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Artificial intelligence approach for detecting and classifying abnormal behaviour in older adults using wearable sensors

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Abstract

The global population of older adults has increased, leading to a rising number of older adults in nursing homes without adequate care. This study proposes a smart wearable device for detecting and classifying abnormal behaviour in older adults in nursing homes. The device utilizes artificial intelligence technology to detect abnormal movements through behavioural data collection and target positioning. The intelligent recognition system and hardware sensors were tested using cloud computing and wireless sensor networks (WSNs), comparing their performance with other technologies through simulations. A triple-axis acceleration sensor collected motion behaviour data, and Zigbee enabled the wireless transfer of the sensor data. The Backpropagation (BP) neural network detected and classified abnormal behaviour based on simulated sensor data. The proposed smart wearable device offers indoor positioning, detection, and classification of abnormal behaviour. The embedded intelligent system detects routine motions like walking and abnormal behaviours such as falls. In emergencies, the system alerts healthcare workers for immediate safety measures. This study lays the groundwork for future AI-based technology implementation in nursing homes, advancing care for older adults.

Keywords

Abnormal behaviour, artificial intelligence, motion recognition, wearable device, older people, nursing house

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Introduction

The population of older people has been growing very rapidly in recent decades. Nutrient-rich foods, excellence in healthcare, and higher living standards have favored the increase in global average life expectancy. By 2050, the number of older people is forecasted to double to 1.5 billion.[1] China is recognized as one of the fastest growing ageing population countries.[2] The population of people more than 60 years old is predicted to rise by 28% in 2040. The global population is aging rapidly, making the challenges of aging more significant. This necessitates new approaches to sustain public health and develop integrated systems that meet the social needs of older adults.

The continuous aging process generally leads to a deterioration of physiological functions or impairments in

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older adults.[3] This increases the risk of falls, often due to carelessness or sudden health events. While traditional nursing homes provide care services, they often rely on observation and monitoring systems with limited support due to the large size of the facilities and the high number of residents requiring care. This can make it challenging to recognize abnormal behaviours in older adults in a timely manner. The development of immersive technologies for healthcare workers[4] and Internet of Things (IoT) devices [5] is becoming increasingly prevalent. Indoor monitoring systems can help detect falls in older adults. Additionally, by identifying abnormal behaviour and relaying key information to apps or medical care platforms, these systems can streamline the work of healthcare workers in nursing homes, enabling them to provide immediate assistance to residents. Therefore, the development of sophisticated software systems and innovative hardware product designs[6] is crucial for recognizing abnormal behaviour in older adults and delivering timely assistance.

Video-based behaviour detection approaches[7] have gained widespread adoption in various applications, including nursing homes. Many facilities utilize cameras to capture images of older adults, detect and track their movements, and extract key behavioural parameters[8] to assess their mobility and overall state. These approaches aim to distinguish between normal and abnormal behaviour in indoor activities. However, a significant limitation is their inability to classify various major movements of older adults, which are crucial for generating timely warnings for healthcare workers. While research has focused on the perceptions of older adults regarding behavioural monitoring technologies, a gap exists in understanding the practical applications and impacts of these technologies in real-world settings.[9]

Inertial Measurement Unit (IMU) and Ultra-Wideband (UWB) sensors serve unique functions within wearable systems for elderly care. IMU sensors excel in measuring joint movements, assessing range of motion (ROM), and recognizing various human behaviours to enhance real-time monitoring and emergency assistance.[10–12] On the other hand, UWB sensors play a crucial role in behaviour evaluation, health monitoring, and emergency detection in localization systems to offer home monitoring capabilities and focus on critical bed-related states with high detection rates.[12–14] The key difference between IMU and UWB sensors is that IMU primarily measures motion and orientation, while UWB focuses on high-precision distance and positioning measurements. Combining the strengths of both sensor types can provide enhanced information for applications like the instrumented Timed Up and Go (TUG) test.[15] UWB sensors are vital for elderly monitoring systems. Homes and care facilities often have many obstacles and moving people, UWB's ability to penetrate obstacles[16] and provide highly accurate location data[13] makes it ideal for these complex environments. Precise tracking of the elderly's location is essential for detecting important events like falls and triggering timely emergency responses.[12] The high localization capabilities of UWB sensors are a key requirement for effective elderly care and safety.

Previous studies have primarily concentrated on operational issues, such as privacy and socio-technical challenges, rather than on the functionality, usability, and real-world effects of these technologies.[17] Furthermore, a majority of research has been conducted within the domain of passive infrared (PIR) motion sensor technology. Despite the widespread adoption of monitoring technologies, many studies have focused solely on demonstrating functionality through simulations using existing datasets or laboratory settings. The real-world needs of older adults in care settings remain largely unexplored. Therefore, there is a critical need to investigate the functionality, effects, and practicality of behavioural monitoring technologies in real-world situations, and complex nursing homes settings and environment. This includes developing AI algorithms capable of accurately detecting activity patterns in older adults.

This study proposes the development of an abnormal behaviour recognition algorithm for use in a sophisticated nursing home environment, utilizing a smart wearable device. The device is designed to collect raw data for human motion detection, tracking, and recognition. To enhance human body detection, we introduce a double background model incorporating a visual background extractor algorithm within the YUV color space. This optimized approach improves sampling, reduces resampling rates, and eliminates shadowing from the traditional ViBe algorithm by leveraging the characteristics of luminance and chrominance separation in the YUV color space. This results in more precise human behaviour detection, enabling accurate segmentation of targeted body movements. In this research, our primary objective is to investigate the effectiveness of integrating these human motion detection, tracking, and recognition capabilities into a real, complex nursing home environment. While the current results are obtained using synthetic data under a simulated nursing home setting for initial analysis and feasibility assessment, our goal is to ultimately demonstrate the system's performance in a real-world, operational nursing home context. This research is important to validate the practical effectiveness of AI-powered approaches in challenging, real-world elderly care environments. For real-time tracking of indoor human activities, we propose a fusion algorithm combining the Kalman filtering and mean-shift algorithms. Through experiments on single and multiple targets, this fusion algorithm demonstrates improved real-time tracking of older adults. Finally, for motion recognition, we propose a Back Propagation (BP) neural network model to extract motion-related features. By integrating these methods, we achieve accurate recognition of abnormal behaviour in older adults.

This research contributes to the field by integrating human motion detection, tracking, and recognition into nursing home operations, developing and researching sensor and network technologies with promising results in complex environments, and demonstrating the integration of AI algorithms with motion recognition to support emerging healthcare applications.

Literature review

Behavioural information acquisition technology

The movement of the human body is often accompanied by a change in acceleration information. Regardless of whether a person is walking, jumping, waving, swinging arms, or even standing or sitting, their acceleration is affected by gravity. This makes acceleration information useful for behaviour recognition in energy consumption assessment, intelligent monitoring, and medical care.[9,17] An acceleration sensor is used to measure acceleration and convert it into an electrical signal for automated detection of movement behaviour.

The acceleration microsensor typically uses a sensitive mass block to measure acceleration. This is obtained by measuring the displacement of the mass block, and the force exerted by the mass block on the frame, or the force required to keep its position unchanged.[18] There are many methods to measure force or displacement, such as strain gauge, capacitance gauge, strain-sensitive resonant beam, tunnel detector, surface acoustic devices, magnetometer, and optical detector (interferometer). Acceleration sensors with adjustable sensitivity ranging from 1.5 g (800 mV/g) to 6g (200 mV/g) are chosen to obtain more accurate movement behaviour of older adults. Micro-acceleration sensors can be classified into piezoresistive micro-sensors, capacitive micro-sensors, resonant micro-sensors, servo micro-sensors, and tunnel-type micro-sensors based on different detection methods. The development of the micro-electro-mechanical system has promoted the miniaturization of sensors, making wearable devices that have less impact on people's lives. Wearable devices are more sensitive to human activities, making them suitable for collecting human behaviour data. Thus, integrating acceleration sensors into wearable devices is crucial for the collection of behavioural information of older adults.[18–22]

Information transfer technology

After using an acceleration sensor to gather data, sensor nodes need to use data transmission technology to send information back to the platform. Sensor data transmission can be accomplished through a two-stage scheme. In the first stage, information is transmitted to the coordinator node via a wireless transfer mode. The wireless approach is preferred as it can cover a large area of a nursing home. In the second stage, information is transferred from the coordinator node to the platform via wired communication technology, which is low-cost, simple, safe, and reliable compared with wireless communication technology.

