IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received January 5, 2020, accepted January 27, 2020, date of publication January 31, 2020, date of current version February 10, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2970813

A Novel Rolling Bearing Defect Detection Method Based on Bispectrum Analysis and Cloud Model-Improved EEMD

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This work was supported in part by the National Natural Science Foundation of China under Grant 51405449 and Grant 51575497, and in part by the Zhejiang Public Welfare Technology Application Research Project under Grant 2016C31067.

ABSTRACT Mechanical signals are not only disturbed by Gaussian noise, but also by non-Gaussian noise. These Gaussian noise and non-Gaussian noise have gravely impeded detecting of rolling bearing defects using traditional methods. In this context, the paper develops a novel detection method for rolling bearing, which combines bispectrum analysis with an improved ensemble empirical mode decomposition (EEMD). To effectively eliminate Gaussian noise in the signal, bispectrum analysis is adopted. In order to effectively reduce non-Gaussian noise, a cloud model-improved EEMD is proposed, where the cloud model is introduced to restrain the mode mixing phenomenon. Then a rolling bearing defect detection plan based on the proposed method is put forward. From theoretical analysis and experimental verification, it is demonstrated that the proposed method has superior performance in reducing multiple background noise. Furthermore, compared with other three methods, the results show that the proposed method can detect the defect of rolling bearings more effectively.

INDEX TERMS Bispectrum analysis, cloud model, defect detection, ensemble empirical mode decomposition, mode mixing, rolling bearing.

I. INTRODUCTION

As a widely used and important part of the rotating machine, rolling bearings often lead to serious consequences of mechanical equipment after their failure. Therefore, the feature extraction and fault diagnosis of rolling bearing has been one of the important issues in the field of fault diagnosis of rotating machinery [1], [2]. When the rotating machinery is in normal operation, its vibration signal is usually a Gaussian signal, but once it fails, its vibration signal will turn into a non-Gaussian signal [3]. However, the traditional power spectrum analysis and time-frequency analysis cannot reflect the phase information between different frequency components, and usually, are disturbed by the non-Gaussian noise. The higher-order spectrum, especially bispectrum analysis, is a powerful tool for the analysis of non-Gaussian signals. It represents random signals from higher-order probabilistic structural and can make up for the defect that second-order statistics (power spectrum) do not contain phase information [4]. Tian *et al.* [5] propose a detector based on bispectrum of modulated signals for bearing fault detection, and can effectively suppress static random noise and discrete aperiodic noise. Shaeboub *et al.* [6] examine the effectiveness of conventional diagnostic features in both motor current and voltage signals using spectrum and modulation signal bispectrum analysis (MSBA), which has a good noise reduction capability. Huang *et al.* [7] use the performance of the conventional bispectrum (CB) method and its new variant, the modulation signal bispectrum (MSB) method to analyze faults from different rotors, and prove that MSB performs significantly better than the CB method. Chasalevris *et al.* [8] use bispectrum analysis to identify bearing fault. Guo *et al.* [9] applied bispectrum analysis for feature extraction of diesel cylinder liner piston rings, then the fault information is extracted by artificial neural network and obtains a high accuracy. Li *et al.* [10] use bispectrum analysis to diagnose the rolling bearing fault. Although these methods can accurately extract the fault features under the background

The associate editor coordinating the review of this manuscript and approving it for publication was Francesco Tedesco.

of complex noise, especially containing Gaussian noise, the non-Gaussian noise will inevitably exist in the measured vibration signals, which often inhibit the extraction of true signal signatures for diagnosis. To improve these methods, Li *et al.* [3] propose a feature extraction method based on wavelet transform and bispectrum analysis which can extract the bearing fault features effectively but cannot detect the multi-frequency component of the fault.

Bispectrum analysis can theoretically completely eliminate Gaussian noise, but it will lose its advantage when non-Gaussian noise is added [11]. In practical application, the fault features of the fault signal are often submerged in the noise, especially when the early fault occurs, the fault features are very weak and hard to extract. The existence of non-Gaussian noise will interfere with the higher-order spectrum of the signal, and will badly affect the extraction and analysis of fault features. Therefore, it is necessary to eliminate non-Gaussian noise in the signal before the bispectrum analysis. Ensemble Empirical Mode Decomposition is a self-adaptive signal decomposition method proposed by Huang *et al.* [12]. Similar to EMD, EEMD can decompose signals into a series of high-to-low frequency bands based on the signal itself [13]. Therefore, the EEMD can be used first to separate the different frequency components of the signal and to remove the non-Gaussian noise mixed in the signal, which can effectively eliminate the adverse effect caused by non-Gaussian noise during the bispectrum analysis. Meanwhile, EEMD is also a noise-assisted data analysis method, which can restrain the mode mixing phenomenon caused by EMD by adding white noise into the signal. Compared with EMD, IMFs obtained by EEMD can better reveal the intrinsic characteristic of the signal. In recent years, EEMD has been widely used in the field of mechanical fault diagnosis [14]–[16]. Wang *et al.* [17] use EEMD with a correlation dimension method to identify diesel engine system failures.

However, some shortcomings of EEMD are discovered gradually. In the process of decomposing complex signals, a certain number of false IMFs are generated. These false IMFs will adversely affect the fault feature extraction. Aiming at this problem, a MEEMD method is proposed to remove the false IMFs by limiting the bandwidth and amplitude of adding white noise [18]. Jiang *et al.* [19] proposed an IEEMD method that uses multiple EMDs to remove false IMFs. Lin and Yu [20] use the correlation coefficient of IMFs and the signal as a criterion to decide which IMFs should be retained and which IMFs should be eliminated. But these methods can cause erroneous judgments sometimes, and cannot identify the true IMFS completely and accurately. To solve these problems, in this paper, a cloud model method is introduced to identify the IMFs obtained by the EEMD and remove the false IMFs, so as to obtain true IMFs.

