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AN IMPROVED FEATURE EXTRACTION METHOD FOR ROLLING BEARING FAULT DIAGNOSIS BASED ON MEMD AND PE

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ABSTRACT

The health condition of rolling bearing can directly influence to the efficiency and lifecycle of rotating machinery, thus monitoring and diagnosing the faults of rolling bearing is of great importance. Unfortunately, vibration signals of rolling bearing are usually overwhelmed by external noise, so the fault frequencies of rolling bearing cannot be readily obtained. In this paper, an improved feature extraction method called IMFs_PE, which combines the multivariate empirical mode decomposition with the permutation entropy, is proposed to extract fault frequencies from the noisy bearing vibration signals. First, the raw bearing vibration signals are filtered by an optimal band-pass filter determined by SK to remove the irrelative noise which is not in the same frequency band of fault frequencies. Then the filtered signals are processed by the IMFs_PE to get rid of the relative noise which is in the same frequency band of fault frequencies. Finally, a frequency domain condition indicator FFR(Fault Frequency Ratio), which measures the magnitude of fault frequencies in frequency domain, is calculated to compare the effectiveness of the feature extraction methods. The feature extraction method proposed in this paper has advantages of removing both irrelative noise and relative noise over other feature extraction methods. The effectiveness of the proposed method is validated by simulated and experimental bearing signals. And the results are shown that the proposed method outperforms other state of the art algorithms with regards to fault feature extraction of rolling bearing.

Keywords: Improved Feature Extraction Method; Rolling Bearing Fault Diagnosis; MEMD and PE

INTRODUCTION

Rolling bearing is widely used in electric power industry, petrochemical industry, military industry and so on. However, rolling bearing is vulnerable and frequently falls out of service for various reasons. Bearing failures may further result in fatal breakdowns or even huge amount of economic losses and casualties. According to the bearing statistical data, about 70% of the mechanical faults are caused by the vibration faults, whereas among the vibration faults, 30% are due to the rolling bearing's failure [1]. Therefore, it is imperative to monitor the work condition of the rolling bearing. Since vibration signal contains much information about machine health condition, fault diagnosis methods based on the vibration signal analysis are really prevalent in current literature. Recently, many signal processing methods to extract features from signals were proposed [2-5].

Rolling bearing is composed of rollers, outer races, inner races, as well as cages. The components of rolling bearing interact with each other to generate complex vibration signals. When the surface of one of these components develops a localized fault, the impacts, generated by other parts of rolling bearing periodically striking the damage spot, will excite bearing fault frequency. And the fault frequency will be further modulated by mechanical resonance of the whole mechanic structure [6]. Thus the measured signals from rolling bearing are usually have the characteristics of non-stationary and non-linear. Moreover, in the early stage of rolling bearing's failure, the information of defects in the measured vibration signals is weak and is usually concealed by large background noise and other structural vibrations. Hence, it is a big challenge to extract the fault frequencies from the raw bearing vibration signals [7].

The fault vibration signals of rolling bearing are usually in the form of amplitude modulation or frequency modulation. So lots of signal analysis methods which are based on either frequency domain or time-frequency domain have been proposed to extract fault frequencies from the measured signals. In frequency domain, the spectrum of the rolling bearing fault vibration signals is composed of fault frequencies and other mechanical noise frequencies. On this basis, the fault frequencies can be obtained from the spectrum of rolling bearing vibration signal. Then, Envelope analysis method, which is one of spectrum analysis methods was presented by McFadden et al [8] to solve the problem of signal modulation in time domain. However, envelope analysis method is decreasingly effective when the signal-to-noise ratio of the rolling bearing vibration signals decreases. To tackle this problems, some optimal frequency-band selection methods based on wavelet and wavelet package [9] have been proposed to complete the function of the band-pass filter and acquire the signals whose frequencies are among the resonance frequency of fault frequencies. However, in order to obtain good decomposition results, the mother wavelet needs to be chosen carefully to ensure that the content of daughter wavelets is similar to the analysed signals. To tackle the disadvantage of wavelet and wavelet package methods, the empirical mode decomposition(EMD) was emerged.

The ensemble empirical mode decomposition(EEMD) was as an improved algorithm of EMD and was put forward by Wu and Huang in 2009 [10]. Many signal analysis methods based on EMD or EEMD [11] have been proposed to decompose the modulation signals into a number of sub-signals, which are also named as intrinsic mode functions(IMFs). However, these methods mentioned previously only decompose the complex signals into a finite number of sub-signals, but they fail to identify the specific sub-signals that contain most of the defect information, especially when the original signals are overwhelmed by large noise.

Spectral kurtosis(SK) is a statistical tool to quantify the presence of transient peak and locate the transients in the frequency domain [12]. The SK algorithm can determine the central frequency and frequency band where the bearing fault frequencies reside. Hence, an optimal band-pass filter can be designed based on the SK algorithm to recover the higher signal-to-noise ratio bearing fault signal from the raw bearing fault signal. Whereas the main drawback of the SK algorithm is that, only the noise which is out of the resonance frequency band of fault frequencies can be removed.

Recently, permutation entropy(PE) has been proposed by Bandt and Pompe in 2002 [13],which serves as a statistical indicator of the time series' complexity. Since PE is sensitive to the signal mutation and can characterize the small intrinsic dynamic changes of signal, it is applied to assist extracting the faults of rolling bearing effectively [14] used the PE as a tool in status characterization of rolling bearing. They found that PE could detect and amplify the dynamic change of rolling bearing vibration signals.

