An Exploration of Dynamic Threshold Wavelet Shrinkage Method for Heart Sound Denoising

Tao Zeng, Jia Li Ma, Bin Bin Fu, and Ming Chui Dong

***Abstract*—Intelligent computer-aided heart sound (HS) auscultation provides quantitative and qualitative HS interpretation for preemptive cardiovascular disease (CVD). However, the noises corruption in electronic stethoscope acquired HS signals will not only pollute the HS pathological characteristics but also deteriorate diagnosis accuracy dramatically. As a consequence, HS denoising plays a pivotal role to obtain qualified HS signals for further analysis and interpretation. Massive pathological information contained in murmurs is vulnerable to be distorted by using traditional wavelet based shrinkage methods. Tackling this, a dynamic threshold wavelet shrinkage (DTWS) method is proposed in this paper. Firstly, characteristic layers containing most HS and murmurs information are identified. Then dynamic threshold shrinkage and traditional shrinkage are conducted on characteristic and noncharacteristic layers respectively. Taking advantage of dynamic thresholds, DTWS could overcome the shortcomings of traditional wavelet shrinkage method and reserve the foremost HS and murmurs information while eliminating noises utmostly. Experiments using HS signals from eGeneral Medical benchmark database validate the high performance of the proposed DTWS method with better denoising results than traditional shrinkage method in terms of both signal-noise ratio (SNR) and root mean square error (RMSE).**

***Index Terms*—Characteristic layers, denoising, dynamic threshold, heart sound, wavelet shrinkage.**

I. Introduction

Tremendous physiological and pathological heart information contained in the heart sound (HS) signal makes it potential for early prediction and preemptive diagnosis of cardiovascular diseases (CVDs) in advance of noticeable symptoms and illnesses. By placing an electronic stethoscope against human chest skin, computer-aided HS auscultation and diagnosis provide an efficient way for qualitative and quantitative HS analysis. Furthermore, it exhibits several advantageous features over traditional HS auscultation paradigm: (1) free from inherent human ears limitation; (2) high efficient to deal with vast amount of HS signals simultaneously; (3) high precise by considering both audible and inaudible HS components during diagnosis; (4) capable to record, replay, and store HS signals efficiently. However, the acquired HS signals from electronic stethoscope suffer a lot from diversified noises corruption by sounds of lung and breathe, contact of electronic stethoscope with skin, environmental noises, and other ambient sounds. These noises will not only pollute the HS pathological characteristics but also deteriorate diagnosis accuracy dramatically. As a consequence, HS denoising plays a pivotal role to obtain the qualified HS signals for further analysis and interpretation.

Recently, wavelet transform methods have attracted extensive attention on HS denoising application [1]–[7], and many wavelet based shrinkage methods have been developed [2]–[4]. With the aid of spatially adaptive technique and shrinkage of empirical wavelet coefficients, the wavelet shrinkage methods are able to choose wavelet reconstructions selectively and adaptively to realize efficient noise reduction [2]. Based on this, several adjustments on shrinkage threshold functions have been made [3], [4]. In [3], the generalized threshold function based on the Stein Unbiased Risk Estimate is employed whereas [4] improves the hard and soft thresholds by inducing two parameters to control the smoothness of signal denoising and adjust the constant deviation between threshold and the original wavelet coefficients correspondingly. Despite their reported high denoising performance for normal murmur-free HS signals, those methods are not applicable for pathological HS signals with murmurs in practical diagnosis. Since murmurs reflect massive pathological information and exhibit comparable amplitudes with noises, a direct application of traditional wavelet shrinkage method on HS signals with murmurs will result in loss of pathological information by mistaking murmurs as noises during denoising process. Therefore, how to make a delicate tradeoff between eliminating noises and keeping pathological information simultaneously when tackling HS signals with murmurs is a bottleneck problem.

In this paper, a dynamic threshold wavelet shrinkage (DTWS) method is proposed. Differ from the traditional wavelet shrinkage method, in DTWS the decomposition layers which contain most HS and murmurs information are found out first as characteristic layers. Then dynamic thresholds and traditional shrinkage thresholds are applied on wavelet coefficients of characteristic layers and noncharacteristic layers respectively. Finally, the reconstructed HS signal is obtained with noises eliminated greatly. Taking advantage of dynamic thresholds, DTWS could overcome the shortcomings of traditional wavelet shrinkage method and reserve the foremost HS and murmurs information while removing noises utmostly.

