Assessment of T-wave morphology for detection of T-wave alternans in ECG signals

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Abstract

In this paper, a robust T-wave Alternans (TWA) detection system based on waveform features is proposed. First of all, some repolarization indices are extracted from T-waves and their relationship with TWA is investigated using statistical t-test to select suitable features for detecting TWA. Then, the series of absolute differences between consecutive even and odd beats are calculated for proper selected features. The alternans amplitude for each feature is quantified as the mean of this series. Global TWA value is determined from single feature values by combining these calculated alternans amplitudes. Singular value decomposition and a feed-forward neural network are applied and compared for combining TWA values. The proposed algorithms were evaluated on the PhysioNet computers in cardiology challenge 2008 database. Simulation study is also performed for evaluating the method on signals with known amount of noise and TWA. Results show an excellent performance on both databases in comparison with two other accepted methods.

Keywords

T-wave alternans, Repolarization features, Singular value decomposition, feed forward neural network, statistical t-test

1-Introduction

When digital electrocardiograms became commonly available, the computational complexity of their signal processing became easier, and more complex attempts to characterize T-wave morphology emerged [1]. One of the first attempts was the so-called T-wave alternans investigating the beat-to-beat changes in the T-wave amplitude.

T-wave alternans (TWA) is a promising electrocardiographic (ECG) index that measures beat-to-beat alternation in T-wave shape, amplitude, or timing. Decades of research now link TWA with inducible and spontaneous clinical ventricular arrhythmias, and with basic mechanisms leading to their initiation [2]. This bench-to-bedside foundation makes TWA a very plausible index of susceptibility to sudden cardiac arrest, and motivates the need to
define optimal conditions for its detection and clinical populations in whom its potential can be realized [3], [4], [5].

In the last two decades, several analysis methods have been proposed to detect and estimate TWA in the ECG [6], [7], [8], [9], [10], [11], [12]. A general framework for TWA analysis methods has been proposed in a recent methodological review, highlighting the current state of the art [13]. The most widely used approaches are the Spectral method and the complex demodulation method, both based on linear spectral estimation. Alternative nonlinear approaches, such as the modified moving average method and the Laplacian likelihood ratio method have been recently proposed and validated.

However, broader application of T-wave alternans analysis in the standard clinical applications of exercise treadmill testing and ambulatory electrocardiogram has been limited. This constraint has been, in part, attributable to the intrinsic properties of spectral analytic methods that have been employed. Spectral analysis is relatively intolerant of changes in data stationarity and motion artifact and generally requires stabilizing heart rate for 2 min [13]. The stationarity requirement is also problematic because major arrhythmias are often precipitated by transient physiological events, such as heightened sympathetic nerve activity, acute myocardial ischemia and reperfusion, and episodes of intense physiological or mental stress.

In this paper, we propose a robust T-wave alternans (TWA) detection system based on waveform features. First, a description of TWA detection system and feature combination algorithms is provided. Then the experimental results obtained with simulated database and the challenge database using the proposed system is presented in comparison with those of two accepted methods.

2-Approach and Methods

2-1TWA detection method
The proposed method is based on differences between even and odd beats in some features extracted from T-wave morphology. The method has three different blocks: preprocessing, feature extraction and combination of proper features.

2-1-1Preprocessing
First of all, frequency components above those associated with the repolarization were attenuated using an 8th order Butterworth digital filter with cutoff frequency equal to 50 Hz. Baseline wander in ECG signals was estimated and suppressed by means of the moving average filter. This filter is used to extract the baseline drift and place the output signal on the isoelectric line of the ECG recording [14]. The QRS detection was done with a robust electrocardiogram detection system based on a continuous wavelet transform. In this algorithm, first, QRS complexes are detected, then, boundaries of each QRS complex are found. In the next step, the T wave peak is detected between the QRS end and the following QRS onset. Finally, the T-wave end is found between the peak of T wave and the following QRS onset.
ECG beats with TP segments that were not relatively isoelectric were marked for elimination, as TP segments that are not flat indicate corruption by electronic noise. The TP segment occurs approximately between 55 and 70% of the R-wave-R-wave interval. To determine whether a particular ECG beat was too noisy to be used, the mean value and the standard deviation of the ECG amplitude within this TP interval were calculated. If the standard deviation was above a predefined threshold (typically 50 μV), then the ECG beat was excluded from analysis.

2-1-2 Feature Extraction and Selection
The repolarization indices analyzed in this study are the T wave width (TW), the T wave amplitude (TA), two symmetry indices defined as: the ratio of the areas at both sides of the T peak (TRA) and the ratio of the T wave time expand at both sides of the T peak (TRT), the mean amplitude of T segments from its start point to its peak, the mean amplitude of T segments from its peak to its end, the mean amplitude of whole the T segment, the T-wave slope and the parameters of the polynomial that approximate the T-wave shape. After many trials, it was found that a sixth-order polynomial was a good trade-off for the approximation of T-wave shapes, and these parameters were used as T-wave morphology features. A representation of some of such repolarization indices is shown in Fig.1 and Fig.2 shows T-wave approximation with polynomial parameters.