In this paper, the SK algorithm is firstly applied to obtain the SOI signal, which contain mainly fault characteristics, and the residual signal which mainly contains noise. Then, the improved IMFs_PE method is used as a tool to recover the bearing fault signal of higher signal-to-noise ratio from the SOI signal. By using MEMD , a series of IMFs are obtained, which include noise, irrelevant components and the real bearing fault signal. Then, the reconstructed bearing fault signal is reconstructed from the IMFs through using the PE value as the criterion. Finally, obtain the fault frequencies by calculating the envelope spectrum of the reconstructed bearing fault signal, and verify the performance of the proposed method in this paper by comparing the FFR values of raw bearing signal and reconstructed bearing fault signal.

The structure of this paper is organized as follows: Section 1 is the introduction, it is mainly introduced the research background of this paper. In section 2, the theory of SK, MEMD and PE algorithms are introduced firstly. Furthermore, the procedure of the proposed feature extraction method based on MEMD and PE is described in detail. In section 3, the proposed method is validated by the simulation bearing signals and experimental bearing signals firstly. Then make comparisons of the proposed method in this paper with some other feature extraction methods to demonstrate the effectiveness of the proposed method. In section4, the conclusion and discussion are drawn.

METHOD

Kurtosis is sensitive to the singular signals and is often used to detect the abnormal responses in the rotating systems. However, kurtosis is a global statistical indicator and sensitive to the noise. To tackle the drawback of kurtosis, spectral kurtosis (SK) was proposed by Dwyer, which is a spectral descriptor. SK is used as a statistic tool for processing the non-stationary signal, it can not only detect the non-stationary components in the signals, but also locate the non-stationary components in the frequency domain. The principle of SK method is to calculate the kurtosis value of each frequency line and then find out the frequency band where the non-stationary characteristics exist, and the definition is explained below:

(1) Taking account of the Wold-Cramer decomposition of conditionally non-stationary process, any a non-stationary signal $x(t)$ can be expressed as $Y(t)$ in frequency domain.

$$Y(t) = \int_{-\infty}^{+\infty} e^{j2\pi ft} H(t,f) dX(f) \tag{1}$$

When $H(t,f)$ is the time-varying transfer function of the system, and it is also a complex envelope. $X(f)$ is the spectrum of the $x(t)$.

(2) Since conditionally non-stationary process has the statistical property of time-independent, 2n-order instantaneous variable $S_{2nY}(t,f)$ is defined to calculate the energy of the complex envelope at time t and frequency f:

$$S_{2nY}(t,f) \triangleq E\left\{\left|H(t,f)\right|^{2n} \mid \omega\right\} \Big/ df = \left|H(t,f)\right|^{2n} \cdot S_{2nX} \tag{2}$$

On the condition that the complex envelope $H(t,f)$ has the properties of stationarity and ergodicity, 2n-order instantaneous variable $S_{2nY}(t,f)$ can be also defined as:

$$S_{2nY}(f) = \left\langle S_{2nY}(t,f)\right\rangle_t \triangleq \lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{+T/2} S_{2nY}(t,f)dt \tag{3}$$

Where $\langle \bullet \rangle_t$ is the time-averaged operator.

(3) According to the definition above, the fourth-order spectral cumulant of conditionally non-stationary process $C_{4Y}(f)$ is defined as:

$$C_{4Y}(f) = S_{4Y}(f) - 2S_{2Y}^2(f) \tag{4}$$

(4) Finally, SK is generated by normalizing the fourth-order cumulant $C_{4Y}(f)$, namely the SK value is used to measure the peakiness of the probability density function of the conditionally non-stationary process at frequency f:

$$K_Y(f) \triangleq \frac{C_{4Y}(f)}{S_{2Y}^2(f)} = \frac{S_{4Y}(f)}{S_{2Y}^2(f)} - 2 \tag{5}$$

Antoni gave the further study of applying the SK to the vibratory surveillance and diagnostics of rotating machines after he gave the formal definition of SK in 2006. When a fault occurs in the rotating machine, the vibration signal of rotating machine usually has a periodic impulse-like repetitive nature. Since the SK algorithm has advantage of having a robust way of detecting and locating the periodic impulse-like signals even in the presence of large noise. The SK algorithm is used as a defect indicator to extract bearing fault signal out of the raw bearing signal overwhelming by large noise in this paper.

Empirical mode decomposition(EMD) is a fully data-driven method for multistate analysis of non-linear and non-stationary signals, so it is widely applied for signal analysis in time-frequency domain. The multivariate empirical mode decomposition (MEMD) algorithm is the extension of EMD for multivariate data, which was proposed by Rahman and Mandaic. MEMD method has the advantage of overcoming the mode alignment problem experienced with EMD by the joint analysis of multiple oscillatory components within a higher dimensional signal.

The detailed procedure of MEMD algorithm is summarized as follows:

(1) The input signal is $\{x(t)\}_{t=1}^{T} = \{x_1(t), x_2(t), \cdots, x_n(t)\}$, and $d^{\theta_k} = \{d_1^k, d_2^k, \cdots, d_n^k\}$ is projected vector according to the angle vector $\theta^k = \{\theta_1^k, \theta_2^k, \cdots, \theta_{n-1}^k\}$ on an $(n-1)$ sphere.

