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Design and implementation of EEMD-assisted ICA joint denoising scheme for ECG signals

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Abstract. Independent Component Analysis (ICA) algorithm is a signal processing method for solving blind source separation(BSS) problem, which can remove noises in observed signals and obtain original signals. This paper designs and implements an EEMD-assisted ICA joint denoising scheme for ECG signals. Firstly, Ensemble Empirical Mode Decomposition (EEMD) is used to perform noise-assisted data analysis on ECG signals, completing pre-denoising of ECG signals and pre-processing for subsequent ICA analysis. Next, to more thoroughly remove noises in ECG signals, ICA separates independent components from pre-denoised signals. Finally, signal reconstruction restores original ECG signals, so as to realize ECG denoising. Experimental results show that the scheme can effectively remove common noises, and get clean ECG signals, which lay a good foundation for accurate diagnosis of heart patients.

1. Introduction

Heart disease has become the most serious death disease in modern society. The global medical community has found that early disease prevention and risk reduction are the most effective diagnosis and treatment ways for heart disease. By measuring and amplifying body surface potentials at electrodes, electrocardiogram (ECG) signal can indicate the current state of the heart. Therefore, the monitoring of ECG signals plays an extremely important role in preventing and diagnosing heart disease [1, 2].

However, the potentials on body surface are so small that ECG usually are corrupted by unwanted interferences such as power frequency noise interference, baseline drift, electrode contact noise, random noise, motion artifacts, instrumentation noise, etc [3]. These interferences will seriously affect the effect of ECG monitoring and diagnosis. Although many efforts have been devoted to refining noise-free ECG signals in past decades, it is still lack of reliable signal processing tools to extract weak ECG components [4, 5].

There are a variety of existing denoising methods. Bandpass filters [6] only can cancel noises out of the frequency range of ECG signal. By virtue of statistical tools, Neural Networks (NNs) [4] can refine signal, but it has difficulty in handling abnormal heart situations. Principle Component Analysis (PCA) and Independent Component Analysis (ICA) [7, 8] can denoise ECG signals by removing uncorrelated components. However, they cannot process single lead ECG signals. Wavelet is only suitable for isolating transient (non-stationary) changes of ECG signals in a time series [9].

The paper focuses on the denoising of ECG signals. According to the drawbacks of existing denoising methods, an EEMD-assisted ICA joint denoising scheme is proposed. Through the joint action of EEMD and ICA, the effective denoising of ECG signals can be realized. The rest of paper is



organized as follows. Section 2 provides some preliminaries in brief. Section 3 presents EEMD-assisted ICA joint denoising scheme in detail. Section 4 shows results and finally Section 5 concludes the paper.

2. Introduction

2.1. Ensemble Empirical Mode Decomposition

EEMD is a noise-assisted data analysis method that adaptively decomposes signals based on local characteristics of signals [10]. All complex signals are composed of multiple simple Intrinsic Mode Functions (IMF), and each IMF is independent. EEMD makes noises to cancel each other by continuously superimposing white Gaussian noises on input signal. In this way, this method can decompose different scales or trend components that really exist in data time series step by step, and generate some data sequences with the same characteristic scale size. Additional noises are gradually eliminated one by one, and final result of denoising is the signal itself, because it is only durable and stable part.

2.2. Independent Component Analysis

Independent Component Analysis refers to finding a linear map without knowing mixed matrix, and separating independent characteristic components that cannot be directly observed from observed mixed signals, that is, recovering basic source signals [7]. There is no other prior knowledge other than known source signals are statistically independent. ICA is developed with blind source problem, so it is also called blind source separation (BSS), where "source" refers to original signals. Its linear mixed model can be expressed as the equation (1).

$$\mathbf{x} = \mathbf{A}\mathbf{s} \quad (1)$$

Here, signal vector $\mathbf{x}$, mixing matrix $\mathbf{A}$ and source signal vector $\mathbf{s}$ converge in the space $\mathbf{R}^n$. Since vector $\mathbf{s}$ and matrix $\mathbf{A}$ are all unknown states, only there is observation vector $\mathbf{x}$, the solution of the equation (1) is not unique. If following assumptions and constraints are made:

- (1) Each component of source signal $\mathbf{s}$ is a zero mean random variable, and each component is statistically independent at any time.
- (2) Source signal $\mathbf{s}$ is a non-Gaussian linear distribution and allows the presence of one Gaussian distribution at most.
- (3) For simplicity, it is assumed that observed signal $\mathbf{x}$ is equal in length to source signal $\mathbf{s}$, that is, mixing matrix $\mathbf{A}$ is a square matrix.

