Denoising Method of ECG Signal with Power Threshold Function Under Wavelet Transform and Smoothing Filter

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Abstract: An electrocardiogram (ECG) is an important tool for doctors to diagnose heart diseases. It is an electrical signal that evolves from the heart and changes over time. It is susceptible to interference from various low-frequency and high-frequency noises. This paper proposes a new adaptive power threshold function to achieve the denoising of ECG signals. On the basis of wavelet transformation and smooth decomposition, the power threshold function is used to perform adaptive threshold denoising on the decomposed signal with high frequency noise. The signal is reconstructed from the denoised high frequency components and useful components. The coefficients of the remaining layers are set to zero. Taking the ECG signal in the MIT-BIH ECG database as the original data, adding different degrees of Gaussian white noise for experimental analysis, it is proved from the quantitative and qualitative aspects that the proposed method has superiority in removing the noise of the ECG signal. The noise effect is better than the traditional threshold function denoising method.

Key words: ECG Signal; Threshold Denoising; Wavelet Transform; Smooth Decomposition; Power Threshold Function

0 Introduction

ECG signals are applied to various examinations such as cardiovascular disease, heart disease and arrhythmia, which can judge people's physical health. It is usually composed of P, QRS and T waveforms. Each characteristic sub waveform of each complete waveform has special electrophysiological significance[1]. ECG is a weak electrical signal, which is easily disturbed by external factors such as mechanical environment and human activities, and some interferences overlap with the frequency of ECG, which makes it difficult to study and judge ECG in the future. Therefore, how to effectively reduce the noise interference in ECG signals is a very important research topic.

Most of the classical signal processing algorithms used to remove and suppress interference noise are based on filtering processing in time domain and frequency domain[1,2], such as discrete wavelet transform (DWT) decomposition[3-5], adaptive filtering [6,7], empirical mode decomposition (EMD) and comprehensive empirical mode decomposition (EEMD) [8-11], Stockwell transform (st), etc. In the case of large noise, the wavelet threshold method has some limitations in ECG denoising, and its denoising performance becomes worse and worse. Therefore, in order to improve the robustness and adaptability of the existing denoising methods and overcome the shortcomings of discontinuity and signal distortion of the traditional threshold function in the process of signal denoising, this paper proposes the power threshold function and adaptive threshold method. Based on wavelet transform and smooth decomposition, the optimal sequence of threshold parameter C is selected by genetic algorithm, The high-frequency noise of the signal is thresholded to achieve the best denoising effect. The experimental data in this paper are from the MIT-BIH arrhythmia public database [13]. Through the three evaluation indexes of root mean square error (RMSE), signal-to-noise ratio (SNR) and correlation coefficient (CR), it is verified that the denoising effect and signal reduction degree of the power threshold function are better than the traditional threshold function. The threshold parameter C makes the power threshold function robust in both decomposition methods.

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1 Decomposition method

1.1 Wavelet transform and reconstruction

1.1.1 Wavelet transform

Wavelet transformation is an effective time-frequency tool that uses different wavelet functions to decompose signals into linear combinations with different scales. When the wavelet basis function is specified, the signal can be completely characterized by coefficients. set up $\psi(t)$ is a basic wavelet, which is expanded and moved:

$$\psi_{a,b} = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) a,b \in R, a \neq 0 \qquad (1)$$

For $f(t) \in L^2(R)$, the continuous wavelet transform is:

$$\begin{aligned} WT_f(a,b) &= \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} f(t)\tilde{\psi}(t)(\frac{t-b}{a})dt \\ &= \langle f, \psi_{a,b} \rangle \end{aligned} \qquad (2)$$

When $a=2^{-j}$, $b=k*2^{-j}$, where $j,k \in Z$, then the discrete wavelet is:

$$WT_f(j,k) = \langle f, \psi_{j,k} \rangle = 2^{\frac{j}{2}}\int_{-\infty}^{\infty} f(t)\psi(t)*(2^j t-k)dt \qquad (3)$$

Here a are the scale factor and b is the translation factor. $\tilde{\psi}(t)$ is the complex conjugate of $\psi(t)$ [9].

