

Retraction

Retracted: Using Wireless Sensor Network to Correct Posture in Sports Training Based on Hidden Markov Matching Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/ participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets 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 own 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

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Research Article

Using Wireless Sensor Network to Correct Posture in Sports Training Based on Hidden Markov Matching Algorithm

Cui Cui 🕩

Depatrment of Sports, Huanghe Jiaotong University, Jiaozuo, Henan 454950, China

Correspondence should be addressed to Cui Cui; 2007070294@zjtu.edu.cn

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This paper combines the research of wireless sensor networks and sports training and proposes a wireless sensor network-based intelligent sports training system. According to the requirements of the system, this design uses the wireless sensor network system as the platform for development and the ZigBee module for wireless communication. The advantage of this system is to transmit the obtained information to the ZigBee coordinator module, and after the processing of information and the resultant decision, a nonwearable unmonitored motion training model based on visual sensing is proposed. The motion terminal collects video data streams of user motion actions and extracts features to establish HMM motion recognition algorithm to achieve recognition of motion actions, automatic counting, and intelligent scoring functions. The template matching algorithm based on dynamic time regularization and weighted Euclidean distance realizes a universal real-time motion recognition algorithm with high standard and low latency and can guide the user's motion action based on similarity calculation. The intelligent sports training system is designed and developed to maintain a high-quality human-computer interaction experience with a real-time feedback client and uploads sports data to a cloud server via the HTTP protocol, which supports real-time sports training system based on the wireless sensor network proposed in this paper is stable and reliable and adds fun and competitiveness to boring sports. The research of this paper has some reference value for the application of wireless sensor networks and the research of the motion recognition algorithm.

1. Introduction

The main task of wireless sensor networks is target monitoring and data collection and sending it to the observer. This process involves the analysis and evaluation of data to facilitate real-time, efficient, and accurate decision-making by decision-makers. The analysis and decision-making of any data depend heavily on the quantity and quality of the data and some relevant information. However, in wireless sensor networks, the quality of the sensed data is an important key factor in the performance of the network, which reflects the actual state of the monitored objects [1]. To be able to interconnect anyone or any device anytime and anywhere, wireless network information and communication technologies are developing rapidly. There are also many important basic technologies widely promoted and practically applied, and the speed of wireless network information communication is developing rapidly [2]. The wireless sensing module is the basic part of wireless sensor technology and embedded technology, intelligent sensors, wireless information communication technology, wireless Internet technology, and distributed data processing technology, and it is the main direction of modern development. With the continuous development and improvement of wireless sensor technology, the national strategic planning and government policies strongly support the requirements of accelerating the development of the sports industry, as well as people's physical health issues that need to be resolved urgently. Therefore, it is urgent to develop a complete set of wireless sensor-based intelligent sports training system to create a personalized sports training platform for athletes [3].

One of the purposes of scientific and technological research and development is to make it easier and more convenient for ordinary users to operate computers and to

change people's production and lifestyle, and it has been a popular area of scientific research. As we all know, human beings rely on vision to obtain information about the external world, and the acquisition of visual data is the basis for people to understand everything in the world. Through the collected image data, the analysis technology allows computers to distinguish human movements and recognize the meaning behind the perception of human actions. Through the cloud, monitoring to collect user movement data, through analysis to achieve different sports training prescriptions customized according to different sportsmen, extract human movement characteristics, establish a standard human movement description model, guide sportsmen to train in line with their physical strength, and improve physical function [4]. Therefore, the original design of this system is to personalize the guided customized sports training program, which can realize the basic sports training while maintaining the personalization of the sportsman and at the same time has relatively wide applicability. This paper proposes a multifunctional sports training system based on a wireless sensor network to solve the sports training needs and some drawbacks of sports training equipment and to facilitate managers to fine and comprehensive control of athletes' sports situation. Through the exploration and mining of wireless sensor networks, this paper has certain exploration and reference significance to the action recognition technology in the field of intelligent sports [5].

