The Use of Sequential RR Distributions to Detect Atrial Fibrillation Episodes in Very Long Term ECG Monitoring

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Abstract

The Sequential RR Distribution (SRRD) is introduced as a diagnostic tool for AF detection and classification. SRRD is obtained by computing consecutive RR histogram distributions in successive temporal windows and plotting them prospectically The validation of SRRD for AF detection was performed using the MIT AF database. A interactive graphic interface was developed to navigate in the SRRD and to manually annotate the onset and offset of the AF episodes. Two expert cardiologists were trained to evaluate the SRRD using an home-made database. They were asked to annotate AF events in the MIT database using RR distributions (without accessing the ECG). The results were: episodes sensitivity 97%, episode P+ 78%, duration sensitivity 98%, duration P+ 95%. These results show that sequential RR histogram distributions are accurate enough to allow the detection of AF events without the need of viewing the ECG signal.

1. Introduction

The true incidence of Atrial Fibrillation (AF) in patients undergoing curative interventions (left atrium RF ablation) is unknown. As a significant percentage of AF episodes are clinically asymtomatic [1], symptoms based follow-up overestimate the success rate [2] and the only way to assess the procedural outcome is a very long-term (weeks or months) ECG monitoring [3][4].

Current "loop-recording" technology allows the long-term ambulatory monitoring using small recorders able to store patient-selected ECG strips, thus documenting symptomatic events. Since these devices cannot store the full ECG signal, on-line AF detection algorithms must be implemented on board (prompting the storage of the ECG only when rhythm transitions occur) to assess asymptomatic AF occurrences. Algorithms perform AF detection by evaluating the ventricular response (VR) to the disorganized atrial activation. Different signal processing techniques are used, including the evaluation of the autocorrelation function [5], the coefficient of variation [6], neural-networks, Markov models [7][8] and the analysis of RR histograms [6][9].

Even if the use of automatic AF detection algorithm may provide information about the occurrence of AF episodes and their durations, the weak point of any algorithmic approach is that nothing is known about most of the monitoring time. In particular, information about normal sinus rhythms, triggering events or about time evolution of the AF event are commonly missed.

We postulated that the continuous storage of a synthetic descriptor of the RR series (in addition to automatically selected ECG strips), could overcome this problem and provide a clinically effective tool for AF characterization and diagnosis.

A synthetic, but fully informative, RR descriptor is the RR histogram distribution. Therefore we computed RR distributions in successive windows and we combine them to obtain the Sequential RR Distributions (SRRD). Aim of this work is the evaluation of the accuracy of SRRD as a detector of AF events.

2. Methods

2.1. Sequential RR Distribution

Sequential RR Distribution (SRRD) is obtained by computing consecutive RR histogram Distributions in successive temporal windows and plotting them prospectically. An example of SRRD is shown in Figure 1. SRRD contains temporal information which are lost in global RR histogram, allowing the detection and timing of significant rhythm changes. For example, episodes of atrial fibrillation may be easily detected because they are characterized by lower and broader distributions.

In this work RR histograms were computed using 500 bins (4ms binsize, 0-2000 ms range). Distributions of normal, aberrant and paced beats may be superimposed using different colors.

The selection of each distribution's temporal window is a critical parameter. The shorter the window the finer

