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Atrial Fibrillation Detection Method Based on Converting ECG to Signal Using Both Symptoms of AF

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Abnormal P wave.

Abstract

Atrial Fibrillation (AF) is one of the most common cardiac arrhythmias that is associated with other kinds of cardiac cases including heart disease, risk of stroke and mortality [1]. The AF case has an irregular heartbeat and an asynchronous rate of the rhythm of the heart compared to the rate of the rhythm of heart of a healthy person. The objective of the research is to highlight AF as an important disease in today's mortality cases and proposed an algorithm to detect AF by using all signs of it by converting Electrocardiogram (ECG) to signals. This paper proposed a statistical method of detecting AF which the techniques included analysis of consecutive RR intervals and detecting the existence or abnormal P wave. To verify the proposed method, the algorithm is tested over 100 pre-recorded ECGs of patients with healthy and AF conditions.

1. Introduction

Arrhythmia is a condition that the heart beats irregularly or has an abnormal rate. Atrial Fibrillation (AF) is the most common cardiac arrhythmia which is announced to be one of the main reasons of stroke. Stroke happens when an obstruction in the blood flow due to blood clots or cut off an artery that feeds the brain. The symptoms of AF could be recognized from ECG which is used as an important diagnostic tool for various cardiac diseases. The ECG is the recording of the electrical activity of the myocardium during one cardiac cycle and is characterized by a sequence of P, QRS, T. ECG is recorded by placing electrodes on the body surface and a standard 12 lead system is used to get an overall view of the heart's activity.

In recent years applications of machine learning, deep learning and signal processing in different research areas has been improved drastically [2-8], of special interest are the improvement in medical science [9-11]. Also the advancements in model reduction techniques, that lead to an equivalent model which demands less computational process than the original model, has improved the decision making process time and also the resulted data analysis seems more reliable [12]. Using machine learning applications allows computational models in different layers to learn representations of data with multiple levels of abstraction and improved the state of art in many domains like object detection [13].

Different methods have been proposed to detect AF which most of the research using MIT_BIH Arrhythmia dataset. Kalsi et al. [14] used PhysioNet ECG signals for detecting AF which is based on R-R intervals and normal or abnormal P waves. The method used statistical analysis for R-R intervals detection and slope analysis by using 4 sample window of ECG signals for present of P waves to detect AF. The result showed that AF has a high variability in Standard Deviation of R-R intervals.

Huang et al, study [15], used R-R intervals and a frame of 1.2 minutes in the automatic detection of atrial fibrillation. The results showed 96.1 % and 98.1 % of sensitivity and specificity, respectively. Escalona et al. [16] proposed a method with has less sensitivity and specificity, 93% and 97 % respectively, compared to the method. They used window length of 35 beats to identify AF, which the processing time for each beat was 129 ms. Ghodrati et al. [17] compared the performance of two methods in detecting atrial fibrillation in real-time ECG monitoring devices. The methods are normalized absolute deviation (NADev) of RR intervals and normalized absolute difference (NADiff). The sensitivity of NADev and NADiff obtained for MIT-BIH Atrial Fibrillation database were 86 % and 89 %, respectively. Dash et al. [18] used R-R interval as a main sign of AF and developed statistical methods to compare the interval to find the AF cases. In these studies the main focus is based on the R-R intervals.

This paper, using data of 100 pre-recorded ECG images and converted them to signals by using image and signal

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processing methods. Furthermore, an algorithm has been proposed to diagnose cardiac arrhythmia based on both signs of AF, differences of the QRS complex and the absence or abnormal of the P wave. The algorithm is designed to classify a heart rhythm into one of two categories: Normal Sinus Rhythm and Atrial Fibrillation. A healthy heart has regular R-R intervals but AF causes different R-R intervals in ECG.

The AF is characterized by finding variability and complexity of the R-R intervals. The irregularly of R-R intervals is assessed by three common statistical tests for measuring heart rate variability(HRV), using turning point ratio (TPR), root mean square of the successive differences (RMSSD) and Shannon Entropy (SE) [18] and [19]. The presence of the P wave or abnormal of the P wave determined by using the mathematical method of measuring. The case determined to be AF when all of the statistical tests and P wave detection classified as AF. The paper using a database of 100 ECG included healthy hearts and diseases one and the algorithm achieved high accuracy in detecting AF. The algorithm first transfers the ECGs to signals by using signal and image processing methods and then implement the proposed statistical methods to determine which ECG is in the AF group.

The remainder of the paper is organized as follows: R-R interval, ECG, and AF representation are in section II, the problem formulation is described in section III, The comparison and discussion of the results are presented in section IV, and section V provides the concluding remarks.

