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Research on Noise Reduction Method Based on CEEMD-WT-SVD and Its Application in Acoustic Signal of Pipeline Blockage

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Abstract. Signal denoising is one of the most important tasks in the application of acoustic detection for pipeline blockage. Aiming at the effects of random noise and impulse noise on acoustic signal from pipeline blockage, a noise reduction method based on complete ensemble empirical mode decomposition (CEEMD), wavelet transform (WT) and singular value decomposition (SVD) is proposed. First, the continuous mean square error criterion is introduced to judge the dominant high-frequency intrinsic mode component obtained by CEEMD. Then wavelet soft threshold is used to denoise and reconstruct the signal, which avoids the loss of high frequency useful signals. Secondly, to achieve the further purpose of suppressing noise, the phase space reconstruction and SVD of the signal are carried out, and the reconstruction order of the signal is determined by using the larger peak position of the singular value energy difference spectrum. Through the analysis of the noise reduction effect of simulation signal and pipeline blockage signal, the results show that this method not only can improve the problem of the modal mixture well, but also can effectively extract the useful features of the signal. Meanwhile, the noise reduction performance is better than the noise reduction method based on ensemble empirical mode decomposition.

Keywords: complete ensemble empirical mode decomposition (CEEMD), noise reduction, singular value decomposition (SVD), wavelet transform (WT)

1 Introduction

As a new way of transportation, pipeline plays an important role in petroleum, chemical and urban infrastructure. However, in industrial production and real life, pipeline blockage is a very common situation. According to the existing research results, pipeline blockage detection technology can be divided into two types, namely direct detection method and indirect detection method, and they have some differences in detection methods and technical means. The direct detection method is to find the pipeline blockage directly by means of ray, optics, wall strain and so on. The indirect detection method detects the blockage of the pipeline by detecting the change of the fluid or sound wave. However, it has been a key and difficult point to study a kind of blockage detection technology with high reliability and high sensitivity. A lot of the research methods in the past are mainly concerned with the complete

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blockage of pipelines. In this way, only when the pressure and flow rate of pipeline are changed obviously, can we identify the blocked working conditions effectively, so the advantage is not obvious. Acoustic detection method is a nondestructive testing technology developed in recent years. It not only has the advantages of high sensitivity with no damage to pipeline equipment and high detection speed [1], but also can make the early identification of pipeline blockage or structural defects. Thus it has been widely used in actual detection. In real life, because of the complexity of background noise, there is a lot of impulse noise and random noise. So it is difficult to distinguish the useful information from the noise signal and effectively extract the fault characteristic information. Therefore, signal denoising is one of the most important tasks in the application of acoustic detection for blockage.

The noise signal is usually expressed as high frequency signal. However, in actual situation, the frequency distribution of the collected acoustic signal for pipeline blockage often walks in the whole frequency space. At present, there is not much research on noise reduction of pipeline fault signals, and most of them focus on the way of wavelet transform. Jiang [2] compared wavelet function with decomposition number, and then realized the noise reduction of ultrasonic signal of pipeline crack by wavelet denoising. Hao [3] used wavelet transform to denoise the negative wave signal of pipeline leak, and analyzed the noise reduction signal to locate the leakage position of the pipeline. By using different methods to analyze the noisy signals with different wavelet threshold quantification methods, Chao and Shanxue [4] made a noise reduction for the pressure signal of the pipeline leakage. Although traditional wavelet analysis has been applied in the field of signal denoising [5-7], there are also some shortcomings: it is not only unable to effectively separate the noise spectrum, but also can easily filter out the mutations information of signal. At the same time, because most of the collected pipeline fault signals are nonlinear and nonstationary, this requires that the decomposition method of the signal should be self-adaptive.

In recent years, signal decomposition technique has become one of the most effective methods to deal with non-stationary and nonlinear signals. Empirical Mode Decomposition (EMD) which was proposed by Huang et al. [8] has a good effect in the treatment of the stationary and non-stationary signal. The advantage of this method is that the base function can be automatically generated, and it has adaptive filtering characteristics and adaptive multiresolution. It can decompose the signal into many Intrinsic Mode Function (IMF) components from high to low frequencies without set the basis functions. Also, it is not only retains the useful information in the signal, but also lays a foundation for deep mining information [9-10]. However, the disadvantage of this method is that the modal mixture phenomenon and the end effect can occur more or less after the signal decomposition. Huang believes that the cause of the pattern aliasing is intermittent phenomenon, which is often caused by abnormal events (such as pulse interference and noise). To overcome the above defects and following his research, Huang and Wu [11] proposed an auxiliary signal noise analysis method——Ensemble Empirical Mode Decomposition (EEMD). To reduce the modal mixture effect, this method add the white noises to the signal which contains singular point, and then carries on EMD decomposition. Whereas it also has some negative effects: IMF will occur a certain degree of deviation in the process of calculating the average approximate value, and it will leave a lot of noise at the reconstructionof the signal. To solve above problems existing in EEMD, Yeh et al. [12] proposed a new method called complete ensemble empirical mode decomposition (CEEMD). Aiming at the problem that there is too much residual noise in the signal reconstruction of EEMD, the auxiliary noise is addedto the original signal in the form of positive and negative pairs, and achieved a good result. CEEMD not only greatly reduce the modal mixture and energy leakage caused by EMD, but also reduce the reconstruction error caused by the addition of white noise. At present, it has been successfully used in the field of signal denoising, and has achieved remarkable results.

