An Improved Spectral Method of Detecting and Quantifying T-Wave Alternans for SCD Risk Evaluation

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Abstract

T-wave alternans (TWA) is widely understood as an important indicator and a predictor of risk of sudden cardiac death (SCD). This research provides an improved spectral method of detecting and quantifying T-Wave alternans. Basically, the algorithm used enhanced TWA spectrum and T-Slope variations to generate two parameters: enhanced alternans ratio (EAR) and range index (RI). Then, the singular value decomposition method was applied to fuse two parameters. The results showed that our method has 82.4% accuracy on MIT-SCD database and 76.7% accuracy on normal healthy individuals. Moreover, the method achieved the 0.636 final score on the official PhysioNet Challenge 2008 dataset.

1. Introduction

T-wave alternans (TWA) was first observed by H.E. Hering [1] at one hundred year ago. Basically, TWA is a pattern in the ECG characterized by two distinct forms of T-waves appearing in alternation. TWA measurements allow detecting the periodic changes of the consecutive T-wave amplitude at microvolt level [2-4]. Furthermore, some recently studies showed that TWA is related to cardiac instability and increased arrhythmogenicity [5-6]. Currently, TWA is widely understood as an important indicator and a predictor [7] of risk of sudden cardiac death (SCD) which is responsible for an estimation of 400,000 deaths per year in the United States and millions of mortalities worldwide.

SCD is a life threatening event which is result of a precipitous loss of heart function. When this occurs, no blood can be pumped to the rest of the body within minutes in a person with known or unknown cardiac disease. Only 1-2% of patients can survive when SCD occurs outside of a hospital [8]. Fortunately, TWA is potentially a SCD risk indicator to prevent the possible loss. In particular, the absence of significant TWA in a patient with congestive heart failure, low ejection fraction, or a recent myocardial infarction is strongly predictive of a low risk of SCD.

Hence, many researchers [2-4][6] provided their methods to detect, to enhance, and to quantify TWA. For examples, Moreno-Martinez *et al*. [9] offers a modified spectral method to increase the alternans significance with regard to the noise in the spectral domain and yield better performance in a noisy environment. Strumillo *et al*. [10] carried out the usefulness of Poincaré mapping in detection of T-wave alternans and its comparison to a well-established Fourier spectrum method for TWA quantification. For comprehensive knowledge of TWA, Martinez *et al*. [6] summarized multiple TWA quantification methods, including energy spectral method (ESM), spectral method (SM), complex demodulation method (CD), correlation method (CM), Karhunen-Loeve transform (KLT), Capon filtering method (CF), Poincaré mapping method (PM), periodicity transform method (PT), statistical tests method (ST), modified moving average (MMA), and Laplacian likelihood ratio method (LLR).

However, according to Janusek *et al*. [4], all spectral methods of TWA are sensitive to physiological interference. Hence, the aim of our research is to propose a more robust spectral method of detecting and quantifying TWA by using fusion technology which combines two different spectral methods.

2. Methods

Our method was implemented by applying seventeen records (with T waves presented) of MIT/BIH Sudden Cardiac Death Holter Database and 30 records of our normal subject database as developing datasets. Then, the official PhysioNet/Computers in Cardiology Challenge dataset at http://physionet.org/challenge/2008/ (PCCC2008) was applied to evaluate the performance of the algorithm.

2.1. System structure

The system structure (fig.1) of our improved spectral method contains three major components, including enhanced spectral method (EnSM), spectral analysis of T-Slope variations (TSV), and singular value

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decomposition (SVD). The details of three components will be described as follows.

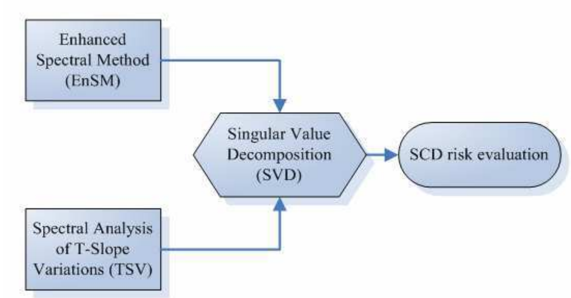

Fig.1 System structure of our improved spectral method

2.2. Preprocessing - T wave extraction

T wave extraction is a critical step for TWA analysis. First, digital filters were utilized to remove general arterial interference and to limit the ECG bandwidth between 1Hz and 50Hz. Second, Tompkins [11] method is used to indicate R waves. With detected R points, T points can be located by cross-checking on the maximum points of ECG and all the zero-crossing points of dECG. After T points are detected, our method captures 0.1 second before and after T points as our T wave window. Finally, there are 128 consecutive T waves which were captured for TWA analysis.

