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Research Article

Computing Cluster and Intelligent Sensor Network in the Analysis and Application of College Students' Physical Exercise Behavior

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Based on computing cluster and intelligent sensor network technology, in view of network delay, this paper uses first-in-first-out buffers to be built at the node sending and receiving ports to convert the random delay of the physical exercise behavior network control system into a fixed delay. First, we analyze and model the controller design of the physical exercise behavior network control system. Through the analysis and synthesis of the current situation and methods of the physical exercise behavior network control system controller at home and abroad, the sensor is driven by time, and the controller and actuator are used. In the event-driven method, the sending and receiving buffers are set on the network ports of the nodes, the delay is changed from random to fixed at the same time, and the problem of data packet timing disorder is improved. Secondly, through the analysis of the internal control system node, the internal AD, DA conversion, data storage, CPU internal tasks, and task scheduling algorithm modules are implemented in the model. Experimental simulations show that, in view of the difficulty of unsatisfactory tracking effect caused by the aliasing of multiple target signals collected by sensor nodes, a combined tracking strategy is adopted; that is, multiple tracking dynamic clusters are combined into one for tracking when the sports behavior is close. In order to avoid the heavy communication and computing requirements in the centralized mode, mobile sensor networks usually adopt a distributed fusion architecture. The dynamic cluster maintenance and positioning strategy are given. In the stage of separation of multiple sports behaviors, a dynamic cluster decomposition algorithm based on boundary search is proposed, which can effectively determine the degree of separation of sports behaviors and provide a basis for establishing new dynamic clusters for follow-up tracking. The results show that the algorithm can effectively realize the merging and decomposition of dynamic clusters of multiple sports behaviors and effectively realize the dynamic tracking of multiple sports behaviors.

1. Introduction

With the development of electronic computers, network communication technology, and sensor technology, the structure of the control system is becoming more and more complex, the network topology is increasing day by day, and the complexity of the exchange and sharing of information between the various components of the system has increased sharply. The centralized control system can no longer meet the increasingly complex control performance requirements [1]. In order to effectively solve the above problems, a networked control system was created, namely, the Netwoked Control System (NCS). The emergence of the NCS effectively solved the limited limitations of the traditional centralized control system. The limitations of computing and communication resources and the spatial layout of system components reduce the structural complexity of the control system to a certain extent and save operation and maintenance costs. It is used in aerospace, vehicle systems, remote control robots, and industrial control with high risks [2–5]. The physical exercise behavior capture system is a technical device used to measure the physical exercise behavior status of physical exercise behavior objects in three-dimensional space. The physical exercise behavior capture system is

widely used in the fields of film digital special effects and animation, games and human-computer interaction, training and simulation, health monitoring and rehabilitation training, and navigation. There are many ways to capture physical exercise behavior. The current mainstream is the acquisition of human physical exercise behavior based on multicamera and the acquisition of human physical exercise behavior based on microsensor. Research on the physical exercise behavior network control system is far from enough to study the control strategy. It is also necessary to fully consider the influence of network factors. Through the research on related scheduling algorithms, the control strategy and network scheduling algorithm can be reasonably modeled and systematically. This analysis has important practical significance for the development of physical exercise behavior network control system [6–9].

Guleria and Verma [10] take some time-varying delay physical exercise behavior network control systems, and the corresponding random delay is converted into a fixed delay by setting the receiving first-in first-out buffer queue at the front end of the controller and the actuator. On this basis, Otoum et al. [11] designed a "delay compensation state observer." The main idea is to use the observer to estimate the state of the object, use the predictor to predict the system state in advance, calculate the corresponding control signal, and realize the delay compensation. The measurement data is stored in the first-in-first-out buffer queue on the controller side, and the controller's signal is stored in the queue. Zhu [12] converts the delay caused by the network in the system into a fixed delay, which can be based on the fixed delay. Aiming at the random physical exercise behavior network control system model where the random time delay is greater than one sampling period and the controller and the actuator are both event-driven, Verma et al. [13] studied single input single output and multiple input multiple. The closed-loop stability of the output is based on the known conditions of the network state variables. Bhushan et al. [14] designed the optimal controller of a long-delay network control system to make the exponential mean square of the system stable. Some researchers have proposed the MEF-TOD dynamic scheduling algorithm. In the event of a network conflict, the sensor message with the largest error is transmitted first, and the message that is not transmitted will be discarded. Research has shown that it is ensuring sufficient network transmission rate. Under the premise of this method, the performance of the system can be guaranteed by using this method. At the same time, the appropriate use of predictors or linear prediction techniques is an effective supplement to the algorithm [15–18]. Some scholars have proposed the MTS (Mixed Traffic Scheduler) scheduling algorithm for the physical exercise behavior network control system using the controller area network (CAN) and combined with the earliest time limit dynamic scheduling algorithm (Earliest Deadline, ED) and time limit monotonic static scheduling; it has higher schedulability than the DM scheduling algorithm and a smaller network load than the ED scheduling algorithm. The effectiveness of the algorithm is verified by comparison [19–25].

