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An IoT-Enabled Wearable System for Tennis Stroke Analysis Using IMU Sensors

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ABSTRACT

The ability to make quick decisions and execute fast movements is essential in lawn tennis and is difficult to assess accurately through visual observation and subjective coaching. Current racquet-mounted and wearable sensing systems can collect stroke information, but many require racquet modifications, are cumbersome during play, or are primarily designed for stroke classification without providing real-time visualization and feedback. Therefore, a lightweight, non-invasive, and cost-effective wearable platform for continuous on-court monitoring is still needed. This paper presents a proof-of-concept Internet of Things (IoT)-based wearable system integrated into a conventional tennis wristband for real-time stroke data collection, processing, and visualization. The system is built around a Nordic nRF52832 System-on-Chip (SoC) and an ICM-20948 inertial measurement unit (IMU) mounted on a custom-designed printed circuit board (PCB) powered by a rechargeable lithium-ion battery. Motion data are validated, noise-filtered, and calibrated before being transmitted to an Android application and cloud backend using Bluetooth Low Energy (BLE). On-court testing demonstrated the successful acquisition and real-time visualization of synchronized linear acceleration, angular velocity, and effective jerk signals during tennis stroke execution. The testing was conducted during five 60-minute on-court sessions involving players aged 13–40 years, and the ball–racquet impact was identified using jerk magnitude peaks exceeding 4,000 meter^2/second^4. These findings demonstrate the technical feasibility of a low-cost, non-invasive wearable IoT platform for real-time tennis stroke monitoring and provide a foundation for future machine learning-based stroke classification and performance analysis.

Keywords: Lawn tennis; Internet of Things (IoT); Inertial Measurement Unit (IMU); Bluetooth Low Energy (BLE); Wearable sensing.

INTRODUCTION

Lawn tennis is a highly technical sport, and there are key fundamental strokes in this game, such as forehand, backhand, serve, etc. It is a highly competitive and popular sport, with data suggesting that there were approximately 106 million players in 2024 across the globe playing this sport, which depicts a 25.6% increase in the number of people playing tennis since 2019 (ITF Global Tennis Report, 2024). At the competitive level, performance depends on micro-decisions at each point, and there is a need to measure parameters such as stroke velocity, sweet spot effectiveness, shot frequency, spin rate, etc. As success in this sport depends on both micro-decisions and the quality of these parameters, it is essential for an athlete to measure and understand their weaknesses through these parameters. Therefore, data analysis of such parameters using sensors helps detect patterns that human observation often ignores. Human observation cannot process high-speed kinematics like racquet edge speed or stroke speed. Coaches and athletes rely on visual memory and qualitative data, which is not always accurate. In the field of sports, coaches and athletes commonly use various platforms and devices to assess and provide valuable feedback, which enhances their sports skills. Such devices can be found in expensive smartwatches, camera-based solutions, or custom gadgets.

A critical review of existing tennis sports analytics devices revealed several limitations in commercially available systems. Most current solutions rely on sensors mounted on the racquet or the player's dominant arm, which may cause discomfort and interfere with natural playing mechanics, thereby limiting user acceptance during prolonged use (Park et al., 2024).

Moreover, research has also found that a few sports sensors, like the Zepp sensor, show inaccurate results when they are being used by high-level players, as the changes in velocity after a training program may be unnoticeable (García, 2022). Hence, there exists a need for an accurate, comfortable, and reliable system for analyzing tennis performance that can make sense of sensor-acquired data.

The current research is using a wearable, IMU-based sensor to measure and analyze the dynamics of tennis strokes. IMUs collect readings from three-axis accelerometers, tri-axial gyroscopes, and tri-axis magnetometers, which collect movement and orientation data. However, having these sensors on is not beneficial unless readings can be wirelessly transmitted, processed, and displayed in a user-friendly way; this is where the use of the Internet of Things comes in. Wearable sensors, when combined with wireless communication and data processing capabilities, have proven effective for real-time monitoring. A study by Naheem and Kim (2022) demonstrated an IMU-based, wearable sensing system that used wireless technologies to monitor and track motion. Similarly, De Fazio et al. (2021) have also demonstrated that IoT-enabled wearable sensing systems can be applied in many domains to support real-time data collection, transmission, and visualization.