Classic Bluetooth, Bluetooth low energy (BLE), and ZigBee are protocols that are widely used in the IoT domain. There are certain trade-offs to consider when deciding which wireless protocol to choose as each protocol has its strengths and limitations. Traditional Bluetooth is relatively power inefficient since it operates on a high bandwidth which requires frequent recharging. Bluetooth iBeacon technology has received increasing attention in recent years as lower-power Bluetooth technology. However, slight changes in the signal intensity of iBeacon can cause significant inaccuracies in distance measurements[23] ZigBee on the other hand is a low-power wireless sensor that is built on top of the Institute of Electrical and Electronics Engineers (IEEE) 802.15.4 protocol. The technology is inspired by the zigzag pattern of the bee colony's communication as they share the newly discovered location of a food source. It supports large number of nodes and improves a variety of network topologies, with speed, reliability, and safety of WSN communication.[24] It is often chosen for a low-cost application in remote controlling of small wireless sensors. Compared with traditional network communication technology, ZigBee wireless communication technology performs efficiently and has convenient characteristics. Table 1 presents a comparison between traditional Bluetooth and ZigBee technology.

ZigBee technology is suitable for applications with small information flow and can be installed in a series of fixed and portable mobile terminals. Considering that the study is mainly focused on behaviour monitoring technology, wireless communication technology needs to be applied in the nursing house to transmit the behavioural information and location information of older adults. In this way, it requires meeting the following features: low power consumption, short transmission distance (10 m - 100m), low transfer rate (100-500 KBPS), low latency, low cost, and convenient networking. ZigBee's transmission distance can network on a large scale (10m-100 m).[26] With the lowest power consumption, small delay, and low cost, ZigBee can be well applied in the transmission of behavioural information to older adults. With the use of routing nodes, this study selects the network structure to provide multiple hop paths for sensor nodes. The ZigBee network ensures the stability of information transmission via the wide coverage of nursing homes effectively. Nevertheless, the system's performance should be investigated in the event of transmitted data loss. Hence, it is important to ensure the stability of the ZigBee network given the complexity of the nursing home environment.

Behaviour recognition algorithm

After the behavioural information of older adults is successfully received through information transmission

Table 1. The comparison between ZigBee and bluetooth.[25]

Specification	ZigBee	Bluetooth
Range (m)	10-100	10-100
Network topology	Ad-hoc, peer to peer, star or mesh	Ad-hoc, very small networks
Frequency (GHz)	2.4	2.4
Complexity	Low	High
Power consumption	Very low	Medium
Security	128-bit AES + application layer security	64 and 128 bits with AES and RSA encryption

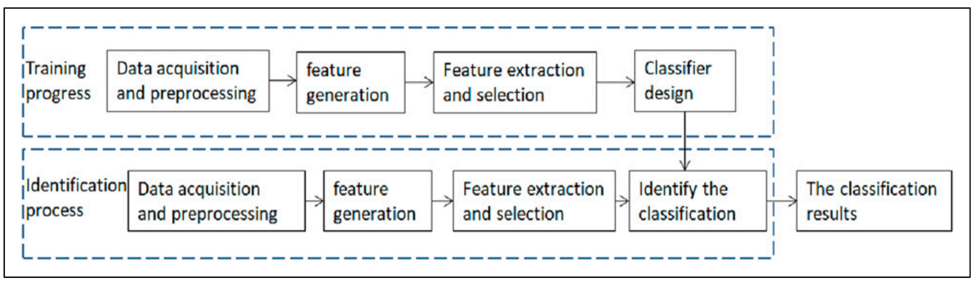

Figure 1. Block diagram of pattern recognition classification system.

technology, the classification algorithm needs to be designed to accurately identify the behaviour of the older adults. In other words, it performs a monitoring role of their behaviour. When an older adult shows abnormal behaviour, the staff can be informed and provide further assistance immediately. When any critical situation occurs, the staff can be notified to aid. According to Wilson, "Behaviour recognition technology can be classified as pattern recognition, and a complete pattern recognition system generally needs to include recognition and Training",[27] as shown in Figure 1.

Neural network for behaviour recognition. The Neural Network (NN) is a nonlinear dynamic system composed of a large number of neurons and shows new approaches and new ideas in pattern recognition, cluster analysis, and expert systems.[26,27] There are many kinds of neural networks, such as BP neural networks, radial basis function neural networks, self-organizing competitive neural networks, and probabilistic neural networks for classification and prediction purposes. The Back Propagation (BP) neural network is a multilayer feedforward network. Propagation is conducted by error inversion of the propagation algorithm.[28,29] The function of the BP neuron is nonlinear. The most used functions are Log-Sigmoid (Logsig) and Tan-Sigmoid (Tansig). Its output is:

$$a = logsig(W_P + b) \tag{1}$$

The two-layer network composed of BP neurons is shown in Figure 2, where p is the input vector, R is the input vector dimension, S is the network dimension, IW represents the weight value, B represents the threshold, N represents the input of the action function, a represents the output of the transmission function, and the superscript on the right represents the number of network layers.

As expected, recognition of an older adult in more behaviour modes requires a large number of behavioural categories in the future. Thus, it will affect the accuracy of the decision tree classification. Data augmentation and generative adversarial network (GAN) approaches [30] are usually used to enhance the accuracy by increasing the dataset. Compared with the other two algorithms, nonlinear mapping ability, self-learning and self-use ability, generalization ability, and fault-tolerant ability of neural networks have great advantages in the classification of large-scale information with noise pollution. In general, there are various types of neural networks, namely linear neural networks, BP neural networks, and radial basis neural networks.[31] One of the important models of the BP neural network is appropriate for pattern recognition and classification. Hence, it is appropriate to apply the BP neural network to the behaviour monitoring of older adults.

Positioning technology. The target of the research study includes both monitoring and locating an older adult. This is not only to realize positioning and abnormal behaviour to prevent deviation activity area in a timely manner, but also to inform the location of the care workers so as to enable monitoring personnel to provide timely rescue. The following sections mainly provide an analysis of the distance

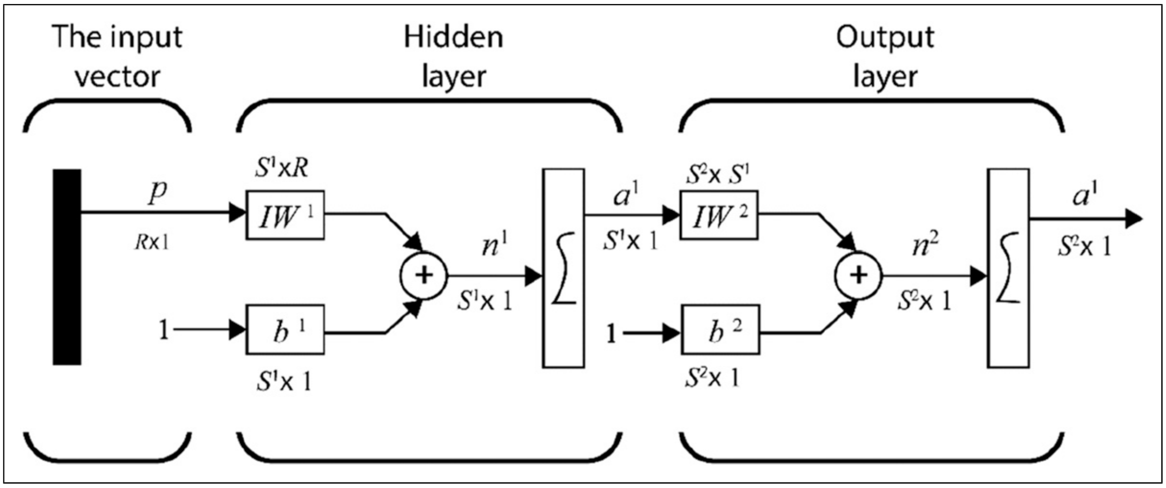

Figure 2. The architecture of the BP neural network model.

