WiCard: A Context Aware Wearable Wireless Sensor for Cardiac Monitoring

Abishek Thekkeyil Kunnath[1], Dilraj Nadarajan[2], Manesh Mohan[3], Maneesha V. Ramesh[4]
AMRITA Center for Wireless Networks and Applications
Amrita Vishwa Vidyapeetham
Amritapuri, Kollam, India
[1] abishektk@am.amrita.edu, [2]dilraj.n@gmail.com, [3] maneshvm@am.amrita.edu, [4]maneesha@am.amrita.edu

***Abstract*— Cardiovascular diseases (CVD) are one of the leading causes of death in rural India. Every year more than 3 million Indian citizens die from CVD [1]. The proposed Wearable Wireless Cardiac Monitoring (WiCard) system, aims to bring home state-of-the-art health care for people living in rural Indian villages, where thousands of death occur each year due to lack of experts and facilities. The architecture involves remote monitoring of the ECG by specialized health professionals via a heterogeneous wireless network. This paper discusses the development of a six lead custom hardware for transmitting data to a Smartphone or a compatible device via a Bluetooth. The data received by the mobile devices will be further processed and transmitted to a central repository located in a specialized hospital. The main disadvantage of wearable cardiac monitoring system is the introduction of Motion Induced Artifacts (MIA), which could mimic a cardiac event. A context aware architecture is proposed here to relate physical activity and physiological signals of the user, with the help of accelerometer sensors. The portion of ECG where the MIA has detected will be tagged and sent to the central repository. Classifications of physical movements are done using statistics based classifiers, which are computationally low cost. The results show that the developed algorithm is capable of classifying the user activity with an accuracy of 94%. The developed hardware achieved a power reduction of 10 %.**

Keywords*— *Artifacts, Context aware, CVD, Wearable sensor, Wireless health care

I. INTRODUCTION

Between 2008 and 2030, global population is expected to grow by 20%, from 6.7 billion to 8.1 billion people [2]. The approximate death rate is expected to remain more or less stable at around 8.4 deaths per thousand. Cardiovascular diseases (CVDs) comprise a major portion of non-communicable diseases. In the year 2030, of all projected deaths worldwide, 23 million people are expected to die due to cardiovascular diseases [2]. A comparison chart of mortality rate from major diseases are shown in Fig.1.

According to a report in Financial Express, 70% of the Indian population is living in and rural areas [3], whereas the 80% of public and private healthcare facilities are located in urban areas. Of the 20% healthcare facilities in rural India, 90% are owned by private organizations. The rise in various kinds of cardio-vascular diseases, cataract and other forms of ailments have increased the need for good and well-equipped surgical facilities in hospitals, especially in rural India. In villages it is quite common for people to die at the age of 40 due to lack of medical facilities.. A large number of these deaths could have been avoided if proper facilities were available. If a citizen lives healthily for another 40 years, they could contribute more to the development of our country.

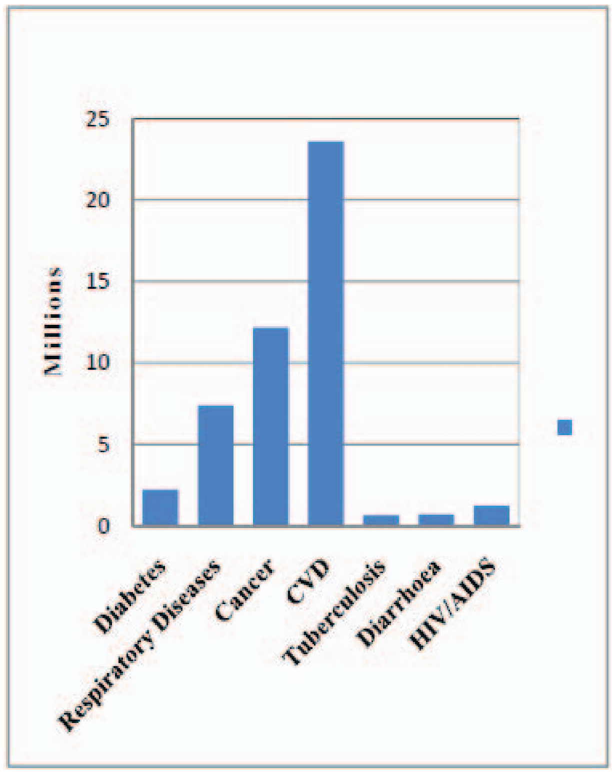

Fig. 1. Mortality from major diseases, 2030[2]

