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Bearing Acoustic Emission Signal Processing based on Improved SGMD

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Abstract: To solve the problems of poor adaptability to fixed thresholds and obvious endpoint effect in traditional Symplectic Geometric Mode Decomposition (SGMD), an improved SGMD (ISGMD) algorithm is proposed to improve the acoustic emission signal processing performance in bearing fault diagnosis. Firstly, a dynamic threshold adjustment model was constructed by fusing the signal Lyapunov exponent and the fractal dimension to realize the adaptive decomposition of signals of different complexity. Secondly, combined with the improved mirror extension and cosine smoothing technology, the endpoint effect is suppressed and the waveform distortion is avoided. Furthermore, the composite multi-scale dispersive entropy (CMSD) is introduced to screen the effective components, and the multi-scale entropy value is used to quantify the signal characteristics, eliminate the noise and reconstruct the components with high information order. Experiments show that ISGMD has excellent decomposition effect in noisy simulation signals, and the decomposition does not produce modal aliasing. In the actual bearing fault signal analysis, the reconstructed signal retains the outstanding peak characteristics, and the noise component is removed to a certain extent. This method significantly improves the robustness of signal decomposition and the ability to extract fault features, and provides an effective tool for the diagnosis of AE bearings under complex working conditions.

Keywords: Symplectic Geometric Mode Decomposition; Acoustic Emission; Signal Reconstruction; Entropy Theory; Bearing Fault Diagnosis.

1. Introduction

As the core component of large-scale rotating machinery, the operation status of rolling bearings is directly related to the economy and safety of industrial production systems. According to statistics, about 30% of rotating machinery failures originate from bearing failure, of which local damage to rolling elements, inner and outer rings and other components accounts for more than 60%. If such faults are not diagnosed in time, they can lead to equipment chain damage and even safety accidents. Therefore, the development of efficient bearing condition monitoring and fault diagnosis technology is of great engineering value [1-3].

Acoustic Emission (AE) technology [4] can sensitively detect early microcracks and local spalling of bearings by capturing the transient elastic waves generated by the release of stress waves inside the material, and has shown unique advantages in the field of bearing fault detection by virtue of its non-sensitivity to materials and strong environmental adaptability. However, acoustic emission signals are susceptible to environmental noise, mechanical friction noise and electromagnetic interference, and their nonlinearity and non-Gausterity make it difficult for traditional time-frequency analysis methods (such as Fourier transform and wavelet analysis) to effectively extract fault features. In addition, existing adaptive decomposition methods, such as Empirical Mode Decomposition (EMD), Local Mean Decomposition (LMD) and Variational Mode Decomposition (VMD), have problems such as modal aliasing, endpoint effects and parameter sensitivity, which limit their application under complex working conditions. The Symplectic Geometric Mode Decomposition (SGMD) proposed by scholar Pan Haiyang solves the eigenvalues of Hamilton matrices through the symplectic geometric similarity transformation, which effectively suppresses the modal confusion while maintaining the intrinsic characteristics of the sequence. Subsequent scholars have extended SGMD to the fields of gearbox fault current analysis [5], photovoltaic DC denoising [6], fault feature clustering extraction [7], and power load prediction [8]. However, the existing SGMD methods have obvious limitations: the decomposition quality depends on the preset similarity threshold, and the fixed parameters are difficult to adapt to signals of different complexity. At the same time, there is endpoint effect interference, which affects the reconstruction accuracy of AE signals.

In this study, an improved SGMD (ISGMD) method is proposed, which improves the adaptability of the algorithm to different signals by constructing an adaptive threshold mechanism, uses the mirror extension technology to eliminate the endpoint effect, and introduces the entropy theory for effective component screening and signal reconstruction.

