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Article

Research on the application and practice of Internet of Things technology in geriatric care

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Abstract: As society moves into the aging stage and the number of elderly living alone is increasing, elderly care has become a key concern. In this paper, a monitoring system for elderly care is developed with the community living environment and physiological data of the elderly as the research object. Indoor temperature and humidity are monitored by temperature and humidity sensors in order to set reasonable comfort parameters for the elderly. The indoor smoke and carbon monoxide concentrations at the collection site are converted into voltage signals to ensure the safety of the environment in which the elderly live. Collect multidimensional parameters such as heart rate, blood oxygen, body temperature, posture and other real-time monitoring of the elderly's physiological data. At the same time, the action signal data of the elderly is collected, and the median filtering processing method is used to accurately extract the characteristics of the action signal to detect whether the elderly fall. Finally, NB-IoT wireless transmission technology is used to upload the detection data to the Internet of Things, realizing the long-distance transmission of nursing information. A comprehensive functional test of the community home-based elderly care monitoring system was conducted, and the system's detection results of the elderly's heart rate, blood oxygen, body temperature, posture and other data basically matched the actual results, and the accuracy of the elderly fall detection reached more than 95%, which met the expectations of the system design. It provides a solution for realizing intelligent and remote community home care.

Keywords: Internet of Things (IoT) technology; elderly care; multidimensional physiological parameters; NB-IoT wireless transmission technology

1. Introduction

It is predicted that by 2035 and 2050, the size of China's elderly population aged 65 years and older will reach 350 million and 450 million, respectively, with the degree of aging reaching 20% and 37% [1]. The rapid development of the aging society has brought new challenges to the cause of elderly care. With the large-scale application of emerging information technologies such as big data, cloud computing, Internet of Things, and "Internet +" in the healthcare industry, geriatric care is gradually moving towards the stage of intelligent care development [2-5]. Intelligent nursing is the collection, storage, evaluation, classification, editing and application of medical data through system computing technology, cloud computing technology, Internet of Things technology and data fusion technology, etc., in order to realize the sharing of medical resources, and to formulate the best clinical decision-making, nursing care plan and health management plan by comparing the basic data of personal information with the public shared data, so as to provide the patients with "end-to-end" nursing care. end-to-end" care services for patients [6-8]. Smart nursing applies Internet of Things (IoT) technology to geriatric nursing services, which can meet the diverse nursing needs of the elderly. Now, we study the application and practice of IoT technology in smart nursing, and put forward corresponding countermeasures, aiming to provide reference for the better application of smart nursing in geriatric nursing.

Geriatric nursing in China started late, and geriatric departments, outpatient clinics and wards were only opened in general hospitals in the 1980s, and with the wide application of information technology in clinical care, information technology has also been applied to geriatric nursing. For example, Ghasemi, F et al. proposed a healthcare system for homebound elderly that uses a set of environmental and wearable sensors to monitor the vital signs and body posture of the elderly [9]. Sendra, S et al. specified the convenience of cell phones in smart aging devices, whereby the caregivers of the elderly can always monitor their physiological indicators, movements, etc. through the smart wearable devices, and transmit the data to the server, which needs to be monitored by the caregiver and dealt with for abnormalities [10]. These smart home systems are connected to the smartphone application, and the monitored data are transmitted to the terminal device through the Internet for processing and analysis, and once abnormal physiological data are found, the system will send them to healthcare personnel or family members of the elderly, so that timely interventions can be taken to reduce the incidence of adverse events, and the frequency of emergency hospitalization of the elderly and the burden of care can be reduced [11-13]. Remote physiologic data monitoring systems are mostly developed to meet the health needs of homebound older adults, but their effectiveness in improving the health outcomes of older adults needs to be further verified.

The applications in safety risk monitoring for the elderly are mainly in monitoring falls, improving medication adherence, screening for urinary tract infections, and preventing nighttime wandering, etc. Coahran, M et al. proposed to install a fall monitoring system on the ceiling of the ward, which sends an alert to the nurse's smartphone when monitoring a fall of an elderly patient, so that the nurse can be the first to know that the patient has fallen and take action [14]. Yin, T et al. designed an intelligent vital signs and safety monitoring system for elderly care by integrating the functions of vital signs collection and safety information monitoring, which realizes the autonomous recognition and judgment of the vital characteristics and safety information of the elderly based on reasonable preset thresholds [15]. Cheung, J et al. designed a sensor-based nighttime monitoring system for nighttime monitoring of the elderly's activities away from the bed to prevent elderly people from wandering at night [16]. Safety risk monitoring reduces the workload of geriatric caregivers and safeguards the health of older adults with safety risks, but the development of a monitoring system requires the joint collaboration of caregivers and scholars in multidisciplinary fields.

Motion measurement techniques can help clinicians in early diagnosis of dementia by assessing gait, balance and postural kinematics, and early monitoring of mood disorders, anxiety and dementia in older adults [17]. Chen, H et al. proposed a time- and space-constrained approach to efficiently identify daily activities of older adults through continuous processing of the monitoring data using low-cost binary sensors [18]. Brenčič, N et al. in the "Active and Assisted Living (AAL)" project detailed techniques for personalized geriatric care that rely on robotic platforms, including the monitoring and assessment of health parameters, sleep and activity patterns [19]. Kaluza, B et al. focused on fall detection in the elderly population aged 65 years and older. Fall detection, the system presented can monitor a variety of behavioral characteristics of older adults in addition to detecting falls, which can help to raise awareness of health risks among older adults [20]. Kim, J et al. were able to provide early warning of depression in older adults by analyzing monitored data on their daily activities, however, no research has been seen on the development and application of emotional and behavioral monitoring systems, and there is a need to develop further emotional and behavioral monitoring systems suitable for the care of older adults [21].

In recent years, the Internet of Things (IoT) has become the focus of research in various countries, and the emergence of IoT has changed the traditional elderly care model, and IoT has been called the third wave of the world's information industry after the computer and the Internet [22]. It refers to a variety of information sensing devices and systems, such as sensor networks, radio frequency tag reading devices, barcode and two-dimensional code devices, global positioning systems and other short-range wireless self-organizing networks based on the mode of inter-object communication (M2M), according to an agreed-upon protocol, connecting any item to the Internet for information exchange and communication, in order to achieve intelligent identification, localization, tracking, monitoring and management of an network [23-25]. Based on IoT technology, the concept of "smart elderly care" has emerged, which actually means utilizing IoT technology to keep the daily life of the elderly in a remote monitoring state through various types of sensors [26-28]. Specifically, the application of IoT in elderly care includes remote monitoring, convenient service and patient tracking. In remote monitoring, Kirbaş, İ and Bayilmiş, C designed Wireless Body Area Sensor Networks Systems (WBASNs), which are wireless sensor nodes placed close to a person or in a person's body, and the WBASNs can provide monitoring of healthcare services at any time, including blood pressure, pulse, respiration, temperature, and other vitals, and then send the data to the healthcare centers, and such remote monitoring technologies can monitor the health of the patient at any time, thus reducing the occurrence of dangerous events in the elderly [29]. Mandal, P et al. stated that IoT technologies are commonly used in home community care for the elderly for smart monitoring systems including automated emergency calls, automated monitoring of activity and falls, vital signs monitoring, reminder services, and automated health assessments [30].

In terms of convenient services, Parker, R et al. designed a medication reminder device for the elderly to support monitoring services, and through the use of the device, medication adherence and the ability of the elderly to take care of themselves at home were improved, in addition, the measured data was directly transmitted to the community health service center, and in the event of data anomalies, the intelligent system automatically activated telemedicine, and if necessary, home health services were provided [31]. Padikkapparambil, J et al. detailed an assisted living system that combines IoT technology, big data, and cloud technology and found that it can help older adults support their daily activities and assist them in staying healthy and safe [32]. Meanwhile, Michard, F states that computer technology can integrate historical, clinical, physiological and psychological information to predict adverse events and suggest the most appropriate geriatric care program. And as data accumulates, the Internet of Things can help make decisions more efficiently and accurately [33].

