# Coupling Fault Feature Extraction Method Based on Bivariate Empirical Mode Decomposition and Full Spectrum for Rotating Machinery

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**ABSTRACT:** To accurately extract the fault characteristics of vibration signals of rotating machinery is of great significance to the unit online monitoring and evaluation. However, because the current feature extraction methods are mainly for single channel, the results of feature extraction are often inaccurate. To this end, a coupling fault feature extraction method based on bivariate empirical mode decomposition (BEMD) and full spectrum is proposed for rotating machinery. Firstly, the two-dimensional orthogonal signal obtained by orthogonal sampling technique is decomposed by bivariate empirical mode decomposition to obtain the intrinsic mode function with phase information. In order to obtain the sensitive modal components, the sensitivity coefficients are constructed on the basis of mutual information. Then, calculate the sensitivity coefficient of each intrinsic mode function, and the intrinsic mode function with the larger sensitive coefficient is selected as the sensitive component. Finally, the full spectrum of the sensitive component is obtained by using the full vector envelope technique, so as to get a comprehensive and accurate characteristic component. The results of simulations experiment and an application example show that this method can extract the fault characteristic component of the rotating machinery comprehensively and accurately. It is of great significance to realize the accurate diagnosis of coupling faults of rotating machinery.

**KEY WORDS：** Rotating machinery; Bivariate empirical mode decomposition (BEMD); Full spectrum; Mutual information; Coupling fault; Feature extraction

## 1. Introduction

Rotating machinery is one of the key parts of large mechanical equipment, such as hydraulic turbine, steam turbine and wind turbine, which have found wide application in various industrial fields [1]. Due to the influence of load, damping, friction and other factors, the rotating machinery usually exhibits complex dynamic behavior, which is related to non-stationarity and nonlinearity [2]. And the vibration signals of rotating machinery often show coupling. In order to ensure the safe and reliable operation of the equipment, the equipment condition monitoring and fault diagnosis technology needs to have higher precision. Whether it can accurately extract the characteristic signal of coupling fault is the key to the condition monitoring and fault diagnosis of rotating machinery [3, 4].

At present, many scholars have done some research on the feature extraction of rotating machinery fault signal, especially in the matter of signal processing methods. The main methods are wavelet transform (WT) [5, 6], Hilbert-Huang transform, empirical mode decomposition (EMD) [7, 8] and variational mode decomposition (VMD) [9, 10] and so on, and the characteristic of different fault feature extraction method as shown in Tab.1. Wavelet transform is the improvement of the Fourier transform, has a certain ability to deal with nonlinear signals. But its essence is the inner product principle characteristic waveform signal decomposition based on basis function, exists the choice problem for basis functions, and the different vibration will show the characteristics of different waveforms [11, 12]. Therefore, the adaptive ability of wavelet transform is poor. EMD has strong adaptability and good local analysis ability, and has been widely used in the field of fault diagnosis. However, the EMD method is lack of rigorous theoretical basis, and there is a serious phenomenon of modal aliasing in the decomposition process [13, 14]. Variational mode decomposition (VMD) is a new adaptive signal decomposition method, which has a solid theoretical foundation, and can solve the problem of mode mixing in EMD, but there are parameter optimization problems in VMD [15].

However, due to the complex mechanism of the fault of rotating machinery, and the vibration signal is often nonlinear, the vibration signals in different directions may represent different fault characteristic information [16]. Through single channel signal feature extraction and fault diagnosis, it often leads to misjudgment and omission [17, 18]. Therefore, it is more accurate to collect the signal of multiple channels, and through the effective information fusion. Therefore, taking into account the rotating machinery generally has two sensors in horizontal and vertical directions, this paper utilize bivariate empirical mode decomposition (BEMD) to decompose the signal collected from two directions.

In 2007, bivariate empirical mode decomposition (BEMD) was firstly introduced by Gabriel Rilling et al [19]. It is not limited to single direction processing of real valued signals, and it can analyze complex signals consisting of two orthogonal directions contained phase information and synchronization [20,21].

**Tab.1 The characteristic of different fault feature extraction method**

| method | characteristic |
| --- | --- |
| WT | Exists the choice problem for basis functions and the different vibration will show the characteristics of different waveforms |
| EMD | Lack of rigorous theoretical basis and there is a serious phenomenon of modal aliasing in the decomposition process. |
| VMD | Solve the problem of mode mixing in EMD, but there are parameter optimization problems in VMD. |
| BEMD | This method can detect synchronous features contained in the two-dimensional signal and comprehensively extract the information of fault signal. |

M.D.Khadmul, Islam Molla, et al. [22] applied bivariate empirical mode decomposition to decompose complex climate signals into simple components and then combined with the classical FFT spectrum to clearly observe the climate change. Then R. Court et al [23] used bivariate empirical mode decomposition of the wind generator state detection, which can overcome the one-dimensional EMD information cannot be fusion defects, more accurately, the wind turbine generator non-stationary vibration signal more powerful processing results, getting good effect.

