Research of Dimensionless Index for Fault Diagnosis Positioning based on EMD

Qinghua Zhang [1] Guangchang Zhao[1,2] Lei Shu[1*]
Aisong Qin[1] Yu Zhang[3]

[1] Guangdong Provincial Key Laboratory of Petrochemical Equipment Fault Diagnosis, Guangdong University of Petrochemical Technology
Maoming Guangdong 525000, China
{qinghua.zhang, guangchang.zhao, lei.shu, aisong.qin}@live.cn
[2] School of Information Engineering, Taiyuan University of Technology
Taiyuan 030024, China
zhaogc6315@163.com
[3] School of Engineering, University of Lincoln
Lincoln, LN6 7TS, U.K.
YZhang@lincoln.ac.uk

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Abstract. Dimensionless index as a new theory tool has been applied in fault diagnosis study, which has shown some progress, however, it will cause some interference to the diagnosis results since no considering the influence of other noise jamming signal is given. Empirical Mode Decomposition (EMD) technique could extract effectively the fault characteristic signal of vibration data. In view of the noise jamming of dimensionless index in analyzing data, dimensionless index processing algorithms based on EMD is proposed. Firstly, EMD method is used to decompose the collected vibration signals, then the first few Intrinsic Mode Functions (IMF) components are obtained which contains the fault characteristic of vibration data, and the effects of other noise signal are removed at the same time. Secondly, fault diagnosis can be achieved by calculating dimensionless parameter values to the IMF components with characteristic signal of vibration data, and obtaining range of characteristic value of their dimensionless index, then diagnosing and analyzing fault characteristics of the equipment. The proposed method is applied to fault diagnosis test analysis of rotating machinery, and the experiment has shown that the proposed method is efficient and effective.

Keywords: Dimensionless index, characteristic signal, fault diagnosis, empirical mode decomposition

1 Introduction

Domestic and international economic started in industrial production, at beginning industrial production depends mainly on manpower to complete, which hinders social production and adverse to the development of the economy. With the development of the society, to satisfy the requirement of the national production, automation machinery arises at the historic moment. The application of automatic mechanical equipment on the production line to greatly expand the production, also make people's living condition better and better. The normal operation of machinery equipment in the process of production, not only relates to the business and personal economic situation, but also has a direct correlation with the national economic lifelines. Besides, the healthy operation of machinery also has a great relationship with staff's personal safety, such as a small screw falls off rotating machinery equipment will result in mechanical movement breaking away from the equipment, causing the personal injury. Fig. 1 and Fig. 2 respectively give frequently used Multi-Fault diagnosis rotating machinery test bed and Industrial units normal and fault fittings in the laboratory. Therefore, the fault diagnosis of mechanical equipment has an important significance.

People currently have some mature diagnostic methods for the fault of mid-term and late-term in the rotating mechanical equipment of rolling bearings. The process of rotating machinery fault diagnosis [1] in the general is shown in Fig. 3, which is divided into four steps: The first step is the information collection of equipment running status; the second step is the extraction of fault feature; the third step is pattern recognition and fault diagnosis; the fourth step is the diagnostic decision. These are the main research problems in the machinery fault diagnosis, in which the second step is the most important and difficult in the diagnostic procedure. This is mainly due to the rotating machinery vibration signals commonly are the complex non-stationary signals [5]. The time-frequency domain characteristics of non-stationary signals can be analysed to determine whether the rotating machinery has the fault characteristics, and then the type of device fault can be determined. So whether it can accurately extract the fault characteristics of the device can be directly related to the accuracy and reliability of machinery and equipment for fault detection and diagnosis. However, the fault feature extraction has a close relationship with the modern signal processing techniques. So we need to further improve the mechanical fault diagnosis theory and develop new method for extraction of fault feature information, which seems to have become a critical research in the rotating machinery fault diagnosis field.

