Detecting Atrial Fibrillation With a Wearable Device

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Abstract

Atrial fibrillation (AFib) is the most common heart arrhythmia in the world but detecting it can be challenging. For this reason, a detection system consisting of a wearable electrocardiogram (ECG) device, a smart phone application and an algorithm was created. The wearable device was designed to be aesthetically simple yet attractive and be worn either as a necklace or a keychain so that it would always be within reach. The overall usability was also a design goal from the start, requiring the user to only touch the device and start a measurement from the smartphone application with a press of a button. The recorded data was processed with an AFib detection algorithm created based on the Chapman university's database with over 10,000 patients with different heart rhythms. The algorithm is a rule-based detection method, which uses heart rate variability and auto-correlation features. Motion artifacts were also taken into account by using an accelerometer signal measured with the device. The algorithm had an accuracy of 95.3% for the original database while all of the healthy volunteers (n = 14) tested with the developed system were correctly predicted to have sinus rhythms. The aim is to continue the study by increasing the test set size and to measure ECG with the device from AFib patients.

1. Introduction

Atrial fibrillation (AFib) is the most common arrhythmia around the world [1–3]. It is a heart condition that presents itself more likely at an older and represents a huge economic burden for health care system [2,4]. It can cause a risk for stroke, heart failure, seizure and even death if it is left untreated [1]. AFib-related hospital admissions have significantly increased in the past few decades, leading to a huge economic burden for the health care system [1].

The gold standard for detecting AFib is to the electrocardiogram (ECG) [1]. AFib causes the heart to beat irregularly, meaning that it is possible to detect it by analysing the heart rate variability (HRV) of a person. Another possible method is to assess atrial depolarization phase of the ECG, the P-wave.

The possibility to detect AFib at home could be highly beneficial. Not only for the patients, but for the whole healthcare system. Regular visits to the hospital just to monitor myocardial health are costly and time-consuming. A wearable device solves these problems by making it possible for the patients to monitor AFib at home. Detecting AFib with a wearable device has been found to be a working solution [4]. The fact that suffering from a COVID-19 infection can cause long-term cardiovascular diseases, including atrial fibrillation [5], increases the demand for such a device. Another reason for demand for this type of device, is the fact that AFib has 30 to 50% recurrence rate after treatment [3]. Active monitoring of the heart after suffering from AFib would be valuable and this could be easily done with a wearable ECG device.

Here we present a custom-made wearable event-based heart measuring device and accompanying software and algorithms to analyze measurements in real-time. Figure 1 demonstrates the overall functionality of the system and the different parts of the system will be introduced in this paper.

2. Materials and Methods

2.1. Wearable Cardiac Monitoring Device

A jewel-like wearable deviced called SAFE was designed around Movesense, which is an open sensor development platform by Movesense Ltd (Finland). The selected sensing unit, Movesense Medical (MD), is a Class IIa Medical Device Accessory according to the EU medical device directive 93/42/EEC [6]. Movesense MD can record single channel ECG together with movement, the latter using a 9-axis inertial measurement unit (IMU). The recorded data can be stored on flash memory or sent to a connected device over Bluetooth Low Energy (LE).

The sensing unit was placed inside a custom-designed casing to give it a stylish look but more importantly to allow ECG recording by applying skin contact on the bottom and top surfaces of the casing. The main plastic frame was 3D printed using digital light processing (DLP) technique to have a detailed finishing. The bottom and top surfaces were produced with computer numerical control (CNC) machining technique using copper as the material.

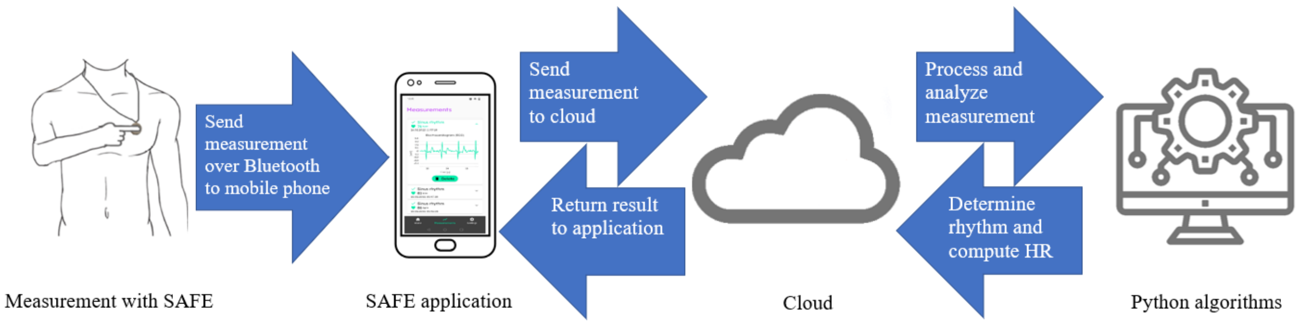

Figure 1. Block diagram of the system.