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2. Theoretical Analysis

2.1. Symplectic Geometric Modal Decomposition Algorithm

2.1.1. Sub-section Headings

The core of Symplectic Geometric Mode Decomposition (SGMD) is to obtain the trajectory matrix $X_{m\times n}(m > n)$by reconstructing the phase space of the acquired signal. Then, the symplectic geometric similarity transformation is carried out to obtain the eigenvalues and eigenvectors under the symplectic geometric framework, and the corresponding eigenvectors are used to reconstruct the single-component signal. The process of the symplectic geometric modal decomposition algorithm can be divided into the following four stages:

(1) Phase space reconstruction

The phase space of the original sequence signal $x = x_1, x_2, \cdots, x_n$ (n represents the signal length) is reconstructed by the Tankens embedding theorem, and the trajectory matrix X of the sequence signal is constructed.

$$X = \begin{bmatrix} x_1 & x_{1+\tau} \cdots & x_{1+(d-1)\tau} \\ \vdots & \vdots \quad \vdots & \vdots \\ x_m & x_{m+\tau} \cdots & x_{m+(d-1)\tau} \end{bmatrix} \quad (1)$$

Among them, d is the embedding dimension, and its value is determined by the power spectral density (PSD) method: the maximum peak frequency of the PSD of the calculated signal is f_{max}, and d=n/3 is taken when the $F_s/f_{max}<10^{-3}$ is taken, otherwise d=$1.2F_s/f_{max}$is taken. The delay time τ is determined by an autocorrelation function.

(2) QR feature decomposition

After the trajectory matrix is constructed, the eigenvalues and eigenvectors are further solved by QR feature decomposition. Firstly, the covariance matrix $A=X^TX$ is constructed, and the Hamilton matrix is established:

$$M = \begin{bmatrix} A & 0 \\ 0 & -A^T \end{bmatrix} \quad (2)$$

Convert M to standard by symplectic geometric similarity transformation:

$$G^TWG = \begin{bmatrix} B & 0 \\ 0 & -B^T \end{bmatrix} \quad (3)$$

where $W = M^2$ is the upper triangular matrix, and its eigenvalues$\lambda_1,\ldots,\lambda d$ satisfy $\sigma_i = \sqrt{\lambda_i}$.

Subsequently, based on the eigenvector Q_i, the initial single-component Z_i is calculated:

$$Z_i = Q_i Q_i^T X^T \quad (4)$$

In this case, the reconstruction matrix Z is composed of the initial single-component reconstruction matrix Z_i group d: $Z = Z_1 + Z_2 + \cdots + Z_d$ that is, Z is a m*d reconstruction matrix.

(3) Diagonal averaging

After solving the reconstruction matrix Z, it needs to be converted into the required one-dimensional time series, so the diagonal averaging method is used. For the element Z in the matrix z_{ij} ($1 \leqslant i \leqslant m, 1 \leqslant j \leqslant d$), let $d^* = min(m, d)$, $m^* = max(m, d)$, $m = n - (d-1)\tau$. If m<d, let $z_{ij}^* = x_{ij}$, otherwise, $z_{ij}^* = x_{ji}$. Then, the one-dimensional time series $Y_i(y_1, y_2, \ldots, y_n)$ is solved by the formula:

$$y_k = \begin{cases} \frac{1}{k}\sum_{p=1}^{k} x_{p,k-p+1}^* \quad 1 < k \le d^* \\ \frac{1}{d^*}\sum_{p=1}^{d^*} x_{p,k-p+1}^* \quad d^* < k \le m^* \quad (7) \\ \frac{1}{n-k+1}\sum_{p=k-m^*+1}^{n-m^*+1} \quad m^* < k \le n \end{cases} \quad (5)$$

Based on the above formula, the Z_i is converted into a one-dimensional time series $Y_i(y_1, y_2, \ldots, y_n)$, which is denoted as a one-dimensional initial single-component signal (SGC), and the sum _i of these initial single-component signals is the original signal.

(4) Component reorganization

After the above operation, the initial single-component signal of group D is obtained. Some of these single-component signals have similar periodic characteristics and are not completely independent of each other, so it is necessary to set a fixed threshold θ for component reconstruction of the components of these similar features, and extract the noise components separately as several components to distinguish them from the active components. However, the fixed threshold cannot adapt to the complexity of different signals, and the signals acquired under different working conditions or at different times have significant differences in essential characteristics (such as nonlinear characteristics and waveform morphology). Improvements are made below.