This thesis treats the design of the intelligent sports training system because of wireless sensor network type as the topic of inquiry. The first chapter is the introduction, which focuses on the research background and significance of the intelligent sports training system, determines the important content of this thesis, and explains the research framework of this thesis. The second chapter is an introduction to related work, focusing on an overview of the implementation of intelligent sports training systems and wireless sensor network application technology, analyzing the current research status and treating it as the basic theoretical foundation for exploration. The third chapter is about the research of the intelligent sports training system based on wireless sensor network. Through the construction of the wireless sensor intelligent model and sports training data processing research, the requirements of the intelligent sports training system are integrated, and its performance and attribute requirements are analyzed and realized. The overall scheme of the intelligent sports training system is designed. Finally, complete the design and implementation of the intelligent sports training system, determine the overall hardware design and the selection of each hardware, including wireless sensor network construction, sensor selection, and design, and access control circuit design and level conversion circuit design. The fourth chapter is the result analysis, testing the function, performance, and reliability of the intelligent sports training system. The fifth chapter is the summary and outlook, mainly summarizing the research work carried out in the full text and looking forward to the details and perfection of the system.

2. Related Work

The application and development of wireless sensing modules also have a broad development future. The use of wireless sensing modules in the present is generally immobile and fixed. The nodes of wireless sensor networks are placed in fixed places, and to monitor the changes of the whole environment, it is necessary to put a large number of wireless sensor nodes, and the cost of using them will therefore become expensive [6]. Cortell-Tormo et al. developed an intelligent sports training system that captures, acquires, tracks, and verifies the patient's hand posture status in real-time through Kinect sensors to effectively intervene and guide the posture trajectory to achieve [7]. Umek et al. developed a smart sports training game by combining virtual reality technology with various games using Unity3D technology [8]. Through the Kinect sensor, the user's movement status and posture in the game are presented in the form of a virtual human skeleton, and the patient can adjust the posture of each part of his body through the feedback movement information to complete the real-time interaction with the virtual human skeleton image, to train the user's body coordination and perception ability [9].

Intelligent sports to sports equipment and fitness equipment are the basis of human-computer interaction technology, Internet of things, cloud computing, big data, other high-tech implantations, the equipment data, network, intelligent, and entertainment. Different from the current traditional fitness and other sports, intelligent sports can break the limitations of time and space [10]. With the fragmented time and space to use, people can have a more intelligent and convenient way of scientific exercise. Smart sports provide a new opportunity to improve the overall physical health of people [11]. Cheng et al. designed and developed a set of intelligent traffic signal control system using Kinect body sensing technology to eliminate noise and other problems based on FAST feature points and PDE video motion compensation algorithm to achieve automatic real-time monitoring of traffic flow information can quickly respond to intersection traffic emergencies and intelligent traffic signal control [12]. Wang et al. developed a training robot that can design motion trajectories that can adjust posture while developing a wearable device for physiological parameter detection, as an auxiliary device for interaction with the robot, and can quickly respond to unexpected user conditions [13]. Wang et al. also developed a virtual reality training system based on machine vision and force-tactile feedback combined with an upper limb training robot, which was trained through human-robot interaction.

People's physical health recognition is an urgent problem, which makes the research of intelligent sports training systems based on wireless sensor networks of great significance. The system combines a wireless sensor network and uses KinectV2 sensors to achieve a small range of fitness exercise training detection and achieve a complete set of intelligence. This system combines wireless sensor network and KinectV2 sensors to achieve a complete intelligent sports training system, which brings scientific and intelligent guidance and management for athletes' daily fitness sports [14]. In this paper, during the research of motion recognition algorithm, a generic motion recognition algorithm model is proposed based on a finite state machine model described by template matching features, which can be reused for adding new motion recognition, reducing the duplication of work and increasing the extension of the system. The study of this system also has implications for exploring the use of wireless sensor networks in addition to the entertainment field, motion recognition, and precise motion recognition [15].

