Comparison of Source Separation Techniques for Multilead T-Wave Alternans Detection in the ECG

Violeta Monasterio*, Gari D. Clifford and Juan Pablo Martínez

Abstract— T-wave alternans (TWA) is a cardiac phenomenon associated with the mechanisms leading to sudden cardiac death. In this work, we evaluate different source separation techniques for multilead detection of TWA in the electrocardiogram (ECG). Two periodicity-based techniques – periodic component analysis (πCA) and the newly proposed spectral ratio maximization (SRM) – are compared to two independence-based techniques – FastICA and JADE – and to principal component analysis (PCA). According to simulation results, the best detection performance is obtained with the periodicity-based schemes.

I. INTRODUCTION

The electrocardiogram (ECG) is extensively used as a clinical tool to study the heart function. It is measured placing electrodes on the body surface, and simultaneously recording the electrical activity of the heart in different chest locations (different channels, also termed leads). A widely used electrode configuration is the Frank lead system, which contains three orthogonal leads that represent the perpendicular X, Y and Z directions. The ECG usually presents five characteristic waves on each beat, labeled from P to T (Fig. 1(a)). The interval between the end of the S wave and the end of the T wave represents the repolarization activity of the heart ventricles, and is known as ST-T segment.

T-wave alternans (TWA) is defined as a consistent fluctuation in the repolarization morphology (ST-T segment) every other beat (Fig. 1(b) and (c)), and is a promising index of susceptibility to sudden cardiac death [1], [2]. TWA amplitudes are in the range of microvolts, and can be even below the noise level, making the detection of TWA a difficult task. There exist several methods to automatically detect TWA [3], which are usually applied to each lead of the ECG individually.

In previous works [4], [5], we presented a multilead analysis scheme that improves the detection performance of single-lead techniques the such as the spectral method (SM) and the Laplacian likelihood ratio (LLR) method. The idea behind this scheme is that separating the TWA from the non-alternating components of the ECG improves the detection of TWA with low amplitudes. The search for a suitable TWA separation technique can be interpreted as a blind source separation problem, and approaches such as principal

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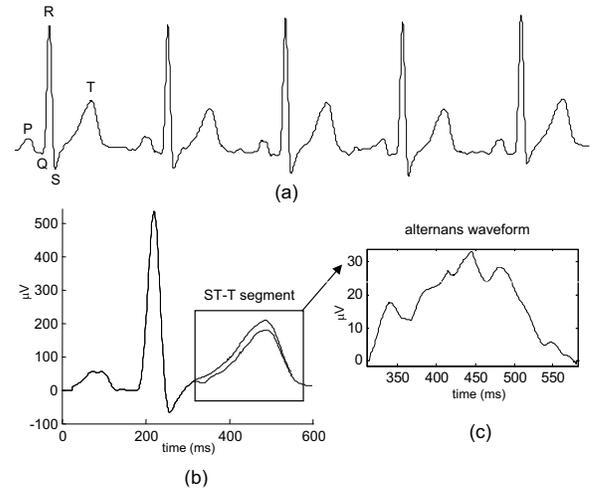
Fig. 1. (a) ECG signal with visible TWA. (b) Superposition of two consecutive beats. (c) Alternans waveform. Reproduced from [4].

component analysis (PCA) or independent component analysis (ICA) can be explored to solve it. In previous works, we evaluated the use of PCA [4] and periodic component analysis (πCA) [5] separation techniques. In this work we propose a new separation technique based on the periodicity of the signal, the spectral ratio maximization (SRM), and also evaluate the applicability of two widely used ICA algorithms: FastICA [6] and JADE [7]. The detection performances obtained with PCA, πCA, SRM, FastICA and JADE are compared by analyzing a set of ECG signals with known TWA.

II. METHODS

A. General multilead analysis scheme

The general scheme for multilead TWA detection consists of three stages: signal preprocessing, signal transformation and TWA detection (Fig. 2). A full description of this scheme can be found in [5]. The three stages are summarized below.

