APPLICATIONS OF WIRELESS SENSOR NETWORKS IN FALL DETECTION FOR SENIOR PEOPLE

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ABSTRACT

Due to the advance of modern medical technology, the average age of global population increases continuously in recent years. In 1993, the society in Taiwan had already reached the criterion of aging population, bringing the country an important issue of looking after old people which could not be ignored by its society. In this study, a wireless sensor device is developed to monitor the activities of old people at home and report fall events in real time. It can decrease the mental and physical injuries caused by fall events, and reduce the cost of looking after the injured old people for a long time. Another objective of this study is to enable the society to realize the problem of looking after old people and pay more attention to the senior citizens living alone as well.

KEYWORDS

Wireless Sensor Networks, Activity Monitoring, Machine Learning, Fall Detection

1. INTRODUCTION

As the advance of information and communication technology (ICT), the applications of various sensing devices have been widespread in our daily life, such as: smoke detectors, central air conditioning systems (with temperature and humidity sensors), and seismic intensity detectors for the piers. Therefore, the communication between users and computers depends not only on the keyboard, mouse, or one-way input button, and it can also be done through wireless sensor networks to receive information from people or environments. Wireless sensor networks can be found in our daily life, and their advantages include no wiring required, low power consumption, less construction costs, and the ability to detect events of interest. By collecting and transmitting data to the terminal equipment, one can understand the status of surrounding environments. Thus, the wireless sensor network is helpful for human life.

At present, the situation of aging population is getting worse in Taiwan. According to the statistics of Council for Economic Planning and Development [1], Taiwan's senior population increased to 2.45 million in 2010, with 10.7% of its people over 65 years. It is estimated to go beyond 20.1% in 2025, and will achieve 41.6% in 50 years. The above data show that the senior population is increasing rapidly. Based on the statistics of Ministry of the Interior in Taiwan [2], the demand for long-term care of senior people had achieved 13.1% in 2010, which became a domestic social issue requiring much attention.

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According to the statistics of Centers for Disease Control and Prevention, U.S.A. [3], falls are the leading cause of accidental death for people of the age above 65. In Taiwan, one fifth of the senior people have experiences of falls, which are the second highest cause of injury death for senior citizens. According to the reports of Taipei City Hospital [4], slip and fall accidents accounted for 22.7 % in the case of accidental injury requiring emergent medical treatments, and the victims were mostly senior people. In the fall events, 17.8% occurred in the living room and 15.8% in climbing ladders. Currently, preventive actions are mainly taken after fall events such as to detect the events quickly and accurately and then report the events immediately to save more time for emergent rescue.

Many studies pointed out that the elderly often delay treatments after falls occur because of comas or muddles. They cannot use phones to inform the medical personnel about the exact fall location or touch the emergency button, simply lying on the ground and missing the best rescue timing, which may even lead to irretrievable consequences [5]. Many old people with fall experiences are not willing to conduct the rehabilitation work in the future because they are afraid to fall again. They often limit the range of actions by themselves, which not only affects their life quality seriously but also results in muscle atrophy; some of them even require long-term care in their daily life.

As the problem of aging population becomes more serious, there is more demand for medical personnel in our society. If we can design a portable sensing device to monitor the activity of old people and report fall incidents immediately, it may decrease the resulted mental and physical injuries and reduce the cost and manpower of looking after the injured elderly for a long time as well. In this study, the device for monitoring senior people's activities and locating their positions is developed using wireless sensor network and machine learning technologies. Analyzing the data obtained from 3-axis accelerometers, the back-end computer can identify the user's activities in real time. When the user falls or in coma, the system can immediately report his or her location and status, and then inform the medical personnel for assistance. The system can also provide the researchers with real-time data for further analyses to understand the needs of senior people living alone.

2. Related Technologies

Currently, Global Positioning System (GPS) is the most common solution for wireless location. GPS has many advantages, such as a global coverage up to 98%, three-dimensional high-precision speed and timing with position error of 5 to 25 meters. However, it cannot be used in sheltered environments. Technologies using radio waves suitable for indoor positioning are Zigbee, Wi-Fi, Bluetooth, RFID, and ultrasonics, etc. In this study, a Zigbee wireless sensor network is used for indoor positioning.

2.1. Wireless Sensor Networks

Wireless sensor networks evolved from Micro Electro Mechanical Systems (MEMS). Initially, it was a research project by University of California, Berkeley, USA, where the researchers developed a tiny sensor with the size of about an aspirin tablet (also called Smart Dust) [6]. Wireless sensor hardware consists of the following basic components:

- Sensing Unit: It is composed of two parts: (1) sensors capable of sensing the environment and expressing the collected data with analog signals, and (2) analog-to-digital converters (ADC) for converting analog signals into digital signals and transmitting data to the processing unit.

- Processing Unit: It acts similarly to the PC's central processing unit (CPU) and is capable of executing the code in storage to collaborate with and control the other nodes to carry out the assigned tasks. Processing unit initiates sensing units according to the commands of stored programs and the back-end computer to collect environmental data and send back the data through the transceiver unit.

- Transceiver Unit: It is responsible for sensor communication and exchanging information with each other through transmission medium such as radio and infrared. It can use different transmission modes based on the application environments.

- Power Unit: It is an important unit because the operation of sensor nodes requires electric power. Usually, a battery is used to provide the electric power, and some power-saving methods are used to remain the sensor's operation for a long time.

2.2. ZigBee Technology

The name of ZigBee comes from the waggle dance of the bee to share information with other bees about pollen locations, and it is used to achieve the purpose of communicating with each other [7]. The protocol of ZigBee is based on the standards of IEEE802.15.4 and ZigBee Alliance; the former is a low-rate wireless personal area network (LR-WPAN), which defines the standard of media access control layer (MAC) and physical layer (PHY); the later defines the related software based on IEEE802.15.4, including the network layer, security service layer, application layer and the application interface specification, and it is responsible for the completion of interoperability testing. ZigBee has become an important standard of wireless communication applications with low power and low data rates [8].

