A Fast and Robust Time-Series Based Decision Rule for Identification of Atrial Fibrillation Arrhythmic Patterns in the ECG

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Abstract

Atrial fibrillation (AF) is an arrhythmic behaviour of the heart, which occurs when the myocardium of the atrial chambers enter into a sustained chaotic and fractionated muscular contraction dynamic. Reliable detection of AF episodes in ECG monitoring devices, is important for early treatment and health risks reduction.

A decision rule for identifying AF arrhythmic patterns was derived from RR-intervals analysis of time-series generated from ECG recordings before, during and after AF episodes. Time-series elements were obtained by consecutive RR intervals time differences (*Δ*RR). In the proposed decision rule, two arguments must be satisfied for identifying an AF pattern within a window of 35 beats: (1) the *number of Δ*RR elements above 50 ms absolute value, is >10, and (2) there is a uniform dispersion of all the corresponding RR-interval elements within the same 35 beat window.

Detection of AF using the proposed decision rule scheme was achieved with 96% exactitude, 93% sensitivity and 97% specificity. The longest case of processing time per ECG beat was of 129ms. This computing time requirement can enable real-time ECG processing algorithms for AF identification.

1. Introduction

Atrial Fibrillation (AF) is an arrhythmia that generates an accelerated and disordered heart rate, and the atrial chambers contract in an abnormal and chaotic manner. During an AF episode, aricular blood pumping into the ventricular chambers is inefficient and unsynchronized. Furthermore, during AF, also ventricular arrhythmia results from excitation pulses conducted into the ventricles irregularly or by non-conducted excitation pulses [1,2]. Among the various consequences of AF, there is a 30% reduction in the ventricular pumping efficiency, an increase in the heart rhythm between 125 and 150 beats per minutes, tachycardia or an irregularity of the ventricular rhythm, and finally, myocardial infarction caused by the formation of blood clots from non-circulating volumes of blood in the atrium chambers [1,3].

In this paper we present the design and performance evaluation of a decision rule scheme capable of identifying, in re-time, patterns of heart rhythm in the time-series of RR intervals (generated from consecutive time difference between an R-wave and the following one) in the ECG, for the study and reliable detection of AF episodes. Functionality and performance evaluation of the proposed decision rule scheme was carried out using two ECG databases available in the public domain: (a) the MIT AF Database, which has 25 AF patient cases of ECG recordings of 10 hour duration each, with a supporting annotation file of AF event start and end; (b) the MIT Arrhythmia Database, which has 48 cases of ECG recordings, each on being of 30 minutes duration. From the latter database, only 10 cases were randomly selected and used in our study; each patient 30 minute ECG recording presenting arrhythmic episodes of diverse types, and in some of them there are short AF episodes.

2. Methods

RR interval time-series and their graphic representations are very useful tools in heart rate variability studies; from normal sinus rhythm studies to cardiac pathologies which produce alterations to this rhythm. This time-series is uniquely constituted by consecutive RR interval elements obtained from the time difference in seconds which there is between two adjacent R waves along the positive time direction of an ECG. Figure 1 graphically illustrates how the time difference elements (RR interval), numbered from 1 to n, are obtained along an ECG; and in table 1, the corresponding numerical RR interval time-series is presented.

The graphical representation of these time series generates a cloud of points in the 2-dimensional (2-D) plane of beats vs. RR-interval (in seconds). From these graphs, we can observe the cardiac rhythm patterns, either from a healthy heart sinus rhythm or from a heart presenting an arrhythmic pattern. Figure 2 illustrates an example 2-D graphic representation of a time-series from and ECG with an AF episode.

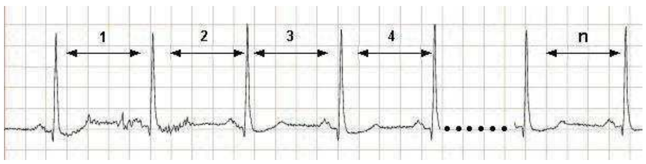

Figure 1. Graphical illustration of elements 1, 2, 3, …, n, in the RR interval time-series.

Table 1. Time series of RR intervals in seconds, corresponding to figure 1.

