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Research Article

A Novel Denoising Algorithm of Electromagnetic Ultrasonic Detection Signal Based on Improved EEMD Method

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In this paper, we propose a new denoising algorithm for electromagnetic ultrasonic signals based on the improved EEMD method, which can adaptively adjust for added noise and average times in different noisy environments, so that the effect of the residual difference of white noise on the results can be eliminated as far as possible. First, the way to add white noise in the EEMD method is processed, and then the permutation entropy algorithm is used to identify the nature of the components obtained during the decomposition. Then the wavelet transform modulus maximum denoising method is used to deal with the IMF components of the high-frequency part obtained before. Finally, the processed IMF results and residual difference are summed up. The results show that after processing, the noise component in the signal is less and the original information is more reserved, which prevents the signal distortion to a great extent and provides more effective data for subsequent processing. In the experiment, the crack defect data collected by the electromagnetic ultrasonic experiment system were processed by the improved EEMD method. Compared with the traditional EEMD method, it can retain the information of crack location more accurately, which proves the effectiveness of the proposed method.

1. Introduction

In recent years, the electromagnetic ultrasonic nondestructive testing technology for pipeline defect detection has been paid more and more attention. Compared with the traditional ultrasonic testing technology, it is simpler and more effective, having a variety of different detection modes. However, due to the influence of environment, human operation, and other factors, there are some singularities in the data collected by the receiving end of the electromagnetic ultrasonic transducer. What is more, it contains a certain degree of noise interference, so that it may cause great disturbance to the identification of signal position and feature in the later period.

Literature [1] proposed an improved denoising algorithm based on wavelet transform modulus maxima reconstruction. This method had a good approximation to the original wavelet transform coefficients of the signal. However, the wavelet denoising method was limited by both the time domain and the frequency domain, and it could not meet the analysis requirements of high resolution in the time domain and frequency domain. In document [2], authors utilized special symmetric matrices to construct the new nontensor product wavelet filter banks, which could capture the singularities in all directions. In document [3], authors proposed an image denoising method based on nonseparable wavelet filter banks and two-dimensional principal component analysis (2D-PCA). This method could achieve both good visual quality and a high peak signal-to-noise ratio for the denoised images. In document [4], the permutation entropy was introduced into the threshold function as the representation parameter of signal denoising, and the permutation entropy of the wavelet packet coefficients of the signal was calculated. Literature [5] proposed a new EEMD (Ensemble Empirical Model Decomposition) harmonic detection method based on new wavelet threshold denoising preprocessing to effectively eliminate the effect of random noise on harmonic detection. However, the EEMD denoising method was to reject the high-frequency partial components directly, which would result in the loss of valid information in the high-frequency components.

The core of the improved algorithm in this paper is to adaptively adjust the added noise and the average times under different noise environments, so that the effect of the residual difference of white noise on the results can be eliminated as far as possible.

In this paper, we first introduce the conception of modulus maxima denoising method based on wavelet transform and EEMD denoising method. Then, the differential threshold method is used to remove the singularities in the data. Next, we make innovative improvements to the EEMD algorithm so that it can adaptively get the ratio coefficient, and the useless residual difference of the added white noise can be reduced to the maximum extent at the same time. Aiming at the added white noise in the EEMD method, we use the permutation entropy algorithm to identify the nature of the components obtained during the decomposition.

For the remaining signal of the low-frequency stationary part, the EMD (Empirical Mode Decomposition) is directly used in the processing, while the other high-frequency IMF (Intrinsic Mode Function) components are continuously obtained by the EEMD decomposition, thereby reducing the influence of noise on the effective part.

Afterwards, the wavelet transform modulus maximum denoising method is used to deal with the IMF components of the high-frequency part obtained before. Finally, the processed IMF components and residual difference are summed up. The results show that after processing, the noise component in the signal is less and the original information is more reserved, which can prevent the signal distortion to a great extent and provide more effective data for subsequent processing.

2. Preliminaries

2.1. Preparation. There are many traditional discrete data denoising methods. At the following, the applicable characteristics of various methods will be combined to explain the relevant knowledge involved in this article algorithm. And then the method proposed in this paper is applied to the processing of electromagnetic ultrasonic nondestructive testing signal. By comparison, the advantages of this article algorithm are highlighted.

In order to compare the denoising effects of several methods, we used the ETG-100 ultrasonic thickness gauge to test three steel plates of the same material as X56 in the laboratory environment. Their length is 50 cm, the width is 30 cm, and the thickness is 12.37 mm, 13.35 mm, and 15.21 mm. Three sets of clean thickness echo signals are obtained. Noise is added to the first set of signals, as shown in Figure 1.

2.2. Introduction to EMD Method. EMD is suitable for the analysis of nonlinear, unsteady signals. The core of the method is to decompose the more complex signals and get the IMF components of the signals. The IMF components obtained by this method represent the characteristics of the data series at different time scales, respectively. In this way, the fluctuation trend of the signal under different scales of the original signal can be decomposed and refined and then analyzed.

For the IMF, Huang et al., had given the qualified conditions [6]:

(1) In the whole data set, the number of extrema and zero-crossings must either be equal or differ at most by one

(2) The average value of the envelope of the maximum and the minimum value of a data sequence is zero

For the signal sequence X_i that needs to be processed, the interpolation function is, respectively, used to obtain the envelopes of the maximum $X_{\max}$ and the minimum point $X_{\min}$ of the signal. Then the average of two envelopes is obtained:

$$X_{\text{mid}} = \frac{(X_{\min} + X_{\max})}{2}. \tag{1}$$

After using the original signal and the average line signal to deal with the difference component, we have

$$H_1 = X_i - X_{\text{mid}}. \tag{2}$$

After getting the component, we first judge whether it is IMF. According to the two principles mentioned above, if the conditions are met, we define $C_{1i} = H_1$. Otherwise, the original sequence is replaced with H_1. The above operation is repeated until a satisfactory sequence function H_{1-k} is obtained, denoted as C_{1i}. The calculation will be stopped, when the following cutoff condition is met:

$$\text{sd} = \sum_{i=0}^{T} \frac{\left|H_{(1-k)i} - H_{(1-(k-1))i}\right|}{H^2_{(1-(k-1))i}}, \tag{3}$$

where sd is generally based on experience value of 0.2–0.3. When meeting the above requirements, we note $C_{1i} = H_{1-k}$.

