

Bearing Fault Feature Extraction Based on EEMD and Autocorrelation Processing

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Abstract

Aiming at the problem of early weak fault feature extraction of rolling bearing, a new method of separating fault signal is proposed. Firstly, the bearing vibration signal is processed according to the principle of autocorrelation De-noising to eliminate the noise interference. Then the vibration signal is decomposed by ensemble empirical mode decomposition (EEMD) method to obtain several IMF components, and the cross-correlation coefficient between each component and the vibration signal is calculated, and the useful components are selected according to the correlation number criterion to complete the reconstruction of the vibration signal. Finally, the reconstruction is eliminated by autocorrelation method. The signal envelope spectrum is obtained and analyzed to obtain the required fault information. The vibration test of rolling bearing shows that the present method can effectively eliminate the interference and noise in the original signal, separate the clear fault vibration signal and obtain useful fault features.

Keywords

EEMD; Autocorrelation denoising; Bearing failure analysis; Correlation coefficient; Feature extraction.

1. Introduction

Bearing is one of the common parts in mechanical rotating equipment, which is easy to be damaged during operation. Therefore, the study of effective bearing fault diagnosis methods, especially for the early weak fault feature extraction method, is of great significance to the safe production of equipment. The fault signal of rolling bearing is often submerged in the strong noise background, so it is difficult to extract. Aiming at the problem of bearing fault signal extraction, Wang et al. [1] denoised the original signal by autocorrelation, reconstructed the denoised signal by empirical mode decomposition, analyzed and processed the reconstructed signal, and obtained the bearing fault feature frequency; Li et al. [2] analyzed and studied the gear fault feature extraction under strong noise background by empirical mode decomposition and morphological filtering; Li et al. [3] proposed a signal processing method combining correlation analysis, wavelet packet transform (WPT) and empirical mode decomposition (EMD) to realize noise suppression and fault feature frequency extraction of vibration signal; Wang et al. [4] proposed a signal processing method combining wavelet packet entropy and EMD decomposition; Li et al. [5] used time-frequency domain analysis method and demodulation technology to implement the signal processing Fault diagnosis. In this paper, a new bearing fault feature extraction method based on correlation coefficient criterion and multi-layer noise reduction is proposed. Through autocorrelation processing and EEMD

method, the interference and noise in the original signal can be effectively eliminated, the clear fault vibration signal can be separated and the useful fault features can be obtained.

2. Principle of Autocorrelation Denoising

Because the autocorrelation function of periodic signal is not attenuated periodic signal, but the autocorrelation function of uncertain signal such as noise and interference is attenuated signal. Autocorrelation denoising is based on this principle to eliminate random noise and interference signal.

If there is a random signal $x(t)$ and its mean value $m(t)$ is 0, then the autocorrelation function of the signal is:

$$R(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T x(t) x(t + \tau) dt \quad (1)$$

Where T is the observation record time.

When signal $x(t)$ is a periodic signal, it becomes $X(t)$ after being polluted by noise signal $n(t)$, then the autocorrelation function of signal $X(t)$ is:

$$\begin{aligned} R(\tau) &= \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T [x(t) + n(t + \tau)] \times [x(t + \tau) + n(t + \tau)] dt \\ &= R_{xx}(\tau) + R_{xn}(\tau) + R_{nx}(\tau) + R_{nn}(\tau) \end{aligned} \quad (2)$$

Where, $R_{xx}(\tau)$ is the autocorrelation function of periodic signal; $R_{nn}(\tau)$ is the autocorrelation function of periodic signal and noise; $R_{xn}(\tau)$ is the autocorrelation function of noise and periodic signal; $R_{nx}(\tau)$ is the autocorrelation function of noise. When $\tau \neq 0$ and the value is large, then the values of $R_{xn}(\tau)$, $R_{nx}(\tau)$ and $R_{nn}(\tau)$ tend to 0, we have:

$$R(\tau) \approx R_{xx}(\tau) \quad (3)$$

3. Information Extraction based on EEMD

According to the characteristics of uniform white noise spectrum distribution, EEMD adds white noise to the signal to be decomposed, which can suppress the mode aliasing produced by EMD, and make the decomposition result better. The decomposition steps are given as follows:

(i) A series of Gaussian white noise $n(t)$ is added to the original vibration signal $x(t)$, and the signal $X(t)$ to be decomposed is obtained:

$$X(t) = x(t) + n(t) \quad (4)$$

(ii) The local wave (EMD) decomposition of signal $X(t)$ with Gaussian white noise is carried out, and n IMF components and remainder terms are obtained:

$$X(t) = \sum_{j=1}^n c_j(t) + r(t) \quad (5)$$

(iii) The signal $x(t)$ is superimposed with different amplitude of Gaussian white noise $n_i(t)$, in which $i = 1, 2, \dots, M$, and different signals $X_i(t)$ to be decomposed can be obtained. EMD decomposition is carried out for these signals $X_i(t)$ respectively, get n intrinsic mode components (IMF) $c_{ij}(j = 1, 2, \dots, n)$, where c_{ij} represents the j th IMF of noisy signal $X_i(t)$. Because the amplitude of the added Gaussian white noise $n_i(t)$ is different, according to the zero mean value characteristics of the Gaussian white noise, the IMF obtained from the above operations is averaged as a whole, so as to eliminate the impact of the superimposed Gaussian white noise on the actual IMF, and the real IMF after the EEMD signal decomposition is obtained as follows:

$$c_j(t) = \frac{1}{M} \sum_{i=1}^M c_{ij}(t) \quad (6)$$

Where $c_j(t)$ is the j th IMF obtained by EEMD processing of signal, and $j = 1, 2, \dots, n$.

4. Selection of Components

The correlation between each IMF component and bearing vibration signal can be expressed by the index of cross-correlation coefficient. The index expression is given as follows:

$$P_{s,cj} = \max[R_{s,cj}(t)] / \max[R_s(t)] \quad (7)$$

Where $R_{s,cj}(t)$ is the cross-correlation function between each component and the signal, and $R_s(t)$ is the autocorrelation function of the vibration signal.

The analysis formula (7) shows that the correlation number of each component and vibration signal is determined by the cross-correlation function composed of them. The effective components with more fault information have great correlation with bearing fault signals, and the calculated correlation number is large. The false component with more noise components has little correlation with bearing fault signal, and the correlation value is also small. Therefore, when selecting IMF components, the components with larger coefficients should be selected as far as possible to reconstruct the vibration signal.

5. Application and Verification of Bearing Vibration Signal

In this paper, the rolling bearing data set published by Case Western Reserve University is used as experimental data, and 6205-2rs deep groove ball bearing is used as experimental object. The relevant parameters of the bearing are given as follows: the number of balls is 9, the diameter of balls is 7.94 mm, the inner diameter of bearings is 25 mm, the outer diameter of bearings is 52 mm, the contact angle is 65° and the inner ring speed is 1750 r/min. The experimental data include inner ring fault and outer ring fault, and the faults are single point damage. The sampling frequency of bearing data is 12 kHz and the number of points is 4096. The theoretical calculation formula of bearing failure frequency is given as follows:

$$f_i = \frac{1}{2}Z \left(1 + \frac{d}{D} \cos \alpha \right) F_r \quad (8)$$

$$f_j = \frac{1}{2}Z \left(1 - \frac{d}{D} \cos \alpha \right) F_r \quad (9)$$

$$F_r = \frac{n_i}{60} \quad (10)$$

Where Z is the number of balls; d is the diameter of the ball; D is the diameter of the pitch circle; α is the contact angle; n_i is the speed of the bearing inner ring.

According to the characteristic frequency calculation formula 8~10 of bearing, the characteristic frequency of inner ring fault bearing is $f_i = 157.76\text{Hz}$, the characteristic frequency of outer ring fault bearing is $f_j = 104.57\text{Hz}$, and the rotation frequency of bearing is $F_r = 29.13\text{Hz}$.

Figure 1 shows the time and frequency-domain waveform of the bearing inner ring fault vibration signal. It can be seen from the figure that the original vibration signal contains a lot of random noise and interference, so it is difficult to extract the bearing characteristic frequency from the frequency domain diagram. In this paper, the self correlation method is used to deal with vibration signals, and the denoised signals are decomposed by EEMD. The correlation coefficient (absolute value) between each component and the signal after autocorrelation processing is calculated, as shown in Table 1. It can be seen from the data in Table 1 that components 1 and 2 have a high correlation with bearing vibration signal, and are likely to be fault signal components. Components 1 and 2 are selected to reconstruct the bearing inner ring fault signal, and the reconstructed signal is processed by autocorrelation method. The processing result is shown in Figure 2. The envelope spectrum of the reconstructed signal after processing is shown in Figure 3, and the inner ring fault frequency and bearing rotation frequency can be obtained. The fault frequency in the figure is 156.7 Hz , while the theoretical fault frequency is $f_i = 157.76\text{Hz}$, and the relative error is only 0.67% , which indicates that the fault characteristics of bearing inner ring are extracted from the original signal.

