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Retraction

Retracted: MEMS Sensors in Tennis Teaching and Training under the Background of Big Data Intelligent Communication

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Wireless Communications and Mobile Computing has retracted the article titled "MEMS Sensors in Tennis Teaching and Training under the Background of Big Data Intelligent Communication" [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process and the article is being retracted with the agreement of the Chief Editor.

References

[1] F. Li and Z. Li, "MEMS Sensors in Tennis Teaching and Training under the Background of Big Data Intelligent Communication," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 4684314, 15 pages, 2022.

[2] L. Ferguson, "Advancing Research Integrity Collaboratively and with Vigour," 2022, https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/.

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Research Article

MEMS Sensors in Tennis Teaching and Training under the Background of Big Data Intelligent Communication

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Racket sports (tennis, pawns, tennis, etc.) are currently very popular sports, and they are a very intense aerobic exercise. The climatic conditions of the competition venue, time difference factors, the size of the competition venue, background, lighting, wind direction, etc. may all have an impact on the performance of the game. In order to fully control and eliminate these risk factors, it is recommended to go to the competition site for adaptive training one month in advance. If you can participate in the prematch training camp organized by the general administration, it is of course the best choice. This research mainly discusses the development of MEMS sensors in tennis teaching and training under the background of big data intelligent communication. Using a single inertial sensor fixed on the bottom of the racket for data collection, a real-time data stream window segmentation method based on the combination of sliding window and action window is proposed. Finally, based on the above recognition method, an intelligent tennis training system software is developed, introduces the processing flow of MEMS sensor data, and gives a specific implementation plan for data preprocessing through in-depth study of the characteristics of inertial navigation data. The tennis training system collects the raw data of tennis players during the training process through the MEMS sensor hardware module placed at the bottom of the tennis racket handle, and the sensor module can upload these raw data to the smart phone terminal through wireless communication. The smart phone terminal can analyze and process the collected raw data and finally feedback the number and proportion of each technical action of the tennis player in the training process and the maximum racquet speed through the mobile phone software in real time. After the practice training, the average CTN score of the control group was 141.73, and the standard deviation of the data was 4.185. After the practice training, the average CTN score of the experimental group was 161.67, and the standard deviation was 6.042. This research will improve the efficiency of tennis teaching and training.

1. Introduction

At present, the recognition and data statistics of racket sports are relatively few. Therefore, an algorithm that can accurately recognize racket sports swings has been developed, and then, a set of real-time recognition and statistics of racket sports has been developed. It is very necessary to use a training system to analyze the sports characteristics of athletes. Make full use of the technical strength of scientific research, medical affairs, and expert groups to provide comprehensive scientific and technological services for the tennis team's prematch training. Organize information exchange meetings with all employees to achieve unified deployment and unified command, give full play to the maximum integration effect of scientific training, and try to do all kinds of services and preparations before going abroad. When forming a team, try to send capable members and talents with multiple skills and expertise to join the team.

Most sports events with statistics athletes in the process of sports data through these data statistics can be very intuitive to show the characteristics of athletes; in addition to these, statistics can be analyzed to guide the movement of athletes and improve the athletic level of athletes. The general situation is that long distances and long intervals between trains make athletes prone to irritability and affect physical recovery. The reason why the tennis team has achieved good results is that it is a very good "risk-off" measure to choose accommodation based on the principle of "nearest." It is not only conducive to rest between games but also avoids many risk factors such as traffic jams and public safety.

Organize athletes to learn related sports psychology knowledge before the game, so that athletes will understand the scientific principles of psychological factors affecting the competition process and start to change the practice of cognitive methods and rationally arrange simulated competitions to gradually master the active control of their mental state and avoid all kinds of the influence of disturbing factors on the mental state which continuously improves the ability of self-adjustment and self-control in the game. Testing and calibration constitute a major part of the overall manufacturing cost of microelectromechanical system (MEMS) equipment. Ozel et al. present a physical stimulation-free built-in self-test- (BIST-) integrated circuit (IC) design that characterizes the sensitivity of capacitive MEMS accelerometers. The BIST circuit can extract the amplitude and phase responses of the acceleration sensor mechanics under electrical excitation, with an error of within 0.55%, relative to its mechanical sensitivity under physical stimulation. A low computational complexity multiple linear regression model was used to characterize the sensitivity. BIST circuits make maximum use of existing analog and mixed-signal readout chains and host processor cores without the need for computationally expensive fast Fourier transform- (FFT-) based methods. The sensor analog front end and BIST circuit are integrated with a three-axis, low-G-capacitance MEMS accelerometer in a sealed package [1]. Wan et al. believe that each atom can interact with gas molecules, providing ultrahigh sensitivity and ultralow detection limits (as low as single molecule detection). Active FET sensors generally exhibit better performance in sensitivity and stability than passive resistance sensors. For mass-sensitive sensors, unique mechanisms can provide new device structures that are different from the other three types. However, considering compatibility with integrated circuit (IC) manufacturing, MEMS sensors may be a good choice. Materials with high specific surface area can provide more adsorption sites. Therefore, the sensor performance can be greatly improved. Specific adsorption sites can be achieved by changing the density and type of functional groups on the graphene surface. Therefore, the capability of selective gas detection is enhanced. In addition, explaining the sensing mechanism and studying the dynamic interaction between gas molecules and graphene would be an ideal basic research. Recently, it is believed that, with the help of a specially designed in situ scaffold, experiments can be carried out on transmission electron microscopy (TEM) to explore this basic research [2]. Kainz et al. believe that small scale and distortion free measurements of electric fields are essential for applications such as atmospheric electrostatic field surveys, lightning research, and protection of areas close to high-voltage power lines. A variety of measurement systems exist; the most common of which is the field mill, which works by taking the differential voltages of the measurement electrodes and shielding them periodically with an earthing electrode. However, all current methods are either bulky, subject to strong temperature dependence, or severely distorted electric fields, requiring clearly defined environments and complex calibration procedures. They demonstrated that microelectromechanical system (MEMS) devices could be used to measure the strength of electric fields without significant field distortion. Pure passive MEMS devices utilize electrostatic induction effects that are used to generate internal forces that are converted into optically tracked mechanical displacements of spring-mounted seismic masses. These devices have a resolution of approximately 100(V/m)/Hz and a quasistatic measurement range of up to tens of kilovolts per meter. It should be possible to achieve this by fine-tuning the sensor embodiments to approximately 1(V/m)/Hz. These MEMS devices are compact in structure and easy to mass produce for wide application [3]. Sharma et al. deposited well-dispersed gold nanoparticles on carbon nanotubes (CNT) by direct current (DC) sputtering and dealloying methods, using nitric acid (HNO 3) to form highly porous films. Fe-sem and AFM confirmed that gold nanoparticles were uniformly dispersed on the CNT matrix, like a highly porous film. The XRD pattern shows the presence of metallic gold particles on the disordered graphite phase. FTIR and Raman spectra confirmed the interaction between gold nanoparticles and CNT matrix. A microhydrogen sensor based on memS was developed from the highly porous film of AU-CNT [4]. Kim et al. suggest that stress caused by moisture saturation on MEMS sensor equipment has been resolved after exposure to the temperature cycle. The humidity, temperature, and time-dependent material properties of the moulds used in MEMS devices are characterized. In order to determine the hygroscopic expansion coefficient and the water diffusion coefficient (D) in the mold, the digital image correlation method combined with the weighing scale was used to monitor the size change and weight loss of the water saturated samples at different temperatures. To obtain the viscoelasticity of the moulds, a series of stress relaxation tests were performed using dynamic mechanical analysis (DMA). In order to explain the viscoelastic behavior caused by moisture, a simple hypothesis was introduced based on the glass transition temperature (Tg) shift of DMA results. Experimental data were used for numerical simulations to estimate temperature and wet-induced stress on MEMS sensor equipment affected by temperature cycles [5]. Mellal et al. describe a noninvasive system for respiratory monitoring using microelectromechanical system (MEMS) flow sensors and IMU (inertial measurement unit) accelerometers. The system is designed to be wearable and used in hospitals or at home to help people with respiratory problems. In order to ensure the accuracy of the system, he proposed a calibration method based on ANN (artificial neural network) to compensate the temperature drift of silicon flow sensor. The SigmoID activation function used in the ANN model was calculated using the CORDIC (Coordinate Rotating Digital Computer) algorithm. The algorithm is also used to estimate the tilt angle of the body position. This design is implemented on FPGA, a reconfigurable platform [6]. Piezoelectric energy collection offers the possibility of using ambient vibration to most beneficially power low-power sensor nodes. Mayrhofer et al. demonstrated the manufacture and characterization of piezoelectric cantilevers with AlN and SCXAl1-XN ($x = 27\%$) films to evaluate their energy collection performance. Characterization mainly focuses on measuring output power under variable load resistors to achieve maximum power output. Compared with AlN films, ScAlN films have proven superior performance in energy collection. In addition, the material parameters of ScAlN are extracted by analytical model. Finally, a detection mass is attached to further increase the output power under optimized load resistance [7]. If the data application and data mining brought by the era of big data are applied to physical education, it will enrich and expand the mode of physical education. It has great influence on improving students' physical literacy, improving students' participation in physical exercise, enhancing their physical fitness, and cultivating students' lifelong physical awareness. It can effectively improve the effect of physical education teaching and promote the depth and breadth of knowledge competition between teaching and learners. Actively communicate with the referee committee, and take the initiative to communicate with referees at all levels in various countries through the use of international competitions held. At the same time, organize high-level referees in the country, give certain international peer communication skills training, improve their diplomatic skills, make full use of all favorable conditions to form a close referee team, and give full play to the role of this team.

