Tennis Stroke Consistency Analysis Using Miniature Wearable IMU

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Abstract – **This paper presents research made on the topic of how consistent a tennis player is when hitting a stroke. The analysis is made preliminarily only for the most common tennis stroke, which is forehand. The analysis results can be very useful for the tennis coaches and other experts on the evaluation of a tennis player's current shape and performance stability. For swing movement acquisition a miniature wearable device is used. It is positioned on a player's forearm above the wrist and uses accelerometer and gyroscope to record acceleration and angular velocity in all three axes. A wearable device is a part of the system-in-a-cloud service where complex and more detailed game/performance analyses can be performed.**

Keywords – **tennis, stroke analysis, IMU, MEMS, stroke statistics**

I. Introduction

Technology has never played so important role in different sports as nowadays. It is used for various purposes and tasks to make sport fairer, measurable, and comparable. For example, video analysis systems are used for goal-line monitoring in soccer and hockey, several different timing systems are used in track and field, race sports, skiing, video replay systems provide support for referees in judo, etc. Technology also plays an important role in athlete's performance monitoring and evaluation. Small, light, and nowadays also cheap wearable devices with embedded inertial measurement units (IMU) are especially suitable for this task. The technology is used for providing useful additional information and statistics for spectators (e.g. live game/match statistics during television video transmission).

Recently, these small and light sport tracking devices have gain popularity and are being widely used in different sports. They can be used for basic movement tracking (like step and fitness trackers), for detecting motion in swing-based sports (like tennis and golf), or for sensing and recording potentially dangerous impacts in sports like boxing or football. Measuring and tracking athlete's performance usually includes many metrics, like acceleration, angular speed, temperature, pulse rate, etc. Miniaturization of sensors, decreases in power consumption, and low power wireless communication technologies have enabled the design of small and non-intrusive embedded devices that can be worn on a wrist, in a shoe or are integrated into the sports equipment. For example, in football, such a device is used to monitor linear and angular head accelerations to detect possible hazardous head impacts. It is mounted on the helmet and it tracks the frequency and severity of helmet impacts [1],[2]. In boxing a small device with the embedded accelerometer is typically fitted into the boxing glove, where microcontroller processes the accelerometer data to detect and distinguish between different punches [3]. Several different devices were proposed also for soccer and basketball. Authors in [4] proposed a low-cost system for a shot and pass statistics during training and competition for soccer.

Although many amateur and professional athletes use smart wearables on a daily basis to optimize their performances or to prevent potential injury, the majority of the sports leagues still hold back on approving the devices for in-game use. One of the first Sports Federations was the International Tennis Federation (ITF). Tennis players are allowed to wear sensors on their bodies and can review critical information during set breaks [5] (as of January 1, 2014). Major League Baseball has also approved wearable biometric devices for use during the game. So far players are allowed to wear a biometric baseball sleeve, and a body-harness for movement tracking [6].

II. Related Work

For tennis, several systems and principles for the game and/or stroke analysis were presented in the past. They are roughly divided into two categories: video-based approach, and sensor-based approach. In video-based approach, one or more video cameras are placed around the court to track and monitor the player and provide information regarding the game. A system with a low-cost camera for video capture for recognition of tennis strokes using key postures was presented in [7]. It tries to detect and classify the main strokes played in tennis, i.e. a serve, forehand, and backhand. In [8] authors proposed a system for automatic annotation of tennis games. The proposed system uses video and audio data to detect and classify events on the court. 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. Multiple cameras system for automatic tennis game indexing is presented in [9]. Several cameras are positioned around the court providing multiple viewing angles of a match. The system indexes several tennis events, such as match, set, game, rally, serve, forehand, etc. The purpose is to provide a visual coaching system for tennis clubs who may wish to enhance their coaching facilities on a cost-effective budget.

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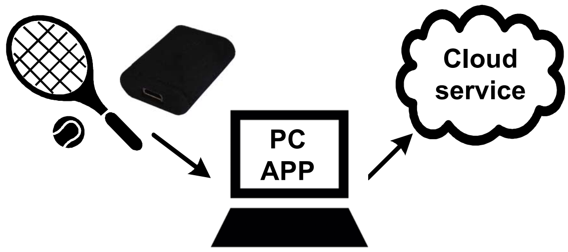

Figure 1. Presentation of the movement and biometric data acquisition system. The data is uploaded via the Internet to a cloud service for more complex signal and/or data analyses.

