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Research on Feature Extraction Method for Low-Speed Reciprocating Bearings Based on Segmented Short Signal Modulation Signal Bispectrum Slicing

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Abstract

Bearing condition monitoring and fault diagnosis (CMFD) can investigate bearing faults in the early stages, preventing the subsequent impacts of machine bearing failures effectively. CMFD for low-speed, non-continuous operation bearings, such as yaw bearings and pitch bearings in wind turbines, and rotating support bearings in space launch towers, presents more challenges compared to continuous rolling bearings. Firstly, these bearings have very slow speeds, resulting in weak collected fault signals that are heavily masked by severe noise interference. Secondly, their limited rotational angles during operation lead to a restricted number of fault signals. Lastly, the interference from deceleration and direction-changing impact signals significantly affects fault impact signals. To address these challenges, this paper proposes a method for extracting fault features in low-speed reciprocating bearings based on short signal segmentation and modulation signal bispectrum (MSB) slicing. This method initially separates short signals corresponding to individual cycles from the vibration signals based on encoder signals. Subsequently, MSB analysis is performed on each short signal to generate MSB carrier-slice spectra. The optimal carrier frequency and its corresponding modulation signal slice spectrum are determined based on the carrier-slice spectra. Finally, the MSB modulation signal slice spectra of the short signal set are averaged to obtain the overall average feature of the sliced spectra.

Keywords

Fault Diagnosis, The Modulation Signal Bispectrum, Short Signal, Low-Speed Reciprocating Bearings, Slewing Bearing

1. Introduction

The application scenarios of low-speed reciprocating bearings are very wide, such as pitch bearings and yaw bearings of wind power generators, slewing platform bearings of space launch towers, slew bearings of cranes and excavators, etc. Among them, pitch bearings are mainly used in variable pitch wind turbines above the megawatt level. The blades are installed on the hub. The pitch bearings and corresponding control devices adjust the windward angle of the blades according to the wind speed to obtain the best windward angle horn. Since the stress conditions of the pitch bearing are complex, the bearings bear relatively large impacts and vibrations, and they are located in a relatively harsh environment, the characteristics of the pitch bearing operating conditions such as low-speed operation or swing, impact load, etc., determine its main failure mode: Failure caused by fretting. With the help of fault diagnosis technology, timely detection of bearing damage in low-speed reciprocating operation can not only avoid major accidents caused by bearing failure but also provide decision support for the health maintenance of equipment. However, compared with rolling bearings that continuously rotate in the same direction, fault diagnosis of low-speed reciprocating bearings is more difficult. First, the rotation speed of this type of bearing is low, so the impact force on the damaging contact is small and the damage signal is weak. Secondly, the phase of the damage impact response sequence jumps after the bearing reciprocates, and the damage impact response sequence covering multiple reciprocating operation cycles is not periodic. In addition, although the damage impact sequence in the uniform section of a one-way stroke is periodic, due to the small stroke and the small number of damage contacts within a stroke, the damage information in the test signal is very weak. Finally, the deceleration and acceleration process of reciprocating commutation will cause commutation shock, and the commutation shock signal will cause serious interference to the bearing damage signal.

In recent years, fault diagnosis of low-speed reciprocating bearings has attracted people's attention. Cassandra and Feng Yang *et al.* successively used the circular domain analysis method to extract the fault characteristics of slewing bearings. This method first resamples the vibration signal in the circular domain, then uses the piecewise aggregation approximation method to compress the resampled signal, and presents the compressed data in the form of a neighborhood correlation diagram. Finally, by observing the shape of the ellipse in the neighborhood correlation diagram to determine whether the bearing is damaged in the tilt direction [1] [2]. Žvokelj *et al.* combined the overall average empirical mode decomposition (EEMD) with multi-scale kernel principal component analysis, and based on the acoustic emission signal, the external slewing bearing was analyzed at 1 rpm, 4 rpm, and 8 rpm. Simulated cracks in the ring raceway were detected [3]. Ding *et al.* combined EEMD with Singular Value Decomposition (SVD) to denoise the vibration signal of the slewing bearing. On this basis, they used a manifold learning algorithm to obtain characteristic indicators describing the degradation trend [4]. Wang *et al.* combined the maximum correlation kurtosis deconvolution and noise reduction method with the complementary ensemble empirical mode decomposition (Complete EEMD, CEEMD) method to diagnose composite faults of slewing bearings [5]. Din *et al.* used the improved variational mode decomposition (VMD) method for life prediction of slewing bearings [6].

