Comparison of two eigenvalue decomposition techniques to detect T Wave Alternans in the ECG

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Abstract—**T-wave alternans (TWA) is a cardiac phenomenon associated with the mechanisms leading to sudden cardiac death. In this work we propose a multilead analysis scheme to improve the detection of TWA in the electrocardiogram (ECG); it is based on Periodic Component Analysis (πCA), an eigenvalue decomposition technique whose aim is to extract the most periodic linear mixtures of the signal. The proposed scheme is evaluated and compared to a previously presented scheme based on Principal Component Analysis (PCA), and to a single-lead scheme. Simulation results show that the πCA-based scheme provides a higher detection power, being able to detect TWA with an amplitude lower than 5 μV.**

Keywords—**T-wave Alternans, ECG, multilead analysis, principal component analysis, periodic component analysis.**

I. Introduction

T-wave alternans (TWA) is defined as a consistent fluctuation in the repolarization morphology on an every-other-beat basis. TWA is presently regarded as a promising index of susceptibility to sudden cardiac death [1], [2]. TWA amplitude is in the range of microvolts, and can be even below the noise level, making its detection a difficult task. Several methods exist to automatically detect and estimate TWA [3]. Most of them work on a single-lead basis. A major drawback of these methods is their low sensitivity to low amplitude alternans [2], [3].

In a previous work [4], we presented a multilead scheme that combines Principal Component Analysis (PCA) with a single-lead TWA analysis method, the Laplacian Likelihood Ratio method (LLR) [5]. In this work we present a new multilead scheme that combines the LLR method with Periodic Component Analysis (πCA), which is a technique that performs eigenvalue decomposition of the input signal to analyze its periodic structure. The πCA technique was first proposed in [6] and later applied to ECG signals in [7]. In this study, PCA-based and πCA-based schemes are compared to a single-lead scheme in terms of detection power.

II. TWA analysis

Three different approaches based on the LLR method are compared: a multilead scheme based on PCA (*multi-PCA*), a multilead scheme based on πCA (*multi-πCA*) and a single-lead scheme (*single*).

A. General multilead scheme

Both *multi-PCA* and *multi-πCA* approaches follow a general scheme that consists of five stages: signal preprocessing, signal transformation, TWA detection, signal reconstruction, and TWA estimation (Fig. 1). The difference between *multi-PCA* and *multi-πCA* is the technique used in the signal transformation stage.

1) Preprocessing: Baseline wandering is removed using a cubic splines interpolation technique. Signal is then low-pass filtered with a cut-off frequency of 15 Hz and decimated to obtain a sampling frequency of $F_s = 31$ Hz. An interval of 300 ms is selected on each beat for TWA analysis (ST-T complex). In the case of 12-lead ECGs, only the eight independent leads (V1-V6, I, II) are considered. Fig. 2(a) shows an example.

Let K be the number of beats in the analysis window, N the number of samples of each ST-T complex, L the number of leads, and $x_{k,l}(n)$ the ST-T complex of the k-th beat and the l-th lead. Each ST-T complex 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 complex, which is periodically repeated in each beat, $a_l(n)$ is the alternans waveform, and $v_{k,l}(n)$ is additive random noise. For each lead l, complexes are concatenated:

$$\mathbf{x}_l(t) = \begin{bmatrix} x_{1,l}(n) & \ldots & x_{K,l}(n) \end{bmatrix} \quad t = 0, \ldots, KN-1 \qquad (1)$$

and $\mathbf{x}_l$ vectors are piled to form the data matrix $\mathbf{X}$

$$\mathbf{X}(t) = \begin{bmatrix} \mathbf{x}_1(t) \\ \vdots \\ \mathbf{x}_L(t) \end{bmatrix} \qquad (2)$$

2) Signal transformation: The objective of this stage is to find a linear transformation $\mathbf{Y} = \mathbf{\Psi}^T\mathbf{X}$ that improves the signal-to-noise ratio (SNR) of TWA by exploiting spatial and temporal information of the multilead ECG. The leads

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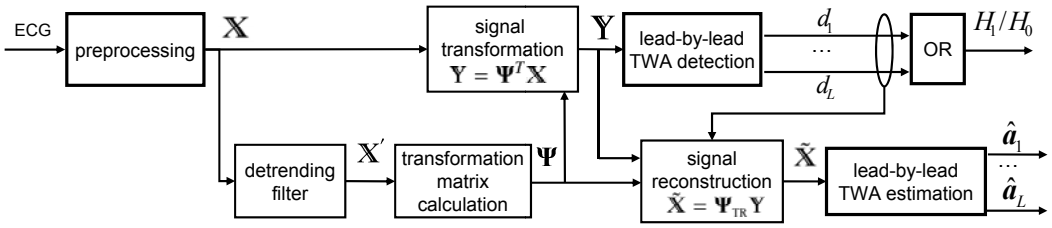

Fig. 1 Block diagram of the general multilead scheme. Blocks in bold line are the ones used in the single-lead scheme, in which $\mathbf{Y} = \mathbf{X} = \tilde{\mathbf{X}}$.

