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PAPER

Hybrid Mechanism to Detect Paroxysmal Stage of Atrial Fibrillation Using Adaptive Threshold-Based Algorithm with Artificial Neural Network

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SUMMARY Automatic detection of heart cycle abnormalities in a long duration of ECG data is a crucial technique for diagnosing an early stage of heart diseases. Concretely, Paroxysmal stage of Atrial Fibrillation rhythms (ParAF) must be discriminated from Normal Sinus rhythms (NS). The both of waveforms in ECG data are very similar, and thus it is difficult to completely detect the Paroxysmal stage of Atrial Fibrillation rhythms. Previous studies have tried to solve this issue and some of them achieved the discrimination with a high degree of accuracy. However, the accuracies of them do not reach 100%. In addition, no research has achieved it in a long duration, e.g. 12 hours, of ECG data. In this study, a new mechanism to tackle with these issues is proposed: "Door-to-Door" algorithm is introduced to accurately and quickly detect significant peaks of heart cycle in 12 hours of ECG data and to discriminate obvious ParAF rhythms from NS rhythms. In addition, a quantitative method using Artificial Neural Network (ANN), which discriminates unobvious ParAF rhythms from NS rhythms, is investigated. As the result of Door-to-Door algorithm performance evaluation, it was revealed that Door-to-Door algorithm achieves the accuracy of 100% in detecting the significant peaks of heart cycle in 17 NS ECG data. In addition, it was verified that ANN-based method achieves the accuracy of 100% in discriminating the Paroxysmal stage of 15 Atrial Fibrillation data from 17 NS data. Furthermore, it was confirmed that the computational time to perform the proposed mechanism is less than the half of the previous study. From these achievements, it is concluded that the proposed mechanism can practically be used to diagnose early stage of heart diseases.

key words: *electrocardiogram (ECG), door-to-door algorithm, paroxysmal stage of Atrial Fibrillation, adaptive threshold of detecting heart beat cycle*

1. Introduction

Signal processing research for the diagnosis of cardiovascular disease has tremendously been activated in the last several decades due to a high number of cardiac-related fatalities [1], [2]. The most widely used method to detect cardiovascular conditions is electrocardiogram (ECG) examination. ECG is a record of the electrical activity of the heart described as wave-forms in chronological order and it shows the depolarization and repolarization processes in the myocardial cells. In a normal heart cycle, ECG consists of five different characteristic wave-forms and each wave includes a peak, which is a spike or a dip. ECG contains a larger number of cardiovascular information, hence, it plays a significant role in guiding clinical diagnoses of heart diseases and their symptoms. Therefore, by identifying the symptoms as early as possible, the treatments for the cardiovascular disease can be effectively made.

Cardiac Arrhythmia is a group of cardiovascular disease that can either suddenly lead to death or gradually lead to heart failure. The most common type of Cardiac Arrhythmia is Atrial Fibrillation, which is a cardiovascular symptom where irregular heartbeats occur at a certain period of time. Atrial Fibrillation is categorized into 3 stages; paroxysmal, persistent and permanent stages. Chronic Atrial Fibrillation normally starts with its Paroxysmal stage, hence, the detection of the Paroxysmal stage of Atrial Fibrillation (ParAF) is indispensable.

There are many studies on detecting Atrial Fibrillation [3]–[5]. Basically, their approaches consist of several stages, such as elimination of baseline drift [6], [7], waveform detection [8], [9], feature extraction [10], and heart disease detection [11], [12]. However, there are two biggest concern and challenge in this study. First, feature extraction process in long duration of ECG data and second is the mechanism to analyze the disease itself. Long duration of ECG data is that the longer the recording time is, the more noise may occur in the ECG data. It has been noticed that a long duration ECG data results in huge noise from various sources like muscular activities, skin stretching and electrode motion, movement of heart due to respiration, etc. that can contaminate the ECG signal. It is difficult to control the environment in such a long period of time consistently and prevent the interference due to some physiological event such as breathing. As a result, an automated analysis requires noise free ECG signal for correct interpretation [13].

Atrial Fibrillation monitoring has been performed in connection with cryptogenic ischemic stroke [14], interventional ablation procedures [15], and pharmacological treatment [16], providing information for evaluating the efficacy of different treatment strategies. The episodes come and go and last for seven days or less, and the possibility of missing an episode is huge if the analysis is done for a short period of time. Therefore, without a long-term monitoring and analysis, lasting from 12 hours and above, all episodes of ParAF cannot be detected precisely, including the very obvious one. A recent study has shown that AF is often overlooked after interventional therapies when the standard strategy for treatment evaluation is used [3]. Based on the expert

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review, a monitoring process of the heart rhythm from day and night will be done when a person is experiencing many symptoms for Atrial Fibrillation, but there is no clinical result shows any sign of abnormalities to the heart.

To overcome the above mentioned issues, in this paper, a new mechanism, which accurately and quickly detects the ParAF from 12 hours ECG data, will be proposed. The new mechanism can mainly be divided into two steps. In the first step, a newly proposed "Door- to-Door" algorithm accurately and quickly detects characteristic wave-forms in the ECG data and discriminates the obvious ParAF from the others. The algorithms have the capability to capture normal heart cycle episode even in a noise environment like base line wander. 3 specific models with 6 adaptive thresholds to handles the noise environment is introduced in this research. In the second step, Artificial Neural is utilized to accurately detect the unobvious ParAF which cannot be easily detected by Door-to-Door algorithm. Therefore, a quantitative classification procedure is proposed in this research. Note that NS symptom will be used as a reference to classify the ParAF. NS symptom represents the characteristic of the healthy human heart condition. By utilizing the error function that describes the deviation of predicted target value, a proper quantification measurement can be used to describe the tendency of the two symptoms.

The remainder of this paper is organized as follows: Sect. 2 will introduce NS and Atrial Fibrillation Rhythms, showing their characteristic wave-forms in ECG data. Section 3 will discuss the related works to clarify the issues of existing methods in detecting heart cycle and Atrial Fibrillation symptoms in ECG data. Section 4 will describe the methodology of the proposed mechanism which elaborately detects characteristic wave-forms in ECG data and identifies the ParAF. In Sect. 5, the evaluation result of the proposed mechanism will be shown based on the two techniques, Door-to-Door algorithm and Artificial Neural Network. In Sect. 6, the conclusion will be made with discussions on possible future study.

2. Principle of Electrocardiograph

Essentially, ECG data is the voltage time series data which is generated by cardiac electrical activity. Medical doctors usually use this data to diagnose the cardiovascular abnormality and assist the patients in the treatment.

A typical ECG waveform periodically repeats 5 main waves in each cycle; P, Q, R, S and T waves. The P wave represents the depolarization of the right and left atria, the Q, R and S waves follow the P wave and depict the activation of the right and left ventricles, and the T wave indicates the repolarization of the ventricles. It is necessary to detect these 5 waves in ECG data to diagnose the cardiovascular abnormality. In this paper, two types of symptoms are mainly focused on, which are NS and ParAF symptoms.

