A Wearable Wireless Sensor for Cardiac Monitoring

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Abstract— **This paper presents a low cost, low power and wireless wearable solution for real-time analysis and monitoring of cardiac activity co-related with physical activity. Utilizing an analogue filter chain for signal conditioning, the device performs continuous measurement of the Electrocardiogram. The wearable also includes an accelerometer enabling it to detect the current physical activity along with body orientation. The device communicates wirelessly, using Bluetooth Smart /Bluetooth Low Energy, with a smart phone, where a complete analysis can be performed on the received data, and decisions about the current health conditions can be made.**

I. INTRODUCTION

According to a recent estimate [1], by the end of 2017 wearable electronics will be facilitating 322.69 million lives around the globe . In everything from healthcare & lifestyle to everyday hassle, wearable devices are introducing newer concepts of convenience, costumer care and novelty. Particularly, with more sophisticated sensing and analytical functionalities, the new generation of medical or clinical wearables is making unmatched growth with an annually rising share of 25-30% in the market [2]. The main motivation being to introduce remote and continuous monitoring of diseases via wearables and thus cater for the dearth of trained medical personnel and lack of available healthcare and thus try to save the loss of millions of lives each year

Most of the physiological diseases encountered by human body have a specific effect on body vitals, like pulse rate, body temperature and blood pressure. Heart Failure, for instance, disrupts human electrocardiogram (ECG) and body skin temperature. Similarly congestive Heart Failure (CHF) is a condition in which the pumping power of the heart gets weaker than normal and this causes the blood to flow through your body slower providing lesser oxygen and nutrients to the body [3]. CHF causes 1 million hospitalizations annually in North America and Europe only and the impact in developing countries is more alarming [4]. [5] Fig. 1 shows the prevalence on CHF among different age groups for both genders.

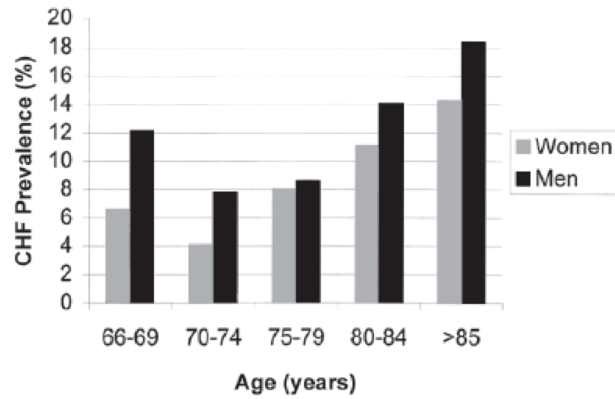

Fig. 1: Prevalence of CHF among different age groups

Medical supervision of a CHF patient is a highly careful procedure that is to be performed 24/7. Previously this was done using hefty ambulatory monitors or Holter monitors. Though it required highly trained staff, this method of supervision was impractical for long term supervision as it restricts the human body movement. Lack of monitoring facilities and an additional possibility of missing out on real time information of body vitals during daily activities of the patient out of the hospital called for a more accurate, portable and easy-to-use medical equipment so that patients could be remotely and continuously monitored.

A number of solutions have been developed to address the aforesaid problems. The commonly proposed solution is based on remote monitoring using wearable bio-sensors that transmit real-time information to the respective medical supervisor. However, to the best of our knowledge the introduction of IoT based wearable patches has not been carried out yet. The solution given in [6] doesn't allow notifications to patient's medical supervisor. Similarly the device described in [7] is expensive and does not support multiuser database and community sharing service. Finally [8], [9] and [10] provide web-based solutions only and do not provide real-time monitoring.

In this paper we propose a wearable wireless sensor that is IoT compliant and provides, real-time remote monitoring of Congestive Heart Failure (CHF) patients. These features are mainly achieved by single lead ECG acquisition along with activity detection using the on board accelerometer and the accompanying mobile application. The proposed solution ensures minimal body restrictions, supervisor notifications and community platform growth. In addition, due to it's cost effectiveness a wider outreach is expected which will lead to timely disease diagnosis of patients.