This research work aims to develop a low power wearable wireless ECG sensor. The device is capable of sensing the Lead I, Lead II signal, and physical activity information from the patient's body. The collected data will be transmitted to a smart phone. The processing of data and derivation of Lead III, Lead aVR, Lead aVL and Lead aVF from Lead I and Lead II data is conducted in the Smartphone. The data received through the smart phone will be further processed and transmitted to a central repository located in a specialized hospital for further analysis or for future reference.

978-1-4673-6217-7/13/$31.00

One of the main disadvantage of monitoring patients using wearable devices such as the motion induced artifacts (MIA), is that it could mimic a cardiac event or degrade the clinical utility of measurements. A context aware architecture is proposed here to relate physical activity and the physiological signals of the user. The context data obtained from a Body Sensor Network (BSN) can be used to monitor long term health care and to collect user activity for accurate event detection [4]. The first step to gather context aware data is to collect low-level sensor readings. Accelerometers are the widely accepted sensors to detect physical activity [5]. Most studies use the waist to place motion sensors because the waist is very close to the center of mass for the entire human body [5]. Accelerations measured by a single sensor placed at waist level can better represent major human activities. Placing motion sensors at waist level causes least restriction in body movements and minimizes level of discomfort.

The proposed system can be used to provide affordable patient monitoring for hospitals, clinics, primary and community health care centers and private practitioners in rural India in an attempt to reduce cost and to provide them access to high quality health monitoring devices. This aids in risk-free operations and enhanced medical care and thereby improves health care for the rural population. The project also aims to stream the monitored medical data in real time to a centrally located server at a multi-specialty medical institution. Additionally, physicians are provided with a greater level of understanding about a patient's condition.

The remaining part of this paper is organized as follows: section II describes related works in the area of wearable wireless monitors for cardiac patients. Detailed system architecture is illustrated in section III. Section IV discusses about the algorithms developed. Section V explains the implementation and test results. Section six concludes with future research ideas.

II. Related Works

Wood et al proposes a wireless sensor system to monitor patients in assisted living facilities and in residences [6]. The system integrates environmental, physiological and activity-based sensors in a scalable heterogeneous architecture. The activity rhythm analysis learns resident's activity patterns and gives them back into the network to aid dynamic privacy policies and context-aware power management.

Landete et al proposes a method with a Context Aware Selection Algorithm (CASA) to select the best ECG signals for babies admitted in Neonatal Intensive Care Unit [7].The accelerometer data correlates well with the presence of movement and changes in ECG signal quality. The algorithm calculates the power spectrum density of ECG data from different sensors. In experiments with adult participants they found that CASA can select the best quality ECG derivation which varies with the context.

Pawar et al proposes a technique to identify the motion artifacts and classify the type of body movement activity (BMA) from the ECG signal itself [8]. They found the motion artifacts due to any two different types of BMA are nearly uncorrelated. A particular class of BMA is classified by applying Eigen decomposition in the corresponding ECG data. When stair climbing was tested using their system it was accurate but there was confusion when testing walking, climbing down stairs and movement of left, right or both arms. The proposed method here uses accelerometer data with computationally less intensive statistical classifiers for detecting the MIA. The cost of power for computations when the device is in continuous monitoring mode has to be kept at a minimum.