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II. Approach

Before denoising, preprocessing should be conducted on the acquired HS signals. Afterwards, the preprocessed HS signals are denoised using the proposed DTWS method.

A. HS Preprocessing

1) Detrending

During HS acquisition, some instrumental noises are introduced, such as periodic baseline drift, DC offset, etc. In order to remove these linear trend items, we usually detrend the acquired HS signal by removing the mean value and best fit of the signal sequence before carrying further denoising process.

2) Band-pass filtering

Since the frequencies of HS components locate from 20 to 1000 Hz, a band-pass filter is usually utilized to filter out unnecessary components beyond the HS frequency band.

3) Normalization

Normalization is to regulate the amplitudes of HS signals from -1 to +1 as defined below:

$$s_{norm}(n) = \frac{s(n)}{|\max(s(n))|} \tag{1}$$

where $s(n)$ is the original HS signal and $s_{\mathrm{norm}}(n)$ is the normalized signal.

B. Mathematical Procedure of DTWS

The proposed DTWS method is based on the noisy signal model shown in (2).

$$f = x + ie \tag{2}$$

where f is the noisy HS signal, x is the clear HS signal without noises, e represents Gaussian white noise with zero mean and unit variance, and i describes the noise intensity.

The mathematical procedure of proposed DTWS method is depicted in Fig. 1. First, the input HS signal is decomposed using discrete wavelet transform (DWT) to obtain wavelet coefficients of different layers. Based on these coefficients, the characteristic layers which contain most of the HS and murmurs information will be selected. After that, traditional shrinkage thresholds are applied on the noncharacteristic layers while dynamic thresholds are performed on the characteristic layers thus to maintain the HS and murmurs information utmostly. Finally, the reconstructed HS signal is achieved through inverse wavelet transform from the wavelet coefficients of both characteristic and noncharacteristic layers after shrinkage.

1) Characteristic layers selection

Since murmurs exhibit comparable amplitudes with noises, a direct application of traditional wavelet shrinkage method on the decomposed HS wavelet coefficients would cause overshrinkage by mistaking murmurs as noises thus result in loss of murmurs information. Therefore, to eliminate the noises while keep the pathological fidelity of murmurs simultaneously, the murmurs should be separated from noises before shrinkage. In this work, the wavelet decomposition layers containing most information of HS and murmurs with few noises are defined as characteristic layers, while layers containing most noises with few HS and murmurs information are defined as noncharacteristic layers. Due to the periodicity difference between noises and HS or murmurs, the characteristic layers could be identified by calculating the autocorrelation of reconstructed signals in each wavelet decomposition layer as shown in (3).

$$r_j = \sum_{n=1}^{l-\eta} s_j(n)s_j(n+\eta) \tag{3}$$

where r_j and $s_j(n)$ are the autocorrelation result and reconstructed signal of jth decomposition layer respectively, l represents signal length, and η is the step length.

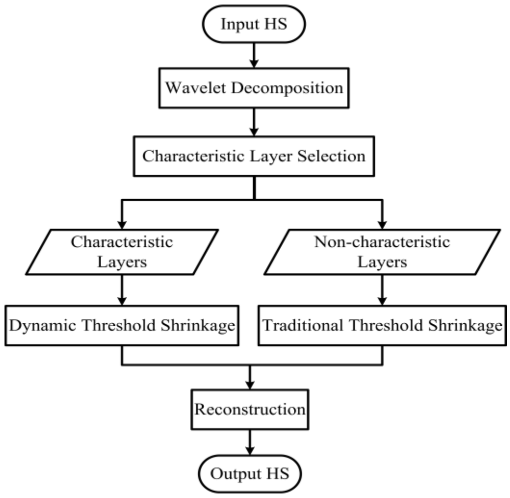

Fig. 1. Mathematical procedure of proposed DTWS method.

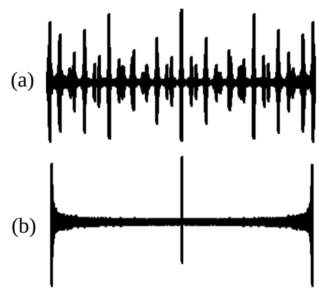

Fig. 2. Autocorrelation results of different signals: (a) periodic signal; (b) aperiodic signal.

