Bearing Fault Feature Extraction based on Kurtosis Index and EMD

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Abstract

Aiming at the problem of early weak fault feature extraction of rolling bearing, a new fault information separation method is proposed. Firstly, the bearing vibration signal is processed according to the principle of wavelet packet transform (WPT) to eliminate the noise interference; the transformed vibration signal is processed by empirical mode decomposition (EMD) method to obtain several IMF components, and the kurtosis value of the components is calculated, and the effective components are selected according to the kurtosis criterion to complete the reconstruction of the vibration signal and realize multi-layer noise reduction; Finally, the signal envelope spectrum is obtained by demodulating the reconstructed signal after de-noising, and the fault information is obtained by analyzing it. 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

Wavelet Packet Transform; Empirical Mode Decomposition; Kurtosis; Feature Extraction; Fault Diagnosis.

1. Introduction

Bearing is one of the common parts in mechanical rotating equipment. Its running state directly affects the safety, reliability and service life of the whole mechanical system. Therefore, it is of great significance to diagnose the bearing fault. However, the fault signal of rolling bearing, especially the early weak fault signal, 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] proposed a rolling bearing fault feature extraction method based on cyclic autocorrelation and cyclostationary model; Luo et al. [2] realized signal denoising and fault identification by ensemble empirical mode decomposition, using correlation coefficient and blind source separation technology; Wang et al. [3] denoised the original signal by autocorrelation, and the de-noising signal is reconstructed by empirical mode decomposition (EMD), and the characteristic frequency of bearing fault is obtained by analyzing and processing the reconstructed signal. According to the characteristics of wavelet packet decomposition, Guo et al. [4] proposed a rolling bearing fault diagnosis method based on the combination of wavelet packet energy spectrum and principal component analysis (PCA), which can accurately identify different fault types. Chen et al. [5] used wavelet packet transform and frequency band energy spectrum to identify the fault frequency band and obtain the bearing fault frequency. In this paper, a bearing fault information analysis method based on kurtosis criterion and multi-layer noise reduction is proposed. In this method, the bearing vibration signal is processed by wavelet packet transform and EMD, and the required bearing fault information can be obtained and the clear fault vibration signal can be separated.

2. Wavelet packet transform principle

From the point of view of mathematical analysis, wavelet packet transform projects the signal into a space composed of wavelet packet basis function. From the signal processing point of view, it uses a series of filters with different central frequency but the same bandwidth to process signals. Given the wavelet function and the orthogonal scale function, there are the following relationships:

$$\phi(t) = \sqrt{2}\sum_k h_{0k}\,\phi(2t-k) \tag{1}$$

$$\psi(t) = \sqrt{2}\sum_k h_{1k}\,\phi(2t-k) \tag{2}$$

Where h_{0k} and h_{1k} represent the corresponding filter coefficients in multiresolution analysis.

In order to further generalize the two scale equation, the following recurrence relations are defined:

$$\begin{cases} w_{2n}(t) = \sqrt{2}\sum_{k\in Z} h_{0k}\,w_n(2t-k) \\ w_{2n+1}(t) = \sqrt{2}\sum_{k\in Z} h_{1k}\,w_n(2t-k) \end{cases} \tag{3}$$

Where h_{0k} and h_{1k} represent filter coefficients in multiresolution analysis. When $n = 0$, $w_0(t) = \phi(t)$, $w_1(t) = \psi(t)$. The function set $\{w_n(t)\}_{n\in Z}$ is the wavelet packet and determined by $w_0(t) = \phi(t)$.

Set $f(t)$ as a time signal, $p_j^i(t)$ represents the i-th wavelet packet on the j-th layer, which is called wavelet packet coefficient. G and H is a wavelet decomposition filter. The fast algorithm of dyadic wavelet packet decomposition is given as follows:

$$\begin{cases} p_0^1(t) = f(t) \\ p_j^{2i-1}(t) = \sum_k H(k-2t)\,p_{j-1}^i(t) \\ p_j^{2i}(t) = \sum_k G(k-2t)\,p_{j-1}^i(t) \end{cases} \tag{4}$$

The reconstruction algorithm is:

$$p_j^i(t)_{=2}\left[\sum_k h(t-2k)\,p_{j+1}^{2i-1}(t) + \sum_k g(t-2k)\,p_{j+1}^{2i}(t)\right] \tag{5}$$

where $j = J-1, J-2, \cdots, 1, 0$; $i = 2^j, 2^{j-1}, \cdots, 2, 1$; $J = log_2^N$, h and g is a wavelet reconstruction filter.