2.2. Improve SGMD Algorithm

(1) Dynamic threshold adaptive mechanism

The dynamic threshold adjustment strategy using nonlinear feature fusion is improved, and the feature evaluation system is constructed by Lyapunov exponent and fractal dimension, so as to better capture the internal structure of the signal under different working conditions, improve the reconstruction quality and enhance the follow-up diagnosis effect. The specific principles and operations are as follows:

Lyapunov Index: quantifies the chaotic properties of a signal, calculated as:

$$\lambda = \lim_{t\to\infty} \frac{1}{t} \ln \left| \frac{\delta x(t)}{\delta x(0)} \right| \quad (6)$$

where δx(t) represents the small perturbation between the initial state of the system and the corresponding trajectory. The higher the exponential value, the more significant the chaotic nature of the system.

Fractal dimension: The complexity of the signal structure is measured based on the box counting method, and the calculation formula is as follows:

$$D = \lim_{\epsilon\to 0} \frac{\ln N(\epsilon)}{-\ln \epsilon} \quad (7)$$

where N(ε) denotes the number of boxes of the signal at scale ε. The signal complexity is quantified based on the box counting method, and the complexity of the signal structure is improved with the increase of the dimension value.

Dynamic Threshold Generation Model: According to the Lyapunov exponent and fractal dimension of each signal, the threshold θ _d of each signal is dynamically adjusted as follows:

$$\theta_d = \theta_{base}.(1 + \alpha \cdot \lambda) \cdot (1 + \beta \cdot D) \quad (8)$$

where θ_{base} is the initial threshold. α. β is the adjustment coefficient, when the signal presents strong chaos (λ ↑) or high complexity (D ↑), the threshold θ_d is automatically reduced to enhance the decomposition sensitivity, so as to ensure that the signal can obtain the optimal component reorganization effect under different working conditions.

(2) Improve image extension

The essence of the image extension method is to symmetrically extend the original signal into a closed ring signal, which fundamentally avoids the endpoint effect [9], but it is easy to introduce distortion in asymmetric signals. A three-stage optimization scheme is proposed:

1. Bidirectional extension: bidirectional image expansion of the original signal x(t) generates x'(t), forms a ring structure to eliminate the endpoints;

2. Waveform symmetry correction: the time-domain flipping process is carried out on the extension section to

eliminate the sudden trend change;

3. Cosine smoothing: The ascending cosine function is used to weighted the fusion extension section:

$$x_l(t) = \omega(t)x(t) + [1 - \omega(t)]x'(t) \tag{9}$$

As shown in Figure 1, a comparison between the normal image extension and the improved image extension, it can be seen that the smooth transition at the endpoint connection does not produce deformities.

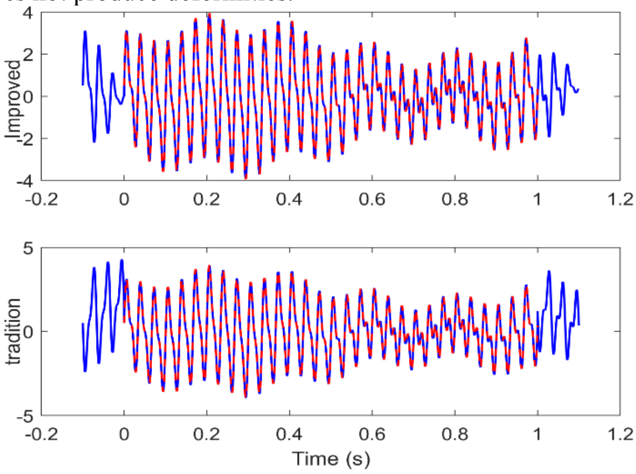
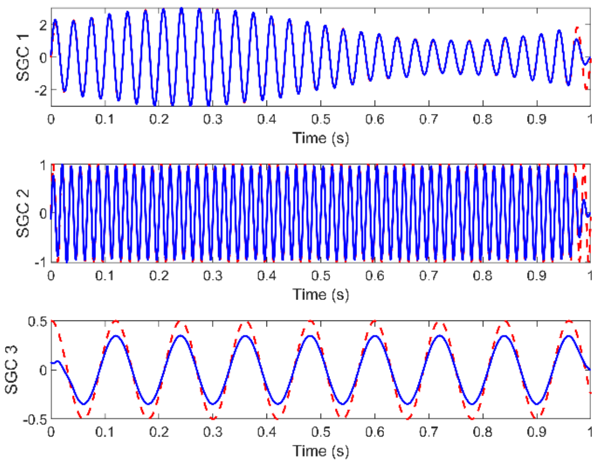
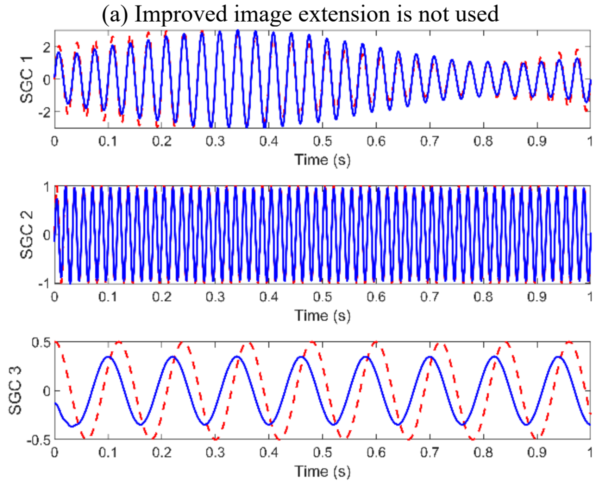