3. Research on the Intelligent Sports Training System Based on the Wireless Sensor Network

3.1. Wireless Sensor Intelligence Model. In WSN network operation, the energy consumption of the nodes in the network is analyzed and calculated based on the structure of the sensor nodes to facilitate our simulation experiments on routing algorithms [16, 17]. The energy consumption model of WSN communication used in this paper includes the case of energy consumption of transmit data module and receive data module. In this model, the energy consumption of the transmitting data module is the sum of the energy consumed by the transmitter circuit and the power amplifier. Its energy consumption is proportional to the transmission distance *m*. The energy consumption of the power amplifier is proportional to the quadratic power of m, and it is proportional to the quadratic power of m. Therefore, we should try to make the transmission path length less than m. When the size of the transmitted data is h bits and the length of the transmission path is m, the energy consumption of the transmitting data module is shown in Equation (1).

$$G(h,m) = \begin{cases} hG(elec) + h\beta_{as}m^2, m < m_0, \\ hG(elec) + h\beta_{bq}m^4, m \ge m_0, \\ G(TX - elec) + G(TX - bq), \end{cases}$$
(1)

where G(h, m) denotes the energy consumption per bit of data in the transmitting circuit, G(h, m) denotes the energy consumption of the power amplifier transmitting hbits of data with a transmission path length of m, and G(elec) denotes the energy consumed per bit of data in the transmitting circuit or the receiving circuit. Use it when the data is transmitted in free space and bq when the data is transmitted in a multipath fading channel.

The energy consumption of the receiving data module is the energy consumption of the receiving circuit, that is, the energy consumption per *h* bits of data received as shown in Equation (2). Assuming the initial and operational state of the nodes in the WSN network, the network model used in this paper has the following characteristics: (1) the size of the monitoring area is $M \times M$, randomly distributed *N* sensor nodes, and the location is fixed and has a unique number. (2) Each sensor node in the network is isomorphic, and the initial energy is the same, the energy consumption, the sensor node is dead, and the energy is not replenished. (3) Each sensor node can communicate with any sensor node or directly with the base station. The transmit power can be adjusted according to the transmission distance, using the same communication energy consumption model. The nodes in the network send the same data with the same energy consumption. (4) The base station is set outside the monitoring area with a fixed location. Also, there is unlimited energy to ensure enough power to send and receive data to the nodes [18, 19].

$$G(h) = G(RX - \text{elec}) + hG(\text{elec}).$$
(2)

The network clustering phase is divided into three phases, the cluster initialization phase, the self-organized cluster formation phase, and the competitive selection of cluster head phase. After the completion of network clustering, each round of cluster head election and data transmission will be carried out, and no more clustering will be carried out. The specific design idea is as follows: in the initialization stage of cluster formation, the base station realizes the vertical division of the network into layers based on the location information of the sensor nodes; in the selforganizing cluster formation stage, the clustering algorithm is carried out for each layer based on the self-organizing feature neural network, the input vector is the sensor nodes of each layer, and the cluster formation is based on the location information of the nodes to realize the horizontal selforganizing cluster formation; in the competitive selection of cluster head stage, the optimal cluster head is selected for each cluster based on the competitive neural network. The input vector is the sensor nodes participating in the competition for cluster head, and the node parameters are selected as the relative residual energy of the node, the number of neighboring nodes of the node, and the number of times the node has been elected as the cluster head.

In the self-organized cluster formation phase, we focus on the location relationship, and in the competitive cluster head selection phase, we focus on the relative remaining energy of nodes and the number of neighboring nodes. Therefore, for the parameters of the SOM input vector, we choose the parameters of the sensor node's horizontal and vertical coordinates and the azimuth angle to the base station. The azimuth of the sensor node is the azimuth of the line that this node is connected to the base station, the angle from the north end of the standard direction, clockwise to that line. Suppose the position coordinates of a sensor node are (a, b) and the position coordinates of the base station node are (a_0, b_0) , then the azimuth angle β of this node to the base station is shown in Equation (3).