This study aims to present an IoT-enabled wearable system for tennis stroke analysis using IMU sensors, which performs real-time data acquisition and graphic visualization of the data collected by the sensors.

LITERATURE REVIEW

The most effective positioning of inertial sensors and the creation of efficient data-processing systems for sports technology are still major challenges in the field of sports technology. In recent years, the combination of inertial measurement units (IMUs) and machine learning algorithms has emerged as a promising approach to enhance stroke detection and classification accuracy. For example, Ebner and Findling (2019) tested the placement of IMU on the wrist and on the racket, with a 98.5% to 99.5% accuracy for stroke detection and an 89% to 99% accuracy for stroke classification. They showed that kinematic information could be obtained from wrist-mounted wearables for accurate stroke recognition without modifying the racket. Likewise, Taghavi et al. (2019) used a commercially available smartwatch to transmit motion data to a local processing system, and a Support Vector Machine (SVM) classifier was used to classify three basic tennis strokes with 99% accuracy. This study demonstrated the potential of consumer-grade wearable technology to accurately identify stroke.

Later studies have gone beyond the laboratory classification to the challenge of real-world game play. Ganser et al. (2021) created a large dataset of 5,682 annotated strokes from both amateur and professional players using a wrist mounted IMU. To overcome the noisy and heterogeneous motion data, deep learning architectures such as Fully Convolutional Networks (FCN) and Residual Networks (ResNet) were used to effectively classify strokes. Various sensor locations have also been considered to improve the comfort and usability of the player. Perri et al. (2022) studied a cervical-mounted IMU system with 98% and 94% classification accuracy for serves and groundstrokes respectively. The system, however, showed decreased performance for volleys with more complex stroke dynamics, specifically spin-intensive volleys, suggesting that the system has a limit in its ability to recognize more complex stroke dynamics. Recently, Agarwal and Vishwakarma (2026b) proposed the SmartDampener prototype which included wireless IMUs in a conventional racket vibration dampener. Their study showed that an unobtrusive embedded sensing platform was able to successfully capture real-time parameters such as impact location, swing speed and vibration characteristics without affecting the usability of the racket.

Research Gap

Previous works have shown high classification accuracy with wrist-worn, smartwatches, cervical-mounted wearables and racket-integrated IMUs, but most of these studies have been limited to stroke detection or performance classification in controlled or offline processing settings. Few studies have been able to build an integrated system that integrates wearable IMU-based sensing, real-time IoT data transmission and live graphical visualization of the stroke kinematics in a single, portable platform. Moreover, the previous studies have focused mainly on the classification accuracy, and have paid little attention to continuous real-time monitoring, intuitive visualization of sensor outputs and user-friendly deployment for coaching and player performance analysis.

MATERIALS AND METHODS

Hardware

Nordic nRF52832 System on a Chip (SoC)

The NRF52832 SoC is a powerful, highly flexible, ultra-low-power multiprotocol SoC microcontroller ideally suited for Bluetooth low energy (BLE) and ultra-low-power wireless applications. The nRF52832 SoC is built around a 32-bit ARM Cortex M4F CPU with 512KB flash and 64KB RAM; hence, most demanding applications with complex arithmetic requirements can be realized in single-chip solutions

(Nordic Semiconductor, n.d.). It supports DSP instructions, a Floating Point Unit (FPU), single-cycle multiply and accumulate, and hardware divide for an energy-efficient process of computationally complex operations. Nordic Semiconductor's SOC nRF52832 collects, processes, and transmits sensor data. The processed data is transmitted to the user's mobile phone using a BLE connection, where it is used by the dedicated app for further analytics.

