An Improved Thresholding Method for Wavelet Denoising of Acoustic Signal

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Abstract: - To minimize the information loss of acoustic signal and get high SNR in the denoising based on discrete wavelet transform, it is important that the thresholding is suitable for the characteristics of acoustic signal. In this paper, we propose an improved thresholding method to be suitable for the characteristics of acoustic signal. In order to minimize the information loss of acoustic signal in White Gaussian noise, we propose new threshold function to improve the modulus square threshold function. We analyze theoretically a continuity and monotonicity of new threshold function and evaluate the performance of wavelet denoising method based on new thresholding, comparing with Hard, Soft and Modulus square thresholding. Also, we perform the simulation experiment using the various acoustic signals such as mixed acoustic signal of the transient signals, speech signal, shot signal, bird's song signal and sound signal of gun. The results of theoretical analysis for an improved thresholding show that new threshold function solves the problems of constant error and discontinuity, and minimizes the information loss of acoustic signal. The results of simulation experiment show that SNR of an improved thresholding is highest but RMSE and Entropy are smallest. The theoretical analysis and simulation experiments show that an improved thresholding is more appropriate for acoustic signal denoising based on discrete wavelet transform than previous methods.

Key-Words: - discrete wavelet transform, non-stationary signal, modulus square threshold function, wavelet thresholding, threshold value, acoustic signal

1 Introduction

Discrete wavelet transform is a powerful mathematic tool in various signal processing fields such as denoising, image processing, pattern recognition, data compression and communication, mechanical fault diagnosis, etc. Many researchers used the discrete wavelet transform for denoising of images and various signals such as shock acoustic wave, acoustic emission, seismic wave, micro wave, EGG signal, electromagnetic wave, and Partial Discharge (PD).

For the non-stationary acoustic signal denoising, one of the effective denoising methods is based on discrete wavelet transform. Also, to improve the denoising performance, it is necessary to choose the mother wavelet, decomposition level, threshold function and threshold value suited for the characteristics of acoustic signal and ambient noise.

The effective denoising based on the discrete wavelet transform is achieved by selecting an appropriate mother wavelet for the characteristics of acoustic signal that contains the target information [1-10]. Snehal S. Laghate showed that the family of Symlet wavelet was symmetrical and orthogonal wavelets efficient in wavelet denoising application and performed better with improved Signal to Noise Ratio (SNR) [7]. And, M.M.Khan proposed new wavelet thresholding algorithm for dropping ambient noise from underwater acoustic signals and demonstrated that 'sym4' was best suited to increase SNR of acoustic signals [1].

Various classical threshold functions are used for the denoising according to the characteristics of signal and noise [1, 5-7, 9, 11-22]. The classical threshold functions used widely for wavelet denoising are Hard and Soft threshold functions. However, Hard threshold function is discontinuous and is prone to vibration during wavelet reconstruction. Also, Soft threshold function has a constant difference problem between the estimated wavelet coefficients.

Yuncheng Du conducted the wavelet denoising with the modified Soft threshold function to reduce noise contained in the low frequency signal of the vertex flowmeter for the application to measuring the flux at low speed [12]. In particular, HongLiang Wang suggested 3 threshold functions based on classical threshold functions annd proved that the compromised method III (modulus square threshold function) between Soft and Hard threshold function is appropriate for the wavelet denoising of acoustic signal [11]. However, this threshold function has an advantage of the good performance in noise level reduction, but doesn't minimize the information loss of the energy component.

Various threshold values are proposed [1, 2, 4-6, 11, 12, 14, 23-27]. Universal threshold value as well as various threshold values are applied to the denoising based on discrete wavelet transform [1, 4, 5, 11, 12, 17, 24-27].

Many kinds of acoustic signal are non-stationary signal including many abrupt changes unlike stationary signals. Typically, acoustic signals generated in the underwater are non-stationary signals whose characteristics change many times in a transient time unlike stationary signal. For non-stationary acoustic signal denoising, an effective denoising approach is based on discrete wavelet transform [1-3, 5-7, 10, 11, 16-22, 27- 31]. And, in order to minimize the information loss of the acoustic signal and to improve SNR for the denoising based on discrete wavelet transform, finding an appropriate thresholding for the characteristics of acoustic signal is very important.