3. Information extraction based on EMD

Empirical mode decomposition (EMD) is used to analyze the time-frequency localization of the signal, that is, the signal is decomposed into a finite number of IMF components. IMF components satisfy the following conditions: in a given interval, the number of extreme points and zeros of components should be equal, or only one difference; the local mean value of the upper and lower envelope determined by the local maximum and local minimum of components is zero. The specific steps of EMD decomposition are given as follows:

(i) The mean value $m_1(t)$ of the upper and lower envelope lines of signal $x(t)$ is obtained, and the new signal $h_{10}(t)$ is obtained by subtracting $m_1(t)$ from the original signal $x(t)$;

(ii) If $h_{10}(t)$ satisfies the condition of IMF component, then $h_{10}(t)$ is the first-order IMF component of signal $x(t)$; if not, then $h_{10}(t)$ is regarded as the new original signal and step 1 is repeated until IMF component $h_{1k}(t)$ satisfying the condition is obtained after the kth time, then $h_{1k}(t)$ is the first-order IMF component of the original signal. It is defined as $c_1(t) = h_{1k}(t)$;

(iii) A new signal $r_1(t)$ is obtained by subtracting the first-order IMF component $c_1(t)$ from signal $x(t)$;

(iv) Repeat the above three steps for signal $r_1(t)$ to get $c_2(t)$ and $r_2(t)$. Perform n times on the original signal according to the steps to get n IMF components and a residual component $r_n(t)$ (RES). When the last residual component $r_n(t)$ is a monotone function or constant, the decomposition stops. After decomposition, the original signal can be expressed as:

$$x(t) = \sum_{i=1}^n c_i(t) + r_n(t) \tag{6}$$

where $c_i(t)$ is the ith IMF obtained by EMD processing of signal, and $i = 1,2,\cdots,n$.

4. Selection of components

The distribution characteristics of signal fault characteristic information can be described by kurtosis index. The function expression is determined as follows:

$$K = \frac{\frac{1}{N}\sum_{i=1}^{N} x(i)^4}{{X_{ms}}^4} \tag{9}$$

$$X_{ms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x(i)^2} \tag{10}$$

where, X_{ms} is the root mean square value of the vibration signal; $x(i)$ is the vibration signal; N is the number of vibration signal points.

Kurtosis is a fourth order dimensionless parameter which obeys normal distribution. Its value is usually independent of the load, speed and size of the machine, while the impact component has a great influence on its value. If there is a running mechanical device, we measure its vibration signal and calculate the kurtosis value k of the signal. When k=3, it means that the machine is running normally; when k>3, it means that the machine has failed; when k value is increasing, it means that the degree of failure is deepening. Therefore, when reconstructing the signal, the component with larger K value should be selected as far as possible.

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 1730 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:

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

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

$$F_r = \frac{n_i}{60} \tag{10}$$

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 $f_i = 155.42$Hz, the characteristic frequency of outer ring fault bearing is $f_j = 102.88$Hz, and the rotation frequency of bearing is $F_r = 28.83$Hz.

Fig. 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 wavelet packet transform is used to process the vibration signal. The number of decomposition layers is set to 3, and the energy distribution of each frequency band in the third layer is calculated. The results are shown in Fig. 2. Analysis of Fig. 2 shows that the energy of the signal is mainly concentrated in the fifth node, which is used to reconstruct the signal. The reconstructed signal is decomposed by EMD, and the kurtosis of each component is calculated, as shown in Table 1. The first five components with kurtosis greater than 3 are used to reconstruct the bearing inner ring fault signal, and the result is shown in Fig. 3. The inner ring fault signal is a periodic impact signal, which has a certain impact characteristics and periodic characteristics. The envelope spectrum of the reconstructed inner ring signal is obtained, as shown in Fig. 4. The inner ring fault frequency and bearing rotation frequency can be known. The separated fault frequency is 155.3 Hz, while the theoretical calculated fault frequency is $f_i = 155.42$Hz, and the relative error is only 0.08%, which indicates that the fault information of bearing inner ring is separated from the original signal.

