation and evaluation for our proposed solution is discussed in Section 4. Finally, we conclude the paper in Section 5.

2. RELATED WORK

Skill assessment is an important research direction in pervasive computing. Existing skill assessment approaches are typically through two methods: the assessment based on domain knowledge and the assessment based on segmentation.

For the assessment based on domain knowledge, for example, in [18] Ladha et al. propose a climbing skill assessment system called ClimbAX, this system uses power, control, stability, speed as the assessment parameter to evaluate the climbing performance. In [21] Robin et al. propose a framework for automatically providing quality feedback about dressage, the evaluation is based on the measurement of six fundamental aspects: (1) Rhythm; (2) Suppleness; (3) Contact; (4) Impulsion; (5) Straightness; and (6) Collection.

In recent years, many research go further and analyze the motion through segmentation methods which evaluate the quality of the motion based on the result of the segmentation. For example, in [13], Joseph proposed an audio-based method for evaluating tooth brushing performance, they use hidden Markov models (HMMs) to recognize various types of tooth brushing actions, such as brushing the outer surface of the front teeth and brushing the inner surface of the back teeth, then use the output of HMMs to build the regression model for the tooth brushing performance evaluation. In [14], Ghasemzadeh et al. using a method called motion transcript to evaluate the performance of the baseball swing, the transcript describes the order and timing of sub-motion, so that the quality of the swing is decided on the coordination of certain sub-motion.

3. SYSTEM DESIGN

In this section, we describe the computational pipeline and design details of our TennisMaster system. We first introduce our serve assessment model and sensing platform, and then describe the system overview, followed by each step of the pipeline.

3.1 8-Stage Serve Evaluation Model

Tennis serve is the most complicated stroke in tennis playing. In this section, we analyze the tennis serve through the 8-stage serve model proposed by Mark et al. [17] to get an intuitive segmentation of the tennis serve. This model uses the kinetic chain theory [12] to analyze the whole process of the serve, which was first studied in nationally ranked tennis players over 25 years ago. According to this model, each tennis serve can be divided into 8 stages: start, release, loading, cocking, acceleration, contact, deceleration and finish. These eight stages map to three phases in the serve: preparation phase, acceleration phase and follow-through phase. The 8 stages of the model are listed in Figure 2. In this study, we use Hidden Markov Models (HMMs) based on IMU characteristics to recognize the above eight stages in the serve process. The performance assessment of the serve is then based on the output of the segmentation.

3.2 Sensing Platform

The players in the studies are asked to wear two IMU sensors in the process of the training. The inertial measure module consists of a 6-axis inertial measurement unit B-MI160 which is an integration of a 3-axis accelerometer and a 3-axis gyroscope and 3-axis compass HMC5983. Each of the sensor transmits the readings to the mobile phone through BlueTooth-V2.0. The modules are also equipped with a 600mAH battery, which could enable the modules work as long as 6 hours. The size of the module is 47*43*17mm, which is comfortable for mounting on the body. The consumption of the module is 240mw, with the sampling rate of 100Hz. The IMU sensors are mounted on the right shank and the bottom of the racquet, as shown in Figure 1.

3.3 System Overview

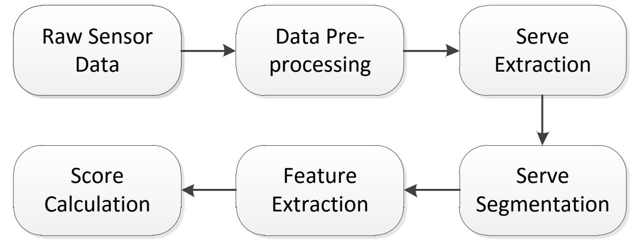


Figure 3: The computational pipeline of TennisMaster.