The C_{1i} is stripped from the original sequence, X_i, and repeated for the rest of the sequence to obtain C_{2i}, and so on, to obtain C_{ji}. The residual sequence obtained by separating all the eigenfunctions from the original data sequence is defined as R_i. Overall expressed as

$$X_i = \sum_{j=1}^{k} C_{ji} + R_i. \tag{4}$$

For the EMD method, it is difficult to ensure that the local mean value limited by condition (2) is equal to zero during the screening process because of the complexity of the electrical signals collected by electromagnetic ultrasound. When the signal is abnormal, it will affect the signal envelope, and the IMF component, resulting in model aliasing, which may lead to the loss of the original physical meaning of the component.

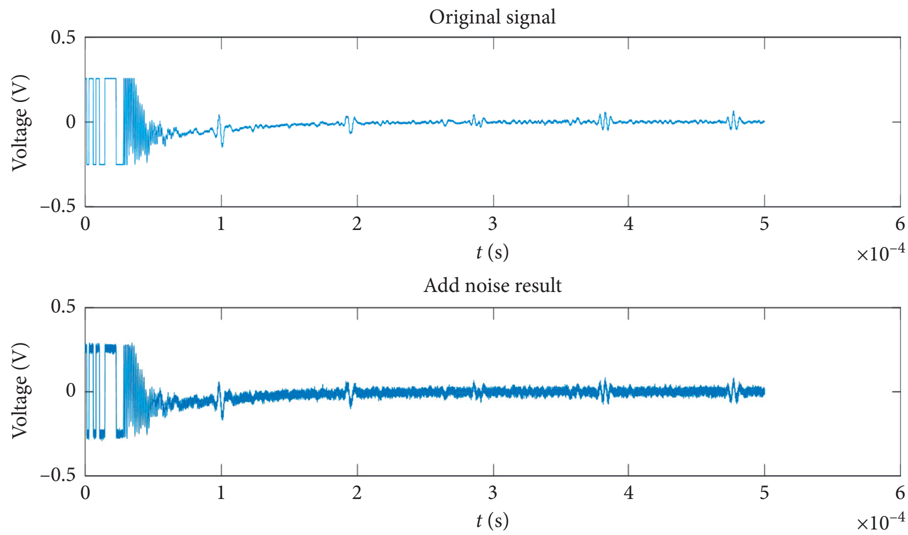

Figure 1: Adding noise to the original signal.

2.3. EEMD Denoising Method. The improvement proposed by Norden. E. Huang to the EMD method in solving the problem of model aliasing is called EEMD [7]. The steps of the EEMD method are as follows:

(1) Add a white noise sequence in the original signal.

(2) Get IMF components with EMD decomposition method.

(3) Repeat the above two steps, and the added white noise is different each time. When a signal is applied to a uniformly distributed white noise background, the signal regions at different scales are automatically mapped to the appropriate scales associated with the background white noise. The decomposed IMF components are shown in Figure 2.

(4) Integrate and average the IMF components obtained each time. Since the noise is different in each individual test, the noise will be removed when the overall mean at a sufficient number of tests is used. After that, the overall mean will eventually be considered as the true result. With more and more repetitions of the above steps, additional noise can be eliminated, and the only permanent part is the signal itself. The general EEMD decomposition flowchart is shown in Figure 3.

The traditional EEMD algorithm is based on the principle of noise-assisted signal processing; the mode aliasing phenomenon is effectively solved by adding a small amplitude of white noise to equalize the signal. The real signal is retained by using the zero-mean characteristic of Gaussian white noise, which is a great improvement to the traditional EMD analysis method.

But the disadvantage of the traditional EEMD method is that the added white noise can not be completely offset from each other in practical application, so the signal is still affected by noise to a certain extent. In the decomposed component, the high-frequency part contains a lot of noise, which is usually removed directly, and then the signal with a large correlation is reconstructed to get the denoised signal.

Because the high-frequency IMF component which is removed directly contains effective information, it will affect the original signal to some extent. In addition, the added white noise and the number of processing have a greater impact on the decomposition results, so that mode aliasing cannot be completely eliminated and may produce more useless components. Therefore, EEMD cannot adjust these decomposition parameters according to the actual situation, especially when the noise is changeable.

3. Abnormal Data Removed

Before the postprocessing of the data, some "damage data" of the data collected by electromagnetic ultrasound needs to be checked and removed. In this paper, the differential threshold method is used to distinguish the numerical changes between the sampling points of the collected data. When the absolute value of the difference between two adjacent points is greater than the set threshold, it is regarded as the wrong data and will be replaced. The principle of differential threshold method is as follows:

$$X_i = \begin{cases} \dfrac{x_{i-1} + x_{i+1}}{2}, & \left|x_i - x_{i-1}\right| > T, \\ x_i, & \left|x_i - x_{i-1}\right| < T, \end{cases} \tag{5}$$

where x_i is discrete data obtained after normalization, X_i is data obtained through algorithm detection and processing, and T is the selected differential threshold and is the maximum value of the difference between adjacent sampling points in the ideal signal.

When the data difference between two adjacent points is less than the selected threshold, the original data will