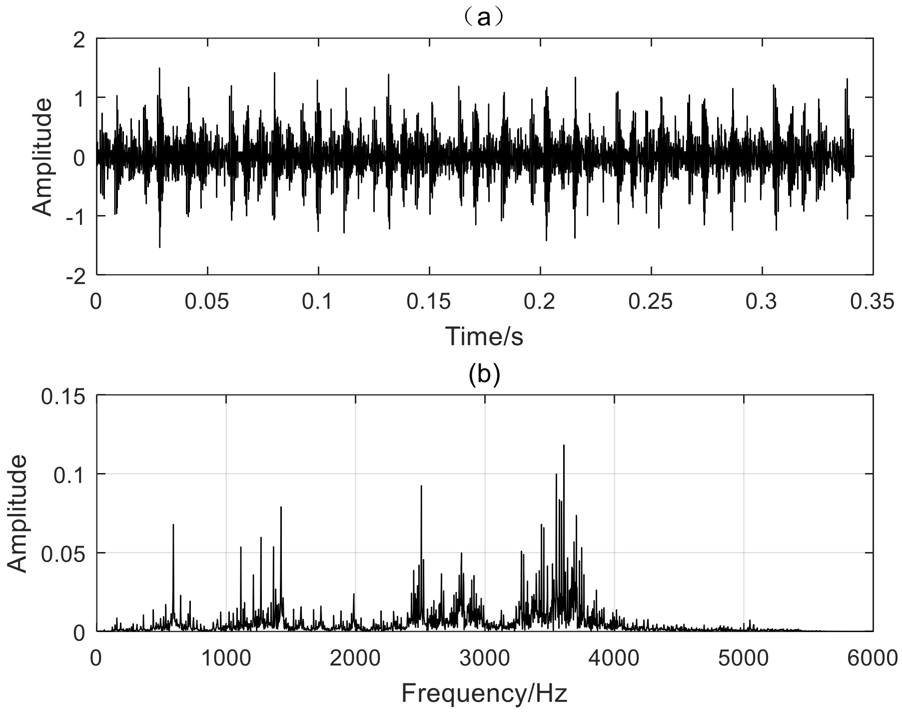

Fig. 1 (a) and (b) are time domain and frequency domain characteristics of inner ring signal respectively

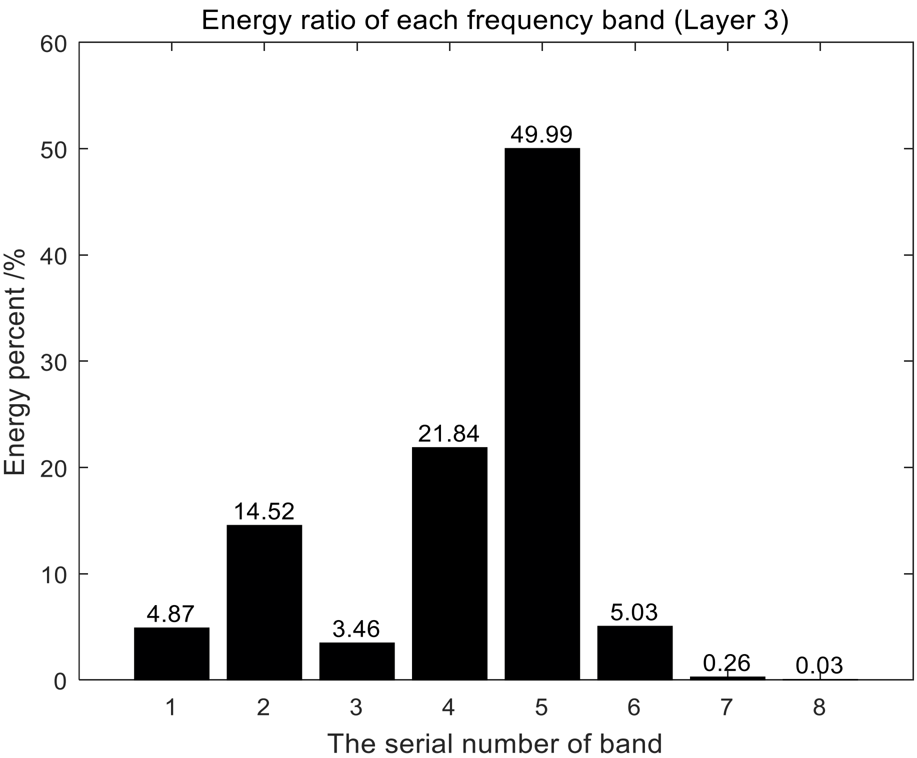

Fig. 2 Energy distribution in the highest frequency band of signal decomposition

Table 1. Correlation coefficient of each component of bearing inner ring signal

IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	IMF 6
5.0216	5.7412	4.0683	3.5562	6.3401	2.8980
IMF 7	IMF 8	IMF 9	IMF 10	Res	
2.5376	1.8339	2.6675	1.8869	1.8929	

