# Rolling Bearing Fault Diagnosis Based on the Coherent Demodulation Model

**YINGHUA SHAO**[ID], **RUI KANG, AND JIE LIU**[ID], **(Member, IEEE)**

School of Reliability and Systems Engineering, Beihang University, Beijing 100191, China

Corresponding author: Jie Liu (liujie805@buaa.edu.cn)

**ABSTRACT** The rolling bearing is an important part of rotary machineries and the health state monitoring is currently a hot research topic. There are four typical failure modes of a rolling bearing: the inner race failure, the outer race failure, the rolling element failure and the support frame failure. Based on the principle of the coherent demodulation, a new method for rolling bearing fault diagnosis is proposed in this work. This method establishes a coherent demodulator simulation model which is usually adopted in the field of radio communications. The proposed method first demodulates the vibration signal with coherent demodulation principle. Then, the characteristic frequencies related the different failures modes are extracted to obtain the fault characteristic amplitudes, to diagnose the ongoing failure mode. The bearing fault data from the Case Western Reserve University Bearing Test Center is taken as an example to verify and analyze the effectiveness of the proposed method. The results show that this method can accurately diagnose the corresponding failure mode with different locations and sizes.

**INDEX TERMS** Bearing fault diagnosis, bearing characteristic frequencies, fault characteristic amplitudes, coherent demodulator simulation model.

## I. INTRODUCTION

The rolling bearing is basic component of rotary machineries, causing about 30% of their failures, especially in gear and shaft drive equipment [1]. After working for a period of time, various minor defects may emerge which can expand gradually in the subsequent operations until the bearing failures. The damage of the bearing can cause economic and social losses, or even threaten the safety of the personnel. Therefore, the monitoring of its status and diagnosis of any incipient faults can promptly favor in detecting the incipient faults of the rolling bearing, and, thus, carry out timely proper maintenance actions to prevent further damage to rotary machineries.

The rolling bearing failure is mainly influenced by the following three factors: the structure damage, including the assembly error and material defect; the over load resulting in accelerated degradation; working environment factors, such as exterior intrusion, moisture intrusion, chemical corrosion etc. [2]. The common failure modes include fatigue spalling, wear, plastic deformation, corrosion, fracture, gluing, and cage damage [3]. With respect to the defect location, rolling

The associate editor coordinating the review of this manuscript and approving it for publication was Yingxiang Liu[ID].

bearings have four typical failure modes: inner race failure, outer race failure, rolling elements failure and support frame failure [4].

Considering different information sources, the methods for rolling bearings fault diagnosis can be categorized into vibration signal-based [5], acoustic emission-based [6], lubricating oil physical and chemical characteristics-based [7], metal debris-based methods [8], etc. However, the latter three methods have relatively some limitations. For example, lubricating oil analysis can only be used for oil-lubricated bearing analysis; metal debris analysis is susceptible to other metal debris in the same environment, such as debris generated by gear running-in and corrosion; acoustic emission test has relatively high demands on the environment and equipment. In practice, vibration signal-based methods are commonly considered for bearing fault diagnosis.

Rolling bearing fault diagnosis process based on vibration signals can be divided into two steps: feature extraction and fault identification. There are in general three directions for feature extraction: time-domain analysis, frequency-domain analysis and time frequency-domain analysis. Due to the computational simplicities, the time-domain analysis has been applied in many simple diagnostic fields of machinery. Three time-domain indexes are compared in [9] for condition

monitoring of rolling element bearings. Time-domain statistics is divided into two categories, the first category is dimensional parameters, mainly including peak-peak value, root mean square value, etc.; the other category is dimensionless parameters, mainly including kurtosis index, peak index, etc. Entropy has also been adopted extraction of rolling bearing fault features, such as approximate entropy [10], permutation entropy [11], sample entropy [12], etc. Frequency-domain analysis means that when the rolling bearing fails, the transformed frequency components of the collected vibration signals change accordingly [13]. Therefore, in order to obtain the characteristics that can represent the fault information in the frequency domain, the Fourier transform is often used to transform the collected vibration signal into the frequency spectrum. The other popular frequency-domain analysis methods are power spectrum analysis [14], kurtosis spectrum analysis [15], order cestrum analysis [16], envelope spectrum analysis [17]. Because of the complex environment in which the machinery is operated, its vibration signal is often nonlinear and non-stationary. And the diagnostic results may be unsatisfactory using solely time-domain or frequency-domain analysis methods. Thus, the time-frequency domain analysis methods based on both time and frequency are proposed. With time-frequency domain analysis methods, the evolvement of the local frequency components can be obtained [18], [19]. There are many time-frequency domain analysis methods, such as wavelet analysis [20]–[22], empirical mode decomposition [23], [24], ReliefF algorithm [25] and other methods. Fault identification is also called fault pattern recognition. The fault characteristic frequency method is commonly used [26], [27]. Other methods, such as hidden Markov models [28], rough set method [29], and neural networks [30] [31], Support Vector Machine [32]–[34] and other artificial intelligence algorithms are also applied to the classification of rolling bearing fault features. Considering the computational complexity and diagnostic accuracy, the envelope spectrum analysis method is widely used in engineering practice. The Hilbert transform method is used to obtain the signal envelope first, and then the Fourier transform is used to decompose the vibration signal. But this method requires more preprocessing actions before it can be used in practical applications such as the use of wavelet transform to reduce noise of the vibration signal collected form the low-speed bearings [35]. Four packages of envelope spectrum analysis algorithm are compared in [36], and it is found that envelope algorithms have different performances in different frequency ranges. In general, the method based on envelope analysis requires a higher sampling rate when processing high-frequency signals, which limits the practical application of this method to a certain extent [36].

In order to solve the limitation of envelope spectrum analysis method, this paper presents a method for rolling bearings fault diagnosis based on the coherent demodulation principle. Following this principle widely used in radio communication technology [37]–[40], a simulation model of a coherent demodulator is established to directly demodulate the vibration signal, collect the vibration signal data of specific frequency bands, extract the fault features, and then diagnose the fault type of the rolling bearing. Three major contributions are made by the method based on coherent demodulation. First, the method can greatly reduce the demand on the sampling frequency of the vibration signal. In order to obtain a valuable envelope spectrum to analyze the fault characteristic frequency response, the collected vibration signal needs to have a higher sampling frequency, which puts forward higher requirements on the sampling equipment and increases the cost of vibration signal analysis. The method based on the principle of coherent demodulation draws on the physical principles of radio communication, and directly demodulates and filters the signal. It does not need to perform mathematical processing on the vibration signal that needs to be analyzed, and does not need to obtain the envelope spectrum, so the sampling frequency of the vibration signal does not need to be that high, which greatly reduces the requirements for sampling equipment. Second, the method proposed in this paper can also greatly reduce the subsequent calculation burden. The envelope spectrum analysis method needs to carry out Hilbert and Fourier transform on the collected vibration signals, and a lot of mathematical calculations. The method based on the principle of coherent demodulation is to establish a simulation model from the physical principle of coherent demodulation of the vibration signal to directly demodulate the collected vibration signal, and calculate the response value at the characteristic frequency of the fault. There is no need to perform mathematical transformation on the vibration signal, the calculation amount is small, and it is easy to popularize and apply in engineering practice. Third, the proposed method reveals the vibration mechanism when the rolling bearing fails and does not rely on experience of data analysts for fault diagnosis. It is easy to understand in principle and can provide information for subsequent operation and maintenance. However, other vibration signal analysis methods such as envelope analysis can only extract the fault characteristics of rolling bearings mathematically and rely highly on the expert knowledge for identifying the characteristic frequencies. It is shown in the case study that it can be applied to the fault diagnosis of various rolling bearings faults.

