

Paper Title* (use style: *paper title*)

Atrial Fibrillation Onset Prediction Using Variability of Electrocardiographic Signals

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which the records were excerpted or at any other time. The length of these records is 30 minutes.

TABLE I. THE DATA BASE USED FOR PAF PREDICTION

Learning set			Test set
non-PAF recordings	PAF recordings		
	Pre-PAF areas	Non-PAF areas	
99	50	50	198

I. INTRODUCTION

Worldwide a large number of both clinical and theoretical studies have been conducted on the subject of paroxysmal atrial fibrillation (PAF), which is defined as short duration episodes of AF lasting from 2 min. to less than 7 days, while chronic AF is defined as lasting more than 7 days. The main reason for this is not the immediate effect of the onset of atrial fibrillation over the patient’s health (AF detection) but the long-term effects: increased risk of cardiac mortality, associated respiratory problems, increase in heart muscle fatigue, increase in thromboembolic and stroke events, etc.

II. DATABASE AND METHODS

The database used for this study was PAF Prediction Challenge Database 2001 from Physionet.org portal [24], mainly its long-term version [25]. The facilities offered by this important data base of ECG recordings are presented in [26], [5]. Each record contains two simultaneously recorded Holter ECG signals, V1 and II leads, digitized at 128 Hz with 12-bit resolution over a 20 mV range. This is an automatically annotated database and consists of 3 types of record sets. The first record set which has records that begin with the letter “n” comes from 50 subjects who do not have documented atrial fibrillation, either during the period from

In order to accurately detect *R* peaks in the ECG signal some *preprocessing steps* are necessary. In this way, false or missed peaks that appear due to noise or artifacts are corrected. Also, ectopic or supraventricular beats have to be removed. We have used an automated preprocessing technique – the “20% filter”, in which *RR* intervals differing more than 20% of the previous interval are replaced by the average value of the 5 preceding and 5 following intervals.

The SDANN indicator is determined using the formula:

$$SDANN = \sqrt{\frac{1}{N} \sum_{i=1}^N (\overline{RR}_i - \overline{\overline{RR}})^2} \text{ [ms]} \quad (1)$$

where \overline{RR}_i is the mean of *RR* intervals in “*i*”-th 5-minute window, $\overline{\overline{RR}}$ is the mean of all means of *RR* intervals in all 5-minute windows, and *N* is the number of analysis windows.

The LF/HF ratio or Sympathovagal balance Index (*SVI*) (2) is the ratio between the low frequency (0.04 Hz–0.15 Hz) and high frequency (0.15 Hz–0.4 Hz) total power components of the *RR* time series. They are obtained by applying the Fourier Transform to the ECG signal and this was done using the HRV analysis software available on physionet.org .

$$HRV_{-LF/HF} = \frac{\text{(Power between 0.04 and 0.15 Hz)}}{\text{(Power between 0.15 and 0.4 Hz)}} \quad (2)$$

The second analysis is based on a newer signal processing method named *morphologic variability (MV)* [18], which highlights the underlying physiological activity of the heart. First, as a preprocessing stage, this method uses *dynamic time-warping technique (DTW)* which is mostly used in voice pattern recognition [28]. The need for DTW of ECG signal comes from the fact that a reliable algorithm has to compute the *energy changes* between consecutive beats, not only differences in amplitude or time axis.

The used algorithm aligns the current QRS complex to the previous two and the next two complexes, then determines the difference between the lengths of each consecutive QRS complex in order to obtain the *morphological difference (MD)* time series:

$$MD = |QRS_{i-2} - QRS_{i-1}| + |QRS_{i-1} - QRS_i| + |QRS_i - QRS_{i+1}| + |QRS_{i+1} - QRS_{i+2}|, \quad (3)$$

where QRS_i is the length of the QRS complex of the i beat.

In this way, the technique described here measures changes in morphology resulting from both amplitude and timing differences between two beats and transforms the original ECG signal from a sequence of beats to a sequence of energy differences. This new signal, comprising pairwise, time-aligned energy differences between beats, is then smoothed using a median filter of length 8.

III. RESULTS

For the training set, as well as for the test set, we have used first the HRV software and computed two indicators: HRV_SDANN and HRV_LF/HF. Then, by means of an algorithm implemented in Matlab® 2008, we computed the morphologic distance between QRS complexes, we obtained morphologic variability (MV) and computed similar parameters: MV_SDANN and MV_LF/HF. The sampling frequency of 128 Hz was enough for the purposes of the study, as we mainly computed RR and QRS intervals, not the exact morphology of the ECG signal. Also, as we studied a prediction method of the AF onset, not an analysis technique of PAF signal, the small 2-5 minutes episodes of AF have no relevance for our study and the obtained results.

A t -test for the parameters of HRV and MV, for the “n” recording set (characterized by a normal ECG signal) and for the „p” set (with PAF), was performed. At this stage we determined confidence intervals for the mean value, for a confidence level of 99% and $p=0,01$.

The t -test results given in Table II show that both „n” set and „p” set do not contain data significantly different from the reference value (mean value). Moreover, for a value $p=0,01$ lower and upper confidence level are specific for each type of HRV or MV indicator, both for normal and pre-PAF ECG signals. The „t” test set from Physionet contains 142 “normal” recordings (without PAF episodes) and 56 recordings with PAF.

IV. CONCLUSION

In this study we have emphasized the synergistic combination of two different automatic prediction methods of PAF, one of them usually used – HRV analysis – and the other – a new technique for surface ECG analysis: morphologic variability (MV) of QRS complexes. Some efficient preprocessing methods, of which the dynamic time-warping (DTW) has a major role, assure better results than those obtained with HRV alone. The experiments emphasized the main and new outcome of our study, that MV is a reliable electrocardiographic risk stratification measure to predict atrial fibrillation onset. In this respect, the experiments demonstrated that low levels of the MV_LF/HF measure are significantly associated with a higher risk of atrial fibrillation.

Also, the experimental work revealed a better accuracy provided by MV in comparison with HRV method. When using both methods and a decision support module, the accuracy of prediction is the best, of about 90%, comparable with the best results in the literature, which were obtained by using special recordings and more complex and time consuming methods. Our method has the main advantage that uses usual Holter recordings and the analysis is a short-term one (on a 5-minute window from 30 minutes total interval).

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