This paper analyzes and models the communication system of the physical exercise behavior network control system and analyzes the current status and methods of the network scheduling research of the physical exercise behavior network control system at home and abroad. The network protocol is the CAN network protocol with high real-time performance. We implement the CAN network protocol data frame format, network scheduling algorithm (CSMA/AMP), model the storage queue system, data encapsulation function, and network message scheduling function involved in the communication process. The core hardware of the physical exercise behavior capture system in this article is the sensor node and the communication base station, to realize the human physical exercise behavior monitoring system based on the human sensor network as the sports behavior, with low cost, low power consumption, high modularity, high reliability, high-precision, and easy-to-wear, and other characteristics are the design guidelines. A set of human physical exercise behavior monitoring system based on a nine-axis wireless sensor platform was developed, which initially achieved the purpose of real-time physical exercise behavior monitoring. One of these sensor nodes will serve as the central node, which is also responsible for the networking and control of the human sensor network; the base station is responsible for controlling the start and stop of the physical activity capture of the human sensor network, as well as receiving physical activity data and transfer it to the computer.

2. Construction of Analysis Model of College Students' Physical Exercise Behavior Based on Computing Cluster and Intelligent Sensor Network

2.1. Computing Cluster Hierarchical Distribution. The computing cluster hierarchical network consists of a large number of deployed sensor nodes and information gathering nodes. Through wireless communication, they form a multi-hop self-organizing distributed network system that can autonomously complete designated tasks based on environmental information. Figure 1 shows the hierarchical distribution of computing clusters.

In the physical exercise behavior network control system, the driving mode of the node is divided into time-driven and event-driven. The time-driven working mode refers to the node sampling the signal according to the sampling clock and then performing related data operations. The clock driving mode needs to pay attention to that the nodes must be synchronized; otherwise, it will cause the action of different nodes in the system. There is a time difference; event-driven means that the activation of a node is related to the arrival of the signal. When a certain node receives a certain signal, the node is activated immediately, and then the data is processed and sent; that is, the node executes a specific mode. The action is "driven" by the arrival of a certain "signal;" so, this working method is called event-driven. Under the premise of comprehensively considering system control performance and system real-time

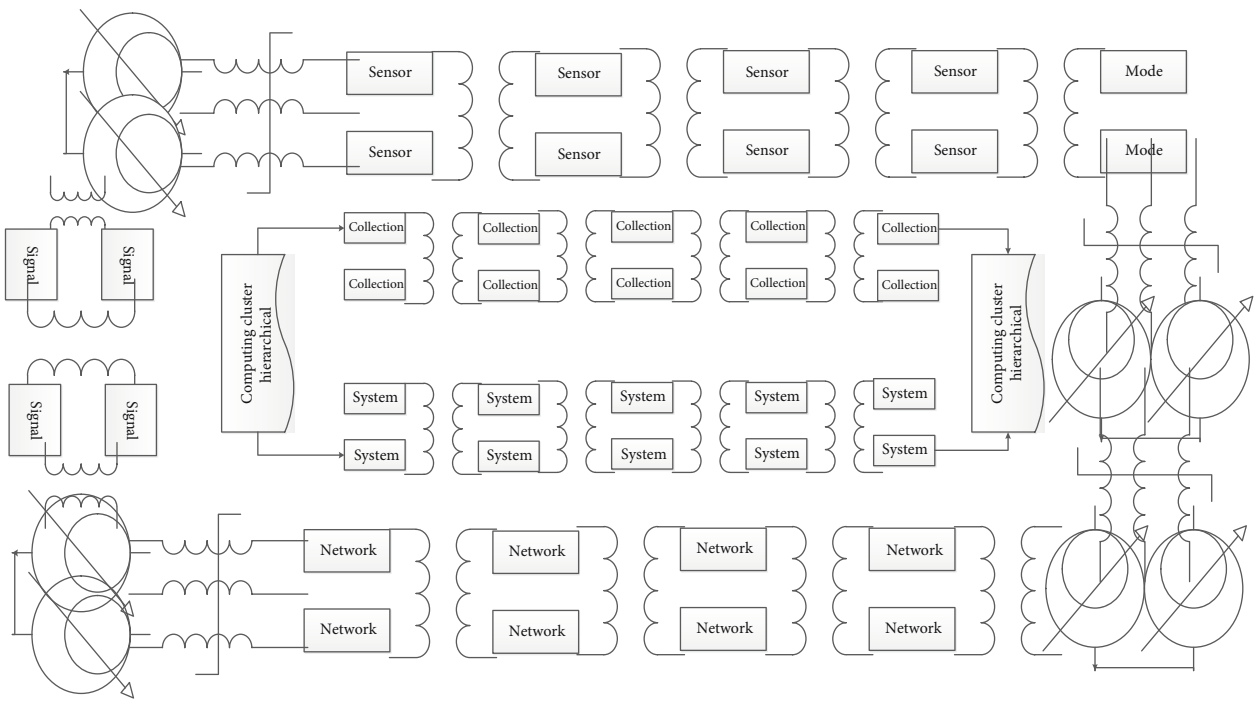

Figure 1: Computing cluster hierarchical structure distribution.

performance, the sensor in this paper is selected as time-driven, timed sampling model data, and controllers, and actuators are event-driven.

$$\begin{aligned} &tf + idf - tf \times idf = 0, \\ &tf(w_i, D_i) = N_{w_1, D_j} \times \sum_{n=1}^{K} N_{w_n, D_j} \times N. \end{aligned} \tag{1}$$

The sensor nodes, controller nodes, and actuator nodes of this system are the final application objects of the control system model. The internal structure of the control system is different for different nodes. The sensor node adopts a time-driven mechanism to realize the function of data collection and package transmission. Its internal AD converter will periodically sample certain parameters of the physical process, and the results will be stored in the RAM inside the CPU. Each task inside the CPU can be used for this purpose. The data is read and written, but at a certain moment, only one task is allowed to read and write.

