A Fault Diagnosis Method for Rolling Bearings Based on Improved EEMD and Resonance Demodulation Analysis

Wei Zhang, Xiange Tian, Guohai Liu, and Hui Liu

Abstract Rolling bearing is a kind of easily damaged mechanical equipment. The quality of rolling bearing is related to the normal operation of the equipment. Because the resonance demodulation method is susceptible to noise interference, and the band-pass filter parameters are largely dependent on personal experience selection. This paper proposes an analysis method based on the combination of Ensemble Empirical Mode Decomposition (EEMD) and the selection criterion of kurtosis-cross-correlation coefficient. Firstly, the vibration signal is decomposed by EEMD to get intrinsic mode functions (IMFs); Secondly, since the decomposed IMF components will produce mode aliasing, two criteria of cross-correlation coefficient and kurtosis are introduced to extract effective IMF components for signal reconstruction; Finally, the reconstructed signal is subjected to Hilbert transform and envelope analysis. Compared with the resonance demodulation analysis method, the EEMD decomposition method is selected to replace the band-pass filter to reduce the noise of the signal, which enhances signal to noise ratio and makes the fault characteristics more obvious. The experimental signal analysis results of rolling bearing faults show that a refinement of methodology presented in this article can effectively extract the fault characteristics of rolling bearing, and has more advantages than traditional envelope analysis methods.

Keywords Ensemble empirical mode · Resonance demodulation · Envelope spectrum · Rolling bearing · Fault diagnosis

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1 Introduction

The rolling bearing is in each kind of revolving machinery applies one of most widespread general machine parts. The normal running state of rolling bearing often directly affects the performance of the whole device, so fault diagnosis is very important [1].

The fault diagnosis of rolling bearing includes four steps: vibration signal acquisition, signal preprocessing, fault feature extraction and pattern recognition. Because there will be interference factors such as noise when the signal is collected, signal preprocessing is an indispensable part of the fault diagnosis process [2]. The signal processing method can be performed in the time domain, frequency domain, and time–frequency domain. Time domain analysis is widely applied in the breakdown diagnosis domain due to their intuitive, easy-to-understand, easy-to-calculate, and high-efficiency advantages [3]. In the time domain index, kurtosis is extremely sensitive to impact characteristics and plays the vital role in the bearing partial expiration [4]. Compared with the time domain analysis, the frequency range analysis mainly separates or the strengthened breakdown characteristic frequency component. When the rolling bearing fails, a modulation component will appear in the collected signal. Envelope spectrum analysis is a powerful tool for processing modulated signals [5]. In these methods, envelope spectrum analysis based on Hilbert transform is the most widely applied. However, the frequency domain analysis method is based on Fast Fourier Transform (FFT). FFT lacks local information for the analysis of non-smooth signals, and is not appropriate for analyzing non-smooth signals [6, 7].

The actual vibration signal is usually unstable. The analysis of nonstationary signal has been studied by many people in the field of signal processing. Empirical mode decomposition (EMD) is a method of analyzing non-stationary signals proposed by Huang [8], and its essence is to process non-stationary signals. EMD is equivalent to an adaptive filter. It can decompose non-smooth signals into a series of Intrinsic Mode Function (IMF). Each IMF component has its physical meaning, and the adaptive and noise reduction characteristics of EMD make it more and more widely used in rolling bearings [9–11]. Literature [12] proposed EMD to reduce the noise of rolling bearing vibration signals, and realizes fault diagnosis of rolling bearing with envelope spectrum analysis. However, the EMD method still has many defects such as modal aliasing, end effect, over-envelope and under-envelope phenomena. In order to improve the modal aliasing phenomenon of EMD, Ref. [13] proposed the total integrated empirical mode decomposition method (EEMD). EEMD through many times joins the white noise to the primary signal in, may suppress the modality aliasing effectively. In Ref. [14], the author used the decomposition method of EEMD and compared it with the EMD decomposition results. Finally, it is concluded that EEMD decomposition has more advantages.

Because the traditional resonance demodulation method needs to select a resonance high frequency band to design a bandpass filter based on personal experience and knowledge reserves. In order to improve this shortcoming, this paper uses EEMD decomposition to replace the filtering method of the band-pass filter, and selects the

IMF component of the reconstructed signal through the cross-correlation coefficient and kurtosis. Then Hilbert transform and envelope analysis are performed on the reconstructed signal, and finally the fault features are extracted. The method proposed in this paper can effectively avoid the interference of artificial selection of bandwidth factors on fault analysis, and the correctness of fault diagnosis and analysis is enormously enhanced.

