Bearing Fault Diagnosis Based on CEMDAN Energy Weighting Method

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Abstract. Bearing fault diagnosis is an important way to ensure the safe operation of equipment. However, the impact caused by some faults in the industrial field is often covered by environmental noise, the weak feature extraction method of vibration signal under strong noise interference is particularly important. In order to solve the problem that weak fault features can’t be extracted by single noise reduction or feature enhancement method under strong noise interference, an energy weighting method based on time-frequency spectrum analysis is proposed in this paper, which combines noise elimination and feature enhancement methods to extract weak impact features under strong noise background. Through the test verification of bearing inner ring fault, the method proposed in this paper has certain practical value in practical application.

Introduction

In the industrial field, there are large vibration disturbances in the operating environment where a large number of devices are located. Because these interference energy is large, the impact caused by some faults is masked, which makes it difficult to monitor the condition of the equipment and diagnose the fault. The industrial field has more urgent requirements for related technologies. A large number of equipments need to ensure operational safety and reduce operation and maintenance costs through monitoring and diagnosis methods. Therefore, it is of great theoretical and practical significance to study the method of extracting weak features of faults under strong noise interference.

During the operation of the device, the fault feature extraction is difficult due to the presence of interference in the external environment or multiple device components. In response to this problem, some scholars first suppress the noise of the collected signal by means of noise reduction, and then analyze the signal after noise reduction. Khemili et al. used adaptive noise cancellation (ANC) technology for noise reduction of faulty bearing vibration signals\textsuperscript{[1]} Shao et al. proposed a hybrid noise reduction method using wavelet denoising combined with ANC \textsuperscript{[2]} Wang et al. proposed a time-varying autoregressive method, and the experimental verification can achieve high-resolution time spectrum analysis by matching other algorithms \textsuperscript{[3]} Antoni proposed a blind source separation method for vibration signal noise separation, which is widely used in the field of equipment fault diagnosis. The spectral kurtosis method detects the frequency position of non-Gaussian components in the signal by calculating the kurtosis value on each spectral line. Due to its theoretical perfectness and practicability, it is widely used in the field of fault diagnosis \textsuperscript{[4]} Some scholars have applied and improved the theory, and proposed optimal bandwidth selection, minimum entropy deconvolution and spectral kurtosis fusion methods, which have achieved good results in gearbox fault diagnosis \textsuperscript{[5,6]} In addition, some scholars have proposed a spectral kurtosis method based on wavelet packet decomposition, a fast kurtosis graph based on LMD, and a spectral kurtosis method based on EEMD and Hilbert-Huang transform. Feature extraction methods combined with multiple time-frequency analysis\textsuperscript{[7-9]}.

However, in a large number of scenarios, the fault feature impact is a weak component and has a
complex coupling relationship with noise, so it is difficult to separate. At the same time, pure noise reduction is easy to cause the loss of impact components. Therefore, in the process of how many scholars study how to demodulate and denoise signals, some scholars have taken a different approach and tried to study the feature extraction of weak faults by enhancing the impact feature. At present, there are few mainstream signal enhancement methods, and the stochastic resonance method can enhance the amplification of weak information through the resonance of nonlinear systems. Leng et al. proposed the theory of bistable stochastic resonance, subsampling stochastic resonance, adaptive stochastic resonance, and parameter-adjusted stochastic resonance \[10-12\], which made the stochastic resonance theory have a certain application in the enhancement of weak characteristics of vibration signals. Harne, Lei, He, etc. also apply stochastic resonance technology in the diagnosis of rotating machinery \[13-16\]. The above method can better extract weak fault impact components in a strong noise environment, but the stochastic resonance method requires cumbersome tuning, and inappropriate parameter selection will greatly affect the diagnostic effect of the device.

Aiming at the problem that weak fault characteristics under strong noise interference are difficult to extract by single noise reduction or feature enhancement method, this paper proposes an energy weighting method based on impact energy enhancement in time spectrum analysis \[17\]. Time-frequency analysis and time-scale multi-scale binarization realizes transient energy extraction and enhancement in the time-frequency domain, and combines noise elimination and feature enhancement to achieve feature extraction of weak impact in strong noise background.