In the process of denoising, wavelet analysis has the characteristics of multi-resolution analysis, which can effectively distinguish the abrupt part of the signal and the noise of different decomposition layers. If s (t) are noisy signal, its expression :

$$s(t) = f(t) + \sigma * e(t) \quad t = 0,1,\ldots,n-1 \qquad (4)$$

Where $f(t)$ is the real signal and $e(t)$ is the noise, σ is the standard deviation of noise [10].

Wavelet transform can decompose the noise signal $s(t)$ into approximation coefficient (CA_i) and detail coefficient (CD_i), representing the low-frequency component and the high-frequency component respectively. Corresponding to non-stationary ECG signals, useful signals are usually low-frequency signals or relatively sTab. signals, while noise signals are distributed in high-frequency areas. At this time, the high-frequency noise is eliminated by shrinking the corresponding coefficient, so as to achieve the purpose of removing signal noise.

1.1.2 Smooth decomposition and reconstruction

The sampling of ECG signal meets Nyquist sampling theorem, and 1/2 of the actual signal sampling frequency is the highest frequency of actual ECG signal. Through three-point smoothing filtering, the filtered signal is identified as the first-order smooth decomposition component (sdc_1), and the highest frequency in the remaining signal is the lower limit of the previous extraction frequency. Continue to extract the new smoothing filter according to 1/2 of the highest frequency of the remaining signal, and the number of smoothing filter points is twice the number of smoothing filter points of the preceding stage minus 1. Until the number of smoothing points is greater than 1/2 of the data length and less than the data length, the decomposition ends.

The smooth decomposition method is outlined below. Set the actual detected ECG signal as $s(n)$, as the sample serial number, and N as the signal length. Record the k-th order smooth decomposition component is, and the remaining signal as, k = 1,2, …, M. M is the maximum decomposition order [12].

When k = 1,

$$sdc_1(n) = s(n) - \frac{1}{4}(s(n) + \sum_{i=n-1}^{n+1} s(i)) \qquad (5)$$

$$r_1(n) = s(n) - sdc_1(n) \qquad (6)$$

When k ≥ 2,

$$sdc_k(n) = r_{k-1}(n) - 1/2(2^{k-1}+1) \times \left(r_{k-1}(n) + \sum_{i=n-2^{k-1}}^{n+2^{k-1}} r_{k-1}(i) \right) \qquad (7)$$

$$r_k(n) = r_{k-1}(n) - sdc_k(n) \qquad (8)$$

In the above formulas, when i < 1 or i > N, $s(i)$ and $r_{k-1}(i)$ take the corresponding data endpoint values.

In order to reconstruct the denoised signal, first set the components of layer 1 and layer 2 to zero, and there are many overlapping parts between noise and ECG signal. Use the power threshold function to denoise the components of layer 3 and 4, and retain the remaining low-frequency components. Finally, add their layers to the remainder of each layer to get the final reconstructed signal, $s_r(n)$ represents the reconstructed signal, and the expression is as follows:：

$$s_r(n) = \sum_{k=1}^{M} sdc_k(n) + r_M(n) \qquad (9)$$

2 Threshold and threshold function denoising

The threshold function should be a function related to the signal noise level, so as to suppress the noise and retain the useful signal components.

2.1 Traditional threshold functions

denoising method is the selection and

quantization of wavelet coefficient threshold. The traditional threshold functions include hard threshold and soft threshold functions [21].

