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# Smart Wearables for Tennis Game Performance Analysis

*Marko Kos and Iztok Kramberger*

## Abstract

For monitoring the progress of athletes in various sports and disciplines, several different approaches are nowadays available. Recently, miniature wearables have gained popularity for this task due to being lightweight and typically cheaper than other approaches. They can be positioned on the athlete's body, or in some cases, the devices are incorporated into sports requisites, like tennis racquet handles, balls, baseball bats, gloves, etc. Their purpose is to monitor the performance of an athlete by gathering essential information during match or training. In this chapter, the focus will be on the different possibilities of tennis game monitoring analysis. A miniature wearable device, which is worn on a player's wrist during the activity, is going to be presented and described. The smart wearable device monitors athletes' arm movements with sampling the output of the 6 DOF IMU. Parallel to that, it also gathers biometric information like pulse rate and skin temperature. All the collected information is stored locally on the device during the sports activity. Later, it can be downloaded to a PC and transferred to a cloud-based service, where visualization of the recorded data and more detailed game/training statistics can be performed.

**Keywords:** smart wearables, inertial sensing, tennis, biometric data acquisition, movement detection, sports tracking

## 1. Introduction

The use of electronic devices in our daily lives is growing constantly; therefore, it is no real surprise that electronic wearable devices are nowadays a big hit. Smart jewelry, smartwatches, fitness trackers, etc. are getting smaller and more capable due to the improvement of sensors, batteries, and microprocessors. Wearable technology has been in use a long time by the military and medical professionals, but the market for smart wearables for private consumers has only recently started to grow. The market for smart wearables is on a rise. In the smart wearables segment, smartwatches are the most valuable, accounting for 60% of market value, followed by fitness and health trackers, smart jewelry and smart fashion [1]. Many solutions and products in the smart wearables industry are developed by young companies and start-ups, which are competing against large international companies for their piece of the smart wearables market. Smart wearables have found their use in several sports applications, for example, for athlete's performance monitoring in sports like swimming, boxing, golf, soccer, tennis, basketball, baseball, etc. Measuring performance, tracking motion, and monitoring biometric data usually includes many metrics (acceleration, temperature, angular speed, pulse rate, etc.). Sensor miniaturization, small power consumption, and low power wireless

communication technologies have enabled researchers and engineers to design miniature, lightweight wearable embedded devices that can be placed in a shoe, worn on a wrist, or are incorporated into the sports equipment (like racket handle). Such devices are also popular for fitness tracking, potential injury prevention, or health monitoring. For example, a miniature wearable device is used for linear and angular head accelerations monitoring in football for detecting the potentially dangerous head impacts. The device is mounted in the player's helmet, and it records the amplitude and frequency of the player's head impacts [2, 3]. A miniature swing tracker was presented in Lightman [2], which can be used for monitoring different swing metrics for baseball and softball. It can monitor information about power, speed, and hitting zone of the swings.

With the popularity of the smartwatches and other smart wearable devices with integrated sensors, there is less need for the application-specific hardware development for specific tasks. Smartwatches generally have built-in MEMS (microelectromechanical systems) accelerometers and gyroscopes, pulse-rate (PR) sensors, etc. Therefore, only software applications for these devices need to be developed. One of these applications was developed for aiding an athlete with baseball pitching action and tennis serve action [4]. The personal sport skill improvement support application is running on Sony's SmartWatch SWR50. Comparative research was made by using the proposed sport skill improvement support and very encouraging results were achieved. Similar to the abovementioned system, authors in Viana et al. [5] proposed an application called GymApp, which is a real-time physical activity trainer. It runs on Android-supported smartwatches, and it supervises physical activities, for example, in fitness. It has two modes of operation: training mode and practice mode. In training mode, an athlete is advised to perform an exercise with lighter weight and with the supervision of a fitness instructor, to guarantee the correctness of the performed exercise. The application then gathers sensory data and builds a model for the performed exercise (e.g., biceps curl). In the practice mode, the recorded sensory data are compared with the previously acquired data and similarity distance is calculated. By evaluation of the similarity distance result, the application estimates how many repetitions of the exercise were performed correctly.

Several systems were developed also for boxing. They provide punch analysis and type statistics. Usually, a small embedded device is fitted into the boxing glove where different punches are detected and distinguished based on accelerometer data [6]. Small embedded devices for tracking, analysis, and statistics were proposed also for basketball and soccer. A shot/pass classification system for activity analysis during a match was presented by Schuldhuis et al. [7]. The proposed system uses a miniature IMU for movement tracking. They developed a low-cost embedded system for a shot and pass statistics, which is especially suitable for use during training and competition. A system for counting shots made or missed was proposed for basketball. It uses double sensor-node principle, where the first sensor is attached on the player's wrist. The wrist sensor records and detects each shot attempt. The second sensor is located on a basket's net where it monitors the statistics of made and missed shots [2].

Although smart wearable devices are nowadays being very popular and are in use by amateur and professional athletes a daily basis, the majority of the sports leagues still do not approve smart wearable devices for in-game use. A safety factor is also an issue, and on the other hand, some athletes expressed their concern about privacy matters. The International Tennis Federation (ITF) was one of the first Sports Federations, which allowed the use of smart wearables. From January 1, 2014, tennis players are allowed to wear sensors during the matches, and they can freely check important information during set breaks [8]. One of the sports

associations, that also approved the use of wearable biometric devices during the game, is Major League Baseball. In their case, players are allowed to wear a special biometric baseball sleeve, which can monitor strain on pitching arm, and a body harness, which can detect and track players' movements on the pitch [9].

The way in which the smart wearable device is designed and the way it performs, it is especially suitable for swing-based sports, like golf or tennis. Although various systems and devices are commercially available, there is not much publicly available information on how they are constructed. In the area of tennis stroke recognition based on a visual approach, much has been previously published [10, 11]. For major tennis competitions, like Grand Slams and others, the ITF approved the use of a sophisticated video system, called Hawk-Eye. The system uses several calibrated high-speed video cameras, which are stationed around the court [12]. The drawback is that it is very expensive, and it takes a lot of time to set up and calibrate. Other systems and principles are more appropriate for everyday use, such as using a device with IMU.

Similar systems, that are IMU based, are also available for other sports. Swing motion detection using an inertial-sensor-based portable instrument was proposed for golf [13]. The miniature device is mounted on a golf club to measure swing motion signals. Procedures for signal collection, signal pre-processing, and swing motion segmentation has been developed. Results show that the instrument can be a promising tool for serving as a training assistant tool for golfers. Authors in Jensen [14] presented a device for golf put analysis. The device uses a removable sensor, and it is built solely from off-the-shelf components. It supports automatic putt detection and parameter calculation in real time.

