ATLANTIS PRESS
Advances in Engineering, volume 126
5th International Conference on Machinery, Materials and Computing Technology (ICMMCT 2017)

A Noise Reduction Algorithm of Heart Sound Based on Wavelet Shrinkage

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Keywords：Heart Sound Signal; Wavelet Shrinkage; Threshold Function; Heuristicthreshold Rule

Abstract. In this paper, a kind of noise reduction algorithm is proposed based on wavelet shrinkage technique to acquire heart sound signal while no distortion. Firstly, Haar, Daubechies, Symlets and Coiflets orthogonal wavelets were studied and according to the statistical results, Coif5 wavelet was chosen for the decomposition and reconstruction of heart sound signal. To get the better noise reduction effects, a smooth and continuous adaptive elastic threshold function was designed for wavelet shrinkage, which could perfectly overcome the discontinuous shortage of hard threshold function, especially under Heursure rule when the SNR was less than 50dB. In addition, the results showed that the energy in each layers of Coif5 wavelet differed significantly among different kinds of heart diseases. So the coif5 wavelet may be suitable for feature extraction of heart sound signal and classifications of pathological heart sounds in future research.

1. Introduction

Heart sound auscultation has become one of the basic methods in the process of clinical diagnosis in the evaluation of whether the heart function is in normal state due to its features of non-invasive, rapid, low cost and so on [1]. By the detection of heart sounds, we can get effective information to diagnose heart diseases. However, because of the patients' movement, the interference of various heart diseases and other factors, heart sound signal will be mixed with many kinds of noise, and will affect the doctor's diagnosis. Therefore, before heart sound signal analysis and diagnosis, we need to denoise the signal to achieve the purpose of efficient and rapid diagnosis and treatment of diseases.

Heart sound signal denoising has always been the focus of many scholars at home and abroad: Singh conducted decomposition application of EMD to noise reduction of heart sound while the effect is not very ideal [2]; F.NazanUcar proposed denoising algorithm of heart sound signal based on multiresolution orthogonal wavelet transform; EM.Agente discussed soft threshold based heart sound signal denoising and so on [3]. Then Donoho and Johnstone proposed wavelet shrinkage denoising theory [4,5], which makes full use of the characteristics of orthogonal wavelet and different characteristics of the signal and noise in orthogonal wavelet transform and the noise can be suppressed greatly when the peak point of the signal feature is kept almost without distortion, that is to say, it can estimate the real signal from the noisy signal perfectly. The wavelet threshold shrinkage denoising algorithm is widely used in many signal processing fields because of its simple implementation and small computation. The key to the effectiveness of the algorithm lies in the selection of wavelet basis and the threshold selection of the denoising algorithm of each scale wavelet component [6].

This paper focuses on the optimization of wavelet shrinkage noise reduction of heart sound signals. The main work is focused on the following two aspects: (1) analyzing the characteristics of the frequency components of heart sound signals and the characteristics of Haar, Daubechies, Symlets and Coiflets orthogonal wavelets according to the principle of frequency band similarity matching,

quantitatively studying discrimination of wavelet generating function and getting the best wavelet base; (2) designing the adaptive elastic threshold function and analysing noise reduction effect of heart sound signal based on fixed threshold (Sqtwolog), unbiased risk threshold (Rigrsure), heuristic threshold (Heursure) and minimax threshold (Minimaxi) at different SNR [7].

2. Wavelet Denoising Theory

Wavelet denoising principle is to preserve the modulus maxima of heart sound signal at various scales of wavelet transform, while set other points to zero or suppress them to the maximum extent, and then to do inverse transform using the processed wavelet coefficients so as to achieve the purpose of suppressing noise [8]. Although orthogonal wavelet can suppress noise to some extent, but in order to achieve better noise reduction effect, according to the level of noise at each scale, different thresholds can be applied, namely multi-scale wavelet threshold denoising, also called wavelet shrinkage (Wavelet Shrinkage).