Zhang et al talks about the pros and cons of Commercial off-the-shelf (COTS) components and use of custom integrated circuits for healthcare monitoring [9]. The main advantages of a COTS based systems is hardware expandability, low power consumption, small size, and interoperability with other commercial devices. The proposed wearable wireless system uses the Commercial off-the-shelf components owing to low time to market and flexibility of redesign.

The main challenge in designing a wearable health monitoring system is power consumption of the device, MIA due to patients' movements and diversity of the context aware environment. Environmental changes, altitude, and pressure could have an effect on ECG results. Sensitivity of electrodes is another major challenge that could deter efficient monitoring. Network traffic congestion could affect continuous data transfer to the central database. This paper discusses the designing and implementation of a low power, light weight context aware wearable wireless sensor for cardiac monitoring. The proposed system provides real time cardiac monitoring without restricting patients activity.

III. Architecture Design

The proposed system consists of a wearable sensor unit, a Smartphone operating on a Android platform and a remote data server connected through GSM network. An overall architecture of the system is shown in Fig. 2.

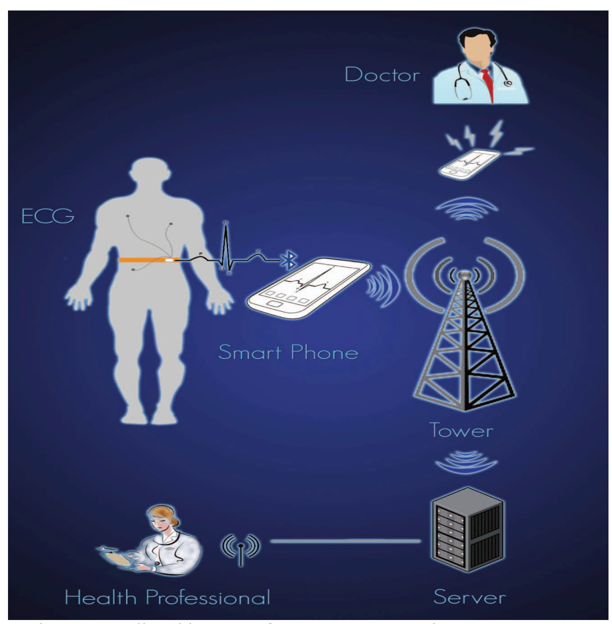

Fig. 2. Overall architecture of context aware sensing system

A. Wearable Sensor unit

o gather data in real time we have developed a low power, and light weight wearable hardware. The architecture of wearable sensor system is shown in Fig 3. The heart of the system is a ADS1292, a front-end single chip analog system for ECG from Texas Instruments. The device is capable of simultaneously measuring two channels with 24-bit resolution and a sampling rate of up to 8KSPS. In this research work the selected sampling rate is 500 samples/second and a gain of six PGA. Right Leg Drive (RLD) is also provided to improve Common-mode Rejection (CMR) in ECG. The device has a lead-off detection mechanism to monitor the connection between the electrode and the skin. We have used a triple-axis accelerometer MMA8452Q, which has the ability to monitor activity in low power mode. We sampled the accelerometer at 50 samples per second. The device has a Bluetooth 2.0 connectivity to transmit data to a Smartphone or to a compatible wireless device. The whole circuit is powered with a 3.7 V, 1500mAH single cell Li-ion Battery.

