31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Adaptive Time-frequency Matrix Features for T wave Alternans Analysis

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***Abstract*— T wave alternans (TWA) has been associated with ventricular arrhythmias. Hence, TWA detection can risk stratify patients with heart disease who may experience sudden death from ventricular arhythmias. However, accurate TWA detection is technically challenging due to the low microvolt TWA signal and the confounding effect of biological noise such as movement, myopotentials or respiration. In this paper, we propose non-negative matrix factorization (NMF)-Adaptive spectral method to increase the robustness of TWA detection in ambulatory electrocardiograms (ECGs). The proposed method applies a non-linear time-frequency (TF) analysis and NMF to the aligned ST-T waveforms. This method separates the TWA signal from the other non-desired ECG signal components, and detects TWA with high accuracy. The performance of our proposed method is validated in a clinical study using ECGs which confirms a TWA detection of 92% compared to 47% using the conventional spectral method.**

I. INTRODUCTION

T wave alternans (TWA), also called repolarization alternans, is a heart rate dependent phenomenon that manifests on the surface electrocardiogram (ECG) as changes in the shape or amplitude of the T wave every second heart beat. TWA is emerging as an important prognostic marker for sudden cardiac death in patients with heart disease. The first cases of TWA were reported at the beginning of the 20th century, but it was not until the 1980s, when non-visible (microvolt-level) TWA were measured with the aid of a computer. TWA can also be measured in ambulatory ECG recordings during activities of daily living, which offers a more practical means of risk classification compared to exercise testing.

In the last two decades, a variety of analysis methods have been proposed to automatically detect TWA from the ECG [1]. The most widely used TWA estimation method in clinical practice is the spectral method (SM), which uses the periodogram to analyze the frequency component 0.5 cycle/beat over the aligned ST-T waveforms. In a previous study [2], we proposed Adaptive time-frequency distribution (TFD) as a powerful means of TWA estimation, and we showed the advantage of Adaptive TFD compared to the currently employed SM.

In this paper, we use the proposed Adaptive time-frequency (TF) analysis for detecting T wave variations. We also propose a new method to improve TWA detection which involves constructing the average Adaptive TFD of the aligned ST-T waveforms. We then consider the TFD as a matrix, and apply non-negative matrix factorization (NMF) to the TF matrix (TFM). The basic idea of applying NMF to the TFM is separating the TWA signal from other ECG signal components. The TWA detection methods are presented in Section II. The results are given and discussed in Section III, and the conclusion is described in Section IV.

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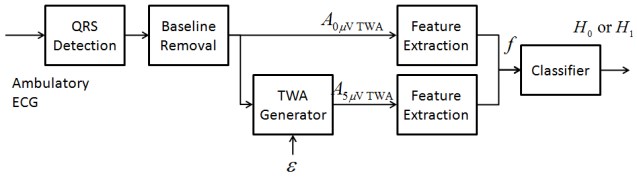

Fig. 1. Schematic of the TWA detection algorithm. '0μV TWA' and '5μV TWA' represent ECG waveforms with 0 and 5μV TWA, respectively. Depending on the TWA feature vector (f), the classifier decides whether there is no TWA in the ECG signal (H_0), or there is TWA in the ECG (H_1).

II. TWA DETECTION METHOD

Microvolt TWA are the beat-to-beat variations in the shape or amplitude of the T wave. Fig. 1 is a schematic of the proposed TWA detection method. After pre-processing the ECG waveform, two groups of ECG waveforms are generated: '0μV TWA' and '5μV TWA'. We chose 5 μV as a cutoff for positive TWA for our study since this approximated the TWA magnitude measured by Klingenheben et al [3] in patients with cardiomyopathy using a similar definition of TWA as our study. For each group, we transform a time series of T wave amplitudes across the entire ST-T segment of consecutive beats to the beat domain. In this process, we construct an $\mathbf{A}_{M\times N}$ matrix using M ST-T waveforms of N samples as follows:

$$\mathbf{A} = \begin{bmatrix} ST_1(1) & ST_1(2) & \cdots & ST_1(N) \\ ST_2(1) & ST_2(2) & \cdots & ST_2(N) \\ ST_3(1) & ST_3(2) & \cdots & ST_3(N) \\ \vdots & \vdots & \cdots & \vdots \\ ST_M(1) & ST_M(2) & \cdots & ST_M(N) \end{bmatrix} \quad (1)$$

where $ST_j(i)$ (for $j = 1$ to M and $i = 1$ to N) represents the ith sample of the jth ST-T waveform in the ECG, M is the number of heart beats used in the analysis, and N is the length of the ST segment. The rows of $\mathbf{A}$ are the individual ST-T waveforms, and the columns are the beat-to-beat variations in these ST-T waveforms. Using this property, we estimate TWA from the columns of the matrix $\mathbf{A}$ for each group. The estimated TWA signals are fed into a linear

