Research on fault feature extraction method of rolling bearing based on improved wavelet threshold and CEEMD

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Abstract. Because bearing fault feature information is not easy to extract in noisy background, this paper proposes an improved rolling bearing fault feature extraction method based on combination of wavelet threshold and complementary ensemble empirical mode decomposition (CEEMD). Firstly, the improved wavelet threshold denoising method is used to reduce the noise of the vibration signal, and the impact characteristics in the signal are enhanced. Then, the CEEMD decomposition is used to obtain a set of Intrinsic Modal Functions (IMFs), and IMFs with larger kurtosis and correlation coefficients are selected for signal reconstruction. At last, the envelope spectrum analysis of reconstructed signal is carried out to extract fault characteristic information. Through the experimental analysis of the vibration signals of the outer ring and inner ring of the rolling bearing, it is proved that this method can effectively extract the fault characteristics of the bearing.

1. Introduction

Rolling bearing fault is one of the most common faults in rotating machinery. When rolling bearing breaks down, it will affect the normal operation of equipment, even cause casualties and economic losses. Therefore, fault diagnosis of rolling bearing has great practical significance [1]. In actual working conditions, the rolling bearing is affected by factors such as the working environment and the transmission path, so that the fault characteristic information in the vibration signal is usually covered by noise, and the fault feature cannot be accurately obtained. Therefore, it is necessary to construct an effective denoising algorithm. Wavelet threshold de-noising algorithm is a classical signal de-noising algorithm, which has the characteristics of de-correlation, multi-resolution and self-adaptation. It has unique advantages in bearing fault signal de-noising [2]. However, in traditional wavelet threshold denoising, both hard threshold function and soft threshold function have great shortcomings, resulting in fixed deviation and discontinuity of denoised signals [3-5]. In view of the shortcomings of traditional threshold denoising methods in processing bearing fault signals, an improved wavelet threshold denoising algorithm is proposed. Here, the improved wavelet threshold denoising method is tried to be combined with CEEMD, and the IMFs are choosen out for reconstruction by using the criteria of maximum kurtosis and larger correlation coefficient, and the envelope spectrum analysis of reconstructed signals is carried out to achieve the extraction of bearing fault characteristic frequency, which is verified in bearing fault diagnosis.

2. Wavelet threshold denoising

2.1. Wavelet threshold denoising method

Wavelet threshold de-noising method uses wavelet transform to carry out multi-order, low-frequency and high-frequency detailed analysis of signals, and quantifies the wavelet coefficients of each layer to achieve the purpose of signal de-noising. Wavelet threshold denoising sets a certain threshold for the wavelet coefficients of each layer, quantify and analyze each wavelet coefficients, retain useful data and eliminate useless data to complete signal denoising. The specific steps are as follows:

1) Choosing appropriate wavelet basis and decomposition layer number, the wavelet coefficients $h_{j,k}$ are obtained by wavelet transform of noisy signals.

2) The threshold λ is estimated according to the threshold rules, and Wavelet coefficient $h_{j,k}$ is processed by threshold function, and the processed wavelet coefficients $\hat{h}_{j,k}$ are obtained.

3) The signal is reconstructed by using the wavelet coefficients and approximate coefficients, and the noise reduction signal is obtained.

In the process of wavelet threshold denoising, the common threshold functions are soft threshold function and hard threshold function. The formula of hard threshold function is as follows:

$$\hat{h}_{j,k} = \begin{cases} h_{j,k} & |h_{j,k}| \geq \lambda \\ 0 & |h_{j,k}| < \lambda \end{cases} \tag{1}$$

The formula of soft threshold function is as follows:

$$\hat{h}_{j,k} = \begin{cases} sign(h_{j,k})(|h_{j,k}| - \lambda) & |h_{j,k}| \geq \lambda \\ 0 & |h_{j,k}| < \lambda \end{cases} \tag{2}$$

Where λ is the threshold, $sign(\,)$ is the symbolic function, $h_{j,k}$ and $\hat{h}_{j,k}$ are wavelet transform coefficients.