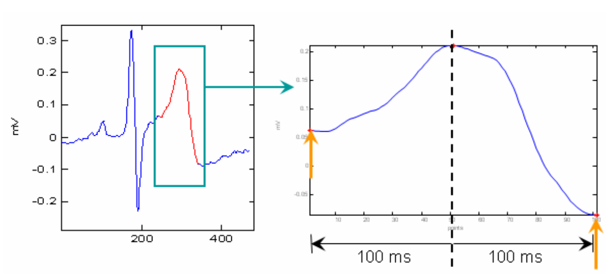

Fig.2 T wave extraction

2.3. Preprocessing - traditional spectral method (SM)

Nowadays, spectral method (SM) is a well-known method to analysis TWA. Briefly saying, the method averages power spectra of 128 time-aligned T-wave with the beat-to-beat amplitude fluctuation on each sampling point of T-wave. The averaged spectrum (PSD_{SM}), the traditional SM spectrum, appears as the spectral peak at the frequency of 0.5 cycles per beat (cpb). Hence, the alternans ratio (AR) can be obtained by:

$$AR = \frac{P_{0.5} - noise}{\sigma_{noise}} \qquad \ldots(1)$$

where $P_{0.5}$ is the amplitude of peak at the frequency 0.5 cpb; *noise* and σ_{noise} are average and standard deviation of the noise registered in the spectrum outside the alternans frequency, 0.5 cpb; however the noise band is not always be the same for researchers. For example, Richter *et al.* [2] defined the reference noise band is between 0.44 and 0.49 cpb, but Moreno *et al.* [9] used the noise band at range [0.33 0.48] cpb. In our research, the noise band is at range [0.42 0.46] cpb, and $P_{0.5}$ is the maximum value at range [0.47 0.5] cpb by considering potentially TWA frequency shifting.

2.4. Enhanced spectral method (EnSM)

As known, the T wave represents the repolarization of the ventricles. The interval from the beginning of the QRS complex to the apex of the T wave is referred to as the absolute refractory period. The last half of the T wave is referred to the relative refractory period. Hence, the idea of the enhanced spectral method (EnSM) is to observe the absolute refractory period, the relative refractory period, and the transition period together.

As mentioned in session 2.2 and fig. 2, the left and right boundary points (so-called $L_{0.1}$ and $R_{0.1}$ points) of our T wave window represent the middle stage of the absolute refractory period and end stage of relative refractory period, respectively. Then other points in between is the transition period.

Next, the new EnSM spectrum averages the traditional SM spectrum (PSD_{SM}), left boundary power spectrum ($PSD_{L0.1}$), and right boundary power spectrum ($PSD_{R0.1}$) together. The PSD_{SM} , $PSD_{L0.1}$, and $PSD_{R0.1}$ are obtained by applying the classical Welch spectrum with 128 points as window size and no overlapping applied. The 128 boundary points came from 128 time-aligned T-waves.

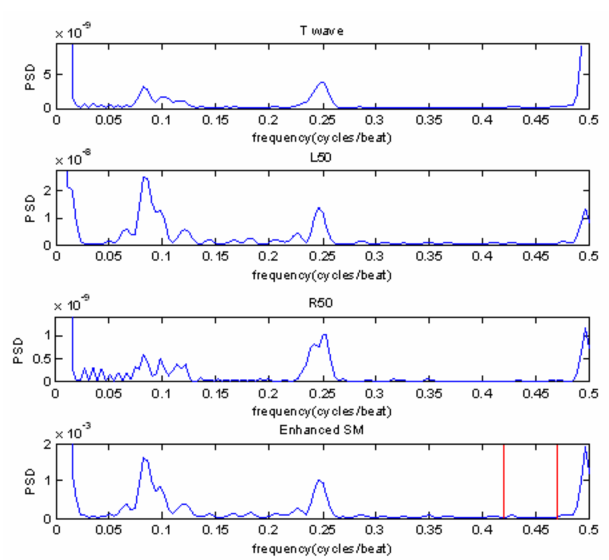

Fig.3 Plot PSD_{SM} , $PSD_{L0.1}$, $PSD_{R0.1}$, and PSD_{EnSM} spectra together (from top to bottom)

