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Real-Time Monitoring System of Exercise Status Based on Internet of Health Things Using Safety Architecture Model

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ABSTRACT As an emerging field of information technology, the Internet of Health Things has attracted great attention from governments, scholars, and related enterprises, and is seen as a major opportunity for development and change in the information field. The European Commission believes that the development and application of the Internet of Health Things will make a significant contribution to solving modern social problems in the next 5 to 15 years. In this paper, the corresponding motion detection algorithms such as pacing detection algorithm, sleep quality and sedentary reminder detection algorithm are designed for real-time detection of motion status. In addition, this paper builds a new safety architecture model based on real-time motion detection, and proposes a time-domain feature-based motion detection method for walking, walking upstairs and walking downstairs. The original acceleration signal is smoothed and denoised using a sliding-average filter. The acceleration signal is segmented by a rectangular window with 50% overlap, and the variance, X-quartile difference, and X-axis bias coefficient are extracted from a single time window.

INDEX TERMS Safety architecture model, real-time monitoring system, exercise status, Internet of Health Things.

I. INTRODUCTION

The basic idea of the Internet of Health Things (IoHTs) emerged in the late 1990s and was first mentioned in 1999 in a networked radio frequency identification (RFID) system proposed by the Massachusetts Institute of Technology's (MIT) Automatic Identification Center (Auto-K) [1]. International Telecommunication Union (ITU) officially defined the concept of the ''Internet of Things'' and subsequently published the Eventide TU Internet Reports 2005 the Internet of Health Things. The main thrust of the Internet of Health Things is that a vast network of sensor devices, such as radio frequency identification devices, infrared sensors, global positioning systems, laser scanners, and other assemblies, can be combined with the Internet [2].

Its purpose is to connect all objects and networks to each other, and through information exchange and communication, realize the system's automatic identification, location, tracking, monitoring and management of objects and other events. IoHTs has a wide range of applications, including smart city, intelligent transportation, smart home, environmental monitoring, lighting control, personal care, food inspection and other fields. In recent years, people's quality of life has been improving, with more and more people suffering from obesity, and the incidence of various chronic diseases such as hypertension, hyperlipidemia, and cardiovascular and cerebrovascular diseases is also increasing [3]–[7]. Therefore, appropriate physical exercise is essential. In the early days, the basic function of pedometers was to count steps, which helped users count the total number of steps in a day for walking, running, and other sports, and to calculate the distance and calorie consumption according to relevant formulas [8]. With the rapid development of sensor technology and people's kinematic malefactors, sports bracelets with integrated heart rate monitor, barometer, gyroscope, three-week acceleration sensor, etc. have entered our daily life, and the new sports bracelets not only add a variety of sports modes, such as walking, running, swimming, etc., but also provide heart rate detection, barometric pressure detection and other new functions [9].

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For people who are increasingly concerned about their health, these new sports bracelets can effectively provide exercise information to help them make reasonable exercise plans and achieve the purpose of exercising and boosting immunity [10]–[14]. In addition, the advancement of science and technology brings the rapid development of society, people's life pace is also accelerating, life pressure is also increasing, and sleep disturbance is becoming more and more prominent. According to a survey by the World Health Organization, 27% of people worldwide are troubled by sleep problems, while the "China Sleep Quality Report" points out that 36.2% of people fail to pass the quality of sleep, which seriously affects people's quality of life. Not only young people face pressure to stay up all night insomnia, unable to sleep and other sleep problems, the elderly are also common among the hard to sleep, easy to wake up, tired after sleep and other sleep problems. Sleep is an essential life activity in people's lives, accounting for nearly 30% of life time, good sleep is critical to human health [15]. Therefore, it is very necessary to monitor human sleep, discover sleep problems in time, and solve sleep problems. Traditional sleep detection sleep detection means mainly include polysomnography sleep monitoring system, sleep detection based on eye movement, heart rate and video sleep detection, etc. With the rapid development of micro-sensors, sleep detection based on body movement has gradually entered into people's vision, and body movement sleep monitoring mainly uses the amount of activity in the detection of human sleep state for discriminant analysis.

Basic human sleep conditions, such as smartphones, sports bracelets, and so on. Wearable devices have small size, simple operation, portable and other characteristics, but the relative range is also relatively lacking, so power consumption has been a constraint on the popularization of wearable devices. In order to improve the user experience, some existing sports bracelets carry out motion and sleep detection functions in parallel, resulting in a sharp increase in power consumption. There are also some sports bracelets that use buttons to manually select functions to reduce power consumption, but this is troublesome for human-computer interaction. There are also some sports bracelets that transmit the recorded movement data to the cell phone via Bluetooth or WiFi, where the algorithm is processed to reduce power consumption, but they require the bracelet and smartphone to stay connected for a long time. To address the above problems, this paper firstly designs corresponding motion detection algorithms for wearable devices, such as pedometer detection algorithm, sleep quality and sedentary reminder detection algorithm; secondly, defines the working mode of the device, and completes the automatic conversion process between the algorithm and the working mode to implement different motion detection algorithms under different working modes, in order to ensure the accuracy of the algorithm performance as much as possible. Then, by integrating each motion detection module into the main flow of the software system, a complete motion detection software system for wearable devices is realized, as shown in Figure 1; finally, it is applied to sports bracelets to complete a wearable device product with practical application value and provide users with a better experience.

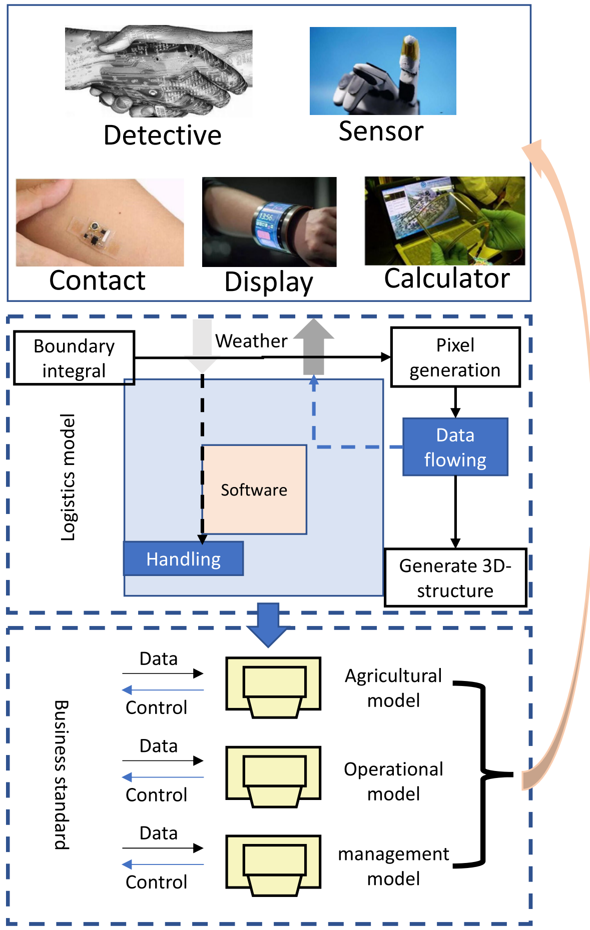

FIGURE 1. Internet of health things-based motion detection system.