The joint information between different sensors such as phase information and synchronization is of significance for rotating machinery condition to evaluate [24]. The signal obtained from multiple sensors is evaluated to contribute to the effective extraction of fault information, so it has received increasing attention in the past years. Okatan A et al. [25]

uses the normalized matrix of the spectral norm to propose the new Calman filter, and proposes a sensor information fusion Calman filter test method, which improves the fusion accuracy. Liu X F et al.[26] proposed a fuzzy fault measurement method and a fuzzy integral information fusion method for rotating machinery. By using multiple classifiers, fuzzy measures and fuzzy integral theory, the diagnosis results are fused and the final diagnosis results are obtained. The full spectrum is a fault diagnosis method based on homologous information fusion technology, which can acquire more comprehensive fault characteristics and reveal the direction of the vibration relative to the direction of the vibration of rotating machinery [27, 28].

In this paper, we proposed a coupling fault feature extraction method based on bivariate empirical mode decomposition and full spectrum for rotating machinery. In order to suppress noise interference in the signal component, the sensitivity coefficients are constructed on the basis of mutual information, and through the sensitive coefficient to extract unique IMFs of the signal. The specific arrangement of this paper is organized as follows. A review on bivariate empirical mode decomposition (BEMD) is illustrated in sections 2. Section 3 describes the sensitive feature extraction based on mutual information. Sections 4 give brief introductions of full spectrum. Section 5 describes the coupling fault feature extraction method based on BEMD and full spectrum. Section 6 applies the proposed method to both simulated data and experimental data obtained from the turbine guide bearing. Conclusions come in Section 7.

## 2. Bivariate Empirical Mode Decomposition

The essence of bivariate empirical mode decomposition (BEMD) is to decompose a two-dimensional signal adaptively into intrinsic mode components with physical meaning. The modal component obtained from the decomposition is a series of single component signals from high frequency to low frequency in two directions. This paper takes the algorithm II in [19] to perform BEMD. For a two-dimensional signal $x(t)$, the basic decomposition process is as follows.

Step 1: Determine the direction of projection $\varphi_k = 2k\pi/N$, where $1 \le k \le N$.

Step 2: The two-dimensional signal $x(t)$ is projected onto the $\phi_k$.

$$p_{\varphi_k}(t) = \mathrm{Re}(e^{-\varphi_k} x(t)) \tag{1}$$

Step 3: Extract the corresponding moment for the local maximum of X $\{t_j^k\}$, then the set $\{t_j^k, e^{i\varphi_k} p_j^k\}$ is interpolated. Get the maximum envelope $e'_{\varphi_k}(t)$ in the direction $\varphi_k$.

Step 4: Calculate the mean of the maximum envelope $e'_{\varphi_k}(t)$ in each direction.

$$m(t) = \frac{2}{N}\sum_{k=1}^{N} e'_{\varphi_k}(t) \tag{2}$$

Step 5: Similar to the EMD decomposition process, the residual component is calculated:

$$S(t) = x(t) - m(t) \tag{3}$$

Determine whether the $S(t)$ meets the requirements of IMF. If satisfied, proceed to step 6, if not, repeat step 2-6. Until $S(t)$ satisfies the conditions of the intrinsic mode function IMF.

Step 6: Record the resulting IMF and remove it from the original signal. And get IMF1 as: $c_1(t) = h(t)$, residual component as:

$$r_1(t) = x(t) - c_1(t) \tag{4}$$

Step 7: Repeat the above steps until you get all the IMFs. The original signal can be expressed as:

$$x(t)=\sum_{k=1}^{K}c_k(t)+r_K(t) \tag{5}$$

Where, $K$ represents the total number of IMFs.

## 3. Sensitive feature extraction based on mutual information

3.1 Mutual information

Mutual information can measure the degree of interdependence between the two variables, which means that the information content is shared between the two variables [29, 30]. Given two random variables X and Y, calculate their respective marginal probability distribution and joint probability distribution $p(x)$、 $p(y)$ and $p(x,y)$. The mutual information between them is:

$$MI(x,y)=\sum_x\sum_y p(x,y)\log\frac{p(x,y)}{p(x)p(y)} \tag{6}$$

3.2 Sensitivity coefficient based on mutual information

The IMFs can be obtained by bivariate empirical mode decomposition (BEMD) the fault vibration signals, and obtain the intrinsic mode functions (IMFs). However, not all the IMFs are important to the evaluate condition of machinery ratoting, so it is of significant to select the sensitive IMFs [31]. Firstly, orthogonal sampling technique is used to collect the vibration signals in the normal and fault state, which are recorded as $x_z(t)$ and $x(t)$. Then the fault vibration signal $x(t)$ is decomposed by BEMD. Get modal component IMFs. $c_1(t)$、 …、 $c_n(t)$.