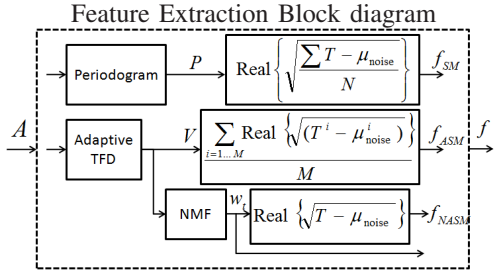

Fig. 2. Three methods are used to extract feature sets (f_{SM}, f_{ASM} and f_{NASM}) from the aligned ST-T waveforms (matrix A). Each feature vector (f) is fed into a classifier to detect TWA.

discriminant analysis (LDA) in order to train the classifier to detect the TWA signals. We then use the trained classifier to group subsequent new ECG signals into '0μV TWA' or '5μV TWA'.

As shown in Fig. 2, three feature sets are extracted: f_{SM}, f_{ASM} and f_{NASM}. The feature extraction methods are explained below:

A. Spectral Method

The presence of TWA within any portion of the ST-T waveform can be measured from two consecutive columns of matrix **A**. This allows measurement of TWA over the entire ST-T segment from the sum periodogram of the columns, as the spectral magnitude at 0.5 cycles/beat:

$$f_{SM} = \text{Real}\left\{\sqrt{\frac{\sum T - \mu_{noise}}{N}}\right\} \tag{2}$$

where $\sum T$ is the TWA magnitude of the periodogram (P) at 0.5 cycle/beat, μ_{noise} is the mean noise estimate calculated at the spectral bandwidth, 0.36 to 0.48 cycle/beat, and N is the ST segment duration.

This method is referred to as the spectral method (SM). Since the development of the SM, a variety of analysis methods have been proposed to automatically detect TWA from the ECG, but SM has always been considered as the only spectral method for TWA estimation, and has widely been applied in clinical practice. However, the SM assumes stationarity of the ST-T segments over M beats, which limits the SM's ability to dynamically track TWA. In order to overcome this shortcoming, a different signal representation is needed that tracks TWA non-stationarity. In our previous study [2], we proposed Adaptive-TFD for TWA estimation, and we refer to the proposed method as Adaptive SM.

B. Adaptive Spectral Method (Adaptive SM)

Adaptive TF analysis provides a positive TF representation of the signal with high time and frequency localization. Therefore, it is a suitable tool for feature extraction of non stationary signals. To construct Adaptive TFD of any arbitrary signal, matching pursuit TFD (MP-TFD) of the signal is first constructed. MP-TFD has been proposed by Mallat and Zhang [4], and it provides a flexible and cross-term free TF representation. MP-TFD decomposes the signal into Gabor atoms with a wide variety of modulated frequency and phase, time shift and duration, and adds up the Wigner distribution of each component. Wigner distribution is a powerful TF representation; however when more than one component is present in the signal, the TF representation will be confounded by cross-terms. Using the MP-TFD, the Wigner distribution of single components are added together, and the summation will be cross-term free. MP-TFD eliminates the cross-term problem with bilinear TFDs, and provides a better resolution for multi-component signals. However, the shortcoming of MP-TFD is that it does not necessarily satisfy the marginal properties, which means that the constructed TF function can not be considered as a true TFD of the signal.