ZigBee transmits at the frequency of 2.4 GHz ISM, 915 MHz and 868 MHz. Channels available for different frequencies are 16, 10 and 1, respectively. The transmission rate of ZigBee is 20 to 250 Kbps, depending on the frequency, and it decreases as the transmission distance extends. However, it can be increased by strengthening the transmission power. In order to guarantee a safe and reliable transmission, ZigBee Alliance provides three kinds of network architectures in the network layer, i.e., star topology, mesh topology, and tree topology (as shown in Figure 1). The role of ZigBee in each node can be divided into the full-function device (FFD) and reduced-function device (RFD). Compared with FFD, RFD is simpler and requires less memory. FFD can function as a controller for data exchange, but RFD can only send data to or receive data from FFD. The network coordinator is responsible for establishing the network and allocating address to sensor nodes.

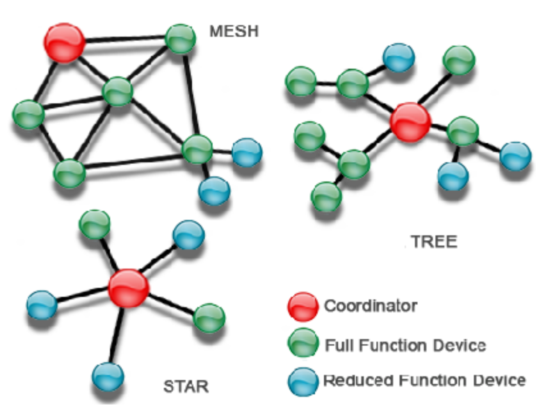

Figure 1. ZigBee's three network architectures

The platform of ZigBee wireless sensor networks can be composed by up to 65000 nodes, similar to the mobile communication of CDMA or GSM networks, and each node is similar to a base station of a mobile network. The nodes can communicate with each other within the entire network area. The advantages of ZigBee include: low complexity, low power, low costs, and a large number of connected peers. At present, locating position in a wireless network area can be achieved by the following methods:

- Angle of Arrival (AOA): It uses directional antennas or antenna arrays to determine the source direction of an active tag. This direction can be decided by a straight line from the starting point of RFID reader on the 2D plane. Two or more RFID readers can be used to measure the direction of the active tags.

- Time of Arrival (TOA): It uses the geometric principles and signal strength to determine the radius parameter instead of signal transmission time.

- Time Difference of Arrival (TDOA): It measures the transmission time of signal from the base station to users by the hyperbolic positioning principle for detecting their positions.

- Received Signal Strength (RSS): It uses the channel propagation model to describe the path loss related to distance, which requires at least three base stations. This study is based on RSS for the comparison in positioning.

2.3. Machine Learning

With the advance of semiconductor technology, the cost of data storage devices is reduced continuously. Therefore, they can be used to create a large database for conducting further analyses, e.g., medical records in a hospital, purchase orders in a store, consumption of calories in walking and exercising, and so on. However, the complex and large amount of data cannot be analyzed easily to obtain implied information using general computation methods. Machine learning is an emerging research area with great potential. It combines statistics, mathematics, information science and other related technologies to provide computers with learning ability. Machine learning is an important research area for many applications and it can use previous data to create association rules for describing the features and relations among these data for predicting the results of some unknown events.

In the training process, a decision tree is a predictive model to describe the mapping relationship between the features of some objects and their values. In the decision tree, each node represents a feature and each path represents a possible attribute value. A decision tree is divided into a number of subsets with similar features based on some recursive methods and finally presented as a tree structure, including the root node, intermediate nodes, and leaves. In this study, the J48 decision-tree model of supervised learning [9] was used as the classifier for activity monitoring. The size of a decision tree is determined by the node number of its branches. It is required to produce the best results using the minimal number of nodes in many applications, and entropy is often used to represent the feature value in machine learning as following.

$$Entropy(S) = \sum_{i=1}^{m} -\frac{|S_i|}{|S|} \log_2 \frac{|S_i|}{|S|}$$

Usually, a good feature can reduce the entropy of its subset, and its value is smaller when the data are of high homogeneity. In the above equation, *S* is the data set and *i* represents a certain class. If each node has S predictive values, then the frequency of occurrence for each value is denoted by $|S_i| \div |S|$. The advantages of using a decision tree include a clear expression of the rules without complex calculations and ability to process continuous and classification variables. Its disadvantage is that the inference process can easily be influenced by missing data.

2.4. Physical Activity Monitoring

In our daily life, the activity monitoring often requires the installation of sensors at some fixed locations and it is classified as indirect and non-adherent. Monitoring of physical activities often requires wearing of sensors for direct measurement of human activities. When wearing sensors, we usually avoid joints and select the big areas with less active parts to improve the accuracy of data. Home activity monitoring can be used for evaluating the activities of old people, and it can be used for the purpose of checking the overall health status. In classification, it can be divided into monitoring activities of daily living (ADL) and physical activities (PA) [10]. ADL refers to basic self-care activities which must be carried out every day by people. However, sustained minor changes are not easy to perceive. ADL monitoring of the elderly enables us to know their long-term behavior patterns or habits at home and predict the changes about functional health status. Examples of ADL monitoring technologies include passive body infrared, reed switch, and real-time image recognition, and they are also often used in security systems.

PA is defined as the body movement consuming calories by muscles and bones. PA monitoring can provide quantitative data as the evaluation index for the activity and health status of the elderly. The commonly used techniques are wearable sensors for PA monitoring (such as pedometers) and sensors to distinguish posture conversion and pace features (such as fall detectors). The ways of sensor data transmission from low-level to high-level can be divided into data recording, data transmission, and data processing. The wireless sensor network used in this study belongs to PA monitoring, and it can record sensor data for real-time transmission and processing as well as reporting fall events immediately.

