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Research Article

Influence of the Athlete's Training Physical State Test Based on the Principle of Artificial Intelligence Sensor

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Artificial intelligence is the study of the laws of human intelligent activities, the construction of artificial systems with certain intelligence, and the study of how to make computers perform tasks that required human intelligence in the past. *Basic Theories, Methods, and Techniques*. With the maturity of the highly integrated hardware technology, the rapid development of sensor technology provides a material basis for the study of sports states based on smart terminals, and the mature model method theory provides a theoretical research basis for the research. The working principle of the sensor is to convert the specific measured signal into a certain "available signal" according to a certain rule through the sensitive element and the conversion element and output it to meet the requirements of information transmission, processing, recording, display, and control. In order to deeply study the application of artificial intelligence sensor theory in athlete training physical condition testing, this article uses theoretical analysis method, formula image combination method, and real person survey method, collects samples, analyzes artificial intelligence sensor, and streamlines the algorithm. In studying the accuracy of smart sensors on athlete training tests, a total of 9 athletes, 4 females, and 5 males are selected. Each experimenter performed three actions of running, jumping, and squatting 10 times, with an interval of more than 20 s. The results showed that the recognition accuracy of running in this paper was 98.51%, and the recognition accuracy of jumping and squatting was 92.59% and 93.33%; we have achieved more than 92% recognition rate for the three kinds of actions. On further study of the real-time performance of the sensor, the average response time of the algorithm is the average value obtained from 80 experimental records in this paper. The average response time of the algorithm proposed in this paper is within 1.5 s. Since the falling process occurs within 2.1 s, the recognition algorithm proposed in this paper has high real-time performance. It is basically realized that starting from the theory of artificial intelligence sensors, a high-precision sensor that can be applied to athlete training is designed.

1. Introduction

In the background of the modern society's quick growth, China's physical education has also achieved significant advances, but the players' fitness and body performance have not been correspondingly enhanced. According to the research results of the physical fitness and health of Chinese athletes in recent years, their physical fitness and health quality are not optimistic. Healthy physical fitness refers to the functions of cardiopulmonary blood vessels and muscle tissue that are closely related to health. Promoting healthy physical fitness can provide protection for the body and avoid chronic diseases caused by sitting lifestyle. Among them, speed and strength quality have declined for ten consecutive years, and endurance quality has declined for 20 consecutive years. At present, there are many problems in the work. For example, there is a lack of supervision mechanism, lack of financial support, and most of the exercise detection of athletes in all schools across the country is that teachers assign fixed test tasks and manually record the completed results, and there is no further data analysis.

With the rise of artificial intelligence sensing technology and micro-electromechanical system technology, motion capture systems using artificial intelligence sensors as signal capture devices have emerged [1]. The artificial intelligence motion capture device collects the inertial motion data of each skeletal joint when the human body is moving through the posture information collection nodes distributed in the specific position of the human body and then drives the digital simulation characters to reproduce the movement process. The information collection nodes are usually accelerometers and gyroscopes. It is supplemented by a magnetometer. The intelligent motion capture system has low cost and good scalability. The above advantages have laid the development advantages of motion capture equipment based on smart sensors. The current development trend of human motion capture systems is to use low-cost smart sensor components to build a human motion data collection platform to obtain accurate human motion information data, analyze and reconstruct the data, and apply it to virtual reality, medical rehabilitation, training and testing, and so on fields [2]. Motion capture relies on mechanical devices to track and measure motion, and a typical system consists of multiple joints and rigid links. An angle sensor is installed in the rotatable joint, and the change of the rotation angle of the joint can be measured; when the device moves, the movement trajectory of point A in space can be obtained according to the data of the angle sensor and the length of the connecting rod.

As the living conditions of athletes get better and better, the pursuit of more scientific training methods has become a hot topic, and many scholars at home and abroad have launched a series of studies. In 2019, Devantara and Ghufron has a direct influence on the evolution of innovation in education. He seeks to identify and diagnose learning styles based on the type of genre. Educational innovation refers to the process of promoting a new concept, system, or method in education for the first time and promoting education to produce progressive results. The method of adoption of the waterfall method is based on the development of a homepage, using the artificial intelligence theory and the forward chain algorithm as an inference engine. To evaluate the system, the program was tested twice by two program experts. The first time it received an average score of 3.68. The second time the average score was 3.89. Then the total score of the learning style analysis system was 3.87, with a criterion of "very good." However, his research objects are biased and inconsistent with the main research purpose [3]. In 2016, Escalante and Wiskott considered SFA as a supervised extension to solve the regression problem and in his paper; they proposed an accurate label learning (ELL) method. The label learning method is a simple way to change our learning ideas from knowledge-oriented to self-oriented, and students to upgrade from primary learners to advanced learners. The ELL method was used in the following categories: (1) gender determination from images of human faces and (2) classification of traffic sign images. This method is universal, supports multiple labels directly, and provides higher accuracy for the problem under consideration than the current graphics. However, they only did research on the coding algorithm and design, which is too theoretical and not suitable for promotion [4]. In 2019, Flah and Mahmoudi collected this information in a database and used it to manage the electricity inside these cars. According to the vehicle communication approach, the best decision will be determined in the building, infrastructure, vehicle, or cloud database. To show the efficiency of this method, the obtained results are compared with the state of charge of the battery and the energy consumption results. They discussed possible connections between vehicles, buildings, and networks for power management problems. Although the application of artificial intelligence sensors is mentioned, the process is too cumbersome, and the research object is a car, not a person [5]. Home air conditioners not only rely on temperature and humidity sensors for self-adjustment, but also automatically select modes through the identification of family members, such as wind direction adjustment and temperature adjustment for children and the elderly. This is the area where AI sensors are most commonly used.

The innovations of this paper are as follows: (1) Below is the premise of performance indicators based on network energy efficiency and balance, a new routing algorithm with self-organization and classification characteristics is given. (2) A dynamic routing algorithm with short-term memory function, which is suitable for cluster routing algorithms in sensor networks, is proposed, which can reduce the energy consumption of node communication and reduce the selection of cluster heads and the determination of clustering cycles. Time consumption balances the total energy of the sensor network. Through the above work, the artificial intelligence sensor can well transmit the physical state of the athlete during the training process, making the data more accurate and efficient.