To realize the monitoring and diagnosis of switching fault for circuit breaker, Sun et al. [13] proposed a fault diagnosis method based on CEEMD, sample entropy and relevance vector machine. First, the vibration signal is denoised by wavelet packet denoising algorithm, and then the sample entropy of the IMF components obtained by CEEMD decomposition is extracted. Finally the fault diagnosis model is constructed. The experiment shows that this method can realize the preliminary evaluation of different fault degree for circuit breaker. However, in the process of noise reduction, they first denoise the signal and then decompose it by CEEMD. This method does not make full use of the adaptive advantages of CEEMD in the analysis signal. In view of the nonlinear and non-stationary characteristics of ECG signals, Bin et al. [14] proposed a wavelet soft threshold denoising method based on different empirical mode decomposition. In the experiment, by comparing the denoising effect between CEEMD and the traditional time-frequency analysis method, they got the conclusion that the combination of CEEMD and wavelet soft threshold is the best way to reduce noise. However, in the process of selecting IMF components, they adopt the method of comparing the result graph of decomposition and make judgment, and there is no definite calculation method. In view of the obvious amplitude modulation characteristics of the cavitation noise of marine propeller, Pan et al. [15] adopt the method of noise reduction based on CEEMD and Wavelet thresholding, the experiment proved that this method can restrain the noise well, and the modulated information is more clear. However, they also have some deficiencies in the process of noise reduction. First, they selected the IMF components that needs to be reduced according to the frequency band information, but it does not specify the specific method. Moreover, the method of personal experience has a great influence on the noise reduction results. It will be very difficult to be effective once the signal and noise frequency bands are mixed badly. Second, it only makes a noise reduction for the selected IMF component, but discards the remaining IMF component. This approach may lose some useful information. Huang et al. [16] introduced the method of combining CEEMD with generalized morphological difference filtering to the fault diagnosis of bearings. In the process of signal preprocessing, the noise is effectively reduced by filtering the reconstructed signal. However, in the process of de-noising, they select only a part of the IMF component to reconstruct, and then filter them. The remaining IMF component was abandoned by them. It should be noted that noise appears in all IMF components, and all IMF components contain a certain amount of useful information. Through CEEMD decomposition, we can get a more complete time-frequency distribution of the signal, and it provides the convenience for further extraction of signal features. This way is feasible to the slowly changing signal with low noise. However, when the complex pulse interference and random noise exist in the actual project, the IMF components obtained by CEEMD decomposition will be distorted to some extent, which affects the characterization of the useful components in the signal. Therefore, it is necessary to reduce the IMF component on the basis of CEEMD decomposition. However, there are some problems in the process of noise reduction. On the one hand, when using CEEMD to reduce noise, the judgment of the IMF components dominated by noise has a great influence on the effect of noise reduction. The dominant energy of many noise pollution signals is concentrated in the low frequency band. The higher the frequency, the stronger the impact of noise on the IMF components. But some of the existing literature on the selection of the IMF is not scientific, and some part of the IMF that is considered minor is not being used well. Therefore, It is needed to adopt an accurate judgement criterion and noise reduction method. On the other hand, the traditional denoising method which only carries out wavelet transform cannot achieve a good effect on the non uniformly distributed signals [17-18]. Singular value decomposition (SVD) is a kind of nonlinear filtering noise reduction method, which can express the information in the form of matrix decomposition, and can achieve the purpose of noise reduction by preserving the singular value of the signal characteristic. It overcomes the disadvantage that wavelet transformhas a poor noise reduction effect on the non-uniform distribution of noise. Now, it has been widely used in the noise reduction of biomedical science [19], acoustic [20], vibration [21], lidar [22] and other signals. However, its effect on the pulse interference denoising is not good [23]. Pulse interference is also a common noise, so it is necessary to consider the influence of various types of noise and study a more suitable signal denoising method.

To sum up, in this paper, proposed a noise reduction method based on complete ensemble empirical mode decomposition (CEEMD), wavelet transform (WT) and singular value decomposition (SVD). First, We decomposed the acoustic signal into a series of IMF components by using CEEMD to obtain a series of IMF components. Secondly, the continuous mean square error criterion was introduced to judge the dominant high-frequency IMF components, and then the dominant role of high frequency noise components were denoised separately by using wavelet soft threshold denoising. Thirdly, the signals were reconstructed. Finally, in order to overcome the problems that the noise reduction effects of the wavelet transform denoising is not good for the signal which is non-uniform in noise distribution, and the residual noise of each type is regarded as useful information in signal reconstruction, the signal was reconstructed by phase space and carried on SVD for reconstruction to achieve the further purpose of suppressing noise. Compared with the work done in previous literatures, the method proposed in this paper scientifically determines the useful signals and noise segmentation points in the CEEMD decomposition results. By comprehensively utilizing the advantages of wavelet transform and singular value decomposition in signal denoising, useful signals from all IMF components can be effectively extracted. The effectiveness of the proposed method is verified by the analysis of the noise reduction of the simulation signal and the pipeline blockage detection signal, and the noise can be eliminated to a large extent. The rest of this paper is organized as follows: Section 2 covers the theory of CEEMD decomposition, wavelet threshold denoising, and SVD decomposition. Meanwhlie, specific procedure of noise reduction based on CEEMD-WT-SVD is also expounded. A simulation signal is used to verify the validity of the proposed method in Section 3. In order to further verify the effectiveness of the proposed method, a diameter of 150 mm pipeline which is blocked is used to show its applications in Section 4, and conclusions are presented in Section 5.

2 Principles and Methods of Noise Reduction

2.1 Noise Reduction Principle

CEEMD Decomposition. Complete ensemble empirical mode decomposition (CEEMD) is a kind of noise assisted analysis method, which is aimed at the deficiency of empirical mode decomposition (EMD). EMD can adaptively decompose the signal according to the time characteristics of the signal. It has a unique advantage in dealing with nonlinear and non-stationary signals. The idea of EMD decomposition is that any signal can be composed of a series of simple non sinusoidal signals. Assuming the original signal is $x(t)$, EMD [24] can decomposes the $x(t)$ into a set of Intrinsic Mode Function (IMF) components c_i and a residual term r_n, namely:

$$x(t)=\sum_{i=1}^{n} c_i + r_n. \tag{1}$$

The idea of ensemble empirical mode decomposition (EEMD) [25] is to add white noise to the signal that contains singular point, and then carry on the decomposition of EMD and reserve the average value of each IMF component as the final result. Aiming at the much residue noise and long computing time in EEMD signal reconstruction, CEEMD take the following measures: the auxiliary noise is added to the original signal in the form of positive and negative pairs, and then carry on the decomposition of EMD. This method not only can greatly suppress the phenomenon of modal mixture and energy leakage in EMD algorithm, but also improve the computational efficiency. The steps are as follows:

(1) Add a pair of white noise to the original signal:

$$\begin{cases} x_1 = x(k) + n(k) \\ x_2 = x(k) - n(k) \end{cases}. \tag{2}$$

(2) x_1 and x_2 in the above steps are decomposed by EMD, and then the overall average of the decomposition results are recorded as IMF_{X1} and IMF_{X2}.

(3) Calculate the average of IMF_{X1} and IMF_{X2}, and the values are used as the result of the decomposition of CEEMD:

$$IMF=\frac{(IMF_{X1}+IMF_{X2})}{2}. \tag{3}$$

Wavelet Threshold Denoising. Wavelet threshold denoising method is proposed by Donobo and Johnstone [26], which has a strong local recognition ability both in time domain and frequency domain. It has a certain effect on suppressing random noise and pulse interference. Wavelet threshold denoising can be divided into the following steps: Firstly, convert the original signal to the wavelet domain. Secondly, threshold processing is performed in the wavelet domain. Finally, try to reconstruct the the signal In general, the threshold processing of wavelet transform can be divided into two kinds: hard threshold processing and soft threshold processing. Compared with soft threshold, the signal after hard threshold processing is rougher and may exist the phenomenon of signal distortion. Therefore, soft threshold processing is usually choosed as the processing method.