In the preprocessing stage, the multilead ECG signal is low-pass filtered and decimated to a sampling frequency of 30 Hz. Baseline wandering is removed using a cubic spline interpolation technique, and beat positions are determined using a wavelet-based algorithm [8]. An interval of 350 ms is selected on each beat for TWA analysis (the ST-T segment). In this work, K represents the number of beats in the analysis window, N the number of samples of each ST-T segment, L the number of leads, and $x_{k,l}(n)$ the n-th sample in the ST-T segment of the k-th beat and the l-th lead. Each ST-T segment

can be modeled as

$$x_{k,l}(n) = s_l(n) + \frac{1}{2}a_l(n)(-1)^k + v_{k,l}(n) \quad n = 0, \ldots, N-1$$

where $s_l(n)$ is the background ST-T segment, which is periodically repeated in each beat, $a_l(n)$ is the alternans waveform, and $v_{k,l}(n)$ is additive random noise. In vector notation, each ST-T segment is denoted as

$$\mathbf{x}_{k,l} = \begin{bmatrix} x_{k,l}(0) & \ldots & x_{k,l}(N-1) \end{bmatrix}.$$

For each lead l, ST-T segments are concatenated to form the lead vectors:

$$\tilde{\mathbf{x}}_l = \begin{bmatrix} \mathbf{x}_{0,l} & \ldots & \mathbf{x}_{K-1,l} \end{bmatrix} \tag{1}$$

$$\tilde{\mathbf{x}}_l^{(m)} = \begin{bmatrix} \mathbf{x}_{m,l} & \ldots & \mathbf{x}_{m+K-1,l} \end{bmatrix}$$

where $\tilde{\mathbf{x}}_l^{(m)}$ is the equivalent to $\tilde{\mathbf{x}}_l$ obtained after sliding the analysis window m beats forward. Two matrices are finally constructed by putting together all the leads:

$$\mathbf{X} = \begin{bmatrix} \tilde{\mathbf{x}}_1 \\ \vdots \\ \tilde{\mathbf{x}}_L \end{bmatrix} \quad ; \quad \mathbf{X}^{(m)} = \begin{bmatrix} \tilde{\mathbf{x}}_1^{(m)} \\ \vdots \\ \tilde{\mathbf{x}}_L^{(m)} \end{bmatrix} \tag{2}$$

The second stage aims to find a transformation that separates TWA from noise. First, background ST-T segments are canceled with a *detrending* filter

$$\mathbf{x}_{k,l}' = \mathbf{x}_{k,l} - \mathbf{x}_{k-1,l}, \ k = 1 \ldots K-1 \tag{3}$$

and the *detrended* beats $\mathbf{x}_{k,l}'$ are arranged as in (1) and (2) to form matrices $\mathbf{X}'$ and $\mathbf{X}^{(m)'}$. Then, the transformation $\mathbf{\Psi}$ is calculated with one of the techniques described in section II-B, and is applied to the original data $\mathbf{X}$

$$\mathbf{Y} = \mathbf{\Psi}^T \mathbf{X} \tag{4}$$

to obtain the transformed signal $\mathbf{Y}$, whose leads (rows of $\mathbf{Y}$) will be denoted as transformed leads.

After signal transformation, TWA detection is performed in the transformed signal $\mathbf{Y}$ using the LLR method [9], [10]. This method decides whether TWA is present or not in each transformed lead by applying the Generalized Likelihood Ratio Test (GLRT) for Laplacian noise, which consists of calculating a detection statistic from the data, and comparing it to a detection threshold. The overall detection is positive if TWA is detected at least in one transformed lead.

B. Transformation techniques

Five techniques to find the transformation matrix $\mathbf{\Psi}$ are compared in this study: PCA, πCA, FastICA, JADE and spectral ratio maximization (SRM).

Principal Component Analysis: PCA separates the orthogonal components of the signal in descending order of variance. In this case, the transformation $\mathbf{\Psi}$ is obtained by solving the equation

$$\mathbf{R}_{\mathbf{X}'}\mathbf{\Psi} = \mathbf{\Psi}\mathbf{\Lambda} \tag{5}$$

where $\mathbf{R}_{\mathbf{X}'} = \dfrac{1}{(K-1)N}\mathbf{X}'\mathbf{X}'^T$ denotes the estimated spatial autocorrelation of $\mathbf{X}'$, $\mathbf{\Lambda}$ denotes the eigenvalue matrix with

the eigenvalues sorted in descending order, and $\mathbf{\Psi}$ denotes the corresponding eigenvector matrix.