Bispectrum analysis and EEMD can effectively eliminate Gaussian noise and non-Gaussian noise. In addition, the cloud model method can improve EEMD to restrain the mode mixing phenomenon. Therefore, this paper, this paper proposed a novel detection method for rolling bearing by the advantages of bispectrum analysis and improved EEMD. First, the signal is decomposed by EEMD into several IMFs with different frequencies from high to low, and then the cloud model method is used to remove the false IMFs. Finally, the bispectrum analysis of the true IMFs is carried out to extract the fault feature information of the fault rolling bearing. The effectiveness of the proposed methods is verified by theoretical analysis and experimental verification.

The remainder of this paper is organized as follows. bispectrum analysis is introduced in section II. EEMD and cloud model method is introduced in section III. The defect detection method based on bispectrum analysis and cloud model-improved EEMD is presented in section IV; Application is presented in section V. Comparison with other methods is presented in section VI. Our main conclusions are given in section VII.

II. BISPECTRUM ANALYSIS

Bispectrum analysis is a higher-order spectrum (third-order spectrum), which has its unique superiority compared with the power spectrum, such as identification of nonlinear systems, retention of phase information and elimination of Gaussian noise [21], usually used to detect quadratic phase coupling in nonlinear signals [22]. The bispectrum is defined as the two-dimensional Fourier transform of the third-order autocorrelation of the signal. There are two ways to obtain the bispectrum of a signal: ① direct method: which computes the bispectrum of the signal by definition, that is, the third-order autocorrelation of the discrete Fourier transform of signal; ② indirect method: The bispectrum is estimated by the parametric model. As the direct method is more convenient and accurate, therefore, this paper adopts the direct method. The specific calculation process is as follows:

(1) Define a discrete signal $\{x(n)\} = \{x^k(0), x^k(1), \ldots, x^k(M-1)\}$,where $k = 1, \cdots, K$.

(2) The signal's discrete Fourier transform coefficients are defined as

$$X^{(k)}(\lambda) = \frac{1}{M}\sum_{n=0}^{M-1} x^{(k)}(n)\exp(-j\frac{2\pi n\lambda}{M}) \tag{1}$$

where $\lambda = 0, 1, \cdots, M/2$; $k = 1, \cdots, K$.

(3) Calculate the third-order autocorrelation of the coefficients

$$b_k(\lambda_1, \lambda_2) = \frac{1}{\Delta_0^2}\sum_{i_1=-L_1}^{L_1}\sum_{i_2=-L_1}^{L_1} X^{(k)}(\lambda_1 + i_1) \cdot X^{(k)}(\lambda_2 + i_2)X^{(k)}(-\lambda_1 - \lambda_2 - i_1 - i_2) \tag{2}$$

where $\Delta_0 = f_s/N_0$, and $M = (2L_1 + 1)N_0$.

(4) The bispectrum of $x(0), x(1), L, x(N-1)$ can be formulated as

$$B(\omega_1, \omega_2) = \frac{1}{K}\sum_{k=1}^{K} b_k(\omega_1, \omega_2) \tag{3}$$

where $\omega_1 = \frac{2\pi f_s}{N_0}\lambda_1, \omega_2 = \frac{2\pi f_s}{N_0}\lambda_2$.

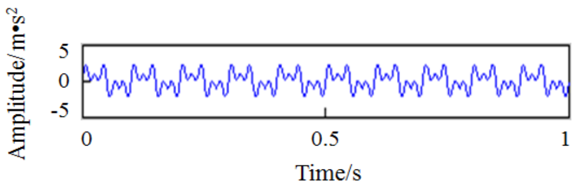


FIGURE 1. Simulated signal f(t).

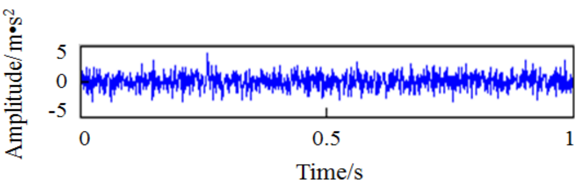


FIGURE 2. Simulated signal g(t).

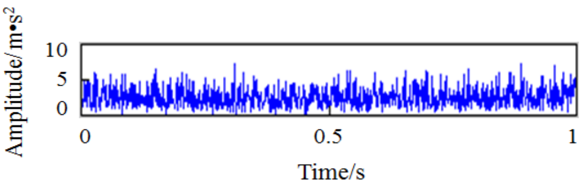


FIGURE 3. Simulated signal r(t).

The bispectrum reflects the distribution of the third moment of the signal in the dual-frequency domain. For a random signal with a symmetrical distribution, the skewness is zero and the bispectrum is also zero. The Gaussian signal is precisely this type of random signal, so the bispectrum has a strong ability to eliminate Gaussian noise. In contrast, the bispectrum of non-Gaussian noise is non-zero, so bispectrum analysis cannot deal with this type of noise.

In the following, the bispectrum is used to analyze a simulated signal to verify that it can effectively eliminate the Gaussian noise but not the non-Gaussian noise. The simulated signal is as follows:

$$x(t) = f(t) + g(t) + r(t)$$
$$= \sin(20\pi t)+\sin(60\pi t)+\sin(100\pi t)+n(t)+r(t) \quad (4)$$

f(t) consists of three sinusoidal signals with frequencies of 10Hz, 30Hz and 50Hz. g(t) is a random signal with Gaussian distribution. r(t) is a random noise with Rayleigh distribution. The sampling rates of f(t), g(t) and r(t) are 1000Hz. x(t) consists of f(t), g(t) and r(t). The time-domain graphics of f(t), g(t), r(t) and x(t) are as shown in Fig.1, Fig.2, Fig.3, and Fig.4.