2. Implementation Method Based on Artificial Intelligence Sensor in Training Body Condition Test

2.1. Training Test Monitoring. Training monitoring is a scientific research work with strong planning, pertinence, and purpose. It not only has the characteristics of rigorous, serious, realistic, and strict operation according to the experimental plan required by scientific research, but also according to the athletes' status and training at any time, the characteristics of flexibility to plan changes and adjust test content [6]. Pay attention to the following principles in the specific operation of physiological and biochemical monitoring exercise training. Physiological and biochemical monitoring refers to the comprehensive use of physiological and biochemical analysis methods to effectively guide exercise training and to translate the adaptive changes within the body through the athlete's hormones and metabolism.

2.1.1. Individualization. Due to the differences in human innate quality and acquired training, it is determined that these differences should be paid attention to when monitoring human dynamic activities, and the relatively stable changes that occur within the limits of one's own conditions can be used for dynamic observation training. The effectiveness and evaluation training methods provide the basis [7].

2.1.2. Systematization. The principle of systematization mainly includes two points: (1) Test conditions, test indicators, test instrument methods, and testers should be kept as consistent as possible so as to eliminate the interference of nontraining factors as much as possible; (2) Test arrangements within the training cycle should be purposeful. Only by formulating a training plan with levels and stages according to a clear purpose, can a corresponding test plan be formulated according to the corresponding training plan to evaluate the training effect of each stage and level [8].

2.1.3. Rationalization of Indicator Selection. The rationalization of the selection of test indicators is embodied in "maximizing effective information by minimizing testing." Minimizing testing refers to minimizing the number, scale, and cost of testing to the lowest level [9].

2.2. Artificial Intelligence Sensor. Artificial intelligence sensors are mainly composed of sensor nodes, master nodes, or convergence nodes, base station controllers, and base station transmission. The base station controller is the connection point between the base transceiver station and the mobile switching center and also provides an interface for exchanging information between the base transceiver station and the operation and maintenance center. In actual sensor network applications, the main nodes or convergence points in the area have stronger communication capabilities and longer transmission distances [10, 11]. Various sensor nodes cooperate in real-time detection, perception, and collection of various environmental factors, such as light intensity, pressure, temperature, electromagnetic, humidity, vibration, and other physical information [12].

It can be seen from Figure 1 that the information is processed through the embedded system in the node, and the processed data is transmitted by the master node to the cluster network, cellular network, or through the wireless communication module in a multihop relay mode. As can be seen, sensor nodes not only process local information, but also fuse and forward data from neighboring nodes [13].

2.3. Training Communication Transmission and System Architecture. The transceiver module of the communication unit in the sensor node can be an active or passive lightwave module, or a star or Bluetooth module. Sensor network is considered to be one of the important technologies affecting human future life, which has the characteristics of self-organization, data-centric, application correlation, dynamic, large network scale, and reliability. Since the data packets between the sensor network nodes are relatively small, the data transmission rate is relatively low, usually less than 1 Hz, and the frequency reusability in short-distance communication is high. Therefore, in most applications, the priority will be selected as a node way of communication. However, the pursuit of high energy efficiency and low duty cycle is still a challenge for the design of the transceiver module circuit. Using Bluetooth technology will frequently switch the transceiver of the node, which will increase more energy consumption [14]. At present, the hardware of most sensor nodes is based on circuit design [15]. In most sensor network applications, frequency bands are mainly concentrated in 3 regions, namely, the 870 MHz frequency band in Europe, the 911 MHz frequency band in the United States, and the global 2.35 GHz frequency band.

2.3.1. Energy Consumption Analysis. Communication protocol refers to the rules and conventions that must be followed by both entities to complete communication or services. The protocol defines the format used by the data unit, the information and meaning that the information unit should contain, the connection method, and other information. Efficient communication protocol is a key factor to reduce the energy consumption of sensor nodes [16]. The statistics of node energy consumption not only need to calculate the energy consumption when the node is activated, but also the energy consumption when the transceiver circuit is started. This article proposes a formula for calculating the total energy consumption of the transceiver module during wireless communication:

$$q_z = o_s\left[q_s\left(s_{\mathrm{off}} + s_{rs}\right) + q_{\mathrm{in}}\left(s_{\mathrm{off}}\right)\right] + o_e\left[q_e\left(e_{\mathrm{off}} + e_{rs}\right)\right]. \quad (1)$$

Among them, q_s and q_e ruler represent the power consumption during transmission and sending, respectively, q_{in} represents the output power consumption of the transceiver, s_{off} and e_{off} represent the online time during transmission and sending respectively, and s_{rs} and e_{rs} represent the startup time during transmission and sending, respectively. o_s and o_e, respectively, represent the number of conversions during transmission and sending in unit time, which is determined by task management strategy and mac [17]. In today's latest low-energy wireless transmission transceivers, q_s is around 18 dbm and q_{in} is close to 0.5 dbm.

The energy consumption model of a single node wireless communication is given, as shown in Figure 2.

