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A review of noise removal techniques in ECG signals

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***Abstract*—In this paper, three improved methods are explored to address the shortcomings of existing ECG signal denoising methods. The first method is based on the empirical identification of the intrinsic mode function (IMF) component of the QRS eigenwave and the reconstruction of the inaccurate identification of the ECG signal, using the statistical properties of the EMD and IMF components to denoise the ECG signal. The second method is out to use a combination of variational modal decomposition and wavelet thresholding to denoise the ECG signal for inotropic interference. The third method is to propose a denoising algorithm based on improved wavelet thresholding-CEEMDAN to address the shortcomings of the wavelet thresholding method. All three schemes have evaluation metrics and criteria and have been tested and proven to be substantially better than traditional methods to a certain extent.**

***Keywords*—ECG, Denoising, Wavelet threshold, modal decomposition, threshold**

I. INTRODUCTION

ECG (Electro cardio graphy) signal is widely used in medicine, the main function is to record the human heart electrophysiological changes in activity, is an important means of clinical diagnosis of various cardiovascular diseases, heart disease, arrhythmias and other diseases. However, ECG is a weak biomedical signal with non-linear and non-smooth characteristics, and it is easy to collect noise during the collection process, and these can affect the detection and identification of low frequency parts of the ECG signal such as P, QRS and T characteristic waves. Therefore, the pre-processing of the ECG signal for noise removal is one of the most important aspects.

A. The main noise in ECG

The human ECG signal is a non-smooth, non-linear, random and weak physiological signal with an amplitude of approximately mV and a frequency of 0.05-100Hz.

1) Baseline drift

Baseline drift is a low frequency disturbance, generally caused by the rhythm of breathing, limb movements and the design of the front-end processing circuitry. The frequency of baseline drift is very low, ranging from 0.05Hz to a few Hz, with the main component being around 0.1Hz, while the frequency of the P-wave, T-wave and ST-segment of the ECG signal is also very low, ranging from 0.5Hz to 10Hz, with the spectrum of both being very close to each other. Baseline drift has the greatest effect on the ECG signal, with significant jitter in amplitude. ECG signals disturbed by this type of noise become distorted and jitter up and down, making it difficult to accurately locate the location of characteristic points in the signal, and this type of noise is essential to eliminate in order to obtain a valid ECG signal.

2) Industrial Frequency Interference

The main source of industrial frequency interference is the electromagnetic field radiated from the transmission lines in the environment around the acquisition stage of the industrial frequency power supply and the device, at a frequency of 50Hz or 60Hz, which appears as periodic small ripples on the ECG, whose frequency components are mainly industrial frequency frequencies and their harmonics, with an amplitude of about 0-0.4mV, which is generally equivalent to 5%-40% of the R-wave amplitude, depending on the situation. Most of the sampled signals will encounter industrial frequency interference, making the SNR of the ECG signal drop or even drown the original signal, so software processing and elimination of such interference is particularly important.

3) Electromyographic disturbances

Myoelectric interference, which is caused by the trembling of muscle fibers, leads to irregular high-frequency electrical disturbances at the body surface, with a short duration, resulting in small ripples in the ECG signal waveform. Because of its wide frequency distribution, the results obtained by conventional noise cancellation methods are not very satisfactory. This is due to the fact that general noise cancellation methods can only remove noise well distributed in specific frequency bands, which has led to myoelectric interference has been a difficult area of research.

B. Classification of existing ECG signal noise removal techniques

On the basis of current technology, ECG denoising methods fall into four different categories. The first category is ECG denoising based on the statistical properties of the EMD and IMF components. Denoising of the ECG signal in the empirical mode decomposition (EMD) domain is usually based on the empirical identification of the intrinsic modal function (IMF) component of the QRS eigenwave and reconstruction of the ECG signal. The introduction of statistical properties of the IMF component to denoise the ECG signal based on EMD can effectively avoid problems such as inaccurate identification due to individual errors. The second type of method is based on wavelet thresholding, and there have been many optimized and improved algorithms as well as processing solutions for this type of method. VMD and wavelet thresholding-based ECG denoising of ECG with myoelectric disturbances is achieved by performing a variational modal decomposition of the noisy ECG signal, determining the signal dominant modal component and the noise dominant modal component, wavelet thresholding of the noise dominant modal component and reconstructing the noise-free ECG signal. The third category is the optimization scheme of the second category, a study of ECG signal denoising based on the improved wavelet thresholding-CEEMDAN algorithm, which is more effective than the empirical mode decomposition (EMD) wavelet denoising and the overall average empirical mode decomposition (EEMD) wavelet denoising algorithms. The filter method, Empirical Mode Decomposition (EMD) method and wavelet thresholding method are useful for ECG denoising, but there are still many problems. The conventional filtering method can remove most of the EMG interference, but this method will clean up part of the ECG signal because the frequency bands of ECG and its noise, especially the EMG interference noise, overlap with each other. The wavelet thresholding method is more capable of local time-frequency analysis, but the wavelet thresholding method is highly dependent on the choice of the threshold value, and setting the threshold value too low or too high will affect the final ECG signal acquisition. Most of the literature is limited to the use of EMD to remove baseline drift, but in practice, EMG interference and baseline drift always co-exist and such schemes can only remove one type of noise. In addition, several papers have attempted to operate the wavelet thresholding method in combination with EMD so that it has the advantages of both EMD and wavelet thresholding, but there is no clear solution to the disadvantages of both, so there is little practical significance in accumulating advantages on top of disadvantages.