3. SYSTEM MODULES AND FUNCTIONS

In this study, the wireless sensor network for activity monitoring is implemented using the CC2430 chip by Texas Instruments (TI) [11], and its advantages include: low cost, low power consumption, small size and easy deployment. The Zigbee blind node in Figure 2 is the essential part of the fall detection module and it can communicate with PIC18F24J microcontroller and the G-Sensor. The latter can convert A/D signals and transmit via the former through RS-232 Port connected to the back-end computer for fall detection. The wireless sensor network was built using five Zigbee chip modules and a CC2430 DBK Board, which was integrated by a back-end computer for obtaining the sensor data in the wireless sensor network.

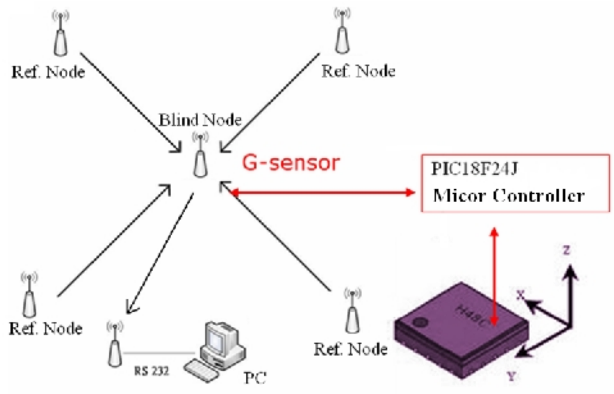

Figure 2. The activity monitoring system using G-sensors

3.1. Fall Detection Module

The fall detection module developed in this study utilizes the FLAG-1609A module of Flag Embedded System. The module adopts the ADXL335 chip of Analog Devices and its schematic diagram is shown in Figure 3. The operating voltages are 3.3V and 5V, and the outputs are analog signals suitable for matching with the Zigbee module. The fall detection module uses the 3-axis accelerometer of ADXL335 with the following features:

- ADXL335 adopts a capacitive accelerometer based on MEMS technology and it is light weighted and small in size, only 4mm×4mm×1.45mm.

- The outputs of 3-axie accelerometer are analog, so they need to be converted into digital signals by the ADC of the microcontroller.

- The 3-axis accelerometer has a sensing range of ±3g and it is more power-saving than other accelerometers. The consumed current is only 350uA, very suitable for long-term wearing to conduct the monitoring of physical activities.

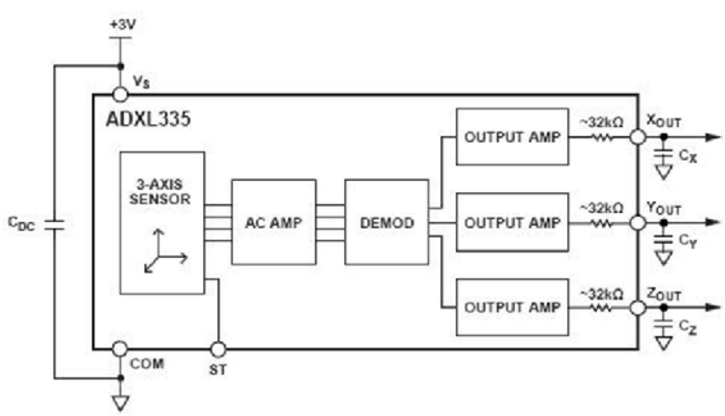

Figure 3. The schematic diagram of ADXL335

3.2. Microcontroller Module

The microcontroller module PIC18F24J is the first Flash PIC microcontroller with full-speed USB 2.0 connectivity, produced by the world's leading semiconductor manufacturer Microchip Technology [12]. Its operating frequency is up to 48 MHz, and the data transfer rate is 12 Mbps. The component combines a variety of on-chip peripheral functions using the technology of nano-watt power consumption management. It is an IC commonly used by embedded system engineers in industrial and medical applications. In this study, we used its 10-bit ADC to convert the 3-axis accelerometer outputs into digital signals and the noise was eliminated by a filter. In this study, the analog signals of ADXL335 are transmitted to the three ADCs of PIC18F24J microcontroller: A/DC0, A/DC1, and A/DC2. The sampling frequency of 3-axis accelerometer is controlled by the timer in the back-end computer's program to obtain data from the three ADCs of 3-axis accelerometer in every sampling period (Figure 4).

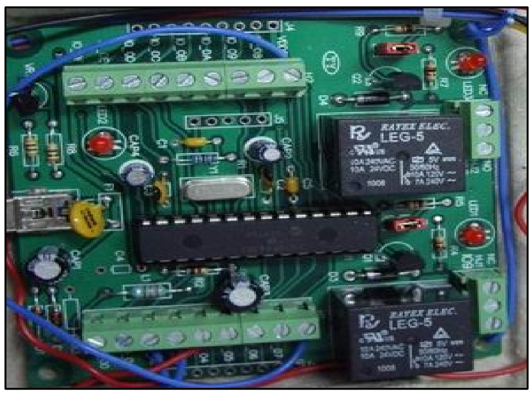

Figure 4. PIC18F24J microcontroller module used in this study

3.3. Compensation of 3-axis Accelerometer Errors

Usually, a 3-axis accelerometer is manufactured with some errors, which must be compensated through a program for correction. In this study, we derived the compensation formulas with the acceleration of gravity. In the calibration tests, the 3-axis accelerometer was set as (*Xout*=1g, *Yout*=0g, *Zout*=0g), (*Xout*=0g, *Yout*=1g, *Zout*=0g), and (*Xout*=0g, *Yout*=0g, *Zout*=1g) for correcting the errors in X-, Y-, and Z-axis. In each case, we sampled 100 times at the frequency of 10 ms in the 3 axes and recorded the values. Then, we calculated the average reading of ADC when X-, Y- and Z-axis accelerations were equal to 0g. When obtaining data, the ADC value is 695 if the X-axis acceleration=0g; the ADC value is 685 if the Y-axis acceleration=0g; the ADC value is 680 if the Z-axis acceleration=0g. The highest voltage provided by ADXL335 chip micro-controller is 3.3V. If its value is 0g, then the voltage falls to 1.65V and the maximum value of the 10-bit sampling is 1024. The relationship between the 3-axis accelerometer and the ADC value in each axis can now be adjusted as follows:

$$X_{out} = \frac{(ADC_x - 695) \times 2.5}{1024} \times 3.3$$

$$Y_{out} = \frac{(ADC_y - 685) \times 2.5}{1024} \times 3.3$$

$$Z_{out} = \frac{(ADC_z - 680) \times 2.5}{1024} \times 3.3$$

The above compensation formulas were employed to test the accuracy of 3-axis accelerometer. We put the sensor in the horizontal direction on the table, so the accelerations in X-axis and Y-axis directions were both 0g while the acceleration in Z-axis was 1g. We obtained an average of 0.01g in X axis after 100 times of measurement, so the error was 1%; we got an average of 0.02g in Y axis after 100 times of measurement, so the error was 2%; we got an average of 0.99g in Z axis after 100 times of measurement, so the error was 1%.

3.4. Zigbee Positioning Module

The ZigBee positioning module used in this study consists of three parts, the Evaluation Board (EB), the ZigBee wireless Evaluation Module (EM), and the power supply Battery Board (BB). The EM module includes an RF antenna and a CC2430 chip to support the full applications in IEEE802.15.4/ZigBee. In addition, the EB and BB boards must be plugged into the CC2430 chip module for usage, and the antenna is also on board. The EB board uses CC2430 ZigBee wireless module plus the structure of EB, and it provides a bitmap-type LCD, a keyboard, a USB to serial port conversion and some light sensors. We can use the human-computer interface consisting of the LCD and keypad to detect the various functions of the CC2430. BB is the simplest module, mainly composed of a power switch, chip module slots, and the REST button, and it is driven by two AAA batteries. Therefore, it is most suitable for use as the external application circuit (Figure 5).

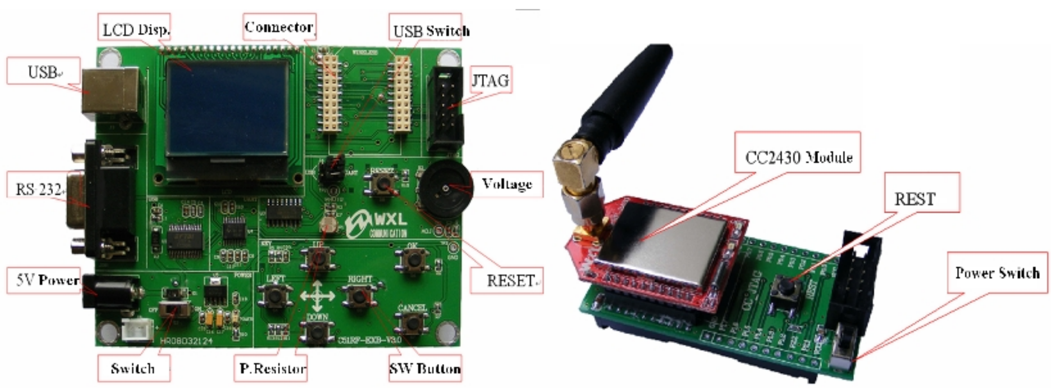

Figure 5. EB and CC2430EM+BB module

3.5. ZigBee Positioning Method

In this study, the Received Signal Strength Indication (RSSI) method proposed by [13] was used as the basis of comparison in ZigBee positioning. With the radio-wave receiver, a Zigbee device has the ability to detect signal strength. Since a single receiver is not sufficient to determine the correct position, we need more than three fixed sensors in order to estimate the distance by the application of regional positioning methods. In Figure 6, the RSSI value of the reference nodes is $-(10n\log 10d + A)$, where n is the signal propagation constant, also known as the spread index, d is the distance from the transmitter, and A is the received signal strength from the transmitter at the distance of one meter.

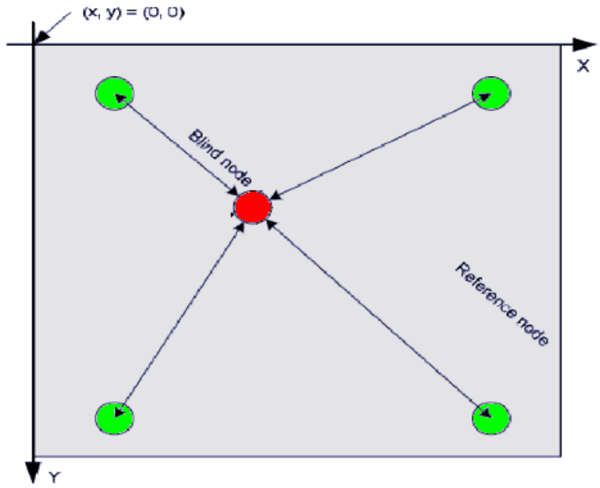

Figure 6. The RSSI ZigBee positioning method

The Zigbee positioning module developed in this study uses the RSSI value of timing detection method to scan ZigBee reference nodes. The method sets the blind node as the center for detecting the neighboring nodes with signal intensity higher than a certain threshold value, and the information of link quality indicator (LQI), signal strength and noise ratio are obtained from these nodes. The blind node scans the neighboring area once in every 100ms and displays the strength of received signals in dB meter. Because each node has a unique physical address (MAC address), which can be used to identify the node, we can use the above information to achieve the goal of regional positioning.

