

Wearable Sensor Data Fusion for Remote Health Assessment and Fall Detection

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Abstract— In this paper, we present the system architecture and design flow for remote user physiological data and movement detection using wearable sensor data fusion. Our design utilizes an Android smartphone to integrate and process multiple body sensor data to enhance the reliability for remote health diagnosis. Various sensor data such as body temperature, current geographical location, electrocardiography, body posture and fall detection data are collected using concurrent Bluetooth connections to the Android smartphone. Our Android application software is designed to handle real-time analysis of collected sensor data to determine current user status, such as instant heart beat rate, body orientation and possible fall recognition. With the help of the Internet connection on the Android smartphone, the system communicates with a remote server and a designated contact person to log sensor data, and to notify authorized professionals in case of an emergency situation. Our system is highly valuable for remote and mobile patient monitoring and diagnosis. This design flow can be extended to condition assessments in various environments and it is not limited to body temperature, current geographical location, electrocardiography, body posture and fall detection.

Keywords—*Body Sensor Network, Fall Detection, Android Smartphone, Sensor Data Fusion, Body Posture Assessment*

I. INTRODUCTION

Our everyday life is enriched by the impact of the smartphone, bringing data mobility as well as real-time data communication. Wearable sensors with wireless data communication capability can be incorporated with the smartphone to collect current user's health status and environment. An example of a wearable sensor can be an electrocardiography (ECG) sensor to determine instant heart beat rate (HBR) [1]. Also, multiple accelerometers placed on specific locations of the body can be used to determine the movement and posture [2]. Measurements of body temperature and current geographical location of the patient can be other valuable sources for remote diagnosis. Therefore, sensor data fusion and real-time information processing is highly desirable for remote health monitoring.

A typical Android smartphone is equipped with the wireless connectivity to the Internet and it allows formation of a personal area network using the Bluetooth protocol. The Bluetooth protocol has the ability to simultaneously connect up to 7 different Bluetooth nodes on a master node [3]. Adding the Bluetooth capability to the sensor modules enables

multiple concurrent sensor data collection on the Android smartphone. Also, the Internet connection provides the flexibility and allows mobility in transferring the collected data to a central database. A central database can be used to store and analyze patients' health status. Also, it can be a server for medical experts to remotely access patients' data. A typical smartphone contains a powerful RISC processing unit and multiple concurrent wireless communication capabilities. This processing unit embedded in the smartphone can be used for various signal processing techniques, preliminary data analysis and patient diagnosis.

In this paper, we extend our existing system design flow [4] by integrating and analyzing multiple body sensor data for remote health assessment and movement detection. Sensor data integration includes multiple accelerometers for body movement and fall detections, ECG sensors for monitoring heart activity, and temperature sensor for monitoring body temperature. Integrated user data is then sent to a central server through the Internet connection, as well as sending a text message to an authorized contact person in case a fall is detected. The proposed system provides real-time patient monitoring where an instant care is needed by an individual at a remote location.

II. SYSTEM DESIGN FLOW

Our system design flow consists of body sensors, a standard Android smartphone, a central server and an emergency contact as shown in Figure 1. Multiple body sensors are chosen to demonstrate our system design. All sensors in our design are equipped with the Bluetooth transceiver to communicate with the Android smartphone. Also, our system design can be used for any types of body sensors for a comprehensive health assessment. In the current system, two accelerometers are used to assess body postures, as well as to monitor movements and detect falls. Furthermore, the ECG sensor data is used to monitor the user's current heart activity. Temperature sensors are also used to determine the body temperature as well as the temperature of the surroundings. These features are crucial for decision making in emergency situations. Our system is not only designed to stream the user's useful body information to a remote location, but also to alert their emergency contacts when the user encounters unsafe situations such as a sudden fall. The method of

contacting the authorized person includes voice calling and texting through the cellular network.

