An Embedded 6-axis Sensor based Recognition for Tennis Stroke

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***Abstract*—In recent years, sensors are widely used in outdoor activities for returning motion information to participants. This paper proposes a product that could send back information about the tennis stroke while playing tennis in real time. This product, consisting of sensor module, controller module and transmission module, is embedded in tennis handle. There are three steps for stroke recognition. Shot detection as the first step in this process uses fluctuation of acceleration based on moving windows. Secondly, data on windows that detected as shots are used to divide those shots into 3 stroke types (forehand, backhand, serve) according to acceleration as well as angular velocity. At last, more information about how the ball rotates would be acquired based on the angular velocity. This step would divide forehand or backhand into topspin or backspin. Different from widespread wearable sensors, this product is embedded in the racket handle without attachment to body and the information of motion would be sent to our mobile phone in real time. The experimental result shows high accuracy for motion recognition with 98% accuracy for shot detection and 96% accuracy for stroke types recognition.**

***Keywords*—motion recognition; sensor; tennis;**

I. Introduction

Sensors have been widely applied in outdoor activities for acquiring more information about motion in order to upgrade their skills. Whereas, sensors did not play an important role in this field in the past when most information for motion recognition came from videos or images. As the development of MEMS (Microelectromechanical Systems), sensors in motion recognition [1] or classification [2] attract more attention because of its reasonable price as well as portability. The 6-axis sensor embedded in this product is used to acquire motion information, such as accelerometer, that would be used for tennis stroke recognition. This paper proposes a simple model for tennis stroke recognition. At first, our model detects the candidate strokes based on standard deviation of resultant acceleration in moving windows, and differentiates candidate strokes from nonstrokes. Then the sensor data during the shot is used to classify strokes into three stroke types (forehand, backhand and serve). At last, the proposed model also returns information about how the tennis rotates (topspin and backspin). It is proved that this model achieves 98% accuracy in shot detection, 96% accuracy in recognizing stroke types, and 80% accuracy in rotation detection.

II. Related Work

Some previous publications have focused on acquiring the movement information in tennis using videos or sensors. In [3], the affordable visual sensing equipment was used to detect key tennis events, and in [4], a sensing platform, consisting of a video network and wearable sensing technology, was proposed to provide athletes with different performance factors. Both of them used visual sensing equipment. A new contribution that can detect the stroke and classify tennis strokes without visual sensing equipment was delivered in [5]. The inertial sensor data from wrist was used to train the classifiers that would be used to detect stroke and classify stroke types. In [6], obtaining data from inertial sensors on the wrist, it used Pan Tompkins algorithm for detecting the shot and time warping based hierarchical shot classifier for classifying stroke types. Compared with [5] and [6], our inertial sensor is embedded in tennis handle rather than worn in wrist. And our model does not need training for classifiers. Our proposed approach makes shots detection and stroke type classification simpler with high efficiency in real time.

III. System Architecture

The proposed system design of this product for recognition of tennis stroke is shown in Fig. 1. This system is made up of the hardware architecture and the algorithm model. For hardware architecture, there are three modules including sensor module, control module and transmission module. Initial data obtained by sensor JY-61 would be transmitted to the control module. The control module, where the proposed model for shot detection and stroke recognition is programmed on, is the core module and the microprocessor STM32F405[7] is selected in this product. Finally, the output about stroke would be transmitted to user through Bluetooth in real time. For the model programmed in the microprocessor would use the sensor data to implement the recognition. The model would detect the shot first and classify those shots later.

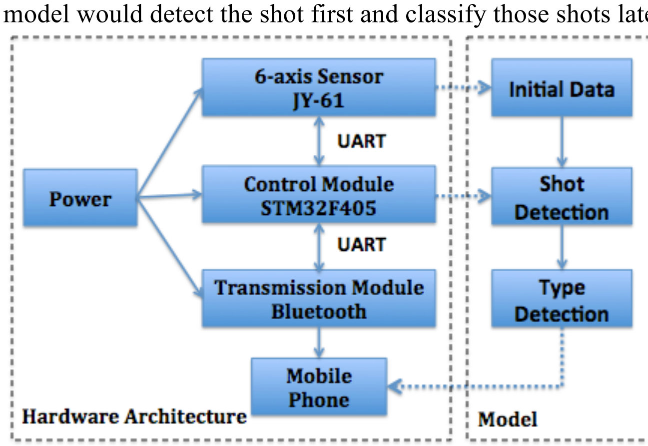

Fig. 1. System design

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IV. Shot Detection

Shot detection is the first step in stroke recognition. The sensor embedded in our product would provide us with motion information, such as accelerations, angular velocities and Euler angles, reflecting the movement of tennis racket. Three steps are necessary to certify whether it is a stroke from initial sensor data. Stroke is quite different from nonstroke because a sudden spike in acceleration would appear during shot.

