Research Article

Bearing Fault Vibration Signal Feature Extraction and Recognition Method Based on EEMD Superresolution Sparse Decomposition

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1. Introduction

At present, the detection and analysis methods and methods for abnormal vibration signals of mechanical equipment have been widely used in the troubleshooting and early warning of equipment. Through long-term and massive monitoring and sample analysis, it is known that the random transformation of abnormal vibration signals presents a certain degree of complexity, characteristic, high-dimensionality, strong nonlinearity, strong coupling, and unsteady state [1]. The abnormal vibration signal is a typical nonlinear and nonsteady random signal. The law of its occurrence and development has great uncertainty, and the postprocessing cost of the signal is high, and the accuracy and stability of the processing cannot be achieved. It satisfies the actual needs very well; while the current conventional vibration signal processing methods are greatly affected by environmental factors at the level of improving the signal-to-noise ratio, feature extraction and intelligent identification methods and the filtering and noise reduction effects are not good. To achieve many problems such as the feature location and extraction under specific conditions and the lack of advancement of intelligent identification methods [2], this article intends to improve the processing method for abnormal vibration signals of mechanical equipment and verify the feasibility of the proposed method through experiments, with certain theoretical significance and application value.

Most of the time, the equipment working under severe working conditions is in the environment of high load, nonlinearity, strong magnetic field, strong vibration, high temperature, and high humidity, due to factors such as nonuniform speed, nonlinear load changes, etc. Vibration waves formed by impact and friction are random and nonrepeatable. The reason is that gear wear will affect the asperity contact and increase the friction, and its generated
sliding vibration is a random signal. This kind of signal is ‘random and nonrepeatable’ [3–5]; field practice and a large number of tests reflect that there are significant differences in waveform changes due to abnormal vibration caused by faults under different conditions: one is in vibration. The change in amplitude is complicated. Second, the frequency and duration of the wave also show obvious differences with the characteristics of the fault source, mechanical structure, location, and medium [6, 7].

In particular, healthy and faulty components experience repetitive collisions in the process of faulty bearing operation. Therefore, the extraction of repetitive transient characteristics caused by bearing faults is one of the most important steps of bearing fault diagnosis. However, the difficulty it faces is that the collected bearing vibration information is usually multicomponent, and it is surrounded by intensive and complex noise from the internal and external environment [8–10], so the repeated transients related to bearing faults that can be collected are often very weak. Especially in the early stage, it will be covered and polluted by the surrounding random mechanical noise, abnormal pulse, gear meshing, and other vibrations [11–13].

As a wide-band wave, the vibration shock wave passes through the filtering effect of the medium, so that, in the process of propagation, the closer to the shock source, the more high-frequency components, and as the wave propagates from near to far, it diverges. The medium and high-frequency components are gradually weakened, while the low frequency can be transmitted to a far distance to be acquired by the sensor [14]. This kind of vibration wave mainly contains one or several main frequency components. This article mainly analyzes the vibration wave frequency in the low-frequency band. The frequency of the low-frequency signal is mainly in the range of 0 ~ 1000 Hz. If it is close to the natural frequency of a certain part of the mechanical equipment, resonance occurs, which increases the damage to the internal structure.

Wang et al. [15] proposed an adaptive spectral pattern extraction method in this paper, which mainly consists of three parts: spectral segmentation, mode extraction, and feedback adjustment. A fault feature mapping method is proposed in the part of spectrum segmentation, and the overdecomposition problem is solved in the variational mode decomposition guided by classical scale space. A method of spectral aggregation factor is proposed in the mode extraction part, and the fusion problem of multiple penalty factors conforming to different intrinsic mode functions is solved. In the feedback adjustment part, the transboundary criterion method is proposed to make the result become a variational model, which is more conducive to the extraction of rolling bearing fault features. Wang et al. [16] proposed an optimization strategy of CYCBD parameters and then proposed an adaptive maximum cyclostationarity blind deconvolution (ACYCBD). Firstly, a cyclic frequency set estimation method based on morphological envelope autocorrelation function is proposed to determine the cyclic frequency, and the method is proved to be effective by simulation and experiments. Secondly, based on the comprehensive consideration of system performance and time cost, the performance efficiency ratio index is put forward. Thirdly, the filter length is adaptively selected by adopting an equal-step search strategy and the method is further confirmed to be effective through simulation and experiments. The method proposed by Levent et al. [17] extracted features from the original vibration signals and acoustic signals and used the network based on 1D-CNN for fusion. The performance of the proposed method is evaluated by a large number of experimental results on 10 groups of bearings. Through the analysis of the loss function and accuracy rate under different signal-to-noise ratios, it is proved that the method has higher diagnostic accuracy rate than the traditional algorithm based on single-mode sensor. Subsequent visualization analysis is also performed to deeply explore the intrinsic mechanism of the 1D-CNN-based method.