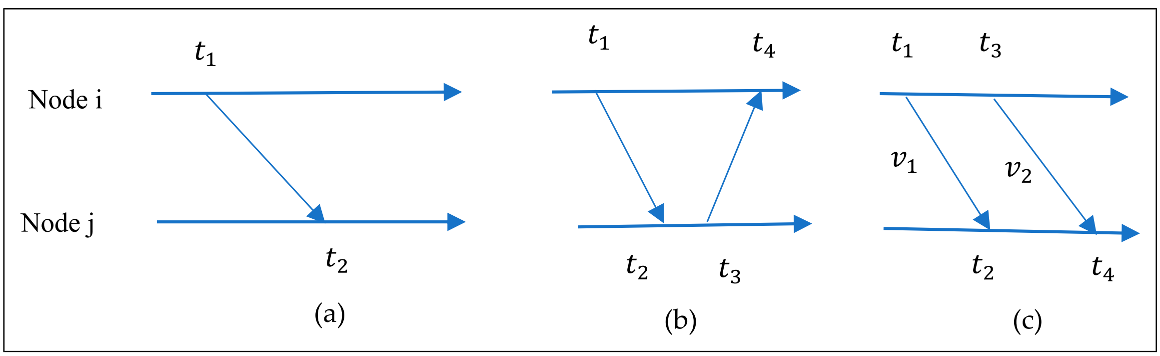

Figure 3. Different ranging methods (a) one-way ToA, (b) round-trip ToA, and (c) TDoA.[31]

measurement algorithm. The time of arrival (ToA) and the angle of arrival (AoA) are the two most used approaches for measuring distances in indoor localization applications.

The Time of Arrival (ToA) distance measurement algorithm uses signal propagation, with the time and propagation rate to determine the distance between two ends of the signal.[32] The signal propagation rate is thus known. The one-way arrival time method measures the signal sending time and arrival time difference, as presented in Figure 3(a), which requires a high-precision clock synchronization mechanism between the sender and receiver. In the two-way arrival time method, the round-trip time of the signal can be measured only on the sending device, as shown in Figure 3(b). There is no need for a high-precision clock synchronization mechanism between the sender and receiver. As such, the two-way arrival time method is easier to achieve.

In the one-way ranging method, the distance between nodes i and j can be determined by the following formula:

$$dist_{ij} = (t_1 - t_2) \times v \tag{2}$$

where, t_1 and t_2 are sending and arrival time of signals, measured by the sending and receiving devices, respectively and v is the signal propagation rate. In the two-way arrival time method, the calculation of distance is given by the following formula:

$$dist_{ij} = \frac{(t_4 - t_1) - (t_3 - t_2)}{2} \times v \tag{3}$$

Among them, t_3 and t_4 are the sending time and arrival time of the response signal. After the transmitting device calculates the location of the receiving device, it informs the receiver of the calculation result.

In the time difference of arrival (TDoA) method, the sending device needs to send two signals with different rates, as exhibited in Figure 3(c).[32] The receiver can determine its position just like in the ToA method. For example, the first signal is a radio signal that starts at time t_1 and arrives at time t_2. The second signal is the acoustic signal, the signal at the time, t_3 arrives in t_4. It can be

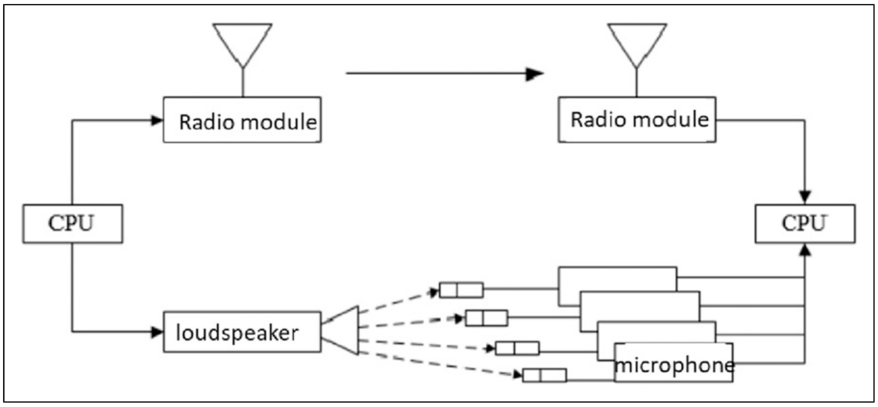

Figure 4. Legal position diagram of arrival angle.

immediately sent out, and can be in t_1 after a fixed time interval to send wait $t_{wait} = t_3 - t_1$. Therefore, the receiver can determine the distance by pressing the following formula:

$$dist_{ij} = (v_1 - v_2) \times (t_4 - t_2 - t_{wait}) \tag{4}$$

where v_1 and v_2 are the propagation rates of the first signal and the second signal, respectively. The TDoA-based approach does not require clock synchronization between sender and receiver. Thus, it can obtain accurate measurements.

Another technique used for positioning is to determine the direction of signal propagation, typically using an antenna array or microphone array to measure the Angle of Arrival. The Angle of Arrival (AoA) is the angle between the signal propagation direction and the reference direction (azimuth). As given in Figure 4, the receiver array is used to achieve angle positioning.[33]

The Received Signal Strength Indicator (RSSI) will decrease with the propagation distance. Also, the received signal strength method is based on this fact to locate the distance.[34] A basic feature of a wireless device is that it has a receiving signal strength indicator which can be used to measure the amplitude of an incoming radio signal. In free space, RSSI decays as the square of the sender's distance.

Although non-ranging algorithms do not directly measure distance or angle, they rely on RSSI, AoA, and ToA information to estimate the node's location, which indirectly measures distance and angle. The centroid algorithm is an outdoor location algorithm according to network connectivity proposed by Bulusu et al.[35] The basic idea is based on the principle of center of mass in geometry. The collection center of polygons is called the center of mass[36] as provided in Figure 5.

In the algorithm, ToA technology requires time synchronization of all nodes in the whole WSN, and the exact time of signal transmission needs to be known. Meanwhile, processing delays and non-line-of-sight propagation of the network will lead to errors. TDoA technology does not need to know the transmission time of the signal. However, it is vulnerable to the impact of non-line-of-sight propagation problems on the system. AoA technology requires sensor nodes to be equipped with directional antennas or antenna arrays, which require too much hardware and do not meet WSN's original intention of low cost and low power consumption. RSSI may cause particular errors due to different working environments. However, compared with the current trend of WSN device miniaturization and low cost, this technology provides expected range finding technology with low accuracy which is more suitable for WSN.

In the positioning algorithm, the three-sided positioning method is simple, but it will not work in case the three circles cannot meet at a point. The centroid algorithm has low requirements on hardware and is easy to implement in software.[37] However, in an environment with a low density of reference nodes, its positioning error is relatively large. To this end, more reference nodes should be distributed evenly to achieve higher accuracy. Since the nursing staff are available for 24-h nursing staff, the positioning algorithm should not necessarily obtain high precision. As long as the positioning is within a certain range, the following work can be completed by the nursing assistants. In addition, the sensor node itself has limited on-chip resources, computing power, and battery power, so it is not suitable for using complex algorithms.

One of the key steps of the centroid positioning algorithm is to determine the polygon region. Basically, there are two methods to determine the polygon region. One method is the algorithm based on network connectivity. The other method is range-based. The disadvantage of this method is that the algorithm is more complex, whereas the advantage is that the researcher can determine the size of the selected polygon by setting a threshold. Hence, the polygon calculation method based on the range is more suitable. Since one of the basic features of a wireless device is an RSSI, no

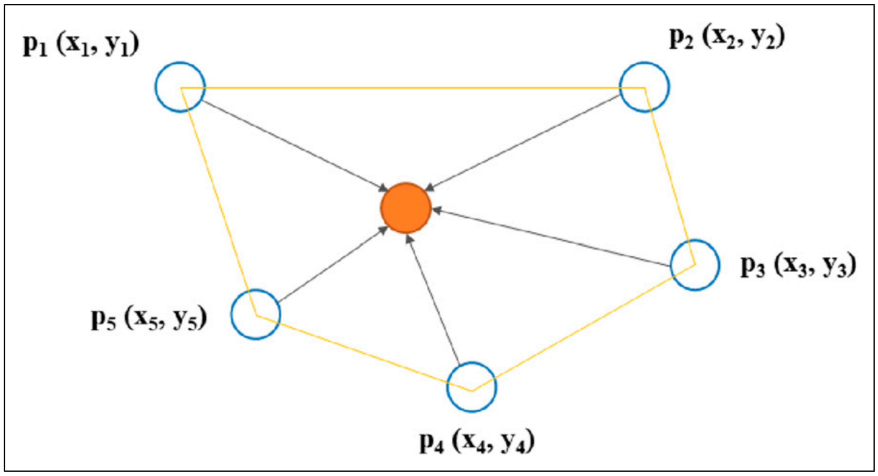

Figure 5. Centroid positioning algorithm diagram.

additional hardware is required, and the power consumption is reduced. Accordingly, we decided to adopt the RSSI-based ranging method and centroid positioning method to locate an older adult.