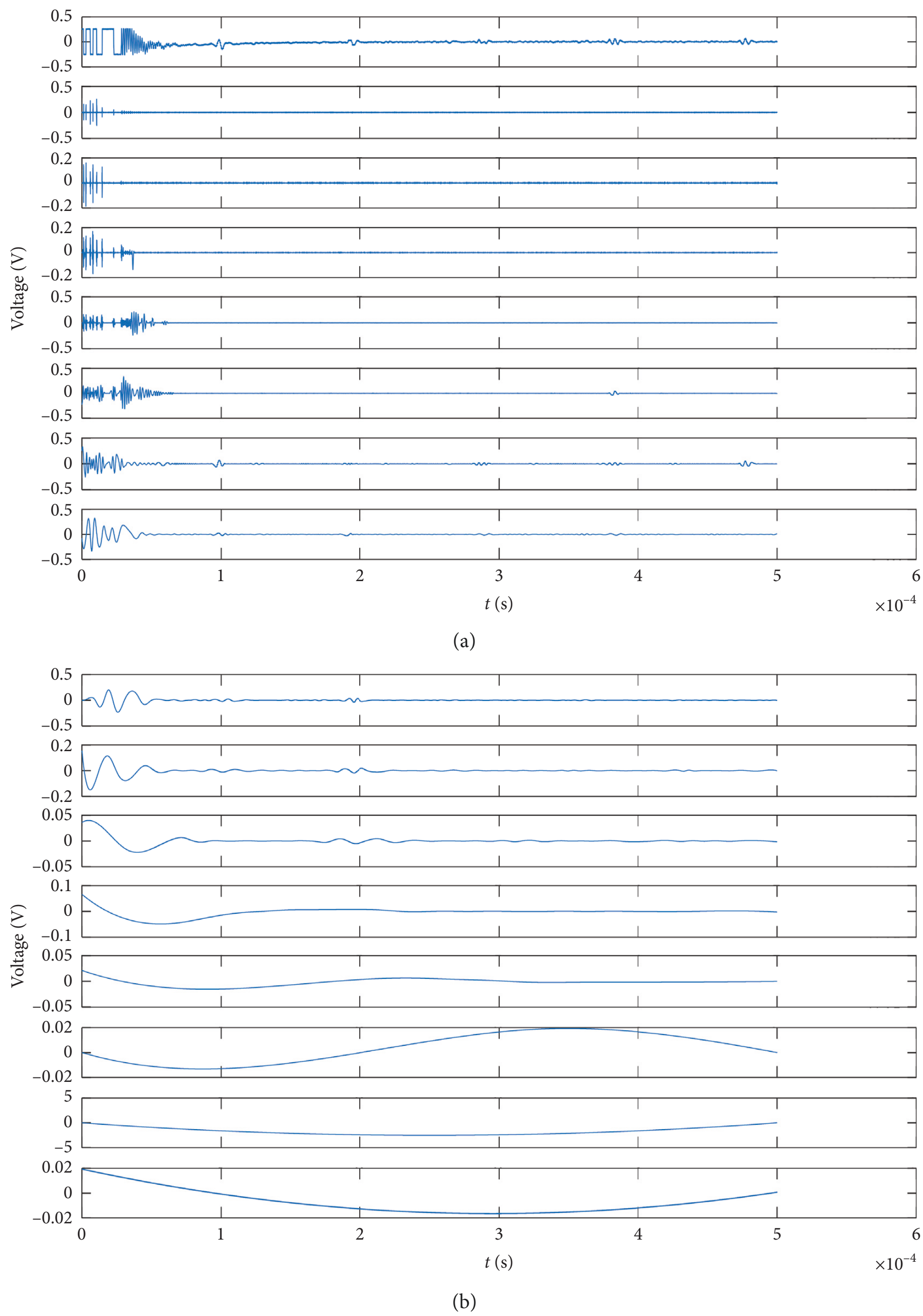

Figure 2: Decomposition results of EEMD method. (a) IMF 1–8. (b) IMF 9–16.

continue to be used. For the mutation data, the data of the two sample points before and after the mutation sample data can be used to supplement.

4. The Improved EEMD Method

In view of the lack of traditional EEMD in electromagnetic ultrasonic testing data processing, for the first time, a new denoising algorithm based on the improved EEMD method, which can adaptively adjust for added noise and integrated average times in different noisy environments, is proposed in this paper.

4.1. Permutation Entropy Algorithm. Permutation entropy [8] is an algorithm used to describe the complexity of time series signals. The algorithm is simple and efficient. What is more, it can be used to analyze the correlation of nonlinear and nonstationary complex signals. In this paper, it is used to identify the properties of the components obtained during the decomposition.

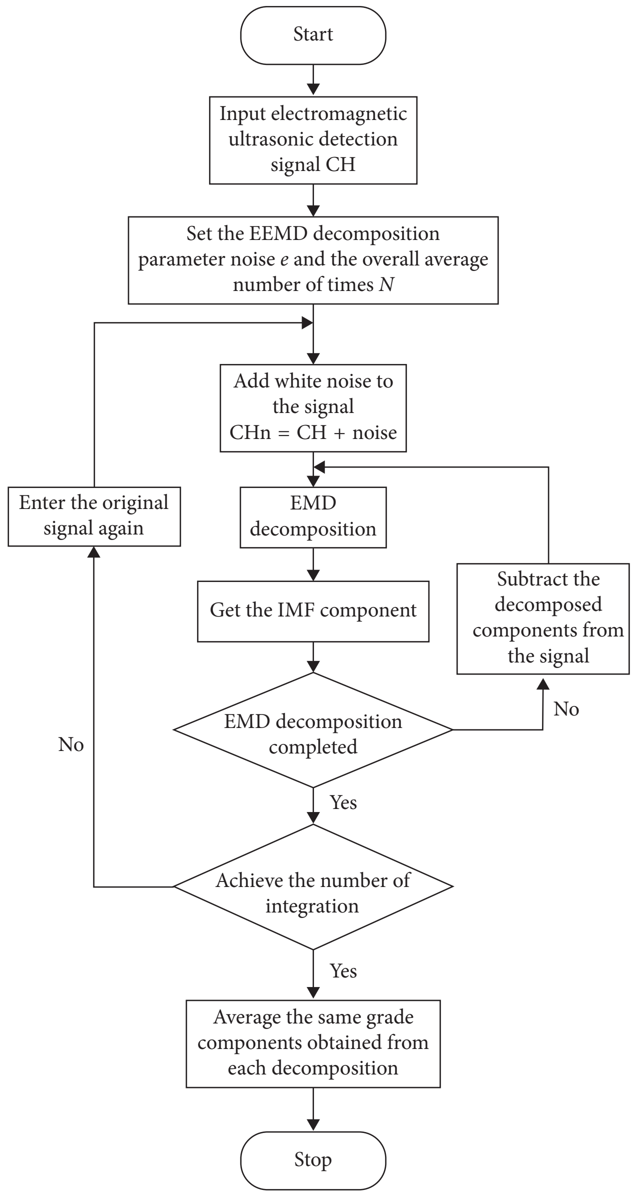

Figure 3: Processing flow of EEMD.

For a time series $S(i)$, the signal is first reconstructed to obtain the following:

$$\begin{bmatrix} s(1) & s(1+\tau) & \cdots & s(1+(n-1)\tau) \\ s(2) & s(2+\tau) & \cdots & s(2+(n-1)\tau) \\ \vdots & \vdots & \ddots & \vdots \\ s(N) & s(N+\tau) & \cdots & s(N+(n-1)\tau) \end{bmatrix}, \quad (6)$$

where τ is the delay time, n is the number of dimensions embedded, and N is the difference between the signal length and $(n-1)$.