Four different principles, that are used for smart embedded solutions integration, exist for tennis: (a) a device is placed in a tennis racket handle [15]; (b) a device is mounted on the racket strings (like a string vibration dampener); (c) a device is attached on the racket grip (at the bottom end); and (d) a device is worn on tennis player's wrist. The option with a sensor being integrated into the racket handle is also the most expensive because one must buy a special tennis racquet. Well-known tennis equipment manufacturer Babolat produces such rackets. The electronic device installed in the racket's handle monitors players' motion and swings. It connects with smart devices via Bluetooth for communication with a mobile app. The data from the device are then synchronized with the mobile app via Bluetooth. The mobile app is used for visualization of most common game statistics and some details regarding basic tennis strokes. The embedded electronics in the racquet handle uses IMU and piezoelectric sensors to detect the strokes [2].

Büthe et al. in their work proposed a system for complete movement monitoring during a tennis match [16]. The system uses three IMU devices. They are attached to each foot and to the tennis racquet. The proposed solution supports the detection and classification of leg and arm movements. Gesture recognition for the active arm based on the longest common subsequence (LCSS) is also supported. The proposed system was tested with four different players, where the results showed highly user-dependent performance. The proposed method achieved 87% recall and 89% precision for stroke detection. Regarding step recognition, the proposed algorithm was able to detect 76% of the steps. The step classification accuracy was 95%.

Tennis serve analysis system with a wearable motion sensor was presented by Sharma et al. [17]. The player gets the feedback from the analytics engine for enhancing their serve performance while preventing potential injuries. Samsung smartwatch Gear S2 was used for sensing and hand movement tracking. It has six-axis IMU with a measuring range of  $\pm 8 \text{ g m/s}^2$  (accelerometer) and  $\pm 2296^\circ/\text{s}$  (gyroscope). The IMU was sampled with the frequency of 100 Hz. For tests and experiments, a database of 1844 serves from various players (professionals,

amateurs, and children) was used. The videos and sensor data are synced timewise 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 consistency, pronation, backswing type, and follow-through are derived from inertial sensor data. Quaternion distance is used for serve consistency evaluation between medoid (general swing model) and the individual stroke.

Authors in Connaghan [18] presented a multi-sensor tennis stroke classification. For tennis stroke recognition, they used a single IMU attached to a player's forearm. Experiments were made during a competitive match. A two-level classification method was used for tennis stroke classification. Firstly, non-stroke events are filtered and after that stroke candidates are classified into three most common tennis strokes: serve, backhand, and forehand. Experiments showed that sensor fusion approach yielded the best tennis stroke classification. Ninety percent accuracy was achieved.

Tennis ball speed estimation using a motion sensor was presented in [19]. TennisEye, as the authors call it, is a system with racket-mounted motion sensor. It senses linear and angular accelerations and sends them to the smartphone device via BLE (Bluetooth low energy) wireless connection. Tennis strokes are detected using a threshold-based method and divided into three categories: serve, ground-stroke, and volley. Authors compared the performance of their system against Zepp [20], which is a similar device mounted on the racket handle. To estimate the serve ball speed, a regression model is proposed. For groundstroke or volley, two models are proposed: a regression model and a physical model. For estimating the ball speed for advanced players, authors use the physical model and regression model for beginners. Using the leave-one-out cross-validation test, the evaluation results show that TennisEye performs better than its competitor.

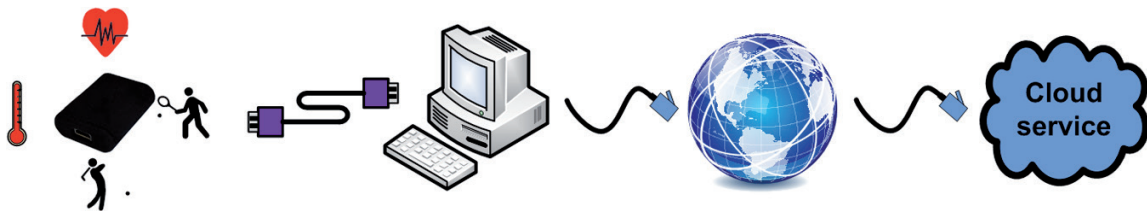
Tennis stroke detection and classification is motion detection and classification problem, which can be observed also as a hand-gesture classification case [21]. For this type of tasks, some popular methods are widely used, like hidden Markov models (HMM) or dynamic time warping (DTW) and similar (like QDTW) [22].

## **2. Movement and biometric data acquisition**

In the following section, we will present a miniature wearable device for tracking tennis swings and strokes. The presented system supports athlete's arm movement tracking, where individual hand gestures can be detected (like strokes etc.), and biometric data monitoring like skin temperature and pulse rate (PR) or even pulse rate variability (PRV). This additional information can be helpful for estimating the physical and mental state of an athlete. The system can work in continuous sampling or in gesture recognition mode, depending on the firmware. The system is presented in **Figure 1**. The system for movement and biometric data acquisition is composed of two parts: (1) a smart wearable module for tracking movement and gathering biometric data and (2) cloud service for detailed data analysis and visualization. A PC or smartphone device with a special application is used to download the gathered information from the wearable device to the cloud via the Internet. The main parts of the system will be presented in more detail further below.

### **2.1 Hardware design of the smart wearable device**

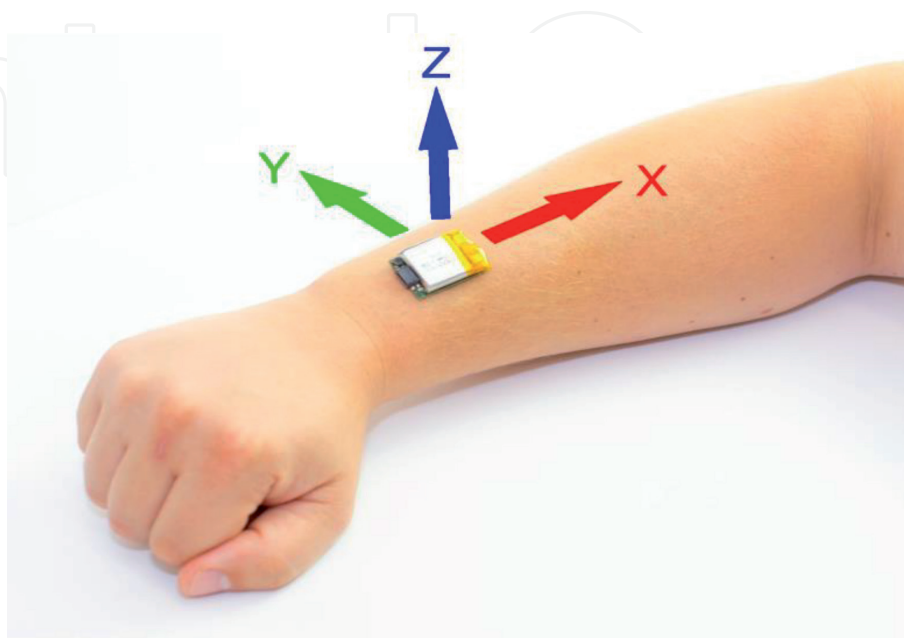
The main objective of the hardware design of the proposed wearable device was to develop a lightweight device for tracking a player's movement and sensing its biometric information. The device should be attached to the player's wrist, and it