It can be seen from Figure 2 that in the state of single hop, no data fusion, and only simple reception and forwarding, at this time, $n = o$, and the energy consumption of each bit of data transmission F_y:

$$F_y = f_{sa} + f_{ea} + f_{ba} \sum_{\exp}^{ab} (sa + ea + ba). \quad (2)$$

$$F_{sa} = f_{sf} + f_{sx} w^{\lambda} \oiint_{uzi} \left[hcc_{sa+eb}\right]. \quad (3)$$

Among them, f_{sa} and f_{ea} represent the energy consumption of sending and receiving one bit of data, respectively [18]. f_{sa} is the energy consumption when the node sending module successfully sends one bit of data, and f_{ea} represents the energy consumption when the node receiving module successfully receives one bit of data [19]. f_{sx} is the energy consumption when the sending module

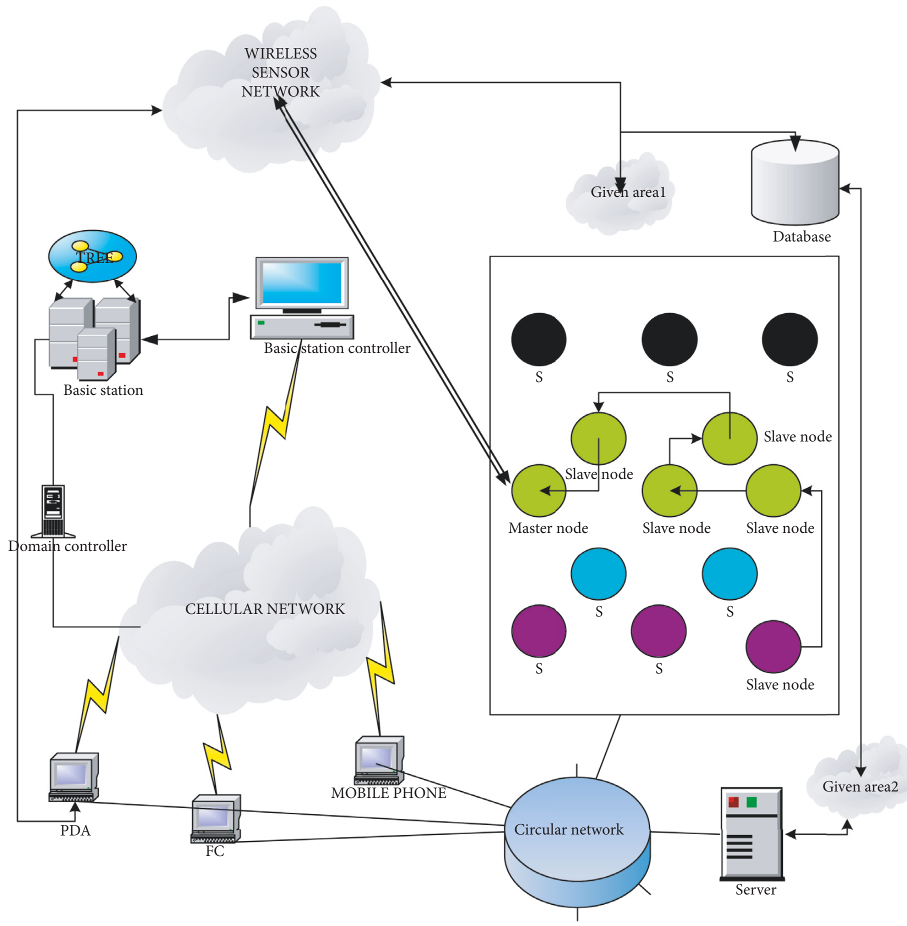

Figure 1: Schematic diagram of wireless sensor network structure.

successfully sends one piece of data for one meter [20]. W is the physical distance from the sending module of a node to the receiving module of another node, and λ is the path loss, which is a constant, which is related to the geographical and transmission environment [21].

Since the hardware energy consumption of the node is mainly the energy consumption of the communication unit during data transmission, it includes data transmission, data reception, and energy consumption when starting the transceiver module, especially for the case of small data packets and short-distance multihop transmission, is in sensor networks, startup energy consumption must also be considered. Now formula (3) is extended to

$$f_y = f_{sa} + f_{ea} + \frac{f_{wfz} + f_{rs} + f_{re}}{i}. \tag{4}$$

On the basis of the original formula (3), f_{wfz} is the energy consumption when the decoder in the communication unit decodes a one-bit data packet. f_{rs} and f_{re} are the energy consumption at the start of sending and the start of receiving, respectively [22]. I represents the effective data bits of the data packet [23].

It can be seen from the improved formula (4) that if the energy consumption of the transceiver module, the decoding energy consumption, and the transceiver startup energy consumption are adjusted reasonably, the communication energy consumption of the sensor node can be effectively reduced, thereby extending the lifetime of the sensor network.

2.3.2. Transmission Delay. Assuming that data transmission is performed between nodes x and y in a single-hop manner, the transmission delay $s_{\text{postpone}X,Y}$ on node y can be defined as

$$s_{\text{postpone}X,Y} = s_{\text{number-inject}} + \frac{e_{\text{index}} \times f_{\text{loose}}}{\text{sandwich}}. \tag{5}$$

Assuming that data is transmitted between nodes X, Y, and Z in a single-hop manner between adjacent nodes, the transmission delay $S_{\text{postpone}X,Y,Z}$ on node Y can be defined as

$$s_{\text{postpone}A,B,C} = S_{\text{number-inject}} + \frac{2\left(e_{\text{index}} \times f_{\text{loose}}\right)}{\text{sandwich}}. \tag{6}$$

Assuming that data is transmitted between nodes $X, Y, Z, \ldots,$ $\sin k$ and adjacent nodes in a single-hop manner, and the number of hops of node x, $\sin k$ is defined as u, the transmission delay $s_{\text{postpone}x,\ \sin k}$ on the node sink can be defined as

$$s_{\text{postpone}X,\ \sin k} = s_{\text{number,inject}} + \frac{e_{\text{index}} \times f_{\text{loose}}}{\text{sandwich}} \times u. \tag{7}$$