1) Periodic Component Analysis: This technique aims to find the projection $\tilde{\mathbf{y}}' = \mathbf{w}^T\mathbf{X}'$ that maximizes the periodic structure of the signal at the TWA frequency. To do so, a measure of periodicity is defined as

$$\epsilon(\mathbf{w}, m) = \frac{\left\| \tilde{\mathbf{y}}'^{(m)} - \tilde{\mathbf{y}}' \right\|^2}{\left\| \tilde{\mathbf{y}}' \right\|^2} \tag{6}$$

where $m = 2$ beats is the period of the TWA. The weight $\mathbf{w}$ that minimizes (6) is given by the generalized eigenvector corresponding to the smallest generalized eigenvalue of the matrix pair $(\mathbf{A}_{\mathbf{X}'}, \mathbf{R}_{\mathbf{X}'})$, where $\mathbf{A}_{\mathbf{X}'}$ is the spatial correlation of $\left(\mathbf{X}^{(m)'} - \mathbf{X}' \right)$ [5], [11]. Note that, with this technique, the transformation matrix $\mathbf{\Psi}$ only contains the column vector $\mathbf{w}$, which can be interpreted as the spatial direction from which the periodic content of the signal is better observed, and therefore the transformed signal $\mathbf{Y}$ will only contain one transformed lead.

Spectral Ratio Maximization: Like πCA, this technique tries to find a projection $\tilde{\mathbf{y}}' = \mathbf{w}^T\mathbf{X}'$ that maximizes the periodicity of the transformed signal. In this case, the measure of periodicity is defined as

$$\xi(\mathbf{w}) = \frac{S_{\tilde{\mathbf{y}}}(f_{0.5})}{\int S_{\tilde{\mathbf{y}}}(f)\, df} \tag{7}$$

where $S_{\tilde{\mathbf{y}}}(f)$ is the power spectral density of the transformed signal, estimated with the modified periodogram, and $f_{0.5}$ is the frequency of TWA (0.5 cycles per beat). To find the $\mathbf{w}$ that maximizes (7), a gradient-based optimization algorithm implemented by MATLAB *fminunc* routine (default options) is applied. Two options are considered to initialize this iterative algorithm: the vector $\mathbf{w} = [1 \ 0 \ \ldots \ 0]^T$, which represents a projection on the first lead axis of the input signal (SRM scheme), and the projection $\mathbf{w}$ obtained with πCA as described above (πCA-SRM scheme). As in the πCA case, the transformed signal $\mathbf{Y}$ will only contain one transformed lead.

FastICA: FastICA is one of the most referenced ICA techniques in the literature [6] and it is freely distributed in [12]. The FastICA algorithm finds the transformation that maximizes the independence of the components by minimizing their mutual information with a fixed point algorithm.

JADE: This widely used algorithm [7] finds the transformation that maximizes the independence of the signal components by jointly diagonalizing fourth-order cumulant tensors. The JADE algorithm is publicly available in [13].

III. DATA SET

To compare the performance of the different separation techniques, we created a set of synthetic ECG signals with known TWA using an artificial multilead ECG model [14]. Synthetic signals were created with TWA amplitudes (V_{alt}) ranging from 0 μV to 200 μV. For a given TWA amplitude, a total of 50 3-Frank-lead ECG records of 5-minute length were generated at a sampling frequency of 500 Hz. A mixture
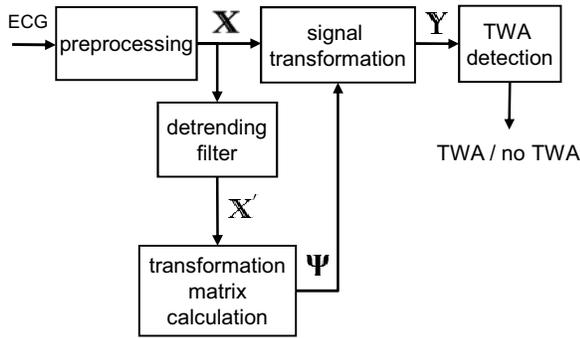
Fig. 2.   Block diagram of the multilead scheme.

