Rolling Element Bearing Fault Diagnosis for Complex Equipment based on MFMD and BP Neural Network

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Abstract: A new fault feature extraction method for rolling element bearing is put forward in this paper based on modified Fourier mode decomposition (MFMD) and multi-scale permutation entropy, and the fault pattern recognition is studied by combining BP neural network. First, introduce frequency band entropy (FBE) to optimize the boundary frequency search and effective modal component selection of Fourier decomposition. Then, use MFMD to adaptively decompose the original vibration signal to several Fourier intrinsic mode functions (FIMFs) and select effective FIMFs. Next, use multi-scale permutation entropy to quantify the fault features. Finally, input the fault feature vector into the BP neural network for fault diagnosis model training and testing. The method proposed in this paper is applied to the rolling element bearing simulation data and the public bearing fault test data set of Case Western Reserve University to verify the feasibility of the method. The results show that the method proposed in this paper has a high identification accuracy for different types of faults, reaching over 98%. The feasibility and superiority of the rolling element bearing fault diagnosis method based on MFMD and BP neural network are verified, and technical support is provided for the health state assessment of rolling element bearings.

1. Introduction
Rolling element bearings are important parts of rotating machinery and equipment. It is of great significance to monitor the running status of rolling bearings and diagnose early bearing faults[1].

The bearing fault vibration signal mainly includes the periodic impact vibration components generated by the fault itself and the high-frequency natural vibration components of the bearing system induced by the impact. In the actual test, the low-frequency part has a lower signal-to-noise ratio due to the strong background noise. Decomposition and reconstruction methods such as wavelet transform (WT)[2], empirical mode decomposition (EMD)[3], integrated empirical mode decomposition (EEMD)[4], and variational modal decomposition (VMD)[5][6]can effectively separate signal and noise and extract some fault features. But it will also lead to signal local information distortion and loss of details, and the eigenmode function needs to be selected artificially. With the fast development of neural networks in the field of fault diagnosis, intelligent fault diagnosis technology that combines signal processing methods with neural networks has achieved many results. Zheng Hua et al.[7], Li et al.[8], and Dibaj Ali et al.[9] combined empirical mode decomposition, ensemble empirical mode decomposition, and variational modal decomposition methods with neural networks to study the fault diagnosis of rolling bearings. However, EMD has problems such as modal aliasing and inability to...
correctly separate components with similar frequencies. VMD has boundary effects, and the number of modes needs to be defined in advance.

Singh P et al. [10] proposed a Fourier Decomposition Method (FDM) based on Fourier theory. Through the search of the boundary frequency from high frequency to low frequency or low frequency to high frequency, a finite length of nonlinear and non-stationary data will be decomposed into the sum of several Fourier intrinsic mode functions (FIMFs). FDM has adaptability, locality, completeness and orthogonality. However, under the actual strong background noise, there are problems of boundary frequency offset and over-decomposition. Zheng et al. [11] improved the boundary frequency search method of FDM and proposed adaptive empirical Fourier decomposition (AEFD). However, there are still some problems such as time-consuming and difficult to select sensitive components.

A rolling bearing fault diagnosis method based on modified Fourier mode decomposition and frequency band entropy is proposed in this paper. Applying this method to the simulation data and experimental data, the accurate diagnosis of bearing faults can be realized. Compared with wavelet transform and empirical mode decomposition, the effectiveness and superiority of the fault diagnosis method are proved, which will provide technical support for the health evaluation of rolling bearing.

2. Modified Fourier mode decomposition and Multi-scale permutation entropy

2.1. Modified Fourier mode decomposition

MFMD introduces band entropy analysis to improve the boundary frequency search of Fourier decomposition and the selection of effective modal components, sets the initial boundary of frequency search and optimizes band-limited Fourier mode decomposition in each interval, and can adaptively decompose any nonlinear and non-stationary signals with limited energy into the sum of a series of FIMFs, that is, \( x(t) = \sum_{k} y_k(t) + r(t) \), where \( r(t) \) is the residual signal and \( y_k(t) \) is FIMF. The analysis shows that the decomposition has completeness, orthogonality, locality and adaptability[10].

For any finite length nonlinear and non-stationary zero-mean real signal \( x(t) \) \( (t \in [t_0, t_n + T]) \), which satisfies the Dirichlet condition:

\( \int_{t_0}^{t_n + T} x(t) \frac{d}{dt} \Psi_n(t) dt = 0 \) .