1) According to the formula (6), the mutual information $MI_i$ between the intrinsic mode components IMF $c_i(t)$ $(i=1,2,\cdots,n)$ and the fault vibration signals $x(t)$ is calculated. And do the normalization as follows.

$$a_i=MI_i/\max(MI_i) \tag{7}$$

2) Calculate the mutual information $MI_i'$ between the intrinsic mode components IMF $c_i(t)$ $(i=1,2,\cdots,n)$ and the normal vibration signals $x_z(t)$. The same normalization is done as follows.

$$b_i=MI_i'/\max(MI_i') \tag{8}$$

3) Calculate the sensitivity coefficient of each modal component IMFs as follows:

$$\lambda_i=a_i/b_i \tag{9}$$

Where, $a_i$ , represent the mutual information between the nth IMFs and their original signals. $b_i$, represent the mutual information between the nth IMFs and the normal signals. In order to make the component better reflect the characteristics of the original signal, $a_i$ should be as large as possible. In order to better monitor the characteristics of the fault signals, $b_i$ should be as small as possible. Considering the characteristics of the early fault signal of rotating machinery, the amplitude of the signal is smaller, and the mutual information between the IMFs and the original signal is relatively small. Therefore, this paper reflects the change of signal characteristic components by increasing the multiple relations**.** That is to say, the higher the $\lambda_i$ value, the more sensitive the IMF.

## 4. Full spectrum theory

There are usually two vertical sensors in the same section of the rotor for rotating machinery to extract vibration information. The full spectrum can fuse the vibration signals of each other in vertical direction, and comprehensively express the intensity and spectrum structure of the rotor vibration [32, 33].

The core idea of the full spectrum: rotating machinery emerges whirling phenomena under the combination of harmonic frequencies. The whirling trajectory is a series of ellipses. The length of the long axis of the ellipse is defined as the principal vibration vector to evaluate vibration intensity. The length of the short axis of the ellipse is defined as the auxiliary vector to evaluate vibration intensity as auxiliary. And through the whirling intensity under the harmonic frequency of rotor, the rotating machinery fault is diagnosed and identified [34].

Set X, Y direction of the data sequence are $\tilde{x}$ and $\tilde{y}$. They can constitute the complex sequence $\tilde{z} = \tilde{x} + i\tilde{y}$. Carry on the Fourier transform for the complex sequence $\tilde{z}$, and get the Frequency domain complex signal $\tilde{Z}$.

$$\tilde{Z} = \tilde{X} + i\tilde{Y} = \mathrm{Re}(Z) + \mathrm{Im}(Z) \qquad (10)$$

The length of the long axis of the ellipse $R_{ai}$ is defined as the main vibration vector.

$$R_{ai} = \frac{1}{2N}\left[|Z_i| + |Z_{N-i}|\right] \qquad (11)$$

The length of the short axis of the ellipse $R_{bi}$ is defined as vice vibration vector.

$$R_{bi} = \frac{1}{2N}\left[|Z_i| - |Z_{N-i}|\right] \qquad (12)$$

$\alpha_i$ is the angle between the main vibration vector and the X axis.

$$\tan 2\alpha_i = \frac{\mathrm{Im}\,Z_i\,\mathrm{Re}\,Z_{N-i} - \mathrm{Re}\,Z_i\,\mathrm{Im}\,Z_{N-i}}{\mathrm{Re}\,Z_i\,\mathrm{Im}\,Z_{N-i} - \mathrm{Im}\,Z_i\,\mathrm{Re}\,Z_{N-i}} \qquad (13)$$

$\phi_i$ is the initial phase angle of the elliptic trajectory at this frequency. According to the property of Fourier transform in the following as (Details of the derivation of the literature [28]):

$$\tan\phi_i = \frac{\mathrm{Im}\,Z_i + \mathrm{Im}\,Z_{N-i}}{\mathrm{Re}\,Z_i + \mathrm{Re}\,Z_{N-i}} \qquad (14)$$

Where, $i = 1, 2, \cdots, N/2 - 1$

Therefore, utilize Fourier transform through the data sequence of the two channels, obtain the characteristic information of each harmonic trajectory which full spectrum required, complex calculated under harmonic is simplified as a simple calculation between complex Fourier parameters. Not only greatly reduce the amount of calculation, but also very robust, in addition, and established a contact with the conventional analysis method. When the information source is a single source, the algorithm is still established, fully meet the requirements of real-time detection and analysis.

