A Portable Real Time ECG Device for Arrhythmia Detection Using Raspberry Pi

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Abstract. Arrhythmia related disorders are one of the leading causes of cardiac deaths in the world. Previous studies have shown that Arrhythmia can further lead to major cardiac diseases like the Sudden Cardiac Death (SCD) syndrome. The difficulty in detecting Arrhythmia in the early stages often results in poor prognosis and presents the need for a costefficient diagnostic device. To this end, we propose a realtime portable ECG device with special emphasis on Arrhythmia detection and classification. The device is centered on a Raspberry Pi 3 (RasPi) module. RasPi with its signal processing and wireless transfer capabilities acts like an adapter between the sensors and a personalized mobile device application that is used for tracking the ECG. A highly sensitive peak detection algorithm was used by RasPi to detect and extract features from the ECG signals at real time. The peak detection algorithm was tested on the standard MITBIH arrhythmia database and reported an accuracy of greater than 95%. Hence, we propose a novel low cost approach towards arrhythmia monitoring and detection with wide applications in mobile health systems.

Keywords: Arrhythmia · Portable · Costeffective · Wireless communication · Mobile health

1 Introduction

Abnormal heart rhythms clinically manifest themselves in the form of arrhythmias. Arrhythmias are relatively quiescent during the initial stages but may provide significant information about the health of an individual and help detect underlying cardiac anomalies [1]. Cardiovascular diseases like atrial fibrillation and ventricular fibrillation represent the more severe cases of arrhythmia. One such disease linked to ventricular fibrillation is the Sudden Cardiac Death (SCD) syndrome which claims 6 million lives worldwide with a low survival rate of 1%–5% [2]. As the disease shows very little symptoms early on, it becomes imperative to come up with diagnostic devices for early detection.

The electrocardiogram (ECG) has been the leading tool for arrhythmia detection and classification, though the bulky 12 lead instrument makes it inconvenient for frequent monitoring while data retrieval and interpretation often needs

P. Perego et al. (Eds.): MobiHealth 2016, LNICST 192, pp. 177–184, 2017.
DOI: 10.1007/978-3-319-58877-3_24

clinical expertise and is expensive in places with limited access to health care [3]. Recently, novel methods have been proposed to use mobile computing for signal processing and data analysis [4]. Previously, use of android based devices for arrhythmia detection using Pan-Tompkins algorithm and feature extraction from mobile devices have been demonstrated [5]. Most of the current algorithms make use of the QRS complex for arrhythmia detection at real time [5,6]. Though these algorithms are quite sensitive to detect the R-R peak intervals, they could fail to abstract other essential features that could detect the presence of other kinds of arrhythmias. The Long QT syndrome characterized by elongation of Q-T interval in ventricular arrhythmias and Premature Atrial Contractions (PACs) associated with Supraventricular arrhythmias are potentially deadly syndromes where characterization of the P and T wave are essential for detection [7]. In our study we present another alternative for ECG tracking with special emphasis on arrhythmia detection. Our approach to this is threefold, (1) Design and development of a portable low cost ECG monitoring device centered on RasPi (2) Developing a highly sensitive algorithm that is capable of detecting P, QRS and T peaks accurately. (3) Developing a mobile application for easy user interface that uses patients medical history for a personalized monitoring of tachycardia or bradycardia. To test the sensitivity and accuracy of our algorithm we tested it on the MIT-BIH arrhythmia and supraventricular arrhythmia database.

2 Design

Raspberry Pi 3 B+. The Raspberry Pi is a portable minicomputer. The Raspberry Pi model B+ has inbuilt wireless LAN 802.11n and Bluetooth 4.1. It has a RAM of 1 GB which makes it ideal for faster calculations and real time implementation. The RasPi model B+ has 40 GPIO pins at its disposal, which allows for greater flexibility to extend the deice for more sensors. The RasPi was booted with Raspbian OS operating system, which is stable open source. Scripting can be carried out using Python 2.7 supported by the Raspbian platform [9]. ECG monitoring system is hardware dependent work, hence Serial Peripheral Interface bus and GPIO pins in RasPi are very useful. The RasPi is powered by 5 V micro USB supply, to make the device portable we have used a standard power bank.

AD8232. AD8232 is a dedicated IC for signal conditioning of ECG signal. In order to achieve the best possible output we are using the AD8232 SparkFun Single Lead Heart Rate Monitor [10]. The evaluation board is mounted with AD8232 and resistors and capacitor. It is designed to filter, amplify ECG signals in the presence of noisy conditions, created by movement or electrode positioning. The board has 3.5 mm jack for connecting sensor pad connection as shown in Fig. 1(C). The usage of 3.5 mm jack reduces the interference of noise. The power supply to the evaluation board is 3.3 V which is provided from the RasPi pinout. The output of the AD8232 is analog, whereas the RasPi read only digital signal. Hence we use MCP3008 for analog to digital convertion.