ICM-20948 Motion Sensor

The ICM-20948 is a multi-chip module (MCM) that integrates two dies within a single QFN package. One die contains a 3-axis gyroscope, a 3-axis accelerometer, and a Digital Motion Processor™ (DMP), while the second die incorporates the AK09916 3-axis magnetometer. This makes the ICM-20948 a compact 9-axis MotionTracking device packaged in a 3×3×1 mm QFN form factor. With its 9-axis integration, embedded digital motion processor, and run-time calibration firmware, the ICM-20948 helps manufacturers avoid the expense and complexity associated with selecting, qualifying, and integrating separate discrete components, while also ensuring optimized motion performance for consumer applications.

Magnetometer

The embedded magnetometer was added to provide heading information and enhance the orientation estimation with wrist movements. It provided geomagnetic reference data along with the data from the accelerometer and gyroscope, which in turn increased the stability of motion tracking and reduced orientation drift when acquiring data for a long period of time, thus making the analysis of stroke trajectory more accurate.

Flash Memory (SPI FlashMX25L3206)

The MX25L3206 is a 32 Mbit Serial Flash memory and interfaces via SPI. It is utilized for storing firmware and sensor data within the system (Macronix International Co., Ltd., 2013).

Rechargeable Battery and RGB LED

The wearable system was powered by a rechargeable lithium-ion battery, which allowed for continuous use during on-court testing. The integrated RGB LED offered visual feedback to the user on the status of the device, such as power, Bluetooth Low Energy (BLE) connection, charging status, and successful data transmission, which allowed for fast user verification without the need to interact with the mobile application.

2.4 GHz Chip Antenna (Cirocomm) and Switch

The 2.4 GHz Cirocomm chip antenna supported the seamless Bluetooth Low Energy (BLE) connection between the wearable device and the Android application, allowing sensor data to be transmitted in real-time. The on-board switch was the main control for powering the wearable system on and off, enabling the user to easily power the system on and off before and after data acquisition sessions.

Printed Circuit Board (PCB)
The PCB serves as the central platform where all components, including the IMU sensor, the microcontroller, and flash memory, are mounted. It electrically connects all these components to ensure the sensor functions properly.

Charging Dock
A custom-developed charging dock with a type-A USB cable connected to a PCB with pogo pins to provide a charging interface for an embedded sensor.

Gloss-Finished Plastic Enclosure
A custom designed, 3D printed plastic enclosure with a gloss finish was designed and manufactured to safely contain the electronic components and charging dock. The enclosure offered structural protection from mechanical damage in the game, but was also lightweight and compact enough to fit into a standard tennis wristband. The prototype was also improved in terms of its overall durability and aesthetic appeal due to the gloss finish.