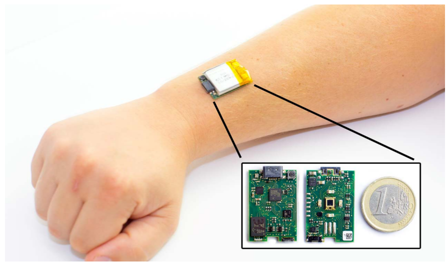

Figure 2. Position of the miniature wearable device during tennis activity. The device is light-weight and it can easily be placed under the player's sweat band.

In IMU sensor-based tennis tracking systems miniature sensing devices can be incorporated into tennis racquet handle [10], they can be worn on a player's wrist, they can be attached on to the strings, or can be attached to the racquet handle. The most expensive option is the first one because one has to buy a new racquet in order to use the system. Our approach is to attach the device to a player's arm above the wrist. This has two benefits: 1.) having the device on a player's arm vibrations that are transferred from the racquet to the arm can be measured and potential risk for injuries can be detected; 2.) player's pulse rate and blood oxidation can be monitored during a match and can be incorporated into a match post-processing statistics. An IMU-based system for a player's full movement tracking during a tennis match was proposed by L. Büthe et al. [11]. Three inertial measurement units are used. One is attached to each foot and one to the tennis racquet. A pipeline was developed to detect and classify leg and arm movement and implement gesture recognition for the shooting arm based on longest common subsequence (LCSS). Tests were performed on four different players. For stroke detection, the algorithm achieved 87% recall and 89% precision, whereas for step recognition the algorithm was able to detect 76% of the steps with a classification accuracy of 95%. System for the tennis serve analysis with wearable motion sensor was presented by Sharma et al. [12]. The analytics engine provides feedback to the player for enhancing their serve performance while preventing potential injuries. For sensing the hand movement Samsung smartwatch Gear S2 was utilized, and for tennis sessions monitoring, 30Hz video recording setup was used. Samsung smartwatch has 6-axis IMU with a measuring range of ±8g m/s^2 for 3-axis accelerometer and ±2296 °/s for 3-axis gyroscope. The sampling rate of the device is 100Hz. A database of 1844 serves from various players (professionals, amateurs, and children) was collected and tagged using a video sync tool build for this task. The videos and sensor data are synced time-wise and further prepared for correctness validation of the developed algorithms. The tennis serve is partitioned into key phases (start, trophy pose, cocking position, impact, and finish), and later features like backswing type, consistency, pronation, and follow-through are derived from inertial sensor data. For consistency evaluation difference between medoid (general swing model) and the individual serve is calculated using quaternion distance.

III. MINIATURE WEARABLE DEVICE

For accurate and unobtrusive player's hand movement tracking during activities, a miniature light-weight wearable device with embedded 6-axis IMU is used. The device is a part of a system for complete performance observation with two main components: 1) A miniature embedded device for movement and biometric information tracking, and 2) Cloud service for information visualization and detailed performance analysis. Because the embedded device itself cannot connect directly to the cloud service, a computer or smart device is used to transfer data from the device and upload it to the cloud for more detailed and integral analyses. The system presentation is depicted in Fig. 1.

The wearable device was designed with special care to be really small and light-weight so it could be attached to a player's wrist without the impact on the player's feeling for the racquet and strokes. The position of the wearable device on the forearm and comparison with a standard coin size is presented in Fig. 2. The embedded accelerometer and gyroscope are sampling the movement with 833 Hz. The device is capable of detecting the tennis strokes and it records only stroke events. This way less memory is needed. The algorithm for tennis stroke detection is described in more detail in [13]. The module's battery is capable of providing enough energy for 6 hours of autonomy, whereas the memory can store more than 8000 individual stroke events. According to the average tennis activity documented in [14], this is enough for almost 6 hours of activity monitoring (on average approx. 20 strokes per player per minute are taken into account). The device also supports PR (Pulse Rate) monitoring of an athlete. The signal for PR monitoring is sampled when the wrist is not moving. Such moments are detected using readings from the IMU. More detailed description of the miniature wearable device is presented in [15].

IV. EXPERIMENTAL SETUP

A. *Tennis stroke database*

For the purpose of this research, several tennis sessions were recorded and recordings were collected to form the Tennis Stroke Database (TSD). For the work in this paper, only forehand strokes were analysed. The recordings took place on different occasions with several 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. 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.