This article mainly studies motion detection algorithms, including exercise intensity classification and detection methods for three daily activities of walking, going upstairs and going downstairs; and designed and implemented software to monitor student exercise intensity, including wearable devices and transit base stations. In Part II, this article first summarizes the relevant reports. In Part III, in view of the low power consumption characteristics of wearable devices, this paper studies the data preprocessing of acceleration signals suitable for transplantation on wearable devices, and then proposes three activities for walking, upstairs and downstairs. In Part IV, this paper studies how to use the acceleration sensor to detect some daily activities and monitor the exercise intensity of students in real time, and study the exercise detection algorithm. This chapter mainly focuses on the detection of the three types of exercises of walking, going upstairs and going downstairs, and the classification of exercise intensity. In Part V, this paper constructs a new type of safety architecture model based on real-time detection of motion status, and proposes a detection method for walking, going upstairs and going downstairs based on time domain features.

II. RELATED WORK

Sensor-based human motion pattern detection is usually divided into two categories from the research content: gesture detection and motion detection. The digital signal processed by motion detection is the acceleration signal generated by the human body during daily activities (for example, walking, running, going upstairs and going downstairs, etc.) [16]–[19]. The acceleration signal processed by the motion detection is long, and the signal contains the repetitive information of the motion. With the rapid development of MEMS technology, MEMS products are widely used in projectors, notebooks, mobile phones, PDAs, etc. Researchers use MEMS for some simple gesture detection.

Ma, Y *et al.* pointed out that in terms of motion detection, basic movements such as walking, running, sitting, and standing in daily life can also be successfully detected [20]. They concluded that the sensors can be used to detect the daily activities of the elderly in real time, especially the occurrence of falls, in order to detect danger in time and ask for help. Human-computer interaction based on acceleration sensors to obtain human body motion information is also attracting attention in the game field. The ''WIISports'' gamepad designed by Nintendo of Japan integrates an acceleration sensor to reflect the movement of the player's upper limbs in virtual games.

Carboni, M and others pointed out that various software such as pedometers can be fully utilized in various fitness applications on mobile phones [21]. Existing studies have shown that sensor-based human motion pattern detection belongs to an emerging branch in the field of pattern recognition [22]. They concluded that the acceleration signal generated by human movement for a period of time is acquired through the acceleration sensor, and the data is transmitted to the motion detection device, and then the data is preprocessed. The preprocessing operations generally include: smoothing, denoising, resampling, and normalization. Then the pre-processed acceleration signals are sent to the feature extraction module, and their feature values are extracted through a certain feature extraction algorithm and selected to form feature vectors. Finally, the type of motion is determined according to the feature matrix formed by extraction. Perform training and testing [23]. Figure 2 shows a typical human motion pattern detection process based on acceleration sensors.

In addition, Pasman *et al.* pointed out that the signal collected by the acceleration sensor not only contains the body acceleration signal generated by human motion, but also the gravity acceleration component and noise [24]. They studied some commonly used denoising methods, including median filter, FIR low-pass filter, moving average filter, Kalman filter, and five-point cubic smoothing method. There are low-pass and high-pass filters for the separation of gravity components. In addition, they also mentioned that combining gyroscope data, they proposed a gravitational acceleration fusion separation preprocessing method. In order to obtain a better recognition effect. They proposed a variety of methods

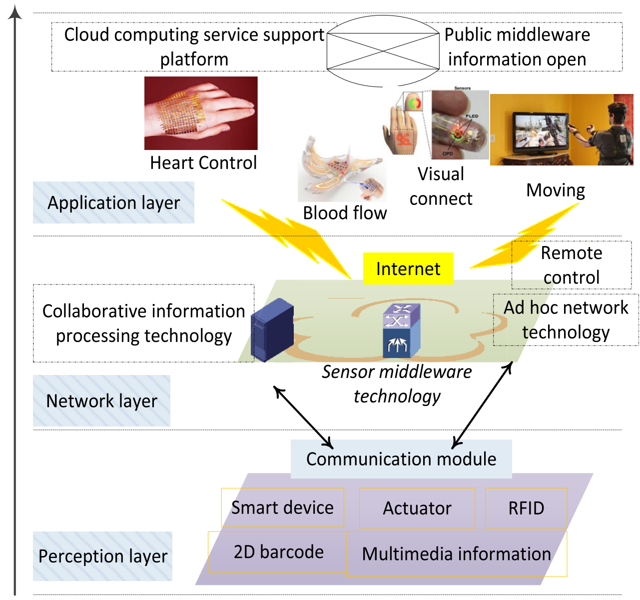

FIGURE 2. **Block diagram of human movement pattern detection.**

for extracting features from acceleration. The methods for extracting features from acceleration mainly include three methods: time domain method, frequency domain method and time-frequency method. The advantage of the time domain method is that the method is simple and the amount of calculation is small; while the frequency domain method and the time-frequency method are relatively complex, but the features extracted by these two methods can achieve high accuracy in pattern recognition [25].

The classifiers often used in human motion detection mainly include C4.5 decision trees, k nearest neighbors, hidden Markov models, dynamic time warping, support vector machines, and hybrid recognition of multiple classification methods. Fan, Z *et al.* proposed a feature extraction algorithm that combines wavelet transform and sample entropy to classify upstairs and downstairs. The extracted features are trained and classified using decision tree classifiers and Bayes classifiers., The three asynchronous states of walking, upstairs and downstairs are detected, but the accuracy of the two classifiers for detecting upstairs and downstairs is not high. Previous scientists placed an acceleration sensor on the human crotch to detect static, walking, running, and jumping actions using support vector machines, and the detection rate reached 92.25% [26]. Someone puts the motion information acquisition device on the waist, and proposes a one-to-one decision tree-based human motion pattern detection method to distinguish between walking on the ground, jogging, going up and down stairs, sitting down, and standing up. Similar motions with similar motion processes still have the disadvantage that the detection results are easily confused. Others fixed two acceleration sensors on the upper limbs of the human body. By collecting acceleration data from two three-dimensional acceleration sensors, the data was preprocessed, and the feature vector was extracted by wavelet transform. Finally, the support vector machine classifies the action to obtain a good distinction effect. Others have proposed motion detection based on the threshold of human acceleration, and proposed a binary judgment method based on the GM threshold, and implemented it on the MCU to detect the daily activities of the human body, such as going upstairs, downstairs, standing, jumping, and walking, etc., [27]–[29].

In summary, the calculations of the algorithms proposed by the researchers are generally too large, and are not suitable for implementation on low-power wearable devices. Moreover, these algorithms cannot quantitatively obtain the physical activity status of students, so it is necessary to study the motion detection algorithm to monitor the amount of exercise of students and detect the type of exercise, and comprehensively consider the calculation and calculation of the algorithm based on the algorithm research. the complexity.

