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An Improved Spatially Selective Noise Filtration for Real-time Denoising of Acoustic Emission Signal

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Abstract

The denoising of acoustic emission (AE) signal plays an important role in structural health monitoring. This paper proposes the improved spatially selective noise filtration (SSNF) which can eliminate the Gaussian white noise well. Firstly, through the comparison of different vanishing moments, "db5" is chose as the mother wavelet. And the Mallat algorithm is used in the composition and reconstruction of signal processing. Secondly, according to the signal noise ratio of wavelet reconstructed coefficients of AE signal, two coefficients are chosen to the next step. Lastly, the denoising algorithm uses the high degree of correlation between coefficients to realize the improved SSNF. Compared with the SSNF, the improved SSNF can avoid "glitches" and realize real-time denoising. And according to the simulation results, the improved SSNF can realize real-time denoising of AE signal.

Keywords: *acoustic emission, real-time denoising, Mallat algorithm*

1. Introduction

Plenty of constructions bring about great convenience by the rapid social progress and continuous technology development. But the structural damages will also bring great loss to the possession and human life. Thus, to avoid these tragedies, the structural health monitoring is necessary and important. The acoustic emission (AE) detection is powerful for the nondestructive evaluation and damage monitoring of structures [1]. The fatigue damage of structures will produce AE signals. There are two types of signals in the AE system; namely burst signals and continuous signals. The duration of burst signal is short (in the range of a few microseconds to a few milliseconds). Meanwhile the continuous signal is emitted close to each other or the burst is very high rate where the signals occurred very close and sometimes even overlap [2]. Many AE phenomena are very weak, so they are difficult to be detected. Due to the sensitivity of fiber sensor, the signals are received by AE detectors [2] [3]. Detectors change mechanical vibration into electrical signal. Then the AE signals will be amplified, processed and recorded.

By processing the AE signal, researchers can determine the location of internal crack and monitor the health of structure accurately. Based on the Kaiser effect, the AE phenomena are irreversible. The AE signals of damages need to be found out as soon as possible. But noises will affect the accuracy of results. Many denoising methods have been presented, such as Donoho and adaptive threshold extimation [4]. Because of the characteristic of AE, these methods are not fit the AE signal. And to the best knowledge of authors, few literatures focus on the real-time denoising of AE signal. Elimination of the noise influence is significantly vital for getting accurate signal [2]. For ensuring the feasible of AE detection, this paper

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proposes the improved spatially selective noise filtration. And the improved algorithm can realize the real-time denoising. According to the simulation results, the proposed algorithm improves the performance of denoising of AE signal.

This paper is structured as follows: Section 2 introduces the AE. And Section 3 introduces the wavelet transform, including Mallat algorithm and vanishing moments of mother wavelet. The improved spatially selective noise filtration is expatiated in Section 4. Section 5 presents the simulation results and analyses. And Section 6 draws the conclusions.

2. Acoustic Emission

The AE is defined as a transient elastic wave generated by the rapid release of energy within a material [5]. Figure 1 shows a typical AE waveform along with feature parameters, such as threshold, amplitude, rise time, duration, *etc.* [5-6].

As shown in Figure 1, maximum amplitude is related to the maximal value of an AE waveform. Rise time means the time between the first overshoot of the predefined threshold and the maximum amplitude. Duration is the time between the first and the last overshoot of the threshold. The waveform shown in Figure 1 is called a hit because it is the result of acoustic signals hitting the AE detectors [7].

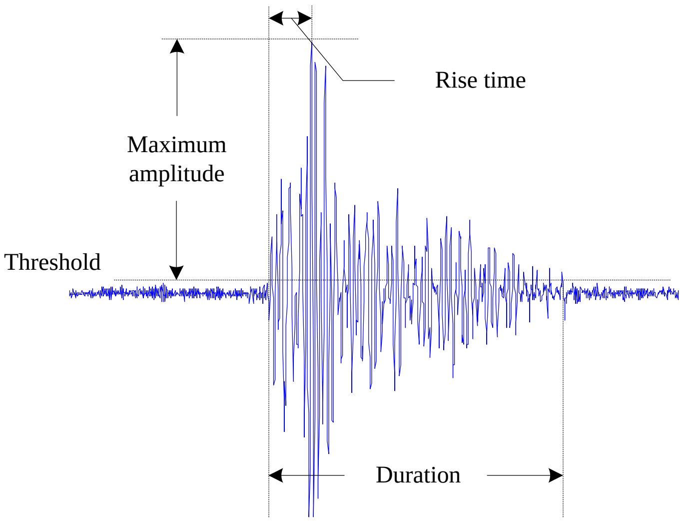


Figure 1. Typical AE Waveform

3. Wavelet Transform

3.1. Mallat Algorithm

There are many ways to process the AE signal, such as wavelet transform (WT), correlation figure, fast Fourier transform (FFT), etc. This paper chooses WT to decompose the AE signal. WT is called as “the digital microscope”. It can process the signal with multi-resolution and it can be applied well in time and frequency.