Fig. 2 depicts an example about autocorrelation results of periodic signal (in Fig. 2 (a)) and aperiodic signal (in Fig. 2 (b)). It is observed that the periodic signal exhibits periodic distribution symmetrically in the autocorrelation results, while for aperiodic signals the autocorrelation only shows peaks at the middle and both ends in the distribution axis. Therefore, the quasiperiodic property of HS components and murmurs makes it possible to differentiate the characteristic layers from the autocorrelation results of reconstructed signals in each decomposition layer.

2) Traditional shrinkage on noncharacteristic layers

After identifying the characteristic layers and noncharacteristic layers, different shrinkage thresholds are performed on wavelet coefficients of those layers for denoising. Since the characteristic layers mainly contain noises information, traditional shrinkage is performed on these layers.

Generally, the traditional shrinkage thresholds are set under four rules: sqtwolog, rigrsure, heursure, and minimax. In HS denoising, the heursure rule based heuristic threshold is proved to be optimal and adopted in this paper [8]. Different functions could be employed to conduct shrinkage based on the selected threshold, namely hard threshold function and soft threshold function as defined in (4) and (5) respectively.

$$y(c)=\begin{cases}c, & |c|\ge T_{heu}\\ 0, & |c|<T_{heu}\end{cases} \tag{4}$$

$$y(c)=\begin{cases}\operatorname{sgn}(c)\times(|c|-T_{heu}), & |c|\ge T_{heu}\\ 0, & |c|<T_{heu}\end{cases} \tag{5}$$

where c is the original wavelet coefficient, T_{heu} stands for the heuristic shrinkage threshold used in this paper, and $y(c)$ describes the wavelet coefficient after shrinkage. In this paper, the soft threshold function is employed for reason that the reconstructed signals become rough by using hard threshold function [9]. Through traditional shrinkage, noises in noncharacteristic layers could be removed efficiently.

3) DTWS on characteristic layers

Different from noncharacteristic layers, the characteristic layers contain lots of HS and murmurs information. The pathological murmurs usually possess weak energy with low amplitudes in both time and frequency domain, thus are extremely sensitive to the shrinkage process. Hence, dynamic shrinkage thresholds are proposed for denoising of characteristic layers in this paper. Furthermore, the Shannon envelope technique based on normalized average Shannon energy [10] is employed before dynamic shrinkage, which could not only perform wavelet coefficients expression and suppression to increase the separation interval between noises and HS or murmurs, but also is beneficial for noises location during dynamic shrinkage [11]. With the aid of a sliding window, the average Shannon energy could be calculated as defined in (6).

$$E_k=-\frac{1}{N}\sum_{m=1}^{N}W_{norm}^2(m)\log W_{norm}^2(m) \tag{6}$$

where E_k is the average Shannon energy of kth window, $W_{norm}(m)$ is the normalized wavelet coefficients within the window and N is window length. Subsequently, the normalized average Shannon energy of each window could be obtained:

$$P_k=\frac{E_k-\text{Mean}(E_k)}{\text{Standard}(E_k)} \tag{7}$$

where P_k is the normalized average Shannon energy of kth window. After calculation, a series of Shannon energy could be achieved $\mathbf{P}=[P_1, ..., P_k, \ldots, P_N]$ is known as Shannon envelop of the wavelet coefficients. Afterwards, the dynamic threshold T_{dyn} in (8) is applied on the wavelet coefficients of characteristic layers based on the Shannon envelope.

$$T_{dyn}=\begin{cases}T_{heu}, & P_k\le TP\\ 0.05T_{heu}, & P_k>TP\end{cases} \tag{8}$$

where T_{heu} represents the aforementioned traditional shrinkage heuristic threshold, and TP is a fixed threshold utilized to identify noises and HS or murmurs as defined in (9).

$$TP=P_{min}+\frac{P_{max}-P_{min}}{1.5} \tag{9}$$

where P_{max} and P_{min} are the maximal and minimum value of Shannon envelope $\mathbf{P}$ respectively. It is observed that an envelope amplitude smaller than TP indicates noises, while an envelope amplitude larger than TP implies HS or murmurs. Therefore, by conducting dynamic shrinkage on noises and HS or murmurs distinctly, DTWS could filter noises while retaining pathological fidelity of HS and murmurs properly.

