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Rolling bearing fault diagnosis method based on modified Fourier mode decomposition and frequency band entropy

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Abstract: [**Objective**] In order to resolve the difficulty of extracting fault features of rolling bearings under conditions of multiple components and strong background noise, this paper proposes a rolling bearing fault feature extraction method based on modified Fourier mode decomposition (MFMD) and frequency band entropy (FBE) analysis. In addition, in order to solve the problem of the boundary frequency offset and over-decomposition of the Fourier decomposition method (FDM) under strong background noise, the paper puts forward a method for selecting sensitive frequency bands and mode components based on FBE and the envelope spectrum. [**Methods**] First, the minimum FBE value is selected as the central frequency of the sensitive band by FBE analysis, and the boundary of the sensitive band is determined. Second, the signal is decomposed by band-limited Fourier mode decomposition in the sensitive frequency band, and several mutually orthogonal Fourier intrinsic mode functions (FIMFs) and their marginal Hilbert spectra are obtained. Next, sensitive FIMFs which can reflect fault features are selected according to the regional dependency relationship between the FIMFs and the FBE of the original signal. Finally, the selected FIMFs are analyzed by envelope spectrum to extract fault features. [**Results**] The bearing simulation and experimental results show that the accurate diagnosis of bearing faults can be realized by applying this method. [**Conclusions**] The results can provide a reference for the health evaluation of rolling bearings.

Key words: rolling bearing; fault diagnosis; feature extraction; modified Fourier mode decomposition (MFMD); frequency band entropy

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0 Introduction

Affected by strong background noise, equipment speed, friction, and load, rolling bearing vibration signals often present the characteristics of low signal-to-noise ratio (SNR), nonlinearity, and non-stationary, so it is difficult to identify fault features [1-2]. To solve this problem, scholars have applied methods of short-time Fourier transform (STFT) [3], Winger-Ville distribution[4], wavelet transform[5], Hilbert-Huang transform (HHT) [6], and variational mode decomposition (VMD) [7-8] in the field of rolling bearing fault diagnosis. However, due to the limitation of the Heisenberg uncertainty principle, the resolution of STFT is low. Winger-Ville distribution will produce quadratic cross-term interference that cannot be eliminated. HHT is an adaptive and efficient time-frequency analysis method, including empirical mode decomposition (EMD) and Hilbert spectrum analysis, but EMD has problems such as

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mode mixing and endpoint effect [9].

On this basis, scholars have proposed a large number of improvement schemes. Wu et al. [10] proposed the ensemble empirical mode decomposition (EEMD) method. Smith [11] proposed the local mean decomposition (LMD) method, and Cheng et al. [12] proposed the local characteristic-scale decomposition (LCD) method. However, these algorithms have problems such as mode mixing and endpoint effect caused by extreme point fitting and lack of a rigorous mathematical basis. Although the VMD method can achieve the adaptive decomposition of signals by searching for the optimal solution of the constrained variational model, it is greatly affected by the number of preset modes and penalty parameters, and the calculation is complex and time-consuming, so the efficiency is low [13].

According to Fourier theory, Singh et al. [14] proposed an adaptive time-frequency analysis method based on zero-phase filter banks, namely, the Fourier decomposition method (FDM). The method can decompose nonlinear and non-stationary data with finite length into the sum of several Fourier intrinsic mode functions (FIMFs) by searching for the boundary frequency from high frequency to low frequency or from low frequency to high frequency. FDM has the advantages of self-adaptability, locality, completeness, and orthogonality. However, under the actual strong background noise, it has the problems of boundary frequency offset, signal over-decomposition, and difficult selection of effective FIMFs. Zheng et al. [15] proposed the adaptive empirical Fourier decomposition (AEFD) by improving the boundary frequency search method of FDM, but there are problems such as long time consumption and difficult selection of sensitive components.

When the rolling bearing has a surface damage fault, its impact will induce the high-frequency inherent vibration component of the system, while the SNR of the low-frequency part is low under strong background noise [16]. Therefore, this paper proposes a rolling bearing fault diagnosis method based on modified Fourier mode decomposition (MFMD) and frequency band entropy (FBE). Firstly, the FBE analysis is used to determine the central frequency and the boundary of the sensitive band. Then, the signal is decomposed by the band-limited Fourier mode decomposition in the sensitive frequency band, and sensitive FIMFs that can reflect the fault features are selected according to the regional dependency relationship between the FIMFs and the FBE of the original signal. Finally, the envelope spectrum analysis and fault feature extraction of the selected FIMFs are performed, and the rolling bearing simulation and experiment are carried out to verify the effectiveness and accuracy of the method.

1 Theoretical analysis

1.1 MFMD

The MFMD method is based on FDM and formed by introducing the methods such as FBE analysis to determine the sensitive frequency band, setting the initial boundary of frequency search, and finally performing the modified band-limited Fourier mode decomposition in each interval. MFMD can adaptively decompose any nonlinear and non-stationary signal $x(t)$ with limited energy into the sum of a series of FIMFs, namely $x(t)=\sum_{i=1}^{I} y_i(t)+r_I(t)$, where t is the time, $y_i(t)$ is the FIMFs (i = 1, 2, …, I), in which I is the number of modes, $r_I(t)$ is the residual signal.