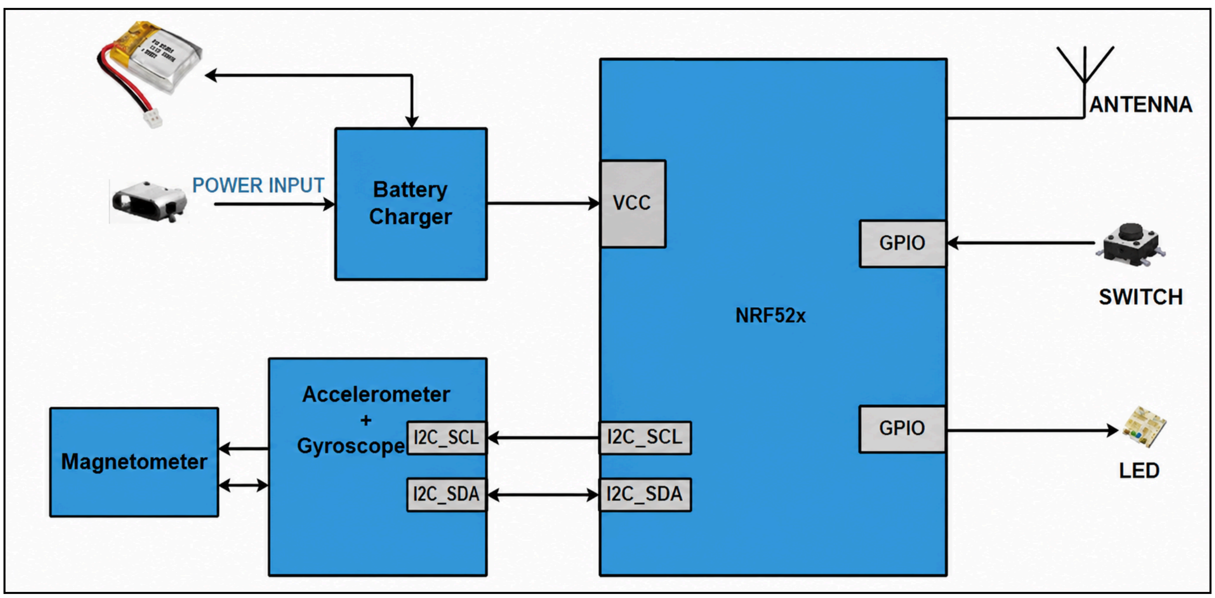

Figure 1: Hardware Schematic. The wearable system is powered by a rechargeable battery through a battery-charging circuit, which supplies power to the nRF52x microcontroller. The microcontroller interfaces with the inertial measurement unit (IMU), comprising an accelerometer, gyroscope, and magnetometer, to acquire motion data. The collected sensor data are processed by the microcontroller and transmitted to the user via an integrated antenna using a Bluetooth Low Energy (BLE) connection. A push

button connected through the general-purpose input/output (GPIO) interface enables user control of the system, while an RGB LED provides visual status indication.

Software and Development Tools

Segger J-Link
A programming and debugging tool for flashing firmware onto the Nordic SoC microcontroller as well as debugging the software (SEGGER J-Link Debug Probes, n.d.).

Visual Studio Code Integrated Development Environment
Visual Studio Code (VS Code): An integrated development environment (IDE) to develop, edit, and manage the system's firmware source code. This includes features to assist in embedded software development, such as code completion, debugging tools, and extension support (Visual Studio Code: The Open Source AI Code Editor, 2021).

OrCAD and Allegro
These applications were used for designing the embedded sensor and defining the charging dock’s hardware schematics. OrCAD was utilized for schematic capture and circuit design, while Allegro was used for printed circuit board (PCB) layout and routing. Their use facilitated the development and implementation of the system hardware.

Miscellaneous

Tennis Wrist Band
A common tennis wristband was used, on which the sensor was stitched.

Android mobile phone
An Android mobile phone (Google Pixel 7) was used, in which the companion mobile application for the sensor was installed.

Tennis Racquet and Balls
These tennis equipment items were used along with the sensor on the court for field trial and data collection.

A portable tripod-stand

This device was used for easy video recording of the player playing along with the sensor in use. The recorded videos enabled a head-to-head comparison of the data collected by the sensor and the actual stroke hit by the player.

Hardware Evaluation Kits
Hardware evaluation kits from Nordic Semiconductor and TDK/Invensys were used for initial development of embedded firmware.

System Architecture

The proposed Proof-of-Concept (PoC) system aims to develop an IoT-enabled wearable sports monitoring platform capable of capturing and transmitting racket motion data in real time. The system consists of four major components: (i) sensor-based data acquisition, (ii) signal conditioning and preprocessing, (iii) wireless data transmission, and (iv) cloud-based visualization and feedback.