Materials and methods

Specification of the nursing home model

As the system is designed specifically for older adults, the characteristics of the information collection and transmission system must consider the layout and size of the nursing home. It is important to note that the study protocol does not require human ethical approval as it does not involve direct human participation. Nonetheless, a model of the nursing home should be established in advance to facilitate the subsequent design of the monitoring system. We have developed a retirement scenario, which considers both experimental and real-world conditions, and includes recreational areas, outdoor spaces, and bedrooms, as depicted in Figure 6. This comprehensive approach ensures the practicality and relevance of the system, as it accurately reflects the diverse environments encountered by older adults in nursing home settings.

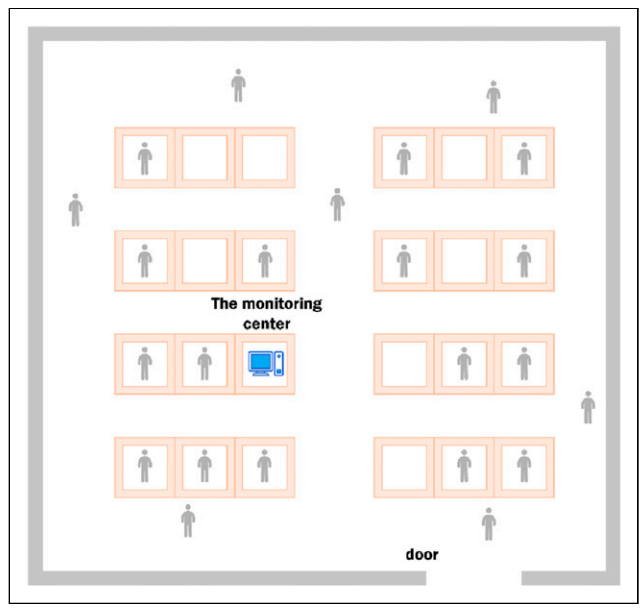

Figure 6. Plan of a nursing home.

Hardware design and system architecture

To obtain more accurate information, a triple-axis acceleration sensor (MMA7361 L) shown in Figure 7, which has a measuring range of ±1.5 g to ± 6g is chosen as the device to obtain the behavioural information. MMA7361 L belongs to a micromechanical acceleration sensor with low power consumption and low-cost capacitance.[38] The acceleration signal from the sensor is then converted to digital format for onward transfer via wireless communication.

ZigBee chip of the CC253X series, with an enhanced model 8051 kernel, 8 KB of RAM, and up to 256 KB of Flash[39] is chosen for the wireless transfer of sensor data. Figure 8 shows the selected ZigBee CC2530 module and the corresponding circuit diagram. The ZigBee module has peripherals including an analog-digital Conversion Period (ADC), timer, AES Security coprocessor, timer, reset circuit, detection circuit, and programmable I/O pins. CC253X series chips are widely used in 2.4 G chip system solutions, built on the IEEE802.15.4 standard protocol. Among them, CC2530 supports other ZigBee types and provides a 101 dB link quality indicator, which has a higher receipt sensitivity and good anti-interference ability.[40]

The hardware circuit design of sensor nodes was designed in the form of a bracelet so that it could be worn on the body. The hardware circuit of the sensor node is mainly composed

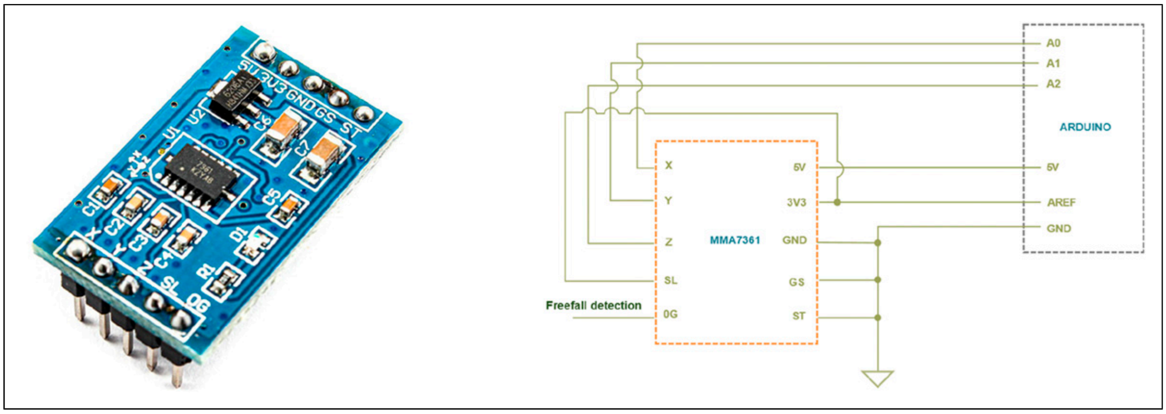

Figure 7. MMA7361L sensor module and block diagram for Arduino interfacing.[35]

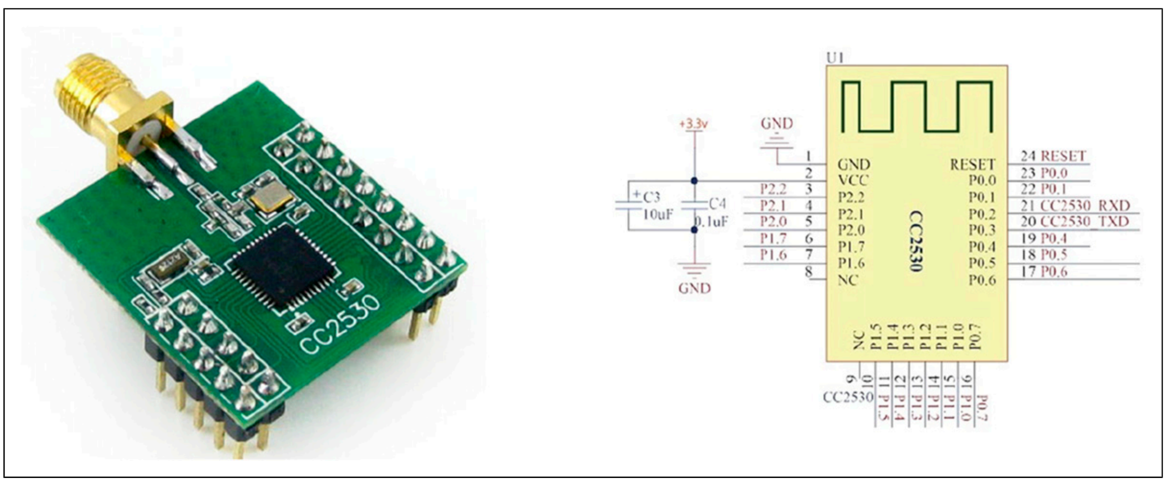

Figure 8. ZigBee CC2530 module and Circuit diagram.[36]

of three parts consisting of the CC2530 peripheral circuit, MMA7361 acceleration sensor circuit, voltage regulator circuit, reset circuit, and Debug circuit.

Concerning the hardware circuit design of the coordinator and router nodes, the coordinator and router node hardware circuit and sensor node constitute the main difference between without acceleration sensor circuit modules, the other does not need to wear in the arm. However, if it is deployed in a fixed position, it is not necessary to design an antenna onboard, in the form of a designed external antenna.

Software design for information acquisition and transmission system

The sensor nodes in the form of a bracelet are worn on the arm for two purposes. Firstly, to send older adults' behaviour data to the monitoring platform based on the acceleration sensor information. Secondly, gather and send the anchor node's RSSI values to the monitoring platform to help the monitoring platform complete the positioning task.

When collecting behavioural information about older adults, the sensor node collects acceleration values of way XYZ of MMA7361 through three ADC (analog to digital conversion) ports P0.0, P0.1, and P0.2 of CC2530. With each information set consisting of 50 sample values and a sampling frequency of 10 Hz, the sensor nodes can collect information about the behaviour of older people every 5s. This will allow the receiver to turn on momentary to received data and then turn off when the data is received, which ensures optimum power consumption while maintaining the integrity of the information by reducing the error rate. However, with the transmission frequency of 5s cannot guarantee the lowest power consumption rate.

Experimental results

Simulation of position data

To conduct a simulation experiment, we created a simulated 2D model of the nursing home environment and then defined the position of anchor nodes and sensor nodes. MATLAB software (version R2020a) was used to simulate the sensor data based on a predefined motion of older adults. To simulate RSSI ranging, we defined the position of anchor nodes and sensor nodes. MATLAB's Wireless Communications Toolbox was used to model the wireless channel and simulate the transmission and reception of wireless signals between the anchor nodes and sensor nodes. RSSI ranging data was then generated based on the simulated transmission and reception of wireless signals between anchor nodes and sensor nodes in a simulated nursing home environment.