III. Experiments

A. Experiment Settings

For method validation and evaluation, several HS signals from eGeneral Medical (eGM) benchmark database [12] are employed with sampling frequency of 4000 Hz and resolution of 16 bits. The experiments are conducted on Matlab platform and "db20" is chosen as the mother wavelet during wavelet decomposition.

B. Performance Measurements

For quantitative measurement and comparison, signal-noise ratio (SNR) and root mean square error (RMSE) are used to evaluate the denoising performance as defined in (10) and (11) respectively.

$$\text{SNR}=10\times\lg\{\sum_{n=1}^{l}x^2(n)/\sum_{n=1}^{l}[x(n)-\hat{x}(n)]^2)\} \tag{10}$$

$$\text{RMSE}=\sqrt{\frac{1}{l}\sum_{n=1}^{l}[x(n)-\hat{x}(n)]^2} \tag{11}$$

where $x(n)$ represents the original clear HS signal without noises, $\hat{x}(n)$ is the reconstructed signal, and l is the signal length. Large SNR and small RMSE are desired for better denoising performance.

C. Parameter Optimization

During DWT decomposition, the decomposition level L is very important for the following denoising since the smaller L leads to incomplete denoising whereas the larger L results in signal distortion. Tackling this, parameter SRR is defined in (12) as a quality factor for optimal L selection.

$$SRR=SNR/RMSE \tag{12}$$

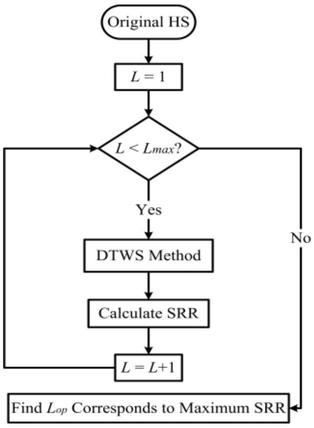

Fig. 3. Diagram for optimal decomposition level selection.

It is obvious that, the maximal value of SRR corresponds to the optimal wavelet decomposition level L_{op}. Fig. 3 illustrates the flowchart of optimal decomposition level selection. Initially, a default value L=1 is employed in the first decomposition. After denoising using DTWS, SRR is calculated and recorded. Then, L increases by 1 and the next iteration starts to obtain the updated SRR value. The loop continues until L reaches the maximal value L_{max} which satisfies condition in (13).

$$\frac{f_s}{2^{L_{\max}}} > f_L > \frac{f_s}{2^{L_{\max}+1}} \tag{13}$$

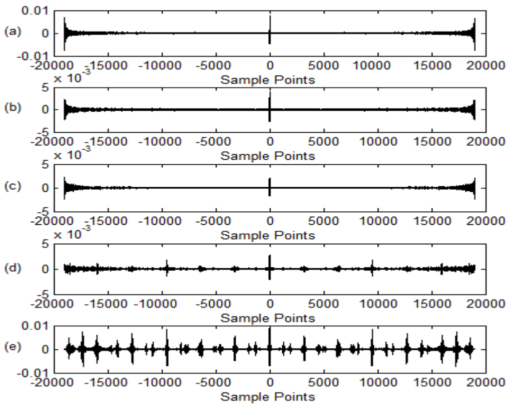

Fig. 4. Autocorrelation results of decomposed EAS signal from different layers. (a) first layer; (b) second layer; (c) third layer; (d) fourth layer; (e) fifth layer.

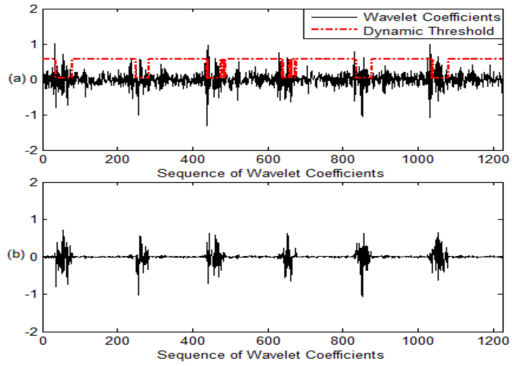

Fig. 5. Dynamic threshold shrinkage on characteristic fourth layer. (a) original wavelet coefficients of fourth layer and dynamic threshold; (b) wavelet coefficients of fourth layer after shrinkage.

where f_s is sampling frequency which is 4000 Hz in this paper and f_L is the minimum frequency of HS signals which is 20 Hz here. Therefore, after all the iterations, the maximal SRR will be obtained thus the optimal decomposition level L_{op} is achieved. The distribution of optimal L for different HS signals from eGM benchmark database is collected through large quantity of tests, and finally the decomposition level is set as 5, which is applicable for most cases.