The reconstructed data are sorted in the ascending order of magnitude. Then the position index of each element in the reconstruction component is labeled as $[j_1, j_2, \ldots, j_n]$, respectively. By this way, we get N sets of different labels such as $[j_1, j_2, \ldots, j_n]_{1,\ldots,N}$. According to the embedding dimension, the symbol sequence has a total of $m!$ kinds. The probability that we get each sequence of sequence numbers is $P_1, \ldots, P_N$. The form as defined by Shannon entropy is shown in Equation (7), and the normalized method is shown in Equation (8), so that the value of entropy is between 0 and 1:

$$H_p(m) = -\sum_{g=1}^{N} P_g \ln P_g, \quad (7)$$

$$H_p = \frac{H_p(m)}{\ln(m!)}. \quad (8)$$

After that, we process the simulation signal for the combined sequence of noise and related sinusoidal signals. According to relevant research experience, we set the parameters $\tau = 1$ and $n = 5$. The signal sequence s is as follows:

(i) $s(1)$: white noise with a signal sequence length of 98000 (with late detection data length)

(ii) $s(2)$: Gaussian random noise and random signal with signal sequence length of 98000

(iii) $s(3)$: mixing of random noise and white noise with a signal sequence length of 98000

(iv) $s(4)$: $\sin(2\pi \cdot 500 \cdot t)$, $t = 0 : 1/97999 : 1$

(v) $s(5)$: $\sin(2\pi \cdot 10 \cdot t)\sin(2\pi \cdot 100 \cdot t)$, $t = 0 : 1/97999 : 1$

(vi) $s(6)$: $[1 + \sin(2\pi \cdot 5 \cdot t)]\sin(2\pi \cdot 50 \cdot t^2 + 2\pi \cdot 10 \cdot t)$, $t = 0 : 1/97999 : 1$

The sequence is processed to obtain the permutation entropy values, which are 0.9897, 0.9722, 0.9815, 0.2443, 0.1159, and 0.2105. We can see that the entropy of the noise is large and irregular, while the entropy of the sinusoidal composite signal is low. We can set a threshold value of 0.58 to provide the parameter support for the improved follow-up study of the EEMD algorithm mentioned below.

4.2. Wavelet Transform Modulus Maxima. Wavelet transform is used to decompose the original signal into high-frequency part and low-frequency part. The low-frequency parameters are retained while the high-frequency part is decomposed again, followed by progress [9].

The modulo-maximum method is a typical method in the wavelet denoising method. Wavelet coefficients can reflect the transient characteristics of the original signal at different scales. Modular-maximum denoising based on wavelet transform is to process the modulus maxima of wavelet decomposition coefficients. Since the modulus maximum point of the signal will increase with the expansion of the scale, the noise maximum modulus point will be opposite, and the signal will be reconstructed from the modulus maxima at different scales by the processed wavelet coefficient, which is the basic idea of WTMM (wavelet transform modulus maxima).

Because of the complexity of the signal processing, the extreme point of the wavelet decomposition coefficient usually corresponds to the abrupt point of the signal, and the singularity of the signal corresponds to the variation rule of the modulus of the wavelet coefficients. Therefore, the paper incorporates the WTMM method into the EEMD denoising algorithm, and a new improved EEMD denoising algorithm is proposed. The following describes the specific implementation process.

4.3. Parameter Selection Criteria. The improved method first determines the principle of adding noise and the average number of times. Different from the traditional empirical judgment, through a considerable number of experimental studies, the specification of adding white noise in the EEMD method has been derived:

$$0 \leq \beta \leq \frac{\rho}{2}, \tag{9}$$

where β is the ratio of the standard deviation σ_{noise} of artificially added white noise to the standard deviation σ_{ch} of the original signal, and ρ is the ratio of the standard deviation σ_h of the high-frequency component of the signal to the standard deviation σ_{ch} of the original signal.

So, Equation (9) can be equivalent to Equation (10):

$$0 \leq \sigma_{\text{noise}} \leq \frac{\sigma_h}{2}. \tag{10}$$

In normal conditions, we choose $\sigma_{\text{noise}} = \sigma_h/4$, that $\beta = \rho/4$.

Another important parameter is the average number of times. Empirical studies have shown that the formula is chosen as shown in

$$e = \frac{\beta}{\sqrt{N}}, \tag{11}$$

where N is the average times, and e is the relative decomposition error, the general value is 1%.

According to the above formula, the average number of integration N is obtained as shown in the following equation:

$$N = \left(\frac{\beta}{e}\right)^2 = \left(\frac{\sigma_{\text{noise}}}{e \times \sigma_{\text{ch}}}\right)^2 = \left(\frac{\sigma_h}{4\sigma_{\text{ch}} \times e}\right)^2. \tag{12}$$

Obviously, the standard deviation of artificially added white noise and the average number of integration are all related to the ratio coefficient β.

4.4. Denoising with the Improved EEMD Method. The core of the improved algorithm is to adaptively adjust the added noise and the average times under different noise environments, so that the effect of the residual difference of white noise on the results can be eliminated as far as possible. Research shows that the white noise added to the high-frequency part of the EEMD method has negligible influence on the mode aliasing, while the white noise added to the low-frequency part has a greater influence factor, so the low-frequency part is directly decomposed by the EMD method to eliminate the influence of mode aliasing.

Firstly, we make improvements to the EEMD algorithm so that it can adaptively get the ratio coefficient. At the same time, it can minimize the useless residual difference caused by added white noise in the result. Secondly, aiming at the way to add white noise to the EEMD method, we use the permutation entropy algorithm to identify the nature of the components obtained during the decomposition. As for the remaining signal of the low-frequency stationary part, the EMD decomposition is directly used in the processing, while the others are continuously obtained by the EEMD decomposition, thereby reducing the influence of noise on the effective part. Afterwards, the wavelet transform modulus maximum denoising method is used to deal with the IMF components of the high-frequency part obtained before. Finally, the processed IMF results and residual difference are summed up. The results show that after processing, the noise content in the signal is less and the original information is more reserved, which prevents the signal distortion to a great extent and provides effective data for subsequent processing.

The flowchart of improvement is shown in Figure 4. The specific steps are as follows:

(1) First of all, the original signal is decomposed by the EMD method to obtain the eigenfunction group, and the first set of high-frequency IMF components in the decomposition result is recorded as the high-frequency component of the original signal. Then, the ratio of the standard deviation of the original signal and the high-frequency IMF components, combined with the previous formula, is used to find the value of β. In this way, we can find out the deviation standard of artificially added noise in the EEMD decomposition operation and the average integral times of this state.

(2) Firstly, the original signal is decomposed into IMF components by EEMD algorithm, and then, all IMF components are sequentially calculated by using the permutation entropy algorithm. If the entropy value is greater than the set threshold, the next component will continue to be calculated.