III. IoHTs-BASED REAL-TIME MOTION MONITORING FOR WEARABLE DEVICES

A. MOTION CHARACTERISTIC DATA ACQUISITION

Motion detection based on acceleration data, of course, requires the acquisition of acceleration signals during human motion through sensors and other hardware devices. The quality of the originally collected acceleration signals directly or indirectly affects all subsequent data processing and calculations, so the proper design of the human motion data acquisition module will affect the performance of the entire motion detection process. Therefore, a motion data acquisition module needs to meet the following requirements: durability, adequate sampling rate, unrestricted motion, portability, data transmission and storage, and power consumption. The sampling rate needs to be sufficient to reflect the most realistic human motion. The data acquisition module should ideally be attached to the body or integrated into a handheld device, such as a cell phone or clothing, to better reflect human movement information. In order to obtain sufficient data, the data acquisition module needs to store data for a long period of time, or it needs to be able to store data continuously for several hours. The test subjects wear the device for a longer period of time, which requires less power consumption and smaller size of the device. Researchers have used the ADXL330's hardware acquisition platform to collect acceleration information for jumping, standing, running, and walking; a multi-sensor acquisition device with an integrated accelerometer was designed at the Technical University of Munich, Germany.

In this paper, a motion data acquisition device is designed. The hardware parts of the data acquisition module include an acceleration signal acquisition module, a Bluetooth radio frequency module, an acceleration data storage module, and a microprocessor module with the CC2541 as the core, etc. The block diagram of the data acquisition module is shown in Figure 3. The block diagram of the data acquisition module is shown in Figure 3. The data acquisition module uses the MCU CC2541 as the platform, on which a 3D acceleration sensor is integrated to collect acceleration data during human body movement, and sends the collected data to the

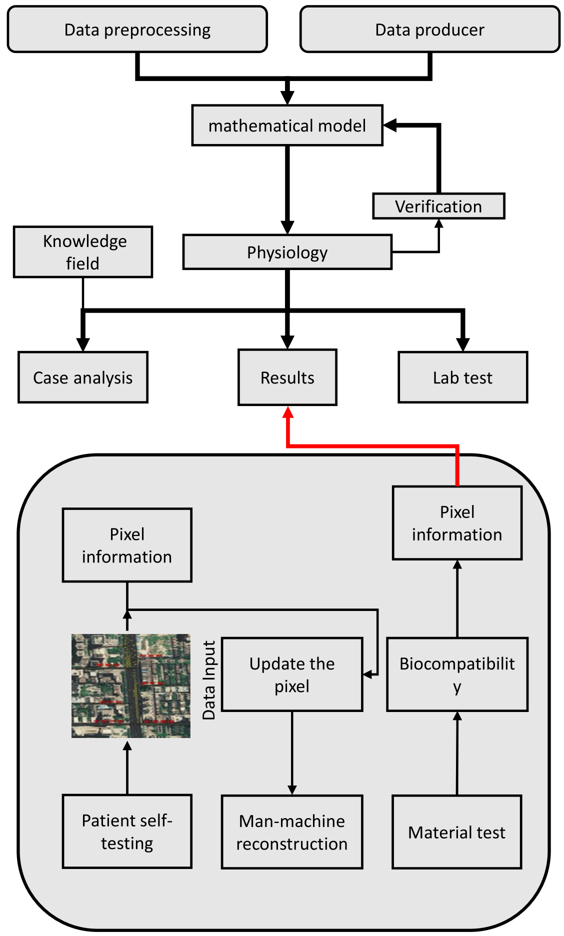

FIGURE 3. Data acquisition module structure diagram.

CC2541. The 3D accelerometer uses a MEMS-based, ultra-low-power ADXL362 3-axis accelerometer. Considering the large size of the motion data and the low power consumption of the device, Bluetooth transmission is not efficient enough for fast real-time transmission, so the 3D acceleration data is dumped from the CC2541 to an off-chip Flash by borrowing the efficiency of SPI transmission. Since a sufficient sampling rate is required to reflect the motion state of the human body, the amount of acceleration data stored for a certain period of time is relatively large. The three-axis acceleration data stored in the Flash is exported by using the software of the host computer to communicate with the serial port for the subsequent study of motion detection algorithms.

The output signal of the acceleration sensor collected by the data acquisition module is superimposed on the following signals: human acceleration component, human gravity component, human jitter, and measurement noise. Since there is a noise component in the human acceleration signal from the accelerometer, the original signal needs to be pre-processed with denoising, smoothing, and windowing. Although non-linear, low-pass, Laplace operator, and high-pass filters can be used to remove high-frequency noise, the gravitational acceleration signal can also be extracted from the raw data by high-pass filters for analyzing the effective components of dynamic acceleration.

When conducting human motion detection experiments with acceleration sensors, since the acceleration sensors can only acquire acceleration signals from specific parts of the human body, how many acceleration sensors are appropriate in order to achieve accurate motion detection accuracy; in which parts of the human body to wear acceleration sensors in order to better detect some daily activities of the human body. In order for accelerometers to accurately capture motion information about daily human activities, the number and location of accelerometer devices should be matched to the type of daily activity being detected. Researchers have used multiple accelerometers positioned on different parts of the body to acquire a more comprehensive picture of the movement of the body in order to accurately capture the movement of some daily activities. One researcher used 30 accelerometers integrated into clothing to detect human movement. Researchers have used 12 accelerometers attached to various joints of the human body to detect movements of the upper and lower limbs of the human body, including walking, standing, and gripping hands. A researcher has designed and implemented a detection system that uses 5 accelerometers simultaneously to detect 20 types of daily movements and achieved a high recognition rate. Although multiple accelerometers worn on different parts of the human body at the same time can improve the accuracy of human motion detection to some extent, the need to wear the sensor device on multiple parts of the body at the same time is awkward and unportable for the tester, which greatly reduces the comfort of wearing it. In addition, the manufacturing cost of the acquisition device and the cost of data processing will increase with the increase in the number of sensors.

B. A CLASSIFICATION OF THE THREE TYPES OF SPORTS

In the actual motion data acquisition process, due to the influence of the external environment and the characteristics of the data acquisition equipment itself, the human motion acceleration signal obtained by the data acquisition module will inevitably be mixed with noise. The noise mixed with the acceleration signal will interfere with the subsequent processing of the acceleration data, so the influence of the noise should be reduced. Here, for typical different sports, we can input different heart, movement indexes to help correct the specific processes. For Basketball, the movement and heartbeats should be more stronger, and the pristine import value was also more large. The output signal of the acceleration sensor collected by the data acquisition module for different sports is superimposed on the following signals: human acceleration component, human gravity component, human jitter, and measurement noise. Since there is a noise component in the human acceleration signal from the accelerometer, the original signal needs to be pre-processed with denoising, smoothing, and windowing. Although nonlinear, low-pass, Laplace operator, and high-pass filters can be used to remove high-frequency noise, the gravitational acceleration signal

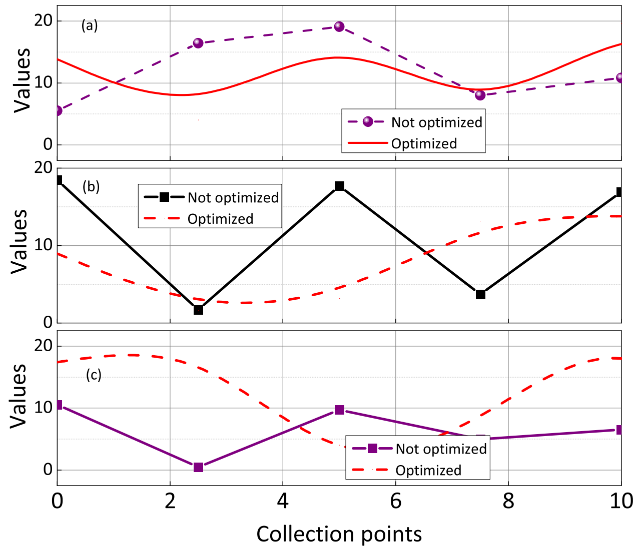

FIGURE 4. Physique monitoring big data platform system architecture.