MCP3008. MCP3008 is capable of taking 8 channel of input and converts it to 10-bit digital value. MCP3008 uses serial peripheral interface (SPI) bus to establish a synchronous serial communication between the master and slave [11]. Here the RasPi is the master and MCP3008 is slave as the clock is being generated by the RasPi. The ADC/MCP3008 is capable of sending 75 Ksps to 200 Ksps based on the supply voltage. The rate at which these samples are read decides the sampling rate. The sampling rate is software programmed by reading after every sampling interval. The ADC is single supply operated and the voltage can be between 2.7 V to 5.5 V. The RasPi has a standard 3.3 V supply, hence we use it to power the MCP3008 which is also used for AD8232 and Vref.

Interface of Components. In order to get a clear ECG signal, 3-electrode method is followed. The sensor pad were placed close to heart forming a right triangle [Fig. 1]. The sensor pads were connected to the tri-conductor sensor cable with the 3.5 mm jack output connected to AD8232. We have developed our device with a three electrode system to have the optimum accuracy as well as make it more user friendly compared to the 12-lead ECG. The analog output of the AD8232 is given to input of the Analog to Digital Converter (MCP3008). The SPI bus was used for serial communication between the MCP3008 and RasPi. The output of the AD8232 varies between 0–3.3 V as per the data sheet, hence the reference voltage of ADC is set as 3.3 V. The ECG output ploted on the Raspi after Digitalisation using MCP3008 is shown in Fig. 1(a)

3 Methodology

In this work, RasPi acts as a central device which analyses the ECG signal and transmits the essential data along with signal to mobile application.

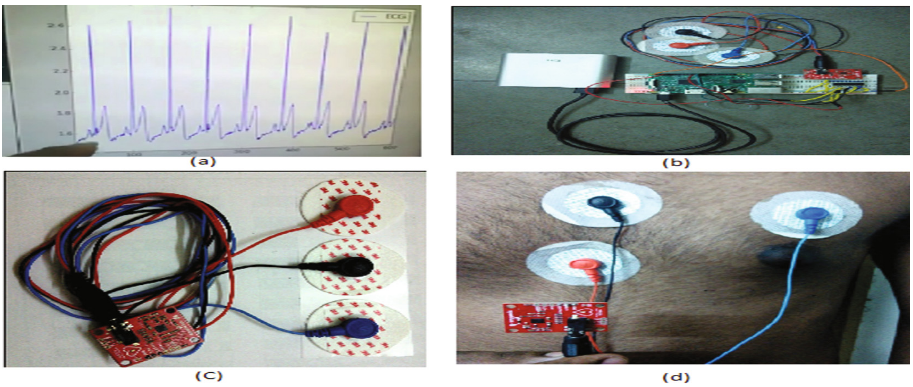

Fig. 1. (a) ECG signals as observed real-time on the RasPi monitor (b) Portable ECG Device powered by a mobile power bank (c) AD8232 with patches (d) Placement of three patches in a right angled triangle

The connectivity between RasPi and the mobile is established by creating a WiFi access point in RasPi. To create hotspot from RasPi, the procedures followed were as given in [9]. The sampling rate is set as 100 samples per second. Every 100th of the second a 10-bit digital value is read by RasPi. The 10-bit value corresponds to a value between 0 to 1024 which is scaled between 0 to 3.3 V. The sampled ECG signal is stored in variable of fixed length of 1000 samples, and updated every 10 s and given as an input signal to the peak detecting algorithm. On the other hand the ECG signal is continuosly transmitter to mobile. This is achieved by using multiple threads. So two variables one stores the current ECG signal incoming and other has the previous 10 s ECG signal for analysis. Time taken for a single run of the algorithm on 1000 samples is on an average 0.080644 s. Every 10 s the stored variable containing the ECG samples is given as input to the peak detecting algorithm. The position of the peaks is being outputed. With these peaks we find the RR interval, PR interval, QT interval and QRS duration (width) which is used to classify the types of pathological condition. This classification is done by mobile application.