Based on CEEMDAN Energy Weighting Method

The energy weighting method is a transient impact energy extraction method based on time-scale multi-scale binarization. The method steps are as follows: Firstly, the time-frequency distribution of the vibration signal is obtained by time-frequency analysis method, and the time-spectrum spectrum is obtained, and then the time-spectrum spectrum is binarized by discriminating the position of the impact energy in the time spectrum, and then obtained by multi-scale bispectrum analysis. The energy weight of the impact can be reflected, and finally the power spectrum analysis is performed to obtain the frequency of the impact component related to the fault.

Time-frequency Analysis Based on CEEMDAN

The empirical mode decomposition (EMD) can adaptively decompose the vibration signal. The Hilbert-Huang transform can obtain the time-frequency distribution of the signal, but the empirical mode decomposition has the problems of end effect and modal aliasing. Wu et al. proposed the Ensemble Empirical Mode Decomposition (EEMD) method, which reduces the influence of abnormal components on the IMF component by noise-assisted analysis, and solves the modal aliasing problem to some extent. \[18\] Colominas, Torres et al. proposed Complete Ensemble Empirical Mode Decomposition (CEEMD) and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) \[19\] to further solve The EEMD method leads to different screening results in the case of adding different white noise. The core of the CEEMDAN method is to add white noise of a specific frequency band in the decomposition process. The algorithm flow is shown in Figure 1. The CEEMDAN signal \(X(t)\) can be expressed as the sum of \(n\) IMFs and the residual amount \(r_n(t)\). By performing a Hilbert transform on each IMF, the instantaneous frequency \(\omega(t)\) and the amplitude \(a(t)\) can be obtained. Then the original signal \(X(t)\) analyzed can be expressed as:

\[
X(t) = \sum_{j=1}^{n} a_j(t) \exp(i \int \omega_j(t) dt)
\]  \hspace{1cm} (1)

By Equation 1, the original signal can be expressed as a function of amplitude and instantaneous frequency with respect to time, so it can be depicted by a three-dimensional time-frequency distribution called the Hilbert amplitude spectrum \(H(\omega, t)\).
Multi-scale Energy Weighting Method

The time spectrum \( H(\omega, t) \) obtained by the Hilbert-Huang transform is a two-dimensional array, and the array size is \( M \times N \), where \( M \) is the number of time domain grids and \( N \) is the number of frequency domain grids.

\[
M = \frac{T}{\Delta t}
\]

\[
N = \frac{1}{n \Delta t} = \frac{T}{n \Delta t}
\]

For rotating machinery, when an abnormal fault occurs in its components, the impact component of the vibration signal is reflected in the form of sudden changes in energy in the time spectrum. Extracting \( n \) time energy sequences representing different frequency intervals from the time spectrum matrix can observe these impacts more effectively and intuitively. Then, by using a variety of windows related to the frequency of the typical fault feature for impact recognition, multi-scale binarization of the energy time series is realized, thereby realizing multi-scale binarization of the time spectrum, thereby obtaining multi-scale binary under different scale features. Spectrum.

The specific implementation method is as follows:

1. Extracting the energy time series \( x_n(t) \), \( n \in (1, N) \) in different frequency intervals from the \( M \times N \) time-spectrum matrix;

2. Set a sliding window of length \( 2d+1 \) in the energy time series \( x_n(t) \). At that time, let \( B_n(t_i)=1 \), otherwise \( B_n(t_i)=0 \). That is, when the midpoint energy value of the window is the local energy extreme value, the weight is set to 1, otherwise it is 0;

3. Binarizing the energy time series on different frequency intervals, repeating \( N \) steps (2), and obtaining \( N \) binarization time series, that is, a binary matrix \( B(t, f) \) having a size of \( M \times N \). This matrix is called a binary spectrum;

