Study on Method of Bearing Fault Detection Based on Vibration Signal Analysis

Guang Yang, Xinrong Liu

Abstract—**This paper introduces a complete method for bearing fault detection. By analyzing the vibration signal when a fault occurs, the type of fault can be detected. The number of high-frequency intrinsic mode functions (IMFs) is determined by calculating the cumulative mean of each IMF. In the modified ensemble empirical mode decomposition (EEMD), only the high-frequency IMFs need to be decomposed out. The scientific calculation process for the parameters of the algorithm is explained in detail. The function of the kurtosis value and the correlation coefficient is analyzed, and the IMFs with the most abundant fault information are selected to restructure the signal. The reconstructed signal is then processed by wavelet algorithm. The fault vibration signal from the bearing inner ring is used as an example for the experiment. The fault characteristic frequency of bearing inner race is calculated by formula. By analyzing the envelope spectrum of the final restructured signal, the fault information is effectively detected. The results demonstrate that the method given by this paper can detect bearing fault information more quickly and efficiently.**

Index Terms—**Fault diagnosis, cumulative mean, rolling bearing, wavelet algorithm, envelope spectrum**

I. Introduction

Most motor failures are caused by rolling bearings. Bearing fault diagnosis has always been an important research content in mechanical fault [1]. When a bearing fault occurs, the vibration signal is often used to analyze it [2]. The vibration fault signal of bearing is a kind of non-linear and non-stationary signal, and empirical mode decomposition (EMD) is very suitable for analyzing its analysis. But EMD has the problem of modal mixing, which limits its use. Today, the ensemble empirical mode decomposition (EEMD) and the application of EEMD in bearing fault detection are being studied. In [3], an example of EEMD in fault diagnosis is given. The EEMD decomposition of the signal can promote all components of the model to obtain better timing, and the diagnostic accuracy of the model can be significantly improved. But the operation process of the algorithm is not detailed enough, and the running speed of the algorithm is slow. In [4], an early warning method for gearbox fault based on EEMD and a broad learning algorithm is put forward, and the results verified that the fusion method of EEMD and the width learning algorithm is feasible in early fault warning. However, many false components are generated during the process of algorithm decomposition, which has a negative impact on the efficiency and accuracy. In [5], a fault diagnosis method for roller bearing based on EMD and spectral kurtosis is discussed, but the decomposition process is prone to mode mixing, which affects the detection effect. In [6], researchers pointed out that the low-frequency white noise plays a major role in eliminating mode mixing, while the high-frequency part has little impact. They proposed to select the white noise with limited bandwidth to save the EEMD operation time, and achieved good results. But the white noise amplitude and the ensemble average operations number cannot be obtained scientifically, which needs to be determined manually.

This paper presents an effective fault detection method. In order to improve the running speed, the EEMD is modified. The relevant parameters are obtained scientifically, and the final reconstructed signal contains richer fault information. The specific implementation process is described in detail as follows.

II. Related algorithms

A. Signal decomposition process

Based on the EEMD algorithm, the signal decomposition process is proposed. The EEMD algorithm comes from EMD algorithm [7]. In application, EMD algorithm has the problem of mode mixing [8]. The mode mixing problem is that an IMF is composed of signals with different scales, or signals with similar scales appear in different IMFs. This problem leads to large errors in the decomposition results [9][10]. Signal discontinuity is the cause of mode mixing. In discontinuous signals, the interval distribution of the extreme points of high-frequency components is dense, and the interval distribution of the extreme points of low-frequency components of signals is sparse. In EEMD, a set of white noise signals is added to the original signal, which changes the distribution characteristics of the low-frequency components. This ensures that the mean value of the upper and lower envelopes can be accurately obtained each time, and avoids the mode mixing in EMD [11], but the running speed become slowly.

For the bearing fault vibration signal, the fault signal is a high frequency periodic signal. It is mainly contained in high-frequency components. Therefore, the low-frequency components and the residual component decomposed by the algorithm are unimportant in bearing fault detection.