2 Methodology

2.1 Resonance Demodulation Algorithm

Resonance demodulation technology uses band-pass filter to extract the high frequency resonance signal of low frequency fault pulse modulation, and then obtains the low frequency signal spectrum through envelope demodulation. The fault type is determined by comparing the actual characteristic frequency with the theoretical fault characteristic frequency. The diagnosis effect mainly depends on the parameter selection of band-pass filter: center frequency and bandwidth. Appropriate band-pass filter can effectively filter noise and other interference factors, and improve the accuracy of fault feature frequency extraction [15]. The specific algorithm is as follows:

(1) The signal is transformed by fast Fourier transform to get the spectrum;
(2) Observe the frequency band where the modulation phenomenon is more obvious from the spectrogram, and select this frequency band as the bandwidth of the band-pass filter;
(3) After determining the bandwidth, design a band-pass filter to filter the signal;
(4) Perform Hilbert transform and envelope analysis on the filtered signal to obtain its envelope spectrum;
(5) Observe the envelope spectrum, extract the characteristic frequency of the fault, and compare it with the theoretical value to judge the fault type.

In the fault diagnosis of rolling bearing, resonance demodulation is the most widely used method, but because the information generated by early small faults of bearing is often disturbed by background noise, the application of resonance demodulation method in improving signal-to-noise ratio is limited, and the diagnosis effect is not obvious. In recent years, some new denoising methods have been developed rapidly. Wavelet denoising has the advantage of multi-resolution. However, the effect of wavelet denoising largely depends on the selection of basis function and threshold, so designers need to have rich experience. EMD is a new signal processing method, which is very suitable for processing nonlinear and non-stationary signals. However, the EMD decomposition is prone to mode aliasing. In order to solve this problem, some scholars put forward the EEMD method based on the research of white noise

EMD decomposition. This method effectively overcomes the shortcoming of mode aliasing in EMD method.

2.2 Ensemble Empirical Model Decomposition

EMD can adaptively process nonlinear and non-stationary signals, but this method has problems and shortcomings, mainly the phenomenon of modal aliasing. The EEMD method adds multiple groups of different white noises to the original signal and then performs EMD decomposition, and then uses the random characteristic of zero white noise to average the IMF components obtained from all EMD decompositions as the components of the EEMD decomposition IMF to eliminate the white noise [16]. At the same time, the problem of modal aliasing is solved. EEMD decomposition steps are as follows:

(1) Select the total average number of decomposition M;

(2) A white noise $n_i(t)$ with normal distribution is added to the original vibration signal $x(t)$ to form a new signal:

$$x_i(t) = x(t) + n_i(t) \tag{1}$$

where $n_i(t)$ represents the ith additive white noise sequence, and $x_i(t)$ represents the additional noise signal of the ith experiment, $i = 1,2\ldots\ldots M$;

(3) The new signal $x_i(t)$ is decomposed by EMD to get the respective IMF:

$$x_i(t) = \sum_{j=1}^{J} c_{i,j}(t) + r_{i,j}(t) \tag{2}$$

where $c_{i,j}(t)$ is the jth *IMF* decomposed after adding white noise for the ith time, $r_{i,j}(t)$ is the residual function, which represents the average trend of the signal, and J is the number of IMF;

(4) Repeat steps (2) and (3) for M times, and add white noise signals with different amplitudes each time to get the set of IMF:

$$c_{1,j}(t)c_{2,j}(t)\ldots\ldots c_{M,j}(t), \ j = 1, 2, 3\ldots\ldots J$$

(5) Based on the principle that the statistical mean value of uncorrelated sequence is 0. The final IMF component can be obtained by calculating the above IMF components, namely:

$$c_j(t) = \frac{1}{M} \sum_{i=1}^{M} c_{i,j}(t) \tag{3}$$

where $c_j(t)$ is the jth IMF decomposed by EEMD, $i = 1,2……M; j = 1,2……J$.

In the EEMD decomposition method, two parameters are needed: the number of average M and the amplitude of white noise. The amplitude of white noise is usually characterized by the ratio of the standard deviation of white noise amplitude to the standard deviation of original signal amplitude [17].