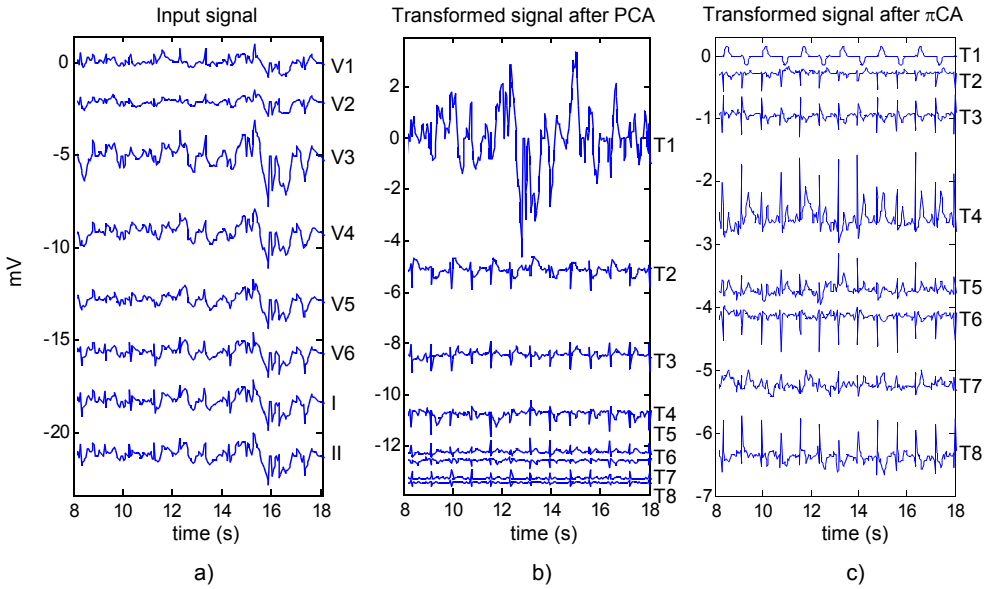

Fig. 2 (a) Input signal with TWA of 200 μV. TWA is invisible to the naked eye due to noise and artifacts. (b) Signal in (a) after PCA transformation. TWA is now visible in T2. (c) Signal in (a) after πCA transformation. TWA is clearly visible in T1.

of the transformed signal $\mathbf{Y}$ will be denoted as transformed leads from here on (T*1* to T*8*). First, a detrending filter is applied to $\mathbf{X}$ to cancel the background ST-T complexes

$$x'_{k,l}(n) = x_{k,l}(n) - x_{k-1,l}(n), \quad k = 1 \ \ldots \ K-1$$

and then $\mathbf{\Psi}$ is calculated from matrix $\mathbf{X}'$ with two different techniques: principal component analysis (PCA) and periodic component analysis (πCA).

Principal Component Analysis: The detrended signal $\mathbf{X}'$ is a zero-mean random process with a spatial correlation matrix $\mathbf{R}_{\mathbf{X}'} = E\left\{\mathbf{X}'\mathbf{X}'^T\right\}$. To obtain the transformation, the eigenvector equation for $\mathbf{R}_{\mathbf{X}'}$ is solved

$$\mathbf{R}_{\mathbf{X}'}\mathbf{\Psi} = \mathbf{\Psi}\mathbf{\Lambda} \tag{3}$$

where $\mathbf{\Lambda}$ denotes the eigenvalue matrix and $\mathbf{\Psi}$ is the eigenvector matrix. Matrix $\mathbf{\Psi}$ defines an orthonormal transformation, that is applied to the original data $\mathbf{X}$

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

thus obtaining the transformed matrix $\mathbf{Y}$, whose lth row contains the lth principal component of $\mathbf{X}$. Fig. 2(b) shows the input signal in (a) after PCA transformation.