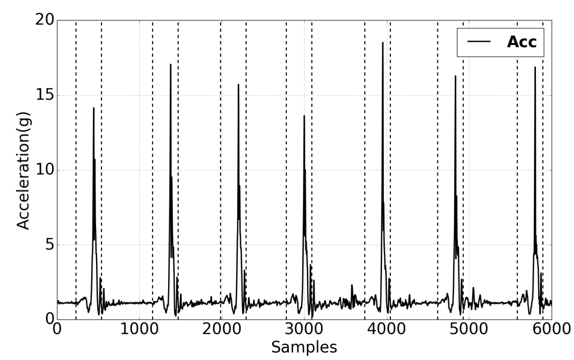
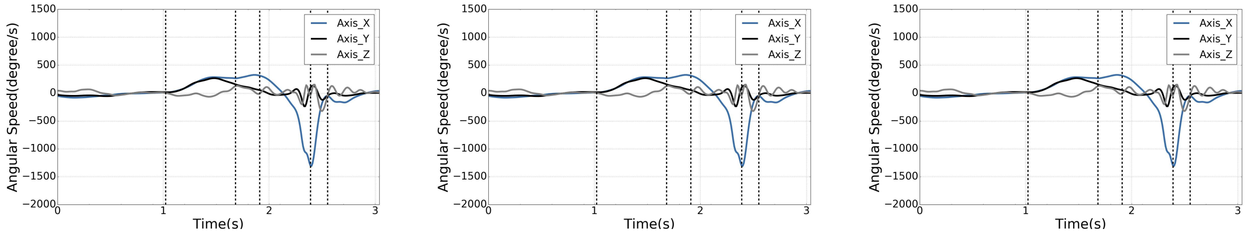


Figure 4: An illustration of serve extraction. When the acceleration exceeds the threshold, the data around the detected point is extracted as candidate event.

Figure 3. presents an overview of the computational pipeline of Tennis Master, which analyzes the raw streaming of the accelerometer and gyroscope data and output the assessment of the serve performance. The first step of the pipeline is to filter the raw data. The second step of the pipeline is the serve extraction process, we first locate the candidate event and filter the non-serve event through Support Vector Machine (SVM). As the third step, we divide the serve into several stages according to the theory of 8-stage serve assessment model. First, we detect the impact stage of the serve, so that the serve segmentation problem is converted to the segmentation before the impact phase and after the impact phase. Then, we use HMM to segment the phases before and after the impact stage into certain stages through Viterbi algorithm [20]. Fourth, we extract features for the assessment of the performance of the serve. The feature extraction protocol is based on the evaluation metric of the first serve emphasizing the speed and placement of the tennis. Our serve evaluation model assesses the serve from three aspect: rhythm, power and gesture, each of the aspects is evaluated through the feature extracted from different stages of the serve. The last step of the pipeline is the score calculation step. The score of the serve is based on the features extracted before. By extracting the features on the basis of the serve segmentation, we propose our serve scoring algorithm based on regression model.

3.4 Serve Extraction



(a) Elite (b) Mid-level (c) Novice

Figure 5: An segmentation result of the serve in the player of three different levels. The five dashed divide a whole serve into several stages through our serve segmentation method. The stages are, from left to right: start, release and loading, cocking, acceleration, deceleration and finish with the fourth dashed as the impact point.

The basis of serve extraction is detecting the candidate events. In this study, we propose the magnitude of the acceleration of racket as detector to detect the candidate events. The magnitude of acceleration is calculated by the 3-axis readings of the accelerometer mounted on the racket, x_t, y_t and z_t representing the acceleration of X-Axis, Y-Axis and Z-Axis, using the equation: $m_t = \sqrt{x_t^2 + y_t^2 + z_t^2}$.

Our serve extraction method contains three steps. First, the algorithm will continuously maintain "listening" at the data sent from the IMU sensor to the smartphone and calculate the magnitude of the acceleration in realtime. Once the magnitude of the acceleration exceeds the threshold of event detection, this means that a candidate event in the training is detected. Based on the detected point x_i, the candidate events are extracted around the detect point in the range $[x_i - a, x_i + b]$, the value of a,b in this step is set through the average length of a serve.