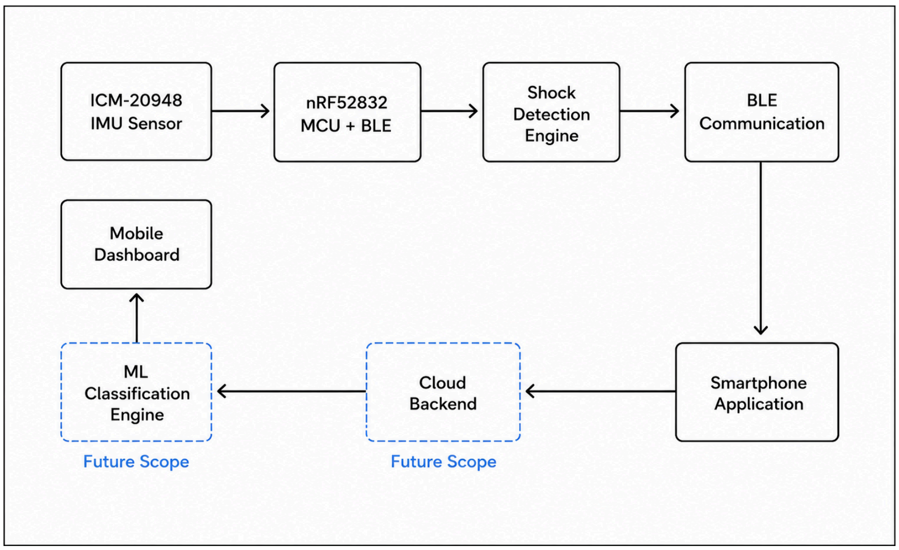

Figure 2: End-to-End Workflow of the Proposed Tennis Analytics System

In general, the design of the wearable sensing system proposed herein is presented in Fig. 2. The system receives data from the ICM-20948 IMU sensor on the nRF52832 microcontroller, processes data, and sends the data for use in the shot detection engine via BLE and on the smartphone, with data visualization on the mobile application and connectivity with the backend cloud; machine learning classification and a mobile dashboard are used to facilitate the user providing feedback regarding the performance.

Hardware Integration and Sensor Placement

The wearable sensor was integrated into a standard tennis wristband by sewing it using a thread and a needle. The sensor was positioned on the player's dominant wrist to capture arm and wrist movements associated with tennis strokes. This placement was selected to minimize interference with gameplay while allowing consistent acquisition of motion data.

The hardware platform consisted of an IMU sensor, microcontroller, flash memory, wireless communication module, battery, and supporting circuitry assembled on a custom-designed PCB. The system was powered by a rechargeable lithium-ion battery, enabling portable operation during on-court testing.

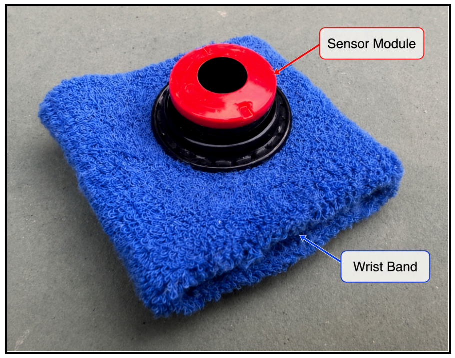

Figure 3: IMU-Based Sensor Integrated with the Wrist Band

Data Acquisition

The wearable sensor continuously captures motion from the IMU sensor that measures the acceleration, angular velocity, and magnetic field of 3 orthogonal axes. The nRF52832 microcontroller captures and processes this data through the embedded firmware.

As depicted in Figure 4, the captured data from the sensor is first filtered using validation to remove incomplete or corrupted data, which then passes through the noise filtering process, where unwanted jitters and vibrations are removed. The data then undergo a calibration process in which sensor offsets are removed to ensure consistent and accurate measurements. Subsequently, the resultant acceleration and angular velocity are computed, with the magnitudes of both parameters represented independently of the sensor's orientation. The extracted features are passed on to the shot detection, which detects the motion that indicates a tennis shot and filters significant shot events. To evaluate this real-time pipeline under live conditions, testing was conducted involving 2 active participants performing serves, groundstrokes, and volleys. Within these sessions, the baseline detection threshold for effective jerk (jEff) was empirically set to a default value of 2,500 $meter^2/second^4$ based on initial calibration trials to isolate true ball-racquet impact shocks from standard playing motion noise, which remains dynamically adjustable via the mobile application settings.