II. DESIGN METHODOLOGY

As depicted in Fig.2 The wearable device consists of four main components i.e. ECG circuitry, Accelerometer, Temperature circuitry, Micro controller combined with BLE transceiver and an accompanying mobile application:

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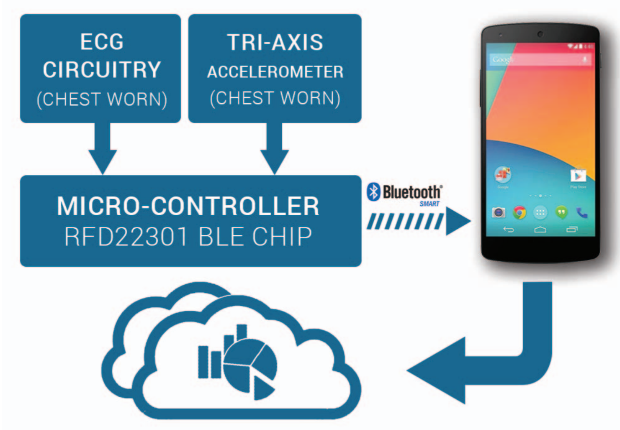

Fig. 2: Block diagram of wearable sensor device

The proposed solution is designed to be a chest worn device. The entire signal conditioning circuitry, along with the accelerometer and micro-controller, is soldered onto a single printed circuit board. The measured values i.e., ECG waveform and the tri-axis accelerations are sent wirelessly to a smart-phone, using the RFD22301 micro controller, where the analysis is performed. This information is further co-related with the current activity of the wearer which is used to draw a meaningful conclusion regarding the current heart condition. The continuous stream of data and analytics is graphically displayed for ease of analysis for short term performance assessment. In addition, the data can be uploaded to the cloud for long term and detailed trend analysis to get an overall picture of hearts health.

III. Hardware and Software Design

The component choice was driven by the motivation to use off-the-shelf components to keep the cost and time to prototype minimal while maintaining low power consumption and high reliability. All of the components were mounted on a double sided PCB made from a FR-14 copper board. The mobile application was tested on a Google Nexus 6P, Nexus 5 and Nexus 4 smart-phones. More details about the components used, circuits designed and algorithms developed are given in the following subsections:

A. ECG Circuitry

ECG signal lies in the range of 0.05 mV to 1.5 mV and is usually accompanied by heavy noise. Hence, the raw signal has to be amplified and filtered from the noise to get a reliable signal. The signal proposed chain consists of a 3 operational amplifier configuration, known as instrumentation amplifier (INA), followed by a series of band pass and notch filters.

One solution is to use an instrumentation amplifier IC and implement the filters using op-amps. This approach not only increases the circuit size and cost but also the power consumed. Another method is to amplify the signal and then filter it digitally, however the filters required to retrieve a reliable signal are of the order of several hundreds. This requires a lot of processing power, which is not feasible in our context since the signal has to be analyzed continuously in real-time.

Hence the solution we opted for, is to use an analog front end specially designed to condition an ECG signal. We have used AD8232 by Analog design [11]. This front end not only possesses a conventional ECG acquisition circuitry but it also possesses a right leg drive (RLD) amplifier, which eliminates noise. In terms of filtering, it includes an adjustable 2 pole high-pass filter along with an adjustable 3 pole low-pass filter with programmable gain. Power consumption is very low, i.e., just 170 μ A during normal operation. Finally, the common mode rejection ratio (CMRR), is high at 80db from DC to 60 Hz.

B. Accelerometer

ADXL-345, which is a tri-axis linear accelerometer by Analogue Design [12], is chosen for gathering inertial movement data because of it's small and thin form factor and ultra low power consumption traits making it suitable for wearable applications. It can operate at $23\mu A$ in measurement mode and just $0.1\mu A$ in the standby mode with a supply voltage of 2.5 Volts with a high resolution of 13 bits. The mounting position for sensor is shown in Fig. 3. X-axis of the accelerometers is along the body from head to feet, Y-axis is from right to left across the chest and Z-axis is out of the chest in forward direction.

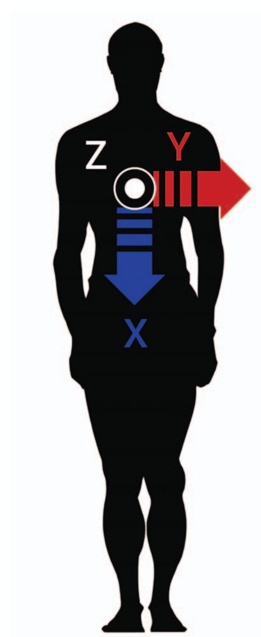

Fig. 3: Orientation of ADXL-345

Calibration of accelerometers is an important consideration for reliable data acquisition. Hence, calibration coefficients were calculated using the method, described in [13], by placing the sensor on a known flat 0^o surface and measuring the offsets for $\pm X$, $\pm Y$ and $\pm Z$ axis.