In this paper, to detect the acoustic signal affected by White Gaussian noise, we popose new thresholding method which plays an important role in the denoising based on the discrete wavelet transform.We propose new threshold function to improve the modulus square threshold function to be suitable for the wavelet denoising of acoustic signal. Also, we analyze a continuity and monotonicity of new threshold function and evaluate the performance of wavelet denoising method based on new thresholding, comparing with Hard, Soft, Modified Soft, Semi-Soft and Modulus square thresholding.

This paper consists of following as. Section 2 summarizes briefly the thresholding methods that are an important factor for the denoising based on discrete wavelet transform. To detect effectively the acoustic signal with White Gaussian noise, Section 3 suggests new thresholding method and theoretically analyzes a continuity and monotonicity of new threshold function. Section 4 shows the results of simulation experiment to evaluate the performance of denoising method based on new thresholding and to compare with the previous methods. Section 5 gives the conclusion.

2 Brief Summary of Thresholding Methods

2.1 Summary of the Threshold Functions

① Hard threshold function

$$\hat{w}_{j,k} = \begin{cases} w_{j,k} & |w_{j,k}| \ge \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \quad (1)$$

where λ represents threshold value, $w_{j,k}$, $\hat{w}_{j,k}$ is kth coefficient and thresholding coefficient at the jth decomposition level of discrete wavelet transform.

② Soft threshold function

$$\hat{w}_{j,k} = \begin{cases} \mathrm{sign}(w_{j,k})(|w_{j,k}| - \lambda) & |w_{j,k}| \ge \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \quad (2)$$

where $\mathrm{sign}(\bullet)$ represents the sign function, with its definition being in the form of Eq. (3).

$$\mathrm{sign}(x) = \begin{cases} 1 & x > 0 \\ 0 & x = 0 \\ -1 & x < 0 \end{cases} \quad (3)$$

③ Modulus square threshold function

$$\hat{w}_{j,k} = \begin{cases} \mathrm{sign}(w_{j,k})\sqrt{(w_{j,k})^2 - \lambda^2} & |w_{j,k}| \ge \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \quad (4)$$

Except these, there are Modified Hard threshold function, Modified Soft threshold function, Semi-Soft threshold function, Modified semi-Soft threshold function, Non-linear threshold function, Super-Soft threshold function, Polynomial threshold function, Non-negative Garrote threshold function, Modified non-negative Garrote threshold function and Modified adaptive threshold function, etc.

2.2 Summary of Threshold Values

① Universal threshold value

This threshold value is a universal one used for thresholding of the denoising based on discrete wavelet transform and is formulated as Eq. (6).

$$\lambda = \sigma\sqrt{2\log N} \quad (5)$$

where σ and N is the standard deviation of noise and length of signal, respectively.

$$\sigma = \frac{\mathrm{median}\{|w_{j,k}|\}}{0.6745} \quad (6)$$

where $\mathrm{median}\{\cdot\}$ is median.

② Local threshold value

The local threshold according to the decomposition level is defined as follows.

— In case of low frequency denoising of Vortex Flowmeter:

$$\lambda_j = \frac{\sigma \ln(1 + 2\sqrt{N_j})}{J + j} A_j \quad (7)$$

— In case of the acoustic denoising:

$$\lambda_j = \frac{\sigma\sqrt{2\ln(N)}}{\ln(j+1)} \quad 8)$$

where $j(j = 0,1,\cdots,J)$ is the decomposition level and J is the maximum value of the decomposition level. N_j and A_j represent the length of signal and the amplitude of extreme points at j th decomposition level, respectively. λ_j means threshold at j th decomposition level.

In addition, there are SURE threshold and Bayes threshold, Smooth threshold, Neigh threshold, Mini-max threshold, Sqtwolog threshold, Rigrsure threshold, Heursure threshold, Energy-entropy adaptive threshold and Approximation-detail threshold, etc.

3 An Improved Thresholding Method for Acoustic Signal Denoising

3.1 An Improved Thresholding Method

Acoustic signal is generated by the ultrasonic electronic instrument in the form of transient impulse group with the energy. The acoustic signal is damaged by the extension and absorption of wave front, the scattering on the non-uniformity of material, the reflection and scattering of boundary surface and the reflection of objects through the propagation in the medium. Also, the characteristics of target and medium are unknown beforehand. Typically, many kinds of acoustic signal generated in the underwater are non-stationary signals that change many times in a transient time unlike stationary signal. Also, the ambient background noise is large while receiving the acoustic signal. In order to increase the target identification ability in the ultrasonic electronic instrument, it must remove the ambient noise and detect the useful signal using effective signal processing methods.

