Tennis Stroke Detection and Classification Using Miniature Wearable IMU Device

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Abstract — **This paper presents work related to tennis stroke detection and classification. For arm movement acquisition a miniature wearable IMU device, positioned on the player's forearm (right above the wrist) is proposed and presented. The device uses a MEMS-based accelerometer and gyroscope with 6-DOF. For reliable and accurate tennis stroke detection the information obtained from the accelerometer data is used, and for tennis stroke classification, information from gyroscope data is extracted and processed. The proposed system is able to detect and classify three most common tennis strokes: forehand, backhand, and serve. Because of limited memory and lack of processing power, the proposed algorithms for stroke detection and classification are quite simple, but are nonetheless capable of achieving high classification rate. Overall 98.1% tennis stroke classification accuracy was achieved.**

Keywords: **tennis, stroke detection, stroke classification, hand gestures, IMU, MEMS**

I. INTRODUCTION

Sport has always been a major part in human history and nowadays it is as popular as ever. In the modern age Olympic Games have more than 50 different summer and winter sport categories, wherein the number of individual disciplines is a lot higher. For example 47 disciplines in athletics alone are planned for the 2016 Olympic Games in Rio [1].

For sports fans, spectators, and also for sport commentators, game/match/event statistics are usually very interesting. Many television broadcast nowadays include live statistics about an event, e.g. a football match. The statistics can show how many goals were achieved, how many shots in and out of goal frame were kicked, how many corners, fouls, outs, off-sides, and penalties an individual football team achieved, how many kilometres has an individual player run, how many free shots were executed, etc. These statistics enrich an event and enable easier inter-event comparison.

For a tennis match, the following statistics are usually available: how many aces a player achieved, how many double faults occurred, first and second serve points won, net points won, break points won, winners, unforced errors, fastest serve, average first and second serve speed, etc. From these numbers tennis coaches and experts can get valuable information about the match and can even discover an individual player's advantages and weaknesses. In modern tennis electronic systems help with obtaining some parts of the final statistics and can also be used to help the tennis judge during the match. The system that can detect a ball out of court (electronic line calling) and provides instant video replays to assist tennis match officials with close decisions on line calls or foot faults is the Hawk-Eye [2]. The system also supports ball-tracking and detailed stroke analysis. It is based on several calibrated high-speed cameras, stationed around the court, and computer software for video processing. Authors in [3] propose a less complex and cheaper system for automatic annotation of tennis games. Their system is based on integration of computer vison, audio signal processing, and machine learning. The input into the system is broadcast tennis video without any manual pre-processing and pre-filtering. The output of the system is ball event detection and ball event classification in five categories: serve, hit, bounce, net, and null, which characterize erroneous event detection.

II. RELATED WORK

Detection and classification of a tennis stroke can be defined also as a hand-gesture problem. Tennis has a variety of strokes, like the serve, forehand, backhand, volley, lob, smash, slice, etc. For example the forehand is a stroke where the open palm of the hand is facing the net, the backhand stroke is when the back of the palm is facing the net, the serve and smash are strokes where the hand is travelling over the head, etc. By recording the hand movement one can retrieve enough information to detect and distinguish tennis strokes. Hand-gesture recognition is an important field in HCI (Human-computer interfaces) area. It provides new input and communication methods that are closer to human nature [4]. Gestures are very popular, effective, and appropriate for virtual environments, especially video games. Authors in [5] propose a system for hand gesture recognition using Kinect for playing racing video games.