In the training process, no one knows the athlete's state best than the athlete himself, who conducts subjective scale evaluation through the pedagogical observation of the athlete himself and the coach. Combined with the objective indicators of training monitoring, the training effect can be evaluated in an all-round and three-dimensional manner within a period of time, which is convenient to promote the process of personalized training and scientific training. Generally speaking, there are many researches on racket sports based on inertial sensors, mainly focusing on the relationship between racket and ball speed and the recognition of swing motions. According to the number of inertial sensors used, it can be divided into the use of single inertial sensors and the use of multiple inertial sensors. According to the different installation positions of the sensor, it is divided into installing the sensor on the racket and fixing the sensor on the key parts of the athlete's movement (such as wrists and ankles). Because the use of multiple sensors fixed on the athlete's body will cause inconvenience to the athlete's movement, this article takes tennis as an example, using a single inertial sensor, installing the sensor on the bottom of the tennis racket for data collection, and researching tennis based on this recognition of sports swings and development of a smart tennis training software. Form an auxiliary training system based on tennis swing motion recognition, integrated sports statistics, motion analysis, sharing, and other functions. Using physiological and biochemical indicators to monitor athletes can objectively and effectively evaluate the size and rationality of the training load, evaluate the athlete's functional state, and reflect the athlete's fatigue and recovery. It provides help for the reasonable and innovative development of training; at the same time, longitudinal comparison of the same athlete's indicators also facilitates an accurate understanding of the athlete's state at a certain stage and can design more personalized training programs.

2. Tennis Teaching and Training Research Methods

2.1. Data Preprocessing. After obtaining the data set, we should not start research in an emergency, but should first evaluate the quality of the delivered data set, review and screen the data files, and deal with dirty data in a timely manner. This step of monitoring and repairing the quality of the data set is called data cleaning.

After the dirty data is found, the processing methods are mainly as follows: data deletion, variable deletion, and variable filling. For example, it is easy to find some record files of nonaction data in the data set. The main manifestation is that the sensor data is always in the 0 input state or the length of the sampling point of the action is obviously lower than the normal value. This kind of data is mostly caused by operator errors. The data itself has no research value, so it can be deleted as a whole.

2.2. Error Calibration. In the zero input state, the output of the sensor often appears as a stable random process after entering a long-term steady state. The statistical characteristic of a stationary random process is that it has a constant mean value β and a constant variance ϕ^2, that is, the output of the sensor changes with a fixed degree of dispersion (mean square deviation) around a fixed value (mean value). The deviation in this initial state will not change with time under the assumption of steady state, so it is a static error and can be eliminated offline [8].

$$\begin{aligned} \beta &= E(z) = \int_{-\infty}^{+\infty} z p(z) dz, \\ \phi^2 &= \left[E(z\text{-}\chi)^2\right] = \int_{-\infty}^{+\infty} (z\text{-}\chi)^2 p(z) dz. \end{aligned} \tag{1}$$

This section only considers the simplified error model to calibrate the static error. This rough calibration scheme is easy to operate and simple to calculate, and it can be easily used by ordinary users. In short-term applications, the accuracy of inertial navigation devices is often relatively stable, and the remaining neglected errors are used as uncontrollable factors along with the data to enter the feature extraction stage. Their influence on the algorithm model is controlled by the robustness of the feature engineering scheme. Through data statistics and many studies and discussions, it is believed that there are two main bottlenecks that hinder the development of men's doubles: one is that the quality of hair extensions is not stable due to the lack of training rigor, and there are more unnecessary errors in multibeat stalemate; the second is special projects. The amount and intensity of training are not ruthless, resulting in insufficient physical fitness for continuous offense and defense. Therefore, in the future, we will pay close attention to the rigor of training and regard "quality" monitoring as an important breakthrough.

In the output model of MEMS gyroscope, when the three-axis turntable $\theta_{\mathrm{ox}}, \theta_{oy}, \theta_{oz}$ only provides x-axis angular rate input, there are [9]:

$$\theta_{ox} = k\theta_{tx} + \theta_{bx} + \theta_{nx}, \tag{2}$$

$$\begin{aligned} \theta_{oy} &= k_1\theta_{tx} + \theta_{bx} + \theta_{nx}, \\ \theta_{oz} &= k_2\theta_{tx} + \theta_{bx} + \theta_{nx}, \end{aligned} \tag{3}$$

Written in the form of a matrix [10]:

$$[\theta_{ox}] = [\theta \quad 1][k \quad \theta_{bx}]^T + [\theta_{nx}], \tag{4}$$

$$\left[\theta_{oy}\right] = \left[\theta \quad 1\right]\left[k \quad \theta_{by}\right]^T + \left[\theta_{ny}\right], \tag{5}$$

$$[\theta_{oz}] = [\theta \quad 1][k \quad \theta_{bz}]^T + [\theta_{nz}]. \tag{6}$$

For multiple experiments, the coefficient matrix can be expressed as [11]:

$$H = \begin{bmatrix} \theta_{tx1} & 1 \\ \theta_{tx2} & 1 \\ \vdots & \vdots \\ \theta_{txn} & 1 \end{bmatrix}. \tag{7}$$

θ_{txi} is the x-axis angular rate input value provided by the three-axis turntable in the ith test.