For the non-stationary acoustic signal denoising, an effective denoising method is based on discrete wavelet transform. Also, minimizing the loss of the acoustic signal and improving SNR, with the denoising based on discrete wavelet transform, it is very important to find a suitable thresholding method for the characteristics of acoustic signal and ambient background noise. In 2009, HongLiang Wang demonstrated that the denoising technique based on discrete wavelet transform is suited to non-stationary acoustic signal denoising and the threshold function and value using Eq. (4) and Eq.(8) are appropriate for acoustic signal denoising [11]. However, this method has an advantage of the high performance of the noise component reduction, but doesn't minimize the loss of the energy component in acoustic signal. That is, when thresholding the wavelet coefficients of acoustic signal, this method subtracts the squared threshold from wavelet coefficients for larger than the threshold; otherwise, it is set to zero. In order to minimize the loss of information in the thresholding for denoising based on discrete wavelet transform, it is necessary to process smoothly the wavelet coefficients to reflect the information of acoustic signal.

In order to minimize the information loss of useful signal in the thresholding for denoising based on discrete wavelet transform, it is necessary to process more smoothly the wavelet coefficients to reflect the information of useful signal.

In order to minimize the energy component loss of the acoustic signal and improve the denoising performance, we propose new threshold function, which improve the modulus square threshold function to be suitable for wavelet denoising of acoustic signal.

New threshold function is defined as follows:

$$\hat{w}_{j,k} = \begin{cases} \mathrm{sign}(w_{j,k}) \cdot \sqrt[4]{(w_{j,k})^4 - \lambda^4} & |w_{j,k}| \geq \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \tag{9}$$

where $\mathrm{sign}(\bullet)$ represents the sign function. λ is threshold value, $w_{j,k}$ and $\hat{w}_{j,k}$ is kth coefficient and thresholding coefficient at jth decomposition level of discrete wavelet transform, respectively.

With the increase of decomposition level for the acoustic signal denoising based on discrete wavelet transform, the wavelet coefficients amplitude of noise can be reduced. On the contrary, the useful signal under large decomposition level can also be enhanced more clearly. Finally, it is not appropriate to apply the same threshold value for each decomposition level. If the threshold value is too small, the effectiveness of denoising falls down because excessive detail information of noise may be reserved. On the other hand, if the threshold value is too large, the loss of useful signal increases.

In order to enhance the adaptation of threshold value, we select the threshold value (Eq. (8)) to decrease logarithmically according to the wavelet decomposition level. In other words, we select large threshold value at the lower decomposition level with large noise component and low threshold value at the larger decomposition level with low noise component.

New thresholding method is a thresholding to minimize the information loss of the acoustic signal by processing the wavelet coefficients with different threshold according to the wavelet decomposition level and improve SNR by removing effectively the noise component.

3.2 Theoretical Analysis of New Threshold Function

Hard threshold function and its modified ones are discontinuous and are prone to vibration during wavelet reconstruction. Soft threshold function and its modified ones are a constant difference between the estimated wavelet coefficients, and the mutation information of the observeignald s is easy to lose.

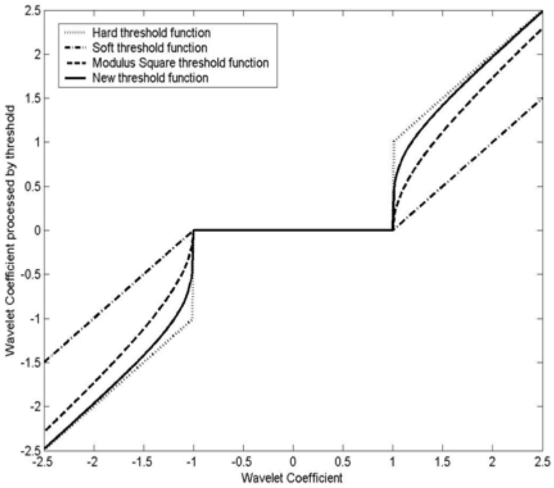

Fig.1 Comparison of wavelet coefficients processed by different threshold functions

Dotted line(…) is Hard threshold function, dash-dot line(-·) is Soft threshold function, dashed line(--) is Modulus Square threshold function and solid line(−) is New threshold function.