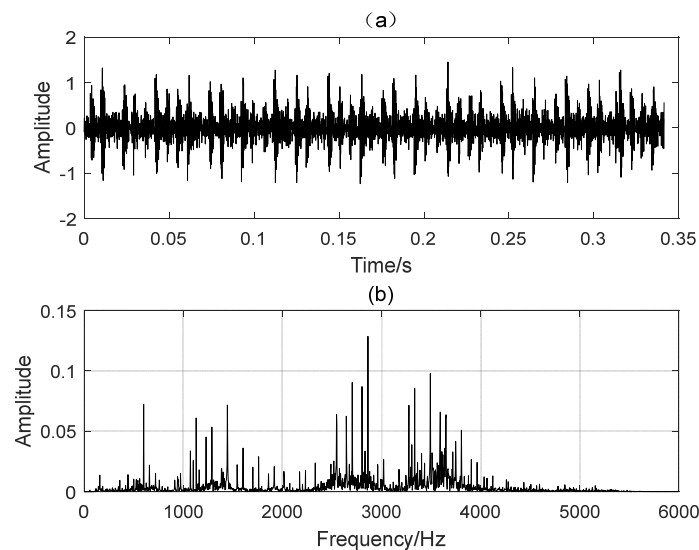
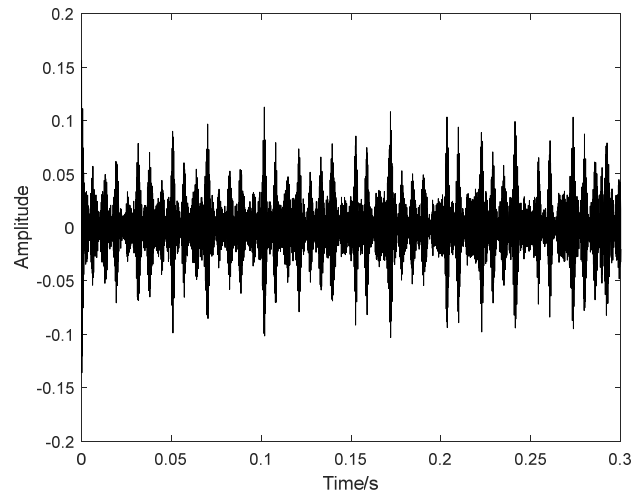
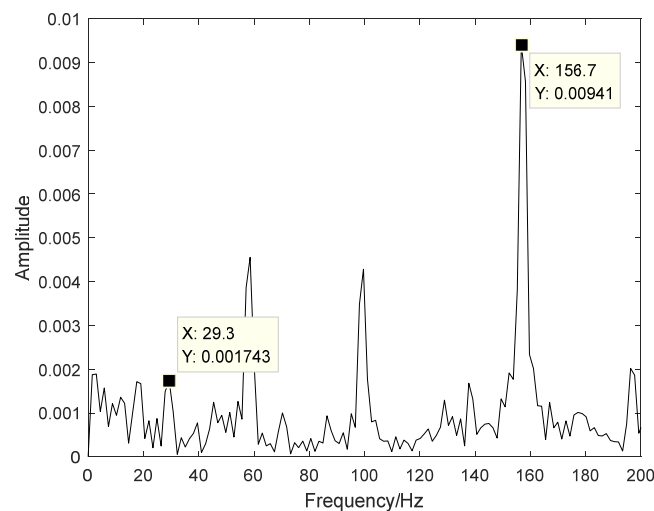


Figure 1. (a) and (b) are time domain and frequency domain characteristics of inner ring signal respectively

Table 1. Correlation coefficient of components obtained from inner ring signal (absolute value)

IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	IMF 6	IMF 7
0.9996	0.9901	0.0043	0.0001	0.0001	0.0001	0.0001
IMF 8	IMF 9	IMF 10	IMF 11	IMF 12	Res	
0.0001	0.0002	0.0001	0.0001	0.0001	0.0001	