Liu *et al.* from the University of Manchester conducted vibration and acoustic emission tests of pitch bearings in a laboratory environment. The bearing tested had been in service in the field for 15 years, and there were multiple spalling damages on the inner ring raceway of the bearing. The test simulates the reciprocating pitch motion. The pitch angle is 100˚. The acceleration and deceleration segment signals at both ends of each stroke are deleted. The uniform speed segment signal of the middle 90˚ stroke is intercepted. The constant speed segment signals of multiple strokes are spliced together to obtain the duration. Signals that are longer contain more damaging impacts. Liu *et al.* conducted empirical wavelet threshold decomposition of vibration signals. The analysis results show that the empirical wavelet threshold method can improve the kurtosis value of the signal. When the rotation speed is greater than 3 rpm, the inner ring damage can be found in the envelope spectrum of the decomposed signal—fault characteristic frequency components [7]. Liu *et al.* used an iterative nonlinear filter to denoise the vibration signal and detected the fault characteristic frequency component of the pitch bearing at 1.27 rpm. For the acoustic emission signal [8], Liu *et al.* used discrete random separation and cepstrum editing to improve the signal-to-noise ratio of the acoustic emission signal. The final envelope spectrum analysis results showed that this method can find the cause of damage to the inner ring of the bearing at a speed of 1.11 rpm—characteristic frequency components [9].

Among the above fault diagnosis methods for low-speed reciprocating bearings, some do not consider that the damage impact sequence covering multiple reciprocating cycles is not periodic, and ignore the impact of the reversing impact caused by the reciprocating motion in the diagnosis process. Some methods intercept and splice the entire long signal. Although the impact of reciprocating motion is eliminated, the uncertainty of the spliced signal itself makes subsequent fault diagnosis more difficult. In some studies, the fault level of the test object has been very serious, and the detection ability of the diagnostic method for low-frequency weak signals needs to be further enhanced.

The Modulation Signal Bispectrum (MSB) proposed by Gu *et al.* is a bispectrum analysis method that considers sidebands. Compared with conventional bispectral analysis, this method can not only conveniently analyze the modulated signal components of the signal, but also better suppress the interference of random noise and non-periodic components [10]. Xu *et al.* proposed a modulated signal bispectrum based on phase linearization. By linearizing the instantaneous phase of the narrow-band signal, the periodic stationary azimuth signal is tuned into a periodic waveform. However, existing research work on MSB diagnostic methods is all aimed at continuously rotating components [11].

This paper aims at problems such as the non-periodic nature of long signals in the current research on low-speed reciprocating bearings, the impact of commutation impact caused by the bearing's reciprocating motion, and the weak damage information caused by slow rotation speed. Based on MSB, a fault of low-speed reciprocating bearings is proposed. The MSB modulation signal slice spectrum overall average feature extraction method comprehensively utilizes the noise reduction ideas of MSB and overall average to improve the fault diagnosis ability of low-speed reciprocating bearings.

2. Modulated Signal Bispectral Slice Ensemble Averaging Method

2.1. Traditional Bispectrum Analysis Theory

As the simplest higher-order spectrum, the bispectrum contains all the characteristics of the higher-order spectrum. Bispectrum estimation using traditional methods is similar to power spectrum estimation using traditional methods. Assuming that $x(t)$ is a stable random signal with a mean value of zero, the autocorrelation function of signal $x(t)$ can be expressed as:

$$r(\tau)=E\{x(t)x(t+\tau)\}$$

where is the mathematical expectation. The third moment of $x(t)$ is:

$$C(\tau_1,\tau_2)=E\{x(t)x(t+\tau_1)x(t+\tau_2)\}$$

The bispectrum is the two-dimensional Fourier transform of $C(\tau_1,\tau_2)$, expressed as:

$$B(\omega_1,\omega_2)=\sum_{\tau_1=-\infty}^{+\infty}\left(\sum_{\tau_2=-\infty}^{+\infty}R(\tau_1,\tau_2)\right)\times\exp\{-j(\omega_1\tau_1+\omega_2\tau_2)\}$$

For a random signal $x(t)$ with finite duration, if its Fourier transform exists, the bispectrum of the signal $x(t)$ can also be expressed by its Fourier transform as:

$$B_x(\omega_1,\omega_2)=X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2)=X(\omega_1)X(\omega_2)X(-\omega_1-\omega_2)$$

where $X^*(\omega_1+\omega_2)$ is the complex conjugate of $X(\omega_1+\omega_2)$.

2.2. Modulated Signal Bispectrum Theory

For the discrete-time signal $x(t)$, considering the nonlinear influence of the modulated signal, the magnitudes of (f_c+f_x) and (f_c-f_x) considered in the bispectrum of the modulated signal. If the signal $x(t)$ has a discrete Fourier transform $X(f)$, its modulated signal bispectrum can be defined as:

$$B_{MS}(f_x,f_c)=E\{X(f_c+f_x)X(f_c-f_x)X^*(f_c)X^*(f_x)\}$$

Among them, f_c is the carrier frequency, f_x is the modulation frequency, $X^*(f_c)$ and $X^*(f_x)$ are the complex conjugates of $X(f_c)$ and $X(f_x)$ respectively, and $E\{\}$ is the collective average of the MSB matrix obtained from the multi-segment modulation signal.

