

Retraction

Retracted: Remote Evaluation System of Tennis Batting Action Standard Based on Acceleration Sensor

Security and Communication Networks

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Y. Ji and S. Ma, "Remote Evaluation System of Tennis Batting Action Standard Based on Acceleration Sensor," *Security and Communication Networks*, vol. 2021, Article ID 9930084, 11 pages, 2021.

Research Article

Remote Evaluation System of Tennis Batting Action Standard Based on Acceleration Sensor

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This paper studies the remote evaluation system of tennis batting action standard based on acceleration sensor, which aims to help improve the standard degree and technical level of tennis batting action. The system includes a data acquisition module to collect original signal data of tennis batting action by the acceleration sensor signal acquisition device in the bracelet and upload to the personal computer (PC) for storage, data preprocessing module to smooth original signal data and extract the key time and frequency domain features as the evaluation basis, and remote evaluation module to assess tennis batting action standard. We applied our system to five tennis trainees from the experimental university, and the results show that the batting action standard level of student *c* and student *e* is lower. Student *c* is weak mainly in the best position of the hitting point and the timing of the lead shot, while student *e* mainly shows poor performance in the timing of movement and the stability of the overall center of gravity. Compared with the proposed system or device, our system has a short real-time delay under the concurrent use of different types of users indicating stable and high real-time evaluation performance. More importantly, our system strictly protects the user's privacy when uploading the user's data remotely. In short, the evaluation results obtained by our system can be used as a scientific basis to improve the tennis batting action standard.

1. Introduction

It is particularly important to evaluate and analyze the technical action standard of tennis batting [1]. Tennis batting is the most important technique in many tennis techniques, and it is the main scoring means for tennis players [2]. Evaluating and analyzing the technical action standard of tennis batting help improve tennis players' skills.

In order to realize the evaluation of the tennis batting action standard, it is necessary to accurately collect the tennis batting action data of the evaluator. At present, most of the methods used to capture motion are video capture. With the help of video equipment, the image information of human motion can be obtained. At the same time, correlation analysis can be carried out to obtain the characteristic parameters of related motion so as to achieve the purpose of collecting action data [3, 4]. However, this kind of collection

method will be affected by external interference such as light, angle, and so on; the collected action data is usually not accurate enough. Therefore, it is not conducive to evaluate the standard degree of tennis batting action accurately. With the popularity and application of micro intelligent wearable devices, as well as the increasing computing power of the built-in processor of intelligent devices, human motion recognition has become a very valuable research. Many applications, including health and fitness monitoring, movement acquisition, and so on, are based on this research [5]. Human motion recognition based on an acceleration sensor is the most commonly used motion recognition method. The wearable device with an acceleration sensor can be worn on the user's chest, wrist, thigh, and calf to monitor the human body's posture and motion. Wearable devices such as smart bracelets can record different movements of users, which can help users understand the situation of

movements in time and make timely adjustments so that users can more scientifically improve the standard of movements. Moreover, this kind of bracelet is equipped with more sensors, such as temperature, acceleration, and pressure sensors; it can collect the user's movement data anytime and anywhere; and the collected movement data is accurate and reliable, which can lay a solid foundation for the research of the standard degree of related movement and the accurate evaluation [6, 7]. Some researchers assess the performance of tennis strokes by this method and provide recommendations to improve tennis skills [8–10]. Recently, a study developed a motion recognition platform for basketball, ping-pong, and badminton that integrated a low-power nine-axis inertial sensor and a low-power environment sensor that can output eleven different characteristics such as triaxial acceleration, triaxial angular velocity, triaxial magnetic field strength, air pressure, and temperature; however, it cannot be used to evaluate the tennis batting level [11]. A research developed a sports skill improvement support system using smartwatch sensors and feedback screen [12], but the model complexity was too high in the above method. Moreover, there was a study [13] that proposed an approach for tennis ball speed estimation based on a racket-mounted motion sensor. Since the sensor was on the racket, there were some errors in the measured results, and it was only used to estimate the speed. A miniature wearable device was proposed by a study [14], which was worn on a player's wrist during the activity. This smart wearable device can monitor athletes' arm movements by sampling the output of the 6 degrees of freedom inertial measurement units (6 DOF IMU). Similarly, it can also gather biometric information such as pulse rate and skin temperature, but its latency increased significantly with the number of users. IMU [15] can detect meaningful differences in angular velocity during tennis groundstrokes to evaluate the tennis batting action standard; however, its measure was not standard. A research used Zepp Tennis Smart Sensor 2 [16] to monitor technical-tactical actions and physical activity during a current tennis competition in the green stage; however, it also had a larger latency. A methodology based on data fusion for sports training [17] has been presented, and a system was developed to assess the performance of a tennis player so as to improve their strokes technique and overall performance (i.e., we call it Brzostowski K.'s system to compare with our system), but it required a large amount of data to train the model, and data collection was difficult. Meanwhile, the model was prone to overfitting resulting in inaccurate evaluation results. Recently, a study focused on fine-grained action recognition in tennis and explored the capabilities of deep neural networks in this task, but this was limited to the classification of actions [18]. A study proposed TenniVis, a novel tennis match visualization system that relied entirely on data that can be easily collected, such as score, point outcomes, point lengths, service information, and match videos that can be captured by one consumer-level camera [19]. Moreover, a study introduced a visual analysis system called Tac-Simur that enabled users to navigate easily through different players and their plays based on their performance in the game to identify players

and plays of interest for further analysis. Users can then use the system to explore different simulation tasks interactively and interpret the simulation results visually. However, the data for this work was obtained visually and was prone to error [20].