3.6. Identifying Normal Events and Suspected Falls

Most PA monitoring systems use the sensors of accelerometers, gyroscopes and horizon gyro indicators to detect users' physical activities. For example, the 3-axis accelerometer's outputs change dramatically when a fall event occurs. Mathie [14] found that a fall may happen if the signal magnitude vector (SMV)>1.8g. Karantonis [15] proposed that the signal magnitude area (SMA), calculated by the absolute value of 3-axis acceleration, is highly related to human motion. The human is in motion when SMA is higher than a threshold, and is static if SMA is lower than the threshold, but it must be verified together with the original SMV value. The formulas for the calculation of SMV and SMA are shown in the following:

$$SMV = \sqrt{a^2_{x\_dynamic} + a^2_{y\_dynamic} + a^2_{z\_dynamic}}$$

$$SMA = \sum_{n=0}^{256} \left(\left| a_{x\_dynamic}[n] \right| + \left| a_{y\_dynamic}[n] \right| + \left| a_{z\_dynamic}[n] \right| \right)$$

Mathie's algorithm is relatively simple and not influenced by directions, but it cannot accurately distinguish among daily-life activities such as walking, sitting down, falling down, lying down and so on. In this study, we used Mathie's algorithm to categorize the activities into two types, normal activities and suspected falls, and then applied the J48 decision-tree model to enhance the recognition rate of fall events.

4. System Setting and Operating Procedure

The operating system of the fall detection system developed in this study is Microsoft Windows XP; the CPU of the back-end computer is Intel P4 3.0G with 4GB memory; the user interface is designed using Microsoft Visual Basic 2008 Express and it adopts a dual-window presentation mode, including body posture recognition interface to show the data of 3-axis accelerometer and regional positioning interface. The embedded application development tools used in this study is C/C++ cross compiler and the debugger is developed by IAR Embedded Workbench, which can support more than 35 types of 8/16/32-bit ARM microprocessor architectures and provides the same intuitive user interface for different microprocessors.

4.1. System Settings

The body posture recognition interface obtains G-sensor data by using RS-232 COM6 Port as the transmission interface and its settings are described as follows: transfer rate = 38400 bps, 8 data bits, and stop bits=1. After connecting to the fall-detection device, one can select COM6 in the drop-down menu and press Connect Button to start the setting program. The program can set the minimum sampling frequency as 0.01, 0.05, 0.1, or 0.5 seconds, and it can also choose to show or cancel the records in X-, Y-, and Z-axis. If there is no need to watch the waveform, one can select the background mode for execution and recording data only. In Figure 7, the vertical axis represents the voltage waveform by the sensor outputs and the horizontal axis represents the elapsed time which is displayed from left to right. If there is no space for displaying, the system will renew the page for continuous recording.

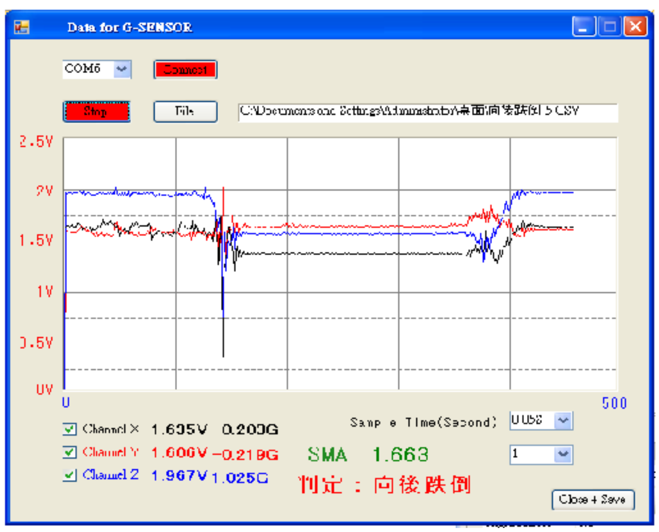

Figure 7. The user interface of body posture recognition

The regional positioning interface can display the floor plan of application environment (Figure 8). When the EM module establishes the sensor network and all reference nodes join the network, the setup tag will display the reference nodes by their address ID, i.e., the physical address of the sensor node (MAC address). The system manager must enter the coordinates of the reference nodes based on the floor plan, and then switch to the setup tag for the blind node. The mobile nodes will start scanning the nearby area and positioning based on the strength of RSSI signals and the associated MAC address. After that, the system interface will display the blind node ID, X, Y coordinates, and its current location on the floor plan.

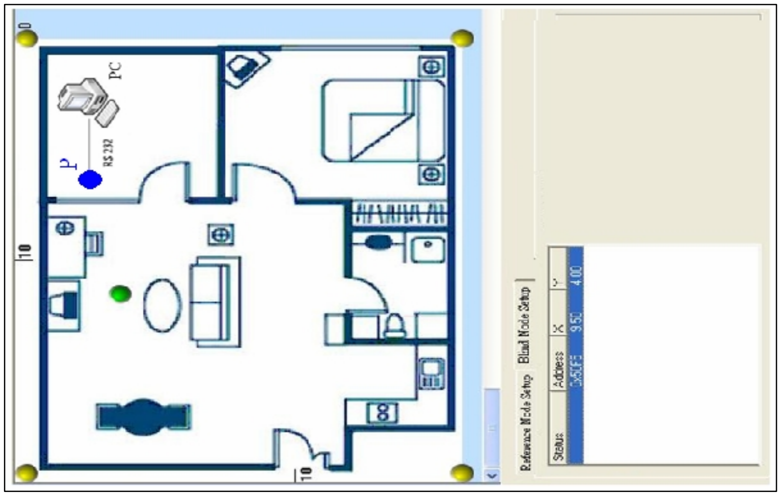

Figure 8. The regional positioning interface to show the blind node

4.2. Operating Procedure

The operating procedure of the activity monitoring system is divided into three stages (Figure 9). First, the system establishes the ZigBee wireless sensor network for regional positioning. Then, it obtains sensor data from the 3-axis accelerometer and sends them to the back-end computer for processing. Finally, the computer uses the J48 decision-tree model to identify the user's activity. The above stages are described in more details as follows:

- Establishing the ZigBee network for positioning

This study deployed four ZigBee reference nodes (CC2430), a ZigBee mobile node (CC2431) and an EB to connect with the back-end computer in an indoor experimental environment, and used the RSSI regional positioning method to obtain the user's real-time coordinates (X, Y). The wireless sensor network sent the coordinates to the CC2430 EM+EB module and the back-end computer via RS-232 COM6 Port. Finally, the system manager can monitor the user's location and activity status on the display.