$x_1(t)$ is a superposition of f(t) and g(t). Calculate the bispectrum of x1(t), the result is shown in Fig.5.

$$x_1(t) = f(t) + g(t) \quad (5)$$

With respect to Fig.5, the maximum peaks exhibit at frequency pair (50, 50) and its Symmetric frequencies [23]. And also, several peaks exhibit at frequency pair (50, 30), (10, 10) and its Symmetric frequencies. The result proves that bispectrum analysis can effectively eliminate Gaussian noise in the signal. However, in the bispectrum, there are also

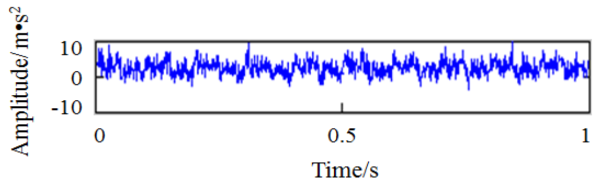


FIGURE 4. Simulated signal x(t).

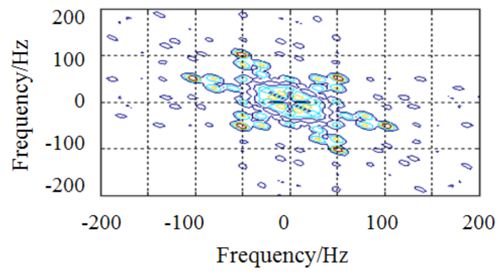


FIGURE 5. Bispectrum of the simulated signal x_1(t).

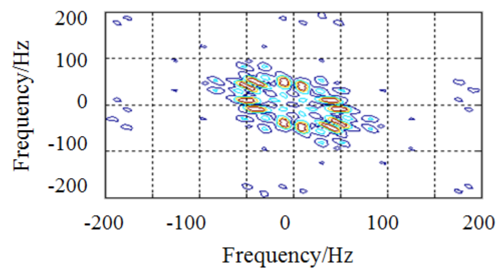


FIGURE 6. Bispectrum of the simulated signal x_2(t).

many low peaks around high peaks, and the quadratic phase coupling phenomenon happens. This is because Rayleigh noise interferes with bispectrum analysis, resulting in more frequency peaks in the bispectrum, which also shows that bispectrum analysis cannot effectively eliminate non-Gaussian noise in the signal.

$x_2(t)$ is a superposition of f(t) and r(t). Calculate the bispectrum of x2(t), the result is shown in Fig.6.

$$x_2(t) = f(t) + r(t) \quad (6)$$

From the bispectrum shown in Fig.6, we can find neither three sinusoidal signals, again verifying that bispectrum analysis cannot deal with non-Gaussian noise.

Calculate the bispectrum of x(t), the result is shown in Fig.7. As can be seen from Fig.7, due to the existence of many frequency components in the signal, and the interference of non-Gaussian noise, the bispectrum is complex, and can find neither three sinusoidal signals. Therefore, it is necessary to de-noising the signal to eliminate the non-Gaussian noise before using bispectrum analysis to obtain accurate analysis results.

III. EEMD AND CLOUD MODEL METHOD

A. EEMD

EEMD is an improved algorithm proposed by Huang to solve the mode mixing phenomenon in EMD. In EMD decomposition, when the time scale of the decomposed signal

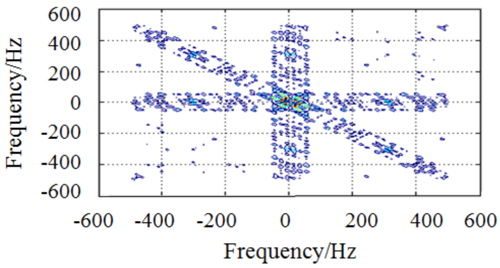


FIGURE 7. Bispectrum of the simulated signal x(t).

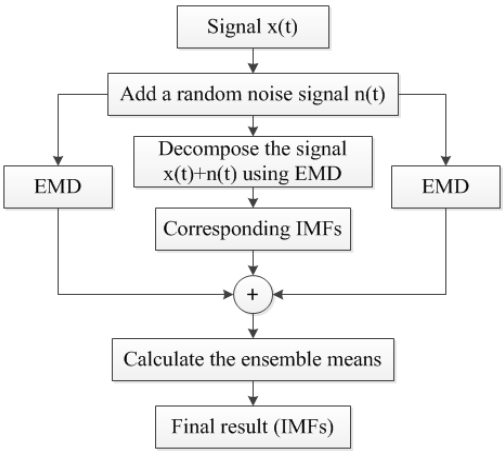


FIGURE 8. Flowchart of EEMD method based on EEMD.

has a sudden change, or the signal contains a lot of noise, a single IMF will contain a large number of frequency components, the phenomenon is called mode mixing [24]. EEMD can restrain the mode mixing phenomenon by adding white noise multiple times into the signal [25]. When the decomposed signal is applied to a background space filled with white noise, the signals of different time scales are automatically mapped to the appropriate frequency scale. Therefore, taking advantage of the zero-mean of noise, after several averaging, the noise will cancel each other and the signal itself will be stable. The result of the integrated mean can be used as the final result. Therefore, taking advantage of the zero-mean of noise, after several averaging, the noise will cancel each other and the signal itself will be stable. The result of the integrated mean can be used as the final result.

The specific calculation process of EEMD is as follows, the flowchart is shown as Fig.8.

(1) Add normal distribution white noise into the decomposition signal;

(2) EMD is performed on the signal which is added with white noise to obtain IMFs;

(3) Repeat steps (1) and (2), adding new white noise each time;

(4) The average value of IMFs obtained each time is taken as the final result.