Based on the above analysis, this paper studies a remote evaluation system of tennis batting action standard based on an acceleration sensor. By using the bracelet embedded with an acceleration sensor, the real-time tennis batting action signal data of the evaluator is collected as the original signal data. After smoothing and feature extraction, the key features are selected as the evaluation basis of the tennis batting action standard of the evaluator. The evaluation model and index are used to realize remote evaluation. In practical application, the evaluation results obtained by this system can be used as the basis for coaches and assessors to understand the standard degree of their tennis batting action and help them improve their tennis batting action standard further. To our knowledge, no previous study has used a bracelet embedded with an acceleration sensor to evaluate the tennis batting action. Moreover, compared with previous methods, our method based on a bracelet embedded with an acceleration sensor is cost-effective, more energy-efficient, not influenced by the lighting environment, and easier to set up. Compared with five related studies that used systems such as IMU gyroscopes [15], Zepp Tennis Smart Sensor 2 [16], Brzostowski K.'s system [17], TenniVis [19], and Tac-Simur [20], our system performance is more stable and has stronger practical applicability. Moreover, our system strictly protects the user's privacy when uploading the user's data remotely. Therefore, we are motivated to explore the way to use it to evaluate the tennis batting action.

The remainder of this paper is organized as follows. In Section 2, we elaborated on the three main parts of our system and their principles. Analysis of evaluating the performance of the system was introduced. We performed an analysis of evaluation results and system performance test that included signal smoothing performance and real-time response in Section 3. In the process of real-time response test of system performance, we compared with five related studies that used the system such as IMU gyroscopes [15], Zepp Tennis Smart Sensor 2 [16], Brzostowski K.'s system [17], TenniVis [19], and Tac-Simur [20]. The results demonstrated the superiority of our system. In the final section, we summed up our work and discussed the merits and limitations of current work, along with a discussion of the future direction of work.

2. Research on the Remote Evaluation System of Tennis Batting Action Standard Based on Acceleration Sensor

2.1. Design of the Overall Architecture of the System. The remote evaluation system of tennis batting action standard based on acceleration sensor mainly includes three parts: data acquisition module for acquiring the original signal data of tennis stroke in real-time, data preprocessing module (smoothing processing and feature extraction units) for

removing redundant noise from the original signal data by smoothing and extracting time and frequency domain features from the smoothed signal, and remote evaluation module for evaluating tennis batting action standard. The overall architecture of the system is shown in Figure 1.

The data acquisition module belongs to the basic module of the system, and its main task is to use the signal acquisition device of the embedded acceleration sensor of the bracelet to obtain the original signal data generated by the tennis player's batting action to be evaluated and upload it to the PC software for storage. The data preprocessing module belongs to the core module of the system, and its main task is to smooth and extract the original signal data of tennis players' batting action collected by the data acquisition module, and on the basis of feature extraction, the key features are selected out and sent to the remote evaluation module as the evaluation basis for the standard level of tennis players' batting action to be evaluated. As the key module of the system, the remote evaluation module constructs the evaluation model and selects the evaluation index. According to the key characteristics conveyed by the data preprocessing module, it implements the standard-grade evaluation of tennis players' batting action.

2.2. Design of Data Acquisition Module. The data acquisition module mainly includes a signal acquisition device of the acceleration sensor and PC software. The signal acquisition device of the acceleration sensor uses the STM32 series processor as the main control chip and collects the three-axis acceleration, three-axis angular velocity, and three-axis attitude angle data of the human body through the YJ901 module. The YJ901 module integrates a three-axis acceleration sensor, a three-axis angular velocity sensor, and a magnetometer [21]. The module uses Kalman filter technology to combine the three-axis acceleration and the three-axis angular velocity signals output by the acceleration sensor and calculates the three-axis attitude angle. The human body data is output through the serial port, while the STM32 processor uses 100 Hz sampling frequency to collect the human body signal output by the YJ901 module and upload the data to the host computer for storage by Bluetooth HC-31 module at 115200 baud rates. In addition, the acceleration sensor signal acquisition device is equipped with the charging management chip, which can realize the charging of a 120 mAh lithium battery. The PC software is mainly responsible for receiving and storing the original signals such as acceleration, angular velocity, and attitude angle from the signal acquisition device of the acceleration sensor so that the system can call the original signal data collected by the signal acquisition device of acceleration sensor at any time. The structure of the signal acquisition device of the acceleration sensor is shown in Figure 2. Therefore, we use this structure of signal acquisition device of acceleration sensor to acquire the original signal data of tennis stroke in real-time.

In Figure 2, for this device, the main control chip is the STM32 series processor; it collects human signal from the YJ901 module and uploads to the host computer for storage

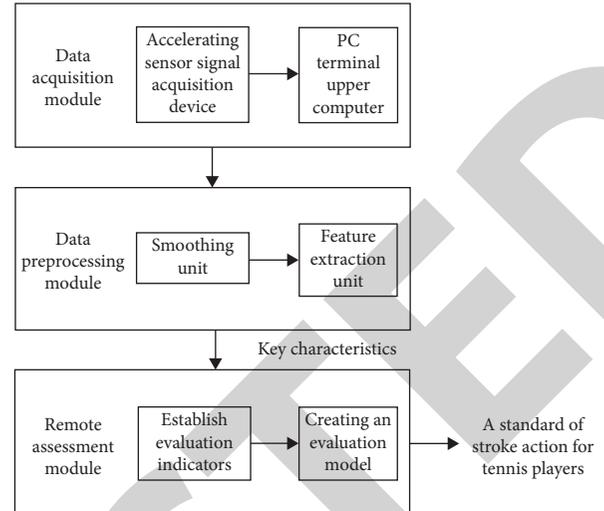


FIGURE 1: Overall architecture diagram of the system.