The traditional hard threshold and soft threshold functions are defined as expressions (10) and (11) respectively:

$$\hat{\omega}_{i,j}=\begin{cases}\omega_{i,j}, & |\omega_{i,j}|\geq\lambda\\ 0, & |\omega_{i,j}|<\lambda\end{cases} \tag{10}$$

$$\hat{\omega}_{i,j}=\begin{cases}\text{sgn}(\omega_{i,j})(|\omega_{i,j}|-\lambda), & |\omega_{i,j}|\geq\lambda\\ 0\quad, & |\omega_{i,j}|<\lambda\end{cases} \tag{11}$$

Hard and soft threshold denoising methods have been widely used in practice, but its function itself has some shortcomings. The principle of hard threshold method is to set a fixed threshold. The wavelet coefficients greater than the threshold remains unchanged, and the wavelet coefficients less than the threshold are directly set to zero. This processing method can completely retain the information greater than the threshold, but the wavelet coefficients near the threshold change from continuous to step before and after denoising, It leads to the pseudo Gibbs phenomenon of the reconstructed signal after hard threshold denoising[14]. In order to avoid this phenomenon, the soft threshold method shrinks the wavelet coefficients greater than the threshold and sets the wavelet coefficients less than the threshold to zero. The processed effect is that the wavelet coefficients near the threshold are continuous and the denoised signal is smooth[14]. Due to the shrinkage of this method, there is a constant difference between the wavelet coefficients before and after processing, leading to the distortion of the reconstructed signal and the blurring of the signal edge.。

2.2 Power threshold function

In view of the shortcomings of soft and hard threshold noise removal methods, combined with the characteristics of soft and hard threshold functions, this paper proposes the following new threshold functions:

$$\hat{\omega}_{i,j}=\begin{cases}\left(1-\dfrac{\lambda^2}{\omega_{i,j}^2}\right)\omega_{i,j}+\text{sgn}\left(\omega_{i,j}\right)\dfrac{\lambda^2}{\omega_{i,j}^2}\left(|\omega_{i,j}|-\lambda\right), |\omega_{i,j}|\geq\lambda\\ \text{sgn}\left(\omega_{i,j}\right)\dfrac{\lambda^2-\omega_{i,j}^2}{c\lambda}, |\omega_{i,j}|<\lambda\end{cases} \tag{12}$$

Where c is the regulatory factor and is a positive number.

The continuity of the power threshold function avoids the pseudo Gibbs phenomenon, overcomes the disadvantage of the constant deviation of the customary threshold function, and improves the accuracy of the reconstructed signal. The power threshold function curve is between the soft and hard threshold function curves, which is equivalent to the transition function between the soft and hard threshold functions; When $\omega_{i,j}$ is large, the value of the power threshold function quickly approaches the curve value of the hard threshold function, which has adaptability. Different from the hard threshold function, and when $\omega_{i,j} = \pm\lambda$,it's still continuous; $\omega_{i,j} < \lambda$,the power function is used to process the wavelet coefficients below the critical threshold, which retains the low-energy signal, which is the merit of the new threshold function.

To sum up, it is concluded that the power threshold function has good continuity, unbiased and asymptotic behavior.

Property1 (continuity) the power threshold function is in ± λ The hard threshold function is eliminated λ The weakness of jumping discontinuity.

Prove: *

$$\lim_{\omega_{i,j}\to\lambda^+}\hat{\omega}_{i,j}=\lim_{\omega_{i,j}\to\lambda^+}\text{sgn}(\omega_{i,j})\frac{\lambda^2-\omega_{i,j}^2}{c\lambda}$$
$$=\lim_{\omega_{i,j}\to\lambda^+}\frac{\lambda^2-\omega_{i,j}^2}{c\lambda}=0$$

When $\omega_{i,j}\to\lambda^-$, Similarly:

$$\lim_{\omega_{i,j}\to\lambda^-}\hat{\omega}_{i,j}=0$$

And：

$$\lim_{\omega_{i,j}\to\lambda^+}\hat{\omega}_{i,j}=\lim_{\omega_{i,j}\to\lambda^-}\hat{\omega}_{i,j}=0$$

Function is continuous in λ:

$$\lim_{\omega_{i,j}\to-\lambda^-}\hat{\omega}_{i,j}=\lim_{\omega_{i,j}\to-\lambda^-}\text{sgn}(\omega_{i,j})\frac{\lambda^2-\omega_{i,j}^2}{c\lambda}$$
$$=\lim_{\omega_{i,j}\to-\lambda^-}\frac{\lambda^2-\omega_{i,j}^2}{c\lambda}=0$$

Property 2 (Unbiased) the threshold function is $(-\infty,\lambda]$ and $[\lambda,+\infty)$ is a hard threshold curve, when $\omega_{i,j}\to\pm\infty$, $\hat{\omega}_{i,j}$ is infinitely close to $\omega_{i,j}$, which overcomes the soft threshold function $\hat{\omega}_{i,j}$ constant deviation from $\omega_{i,j}$.