Before the wavelet denoising, 120 groups of heart sound signals were pretreated. The original sampling frequency of the noisy heart sound signal was 44100Hz. Because of the frequency of useful components in heart sound signal are generally lower than 800Hz, in order to reduce pressure and improve running speed for subsequent data processing, as well as better effect for wavelet decomposition later, we usually resample the signal sampling frequency to 1102Hz. Then the notch filter is used to denoise the power frequency. Fig.1 shows the corresponding flow chart of the optimal noise reduction scheme for heart sound signal.

2.1 Mallet Wavelet Algorithm

This study uses Mallet algorithm for wavelet decomposition [9]. Assuming that X(n) is heart sound signal mixed with Gauss white noise, S(n) is the original heart sound signal, and e(n) represents the white noise N(0,1), thus X(n)=S(n)+e(n). This study is to realize the original research by wavelet denoising, which is the effective separation of original heart sound signal by wavelet denoising. The wavelet denoising process designed in this study is shown in Fig.1, where A represents the overview and D represents the details. This algorithm can realize the decomposition of signal X (n), as well as the detail subdivision of the frequency band. It also ensures the constant Q characteristic of each frequency band and the invariance of A (t) and D (t).

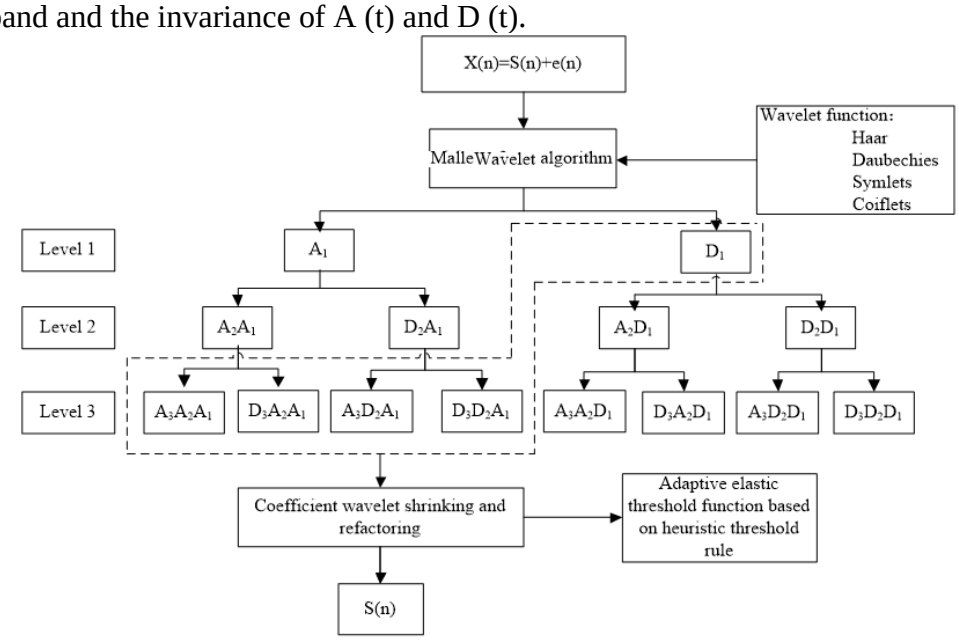

Fig.1 Wavelet denoising flow chart

2.2 Wavelet Function

In the process of wavelet decomposition, different decomposition layers and wavelet generating functions have different effects on heart sound noise reduction. So wavelet decomposition has the characteristic of diversity. Generally speaking, the symmetry and orthogonality of wavelet bases are not compatible. So when studying heart sound signal, orthogonal function wavelet function is usually selected. Common orthogonal wavelets are: Haar, Daubechies, Symlets and Coiflets, etc, in which wavelet and scaling functions of orthogonal wavelet Coif5 have prominent symmetry properties, and then conduct quantitative analysis of orthogonal wavelet Coif5 partition by experiment. Analysing data normalization with frequency section determined by optimal wavelet packet, and respectively studying the energy values contained in different levels of four wavelets to obtain the optimal wavelet generating function.