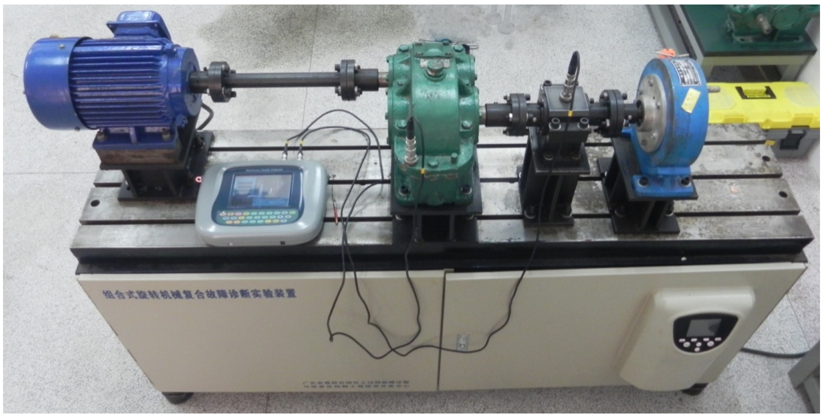

Fig. 1. Multi-Fault diagnosis rotating machinery test bed

Fig. 2. Industrial units normal and fault fittings

2 Background Knowledge

2.1 Dimensional Index

Fault diagnosis based on dimensional index analysis generally started studying from the time domain. It contains four kinds of forms: two of which were reflected by the form of the square root and the average amplitude, the other two are the peak value and the root mean square value. If the random process x(t) accords with the smooth process, then set x is the amplitude, p(x) is the probability density function of the amplitude. Thus we think x(t) is the frequency falling into $x \le x(t) \le x + \Delta x$ range in the observation time *t*. The dimensional index can be defined as follows [2], [3]:

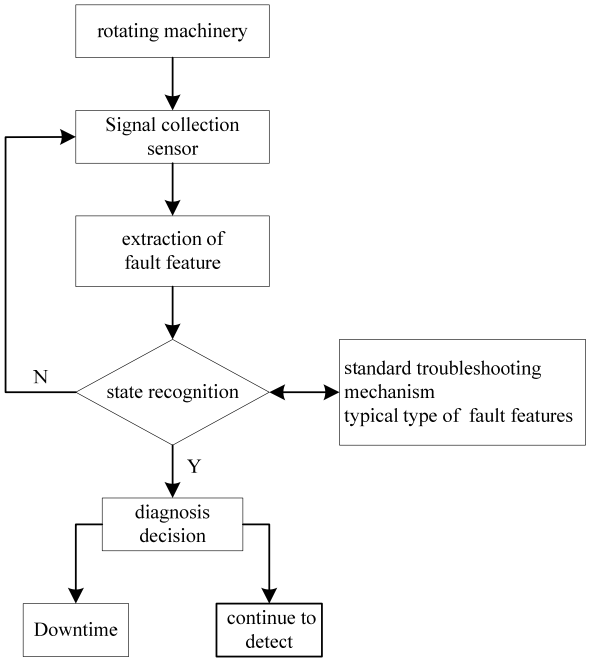

Fig. 3. Flowchart of rotating machinery fault diagnosis

$$x_d = \left[\int_{-\infty}^{+\infty} |x|^l p(x) dx \right]^{\frac{1}{l}} \quad \textbf{(1)}$$

When $l = \frac{1}{2}$,
$$X_r = [\int_{-\infty}^{+\infty} \sqrt{|x|} p(x) dx]^2 \quad \textbf{(2)}$$

When $l = 1$,
$$\overline{X} = \int_{-\infty}^{+\infty} |x| p(x) dx \quad \textbf{(3)}$$

When $l = 2$,
$$X_{rms} = \sqrt{\int_{-\infty}^{+\infty} x^2 p(x) dx} \quad \textbf{(4)}$$

When $l \to \infty$,
$$X_p = \lim_{l \to \infty} \left[\int_{-\infty}^{+\infty} |x|^l p(x) dx \right]^{\frac{1}{l}} \quad \textbf{(5)}$$

where X_r is the square root amplitude, $\overline{X}$ is the average amplitude, X_{rms} is the root mean square value, X_p is the peak value.

All of the above values are dimensional index, where T is the recording time, the graphical representation of the above four kinds of dimensional index is shown in Fig. 4.

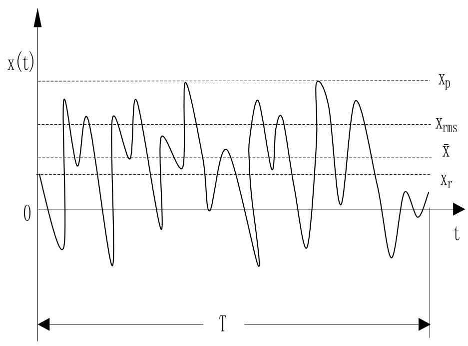

Fig. 4. Dimensional indicators

General fault diagnosis methods are diagnosis analysis methods based on dimensional index. The size of the dimensional parameter values is directly proportional to the severity of the fault, but it is affected easily by environmental and working conditions. Such indicators often cannot recognize the normal state and the fault condition in the field application [3]. In view of deficiency of dimensional index, we use the dimensionless index to diagnose the fault. The following section will introduce the dimensionless index in detail.

