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Wearable human motion posture capture and medical health monitoring based on wireless sensor networks

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ABSTRACT

Wireless wearable technology is widely used in health monitoring, rehabilitation training and other fields. In this paper, motion capture sensors are used to collect human motion data, and the collected data format is processed accordingly. We study the characteristics of different posture signals, and select the signal feature sequence that can identify the posture of the signal. According to the signal feature sequence of the pose in the pose database, a multi-level hierarchical recognition algorithm for human pose is designed. Only three-layer recognition algorithm is used to accurately recognize various poses. Through simulation experiments, it is verified that the recognition rate of the designed algorithm meets the monitoring requirements. Experiments were carried out on the physiological parameters of the experimenters. The experimental results show that the entire system has applicability and reliability, and can meet the needs of physicians for real-time monitoring of patient physiological parameters during medical health monitoring.

1. Introduction

As a current hot research field, wireless sensor network technology is playing an increasingly important role in daily life due to its cheap, portable and universal characteristics [1]. Remote health monitoring is a new means of monitoring human health status with the help of modern communication technology, computer technology and physiological signal detection technology [2–4]. Its key points are physiological signal collection and remote transmission of information. The system provides important data references for clinical health monitoring by classifying and identifying the daily movements of the monitored objects [5–7]. The system realizes the acquisition and wireless transmission of human daily posture and physiological information under the condition of low physiological and psychological load of testers, and analyzes and processes data through the background monitoring center to determine the health level of the tester [8,9].

Compared with behavior recognition based on vision, the behavior recognition based on wearable sensors has the advantages of strong anti-interference ability, comfortable wearing, and protection of the privacy of the wearer [10–12]. Sensors that have been used for wearable behavior recognition research include Shimmer and Imote2 [13]. Wearable sensors can be applied not only to intelligent human–computer interaction, but also to areas such as intelligent monitoring, health monitoring, environmental monitoring, context awareness based on handheld devices, and energy consumption assessment of human motion [14–17]. Since acceleration is ubiquitous in daily life, whether it is running, fighting, falling and other violent sports, or walking, sitting and other relatively gentle movements will produce acceleration. Therefore, among the many wearable sensors, the use of acceleration signals measured by acceleration sensors to recognize the movement state of people has been widely valued by researchers around the world [18–20]. After analyzing and processing the motion signal, the corresponding action of generating the signal can be judged [21,22]. Wearable health monitoring technology overcomes the limitations of traditional medical detection technology [23–25]. The sensor uses a wearable design that does not limit the daily activities of the tester, monitors various parameters in real time, and stores, processes, and remotely transmits information for patients [26,27]. The blood pressure meter developed by the center can carry out continuous non-invasive blood pressure monitoring anytime and anywhere, overcoming the shortcomings of the traditional cuff-type blood pressure meter, such as poor mobility, inconvenience to wear, and large power consumption [28–30]. Relevant scholars use mutually perpendicular biaxial acceleration sensors to measure three-dimensional motion acceleration, and

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use correlation methods and two-variation data distribution statistical methods to perform posture judgment and gait tracking on testers of portable devices [31,32]. The researchers designed a gesture recognition system based on a multi-layer hierarchical algorithm [33–37]. The human body posture is divided into simple posture and complex posture for recognition, and the recognition rate is 82.87% [38]. However, the system relies on the collected database and cannot add gestures or delete gestures. Relevant scholars use two-axis acceleration sensors placed on the back and head of the human body to perform human body gesture recognition [39–41]. The algorithm can recognize the postures of standing, walking and running, and has the characteristics of free movement. The disadvantage is that the gesture recognition rate is only 80%. Relevant scholars have designed a wearable device for the fall that is easy to occur on the treadmill [42]. Wearing it can remind the user of the running speed of the treadmill in real time and effectively prevent the fall on the treadmill.

A human skeleton model suitable for human motion capture based on inertial sensors and suitable for three-dimensional reconstruction is established. On the basis of researching and summarizing a large number of human movements, an analysis and comparison of commonly used human posture models are used to establish a hierarchy model based on constraints. Specifically, the technical contributions of this paper can be summarized as follows:

First: We realize the three-dimensional dynamic reconstruction of human action posture capture. After collecting human motion posture data through motion capture sensors, in order to facilitate the subsequent behavior analysis, this paper uses a hierarchical three-dimensional human model to achieve dynamic three-dimensional reconstruction of human behavior.

Second: We propose a multi-level hierarchical recognition algorithm for human posture based on wireless body area network. The algorithm preprocesses the posture signal, filters out the outliers and samples it, extracts and selects the characteristic signal of the posture signal with the posture identifier, and uses only three levels of judgment conditions to accurately identify the four posture signals.

Third: Experimental analysis verified the reliability, stability and applicability of the medical health monitoring system. The medical health monitoring system can meet the demand for real-time monitoring of physiological parameters.

The rest of this paper is organized as follows. Section 2 analyzes the wearable human body motion posture signal collection and human body motion reconstruction under the wireless body area network. Section 3 studies the multi-level hierarchical capture algorithm of human posture based on WSN wireless body area network. Section 4 analyzes the medical health monitoring of wearable wireless sensor networks. Section 5 summarizes the full text.

2. Wearable human body motion posture signal acquisition and human body motion reconstruction under wireless body area network

2.1. Wireless body area network system structure

The wireless body area network has different network architectures according to different scenarios. So far, the basic architecture of the wireless body area network is summarized in Fig. 1. The figure shows the communication method and signal transmission diagram of different levels of wireless body area network. Sensors capable of sensing different kinds of physiological parameters and posture information are placed on the body surface of the human body. These sensors transmit the collected signals to the AP node in a certain period of polling. The AP node here can be a sink node placed on the body, or it can be a smartphone or a personal tablet. The AP nodes placed on the body surface can transmit signals in a wired manner, while the APs outside the body must use wireless methods to aggregate the signals from the sensors, among which the ultra-wideband methods include ultra-wideband, Zigbee, and Bluetooth. Another task of the sink node is to manage, schedule, and preprocess the transmitted signals, and then transmit them to remote devices through various mobile communication methods. After the signal transmitted to the remote device through the AP node is received by the corresponding application device, through the processing and analysis of the received signal and the interpretation of the experienced staff, important information can be obtained at the remote end.

The wireless body area network has typical applications and some commonly used equipment in the field of army information construction, leisure life and intelligent diagnosis. There are many applications of wireless body area networks in the medical field, such as some testers for asthma patients and sleep recorders for patients with sleep.

The solution based on MEMS sensor is relatively inexpensive, the experiment operation is simple, it is not afraid of occlusion and other external interference, the requirements on environment and space are low, the collected data is more accurate, and at the same time, it is less intrusive to human privacy. Compared with other schemes including optics, it has obvious advantages, so the motion capture and behavior recognition system studied in this paper is based on this scheme.

The human behavior recognition technology based on motion capture sensors studied in this paper is a comprehensive technology that combines sensor technology, human dynamics, computer graphics, pattern recognition and other disciplines. The technology consists of front-end hardware and back-end software. The main functions and content of the front-end hardware include the use of motion capture sensors to collect human motion data and transfer these motion data to the computer; the main functions and content of the back-end software are to use the computer to effectively process the collected motion data, so that the computer can automatically recognize the action category of the captured object, so as to realize the reproduction of the action and human–computer interaction. The content of this paper is the design and operation of the front-end action data transmission and processing and the classification and recognition algorithm of the back-end program.