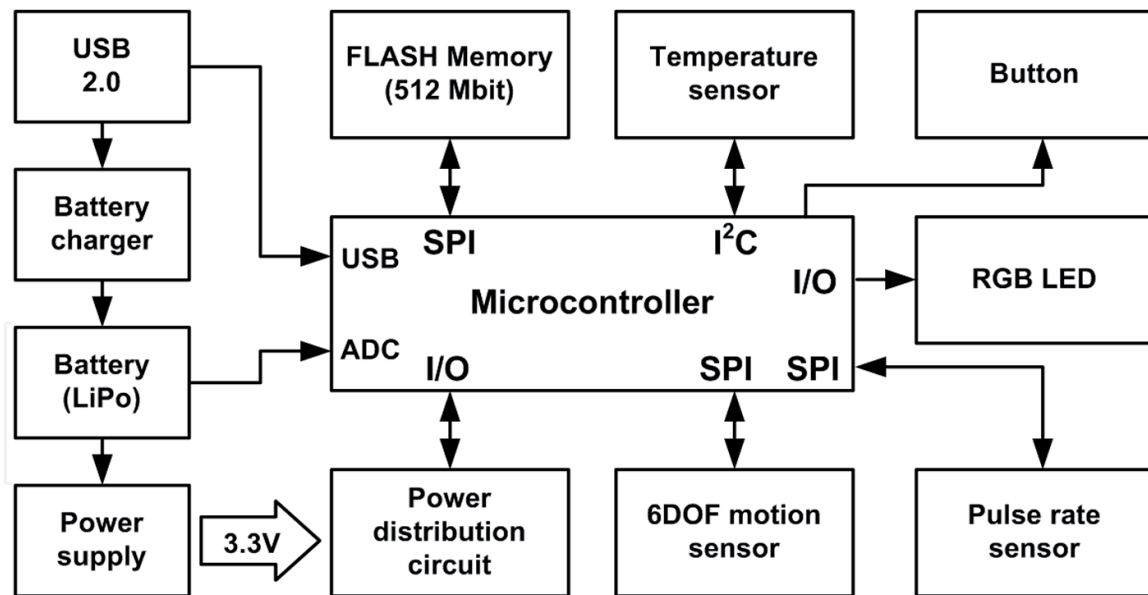
**Figure 1.**  
*Architecture of the movement and biometric data acquisition system. The gathered information is uploaded to a cloud service via the Internet.*

should not influence the player's abilities for sports performance. One of the better places for device's attachment on the hand is right above the wrist (ulnar head), where there is enough soft tissue between the bones (the ulna and the radius) to successfully detect and measure pulse rate using photoplethysmography (PPG) method. The spot of attachment of the smart wearable device on the sportsman's forearm and the orientation of the individual IMU's axes are visible in **Figure 2**. The axes of the gyroscope are pointing in such a way that the angular rate is positive in a counter-clockwise direction if the accelerometer arrow is facing toward you.

We developed the wearable device with the wish for independent operation and the possibility to detect and classify basic strokes in real time. For this task to be successful, the sampling rate of the IMU unit must be high enough. We estimated that a sample rate of 1000 sps should suffice, after studying literature on racket body and racket strings vibration [23]. To be able to handle such amount of data, the wearable device must have large memory space to be able to store movement and biometric information reading for at least an average tennis match. An average tennis match lasts for about 2 h, and we rarely can see a match longer than 5 h. The record for the longest tennis match is held by Isner and Mahut. Their match lasted for 11 h and 5 min. It happened in Wimbledon in 2010. The percentage of total playing time for a tennis match is around 23–30% on clay and 10–15% on fast courts [24]. For maximum battery life, we implemented wired USB connection (instead of wireless, e.g., Bluetooth) for movement and biometric readings. The USB connection is also faster, and the USB connector can at the same time be used for battery charging. Detailed composition with the presentation of individual subsystems of the smart wearable device is presented in **Figure 3**.



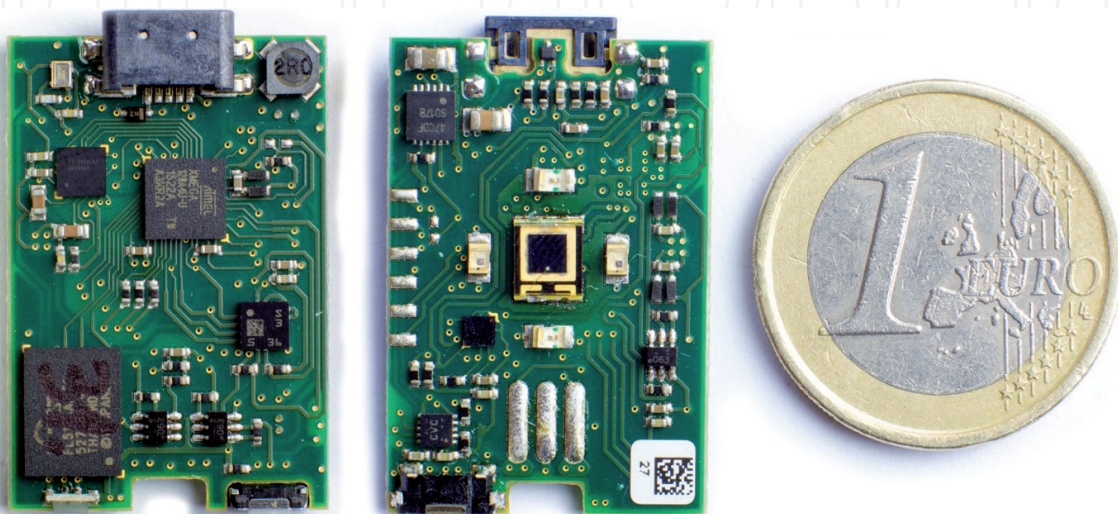
**Figure 2.**  
*Smart wearable device position and IMU orientation. The device is attached above the wrist.*



**Figure 3.**  
Block representation of the smart wearable device with connections to individual subsystems.

The physical presentation of the smart wearable device is depicted in **Figure 4**. The device is implemented on a four-layer FR4 PCB (printed circuit board) with 1 mm thickness. The physical dimensions are 20 × 29.5 × 7.2 mm (W × L × H) including the battery. It weighs 5.8 g, and because of its miniature size, it can easily be placed under a sweatband. The top layer of the PCB is populated by a microcontroller, IMU unit, FLASH memory, and battery charger. On the bottom side, the power supply, temperature sensor, and the LEDs for pulse rate sensing are placed. Opposite to the USB connector, the RGB LED and the push button are placed. The heart of the smart wearable module is a low power high-performance 8/16-bit RISC microcontroller. It supports 128 kB of FLASH memory, 8 kB of SRAM memory, and 2 kB of EEPROM. It can run with 32 MHz clock (it has an internal calibrated clock source), and it supports various peripheral and communicational interfaces (ADC, SPI, I2C, USB etc.).