Soft thresholding and hard thresholding have their own advantages. But both soft and hard thresholds have some shortcomings. For example, there will be constant deviation between the signal and the real signal after denoising by soft threshold method, which will lead to signal distortion. As for the hard threshold function, the signal processed by the hard threshold noise reduction method will produce the problem of signal oscillation.

2.2. An improved threshold function

Aiming at the problems of traditional soft threshold and hard threshold functions, this paper introduces an improved threshold function between hard and soft thresholds. The expression of the improved threshold function is as follows:

$$\hat{h}_{j,k} = \begin{cases} sign(h_{j,k})(|h_{j,k}|^n - \lambda^n)^{1/n} & h_{j,k} \geq \lambda \\ 0 & h_{j,k} < \lambda \end{cases} \tag{3}$$

Where $n \geq 1$. When $n \to +\infty$, the improved threshold function is equivalent to the hard threshold function, and when $n = 1$, the improved wavelet threshold function is equivalent to the soft threshold function. It can be seen that the improved threshold function is based on the hard threshold function and the soft threshold function, which can adjust the change. When $|h_{j,k}| = \lambda$, $\hat{h}_{j,k} = 0$; when $|h_{j,k}| \to \lambda$, $\hat{h}_{j,k} \to 0$, that is, $\hat{h}_{j,k}$ is continuous in $|h_{j,k}| = \lambda$, and with the gradual increase of $|h_{j,k}|$, the deviation between $|h_{j,k}|$ and $\hat{h}_{j,k}$ decreases gradually.

It can be seen from the above analysis that the improved threshold function reduces the oscillation problem of hard threshold function and reduces the constant deviation problem of soft threshold method. Therefore, compared with hard and soft thresholds, the improved wavelet threshold function can improve the denoising effect more effectively and achieve higher signal reconstruction accuracy.

3. CEEMD algorithm

Empirical Mode decomposition (EMD) method decomposing complex signals adaptively into different IMFs based on different time-scale characteristics by looking for local maxima and minima points and their envelopment in signals, and recombining IMFs can realize the reconstruction and noise reduction of original signals. This method is suitable for non-stationary signal analysis and also widely used in mechanical vibration signal processing. However, when EMD decomposes signals, it is easy to generate modal aliasing. Yeh et al. proposed CEEMD method that can effectively suppress modal aliasing [6]. This method adds two groups of positive and negative white noise in pairs to the original signal, and then decomposes them by EMD. The IMFs obtained are averaged by two groups of IMF components of residual positive and negative white noise. The process of CEEMD algorithm is as follows:

1) A pair of positive and negative white noise $n(t)$ is added to the original signal $x(t)$:

$$\begin{cases} x^{+}(t) = x(t) + n(t) \\ x^{-}(t) = x(t) - n(t) \end{cases} \tag{4}$$

2) The EMD method is used to decompose $x^{+}(t)$ and $x^{-}(t)$ to obtain IMF_k^{+} and IMF_k^{-}.

3) Calculate the average values of IMF_k^{+} and IMF_k^{-}:

$$\overline{IMF} = \frac{IMF_k^{+} + IMF_k^{-}}{2} \tag{5}$$

4) The original signal can be expressed as:

$$x(t) = \sum_{k=1}^{K} \overline{IMF}_k + r(t) \tag{6}$$

Where $r(t)$ is the residual amount.

4. Fault feature extraction of rolling bearing based on improved wavelet threshold and CEEMD

In this paper, a fault feature extraction method of rolling bearing based on improved wavelet threshold and CEEMD is proposed. Firstly, the improved wavelet threshold is used to de-noise the vibration signal to reduce noise interference and enhance the impact characteristics. Then, CEEMD is used to decompose the noise reduction signal into a group of IMFs with different scales. False components are eliminated according to kurtosis and correlation coefficient, IMFs representing fault characteristics are selected and used for signal reconstruction. At last, the envelope spectrum analysis of reconstructed signal is carried out to extract fault characteristic information. The process of fault feature extraction is shown in Figure 1.