Wang and Qing [18] proposed that the system directly uses the original time series sensor data as input, and the optimal features can be effectively learned through appropriate training based on 1D-CNN method. The main advantages of this method are as follows: (1) the architecture is compact, only 1D convolution is performed, and it is suitable for real-time mechanical fault monitoring; (2) the cost-effectiveness is controllable and the hardware real-time performance is good; (3) without any predetermined transformation (such as FFT or DWT) and artificial feature extraction, it has strong ability of adaptive feature selection; (4) it can provide effective classifier training ability under limited training data sets and limited BP iterations. This method is applied to two commonly used benchmark real vibration data sets and compared with other traditional intelligent fault diagnosis methods, which verifies the effectiveness, feasibility, and practical value of this method.

This article uses multiparameter, distributed online detection and corresponding signal analysis and processing methods for the large load and limit speed conditions of the rotating machinery system, so as to avoid adverse effects that come from sensor noise, signal disturbance, or instrument performance degradation while obtaining effective information [19]. Feature extraction methods based on numerical optimization calculations and artificial intelligence, such as self-associative memory neural networks, provide a good theoretical support for the fault diagnosis and decision-making of rotating machinery [20]; Eklund et al. [22] used the Rank Permutation Transformation (RPT method). Reduce the influence of noise in the state measurement, and make the statistical state events more clear through the classification method [20]. The exponential smoothing and average filtering methods are widely used in signal processing because of their good noise reduction effects. The linear filter used by PM Pawar et al. [22] usually filters out the peak signal in the signal during noise reduction, resulting in signal errors. This method cannot achieve good reduction in signal processing applications that include multiple types of time-frequency characteristics. Noise effect: For this kind of problems, nonlinear filters have been widely used because they can reduce the impact of coupled noise while retaining the peak signal [22]. For online detection of equipment operating status, the signals collected by sensors are
inherently nonsteady and nonlinear and are extremely complex due to the influence of multifield environments. It is difficult to meet narrowband conditions and symmetry conditions, so it needs to be more suitable for signal analysis and processing methods.

As a new method proposed by Tsinghua University, the robust and flexible morphological filtering technology was first applied to the defect diagnosis of rolling bearings under strong noise background. This method can efficiently extract the signal shape and edge contour features and is of great reference value [23]. The research team of Professor Zhou Zude of Wuhan University of Technology has applied the HHT analysis method to the detection and diagnosis of bearing vibration faults in rotating machinery equipment, extracting state characteristic signals under severe working conditions, and has achieved a series of scientific research results [24, 25].

By analyzing the changes of various parameters of the mechanical vibration signal, such as the changes in the time domain, frequency domain, and amplitude domain, the mechanical failure can be studied and early warning implemented. At present, the extraction methods of fault features have been developed from conventional methods (such as fast Fourier transform, power spectrum estimation, time-frequency analysis, and axis trajectory) to a higher level (angle domain analysis, holographic spectrum and fractal dimension, etc.) [26]. For example, the holographic spectrum theory, which combines the amplitude, frequency, phase, angular momentum, and other information of mechanical vibration for research and judgment, is of great significance for improving the diagnosis level of mechanical faults.

2. The Mechanism of the Time-Frequency Feature Extraction Method of the Overall Average Ensemble Empirical Mode Decomposition (EEMD) Vibration Signal

Feature extraction is required after filtering the collected fault vibration signals. With the development of technology, the classical method is gradually being replaced by empirical mode decomposition (EMD) and overall average Ensemble Empirical Mode Decomposition (EEMD). The mainstream methods are discussed separately.

In the actual signal analysis and processing process, most of the objects do not have IMF component characteristics, and unstable fluctuations may occur at any point in the signal. For the original signal that does not fit the IMF conditions, it needs to be resolved by EMD. Decompose its IMF component. In any case, a changeable signal can be decomposed into the sum of several IMF components and residual values by EMD, but after EMD decomposes the unsteady signal, modal aliasing will occur. For solving this problem, the overall average empirical mode - EEMD method can well contain the modal aliasing phenomenon in the application of EMD method [27].