Then, after getting the candidate events, we need filter the non-serve events from the candidate events. Since the characteristics between the stroke events and non-stroke events are obvious, we first make a classification between stroke events and non-stroke events. We use the features of the accelerometer readings from different players to train a classifier between stroke events and non-stroke events. The classification method we use is Support Vector Machine (SVM), which is proved to be useful in most of the classification problems. The third step is to recognize the serve events from the stroke events, this is a problem of classification between the forehand, backhand and serve. Similarly, the classifier between the three stroke events is trained using SVM through the features of the accelerometer readings.

The features use to train the classifiers are computed using the acceleration readings from the racket, and do not involve the data from the other sensor. These features involve the time-domain features and heuristic features et al., which are proved to be useful in stroke classification [9]. In our experiment, the threshold of the event detection is empirically set to 5g, this threshold could filter out most of the slight movement in the tennis training, and keep the intense movement, such as the fast running. Figure 4 illustrates an serve extraction example using racket acceleration.

3.5 Serve Segmentation

The next step of serve assessment is serve segmentation. In this study, we use HMM based on IMU readings to recognize the eight stages described above. To correctly divide the serve into eight stages, a signal processing chain was developed:

- detect the impact stage of the serve.
- segment and extract features of the IMU readings before and after the impact stage.
- apply hidden Markov models to divide the rest stages of the serve.

First, we detect the impact stage of the serve, thus the segmentation of the serve can be changed into the segmentation of the stage before the serve, and the segmentation after the serve. This usually improve the accuracy of the segmentation, since the impact stage has obvious characteristics. The impact stage detection is based on the observation that when the tennis impact the racket, there will be a hop in the acceleration of the racket, and the acceleration always get maximum before the hop, after getting the minimum of the acceleration, a second hop will cause the acceleration to another maximum.

The second step of the segmentation is segmenting the serve and extract the features from each of the segments. We segment the serve through a window of 80ms with 50% overlap. The features of the segment involves the readings from both accelerometer and gyroscope of the racket.

The third step of the segmentation is using HMM to segment the sensor data before and after the impact stage into certain stages according to the 8-stage model. The motion of serve is an 8-stage process with obvious boundary between each stage, which can be described by Hidden Markov Model (HMM). Considering a HMM with N observation states and M hidden states, the observation states and hidden states in HMM can be defined as:

$$S = \{S_1, S_2, \cdots, S_N\} \quad (1)$$

$$V = \{V_1, V_2, \cdots, V_N\} \quad (2)$$

We can use a five-item tuple $\lambda = \{M, N, \pi, A, B\}$ to define it. $A = \{a_{ij}\}$ donates the transition matrix which contains the probability transits from state i to state j, where:

$$a_{ij} = P(q_t = s_j | q_{t-1} = s_i) \quad (3)$$

$\pi = \{\pi_i\}$ is the initial probability, where:

$$\pi_i = P(q_0 = s_i) \quad (4)$$

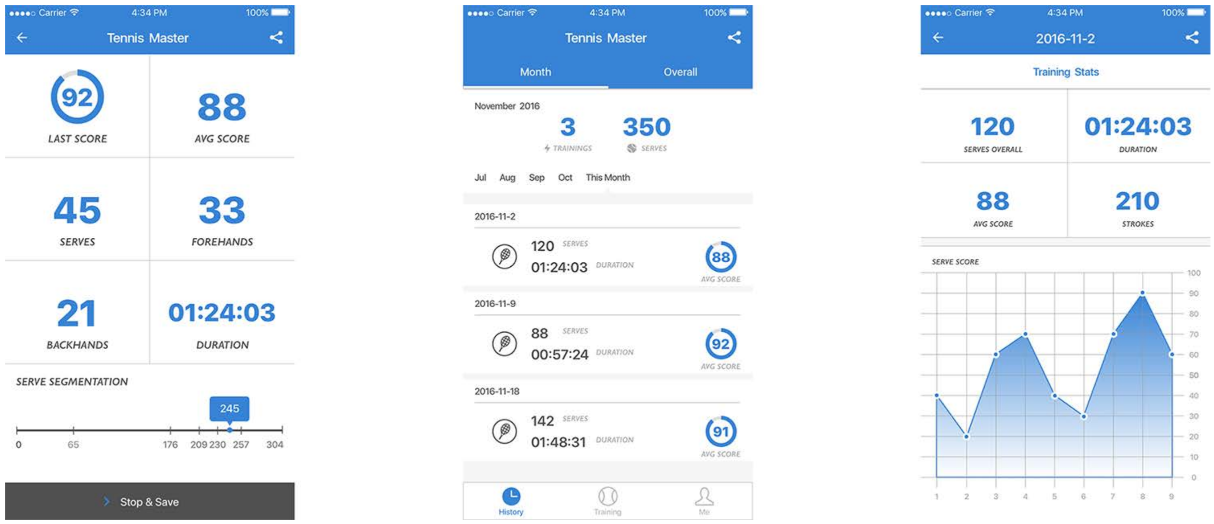


Figure 6: The APP screenshots of our system. (a) The screen showing the serve score and stroke numbers of the player during the training. (b) The screen showing the history of the user. (c)The screen gives an detailed description of a former training with the score of every serve in the training process.

$B = \{b_j(k)\}$ denotes the observation matrix which contains the probability of observation state k related from hidden state j, where:

$$b_j(k) = P(O_t = v_k | q_t = s_j) \tag{5}$$

In this problem, $O = \{o_0, o_1, o_2, ..., o_t\}$ which denotes the sequence of observations is modeled as the IMU readings, $S = \{s_0, s_1, s_2, ..., s_t\}$ which denotes the sequence of hidden states is modeled as the serve stage sequence. The problem of serve segmentation is equivalent to finding the most probable serve state sequence from the IMU readings which can be defined as:

$$S^* = arg\max_s P(O, S|\lambda) = arg\max_s \{P(O, S|\lambda) \cdot P(S|\lambda)\} \tag{6}$$

through Viterbi algorithm we can solve this problem using the Viterbi likelihood (score):

$$S^* = arg\max_s \pi_s b s_1(O_1) \prod_{t=2}^{T} a_{S_{t-1}S_t} b_{S_t}(O_t) \tag{7}$$

In this problem, we use Gaussian Mixture Model (GMM) to model the observation matrix $b_j(O)$, where:

$$B = \{b_j(O)\}, b_j(O) = \sum_{l=1}^{M} c_{jl}(0, \mu_{jl}, U_{jl}) \tag{8}$$

O in this equation is the observation vector, M is the number of mixed Gaussian elements contained in each state, G donates the normal Gauss probability density function, c_{jl},μ_{jl},U_{jl} is the weight, mean vector, covariance matrix of the jth mixed Gauss elements in lth states.

A_{ij} can be calculated as the number of segments in the training set extracted in the last step with a transition from stage q_i to stage q_j divided by the total number of segments labeled as stage q_i. Generally, we can estimate the transition matrix as follows:

$$P(q_t = s_j | q_{t-1} = s_i) = \frac{Count(q_{t-1} = s_i | q_t = s_j)}{Count(q_{t-1} = s_i)} \tag{9}$$

We use the video of each serve as the ground truth of the segmentation, the video of each serve is segmented manually as the reference of the segmentation. We limit the least time of each stage based on the statistical results of the experiments. Figure 5 illustrates an example of segmentation in different levels of player.

