Research Article

Monopulse Feature Extraction and Fault Diagnosis Method of Rolling Bearing under Low-Speed and Heavy-Load Conditions

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According to the rolling bearing local fault vibration mechanism, a monopulse feature extraction and fault diagnosis method of rolling bearing under low-speed and heavy-load conditions based on phase scan and CNN is proposed. The synchronous collected speed signal is used to calculate bearing phase function and divide fault monopulse periods. The monopulse waveforms of multiple fault periods are scanned and ensemble averaged to suppress noise interference and detail feature loss at the same time of feature extraction. By iteratively calibrating phase function, the feature matrix containing bearing fault information can be obtained. Finally, CNN is used to recognize and classify different bearing states. The experimental and analysis results show that bearing fault diagnosis can be achieved. The total recognition rates of constant and variable speed samples are 99.67% and 99.89%, respectively. The trained network has fast convergence speed and good generalization ability for different fault sizes and working conditions. Further experiments show that the method can also accurately identify different bearing degradation states. The total recognition rates of constant and variable speed samples are 96.67% and 95.56%, respectively. The limited errors are concentrated between the degradation states with the same type weak fault. The experimental results using Case Western Reserve University bearing data show that feature extraction and network training are better, and the recognition rates of 5 bearing states are all 100%. Therefore, the proposed method is an effective rolling bearing feature extraction and fault diagnosis technology.

1. Introduction

Rolling bearing is an important part of rotating machinery, which is widely used in various industries. However, poor working conditions make the bearing performance degenerate and produce faults, which will threaten the equipment operation safety. Furthermore, the technology requirements of accurately quantifying bearing fault degree and overcoming the influence of complex working conditions are increasing [1–3]. Thus, novel bearing fault diagnosis and degradation state identification technology need to be studied.

Feature extraction is an important part of fault diagnosis technology [4]. Its goal is to extract and purify low dimensional data containing fault feature information from

original data. So far, many feature extraction methods have been proposed [5, 6]. Li et al. [7] improved the frequency band entropy method based on the maximum kurtosis principle and applied it with singular value decomposition and singular value kurtosis to extract bearing fault feature. Zhou et al. [8] proposed a novel sparse dictionary based on attenuated cosine basis. It was used to extract rolling bearing weak fault combined with an improved basis pursuit algorithm with feature sign search. Jiao et al. [9] presented a hierarchical discriminating sparse coding method, which can extract weak fault feature with strong noise and ambient interferences.

After obtaining the equipment fault feature information, it is necessary to carry out effective classification and recognition. Many traditional classifiers have been applied by

researchers [10, 11]. However, the algorithm performance still needs to be improved for complex conditions and accurate diagnosis requirements. In recent years, various deep learning algorithms have been developed rapidly [12, 13]. Zhang et al. [14] used stacked sparse autoencoder to solve simultaneous fault diagnosis issue. The method achieves high diagnosis performance on unseen simultaneous faults of the solid oxide fuel cell system. Yu [15] proposed a selective stacked denoising autoencoders with negative correlation learning for gearbox fault diagnosis. Nasiri et al. [16] constructed a deep learning model for intelligent fault diagnosis of radiator based on convolutional neural network, and the infrared thermal images are directly used as input.

Convolutional neural network (CNN) is an effective algorithm for processing images or other multidimensional data [17, 18]. Because of its excellent performance, it is also used in mechanical fault diagnosis field [19]. Chen et al. [20] proposed a novel diagnosis model integrating CNN and Extreme Learning Machine to achieve higher classification accuracy with less computational time. Han et al. [21] introduced the adversarial learning as a regularization into CNN and proposed a novel deep adversarial CNN to achieve the intelligent diagnosis of mechanical faults. Wang et al. [22] optimized CNN using the bottleneck layer with efficient convolution kernel to fuse data at the same time.

Most of the existing methods are aimed at common working conditions. In mining, construction machinery, and many other fields, the rolling bearings usually have to face low-speed, heavy-load, and variable speed conditions. This increases the diagnosis difficulty and limits the traditional fault diagnosis method application. In addition, the classification and recognition mostly rely on the data differences between sample features. The actual physical meanings of the extracted feature indexes are usually not clear enough. The redundant information is often retained, but detailed features may be lost. These have put forward higher requirements for algorithm performance and are not conducive to diagnosis accuracy.