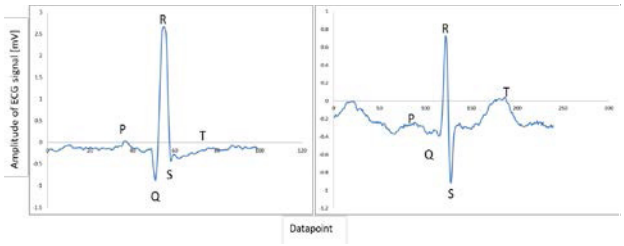

Fig. 1 Normal Sinus Rhythm pattern (left) and Premature Atrial Fibrillation Rhythm pattern (right) with P, Q, R, S and T peaks

2.1 Normal Sinus Rhythm

Sinus rhythm is the set of heart's normal regular rhythms by the heart's natural pacemaker called sinoatrial node. Normal cardiac impulses start at the right atrium wall and are transmitted to the atria, then down to the ventricles. Additionally, it is a reflection of normally functioning conduction system in the body. This electrical current is following the normal conduction pathway without interference from other bodily system or disease processes [17].

2.2 Atrial Fibrillation Rhythm

Atrial Fibrillation rhythm is a situation where many different impulses rapidly fire at once, causing an unstable rhythm in the atria. Due to these unstable electrical impulses, the atria cannot contract or squeeze blood effectively into the vertical. Atrial fibrillation is the most common irregular heart rhythm that starts in the atria area.

2.3 P, Q, R, S, T Wave Morphology

A normal ECG signal is considered as a periodic signal. This electrical signal of the heart consists of a sequence waves, named P, Q, R, S and T. Each wave basically has a peak (hereafter P, Q, R, S or T peak), which is a spike or a dip. This sequence constitutes the sinus waveform of the heart signal. If there are irregularities in these waves, they could be signs of the heart problem. From the comparison in Fig. 1, which represents NS and premature Atrial Fibrillation, both waveforms show a huge similarity in many ways. In this research, the five main peaks are considered as important parameters which are used for analysis of ECG data. The process of detecting and collecting each peak in each cycle is the main concern.

3. Related Works

Felix et al. [18] proposed an automatic multiscale-based peak detection algorithm in noisy periodic and quasi-periodic ECG signals. The achievement of this study is that the accuracy of R peak detection is 100% for 200 seconds of ECG data. However, it is skeptical that the proposed algorithm can be applied to several hours of ECG data. In

general, there are many ways to detect peaks for signal processing such as the use of wavelet transform [19]–[24], artificial neural network [25], [26], nonlinear filtering [27], linear prediction analysis [28], hidden Markov models [29], momentum [30] and window-threshold techniques [31]–[34]. The disadvantage with most of the existing peak detection algorithms is that different algorithms require different parameters to detect peaks. Therefore, these methods cannot be easily combined to achieve a high performance. Moreover, the issue of signal noise is one of the biggest challenges.

Shadnaz et al. [4] proposed an automatic detection of Atrial Fibrillation using stationary wavelet transform and support vector machine. The proposed method achieved a sensitivity of 97.0% and specificity of 97.1% without relying on the detection of P wave, R wave and heartbeat. However, the method induces a computational complexity. During ECG feature extraction stage, data with a different frequency band requires a different stationary wavelet transform process. Moreover, the proposed method does not dynamically choose the most effective wavelet scale for noise reduction, resulting in less flexibility in implementation.

Likewise Andrius et al. [3] designed a low-complexity method to detect Atrial Fibrillation by observing the irregularity of R to R interval and associating it with the increase of heart rate. The proposed method achieved a sensitivity of 97.1% and specificity of 98.3 % with low space complexity. The proposed method relies on several processes which are preprocessing data, R to R interval irregularity analysis, bigamy suppression analysis, signal fusion and detection analysis. There are two drawbacks in this method. First, it has not been fully automated to analyze the ECG data. Second, this method is impractical because it requires a lot of time to analyze a long duration of ECG data.

Sujit et al. [35] reviewed several techniques for detecting Atrial Fibrillation from Non-Episodic ECG data. Several features have been defined to describe the behavior of Atrial Fibrillation by focusing on P wave, QRS waves cycle and R to R interval. However, most of the reviewed techniques do not focus on the data distribution model of NS heart cycle to distinguish ParAF. Since the ParAF symptom has similarities in rhythm to NS symptom. Therefore, a constructive data distribution model for NS is required to classify the diseases. This data distribution model is basically regarded as a series of P, Q, R, S and T peak values in millivolt in ECG data. Some of the techniques to detect Atrial Fibrillation are K-nearest neighbor (KNN) [36], [37], Bayer Optimal classier [36], Artificial Neural Network (ANN) [36], [38], [39], Linear Discrimination Analysis [35] and Empirical Detector [40]. However, there exist a few drawbacks. Some methods have defined too many ECG parameters to characterize Atrial Fibrillation, resulting in the increase of computational complexity. Although, some methods [36], [37] attempted to overcome this issue by reducing the number of parameters in characterizing the Atrial Fibrillation, but the relation of the trade-off of the computational complexity and the classification performance cannot be solved.

4. Automatic Detection of Paroxysmal Stage of Atrial Fibrillation Symptoms

In this section, an automatic mechanism to detect ParAF symptoms is proposed. Door-to-Door algorithm, which is a new algorithm with the capability to accurately extract heart cycle in ECG data, is proposed in this research. This algorithm captures normal heart cycle episodes even in a noise environment like base line wander. "Door-to-Door" is derived from a continuous process of finding the right heart cycle among a series of local maximums in the ECG data. The word "Door" refers to the highest local maximum detected among a group of data for local search. Each "Door" represents the entrance or starting point for the deep investigation, which is performed to the surrounding data of the local maximum. Once the investigation is done to one local maximum, this "Door" will be used again as an exit to search for another "Door". This process will be continued until the end of data. Therefore, "Door-to-Door" was named after this investigation process. The flowchart of the mechanism is described in Fig. 2.

The five significant peaks in ECG data, which are P, Q, R, S and T peaks, are extracted using "Door-to-Door" algorithm and the number of detected peaks is counted. If the number of detected peaks is smaller than a certain threshold value (e.g. when a 12 hours ECG data is utilized, the threshold value is set to 46,000), the ECG data is regarded as an obvious ParAF rhythm or the advanced one. This is because it shows that the five significant peaks are not fully detected due to the unstable heart cycle. On the other hand, if the number of detected peaks is larger than the threshold value, the ECG data may be NS rhythm, but there is still the possibility that it is an unobvious ParAF rhythm. In this case, it must be discriminated from NS rhythm.