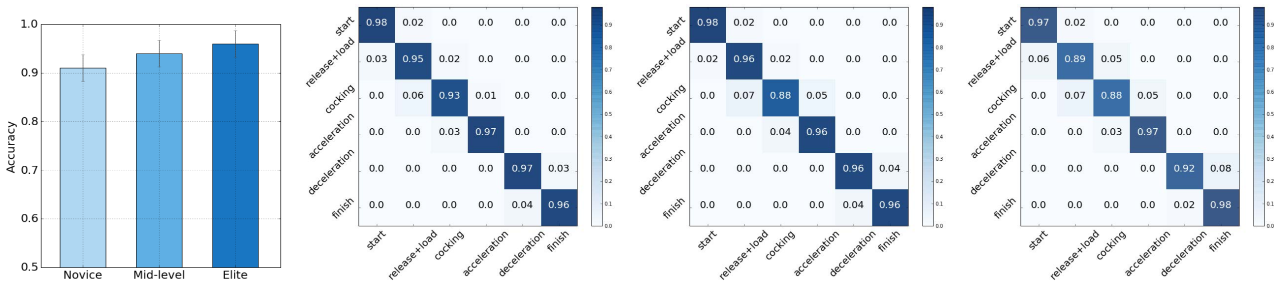
3.6 Feature Extraction

The scoring metric is based on the segmentation result of the step above. Since a whole serve can be divided into eight stages, each stage has a distinct impact on the serve. For example, at ball contact stage, ball velocity is determined by shoulder internal rotation and wrist flexion. What is more, as is described in [17], the power and angle variance of the joint in each of the stage is the vital contributor to the performance of the serve. We evaluate the performance of a serve in three aspects: rhythm, gesture and power. The feature extraction protocol is based on the three aspects.

For the assessment of rhythm, we use the duration of the 5 stages: release, loading, cocking, acceleration, deceleration, except the stage of start, finish and impact as the rhythm feature. The duration of these stages usually different among different levels of serve, since the high quality and low quality finish of different stages usually cause different time duration.

For the assessment of gesture, we use the orientation characteristics for the evaluation, since different orientation of the sensor usually reflects different motion. On the basis of this consideration, we use the average of pitch and roll of the IMU sensors in each stage except the impact stage as the gesture feature to evaluate the gesture performance in the serve. The angle of the sensors mounted on the shank and the racket are both used for the gesture evaluation, since the serve is a motion corresponding to the whole body, and the upper and lower body are both involved in the serve.

For the assessment of power, we use the average signal energy of the IMU sensors in the acceleration stage,impact stage and deceleration stage to evaluate the power perfor-



(a) 3-level Accuracy (b) Elite (c) Mid-level (d) Novice

Figure 7: (a)Shows the accuracy of serve segmentation of 3 different level of players. (b)-(d)Shows the corresponding confusion matrix of 3 different levels.

mance in the serve, since the acceleration stage is the stage to build up the power for the impact point, and the energy of the impact stage always reflect the ball hitting strength. These two stages along with deceleration stage form the three most powerful stages in the serve. The signal energy of the stage can be calculated using the 3-axis accelerometer signals of the X-axis $a_x(t)$, the Y-axis $a_y(t)$ and the Z-axis $a_z(t)$ as follows:$E(t) = a_x^2(t) + a_y^2(t) + a_z^2(t)$

3.7 Score Calculation

The last step of our serve assessment pipeline is to predict the serve score with the features extracted in the above subsection. We model it as a regression problem, which aims at performing the serve score to the user with least error. In order to choose the regression model with best performance, we compare various kinds of regression models, such as regularized linear regression, regression trees, and support vector regression using cross-validation. After comparing the predicting result of these models, we choose linear regression model as our serve assessment model. In order to avoid overfitting, we also use L1 regularization as the feature selection method.

4. IMPLEMENTATION AND EVALUATION

We have finished an Android-based app as the implement of our system. The whole data processing pipeline of Tennis Master from serve detection to serve evaluation is performed on a smartphone. Our application could inform the player with the score after the player perform a serve in the training, the user can also get the number of the serve and strokes that performs in the training. Before starting the training, the user should click the start button to enable the system start the built-in algorithm. After that, the player can start training, every time the system detect a serve in the training, the view serves will be added, and inform the player with the score of the serve. The user can also use the app to watch former training, to get a view of the former training log, and each score of the serve can be achieved from the former training log. The screen shots are shown in Figure 6. The complete serve detection and analysis algorithm is implemented using the Java language. The serve detection algorithm is running during the whole training process.