(2) According to the Hamersley sequence[4], an appropriate set of sampling points on $(n-1)$ sphere is obtained.

(3) Calculate a projection $\{p^{\theta_k}(t)\}_{t=1}^{T}$, which is the projection of the input signal $\{x(t)\}_{t=1}^{T}$ along the direction vector d^{θ_k}, for all k, giving $\{p^{\theta_k}(t)\}_{k=1}^{K}$ as the set of projections.

(4) Find all maxima of the set of projected signals $\{p^{\theta_k}(t)\}_{k=1}^{K}$ at time instants $\{t_i^{\theta_k}\}$. Then interpolate the sequences $\left[t_i^{\theta_k}, v(t_i^{\theta_k})\right]$ to obtain multivariate envelope curves $\{e^{\theta_k}(t)\}_{k=1}^{K}$. Finally, for a set of K direction vectors, calculate the mean $m(t)$ of the envelope curves as $m(t) = 1/K\sum_{k=1}^{K} e^{\theta_k}(t)$

(5) Extract the detail signal $d(t)$ by using $d(t) = x(t) - m(t)$. If the detail signal $d(t)$ fulfills the stop criterion for a multivariate IMF, apply the above (2) procedure to $x(t) - d(t)$, otherwise apply it to $d(t)$.

In this paper, MEMD is used as a tool for decomposing the filtered bearing vibration signal by SK through adding extra channels containing independent white noise. By using MEMD, a series of IMFs are obtained.

Permutation entropy (PE) is a statistical method for measuring the complexity and detecting the dynamic changes of one dimensional time series, which was first proposed by Bandt and Pompe in 2002. PE has the advantage of simple and fast calculation. Furthermore, Yan et al had applied PE for status characterization of rotating machine and demonstrated that PE had the advantage of effectively characterizing the working status of rotating machine.

PE was calculated by the comparison of neighboring values and its definition is given as follows.

(1) For a given time series $\{x(i), i = 1, 2, 3, \cdots, N\}$, according to the time delay τ and embedding dimension m, the $m-$ dimensional reconstructed matrix Y^m is defined as Eq. (6):

$$Y^m = \begin{bmatrix} Y(1) \\ \vdots \\ Y(j) \\ \vdots \\ Y(N-(m-1)\tau) \end{bmatrix} = \begin{bmatrix} x(1) & x(1+\tau) & \cdots & x(1+(m-1)\tau) \\ \vdots & \vdots & \vdots & \vdots \\ x(j) & x(j+\tau) & \cdots & x(j+(m-1)\tau) \\ \vdots & \vdots & \vdots & \vdots \\ x(N-(m-1)\tau) & x(N-(m-2)\tau) & \cdots & x(N) \end{bmatrix} \tag{6}$$

(2) Rearrange the reconstructed matrix Y^m, each row in matrix Y^m $Y(i) = \left(x(i) \quad x(i+\tau) \quad \cdots \quad x(i+(m-1)\tau)\right)$ is rearranged in an increasing order as in Eq. (7).

$$x(i+(j_1-1)\tau) \le x(i+(j_2-1)\tau) \le \cdots \le x(i+(j_m-1)\tau) \tag{7}$$

Where $j_1, j_2, \cdots, j_m$ refer to the index of column in matrix $Y(i)$. If there are two same values in $Y(i)$, for example, if $x(i+(j_1-1)\tau) = x(i+(j_2-1)\tau)$, then the order can be rearranged by the value of j_1 and j_2. That is to say, when j_1 is small than j_2, it can be rearranged as $x(i+(j_1-1)\tau) \le x(i+(j_2-1)\tau)$.

(3) After rearranging, each row $Y(j)$ of the matrix Y^m can be uniquely mapped into an ordinal permutation as Eq. (8).

$$S(l) = \left(j_1, j_2, \cdots, j_m\right) \tag{8}$$

Where $l = 1, 2, \cdots, K$, and $K \le m!$.

(4) It is clearly that there is $m!$ permutations for m dimensional delay vectors at most. And each $S(l)$ represents a permutation pattern. Assume that the probability distribution of each permutation pattern can be calculated with Eq. (9)

$$P_l = \frac{\{the \quad number \quad of \quad S(l)\}}{K} \tag{9}$$

Where $l = 1, 2, \cdots, K, K \le m!$.

(5) Finally the normalized permutation entropy is defined as Eq. (10):

$$0 \le H_p = \frac{-\sum_{i=1}^{K} P(l)\ln P(l)}{\ln(m!)} \le 1 \tag{10}$$

Thus H_p gives a complexity measure of a time series. The smaller the value of H_p, the more regular the time series is. Bandt and Pompe recommend that the value of m should be in the scope $m = 3, \cdots, 7$.

As known, fault information of rolling bearings is mostly reflected by singular points of abrupt changing signals and is usually non-stationary and non-linear. PE is effective to detect the dynamic changes of non-stationary and non-linear signals in complex systems . Moreover, the PE is insensitive to the noise. In this paper, the PE is used as the criterion to select the corresponding IMFs of bearing fault signal to reconstruct the high signal-to-noise ratio bearing fault signal. The procedure of calculating PE is described as follows: First, the raw data is partitioned into blocks of data subsets with length w, which may overlap each other or not. Then the embedding dimension m and the delay time τ are determined. Finally, the permutation entropy H_p is calculated for each data subset, so its change with time varying is obtained. In this paper, the parameters are chosen as: $w = 1024, m = 5, \quad = 1$. For more details about the parameter selection, refer to Yan and Zheng.