Figure 1. Comparison of image extensions

Figure 2 shows the original signal decomposed using SGMD and the signal processed using improved image extension.



(a) Improved image extension is not used



(b) Improve image extension

Figure 2. Break down the contrasts

It can be seen that the component endpoint effect of the decomposition after image extension is significantly improved, which improves the robustness of the decomposition algorithm, which is helpful to retain the key features of the signal in the subsequent actual signal decomposition process, and also provides reliability for subsequent reconstruction and analysis. It is worth noting that the waveform of the two decomposition components of the same signal is not synchronized, which is caused by the change of the length of the decomposition signal under the image extension, and does not change the frequency and other characteristics of the signal, which does not affect the results.

2.3. Signal Reconstruction

According to the entropy value theory, the Composite Multiscale Entropy (CMSD) is used to capture the multi-level changes of the signal through the multi-scale entropy value, deal with the transient changes or prominent peaks in the signal components, and select the effective components.

As an entropy measurement method based on signal multiscale analysis, compound multi-scale dispersion entropy aims to measure the complexity and uncertainty of signals at different scales. Capturing the multi-level changes of the signal from a multi-scale perspective has the advantage of interpreting the local and global characteristics of the signal at different scales, and is more effective for the non-stationary signal of the acoustic emission signal.

(1) Dispersion entropy calculation:

The phase space of the component signal x(t) is reconstructed to generate an embedding matrix:

$$X_m = [x(t), x(t+1), \dots, x(t+m-1)] \tag{10}$$

(2) Calculate the window divergence value:

Divergence measurements are performed on the embedding matrix to calculate the divergence within each window:

$$\mathrm{d}(t) = \frac{1}{a}\sum_{t=1}^{a} \|X_m(t) - X_m(t+k)\|^2 \tag{11}$$

where a=N-m+1.

(3) Calculate the entropy value by probability distribution:

$$H_s = -\sum_{i=1}^{N-m+1} p_i \log p_i \tag{12}$$

where p_i is the probability of each divergence value.

(4) Multi-scale fusion:

The dispersion entropy is calculated in the range of scale s=1 to s, and the composite entropy value is weighted to be generated:

$$H_E = \frac{1}{S}\sum_{s=1}^{S} H_s \tag{13}$$

(5) Threshold screening:

Calculate the mean entropy of all components Threshold as the baseline threshold:

$$\text{Threshold} = \frac{\sum_{i=1}^{n} H_{Ei}}{n} \tag{14}$$

According to the entropy theory [10]: the smaller the entropy, the lower the uncertainty of the system and the more information it contains, that is, the smaller the entropy value, the more "useful" or "orderly" the information in the system can better help understand or predict the characteristics of the system. Therefore, the benchmark threshold is taken as the filter condition, and the components that meet the $H_{E_i} < Threshold$ are retained (low entropy value represents high information ordering), and the high entropy noise component is eliminated.

3. Experimental Analysis

In order to verify the effectiveness and robustness of the improved SGMD (ISGMD) algorithm, experimental analysis of simulated signals and actual bearing signals is carried out. The experimental part aims to compare the performance of ISGMD with traditional empirical mode decomposition (EMD) and variational mode decomposition (VMD) algorithms, especially in dealing with noisy signals and complex fault modes.

