# Predicting atrial fibrillation termination using ECG features, a comparison

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***Abstract* - In this study, surface ECG recordings have been used to accomplish a non-invasive method which can predict spontaneous termination of Atrial Fibrillation (AF) and discriminate terminating (T) and non-terminating (N) AF episodes. The data set was provided by Physionet including holter recordings of 50 patients (20 training and 30 test sets). Concerning that most relevant information about the AF exists in the atrial fibrillatory wave, Several spectral and time-frequency parameters were extracted from the ECG signal after canceling the QRST complex. Also a temporal feature, RR interval variation, representing the ventricular activity was calculated. These parameters were evaluated using a scattering criterion with the purpose of selecting best features. The performance of our method was assessed using a Linear Discriminant Analysis (LDA) technique to classify the N and T groups. The result revealed accuracy of 100% for both training and test sets which shows a significant improvement in comparison with previous studies.**

***Keywords* – atrial fibrillation, ECG, non-invasive arrhythmia, cancellation, non-terminating, terminating**

## I. INTRODUCTION

Atrial Fibrillation (AF) is the most common human cardiac arrhythmia. It is responsible for about one third of hospitalizations for arrhythmia problems [1]. Most often atrial fibrillations are classified in 3 forms including Paroxysmal AF (PAF) which is terminated spontaneously, Persistent AF in which the atria fibrillates more than 7 days or until intervention, and Permanent AF (non-terminating) [2]. PAF can be a precursor of sustained AF that requires a pharmacological or external electrical cardioversion to terminate. Risks of sustained AF are hemodynamic impairment and thromboembolic events. Thus distinguishing between paroxysmal and sustained AF may lead to a better understanding of the mechanisms of AF termination and an improved treatment for AF. Also the cost associated with useless therapeutic treatments and hospitalizations are reduced.

Aim of this study is to develop a non invasive method using surface ECG signals to investigate characteristics of both atrial and ventricular electrical activity and consequently predicting the spontaneous termination of AF. In this way we extracted a set of spectral, time domain and time frequency features. Then to evaluate the features we used a scattering criterion to select those ones that best distinguish the terminating and non-terminating groups.

## II. MATERIALS

Physionet provided free access to 50 one minute ECG recordings extracted from 24-hour holter recordings from 50 different patients, which are available through physiobank [3]. This database includes non-terminating AF (group N), which were observed to continue for at least one hour and AF terminating immediately after the end of the extracted segment (group T).Ten labelled recordings of each group were supplied as a learning set. The remaining 30 recordings were provided as the test set.

## III. METHODS

### *A. Preprocessing*

We first applied a moving average filter of order 5 to the signal that contains high frequency and low frequency components. The filter suppresses high frequency noise like muscle noise. Then, high pass filter removes drift from resulting signal with a cut off frequency of 1 Hz. Finally, a low pass Butterworth filter with a limiting frequency of 30 Hz is applied to the signal.

### *B. QRS detection*

We used the Lai et al [4] method which is based on the first derivative of the ECG data to detect QRS complex. Let X(n) represents the amplitude of the ECG data at discrete time n. The slope of the ECG waveform is obtained by

$$slope(n) = -2\mathrm{X}(\mathrm{n}-2) - \mathrm{X}(\mathrm{n}-1) + \mathrm{X}(\mathrm{n}+1) + 2\mathrm{X}(\mathrm{n}+2) \quad (1)$$

$$slope\_thresh = \frac{thresh\_param}{16} * \max i \quad (2)$$

When two consecutive ECG data satisfy the condition that slope(n) > slope_thresh, the onset of the QRS complex is detected. The parameter thresh_param can be set as 2, 4, 8 or 16. After the detection of the onset of the QRS complex, the height of the onset is taken as the minimum. The maximum point following the onset is taken as the R point. The maximum (max *i*) is then updated by Equ. (3) as shown below which incorporates an one-pole filter to smooth out the effect of any abrupt change.

$$\max i = \frac{first\_\max i}{filter\_param} + \max i \qquad (3)$$

$$first\_\max = height\ of\ R\ point - height\ of\ onset \qquad (4)$$

The parameter filter_param can be set as 2, 4, 8 or 16 [4].

*C. Cancellation*

In order to well characterize the AF we need to analyse the atrial fibrillatory wave (FW). For this aim we used morphological classification and average beat subtraction to extract the residual ECG (rECG), i.e. FW, in which the ventricular activity, the QRST complex, is cancelled [5, 6].