The experimental protocol involves fixing the position of the first node while moving the second node within a range of 1~50 m (RSSI threshold). The corresponding RSSI reading of the mobile node was then simulated for each distance. The distance over which the information is to be sent should be within the threshold calculated according to the RSSI router node location.

The relationship between RSSI and the transmission distance d was calculated using the following formula where lgd denotes the logarithmic Gaussian distance.

$$\mathrm{RSSI} = \mathrm{A} - 10\, n\, lgd \tag{5}$$

Using the experimental data, the values of the coefficients were obtained as $\mathrm{A} = 45.3$, $n = 18.38$. The values were then used to fit the RSSI expression. Figure 9 shows the simulated RSSI ranging data which was generated using MATLAB. Figure 10 shows the actual RSSI readings, and the corresponding fit obtained. The result reveals that the closer the distance between the two nodes, the stronger the RSSI, and vice versa.

Based on the experimental result, the localization of unknown nodes is done based on the centroid algorithm as follows. First, the unknown nodes collect the RSS values of anchor nodes within 50 m of distance (threshold). The centroid of the anchor nodes whose RSS values >76.53 (threshold) is used as the positioning coordinate of the unknown nodes. When the sensor node receives a locate command and radio RSSI request, it collects the RSSI values from all anchor nodes for processing. If an RSSI value is above a certain threshold, the sensor node sends it to the router node, which in turn sends it to the coordinator. The sensor node continues to wait for new commands after sending the RSSI values. Once the sensor node collects acceleration data within 5 s from the triaxial numerical MMA7361 sensors, it sends them to the coordinator node. In normal operation, the sensor node waits for confirmation from the coordinator node after sending data or commands.

The main functions of the router nodes are to establish the network topology and assist unknown nodes with positioning. When a router node joins the network, it can assist sensor nodes in transmitting RSSI values and other information to the coordinator node.[27,41,42] Before connecting to the network, the sensor node undergoes equipment initialization and then connects to the network. The coordinator then assigns an address to the sensor node and waits to receive information. When the sensor node receives a locate request, it sends its RSSI value and position to the router node. After the router node has received this information, it waits for confirmation before forwarding it to the coordinator node. Finally, the router node waits for the result of the positioning.

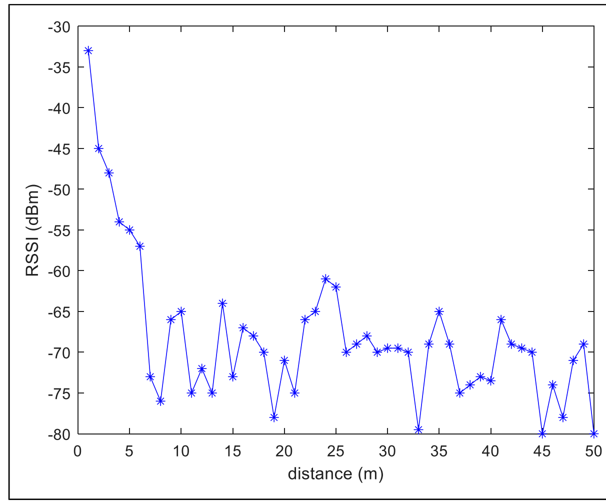

Figure 9. The relationship between distance and RSSI.

As the core of WSN, the coordinator is mainly responsible for initiating a network, assigning addresses to the nodes, and managing the routing of data within the network. The sensor nodes will collect the information, and then connect with the platform of the PC terminal by a universal asynchronous receiver-transmitter (UART). Figure 11 shows the flow chart of the coordinator software.

Simulation of acceleration data and behaviour recognition

In addition to simulating the positioning data, we generated simulated acceleration data for five motion behaviours in MATLAB. This simulation was based on realistic assumptions about the acceleration patterns corresponding to these behaviours. To generate the simulated acceleration data, we first studied the typical acceleration profiles for the behaviours of interest such as walking, lying, standing, and sitting down.[43] For instance, for walking, we simulated rhythmic, alternating patterns of acceleration and deceleration in the X and Y axes. For motion behaviour involving lying down, the acceleration data exhibits a significant decrease in the Z axis. Thus, the simulated values of acceleration data in the X-Y-Z axes corresponding to each behaviour were based on typical

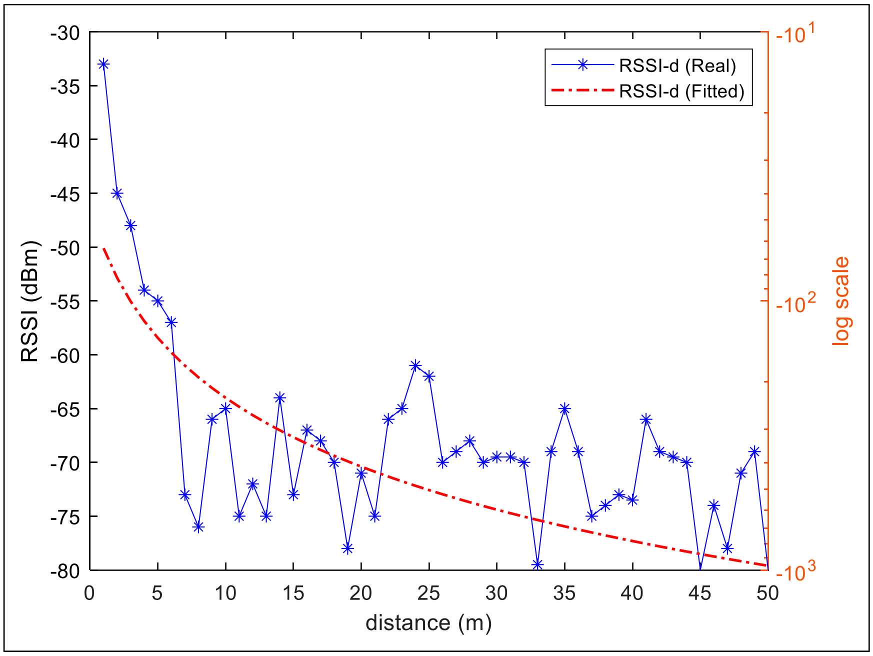

Figure 10. RSSI-D fit.

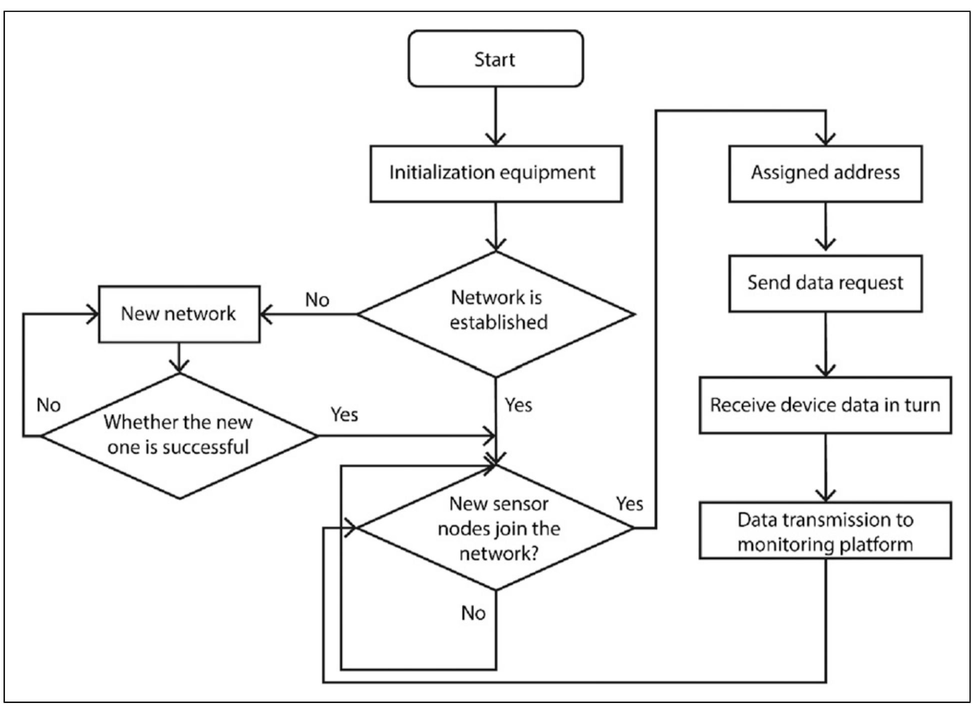

Figure 11. Flow chart of coordinator node software.

acceleration profiles for these movements. To emulate the variability typically encountered in real-world data and create a more realistic simulation, we also incorporated random noise into our data. The simulated data was subsequently used as input to the behaviour recognition system.