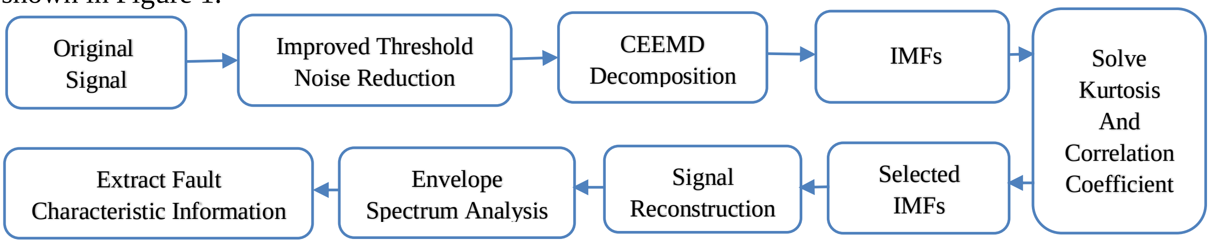


Figure 1. Fault features extraction process

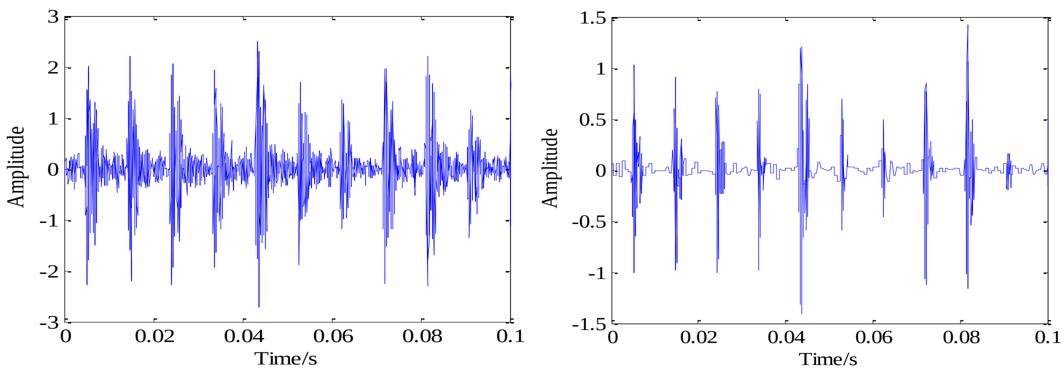
5. Experimental analysis
The bearing data of Case Western Reserve University were used to analyze the experiment. The driving end bearing is selected as the object of this study, and the bearing model is 6205-2RS JEM SKF, with diameter of inner ring 25 mm, diameter of outer ring 52 mm, thickness 15 mm, diameter of rolling body 7.94 mm, pitch 39.04 mm, nine rolling bodies, contact angle 0 degree, sampling frequency 12 KHz, sampling points 2048, rotating speed 1772 r/min, load 746 W. The theoretical characteristic frequency of inner ring fault is 156.14 Hz, and that of outer ring fault is 103.36 Hz.

First, take the fault signal, and then the wavelet base is selected as $sym5$, with four decomposition layers and a threshold $\lambda = \sigma\sqrt{2\ln N}$ selected. Among them, σ is noise standard variance and N is sampling signal length. The fault signals of inner and outer rings of rolling bearings are analyzed by using the fault feature extraction method based on improved wavelet threshold and CEEMD.