D. *Experimental Results*

The detailed experimental results of HS signal with early aortic stenosis (EAS) disease are given here. 5dB white noises are added to the original EAS signal for further denoising and test.

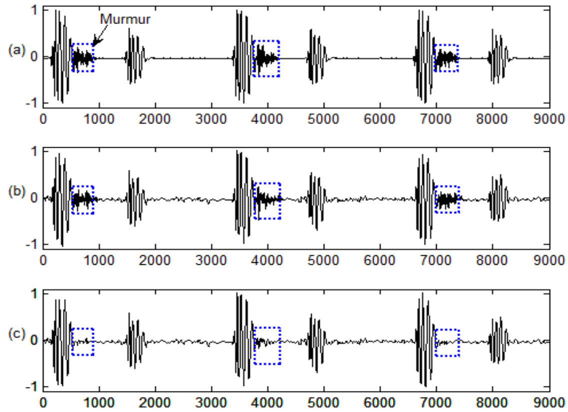

Fig. 6. Denoising results of EAS signal: (a) original EAS signal; (b) de-noised EAS signal using DTWS; (c) denoised EAS signal using traditional shrinkage method.

TABLE I: DENOISING RESULTS COMPARISON BETWEEN PROPOSED DTWS AND TRADITIONAL SHRINKAGE METHOD

HS Record	Traditional Shrinkage Method		DTWS	
	SNR (dB)	RMSE (%)	SNR (dB)	RMSE (%)
EAS	12.54	5.16	15.16	3.74
MAS	11.61	6.38	13.48	4.60
DAR	10.24	5.62	11.59	4.12

First, the EAS signal is decomposed to five wavelet layers and autocorrelation results of each layer are calculated as shown in Fig. 4. It is observed that the first three layers mainly contain noises information thus are classified as noncharacteristic layers whereas the fourth and fifth layers show quasiperiodic results in autocorrelation distributions and are identified as characteristic layers. Subsequently, the dynamic threshold shrinkage is applied on the characteristic layers. Fig. 5 (a) depicts the original wavelet coefficients in fourth layer as well as the dynamic thresholds, and Fig. 5 (b) shows the wavelet coefficients of fourth layer after dynamic shrinkage. Finally, the reconstruction results after denoising are obtained as illustrated in Fig. 6, where (a) is the original EAS signal without white noises, (b) is the reconstructed signal after DTWS denoising. For comparison usability, the denoising result of the same EAS signal by using traditional shrinkage method is also plotted in (c). It is clearly seen that the pathological murmurs are well remained in (b), and in (c) the murmurs are distorted.

Furthermore, the denoising results by using both traditional shrinkage method and DTWS method are listed in

Table I. Three HS signals, including EAS, MAS (mild aortic stenosis), and DAR (diastolic aortic regurgitation) from eGM benchmark database are employed with 5 dB white noises added. It is observed from Table I that for all the test signals, the proposed DTWS method achieves better results than the traditional shrinkage method in terms of both SNR and RMSE.

IV. Conclusion

A DTWS method is proposed for denoising of HS signals with murmurs. By dividing the wavelet decomposition layers into characteristic layers and noncharacteristic layers, dynamic threshold shrinkage is performed on the characteristic layers whereas the noncharacteristic layers are processed with traditional shrinkage method. Therefore, DTWS is able to eliminate utmostly noises while keeping the pathological fidelity of HS signals and murmurs. In conclusion, the proposed DTWS method provides a reliable HS denoising method for further clinical applications.

In future, the effectiveness and reliability of DTWS method will be verified by a series of clinical diagnostic HS signals collected from hospitals. Furthermore, the parameters of threshold setting (e.g. TP, T_{heu}) will be adjusted to obtain the optimal results according to different kinds of CVDs through some machine learning techniques.

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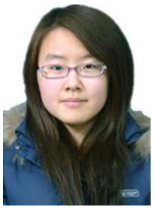

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