Compare traditional bispectrum and modulated signal bispectrum definitions, it can be found that MSB can not only obtain the carrier frequency f_c component and the modulation frequency f_x component, but also obtain the independent upper sideband frequency $f_c + f_x$ component and lower sideband frequency $f_c - f_x$ component. Compared with traditional bispectrum, MSB uses the overall average, so it has good noise suppression capabilities.

It can be obtained from Fourier series integration that f_c and f_x are coupled through amplitude modulation (AM) or phase modulation (PM), and their phases satisfy the relationship:

$$\phi(f_c + f_x) = \phi(f_c) + \phi(f_x)$$
$$\phi(f_c - f_x) = \phi(f_c) - \phi(f_x)$$

For AM signals, the phase of $(f_c + f_x) X(f_c - f_x) X^*(f_c) X^*(f_x)$ is zero, and for PM signals, its phase is ±π. If the signal contains both AM and PM components, the final phase will be in the range (0, ±π).

2.3. Fault Diagnosis Method for Reciprocating Bearings Based on the Overall Average of Bispectral Slices of Modulated Signals

Although MSB has better weak signal detection capabilities than traditional bispectral analysis methods or envelope demodulation methods, due to the large commutation impact of reciprocating bearings during deceleration and commutation, these impact components will cause serious interference to the fault impact signal, so MSB is not suitable for directly processing the test signals of reciprocating bearings. To this end, it is proposed to first segment the original test signal according to the motion direction stroke to obtain a short signal set of a single direction stroke, then extract the MSB features of the short signals respectively and finally average the extracted MSB features to further analyze the fault characteristics—enhanced effect. The flow of the diagnostic method is shown in Figure 1.

1) Short signal segmentation. After distinguishing the single reciprocating stroke of the original vibration signal according to the rotation speed map, the short signal set of the single-direction stroke is separated from the original test signal based on the encoder signal.

2) Obtain the MSB three-dimensional spectrum. Use the MSB calculation method of the modulated signal bispectrum definitions to perform noise reduction and demodulation processing on the short signal to obtain the MSB three-dimensional spectrum.

3) Construct carrier frequency slice spectrum. Use the formula:

$$B(f_c) = \sum_{N=1}^{1} B_{MS}(f_c^n, f_x)$$

Calculate the average of the MSBs in the direction of f_x increment, resulting in f_c slices. The optimal carrier frequency f_c^{best} can be found from the f_c slice spectrum.

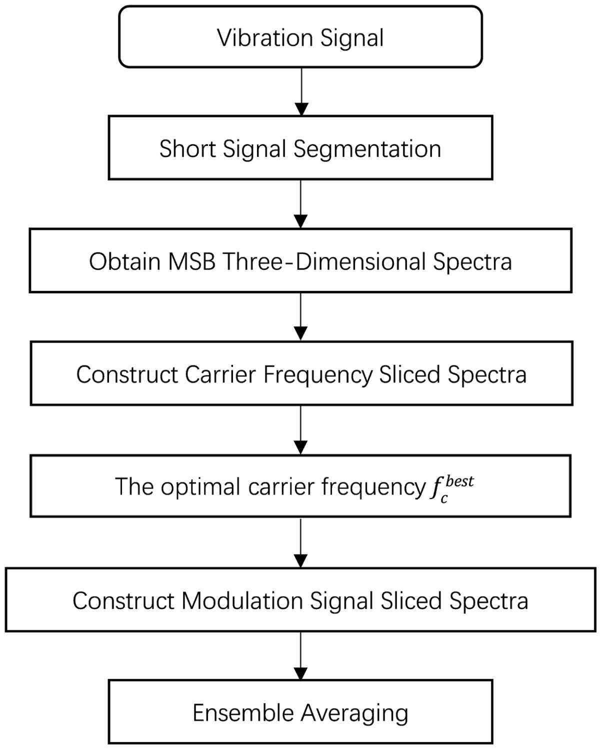

Figure 1. Modulation signal bispectrum slice overall average flow chart.

4) Construct the slice spectrum of the modulated signal. Based on the optimal carrier frequency, use the formula:

$$B(f_c) = \frac{1}{M-1}\sum_{m=2}^{M} B_{MS}\left(f_c^{bet}, m\Delta f\right)$$

5) Overall average. After analyzing the short signal set by the modulated signal bi-spectrum slicing method, a modulated signal slice spectrum set is obtained. After performing overall average processing on the modulated signal slice spectrum set, the overall average feature of the slice spectrum is obtained.