For each ECG recording, the temporal series of the above parameters are considered for the analysis. To remove potential outliers from each of the measured series, a technique that is described below is applied [15].

The quantity that is commonly used to examine x-values in multiple regressions can be written as:

$$h_{ii} = x_i (X^T X)^{-1} x_i$$  \hspace{1cm} (1)

Where X is the matrix of data, and $x_i$ is the row-vector made up of the ith observations xvalues. The $h_{ii}$ then is the ith diagonal element of the “hat matrix” $h_{ii} = x_i (X^T X)^{-1} x_i$.

The observation with the largest $h_{ii}$ can be said to have the most extreme predictor variables, while the observation with the smallest $h_{ii}$ values might be said to be the most typical. As a rule of thumb we say that any observation with $h_{ii}$ twice the average of all of the $h_{ii}$s is a leverage point, and has the potential to change the model.

After removal of potential outliers, features are classified in two groups as even and odd beats. From the definition of TWA, repolarization features related to alternans must appear in two separate groups. So, the series of absolute differences between consecutive even and odd beats are calculated and then the mean of the series is applied for quantifying alternans. In this work, we evaluate first the performance of each feature separately to identify which parameters are relevant to the alternans.

Experimental analysis showed that of those features extracted from T-waves, only five features are determined to be proper for detecting the T wave alternans, since their odd and
even features are significantly different in the signals that contain TWA. Student t-test was used for analyzing the significance of the mean difference between two groups of features. The results show that the peak amplitude, the ratio of the area at both sides of the T peak, the mean amplitude of the whole T-wave, the mean amplitude of the T segments from its start to its peak and one of polynomial parameters have respectively better performance in quantifying TWA. The 6th order polynomial approximating the T wave has 7 parameters ($p_1 x^6+p_2 x^5+p_3 x^4+p_4 x^3+p_5 x^2+p_6 x+p_7$). Several trials for approximating different T waves show that parameters $p_1$ through $p_5$ have small values, so only $p_6$ and $p_7$ are considered for characterizing the TWA. Of these two parameters, student t-test shows that only $p_6$ has significant relationship with TWA.

![Figure 1 – Representation of repolarization indices](image1)

![Figure 2 – Representation of T-wave approximation with 6th order polynomial](image2)

2-1-3 Feature combination

In the next step, we must combine these proper indices obtained from various features for final decision about TWA value. Singular value decomposition and feed-forward neural networks were used and compared for combination of five different features to obtain a single value for quantifying TWA.

2-1-3-1 Feature combination using SVD

To extract essential orthogonal functions of a feature vector, singular value decomposition is applied [16]. Application of SVD to the vector
Yields a set of \( M \) orthogonal functions \( u^{(r)}[n], \ r=1,\ldots,M \). Original feature vector can be reconstructed by these orthogonal functions as

\[
y(m)[n] = \sum_{r=1}^{M} a_r u^{(r)}[n], n = 1,\ldots,N
\]

Here \( u^{(r)} \) is the \( r \)th singular vector multiplied by \( \sigma_r \). Singular values are arranged in descending order of its values. In other words, \( u^{(r)} \) is the \( r \)th row of the matrix \( U \) in the following SVD formula

\[
Y = A \Sigma V^T
\]

Here \( Y \) is the matrix with \( m \)th row being the \( m \)th feature for each record. \( A \) is the coefficient matrix for the original matrix reconstruction from decomposed orthogonal functions. \( \Sigma \) is a diagonal matrix with main diagonal elements being singular values. \( V^T \) is the matrix with \( r \)th row being the \( r \)th orthonormal singular vector. Vector reconstruction using the first \( r_0 \) orthogonal functions is

\[
y(m)[n] = \sum_{r=1}^{r_0} a_r u^{(r)}[n], n = 1,\ldots,N
\]

In this work, the first singular vector is used as an index for detecting TWA. In many situations where the SVD is computed, only the first few singular components are desired; smaller singular values are treated as negligible. The problem of interest in this work is that of finding the largest singular value and associated vector of a matrix. The used algorithm, which is based on the power method for eigenvalues and eigenvectors, allow the computation of the singular values and vectors, one set at a time, in order of decreasing size of the singular values [17]. The power method is particularly suited to large matrices of which only the dominant singular components are of interest. The performance of this combination method is evaluated on both simulated database and the challenge database [18].

2-1-3-2 Feature combination using neural networks

In this work, a feedforward neural network is also used for nonlinearly combining the feature vector and its results are compared with those of the SVD.

The parameters extracted from simulated signals with known amount of TWA are used for training the neural network.

