Rolling Bearing Fault Diagnosis Method With Adaptive CEEMD and Cyclic Spectrum Coherence

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Abstract. Rolling bearings are the key components of rail trains, and ensuring their normal operation is very important to the safety of trains. Aiming at the problem of bearing fault diagnosis, this paper proposes a bearing fault diagnosis algorithm based on adaptive CEEMD and cyclic spectrum coherence. Firstly, for noise reduction on the original signal, the adaptive CEEMD algorithm is proposed. This algorithm realizes the selection of the optimal parameter combination of CEEMD, solves the traditional EMD algorithm mode mixing problem, the reconstruction error problem of the EEMD algorithm, and the problem that CEEMD algorithm caused the difference of analysis results due to parameter settings. Secondly, the cyclic spectrum coherence analysis uses the characteristics of the cyclostationarity of the faulty bearing signal to reveal the hidden periodic characteristics in the signal, and calculates its improved envelope spectrum to make the fault characteristic information of the bearing more convenient to identify. Finally, this paper will compare the proposed algorithm with other current fault diagnosis algorithms to further verify the superiority of this algorithm.

Keywords: Fault diagnosis, Adaptive CEEMD, Cyclic spectrum coherence

1 Introduction

As the speed of high-speed trains continues to increase, the operating environment of rolling bearings in train bogies has become more and more complex. Long-term operation under severe conditions such as high speeds and heavy loads is prone to fatigue failure. Once a failure occurs, the train will be directly affected. Therefore, it is particularly important to conduct timely state detection of rolling bearings, accurately diagnose their faults, and repair or replace them in time to ensure their healthy operation.

Due to the complex operating environment, there is usually a large amount of noise pollution in the vibration data of rolling bearings, so it is particularly important to denoise the bearing vibration data. At present, common signal noise reduction methods include Empirical Mode Decomposition (EMD) [1], Local Mean Decomposition (LMD) [2], etc. In 2021, Zhao et al. proposed a blind source extraction of rolling bearing fault diagnosis based on EMD and time correlation. This method can extract bearing fault signals well and can extract periodic fault signals for bearing fault diagnosis [3]. However, the above methods all have the problem of mode mixing. To solve this problem, Zhaohua Wu et al. proposed the Ensemble Empirical Mode Decomposition (EEMD) algorithm [4], but the addition of white noise will change the original signal and cause reconstruction errors. To solve this problem, Jia-Rong YEH et al. proposed a Complementary Ensemble Empirical Mode Decomposition (CEEMD) algorithm [5]. It solved the mode mixing and reconstruction errors. However, the difference in the amplitude and amount of white noise added to the CEEMD algorithm will have a greater impact on the results of the algorithm. Based on this problem, this paper proposes an adaptive CEEMD algorithm, which selects the optimal parameter combination for CEEMD decomposition intending to minimize the envelope entropy to achieve a better noise reduction effect.

To better identify the fault, it is necessary to perform spectrum analysis to highlight the fault information. At present, common frequency domain analysis methods include envelope analysis, Fast Spectral Kurtosis (Fast SK) [6], etc. Because of the cyclostationary characteristics of fault signals, cyclic spectrum analysis [7] has gained more and more attention and application in the field of fault diagnosis in recent years. Therefore, in this paper, after performing the adaptive CEEMD algorithm, the cyclic spectrum coherence analysis is performed, and the improved envelope spectrum is calculated, to achieve the highlight of the fault information and the accurate identification of the bearing fault.

The rest of the article is arranged as follows: In chapter 2, the principle of the adaptive CEEMD algorithm will be explained in detail; in chapter 3, the cyclic spectrum coherence and improved envelope spectrum will be introduced in detail; in chapter 4, the principle of fault diagnosis algorithm based on adaptive CEEMD and cyclic spectrum coherence will be explained in detail; in chapter 5, the performance indicators of the fault diagnosis algorithm will be introduced, and the proposed algorithm will be compared with other algorithms based on the real fault data to further prove the superiority of the algorithm; in Chapter 6, the conclusion of this article will be explained.

2 Principle of adaptive CEEMD algorithm

2.1 Complementary Ensemble Empirical Mode Decomposition

The Empirical Mode Decomposition (EMD) algorithm [1] has been widely applied in the field of vibration signal processing for bearing fault diagnosis. This algorithm can decompose any complex vibration signal $x(t)$ into several single-component signals, namely the Intrinsic Mode Function (IMF) and a non-zero average residual signal $r(t)$.