2.3 Optimal Wavelet Packet

According to the three order decomposition in Fig.1, the better frequency resolution of the low-frequency part can be obtained. According to the frequency domain characteristics of heart sound signal, the useful component frequency is generally lower than 800Hz. Therefore, when determining the optimal wavelet packet, we should consider the frequency component within 800Hz. The most suitable wavelet packet constructed in this study can achieve high frequency resolution in the frequency domain of the heart sound effective information, and reflect the high temporal resolution in the high-frequency part. The final corresponding frequency range of the optimal wavelet packet:

Tab.1 Pass band of equivalent filter

	Pass band
$\mathbf{A_3A_2A_1}$	0Hz-138Hz
$\mathbf{D_3A_2A_1}$	138Hz-275Hz
$\mathbf{A_3D_2A_1}$	275Hz-413Hz
$\mathbf{D_3D_2A_1}$	413Hz-551Hz
$\mathbf{D_1}$	551Hz-1102Hz

2.4 Wavelet Coefficient Shrinkage

The key of wavelet threshold denoising is the selection of threshold function and threshold rule. The traditional threshold function is divided into soft threshold and hard threshold. Hard thresholding is a simple zero setting method, but with poor continuity and there will be a shock in the reconstructed signal; Soft threshold is to make the coefficient with a larger absolute value reduce on the basis of the original, and then reconstruct the signal directly using processed wavelet coefficients to make the input-output curve become continuous and consequently achieve the purpose of noise reduction. However, some singular points will be submerged, and there will be a large distortion in reconstruction signal. Therefore, an adaptive elastic threshold function is proposed in this study.

$$f(x)=\begin{cases} -\frac{a}{2}(e^{\frac{x+T}{a}}-e^{\frac{-T-x}{a}}) & x\le -T \\ 0 & |x|<T \\ \frac{a}{2}(e^{\frac{x-T}{a}}-e^{\frac{T-x}{a}}) & x\ge T \end{cases} \tag{1}$$

X is the coefficient of wavelet decomposition, a is a regulating parameter.

The new threshold function has the following advantages:

1 New threshold function is $\lim_{x\to -T^-} f(x)=\lim_{x\to -T^+} f(x)=0$ and $f(x)$ is continuous differentiable when $x=\pm T$.

2 $f(x)$ is odd function and the curve is smooth and monotonically increasing.

3 $f(x)$ can overcome the problem of discontinuous point of hard threshold function, so that the reconstructed signal retains more details of the signal under the premise of fully ensuring noise reduction effect.

Wavelet threshold T also plays a key role in the process of noise reduction. If the threshold T is selected too large, the signal distortion will be caused, that is to say, it will filter too many effective components of heart sound signals; If the threshold value of T is too small, there will still be noise components mixed in the signal after noise reduction. The noise reduction effect is not obvious [11]. So it is very important to select appropriate threshold T. Experimental analysis of the denoising effect of the fixed threshold, unbiased risk threshold, heuristic threshold and Minimax threshold is conducted to select optimal scheme.

In order to evaluate the noise reduction effect of various threshold rules, this paper make use of a class variance index V which is defined as the average of each data and the square value of mixed noise to evaluate. When V reaches minimum threshold rule is optimal. Firstly, to add Noise E (n) with different signal to noise ratio to the denoised heart sound signal S(n) in order to get X(n). Then apply the above threshold rules to denoise the mixed signal to get the denoised signal S(n). Calculate evaluation index V, the smaller V shows that the threshold rule has better noise reduction effect under this signal to noise ratio.

$$V = \frac{(signal\ after\ the\ reduction - original\ signal)^2}{Number\ of\ data} \tag{2}$$

3. Experiment and Data

3.1 Sources of Data

The heart sound data in this paper comes from the General Hospital Affiliated to Tianjin Medical University and Nankai Hospital. Five typical heart sound data of patients with heart disease are contained: stenosis of right ventricular outflow tract, tetralogy of fallot, pulmonary artery stenosis, and mitral inadequacy as wewll as stenosis of right ventricular outflow tract, aortic stenosis, polyarteritis. Simultaneously, in order to avoid the heart sound signal distortion, we invited expert team from these hospitals for artificial discrimination to reconfigure the noise reduction parameters of the distorted heart sound to reprocess.