2. R-R Interval, ECG and AF Representation

ECG is a test that records and measures the electrical activity of the heart through small electrode patches that were attached to the skin of the body. As it represents in Figure 1, ECG includes three main parts. The first wave called P wave represents atrial depolarization, next wave called QRS Complex which represents Ventricular depolarization, and the last wave called T wave shows Ventricular repolarization. The important parts of ECG for measuring are the existence of the waves such as P and T and the interval between consecutive QRS complexes which are conventionally called R-R interval.

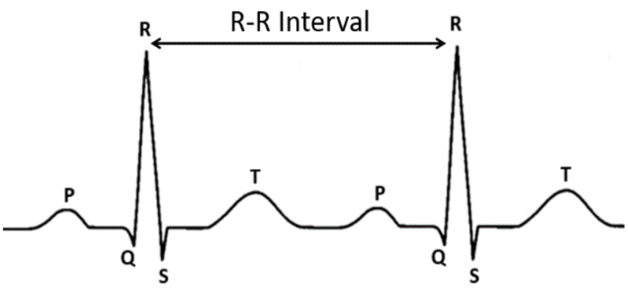

Figure 1. Schematic representation of an ECG wave

In Figure 2, a normal hearts rhythm and AF heart rhythm are shown. Using the differences between these two rhythms the AF is diagnosed**.** Normal heart rhythm has a completely regular RR intervals and P waves are exist but the AF rhythm has a completely irregular R-R intervals and P waves are not identifiable.

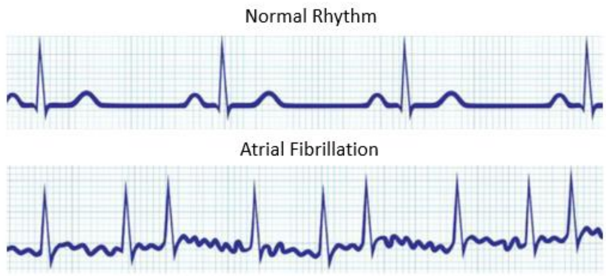

Figure 2. Normal Rhythm and Atrial Fibrillation of Heart

3. Problem Formulation

The data of this study prepared from converting ECG of 100 samples to signals. The Atrial Fibrillation algorithm should be able to detect irregular R-R intervals and also absent of P waves. The proposed algorithm using three statistical methods, turning point ratio (TPR), root mean square of the successive differences (RMSSD) and Shannon Entropy (SE), and comparing to the threshold for detecting irregular R-R intervals and mathematical analysis for identifying P waves. The sample was flagged as AF if all the three statistical methods and also P wave detection determined it to be AF. The algorithm was designed for using eight "QRS complex" for each sample. The proposed method is explained in the following subsections.

3.1. Convert ECG to Signal

The 100 samples from the patients with AF cases and healthy cases are converted to signals by using image and signal processing methods. The samples are converted from color images to gray form and then peaks are identified by using different methods of edge detection. The flowchart of the proposed method is shown in Figure 3.

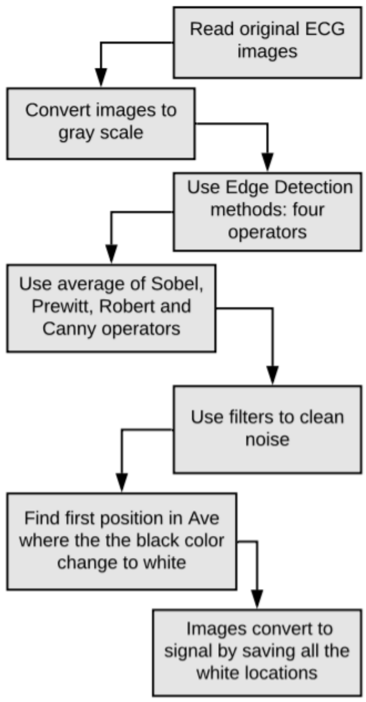

Figure 3. Algorithm flowchart

3.1. Root Mean Square of the Successive Differences (*RMSSD)*

The process of taking out the parameters related to analysis for Hearts health is called Heart Rate Variability (HRV) feature extraction [14]. The most widely accepted features are: mean heartbeat intervals (mean RR) and root mean square of successive differences (RMSSD). RMSSD is a parametric statistic that measures the variability in a data set and it is sensitive to outliers so it removes shortest and longest of each 8 beat segment prior doing RMSSD calculation. It is calculated by the Eq. (1)

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N-1}(\boldsymbol{\alpha}_{j+1} - \boldsymbol{\alpha}_j)^2} \quad (1)$$

where, N is the number of the intervals and $\boldsymbol{\alpha}$ represents R-R intervals. Because of changing in heart rate overtime and premature Ventricular contractions, RMSSD is divided by mean RR. The reached threshold for detecting AF is calculate by Eq. (2)

$$\frac{RMSSD}{mean\ RR} > 0.1 \quad (2)$$

3.2. Turning Point Ratio (TPR)

Turning Point ratio is a non-parametric statistic that measures the randomness of changing in data set and it is not sensitive to outliers. It compares the amount of turning point to the maximum number of possible turning points. For the arbitrary length [20],l, the expected number of turning point calculated by Eq. (3)

$$Expected\ Number\ of\ TP = \mu = \frac{(2\boldsymbol{l}-4)}{3} \quad (3)$$

where, the standard deviation is defined by Eq. (4)

$$\sigma = \sqrt{\frac{(16l-29)}{90}} \quad (4)$$

The study uses a confidence interval of μ- 2.2l and for length of 8 beat segment, if TPR >0.21 the sample will be marked as AF.