Four spectra are compared in fig. 3, which include traditional TWA spectrum (PSD_{SM}), $L_{0.1}$ spectrum ($PSD_{L0.1}$), $R_{0.1}$ spectrum ($PSD_{R0.1}$) and enhanced TWA spectrum (PSD_{EnSM}). Similarly, the enhanced alternans ratio (EAR) inherited from eq. (1) can also be calculated from the new EnSM spectrum.

2.5. Spectral analysis of T-slope variations (TSV)

The spectral analysis of T-slope variations (TSV) is defined as Fourier transform analysis on T-wave slope variations. Here, the T-wave slope is defined as either the slope between $L_{0.1}$ and T point or the slope between $R_{0.1}$ and T points (fig.4). We expected to obtain the AB mode on slope variations, as same as traditional TWA. Then, the consecutive 128 slopes on each side were obtained. Again, the classical Welch spectrum is applied on beat-to-beat slope variability to quantify the AB mode (fig.5).

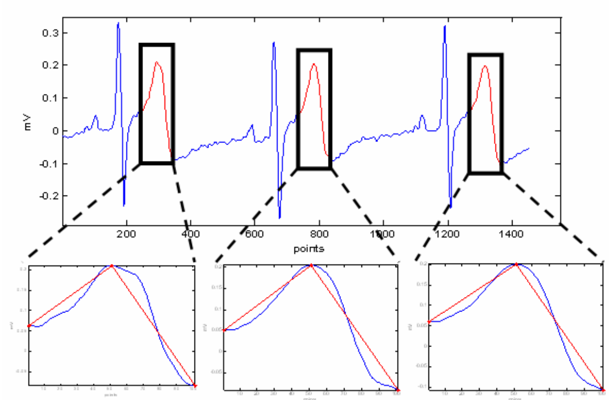

Fig.4 Describe the slope between $L_{0.1}$ and T point; the slope between $R_{0.1}$ and T points.

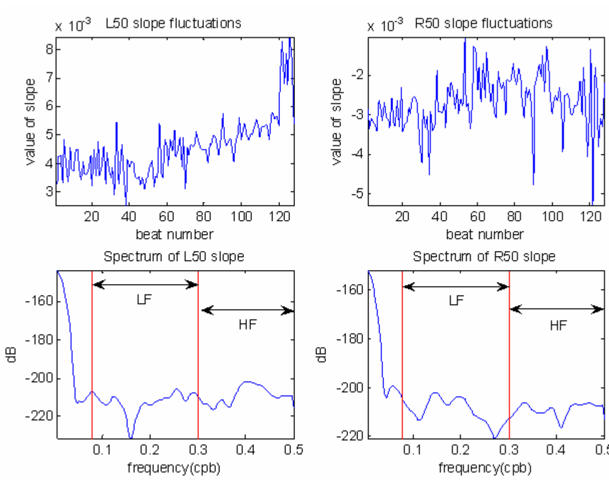

Fig.5. Upper: slope variation tachograms; Lower: the spectra of both slope variations.

The low frequency (LF) and high frequency (HF) bands of T-slope variations is set at [0.078 0.3] cpb and [0.3 0.5] cpb, respectively. The very low frequency (lower than 0.078 cpb) casued by baseline wonder is ignored on our TSV analysis.

To quantify the spectra of T-slope variations, the range index (RI) is defined as the difference of maximum and minimum of LF and HF magnitudes in dB (fig. 6). The minimum value can be considered as background noice magnitude, and the maximum value can be considered as alternan frequency. According to our investigation, $RI_{L0.1}$ is more significant than $RI_{R0.1}$. Hence, the $RI_{L0.1}$ is selected to fuse with EAR.

