Continuous Time Analysis Method for T–Wave Alternans Detection

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Abstract

T-wave alternans (TWA) or repolarization alternans have been closely linked to electrical instabilily of the heart. Recent studies have demonstrated that TWA ocurrence is related with ventricular arrhythmias. Accordingly, TWA detection may help in the diagnosis of heart diseases and sudden cardiac death. It consists of every–other–beat subtle fluctuations in the repolarization section ranged in the order of μV. For such small variations, noise is a critical factor. Noise amplitudes similar to the alternant wave may make TWA detection difficult. In this work, a new time domain method for TWA detection is presented. The performance evaluation is carried out with simulated signals through comparative studies against the well known Spectral Method (SM). The proposed method yields better performance in a noisy environment with a decreased computational cost, and is suitable for embedded real time implementation.

1. Introduction

T-wave alternans (TWA) or repolarization alternans has been proposed as an indicator to detect abnormalities in ventricular repolarization and ventricular arrhythmias [1]. Recent studies have shown TWA as a risk stratifier for sudden cardiac death [2].

It consists of a beat–to–beat variation in amplitude, waveform and duration of the ST-T complex. In most of the cases, TWA are ranged within an interval of few microvolts making the visual assessment impractical and unfeasible. Accordingly, many digital signal processing techniques for TWA identification have been recently reported. The review of the most important contributions is sumarized in [3]. One of the main concerns in TWA detection is noise. A decreased SNR, specially in the repolarization section, leads to significant noise amplitudes that may cover the small variations associated with alternans. This is common for all the reported methods while limited solutions have been provided, except the inclusion of preprocessing stage for denoising. Thus, robust detection techniques against noise are welcome.

Among all the TWA detection techniques, the Spectral Method (SM) [4], [5] is the most widely used. The basic detection of the SM algorithm consists of first aligning successive ST-T complexes to get a set of temporal series of samples at the same phase taken from successive ST-T segments. The presence of alternans is reflected as a maximum of energy of the temporal series at the frequency of 0.5 cycles per beat (cpb). The main drawback of processing temporal series obtained from ST-T complexes is that a relatively high number of beats are needed, at least from 64 to 128. In this work, a novel easy to use time domain technique for TWA detection is presented. It is based on spectral analysis but instead of processing time series, such as in the SM, it takes the raw ECG as the original signal to process.

To assess the performance of the new algorithm, a wide set of long–term simulated ECG records from different SNR values with TWA included is analyzed. To get realistic signals, these ECG records have been synthesized adding physiological noise at different scales.

The paper is organized as follows. Section 2 presents an introduction to the SM. Subsequently, our approach is introduced in Section 3. The performance of the SM and the proposed method is evaluated in Section 4. Finally, conclussions are given in Section 5.

2. Brief description of the spectral method

The spectral method operates over the matrix $\mathbf{M_S}$,

$$\mathbf{M_S} = \begin{bmatrix} \mathbf{A}_1 - \mathbf{B}_1 \\ \mathbf{B}_1 - \mathbf{A}_2 \\ \vdots \\ \mathbf{A}_{\frac{M}{2}} - \mathbf{B}_{\frac{M}{2}} \\ \mathbf{B}_{\frac{M}{2}} - \mathbf{A}_{\frac{M}{2}+1} \end{bmatrix} = \begin{bmatrix} -\varepsilon \\ +\varepsilon \\ \vdots \\ -\varepsilon \\ +\varepsilon \end{bmatrix} + \begin{bmatrix} \mathbf{v}_{d1} \\ \mathbf{v}_{d2} \\ \vdots \\ \mathbf{v}_{dM-1} \\ \mathbf{v}_{dM} \end{bmatrix}. \quad (1)$$

$\mathbf{A}_i$ and $\mathbf{B}_i$ are row vectors containing consecutive ST–T complexes. Subtraction allows background ECG elimination remaining the alternant wave $\boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1, & \varepsilon_2, & \cdots, & \varepsilon_N \end{bmatrix}$ plus noise $\mathbf{v}_{di} = (\mathbf{v}_i - \mathbf{v}_{i+1})$.