## 5. Coupling fault feature extraction method based on BEMD and full spectrum

Owing to the complexity, coupling and uncertainty of rotating machinery faults, the intrinsic dynamic characteristics of the faults are more complicated. The external manifestation is that the vibration signals in different directions may indicate different characteristic information, and the single-channel signal characteristics diagnosis for rotary machinery is prone to misjudgment and leakage judgment. And BEMD and full spectrum have advantages in the processing of two dimensional signals and information fusion. Therefore, this paper proposes a new coupling fault feature extraction method based on BEMD and full spectrum for rotating machinery. To select the sensitive IMF, use the sensitivity coefficient based on mutual information as the screening criteria. The extraction process of this method is shown in Fig 1. Specific steps are as follows:

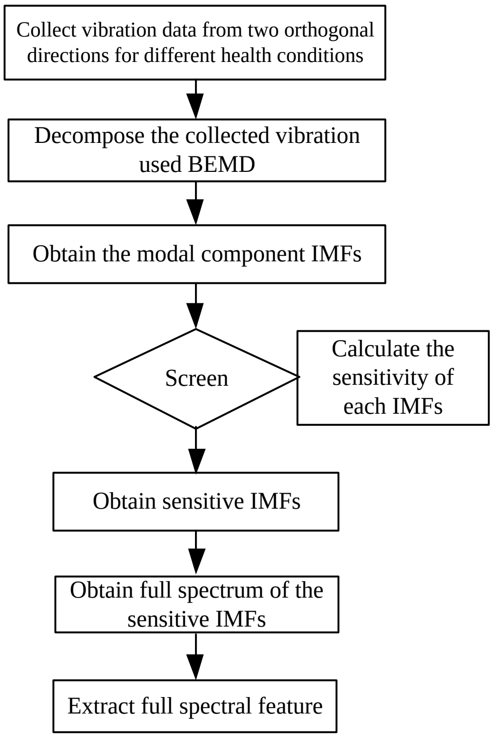



Fig. 1 Flow chart of the proposed method

Step 1: Collect the orthogonal vibration signal of the rotating machine in the normal and fault condition by the sensor.

Step 2: The orthogonal fault vibration signal is decomposed by BEMD to obtain K intrinsic mode components $c_k(k=1,2,\cdots,K)$.

Step 3: Calculate the sensitivity of each modal component IMFs.

Step 4: Select the modal component IMFs with the larger sensitive coefficient as sensitive modal components IMFs.

Step 5: Full spectrum analysis of the selected modal components IMFs is carried out to detect the characteristic frequency of coupling fault signals.

## 6. Experiment results

6.1 Simulation experiment

There are two common phenomena that a change in amplitude at the typical frequency [35] and a new frequency appearance [36] when rotating machinery fault. In this paper, the vibration signal of the hydropower unit bearing is simulated. Suppose that the rotating frequency of hydropower unit is $f_0$ , It is considered that the vibration fault signal of the actual hydroelectric generating set often contains $f_0$, $2f_0$, $3f_0$, 50Hz, 100Hz and some common characteristic signals and noise. In order to make the simulation result more fitting with the actual situation and verify the effectiveness of the proposed method, this paper in the processing of two-dimensional signals, simulate the normal and fault signals of the hydropower unit to verify. The specific simulation vibration signal is as follows.

$$x_z = 8\sin(\omega t) + 5\sin(5\omega t) + 3\sin(100\pi t) + 2rand(1,N)$$

$$y_z = 8\cos(\omega t) + 5\cos(5\omega t) + 3\cos(100\pi t) + 2rand(1,N)$$

$$x = 8\sin(\omega t) + 5\sin(5\omega t) + 5\sin(100\pi t) + 2rand(1,N) + 5\sin(2\omega t)$$

$$y = 8\cos(\omega t) + 5\cos(5\omega t) + 5\cos(100\pi t) + 2rand(1,N) + 5\cos(2\omega t)$$

Where, the $x_z$ and $y_z$ are used to simulate the normal signals, which are composed of a rotating component at a frequency of $f_0$ with amplitude of 8, a rotating component at a frequency of $5f_0$ with amplitude of 5, a rotating component at a frequency of 50Hz with amplitude of 3 and the noise generated randomly with amplitude of 2. Each component of the normal vibration signal is shown in Fig.2(a). Fig.2(a) separately represent the rotating component at a frequency of $f_0$, $5f_0$, 50Hz and the noise generated randomly in turn.

The $x$ and $y$ are used to simulate the fault signals, which not only are composed components of the normal signal, but also have the rotating component at a frequency of $2f_0$ with amplitude of 5 and the rotating component at a frequency of 50Hz with increased amplitude of 2. Each component of the fault vibration signal shown in Fig.2(b). And Fig.2(b) separately represent the rotating component at a frequency of $f_0$, $5f_0$, 50Hz ,the noise generated randomly and the rotating component at a frequency of $2f_0$ in turn.