Interval RR1	**Interval RR2**	**Interval RR3**	**Interval RR4**	**Interval RRn**
0.93 s	0.90 s	0.92 s	0.97 s	0.99 s

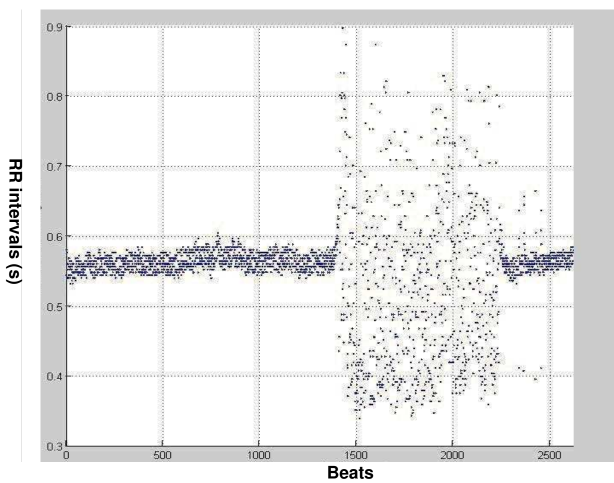

Figure 2. Graphical representation of a RR interval time-series with an AF episode (MIT AF Database, Patient 04043. dat).

By observing a considerable number of ECG recordings from patients with AF, we generated the following set of **basic criteria** for the development of a decision rule scheme for the identification of AF arrhythmic patterns in the ECG, using a processing window of N beats:

1- Determine the longest and the shortest RR interval. The difference between the maximum and the minimum values is named ΔRRmax, in seconds.
2- The dispersion of the points (RR intervals), can be considered to be quite uniform, so we can assume that there will not be a clear space greater than ΔRRmin seconds.
3- There will be at least M time differences between an RR interval and the next greater than 0.05 s, where M is approximately a 30% of N.
4- The uniform dispersion of the points (RR intervals), allows the detection of AF, and at the same time, discard other types of arrhythmias, such as the cases of arrhythmias 2:1, 3:1 and 4:1; as their RR interval time-series graphical representation would produce a saw tooth type of graphic, leaving clear spaces greater than ΔRRmin seconds in the graphic, and this behavior does not occur during AF episodes. This important characteristic allows the creation of an algorithm structure that could reliably detect the saw tooth occurrences and classify them as non AF, thus helping to minimize the generation of false positives and false negative.

After setting these defining criteria we proceeded to design the supporting software to process ECG signals for the proof of concept of the above set of criteria. All the software was developed and implemented using Matlab version 6.5. The computer used for this study was an AMD Athlon of 2.4 GHz, with 512 MB RAM memory and 512 K of cache memory. In general, the processing stages are as follows:

- Acquiring de ECG signal
- Digital filtering
- QRS detection
- RR interval time-series generation
- Detection of AF

Digital filtering was oriented to facilitate de reliable detection of QRS complexes, leading to the generation of the RR intervals time-series. For this, a digital band-pass Butterworth filter of 3-30 Hz was used for the ECG signal conditioning requirement prior to the QRS detection process.

QRS detection was carried out in several stages. First, the derivative of the band-pass filtered signal is computed, then the absolute value of the resulting signal is operated, and finally, the highest peaks of this are compared with an adapting threshold value [4].

Once obtained the RR intervals time-series, a graphic representation of this was studied. After a detailed and meticulous observation of these graphic representations, recording by recording in both the MIT AF Database and the MIT Arrhythmia Database, four decision rules were hypothesized. The processing is performed on a window of 35 beats, which is shifted forward beat by beat, and the following decision rules processes are performed:

1- Every time the window is shifted a search is carried out among the 35 RR intervals in the window and the longest and shortest RR values are noted. If the difference between these maximum and minimum RR values is greater than 0.15 s, the processing continues to the next decision rule, otherwise the window is shifted forward by one beat, and the search is repeated on the new 35-beat window.

2- Having detected such a time difference (> 0.15 s), a dispersion test is carried out on the points (RR intervals in the beat-RRinterval plane). This is implemented by counting how many time differences are greater than 0.05s in adjacent RR intervals, within the window being processed. If the count reaches or exceed 10 differences greater than 0.05 s, the process continues to the next decision rule , otherwise the window is shifted forward and the search in step 1 above is repeated.

3- Finally an arrhythmia test is carried out in order to reject type 2:1, 3:1 and 4:1 arrhythmias. These arrhythmias produce graphic representations with saw tooth shapes, and leave time spaces greater than 0.1 s, a situation that does not occur during an AF episode.

It is worth pointing out that the above explained decision rules based process for AF pattern identification, was evaluated under four different schedules of window (35 beats) stepwise shifting: 1-beat step, 2-beat step, 5-beat step and 35-beat step, in order to analyze and find which stepwise shifting schedule was most efficient from a processing time point of view.

