Implementation of a Physical Activity Monitoring System for The Elderly People With Built-in Vital Sign and Fall Detection

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Abstract

Physical activity monitoring of the elderly people provides valuable information for health aware services. This paper presents the implementation of a system to sense, send, display and store physiology activity. The system includes a wearable device to be worn by the individual to collect physical activity data, a wireless communication link between the patient and the monitoring network. A fall detection and heart beat measurement are also included to provide better monitoring. Testing results show the system function properly and provide accurate fall detection and data for monitoring purpose..

1. Introduction

Most older adults have one or more health problems, their day-to-day and long-term attention has great relevance to primary healthcare providers and their loved ones [1]. Identification and tracking of daily physical activities are key factors to evaluate the quality of life and health status of that person [2]. Continuous health condition monitoring of aged is necessary to prevent injuries and guarantee safety social environment in order that old people can enjoy their social actions [3]. The ability to record and classify the movements of an individual is essential when attempting to determine his or her degree of functional ability and general level of activity. Furthermore, the real-time monitoring of human movement can provide an automated system of supervising functional status over extended time periods [4]. Numerous physical activity monitoring have been developed in the past. Some of the systems use accelerometers mounted in various locations on the body to record the physical motions [3-8], the others uses kinematic sensors [9]. Similar systems can be found using video recording with complicated algorithms to determine activities.

This paper presents an implementation of a complete system for monitoring of physical activity for the elderly people. The system includes a wearable device mounted with sensors, a wireless connection for the communication link between the sensors and a computer; the computer receives, stores and transfers the sensor data to the monitoring network. The wearable device detects physical activities using a set of sensors consists of a 3-axial accelerometer, a 2-axial gyroscope, and a heart beat detection circuit. The device is worn on the chest of an individual elderly to sense his or her movement and vital sign. The device is capable of sending sensor data wirelessly using the ZigBee protocol to the computer. Besides monitoring physical activity using accelerometer and gyroscope, the system also provides vital sign information and gives fall detection alert to the monitoring station. Previous studies into ambulatory monitoring of human motion have involved the processing and analysis of raw accelerometer signals after transmission to a local computer [4]. Data processing was often performed offline, after a recording had been completed. The advance of the proposed system is to perform some of the signal processing onboard of the wearable device. This includes vital sign and fall detection to provide prompt warning or alert signal to appropriate personnel. Other physical activities can be processed on the receiving computer and fed to the network.

2. System architecture

One criteria of the design is to have a small, light weight device, easy to use by the elderly people. Trapping the device on the chest is the wearing method for this design. In addition, the system should be wireless to transfer physical activity to provide freedom of movement of the wearer in his or her dwelling. Low power design is another constraint in this implementation since the device intends to be used for an extended period of time. This requirement enhances the system usability by ensuring the

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longevity of battery life in the wearable device and relieving the wearer from regularly recharging the battery. Numerous wireless data transfer protocol can be employed for this application but up-to-date, ZigBee seems to be the best choice due to its low power consumption for a reasonable transmission range.

Shown in Figure 1 is the system set-up in which the wearable device is to be worn by an elderly individual, the laptop computer connected to the receiver end of the wireless link is to receive physical activity and vital sign data, process if necessary, store the data and send to the monitoring network. The wearable device is mounted with a 3-axial accelerometer, a 2-axial gyroscope to capture the wearer motion, a heart beat sensor to detect heart beat signal, an RF-ready microcontroller collecting physical activity and vital sign and sending the data through a wireless link, and a rechargeable battery to power the device. The wireless receiver is to receive and transfer the data to a laptop computer using USB connection. The computer stores, sends and displays physical activity data along with the vital sign. Healthcare personnel can tap into the network for monitoring purposes. The system also sends alert signal to the love ones in case of emergency (a fall or irregular vital signs).

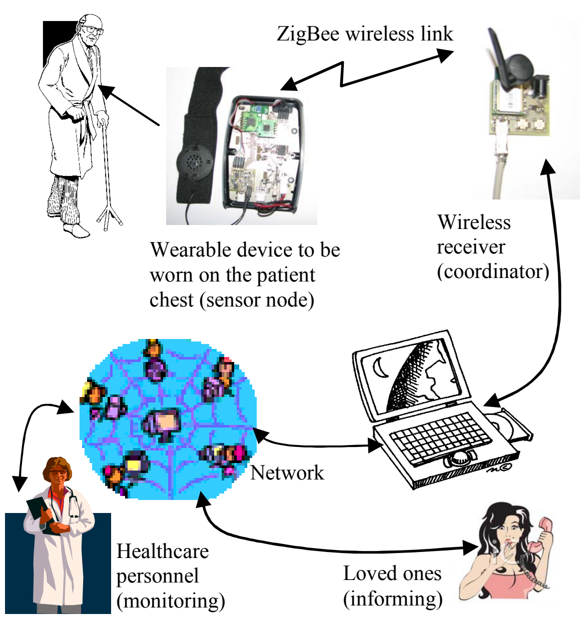

Figure 1. System set-up includes a wearable device, a wireless link, a local computer connected to the monitoring network.