$$\begin{aligned} f(m,t) &= \frac{n * f(m,t)}{\sum_{i=1}^{n} f(i,t)}, \\ g(m,t) &= \frac{n * (h(m,t)/k(i,t))}{\sum_{i=1}^{n} h(i,t)/k(i,t)}. \end{aligned} \tag{2}$$

The controller node uses an event-driven mechanism to achieve the following functions: read data from the network, calculate the control amount, encapsulate it into a network message frame, and send it to the transmission network. Specifically, the internal network message receiving task of the controller node reads the network message frame from the network through the port connected to the network inside the controller, decapsulates it by the internal transceiver of the controller, reads the valid data therein, and stores it in the internal RAM of the CPU. This RAM is shared by all nodes inside the CPU. It is the same as the sensor node. Only one task is allowed to obtain the right to use the CPU at a time and read and write the RAM.

$$\begin{aligned} &\begin{cases} V_{(i,f)} = \dfrac{J_i^f + J_i^{f-1}}{T}, \\ V_i = \left(V_{(i,\mathrm{i})}, \cdots, V_{(i,f)}\right), \end{cases} \\ &\min \sum_{i=1}^{N} a_i + \frac{1}{2} \times \sum_{i=1}^{N} \sum_{j}^{N} a_i y_j a_j y_i k\left(x_i^2, x_j^2\right) = 0. \end{aligned} \tag{3}$$

The data acquisition process of the physical exercise behavior capture system in this article is as follows: the system starts and keeps the node in the standby state, then the PC sends the start physical exercise behavior capture command wirelessly through the base station, and the node in the BSN starts after receiving the start capture command. The centralized tracking system is suitable for the situation where the number of sensors is small. In this state, the node transmits the data wirelessly to the base station while collecting and storing data, and the base station then transmits the data back to the computer for corresponding processing.

2.2. Smart Sensor Network Topology. The physical exercise behavior network control system has a delay between the sensor controller and the controller actuator. When calculating the control amount inside the controller, there is also a

certain delay. The cause of network data packet loss is that during the process of data packet transmission, transmission errors caused by network congestion, transmission timeout exceeding a certain error rate, connection interruption caused by node failure, etc. are caused by unknowable reasons. If the error rate is not set, the default error rate of the network is 0, and no loss will occur during data packet transmission; if the error rate of the network is set to 0.1, it will be transmitted after 10 times. During the process, there will be a transmission error. In this case, you can choose to resend or discard the data packet. This measure can simulate the network data packet loss and the corresponding processing error. Figure 2 shows the distribution of nodes in a smart sensor network.

The sensor node in this article is mainly composed of microcontroller, physical exercise behavior sensor, wireless module, power management module, and so on. Because the node needs to be small (easy to wear) and must be able to work continuously for a long time, the microcontroller must support low power consumption mode; the node integrates a nine-degree-of-freedom physical exercise sensor, and the amount of data that needs to be processed is large; so, the microcontroller memory is required; due to the real-time requirements of the system, the microcontroller needs to have a fast processing speed. According to whether the coordinate location information is obtained or not, the network nodes can be divided into beacon nodes and nodes with unknown locations. A beacon node is a node that actively obtains its own location information in some way after being deployed and sends its own information to the location node for other nodes to locate its location; nodes with unknown locations need the location information of the beacon node. Usually, triangulation, trilateral measurement, and maximum likelihood estimation method can be used to accurately calculate the position of the node.

2.3. Analysis of College Students' Physical Exercise Behavior. When the human physical exercise behavior capture system is working, the measured person wears more than a dozen sensor nodes for physical exercise behavior capture. We need to implement network interconnection between these nodes to compensate for the rather limited sensor software and hardware resources to realize the optimal use of resources. In addition, the system needs to integrate the data collected by each node at the same time at the data processing end; otherwise, it will cause incoherent and deformed movements when restoring the physical exercise behavior data. It is only designed for channel resource allocation and conflict avoidance. Therefore, the traditional synchronization mechanism cannot guarantee that the data collected at the same time can reach the data processing end at the same time. Figure 3 is the composition of the physical exercise behavior module.

The sampling frequency of the physical exercise behavior data of the sensor node mainly depends on the application, the type of physical exercise behavior, or the different parts of the joint. In general, we believe that the lowest sampling frequency that can be used to describe people's daily activities is 20 Hz, and the medium sampling frequency is about

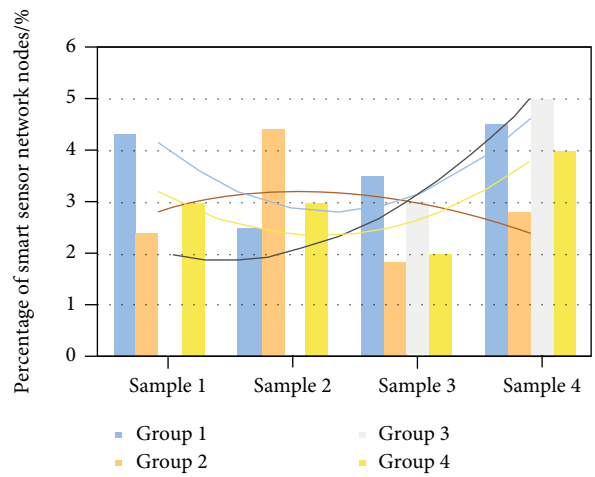

Figure 2: Distribution of smart sensor network nodes.

