Atrial Fibrillation Analysis for Real Time Patient Monitoring

Ragheed Allami[1], Andrew Stranieri[1], Faezeh Marzbanrad[2], Venki Balasubramanian[1], Herbert F. Jelinek[3]

[1]Centre for Informatics and Applied Optimisation, Federation University, Victoria, Australia
[2] School of Electrical and Computer Systems Engineering, Monash University, Victoria, Australia
[3] School of Community Health, Charles Sturt University, NSW, Australia

Abstract

Atrial Fibrillation (AF) can lead to life-threatening conditions such as stroke and heart failure. The instant recognition of life-threatening cardiac arrhythmias based on a 3-lead ECG to record a Lead II configuration for a few seconds is a challenging problem of clinical significance. Five consecutive ECG beats that were identified by a cardiologist to characterise an AF episode and five consecutive heartbeat intervals representing an irregular RR intervals episode were analysed. The detection and analysis of P waves as the morphological features of AF was executed based on two template matching methods. An AF detector was developed by combining the correlation coefficients based on the template matching methods and the standard deviation of the RR intervals. The AF detector was then applied to classify 5 consecutive beats as AF or non-AF based on thresholding the calculated irregularity.

The proposed algorithm was tested on the MIT-BIH Atrial Fibrillation and the Challenge 2017 databases. The proposed method resulted in an improved sensitivity, specificity and accuracy of 97.60%, 98.20% and 99% respectively compared to recent published methods. In addition, the proposed method is suitable for real-time patient monitoring as it is computationally simple and requires only a few seconds of ECG recording to detect an AF rhythm.

1. Introduction

An Electrocardiogram (ECG) records the electrical impulses of the heart and indicates rhythm anomalies for diagnostic purposes [1]. A typical ECG tracing of the cardiac cycle consists of a P wave, QRS complex, and T wave [2]. The performance of an ECG analysis system depends upon the accurate and reliable detection of the QRS complex, as well as the T and P waves [3].

Atrial Fibrillation (AF) are irregular heartbeats caused by obstruction along electrical impulse pathways of the heart atria hence [4]. AF is linked to fast uncoordinated atrial fluctuations where the contraction rate may exceed 600 beats per minute. Hence, it often leads to a sudden vanishing of P-waves, which is usually linked with synchronous functioning of the atria. P waves are substituted by an oscillating baseline that is composed of fibrillatory wavelets of low amplitude.

AF represents one of the most common chronic cardiovascular arrhythmias, appearing in 2% of the population globally [4]. AF is linked with stroke, heart failure, risk of death and coronary artery disease and found to be connected with significant morbidity and mortality [4, 5]. Approximately 12 million North Americans and Europeans suffer from AF and this is estimated to triple in the next 30 to 50 years [6]. The prevalence of AF rises with age. It is affecting 0.5% of people at the age between 40 and 50 years and 5-15% at the age of 80 years [7]. The automated detection and classification of AF based on a simple and fast method over a few heartbeats is important for prompt, accurate diagnosis and treatment to reduce morbidity and mortality.

Figure 1 illustrates typical ECG diagnostic features in a segment of normal rhythm including the distance between R waves called the RR interval. RR intervals in normal rhythms are regular as shown in figure 1 whereas in AF rhythms, they are irregular as demonstrated in figure 2. Therefore, many studies described below have used RR intervals to detect AF.
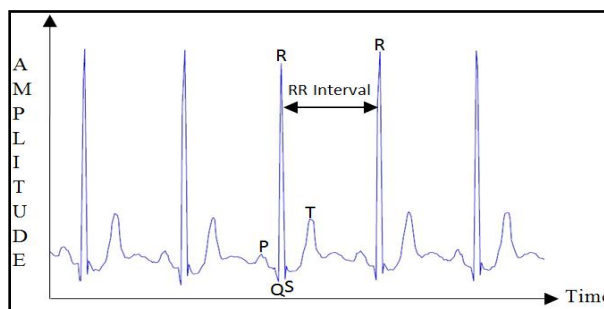

Figure 1. A segment of Normal ECG for Record No. A00823 readings from Challenge 2017 database showing P, QRS and T and RR interval.
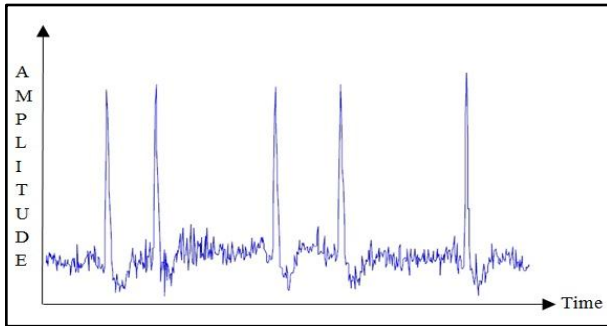
Figure 2. A segment of AF rhythm for Record No. 06995 reading from MIT-BIH Atrial Fibrillation database.