In this paper, the inner and outer ring faults of rolling bearings are studied, and a monopulse feature extraction method is proposed to obtain detail fault information. Combined with CNN, the feature extraction and fault diagnosis of rolling bearing under low-speed and heavy-load conditions are realized. The remainder of this paper is composed as follows: in Section 2, the theoretical basis is introduced. In Section 3, the mathematical model and calculation process of proposed method are established. In Section 4, the experimental equipment is introduced, and the vibration signals of tested bearing are collected. In Section 5, the proposed method is used to deal with the original bearing signals with different fault states. The experimental results are analyzed and discussed to verify method effectiveness. In the last section, the conclusions are summarized.

2. Basic Theory

When rollers contact with the bearing local fault, the additional displacement will be generated as shown in Figure 1.

If the fault is located in loading area, the additional displacement will make the compressed roller lose and regain compression. This process will make bearing support stiffness change suddenly and produce impact components in vibration signals. The impact frequency corresponding to bearing fault type is called fault characteristic frequency (FCF). Its ratio to instantaneous shaft rotation frequency (ISRF) is a fixed value, which is called fault characteristic coefficient (FCC). When bearing outer ring is fixed, the inner ring speed is ISRF, and FCC can be calculated as follows [23]:

$$\begin{aligned} \text{FCCI} &= -0.5Z \left(1 + \frac{d}{D} \cos(\alpha) \right), \\ \text{FCCO} &= -0.5Z \left(1 - \frac{d}{D} \cos(\alpha) \right), \end{aligned} \quad (1)$$

where FCCI is inner ring FCC, FCCO is outer ring FCC, Z is number of rollers, d is roller diameter, D is pitch diameter, and α is contact angle.

In addition to overall wear and other conditions, early bearing deterioration can be considered as the diffusion of local faults. The contact process between roller and local fault results in an impact characteristic with two peaks in bearing vibration signal, as shown in Figure 2. It can be seen that local fault can directly affect the monopulse waveform of vibration signal, and plenty of fault information is contained in it. This phenomenon will become more obvious in low-speed and heavy-load conditions, and the conventional method is limited. Some researchers have already noticed and tried to use this phenomenon to measure local fault size [24, 25]. However, there are noise and interference in actual collected signals, and the monopulse waveform details are easy to be lost or destroyed. Therefore, based on the above theory, extracting monopulse waveform features and combining with efficient classification and recognition algorithms is a natural idea to overcome the limitations of traditional methods and achieve bearing fault degradation identification.

3. Model Establishment

In this section, the mathematical model of rolling bearing monopulse feature extraction and fault diagnosis method is established. Phase scan and ensemble average are used to suppress noise and detail loss. Then, a deep learning network is established based on CNN to realize bearing fault diagnosis and degradation identification.

3.1. Monopulse Feature Extraction. To extract detail waveform feature, the vibration signal should be divided, and each segment contains a single fault pulse. Although the completely constant speed signal can be divided equally, the speed is usually variable in actual conditions. Therefore, a monopulse feature extraction method is proposed in this paper. The method flow is shown in Figure 3, and the specific steps are as follows.

FIGURE 1: Additional displacement path of rolling bearing local fault.

FIGURE 2: Dual-peak characteristics in fault bearing vibration signal.

FIGURE 3: The flow of monopulse waveform feature extraction.

Step 1: For the bearing vibration signal $x(t)$ with time length T , its corresponding fault phase function $p(t)$ can be calculated as follows:

$$p(t) = \text{mod}\left(F \int_0^t f(\tau) d\tau, 2\pi\right), \quad (2)$$

where $f(\tau)$ is ISRF, F is the FCC of current fault type, and $\text{mod}(\cdot)$ is remainder operator. The fault phase function $p(t)$ takes $[0, 2\pi]$ as the period and changes repeatedly with time t . The point in $x(t)$ with phase in the same period belongs to the same monopulse. In this way, $X(T)$ is preliminarily divided into several monopulse periods. Due to the noise interference, any single fault pulse is not suitable to be directly selected to be the fault characteristic, and further processing is necessary.

