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Detection and Quantification of T-Wave Alternans in Ecg by Spectral Method

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ABSTRACT *T-wave alternans (TWA) is a cardiac phenomenon related to the mechanisms leading to ventricular arrhythmias and sudden cardiac death (SCD). It appears in the surface electrocardiogram (ECG) as a beat-to-beat alternation in the morphology of the repolarization, and its amplitude can be so low that it is imperceptible to the naked eye. Several signal processing methods proposed to detect TWA in the ECG and to quantify its amplitude. The objective of this project is to develop multilead analysis schemes for TWA analysis that improve the detection and quantification of TWA in the ECG. 50 ECG recordings provided by the 2008 PhysioNet/Computers in Cardiology Challenge were analyzed. After ECG pre-processing, Fast Fourier Transform (FFT) spectral analysis and principal component analysis (PCA) were used for TWA determination and quantification. The work carried out to achieve this goal is divided in two parts: The first part of the project introduces a general scheme for multilead analysis of TWA. The second part of the paper presents the methodological evaluation of the multilead scheme based on the different transformation techniques. Using spectral method, accuracy of TWA detection increased up to 94 %. Furthermore analyse the precision and recall parameters.*

KEYWORDS : ECG, multilead analysis, principal component analysis (PCA), T-wave alternans (TWA).

INTRODUCTION

ECG signals are electrical signal which are measured by placing electrodes on the body surface and recording the electrical activity of the heart. The instantaneous recording of the ECG on different chest positions (channels or leads) delivers a spatial perception of cardiac events. The standard 12-lead system is the furthermost widely used system in clinical practice, and consists of eight independent leads, entitled V1–V6, I, and II, and four additional leads that can be derived from the independent ones. The ECG has three characteristic waves on each beat: P-wave, QRS complex, and T-wave. The interval between the end of the QRS complex and the end of the T-wave is known as ST-T complex, and reflects the repolarization activity of the ventricles. TWA is defined as a consistent variation in the repolarization morphology on an every-other-beat basis. TWA amplitude is in the range of microvolts. So it can be even below the noise level, making its detection a difficult task & invisible to naked eye. Many signal processing methods occur to detect and estimate TWA. The utmost widely used techniques are the spectral method (SM) [1], [4] and Laplacian likelihood ratio method (LLR) the [5]. Alternative techniques are the complex demodulation method [6] and the recently proposed modified moving average method [7], [8]. The outcomes of existing techniques is with high amplitude their sensitivity to the presence of nonalternant components or less sensitivity to low-level TWA [2], [3]. Also, some of these techniques measure TWA amplitude. But they do not estimate the TWA waveform. An accurate waveform estimation is necessary because, in addition to the presence and magnitude of TWA, the distribution of TWA within the ST-T complex has been shown to specify arrhythmic risk [9]. TWA analysis systems have been commonly applied to each lead individually. In commercial TWA analysis systems, only basic multilead strategies are performed, such as analyzing the vector-magnitude lead. However, ECG signals has a high spatial redundancy that can be better exploited with techniques based on the Eigen analysis of input data, such as principal component analysis (PCA) or Karhunen–Lo`eve transform (KLT) [10].

These techniques have been applied to ECG data compression and noise reduction [11]–[14], characterization and diagnosis of ischemia [15], [16], repolarization heterogeneity [17]–[19], atrial fibrillation [20], [21], and separation of maternal and fetal ECG [21]. The hypothesis of this paper is that TWA analysis can be improved by exploiting the spatial redundancy of ECG signals with PCA. In this paper, we have proposed a multilead TWA analysis scheme that syndicates PCA with the LLR method & FFT method [7], [8]. Methodological evaluation of a new technique (i.e., the estimate TWA accuracy) is a prior step to clinical validation (which quantifies the adequateness of the TWA test as a risk stratifier). The improvements in the detection performance and in the accuracy of TWA estimation over a single-lead-scheme are quantified for all the multilead alternatives. 50 ECG recordings provided by the 2008 PhysioNet/Computers in Cardiology Challenge were analyzed. After ECG pre-processing stage, Fast Fourier Transform (FFT) and principal component analysis (PCA) were used for TWA determination and quantification.

This paper intentions to deliver a methodological overview of the different approaches to TWA analysis. Framework of this paper is as follows: In Section II, recognition and estimation methods for TWA, Section III, is dedicated to PhysioNet Database Finally result and discussion are expressed in Section IV, and conclusions are given in Section V.

