Design Flow of Wearable Heart Monitoring and Fall Detection System using Wireless Intelligent Personal Communication Node

Won-Jae Yi, Oishee Sarkar, Sivisa Mathavan and Jafar Saniie

Department of Electrical and Computer Engineering
Illinois Institute of Technology
Chicago, Illinois, United States

***Abstract*— Most current remote health monitoring systems provide limited physiological information on the user end. Raw physiological data collected from the on-body sensors are sent to a distant location for data storage and analysis without being analyzed on the user end. In this paper, we present the design flow of a system utilizing the Wireless Intelligent Personal Communication Node (W-iPCN) for analyzing heart activities and detecting sudden fall situations of a remote patient. The W-iPCN is a small, compact and lightweight system which has the ability to process and analyze body sensor data. Furthermore, this system is capable of communicating with other devices through wireless protocols. The purpose of having the W-iPCN for wireless body sensor network system is to provide in-depth biomedical data to the user in real-time. As an example, we emphasize on electrocardiography (ECG), accelerometer and gyroscope data analysis to show the feasibility and capability of the W-iPCN. The ECG sensor data is useful to determine current heart conditions of the user. Accelerometer and gyroscope data are useful to detect sudden collapse events. In this paper, we expand our system design to an Android smartphone to present acquired analyzed sensor data to the user. In addition, the Android smartphone transmits the data to the distant server for data logging and history keeping through the Internet in real-time. Our system targets standard Android smartphone users to be able to install and run our Android application software without requiring expert software knowledge.**

Keywords—Wireless Body Sensor Network, Heart Monitoring, Sudden Collapse, Fall Detection, Android Smartphone

I. Introduction

Monitoring and detecting physiological condition of a person outside of the medical facilities has become a part of our lives in the 21st century. With handheld devices, it is now possible to run a simple diagnosis of the user including blood sugar levels, oxygen saturation, blood pressure and more [1]. Additional requirements for these handheld devices are powerful processing capability for in-depth physiological diagnosis on the user-end, as well as low power consuming sensor devices for long-lasting monitoring and detection systems. In our previous work [2], we have tested the feasibility and usability of a standard Android smartphone as the key tool of body sensor data integration and processing.

In this paper, we extend and explore an improved design flow of the wearable body sensor system using Wireless Intelligent Personal Communication Node (W-iPCN). The W-iPCN is a system which collects various sensor data, and processes and analyzes the data using appropriate algorithms. Also, the W-iPCN wirelessly communicates with the standard Android smartphone to provide user diagnosis data on the display. This approach is an enhancement over the previous work where the Android smartphone act as the central node for collecting different sensor data [2]. Also, the smartphone acted as a preliminary body sensor data analysis tool in the previous work, but the smartphone in this paper concentrates on transmitting incoming raw body sensor data to the distant server [3]. In this work, three types of sensor data analysis were considered on the W-iPCN to show the feasibility and capability of the system.

In Section II, the design flow of our system is introduced to show the overall capability of the system. In Section III, electrocardiography (ECG) data processing and analysis will be presented to show what types of algorithms and heart failure symptoms can be detected remotely. In Section IV, the detection of sudden collapse or fall of the user is presented with an effective fall detection algorithm. In Section V, we describe how the standard Android smartphone acts in our design. Finally, Section VI concludes our paper.

II. System Design Flow

Our system follows an approach that is similar to our previous work [2], where the Android smartphone is the central device that collects data from all body sensors through the Bluetooth connection. Instead of concentrating the workload on the Android smartphone, we introduce the Wireless Intelligent Personal Communication Node (W-iPCN) into our system design flow to reduce the amount of processing workload on the Android smartphone. This configuration will reduce the CPU processing power consumption on the Android smartphone to conserve more battery life. Additionally, it makes the system more flexible with wireless communication protocol on the sensor node level. Figure 1 shows the overview of our system design flow. The W-iPCN is the central node that communicates with the body sensors instead of the Android smartphone. In this study, we have chosen Raspberry Pi Model B+ [4] as the W-iPCN to show the feasibility of W-iPCN in our system design. Raspberry Pi is a small and compact single board computer that integrates a Broadcom BCM2835 System-on-Chip (SoC). This SoC comes with an ARM based CPU running at 700MHz with a GPU and 512MB of RAM. It is equipped with

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USB ports so that the USB dongles like the Bluetooth or Wi-Fi modules that can be attached as important peripherals.