A. Data partitioning and feature extraction

A suitable window with 50% overlap is applied in initial data for data partitioning. For each window, the feature values are proposed to represent this period. Some characteristic parameters are introduced to reflect the volatility and detect shot based on those feature values because shots generate specific fluctuation that would make quite difference in feature values. The size of windows could not be too large or too small, resulting in no shot or more than one shot are contained in a window. Different characteristic parameters selected for shot detection results in different accuracy. The detection accuracy results using different characteristic parameters are shown in TABLE I.

B. *Detection* of stroke candidate

The feature value that reflects the volatility is used for shot detection. The larger value it is, the more volatility it has, and the higher probability it would be a shot. Only when the feature value reaches a threshold, it can be detected as a stroke candidate.

C. Confirmation of shot from candidates

This step is necessary because some swings without shot would be likely detected as a stroke candidate. For each candidate, the difference in the acceleration between adjoining points is calculated and the shot points are detected while the maximal difference in the window reaches another threshold because the impact makes greater difference in short period.

TABLE I
ACCURACY OF SHOT DETECTION WITH DIFFERENT PARAMETERS

Characteristic Parameter	**Strokes**	**Swings**	**Accuracy %**
Maximal Acceleration	160	160	96.56
Standard Deviation	160	160	98.75
Single Range	160	160	96.25

For each parameter, 320 samples (160 strokes and 160 swings) are tested. The maximal acceleration is the maximum of resultant acceleration while the single range is the difference between the maximum and minimum. As the table shows, the standard deviation works well in shot detection.

V. Stroke Recognition

After the shot was detected, the information around the shot point could be used to classify the stroke types (forehand, backhand and serve). For each stroke types, the additional work in this model is to describe the tennis rotation mode, in other words, whether it is a topspin or backspin.

A. Preprocess of raw data

Initial data from sensor contains accelerations, angular velocities and Euler angles. The Euler angles could be used to calculate the gravity for 3 axes. The transformation is shown in Fig. 2.

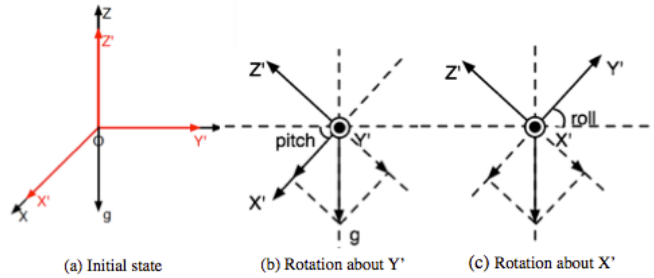

Fig. 2. Initial state and rotation

Euler angles include yaw (rotation about Z'-axis), pitch (rotation about Y'-axis) and roll (rotation about X'-axis). Here we use g_x, g_y and g_z to represent the gravity in X'-axis, Y'-axis and Z'-axis respectively.

1) *Rotating yaw about Z'-axis*

Since the gravity is on Z'-axis completely, the rotation about Z'-axis makes no difference for the gravity. The distribution of gravity is described in (1).

$$g_x = 0, \quad g_y = 0, \quad g_z = -g \tag{1}$$

2) *Rotating yaw about Y'-axis*

This rotation leads to decomposition of gravity in Z'-axis shown in Fig.3 (b). The update of distribution of gravity is described in (2).

$$g_x = g * \sin(pitch), \;\; g_y = 0, \;\; g_z = -g * \cos(pitch) \tag{2}$$

3) *Rotating yaw about X'-axis*

The rotation makes gravity redistribution as shown in Fig. 3(c), which is the orthographic views in the X'-Y'. The update of gravity is shown in (3).

$$\begin{aligned} g_x &= g * \sin(pitch) \\ g_y &= -g * \cos(pitch) * \sin(roll) \\ g_z &= -g * \cos(pitch) * \cos(roll) \end{aligned} \tag{3}$$

The distribution of gravity converting from Euler angles with (3) would be used for obtaining the real gravity on 3 axes and reflecting the orientation of the tennis handle.

B. *Classification of stroke types*

Strokes can be classified into forehand, backhand and serve. For all shots detected above, they belong to one of those types.

1) *For serve or smash*

Different from forehand or backhand, the serve and smash hit the tennis over plays' head leading to more gravity contribution on Y'-axis. Only when the absolute value of g_y exceeds a threshold, it can be described as a serve/smash. There would be a long time between a serve and last stroke while a short time between a smash and last stroke. The time duration between two strokes would separate serves from smashes.