Features are extracted from signals with 5db signal to noise ratio. TWA values are varied between 10 to 100 \( \mu \text{v} \). Therefore, for different values of TWA, the feature vector is obtained and set as an input for the feedforward neural network. The network output is set to be the known alternans value. The low amount of SNR is used for training the network to prepare it for a better performance in noisy situations. The training method was the back propagation algorithm. Then, the trained network is used for combining feature values and a single value
is obtained as alternans amplitude in the output. Therefore, the network is trained on the simulated database and tested on the challenge database.

2-2-Simulation study
In actual ECG recordings, the exact value and timing of the TWA episodes are unknown. Thus, a simulation study is used to evaluate the TWA detector performance. The simulated alternans ECG signal was synthesized as a repetitive beat to which different kinds of noise and alternans episodes were added.

Four different noise sources were considered: simulated Gaussian and Laplacian noise and two recordings of physiological noise from MIT-BIH Noise stress Test database, electrode motion and muscular activity. To compare the effects of different noise types, the noise were scaled as depicted in Fig.3.

TWA was simulated by adding and subtracting a hanning window to the ST-T complex of the simulated beats. The amplitude of this waveform was modulated beat-by-beat by a trapezoidal episode shape of 40 beats of duration and being 18 beats at its maximum value. The episodes were centered in the 128 beat segments. The noise type and level and the TWA amplitude were the parameters of the proposed simulation. A sample of the simulated ECG signal with different types of noise and alternans is shown in Fig.4.

![Figure 3 – Representation of construction the simulated ECG signal with noise and TWA](image)

![Figure 4 – A simulated ECG signal with noise and TWA](image)
2-3-The challenge database
The 9th annual PhysioNet/Computers in Cardiology challenge invited participants to measure T-wave alternans (TWA) in a set of 100 two-minute electrocardiograms that included subjects with a variety of risk factors for sudden cardiac death (including ventricular tachyarrhythmias, transient myocardial ischemia, and acute myocardial infarctions), healthy controls, and synthetic ECGs with calibrated amounts of artificial TWA[18]. The participants’ TWA estimates were used to develop a ranking of the 100 test cases in order of TWA content, and the Kendall rank correlation coefficient between this reference ranking and each individual participant’s ranking of the 100 cases was calculated as a score [19].

3-Results and discussions
3-1-Results for simulation study
The performance of TWA detector system using SVD for combining indices is evaluated on simulated database in various situations of noise. The SNR is varied between 20db to 5db. For each SNR, simulated TWA amplitude is varied between 0 to 100 μV.

A calculated index of alternans amplitude is perfectly sensitive to the presence of alternans and detection sensitivity and specificity is 100% and no alternans is detected when the simulation has different kinds of noise but no alternans. Sensitivity and specificity of calculated index is not affected even at SNR=5 dB. Figure 5 illustrates the mean performance of the calculated index with increasing noise in multiple simulations with different alternans value.
Figure 5 – TWA amplitude in different SNRs for 100, 50 and 0 microvolt simulated alternans.

3-2-Results for the challenge database

Applying the proposed TWA detector to the entire 9th annual PhysioNet/Computers in Cardiology challenge 2008 database using SVD for feature combination, the following result is obtained.

Each ECG recording in this database is analyzed and the alternans amplitude is estimated using the proposed method. Then, TWA amplitudes are used to develop a ranking of the 100 test cases in the order of TWA content, and the Kendall rank correlation coefficient between this rank and the reference ranking of the 100 cases is calculated as a score of 0.74.

This procedure is also repeated using the trained neural network with simulated database for feature combination and the score of 0.77 is found. This better result may show that nonlinear combination of features obtained with neural network works better than linear combination using SVD.

Two accepted methods (spectral Method and GLRT approach [13]) are also applied for this database to compare with results of the proposed methods. The results are shown in Table 1.

<table>
<thead>
<tr>
<th>Method</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed Method using Neural Networks</td>
<td>0.77</td>
</tr>
<tr>
<td>Proposed Method using SVD</td>
<td>0.74</td>
</tr>
<tr>
<td>GLRT approach</td>
<td>0.57</td>
</tr>
<tr>
<td>Spectral Method</td>
<td>0.33</td>
</tr>
</tbody>
</table>

4-Conclusion

A TWA detector based on combination of waveform features have been tested with ECG signals containing alternans. Singular value decomposition and a feedforward neural network are proposed for combining waveform features. The results of the simulation study indicated that the detector performance is suitable for any TWA amplitude at signal to noise ratio between 20 to 5 dB.
The detector was also applied to the 9th annual PhysioNet/Computers in Cardiology challenge database, the Kendall rank correlation coefficient between this rank and the reference ranking of the 100 cases is calculated as a score of 0.74 for SVD feature combination and 0.77 for neural network feature combination that are better than those of two accepted methods.

References


