A Smartphone App for Real-time Heart Rate Computation from Streaming ECG/EKG data

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***Abstract*—Cardiac disease, also known as cardiovascular disease, refers to a group of conditions that affect the heart and blood vessels. Diagnosis of cardiac disease typically involves a combination of medical history, physical examination, and various tests, such as electrocardiograms (ECG/EKG), echocardiograms, and stress tests. To address this concern, we introduce a mobile application called Smart-Health application, which can continuously monitor electrocardiogram signals and display Average Heart Rate (HR) along with the instantaneous HR. The aim of this project is to discover cardiac diseases so that doctors can monitor the accurate heart rate and take further actions based on the results. Smart-Health application typically works by collecting data from wrists or chest by electrodes. This data is then processed and analyzed to provide the user with insights into their health. We collected data from 10 participants and compared it with KardiaMobile (AliveCor®, Mountain View, CA, USA) commercial application. The error rate of the proposed algorithm depends on several factors, including the accuracy of the sensors used to capture the ECG signal, the algorithms used to process the signal, and the quality of the hardware and software components used to build the application. Experimental results show an accuracy of up to 95-99%. This Smart-Health application has the potential to improve health outcomes and reduce healthcare costs, making it a valuable tool for both individuals and healthcare providers.**

***Index Terms*—Electrocardiogram (ECG), Instantaneous Heart Rate (HR), KardiaMobile, Smart-Health Application.**

I. Introduction

Cardiovascular diseases (CVDs), which include ischemic heart disease, stroke, heart failure, peripheral arterial disease, and several other cardiac and vascular illnesses, are the world's leading cause of death and a significant factor in decreased quality of life [1]. Without appropriate treatment, heart disease can lead to heart attacks or strokes [2]. There are several methods and tools that can be used to monitor heart disease, including monitoring ECG signal that measures the electrical activity of the heart and can detect irregular heartbeats or other abnormalities. Mobile health applications, or "mHealth" apps, are becoming increasingly popular for monitoring heart disease and promoting heart health [3]. These apps can provide a range of tools and features to help users manage their heart health, track their symptoms, and communicate with healthcare providers.

Holter monitors are small, portable devices that record the heart's electrical activity over an extended period, typically 24 to 48 hours, while the patient goes about their daily activities [4]. The device consists of several leads that are attached to the chest and connected to a small recording device that the patient carries with them. KardiaMobile is a small, portable electrocardiogram (ECG) device that allows individuals to monitor their heart health and detect potential cardiac issues at home or on the go [5]. It works by recording a single-channel ECG through two electrodes on the back of the device. It has demonstrated effectiveness in clinical studies for detecting atrial fibrillation (AF), with a sensitivity of 96.6% and a specificity of 94.1% [6]. Similar to KardiaMobile, an ECG check is a portable electrocardiogram (ECG) device that uses two or more electrodes to record the heart's electrical activity [7]. ECG check's app sends the recorded ECG data to a server for analysis, which can take a few minutes to several hours to complete. Another device to monitor the ECG signal and measure heart rate is Apple Watch. The ECG feature, available on Apple Watch Series 4 and later, allows users to record an electrocardiogram, which is a test that measures the electrical activity of the heart [8]. The watch can detect abnormal heart rhythms, such as AF, and notify the user if an irregularity is detected. Along these, there are several mHealth applications available on the market for monitoring heart diseases such as iHealth Rhythm [9], and QuardioCore [10]. Previously, another smart health framework [11] was developed by our research group with body-worn flexible Inkjet-printed (IJP) sensors, commercial wearables such as smart wristbands, a scanner on a printed circuit board, and a custom SSC-Health smartphone app.

In this work, a low-cost, wearable, real-time ambulatory ECG monitoring system based smartphone app is described. We have developed a smartphone-based application with real-time ECG trace visualization and heart rate detection for monitoring, assessment, and diagnosis. This application is based on *Smart Health Integrated Framework and Topology (SHIFT)* architecture that preserves Mobile Health (mHealth) for individuals to self-monitor their own health and allows participants to share individual health severity data with doctors for further inspection [12]. This application has high scalability and low latency in addition to being low-cost and real-time.

