

Adaptive Frequency Tracking on the ECG Used to Predict the Success of Electrical Cardioversion of Atrial Fibrillation

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Abstract

One of the rhythm control strategies in atrial fibrillation management consists in the application of a brief single electrical shock to the atria. This electrical cardioversion does not always succeed, and the long-term success of this therapy is not sufficiently predictable on the basis of clinical and echocardiographic parameters. In noninvasive atrial fibrillation studies, the frequencies observed in the atrial ECG signals are considered as an indicator of the underlying dynamics. In this study, we examine the use of frequency tracking techniques in predicting the success of electrical cardioversion.

A clinical database of 18 patients in sustained AF prior to an electrical cardioversion attempt was employed. The signal processing steps performed on 5-minute standard 12-lead ECG signals were: baseline correction, ventricular activity cancellation followed by an adaptive frequency tracking algorithm. Fisher's linear discriminant function yielded up to 94% correct classifications ($p = 10^{-3}$).

1. Introduction

Atrial fibrillation (AF) is frequently responsible for morbidity and fatal complications. The diagnosis of AF as such has been based mainly on visual inspection of the surface electrocardiogram (ECG) [1]. Neither the natural history of AF nor its response to therapy is sufficiently predictable from clinical and echocardiographic parameters. Thus, it seems appropriate to develop tests that quantify AF disease states and guide AF management [2]. The underlying mechanisms of the wavefront dynamics of AF relate to their substrates, which manifest themselves on different time scales.

Invasive electrophysiological as well as noninvasive studies based on the surface ECG have commonly used two types of analysis to characterize these time scales: the Fourier-based spectral and the time-frequency analysis [3, 4]. In Fourier-based spectral analysis, the modal frequency (MF), also known as dominant frequency, ob-

served from the electrogram or the ECG lead is believed to determine the mean firing rate [3] or the most common fibrillatory rate of nearby endocardial sites [5], respectively.

In noninvasive analysis situations, the correspondence between the atrial fibrillatory rate during AF and the MFs observed on the ECG lead signals is assumed. This correspondence was studied in [6]. The MF is usually estimated after first cancelling the ventricular activity (VA). Two approaches are generally used to perform VA cancellation: independent component analysis or average beat subtraction based approaches [7–9]. Subsequently, the MF is generally estimated on lead V1 intervals (typically 5 seconds long) by using classical power spectral density (PSD) estimation techniques [4]. However, even after VA cancellation, MF estimation is often hampered by the presence of residual cancellation artifacts. The other leads, for which VA cancellation performance is poorer, are generally not considered, but it has been demonstrated that these other leads may yield important information about AF complexity [6].

Adaptive tracking of noisy sinusoidal signal components receives a great interest in many engineering applications such as communications [10], biomedical engineering [11], and speech processing [12]. Over the years, several dedicated algorithms have been proposed in the literature. Some rely on a Kalman- [13] or an RLS-based [14] prediction algorithm, but most are based on an adaptive notch filter (ANF) or bandpass filter (BPF) structure. In the latter methods, criteria relating to the output of the adaptive filter are used to update the filter parameters in order to provide the tracking feedback. In 2005, Liao proposed an interesting adaptive frequency tracking algorithm for sinusoids embedded in a noisy environment [15]. The novelty of his technique is that derivations of the coefficients-updating algorithms for the adaptive mechanisms are based on the discrete oscillator model.

In this paper, we use this adaptive frequency tracking method applied to the atrial signal of the standard 12-lead ECG to obtain an instantaneous estimate of the MF and its corresponding signal component. From the instantaneous

estimated frequency and the filter output, we compute five features to be used in a discrimination procedure between successful and unsuccessful electrical cardioversion.

Prior to the application of this method, we briefly describe the principle of the adaptive frequency algorithm used and the characteristics of a clinical database.

2. Methods

2.1. Adaptive frequency tracking algorithm

Frequency tracking on the atrial signal is realized using the algorithm called OSC-MSE (oscillator based mean square error) BPF-based algorithm. The input signal $u(\cdot)$ is assumed to be :

$$u(n) = d(n) + b(n), \quad (1)$$

where $d(\cdot)$ is a sinusoid at frequency ω_0 and $b(\cdot)$ is an additive noise. The sinusoidal component $d(\cdot)$ should satisfy the oscillator equation :

$$\begin{aligned} d(n) &= 2d(n-1) \cos \omega_0 - d(n-2) \\ &\equiv 2\alpha_0 d(n-1) - d(n-2). \end{aligned} \quad (2)$$

The adaptive coefficient $\alpha(\cdot)$, which tracks $\alpha_0 = \cos \omega_0$, determines the central frequency of the BPF. Its transfer function is defined as

$$H(z; n) = \frac{1 - \beta}{2} \frac{1 - z^{-2}}{1 - \alpha(n)[1 + \beta]z^{-1} + \beta z^{-2}}, \quad (3)$$

where $0 < \beta < 1$ controls the bandwidth of the BPF.