$$\beta = \sec\left(\frac{a-a_0}{\sqrt{(a-a_0)^2 + (b-b_0)^2}}\right) + \csc\left(\frac{b-b_0}{\sqrt{(a-a_0)^2 + (b-b_0)^2}}\right).$$
(3)

In this paper, we assume that a certain number of sensor nodes are distributed in a certain area, and the base station is set outside the area. The improved wireless sensor smart network model is as follows: at the start of network operation, the base station sends broadcast signals to the whole network to collect sensor node information [20–22]. The node feeds back its location information, including location coordinates, distance, and azimuth to the base station and also sends the number of neighboring nodes. The base station divides the network into layers according to the distance between the nodes and the base station and calculates the number of nodes in each layer of the network and the optimal number of cluster heads in each layer. The SOM clustering algorithm is run according to the position coordinates of the nodes and the azimuth angle to the base station, each layer is clustered according to the optimal number of cluster heads, and the broadcast message of the cluster to which the node belongs is sent at the end. The hamming competitive neural network is used to select the optimal cluster head for each cluster that has relatively more nodes with relatively more remaining energy, relatively more neighboring nodes, and relatively fewer elected cluster heads.

3.2. Sports Training Data Processing. The motion recognition algorithm proposed in this system adopts the method of DTW template matching by a finite state machine describing the spatial characteristics of the angle between skeletal joints, which can meet the requirement of low latency for the motion recognition process, match the standard motion of each frame decomposition with high accuracy, and can exclude the influence of individual differences on motion recognition. It is a general motion recognition algorithm with high reusability, and the main flow of the algorithm is shown in Figure 1.

The real-time data stream collected by Kinect V2 is accepted, including the depth data stream, skeletal data stream, and color image stream. The skeletal data stream will be used for the subsequent motion recognition process, and the other data will be used for client-side interaction and storage in the application layer. The skeletal data stream of data acquisition is firstly filtered by applying the joint filtering method based on the combination of jitter removal and double exponential smoothing, and the smoothed skeletal data lays the foundation for the smooth output of skeletal features. Then, the spatial vector method is adopted to extract the joint angle features of the skeletal data. After processing the skeletal data, a motion finite state machine template based on the joint angle features is established for different motions, and the motion recognition of the formulated motion is performed by matching the DTW template matching algorithm with the real-time motion data. The above motion recognition is only for one cycle of the moving process, but it is necessary to continuously identify and settle the motion process, and the client needs to do the main interaction feedback according to the different finite state machine states. Eventually, the data is stored on the server side for other applications.

According to the features of the target motion to be recognized, a set of discrete action state time series can be designed to reflect the motion process. The spatial feature vectors extracted from the skeletal data, such as the angle of multiple joints and the rotation angle, are used as the features of the discrete movements and as the basis for judging the state switching conditions. The specific description of these features needs to be set by human beings, and the scientific nature of the setting will also affect the user experience and the effect of fitness. The system is designed to identify the three movements combined with national standards and professional sports instructors for the specific description of the skeletal features of the movements, which will be described later [23]. Since the starting movement of each sport is different, we can distinguish the sports to be tested according to the preparatory movements of the testers. Once the test sports are identified, the system can select the reference template skeletal characteristics and standard sports data that need to be matched according to the different requirements of different sports.

In the skeletal feature matching, the reference template and the user's test template are calculated using the DTW algorithm, and this system incorporates a weighted Euclidean distance calculation in the process, weighting for the skeletal nodes with high motion influence. The reference template and test template in the DTW algorithm correspond to the standard skeletal feature sequences in the motion template and the real-time skeletal feature sequences of the user, respectively, in this system. Therefore, the test template and the reference template are represented in this system as

$$\begin{cases} P = \sum_{i}^{m} P(i), \\ Q = \sum_{i}^{n} Q(i), \end{cases}$$
(4)

where P(i) and Q(J) can be expressed as Equation (5), P(i) denotes the specific composition of the feature vector P(i) in the *P*-featured time series at time *m*, consisting of multiple sets of spatial feature pair angles between multiple joints, and similarly, Q(j) denotes the *Q*-featured time series.

