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Detection of T-wave Alternans in ECG Signals Using FRFT and Tensor Decomposition

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Abstract: T-wave alternans (TWA) refers to the periodic beat-to-beat variation in the amplitude of T-wave in the electrocardiogram (ECG) signal in an ABAB-pattern. TWA has been proven to be a very important indicator of malignant arrhythmia risk stratification. A new method to detect TWA by combining fractional Fourier transform (FRFT) and tensor decomposition is proposed. First, the T-wave vector is extracted from the ECG of each heartbeat, and its FRFT amplitudes at multiple orders are arranged to form a T-wave matrix. Then, a third-order tensor is composed of T-wave matrices of several consecutive heart beats. After tensor decomposition, projection matrices are obtained in three dimensions. The complexity of the projection matrix is measured by Shannon entropy to obtain feature vector to detect the presence of TWA. Results show that the sensitivity, specificity, and accuracy of the algorithm on the MIT-BIH database are 91.16%, 94.25%, and 92.68%, respectively. This method effectively utilizes the fractional domain information of ECG, and shows the promising potential of the FRFT in ECG signal processing.

Keywords: T-wave alternans (TWA); electrocardiogram (ECG); fractional Fourier transform; tensor decomposition

1 Introduction

Cardiovascular diseases have the highest prevalence and mortality worldwide [1]. T-wave alternans (TWA) is an important non-invasive electrophysiological predictor of these malignant arrhythmias. Many clinical trials and studies have revealed the clinical relationship between the basic mechanisms underlying TWA and malignant arrhythmia. They show TWA is an informative factor of sudden cardiac death risk stratification [2]. TWA is defined as the periodic beat-to-beat variation in the amplitude of T-wave in the electrocardiogram (ECG) signal in an ABAB-pattern [3]. However, in many cases, the difference between two subsequent T-waves is only a few microvolts, which is extremely small to detect with the naked eyes. Finding a method for the automatic and precise detection of TWA is important. Existing methods for TWA detection include spectrum analysis and nonlinear methods [3,4]. Simple methods for spectral analysis do not involve time-resolution information and are susceptible to noise. The accuracy of the existing nonlinear methods should therefore be improved.

This paper introduces a new method that combines fractional Fourier transform (FRFT) and tensor decomposition to effectively extract TWA features. This method is tested on the MIT-BIH database and a support vector machine (SVM) is used to classify.

2 Materials and Methods

Methodology: This work proposes an algorithm to detect TWA based on FRFT and tensor analysis. Fig. 1 shows the process of TWA detection.

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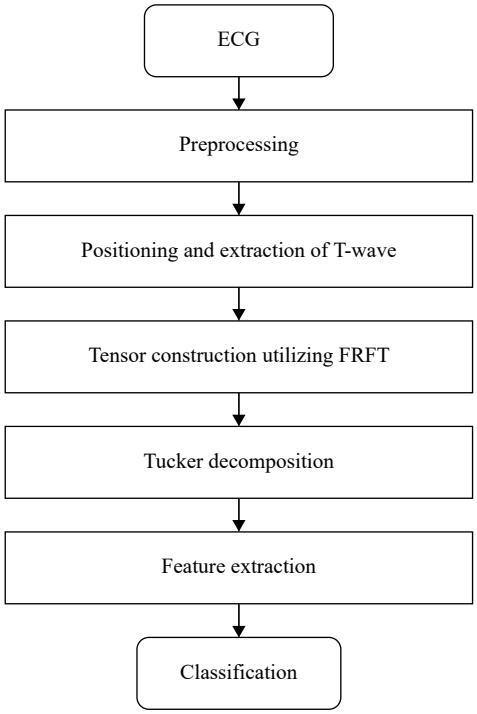

Fig. 1 TWA detection process

2.1 Data Preprocessing

The databases used in this study include T-Wave Alternans Challenge Database and MIT-BIH Normal Sinus Rhythm Database. Twenty-nine synthetic TWA electrocardiogram (ECG) signal records are selected from the T-Wave Alternans Challenge Database. All records contain 12 channels sampled at 500 Hz in 2 min long. Eighteen normal sinus rhythm (NSR) ECG signal records are selected from the MIT-BIH Normal Sinus Rhythm Database, and all records contain 2 channels sampled at 128 Hz in several hours [5].