In general, gesture recognition systems use three basic approaches [6]: (1) sensor-based, (2) touch-based, and (3) vision-based approach. For sensor-based approach users have to wear special gloves or extra devices to be worn on hands [7]. In [8] authors propose a framework for hand gesture recognition based on 3-axis accelerometer and multichannel electromyography (EMG) sensors. Start and end points of the gesture segment are automatically detected by intensity of the EMG signals. For classification of gestures hidden Markov models (HMM) are used. Touch-based approach is popular with smart phones and tablets, where different single and multi-touch gestures are used to interact with the user interface or applications (e.g. tap, double tap, drag, flick, touch and hold, spin, etc.). The vision-based approach uses one or more video capturing devices to capture arm, hand or

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palm gesture or movement [9]. Till now many vision-based hand gesture methods have been proposed. These can be divided into two main categories: model-based approach and appearance-based approach. In general robust vision-based hand gesture recognition is often a challenging task, because of various scene backgrounds and illumination changes. Complex backgrounds with similar-to-skin colour can interfere with the detection and segmentation of the hand, while illumination can produce shadows and can interfere with the appearance of the hand [5].

Our system uses a sensor-based approach for the hand gesture recognition. This approach has been used in the past for various tasks and applications. Authors in [10] propose a wheel chair control based on 3-axis MEMS (microelectromechanical system) accelerometer movement detection. Based on the gesture the translated command for the wheelchair movement is left, right, forward, and stop. An acceleration-based gesture recognition approach, called FDSVM (Frame-based Descriptor and multi-class SVM) is presented in [11]. The proposed system uses a Nintendo Wiimote controller with Bluetooth connectivity to record the acceleration of the movement. 12 different gestures were analysed from a set of 3360 gesture samples. Tests on user-dependent and user independent cases were evaluated. In [12] authors propose a MEMS accelerometer based nonspecific-user hand gesture recognition system. The system is capable of distinguish between seven different hand gestures: up, down, left, right, tick, circle, and cross. Three different gesture recognition models were evaluated. The best model achieved a 95.6% overall recognition accuracy.

In the field of tennis stroke detection and classification some of the previous work can be found. A system for recognition of tennis strokes using key postures was presented in [13]. The system uses a single low cost camera for video capture. It tries to detect and classify the main strokes played in tennis, i.e. a serve, forehand, and backhand. The proposed approach is tested on a real-world dataset, obtained from players in a competitive training match. Researchers in [14] did an analysis of a tennis swing motion using a 3D gyro sensor and a microphone. The hybrid sensor was placed in the centre of the back of the waist, where the angular velocity of the body rotation was measured. Comparison between the advanced and novice players was performed. In [15] authors presented a framework to improve the detection of ball hit events in tennis games by combining audio and visual information. Their approach is to first attempt to track the ball visually and estimate the coarse detection of the ball-hit events. This information is used as a constraint for audio detection. Audio information is then used to refine coarse estimate of the ball hit event timing.

A well-known tennis equipment company Babolat developed a system, called Babolat PLAY, for evaluation and analysis of a tennis game. The system is integrated into the racket handle and it uses a Bluetooth connection to connect with a smart mobile device. The racket logs different strokes and also the nature of the strokes, which are then synchronized with the mobile device. The application on the device is used for visualization of the game/training statistics, e.g. how many and which kind of strokes were played (serve, smash, forehand, backhand, volley), what was their velocity, etc. The system has 6 hours of autonomy with one battery charge. It uses accelerometer, gyroscope and piezoelectric sensors to detect the strokes [16]. Not much is publicly known about the system's design, therefore it cannot be compared in detail with our proposal. Babolat also has a wrist-worn device, called Babolat POP with similar performances as the Babolat PLAY. Similar systems that can be attached on the handle of the racket are manufactured by Sony and Zepp.

III. Stroke Detection and Classification System

A. Design of the IMU data acquisition module

Tennis players are very sensitive about their tennis rackets and individual player has his own favourite tennis racket manufacturer and model. It is understandable because the racket acts as an extension of the players arm. The racket mass, mass centre, racket string tension, racket size, and racket handle are customized to ideally suit the player [17]. We therefore decided that our device will be located on the player's writs and attached with a rubber band. Device placement and sensor orientation is shown in Fig. 1. Block diagram of the proposed IMU (inertial measurement unit) data acquisition module is depicted in Fig. 2.