Periodic Component Analysis: This technique aims to find the transformation $\mathbf{y}(t) = \mathbf{w}^T\mathbf{X}'(t)$ that maximizes the periodic structure of the signal at frequency $f_0 = 0.5$ cicles per beat (cpb), or equivalently at period $\tau = 1/f_0 = 2N$ samples. The desired transformation must minimize the following measure of periodicity

$$\epsilon(\mathbf{w}, \tau) = \frac{\sum_t |\mathbf{y}(t+\tau) - \mathbf{y}(t)|^2}{\sum_t |\mathbf{y}(t)|^2} \tag{5}$$

As shown in [7], (5) can be rearranged as

$$\epsilon(\mathbf{w}, \tau) = \frac{\mathbf{w}^T\mathbf{A}_{\mathbf{X}'}(\tau)\mathbf{w}}{\mathbf{w}^T\mathbf{R}_{\mathbf{X}'}\mathbf{w}} \tag{6}$$

where

$$\mathbf{A}_{\mathbf{X}'}(\tau) = E_t\left\{\left[\mathbf{X}'(t+\tau) - \mathbf{X}'(t)\right]\left[\mathbf{X}'(t+\tau) - \mathbf{X}'(t)\right]^T\right\}. \tag{7}$$

The weight $\mathbf{w}$ that minimizes (6) is given by the generalized eigenvector corresponding to the smallest generalized eigenvalue of the matrix pair $(\mathbf{A}_{\mathbf{X}'}(\tau), \mathbf{R}_{\mathbf{X}'})$ [7], [6]. Transformation matrix $\mathbf{\Psi}$ is chosen as the generalized eigenvector matrix of $(\mathbf{A}_{\mathbf{X}'}(\tau), \mathbf{R}_{\mathbf{X}'})$, with the eigenvectors (columns) sorted according to the corresponding eigenvalues in ascending order. In this way, the transformation $\mathbf{Y} = \mathbf{\Psi}^T\mathbf{X}$ gives the most periodic components of $\mathbf{X}$ in descending order of periodicity, that is, the alternans component is projected to the first transformed lead (first row in $\mathbf{Y}$). Fig. 2(c) shows the input signal in (a) after πCA transformation.

3) TWA detection: After signal transformation, TWA detection is performed in the transformed signal. The Generalized Likelihood Ratio Test (GLRT) for Laplacian noise is applied to each transformed lead (rows in $\mathbf{Y}$) as proposed in [5]. To decide whether alternans is present or not, a detection statistic Z is computed from the data, and is compared to a threshold γ. The result of this lead-by-lead detection is denoted as d_l: $d_l = 1$ if TWA is detected in the lth transformed lead, and $d_l = 0$ otherwise. The overall TWA detection is positive if TWA is detected at least in one transformed lead ('OR' block in Fig. 1).

4) Signal reconstruction: TWA must be measured in the original leads to be clinically useful. Therefore, a new signal in the original lead set is reconstructed, considering only the transformed leads where TWA was detected. Matrix $\mathbf{\Psi}$ is truncated by inserting zeros in columns corresponding to leads without TWA, thus obtaining matrix $\mathbf{\Psi}_{\text{TR}}$, and then the reconstructed signal is obtained as

$$\tilde{\mathbf{X}} = \mathbf{\Psi}_{\text{TR}}\mathbf{Y}. \tag{8}$$

5) TWA estimation: Finally, the Maximum Likelihood Estimation (MLE) for Laplacian noise is applied to the reconstructed data as described in [5] to estimate the TWA waveform in each lead l, $\hat{a}_l(n)$, and its amplitude V_{alt}.

B. Single-lead scheme

The single-lead scheme handles each lead independently throughout the process. It consists of the same preprocessing, TWA estimation and TWA detection stages as the multilead scheme, but without the intermediate transformation/reconstruction stages. That is, with the single-lead scheme $\mathbf{Y} = \mathbf{X} = \tilde{\mathbf{X}}$. The stages of the single-lead scheme are shown in bold line in Fig.1.

III. Data set

To compare the analysis schemes, we designed a simulation study where a known TWA waveform was added to real 12-lead ECGs. Records belonging to 277 healthy subjects (negative stress test both clinically and electrically) were chosen from a stress test ECG database [8]. For each record, the initial fragment in which heart rhythm was < 100 beats/minute was selected and divided into segments of 32 beats. 1744 ECG segments were obtained in total. A real TWA waveform was detected and extracted from a 12-lead record of the STAFF-III database, using the LLR method as described in [5]. TWA was scaled with amplitudes (V_{alt}) from 0 to 200 μV, and added in each case to all ECG segments.

IV. Results

Signals were processed with the single-lead and the two multilead schemes. The value of the detection threshold γ was set so that the probability of false alarm (P_{FA}) was 0.01 for all schemes, and the resulting probability of detection (P_{D}) was compared (Fig. 3). TWA of 5μV was detected with a $P_{\text{D}} = 98\%$ with the *multi-πCA* scheme, and with a $P_{\text{D}} = 60\%$ with the *multi-PCA* scheme.