50~100 Hz; it can be seen that the communication data volume of the network in the data transmission state is quite large; so, the communication protocol must minimize its overhead in other states. However, the network access of nodes and network control will occasionally require communication time slots. In order to make more reasonable use of channel resources, we introduce a competition mechanism in TDMA communication based on the scheduling mechanism, referring to the multisuperframe structure of the MedMAC protocol. A single-hop star network is formed between all nodes and the central unit (CU)/central node. Each measured object has a central unit/central node responsible for data relay from node to base station and control from base station to node. This method has many advantages. First, all nodes except the central node do not need a large transmission power, which not only ensures the effective use of resources but also reduces the radiation hazard to the human body. Second, the star-shaped network is simple in networking, reducing routing overhead. Third, if we need to capture long-distance and large-scale physical exercise behaviors, we can increase the transmission power of the central node, since the signal coverage of nodes other than the central node is very small, which ensures the transmission distance and the stability of the system.

2.4. Model Iteration Factor Update. The sequence of messages transmitted in the network is out of order, indicating that the order in which the destination node receives the message is different from the order in which the sending node sends it. That is, the message sent after the sending node arrives at the destination node before the message sent by the node before. That is, if the above situation occurs, if it is a multipacket transmission, it will cause the sending node to send data disorder, disturb the corresponding controller to calculate the corresponding control amount, and have a greater impact on the control effect. In this study, using internal time, messages transmitted in the network have corresponding timestamps, namely, the generation time and the reception time. If the generation time is late and the reception time is early, it means that the data packet sequence is disordered, and the message is discarded. The sending and

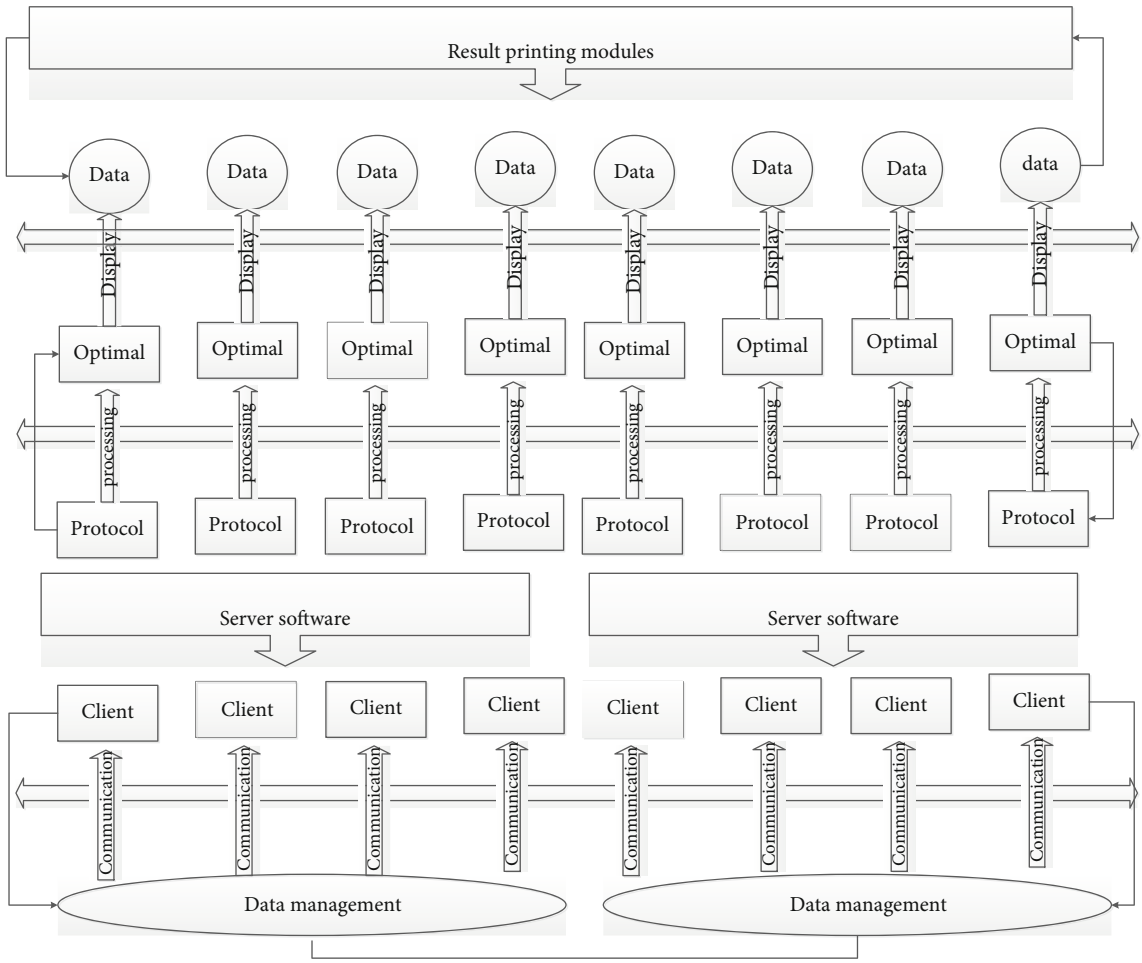

Figure 3: The composition of the physical exercise behavior module.

receiving buffer queues are, respectively, used inside the node, so that the messages sent from the node enter the network in the corresponding order, which reduces the disorder of the data packet sequence to a certain extent. Its accuracy greatly depends on the distribution density of nodes and the distribution of node positions and is easily affected by the accumulation of errors. Based on this, someone proposed to use a weighted method to weigh the impact of sports behaviors on network nodes. After using the weighted centroid algorithm, the positioning accuracy weakens the impact of uneven distribution of nodes on positioning, but the positioning effect still depends more on the distribution density of nodes. Figure 4 shows the iterative factor distribution of the calculated cluster model.