Hard threshold processing:

$$\omega_\lambda = \begin{cases} \omega & |\omega| \geq \lambda \\ 0 & |\omega| > \lambda \end{cases}. \tag{4}$$

Soft threshold processing:

$$\omega_\lambda = \begin{cases} sgn(\omega)(|\omega| \text{-} \lambda) & |\omega| \geq \lambda \\ 0 & |\omega| < \lambda \end{cases}. \tag{5}$$

Where ω is the original signal; λ is the specified threshold.

SVD decomposition for noise reduction and Selection of Noise Reduction Order. Singular value decomposition (SVD) is a special kind of matrix transformation. In recent years, because it can represent the essential characteristics of the signal, it has been widely used in the signal noise reduction and the extraction of periodic components. To achieve the purpose of noise reduction, the SVD decomposes the matrix of the signal, and preserves the singular values that can represent the characteristic of original signal.

Assuming a discrete signal $x = \{x_1, x_2, ..., x_N\}$, it can be expressed as:

$$x = s_k + \omega_k \;\; k{=}1,2,\cdots N. \tag{6}$$

Where s_k is the real signal; ω_k is the noise signal. The following hankel matrix is constructed by using the above data:

$$H = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \\ x_2 & x_3 & \cdots & x_{n+1} \\ \vdots & \vdots & \vdots & \vdots \\ x_m & x_{m+1} & \cdots & x_N \end{bmatrix} = S + W. \tag{7}$$

Where $m{=}N{+}n{-}1$, $H \in R^{mxn}$. This matrix is called reconstructed attractor orbit matrix. No matter whether the row and column of the above matrix is relevant, there are always two orthogonal matrixes U and V, which makes:

$$H = U \Sigma V^T. \tag{8}$$

Where $\Sigma = \begin{bmatrix} \Sigma_r & O \\ O & O \end{bmatrix} \in R^{m \times n}$; $\Sigma_r = diag(\sigma_1, \sigma_2, \cdots \sigma_r)$. $\sigma_i (i = 1,2,\cdots,r)$ is called the singular value of H. $r(r \leq \min(m,n))$ is the rank of H. When the signal mixed with the noise, the track matrix which corresponds to it must be a full rank matrix. Fundamentally speaking, SVD is to divide the signal which contain the noise into two spaces: real signal space and noise space, and these two spaces are irrelevant.. Therefore, it is necessary to remove the noise space to complete the signal noise reduction. According to matrix optimal approximation theorem of frobenious norm sense, as long as the first n singular values of the matrix H are retained, and the other singular value are set to 0, then the new matrix can be reconstructed through the inverse process of SVD. In this process, the determination of the order of noise reduction is the core of the reconstruction. So, in order to obtain the reconstruction of the order, the singular value energy difference spectrum is defined as follows:

$$b_i = \sigma_i^{\,2} - \sigma_{i+1}^{\,2}, \; i = 1,2,\cdots,q-1. \tag{9}$$

The sequence $B = [b_1, b_2, \cdots, b_{q-1}]$ that formed by all of b_i is called singular value energy difference spectrum sequence. It shows the process of value changes in adjacent singular. In general, the real signal energy is relatively concentrated. So according to the definition of singular value energy difference spectrum, it will contain a relatively large peak that separate the signal from the noise. Namely: the singular values after the peak value are dominated by the noise, and the different of the energy between the neighboring singular values are also very small. At the same time, the singular values before the peak are mainly dominated by the real signal, and the generated spectrum summit are very steep. Therefore, we can select a boundary point k that meets the above conditions to make that peak value larger, and the peak value after it will be significantly smaller. Namely: the first k singular values that corresponding to components represents the true signal and the k singular values after the point represents the noise components.

2.2 Noise Reduction Method Based on CEEMD-WT-SVD

In order to make full use of the advantages of the above methods, a noise reduction method based on CEEMD-WT-SVD is proposed. First of all, carry on the decomposition for the orignal signal to obtain a multiple frequencies of IMF components from high to low by means of CEEMD. Because the dominant energy of the signal contaminated by noise is concentrated in the low frequency band, the more to the high frequency segment, the less useful signal it contains. Therefore, there must be a segmentation point, which turns the IMF signal into the leading mode after the split points. If the split point is not suitable, it will result in a poor noise reduction effect. Based on this, this paper intends to judge the critical point of IMF by using the continuous mean square error criterion proposed by Boudrra [27]. And then, all the dominant roles of high frequency noise components are denoised separately by using the wavelet soft threshold denoising. The definitions of continuous mean square error (CMSE) are as follows:

$$CMSE(y_k{}', y_{k+1}{}') = \frac{1}{n}\sum_{i=1}^{n}[y_k{}'(t_i) - y_{k+1}{}'(t_i)]^2 = \frac{1}{n}\sum_{i=1}^{n}[IMF_k\ (t_i)]^2,\ k=1,2,...,c\text{-}1. \tag{10}$$

Where $y_k{}'$ represents the first k components of IMF; $y_k{}' = [y_k{}'(t_1), y_k{}'(t_2), .., y_k{}'(t_N)]^T$. When $k = 0$, $y_k{}'$ is the original noise signal, and n is the length of the signal. Where c is the sum of the IMF components and the residual term that decomposed by CEEMD; f is the label of continuous value of minimum mean square error.

After a series of continuous mean square error coefficients are obtained by the above formula, they are searched sequentially. When the first continuous mean square error coefficient achieved a relatively small value, record the the corresponding label f. In the first f IMF components, it means that the dominant mode is noise. So, firstly the first f IMF components are denoised separately by using wavelet soft threshold denoising. secondly, try to reconstruct the signal. Thirdly, the signal is reconstructed by phase space and carried on SVD. According to the singular value difference spectrum, we can find a relatively large energy peak value, and then determine the reconstructed order. Finally the signals are reconstructed again. The specific steps are as follows:

(1) The original signal is decomposed into a number of IMF components and a residual term R by means of CEEMD;

(2) According to the continuous mean square error criterion to calculate the continuous mean square error between several consecutive IMF, and choose the f as the dividing point. Afterwards, the first f IMF components are denoised separately by using wavelet soft threshold denoising. Then, the first f IMF components w and the rest of the IMF componentsare reconstructed.;

(3) Construct the hankel matrix for the reconstructed signal;

(4) Carry on the Singular value decomposition of hankel matrix;

(5) Find the singular values of the differential spectrum, and then draw the singular value energy difference spectrum. Afterwards, the location of the peak point is used to determine the reconstruction order of the signal;

(6) Signal reconstruction.

