Atrial Fibrillation Detection Algorithms for Very Long Term ECG Monitoring

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Abstract

In this paper, we describe two algorithms suitable for the detection of Atrial Fibrillation episodes in very long terms (weeks) ECG monitoring, were the need of on-board implementation requires the development of reliable but simple and easy-to-implement methods. The proposed algorithms are based on the extraction of simple geometric features from the histogram of RR prematurity and delta RR. On the MIT Atrial fibrillation database, the RR prematurity algorithm provides the following performances: episodes sensitivity (S) 91%, episode positive Predictivity (P+) 92%, duration S 93%, duration P+ 97%. For the delta-RR algorithm the results were: episodes S 92%, episode P+ 78%, duration S 89%, duration P+ 90%.

1. Introduction

The true incidence of asymptomatic Atrial Fibrillation (AF) in general population [1][2], and especially in patients undergoing curative interventions [3][4], is still unknown. Recently has been suggested that asymptomatic episodes may occur and significantly increase after catheter ablation of AF [5] and that symptoms-only based follow-up overestimate the success rate. Although random daily transtelephonic ECG transmission and Holter function of implantable devices suggest that a significant percentage of AF episodes are clinically silent (up to 20% in asymptomatic general population [1] and up to 50% in symptomatic AF patients [6]), only very long term (weeks or months) ECG monitoring will probably increase our knowledge in this field [5]. Therefore, there is the need for automatic, reliable detectors of clinically significant (lasting more than 2 minutes) but asymptomatic AF episodes. As these algorithms must be implemented on-board they should have low memory requirement and computational burden.

The idea to detect AF from the analysis of RR interval dynamics have been widely explored in the past. Different signal processing techniques were employed including evaluation of the autocorrelation function [7], the coefficient of variation [8], neural-networks or Markov models [9][10]. Recently, analysis of density histograms of RR and delta-RR (i.e. the difference between two consecutive RR intervals) have been also proposed [8]. These methods need the evaluation of some a-priori information such as transition probabilities for the Markov models, the training of neural network, or some 'golden-reference' density histograms.

In this paper, we describe two algorithms based on the extraction of simple geometric features from the density histogram of both RR prematurity and delta-RR (Δ_{RR}).

We developed the proposed algorithms on an home-made database including 25, 24-h Holter recordings of patients with AF and/or other atrial disturbances and we tested them on the MIT AF database.

2. Methods

2.1. Databases

To develop and test our algorithms we used 2 separate datasets. The development dataset was an home-made database including twenty-five, manually annotated 24-h Holter recordings of patients with AF and/or other atrial disturbances (iterative or multifocal atrial tachycardia, atrial flutter, frequent atrial premature beats or extreme respiratory arrhythmia). The records include 3 simultaneously recorded ECG leads sampled at 250 Hz.

A subset of 5 records (named Subset A throughout the text), that we considered particularly representative of the difficulties encountered by an AF detector, was selected for the very early development phase. In details, Subset A included the following records. Record #1: sinus rhythm with extreme respiratory arrhythmia and very frequent SVEB and SV Bigeminy (20% of the total QRS number); Record #2: Sinus Rhythm (SR) with iterative atrial tachycardia, accounting for 35% of the QRS; Record #3 and #4: stable AF with variable ventricular rate, from very low (night-time) to very fast; Record #5: SR with several episodes of parossistic AF (total AF time: roughly 4 hours).

Once defined the best setup on the development database, the algorithms performance was evaluated on the MIT AF database (www.physionet.org)[11].

2.2. Histogram analysis

We investigated two algorithms based respectively on histogram of RR prematurity and Delta-RR (Δ_{RR}). A set of geometric features was defined and extracted from the two distributions as described below.

Δ_{RR} histogram: The first step of both algorithms includes detection, timing and classification of QRS complexes. The sequence of RR intervals was generated, but only the Normal-to-Normal (NN) intervals were considered for successive analysis. Δ_{RR} histogram was build by considering the difference between two successive NN intervals. To synthetically characterize the histogram, only one geometric index was computed: we searched for the first empty bins on the right and on the left of the modal value and the difference between these two bins was taken as representative of the main distribution width (MDW) and used to discriminate between non-AF and AF distributions.

Prematurity histogram: The prematurity (P) of each NN interval was computed as the percentage variation from the current heart rate:

$$P(i) = \frac{NN(i) - NN_{mean}}{NN_{mean}} * 100$$

where $NN(i)$ is the actual NN and NN_{mean} is a running average of NN; NN_{mean} is calculated as the mean of the last n intervals, where n is shorter for rhythmic beats (fast update) and longer for premature or delayed beats (slow update). Prematurity directly provides a normalization for the current heart rate, accounting for the decrease of the interbeat variability at higher rates.