Therefore, it can be obtained that the complex form of the Fourier series expansion of \( x(t) \) is:

\[
 x(t) = \sum_{k=-\infty}^{\infty} c_k \exp(-j2\pi k f t)
\]

Where Angular frequency \( \omega_0 = 2\pi / T \), \( c_k = \frac{1}{T} \int_{t_0}^{t_n + T} x(t) \exp(-j2\pi k f t) dt \). The complex coefficient of \( x(t) \) is \( F(f) = \int_{-\infty}^{\infty} x(t) e^{-j\beta f} dt \), which is obtained by fast Fourier transform.

(2) The accuracy of frequency boundary has a decisive influence on the results of Fourier mode decomposition, while the frequency search of FDM boundary is greatly affected by background noise, so the decomposition efficiency and effect are not ideal. Therefore, this paper proposes a boundary frequency search method based on FBE[12], which determines the frequency boundary set according to the following methods:

1. Firstly, the original signal is analyzed by FBE and short-time Fourier transform, the minimum point of regional entropy is selected as the central frequency, and the boundary of the sensitive band is determined by the maximum point of band entropy envelope nearest to the central frequency.

2. Then the initial boundary frequency set in the whole frequency band to be searched is divided according to the boundary of the sensitive frequency band.

\[
 \{ B_k \} = \bigcup_{k=1}^{k} [f_{k-1}, f_k) = [0, F_s / 2)
\]
Where \( f_0 = 0, f_k = F_s/2 \).

③ According to the initial boundary frequency set, the boundary frequency is searched twice in each interval, and the judgment method is to obtain the minimum number of analytical FIMFs when the instantaneous amplitude \( a_i(t) \geq 0 \) and instantaneous frequency \( f_i(t) \geq 0 \) are satisfied. The final optimized frequency boundary set is obtained: \( \{ B_i \} = \bigcup_{i=1}^{J} [f_{i-1}, f_i] = [0, F_s/2], \) where \( f_0 = 0, f_J = F_s/2 \)

(3) The inverse fast Fourier transform is applied to the signal in the interval \( B_i = [f_{i-1}, f_i] \), and the analytical FIMF component in each interval is obtained: \( I_i(t) = x_i(t) = a_i(t) \exp\left(j\phi_i(t)\right) \), \( i = 1, 2, \cdots, J \). Thus, the original signal can be expressed as:

\[
x_i(t) = \sum_{i=1}^{J} f_i(t) = \sum_{i=1}^{J} \rho_i(t) \exp(i\phi_i(t))
\]

Its discrete form can also be expressed as:

\[
x[n] = \sum_{i=1}^{J} a_i[n] \exp\left(i\phi_i[n]\right)
\]

(4) The instantaneous amplitude \( a_i(t) \) and instantaneous frequency \( f_i(t) \) of each FIMF are functions of time, so we define the three-dimensional time-frequency energy distribution \( \{ t, f_i(t), a_i(t) \} \) as the Fourier Hilbert spectrum, marked as \( H(f, t) \). The marginal Hilbert spectrum is defined as:

\[
h(f) = \int_0^T H(f, t) \, dt
\]

2.2. Multi-scale permutation entropy

The amount of calculation will be too large if the MFMD decomposition envelope spectrum of a large number of samples is directly input into the neural network for fault diagnosis. Therefore, in this paper, the multi-scale permutation entropy algorithm is used to quantify the fault features, and the target sequence change information is mined deeply from the multi-scale.

Aziz et al.\[13\] put forward the concept of multi-scale permutation entropy (MPE), which overcomes the limitation that permutation entropy only measures the complexity of time series in a single scale. The arrangement entropy at different time scales can be obtained by coarse-grained time series, which can more comprehensively characterize the complexity and variation of the signal. The calculation of multi-scale permutation entropy is mainly divided into two parts: finding the coarse-grained time series and calculating the permutation entropy.