According to the output vector θ_{oi} of each axis MEMS gyroscope in the test, it can be calculated by the least square algorithm [12]:

$$[k_{11} \quad \theta]^T = \left(H^T H\right)^{-1} H^T \theta_{ox}, \tag{8}$$

$$[k_{21} \quad \theta]^T = \left(H^T H\right)^{-1} H^T \theta_{oy}, \tag{9}$$

$$[k_{31} \quad \theta]^T = \left(H^T H\right)^{-1} H^T \theta_{oz}. \tag{10}$$

Control the three-axis high-precision turntable to provide a series of y-direction standard angular rate inputs and a series of z-direction standard angular rate inputs for the MEMS gyroscope in the attitude measurement unit to obtain the MEMS gyroscope calibration coefficient matrix K and the gyroscope zero bias estimate.

$$k_{11}^2 + k_{12}^2 + k_{13}^2 = k_{1x}^2, \tag{11}$$

$$k_{21}^2 + k_{22}^2 + k_{23}^2 = k_{2y}^2, \tag{12}$$

$$k_{31}^2 + k_{32}^2 + k_{33}^2 = k_{3z}^2. \tag{13}$$

Due to the practical significance of the scale factor of the MEMS gyroscope, solving the equation can be obtained [13]:

$$\begin{aligned} k_{1x} &= \sqrt{k_{11}^2 + k_{12}^2 + k_{13}^2}, \\ k_{2y} &= \sqrt{k_{21}^2 + k_{22}^2 + k_{23}^2}, \\ k_{3z} &= \sqrt{k_{31}^2 + k_{32}^2 + k_{33}^2}. \end{aligned} \tag{14}$$

Therefore, the scale factor error of the MEMS gyroscope is [14, 15]:

$$\begin{aligned} s_{GX} &= K_x - 1, \\ s_{GY} &= K_{\mathrm{y}} - 1, \\ s_{GZ} &= K_{\mathrm{z}} - 1. \end{aligned} \tag{15}$$

(1) Gyroscope

With the continuous renewal and deepening of the understanding of the rules of the event, the training and monitoring of athletes have received extensive attention. Reasonable training monitoring can enable coaches to obtain considerable data and then help coaches to understand training effects, evaluate training methods, and adjust training programs in a targeted manner and in a timely and effective manner.

The static drift error of the gyroscope is the main source of error when the quaternion is used to solve the attitude in the inertial navigation calculation. The data output by the gyroscope when it is stationary in tennis training is shown in Figure 1. The comparison of the real value and the measured value in Figure 1 can clearly distinguish the static drift noise output by the gyroscope when it is stationary.

Multiball technical training mainly solves the problems of positioning and matching lines and hitting points, strengthening the awareness of skills and tactics, and running in fewer times and more sets, such as rotation after backcourt attack, as well as defensive positioning and catching, the division of labor and so on. This should be practiced as a key project, and it is necessary to try more multiball training methods.

The output data of the gyroscope when the tennis training is normal walking is shown in Figure 2, which can intuitively show that the angular velocity amplitude of the gyroscope when the pedestrian is moving is obviously greater than the angular velocity when the pedestrian is walking normally.

(2) Accelerometer

The output of the MEMS accelerometer includes the actual motion acceleration data a of the carrier, the gravitational acceleration g generated by the rotation of the earth, and the static drift noise v generated by the error of the inertial navigation element itself. The specific expression is [16]:

$$\mathrm{y} = a - g + v. \tag{16}$$

When selecting tennis men's doubles athletes, they are usually selected according to their age characteristics,

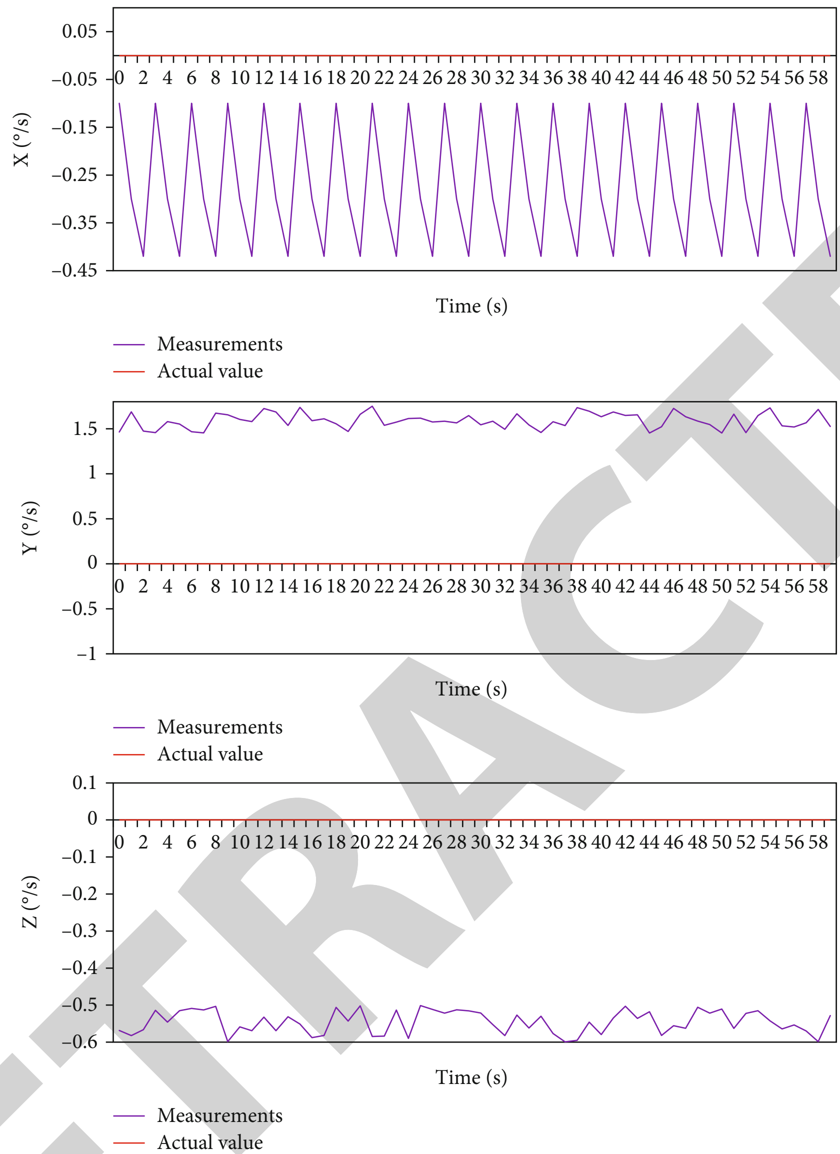

Figure 1: Data output by the gyroscope when stationary in tennis training.

specific technical and tactical characteristics, form, function, physical fitness, and psychological characteristics. Shape selection is an important part of the selection of athletes. Height and weight have high stability and good correlation. Tennis is a sport based on aerobic endurance and anaerobic capacity as a special ability.

Obtained: MEMS acceleration output contains large static drift noise, which needs to be filtered out in later data processing. The sampled data when the trainer walks normally is shown in Figure 3.

(3) Magnetometer

Like accelerometers, magnetometers also have zero bias errors. The zero-bias error mainly refers to the drift of the magnetic sensor caused by the drift of the internal circuit and the residual magnetism when the magnetometer is in a static state. According to the performance and injury situation of the participating players, different degrees of relaxation and adjustment are carried out. The training is mostly based on strength training, and the maintenance training will be carried out in terms of physical fitness. Technically, it will be based on basic skills and a single individual. Part of the need to strengthen technical training, each pair of meticulous summary works after training, a comprehensive analysis of the gains and losses in the game.

2.3. Zero Speed Detection. Zero speed detection is to detect the "zero speed" state information at the time when the foot touches the ground during walking.