(3) The WTMM method is used to denoise the components whose entropy values are greater than the threshold. Then, the IMF components and the residuals of the high-frequency part can be obtained.

(4) These high-frequency components whose entropy values are greater than the threshold are removed from the original signal, the remaining part of the signal is decomposed by the EMD method to get the low-frequency partial IMF components.

(5) By summing the IMF components and the residuals obtained in the above two steps, the processed result is as shown in the following equation:

$$X(t) = \sum_{i=1}^{m} \mathrm{IMF}_i + p_i. \tag{13}$$

After calculation, the 2–5 in the IMF component diagram needs to be processed. Using the modulus maxima denoising method based on the wavelet transform, the IMF component image after processing is shown in Figure 5.

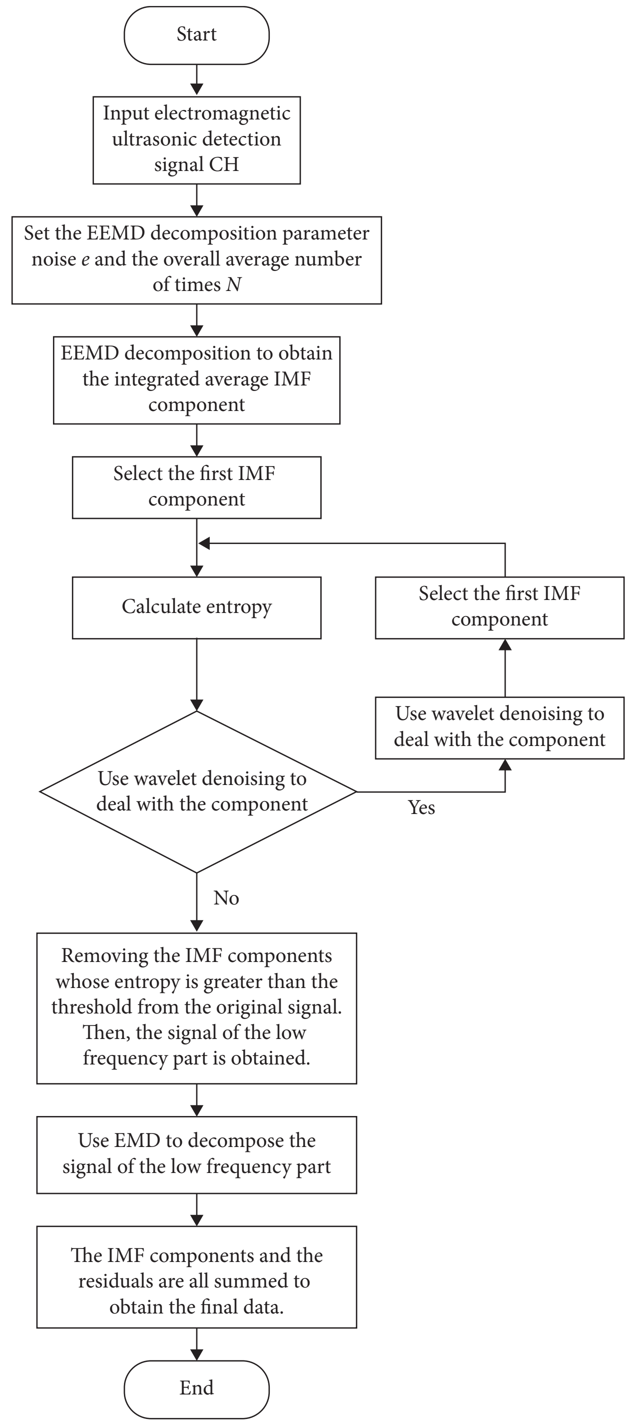

Figure 4: Improved method to handle flowchart.

4.5. Methods Comparison. In order to prove that the improved method is superior to the traditional EEMD method in the processing of electromagnetic ultrasonic detection signals and to verify that it has sufficient stability, the corresponding experiments have been carried out through simulation.

We used the ETG-100 ultrasonic thickness gauge to test three steel plates of the same material as X56 in the laboratory environment. Their length is 50 cm, the width is 30 cm, and the thickness is 12.37 mm, 13.35 mm, and 15.21 mm. Three sets of clean thickness echo signals are obtained.

In the first set of simulation experiments, the original signal is the clear thickness measurement data used in the previous section. The original signal is artificially added with noise and then denoised by the traditional EEMD method and the improved EEMD method, respectively. The comparison chart of denoising effect is shown in Figure 6.

The SNR (signal-noise ratio) of the original signal, the traditional EEMD method, and the improved EEMD method is calculated, which are shown in Table 1.

In the second and third sets of simulation experiments, the original signal uses different clean thickness echo data