The implementation process of this method is shown in Fig. 1.

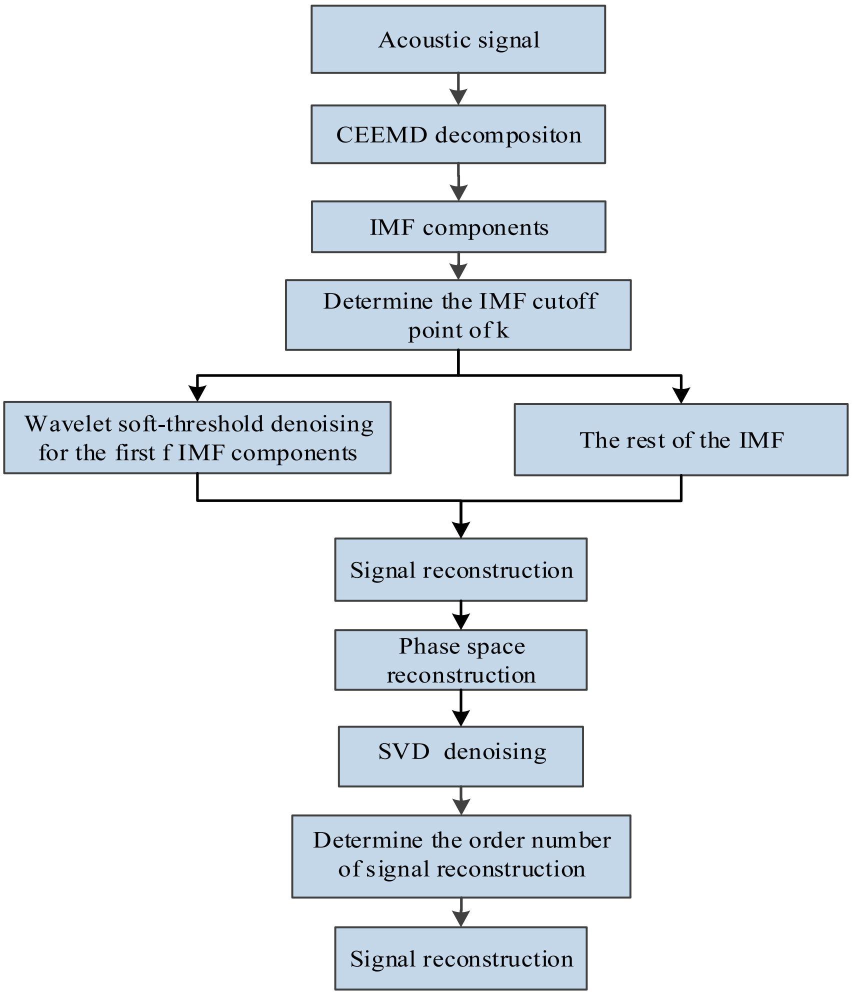

Fig. 1. Noise reduction process based on CEEMD-WT-SVD

On the basis of CEEMD decomposition and continuous mean square error criterion, this model makes full use of the advantages of wavelet transform and singular value decomposition (SVD) in the noise reduction. Firstly, the model is used to denoise the high frequency noise dominated IMF. Then the reconstructed signal is used for further denoising. Theoretically, this model can suppress most of the noise, so that the useful information in the signal can be preserved.

3 Experimental Simulation

To verify the validity of the method proposed in this paper, we designed a simulation signal and added noise as follows:

$$x(t) = s(t) + \omega(t) = 2sin(40\pi t + \frac{\pi}{2}) + cos(16\pi t + \frac{\pi}{2}) + n(t) + z(t). \quad \textbf{(11)}$$

Where $s(t)$ is the original signal; $\omega(t)$ is the addition of noise signal; $x(t)$ is the synthesis signal; $n(t)$ is random noise; $z(t)$ is pulse noise. The waveform of the signal $s(t)$ and $x(t)$ are shown in Fig. 2 and Fig. 3 respectively. The sampling frequency is 1.2 kHz, and the sampling point is 1000.

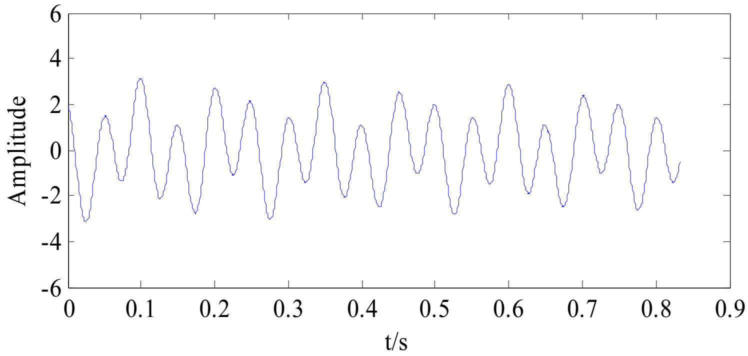

Fig. 2. Original signal

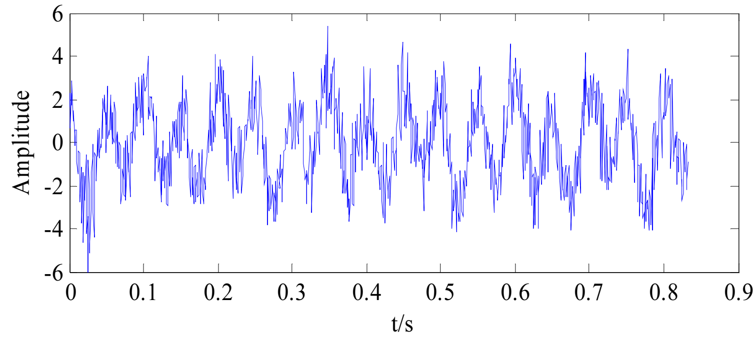

Fig. 3. Synthesis Signal

For comparison purposes, EEMD and CEEMD method were adopted to decompose the signal and obtained a series of IMF components. The obtained IMF components are shown in Fig. 4. As shown in Fig. 4 (left), the sine and cosine signal which are the components parts of the synthesis signal are IMF4 and IMF5 respectively. It can be seen that the signals are not well decomposed and there still has the phenomenon of modal mixture. This indicates that the white noise that added to the original signal has not been completely neutralized. Meanwhile, some IMF components are also mixed with other components, which make the signal analysis become more complicate. As shown in Fig. 4 (right), the sine and cosine signal which are the component part of the synthesis signal are IMF4 and IMF5 respectively. It can be seen that the mode mixing phenomenon has been greatly reduced through the decomposition of CEEMD. Furthermore, the useful components in the signal are decomposed, and the neutralization effect of the noise is better than that of EEMD method.