The remainder of the manuscript is structured as below. Section II introduces the vibration of rolling bearings, including its structure, natural vibration frequency and bearing characteristic frequencies. Then the principle and process of rolling bearing fault diagnosis based on coherent demodulation is given in Section III, and the validity of the coherent demodulation is analyzed by comparison with the common envelope spectrum analysis method. After that, a case study is carried out to verify the effectiveness of the method and analyze the influence of factors on the diagnosis result of the method in Section IV. And last, a conclusion is made to evaluate the applicability and improvement direction of the method.
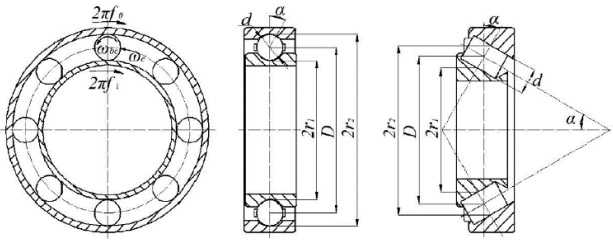
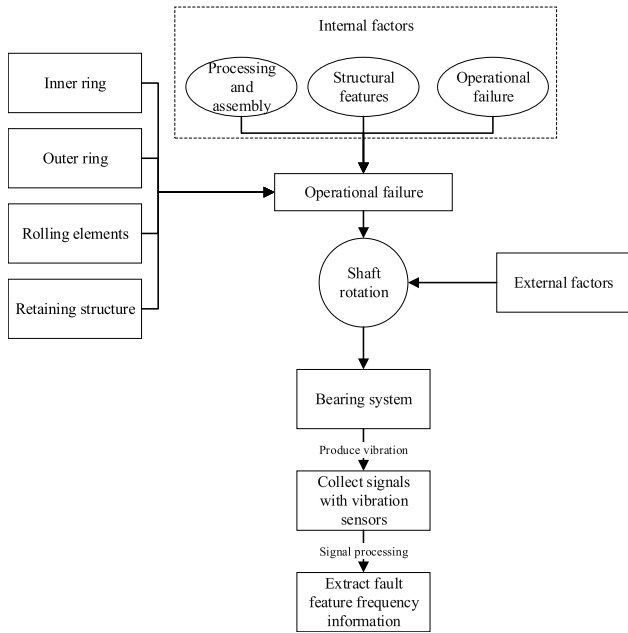**FIGURE 1.** Typical structure of a rolling bearing.



**FIGURE 2.** Typical structure diagram of rolling bearing.

## II. VIBRATION OF ROLLING BEARINGS

### A. VIBRATION MECHANISM OF ROLLING BEARINGS

Rolling bearings are generally composed of an inner race, an outer race, rolling elements (i.e. ball), and a support frame, as shown in FIGURE 1.

During the operation of a mechanical equipment, there are many sources causing the vibration of the rolling bearings, such as partial that degradations, malfunctions, roller roughness, assembly error, inner raceway, outer raceway, surface problems, etc. [41] The vibration mechanism is shown in FIGURE 2. Vibration signal acquisition is relatively easy and sensitive to early faults. In the diagnosis process, the signal from the acceleration sensor placed on the bearing support is the joint excitation of all the above factors. However, if the structure and environment factors are avoided, the vibration signal is mainly affected by the bearing faults during operation.

If the rolling bearing surface has a defect or damage, the remaining part collides with the defective part to produce a low-frequency impact vibration. The frequency of this impact vibration is called Bearing Characteristic Frequencies (BCFs) [42]. When the bearing is working normally, its own vibration has also a natural high-frequency vibration

frequency [43]. The vibration signal of a faulty bearing measured by an acceleration sensor is a signal generated by modulating both the characteristic frequency of the fault and the natural vibration frequency of the bearing.

### B. NATURAL VIBRATION FREQUENCY OF ROLLING BEARING

During operation, each element in the rolling bearing will vibrate at its natural frequency due to local defects and irregular structure impact. The natural frequency of the bearing element is mostly in the high frequency band of several kHz to tens of kHz. The frequency depends on the material, shape and quality of the bearing components, and is affected by the bearing assembly conditions, regardless of the operating speed. The equations for calculating the natural frequencies of the bearing inner and outer raceways and rolling elements are given below.

#### 1) NATURAL VIBRATION FREQUENCY OF INNER AND OUTER RACEWAYS

The natural frequency of the inner and outer raceways is divided into the natural frequencies of the pure radial direction, the torsional direction and the bending direction. The following Equation (1) gives the natural frequency of the inner and outer raceways of the bearing in the plane of the ring, that is, the radial bending natural vibration frequency.

$$f_{nr} = \frac{n(n^2 - 1)}{2\pi (D/2)^2 \sqrt{n^2 + 1}} \sqrt{\frac{EI}{M}} \tag{1}$$

In Equation (1), $E$ means the elastic modulus of the material; $I$ means moment of inertia of the longitudinal section of the bearing ring; $M$ means quality within unit length of bearing ring; $D$ means the diameter of the neutral shaft of the bearing ring; $n$ means order of natural frequency.

#### 2) NATURAL VIBRATION FREQUENCY OF ROLLING ELEMENT

Due to its elastic properties, the rolling elements of the bearing will also elastically deform like a spring, but its rigidity is high and it has nonlinear characteristics. If the lubrication is poor, nonlinear vibration is prone to occur. When the bearing is subjected to radial load or is running at low speed, the rolling element enters the non-load area from the load area and becomes free movement. Due to the gravity of the rolling element, the position of the rolling element advances or lags, which will collide with the cage or the collar. The imperfection of the component produces free vibration. The natural vibration frequency of the rolling element can be calculated by Equation (2):

$$f_{nb} = \frac{0.848}{d} \sqrt{\frac{E}{2\rho}} \tag{2}$$

In Equation (2), $d$ means diameter of rolling element; $E$ means the elastic modulus of the material; $\rho$ means the density of the material.

It can be seen from Equation (1) and (2) that the natural vibration frequency of the elements of rolling bearings is

only related to the inherent material properties and geometric characteristics of rolling bearings. In practice, it may also be affected by assembly conditions. The initial vibration frequency of the flawless rolling bearing system measured by the accelerometer is taken as the natural vibration frequency of the rolling bearing.

### C. BEARING CHARACTERISTIC FREQUENCIES OF ROLLING BEARING

During the operation of the rolling bearing, when the rolling element encounters a local defect at the raceway of the inner raceway or the outer raceway, an impact signal is generated through contact collision. At a certain speed, while the defect is on different bearing components, the frequency of the contact point passing through the defect is also different. These frequencies are called the BCFs, which reflects the location of bearing defects. Thus bearing fault diagnosis can be realized by analyzing BCFs.

The calculation model of BCFs is based on the following assumptions: the angular velocity of the inner and outer raceways of the bearing and the rolling elements is constant during the observation time; There is no slippage between the rolling body and the inner and outer raceways; And the pressure angle is unchanged [35].

If the operating contact angle is $\phi$, the rolling element (spherical) diameter is $d$, the rolling pitch circle diameter is $D$, the inner raceway angular frequency is $f_i$, the outer raceway angular frequency is $f_o$, the number of rolling elements is $N$, and the characteristic vibration frequency of each part of the bearing can be calculated as follows [35]:

Ball pass frequency of inner race (BPFI),

$$f_{BPFI} = \frac{N}{2}(f_i - f_o)\left(1 + \frac{d}{D} \times \cos\phi\right) \quad (3)$$

Ball pass frequency of outer race (BPFO),

$$f_{BPFO} = \frac{N}{2}(f_i - f_o)\left(1 - \frac{d}{D}\cos\phi\right) \quad (4)$$

Ball spin frequency (BSF),

$$f_{BSF} = \frac{D}{2d}(f_i - f_o)\left(1 - \left(\frac{d}{D}\cos\phi\right)^2\right) \quad (5)$$

Fundamental train frequency (FTF),

$$f_{FTF} = \frac{1}{2}(f_i - f_o)\left(1 - \frac{d}{D}\cos\phi\right) \quad (6)$$

The above four vibration frequencies are collectively referred to as BCFs, which correspond to four types of failures: inner raceway failure, outer raceway failure, rolling element failure and support frame failure. In this article, we will use the characteristics of these four fault vibration frequencies to carry out fault diagnosis of rolling bearings.

### D. WORKING VIBRATION FREQUENCY OF ROLLING BEARING

In the actual working process, rolling bearings have both their own natural vibration frequency and the characteristic

vibration frequency of the bearing due to defects. Therefore, the working vibration frequency of the rolling bearing is the vibration frequency generated by modulating the characteristic vibration frequency to the natural vibration frequency. If only single-point failures are considered, the impact vibration frequency BCFs due to bearing defects or damage can be expressed as:

$$f_{BCFs} = \cos(\omega t + \varphi) \quad (7)$$

The natural vibration frequency (NF) of the bearing can be expressed as:

$$f_{NF} = \sum_{i=1}^{n} \sin(\omega_i t + \varphi_i) \quad (8)$$

Then the working vibration frequency of the rolling bearing modulated by BCFs and NF, which can be measured by the acceleration sensor can be expressed as:

$$\begin{aligned} f_{in} &= f_{BCFs} \cdot f_{NF} \\ &= \cos(\omega t + \varphi) \cdot \sum_{i=1}^{n} \sin(\omega_i t + \varphi_i) \\ &= \underbrace{\frac{1}{2}\sum_{i=1}^{n} \cos[(\omega - \omega_i)t + (\varphi - \varphi_i)]}_{\text{Low frequency}} \\ &\quad + \underbrace{\frac{1}{2}\sum_{i=1}^{n} \cos[(\omega + \omega_i)t + (\varphi + \varphi_i)]}_{\text{High frequency}} \quad (9) \end{aligned}$$

It can be seen from Equation (9) that the actual measured vibration signal is actually the result of the modulation of the natural vibration signal and the impact vibration signal generated by the fault, which is the working vibration frequency. If we can separate the characteristic vibration frequency from the measured signal, and then it can be used to diagnose the failure mode of the rolling bearing in the actual working process.