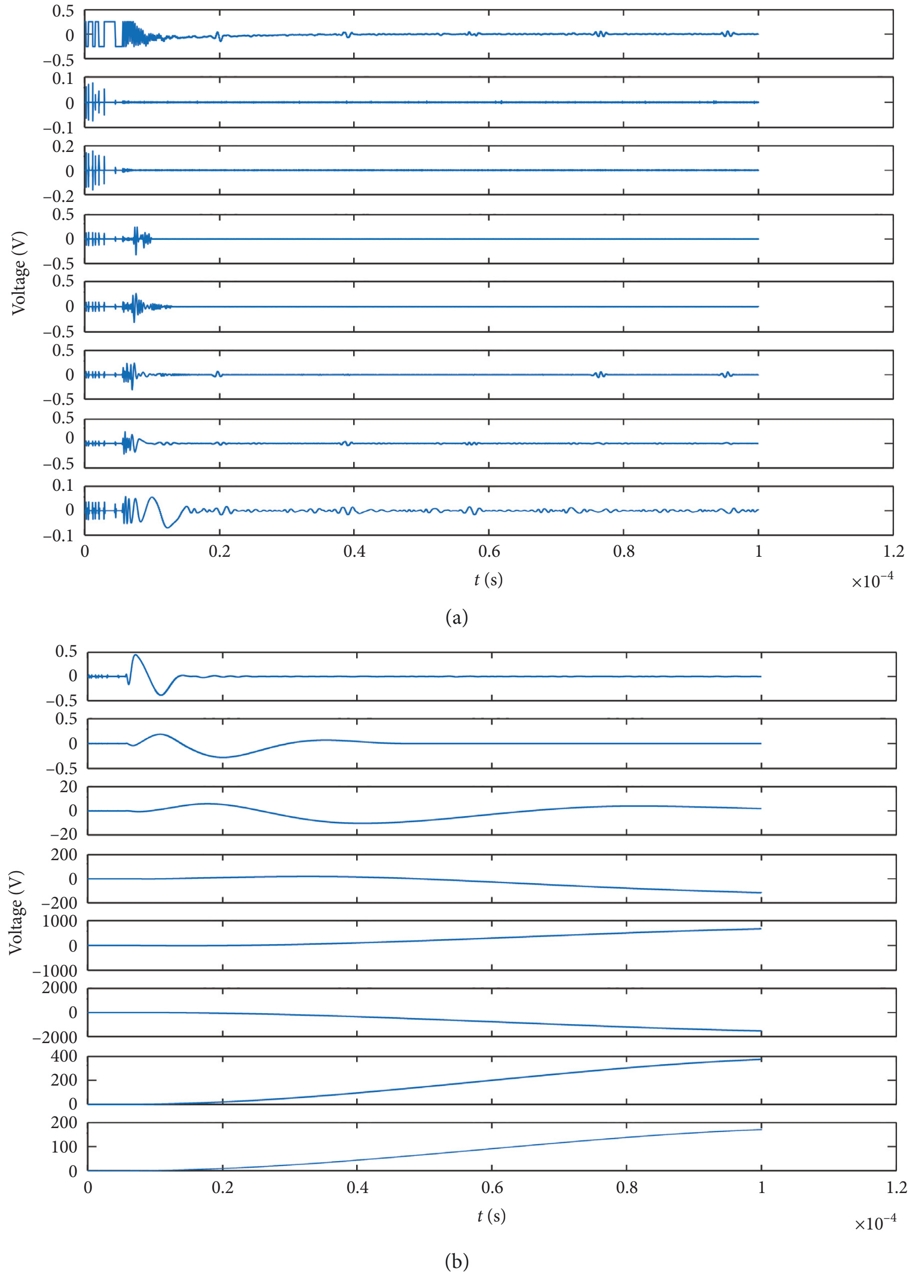

Figure 5: IMFs obtained by the improved method. (a) IMF 1–8. (b) IMF 9–16.

which are also artificially added with noise later, and the original signal is processed by the traditional EEMD method and the improved EEMD method, respectively. The SNR of the original signal, the traditional, and the improved EEMD method is presented below.

As can be seen from Tables 1 and 2, the SNR obtained by the improved method is closer to the original SNR. The improved method can not only solve the shortcomings of the EEMD method, but also get closer to the original data, so that the processed signal can better maintain the characteristics of the original signal. Therefore, the improved method is superior to the traditional EEMD method in the processing of electromagnetic ultrasonic detection signals, and it has sufficient stability.

5. Experiment

In order to verify the validity of the improved method, we used the EMAT2000 electromagnetic ultrasonic crack detector on Central Offshore Oil Pipeline Test Platform to test the crack defects at Tanggu, Tianjin. The actual metal spline crack depth of the pipe wall was 0.5 mm. The echo signals obtained from electromagnetic ultrasonic testing are processed by the traditional method and improved method, respectively. Then, the denoising effects of the two methods are compared.

The collected signal data are shown in Figure 7. Obviously, the collected data contain noise, so that it is also necessary to remove singular values and denoising.

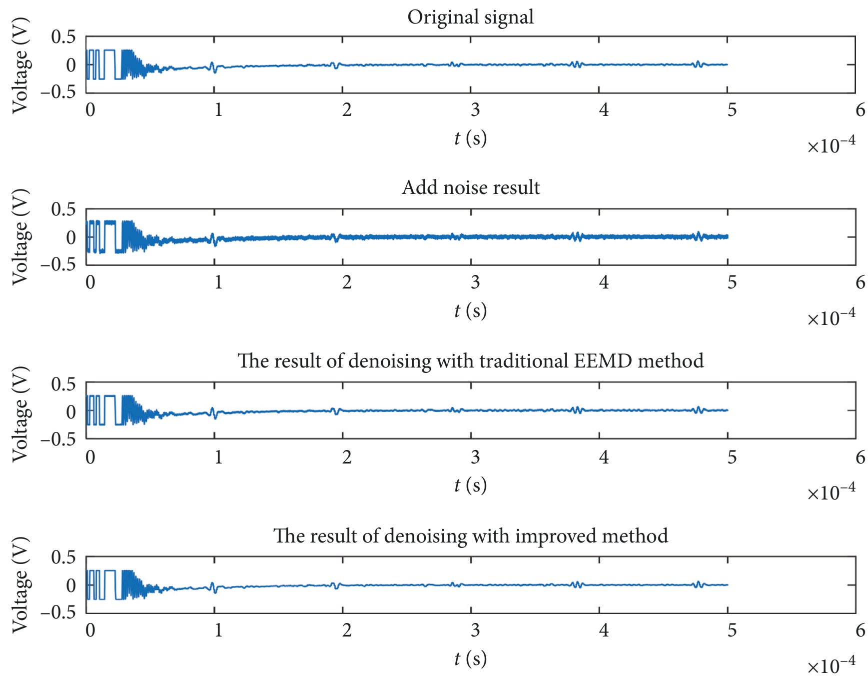

Figure 6: Denoising effect comparison chart.

Table1: Denoising effect comparison.

Method	The original signal-to-noise ratio	The traditional EEMD method	The improved EEMD method
SNR	11.53	10.12	11.15

Table 2: The other two sets of denoising effects comparison.

Method	The original signal-to-noise ratio	The traditional EEMD method	The improved EEMD method
SNR of the second set of experiments	11.78	11.23	11.59
SNR of the third set of experiments	10.45	9.68	10.23

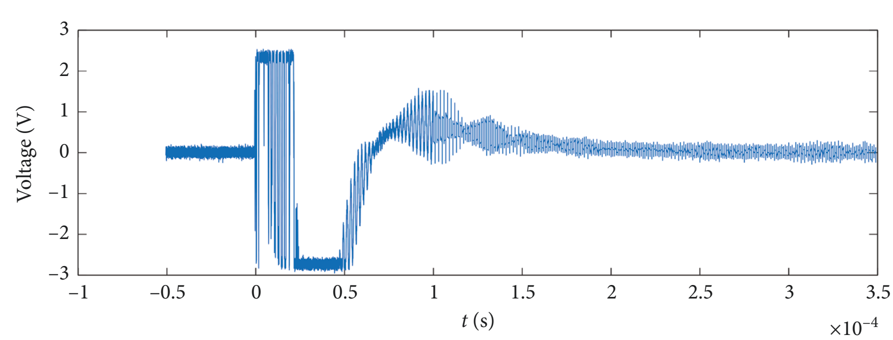

Figure 7: The original electrical signal of crack defects detected.