B. OBTAINTRUE IMFs USING CLOUD MODEL METHOD

EEMD is similar to EMD and is a self-adaptive method of signal decomposition [26], [27]. However, due to the end effect in the decomposition process, false IMFs will be generated,

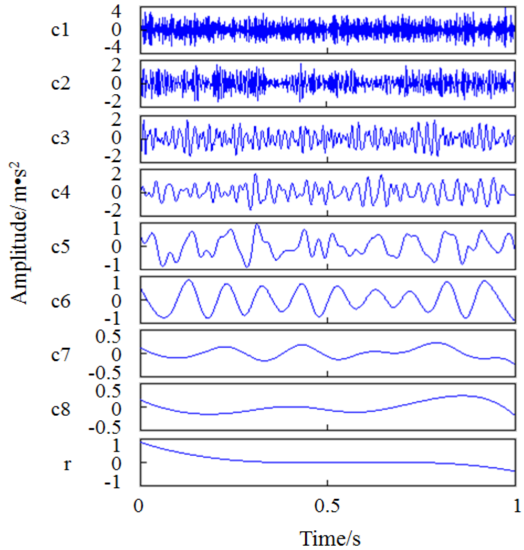


FIGURE 9. EEMD of the simulated signal x(t).

which will badly affect the extraction of fault feature and the accuracy of fault diagnosis. Therefore, this paper proposes the parameter of the cloud model to identify the true IMFs, remove the false IMFs.

Whether IMFs of bearing signal decomposed by EEMD is true or not, which is qualitative, and the parameters of cloud model C (Ex, En, He) are an expression of some qualitative features. So, it can judge which are true IMFS effectively. Where Ex is Mean Value, En is Feature Entropy, He is Excess Entropy.

$$Ex = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{7}$$

$$En = \sqrt{\frac{\pi}{2}} \times \frac{1}{n}\sum_{i=1}^{n} |x_i - Ex| \tag{8}$$

$$He = \sqrt{S - En^2} \tag{9}$$

where S is Second-order central moment of x.

Since the IMF component is derived from the same signal by the EEMD method, there is little difference in Ex of each IMF component. Where En is the dispersion of IMFs, and He is the uncertainty measure of En. In this paper, the similarity between IMFs and the original signal is measured by parameter En and parameter He ratio of IMFs and the original signal, so that the false IMF is eliminated.

The following example of a simulated signal verifies the effectiveness of the cloud model method in removing the false IMFs. Consider the signal x(t) given in formula (4). The signal x(t) consists of three sinusoidal signals with frequencies of 10 Hz, 30 Hz and 50 Hz and amplitudes of both 1. The results of EEMD of the simulated signal x(t) are shown in Fig.9. Calculate the ratio of the cloud model parameters (En, He) and correlation coefficient ($|\rho xy|$) [17] of each IMF and the original signal. The results are shown in Tab.1.

TABLE 1. Results of two false component identification methods.

Para.	C3/C	C4/C	C5/C	C6/C	C7/C	C8/C	C9/C
En	0.576	0.442	0.393	0.042	0.029	0.047	0.078
He	0.760	0.057	0.510	0.070	0.045	0.063	0.005
|ρxy|	0.473	0.437	0.425	0.321	0.102	0.589	0.554

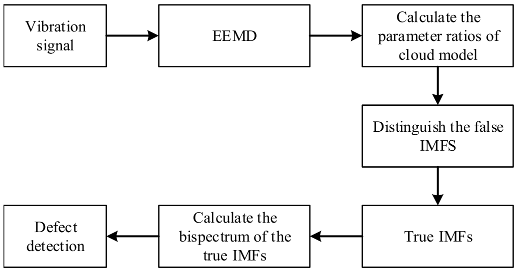


FIGURE 10. Flowchart of the proposed method.

It can be seen from Tab.1 that the En and He parameter ratios of IMF3, IMF4, and IMF5 are much larger than the remaining IMFs, so IMF3, IMF4, and IMF5 are true components. Based on a large number of experiments, IMF3-IMF5 usually needs to be considered. On the contrary, the correlation coefficients of IMF5 and IMF6 are similar, and the authenticity of the IMF cannot be effectively recognized by the correlation coefficient method. It can be seen that the cloud model method proposed in this paper can effectively identify the real IMFs and remove the false IMFs, and the effect is better than the correlation coefficient method.

IV. DEFECT DETECTION METHOD BASED ON BISPECTRUM ANALYSIS AND CLOUD MODEL-IMPROVED EEMD

The practical engineering signals collected from machines are often complex and usually contain interference noise such as Gaussian and non-Gaussian noise. Bispectrum analysis can only eliminate Gaussian noise, so we use EEMD before bispectrum analysis to decompose the complex noise into a series of high-to-low frequency bands and eliminate the non-Gaussian noise in the signal first. The steps of this method are as follows: first, decompose the signal using EEMD to obtain a series of high-to-low frequency bands. Usually, the frequencies of noise are high and the frequencies of fault features are low [28]. Then, the cloud model method is used to choose the true and useful IMFs. Finally, bispectrum of these true IMFs is calculated to extract fault feature information hiding in the signal. The flowchart is shown in Fig.10.

Known in section 3, IMF3, IMF4, and IMF5 are true IMFs, so calculate the bispectrum of them, the results are shown in Fig.11. As we can see, the maximum peaks exhibit at frequency pair (50, 50), (30, 30), (10, 10) and their Symmetric frequencies, represent the frequencies of three sinusoidal signals. This example proves that the proposed method can effectively eliminate the Gaussian and non-Gaussian noise in the signal and extract the fault feature information from the complex noise.