In 1988, Mallat put forward the multiresolution analysis (MRA). In order to obtain wavelet coefficients quickly, fast wavelet transform (FWT) has been presented, namely Mallat algorithm [8]. Mallat algorithm can be comparable with the FFT. It reduces the difficulty of getting wavelet coefficients greatly, and opens up a shot cut of wavelet analysis application [9]. Because of Mallat algorithm, wavelet analysis reveals the actual value. Mallat algorithm is based the following thought.

If $\{V_j\}$ is a given MRA, it can be decomposed into two subspace $\{V_{j+1}\}$ and $\{W_{j+1}\}$. $\{\varphi_{j,k}(x)\}_{j,k\in\mathbf{Z}}$ and $\{\psi_{j,k}(x)\}_{j,k\in\mathbf{Z}}$ respectively are the orthonormal basis of the scale space $\{V_j\}$ and the wavelet space $\{W_j\}$. For the function $f(x)\in V_J$, the composition can be expressed as $\{\varphi_{J,n}\}$ or $\{\varphi_{J+1,k},\psi_{J+1,k}\}$:

$$f(x)=\sum_{n\in\mathbf{Z}}c_{J,n}\varphi_{J,n}=\sum_{k\in\mathbf{Z}}c_{J+1,k}\varphi_{J+1,k}+\sum_{k\in\mathbf{Z}}d_{J+1,k}\psi_{J+1,k} \tag{1}$$

where $J\in\mathbf{Z}$, $\{c_{J+1,k}\}$ is the approximation sequence, and $\{d_{J+1,k}\}$ is the detail sequence.

$V_{j+1}\perp W_{j+1}$, so we can get $c_{J+1,k}=\langle\sum_{n\in\mathbf{Z}}c_{J,n}\varphi_{J,n},\varphi_{J+1,k}\rangle=\sum_{n\in\mathbf{Z}}c_{J,n}\langle\varphi_{J,n},\varphi_{J+1,k}\rangle$ according to Eq. (1). And because of $\varphi(x)=\sqrt{2}\sum_{m\in\mathbf{Z}}h_m\varphi(2x-m)$ and $\psi(x)=\sqrt{2}\sum_{m\in\mathbf{Z}}g_m\varphi(2x-m)$, we can get:

$$\begin{cases}\langle\varphi_{J,k},\varphi_{J+1,m}\rangle=\bar{h}_{k-2m}\\ \langle\psi_{J,k},\psi_{J+1,m}\rangle=\bar{g}_{k-2m}\end{cases} \tag{2}$$

So the decomposition algorithm is calculated as:

$$\begin{cases}c_{J+1,k}=\sum_{n\in\mathbf{Z}}c_{J,n}\bar{h}_{n-2k}=\sum_{n\in\mathbf{Z}}c_{J,n}\bar{h}_{n-k'}\Big|_{k'=2k}\\ d_{J+1,k}=\sum_{n\in\mathbf{Z}}c_{J,n}\bar{g}_{n-2k}=\sum_{n\in\mathbf{Z}}c_{J,n}\bar{g}_{n-k'}\Big|_{k'=2k}\end{cases} \tag{3}$$

It is observed that $\{c_{J+1,k}\}$ and $\{d_{J+1,k}\}$ are calsulated by $\{c_{J,k}\}$; $\{c_{J+2,k}\}$ and $\{d_{J+2,k}\}$ are calsulated by $\{c_{J+1,k}\}$, etc.