## III. ROLLING BEARING FAULT DIAGNOSIS BASED ON COHERENT DEMODULATION

### A. COHERENT DEMODULATION

The commonly fault diagnosis method based on the vibration signal of the rolling bearing combines the envelope analysis method and the Fourier Transform method. That is, after removing the noise, the envelope spectrum analysis is carried out. The frequency spectrum of the vibration signal is obtained through the Fourier Transform, and then the response at the characteristic frequency of the fault (BCFs) is analyzed to determine its failure mode. This method often requires over-sampling of the collected signal and a higher sampling frequency to obtain a complete signal waveform, which may reduce the versatility of the system and increase the cost [44]. This paper presents a method for processing the measured vibration signal of the rolling bearing using coherent demodulation technology. Based on the principle of
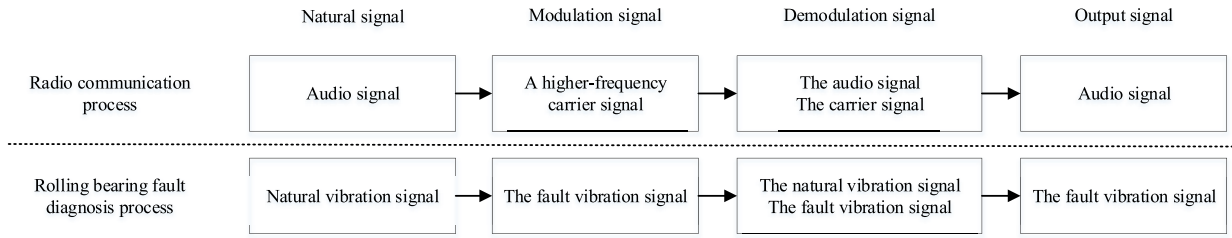
**FIGURE 3.** The signal processing analogy of radio communication process and rolling bearing fault diagnosis process.

coherent demodulation similar to the traditional superheterodyne radio [45], the measured signal data is first demodulated by frequency reduction and, then, the fault characteristic data is extracted and, at the end, the fault type of the rolling bearing is identified.

The concept of coherent demodulation comes from radio communication. At the transmitting end of radio communication signals, low-frequency information-containing signals, such as audio signals, cannot usually be directly transmitted. It is needed to use these signals to modulate a higher-frequency carrier signal and then transmit. This process is called modulation. At the receiving end of radio communication signals, the received signal is demodulated. Demodulation is the inverse of the modulation process. It is used to divide the received signal into two parts, the signal carrier with a higher frequency and the signal containing information with a lower frequency. So the signal containing information can be used to carry out analysis.

Demodulation methods can be divided into two categories: coherent demodulation and non-coherent demodulation. Coherent demodulation [46], [47] is also called synchronous detection, which is applicable to the demodulation of all linear modulation signals. The key to realizing coherent demodulation is that the receiver needs to recover a coherent carrier that is strictly synchronized with the modulated carrier. Non-coherent demodulation [48], [49] is also called envelope detection. Envelope detection is to directly recover the original modulated signal from the amplitude of the modulated wave without a coherent carrier. Compared with non-coherent demodulation, the coherent demodulation method has a wider application range and higher demodulation accuracy.

After the analogy with the radio communication signal processing process, the rolling bearing fault diagnosis signal processing process is illustrated in FIGURE 3. When the rolling bearing is working normally, there will be a natural vibration signal. Then when a fault occurs, the signal collected by vibration sensors is the modulated signal of the natural vibration signal and the fault vibration signal. In order to get the fault vibration signal, the demodulation is carried out to decompose the vibration signal into two parts: the inherent vibration signal and the fault vibration signal. The fault vibration signal can, then, be used for fault diagnosis purpose.

The feature extraction method of rolling bearing vibration signal based on coherent demodulation technology proposed in this paper works as follows: the input signal is mixed with the signal of the specified frequency, that is, the signal generated by the local oscillator, and then passed through a low-pass or band-pass filter to obtain the required signal to realize the extraction of the specified frequency signal. The block diagram of the coherent demodulator based on MATLAB Simulink simulation used in this paper is shown in FIGURE 4, and its process is shown in FIGURE 5.

As shown in FIGUREs 4 and 5, it is assumed that the collected vibration signal is composed of several sine waves with different frequencies, and its frequency can be expressed as:

$$f_{in}(t) = \sum_{i=1}^{n} \cos\left(2\pi f_i t + \phi_i\right) \tag{10}$$

The phase-locked loop (PLL) [46] in FIGURE 4 is composed of a voltage-controlled oscillator (VCO), a mixer, and a loop filter. Its function is to generate a signal with a specified frequency $f_j$ and the same phase as the input signal to be diagnosed. Therefore, by inputting the natural vibration frequency of the rolling bearing, the frequency of the natural vibration signal $l_o$ generated by the local oscillator PLL in phase with the vibration signal to be diagnosed can be expressed as:

$$f_o(t) = \cos\left(2\pi f_j t + \phi_j\right) \tag{11}$$

In Equation (11), $f_j$ can be set and adjusted by the users, and $\phi_j$ is synchronized using PLL. Next, mix $l_{in}$ and $l_o$ in the multiplier. This process is coherent. The frequency of the signal obtained after coherence can be expressed as:

$$\begin{aligned}
f_x &= f_o(t) \cdot f_{in}(t) \\
&= \cos\left(2\pi f_j t + \phi_j\right) \cdot \sum_{i=1}^{n} \cos\left(2\pi f_i t + \phi_i\right) \\
&= \underbrace{\frac{1}{2} \sum_{i=1}^{n} \cos\left[2\pi\left(f_j - f_i\right)t + \left(\phi_j - \phi_i\right)\right]}_{Low\ frequency} \\
&\quad + \underbrace{\frac{1}{2} \sum_{i=1}^{n} \cos\left[2\pi\left(f_j + f_i\right)t + \left(\phi_j + \phi_i\right)\right]}_{High\ frequency} \tag{12}
\end{aligned}$$

**FIGURE 4.** Coherent demodulator simulation model.



**FIGURE 5.** Coherent demodulation process.



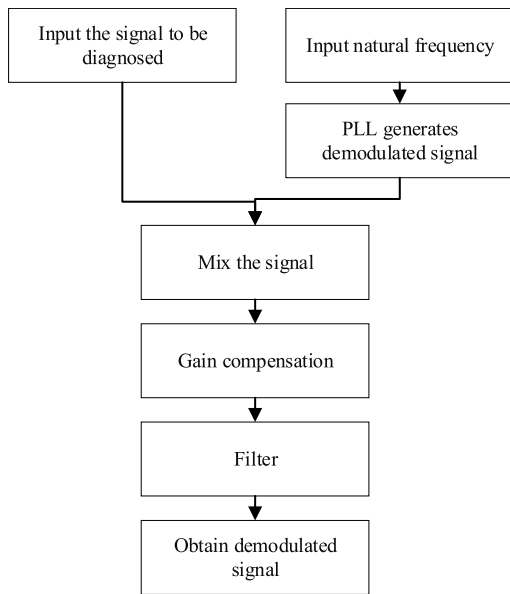**FIGURE 6.** Technical process of rolling bearing fault diagnosis based on coherent demodulation principle.