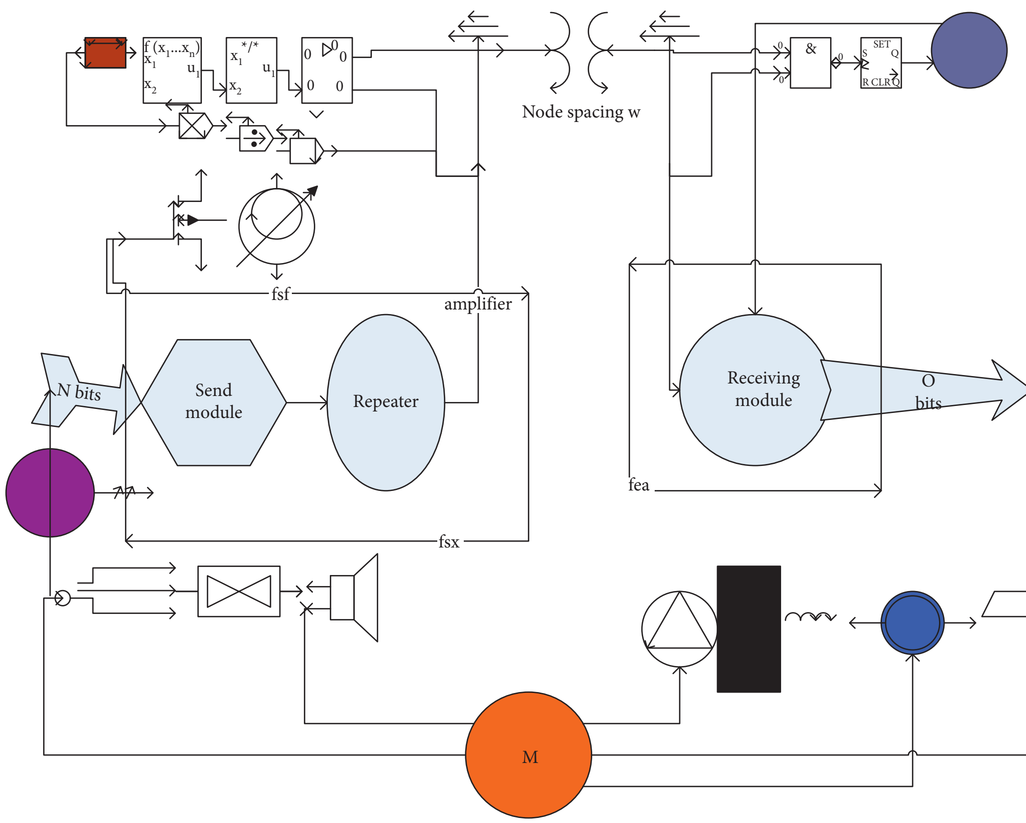

FIGURE 2: Energy consumption model for wireless communication of sensor nodes.

2.3.3. Node Analysis. Let ε be the proportion of working time in a frame. q_{work} is the working power consumption, which is mainly the power consumption during node communication, q_{sleep} is the power consumption during sleep, and q_{idle} is the power consumption when in the idle state. Then, the average node power consumption $\overline{q}$ can be defined as

$$\overline{q} = \varepsilon q_{\text{work}} + (1-\varepsilon)q_{\text{sleep}} + q_{\text{idle}}. \quad (8)$$

Considering $q_{\text{idle}} \approx 0$, the above formula can be rewritten as

$$\overline{\text{q}} = \varepsilon q_{\text{work}} + (1-\varepsilon)q_{\text{sleep}}. \quad (9)$$

Since the energy consumption of nodes during operation is mainly generated during wireless communication, the energy consumption model of node wireless communication in Section 9 is rewritten, and the wireless communication energy consumption q_{frame} when transmitting a frame of data is defined as

$$q_{\text{frame}} = \left(q_{sa} + q_{ea} + \frac{q_{wfz} + q_{rs} + q_{re}}{i}\right) \times d_{yus}. \quad (10)$$

Among them, the parameter q_{sa} is the energy consumption when sending, q_{ea} is the energy consumption when receiving, q_{wfz} is the energy consumption when the decoder in the communication unit decodes a one-bit data packet, and q_{rs} and q_{re} are when sending and receiving are started, respectively. For energy consumption, i represents the number of effective data bits of the data packet, and d_{yus} is the number of bits of one frame of data.

The average power consumption $\overline{q}$ of the nodes that can be obtained by combining (9) and (10) is

$$\overline{q} = \varepsilon \times \left(q_{sa} + q_{ea} + \frac{q_{wfz} + q_{rs} + q_{re}}{i}\right) \times d_{yus} + (1-\varepsilon)q_{\text{sleep}}. \quad (11)$$

Analyzing (11), it can be seen that after the data fusion technology is used on the sink, the number of effective data bits in the data packet is fixed due to the removal of redundant control bits, which significantly reduces the number of bits in a frame of data.

2.3.4. Balance Analysis. Given a topology $h = \{m, i, f, d\}$, where $m = \{m1, m2, \ldots mo\}$ is the subdomain in the network, $i = \{i_{ul}|u, \quad l \in o\}$ is the edge set in the graph, d is the weight of the edge, the length of the edge here, the distance between nodes, and $f = \{f1, f2, \ldots f_o\}$ is the power of a single sensor node. In round $s+1$, the path transition probability $q_{u,l}(s+1)$ of data from sensor node u to node l is defined as

$$q_{u,l}(s+1) = \frac{e_{ul}^{\varepsilon}(s) \times \theta_{ul}^{\lambda}}{\sum_{n\in h, n\neq l} e_{un}^{x}(s)\theta_{un}^{\lambda}}. \quad (12)$$

Among them, l is the parent node of u, h_u is the set of parent nodes of node u; θ_{ul} is called a priori knowledge, which is related to the distance between nodes, take $\theta_{ul} = 1/w_{ul}$, w_{ul} is the distance between nodes u and l, and ω is the path. The magnitude of the link evaluation quality on u, l, λ is the importance of path selection; $e_{ul}(s)$ is the energy balance on the path of nodes u, l after the end of the s round, which is related to the energy of node l.

$$e_{ul}(s) = \frac{z \times f_l(s)}{f_{\text{all}}(s)}. \tag{13}$$

Among them, z is a constant, $f_l(s)$ is the remaining energy of node l at the end of the s round, and $f_{\text{all}}(s)$ is the total remaining energy of all nodes at the end of the s round; at the initial state of the network ($s = 0$), in each path, the upper pheromone is equal.