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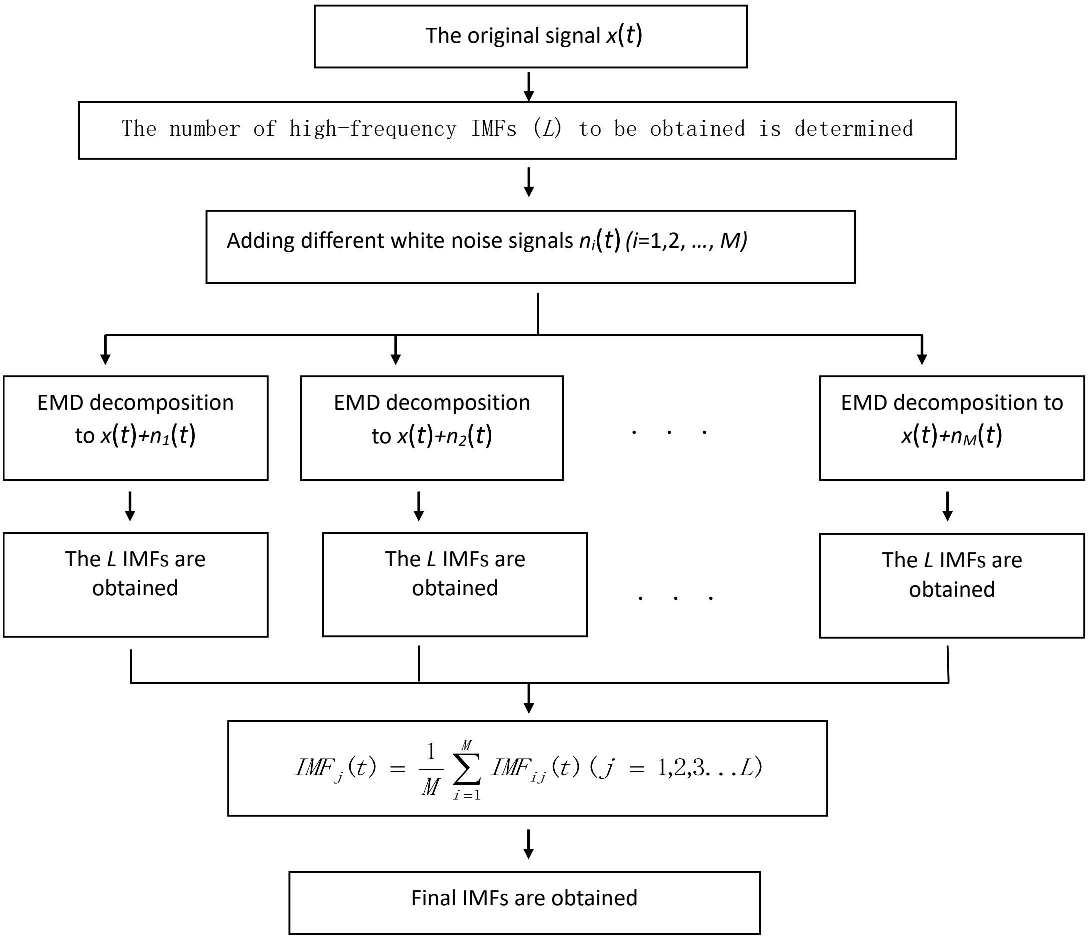

Fig. 1. The algorithm of modified EEMD

In this paper, the EEMD algorithm is modified. During the operation of the algorithm in this paper, after all high-frequency IMFs are decomposed out, the algorithm will be ended. The low-frequency IMFs and the residual need not be worked out. The parameter of cumulative mean is introduced in the process. The main function of cumulative mean is to distinguish high-frequency components from all IMFs [12]. When the cumulative mean value of an IMF is close to zero, the IMF is regarded as a high-frequency component. If the cumulative mean deviates too much from the zero value, the IMF is regarded as a low-frequency component. The cumulative mean is given by the following formula:

$$L = mean\left(\sum_{i=1}^{n}(IMF_i - \frac{mean(IMF_i)}{std(IMF_i)})\right) \quad (1)$$

Here the L is cumulative mean; the *mean(·)* is function for averaging. The *std(·)* is the standard deviation. The $mean(IMF_i)$ is the average value of each number in IMF_i .

The modified EEMD algorithm in this paper are described as follows:

1) The original signal is decomposed with EMD, and all IMFs are obtained. The number of high-frequency IMFs are determined according to the L value of each IMF. The number of high-frequency IMFs is expressed by j.
2) White noise $n_i(t)$ with zero mean and constant amplitude standard deviation is added to the original signal $x(t)$ for many times.

$$x_i(t) = x(t) + n_i(t) \quad (i=1, 2\ldots M) \quad (2)$$

Where, $x_i\ (t)$ is the signal after adding white noise for the ith time, and $n_i(t)$ is the white noise added for the ith time.