3. Experimental Verification

To verify the effectiveness of the overall average feature extraction method of bispectral slices of modulated signals, a low-speed reciprocating bearing raceway fault simulation test was carried out in a laboratory environment to simulate wind turbine pitch-bearing raceway damage test data. Based on the obtained test data, a comparative analysis is conducted between the traditional MSB method and the fault diagnosis method proposed in this article.

3.1. Experiment Introduction

The bearing reciprocating operation test bench used is shown in **Figure 2**. It consists of a drive motor, a ball screw, a rack and pinion, a rotating shaft (vertical axis), a counterweight, and a control system. The test bench is connected by the ball screw and the rack and pinion. The meshing drives the rotating shaft to

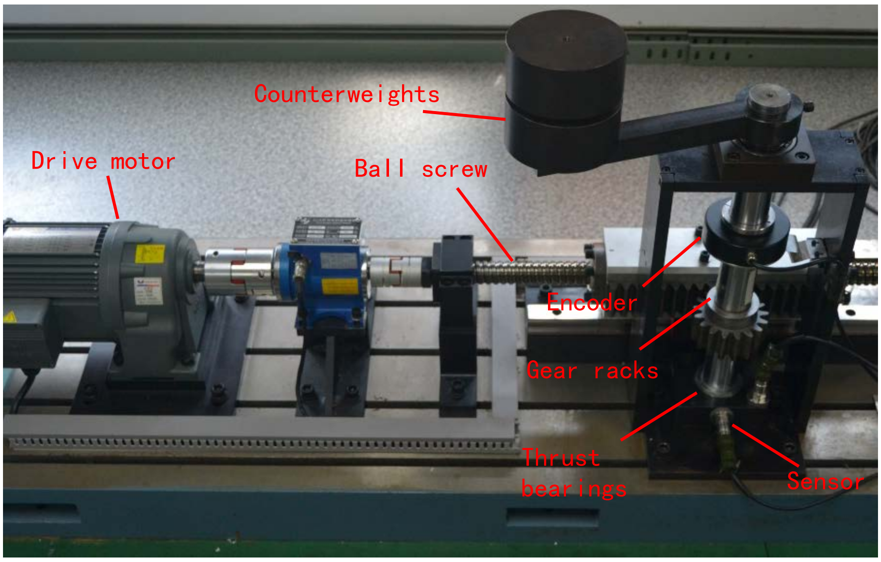

Figure 2. Low-speed reciprocating bearing damage simulation test bench.

reciprocate, and the reciprocating angle is adjusted by the limiter, with the angle ranging from 90˚ to 360˚. The test system used consists of a vibration acceleration sensor, a photoelectric encoder, a collection card, and a data conditioning module. The vibration acceleration sensor has a sensitivity of 10.20 $mv/m \cdot s^{-2}$ and is installed on the bearing seat at the bottom of the rotating shaft. The photoelectric encoding used the device generates 1024 speed pulses per revolution.

The test bearing is a one-way thrust bearing, model SKF 51109. A damaged ferrule is implanted on the raceway and is fixed in the bearing seat at the bottom of the rotating shaft. It does not rotate with the rotating shaft. The damaged bearing implanted is shown in **Figure 3**. The damage was a crack 0.2 mm wide and 1.5 mm deep. The parameters of the SKF 51109 bearing are shown in **Table 1**.

The characteristic frequency coefficient of raceway failure of this bearing is 11. That is, for every revolution of the bearing, the damage on the ring raceway contacts the rolling element 11 times, resulting in 11 damage contact instantaneous impacts.

During the experiment, the rotating speed was set to 4.68 rpm, and the fault characteristic frequency of the bearing at this rotating speed was 0.858 Hz. The reciprocating stroke of the bearing is set to 332˚, so the commutation frequency of the bearing is 0.0417 Hz. Set the sampling frequency to 25.6 kHz and the sampling time to 180 s.

Figure 4 shows the vibration signal and local encoder pulse signal obtained from a test. The 180 s signal contains 7 complete reciprocating operation cycles. During reciprocating commutation, the vibration signal has a commutation impact with a larger amplitude, and the encoder signal has a wider commutation pulse. The speed calculated using the zero-crossing detection method and the encoder signal is shown in **Figure 5**. It can be seen from the figure that there is a

Table 1. Main parameters of SKF 51109 bearing.