The EEMD algorithm is an effective method to deal with non-linear and non-stationary signals. It solves the mode aliasing in the process of signal decomposition, but it also has some disadvantages, such as residual white noise in the process of signal decomposition. The choice of an effective IMF depends entirely on experience. All these affect the accuracy of EEMD decomposition and reconstruction. For this reason, two criteria, cross-correlation coefficient and kurtosis, are introduced to select and reconstruct IMF components.

2.3 Kurtosis and Cross-Correlation Coefficient

Kurtosis is a measure of how much the distribution of a set of random variables deviates from the Gaussian distribution. The signal of normal rolling bearing is close to Gaussian distribution, and its kurtosis value is about 0. When the rolling bearing fails, its kurtosis value is greater than 0, and the impact component of the fault signal is prominent. The magnitude of the kurtosis value reflects the degree of impact of the impact component, and a value between 3 and 8 has a significant effect on the extraction of weak faults.

The cross-correlation coefficient indicates the degree of correlation between two signals. The greater the correlation coefficient between two random signals, the stronger the correlation degree [18]. Generally, the correlation coefficient should be greater than 0.1. Equation (4) is the definition of the correlation coefficient in this article:

$$R(x, imf) = \frac{\sum_{i=1}^{N} [x(t) - \overline{x}][imf(t) - \overline{imf}]}{\sqrt{\sum_{i=1}^{N} [x(t) - \overline{x}]^2} \sqrt{\sum_{i=1}^{N} [imf(t) - \overline{imf}]^2}} \tag{4}$$

where N is the number of sampling points; $x(t)$ is the original vibration signal; $imf_i(t)$ is the ith IMF component, and $\overline{x} = \frac{1}{N} \sum_{i=1}^{N} x(t)$.

From the cross-correlation coefficient between each IMF component and the original signal, we can find the first imf_k with the local minimum value of the cross-correlation coefficient and the imf_{k+1} is considered to be the modal aliasing component. Then the first k IMF components are highly correlated with the original signal and contain more fault information. In addition, since the IMF component is from high frequency to low frequency, the high frequency part contains more fault information, so we give priority to the high frequency part. The remaining components can be directly eliminated, and then the selected components can be accumulated and reconstructed to obtain the denoised signal [19, 20].

3   Improved EEMD Decomposition Algorithm

Due to the modal aliasing phenomenon in the IMF components decomposed by the EMD method, and the end effect affects the decomposition effect. In order to avoid such problems in the experiment, this paper chooses to improve the EMD method, that is, the EEMD method, which effectively solves the above problems. Because the spectrum of white noise is evenly distributed, when we add white noise to the signal to be analyzed, it will be automatically distributed to the appropriate location. Because the mean value of noise is 0, the influence of white noise can be eliminated after several average calculations. The final result can be obtained by integrating and averaging each IMF. Therefore, the shortcomings of EMD decomposition are improved. The signal is decomposed by EEMD to get IMF component. Generally, the first component will be selected as the next signal to be studied, which will lose some fault information. Here, we make a little improvement: by calculating the kurtosis of IMF component and the cross-correlation coefficient between IMF component and original signal, we select the component reconstruction signal according to the selection criteria in Sect. 2.3. The steps of the improved EEMD algorithm are as follows:

(1)   EEMD decomposition of the vibration signal will result in a number of IMF components;
(2)   Compute the kurtosis of IMF and the cross-correlation coefficient between IMF and signal;
(3)   According to the selection criteria proposed earlier in the thesis, compare the correlation values and kurtosis values, and select the appropriate IMF component to reconstitute the signal;
(4)   Perform Hilbert transform on the reconstructed signal, and perform envelope demodulation analysis to obtain an envelope spectrogram;
(5)   Observe the envelope spectrum, look for the characteristic frequency of the fault, and compare it with the theoretical value to judge the fault type.