3) EMD decomposition is carried out on $x_i(t)$. After j times of decomposition, EMD stops operation. Each $x_i(t)$ is decomposed into j components, and the result is recorded as IMF_{ij}.
4) After averaging the corresponding IMF components according to the following formula, the final decomposition result is obtained.

$$IMF_j(t) = \frac{1}{M}\sum_{i=1}^{M} IMF_{ij}(t) \quad (j=1,2,3\ldots) \quad (3)$$

The Fig. 1 shows the running process of the algorithm.

It can be seen from the above process that the algorithm can run faster than EEMD since only j IMFs are decomposed out, and other IMFs and residual component need not to be obtained.

In the above algorithm, the amplitude and number of white noise need to be determined. The magnitude of white noise directly determines the effect of eliminating mode mixing, and the number of ensemble average operations can determine the degree of white noise elimination [13].

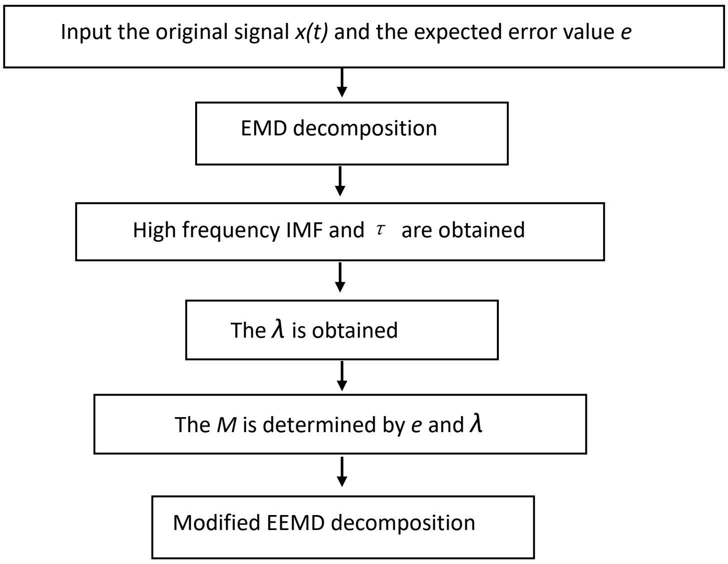

Fig. 2. The parameters calculation process

B. Method of determining parameters

Before the process of the above algorithm, two parameters should be determined in the algorithm of this paper. One parameter is the amplitude of the white noise signal; the other is the total number of white noise signals that will be added to the process. The two parameters are usually decided by experience, and that lacks a theoretical basis. This paper gives the calculation method. The following section describes the parameters calculation process.

The relationship between the two parameters can be given by the following formula:

$$e = \lambda / \sqrt{M} \tag{4}$$

Here e is the expected error value between the original signal and the decomposition result. The λ is the ratio of the white noise signal amplitude standard deviation to the original signal amplitude standard deviation; The M is the ensemble average number.

The e must be defined to a small value in order to get a better decomposition result. From above formula we can see that the e can become small by decreasing λ or increasing M. But when λ is too smaller, the effect of adding white noise signal is not obvious. Similarly, the larger the M is set, the longer the running time of the algorithm will be.

Usually, the e can be determined by our expectations. The λ can be obtained by following formula:

$$0 < \lambda < \frac{\tau}{2} \tag{5}$$

The τ is the ratio of the high frequency signal amplitude standard deviation to the original signal amplitude standard deviation. Usually, the parameter value of λ is $\tau/4$.

In order to determine τ, the high frequency IMF must be selected. The original signal is decomposed by EMD algorithm at first, and some IMFs are obtained. The first IMF usually has the highest frequency. So, the first IMF is selected to determine τ.

The Fig. 2 shows the calculation process for the two parameters.