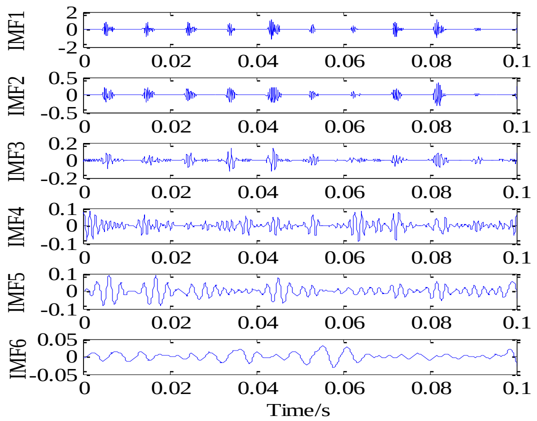
5.1. Outer circle fault analysis
The fault signal of bearing outer ring is analyzed. The time domain waveform of the outer ring fault signal is shown in Figure 2(a). It is obvious from the graph that the background noise of the original vibration signal is large and the impact characteristics are not obvious. The time-domain waveform of outer-loop fault signal denoised by improved wavelet threshold is shown in Figure 2(b), and it can be seen that the impulse component in the signal increases, and the fault characteristics are more obvious. CEEMD algorithm is used to decompose the denoised signal, and the first six IMFs are shown in Figure 2(c). The kurtosis and correlation coefficients of the first six components of CEEMD decomposition are shown in Table 1. It can be seen that the kurtosis and correlation coefficients of the first two components are larger. Then two IMFs, IMF1 and IMF2, are selected to represent the fault information of the signal, and use them to reconstruct signals, and envelope spectrum of reconstructed signal, as shown in figure 2(d). It can be seen from the envelope spectrum that the fundamental frequency of the fault is 105.5 Hz, which is approximately 103.36 Hz, the theoretical value of the fault characteristic frequency of the outer ring, and its double, triple and quadruple frequency etc can be obtained. Therefore, within the allowable range of errors, bearing outer ring damage can be determined.

Table 1. Kurtosis and correlation coefficient of IMFs

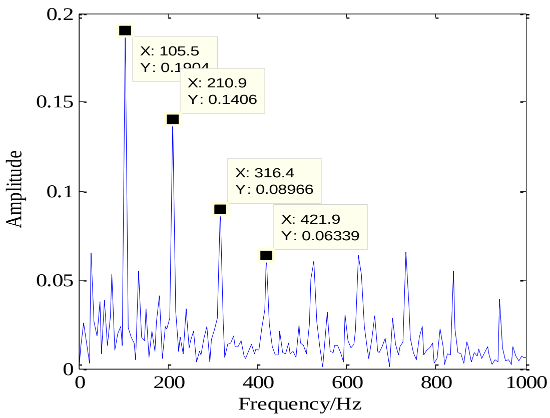
IMFs	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6
Kurtosis	8.6963	9.7282	8.4267	6.2198	3.7438	3.2045
Correlation coefficient	0.9499	0.4720	0.0737	0.0789	0.0429	0.0200



(a) Time-domain waveform of fault signal (b) Noise reduction signal waveform



(c) Decomposition results of CEEMD



(d) Envelope spectrum of reconstructed signal

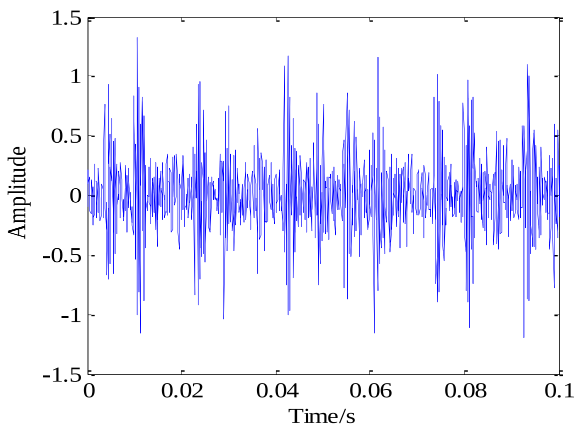
Figure 2. Analysis of outer circle fault signal