II. ECG NOISE REMOVAL TECHNIQUES

A. ECG noise removal based on the statistical properties of EMD and IMF components

This method is modified and optimized to address the shortcomings of the EMD method for ECG noise removal. The statistical properties of the EMD and IMF components are used to denoise ECG signals containing baseline drift noise and electromyographic interference noise. Firstly, the EDM method is used to decompose the noisy ECG signal to obtain a series of IMF components, then all the noisy IMF components are identified using the statistical properties of the noisy IMF components, and the remaining IMF components are the ECG signal components, and finally, the ECG signal is reconstructed using the signal attribute IMF components.

1) Methodologies

The EMD decomposition of the noisy ECG signal yields a series of IMF components in the high-frequency noise IMF component, the ECG signal IMF component, and the low-frequency noise IMF component, respectively.

(a) The high-frequency noise IMF components are generally high-frequency signals with myoelectric interference, and the EMD decomposition of Gaussian white noise is equivalent to a binary filter bank with constant quality factors. are normally distributed and the area of the power spectrum of the IMF is the same on the (logarithmic) plot of the average period of the power spectrum. Based on (1) and (2), the sum of the IMF energy density and the logarithm of its corresponding mean period is obtained as a constant.

$$\mathrm{lgEn} + \mathrm{lgTn} = \mathrm{constant} \tag{1}$$

where En is the energy density of the first IMF component and Tn is the average period of the IMF component.

For a normalized Gaussian white noise sequence, the constant in equation (1) is zero.

$$\mathrm{lgEn} + \mathrm{lgTn} = 0 \tag{2}$$

$$y = -x \pm k\sqrt{\frac{2}{N}}e^{x/2} \tag{3}$$

Eq. (3) represents the expansion function of the energy density, where x = lgT and k is a constant determined by the percentile of the standard normal distribution, with k = 1.645 for a 95% confidence interval.

The noise IMF component of the data is estimated based on IMF1 and using the statistical properties of white noise described above. The IMF is identified as a noisy IMF component if it falls within the confidence interval of the noisy expectation line constructed based on IMF1.

(b) The low-frequency noise IMF component, in general, belongs to the baseline drift component with the data finite length causing pseudo-component superimposed noise, so relying on the (a) approach cannot identify the superimposed component contained in the low-frequency noise IMF component of the noisy ECG signal.

The EMD decomposition process is an averaging filtering process. As the IMF order increases, the frequency decreases, the local scale increases, and the edge error increases, so that the deviation of the IMF mean from the 0 mean increases with the IMF orders. The frequency of the IMF component of low-frequency noise is typically smaller than the IMF frequency of the ECG signal (typical frequencies of baseline drift noise are typically 0.15 to 0.30 Hz, and the frequency of the ECG signal is typically greater than 1 Hz (60 bpm), and the local time scale of the polar definition, particularly the end local time scale, is much larger than the local time scale of the IMF component of the ECG signal, so the end The estimation error causes a larger mean error, which is well represented by the abrupt change in the non-linearity of the mean curve of the IMF component, and is able to identify the low-frequency noisy IMF component.

(c) ECG denoising method with statistical properties of IMF components ECG denoising method based on EMD with statistical methods of IMF components, the method steps are as follows: (1) ECG containing noise is decomposed into a series of IMF components by EMD; (2) lgT and lgE of each IMF component are determined, and all IMF components are checked for validity based on the fact that IMF 1 is high-frequency noise , identifying the high-frequency noise IMF components. (3) Perform a 0-average check on each IMF component, and if an IMF component deviates significantly from the 0-average, that IMF component is identified as low-frequency noise, after which all IMF components are also identified as low-frequency noise. (4) The remaining IMF components not identified in steps (2) and (3) are the ECG signal components, and if the IMF components of the ECG signal are reconstructed, the ECG signal after noise removal is obtained