3.3. Shannon Entropy (SE)

Shannon Entropy is a parametric statistic that measure the uncertainty of a random variable and it is sensitive to outliers, so it removes shortest and longest of each 8 beat segment. For any data SE is between zero and one. The SE of a random data like white noise is about one and the SE of the constant value which is predictable is zero. The 8 beat segment are used to build a histogram with 3 equally spaced bins. The number of bins was found empirically for minimizing distortion. The probability for each bin is computed by Eq. (5)

$$P(i) = \frac{Ni}{l - N_{outliers}} \quad (5)$$

where, Ni is the number of beats in the specific bin. Shannon Entropy is then calculated by Eq. (6)

$$SE = \sum_{i=1}^{2} p(i)\frac{\log(p(i))}{\log(\frac{1}{2})} \quad (6)$$

To detect AF cases, the algorithm selected SE>0.5

3.4. P Wave Detection

Absence P wave is another identification parameter for Atrial fibrillation. When algorithm detects the R peaks, it easier to detect the other waves such as P waves. The study trying to find a notable peak compared with R peak, before QRS complex. The algorithm finds the middle point between Ri and $Ri+1$, and then finding a notable peak between middle and, $Ri+1$ if the algorithm could not find any appropriate peak, the sample marked as AF.

4. Results and Discussion

This section presents results for applying the proposed method on the test system. First, to show the performance of converting an image to signal, one of the healthy ECG image and the process to get the readable image is shown in figure 4 and then converted the image to signal for a healthy person is shown in Figure 5.

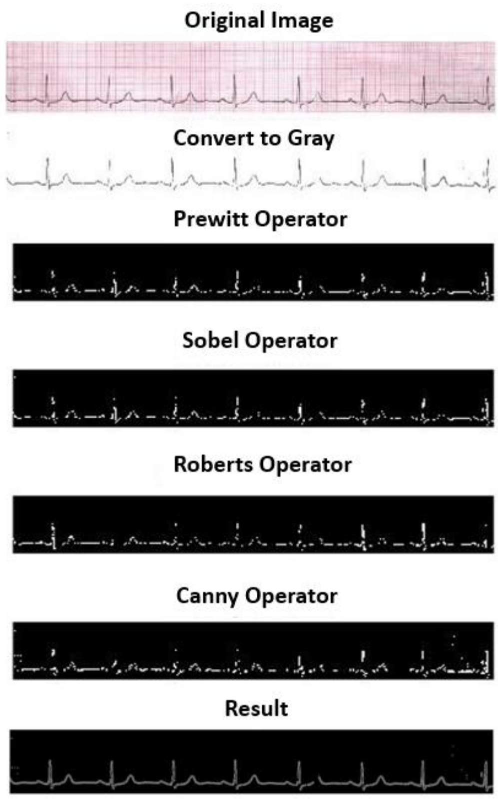

Figure 4. Converting original ECG to readable ECG for healthy person

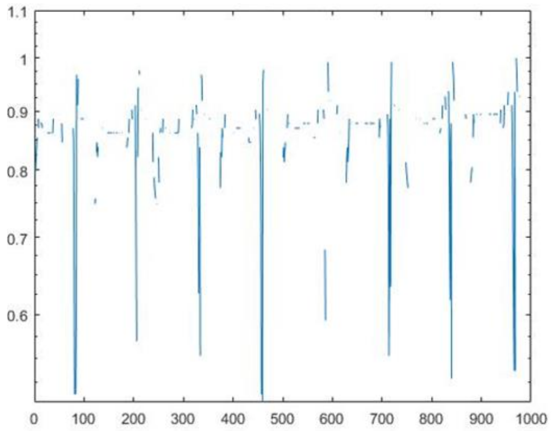

Figure 5. Converting readable ECG to signal for a healthy person

Figure 6 show the same procedure for the person with the AF condition. In Figure 7, the last readable image converted to signal using the proposed method. The quality of figures for ECGs is the same as the data.