In this research, therefore, the values of significant five peaks in each heart cycle are investigated using Artificial Neural Network (ANN). ANN outputs a numerical value

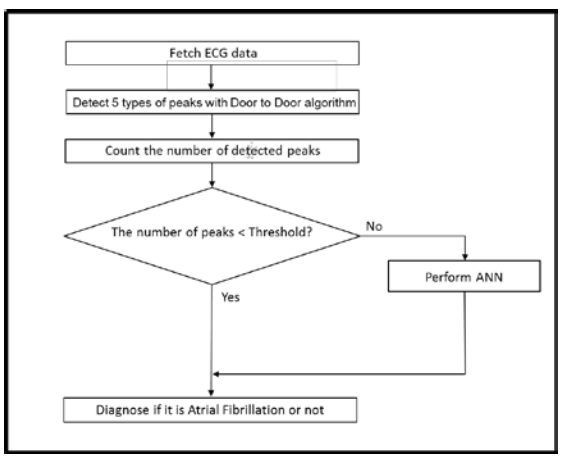

Fig. 2 Proposed automatic mechanism to detect ParAF

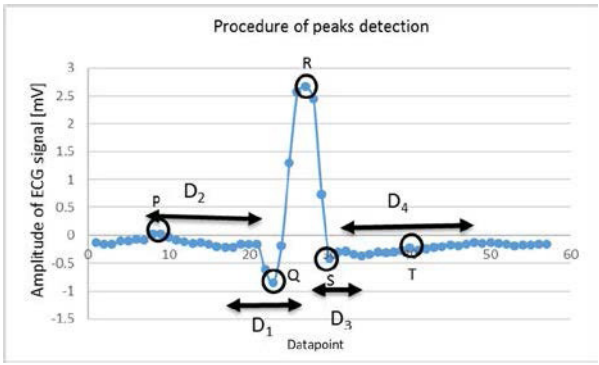

Fig. 3 P, Q, S, T peaks detection mechanism based on R peak position

to each heart cycle which indicates how much tendency of Atrial Fibrillation rhythm or NS rhythm the heart cycle has. Based on the numerical values for whole heart cycles of the ECG data, the unobvious ParAF rhythm is detected. The details of Door-to-Door algorithm and ANN will be stated in Sects. 4.1 and 4.2.

4.1 Door-to-Door Algorithm for Five Significant Peaks Detection

Figure 3 illustrates the procedure of Door-to-Door algorithm. R peak, Q peak, P peak, S peak and T peak are detected in a sequential order. When R peak is searched for, adaptive thresholds to the neighboring data points are introduced. Here, let D_1, D_2, D_3 and D_4 be the relative horizontal distances from R peak to the direction of Q peak, from Q peak to the direction of P peak, from R peak to the direction of S peak and from S peak to the direction of T peak, respectively. Note that the relative horizontal distance is expressed as data point unit. Q peak and S peak are detected as the minimum values in the range of D_1 and D_3, respectively. In the same way, P peak and T peak are detected as the maximum values in the range of D_2 and D_4, respectively. The values of D_1, D_2, D_3 and D_4 are determined by investigating the MIT-BIH Normal Sinus rhythm database [36]. The detailed procedure of each peak detection is described in the following sections.

4.1.1 R Peak Detection with Adaptive Thresholds

R peak detection is a fundamental pre-requisite for the detection of other peaks and its detection accuracy is crucial for diagnosing the ParAF. R peak detection based on an absolute threshold has a significant weak point. Figure 4 depicts two different waveforms of NS rhythm in ECG data. As seen from this comparison, it is not appropriate to use the absolute threshold value of 2.5mV since the value of R peak fluctuates so much. In contrast, R peak detection by Door-to-Door algorithm relies on the adaptive thresholds to overcome the difficulty.

In this paper, three types of heart cycles in ECG data are considered to detect R peak in different ways. These

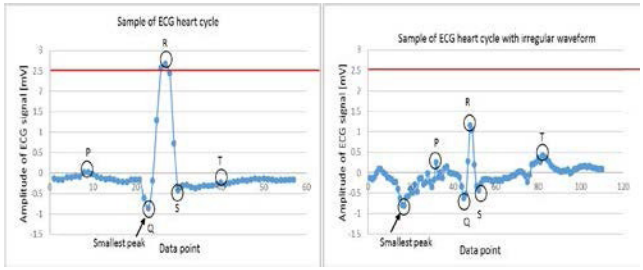

Fig. 4 Different ECG heart cycle behaviors in Normal Sinus rhythm

three types of heart cycles correspond to normal rhythm scenario, irregular rhythm scenario and off-the-baseline scenario. The detail of each procedure to detect R peak is mentioned below.

(1) Detection of Local Maximum Point
When Door-to-Door algorithm starts, it searches for the local maximum point in the range of successive seven data points from the beginning of ECG data. If the local maximum point is not detected, the considered successive seven data points are shifted one data point onward and the local maximum point is searched for again. This procedure is repeated until the local maximum point is detected.

Let V_i denote the value of the detected local maximum point at i-th data point. Hereafter, the local maximum value is described as V_i for the sake of simplicity.

(2) Identification of R Peak
In this study, 6 adaptive threshold values have been introduced to accurately extract all heart cycles in ECG data. False Acceptance Rate (FAR) analysis has been done to determine the most optimal value to be used as each adaptive threshold value for this algorithm.

(a) Normal Rhythm
When ECG data shows a normal rhythm, the five significant peaks can easily be seen at the standard positions as shown in the figure on the left side of Fig. 4. In this case, no abnormal waveforms such as noisy or unexpected signals are observed. However, there need some restrictions to V_i in order to regard the local maximum point as R peak. Here, three types of adaptive threshold values are introduced, which restrict the relative position of the local maximum point to the neighboring data points. The values of five data points, V_i, V_{i-2}, V_{i-4}, V_{i+2} and V_{i+4}, are utilized to identify R peak as shown in Fig. 5.

When all the following conditions are fulfilled, V_i is identified as the value of R peak:

(1) $V_{i+2} < V_{i+1} < V_i$
(2) $V_{i-2} < V_{i-1} < V_i$
(3) $V_{th1} \leq V_i - V_{i+2}$
(4) $V_{th2} \leq V_i - V_{i-2}$
(5) $V_{i+k\,(k=1,15)} < V_i$

For this research, V_{th1} and V_{th2} are 0.35. $V_{i+k\,(k=1,15)}$ repre-

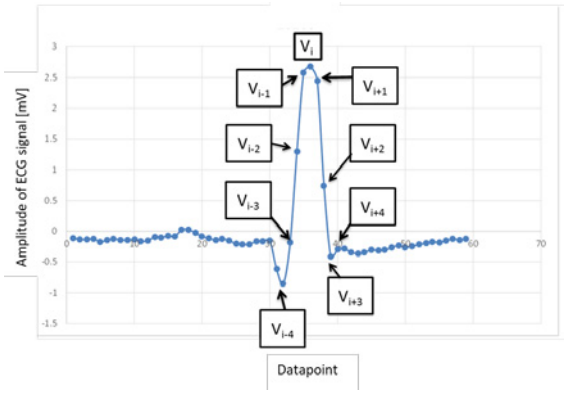

Fig. 5 R peak detection in a normal rhythm scenario

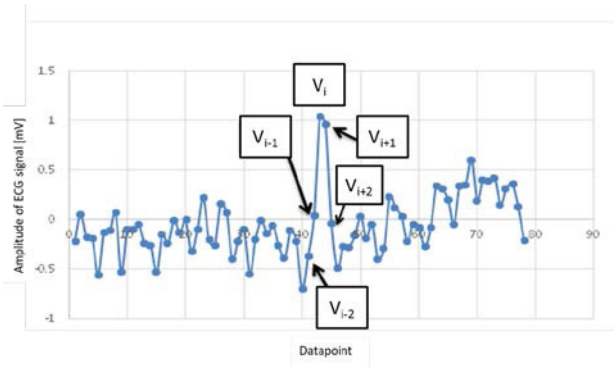

Fig. 6 R peak detection in an irregular rhythm scenario

sents the range of data which is used to check if other local maximums close to the current local maximum exist or not. k = 15 is determined by using False Acceptance Rate (FAR) analysis where the most optimal value to be used is selected. This process is very important to ensure the only the right heart cycle detection, not a noise signal.