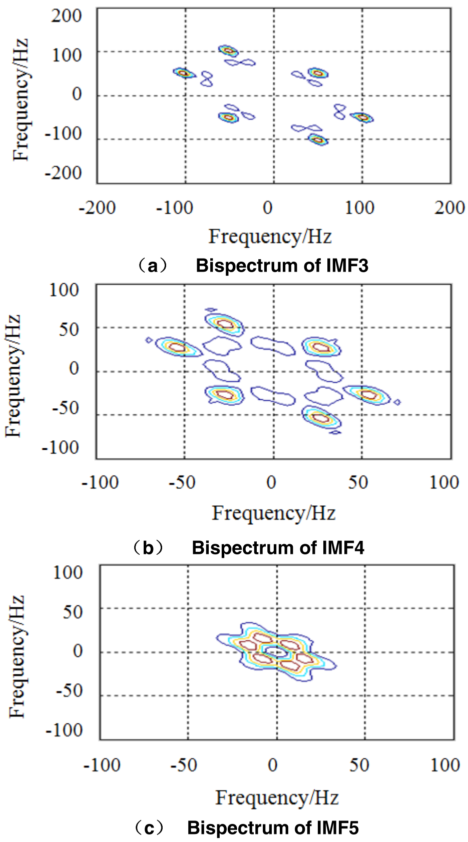


FIGURE 11. Bispectrum of IMFs of the simulated signal x(t).

V. APPLICATION

In practical industrial production, when the bearing failure happens, its internal parts will periodically collide with the fault part as it rotates at a high speed, resulting in a series of impact excitation. Generally, the characteristic frequencies of various fault can be calculated according to the bearing parameters, then the fault can be diagnosed according to the fault feature frequency. However, since the energy of the vibration is often spread over a relatively wide frequency band, the frequency spectrum contains the harmonics of the fault feature frequencies, which will easily be disturbed by noise. Therefore, if different noises can be handled separately during the feature extraction, the fault diagnosis accuracy can be greatly improved. Next, we apply the proposed method to analyze vibration signals of rolling bearings.

A. INNER-RACE FAULT BEARING DETECTION

The bearing vibration signals analyzed in this paper are provided by Case Western Reverse Lab. The rolling bearing inner-race fault experiment uses 6205-type rolling bearing manufactured by SKF Co., the bearing pitch diameter is 39.04mm, the ball diameter is 7.94mm, the number of balls is 9, the contact angle is 0°. The signal was collected with a sampling rate of 12000Hz, speed of 1797r/min, the vibration acceleration signal is shown in Fig.12. The fault feature frequency of the inner-race fault is calculated to be 162Hz.

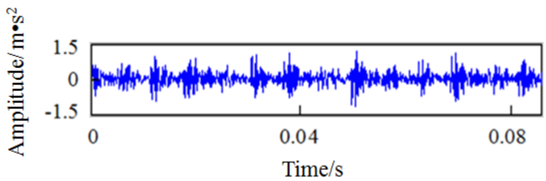


FIGURE 12. Signal of the rolling bearing with inner- race fault.

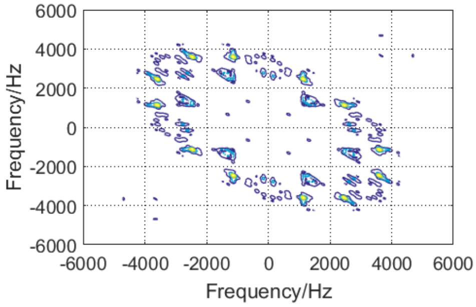


FIGURE 13. Bispectrum of rolling bearing with inner- race fault.

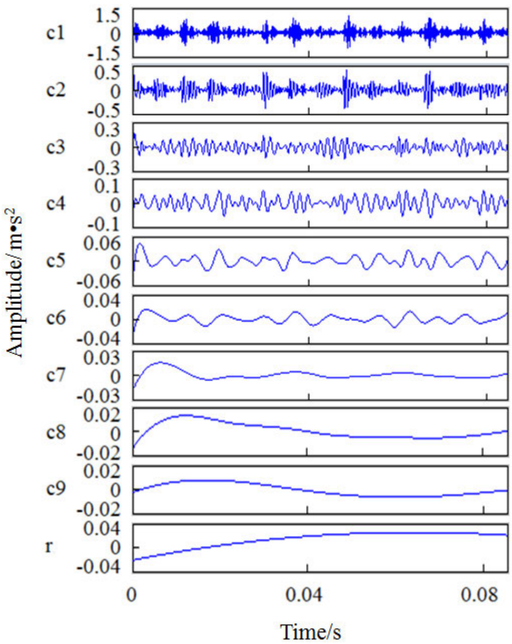
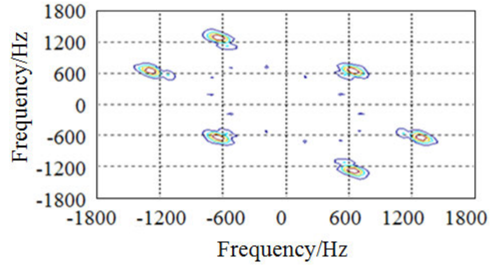


FIGURE 14. EEMD of rolling bearing with inner-race fault.

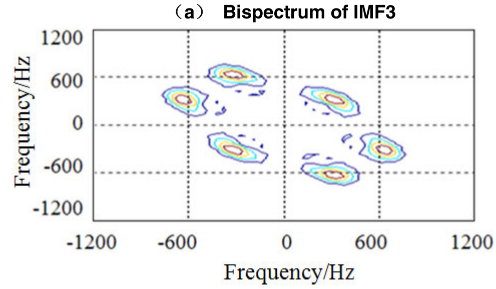
The bispectrum of rolling bearing with the inner-race fault is shown in Fig.13. From Fig.13, we cannot find any fault feature in it. Analyze the signal using the proposed method. First, the signal is decomposed by EEMD into several IMFs, as shown in Fig.14. IMF1 and IMF2 are noise due to the high frequencies, which does not contain fault feature information of the bearing, so it is eliminated directly. Calculate the cloud model parameter ratios of IMF3-IMF9 with the original signal, the results shown in Tab.2. It can be seen that the ratio of the cloud model parameters of IMF3, IMF4, IMF5 and the original signal is large, and the difference is obvious, while the ratio of IMF6 to IMF9 is small, and the change of ratio is few, so choose these three IMFs with largest parameter ratios as the true IMFs and then calculate the bispectrum of them. The results are shown in Fig.15(a), 15(b) and 15(c) respectively. It can be clearly seen from Fig.14 that maximum peaks exhibit at frequency pair (648,648), (324,324), (162,162) and their Symmetric frequencies, not only reflecting the bearing inner-race fault feature frequency of 162Hz and its second and fourth harmonics, but also reflects the signal phase information.