4.1 Data Collection

In order to evaluate Tennis Master, we recruited 12 subjects and collected data from 40 trainings in total (1,030 serves). Based on their self-report information, we divided the subjects into three categories: *Novice level*, *Mid-level*, and *Elite level*. Our experiments for data collection was conducted in a tennis court of our university. In order to collect data, each subject used a smartphone (Google Nexus 5) and two IMU sensors during the experiment. The IMU sensor nodes are mounted on the right shank and the bottom of the racket.

The ground truth for serve evaluation is collected in the following two ways. For the ground truth for the evaluation of the serve, we invited the professional tennis coach to give score to each of the serve in the training set. The level of the player forms the nominal score of the serve, and the placement and speed of the serve form the performance score of the serve. The score of each serve is the sum of nominal score and performance score. For the evaluation of the ground truth of the segmentation, we take video for each of the serve, and segment each of the serve into eight stages manually.

Table 1: The performance of serve extraction.

Session	Precison(%)	Recall(%)	F1-score(%)
Stroke detection	97.02	90.76	93.16
Serve detection	98.96	96.13	97.04

4.2 Performance of Serve Extraction

We first examine now how well we can recognize the serve event during the whole process of a training. First, we evaluate how well individual stroke events can be detected by the Support Vector Machine (SVM) classifier which examines each segment independently of the others. Then we evaluate the performance of the SVM that infers the type of stroke for each segment. And we perform 5-fold cross validation towards the two classification problem involving all the stroke events and non-stoke events detect using our serve extraction method. We can see that the precision in the stroke event detection using Support Vector Machine classifier is over 97.02%. The detection precision in the serve events detection among the stroke events is 98.96%. Considering the 2 steps together, the overall precision of serve detection in the all data is 96.01%. The result of serve extraction is shown in Table 1. We can see that our serve detection algorithm performs well in the experiment. It is apparent that our serve event detection is sufficiently accurate.

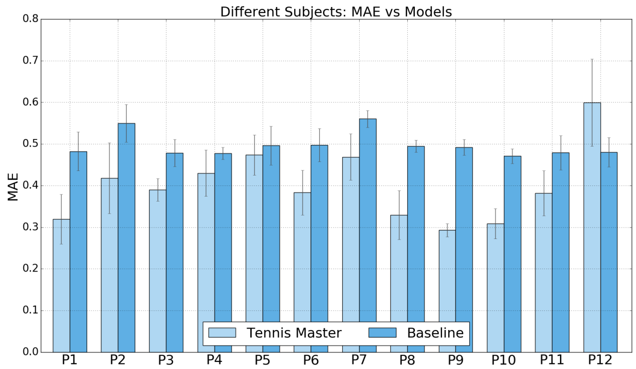


Figure 8: The assessment performance between different number of sensors.

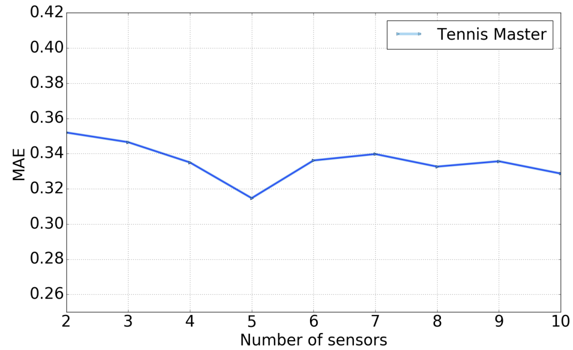


Figure 9: The assessment performance between different number of sensors.

Table 2: The serve segmentation performance of all the stages.