The sensor network can be regarded as a distributed database, and each node is a storage unit. Applying the database management method to the sensor network, the virtual view seen by the end user can represent the actual node information in the network. The user only needs to care about the event information of the terminal interface and does not need to care about the status information of each node in the implementation. This data management method based on database technology can significantly enhance the usability and practicability of the sensor network, making the management of network nodes more convenient and more efficient. The service life of sensor networks is limited by energy supply, and reducing the amount of transmitted data can effectively save energy. In the centralized tracking architecture, the measurement values of all sensors are sent to the central tracker or the fusion center, and the fusion center performs measurement-trajectory correlation and fusion. Therefore, data can be fused during the process of collecting and forwarding data from various sensor nodes to reduce the length of data packets and remove redundant information. At the same time, the forwarded data and the locally collected data can be analyzed and processed to improve the accuracy of the information. The microembedded system of sensor nodes has the following characteristics: one is the high degree of concurrency; that is, sometimes, there are multiple simultaneous tasks, but the execution time of a single task is very short; so, the operating system should have a mechanism to handle such concurrent tasks. The operating system is required to simplify the difficulty of operating the hardware of the application program and to release more operation permissions to the application program.

3. Results and Analysis

3.1. Data Preprocessing of Smart Sensor Network. When the polling algorithm is used in the experiment, the scheduler

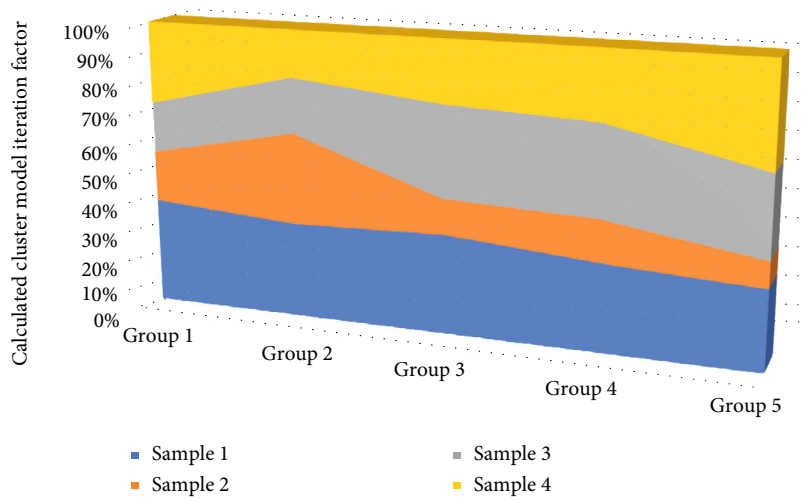

Figure 4: Calculating the distribution of the iterative factor of the cluster model.

usually uses time-sharing technology to give each process a time slice (a single allowable CPU execution time). If the process cannot complete the task at the end of the time slice, it will be replaced by other processes. When the CPU execution processing time is regained through scheduling next time, the process will be executed from the current interrupted location. If the time slice is 20 milliseconds, and process 1 needs 50 milliseconds to complete, at the end of 20 milliseconds, the system sends a signal to notify the scheduler. The scheduler stops the execution of the process according to this signal, temporarily suspends the task, and stops the execution of the CPU processing time is given to other processes. When all other processes have sequentially obtained 20 milliseconds of running time, process 1 will regain 20 milliseconds of CPU execution time and so on. This method can ensure that all processes in the run queue can obtain a time slice of CPU processing time within a given time period. Figure 5 is the data progress curve of the smart sensor network.

If the relative position of the sports behaviors in the multisports behavior dynamic cluster does not change much during the progress, and the sports behaviors are relatively evenly distributed, the weighted centroid positioning method is used to determine the geometric centroid of the sports behavior cluster as the positioning result based on all the measurement information. Regarding the sports behavior cluster as a whole, the measurement received by the nodes in the edge area of the sports behavior cluster should be smaller than the measurement of the nodes in the central area. Therefore, the geometric center of mass of the sports behavior cluster can be roughly determined according to the node coordinates of the edge area and its measurement. As the error rate increases, the overshoot increases, and the response time becomes longer. In the case of an error rate of 0.3, the inverted pendulum system can eventually remain stable; but when the error rate is 0.5, the inclination angle of the inverted pendulum cannot remain stable. The network cannot transmit the sensor collection data information and the controller node control information in time, so that the actuator node cannot obtain the control amount that acts on the inverted pendulum model at the corresponding time.

3.2. Simulation of Physical Exercise Behavior Model Based on Computing Cluster. The output of the IDG650 dual-axis gyroscope and ISZ650 single-axis gyroscope used in the simulation system are both analog voltage values, which need to be converted into corresponding measured values by the 12-bit ADC sampling module of the microcontroller. When the operating voltage of the microcontroller is 3.6 V, the accuracy of the 12-bit ADC is about 0.25 mV, which is higher than that of the gyroscope. The three-axis magnetometer uses PNI's MicroMag module, which reduces the development difficulty and shortens the development cycle. The working current of this module is only 500A at 3VDC, the magnetic field range is ±11, the resolution is 0.015, and SPI digital interface is provided. The experimental design controller contains three tasks, namely, the network message sending task, the network message receiving task, and the control quantity calculation task. Therefore, the internal scheduler of the controller must schedule these three subtasks. It can be seen that the time is 0.2 s. Inside, three concurrent tasks compete for CPU time. At a certain time, only one task can get the right to use the CPU. Using the FIFO scheduling algorithm, to apply for scheduling a new task, first find out whether the waiting task queue already contains the task. If the task does not exist in the queue, add the task to the end of the queue; otherwise, go directly to the next step and schedule it through query. If there is no task and the task queue is not empty, then take out a task at the head of the task queue and schedule its running parameter to run. Otherwise, if there is a task running, but the task is already running at the moment when it is finished, it is judged whether the task queue is empty. If the task queue is not empty, the first task of the task queue is taken out for scheduling operation; otherwise, the next scan scheduling is performed. Figure 6 shows the distribution of task scheduling in computing clusters.