For any nonlinear and non-stationary zero-mean real signal $x(t)$ ($t\in[t_0, t_0+T]$, where t_0 is the starting time, T is the period) that has a finite length and satisfies the Dirichlet condition, the following steps are carried out.

1) The periodic extension of $x(t)$ is constructed, and its fast Fourier transform is performed. Let $x_T(t)=\sum\limits_{k=-\infty}^{\infty} x(t-kT)$, where $k\in[-\infty, \infty]$, and k is the number of periods. Let $x(t)=x_T(t)w(t)$, when $t_0 \leqslant t \leqslant t_0+T$, $w(t)$ = 1, or otherwise $w(t)$ = 0. Therefore, the complex form of Fourier series expansion of $x_T(t)$ is

$$x_T(t)=\sum_{n=-\infty}^{\infty} c_n \exp(-\mathrm{j}n\omega_0 t) \tag{1}$$

where $n\in[-\infty, \infty]$, and n is the number of waves; j is the imaginary unit; the angular frequency $\omega_0=2\pi/T$; $c_n=\dfrac{1}{T}\int_{t_0}^{t_0+T} x_T(t)\exp(-\mathrm{j}n\omega_0 t)\mathrm{d}t$. The complex coefficient of $x_T(t)$ can be obtained by the fast Fourier transform: $F(f)=\int_{-\infty}^{+\infty} x(t)\mathrm{e}^{-ift}\mathrm{d}t$, where f is the frequency.

2) The accuracy of the frequency boundary will directly affect the results of Fourier mode decomposition, and the FDM boundary frequency search is greatly affected by the background noise. To obtain an ideal decomposition effect, this paper proposes a boundary frequency search method based on FBE. The steps to determine the frequency boundary set are as follows.

(1) Firstly, the original signal is analyzed by FBE and STFT. The minimum regional entropy value is selected as the central frequency, while the boundary of the sensitive band is determined by the maximum value of the FBE envelope nearest to the central frequency.

(2) Then, according to the boundary of the sensitive frequency band, the initial boundary frequency set in the whole frequency band to be searched is divided as $\{B_s\}=\bigcup_{s=1}^{S}[f_{s-1},f_s)=[0,F_s/2)$, where s=1, 2,..., S, and S is the number of initial intervals. The minimum value f_0 equals 0; the maximum value $f_s=F_s/2$, and F_s is the upper-frequency limit.

(3) According to the initial boundary frequency set, the boundary frequency is then searched in each interval. The criterion is to obtain the minimum number of analytical FIMFs when the conditions that instantaneous amplitude $a_i(t)\geqslant 0$ and instantaneous frequency $f_i(t)\geqslant 0$ are satisfied. Set the finally optimized frequency boundary set as $\{B_i\}=\bigcup_{i=1}^{I}[f_{i-1},f_i)=[0,F_s/2)$, where f_0 equals 0, and the maximum value $f_I=F_s/2$. Then the real part Re $\{F(f)\}$ of the complex coefficient is adaptively segmented according to the boundary frequency.

3) The inverse fast Fourier transform is performed on the signal in the interval $B_i=[f_{i-1},f_i)$ to obtain the analytical FIMF component $I_i(t)=a_i(t)\exp(\mathrm{j}\phi_i(t))$ in each interval B_i. Specifically, $a_i(t)$ is the instantaneous amplitude, and $\phi_i(t)$ is the instantaneous phase.

Therefore, the original signal can be expressed as

$$x_T(t)=\sum_{i=1}^{I}I_i(t)=\sum_{i=1}^{I}a_i(t)\exp(\mathrm{j}\phi_i(t)) \qquad (2)$$

Its discrete form is

$$x[n]=\sum_{i=1}^{I}a_i[n]\exp(\mathrm{j}\phi_i[n]) \qquad (3)$$

where $x[n]$, $a_i[n]$, $\phi_i[n]$ are the discrete forms of $x_T(t)$, $a_i(t)$, $\phi_i(t)$, respectively; n = 1, 2, …, N, and N is the length of the discrete signal.

4) The $a_i(t)$ and $f_i(t)$ of each FIMF are time-dependent functions, so the three-dimensional time-frequency energy distribution $\{t, f_i(t), a_i(t)\}$ is defined as Fourier Hilbert spectra, which is denoted as $H(f, t)$. Its marginal Hilbert spectra $h(f)$ is

$$h(f)=\int_0^T H(f,t)\mathrm{d}t \qquad (4)$$

1.2 FBE

FBE is a signal analysis method combining time-frequency analysis and information entropy [17]. The calculation method of FBE based on the amplitude spectrum entropy is as follows.

1) Firstly, the signal $y(z)$ (z = 1, 2, ..., Z, and Z is the signal length) is subjected to the STFT to obtain the time-frequency distribution ***TER***.

$$\boldsymbol{TER}=\begin{bmatrix} r_{1.1} & \cdots & r_{1.C} \\ & \cdots & \\ r_{M.1} & \cdots & r_{M.C}\end{bmatrix} \qquad (5)$$

where M is the number of frequency points; $C=Z/L$, is the number of Fourier transforms, in which L is the step size; $r_{M.C}$ is the estimated value of the frequency component M of the signal in a certain time corresponding to the C-th window.