The filter defined by (3) has a zero phase shift and a unitary gain at the central frequency $\alpha(\cdot)$, so the reference signal $x(\cdot)$ (output of the filter) used in the adaptive mechanism is the component of $u(\cdot)$ at the frequency $\alpha(\cdot)$.

In short, the adaptive algorithm is driven by a line-enhanced version of the input signal. In the OSC-MSE algorithm, the goal is to determine the value of $\alpha(n+1)$ that satisfies the discrete oscillator model. This is done by minimizing the following cost function, based on the discrete oscillator model:

$$J = E \{ [x(n) - 2\alpha(n+1)x(n-1) + x(n-2)]^2 \}. \quad (4)$$

By setting $\partial J / \partial \alpha(n+1) = 0$, the optimal solution for this MSE criterion is

$$\alpha(n+1) = \frac{E\{x(n-1)[x(n) + x(n-2)]\}}{E\{2x^2(n-1)\}}. \quad (5)$$

However this expression for $\alpha(n+1)$ is not real-time computable. Instead, the numerator and the denominator

are replaced by their exponentially weighted time-average estimates, and the coefficient-updating algorithm becomes

$$\alpha(n+1) = \frac{Q(n)}{2P(n)}, \quad (6)$$

where

$$\begin{aligned} Q(n) &= \delta Q(n-1) + (1-\delta)x(n-1)[x(n) + x(n-2)], \\ P(n) &= \delta P(n-1) + (1-\delta)x^2(n-1). \end{aligned} \quad (7)$$

The parameter δ ($0 \ll \delta < 1$) controls the estimation update rate. This algorithm was shown to be unbiased (see [15] for details).

The OSC-MSE algorithm, as all adaptive algorithms, presents a delay due to its adaptation to frequency changes in the signal. The quality of the extracted component can be improved by compensating for this adaptation delay m . To this end, the extracted component is obtained by filtering the input signal $u(\cdot)$ with the transfer function (3), where the central frequency is the estimated frequency, obtained with the OSC-MSE algorithm, with a m -sample shift. The optimal delay m is found by applying an exhaustive search of the number of samples specifying the delay that maximize the filter output.

2.2. Clinical Database

The discrimination procedure was tested on a clinical database comprising 18 5-minute standard 12-lead ECGs of patients observed in sustained AF. The signals were recorded prior to electrical cardioversion attempt. Cardioversion succeeded in eight patients (referred as the SEC group) and failed in the ten others (referred as the FEC group). The signals were recorded and stored using a commercial recording system (CardioLaptop[®] AT-110, SCHILLER). The electrocardiographic filter settings used were 0.05 to 150 Hz. The system has a dynamic range of ± 10 mV AC (resolution of 5μ V) and a sampling rate of 500 Hz.

2.3. Procedure

The following processing steps were applied to all 12-lead ECG signals present in the database.

- Baseline correction and VA cancellation on the ECG signals as described in [16].
- Downsampling at 50 Hz and highpass filtering (Butterworth filter, cutoff frequency at 1.5 Hz).
- Adaptive frequency tracking with the algorithm described in section 2.1, with parameters $\beta = 0.94$ and $\delta = 0.95$ in equation (3) and (7), respectively.
- The optimal adaptation delay m for the application to the ECG data was found to be 25 samples.

- Extraction of the signal component corresponding to the estimated instantaneous frequency by filtering with the optimal adaptation delay.

In the discrimination procedure, the following five features were computed from the estimated frequency and its corresponding signal component: mean and standard deviation of the estimated frequency (F_{mean} and F_{std} , respectively), mean and standard deviation of the envelop of the extracted signal (E_{mean} and E_{std} , respectively) and the power ratio (R) between the extracted component and the atrial signal. The quality of the discrimination based on Fischer's linear discriminant function was tested for all possible selections of two features out of the five specified above in their application to all of the leads of the standard 12-lead system.

3. Results

Figure 1 shows the result of the frequency tracking algorithm on a 15-second ECG signal on lead V1 after VA cancellation. The estimated frequency is displayed by the black trace. A classical time-frequency plane is also displayed in the background, high and low power regions represented in yellow and black, respectively.

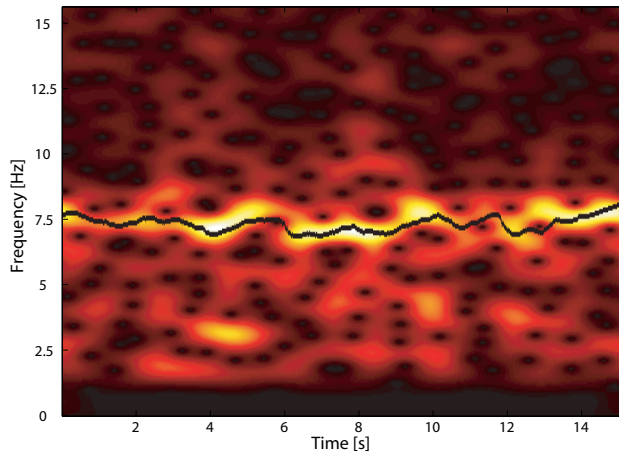


Figure 1. Result of the frequency tracking algorithm on a 15-second ECG signal on lead V1 after VA cancellation. The estimated frequency is displayed by the black trace against the background of a classical time-frequency plane. High and low power regions represented in yellow and black, respectively.