$$\begin{cases} P(i) = \left[\beta_{pi}\right], i \subseteq [1, m], \\ Q(j) = \left[\beta_{qi}\right], j \subseteq [1, n]. \end{cases}$$
(5)

The mapping between the reference skeletal sequence and the feature skeletal sequence in this system is shown in Equation (6).

$$f(x) = \sum_{i}^{m} \sum_{j}^{n} m_{i} * n_{j}, m_{i} = n_{i}, m_{j} = n_{i},$$
(6)

where m_i and n_j are the labels of the feature skeletal sequence frame f (x) corresponding to the standard skeletal sequence. The total distance between the two sets of feature



FIGURE 1: Motion recognition algorithm flow.

sequences is shown in Equation (7).

$$D(P,Q) = \sqrt{\sum_{i,j}^{f(x)} (d(P(n_j)) + d(Q(m_i)))}.$$
 (7)

The optimal path solution of DTW is shown in Equation (8).

DTW(P,Q) =
$$\sqrt{\frac{\min(D(P,Q)) + \max(D(P,Q))}{2}}$$
. (8)

The system searches for the shortest neighboring nodes by matching the templates of the temporal feature sequence matrix composed by the finite state machine in the motion recognition to complete the matching of the complete cycle and realize the motion recognition. This system extracts the skeletal data in motion in real-time, and after filtering and feature extraction to form a test template skeletal feature sequence, the length of the extracted sequence in one cycle is greater than the reference template, that is M > N. The system uses weighted Euclidean distance to calculate the distance between the nodes in the graph and the template; taking the temporal coordinates (1.0,1.0) as an example, the distance will be calculated with the three temporal point features with coordinates (1.0,2.0), (2.0,1.0), and (2.0,2.0) in turn and find the temporal coordinate point (2.0,2.0) with the smallest distance, while comparing with the system threshold, whether the action is standard, if it is less than the threshold value that indicates a successful match, calculates the difference, in turn to find the next optimal path point for comparison, and finally, get the optimal path. That is the similarity of the test template with the highest similarity.

3.3. Design and Implementation of the Intelligent Sports Training System. The sensor subnodes in this system assume a very important role. In the intelligent sports training operating system described in this design, the nodes are mainly divided into regulation nodes, home gateway nodes, monitoring nodes, and routing nodes when there are a large number of sensors, and different functions of the communication nodes have different functions. The terminal nodes in this system can be divided into two categories according to their functions: acquisition nodes and control nodes, which do not interfere with each other and exist independently. The power supply for the terminal nodes is used to ensure that the sensor nodes can work for a long time. The difference between the control node and the acquisition node is that the control node end is connected to the relay, and the acquisition node end is connected to the sensor. The data in the environment is collected by the sensor and sent through the node to the route, which is forwarded to the coordinator or directly to the coordinator. The two nodes differ only in their functionality. In the development of the program, they are identical in their hardware structure.

The terminal node plays a very important role in the intelligent sports training system, both in terms of its role in sensing the underlying environment and executing pulling commands and in terms of its role in processing the network data. Since the end nodes use wireless communication technology to achieve data communication, more attention is paid to the power consumption of the nodes in the sensor network and the optimization of the network performance.



FIGURE 2: System design and implementation.

After comparing wireless communication technologies such as ZigBee, Bluetooth, and WIF, we finally choose ZigBee as the communication solution for the wireless sensor network because the data transmission volume of the intelligent sports training system is relatively small, the system should meet the many-to-one networking mode, and the sensor network should also have strong self-adaptation; so, these factors are considered. Therefore, we finally choose ZigBee as the communication solution for the wireless sensor network.