2.2 Dimensionless Index

2.2.1 The definition of Dimensionless Index

Dimensionless index are the ratio of two-dimensional index. The dimensionless index has a characteristic which is sensitive to the mechanical equipment failure but not sensitive to the signal amplitude and frequency, which has little relationship with the condition of the machine running. It only depends on the shape of the probability density function curve, which is good device diagnostic parameters [4]. Generally, the dimensionless parameters are defined as follows:

According to

$$\zeta_x = \frac{\left[\int_{-\infty}^{+\infty} |x|^l \, p(x)dx\right]^{\frac{1}{l}}}{\left[\int_{-\infty}^{+\infty} |x|^m \, p(x)dx\right]^{\frac{1}{m}}} \tag{6}$$

In the above formula: x denotes the vibration amplitude, and $p(x)$ denotes the probability density function of vibration amplitude.

According to the different l and m, you can get different dimensionless indicator [5]:

If $l = 2, m = 1$ get waveform indicator

$$S_f = \frac{\left[\int_{-\infty}^{+\infty} |x|^2 \, p(x)dx\right]^{\frac{1}{2}}}{\left[\int_{-\infty}^{+\infty} |x| \, p(x)dx\right]} = \frac{X_{rms}}{|\overline{X}|} \tag{7}$$

If $l \to \infty, m = 1$ get pulse indicator

$$I_f = \frac{\lim\limits_{x\to\infty}\left[\int_{-\infty}^{+\infty} |x|^l \, p(x)dx\right]^{\frac{1}{l}}}{\left[\int_{-\infty}^{+\infty} |x| \, p(x)dx\right]} = \frac{X_{\max}}{|\overline{X}|} \tag{8}$$

If $l \to \infty, m = \frac{1}{2}$ get margin indicator

$$CL_f = \frac{\lim\limits_{x\to\infty}\left[\int_{-\infty}^{+\infty} |x|^l \, p(x)dx\right]^{\frac{1}{l}}}{\left[\int_{-\infty}^{+\infty} |x|^{\frac{1}{2}} \, p(x)dx\right]^2} = \frac{X_{\max}}{X_r} \tag{9}$$

If $l \to \infty, m = 2$ get peak indicators

$$C_f = \frac{\lim\limits_{x\to\infty}\left[\int_{-\infty}^{+\infty} |x|^l \, p(x)dx\right]^{\frac{1}{l}}}{\left[\int_{-\infty}^{+\infty} |x|^2 \, p(x)dx\right]^{\frac{1}{2}}} = \frac{X_{\max}}{X_{rms}} \tag{10}$$

In addition, also get kurtosis indicators [5]

$$K_v = \frac{\beta}{\left\{\left[\int_{-\infty}^{+\infty} |x|^{\frac{1}{2}} p(x)dx\right]^{\frac{1}{2}}\right\}^4} = \frac{\beta}{X_{rms}^4} \quad \textbf{(11)}$$

From the formula (11), β is the kurtosis, $\beta = \int_{-\infty}^{+\infty} x^4 p(x)dx$

From the above, we can obtain

$$I_f = C_f \times S_f = \frac{X_p}{X_{rms}} \times \frac{X_{rms}}{\overline{X}} = \frac{X_p}{\overline{X}} \quad \textbf{(12)}$$

Moreover, it represents different dimensionless index when l and m have different value.

2.2.2 The Advantages of Dimensionless Index

Computing the dimensionless index ξ_y of signal $y = ax$, according to the definition of the dimensionless index type

$$\xi_y = \frac{\left[\int_{-\infty}^{\infty} |y|^l p(y)dy\right]^{1/l}}{\left[\int_{-\infty}^{\infty} |y|^m p(y)dy\right]^{1/m}} = \frac{\left[a^l \int_{-\infty}^{\infty} |x|^l p(ax)d(ax)\right]^{1/l}}{\left[a^m \int_{-\infty}^{\infty} |x|^m p(ax)d(ax)\right]^{1/m}} = \xi_x \quad \textbf{(13)}$$

where $p(ax) = \frac{1}{a} p(x), d(ax) = adx$

That is to say, dimensionless index does not vary with the changes in the amplitude of the random process, which is not affected by changes in working conditions, but only be sensitive to the change in the shape of the probability density function $p(x)$. The advantages of dimensionless index is summarized as follows: 1) complete with the ability to reflect the characteristics of the fault; 2) almost independent of the absolute level of vibration signal; and 3) there are different sensitivities for different types of fault; and 4) insensitive to the composite concurrent fault; 5) not affected basically by the conditions, load, speed and other changes. So a large number of scholars are attracted to dimensionless index just proposed, and getting a certain application in some areas. But most of them were confined to researches on dimensionless analysis of original data, without further processing, which can lead to bring other interfering signal in the calculation of the dimensionless indicators, resulting in the error of the dimensionless index, influencing the analysis result.