Modulus Square Threshold Function is an almost Hard thresholder with the continuity property. However, this function has an advantage of the good performance in noise reduction, but it doesn't minimize the useful information loss of acoustic signal.

Fig.1 shows the Hard, Soft, Modulus square and new threshold function in the form of graphics. Here, the threshold value is $\lambda = 1$ and $-2.5 \le w_{jk} \le 2.5$.

In Fig.1, transverse axis is wavelet coefficients and longitudinal axis is thresholding wavelet coefficients. As shown in Fig.1, new threshold function solves the problem of constant error and discontinuity, wavelet coefficients are reaching λ it gradually become close to zero than previous threshold functions.

3.2.1 Proof the continuity of new threshold function

The equation (9) is rewritten as follows.

$$f(x) = \begin{cases} \mathrm{sign}(x) \cdot \sqrt[4]{x^4 - \lambda^4}, & |x| > \lambda \\ 0, & |x| \le \lambda \end{cases} \tag{10}$$

where $f(x) = \hat{w}_{j,k}$, $x = w_{j,k}$.

It proves that $f(x)$ is continuous at threshold value $\pm\lambda$.

Firstly, it proves when $x \to +\lambda$.

$$\begin{aligned} \lim_{x\to\lambda+0} f(x) &= \lim_{x\to\lambda+0} \mathrm{sign}(x) \cdot \sqrt[4]{x^4 - \lambda^4} \\ &= +1 \cdot \sqrt[4]{\lambda^4 - \lambda^4} = 0 \end{aligned} \tag{11}$$

$$\begin{aligned} \lim_{x\to\lambda-0} f(x) &= \lim_{x\to\lambda-0} \mathrm{sign}(x) \cdot \sqrt[4]{x^4 - \lambda^4} \\ &= +1 \cdot \sqrt[4]{\lambda^4 - \lambda^4} = 0 \end{aligned} \tag{12}$$

Secondly, it proves when $x \to -\lambda$.

$$\begin{aligned} \lim_{x\to-\lambda+0} f(x) &= \lim_{x\to-\lambda+0} \mathrm{sign}(-x) \cdot \sqrt[4]{(-x)^4 - \lambda^4} \\ &= -1 \cdot \sqrt[4]{(-\lambda)^4 - \lambda^4} = 0 \end{aligned} \tag{13}$$

$$\begin{aligned} \lim_{x\to-\lambda-0} f(x) &= \lim_{x\to-\lambda-0} \mathrm{sign}(-x) \cdot \sqrt[4]{(-x)^4 - \lambda^4} \\ &= -1 \cdot \sqrt[4]{(-\lambda)^4 - \lambda^4} = 0 \end{aligned} \tag{14}$$

Thus, new threshold function is a continuous function and wavelet coefficients gradually become close to zero when $x \to \pm\lambda$.

3.2.2 Proof the monotonicity of new threshold function

New threshold function increases monotonically for $|x| > \lambda$.

Assuming $f(x)'$ is the first derivative of $f(x)$.

Firstly, for $x > \lambda$, $f(x)'$ is following as.

$$f(x)' = \frac{1}{4} \cdot \frac{4 \cdot x^3}{\sqrt[4]{(x^4 - \lambda^4)^3}} = \frac{x^3}{\sqrt[4]{(x^4 - \lambda^4)^3}} \quad (15)$$

When $x > \lambda$, $(x^4 - \lambda^4)^3 > 0$ and $x^3 > 0$. So $f(x)' > 0$.

Secondly, for $x < -\lambda$, $f(x)'$ is following as.

$$f(x)' = -\frac{1}{4} \cdot \frac{4 \cdot x^3}{\sqrt[4]{(x^4 - \lambda^4)^3}} = -\frac{x^3}{\sqrt[4]{(x^4 - \lambda^4)^3}} \quad (16)$$

When $x < -\lambda$, $(x^4 - \lambda^4)^3 > 0$ and $x^3 < 0$. So $f(x)' > 0$.

Through the above analysis, when $x > \lambda$, $f(x)' > 0$ and when $x < -\lambda$, $f(x)' > 0$. Thus, this threshold function increases monotonically for $|x| > \lambda$.