The main aspects of the proposed application include:

- The application connects to the embedded systems which collect ECG signals from the electrodes via Bluetooth Low Energy (BLE) V5.3.

- The users can monitor ECG signals on the screen of the application where the noise of the signal is mostly filtered out.
- Users can track their heart rate and rhythm over time in the application. Also, they can see their instantaneous heart rate over a long period of time.
- The application allows users to share ECG recordings with their healthcare providers, enabling remote monitoring and diagnosis.

II. Materials and Methods

A. System Architecture

The system consists of a front-end ECG data collection device based on an AD8232 chip (Analog Devices, Wilmington, MA). Sparkfun nRF 52840 mini (where electrodes are attached) is connected to the application via Bluetooth Low Energy (BLE) V5.3. Figure 1 shows the overall architecture of the system. The Smart-Health application collects ECG signals from the patients and displays them on the screen. Patients with heart disease can use the app to monitor their heart health and detect any changes that may require medical attention. The app allows patients to share ECG recordings with their healthcare providers, enabling remote monitoring and diagnosis. This can reduce the need for in-person appointments and improve access to care, especially for patients who live in rural or underserved areas.

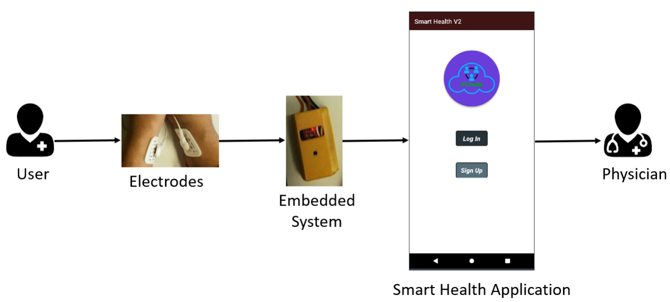


Fig. 1: Architecture of the proposed system.

B. Application Design and Implementation

Figure 2 shows the block diagram of the Smart-Health Application. At first, the user is required to register his/her details on the application. After clicking *Device Connect* on the Dashboard screen, the smartphone displays the available devices that can be connected via BLE connection. When the *Connect* button is pressed, the application makes a connection with the device via BLE and is ready to collect the data. It can be disconnected by pressing the *Disconnect* button. Then the user will go to the *Modules* segment, from where he/she can monitor the *Data* or watch the ECG signals in the *Plotter*. Here, users can also monitor their heart rate over a long period of time and see if there is anything to worry about.

For heart rate calculation, firstly we collect the incoming data. Then we used *Pan-Tompkins* algorithm to detect the R-peaks of the ECG signal. Data came from the embedded ECG data collection system at a rate of 20kHz. In other words, the signal is divided into small time intervals, and at each interval, a sample is taken to represent the value of the signal at that specific time.

Algorithm 1: R-Peak Detection Algorithm

Input: Input data: ECG signal $x(t)$
Output: Output data: R-peak times $r_1, r_2, ..., r_n$
Data: Parameters: alpha= 0.75

