Spatial ECG filtering by Periodic component analysis for improved QT delineation in stress test recordings

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The electrocardiogram signal (ECG) represents the electrical activity of the heart at body surface. Characteristic waves and their delineation marks are studied to define biomedical markers without using invasive procedures. For example, slowed adaptation of the QT interval to sudden abrupt changes in Heart Rate (HR) has been identified as a marker of arrhythmic risk. Such abrupt HR changes are difficult to induce, leading here to explore estimation of this delay from the ramp-like HR variations observed in exercise stress test. However, stress test ECG signals are very noisy. The aim of this study is to find proper methods to emphasise T wave for optimal end determination. Stress test ECG recordings from 250 subjects were analyzed. The first spatially transformed lead from six different methods, based on two lead-space reduction (LSR) techniques, were delineated to obtain the QT series. The lower fitting error power was obtained with periodic component analysis technique exploiting 1, 2 and 3-beats periodicities.

***Index Terms*—Periodic component analysis, QT interval, biomedical marker.**

I. EXTENDED SUMMARY

In recent years, different biomarkers for ventricular arrhythmia risk patients stratification, eventualy leading to Sudden Cardiac Death (SCD), have been proposed. Several are based on the electrocardiogram signal (ECG) due to their non-invasive character. The adaptation time of the QT interval to sudden changes in Heart Rate (HR) is just one example that has been identified as a biomarker for arrhythmic risk [4][5]. The QT response to these sudden HR changes were modeled as a the response of a first-order system to a step input, so characterized by a time adaptation constant. However, abrupt HR changes, from where to estimate the time constants, are not always easily observed. The response to a ramp of a first-order system is characterized by the same time constant as the step-response [3], so ramp-like HR changes are alternatively suggested to measure this delay. Ramp-like inputs are typically observed in exercise stress tests, where the cardiac system is subject to an approximately linear HR input both during the exercise and recovery phases of the test, suggesting the use of stress test for this purpose. However, ECG signals recorded during a stress test are very noisy, representing a limitation for QT interval estimation, T-wave end (T_e) minus QRS complex onset (QRS_o), particularly if measured from single lead analysis.

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Two different lead-space reduction (LSR) techniques have been analysed in the context of multi-lead QT delineation improvement: *Principal Component Analysis* (PCA) [1] and *Periodic Component Analysis* (πCA) [6]. Their common objective was to find a linear transformation, $\mathbb{Y} = \mathbf{\Psi^T}\mathbb{X}$, which emphasizes the ECG waves at the transform leads of interest in $\mathbb{Y}$ matrix, transformed from the original ones in $\mathbb{X}$ matrix. The learning phase to estimate the transform $\mathbf{\Psi^T}$, is restricted to the T-wave of each beat along of the 8 independent standard leads. This learning was done using in total six variants of the two LSR techniques:

- $\pi\mathbf{CA_w}$: πCA technique with 1-beat periodicity, and $\mathbf{\Psi}$ matrix recalculated in each ECG signal segment of 120 seconds.
- $\pi\mathbf{CA_{w_{ext}}}$: $\mathbf{\Psi}$ was calculated as for $\pi\mathbf{CA_w}$ but mixing the information of 1-beat, 2-beats and 3-beats periodicity of the T waves.
- $\pi\mathbf{CA_o}$: πCA technique restricted to 1-beat periodicity and $\mathbf{\Psi}$ matrix calculated once for the whole recording using the information of the first 120 seconds.
- $\pi\mathbf{CA_{o_{ext}}}$: $\mathbf{\Psi}$ matrix was calculated once mixing the information of 1-beat, 2-beats and 3-beats periodicity during the first 120 seconds.
- $\mathbf{PCA_w}$: PCA technique whose $\mathbf{\Psi}$ matrix was recalculated in each window of 120 seconds.
- $\mathbf{PCA_o}$: PCA technique whose $\mathbf{\Psi}$ matrix was calculated once using the information of the first 120 seconds.

In each case, the delineation procedure, which was based on a wavelet-based algorithm [2], was applied in the first transformation signal (TL1) to obtain the QT series. Fig.1 shows an example of the 8 independent standard leads from a subject (Fig.1(a)).