For the continuous long-term physical exercise behavior of the measured object, the posture estimation mainly relies

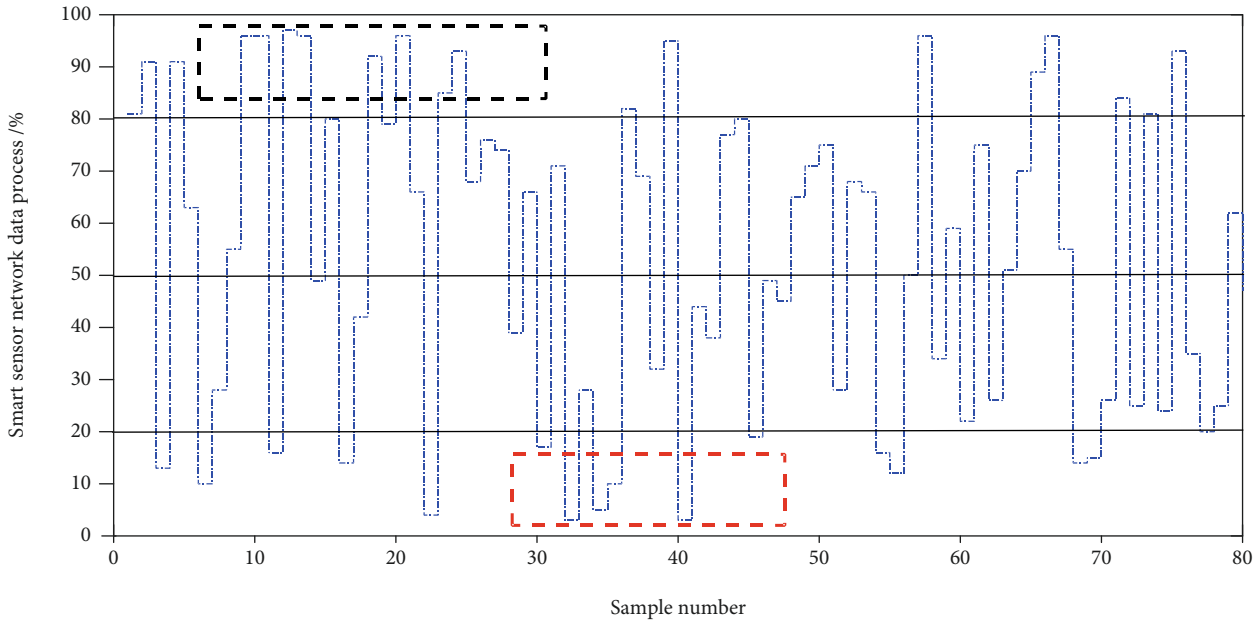

Figure 5: Data process curve of smart sensor network.

on the integration of the output value of the gyroscope. If the system cannot get the acceleration and magnetometer attitude correction over time, the deviation and drift of the gyro will make the attitude estimation accuracy. In the case of continuous motion of the object under test, we separately analyze the attitude output of the gyroscope, and the error of its Euler angle is as follows. They can not only estimate the state of multiple targets but also realize trajectory correlation. During the experiment, we used 4 miniature sensors to capture and reproduce the physical exercise behavior of the lower body of the human body. The node on the calf is fixed on the outer side above the ankle 10era, the node on the thigh is fixed on the outer side 10 cm above the knee, and two sensor nodes are placed on the torso. The sampling frequency of the node is 50 Hz. Each sensor node collects the physical exercise behavior information of the corresponding limbs, such as the thigh sensor collects the physical exercise behavior information of the thigh, and the calf sensor collects the calf physical exercise behavior information. Figure 7 is the cluster distribution of physical exercise behavior information calculation.

The multisports behavior test plan in this article is defined in the area plane with a range of $2\,\Omega = 100 \times 100\,\mathrm{m}$. 400 network nodes are randomly scattered in the area as the test environment for the content of this section. The nodes all belong to a cluster, and the network environment and the physical location information of the nodes are as written. Starting from nodes A, B, C, and D, each node starts to traverse the information of its surrounding nodes in a clockwise direction. After a round of boundary traversal, if it is a complete continuous dynamic cluster, there should be four traversal results $A \longrightarrow B$, $B \longrightarrow C$, $C \longrightarrow D$, and $D \longrightarrow A$. If not, it means that the dynamic cluster is separated, and a new dynamic cluster head management should be established. The separated dynamic cluster nodes continue to track sports behaviors.