2.2. Action data collection based on inertial sensors

Data collection is the process of using special equipment to collect data from outside the system and input it into the system. Commonly used data collection equipment can be scanners, microphones, cameras, sensors, etc. This paper uses a sensor-based data acquisition system. In the experiment, we chose Nuo Yiteng's sensor-based motion capture Truemotion data acquisition system. Using Truemotion to obtain human motion posture data has the advantages of simple and reliable operation and high accuracy of data. It is used for bone modeling and behavior recognition of human motion posture.

Truemotion is a set of inertial motion capture system. Like other motion capture devices, Truemotion system includes three main components: (1) The sensor can sense external signals and is responsible for collecting data; (2) The signal collection and transmission device is responsible for collecting each sensor The collected signals can be transmitted to the PC. The data transmission uses wireless Bluetooth transmission technology and USB interface transmission technology; (3) The signal processing equipment is mainly computer hardware and software equipment. The software equipment is Truemotion data processing

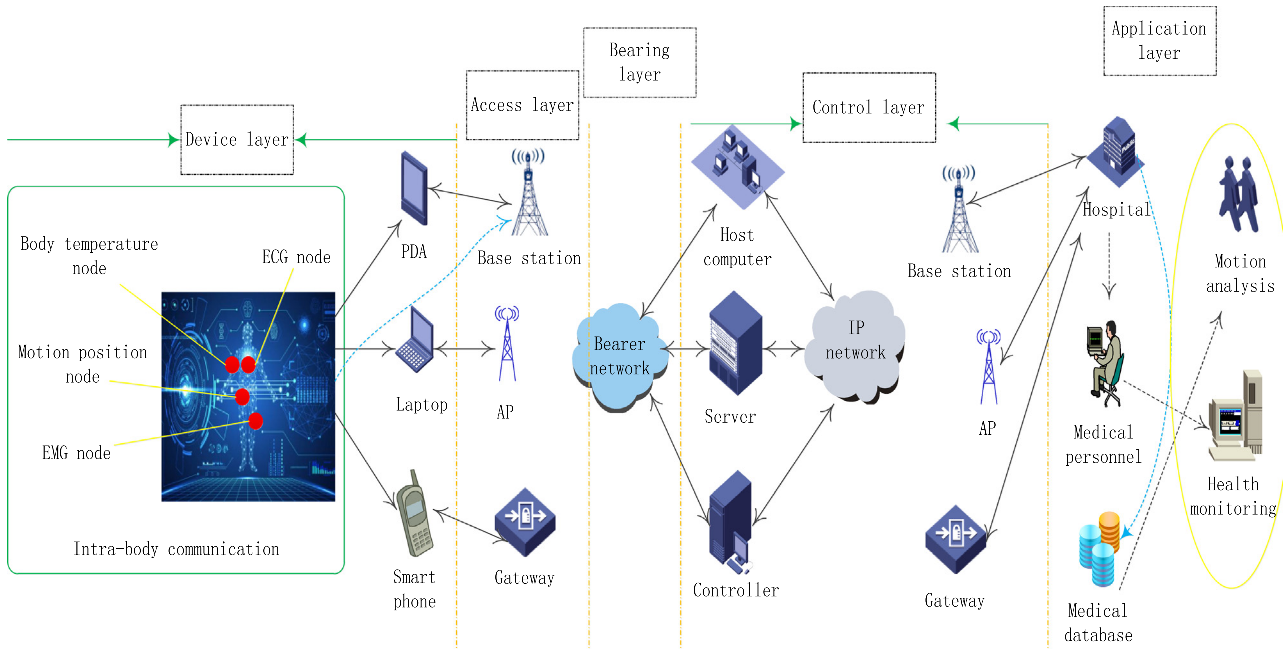

Fig. 1. Wireless body area network system architecture.

software, which is responsible for the original processing of the collected signals.

The Truemotion system combines a navigation system and an angular positioning system. The signal obtained by the sensor is processed in real time by a signal processing device to calculate the relative offset position of each joint of the body, so that it can be developed again for us and realize the acquisition of human motion data and three-dimensional reconstruction.

Among them, the sensor is an important part of the Truemotion system. The sensor used in this paper is mainly composed of two modules: MEMS sensing unit and node attitude analysis. The three motion sensing chip components of the axis magnetometer incorporate more magnetic field measurement than the standard six-axis sensor, making their measurement more accurate and reliable.

The data collection of the inertial motion capture process is to use the motion capture sensor to automatically sense the signal and capture the rotation angle and offset information of the human body motion, and transmit the information to the entire process of the PC side. The Truemotion device collects the sensor's offset and rotation angle information during human body motion through the motion capture sensor on the equipment, and transmits it to the PC side through wireless transmission technology, and performs related processing on the PC side, and then displays it in real time. The computer software used in the experiment was Truemotion. The operation steps are as follows:

(1) We bind a full set of sensors of Truemotion equipment to the experimenter, note that it is necessary to ensure that each sensor is tightly fixed on each specific part of the human body, and record that all parts of the human body are properly worn.
(2) We install Truemotion software. The motion capture sensor capture device cannot be used alone, it needs to be combined with the official software Truemotion on the PC.
(3) After the hardware wearable sensor and signal transmitter and software Truemotion are installed, the tester needs to perform pre-defined motion calibration. Then you can record the animation, note that when you start recording human movements, you also need to save the human animation data.
(4) There are two kinds of .raw and .bvh human animation formats recorded and saved by the software. The .bvh format is the file format of human body animation supported by various popular animation production software, so it can be exported to other animation production software and applications.

2.3. Model establishment and analysis of human movement posture

The architecture of the human motion posture capture system is shown in Fig. 2. According to the signal extraction process, from a spatial point of view, there are two types of geometric human models, one is a three-dimensional human body model, and the other is a two-dimensional human body model. The three-dimensional human body model, as the name implies, can describe the human posture in a real way through changes in three-dimensional space. The three-dimensional human body model has two commonly used models, a three-dimensional face model and a three-dimensional geometric model. Among them, the three-dimensional patch is based on the external structure of the human body, and the human body is modeled independently with a large number of patches, and then the entire human body is organically combined. This way can more truly characterize the external features of the human body. The three-dimensional geometry model is to use the most commonly used geometric shapes to abstractly model the important limbs of the human body, and to reflect the movement of the human body by controlling the changes of the geometric shapes. For example, in the field of motion capture, points are often used to represent joint points, a line between two points is used to describe joints and joint points, and a sphere is used to describe the head model. The two-dimensional human body model refers to a model that can truly describe the posture of the human body through changes in the two-dimensional space.