Although the traditional EMD algorithm has been widely used in fault diagnosis, it still has many problems, among which the main problem is mode mixing. The main cause of this problem is impulse signals or noise interference. To solve this problem, Zhaohua Wu et al. proposed the Ensemble Empirical Mode Decomposition (EEMD) algorithm [4]. This algorithm adds different white noise signals to the original vibration signal several times, and performs EMD decomposition, and finally obtains the final IMF sequence by averaging the obtained different IMF sequences.

Although the EEMD algorithm solves the mode mixing problem of the traditional EMD algorithm, the original signal is changed due to the added white noise, which will cause reconstruction error. To solve this problem, Jia-Rong YEH et al. proposed a Complementary Ensemble Empirical Mode Decomposition (CEEMD) algorithm [5]. The CEEMD algorithm solves the reconstruction error problem caused by the addition of white noise in the EEMD algorithm by adding several pairs of Gaussian white noise signals with zero mean to the original signal and taking the average value after EMD decomposition. The specific steps of the CEEMD algorithm are as follows:

Step 1. Add N_e pairs of Gaussian white noise signals with zero mean to the original signal $x(t)$, and obtain N_e pairs of noise-added signal $x_i^+(t)$ and $x_i^-(t)$ $(i=1,2,\ldots\ldots,Ne)$.

$$\begin{cases} x_i^+(t)=x(t)+s_i*w_i(t) \\ x_i^-(t)=x(t)-s_i*w_i(t) \end{cases} \tag{1}$$

Among them, $w_i(t)$ $(i=1,2,\ldots\ldots,Ne)$ is Gaussian white noise, and s_i $(i=1,2,\ldots\ldots,Ne)$ is the proportion of noise in the original signal.

Step 2. Perform EMD decomposition on $x_i^+(t)$ and $x_i^-(t)$ respectively to obtain N_e pairs of IMF sequences $\left\{imf_{i,j}{}^+(t)\right\}$ and $\left\{imf_{i,j}{}^-(t)\right\}$ $(i=1,2,\ldots\ldots,Ne;j=1,2,\ldots\ldots,N)$.

Step 3. Take the average of IMF sequence pairs to obtain N_e groups of IMF sequences $\left\{imf_{i,j}(t)\right\}$ $(i=1,2,\ldots\ldots,Ne;j=1,2,\ldots\ldots,N)$.

$$imf_{i,j}(t)=\frac{1}{2}\left[imf_{i,j}{}^+(t)+imf_{i,j}{}^-(t)\right] \tag{2}$$

Step 4. The obtained N_e sets of IMF sequence $\left\{imf_{i,j}(t)\right\}$ are respectively summed and averaged to obtain the final IMF sequence $\left\{imf_j(t)\right\}$ $(j=1,2,\ldots\ldots,N)$.

$$imf_j(t) = \frac{1}{Ne}\sum_{i=1}^{Ne} imf_{i,j}(t) \tag{3}$$

2.2 Adaptive CEEMD algorithm

Although the CEEMD algorithm not only solves the mode mixing problem of the traditional EMD algorithm, but also optimizes the reconstruction error of the EEMD algorithm, but adding the amplitude and amount of Gaussian white noise will have a greater impact on the CEEMD analysis results. Therefore, this paper proposes an adaptive CEEMD algorithm, which takes the amplitude and amount of white noise added in the CEEMD algorithm as the parameters to be optimized, and takes the minimum envelope entropy of the first IMF component obtained after CEEMD decomposition as the goal, using Particles Swarm Optimization (PSO) algorithm optimizes the CEEMD algorithm to find the optimal combination of parameters.

Objective function optimized by Adaptive CEEMD algorithm. TANG Guiji et al. proposed envelope entropy based on the concept of Shannon entropy [8]. The envelope entropy value E_p can reflect the sparse nature of the original signal. The specific calculation formula is as follows:

$$\begin{cases} E_p = -\sum_{i=1}^{N} p_i \, lg\left(p_i\right) \\ p_i = \frac{a(i)}{\sum_{j=1}^{N} a(j)} \end{cases} \tag{4}$$

Among them, $a(j)$ represents the envelope signal of the original signal after Hilbert transform.If the IMF component after CEEMD decomposition contains more noise components, the sparsity of the IMF is weaker, that is, the envelope entropy value is larger.

Adaptive CEEMD algorithm flow.