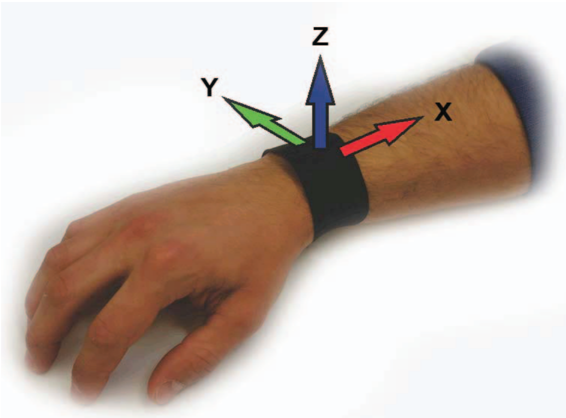

Figure 1. IMU device placement and sensor orientation.

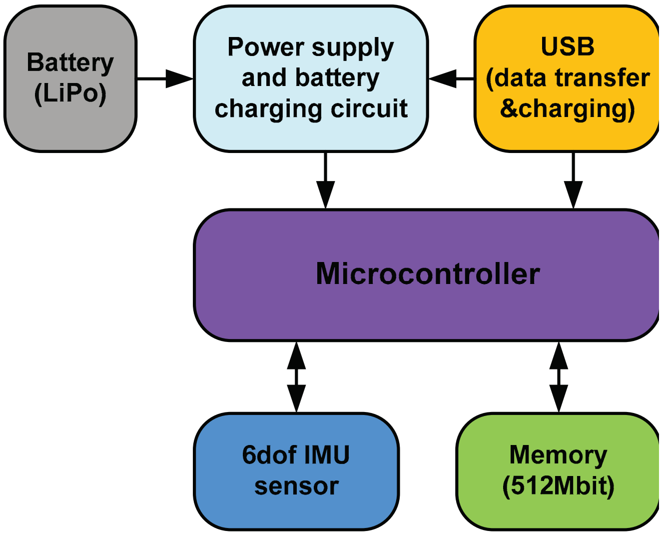

Figure 2. Block scheme of the proposed IMU data acquisition module.

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Before the detailed description of the module's individual units is given, explanation of the motivation behind the system's design is needed. The goal was to design a light-weight IMU acquisition device that can be attached on the wrist of a tennis player without influencing on the player's performance. The device has to operate in a stand-alone mode and detect and classify strokes in real-time. The device should have the maximum battery autonomy possible, therefore a low power consumption design has to be considered. For this reason, wireless connectivity was not an option (USB interface was used). The device also has to have enough memory for continuous game play recording with a sampling frequency large enough that will allow a detailed stroke analysis.

The main unit of the IMU data acquisition module is a microcontroller. It is an AVR type 8-bit microcontroller running at 32MHz. The IMU sensor is an integrated MEMS 3-axis accelerometer and 3-axis gyroscope, providing 6 degrees of freedom (6-DOF). Accelerometer and gyro support ±16G 16-bit acceleration and angular velocity sensing. The sensor is connected with the microcontroller via a dedicated SPI bus for maximum data throughput. Sensor is sampling the acceleration and gyro data with the rate of 1000 samples per second. Information is stored in memory with a storage capacity of 512MBit. In continuous-sampling mode this memory capacity is enough for almost 1.5h of recording. When a new recording session is initiated, time stamp information is also written to the beginning of the record-block in memory for easier video and IMU data synchronization. For time-keeping, a RTC (real time clock) unit of the microcontroller is used. The power supply unit provides a stable 3.3V voltage supply for the module and it is also responsible for the battery charging process. The power source is a 155mAh Li-Po battery. The module draws approximately 30mA of current, when in working mode. In stand-by mode current consumption drops down to 400uA. The battery has enough energy for over 5h of operation in working mode and over two weeks in stand-by mode.