Peak Detection Algorithm. An Input signal of 1000 samples was given to the peak detection algorithm. Baseline wandering from the input signal was removed using a moving average filter and the power line noise removal was done by a notch filter designed at 60 Hz. A padding of 100 zeros was then introduced in the start and end of the input signal [12].
To accurately detect R peaks a threshold value was set based on the analysis of all normal ECG signal and all values above the threshold were selected. Threshold value was set as follows:

$$ThresholdValue \geq Mean(Mean(samples) + Max(samples)) \tag{1}$$

Peaks above the threshold value were further filtered into peaks having less than 10 samples between each of them and the maximum value in this set represents the R- peak. A window of length 20 was chosen to the left and right of the R peak and the minimum values were assigned to Q and S peaks respectively. Further a window of 30 samples was taken to the left of the Q peak and another window of 50 samples was taken to the right of the S peak. The maximum values in this region were assigned to P and T peaks (Fig. 2). At this step the sample numbers of all the peaks are stored. These windows were decided based on the sampling rate. To get the absolute position of the peaks, the padding of 100 zeros from the start is removed from the detected position to get the absolute position. As a check for the abnormal cases, any value below zero or greater than 1000 means that the peak didnt exist. To test the accuracy of the algorithm, samples from the MIT-BIH arrhythmia were taken.

Classification Based on the ECG Wave Characteristics Using Peak Detection Algorithm. In this section, we provide the basis for arrhythmia classification using previously reported classifiers [12], all of which are

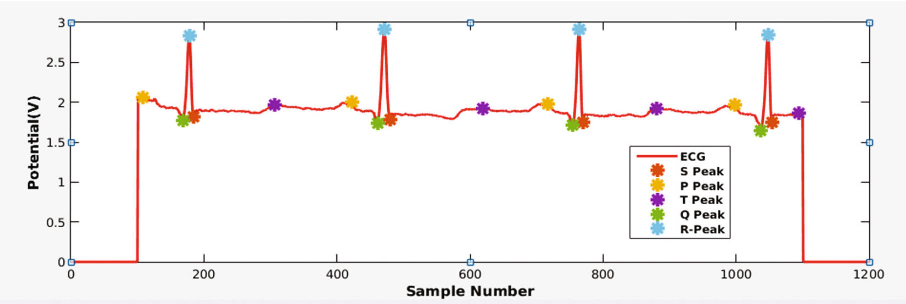

Fig. 2. The P(Yellow), Q(Green), R(Cyan), S(Red), T(Violet) peaks detected by the Peak Detection Algorithm (Color figure online)

incorporated in our algorithm. We are using the peaks detected by using the algorithm and calculating the RR, PR, QRS and QT intervals. Using the R-R interval(samples between R-R peaks) we calculate the heartbeats per minute. Here Fs = Sampling frequency

$$HeartRate = \frac{60 * Fs}{R - Rinterval} \tag{2}$$

Classification based on rhythmic, intervals we also include the conventional heart rate approaches to accurately classify arrhythmia into its specific subclasses as shown in Table 1.

Long QT Syndrome. From the peak position we find the QT interval using (Formula-3). Using Bazetts formula to calculate QTc Values for detecting QT Prolongation [8,13] Where QT and RR are the represent the peak durations respectively.

$$QTc = \frac{QT}{\sqrt{RR}} \tag{3}$$

Mobile Application. The application lets the user create their own account. As soon as RasPi is switched on, it turns on WiFi access point. The user needs to connect the phone to the WiFi hotspot, user can login and start the ECG recording. The transfer of data to mobile from RasPi is achieved using the socket library. The socket library transfers data using UDP protocol. The RasPi does the analysis on the ECG signal and every 10 s data (1000 samples) and updates the information about the peaks during that 10 s interval. The mobile application plots the ECG signal, heart beat per minute, and RR intervals. Concurrently, it also receives data on the PR, QT and QRS intervals from the RasPi, which are used classification of the signal, which are then displayed in the session log window after recording. The mobile app also helps in heart beat range for the user. Based on the personal information collected from the user for nonsmoking people the lower limit is set to $0.7 * 75$ and the upper limit is set to $220 - 0.48 * Age$.

Table 1. Table showing parameters and criteria for arrhythmia classification.

Parameter	Criteria for detection	Type of disorder
Heart rate	60–100 Bpm	Normal sinus rhythm
Heart rate	100–150 Bpm	Sinus tachycardia
Heart rate	40–60 Bpm	Sinus bradycardia
Rhythm and Heart rate	Irregular rhythm and 40–60 Bpm or 60–100 Bpm	Sinus arrhythmia
QRS width	Width > 0.13 s	Bundle branch block
QRS width	Width < 0.045 s	Premature ventricular contractions
PR interval	Interval > 0.2 s, consistent with every beat	First Degree AV Block
RR interval	Interval > Avg. R-R interval	Escape/AV Block
QTc values	Male > 0.45 Female > 0.47 1–15years: > 0.46	QT syndrome

Studies have shown that people who smoke, their heartrate changes by 11 as compared to people who don't smoke. Hence for smokers, the lower limit increased by 11 and upper limit decreased by 11. A separate thread is created, which keeps track of all the heart-rate measured. The thread keeps running in parallel to check whether the heart-rate falls in the above mentioned range else a message alert is passed to the contacts (Fig. 3).