To better understand the effects of PCA and πCA transformations, the evolution of the GLRT statistic Z in the transformed leads vs. TWA amplitude was analyzed for all signals. Fig.4 shows an example where the same ECG signal is transformed using PCA (left) or πCA (right).

V. Discussion and Conclusions

The best detection performance is obtained with the *multi-πCA* scheme (Fig.3). ECG signals do not usually contain any components at frequency 0.5 cpb, as long

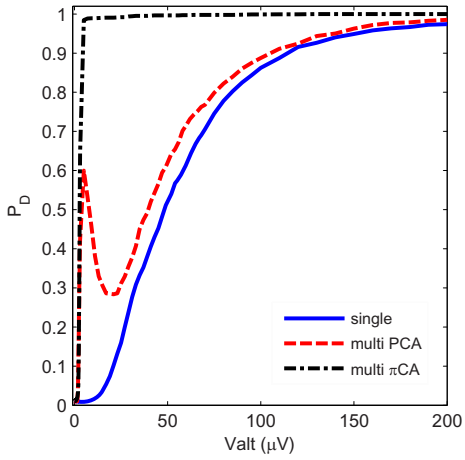

Fig. 3 P_D for $P_{FA} = 0.01$ of *multi-PCA*,*multi-πCA* and single-lead schemes vs. TWA amplitude.

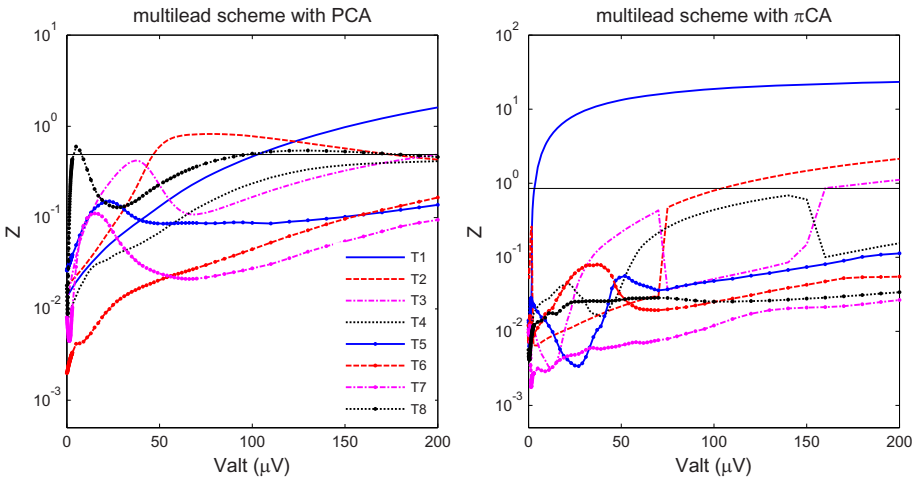

Fig. 4 Comparison of *multi-PCA* (left) and *multi-πCA* (right) applied to the same ECG signal with different amounts of TWA. Curves show the values of the detection statistic in the eight transformed leads for each TWA amplitude. Horizontal black line indicates the detection threshold (P_{FA} = 0.01 for both schemes). Legend is the same in both panels.

as baseline wander is correctly removed, so the content projected by πCA to the first transformed lead (T*1*) is mainly the TWA component; therefore, even TWA with an amplitude as low as 5μV becomes detectable in the transformed signal. This effect can be clearly observed in left panel of Fig.4, where the detection statistic passes the threshold at V_{alt} = 3.5μV.

With *multi-PCA* scheme, P_D improves fast for $V_{alt} \leq 5\mu$V and then drops suddenly (Fig.3). This happens because PCA projects the components of the signal with higher variance into the highest transformed leads (T*1*- T*3*); therefore, when TWA amplitude is low, PCA mainly concentrates the noise in the highest transformed leads, whereas TWA remains present in all leads (as long as spatial correlations of TWA and noise are different), making TWA detectable in the lowest leads. As V_{alt} increases, TWA starts to be projected to higher leads, so it gets masked by noise again, and therefore P_D decreases. Finally, when V_{alt} is high enough, PCA mainly concentrates TWA in the highest leads, but in this case there is little advantage in using the *multi-PCA* scheme since TWA is detectable even by the single-lead scheme. In the example of Fig.4, TWA is detected in T*8* for $V_{alt} < 5\mu$V, becomes undetected for $5 < V_{alt} < 50\mu$V, and then is detected again in T2 for $V_{alt} = 50\mu$V.

According to simulation results, the multilead scheme based on periodic component analysis improves significantly the detection of TWA, outperforming the multilead scheme based on PCA and the single lead scheme. Although further validation with real signals is needed, it may find application in noisy signals such as stress test ECG, which is one of the main clinical scenarios where TWA analysis is performed.

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