can also be extracted from the raw data by high-pass filters for analyzing the effective components of dynamic acceleration. However, the above methods are generally computationally intensive and are not suitable for implementation in wearable devices with low power consumption characteristics. In order to filter out the effects of the postures of the collecting device, such as rotation and swaying, on the collected human acceleration, the triaxial acceleration data are synthesized into a one-dimensional acceleration vector. This vector represents the acceleration of the human body during motion, ignoring the influence of positive, negative, and direction, and can accurately describe the overall motion changes of the human body as shown in Figure 4. The acceleration vector values are defined by the following formula.

$$\alpha^2 = x^2 + y^2 + z^2 \tag{1}$$

If the video object area is at time t0, the centroid of the video object can be defined as:

$$D_A(x, y, i_0) = \frac{\int_{(x,y)\in B(i_0)} xdxdy}{\int_{(x,y)\in B(i_0)} ydxdy} \tag{2}$$

Therefore, the displacement change law of the object can be obtained:

$$\frac{dT}{dS} = w_0 + \frac{P(S)S}{n} \tag{3}$$

Due to the limited speed and force of the object and the non-zero mass, the displacement curve of the object is always smooth. Suppose the plane coordinates perpendicular to the camera are X, Y, and the direction parallel to the camera is Z, then the displacement of the object in the X-Y plane shows a change in position in the video, and the displacement in the Z direction shows a change in size. Decomposing the force P(T) into the X-Y plane, the position change of the same object in the video is smooth. So, if A(t) is the imaging of the same object in the video, then is a smooth curve.

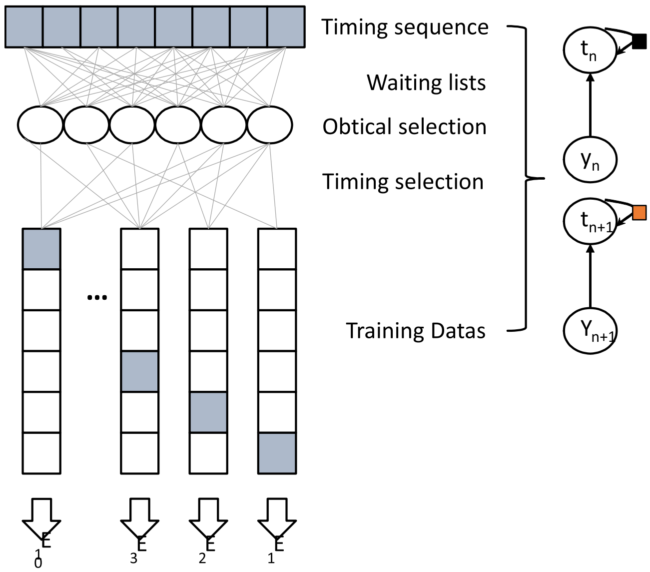

FIGURE 5. Variance distribution per time window.

C. EXTRACTION OF FEATURES

In general, feature extraction is the foundation and key to motion detection. The quality of feature extraction will directly affect the accuracy of the detection results. Feature extraction is to discover the most useful information for motion detection from the original signal, to compress the space with more dimensions to the space with fewer dimensions, and to combine many features in the original feature space to reduce the number of feature dimensions. In this paper, the smoothed and denoised data is processed by adding windows, using a single rectangular window of 128 samples to slide over the original acceleration signal, with two adjacent windows overlapping by half a window. The behavior is characterized by extracting multiple eigenvalues from the acceleration signal of a single rectangular window to form an eigenvector. The following is a description of the feature set extracted in this paper to characterize the motion behavior.

The definitions of variance and standard deviation are given by Eq.

$$s^2 = \frac{\sum (x_i - x)^2}{N} \tag{4}$$

$$s = \sqrt{\frac{\sum (x_i - x)^2}{N}} \tag{5}$$

where N is the sample size and x is the sample mean. Variance and standard deviation are among the most important and commonly used statistical characteristics. The greater the variance, the greater the degree of fluctuation and dispersion of the data. The standard deviation reflects the degree of dispersion of the accelerometer data. From the distribution of variance for each time window after the window is added in Figure 5, the three color curves of green, black, and magenta represent the variance of the three types of motion: walking, walking, and walking upstairs, respectively, and we can see that the standard deviation can distinguish the two types of motion: walking downstairs and upstairs.

The idea of nonlinear decreasing inertia weights is similar to linear decreasing in that the value of inertia weights gradually decreases as the number of algorithm iterations increases. Compared to the linear decreasing strategy, the nonlinear strategy better controls the ability to explore and develop the algorithm and has better algorithm performance, which is calculated as follows.

$$w = w_{\max} - R \times w_{\min} \tag{6}$$

Both linear and nonlinear decreasing approaches argue that the algorithm should be searched locally at a later stage, a strategy that R is prone to local optimality and leads to slow convergence at a later stage. The researchers believe that the inertia weight is a random value, the value of which can be taken as long as it can solve the optimization target changes:

$$w = \nabla\phi \frac{\partial w}{\partial t} + \frac{\partial r}{\partial t} \tag{7}$$

The $\frac{\partial r}{\partial t}$ has the same evolutionary strategy as the elementary particle swarm algorithm, except that $\frac{\partial w}{\partial t}$ is introduced in the velocity update process to enhance the search ability and convergence velocity of the individual, which is expressed as follows.

$$V_i(t+1) = \frac{\nabla\phi}{|\nabla\phi|} + k[V_i(t) - X_i] \tag{8}$$

The algorithm can effectively guarantee the convergence of the algorithm, and it is found that when $X = 4.1$, i.e., the contraction factor $k = 0.729$, then the algorithm has a good convergence performance. Mathematically, the two parameters, inertial weights and contraction factor k, are equivalent.

