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Bridge Monitoring Signal Noise Reduction Method for EMD Joint Improvement of Wavelet Threshold

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Abstract

When the bridge conducts status assessment and health monitoring, the obtained bridge signals are susceptible to the interference of the external environment and are difficult to reflect the true response of the bridge structure. Based on the bridge monitoring signal noise reduction method for EEMD to improve the wavelet threshold. This method first uses EEMD to perform adaptive decomposition of the signal containing noise, then removes the modes with small variance contribution rate, and finally performs the wavelet threshold denoising of the remaining modes to reconstruct the real signal after denoising. On the simulated signals, the results show that the noise reduction method of EEMD can filter the interference noise signal effectively, and the noise effect is better than the single improvement, EMD and EMD denoising, and the research results can provide meaningful reference for the bridge signal denoising processing.

Keywords

Bridge Monitoring Signal; Set Empirical Mode Decomposition; Noise Reduction at the Wavelet Threshold; Analog Signal.

1. Introduction

In order to ensure the safe operation of the bridge and avoid serious accidents, it is particularly important to carry out the condition assessment and health monitoring of the bridge structure. In the health monitoring of the bridge, it is necessary to install various sensors (such as strain sensors, displacement sensors, etc.) on the measuring points of the bridge structure to collect relevant data. These data can reflect the real-time response of the bridge structure, and then the response is processed and analyzed to assess the status of the structure. However, in the actual engineering application, the external environment of the bridge structure is usually more complex, and its health monitoring system is always affected by various interference factors, so that the collected data is unable to accurately infer the real information of the structure. In some cases, interference can even completely drown out the real information and cause the phenomenon of fake. Therefore, in order to accurately judge the state information of the structure, we need to reduce the sampled signal in the signal analysis, so as to eliminate the influence of noise on the structure of the state information. Therefore, using reasonable and efficient algorithms for data denoising has become one of the important problems in bridge health monitoring data processing.

In the investigation of monitoring signal preprocessing method, it is found that the preprocessing theory and method of signal data involve a variety of interdisciplinary disciplines, and the commonly used methods include empirical mode decomposition method, Kalman filter method[4], wavelet threshold noise reduction method, etc. The empirical mode decomposition method is a new data preprocessing method proposed by Huang'e in 1998 for how to extract useful information from a large number of noise signals[1]. Although the empirical mode decomposition method shows its effectiveness in the engineering field, it still has limitations such as generating spurious components, mode aliasing and endpoint effects. The Kalman filter

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method was proposed by the mathematician Kalman in the middle of the 20th century. It was first used to find the optimal estimate of the prediction algorithm to dynamically filter the real-time signal. Although the Kalman filtering algorithm has the characteristics of fast operation and small memory for the monitoring data, it is usually difficult to achieve the optimal preprocessing effect when filtering or predicting the monitoring signal due to the limitations of the method. The wavelet threshold noise reduction method was proposed in 1994 by Donodo and Johnstone based on the wavelet analysis theory to reduce the noise with a large number of random noise signals. Wavelet threshold noise reduction method is the most commonly used signal noise reduction method. It is widely used in practical engineering because of its advantages of good noise reduction effect, simple and easy to realize[2].

Based on this, this paper proposes the noise reduction method of jointly improving wavelet threshold jointly. First, because the empirical mode decomposition of the same feature scale sequence can coexist in multiple eigenmode function components, in order to optimize this problem, ZHAOHUA et al. proposed the ensemble empirical mode decomposition method in 2005. Secondly, because the threshold function is particularly important in the wavelet threshold noise reduction method. At present, the commonly used threshold function is the soft threshold function and the hard threshold function proposed by Donoho in 1995, but the hard threshold function directly causes the phenomenon when the noise level is too high. Although the overall continuity of the soft threshold function is good, when the wavelet coefficient is large, which will directly affect the approximate degree of the reconstruction signal, so the improved threshold function is introduced to avoid such problems. Finally, the noise-containing signal is decomposed by the set empirical mode decomposition, and then the wavelet threshold noise reduction method is used to achieve the noise reduction of the bridge monitoring signal[3].