(b) Irregular Rhythms

When ECG data shows an irregular rhythm, it is difficult to identify the local maximum point as R peak only by comparing the value to the neighboring data points. This is because the values of data points around the baseline fluctuate so much, and thus it is necessary to confirm that V_i is only the local maximum value within a certain range of data points. Therefore, in addition to the value differences of $V_i - V_{i+2}$ and $V_i - V_{i-2}$, V_i must be compared to the other data points values onward as shown in Fig. 6.

When all the following conditions are fulfilled, V_i is identified as the value of R peak:

(1) $V_{i+2} < V_{i+1} < V_i$
(2) $V_{i-2} < V_{i-1} < V_i$
(3) $V_{th3} \leq V_i - V_{i+2}$
(4) $V_{th4} \leq V_i - V_{i-2}$
(5) $V_{i+k(k=1,15)} < V_i$

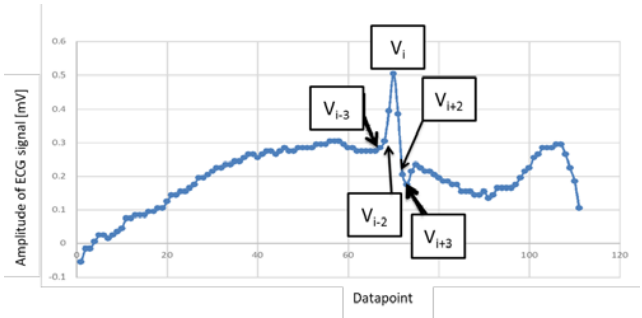

Fig. 7 R peak detection in an off-the-baseline rhythm scenario

For this research, V_{th3} is 0.35 and V_{th4} is 0.4. $V_{i+k\,(k=1,15)}$ represent the range of data to be check for any possible of other local maximum value exist that close to the current local maximum value location. k = 15 is determined by using False Acceptance Rate (FAR) analysis where the most optimal value to be used is selected. This process is very important to ensure the only right heart cycle is detected and not a noise signal.

(C) Off-the-baseline Rhythms

When the heart rhythm is off the baseline of ECG data, it is also difficult to identify the local maximum point as R peak only by comparing the value to the neighboring data points. This is because the absolute value of V_i is meaningless due to the offset of the baseline. To avoid the miss-detection of R peak, the values of adjacent data points around the local maximum point must be carefully investigated, considering the offset of the baseline. Therefore, in addition to the value differences of $V_i - V_{i+2}$ and $V_i - V_{i-2}$, it must be confirmed that V_i is the local maximum value at the center of the successive seven data points and each data point value decreases from V_i to V_{i-3} and from V_i to V_{i+3} as shown in Fig. 7.

When all the following conditions are fulfilled, V_i is identified as the value of R peak:

(1) $V_{i+3<}V_{i+2} < V_{i+1} < V_i$
(2) $V_{i-3<}V_{i-2} < V_{i-1} < V_i$
(3) $V_{th5} \leq V_i - V_{i+2}$
(4) $V_{th6} \leq V_i - V_{i-2}$
(5) $0 < V_{i+k\,(k=1,6)}$
(6) $0 < V_{i-k\,(k=1,6)}$

For this research, V_{th5} and V_{th6} are 0.2. $V_{i+k\,(k=1,6)}$ and $V_{i-k\,(k=1,6)}$ represent the range of data to be check for any possible of other local maximum value exist that close to the current local maximum value location. k = 6 is determined by using False Acceptance Rate (FAR) analysis where the most optimal value to be used is selected. This process is very important to ensure the only right heart cycle is detected and not a noise signal in the off-the-baseline rhythms.

4.1.2 Q Peak Detection

After R peak in a heart cycle is detected, Q peak detection is performed. Q peak is searched for in the range of D_1. The data point, which has the minimum value in the range, is identified as Q peak as shown in Fig. 3.

4.1.3 P Peak Detection

After Q peak in the heart cycle is detected, P peak detection is performed. P peak is searched for in the range of D_2. The data point which has the maximum value in the range is identified as P peak as shown in Fig. 3.

4.1.4 S Peak Detection

After P peak in the heart cycle is detected, S peak detection is performed. S peak is searched for in the range of D_3. The data point which has the minimum value in the range is identified as S peak as shown in Fig. 3.

4.1.5 T Peak Detection

After S peak in the heart cycle is detected, T peak detection is performed. T peak is searched for in the range of D_4. The data point which has the maximum value in the range is identified as T peak as shown in Fig. 3.

4.2 Artificial Neural Network (ANN) Classifier

Artificial Neural Network (ANN) is one of the machine learning methods which imitate human's way of thinking to decide the most suitable solution to an issue. In this research, ANN is used to classify an ECG data into unobvious ParAF rhythm or NS rhythm based on the values of P, Q, R, S and T peaks.

When ANN is performed with the values of P, Q, R, S and T peaks in a heart cycle as an input dataset, a numerical value is output. In this research, the output values of 0 and 1 indicate a typical NS rhythm and an unobvious ParAF rhythm, respectively. Therefore, the middle value of 0.5 can be the border. Note that the output value is sometimes larger than 1 or smaller than 0 since it can be overestimated or underestimated by ANN, depending on the training dataset. When ANN is performed for the whole ECG data, the same number of output values as the heart cycles is obtained. Figure 8 and Fig. 9 show the output values obtained from a NS data and an unobvious ParAF data, respectively. In these figures, the horizontal axis indicates data point for each heart cycle, however, it is arranged in ascending order.

Let N_{ns} and N_{af} be the number of data points that has the output value less than 0.5 and the number of data points that has the output value more than 0.5. In Fig. 8, N_{ns}/N_{af} is obviously larger than 1. On the other hand, N_{ns}/N_{af} is much smaller than 1 in Fig. 9. It revealed that the unobvious ParAF rhythm can clearly be discriminated from the NS rhythm by using ANN.

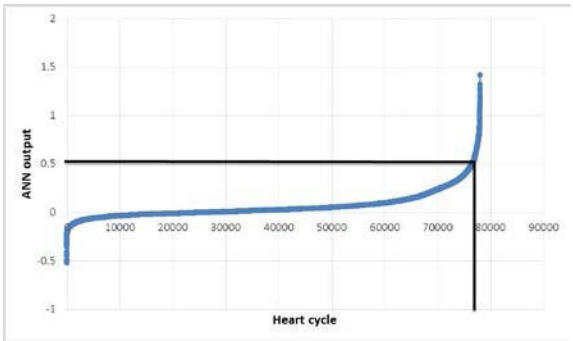

Fig. 8 ANN output values obtained from an ECG data of a Normal Sinus patient.

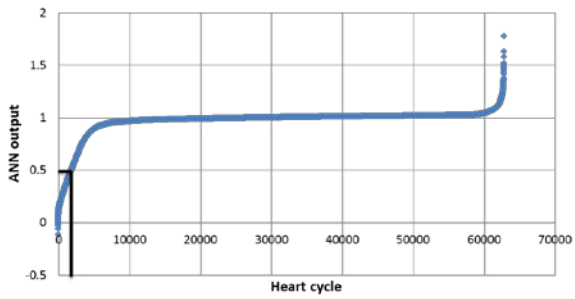

Fig. 9 ANN output values obtained from an ECG data of an Atrial Fibrillation patient.