3 Related Work

The early fault diagnosis technology is mostly based on dimensional analysis research [6], such as the analysis of the square root amplitude, the average amplitude, the root mean square value and the peak value. But these indicators are susceptible to the influence of mechanical load and speed. Currently, there are plenty of fault diagnosis methods based on roller bearing. For example, Sun et al. combined discrete wavelet transforming with envelopment analysis and applied it in the roller bearing fault diagnosis [7]; Qin et al. proposed a method of rolling bearing fault diagnosis based on high density wavelet transforming and envelope spectrum for the recognition problem of rolling weak signals [8]; Xue et al. used the Hilbert envelope power spectrum and M distance function to analyze the rolling bearing failure [9]; Fu proposed the fast wavelet filter bank decomposition method used the envelope spectrum to process the signals and applied in the rolling bearing fault diagnosis for the traditional combination of wavelet envelope analysis [10]; Lu combined the support vector machine with window functions and applied it the fault diagnosis of rolling bearing [11]; Hu et al. introduced the STFT into vibration signal demodulation analysis of rolling bearing and determined the best band of the band-pass filter according to the kurtosis values of different bands of the demodulated signal [12]; Shi proposed an improved method based on continuous wavelet transforming and spectral kurtosis analysis and applied it in the fault diagnosis of rolling bearing, and confirming the truth of its efficiency [13].

Dimensionless index is not sensitive to changes of amplitude and frequency and is not related to the machine movement condition, which only depends on the shape of the probability density function [14], so a hot wave of dimensionless index research is raised in a period of time. Many scholars apply dimensionless index to analyze the fault feature based on the mentioned characteristics of dimensionless index. However, this analysis has not taken into account the preprocessing of the sampling vibration data, which adopts the method of calculating directly the dimensionless index data. These methods will bring other interfering signals such as noise influencing the final analysis result in the calculation of dimensionless index [15]. The EMD technique has a certain advantage in dealing with nonlinear and non-stationary signals [16], and can separate the characteristic signal of the vibration data, eliminating the influence of other interfering signal. In recent years, many scholars are trying to use the decomposition approach of empirical mode to diagnosis the fault of rolling bearings. Cai et al. improved a fault feature extraction method of rolling envelope spectrum based on EMD and spectral kurtosis for the defects of characteristic of roller bearing fault vibration signal modulation and traditional envelope analysis method [17]. Zhang et al. proposed a bearing fault diagnosis method based on EMD and singular value of the differential spectrum for the failure of bearing vibration signal with a strong background noise, which is difficult to extract the reality of failure frequency [18]. Zhou et al. used the demodulation method based on EMD and adaptive morphological filtering to separate the fault information of rolling bearing and extract the fault feature frequency [19]. Cheng et al. introduced the empirical mode decomposition and partial Hilbert energy spectrum into the rolling bearing fault diagnosis [20]. Luo et al. proposed a demodulation method based on multi-scale morphology of EMD combining the decomposition method of EMD signals with multi-scale morphology demodulation. These methods enrich the application of EMD in fault diagnosis [21]. Therefore, this research work has the following theoretical and practical contributions.

1) The paper proposes first the dimensionless index troubleshooting localization algorithm based on EMD, and makes the use of EMD to preprocess vibration data, then obtains the dimensionless index value of new data, which can be further analyzed and explains this algorithm outperforms the existing algorithms from the perspective of theory;

2) In practical, the paper has made a deep study on the feature extraction method which is based on the vibration signal processing in the background of strong noise, and explored the intelligent diagnosis methods to the bearing fault with the latest achievements in the field of non-dimensional index. These researches can give help to increase the efficiency of fault feature extraction, the robustness and efficiency of diagnosis, which can improve the fault diagnosis level of mechanical equipment. Finally, this paper applied the proposed analysis algorithm on fault diagnosis of rotating machinery and the experimental results have validated the feasibility and effectiveness of the proposed method.