In order to detect the energy of TWA at 0.5 cycle/beat, the constructed TFD requires preservation of the correct time and frequency location of the estimated energy. The marginal property guarantees that the energy of each point in the constructed TFD represents the true value. Therefore, as described by Krishnan et al [5], we perform minimum cross-entropy (MCE) optimization on MP-TFD to construct Adaptive TFD, which is cross-term free, and satisfies the time and frequency marginals. MCE optimization is proposed to construct an optimal estimate of the positive TFD, $\mathbf{V}(t,f)$, given an initial TFD estimate, $\hat{\mathbf{V}}(t,f)$, which is positive but does not satisfy the marginal conditions. This method modifies the initial positive TFD to satisfy the marginal properties by multiplying and then dividing it by the desired and the current marginals respectively. This iteration continues until the constructed TFD satisfies the marginal properties. The constructed TFD is called Adaptive TFD. Adaptive TFD is cross term free and promises a high TF localization.

According to our definition of TWA as the average TWA magnitude for the series of odd and even beats over ST segments, we construct the average Adaptive-TFD of all the aligned ST segments, and denote it with $\mathbf{V}_{M\times M}$. We use the energy of the average Adaptive-TFD at 0.5 cycle/beat as a TWA feature:

$$f_{ASM} = \frac{\sum_{i=1\ldots M} \text{Real}\left\{\sqrt{(T^i - \mu^i_{noise})}\right\}}{M} \tag{3}$$

where T^i is the magnitude of the ith column of the TFD, $\mathbf{V}$, at 0.5 cycle/beat, μ^i_{noise} is the noise estimate calculated at the spectral point bandwidth, 0.36 to 0.48 cycle/beat from the ith column of the average TFD, and M is the number of heart beats used in the analysis.

Although performing the Adaptive-TFD increases the detection of T wave variations, the presence of noise and data non-stationarity in the ECG record can cause the method to underestimate the TWA. We can write the matrix of the average Adaptive TFD of the aligned ST-T waveforms with as a combination of the TWA matrix (**TWA**) and all the other non-desired ECG signal components (**K**):

$$\mathbf{V} = \mathbf{TWA} + \mathbf{K} \tag{4}$$

Based on this equation, if we separate the T wave matrix from the noise component (**K**), we are able to detect the

TWA signal from the separated TWA matrix with higher accuracy.

C. Non-negative Matrix Factorization Adaptive SM (NMF-Adaptive SM)

To separate TWA signal from noise, we apply non-negative matrix factorization (NMF) to the TFM, **V**. NMF was performed in the middle of the 1990s under the name positive matrix factorization (PMF). In 1999, Lee and Seung [6] introduced some simple algorithms for the factorization, and demonstrated the success of the technique on some applications. NMF decomposes a non-negative matrix, and constraints the matrix factors **W** and **H** to be non negative; therefore, NMF attempts to extract part-based features. Various alternative minimization strategies for NMF decomposition have been proposed. In this study, we use a projected gradient bound-constrained optimization method by Lin et al. [7]. This method is computationally competitive and offers better convergence property than the standard approach.

We apply non-negative matrix factorization to the TFM, and decompose the TFM into two matrices, **W** and **H**:

$$\begin{aligned} \mathbf{V}_{l\times M} &= \mathbf{W}_{l\times r}\mathbf{H}_{r\times M} \\ &= \textstyle\sum_{i=1}^{r} w_i h_i \end{aligned} \tag{5}$$

where r is the order of the decomposition, w_i is the ith column of the matrix **W** and h_i is the ith row of the matrix **H**. NMF estimates matrices **W** and **H** in a way that the columns of matrix **W** contain the spectral components presented in the TFM, and the rows of matrix **H** contain the corresponding temporal location of each spectral structure in the TFM. Next, we use Eqn. 3 to calculate the TWA values of each spectral component. The component with the highest TWA value is denoted as w_t, and Eqn. 5 is written as following:

$$\mathbf{V} = w_t h_t + \sum_{\{i=1,..,r\}-\{i=t\}} w_i h_i \tag{6}$$

In this equation, the first term of the right hand side represents the major TWA, and the second term contains noise and the other non-desired components. Comparing Eqn. 6 with Eqn. 4, we can conclude that using NMF on TFM of the aligned ST-T waveform, we are able to separate the $\mathbf{TWA} = w_t h_t$ matrix from the undesired ECG components.