(1) Acceleration amplitude detection

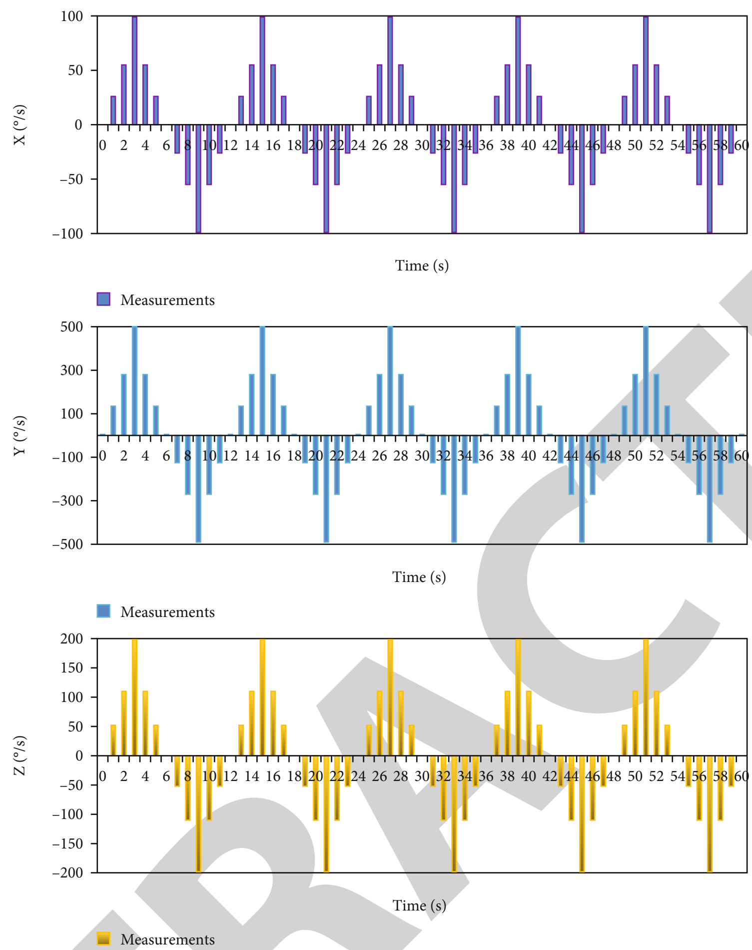

FIGURE 2: The output data of the gyroscope during normal walking in tennis training

The acceleration amplitude $|a_k^b|$ is:

$$\left|a_k^b\right| = \sqrt{\left[\left(a_{1k}^b\right)^2 + \left(a_{2k}^b\right)^2 + \left(a_{3k}^b\right)^2\right]}. \tag{17}$$

(2) Acceleration variance detection

The acceleration variance ϕ_{m}^2 formula is [17]:

$$\phi_m^2 = \frac{1}{2s+1}\sum_{j=k-s}^{k+s}\left(a_j - a_k\right)^2. \tag{18}$$

(3) Angular velocity energy detection

Based on objective test indicators, the study summarizes the time-domain characteristics of key athletes' physiological state regulation and comprehensively activates nutrition regulation and psychological regulation procedures to help athletes form a healthy and peaceful prematch mentality, full of energy, and good self-confidence.

The angular velocity output data $|\alpha|$ is close to zero at the zero velocity moment when the footsteps of the personnel are in contact with the ground, while the angular velocity output data changes greatly when the personnel are in motion. Therefore, it is possible to detect the moment of pedestrian landing by detecting the magnitude of the angular velocity at the moment [18].

$$|\alpha| = \sqrt{\left[\alpha_k^b(1)^2 + \alpha_k^b(2)^2 + \alpha_k^b(3)^2\right]}. \tag{19}$$

2.4. MEMS Action Data Collection. The model of the MEMS inertial sensor used in this article is WT901BLE5.0C, its acceleration measurement range is ±16 g, the gyroscope's range is ±2000°/sec, the angle is ±180°, the magnetometer can reach 4800 uT, and the acceleration stability is 0.01 g, The angular velocity stability is 0.05°/sec, the frequency is set to 50 HZ, and the baud rate is 9600. The MEMS inertial sensor fixed on the human body is integrated by an accelerometer, a gyroscope, and a magnetometer, which can measure the acceleration, angular velocity, and magnetic field

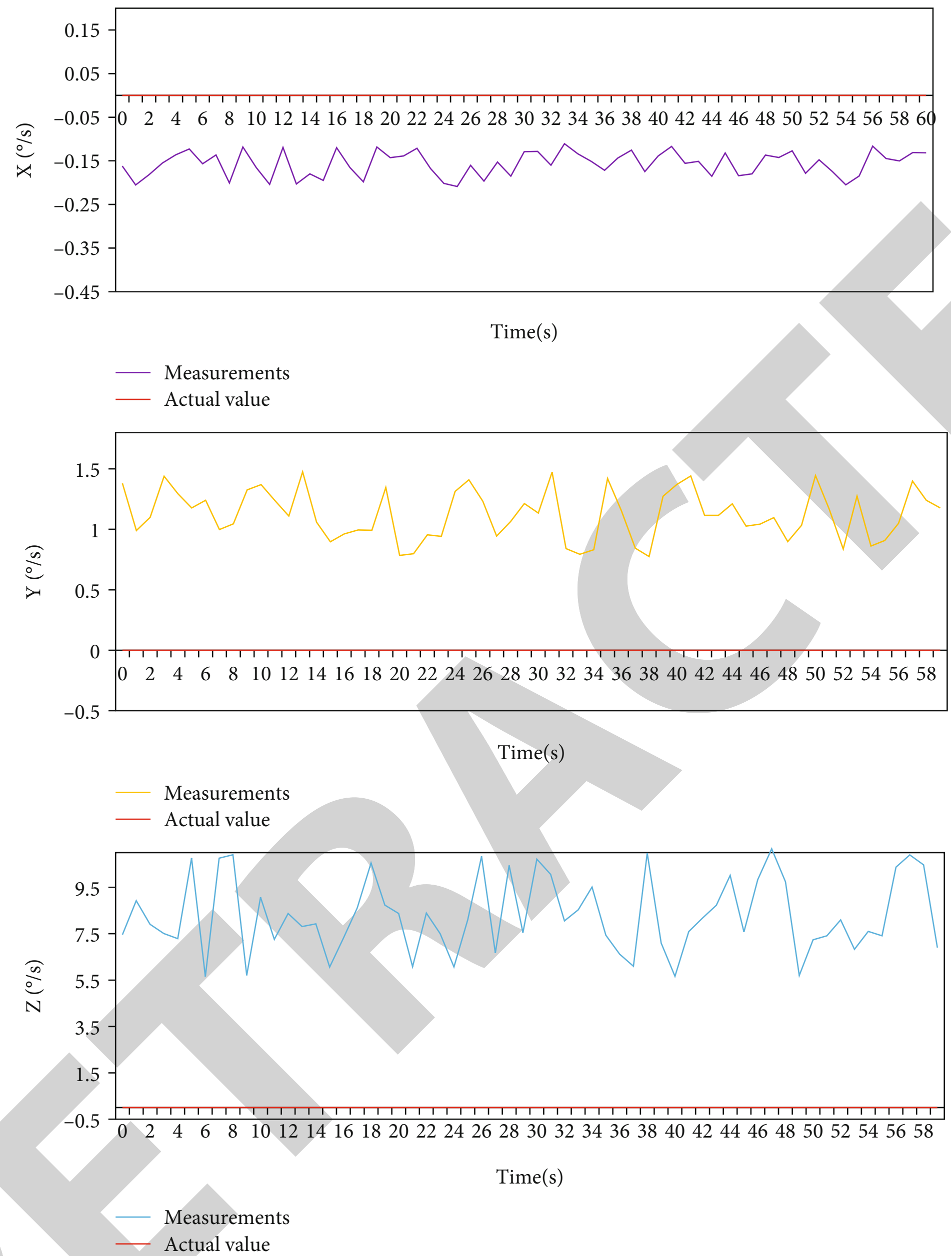

Figure 3: Sampling data when the trainer walks normally

strength of the X, Y, and Z axes, respectively. It uses the STM32 main control chip and uses the quaternion method. Calculate the attitude angle of each node, and use the wireless module to send the attitude value to the PC. The MEMS inertial sensor module is shown in Figure 4.