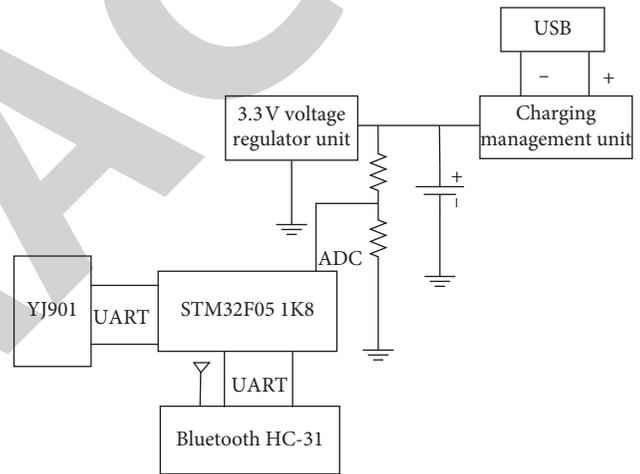


FIGURE 2: Structure diagram of signal acquisition device of the acceleration sensor.

by Bluetooth-31 HC module. Meanwhile, there are equipped with a charging management chip and a voltage regulator chip.

2.3. Design of Data Preprocessing Module

2.3.1. Smoothing. In the practical application of the signal acquisition device of the acceleration sensor, the collected acceleration signal is inevitably affected by a hardware circuit, transmission noise, disturbance frequency noise, and jitter, and the output signal is often mixed with a lot of irrelevant signals such as noise [22]. Before using the original signal data collected by the signal acquisition device of the acceleration sensor to implement the remote evaluation of the tennis batting action standard, the original signal data needs to be smoothed to eliminate the noise of the original signal data. The smooth filtering method is used to remove a small number of local peaks and troughs on the original signal waveform, and a smooth curve is obtained, which is

convenient for the next step to find the peaks, troughs, and zeros. In this paper, the smoothing filtering algorithm, also known as the moving average filtering method, is used to denoise by calculating the mean value of the signal in the sliding field so as to make the curve smoother and highlight the overall curve change trend, which is similar to low-pass filter [23]. When the width is large, the smoothness is high, but the sensitivity is low, and the signal loss is serious; when the width is small, the smoothness is low, but the sensitivity is high. In this paper, we hope that the smoothed signal has better smoothness while minimizing signal loss. Through the experimental summary, the effect of smoothing filter with a window width of 5 is better. The following is the smoothing filtering equation with a window width of 5:

$$\left\{ \begin{array}{l} y'(1) = y(1), \\ y'(2) = \frac{(y(1) + y(2) + y(3))}{3}, \\ y'(3) = \frac{(y(1) + y(2) + y(3) + y(4) + y(5))}{5}, \\ y'(4) = \frac{(y(2) + y(3) + y(4) + y(5) + y(6))}{5}, \\ M, \\ y'(n-2) = \frac{(y(n-4) + y(n-3) + y(n-2) + y(n-1) + y(n))}{5}, \\ y'(n-1) = \frac{(y(n-2) + y(n-1) + y(n))}{3}, \\ y'(n) = y(n). \end{array} \right. \quad (1)$$

Generally, the arm movement of tennis players with racket from start to end and then to the next action can be considered as the process of z -axis angular velocity increasing from 0 to positive maximum, then decreasing to 0, then decreasing from 0 to negative minimum, and finally increasing to 0. Taking this process as a complete action, the starting and the ending points of an action are determined by finding the zero point of the smoothed signal [24]. For the sake of simplicity, we use the smoothing filtering equation to remove redundant noise from the original signal data.

2.3.2. Feature Extraction. After smoothing the original signal, the related feature quantity is extracted from the time and the frequency domains [25]. In order to make full use of the information in the original signal, 14 eigenvalues are extracted from 9 original signals, such as triaxial acceleration, triaxial angular velocity, and attitude angle of three axes, respectively, which are the mean value of acceleration, the mean value of synthetic acceleration, the variance of synthetic acceleration, the peak valley value of synthetic acceleration, the average synthetic angular velocity, the variance of synthetic angular velocity, the peak valley value

of synthetic angular velocity, the covariance of synthetic acceleration and synthetic angular velocity, the change of attitude angle in X , Y , and Z directions in the time domain, and the energy value of acceleration signal in the frequency domain.

(1) *Feature Extraction in the Time Domain.* The mean acceleration in three directions reflects the average state of the signal in the X , Y , and Z directions and can reflect the intensity of an action in three directions. The expressions are \bar{a}_x , \bar{a}_y , and \bar{a}_z , respectively. The calculation equation is as follows:

$$\left\{ \begin{array}{l} \bar{a}_x = \frac{\sum_{k=1}^n a_{x,k}}{n} \\ \bar{a}_y = \frac{\sum_{k=1}^n a_{y,k}}{n}, \\ \bar{a}_z = \frac{\sum_{k=1}^n a_{z,k}}{n} \end{array} \right. \quad (2)$$

where $a_{x,k}$, $a_{y,k}$, and $a_{z,k}$ are the three-axis acceleration signals of X , Y , and Z , respectively, obtained from the k th sampling point in an action; n is the sampling points of an action.

The average value of the combined acceleration \bar{a} , that is, the average value of the combined three-axis acceleration signal of an action, can reflect the comprehensive intensity of the action. The formula is as follows:

$$\bar{a} = \frac{\sum_{k=1}^n a_k}{n}, \quad (3)$$

where $a_k = \sqrt{a_{x,k}^2 + a_{y,k}^2 + a_{z,k}^2}$, and a_k is the modes of triaxial composite acceleration at the k th sampling point in an action.