The parameter μ is used to indicate the degree of dispersion on the edges, and the pheromone of each edge on $h = \{m, i, f, d\}$ is adjusted according to the following formula:

$$e_{ul}(s+1) = \mu e_{ul}(s) + \Delta e_{ul}. \tag{14}$$

$$\Delta e_{ul} = g\left(1 - \frac{\Delta f_l(s)}{\Delta f_{xii}(s)}\right). \tag{15}$$

Write (14) and (15) as an expression:

$$e_{ul}(s+1) = \mu e_{ul}(s) + g\left(1 - \frac{\Delta f_l(s)}{\Delta f_{xii}(s)}\right). \tag{16}$$

Among them, g is a constant; Δe_{ul} represents the increase in energy balance on nodes u and l in the s round; $\Delta f_l(s)$ is the energy change of node l in the s round; $\Delta f_{xii}(s)$ is the s round, all the total energy change of the node; $\Delta f_l(s)/\Delta f_{xii}(s)$ represents the ratio of node i's energy consumption to the total energy consumption of the entire network in the s round.

3. Experiments Based on the Design and Implementation Method of Artificial Intelligence Sensors in Training Body State Testing

3.1. Experimental Platform

3.1.1. Hardware Platform. The experimental hardware platform is not easy to describe in words, as shown in Figure 3, described with words and pictures together (http://www.ixueshu.com).

As can be seen from Figure 3, A is a multisensing unit module, which is bound to various areas of the body to gather motility information. The core problem of multisensor system is the synthesis of information. The so-called multisensor synthesis refers to the process of collecting, providing, gathering, or combining the information provided by multiple sensors. The multisensing unit transmits the required data to the data control unit through the PH2.0 electronic connection line. B is the internal structure of the multisensing unit. It contains a processor, and the sensor uses a chip integrated with a gyroscope and accelerometer

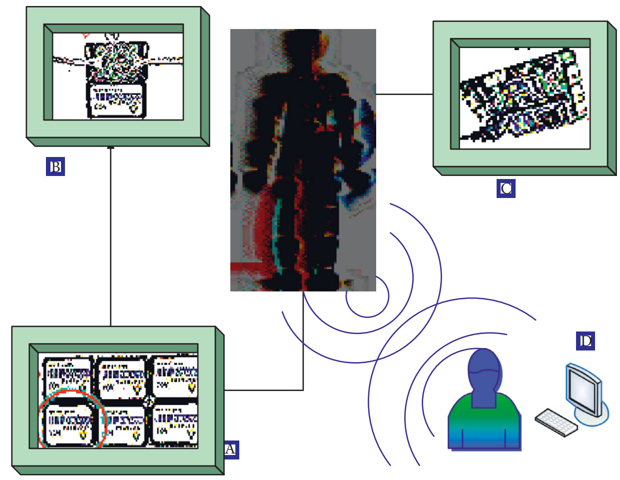

Figure 3: System hardware platform.

and a magnetometer chip. C is the data control unit, using a processor, and the sampling frequency is 110 Hz. The data control unit gathers and packs the posture information of each sensor unit and then transmits it to the upper computer through the wireless communication module. The arrow indicates the data flow direction. D is the upper computer, which receives sensor data wirelessly and synthesizes human body movement posture data. The posture angle information and sensor data of each node transmitted to the host computer can be synthesized with the human body motion posture measurement algorithm through the human body motion posture measurement algorithm and then drive the virtual character model to reproduce the human body posture motion.

3.1.2. Software Platform. Software development is based on the windows integrated development environment, using programming languages, Microsoft basic class libraries, and graphical programming ideas. The human body motion posture data collection interface, posture display interface, and implementation schematic diagram are shown in Figure 4, respectively.

As shown in Figure 4, the experimental software platform is divided into two parts: the data transfer station software and the posture display software. The data transfer station software is responsible for the reception and synthesis of human movement data, and the posture display software is responsible for driving the virtual character's movement with the synthesized human movement data. The posture display software realizes the reproduction of the human body movement posture, while saving the movement data for various research and analysis.

3.2. Sensor Selection

3.2. Sensor Selection. The detection terminal of this system is powered by a lithium battery. Lithium batteries have high working voltage, large specific capacity, high energy density, good safety performance, and long cycle life. Moreover, the lithium battery is clean and pollution free, and very little gas is released during use, which does not cause pollution to the