The preprocessing stage mainly includes the removal of baseline wander, denoising high frequency noise and resampling. A method based on the wavelet transform is considered to complete the two former processes. Then, NSR signals are resampled to 500 Hz which is the same as the TWA signals. To detect TWA in single channel ECG signals, the signals from different channels are considered as independent samples. Finally, 348 samples with TWA and 360 normal samples without TWA are obtained. All samples are 2 min long and sampled at 500 Hz.

2.2 T-wave Positioning and Extraction

Given its small amplitude of, directly identifying the T-wave is relatively difficult. Hence, other characteristics, such as R-wave, must be detected first. The classical Pam–Tompkins algorithm is initially used to detect the QRS complex, and after which the T-wave peak is located according to the R-wave peak. The T-wave peak is set as the middle point and a window with length L ($L = 2n + 1$) is used to extract $(2n + 1)$ sample points as one T-wave.

2.3 Tensor Construction Utilizing FRFT

Fractional Fourier transform (FRFT) is a generalization of the ordinary Fourier transform. An order parameter α exists in FRFT. For $\alpha = 0$ and $\alpha = 1$, the FRFT reduces to the identity transform and the conventional Fourier transform, respectively. Any intermediate value of α $(0 < \alpha < 1)$ produces a signal representation that can be considered as a rotated time–frequency representation of the signal [6].

Utilizing FRFT, a T-wave vector is transformed into a T-wave matrix with dimensions of orders × characteristic parameters which contains abundant time--frequency information of the T-wave. The process is shown in Fig. 2.

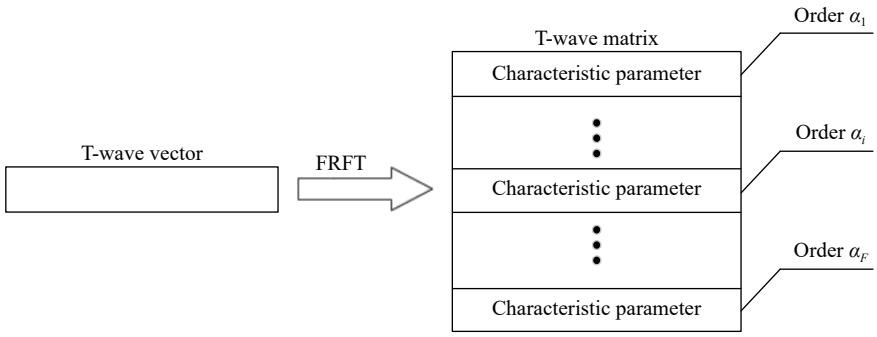

Fig. 2 T-wave vector is transformed into T-wave matrix utilizing FRFT

A tensor can be regarded as an extension of high order vector with the intrinsic relationship between elements preserved. Here, to construct the tensor, here, a third dimension-heartbeats, are created by aligning the T-wave in order. One T-wave represents one heartbeat, and TWA is a beat-to-beat fluctuation. Thus, the beat-to-beat change information lies in adjacent heartbeats can be maximally emphasized by aligning T-wave in order. Consequently, one tensor is constructed for each ECG signal sample. Let M be the number of heartbeats and F be the number of FRFT orders. The resultant tensor will have a size of $(L \times F \times M)$. Fig. 3 shows the construction of a third-order tensor.

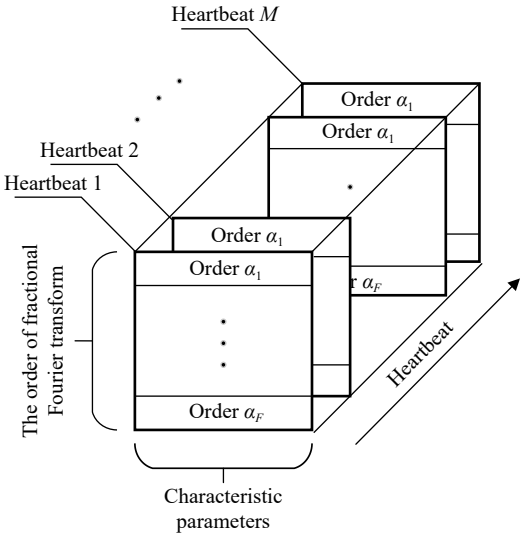

Fig. 3 Construction of a third-order tensor

2.4 Tensor Decomposition

Tensor decomposition is a dimension reduction process. This method can also extract the essential factor of signals while maintaining their correlation. On this basis, the superior performance of the internal structure inside the signal tensor is rendered. In this letter, the Tucker decomposition is taken.