According to Eq. (1), if the decomposition level is N_1-N_2. The function $f(x)$ can be decomposed as:

$$f(x)=\sum_{k\in\mathbf{Z}}\left(c_{N_1,k}\varphi_{N_1,k}+\sum_{j=N_2+1}^{N_1}d_{j,k}\psi_{j,k}\right) \tag{4}$$

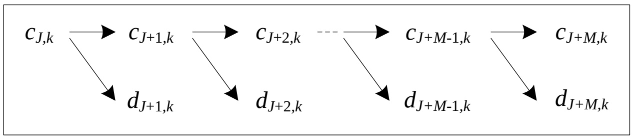
Because of $c_{J,n}=\langle\varphi_{J,n},\sum_{n\in\mathbf{Z}}c_{J,n}\varphi_{J,n}\rangle=\langle\varphi_{J,n},\sum_{k\in\mathbf{Z}}c_{J+1,k}\varphi_{J+1,k}\rangle+\langle\varphi_{J,n},\sum_{k\in\mathbf{Z}}d_{J+1,k}\psi_{J+1,k}\rangle$, we can get $c_{J,n}=\sum_{k\in\mathbf{Z}}c_{J+1,k}\langle\varphi_{J+1,k},\varphi_{J,n}\rangle+\sum_{k\in\mathbf{Z}}d_{J+1,k}\langle\psi_{J+1,k},\varphi_{J,n}\rangle$.

So the reconstruction algorithm is defined as:

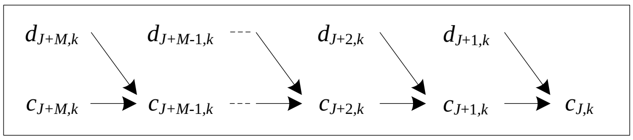
$$\begin{aligned}c_{J,n}&=\sum_{k\in\mathbf{Z}}(h_{n-2k}c_{J+1,k}+g_{n-2k}d_{J+1,k})\\&=\sum_{k\in\mathbf{Z}}(h_{n-2k}c_{J+1,k}+g_{n-2k}d_{J+1,k})+\sum_{k\in\mathbf{Z}}(h_{n-2k+1}\cdot 0+g_{n-2k+1}\cdot 0)\\&=\sum_{k\in\mathbf{Z}}(h_{n-k}c'_{J+1,k}+g_{n-k}d'_{J+1,k})\end{aligned} \tag{5}$$

where $\{c'_{J+1,k}\}$ and $\{d'_{J+1,k}\}$ are obtained from $\{c_{J+1,k}\}$ and $\{d_{J+1,k}\}$ by adding zero in odd index.

In Mallat algorithm, the space pyramidal decomposition is shown as Figure 2(a). And Figure 2(b) illustrates the space pyramidal reconstruction.



(a) Mallat Decomposition



(b) Mallat Reconstruction

Figure 2. The Space Pyramidal of Mallat

To sum up, the Mallat algorithm use filter and down sampling to realize the wavelet decomposition. And then up sampling and reconstruction filter are used to reconstruct the wavelet coefficients [10]. Figure 3 shows the diagram of Mallat algorithm. Boundary extension is necessary in Mallat algorithm of time-limited signal processing. There are many kinds of boundary extension methods. Periodic extension is used in this paper.

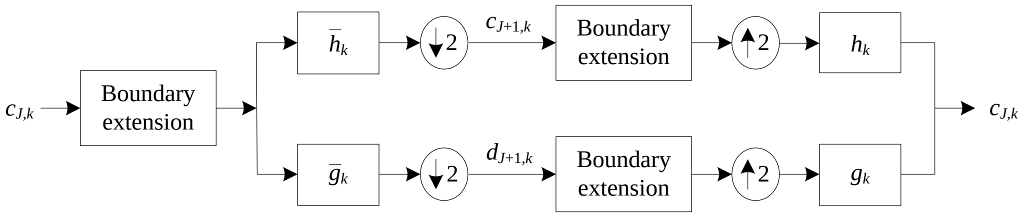
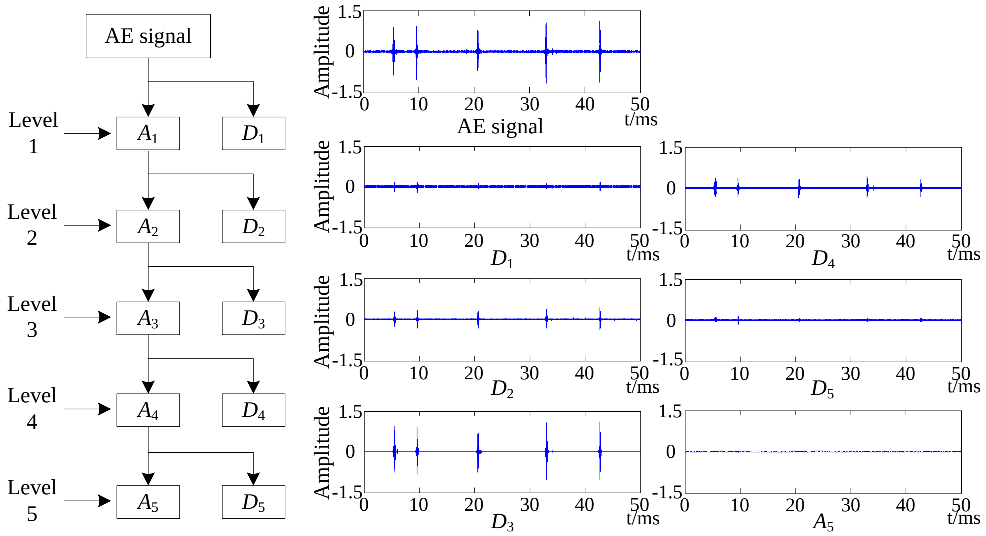