TABLE 2. Parameter ratios of IMFs and bearing signal.

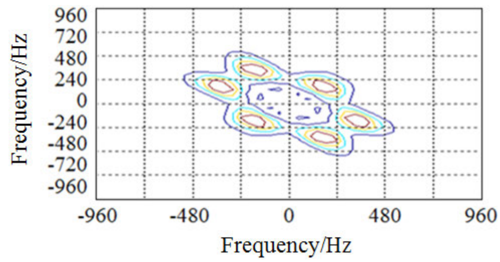
Para.	C3/C	C4/C	C5/C	C6/C	C7/C	C8/C	C9/C
En	0.225	0.096	0.048	0.015	0.017	0.018	0.015
He	0.079	0.025	0.016	0.009	0.008	0.004	0.008



(a) Bispectrum of IMF3



(b) Bispectrum of IMF4



(c) Bispectrum of IMF5

FIGURE 15. Results of rolling bearing with inner-race fault obtained by method based on EEMD and bispectrum analysis.

B. OUTER-RACE FAULT BEARING DETECTION

Fig.16 shows the vibration acceleration signal of the 6205-type rolling bearing with an outer-race fault with a sampling rate of 12000Hz and speed of 1797r/min. The out-race fault feature frequency is calculated to be 107Hz.

Tab.3 and Fig.17 are the cloud model parameter ratios and bispectrum obtained by the proposed method based on EEMD and bispectrum analysis. From the Tab.3, It can be seen that IMF3, IMF4, and IMF5 are the true IMFs. And from the Fig.17, It can be seen that the maximum peaks exhibit at frequency pair (428,428), (214,214), (107,107) and their Symmetric frequencies, represent the feature frequency of the

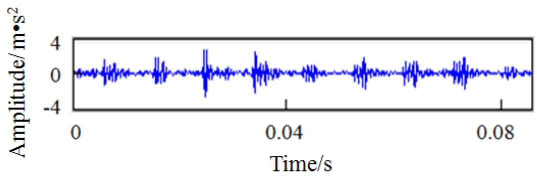
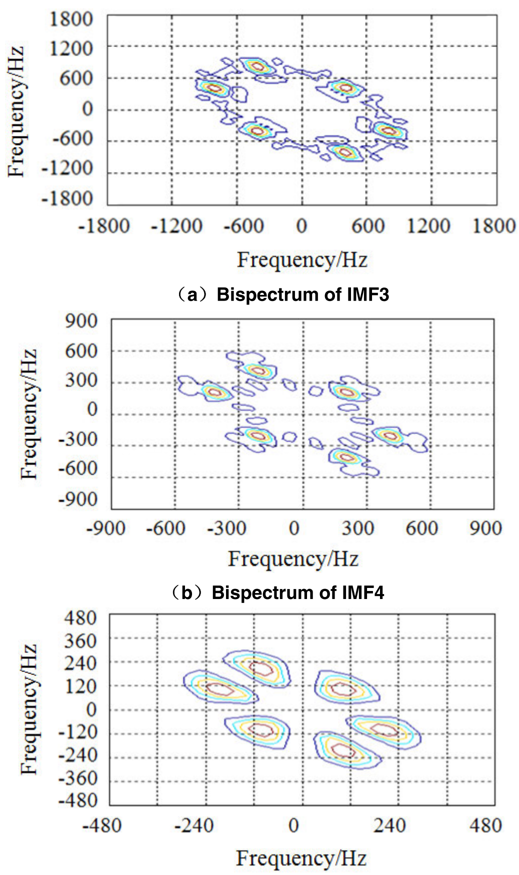


FIGURE 16. Signal of the rolling bearing with outer-race fault.

TABLE 3. Parameter ratios of IMFs of bearing signal.

Para.	C3/C	C4/C	C5/C	C6/C	C7/C	C8/C	C9/C
En	0.118	0.047	0.034	0.013	0.011	0.007	0.011
He	0.074	0.024	0.013	0.008	0.006	0.006	0.005



(a) Bispectrum of IMF3

(b) Bispectrum of IMF4

(c) Bispectrum of IMF5

FIGURE 17. Results of rolling bearing with outer-race fault obtained by method based on EEMD and bispectrum analysis.

outer race fault and its second and fourth harmonics. This experiment also verifies the effectiveness of the proposed method.

C. ROLLING ELEMENT FAULT BEARING DETECTION

Fig.18 shows the vibration acceleration signal of the 6205-type rolling bearing with a rolling element fault with a sampling rate of 12000Hz and speed of 1797r/min. The out-race fault feature frequency is calculated to be 137Hz.