2) Evaluation metrics

In this paper, three evaluation metrics, Signal to Noise Ratio (SNR), Mean Square Error (MSE), and Autocorrelation Coefficient (AC), are used to evaluate the noise cancellation effect of this method is as follows.

$$SNR = 10\lg \frac{\sum_{i=1}^{n} x^2(i)}{\sum_{i=1}^{n} [x(i) - f'(i)]^2} \quad (4)$$

$$MSE = \frac{1}{N} \sum_{i=1}^{n} [x(i) - f'(i)]^2 \quad (5)$$

$$AC = \frac{\sum_{i=1}^{n} (x(i) - \bar{x})(f'(i) - \bar{f}')}{\sqrt{\sum_{i=1}^{n} (x(i) - \bar{x})^2 \bullet \sum_{i=1}^{n} (f'(i) - \bar{f}')^2}} \quad (6)$$

where x(n) is the original ECG signal and f' (n) is the reconstructed ECG signal. The larger the SNR and the smaller the MSE, the better the denoising effect of the denoising method. The larger the AC signal, the smaller the deviation of the reconstructed ECG signal from the "clean" ECG signal, and the better the denoising effect of the denoising method.

B. VMD and wavelet thresholding-based ECG myoelectric interference noise removal processing

It outperforms EMD because the signal can be decomposed adaptively to obtain a range of mode components and the Centre frequency and bandwidth of each mode component can be determined, and the mode mixing in EMD can be effectively mitigated [3], but both signal and noise are also included in each mode component obtained by VMD decomposition. The optional removal of arbitrary mode components may significantly affect the accuracy of the reconstruction of the ECG signal. The method combines VMD and wavelet thresholding methods to decompose ECGs containing noise, determine signal-dominated mode components and noise-dominated mode components, wavelet threshold noise removal for noise-dominated mode components, and finally reconstruct all mode components as noise-free ECGs.

1) Methodologies

In the noisy ECG after VMD decomposition can be adaptively decomposed to obtain a series of modal components all containing useful 'clean' ECG signals as well as noise, using the strong local time-frequency analysis capability of the wavelet thresholding method, it is more suitable for ECG myoelectric interference denoising by combining it with VMD.

First, the number of decomposition layers k is set. If the value of k is too small, the signal is not sufficiently decomposed, leading to severe modal mixing results. When the value of k is too large the resulting pseudo-component affects the accurate analysis and reconstruction of the signal [9]. After determining the k-value the noisy ECG is adaptively decomposed into k modal components after VMD decomposition. The second step uses the correlation coefficient between the modal components belonging to the signal-dominated or noise-dominated ECG and the noise-containing ECG as the characteristic quantity and distinguishes whether the modal components belong to the signal-dominated or noise-dominated ECG. This is done by setting 0.5 as the threshold for distinguishing the mode components: with a correlation coefficient greater than 0.5, the mode components are considered to signal dominant; those less than 0.5 are noise dominant. The third step is to remove the noise-dominated mode components using the wavelet thresholding method. Finally, the signal reconstruction is performed on the mode components after removing the wavelet threshold noise and the signal-dominated mode components to obtain the ECG signal after removing the noise.

2) Evaluation metrics

The effectiveness of this method in ECG electromyographic interference denoising was evaluated using Signal to Noise Ratio (SNR), Mean Square Error (MSE), and Autocorrelation Coefficient (AC) as evaluation metrics.

The equations for SNR and MSE are as follows.

$$SNR = 10lg \frac{\sum_{i=1}^{n} x^2(i)}{\sum_{i=1}^{n} [x(i) - t'(i)]^2} \quad (7)$$

$$MSE = \frac{1}{N} \sum_{i=1}^{n} [x(i) - f'(i)]^2 \quad (8)$$

Where: x(n) is the original ECG without noise and f'(n) is the denoised ECG. a larger SNR and smaller MSE means better denoising performance of the method.

The autocorrelation coefficient AC represents the deviation of the reconstructed ECG from the original ECG and is given by:

$$AC = \frac{\sum_{i=1}^{n} [x(i) - \bar{x}]\left[f'_{(i)} - \bar{f'}\right]}{\sqrt{\sum_{i=1}^{n} [x(i) - \bar{x}]^2 \cdot \sum_{i=1}^{n} \left[f'(i) - \bar{t'}\right]^2}} \quad (9)$$

The larger the AC, the smaller the deviation of the reconstructed ECG from the original ECG after denoising by the method, and the higher the similarity.

C. ECG signal denoising based on improved wavelet thresholding-CEEMDNA algorithm

The method is based on improved wavelet thresholding [10,11] algorithm for noise removal of ECG signals. the ECG signals are decomposed by CEEMDAN using a correlated frequency method to find the noise-dominated high-frequency noise eigenmode function IMF components, and wavelet improved thresholding noise removal is performed. For the IMF component, the IMF component lower than this threshold is determined as the baseline drift signal by setting a fixed threshold, removing this IMF component and finally reconstructing the IMF component. This algorithm is more effective than the EMD wavelet noise removal and the overall averaging empirical mode decomposition EEMD (Ennsemble Empirical Mode Decomposition) [6] wavelet noise removal algorithm, and good noise removal results are obtained.