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2) *For forehand and backhand*

Because the sensor stays static in tennis handle, the key for detection is to recognize stroke types correctly no matter how the player holds the racket. It is obvious that there are two sides (side A and side B) in each racket, and the tennis hit on different sides would generate opposite values for each axis. The reference coordinate in tennis racket and the tangible product are shown in Fig. 3. In the following analysis, w_x, w_y and w_z represent the angular velocity on X'-axis, Y'-axis and W-axis respectively.

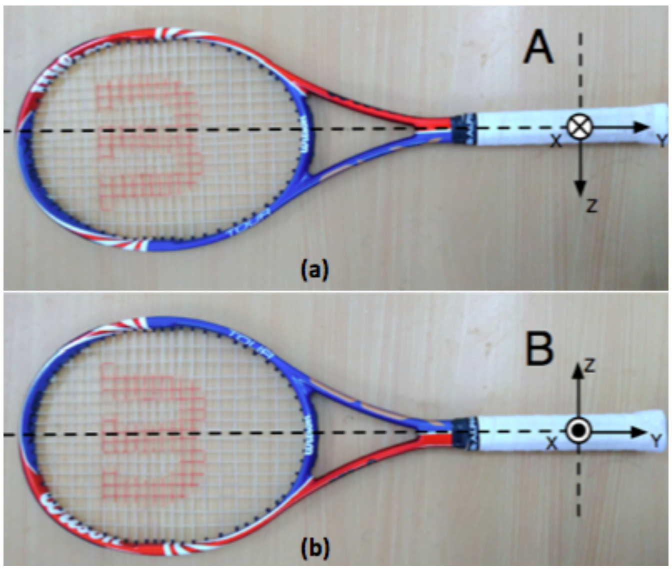

Fig. 3. (a)Reference coordinate in racket while side A is up. (b)Reference coordinate in racket while side B is up.

a) Forehand: As for forehand, if the player grips the handle with side A facing the opponent, which means the side A would hit the tennis and g_z is positive and w_z is negative because the racket trace is from right to left. The same analysis for griping the handle with side B facing the opponent shows that g_z is negative and w_z is positive.

b) Backhand: As for backhand, similar analysis is created for both side A and side B. The result shows that both g_z and w_z are positive using side A to hit tennis and negative while using side B.

Based on the analyses above, the product of g_z and w_z could distinguish the forehand and backhand as shown in (4). The waveform data of the sensor output is shown in Fig. 4, which (a) and (b) exhibit the forehand stroke and the backhand stroke respectively. Here we used the sign function to make the result directly. The sign function makes the negative product equal to -1 while the positive product to 1.

$$\begin{aligned} & g_z * w_z < 0, forehand \\ & g_z * w_z > 0, backhand \end{aligned} \tag{4}$$

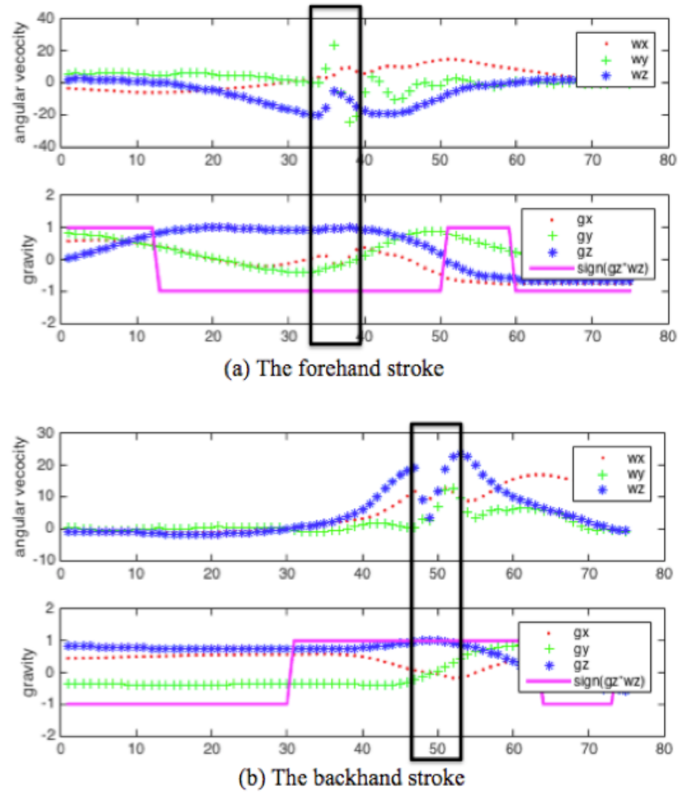

Fig. 4. The product embedded in racket handle

C. *Classification of tennis rotation mode*

As for tennis rotation, the topspin is a ball that rotates forward through lifting the tennis while the backspin describes a ball that rotates backwards. The angular velocity in X'-axis, w_x, makes a critical difference in tennis rotation. For a forehand stroke, either topspin or backspin is created through a certain rotation about X'-axis. The similar analysis for rotation styles shows that the product of g_z and w_x is positive in topspin while negative in backspin as in (5).

$$\begin{aligned} & g_z * w_x > 0, w_x > threshold, topspin \\ & g_z * w_x < 0, w_x > threshold, backspin \end{aligned} \tag{5}$$

For topspin or backspin, the w_x must be larger than a threshold, or it would be detected as a plat that holds little rotation while in moving. Based on the analysis above we can use this simple model to recognize the strokes in real time.