C. Wavelet algorithm

After running the modified EEMD algorithm, some IMFs are selected to reconstruct the signal. In order to obtain a better fault detection effect, wavelet algorithm is used to further process the reconstructed signal. During the operation of wavelet algorithm, a series of high-frequency detail coefficients and a low-frequency approximation coefficient are generated. In the usual wavelet denoising algorithm, some high-frequency detail coefficients are removed as noise. However, for the bearing fault signal, the fault feature information is mainly included in the high frequency signal. Therefore, this paper uses some high frequency detail coefficients to further reconstruct the signal, and the low frequency approximation coefficients are removed.

The final reconstructed signal contains more obvious fault information.

III. Bearing Fault Detection Method

A. Kurtosis

Kurtosis is a parameter that describes the peak of waveform, which is very sensitive to the instantaneous impact characteristics in the signal [14]. Kurtosis is widely used in bearing fault diagnosis, and its calculation formula is given as below:

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \overline{x}}{\lambda}\right)^4 \tag{6}$$

The K is kurtosis value; N is the number of samples; the x_i is amplitude of signal; $\overline{x}$ is mean value of signal; λ is standard deviation of signal.

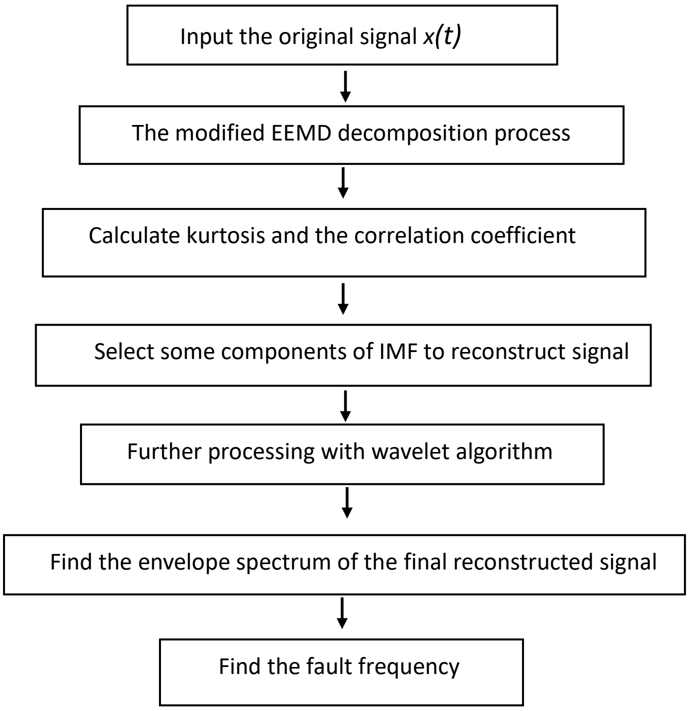

Fig. 3. The bearing fault detection process

Kurtosis is very sensitive to impact signals, which is especially suitable for the diagnosis of surface damage faults [15]. For the normal bearing vibration signal, the kurtosis value K=3, but for the fault bearing, the kurtosis value of the vibration signal will become larger. The higher the kurtosis value, the more obvious the fault impact component contained in the signal [16]. When the kurtosis value K>8, the bearing may have great faults. In the process of bearing fault detection, the IMF component with a large kurtosis value can better reflect the fault characteristics.

B. Correlation coefficient

The correlation coefficient can be used to assess whether two signals are related [17]. Because the bearing vibration signal contains noise, the IMFs decomposed by EEMD may contain many false components. The false IMFs are irrelevant to the original signal, and they should be eliminated [18][19]. For the real IMF component, its correlation coefficient is relatively large, whereas for the false IMF component, the correlation coefficient is relatively small. By calculating the correlation coefficient between each IMF component and the original vibration signal, the false IMFs can be picked out.

The following formula gives the calculation method for correlation coefficient:

$$r_i = \frac{\sum_{k=1}^{N} x(k) \times IMF_i(k)}{\sum_{k=1}^{N} x(k)^2 \times IMF_i(k)^2} \tag{7}$$

The IMF_i is the ith IMF component; r_i is correlation coefficient between original signal and IMF_i; $x(k)$ is the kth sampling point of the original signal; $IMF_i(k)$ is the kth sampling point of IMF_i; N is the number of samples.

C. Bearing fault detection process

1) The original bearing vibration signal is decomposed by the above modified EEMD algorithm, and j IMFs are obtained.
2) The kurtosis values for each IMF are calculated.
3) The correlation coefficients between each IMF and the original signal are calculated.
4) Those IMFs with a large correlation coefficient and a kurtosis value are selected to reconstruct the signal.
5) The reconstructed signal is further processed by wavelet algorithm, and the final reconstructed signal is obtained.
6) Find the envelope spectrum of the final reconstructed signal, and the fault frequency is found.