`// Apply a bandpass filter to the ECG signal`
$f(t) \leftarrow \sum_{i=1}^{length(x)} (alpha * f(i-1) + (1-alpha) * x(i))$;
`// Differentiate the filtered ECG signal`
$z(t) \leftarrow f(t) - f(t-1)$;
`// Square the differentiated ECG signal`
$p(t) \leftarrow z(t) * z(t)$;
`// Integrate the squared ECG signal using the trapezoidal rule`
for $t = 0$ **to** n **do**
  if $t == 0$ **then**
    $q(t) \leftarrow p(t)$;
  end
  else
    $q(t) \leftarrow q(t-1) + (p(t) * p(t-1))/2$;
  end
end
`/* Find the R-peaks by locating the maximum values in the integrated signal. First, find the threshold from the integrated signal. */`
$mean \leftarrow (\sum_{i=1}^{length(q)} q(i))/length(q)$;
$std \leftarrow (\sum_{i=1}^{length(q)} (q(i) - mean)^2)/length(q)$;
$threshold \leftarrow mean + std * 2$;
`// Then, apply the threshold for finding R-peaks`
for $t = 0$ **to** $length(q)$ **do**
  if $q(t) > threshold$ **then**
    $s(t) \leftarrow 1$;
  end
  else
    $s(t) \leftarrow 0$;
  end
end
`// Now, find the position of R-Peaks`
for $t = 0$ **to** $length(s)$ **do**
  if $s(t) == 1$ **then**
    $r_n \leftarrow t$;
  end
end

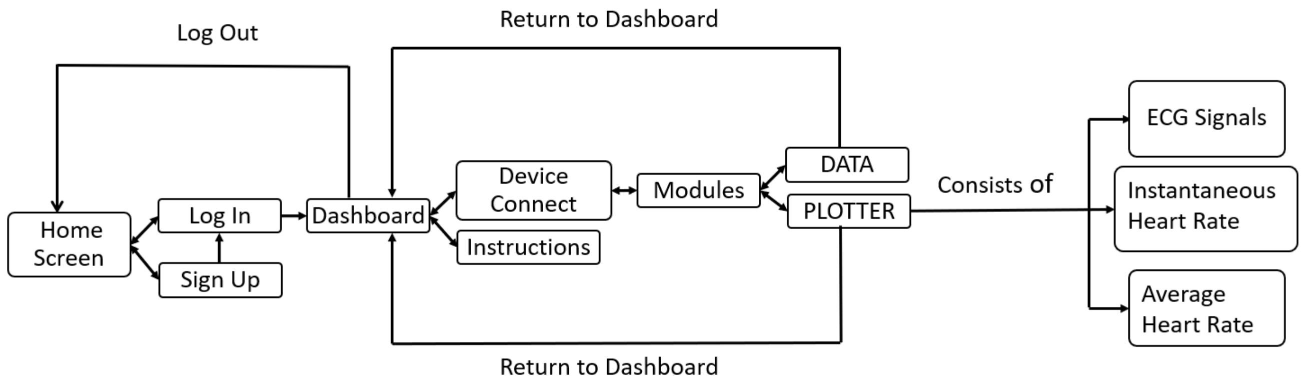


Fig. 2: Block Diagram of Smart-Health Application.

Algorithm 1 shows how we detected the R-Peaks from incoming ECG signals that are collected from electrodes. Then, we use *Algorithm 2* to determine the heart rates from R-Peaks. Also, we showed the Average Heart Rate on the application to get a better view of the heart conditions of the user. We used *Sliding Window* technique for that. With a window size of 30, we examined 30 heart rate readings simultaneously. Next, after shifting the window by one heart rate value, the same statistic was computed for the following 30 values. So, users can easily monitor their heart rate and see if there are any rapid changes.

III. Results and Discussions

We have collected 10 participants' (Age range: 25-35 years old) data through the application. Participants were encouraged to take part in two data collection sessions, first, we took the data from their *resting* position, and later we took the data after some sort of activities they had done. Figure 3. indicates a whole setup for data collection from the application and KardiaMobile also. We collected data from KardiaMobile in a continuous manner at the same time of collecting data from the Smart-Health Application so that we could find the error rate using our custom ECG data collection device [13]. Collecting data from each person in every state includes:

1) First, we attached electrodes to the wrists of the participants. Then an embedded system (consisting of Sparkfun nRF 52840 mini) collected data and transferred it to the application via BLE.
2) Participants held two metal electrodes (for KardiaMobile) on their fingers, index, and middle at the same time.
3) Then we started the data collection process in the Smart-Health application (Fig. 4) and KardiaMobile at the same time.
4) As the KardiaMobile application shows an average HR after 30 seconds, we collected data 10 times.
5) In the meantime, ECG signals from wrists were saved in a CSV file on the application.