For the data collected from the crack defect, after eliminating the singular value of the data, the IMF components obtained by the traditional EEMD method are shown in Figure 8, and the IMF components obtained by the improved EEMD method are shown in Figure 9.

Finally, the IMF components and the residual difference are reassembled, and the comparison results of the traditional EEMD method and the improved EEMD method are shown in Figure 10.

As can be seen from Figure 10, the data obtained by the improved EEMD method are cleaner than those obtained by the traditional EEMD method. The valid region is partially enlarged to get Figure 11, from which the resulting echo signal from the EMAT (Electromagnetic Acoustic Transducer)

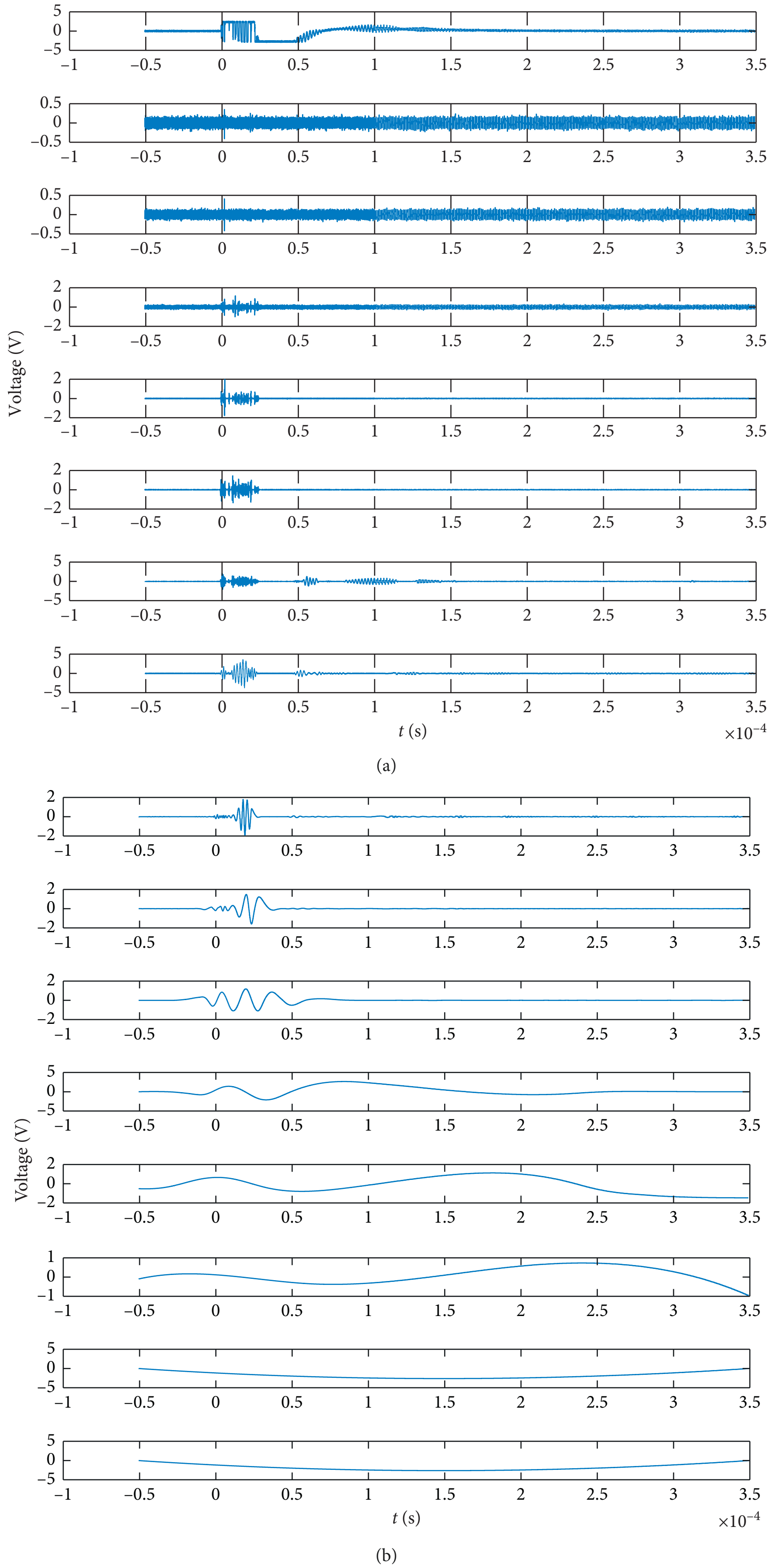

FIGURE 8: The IMF components obtained by the traditional EEMD method. (a) IMF 1–8. (b) IMF 9–16.