Main Parameters	SKF 51109 bearings.		
	Inner Diameter	Outer Diameter	Number of Rolling Elements
size	45 mm	65 mm	18

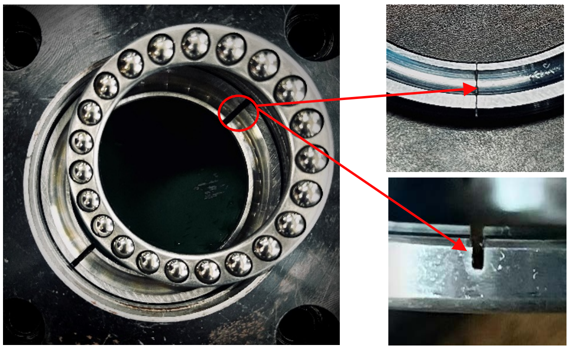

Figure 3. The axial thrust bearing failure parts.

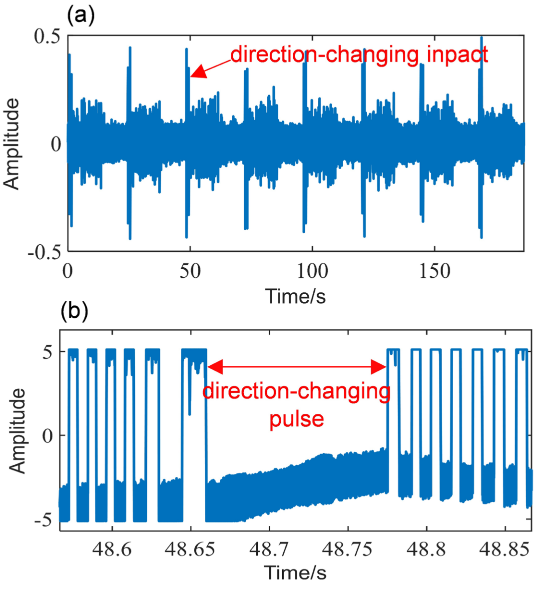

Figure 4. Experimental bearing vibration signal and local encoder pulse signal.

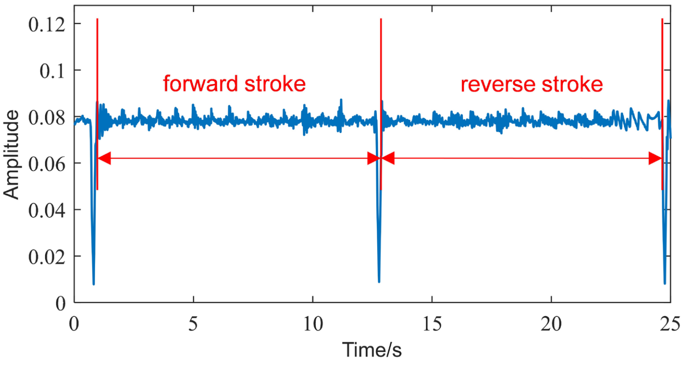

Figure 5. Revolution speed.

rapid speed reduction and speed increase process during commutation. A reciprocating cycle contains two commutations. As a distinction, the process of clockwise rotation of the bearing is called forward stroke, and vice versa is called reverse stroke.

3.2. MSB Feature Extraction

Perform traditional MSB analysis on the vibration signals obtained from the test. Figure 6 shows the amplitude spectrum of the vibration signal. There is a frequency band with greater energy at about 8 kHz. Therefore, [7000 Hz - 9000 Hz] is used as the best frequency band to select the optimal carrier frequency. This frequency band is used as the carrier frequency band to calculate the MSB of the vibration signal. , the MSB three-dimensional spectrum is obtained as shown in Figure 7. By calculating the frequency component with the largest amplitude in this frequency band, the optimal carrier frequency is 8051.77 Hz.

The modulated signal slice spectrum of the vibration signal obtained at the optimal carrier frequency is shown in Figure 8.

As can be seen from Figure 8, the fault characteristic frequency component and its frequency multiplier component are annihilated by the noise and direction change frequency, indicating that the traditional MSB is ineffective in fault diagnosis of low-speed reciprocating bearings.

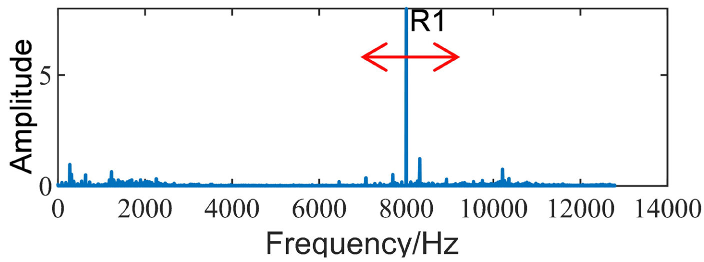

Figure 6. Vibration signal amplitude spectrum.