B. Tennis stroke detection and classification

For the task of tennis stroke detection and classification we limited ourselves on classifying the three most often tennis strokes: serve, forehand, and backhand. Because of the low processing performance and limited memory capacity, the stroke detection and classification method has to be simple and fast. We first started with the observation of the accelerometer and gyro data of all three different strokes. Graphical representation of the mentioned strokes is in Fig. 3.

From observation of Fig.3 it can be concluded, that there is some similarity between strokes. E.g. serve and forehand have very similar acceleration curves, and also peak acceleration value is not a discriminative feature. By close observation of the gyroscope data more discriminative features between the strokes can be found. It can be seen that different peak values of individual gyro axes are achieved for serve, forehand and backhand around the point of impact (this is the moment when tennis ball hits the racket). E.g. for the serve min. and max. gyro values are achieved in the Z and X axis, whereas for the forehand min. and max. gyro values are achieved in the Y and X axis. Min. and max.

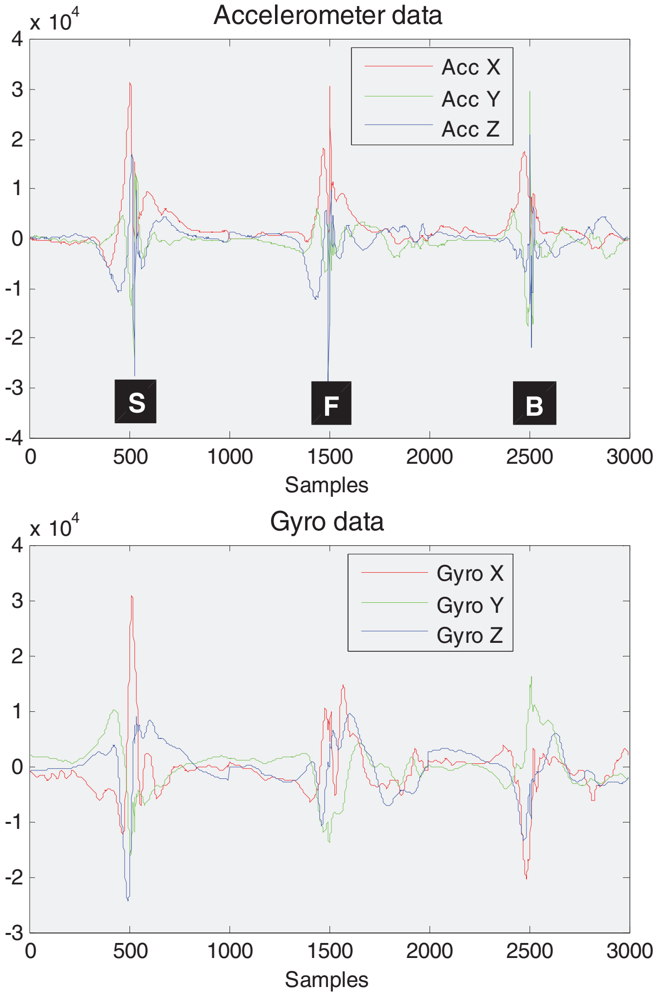

Figure 3. Graphical representation of accelerometer and gyro data: S – Serve, F – Forehand, and B – Backhand.

values are looked for in last 50 samples per individual axis. If no stroke classification is successful, the label UNKNOWN is recorded for present stroke. The flowchart diagram of the tennis stroke classification algorithm is depicted in Fig. 4.