1. Randomly generate a certain number of white noise addition specific gravity s and times Ne of the CEEMD algorithm, use the parameter combination $[s,Ne]$ as the initial position of the particle swarm, and initialize a certain number of particle swarm velocities randomly.
2. The original signal is decomposed by CEEMD according to different parameter combinations $[s,Ne]$, and the envelope entropy of the first IMF component is calculated.
3. By comparing the envelope entropy, the local optimal solution and the global optimal solution of the particle swarm are updated.
4. Update the position and velocity of the particle swarm and repeat the above steps until the maximum number of iterations is reached.
5. Perform CEEMD decomposition according to the global optimal solution of the parameter combination$[s,Ne]$obtained in the final iteration, and obtain the decomposed IMF sequence.

3 Principle of Cyclic Spectrum Coherence

After the original signal is decomposed by the adaptive CEEMD algorithm, to achieve a better fault diagnosis effect, it is necessary to select an appropriate time-frequency analysis method to analyze the IMF components. In recent years, cyclostationary theory has received extensive attention. For rotating machinery, the vibration signal of a faulty bearing is a modulation signal generated by its fault characteristic frequency. This type of signal has second-order periodicity and can be separated from other interference signals. The cyclic spectrum analysis [7] is an effective second-order statistical tool for cyclostationarity.

For a cyclostationary signal $x(t)$, the second moment of its cyclostationarity is defined as an Auto Correlation Function (ACF) with a cycle period of T, as follows:

$$R_{xx}(t,\tau)=R_{xx}(t+T,\tau)=E\left\{x\left(t+\frac{\tau}{2}\right)x\left(t-\frac{\tau}{2}\right)^*\right\} \tag{5}$$

Among them, * Means complex conjugate; τ means time lag; E means expected value operation.

The cyclic ACF is defined as the Fourier coefficient of ACF, as follows:

$$R_{xx}(\tau,\alpha)=\int R(t,\tau)e^{-j2\pi\alpha t}dt \tag{6}$$

Among them, α represents the cycle frequency.

Cyclic Spectral Correlation (CSC) can be estimated by the Fourier transform of the cyclic ACF to estimate the Cyclic Spectral Correlation (CSC), as follows:

$$CSC(\alpha,f)=\int R_{xx}(\tau,\alpha)e^{-j2\pi ft}d\tau=\iint R(t,\tau)e^{-j2\pi(\alpha t+ft)}dtd\tau \tag{7}$$

The cyclic spectrum correlation is a function of the frequency f and the cyclic frequency α, the frequency f is related to the carrier, and the cyclic frequency α is related to the modulation. Further, to minimize the uneven distribution, the concept of Cyclic Spectrum Coherence (CSCoh) [9] is proposed, and its calculation formula is as follows:

$$CSCoh(\alpha,f)=\frac{CSC(\alpha,f)}{\sqrt{CSC(0,f)CSC(0,f-\alpha)}} \tag{8}$$

Cyclic spectrum coherence can also be understood as the cyclic spectrum correlation of the signal after whitening processing. After obtaining the cyclic spectrum coherence, integrate f in the specified frequency band $[f_1,f_2]$ to obtain the enhanced envelope spectrum (EES) of the cyclic spectrum coherence. The enhanced envelope spectrum is an improvement of the square envelope spectrum (SES). The improved envelope spectrum (IES) [10] can be obtained by averaging it, as follows:

$$S_x^{IES}(\alpha)=\frac{1}{f_2-f_1}\int_{f_1}^{f_2}|CSCoh(\alpha,f)|\,df \tag{9}$$

4 Bearing fault diagnosis method based on adaptive CEEMD and Cyclic Spectrum Coherence

Based on the research content of Chapter 2 and Chapter 3, this chapter proposes a bearing fault diagnosis method based on adaptive CEEMD and CSCoh, hereinafter referred to as Adaptive CEEMD-CSCoh. This algorithm can identify bearing faults under the background of noise. The specific process of the algorithm is as follows:

Step 1. Perform adaptive CEEMD decomposition on the original signal $x(t)$ to obtain the decomposed IMF component sequence $\{imf_i(t)\}$.

Step 2. Carry out cyclic spectrum coherence analysis on $imf_1(t)$, and obtain its cyclic spectrum coherence matrix $CSCoh_{imf_1}(\alpha,f)$. And then Calculate the improved envelope spectrum $S^{IES}_{CSCoh_{imf_1}}(\alpha)$ of $CSCoh_{imf_1}(\alpha,f)$, and perform fault identification on it.