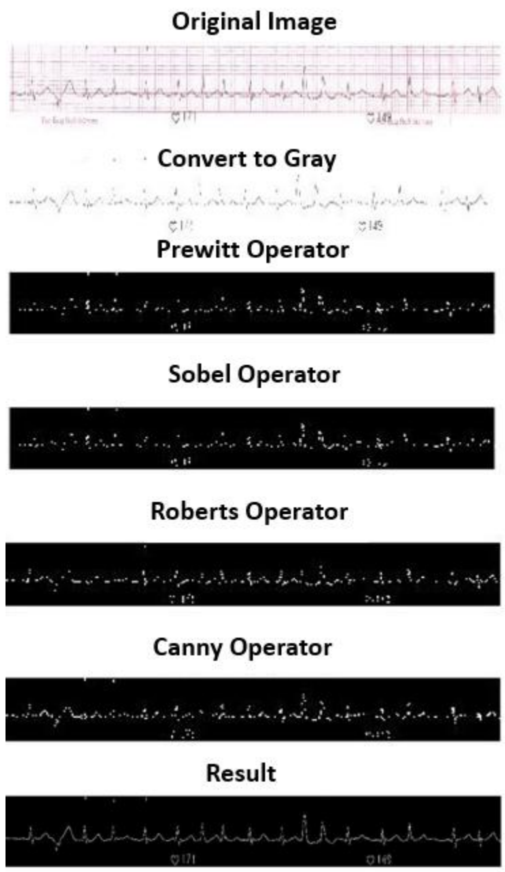

Figure 6. Converting original ECG to readable ECG for person with AF case

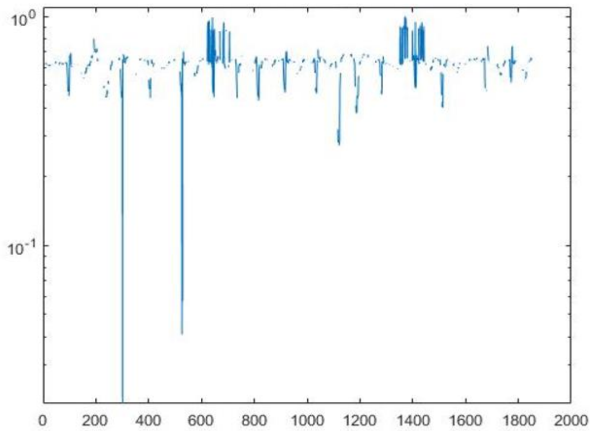

Figure 7. Converting readable ECG to signal for a person with AF case

After converting all the images to signal, the detection code for finding the AF cases is used for 100 ECGs, which has healthy and with AF cases. For all the statistical methods, there is a threshold which determines if the case has AF or not. If the results for statistical methods are above the threshold the statistical methods confirm that the person has AF and also not detecting or abnormal P wave results in conclusion (if there is no appropriate P wave the result shows 1 in detection function). Figure 8 shows the result of using the detecting algorithm for a sample, the thresholds are shown in red color and the numerical numbers for the cases are shown in blue. As it is showed each detected method

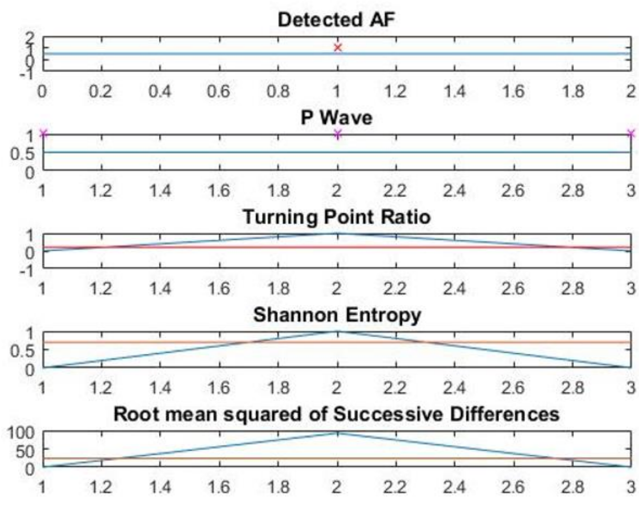

Figure 8. The result of detection as AF sample

depicts that the sample is above the threshold and also P wave detection is in one state, so detected AF function is in one state and the sample marked as AF.

5. Conclusions

In this paper, an algorithm to convert image to signal and an enhanced method to detect the most common cardiac arrhythmia, Atrial Fibrillation, is proposed. The method used 100 samples of ECG and converted them to signal and then based on all the signs of the AF, detected if the sample is healthy or has AF. To verify the effectiveness of the proposed method, a dataset of 100 ECGs is used. The method can determine all the healthy ECG samples and 98 percent of AF cases. The conclusion from these results is that the algorithm is able to detect both symptoms of Atrial Fibrillation and determine the case is healthy or has AF. Furthermore, the method can use any ECG samples to detect the diseases because of using the methods to convert ECG images to signals.

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