3. Results

The parameters used to evaluate the degree of accuracy and reliability of the proposed decision rule scheme use as input values the beats that are true positive (TP, beats within an AF episode), true negative (TN, non-AF beats), false positives (FP) and false negatives (FN). The following parameters were evaluated in each particular ECG recording of the database: **exactitude**, expressed in percentage of the division of the sum of correctly detected AF beats (TP+TN) by the sum of all the beats (TP+TN+FP+FN), provides a measure of the precision of the algorithm; **sensibility**, expressed in percentage of the division of all true AF beats (TP) by the sum of TP + FN, provides a measure of the capacity of the algorithm to detect AF; **specificity**, expressed in percentage of the division of all non-AF beats (TN) by the sum of TN + FP, provides a measure of the capacity of the algorithm to confirm the non-presence of AF episodes in the ECG. Table 2 shows the parameters figures obtained in a particular study with the 25 ECG recordings in the MIT AF Database; for the case when the processing window was shifted by 1-beat steps (i.e., beat by beat).

Similar studies of the algorithm performance using the above parameters were carried out for the following different cases of processing window shifting: 2-beat steps, 5-beat steps and 35-beat steps. This task was done in order to find which particular shift stepwise for the processing window was most efficient, for both the MIT AF Database and the MIT Arrhythmia Database. The averaged overall results using both databases for the particular case of processing window shifting by 1-beat steps, are shown in table 3.

Table 2. AF detection performance of the proposed decision rule scheme, using 1-beat stepwise window shifting, for the 25 recordings in the MIT AF Database.

AF detection input values: figures are in number of beats MIT AF Database				
ECG #	**TP**	**TN**	**FN**	**FP**
00735	292	39835	40	14
03665	10582	41412	475	244
04015	461	40778	64	2650
04043	11003	47140	3631	89
04048	402	38987	411	82
04126	2693	38509	600	1006
04746	29991	16773	882	175
04908	5573	55615	237	283
04936	31737	13556	7944	357
05091	69	34882	1512	278
05121	28334	16253	1435	3807
05261	432	43965	502	583
06426	51489	1385	1595	634
06453	278	33901	167	439
06995	26993	26003	481	1660
07162	35689	0	3557	0
07859	50409	0	9824	0
07879	39892	15972	143	535
07910	6697	29112	23	715
08215	32312	9855	768	369
08219	13393	43225	801	1822
08378	1522	39714	433	3794
08405	43821	13295	1224	464
08434	2206	36822	104	666
08455	43771	14934	443	352
TOTAL	**470041**	**691923**	**37296**	**21018**
Calculated parameters figures:				
Exactitude= 95.2%	**Sensitivity= 92.7%**	**Specificity= 97.1%**		

Table 3. Average overall performance of the decision rule scheme using both the MIT AF Database and the MIT Arrhythmia Database, for 1-beat stepwise window shifting.

Parameter	Calculated Value (%)
Exactitude	96
Sensibility	93
Specificity	97

4. Discussion and conclusions

This research and development work demonstrated how the diagnosis of AF by means of RR intervals time-series analysis can be implemented in an effective way, as also other recent investigations have demonstrated [5,6]. The obvious advantage of detecting AF only by means of the RR intervals data sequence, is that a high resolution ECG signal is not required for reliable algorithm performance. In the two MIT ECG databases used, sampling frequencies are 250 Hz and 360 Hz, thus, a large volume of data handling was not involved. With regard to the processing time required by the proposed algorithm, it can be reported that it was able to process a 35-beat window (the longest window considered) in approximately 129 ms, which is an acceptable processing time for enabling the decision rule scheme to run in any of its different modes of window width (1, 2, 5 and 35 beats), as during the whole study with both ECG databases, there was no RR interval below 129 ms; and in general, such a RR interval is unlikely to happen in the human heart, as this would imply an extremely high heart rate of about 480 bpm. We examined both ECG databases used and found that the minimum RR value in them is about 200ms. The mean RR value for the MIT AF Database is 0.735 s, and in the MIT Arrhythmia Database, it is 0.825s. Therefore, having a longest processing time case of 129 ms, which compared with the minimum and average RR values in both ECG databases and the fact that a relatively below-average performance specification laptop computer was used during the study, the proposed decision rule scheme can be adopted for real-time implementable algorithms for the detection of AF with reasonably good accuracy and reliability, as reflected by parameter values in table 3.

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