In terms of patient tracking, Azimi, I et al. constructed a monitoring system for the elderly using Internet of Things (IoT) technology, which provides a new perspective on geriatric care by introducing a hierarchical model of monitoring centered on the elderly, as well as restricting the elderly patients from going to certain non-safety zones and preventing the elderly patients with intellectual disabilities or the elderly from leaving their homes and getting lost [34]. Sie, J et al. proposed the Smart Home Platform for Long-Term Care (LAESO), which integrates technologies such as cloud, IoT, sensor networks, GPS localization, and crowd sensing, and allows for timely reporting of the exact location to the guardians of the elderly through a GPS localization system [35]. In summary, through IoT technology, even when the elderly are alone at home in a dangerous situation, they can be detected in time, which makes community home care more convenient, saves human resources, reduces the burden on society and the family, and is in line with the traditional Chinese culture of aging at home. With the change of consumer attitudes and the improvement of infrastructure, the application of IoT technology to care will become more and more common.

Population aging is one of the great challenges facing the world today, and how to use science and technology to ensure the health and safety of the elderly has become a focus of attention in the academic and medical communities. The traditional methods of monitoring care have the defects of untimely feedback and more blind spots of perspective. This study constructs an all-round monitoring system for community home-based elderly care based on the Internet of Things (IoT) technology. Firstly, the data acquisition methods of environmental sensors such as temperature, humidity and gas and physiological behavioral sensors such as heart rate, blood oxygen, body temperature and posture were designed, and the fall detection algorithm based on median filter processing method and behavioral feature extraction was developed to accurately identify the fall of the elderly. Multi-functional testing of the system and practical application experiments were designed to verify the reliability of the system and realize the complete closed loop from data sensing to the risk warning of elderly care.

2. Design of a monitoring system for community-based home care for the elderly

2.1. Environmental data acquisition software design

2.1.1. Temperature and humidity

The temperature and humidity data acquisition process first detects whether the DHT11 temperature and humidity sensor [36] exists, and if it does, it carries out the DHT11 data IO port initialization operation, and then reads the sensor's 40-bit data, and then calculates the temperature and humidity data, respectively, after calibrating correctly.

2.1.2. Gas concentration acquisition

Gas Concentration Acquisition Process [37] Firstly, the ADC is initialized, then the collected smoke concentration signal and carbon monoxide concentration signal are converted into voltage signals, which are converted by A/D to get the digital signals, and finally the main controller processes the collected data to get the smoke concentration and carbon monoxide concentration.

2.1.3. Illuminance

The illuminance sensor has a built-in 16-bit analog-to-digital converter and communicates with the main controller through the I^2C protocol.After the initialization operation of the BH1750FVI, the main controller sends startup commands and start measurement commands to the sensor through the I^2C protocol, the sensor receives the measurement commands and starts to measure the current illuminance, and the main controller reads the sensor data and calculates the light intensity. The sensor receives the measurement instruction and starts to measure the current illumination, and the main controller reads the sensor data and calculates the light intensity. The light intensity calculation formula is shown in equation (1):

$$Lux = \frac{(HB + LB)}{1.2}(\text{Units:lx}) \tag{1}$$

2.2. Physiological data acquisition software design

2.2.1. Heart Rate Oximetry Collection

In this paper, the photoelectric volumetric pulse wave tracing method is chosen to realize the measurement of human heart rate and blood oxygen.MAX30102 consists of a light source and a photoelectric converter, and the light source part adopts the light-emitting diode of a specific wavelength in the arterial blood that is selective to $\mathrm{HbO_2}$ and Hb. The light absorption coefficient of $\mathrm{HbO_2}$ is higher for 800~1000nm and Hb is higher for 600~800nm. In this paper, we use infrared light around 850nm and red light around 650nm as the incident light source.

Heart rate calculation: the number of heartbeats per minute $\mathrm{BPM{=}60/T}$.

Oxygen saturation is the percentage of the $\mathrm{HbO_2}$ volume of blood to the whole hemoglobin volume. The formula is shown in equation (2):

$$SpO_2 = \frac{C_{HbO_2}}{C_{HbO_2} + C_{Hb}} \times 100\% \tag{2}$$

The system realizes SpO_2 measurements according to the different light transmittance of human tissues during vascular pulse beats. According to Lambert's law, when monochromatic light of intensity I_0 passes through a solution of concentration C, the transmitted light intensity is:

$$I = I_0 e^{-\varepsilon CD} \tag{3}$$

where I_0 is the incident light intensity, I is the transmitted light intensity, C is the solution concentration, D is the thickness of light passing through the solution, and ε is the light absorption coefficient.

When the artery is not pulsating, the light intensity is I_0 incident light shining on the finger, when the transmitted light intensity is:

$$I_{DC} = I_0 e^{-\varepsilon_0 C_0 L} e^{-\varepsilon_{HbO_2} C_{HbO_2} L} e^{-\varepsilon_{Hb} C_{Hb} L} \tag{4}$$

where ε_0 is the absorption coefficient of the nonpulsatile and venous components; C_0 is the concentration, L is the optical range; and $\varepsilon_{Hb}, \varepsilon_{HbO_2}$ are the absorption coefficients of HbO_2 and the light absorption coefficient of Hb.

When the human pulse beats, the blood vessels are dilated, and let the amount of light range change caused be ΔL, then the transmitted light intensity is $I_{DC} - I_{AC}$, then:

$$I_{DC} - I_{AC} = I_{DC} e^{-\left(\varepsilon_{Hb} C_{Hb} + \varepsilon_{HbO_2} C_{HbO_2}\right)\Delta L} \tag{5}$$

Taking the logarithm of e for equation (5) yields:

$$\ln \frac{I_{DC} - I_{AC}}{I_{DC}} = -\left(\varepsilon_{Hb} C_{Hb} + \varepsilon_{HbO_2} C_{HbO_2}\right)\Delta L \tag{6}$$

Considering that the AC component of transmitted light is much smaller than the DC component:

$$\frac{I_{AC}}{I_{DC}} = -\left(\varepsilon_{Hb} C_{Hb} + \varepsilon_{HbO_2} C_{HbO_2}\right) \tag{7}$$

MAX30102 uses red light and infrared light as incident light, so the calculation of blood oxygen saturation only needs to calculate the red light AC and DC ratio respectively, the calculation formula is as equation (8):

$$R = \frac{AC_{red} / DC_{red}}{AC_{ired} / DC_{ired}} \tag{8}$$

Let the wavelengths of red and infrared light be λ_1, λ_2 , respectively:

$$R = \frac{AC_{red} / DC_{red}}{AC_{ired} / DC_{ired}} = \frac{AC^{\lambda_1} / DC^{\lambda_1}}{AC^{\lambda_2} / DC^{\lambda_2}} = \frac{\varepsilon_{HbO}^{\lambda_1} C_{HbO} + \varepsilon_{HbO_2}^{\lambda_1} C_{HbO_2}}{\varepsilon_{HbO}^{\lambda_2} C_{HbO} + \varepsilon_{HbO_2}^{\lambda_2} C_{HbO_2}} \tag{9}$$

Substituting Eq. (9) into Eq. (2) yields Eq. (10):

$$SpO_2 = \frac{\varepsilon_{Hb}^{\lambda_1} R - \varepsilon_{Hb}^{\lambda_1}}{\left(\varepsilon_{Hb}^{\lambda_2} R - \varepsilon_{HbO_2}^{\lambda_2}\right) R - \left(\varepsilon_{Hb}^{\lambda_1} - \varepsilon_{HbO_2}^{\lambda_1}\right)} \times 100\% \tag{10}$$

Usually, there are two fitting methods for blood oxygen saturation, one is primary function and the other is quadratic function, and the system chooses the quadratic fitting function to realize the calculation of blood oxygen saturation, and its quadratic fitting function is:

$$SpO_2 = AR^2 + BR + C \tag{11}$$

Where A, B and C are calibrated according to the measured R-value and the standard SpO_2 -value, the following fitted calibration equations are chosen for the design of this system:

$$SpO_2 = -45.060R^2 + 30.054R + 94.845 \tag{12}$$

The main controller reads the AC and DC signals of MAX30102, and after filtering and other operations, stores them in the internal RAM of the module, calculates the AC signal, DC signal, T and R values between the two peaks of AC, and finally calculates the heart rate and blood oxygen according to the above equation (12). The flow of heart rate and blood oxygen acquisition is shown in Fig. 1.