CEEMD maintained abinary filter property of EMD, and the obtained IMF components meet the series distribution rules from high frequency to low frequency. The first few IMF components are high frequency components, and the random noise will be distributed among them. Through the calculation of continuous mean square error criterion, we obtained the boundary point of IMF. Afterwards, all the dominant roles of high frequency noise components were denoised separately by using the wavelet soft threshold denoising. And then, the signal was reconstructed. The result of signal reconstruction is shown in Fig. 5. It can be seen from Fig. 5 that lots of random noise and pulse interference is effectively filtered, but the reconstructed waveform has a clear distortion, and the noise has not been completely eliminated.

Therefore, the next step was to build the hankel matrix of the signal and then it was decomposed by SVD. The singular value spectrum and singular value energy difference spectrum are shown in Fig. 6 (left) and Fig. 6 (right) respectively. For the convenience of view, this paper only selected the first 100 points. As we can see from Fig. 6 (right), the fourth peak of the signal energy is larger, and all of the peak points after it are significantly smaller. So, the selected number of reconstruction is 4. The result of signal that carried on SVD and then was used for reconstruction is shown in Fig. 7.

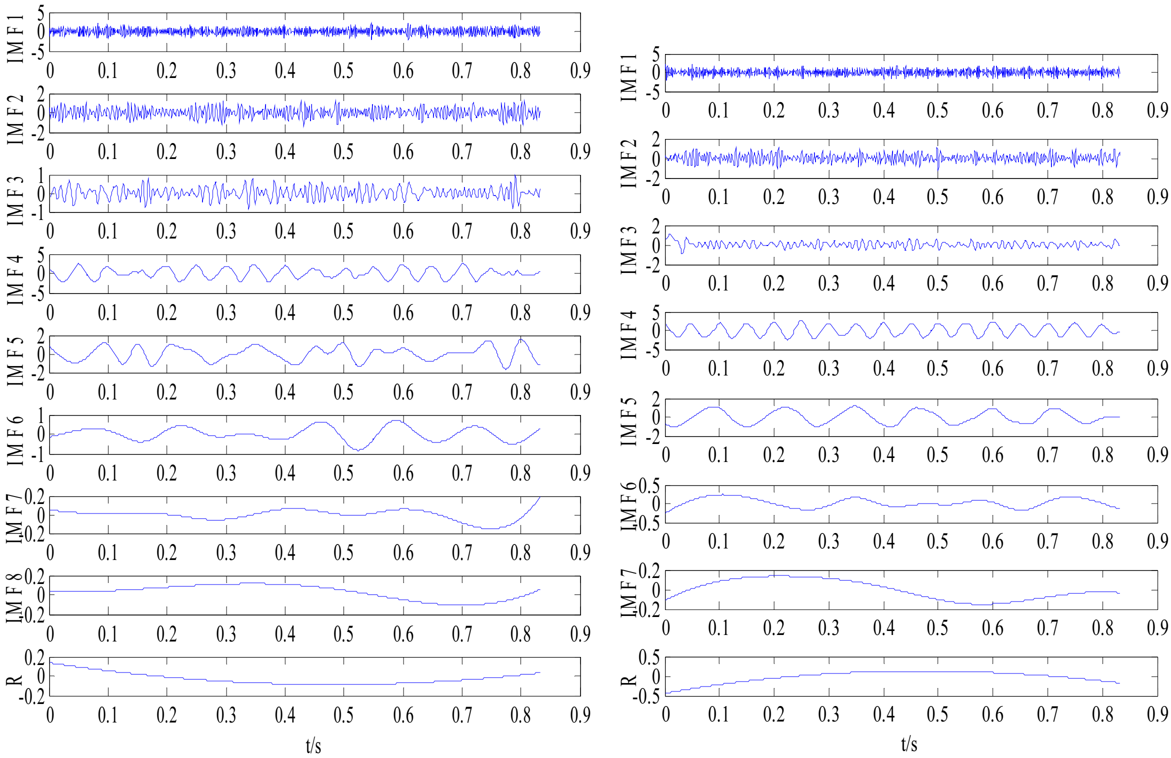

Fig. 4. Decomposition results of EEMD (left) and CEEMD (right)

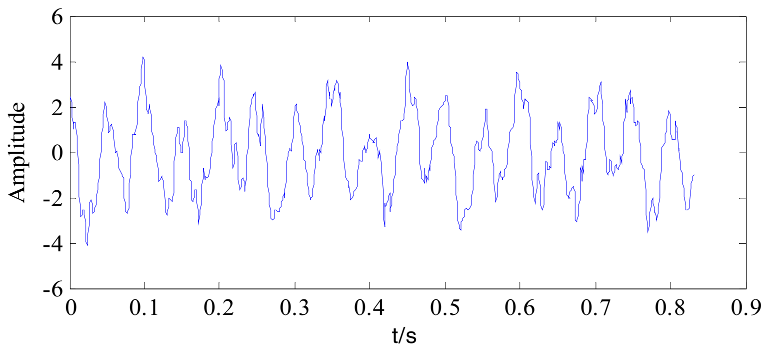

Fig. 5. Signal reconstruction results

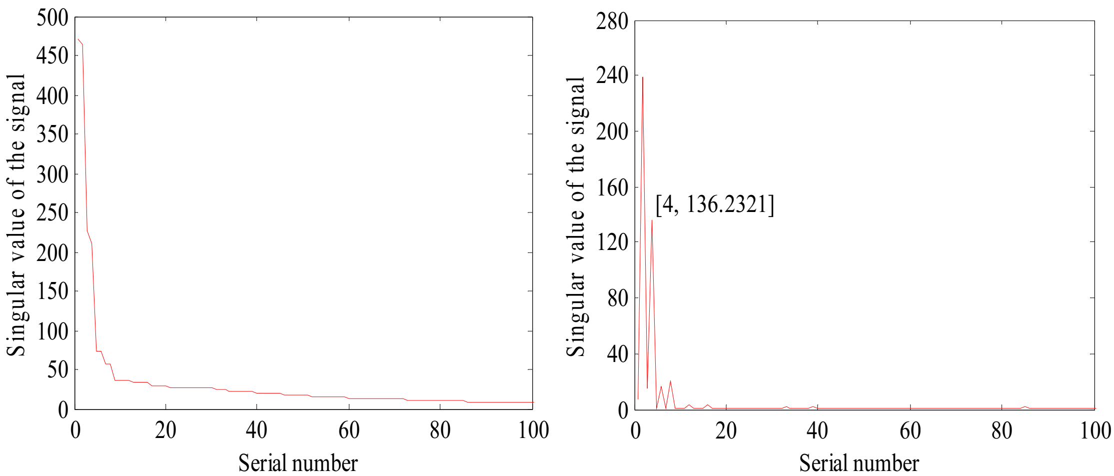

Fig. 6. Singular value spectrum (left) and Singular value energy difference spectrum (right)