Where $\omega$ represents the angular velocity, in actual hydroelectric generating set, the rated speed is 107.1r/min, the sampling frequency is

227Hz and the sampling point is 1024. Considering the consistency with the actual operation of hydropower units and the simplicity of simulation, it can be assumed that the unit speed is 107r/min, sampling frequency is 250Hz, and sampling point N is 1000. The normal and the fault raw signal is shown in Figure 3, followed are from the normal signal of the X direction to the normal signal of the Y direction to the fault signal of the X direction and to the fault signal of the Y direction.

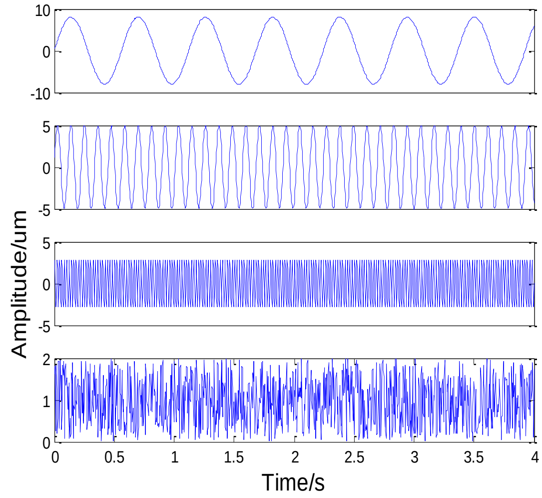
The proposed method is used to extract the feature of the simulation signal in figure 3. Firstly, the orthogonal fault raw signal is decomposed by BEMD, and the results are shown in figure 4. Where the blue curve represents the real part and the black one represents the imaginary part of the decomposition results by BEMD. Then calculate the sensitivity coefficient of each IMF, as shown in table 2.

**Tab.2 Sensitivity coefficient of each characteristic component**

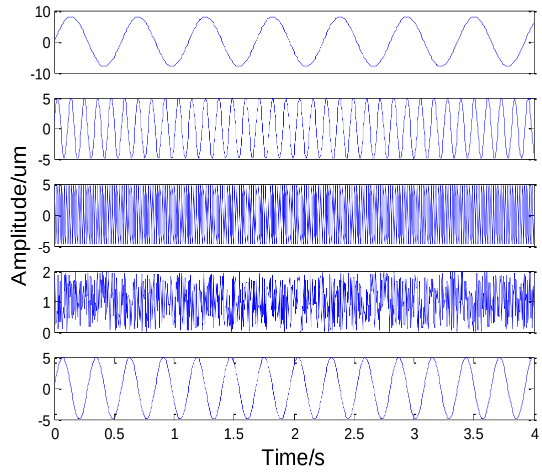
| IMF | IMF1 | IMF2 | IMF3 | IMF4 | IMF5 |
|---|---|---|---|---|---|
| Sensitivity coefficient | **2.881** | 0.693 | **1.078** | 0.767 | 0.654 |

The IMF1 and IMF3, whose sensitivity coefficient is greater than 1, are selected as sensitive IMFs. Utilize the full vector envelope technique to fuse the sensitive IMFs are selected, and obtain full spectrum of the sensitive IMFs. As shown in Fig. 5.

Based on the full spectrum of the sensitive IMFs in Fig.5, this method proposed in the paper can fuse the orthogonal signals in two directions. And it can accurately detect the new frequency appearance at a frequency of $5f_0$ and the change in amplitude at the typical frequency of 50Hz. Obviously, the method has strong compatibility and effectiveness.