- Conversion and transmission of 3-axis accelerometer data

When the ZigBee blind node (CC2431) is embedded with the 3-axis accelerometer sensor chip (FLAG-1609A), it can convert the analog signals into digital signals through the ADC, and then transmit the data to CC2430 EM+EB module by the wireless sensor network. The latter passes the collected data to the back-end computer via RS-232 COM6 Port for further processing. The system manager can monitor the acceleration data when the user changes body postures.

- Back-end computer processing

The back-end computer combines the data of position and 3-axis accelerometer to identify the user's activity by the application of the J48 decision-tree model. If the results show that the user falls or is in coma, the system will report the user's position and fall status through the network to notify medical personnel for assistance immediately.

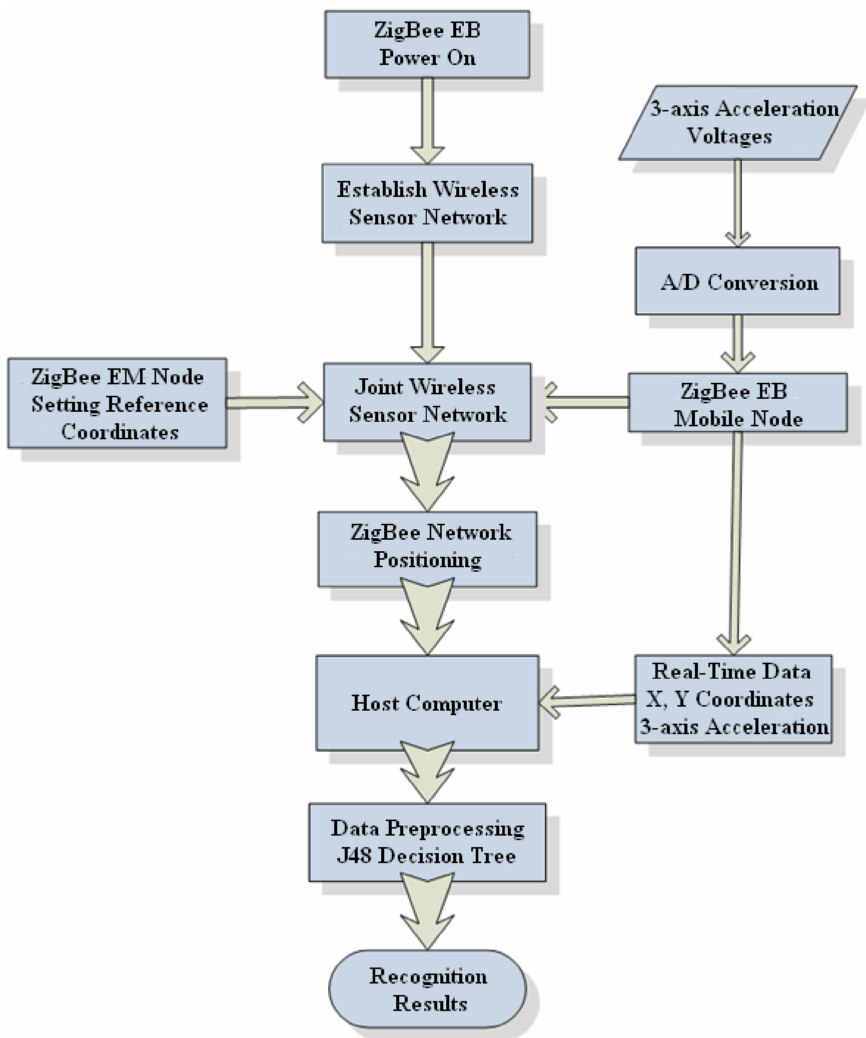

Figure 9. Operating procedure of activity monitoring system

4.3. Data Processing and Feature Extraction

In the proposed activity monitoring system, the 3-axis accelerometer uses the front direction of user's body as the positive X-axis, the right direction as the positive Y-axis, and the up direction as the positive Z-axis. The condition of SMV>1.8 is set as the first threshold (with the sampling time of 50 millisecond). When the condition is satisfied, it is determined as a suspected fall and the system begins to retrieve the related information. Since the human body usually remains stable during walking or sitting down, the SMV will not change too much. Falls or lying down will cause a sudden change of SMV value, so the fall characteristics may appear at both ends of the motion. Hence, SMV>1.8 can be used to determine if it is a normal activity or not. The system creates a temporary storage area for the condition of SMV> 1.8 and captures the sensor data within a second. Then, it uses a quick sorting algorithm to sort the SMV values from small to large. Eight types of features based on the SMV peaks at both ends are captured, including the minimal and maximal SMV values in X-, Y-, and Z-axis directions. Finally, the data are fed into the trained J48 decision-tree model to identify if it is walking, sitting-down or fall events. The procedure of feature extraction for fall detection is shown in Figure 10.