D. INTENSITY OF MOTION CLASSIFICATION METHOD

Double-labeled water and indirect calorimetry are the "gold standard" for accurate energy consumption, but they have many limitations in measuring energy consumption and intensity of body movement in free conditions. Three-dimensional acceleration sensors provide a better option for laboratories, providing new methods for objective evaluation of human movement from a physical perspective, and new ideas for constructing new types of motion data analysis and processing. Numerous experiments have demonstrated that the absolute value of the body motion acceleration is linearly related to the integration over time and the amount of energy or oxygen consumed, which provides a theoretical basis for evaluating human motion with 3D accelerometers. The human body acceleration vector amplitude (a) is an important parameter to distinguish the motion state of the human body, and to characterize the intensity of the human body motion through the acceleration amplitude, the larger value indicates the more intense motion. It is defined as follows.

$$x = |x_1| + |x_2| + |x_3|$$

Considering the low power consumption of the wearable device and the noise contained in the data obtained from the accelerometer, a sliding-mean filter was used as a pre-processing method to calculate the sum of the absolute values of the three-axis acceleration for each second as a statistic using the equation (2-8). Afterwards, the minute is divided into four equal parts, and the average value of a in each 15 seconds is calculated as the value of a in those 15 seconds. The underlying statistics are the four average a-values for one minute, and these a-values are uploaded to the server via the base station, where the appropriate thresholds are set to classify the intensity of the exercise into low, medium, high, and high. Finally, the exercise intensity classification method is transferred to a wearable device. In this paper, the acceleration data of a number of distinct sports were collected using a motion data acquisition module worn in the waist position, including sedentary, walking, 800 m running, 100 m fast running, jogging, cycling, playing basketball and badminton, etc. The data were repeated 10 times. Each sport, except for the two types of 800 m and 100 m, lasted for 30 minutes. The 3D acceleration recorded in real time was extracted from the data acquisition software of the PC, pre-processed on matlab, and calculated the amplitude of acceleration for each second using the formula, and then calculated the four average amplitude of acceleration for each minute. The threshold value for intensity yields a recommended value of 1000 mg for moderate intensity.

E. EXPERIMENTAL RESULTS

In this paper, the acceleration signals of the movements of 10 individuals located at the waist were selected as raw acceleration signals, each with 10 sets of acceleration signals for each movement, for a total of 100 raw acceleration signals. The raw acceleration signals are smoothed and denoised using a sliding mean filter with a window value of 6, and then a rectangular window with a window length of 128 samples is slid over each acceleration signal with a 50% overlap window. From each acceleration signal, 10 windows are extracted, each containing 128 samples, making a total of 3*10*10 300 accelerometer data, 100 for each activity, and for each data, variance (standard deviation), x-quartile difference, and x-axis bias coefficient are extracted to form a 3-dimensional eigenvector, which is finally composed of the 3*300 feature matrix. There are 100 feature vectors for each of the three actions.

The feature matrix was divided into five equal parts, and four of them were selected as training matrix and the remaining one as test matrix by leaving one of the five parts for cross-validation, and then the SVM classifier was used for classification and identification five times. The FFT coefficient, wavelet coefficient, and wavelet energy were also extracted as features for training and modeling using the same process as above. Figure 6 shows the training and detection of three types of motions: walking, going upstairs and going downstairs with different eigenvalues. For different sports, the variance, X-quartile difference, and X-skewness coefficients are used as eigenvectors to distinguish the three types of activities: walking, going upstairs, and going downstairs, with an average recognition rate of over 90%. The eigenvectors composed of variance, X-quadratic disparity, and X-skewness coefficients have obvious advantages over the commonly used FFT coefficients, wavelet energy, and wavelet coefficients - the average recognition rate is higher, and the calculation is relatively simple. Therefore, the eigenvalues extracted in this paper can effectively distinguish walking, walking upstairs and walking downstairs movements.

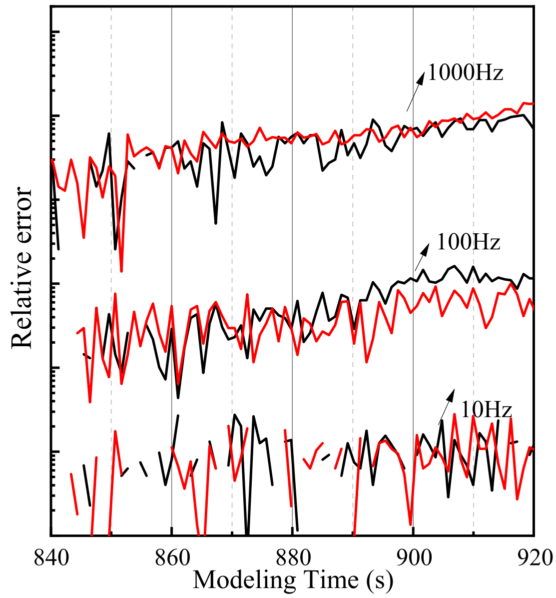

FIGURE 6. Average recognition rate of eigenvalues on walking, walking up and down stairs.

IV. REAL-TIME DETECTION OF ACCELERATION SENSORS

A. REAL-TIME DETECTION BASED ON STAGING BASE STATIONS

The process of transferring Bluetooth data from the module of the relay base station to the wearable device is obtained from the real detection, and the data from the wearable device is uploaded to the module of the base station by means of characteristic operations. In addition to the transmission of the most important motion data, it is also possible to perform a time check on the wearable. The relay base station mainly receives and temporarily stores the data uploaded by the wearable device and forwards it to the base station server. Depending on the functions to be achieved and the convenience of wireless communication, the hardware structure of the base station includes a Bluetooth module based on CC2541, a GPRS module for communication with the server, and a microcontroller module based on STM32. The CC2541-based Bluetooth module is responsible for receiving Bluetooth data from wearable devices, and the STM32 host processor reads the data received from the CC2541 module via the serial port. For the core control module, the STM32F103 microcontroller is selected as the main processor, which operates at a maximum frequency of 72MHz.

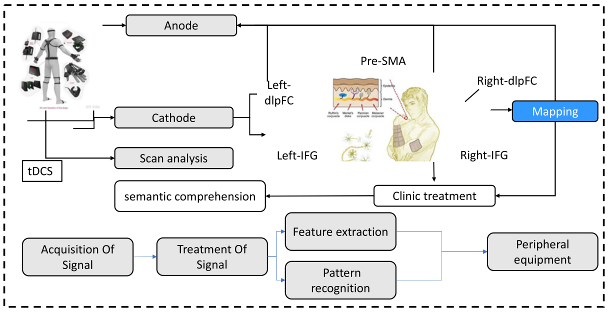

FIGURE 7. Real-time detection of staging base stations.

The transit base station uses STM32 series microcontrollers, the STM32 microprocessors are based on ARM. u Vision4 IDE is a software development platform for microcontrollers developed by Keil (now part of ARM), a well-known German software company, and is the mainstream tool for ARM microcontroller development. u Vision4 IDE is a software development platform that integrates editing, compiling, and project management in one window-based software development environment. The transit base station is designed and debugged in the u Vision4 IDE development environment. The main function of the transit base station is that it scans at regular intervals to see if there are any wearable devices in the vicinity that need to be connected, and if so, connects the wearable device, receives and stores the data sent by the wearable device, and sends it to the base station server via the wireless network as shown in Figure 7.

The CC2541 module at the relay base station needs to receive data from multiple wearable devices, so the CC2541 module at the relay base station is in host mode and the wearable device is in slave mode. The CC2541 module at the base station initiates a scan request at intervals to scan for Bluetooth devices that are sending advertisements, and the relay base station can scan for the device if the wearable happens to open a Bluetooth advertisement at that time, and if the UUID of the GAP master service is "The CC2541 module on the relay base station makes GATT data service discovery through mutually agreed UUIDs; GATT is discovered. After the data service, the CC2541 module at the relay base station sends the UUID of the "feature" for which the data operation is to be performed, and the wearable device returns the handle of this "feature" to the CC2541 module at the relay base station; the relay base station.