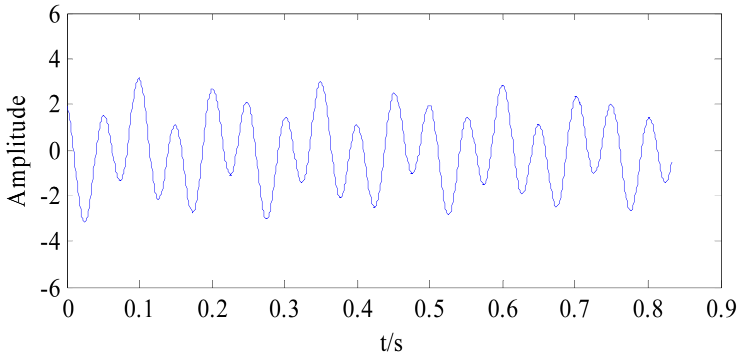

Fig. 7. Noise reduction result based on CEEMD-WT-SVD

It can be seen from Fig. 7, the noise interference in the signal has been effectively filtered, and the useful part is preserved. In order to evaluate the noise reduction effect of different models, the signal to noise ratio (SNR) and the root mean square error (RMSE) are used as the evaluation index. This experiment has recorded the evaluation index value of signal that first decomposed by CEEMD and EEMD, and then denoised by using wavelet soft threshold denoising based on the continuous mean square error criterion for IMF components. Afterwards, the signal is reconstructed by phase space and carried on the SVD for reconstruction, and the experiment once again recorded a set of evaluation index value for comparison. Meanwhile, the test also used wavelet soft threshold noise reduction for comparison. The results are shown in Table 1.

Table 1. Comparison of the noise reduction effects of different models

	Synthesis signal	WT	EEMD-WT	CEEMD-WT	EEMD-WT -SVD	CEEMD-WT -SVD
SNR (dB)	4.3125	8.7452	19.461	20.2660	45.9015	49.4349
RMSE	0.8060	0.6458	0.393	0.3630	0.1008	0.0844

The signal to noise ratio (SNR) and root mean square error (RMSE) are defined as follows:

$$SNR = 10lg\left(\frac{\sum S(t)^2}{\sum \left[S(t) - S(t)'\right]^2}\right). \tag{12}$$

Where S is the original signal; S' is the signal after noise reduction.

$$RMSE = \sqrt{\frac{\sum \left[S(t) - S(t)'\right]^2}{n}}. \tag{13}$$

Where S is the original signal; S' is the signal after noise reduction; n is the number of measurements.

As shown in Table 1, through the comparison of different models of noise reduction in two indicators, we can see that the above models have some effect on improving the quality of the signal. But the CEEMD-WT-SVD method is more prominent than the other methods, and it can not only improve the SNR of signal, but also can obtain a high similarity waveform when compared with the original signal. By comparison, the results shows that the method proposed in this paper can preserve the characteristics of the original signal.

4 Case Analysis

In order to further verify the effectiveness of the method proposed in this paper, our test used a total length of 14.2 m, and a diameter of 150 mm pipeline. In the experiment, a blockage was placed inside the pipeline. The collection of the blocking signals of pipeline was based on the acoustic detection method. The detection principle of pipeline blockage is shown in Fig. 8. The acoustic sensor device was installed on one end of the pipeline, and the other end of the pipeline was open. Meanwhile, in order to simulate the actual working conditions, a certain degree of noise was added to the collected acoustic signals. The distance between the speaker and the blocking object was d1, and the distance between the speaker and the microphone was d2. Meanwhile, the sampling frequency of the signal was 44100HZ. Through an amplifying circuit driving a speaker to produce a wave of sound which can travel along the pipeline, the experimenters can determine whether there is a blockage. When the sound met the blockage, we used a microphone to record the signal received by the whole process. So, the detailed information of blockage can be obtained by further analysis of the response signals.

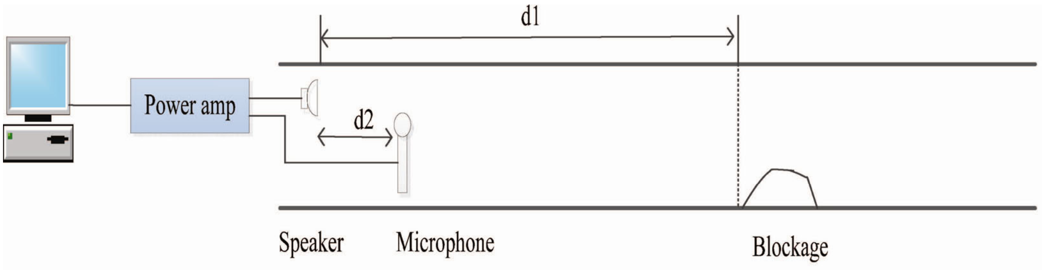

Fig. 8. Schematic diagram of pipeline blockage detection

At present, many acoustic detection methods are based on impulse response. Because these signals carry sufficient information to identify pipeline structural defects and blockage created by sediment or other things [28], we can analyze it and get the desired results. So, for further analysis of the detection signal, the collected signal in this experiment is preprocessed to get the acoustic impulse response. It is assumed that a time-varying excitation signal $x(t)$ is applied to a linear time invariant system, and its output can be represented as a mathematical convolution integral:

$$y(t) = \int_0^\infty h(\tau)x(t-\tau)d\tau. \quad \textbf{(14)}$$

Where $h(t)$ is the impulse response of the system, and τ is the auxiliary integral variable corresponding to the time delay. The impulse response can be obtained by deconvolution of the signal [29].