3.1. Analysis of Noisy Simulated Signals

The decomposition effect and noise robustness of the improved algorithm ISGMD were verified, and the simulated signal analysis was carried out, and the experimental part was aimed at comparing the performance of ISGMD with the traditional empirical mode decomposition (EMD) and variational mode decomposition (VMD) algorithms.

Construct the following simulation signal:

$$\begin{cases} x_1(t) = 2\sin(60\pi t) \times (1 + 0.5\sin(2\pi t)) \\ x_2(t) = \sin(12\pi t) \\ x_3(t) = 0.5\cos(10\pi t) \\ x(t) = x_1(t) + x_2(t) + x_3(t) \end{cases} \tag{15}$$

Add a noise n(t) with a signal-to-noise ratio of 20dB to x(t), and the noise simulation signal is as follows:

$$x(t) = x_1(t) + x_2(t) + x_3(t) + n(t) \tag{16}$$

The decomposition was carried out by ISGMD, and the EMD decomposition and VMD decomposition were used for comparison, and the decomposition results are shown in Figure 3, Figure 4, and Figure 5.

For better observation, only the first three components of the decomposition are shown in the SGMD exploded view, and the residual components are not shown. In the face of noisy signals, SGMD can still be effectively decomposed, and the first three components of the separation are basically the same as the components of the original signal. Observing the frequency domain diagram, it is found that there is no modal aliasing for each component. It shows that the SGMD decomposition algorithm does not produce modal aliasing during the decomposition process, and has good noise robustness.

Observing EMD, it can be seen that the decomposition effect is not ideal, and many false components are generated, and the decomposed components are not similar to the original signal components, and the observation of the frequency domain can be seen that the modal aliasing is serious. Therefore, the EMD decomposition algorithm is not noise robust and cannot suppress modal aliasing.

Observing the decomposition effect of VMD, it can be seen that the first two components of the decomposition are roughly similar to the first two components of the original signal when the decomposition parameter is set to 4, but there are also deviations, while the third component is not decomposed. At the same time, the frequency domain was observed, and it was found that the first component was mixed with the components of the third component, and the second component was not mixed with the other components. Therefore, the VMD decomposition algorithm is not very ideal in the decomposition of simulated signals containing noise, and the decomposition effect is not as good as ISGMD, and it also does not have the effect of noise robustness and suppressing modal aliasing.