In the EEMD method, the original signal is added with Gaussian white noise to make its frequency present a statistical characteristic of uniform distribution. After adding the white noise, the vibration signal shows continuous characteristics on different scales, and its main function is to reduce the modal aliasing caused interference; the specific steps are as follows:

Step 1: add white noise to the original signal multiple times. Since its mean value is 0 and the amplitude standard deviation is constant, the white noise amplitude level is added to reflect the shielding effect on modal aliasing.

Step 2: use EMD to decompose the signal with Gaussian white noise added for the Nth time, and get IMF components and a residual term. After M times of adding white noise, decompose the original signal to get any IMF component characterization.

Step 3: repeat steps 1 and 2 several times. For each independent IMF component, use the characteristic of uncorrelated random sequence statistical average to be 0 to implement overall average, and finally get the IMF component after applying EEMD decomposition.

To sum up, the significant advantage of EEMD is that it can curb the inherent defects of EMD’s insufficient adaptability to decomposing unsteady signals. It can decompose any signal into the sum of several IMFs and a residual component, which is effective for modal aliasing to a very good containment effect.

3. Research on EEMD Superresolution Sparse Feature Extraction and Recognition Method of Fault Vibration Signal

Synthesizing the above vibration signal characteristics, this paper processes the signal according to the law of signal frequency changing with time and uses the EEMD superresolution sparse decomposition method as an effective adaptive algorithm, especially for nonstationary signal processing. For each independent IMF component, in other words, they all have the scale characteristic of the signal and have the characteristic that changes accordingly. In order to further clarify the difference between fault and nonfault events, the focus of research on independent IMF components is carried out, and then the energy distribution of fault vibration signals in different frequency bands is analyzed based on the characteristic distribution of IMF and then compared with the energy distribution under normal conditions. At the same time, the judgment method of energy entropy is used to judge the type of fault behavior.

The flowchart of fault vibration signal feature extraction and identification is shown in Figure 1. The processing steps described in Figure 1 are first to collect vibration signals, again to obtain refined IMF components through EEMD superresolution sparse decomposition, then to extract the characteristics of the vibration signals and calculate the energy entropy of the corresponding IMF, and finally to perform classification and recognition operations. Get the final result.

The specific processing steps are as follows:
Step 1: collect low-frequency fault vibration signals with a frequency not higher than 1000 Hz; the detection system converts the low-frequency vibration signals collected by the set vibration sensor in the same period into electrical signals \( x(t) \).

Step 2: EEMD superresolution sparse decomposition: add the electrical signal to a certain amplitude of Gaussian distributed white noise, use this method to construct the IMF component and a residual term, then refine the sparse processing of the IMF component, and then target each eigenmode. The signals are, respectively, added with different Gaussian white noises with the same root mean square and then decomposed into several IMF components and a residual term through the empirical mode. Take an appropriate number of iterations from 100 to 400, and finally calculate the overall average of the same-order IMF.

Step 3: calculation of energy entropy: apply \( E_1, E_2, E_3, E_4, E_5, E_6 \) to characterize the energy of the aforementioned IMF component, and use \( E_1, E_2, E_3, E_4, E_5, E_6 \) as the energy distribution of the signal, and calculate the energy entropy value.

Step 4: feature extraction of the fault vibration signal: after decomposition in step 2, the normalization operation of the steady-state components of each scale is implemented through the \( H = -\sum^m P_j \log P_k \) fixed formula.

The steps flowchart is shown in Figure 2.

As described above, in step 2, the EEMD superresolution sparse decomposition method is used to perform more refined superresolution sparse processing on the IMF components. First, create a redundant dictionary in vector form as \( D = (d_1, \ldots, d_n) \in \mathbb{R}^{ncm} (n < m) \), and for IMF component samples \( Y = (y_1, \ldots, y_K) \in \mathbb{R}^{nk} \), the main purpose of using dictionary training is to find suitable redundant items to ensure that IMF component samples can be expressed as sparse matrices like \( X = (x_1, x_2, \ldots, x_K) \in \mathbb{R}^{nk} \) in turn form. The dictionary training process is shown in the following equation (1):

\[
\begin{align*}
\min_{D, X} & \quad \|Y - DX\|_F^2, \\
\text{s.t.} & \quad \|x_k\|_{l_0} < T_0, \quad \forall k.
\end{align*}
\]  