Then, the gain of 1/2 produced by mixing is compensated. The frequency of the signal $l_{x2}$ obtained after gain compensation can be expressed as:

$$f_{x2} = \underbrace{\sum_{i=1}^{n} \cos\left[2\pi\left(f_j - f_i\right)t + \left(\phi_j - \phi_i\right)\right]}_{\text{Low frequency}}$$
$$+ \underbrace{\sum_{i=1}^{n} \cos\left[2\pi\left(f_j + f_i\right)t + \left(\phi_j + \phi_i\right)\right]}_{\text{High frequency}} \quad (13)$$

Assuming that for a certain frequency $i$, $f_i$ is close to or equal to $f_j$, $\phi_i$ equal to $\phi_j$, obviously at this time, a low-frequency part will appear as a direct-current (DC) component, which can be extracted with a low-pass filter. The low-pass filter can then be used to remove high-frequency components, leaving low-frequency components.
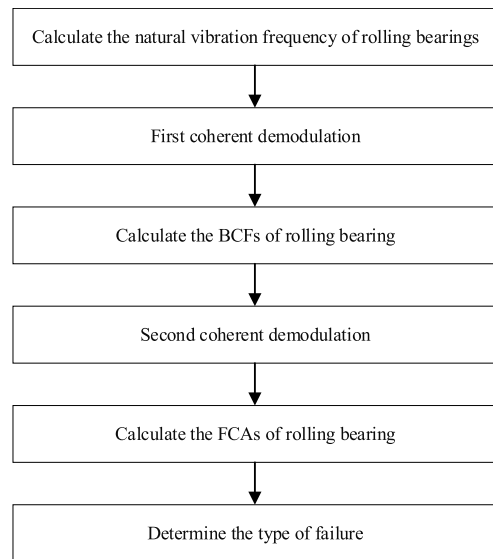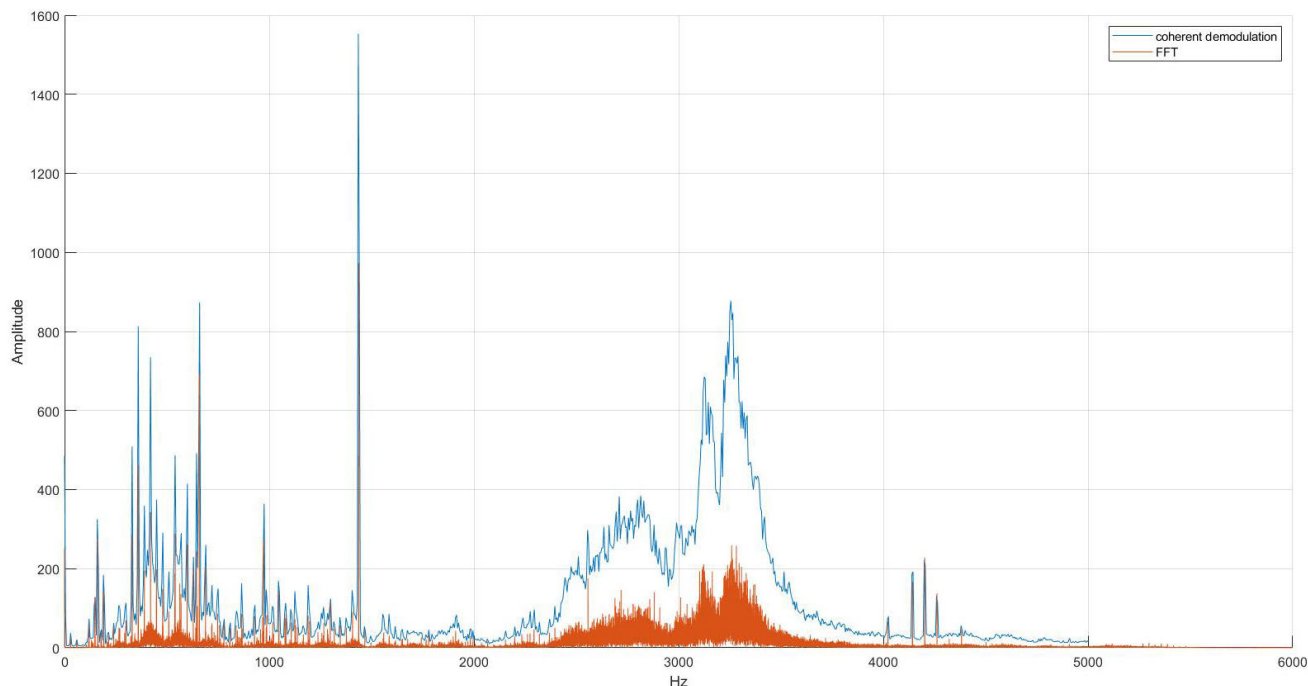
The low frequency component obtained after demodulation is the vibration signal containing the rolling bearing fault information.

### B. FAULT DIAGNOSIS USING COHERENT DEMODULATION

The technical process of rolling bearing fault diagnosis based on coherent demodulation principle consists of the following six steps, as shown in FIGURE 6.

The first step is to calculate the natural vibration frequency. According to the parameters of the rolling bearing, Equation (1) or (2) are used to calculate the natural vibration frequency of the bearing during operation; or the natural vibration frequency can be obtained by analyzing the vibration signal of the bearing working without failure.

The second step is the first coherent demodulation. The natural vibration frequency of the bearing obtained in the first step serves as input of a coherent demodulator and is mixed with the collected vibration signal of the bearing to be

**FIGURE 7.** Comparison of frequency response between the envelope spectrum analysis method and the coherent demodulation proposed in this work.

diagnosed. The mixed signal is separated by a low-pass filter to obtain a low-frequency vibration signal containing bearing fault information. The frequency bandwidth of the low-pass filter in the first coherent demodulation should at least include both the natural vibration frequency and the BCFs.

The third step is to calculate the BCFs. By entering the size and speed of the target rolling bearing, the fault characteristic frequency are obtained according to the Equation (3) (4) (5) (6).

The fourth step is the second coherent demodulation. The BCFs of the bearing fault obtained in the third step is fed into the coherent demodulator and mixed with the low-frequency vibration signal obtained by the first coherent demodulation in the second step. Separated by a band-pass filter, the bearing discrete low-frequency vibration signal of fault information is obtained. The frequency bandwidth of the band-pass filter in the second coherent demodulation is generally about 10Hz. According to the test results, when the bandwidth is larger than 10Hz, the calculation of the fault characteristic amplitude will increase the amount of calculation; when the bandwidth is less than 10Hz, the accuracy of calculating the fault characteristic amplitude for fault diagnosis will decrease. Therefore, in this paper, the optimal bandwidth of the filter in the PLL is 10Hz.

The fifth step is to calculate Fault Characteristic Amplitudes(FCAs). According to the fourth step, several discrete vibration signals corresponding to the BCFs are obtained, and their amplitudes are taken as the fault characteristic amplitude corresponding to the BCFs.

The sixth step is to determine the fault type. The fault type corresponding to the BCFs with the larger FCAs in the fifth step is the main cause of the rolling bearing fault.

## C. METHOD VALIDITY ANALYSIS BY COMPARISON
In order to verify the effectiveness of the coherent demodulation method, comparisons with the envelope spectrum analysis method are considered, and the effectiveness of both methods is verified by the frequency response method [50] usually used in spectrum analysis. The fault diagnosis results are also compared and analyzed.

Envelope spectrum analysis [51] is commonly used to analyze vibration signals. First, the vibration signal is subjected to Hilbert Transform to extract the envelope spectrum of the vibration signal, and then the Fourier Transform is used to obtain the frequency domain characteristic map of the vibration signal. After coherent demodulation of the vibration signal, the method proposed in this paper obtains a very narrow (generally 10Hz bandwidth) vibration signal at each frequency point. The absolute value of this signal is integrated in the time domain, and the outcome is regarded as the amplitude value at the frequency point, and then we plot it to get the frequency domain characteristic map. The data concerns the single-point fault in ball spin with a diameter of 14 mils in the bearing fault data published by the Case Western Reserve University Bearing Data Center [52]. The spectrum obtained by this method is shown in FIGURE 7, where the red curve (FFT) is the spectrum obtained by the benchmark method, and the blue curve (coherent demodulation) is the spectrum obtained by the proposed method.