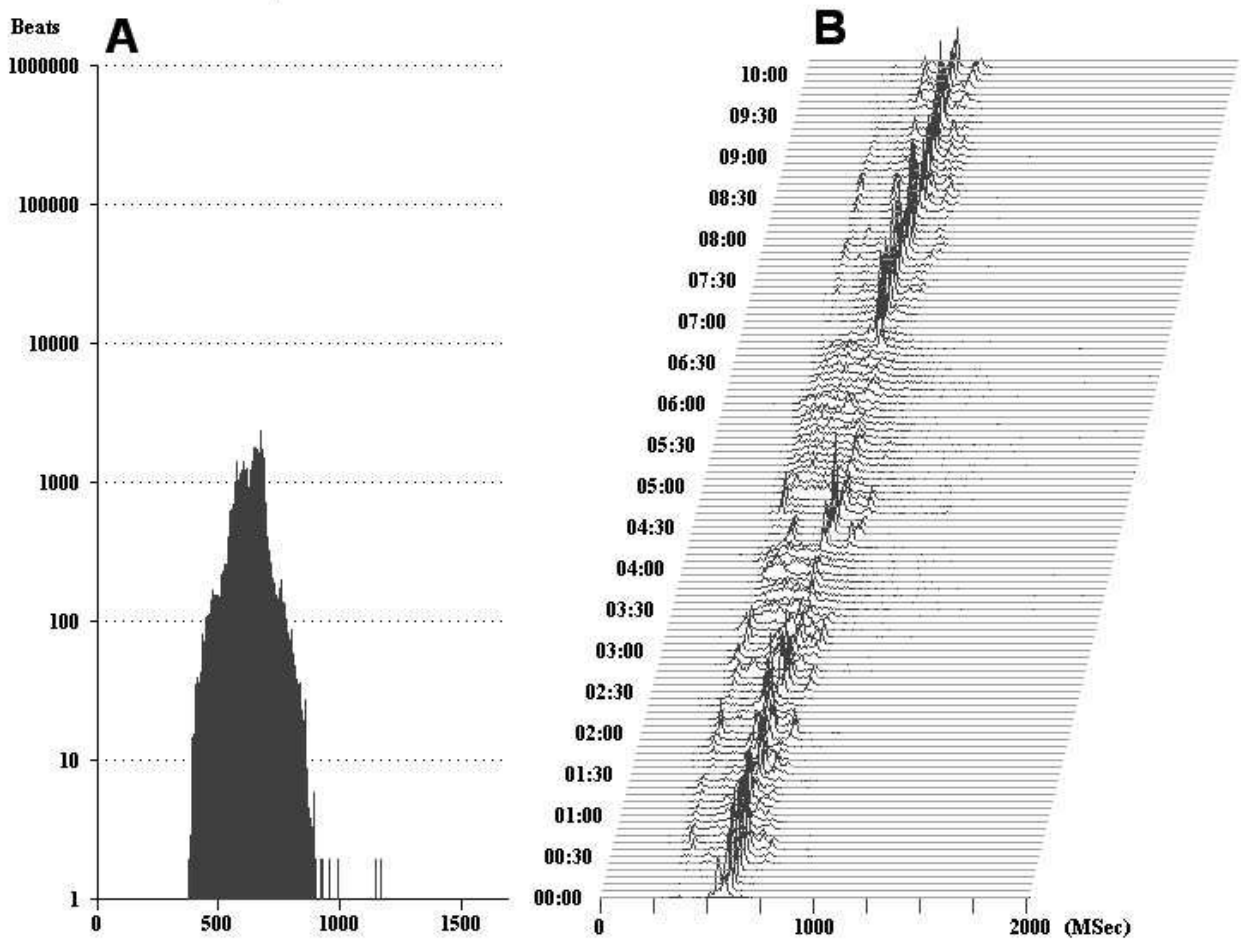

Figure 1. A: a single RR distribution is obtained from Record 8219 of the MIT AF Database, containing 10 hours of ECG: the time window is too long to provide diagnostic rhythm informations. The X axis represents the RR (or cycle length) in ms, while the number of occurrences is on Y axis (logarithmic scale). B: Sequential RR Distribution is obtained from the same Record. In this 3D plot, several episodes of AF (lower and broader distributions) are clearly evident. The longest is located between 05.00 and 07.00. A significant atrial ectopic activity during sinus rhythm, represented by multiple, early peaks is also evident. The X axis represents the RR duration (or cycle length) in ms, while the number of occurrences is on Z axis (scale not displayed). Time elapses from bottom to top, the time scale on the left side being provided in hours and minutes.

the description of the rhythm changes and larger the memory requirement. We empirically found that a 3 to 5 minutes epoch is a good compromise between diagnostic accuracy and memory requirements in most clinical settings. However, for the purpose of this validation we select a value of 1 minute, to detect unambiguously AF episodes lasting more than 2 minutes. Two consecutive windows were not overlapped.