2. The Theoretical Part

2.1. Empirical Modal Decomposition

Any complex signal can be regarded as the sum of the superposition of multiple different intrinsic mode functions, any modal function can be linear or nonlinear, and any two modes are independent of each other. Based on this assumption, the EMD decomposition steps of the complex signals $x(t)$ are as follows[2]:

(1) Find all the extreme points of the signal $x(t)$, connect the local maximum points into the upper envelope through the cubic spline, and connect the local minimum points into the lower envelope. The upper and lower envelope contain all the data points.

(2) From the average value $m_1(t)$ of the upper envelope $e_{\max}(t)$ and the lower envelope $e_{\min}(t)$.

$$m_1(t) = \frac{e_{\max}(t) + e_{\min}(t)}{2} \tag{1}$$

(3) Using the signal $x(t)$ minus the mean envelope $m_1(t)$, the first component can be obtained. The calculation formula is as follows:

$$h_1(t) = f(t) - m_1(t) \tag{2}$$

If the eigenmode function requirement $h_1(t)$ is met, it is the first order eigenmode function of the signal, skip to step (5); if the requirements are not met, continue to step (4).

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(4) Repeat steps (1) ~ (3) as a signal, and the calculated mean envelope and new components. And to judge whether the new component of the component meets the requirements of the intrinsic mode function.

If it is still not satisfied, repeat step (4) until the definition of the eigenmode function is met, and then the new component is the first-order eigenmode function.

(5) The residual amount can be obtained by subtracting the first order IMF. The calculation formula is as follows:

$$r_1(t) = f(t) - C_1(t) \tag{3}$$

(6) Take the residual amount as the new signal, and repeat the steps (1) ~ (5) to obtain the new residual amount of the second order eigenmode function. Repeat the above steps until the termination condition is reached. The termination condition for order i residue is a monotonic function or constant.

The EMD decomposition signal can be expressed as:

$$f(t) = \sum_{i=1}^{I} C_i(t) + r_I(t) \tag{4}$$

The intrinsic mode function shall satisfy the following two conditions: 1. In the whole time series, the number of signal extreme points and the number of passing zero, must be equal or at most one difference; 2. At any time series, the mean of the upper and lower envelope of this time series is determined as zero by the signal local maxima and local minima, respectively[6].

2.2. Set Empirical Mode Decomposition

The principle of EEMD method is to add several white noise in the original signal, the combination of signal and noise as a signal to decomposition signal, using the uniform distribution characteristics of white noise spectrum, when the signal load throughout the white noise background, the signal of different time scales will automatically distributed to the appropriate reference scale, and due to the characteristics of zero mean noise, then EMD processing, finally average to approximate the true mode.

Step 1: Set the average number of treatments to M, and the initial i=1,2,..., M;

Step 2: Add a random white noise of a certain amplitude to form a new series of signals[2]:

$$x_i(t) = x(t) + n_i(t), i = 1,2,3,\ldots,M \tag{5}$$

Step 3: EMD decomposition of the new sequence signal workers.

$$x_i(t) = \sum_{n=1}^{n} c_{i,n}(t) + r_{i,n}(t) \tag{6}$$

Step 4: Repeat step 2~3M times, and add white noise with different amplitude each time to obtain a series of eigenmode functions. We find their components by calculating the average of these eigenmodal functions of EEMD.

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2.3. Wavelet Threshold Function

The wavelet threshold method is the threshold denoising proposed based on the wavelet transform, and is the wavelet threshold denoising method proposed by D.L.Dohonn in 1995. The wavelet threshold denoising method is to decompose the collected one-dimensional signal through the wavelet and extract the signal high frequency coefficient and low frequency coefficient. According to relevant studies, the effective signal is mainly concentrated in the low frequency coefficient, and the noise signal and a small number of effective signal are distributed in the high frequency coefficient. The appropriate threshold value is selected according to the characteristics of the high and low frequency coefficient, and the wavelet coefficient outside the threshold range is retained, and the wavelet coefficient within the threshold range is removed, so as to realize the signal noise reduction.

Noise reduction steps by wavelet thresholding method[3]:

(1)Wavelet decomposition. Select the appropriate wavelet basis function, and decompose the N layer of the collected original signal to obtain the corresponding wavelet coefficient of each layer;

(2) Thresholding value processing. Select the appropriate threshold value, select the corresponding threshold function, and conduct the threshold processing of the wavelet coefficient obtained by the wavelet decomposition;

(3) wavelet reconstruction. The wavelet reconstruction reconstructed the wavelet coefficient to obtain the effective signal.