Fig. 3. P_D of the different schemes vs. simulated TWA amplitude. $P_{FA} = 0.01$ for all schemes.

of noises from the MIT-BIH Noise Stress Test Database [15] - electrode motion (*em*), muscular activity (*ma*) and baseline wander (*bw*) - was added to the signals. For each synthetic ECG signal, two-lead segments of 5 minutes were extracted from *em*, *ma* and *bw* records beginning at a random position. These records only contain two leads, so a third lead of spatially correlated noise was computed as the first principal component of the two available leads. Finally, the three noise leads were scaled to obtain an SNR of 20 dB with respect to the ECG, and added to the synthetic signal.

IV. RESULTS

Signals were processed with PCA, πCA, SRM, πCA-SRM, FastICA and JADE schemes using a 32-beat analysis window. The execution time (in seconds) for the analysis of the entire dataset was 64 s with PCA, 68 s with πCA, 6678 s with SRM, 5345 s with πCA-SRM, 1254 s with FastICA and 129 s with JADE.

The detection performance of the schemes was compared as follows. Probability of false alarm (P_{FA}) was defined as the ratio between the number of positive TWA detections in signals with $V_{alt} = 0$ (false detections) and the total number of decisions made in those signals. Probability of detection (P_D) was defined as the ratio between the number of positive TWA detections in signals with a given V_{alt} and the total number of decisions made in those signals. For each scheme, a detection threshold was set so that (P_{FA}) was 0.01, and the resulting P_D was compared. The best performance was obtained with schemes πCA, SRM and πCA-SRM, that presented similar P_D for every V_{alt} (Fig. 3).

The projection directions obtained with πCA, SRM and πCA-SRM schemes were also studied. For each V_{alt} value, the vectors **w** obtained with each scheme were normalized and averaged. The average directions obtained with SRM and πCA-SRM schemes coincided in all cases. The directions of πCA and SRM schemes were similar for low V_{alt} (Fig. 4(a)), and the difference between them decreased as V_{alt} increased (Fig. 4(b)).

V. DISCUSSION AND CONCLUSIONS

The best detection performance is obtained with the periodicity-based schemes. Both πCA and SRM search for the direction from which the periodicity of the transformed

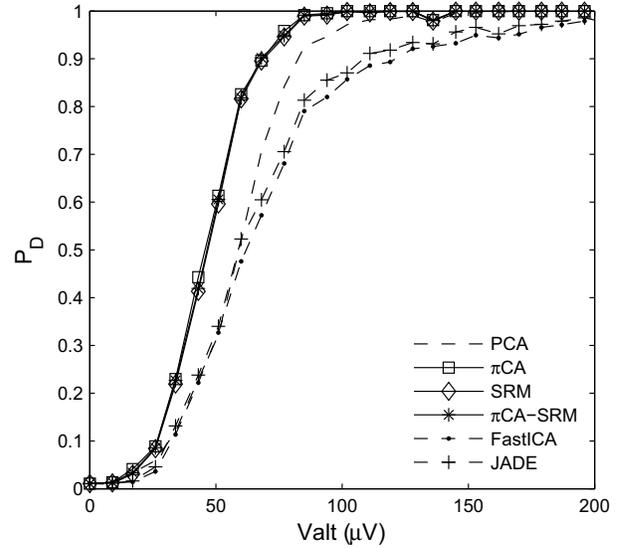signal is maximum, following a temporal and a spectral criterion respectively. These criteria offer equivalent detection results; the directions obtained by the two schemes tend to converge as TWA increases, and for low V_{alt} values, πCA and SRM directions are close enough to produce the same P_D. The projections obtained with SRM and πCA-SRM schemes coincide in all cases. Initializing the optimization algorithm with πCA - a closer point to the solution - reduces convergence time, but even in that case the computational cost is more than 70 times higher than the cost of the πCA scheme.

PCA is the fastest among the compared schemes, although the execution times of PCA and πCA are comparable. The maximum-variance criterion of PCA produces a *denoising* effect on the multilead signal that improves the detection of TWA over a single-lead scheme [5], but this improvement is not high enough to outperform the periodicity-based schemes.