Prove：*

$$\lim_{\omega_{i,j}\to+\infty}\left(\hat{\omega}_{i,j}-\omega_{i,j}\right)=\lim_{\omega_{i,j}\to+\infty}\left((1-\frac{\lambda^2}{\omega_{i,j}^2})\omega_{i,j}+\frac{\lambda^2}{\omega_{i,j}^2}(\omega_{i,j}-\lambda)-\omega_{i,j}\right)$$
$$=\lim_{\omega_{i,j}\to+\infty}\left(\omega_{i,j}-\frac{\lambda^2}{\omega_{i,j}^2}-\omega_{i,j}\right)=0$$

$$\lim_{\omega_{i,j}\to-\infty}\left(\hat{\omega}_{i,j}-\omega_{i,j}\right)=\lim_{\omega_{i,j}\to-\infty}\left((1-\frac{\lambda^2}{\omega_{i,j}^2})\omega_{i,j}-\frac{\lambda^2}{\omega_{i,j}^2}(-\omega_{i,j}-\lambda)-\omega_{i,j}\right)$$
$$=\lim_{\omega_{i,j}\to-\infty}\left(\frac{\lambda^2}{\omega_{i,j}^2}\right)=0$$

To sum up:

$$\lim_{\omega_{i,j}\to+\infty}\left(\hat{\omega}_{i,j}-\omega_{i,j}\right)=\lim_{\omega_{i,j}\to-\infty}\left(\hat{\omega}_{i,j}-\omega_{i,j}\right)=0 \quad *$$

Property 3 (Asymptotic) $\omega_{i,j}$ picks up the straight line $\hat{\omega}_{i,j}$ $\omega = \omega_{i,j}$ as the asymptote. When $|\omega_{i,j}| \to \infty$, $\omega_{i,j}$ takes the straight line $\hat{\omega}_{i,j} = \omega_{i,j}$ as the asymptote. With the increase of $\omega_{i,j}$, $\hat{\omega}_{i,j}$ approaches $\omega_{i,j}$ infinitely.

Prove：* when $\omega_{i,j} \to -\infty$,

$$\lim_{\omega_{i,j}\to-\infty}\left(\frac{\hat{\omega}_{i,j}}{\omega_{i,j}}\right)=\lim_{\omega_{i,j}\to-\infty}\frac{(1-\frac{\lambda^2}{2\omega_{i,j}^2})\omega_{i,j}+\frac{\lambda^2}{2\omega_{i,j}^2}(-\omega_{i,j}-\lambda)}{\omega_{i,j}}$$

$$=\lim_{\omega_{i,j}\to-\infty}\frac{1+\frac{\lambda^2}{2\omega_{i,j}^2}(-\omega_{i,j}-\lambda)}{\omega_{i,j}}=1$$

$$\lim_{\omega_{i,j}\to+\infty}\frac{\hat{\omega}_{i,j}}{\omega_{i,j}}=\lim_{\omega_{i,j}\to+\infty}\frac{(1-\frac{\lambda^2}{2\omega_{i,j}^2})\omega_{i,j}+\frac{\lambda^2}{2\omega_{i,j}^2}(\omega_{i,j}-\lambda)}{\omega_{i,j}}$$

$$=\lim_{\omega_{i,j}\to+\infty}\frac{1+\frac{\lambda^2}{2\omega_{i,j}^2}(\omega_{i,j}-\lambda)}{\omega_{i,j}}=1$$

There we get：

$$\lim_{\omega_{i,j}\to+\infty}\left(\hat{\omega}_{i,j}/\omega_{i,j}\right)=\lim_{\omega_{i,j}\to-\infty}\left(\hat{\omega}_{i,j}/\omega_{i,j}\right)=1*$$

These properties compared with soft threshold function, effectively corrects the estimated coefficient of wavelength and wavelength after decomposition coefficient between the standard deviation and threshold function continuous in the $|\omega_{i,j}|=\lambda$, avoided due to the hard threshold with discontinuous function potential signal distortion.