The net filtered jerk (jNet) is derived from the first-order low-pass filtered accelerometer components (xF,yF,zF) across all three orthogonal axes:

$$jNet = xF + yF + zF$$

The effective jerk (jEff) is subsequently calculated using the magnitudes of the current and prior net jerk iterations to isolate the primary impact shock:

$$jEff = |jNet| \cdot (||jNet_{prev}| - |jNet|| + ||jNet_{prevPrev}| - |jNet||)$$

The effective jerk (jEff) calculation is mathematically performed with a unit of meter^2/second^4 using a fixed time delta scalar ($\Delta t=1$). The baseline detection threshold default of 2,500 meter^2/second^4 is a good generalisation for different players and racquets because the shock of a true ball-racquet impact produces a distinct, high-amplitude kinetic spike that always exceeds the lower-amplitude acceleration changes that occur from normal playing motions and individual swing variations, regardless of the racquet and player.

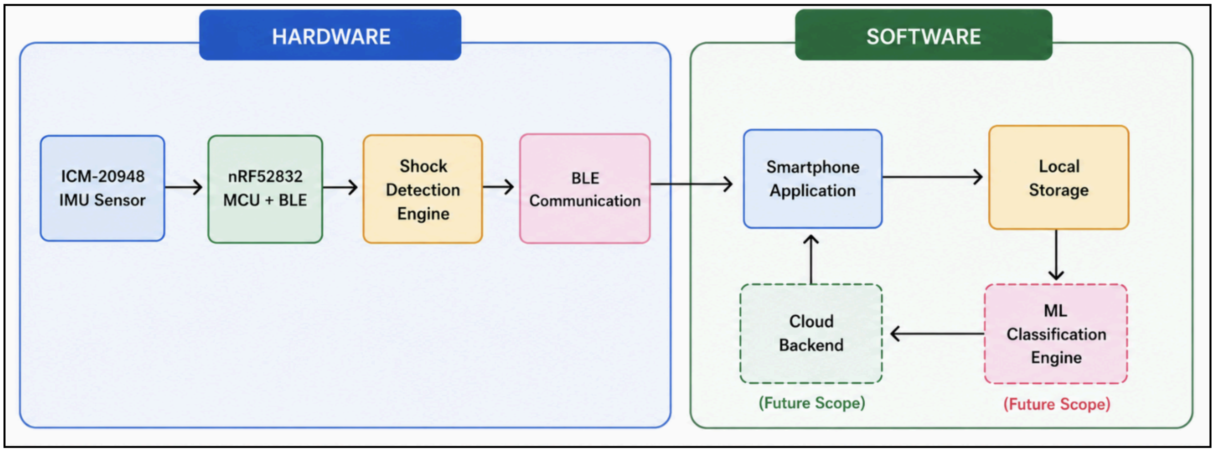

Figure 4: Signal Processing Workflow: Motion Signal Processing Pipeline

Wireless Communication and IoT Integration

Bluetooth Low Energy (BLE) was used to transmit the processed sensor data wirelessly. The nRF52832 microcontroller served as the BLE peripheral, and the application on the smartphone served as the central, where the connection was established and maintained.

An Android application was designed to retrieve and visualize the stream of sensor data in real-time. The application visualizes graphs for the accelerometer readings along each axis and the gyroscope readings along each axis, and the values are constantly being updated as the player plays the game, making the changes more evident.

Dashboard Development and Visualization

The mobile app provided a dashboard for real-time visualization of the sensor data and manipulation of the device. This dashboard has options for discovering sensors, Bluetooth connection, viewing the current session, and checking battery status.

Since the accelerometer and gyroscope data were presented in graphical form, it was useful for being able to visually follow the players' movements and patterns associated with strokes in real-time. It also showed the relevant data, such as swing speed, ball speed, ball spin, and impact score via an intuitive-to-understand user interface to monitor the sensor's outputs in the training session.

DISCUSSION

The field testing was carried out on a tennis court using the wearable sensor setup. To obtain data for this study, the sensor was tied on the dominant wrists of 2 tennis players, with their ages ranging between 13 and 40 years. Data collection was carried out over 5 sessions, with each session lasting approximately 60 minutes.