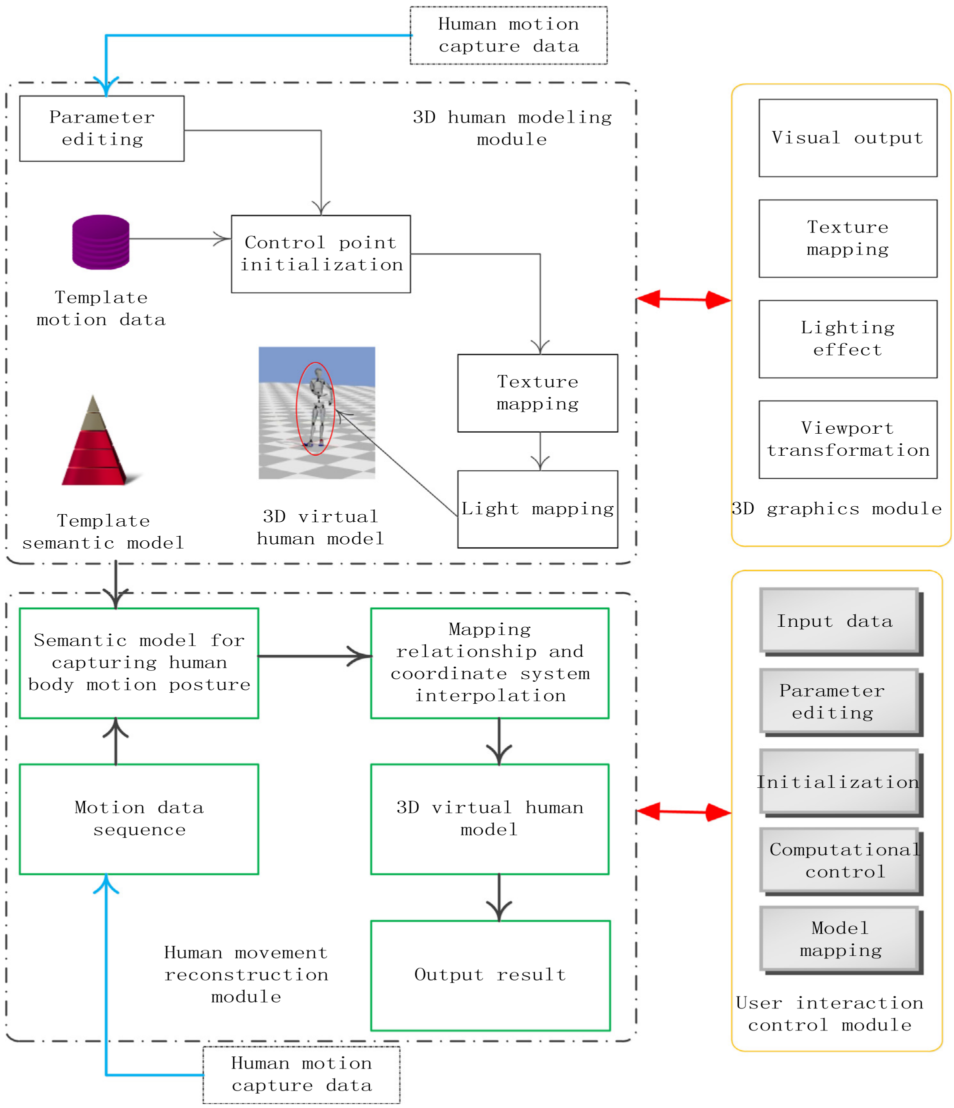

Fig. 2. Architecture of human motion posture capture system.

In this paper, we need to describe our gestures in three-dimensional space, so the model to be built is three-dimensional, so the three-dimensional geometry model is used.

The function of the data collection module is to use sensors to obtain acceleration data related to human posture, and to transmit the data to the smart terminal through the wireless transmission module to provide the original data for the entire recognition system. The data collection module is at the bottom of the entire gesture recognition system. The quality of the acceleration data collected by the sensor will affect the final result of the entire human gesture recognition system.

The human posture is very complicated. Different postures of the human body will involve different parts, and the motion intensity of different postures is also different, so the position where the acceleration sensor is worn also has a greater impact on the classification result.

Denoising is one of the most commonly used data preprocessing methods in human posture recognition, because the original acceleration data collected by the sensor will be mixed with the measurement noise of the system and the noise signal due to human body shake.

In the process of collecting data, due to the tilt or rotation of the data collection module, there will be a deviation between the actual vertical acceleration signal and the theoretical vertical acceleration signal. To solve this problem, a kind of tilt correction is applied to the vertical acceleration signal The method uses the characteristic that the gravity acceleration component of the data acquisition module is stationary vertically downward at rest, and corrects the actual acceleration signal in the vertical direction when the user is active. After correcting the acceleration signal in the vertical direction, the accuracy rate is identified. There is a big improvement. According to different research and application requirements, choosing the appropriate data preprocessing method will directly affect the subsequent feature extraction and classification and recognition, and will play an important role in the entire human posture recognition system.

The pattern recognition method based on statistics is generally adopted in human gesture recognition based on acceleration sensors. After feature extraction and selection, we use a suitable classification algorithm to classify different poses of the human body correctly according to the selected feature vectors. Among them, the difference in the selection of the classifier will have a great impact on the final result of the entire human body gesture recognition system.

The processing of three-axis angular velocity and three-axis acceleration signals mainly includes filtering, attitude calculation, and attitude update. When the gyro sensor alone is used to solve the attitude angle, the cumulative error will be generated due to the integration operation, while the acceleration sensor alone is used to solve the attitude angle, its shortcomings are obvious. Therefore, in order to get a more accurate attitude angle, this paper combines these two methods to solve the attitude angle.

(1) The MPU6050 sensor is at rest by default at the beginning;
(2) You read three-axis acceleration to initialize attitude angle;
(3) You read the three-axis angular velocity value and apply Kalman filter to it, and use the filtered three-axis angular velocity to calculate the attitude angle.
(4) You determine whether the MPU6050 sensor is in motion, if it is in motion, output the calculated attitude angle, and return to step (3); if it is at rest, use three-axis acceleration to solve the attitude angle, correct the current attitude angle, and output the attitude angle and return to step (3).

2.4. 3D human body reconstruction based on sensor data

How to convert the correct position and dynamics of bones into animation, the matrix algorithm has proved to be a feasible bvh analysis algorithm, as shown in the following formula:

$$v' = vM \tag{1}$$

where v' represents the transformation point, v represents the original point, and M represents the transformation matrix. This formula is particularly important when the matrix multiplication is a non-commutable 3 separate Euler angles to construct a rotation matrix. Rotation matrix R is the rotation parameter of each axis based on a separate rotation matrix, Rx, Ry, Rz, as shown in the following formula:

$$R = R_x \times R_y \times R_z \tag{2}$$

Among them, R represents the rotation matrix, R_x represents the y axis rotation parameter, R_y represents the z axis rotation parameter, and R_z represents the x axis rotation parameter.

$$M = S \times R \times T \tag{3}$$

Among them, S represents the bone size, T represents the translation matrix. We can find all the relevant node positions we need.

$$v'_0 = [0, 0, 0, 1]M_{Leftfoot}M_{Hips}M_{Leftleg}M_{Leftupleg} \tag{4}$$

$$v' = vM_{Local1}M_{Local2}M_{Local3}M_{Hips} \tag{5}$$

v'_0 indicates the position of Left Foot, and v 'indicates the position of a general point, where the M matrix needs to be changed accordingly.

We can obtain the positions of the 15 important joint points that we need to reconstruct the human body, and over time, accurately obtain the behavior data of each frame, so we can realize the reconstruction of the three-dimensional model of the human body. Fig. 3 is a three-dimensional human body pose reconstructed by using sensor data to analyze the data.

2.5. Analysis of spatial kinematic parameters of human motion

The human actions studied in this paper are based on the daily behavior of the human body, and its significance lies in that it can provide us with valuable movement information. To analyze the different behaviors of the human body, we need to understand some basic spatial kinematic parameters of human motion, mainly including: displacement, velocity, acceleration, joint angle change, joint angular velocity, trunk angle, rotational inertia, etc. The relevant parameters of the main research content of this paper are shown in Table 1.

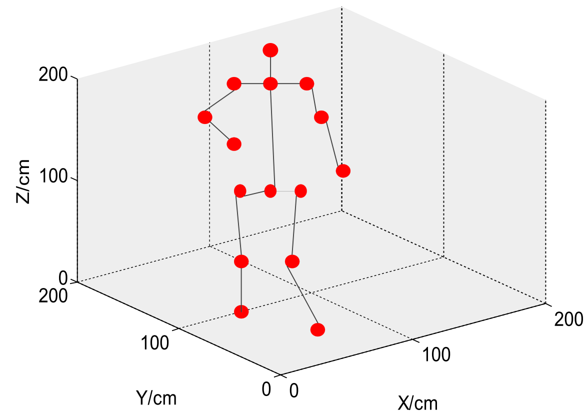

Fig. 3. Reconstructed 3D human body posture using sensor data.