The CC2541 module at the base station reads and writes application data via a handle. If the time on the wearable does not match the time on the base station, the time on the wearable is updated to avoid time errors on the wearable, and the current battery information of the wearable is transmitted to the base station. When a wearable is ready to transmit data, it disconnects from the wearable and instead queries the list to see if there are any other connected devices, and if so, connects to the next device; otherwise, it rescans the vicinity to see if there are any other connected devices.

The CC2541 module of the staging site is in host mode, so the staging site can maintain a network connection with three wearable devices at the same time, and when one of the wearable devices in the network sends data and is disconnected, a new wearable device can join the network. Each wearable can join another network after it is disconnected from the relay station. The network topology between the relay station and multiple wearable devices is shown above.

B. EMBEDDED REAL-TIME OPERATING SYSTEM

The STM32 transit base station software is designed using the embedded operating system UCOSII, which meets the system's real-time requirements with a small kernel and a high degree of real-time and portability. UCOSII is widely used in embedded products today, managing up to 64 tasks, each of which is assigned a certain priority according to its importance, but each task has a different priority and its own stack space. Therefore, UCOSII needs to be ported, where the files that need to modify the source code include the header file OS_CPU.

The UCOSII operating system kernel is real-time deprivable, which means that as soon as a new higher priority task is ready, either during task execution or in the interrupt service subroutine, the kernel schedules the new task to run, which means that the response time to the task is immediate and certain. According to the functions implemented in the relay base station, the relay base station task layer is designed with the following five tasks: Bluetooth data processing task, motion data upload task, GPRS task, heartbeat packet task, and system task, which exist in parallel.

Each task has the following three components: application, task stack, and mission control block. The task stack is used to store the CPU register contents. When a task changes from a running state to another state, the operating system manages the task by querying the contents of the task controller. UCOSII assigns a different priority to each task to ensure real-time performance. When a task switchover occurs, it always switches to the highest priority task that is ready. The priority setting is determined by the order in which each task is executed and its impact on system security. The priority order is: Bluetooth data processing task, GPRS task, motion data upload task, heartbeat packet task, and system task, in descending order of priority. The transit base station adopts static priority setting, which means that the priority of tasks remains unchanged during operation.

The Bluetooth data processing task is the highest priority task among the five tasks. Subsequent uploads of motion data to the base station server can only be achieved if the motion data is received from the wearable device's Bluetooth. But Bluetooth transmits not only motion data, but also other useful information such as time, battery level, and heartbeat packets. The Bluetooth data processing task is to take the data received by the CC2541 module of the relay base station and process it accordingly. The CC2541 receives the Bluetooth data from the wearable device and dumps it to the STM32 processor via the DMA of the STM32 serial port, where it analyzes and processes the packet information in the

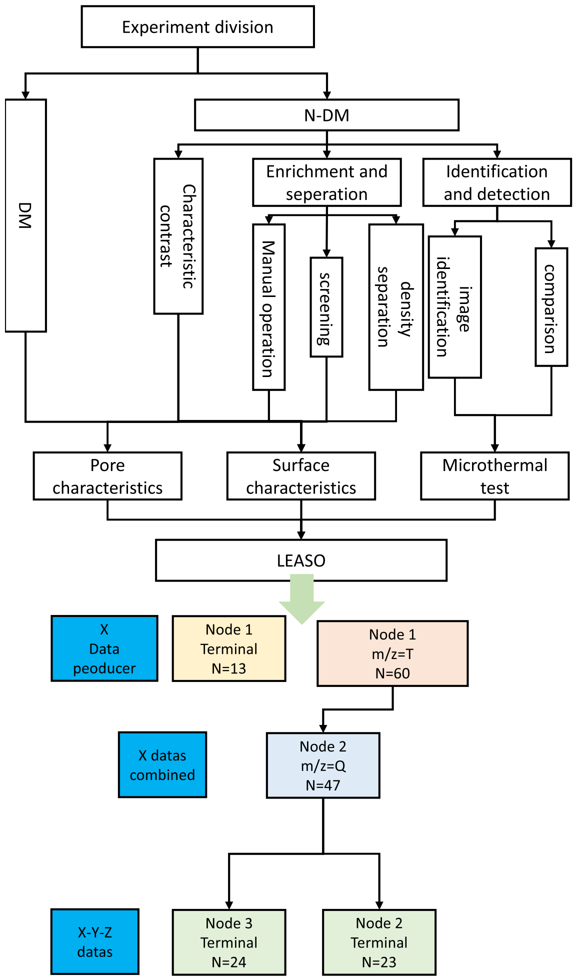

FIGURE 8. Bluetooth time processing flow.

receive function. Other corresponding treatments are shown in Figure 8.

C. MOTION DATA UPLOAD TASKS

The motion data upload task is to check whether there is motion data in the flash that comes with STM32, and if so, to read the fixed-length motion data from the flash, encapsulate the motion data in corresponding packets according to the data communication protocol, put them in the sending queue of the GPRS task, and send them out via the sending function of the GPRS task. The human motion acceleration signal obtained by the data acquisition module will inevitably be mixed with noise. The noise mixed with the acceleration signal will interfere with the subsequent processing of the acceleration data, so the influence of the noise should be reduced.

The output signal of the acceleration sensor collected by the data acquisition module is superimposed on the following signals: human acceleration component, human gravity component, human jitter, and measurement noise. Since there is a noise component in the human acceleration signal from the accelerometer, the original signal needs to be pre-processed with denoising, smoothing, and windowing. Although nonlinear, low-pass, Laplace operator, and high-pass filters can be used to remove high-frequency noise, the gravitational acceleration signal can also be extracted from the raw data by high-pass filters for analyzing the effective components of dynamic acceleration.

It responses from the base station server. If the BTS server's response is received, check whether there is data in Flash again, and keep repeating the above process until there is no movement data in Flash; if no response is received from the BTS server within a certain period of time or if the response is received from the BTS server, and the resolution response is a storage failure, then resend the last sent movement data packet. The heartbeat packet task is to send heartbeat packets to the BTS server at regular intervals to check the connectivity of the communication link with the BTS server. The BTS sends heartbeat packets to the BTS server at regular intervals, and the BTS server receives them and responds. If the STM32 SCM does not receive the corresponding response from the BTS server to the heartbeat packets five times in total, this document considers that there is a communication problem with the current session, which may result in subsequent communication quality.

D. SYSTEM TASKS

The system tasks are mainly to complete the parameter settings for the relay base stations, as well as to restart the GPRS module and establish a new session with the base station server. For example, setting the time, setting the ID of the base station, and so on. Each time the BTS sends a heartbeat packet to the BTS server, which contains the current time of the BTS. The BTS server receives the heartbeat packet from the BTS and uses the parsing function to obtain the content of the packet.

The output signal of the acceleration sensor collected by the data acquisition module is superimposed on the following signals: human acceleration component, human gravity component, human jitter, and measurement noise. Since there is a noise component in the human acceleration signal from the accelerometer, the original signal needs to be pre-processed with denoising, smoothing, and windowing. Although nonlinear, low-pass, Laplace operator, and high-pass filters can be used to remove high-frequency noise, the gravitational acceleration signal can also be extracted from the raw data by high-pass filters for analyzing the effective components of dynamic acceleration. The system task parses the packets and adjusts the time of the base station. Each base station has a corresponding base station ID, and the base station server can send a command to set the ID. The system task receives the GRPS failure packet, reboots the GPRS module, and reconnects to the base station server to establish a new TCP connection. The flow of the system task is shown in Figure 9. For D0, D1 and D2 movement, which means three different process in the whole system, an obvious difference can be observed.