The variance of the composite acceleration is expressed in σ_a^2 , and the equation is as follows:

$$\sigma_a^2 = \frac{\sum_{k=1}^n (a_k - \bar{a})^2}{n}. \quad (4)$$

The peak valley value of the composite acceleration is expressed as a_{pv} , which is the difference between the maximum and the minimum values of an action synthetic acceleration signal. The equation is as follows:

$$a_{pv} = \max(a) - \min(a). \quad (5)$$

The average synthetic angular velocity is expressed by $\bar{\omega}$, that is, the average value of the synthetic three-axis angular velocity signal of an action. The calculation equation is as follows:

$$\bar{\omega} = \frac{\sum_{k=1}^n \omega_k}{n}, \quad (6)$$

where $\omega_k = \sqrt{\omega_{x,k}^2 + \omega_{y,k}^2 + \omega_{z,k}^2}$, where $\omega_{x,k}$, $\omega_{y,k}$, and $\omega_{z,k}$ are the three-axis angular velocity signals of X , Y , and Z ,

respectively, obtained from the k th sampling point in the first action.

The variance of the resultant acceleration is expressed as σ_ω^2 , and its equation is as follows:

$$\sigma_\omega^2 = \frac{\sum_{k=1}^n (\omega_k - \bar{\omega})^2}{n}. \quad (7)$$

The peak valley value of the synthetic angular velocity is expressed by ω_{pv} , that is, the difference between the maximum and the minimum values of synthetic angular velocity signal of an action. The calculation equation is as follows:

$$\omega_{pv} = \max(\omega) - \min(\omega). \quad (8)$$

The covariance of synthetic acceleration and synthetic angular velocity is expressed by $\text{Cov}(a, \omega)$, and its equation is as follows:

$$\text{Cov}(a, \omega) = \frac{\sum_{k=1}^n (a_k - \bar{a})(\omega_k - \bar{\omega})}{n-1}. \quad (9)$$

The attitude angle variations of X , Y , and Z axes are represented by R_x , R_y , and R_z , respectively, and its equation is as follows:

$$\begin{cases} R_x = \sum_{k=2}^n |\phi_{x,k} - \phi_{x,k-1}| \\ R_y = \sum_{k=2}^n |\phi_{y,k} - \phi_{y,k-1}|, \\ R_z = \sum_{k=2}^n |\phi_{z,k} - \phi_{z,k-1}| \end{cases} \quad (10)$$

where $\phi_{x,k}$, $\phi_{y,k}$, and $\phi_{z,k}$ are the attitude angle signals in X , Y , and Z axes obtained from the k -th sampling point in the first action.

In summary, we extract the features in the time domain from the smoothed signal according to the above equation.

(2) *Feature Extraction in the Frequency Domain.* This part uses the multiscale spatial energy distribution feature extraction method of the wavelet transform. The component of wavelet is a set of wavelet basis functions, which can describe the characteristics of signal in time (space) domain and frequency (scale) domain in a local range, which is also the advantage of wavelet transform over Fourier transform. In any time or space domain, wavelet analysis can effectively analyze the signal. The requirements of adaptive signal analysis are conducive to focus the details of the signal, and these characteristics are particularly important for signal analysis [26]. The commonly used wavelet functions are Haar, Daubechies (DBN) wavelet, and so on. After wavelet analysis, the energy characteristics of each level can be obtained. The dyadic wavelet decomposition of the signal can be expressed as follows:

$$f(t) = A^t + \sum D^t, \quad (11)$$

where A is the approximate signal, which is the low-frequency part; D is the detail signal, which is the high-frequency part. At this time, the frequency band distribution of the signal is shown in Figure 3.

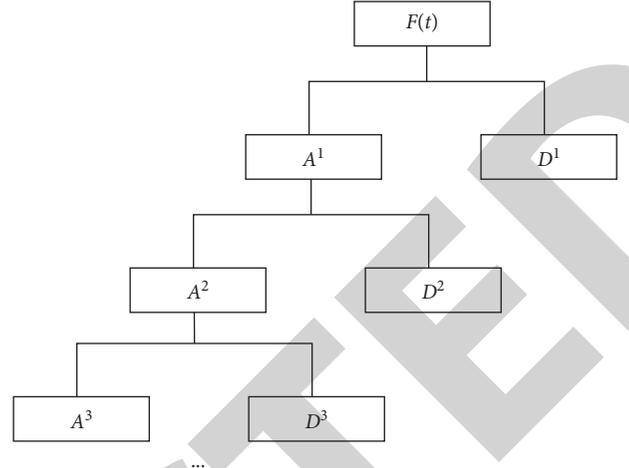


FIGURE 3: Signal frequency band distribution of multiscale decomposition.

In Figure 3, the signal can be decomposed into lower- and higher-frequency bands on multiscale where A represents the low-frequency part, and D represents the high-frequency part.

The total energy of the signal is as follows:

$$E = EA_i + \sum ED_j. \quad (12)$$

The energy of the approximate signal of the j th layer and the detail signal of each layer are selected as features to construct the feature vector:

$$F = [EA_j, ED_1, ED_2, \dots, ED_j]. \quad (13)$$

This feature extraction directly calls PyWavelets signal processing library in Python, sets j to 2, extracts the feature of the signal, and outputs the feature vector:

$$F = [EA_2, ED_1, ED_2]. \quad (14)$$

In brief, we use the above model to extract features in the frequency domain from the smoothed signal.

(3) *Feature Selection.* Feature selection is an important “data preprocessing” process, which can remove features irrelevant to the current task so as to reduce the burden of the system and the difficulty of system evaluation. There are four common feature selection algorithms based on filter, wrapper, embedding, and information gain [27, 28]. Because of the complexity of the first three kinds of algorithms, both memory and time costs are very large; we use the feature selection algorithm based on information gain (IG), which is also a common and efficient feature selection algorithm [29]. In our study, we select some important features from the above-extracted features for subsequent evaluation of the action.