Select the IMF component with larger amplitude and front IMF component and the IMF component with lower amplitude and lower amplitude from the IMF component set. Through the downsampling mode, the later IMF component and the front IMF component are interpolated in pieces, which is similar to other modes. In contrast, the interpolation polynomial value on the node is equivalent to the value of the interpolation function within the node, and the piecewise interpolation process is shown in the following equation (2):

\[
H(x) = \alpha_j(x)f_j + \alpha_{j+1}(x)f_{j+1} + \beta_j(x)f'_j + \beta_{j+1}(x)f'_{j+1}.
\]  

The basic function values of the piecewise interpolation are shown in

\[
\begin{align*}
\alpha_j(x) &= \left( \frac{x - x_{j+1}}{x_j - x_{j+1}} \right)^2 \left( 1 + 2 \frac{x - x_j}{x_{j+1} - x_j} \right), \\
\alpha_{j+1}(x) &= \left( \frac{x - x_{j+1}}{x_{j+1} - x_j} \right)^2 \left( 1 + 2 \frac{x - x_{j+1}}{x_j - x_{j+1}} \right), \\
\beta_j(x) &= \left( \frac{x - x_{j+1}}{x_j - x_{j+1}} \right)^2 (x - x_j), \\
\beta_{j+1}(x) &= \left( \frac{x - x_j}{x_{j+1} - x_j} \right)^2 (x - x_{j+1}).
\end{align*}
\]
Collect the low-frequency fault vibration signals with a frequency lower than 1000Hz, then transform to the electric signal.

EEMD super-resolution sparse decomposition

Calculate the energy entropy value

Feature Extraction of Fault Vibration Signals

Figure 2: The specific processing steps chart.

processing method also needs to process its high-frequency part; here S groups of high-pass filters are used to extract high-frequency characteristics, expressed as $f_j \otimes y'_j$; after this process, the high-amplitude IMF components and low-amplitude IMF components can be decomposed into blocks $\sqrt{n} \times \sqrt{n}$ with overlapping sizes, and then K blocks are randomly obtained. The reconstructed IMF component sample is $\{P_{k, h}, P_{k, l}\} (k=1, 2, 3, ..., K)$.

The training dictionary $\{A^h, A^l\}$ is obtained according to the established sample $\{P_{k, h}, P_{k, l}\}$ and combined with the processing process. There are $P^h = \{P_{1, h}, P_{2, h}, ..., P_{k, h}\}$ and $P^l = \{P_{1, l}, P_{2, l}, ..., P_{k, l}\}$; the dictionary training process of the high-amplitude IMF component is shown in the following equation (7):

$$\begin{align*}
\min_{A^h, Q} \quad & \frac{1}{n} \|P^h - A^hQ\|_F^2 \\
\text{s.t.,} \quad & \|q_k\|_0 \leq T_0 \quad \forall k.
\end{align*}$$

The dictionary training process of low-amplitude IMF components is shown in the following equation (8):

$$\begin{align*}
\min_{A^l, Q} \quad & \frac{1}{nS} \|P^l - A^lQ\|_F^2 \\
\text{s.t.,} \quad & \|q_k\|_0 \leq T_0 \quad \forall k.
\end{align*}$$

The dictionary training process integrating high- and low-amplitude IMF components can be expressed as shown in the following equation:

$$\begin{align*}
\min_{A^h, A^l, Q} \quad & \frac{1}{n} \|P^h - A^hQ\|_F^2 + \frac{1}{nS} \|P^l - A^lQ\|_F^2 \\
\text{s.t.,} \quad & \|q_k\|_0 \leq T_0 \quad \forall k.
\end{align*}$$

The dictionary training weights of the high and low IMF components are, respectively, $1/n$ and $1/nS$, and formula (9) can be abbreviated as shown in the following formula:

$$\begin{align*}
\min_{A^h, A^l} \quad & \|P - A^hQ\|_F^2 \\
\text{s.t.,} \quad & \|q_k\|_0 \leq T_0 \forall k.
\end{align*}$$

The parameters $P$ and $A$ in equation (10) are shown in the following equation:

$$\begin{align*}
P &= \begin{bmatrix} \frac{1}{\sqrt{n}} P^h \\ \frac{1}{\sqrt{nS}} P^l \end{bmatrix} \\
A &= \begin{bmatrix} \frac{1}{\sqrt{n}} A^h \\ \frac{1}{\sqrt{nS}} A^l \end{bmatrix}.
\end{align*}$$

Taking the matrix elements as the elements of matrix $Q$, $E_j = P - A_0 \sum_{k=1}^{m} z_j q_k$ $E$ obtains the sparse matrix as shown in the following equation:

$$\|P - A_0 ZQ\|_F^2 = \left\|P - A_0 \sum_{j=1}^{m} Z_j q_j\right\|_F^2 = \left\|E_j - A_0 z_j q_j\right\|_F^2.$$  \hspace{1cm} (12)

The EEMD superresolution sparse method is used as an effective adaptive algorithm, especially for nonstationary signal processing. For each component of the independent IMF, they all have the scale characteristics of the signal and have the characteristics that change accordingly.