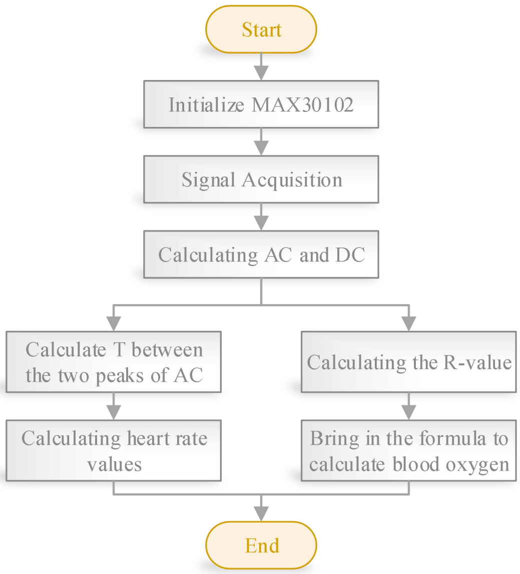


Figure 1. heart rate blood oxygen collection flow chart.

2.2.2. Body temperature collection

The temperature acquisition process is shown in Figure 2, the main controller sends a reset command to the sensor to reset the sensor, then detects whether the sensor exists or not, and if the sensor exists, it carries out the initialization operation and sends the relevant instructions to read the data collected by the sensor, and finally, it is verified by the CRC to derive the human body temperature data. The temperature conversion formula is as follows:

$$Tem = t \times 0.0625 \tag{13}$$

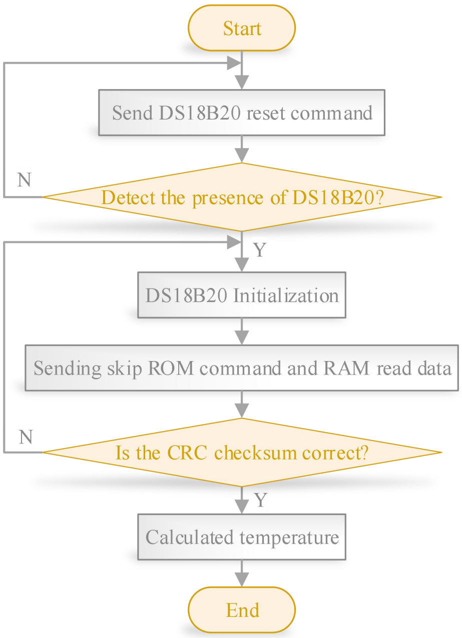


Figure 2. Temperature collection flow chart.

2.2.3. Attitude data acquisition

The MPU6050 six-axis sensor is selected for human posture data acquisition. Initialization operation of MPU6050 is carried out to complete the communication between the main controller and MPU6050, in which the initialization operation includes: I^2C interface initialization, sensor reset operation, setting the sensor range range, sampling frequency, low-pass filter and other operations, and enabling the relevant clock source. The acceleration and angular velocity inside the sensor are read as raw data through the main controller, and need to be solved by the attitude to obtain the Euler angles required by the system. There are two attitude solution methods, one is the attitude fusion settlement, which realizes the calculation of the Euler angle through the theoretical formula, and the process is more complicated. The second is to convert the raw data into quaternions according to the MPU6050's own DMP, and the main controller calculates the Euler angle according to the reading of quaternions, so as to calculate the heading angle, roll angle and pitch angle of the human body's attitude data, and the system adopts the built-in DMP unit to realize the human body's attitude solving.

2.2.4. Positioning module acquisition

Communication between the positioning module and the main controller is realized through the serial port. The module uses NMEA-0183 protocol to send data to the main controller, and the NMEA-0183 protocol conveys GPS positioning information with ASCII code. Positioning module data acquisition is done by setting baud rate 9600bps, 8 data bits, no parity bit, and completing the serial port 2 initialization operation. After the main controller receives GPS data, it needs to parse the data according to the protocol format of the positioning module, and the parsed latitude and longitude information is sent to the upper computer and APP through the BC26 module.

2.3. Fall detection in the elderly

The elderly community home care monitoring system realizes real-time detection of the elderly fall situation, through the built-in MPU6050, L80-R, STM32 main controller, BC35-G communication module and other hardware circuits of the belt placed on the waist of the elderly to collect the elderly's action signal data, and then after the median filtering process, feature extraction, the elderly's behavioral analysis, to determine the elderly Whether the elder falls or not, and upload the result, and upload the location information of the elder at the same time.

Taking the position of the device worn by the elderly as the origin, a spatial right-angled coordinate system is established, defining the front and back sides of the elderly as the X-axis, the left and right sides as the Y-axis, and the side perpendicular to the ground as the Z-axis. Therefore, after median filtering, the corresponding acceleration of X-axis, Y-axis and Z-axis are a_x, a_y, a_z, and the angular velocity is w_x, w_y, w_z, respectively.

In this paper, the human posture motion state is specifically described by signal magnitude vector (SMV). According to the spatial calculation method, the combined acceleration SMV_a and the combined angular velocity SMV_w are obtained, where the combined acceleration and the combined angular velocity are calculated as shown in Eq. (14) and Eq. (15).

$$SMV_a = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{14}$$

$$SMV_w = \sqrt{w_x^2 + w_y^2 + w_z^2} \tag{15}$$

In order to improve the accuracy of fall detection events for the elderly, this paper introduces the concept of human body angle of inclination (AoI) parameter to further analyze the behavioral postures of the elderly, where the angle of inclination defined by AoI is the spatial angle established with respect to the Z-axis. Its calculation is shown in equation (16).

$$AoI = \arctan\left(\sqrt{a_x^2 + a_y^2} \,/\, a_z\right) * (180/\pi) \tag{16}$$

Normally, when the human body is standing normally, the AoI of the human body to the Z-axis is 0°, then when the human body and the smooth ground are in a horizontal state, i.e., lying down, the a_z is approximated to be 0, and then the AoI is 90°. Due to the irregularity of the ground, in general when the human body is in the standing state, the AoI fluctuates between 0° and 20°; in the tilted state, the AoI fluctuates between 20° and 60°; in the lying state, the AoI fluctuates between 60° and 90°. Therefore, by analyzing the AoI values, the active posture situation of the elderly can be detected more accurately, so as to improve the accuracy of the fall determination of the elderly.

2.3.1. Signal Filtering and Feature Extraction

In this paper, median filtering [38] is used to eliminate noise interference and reduce the impact of noise on the performance of fall detection. Taking X-axis as an example, the original acceleration sequence of X-axis is defined as $a'_x(i), i = 1, 2, \ldots, n$, and the acceleration after median filtering is $a_x(i)$. Similarly, the original angular velocity sequence of X-axis is defined as $w'_x(i), i = 1, 2, \ldots, n$, and the angular velocity after median filtering is $w_x(i)$. The calculations are shown in Eq. (17) and Eq. (18).

$$\begin{aligned} a_x(i) &= Med\left(a'_x(1), a'_x(2), \ldots, a'_x(m)\right) \\ &= \begin{cases} a'_x\left(\dfrac{m+1}{2}\right), & m = 2n+1, n \in Z \\ \dfrac{1}{2}\left[a'_x\left(\dfrac{m}{2}\right) + a'_x\left(\dfrac{m+2}{2}\right)\right], & m = 2n, n \in Z \end{cases} \end{aligned} \tag{17}$$

$$\begin{aligned} w_x(i) &= Med\left(w'_x(1), w'_x(2), \ldots, w'_x(m)\right) \\ &= \begin{cases} w'_x\left(\dfrac{m+1}{2}\right), & m = 2n+1, n \in Z \\ \dfrac{1}{2}\left[w'_x\left(\dfrac{m}{2}\right) + w'_x\left(\dfrac{m+2}{2}\right)\right], & m = 2n, n \in Z \end{cases} \end{aligned} \tag{18}$$

After the data are processed by median filtering, the spatial joint acceleration and joint angular velocity computations obtained from SMV_a and SMV_w are more accurate, and the results of the fall detection and analysis of elderly people are more accurate, which effectively reduces the misjudgment rate of the system.

The data after preprocessing needs to be feature extracted for training and building a fall detection model. In this paper, the system adopts the method of time domain analysis and frequency domain analysis for the feature extraction of elderly behavioral information, and the two feature extraction methods extract different feature quantities, and the extracted feature quantities are combined into one feature quantity to be input into the Support Vector Machine (SVM) classifier for further recognition of human behavior, to discriminate the elderly's daily behavioral actions, and to avoid under-reporting of the fall events as daily behavioral actions.