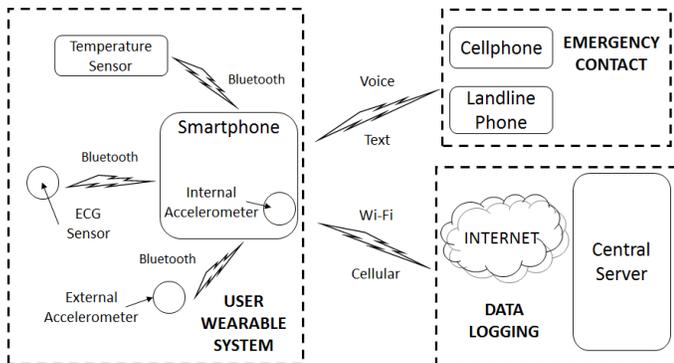


Figure 1. System design flow

We have selected a low-power and Bluetooth-enabled module, eZ430-RF2560, to demonstrate our system's capability. This module includes a MSP430 microprocessor, a Bluetooth transceiver module, embedded accelerometer, temperature sensor, and external input/output ports for analog/digital signals [5] for other sensors such as ECG sensor. In our study, we deployed three eZ430-RF2560 modules to transmit ECG, temperature and accelerometer data to the Android smartphone. Table I describes the estimated power consumption of this module. This table shows that eZ430-RF2560 meets the power requirements using 2xAAA regular batteries for a portable smart sensor module.

TABLE I. POWER CONSUMPTION OF EZ430-RF2560

	Power Consumptions	
	Maximum (Active)	Minimum (Idle)
MSP430BT5190 Microcontroller [6]	0.88mA – 1.84mA	1.2 μ A – 2.1 μ A
CC2560 Bluetooth Transmitter [7]	39.2mA	40 μ A
CMA3000-D01 Accelerometer [8]	70 μ A – 90 μ A	Unknown
TMP106YZC Temperature Sensor [9]	100 μ A	50 μ A – 85 μ A
Typical ECG Module	180 μ A	-
Total	40.43mA – 41.41mA	91.2μA – 127.1μA
Possible Operational Time	1 day	327 – 456 days

Our customized Android smartphone application software is the core of our system design. It integrates, analyzes, displays and streams all body sensor data in real-time. Using three concurrent Bluetooth connections to the eZ430-RF2560 module, it constantly monitors the heart's function, body temperature and body orientation. Any type of emergency alarming mechanism can be applied to our design, including a heart failure, a sudden drop or increase in the body temperature, or a change of the body orientation. Figure 2 describes the Android application software flow when a fall is detected. The Android application software receives and analyzes multiple body sensor data until it detects a sudden

fall. In case a sudden fall is detected, the software combines all sensor data into one package. Then, it reports to the central server, and connects to a predefined emergency contact person.

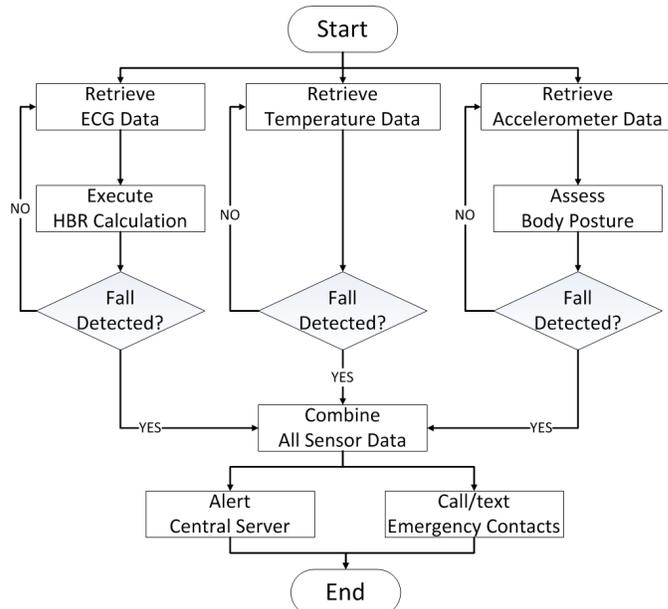


Figure 2. Example of Android application software flow

III. SENSOR DATA ANALYSIS

Three different sensor data are used for user health assessment and movement detection in our design. In particular, ECG and accelerometer data requires extensive data analysis to assess instant HBR, body posture and fall detection.

A. Heart Beat Rate(HBR) Calculation

One of the general methods for determining the HBR is to count the number of heart beats in one minute. The ECG signal is band-pass filtered with threshold adjustments and the utilization of a signal processing technique called QRS detection [10] is applied to determine the HBR. This method detects the QRS complex (Q, R and S waves) which is the dominant peak of the ECG signal. By calculating the time interval between the R-waves, instant HBR is calculated as described in Figure 3.