The copper electrodes were connected to the ECG pins of the Movesense MD sensing unit using short wires. The compact design of the casing along with its large electrode surfaces give the resulting device a wearable form factor with good-quality signal output. The main device parts together with an assembled device have been presented in figures 2(a) and 2(b), respectively.

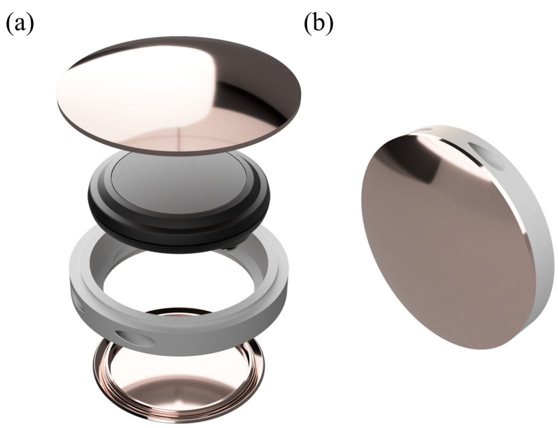

Figure 2. Rendered pictures of the developed SAFE device. (a) The main parts of the device, from bottom to top: chest bottom electrode, 3D printed frame, Movesense MD, and finger top electrode. The electrodes are made out of copper and they are connected to the Movesense MD device with a pair of short wires (omitted from the picture for clarity). (b) Front view of an assembled device without the necklace chain.

2.2. Data

A database from Chapman University containing 10,646 patients was used to create the detection algorithm [7]. This database includes patients with multiple different heart rhythms, labeled by professional experts. For this study, only patients with AFib (n=1780), sinus rhythm (SR, n=1826), sinus tachycardia (ST, n=1568) and sinus bradycardia (SB, n=3889) were included. The database has a 10-second recording of 12-lead ECG sampled at 500 Hz, for each patient. However, only lead II was used in the detection algorithm since it represented the SAFE measurements the best.

To test the detection algorithm, ECG data with the SAFE device was gathered. Data was gathered from 14 (9 women) healthy people with no known heart diseases. All subjects took several measurements with the device, totaling 43 different recordings. The age of the patients varied from 19 to 52 (mean=27) years.

2.3. Algorithms

The created classification algorithm is based on heart rate (HR), HRV and auto-correlation features extracted from the data. The ECG signals were filtered with a 2nd order Butterworth band-pass filter with cutoff frequencies of 0.5 Hz and 25 Hz before feature extraction. The R-peaks were identified from the filtered signals using the Pan-Tompkins algorithm. HR and HRV were then computed based on the R-peaks. The extracted features were analyzed and a threshold value for each feature was established. With these threshold values, an algorithm similar to a decision tree was created. Working with simple if-else statements based on the features, the algorithm returns the predicted heart rhythm: AFib, SR, ST, or SB.

The algorithm was tested with our own data gathered with the SAFE device. Since the ECG signals in the original database are 10-second long, the ECG signals gathered with the SAFE device were segmented into 10-second segments. The signals were originally 40-seconds long, meaning that the signals were split into four segments. The heart rhythm was calculated for all four segments and the rhythm that occurred the most was the one that was predicted. This should increase the reliability of the detection, since it does not rely on one prediction, but four.

The measurement can be vulnerable to movement. For this reason, the accelerometer signals of the device were used to detect movement. If too much movement was detected, the rhythm detection was canceled, and the patient was asked to repeat the measurement. This was done to ensure the reliability of the algorithm since movement could significantly affect the auto-correlation results.

2.4. Mobile Application

The SAFE device is controlled with a mobile application over Bluetooth LE. The application was developed with the Flutter software development kit (SDK) because it enables to develop cross-platform applications with a single codebase. The home view of the application shows the device connection status, battery level and houses a button to start a 40-second measurement during which the subject has to hold the bottom electrode of the device against the chest by pressing the top electrode with both index and middle fingers. After a successful completion of the measurement, the data is sent to a cloud service where the developed algorithm analyzes the ECG signal. The analysis result of the rhythm along with the computed heart rate and the recorded ECG signal are displayed to the user. Figure 3 shows the *measurements* view, one of the three views of the application, where the user can see all past measurements.