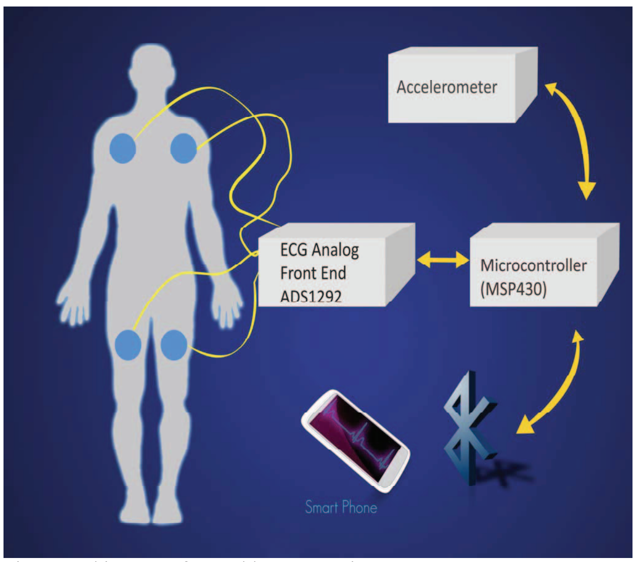

Fig. 3. Architecture of wearable sensor unit

B. Smartphone application

The Android operating system has emerged as a dominating Smartphone platform in the recent years. Features of Android such as open-source, user friendly and world's most broadly used Smartphone platform made us choose that operating system as a backend resource for data collection in our proposed system. Android application operating in the Smartphone application uses Bluetooth serial port profile (SPP) to connect with the wearable hardware. ECG signal is transmitted at a sampling rate of 500 sps. After receiving the raw ECG data the algorithm uses a FIR band pass digital filter to remove the unwanted noise and a notch filer to remove 50Hz line frequency after which the data is displayed. The scale for the ECG plot is the same as the clinical standards, 0.5 mV in y axis and 200 ms in x axis. A back-end QRS detection and RR peak detection algorithm is run to calculate and display the average heart beat. In addition to plotting the real-time ECG signal, the application will derive Lead III, Lead aVR, Lead aVL and Lead aVF from Lead I and Lead II data.

C. Remote Data Server

The wearable sensor system is connected to a remote data server (RDS) through GSM network. The acquired ECG data along with the wearable sensor is tagged with user activity and sent to RDS for detailed analysis. The MIA removal algorithms are run in this server. This architecture helps to the continuously monitor CVD patients. The patients data stored in the RDS can be used for future reference and easy diagnosis of the disease.

IV. ALGORITHMS

Different algorithms are developed to classify activity and manage power. The activity classification algorithm is used in Smartphone and the power management algorithm is used in WiCard. Fig. 4 shows the work flow of algorithm that runs on Smartphone.

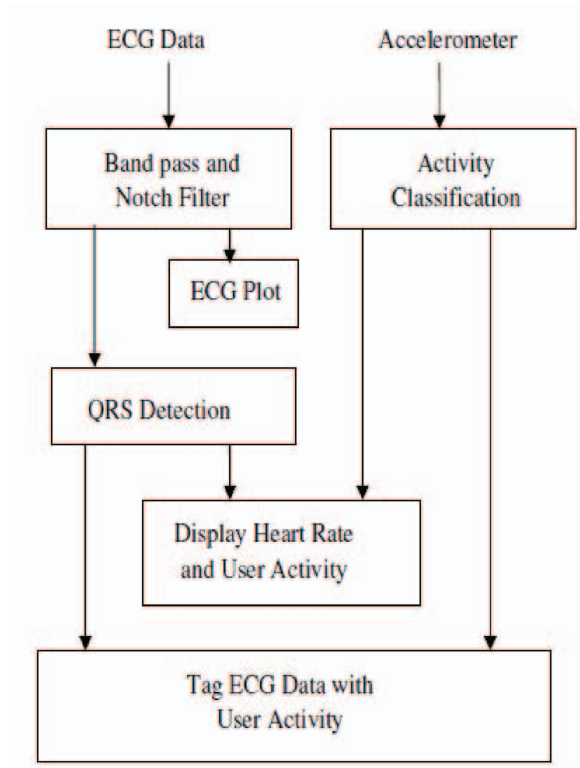

Fig. 4. Flow of Algorithm running in the Smartphone

a) Activity classification

One of the main drawback of wearable health monitoring system is MIA getting activated by the movements of the user. These artifacts degrade the quality of ECG signals measured from the body. To remove the unwanted artifacts and get real ECG data, a context aware mechanism is required to detect user's movement. In this proposed architecture an accelerometer sensor is used to detect and classify patients' activities. The data from the Accelerometer sensor is collected and sent to the Smartphone via Bluetooth. Android application operating on Smartphone will classify the signals and accordingly tag the ECG data with the classified user's activity. The tagged data will be sent to the remote server. The server at the back-end houses artifact removal algorithm to remove the artifacts and obtain clear ECG data.