Data for the three axis from the ADXL-345 was collected using the I^2C protocol at a baud rate of 115200 and sampling rate of 25 Hz. A high sampling rate was chosen to ensure reliable collection even under high frequency movements.

C. Temperature circuitry

Skin temperature was acquired using a Negative temperature coefficient (NTC) thermistor. Particularly, a 2 $k\Omega$ NTCLE203E3 [14] was used. Official look up tables to match resistance to temperature are available but we generated one ourselves by comparing with a reference thermometer. As is evident by the plot in Fig. 4, the response is quite linear in the range of human body temperatures.

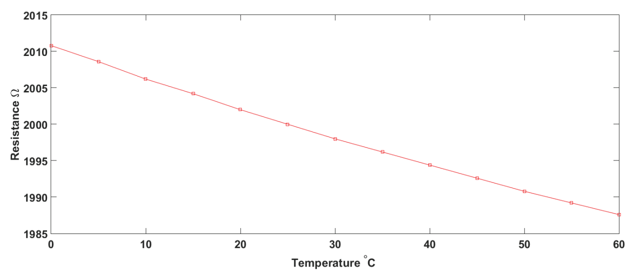

Fig. 4: Linearity of NTC Thermistor NTCLE203E3

D. Micro-controller

We used the RFduino SMT module, i.e., the RFD22301, by RF Digital [15] as the controller for data acquisition and transmission. It is based on a 16 MHz ARM Cortex-M0 CPU and has built in Bluetooth Low Energy (BLE) 4.0 transceiver . It's small size, i.e., $15mm \times 15mm \times 3.5mm$, provides an ideal form factor for wearable devices.

Since it posses an inbuilt 10-bit Analog to Digital converter, ECG values can be acquired directly from the signal conditioning block. A coin cell battery, such as the CR 2032 by Energizer [16], can be used to power it up. It is programmed to remain in the Ultra Low Power mode of $4\mu A$ between sampling intervals and when it is outside the transmission range of the smart phone. The average current drawn by the complete circuit is about 4.8 mA, which gives an approximate operating time of about 52 hours on a 250 mAh CR 2032 battery.

E. Android Application

Fig. 5 shows the proposed layout of the android application. The user interface (UI) has been designed with a layman in mind, hence the UI is simple and straightforward. It provides a real-time ECG graph, Stats and Analysis of the ECG and other features, such as history and doctor notification.

IV. Testing and Results

Before describing the results and their analysis, it is to be pointed out the subjects used for data acquisition were the authors themselves and acquaintances thereof, all of whom willingly consented to serve as test subjects and to the sharing of their biomedical data.

The testing phase for the proposed wearable is divided into two separate categories as follows:

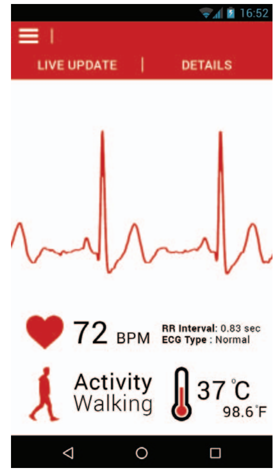

Fig. 5: Android Application User Interface

A. Algorithm Verification for ECG Analysis

The algorithm used in the proposed wearable is a modified version of Pan Tompkins QRS complex detection algorithm [17]. It has been designed to operate in real-time on 6 second long window of ECG values sampled at a constant rate of 250 Hz. Figs. 6 and 7 show the plots for recorded sample and the output of QRS Detection overlayed on top of it, respectively. Finally, Table I details the percentage of correctly detected complexes (tolerance of $\pm 1 sample$ / $\pm 4 ms$).

The plots in Figs.6 and 7 are generated using MATLAB while the results presented in Table. I are generated in MATALB, C++ and JAVA. The final implementation of the algorithm is in JAVA.