Table 1
Spatial kinematic parameters of human motion.

Parameter number	Parameter description
Speed	The displacement increment per unit time is the speed. The joint velocity is a vector, it also contains direction information, and its direction is the direction of change of the joint position.
Human joint angle change value	The movement system of the human body is actually the movement of the limbs around the joints, so the joint angle is a very important change in the analysis of human movement, that is, the angle change of each joint when it moves.
Moment of inertia	The rotational inertia of a person rotating in situ is the product of the mass of each point of the human body and the square of the distance from that point to the axis of rotation.
Joint angular velocity	Joint angular velocity is the change value of joint angular displacement per unit time. The change of human joint angle is a very important parameter in human behavior analysis.
Torso angle	According to the definition of human kinematics, the angle between the trunk of the human body refers to the angle. The angle of the torso also characterizes the posture of these movements. Therefore, the angle of the torso is also a very important spatial gesture.
Acceleration	The speed increment per unit time is acceleration. The joint acceleration is a vector like the speed, which reflects a change in the speed of the joint motion of the human body.

3. Multi-level hierarchical capture algorithm of human posture based on wsn wireless body area network

3.1. Human posture feature selection

In order to make human posture easy to learn and apply, the following two principles need to be grasped when designing human posture actions: (1) Human posture should be easily recognized by the computer, no matter what technology is adopted, the human posture is executed so that it can be correctly recognized for the ultimate goal; (2) Human posture should be as simple as possible, so that the operator does not need to spend too much time in learning this posture, and also reduces the burden of understanding. In this way, the posture of the human body is convenient for the operator to grasp and use, and is convenient for application in actual operation. Therefore, the human postures defined in this article are all common human postures in daily life.

In this paper, the following four characteristic parameters are used to recognize human posture, as follows:

(1) Human acceleration vector magnitude

SVM (Signal Vector Magnitude) is the square of the acceleration values of the three axes collected by the system and the modulus value. SVM characterizes different intensities of movement corresponding to different values. The more intense the exercise, the greater the value, which is an important parameter for identifying the human body's movement status. The movement state of the human body can be divided into violent exercise and non-vigorous exercise. When the human body performs vigorous exercise, the SVM value will increase accordingly. We choose an appropriate threshold to distinguish between vigorous exercise and non-vigorous exercise, and initially classify the state of human movement.

$$SVM = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{6}$$

In the formula, a_x, a_y, a_z are the acceleration of X, Y, Z axis respectively.

(2) Heading angle θ_x, pitch angle θ_y, roll angle θ_z and range R

θ_x is the heading angle. When rotating around the X axis, turning left is the positive angle parameter. θ_y is the pitch angle. When rotating around the Y axis, the backward angle is the forward angle parameter. θ_z is the roll angle. When rotating around the Z axis, the right angle is the forward angle parameter. We calculate the maximum angle R_x, R_y and R_z of the rotation of the human body posture in a sampling time that can be represented by the range R of each coordinate axis angle. According to the collected angle data, it can be preliminarily judged whether the user's running motion is smooth or a sudden fall occurs.

$$R_y = \theta_{y\max} - \theta_{y\min} \tag{7}$$

In the formula, θ_{ymax} is the maximum value of the angle of rotation in the unit time of data collection, and θ_{ymin} is the minimum value of the angle of rotation in the unit time of data collection.

(3) Three-axis angular acceleration ω_x, ω_y, ω_z and range r

The hardware system adopted in this paper can collect the angular acceleration ω of the three axes of the human body coordinate system when the human body changes its posture in real time. Different postures have different rotation angles around the human body coordinate system, and the rotation speeds are also different. When the body is violently swaying, it may be that the stroke patient suddenly twitched, so the real-time detection of the extreme r of angular acceleration is important for the doctor to quickly find the condition.

$$w = \frac{d\theta}{dt} \tag{8}$$

$$r = w_{\max} - w_{\min} \tag{9}$$

where θ is the angle of rotation, ω is the angular acceleration, t is the infinitely small time period, ω_{max} is the maximum value of the angular acceleration in the collected data, and ω_{min} is the minimum value of the angular acceleration in the collected data.

(4) Three-axis displacement S

The hardware system adopted in this paper can collect the acceleration of the three axes of the human body coordinate system. Integrating the collected acceleration value once is the speed in that direction, and integrating it twice results in the displacement in that direction. Different displacements will be generated according to different postures, which can facilitate the doctor to calculate the amount of exercise and movement method for the reconstructed patient. The three-axis displacement will be used as an important attitude detection parameter.

$$S = \iint a dt \tag{10}$$

where a is the acceleration of any number of axes, and S is the displacement of the attitude on the corresponding axis.

3.2. Multi-level hierarchical recognition algorithm for human pose

The multi-level hierarchical recognition algorithm of human posture is mainly used to recognize the different actions of the human body when the wireless body area network is applied. This paper recognizes a total of four postures, from standing to sitting, from standing to squatting, from standing to running and walking. The designed multi-level hierarchical human pose recognition algorithm is mainly divided into 3 levels, each level is classified according to the characteristics of the gesture itself, and the latter

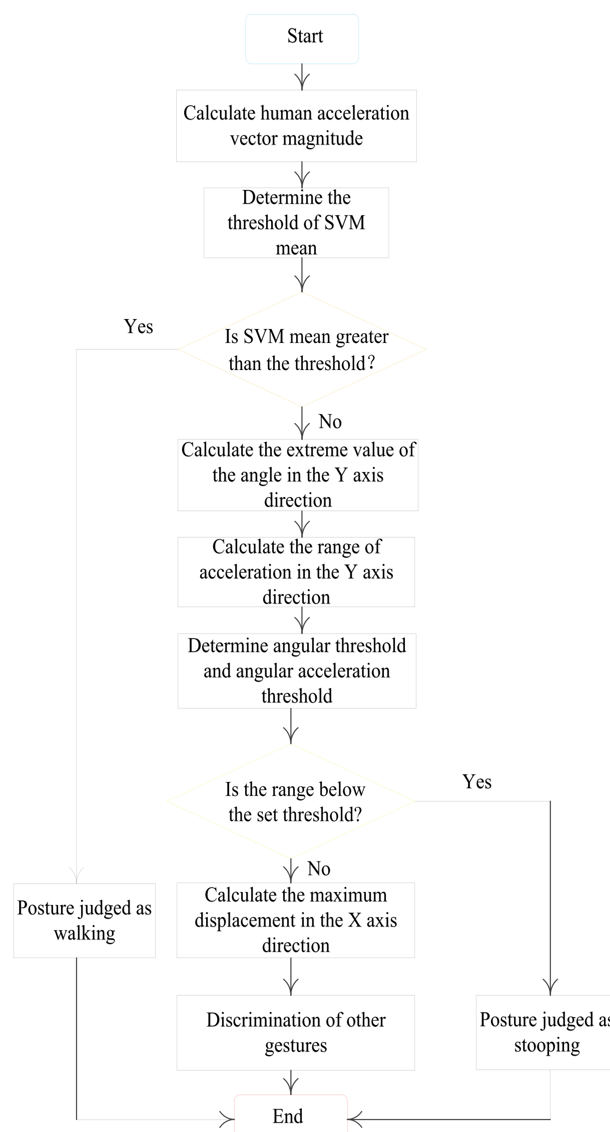

Fig. 4. Flowchart of multilevel hierarchical recognition algorithm for pose.

level algorithm continues and refines the gesture recognition of the previous level. The specific recognition process is shown in Fig. 4.