EEMD decomposition can effectively denoise the signal. The selection component is improved slightly. In the next analysis, it is used to replace the band-pass filter, which avoids the shortcomings of choosing the band-pass filter parameters according to personal experience. This paper considers the shortcomings of traditional methods, and uses an improved EEMD method instead of a band-pass filter to analyze the signal. Figure 1 shows the algorithm flow of the traditional Hilbert envelope spectrum, and Fig. 2 shows the algorithm flow of the Hilbert envelope spectrum based on the improved EEMD method.
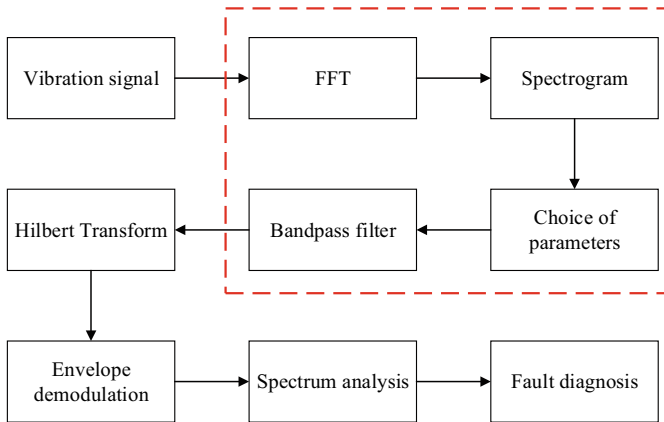
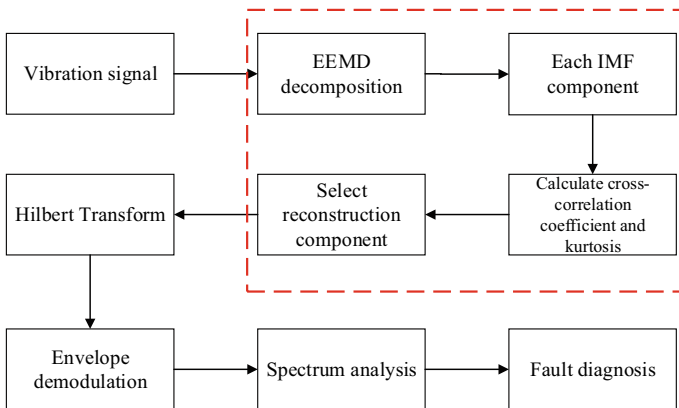**Fig. 1** Flow chart of resonance demodulation method based on fixed bandwidth

Fig. 2 Flow chart of resonance demodulation method based on improved EEMD

4 Experiment and Analysis

4.1 Data Sources

The data used in this paper are from the life cycle bearing data provided by the University of Cincinnati [21]. Figure 3 shows the physical picture of the bearing in the experiment and the simulation picture which is easy to watch. The experimental equipment consists of an AC motor, four bearings (Rexnord za-2115 double row bearings) and a vibration sensor. In this experiment, the number of rolling elements is 16 ($z = 16$), and the pitch diameter of bearing raceway is 2.815 inches ($D = 2.815$ in); The diameter of rolling element is 0.331 inch ($d = 0.331$ in); The contact angle
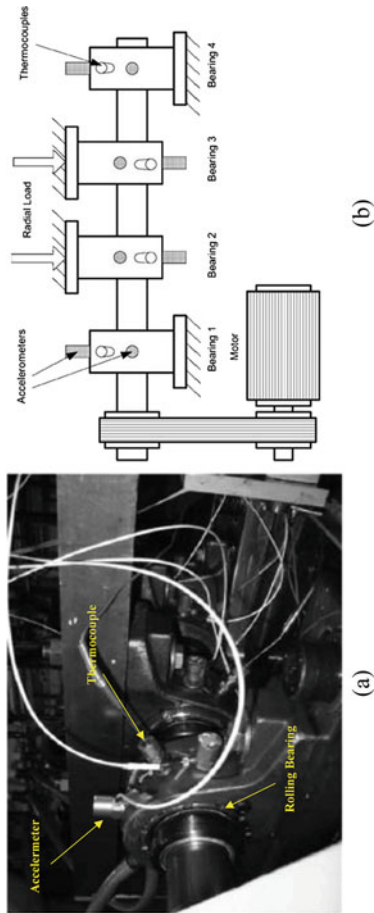
Fig. 3 The experimental platform: **a** Experimental platform of bearing. **b** Simulation experimental platform of bearing

is 15.17°($\alpha = 15.17°$). The rotation speed of the bearing is 2000 rpm ($f_r = 33.33$ Hz) and the sampling rate is 20 kHz. The vibration signal is collected every ten minutes. Each file in the dataset consists of 20,480 points. NI DAQ 6062E was used to collect data in the experiment.