To detect and sense tennis strokes, a MEMS inertial measurement unit is used. It incorporates a three-axis accelerometer and a gyroscope, and together, they form a 6-DOF unit (DOF—degrees of freedom). Linear accelerations are measured by



**Figure 4.**  
The physical implementation of the smart wearable module (top and bottom sides of the PCB).

MEMS digital accelerometer. It supports measuring ranges from  $\pm 2$  to  $\pm 16$  G, and it supports 16-bit resolution of output readouts. For angular velocity sensing, MEMS digital gyroscope is used. It supports angular several measuring ranges, from  $\pm 125$  to  $\pm 2000$  dps and 16-bit resolution. Due to the integrated 8 kB FIFO memory, burst mode reading of the measured data is possible. This type of readout also helps to reduce the power consumption of the device. For communication with the microcontroller, the SPI digital bus is used. The accelerometer is capable of maximum 6664 sps data rate, and the gyroscope is capable of 1666 sps data rate. Current consumption of the IMU unit is 0.9 mA in normal operation mode and 1.2 mA in high-performance mode. It is placed in a miniature LGA-16L package and because of its miniature dimensions, it is ideal for implementation in the presented smart wearable device.

For sensing the pulse rate of a player wearing the smart wearable device, a pulse rate sensor with integrated analog front-end part is implemented. It has a low-noise receiver with an integrated ADC for reflected signal detection and a LED transmitter. For pulse-rate measurement, it uses a photoplethysmography (PPG). More about the PPG method is presented in Refs [25, 26].

To measure the skin temperature during the sports activity, a contactless temperature sensing is used. The principle is based on IR (infrared) thermopile sensor, which measures the temperature of the surface by detecting the passive infrared radiation with a wavelength from 4 to 16  $\mu\text{m}$ . The accuracy of the used thermopile temperature sensor is  $\pm 1^\circ\text{C}$  in the temperature range between 0 and  $+65^\circ\text{C}$ . Similar integrated circuits are used also in medical contactless temperature measuring devices. The temperature sensor also supports calibration. For this, it has NV-MEM (non-volatile memory), which is used for storing the calibration coefficients. Calibration is necessary in the case when the default emissivity factor is not correct.

For storing the recorded accelerometer and gyro information, external NV-MEM is used with the capacity of 512 Mbits. It is used also for storing the temperature measurements and saving the timestamp data. The memory is large enough to store approximately 1.5 h of non-stop sports activity. When in stroke detection mode (only stroke actions are detected, timestamped, and recorded), it can store approximately 8000 events. This is enough for storing almost 6 h of an average tennis play, where an average of 20 strokes per player per minute is considered [27].

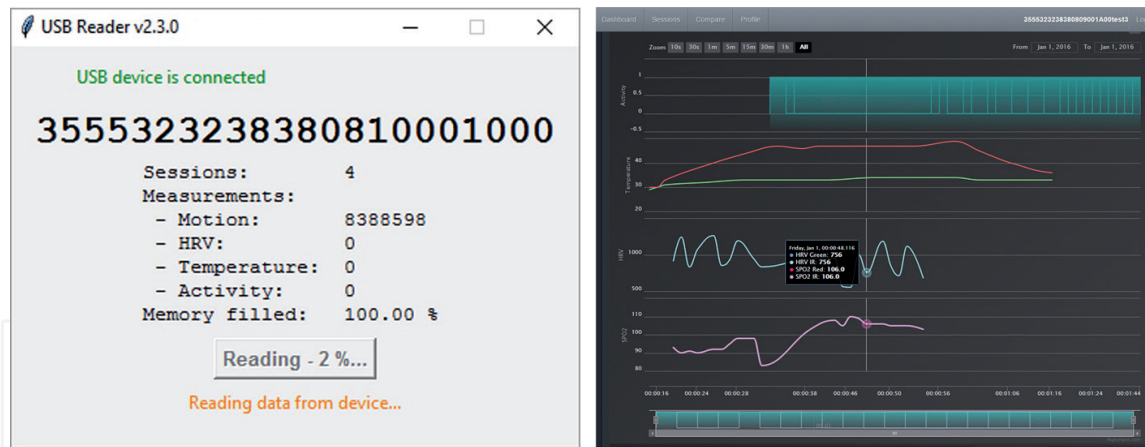
As already mentioned, a USB is used for the connection between the smart wearable module and a personal computer. The connector used must be water-proof due to the exposure to moisture and sweat. For battery management, a dedicated integrated circuit is used. It charges the batter to correct levels, and it also monitors and protects the battery from getting too discharged. This can happen because we use Li-Po battery type, which is sensitive to discharge voltages below 2.7 V (can get damaged). The batter has a capacity of 155 mAh. The charging current is set to 100 mA, which suffices for the battery to be fully charged in approximately 1.5 h.

For more efficient power consumption and achieving longer battery autonomy, power supply switches are implemented. They are used to cut off power to individual subsystems and can reduce the overall current consumption of the smart module. Power switches are P-type MOS-FET transistor with low serial resistance. They are used to distribute power to the IMU unit, PPG measuring subcircuit, the temperature measuring subcircuit, and the external FLASH memory. More about the miniature wearable movement and biometric data acquisition device can be found in [28].

## 2.2 PC application and cloud service

For downloading recorded data from the smart wearable device, a custom PC application was developed. The USB reader is also capable of erasing the module (it erases the internal memory for storing the recorded info), for clock





**Figure 5.** PC application graphical user interface (left) and cloud service graphical web interface (right).

synchronization, uploading the data to the cloud, and for eventual firmware upgrades. When the wearable module is connected to the PC, it is detected as a generic HID device. The graphical user interface of the PC application is presented in **Figure 5** (left side).

When the recorded smart wearable data is uploaded to the cloud, it is visualized and processed. Due to the larger processing power being available and bigger memory space, more complex analyses on the recorded data are possible. Comparison of individual athletes is also possible. Because data from several different players and from different events can be stored in the cloud, big data analytics can be performed, and even more, information can be extracted. The visual representation of the proposed cloud service web interface is depicted in **Figure 5** (right side).