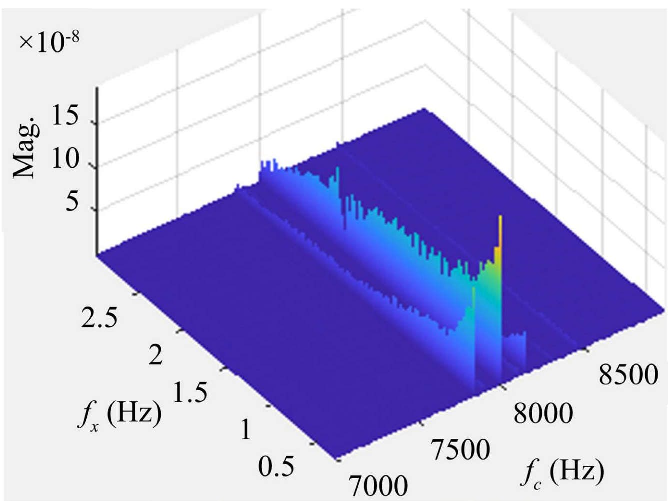

Figure 7. Vibration signal MSB three-dimensional spectrum.

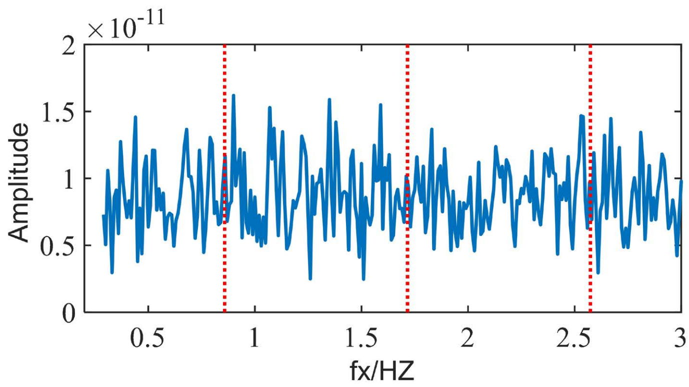

Figure 8. Vibration signal modulation signal slice spectrum.

3.3. Segmentation Signal MSB Slice Overall Average Feature Extraction

The reason why traditional MSB analysis is ineffective in low-speed reciprocating bearing fault diagnosis may be that there is a commutation impact with large amplitude in the long signal covering multiple strokes, and both the commutation impact and the fault impact are in the low-frequency band below 1 Hz. The commutation shock component causes serious contamination to the fault shock component. Therefore, this paper proposes to first segment the original test signal, then conduct MSB analysis on the segmented short signals respectively to generate the MSB modulated signal slice spectrum, and finally average the MSB modulated signal slice spectrum of the short signal set to generate the overall average feature of the slice spectrum.

The test uses the pitch bearing of the wind turbine generator as the simulation object. The size of the wind turbine pitch-bearing ring is large, the number of rolling elements is large, and the failure frequency coefficient is large. For example, the pitch bearing manufactured by Rollix Company in literature [7] has an inner ring fault characteristic frequency coefficient of 31.04. Therefore, during the 90˚ uniform pitch stroke, 31.04 × 90˚/360˚ = 7.76 damage impacts will occur. The SKF 51109 bearing tested in this article is small in size and has a failure frequency of only 11. To simulate the 7.76 damage impacts produced by the pitch bearing in the literature [7] during a 90˚ uniform pitch stroke, the SKF 51109 bearing needs to run at a constant speed. 253.96˚, the corresponding segmented signal length is 9.33 s. The encoder signal is used to realize short signal segmentation. The segmentation is performed at the rising edge of the 100th pulse and the falling edge of the 845th pulse after a single forward stroke commutation pulse. The length of the segmented short signal is close to 9.33 s. The operating angle corresponding to the segmented short signal is approximately 254˚.

Figure 9 shows the segmented forward stroke short signal and its amplitude spectrum. It can be seen from the amplitude spectrum that there are three frequency bands with relatively large energy at approximately 4 kHz, 8 kHz, and 12 kHz. Therefore, [3000 Hz - 5000 Hz], [7000 Hz - 9000 Hz], and [11,000 Hz -