5.2. Fault analysis of inner ring

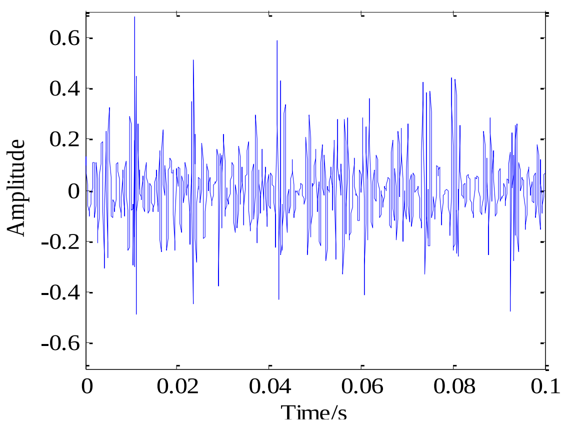
The fault signal of bearing inner ring is analyzed. The time domain waveform of the inner ring fault signal is shown in Figure 3(a). It is obvious from the graph that the background noise of the original vibration signal is large and the impact characteristics are not obvious. The time-domain waveform of inner-loop fault signal denoised by improved wavelet threshold is shown in Figure 3(b). It can be clearly seen that the impulse component in the signal increases and the fault characteristics are prominent. The noise reduction signal is decomposed by CEEMD algorithm. Its first six IMFs are shown in Figure 3(c). The kurtosis and correlation coefficients of the first six IMFs are shown in Table 2. It can be seen that the kurtosis and correlation coefficients of the first three IMFs are larger. So three IMFs, IMF1, IMF2 and IMF3, are selected to represent the fault information of the signal, and use them to reconstruct signals, and envelope spectrum of reconstructed signal, as shown in Figure 3(d). It can be seen from the envelope spectrum that the fundamental frequency of the fault is 158.2 Hz, which is approximately 156.14 Hz, the theoretical value of the fault characteristic frequency of the inner ring, and its double, triple and quadruple frequencies etc can also be obtained. Therefore, within the allowable range of errors, bearing inner ring damage can be determined.

Table 2. Kurtosis and correlation coefficient of IMFs

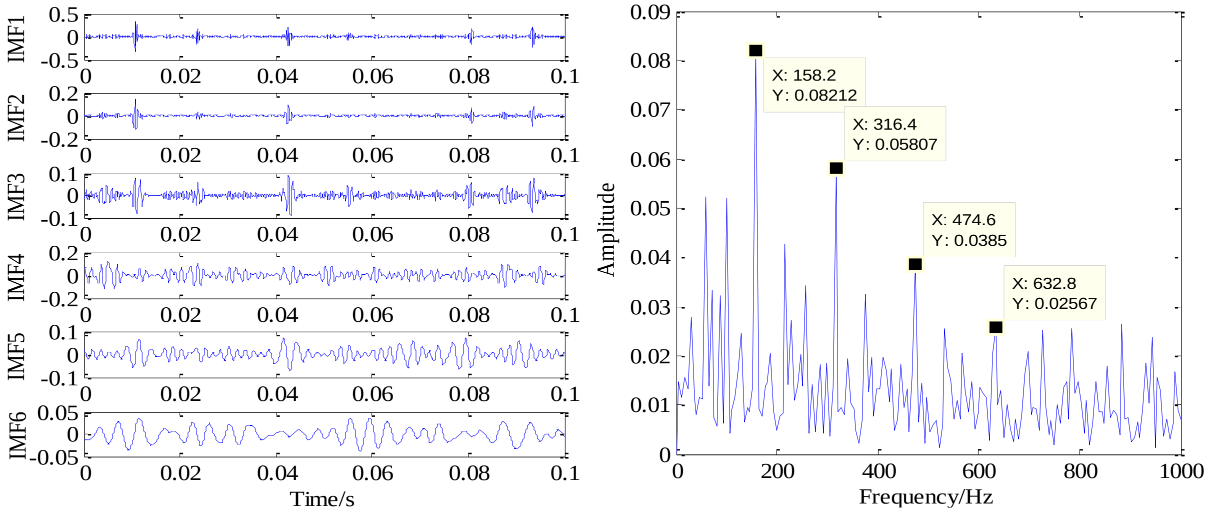
IMFs	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6
Kurtosis	21.7805	19.8798	16.3396	3.7059	3.8074	3.5406
Correlation coefficient	0.8010	0.6205	0.3910	0.1677	0.0626	0.0093