3.3. Analysis of Experimental Results. The MSP430 series single chip microcomputer used in the experiment is a 16-bit ultra-low power mixed signal processor, which is called a mixed signal processor. It is integrated with a microprocessor on a chip to provide a "single-chip" solution. In terms of operating speed, MSP430 series single-chip microcomputers can realize 125 ns instruction cycle under the drive of 8 MHz crystal. The 16-bit data width, 125 ns instruction cycle, and the multifunctional hardware multiplier (which can realize multiplication and addition) can realize certain algorithms of digital signal processing (such as FFT). The MSP430 series single-chip microcomputers have many interrupt sources and can be nested arbitrarily, which is flexible and convenient to use. When the system is in a power-saving standby state, it only takes 6us to wake it up with an interrupt request. Due to the instability of wireless transmission, the physical exercise behavior data sent by the node to the base station may be lost; so, an external expansion storage device is required for data backup. In this way, even if the wireless communication is not smooth, the upper computer can send a repacking command to upload the missing data. The expansion storage device selects the flash chip of AT25DF641, which is fast to write and erase, the working voltage is 2.7 V-3.6 V, the capacity is 64 Mbit, the minimum erasable capacity is 4 K bytes, and the SPI digital interface is provided. Figure 8 shows the periodic data distribution of the smart sensor network.

In this system, 4 frequencies are allocated to each base station for frequency hopping, and the intervals between frequencies are equal. Frequency hopping is started when the number of data packets received by the base station in 1 s is less than the threshold, and the threshold is selected through experiments. The algorithm framework and solution for the joint search and tracking of regional multimaneuvering targets can handle situations where the number of targets is unknown and may change dynamically. If the

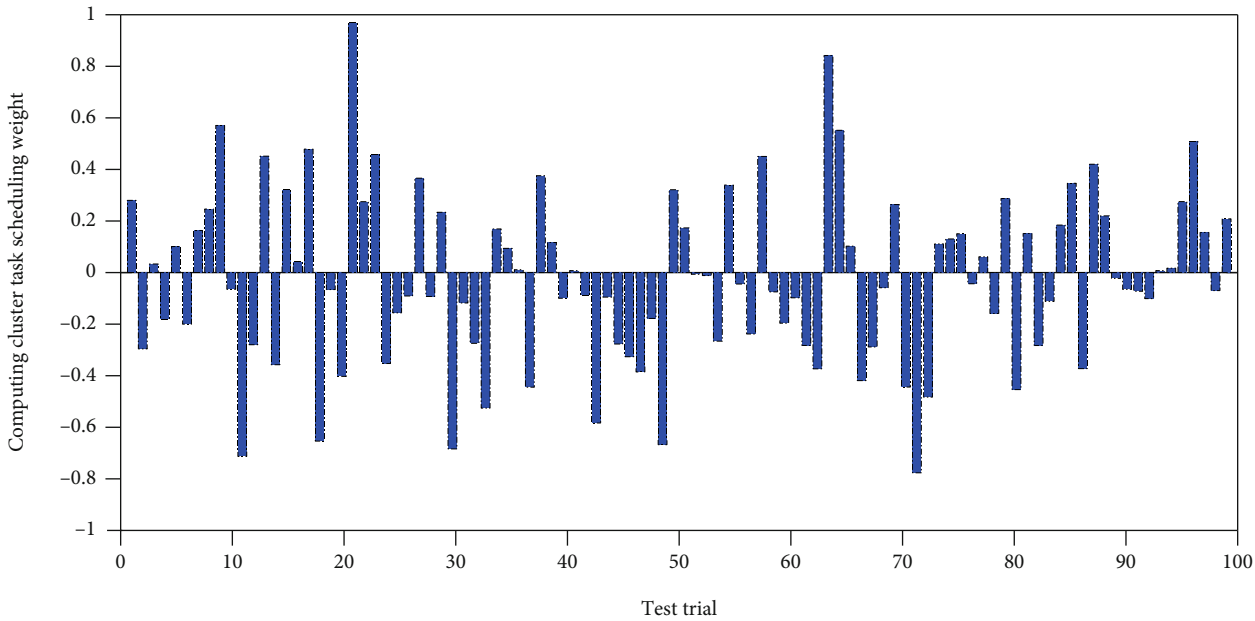

Figure 6: Computing cluster task scheduling distribution.

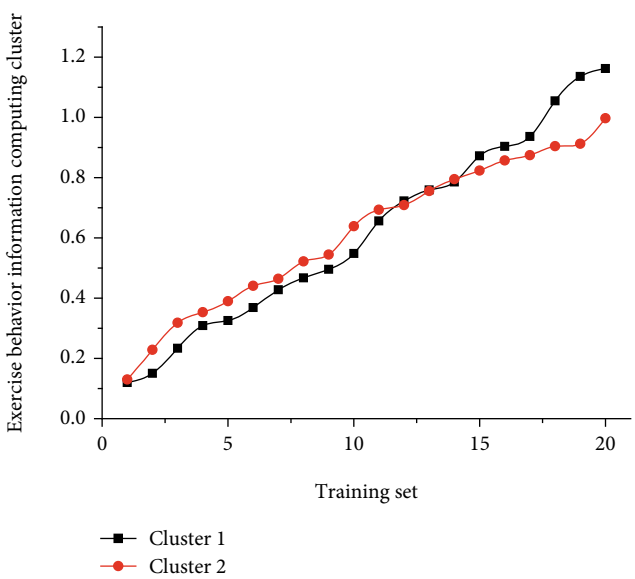

Figure 7: Physical exercise behavior information computing cluster distribution.

threshold is too large, the packet loss rate cannot be effectively controlled; if the threshold is too small, frequency hopping will occur frequently, and the chance of frequency hopping disorder will increase significantly. After the frequency hopping is disorderly, the base station and the node lose communication, the base station will hop back until it establishes communication with the node after hopping to a certain frequency. In this system, the longest time required for reestablishing the connection after frequency hopping is 4 s, the shortest time is 1 s, and 200 data packets will be lost during this time. For this reason, the frequency hopping threshold must be selected reasonably. The system has undergone repeated tests, and the selected frequency hopping threshold is 5 data packets lost within 18. Figure 9 shows the distribution of thresholds for selection of smart sensor networks.