In the process of extracting the fault frequencies of rolling bearing vibration signals, there are two big challenges that we have to face. 1) the irrelevant interference which is not in the same frequency band of fault frequencies; 2) the relevant interference which is in the similar frequency band of fault frequencies. As for the irrelevant interference, since it has the property of the irrelevant interference having different frequency band range with the fault frequencies in frequency domain. Some time-frequency signal analysis methods have successfully removed the irrelevant interferences, such as SK, ,wavelet package transfer, EEMD and so on. And it has appeared large amount of excellent research achievements. However, there fewer research on solving the problem of getting rid of the relevant interferences except for blind source separation algorithm. On this basis, the IMFs_PE method in this paper is mainly aimed at removing the relevant interference. The improved feature extraction method based on the MEMD and PE in this paper take both irrelevant and relevant interferences into account. And it recover the bearing fault signal from the raw noisy bearing signal very well.

Before introducing the improved feature extraction method clearly, in order to validate the effectiveness of the proposed feature extraction method based on MEMD and PE quantitatively, the fault frequency ratio(FFR) is introduced firstly.

For a bearing fault signal $x(n)$, let $X(f) = F[x(n)]$, where F is the envelope spectral transform. Then the FFR is defined as:

$$FFR = \frac{\left|X(f_{fault})\right|}{\sum_{i=1}^{N}\left|X(f_i)\right|^2} \tag{11}$$

Where $\left|X(f_i)\right|$ is the modulus of $X(f_i)$, and f_{fault} is the fault characteristic frequency of the bearing fault signal.

In this paper, an improved feature extraction method applied to fault diagnosis of rolling bearing based on MEMD and PE is proposed, and the whole processing procedure is shown in Fig. 1. And the procedure of the proposed method is summarized as follows:

THE PROCEDURE OF FILTERING SIGNAL BY SK

Obtaining the central frequency f_c and bandwidth B_w by using the SK algorithm firstly. Then design the optimized band-pass filter and optimized band-stop filter according to the central frequency f_c and bandwidth B_w. Extracting the SOI signal by the optimized band-pass filter, and the SOI signal contains more of fault characteristics. Obtaining the residual signal by the corresponding band-stop filter. The procedure of filtering signal by SK is mainly to get rid of the irrelevant interference which is not in the same frequency band of the fault frequencies.

THE PROCEDURE OF PROCESSING SIGNAL BY MEMD AND PE

(a) Decompose the SOI signal by MEMD, and a series of IMFs are obtained;

(b) Calculate the PE value of each IMF to get PE_{IMFi}. Then calculating the PE value of the residual signal to get the $threshold\_B^*$ and the PE value of the normal bearing signal to get the $threshold\_A^*$;

(c) Reconstruct the bearing fault signal from the IMFs by comparing the PE value of each IMF PE_{IMFi} with threshold values $threshold\_A^*$ and $threshold\_B^*$, the IMF which fulfil the equation $PE_{IMFi} > threshold\_A^*$ *and*

$$\left|PE_{IMFi} - threshold\_B^*\right| is\max imum$$

is used to reconstructed the bearing fault signal. The procedure of processing signal by MEMD and PE is mainly to remove the relevant interference which is in the similar frequency band of the fault frequencies.

THE PROCEDURE OF EXTRACTING THE FAULT FREQUENCY

Calculate the spectral envelope of the reconstructed bearing fault signal, and then calculating the FFR value of the reconstructed bearing fault signal based on the spectral envelope.

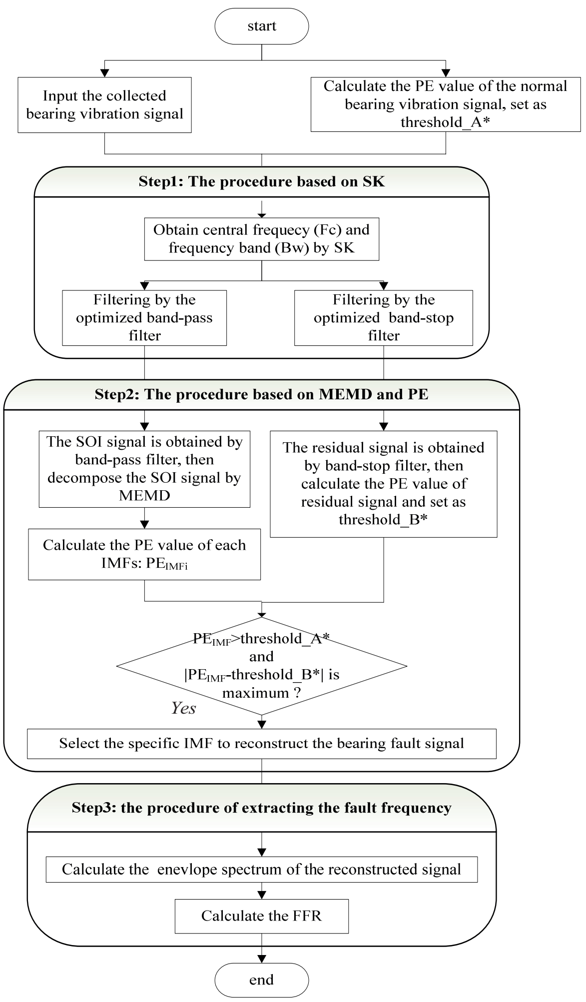


Fig. 1. The processing procedure of the proposed method

To verify the proposed feature extraction method in this paper, a simulated bearing fault signal is used to verify the correctness of the proposed method. According to the fault model of rolling bearing, the formula for inner fault model of rolling bearing under noise is defined as:

$$y(t) = [1 + Cx_{inner}(t)] * \cos(2\pi * f_z * t) + n(t) \quad (12)$$

Where f_z is the resonant frequency of the rolling bearing system, $n(t)$ is the noise, and $x_{inner}(t)$ is the inner fault signal, and the definition is as follows:

$$\begin{aligned} x_{inner}(t) &= A * [1 + B * \cos(2\pi * f_a * t)] \\ &* \cos(2\pi * n * f_i * t), n = 1, 2, \cdots \end{aligned} \quad (13)$$

Where f_a is the rotating frequency, and f_i is the inner fault frequency.

The simulated bearing inner signal is shown as Fig.2(a), it is clearly that the fault frequency is 106.2Hz, which agrees with the theoretical value. Then the simulated signal is processed by the proposed method in this paper, and the de-noised simulated signal is obtained and is shown in Fig.2(b). In the envelope of the de-noised simulated signal, the fault frequency 106.2Hz is well preserved and the interferences are suppressed effectively. In order to describe the result intuitively, FFR is calculated and the results are shown in Table 1.

According to the Table1, the FFR value of the simulated signal is 0.5245, while the FFR value of the De-noised simulated signal which is obtained by the proposed method in this paper is 0.6682. It has improvement of 27.3% according to the FFR value of the simulated signal. In a word, the improved feature extraction method based on MEMD and PE is effective in the feature extraction of the rolling bearing vibration signals.

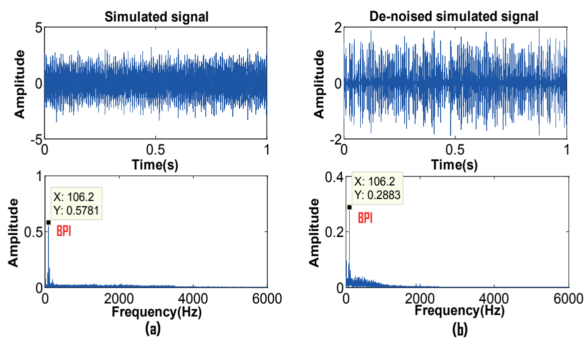


Fig. 2. The simulated inner fault signal; (a) The time domain and envelope spectrum of the simulated inner fault signal; (b) The time domain and envelope spectrum of the de-noised simulated signal which is obtained by the proposed method

Tab. 1. The FFR of inner fault simulated signal

Signal	FFR	$\triangle FFR$
Simulated signal	0.5245	27.3%
De-noised simulated signal	0.6682	

EXPERIMENT AND RESULT

All the bearing vibration signals analyzed in this paper are downloaded from the Case Western Reserve University (CWRU) Bearing Data Centre. As shown in Fig. 3, the test stand consists of a 2 horsepower, three-phase induction motor (left), a torque sensor (middle), a dynamometer (right) and a self-aligning coupling (middle). The type of the tested bearing used in the experiment is the deep groove ball bearings 6205-2RS JEM SKF, and the information of the tested bearing are shown in Table 2. Single pointe fault is arranged in the bearing by electric discharging machining (EDM) technique and the defect size is 0.007inch in diameter, 0.0011inch in depth. The sampling frequency is 12KHZ and the shaft rotating speed of the motor 1730rpm. Under this environment, the normal bearing signal (NORM), the inner race fault bearing signal (IRF), the outer race fault bearing signal (ORF) and the rolling element fault bearing signal (REF) are collected by using the accelerometers. The time-domain waveforms of the four kind signals are shown in Fig. 4. In Table 3, the fault characteristic frequency (defect frequency) of the inner race fault, outer race fault and rolling element fault are listed.