New threshold function is a continuous function and increases monotonically. And, it minimizes the distortion and information loss of acoustic signal. Thus, denoising effect of new threshold function is better in theory.

4 Simulation Experiment Results

Through the simulation experiments for wavelet denoising of various acoustic signals, we evaluate the performance of new thresholding method. The processing results are treated by using the SNR (Signal to Noise Ratio), RMSE (Root Mean Square Error) and Entropy.

$$SNR = 10\log\left(\frac{\sum_{k=1}^{N} f^2(k)}{\sum_{k=1}^{N}\left(\tilde{f}(k) - f(k)\right)^2}\right) \quad (17)$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}\left(\tilde{f}(k) - f(k)\right)^2}{N}} \quad (18)$$

$$Entropy = -\sum_{k=1}^{N} \frac{\tilde{f}(k)}{f_T} \cdot \ln\left(\frac{\tilde{f}(k)}{f_T}\right) \quad (19)$$

$$f_T = \sum_{k=1}^{N} \tilde{f}^2(k) \quad (20)$$

where f is the source signal, $\tilde{f}$ is the denoising signal and N is the length of signal. In Eq. (19), 0ln0 = 0.

The mother wavelet used for the discrete wavelet transform is '*sym4*' wavelet, which is best to improve SNR of signal [1, 6, 21]. And the wavelet decomposition level is 5. Hard and Soft thresholding use the universal threshold value (Eq. (5)). Modulus Square thresholding and new thresholding use the local threshold value (Eq. (8)).

The simulation experiments are performed by using MATLAB 6.5. The results are computed by averaging over 1000 Monte Carlo simulations. Also, White Gaussian noise is formed by *randn()* function to generate normally distributed random numbers.

4.1 Wavelet Denoising for Mixed Acoustic Signal of the Transient Signals

The acoustic signal used for the first simulation experiment is the mixed acoustic signal of the transient signals. It is the non-stationary signal with the non-stationary characteristics because of short delay time. The sampling frequency is 20kHz and the number of samples is 15000. This signal consists of three signals decreasing exponentially and is defined as follows:

$$S_1 = \exp(-j \cdot 2 \cdot \pi \cdot f_1 \cdot k_1) \cdot \exp(-200 \cdot k_1),\ k_1 = 1,2,\cdots,250$$
$$S_2 = \exp(-j \cdot 2 \cdot \pi \cdot f_2 \cdot k_2) \cdot \exp(-200 \cdot k_2),\ k_2 = 1,2,\cdots,200 \quad (21)$$
$$S_3 = \exp(-j \cdot 2 \cdot \pi \cdot f_3 \cdot k_3) \cdot \exp(-200 \cdot k_3),\ k_3 = 1,2,\cdots,150$$

where, $f_1 = 3000Hz$, $f_2 = 3500Hz$ and $f_3 = 4000Hz$. S_1 is apart from S_2 at the distance of 2000 samples and S_2 is apart from S_3 at the distance of 1000 samples.

Fig.2 shows the denoising signals of the wavelet denoising methods based on various kinds of thresholding for the noisy mixed acoustic signal (SNR=-6dB). In Fig.2, a) and b) are the original signal and the noisy signal, respectively. Also, c), d), e) and f) are the denoising signals of the wavelet denoising methods based on Hard, Soft, Modulus Square and new method, respectively. Fig.2 shows that the performance of wavelet denoising methods based on Modulus square and new thresholding are better with the naked eyes.

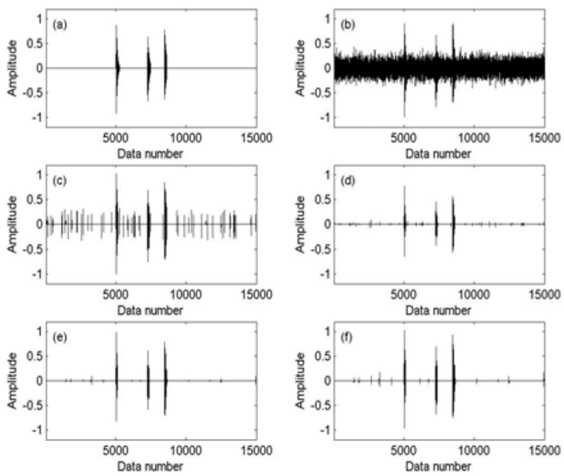

Fig.2 Wavelet denoising results of mixed acoustic signal (SNR=-6dB). a) and b) are the original signal and the noisy signal, respectively. Also, c), d), e) and f) are the wavelet denoising signals based on Hard, Soft, Modulus Square and new method, respectively.