In order to be able to build the SRRD the QRS detection must be performed. We did not use the QRS annotation provided by the MIT database, but those obtained by our QRS detectors and classifier [10].

2.2. Performance evaluation

To test the method we used 2 separate datasets. The *training* 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 [9].

The *test* dataset was the MIT AF database (www.physionet.org) [11], which includes 24 ECG recordings (duration 10 hours each, 2 ECG leads,

sampling rate 250 Hz, resolution 10 bit) annotated for AF episodes.

The performance evaluation was obtained by comparing the *true* annotation with our ("Test") annotation. The comparison was automatically performed using the "epicmp" freely available software [11], provided with the MIT Database, wich implements the AF episode-by-episode algorhitms specified by the current American National Standard for ambulatory ECG analyzers (ANSI/AAMI EC38:1998). The following performance evaluation indexes are generated: AF Episode sensitivity and predictive accuracy, AF Duration sensitivity and predictive accuracy.

Two expert cardiologists, which were unaware of the AF MIT signals were trained to evaluate the SRRD distribution plots using the *training* dataset. An interactive graphic interface was developed to easily navigate along multiple, perspectively plotted distributions and to annotate the onset and offset of the AF episodes. In the training phase, ECG traces were available to help annotators to associate SRRD shape to various cardiac rhythms.

The average time required by the annotators to get accustomed with the tool was about 2 hours. Then they were asked to annotate AF events in the MIT database using SRRD plots only (i.e. without accessing the ECG). Annotations were generated with a discretization related to the SRRD temporal window (i.e. 1 minute).

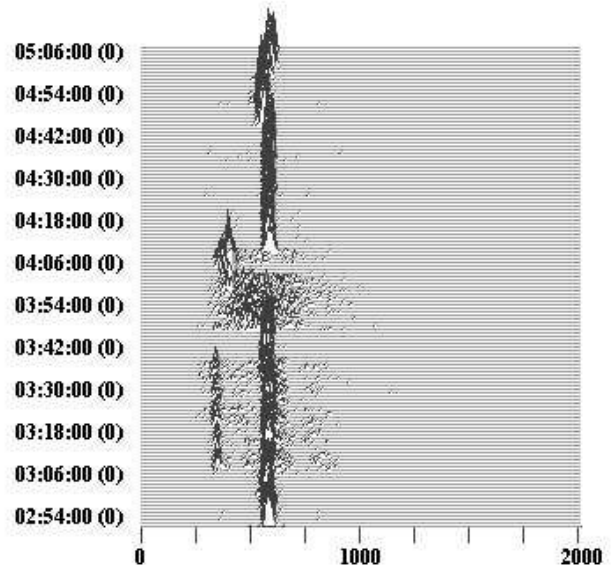

Figure 2. Example of SRRD during AF episode. See text for details.

3. Results

An examples of SRRD distribution is shown in Fig 2. The initial rhythm is sinus rhythm with a cycle length of about 600 ms. A few minutes later a new peak appears, indicating supraventricular ectopic activity. This peak disappears and, some minutes later a brief AF episode begins. The sinus rhythm restoration is preceded by a period of synchronized atrial tachycardia. Sinus rhythm restores (F), without any residual ectopic activity. Note the narrow sinus distributions, suggesting a reduced RR variability. This plot refers to Record 4908 of the MIT-BIH AF Database.

A second example is shown in Figure 3.