2) The change of the amplitude of the q-th frequency component with time is defined as $X_{fq}=(r_{q,1},r_{q,2},\cdots,r_{q,C})$, and then the FBE of a single frequency component is

$$\begin{cases} H_{sq}=\dfrac{-\left(\sum\limits_{m=1}^{C}p_{m,q}\ln p_{m,q}\right)}{\ln C} \\ p_{m,q}=\dfrac{X_{fq}(F_m)}{\sum\limits_{m=1}^{C}X_{fq}(F_m)} \\ \sum\limits_{m=1}^{C}p_{m,q}=1 \end{cases} \qquad (6)$$

where m = 1, 2, ..., C; q = 1, 2, ..., M; $p_{m,q}$ is the proportion of the q-th frequency component in the entire spectrum; H_{sq} is the FBE value of the q-th frequency component; F_m is the spectral distribution of the frequency component X_{fq} along the time axis.

3) By calculating the FBE value of each frequency component, the FBE distribution H_{sf} of the whole frequency band can be obtained as follows.

$$H_{sf}=(H_{s1},H_{s2},\cdots,H_{sM}) \qquad (7)$$

If X_{fq} changes smoothly or regularly with time, its FBE value will be small. Otherwise, it will be large. Therefore, it can be used to find the resonance frequency of the equipment in fault diagnosis [18] and provide a reference for the setting of adaptive filtering parameters.

2 Simulation signal analysis

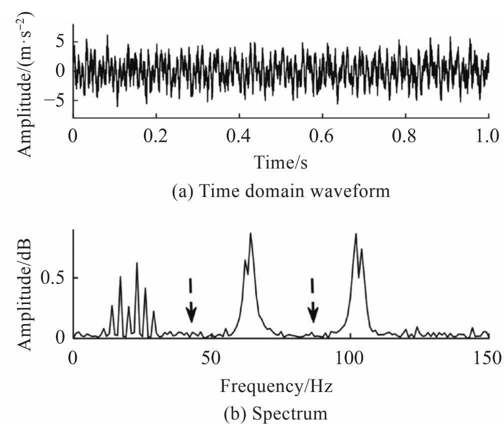
In this section, the feasibility of the MFMD will be verified through the simulation signal analysis, and the superiority of the fault diagnosis method based on MFMD and FBE will be clarified through the bearing fault simulation signal analysis.

2.1 MFMD

The simulation signal is set as follows:

$$x_1(t) = [1 + 0.2\cos(6\pi\ ) \cdot \cos[40\pi\ + 2\sin(6\pi\ )]$$
$$x_2(t) = (1+t)\cos\left(120\pi\ + 6\pi\ ^2\right)$$
$$x_3(t) = 2\exp(-0.5t)\sin\left(200\pi\ t + 6\pi\ ^2\right)$$
$$x(t) = x_1(t) + x_2(t) + x_3(t) + n(t), \quad t \in [0,1]$$
$$F_s = 4\ 096\ \text{Hz} \tag{8}$$

where the simulation signal $x(t)$ is composed of three amplitude modulation (AM)-frequency modulation (FM) time-varying mode signals, namely, $x_1(t)$, $x_2(t)$, $x_3(t)$. The sampling frequency F_s is 4 096 Hz. $n(t)$ is the Gaussian white noise with an SNR of 5 dB. The time domain waveform and spectrum of $x(t)$ are shown in Fig. 1.