Table 1 shows SNR, RMSE and Entropy of wavelet denoising methods based on various kinds of thresholding for noisy mixed acoustic signal. As shown in Table 1, SNR of new thresholding is highest. Also, RMSE and Entropy of new thresholding are smallest. For the noisy mixed acoustic signal of SNR=-6dB, SNR improved by the wavelet denoising method based on the new thresholding is about 11.4663dB.

Table 1 SNR, RMSE and Entropy of various kinds of thresholding for mixed acoustic signal (SNR=-6dB)

Thresholding	SNR(dB)	RMSE	Entropy
Hard	4.9446	0.0330	56.9869
Soft	4.6114	0.0343	51.0579
Modulus square	5.1905	0.0321	47.7076
New Method	**5.4663**	**0.0311**	**47.5078**

As a result, the performance of wavelet denoising method based on the new thresholding is best of the four methods for the noisy mixed acoustic signal.

4.2 Wavelet Denoising for Speech Signal

The acoustic signal used for the second simulation experiment is the speech signal collected in the real environment. The original signal uses a relatively pure man speech signal in order to facilitate the observation of the effect of noise.

Fig.3 shows the denoising signals of the wavelet denoising methods based on various kinds of thresholding for the noisy speech signal (SNR=2dB). In Fig.3, a) and b) are the original speech signal and the noisy speech signal, respectively. Also, c), d), e) and f) are the denoising speech signals of the wavelet denoising methods based on Hard, Soft, Modulus Square and new method, respectively. Fig.3 shows that the performance of wavelet denoising methods based on Hard and new thresholding are better with the naked eyes.

Table 2 shows SNR, RMSE and Entropy of wavelet denoising methods based on various kinds of thresholding for noisy speech signal. As shown in Table 2, SNR of new thresholding is highest. Also, RMSE and Entropy of new thresholding are smallest. For the noisy speech signal of SNR=2dB, SNR improved by the wavelet denoising method based on the new thresholding is about 2.0509dB.

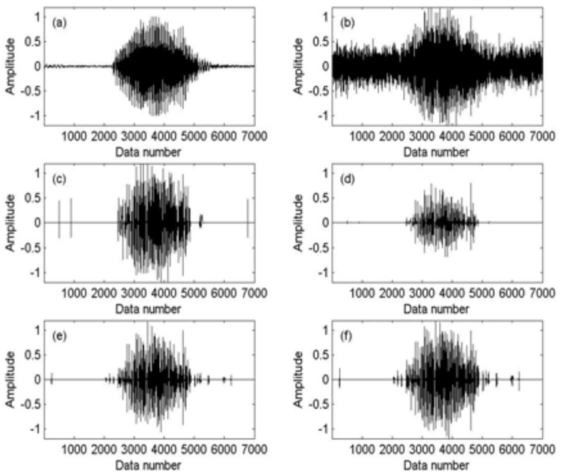

Fig.3 Wavelet denoising results of speech signal (SNR=2dB). a) and b) are the original signal and the noisy signal, respectively. Also, c), d), e) and f) are the wavelet denoising signals based on Hard, Soft, Modulus Square and new method, respectively.

Table 2 SNR, RMSE and Entropy of various kinds of thresholding for speech signal (SNR=2dB)

Thresholding	SNR(dB)	RMSE	Entropy
Hard	3.9481	0.1326	303.9117
Soft	2.3301	0.1597	381.8679
Modulus square	3.8053	0.1348	310.6859
New Method	**4.0509**	**0.1310**	**301.0193**

As a result, the performance of wavelet denoising method based on the new thresholding is best of the four methods for the noisy speech signal.

4.3 Wavelet Denoising For Shot Signal

The acoustic signal used for the third simulation experiment is the shot signal.

Fig.4 shows the denoising signals of the wavelet denoising methods based on various kinds of thresholding for the noisy shot signal (SNR=0dB). In Fig.4, a) and b) are the original shot signal and the noisy shot signal, respectively. Also, c), d), e) and f) are the denoising shot signals of the wavelet denoising methods based on Hard, Soft, Modulus Square and new method, respectively. Fig.4 shows that the performance of wavelet denoising methods based on Modulus Square and new thresholding are better with the naked eyes.