3. The wearable device and the wireless link

Figure 2 provides a closer look at the wearable device. This device (i.e., a sensor node) comprises of a high precision accelerometer sensor (ST LIS3LV02DQ), a gyroscope (InvenSense IDG-300), a heart beat sensing circuit, an RF-ready microcontroller (Jennic 5139-Z01) and a 3.7V rechargeable battery, the battery is mounted underneath the circuit board. A battery charging circuit is also built on the printed circuit board.

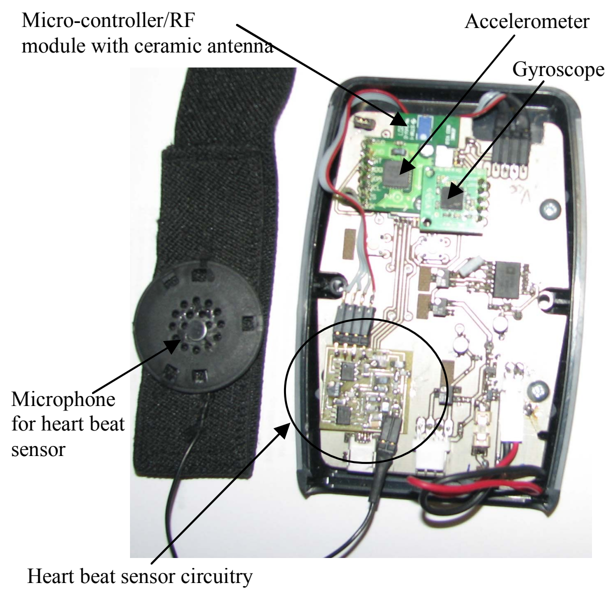

Figure 2. Wearable device

The LIS3LV02DQ is a three axes 12-bit digital output linear accelerometer that includes a sensing element and an IC interface. The I^2C/SPI serial interface takes information from the sensing element and provides measured acceleration signals to the external world. The sensor operates on a 2.2V-3.6V supply and a selectable full scale of ±2g or ±6g. The device may be configured to generate an inertial wake-up/free-fall interrupt signal when a programmable acceleration threshold is crossed at one of the three axes. This feature is very useful in this application: 1) our wearable device can reduce power consumption by putting the sensor into the sleep mode and 2) the sensor can be programmed to detect a fall for a certain threshold to be determined by a particular individual after a pre-fall analysis.

The dual-axis gyros is also a MEMS device operating at a single supply voltage of 3.0-3.5V. The sensor provides analog outputs of x and y rates with a full scale of $\pm 500^0$/sec. The output voltages of the rotations are connected to the onboard ADC of the microcontroller/RF module. One of the drawbacks of the gyros is its output drifting. This is due to the nature of the gyroscope and the error requires further filtering to correct. This rate sensor consumes power continuously due to its long wake-up time. Both the accelerometer and the gyroscope have very high shock survivability of at least 500g. The combination of accelerometer and gyroscope provides a better postural activity measurement as proved in the testing results.

The heart beat sensing consists of an acoustic sensor (a microphone) to listen and pick up the sound of the heart beat. The microphone used is a low cost electret condenser type having a flat response from dc to 10kHz for a near field of 6mm. The microphone is attached to the belt which is trapped around the chest at the heart location. With appropriate amplification and filtering, the heart beat signal will be obtained as shown in the circuit block diagram of Figure 3. The filtering and amplification circuitries were built using discrete components on a small PCB.

The wireless transmitter JN5139 is a low-cost, off-the-self microcontroller and wireless communications in a single unit made by Jennic [10]. This low power module ZigBee-Based WPAN also includes a built-in ceramic antenna. One of the useful features of this module is that the unit can be put into the sleep mode which requires only 3μA of current to run the active sleep timer. Sleep mode is used extensive in this system to reduce power consumption of the sensor node which is running on a rechargeable battery. The module also contains a 32-bit RISC CPU provides the ability to perform other tasks such as processing data, controlling the SPI output of the accelerometer, performing ADC conversion of the gyroscope and the heart beat sensor signals.