Finally, we derive the NMF-Adaptive SM feature vector as given below:

$$f_{NASM} = \{w_t, \alpha\}, \quad \alpha = \text{Real}\left\{\sqrt{T - \mu_{noise}}\right\} \tag{7}$$

where w_t is the decomposed spectral component with the highest TWA value, T is the magnitude of that component at 0.5 cycle/beat, μ_{noise} is the noise estimate calculated from w_t at the spectral point bandwidth, 0.36 to 0.48 cycle/beat, and l is the length of w_t.

III. Results

Ambulatory ECGs with physiological noise were obtained from MIT-BIH Normal Rhythm Database (NSRDB) from Physiobank [8]. NSRDB includes 2-channel ambulatory ECGs recorded at a sampling rate of 128 Hz from 18 normal subjects (5 men) aged 20-50 years with no arrhythmias. Each ECG channel is included as a separate record. As shown in Fig. 1, QRS detection is performed automatically and verified manually. Baseline wander is corrected by subtracting a cubic spline interpolation of isoelectric points preceding the QRS onset. The first 64-beat segment of each NSRDB ECG record with a mean heart rate less than 100 beat/minute is analyzed in order to ensure the absence of inherent TWA signal. Two groups of ECG signals are generated: '0μV TWA' and '5μV TWA'. To generate the group with TWA of 5μV, a synthetic TWA waveform with amplitude of ϵ = 5μV is added to the physiological ECG. This is achieved by increasing T wave amplitude of even beats and decreasing T wave amplitude of odd beats uniformly across the ST segment from a point 40 ms after QRS offset to the end of the T wave.

TWA feature extraction methods are performed on each 64-beat segment, and three feature sets are extracted: f_{SM}, f_{ASM} and f_{NASM}. Before we present the performance of the proposed features, we demonstrate the effectiveness of NMF-Adaptive SM through an illustrative example.

Matrix decomposition procedure of TFM is shown Fig. 3. From the group with TWA of 5μV, we choose an ECG signal, in which SM and Adaptive SM fail to detect the TWA, and construct the average TFM, **V**, of the aligned ST-T segments. The aligned ST-T waveform are shown in Fig. 3(a), and Fig. 3(b) illustrates the reconstructed TFM, $\mathbf{V}_{l\times M}$, where l corresponds to the point 0.36 cycle/beat. Since we are interested in the TF structure of this matrix only in the spectral bandwidth of 0.36 to 0.5 cycle/beat, we illustrate this range of the TFM in Fig. 3(b), and apply the NMF to this part of the matrix rather than the whole matrix.

The decomposed matrices, **W** and **H**, resulted from NMF with decomposition order of three ($r = 3$) are shown in Figs. 3(c) and (d), respectively. As evident in these figures, the columns of matrix **W** represent the components present in the TFM of the ST-T segments, and the rows of matrix **H** show the location of each corresponding component. We calculate TWA for each decomposed component using Eqn. 3, and choose the component with the highest TWA value. As shown in Fig. 3(c), the third component, which is indicated by a dashed box, has the greatest T wave variation. Fig. 3(e) illustrates the TFM represented by the third component ($\mathbf{TWA} = w(3)h(3)$), and Fig. 3(f) shows the TFM represented by the rest of the components ($\mathbf{K} = w(1)h(1) + w(2)h(2)$). By applying NMF to the TFM, we determined an estimate of the **TWA** matrix.

In order to compare the accuracy of the methods for detecting TWA, receiver operating curves (ROC) are computed with the area under the curve indicating relative TWA signal discrimination (Fig. 4). The area under the ROCs for f_{NASM}, f_{ASM} and f_{SM} are 0.98, 0.91 and 0.73, respectively, indicating TWA discrimination for NMF-Adaptive SM and Adaptive SM compared to SM. Based on the ROCs, the maximum sensitivity for TWA detection while preserving 100% specificity is 89% for NMF-Adaptive SM, 42% for Adaptive SM and 44% for SM. These results show that the proposed NMF-based method (1) successfully discriminates