To calculate information gain, information entropy is defined first. Information entropy is generally used as an index to reflect the purity of the sample set. Assuming that pk ($k = 1, 2, \dots, |y|$) is the proportion of the k -th type of sample in the current sample set D , the information entropy of D is defined as

$$\text{Ent}(D) = - \sum_{k=1}^{|y|} pk \log_2 pk, \quad (15)$$

where $|y|$ represents the number of tag categories. The smaller the value of entropy $\text{Ent}(D)$, the larger the purity of set D . Information gain is defined below.

Since the features extracted from the signal are all continuous values, the number of values of continuous value attributes is not limited, so the information gain cannot be calculated directly according to the continuous value; thus, the continuous value discretization technology is adopted here [30]. Given sample set D and continuous attribute v , assuming that v has n different values $\{v^1, v^2, \dots, v^n\}$ on D , and D can be divided into subsets D_t^- and D_t^+ based on partition point t . For the adjacent attribute values v^j and v^{j+1} , the partition result is the same when t takes any value in the interval $[v^j, v^{j+1})$. A set of candidate partition points with $n - 1$ elements is defined as follows:

$$T_a = \left\{ \frac{v^j + v^{j+1}}{2} \mid 1 \leq j \leq n - 1 \right\}. \quad (16)$$

Taking the median point of interval $[v^j, v^{j+1})$ as the candidate partition point, the optimal partition point is selected to divide the sample set, namely

$$\text{Gain}(D, v) = \text{Gain}(D, v, t) = \text{Ent}(D) - \sum_{\lambda \in \{-, +\}} \frac{|D_t^\lambda|}{|D|} \text{Ent}(D_t^\lambda), \quad (17)$$

where $\text{Gain}(D, v, t)$ is the information gain of the sample set D based on the partition point t . In this way, each feature v can be brought in to get the information gain value of all features, and then the importance value of each feature can be calculated. According to the importance value, we select 10 key features of tennis players' batting action and input them into the remote evaluation module to implement the remote evaluation of tennis batting action standard.

2.4. Design of Remote Evaluation Module. After receiving the key characteristics of the tennis batting action of the players to be evaluated, the remote evaluation module uses the evaluation model in the module to implement the remote evaluation according to the established evaluation index and obtains the standard level of the tennis batting action of the players to be evaluated.

2.4.1. Establishment of Evaluation Index. Through the questionnaire survey, the tennis players' scoring criteria are set up [31, 32]. The content of the questionnaire is divided into two parts: the first part is "evaluation indicators." Through repeated interviews with a normal university athlete and tennis teacher, data on 18 evaluation indicators are collected. Each indicator is represented by 1, 2, and 3 index, respectively. The higher the importance and accuracy of the target, the more important and accurate the corresponding index evaluation; the second part of the

"evaluation index" is the evaluation standard of 18 indicators that have been developed.

A total of 500 questionnaires are distributed to the tennis teachers and athletes in 5 professional sports colleges, and 490 valid questionnaires are recovered, with a recovery rate of 98%. After recycling, the indicators that are not selected in levels 1 and 2 are deleted. After experts' evaluation and modification, 9 evaluation indicators and evaluation standards of each indicator are finally obtained, as shown in Table 1.

2.4.2. Construction of Evaluation Model. (1) *Establish the Grading Standard of Evaluation Index.* According to the experts' opinions and the level of athletes, the grading standard of each evaluation index is established. The grades of the evaluation index are divided into four grades: "excellent", "average", "bad", and "poor", and the corresponding scores are 81–100, 61–80, 41–60, and below 40, respectively.

(2) *Create Index Evaluation Matrix.* A group of relevant index data of athletes (10 shots) are collected to carry out statistics and then get the ratio of the athlete to four grades of "excellent", "general", "bad", and "poor", respectively, in each evaluation index. The evaluation vector $S_i = (s_{i1}, s_{i2}, \dots, s_{ik})$ is used to express it; thus, the fuzzy evaluation matrix H_i can be obtained.

(3) *Fuzzy Operation.* The weight of each evaluation index is obtained by expert evaluation method [33]; the weight coefficient fuzzy subset B_i and the fuzzy evaluation matrix H_i are combined to obtain the evaluation vector U_i of the i -th evaluation index, expressed as follows:

$$U_i = B_i \times H_i = (a_{i1} a_{i2} \dots a_{im}) \times \begin{bmatrix} s_{i1} & s_{i2}L & s_{ik} \\ s_{21} & s_{22}L & s_{2k} \\ M & M & MM \\ s_{j1} & s_{j2}L & s_{jk} \end{bmatrix}. \quad (18)$$

(4) *Fuzzy Comprehensive Evaluation.* The single factor fuzzy evaluation result $U_i (i = 1, 2, \dots, n)$ is integrated to form a higher-level fuzzy evaluation matrix H . The standard level of tennis players' batting action can be obtained by combining $U = B \times H$ with the principle of maximum membership.

2.5. Analysis of Evaluating the Performance of System. We use the following measures to evaluate the performance of the proposed method. (1) Signal smoothing performance: The waveform of the acceleration signal before and after the smooth processing is compared, and the signal smooth processing effect of this system is tested. (2) Real-time response performance: With the growth of the number of concurrent users, the change of the response delay of our system is tested as well as compared with five related studies that used the system such as IMU gyroscopes, Zepp Tennis Smart Sensor 2, Brzostowski K.'s system, TenniVis, and Tac-Simur.

TABLE 1: Evaluation index and evaluation standards of tennis batting action.