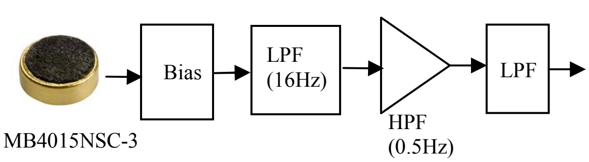

Figure 3. Heart beat sensor block diagram.

Figure 4 provides a closer look at the wireless receiver in which the same JN5139 in the wearable device is programmed to perform a receiving function. The receiver can be connected to an external antenna or a ceramic antenna (see Figure 2) to extend the transmission range. As shown in Figure 1, the receiver (i.e., the coordinator) is the main controller connected to the computer. The coordinator communicates directly to the sensor node. The computer is connected to the coordinator to receive physiological activity data sent by the wearable device. The computer displays the x,y,z coordinate of the accelerometer, the x,y rates of the gyroscope, and the heart beat signal for real time observations. The computer also stores data for later use.

This system is a hardware/software co-design in which the software must be written to run the microcontroller in the Jennic module. On startup, the coordinator initializes itself and sets up the network. When a sensor node joins, the coordinator will receive data from that node and forward data to the computer. The sensor node, when turned on, initializes all the required subsystems and begins searching for a local wireless network (which is initialized by the coordinator). When the sensor node finds a coordinator, it will join the network, turn on the sensors, and begin the main loop. The loop checks to ensure the battery voltage is good, then reads the sensors and sends the data to the coordinator. The Jennic module in the sensor node then sleeps for 20ms or until the next accelerometer data sample is ready at a sampling rate of 40samples/second. If the battery voltage is low, the module will turn off the sensors to save power, and emit a pulse with the buzzer alerting the user to recharge the battery. When the voltage gets low enough that there is a risk of damaging the lithium polymer cell, the sensor node will turn itself off and no longer transmitting data.

Figure 4. The receiver receives data from the wearable device and transfers to the computer via USB connection.

4. Experiment results

One of the wearable devices was trapped on the thorax of healthy participants to test the system functionalities including data storage, data display and data analysis.

4.1. Data collection for physical activity monitoring

Figure 5 shows an example of the data stored with time stamped. The sampling rate is 40 samples per second. Data are stored in a file upon starting the system and the user can name the file. In this example, the 1st column lists the time of the computer receives data from the coordinator. The next 3 columns contain x, y, and y values of the accelerometer. The 6th and 7th column store x and y rates of the gyroscope and the last column contains digital values of the heart beat signal. The raw data can be sent to the network for monitoring purpose or processed at any point. The size of the data file is to be determined by the data polling rate and the number of days to be observed.

Figure 6 is an example of the screen captured of the display for the three-axis accelerometer, the rotational data from the dual-axis gyroscope and the heart beat signal. The data display is for the random and sometime rigorous postural movements.

	A	B	C	D	E	F	G
1	1:27:38 PM	0.566	-0.343	-0.683	297.949	324.615	987
2	1:27:38 PM	0.566	-0.343	-0.683	297.363	326.96	992
3	1:27:38 PM	0.554	-0.343	-0.703	296.484	324.908	986
4	1:27:38 PM	0.563	-0.349	-0.706	298.828	325.202	986
5	1:27:38 PM	0.557	-0.343	-0.709	298.535	324.322	988
6	1:27:38 PM	0.557	-0.34	-0.706	299.707	325.202	990
7	1:27:39 PM	0.557	-0.349	-0.698	299.707	324.615	984
8	1:27:39 PM	0.554	-0.352	-0.709	295.897	324.615	988
9	1:27:39 PM	0.574	-0.349	-0.721	299.707	324.908	988
10	1:27:39 PM	0.542	-0.352	-0.709	309.963	322.857	988

Figure 5 Data storage includes time stamped, accelerometer data (x,y,z), gyroscope data (x,y), and heart beat signal.