(a) Time-domain waveform of fault signal



(b) Noise reduction signal waveform

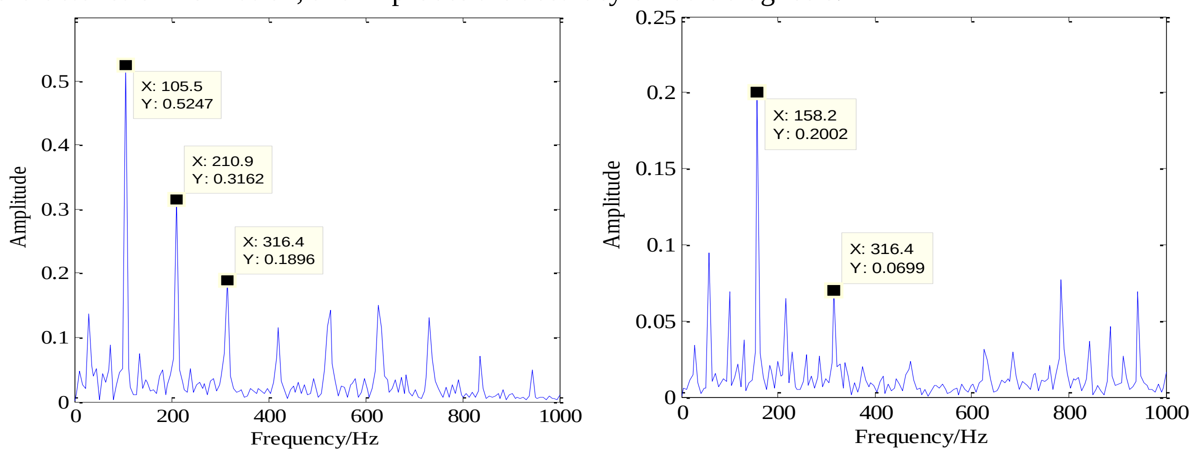


(c) Decomposition results of CEEMD (d) Envelope spectrum of reconstructed signal

Figure 3. Analysis of inner circle fault signal

5.3. Comparative analysis

When the fault signal is not denoised, the CEEMD method is directly adopted to decompose the fault signal and conduct envelope spectrum analysis. The envelope spectra of the outer ring and inner ring signals of the bearing are shown in figure 4. It can be found that the middle and high frequency part of the fault signal is drowned by noise due to the influence of noise, and the fault impact characteristics of the middle and high frequency part of the signal are not obvious, which reduces the accuracy of fault diagnosis. Compared with it, the method adopted in this paper reduces the noise interference, features obvious fault impact, highlights the fault characteristic frequency, effectively extracts the fault characteristic information, and improves the accuracy of fault diagnosis.



(a) Envelope spectrum of outer-loop signal (b) Envelope spectrum of inner circle signal

Figure 4. Fault signal analysis of inner and outer rings

6. Conclusion

This paper presents a fault feature extraction method for rolling bearings based on improved wavelet threshold and CEEMD. The improved wavelet threshold de-noising algorithm is used as the pre-filter of CEEMD decomposition to filter out the noise interference and enhance the impact characteristics. The noise reduction signal is decomposed by CEEMD algorithm, and the false components are eliminated according to the kurtosis and correlation coefficient of components, and the components representing the fault impact characteristics are selected for reconstruction. The fault feature information is extracted by envelope spectrum analysis. Through experimental analysis, this method is helpful for rolling bearing fault diagnosis.

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