II. RECOGNITION AND ESTIMATION METHODS FOR TWA

The block diagram of the proposed multilead scheme [21] is shown in Fig. 1.

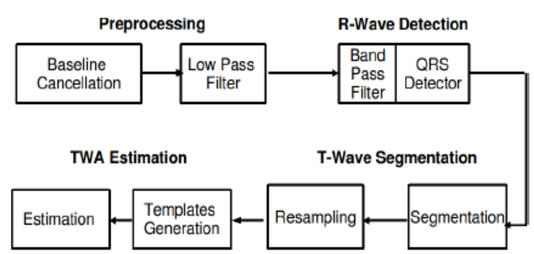

Fig. 1. Multilead Analysis System [21].

It consists of five stages: signal reprocessing, signal transformation with, TWA detection, signal reconstruction, and TWA estimation.

A. ECG pre-processing:

Preprocessing is very important step in the diagnosis of different kinds of heart diseases because ECG signal is contaminated with different kinds of noises. If we analyse signal without removing these noises then there is prospect of wrong diagnosis. ECG signal consists of very important information about heart.

B. Signal transformation:

The second stage aims to find a spatial transformation of the original leads set that separates TWA from noise as much as possible. First, background ST-T segments are cancelled with a detrending filter. The application of the detrending filter is projected to remove the background ECG. This is necessary because otherwise the separation techniques described later would tend to separate the background ECG, not the TWA, from noise, since the background ECG has greater power than the TWA component. Then, the transformation is calculated using a technique that separates TWA from the rest of the ECG components. Two techniques are engaged to find the transformation matrix: 1). Fast Fourier Transform (FFT) & 2) Principal component analysis (PCA). The objective of the linear transformation is to increase the separation between TWA and noise by projecting most of the TWA component onto one subset of transformed leads, and most of the noise onto a different subset of leads. Therefore, TWA and noise will appear more separated in the transformed signal than in the original signal, and the detection of TWA will be easier. In which TWA becomes easily detectable in the transformed signal after PCA transformation. Signal transformation techniques used in this algorithm are as follows

a. Fast Fourier Transform

In the FFT-based method, power spectrum for each sample point (columns of Amxn matrix) of 128 time aligned T-waves is calculated by squaring the magnitude of the fast Fourier transform. The cumulative power spectrum is projected by summing the power spectra got for all sample point. In the cumulative spectrum, the beat-to beat fluctuation of the T wave amplitude looks as the spectral peak at the frequency of 0.5 cycles per beat; hence, the magnitude peak is a direct marker of the alternans. The FFT-based detector enables the registration of the Alternans along the T-wave by analysis of the power spectrum for each sample point.

b. Principal Component Analysis

Principal component examination is a statistical technique which converts a set of associated variables into a set of uncorrelated variables ("principal components"). In general, the objective of PCA is to condense the information of a large set of variables into a few variables, while maintaining the variability present in the dataset [Joliffe, 2002]. In this paper, however, the main objective of PCA is to separate TWA from noise as much as possible, since TWA and noise originate from different physical processes, and therefore it is sensible to assume that they are uncorrelated.

c. TWA Finding

Next PCA transformation, TWA detection is executed in the transformed data. The generalized likelihood ratio test GLRT is applied to each transformed lead. The outcome of this lead-by-lead detection is denoted as dl: dl = 1 if TWA is detected in the l^{th} transformed lead and dl = 0 otherwise. The overall TWA detection is positive if TWA is detected at least in one transformed lead.

d. Signal Reconstruction with Inverse PCA

After TWA detection, a new signal in the original lead set is reconstructed. This is necessary because TWA must be measured in the original leads to be useful in clinical practice. A diagonal matrix is defined from the lead-by-lead detection.

TWA Estimation

To estimate the TWA waveform and amplitude, the maximum likelihood estimation is applied to the reconstructed data

Physionet T-Wave alternans database

The Physionet T-Wave alternans database is a publicly available resource compiled for the PhysioNet/Computers in Cardiology Challenge 2008 [Moody, 2008]. It covers one hundred real ECG records, sampled at 500 Hz. The synthetic subset of the database consists of thirty-two 12- lead ECGs containing artificial TWA in calibrated amounts. The remaining 68 records are real signals from different databases, 56 of which belong to patients with known cardiac risk factors. Synthetic records have 12 leads, and real records have 2, 3 or 12 leads. We havedeveloped Matlab based software tool for detection of abnormalities. Also we have tested the proposed estimation and detection algorithm on the 100 ECG recordings included in the 2008 Challenge data base in which the presence of alternans was not known. Finally studied the detection performance and the accuracy of the estimation.