### 3. Motion and biometric data acquisition

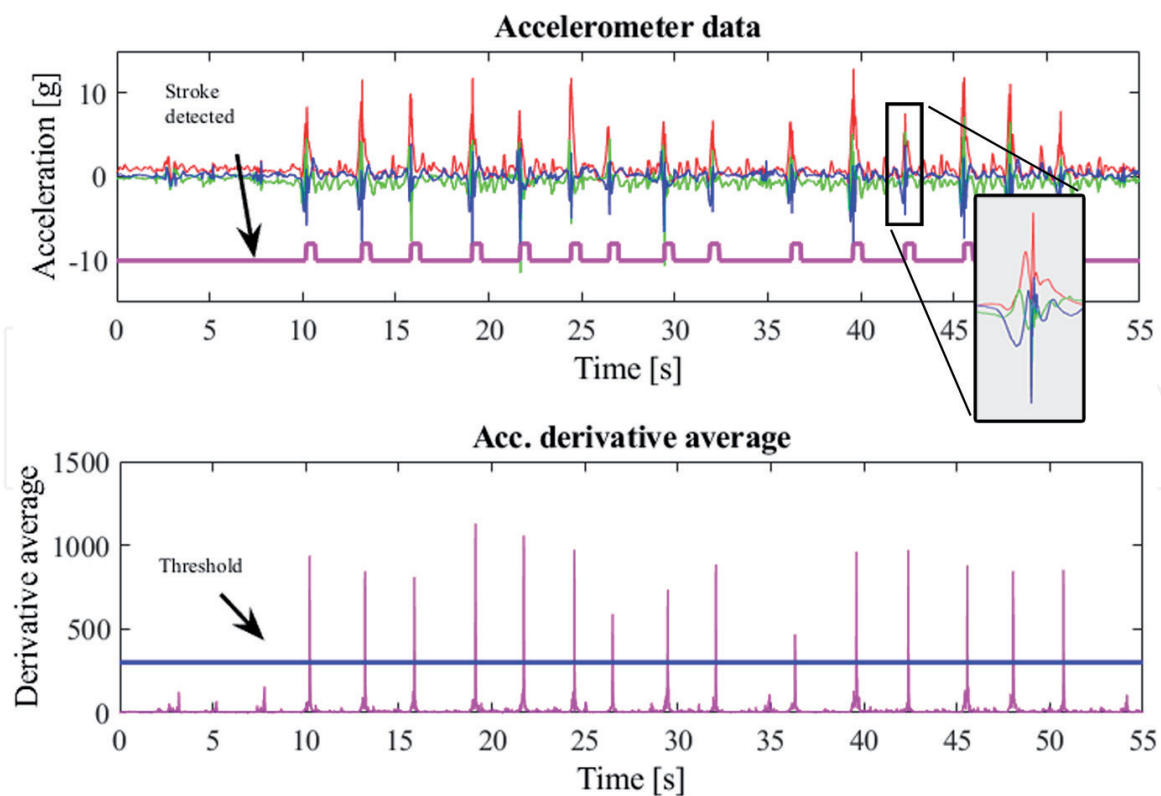
Details regarding the motion detection and tracking, as well as biometric data acquisition, are covered in the following section. As mentioned earlier, the proposed smart wearable device could be used for several different sport applications, but due to being so miniature and lightweight plus with the battery autonomy of more than 5 h, it is especially suitable for sports like golf or tennis. We chose tennis to test the performance of the proposed system in a real environment. Tests were performed during competitive training. Challenges on tennis stroke detection and classification will also be addressed in this section.

#### 3.1 Tennis stroke detection and classification

##### 3.1.1 Tennis stroke detection

For successful tennis stroke classification process, individual tennis strokes must first be accurately detected. We focused on detecting and classifying the three most common tennis strokes: forehand, backhand, and serve.

**Figure 6** presents the accelerations of individual axes during the tennis game. As expected, there are spikes in accelerometer data for every tennis stroke, where the maximum values of acceleration are usually higher than 10 G (for more powerful strokes like serve the maximum values can reach up to the 16 G). For stroke detection, one could easily compare the acceleration spike values with the predefined threshold. The stroke would then be detected if the acceleration values would surpass it. This is one of the most common methods that researches use for stroke



**Figure 6.** Graphical representation of the accelerometer data ( $x$ -axis = red,  $y$ -axis = green,  $z$ -axis = blue). The second subplot represents the average derivative of accelerometer data with a predefined threshold for tennis stroke detection.

detection. The problem with this method is that it can produce false positives because the accelerometer values can be high even during the swing part of the stroke before the ball touches the racket. Therefore, we decide to use a different method for tennis stroke detection. We focused on the point of contact, where abrupt changes in the acceleration readings happen.

The moment of contact can most effectively be detected by calculation a two-point derivative of the acceleration values. We calculate the derivative average for all three axes because rotation normalization is not used. Rotation normalization is usually performed to normalize the acceleration readings orientation between individual players due to the fact that different players hold the racket differently and therefore the axes of the IMU unit are not aligned to the racket in the same way. The following expression is used for derivative average calculation:

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

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 the predefined threshold. Other arm movements can also trigger a tennis stroke detection. By observing **Figure 6**, one can notice small spikes in acceleration between time 0 and 10 s. They happened when the player was picking up the tennis ball with the racket. Acceleration spikes can also occur when the player is twirling the racket during the waiting for the opponent to serve, which is a very common thing [18]. Such events are not actual strokes and are undesirable to be detected. Therefore, the threshold for tennis stroke detection must be selected carefully. It is a tunable parameter and can be adapted to different conditions and different players.

### *3.1.2 Tennis stroke classification*

We worked on the problem of tennis stroke classification in one of our previous works presented in [29], where we proposed a classification method which is especially suitable for use with small embedded systems with low processing power because it is very simple but effective. The tests were performed on the strokes gathered from several different tennis players. In Kos and Kramberger [28], we extended the database and slightly modified the algorithm for tennis stroke classification. For test and experiments, we used our tennis stroke database (TSD). The database is composed of tennis stroke recordings of seven different players with different levels of tennis knowledge. The recordings were performed on several different occasions and in different conditions (different court surfaces, different tennis balls, and rackets). The recordings are a mix of individual stroke sequences during warm-up and recordings made during competitive training. Overall, the database is composed of 446 strokes. For easier TSD annotation, for each tennis player, a video was recorded in parallel with the wearable embedded device recordings. Other types of tennis strokes are also included in the recordings (e.g., slices, volleys, smashes, etc.), which are not used for tests and in the evaluation.

The main starting point for the tennis classification is that the accelerometer information alone does not have enough discriminative information for the tennis stroke classification task. Therefore, we looked at the gyroscope readings and analyzed them for different tennis strokes. It happens that there is enough difference for simple but successful implementation for the classification algorithm. The algorithm works in such a way that it first looks for minimum and maximum gyroscope values around the point of contact event (the ball touches the tennis racket strings), and it searches for the axes in which the extreme values occur. The observation interval for minimum and maximum searching is 50 ms before the point of contact event. The gyroscope values for all three axes are sampled and stored in a buffer for maximum and minimum search. When the stroke detection event occurs, the buffer with gyroscope readings is swept for extreme values. Based on the information for which axis and in which direction the extreme value was found, the decision on which stroke happened, is made. For example, if the maximum angular velocity during the swing happened along Y-axis, the stroke is classified as a backhand. If the maximum corresponds to the X-axis, and the minimum is found in the Z-axis, the stroke is classified as a serve. If the maximum and minimum gyroscope values correspond to the X and Y axes, an additional condition is checked for the minimum Z-axis angular rate. If the angular rate is lower than  $-1500$  dps, the stroke is classified as a serve; otherwise, the stroke is classified as a forehand. This condition was added to the classification algorithm because some tennis players tend to rotate the hand differently during the execution of the serve. If none of the abovementioned combinations is true, the detected stroke is classified as unknown (UNKN). This was introduced because sometimes the players make the shots very close to the body or out of balance and are therefore difficult to categorize as one of the basic strokes. The algorithm described is for a right-hand player. For a left-hand player, the accelerations of Y-axis and angular velocities of X and Z axes must be inverted.