5 Instance verification

5.1 Performance evaluation index of fault diagnosis algorithm

To be able to quantitatively evaluate the performance of different fault diagnosis algorithms, it is necessary to introduce a suitable fault diagnosis effect evaluation index. Feature Energy Factor (FEF) [11] is a more stable and accurate indicator. The calculation formula of FEF is as follows:

$$FEF=\frac{E^*}{E}=\frac{\sum_{i=1}^{m} Y^2(i)}{\sum_{j=1}^{N} Y^2(j)} \tag{10}$$

Among them, E^* represents the energy of the fault information, E represents the total energy of the spectrum, $Y(i)(i=1,2,\ldots,m)$ represents the peak value at the fault frequency, $Y(j)(j=1,2,\ldots,N)$ represents the peak value of the frequency spectrum at point j.

The FEF index reflects the prominence of the fault information in the frequency spectrum by calculating the proportion of the energy of the fault information in the total energy of the frequency spectrum. The larger the FEF, the more prominent the fault information, and the better the performance of the fault diagnosis algorithm.

5.2 Verification of vibration data of freight train bearings

In this section, we select the vibration data of the bearing with outer race fault to verify and compare the algorithm. The bearing models of the faulty bearing is 197726TN. The running speed is 90km/h, the vertical load is 56kN, and the data sampling frequency is 32768Hz. Referring to the theoretical fault frequency formula of the bearing, the theoretical fault frequency of the outer race is calculated to be 85.51 Hz.

Before verifying the Adaptive CEEMD-CSCoh algorithm, the parameters of Adaptive CEEMD need to be preseted. To reduce the influence of adding Gaussian white noise on the original signal, and to ensure the algorithm's processing effect on the mode mixing problem and the reconstruction error problem, S_i is set between [0.1, 0.3], Ne is set between [20,50].

Firstly. The Adaptive CEEMD-CSCoh algorithm is used to analyze the fault data. Fig.1 is the iterative result of Adaptive CEEMD. The optimal S_i is 0.25 and the optimal *Ne* is 47. Fig.2 is the cyclic spectrum coherence spectrum of the first IMF. Fig.3 is the improved envelope spectrum. From the figure, we can clearly see the fault information from the fault frequency pointed to by the red arrow to its five times the frequency.

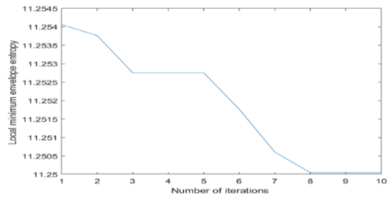

Fig. 1. Adaptive CEEMD iteration result of the fault data

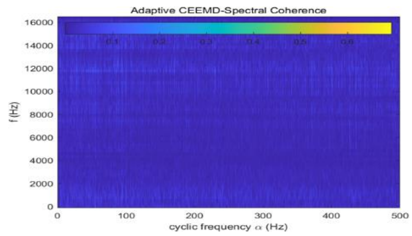

Fig. 2. Adaptive CEEMD-CSCoh result of the fault data

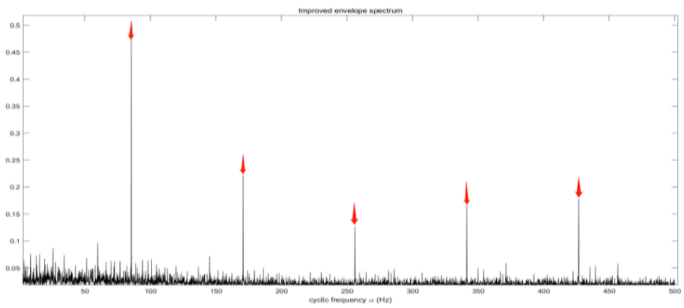

Fig. 3. IES of Adaptive CEEMD-CSCoh

Secondly. The Fast SK algorithm is used to analyze the fault data. Fig.4 is the fast kurtogram of the fault data. The optimal filter bandwidth B_w is 682.6667 Hz, and the center frequency f_c is 11946.6667 Hz. Fig.5 is the squared envelope spectrum obtained after filtering. It can be seen that the diagnostic effect of this algorithm is obviously not as good as the algorithm proposed in this article.