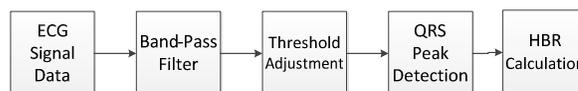


Figure 3. Instant HBR calculation flow

B. Body Posture and Fall Detection Analysis

Tri-axial accelerometers are used to perform body posture detection. This will be useful for surveillance of the elderly or of human workers during rescue operations and other potentially dangerous activities. An accelerometer can be used as a wearable device. Consequently, it does not require

additional effort by the user for posture detection. The human body is a complex machine, and using a single accelerometer does not provide sufficient information for efficient and accurate detections without the use of additional sensors or complex operations [11]. In practice, two body postures, upright and lying down, can be tracked by using two 3-axes accelerometers. As shown in Figure 4, the accelerometers are placed on the chest and the thigh of the user. For this configuration, three body orientations are determined: standing straight, lying down and sitting down. Differentiating these body postures are achieved by processing the accelerometer data on a set of axes (X, Y and Z). Thresholding on these 3-axis outputs is applied to determine body orientations. X-axis outputs are used to determine the roll position of the body. Y-Axis outputs are used to determine the yaw motion of the body. Finally, Z-axis outputs are used to determine the pitch of the body. Another approach is to take the magnitude and phase by combining the measurements from all 3 axes to compute a net acceleration independent of orientation [12-14].

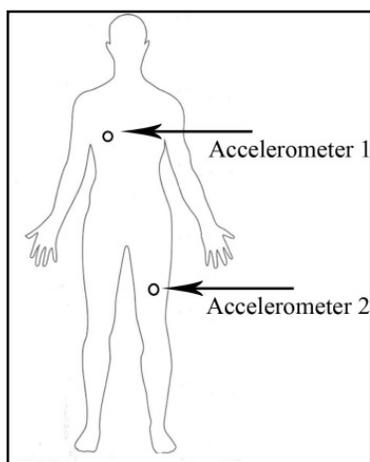


Figure 4. Accelerometer layout for body posture assessment

For fall detection, similar approaches are applied as introduced in body posture assessment. There are several different methods that can be applied to detect such an event. The simplest algorithm is to record the data in numerous attempts during the normal movements of the user. An axis-based threshold value will be set based on the normal conditions, to determine if a fall has taken place. Another similar algorithm is to process the data in time and frequency domains using a model known as Naïve Baye's Classifier [15]. In this study, for fall detection, the Signal Vector Magnitude (SVM) is calculated based on the following equation [16]:

$$SVM = \sqrt{x_i^2 + y_i^2 + z_i^2} \quad (1)$$

where x_i is the i -th sample of the x -axis signal (similarly for y_i and z_i). Based on the test results, a threshold of 2.5 times the mean value of SVM for normal movement conditions is used to determine the fall events.

IV. EXPERIMENTAL RESULTS

Our Android application software requires connection to individual Bluetooth modules prior to assessing body posture, HBR and falls. For body posture assessment, we utilize the internal accelerometer inside the Android smartphone and the external accelerometer fixed on the thigh as shown in Figure 5.

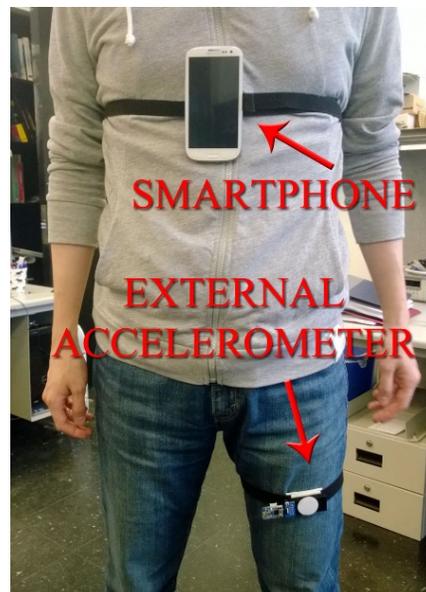


Figure 5. Body posture assessment accelerometer configuration

Our application software is able to identify three different body orientations (standing straight, lying down, and sitting down) by integrating the data collected from the two accelerometer units. By applying the SVM algorithm, our developed Android application software successfully recognizes the three body orientations and detects falls. The Z-axis outputs dominate the X and Y axis outputs in determining the fall (For clarification, see results shown in Figure 6 and 7). Table II represents the experimental threshold results for characterizing three body orientations using the magnitudes of Z-axis outputs ($|Z|$).