(1) Time series \( y(k), k = 1, 2, \cdots, N \), after coarse granulation treatment, the coarse granulation sequence \( \{ y^{(r)} \} \) is obtained. Its expression is:

\[
y^{(r)}_j = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} y_i \quad j = 1, 2, \cdots, \lfloor N/\tau \rfloor
\]

Where \( \lfloor N/\tau \rfloor \) means to round \( N/\tau \), \( \tau \) is the scale factor, \( \tau = 1, 2, \cdots \). The original sequence is coarse-grained into a signal of length \( \lfloor N/\tau \rfloor \) and Coarsening makes sense when \( \tau \geq 2 \). The value of the scale factor needs to ensure that the length of the coarse-grained sequence does not affect the calculation of entropy. In this paper, in order to ensure the efficiency and the adequacy of the amount of data, \( \tau = 60 \) is selected.

(2) The arrangement entropy of each coarse-grained sequence is calculated respectively, and the result of multi-scale arrangement entropy can be obtained. In order to calculate MPE, we also need to consider the appropriate number of embedded bits. If the value of \( m \) is too small, the change of PE value
with the increase of scale factor is too small, but the larger the value of m is, the longer the calculation time is. In this study, m=5.

2.3. The Proposed Bearing Fault Diagnosis Method

The improved Fourier mode decomposition method (MFMD) is an adaptive time-frequency analysis method based on zero-phase filter banks. MFMD method determines the sensitive frequency band by FBE analysis, sets the initial boundary of frequency search and performs adaptive Fourier mode decomposition in each sensitive interval. The analysis shows that the decomposition has completeness, orthogonality, locality and adaptability[10]. BP neural network has the characteristics of strong nonlinear mapping ability, clear structure, easy to use and so on. The fault feature extraction algorithm based on MFMD and multi-scale permutation entropy (MPE) has obvious efficiency advantages in processing rolling fault signals and can greatly alleviate the computational pressure of neural network, which is very consistent with the neural network fault diagnosis system which needs a large number of data samples to learn and train. The fault diagnosis process of rolling bearing based on MFMD and BP neural network is shown in figure 1.

3. BP neural network

BP learning algorithm is a kind of artificial neural network with the most in-depth research, the most concise operation mechanism and the most widely used[14]. BP neural network consists of input layer, hidden layer and output layer, including forward calculation process and error back propagation process [14]. In this paper, BP neural network is introduced to recognize the bearing fault features obtained by MFMD-MPE analysis, and the topology diagram is shown in figure 2.
In the process of feedforward calculation of BP neural network, the input and output of each layer are calculated in turn from the input layer, and finally the output results from the output layer are input into the SoftMax classifier, and the cross entropy loss function (Cross Entropy Error Function) is used to calculate the loss of the output result and the target result. Then the connection weight between the neurons in each layer is adjusted by the gradient descent algorithm, so that the loss function changes in the direction of reduction, and the weight correction formula is as follows:

$$\Delta w_{ij} = -\eta \frac{\partial E_k}{\partial w_{ij}}$$

(7)

Where $\eta$ is the learning rate, $E_k$ is the mean square error of the network, and $w_{ij}$ is the connection weight.

4. Application

4.1. Application to simulation data
In order to verify the effectiveness of the fault feature extraction method of MFMD and MPE, the fault simulation signal of rolling bearing inner ring is considered.

$$x(t) = \sum_{i=1}^{M} A_i s(t - iT - \tau_i) + n(t)$$

$$A_i = A_0 \cos \left(2\pi f_r t + \varphi_A\right) + C_A$$

$$s(t) = \exp(-Bt) \sin \left(2\pi f_m t + \varphi_m\right)$$

(8)

Where the sampling frequency of the system is $f_s = 12000\text{Hz}$, $f_m = 4000\text{Hz}$ is the structural resonance frequency, the inner ring fault frequency and the rotation frequency, and $B=500$ represents the attenuation coefficient of the system. $n(t)$ is Gaussian white noise with a signal-to-noise ratio of -10dB. The time domain waveform and envelope spectrum of the simulation signal are shown in figure 3. Due to the influence of strong background noise, 50 FIMFs are obtained by FDM decomposition and it is very difficult to select effective components as shown in the figure4. But MFMD can solve this problem.
Through the FBE analysis of the original signal, the frequency band entropy distribution of the signal with different window length is obtained, as shown in figure 5.

Select the sensitive interval as \([3500 \text{ and } 4500]\) Hz, and get the decomposition result as shown in figure 6. According to the subordinate relationship between FIMFs and the frequency band entropy analysis of the original signal, the effective modal components FIMF2 are selected. From the results, it can be seen that MFMD can effectively select the sensitive interval and effective modal components, and has high efficiency and accuracy.