As for behavioural information collection, the sensor node is used for collecting the behaviour of older adults through MMA7361. The wearable sensor which is worn on a wrist is shown in Figure 12. The sensor's position can be described using the X-Y-Z coordinate system as follows. The X-axis is aligned with the arm's length, with positive values towards the hand and negative values extending away from the hand. The Y-axis is aligned with the arm's width, with positive values toward the little finger and negative values extending toward the thumb. The Z-axis is aligned with the arm's thickness, with positive values towards the skin surface and negative values extending away from the skin surface."

Behaviour recognition using acceleration sensors requires extraction of features from the time-, frequency, and time-frequency domains. The proposed algorithm identifies five kinds of motion of older people: walking, sitting down, lying down, standing, and sudden falling. For each type of motion, we simulated 50 samples of motion data at a 10 Hz sampling frequency. These samples were then used to analyze the characteristics of acceleration curves in the x, y, and z axes corresponding to each motion behaviour. Figure 13 illustrates that the X-axis acceleration does not undergo significant changes during activities with minimal horizontal movement, such as sitting, lying, and standing. In contrast, activities that involve a wider range of motion, like sudden walking and falling, are characterized by a large fluctuation in the X-axis acceleration values. The figure also depicts the acceleration patterns of the y-axis and z-axis for the same type of motion. The patterns of fluctuation for these axes are like those observed in the X-axis, as they also capture the variety of movements involved in each type of motion.

As for the results, these five behaviours can be divided into 5 key parts including stillness and movement. Three-axes acceleration values for sitting behaviour typically stay near (0.34, 0.34, 0.78), while acceleration values for laying down behaviour are maintained near (0.06, 0.05, 0.93). Acceleration values for standing behaviour typically remain close to (0.84, 0.20, 0.07). Walking and sudden falling are two kinds of behaviour. The x, y, and z three-axis accelerations show varying degrees of apparent fluctuation, especially during sudden falls. The acceleration values during walking exhibit more cyclical volatility, while the acceleration curve during sudden falling has steeper peaks and troughs. The absolute value of the acceleration is also larger during sudden falling.

Based on the above analysis, the average and standard error of the acceleration components along the x, y, and z axes can be used to distinguish features for sitting, standing, and lying down behaviour. Thus, an older adult can be classified as sitting, lying, standing, walking, and suddenly falling. A behaviour is detected as abnormal according to the system when the acceleration data deviates significantly from the expected patterns for a given behaviour. At rest, it can be seen from the above analysis that sitting, lying down,

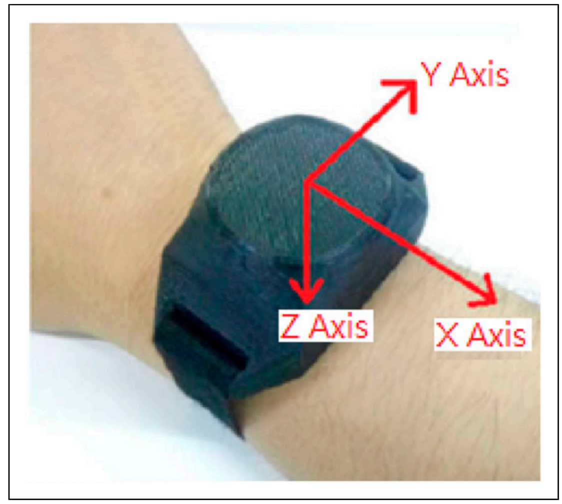

Figure 12. Wearing mode of sensor nodes on the arm.

and standing on the three axes are remarkably different in orientation along the three axes. During motion, there are noticeable differences in the degree of fluctuation and correlation in the acceleration components along the three axes for walking and sudden fall behaviour. To effectively differentiate between these behaviours, the study utilized time-domain feature peaks and other ratios. Specifically, the study extracted the average value, standard deviation, and kurtosis of the acceleration components along the x, y, and z axes between two consecutive time intervals to form a 12-dimensional feature vector that represents the behavioural characteristics.

MATLAB was used to construct the BP neural network for identifying and classifying motion behaviour. The neural pattern recognition system automatically normalizes the sample data, and determines the number of iterations, vectors, and target error arithmetic, simplifying the process. Once the neural network classifier training is completed, the trained neural network threshold and weight can be examined, which facilitates the deployment of the neural network classifier. Therefore, the neural network recognition toolbox was appropriate for constructing the BP neural network used in this study to classify older adults' behaviour.

We implemented a 70/15/15 split for training, testing, and validation, respectively. The dataset was randomly reshuffled before splitting it into training, testing, and validation sets to ensure that the data was representative and not biased towards any motion behaviour. The model was trained for 25 epochs which showed convergence around the 22nd epoch, indicative of the optimal validation performance as shown in Figure 14. The model achieved a training accuracy of 97.1%, while both the validation and testing accuracies were consistent at 87.5%. Additionally, the model has achieved an overall precision of 86.0% and an

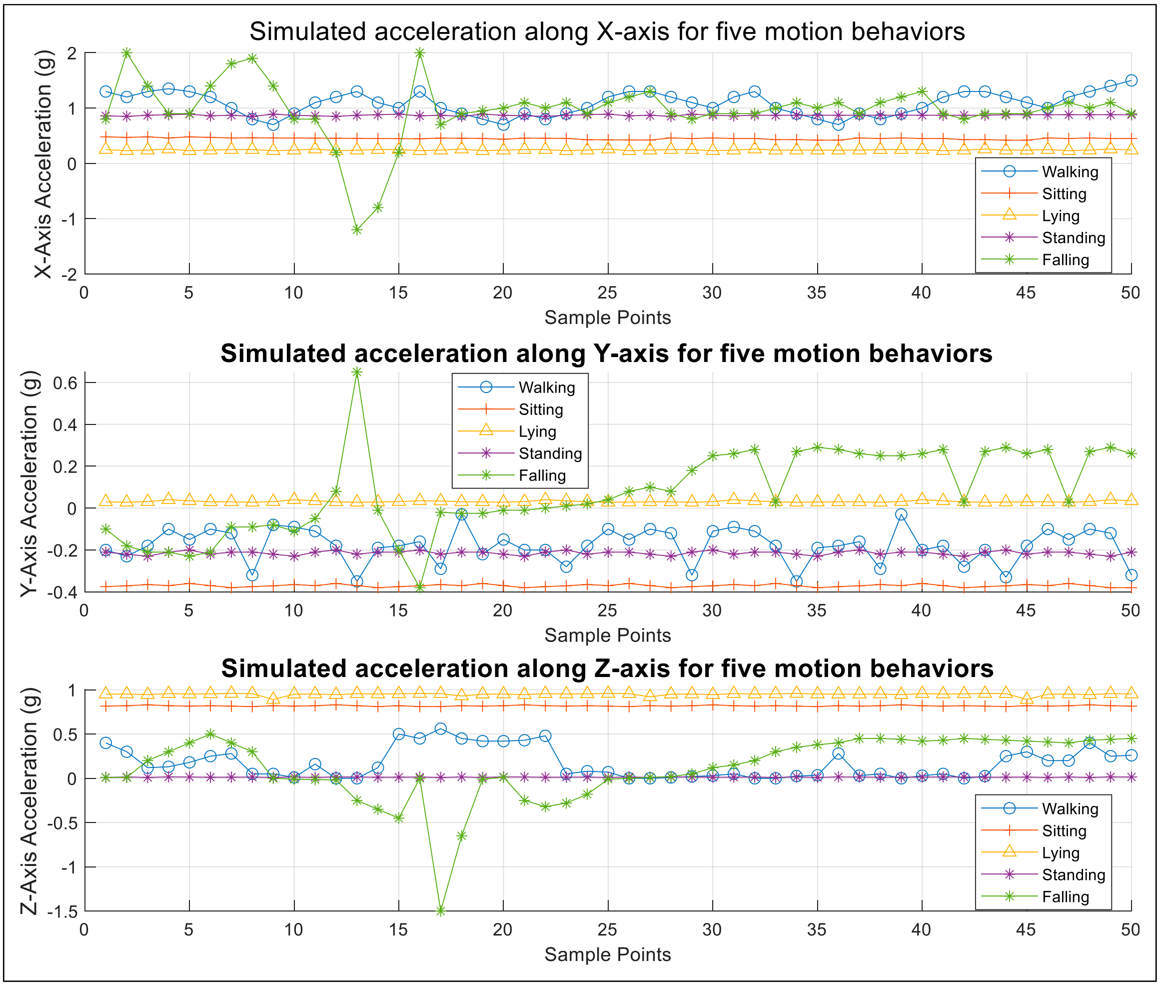

Figure 13. The acceleration changes in *X*, *Y* and *Z* axes.

overall recall of 96.0%. The confusion matrices for both the validation and testing performance are illustrated in Figure 15. The results reveal that our model is highly accurate, with only one class being misclassified. This suggests that the model has largely learned to distinguish accurately between the different motion behaviours.