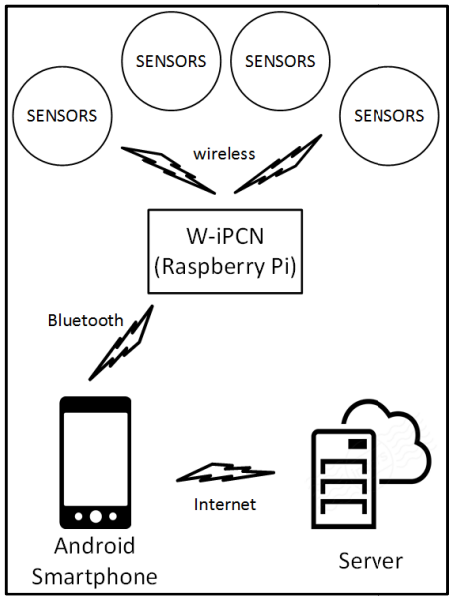

Figure 1. System Design Flow

In addition, there are 17 General Purpose Input/Outputs (GPIOs), UART, and I2C bus on the board which help developers to attach other external modules with the Raspberry Pi. General power consumption of this device is around 600mA to 700mA at 5V [5], which is quite low for a single board computer. Other wireless transceivers without any USB interface can utilize the external pinouts on the Raspberry Pi to enable wireless communication. We experimented the usability of these ports for integrating accelerometers and gyroscope sensors into Raspberry Pi for fall detection system, which will be discussed in the later section.

In our system, we have installed the Bluetooth and Wi-Fi USB dongles to add wireless communication capabilities on the W-iPCN as shown in Figure 2. The Bluetooth USB dongle is used to establish connection to the Android smartphone, and the Wi-Fi USB dongle is used to connect to the Raspberry Pi through SSH connection for system development.

Figure 2. Raspberry Pi with Bluetooth and Wi-Fi USB Dongles

As per the requirement for W-iPCN, the Raspberry Pi is capable of running complex signal processing algorithms under the environment of user-friendly operating system such as Linux. The W-iPCN collects data from all body sensors that are deployed on the user. Then, the system analyzes the sensor data according to their characters where the algorithms may vary. As an experiment, we have explored the concepts of heart monitoring and implementation of a fall detection system utilizing the W-iPCN, where in, the thoroughly analyzed data is displayed on the smartphone display. The smartphone then relays the received data to the distant server for data logging and history keeping for the user. In the upcoming sections, we will present the possible data analysis algorithms on the heart activity monitoring using the ECG sensor data, and also combined accelerometers and gyroscope data for fall detection. All the collected data are interpreted and provided to the user from the W-iPCN system.

III. ECG Data Processing and Analysis

Processing series of ECG data requires fairly powerful computational ability on a device. Multiple band-pass filtering and other computationally complex mathematical operations such as fast Fourier transform (FFT) or Discrete-time Fourier transform (DTFT) can be executed on the W-iPCN. The ECG analysis such as QRS (Q, R, S waves of the ECG signals) detection and heart rate calculation [6] can be implemented on the W-iPCN. By monitoring these two, we could easily detect bradycardiac [7] and tachycardiac conditions [8], which are two major heart conditions that could be fatal to the patient. The following ECG analysis methods can all be practically realized in the W-iPCN.

A. QRS Wave Time Period Detection

Detecting time difference between the QRS points can be a very useful tool to determine atrial fibrillation (AFib) condition which happens randomly in patients without their knowledge [9]. AFib is hard to detect as their symptoms are very mild or non-existent. This QRS based method, when incorporated in an ambulatory device, helps the patients who suffer from arrhythmias, to identify the presence of AFib in an effective and efficient way. Thus, they can work with their doctors to manage their condition.

To efficiently detect the QRS waves in the ECG data, Pan-Tompkins algorithm [10] can be applied and implemented on the W-iPCN, based on the received ECG data from the sensor. Figure 3 shows a brief description of the algorithm.

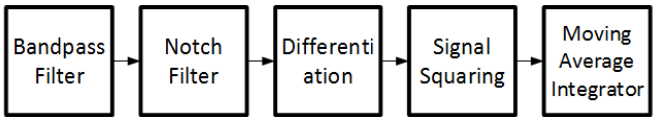

Figure 3. Pan-Tompkins Algorithm

In this algorithm, noise filter is used to remove baseline wander, high frequency noise and power line interference on the received ECG data. Differentiator is used to detect the rapid change in slope. Thus, in case of a QRS complex, there is a rapid change in the slope. Finally, the coarse signal obtained by squaring operation can be smoothened using the moving average integrator. This is performed for efficient

signal peak detection. Figure 4 shows the Pan-Tompkins algorithm result waveforms after each step. Based on the detected signal peaks in the ECG signals, it is possible to determine the heart beat rate by calculating the difference between two or more peak points.