In this way, ICA finds a matrix $\mathbf{W}$ by demixing operation, as shown in the equation (2), through which optimal forced output $\mathbf{y} = \mathbf{W}\mathbf{x}$ can be obtained, so that optimal estimated value of source signal $\mathbf{s}$ can be obtained, so as to achieve noise removal.

$$\mathbf{y} = \mathbf{W}\mathbf{x} = \mathbf{W}\mathbf{A}\mathbf{s} \quad (2)$$

It can be known from the nature of matrix operation that the size and order of independent components have the characteristics of uncertainty, so ICA can only estimate the vector $\mathbf{y}$ that is similar to source signal. In order to facilitate data processing and the simplification of ICA algorithm, mixed observation signal $\mathbf{x}$ need to be pre-processed: centralization processing and whitening processing, so that observed signals have a unit variance of zero mean characteristics.

3. EEMD-assisted ICA joint denoising scheme

3.1. Proposed scheme

Aiming at nonlinear and non-stationary characteristics of ECG signals, an EEMD-assisted ICA joint denoising scheme is proposed. The schematic diagram of the scheme is shown in figure 1. Firstly, Ensemble Empirical Mode Decomposition (EEMD) is used to decompose noisy ECG signals into a number of Intrinsic Mode Functions (IMF) to achieve pre-denoising of ECG signals and complete pre-processing for subsequent ICA analysis. Then, on the basis of independent IMFs, ICA

algorithm is used to denoise IMFs decomposed by EEMD, and effective components of ECG signal are separated. Finally, the estimated value $y(t)$, which is infinitely close to source signal s , is obtained by reconstructing ECG signal, so as to eliminate noises.

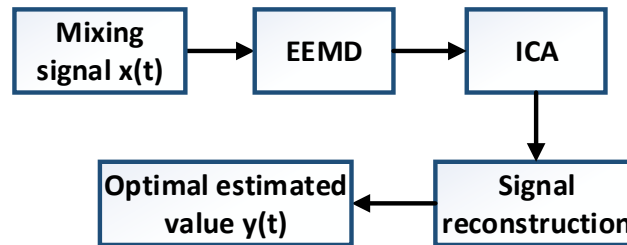


Figure 1. The schematic diagram of the scheme

3.2. Ensemble Empirical Mode Decomposition

The EEMD algorithm flow is shown in figure 2. The steps are as follows:

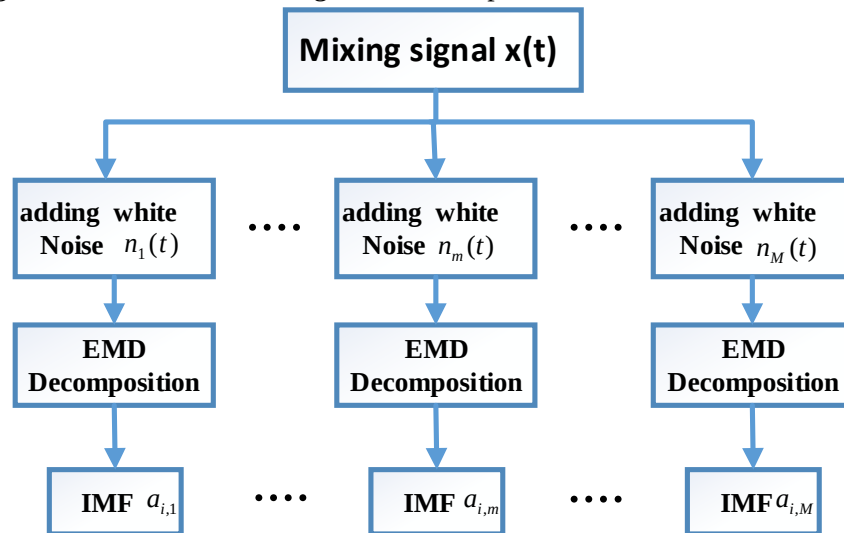


Figure 2. The EEMD algorithm flow

- (1) Obtain a population by adding a set of Gaussian white noise to the target signal;
- (2) Decompose the overall signals to obtain $IMF a_{i,1}$;
- (3) Continue above steps to decompose the target signal into multiple groups;
- (4) After decomposing multiple groups, the respective $IMF a_{i,m}$ are obtained;
- (5) The results of multiple sets of decompositions are summarized into $IMF a_i$ groups.