Figure 2 shows an example of the extracted signal component corresponding to the estimated instantaneous frequency as described in section 2.3. The solid trace represents the original 4-second ECG signal on lead V1 after VA cancellation. The dashed trace represents the extracted component.

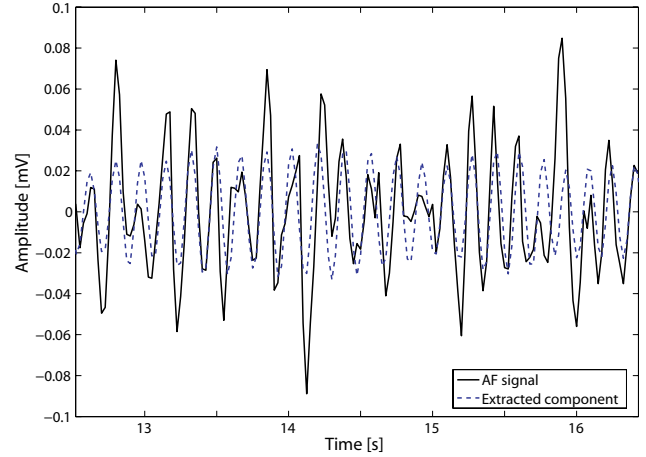


Figure 2. Example of extracted signal component corresponding to the estimated instantaneous frequency. The solid trace represents the original 4-second ECG signal on lead V1 after VA cancellation. The dashed trace represents the extracted component.

Features		V1	V2	V3
R	E_{std}	94.4%	77.8%	83.3%
R	E_{mean}	77.8%	72.2%	72.2%
F_{std}	E_{std}	72.2%	88.9%	83.3%
F_{std}	E_{mean}	77.8%	77.8%	77.8%
F_{mean}	E_{std}	77.8%	61.1%	83.3%

Table 1. Percentage of correct classifications of SEC and FEC groups on leads V1, V2 and V3 for the five feature combinations yielding the highest correct classification percentages.

Table 1 summarizes the results obtained for the classification of the SEC and FEC groups for leads V1, V2 and V3 that correspond to the third, fourth and fifth column, respectively. The five feature combinations yielding the highest correct classification percentage correspond to the rows.

Figure 3 illustrates the performance of the discrimination procedure applied to lead V1 for the R and E_{Std} features. The Fischer's linear discriminant function separating both groups is characterized by a slope $s = 0.024$ and an intercept $i = 6 \cdot 10^{-4}$. A 94.4% of correct classifications is obtained, with a p value of 10^{-3} .

4. Discussion and conclusion

This study suggests that frequency tracking can be a useful tool for obtaining an estimate of the time course of the MF of atrial signals. The statistical analysis of features extracted from this time course and the corresponding ex-

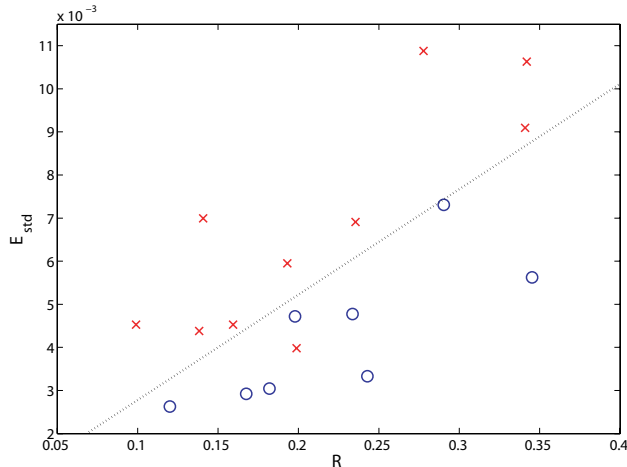


Figure 3. Scattergram showing the performance of the separation based on R and E_{Std} applied to lead V1. Elements of SEC are indicated by blue circles and those of FEC by red crosses. The dotted line represent the Fischer's linear discriminant function.

tracted component was demonstrated to be highly effective in the discrimination between successful and unsuccessful attempts at electrical cardioversion. Based on this database, comprising notably only 18 subjects, the optimal combination of features was found in the application to lead V1, while using as features the power ratio between the extracted component and the atrial signal and the standard deviation of the extracted component (94.4% of correct classifications).

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