The ICA algorithms, FastICA and JADE, present the worst detection performance among the compared schemes. ICA has been successfully applied to ECG problems in the past [16], but, according to our results, it is not the best approach for TWA analysis. FastICA and JADE algorithms are based on the classic ICA model, which assumes that the input signal is an instantaneous stationary linear mixture of independent sources, whose number equals the number of signal channels. This is not a very realistic assumption for TWA analysis in 3-lead ECGs, in which the signal after the preprocessing stages, besides the TWA component, may still contain different types of residual noise (electrode movement, baseline wander, motion artifacts) and residual activity of the ventricles due to a non-perfect *detrending* filter. In this case, assuming only three sources could be unrealistic, and independence between sources is not assured
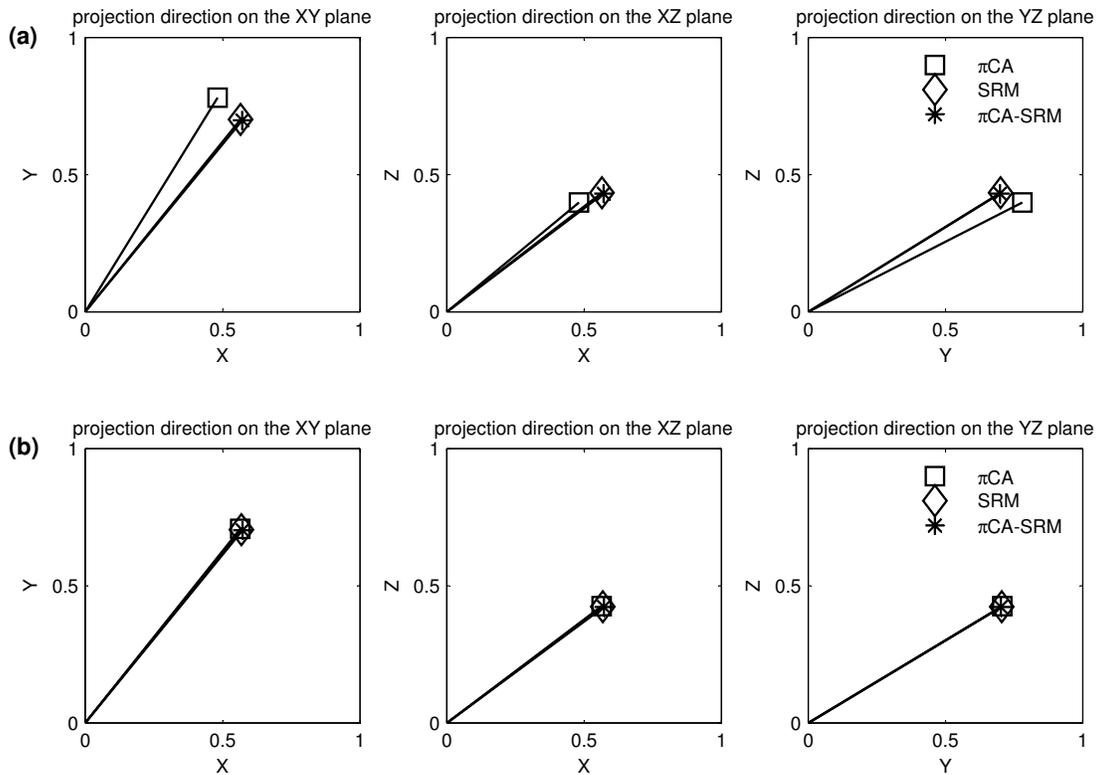
Fig. 4. Average direction of the projections obtained with the πCA scheme (squares), the SRM scheme (diamonds) and the πCA-SRM scheme (asterisks) in signals with (a) V_{alt}=10 μV and (b) V_{alt}=60 μV.

either. ICA algorithms could yield better results with 12-lead ECGs, such as those obtained in TWA clinical stress tests, but their utility with ambulatory 2 or 3-lead ECGs seems limited. According to our results, the preferred option for TWA analysis in ambulatory ECG signals should be the πCA scheme.

VI. ACKNOWLEDGMENTS

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