3.2 Data Processing

In this study, five kinds of pathological heart sound signals were selected to analyze the energy of frequency division. Tab.2 corresponds to four mother wavelets which are Haar, Daubechies, Symlets and Coifletst. Because of the highest energy value in the corresponding frequency band of A3A2A1, in order to facilitate subsequent data analysis, we make band value of 0-138Hz be 1 while other frequency bands for numerical normalization analysis.

Tab.2 Four wavelets corresponds to different levels of energy

		$D_3A_2A_1$	$A_3D_2A_1$	$D_3D_2A_1$	D_1			$D_3A_2A_1$	$A_3D_2A_1$	$D_3D_2A_1$	D_1
Haar	1	0.6259	0.2268	0.0482	0.0123	Sym8	1	0.6350	0.1923	0.0300	0.0021
	2	0.6305	0.2615	0.0851	0.0194		2	0.6427	0.2586	0.0783	0.0082
	3	0.7555	0.4139	0.1911	0.0318		3	0.7203	0.4339	0.2485	0.0117
	4	0.7725	0.3567	0.1071	0.0325		4	0.8307	0.4055	0.1180	0.0204
	5	0.8229	0.5058	0.2503	0.0681		5	0.9102	0.5283	0.2823	0.0427
Db3	1	0.6421	0.2113	0.0280	0.0022	Coif5	1	0.5337	0.2176	0.0343	0.0034
	2	0.6529	0.2620	0.0763	0.0095		2	0.6121	0.2631	0.0796	0.0099
	3	0.7396	0.4684	0.2224	0.0132		3	0.7080	0.3783	0.2178	0.0137
	4	0.8224	0.3900	0.0953	0.0223		4	0.8005	0.4246	0.1181	0.0230
	5	0.8945	0.5105	0.2613	0.0442		5	0.8869	0.5359	0.2676	0.0462

Now by evaluating different levels of energy corresponding to different wavelet we get Fig.2. It can be concluded that the level of energy Coif5 corresponding to has the Maximum sum variance. Therefore, the variance of Coif5 is the largest, which can be used to effectively distinguish the energy values of each hierarchy. So in this study, we choose Coif5 wavelet as wavelet generating function.

Based on the new threshold function, this study compared noise reduction effect of threshold rules selection under different SNR getting Tab.3. Tab.3 is the threshold variance comparison chart of 10dB. By experimental comparison, of the 10 kinds of heart sounds, there are 7 kinds of heart sound signal with the minimum variance under heuristic threshold. For other three signals, the best effect exists in corresponding unbiased risk threshold. But it can be found from the data that the difference between unbiased risk threshold and heuristic threshold is less than 1×10^{-6} which is very small. Therefore, heuristic threshold can be applied to the 10 kinds of heart sound signals in the experiment group.

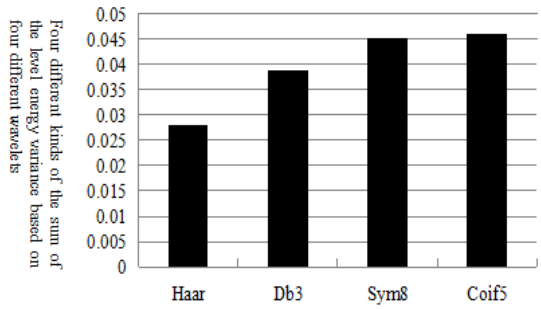

Fig.2 A variance sum of wavelet corresponding hierarchical energy.