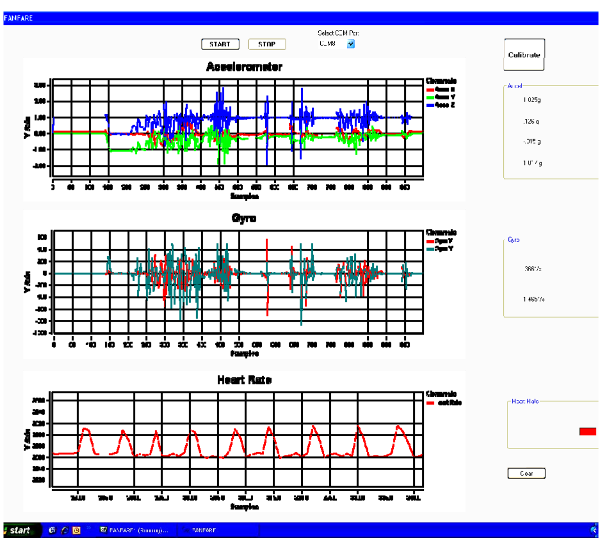

Figure 6. Sensor node display.

4.2. Fall detection

The time stamped data stored in the computer can be retrieved and analyzed using any fall detection analyzing methods. One such method is the data classification using support vector machines described in [11]. An algorithm to detect the fall using acceleration data has been developed by Hwang, et.al in [12] while Luo and Hu applied a 3D body motion model to represent acceleration vector in 3D space to detect the fall using a three stage dynamic process [13].

In this implementation, machine learning method was used to identify the fall and some of the simple physical activities. Test data are classified into 7 different postural movements: standing, walking, lying, forward fall, backward fall, left fall, and right fall. Five algorithms have been used for the machine learning methods to test the data: Naive Bayes [13], support vector machine, C4.5, ripple down rule learner, and radial basis function network. Due to its high accuracy and fast model building, the Naïve Bayes algorithm was chosen to use in the Java based data mining tool WEKA (Waikato Environment for Knowledge Analysis) [14]. Table I below shows the results of three algorithms used in the tested data to identify the fall in which the Naïve Bayes showing its best performance. It has also been observed that the data from the accelerometer achieved only 90% of accuracy but when they are combined with the gyroscope data, the detection probability has increased to 97%. This agrees with the finding in [12] in which the simultaneous use of accelerometer, gyroscope and tilt sensor increases the fall detection accuracy.

Table 1. Fall detection using stored data

Algorithm	Correct classified instances (%)	Incorrect classified instances (%)
Naïve Bayes	97.3	2.7
Support vector machine	92.3	7.7
Ripple down rule learner	95.8	4.2

Numerous methods to classify human movement using accelerometer data have been published [4,5,8,15]. With the aid of powerful processing on the computer, real-time physical activity monitoring can be performed with ease.

4.3. Instrumentation performance

When developing the code to execute the Jennic JN5139, careful consideration was given to reduce the power consumption as much as possible. The wearable device micro-controller is programmed to spend most of its time in the sleep mode to conserve energy unless the data are transmitted. The micro-controller sleeps for 20ms drawing only 1.3µA then wakes up to transmit data. During transmission, the module draws 30mA from the 3.3V supply. The chosen microcontroller has enough memory to program further tasks of filtering the acceleration and gyroscope data. One of such tasks is the implementing a Kalman filter to reduce drifting of the gyroscope. This is useful since the accuracy of fall detection is improved with the assistance of gyroscope data.

The on-board processor also provides the necessary resources to design a wireless sensor network with multiple sensor nodes using the ZigBee protocol. Data rate of the chosen wireless protocol of 250kbit/s is more than sufficient for this application. The combination of ceramic antenna in the transmitter and external antenna at the coordinator provides a tested transmission range of at least 15m non-line-of-sigh.

The 12-bit ±2g accelerometer used in this design provides enough accuracy for the purpose of identifying simple physical activities such as sitting, standing, walking and lying. The accelerometer can also be programmed to detect the free fall by setting the thresholds in one or all of its 3 axis.

Test results on a full-charge battery (2000mAh) showing the wearable device can properly operate for 70 hours. The gyroscope and the heart beat circuit use power continuously while the accelerometer can be put into sleep mode if desired. As the battery voltage falls below 3.0V, the gyroscope stops functioning while the other parts of the sensor node still operate.

5. Discussion and conclusion

A physical activity monitoring system on the elderly people was successfully designed and built. The system is also embedded with vital sign and fall detection. Using low power devices and design techniques increase battery life on the wearable device. The system provides accurate physiological activity data to the needs of real-time monitoring. The tests were not conducted on the elderly people as the system is designed for. Further experiments are required in order to evaluate the performance of the system on the target group of people. To aid the accuracy of the free fall detection of the accelerometer, real-time fall detection is to be developed in the computer or network to promptly provide accurate fall alarm signal to healthcare personnel and the love ones. Multiple wearable devices also need to be developed to monitor more elderly people at the same time in a community-dwelling facility.

6. References

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