The formula for outer ring fault frequency [22] is

$$f_o = \frac{N}{2}\left(1 - \frac{D}{d}\cos\alpha\right)f \tag{5}$$

According to Eq. (5), the outer ring fault frequency is 236.4 *Hz*.

4.2 Data Analysis Based on Fixed Bandwidth

Firstly, we select four time-domain indicators of RMS, absolute average, variance and kurtosis to make a preliminary analysis and judgment on the signal. Figure 4 shows the waveforms of the four indicators of this signal. RMS is the reflection of signal impulse characteristics. The absolute average reflects the energy of the signal. Variance reflects the degree of signal dispersion. From the change trend of the four indicators in Fig. 4, we can determine that the bearing must have a fault in the later stage.

According to the changing trends of the four indicators, the failure of the entire cycle initially occurred near Document 500. Next, we use the content of Sect. 2.1 to analyze the vibration signal. Because the traditional resonance demodulation method needs to rely on experience to select the bandwidth of the band-pass filter. In order to better select the bandwidth, here we select the data collected without failure (file number 30), the data collected at the initial stage of the failure (file number 533), and the data collected after the failure (file number 800) for analysis. Figure 5 shows
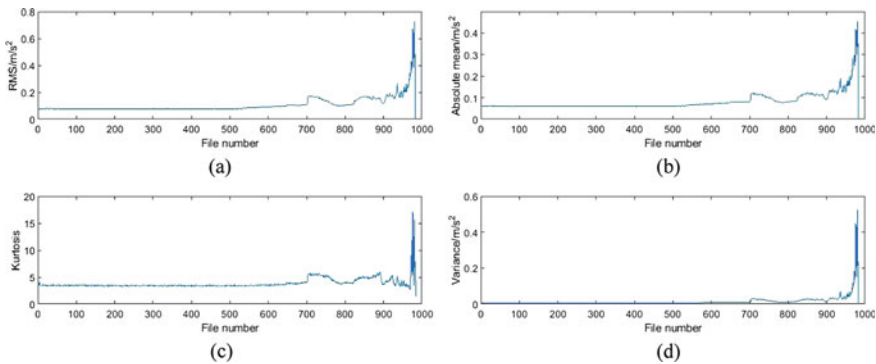

Fig. 4 Four time-domain indicators of vibration signals: **a** RMS. **b** Absolute mean. **c** Variance. **d** Kurtosis
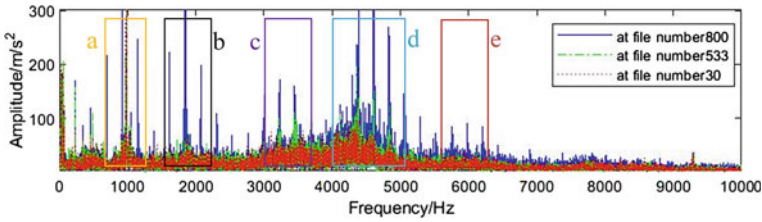
Fig. 5 Resonance frequency band: **a** [600, 1400 Hz]; **b** [1600, 2400 Hz]; **c** [3000, 3800 Hz]; **d** [4000, 5000 Hz]; **e** [5500, 6500 Hz]

the selection of resonance frequency band in the spectrum of the three files. It can be found from the figure that when the center frequency is 1000, 2000, 3400, 4500 and 6000, the resonance frequency band is more prominent. Based on this, the bandwidth of the band-pass filter is designed to be [600, 1400 Hz], [1600, 2400 Hz], [3000, 3800 Hz], [4000, 5000 Hz], [5500, 6500 Hz] to band-pass filter the signal. Choose different bandwidths to design the band-pass filter, and then analyze the signals separately according to Sect. 2.1. Finally, it is found that the envelope spectrum obtained by [4000, 5000 Hz] has the most obvious fault characteristics. Figure 6 shows the envelope spectrum at file numbers 30, 500, and 800, with a bandwidth of [4000, 5000 Hz].