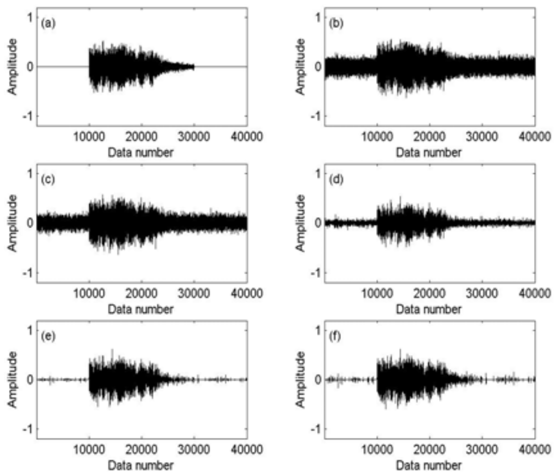

Fig.4 Wavelet denoising results of shot signal (SNR=0dB). a) and b) are the original signal and the noisy signal, respectively. Also, c), d), e) and f) are the wavelet denoising signals based on Hard, Soft, Modulus Square and new method, respectively.

Table 3 SNR, RMSE and Entropy of various kinds of thresholding for shot signal (SNR=0dB)

Thresholding	SNR(dB)	RMSE	Entropy
Hard	4.2227	0.0577	623.5258
Soft	7.5295	0.0395	318.8234
Modulus square	7.6411	0.0390	302.1897
New Method	**7.7923**	**0.0383**	**296.4077**

Table 3 shows SNR, RMSE and Entropy of wavelet denoising methods based on various kinds of thresholding for noisy shot signal. As shown in Table 3, SNR of new thresholding is highest. Also, RMSE and Entropy of new thresholding are smallest. For the noisy shot signal of SNR=0dB, SNR improved by the wavelet denoising method based on the new thresholding is about 7.7923dB.

As a result, the performance of wavelet denoising method based on the new thresholding is best of the four methods for the noisy shot signal.

4.4 Wavelet Denoising for Bird’s Song Signal

The acoustic signal used for the fourth simulation experiment is the bird’s song signal.

Fig.5 shows the denoising signals of the wavelet denoising methods based on various kinds of thresholding for the noisy bird’s song signal (SNR=-6dB). In Fig.5, a) and b) are the original bird’s song signal and the noisy bird’s song signal, respectively. Also, c), d), e) and f) are the denoising bird’s song signals of the wavelet denoising methods based on Hard, Soft, Modulus Square and new method, respectively. Fig.5 shows that the performance of wavelet denoising methods based on Hard and new thresholding are better with the naked eyes.

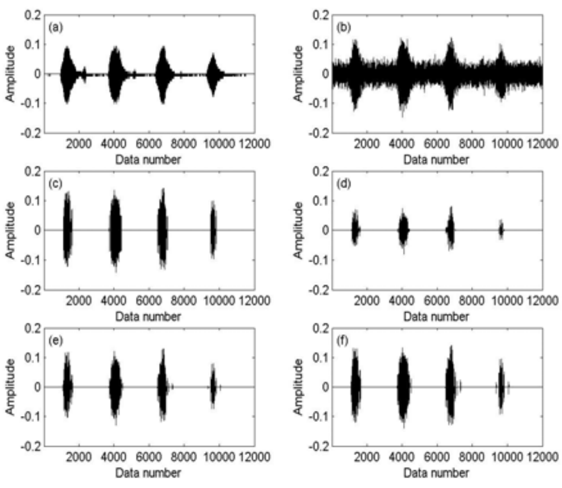

Fig.5 Wavelet denoising results of bird’s song signal (SNR=-6dB). a) and b) are the original signal and the noisy signal, respectively. Also, c), d), e) and f) are the wavelet denoising signals based on Hard, Soft, Modulus Square and new method, respectively.

Table 4 shows SNR, RMSE and Entropy of wavelet denoising methods based on various kinds of thresholding for noisy bird’s song signal. As shown in Table 4, SNR of new thresholding is highest. Also, RMSE and Entropy of new thresholding are smallest. For the noisy bird’s song signal of SNR=-6dB, SNR improved by the wavelet denoising method based on the new thresholding is about 10.1320dB.