Step 2: Through the difference operation, the mutation points of fault phase function $p(t)$ between different fault periods can be identified. The key phase function $p_0(t)$ can be constructed as

$$p_0(t) = \begin{cases} 1, & \text{diff}(p(t)) < 0, \\ 0, & \text{else,} \end{cases} \quad (3)$$

where $\text{diff}(\cdot)$ is difference operation.

Step 3: Calculate the average of signal envelope at key phase points:

$$P_0(\theta) = \frac{\sum_{t=0}^T p_0(t)h(t)}{\sum_{t=0}^T p_0(t)}, \quad (4)$$

where $P_0(\theta)$ is the current phase waveform value obtained using ensemble average and $h(t)$ is the envelope of signal $x(t)$. By calculating the sum of $p_0(t)$, the number of key phase points (i.e., the number of fault pulses or fault periods) can be obtained. Similarly, by calculating the sum of $p_0(t)h(t)$, the amplitude sum

of multiple fault pulse waveforms can be obtained. Using their ratio as the ensemble average result, the waveform feature value of current scanning phase can be obtained. Ensemble average is a simple and effective signal processing method. It can suppress noise interference and highlight the required time-frequency characteristics.

Step 4: Establish new fault phase function and set the current scanning phase:

$$\theta = \theta + \frac{2\pi}{n}, \quad (5)$$

$$p(t) = \text{mod}\left(F \int_0^t f(\tau) d\tau - \theta, 2\pi\right),$$

where θ is the current scanning phase with the initial value is 0, and $0 < \theta < 2\pi$. n is the number of phase scan steps. The new fault phase function $p(t)$ is used to repeat Steps 2, 3 and 4, and all divided fault periods are scanned by the moving key phase function $p_0(t)$. The nearest data points are automatically selected for ensemble average, and the fitting and resampling are avoided because of the high sampling frequency. Then, the waveform vector P_0 with length n can be obtained.

Step 5: The theoretical FCC is calculated according to bearing structural parameters, and pure rolling is taken as a prerequisite. Due to size error and relative slip, there is error between the theoretical FCC and actual value, and the waveform obtained by ensemble average is smeared. In order to calibrate FCC, the calibration step s_i and calibration step number N are set to obtain $F_i = F[1 + s_i(i - N - 1)]$, where $i = 1, 2, \dots, 2N + 1$. F_i is used to replace F and repeat Steps 1 to 4 to obtain the corresponding waveform vector P_i . When $\max(P_i)$ is maximum, it is proved that F_i coincides with the actual FCC. At this time, the waveform vector P_i is selected as P_m .

Step 6: When $x(t)$ is divided, the pulse phase position may not be appropriate. By translating the elements of P_m , the wave crest is moved to the vector center $n/2$. The vacancy at one end is cyclically filled in by elements at the other end. Finally, P_m is standardized and adjusted to $[0,1]$ to further eliminate speed and load influence, and the monopulse feature of current FCC can be extracted as P .

3.2. Convolutional Neural Network. CNN is a kind of deep learning network with special structure. Its weight sharing can significantly reduce the calculation complexity. The principle and structure are simple and effective, and the network is easy to be extended to data with multichannel and different dimensions. Therefore, CNN with different structures has already been widely used in signal analysis, feature extraction, and image-processing field. The typical CNN structure is shown in Figure 4. The convolution operation of convolution kernel $k(x, y)$ and input matrix $M(x, y)$ can be expressed as follows:

$$Mc(m, n) = M(x, y) * k(x, y)$$

$$= \sum_{x=1}^a k(x, y) \sum_{y=1}^b M((m-1)s_{cx} + x, (n-1)s_{cy} + y), \quad (6)$$