For accurate point of impact detection using only raw accelerometer data is not sufficient. Comparing the individual axis accelerations or average axis acceleration with a threshold would detect a stroke, but the moment of detection would often be different from the point of impact. By observing accelerometer data of strokes, one can see that at the point of impact, abrupt changes in the acceleration occur. These changes are easily detected by calculating a simple 2-point derivative of the acceleration curves. Because rotation normalization (i.e. different players hold the racket differently for the same type of stroke) is not performed, the derivative average of the all three gyro axes is calculated by the following expression:

$$D[n] = \frac{1}{3} \cdot \sum_{i=1}^{3} \left|\left[A_i[n] - A_i[n-1]\right]\right|. \qquad (1)$$

Where n is the sample data index, $D[n]$ is the average derivative value, and i is the gyro axis index (1 = X axis, 2 = Y axis, and 3 = Z axis). The stroke is detected when the value D[n] exceeds a predefined threshold.

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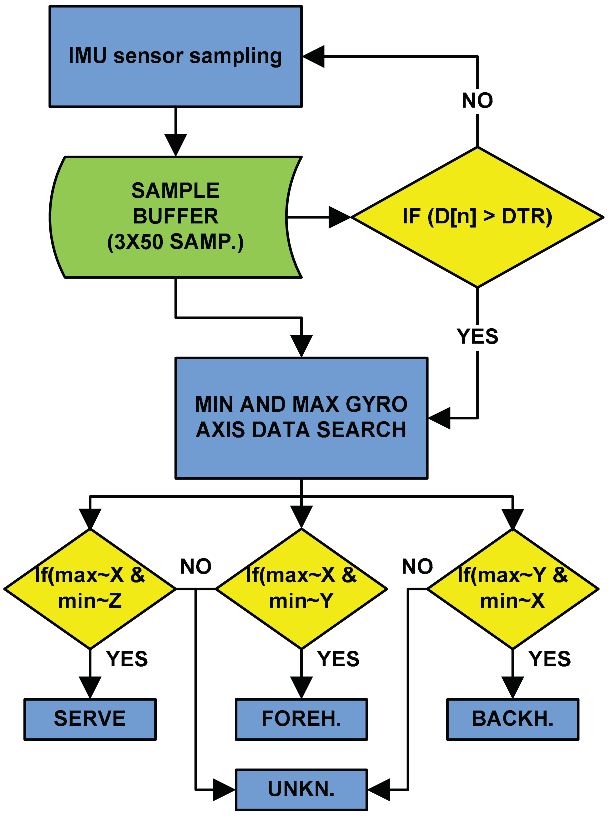

Figure 4. Tennis stroke classification algorithm flowchart diagram.

IV. Evaluation and Results

A. Tennis stroke database

To get research material and also to test the proposed algorithms for tennis stroke detection and classification, a Tennis Stroke Database (TSD) was recorded. The recording took place on several occasions with three different players with different level of tennis experience and knowledge. Recordings are a mix of individual stroke sequences and a competitive training with a mixture of strokes and game elements. Overall 147 strokes were recorded. For easier TSD annotation, video recording of a tennis player was made in parallel with the IMU device recordings. Recordings also include other types of tennis strokes (e.g. volleys, slices, smashes, etc.), which were not considered in the evaluation.

B. Results

The results of the tennis stroke detection and classification algorithm are presented in Table 1. The results show very good classification accuracy for such a simple system. Stroke detection performance is also very good, although it is not evaluated separately. All of the 147 strokes in the database were successfully and accurately detected. Overall 98.1% average tennis stroke classification accuracy was achieved.

TABLE I. Results of Tennis Stroke Classification

	Serve	Foreh.	Backh.	Unkn.	Acc (%)
Serve	41				**100,0**
Forehand	2	51			**96,23**
Backhand			52	1	**98,11**

V. Conclusion and Future Work

In this paper an autonomous wearable IMU device for tennis stroke detection and classification is presented. The device is composed of microcontroller, 6-DOF IMU sensor, memory, and Li-Po battery. For external connectivity USB bus was used. The system successfully detects and classifies three most common tennis strokes: serve, forehand, and backhand. Overall 98.1% average stroke classification accuracy was achieved. Because low memory capacity and processing power, detection and classification principles are quite simple, but still very effective. For future work additional stroke classification and metrics (e.g. speed, quality) could be investigated.

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