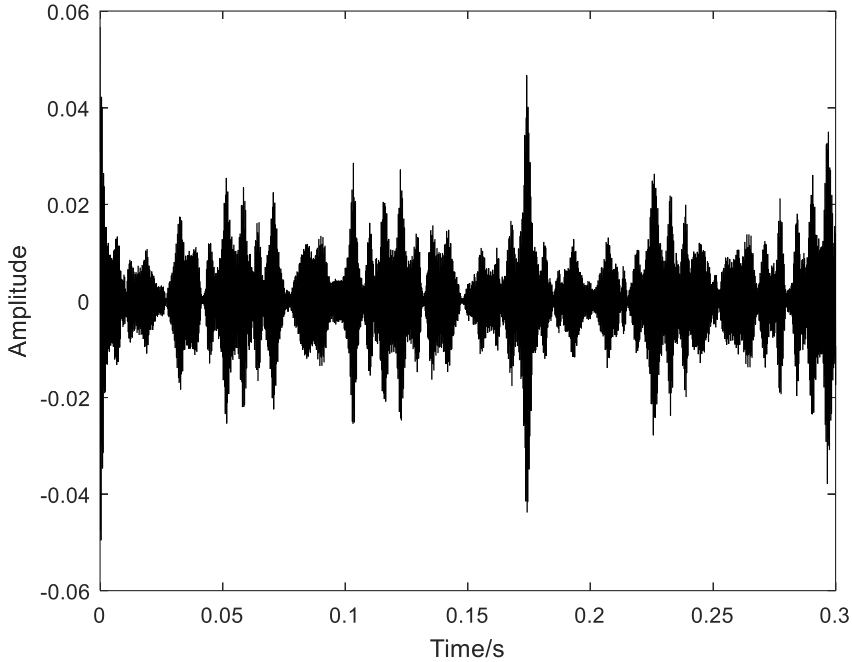

Fig. 3 Inner ring fault reconstruction signal

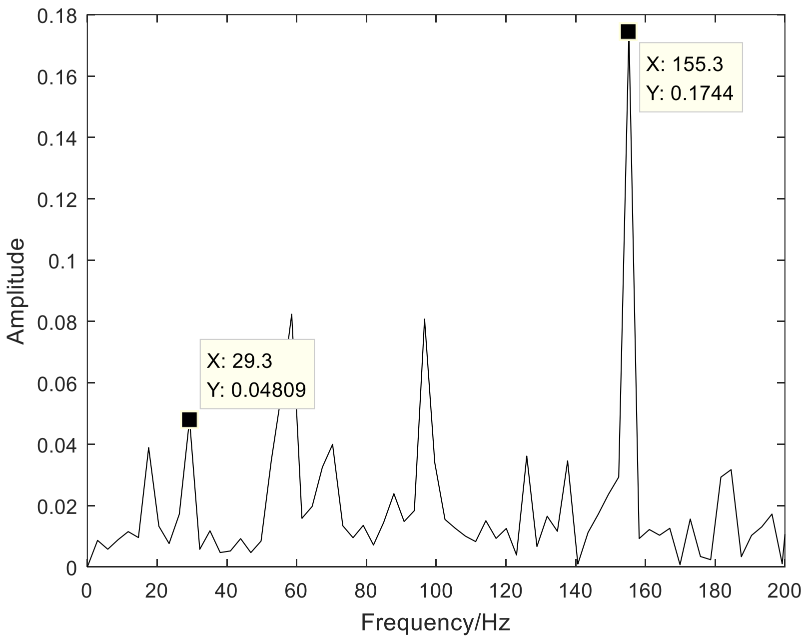

Fig. 4 Envelope spectrum of inner ring fault reconstruction signal

In the same way, the bearing outer ring fault signal is processed, and the kurtosis value of the component is calculated, as shown in Table 2. According to the kurtosis criterion, the first six components are selected to reconstruct the bearing outer ring fault signal, and the results are shown in Fig. 5. The outer ring fault signal is also a periodic impact signal, and its impact characteristics and periodic characteristics are obvious. Fig. 6 shows the envelope spectrum of bearing outer ring fault.

The fault frequency is 102.5 Hz by analyzing the envelope spectrum, while the theoretical fault frequency is $f_j = 102.88$Hz. The relative error is only 0.37%, which indicates that the outer ring fault frequency is separated from the original signal. At the same time, comparing with Fig. 3 and Fig. 5, it can be found that both inner ring fault signal and outer ring fault signal can highlight the periodic characteristics and impact characteristics of fault signal through processing, but the outer ring signal processing result is more obvious.