The human-computer interaction interface is used to provide users with information query, command control, system configuration, and other visualization operations. In this system, users can use mobile terminals such as computers and cell phones to realize the query and display of information such as temperature, humidity, and motion control status in motion, and to ensure that the identity information of the logged in user is legal, an account password is set up in the cell phone terminal to log in. The function of the gateway part is mainly used to send commands, receive data, and data processing. The national gateway application is used to achieve data fusion between the ZigBee protocol and WIFI protocol, which is more similar to the router we usually see, both play a role in data interaction, and it is different from the router that exists in the interconnection layer. The role of the gateway is to achieve to help realize the communication between the internal LAN and the external public network. The specific design and implementation are shown in Figure 2.

The user can enter the application login screen by opening the mobile phone, enter the account and password to complete the information verification, and then automatically jump to the device list interface. The device list is divided into two columns: online and offline devices. If the intelligent sports training control system is not connected to the network, it will show the offline status; when the system is online, you can click on the system to enter the total view and control interface, and the application will receive the sensor data and equipment operation status from the cloud server platform every few seconds. Firstly, the wireless sensor network coordinator establishes a connection with the terminal node and starts to receive information sent from the terminal node and then uploads the information to the cloud server through the WIFI module; secondly, it receives control commands from the cloud server platform through the WIFI module, and then the gateway sends the control commands to the target control node through the coordinator to execute the corresponding control actions. In addition, the design of the smart gateway part uses a multithreaded mechanism to achieve real-time data processing at the same time, and the ZigBee protocol stack also adds a task scheduling mechanism to better meet the gateway performance design requirements.

4. Simulation Results and Analysis

4.1. Model Algorithm Analysis. Considering the computational time complexity, the method improves the computational time complexity of the algorithm from both the

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FIGURE 3: Training time and test time results.

training phase and the decision phase. Using the wireless sensor network system constructed in this chapter, the corresponding dataset is obtained, the three outlier point detection algorithms, new SVDD, SMO2-SVDD, and SVDD, are applied to this dataset, and they are computational. The results are shown in Figure 3. From Figure 3, it can be seen that the training time of the SVDD method is significantly higher than that of the new SVDD and SMO2-SVDD methods, for example, the average training time of new SVDD and SMO2-SVDD is 1.8772s for node 2, while the average training time of the traditional SVDD is 3.3681 s, which is because of the former. This is because the first two methods adopt the second-order approximation SMO algorithm to train the target sample set by the working set selection method proposed in this paper, which results in the reduction of the training computation time complexity. Meanwhile, the decision time of the new SVDD method is very short, which is significantly better than that of the SVDD and SMO2-SVDD methods. The average decision time of the new SVDD method is 0.0017 s, while the average decision time of SVDD and SMO2-SVDD methods is 0.8825 s, which is because the former adopts the fast decision method proposed in this paper to reduce the decision computation time complexity of the algorithm from O (|SVs|) to O (1), which makes the decision time of the improved method significantly shorter than that of the traditional method.

The number of surviving network nodes and the remaining energy of the network is compared. Figure 4 shows the number of surviving nodes in the network, and it can be seen that the number of remaining nodes without partitioned chaining is gradually smaller than the routing algorithm with partitioned chaining from 280 rounds. Figure 4 shows the residual energy of the network, and it can be seen that from 120 rounds, the gap between partitioned chaining and partitioned chaining is slowly widened, and overall, the partitioned chaining algorithm is better than the partitioned chaining algorithm.

4.2. Training Data Test Analysis. In the process of system testing, the motion recognition algorithm was tested several times by multiple people. Thirty male and 20 female students were invited to use the system once a day for 10 days. 400 test samples were obtained, the accuracy of the motion recognition rate and the judgment of the motion results were calculated, and the results are shown in Figure 5.

The test results show that the system has a very high recognition rate for motion, and the motion recognition



FIGURE 4: Chain formation simulation diagram.



FIGURE 5: Experimental test analysis results.

function is very reliable, but the accuracy rate, except for the standing long jump, the pull-up, and deep squat can still reach the level of consumer grade products. To investigate the problem of low accuracy of standing long jump, a more detailed investigation was conducted, and a comparison between the standing long jump test and the actual distance was obtained from the KinectV2 effective visual range of jumping from near too far in sequence in Figure 6.