Table 4 SNR, RMSE and Entropy of various kinds of thresholding for bird’s song signal (SNR=-6dB)

Thresholding	SNR(dB)	RMSE	Entropy
Hard	3.7911	0.0151	18.3987
Soft	1.7481	0.0190	27.1001
Modulus square	3.7036	0.0152	18.6617
New Method	**4.1320**	**0.0145**	**17.2171**

As a result, the performance of wavelet denoising method based on the new thresholding is best of the four methods for the noisy bird’s song signal.

4.5 Wavelet Denoising for Sound Signal of Gun

The acoustic signal used for the fifth simulation experiment is the sound signal of gun.

Fig.6 shows the denoising signals of the wavelet denoising methods based on various kinds of thresholding for the noisy sound signal of gun (SNR=2dB). In Fig.6, a) and b) are the original sound signal of gun and the noisy sound signal of gun, respectively. Also, c), d), e) and f) are the denoising sound signals of gun of the wavelet denoising methods based on Hard, Soft, Modulus Square and new method, respectively. Fig.6 shows that the performance of wavelet denoising methods based on Modulus Square and new thresholding are better with the naked eyes.

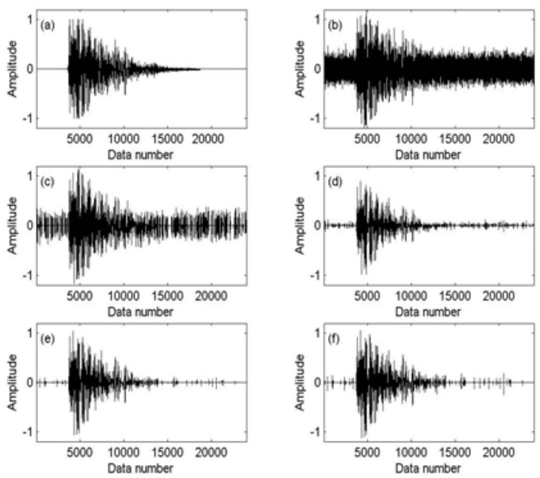

Fig.6 Wavelet denoising results of sound signal of gun (SNR=2dB). a) and b) are the original signal and the noisy signal, respectively. Also, c), d), e) and f) are the wavelet denoising signals based on Hard, Soft, Modulus Square and new method, respectively.

Table 5 shows SNR, RMSE and Entropy of wavelet denoising methods based on various kinds of thresholding for noisy sound signal of gun. As shown in Table 5, SNR of new thresholding is highest. Also, RMSE and Entropy of new thresholding are smallest. For the noisy sound signal of gun of SNR=2dB, SNR improved by the wavelet denoising method based on the new thresholding is about 6.2784dB.

Table 5 SNR, RMSE and Entropy of various kinds of thresholding for sound signal of gun (SNR=2dB)

Thresholding	SNR(dB)	RMSE	Entropy
Hard	7.0962	0.0680	424.2944
Soft	8.0068	0.0612	351.6692
Modulus square	8.1755	0.0600	347.1073
New Method	**8.2784**	**0.0593**	**343.4286**

As a result, the performance of wavelet denoising method based on the new thresholding is best of the four methods for the noisy sound signal of gun.

5 Conclusion

In this paper, to reduce an ambient noise and to detect effectively the acoustic signal, we proposed an improved thresholding method to be suitable for the characteristics of acoustic signal. To minimize the information loss of the acoustic signal during wavelet denoising, we proposed new threshold function to improve the modulus square threshold function suitable for the acoustic signal denoising. Firstly, we theoretically analyzed a continuity and monotonicity of an improved threshold function. The results of theoretical analysis show that an improved threshold function solves the problems of constant error and discontinuity, and minimizes the information loss of acoustic signal. Next, we evaluated the performance of wavelet denoising method based on new thresholding, comparing with Hard, Soft and Modulus square thresholding. Also, we performed the simulation experiment using the various acoustic signals such as mixed acoustic signal of the transient signals, speech signal, shot signal, bird’s song signal and sound signal of gun. The results of simulation experiment using the various acoustic signals show that SNR of an improved thresholding is highest, but RMSE and Entropy are smallest. The theoretical analysis and simulation experiments show that an improved thresholding is more appropriate for acoustic signal denoising based on discrete wavelet transform than previous methods.

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