Detection of Atrial Fibrillation Using Model-based ECG Analysis

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Abstract

Atrial Fibrillation (AF) is an arrhythmia that can lead to several patient risks. This kind of arrhythmia affects mostly elderly people, in particular those who suffer from heart failure (one of the main causes of hospitalization). Thus, detection of AF becomes decisive in the prevention of cardiac threats. In this paper an algorithm for AF detection based on a novel algorithm architecture and feature extraction methods is proposed. The aforementioned architecture is based on the analysis of the three main physiological characteristics of AF: i) P wave absence ii) heart rate irregularity and iii) atrial activity (AA). Discriminative features are extracted using model-based statistic and frequency based approaches. Sensitivity and specificity results (respectively, 93.80% and 96.09% using the MIT-BIH AF database) show that the proposed algorithm is able to outperform state-of-the-art methods.

1. Introduction

Atrial Fibrillation, the most common atrial sustained arrhythmia, is a result of multiple re-entrant wavelets in the atria, which conducts to its partial disorganization. Although it is not a lethal disease, it may lead to very disabling complications such as cardiac failure and atrial thrombosis, with the subsequent risk of a stroke. One of the characteristics of AF episodes is the absence of P waves before the QRS-T complex of the ECG, which are replaced by 'sawtooth'-like pattern waves along the cardiac cycle (see Figure 1). Additionally, these waves are associated with irregular cardiac frequency. During the last years, these two main characteristics of AF have been object of intense research for the detection and prediction of AF.

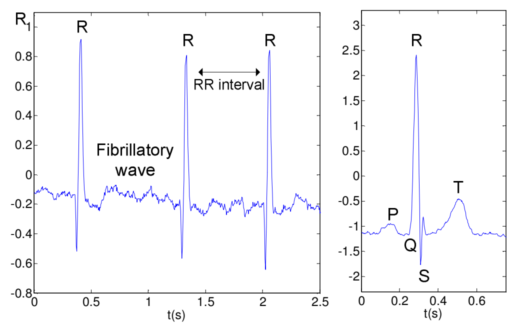

Figure 1. (Left) AF episode. (Right) Cardiac cycle.

Moody and Mark [3] constructed a Hidden Markov (HM) model and used the transition probabilities to detect AF episodes. Cerutti *et al.* [4] proposes the use of linear and non-linear indexes for characterization of RR series and consequent AF detection. Tateno and Glass [5] estimate the similarity between standard and test RR interval histograms to reveal the presence or absence of AF episodes.

Extraction of atrial activity (AA) is of crucial importance in the detection of AF. Techniques like Blind Source Separation, Spatio-Temporal Cancellation and Artificial Neural Networks are the most promising in this field of research. Despite the satisfactory results achieved by these approaches, most of them need several ECG leads to be implemented - a serious drawback for pHealth applications, where usually only one ECG lead is available. Senhadj *et al.* [6] presents an algorithm for QRS-T cancellation based on dyadic wavelet transform. Similarly, Sanchez *et al.*

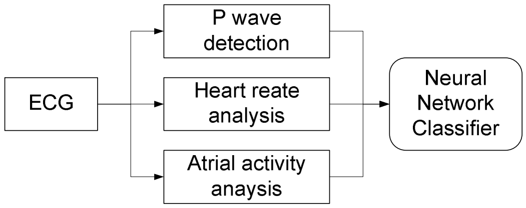

Figure 2. Architecture of the proposed algorithm.

[7] proposes an algorithm where Discrete Packet Wavelet Transform is used for the extraction of AA.

Shkurovich *et al.* [8] uses a median template based approach to cancel ventricular activity. None of the above mentioned authors dedicated special attention in frequency analysis and consequent feature extraction.

Although, the algorithms reported in the literature cover the most important characteristics of AF, a robust algorithm for AF detection has not yet been presented. Furthermore, the most significant existing methods concentrate on one of the physiological characteristics of AF. In this paper, an algorithm for AF detection is presented, which is based on the extraction of features related to the three principal characteristics of AF. The architecture of the proposed algorithm is presented in Figure 2. Some new feature extraction methods, based on estimated models using data driven approaches are also presented.