Figure 3. The Diagram of Mallat Algorithm

3.2. Vanishing Moments of Wavelet

In order to detect kinds of singularities in signal, the wavelet function should have enough vanishing moments during the singular signal detection. And the wavelet function should be chose based on the singularity of signal. AE signal processing use many kinds of mother wavelets. The Daubechies family of wavelets has the characteristics of orthogonality and compact support [11-12]. It can avoid energy cross leakage, so frequency resolution can be ensured easier. It could display every mutation of AE signals. So "db*N*" of Daubechies wavelet is used as the basis function for processing the AE signal. "*N*" is the vanishing moment of wavelet function. Greater vanishing moment will make flatter filters. Vanishing moment can change the wavelet coefficients of each layer. It can also influence the computation speed. So the proper vanishing moment need to be chose.

Mallat algorithm is used to decompose and reconstruct the AE signal with noise. A signal is split into an approximation and details. The sampling rate of the AE signal of this paper is 2MHz. As illustrated in Figure 4, the signal can be decomposed into a tree structure with wavelet details and wavelet approximations at 5 levels. $A_i(t)$ stand for the wavelet approximations and $D_i(t)$ denote the wavelet details, where $i = 1, 2, \cdots, 5$.



(a) DWT Tree (b) AE Signal and Each Layer of Coefficients

Figure 4. Wavelet Transform Tree and Wavelet Coefficients

Table 1 shows both the energy percentage of each layer and simulation time of decomposition and reconstruction by using different vanishing moments of mother wavelet.

Table 1. Energy Percentage of Each Layer

db*N*	Energy Percentage (%)					Simulation Time (ms)	
	D_1	D_2	D_3	D_4	D_5	Decomposition	Reconstruction
db1	8.9	22.5	54.3	9.2	4.4	7.12	17.68
db2	1.3	12.1	78.7	6.9	0.8	7.57	21.97
db3	0.5	9.9	82.3	6.5	0.7	7.97	23.68
db4	0.7	6.7	85.1	7.0	0.4	8.52	25.31
db5	0.7	5.5	86.5	6.7	0.5	8.69	25.37
db6	0.5	6.0	87.3	6.0	0.2	9.19	26.77
db7	0.5	4.3	88.4	6.4	0.3	9.61	27.77

According to Figure 4 and Table 1, the energy of wavelet coefficients becomes more concentrated while the vanishing moment becomes greater. With the increase of vanishing moment, the energy of the third layer becomes higher and higher. The energy of the fourth layer has almost no change. And the energy of the other three layers become lower and lower. So the vanishing moment changes the distribution of wavelet coefficents energy. At the same time, with the growing of vanishing moment, decomposition and reconstruction spend more and more time. In this paper, based on comprehensive consideration of the simulation time and the energy of wavelet coefficients, “db5” is chose as the mother wavelet.

4. Improved Spatially Selective Noise Filtration

4.1. Basical Spatially Selective Noise Filtration

Firstly, there is a characteristic of AE signal is that the decomposed wavelet coefficients have a high degree of correlation. But the coefficients of the noise signal do not have it. Secondly, the lengths of decomposed wavelet are all same. These two characteristics have been found by some researches, and spatially selective noise filtration (SSNF) has been proposed [13-15]. SSNF is described briefly as follows.