The three-axis gyroscope and the three-axis magnetometer, respectively, measure the angular velocity component and the magnetic field component in the three-dimensional space. The gyroscope uses a combination of a single-axis gyroscope and a dual-axis gyroscope, and their sensitive axes are perpendicular to each other. Randomly, we simulate the composition of dynamic clusters from different physical exercise behaviors to different positions. Because the nodes are not evenly distributed in the two-dimensional space, the size, scope, and composition of the dynamic clusters are always changing dynamically. When the node density is sparse, because the number of nodes that can be judged is small or no, and the sports behavior positions are already very close, it is easier to cause misoperation in this case. The analog data of the gyroscope on the node bottom board is sent to the microcontroller on the node core board through the interface with the node core board. The sampled signal value of the angular velocity measured by the sensor obtained by ADC conversion needs to be converted into the corresponding measured value, and the measured value represents the obtained angular velocity component value. Strictly speaking, the resolution of the ADC should be higher than the resolution of the sensor; otherwise, the high-resolution sensor will not be effectively used.

4. Conclusion

Based on computing clusters and smart sensor network technology, this paper designs college students' physical exercise behavior experiments, using the output of posture tracker as a reference signal, taking the acceleration signal of physical exercise behavior as an example to analyze and

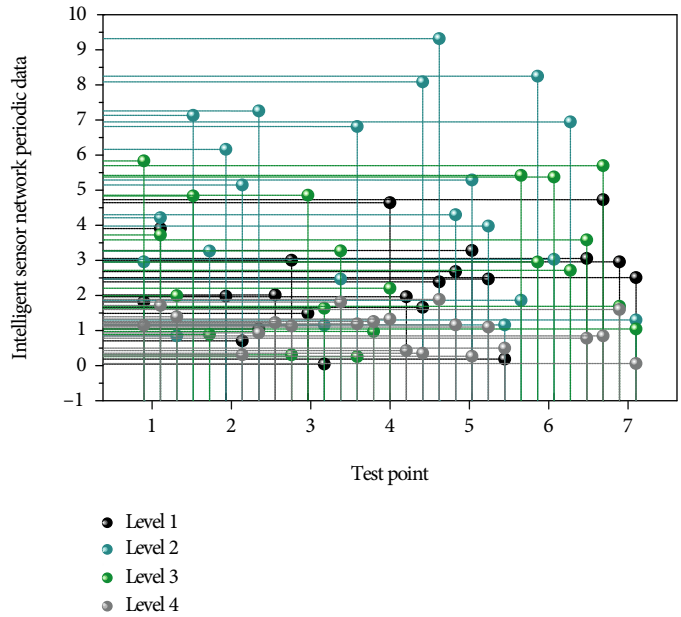

Figure 8: Periodic data distribution of smart sensor network.

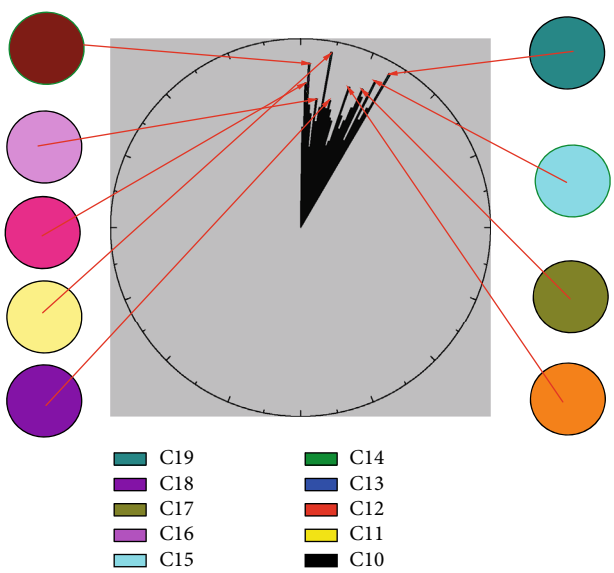

Figure 9: Distribution of thresholds for selection of smart sensor networks.

compare the commonly used data filtering methods of physical exercise behavior sensors. The experiment builds an inverted pendulum model based on CAN network protocol and a control model of continuous control system inverted pendulum and analyzes and studies the timing of the physical exercise behavior network control system model based on CAN network. The phenomenon of unexpected loss of behavior gives a recovery strategy. The simulation results show that the combination of these two methods for mobile sports behavior tracking improves the effect of sports behavior positioning and sports behavior location prediction and obtains the effects of higher tracking accuracy and lower network computing overhead. At the same time, the control communication system model of a certain type of obstacle avoidance car is built, and the delay of the communication process, data packet loss, single-packet and multipacket transmission, data packet timing disorder, and network scheduling are simulated and analyzed. It effectively proves the effectiveness of the unified modeling method of the control and communication model proposed in this paper. At the same time, two simple experiments are designed to analyze the errors of the two methods, use the real-time attitude angle calculation method to try the physical exercise behavior and physical exercise behavior of human bones and initially realize the physical behavior of real-time physical exercise behavior supervision.

Data Availability

All data, models, and code generated or used during the study appear in the submitted.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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