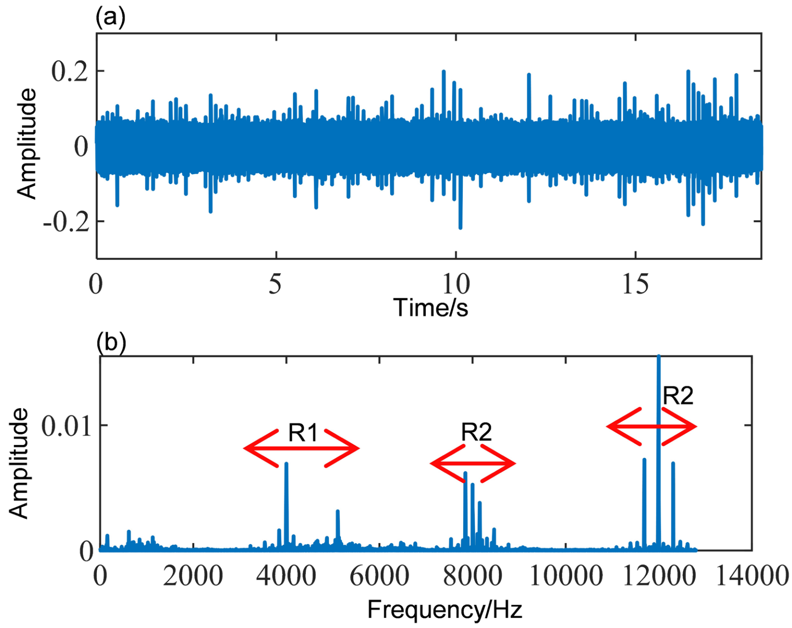

Figure 9. Short signal time signal and spectrum.

13,000 Hz] are selected as the candidate frequency bands for selecting the optimal carrier frequency. Perform MSB analysis on the short signal to obtain the MSB three-dimensional spectrum of the short signal. The local MSB three-dimensional spectrum in the second candidate frequency band is shown in Figure 10.

As can be seen from Figure 10, the MSB three-dimensional spectrum has large peaks at certain carrier frequencies. Calculate the average value of the MSB in the increment direction of the modulation frequency, and the carrier frequency slice spectrum can be obtained as shown in Figure 11. After calculation, the frequency component with the largest amplitude in this frequency band, that is, the optimal carrier frequency is 7999.85 Hz. The slice spectrum of the modulated signal extracted at the optimal carrier frequency is shown in Figure 12.

As can be seen from Figure 12, in the slice spectrum of the MSB modulated signal at the optimal carrier frequency of 7999.85 Hz, there is a clear fault frequency component of 0.858 Hz and its second harmonic component.

According to the same process, short signals are segmented on the remaining six complete forward strokes to form a short signal set. The modulation signal slice spectrum of each short signal is calculated to obtain a short signal modulation signal slice spectrum set. The set of modulated signal slice spectra obtained from seven forward-travel short signals is collectively averaged, and the overall average characteristics of the slice spectrum are obtained, as shown in Figure 13. In the overall average characteristics of the slice spectrum shown in Figure 13, the fault characteristic frequency component and its 2-octave and 3-octave frequency components are clearer than those in Figure 9. This illustrates the effectiveness and superiority of the MSB slice overall average feature extraction method proposed in this paper for low-speed reciprocating bearings.

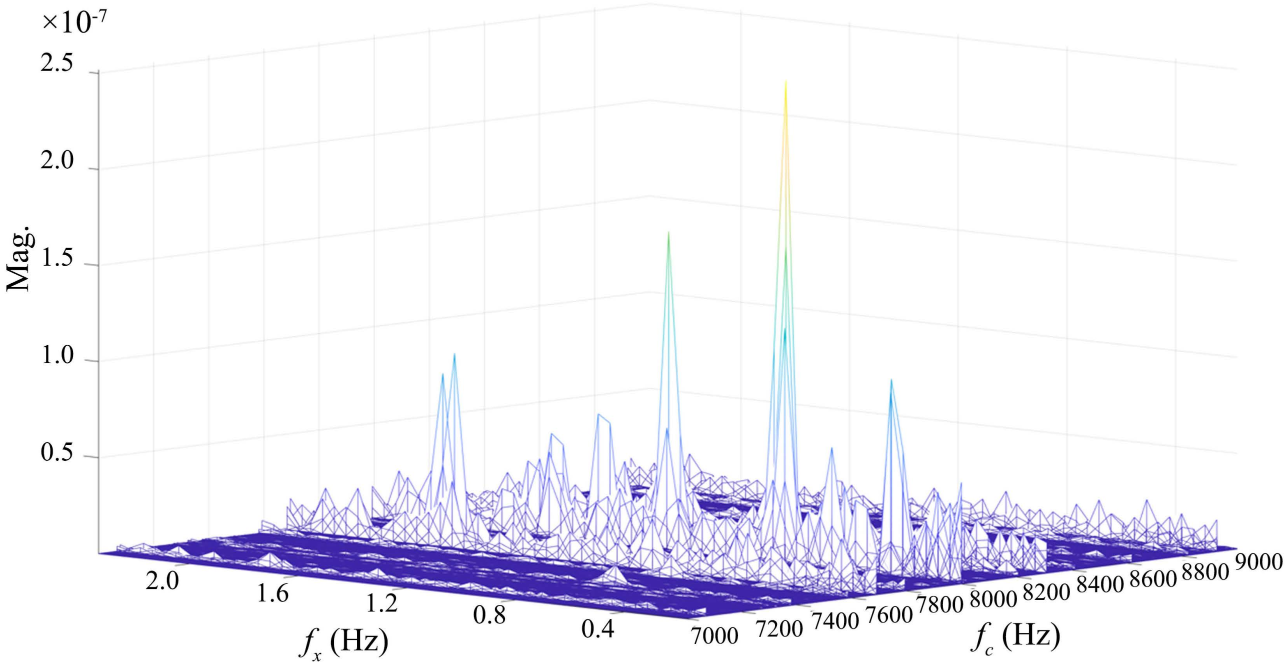

Figure 10. Short signal MSB three-dimensional spectrum.