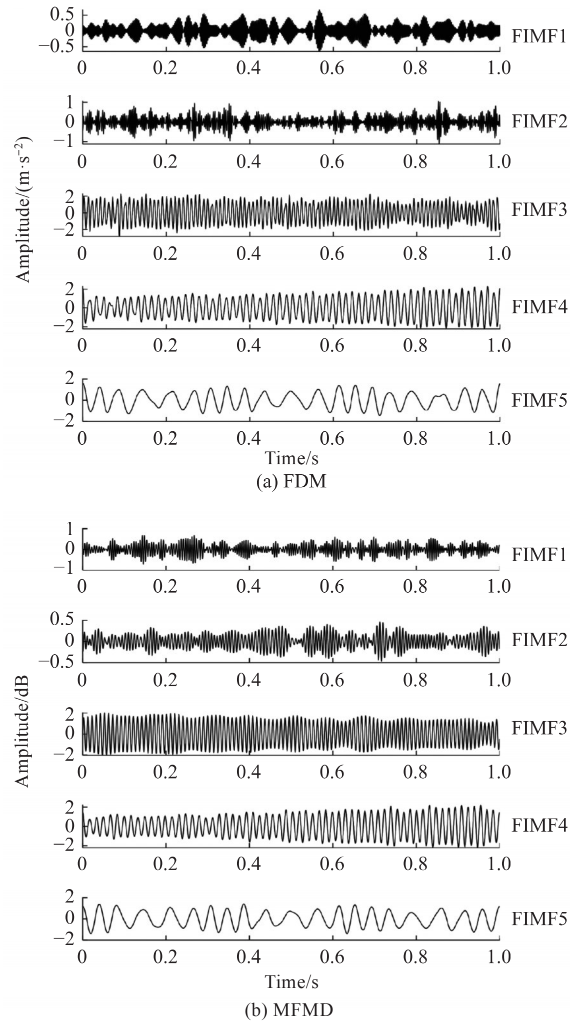
(a) Time domain waveform

(b) Spectrum

Fig. 1 Time domain waveform and spectrum of analog signals

FDM and MFMD were performed on $x(t)$, and FDM adopted the frequency boundary search from low frequency to high frequency. Since MFMD was essentially a band-limited FDM, the initial decomposition frequency boundary of the simulation signal was determined as [40, 90, 200] according to the signal spectrum, and the MFMD was carried out under the initial boundary. The first five components obtained by the algorithm were selected and named FIMF1, FIMF2, FIMF3, FIMF4, and FIMF5, respectively, and the results are shown in Fig. 2. Affected by the noise signal $n(t)$, the boundary frequency searched by FDM offsets, and the accurate signal mode information cannot be obtained in the low-frequency part. Therefore, the error between the decomposed FIMFs and the expected results is large, while MFMD obtains three FIMFs corresponding to their mode components and achieves an ideal decomposition effect.

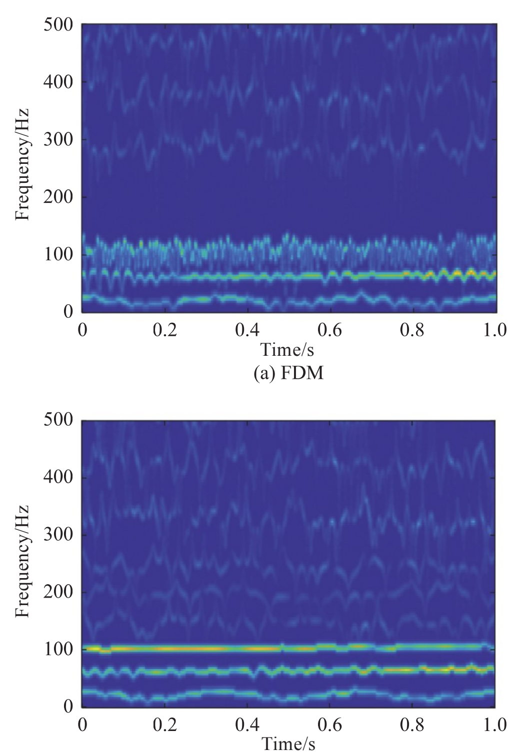
The time-frequency distribution characteristics were further analyzed by Fourier Hilbert spectra, and the results are shown in Fig. 3. The overall fluctuation of FIMFs decomposed by FDM is large, and there is a large boundary frequency identification error under strong background noise. MFMD has the



(a) FDM

(b) MFMD

Fig. 2 Signal decomposition results of FDM and MFMD



(a) FDM

(b) MFMD

Fig. 3 Time-frequency distribution of analog signals completeness and orthogonality of Fourier decomposition. The obtained mode components are in line with expectations and have high accuracy.

2.2 Fault feature extraction based on MFMD and FBE

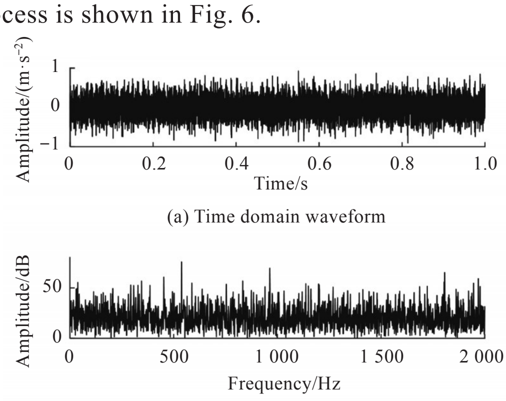
In order to verify the feasibility and superiority of the fault feature extraction method based on MFMD and FBE, the fault simulation signal of the inner ring of the rolling bearing is set as

$$\begin{cases} x(t)=\sum_{e=1}^{E} A_e h(t-eT-\tau_e)+z(t) \\ A_e=A_0\cos(2\pi f_r t)+1 \\ h(t)=\exp(-Bt)\sin(2\pi f_n t) \end{cases} \tag{9}$$

where $x(t)$ is the analog signal; A_e is the AM signal of the e-th impact (e =1, 2, ..., E, and E is the maximum number of impacts); τ_e is a small fluctuation of the e-th impact; $z(t)$ is the Gaussian white noise with an SNR of −10 dB; A_0 is the amplitude of the impact; f_r equals 28 Hz and is the rotation frequency; $h(t)$ is the FM signal; B=500 and is the attenuation coefficient of the system; f_n =4 000 Hz and is the structural resonance frequency. The sampling frequency of the system F_s=12 000 Hz, and the number of the analysis points is 12 000. The inner ring fault frequency $f_1=1/T$ =80 Hz.