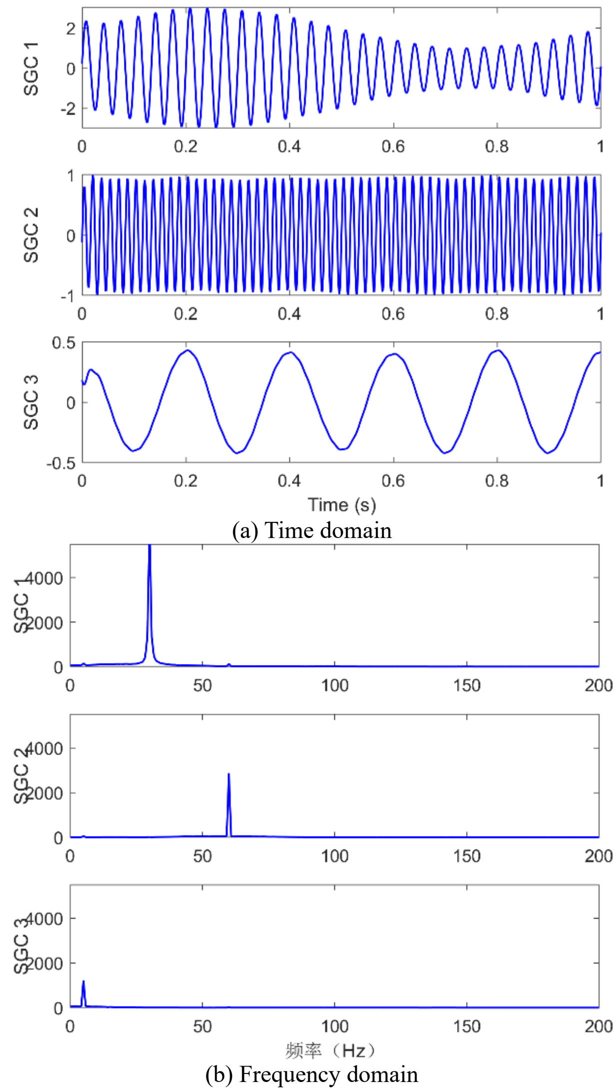


Figure 3. ISGMD decomposition results

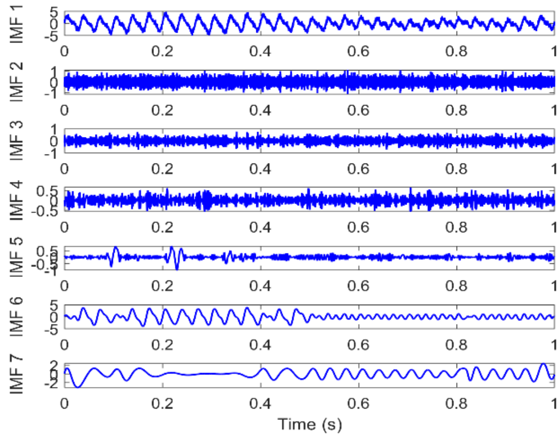
3.2. Actual Signal Analysis

The simulation signal decomposition with noise proves that the ISGMD algorithm has the robustness of suppressing modal aliasing and noise, and the actual signal decomposition analysis is carried out below. As shown in Figure 6, the acoustic emission signal in the healthy state of the rolling bearing in the actual engineering - the fault signal of the inner ring of the acoustic emission can be observed, and the characteristic part is not obvious, and there is a large amount of noise to cover the real signal.

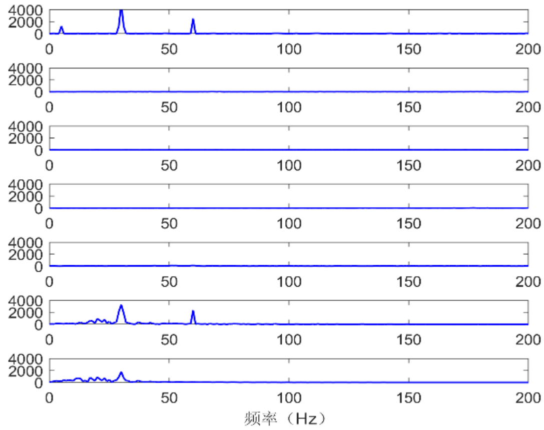
Observing the components of the decomposition, it can be seen that:

1. Each component shows different amplitude and frequency changes, and the waveform of some components has strong periodic or abrupt characteristics, which indicates that decomposition can effectively distinguish different signal components.

2. From the third component onwards, the amplitude of the subsequent components is relatively small, meaning that they contain less energy or are just a fraction of the components in the original signal, representing noisy or irrelevant parts. Some components, such as SGC1, show large fluctuations and represent the main components of the signal.