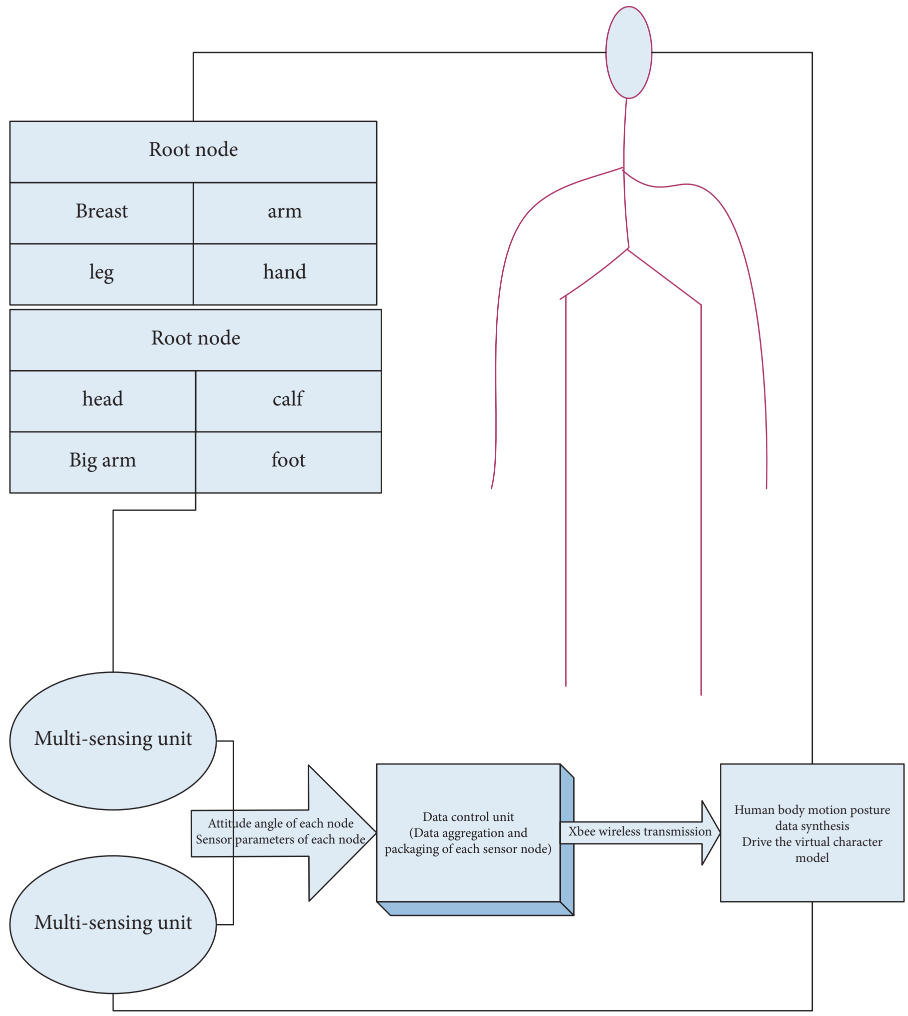

FIGURE 4: Schematic diagram of system function realization.

environment. It receives light in a transmissive manner and detects the characteristics of fingertip blood volume changes caused by heartbeat. Through circuit processing, a digital pulse signal synchronized with the pulse change is output to calculate the heart rate, which is mainly used for clinical heart rate measurement and detection. The technical parameters of HA are listed in Table 1.

TABLE 1: HA technical parameters.

Parameter	Minimum	Typical value	Max	Unit
Operating voltage	—	4	5.5	Volt
Working current	—	4	—	Milliampere
Working temperature	−39	—	83	Celsius
Storage temperature	−39	—	15.5	Hertz
Output pulse amplitude	—	Mzz-1	—	Volt

3.3. Coordinator Design. The function of the coordinator is mainly to establish and maintain an artificial intelligence sensor network, conduct unified management of all router nodes in the entire motion network, provide routing information, and receive data transmitted by each subpoint; although it does not perform specific application operations, it can communicate with the upper computer communicates and sends the data packet to the upper computer for storage for further analysis. The software design process of the coordinator in the human motion energy consumption detection system based on the ZigBee artificial intelligence sensor network is shown in Figure 5.

As can be seen from Figure 5, the coordinator first completes the node initialization through the initialization function. The initialization needs to complete the initialization of the system clock, detection chip, stack, various hardware modules, and other parts, as well as initialize the equipment and each layer protocol, complete the node hardware and network-related parameter settings, so that the system is ready for operation at any time. The establishment of a new network is preset by the protocol stack and can be completed automatically. It is generally done by scanning the specified channel and selecting a network in the list. The coordinator starts to build the network. After configuring all the parameters, call the function to form the

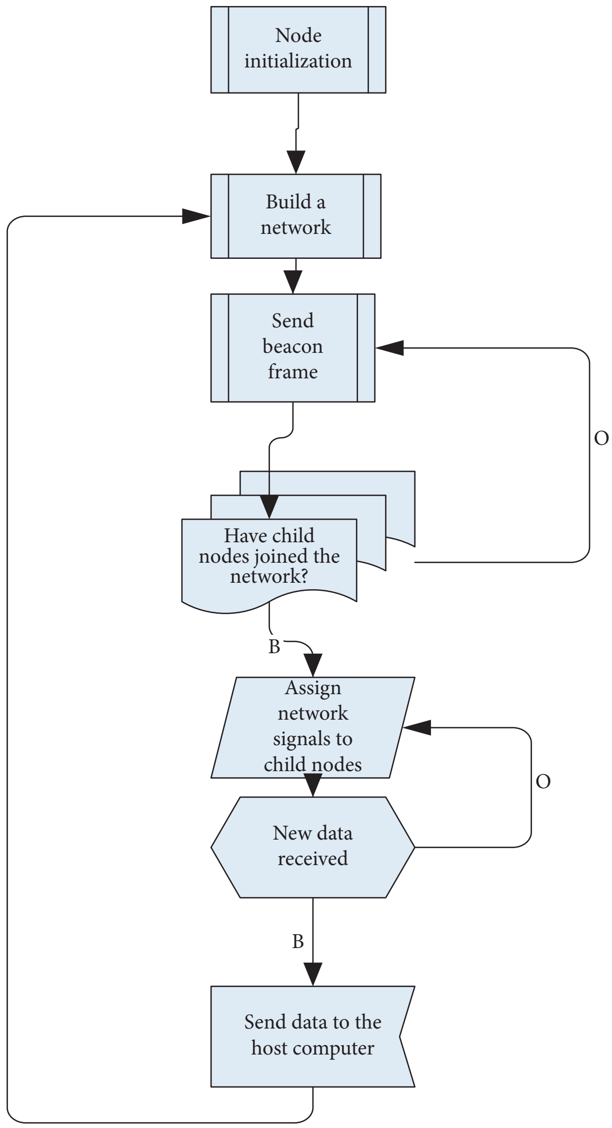

FIGURE 5: Software flowchart of the coordinator node.

web. When new data is received, the coordinator will periodically transmit the received data packets to the host computer monitoring system through the USB serial port.

4. Experimental Results Based on the Design and Implementation of Artificial Intelligence Sensors in Training Physical State Testing

4.1. Survey Samples and Analysis. There are 9 athletes in the experiment, including 4 females and 5 males, aged 21–25 years old, height 155 cm–175 cm, and weight 15 kg–72 kg. The mobile terminal equipped with the LIS3DH artificial intelligence sensor was placed in the chest pocket of the experimenter, and the experiment site was selected in an open outdoor. Each experimenter performed three actions of running, jumping, and 10 times each, with an interval of more than 20 s between actions, so that the experimenters could adjust themselves to a normal state. Among them, the take-off and squat are both in situ actions. The experimenter performs the test according to his normal state. We have no specific restrictions on the actions made by the experimenter. The test is completely based on his usual state. For the test process of running, the experimenter is required to run more than 10 steps and test according to his normal running state.