(a) Component of normal vibration signal




(b) Components of fault vibration signal

Fig.2 Components of normal and fault vibration signal

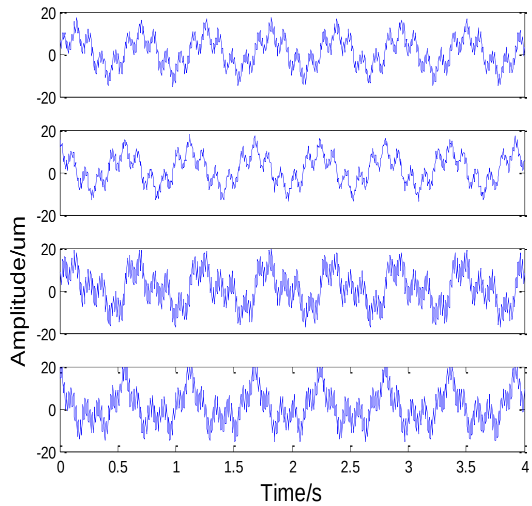



Fig.3 Observation signal of normal and faulty

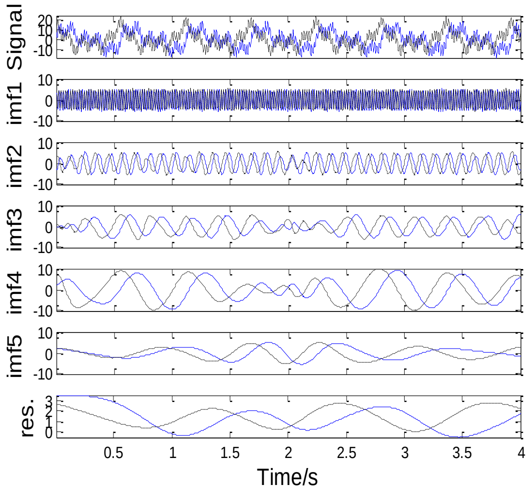



Fig.4 Results of BEMD decomposition for fault signal

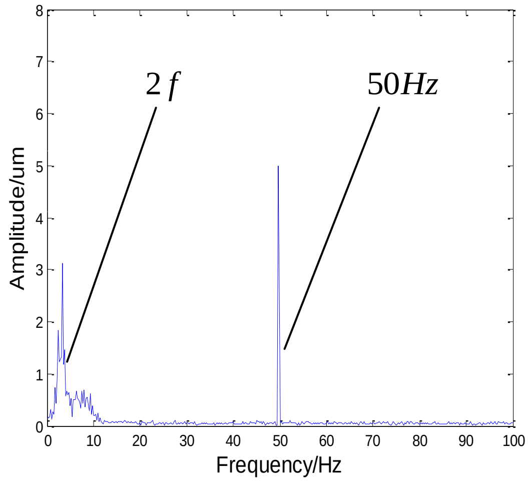



Fig.5 Full spectrum of sensitive IMFs

### 6.2 Coupling fault feature extraction of turbine guide bearing

To verify the effectiveness of proposed method in coupling fault feature extraction for rotating machinery, the experimental studies on a hydroelectric turbine in upper reaches of Yellow River are conducted. The experimental signals are acquired from the prototype of hydroelectric turbine with 5 blades and 16 guide vanes, the maximum water head is 25.7m, the rated head is 16m, and the rated power of the turbine is about 49 MW and the rated speed is 107.1r/min (1.79Hz). Figure 6 describes specific layout of measuring points of pressure fluctuation signals in the turbine [37].

The measured data are collected turbine guide bearing by the vibration and throw monitoring sensors turbine guide bearing (As shown in Fig.6), which are from horizontal and vertical direction. Randomly select a segment of signal from normal and fault condition to verify the effectiveness of proposed method, as shown in Fig.7. From top to bottom: the normal signal of the X direction, the normal signal of the Y direction, the fault signal of the X direction and the fault signal of the Y direction. Where, the sampling frequency is 227 Hz and the sampling point M is 1024. Under the same load, the fault raw data is collected when the unit is abnormal.

Using the method proposed in this paper to extract the Coupling fault feature of turbine guide bearing. Firstly, the fault signal is decomposed by