RESULT DISCUSSION

- Signals were processed with the multi-lead using PCA multilead scheme.
- ECG signal is affected by various kinds of noises, among which baseline wander is the important artifact. Hence median filter is used to remove baseline wander.
- Median filter removes baseline wander more effectively and gives more stable ECG waveform.
- Wavelet transform is used to remove high frequency components (noise) from ECG signal. Fig 2 shows filtered outputs of various leads.
- Various features are extracted from input ECG signal which shown in fig 3. Finally principle multilead analysis system is implemented for automatic classification of normal and abnormal signal.
- Using FFT method we find mean of FFT of T wave as shown in fig.4.
- The PCA method gives us TWA detection as shown in fig.5.
- Analysis of various parameter is done in Table.1

CONCLUSION

- ECG signal is affected by various kinds of noises, among which baseline wander is the important artifact. Hence median filter is used to remove baseline wander.
- Median filter removes baseline wander more effectively and gives more stable ECG waveform.
- Wavelet transform is used to remove high frequency components (noise) from ECG signal.
- Multilead analysis system is implemented for automatic classification of normal and abnormal signal.
- The PCA method gives us TWA detection.
- Using spectral method, accuracy of T wave alternans detection increased up to 94 %.

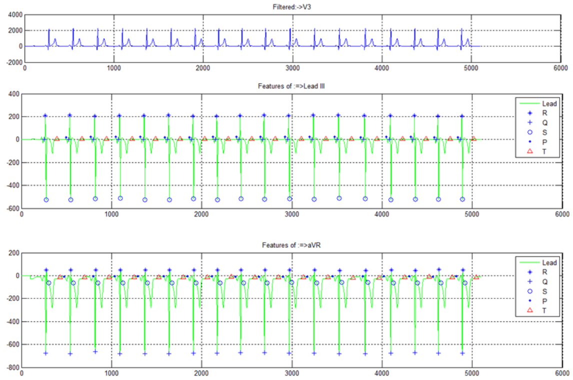

Fig.3.Various features are extracted from input ECG signal

Table No. 1. Analysis of various parameter of TWA Output Signal

Sample Signal	FFT ANALYSIS				PCA ANALYSIS			
	Normal/ Abnormal Signal	Accuracy	Precision	Recall	Normal/ Abnormal Signal	Accuracy	Precision	Recall
twa06m	Abnormal	90.2339	0.0106	1.3108	Abnormal	91.463	0.0556	1.2353
twa09m	Abnormal	90.1568	0.0108	1.2968	Abnormal	91.4	0.0526	1.3039
twa28m	Abnormal	90.57	0.0108	1.2968	Abnormal	91.7596	0.0556	1.2353
twa29m	Abnormal	90.395	0.0108	1.2968	Abnormal	91.599	0.0556	1.2353
twa30m	Abnormal	90.7288	0.0109	1.2829	Abnormal	91.8701	0.0556	1.2353
twa33m	Abnormal	90.532	0.0108	1.2968	Abnormal	91.7023	0.0556	1.2353
twa34	Abnormal	90.0353	0.0106	1.3108	Abnormal	91.3017	0.0526	1.3039
twa64	Abnormal	90.5058	0.0108	1.2968	Abnormal	91.7246	0.0556	1.2353

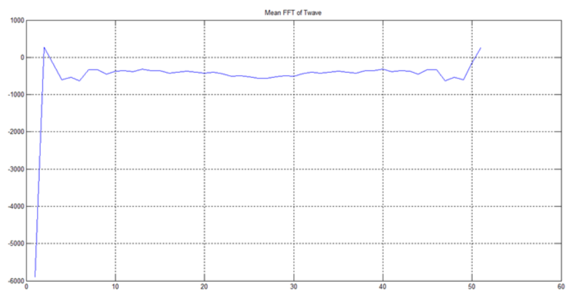

Fig.4. Mean of FFT of T wave

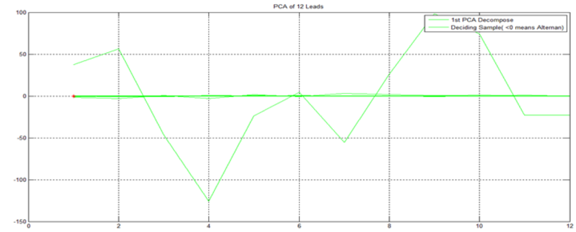

Fig. 5. TWA detection using PCA multilead analysis system

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