4 Dimensionless Index Analysis Based on EMD Decomposition

4.1 EMD Technique

Hilbert transform demodulation methods are employed to gain the instantaneous characteristics, such as single-component signal, instantaneous frequency and instantaneous amplitude, et al. [22]. But the measured signals usually contain many components, including stationary signals, transient signals, linear signals, and nonlinear signals. Then we need to process the unstable and nonlinear signals, these signals are decomposed into a large number of intrinsic mode functions by EMD technique, and then analyzing the characteristics of the functions, we will obtain the instantaneous characteristics of the signals.

EMD technique can obtain the global and local information of the signals, especially when dealing with a local signal, it can make the local information clearer, and play the role of a magnifying glass. The collected vibration signals are decomposed into several (intrinsic mode function) IMF components [23] by EMD technique, including high frequency information and low frequency information in these components. But we often deal with some high frequency information when analyzing fault status, because fault information of some equipment is often hidden in the high frequency information, such as bearing fault information. In fact, we often take into account the frequency and the surrounding environment when collecting the signal before processing the signal. Thus we will preferably consider various factors when using technology methods to deal with signals, and can grasp comprehensive data information.

EMD technique has certain advantages to remove the noise and other interference signals, such as Cheng [24] applies EMD technique to decompose the collected rotor signals, removing the noise signals and excluding the interference of signals themselves at the same time, only retaining the useful fault signals, and has verified that the EMD technique can remove effectively noise signals by rub-impact fault diagnosis test. Therefore, EMD technique can be applied to the field that need to remove noise of the original data, in which way, the noise signal of data needs to be removed in advance, and then the data can be analyzed and processed only including fault characteristic signal by other techniques.

4.2 Dimensionless Index Analysis Based on EMD

4.2.1 Existing Dimensionless Index Methods of Fault Feature Extraction

Currently, the method uses the dimensionless index to extract fault feature by the test, and groups the continuous samples online and computes each dimensionless parameter index when different fault occurs. Then the average of each group of indicators is calculated and the average value of each index is taken as each fault characteristic parameter. There are two common comparison methods [25].

Method 1: It is determined that it has some faults as the average value is same, otherwise there is no fault.

Method 2: Using the threshold comparison method (or cluster comparison method), and defining the minimum allowable misalignment value of feature value and the detected value as a threshold value (the threshold value is a distance function). If the misalignment value is less than the threshold value, we can judge that there has been a fault. If the misalignment value is greater than the threshold value, we can determine that the fault does not occur. The form of the algorithm is described as follows,

$$Y = \mu(\delta - \sqrt{(l-k)^2}) \tag{14}$$

where Y is the fault variable, when $Y = 0$, it represents non-fault, when $Y = 1$, it represents fault.

δ represents threshold;

l represents element values of fault feature extracted from dimensionless index;

k represents element values of fault feature (template value) from dimensionless index which is tested accurately;

$\mu(x)$ represents the unit step function, $x < 0,\ \ \mu(x) = 0$; $x \ge 0,\ \ \mu(x) = 1$.

The above methods can determine whether there is a fault and the fault type and receive certain diagnostic results, especially the second method is more reasonable. But these methods make the average value of the dimensionless index as a model value. In practical, the first method determine whether there is a fault by comparing the sample value with the detected value to the real-time line, because the measurement accuracy, the measurement position or change in operating conditions, and various changes in the load situation is often some deviation; so using the second method is more accurate, but how to determine or whether it can accurately determine the threshold has an impact of the presence of diagnostic results.

4.2.2 Dimensionless Index Analysis Based on EMD

Actually, EMD is a process of screening the signal, specific steps are as follows: a real signal is composed by a multiple IMF component set, and the process of screening IMF is as follows [26], [27], [28]:

(1) Determining all local extreme points of the signal $x(t)$ and calculating the upper and lower envelopes. All the original signal data must be within the two envelopes;

(2) The average of two envelopes is recorded as μ_1, then calculating

$$y_1(t) = x(t) - \mu_1 \tag{15}$$

(3) Determining $y_1(t)$ whether it can satisfy the conditions of getting IMF. When the condition does not meet, $y_1(t)$ is seen as a new signal $x(t)$ and steps (1) and (2) are repeated. $y_1(t) = c_1(t)$ is defined until the IMF's condition is met. The signal $c_1(t)$ is the first IMF component of the signal $x(t)$, also representing the highest frequency component of the signal $x(t)$.