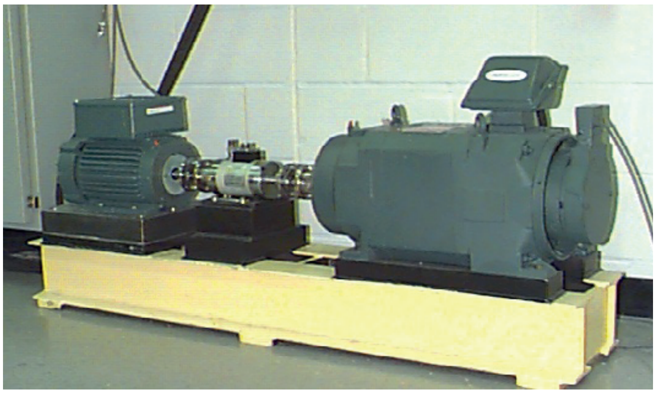


Fig. 3. The test stand of bearing

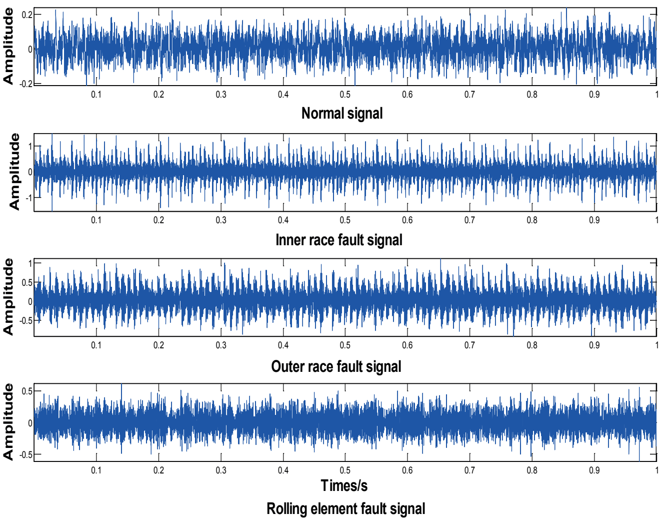


Fig. 4. NORM signal and IRF, ORF, REF fault signals

Tab. 2. The information of the tested bearings

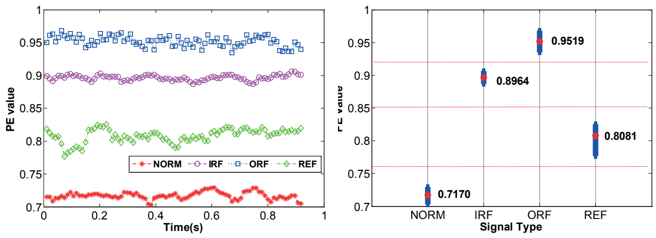
Inside Diameter (inch)	Outside Diameter (inch)	Thickness (inch)	Ball Diameter (inch)	Pitch Diameter (inch)	Number of Balls (inch)
0.9843	2.0472	0.5906	0.3126	1.537	9

Tab. 3. Characteristic frequency of the tested bearing

Characteristic frequency	Rotating speed r(RPM)	Equation	Value (Hz)
Defect on inner race (BPI)	1721	$BPI = \frac{r}{2} \bullet N$ $(1 + \frac{d}{D} \cos \alpha)$	155.3
Defect on outer race (BPO)	1725	$BPO = \frac{r}{2} \bullet N$ $(1 - \frac{d}{D} \cos \alpha)$	103.6
Defect on rolling element (BS)	1722	$BS = \frac{r}{2} \bullet \frac{D}{d}$ $(1 - \left(\frac{d}{D}\right)^2 \cos^2 \alpha)$	67.6

Where N is the number of balls, d is the ball diameter, D is the pitch diameter, and α is the contact angle.

In this paper, PE is used as a criterion to select the IMF components which contain more fault information in the bearing vibration signals. First of all, the PE of the NORM signal, IRF signal, ORF signal and REF signal are studied, and the result are shown in Fig.5.

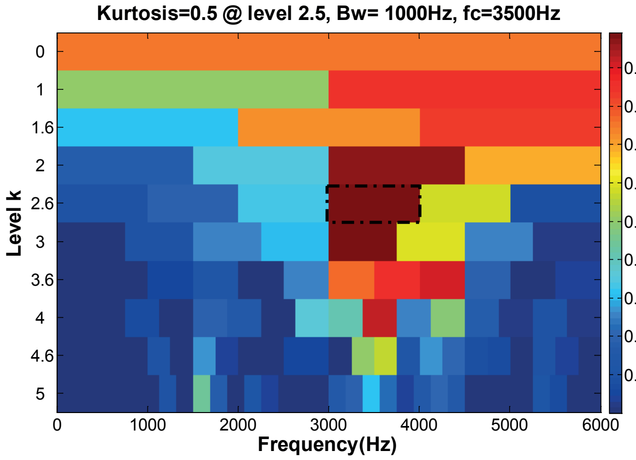


(a) (b)

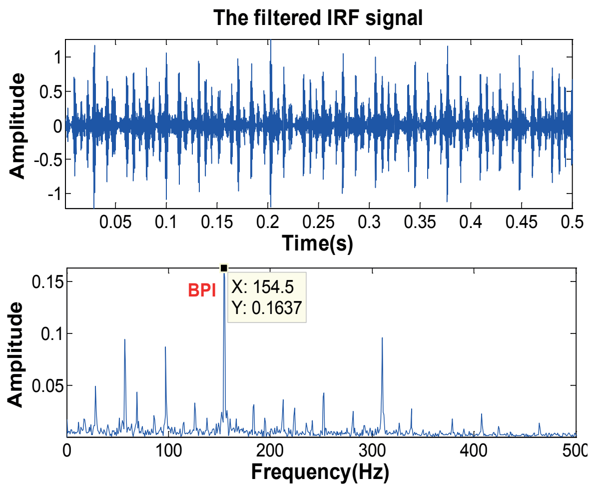
Fig. 5. The PE values of the NORM, IRF, ORF and REF signals;
(a) The PE value changes over time;
(b) The mean value and range of variation of the PE value

In Figure 5(a), it is clearly that the PE of NORM signal, IRF signal ORF signal and REF signal could be clearly separated. According to the theoretical analysis, when a localized fault occurs on the bearings, the measured bearing vibration signals will contain more internal modes and the value of PE will increase. This confirms the results in Fig.5(a). Namely, the PE values of bearing fault signals (IRF signal, ORF signal and REF signal) are higher than the PE value of normal bearing signal. The mean PE values of NORM signal, IRF signal ORF signal and REF signal are 0.7170, 0.8964, 0.9519 and 0.8081 respectively. In a word, PE is suitable to be used as a criterion for selecting the components which contain the information of the faults in rolling bearings to reconstruct the bearing fault signals.