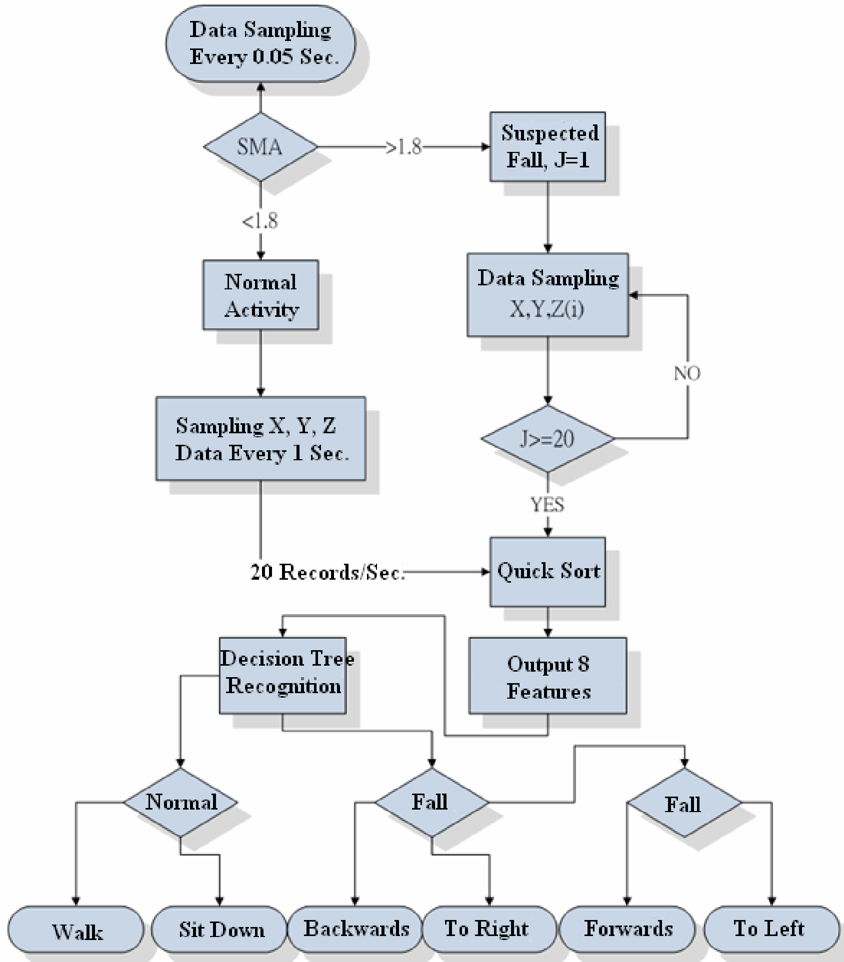

Figure 10. Feature extraction and identification procedure

5. Simulation Experiment and Results

In this study, a simulation experiment described was conducted to evaluate the recognition rates of fall events with different body postures using the activity monitoring system. Ten people were invited to wear the fall-detection module and simulate a variety of activities. Then, the system identified the posture of each user by the J48 decision-tree model according to the sensor data obtained from the wireless sensor network.

5.1. Experimental Environment

To simulate the general residential application, one of the researchers used his apartment as the experimental environment, with the size of about 10 square meters, and the space included a living room, a bedroom, a bathroom, and a storeroom (as shown in the floor plan of Figure 8). This study deployed four Zigbee 2430 EM modules at the corners as reference nodes (expressed by the yellow dots). A Zigbee 2430 EB module was placed at the position P (denoted by the blue dot) to communicate with the back-end computer through RS-232 COM6 Port. The user wearing the posture recognition module (the blind node) was expressed by the green dot.

5.2. Wearing Posture Recognition Module

The posture recognition module was installed in a box with an elastic band for easy wearing. The user tied the module outside of his thigh (Figure 11). The directions of 3-axis accelerometer were defined as: the positive X axis was the front direction of user's body, the positive Y axis was the right direction, and the positive Z axis was the up direction.

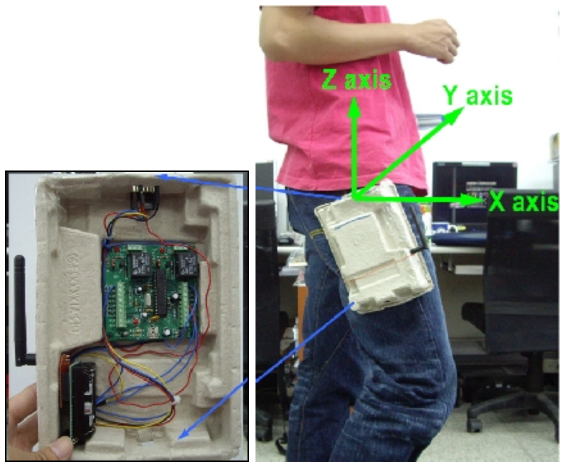

Figure 11. The user wearing the posture recognition module

When training the J48 decision-tree model, this study invited 10 users to simulate the six postures: walk, sit down, fall forward, fall backwards, fall to left, and fall to right to generate the training data (Figure 12). Because the postures for each user are different, the distribution of SMV parameters used to identify these postures may also be different. The decision-tree model can easily find the upper bound of the maximal SMV value for the activities of normal people, for example, the SMV values of walk in Figure 13. Hence, it is better to invite more people to generate training data to avoid triggering false alarms due to some personal habits.