During the normal action behavior, the angular velocity is almost 0, which can be ignored, so this paper only extracts the features of acceleration in time and frequency domains. The elderly behavior data model $\left\{a_x, a_y, a_z\right\}$ is established, and the acceleration data in the window is computed to extract the time-domain feature quantities, and then it is analyzed in the frequency domain to extract the frequency-domain feature quantities. The specific calculation of each feature quantity is shown in the following equation:

$$mean(S) = \frac{\sum_{i=1}^{n} S_i}{n} \tag{19}$$

$mean(S)$ is the mean eigenvolume, where $S \in \left\{a_x, a_y, a_z\right\}, S_i$ denotes the i th sampling point and 1 is the window length.

$$std(S) = \sqrt{\frac{\sum_{i=1}^{n} \left(S_i - mean(S)\right)^2}{n}} \tag{20}$$

$std(S)$ is the standard deviation eigenvolume, where, denotes the first sampling point and 1 is the window length.

$$correlation = (S, A) = \frac{\operatorname{cov}(S, A)}{\sigma_S \cdot \sigma_A}, S \neq A \tag{21}$$

$correlation(S, A)$ is the correlation coefficient eigenvolume of the sensor's data in any of the two different axes, where $S, A \in \left\{a_x, a_y, a_z\right\}, A$ is the sampled data in the other axis, $\operatorname{cov}(S, A)$ is the covariance of S and σ_S and σ_A are the standard deviation of and respectively.

$$F(k) = \sum_{i=0}^{n-1} S_i e^{-j\frac{2\pi}{n}ik}, k = 0, 1, \ldots, n-1 \tag{22}$$

$F(k)$ is the Fourier transform eigenvolume in the first k dimensions of the FFT, and 1 is the window length.

$$energy(S) = \sum_{i=1}^{n} \left|F_i\right|^2 \tag{23}$$

$energy(S)$ is the energy eigenvolume, which represents the sum of squares of the amplitudes of the components of the signal after the discrete Fourier transform, where $S \in \left\{a_x, a_y, a_z\right\}, \left|F_i\right|$ denotes the i th component magnitude, and 1 is the window length.

The SVM classifier is designed to collect the action signal data of multiple sample behaviors from the wearable fall detection device, and then carry out feature extraction after time domain and frequency domain analysis, so as to obtain multiple corresponding time domain and frequency domain feature quantities. In the actual fall detection process, the multiple corresponding feature quantities obtained from the collected human action signal data after feature extraction are combined into a single feature quantity, which is input into an SVM classifier, and at the same time, the actual output results are predicted according to a pre-trained set of models, and the actual behavioral results of the human body are obtained.

After calculating each time domain and frequency domain feature quantity, the extracted multiple feature quantities are merged into one feature quantity, this is the feature quantity corresponding to all the behavioral information in a window, and the feature quantity is inputted into the SVM classifier to judge the posture behavior of the elderly, to differentiate between the fall behavior and the daily action behavior, and to avoid the system omission.

2.3.2. Flow of fall detection algorithm

The acceleration, angular velocity and GPS data are collected in real time by MPU6050 and L80-R, and then the collected human body movement signal data are calculated and processed by median filtering method. After the data are processed by median filtering, its combined acceleration SMV_a and combined angular velocity SMV_w as well as the human body posture tilt angle AoI value are calculated. Usually, the fall situation of the elderly can be divided into three kinds, forward fall, backward fall and lateral fall, because the SMV values generated during the collision with objects and fall of the elderly are usually higher than the daily activity behaviors (ADLs) such as walking, sitting, etc., so that when the elderly fall situation occurs, the combined acceleration and combined angular velocity will change drastically within a short period of time and generate higher peak values.

Since jogging, squatting, and other actions also show the characteristics of large changes in the amplitude of the combined acceleration and combined angular velocity, the algorithm proposed in this paper adopts the combined threshold method and utilizes the human posture parameters to determine whether the human body has experienced a fall condition as well as to distinguish between fall events and ADL behaviors at the same time, so as to reduce the rate of misjudgement of the human action behaviors, and then through the feature extraction of the information of the human action behaviors, using the time domain and the frequency domain feature analysis method, to obtain multiple feature quantities, and then merge the feature quantities and input them into the SVM classifier for analysis, so as to further obtain the results of the human posture behavior, thus preventing the fall behavior of the elderly from being treated as daily life behaviors and occurring underreporting, and further improving the accuracy of the fall detection rate. The specific detection algorithm flow is shown in Figure 3.

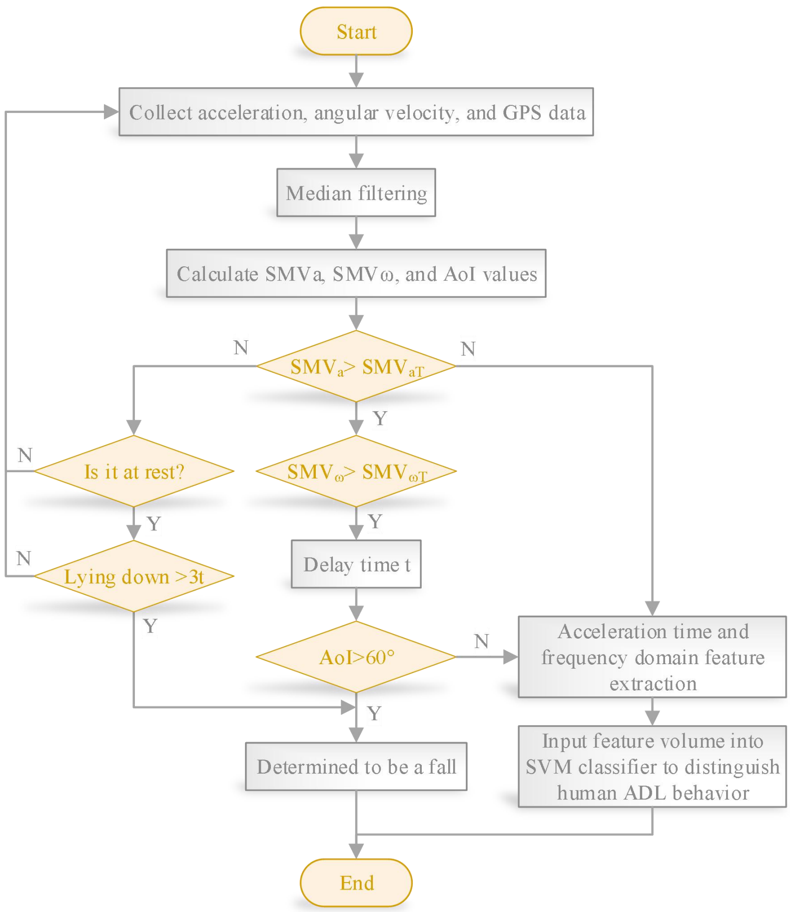


Figure 3. Falls detection process.

2.4. NB-IoT communication design

NB-IoT communication flow is shown in Figure 4, through the configuration of the serial port, clock, interrupts and other resources to complete the initialization operation of the module, first check whether the network is active or not, if it is in the activated state, then create a SOCKET socket, otherwise continue to detect the network activation state; and then detect the network logon, if the network logon is successful, the module will be sent to send the data, and after the successful sending BC26 The module will enter the low power consumption mode, in daily situation the module enters Idle state and set the timer wake-up time as 7 seconds, when a fall occurs, the system wakes up the module and it is in Connected state; late at night, the module enters the PSM state and set the wake-up time as 1 hour, so as to ensure that the system power consumption is lower.

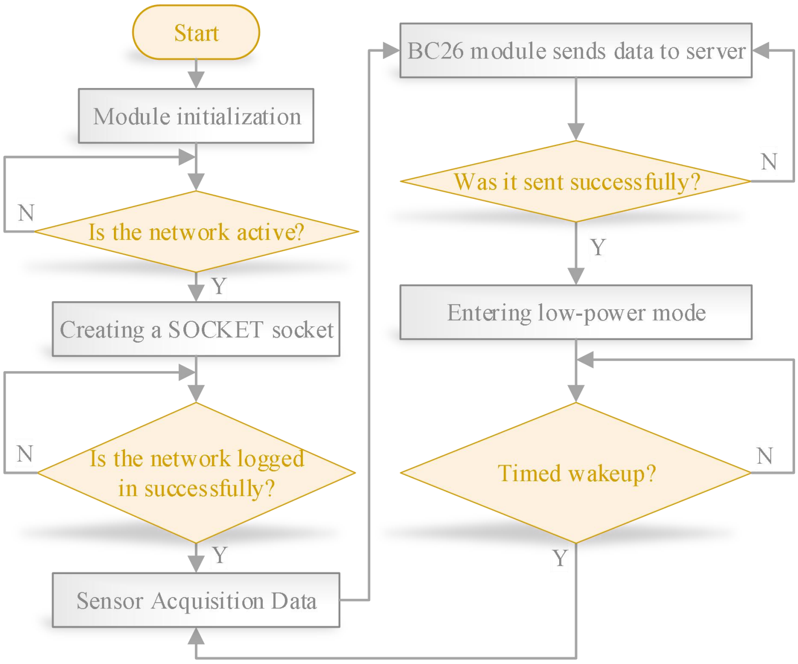


Figure 4. NB-IoT communication flowchart.