The time domain waveform and envelope spectrum of the simulation signal are shown in Fig. 4. Due to the influence of strong background noise, the fault feature frequency, frequency doubling, or rotation frequency cannot be directly extracted from the envelope spectrum. The FDM analysis results are shown in Fig. 5. It is difficult to extract the fault features of rolling bearings due to the over-decomposition, boundary frequency offset, and difficult selection of effective FIMFs.

Therefore, this paper proposes a fault feature extraction method based on MFMD and FBE, and its process is shown in Fig. 6.



(a) Time domain waveform

(b) Spectrum

Fig. 4 Time domain waveform and spectrum of bearing fault simulation signals

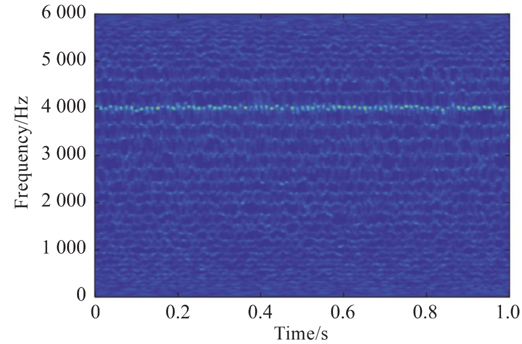


Fig. 5 Time-frequency distribution of bearing fault simulation signals

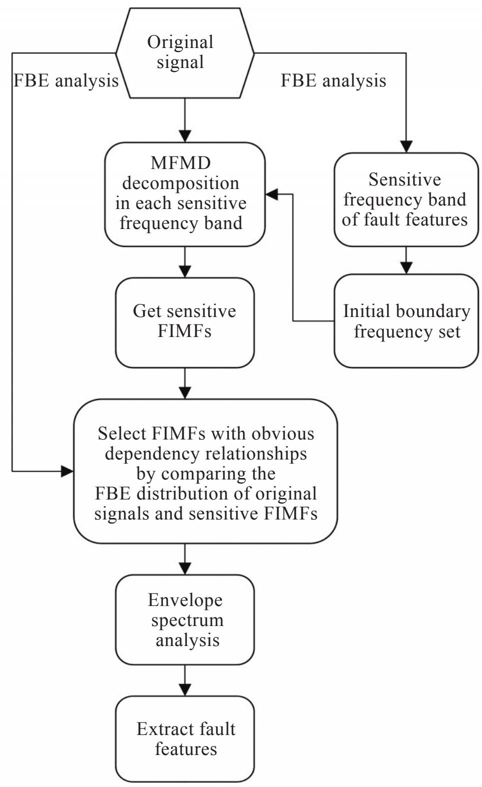


Fig. 6 Fault diagnosis process

Through the FBE analysis of the original signal, the FBE distribution at the window length of 16, 32, 64, 128, 256 can be obtained, respectively. As shown in Fig. 7, the minimum entropy value appears at 4 000 Hz, which indicates that the natural frequency of the bearing is also near this value. When the surface damage fault of rotating machinery appears, the impact will induce the high-frequency inherent vibration component of the system and thus amplify the fault features. Therefore, this paper selected the region with the minimum entropy value as the central frequency and took it as the sensitive frequency band. The boundary of the frequency interval was determined by the maximum entropy value of the frequency band nearest to the central frequency. The sensitive band ranged from 3 500−4 500 Hz in this paper, and the MFMD of the signal was performed in the sensitive band, with results shown in Fig. 8. It can be seen from the time domain waveform that the periodic impact fault features of FIMF4 are obvious.