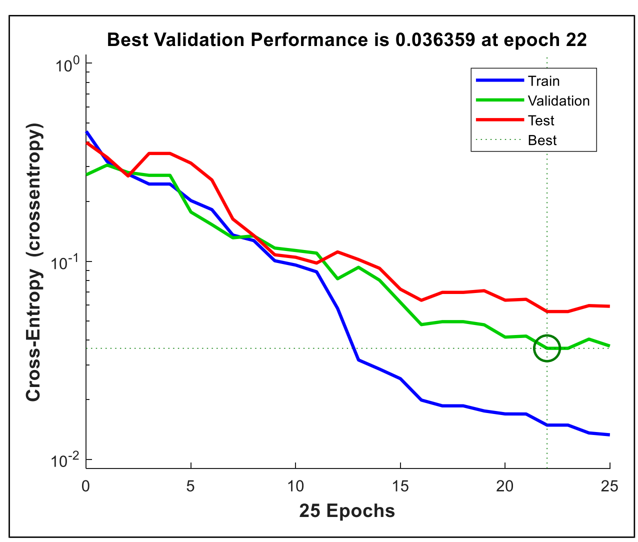

Figure 14. Cross-entropy loss of the proposed neural network model.

Centroid localization based on RSSI ranging

The configuration of the monitoring platform requires the integration of the anchor node location information for the proper functioning of the centroid localization algorithm. It uses the centroid localization algorithm to determine the location of sensor nodes based on measurements of the distances between the sensor node and nearby anchor nodes using RSSI ranging. The positioning precision improves with an increase in the number of anchor nodes and their even distribution. However, using several anchor nodes can increase operational costs. Based on the nursing home area

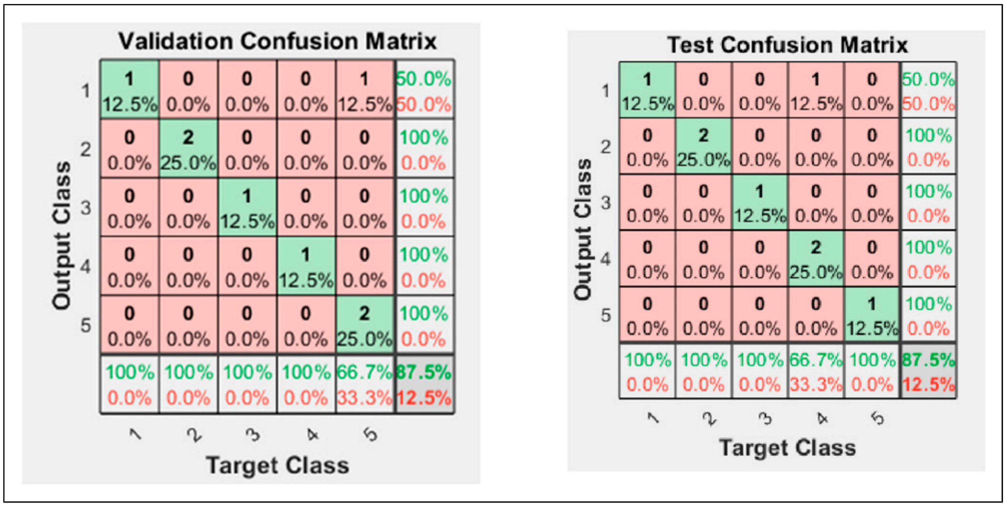

Figure 15. Validation and testing confusion matrices.

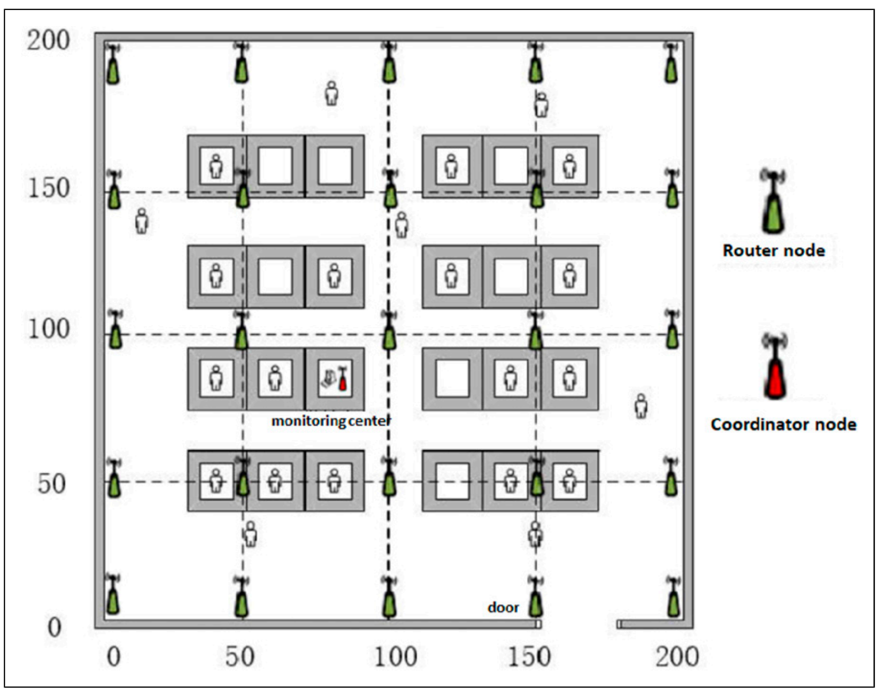

Figure 16. Deployment mode of WSN in a nursing home.

designed in this study, WSN nodes were deployed in the nursing home as shown in Figure 16. The figure illustrates that the nursing home was divided into 16 areas, each with a length and width of 50 m, resulting in an area of 2500 square meters. Router nodes were deployed at each vertex of each area, and sensor nodes were attached to the elderly as bracelets.

The coordinator node was placed in the monitoring center while sensor nodes, router nodes, and coordinator nodes communicated wirelessly. The location of the router node was used as an anchor node for the centroid localization algorithm. The sensor node, which is worn by older people was the node whose location was to be determined and was treated as an unknown node.

Next, MATLAB was used to simulate the centroid positioning method based on RSSI ranging. This method was employed to calculate the position of an unknown node and consists of two main steps:

1. Using the RSSI ranging technique to calculate the range of the unknown node and the anchor nodes.
2. Computing the center of mass of the anchor nodes using the formula $(x, y) = \left(\frac{x_1+x_2+\ldots+x_n}{n}, \frac{y_1+y_2+\ldots+y_n}{n}\right)$ where x_1, x_2, ..., x_n and y_1, y_2, ..., y_n are the x-coordinate and y-coordinate of each anchor node, respectively. Here, n is the number of anchor nodes. The resulting coordinates (x,y) represent the center of mass of the anchor nodes and are used to estimate the position of the unknown node.

According to the deployment mode of WSN in nursing homes indicated in Figure 16, the threshold value was set to 50. The simulation results are presented as follows.

In Figure 17, the black five-pointed star "☆" depicts the anchor node, which is consistent with the deployment mode of the middle route node shown in Figure 13. The red "O" depicts the uncharted node while the "*" indicates the calculated position. Figure 18 shows the errors generated by the centroid positioning method used in this study. The results illustrate that the maximum error was less than 20 m, and the average error was less than 11 m. In other words, the proposed positioning algorithm enables a caregiver to obtain the location information of an older adult quickly.

Design of monitoring platform

The proposed behaviour recognition algorithm was evaluated, and a simulation experiment was conducted to verify the performance of the system. The software system of the monitoring platform was designed using C# language in Visual Studio 2013 and SQL Server 2008 database. The platform was developed using the Windows 7 operating system to receive information on older adults' behaviour and position. The monitoring platform utilizes the BP neural network classification algorithm and centroid localization algorithm to process the received information. These algorithms were simulated in MATLAB, and their performance was evaluated. The algorithm design of the monitoring platform only requires MATLAB programs, and the information can be easily transplanted into C#.