where the size of $k(x, y)$ and $M(x, y)$ is $a \times b$ and $c \times d$, respectively. Mc is the convolution result. When there is no edge filling, $1 \leq m \leq ((c-a)/s_{cx} + 1)$ and $1 \leq n \leq ((d-b)/s_{cy} + 1)$. s_{cx} and s_{cy} are convolution steps. The ReLU function is chosen as the activation function to avoid gradient disappearance and simplify calculation process. The calculation of ReLU function is as follows:

$$f_{\text{ReLU}} = \max(0, x). \quad (7)$$

The calculation process of typical convolution layer can be expressed as follows:

$$M_j^l = f_{\text{ReLU}} \left(\sum_{i \in S_j} (M_i^{l-1} * k_j^l) + B_j^l \right), \quad (8)$$

where M_j^l is the j -th output characteristic matrix of current convolution layer and l is the corresponding convolution kernel. S_j is the serial number of a set of upper layer's output feature matrices M_i^{l-1} corresponding to M_j^l . The M_i^{l-1} with the same S_j share the same k_j^l . B_j^l is the bias of M_j^l .

In order to reduce the amount of data and prevent overfitting, pooling layer is used to down sample the output feature matrices of convolution layer. For $c \times d$ input matrix q , the calculation process of average pooling Q_a and maximum pooling Q_m are as follows:

FIGURE 4: Typical CNN structure.

$$Q_a(m, n) = \frac{1}{ab} \sum_{x=1}^a \sum_{y=1}^b q((m-1)s_{px} + x, (n-1)s_{py} + y),$$

$$Q_a(m, n) = \max[q((m-1)s_{px} + x, (n-1)s_{py} + y)], \quad (9)$$

where pooling area size is $a \times b$, $1 \leq m \leq ((c-a)/s_{px} + 1)$, $1 \leq n \leq ((d-b)/s_{py} + 1)$. s_{px} and s_{py} are pooling steps. By stacking layers and modifying parameters, CNN with different structures can be established.

3.3. The Proposed Bearing Feature Extraction and Fault Diagnosis Method. Based on the above, a monopulse feature extraction and fault diagnosis method of rolling bearing under low speed and heavy load is proposed. The method flow is shown in Figure 5, and the specific steps are as follows.

Step 1: Use data acquisition equipment to synchronously collect vibration signal and speed signal of rolling bearing.

Step 2: The proposed monopulse feature extraction method is used to extract feature vectors with different FCC. In this paper, P_{in} and P_{out} are mainly extracted for inner and outer ring fault.

Step 3: P_{in} and P_{out} are combined to form the feature matrix P_b to represent bearing state, and P_b can be expressed as

FIGURE 5: Bearing fault diagnosis method flow based on monopulse feature extraction and CNN.

$$P_b = \begin{bmatrix} P_{out}(1) & P_{out}(2) & \dots & P_{out}(n) \\ P_{in}(1) & P_{in}(2) & \dots & P_{in}(n) \end{bmatrix}. \quad (10)$$

P_b contains bearing fault state information of inner and outer rings.

Step 4: P_b is used as sample data to construct and train the deep learning network based on CNN, so as to realize the fault diagnosis and degradation identification of rolling bearing under different working conditions.

4. Test Equipment and Data Acquisition

In order to verify the effectiveness of the proposed method, cylindrical roller bearing NU1007 was selected as the study object, and the bearing parameters are displayed in Table 1. As shown in Figure 6, the experimental device is mainly composed of AC variable frequency motor, torque speed sensor, reducer, test shaft, hydraulic loading device, magnetic brake, and other devices. The test point and the installation position of vibration sensor are outside the bearing seat, as shown in Figure 7. The triaxial vibration acceleration sensor was used to collect vibration signals, and Z-axis signal was selected for analysis. Under different working conditions, the vibration and speed signals of inner and outer ring fault bearings with four degradation states, as well as normal bearing, were collected, respectively, and the sampling frequency is 20 kHz. The 8 tested fault bearings are shown in Figure 8, and four fault sizes are 0.5 mm, 0.7 mm, 1.1 mm, and 1.6 mm, respectively. They were installed in the right-hand bearing housing for the test.