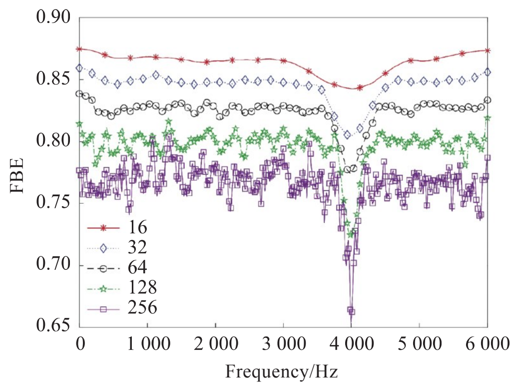


Fig. 7 FBE analysis of original signals with different window lengths

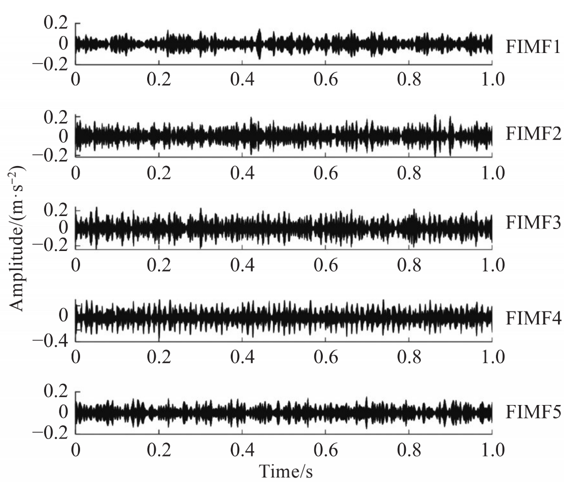
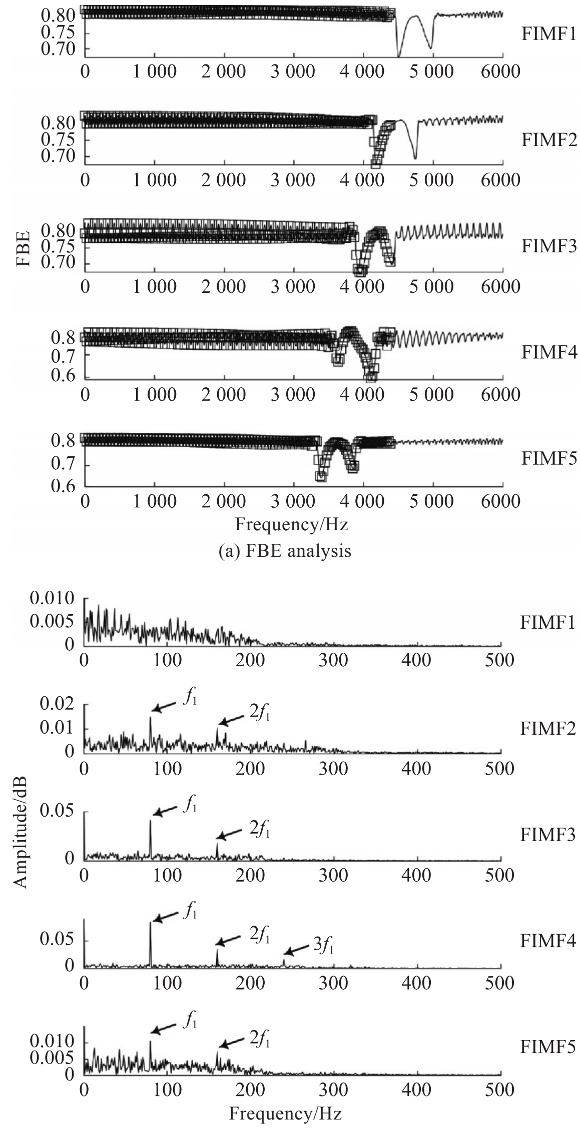


Fig. 8 Signal decomposition results in sensitive intervals

In order to select sensitive FIMFs, the FBE analysis for each component was performed, as shown in Fig. 9(a). The results show that the FBE distribution of FIMF3 and FIMF4 has a high regional dependency relationship with the original signal at the natural frequency of 4 000 Hz, and the dependency feature of FIMF4 is more obvious. To verify the selection accuracy of sensitive FIMFs and extract the fault features, this paper analyzed the envelope spectrum, as shown in Fig. 9 (b). The results show that FIMF1, FIMF2, FIMF3, FIMF4 all present fault feature frequencies that take $f_1 = 1/T = 80$ Hz as the fundamental frequency, and the fault features of FIMF4 are the clearest, which is consistent with the selection results of sensitive FIMFs based on the FBE analysis.

To verify the superiority of this method in extracting fault features under strong background noise, this paper compared the performance of discrete wavelet transform and EMD in processing simula-



(a) FBE analysis

(b) Envelope spectrum analysis

Fig. 9 FBE and envelope spectrum analysis of FIMFs

tion fault signals, and the results are shown in Fig. 10 and Fig. 11. Under strong background noise, both discrete wavelet transform and EMD have problems such as the difficult selection of effective components and obvious influence of noise on fault features. Therefore, the fault feature extraction algorithm based on MFMD and FBE has high feasibility and superiority.

3 Experimental signal analysis

In this section, the fault diagnosis experiment of

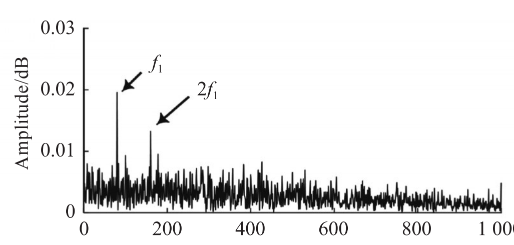


Fig. 10 Analysis results of wavelet envelope spectrum

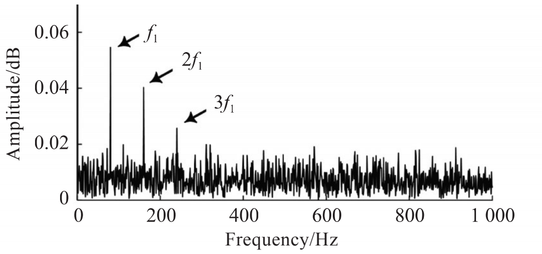
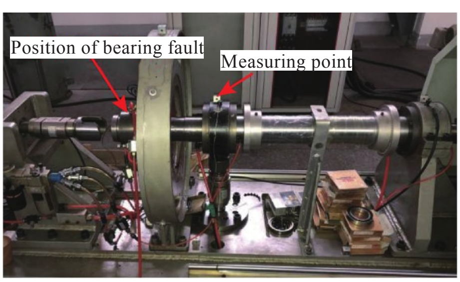
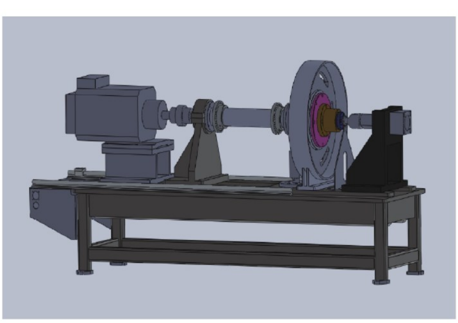