4 Results

Performance of the Peak Detection Algorithm. In this paper we randomly selected data 100, 101, 109, 113 & 115 from MIT-BIH Arrhythmia Database [14]. Table 2 shows the predicted and the actual heart rate along with the number of peaks in the ECG signal pedicted by our algorithm as compared to MIT-BIH database results.

From Table 3 for data 100, the RR interval, PR interval, are well within the bound whereas the QRS interval wanders around 0.045 s which has a possibility of Premature ventricular contraction & QTc value slightly goes beyond the 0.45. This ECG data corresponds to adult male, so the subject may have prolonged QT syndrome. Similarly for data 101 the all interval (Mean ± std) as shown in are within the bound hence the subject has a normal heart beat. Data 109

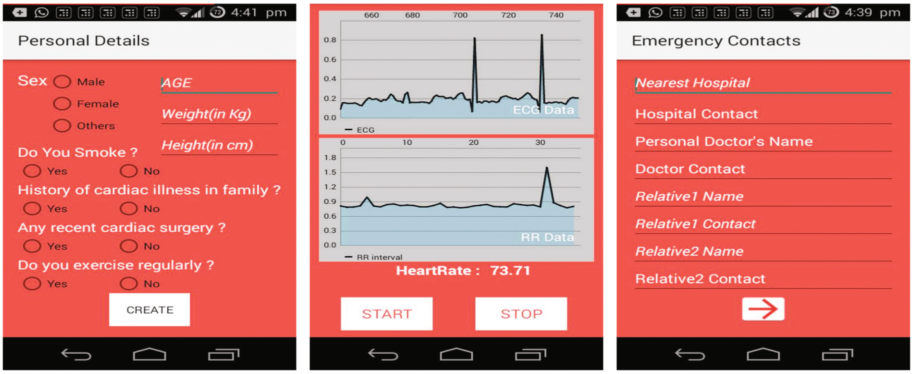

Fig. 3. Screenshot of the personalised mobile application

Table 2. Performance of the peak detecting algorithm.

Data	Predicted HBP	Actual HBP	Predicted R peaks	Actual R peaks
100	75 ± 1	70–89	2268	2273
101	61 ± 3	55–79	1855	1865
109	83 ± 4	77–101	2495	2532
113	62 ± 5	48–87	1865	1795
115	64 ± 5	50–84	1945	1953

Table 3. Results of our analysis on MIT-BIH arrhythmia database

Data	RR	PR	QTc	QRS	HeartRate
100	0.793 ± 0.019	0.152 ± 0.005	0.443 ± 0.013	0.04 ± 0.006	75.62 ± 1.91
101	0.973 ± 0.046	0.152 ± 0.003	0.360 ± 0.083	0.065 ± 0.001	61.78 ± 3.27
109	0.722 ± 0.044	0.196 ± 0.029	0.448 ± 0.078	0.081 ± 0.001	83.28 ± 4.50
113	0.966 ± 0.776	0.131 ± 0.008	0.360 ± 0.029	0.043 ± 0.002	62.52 ± 5.41
115	0.930 ± 0.050	0.184 ± 0.003	0.389 ± 0.018	0.060 ± 0.001	64.70 ± 5.45

has PR interval as 0.1969 ± 0.0290 s hence the subject may suffer from First Degree AV Block. Towards detecting more than one kind of arrhythmia. Further, we also analyzed data 113 and 115. Samples 113 and 115 showed signs of sinus arrhythmia and PVC. Data 115 may have a condition of a AV block, thus the results confirm a strong correlation between the Peak Detection Algorithm and MIT-BIH arrhythmia database. Thus, we were able to predict occurrences of arrhythmia in these sample with high accuracy. In addition to this, our algorithm also picked up instances of the long QT syndrome in Data 100, which werent reported by the database. This may potentially be a case of Ventricular Fibrillation that was detected by our algorithm.

5 Conclusion

In this work, we present a novel device capable of detecting different types of arrhythmia. We have synchronized the RasPi centered device through a wireless LAN, to a mobile app that is user friendly and generate log files, that can be shared with a personal doctor. We also present a highly accurate Peak Detection Algorithm that is sensitive at detecting various types of arrhythmias. Though we have intended to make this device portable, issues like power supply, noise reduction and reducing the overall hardware complexity without compromising on the quality of the signal processing are still major challenges in building real-time tracking devices. In our model, we have tried to reduce these variants to a minimum by introduce a portable USB charger and two peripheral chips along with a RasPi module, to make it a viable prototype for a wearable device.

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