4. Set different window lengths \( 2d+1 \), repeat steps 2 and 3 multiple times to obtain multi-scale binary spectrum.

In the process of binary spectrum calculation, the parameter \( d \) in the window length \( 2d+1 \) is an important parameter that plays a decisive role. If the parameter \( d \) is too large or too small, the calculation result will be affected, and the diagnosis result will not be affected. In order to effectively extract the sudden change of the impact energy and reduce the noise interference as much as possible, the window length \( 2d+1 \) should be satisfied when calculating the first binary spectrum: the number of intervals between the two impacts generated by the fault < \( 2d+1 \) < the number of intervals between the three impacts caused by the fault. However, due to the complex coupling relationship between noise and fault impact, the first binary spectrum obtained is still doped with many false energy shocks from noise interference. Therefore, it is necessary to increase the window length parameter \( d \) and repeatedly calculate the binary spectrum at different scales. The window length parameter \( d \) can be selected according to Equation 4:

\[
d = \left\lfloor \frac{f_s \cdot c}{2f_f} \right\rfloor
\]

Where \( f_s \) is the sampling rate, \( c \) is the number of calculations, and \( f_f \) is the frequency of the fault feature, which is the upward even operator.

By calculating the binary spectrum \( B_1(t, f) \), \( B_2(t, f) \), \( \cdots \), \( B_C(t, f) \) at different scales, the frequency domain summation is obtained by frequency domain summation:

\[
W_\epsilon(t) = \sum_{f=1}^{N} B_\epsilon(t, f)
\]

The power spectrum analysis of the energy weight time series can obtain the enhanced spectrum of the signal.
Bearing Fault Diagnosis

Taking an inner ring fault bearing as an example, the bearing is a 352226X2-2Z axle box bearing widely used in China railway freight trains, and its parameters are shown in Table 1. The inner ring fault is shown in Fig. 2, which is irregular wear caused by the use process, and is about 10 mm long, about 2 mm wide, and about 0.1 mm deep.

| Bearing average diameter D/mm | Roller diameter d/mm | Contact angle α | Number of rollers/piece |
|-------------------------------|----------------------|-----------------|------------------------|
| 176.29                        | 24.74                | 8.833           | 20                     |

When the rotational speed is 461 rpm, the fault characteristic frequency is 87.26 Hz. The collected vibration signal X(t) is shown in Fig. 3, the sampling rate is 5120 Hz, and the sampling duration is 2 s.
Envelope spectrum analysis is performed on the acquired vibration signal, and its spectrum is shown in FIG. 4. It is impossible to distinguish from the figure whether there is a fault characteristic frequency component, and even the bearing frequency conversion component cannot be distinguished.

In addition, the wavelet packet denoising method and the stochastic resonance based signal enhancement method are used for signal processing. Figure 5 shows the envelope spectrum of the noise-reduced signal obtained by setting the 1-5 layer noise reduction thresholds to 169.68, 111.6, 68.8, 38.2, and 15.01 after the 5-layer wavelet packet decomposition is performed on the haar wavelet basis. Fault related features.

Fig. 6 is a frequency-reduced amplitude spectrum obtained by random resonance method, parameter selection $\mu = 1$, $a = 0.1$, $fs = 5120$ Hz, $fsr = 1000$ Hz, and the fault characteristic component can not be seen from the figure.

A time-frequency diagram as shown in FIG. 7 is obtained by performing CEEMDAN-based Hilbert-Huang transform time-frequency analysis on the acquired vibration signal.

Perform a binary spectrum analysis on the time-frequency diagram. The parameters in Equation 4
take $f_s=5120$, $f_f=88.8$, and perform 6 times of binary spectrum calculation. Then $d_1=30$, $d_2=60$, $d_3=90$, $d_4=120$, $d_5=150$, $d_{\text{max}}=d_6=180$, and the obtained 6 binary spectra are as shown in FIG. 8.

Figure 8. Vibration signal binary spectrum.

The calculated set energy weights are shown in Figure

![Compound weight of energy $\tilde{W}(t)$](image.png)

Figure 9. Compound weight of energy $\tilde{W}(t)$.

The power spectrum of the signal $W(t)$ is calculated as shown in FIG. The power spectrum obtained in Fig. 9 shows a clear frequency shift at 7.7 Hz and a fault characteristic frequency at 87.3 Hz. Through the above experiments we can see the effectiveness of the proposed algorithm.

**Conclusion**

According to the bearing vibration acceleration signal obtained by the experimental device, the time-frequency analysis based on CEEMDN is carried out and the fault characteristic component is enhanced by multi-scale energy weighting method. Finally, the power spectrum of the signal is calculated. The experimental results demonstrate the effectiveness of the proposed algorithm and are suitable for engineering applications.
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