2.3 Selection of decomposition layers

Each step of signal processing will affect the final result of denoising. If the decomposition layer number is too low or too high, the ideal denoising effect cannot be achieved. Different ECG signal decomposition layer number is also different. In order to remove noise better, wavelet transform and smooth decomposition were used to test decomposition layers of 103 ECG signal from MIT-BIH arrhythmia database. Through the experiment, the best denoising effect was achieved when the decomposition layers were 8 and 10 respectively.。

2.4 Selection of threshold

Using signal denoising threshold method, the most important thing is to set a reasonable threshold for wavelet coefficients λ, If λ If it is too large, some wavelet coefficients generated by the useful signal will be filtered out, but if λ If it is too small, the wavelet coefficients generated by noise will be retained and the denoising is incomplete[16]. Therefore, the size of the threshold determines the final denoising quality. Tackling the uncomforTab. signal of ECG signal, after wavelet decomposition, the amplitude difference between different wavelet coefficients is large, and the signal-to-noise ratio is also different. Therefore, different threshold expressions are used to denoise the signal, and the optimal threshold expression is chosen according to the experimental results.

Donoho proposed a unified threshold method λ Defined as:：

$$\lambda=\sigma\sqrt{2\ln N} \tag{13}$$

In equation (13), n is the length of the signal, σ Is the standard deviation of noise, which can be estimated by the median of wavelet coefficients of the first layer lifting wavelet decomposition. If it represents the wavelet coefficients of the first layer, then：

$$\sigma=\text{median}\left(\left|\omega_{1,n}\right|\right)/0.6745 \tag{14}$$

This threshold estimation can separate most signals from noise, but when the signal amplitude is close to or less than noise, the signal is easy to be filtered into noise and affect the noise reduction effect. Based on the threshold estimation formula in reference [17-19], this paper proposes a new threshold estimation expression to adjust the threshold estimation. Subsequent experiments use the new threshold λ_ New estimate threshold.

$$\lambda\_new=\sigma_i\frac{\sqrt{2\ln N_i}}{\ln(i+1)} \tag{15}$$

Estimate the standard deviation according to equation (16):：

$$\sigma_i=\text{median}\left(\left|\omega_{i,j}\right|\right)/0.6745 \tag{16}$$

In the above threshold calculation expression, σ_i represents the noise standard deviation of the i-layer wavelet decomposition coefficient, $\omega_{i,j}$ are the detail coefficients of each layer wavelet decomposition, and N_i is the length layer decomposition of the i-layer wavelet decomposition coefficient.

3 Experimental results and analysis

3.1 Experimental data source

The ECG signal was derived from no. 103 ECG signal data of MIT-BIH Arrhythmia database (MITDB), with a sampling frequency of 360Hz and

1000 intercepted data points. The ECG signal was extracted from no.103 data was regarded as the original signal, denoted as $s_o(n)$.