Table 2. Correlation coefficient of each component of bearing inner ring signal

IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	IMF 6
5.0216	5.7412	4.0683	3.5562	6.3401	2.8980
IMF 7	IMF 8	IMF 9	IMF 10	Res	
2.5376	1.8339	2.6675	1.8869	1.8929	

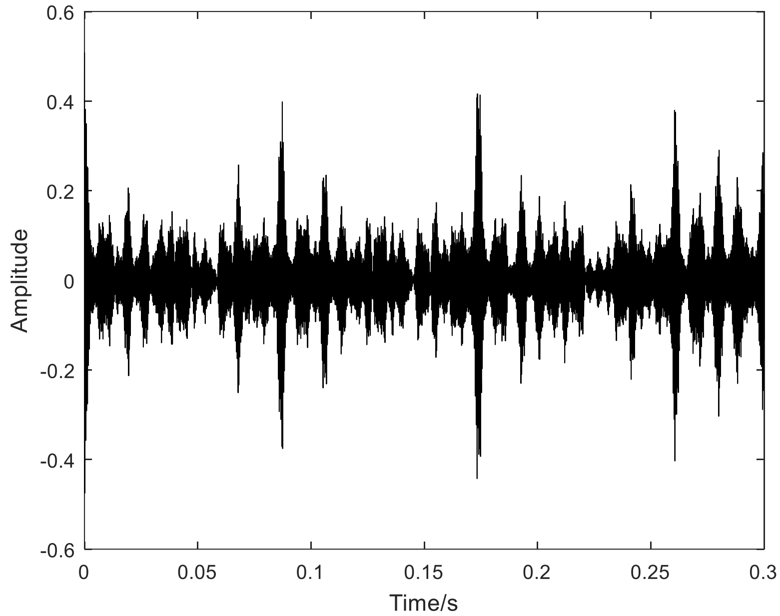

Fig. 5 Outer ring fault reconstruction signal

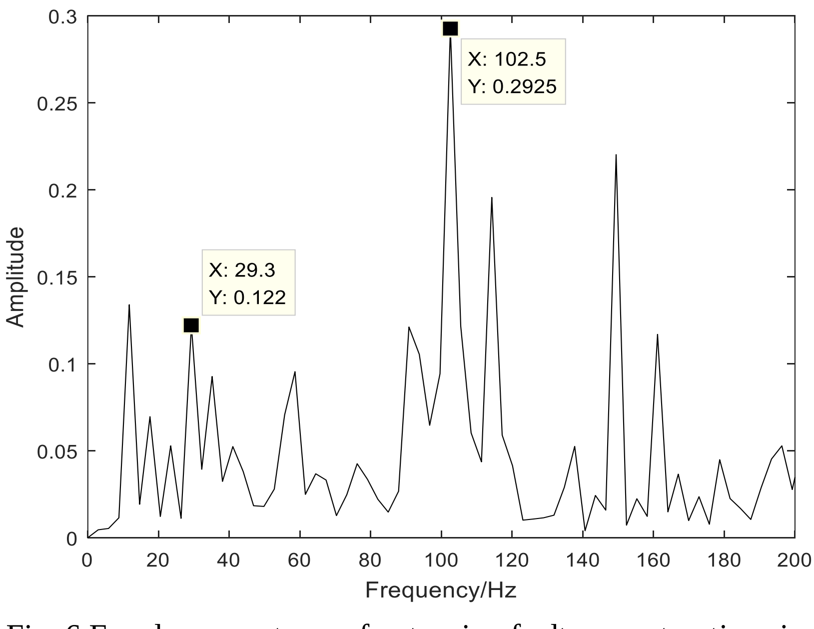

Fig. 6 Envelope spectrum of outer ring fault reconstruction signal

6. Conclusion

The proposed method in this paper firstly decomposes the original signal by wavelet packet, selects the highest level energy most concentrated frequency band node to reconstruct, and eliminates most of the interference signals. Then, the signal after de-noising is decomposed by empirical mode decomposition (EMD), and several intrinsic modal functions (IMF) components are obtained. Taking kurtosis as the index, the effective IMF component is retained and reconstructed. The reconstruction signal is used to analyze the envelope spectrum to obtain the characteristic frequency. Through the signal processing and analysis of two different types of bearing vibration, the conclusions are obtained as follows:

(i) The proposed method can effectively eliminate the interference noise, accurately extract the fault characteristic signal, and realize the accurate diagnosis of bearing inner and outer ring fault.

(ii) The present method can effectively enhance the impact characteristics of bearing early fault signal, highlight the weak fault characteristics, and obtain effective fault information.

(iii) Some IMF components are obtained by wavelet packet transform and EMD decomposition. The components may contain noise components, and the authenticity of IMF components can be distinguished according to the kurtosis of components.

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