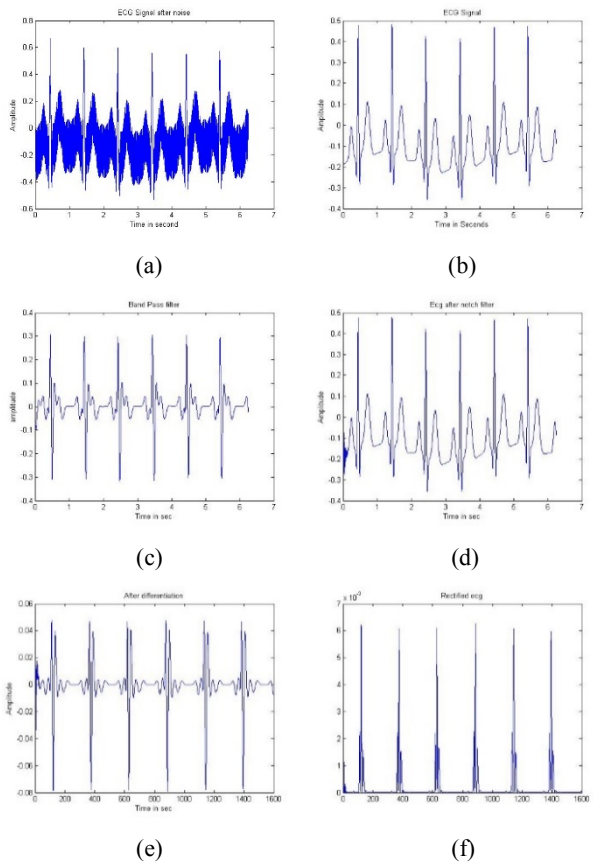

Figure 4. Pan-Tompkins Algorithm Results where (a) ECG with noise; (b) ECG after Denoising; (c) ECG after Bandpass Filter; (d) ECG after Notch Filter; (e) ECG after Differentiation; (f) Rectified ECG

B. Heart Murmurs

This could be one of the next generation methods for ambulatory monitoring. Heart murmurs are used to detect valvular failure of the heart [11]. It is usually detected by listening to the sounds of the heart called echocardiography. Therefore, this will be a combination of two data. Thus, it would be a great tool to record the sound of the heart for two minutes every day at the same time to check for the heart murmurs. A signal processing algorithm is used to compare the patient's echocardiography with a standard sound wave and to detect the abnormalities.

C. ST Wave Segmentation

Detecting the time period of the S and T waves can be used to detect whether any backflow of blood [12] exists or not. The blood flow in the heart is in one direction for a normal person. Therefore, whenever there is a back flow, it is used to identify future valve failures. It is an important parameter that physicians would like to have in their ECG analysis.

IV. Fall Detection using Accelerometers and Gyroscope

A fall can be detected even from a single accelerometer placed at a sufficiently rigid position of the human body (the chest, for example) by setting proper thresholds. However, our focus is to develop a more accurate and advanced system of fall detection that identifies a fall from other ADLs (Activities of Daily Living) and not just the stationary state. Additionally, the accuracy of fall detection using a single accelerometer is low. This is why additional sensors were used. In addition to a second accelerometer, a gyroscope has also been employed. A gyroscope is a device for measuring or maintaining orientation, based on the principles of angular momentum. The data acquired from the sensors need to be processed in order to detect the fall. The data is sent in real time to the W-iPCN, in this case the Raspberry Pi, in order to be processed in real-time. The sensors are described in detail below. Also, Table I shows that each sensor modules are suitable as wearable devices and capable of being powered by batteries.

A. Accelerometer ADXL345

This is a small, thin, low power, 3-axis accelerometer with high resolution (13-bit) measurement at up to ±16*g*. It uses the I2C module to connect with the Raspberry Pi [13].

B. Adafruit 9-DOF IMU Breakout - L3GD20H & LSM303

This board has three sensors, of which we use the accelerometer LSM303 and the gyroscope L3GD20H in our algorithm. It also uses the I2C module to connect to the Raspberry Pi. Thus we can connect all the sensors to the same I2C port on the Raspberry Pi [14], [15].