TABLE II. BODY ORIENTATION DETECTION THRESHOLDS

	Smartphone Accelerometer (Chest)	External Accelerometer (Thigh)
Standing Straight	$ Z \leq 0.3$	$ Z \leq 0.3$
Lying Down	$ Z \geq 0.7$	$ Z \geq 0.7$
Sitting Down	$ Z \leq 0.3$	$ Z \geq 0.7$

Figure 6 shows sample results of the Android application software capturing postures for sitting down and standing up straight. In addition to displaying the recognized body posture, our application sends the body orientation changes to a central server for data logging.

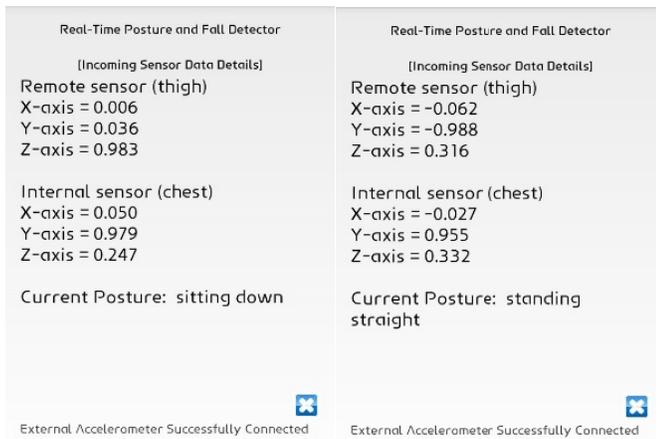


Figure 6. Example of body posture recognition on Android application software

In case a fall is detected, the Android application software displays the direction of the fall. The directions include north (falling forward), south (falling backwards), west (falling left), east (falling right), northwest (falling forward and left), northeast (falling forward and right), southwest (falling backwards and left) and southeast (falling backwards and right). Figure 7 shows an example result of when the user fell down backwards.

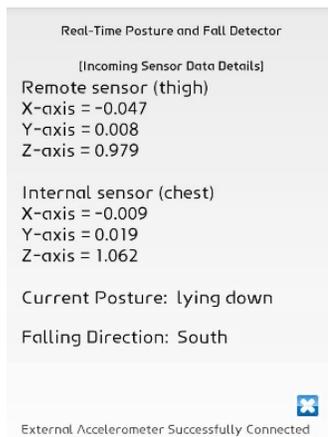


Figure 7. Example of body posture recognition on Android application software with falling direction

Along with the detected body posture data, the Android application software captures and integrates the current HBR, body temperature and current user geographical location into a package. This package is transmitted over the Internet to a central server with its timestamp. Figure 8 is an example of how the server would react upon receiving the user data. The user data includes current location, last known body posture, direction of the fall, current body temperature and the HBR. The body temperature is denoted as in degree Celsius, and the HBR is denoted as beats per minute (BPM) in this example.

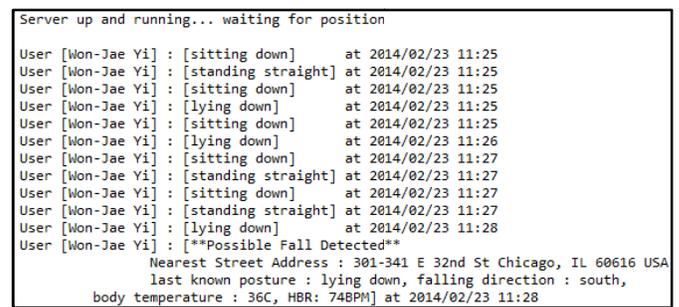


Figure 8. Example of central server displaying received user information

Furthermore, the alert is sent to an authorized emergency contact person through either voice calling or texting using our customized Android application software. This alert message is sent only when a fall is detected. Figure 9 shows an example of a received text on the emergency contact person's cellphone.

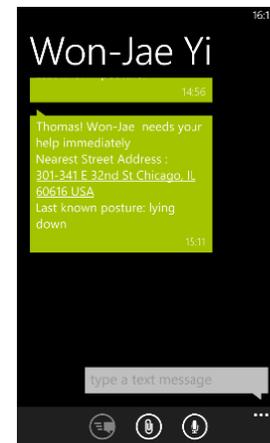


Figure 9. Example of received text when the fall is detected

V. CONCLUSION

In this paper, we have explored the system design flow of a remote health assessment using wearable body sensor data fusion. Sensor data integration includes multiple accelerometers for body posture and fall detection, ECG module for monitoring heart activity, and temperature sensor for observing current body temperature of the user. Our customized Android application has the capability to integrate all sensor data simultaneously using the concurrent Bluetooth connections. The requirements for a mobile sensor module, including portability, power efficiency and lightweight, is satisfied in our design. In the case of a fall being detected, our Android application software combines all data and contacts an emergency contact person and transfers data to a central server for extensive data analysis. For determining the user's symptoms at an earlier stage, our software has the capability to analyze heart activities, direction of the fall, body temperature, and the current user geographical location by employing the processor embedded on the Android smartphone. Our system is adaptable to more sensor data integration, in order to achieve highly accurate health