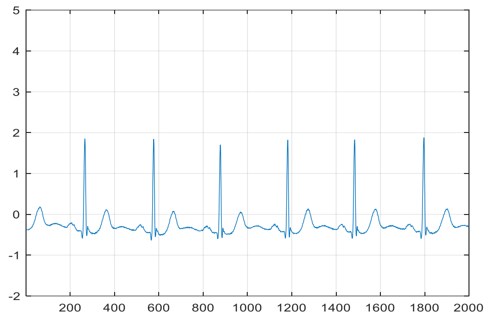
Three kinds of noise are involved in this experiment, which are baseline wandering (BW), electromyogram (EMG), White noise (WN) and hybrid noise (HN). Mixed noise HN is produced by mixing the above three kinds of noise. Three different types of noise information changed to the original signal are given below:

(1) 0.2Hz baseline drift noise (BWN) :

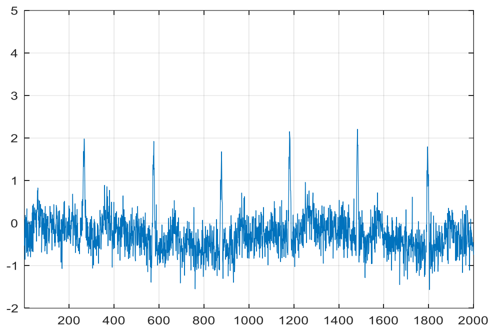
(2) EMG is derived from the myoelectric interference of the original ECG signal in MIT-BIH, and the sampling frequency is 360 Hz.

(3) Gaussian white noise (WGN) with the power of 20dB is generated by Matlab2018's random function.

As shown in Fig. 3-1, Fig. 3-1 (a) is the original normal ECG signal, and (b) is the noisy ECG signal.



(a) Original signal



(b) Noisy signal

Fig. 3-1 ECG waveform before and after adding simulation noise

3.2 Evaluation method of denoising results

In this paper, we choose the root mean square error (RMSE), signal-to-noise ratio (SNR) and correlation coefficient (CR), to quantitatively analyze the proposed denoising method and the existing denoising method. These performance metrics statistically evaluate the quality of the output generated after simulation.

The calculation formula for performance indicators is::

$$RMSE=\sqrt{\frac{\sum_{n=1}^{N}\left[s_o(n)-s_r(n)\right]^2}{N}} \quad (17)$$

$$SNR=10\log\frac{\sum_{n=1}^{N}s_o^{\,2}(n)}{\sum_{n=1}^{N}(s_r(n)-s_o(n))^2} \quad (18)$$

$$CR=\frac{\sum_{n=1}^{N}\left(s_r(n)-\overline{s_r(n)}\right)\left(s_o(n)-\overline{s_o(n)}\right)}{\sqrt{\sum_{n=1}^{N}\left[s_r(n)-\overline{s_r(n)}\right]^2}\sqrt{\sum_{n=1}^{N}\left[s_o(n)-\overline{s_o(n)}\right]^2}}\times 100 \quad (19)$$

Where $s_o(n)$ is the original ECG signal, $s_r(n)$ is the reconstructed denoised signal, and N is the length of the signal.

Usually, visual examinations are used for clinical acceptability of denoised signals. At the same time, quantitative analysis is carried out to measure the degree of denoised signal compared with the original signal. The measurement parameter RMSE is used to measure the error between the original signal and the reconstructed (denoised) signal. The smaller its value is, the more complete the information saved is. SNR reflects the difference between noise levels before and after the application of the algorithm, and the greater the value, the better the effect. CR is defined as the correlation coefficient between the denoised signal and the noiseless source signal, which is used to express the similarity between the denoised signal and the source signal, and to evaluate the denoising effect from the aspect of waveform form.

3.3 Performance evaluation based on threshold function and decomposition method

In order to verify the feasibility of the proposed method, two decomposition methods, smooth decomposition and wavelet decomposition, are used to denoise the ECG signal, including soft threshold, hard threshold and power threshold function. In the decomposition process, flat decomposition uses the way of weight to filter and extract points, and wavelet transform uses a series of functions labeled wavelet. Different wavelet functions have different scales, which are decomposed by the decomposition scale of the wavelet function used.

Here, the ECG signal extracted from 103 data after adding the above mixed noise (HN) is used for experiments. The soft and hard threshold functions and power threshold functions are applied to two different decomposition methods. The above three evaluation indexes RMSE, SNR and Cr are used to evaluate the performance of the three threshold functions, and the denoising effect is analyzed through the graph shape and performance index values, The denoising effect is shown in Fig. 3-2 and Fig. 3-3.