The Fig. 3 shows the bearing fault detection process.

IV. EXAMPLE OF DETECTION PROCESS

The bearing fault signal data comes from the experimental data provided by Western Reserve University in the United States. From the inner circle fault data file, 1200 data are selected as the original signal. Fig. 4 shows the original signal waveform. In this paper, the fault data of the bearing inner ring for driver end is adopted. The sampling frequency is 12KHZ, and the bearing speed r=1797r/min; Number of balls n=9; Rolling element diameter d=7.938mm; Bearing diameter D=39mm; Contact angle of rolling element α=0.

The calculation formula for bearing inner ring fault frequency is given below:

$$f_i = \frac{r}{60} \times \frac{1}{2} \times n \times \left(1 + \frac{d}{D}\cos\alpha\right) \tag{8}$$

The f_i is inner ring fault frequency; r is bearing speed; n is number of balls; d is rolling element diameter; D is bearing diameter; α is contact angle of rolling element.

The calculation result shows that the inner ring frequency

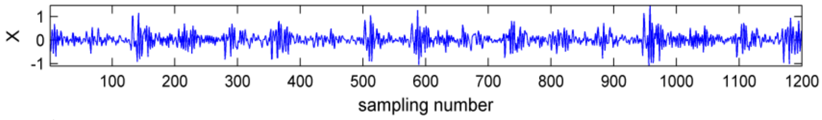

Fig. 4. Original signal waveform

TABLE I
THE CALCULATION RESULTS FOR EACH IMF

Cumulative mean (×10-2)	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9
L	0.36	0.30	-0.17	0.12	3.50	4.20	6.90	10.34	24.25

fault is 162.2HZ, after substituting the above experimental data into the formula.

A. Modified EEMD decomposition process

Before running the modified EEMD, the L value in the formula (1) and the three parameters in formula (4) are determined. The calculation process is described as follows.

First, the original signal is decomposed by EMD algorithm. Nine IMFs and a residual component are generated. The L value of each IMF is calculated, and the results are given in Table 1. It can be seen from Table 1 that the deviation from zero increases significantly after the fourth L value. So, the first four IMFs are considered to be high-frequency components, and j=4. This means that in the subsequent EMD decomposition, only four IMFs need to be decomposed each time. This makes the algorithm run faster.

The IMF1 is taken as the high frequency component to calculate τ. The standard deviation of original signal is 0.2876, and the standard deviation of IMF1 is 0.2553. τ= 0.2553/ 0.2876=0.8877. Therefore, the λ is finally determined as $\lambda=\tau/4=0.222$.

The expected error value e is set to 0.015, and the final value of M is 219 by the calculation of formula 4.

The original signal is decomposed with the modified EEMD, and four IMFs are obtained. The Fig. 5 shows the decomposition results.

B. Signal reconstruction

The kurtosis value and the correlation coefficient of the four IMFs are calculated. The results of the calculation are presented in Table 2.

The vibration signal of normal bearing approximately obeys the normal distribution, and the kurtosis value is about

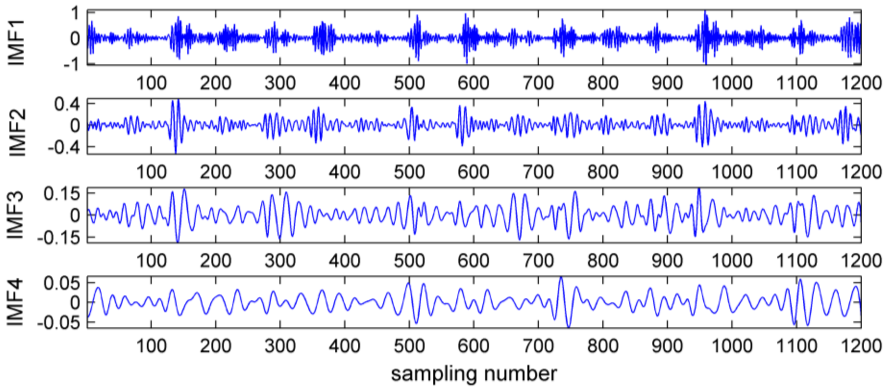

Fig. 5. The decomposition results

TABLE 2
KURTOSIS AND CORRELATION COEFFICIENT OF THE IMFS

	IMF1	IMF2	IMF3	IMF4
Kurtosis	5.0426	5.6002	3.1851	3.2005
Correlation coefficient	0.8433	0.4156	0.2448	0.1356