**Figure 2.** Autocorrelation processing results of inner ring fault reconstruction signal**Figure 3.** Envelope spectrum of reconstructed inner ring fault signal after processing

The fault signal of bearing outer ring is processed by the present method, and the cross-correlation coefficient (absolute value) of the components after processing is calculated, as shown in Table 2. We select the first three components to reconstruct the bearing outer ring fault signal and carry out autocorrelation processing, the results are shown in Figure 4. Figure 4 shows that the outer ring fault signal is also a periodic impact signal, and its impact characteristics and periodic characteristics are obvious. Figure 5 shows the envelope spectrum of bearing outer ring fault. The extracted outer ring fault frequency is 105.5 Hz, while the theoretical calculated fault frequency is $f_j = 104.57\text{Hz}$. The relative error between them is only 0.88%, which indicates that the outer ring fault feature is extracted from the original signal. Through comparative analysis of Figure 3 and Figure 5, it can be found that the vibration signals

of bearing inner ring and outer ring show certain periodic characteristics and impact characteristics, but the results of outer ring signal processing are more obvious.

Table 2. Correlation coefficient of components obtained from outer ring signal (absolute value)

IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	IMF 6	IMF 7
0.9995	0.9978	0.0636	0.00057	0.0001	0.0001	0.001
IMF 8	IMF 9	IMF 10	IMF 11	IMF 12	Res	
0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	

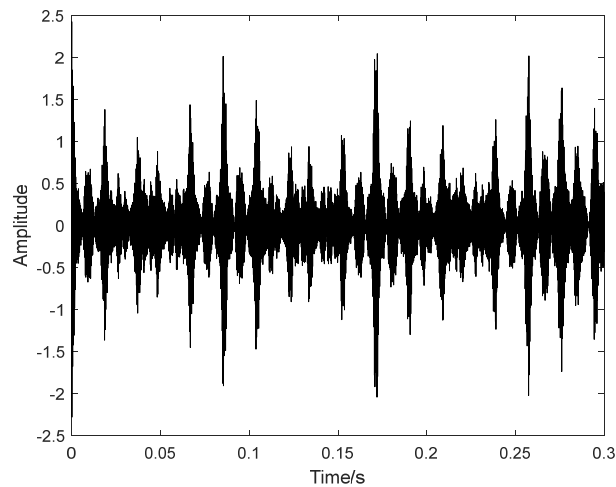


Figure 4. Autocorrelation processing of outer ring fault reconstruction signal

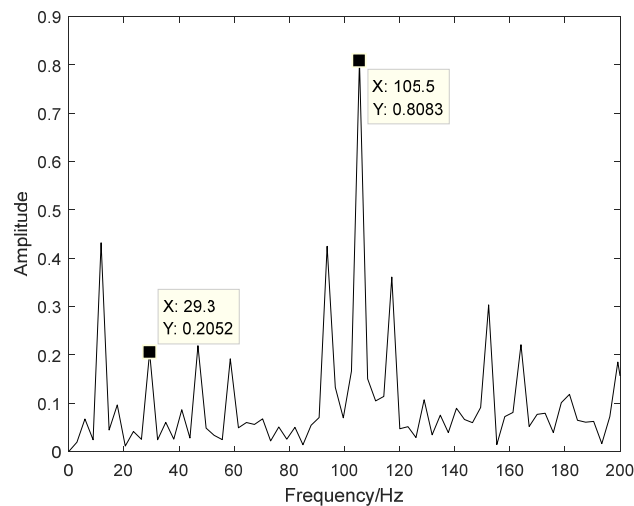


Figure 5. Envelope spectrum of reconstructed outer ring fault signal after processing

6. Conclusion

In this paper, a bearing fault information analysis method is proposed, which uses correlation coefficient criterion to screen components and realizes multi-layer noise reduction. Through the experimental results and analysis, the following conclusions are drawn:

(i) The bearing fault information analysis method with multi-layer noise reduction processing proposed in this paper can effectively enhance the impact characteristics of bearing early fault signal and highlight the weak fault characteristics..

(ii) Several IMF components can be obtained by EEMD decomposition of vibration signals, and the authenticity of IMF components can be distinguished according to the value of correlation coefficient between components and signals.

(iii) By processing and analyzing the measured vibration signal of bearing, it is found that the proposed method can effectively eliminate the noise component and separate the fault characteristic signal from the original signal, so as to realize the accurate diagnosis of bearing inner and outer ring fault.

Acknowledgments

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