The first level designs the SVM value as the criterion. According to the analysis of experimental data, we select the appropriate threshold. According to the selected threshold a, the four postures are divided into vigorous exercise and non-vigorous exercise. SVM values greater than the threshold are defined as vigorous exercise, including running. SVM values below the threshold are defined as non-vigorous exercise, including sitting, squatting, running, and walking. The first level judges that the four postures involved in this paper continuously appear within 60 s. The posture with 3 peak sampling points above the threshold is regarded as walking, which is defined as A1 posture, and the one below the threshold is defined as A2 posture.

In the second stage, the range R_Y of the angle in the Y axis direction and the range r_y of the angular acceleration in the Y axis direction are used as criteria. According to the characteristics of different postures of the human body, it can be found that in A2, when the human body walks, the three angles of θ_x, θ_y, and θ_z will hardly change much, and the calculated range of the Y-axis direction angle is $R_{Y.}$ The value of the range r_y is relatively small. When the human body is in the three postures of sitting, squatting and running, R_Y and r_y will change greatly. Therefore, according to the set angle threshold b and angular acceleration threshold c, when R_Y is greater than b and r_y is greater than c, it is judged as "sitting, squatting, walking".

The third level integrates the acceleration of the measured data in the X-axis direction twice to obtain the displacement of the human body in the X-axis direction (d_x) as the criterion. The displacement of the waist when the body changes from the standing position to the sitting position should be less than the length of the thigh (d_1). When the human body changes from a standing position to a squatting position, the displacement of the waist is greater than the length of the thigh (d_1) and less than the length of the entire leg (d_2). According to the characteristics of the above three postures, different thresholds for the displacement in the X-axis direction are selected according to the experimental data to distinguish the three postures.

3.3. Simulation experiment and result analysis

The design of the experimental system is mainly to collect the original data for the human body gesture recognition algorithm. The system is suitable for the transmission protocol of the wireless body area network. The system has the functions of recording, playing back and storing the original data, recording the experimental data into the original data set of the verification algorithm. In addition, the device is required to have the characteristics of wearability, real-time data measurement and high stability.

To sample the collected data, in order to make gesture recognition more accurate, the sampling frequency used is 120 Hz. The pose data set has four kinds of pose data, a total of 240 sets of data for each 60 groups as the sample population. After normalization and standardization, the data is put into the data set and stored in excel format files, with a total of 240 excel files. An excel file includes the angle, angular acceleration, and acceleration data of a posture, and the length of time is 60 s. There are 300 rows of data and 3 columns of data in each excel file.

Normally, the raw data collected by the acceleration sensor includes not only acceleration data generated by different motion behaviors, but also some gravity acceleration data and noise data. Noise data is generally caused by factors such as measurement noise of the acquisition equipment and human body shake, which is not conducive to subsequent feature extraction and gesture recognition, so researchers generally preprocess the original data before feature extraction and selection. Common data preprocessing methods usually include windowing, denoising, normalization, correction, etc.

In the process of monitoring and recognizing human posture, generally the user's acceleration data in a period of time is acquired, and its length is very long, which is not suitable for direct feature extraction and posture recognition. Therefore, the raw acceleration data is usually windowed. Windowing refers to dividing long acceleration data into many time segments with the same length. Each time segment is called a window, and the overlap between different windows is 50%. By windowing the original acceleration data, it can not only be regularized, the length of the acceleration data of different users is also conducive to researchers to choose the appropriate data length according to the actual situation, which is obviously very important for subsequent feature extraction and gesture recognition.

(1) The first level algorithm

We calculate the SVM value of each posture. According to a large number of experimental data, the SVM value during running will be significantly greater than the other three postures. The value of threshold a is 1.2 g, and the SVM value of three consecutive sampling points is greater than 1.6 g (that is, the duration exceeds 30 ms) as the criterion of the first-level algorithm. The peak group with three points exceeding 1.6 g within three seconds of running is judged as running, otherwise it is judged as walking, sitting and squatting (see Fig. 5).

(2) Second level algorithm

According to the measured experimental data, Fig. 6 (a) and 6 (b) are the sampling data of the angles and angular accelerations of the four attitudes in A2. We calculate the angular range R_Y and angular acceleration range r_y of the four postures. When selecting the angular range threshold b and the angular acceleration range threshold c, the recognition rate under different values of b and c needs to be weighed.

(3) The third level algorithm

The representation of the human posture is mainly based on the characteristics of the sensor signal when the operator performs specific actions to complete the establishment of the human posture model. The selection of human posture model is very important for wireless human posture recognition system. The choice of model should depend on the specific application. To realize the free operation of the operator and the natural human–machine

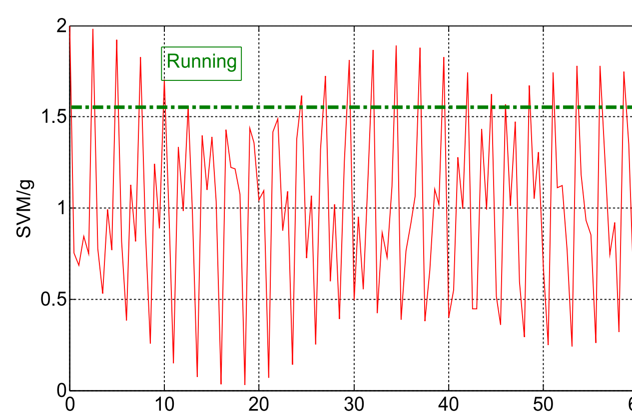

Fig. 5. SVM value change of running posture.

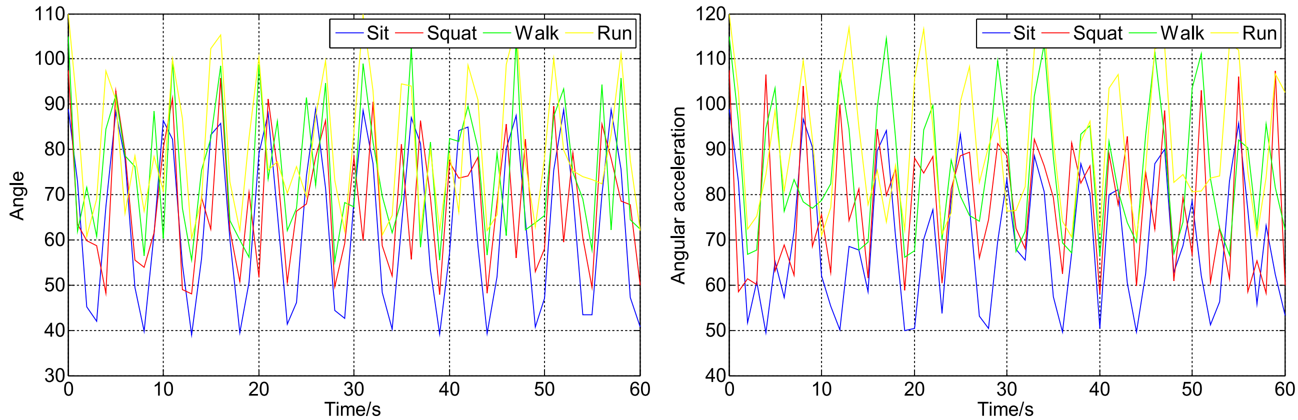

Fig. 6. Changes in angle and angular acceleration of sitting, squatting, walking and running.