The problem of modal aliasing will appear when the traditional empirical modal decomposition method is used. This part uses the uniform distribution of the frequency after the addition of white noise to avoid this problem and obtain the time-frequency information at the same time, with real attributes.

The added white noise component can also achieve complete noise reduction under the calculation of the overall average of the same-order IMF. However, the actual decomposition effect does not have a linear relationship with the increment of the iteration rounds, so the selection of the iteration number should be specifically selected according to the experimental results. Compared with similar methods, this method can better achieve denoising and refined processing of vibration signals.

The front-end sensor array has different frequencies of vibration signals, and the angle and orientation of the received vibration signals are random and uncertain [15, 16].
To sum up: each time the vibration wave frequency collected by all vibration sensors is compared, more than 3 vibration signals with larger amplitude and lower frequency are selected for processing. The frequency of the vibration wave reflected on each sensor is different; and the frequency of the main vibration plays a vital role in signal analysis. Therefore, the principle of selecting the main vibration frequency and other component frequencies among the selected vibration waves is as follows. Among the several vibration waves measured in the sensor, the vibration wave with the highest amplitude is the main vibration frequency, and the others are the components.

4. Research on EEMD Superresolution Sparse Feature Extraction and Recognition Method of Bearing Fault Vibration Signal

4.1. Experimental Platform Construction. The physical diagram corresponding to this experimental platform is shown in Figure 3. The type of servo motor used is M48015-H, Servo motor controller adjusts speed, and rotational speed measuring instrument measures the actual rotational speed. Choosing FBG accelerometer to collect vibration signal, the measuring frequency range is 10–1000 Hz. The sensitivity is 490 mv/g. The type of cylindrical roller bearing is N205EM.

Set sampling frequency to 5 KHz in test. Collect vibration signal by FBG accelerometer. When the rolling speed is 1200 r/min, then replace the previous defective bearings in turn and repeat the experiment again and record the data. Several faults that often occur in rolling bearings are simulated by experiments including outer ring wear, inner ring wear, roller wear and belt wear, shaft wear, ball failure, drive end, fan wear, and so on, with comparison between intact bearings and three types of example defective bearings in Figure 4.

4.2. EEMD Superresolution Sparse Decomposition of IMF Component Features. Under normal operating conditions of the bearing, the energy distribution of the vibration signal is uniform and does not fluctuate much. If a fault condition occurs, resonance will be detected in the corresponding frequency band, and the energy will also be concentrated in this frequency band. The energy entropy value will also change accordingly.

By calculating the energy entropy value and comparing it with the data in the rolling bearing fault energy entropy empirical database, the comprehensive energy distribution status can be used to preliminarily judge the fault type and provide timely warning.

Next, analyze the characteristics of the vibration signal of the bearing under fault conditions. When the motor speed is 1200 r/min, the frequency domain waveform of the fault vibration signal collected by the FBG acceleration sensor is shown in Figure 5.

After performing noise reduction and conditioning processing on the above signal, and then performing EEMD superresolution sparse decomposition, 9 IMF components and one residual component will appear. With the gradual increase of IMF components, the resulting “end effect” becomes more and more significant, and the impact on the energy situation of IMF components also increases. The superiority of EEMD super-resolution sparse method can be demonstrated when solving the above problems. It can be realized that, by reducing the attenuation caused by the “end effect” on the signal energy, the typical IMF characteristic components are selected and their energy distribution and entropy value are calculated to achieve the goal.

4.3. Analysis of Energy Entropy Characteristics of Bearing Fault Vibration Signal. The IMF component carries both the original signal locality and the time-varying scale characteristics. Through theoretical analysis, it is known that, by comparing the energy entropy, the energy change under different conditions can be grasped to judge the fault event and the normal event.

It can be seen from Table 1 that the energy entropy value of each working part of the bearing is the largest and stable under normal operating conditions. As the fault continues to deteriorate, the energy entropy value will continue to decrease. Compare the energy entropy value under the same type of fault condition. The order of size is inner ring, outer ring, and roller. According to this law analysis, the energy entropy value under various fault conditions can be used as the basis for fault diagnosis.

