ECG De-Noising using improved thresholding based on Wavelet transforms

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Summary
The electrocardiogram (ECG) is widely used for diagnosis of heart diseases. Good quality of ECG is utilized by physicians for interpretation and identification of physiological and pathological phenomena. However, in real situations, ECG recordings are often corrupted by artifacts. Noise severely limits the utility of the recorded ECG and thus need to be removed, for better clinical evaluation. Donoho and Johnstone [4, 5, 10] proposed wavelet thresholding de-noising method based on discrete wavelet transform (DWT) with universal threshold is suitable for non-stationary signals such as ECG signal. In the present paper a new thresholding technique is proposed for de-noising of ECG signal. This new de-noising method is called as improved thresholding de-noising method could be regarded as a compromising between hard- and soft-thresholding de-noising methods. The proposed method selects the best suitable wavelet function based on DWT at the decomposition level of 5, using mean square error (MSE) and output SNR. The advantage of the improved thresholding de-noising method is that it retains both the geometrical characteristics of the original ECG signal and variations in the amplitudes of various ECG waveforms effectively. The experimental results indicate that the proposed method is better than traditional wavelet thresholding de-noising methods in the aspects of remaining geometrical characteristics of ECG signal and in improvement of signal-to-noise ratio (SNR).

Key words:
ECG signal, wavelet de-noising, discrete wavelet transform, improved thresholding

1. Introduction

Electrocardiogram (ECG) signal, the electrical interpretation of the cardiac muscle activity, is very easy to interfere with different noises while gathering and recording. The most troublesome noise sources are the Electromyogram (EMG) signal, instability of electrode-skin effect, 50 / 60 Hz power line interference and the baseline wandering. Such noises are difficult to remove using typical filtering procedures. The EMG, a high frequency component, is due to the random contraction of muscles, while the abrupt transients are due to sudden movement of the body. The base line wandering, a low frequency component is due to the rhythmic inhalation and exhalation during respiration. J. Pan *et al*. showed that the QRS complex power spectrum density (PSD) –(5-15 Hz) overlaps with the muscle noise [1], while P and T waves PSD overlaps with respiration action and blood pressure at low frequency band (usually from 0.1 to 1 Hz)[2]. Furthermore, the non-stationary behavior of the ECG signal, that becomes severe in the cardiac anomaly case [3], incites researchers to analyze the ECG signal. Wavelet thresholding de-noising method based on discrete wavelet transform (DWT) proposed by Donoho *et al.* is often used in de-noising of ECG signal [4, 5]. In 1999, Agante used it in de-noising of ECG signal [6].

Wavelet thresholding de-noising methods deals with wavelet coefficients using a suitable chosen threshold value in advance. The wavelet coefficients at different scales could be obtained by taking DWT of the noisy signal. Normally, those wavelet coefficients with smaller magnitudes than the preset threshold are caused by the noise and are replaced by zero, and the others with larger magnitudes than the preset threshold are caused by original signal mainly and kept (hard-thresholding case) or shrunk (the soft-thresholding case). Then the de-noised signal could be reconstructed from the resulting wavelet coefficients. These methods are simple and easy to be used in de-noising of ECG signal. But hard-thresholding de-noising method may lead to the oscillation of the reconstructed ECG signal and the soft-thresholding de-noising method may reduce the amplitudes of ECG waveforms, and especially reduce the amplitudes of the R waves. To overcome the above said disadvantages an improved thresholding de-noising method is proposed [13, 14, 15, and 16].

2. Methods

ECG signal is easy to be contaminated by random noises uncorrelated with the ECG signal, such as EMG, baseline wandering and so on, which can be approximated by a white Gaussian noise source [6, 7].

The method can be divided into the following steps:

Noise Generation and addition: A random noise is generated and added to the original signal. So, the noisy ECG signal can be assumed with finite length as follows:

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$$y(n) = x(n) + d(n), \quad n = 1,2,\ldots,N. \tag{1}$$

where x (n) is the clean original MIT-BIH ECG data signal with DC component rejected, d (n) is Gaussian white noise with zero mean and constant variance, y(n) is the noisy ECG signal.