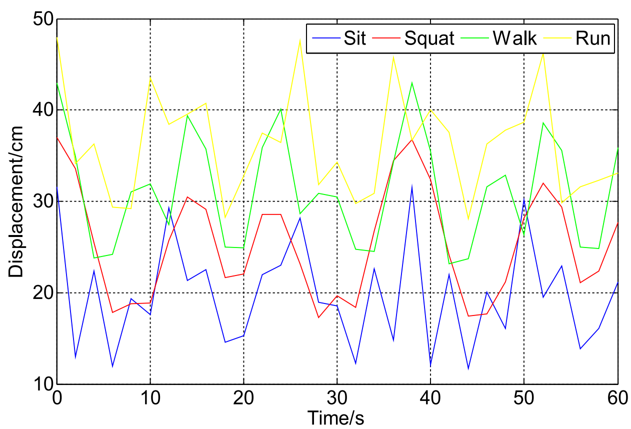

Fig. 7. X-axis displacement diagram of sitting, squatting, walking and running.

operation, an accurate and effective human posture model needs to be established.

The X-axis acceleration a_x data measured in the experiment is integrated twice in succession to calculate the maximum displacement in the X-axis direction. In the experiment, the average length of the experimenter from the waist to the knee is 30 cm, and the average length from the waist to the heel is 45 cm. Through 60 experiments, the maximum displacement of running is 48 cm. In this paper, β is selected as 15 cm. Fig. 7 is the displacement curve after two integrations in one experiment.

Based on the above experimental methods and algorithms, we have done 60 sets of experiments. The results of the experiments, that is, the error rate of the gesture recognition algorithm, are shown in Table 2. The recognition rate for sitting position is 90%, the recognition rate for squatting is 97%, the recognition rate for running is 100%, and the recognition rate for walking is 91%. The overall recognition rate achieved in this experiment is 94.5%.

4. Medical health monitoring of wearable wireless sensor network

4.1. Performance analysis of wireless sensor networks

Through the establishment of wireless sensor networks, data transmission between sensor nodes and nodes, and between nodes and gateway nodes is realized. According to the analysis of networking requirements, the goals of the wireless mesh networking test of this system are:

(1) Whether all nodes except the gateway node have routing function;
(2) Whether each node has self-organizing network function and has high stability;
(3) Whether the wireless sensor network has strong network self-healing ability;
(4) Whether the gateway node has high gateway reliability.

The interference when only considering the channel propagation of the node without adding any network protocol is called the original interference. The essence of the original interference is the collision caused by a node processing the concurrent events. The research community subdivides the original interference problem into the first and second types of interference problems.

The first type of interference problem is the interference caused by two or more data sending nodes accessing the same channel at the same time. The interference caused by a node transmitting and receiving data at the same time is also called the first type of interference.

The second type of interference problem is the interference caused by a node receiving data packets from multiple nodes at the same time. In this case, all data sending nodes compete for the only receiving node, and finally only one node can successfully compete, while the other sending nodes become interfering nodes of this node.

Table 2
Error rate of multilevel hierarchical recognition algorithm.

	Experiments	Sitting	Squatting	Walking	Running	Correct times	Wrong times	Recognition rate
Sitting	60	54	4	1	1	54	6	90.1%
Squatting	60	1	58	1	0	58	2	97.3%
Walking	60	1	1	55	3	55	5	91.0%
Running	60	0	0	0	60	60	0	99.8%
Overall	240	56	63	57	64	227	13	94.5%

Physical interference refers to the comprehensive consideration of multiple technologies such as codec and modulation and demodulation of the physical layer of the network, and directly measures the amount of interference received by the node at the physical layer. As a common open resource, wireless spectrum allows multiple nodes to access the same channel at the same time, which will lead to the collision of data packets, so that the data packets cannot be correctly received by the receiving node, thereby affecting the quality of data transmission.

The physical interference model comprehensively considers factors such as concurrent transmission node set, node transmission and reception power, transmission distance and channel attenuation. It clarifies the nature of wireless network interference from the perspective of the physical layer and gives the amount of interference received by the node. Compared with the protocol model, this model can reflect the interference situation of the nodes more realistically, but it is not intuitive enough. Since the interference caused by the multi-hop shared wireless channel is directly related to the specific geographic location of the node, the interference model can be further transformed into a network graph model. The geometric process of the above interference model will be more conducive to the research and development of WSN communication protocols design.

Since WSN nodes have limited transmit power, each node has a limited signal coverage. The sending activity of a node can be sensed by the nodes within the coverage area, and the closer the node is to the node, the stronger the signal strength is. Conversely, the node farther away from this node will perceive the signal strength.

In a wireless communication system, if a signal is within the perception range of a node in the network, it does not mean that the signal can be successfully received. Only when the signal strength received by the receiving node is higher than the node's receiver sensitivity can the signal be correctly received by this node.

The transmission power of a node has a direct impact on the degree of network competition. Nodes can change the size of their transmission radius by adjusting the transmission power, and then adjust the size of the collision domain of the network to achieve the purpose of reducing network interference. However, lower transmission power will weaken the capture effect at the receiving end, but will increase the network interference.

Generally, the product of the transmit power and the sensing threshold satisfies the condition that the product of the two is a constant. Therefore, the anti-interference can also be achieved by adjusting the sensing threshold of the receiving node, which has the same effect as adjusting the transmitting power of the transmitting node.

Each sending node has its own shielding area, which requires the node's perception radius to be greater than the transmission radius. This determines that the node can adjust its transmission radius and perception radius through power control to meet the sufficient and necessary conditions that the node defined in the model can successfully send data, so as to achieve the goal of reducing network interference.

Transmission on channels with poor channel quality requires more energy to retransmit data or resist interference. Similarly, the channel switching to a channel with a large difference from the original channel also consumes more energy. In view of the fact that WSN belongs to an energy-constrained network, the channel allocation designed by this algorithm is based on the principle of energy saving. The channel with the higher anti-interference and channel switching energy cost has a lower probability of being selected. The anti-jamming capability results are shown in Fig. 8.

The working frequency band of the wireless sensor network is 2.4 GHz, which is in the same frequency band as common communication technologies Wi Fi and Zigbee. For example, if wireless sensor networks are used in hospitals, homes, or public areas, there may be other devices that use Wi Fi or Zigbee, whether they will affect and interfere. Compared with Zigbee, due to the widespread use of Wi Fi, there is a greater chance of impact or interference on the wireless sensor network.

Although the non-overlap of wireless sensor network channels and good channel allocation strategy can be distributed to different channels of nodes, the channel and frequency of wireless sensor network and Wi Fi will overlap. It is also highly likely to coincide with other wireless devices on the same frequency channel. Therefore, when the wireless sensor network coexists with Wi Fi, it is highly likely that performance interference will occur.

4.2. ECG terminal node monitoring and body temperature node monitoring

Fig. 9 shows the result of denoising the ECG signal using db5 wavelet in the Matlab environment. As can be seen from the two marks in the figure, the abnormal noise between the two pulses is largely eliminated. We can judge that the denoising algorithm is effective.