Table I. Power Consumption of the External Sensors

	Maximum (Active)	Minimum (Standby)
ADXL345 (Accelerometer A2)	23 µA	0.1 µA
LSM303 (Accelerometer A1)	110 µA	1 µA
L3GD20H (Gyroscope G1)	6.1 mA	2 mA

The algorithm that we are employing is described later in this paper. We have two accelerometers; say A1 and A2, and a gyroscope G1. A1 and G1 exist on the same board and this is placed on the chest of a person. The second board with A2 is placed on the thigh of the person. Both boards are connected to the Raspberry Pi (noted as RPi in the figure) through I2C module as shown in Figure 5.

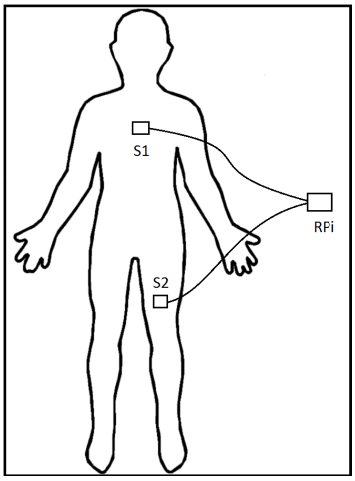

Figure 5. Position of the sensors where S1 contains Accelerometer A1 (LSM303) and the Gyroscope G1 (L3GD20H), S2 contains Accelerometer A2 (ADXL345)

All sensors send real-time data to the Raspberry Pi that is stored with a timestamp. Prior to this, a trial and error method has been employed to observe the change in the magnitude of the sensor outputs in the event of a fall. The Raspberry Pi monitors the data of A1, A2 and G1 separately and compares it with the prerecorded data to determine the possibility that a fall has occurred. If a fall is detected in any one sensor, the Raspberry Pi checks the other sensor data for a confirmation, i.e., if G1 detects a fall, Raspberry Pi checks A1 and A2 for an extended threshold margin fall detection.

Consider the coordinate system in Figure 6. The R arrow denotes the direction in which the device moves. According to Pythagoras' theorem,

$$R_t^2 = R_x^2 + R_y^2 + R_z^2$$

which is the representation of the R vector in terms of the x, y and z axes. The magnitude of change in position can thus be given as:

$$R_t = \sqrt{R_x^2 + R_y^2 + R_z^2}$$

There is a similar algorithm for the gyroscope where the magnitude of change in roll, pitch and yaw is measured.

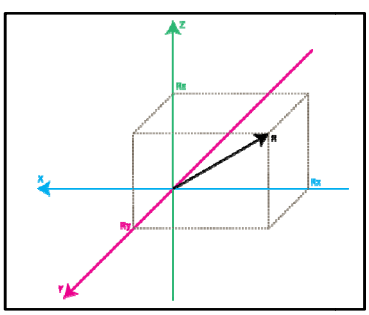

Figure 6. Coordinate System

The sensor readings are taken at regular time intervals based on a standard assumption of how much time it takes for a person to fall. If the time interval is too small, the fall may not be detected. If it is too large, the fall may be falsely detected when the patient is carrying out some ADL. We have selected a time interval of 20ms between subsequent readings from the sensor as an optimum between unnecessary power consumption and timely detection of the fall. When a fall is detected, the system is intimated to carry out the communications.

Figure 7. Fall detection sample output on the W-iPCN

The output on the Raspberry Pi is shown in Figure 7. When the patient is in natural state, the output shows "Upright". As soon as the fall occurs, the output shows that the fall has been detected. It also shows the direction in which the patient has fallen – front, back, or either side, denoted as the directions N (North), S (South), E (East) and W (West).

The raw data obtained from both the accelerometers are in mG (milli-G) units where G stands for the G-force of the Earth (9.8 m/s^2), and the raw data obtained from the gyroscope can be converted into degrees with the help of a simple calculation. Employing a trial and error method, we have determined that a fall has occurred when the values obtained from the respective sensors meet the thresholds mentioned in Table II.