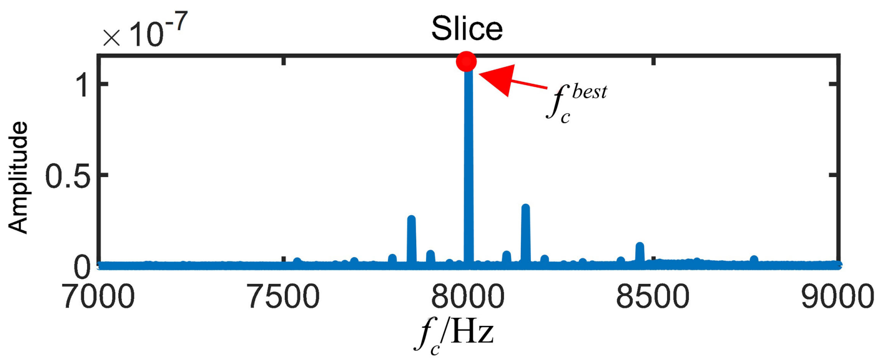

Figure 11. Short signal MSB carrier slice spectrum.

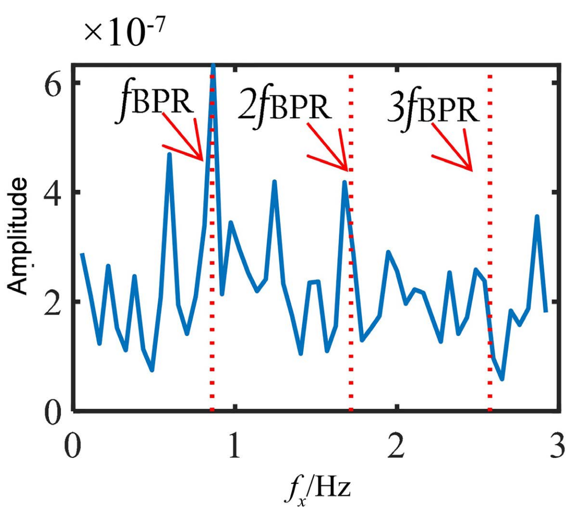

Figure 12. Short signal MSB modulation signal slice spectrum.

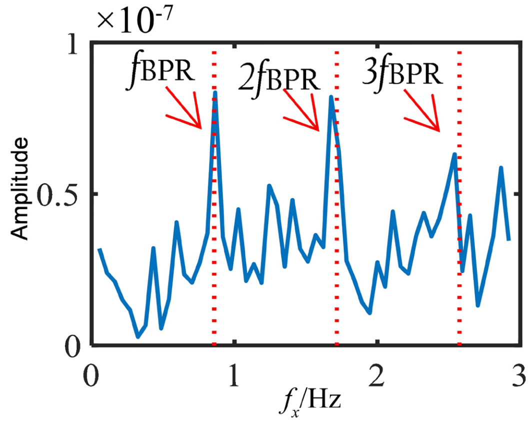

Figure 13. Overall average characteristics of slice spectrum.

4. Conclusions

Aiming at the problem of early fault diagnosis of low-speed reciprocating bearings, this paper uses wind turbine pitch bearings as simulation objects to conduct experimental research from three angles and proposes a bispectral slice overall average feature extraction method of modulated signals.

1) Given the problem that the bearing vibration signal is not periodic under reciprocating operation conditions and the commutation process causes commutation impact, it is proposed to divide the vibration signal stroke and then perform short signal segmentation based on the encoder signal to obtain the short signal of the uniform running section within a single stroke collection, and then perform MSB processing on the short signal to avoid the interference of the commutation impact on the bearing damage signal during the MSB processing process.

2) The fault frequency of the test signal when the bearing is running at low speed is extremely low. The fault diagnosis method based on MSB has a strong detection ability for low-frequency signals and can accurately identify fault characteristic frequencies below 1 Hz.

3) The number of damaged contacts in a single stroke is small, and the damage information in the segmented short signal is very weak. The short signal set is processed based on MSB to obtain the modulated signal bispectrum set and then the overall average can make the fault characteristic frequency component clearer.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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