In FIGURE 7, the abscissa is the frequency; the ordinate is the relative amplitude. It can be seen from the spectrum diagram that for the same vibration signal, the frequency responses of the spectrum diagram obtained by the envelope spectrum analysis method and the coherent demodulation method are generally consistent, showing that the
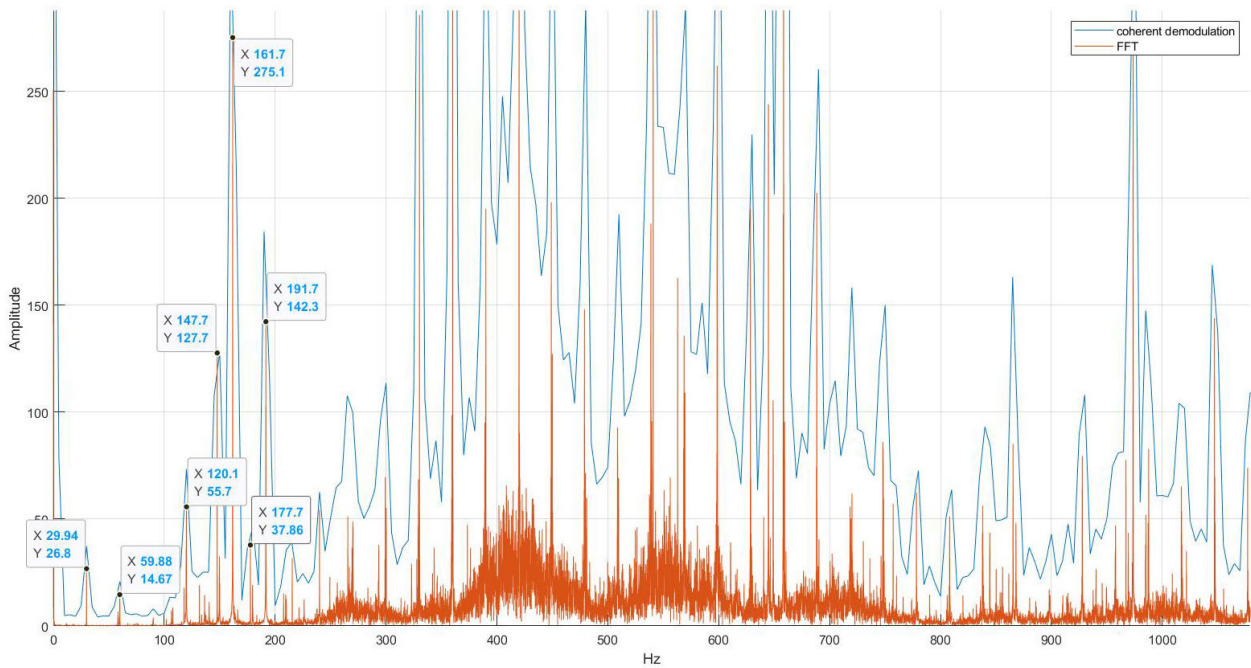
**FIGURE 8.** Spectrum diagram for fault diagnosis using envelope spectrum analysis method.
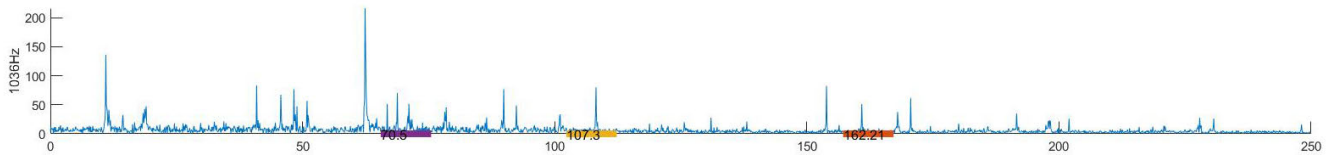


**FIGURE 9.** Spectrum diagram of fault diagnosis using coherent demodulation method.

**TABLE 1.** Fault characteristic amplitude of 14 mil single point fault of rolling bearing.

| Number | True fault location | BPFI | BPFO | BSF |
|--------|---------------------|------|------|-----|
| *1* | rolling element failure | 567.56 | 462.91 | **892.04** |

coherent demodulation method proposed in this paper for analyzing the vibration signal in the frequency domain is effective.

Following equation (3) (4) (5), the BCFs can be calculated in TABLE 1. Usually, the low frequency part (0-200Hz) in the FIGURE 7 contains the fault characteristic information, as shown in FIGURE 8. Through the envelope spectrum analysis method, we can directly observe the response value of the fault characteristic frequency in the spectrogram to obtain the bearing fault diagnosis result. It can be seen from FIGURE 8 that the frequency value at the maximum response of the spectrogram frequency obtained by mathematical transformation of the bearing vibration signal is not completely consistent with the fault characteristic frequency of the bearing, and there are multiple peaks, such as 161.7Hz, 191.7Hz, 147.7Hz, 120.1Hz etc., which cannot easily be used to carry out fault diagnosis especially under the influence

of environmental factors. Through the coherent demodulation method, we can calculate the FCAs at BCFs as shown in TABLE 1 based on FIGURE 9. The fault characteristic amplitude at the BSF is the largest, whose value is 892.04. So the fault diagnosis result is a rolling element fault, which is consistent with the selected vibration signal data. This fully demonstrates the effectiveness of the proposed method based on coherent demodulation.

## IV. CASE STUDIES

In this part, case studies are considered to elaborate on the application of the proposed method for rolling bearings fault diagnosis considering different fault sizes and locations.

### A. DATA DESCRIPTION

The bearing failure data published by the Case Western Reserve University Bearing Data Center is considered in the case studies [53]. As shown in FIGURE 10, the Western Reserve University Bearing Test Bench consists of a 2 horse-power motor (left), torque sensor / encoder (center), dynamometer (right), and control circuit. The test bearing supports the motor shaft. The drive end bearing is SKF6205, whose sampling frequency is 12KHz and 48KHz; The fan end bearing is SKF6203, whose sampling frequency is 12Khz. A single point failure is introduced into the test bearing
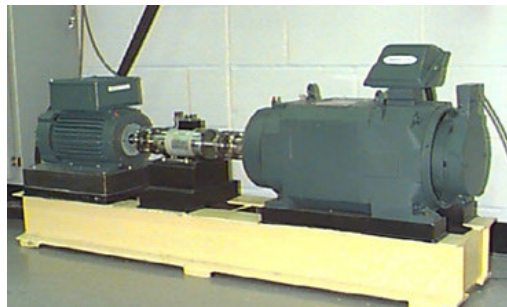
FIGURE 10. Apparatus & Procedures.

using electrical discharge machining. The diameter of the failure is divided into 7mil, 14mil, 21mil, and 28mil (1mil = 0.001 inch). There are three types of failure location: inner raceway, outer raceway, and rolling element. The data is the SKF6205-2RSJEM bearing single-point fault vibration data measured by the bearing drive end acceleration sensor, and the speed is 1797 rpm. The sampling rate is 12KHz. The details of the bearing: the number of balls $n = 9$; the rolling element diameter $d = 7.938mm$; bearing pitch diameter $D = 39mm$; rolling element contact angle $\phi = 0$.

In this section, the rolling bearing fault diagnosis technology based on coherent demodulation technology will be used to process the bearing fault vibration data and carry out fault diagnosis. The accuracy and effectiveness of the proposed method are verified in the case studies.

### B. ANALYSIS OF THE EXPERIMENTAL RESULTS

#### 1) THE NATURAL VIBRATION FREQUENCY CALCULATION

This section analyzes the natural vibration frequency of the bearing at a speed of 1797 RPM [49]. When the bearing is working normally, the vibration data measured by the accelerometer is transformed with Fourier transform, and the frequency values with significant vibration amplitude are obtained. The specific rules are: the frequency with an amplitude greater than 4000 is considered as a significant frequency; the frequency with the largest amplitude within 100Hz around the significant frequency is considered as the fundamental frequency; the rest are the beat frequencies generated by the fundamental frequency and other low-frequency signals. Therefore, the beat frequency
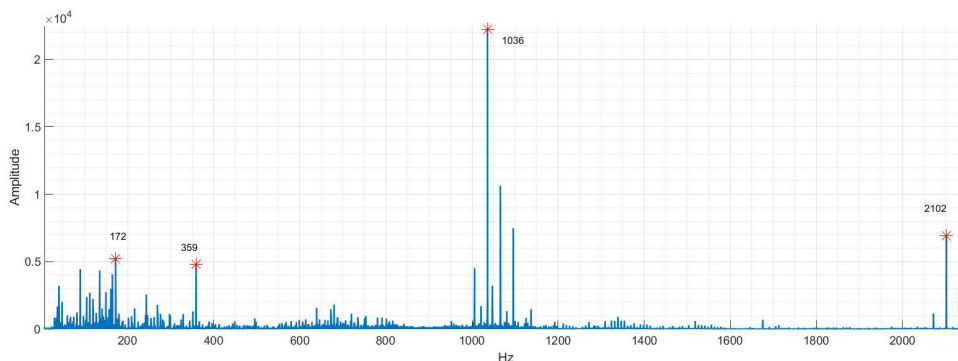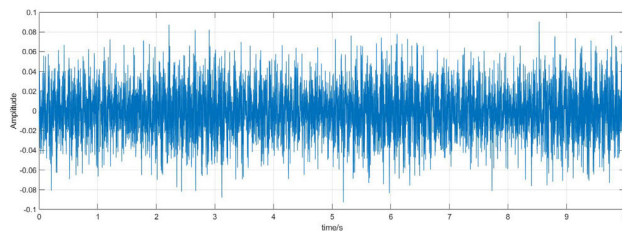


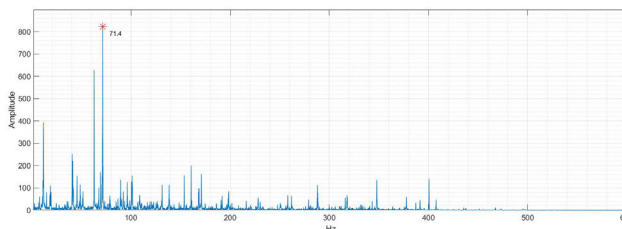FIGURE 12. Time domain characteristics of the signal after the first coherent demodulation.