Later, we compared *Average Heart Rate* from the application with the heart rates from KardiaMobile.

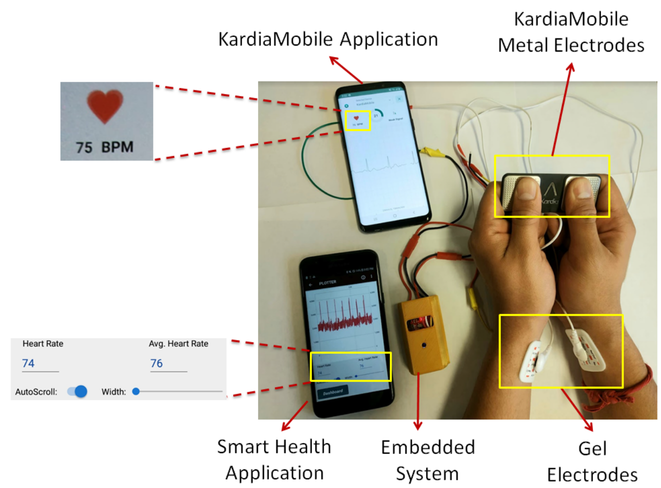
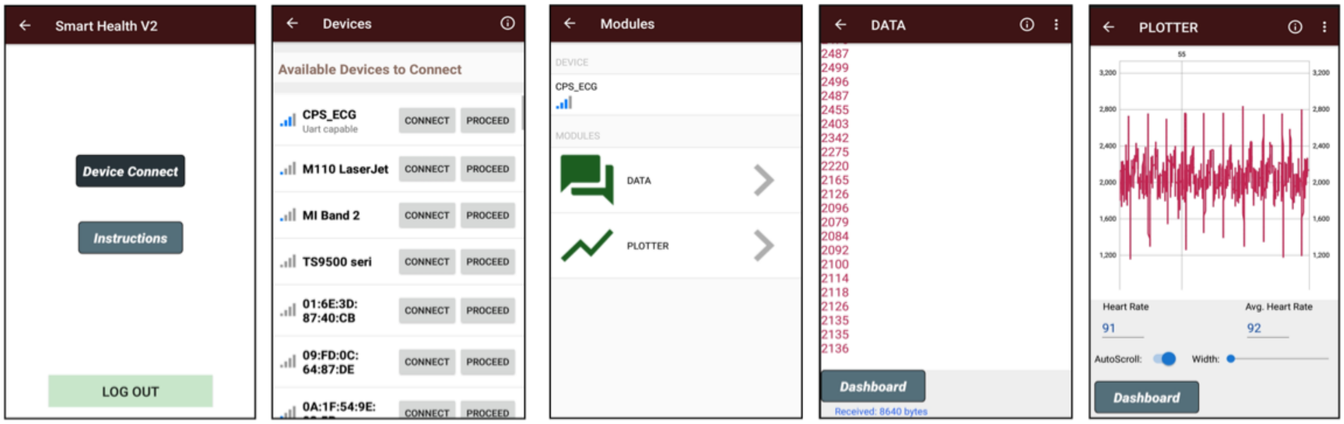


Fig. 3: Data collection in Real Time from the Smart-Health Application and KardiaMobile.