The work presented here mainly focuses on the classification of MIA using a threshold based approach. The classifiers used are root mean square value, peak to peak duration and the range of the accelerometer data. There is a distinguishable difference that occurs in these parameters during the different activity of the user. The average observed values of classifiers are shown in Table. 1. The scope of this study is limited to four activities: lying down, standing, walking, and jogging. The definitions of all the four activities that was used for our study is given in Section V.

TABLE 1: Acceleration parameters for different activities

	Walking	Jogging
RMS_X(g)	0.45	0.76
RMS_Y(g)	1.01	1.13
RMS_Z(g)	0.35	0.46
Y-peak to peak(g)	1.62	2.97
Y-peak to peak(Sec)	0.5	0.25

When the patient is walking or jogging there is repetitive pattern in the x, y and z axes values and a relatively high acceleration occurs in y-axis. These two movements can be distinguished with the time period between the peaks and relative magnitude x, y and z axes values. The algorithm used to classify the user activity is shown in Fig. 5.

Algorithm 1 Classify Activity

```
for i = 1 → 100 do
    axis_data ← get_values()
end for
(T_x, T_y, T_x) ← calc_interval(x, y, z) {time between peak to peak}
(X_d, Y_d, Z_d) ← peak_to_peak(x, y, z) {peak to peak gravity}
(X_rms, Y_rms, Z_rms) ← calc_rms(x, y, z) {RMS value of each axis}
if (X_d, Y_d, Z_d) < Threshold then
    if (X_rms = −1g&&Y_rms = 0g&&Z_rms = 0g) then
        Activity ← UPRIGHT
    else if (X_rms = 0g&&Y_rms = 0g&&Z_rms = 1g) then
        Activity ← LYING
    else
        Activity ← NO_MOVEMENT
    end if
else
    if (T_x, T_y, T_x) < Threshold then
        Activity ← WALKING
    else
        Activity ← JOGGING
    end if
end if
```

Fig. 5. Algorithm for user activity classification

b) Power Management

Power management is another main challenge of wearable devices used for continuous monitoring. An analysis of power for the developed hardware was done. It was observed that the Bluetooth module was the main power hungry device. The Bluetooth module could not be put in power down mode due to problems of disconnection and re-initialization requirements. The solution that was used to reduce the power consumption was by adjusting the duty cycle of microcontroller and the accelerometer. The hardware could be put in power down mode and re activated with an external interrupt from ADS1292. The power consumption of different devices used in this work is given in Fig. 6.

Current Consumption				
	MSP430F2416	ADS1292	Bluetooth	Accelerometer
Active(μA)	515	111.6666667	30000	24
Standby(μA)	25	53.33333333	26	14
Connected(μA)	-	-	3000	-

Fig. 6. Current consumption of different modules in active and standby states

The packet format of messages from wearable sensor unit to the smart phone is shown in the Fig.7. The data is formed as a fixed length packet, which contains two bytes packet header, two channel ECG data (each channel has two bytes of data), one byte status contains lead off status, tri-axis accelerometer data (each axis has 1 byte data), the voltage and two bytes of check sum for error detection. The first byte of the check sum is the XOR of all bytes in the even position and second byte is the XOR of all bytes in the odd position.