Real-time data stream window segmentation: real-time motion data enters the real-time recognition system in the form of data stream, so it needs to receive a certain amount of data before the action window can be intercepted. The function of the sliding window interception is to process the data once when the received data reaches a certain amount. After the sliding window is intercepted, it is necessary to determine whether there is a swing action in the sliding window. If there is a swing action, determine the hit point and perform the interception of the action window. If there is no swing action in the sliding window, the data in this window will be discarded. The data enters the next sliding window, so that the motion data of the real-time data stream can be intercepted by repeating this.

For circuit devices, there is the same transmission line effect. The output current of 2 cm in-line resistors in the circuit under different frequency signals is shown in Figure 5. When a current signal with a frequency of 100 MHz and a wavelength of 3 m passes through the resistor, the output current does not change significantly compared with the input current, and the resistance length at this time is less

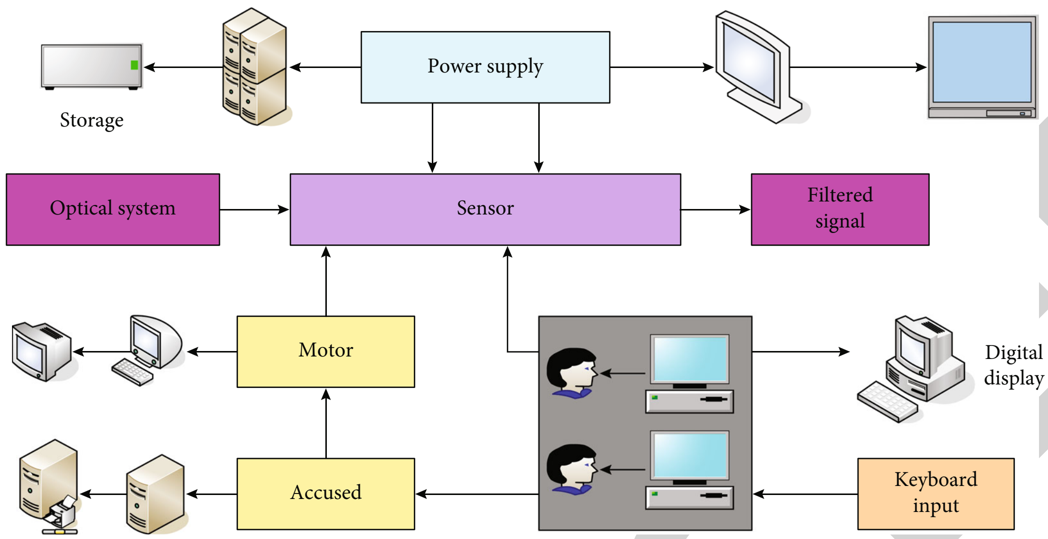

Figure 4: MEMS inertial sensor module.

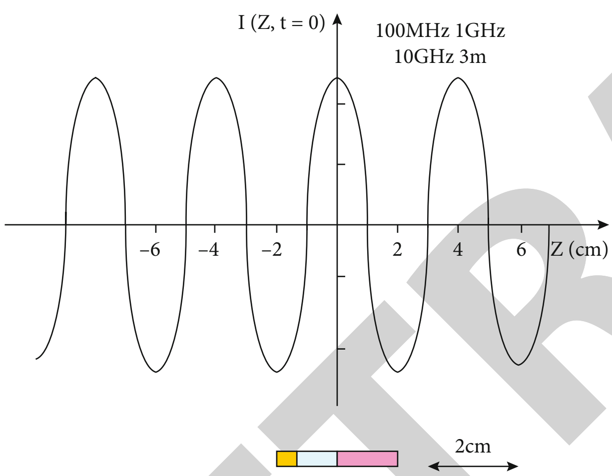

Figure 5: The output current of the 2 cm in-line resistor in the circuit under different frequency signals.

than one percent of the wavelength; when the frequency is 1 GHz, the current is with a wavelength of 30 cm. The signal passes through the resistor, and the length of the resistor at this time is between twentieth of a wavelength and a hundredth of a wavelength [19].

By comparing the effects before and after the experiment on the teaching objects, it explores the learning effects of students in the teaching process and the specific application of smart sensors in tennis teaching in colleges and universities. To verify whether this comparative analysis of the numerical feedback parameters in the practice process can effectively guide the students to correctly experience the power of the action, clarify the differences in each link in the teaching of tennis hitting techniques, and recognize them in a shorter time. The essence and key of the technical movements of this link enhance the learning initiative and the ability to master the essentials of tennis technology and then achieve the purpose of improving the teaching effect and learning efficiency. Provide theoretical research and practical basis for the implementation and development of intelligent sensor-assisted teaching methods in physical education in the future. In the impedance matching circuit design of this research, the capacitor and inductance are selected as Murata brand, and the main parameters are shown in Table 1.

Table 1: Main parameters.

Component label	Device value	Encapsulation
L1	2.2 nH	0505
L4	3.7 nH	0505
L5	4.7 nH	0505
C13	1 pF	0505
C16	2.2 pF	0505
C17	1.5 pF	0505

2.5. Mobile APP Design. According to system functional requirements, the mobile phone software of this system is mainly divided into three parts: Bluetooth BLE wireless sports data real-time collection, data conversion and storage, and data analysis. Among them, real-time data collection uploads the raw motion data collected by the hardware sensor module to the smartphone via Bluetooth BLE; data conversion and storage refers to the decimal conversion of the collected raw motion data and saves it through the mobile phone file system; data analysis refers to the feature value extraction and feature selection of the converted motion data, to obtain an algorithm for judging each action and use the integral of the three-axis acceleration to estimate the bat speed of each action.

(1) Real-time collection of Bluetooth BLE data

Step 1. Search and obtain Bluetooth peripherals. To search for the device, first turn on the Bluetooth of the Android device, and obtain the scan result in LeScanCallBack by calling the callback

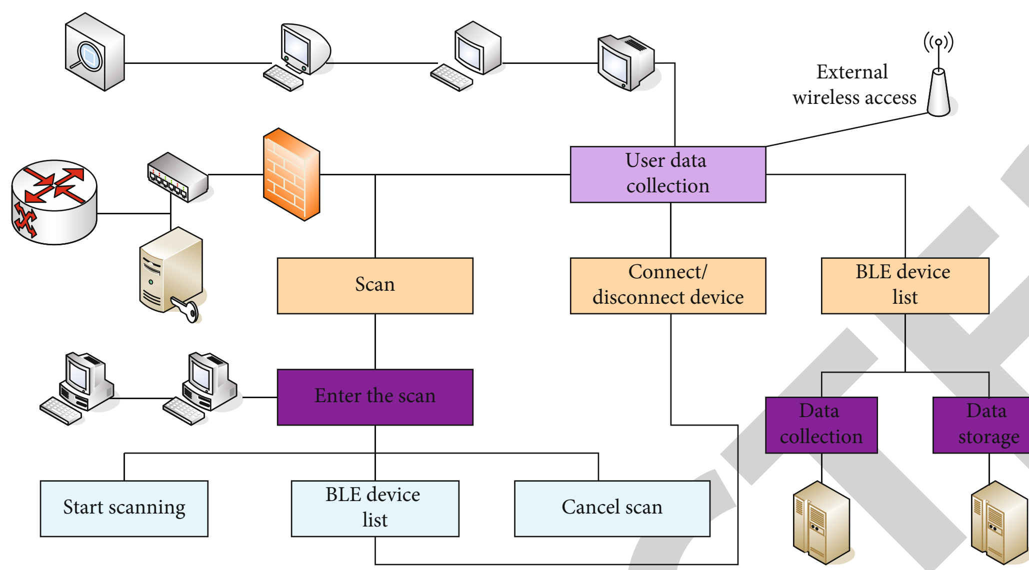

Figure 6: The main data acquisition interface software design based on this article.