To characterize the prematurity histograms the following parameters were computed: i) number of non-empty bins (NEB); ii) main distribution width (MDW); iii) difference between mean and median and iv) geometric test of bimodality (i.e. searching for a secondary significant modal peak and computing the distance from the main mode). The last parameters were used to discriminate uni-modal from bi-modal distributions. They will be therefore indicated in the following as bimodality tests.

2.3. Rhythm Classification

Firstly, each histogram is labeled as representative of AF or not-AF rhythms. For the Δ_{RR} histogram the classification was only based on the analysis of MDW. Conversely, for the prematurity histogram a more complex rule was designed combining the various parameters with the information on the actual rhythm. Different decision rules and thresholds were defined for the detection of the onset and the offset of AF as explained in Table 1.

For both algorithms multiple distributions were obtained by 10 seconds shifting the analysis window along the records, thus reducing the detection latency. Because each 10 seconds-segment is analyzed several times (depending on the window length) in an evolving context, a score system was introduced to finally classify it as non-AF or AF period.

Table 1. AF vs. Not-AF rhythms transition rules

Stauts	*Rule*	*Outcome*
Not-AF	(MDW>S1 OR NEB>S2) AND ALL DIMODALITY TESTS=FALSE	AF
AF	(MDW<S3 OR NEB<S4) OR ONE DIMODALITY TEST=TRUE	Not-AF

2.4. Setup and validation

The first step of our developmental phase was the selection of the best time-window length (i.e. the duration in seconds of the ECG strip) used for histogram generation. The selection of the most appropriate time-window length is crucial to maximize the differences between AF and non-AF distributions. This critical parameter has been optimized using the Subset A of the development database and the MDW as the discriminant parameter.

For example, Figure 1 shows the MDW behaviour as a descriptor of the true non-AF (dark bars) versus the true AF segments (gray bars), calculated over the whole dataset A using both algorithms.

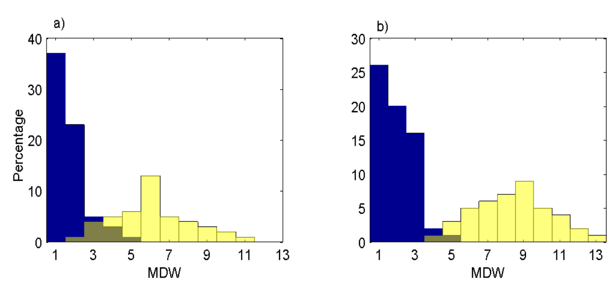

Figure 1 Distribution of MDW obtained for AF (gray bars) and not-AF (dark bars) rhythms. a) Δ_{RR} histogram and b) prematurity histogram.

The best time-window length is selected by searching the value that minimize the overlapping region. In Figure

2, the percentage of overlap is plotted as a function of the window length. Data refer to prematurity histogram. The minimum is obtained for a window length of 40 seconds.

The best window for Δ_{RR} histogram algorithm was found to be equal to 60 seconds.

Next, all records of the development database were used to assess the power of each geometric descriptor, taken individually, in differentiating non-AF from AF rhythms. For each of them the best preliminary threshold were defined. Since SR and AF, once established, tend to perpetuate themselves rather than to alternate frequently, the algorithms must be adapted according to the actual rhythm. Therefore, once AF is initiated the thresholds are adjusted in such a way to facilitate the perpetuation of the event, while detection of not-AF rhythm is made more restrictive to avoid frequent alternans of AF and not-AF rhythms. Finally, for prematurity histogram algorithm, multiple parameters (and hence multiple interdependent thresholds) must be set. These setup operations have been performed by iterative evaluations of the whole development database.

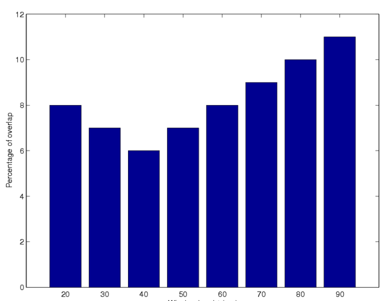

Figure 2. Percentage of overlap between the curves of Figure 1 as a function of time-window length. The minimum is located for window length of 40s (Prematurity histogram).

3. Results

The Δ_{RR} and the prematurity histograms obtained during different rhythms are shown in Figure 3 and 4, respectively.

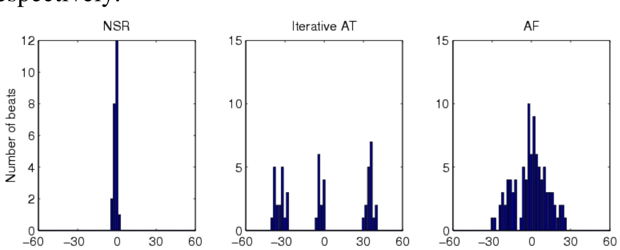

Figure 3. Δ_{RR} histograms obtained during Normal Sinus Rhythm (NSR) Iterative Atrial Tachycardia (AT) and Atrial Fibrillation (AF).