TABLE II. THRESHOLD VALUES FOR FALL DETECTION

Threshold Values	Accelerometer A1 (mG/LSB)	Accelerometer A2 (mG/LSB)	Gyroscope G1 (degrees)
N (North)	Z < -200	Z > 200	X ~ 90
S (South)	Z > 200	Z < -200	X ~ (-90)
E (East)	X > 200	X > 200	Z ~ (-90)
W (West)	X < -200	X < -200	Z ~ (-90)
Upright	Y > 200	Y < -200	X ~ 0 Z ~ 0

V. Android Smartphone and Remote Server

In our design flow, the standard Android smartphone is used to present the analyzed sensor data from the W-iPCN to the user. Analyzed results from the W-iPCN are transmitted to the Android smartphone through the Bluetooth connection. Then, the results are displayed on the screen for the user in real-time. As a background service of our Android application software, it sends the data to a remote server, where the server can be used for data logging and heavy computation analysis. Figure 8 represents the received sensor data from the W-iPCN on the Android smartphone. The Android application software provides the raw sensor data, as well as the processed data from the W-iPCN. Figure 9 shows the received data on the remote server from the Android smartphone over the Internet.

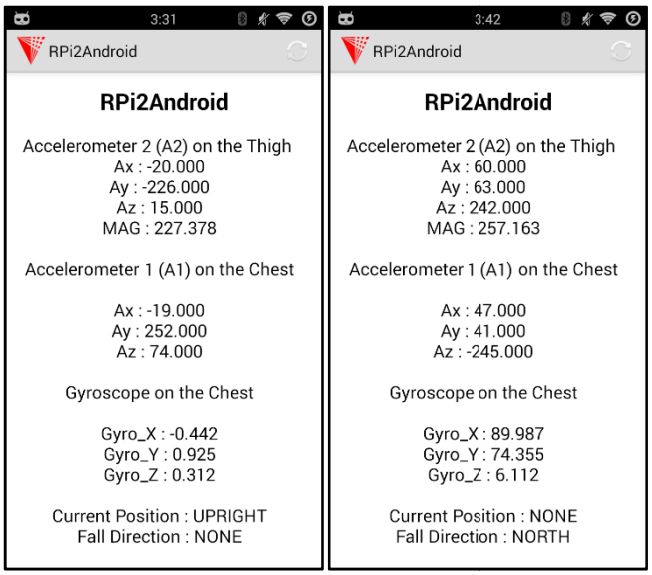

Figure 8. Android Application Software Display Results

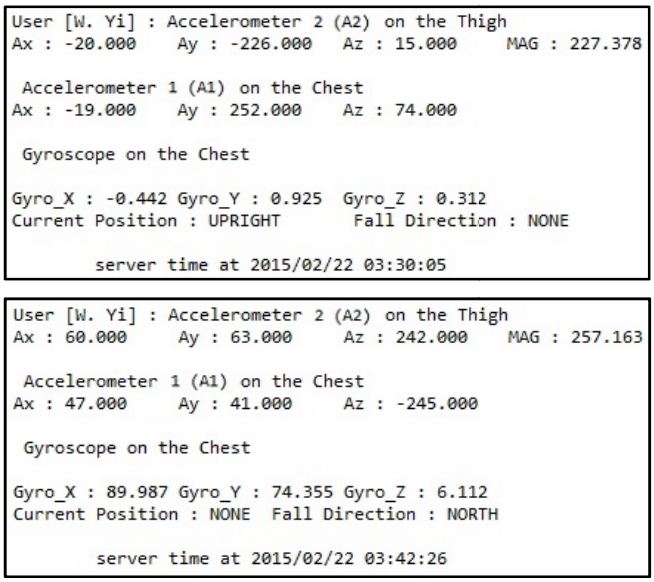

Figure 9. Received Sensor Data on the Remote Server

VI. Conclusion

In this paper, we discussed and presented the design flow of a health monitoring system using Wireless Intelligent Personal Communication Node (W-iPCN) for wearable body sensors including ECG, accelerometer and gyroscope. The W-iPCN is designed to communicate with body sensors that require intensive data analysis. We have chosen Raspberry Pi as a model for the materialization of the W-iPCN. By adding wireless communication features on the Raspberry Pi, the W-iPCN is able to transmit sensor data in real-time. Furthermore, we have implemented sensor data analysis algorithm in the W-iPCN to present real-time processing capability of the system. The low power consuming processing unit on the Rapsberry Pi is adequate to analyze accelerometer and gyroscope data to detect sudden fall situation of the user. The processed sensor data is transmitted to the Android smartphone to display the analyzed result to the user, and relayed to a remote server in real-time. Our design flow shows that deploying a central processing unit for wireless body sensor network system is helpful to determine current health status on the user end. Moreover, this reduces the workload on the Android smartphone, which uses less processing power which in turn conserves battery life. Our system design flow is superior to the basic wireless body sensor network system which provides only raw and limited analyzed sensor data to the user.

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