(4) The obtained high-frequency signals will be removed from the original data, which means a new data information $r_1(t)$ is gotten. That is to say $c_1(t)$ is decomposed from the signal $x(t)$, there are:

$$r_1(t) = x(t) - c_1(t) \tag{16}$$

(5) Repeating the above steps until the residual signals meet the given termination conditions, we can obtain decomposition formula as follows:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{17}$$

where $r_n(t)$ is the final remaining function, indicating steady trend of the signal. All components of IMF contain the stable characteristic of the signal, which can be used for analyzing and processing the signal.

In step (1), it may not be able to determine that the ends of the signals are extreme points when applying extreme value points of the signals to solve the upper and lower envelopes, this will lead to the end effect problem. The polynomial fitting algorithm proposed by Liu [29] can be used to deal with the problem to obtain complete characteristic signals. Furthermore, due to the first few IMF components often contain major energy and frequency of the signals by EMD, and the noise and other interfering signals are removed, we can deal with the first few IMF components to analyze and study the fault feature by other methods.

When dimensionless index is used to analyze the data, we need to preprocess the collected vibration data in advance, and remove noise and other interfering signals. Therefore, we may apply the EMD decomposition technique to preprocess data, and then calculate the dimensionless indicators of the processed data, further analyzing and studying the failure information. So this paper proposes the dimensionless index analysis method based on the EMD decomposition. The flow block diagram of the analysis method is shown in Fig. 5.

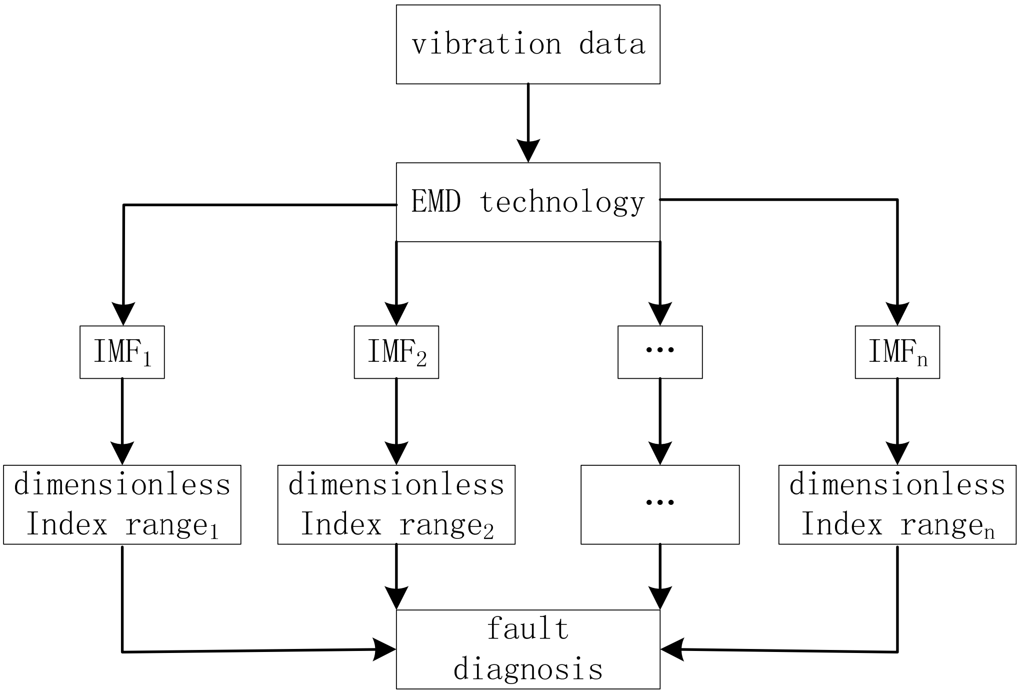

Fig. 5. The flow chart of Algorithm

As shown in Fig. 5, firstly, the collected vibration data signals are decomposed into a finite number of IMFs by EMD, and then the dimensionless indicators of the first few IMF components is calculated. We can obtain dimensionless index range of the fault signals, further performing fault diagnosis analysis and research. Since this algorithm removes other interfering signals in advance and calculates the dimensionless indicators of fault characteristic signals, the algorithm is more persuasive than no preprocessing dimensionless index analysis method. Finally the proposed method was applied to fault diagnosis tests of roller bearing.