All players involved in this study were recorded while performing different types of tennis shots like forehand, backhand, volley, serve, etc. To ensure that the data collected was valid, the testing was simultaneously accompanied by video recording on a smartphone that was stabilized on a tripod. The recording camera was placed 5 meters away from the player with a view of the court at a height of 4 feet from the ground.

The view on the camera covered the body of the player, the wrist, the hand movements, and the stroke application performed by the player. This enabled effective comparison of the sensor-acquired data with the actual stroke. To ensure reliable data collection, all tests were conducted in the same conditions and on synthetic tennis courts. At the beginning of every testing session, it was ensured that the sensor was properly stitched into the wristband and confirmed if it was working correctly and connected via Bluetooth to the mobile phone. Finally, the collected sensor data and the video files were examined for the quality of the sensor and transmission.

Figure 5: On-court Data Collection using Sensor

The accelerometer data collected by the proposed wearable system showed clear high amplitude peaks at the time of ball–racquet impact, followed by a sudden drop in the signal amplitude, which is consistent with the characteristic ball–racquet impact signatures reported in previous IMU based tennis studies (Ganser et al., 2021; Anand, 2017). These observations corroborate the potential of real-time stroke event detection using acceleration derived features. Following the method presented by Ganser et al. (2021) and Anand (2017), jerk was calculated along the x-axis, y-axis and z-axis and then added together to get the effective jerk. The effective jerk profiles were analyzed and the results showed that the ball–racquet impact point could be identified reliably and the impact timestamp could be calculated from the effective jerk profile using a threshold based approach. The feasibility of real-time impact detection in the proposed wearable platform is demonstrated in the present work, but the characteristics of the observed signals are very similar to those described in previous studies, suggesting that the proposed proof-of-concept is able to record meaningful stroke kinematics and could serve as a basis for future development of advanced stroke classification and performance analysis algorithms.