From figure 2, it is apparent that RR intervals are irregular and most P waves are absent or have low amplitude. Accordingly, numerous investigations harnessed these two key points to classify and detect AF.

AF detection methods can be grouped under ventricular function analysis-based and atrial function analysis-based approaches. Classification based on ventricular function analysis using RR intervals is the most common method in real-time studies to detect AF [8]. For example, RR data that was generated from a 30 second trace, was employed to classify AF using statistical detrended fluctuation analysis (DFA), the local dynamics score (LDs) and sample entropy (COSEn). The results indicated that the positive predictive values for AF were 97% [8]. In addition, A low complexity method introduced by Petrenas et al. [9] based on statistical techniques of RR data from a sliding window of 8 beats was utilized to discern AF from normal rhythms. The results for sensitivity and specificity were 97.1% and 98.3% respectively. Moreover, Zhou et al. [10] presented a novel approach using Shannon entropy and symbolic dynamics with sensitivity, specificity and accuracy values were 96.14%, 95.73%, 95.97% respectively.

Combining both ventricular and atrial features could plausibly achieve improved performance by including ventricular and atrial features to detect AF disease. Babaeizadeh et al. [11] employed a Markov modeling technique to compute irregular RR intervals and two morphology features P and PR intervals were then applied to three statistical classifiers to detect AF rhythms with 92% sensitivity and 97% specificity. A four features-based classification included RR intervals, P wave absence, f wave presence and noise level and submitted to a fuzzy logic classifier to detect AF episodes. The fuzzy logic classifier provided sensitivity, specificity and accuracy of 100%, 76% and 88% respectively. Other techniques have been applied to classify AF rhythm including nonlinear complexity measures, wavelet transform and artificial neural networks such as described in [12-15] However, these techniques may not always be technically feasible for real-time processing of ECG data due to the requirement of high computational resources [16].

Brief periods, usually less than 30 seconds, play an important role in cardiac research to detect AF rhythm [17]. Recent investigations have recommended that the use of short time intervals such as five seconds may be sufficient for the detection of AF due to increased risk of stroke [17-19]. Real time, continuous cardiac monitoring platforms have emerged that utilize wearable ECG sensors and smartphones for biosignal interpretation. However, these devices have limited power, memory and processor capacity and are not suitable for implementation of complex AF classification algorithms as data streaming through these devices consumes considerable power resources. Hence, computationally simple and fast algorithms based on ventricular and atrial features that can accurately detect an AF rhythm from only a few ECG signals is crucial.

The method advanced here applies two templates to identify the presence or absence of P waves. The standard deviation of normal to normal RR cycles is computed to find the irregular RR data then two simple rules are employed to detect an AF episode from non-AF.

The algorithms are described in the materials section next before experimental results are reported.

2. Materials

Trials of the AF detection algorithm advanced here were applied to the MIT-BIH Atrial Fibrillation (MIT-BIH AF) database [20] for testing and the Challenge 2017 database [21] was employed for measuring the generalization capability performance of the algorithm. The MIT-BIH AF database is commonly used in AF analysis because it includes about one million ECG beats with 43% classified as AF beats. It contains 25 ECGs of 10 hours recording lengths. Furthermore, it has two channel ambulatory ECG recordings in digital format with a 250 Hz sampling rate. The Challenge 2017 database [21] consists of 8528 recordings with 5154 records classified as Normal of 9 minutes recording lengths, 771 records classified as AF of 10 minutes recording lengths, 2557 records classified as other rhythm of 9 minutes recording lengths and 46 records classified as Noise and again of 9 minutes recording lengths. Signals were extracted from an AliveCor device at a sampling rate 300 Hz. To match the MIT-BIH AF database the ECG recordings of the Challenge 2017 database were resampled to 250 Hz.