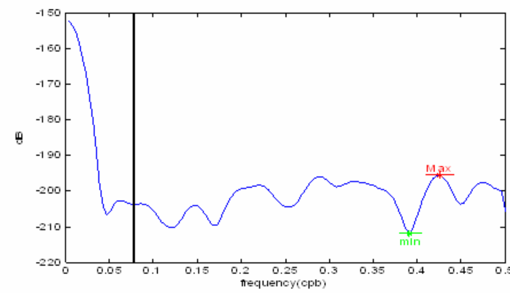

Fig.6 Explanation for range index (RI)

2.6. Fusion by using singular value decomposition (SVD)

The singular value decomposition (SVD) is widely applied on many applications, such as computing the pseudoinverse, matrix approximation, and determining the rank, range. SVD which belongs to the batch category can compute principle components [13]. Hence, SVD is used to fuse EAR and RI to reduce physiological interference.

From a numerical perspective, a better method is to use singular value decomposition by applying it directly to the data matrix [13]. The data matrix A(n), contained both EAR and RI values, is decomposed as follows:

$$A = U\Sigma V^T \qquad \ldots(2)$$

where U and V are orthogonal matrices and called the left singular vectors and the right singular vectors. The matrix Σ contains the singular values ($\sigma_1,\sigma_2,\ldots\sigma_k$) of the data matrix A, which can be thought of as scalar by which each corresponding input is multiplied to give a corresponding output.

In our research, EAR has more contribution on first singular value σ_1 than RI, so the developing fusion formula has more proportion on EAR. In eq.3, a new index, S is described as follows,

$$S = \frac{\sigma_1}{\sigma_1+\sigma_2} EAR + \frac{\sigma_2}{\sigma_1+\sigma_2} RI \qquad \ldots(3)$$

where $\sigma_1/(\sigma_1+\sigma_2) = 0.77$ and $\sigma_2/(\sigma_1+\sigma_2) = 0.23$.

3. Results

For developing data sets (MIT/BIH Sudden Cardiac Death Holter Database and our normal subject database), our improved spectral method successfully indicates 82.4% of people within SCD database at high risk, and 76.7% of people within normal database at low risk. The details of our results are listed in table 1.

Table 1. The accuracy table of developing data.

	SCD database (17 records)		Normal database (30 records)	
	# of exception	Accuracy	# of exception	Accuracy
AR (TH=2.5)	9	47.1%	8	73.3%
EAR (TH=2.5)	5	70.6%	9	70%
RI (dB) (TH=24)	4	76.5%	9	70%
S: SVD (TH=5)	3	82.4%	7	76.7%

For testing data set (PCCC2008 with 100 samples), our proposed methods got the score of final reference ranking, 0.636 [14]. However, score 0.549 is achieved when only ERA method was applied. Table 2 lists standard statistic results of EAR and RI for both SCD and PCCC2008 databases. The t-test probability of SCD database is not calculated because the sample size is less than 30 samples.

Table 2. The standard statistics analysis of ERA and RI

	Mean±Std.	Max	Min	t-test Prob.
EAR (SCD)	4.99±6.55	25.60	-1.41	n/a
EAR (PCCC 2008)	27.01±107.90	900.89	-1.60	< .0001
RI (dB) (SCD)	34.92±12.29	62.72	21.45	n/a
RI (PCCC 2008)	32.52±15.33	63.27	7.67	0.0139

4. Discussion and conclusions

The traditional AR is considered as our standard result. It is interested to compare our parameters (EAR/RI/SVD) with traditional AR values. Hence, based on the PCCC2008 database, the correlation coefficients were calculated in Table 3. We found that EAR and SVD values is somewhat correlated with AR values, but RI has low correlation.

Table 3. Correlation coefficient matrix for traditional AR comparison

	EAR	RI	SVD
AR	0.6629	0.3345	0.6656

Overall, according to our results by analyzing SCD and PCCC2008 databases, the traditional TWA method still has the room to improve. In addition, our method is potentially able to estimate the levels of the SCD risk.

Acknowledgements

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