5. Performance Evaluation

In this section, the performance of the proposed mechanism to detect five significant peaks and to discriminate Atrial Fibrillation data from NS data is evaluated. In addition, the computational time of the proposed mechanism is also discussed. In the following subsections, the databases utilized for the evaluation, ANN setup, the performance metrics and the evaluation results will be presented.

5.1 Databases Used for Evaluation

In this research, two types of databases, which are "MIT-BIH Normal Sinus" and "MIT-BIH Atrial Fibrillation", were utilized in order to evaluate the performance of the proposed mechanism. These two databases have been provided by PhysioNet [41]. PhysioNet is a research resource, providing a large number of recorded physiological data and the related open-source software.

17 patients' ECG data from the Normal Sinus database and 15 patients' ECG data from the Atrial Fibrillation database were selected for the evaluation. Each patient's data consists of a time series ECG data for 12 hours, which is one of the most important criteria to select the data. Note that the 15 patients' data from the Atrial Fibrillation database show the ParAF. Therefore, the characteristics of

their ECG waveforms are quite similar to the ones of NS. The proposed mechanism was performed to discriminate these 15 ParAF data from the 17 NS data. The sampling frequency of all the ECG data utilized in this evaluation is 129 Hz. The amplitude range of typical ECG signals is from −5 mV to 5 mV. For a routine recording, most electro cardiographers agree that visual diagnostic accuracy can be maintained with a high frequency specification between 50 and 100 Hz [42]. In this experiment, the sampling frequency of 129 Hz is acceptable for measuring the consecutive R-peak of electrocardiogram. A small difference in sampling frequency does not influence the adaptive threshold setting and the detection performance itself. Therefore, in this research, ECG data with sampling frequency of 129 Hz, which is the original data configuration provided by Physionet, was utilized.

5.2 ANN Setup

As mentioned in Sect. 4, the obvious ParAF data were discriminated from NS data by counting the number of detected five significant peaks using Door-to-Door algorithm. After that, ANN was performed to discriminate the unobvious ParAF data from the NS data. The input parameters to ANN were the voltage values of P, Q, R, S and T peaks in each heart cycle. These five values constitute a dataset for a heart cycle. In this experiment, a conventional two-layered neural network with a single output neuron was used for ANN model development. As a result of network training, a decision function is chosen from the family of functions represented by the network architecture. This function family is defined by the complexity of the neural network: number of hidden layers, number of neurons in these layers, and topology of the network. The decision function is determined by choosing the appropriate weights for the neural network. Optimal weights usually minimize an error function for the particular network architecture. The error function describes the deviation of predicted target values from the observed or desired values. In this research, class/nonclass classification problem the target values is 1 for class (Atrial Fibrillation) and 0 for nonclass (Normal Sinus). The number of hidden layers is 20. Training of neural network is performed on variations of ECG peak value based on Levenberg-Marquardt algorithms by trying to minimize an error function with 60% of dataset is allocated from the whole dataset. To avoid over fitting and under fitting, cross validation is used to find an earlier point of training by providing about 5% of validation data from the whole dataset. Finally, 35 % dataset is allocated to provide an unbiased evaluation of a final model fit on the training dataset. As shown in Table 2, the data divisions for each set are stated in this table. The main aim of the separation into 5% validation and 35% testing is to create a balance prediction model between over fitting and under fitting. Since the prediction model may perfectly predict predefine training data, but it is very unlikely to perfectly predict any other data, a balance prediction model is required to support the case. Hence, the proposal is used to get the balance prediction model. In order to provide a balance prediction model, the average mean square errors of training, testing and validation values are used to evaluate. Mean square errors represent the average square difference between output and targets. The lowers values of mean square errors are better for prediction. The equation for Mean square errors (MSE) of the predictor are shown below.

$$MSE = \frac{1}{n}\sum_{i=0}^{n}(Y_i - \hat{Y}_i)^2$$

$\hat{Y}$ is a vector of n predictions, and Y is the vector of observed value of the variable being predicted. In order to get the best ratio, a series of experiments are conducted where 10 different ECG datasets with 3 different ratios for testing, validation and training data were investigated. Moreover, 270 times of training model was tested to find the best ratio to be used in this research. As the result, over fitting

Table 1 Average Mean Square error for training, testing and validation for different ratio

Training dataset (%)	Testing dataset (%)	Validation dataset (%)	Average Training Mean Square error	Average Testing Mean Square error	Average Validation Mean Square error
100	40	0	0.001109	0.001175	0.001222
60	15	5	0.001660	0.001874	0.001640
55	15	10	0.001696	0.001923	0.001983

Table 2 Data division for testing, training and validation for ANN experiment

Validation data (5%)	Testing data (35%)	Training data (60%)
3,094	21,662	37,135
2,458	15,732	29,499
2,828	19,781	33,940
3,065	22,428	36,775
3,204	22,428	38,445
2,954	20,678	35,449
2,704	18,928	32,449
2,798	19,591	33,584
2,827	19,791	33,927
3,187	22,312	38,249
3,439	24,072	41,266
3,107	21,751	37,288
3,251	22,754	39,007
2,611	18,276	31,330
2,340	16,379	28,078
3,069	21,488	36,829
3,543	24,804	42,521
3,142	21,996	37,708
2,867	20,067	34,400
2,791	19,535	33,489
3,289	23,023	39,467

Table 3 The sensitivity of heart cycle detection on MIT-BIH Normal Sinus database with Door-to-Door algorithm

Peak	P	Q	R	S	T
True Positive	100%	100%	100%	100%	100%
False Negative	0%	0%	0%	0%	0%
Sensitivity	100%	100%	100%	100%	100%

occurred when mean square errors values are very low for training data compared to the others two, while under fitting occurred when Mean Square Error value are very high for testing and validation data. Here, the investigation result was described in Table 1. As seen in Table 1, the best ratio is the one with validation 5 %, testing 35 % and training 60% comparatively.

5.3 Results of Performance Evaluation

The performance of Door-to-Door algorithm was evaluated in quantitative ways. The performance evaluation was divided into two: (1) How correctly five significant peaks in 12 hours ECG data of NS is detected, (2) How correctly the obvious ParAF data is discriminated from the NS data.

To evaluate the peaks detection performance, *"Sensitivity"* was selected as the evaluation metric. It indicates how correctly each peak can be detected. The detection sensitivity of the five peaks (expressed as *"Sensitivity"*) is defined as follows:

$$\textit{Sensitivity} = \textit{True Positive}/(\textit{True Positive} + \textit{False Negative})$$

where,
True Positive: The number of actual peaks that are correctly detected as peaks.
False Negative: The number of actual peaks that are not detected as peaks.

Since there were a huge number of heart cycles in a 12 hours ECG data for 17 NS data, 1000 heart cycles data randomly sampled from each Normal Sinus data were manually investigated. In other words, 1000 (heart cycles) x 5 (peaks) x 17 (data) = 85,000 (peaks) were validated. As the result, the detection sensitivity of the five significant peaks for the sampled data was 100%. This surprising accurate sensitivity concludes that Door-to-Door algorithm works very well to detect heart cycles of ECG data with adaptive thresholds as shown in Table 3.