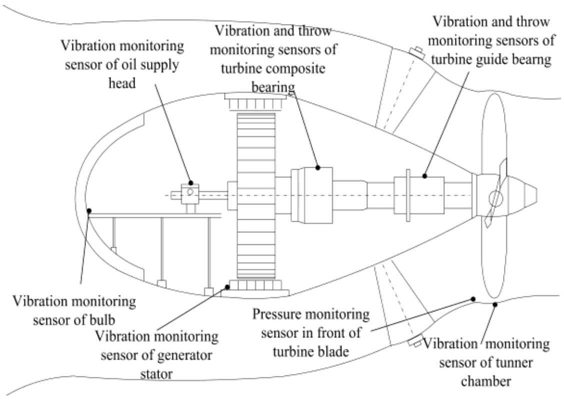



Fig.6 Specific layout of measuring point in hydroelectric turbine

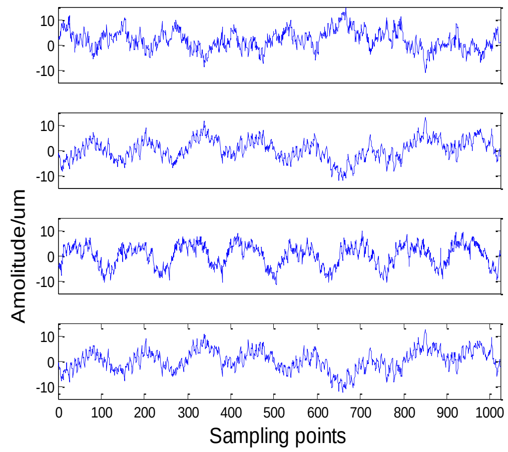



Fig.7 Raw vibration data of normal and fault signals

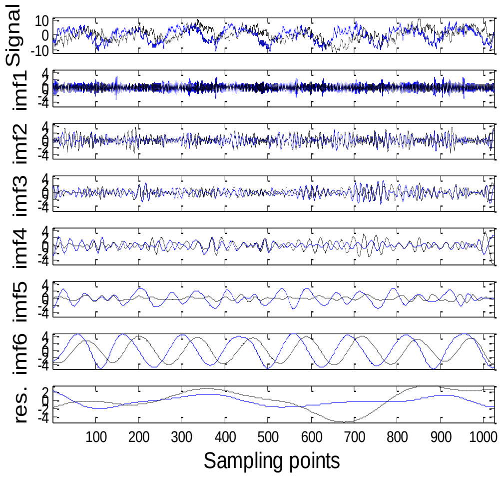



Fig.8 BEMD decomposition results of measured fault signal

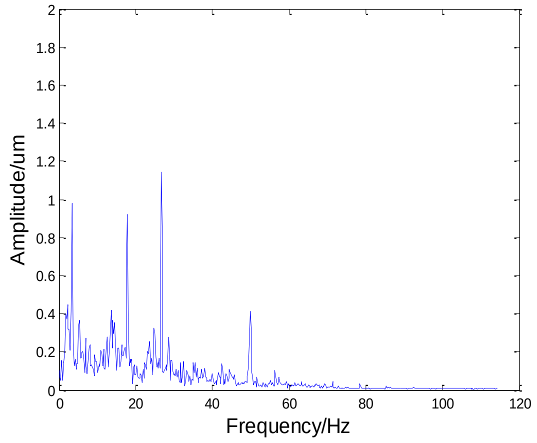
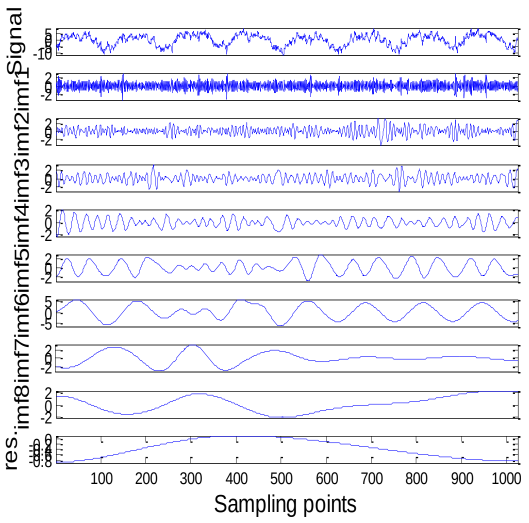
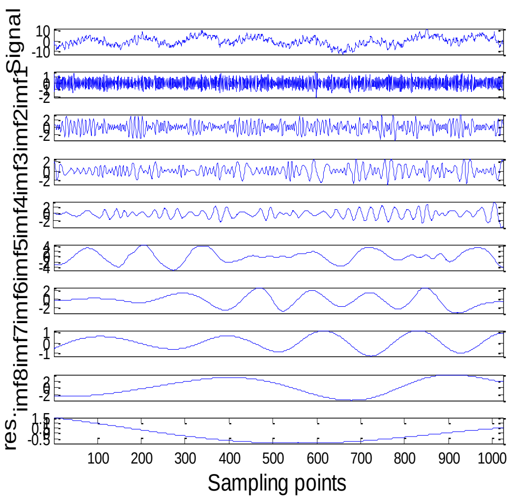



Fig.10 Full vector envelope spectrum of BEMD




(a) The decomposition results of real fault signal




(b) The decomposition results of imaginary part fault signal

Fig.9 EMD decomposition results of real and imaginary part of measured fault signal