In these graphs differences in the distributions are evident: MDW is larger in AF than in not-AF rhythms and it is always unimodal. Larger distributions can be obtained also for non-AF rhythm (Atrial tachyarhhythmias), but the resulting histograms are often bi-modal.

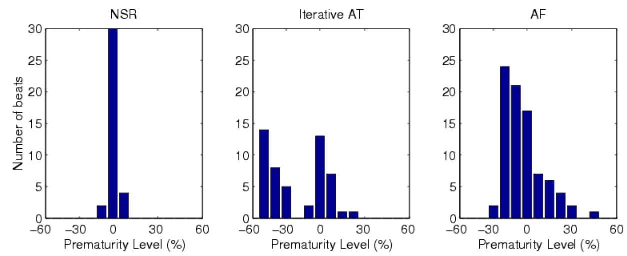

Figure 4. Prematurity histograms obtained during Normal Sinus Rhythm (NSR), Iterative Atrial Tachycardia (AT) and Atrial fibrillation (AF).

Performances of the two algorithms on the MIT AF database are reported in Table 2. According to our working hypothesis, in the evaluation of the performance only episodes longer that 2 minutes were included. We believe that shorter episodes are, in the context of a long-term monitoring, less relevant from a clinical viewpoint. In addition, the attempt to capture such short episodes may result in an undesiderable reduction of P+.

Table 2. Global results on the MIT Database

Algos		*Epi S*	*Epi P+*	*Dur S*	*Dur P+*
Δ_{RR}	Gross	92	78	89	90
	Aver	93	70	88	76
Premat.	Gross	91	92	93	97
	Aver	92	92	87	90

In the test phase, it is worth noting that we did not used the MIT database QRS annotations, but our own QRS detectors and classifier [12].

4. Discussion and conclusions

It is now well known that AF is frequently characterized by a variable spontaneous course [13] and that highly symptomatic and totally silent episodes may coexists in the same patient. Thus, in addition to a careful documentation of symptomatic recurrences, intensive long term monitoring is needed for accurate assessment of the true success rate of any treatment option, pharmacologic or ablative. This is more than an academic issue, since ongoing AF exposes to haemodinamic deterioration and make mandatory oral anticoagulation to prevent thromboembolic stroke [14].

Attempts have been made in the past to detect AF in long term ECG recordings, mainly because the underlying irregular rhythm make the arrhythmias diagnosis difficult or impossible. However, in this new scenario, automatic detection of AF is of clinical relevance, due to the need of quantify silent episodes recurrences in the follw-up.

In this paper we described and evaluated 2 algorithms of different complexity, designed to work in realtime in the setting of a very long-term rhythm monitoring.

From the electrocardiographic viewpoint, AF is characterized by: i) absence of P waves ii) irregularly fluctuating baseline and iii) widely irregular QRS timing. Because P wave and baseline analysis require a good and stable signal quality, difficult to obtain in long term real-time recordings, we focused our attention on RR intervals analysis. The basic idea was that, in well defined conditions, the totally irregular RR sequence of AF could be translated in a typical pattern of RR distribution, and that simple rules could be used to differentiate AF from other, non-AF rhythms.

The first step was to extract from the RR series an estimate of the short term (beat to beat) variability and to obtain distribution plots of these estimates (respectively Δ_{RR} and prematurity histograms). By visually inspecting these distributions, we found that AF, when observed on appropriate time-windows, is characterized by lower and wider, but still unimodal histograms than normal sinus rhythm or other sustained supraventricular arrhythmias.

The second step was to extract from the histograms simple (easy to calculate) geometric features to define the width of the histogram base, its height as well as some pattern descriptors of unimodal or multimodal distribution.

The philosophy behind the selection of the two algorithms was different. Δ_{RR} historgam was designed as simple as possible. In fact, it considers only one feature (the MDW) and a simple decision rule. In addition, for this simpler classifier, Δ_{RR} was preferred to prematurity to avoid divisions and the need to compute the mean RR. Computational efficiency rather than performance were optimized. Conversely, in the prematurity histogram algorithm, the complexity was increased either in the feature extraction (other parameters were considered with MDW) and in the implemented decision logic. In this case the discriminating power of the histogram was deeply stressed and performance were increased, with a only little expense in terms of computational burden. Our results show that the simpler Δ_{RR} histogram algorithm yields acceptable performance. However, the use of a more complex approach is justified by a significant performance increase, as shown by results of prematurity based algorithm.

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