The input signal is: $f(N)=s(N)+n(N)$, where $s(N)$ is the original signal, $n(N)$ is the noise signal, N is the length of the input signal. In this paper, $N=100000$. Then SSNF perforems following five steps:

1) Compute the spatial correlation matrixes $Corr(m,k)$ for every wavelet scale:

$$Corr(m,k)=w(m,k)*w(m+1,k) \tag{6}$$

where $w(m,k)$ denote the wavelet coefficient data, m is the scale index, $k=1,2,\cdots,N$. Estimate the standard deviation σ_m of $w(m,k)$.

2) Then the normalization of the correlation coefficient is got as:

$$Nor(m,k)=Corr(m,k)\sqrt{\frac{P_w(m)}{P_{Corr}(m)}} \tag{7}$$

where $P_w(m)=\sum_{k=1}^{N}\left(w(m,k)\right)^2$, $P_{Corr}(m)=\sum_{k=1}^{N}\left(Corr(m,k)\right)^2$.

3) If $|Nor(m,k)|\geq|w(m,k)|$, we assume $Nor(m,k)$ is produced by signal. Set $w(m,k)$ to $W_s(k)$, then $w(m,k)$ and $Corr(m,k)$ are set to zero. If $|Nor(m,k)|<|w(m,k)|$, $w(m,k)$ and $Corr(m,k)$ remain constant.

4) Repeat step 2 and step 3 until $P_w(m)\leq(L-1)\sigma_m^2$, where L is the number of nonzero data in $w(m,k)$.

5) Got the wavelet coefficients $W_s(k)$ after de-noising.

There are two important stages: the first stage is step 1 and step 2; the second stage is step 4. Step 3 is complicated. It will waste too much time to the calculation. Because of the high sampling rate, the denoising of AE signal needs to be sample enough. But the step 3 and step 4 will spend too much time. So the SSNF needs to be improved.

4.2. Improved Spatially Selective Noise Filtration

The concrete steps of the improved SSNF algorithm are as follows:

a) Conduct the WT of the AE signal in m scales and get the wavelet coefficients $w(m,k)$, where $m=1,2,\cdots,5$, $k=1,2,\cdots,N$, N is the length of input signal.

b) Calculate the signal noise ratio (SNR) of each wavelet coefficients. Choose $w(m,k)$ and $w(m+1,k)$ which SNRs are bigger than others.

c) Because of the high degree of correlation between $w(m,k)$ and $w(m+1,k)$. Compute the spatial correlation matrixes $Corr(m,k)$ as Eq. (6).

d) Then Eq. (7) is improved as:

$$Nor(m,k)=\left(Corr(m,k)\right)^2\sqrt{\frac{P_w'(m)}{P_{Corr}(m)}} \tag{8}$$

where $P_w'(m)=\frac{\sum_{k=1}^{N}\left(\left(w(m,k)\right)^2+\left(w(m,k)\right)^2\right)}{2}$, $P_{Corr}(m)=\sum_{k=1}^{N}\left(Corr(m,k)\right)^2$.

$\left(Corr(m,k)\right)^2$ can make the AE phenomenon more clearly than the $Corr(m,k)$ in Eq. (7). And if the energy of $w(m,k)$ and $w(m+1,k)$ are too different, $\sqrt{\frac{P_w'(m)}{P_{Corr}(m)}}$ can make sure the amplitude of denoised signal will not be too small.

e) At last $Nor(m,k)$ is changed as:

$$I_{\text{SSNF}}(m,i) = \sum_{k=1+100(i-1)}^{100i} Nor(m,k) \tag{9}$$

where $i = 1,2,3,\cdots,\frac{N}{100}$. Compared with $Nor(m,k)$, AE phenomenon will be clearer in $I_{\text{SSNF}}(m,i)$. Step e can reduce the number of "glitches". So it will make the denoised signal smoother.

5. Simulation Results and Analyses

The simulation environment of this paper is using MATLAB2010. CPU is Intel Core i7-2600, and the main frequency of CPU is 3.4GHz. The memory of computer is 4GB.

Gaussian white noise is added to the AE signal which SNR is -15dB, as shown in Figure 5. This signal is used to analyze the performance of the improved SSNF. The wavelet coefficients of signal with noise are shown in Figure 6.