Evaluation indicators	Evaluation criteria
Mobile time C1	A move that begins when the ball is not over the net and is hit by an opponent
The degree to which the pace moves into position C2	Able to reach the hitting position, steady body weight, and accurately hit the ball
Overall movement rhythm C3	The lead shot, there is a momentary pause; hit the ball coherently and fluently with the swing
Global barycentric stability C4	Keep the center of gravity steady and unchoppy from the start to the end of the shot
Lead the racket to end position C5	The racket swings to the side of the body; the racket holder arm is slightly bent; and the racket head extends to the maximum back of the court
Racket back time C6	When the opponent hits the ball, the racket is drawn when the ball is not over the net
Rhythm of batting swing C7	Instant acceleration and a consistent, fluid swing
The best position for hitting C8	The height in front of the pivot foot at waist level
Direction of strike C9	Hit the ball in the planned direction

3. Analysis and Comparison of Experimental Results

Taking the tennis major of a sports university as the experimental object, this paper uses the system to implement the remote evaluation of the tennis batting action standard, analyzes the evaluation results, and detects the signal smooth processing performance and real-time response performance in the evaluation process of the system. Moreover, we compared our evaluation results and system performance with five related studies that used the system such as IMU gyroscopes, Zepp Tennis Smart Sensor 2, Brzostowski K.'s system, TenniVis, and Tac-Simur.

3.1. Analysis and Comparison of Evaluation Results. Five tennis trainees (*a~e*) are randomly selected from the tennis major of experimental colleges and universities to make four tennis batting actions. Through the system in this paper, the five tennis trainees are remotely evaluated for four tennis batting actions each. The final evaluation results are shown in Table 2.

We, respectively, tested the average scores of the four strokes of the five trainees in our system and five related studies that used the system such as IMU gyroscopes, Zepp Tennis Smart Sensor 2, Brzostowski K.'s system, TenniVis, and Tac-Simur. The results are shown in Figure 4. It can be concluded from Figure 4 that the average levels of the four tennis strokes of the five tennis trainees *a~e* from our system are in the order of average, excellent, bad, average, and bad, so are other five works' results, and it reflects that our results are very reliable. As can be seen from Figure 4, the score of each student evaluated by our system is more stable compared with the other five systems. For our results, it can be seen that among the five tennis trainees selected, the tennis strokes of student *b* are the most standard; the tennis strokes of trainees *a* and *d* are in the middle, while the tennis strokes of trainees *c* and *e* are not standard enough, so we need to pay attention to them in the future teaching to improve the tennis batting action standard of the two trainees.

In order to make the experimental colleges and universities more targeted to improve the tennis batting action standard of trainees *c* and *e*, the tennis coaches of

TABLE 2: The remote evaluation results of the tennis stroke of the five tennis trainees.

Tennis cadet no.	Hit number	Evaluation score	Assessment level
<i>a</i>	First time	62.53	General
	Second time	58.77	Bad
	Third time	68.79	General
	Fourth time	79.12	General
<i>b</i>	First time	81.56	Good
	Second time	76.45	General
	Third time	80.93	Good
	Fourth time	83.21	Good
<i>c</i>	First time	50.13	Bad
	Second time	48.95	Bad
	Third time	44.79	Bad
	Fourth time	62.35	General
<i>d</i>	First time	83.44	Good
	Second time	54.13	Bad
	Third time	70.68	General
	Fourth time	78.21	General
<i>e</i>	First time	38.95	Poor
	Second time	61.25	General
	Third time	55.15	Bad
	Fourth time	66.11	General

experimental colleges and universities need to understand the shortcomings of the two trainees' tennis batting action accurately. Therefore, the ratio of the two trainees reaching different levels in each evaluation index should be counted. The statistical results obtained by our system in this paper are shown in Figure 5.

In Figure 5, the horizontal coordinate is nine evaluation indicators; each indicator contains four levels; and the vertical coordinate indicates the proportion. Moreover, (a) and (b), respectively, show the proportions of trainees *c* and *e* at different levels under the nine indicators. By analyzing Figure 5, it can be concluded that student *c*'s tennis batting action is insufficient in the best batting point C8, timing of shooting C6, batting rhythm C7, and stability of global center of gravity C4 and needs to be improved; student *e*'s tennis batting action is not standard in positions moving opportunity C1, stability of

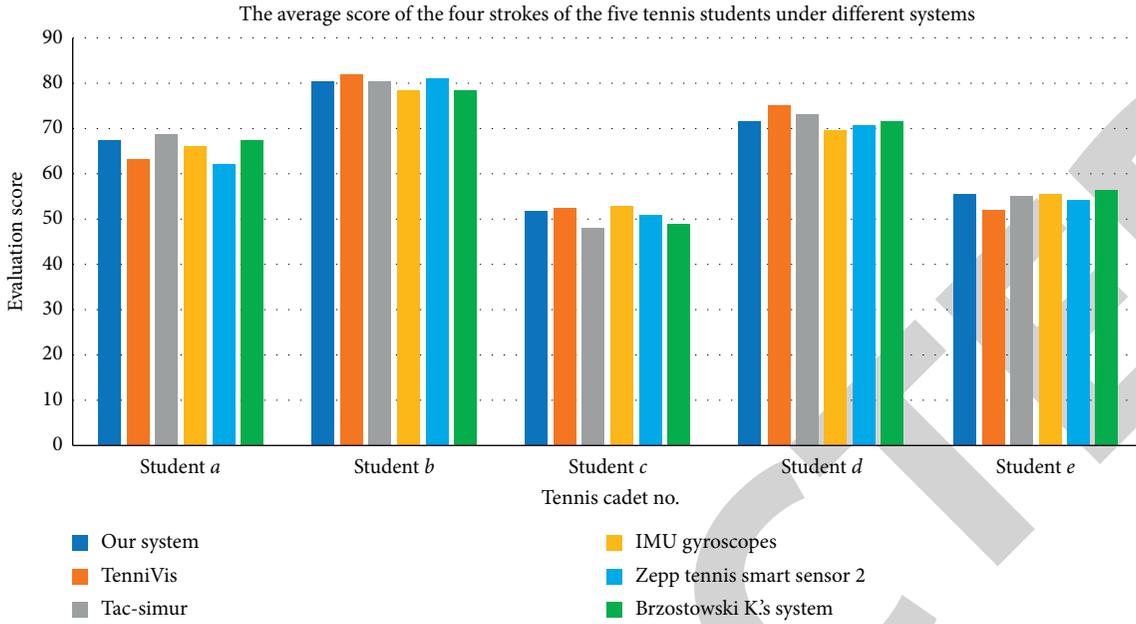


FIGURE 4: The average score of the four strokes of the five tennis trainees under our system and the other five comparable systems.