3. Results of the realization of the community-based home-based elderly care monitoring system

3.1. Analysis of Attitude Data Changes

In this study, backward and forward falls, and lateral falls were categorized as falls. Behaviors such as standing still, walking, bending, sitting up, walking up and down stairs, running, and jumping are classified as non-falls. The classification can be continued in non-falling behaviors as strenuous and non-strenuous exercise. The final categorization result in this study only requires a distinction between falls and non-falls. The classification problem requires a decision boundary for distinguishing different classes, which can be determined by different features. The system was worn in the center of mass position near the waist of the experimenter. Considering the life characteristics of the elderly, six normal behaviors such as walking, jogging, jumping, bending, standing and sitting, going up and down the stairs, and four fall behaviors, such as forward fall, backward fall, left fall, and right fall, were collected in the experiment. The above 10 behaviors were randomly performed by 10 experimenters wearing the fall warning module to reduce the effect of movement habits. The collected posture data was sent to PC via Bluetooth and USB to serial port. The data were output in float format with time in front and two data separated by a space.

The combined acceleration, combined angular velocity, and combined attitude angle of different behaviors will be analyzed in a comprehensive comparison. If the original three-axis acceleration components are taken as the research object, the number of feature dimensions is large and the change trend is different, and the complexity of algorithm design is very high. Therefore, in order to simplify the algorithm, the mode of the three-axis acceleration vector can be taken to characterize the acceleration features. That is, the combined acceleration Acc, denoted as:

$$Acc = \left(a_x^2 + a_y^2 + a_z^2\right)^{\frac{1}{2}} \tag{24}$$

Angular velocity is an important feature in human posture data, and due to the differences in the direction of fall, the angular velocity feature can be characterized by taking the mode of the three-axis angular velocity vector. That is the combined angular velocity Gyr, denoted as:

$$Gyr = \left(gyr_x^2 + gyr_y^2 + gyr_z^2\right)^{\frac{1}{2}} \tag{25}$$

where Gyr_x, Gyr_y, Gyr_z are the data output from the gyroscope respectively.

The spin angle mainly points to the facing direction of the human body, which changes ±180deg when the human body turns back and forth. Therefore the spin angle is weak to distinguish the behavioral characteristics. And as previously analyzed in the lateral fall behavior, relative to the lateral roll angle, the time period in which the spin angle undergoes drastic changes is delayed for a period of time, which is a weak correlation to the early warning of the fall. Therefore, the combined pitch and roll angles are taken as the attitude angle characteristics. Define the combined attitude angle Angle as follows:

$$Angle = |roll| + |pitch| \tag{26}$$

In fall behavior, the change of stance angle when lateral fall behavior occurs is mainly distinguished by the traverse roll angle, and the change of stance angle when anterior-posterior fall behavior occurs is mainly distinguished by the pitch angle, and in order to unify the study, the combined stance angle is taken as the characteristic in this paper.

Fig. 5 and Fig. 6 show the change curves of combined acceleration, combined angular velocity and combined stance angle of fall behavior and normal behavior, respectively. (a)~(d) in Fig. 5 are the change curves of forward, backward, left, and right behaviors, respectively, and (a)~(f) in Fig. 6 are the change curves of walking, running, jumping, going up and down the stairs, bending, and getting up and sitting behaviors, respectively.

From the figure, it can be seen that there is a large change in the combined posture angle when the fall behavior occurs. The value of the joint posture angle increases in the positive direction from the beginning of the fall behavior and the rate of change is increasing. With high probability, the maximum value is reached when the human body collides with a low-potential object, and then oscillates and smoothes out to a range of 75-110deg. Specifically, the increasing trend of the joint posture angle is relatively smooth when the forward fall behavior occurs, and the joint posture angle will reach an extreme point when the joint acceleration reaches a very small value, and then there will be a transient decrease, which is reflected in the instinctive cushioning of the human body with the hand before colliding with the low-potential object in the forward fall behavior, and then it will reach the extreme point of the joint posture angle in the whole process of the forward fall behavior, and then it will be stable in the final oscillation; when the backward fall behavior occurs, the human body will be in the low potential object after falling, and then it will be stable in the range of 75-110deg. In the case of backward-facing fall, the human body will instinctively collide with the low-potential object in a posture close to the sitting posture after the fall, which is reflected in a relatively small rate of change of the joint posture angle, which increases rapidly to the point of maximal value after the collision, and then oscillates steadily; the change of the joint posture angle of the two lateral-facing fall behaviors has a large degree of similarity, and after the lateral-facing fall behavior occurs, the joint posture angle increases in a relatively gentle rate of change, and then increases to a point of maximal value at the moment of joint acceleration reaching the minimal value, and finally oscillates steadily. acceleration reaches a minimal value near the moment point where the combined acceleration increases sharply at a large rate of change to a point of great magnitude, which is reflected as the process of the human body changing from sideways to lying down after a collision with a low-potential object in the lateral fall behavior, and then oscillating to a steady state. There is a certain correlation between the change trend of the joint posture angle and the joint angular velocity and the change of the joint acceleration in the normal behavior. After statistical analysis, the joint posture angle in the walking, running, and going up and down the stairs behaviors are all within 25deg of regular oscillation, the change amplitude of the joint posture angle in the jumping behavior is 20-30deg, the change amplitude of the joint posture angle of the bending behavior and the sitting up behavior is in inverted U shape, and the change amplitude of the bending behavior is 85-105deg, and the change amplitude of the bending behavior is 85-105deg, and the change amplitude of the sitting up behavior is 85-90deg. 105deg for the bending behavior and 50-70deg for the sitting up behavior.

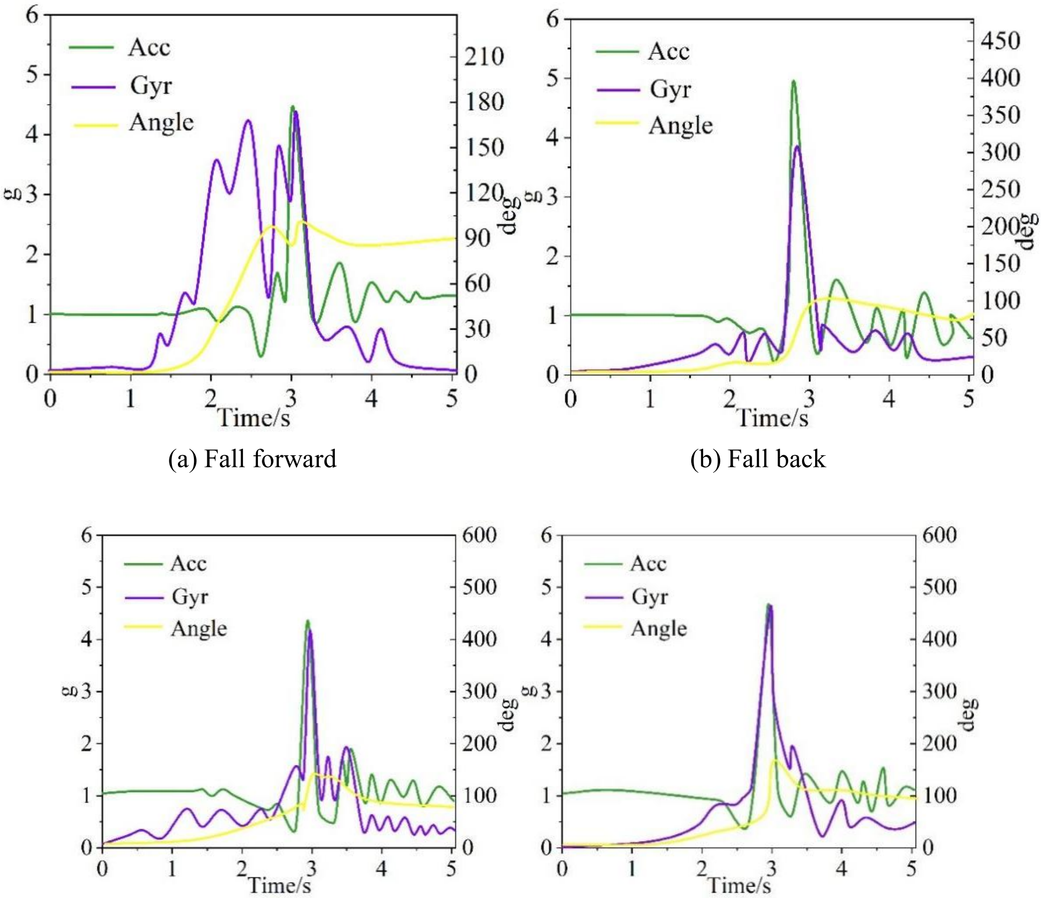
Therefore, it can be concluded that:

(1) The selection of suitable acceleration thresholds can basically classify human behavior into two

categories. One category is fall behavior, running, jumping. The other category is walking, going up and down stairs, sitting up, bending and other behaviors.

(2) Selecting the suitable posture angle threshold can basically classify the strenuous behavior into two categories. One category is fall behavior. The other category is running and jumping behavior.

(3) The selection of suitable posture angle threshold can basically classify human behavior into two categories. One category is fall behavior, bending, sitting up. The other category is walking, running, jumping, going up and down stairs and other behaviors.



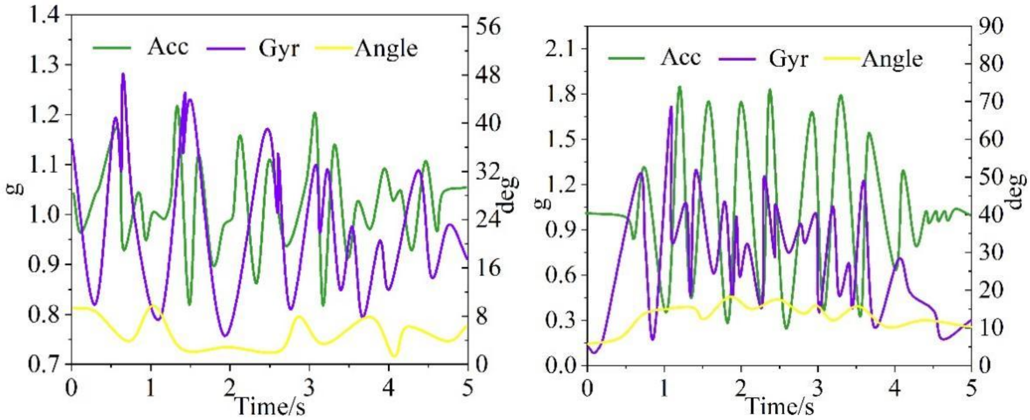
(a) Fall forward

(b) Fall back

(c) Fall to the left

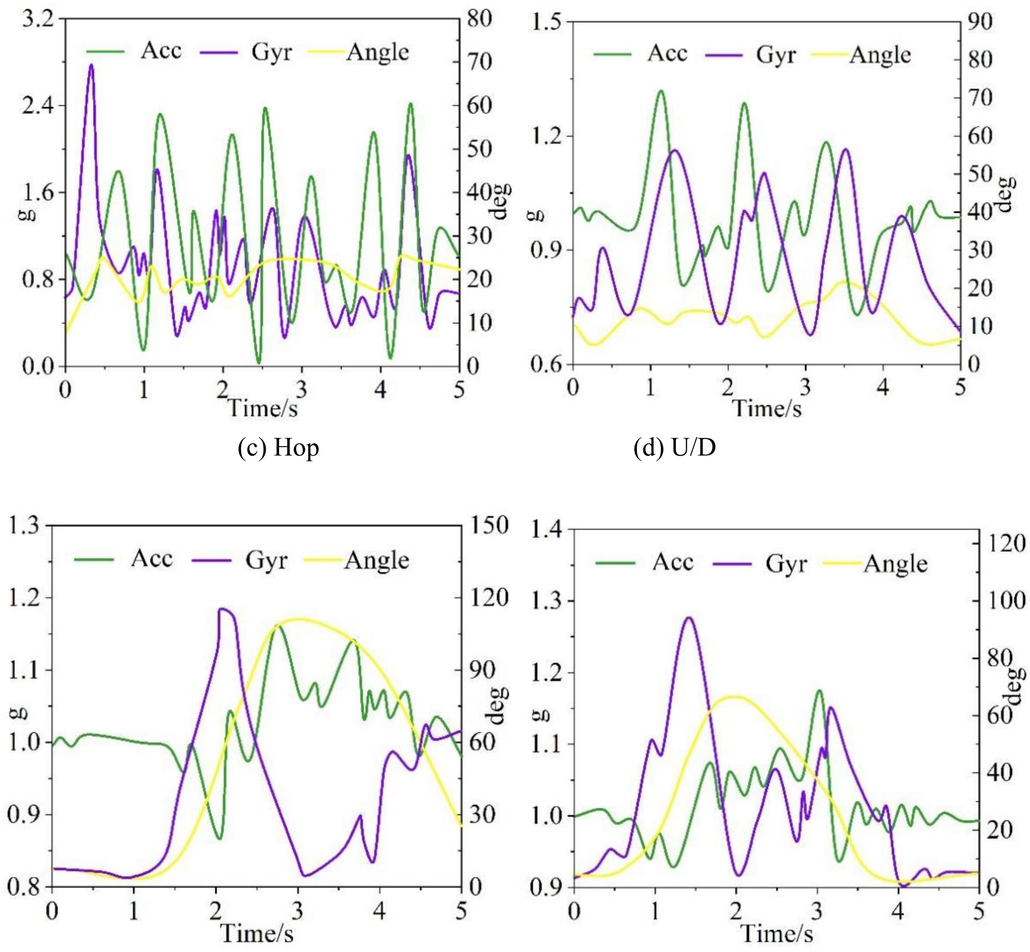
(d) Fall right

Figure 5. The attitude data change curve of the fall behavior.



(a) Walk

(b) Run



(c) Hop (d) U/D

(e) Stoop (f) Sit

Figure 6. Attitude data change curve of normal behavior.

3.2. Analysis of numerical changes in eigenvalues

The body wear sensor system developed in this paper is battery powered and small in size. Experimenters simulated a fall while wearing the monitoring sensor, and the measured sensor data SVM, w are shown in Figure 7 and Figure 8. It can be seen that in the process of falling, i.e., when the time series is about 60, the values of the body-worn sensor data have changed significantly, and it can be very obvious to interpret the occurrence of abnormal falling events. The validation through multiple measurements shows that the proposed accidental fall detection system for elderly users based on NB-IoT communication and localization has a fall detection rate of more than 96% in a multi-user situation.

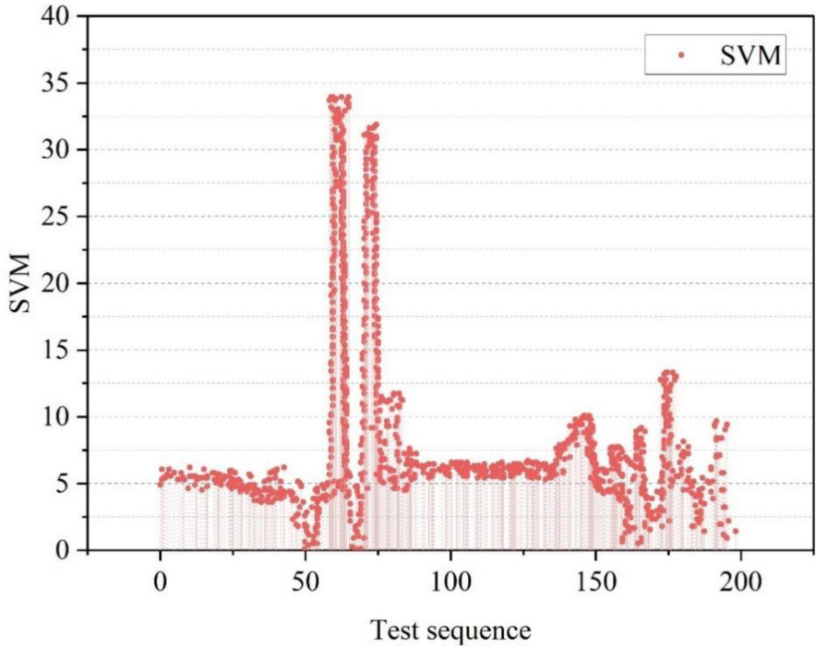


Figure 7. Measured sensor data SVM.