In the two steps of wavelet decomposition and reconstruction, different types directly affect the effect of signal decomposition and reconstruction, thus determining the quality of the signal; the signal characteristics and experience, but the selection of the wavelet threshold noise algorithm also depends on the selection of the threshold. If the threshold selection is too small, the denoising effect will be unsatisfactory, if the threshold selection is too large, the elimination of some effective signals.

(1) Criteria for wavelet threshold

In the process of denoising of wavelet threshold, the determination of wavelet threshold selection criterion is a key step. The selection method of wavelet threshold generally includes four criteria: unbiased risk estimation threshold, fixed threshold, heuristic threshold, and maximal threshold. The unbiased risk threshold is mainly aimed at the noise is approximated to additive Gaussian white noise, with fixed frequency spectrum and relatively large noise intensity, and retains more high frequency information, which is suitable for high frequency signals. Maxima do not need to know the noise variance, have a relatively small noise dependence, and are more suitable for low signal-NR-signal filtering denoising. The fixed threshold is more applied in engineering, and the noise reduction effect is obvious when the noise is more. The heuristic threshold is a combination of unbiased risk estimation threshold and fixed threshold, which can get better denoising while retaining more high-frequency information. Both unbiased risk estimation thresholds and minimax thresholds are conservative to extract weak signals, but noise removal is often less effective. The fixed and heuristic threshold denoising are more thorough, while the bridge has lower ambient vibration natural frequency, so using the fixed threshold criterion is more effective in denoising compared to the heuristic threshold. Therefore, the fixed threshold estimation method is used to denoise the bridge signal.

The fixed threshold expression is as follows[5]:

$$\lambda = \sqrt{2 \ln N} \tag{7}$$

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λ: Threshold value; N: signal length.

(2) Wavet threshold function selection

1)Hard threshold function

$$\hat{\omega}_{j,k} = \begin{cases} \omega_{j,k}, & \omega_{j,k} \geq \lambda \\ 0, & \omega_{j,k} < \lambda \end{cases} \tag{8}$$

2)Soft threshold function

$$\hat{\omega}_{j,k} = \begin{cases} sign(\omega_{j,k})(|\omega_{j,k}| - \lambda), & |\omega_{j,k}| \geq \lambda \\ 0, & |\omega_{j,k}| \leq \lambda \end{cases} \tag{9}$$

3)Improved threshold function

$$\hat{\omega}_{j,k} = \begin{cases} sign(\omega_{j,k})(|\omega_{j,k}| - \dfrac{(1-a)\lambda}{1+e^{b(\omega_{j,k}-\lambda)^2}}), & |\omega_{j,k}| \geq \lambda \\ sign(\omega_{j,k}) a e^{b(\omega_{j,k}-\lambda)^2} |\omega_{j,k}|, & |\omega_{j,k}| \leq \lambda \end{cases} \tag{10}$$

(3) Wavelet basis function and decomposition layer number selection

When the signal is denoised, the wavelet basis function is generally selected through experience, and it is often difficult to choose the optimal wavelet basis function. In this paper, the optimal wavelet basis function and wavelet decomposition layer number are selected by comparing the SNR of different wavelet bases and different wavelet decomposition layers. The coif 2 wavelet basis function is selected as 4 layers.

2.4. This Paper Reduces the Noise Method

In this paper, the method of set empirical mode decomposition is adopted to achieve the purpose of accurate decomposition, calculate the variance contribution rate of the decomposition component, remove the components with low variance contribution rate, and then transfer the remaining signals to wavelet threshold processing. The whole specific implementation process is as follows:

(1) The simulation signal is decomposed by the ensemble empirical mode decomposition;

(2) Calculate the variance contribution rate of the component obtained by decomposition, and remove the modal component with a small contribution rate of the variance, then the retained modal component can generally express the characteristics of the original signal with less information loss.

(3) The wavelet threshold is denoised by the retained mode components.