Tucker decomposition [7] was first introduced in 1966 and is a high-order number of principal component analysis. In this method, a tensor is expressed as a core tensor multiplied by a matrix along each mode, defined as

$$X \approx \boldsymbol{G} \times \boldsymbol{U}_1^{(1)} \circ \boldsymbol{U}_2^{(2)} \circ \ldots \circ \boldsymbol{U}_n^{(N)} = [[\boldsymbol{G}, \boldsymbol{U}^{(1)} \boldsymbol{U}^{(2)}, \ldots, \boldsymbol{U}^{(N)}]] \tag{1}$$

where $\boldsymbol{U}_n$ is the principal component along each mode, and $\boldsymbol{G}$ is the core tensor.

In Tucker decomposition a third-order tensor is projected into matrices. The tensor is transformed into a tensor $\boldsymbol{G}$ with the same order of low-dimension, and the projection matrices are reflected in three directions. Fig. 4 shows the Tucker decomposition of a third-order tensor.

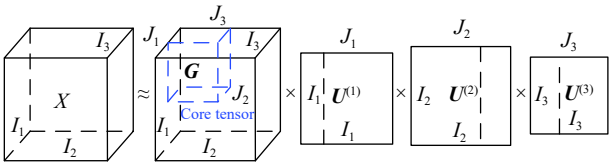

Fig. 4 Tucker decomposition of the third-order tensor

2.5 Feature Vector Calculation and TWA Detection

In constructing a third-order tensor, the third direction is composed of aligning adjacent T-wave matrices; therefore, its projection can best detect the existence of TWA. After decomposition, the projection matrix in the third direction is used to detect TWA. The Shannon entropy of each column vector in this projection matrix is calculated as the final feature vector for TWA detection. As shown in Fig. 5, the feature vector calculated in the third direction are distinguishable between two groups of samples.

To assess the proposed algorithm, SVM with radial basis kernel function is used to classify TWA and NSR samples and a 10-fold cross validation is used for performance evaluation.

3 Results and Discussion

After preprocessing, 348 samples with TWA (i.e., TWA group) and 360 samples without TWA (i.e., NSR group) are obtained, and all samples are in 2 min long. A 20-order FRFT is conducted in different domains to build a third-order tensor. Then, the feature vectors are calculated