Figure 12. Simulating six postures to obtain the training data

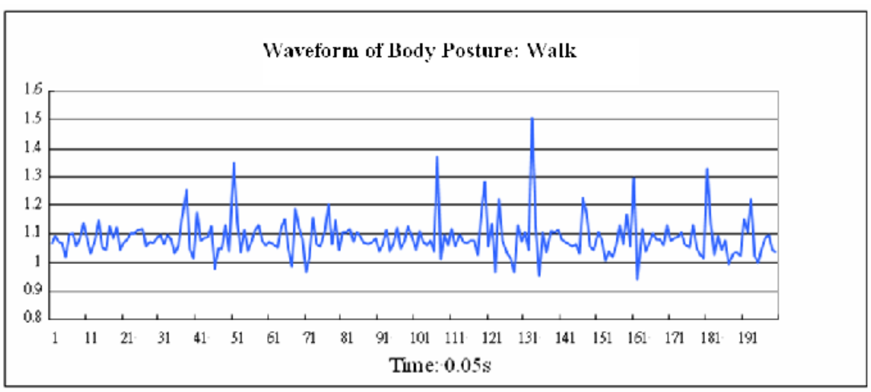

Figure 13. The SMV waveform for the walk posture

5.3. Training the J48 Decision-Tree Model

To train the J48 decision-tree model, each user had to simulate the six activities, i.e., walk, sit down, fall forward, fall backwards, fall to left, and fall to right, each for 10 times to produce 60 records as training data (a total of 600 records were collected). The J48 decision-tree model after training is shown in Figure 14. This study also recorded (X, Y) coordinates of the fall position for each user during the training process to compare with the actual location obtained by the activity monitoring system for the calculation of positioning error.

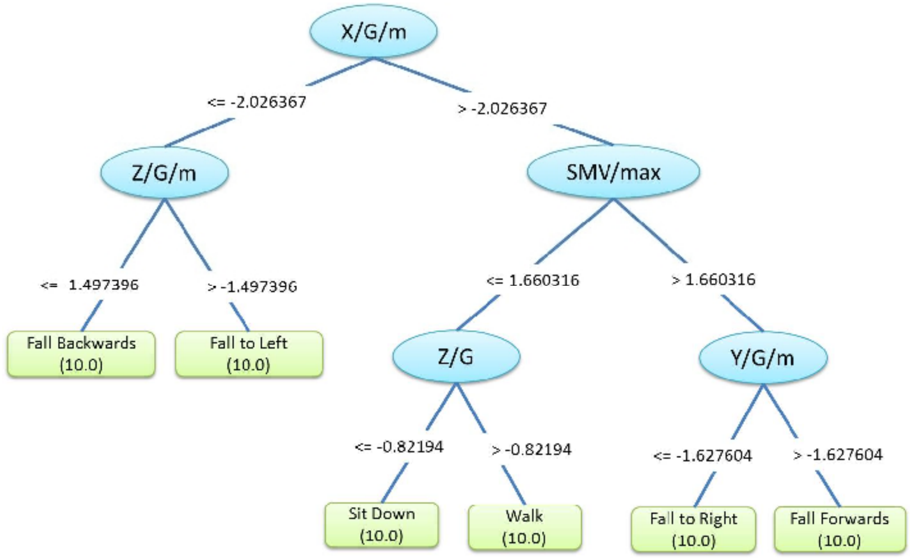

Figure 14. The J48 decision-tree model after training

5.4 Recognition Results of Six Postures

After the training of J48 decision-tree model was completed, the 10 users simulated 6 different postures again for 5 times to produce 300 records of testing data. The activity monitoring system used the data to calculate the recognition rates of various postures, and the results are shown in table 1. As for the positioning accuracy, each user stayed in the living room, bathroom, bedroom and storage room for 5 seconds. The system obtained a total of 400 (X, Y) coordinates (recorded once in every 0.5 seconds) and compared with the actual coordinates to calculate the average positioning error as 0.283 meter within the area of 10 square meters.

Table1. The recognition results for the 6 postures

	Normal Activities		Fall Events			
Actual Events / Identification	Walk	Sit Down	Fall Forwards	Fall Backwards	Fall to Left	Fall to Right
Walk	50	0	0	0	0	0
Sit Down	0	50	0	0	0	0
Fall Forwards	0	0	50	0	0	0
Fall Backwards	0	0	0	49	1	0
Fall to Left	0	0	16	3	31	0
Fall to Right	0	0	10	1	6	33

In this study, the six body postures were divided into two categories at first for identification, i.e., normal activity and fall events, and the latter were further divided into fall forwards, fall backwards, fall to left and fall to right. After the experiment, the researchers found that the lower recognition rates in fall to left (62%) and fall to right (66%) were due to the results from a certain users. However, the system could still distinguish between normal activities and fall events accurately for all users, so the recognition rates for normal activities and fall events are both 100%. The overall recognition rate is 87.66% (as shown in Table 2). This study inferred that fall is a reflex action which doesn't often occur to left or to right, so the simulated postures were not very natural and sometimes identified as falls in other directions. However, the recognition rate is still within the acceptable range in this application.

Table2. Recognition rates for different postures

<table>
<tr><td rowspan="2">Recognition Rate</td><td>Walk</td><td>Sit Down</td><td>Fall Forward</td><td>Fall Backward</td><td>Fall to Left</td><td>Fall to Right</td></tr>
<tr><td>100%</td><td>100%</td><td>100%</td><td>98%</td><td>62%</td><td>66%</td></tr>
<tr><td>Normal Activities</td><td colspan="2">100%</td><td colspan="4" rowspan="2">Overall Recognition Rate=87.66%
Indoor Positioning Error=0.283m</td></tr>
<tr><td>Fall Events</td><td colspan="2">100%</td></tr>
</table>

6. CONCLUSION

In this study, a residential activity monitoring system was designed using G-sensor and wireless sensor network technologies. It can send the user activity and position data via ZigBee wireless sensor network to the back-end computer for recording and analysis. The computer uses the J48 decision-tree model to distinguish between different body postures such as walking, sitting down and falling in different directions. The simulation results show that the indoor positioning error is 0.283 meter, the recognition rates for normal activities and fall events are both 100%, and the average recognition rate is 87.66% for the 6 postures.

In the future, we hope to cooperate with some healthcare departments and research centers to conduct more experiments with the elderly for long-term wearing the fall detection module. By using more machine learning algorithms to record and classify the elderly's activities, we hope the system can make more accurate identifications in detecting anomalies based on past experiences to provide a better care for the elderly.

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