In the following section the proposed feature extraction algorithm will be outlined. In section 3 the results achieved with proposed features will be presented and discussed. In the last section some main conclusions will be drawn.

2. Methods

In the proposed algorithm, the analysis starts with the detection of major characteristic waves, namely the QRS complexes, P and T waves. Difficulties in this task are mainly due to oscillation in the baseline, presence of noise, artifacts and frequency overlapping. To avoid these situations noise filtering and baseline removal is essential. In the proposed AF detection algorithm, these steps are performed using morphologic transform concepts, such as erosion and dilation operations, and opening and closing operators. For ECG segmentation, the algorithm proposed by Sun *et al.* [9] has been adopted.

2.1. Features extraction

Real time AF detection is one of the main priority aspects of the proposed algorithm. Since the information contained in single beats is not sufficient to discriminate AF episodes, a sliding window analysis is used. A minimum of 12 beats per analysis window is established. For real time applications, the length of the present analysis window is estimated based on the heart rate frequency observed in the previous window. For offline operation, each window length is set according to the established number of beats.

In each analysis window a set of five features $(f_i, i = 1, ..., 5)$ is extracted, belonging to one of the three AF characteristic types. P wave absence is quantified by measuring the correlation of the detected P waves to a P wave model. Heart rate variability is accessed by assuming that the observed ECG is a non-linear transformed version of a model. The statistical similarity is determined from the Kullback - Leibler divergence. AA is extracted using a wavelet analysis approach, based in the algorithms reported in [6] and [7].

P wave detection: The absence of P waves during the fibrillatory process before the QRS complexes is an important characteristic of AF episodes. Although segmentation methods can be very accurate in the detection of most ECG fiducial points, it is observed that these algorithms tend to breakdown for the detection of P waves during AF episodes. To avoid these misclassification errors, a template based P wave detection approach is proposed. First a P wave model is extracted by averaging all annotated P waves found in the QT Database from Physionet. Let $\overline{P_{wave}}$ be the aforementioned model (see Figure 3) and let $P_{wave}(i)$ be the P wave under analysis. The existence of a P wave is assessed by (2) using the correlation coefficient between $P_{wave}(i)$ and $\overline{P_{wave}}$ (1).

$$cc(i) = \left| corrcoef\left(P_{wave}(i), \overline{P_{wave}}\right)\right|, i = 1, ..., n_{beats} \quad \textbf{(1)}$$

$$S(i) = \max(cc) - cc(i), i = 1, ..., n_{beats} \quad \textbf{(2)}$$

The rate of P waves in each window, equation (3), is accessed by relating the number N_S of selected P

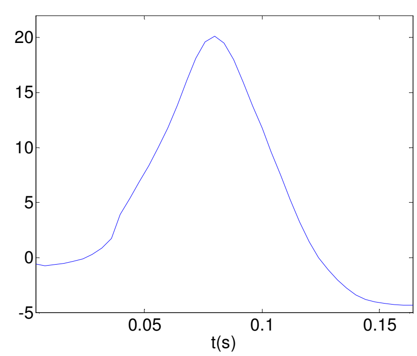

Figure 3. P wave model.

waves (P waves whose index S is greater than 0.2) and the number N_{CB} of cardiac beats.

$$R = \frac{N_S}{N_{CB}} \tag{3}$$

Heart rate analysis: The principal and most important objective of heart rate analysis is to access the variability/irregularity of the RR intervals.

Following the algorithm proposed by Moody *et al.* [3], the RR sequence was modelled as a three state Markov process (see Figure 4). Each interval is characterized as small, regular or long. Based on the transitions between states ($T_i, i = 1,...,9$), a transition probability matrix is derived, describing the cardiac rhythm. The regularity of heart rate is characterised by the probability of transition from state R to itself, since this transition is more likely to occur when the RR intervals present approximately the same length. This is the first feature applied in order to assess RR regularity.