assessment. Furthermore, this system is valuable in applications which require remotely monitoring the posture of an individual who may be at high risk, such as firefighters, senior citizens, and manual laborers.

REFERENCES

- [1] I. Korhonen; J. Parkka; M. Van Gils; "Health monitoring in the home of the future," *IEEE Engineering in Medicine and Biology Magazine*, vol. 3, no. 4, pp. 66-73, May-Jun. 2003.
- [2] H. Tanaka; R. Kimura; S. Ioroi; "Equipment Operation by Motion Recognition with Wearable Wireless Acceleration Sensor," *Third International Conference on Next Generation Mobile Applications, Services and Technologies (NGMAST '09)*, pp. 114-118, 15-18 Sept. 2009.
- [3] I.H. Mulyadi; E. Supriyanto; N.M. Safri; M.H. Satria; "Wireless Medical Interface Using ZigBee and Bluetooth Technology," *Third Asia International Conference on Modelling & Simulation*, pp. 276-281, 25-29 May 2009.
- [4] W.-J. Yi; J. Saniie; "System Architecture and Design Flow of Smart Mobile Sensing Systems," *Journal of Sensor Technology*, vol. 3, no. 3, pp. 47-56, Sep. 2013.
- [5] Texas Instruments. (2013) EZ430-RF256x. [Online]. Available: http://processors.wiki.ti.com/index.php/EZ430-RF2560?DCMP=wtbu_ez430rf2560_pan1315&HQS=Other+OT+ez430-rf2560wiki
- [6] Texas Instruments, MSP430BT5190 Mixed Signal Microcontroller, Apr. 2010.
- [7] Texas Instruments, CC2560 Bluetooth single-chip solution, Jul. 2010.
- [8] Murata Electronics, CMA3000-D01 3-Axis Ultra Low Power Accelerometer with Digital SPI and I2C Interface, Aug. 2012.
- [9] Texas Instruments, Digital Temperature Sensor with Two-Wire Interface, Jan. 2006.
- [10] H.C. Chen; S.W. Chen; "A Moving Average based Filtering System with its Application to Real-time QRS Detection," *Computers in Cardiology*, pp. 585-588, 21-24 Sept. 2003.
- [11] D. Curone; G.M. Bertolotti; A. Cristiani; E.L. Secco; G.Magenes; "A Real-Time and Self-Calibrating Algorithm based on Triaxial Accelerometer Signals for the Detection of Human Posture and Activity," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 4, pp. 1098-1105, Jul. 2010.
- [12] M. Tolkiehn; L. Attalah; B. Lo; G.-Z. Yang; "Direction Sensitive Fall Detection using a Triaxial Accelerometer and a Barometric Pressure Sensor," *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 369-372, 30 Aug. - 3 Sept., 2011.
- [13] M. Van Wieringen; J.M. Eklund; "Real-Time Signal Processing of Accelerometer Data for Wearable Medical Patient Monitoring Devices," *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS)*, pp. 2397-2400, 20-25 Aug. 2008.
- [14] Y. Li; G. Chen; Y. Shen; Y. Zhu; Z. Cheng; "Accelerometer-based Fall Detection Sensor System for the Elderly," *2012 IEEE 2nd International Conference on Cloud Computing and Intelligent Systems (CCIS)*, vol. 3, pp. 1216-1220, 30 Oct. - 1 Nov. 2012.
- [15] X. Yang; A. Dinh; L. Chen; "A Wearable Real-Time Fall Detector based on Naïve Bayes Classifier," *2010 23rd Canadian Conference on Electrical and Computer Engineering (CCECE)*, pp. 1-4, 2-5 May 2010.
- [16] W.-C. Cheng; D.-M. Jhan; "Triaxial Accelerometer-based Fall Detection Method using a Self-Constructing Cascade-AdaBoost-SVM Classifier," *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 2, pp. 411-419, Mar. 2013.