Step 2. Stop scanning. When the smartphone side searches for the required Bluetooth peripheral and needs to stop scanning, call Bluetooth Adapter.startLeScan

Step 3. Equipment connection and data interaction guarantee

Step 4. Send instructions and receive data

Based on this text, the data acquisition interface software design is shown in Figure 6.

UUID (universally unique identifier) is a universally unique identifier. The Bluetooth Technology Alliance has stipulated two types of UUID codes, namely, the basic Bluetooth UUID code and the simplified UUID code. The UUID codes of the characteristics defined in this article are shown in Table 2.

Table 2: UUID codes of the features defined in this article.

Feature type	Characteristic UUID code
Bluetooth interactive service	0×01
Bluetooth send data	0×02
Bluetooth receive data	0×03

Athlete selection is the beginning of training an athlete, the process of selecting outstanding sports reserve talents, and an indispensable link in the whole process of cultivating outstanding sports talents and improving the level of competitive sports. Therefore, how to scientifically select athletes plays a vital role in cultivating outstanding men's doubles.

After two Bluetooth devices are connected, they form a bridge that can transmit data to each other, and the two Bluetooth devices that form a connection can be called pairing through this bridge. This article configures security mode 1 and horizontal mode 2. The encryption link is not required for MITM protection. The safe connection mode is shown in Table 3.

(2) Data conversion and storage

The so-called special physical training is a physical training method and training process designed in accordance with the competition parameters under the premise of following the rules of special winning. According to this idea, the design of special physical training methods should first analyze the similarity between all the characteristics of the body (including training, physiology, anatomy, and biomechanics) and the characteristics of the special competition during tennis.

After the Android device receives the data of the connected Bluetooth, in order to analyze the data later, it must be analyzed and transformed before it can be stored. After the data received by the Android device is finally unpacked, it will eventually receive a byte type array with a length of 12. For convenience, it is named txValue; among them, every two words in the first 6 bytes of txValue of the sections, respectively, represent the raw data of X, Y, and Z axis acceleration. The sensitivity values corresponding to different ranges are shown in Table 4.

(3) Collected data processing

In the real-time data processing stage, the stored training data must be used to analyze the data to obtain an algorithm basis that can identify the five tennis movements. And the algorithm is improved to ensure the real-time performance of the algorithm, through the real-time collection of test data and through the existing recognition algorithm and real-time recognition, and finally, the recognition result is displayed on the screen. In the data processing stage, first, intercept the collected data in a sliding window, and then, judge whether there is a shot in the window based on the intercepted data. If there is a hitting action, the data window of the movement is intercepted in the sliding window according to the hitting point. If there is no hitting action, slide to the next window. After the motion data is

Table 3: Security mode.

Horizontal mode	Safe mode	Safe mode level
Horizontal mode 0	Safe mode 0	Connection not allowed
Horizontal mode 1	Safe mode 1	No safety requirements
Horizontal mode 1	Safe mode 2	Signature or encryption, no MTTM protection
Horizontal mode 2	Safe mode 1	Need to encrypt the link, no MITM protection
Horizontal mode 2	Safe mode 2	MITM protected signature or encrypted link
Horizontal mode 3	Safe mode 1	Encrypted connection and MITM protection

Table 4: Sensitivity values corresponding to different ranges.

a_sensitivity	w_sensitivity
4048 (±36 g)	36.4 (±4000 dps)
4096 (±8 g)	34.8 (±3000 dps)
8394 (±4 g)	61.1 (±100 dps)
36384 (±4 g)	333 (±410 dps)

intercepted, the eigenvalues are extracted according to the data of the motion window, and then, the extracted eigenvalues are normalized. Finally, according to the difference of the eigenvalues of different actions, it is selected as the eigenvalue of the different sports to classify the tennis technical actions.

3. MEMS Sensor in Tennis Teaching and Training Results

Figure 7 shows the output curve of the tennis motion posture angle recorded by the wearer using the device. It can be observed that, because the output range of the attitude angle is limited to $[180^\circ,180^\circ]$, the attitude angle curve tends to show the phenomenon of two-pole jump, which leads to the deterioration of the continuity of the curve. In the subsequent signal analysis link, the jump point can easily show extremely special properties and introduce interference frequency components.

Before extracting time-domain features, it is necessary to standardize features to eliminate the impact of different dimensions on classification performance. It is also to speed up the operation of subsequent pattern recognition methods. The data is specified in a certain area. The standardization interval in this article is (0, 1). Taking 10 samples of the head sensor from standing to squatting as an example, the results of the roll angle time domain feature extraction are shown in Table 5. 11 sensors obtain time-domain feature data in 3 directions, and each direction contains 10 time-domain features, so there are 330 time-domain features in total.

Table 6 shows the number of samples of the action category labels used in this article.

The scores of the students in the experimental group before and after the experiment of the various techniques of CTN were tested by paired-sample T-test through the spas software, and the results are shown in Figure 8. The total CTN score of the experimental group students before the practical training was 125.03, and the standard deviation was 4.165, and the CTN total score after the practical training was 161.67, and the standard deviation was 6.042. Through the calculation of the spas software, the test t value of the total CTN score of the experimental group students before and after the experiment is -45.299, and the significance p value corresponding to the data is 0.000. Since the p value is less than 0.05, it indicates that the experimental group has CTN after practical training. The total score is significantly higher than the CTN total score before the practical training. Similarly, in the CTN technical scores of the four technical links of the depth of the ground, the depth of the volley, the accuracy of the ground, and the serve, the experimental group students' CTN technology after the practical training scores are significantly higher than the scores.

After the 6-week training of the two groups of students, the data of various technical scores and total scores calculated by the International Tennis Federation and the Chinese Tennis Technical Rating Method (CTN) were used to perform an independent sample T test through the spas software, and the results were obtained. As shown in Figure 9, it can be clearly seen from Figure 9 that after the practical training, the average CTN total score of the control group students is 141.73, and the standard deviation of the data is 4.185, while the average CTN total score of the experimental group after the practical training is 161.67. The standard deviation is 6.042. The test t value of the total CTN score of the two groups of students was -14.855, and the corresponding significance p value was 0.0000. Because the p value is less than 0.05, there is a significant difference between the two groups of data. From the obtained data, it can be seen that the total CTN score of the experimental group after practical training is significantly higher than the total CTN score of the control group after practical training. After the practical training, the CTN scores of the students in the experimental group were significantly higher than those in the control group.

The above experimental results show that after the experiment, the four technical indicators of the control group and the experimental group, including the depth of the ground, the depth of the volley, the accuracy of the ground, and the serve, have improved. Among them, the students of the experimental group have improved significantly, with highly significant differences. In the same venue, the same amount of training time, and the same level of starting point, this fully shows that the smart tennis sensor has a good effect in daily teaching and training.