For the further research, the acceleration signal generated by human movement for a period of time is acquired

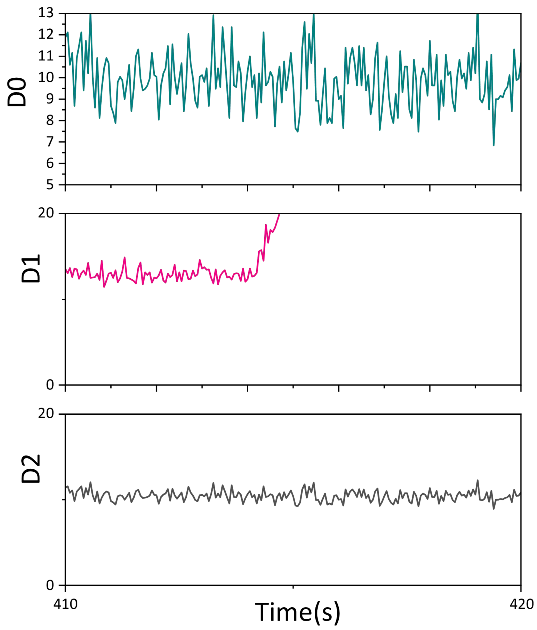

FIGURE 9. System task flow.

through the acceleration sensor, and the data is required to be transmitted to the motion detection device, and then the data should be preprocessed. The preprocessing operations generally include: smoothing, denoising, resampling, and normalization.

V. SYSTEM SECURITY ARCHITECTURE ANALYSIS

The relay base station receives data from the wearable device through the CC2541 module, saves the motion data in the flash of the relay base station, and finally sends it to the base station server via GPRS wirelessly. Data communication is needed between the relay base station, wearable device and base station server, so this paper needs to design a corresponding data communication protocol. The communication between the relay base station and the wearable device is carried out wirelessly via Bluetooth for data transmission. The operation of Bluetooth application data requires ''features'' to operate. In this paper, we need to consider how to transfer the motion data from the CC2541 module of the relay base station to the Flash of the STM32 of the relay base station, and then to the server of the base station via the GPRS network. The CC2541 module communicates with the base station and receives motion data transmitted by Bluetooth using the DMA operation of the serial port and saves them to Flash.

The interaction between the CC2541 module on the base station and the STM32 main processor is done via the serial port. Each time the CC2541 module on the base station sends data to the STM32 main processor, it calls the packet function to encapsulate what it wants to send into a specific packet to be sent out. each time the STM32 receives a complete packet, it first determines the validity of the packet header information and, if the header is wrong, does not receive subsequent packet contents. If the header is correct, it parses the packet's the command section calls different data processing functions

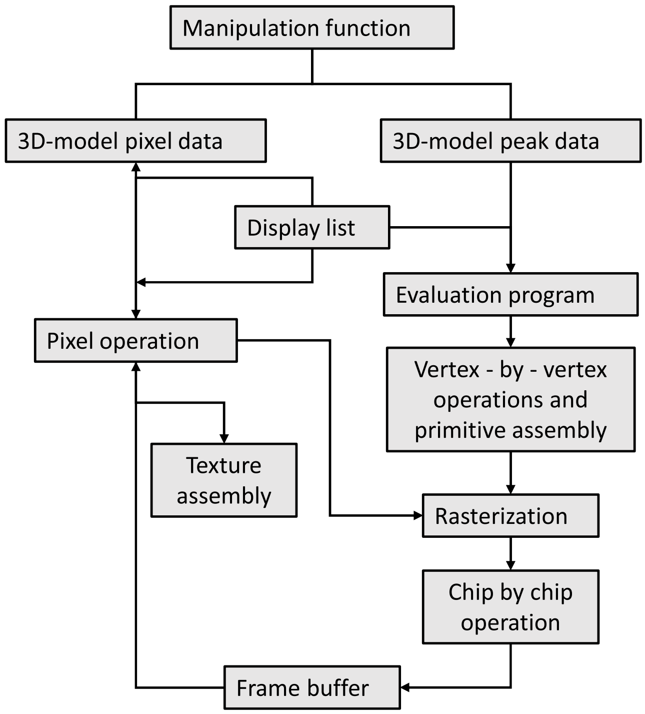

FIGURE 10. Program flowchart.

according to the contents of the command section for processing. At the same time, the parsed packets are deleted from the receive queue of the Bluetooth data processing task. The program flow diagram is shown in Figure 10.

The interaction between the base station and the base station server is based on the reliable TCP protocol. Each time the base station sends data to the base station server, it calls the packet function to encapsulate what it wants to send into a specific packet to be sent out. This way, users do not have to worry about data integrity. Each time the base station receives a complete packet of data, it interacts with the STM32 host processor in a similar way as the CC2541 of the base station. The packet is parsed from the packet header and instructions in turn, and different processing functions are called according to the instructions, such as time setting, ID setting, etc. At the same time, the parsed packet is parsed from the main processor. At the same time, the parsed data is deleted from the receiving queue of GPRS tasks. The authentication command, the upload data command and the heartbeat packet command are required to upload motion data from the BTS. When the BTS starts the GPRS module online, it starts to send authentication packets to the BTS server. After the authentication packets are received by the BTS server, it starts to parse the authentication packets to get the BTS number, and queries whether the number exists in the local database. The base station does not know that it has not received a response from the base station's server for only 5 heartbeat packets.

However, the base station does not know that it has not received any response to the heartbeat packet from the base station server only 5 times in total, so it restarts GPRS and sends the authentication packet. After passing the

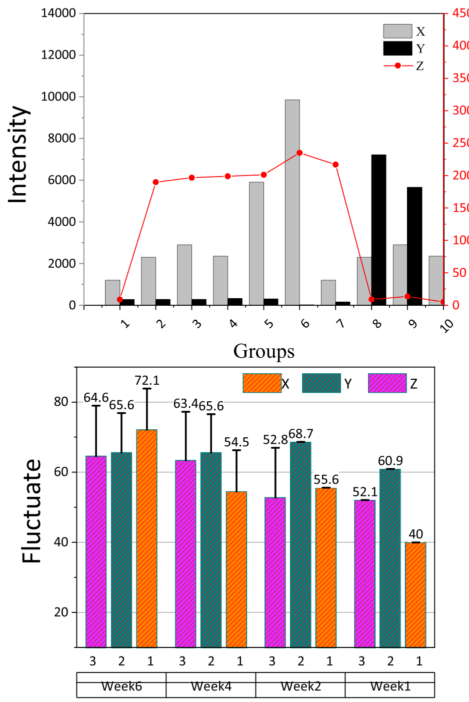

FIGURE 11. Number of data returns.

authentication of the BTS server, the BTS sends heartbeat packets at regular intervals to check the connection status with the BTS server, and then sends the movement data to the BTS server using the encapsulation function to encapsulate the movement data into predefined format. If the storage succeeds, it sends a successful response packet to the base station. If the storage fails, it sends a motion data retransmission packet to the base station to request retransmission. Until all the motion data stored in Flash is uploaded to the BTS server. The specific number of data retransmission is shown in Figure 11. In the first figure, for different groups of detection researching, in the Z axe, the intensity obviously shows a peak, which means it actively establishes a network connection with the base station server in this direction.