1. Decomposing of the noisy signals using wavelet transform:

Using the discrete wavelet transform by selecting mother wavelet, the noisy signal is decomposed, at the decomposition level of 5. As a result approximate coefficients a_j and detail coefficients d_j are obtained.

2. Apply thresholding, to obtain the estimated wavelet coefficients $\hat{d}_j$.

For each level a threshold value is found, and it is applied for the detailed coefficients d_j.

(a) Hard-thresholding method:

$$\hat{d}_j = \begin{cases} d_j, & |d_j| \geq T_j \\ 0, & |d_j| \leq T_j \end{cases} \tag{2}$$

where preset threshold is $T_j = \sigma\sqrt{2\log\|d_j\|}$ (3)

The σ can be estimated by the wavelet coefficients with $\sigma = \left(\text{median}\left(|d_j|\right)\right)/\ 0.6745$. Here median ($|d_j|$) denotes the median value of the absolute values of wavelet coefficients d_j.

3. Reconstructing the de-noised ECG signal $\hat{x}(n)$ from $\hat{d}_j$ and a_j by inverse discrete wavelet transform (IDWT).

The same steps are to be followed for soft thresholding, and improved thresholding de-noising methods.

(b) Soft-thresholding method:

$$\hat{d}_j = \begin{cases} \text{sgn}(d_j)(|d_j| - T), & |d_j| \geq T_j \\ 0, & |d_j| \leq T_j \end{cases} \tag{4}$$

(c) Improved thresholding method:

$$\hat{d}_j = \begin{cases} \text{sgn}(d_j)(|d_j| - \beta^{(T_j - |d_j|)}.T_j), & |d_j| \geq T_j \\ 0, & |d_j| \leq T_j \end{cases} \tag{5}$$

where $\beta > 1$ *and* $\beta \in R$. Because the magnitudes of the wavelet coefficients related to the Gauss white noise decreases as the scale j increases, hence the threshold value will be chosen as

$$T_j = \sigma\sqrt{2\log\|d_j\|}\,/\log(j+1) \tag{6}$$

For each level, find the threshold value that gives the minimum error between the detailed coefficients of the noisy signal and those of original signal.

From equation (5), the improved wavelet thresholding de-noising method has the following characters:

Assured the continuity of estimated wavelet coefficients d_j at position $\pm T_j$, so that the oscillation of the reconstructed ECG signal is avoided.

Once β is fixed the deviations between $\hat{d}_j$ and d_j decrease with the increase of the absolute values of d_j, when $|d_j| \geq T_j$, if equation (5) satisfies :

$$\lim_{|d_j| \to \infty} \hat{d}_j = d_j \tag{7}$$

It makes the reconstructed ECG signal remain the characteristics of the original ECG signal and keep the amplitudes of R waves effectively.

Equation (5) will be equivalent to hard-thresholding when $\beta \to \infty$ and will be equivalent to soft-thresholding, when $\beta \to 1$. This shows that the improved threshold de-noising method can be adapted to both hard- and soft-thresholding de-noising methods. Therefore, the improved thresholding de-noising method could be regarded as a compromise between the hard- and soft-thresholding de-noising methods. So, that the improved thresholding de-nosing method presented in this paper could choose an appropriate β by trail –and-error to satisfy the request of de-noising of the ECG signal.

Evaluation Criteria: We utilize both the mean square error (MSE) value and SNRo value between the constructed de-noised ECG signal $\hat{x}(n)$ and the original ECG signal with DC offset rejected $x(n)$ (the reference ECG signal to evaluate our method).

Determination of Mean square error: For ECG signal de-noising, the best suitable wavelet function is achieved based on the mean square error (MSE) value between the de-noised ECG signal $\hat{x}(n)$ and the original with DC component rejected signal $x(n)$.

$$MSE(w,l) = \frac{1}{N}\sum_{i=1}^{N}(x(i)-\hat{x}(i))^2 \qquad (8)$$

where w is the wavelet function, l is the level of wavelet de-noising and N is the length of the ECG segment[17].