5. Experimental Verification

In this section, the collected original bearing vibration signals are displayed. The monopulse waveform features

under different working conditions are extracted, and the extraction effect is analyzed. Finally, the process and results of bearing fault diagnosis and degradation identification are presented and discussed, and the method effectiveness can be verified.

5.1. Original Vibration Signal Analysis. For 9 bearing states, 5 kinds of speed conditions and 2 kinds of load conditions were set. The load conditions include 1 kN and 2 kN radial load, and the speed conditions include 2 Hz, 3 Hz, 4 Hz, and 5 Hz and a variable speed condition. A total of 90 groups of experimental data include vibration and actual speed signals were collected, and some of them are displayed in Figures 9 and 10, respectively.

It can be seen that there are some differences between original vibration signals. The fault bearing signals generally contain impact characteristic, but the fault type and degradation state cannot be diagnosed directly. Due to different working conditions, the signal characteristics of the same bearing will also change. Besides the variable speed condition, there are some fluctuations appearing in theoretical constant speed condition. Some special working conditions and random events will also produce similar characteristics, which will interfere in diagnosis results.

5.2. Monopulse Waveform Feature Extraction Analysis. Based on bearing vibration mechanism, the monopulse can be used for fault diagnosis. However, it is not reliable to separate monopulse directly. As shown in Figure 11, although the tested fault bearing is the same as that in Figure 2, there is detail feature loss and noise interference. The duration and amplitude of monopulse also change with working conditions. These differences will mask the real fault information. The proposed method was used to extract monopulse waveforms of inner ring fault, outer ring fault,

TABLE 1: Basic parameters of test bearings.

Outer race diameter	Inner race diameter	Pitch diameter	Roller diameter	Roller number
55 mm	42 mm	48.5 mm	6.5 mm	16
FCC	Outer race fault 6.93		Inner race fault 9.07	
Fault size	0.5 mm	0.7 mm	1.1 mm	1.6 mm
Code name	1	2	3	4

FIGURE 6: Signal acquisition experimental device.

FIGURE 7: Arrangement of test points and vibration acceleration sensors.

and normal bearings. The length of each sample is 1s, the phase scan step number is 500, the FCC calibration step length is 0.02%, and the calibration step number is 50. Some typical extraction results are shown in Figures 12, 13, and 14.

In Figure 12, the feature extraction results of outer ring fault with 4 Hz and 2 kN condition were selected as examples. The monopulse waveforms of different degradation states with the same working condition are different. These differences contain degradation degree information of local faults. The waveform of large fault has obvious dual-peak characteristics, and the interval corresponds to fault size. The waveforms of small faults have only one obvious peak. These are consistent with the vibration mechanism in Section 2, which means the most direct bearing degradation information is obtained by the proposed method.

In Figures 13 and 14, 1.1 mm inner and outer ring faults were selected as examples. Although the working conditions are different, the monopulse waveform characteristics of fault bearing with the same degradation state are basically similar. The proposed method selects sampling points according to fault pulse phase and standardizes the length and amplitude of extracted waveform. In Figures 12, 13, and 14, there is no clear fault pulse waveform appearing in the extraction results while using the FCC not corresponding to the real fault type. This is because the fault pulses are smeared and dispersed after ensemble average. No matter which FCC is adopted, the waveform characteristics of normal bearing are always cluttered. This means there is no fault in corresponding position of bearing, and the feature matrix can be formed together with the fault pulse waveform to represent overall bearing state. In addition, the extracted waveform is smoother than original signal's monopulse, because the ensemble average can suppress noise interference and detail loss. Therefore, the proposed method can effectively extract local fault feature information and describe bearing fault type and degradation state. Moreover, it eliminates the influence of working conditions and provides a standardized feature extraction result.

5.3. Fault Diagnosis and Degradation Identification Analysis. In order to accurately diagnose fault state of rolling bearings under different working conditions and further realize the degradation identification of different size faults, a CNN was established. The network structure and parameters of each layer are shown in Table 2.