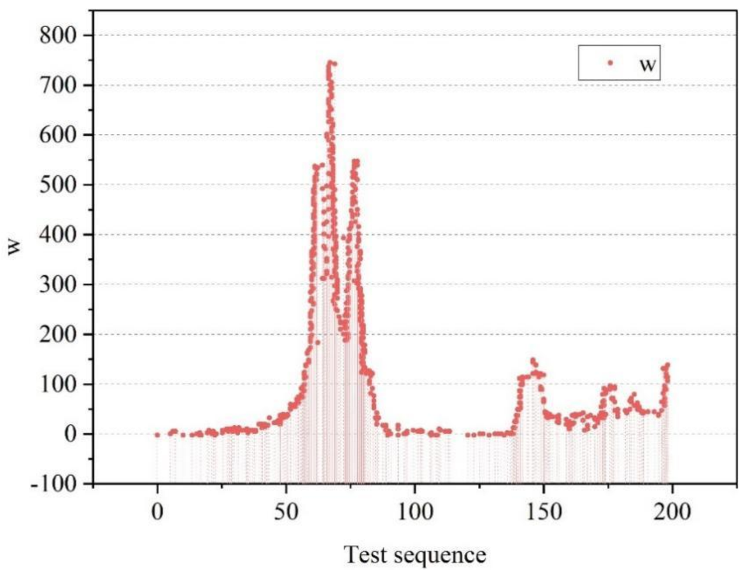


Figure 8. Measured sensor data w.

3.3. Elderly Care Monitoring System Test Results

The comparison of the functional completeness of this system and the test results of each part are shown in Table 1. The results show that the function of each part of this system is realized normally and meets the expectation, and the system is more complete and the applicability is further enhanced.

Table 1. The system is compared to the functionality of his system.

System	Heart rate and blood oxygen	Blood pressure test	Temperature detection	Fall detection	GPS positioning	Data upload

	test					
Based on PPG's heart rate and blood oxygen monitoring system	Yes	No	No	No	No	No
Multiparameter physiological monitoring system	Yes	Yes	Yes	No	No	No
Wearable health data collection and upload system	Yes	Yes	Yes	No	No	Yes
This system	Yes	Yes	Yes	Yes	Yes	Yes

3.3.1. Health Information Detection Partial Test Results

The health information detection part is tested using the logic analyzer (ILA), an online waveform debugging tool integrated in the Vivado software. When the test is completed, the state changes from TEST to WAIT, while the end signal sto goes high, and after one clock cycle it changes to STOP state, and the control command changes to 85, indicating that the test has been completed. The health data collected by the system at this time are oxygen saturation value of 98%, high pressure value of 125 mmHg, low pressure value of 78 mmHg, and heart rate value of 66 beats/min.

The use of this system and the market common Yuyue brand electronic sphygmomanometer for multiple measurements, respectively, to the electronic sphygmomanometer measurement value as the actual value, blood pressure, heart rate, blood oxygen measurement value and the actual value of data comparison results are shown in Figure 9 ~ Figure 11, respectively. It can be seen that the data obtained from the measurement of this system and the sphygmomanometer are not much different, and can realize the expected requirements of health monitoring, and the compliance of the blood oxygen measurement value with the actual value is 100%.

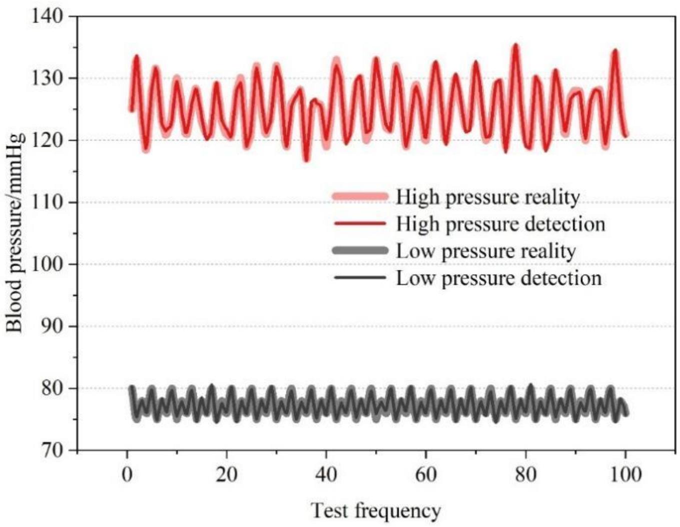


Figure 9. Blood pressure data contrast.

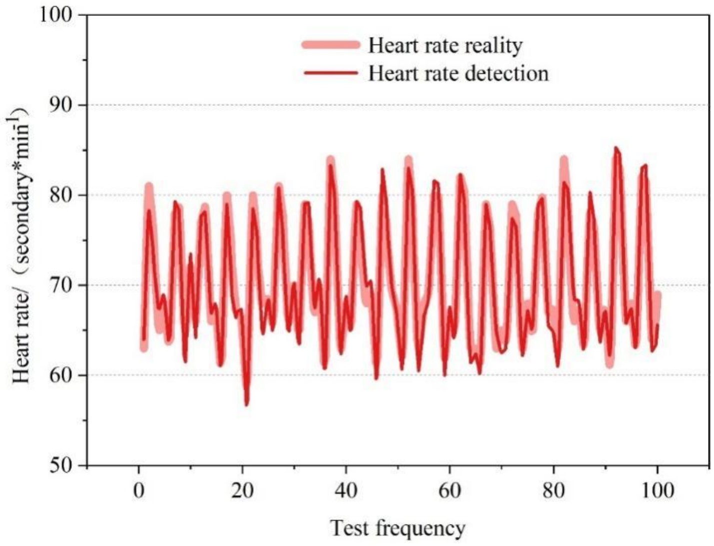


Figure 10. Heart rate data contrast.

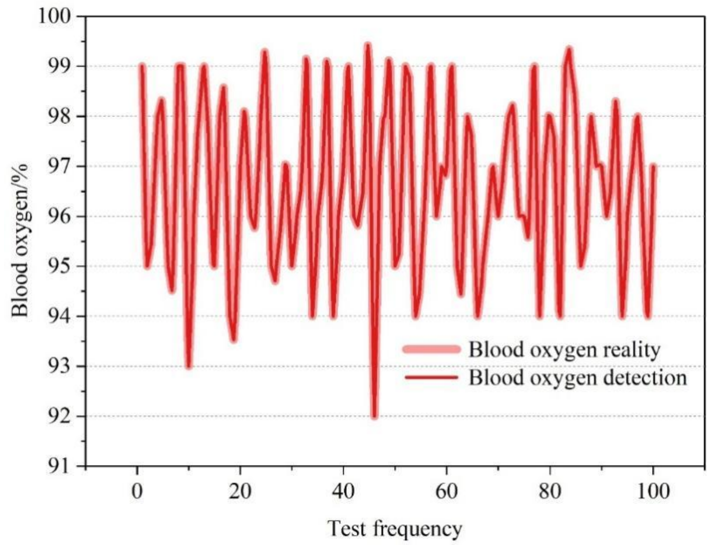


Figure 11. Blood oxygen data contrast.

3.3.2. Test results of temperature detection section

Body temperature detection respectively using infrared thermometer gun and this system to measure the axillary temperature, measurement 20 times to ensure the availability of data, the results of the measurements are shown in Table 2, the two data basically coincide with the maximum difference between the body temperature measurement is only 0.2 ℃.

Table 2. Temperature measurement result.