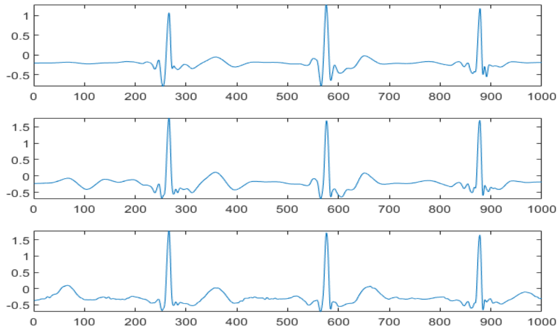


Fig. 3-2 Denoising effect of three threshold functions after wavelet transform

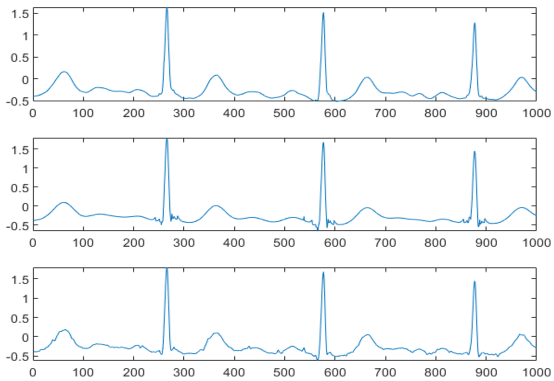


Fig. 3-3 Denoising effect of three threshold functions after smooth decomposition

From top to bottom, the denoising effects of soft threshold, hard threshold and power threshold function are shown respectively; The denoising results are shown in Tab. 3-1 and Tab. 3-2.

Tab. 3-1 Denoising results of three threshold functions after wavelet transform

Threshold function	*SNR*	*RMSE*	*CR(%)*
Soft threshold	15.7094	0.1828	86.90
Hard threshold	21.3720	0.1378	91.32
Power threshold function	39.4531	0.0558	98.36

Tab. 3-2 Denoising results of three threshold functions after smoothing decomposition

Threshold function	*SNR*	*RMSE*	*CR(%)*
Soft threshold	35.3429	0.0685	98.04
Hard threshold	40.0628	0.0541	98.71
Power threshold function	43.0734	0.0465	98.98

After wavelet decomposition, the wavelet coefficients of 3-6 layers are denoised by the power threshold. The reconstructed waveform can remove noise well and restore the waveform characteristics of cardiac signal completely; The denoising effect of uniform decomposition combined with threshold function is better than that of wavelet transformation. It can be seen from the graph that the QRS wave of ECG signal is preserved and can restore the waveform characteristics of ECG signal. Moreover, from the denoising result, the results of RMSE, SNR and Cr are similar to those under wavelet decomposition, But the calculation speed of smooth decomposition is faster than that of wavelet transform.

In the comparison of threshold functions, the noise reduction effect of the power threshold function surpassed the performance of the traditional soft and hard threshold function, has good signal reduction and high denoising efficiency, and the power threshold function makes up for the fixed deviation of the soft threshold and avoids the loss of some useful information.

In conclusion, the power threshold function has good adaptability to different decomposition methods. For the traditional threshold function, the denoising effect of the power threshold function is better.

3.4 Method performance evaluation based on experimental parameters

Different degrees of noise correspond to different parameters, and the denoising effect is different. In order to better eliminate different noises, the parameter most suiTab. for the current noise is identified through parameter adjustment. As mentioned earlier, the new method has one degree of freedom: threshold parameter c, which provides greater flexibility for denoising. Basically, finding the best value for the threshold and threshold function parameters means that the ECG information overlaps less with the noise in the detail part of the signal, and the quality of the denoised signal is better [20].