4.4. Recognition of Energy Entropy Feature of Bearing Fault Vibration Signal. For bearing fault identification based on energy entropy, the preliminary judgment of bearing fault type can be achieved by comparing with the threshold value in the energy entropy subdatabase in the rolling bearing standard database of Case Western Reserve University.

The rolling bearing data of Case Western Reserve University in the United States is widely concerned around the world and cited as a standard database for fault diagnosis. It is also widely used in China. It collects signals through a 16-channel DAT recorder and performs post-processing in MATLAB.

The results of comparing the energy entropy value calculated by selecting several typical fault characteristics with the database are shown in Table 2.

The results in Table 2 show that the energy entropy value judgment method can be effectively used as a characteristic value in the judgment of typical failures of rolling bearings.

5. Experimental Research on Feature Extraction and Recognition of Bearing Fault Vibration Signals

5.1. Experimental Plan Design. This experimental research mainly involves the EEMD superresolution sparse feature extraction and energy entropy calculation of the fault vibration signal during the bearing rotation process and then the preliminary judgment of the fault category. The energy entropy method is used to calculate the energy distribution and energy entropy of various fault signals under different fault states and compare them. A total of three sets of fault
Figure 3: Rolling bearing experimental platform.

Figure 4: Comparison between intact bearing and three types of example defective bearing comparison diagram.

Figure 5: Time-domain and frequency-domain diagrams of bearing fault vibration signal at 1200 r/min speed.
characteristics analysis and comparison were carried out in the experiment, described as follows:

1. Calculate the energy distribution and entropy value of the scratch damage of the inner ring, outer ring, and roller to compare and analyze the energy entropy value of each component under normal operating conditions.

2. Calculate the energy distribution and entropy value of the shaft, belt, and ball wear damage, respectively, and compare and analyze the energy entropy value of each component under normal operating conditions.

3. Calculate the energy distribution and entropy value of drive end, fan, and gear wear damage and compare and analyze the energy entropy value of each component under normal operating conditions.

Finally, through comparison with various fault data in the typical energy entropy value database of rolling bearings of Western Reserve University in the United States, preliminary judgments and determinations of fault types are made. The processing steps of abnormal bearing vibration signal are as follows:

Step 1: Perform noise filtering on the input signal.

Step 2: Perform EEMD superresolution sparse decomposition of the fault vibration signal after noise reduction and conditioning, and obtain each of its different IMF components and a residual value; analyze the energy distribution state of each IMF component and calculate its energy entropy.

Step 3: Compare the calculated energy entropy value with the threshold data in the vibration fault energy entropy database in the standard bearing database of Western Reserve University, and preliminarily judge the fault type.

The EEMD superresolution sparse decomposition method can avoid the interference caused by the "end effect" on the signal energy as much as possible, select the limited IMF component for analysis, calculate its energy distribution and entropy, and discard the remaining IMF components. Here, each time the first seven IMF components are selected as features and their energy states are calculated.

5.2. Improved Wavelet Packet Decomposition and Reconstruction Noise Reduction Test Experiment Aimed at Bearing Fault Vibration Signal. Generate a pulse signal with a pulse width of 10 nm and a period of 2K. This signal is used as a modulation signal of continuous light generated by a semiconductor optical amplifier (SOA). Continuous light is emitted by a laser and modulated into optical pulses by SOA. The optical pulse is amplified by an erbium doped fiber amplifier (Erbium Doped Fiber Amplifiers, EDFA) and then sent into SF (sensing fiber-sensing fiber) via a 3 dB optical fiber coupler, winding the sensing optical fiber with 0.5 m length at the end of the sensing fiber on the PZT vibrator. The sine waves with different frequencies are used as excitation signals to tremble the PZT; the data is collected by PXIE-5122 data acquisition card.

First of all, a sinusoidal excitation signal with 600 Hz frequency is used to drive the PZT, the vibration corresponding to the optical fiber at the excitation point. Based on the optical fiber vibration point, the several points values on the left and right sides of the optical fiber are obtained; then drawing a continuously changing waveform curve according to the corresponding time, 4 s is the intercept unit time range aim at each sampling point. The waveform changing situation can be described completely by this distance, and then implement the Hilbert transform as shown in Figure 6. Taking a single point for example, a signal with 1/4 s time length is selected to represent the situation change even better. As shown from Figure 6, with the passage of time, the fluctuation of the sampling point is similar to the fluctuation of the sine wave. A spectral peak near the approximate 600 Hz frequency was observed with Hilbert transform, while the rest of the sampling points were transformed and it was observed that there was no spectral peak at the same position.