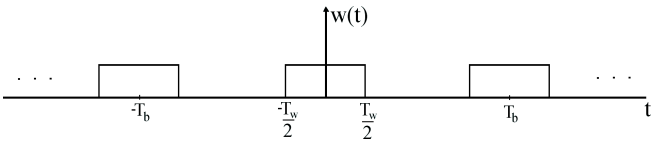

Figure 1. Periodic pulse used for ST-T complexes extraction.

Column-wise, $\mathbf{M_S} = \left[\begin{array}{cccc} \mathbf{S}_1 & \mathbf{S}_2 & \cdots & \mathbf{S}_N \end{array} \right]$ gives the time series $\mathbf{S}_j$ across beats. The spectral method analyzes TWA through the averaged power spectrum obtained as

$$P = \frac{1}{N} \sum_{j=1}^{N} P_j, \tag{2}$$

where P_j is the periodogram of every time series. The statistic to perform a hypothesis test on TWA is the T–Wave Alternans Ratio (TWAR):

$$TWAR = \frac{\sum T - \mu_{noise}}{\sigma_{noise}}, \tag{3}$$

where $\sum T$ is the magnitude of P at 0.5 cycles–per–beat (cpb), and μ_{noise} and σ_{noise} are the mean and the standard deviation respectively of the equivalent noise in the range $[0.33\ 0.48]$ cpb. The spectral method is extensively used in research and it is included in several commercial units. Therefore, there already exists a decision rule to decide whether TWA is positive or not. The decision threshold for the spectral method is tipically set to be 3 [6].

3. Proposed method

The proposed method is based on the theoretical relationship between the cardiac frequency and the alternans frequency. Let consider f_b as the frequency of the heartbeat at a specific time. Given that TWA is manifested with a period of two beats, it will be reflected at one half the heartbeat frequency $f_b/2$. The ECG signal $p(t)$ may be described as a sum of two components: the iteration of a single beat $q(t)$ plus the TWA component $\epsilon(t)$ included every other beat:

$$p(t) = \sum_{l=0}^{L} q(t - lT_b) + \sum_{l=0}^{L/2} \epsilon(t - 2lT_b). \tag{4}$$

Its Fourier Transform:

$$P(\omega) = 2\pi \sum_{k=-\infty}^{\infty} a_k \delta(\omega - \frac{2\pi k}{T_b}) + 2\pi \sum_{k=-\infty}^{\infty} b_k \delta(\omega - \frac{\pi k}{T_b}), \tag{5}$$

where $1/T_b$ is the heartbeat frequency f_b, a_k are the Fourier series cofficients of the periodic extention of $q(t)$ and b_k are the Fourier series coefficients of the repolarization segment alternans $\epsilon(t)$. In a noisy scenario, we consider the additive model, so the ECG is then $x(t) = p(t) + v(t)$, whose spectrum is,

$$X(\omega) = P(\omega) + V(\omega). \tag{6}$$

The information from the ST–T complex is obtained by windowing with a periodic pulse $w(t)$ whose period is chosen to be as that of the heartbeat, i.e., T_b, as shown in Fig. 1. The result is the windowed ECG

$$x_w(t) = x(t) \cdot w(t) = p(t) \cdot w(t) + v(t) \cdot w(t). \tag{7}$$

Useless information such as the background ECG and some other slow variations is rejected through the substraction of consecutive repolarization segments. After this preprocessing step, the differential windowed ECG $x_{wd}(t)$ is obtained, which is the signal to be processed in the frequency domain:

$$x_{wd}(t) = x_w(t) - x_w(t - T_b) = p_{wd}(t) + v_{wd}(t), \tag{8}$$

where,

$$p_{wd}(t) = p_d(t) \cdot w(t) = [p(t) - p(t - T_b)] \cdot w(t), \tag{9}$$

and,

$$v_{wd}(t) = v_d(t) \cdot w(t) = [v(t) - v(t - T_b)] \cdot w(t). \tag{10}$$

Assuming that the noise is a wide sense stationary process, it can be shown that the power spectral density function for the differential windowed ECG is:

$$\begin{aligned} S_{v_{\omega d}}(\omega) =& 4 \sin^2 \left(\pi \frac{\omega}{\omega_d} \right) \\ & \cdot \sum_k \frac{\sin^2 \left(k 2\pi \frac{T_w}{T_b} \right)}{k^2 \omega^2} S_v(\omega - k\omega_b). \end{aligned} \tag{11}$$

The choice $T_w = T_b/4$ is a good trade–off between noise reduction and efficiency. Additionally, the even coefficients of the windowed ECG are cancelled.