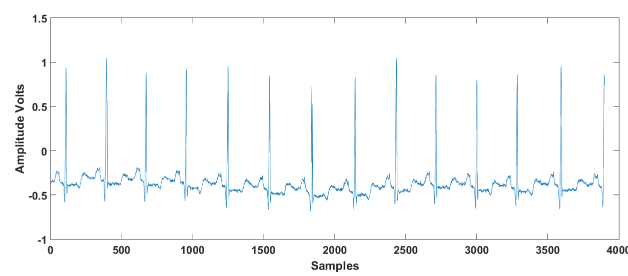

Fig. 6: ECG Input to Algorithm

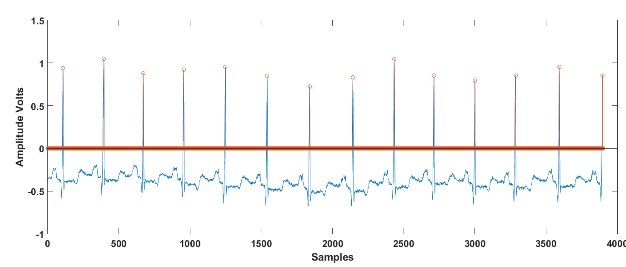

Fig. 7: ECG Peak Amplitude and Location Output from Algorithm

Subject	Total Beats	Total Failed	% Correct
subject A	1307	25	98.08
subject B	1263	19	98.50
subject C	1358	32	97.64
subject D	1386	36	97.40
subject E	1370	57	95.83
subject F	1294	11	99.14
Overall	**7978**	**180**	**97.74**

TABLE I: Pan Tompkins Results

As is evident from Table.I, the overall performance of the algorithm is satisfactory since the error rate is below 5% across all patients and less than 4% on average. Hence we can safely conclude that the quality of the data acquired is good enough to perform further analysis.

B. Classifier Verification for Activity Detection

The classifier design is based on a support vector machine using a 7-feature set space. It first calculates the body orientation and then moves on to activity classification. The features extracted from the 3-axis acceleration data is listed in Table II.

Time Domain
Co-relation X-Y axis
Co-relation Y-Z axis
Kurtosis X-axis
Skewness X-axis
Standard Deviation X-axis
Minimum value X-axis
$\sum Mag_i = \sum \sqrt{A_{xi}^2 + A_{yi}^2 + A_{zi}^2}$
such that $Mag_i < 25^{th}$ percentile of Mag

TABLE II: Features Time Domain

A major problem in classifier verification is over fitting of data. While it gives pretty high accuracies, it is not representative of how the classifier will perform in general. Hence we have employed two separate testing methods to ensure that our classifier will perform well as a generalized model. The results for Hold-out testing and Cross fold testing are presented in Tables III and IV, respectively. The activities are classified into Running, Walking, Upstairs, Downstairs and being idle.

For Hold-out testing, the split was made at random and then the same percentage split was averaged over 3 times to generate a final count, e.g 3 different random splits were made for 70 % training data and 30 % testing data and the final count for correctly classified samples was taken as average of the 3 tests.

All tests are first performed in MATLAB and then cross validated in Python using the Scikit Learn package. For the results in Tables.III and IV, the total number of feature vectors (instances) calculated, from the collected raw data, are 1292. The accuracy is measured as percentage i.e.,

$$Accuracy = \frac{Correctly\ Classified}{Total\ Instances} \times 100 \qquad (1)$$

Table. III shows promising holdout testing results. Even when just 20% of the 1292 samples are used for training, the accuracy is 98.30 %. This means that even if the learning set is small, the chosen features are good enough to generate a classifier with accuracy of 95% or above.

% Data Split	Total Instances	Correctly classified	Accuracy
80% Training	1292	1287	99.61 %
70% Training	1292	1288	99.39 %
60% Training	1292	1263	97.76 %
50% Training	1292	1273	98.52 %
40% Training	1292	1273	98.52 %
30% Training	1292	1271	98.37 %
20% Training	1292	1270	98.30 %
Overall Accuracy			**98.638** %

TABLE III: Hold out testing

% No. Folds	Total samples	Accuracy
10 Fold	1292	97.454 %
11 Fold	1292	96.308 %
12 Fold	1292	98.358 %
13 Fold	1292	97.462 %
14 Fold	1292	98.689 %
15 Fold	1292	98.272 %
Overall Accuracy		**97.757** %

TABLE IV: Cross fold testing

The cross fold test is a much better measure of classifier accuracy than the hold out test. The results produced by this method as shown in Table.IV, hold true for actual device performance.

V. CONCLUSION

A wearable cardiac monitoring device has been developed along with a framework to analyze the acquired data from it. The device is enabled to be online at all times and thus is suitable for both short and long term analysis. It consumes only 20.32 mW and the development cost is very low at $95. The companion android application processes the raw data and displays meaningful information on a simple and easy to use graphical interface. The processed data is then stored in the cloud for further analysis if required. The device in addition to cardiac patients can be used for athletes, mine workers, astronauts and in many other applications.

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