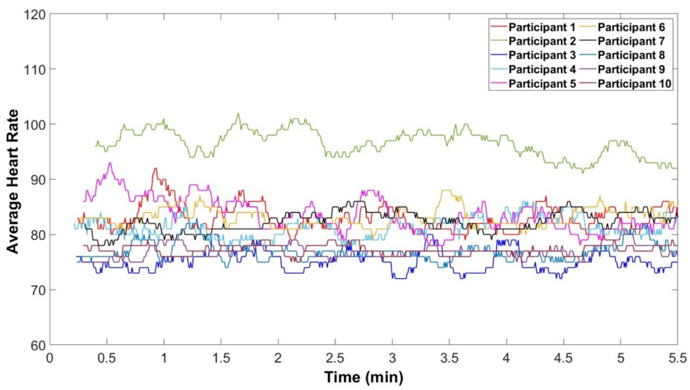
All participants resting state HR was shown in Fig. 5(a). Also, we collected data from the participants after walking or some sort of workout. At that time, HR got increased which is shown in Fig. 5(b). But there are no significant changes in HR as we collected data after some sort of activities, not during that time. It got increased by more or less 5 BPM per person. Also, in Fig 6, we have shown a comparison of the HR collected from the application with the KardiaMobile commercial application. Fig. 6(a) indicates a comparison between the application and KardiaMobile in terms of resting state HR. Also, resting state HR after some activities in the Smart-Health application and KardiaMobile are shown in Fig. 6(b) bar chart.

From the experiment, we have found that in KardiaMobile, the ECG signals are much smoother than in our application although we have filtered the noise also. It indicates that filtration is performed much better in KardiaMobile. But there

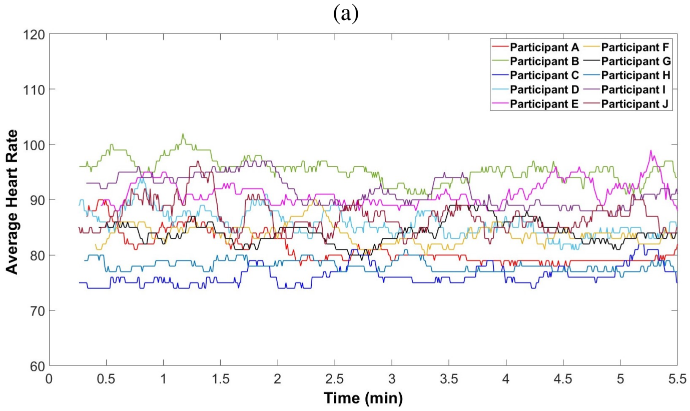


(a) (b) (c) (d) (e)

Fig. 4: Snapshots from the application (a) Dashboard (b) Available Devices (c) Modules (d) Incoming Data (e) Real-time plot of ECG trace and Heart Rate.

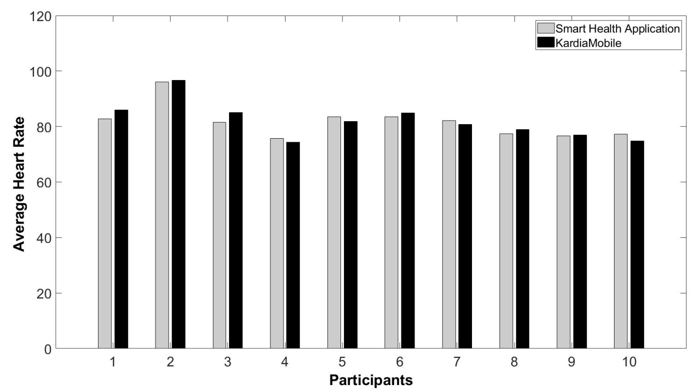


(a)

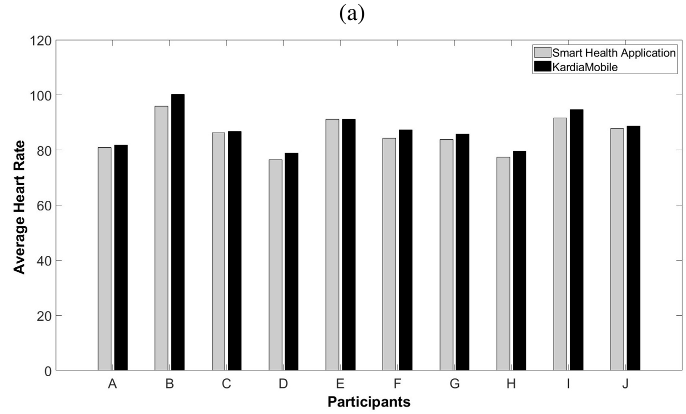


(b)

Fig. 5: Heart Rate of the participants (a) In *resting state* (b) In *resting state after some activities*.