3.3. Independent Component Analysis

This scheme adopts adaptive maximum entropy ICA algorithm [11], and its schematic diagram is shown in figure 3.

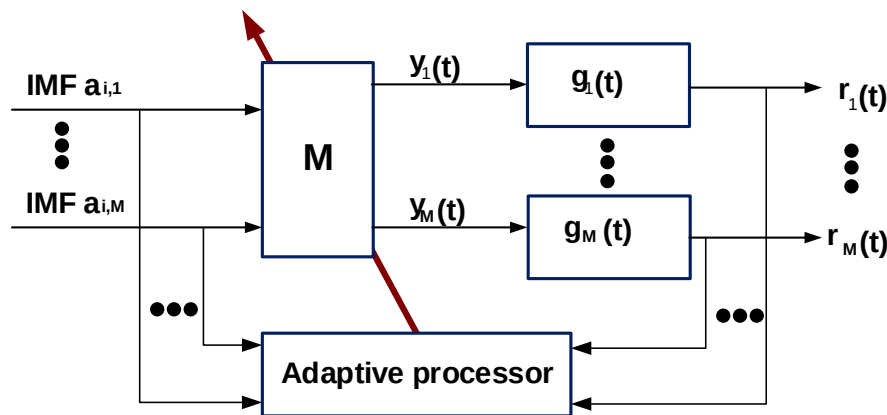


Figure 3. The schematic diagram of ICA

The basic idea of the algorithm is to introduce a group of nonlinear functions $r_i = g_i(y_i)$ after output $y(t)$, and to replace the estimated values of the higher-order statistics component by component. The criterion of optimal force is to maximize total entropy amount $H(\mathbf{R})$ of output $\mathbf{R} = [r_1, r_2, \dots, r_M]$ given appropriate $g_i(y_i)$ [12]. The coefficients of separation matrix $\mathbf{B}$ are adjusted by the gradient algorithm in the equation (3), where μ is iteration step and k is the number of iterations.

$$\Delta \mathbf{B}(k) \propto \frac{\partial H(\mathbf{r}, \mathbf{B})}{\partial \mathbf{B}} \mathbf{B}(k)^T \mathbf{B}(k), \mathbf{B}(k+1) = \mathbf{B}(k) + \mu \Delta \mathbf{B}(k) \quad (3)$$

3.4. Signal reconstruction

The output $\mathbf{R} = [r_1, r_2, \dots, r_M]$ of ICA is a plurality of independent ECG components. So, $\mathbf{R}$ needs a lumped average to realize the reconstruction of ECG signal, so as to obtain an estimated value $\mathbf{y}$ that is infinitely close to the source signal.

4. Experimental results

The scheme is implemented by using MATLAB software programming. By using the records from the MIT-BIT arrhythmia database as inputs and adding various types of noises, the scheme is simulated. The following simulation results are obtained.

4.1. The denoising of power frequency noise

The $\sin(2\pi \cdot 50 \cdot t)$ is used as the power frequency noise to mix original ECG signal. The mixed signal is used as an input signal, as shown in figure 4(a), and the outputted waveform is shown in figure 4(b). It can be seen that the power frequency noise is well eliminated and the source signal is not too much distortion.