In order to verify the superiority of this method in extracting fault features under strong background noise, the fault simulation signal is processed by discrete wavelet transform and empirical mode decomposition, and the results are shown in figures 7 and 8. Under strong background noise, it is difficult to select effective components and fault features are obviously affected by noise signals in both discrete wavelet transform and EMD. The results show that the fault feature extraction algorithm based on MFMD and FBE has high feasibility and superiority.
4.2. Application to experimental Data

4.2.1. Experimental Data
In order to verify the method proposed in this paper, the test and analysis is carried out by using the sample data of the open bearing database of case Western Reserve University (CWRU) in the United States. The bearing fault test-bed is shown in figure 9. This paper takes the drive end bearing (6205-2RS JEM SKF) as the research object, and analyzes the measured data when the load is 745.70W and the rotational speed is 1772. The accelerometer is placed at 12 o'clock on the drive end of the motor housing and the fan end, and the sampling frequency is 48KHz.

Seven typical fault categories are considered in this paper, as shown in the table2. It includes three kinds of cases: normal, inner ring failure and outer ring failure. Among them, the fault conditions include three fault degrees with loss diameters of 0.07, 0.14, 0.21 inch respectively, and the fault characteristic order is shown in the table 1. Each type of fault consists of 200 samples, including 150 training samples and 50 test samples.

| Tab.1 Defect frequencies: (multiple of running speed) |
|-----------------------------------------------------|
| Position                                             |
| Inner Race Frequency                                 |
| Frequency                                           |
|                                                      |
| 5.4152                                              |
| 3.5848                                              |

| Tab.2 Bearing data sample statistics                 |
|-----------------------------------------------------|
| Type       | Fault Diameter /inch | Number of samples | Label |
| Normal     |                       |                   |       |
| 0.07       | 200                   | 0                 |
| 0.14       | 200                   | 1                 |
| 0.21       | 200                   | 2                 |
| Inner Race |                       |                   |       |
| 0.07       | 200                   | 3                 |
| 0.14       | 200                   | 4                 |
| 0.21       | 200                   | 5                 |
| Inner Race |                       |                   |       |
| 0.14       | 200                   | 6                 |
| 0.21       |                       |                   |       |
| Total      |                       | 1400              |       |
The fault characteristics are obtained by MFMD decomposition of the above sample data, and the envelope spectrum of the effective modal components is shown in figure 10. The fault feature whose fundamental frequency is 109Hz is extracted in figure 9, which is consistent with the theoretical value of 3.5848 order.

The bearing fault features have been obtained by MFMD decomposition, and then the obtained fault features are quantified by multi-scale permutation entropy. The scale factor of multi-scale permutation entropy is 60, and the embedding dimension m is 5. Multi-scale permutation entropy can deeply mine data change information under different scales and quantify bearing fault characteristics. After processing, each bearing fault data sample changes from an one-dimensional vector.

4.2.2. Experimental analysis.
The fault feature vector is divided into training set and test set. The number of samples for each type of fault training set is 150 and the number of test set is 50. In practical work, the data set can be continuously supplemented. In this paper, a neural network with five hidden layers is selected and the optimization algorithm of random gradient descent (SDG) is adopted. The change of the accuracy of loss function and test set fault identification with the increase of iterations is shown in figure 11:

Finally, after several rounds of training, the internal parameters of BP neural network tend to be stable, and the change of recognition accuracy also tends to be stable. For all kinds of faults, the neural network recognizes them as shown in figure 12, and the recognition results are statistically shown in Table 3.
### Tab.3 Bearing fault diagnosis results

| Type          | Fault Diameter (inch) | Correct/total | Accuracy (%) |
|---------------|-----------------------|---------------|--------------|
| Normal        | 0.07                  | 49/50         | 98           |
|               | 0.14                  | 49/50         | 98           |
|               | 0.21                  | 49/50         | 98           |
|               | 0.07                  | 50/50         | 100          |
| Inner Race    | 0.14                  | 48/50         | 96           |
|               | 0.21                  | 49/50         | 100          |
| Total         |                       | 344/350       | 98.28        |

According to statistics, the recognition accuracy of all kinds of bearings by BP neural network is more than 96%, and the overall recognition accuracy is 98.28%. The results show that the rolling bearing fault diagnosis method based on MFMD and BP neural network has high efficiency and accuracy.