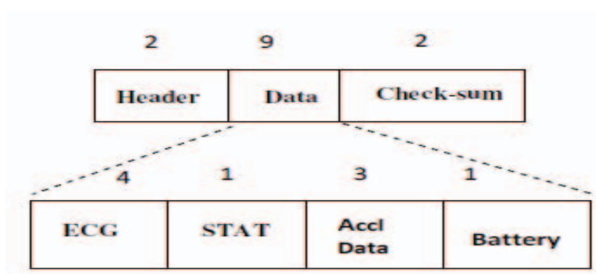

Fig. 7. Packet format of Data from WiCard to Smartphone

V. RESULTS AND DISCUSSION

As previously mentioned, the aim of this research work was to develop a context aware wearable wireless sensor to monitor CVD. To prove the feasibility of this research we conducted tests with real device. The developed wearable platform WiCard was tested on 10 healthy male candidates. The data from the developed system was streamed through Bluetooth to a Smartphone and PC. The ECG as well as user activity data streamed from the WiCard was logged for future reference. The implementation and validation of the algorithms were performed using MATLAB 7.3.0.

The GUI shown in Fig. 8 is capable of plotting 6 leads from the ECG data which displays average heart rate of the user activity. When the heart beat becomes abnormal the application will give a warning to the user. The validation of algorithm was first tested using data from the MIT-BIH Arrhythmia Datasets of PhysioNet [10] and then tested using the real time data collected from the WiCard system.

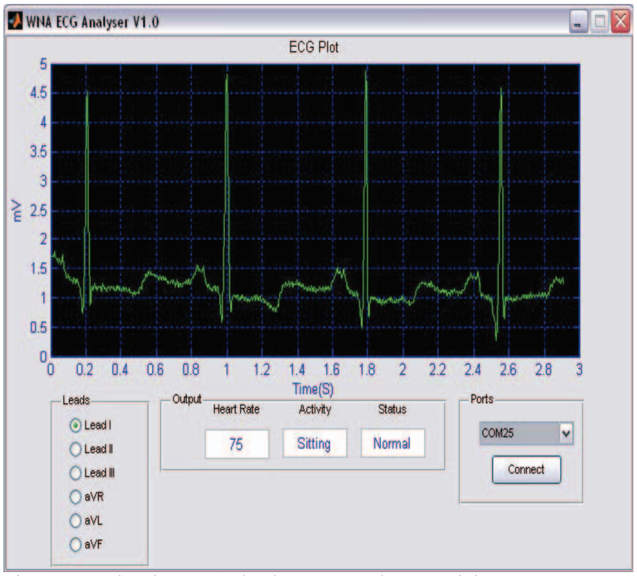

Fig. 8. GUI showing ECG plot, heart rate and User activity

The activity detection test was performed on 15 adults (10 male and 5 female) ranging in ages 20 – 30. The accelerometer was placed on the hip of adults in the upright position. A total of 75 data sets for each activity were given to the classifier.

In our experimental setup the x-axis value represents the horizontal movements, y-axis represents the up-down movements and z-axis represents the forward movements of the body. In lying down and standing posture there was no repetitive pattern but it was distinguished with the magnitude of x, y and z axes values.

Context awareness was tested using four activities: lying down, standing, walking, and jogging. The standing position is defined as the body in upright position only supported by legs. Walking activity in this experiment is normal walking with an average speed of 3.5 kilometer per hour. Jogging activity is normal jogging with an average speed of 5 kilometer per hour. All our experiments detailed here with the help of single tri-axial accelerometer worn at the hip level were recorded with the data of three axes for each movement.

The performance of the developed algorithm was analyzed using a confusion matrix. The confusion matrices are commonly used to evaluate the accuracy of classifiers. The details are shown in Fig. 9. The accuracy or AC parameter could be derived from the represented confusion matrix. A 94% accuracy for classifying the activities were obtained.

		Predicted Class			
Actual Class		Lying	Standing	Walking	Jogging
	Lying	**72**	3	0	0
	Standing	2	**73**	0	0
	Walking	0	0	**68**	7
	Jogging	0	0	5	**70**

Fig. 9. Confusion matrix of classification algorithm

Power management was done with dynamically adjusting the duty cycle of microcontroller and the accelerometer. A comparison of power consumption with power management and without power management is shown Fig. 10. With the help of power management algorithm a 10% reduction in power was achieved.