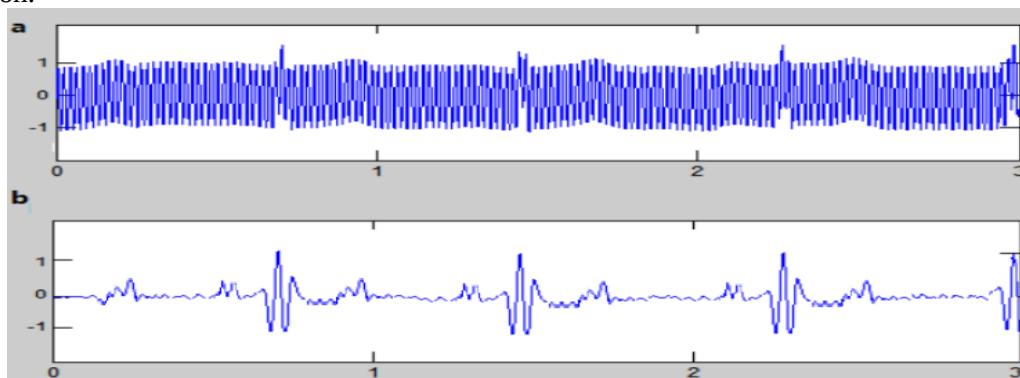


Figure 4. The denoising waveform of power frequency noise

4.2. The denoising of baseline drift

Using $0.15 \cdot \sin(2\pi \cdot 0.2 \cdot t)$ shown in figure 5(a) as baseline noise and mixed signal shown in figure 5(b) as input, the denoising result of this scheme is obtained, as shown in figure 5(c). The denoising result shows that original signal has almost no distortion. The denoising scheme has a very good effect on baseline noise.

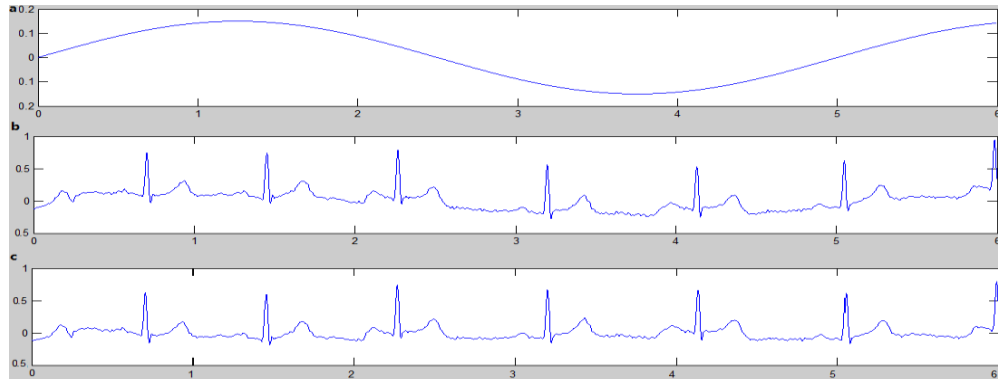


Figure 5. The denoising waveform of baseline drift

4.3. The denoising of random noise

As shown in figure 6, the ECG signal with random noise is inputted in figure 6(a), and the result in figure 6(b) is obtained. It can be seen that the waveform of the denoising result is more chaotic and there are more burrs after EEMD-assisted ICA joint denoising, but it can still distinguish the waveform of each ECG characteristic vector.

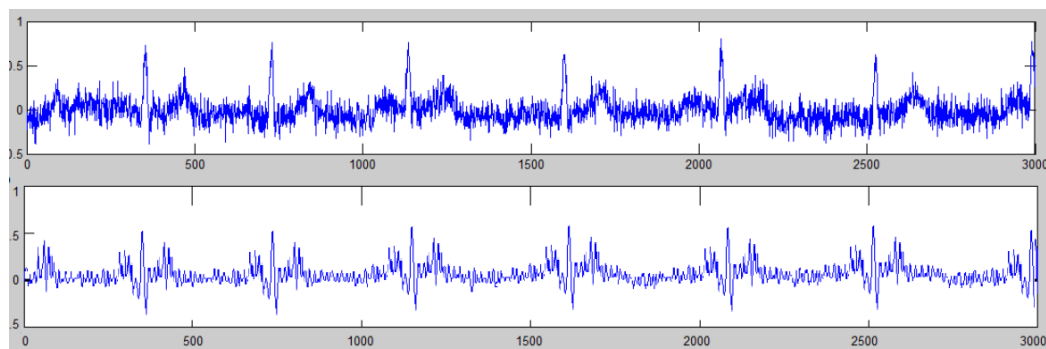


Figure 6. The denoising waveform of random noise

5. Conclusion

This paper designs and implements an EEMD-assisted ICA joint denoising scheme for ECG signals. The scheme firstly uses EEMD to perform noise-assisted data analysis on ECG signals, completing pre-denoising and pre-processing. Then, ICA is used to blindly separate pre-denoised signals, restoring original ECG signals. The experimental results show that the scheme can effectively remove common types of noises, retain its useful information, and have less signal distortion, which can lay a foundation for accurate diagnosis of heart patients.

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