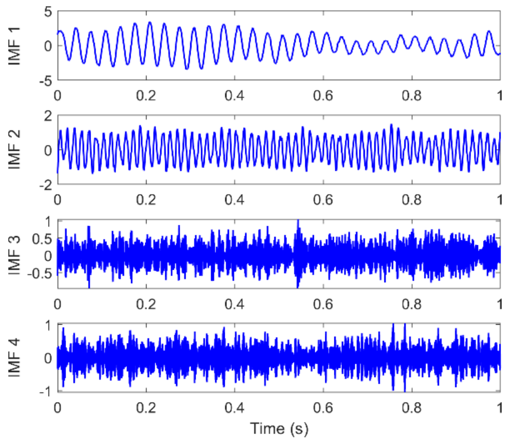


(a) Time domain

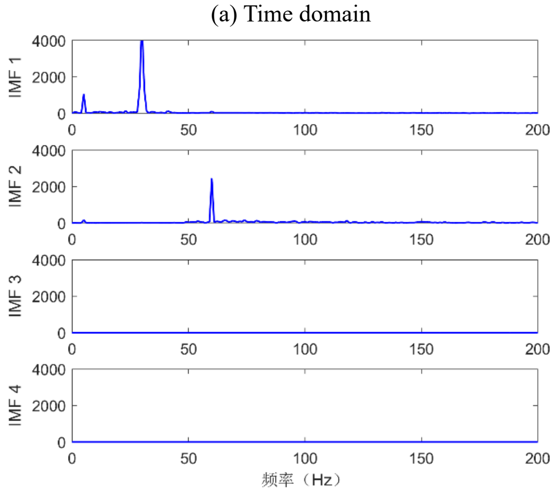


(b) Frequency domain

Figure 4. EMD decomposition results



(a) Time domain



(b) Frequency domain

Figure 5. VMD decomposition results

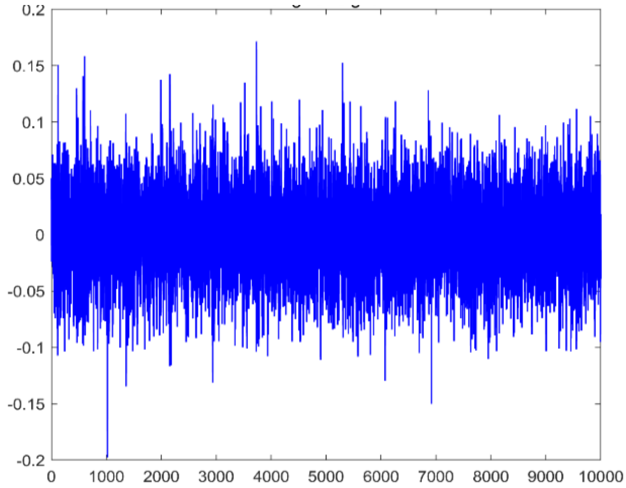


Figure 6. Acoustic emission inner ring fault signal

The signal is broken down below. The components decomposed by ISGMD are shown in Figure 7, and only the first six components are shown for ease of display.

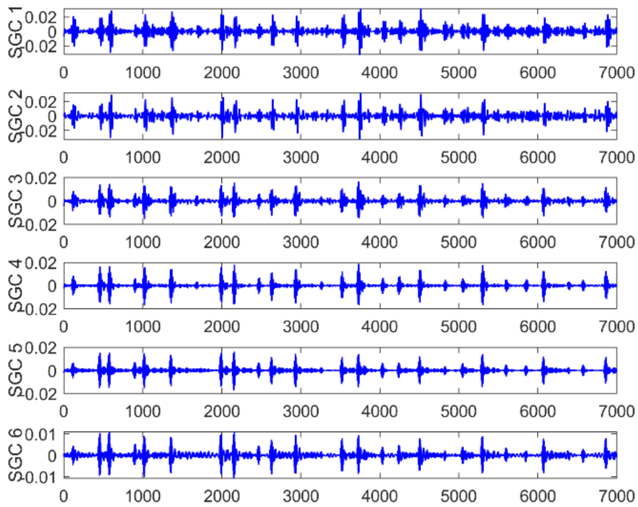


Figure 7. ISGMD decomposition results

3. As can be seen from the figure, although there is a large difference between the components, they can show a certain regularity in the time domain, which shows that the ISGMD decomposition effect is very good, and different features are extracted through reasonable decomposition, which correspond to the important dynamic changes in the bearing signal.

These characteristics show the effectiveness of the ISGMD decomposition algorithm and the advantages of the AE signal: it can extract components with different characteristics from the AE signal, and these components can correspond to the specific failure modes or characteristic frequencies in the signal, which can provide help for subsequent signal analysis and component reconstruction.

Then, the composite multi-scale dispersive entropy is used to reconstruct the components, and the reconstructed signal is shown in Figure 8.

By observing the reconstructed signals, it can be seen that the two types of reconstructed signals retain outstanding peak characteristics, and their mean square error and root mean square error are very small, indicating that the quality of the reconstructed signal is good, and the noise component is removed to a certain extent. Among them, the decrease in the amplitude at some peaks compared to the original signal is caused by the amplitude of the removed noise, which is a normal situation.