The time domain and frequency domain of the collected acoustic impulse response signal are shown in Fig. 9 and Fig. 10 respectively. It can be seen from the Fig. 10 that the frequency distribution of blockage signal is in 0~2.1x10^4 Hz frequency range, and there is a lot of noise. Therefore, it is necessary to reduce the noise in order to obtain the signal sequence.

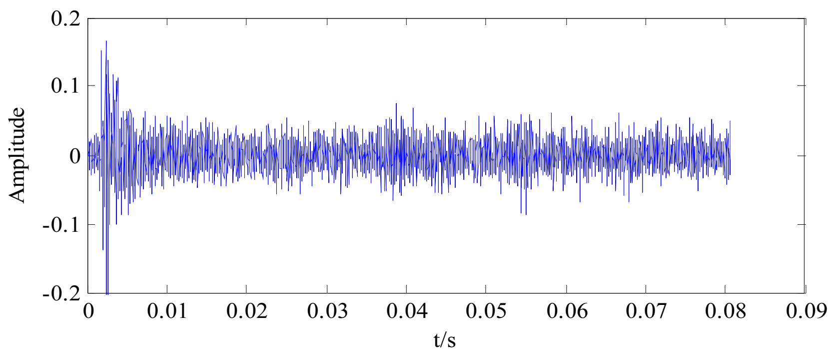

Fig. 9. Time domain of blockage signal

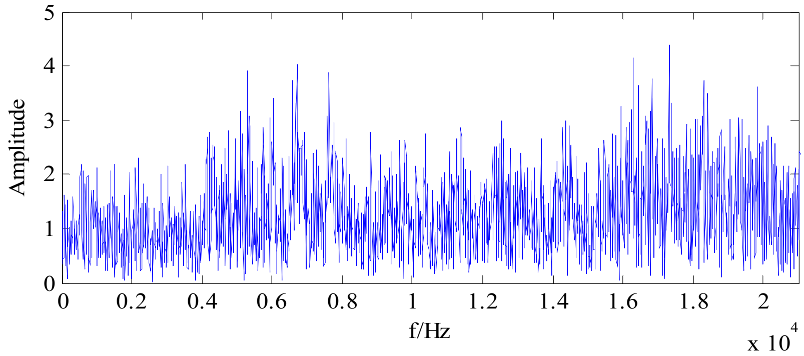

Fig. 10. Frequency domain of blockage signal

Firstly, CEEMD method was adopted to decompose the acoustic signal and obtained a series of IMF components. The first seven components of the decomposition results are shown in Fig. 11. It can be seen from the Fig. 11 that the spectral characteristics of high frequency IMF components are similar to the noise spectrum. Because the original signal is contaminated by a certain degree of noise, it can result in poor noise reduction effect if the IMF component of the high frequency selection is not accurate. So, it is necessary to determine the boundaries of IMF. By calculating the continuous mean square error, the experiment determined the cut-off point, and then the related IMF components were denoised separately by using wavelet soft threshold denoising. Secondly, the signals were reconstructed. The reconstruction result of the signal is shown in Fig. 12.

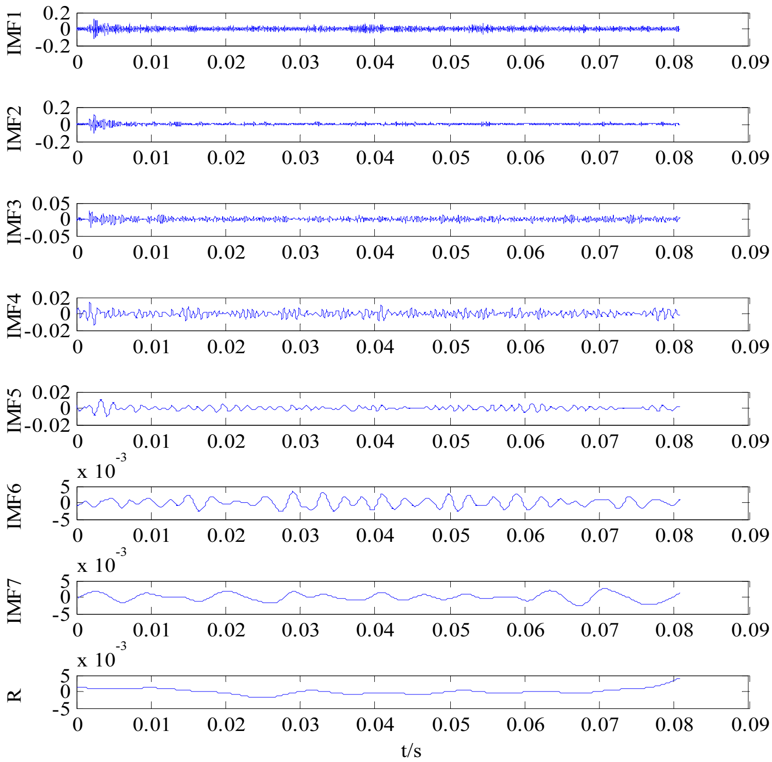

Fig. 11. CEEMD decomposition results of blockage signal

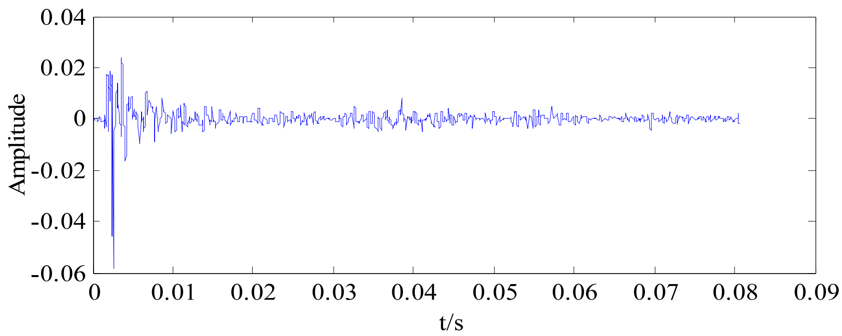

Fig. 12. Signal reconstruction results

Because the wavelet soft threshold denoising is only used in the high frequency IMF components, and not directly to the whole signal, it improves the defects that wavelet soft threshold denoising may eliminate some of the real signals in practical applications. This approach not only improves the precision of analysis, but also can better reflect the fault feature of the signals. It can be seen from the Fig. 12 that a certain degree of the random noise is effectively filtered out, but there still exists some noise. Therefore, the next step was to build the hankel matrix of the signal and then it was decomposed by SVD. The singular value spectrum and singular value energy difference spectrum are shown in Fig. 13 (left) and Fig. 13 (right) respectively. For the convenience of view, this paper only selected the first 100 points. From Fig. 13 (right), it can be see that the twelfth peaks of the signal energy is larger, and all of the peak points after it are significantly smaller. So, the selected number of reconstruction is 12. The noise reduction result in time domain and frequency domain based on CEEMD-WT-SVD are shown in Fig. 14 and Fig. 15 respectively.