After validating the effectiveness of the PE criterion, the analysis of the bearing fault signals (IRF signal, ORF signal and REF signal) by our proposed method are carried out. The first process of the process method is to remove the noise from the raw bearing vibration signals by using the SK method. The results of filtered signals by SK are shown in Figs. 6–8. In Figs. 6-8, the x-axis is limited to the range of 0-500Hz so that the characteristic frequencies can be observed clearly. In Fig. 6(a), the maximum kurtosis of the IRF signal is 0.5, as shown in the red dash-line rectangle. The central frequency and band width is 3500Hz and 1000Hz, respectively. Based on the central frequency and band width, the optimal band-pass filter is designed. The filtered IRF signal and its envelope spectrum are shown in Fig. 6(b). It is clearly that the fault characteristic is well reserved in the filtered IRF signal. The same analysis process for ORF and REF signals and the results are shown in Figs. 7-8, and the fault characteristic frequencies are also well preserved in the filtered signals which obtained by the SK method.

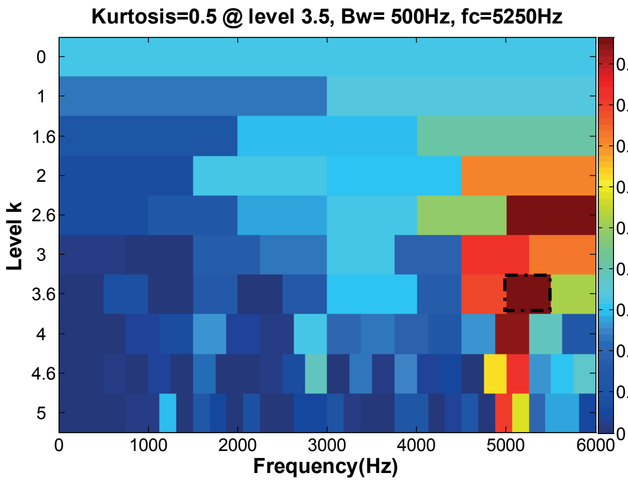


(a)

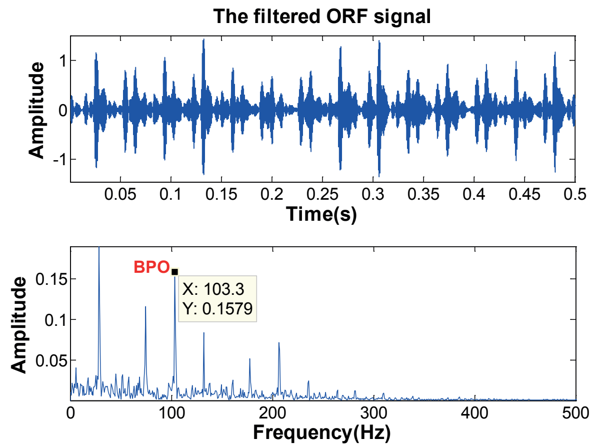


(b)

Fig. 6. The results of IRF signal by SK. (a) The 2-D SK of IRF; (b) The filtered IRF and its envelope spectrum



(a)



(b)

Fig. 7. The results of ORF signal by SK. (a) The 2-D SK of ORF; (b) The filtered ORF and its envelope spectrum

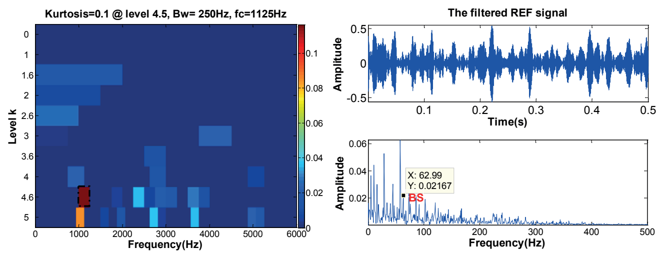


Fig. 8. The results of REF signal by SK. (a) The 2-D SK of REF; (b) The filtered REF and its envelope spectrum

After obtaining the filtered bearing fault signals through SK, MEMD and PE are further used to recover the bearing fault signals. Firstly, IMFs are obtained by decomposing the filtered bearing fault signals through MEMD. Then calculate the PE of each IMF and choose the specific IMF which contain the fault information to reconstruct the bearing fault signals by comparing the PE value of each IMF with the threshold values. Figures 9 shows the MEMD decomposition results of the filtered bearing fault vibration signals.

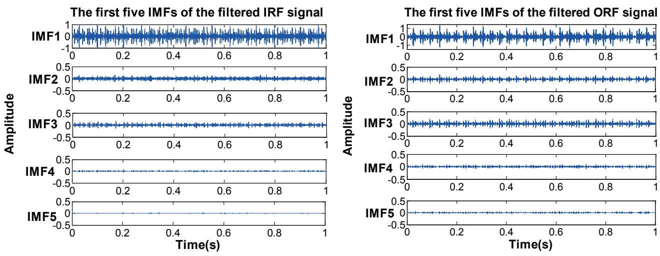


Fig. 9. The first five IMFs of the filtered IRF, ORF and REF signals; (a) The first five IMFs of filtered IRF signal; (b) The first five IMFs of filtered ORF signal; (c) The first five IMFs of filtered REF signal

The PE of the first five IMFs of filtered IRF signal, filtered ORF signal and filtered REF signal are listed in Tables 4–6. Besides, the threshold values of PE of the corresponding residual signal and NORM signal are also listed in Tables 4-6.