In this research, it was assumed that when the number of detected peaks (including P, Q, R, S and T peaks) is smaller than 46,000 in a 12 hours ECG data, it is identified as an obvious ParAF data. Therefore, 32 ECG data (15 Atrial Fibrillation data and 17 NS data) were investigated if each data is an obvious ParAF data or not. As the result, 11 out of 32 ECG data were regarded as obvious ParAF data and actually they were correctly identified.

Table 4 N_{ns}/N_{af} for the 21 ECG data

ECG data number	N_{ns}/N_{af}
NS16265	1048.000
NS16272	246.075
NS16273	1177.458
NS16420	424.638
NS16483	2287.536
NS16539	808.328
NS16773	1039.019
NS16786	3997.143
NS16795	276.181
NS17453	826.896
NS18177	437.063
NS18184	738.845
NS19088	138.209
NS19090	599.195
NS19093	1455.75
NS19140	229.759
NS19830	119.320
AF04043	0.0566
AF05261	0.153
AF06995	0.049
AF08455	0.091

At this moment, the rest of 21 ECG data have not as yet identified with either unobvious ParAF data or NS data since the number of detected peaks was larger than 46,000. Then, subsequently, ANN was performed to the 21 ECG data as stated in Sect. 4.2. The value of N_{ns}/N_{af} for each ECG data was obtained as the result as shown in Table 4.

As clearly seen from Table 4, N_{ns}/N_{af} is much larger than 1 in the first 17 ECG data, and in the other 4 ECG data, N_{ns}/N_{af} is much smaller than 1. Therefore, the 17 ECG data and the 4 data were regarded as NS data and unobvious ParAF data. As a matter of fact, these 21 ECG data were correctly identified.

To compare the discrimination performance of the proposed mechanism with other existing studies, *"Sensitivity"* and *"Specificity"* were selected as the evaluation metrics. The sensitivity and specificity are considered as the best paired performance metrics to evaluate the discrimination accuracy of Atrial Fibrillation from NS [26]. The discrimination sensitivity of Atrial Fibrillation indicates the true positive rate in identifying Atrial Fibrillation. On the other hand, the discrimination specificity of Atrial Fibrillation indicates the true negative rate in identifying Atrial Fibrillation, which means the rate how correctly NS is identified. The discrimination sensitivity and specificity (expressed as *"Sensitivity"* and *"Specificity"*, respectively) are defined as follows:

$$\textit{Sensitivity} = \textit{True positives}/(\textit{True positive} + \textit{False negative})$$

Table 5 Overall performance evaluation results comparing this research with conventional SVM, Decision Tree and KNN using same dataset

ECG data number	SVM Accuracy (%)	Proposed method Accuracy (%)	Decision Tree Accuracy (%)	KNN Accuracy (%)
NS16265	99.9	100	99.9	99.9
NS16272	96.7	100	98.0	99.4
NS16273	99.8	100	99.9	99.9
NS16420	99.5	100	99.8	99.8
NS16483	99.9	100	99.9	99.9
NS16539	100	100	100	100
NS16773	99.8	100	99.9	99.9
NS16786	100	100	100	100
NS16795	98.3	100	99.2	99.4
NS17453	99.8	100	99.9	99.9
NS18177	99.5	100	99.7	99.7
NS18184	99.7	100	99.8	99.9
NS19088	96.2	100	97.5	97.1
NS19090	99.2	100	99.8	99.8
NS19093	99.6	100	99.9	99.9
NS19140	99.0	100	99.3	99.2
NS19830	97.8	100	98.0	98.4
AF04043	85.6	100	95.1	96.6
AF05261	58.4	100	86.4	90.7
AF06995	86.1	100	94.9	96.6
AF08455	61.8	100	89.9	94.7

Specificity
= *True negatives / (True negative + False positives)*

where,

True positive: The number of Atrial Fibrillation data correctly identified as Atrial Fibrillation data.
False negative: The number of Atrial Fibrillation data incorrectly identified as NS data.
False positive: The number of NS data incorrectly identified as Atrial Fibrillation data.
True negative: The number of NS data correctly identified as NS data.

In this evaluation, to discriminate ParAF data from NS data, two steps were taken, that is to say, the steps using Door-to-Door algorithm and ANN. Based on the definitions of sensitivity and specificity for the discrimination performance, the overall results for both are 100%. In order to ensure the proposed method are the most suitable model for classification, 3 different classification model have been selected to compare with, which are conventional Support Vector Machine (SVM), Decision Tree, and K-Nearest Neighbor (KNN) with 5 folds cross-validation. Since all those techniques are highly effective in data classification, hence, this result may describe the significance of the ANN and the study itself. The same dataset is used to test the performance of these 3 models. However, ANN has shown more advantages in predicting medical outcome compared to the other 3 classification model. The results are shown in Table 5.

Table 6 shows the results of the sensitivity and specificity of other studies with this research using the same database with duration more than 10 hours long. It is revealed that the proposed mechanism in this research outperformed the other studies.

Table 6 Overall performance evaluation result comparing this research with other studies. The bold font shows the results re-evaluated by Larbruru et al. [43]

Algorithm name	Sensitivity (%)	Specificity (%)
Slocum et al. [44]	**62.8**	**77.5**
Babaeizadeh et al.[45]	**87.3**	**95.5**
Tateno et al. [46]	**91.2**	**96.1**
Couceiro et al. [47]	**93.8**	**96.1**
Dash et al.[48]	94.4	95.1
Huang et al.[49]	96.1	98.1
Sarkar et al.[50]	97.5	99
Lee et al.[51]	98.2	97.7
Jiang et al.[52]	98.2	97.5
Shadnaz et al.[4]	97.0	97.1
Zhou et al. [53]	96.9	98.3
Carvalho et al. [54]	93.8	96.1
Huang et al. [49]	96.1	98.1
Lake et al. [55]	91	94
Lian et al. [56]	95.8	96.4
Dash et al. [57]	94.4	95.1
Tateno & Glass [45]	94.4	97.2
Proposed method	100	100

To complete research, the computational time of detecting heart cycle was evaluated. The computational time of Door-to-Door algorithm implemented on a personal computer (with Intel® Core™ i7 2.50 GHz, 16 GB RAM, 64 bit OS) was approximately 15 ms for a 30 second of ECG data. To the best of our knowledge, few research has mentioned the computational time of heart cycle detection for a long duration of ECG data. One research [4] stated that the computational time to detect heart cycle for a 30 second of ECG data was 40ms, which is more than two times longer than Door-to-Door algorithm. The computational time of Door-to-Door algorithm for a 12 hour of ECG data varied from 30 seconds to 360 seconds. Even in the longest case, it takes only six minutes, which is clinically acceptable for diagnosis. Given this short computational time, the proposed mechanism can effectively be used in diagnosing a long duration of ECG data, especially to detect ParAF.