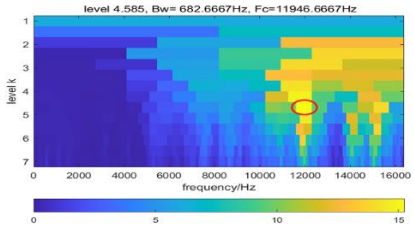

Fig. 4. Fast Kurtogram

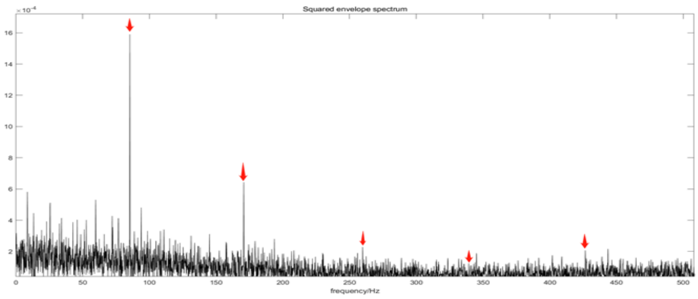

Fig. 5. SES of filtered signal

In order to quantify the performance indicators of the four algorithms, it is necessary to calculate the FEF of the four algorithms, and choose to calculate the ratio of the energy value from the fault frequency to its fifth frequency to the total spectrum energy. The results are shown in the following table:

Table 1. The comparison result of Adaptive CEEMD-CSCoh and Fast SK

Method	FEF(%)
Adaptive CEEMD-CSCoh	33.51
Fast SK	4.45

It can be seen that the performance of the algorithm proposed in this paper is significantly better than the existing algorithm.

6 Conclusion

Bearings are the key components of rail trains, and ensuring their normal operation is very important to the safety of trains. Aiming at the problem of bearing fault diagnosis, this paper proposes a bearing fault diagnosis algorithm based on adaptive CEEMD and cyclic spectrum coherence. Among them, the adaptive CEEMD solves the problem of modal aliasing in the traditional EMD algorithm, and the reconstruction error caused by the parameter setting of the CEEMD algorithm. The cyclic spectrum coherence takes advantage of the cyclic stability of the faulty bearing signal, revealing the hidden periodic characteristics in the signal.

This article first introduces the principle of the adaptive CEEMD algorithm, introduces the concept of envelope entropy to select the optimal parameter combination for CEEMD decomposition. Secondly, the cyclic spectrum coherence analysis is performed, and then the improved envelope spectrum is further calculated. Based on this, the bearing fault identification is carried out. Finally, the algorithm proposed in this paper is compared with the Fast SK algorithm. Compared with the quantitative evaluation of the performance of each algorithm based on the FEF index, it further verifies the superiority of the proposed algorithm.

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References

1. Huang N E, Shen Z, Long S R, et al: The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. In: Proceedings A, 454(1971):903-995 (1998)
2. Smith, Jonathan S: The local mean decomposition and its application to EEG perception data. In: Journal of The Royal Society Interface, 2(5):443-454 (2006)
3. Zhao, X., Qin, Y., Fu, H., Jia, L. and Zhang, X.: Blind source extraction based on EMD and temporal correlation for rolling element bearing fault diagnosis. In: Smart and Resilient Transportation, 3(1):52-65 (2021)
4. ZHAOHUA WU, NORDEN E. HUANG: ENSEMBLE EMPIRICAL MODE DECOMPOSITION: A NOISE-ASSISTED DATA ANALYSIS METHOD. In: Advances in Adaptive Data Analysis (2009)
5. Yeh J R, Shieh J S, Huang N E: Complementary Ensemble Empirical Mode Decomposition: a Novel Noise Enhanced Data Analysis Method. In: Advances in Adaptive Data Analysis, 2(2):- (2010)
6. Antoni J: Fast computation of the kurtogram for the detection of transient faults. In: Mechanical systems and signal processing, 21(1):108-124 (2007)
7. Antoni J: Cyclic spectral analysis in practice. In: Mechanical Systems & Signal Processing, 21(2):597-630 (2007)
8. TANG Guiji, WANG Xiaolong: Parameter Optimized Variational Mode Decomposition Methodwith Application to Incipient Fault Diagnosis of Rolling Bearing. In: Journal of Xian Jiaotong University, 549(005):73-81 (2015)（in Chinese）
9. Antoni J, Xin G: Hamzaoui N. Fast computation of the spectral correlation. In: Mechanical Systems & Signal Processing, 92(AUG.):248-277 (2017)
10. Liu C, Gryllias K: A Semi-supervised Support Vector Data Description-based Fault Detection Method for Rolling Element Bearings based on Cyclic Spectral Analysis. In:Mechanical Systems and Signal Processing, 140 (2020)
11. Luo Y, Chen C, Zhao S, et al: Rolling Bearing Fault Diagnosis Method With Enhanced Top-Hat Transform Filtering and Cyclic Spectrum Coherence. In: IEEE Access, 8:163715-163729 (2020)