### **3.2 Pulse rate and pulse rate variability**

To evaluate an athlete's physical and mental levels, pulse rate and pulse rate variability information is recorded during the athlete's activity. For monitoring the pulse rate, we selected the reflective photoplethysmography. The method is noninvasive, and it still gives a good result. Two different light sources with different light

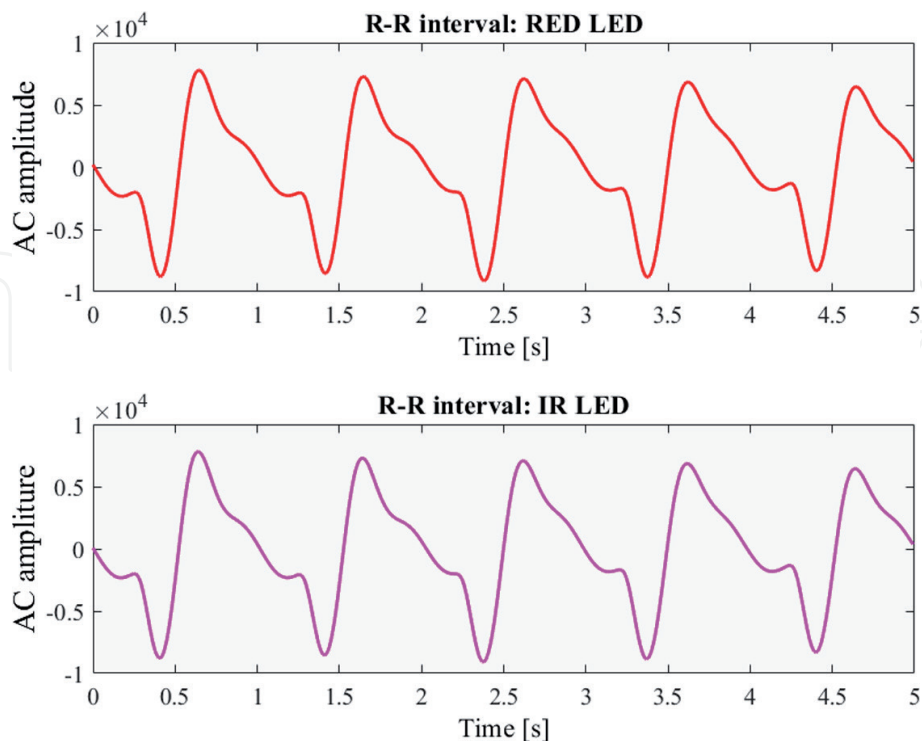
wavelengths (RED and IR LED) were used for tissue illumination. The receiving photodiode detects the reflected light. The intensity of the reflection is modulated by the difference in the blood flow; therefore, minimal ripple is present from which the pulse rate can be evaluated. The signal is sampled with 100 Hz. Every heartbeat is represented with a so-called R wave and the distance between individual R waves is called the R-R interval. PR and PRV can be calculated by measuring this interval. Some PR and PRV experiments were performed in our previous work, and the results are presented in [26]. R-R intervals from RED and IR LED illumination are depicted in **Figure 7**.

### 3.3 Temperature measurement

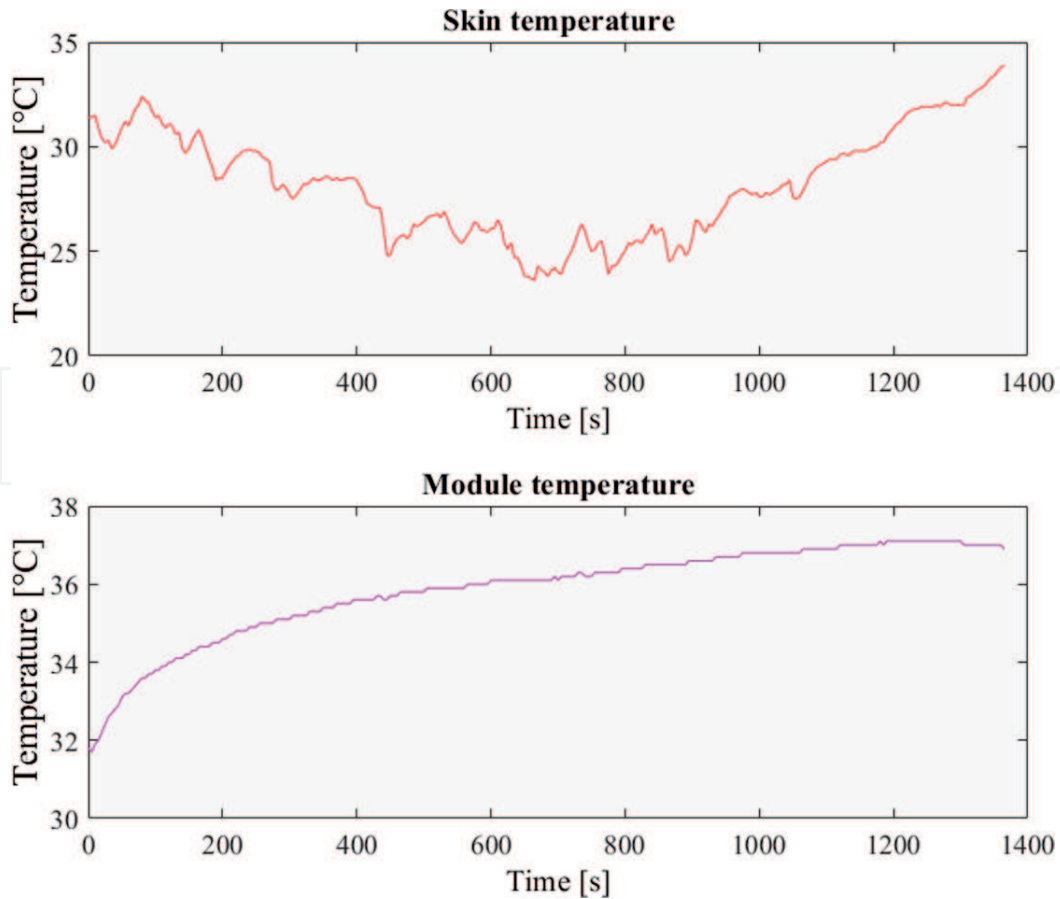
The player's skin temperature was measured with a contactless thermopile sensor. For accurate temperature measurements, the local temperature of the cold-junction temperature reference is measured. This is necessary because this type of sensors can only sense the temperature difference, not absolute temperatures. **Figure 8** presents the skin and module temperature readings during a short practice. For high precision, the sensor must be calibrated because different surfaces have different emissivity (even different skin tones have influence). Plots in **Figure 8** show that the wearable module was slightly heating over time because of the LEDs for pulse rate measurement (they are close to the sensor and they generate heat). This could be the reason that the module achieved a temperature higher than 37°C.