The body temperature sensor is integrated on the sensor board. When the sensor board is worn on the patient's body, the sensor

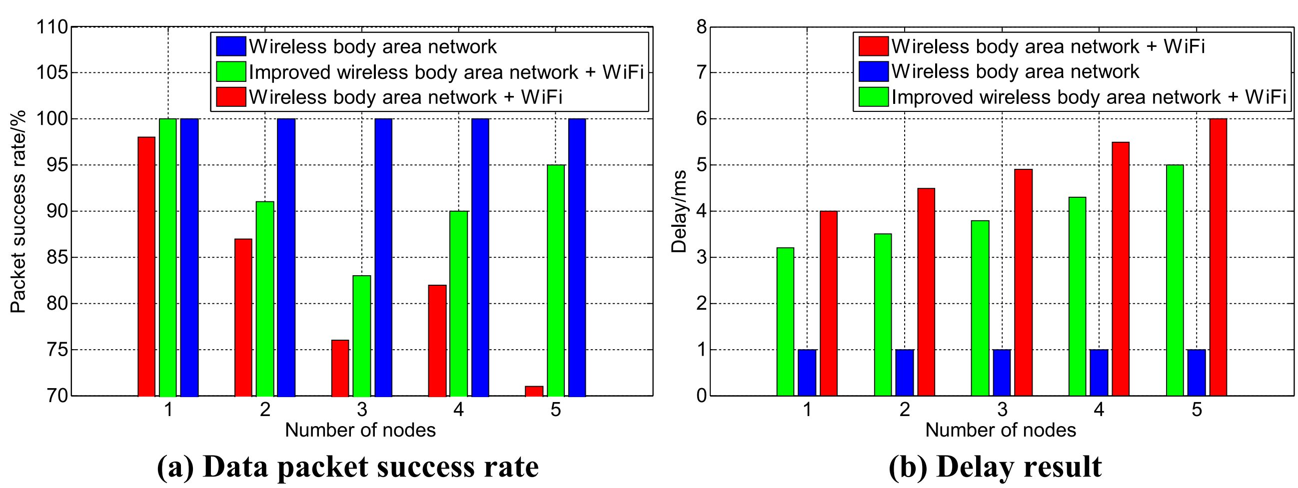

Fig. 8. Anti-jamming capability results.

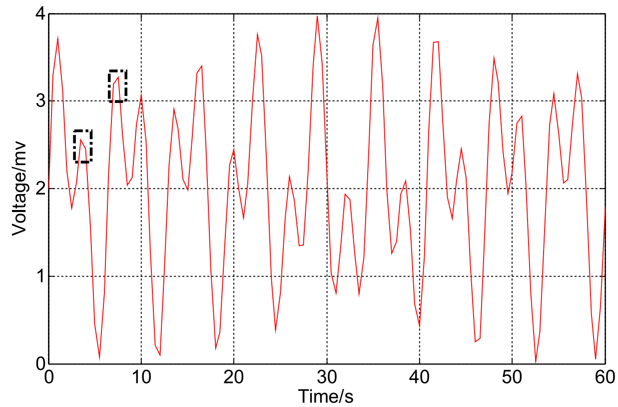

Fig. 9. db5 wavelet denoising the ECG signal.

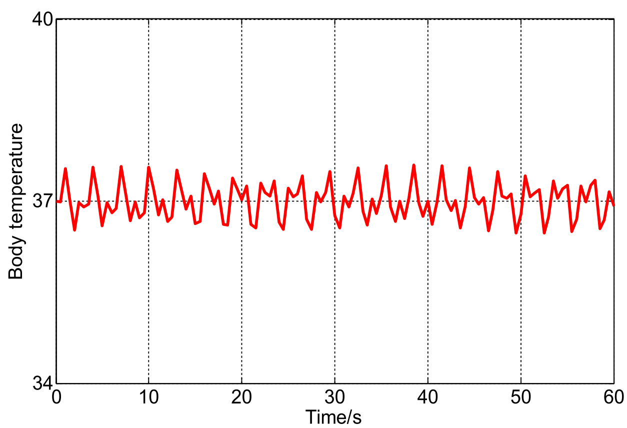

Fig. 10. Body temperature collection and monitoring results.

contacts the body and can collect body temperature in time. The temperature change of a patient is shown in Fig. 10.

4.3. Monitoring of EMG terminal nodes

The waveform of the EMG signal acquired when the arm is relaxed to the tight state is shown in Fig. 11.

This paper specifically uses sym8 wavelet to de-noise multiple sets of EMG signals collected continuously. Fig. 12 is the result diagram of denoising the surface signal using sym8 wavelet under matlab environment. The result shows that the EMG signal after

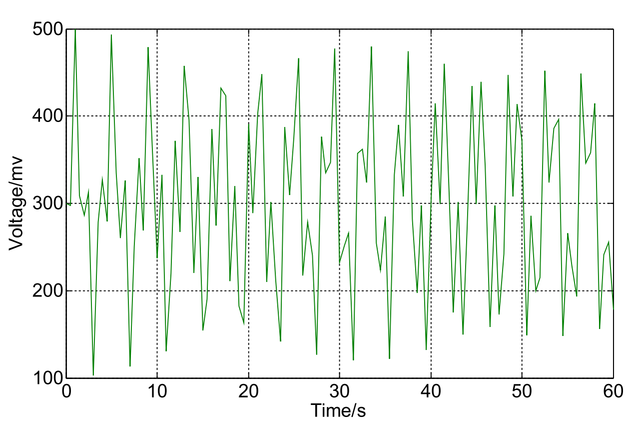

Fig. 11. EMG signal acquisition waveform.

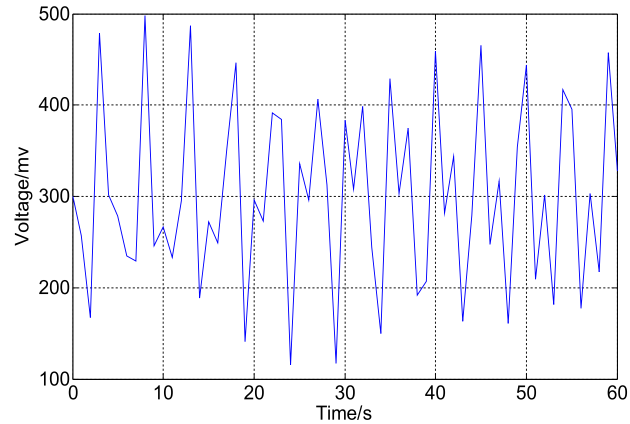

Fig. 12. Result of EMG signal denoising.

noise reduction is smoother. It can be seen from the figure that the EMG signal after denoising is smoother and the abnormal noise is significantly less.

Fig. 13 is a diagram of the feature recognition of the main wave of EMG signal in Matlab environment. The original signal is the signal collected by the subject continuously performing arm muscle contraction and relaxation exercises.

4.4. Movement position node monitoring

The reason for the gyro sensor drift is the disturbance torque acting on the gyro sensor. There are many factors that can generate interference torque, and they can be divided into two categories according to their nature and changes. One is deterministic interference torque, and the other is random interference torque. The size and change law of the first type of interference torque can be obtained through experiments or calculations. Therefore, the drift caused by this type of interference torque is regular and determined, which can be called a systematic drift, which is carried out systematically when manufacturing gyro sensors make up. The other type is that the disturbance torque is random. The drift caused by this kind of disturbance torque is called the random drift of the gyro sensor. The random drift can only be statistically estimated to estimate its probability and statistical characteristics, and then be compensated.

Random drift is difficult to express by a fixed mathematical formula, because it is constantly changing with time. The usual method of signal processing for gyro sensors is to conduct statistical tests on the gyro sensor signals. We perform statistical analysis on the data obtained from the experiment, calculate the variance and correlation function, use the variance and correlation function to express its random process, and finally use it to represent the random drift of the gyro sensor. Kalman filter technology is commonly used to reduce the effects of random drift. Because the randomness of most interference factors causes the gyro sensor drift, the gyro sensor drift can be regarded as a random process. Even if the conditions remain unchanged during the drift test, the obtained test data will be a random time series. The mathematical model of the gyro sensor drift can be expressed by statistically related mathematical expressions of random time series.