Since KinectV2 is a sensor based on optical sensing technology, the ambient light and the recognition distance of Kinect will probably affect the accuracy of KinectV2 for environmental sensing, resulting in errors. Since the infor-

mation received by the KinectV2 sensor is captured by a one-point camera, there will be some image distortion, especially at the edge of the image, which may lead to system errors when combined with the height of the Kinect placement. The complexity of the algorithm is much higher than that of the other two sports, where the fast movement of the vertical jump has already had an impact on the accuracy of the algorithm by calculating the distance of the estimated foot size. All of them have an impact on the accuracy of the algorithm. This system, although the function of the standing long jump movement still has certain shortcomings, the success of the universal recognition algorithm on the pull-up and deep squat movement, can be judged that this algorithm has a good recognition effect in the movement without the movement position fast movement and can be accurate recognition of the movement decomposition movement, and this system has been applied in the campus for some time and has been praised by the teachers and students; "Strong sense of technology" and "interesting" are the two words most evaluated by teachers and students. Also, in the application process, the client software and the cloud server did not show any major abnormalities.

4.3. System Test Analysis. The performance test in this system is mainly to test the user input or submit the relevant data, these data after the system backend and the database to operate between the processing to return to the browser the user can see the response time, and these returned data is correct and other related requirements. The main purpose of the test is to test whether the performance of the system meets the basic needs of the user and for special





requirements of the module also requires faster response time. The results of the test using Load Runner are shown in Figure 7. From the test results, the system is mainly used in the unit; so, it can meet the basic needs of the unit system and meet the performance requirements. The reliability of the system mainly depends on the leakage rate and the false alarm rate of the system, and the error rate of the system is the sum of the two, where the error rates of the three network models during the ten repetitions of the experiment are shown in Figure 8. The error rate of the RBF



FIGURE 8: System recognition error rate.

network fluctuates from 0 to 0, and the error rate stabilizes at a relatively low value; the error rate of the FRBF network fluctuates between these two, and the error rate is smaller than that of the RBF network. FRBF network is smaller than the RBF network. Therefore, from the reliability point of view, FRBF is better than BP and RBF networks.

The wireless sensor network-based intelligent sports training system has been widely used to detect the temperature, humidity, and light of various environments in sports training and to control some sports training equipment. After a simple practical debugging and operation, the designed system can work normally and smoothly and achieve the requirements and functions of monitoring in all aspects, and the system is built with low cost, low power consumption, easy and fast operation and can guarantee the user to achieve long-distance monitoring and control of sports training environment, providing a user-friendly and fast sports training system.

5. Conclusion

The design of this system mainly uses Zigee technology as the technology of wireless sensor network networking to build up the intelligent sports training system, and the system equipment consists of three main parts, the distribution of remote access devices, gateway modules, and wireless sensor network module. Among them, the remote access device mainly refers to the user's computer, cell phones, and other mobile devices; the gateway module has a router, wireless network module, etc.; the wireless sensor network module is mainly Zigee coordinator, sports training equipment control part, and sensor detection part. The system provides scientific body strength training for sports and fitness people

and multifunctional and networked design for users in fragmented time that can break the limitations of time and space to complete scientific sports training and can view the progress of sports and develop training plans. The analysis of the requirements of the motion recognition algorithm proposes an efficient general motion recognition algorithm model based on the combination of DTW and finite state machine. Based on the above algorithm, the feature vector of the relationship between multiple joints in the motion skeletal data is extracted using the space vector method as a specific description of the finite state machine to develop a motion reference template. Similarity template matching based on the DTW algorithm is performed to complete the implementation of motion recognition. In this paper, we focus on the improvement of the recognition rate and accuracy rate of sports actions and aim to solve the drawbacks of traditional sports training equipment and realize the scientific, standardized, and unified management of sports training, because there is little research on the recognition of continuous actions in actual scenes in the current popular direction of human behavior detection and recognition.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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