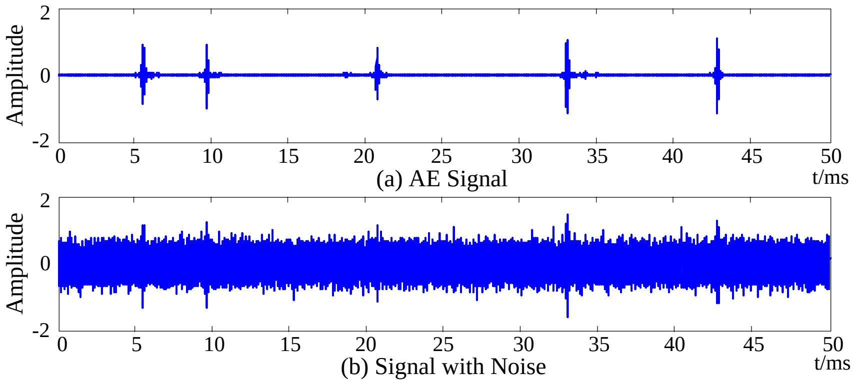


Figure 5. AE Signal and Signal with Noise

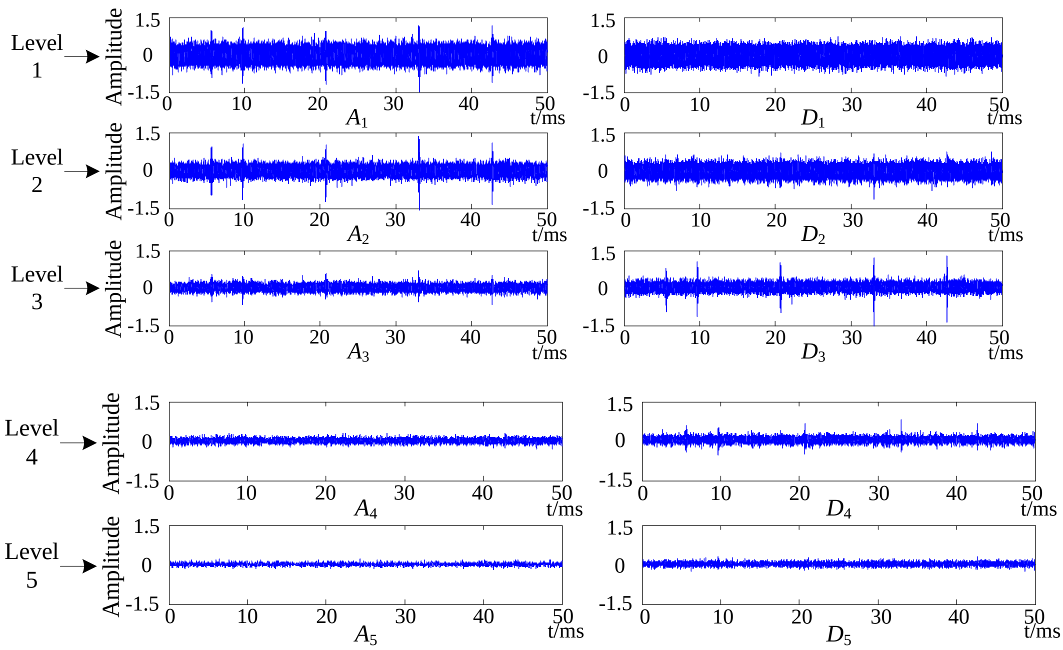


Figure 6. Wavelet Coefficients of Signal with Noise

In Figure 6, the SNRs of $D_1 \sim D_5$ respectively are -24.45dB, -19.18 dB, -7.53 dB, -11.56 dB, -19.41 dB. And the SNR of A_5 is -26.49 dB. So the SNRs of D_3 and D_4 are bigger than the others. We use these two coefficients to analyze the performance of SSNF. Then the improved SSNF uses $w(3,k)$ and $w(4,k)$ in step b. So $m=3$ in Eq. (8). The simulation results of SSNF and improved SSNF are shown as Figure 7.