The human motion acceleration signal obtained by the data acquisition module will inevitably be mixed with noise. The noise mixed with the acceleration signal will interfere with the subsequent processing of the acceleration data, so the influence of the noise should be reduced. The output signal of the acceleration sensor collected by the data acquisition module is superimposed on the following signals: human acceleration component, human gravity component, human jitter, and measurement noise. Since there is a noise component in the human acceleration signal from the accelerometer, the original signal needs to be pre-processed with denoising, smoothing, and windowing. Although nonlinear, low-pass, Laplace operator, and high-pass filters can be used to remove high-frequency noise, the gravitational acceleration signal can also be extracted from the raw data by high-pass filters for analyzing the effective components of dynamic acceleration.

Common classifiers include decision trees, BP neural networks, KNN algorithms (K-Nearest Neighbour), plain Bayesian, and support vector machines, etc. Decision trees ignore correlations between attributes in a data set and can cause overfitting problems. BP neural network is the most widely used and well studied model in artificial neural networks, but the training of BP neural network requires a large number of samples. However, the training of BP neural network requires a large number of samples, the convergence speed of BP neural network algorithm is slow, and there is no unified and complete theoretical guidance on the selection of hidden layers and number of units in BP neural network. In addition, the learning and remembering of BP neural networks is unstable, and the KNN algorithm is a lazy learning method with a large computational volume, and the selection of K-values affects the classification results of the KNN algorithm, which is limited by the number of samples and the degree of dispersion. Simple Bayesian classifiers require prior knowledge of a priori probabilities, and classification decisions are subject to error rates.

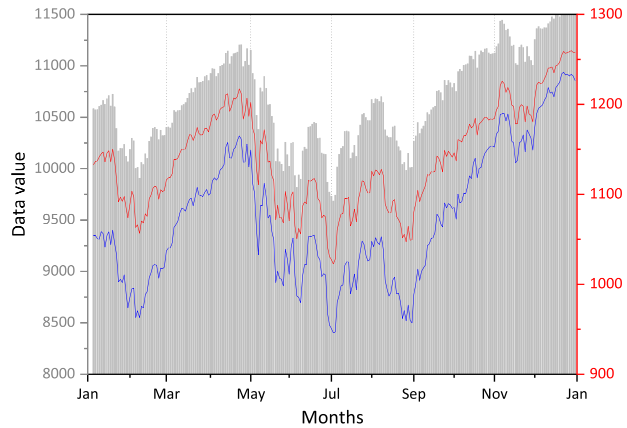

FIGURE 12. Variation of the inner product of a vector of samples.

The Support Vector Machine is a new tool that has emerged in recent years in the field of pattern recognition and machine learning testing, and is the youngest and most practical part of statistical learning. The Support Vector Machine (SVM) was introduced by Vapnik *et al.* in 1995. Since then, with the development of statistical theory, support vector machines have gradually received the attention of researchers in various fields, and have been widely used in a very short time. It is based on the VC theory and structural risk minimization principle of statistical learning theory, and seeks the best compromise between model complexity and learning ability according to the limited sample information to obtain the best generalization ability. It also exhibits many remarkable properties in machine learning problems such as small samples, nonlinearities, and high dimensionality of data, and is therefore widely used in pattern recognition, data mining, and other fields as shown in Figure 12. With the time gone on, the data value shows obvious periodicity, and in the May, the value shows a peak due to the best generalization ability.

Support Vector Machine (SVM) is a learning method based on the structural risk minimization criterion, which is not only a simple algorithm, but also has a good "robustness", and

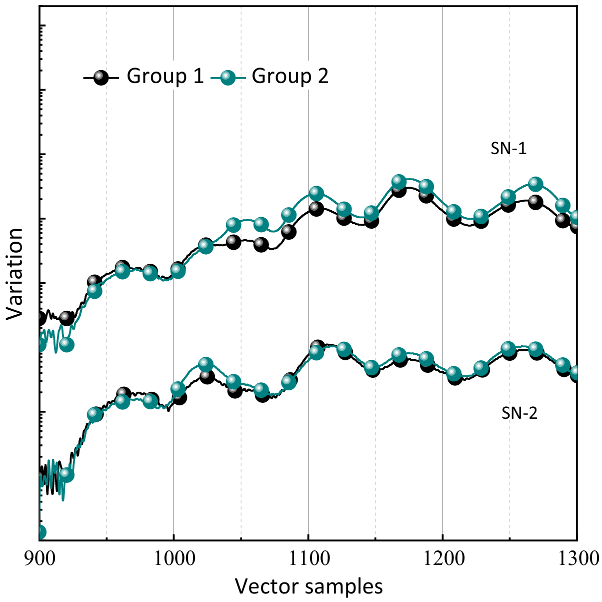

FIGURE 13. Variation of the inner product of a vector of samples.

has been widely used in speech recognition, face recognition, handwritten number recognition, and article classification. It is nonlinear mapping and has a solid theoretical foundation, which basically does not involve probability measurements and laws of large numbers, and is therefore different from existing statistical methods. The basic idea of the support vector machine is to map the training data into a higher dimensional feature space by a nonlinear transformation, where a hyperplane is found to maximize the separation edge between the positive and negative cases. This nonlinear transformation is achieved by defining an appropriate inner product function. The classification function obtained by the support vector machine is similar in form to a neural network, and its output is a linear combination of several intermediate nodes, each of which corresponds to the inner product of an input sample and a support vector, as shown in Figure 13.

VI. CONCLUSION

The rapid development of microprocessor technology, wearable technology, and embedded technology has created the conditions for the development of powerful, low-power human motion detection devices. To address the gradual decline in the physical fitness and health of the student population, this paper studies motion detection algorithms, including three types of motion detection methods: walking, walking upstairs and walking downstairs, and a classification method of motion intensity implemented on a wearable device, and designs and implements software to monitor students' motion intensity. The main contribution of this paper can be summarized as:

(1) The acceleration signal is collected from the waist, pants pocket, and wrist of the human body; the collected acceleration data is smoothed and denoised using a sliding mean filter with window 6, and the acceleration signal is segmented by adding a window.

(2) The variance, X-quartile difference, and X-axis bias coefficient are used as eigenvalues to train and detect the movement types of human body using a radial basis function-based support vector machine (SVM).

(3) The experimental results show that the features extracted in this paper are able to distinguish between three daily activities: walking, walking upstairs and walking downstairs. The paper also proposes a classification of exercise intensity into four intensity levels: low, moderate, high and vigorous.

Based on the functions achieved by the wearable device, a hardware structure diagram of the wearable device is proposed. On this basis, the internal implementation process of wearable device software is analyzed in detail from the modules of acceleration data acquisition, data processing, Flash memory design, and Bluetooth 4.0 wireless communication, respectively. The data processing module includes data pre-processing and calculation of human motion intensity. TI's packet capture software verifies the accuracy of data communication between the wearable device and the transit base station; the power consumption test results of the wearable device show that the wearable device designed and implemented in this paper meets the characteristics of low power consumption.

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