A sub-cohort of 250 patients which belongs to a database of Tampere University Hospital, targeted to characterize patients with high risk of cardiovascular morbidity and mortality, was used in this study. A continuous ECG was recorded during a stress test done in a bicycle ergometer and the 8 independent standard leads were available to apply the six transformation matrix. The QT series was calculated delineating the TL1 of each method. To evaluate the appropriated technique to obtain

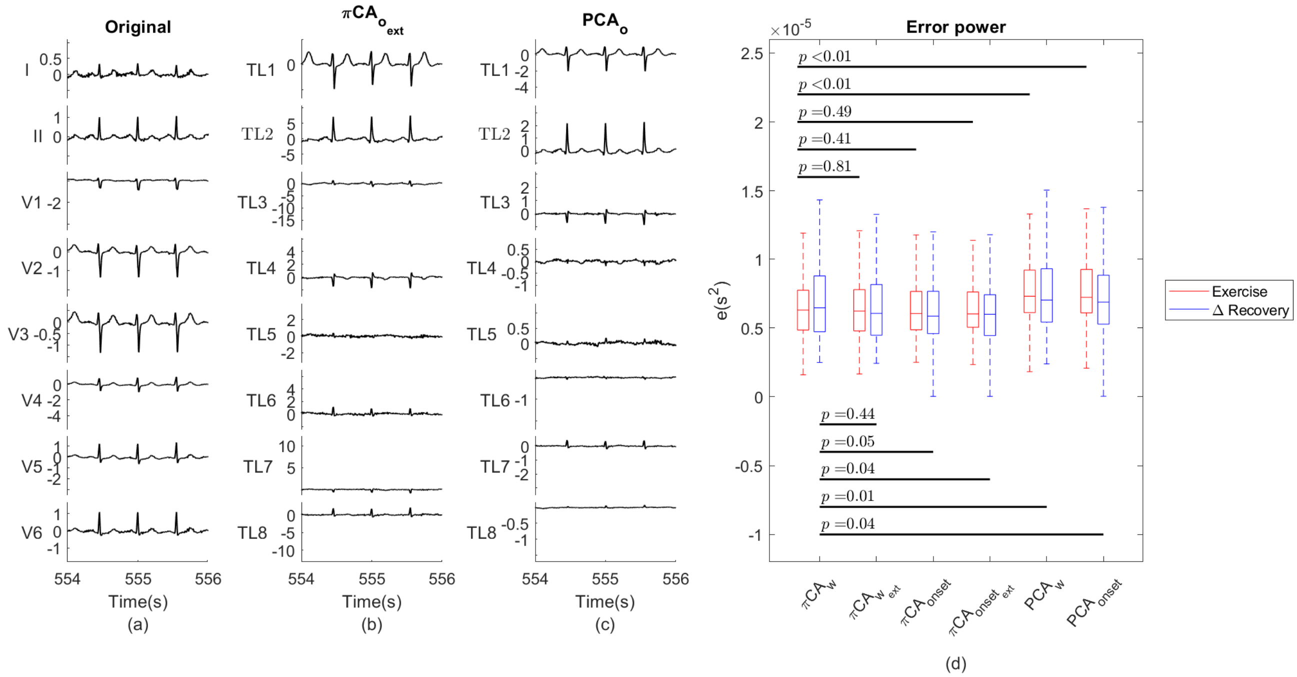

Fig. 1. (a) An example of ECG from 8 independent standard leads recorded during a stress test. (b) Their corresponding 8 transformation leads obtained with $\pi CA_{w_{ext}}$ and (c) with $\pi CA_{o_{ext}}$, where the emphasized T-wave can be shown. (d) QT trend fitting error power values calculated both in the exercise and in the recovery areas independently for each 6 transformation method.

the best QT series, the low-frequency QT trend deviation error power was calculated applying a high-pass filter with a cut-off frequency of 0.04Hz. This value was obtained in the exercise and in the recovery areas independently for each 6 transformation method. The results are shown in Fig.1(d), where we can see that the lowest median value and the least dispersion in exercise is obtained with $\pi CA_{w_{ext}}$, while in recovery is obtained with both πCA_o methods. An example of the 8 transformation leads obtained with $\pi CA_{w_{ext}}$ and $\pi CA_{o_{ext}}$ are shown in Fig.1(b) and Fig.1(c) respectively, where the T-wave is emphasized in the TL1. The Mann–Whitney–Wilcoxon statistic test disclose that there is not significant differences between the four πCA methods.

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