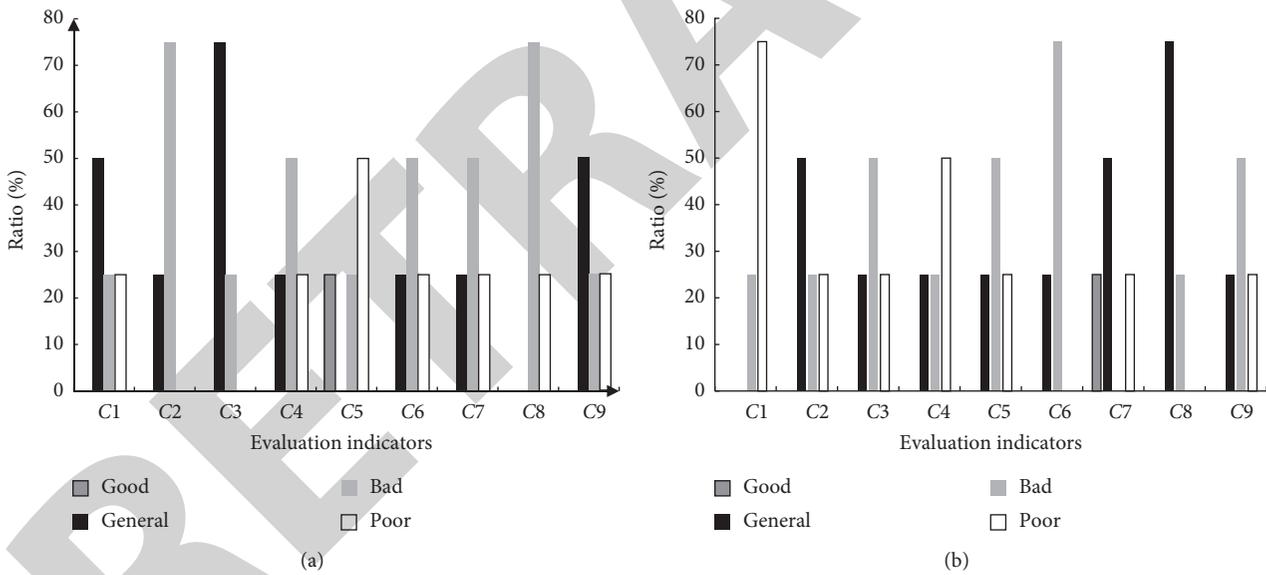


FIGURE 5: Statistical results of trainees c and e reaching different grades in each evaluation index: (a) the rate at which trainee c achieves each grade in each evaluation indicator and (b) the rate at which student e achieves each grade in each evaluation indicator.

global center of gravity C4, overall movement rhythm C3, the end position of shooting C5, and batting direction C9 and needs to be improved.

Based on the above, the system in this paper can realize the remote evaluation of the tennis hitting action standard of each student of tennis major in experimental colleges and universities, and the evaluation results can provide an effective scientific basis for improving the tennis hitting action standard of trainees in experimental colleges and universities.

3.2. Analysis and Comparison of System Performance

3.2.1. Signal Smoothing Performance. A group of the original acceleration signal of a student's tennis batting action collected by the system in this paper is randomly selected. Through the smooth processing of this system, the waveform of the acceleration signal before and after the smooth processing is compared, and the signal smooth processing effect of this system is tested. The comparison results are shown in Figure 6.

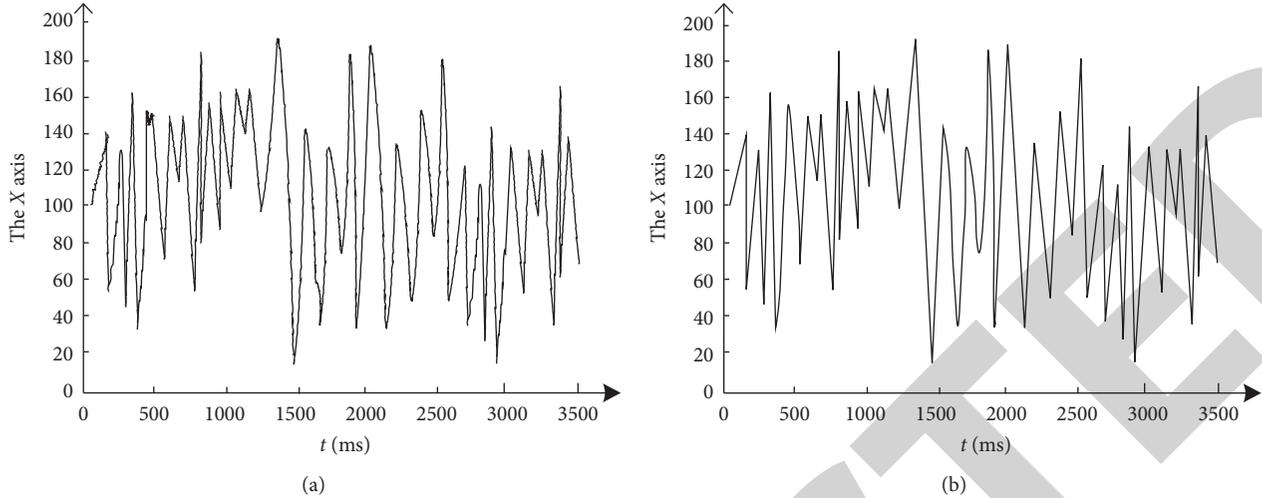


FIGURE 6: Acceleration signal waveform before and after system smoothing processing in this paper: (a) acceleration signal waveform before smoothing processing and (b) the acceleration signal waveform after smoothing processing.