Total Current(μA)		
Devices	**With Powermanagement**	**Without Powermanagement**
MSP430F2416	41.84715278	515
ADS1292	111.6666667	111.6666667
Bluetooth	3820.3125	3820.3125
Accelerometer	15	24
Sum	3988.826319	4470.979167

Fig. 10. Comparison of current consumption of two modes

VI. CONCLUSION AND FUTURE WORK

A low power light weight wearable system with two channels ECG was designed and implemented. The collected ECG data was transmitted to a Smartphone via Bluetooth. In order to analyze the variation in ECG data due to body induced movements an accelerometer was used to log the movements. The data used for this study were classified into the following four activities: lying down, standing, walking, and jogging. Physical movements were classified using statistics-based classifiers, which were computationally low cost. The results show that the developed algorithm is capable of classifying user activity with an accuracy of 94%. In the threshold-based approach high speed walking maybe classified as jogging. A frequency based classification of activities can increase the accuracy of the algorithm. The developed hardware achieved power reduction by 10 %.

As a future research goal, more user activities will be incorporated and tested using the analysis of frequency based classification which is being developed. A suitable signal processing algorithm will be developed to remove MIA from the physiological signals.

ACKNOWLEDGEMENT

We would like to express our immense gratitude to our beloved Chancellor Shri. Mata Amritanandamayi Devi, who provided inspiration and motivation to complete this research work. We also want to acknowledge Prof Unnikrishna Menon, Mr. Kaushik, Dr Prem Nair, Dr Prakash Kamat, Dr Jaggu, Mr. Vaishak, and Mr. Tinu Vinod who helped us in various stages of our research. This work is part of the WIreless Networks for SOcietal Needs (WINSON) - an Indo-Brazil Project funded by Department of Science and Technology (DST) India.

REFERENCES

[1] Tsunami of Heart Disease in India [Online]. Available: http://www.cadiresearch.org/topic/asian-indian-heart-disease/cadi-india/tsunami

[2] Dilip Modi, "Cardiovascular diseases in India challenges and way ahead," International Heart Protection Summit, September 2011

[3] Low cost healthcare for great Indian middle class[Online]. Available: http://www.thefifthconference.com/topic/health/low-cost-healthcare-great-indian-middle-class

[4] T. Korel and S.G.M. Koo, "A survey on context-aware sensing for body sensor networks". Wireless Sensor Network, pp.571-583, 2010.

[5] Yang, C.-C.; Hsu, Y.-L. "A Review of Accelerometry-Based Wearable Motion Detectors for Physical Activity Monitoring". Sensors 2010, no. 8, pp. 7772-7788, 2010.

[6] Anthony D. Wood, John A. Stankovic, Gilles Virone, and Radu Stoleru ," Context-Aware Wireless Sensor Networks for Assisted Living and Residential Monitoring", IEEE Network, vol. 22, no. 4,pp. 26–33, Jul./Aug. 2008.

[7] F.J. Piqueras Landete, W. Chen, S. Bouwstra, L.M.G. Feijs, S. Bambang Oetomo M.D.," Context Aware Sensing for Health Monitoring", 34th Annual International Conference of the IEEE EMBS, pp.1294-1297 August/September 2012.

[8] Tanmay Pawar, N. S. Anantakrishnan, Subhasis Chaudhuri, and Siddhartha P. Duttagupta," Transition Detection in Body Movement Activities for Wearable ECG", IEEE Transactions On Biomedical Engineering, pp 1149-1152, June 2007

[9] Zhang et al ," Energy Efficient Design for Body Sensor Nodes", Journal of Low power Electronics and Applications, Appl. 2011

[10] A. L. Goldberger et al., "PhysioBank, PhysioToolkit, and PhysioNet:Components of a new research resource for complex physiologic signals,"Circulation, vol. 101, no. 23, pp. e215–e220, Jun. 2000.