By adjusting the experimental parameters and using the formula calculation, it is concluded that the simulated vibration system can effectively distinguish the vibration signal within the range of 1 m. In this experiment, the length of the optical fiber wound on the PZT vibrator is 0.5 m. This simulation method is used to simulate the generation of mechanical vibration signals and sequentially detect the vibration signals of the corresponding sampling points. By observing the spectrum of each sampling point, it is known
that, in a series of sampling points, the spectrum of only one point can be fitted with the frequency of the driving signal, so the actual measured resolution is also 1 m.

By analyzing the characteristics of the simulated signal, the wavelet function-sym6 wavelet basis which is most suitable for practical needs is selected from among many wavelet functions. Because of its regularity and symmetry, it is better than other wavelet functions. Figure 7 is a comparison of waveforms after denoising through 2, 3, 4, and 5 layers of wavelet packet decomposition. It is also stimulated by a 600 Hz sinusoidal excitation signal, and a signal with a time length of 1/4 s is also selected to better observe its changing situation. It can be seen from the observation diagram that the more the layers of decomposition, the higher the corresponding sensitivity to noise filtering; however, as the number of decomposition layers increases, it does not mean that the denoising effect will change linearly. In the experiment, when the number of decomposition layers is 4 or even higher, it is found that the effective signal will almost be mistakenly filtered out in most cases. After repeated analysis and comparison, it was finally determined that 4 layers were the most suitable number of decomposition layers.

By observing Figure 6, we know that the DC offset with higher components exists objectively in the original signal, and it mainly concentrates in the low-frequency part of the signal, while the energy of the signal itself is less than that of the DC offset component. The DC part can be filtered out by means of isolation filtering. However, due to the frequency doubling effect during vibration, another spectral peak also appears together at the frequency position of an integer multiple of 600 Hz. However, the signal will be smoother after the wavelet packet decomposition and noise reduction processing, and the spectral components of the high-frequency part of the signal will almost disappear. Through observation, it is found that there is a spectral peak with the same value before noise reduction near 600 Hz, which means that the useful part of the signal is completely preserved after wavelet packet decomposition and noise reduction, which also verifies the use of this method for noise reduction with effectiveness. Figures 8 and 9 are the time-frequency domain of the original vibration signal obtained and the signal after denoising by wavelet packet decomposition based on Hilbert operator when 600 Hz and 900 Hz sine waves are used as excitation signals to drive the PZT. Compared with the waveform diagram, it is verified that the above wavelet packet decomposition noise reduction method can achieve better denoising effect.

In this section, the wavelet packet decomposition noise reduction method based on the Hilbert operator is used to filter the original vibration signal in the early stage, and the optimal wavelet basis function symlet is selected according to the signal characteristics. The actual number of decomposition layers is required, and finally compare the effects before and after denoising in the frequency domain. Using the above wavelet packet decomposition noise reduction method can achieve a better purpose of denoising.

5.3. Experimental Data Processing and Analysis. First, select the inner ring, outer ring, and roller scratch failure phenomenon as an example to evaluate the energy entropy calculation method. The energy distribution and entropy value distribution of each state are shown in Tables 3 and 4. The selected failure phenomena of the outer ring, roller, and inner ring are calculated and evaluated as an example of using energy entropy as shown in Table 4.
It can be seen from Table 3 that the energy of the vibration signal is mainly concentrated in the first five components, and the energy distribution is different for each type of fault.

The following conclusions are obtained from Tables 3 and 4:

1. The first five components mainly converge the main energy of the signal, and the energy distribution in each fault state is different.

2. The energy entropy value of the bearing under normal operating conditions is the largest. As the operating environment and conditions continue to deteriorate, the fault becomes more serious, and the corresponding energy entropy value gradually decreases.

3. The energy entropy value of the same fault characteristic of the inner ring, outer ring, and roller shows a trend of change from large to small.

Subsequently, the second category (rotation shaft, belt, ball) wear failure phenomenon is selected as an example and evaluated using energy entropy calculation. The energy distribution and entropy value of each state are shown in Tables 5 and 6.

It can be seen from Table 5 that the energy of the vibration signal is mainly concentrated in the first four components, and the energy distribution is different for each type of fault. The following conclusions are obtained from Tables 5 and 6:

1. The first four components mainly converge the main energy of the signal, and the energy distribution in each fault state is different.