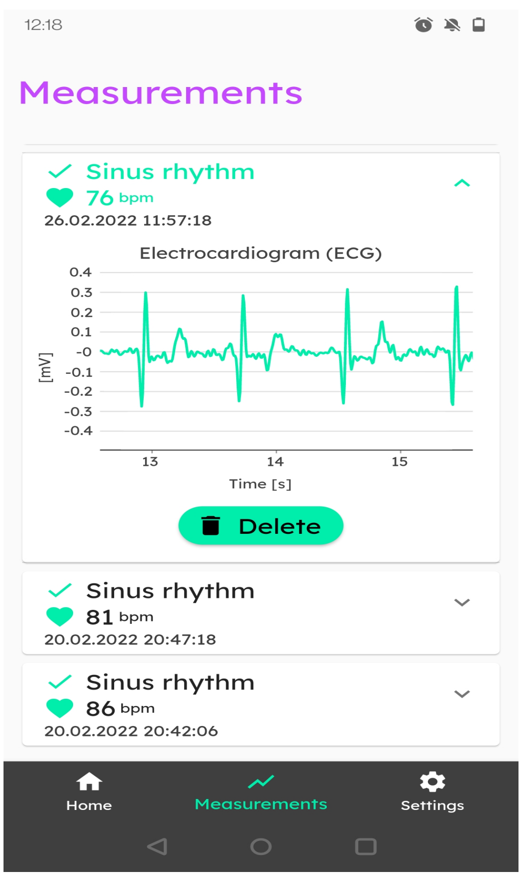

Figure 3. Screenshot of the smartphone application.

3. Results

Table 1. Results of the algorithm.

Database	Chapman University	SAFE
Measurements	9063	43
Accuracy	95.3%	100%
Precision	94.6%	100%
Recall	95.2%	100%
F1 score	94.8%	100%

The algorithm performs well on both datasets, as shown by the performance metrics in table 1. For the SAFE dataset the algorithm correctly predicts all of the signals to have SR. For the Chapman University dataset with more challenging rhythms, the performance metrics are predictably lower but still very high with an accuracy measure of 95.3%. For reference, one study working on the same database was able to achieve a very similar result with the accuracy of 95.35%, but with much more complicated machine learning system [8]. Figure 4 demonstrates the confusion matrix for our results of the Chapman University database and gives more insight into the accuracy of the algorithm.

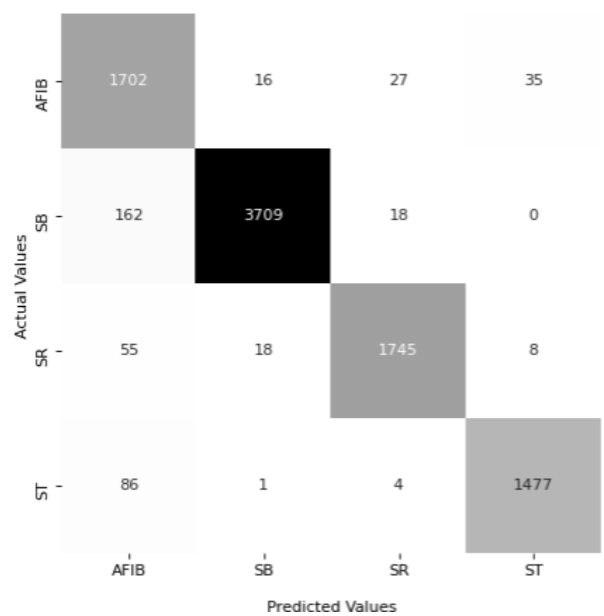

Figure 4. Confusion matrix of the Chapman University dataset.

Figure 4 shows that the accuracy of predicting AFib is high, 95.6%. All of the sinus rhythms (SR, SB, ST) are being predicted correctly most of the time, but there are some false negatives. Most of these come from the SB rhythm. In the data analysis, this seemed to be a common problem, but the accuracy of predicting sinus bradycardia correctly is, however, quite high, 95.3%. Predicting sinus tachycardia produces the worst result, giving an accuracy of 94.2%. Sinus rhythm is predicted correctly with 95.5% accuracy.

4. Discussion

This article presented a wearable ECG device and an AFib detection algorithm for analyzing the recorded signals. The device has a compact and stylish wearable form factor providing a convenient way to record a single channel ECG even in home setting. The developed AFib detection algorithm was shown to have good performance against both datasets. The developed system received praise from the study participants for its usability and the system was seen as a potential solution for home monitoring.

The results are encouraging to develop the system, from the device to the algorithms and software, further. Future work will focus on collecting data from AFib patients to determine how the algorithm and the system in general perform in a real-life setting. Future work could also include the study of other heart diseases.

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