It is obvious from the Fig. 6 that the fault has occurred in the later stage of the signal, and the characteristic frequency is 230.5 Hz, which is very close to the result
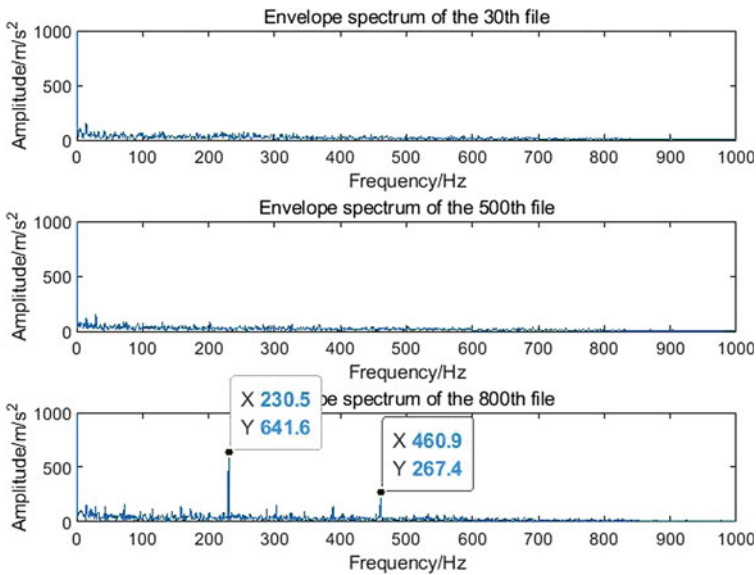

Fig. 6 Envelope spectrum obtained with a bandwidth of [4000, 5000 Hz] at file number 30 500 and 800
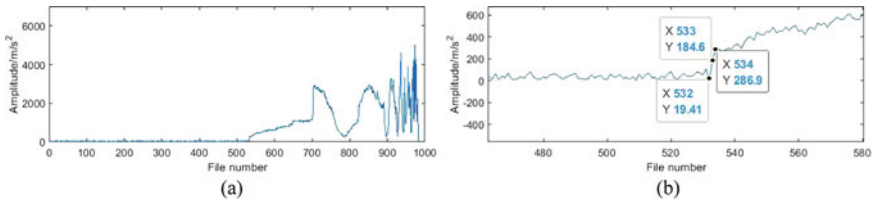
Fig. 7 Trend chart of fault characteristic frequency: **a** Whole cycle; **b** Partially enlarged trend graph
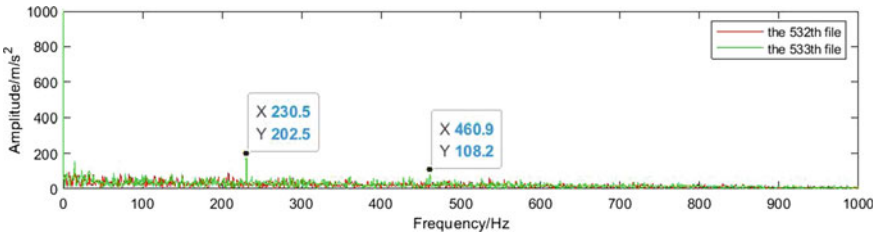

Fig. 8 Envelope spectrogram at file number 532 and 533

calculated by Eq. (5) of 236.4 Hz, and it also can find that the twice fault characteristic frequency. Based on this, it can be judged that the actual fault characteristic frequency is 230.5 Hz.

In order to know the time of the initial failure of the fault more accurately, we know the fault characteristic frequency of the bearing through the above analysis. Figure 7 shows the trend diagram of the extracted fault feature frequency and its partial enlarged diagram.

It can be found from Fig. 7b that the rolling bearing failure at file number 533 began to occur. Then the file number 532 and 533 are analyzed by the resonance demodulation method to obtain the envelope spectrum. Figure 8 shows the envelope spectrogram obtained after the resonance demodulation method at file number 532 and 533. We can find that no clear fault characteristic frequency can be found in the envelope spectrum at file number 532. The fault characteristic frequency and its twice fault characteristic frequency can be found at file number 533. Therefore, it can be known that the bearing started to fail at file number 533.