3. Analyses of Simulated Signals

Establish the simulation signal, using the noise reduction algorithm, EMD noise reduction method, improve wavelet threshold noise reduction method, EMD joint improve wavelet threshold noise reduction method, through the comparison of different noise reduction performance index, verify the proposed method in signal decomposition and reconstruction noise reduction performance. Firstly, the analog signal is established, and the white noise of

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1dB, 1 dB, 5dB, 10dB, 15dB and 20dB respectively are added to verify the retention performance and noise reduction effect of the noise-containing signal after the noise reduction of this method. Establish analog signals including 1Hz, 1.5Hz and 5Hz frequencies, and add white noise n (t) of 1dB, 5dB, 10dB, 15dB and 20dB respectively. The sampling frequency is 100Hz and the sampling time is 10s. The mathematical model is as follows:

$$x(t) = 15\cos(2\pi t + \frac{\pi}{3}) + 12\cos(3\pi t + \frac{\pi}{3}) + 12\cos(10\pi t + \frac{\pi}{8}) + n(t) \tag{11}$$

The simulated signal without noise signal is shown in Figure 1 and with 5dB noise signal $x(t)$ is shown in Figure 2.

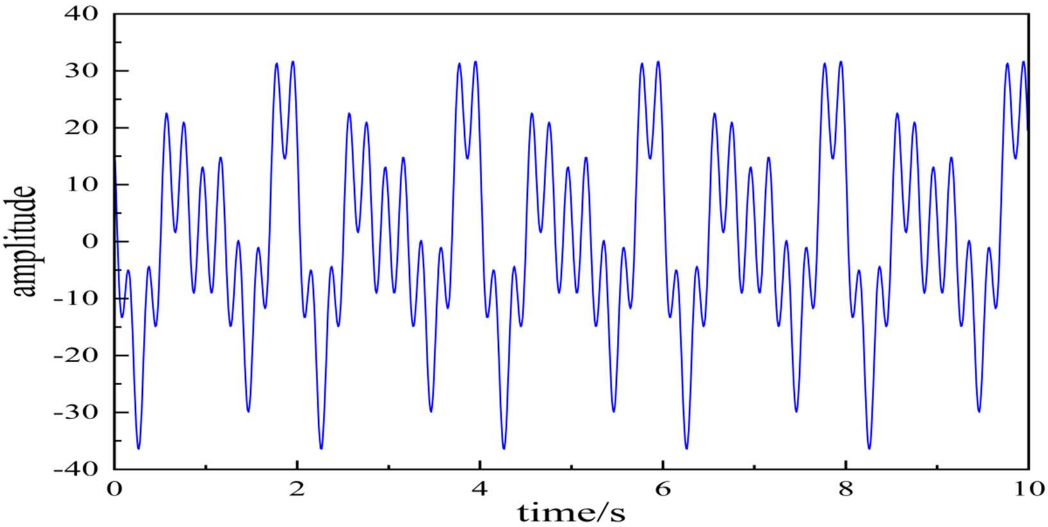

Figure 1. adds no noise analog signal

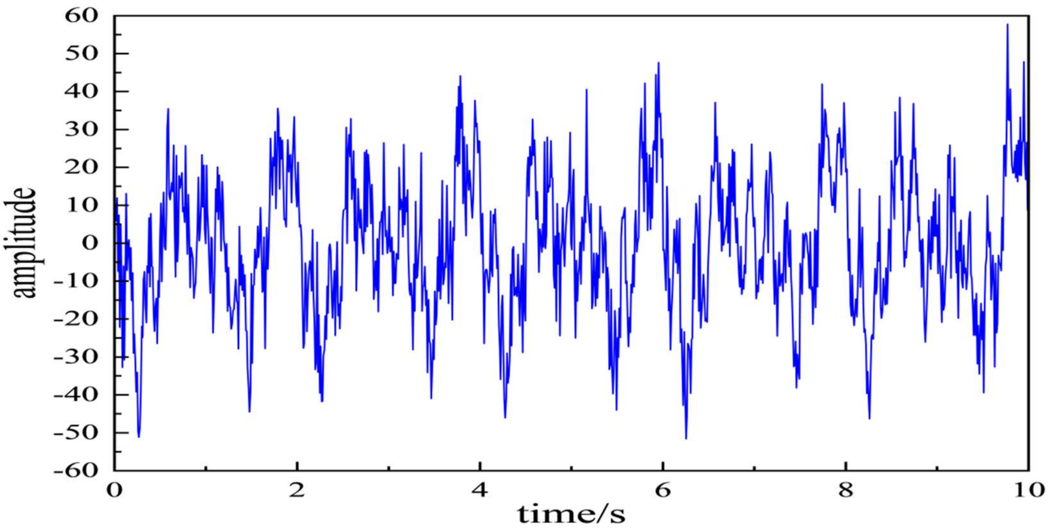

Figure 2. adds a 5dB noise analog signal

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3.1. Denoising Process Analysis