### 5. Conclusions

For the original vibration signal, the processes of preprocessing, fault feature extraction and pattern recognition are integrated to realize the end-to-end rolling bearing fault diagnosis. Compared with the traditional rolling bearing fault diagnosis method, this method has the following advantages:

1. Many bearing fault features can be better characterized and quantified by MFMD-MPE algorithm, which can greatly alleviate the calculation pressure of neural network and improve the efficiency of fault diagnosis.
2. The robustness of BP neural network can be improved with the increase of data type and amount of data, and the corresponding fault diagnosis accuracy will also be improved. By combining MFMD-MPE method with BP neural network, this paper provides a new idea for extracting fault features from strong background noise and non-stationary rolling bearing fault vibration signals and fault pattern recognition under big data fault samples.

### References

[1] Yu Yang, Haiyang Pan, Li Ma, Junsheng Cheng. A roller bearing fault diagnosis method based on the improved ITD and RRVPMCD[J]. Measurement, 2014, 55.
[2] Shu’e Li, Feng Lv, Chao Fu. Wavelet Selection in Fault Diagnosis of Wavelet Transform[J]. Advanced Materials Research,2012,2076.
[3] Niu Xiaodong, Lu Lijing, Wang Jian, Han Xingcheng, Li Xuan, Wang Liming, Ponomariov Volodymyr. An Improved Empirical Mode Decomposition Based on Local Integral Mean and Its Application in Signal Processing[J]. Mathematical Problems in Engineering, 2021,2021.
[4] Teng Lehua. Fault Diagnosis of Rolling Bearing Based on EEMD and MMTS[J]. Journal of Physics: Conference Series,2021,1865(3).
[5] Wei Jiajia, Xie Tao, Shi Ming, He Qianqian, Wang Tianzhen, Amirat Yassine. Imbalance Fault Classification Based on VMD Denoising and S-LDA for Variable-Speed Marine Current Turbine[J]. Journal of Marine Science and Engineering, 2021,9(3).
[6] MeiYing Qiao, XiaXia Tang, YuXiang Liu, ShuHao Yan. Fault diagnosis method of rolling bearings based on VMD and MDSVM[J]. Multimedia Tools and Applications, 2021 (prepublish).
[7] Zheng Hua, Wu Zhenglong, Duan Shiqiang, Zhou Jiangtao, Song Zhiguang. Research on Feature Extraction Method for Flutter Test Based on EMD and CNN[J]. International Journal of Aerospace Engineering,2021,2021.
[8] Li Siqi, Jiang Zhijian. Fault diagnosis method of rolling bearing based on EEMD-CNN [J].
Mechanical strength, 2020, 42 (05): 1033-10.

[9] Dibaj Ali, Ettefagh Mir Mohammad, Hassannejad Reza, Ehghaghi Mir Biuok. A hybrid fine-tuned VMD and CNN scheme for untrained compound fault diagnosis of rotating machinery with unequal-severity faults[J]. Expert Systems With Applications, 2021, 167.

[10] Singh P, Joshi S D, Patney R K, et al. The Fourier Decomposition Method for nonlinear and nonstationary time series analysis[J]. Proceedings Mathematical Physical & Engineering Sciences, 2015, 473(2199).

[11] Zheng Jinde, Pan Haiyang, Cheng Junsheng, et al. Mechanical fault diagnosis method based on adaptive empirical Fourier decomposition [J]. Journal of Mechanical Engineering, 2020, v. 56 (09): 139-150.

[12] Liu T, Chen J, Dong G, et al. The fault detection and diagnosis in rolling element bearings using frequency band entropy[J]. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, 2012.

[13] Chen Dongning, ZHANG Yundong, Yao Chengyu, et al. Fault diagnosis based on variational mode decomposition and multi-scale permutation entropy [J]. Computer Integrated Manufacturing Systems, 2017, 23(012):2604-2612.

[14] Zhen Bo Wang, Shu Zhi Li, Liang Zhang. High-Speed Machining Time Model Prediction of Combination Framework Based on BP Neutral Network[J]. Materials Science Forum, 2014, 3256.