### 3.4 Tennis stroke consistency estimation

Readings of the smart wearable module, if they are stored and properly analyzed, can be used also for the analysis of how consistent a player is when hitting a



**Figure 7.** Graphical representation of R-R intervals obtained with the PPG method. The upper plot represents a signal obtained with red LED tissue illumination and the lower plot represents a signal obtained with IR LED tissue illumination.



**Figure 8.** Temperature readings during a short (20 min) tennis practice. The upper graph represents the temperature of the skin, while the lower plot represents the sensor's internal cold-junction temperature readings.

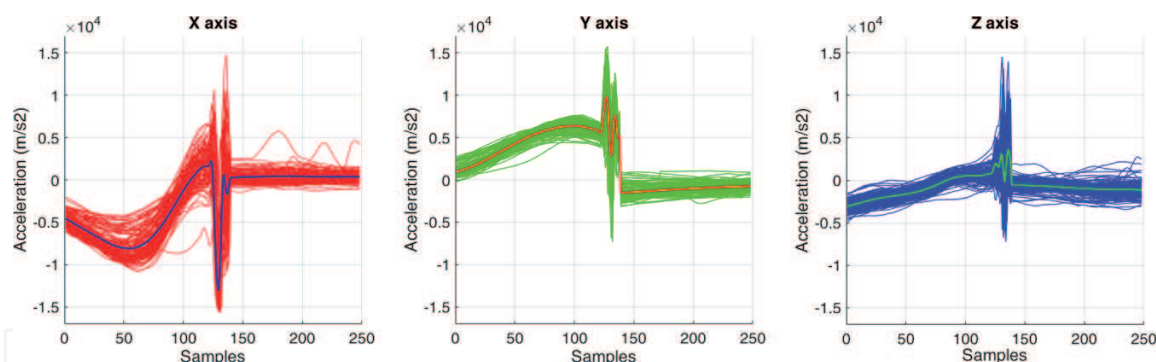
stroke. This kind of analysis can be very useful for tennis coaches and other experts on the evaluation of the tennis player's current shape and performance ability. If combined with the information of which stroke was a winner or a fault, even more valuable information can be extracted [30].

#### 3.4.1 Forehand stroke models

For the task of tennis stroke consistency evaluation, we made a general forehand stroke model. A separate model was built for each individual player. The model was made by calculating an average of acceleration sample bins for every accelerometer axis separately. We paid special attention that the accelerometer readings were aligned fairly good with the stroke detection point. About 150 ms before and after, the point of contact was used for making the model. That interval corresponds to 248 sample bins in total. An individual player's forehand stroke model for one axis is determined by using the following expression:

$$FSM(i) = \frac{1}{N} \sum_{j=1}^N fh_{acc}[i][j], \quad i = 1:248, \quad (2)$$

where  $FSM(i)$  corresponds to the axis bin of the forehand stroke model,  $fh_{acc}[i][j]$  is an array of accelerometer readings,  $N$  is the number of different stroke acc. recordings,  $i$  is the index of accelerometer sample bins, and  $j$  is the player's stroke record index. For a specific player, the general forehand models (separate for individual axes) are presented in **Figure 9**. The model is seen as the thick line in the middle of the curves.



**Figure 9.** General forehand stroke model for a tennis player. For each axis, a separate model is presented.

By observing the acceleration plots, we can notice that the trajectories are quite sparse. If the plots are closer together, then the ability of the player, to hit the strokes in a repeating manner, is very high. In this case, consistency is also very high. From a closer observation of the graphical plots of the individual axis, we can conclude, that the player, whose strokes are presented in **Figure 9**, is the most consistent via Y-axis, where the X-axis is the one with the most scattered plots. This estimation is made on observing the scatter thickness around the thick middle line, which represents the general axis stroke model. Plots show us also the three most obvious swing segments, where at the beginning of the plot from bin 1 to bin 120 is the swing segment. From the bins 120 till 140, the ball impact segment occurs. The last segment, called follow-through is from bins 140 till 248. The thick emphasized line plotted in the middle of the axis's acceleration curves is the graphical representation of a stroke model.

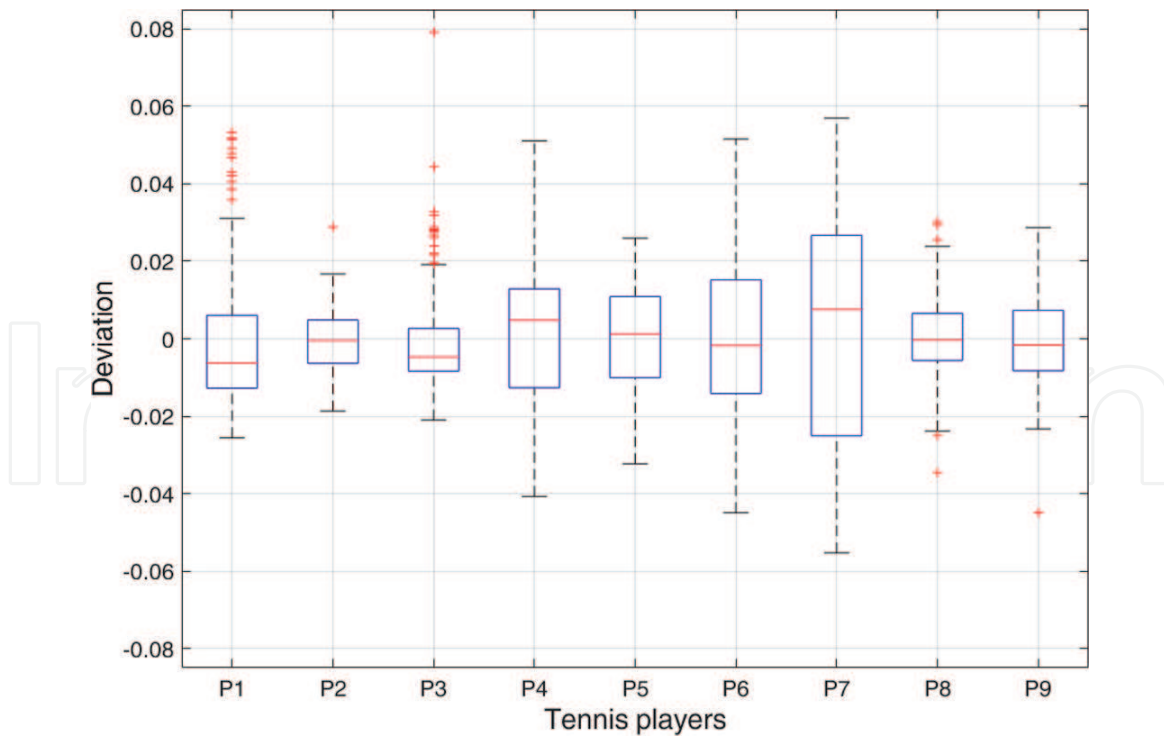
### 3.4.2 Stroke consistency evaluation

To evaluate the tennis player's forehand stroke consistency, the general player's forehand model is compared to the players' recorded forehand strokes. To be able to derive the forehand stroke models, a database of forehand strokes was built. For estimation of the individual player's forehand consistency, an average distance between individual acceleration bins of stroke recordings and stroke model is calculated. The mathematical expression is:

$$dist(i) = \frac{1}{N} \sum_{j=1}^N (fh_{acc}[i][j] - FSM[i]), \quad (3)$$

where  $dist(i)$  is distance (for one axis) between the player's stroke and the stroke model,  $FSM[i]$  is the player's forehand stroke model,  $fh_{acc}[i][j]$  is the array of player's forehand strokes,  $N$  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. Around 100–150 strokes for a player were typically captured.

After that, average value of distances for all the three axes is calculated to get the common distance between the model and the individual stroke recording. Some valuable information is lost by doing that, but the reason for doing it this way is that the sign of the bin differences gets preserved. This is a piece of valuable information which tells us if the player is making the swing “under” or “over” compared to the forehand model. If we would use some other distance metrics (like Euclidean distance) to calculate the distance between acceleration bins of the strokes and the model, the outcome would have an only positive sign and the information about the error direction would be lost. A box plot is used for results presentation. **Figure 10** shows the statistical representation of the forehand stroke consistency for players P1–P9.



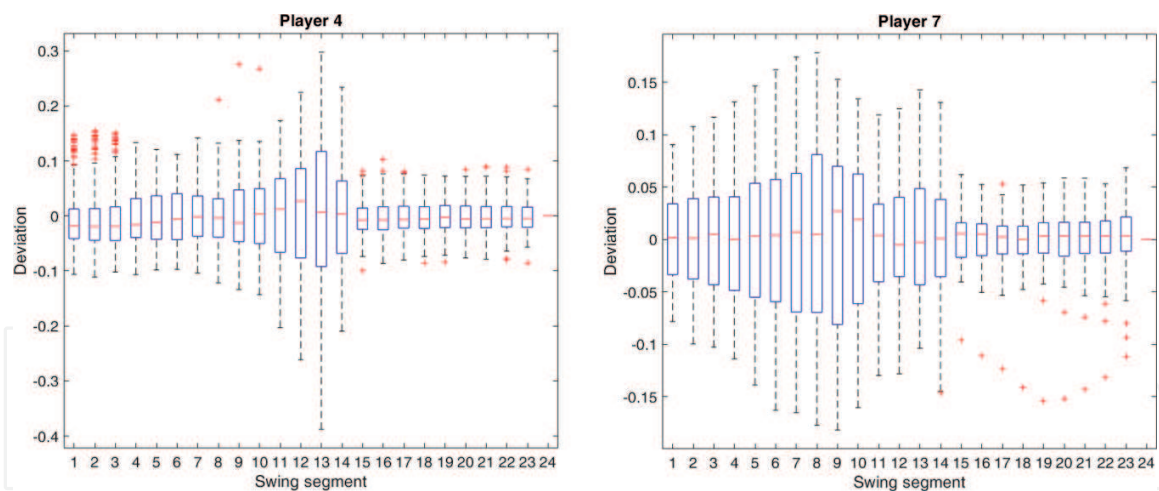
**Figure 10.**

Box-plot representation of the tennis stroke consistency evaluation. Lower and upper lines of the boxes represent the 25th and 75th percentile of the deviation interval, respectively.

A comment on the presented data is necessary to properly interpret the provided information. As mentioned, we used a box plot to represent the consistency analysis. A rectangle (box) is presenting each player. The red line in the box represents the average (median) value of the forehand stroke deviation from the model. Players P2 and P8 have near 0 deviation. The upper line of the box represents the 75th percentile of the deviation interval, and the lower line of the box represents the 25th percentile of the deviation interval. Its distance (between lower and upper box border) is known also as the interquartile range. Each box is also extended by a line, called a whisker. Whisker is a dotted line that is drawn from the box border to the far border of the observation interval. They are determined beforehand, and in our case, they represent the border for the outlier values. In our case, they are set to 1.5 of the interquartile range. Values of the deviation that exceed this range are represented by red crosses and are called outliers. Box plots in **Figure 10** show that the players P2, P3, and P8 are the most consistent among the tested group because their box plots are the smallest. They have some outliers, but they can be a consequence of an off-balance/close-to-body forehand stroke made. Regarding stroke consistency estimation, the worst player is the player P7. It has the biggest box plot and the red line (average value) is also off center, which suggests that the stroke deviation distribution is somewhat skewed to the positive values.

A more detailed stroke consistency estimation can be made for individual players. In **Figure 11**, detailed segmental stroke analysis is presented, also using a box plot.

As we can conclude from **Figure 11**, detailed segmental stroke analyses for players P4 and P7 are presented. The analyses presented in **Figure 10** gave us the overall forehand swing consistency estimation. On the other hand, the segmental analysis presented in **Figure 11** gives us the insight in which part of the forehand stroke the players are the most or the least consistent. We can see that player P4 has the highest box plots at segments 12–14, which are the segments, where the racket contacts the tennis ball. This deviation in this segment is to be expected and is common because of the oscillations and vibrations due to the ball contact. But the player P7 has the



**Figure 11.** Segmental forehand swing consistency analysis presentation for players P4 and P7. Player P7 is inconsistent in the swing phase of the tennis stroke.

least inconsistent forehand around the segments 7–10, which is a swing stage of the tennis stroke. This information can be valuable for the player and the tennis coach. Based on such analyses, they can make a strategy on how to improve the training and performance of a tennis game.

## 4. Conclusion

In this chapter, smart wearables in sport were presented, using a case of a system for tennis game analysis. A miniature wearable device for detecting and recording the movement and biometric data is presented in detail, along with the procedures and algorithms for tennis stroke detection and classification. The presented system also incorporates a cloud service for information visualization and possibly more sophisticated game/athlete's performance analysis. The performance of the proposed system was tested for tennis. The wearable device supports tennis stroke detection and classification of the three most basic strokes: forehand, backhand, and serve. It also supports pulse-rate measurements and skin temperature measurements. A principle of tennis stroke consistency evaluation was also presented. The smart wearable device with cloud processing support and presented stroke analyses can give an athlete or a coach a good insight into an athlete's skills and abilities and can be a great tool for sport performance improvements.

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