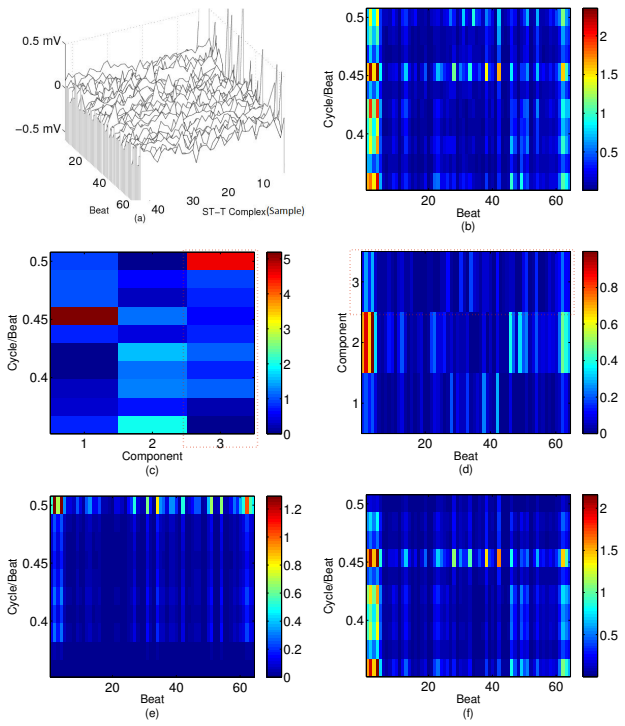

Fig. 3. NMF-Adaptive Method is demonstrated. (a) The aligned ST-T waveform for a 64 beat ECG segment. (b) The average of Adaptive TFD of the aligned ST-T segments. (c) The decomposed spectral components. (d) The decomposed temporal components. (e) The TWA matrix separated from the TFD. (f) The remained part of the TFD.

TABLE I
TWA DETECTION RATE

Method	Class	0μV TWA	5μV TWA
SM	0μV TWA	97%	3%
	5μV TWA	53%	47%
Adaptive SM	0μV TWA	95%	5%
	5μV TWA	33%	67%
NMF-Adaptive SM	0μV TWA	95%	5%
	5μV TWA	8%	92%

TWA from the rest of the TFD, (2) increases the area under ROC by 34% compared to SM, and (3) improves TWA detection (with no false TWA detection) by more that 102% compared to the other two methods.

Table I shows the TWA detection accuracy at cut-points of 0.8, 4.5 and 0.9 for f_{SM}, f_{ASM} and f_{NASM}. The boxed numbers show the detection rate for each method. SM has a detection rate of 97% for 0μV TWA group, and 47% for 5μV TWA group. The Adaptive SM increases detection of 5μV TWA to 67% while the new proposed NMF-Adaptive spectral method detects 92% of 5μV TWA which is a significant increase compared to the detection rate of SM. The results of this experiment demonstrate that Adaptive-TFD and NMF take an important role in separating TWA from physiological non-stationarities, and they increase the robustness of TWA detection in ambulatory ECGs.

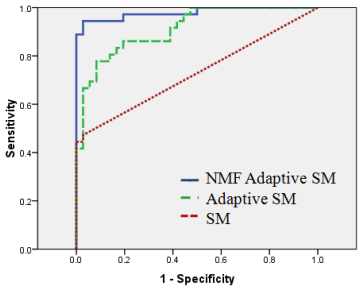

Fig. 4. Receiver operating curves for the three methods are plotted. In this analysis, ambulatory ECGs without added TWA are considered negative, while the ECGs with added TWA of 5μV are considered positive. The area under the ROC for f_{NASM}, f_{ASM} and f_{SM} is 0.98, 0.91 and 0.73, respectively.

IV. CONCLUSION

In this paper, we proposed two methods for TWA detection: Adaptive SM and NMF-Adaptive SM. The former employs Adaptive TFD, which is an adaptive non-linear signal decomposition technique, to detect TWA, and the latter applies NMF, which is a matrix decomposition technique, to separate the TWA from undesired ECG components. We applied the proposed methods to ambulatory ECGs, and showed their advantages compared to the currently employed SM. The area under the ROC for NMF-Adaptive SM and Adaptive SM was 0.98 and 0.91 respectively vs. 0.73 for SM. NMF-Adaptive SM resulted in a detection rate of 92% which is a significant increase compared to SM and Adaptive SM. Our future work will implement the proposed approaches in the presence of data non-stationarity from changing heart rate, ectopic beats and varying TWA signal which can limit accurate TWA detection using SM. Applying NMF to Adaptive TFD has the potential to control noise and accurately detect TWA under these conditions.

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