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B. *Forehand stroke models*

In order to be able to evaluate the stroke consistency for an individual player, we had to build a general forehand stroke model for that player. This was done by calculating a median acceleration value for individual sample bin. The model was built for every accelerometer axis individually. This way information regarding the wrist rotation differences for the individual player was preserved. The accelerometer data was fairly good aligned with the stroke detection point (point of contact of the ball with the racquet). 150ms before and after the contact point was taken into consideration for the model, which corresponds to 248 sample bins in total. An individual acceleration bin value (for one axis) for player's forehand stroke model is estimated using the following expression:

$$FSM(i) = \frac{1}{N}\sum_{j=1}^{N} fh\_acc[i][j],\ i{=}1{:}248; \qquad (1)$$

where *FSM(i)* corresponds to forehand stroke model axis bin, *N* is the number of different stroke acc. recordings for individual player, and *fh_acc[i][j]* is an array of accelerometer readings for individual player and individual axis (*i* is the index of accelerometer sample bins, and *j* is the player's stroke record index). Graphical representations of general player's forehand stroke models for individual accelerometer axes are presented in Fig. 3.

As we can see from observing the individual axis acceleration plots, trajectories quite differ from axis to axis. In general, if the plots are close together, the player's stroke consistency is greater because the acceleration trajectories are less scattered. From the observation of the plots for individual axes we can roughly estimate, that the player is most consistent via Y-axis, and the least consistent via X-axis. This estimation is made on the basis of the acceleration plot scatter around the general serve stroke model. From the plots in Fig. 3 three basic swing segments can be noticed. At the beginning of the stroke is a swing segment, ranging from sample bin 1 to 120, from sample bin 120 to 140 is the ball impact segment, where typically oscillations and acceleration spikes can be seen, and the follow-through segment of the stroke, ranging from sample bins from 140 to 248. The stroke model is presented as a thick line in the middle of the individual axis acceleration plots.

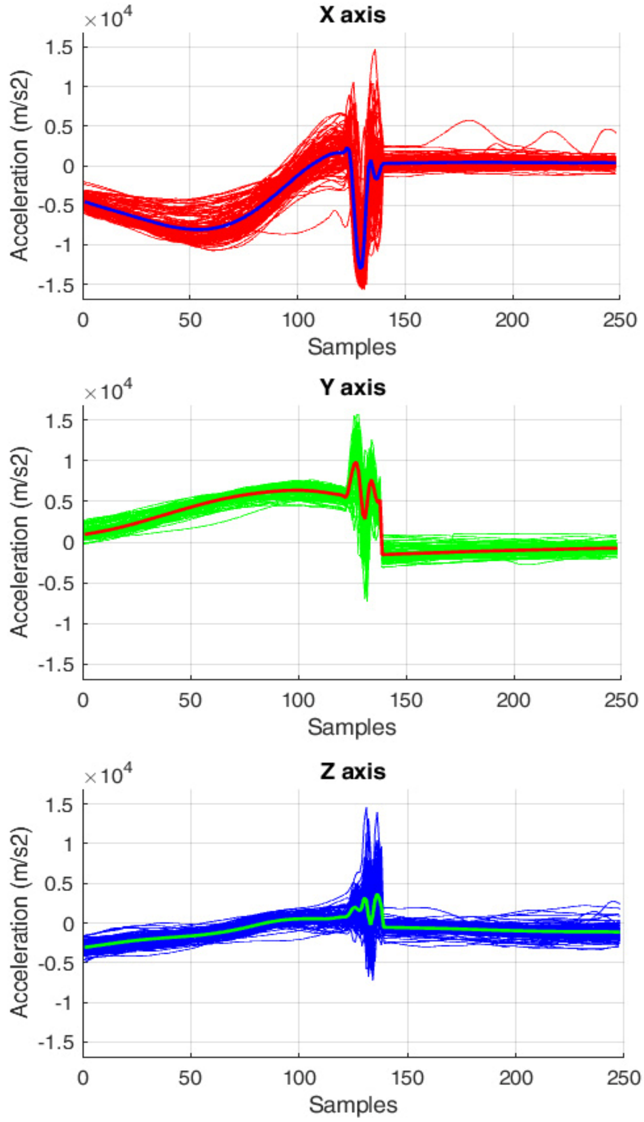

Figure 3: Individual player's general forehand stroke model. For each accelerometer's axis separate model is made.