Fig. 11 Analysis results of EMD decomposition and envelope spectrum

bearings in the bearing fault simulation platform was carried out, as shown in Fig. 12. The bearing model was NSK7010C, with an outer diameter of 80 mm, an inner diameter of 50 mm, and a contact angle of 15°. The diameter of the rolling element was 8.7 mm, and there were 19 rolling elements in total. The bearing fault was artificially simulated by machining a groove with a width of 0.5 mm and a depth of 0.5 mm parallel to the bearing axis by laser in the outer ring. The rotation frequency of the motor was 50 Hz, and the sampling frequency in the experimental process was 65 536 Hz. The theoretical feature frequency of the bearing fault in the outer ring was 412 Hz.



(a) Bearing fault simulation platform



(b) Experimental platform model

Fig. 12 Bearing fault simulation platform and model

Based on the fault simulation platform, the radial vibration acceleration data inside the bearing were collected, and the number of analysis points was 65 536. Firstly, the original vibration signal was analyzed by STFT and FBE, as shown in Fig. 13 and Fig. 14. The results show that the vibration component of the bearing in the low-frequency part is complex, and its energy is dispersed in a wide frequency band, so it is difficult to determine the frequency band range where the natural frequency of the bearing is located. The vibration signal has high energy in the frequency band of about 20 000 Hz, and the FBE tends to decrease in this range, which conforms to the judgment standard of natural frequency. Thus, it can be judged that the bearing in the experiment has a certain natural frequency of about 20 000 Hz.

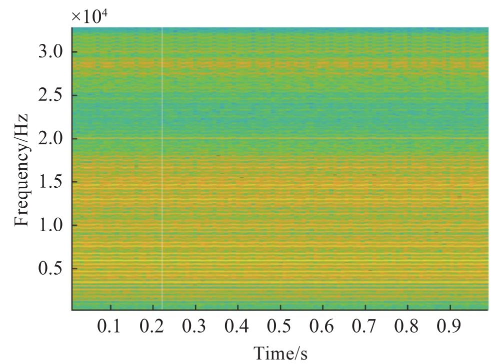


Fig. 13 STFT of bearing vibration signals

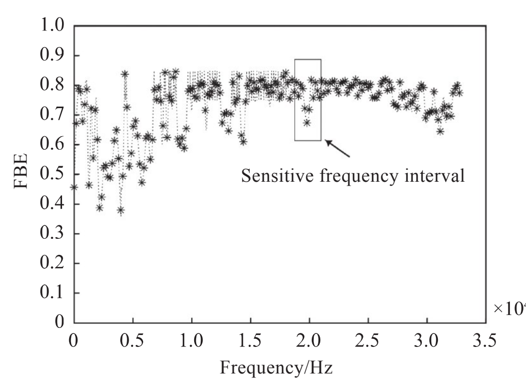


Fig. 14 FBE analysis of bearing vibration signals

According to the FBE analysis, it is found that the sensitive frequency band interval may range from 19 000−21 000 Hz. Four FIMFs could be obtained by MFMD of the signal in this interval, as shown in Fig. 15. In order to select sensitive FIMFs, the FBE analysis for each component was carried out, as shown in Fig. 16(a). The results