Figure 2 shows the Fourier Transform of the differential windowed ECG, $x_{wd}(t)$, for a cardiac rhythm of 71.2 bpm that corresponds with $f_b = 1.1867$ Hz. As can be seen, the TWA is manifested at half the frequency of the cardiac rhythm, i.e., $f_b/2 = 0.5941$ Hz. Note that the harmonics of the heartbeat frequency are eliminated.

To assess TWA, the relationship between the peak value at $f_b/2$ and the noise in its neighborhood is obtained by means of the Half–Beat Frequency Ratio ($HBFR$):

$$HBFR = \frac{1}{2\sigma_l \sigma_r} \left[X_{wd}(\frac{\pi}{T_b}) \cdot (\sigma_l + \sigma_r) \right] - \frac{\mu_l}{\sigma_l} - \frac{\mu_r}{\sigma_r}, \tag{12}$$

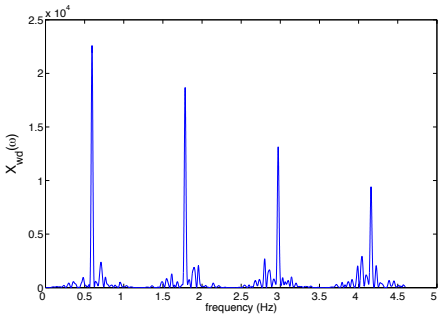

Figure 2. Fourier Transform $X_{wd}(\omega)$ of a differential windowed ECG of 32–beats block with $ANR = -20.4$ dB.

where $X_{wd}(\omega)$ is the Fourier transform of the differential windowed ECG, μ_l and σ_l are the mean and the standard deviation of the equivalent noise on the left of $X_{wd}(\pi/T_b)$, and μ_r and σ_r are the mean and the standard deviation of the equivalent noise on the right. In the experiments carried out in this work, a TWA is considered to be positive when $HBFR \geq 7.5$, which gives a similar false alarm probability than the criterion $TWA > 3$ for the SM.

4. Experimental study

The lack of specific annotated databases for TWA study makes the methodological validation very difficult, but the use of simulated ECG is commonly accepted [3]. The major concern would be to design the most realistic signal as possible. In this way, synthetic noise like additive white Gaussian noise is not recommended, since it does not simulate the non-stationary conditions of a clinic environment. Our strategy consists of the periodic replication of a clean heartbeat followed by the addition of physiological noise as proposed in [3], [7]. A synthetic alternant wave at different amplitudes is added to every other beats to obtain a simulated ECG with TWA.

A single beat was isolated from record 103 of the MIT–BIH Arrhythmia Database [8]. Physiological noise records from the MIT–BIH Noise Stress Test Database [8] are used to obtain a realistic and non-stationary ECG. In this work, the '*ma*' (muscle artifact) and the '*em*' (electrode motion) records are used, but prior to the addition to the synthetic ECG, the baseline wander in each record is eliminated by lowpass filtering. As mentioned before, the non-visible alternans are very much affected by the noise level in the ECG, although the most concerning one is that part of noise that falls into the repolarization segment. The Alternant to Noise Ratio (ANR) is used for measuring the noise level in the ST-T complex. It is calculated as the averaged relationship between the alternant wave power and the noise power in the ST-T complex for those beats with positive TWA:

$$ANR = \frac{1}{N_2 - N_1} \cdot \sum_{i=N_1}^{N_2} 10 \log \left(\frac{\|\boldsymbol{\epsilon}_i\|^2}{\|\mathbf{n_i}\|^2} \right), \qquad (13)$$

where N_1 is the first heartbeat with alternan wave and N_2 is the last one; $\boldsymbol{\epsilon}_i$ is the alternant wave corresponding to the *i*-th TWA heartbeat and $\mathbf{n_i}$ is the noise in the *i*-th ST–T complex. The proposed method is compared against the SM over a wide set of signals with different ANR.