5 Experiments and analysis of mechanical fault location

5.1 Experiment Devices

The test bed is a platform with combined rotating machinery device in the Key Laboratory of fault diagnosis of Guangdong Province and is used to generate varieties of faults, as shown in Fig. 6. The rotating machinery of combined experimental device requires the apparatus which are equipment rack, low-noise axial fan, frequency control three asynchronous motor, reduction gear and bearing.

The studied object of test is rotating machinery rolling. After the basic level, the shaft balance and the shafting alignment calibration on the unit. First we can use the EMT390 [30], [31] data collector which produced by Beijing EMT Technology company to collect the acceleration vibration signals during the normal operation of combined rotating machinery device. Before collecting the acceleration vibration signals of the bearing faults of combined rotating machinery device, we need to replace the roller bearing fault units (the common faults of roller bearing include shortage of bearing balls, wear of bearing balls, outside crack of bearing and inside crack of bearing, as shown in Fig. 7 to Fig. 10). The EMT390 is used to collect data by the sensors which are put on the bearing housing and set up the motor speed 1950 rpm, sampling frequency 1000Hz and the sampling points 1024.

In the experiment figure, the bearing model is YFZH30205. Inner diameter is 25 mm. Outer diameter is 45 mm, Thickness is 15 mm, and number of balls is 18. The experiment method is based on EMD and a dimensionless index algorithm to diagnose the faults.