2. The energy entropy value of the bearing under normal operating conditions is the largest. As the operating environment and conditions continue to deteriorate, the fault becomes more serious, and the corresponding energy entropy value gradually decreases.

3. The energy entropy value of the same fault feature of the shaft, belt, and ball is showing a gradual decline.

Finally, select the third category (drive end, fan, gear) failure phenomenon as an example to use energy entropy calculation method for evaluation. The energy distribution and entropy value of each state are shown in Tables 7 and 8.

It can be seen from Table 7 that the energy of the vibration signal is mainly concentrated in the first three components. The energy distribution under various fault conditions is different.

The following conclusions are obtained from Tables 7 and 8:

1. The first three components mainly converge the main energy of the signal, and the energy distribution in each fault state is different.

2. The energy entropy value under normal operating conditions is the largest. With the continuous deterioration of the operating environment and conditions, the fault will become more serious, and the corresponding energy entropy value will gradually decrease.

3. The energy entropy value of the same fault feature of the drive end, fan, and gear is also showing a gradual decline.
Figure 8: Comparison diagram of original signal and signal and spectrum after wavelet packet decomposition and noise reduction under 600 Hz sine wave excitation.

Figure 9: Comparison diagram of original signal and signal and spectrum after wavelet packet decomposition and noise reduction under 900 Hz sine wave excitation.
Here, through the calculation and comparison of the energy distribution and energy entropy value of the above three different types of failure phenomena, it is concluded that the scheme of predicting bearing failure phenomena with energy entropy as the characteristic value is completely feasible.

For the preliminary judgment of rolling bearing faults by means of energy entropy, the preliminary judgment of rolling bearing fault types based on energy entropy can be achieved by comparing with the thresholds in the energy entropy sub-database in the Rolling Bearing Standard Database of Western Reserve University.
The rolling bearing data of Case Western Reserve University in the United States, as a database widely used worldwide and cited as a fault diagnosis standard, is widely used in China [17]. Its vibration signals are collected by a 16-channel DAT recorder and later performed in the MATLAB environment. The sampling frequency of the digital signal is 12000 S/s, and each bearing fault data is also collected at a sampling rate of 48000 S/s. The ultra-high sampling rate can fully guarantee the situation capture of vibration signal changes.

Select the energy entropy values calculated from the abovementioned typical failure phenomena and input them into the database for query. Fault type database is as shown in Table 9.

The results show that the energy entropy value of each type of typical fault input is basically consistent with the energy entropy threshold range of the corresponding fault type in the standard database, which proves that the energy entropy value judgment method can be effectively used as a characteristic value in the judgment of typical rolling bearing faults.

### 6. Conclusion

In view of the shortcomings of nonlinear and nonstationary rolling bearing vibration signals in improving signal-to-noise ratio and fine feature extraction and recognition, a feature extraction and recognition method of abnormal vibration signals based on EEMD superresolution sparse decomposition is designed in this paper.

In this method, the superresolution sparse decomposition method is used to refine the set of IMF components of bearing vibration signals after EEMD decomposition, and then the features of the set are extracted and their corresponding energy entropy is calculated, so as to identify the fault types and compare them with other methods. The practice shows that this method has strong noise reduction ability and is easy to implement; it can effectively extract the fault feature information of rolling bearing inner ring, outer ring, and rolling body; the diagnosis effect is different with different measuring points. At the same time, this method provides an important means for feature extraction and recognition of bearing fault feature signals and has high engineering application value.

### Data Availability

The raw/processed data required to reproduce these findings cannot be shared at this time as the data also form part of an ongoing study.

### Table 9: Comparison table of fault type database.

| Serial number | Energy entropy | Range of energy entropy data in American Western Reserve rolling bearing database | Fault type judgment |
|---------------|----------------|---------------------------------------------------------------------------------|---------------------|
| 1             | 0.0753         | 0.0425 ~ 0.0823                                                                  | Scratches on the outer ring |
| 2             | 1.3175         | 1.3005 ~ 1.3273                                                                  | Inner circle scratches  |
| 3             | 1.2364         | 1.1540 ~ 1.2756                                                                  | Roller scratches       |
| 4             | 1.4434         | 1.3504 ~ 1.4823                                                                  | Shaft wear             |
| 5             | 0.6392         | 0.439 ~ 1.1046                                                                   | Ball wear              |

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

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