FIGURE 13. Frequency domain characteristics of the signal after the first coherent demodulation.

is ignored during processing, and only the significant fundamental frequency is retained as shown in FIGURE 11.

According to FIGURE 11, the series of fundamental frequency points are 172 Hz, 359 Hz, 1036 Hz, and 2102 Hz, respectively. We select the fundamental frequency point of 1036 Hz with the largest vibration amplitude as the natural vibration frequency of the rolling bearing.

#### 2) THE FIRST COHERENT DEMODULATION

The bearing natural vibration frequency of 1036 Hz is fed into the coherent demodulator to obtain the demodulated signal, which is mixed with the collected bearing vibration signal. In order to keep the complete information of BCFs to the greatest extent and reduce the amount of data processed, the first coherent demodulation uses a low-pass filter, the filter bandwidth is set to 0-600Hz, that is, after the first coherent demodulation, the frequency of the signal is reduced to below 600 Hz. Taking the data of 7 mil single-point fault data of the rolling element [53] as an example, the results are shown in FIGURE 12 and FIGURE 13.
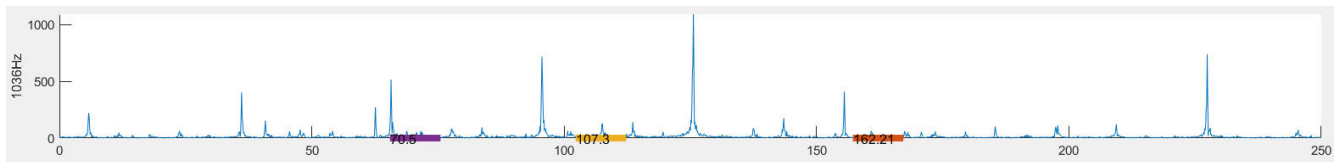


FIGURE 11. Rolling bearing natural vibration spectrum.

**FIGURE 14.** Frequency domain characteristic diagram of the signal after the second coherent demodulation.

**TABLE 2.** BCFs calculated results.

| Number | BCFs | Frequency(Hz) |
|--------|------|---------------|
| 1 | BPFI | 162.2 |
| 2 | BPFO | 107.3 |
| 3 | BSF | 70.5 |

**TABLE 3.** Fault characteristic amplitude at 7 mil inner raceway single point fault Bcfs of rolling bearing.

| Number | BCFs | Value of BCFs(Hz) | Value of characteristic amplitude |
|--------|------|-------------------|-----------------------------------|
| 1 | BPFI | 162.2 | **1213.62** |
| 2 | BPFO | 170.3 | 784.80 |
| 3 | BSF | 70.5 | 634.40 |

### 3) THE BCFs CALCULATION

By analyzing the generation mechanism of BCFs, and substituting bearing size and speed information into Equation (3) (4) (5), the BCFs are calculated and shown in TABLE 2.

### 4) THE SECOND COHERENT DEMODULATION

Bearing characteristic frequency BPFI, BPFO and BSF obtained in the third step are fed respectively into the coherent demodulator as the natural vibration frequency of the bearing, and are mixed with the low-frequency vibration signal obtained by the first coherent demodulation in the second step. The discrete low frequencies containing bearing fault information corresponding to the three fault characteristic frequencies are separated through a band-pass filter with a bandwidth of 10 Hz (that is, the band-pass range is $[f_i - 5, f_i + 5]$, ).The vibration signal is shown in FIGURE 14, and the band frequencies marked as purple, yellow and read correspond to the rolling element fault characteristic frequency, the outer loop fault characteristic frequency and the inner loop fault characteristic frequency, respectively.

### 5) FCAs CALCULATION

By summing separately the amplitudes of the three low frequency vibration signals corresponding to BPFI, BPFO and BSF, the FCAs are obtained and shown in TABLE 3.

### 6) THE FAULT TYPE IDENTIFICATION

It can be seen from TABLE 3 that the inner-loop fault FCA reaches a maximum value of 1213.62. Therefore, the vibration data corresponds to the inner-loop fault which is consistent to the fact of a 7 mil inner raceway single-point failure data, proving the effectiveness of the method.

In order to further verify the effectiveness the rolling bearing fault diagnosis method proposed in this paper, various data of the Case Western Reserve University Bearing

**TABLE 4.** Fault characteristic amplitude of 21mil single point fault of rolling bearing.

| Number | True fault location | BPFI | BPFO | BSF |
|--------|---------------------|------|------|-----|
| 1 | inner raceway failure | **1323.08** | 659.55 | 874.52 |
| 2 | outer raceway failure | 306.31 | **330.97** | 261.14 |
| 3 | rolling element failure | 354.32 | 207.80 | **558.97** |

**TABLE 5.** Fault characteristic amplitude of single-point failure of bearing inner raceway.

| Number | Fault size | BPFI | BPFO | BSF |
|--------|-----------|------|------|-----|
| 1 | 7mil | **1213.62** | 784.80 | 634.40 |
| 2 | 14mil | **303.81** | 180.43 | 95.02 |
| 3 | 21mil | **283.68** | 216.80 | 55.34 |
| 4 | 28mil | **418.26** | 190.92 | 154.37 |

Data Center [53] is considered following the process of FIGURE 6.

The influence of the fault location of rolling bearings on the diagnosis results is analyzed in this section. Single-point failure data with bearing speed of 1797RPM and bearing defect diameter of 21mil were used to analyze three single-point failure data of inner raceway failure, outer raceway failure and rolling element failure, respectively. With the coherent demodulation method proposed in this paper, the FCAs for the fault characteristic frequency corresponding to three possible fault locations are obtained and shown in TABLE 4.

From TABLE 4, the identified faults are marked bold and are consistent with true fault locations in the second line of the table. This shows that the coherent demodulation method is suitable for diagnosing faults at different fault locations.

Then the influence of the fault size on the diagnosis results is analyzed. Single-point fault data with a bearing speed of 1797RPM is used to check the defect location for the inner raceway fault. The fault data of the bearing defect diameters of 7mil, 14mil, 21mil and 28mil are considered. It can be seen from the TABLE 5 that the proposed method identified correctly the corresponding fault location, i.e. the inner raceway. It shows that the proposed method is suitable for carrying out fault diagnosis for fault of different sizes.

In summary, the rolling bearing fault diagnosis method based on the principle of coherent demodulation proposed in

this paper is applicable to the diagnosis of different fault locations and different fault sizes. Moreover, the above conversion process can be realized by a simple simulation hardware circuit. Compared with the traditional method of envelope spectrum analysis, it has lower calculation complexity and higher calculation speed. Therefore, the application of the principle of coherent demodulation in the field of fault diagnosis of rolling bearings is practical and efficient.

## V. CONCLUSION

This paper proposes a new method for rolling bearings fault diagnosis using the principle of coherent demodulation in radio communication. The proposed method demodulates the collected vibration data and extract fault features to obtain the FCAs of the BCFs. This method is simple to implement on a printed circuit board, and has low calculation complexity and high diagnosis efficiency. This method has a wide range of application value in fault diagnosis of rotating equipment including rolling bearings, such as wind turbines and centrifugal pumps.

This paper shows, in the case studies, two typical applications of the proposed method in rolling bearing fault diagnosis, showing that the method taken from the field of radio signal processing is feasible in the field of rolling bearing fault diagnosis. It gives certain enlightenment to the research of fault diagnosis theory and practice.