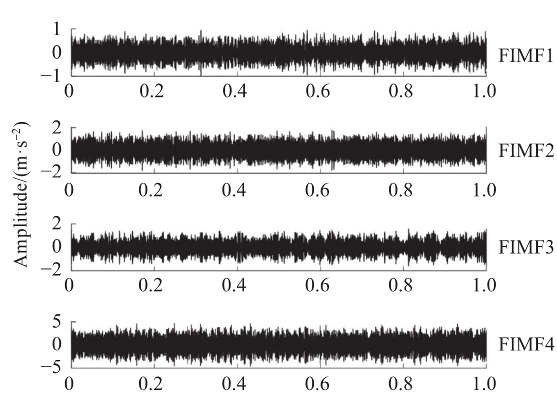
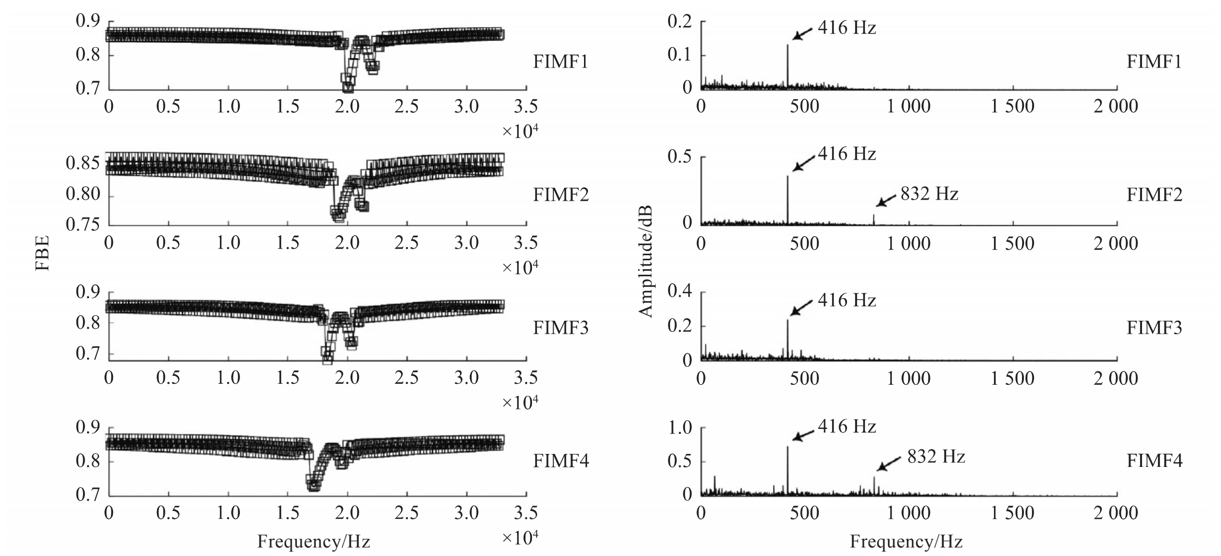


Fig. 15 Signal decomposition results in sensitive intervals

show that the FBE of FIMF1, FIMF2, FIMF3, FIMF4 is distributed at near 20 000 Hz and has a regional dependency with the original signal, and the dependency feature of FIMF2 is the most obvious. To verify the selection accuracy of sensitive FIMFs, this paper analyzed the envelope spectrum of FIMFs, as shown in Fig. 16(b). The results show that FIMF1, FIMF2, FIMF3, FIMF4 all present fault feature frequencies that take 416 Hz as the fundamental frequency, which is consistent with the theoretical result of 412 Hz. The fault features of FIMF2 are the clearest, and the first-order and second-order fault feature frequencies can be observed, which is consistent with the selection results of sensitive FIMFs based on the FBE analysis. Thus, the machinery fault feature extraction algorithm based on MFMD and FBE has high feasibility and accuracy.



(a) FBE analysis (b) Envelope spectrum analysis

Fig. 16 FBE and envelope spectrum analysis of FIMFs

4 Conclusions

In this paper, a rotating machinery fault diagnosis method based on MFMD and FBE was proposed, which was suitable for the early fault diagnosis of rolling bearings under conditions of multiple components and strong background noise. The main conclusions are as follows.

1) In terms of the problems such as long time consumption, poor accuracy, poor anti-noise performance, and over-decomposition of Fourier decomposition in searching for the frequency boundary in the whole frequency range, a sensitive frequency band selection method of fault features based on FBE and an MFMD algorithm based on the initial sensitive frequency interval were proposed. The simulation and experimental signal analysis results show that the effect of MFMD is better than that of FDM, wavelet transform, and EMD. It has high effectiveness and accuracy and is equipped with advantages of self-adaptability, locality, orthogonality, and completeness of Fourier decomposition.

2) In terms of the difficult selection of sensitive components, a selection method for sensitive FIMFs based on FBE and envelope spectrum analysis was proposed. Firstly, sensitive FIMFs were selected according to the similarity between the FBE distribution of FIMFs and the original signal near the natural frequency. Then, the fault features were extracted by envelope spectrum analysis. Finally, the selection of sensitive components was verified.

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基于改进傅里叶模态分解和频带熵的滚动轴承故障诊断方法

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摘　要:［目的］针对多分量、强背景噪声下滚动轴承故障特征提取困难的问题,提出一种将改进傅里叶模态分解(MFMD)和频带熵(FBE)分析相结合的滚动轴承故障特征提取方法。针对傅里叶分解(FDM)在强背景噪声下边界频率偏移和过分解等问题,提出频带熵和包络谱相结合的敏感频带和敏感模态分量选取方法。［方法］首先,通过FBE分析选取频带熵区域的极小值,将其作为敏感频带的中心频率并确定敏感频带边界;然后,在敏感频带区间内对信号进行带限傅里叶模态分解,从而获得若干个相互正交的傅里叶本征模态函数(FIMF)及其边际希尔伯特谱;其次,根据FIMFs与原信号频带熵的区域从属关系,选取可以反映故障特征的敏感FIMFs;最后,对所选取的FIMFs进行包络谱分析并提取故障特征。［结果］轴承仿真和实验结果表明,该方法可以实现轴承故障的精确诊断。［结论］研究成果可为滚动轴承的健康状态评估提供参考。

关键词: 滚动轴承; 故障诊断; 特征提取; 改进傅里叶模态分解; 频带熵