Stage	Precison(%)	Recall(%)	F1-score(%)
start	97.59	96.04	96.81
release+loading	93.88	91.40	92.62
cocking	90.06	93.83	91.91
acceleration	96.71	96.40	96.56
deceleration	94.90	96.40	95.64
finish	96.84	97.14	96.99

4.3 Performance of Serve Segmentation

We then explore the segmentation performance achieved by Tennis Master. Twelve players participated in the experiments. Table 2. shows segmentation performance of Tennis Master with different players in the 6 stages. We can see that the average F1-score in the six phase is over 95%. Considering the 6 stages together, the highest F1-score is 96.99%, the lowest F1-score is 91.91%. We can see that TennisMaster performs well in our serve dataset at the 6 different stages. The difference between the maximum and the minimum F1-score is 5.1%.

The players of different level may perform serve with different quality, the serve between high level and low level is usually very different, thus we further investigate the impact of the level of the players on the performance of Tennis Master. The classification result of 3 different level of players are shown in Figure 7. It can be seen that Tennis Master achieves good accuracy both on level elite and mid-level players with accuracy of 96.28% and 94.03%, but the accuracy is slightly lower on novice level with accuracy of 90.86%. This is because the players of high level usually perform the serve with standard, and the player of low level usually perform the serve with bad quality, and these serves usually different from person to person. In addition, the serve of the low level players usually tend short in some of the stages, this makes the recognition of these stages more difficult. These stages are usually falsely recognized into other stages.

4.4 Performance of Score Calculation

We use the mean absolute error (MAE) and Pearson correlation to measure the performance of score prediction. MAE measures how close predictions are to the outcomes. We also use Pearson correlation to measure the linear relations between the ground truth and the predictive score.

For comparison, we choose another knowledge-based serve assessment method as baseline. For the knowledge based assessment, we use the peak values of the upper arm internal rotation, wrist flexion, and shoulder rotation before impact stage as the feature representation of a serve, since these three motions are the main contributors to the performance of a serve. The calculation method of these three elements can be get in [5]. The score of the serve evaluation is based on the 5-point scale. And we perform 5-fold cross validation using the two assessment method on all of 12 players. We use P1, P2,..., P12 to denote them respectively. We use half of the serve sets of all the 12 players as training set, and use the rest serves with each of them to test the performance of the two models. The average MAE of tennis master is 0.398 through the evaluation of 12 players, which is much better than the average MAE of baseline: 0.458, the result is shown in Figure 8. The predicted serve performance strongly correlates with the ground truth , with the Pearson correlation of 0.702.

4.5 Performance of Various Sensor Placements

In this system, we use two sensors to evaluate the performance of the serve, this design choice is based on the result of our sensor selection protocol. At first, we mount sensor on all of the eight limb of the body as well as the chest and the bottom of the racket. The power features and gesture feature were extracted from all of the ten sensors. Then, we perform feature selection method through the RRelief-F algorithm, this algorithm can calculate the weight of the feature which indicates the importance of the feature. And the importance of the sensor in the system is indicated by the sum of the feature extracted from it [13]. Through this we sort the importance of the ten sensors in the system.

Figure 9 shows the MAE of the serve assessment with different number of sensors. At first we use all of the 10 sensors to assess the performance of the serve, and each time we discard the least important sensor through the method above. We can see from the figure, that when the number of sensor is larger than 5, the MAE tends not to become smaller with the raise of sensor number and the MAE various small when the sensor number is 2, 3, and 4. In consideration of the mounting comfort, price and accuracy, we choose the sensor number as two.

5. CONCLUSION

Wearable devices play an important role in the research and application of cyber physical systems. In this paper, we present the design, implementation, and evaluation of TennisMaster, an IMU-based online feedback system to perform on-line assessment of tennis serve to the player during the training process. TennisMaster provides accurate and real-time evaluation of serve performance. The evaluation is based on the segmentation of the serve and makes assessment through the fields of power, gesture and rhythm. Experimental results demonstrate that our system achieves excellent accuracy in the recognition, segmentation and performance evaluation of tennis serve.

6. ACKNOWLEDGMENT

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