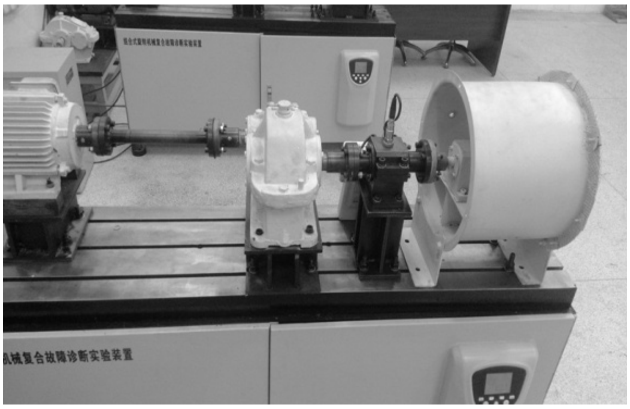

Fig. 6. Rotating machinery of combined experimental device

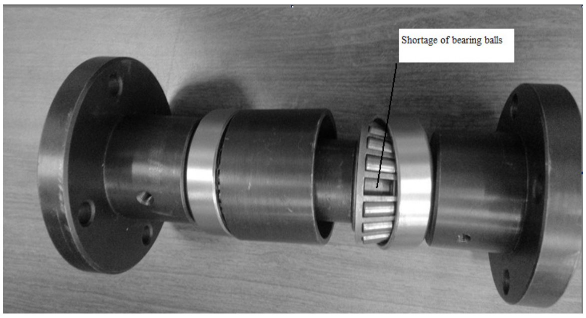

Fig. 7. Shortage of bearing balls

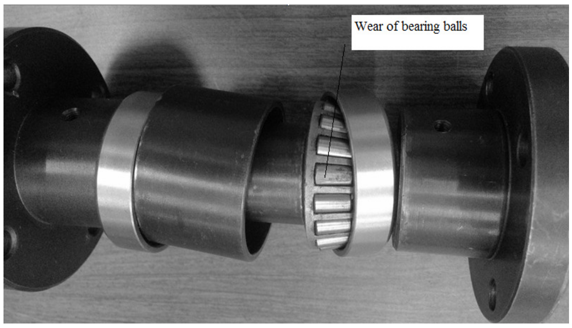

Fig. 8. Wear of bearing balls

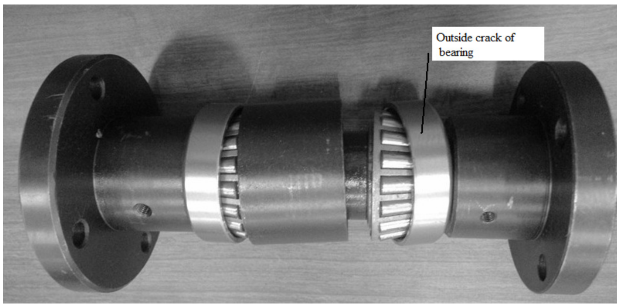

Fig. 9. Outside crack of bearing

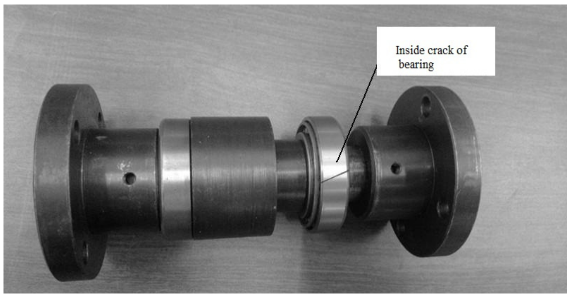

Fig. 10. Inside crack of bearing

5.2 Bearing fault localization experiments

Bearing fault signal contains high-frequency information, so the first IMF component of EMD represents the fault information of the bearing. The acceleration vibration signal sampling of each bearing mode needs 120 groups of data, and then using dimensionless index algorithm based on EMD decomposition to get a dimensionless index range of acceleration vibration signals and obtaining the dimensionless index range of bearing fault mode, as shown in Table 1.

From the experimental results of dimensionless index ranges of various models, there is no phenomenon of overlapping between the same dimensionless index among these fault models, so we can use this method to analyse the roller bearing fault. In the following under the same experimental conditions, we again respectively capture 120 groups of acceleration vibration signals of each type in various bearing modes and randomly select a group of data from each mode to verify the validity of the analysis results. Randomly selecting a group of data, five kinds of dimensionless index values are: waveform index is 6.8526, pulse index is 6.5536, margin index is 8.4258, peak indicator is 5.5356, kurtosis index is 6.6578. Comparing with the dimensionless index range of various fault modes from Table 1, we can obtain that several indicators fall within the target range of outside crack of bearing, which determines the fault mode of this data is outside crack of bearing. To verify the accuracy of this method, the determination results are compared with the actual situation of the data and find that it is this sample data for the outside crack of bearing, which has shown the validation of this method. To further analyze the technique based on EMD with dimensionless index algorithm, we have study the other four running states of bearing and finally all of them are correctly determined according to the running state of the bearing. This has shown that the proposed method can correctly detect faults and identify the type of the fault.

Table 1 the dimensionless index range value of roller bearing acceleration vibration signal

Fault model	Waveform index	Pulse index	Margin index	Peak index	Kurtosis index
Normal	1.388~2.503	3.048~4.960	3.989~5.065	1.695~3.576	2.330~4.827
Shortage of bearing balls	4.385~5.124	5.246~6.234	6.268~6.802	3.863~4.165	8.024~9.124
Wear of bearing balls	3.608~4.125	7.684~8.154	5.201~6.189	6.248~6.843	5.256~6.421
Inside crack of bearing	5.434~6.245	6.989~7.452	7.015~7.524	4.358~5.024	7.346~7.982
Outside crack of bearing	6.453~7.371	6.356~6.846	8.034~8.654	5.346~5.834	6.580~7.128

The experimental results show that the effect of EMD is significantly better than the Fourier transform, window Fourier transform and wavelet decomposition results. The main reasons as follow: (1) Fourier transform is a global transformation, which merely obtains the information of time domain or the frequency domain, and cannot provide the information of time domain and frequency domain simultaneously; (2) even though the window Fourier transform can provide the information of time domain and frequency domain simultaneously, the size and shape of the window is fixed, therefore, it is not sensitive to reflect the mutation of windowed Fourier transform signals; (3) the wavelet transform has adaptive window to reflect the mutant signal, but once the decomposition scale and wavelet were selected which only can get a signal at a fixed frequency band. From this point we can say that the wavelet decomposition do not have adaptability while in the decomposition process of EMD basis functions are determined by the signal itself, but not determined in advance. Thus, (1) EMD method is an adaptive signal processing method that can accurately be applied to process non-linear, non-stationary signals; (2) the EMD method can accurately determine the fault type and fault location with the non-dimensional analysis theory in the fault diagnosis.

6 Conclusion

This paper proposes the dimensionless index analysis algorithm based on EMD, and regarding the combined experiment device of rotating machinery as the test platform, the fault pattern of rotating machinery rolling bearing as the research object. We remove the noise and other interfering signals of the collected acceleration vibration signals by EMD technique, then applying the dimensionless index analysis algorithm to deal with the new data, further determining the pattern of mechanical bearing fault. The proposed algorithm preprocesses the sampling data in advance, eliminating the influence of noise and other interfering signals, which is more efficient than general dimensionless index analysis algorithm; finally it outperforms the feasibility and effectiveness. The research object of this paper is one failure mode; however, mechanical fault types are mostly composite fault modes in the actual production process, which are needed to analysis and research further.

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