6. Conclusion

In this paper, a novel and hybrid mechanism, which automatically detects ParAF symptom using Door-to-Door algorithm and ANN classifier, was proposed. To show the effectiveness of the proposed mechanism, the performance was thoroughly evaluated. The sensitivity of peaks detection in NS data by Door-to-Door algorithm was 100% and the obvious ParAF data were perfectly discriminated from NS data based on the number of detected heart cycles. By

performing ANN, the overall unobvious ParAF data were discriminated from NS data with the accuracy of 100%. The comparison result between this research and other studies shows that the proposed mechanism outperformed in sensitivity and specificity of the discrimination performance. Moreover, the proposed mechanism holds strong advantages, that is to say, the computational cost and time are less than the other studies. It is concluded that this research can contribute to the medical field as one of the best technologies in diagnosing ParAF symptoms.

References

[1] P. Groves, B. Kayyali, D. Knott, and S.V. Kuiken, "The big data revolution in healthcare," McKinsey & Company, center for US Helath System Reform Business Technology Office, pp.1–2, Jan. 2013.
[2] World Health Organization, Cardiovascular disease (CVDs), Fact sheet N317 [Online. Available: http://www.who.int/mediacentre/facsheets/fs317/en/, accessed July 2016.
[3] A. Petrėnas, V. Marozas, and L. Sörnmo, "Low-complexity detection of atrial fibrillation in continuous long-term monitoring," Computers in Biology and Medicine, vol.65, pp.184–191, 2015.
[4] S. Asgari, A. Mehrnia, and M. Moussavi, "Automatic detection of atrial fibrillation using stationary wavelet transform and support vector machine," Computers in Biology and Medicine, vol.60, pp.132–142, 2015.
[5] K. Padmavathi and K.S. Ramakrishna, "Classification of ECG Signal during Atrial Fibrillation Using Autoregressive Modeling," Procedia Computer Science, vol.46, pp.53–59, 2015.
[6] O. Sayadi and M.B. Shamsollahi, "Model-Based Fiducial Points Extraction for Baseline Wandered Electrocardiograms," IEEE Trans. Biomed. Eng., vol.55, no.1, pp.347–351, 2008.
[7] M. Zivanovic and M. González-Izal, "Simultaneous powerline interference and baseline wander removal from ECG and EMG signals by sinusoidal modeling," Medical Engineering & Physics, vol.35, no.10, pp.1431–1441, 2013.
[8] M. Merino, I.M. Gómez, and A.J. Molina, "Envelopment filter and K-means for the detection of QRS waveforms in electrocardiogram," Medical Engineering & Physics, vol.37, no.6, pp.605–609, 2015.
[9] C. Ye, B.V. Kumar, and M.T. Coimbra, "Heartbeat Classification Using Morphological and Dynamic Features of ECG Signals," IEEE Trans. Biomed. Eng., vol.59, no.10, pp.2930–2941, 2012.
[10] Y.-C. Yeh, W.-J. Wang, and C.W. Chiou, "Feature selection algorithm for ECG signals using Range-Overlaps Method," Expert Systems with Applications, vol.37, no.4, pp.3499–3512, 2010.
[11] M. Llamedo and J.P. Martíez, "Heartbeat Classification Using Feature Selection Driven by Database Generalization Criteria," IEEE Trans. Biomed. Eng., vol.58, no.3, pp.616–625, 2011.
[12] O.T. Inan, L. Giovangrandi, and G.T.A. Kovacs, "Robust Neural-Network-Based Classification of Premature Ventricular Contractions Using Wavelet Transform and Timing Interval Features," IEEE Trans. Biomed. Eng., vol.53, no.12, pp.2507–2515, 2006.
[13] S. Chaudhuri, T.D. Pawar, and S. Duttagupta, Review of ECG Analysis, In: Ambulation Analysis in Wearable ECG, Springer, Boston, MA, 2009.
[14] A.C. Flint, N.M. Banki, X. Ren, V.A. Rao, and A.S. Go, "Detection of Paroxysmal Atrial Fibrillation by 30-Day Event Monitoring in Cryptogenic Ischemic Stroke: The Stroke and Monitoring for PAF in Real Time (SMART) Registry," Stroke, vol.43, no.10, pp.2788–2790, July 2012.
[15] T. Hanke, E.I. Charitos, U. Stierle, A. Karluss, E. Kraatz, B. Graf, A. Hagemann, M. Misfeld, and H.H. Sievers, "Twenty-Four-Hour Holter Monitor Follow-Up Does Not Provide Accurate Heart Rhythm Status After Surgical Atrial Fibrillation Ablation Therapy: Up to 12 Months Experience With a Novel Permanently Implantable Heart Rhythm Monitor Device," Circulation, vol.120, no.11_suppl_1, 2009.
[16] P. Zimetbaum, "Antiarrhythmic Drug Therapy for Atrial Fibrillation," Circulation, vol.125, no.2, pp.381–389, 2012.
[17] S. Uchida, A. Mori, R. Kurazume, R. Taniguchi, and T. Hasegawa, "Logical DP Matching for Detecting Similar Subsequence," Computer Vision – ACCV 2007 Lecture Notes in Computer Science, pp.628–637, 2007.
[18] F. Scholkmann, J. Boss, and M. Wolf, "An Efficient Algorithm for Automatic Peak Detection in Noisy Periodic and Quasi-Periodic Signals," Algorithms, vol.5, no.4, pp.588–603, 2012.
[19] P. Du, W.A. Kibbe, and S.M. Lin, "Improved peak detection in mass spectrum by incorporating continuous wavelet transform-based pattern matching," Bioinformatics, vol.22, no.17, pp.2059–2065, April 2006.
[20] K.R. Coombes, S. Tsavachidis, J.S. Morris, K.A. Baggerly, M.-C. Hung, and H.M. Kuerer, "Improved peak detection and quantification of mass spectrometry data acquired from surface-enhanced laser desorption and ionization by denoising spectra with the undecimated discrete wavelet transform," Proteomics, vol.5, no.16, pp.4107–4117, 2005.
[21] O. Singh and R.K. Sunkaria, " A robust R-peak detection algorithm using wavelet transform," Int. J. Comput. Appl., vol.36, pp.37–43, 2011.
[22] Z. Nenadic and J.W. Burdick, "Spike Detection Using the Continuous Wavelet Transform," IEEE Trans. Biomed. Eng., vol.52, no.1, pp.74–87, 2005.
[23] C. Li, C. Zheng, and C. Tai, "Detection of ECG characteristic points using wavelet transforms," IEEE Trans. Biomed. Eng., vol.42, no.1, pp.21–28, 1995.
[24] J.M. Gregoire, D. Dale, and R.B.V. Dover, "A wavelet transform algorithm for peak detection and application to powder x-ray diffraction data," Review of Scientific Instruments, vol.82, no.1, pp.1–8, 2011.
[25] Q. Xue, Y.H. Hu, and W.J. Tompkins, "Neural-network-based adaptive matched filtering for QRS detection," IEEE Trans. Biomed. Eng., vol.39, no.4, pp.317–329, 1992.
[26] G. Vijaya, V. Kumar, and H.K. Verma, "ANN-based QRS-complex analysis of ECG," Journal of Medical Engineering & Technology, vol.22, no.4, pp.160–167, 1998.
[27] Y. Ferdi, J.P. Herbeuval, A. Charef, and B. Boucheham, "R wave detection using fractional digital differentiation," Itbm-Rbm, vol.24, no.5-6, pp.273–280, 2003.
[28] K.-P. Lin and W.H. Chang, "QRS feature extraction using linear prediction," IEEE Trans. Biomed. Eng., vol.36, no.10, pp.1050–1055, 1989.
[29] D.A. Coast, R.M. Stern, G.G. Cano, and S.A. Briller, "An approach to cardiac arrhythmia analysis using hidden Markov models," IEEE Trans. Biomed. Eng., vol.37, no.9, pp.826–836, 1990.
[30] K. Harmer, G. Howells, W. Sheng, M. Fairhurst, and F. Deravi, "A Peak-Trough Detection Algorithm Based on Momentum," 2008 Congress on Image and Signal Processing, 2008.
[31] J. Pan and W.J. Tompkins, "A Real-Time QRS Detection Algorithm," IEEE Trans. Biomed. Eng., vol.BME-32, no.3, pp.230–236, 1985.
[32] A. Jacobson, "Auto-threshold peak detection in physiological signals," 2001 Conference Proc. 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2001.
[33] G. Vivó-Truyols, J.R. Torres-Lapasió, A.M. van Nederkassel, Y.V. Heyden, and D.L. Massart, "Automatic program for peak detection and deconvolution of multi-overlapped chromatographic signals," Journal of Chromatography A, vol.1096, no.1-2, pp.133–145, 2005.
[34] J.L. Excoffier and G. Guiochon, "Automatic peak detection in chromatography," Chromatographia, vol.15, no.9, pp.543–545, 1982.
[35] S.K. Sahoo, W. Lu, S.D. Teddy, D. Kim, and M. Feng, "Detection of Atrial fibrillation from non-episodic ECG data: A review of methods," 2011 Annual International Conference of the IEEE Engineer-