(a)



(b)

Fig. 6: Comparison of HR between Smart-Health application and KardiaMobile (a) In *resting state* (b) In *resting state after some activities*.

Algorithm 2: Calculate heart rate from R peaks

Input: Input data: $rPeaks$, $windowSize$
Output: Output data: $heartRate$
`// Get the difference in time between each R peak`
for $i \leftarrow 1$ *to* $rPeaks.size()$ **do**
  $rrInterval \leftarrow rPeaks[i] - rPeaks[i-1]$
  $rrIntervals$.add($rrInterval$)
end
`// Initialize a moving average window`
$window \leftarrow$ array of size $windowSize$
$windowIndex \leftarrow 0$
`// Calculate the moving average of the R-R intervals`
$movingAvgRRIntervals \leftarrow$ empty list **for** $rrInterval$ *in* $rrIntervals$ **do**
  $window[windowIndex] \leftarrow rrInterval$
  $sum \leftarrow 0$
  for $interval$ *in* $window$ **do**
    $sum \leftarrow sum + interval$
  end
  $avgRRInterval \leftarrow sum/windowSize$
  $movingAvgRRIntervals$.add($avgRRInterval$)
  $windowIndex \leftarrow (windowIndex + 1)$ mod $windowSize$
end
`// Calculate heart rate in beats per minute`
$sum \leftarrow 0$
for $avgRRInterval$ *in* $movingAvgRRIntervals$ **do**
  $sum \leftarrow sum + avgRRInterval$
end
$avgRRInterval \leftarrow sum/movingAvgRRIntervals$.size()
$heartRate \leftarrow 60/avgRRInterval$

might be a problem. By eliminating too much noise, some peaks of ECG signals might be removed. Therefore, we might not get the exact HR. Also, we are collecting data from the fingers in KardiaMobile which is a widely used method and is considered to be a relatively easy and non-invasive approach [14]. Yet, wrist-worn devices allow for long-term monitoring during normal activities and are more comfortable than finger-worn acquisition methods [15]. The quality of the ECG signal obtained from the finger or wrist can depend on several factors, including the accuracy of the device used to measure the signal and the position of the device relative to the heart. In general, ECG signals obtained from the chest tend to be of higher quality and more reliable than signals obtained from the finger or wrist [16].

IV. Future Work

As the setup of our system is very complex, it is very hard to collect data while walking, running, or doing some sort of activity. The package consists of some IoT devices that might be optimized in the future and then we can easily attach those devices to the body which will help us to collect data. Also, we couldn't collect data from the chest of the participants. Although the traditional method of collecting ECG data involves placing electrodes on the chest, it is not always feasible or practical to collect ECG data from the chest in all situations.

At present, the Smart-Health application can show ECG signals and instantaneous Heart Rate, but does not detect any cardiac disease. There are many different types of cardiovascular diseases, including Arrhythmia, Valve disease, Coronary Artery Disease, Peripheral Artery Disease, etc that can be identified [17]. As we can now monitor ECG signals and measure Heart Rate in the application, our next goals are,

1) Apply Machine Learning algorithms to detect cardiac diseases.
2) Plot study of the application with cardiac patients at a cardiac clinic.

V. Conclusion

We developed a Smart-Health application that can plot ECG signals and measure heart rate have the potential to improve healthcare outcomes by allowing patients to monitor their cardiovascular health and detect abnormalities in a timely manner. In conclusion, the development of smart health applications that can accurately plot ECG signals and measure heart rate is an important step towards improving healthcare accessibility, quality, and affordability. By enabling patients to take an active role in their health management, these applications can help to prevent and manage cardiovascular diseases, leading to better health outcomes and improved quality of life.

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