Consider the matrix of transition probabilities as a probabilistic distribution $P(E_i, E_j) = P(E_i \mid E_j) \times P(E_i)$ where $\{E_1, E_2, E_3\} = \{S, R, L\}$.

Table 1. (Left) AF episode probabilistic distribution. (Right) Normal sinus rhythm probabilistic distribution.

	S	R	L
S	0,06	0,11	0,06
R	0,10	0,35	0,10
L	0,06	0,11	0,04

	S	R	L
S	0,01	0,02	0,01
R	0,01	0,91	0,01
L	0,02	0,01	0

In Table 1 the probabilistic distributions of an AF episode (left) and a normal rhythm (right) are presented. The high regularity of normal rhythms is represented by a dirak-impulse-like distribution centred in the transition between two regular states (R). In this kind of rhythm almost no transition between other states can be observed. On the other hand, when studying AF episodes, the presence of various RR interval lengths result in a flatter probabilistic distribution. Based on this observation the concentration/dispersion is assessed using the entropy of the distribution as described by (4).

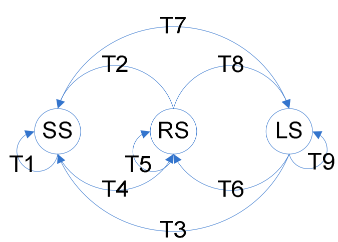

Figure 4. States and transitions of the HM model [3].

$$H = -\sum_{i=1}^{3} P(E_i) \times H(E_i) \tag{4}$$

$$H(E_i) = -\sum_{j=1}^{3} P(E_j \mid E_i) \times \log_2 P(E_j \mid E_i) \tag{5}$$

The specificity of the probabilistic distributions for both normal rhythms and AF episodes is also object of study. The objective is to determine the similarity between a probabilistic distribution under analysis and a model that represents AF episodes. Based on the MIT-BIH Atrial Fibrillation database, a model for the AF episode probability distribution (defined by $\overline{P_{AF}(x,y)}$) was extracted (see Table 1 (Left)). Using the *Kullback–Leibler* divergence (D_{KL}) the similarity between the distribution $\overline{P_{AF}(x,y)}$ and the distribution under analysis ($P(x,y)$) is evaluated. This feature is described by (6).

$$D_{KL}\left(P(x,y), \overline{P_{AF}(x,y)}\right) = = \sum_{x=1}^{3}\sum_{y=1}^{3} P(x,y) \log\left(\frac{P(x,y)}{\overline{P_{AF}(x,y)}}\right) \tag{6}$$

Atrial activity analysis: AF episodes are characterized by a fibrillatory wave with specific frequency between 4 and 10 Hz. To obtain a valid frequency domain characterization of AF episodes, the extraction or cancellation of the signal components associated to the ventricular activity (VA) is needed. That is, the QRS complex and the T wave are cancelled out.

For this propose, the methods reported by Senhadj *et al.* [6] and Sanchez *et al.* [7] has been the basis for our algorithm. The QRS-T cancellation is conducted in the frequency domain by excluding the values corresponding to the QRS-T segments and the values above a predefined threshold. This approach guaranties that the influence of miss-segmented QRS-T complexes in the cancelled signal is minimized. Spectral analysis is performed on the residual ECG signal using a Fast Fourier Transform. Once the frequency spectrum has been calculated, it is parameterized in order to find specific characteristics for AF episodes. The two main characteristics of AF episodes, observed in the frequency spectrums, are the level of concentration around the main peak and its position in the interval [4, 10] Hz. The concentration of each spectrum is assessed by calculating the entropy of each normalized cancelled ECG window spectrum.

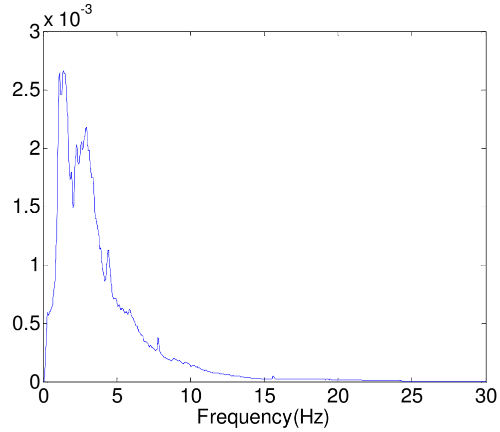

Figure 5. Normalized frequency spectrum model of an AF episode.