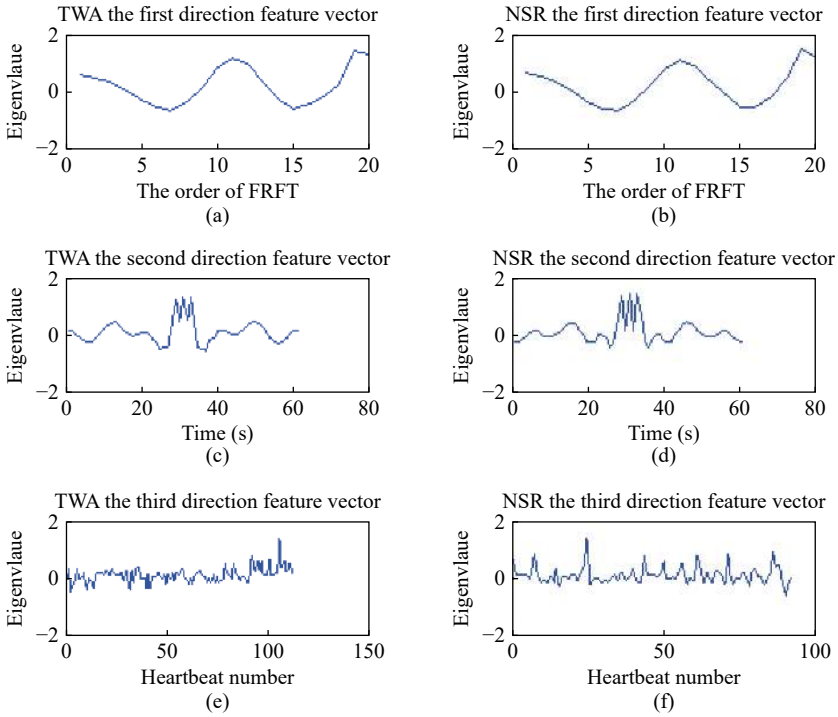

Fig. 5 The eigenvalue of feature vector in three directions after decomposition between TWA and NSR groups: (a) The first direction of TWA sample; (b) The second direction of TWA sample; (c) The third direction of TWA sample; (d) The first direction of NSR sample; (e) The second direction of NSR sample; (f) The third direction of NSR sample

and inputted into the SVM classifier for the automatic classification of the TWA and NSR groups. Tab. 1 presents the classification results.

Tab. 1 Experimental results with different FRFT domain range

FRFT domain	0-0.5	0.3-0.6	0.5-1.0	0-1.0
Sensitivity (%)	91.16	87.03	88.54	88.64
Specificity (%)	94.25	94.17	92.95	95.59
Accuracy (%)	92.68	90.54	90.71	92.06

The highest accuracy is 92.68% when the FRFT domain range is 0 –0.5, and the highest sensibility is 91.16% in the same range. The highest specificity is 95.59% when the FRFT domain range is 0–1.

4 Conclusion

In this work, an algorithm based on FRFT and tensor analysis is proposed for TWA detection. The results show that the proposed algorithm has a promising application prospect for T-wave feature extraction and alternation detection, and it can accurately detect the occurrence of micro-level TWA. Compared with the work in 2018 [8], our proposed algorithm is more robust with higher recognition ability for TWA detection. This algorithm can be used in ECG monitoring and malignant arrhythmia risk stratification, and it can also be applied in identification and classification of other weak physiological signals.

References:

[1] K. V. Nyombi, S. Kizito, D. Mukunya, A. Nabukalu, M. Bukama, J. Lunyera, M. Asiimwe, I. Kimuli, and R. Kalyesubula,"High prevalence of hypertension and cardiovascular disease risk factors among medical students at Makerere University College of Health Sciences, Kampala, Uganda," *BMC Research Notes*, vol. 9, no. 1, pp. 110, 2016.

[2] L. Burattini, W. Zareba, and R. Burattini,"Assessment of physiological amplitude, duration, and magnitude of ECG T-wave alternans," *Ann Noninvasive Electrocardiol*, vol. 14, no. 4, pp. 366-374, 2009.

[3] G. Goovaerts, B. Vandenberk, R. Willems, and S. Huffel,"Automatic detection of T wave alternans using tensor decompositions in multilead ECG

signals," *Physiological Measurement*, vol. 38, pp. 1513-1528, 2017.

[4] M. A. Hasan, V. S. Chauhan, and S. Krishnan,"Beat-to-beat T-wave alternans detection using the ensemble empirical mode decomposition method," *Comput. Biol. Med.*, vol. 77, pp. 1-8, 2016.

[5] A. L. Goldberger, L. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C-K Peng, and H. E. Stanley,"Components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. 215-220, 2000.

[6] S. Ervin, I. Djurović, and J. Jiang,"Time-frequency feature representation using energy concentration: An overview of recent advances," *Digital Signal Processing*, vol. 19, no. 1, pp. 153-183, 2009.

[7] S. Weiland and F.V. Belzen,"Singular value decompositions and low rank approximations of tensors," *IEEE Transactions on Signal Processing*, vol. 58, no. 3, pp. 1171-1182, 2010.

[8] O. Karnaukh, Y. Karplyuk, and N. Nikitiuk, "Evaluation of machine learning techniques for ECG T-wave alternans", in *2018 IEEE 38th International Conference on Electronics and Nanotechnology (ELNANO)*, Kiev, 2018, pp. 346-350.

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