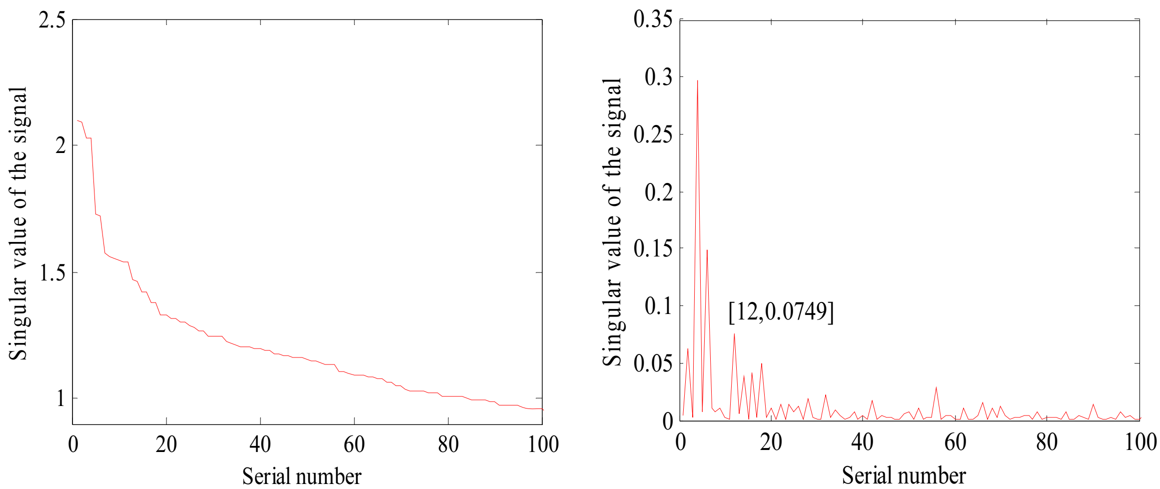

Fig. 13. Singular value spectrum (left) and Singular value energy difference spectrum (right)

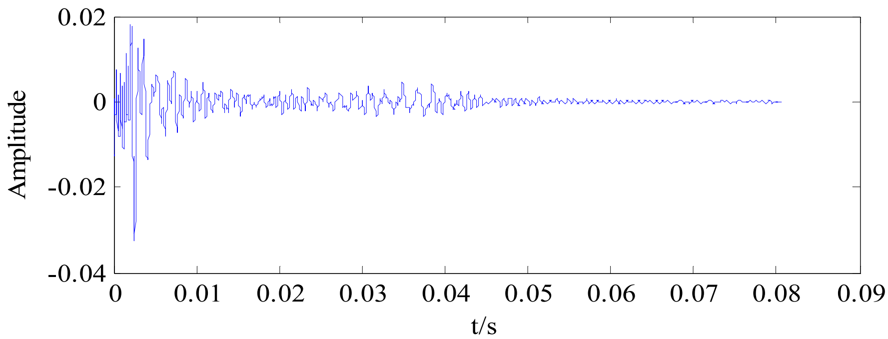

Fig. 14. Noise reduction result in time domain based on CEEMD–WT–SVD

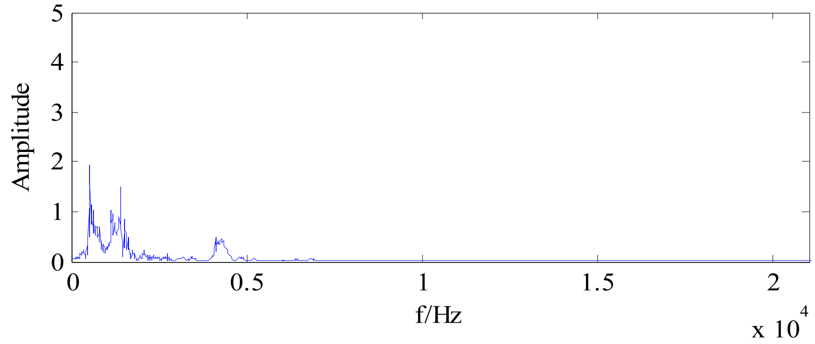

Fig. 15. Noise reduction result in frequency domain based on CEEMD–WT–SVD

As is shown in Fig. 14 and Fig. 15, the noise reduction of the signal has preserved the part of the useful signal very well. The result shown that the noise reduction method based on CEEMD-WT-SVD can not only effectively retain the original signal characteristics, but also can filter out the noise. Meanwhile, it can be seen from the frequency spectrum of the signal, the noise reduction signal retains the useful information of the signal, and filter out the high frequency interference noise. This method provides a new way for the noise reduction of acoustic signals.

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5 Conclusions

Under the actual operating conditions, the acoustic signal of the pipeline blockage can be affected by the random noise and the pulse interference, which will cause difficulties to the identification of the useful signal. In order to solve the above problems, the method based on CEEMD-WT-SVD is applied to reduce the noise of the acoustic signal from pipeline blockage. This paper makes the following contributions:

(1) By comparing the decomposition results of CEEMD and EEMD for simulation signals from Fig. 4 (left) and Fig. 4 (right), it can be seen that the CEEMD method has better neutralization effect for the added white noise, which can suppress the modal mixture and reduce the reconstruction error. However, By using EEMD method, more IMF components were obtained in the experiment, and there is also a phenomenon of modal mixture. CEEMD not only keeps the useful information in the signal, but also plays a key role in the deep mining of information.

(2) By using the continuous mean square error criterion, the problem of determining the useful signal and the noise segmentation point in the use of CEEMD method is solved. Based on this, we utilized the advantages of wavelet transform and singular value decomposition, and applied it to the signal noise reduction. So, the useful signals from all IMF components have been effectively extracted. By comparing the SNR and RMSE index in Table 1, the result shows that after CEEMD-WT-SVD noise reduction, we can get a better evaluation index than other traditional noise reduction methods.

(3) Through the noise reduction analysis of the acoustic signal collected by pipeline blockage experiment, it can be seen from Fig. 10 and Fig. 15 that the high-frequency noise in the original signal has been greatly filtered, it proved the effectiveness of the proposed method, which can eliminate the noise and retain the characteristics of the original signal. It provides an effective basis for the further feature extraction and pattern recognition of the signal, and has a certain application prospect.

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