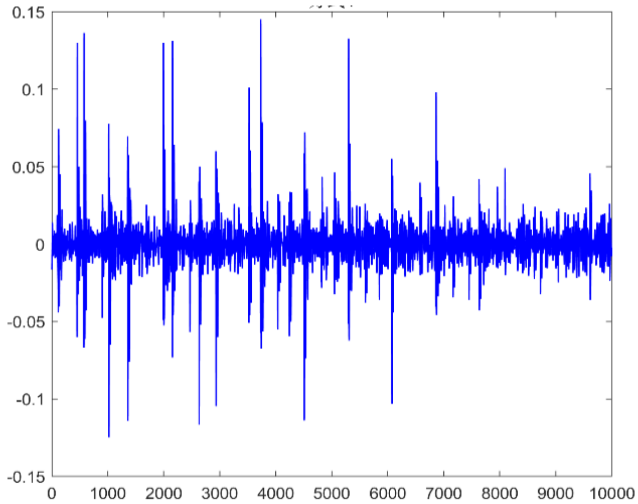
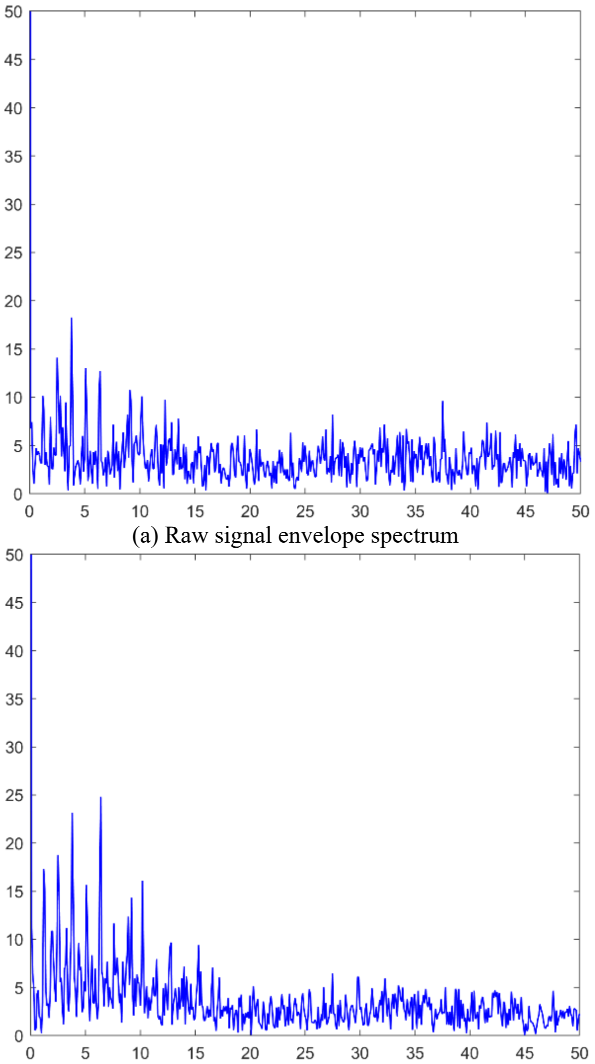


Figure 8. Reconstruct the signal

Then, the envelope spectrum transformation of the reconstructed signal and the original signal is performed, as shown in Figure 9.


(a) Raw signal envelope spectrum
(b)Reconstruct the signal envelope spectrum
Figure 9. Comparison of envelope spectrum

Observing the reconstructed envelope spectrum, it can be seen that the fault energy is mainly concentrated in the low frequency range, which is consistent with the fault energy concentration area of the inner ring fault, and it can be seen that the energy is enhanced and highlighted, indicating that the reconstruction signal reduces the noise component and highlights the fault pulse.

4. Conclusion

The symplectic geometric mode decomposition algorithm is improved, and the SGMD can be appropriately decomposed according to the characteristics of different signals through adaptive threshold adjustment. At the same time, the improved mirror extension method is used to effectively suppress the endpoint effect of the components. Experiments have proved that the ISGMD algorithm is effective and noise robust.

According to the entropy value theory, the multi-scale dispersion entropy is used to select the effective components to reconstruct the signal, and through the observation of multiple scales and the selection of the retained signal components, the prominent peak characteristics are retained, and the noise component is removed to a certain extent. Through experiments, the effectiveness of the reconstruction method is proved.

The improved symplectic geometric mode decomposition provides a technical basis for real-time monitoring of industrial sites, and provides a possibility for the subsequent exploration of the deep integration of the algorithm with other deep learning models to further improve the generalized diagnosis ability of complex failure modes.

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