Tab. 4. The PE valued of the first five IMFs of filtered IRF Signal, residual IRF signal and NORM signal

	PE		
	Filtered IRF signal	residual IRF signal	NORM signal
IMF1	0.798	0.826	0.717
IMF2	0.846		
IMF3	0.611		
IMF4	0.431		
IMF5	0.319		

Tab. 5. The PE values of the first five IMFs of filtered ORF signal, residual ORF signal and NORM signal

	PE		
	Filtered ORF fault signal	residual ORF signal	NORM signal
IMF1	0.70	0.899	0.717
IMF2	0.91		
IMF3	0.606		
IMF4	0.479		
IMF5	0.53		

Tab. 6. The PE values of the first five IMFs of filtered REF Signal, residual REF signal and NORM signal

	PE		
	Filtered REF fault signal	Residual REF signal	NORM signal
IMF1	0.876	0.801	0.717
IMF2	0.508		
IMF3	0.482		
IMF4	0.357		
IMF5	0.265		

According to the procedure of the improved feature extraction method based on MEMD and PE mentioned in Fig.1, the reconstructed bearing fault signal is composed of the specific IMF which fulfills the conditions $PE_{IMFi} > threshold\_A^*$ and $\left|PE_{IMFi} - threshold\_B^*\right| is \max imum$. Table 4 shows the PE value of the first five IMFs of filtered IRF signal, the residual IRF signal and the NORM signal, the $threshold\_A^*$ is 0.717, $threshold\_B^*$ is 0.801, and the PE values of the first IMFs of the filtered IRF signal are 0.798, 0.8466, 0.611, 0.431 and 0.319 respectively. Therefore, the reconstructed IRF bearing fault signal is the IMF2 of the filtered IRF signal. Applying the same analysis process to the ORF signal and REF signal, so the reconstructed ORF bearing fault signal is the IMF2 of the filtered ORF signal, and the reconstructed REF bearing fault signal is the IMF1 of the filtered REF signal. Finally, the reconstructed bearing fault signals of IRF, ORF and REF and their envelope spectrums are shown in Fig.10. It is clearly that the characteristic frequencies are well reserved in the reconstructed bearing fault signals.

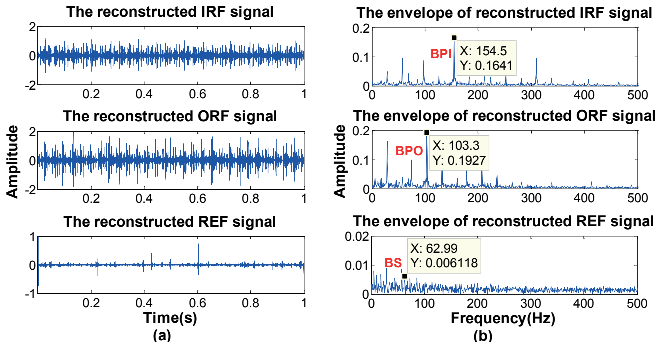


Fig. 10. The reconstructed signals and their envelope spectrums

In Table 7, the FFR of the raw bearing vibration signals, filtered bearing vibration signals and reconstructed bearing vibration signals are shown. It is obviously that, the FFR value of reconstructed signals (reconstructed IRF signal, reconstructed ORF signal and reconstructed REF signal) are higher than the FFR value of raw signals (IRF signal, ORF signal and REF signal). Therefore, it is distinct that the improved collaborative method based on MEMD and PE is effective to extract the fault characteristics of the rolling bearings.

Tab. 7. The FFR values of the raw signals, filtered signals and reconstructed signals

FER / Fault category	Raw signal	Filtered signal	Reconstructed signal
Inner race fault(IRF)	0.91	1.27	1.91
Outer race fault(ORF)	1.64	1.92	2.93
Rolling element fault(REF)	0.56	2.07	7.23

According to the results in Table 8, as for the inner race fault, outer race fault and rolling element fault, the proposed method in this paper has improvement of 6.8%, 7.9% and 5.9% respectively compared with the method proposed by Guo et al, and 15.1%, 14.6% and 12.3% respectively compared with the method proposed by Wu et al. Therefore, it is distinct that, our improved collaborative method based on MEMD and PE is more effective to recover bearing fault signals from noisy raw signal, and also the fault characteristic frequencies are amplified in the reconstructed bearing fault signals.

CONCLUSION

In this paper, an improved feature extraction method for rolling bearing fault diagnosis based on MEMD and PE was proposed to extract the bearing fault features from the noisy bearing vibration signal. The proposed method solves two big problems. (1) To get rid of the irrelevant interferences of the fault frequencies by filtering the signal by optimal band-pass filter which determined by SK algorithm; (2) Combine the MEMD and PE algorithms, a novel method to get rid of the relevant interferences of the fault frequencies is put forward. Then, the proposed method is validated by the simulated signals and real bearing vibration signals. Further, some comparisons of the proposed method with the other feature extraction methods proposed in recent three years are done, and it further prove that our proposed method has better performance in the feature extraction of rolling bearing signals.

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