According to the experimental plan designed in this article, we have counted the three types of movements made by a total of 9 male and female athletes and asked each person to repeat each type of movement 15 times. We separately performed each person take-off and running. The correct recognition times of the three movements of squatting and squatting are recorded, and the experimental results are shown in Table 2.

This paper makes statistics on the correct recognition rate, false alarm rate, and false alarm rate of the three actions. Among them, correct recognition means that the system can correctly recognize the action after the experimenter makes a certain action; false alarm means that the system does not recognize the action after the experimenter makes a certain action; and false alarm means that the experimenter makes a certain action. After this action, the system judges it as another action. The statistics of the experimental results of the three actions are shown in Table 3.

It can be seen from the above results that the recognition rate for running in this article is high, with a recognition accuracy rate of 98.51%, while the recognition rate for take-off and squat actions is relatively low. The recognition accuracy rates for take-off and squat are 92.59% and 93.33%, respectively; this is because we did not restrict the experimenter's movements. In the process of squatting and take-off, different experimenters made different motion amplitudes and different take-off speeds. Some motions that did not reach the threshold would cause false negatives. It can be seen from the table that the number of take-offs recognized by women is significantly lower than that of men. This is due to the different weights and different take-off amplitudes of men and women.

In summary, we have achieved a recognition rate of over 92% for the three types of actions. Therefore, the correct recognition rate obtained from the experiment shows that the method we proposed has a high recognition effect on the three actions of jumping, running, and squatting and has certain practical application value.

4.2. Motion Drop Monitoring. There are a total of 10 athletes, including 5 women and 5 men, aged 20–33 years old, 155–177 cm tall, and weighing 51–74 kg. The drop test was performed indoors with a foam mat of 15 cm height on the floor. We placed the mobile terminal equipped with the LIS3DH artificial intelligence sensor in the chest pocket of the experimenter. The program running on the mobile terminal implemented the fall detection algorithm proposed in this article and recorded the detection results of each fall and the response time of the algorithm. We documented the tests, as shown in Figure 6.

It can be seen from Figure 6 that the accuracy of the algorithm proposed in this paper has reached more than 90% in the recognition of falling behavior, and there was no false

Table 2: The correct identification frequency table of the three actions.

Experimenter	Take-off (number of correct identifications/total number of times)	Run (number of correct recognition/ total number of times)	Squat (number of correct recognition times/total number of times)
Woman1	14/15	15/15	15/15
Woman2	12/15	15/15	14/15
Woman3	14/15	15/15	13/15
Woman4	12/15	14/15	15/15
Man1	15/15	15/15	15/15
Man2	13/15	14/15	14/15
Man3	15/15	15/15	15/15
Man4	15/15	15/15	11/15
Man5	15/15	15/15	14/15
Total	125/135	133/135	126/135

Table 3: Statistical table of experimental results of three actions.

Action	Total number of experiments	Correct recognition times	Correct rate (%)	Number of false negatives	False negative rate (%)	Number of false positives	False alarm rate (%)
Take-off	135	125	92.59	8	5.9	2	1.48
Run	135	133	98.51	2	1.49	0	0.00
Squat	135	126	93.33	9	6.67	0	0.00
Total	405	384	94.81	21	4.68	2	0.49

alarm in the whole experiment process. The recognition rate of falls in various directions is different, the recognition rate of falling forward is lower, and the recognition rate of falling in the other three directions is higher. Because the fall experiment in this article was carried out by people consciously, the psychology of the experimenter will have a certain influence on the results of the experiment. In the process of falling forward, the experimenter's simulation of the real fall is not enough, so sometimes the threshold set by the algorithm is not reached, which will cause underreporting. After analyzing the results of the experiment, it is found that the fall recognition rate of men in this article is significantly higher than that of women. This is because the psychological condition of the male experimenter is stronger than that of the female, and the fall speed and amplitude are larger, and the experiment is closer to the real situation.

In order to make statistics, the system will falsely report it as whereabouts when there are no whereabouts. We asked 10 athletes to do jump, run, squat, lie down, bend down, and go up and downstairs 7 times each. Table 4 records the specific conditions of the experiment. The experimental results show that the algorithm proposed in this paper has a low false alarm rate for fall detection.

The response time of the algorithm refers to the period of time from the time when the SA reaches the specified threshold to the judgment of the falling situation and the direction of the fall. It is used to measure the real-time nature of the algorithm. The average response time of the algorithm is the response time of this article to 80 falling experiments.

The statistical average value is obtained during the recording.

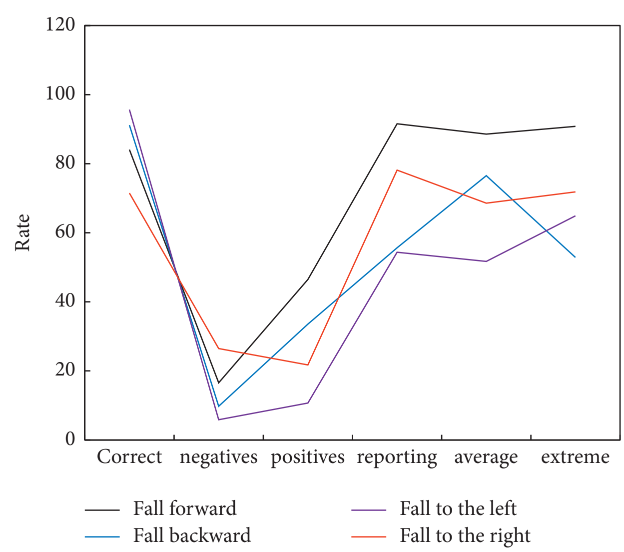

Figure 6: Test results of different types of falls.

Figure 7 indicates that the mean response time of the proposed method is within 1.5 s. Since the fall process generally occurs within 2.1 s, the fall recognition algorithm proposed in this paper has high real-time performance.