The noise reduction algorithm, EMD noise reduction method, improved wavelet threshold noise reduction method and EMD joint improved wavelet threshold noise reduction method are adopted. The results of the original and denoised signals are shown in Figure 3 to Figure 4.the results show that, The above four denoising methods can effectively eliminate most of the noise of the simulation signal; For the denoised signal and the original signal pair as shown in Figure 6, Although there are still smaller deviations at some peak positions, But largely consistent, It can be shown that this method has a good denoising effect; By observing the enlarged regions A, B, C and D of the remaining three denoising effects, EMD noise reduction method, improved wavelet threshold noise reduction method, EMD joint improvement of wavelet threshold reduction noise denoising signal peak part and the original signal without noise have obvious deviation, Its denoising effect is not very ideal; on the whole, In contrast to the remaining three denoising methods, The denoising method in this paper achieves a better denoising effect on the peak part of the signal.

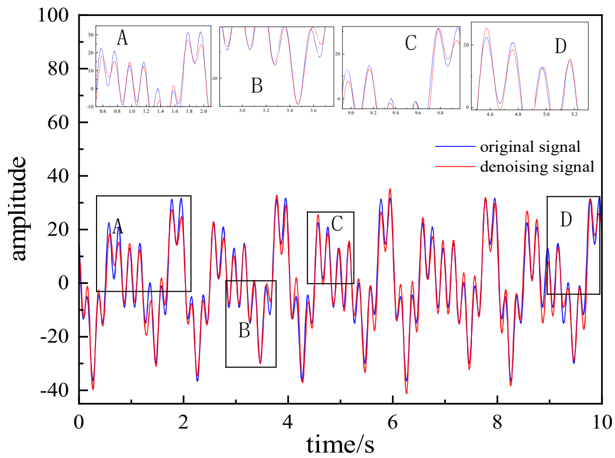

Figure 3. Noise reduction effect diagram of EMD

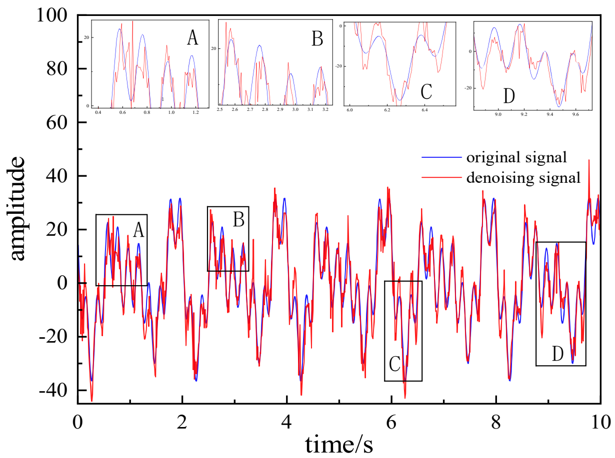

Figure 4. Noise reduction effect diagram of EMD

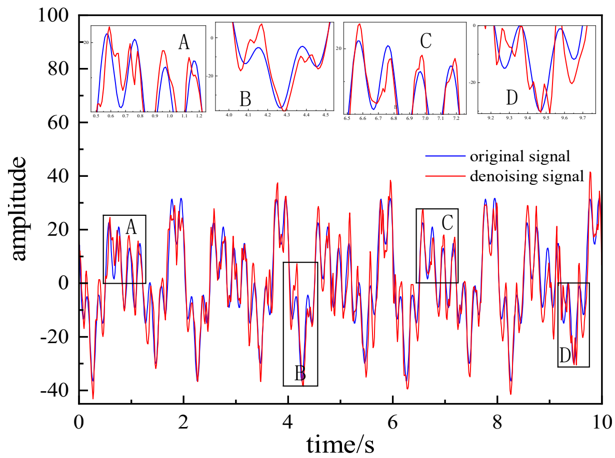

Figure 5. Effect reduction of EMD jointly improved wavelet threshold

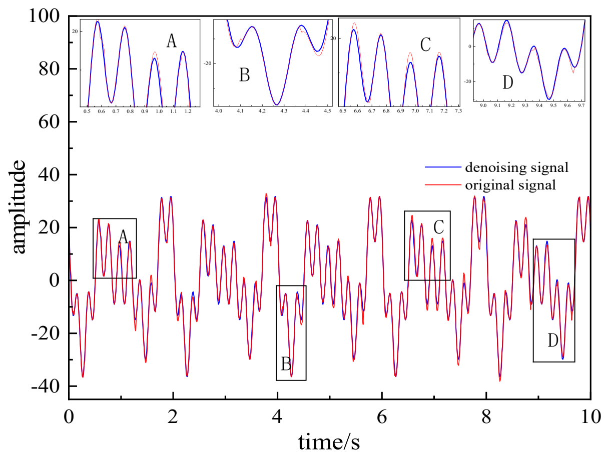

Figure 6. The effect diagram of the noise reduction method in this paper

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To further evaluate the advantages of this method, the signal denoising is quantitatively analyzed by two common denoising performance indexes: signal-to-noise ratio and mean variance root error:

(1) The SNR is the dimensionless ratio of the noise power included in the signal power. The larger the SNR value, the smaller the noise signal ratio in the original signal, the better the noise reduction effect is.

$$SNR = 10\lg \frac{\sum_{i=1}^{N} x_i^2}{\sum_{i=1}^{N} (x_i - \widehat{x_i})^2} \tag{12}$$

(2) The root mean square error represents the square root of the variance of the signal and the original signal. As an indicator to measure the deviation between the observed value, the smaller the RMSE value indicates that the smaller the difference between the signal and the original signal, the closer the observed value is to the true value, indicating that the better the noise reduction effect is.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \widehat{x_i})^2} \tag{13}$$