ing in Medicine and Biology Society, 2011.
[36] E. Ros, S. Mota, F. Fernandez, F. Toro, and J. Bernier, "ECG characterization of Paroxysmal atrial fibrillation: Parameter extraction and automatic diagnosis algorithm," Computer in Biology and Medicine, vol.4, no.8, pp.679–696, 2004.
[37] B. Pourbabaee and C. Lucas, "Automatic Detection and Prediction of Paroxysmal Atrial Fibrillation based on Analyzing ECG Signal Feature Classification Methods," 2008 Cairo International Biomedical Engineering Conference, 2008.
[38] N. Kikillus, M. Schweikert, and A. Bolz, "Identifying Patients Suffering From Atrial Fibrillation During Atrial Fibrillation and Non-Atrial Fibrillation Episodes," IFMBE Proceedings 4th European Conference of the International Federation for Medical and Biological Engineering, pp.1349–1352, 2009.
[39] Y.V. Chesnokov, A.V. Holden, and H. Zhang, "Screening patients with Paroxysmal atrial fibrillation (PAF) from non-PAF heart rhythm using HRV data analysis," 2007 Computers in Cardiology, pp.459–462, 2007.
[40] B. Hickey, C. Heneghan, and P.D. Chazal, "Non-Episode-Dependent Assessment of Paroxysmal Atrial Fibrillation Through Measurement of RR Interval Dynamics and Atrial Premature Contractions," Annals of Biomedical Engineering, vol.32, no.5, pp.677–687, 2004.
[41] "PhysioNet," https://physionet.org/, accessed 2017.
[42] G.D. Pinna, R. Maestri, A.D. Cesare, R. Colombo, and G. Minuco, "The accuracy of power-spectrum analysis of heart-rate variability from annotated RR lists generated by Holter systems," Physiological Measurement, vol.15, no.2, pp.163–179, Jan. 1994. https://physionet.org/physiobank/database/, accessed July 2, 2016.
[43] N. Larburu, T. Lopetegi, and I. Romero, "Comparative study of algorithms for Atrial Fibrillation detection," Computing in Cardiology, vol.38, pp.265–268, 2011.
[44] J. Slocum, A. Sahakian, and S. Swiryn, "Diagnosis of atrial fibrillation from surface electrocardiograms based on computer-detected atrial activity," Journal of Electrocardiology, vol.25, no.1, pp.1–8, 1992.
[45] S. Babaeizadeh, R.E. Gregg, E.D. Helfenbein, J.M. Lindauer, and S.H. Zhou, "Improvements in atrial fibrillation detection for real-time monitoring," Journal of Electrocardiology, vol.42, no.6, pp.522–526, 2009.
[46] K. Tateno and L. Glass, "Automatic detection of atrial fibrillation using the coefficient of variation and density histograms of RR and ΔRR intervals," Medical and Biological Engineering & Computing, vol.39, no.6, pp.664–671, 2001.
[47] R. Couceiro, P. Carvalho, J. Henriques, M. Antunes, M. Harris, and J. Habetha, "Detection of Atrial Fibrillation using model-based ECG analysis," 2008 19th International Conference on Pattern Recognition, 2008.
[48] S. Dash, K.H. Chon, S. Lu, and E.A. Raeder, "Automatic Real Time Detection of Atrial Fibrillation," Annals of Biomedical Engineering, vol.37, no.9, pp.1701–1709, 2009.
[49] C. Huang, S. Ye, H. Chen, D. Li, F. He, and Y. Tu, "A Novel Method for Detection of the Transition Between Atrial Fibrillation and Sinus Rhythm," IEEE Trans. Biomed. Eng., vol.58, no.4, pp.1113–1119, 2011.
[50] S. Sarkar, D. Ritscher, and R. Mehra, "A Detector for a Chronic Implantable Atrial Tachyarrhythmia Monitor," IEEE Trans. Biomed. Eng., vol.55, no.3, pp.1219–1224, 2008.
[51] J. Lee, Y. Nam, D.D. Mcmanus, and K.H. Chon, "Time-Varying Coherence Function for Atrial Fibrillation Detection," IEEE Trans. Biomed. Eng., vol.60, no.10, pp.2783–2793, 2013.
[52] K. Jiang, C. Huang, S.-M. Ye, and H. Chen, "High accuracy in automatic detection of atrial fibrillation for Holter monitoring," Journal of Zhejiang University SCIENCE B, vol.13, no.9, pp.751–756, 2012.
[53] X. Zhou, H. Ding, B. Ung, E. Pickwell-MacPherson, and Y. Zhang, "Automatic online detection of atrial fibrillation based on symbolic dynamics and Shannon entropy," BioMedical Engineering OnLine, vol.13, no.1, p.18, 2014.
[54] P.D. Carvalho, J. Henriques, R. Couceiro, M. Harris, M. Antunes, and J. Habetha, "Model-Based Atrial Fibrillation Detection," ECG Signal Processing, Classification and Interpretation, pp.99–133, Nov. 2011.
[55] D.E. Lake and J.R. Moorman, "Accurate estimation of entropy in very short physiological time series: the problem of atrial fibrillation detection in implanted ventricular devices," AJP: Heart and Circulatory Physiology, vol.300, no.1, 2010.
[56] J. Lian, L. Wang, and D. Muessig, "A Simple Method to Detect Atrial Fibrillation Using RR Intervals," The American Journal of Cardiology, vol.107, no.10, pp.1494–1497, 2011.
[57] S. Dash, K.H. Chon, S. Lu, and E.A. Raeder, "Automatic Real Time Detection of Atrial Fibrillation," Annals of Biomedical Engineering, vol.37, no.9, pp.1701–1709, 2009.

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