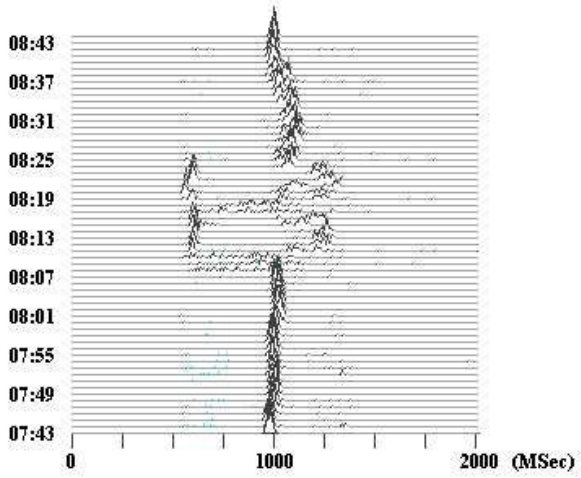

Figure 3. Example of SRRD during AF episode. See text for details.

In this case is shown an episode of atrial bigeminy (double peaks with 1:1 ratio) from 8:13 to 8:25. Two short episodes of parossistic AF (PAF) are also evident. This SRRD plot referes to record 6453 of MIT database.

The results of the test phase (as the mean of the results of the two annotators) on the whole MIT AF database are reported in Table 1. According to our working hypothesis, only episodes longer that 2 minutes were included, shorter episodes being, in the context of a very long-term monitoring, less relevant from a clinical viewpoint.

Table 1. AF detection Results

	Epi S	Epi P+	Dur S	Dur P+
Gross	97	88	98	95
Aver	99	83	98	89

4. Discussion and conclusions

In this paper we describe and evaluate a simple imaging technique to represent the RR variability in long term recordings: the Sequential RR histograms

distribution, obtained in successive, non overlapped windows (1 minute length). This method allows the generation of a tridimensional plot from which rhythm informations can be extrapolated. AF is characterized by a typical enlarged distribution, with variable shape, symmetric or asymmetric but usually unimodal.

In the setting of a very long-term rhythm monitoring the SRRD approach provides continuous, although not conventional informations, including the assessment of the precipitating events and the evolution of AF episodes. Our results show that, even with a limited training, this parametric technique has an excellent diagnostic power with respect to detection of AF episodes; the comparison of our results with literature data show that sensitivity is very good, while the lower positive predictivity (ie high false positive rate) is mainly due to the low discretization (1 min) of the method with respect to the short duration of AF episodes in some MIT AF Database records.

The RR distribution representation not only allows the immediate detection and timing of AF episodes, but also provides context informations often difficult to detect even by visual inspection of the ECG traces. These information include: i) sinus heart rate changes before and after the AF episode, well represented by fluctuations of the modal values of the RR distributions: most parossistic AF(PAF) episodes are, in fact, preceded by a reduction of HR, with a gradual shift to the right of the modal peak (longer RR); ii) Heart Rate Variability (HRV) changes before and after the AF episodes, represented by narrow (or large) distributions roughly indicating low (or high) HRV; iii) organized, sustained SV tachyarrhythmias preceding PAF onset or its termination (as in Figure 2) are easily detected; SV tachycardia is characterized by a single, narrow peak with short modal RR suddenly appearing in the graph; iv) the firing activity triggering the PAF episodes is evaluable if the foci's discharge is conducted to the atria and subsequently to the ventricles, thus affecting the RR interval. In the SRRD plots this pre-AF ectopic activity is represented by one or more discrete, usually growning peaks, associated with, but well separated from the sinus modal peak. The ratio between the height of the various peaks indicate the frequency of the ectopic discharge, with 1:1 ratio suggesting bigeminy . If beats are colour-coded, SV and Ventricular ectopies can be also differentiated.

In conclusion, tridimensional display of RR distributions is a synthetic, multiparametric view of a long term ECG recording, which allows a fast and selective review of the ECG trace while providing unique context informations. Some arrhythmias, namely AF episodes, show a typical pattern and in most cases the diagnosis can be made directly (whithout reviewing the ECG) with a high degree of confidence.

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