*D. Feature Extraction*

As we mentioned above we selected features from rECG in frequency and time domain and also a time-frequency parameter.

*1) Spectral analysis:* Frequency analysis was applied to rECG using the Welch methods (Hanning window: 128 points, overlap: 32 points and zero-padding: 512 points). Then we computed some features which were used in earlier studies including: main peak frequency ($f_p$), bandwidth (BW) and spectral concentration (SC) [1, 7, 8, 9].

In order to obtain more precise feature we dissected each 1 min ECG signal into 6 sub-segments each of which containing 10 sec. Fourier analysis was used to calculate the peak frequency in the 3-9 Hz band of each sub-segments and the average value of the 6 contiguous sub-segments was obtained and assigned as the peak frequency for that ECG segment.

Spectral band width (BW) was calculated as the width of main spectral peak at 75% of its maximum amplitude.

Spectral concentration is a point where the spectral density function has a local maximum.

*2) RR interval:* In AF the loss of synchronicity between the atria and the ventricles leads to large variations in the interval between ventricular beats. Given the hypothesis that termination of AF is preceded by organisation of the atrial rhythm, this may be reflected in more stable ventricular activation which can be measured by the inter-beat spacing or RR interval [10].

Intervals between ventricular beats were calculated from the row ECG. A time domain parameters were computed from the RR interval data which is called ΔRR. Figure (1) shows a typical 1 min ECG signal and its associated RR peaks and ΔRR.

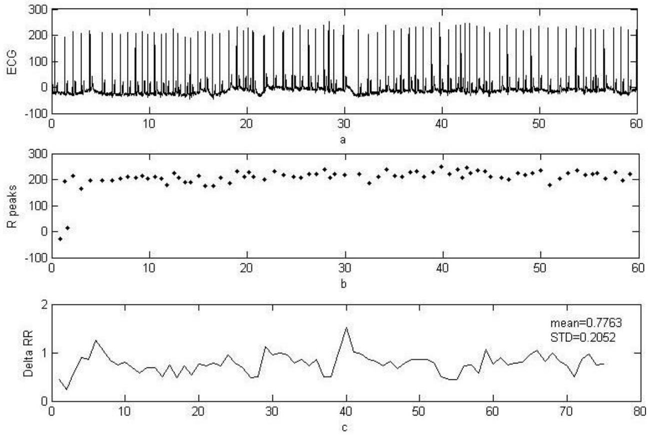


Fig. 1 Patient n01 (from non-terminate group) (a) 1 min ECG data, (b) R peaks and (c) ΔRR.

*3) Time-frequency analysis:* Spectral analysis cannot reflect the temporal variations of atrial fibrillation. Subsequently, we used time frequency features to investigate short time variations in rECG. The residual signal were analysed by Short Time Fourier Transform (STFT). A Gaussian window of 2 s was used, the power spectra were averaged over time discarding 10% percentiles and two features from resulting spectrum, in the band 3-10 Hz, was found: Instantaneous main frequency ($f_m$) and Instantaneous secondary frequency ($f_s$) [8,11].

*E. Feature Selection*

In order to reduce the complexity of feature space for online applications we intended to choose best features.

Generally, two methods are used in evaluation of features: applying features onto the classifier, and evaluation of the feature space by statistical criteria. The first method is dependent on the classifier type (neural network, statistical classifier, neuro-fuzzy classifier, etc) while the second one is not problematic in this sense. It tries to quantify the suitability of the feature space straightforwardly, and directly addresses the issue of class separability in the feature space.

We employed the second method using a scattering criterion. The most important advantage of this method is that can asses all clusters simultaneously. In order to calculate a formula that offers this criterion, first, the covariance matrix of between cluster means is determined and then the covariance matrix of the classes is determined. To achieve the value of the scattering criterion, the trace of covariance matrix of between cluster means is divided into the trace of the summation of the covariance matrix of all classes [12]. We defined the matrix as follows:

$$S_w = \sum_{i=1}^{k} p_i E((x-m_i)(x-m_i)^T). \qquad (5)$$

$S_w$ is the covariance matrix of all classes in which $m_i$ is the mean of the $i^{th}$ class and x is the sample vector.

$$S_B = \sum_{i=1}^{k} p_i (m_i - m_{mean})(m_i - m_{mean})^T). \qquad (6)$$

$S_B$ is the covariance matrix of between-classes means in which $m_{mean}$ is the mean of all classes' means. Finally, the value of the scattering criterion is calculated as

$$J = trace(S_w)/trace(S_B) \qquad (7)$$

It is obvious that the quality of the space feature will improve when the value of the criterion decreases [12].