Next, analyze and verify the influence of the change of parameter c in the power threshold function on signal denoising. In order to find the optimal value set of the involved parameter c, we use the genetic algorithm to find the sequence of the optimal parameter values, lastly obtain the optimal parameter values. The numerical results calculated based on the evaluation method record the performance of the proposed method for comparison. Tab. 3-3 and Tab. 3-4 reflect the influence of parameters on signal denoising under the two methods of wavelet transformation and smooth decomposition.

Tab. 3-3 Changes of noise performance with c under wavelet transform

c	*SNR*	*RMSE*	*CR*(%)
3.1	39.4134	0.0559	98.38
3.3	39.8021	0.0548	98.42
3.5	40.5651	0.0528	98.52
3.7	39.8826	0.0546	98.42
3.9	39.1730	0.0566	98.30

According to the experiment, we determine the best sequence of c. It can be seen from the data in Tab. 3-3 that when c = 3.5, the RMSE value we get is 0.0528 and the SNR value is the largest, which shows that when c is 3.5, the distortion of the denoised ECG signal is much smaller than that of the noisy ECG signal, the denoising effect is the best, and the useful ECG information can be retained.

Tab. 3-4 Variation of noise performance with c after smooth decomposition

c	*SNR*	*RMSE*	*CR*(%)
0.5	41.0066	0.0516	98.63
0.7	41.9951	0.0491	98.87
0.9	42.3847	0.0482	98.83
1.1	44.6620	0.0430	99.06
1.3	43.9936	0.0445	99.02
1.5	45.0100	0.0422	99.28

For the power threshold denoising under smooth decomposition, the sequence of parameter c changes. Since the waveform of ECG signal is relatively intact after smooth decomposition, the value of c should not be too large and needs to be adjusted within a small value range. After selecting the appropriate parameter sequence by genetic algorithm, the experimental results show that when c = 1.5, the SNR value is the largest and the similarity can reach 99.28%, The denoising effect is the best, which can well restore the waveform and characteristics of ECG signal.

3.5 Denoising effect under different noise levels

In order to simulate the noise removal process, AWGN noise with different levels of 0dB, 5dB, 10dB, 15dB and 20dB generated by MATLAB is used to add noise to the ECG signal for experiments. The denoising methods based on wavelet transform and smooth decomposition power threshold are compared in different noise environments, and the quantitative analysis is carried out intuitively according to the performance measurement parameters.

Tab. 3-5 Denoising results of different levels of noise under wavelet transform

AWGN(dB)	*SNR*	*RMSE*	*CR*(%)
0	2.7894	0.3488	64.18
5	12.7750	0.2117	79.30
10	22.2295	0.1320	90.97
15	33.5262	0.0750	97.07
20	40.2155	0.0537	98.47

Tab. 3-6 Denoising results of noises at different levels under smooth decomposition

AWGN(dB)	*SNR*	*RMSE*	*CR*(%)
0	3.5822	0.3353	65.02
5	15.4439	0.1853	83.26
10	26.3656	0.1073	93.82
15	35.7845	0.0670	97.68
20	44.6702	0.0430	99.12

Under different levels of Gaussian white noise, the denoising effect of power threshold function is still very good. For the removal of depth noise, the effect of the two decomposition methods is not different, but when the noise is relatively small, the denoising effect of smooth decomposition combined with power threshold is better than that of wavelet transform; From the comparison of signal-to-noise ratio and similarity results, under different degrees of Gaussian white noise, the power threshold function stated in this paper still obtains good results after denoising, which shows that the proposed method has good performance and robustness for the removal of different levels of noise.

Conclusion

In this paper, a new ECG denoising method based on power threshold function based on wavelet transformation and smooth decomposition method is proposed. Experiments have proved that this method is conducive to removing the noise interference of non-stationary ECG signals, and shows good applicability and superiority in both decomposition methods. Through the analysis of the experimental results, the power threshold denoising method in this paper has greatly improved the signal-to-noise ratio, the correlation coefficient is generally more than 95%, the ECG waveform distortion after denoising is small, the P wave, T wave and QRS complex are complete and clear, and their position, shape and amplitude are consistent with the source signal, reaching the level of practical clinical application.

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