4.3 Data Analysis Based on Improved EEMD

Through the analysis of the traditional resonance demodulation method, we know that the initial fault location is at file number 533, and then use the improved method proposed in this paper for this set of data. The signal is decomposed by EEMD, and then each IMF component can be obtained. The kurtosis of each component and the cross-correlation coefficient between each IMF component and the original signal

Table 1 Cross-correlation coefficients and Kurtosis

IMF	Cross-correlation coefficients	Kurtosis
IMF1	0.7614	3.7983
IMF2	0.4543	3.6152
IMF3	0.4630	2.4166
IMF4	0.2171	3.1758
IMF5	0.1393	3.3171
IMF6	0.1061	2.8522
IMF7	0.1643	3.0198
IMF8	0.1287	2.3135
IMF9	0.0256	2.7608
IMF10	0.0070	3.7430
IMF11	0.0020	3.2776

are calculated. Table 1. shows the cross-correlation number and kurtosis of each IMF component.

Because the resonance caused by the fault is mostly obvious in the high frequency part, and the IMF component is from high frequency to low frequency. Therefore, we prefer to choose the kurtosis and cross-correlation coefficients of the first few IMF components to observe and compare. According to the selection rules described in Sect. 2.3, from Table 1, we can find that the kurtosis of IMF1 and IMF2 components are between 3 and 8, while the kurtosis of IMF3 is not in this range, so IMF1 and IMF2 contain more fault characteristics. Similarly, it is found that the cross-correlation coefficients of IMF1 and IMF2 components are both greater than 0.1, and the first local minimum cross-correlation coefficient is found at IMF2. Therefore, the kurtosis and cross-correlation coefficients of IMF1 and IMF2 components conform to the selection rules, so we choose IMF1 and IMF2 to reconstruct the signal. Figure 9 shows the envelope spectrum at file number 533 obtained using the method in Part 3.

Comparing Fig. 9. with Fig. 8, in the analysis of the same initial fault, the fault frequency obtained by the method proposed in this paper is more obvious, and the twice frequency, three times frequency, and four times frequency can all be clearly found. The fault diagnosis has a very intuitive judgment function.
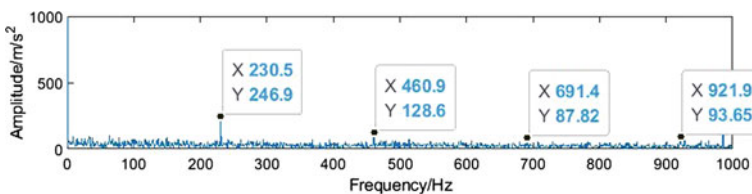

Fig. 9 The envelope spectrum at file number 533 based on the improved EEMD

Table 2 SNR of the two methods

File number	The SNR of traditional method	The SNR of the method in this paper
533th file	−1.1795	5.7100
540th file	−1.3481	6.2237
600th file	−1.8977	6.5063
700th file	−2.7630	7.9383
800th file	−2.0808	6.9007
850th file	−6.1887	10.5551

The above analysis shows that the method proposed in this paper has a better filtering and denoising effect than the band-pass filter, and has more advantages in the extraction of fault signals. Here we use the signal-to-noise ratio (SNR) [23] to quantitatively analyze the denoising effect. The calculation expression of SNR is

$$SNR = 10 \lg \left[\frac{\sum_{n=0}^{N-1} S_n^2}{\sum_{n=0}^{N-1} \left(S_N - S_n' \right)} \right] \tag{6}$$

where S_n is the original signal; S_n' is the signal after noise reduction; N is the number of sampling points.

Table 2 shows the SNR calculated by the resonance demodulation method using a fixed frequency band and the method proposed in this paper after denoising the signal. Select several sets of data from the early stage to the later stage of the failure for analysis and calculation. It can be found from the table that the SNR after denoising the signal using this method has been greatly improved.

5 Conclusion

In this paper, the resonant demodulation method is vulnerable to noise interference and the parameters of band-pass filter are difficult to determine. In most cases, the design of band-pass filter depends on experience to select the bandwidth, which has a great impact on the signal diagnosis. Therefore, this paper proposes an improved EEMD method instead of band-pass filter to remove the noise in the vibration signal. The measured vibration signal is decomposed by EEMD, and the appropriate IMF component is selected for reconstruction by combining the cross-correlation coefficient criterion and kurtosis criterion. Finally, the reconstructed signal is processed by Hilbert transform and envelope demodulation to get the envelope spectrum. By observing the envelope spectrum obtained by the two methods and comparing the SRN of the two methods, it can be seen that the proposed method has greater advantages than the traditional envelope analysis method.

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