VI. Experimental Setup and Result Analysis

A. *Experimental setup*

Our product consists of three modules, including a sensor module, a control module and a transmission module. For sensor module, JY-6 is selected as a 6-axis sensor that has a 3-axis accelerometer with range of ±16g, and a 3-axis gyroscope with range of ±2000 degrees/s. The sampling rate is 100Hz and the baud rate between the sensor and the controller is 115200 bits/s. In control module, the STM32F405

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has a 32-bits floating-point unit and its frequency is up to 168 MHz. The baud rate of Bluetooth is 9600 bits/s. More details about our product embedded in tennis handle is shown in Fig.5.

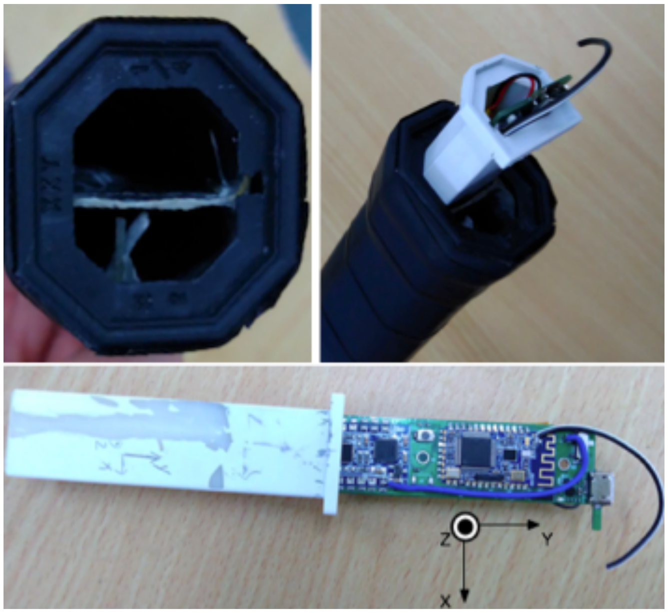

Fig. 5. The product embedded in racket handle

B. Result analysis

The accuracy of stroke recognition is shown in Table II. It turns out that the proposed model acquires more than 98% accuracy for shot detection and 96% accuracy for stroke recognition. The accuracy of the rotation detection is not as high as stroke recognition because there is no specific standard for topspin or backspin.

TABLE II
ACCURACY OF SHOT DETECTION WITH DIFFERENT PARAMETERS

Stroke types	Sample	Accuracy %
Forehand	350	96.8
Backhand	350	96.2
Topspin	350	80.6
Backspin	350	82
Serve	100	94
Smash	100	96
Stroke	1600	98.1

The comparison of our product with previous work is shown in Table III. The advantages of our product are shown as following.

1) *High accuracy:*

Compared with [5] which achieves 90% accuracy in shot detection and stroke recognition, our product achieves higher accuracy.

2) *More simplicity:*

Though [6] gets a higher accuracy with 99% accuracy in shot and stroke detection, our proposed model works in a simpler way without training and matching.

TABLE III
COMPARISON

	Accuracy %			Performance	
	Shot detection	Stroke type detection	Rotation detection	Simplicity	Real-time
Our work	98.1	95.75	81.3	Max	Max
[5]	<90	90	None	Medium	NA
[6]	99.41	99.45	88.45	Min	NA

[a] The accuracy of stroke detection is the average of the accuracy of all stroke (forehand, backhand, serve and smash). The accuracy of rotation detection is the average of the accuracy of topspin and backspin.

VII. CONCLUSION

We have described a product embedded in tennis handle that could recognize tennis stroke. We introduced the hardware architecture in this product and the simple model for shot detection and stroke recognition. At last, the experimental result and analysis show the high efficiency and accuracy of our product. The key of this product is the proposed model programmed in microprocessor for shot detection and stroke classification by making use of the information obtained by sensor. The experimental result turns out that our product works with high efficiency in real time. This product also needs to be improved for higher accuracy, particularly for the rotation. The model with higher efficient would be built and more useful information would be acquired in the future work.

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