3. Methodology

Template matching techniques have been widely used to identify similarities between waveforms. As described above, in AF rhythms, P waves either disappear or change to be appear like a sawtooth pattern. In this study, two templates called P presence and P absence were used to

determine P wave presence or absence. The P presence template represented the normal P wave morphology as symbolized in figure 1 and identified from [22]. The P wave absence template consisted of a sawtooth morphology and a disappear morphology generated from the MIT-BIH AF database. The both models were identified using probability based data adaptive techniques from nonconsecutive 10 minute traces, randomly selected, from each ECG record.

The standard deviation of five consecutive RR intervals was used to determine irregular RR intervals. The Standard deviation threshold (SDRR) was identified empirically based on RR intervals obtained from MIT-BIH AF database. Five consecutive RR intervals were selected following advice from senior cardiologists associated with the investigators.

4. AF detection technique

The presence of noise, especially in the baseline, leads to inaccurate detection of P wave presence or absence. Therefore, a real-time ECG reduction method reported by Allami et al. [23] was applied in order to suppress noise in the baseline. The AF detection method was implemented in four steps. First, the real-time QRS detection algorithm [24] was applied to extract six RR intervals. In the second step, five P waves were detected and the average correlation coefficient for P wave presence and absence computed. In the third step, the standard deviation of RR data (SDRR) was computed. Finally, if-then rules were applied to classify 5 consecutive beats as AF or non-AF episodes based on thresholding the calculated irregularity.

The algorithm for the detection of AF and non-AF episodes is as follows:

Input: Six consecutive ECG signals
Output: Classification of AF or non-AF

Step 1: Apply real-time ECG reduction method [23] to suppress noise from the baseline
Step 2: Apply real-time Pan and Tompkins [24] QRS detection algorithm to extract RR data from six ECG signals
Step 3: $SDRR = \sqrt{\frac{\sum_{i=1}^{5}(Xi-\mu)^2}{5-1}}$
Step 4: For each beat compute the correlation coefficient (Corrcof) based on the P presence template (PP) and P absence template (Pa)
Cpp=Corrcof (P(i), PP) where i=1,2,...5
r1= Average (Cpp)
if (r1>0.80 and $SDRR$<0.059) then non AF Else
Cpa=[Cpa1=Corrcof (P(i),Pa1), Cpa2=Corrcof (P(i),Pa2)]
r2= Max(Average (Cpa1), Average(Cpa2))

Step 5: if (r1<0.50 and r2>0.50 and $SDRR$ >0.059) then AF Else unknown

5. Results

The performance of the suggested AF detection algorithm was quantified by calculation of sensitivity (Se), specificity (Sp) and accuracy (Ac) for each six ECG signals during 10 hours as described in formulas below

$$Se=TP/(TP+FN) \times 100 \tag{1}$$

$$Sp=TN/(TN+FP) \times 100 \tag{2}$$

$$Ac=(TN+TP)/(TP+FP+TN+FN) \times 100 \tag{3}$$

where True Positive (TP) refers to AF episodes correctly recognized, False Negative (FN) refers to missed AF episodes, False Positives (FP) refers to nonAF episodes recognized as AF's and True Negative (TN) refers to correctly recognized non-AF episodes.

Overall validation results of the proposed algorithm, including the results from the testing process based on the MIT-BIH Atrial Fibrillation database and generalization evaluation based on the Challenge 2017 database are depicted in Table 1.

Table 1. Overall performance in the testing databases of MIT-BIH AF database and the Challenge 2017 database.

Database	Se%	Sp%	Ac%
MIT-BIH AF	97.60	98.02	99
Challenge 2017	95.27	90.60	96.80
Other MIT-BIHAF [10]	96.14	95.73	95.97

The method advanced here incrementally displays better sensitivity, specificity and accuracy over recently published methods [8 – 11] of AF detection. The approach generalizes well to data sets not deployed in the training as observed by results from the (Challenge 2017) dataset.

6. Conclusion

The two template matching methods improved the detection accuracy by combining the similarity with irregular RR intervals results. Our results indicate that six consecutive ECG signals, are suffient to discern AF episodes from non-AF episodes with a high level of accuracy. The algorithm presented suits real-time cardiac monitoring as it requires only a few beats of ECG and is computationally simple. It is anticipated the proposed algorithm is clinically relevant since short AF episodes can be diagnosed in asymptomatic conditions.

Acknowledgements

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Address for correspondence:

Ragheed Allami
Federation University
University Drive, Mt Helen VIC 3350
Melbourne, Australia
ragheed.dawood@yahoo.com