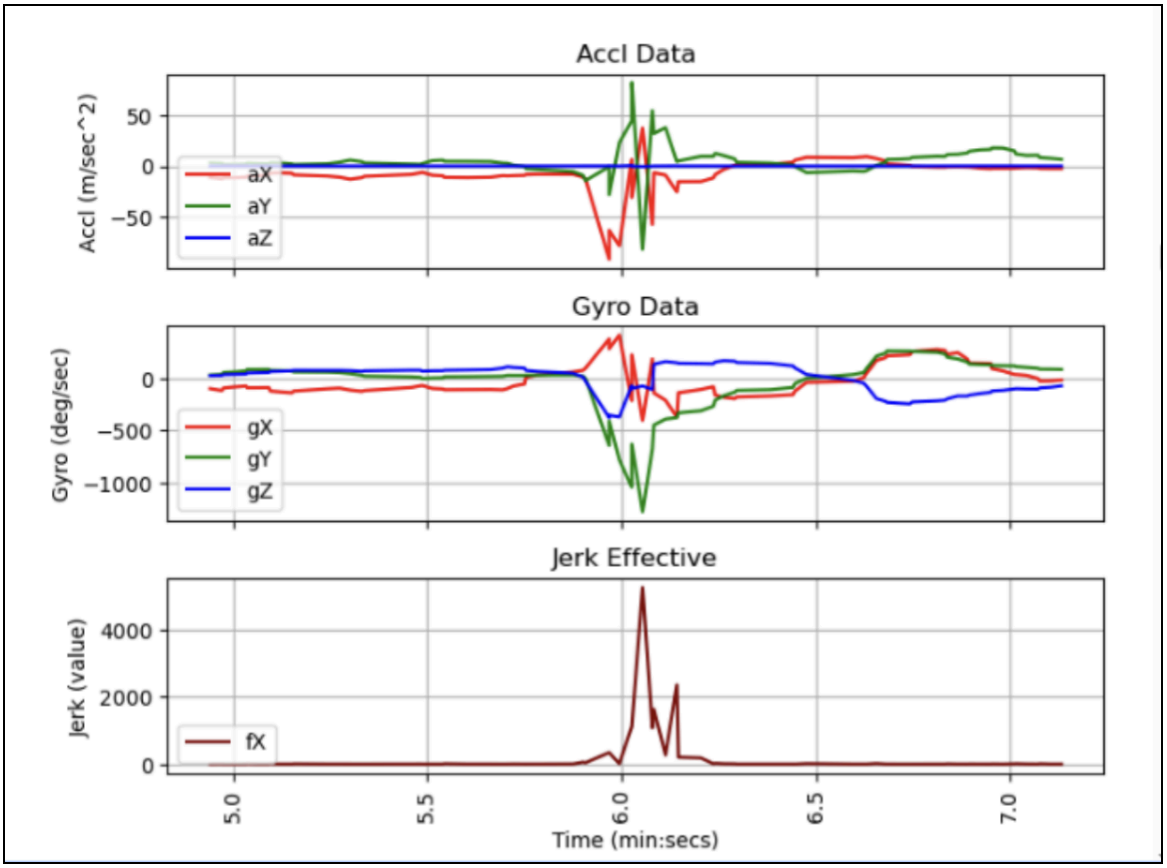

Figure 6: Graphs Illustrating Real-Time Sensor Measurements

The acceleration, gyroscope, and effective jerk measurement results are illustrated in Figure 6. The accelerometer signal indicates a sudden, large change in linear motion due to high-frequency changes across all three axes just before and after impact. The gyroscope also shows many high-frequency changes in angular velocity in relation to the movement of the wrist and racquet as the stroke occurs. These peaks occurred at virtually the same time, demonstrating that the wearables had recorded the dynamic motion during a stroke.

When looking at the effective jerk, there is a significant peak at approximately 6.0 seconds, which correlates with the time of ball impact. The magnitude of the effective jerk at this moment is substantially

greater than the values before and after this point, indicating that this moment caused a very large change in acceleration due to a high-impact force created when the ball contacts the racquet.
These results confirm that the proposed system is capable of continuously acquiring, transmitting, and visualizing motion data generated during tennis play. These distinctions reveal that useful stroke-related information could be derived from the collected sensor signals, which could pave the way for classification algorithms, such as strike, impact event, swinging, and player performance analysis.

CONCLUSION

This study aimed to present a proof-of-concept IoT-based Wearable Tennis Stroke Analysis System with Inertial Measurement Unit (IMU) sensors. The developed system was successfully used to show the acquisition, transmission and visualization of motion data associated with tennis strokes, showing the viability of the application of wearable sensing technologies to the objective monitoring of human motion in a sporting context. The prototype combines IMU motion capture with an IoT communication system to enable the collection of kinematic data in an environment outside the laboratory setting, in a portable and cost-effective manner.

The findings indicate that wearable IMU sensors could provide useful information regarding the players' movements and how they execute their tennis strokes, which could help to quantify player technique and movement patterns. While this work was not designed to conduct a full biomechanical validation or advanced performance analysis, it showcases the potential of low-cost wearable technologies as a basis for data-driven sports analysis.

Several aspects of this investigation are limited as a proof-of-concept study: testing conditions are limited, number of participants is limited, and there are no automated analytical models. Furthermore, the system development and feasibility evaluation are highlighted in the current implementation, and the validation and predictive analysis have yet to be performed on a large scale. The suggested method needs to be further researched to determine its validity, reliability and applicability to other stroke types and ability levels of players.

The potential future directions for research include incorporating more than one wearable sensor, creating machine learning algorithms to classify strokes and analyze performance, and developing real-time feedback systems to enable coaching and training. The information collected during the motion can also be utilized to develop clever sports monitoring systems that can provide valuable insights to athletes and coaches, which can be utilized to improve their performance.

Finally, the proposed system proves the technical feasibility of integrating an IMU sensing system with an IoT system in order to monitor the tennis stroke. This successful implementation of the proof-of-concept lays the groundwork for future research on scalable, data-driven approaches to sports performance analysis and athlete development.

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