Tab.4 and Fig.19 are the cloud model parameter ratios and bispectrum obtained by the proposed method based on

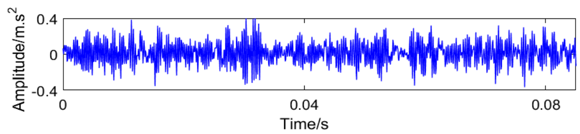
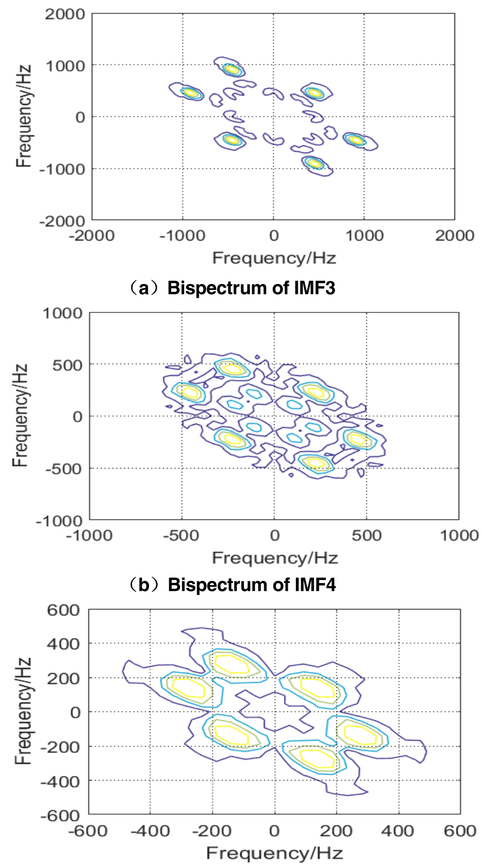


FIGURE 18. Signal of rolling bearing with rolling element fault.

TABLE 4. Parameter ratios of IMFs of bearing signal.

Para.	C3/C	C4/C	C5/C	C6/C	C7/C	C8/C	C9/C
En	3.704	2.721	2.708	0.883	0.809	0.368	0.038
He	0.282	0.143	0.137	0.044	0.045	0.015	0.002



(a) Bispectrum of IMF3

(b) Bispectrum of IMF4

(c) Bispectrum of IMF5

FIGURE 19. Results of rolling bearing with rolling element fault obtained by the method based on EEMD and bispectrum analysis.

EEMD and bispectrum analysis. From the Tab.4, It can be seen that IMF3, IMF4, and IMF5 are the true IMFs. And from the Fig.19, It can be seen that the maximum peaks exhibit at frequency pair (548,548), (274,274), (137,137) and their Symmetric frequencies, represent the feature frequency of the rolling element fault and its second and fourth harmonics. This experiment further verifies the effectiveness of the proposed method.

D. ANOTHER INNER-RACE FAULT BEARING DETECTION

In order to validate the robustness and versatility of the proposed method, another inner-race fault bearing detection

FIGURE 20. Drivetrain Dynamics Simulator.

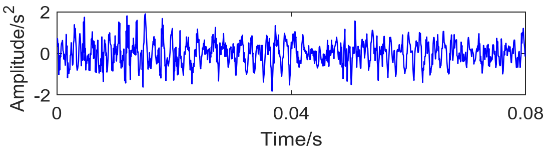


FIGURE 21. Signal of the rolling bearing with inner-race fault.

TABLE 5. Parameter ratios of IMFs of bearing signal.

Para.	C3/C	C4/C	C5/C	C6/C	C7/C	C8/C	C9/C
En	0.536	0.198	0.125	0.084	0.055	0.025	0.006
He	0.459	0.363	0.431	0.198	0.119	0.106	0.024

is carried out using SpectraQuest's Drivetrain Dynamics Simulator (DDS), which is showed in Fig.20. The experiment uses ER16K-type rolling bearing, the bearing pitch diameter is 15.16mm, the ball diameter is 3.125mm, the number of balls is 9, the contact angle is 0°. The signal was collected with a sampling rate of 12800Hz, speed of 1200r/min, the vibration acceleration signal is shown in Fig.21. The fault feature frequency of the inner-race fault is calculated to be 108Hz.

Tab.5 and Fig.22 are the cloud model parameter ratios and bispectrums obtained by the proposed method based on EEMD and bispectrum analysis. It is obvious from Table 5 that IMF3, IMF4, and IMF5 are real IMF components. The results of the bispectrum analysis are shown in Fig.22 (a), 22 (b), and 24 (c), respectively. And from the Fig. 22, It can be seen that the maximum peaks exhibit at frequency pair (108,108), (324,324), (648,648) and their Symmetric frequencies, represent the feature frequency of the inner race fault and its third and sixth harmonics. This experiment further verifies the robustness and versatility of the proposed method.

VI. COMPARISON

In this section, we take several other methods, such as power spectrum analysis, bispectrum analysis, and wavelet de-noising bispectrum analysis, to compare with the proposed method so as to verify the effectiveness and superiority of it.

Consider the signal of the rolling bearing with an outer-race fault in section 5.2. Fig.23, Fig.24 and Fig. 25 are

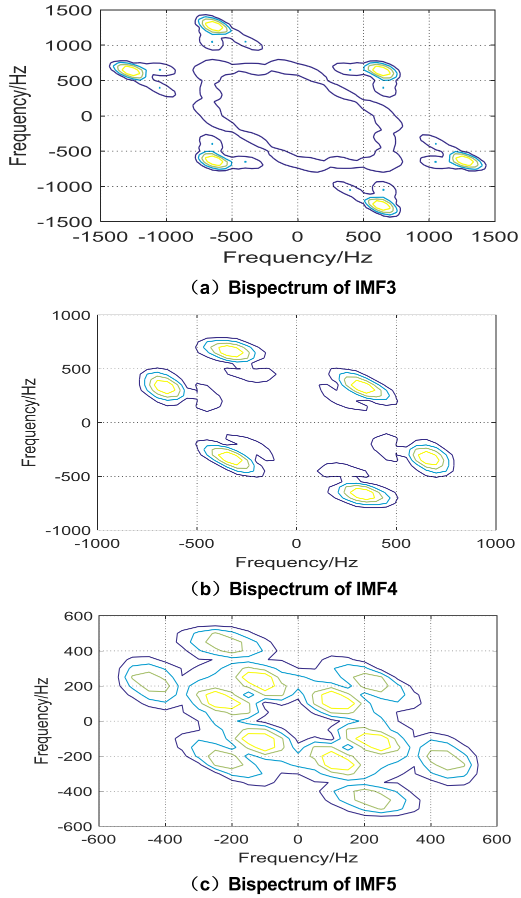


FIGURE 22. Results of rolling bearing with inner-race fault obtained by method based on EEMD and bispectrum.