The comparison of the evaluation indexes of the four noise reduction methods is shown in Table 1:

Table 1. The comparison of the evaluation indexes of the four noise reduction method

	1dB		5dB		10dB		15dB		20dB	
	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE	SNR	RMSE
The noise-reduction algorithm presented in this paper	9.04	0.5625	14.16	0.3139	18.31	0.1947	22.95	0.1241	26.08	0.1123
The EMD noise-reduction method	5.99	0.6195	10.63	0.5509	14.22	0.3947	18.04	0.2713	22.47	0.1955
Improved wavelet threshold noise reduction method	6.91	0.5471	10.97	0.5282	14.45	0.3404	18.42	0.2788	22.91	0.1522
EMD jointly improves the wavelet threshold for noise reduction	7.82	0.5664	12.31	0.5766	15.07	0.3559	19.40	0.2720	23.03	0.1544

The RMSE values of the denoising method at different noise levels are 0.5625, 0.3139, 0.1947,0.1241 and 0.1125, which are the smallest among the four denoising methods. The RSME value reflects the degree of similarity between the filtered signal and the original signal, indicating that the denoising method in this paper can better retain the original signal information compared with other denoising methods.

By analyzing the SNR of four denoising methods for bridge signals at different noise levels, the method has higher noise ratio of 9.04,14.16,18.31,22.95 and 26.08, respectively. The signal

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noise ratio increases by 6dB~10dB, which is suitable for simulated signals with different noise intensity. In this paper, the denoising method has a higher signal to noise ratio than the other three denoising methods, so the signal denoising is more thorough. In conclusion, compared with the other four denoising methods, whether using detailed contrast map analysis or quantitative analysis of signal denoising performance index, this method has higher denoising ability for both nonlinear and non-stationary random signals while retaining more signal details.

4. Conclusion

In order to reduce the influence of the bridge signal by external environmental noise, and conduct the state assessment and health monitoring of the bridge more accurately, the denoising method based on EEMD joint improvement wavelet threshold is proposed. Through numerical simulation test, the method based on EEMD joint improvement wavelet threshold can effectively separate the useful signal and noise signal from the mixed signal, while retaining the original characteristics of the signal, which is suitable for the denoising of the bridge signal.

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