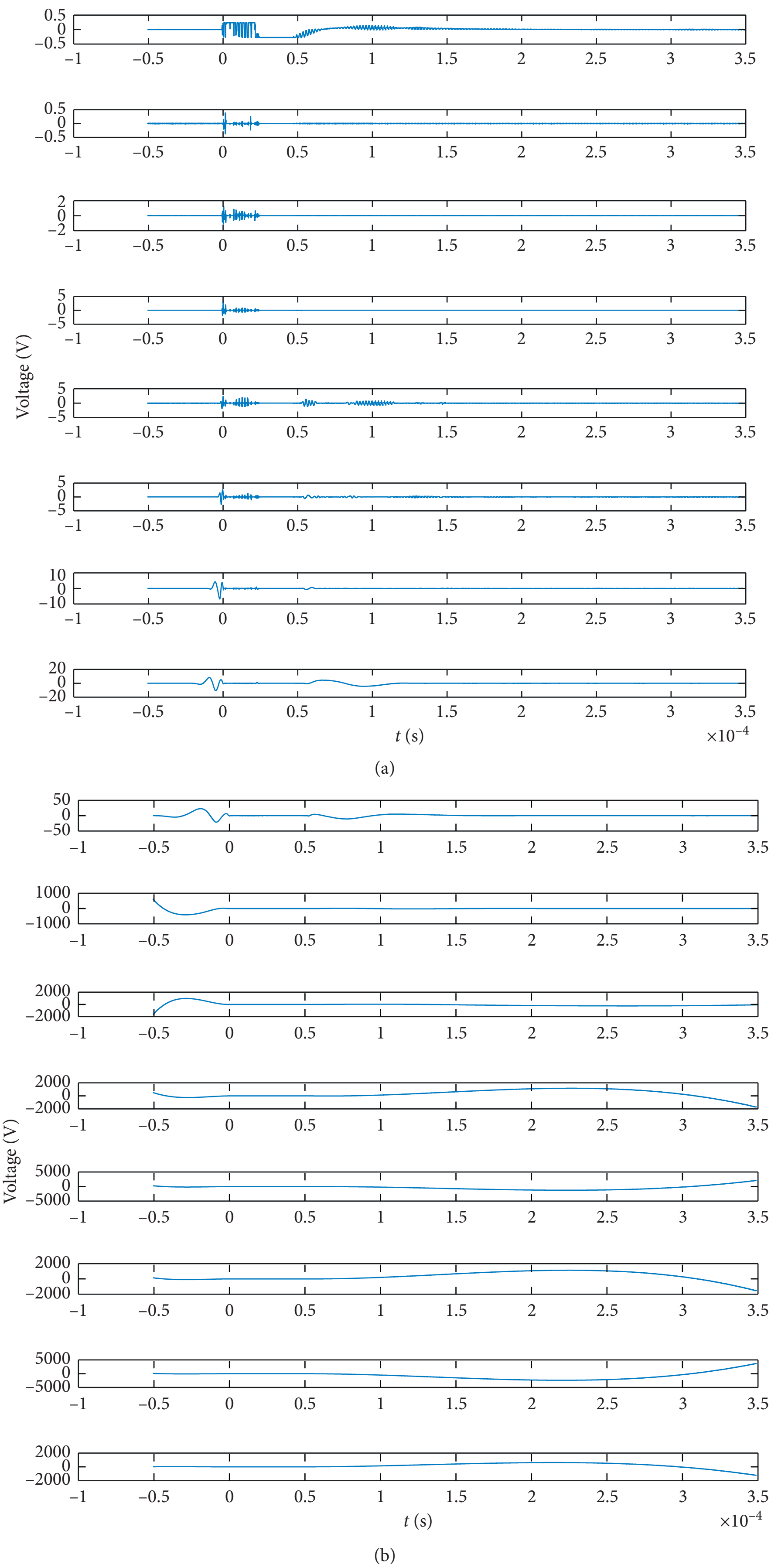

FIGURE 9: The IMF obtained by the improved EEMD method. (a) IMF 1–8. (b) IMF 9–16.

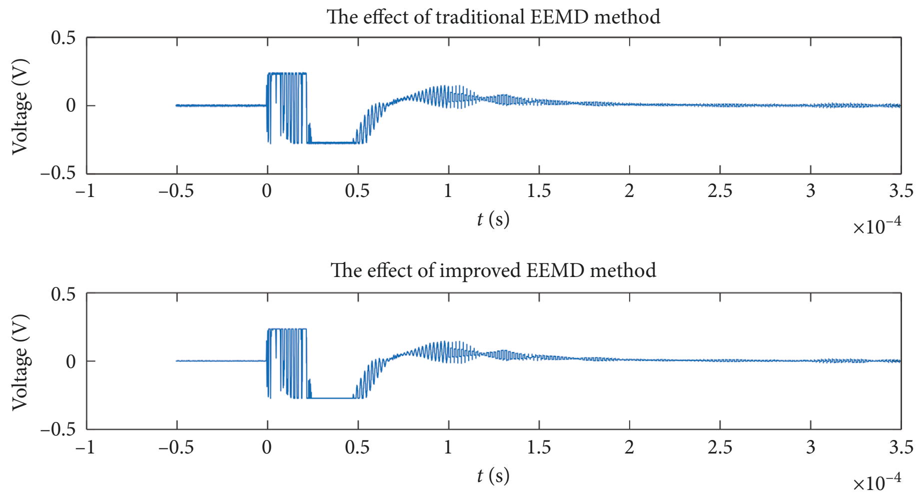

Figure 10: The comparison results of the two methods.

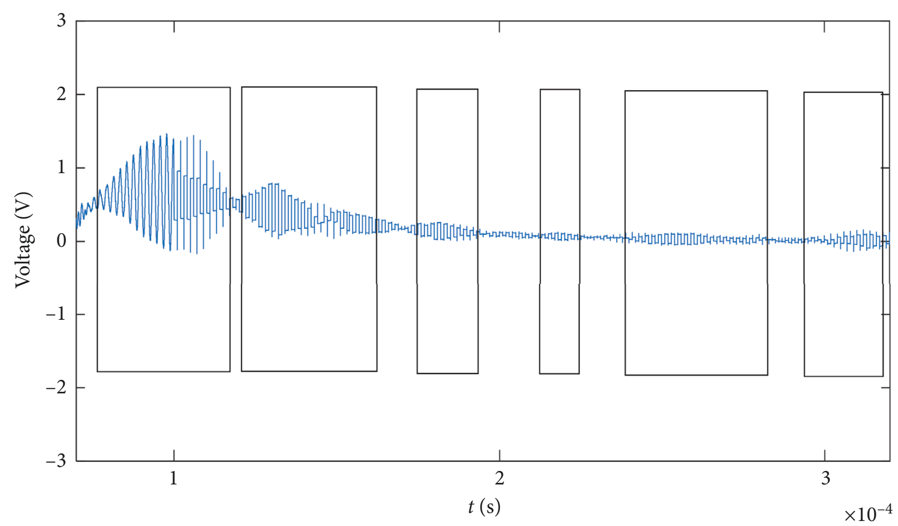

Figure 11: Effective signal denoising location.

receiver can be obtained. The interior of the black box is the received echo signal. Obviously, it can accurately reflect the effective information of the cracked position, and later, it can identify the location information of the defect according to the feature extraction method.

6. Conclusion

In this paper, a new denoising algorithm of electromagnetic ultrasonic testing signal based on the improved EEMD method is used to process the collected data. First of all, singular values in the data are removed. Then, aiming at the way that white noise is added to the EEMD method, the permutation entropy algorithm is used to identify the nature of the components obtained during the decomposition. Furthermore, the components of low-frequency signal are decomposed by EMD directly, while the components of other high-frequency IMF components are decomposed by EEMD. Afterwards, the wavelet transform modulus maximum denoising method is used to deal with the IMF components of the high-frequency part obtained before. Finally, the processed IMF results and residual difference are summed up. In the experiment, crack defect data collected by electromagnetic ultrasonic experiment system were processed by the improved EEMD denoising method. The results show the effectiveness and superiority of the proposed method.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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