Based on the spectrums extracted from the MIT-BIH Atrial Fibrillation database, an AF specific spectrum model has been extracted (see Figure 5). Let $P(x)$ be the spectrum under analysis and $Q(x)$ be the aforementioned model. The similarity between $P(x)$ and $Q(x)$ is related to the likelihood of the time window under analysis to be an AF episode. This similarity is evaluated by the *Kullback–Leibler* divergence (D_{KL}) between the two distributions.

3. Results

3.1. Dataset and classifier

A set of 23 available records from the 25 MIT-BIH Atrial Fibrillation Database long term records were used for testing the proposed algorithm (two records have been excluded, since they are not available in the database). The records were collected from patients with Atrial Fibrillation (mostly paroxysmal). The recordings are each 10 hours in duration, two leads ECG, each sampled at 250 Hz.

The proposed classifier consists of a three layer (six-six-one) feed-forward neural network with sigmoid activation functions, trained with the Levenberg-Marquardt algorithm.

3.2. Classification results

To validate the proposed AF detection algorithm, 23 records from MIT-BIH Atrial Fibrillation were used (lead MLII). Respectively, 19161 and 29893 windows of 12 seconds, corresponding to AF and non AF episodes, compose the training dataset. Validation has been performed using all 23 dataset records (238321 and 59785 AF and non AF episodes, respectively). The results obtained by the proposed algorithm are presented in Table 2, along with the results present in the literature.

Table 2. Sensitivity (Se) and Specificity (Sp).*These values correspond to Positive Predictiveness (+P).

	Se (%)	Sp (%)
Proposed algorithm	93.8	96.09
Moody and Mark [3]	93.58	85.92*
Cerutti *et al.* [4]	93.3	94*
Tateno and Glass [5]	93.2	96.7
Shkurovich *et al.* [8]	78	92.65

3.3. Discussion

The proposed algorithm presents 93.80% and 96.09% of sensitivity and specificity, respectively (see Table 2). Moody and Mark [3] proposed an algorithm whose sensitivity is similar to the proposed algorithm. The use of P^+ to evaluate the correct detection of non AF episodes prevents a realistic comparison with the proposed algorithm. Tateno and Glass [5] algorithm achieved slightly higher specificity (+0.61%) however slightly lower sensitivity (-0.6%) than the proposed algorithm. Although this algorithm presents similar results with only one feature, the need of a 100 beat segment to classify each beat makes it unusable in real time detection of AF episodes. When comparing with the remaining algorithms, higher sensitivity and specificity have been achieved by the algorithm presented in this paper. It should be noted that the results reported by these authors are not only based on the MIT-BIH Atrial Fibrillation records, but also on individual patient records. These results outline the accuracy of the proposed algorithm, suggesting its reliability for the detection of AF episodes.

4. Conclusions

In this paper an algorithm for the detection of AF episodes was presented. The architecture used in the proposed algorithm, approaches the three main physiological characteristics of AF using a pre-defined model-based setup. The use of template based approaches, along with information theory concepts together with the simultaneous application of features related to the main physiological characteristics of AF were the main innovative aspects presented in the present paper. Experimental results revealed that the proposed algorithm presents overall better discrimination performance compared to the state-of-the-art methods reported in literature. Based on these evaluations, it is possible to conclude that the proposed architecture, while using features related to the main areas of AF detection research, can be the direction to solve some of remaining issues in the AF detection area. The algorithm is currently integrated into the Heart Failure Management concept of the MyHeart project, a large EU integrated project in the pHealth area, which will initiate soon its clinical trial using 200 patients. This will provide the opportunity to fine tune the algorithm, based on data collected using wearable ECG sensors.

5. Acknowledgments

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