The 90 groups of original data were randomly separated with a length of 1s, and 50 signal segments were obtained from each group. Using the proposed feature extraction method to process these signal segments, a total of 4500 samples were obtained. In constant speed samples, 300 samples were randomly selected as the training set from each bearing degradation state, and the remaining samples were combined with variable speed samples as the test set. Finally, a training set containing 2700 samples and a test set containing 1800 samples were obtained. They are used to train and test CNN. The maximum training epoch number is 10, and the learning rate is 0.001.

Firstly, the fault diagnosis performance of the proposed method is verified. The experimental results are shown in Figures 15, 16, and 17. For constant speed test samples, the total recognition rate is 99.67%. The recognition rates of outer ring fault, inner ring fault, and normal state are 97%, 100%, and 100%, respectively. For variable speed samples, the total recognition rate is 99.89%. The recognition rates of

FIGURE 8: Tested fault bearings.

FIGURE 9: Part of bearing vibration signals with different working conditions and fault sizes.

FIGURE 10: 5 speed conditions.

FIGURE 11: Original monopulse with missing detail characteristics.

outer ring fault, inner ring fault, and normal state are 100%, 99.75%, and 100%, respectively. It can be seen from Figure 15 that the network convergence speed is very fast, and the high recognition rate can be obtained after one epoch. In Figures 16 and 17, there are only sporadic errors occurring in diagnosis results. There is no significant difference between the verification results of variable speed samples and constant speed samples. Different load and fault sizes also have no obvious influence on the diagnosis results. This means the extracted features are completely based on fault information rather than data differences between samples.

Secondly, the degradation identification performance of the proposed method is verified. The experimental results are shown in Figures 18, 19, and 20. For constant speed test samples, the total recognition rate is 96.67%. For variable

speed test samples, the total recognition rate is 95.56%. The identification results of each degradation state are shown in Table 3. In Figure 18, the network convergence speed is a little slower than that of fault diagnosis network. However, after the 4th epoch training, the total recognition rate can reach and maintain a high level. Most errors are concentrated in the degradation states with 0.5 mm and 0.7 mm faults. This may be because the smaller fault size makes the monopulse waveform more similar, and the happening probability of interference and misjudgment in feature extraction results increases. However, the recognition rate of these two degradation states is still higher than 80%, and there are only sporadic errors in other degradation states. However, the recognition rates of these two degradation states are still higher than 80%, while there are only sporadic

FIGURE 12: Outer ring fault feature extraction results under 4 Hz and 2 kN conditions.

errors in other degradation states. Therefore, the proposed method can realize bearing degradation identification of inner and outer ring faults under different working conditions. It should be noted that the variable speed samples are not included in the training samples for fault diagnosis and degradation identification networks. Under this premise, the CNN network with simple structure can still achieve relatively good results. This further proves that the feature extraction is successful and effective, and the proposed method has good generalization and recognition ability for different working conditions and degradation states.

5.4. Degradation Identification Analysis of CWRU Bearing Data. To verify the effectiveness of proposed method on different data sets, Case Western Reserve University (CWRU) bearing data are used for degradation

identification analysis. As shown in Figure 21, the experimental device consists of motor, torque and speed sensor, dynamometer, and control system. The drive end bearing type is 6205-2RS JEM. Its vibration signals were selected and analyzed, and the sampling frequency is 12 kHz. The outer and inner ring FCCs are 3.5848 and 5.4152, respectively. The five bearing states are normal, 0.18 mm and 0.53 mm inner and outer ring faults (i. e., Normal, Inner 1, Inner 2, Outer 1, and Outer 2). Each state adopts two working conditions: (1) 29.95 Hz and 0HP; (2) 28.83 Hz and 3HP. A total of 10 original vibration signals were used, and some of them are shown in Figure 22. It can be seen that the overall characteristics are similar to the previous experiment.

The proposed method was used to extract the monopulse waveforms, and the method parameters are the same as those of previous experiment. Some of the extraction results are shown in Figure 23. The waveform of 0.18 mm fault has obvious dual-peak characteristics. The waveform of 0.53 mm

FIGURE 13: Feature extraction results of 1.1 mm outer ring fault under different working conditions.

fault has stronger fluctuation characteristics. These obviously carry the fault information of corresponding bearing degradation states. The 0HP and 3HP conditions have no significant effect on the extraction results. Due to higher speed, the fault characteristics are more obvious and the fault periods are also more, which makes the extracted waveform smoother than previous experiment. The waveforms extracted using incorrect FCC are basically similar to the previous experiment, and they are not displayed here due to space limitation.