Determination of SNR Criteria: The output SNR is given by

$$\text{SNRo} = 10\log\left(\frac{\sum_{i=1}^{N}x^2(i)}{\sum_{i=1}^{N}(x(i)-\hat{x}(i))^2}\right) \qquad (9)$$

SNR_o values to determine the wavelet function for de-noising ECG signal [17].

3. Results and analysis

To validate the superiority of the proposed improved thresholding de-noising method, ECG signal in MIT-BIH database is intercepted to be the original ECG signal. The length of the original ECG signal (i.e., the number of the sample points) is N=1024 (see Fig 1(a)). Gauss white noise is added to the original ECG signal, the noisy ECG signal is shown in Fig 1(b). Noise reduction Procedures were implemented in Mat lab 7.0.1. The effectiveness of de-noising process for 14 wavelet functions are tested [18]: Daubechies proposed functions [5] (db2, db3, db4, db5, db6, db7, db8), and their modifications so-called Symlets wavelets (sym2, sym3, sym4, sym5, sym6, sym7, sym8), at the decomposed scale of 5. The DWT wavelet de-noising is performed for hard-thresholding, soft-thresholding and improved thresholding de-noising methods respectively to de-noise the noisy ECG signal.

In improved thresholding de-noising method with DWT, the coefficient β is chosen as β =21. The fig. 1(c)-(e) shows that the de-noised the ECG signals by using the hard-, soft- and improved-thresholding de-noising methods respectively. From fig. 1(c), it can see that hard–thresholding using DWT is better in remaining the characteristics of original ECG signal and the loss of the amplitudes of R waves is not obvious. It is seen from fig.1(d) soft-thresholding de-noising using DWT gains good smoothness but the amplitude of R waves in reconstructed ECG signal is reduced obviously. From fig 1(e), the improved thresholding de-noising method via DWT can not only remain the geometrical characteristics of original ECG signal and gain good smoothness, but also keep the amplitudes of R waves in reconstructed ECG signal efficiently.

The proposed method is based on choosing threshold value by finding minimum error of denoised signal and original wavelet subsignal (coefficients). Therefore, high quality denoised signal can be accomplished. Our study establishes particular approach to fit ECG signal that has nonstationary clinical information. To preserve the distinct ECG waves and different low pass frequency shapes, the method thresholds detailed wavelet coefficients only.

This concept is used to return the low frequencies (P-wave where the frequency is less than 8Hz and T-wave where the frequency is less than 11Hz) by inverse discrete wavelet transform (IDWT). Donoho's method deforms, slightly, low frequency P and T-waves, by creating small wave at the beginning of these waves.

Comparative Analysis:

The comparative analysis was carried out on the ECG data record with SNR = -10 of the reference ECG signal and β -value at 21 in the improved thresholding de-noising method. The table.1 summarizes the obtained output MSE and SNR values for hard-, soft-, and improved thresholding de-noising methods respectively. This will ensure the performance superiority of improved thresholding de-noising method algorithm over hard- and soft- thresholding methods. The db5 and sym8 are showing better suitable wavelets for de-noising of ECG signal.

4. Conclusion

The wavelets transform allows processing of non-stationary signals such as ECG signal. The proposed method shows a new experimental threshold value for each decomposition level of wavelet coefficients of d_j. This threshold value is accomplished at β =21 providing better MSE and SNR values comparative to hard- and soft- thresholding methods. In this study, it shows that proposed improved thresholding de-noising method in this paper is superior to other traditional thresholding de-noising methods in many aspects such as smoothness, remaining the geometrical characteristics of the original ECG signal with DC offset rejected. Though, the β value has taken at 21 based on the maximum SNR value using trial and error method. So, it is valuable to study further to find appropriate β value exactly. On other hand, to develop more appropriate and effective thresholding representation is also a valuable problem to study further.