In Figure 6, the horizontal coordinate represents the time in milliseconds, and the vertical coordinate is the value of the raw acceleration signal collected by the system, while the student was performing the tennis stroke where (a) and (b), respectively, represent the original and smoothed acceleration signal waveforms. It can be seen from Figure 6 that the acceleration signal waveform before smoothing has interference such as burr noise. After smoothing, the burr is filtered out by the acceleration signal waveform of the system in this paper, and the signal waveform is smoother. It shows that the system in this paper has better signal smoothing performance, which can effectively remove redundant noise and improve signal accuracy.

3.2.2. Real-Time Response. We test the real-time performance of the actual evaluation response of our system under the concurrent use of different numbers of users in this paper, and the response delay is taken as the measurement index. Moreover, we test the change of the response delay of the actual evaluation of five related studies that used the system such as IMU gyroscopes, Zepp Tennis Smart Sensor 2, Brzostowski K.'s system, TenniVis, and Tac-Simur as a comparison. The results are shown in Figure 7.

In Figure 7, the horizontal coordinate is the number of users using the system concurrently, and the vertical coordinate is the delay time in milliseconds. Specifically, we tested the latency of our system against 5 other systems with 25 to 200 concurrent users to compare the performance of each system. Roughly, it seems that the latency of these 6 systems is between 280 and 340 ms. It can be seen from the analysis of Figure 7 that the actual evaluation response delay of the system in this paper presents a gradual upward trend with the growth of the number of concurrent users in all systems; however, the latency of our system is relatively low, and the overall increase rate in the test is only 0.0458 s. The IMU gyroscope, Zepp Tennis Smart Sensor 2, Brzostowski K.'s system, TenniVis, and Tac-Simur and other devices have greater response delay changes than our system. To sum up,

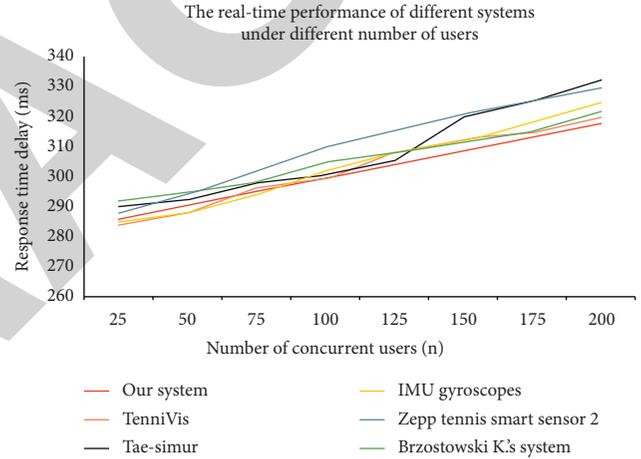


FIGURE 7: Actual response delay of the system in this paper under the different number of concurrent users.

the results show that our system is stable. It can be concluded that the real-time response of the system in this paper is high, which is less affected by the growth of the number of concurrent users, and the system performance is stable and has strong practical applicability.

4. Conclusion

In playing tennis, the standard degree of batting action directly affects the final score. Improving the standard of tennis batting action is the key to get a high score in tennis. In this paper, the remote evaluation system of tennis batting action standard based on the acceleration sensor is researched to provide a scientific basis for real-time evaluation of the standard degree of tennis batting action based on remote monitoring. The bracelet embedded with the acceleration sensor is worn on the wrist of the evaluator to collect and store the original signal data of tennis stroke in real-time. The redundant noise of the original signal data is

eliminated by smoothing, and the accuracy of the signal is improved. The features of the time and the frequency domains are extracted from the smoothed signal data, and the key features are obtained by feature selection as the evaluation criteria of the evaluator's tennis stroke. According to the key characteristics of the long-distance evaluation of the tennis batting action standards of the subjects to be evaluated, this paper uses the system to implement the long-distance evaluation of the tennis batting action standards of the tennis majors in a sports university. The results show that among the five tennis trainees, the standard degree of tennis batting action of trainees c and e is relatively low, among which student c 's tennis batting action is not enough in the best position of the batting point, the timing of leading the racket, and the rhythm of batting, while student e 's tennis batting action is not standard in the timing of moving, the stability of the overall center of gravity, and the rhythm of the overall action. In the future, we need to focus on the shortcomings of both.

The system in this paper has superior signal smoothing processing performance and good real-time response performance. In practical application, it can realize the remote evaluation of different tennis batting action standards and has high practical application value. Moreover, our method is cost-effective, more energy-efficient, easier to set up, and not influenced by the lighting environment. Importantly, our system strictly protects the user's privacy when uploading the user's data remotely. However, our method also has some limitations. Whether it can accurately assess the standardization of the tennis batting action also depends on whether the sensor has a high sampling rate. Therefore, it would be interesting to investigate whether the accuracy will be further improved or not with a higher sampling rate. This will be explored in the future. At the same time, the sample size of statistical measurements in this study was not sufficient, and we will continue the study to obtain more valid results.

Data Availability

The data used and/or analyzed in this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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