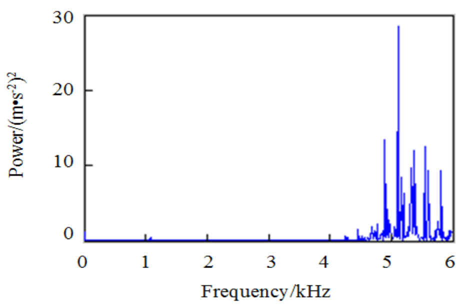


FIGURE 23. Power spectrum of the rolling bearing with outer-race fault.

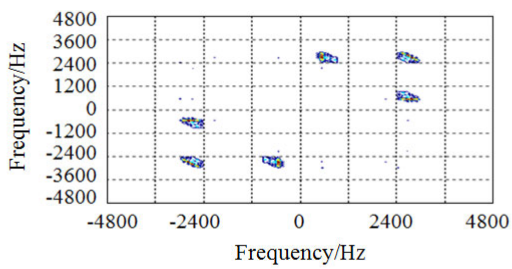


FIGURE 24. Bispectrum of the rolling bearing with outer-race fault.

the results obtained by power spectrum analysis, bispectrum analysis, and wavelet de-noising bispectrum analysis.

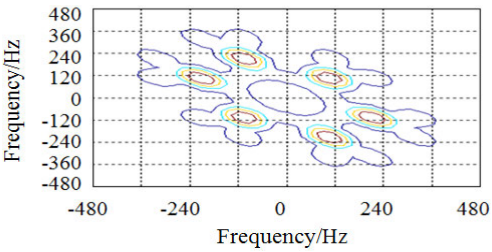


FIGURE 25. Results of rolling bearing with outer-race fault obtained by method based on wavelet denoising and bispectrum analysis.

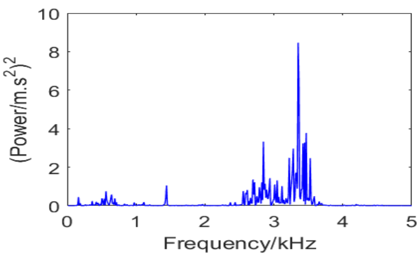


FIGURE 26. Power spectrum of rolling bearing with rolling element fault.

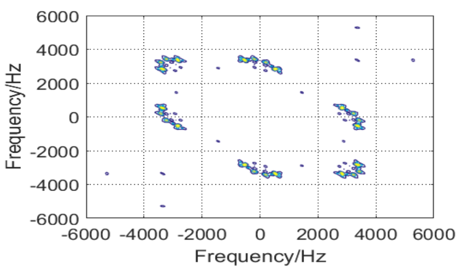


FIGURE 27. Bispectrum of rolling bearing with rolling element fault.

The steps of the method of wavelet de-noising bispectrum analysis are as follows: the fault signal is first decomposed and denoised by wavelet, then after demodulated by Hilbert transform, the bispectrum analysis is applied to extract the fault feature.

From Fig.23 and Fig.24, It can be seen that the fault feature frequency of the rolling bearing cannot be identified from the power spectrum and the bispectrum due to the noise interference. The fault information has been completely buried in the strong noise. Therefore, the power spectrum analysis, and bispectrum analysis cannot extract the fault features of rolling bearings. With respect to Fig.17, the maximum peaks exhibit at frequency pair (107, 107) and its Symmetric frequencies, represent the feature frequency of the outer race fault. However, compare Fig.25 with Fig.17, peaks in Fig.17 (c) are sharper than peaks in Fig.25, and there are second and fourth harmonics of the fault feature frequency finding in Fig.17 but not Fig.25. Therefore, compared with the power spectrum analysis, bispectrum analysis and wavelet de-noising bispectrum analysis, the proposed method can detect the defect of rolling bearings more effectively, which provides a new method for fault diagnosis of rolling bearings.

Consider the signal of the rolling bearing with a rolling element fault in section 5.3. Fig.26, Fig.27 and

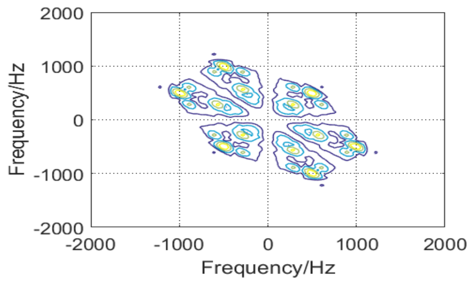


FIGURE 28. Results of rolling bearing with rolling element fault obtained by method based on wavelet denoising and bispectrum analysis.

Fig.28 are the results obtained by power spectrum analysis, bispectrum analysis, and wavelet de-noising bispectrum analysis. Compared with the power spectrum analysis, bispectrum analysis, and wavelet de-noising bispectrum analysis, the result is the same as the analysis of the rolling bearing with an outer-race fault, the proposed method can detect the defect of rolling bearings more effectively.

VII. CONCLUSION

The research presented in this paper focused on rolling bearing defect detection in multiple background noise. Bispectrum analysis has been utilized to effectively reduce Gaussian noise of rolling bearing defect detection signals. A novel cloud model-improved EEMD has been proposed for non-Gaussian signal denoising, where the cloud model has been introduced to restrain the mode mixing phenomenon so as to improve the accuracy of EEMD. After theoretical and experimental investigations, the necessity and benefit of the cloud model have been demonstrated. After comparing the results obtained by five methods, it can be concluded that the proposed method based on bispectrum analysis and cloud model-improved EEMD can extract fault feature information of rolling bearings more effectively and outperforms traditional methods with better capability of defect detection.

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