V. Stroke Consistency Evaluation

To evaluate forehand stroke consistency, individual player's strokes are compared to the general player's forehand model. As mentioned before, a database of forehand strokes was recorded and from these recordings, average player's forehand stroke model was estimated. To estimate the stroke consistency, we calculate a regular average distance bin by bin between individual forehand and general forehand stroke model. The expression used for this task is:

$$dist(i) = \frac{1}{N}\sum_{j=1}^{N}(\, fh\_acc[i][j] - FSM[i]\,), \qquad (2)$$

where *dist(i)* is distance (for one axis) between stroke model and individual player's stroke, *fh_acc[i][j]* is the array of player's forehand strokes, *FSM[i]* is the player's forehand stroke model, *N* is the number of different strokes, *i* is the individual stroke sample bin (i=1:248), and *j* is the player's stroke record index. Typically around 100 to 150 strokes for a player were captured.

The overall distance for individual player's stroke is then averaged for all three axes. We are aware, that some valuable information is lost by calculating the axes average distance, but to present a general player's stroke consistency, the average is presented. The reason we decided to calculate a regular distance between individual player's strokes and the player's general model is that the sign of difference is preserved. This way we can estimate if the players tend to swing "over" or "under", compared to the general forehand model. If we would use Euclidean distance to calculate the distance between strokes and the model, the result would be only positive and the information about the swing error direction would be lost. To

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present the results of forehand stroke consistency for a group of nine players, we decided to use a box plot. A box plot is a well-known and widely used principle for presenting statistical information. The statistical representation of forehand stroke consistency is presented in Fig. 4.

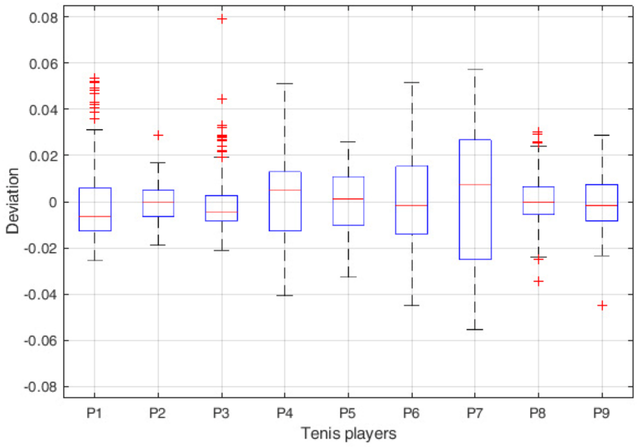

Figure 4: Forehand swing consistency analysis presentation for nine players (P1-P9). Y axis represents deviation from the general forehand model.

To properly interpret the information provided by the box plot in Fig. 4, we need to comment the presented data. For each player, a rectangle with the red horizontal line is presented. The red line represents median value of the player's forehand stroke deviation. The upper rectangle border represents the 75th percentile of the deviation limit, whereas the lower rectangle border represents the 25th percentile of the deviation limit. The distance between top and bottom rectangle border is also known as the interquartile range. Each rectangle is extended by a dotted line, which is called a whisker. Whiskers are drawn from ends of the interquartile ranges to the furthest value within the observation interval. In our case the whisker length is set to 1.5, this means that the outlier value is set to 1.5 times of the interquartile range. Values out of this range are called outliers and are seen in the figure as little red crosses.

Stroke consistency results in Fig. 4 show, that the players with the most consistent forehand stroke are players P2, P3, and P8. They all have small box plot with relatively short whiskers. Player P2 only has one outlier, whereas player P8 has many. Player P3 also has narrow box plot, showing that his consistency is good, but the median line is not in the centre. It also has many outliers in plus direction, which indicate extreme deviations from the general stroke model. The worst player regarding the stroke consistency is the P7. The box plot is the widest and also the median deviation of the stroke is not in the centre, which suggests that the stroke deviation distribution is somewhat skewed.

VI. CONCLUSION

In this paper tennis stroke consistency analysis method is presented. For this purpose forehand stroke database was built with arm acceleration recordings of several different tennis players during competitive training and tennis matches. For arm movement acquisition a miniature wearable device is used. It is positioned on a player's forearm above the wrist and it uses an accelerometer and a gyroscope to record acceleration and angular velocity in all three axes. The analysis results can be very useful for tennis coaches and other experts evaluating a tennis player's current shape and performance stability. For more detailed stroke consistency a stroke swing could be divided into segments, where consistency evaluation could be done for each individual segment. This way exact analysis could be made in which part of the swing trajectory a player is making a bad swing.

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