Tab.3 10dB/50dB variance value comparison chart

	10dB				50dB			
	Minimaxi	**Sqtwolog**	**Heursure**	**Rigrsure**	**Minimaxi**	**Sqtwolog**	**Heursure**	**Rigrsure**
1	3.80990	6.18510	0.99210	1.19910	3.80990	6.18510	0.99210	1.19910
2	2.70020	4.30390	0.68528	0.82771	2.70020	4.30390	0.68528	0.82771
3	3.16260	5.02650	0.78463	0.85750	3.16260	5.02650	0.78463	0.85750
4	0.99618	1.55450	0.24163	0.25009	0.99618	1.55450	0.24163	0.25009
5	0.52947	0.71658	0.20707	0.19860	0.52947	0.71658	0.20707	0.19860
6	0.50541	0.68863	0.15723	0.15729	0.50541	0.68863	0.15723	0.15729
7	1.40480	0.21555	0.37017	0.36462	1.40480	0.21555	0.37017	0.36462
8	3.80990	6.18510	0.99210	1.19910	3.80990	6.18510	0.99210	1.19910
9	2.70020	4.30390	0.68528	0.82771	2.70020	4.30390	0.68528	0.82771
10	3.16260	5.02650	0.78463	0.85750	3.16260	5.02650	0.78463	0.85750

Fig.3 Shows denoising effect by heuristic threshold under different SNR. The comparison shows that when SNR is greater than 50dB, the optimal proportion of heuristic threshold is reduced to 50%. Referencing Tab.3 simultaneously, because the noise is too low, it can be seen that the discrimination of heuristic threshold and unbiased risk threshold is small.

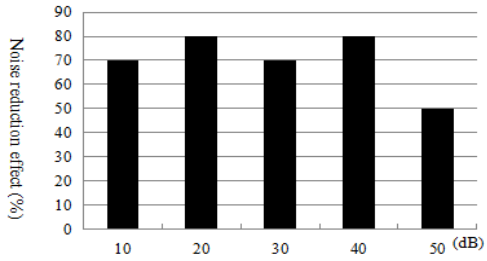

Fig.3 Heursure noise reduction effect under different SNR

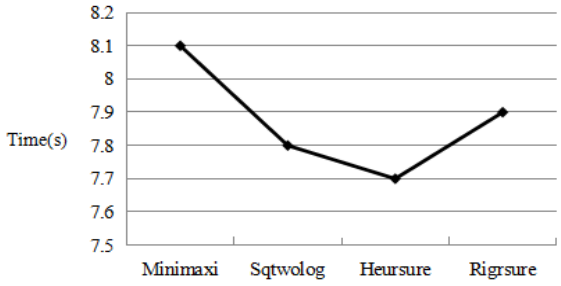

Fig.4 Denoise time with different threshold rules

Fig.4 shows the comparison of reduction time of different threshold noise. Computing environment: CPU Intel i5 processor, 3.2GHz, memory 4GB, win7 system, Matlab R2014a. Subsequently, we evaluate various algorithms. The results of all threshold methods come out around 7.8s basically in which Minimax threshold rule is a little longer, around 8.1s. The time required to run the program is not significantly different. Therefore, we find that when applying heuristic threshold for noise reduction in heart sound signal with noise whose SNR is less than 50dB, we get the best effect. The time required is not inferior to other methods either, which indicates that it can be widely used in clinical diagnosis in hospital.

4. Conclusion

In this paper, the wavelet denoising optimization scheme of heart sound signal is studied. According to the wavelet domain frequency energy characteristics of heart sound signals, we select Coif5 wavelet for three layer decomposition, and select {A3A2A1,D3A2A1,A3D2A1,D3D2A1,D1} for wavelet packet decomposition. Combined with artificial evaluation of medical experts, we conduct quantitative analysis of threshold value under fixed threshold, unbiased risk threshold, heuristic threshold and minimax threshold in view of the threshold function. The results show that when SNR is lower than 50dB, the adaptive elastic threshold function combined with heuristic threshold can effectively reduce noise.

Acknowledgments

In this paper, the research was sponsored by the science and technology support program of Tianjin (Project No. 16YFZCNC00690) .

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