At present, this method is only verified for diagnosing the single rolling bearing fault. The vibration of rolling bearings caused by multiple faults needs to be further studied in conjunction with experiments.

## APPENDIX
### ABBREVIATION

| | |
|---|---|
| BCFs | Bearing characteristic frequencies |
| FCAs | Fault Characteristic Amplitudes |
| NF | Natural vibration frequency |
| BPFI | Ball pass frequency of inner race |
| BPFO | Ball pass frequency of outer race |
| BSF | Ball spin frequency |
| FTF | Fundamental train frequency |
| PLL | Phase locked loop |
| DC | Direct current |
| FFT | Fast Fourier Transform |
| VCO | Voltage-controlled oscillator |

### A. NOTATION

| | |
|---|---|
| $f_{nr}$ | The natural frequency of the inner and outer raceways of the bearing |
| $f_{nb}$ | The natural vibration frequency of the rolling element |
| $f_i$ | The inner raceway angular frequency |
| $f_o$ | The outer raceway angular frequency |
| $f_{BPFI}$ | Ball pass frequency of inner race |
| $f_{BPFO}$ | Ball pass frequency of outer race |
| $f_{BSF}$ | Ball spin frequency |
| $f_{FTF}$ | Fundamental train frequency |
| $f_{BCFs}$ | Bearing characteristic frequencies |
| $f_{NF}$ | The natural vibration frequency |
| $l_{in}$ | The collected vibration signal to be diagnosed |
| $l_o$ | The natural vibration signal generated by the local oscillator PLL |
| $f_{in}(t)$ | The frequency of the collected vibration signal to be diagnosed |
| $f_o(t)$ | The frequency of the natural vibration signal generated by the local oscillator PLL |
| $l_x$ | The signal obtained after coherence |
| $f_x$ | The frequency of signal obtained after coherence |
| $l_{x2}$ | The signal obtained after gain compensation |
| $f_{x2}$ | The frequency of the signal obtained after gain compensation. |

## REFERENCES

[1] J. Lee, F. Wu, W. Zhao, M. Ghaffari, L. Liao, and D. Siegel, "Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications," *Mech. Syst. Signal Process.*, vol. 42, nos. 1–2, pp. 314–334, Jan. 2014.

[2] Q. Li and S. Y. Liang, "Degradation trend prognostics for rolling bearing using improved R/S statistic model and fractional Brownian motion approach," *IEEE Access*, vol. 6, pp. 21103–21114, Dec. 2018.

[3] *Rolling Bearing-Damage and Failures-Terms, Characteristics and Cause*, ISO Standard 15432, 2004.

[4] A. Sharma, M. Amarnath, and P. K. Kankar, "Life assessment and health monitoring of rolling element bearings: An experimental study," *Life Cycle Rel. Saf. Eng.*, vol. 7, no. 2, pp. 97–114, Mar. 2018.

[5] S. A. McInerny and Y. Dai, "Basic vibration signal processing for bearing fault detection," *IEEE Trans. Educ.*, vol. 46, no. 1, pp. 149–156, Feb. 2003.

[6] A. Choudhury and N. Tandon, "Application of acoustic emission technique for the detection of defects in rolling element bearings," *Tribol. Int.*, vol. 33, no. 1, pp. 39–45, Jan. 2000.

[7] B. T. Kuhnell and S. Jacek, "Correlation of vibration, wear debris analysis and oil analysis in rolling element bearing condition monitoring," *Maintenance Manage. Int.*, vol. 5, pp. 105–115, May 1985.

[8] Z. Li and X. Yan, "Study on data fusion of multi-dimensional sensors for health monitoring of rolling bearings," *Insight - Non-Destructive Test. Condition Monitor.*, vol. 55, no. 3, pp. 147–151, Mar. 2013.

[9] B. Tao, L. Zhu, H. Ding, and Y. Xiong, "An alternative time-domain index for condition monitoring of rolling element bearings—A comparison study," *Rel. Eng. Syst. Saf.*, vol. 92, no. 5, pp. 660–670, May 2007.

[10] Y. Li, W. Pan, K. Li, Q. Jiang, and G. Liu, "Sliding trend fuzzy approximate entropy as a novel descriptor of heart rate variability in obstructive sleep apnea," *IEEE J. Biomed. Health Informat.*, vol. 23, no. 1, pp. 175–183, Jan. 2019.

[11] M. Kuai, G. Cheng, Y. Pang, and Y. Li, "Research of planetary gear fault diagnosis based on permutation entropy of CEEMDAN and ANFIS," *Sensors*, vol. 18, no. 3, p. 782, Mar. 2018.

[12] A. Khoshnami and I. Sadeghkhani, "Sample entropy-based fault detection for photovoltaic arrays," *IET Renew. Power Gener.*, vol. 12, no. 16, pp. 1966–1976, Dec. 2018.

[13] Y.-T. Su and Y.-T. Sheen, "On the detectability of roller bearing damage by frequency analysis," *Proc. Inst. Mech. Eng., C, J. Mech. Eng. Sci.*, vol. 207, no. 1, pp. 23–32, Jan. 1993.

[14] M. Akram, S. Khushnood, S. Tariq, H. Ali, and L. Nizam, "Vibration based gear fault diagnosis under empirical mode decomposition and power spectrum density analysis," *Adv. Sci. Technol. Res. J.*, vol. 13, no. 3, pp. 192–200, Sep. 2019.

[15] W. Bao, X. Tu, Y. Hu, and F. Li, "Envelope spectrum L-Kurtosis and its application for fault detection of rolling element bearings," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 5, pp. 1993–2002, May 2020.

[16] H. Tian, X. Y. Kang, Y. J. Li, and J. N. Zhang, "Fault diagnosis of gear wearing based on order cepstrum analysis," *Appl. Mech. Mater.*, vols. 543–547, pp. 922–925, Mar. 2014.

[17] H. N. Nguyen, J. Kim, and J.-M. Kim, "Optimal sub-band analysis based on the envelope power spectrum for effective fault detection in bearing under variable, low speeds," *Sensors*, vol. 18, no. 5, p. 1389, Mar. 2018.

[18] B. Yazici and G. B. Kliman, "An adaptive statistical time-frequency method for detection of broken bars and bearing faults in motors using stator current," *IEEE Trans. Ind. Appl.*, vol. 35, no. 2, pp. 442–452, Apr.1999.

[19] J. Ma, J. Wu, and X. Yuan, "The fault diagnosis of the rolling bearing based on the LMD and time-frequency analysis," *Int. J. Control Autom.*, vol. 6, no. 4, pp. 357–376, Jan. 2013.

[20] J. D. Zheng, H. Y. Pan, X. L. Qi, X. Q. Zhang, and Q. Y. Liu "Enhanced empirical wavelet transform based time-frequency analysis and its application to rolling bearing fault diagnosis," *Acta Electronica Sinica*, vol. 46, no. 2, pp. 358–364, Feb. 2018.

[21] C. M. M. Malla, J. Sadarang, and P. Isham, "Deep groove ball bearing fault diagnosis and classification using wavelet analysis and artificial neural network," *Int. J. Eng. Adv. Technol.*, vol. 8, pp. 307–313, Jun. 2018.

[22] W. Fan, Q. Zhou, J. Li, and Z. Zhu, "A wavelet-based statistical approach for monitoring and diagnosis of compound faults with application to rolling bearings," *IEEE Trans. Autom. Sci. Eng.*, vol. 15, no. 4, pp. 1563–1572, Oct. 2018.

[23] R. Abdelkader, A. Kaddour, and Z. Derouiche, "Enhancement of rolling bearing fault diagnosis based on improvement of empirical mode decomposition denoising method," *Int. J. Adv. Manuf. Technol.*, vol. 97, no. 13, pp. 1–19, Jul. 2018.

[24] J. Wang, H. Wang, L. Guo, and D. Yang, "Rolling bearing fault detection using autocorrelation based morpho-logical filtering and empirical mode decomposition," *Mechanics*, vol. 24, no. 6, Jan. 2019.

[25] T. Tang, L. Bo, X. Liu, B. Sun, and D. Wei, "Variable predictive model class discrimination using novel predictive models and adaptive feature selection for bearing fault identification," *J. Sound Vib.*, vol. 425, pp. 137–148, Jul. 2018.

[26] Y. P. Guo, Y. Xiong, and G. C. Song, "Rolling bearing fault diagnosis with EMD-based fault characteristic frequency difference analysis," *Appl. Mech. Mater.*, vol. 596, pp. 437–441, Jul. 2014.