## IV. Results

For each feature mean and standard deviation were calculated over the training sets related to group T and N. Table 1 illustrates that $f_p$ obtains more distinct values in relation with other spectral features. It is obvious from the table that $f_p$ decreases moving from non-terminating to terminating class. This suggests that slowing of fibrillatory frequency may be a potential indicator of spontaneous termination of paroxysmal AF (self-terminating).

Time frequency parameters ($f_m$, $f_s$) are also far enough in different classes which may yield to good discrimination results. Moreover, the single temporal feature, RR, which is representative of ventricular activity, takes separate measures over classes.

Table1. Feature values (mean±std) over training sets

| Feature | Group T | Group N |
|---|---|---|
| $f_p$ | 4.94 ±0.49 | 6.52±0.58 |
| *BW* | 2.6±0.79 | 2.4±1.01 |
| *SC* | 0.49±0.09 | 0.5±0.1 |
| $\Delta RR$ | 0.53±0.21 | 0.73±0.29 |
| $f_m$ | 5.1±0.32 | 6.51±0.54 |
| $f_s$ | 5.3±0.3 | 6.9±0.63 |

We imposed all of the above mentioned features into the scattering criterion to find out which can best distinguish non-terminate and terminate classes. It is obvious from table 2 that peak frequencies which are obtained from both spectral and time-frequency analysis well discriminate the classes. Peak frequency ($f_p$) has the lowest value and consequently is the best feature. Instantaneous main ($f_m$) and secondary ($f_s$) frequency values are also remarkable.

In order to study feature vectors the scattering criterion was determined for pair features. Table 3 shows the subsequent values.

Table2. Scattering criterion for different features

| **Feature** | ***fp*** | ***RR*** | ***BW*** | ***SC*** | ***fm*** | ***Fs*** |
|---|---|---|---|---|---|---|
| **Scattering criterion** | **0.0489** | 0.0965 | 0.1446 | 0.0847 | **0.0510** | **0.0772** |

Table3. Scattering criterion for pair features

| **feature** | ***fp*** | ***RR*** | ***BW*** | ***SC*** | ***fm*** | ***fs*** |
|---|---|---|---|---|---|---|
| ***fp*** | - | **0.021** | 0.030 | 0.055 | 0.050 | 0.052 |
| ***RR*** | **0.021** | - | 0.108 | 0.090 | 0.026 | 0.028 |
| ***BW*** | 0.030 | 0.108 | - | 0.311 | 0.038 | 0.044 |
| ***SC*** | 0.055 | 0.090 | 0.311 | - | 0.060 | 0.068 |
| ***fm*** | 0.050 | 0.026 | 0.038 | 0.060 | - | 0.058 |
| ***fs*** | 0.052 | 0.028 | 0.044 | 0.068 | 0.058 | - |

As it can be observed some of feature vectors show superior behavior in comparison with single ones. $f_p$ -RR which showed the most significant value in this evaluation was selected as the pair feature and feed to our Linear Discriminant Analysis (LDA) classifier.

LDA partitions the feature space into the different classes using a set of hyper-planes. Optimization of the model is achieved through direct calculation and is extremely fast relative to other models.

We trained our classifier with the 10 labeled signals for N (non-terminate) and T (terminate) group. These learning sets were plotted in a plane with the averaged RR and fp on x and y axis respectively. A linear classifier was applied and the two half-planes were separated by a straight line.

Then, we assessed the classification performance by applying both training and test sets separately. The classification accuracy was 100% for both training (20/20) and test (30/30) which showed a great improvement in comparison with previous studies.

## V. Conclusion and Discussion

In this study we inspected different features (single ones and vectors) and evaluated their performance in distinguishing between terminate and non-terminate groups using a scattering criterion. Both ventricular and atrial activities were taken into account. It was demonstrated that peak frequency in according with ΔRR can well discriminate between these classes. Time-frequency parameters were also extracted to assess short term information in the residual ECG. Our presented technique could completely predict termination of AF fibrillation. As well as the presented feature selection method, the ventricular activity cancellation seems to be very fundamental in the processing procedure. The applied cancellation technique in this paper offers satisfactory results.

However, further studies on extended datasets are necessary to validate the clinical application of our proposed method in order to optimize therapeutic treatments. This study reflects that noninvasive techniques utilizing ECG analysis may lead towards the development of improved therapeutic interventions for the treatment of AF.

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