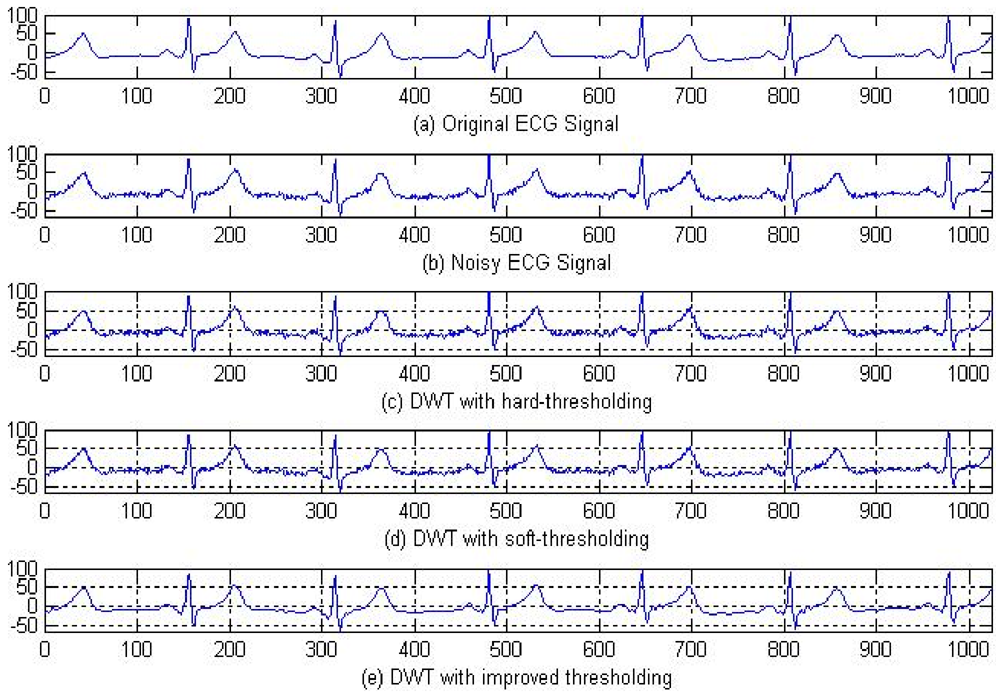

Fig.1 De-noising of ECG signal using threshold methods with Sym8

Table 1: MSE and SNR values for the de-noising methods using Daubechies wavelets and Symlet wavelets

Daubechies wavelets				**Symlet wavelets**			
Wavelet	**Denoising method**	**MSE**	**SNRo**	**Wavelet**	**Denoising method**	**MSE**	**SNRo**
db2	Hard	10.0379	14.4833	**sym2**	Hard	10.3987	14.2894
	Soft	9.1424	14.8544		Soft	9.6900	14.5527
	Improved	8.1042	15.1877		Improved	7.3250	15.6014
db3	Hard	10.0257	14.4590	**sym3**	Hard	9.7569	14.5024
	Soft	9.2329	14.7818		Soft	9.0883	14.7639
	Improved	6.7172	15.9901		Improved	6.4657	16.0977
db4	Hard	10.1304	14.4104	**sym4**	Hard	10.2239	14.3775
	Soft	9.3490	14.7232		Soft	9.4295	14.6844
	Improved	6.4488	16.1768		Improved	6.2522	16.3072
db5	Hard	9.7859	14.5275	**sym5**	Hard	10.0501	14.4386
	Soft	8.8397	14.9290		Soft	9.3407	14.6972
	Improved	5.6444	16.7279		Improved	6.4077	16.1811
db6	Hard	10.1955	14.3753	**sym6**	Hard	10.1919	14.3517
	Soft	9.3151	14.7343		Soft	9.3550	14.6959
	Improved	6.5840	16.0738		Improved	6.3105	16.2333
db7	Hard	9.8823	14.4861	**sym7**	Hard	10.0422	14.3989
	Soft	9.0764	14.8007		Soft	9.1510	14.7601
	Improved	6.4528	16.1318		Improved	6.3309	16.1981
db8	Hard	10.1248	14.3846	**sym8**	Hard	10.1374	14.3713
	Soft	9.3411	14.6935		Soft	9.4309	14.6522
	Improved	6.5094	16.1057		Improved	6.2854	16.2472

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