A 2000-heartbeats long ECG is considered for the evaluation. The alternant wave is included from the start of the signal up to the end. For the SM, the *m* value in (1) is set to be 64 or 128, i.e., 64 or 128 hearbeats are used to obtain each time series $\mathbf{S_j}$. The ST-T onset is taken at 0.06 s from the fiducial point with a duration of 0.3 s.

The graphs in Figs. 3 and 4 show the sensitivity against ANR of the proposed method and the SM for *'ma'* and *'em'* noise respectively. The proposed method is applied with a window length of 32 heartbeats while two different lengths are considered for the SM: 64-long heartbeats and the most commonly used of 128 beats. As it can be seen, in a severe noisy environment, the proposed method outperforms even with less beats. In both cases, the achieved improvement is of about -15 dB. Our approach shows several advantages: 1) better performance in noisy conditions, and 2) less number of beats to assess positive TWA. Note that this leads to a reduced computational cost algorithm. The performance study of our approach for different blocks is also carried out. Note that this is very important because the lesser the length block, i.e. the window length, the lower the computational cost. Also a shorter window would allow a faster tracking of TWA with very much less cardiac variability. All of these features are essential for real time implementation with long-term records such as Holter. Figure 5 shows the results of the proposed method for window lengths of 16 and 32 heartbeats. Naturally, results worsen for shorter window. Nonetheless, even for the 16-beats length case, the proposed method yields better performance than the 64-beats length SM as compared in Figs. 3 and 4.

5. Conclusions

In this work, a novel technique for TWA detection based on the continuous time analysis of the ECG is presented. The first advantage of the method is the reduced use of beats in TWA detection, in our case from 16 to 32. This fact involves several advantages: 1) the computational cost is decreased making the proposed approach suitable for real time implementations, 2) the cardiac variability dependence is less significant, and 3) the resolution analysis is increased allowing fast TWA tracking.

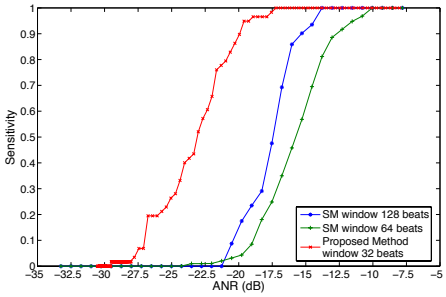

Figure 3. Comparison of the proposed method against SM for '*em*' noise.

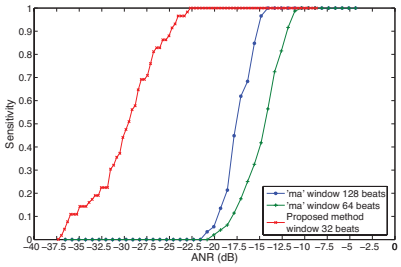

Figure 4. Comparison of the proposed method against SM for '*ma*' noise.

The method itself includes a technique which gives it higher robustness against noise. The comparison with the commonly accepted SM is performed, achieving better results for lower ANR, i.e., noisier environment.

The results and the aforementioned features makes the proposed method appropriate to use with long-term records such as Holter, which is the desired situation for future research. Also, its robust behavior against noise allow its use as a clinical routine method such as stress test. The experimental study is limited to synthetic ECG. Therefore, extended evaluations with other databases have to be done to study the effects of the heart rate variability using this method.

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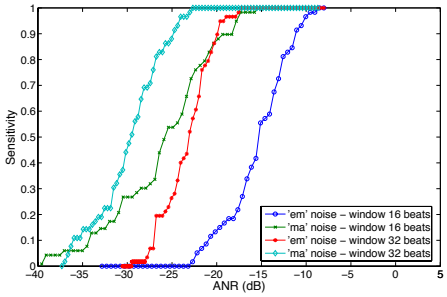

Figure 5. Results of the proposed method for window lengths of 16 and 32 heartbeats.

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