1) Methodologies

Based on EMD, an EEMD algorithm has been proposed in an attempt to solve the pattern mixing problem by applying normally distributed white noise to the original signal. However, experimental results show that this method cannot guarantee accuracy as the reconstruction error after decomposition is difficult to be completely eliminated. Therefore, CEEMDAN combines EMD and EEMD, based on which the proposed fully integrated empirical mode decomposition algorithm with adaptive white noise inherits the advantages of both well, while overcoming the experimental shortcomings of both.

Find the first order modal component. The new signal $x(t)+(-1)^m \varepsilon n^i(t)$ is formed by adding a positive and negative pair of Gaussian white noise $(-1)^m \varepsilon n^i(t)$ to the original signal x(t), where m is the coefficient, ε is the amplitude, and m $\in \{1, 2\}$, $n^i(t)$ is the white noise sequence that obeys the standard normal distribution for the ith addition, and i is the number of times the auxiliary noise is added. The EMD decomposition of the new signal yields

$$x(t)+(-1)^m \varepsilon n^i(t)=IMF_1^i(t)+r_1(t) \tag{10}$$

Multiple first-order components $IMF_1^i(t)$ are obtained. The first-order final component is then obtained by averaging over N*$IMF_1^i(t)$:

$$\overline{IMF(t)}=\frac{1}{N}\sum_{1=1}^{N} IMF_1^i(t) \tag{11}$$

From Equation (1) and (2), the first order residual component is obtained as:

$$r_1(t)=x(t)+(-1)^m \varepsilon n^i(t)-\frac{1}{N}\sum_{i=1}^{10} IMF_1^i(t) \tag{12}$$

b: Find the second order modal component. Add positive and negative pairs of Gaussian white noise to the remaining components to form the new signal $r_1(t)+(-1)^m \varepsilon n^i(t)$, which is again decomposed for N times as follows.

$$r_1(t)+(-1)^m \varepsilon n^i(t)=IMF_2^i(t)+r_2(t) \tag{13}$$

The second order component is then obtained by averaging over the N*$IMF_1^i(t)$ as follows.

$$\overline{IMF_2}(t)=\frac{1}{N}\sum_{i=1}^{\mathbb{N}} IMF_2^i(t) \tag{14}$$

The final second order residual component is obtained as:

$$r_2(t)=r_1(t)+(-1)^m \varepsilon n^i(t)-\overline{IMF_2}(t) \tag{15}$$

(c) Repeat (b) until the remaining signal can no longer be decomposed. Let K average IMF components be obtained at the end of the algorithm, then the final remaining signal R(t) obtained is:

$$R(t)=x(t)+(-1)_\varepsilon^n n^i(t)-\sum_{i=1}^{k}\overline{IMF_\iota}(t) \tag{16}$$

Therefore, the original signal can be expressed as follows:

$$x(t)=\sum_{i=1}^{k}\overline{IMF_\iota}(t)+R(t)-(-1)^m \varepsilon n^i(t) \tag{17}$$

III. Conclusion

ECG signals are used in various examinations for cardiovascular disease, heart disease and arrhythmias, and their application in the medical field is quite extensive, so ECG signal denoising pre-processing is very important. This paper lists and analyses three different existing research methods for signal denoising, namely ECG denoising based on the statistical properties of EMD and IMF components, ECG inotropic noise removal processing based on VMD and wavelet thresholding, and ECG signal denoising based on the improved wavelet thresholding CEEMDNA algorithm, all of which are optimised on the traditional denoising processing schemes. Compared to the traditional EMD denoising and wavelet thresholding denoising methods, the errors in the traditional methods can be well avoided by using the combined and optimised algorithms. However, when testing the ECG denoising method based on the statistical properties of the EMD and IMF components proposed in this paper in experiments, it was concluded that this method is of general interest but still has limitations. In reality, the amplitude of the mixed EMG interference noise in a well acquired ECG signal is typically 10% of the peak ECG value, which can be effectively removed by the proposed denoising method. However, for some poorly acquired ECGs, the ECG signal is completely drowned out by the EMG interference noise, so that the noisy ECG does not have the obvious QRS characteristics of the ECG signal, and the modal components after VMD decomposition are all approximately white noise, which makes this method less effective or even ineffective. This shows that there are still many shortcomings in the field of ECG signal denoising, and there is still a need to optimize the denoising mechanism in the future.

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