Discussion

Comparison with previous research

This research employs a BP neural network utilizing three-axis acceleration data to classify various behaviours commonly observed in older adults, including sitting, lying down, standing, walking, and sudden falling. The findings reveal distinct acceleration patterns for each behaviour, highlighting significant differences in both static and dynamic states. Overall, this study contributes to the existing body of knowledge on behaviour classification in older adults and demonstrates the effectiveness of BP neural networks for this purpose. The results are consistent with previous research conducted in different contexts, suggesting a promising direction for further exploration and real-world application, particularly in fall detection and monitoring systems for older adults in nursing home environments.

To contextualize the significance and reliability of our findings, we compared acceleration values for sitting, lying down, and standing behaviours, which showed marked

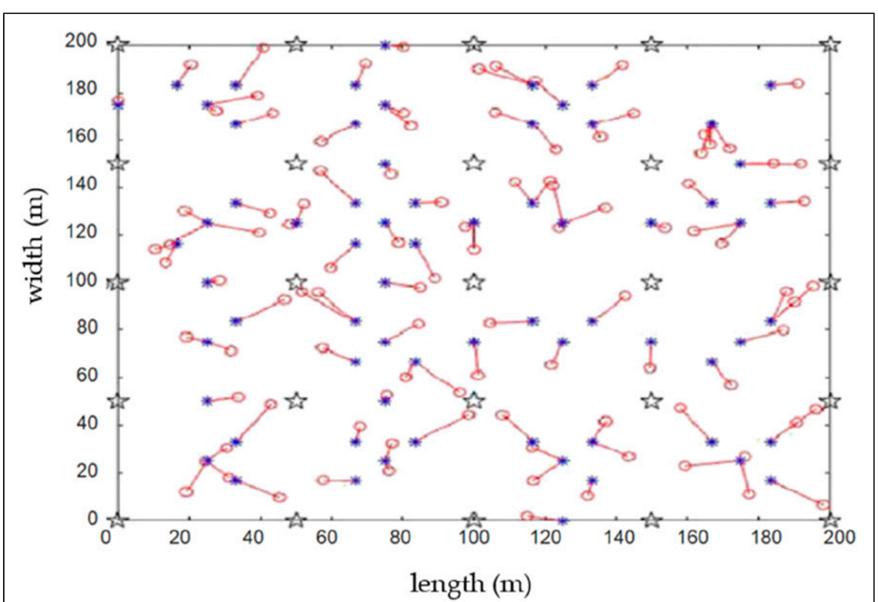

Figure 17. Simulation of the positioning of older people.

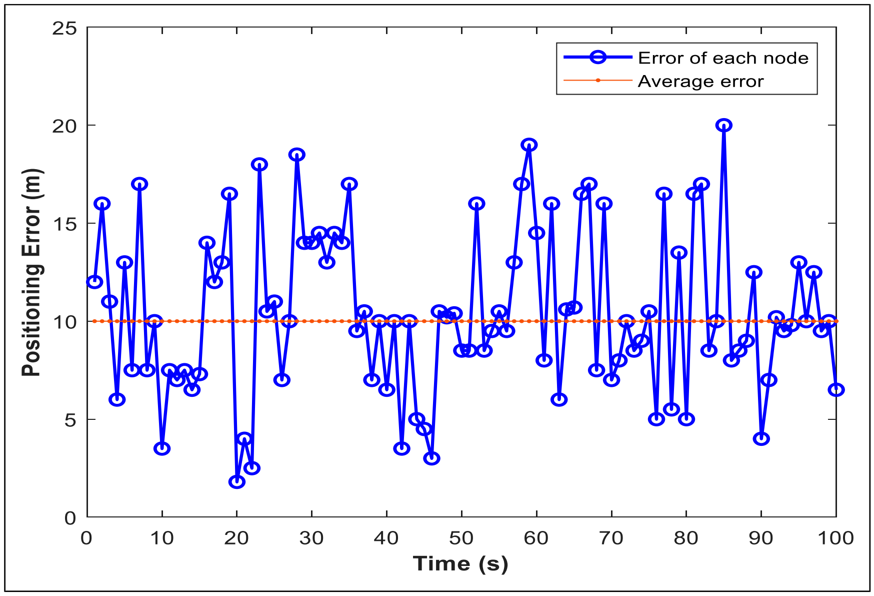

Figure 18. The error of the positioning method.

differences across the three axes. This observation aligns with prior studies that have identified distinct acceleration profiles for various postures[44]. Differentiating these behaviours based on acceleration data is crucial for developing effective monitoring systems for older adults, as emphasized in the literature[45]. Our research also identified cyclical volatility in walking behaviour and pronounced peaks during sudden falls. These patterns support findings by Biswas et al.[46], who noted that sudden falls generate distinct and recognizable acceleration signals. The larger absolute acceleration values observed during sudden falls further indicate that fall detection systems should focus on these unique characteristics to enhance their accuracy.

The study utilizes a 12-dimensional feature vector derived from time-domain features, a method supported by prior research underscoring the importance of comprehensive feature extraction in behavioural classification[47,48]. Incorporating metrics such as average value, standard deviation, and kurtosis into the feature vector enhances the model's robustness, consistent with methodologies applied in similar research[49]. The BP neural network achieved a training accuracy of 97.1%, with consistent validation and testing accuracies of 87.5%. These results are comparable to those reported in the literature, though our model demonstrated superior precision in recognizing physical activities[50]. The overall precision of 86.0% and recall of 96.0% indicate that the model is particularly effective at identifying true positive instances, which is critical for applications such as fall detection, where false negatives can have serious consequences[51]. This research shows promising results in the field by integrating human motion detection, tracking, and recognition within nursing home operations. It successfully combines sensor and network technologies with AI algorithms for motion recognition, yielding effective outcomes in complex environments to support emerging healthcare applications.

Limitations and future research

Our proposed intelligent monitoring system has demonstrated promising results in recognizing and classifying five types of motion behaviour in older individuals. The simulation results suggest that our system can provide timely and accurate identification and classification of abnormal behaviours in older adults, thereby enabling prompt warning feedback to nursing staff to improve the safety of nursing homes. However, while these findings are encouraging, there are several limitations that need to be considered.

Firstly, although designed to mimic real-world human motion, our simulated data lacks the complexity and variability inherent in the movements of actual individuals. Consequently, our model's performance may be overestimated in the current study. Secondly, the predefined motion behaviours we focused on, which, though based on typical movements observed in older adults, may not exclusively capture the full range of possible behaviours. Additionally, the simulated data encompasses both 'normal' and 'abnormal' behaviours, with the latter defined as significant deviations from the typical movement patterns. This binary categorization might not fully reflect the nuanced continuum of human movement behaviours in real-world settings. Lastly, our current model has been tested solely on simulated data, and its performance on real-world data remains unverified. Future research can be conducted to validate our model using real-world data collected from older adults in various settings to ensure it can accurately identify and classify a wider range of human motion behaviours.

Conclusions

Identifying the behaviour patterns that may indicate potential health or safety issues for older adults is critical in nursing homes. Effective identification and classification of older adults' behaviour enables nursing staff to intervene early and provide appropriate care. This study proposed an intelligent system based on wearable sensors and artificial intelligence for the monitoring of abnormal behaviour of older people in nursing homes. The focus of the study is to explore how motion detection, tracking, and recognition can be implemented in a real nursing home setting using sensors, and how these technologies can be integrated with AI algorithms to improve the quality of care for older adults. The proposed intelligent monitoring system has shown promising results in recognizing and classifying five types of motion behaviour of older people. The simulation study results show that the system can provide timely and accurate identification and classification of abnormal behaviours of older adults in nursing homes such as fainting episodes. The results can be used to provide timely warning feedback to the nurses and doctors, significantly improving the safety of nursing homes.

Compared with emerging self-powered sensors that rely on triboelectric or piezoelectric effects, the proposed system can be effectively integrated with human-machine interaction (HCI), VR/AR, and intelligent robot systems One of the specific characteristics of the triboelectric or piezoelectric effects are that it is reversible. This means that when two films with extremely distinguishing electronegativity are rubbed together, they create a possible difference and carry opposite charges. This may affect the stability, sensitivity, industrial production, and durability of the sensors.

The current system is equipped with sensors that are worn on the arm. In the next experiment, sensors that can be mounted on different body locations can be investigated to determine the optimal performance of the system. Besides, although the simulation results for localization are promising, understanding the real-world testing of the system with older adults is critical to verify the results. Thus, future studies should consider testing the system on a sample of the human population. To this end, the implementation and evaluation of the system in a real-world setting is the future direction of this study. Furthermore, this study focuses on the sensor and how it is integrated with the deep learning approach. With the growth of AI technology, further investigation and comparison of deep learning algorithms can be considered in future works.

Declaration of conflicting interests

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