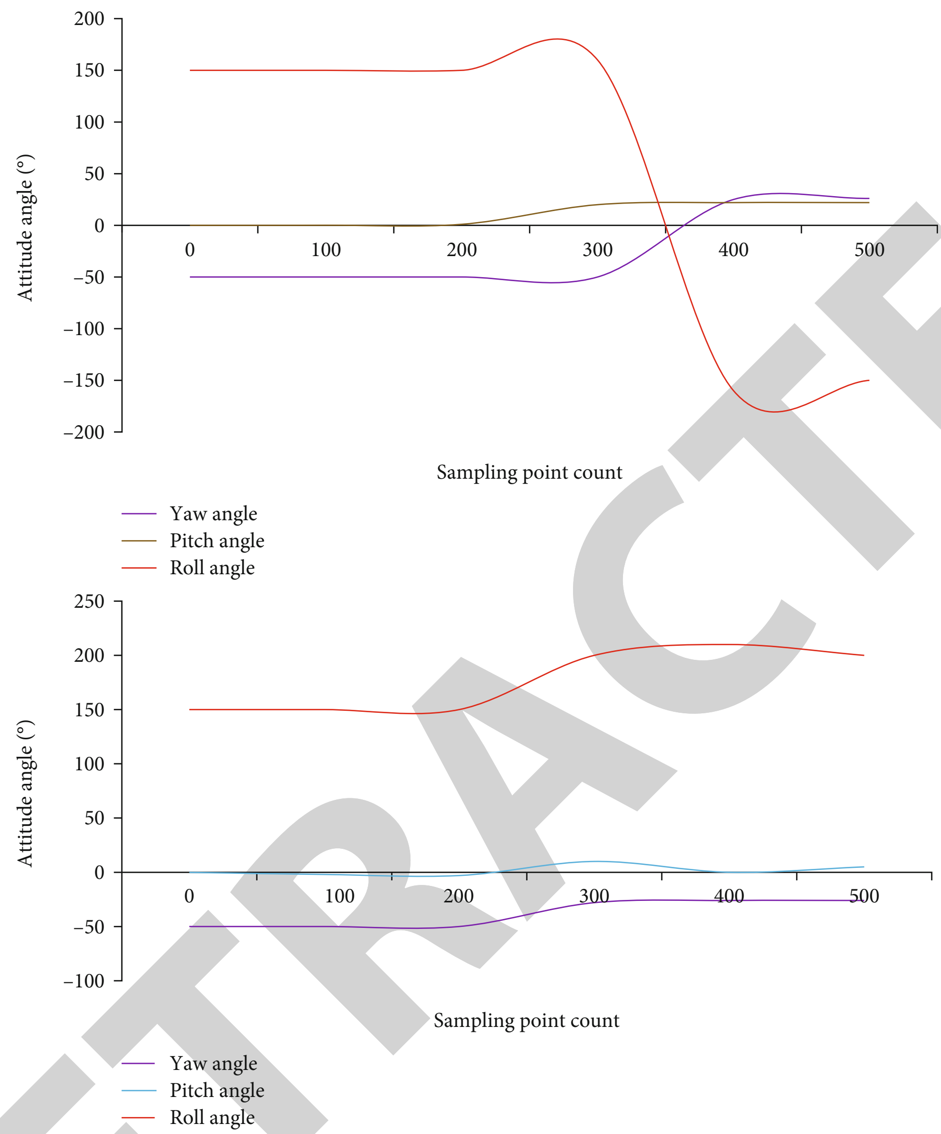

Figure 7: The output curve of the posture angle of the tennis movement recorded by the wearer using the device.

Table 5: The results after the time domain feature extraction of the roll angle.

No.	1	2	3	4	5	6	7	8	9	10
1	0.15	0.32	0.29	0.53	0.40	0.34	0.31	0.51	0.51	0.37
2	0.14	0.39	0.22	0.50	0.44	0.39	0.33	0.34	0.32	0.51
3	0.12	0.29	0.27	0.47	0.38	0.34	0.31	0.53	0.50	0.58
4	0.17	0.24	0.21	0.56	0.46	0.39	0.34	0.31	0.56	0.33
5	0.18	0.22	0.19	0.33	0.47	0.30	0.32	0.27	0.30	0.47
6	0.13	0.28	0.17	0.55	0.46	0.32	0.30	0.32	0.47	0.52
7	0.14	0.36	0.19	0.56	0.47	0.38	0.25	0.49	0.53	0.34
8	0.15	0.22	0.22	0.49	0.38	0.29	0.29	0.47	0.37	0.49
9	0.14	0.33	0.26	0.59	0.27	0.39	0.32	0.41	0.56	0.56
10	0.11	0.21	0.25	0.36	0.35	0.40	0.31	0.50	0.52	0.31

Table 6: The number of samples of the action category labels used in this article.

Human action category	Category label	Number of samples
Stand	1	15
Sit upright	2	15
Prone	3	15
Squat	4	15
Push	5	15
Arms folded	6	15
Front kick	7	15
Forward kick	8	15
Lunge	9	15
Side step	10	15

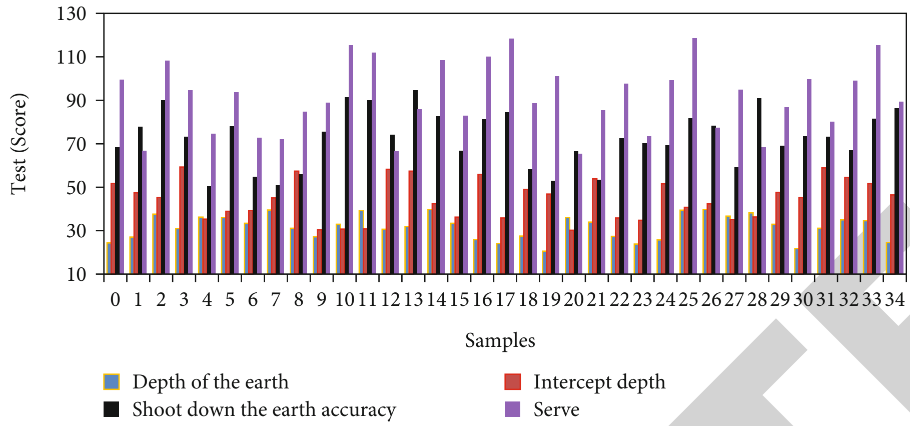

Figure 8: The scores of the students in the experimental group before and after the experiment in various CTN techniques.

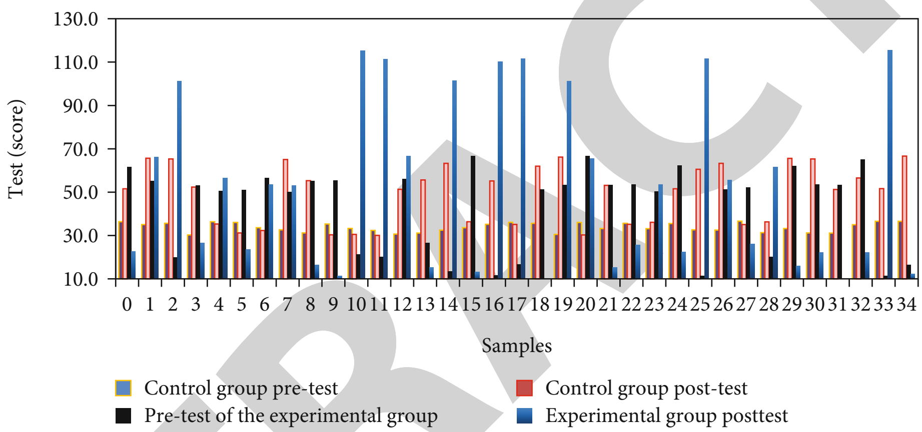

Figure 9: Independent sample T test by spass software.