It is moved at different angles, and the horizontal movement is defined as the X axis, the horizontal forward and backward movement is the Y axis, and the longitudinal movement is the Z axis. Fig. 14 shows the four groups of motion sensor parameters.

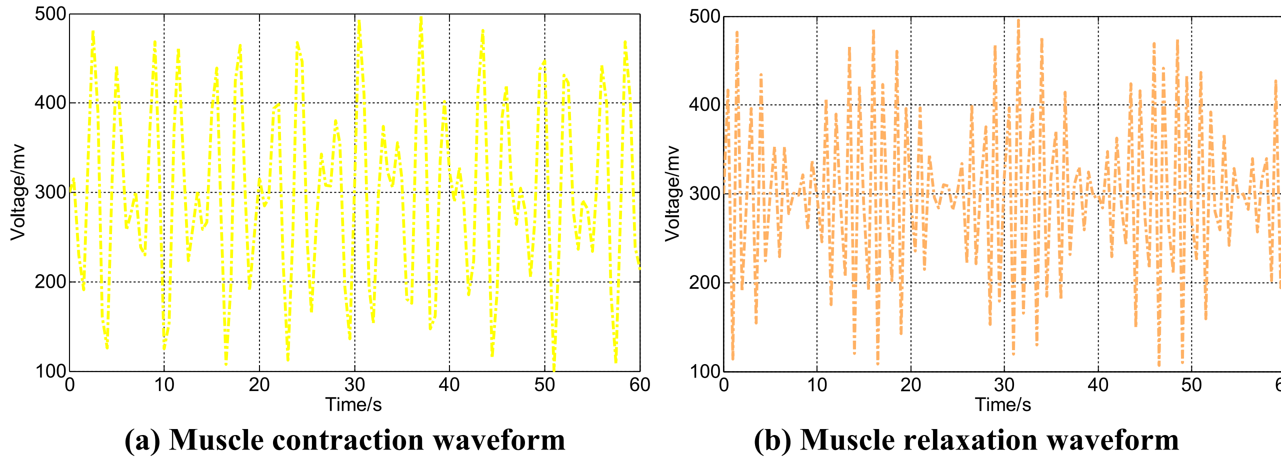

Fig. 13. EMG signal characteristic main wave extraction diagram.

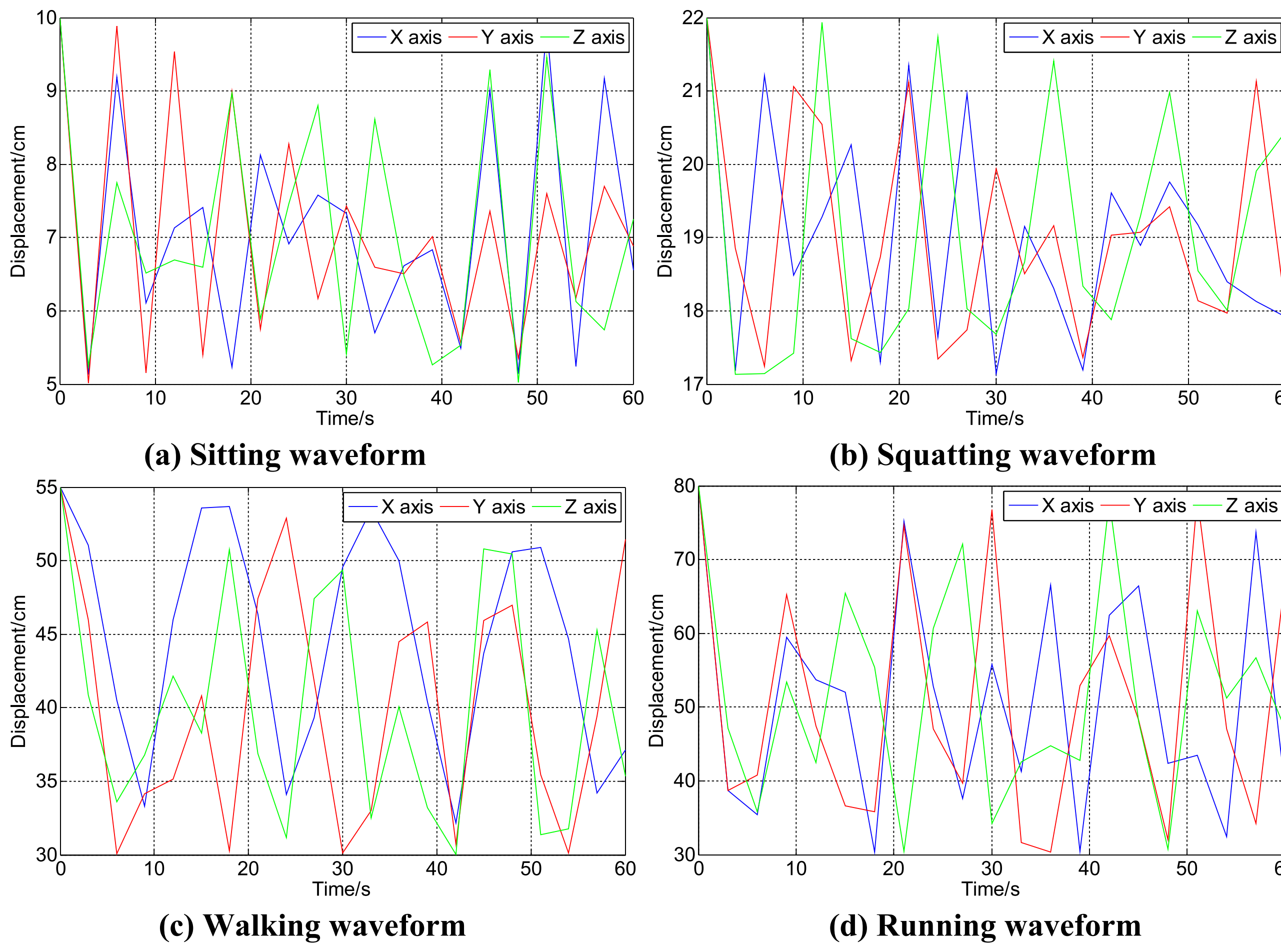

Fig. 14. Movement position waveform.

5. Conclusion

By introducing the motion signal capture and original processing equipment of the motion sensor, the selected human body model method is analyzed. The three-dimensional hierarchical model of the human body based on constraints in three-dimensional space is selected for design. The spatial pose of human motion is analyzed, which lays the foundation for the design of recognition algorithms for daily behaviors. A multi-level hierarchical recognition algorithm for human posture based on wireless body area network is proposed. The structure and calculation method of the entire algorithm are clarified in detail. A large number of data measurements are collected through the MEMS nine-axis acceleration gyroscope. Using the acceleration vector amplitude, angle, angular acceleration and displacement and other parameters, as well as the analysis of the actual measurement data, the four postures of sitting, squatting, walking and running can be accurately identified. Experimental results show that compared with traditional recognition algorithms, the proposed algorithm has high recognition rate, fast speed and simple and reasonable recognition result. This algorithm has laid the foundation for human body posture recognition system in wireless body area network. The next step is to design a database to store the patient's posture and physiological information for the monitoring staff to track and observe the patient's condition, and design a remote data transmission mechanism, so that patients can transfer information to the hospital's monitoring system without leaving the house, thereby enjoying the convenience brought by telemedicine.

Declaration of Competing Interest

The authors declare 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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