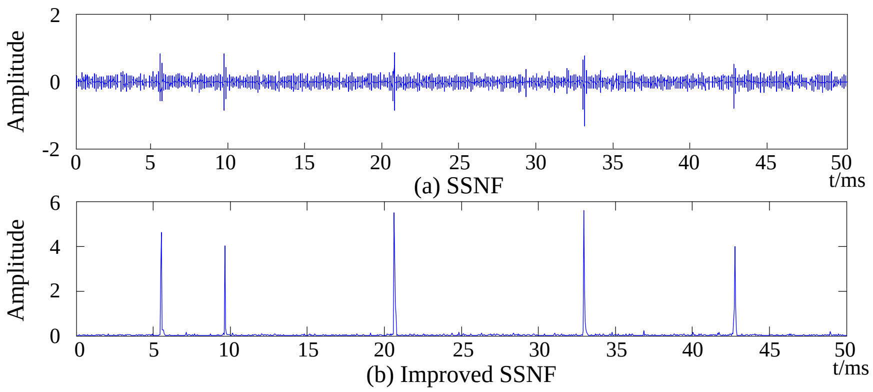


Figure 7. Simulation Results of SSNF and Improved SSNF

Figure 7 exhibits the differents between SSNF and improved SSNF. Compared with the SSNF, the improved SSNF has less "glitches" in the simulation results. This indicates the AE phenomenon of the result of improved SSNF is clearer than SSNF. There are three more simualtion results in Figure 8. The SNRs of Gaussian white noise signal are all -15dB in Figure 8(a). And the results of improved SSNF are shown in Figure 8(b). To sum up, these simulation results can prove that the improved SSNF has a good noise smoothing capability.

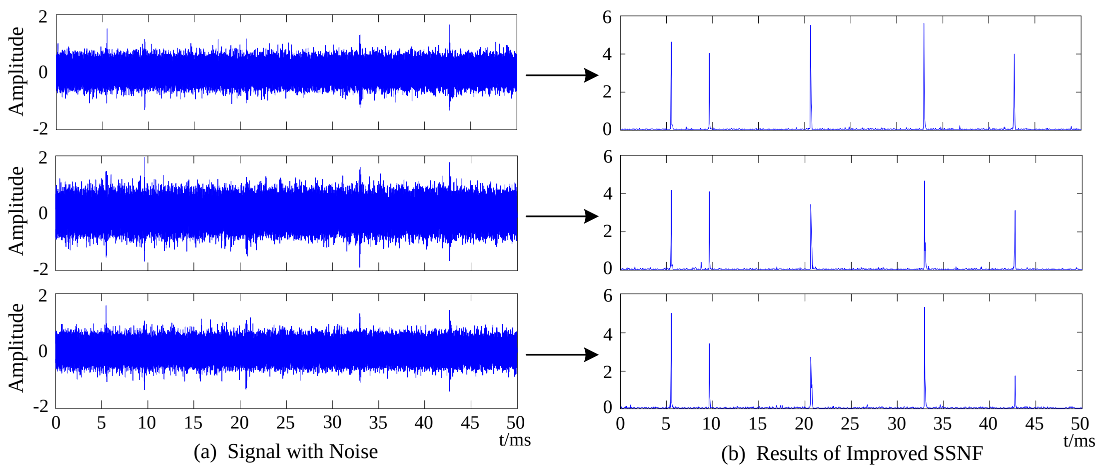


Figure 8. Simulation Results of the Improved SSNF

In addition, the simulation time is also important for an algorithm. The time of input signal is 0.05s, and the simulation time of SSNF is about 8.393s. So the SSNF cannot realize real-time denoising in the simulation environment of this paper. Compared with the SSNF, the average simulation time of improved SSNF is only 0.01996s. It is less than 0.05s. So the improved SSNF can realize real-time denoising of AE signal.

6. Conclusions

This paper proposes an improved SSNF for denoising AE signal. The Mallat algorithm is used to decompose the AE signal. Then by comparing the simulation results of different vanishing moments, "db5" is chose as the mother wavelet. According to the SNRs of wavelet coefficients, D_3 and D_4 are chose for the improved SSNF. By simulation, the improved SSNF has better performance in denoising compared with SSNFB. And the most important is that it has better time efficiency in algorithm complexity, which means it can realize real-time denosing of AE signal.

Acknowledgements

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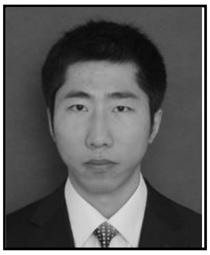
Authors



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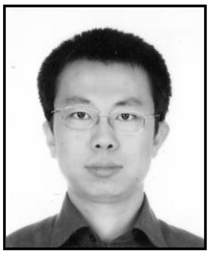

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