Finally, the degradation identification performance of the proposed method was verified. 100 samples were obtained from each bearing state. 50 samples were randomly

selected as the training set and the remaining samples as the test set. In this way, the test set and training set each contain 250 samples. The network structure and training parameters are basically the same as previous experiment, except that the output number of fully connected layer is 5. The experimental process and results are shown in Figures 24 and 25. It can be seen that the network convergence speed is faster than previous experiment due to the better feature extraction results. After 2 epochs of training, the train and test accuracy rates can reach 100%. The test set was used to verify, and the recognition rates of five bearing states are all 100%. Therefore, the proposed method is also effective for different data sets.

FIGURE 14: Feature extraction results of 1.1 mm inner ring fault under different working conditions.

TABLE 2: CNN structure and parameters.

Layer	Output number	Output size	Kernel size	Step length
Input layer I1	1	2*500	—	—
Convolution layer C2	20	2*243	1*16	1*2
Pooling layer P3	20	2*121	1*2	1*2
Convolution layer C4	40	2*55	1*12	1*2
Pooling layer P5	40	2*27	1*2	1*2
Convolution layer C6	80	2*10	1*8	1*2
Fully connected layer F7	9	1	—	—

FIGURE 15: Training and verification process of fault diagnosis network.

FIGURE 16: Fault diagnosis results of constant speed samples.

FIGURE 17: Fault diagnosis results of variable speed samples.

FIGURE 18: Training and verification process of degradation identification network.

FIGURE 19: Degradation identification results of constant speed samples.

FIGURE 20: Degradation identification results of variable speed samples.

TABLE 3: Degradation identification results.

Degradation state		Recognition rate	
		Constant speed (%)	Variable speed (%)
Normal state		98	100
	0.5 mm	91	81
	0.7 mm	91	91
	1.1 mm	100	100
Outer ring fault	1.6 mm	100	97
	0.5 mm	96	97
	0.7 mm	96	95
	1.1 mm	100	99
Inner ring fault	1.6 mm	98	100

FIGURE 21: Experimental device.

FIGURE 22: Part of bearing vibration signals.

FIGURE 23: Feature extraction results using correct FCCs under different working conditions.

FIGURE 24: Network training and verification process.

FIGURE 25: Degradation identification results.

6. Conclusion

In this paper, a monopulse feature extraction method is proposed. Combined with CNN, a rolling bearing fault diagnosis and degradation state identification method is further proposed. Nine bearing samples of outer ring fault, inner ring fault, and normal state were selected as the research objects. The proposed method was used to analyze the bearing vibration signals collected under different working conditions. The fault diagnosis results under constant speed conditions show that the recognition rates of outer ring, inner ring fault and normal state are 97%, 100% and 100% respectively, and the total recognition rate is 99.67%. The recognition rates of three bearing states under variable speed conditions are 100%, 99.75%, and 100%, respectively, and the total recognition rate is 99.89%. The proposed method can also identify different bearing degradation states, and the total recognition rates under constant and variable speed conditions are 96.67% and 95.56%, respectively. The limited errors are concentrated between the degradation states with the same type weak fault, while other degradation states still maintain high recognition rates. The experimental results show that the proposed method can effectively extract fault features under different working conditions. The extracted features have clear physical meaning and carry bearing fault information directly. After less training, the CNN with simple structure can accurately identify bearing fault types and degradation states. It also has good generalization ability for samples with different working conditions and fault sizes. The experimental results using Case Western Reserve University bearing data show that the recognition rate is 100%. The proposed method is also effective for different data sets. Therefore, the proposed method is an effective feature extraction and fault diagnosis technology for rolling bearing under low-speed, heavy-load, and unsteady state conditions.

Data Availability

The original data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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