[27] T. Y. Wang, J. Y. Li, and W. D. Cheng, "The instantaneous fault characteristic frequency and fault characteristic order template based fault diagnosis algorithm for rolling bearing under time-varying rotational speed," *J. Vib. Eng.*, vol. 28, no. 6, pp. 1006–1014, 2015.

[28] H. Darong, K. Lanyan, C. Xiaoyan, Z. Ling, and M. Bo, "Fault diagnosis for the motor drive system of urban transit based on improved hidden Markov model," *Microelectron. Rel.*, vol. 82, pp. 179–189, Mar. 2018.

[29] J. Yu, B. Ding, and Y. He, "Rolling bearing fault diagnosis based on mean multigranulation decision-theoretic rough set and non-naive Bayesian classifier," *J. Mech. Sci. Technol.*, vol. 32, no. 11, pp. 5201–5211, Nov. 2018.

[30] X. Zhang, G. Chen, T. Hao, and Z. He, "Rolling bearing fault convolutional neural network diagnosis method based on casing signal," *J. Mech. Sci. Technol.*, vol. 34, no. 6, pp. 2307–2316, May 2020.

[31] X. Li, W. Zhang, and Q. Ding, "Cross-domain fault diagnosis of rolling element bearings using deep generative neural networks," *IEEE Trans. Ind. Electron.*, vol. 66, no. 7, pp. 5525–5534, Jul. 2019.

[32] J. Liu and E. Zio, "Integration of feature vector selection and support vector machine for classification of imbalanced data," *Appl. Soft Comput.*, vol. 75, pp. 702–711, Feb. 2019.

[33] M. M. M. Islam, J. Kim, S. A. Khan, and J.-M. Kim, "Reliable bearing fault diagnosis using Bayesian inference-based multi-class support vector machines," *J. Acoust. Soc. Amer.*, vol. 141, no. 2, pp. EL89–EL95, Feb. 2017.

[34] Y.-K. Gu, X.-Q. Zhou, D.-P. Yu, and Y.-J. Shen, "Fault diagnosis method of rolling bearing using principal component analysis and support vector machine," *J. Mech. Sci. Technol.*, vol. 32, no. 11, pp. 5079–5088, 2018.

[35] C. Mishra, A. K. Samantaray, and G. Chakraborty, "Rolling element bearing fault diagnosis under slow speed operation using wavelet de-noising," *Measurement*, vol. 103, pp. 77–86, Jun. 2017.

[36] B. Betea, P. Dobra, M.-C. Gherman, and L. Tomesc, "Comparison between envelope detection methods for bearing defects diagnose," *IFAC Proc. Volumes*, vol. 46, no. 6, pp. 137–142, 2013.

[37] A. Matsuoka, M. Orihashi, and K. Takahashi, "Demodulator apparatus for digital radio communication receiver providing pseudo-coherent quadrature demodulation based on periodic estimation of frequency offset," U.S. Patent 5 809 009, Sep. 15, 1999. [Online]. Available: FreePatentsOnline

[38] J. C. I. Chuang and N. R. Sollenberger, "Burst coherent demodulation with combined symbol timing, frequency offset estimation, and diversity selection," *IEEE Trans. Commun.*, vol. 39, no. 7, pp. 1157–1164, Jul. 1991.

[39] R. de Buda, "Coherent demodulation of frequency-shift keying with low deviation ratio," *IEEE Trans. Commun.*, vol. 20, no. 3, pp. 429–435, Jun. 1972.

[40] J. Zheng, "A dual-polarization coherent communication system with simplified optical receiver for UDWDM-PON architecture," *Opt. Express*, vol. 22, no. 26, pp. 31735–31745, Dec. 2014.

[41] C. S. Sunnersjö, "Rolling bearing vibrations—The effects of geometrical imperfections and wear," *J. Sound Vib.*, vol. 98, no. 4, pp. 455–474, Feb. 1985.

[42] W. Su, F. Wang, H. Zhu, Z. Zhang, and Z. Guo, "Rolling element bearing faults diagnosis based on optimal Morlet wavelet filter and autocorrelation enhancement," *Mech. Syst. Signal Process.*, vol. 24, no. 5, pp. 1458–1472, Jul. 2010.

[43] O. Hiroyuki and Y. Masanori, "Studies on the vibrations of ball bearing under radial load: 3rd report, flexural natural vibration of outer raceway," *Trans. Jpn. Soc. Mech. Eng. C*, vol. 59, no. 562, pp. 1857–1861, Jun. 1993.

[44] B. Van Hecke, J. Yoon, and D. He, "Low speed bearing fault diagnosis using acoustic emission sensors," *Appl. Acoust.*, vol. 105, pp. 35–44, Apr. 2016.

[45] R. T. Enderby, "Fully integratable superheterodyne radio receiver utilizing tunable filters," U.S. Patent 4 580 289, Apr. 1, 1986.

[46] S. Chen, B. Yang, Y. He, Z. Xie, M. Su, J. Liu, J. Xiao, Y. Li, G. Zhao, and D. Fan, "Optical orbital angular momentum shift-keying communication based on coherent demodulation," *Opt. Commun.*, vol. 452, pp. 405–410, Dec. 2019.

[47] C. Wang and F. Gao, "A coherent demodulation method for short burst communication," in *Proc. IEEE 8th Joint Int. Inf. Technol. Artif. Intell. Conf. (ITAIC)*, Chongqin, China, May 2019, pp. 935–938.

[48] T. R. Giallorenzi and S. G. Wilson, "Noncoherent demodulation techniques for trellis coded M-DPSK signals," *IEEE Trans. Commun.*, vol. 43, no. 8, pp. 2370–2380, Sep. 1995.

[49] S. Lee, H. Kwon, Y. Jung, and J. Kim, "Efficient non-coherent demodulation scheme for IEEE 802.15.4 LR-WPAN systems," *Electron. Lett.*, vol. 43, no. 16, pp. 879–880, Aug. 2007.

[50] M. Rice and P. Hall, "Digital communications: A discrete-time approach: United States edition," *J. Pathol. Bacteriology*, vol. 94, no. 94, pp. 417–427, Aug. 2008.

[51] R. G. Jordi and D. D. Do, "Analysis of the frequency response method for sorption kinetics in bidispersed structured sorbents," *Chem. Eng. Sci.*, vol. 48, no. 6, pp. 1103–1130, 1993.

[52] X. He, Y. Yu, D. Huang, R. Zhang, W. Liu, and S. Jiang, "Spectrum envelope analysis for interleaved sampled gratings with phase-shift," *Opt. Commun.*, vol. 281, no. 3, pp. 415–420, Feb. 2008.

[53] Bearing Data Center, USA, University of the Case Western Reserve University. *Seeded Fault Test Data*. Accessed: 2014. [Online]. Available: https://csegroups.case.edu/bearingdatacenter/home.

**YINGHUA SHAO** received the B.S. degree in control science and engineering from Beihang University, in 2015, where he is currently pursuing the Ph.D. degree with the Science and Technology on Reliability and Environmental Engineering Laboratory, School of Reliability and Systems Engineering. His research interests focus on basic theory and method of faultology and fault prediction and health management.

**RUI KANG** received the bachelor's and master's degrees in electrical engineering from Beihang University, Beijing, China, in 1987 and 1990, respectively. He is a Changjiang Scholars and Distinguished Professor at the Chinese Ministry of Education. He is currently the Chinese Director of the International Center for Resilience and Safety of Critical Infrastructure.

He is also with the School of Reliability and Systems Engineering, Beihang University. He has authored or coauthored eight books and more than 150 research articles. His main research interests include belief reliability theory, reliability-centered systems engineering, reliability design and testing theory, methods for high-reliable and long-lifetime product and resilience modeling, and evaluation for cyberphysical system.

He is also a famous Reliability Expert in the Chinese industry. He received several awards from the Chinese government for his outstanding scientific contributions, including the First Prize for the National Science and Technology Progress Award and the First Prize for Science and Technology Progress Award of Ministry of Industry and Technology. He is also an Associate Editor of the IEEE TRANSACTION ON RELIABILITY and an Associate Editor of *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*. He is the Founder of China Prognostics and Health Management Society.

**JIE LIU** (Member, IEEE) received the bachelor's degree in mechanical engineering and the master's degree in physics from Beihang University, in 2009 and 2012, respectively, and the Ph.D. degree in industrial engineering from Centrale-Supélec, in 2015. He is currently an Associate Professor with Beihang University. His current research interests concern diagnostics, prognostics, and health management with data-driven methods.

● ● ●