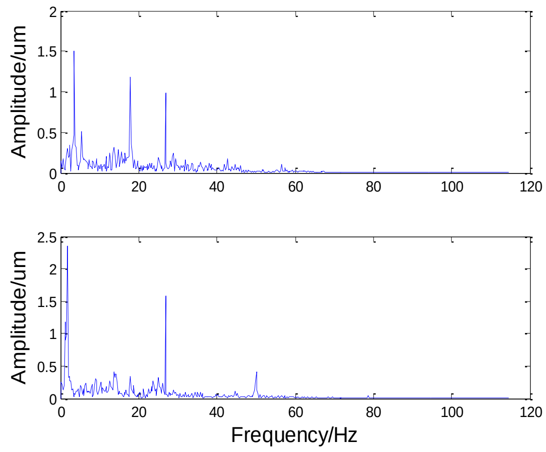



Fig.11 Spectrum of EMD decomposition sensitive component

decomposition sensitive component

BEMD, the results of the decomposition are shown in Fig 8 (where the blue represents the real part and the black represents the imaginary part). As shown in figure 8, the BEMD decomposition can effectively preserve the phase information of the orthogonal two-dimensional signal, and the decomposition results have good synchronization. In order to illustrate the advantages of BEMD, the real and imaginary parts of the fault signal are separately decomposed by EMD, the results are shown in Fig.9. Obviously, when utilize EMD to decompose the orthogonal two-dimensional signal, the phase information contained in the orthogonal signal lost. In addition, compared to the decomposition results of BEMD, the decomposition component of EMD is too much, that is the phenomenon of over decomposition.

On the basis of BEMD decomposition, the sensitivity coefficients of each IMFs are calculated, as shown in Table 3. And select the sensitive coefficient of large IMF2, IMF3 and IMF5 as the sensitive component IMFs. Then utilize the full vector envelope technique to fuse the sensitive IMFs are selected, and obtain the full spectrum of the sensitive IMFs. As shown in Fig. 10. Obtain the decomposition results of EMD to compare with the decomposition results of BEMD as shown in Fig 11. Calculate the sensitivity coefficients of the IMFs obtained by EMD in two directions, as shown in table 4. In the IMFs of the real part, IMF2, IMF3 and IMF6 with the larger sensitivity coefficient are selected as the sensitive IMFs, and In the IMFs of the imaginary part, IMF2, IMF4 and IMF5 with the larger sensitivity coefficient are selected as the sensitive IMFs. The frequency spectrum analysis of the sensitivity coefficient in each direction is carried out. The frequency spectrum of the EMD sensitive IMFs is shown in figure 11 (where, the upper part represents the real part and the lower part represents the imaginary part of the decomposition results by BEMD).

Tab.3 **Sensitivity coefficients of BEMD modal components**

| IMFs | IMF1 | IMF2 | IMF3 | IMF4 | IMF5 |
|---|---|---|---|---|---|
| Sensitivity coefficient | 0.661 | **1.043** | **1.172** | 0.564 | **0.984** |

Tab.4 **Sensitivity coefficients of EMD modal components**

| IMFs | IMF1 | IMF2 | IMF3 | IMF4 | IMF5 |
|---|---|---|---|---|---|
| Real part | 0.831 | **1.634** | **1.875** | 0.73 | 0.455 |
| Imaginary part | 0.76 | **2.292** | 0.877 | **1.12** | **1.853** |
| IMFs | IMF6 | IMF7 | IMF8 | IMF9 | |
| Real part | **1.344** | 0.495 | 0.393 | 0.543 | |
| Imaginary part | 0.742 | 0.436 | 0.874 | 0.432 | |

It can be seen from Fig.11 that the vibration signal (real part) in the horizontal direction can be divided into $2f_0$, a small number of the 3 frequency $3f_0$ and $15f_0$. But the vibration signal in the vertical direction (imaginary part) contains $1f_0$, $15f_0$. And the small 50Hz vibration signal. Thus, the vibration signal due to a certain interference, the results of the extraction of the two directions are different, which often brings trouble to feature extraction. Compared with this, the method proposed in this paper can solve the problem of the inconsistency between the two channels. As shown in the Fig.10, this method can better fuse the information in two orthogonal directions of vibration signal. This method has good compatibility, which can be more comprehensive and accurate to detect the vibration signal in the rotating machinery, and the feature extraction results are more reliable.

## 7. conclusions

This paper proposed a method to extract a feature from orthogonal signals in two directions sensors for the condition monitoring of rotating machinery based on bivariate empirical mode decomposition (BEMD) and full spectrum.

BEMD is employed to decompose signals from two orthogonal sources together, thus a complicated rotation can be represented by a set of simpler rotation components. BEMD is proved to outperform standard EMD for two orthogonal signals, because the intrinsic mode functions (IMFs) derived by BEMD preserve the signal phase information, and detect synchronous features contained in the two-dimensional signal. And effectively solve the problem of misjudgment and leakage judgment in extract feature method by single-channel signal for rotary machinery. Thus the comparison of IMFs for different health conditions is made reasonable and easy.

A criterion based on mutual information is proposed for selecting the most sensitive IMF.

The definition of this standard is to better represent the IMF of the original signal and penalize IMFs that cannot distinguish between different health conditions. Therefore, the IMF selected always ensures that it retains unique information about a particular health condition.

The performance of proposed method has been evaluated of the hydroelectric turbine in upper reaches of Yellow River. Experiments results verified the effectiveness of the proposed method in two orthogonal directions fault feature extraction and fault diagnosis for rotating machinery.

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