4. Discussion

Although motion recognition based on image data has been widely used and proved to have a good recognition effect, its data collection and processing are often restricted by the venue and equipment (need to be in a specific venue). For example, in sports projects that require a larger space for motion, image data collection cannot be performed well. The image data collection equipment cannot be installed on sports equipment or the human body, so it cannot move with the athlete. In the process of image collection data, the collection equipment is easily affected by the environment of the shooting site, such as the occlusion of characters, the intensity of light, the color of the subject's clothing, the angle of shooting, and other external factors, which affect the quality of data collection and eventually affect the accuracy of action recognition. Image acquisition equipment is often relatively expensive, complicated to install, and requires higher computer performance in the process of algorithm research. In addition, the image acquisition equipment cannot directly collect the intuitive motion data such as acceleration and angular velocity generated by the athlete during exercise. Finally, due to the relatively large amount of data collected based on images, the algorithm used is time-complex and difficult to realize real-time recognition [20, 21].

At present, the teaching of tennis skills in colleges and universities still mostly stays in a single teaching mode based on the subjective experience of teachers. In the process of teaching practice, because many technical actions are completed in an instant, there are many students in the classroom. Students' understanding and mastery of technical movements only follow the teacher's pure language expression and the guidance of error correction one by one. The movements learned by themselves rely only on self-perception and impromptu imitation, and the subtleties are difficult to identify. Such learning is easy to float on the surface; it is not easy to solidify and form the correct concept of action, which directly affects the teacher's classroom teaching effect and the efficiency of students' mastery of technical movements [22].

Under such a background, it is impossible for competitive sports to be independent, and it is impossible not to be surrounded by "big data." In fact, the detection data provided by various wearable devices, the video information provided by various multimedia devices, and all kinds of information provided by the developed Internet, etc., are the basis of competitive decision-making. There is no doubt that collecting data at the first time, rationally analyzing, correctly transforming the connotation of the data, and applying it to sports practice are the necessary qualities of an excellent coach. The coaches of the national team must be good at acquiring, analyzing, and using big data, and use boring data for my use, be targeted, make correct decisions, and continuously improve the ability to grasp the laws of big data development, so that big data can play more in competitive sports. The opening of tennis courses in colleges and universities is an important way to spread tennis culture, and it is also an inevitable result and a good trend of the rapid development of Chinese tennis. The vast majority of social elites are from colleges and universities. The experience on campus is often the best memory in life. During this period, if they have accumulated experience in tennis, they are more likely to share the tennis skills they have learned with their colleagues and friends, so as to introduce tennis to more people and promote the development and popularization of tennis. It is of great significance to the Chinese tennis industry. At the same time, strengthening the construction of campus tennis culture plays an important role in creating a harmonious campus atmosphere, establishing a civilized campus image, and enriching the connotation of sports culture. It has a guiding significance for improving the overall level of running a university [23, 24].

Nowadays, Chinese and Western cultures continue to conflict and merge. As teachers and students of colleges and universities, this special group has higher recognition and acceptance of foreign culture and knowledge than ordinary people. Tennis is an imported sport that they accept foreign culture, a way of doing it by yourself, the understanding of the rules, the curiosity of new things, the evolution of the history of tennis, etc. The influence of foreign culture on college teachers and students' willingness to play tennis cannot be ignored. In addition, it is precisely because of the aristocratic atmosphere of tennis that participating in tennis has become a means to improve one's own grade. Tennis has gradually become a sport that gathers the attention of teachers and students in colleges and universities. If the data application and data mining brought by the big data era are applied to physical education, it will enrich and expand the physical education model. Effectively promote the depth and breadth of knowledge competition between teaching and learners. Nowadays, in the era of big data, college students are more inclined to use the Internet for learning. College students also look forward to the spark and novelty of the collision of the subject of sports with the Internet. Therefore, combined with big data, the college tennis teaching model is implemented. Time does not wait for reform [25].

At present, the daily training and teaching of amateur tennis clubs are mainly based on the subjective experience teaching of the coach. However, in the actual teaching process, because the technical movements and power chain of tennis are difficult to master, it needs to be practiced with and without the ball. Combination of exercises and training can enable students to deepen their proficiency and muscle memory so as to master the technical movements and the sequence of force exertion. However, in the process of teaching practice, coaches often teach one-to-many, and students' understanding and mastery of technical movements can only follow the coach's language guidance and short-term error correction one by one. The understanding of technical movements and the power chain of hitting is only superficial; it is difficult to fix the technical movements and form the correct order of hitting force. Therefore, this research is aimed at the pain points of low efficiency of traditional training modes and pioneered the use of smart tennis sensors to assist coaches in daily training. The traditional tennis training methods and methods are combined with the data collected by smart tennis sensors and its supporting applications; use it reasonably during training [26].

Smart sensors can accurately monitor the state of motion, and numerically quantified synchronous feedback can deepen students' experience of performing actions (such as exercise duration, speed, sequence, strength, and rhythm) and use the 3D mode to intuitively restore the state of motion [27–29]. It also allows practitioners to clearly observe the spatial characteristics of their movements such as movement orientation, movement trajectory, movement range, movement range, and so on. In the simulation of motion trajectory restoration, the practitioner can select the motion parameters at key time points, combined with the trajectory for selective reproduction, and carefully observe the practitioner's movement execution, thereby improving the accuracy of feedback and helping the practitioner to realize self-technical movements. This novel teaching method is not only conducive to the mastery of technical movements of students and enhances the experience of learning effects but also helps to realize the emotional interaction between teachers and students in the learning process. On the other hand, in the actual classroom motor skills learning, it is impossible for teachers to guide every student's every practice action, and the use of this kind of sensing equipment can be more targeted for every student. Providing individualized real-time comments truly embodies the teaching principle of "differential treatment" [30–32].

Taking computer and multimedia teaching aids in traditional classroom teaching as an example and physical education as a special education discipline (with training ground as the classroom and physical exercise as the main method), the changes in the new era are not significant. Taking the form of microclasses of college physical education as an example, when college physical education teachers use video as the main medium to explain courses, they do provide students with a fragmented learning experience that can learn anywhere, but physical education is missing. It is very different from the traditional model. First, it ignores the mechanism of outdoor activities in college physical education. Second, it ignores the differences in the acceptance and understanding capabilities of different students when watching video explanations. Individual differences between students will lead to video teaching content. Third, the microclass videos of physical education classes cannot solve the temporary problems of students, especially physical education classes are different from other subjects. Each student's physical structure, including flexibility, coordination, and strength, is different. A considerable number of student teachers are required to teach the actions themselves, which results in limitations [27].

5. Conclusion

Seek opportunities to investigate the conditions of the venues, choose similar environments for prematch adaptive training; carefully track the changes in the competitive state of the main opponents, study and formulate detailed forward-looking combat plans, and conduct simulation training in a timely manner. Big data has its basic connotations and characteristics. A simple overview can be carried out with large volume, many types, low value density, and fast processing speed. Undoubtedly, the data volume of big data is huge and rich in types. The data types may be in the form of text, pictures, and videos. At the same time, when analyzing and using data, continuous real-time monitoring is needed to obtain useful and high-value information. Intelligent sensor-assisted teaching is the reasonable application of wireless sensing technology in the exercise of traditional tennis techniques, helping students to objectively record the speed, intensity, and arc of action during each tennis swing, and reproduce the swing. The specific trajectory of the slap shot process can be more clearly restored and reproduced in a 3D simulation of every technical action. This design not only enriches the information resources of tennis training in the era of big data and provides real-time feedback on the players' batting performance. On the other hand, it also deepens the education reform and builds a new teaching situation for big data in the methods and methods of physical education. The value of sports science has been raised to a new height. In the future, people with big data thinking and the ability to transform data to dig into industries that have not been touched by big data will become the most potentially valuable event in the big data field.

Data Availability

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Conflicts of Interest

The authors state that this article has no conflict of interest.

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