Measuring number	Measuring equipment		Measuring number	Measuring equipment	
	Infrared thermometer gun	Current system		Infrared thermometer gun	Current system

1	36.6	36.7	11	37	37.0
2	37.3	37.2	12	36.3	36.4
3	36.9	36.8	13	36.8	36.9
4	36.4	36.4	14	37.3	37.2
5	36.7	36.6	15	36.9	36.8
6	37.0	36.9	16	36.2	36.2
7	37.0	37.0	17	36.9	37.1
8	36.3	36.3	18	36.8	36.7
9	36.4	36.4	19	36.7	36.4
10	37.3	37.2	20	36.1	36.1

3.3.3. Positioning section test results

The longitude of the GPS location test result is E12024.83271 and the latitude is N3607.35945. After converting the raw data to the degree-minute format used by Google Maps and correcting the deviation, the location information obtained is N3607.35885 and E12024.81942. The location information is consistent with the author's test location. There is a slight error due to the occlusion of buildings and other structures, but it is within the acceptable range.

3.3.4. Results of the fall detection component of the test

Ten volunteers were invited to simulate the daily activities of slow walking, going up and down stairs, and falling of the elderly in the laboratory, and the test was repeated for 25 times, and the test results are shown in Table 3. It can be seen that the fall detection algorithm in this paper can achieve the expected goal, and the detection accuracy is above 95% in all cases. Because the fall confirmation time threshold set is 3.5s and the angle threshold is 55°, it can better distinguish between normal activities and falls, and there are very few misjudgments.

Table 3. The fall test results.

Number	Walk slowly		Up and down stair		Fall down		Acc/%
	Fall	No fall	Fall	No fall	Fall	No fall	
1	0	25	1	24	25	0	98.67
2	0	25	0	25	25	0	100.00
3	0	25	1	24	24	1	97.33
4	0	25	2	23	24	1	96.00
5	0	25	0	25	25	0	100.00
6	0	25	0	25	25	0	100.00
7	0	25	0	25	25	0	100.00
8	0	25	0	25	25	0	100.00
9	0	25	1	24	25	0	98.67
10	0	25	0	25	23	2	97.33

Checking the uploaded data of this system on the cloud platform, all the data are successfully uploaded, there is no phenomenon of data loss or messy code, the system works normally.

4. Practical application of community-based home-based geriatric care monitoring system

4.1. Information and Methodology

The 140 cases of geriatric patients admitted to the ward of a community hospital from January 2023 to January 2014 were divided into observation group and control group according to the randomized numerical table method, each with 70 cases. Inclusion criteria: (1) age ≥ 60 years old; (2) are in the "medical" or "nursing" state (medical: hospitalization of the patient at the onset of the disease; nursing: in a period of stabilization or recovery); (3) the patient and his family gave informed consent and signed an informed consent form. Exclusion criteria: (1) those who died during hospitalization and nursing; (2) those who cannot cooperate with treatment and care. Observation group 33 cases of men, 37 cases of women; age 60-85 years old. In the control group, there were 35 men and 35 women, aged 62-86 years old.The differences in general data such as gender, age, and type of disease between the two groups were not statistically significant (P>0.05), and they were comparable.

The patients in the control group adopted routine nursing measures, and were given psychological care and health education. The patients in the observation group were assisted with nursing care by the community-based home geriatric care monitoring system.

Compare the incidence of adverse events of fall care during hospitalization in the 2 groups. The self-made nursing quality questionnaire was used to evaluate from 4 aspects of responsibility awareness, service attitude, health education, nursing skills, each dimension full score is 100 points, a total of 140 questionnaires were issued, 140 were recovered, all of which were valid questionnaires. The scale had a reliability of 0.89, a Cronbach's alpha of 0.85, and a structural validity of 0.84, with good reliability. A self-made fall prevention knowledge questionnaire was used to evaluate the patients before discharge, including 4 dimensions of fall prevention facilities, fall prevention knowledge, fall prevention skills, and fall prevention response knowledge, with a full score of 10 points for each dimension. A total of 140 questionnaires were distributed and 140 were recovered, all of which were valid questionnaires. The scale had a reliability of 0.88, a Cronbach's alpha of 0.86, and a structural validity of 0.92, with good reliability.

4.2. Results of practical application

The results of the comparison of the incidence of falls between the two groups are shown in Table 4, and the incidence of falls in the study group was lower than that in the control group, with a P value of 0.015, and the difference was statistically significant (P < 0.05). After applying the nursing intervention of community home geriatric nursing monitoring system in the intervention group, the incidence rate of falls was 0.00%, which was lower than that of the control group by 11.43%, which verified the role of community home geriatric nursing monitoring system in improving the prognosis of patients.

Table 4. The incidence of falls in the two groups was compared.

Group	N	Light	Medium	Severity	Death	Total incidence
Control group	70	3	2	2	1	8
Research team	70	0	0	0	0	0
χ^2	5.589					
P	0.015					

Comparison of the quality of care of patients in the two groups is shown in Table 5, and the quality of care scores of the study group in all dimensions were higher than those of the control group, with all P-values < 0.001, and the difference was statistically significant (P < 0.05). In terms of quality of care, the quality of care scores of the study group in the four dimensions of responsibility awareness, service attitude, health education, and nursing skills were higher than those of the control group, indicating that the application of the program of the community-based home geriatric care monitoring system can significantly improve the quality of care.

Table 5. Comparison of nursing quality in both groups.

Group	Responsibility awareness	Service attitude	Health education	Nursing skill
Control group	89.56±5.78	90.38±6.56	84.18±4.35	87.36±6.28
Research team	94.32±4.11	95.87±4.13	94.59±4.29	94.39±5.28
t	5.716	5.437	8.206	5.509

P	<0.001	<0.001	<0.001	<0.001

Comparison of the effect of health education between the two groups of patients is shown in Table 6, and the mastery scores of the research group in fall prevention facilities, fall prevention knowledge, fall prevention skills, and fall prevention coping knowledge were higher than those of the control group, suggesting that the program can improve the level of patients' knowledge of fall prevention, which in turn can improve their ability to prevent falls. The difference was statistically significant ($P < 0.05$).

Table 6. Comparison of health education effect of the two groups.

Group	Fall prevention facility	Crime prevention	Fall prevention technique	Anti-fall coping
Control group	5.79±2.10	6.12±2.08	5.38±2.01	5.12±2.14
Research team	8.56±1.19	8.89±1.22	8.49±1.34	8.36±1.29
t	8.895	8.671	10.123	10.048
P	<0.001	<0.001	<0.001	<0.001

Elderly hospitalized patients fall and other nursing adverse events are likely to aggravate the psychological burden of patients, leading to trauma, and in severe cases can lead to fractures, organ damage, etc., which has a serious adverse impact on the recovery of patients, so the clinic should pay attention to strengthen nursing care, in order to reduce the risk of the patient's hospitalization period. The application of community home geriatric nursing monitoring system is a new nursing model, which supports the adoption of targeted nursing measures according to the physiological and psychological state of patients and individualized needs, and is conducive to promoting the improvement of nursing quality. Specifically, the application of community-based home geriatric nursing monitoring system in this study can effectively identify the risk level of patients, and then differentiated nursing measures can be taken in combination with the risk, which can meet the needs of patients on the one hand, and realize the rational allocation of nursing resources on the other. Regular health education and the supporting role of family members in explaining the precautions for getting up, walking, toileting, etc., can avoid patients' risky behaviors and further reduce the incidence of falls.

5. Conclusion

In this paper, we design a community-based home geriatric care monitoring system based on Internet of Things (IoT) technology, and realize remote monitoring of the physical state of the elderly by building a multi-sensor data acquisition module, and a real-time fall detection module.

(1) Through experimental tests, it shows that the detection effect of the community home-based elderly care monitoring system is good, and the functions of the system such as health information detection, body temperature detection, positioning and fall detection are all normal, and the maximum error of body temperature detection is only 0.2℃, and the detection accuracy of the fall detection module, which is the highest correlation with the life and safety of the elderly, reaches more than 95%, so that real-time all-around monitoring and care for the elderly who live alone can be realized.

(2) The main contribution of this paper is to provide a referable case of integrated technology and application practice for the construction of a smart elderly care service system, exploring the application method of multi-source IoT data in elderly care, which significantly improves the safety level of the living environment of the elderly who live alone and realizes early detection of risks and timely intervention, which has an important social application value.

(3) This system also has certain limitations, and the privacy protection of elderly users and the sensitivity of the sensors when used for a long period of time are issues that need continuous attention. Future research will be devoted to the development of more sensitive and miniature sensing devices to further optimize the intelligent level of the system and the user's experience.

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