4.3. System Architecture. On the theoretical basis of the action recognition method proposed in Sections 2 and 3, this section mainly designs an athlete training test monitoring system based on artificial intelligence sensors. The system realizes real-time monitoring of athletes' daily sports, records daily sports conditions, and the system also has the

Table 4: False report of human daily behavior as a fall.

Action	Experimental times	Number of false positives	False alarm rate (%)	False positives
Stand-jump	70	0	0.00	None
Run	70	0	0.00	None
Standing-squatting	70	0	0.00	None
Sit-lie down	70	5	3.50	5 false positives as falling backwards
Standing-bending over	70	4	2.86	4 false positives for falling forward
Downstairs	70	0	0.00	None
Total	420	9	2.25	9

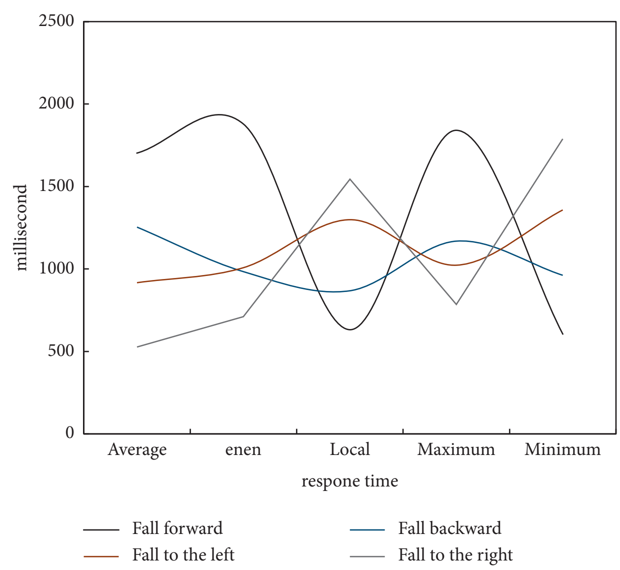

Figure 7: Algorithm average response time.

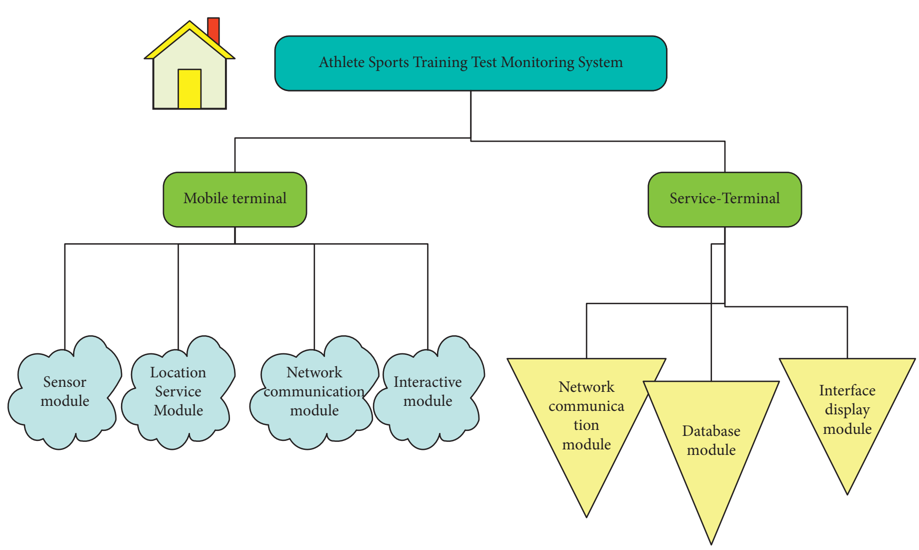

Figure 8: Overall structure of system functions.

function of handling abnormal behaviors, such as falling, and can effectively rescue the monitored objects through the alarm mechanism. It is of great significance in human health and medical monitoring. The athlete's exercise state training test monitoring system adopts a typical C/S structure, which mainly includes two parts: a terminal for cellular and a container. The overall architecture of the system is shown in Figure 8.

As shown in Figure 8, the mobile terminal uses artificial intelligence agents to capture human data and provides interaction with the server in the form of an operator interface. The athlete can send alarm information to the mobile terminal during training and can process the feedback information from the mobile terminal.

5. Conclusions

Taking the athlete's motion capture as the research background, this paper mainly studies the human motion posture measurement algorithm applied to the human motion capture system and designs an intelligent model based on the theory of artificial intelligence sensors. In order to deeply study the application of artificial intelligence sensor theory in athlete training physical condition testing, this article uses theoretical analysis method, formula image combination method, and real person survey method, collects samples, analyzes artificial intelligence sensor, and streamlines the algorithm. And a smart sensor that can act on athletes is created. In studying the accuracy of the smart sensor on the training test of athletes, a total of 9 athletes, 4 women, and 5 men were selected. Each experimenter performed three actions of running, jumping, and squatting 10 times, with an interval of more than 20 s. The results showed that the recognition accuracy of running in this paper was 98.51%, and the recognition accuracy of jumping and squatting was 92.59% or 93.33%; we have achieved more than 92% recognition rate for the three kinds of actions. Further, the real-time performance of the sensor is studied; the average response time of the algorithm is the average value obtained from 80 experimental records in this paper. The average response time of the algorithm proposed in this paper is within 1.5 s. Since the falling process occurs within 2.1 s, the recognition algorithm proposed in this paper has high real-time performance. The shortcomings of this paper are as follows: First, although the amount of calculation for the recognition of athletes' daily sports behaviors has been reduced to a certain extent, the method proposed in this paper is only suitable for simpler actions and is not effective for more complex actions. Secondly, the training detection algorithm proposed in this paper still has a small amount of underreporting in the recognition of training behaviors, and further optimization of the algorithm is needed. Therefore, in the next stage of research, in the future, we can consider combining multipoint data from artificial intelligence sensors for further research, especially identifying more types of different actions, implementing algorithm optimization, and simplifying the process, thereby making the effect of the artificial intelligence sensor more effective.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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