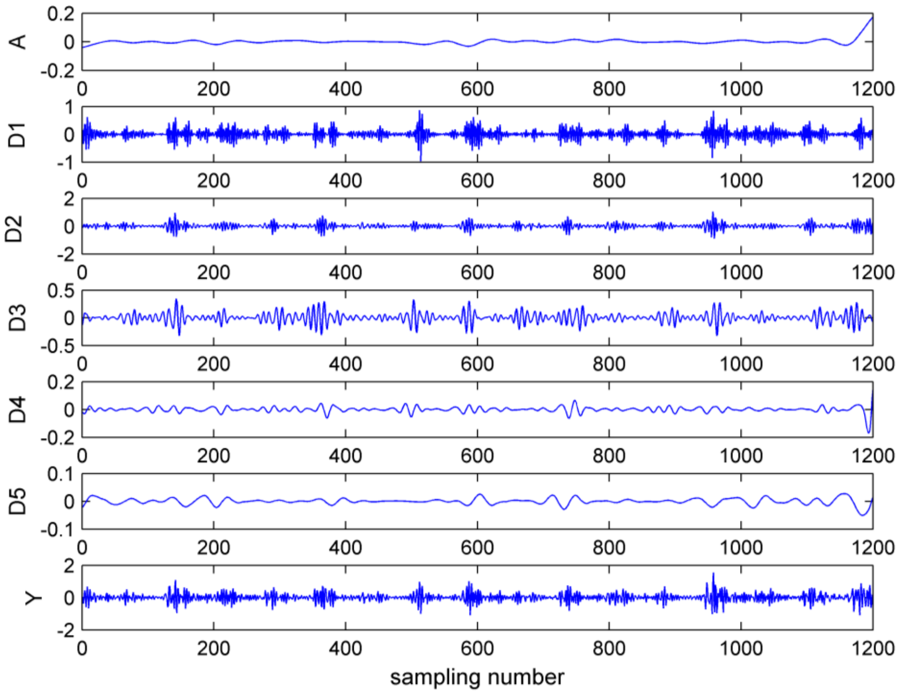

Fig. 6. The results of wavelet decomposition and the final reconstructed signal

3. When the rolling bearing fails, the kurtosis value increases significantly. So, the IMFs with a kurtosis value greater than 3 contain more fault information. The kurtosis value of the original signal is 5.4996.

It can be seen from the Table 2 that the correlation coefficient and kurtosis value of IMF1 and IMF2 are large, and the kurtosis value is greater than 3. They retained the most fault information in the original signal, so the first two IMFs are used for the signal reconstruction.

The reconstructed signal is further processed with wavelet algorithm. The signal is decomposed into five layers of wavelet. Five high-frequency detail coefficients and one low-frequency approximation coefficient are obtained. The first two high-frequency detail coefficients contain the most fault information, and they are selected to further reconstruct the signal. The further reconstructed signal is used for subsequent fault analysis. The results of wavelet decomposition and the final reconstructed signal are shown in the Fig.6. A is the approximation coefficient; D1-D5 are the detail coefficients; Y is the final reconstructed signal.

C. Envelope Spectrum Analysis

In order to obtain the final fault detection results, envelope spectrum analysis is required. The Fig.7 shows the envelope spectrum of the final reconstructed signal.

From the envelope spectrum, it can be seen that there is a prominent pulse signal, which is much higher than the other parts. The frequency corresponding to the pulse is around 162Hz, and that is the inner ring fault frequency calculated previously. Therefore, the fault frequency is finally detected perfectly through the envelope spectrum.

V. Conclusions

This paper studies the bearing fault detection method. The fault data from the bearing inner ring is used in the experiment. The application of the modified EEMD algorithm in detection is introduced in detail, and the calculation process of relevant parameters is well explained. In the modified EEMD, only high-frequency IMFs need to be decomposed, which greatly accelerates the operation speed of the algorithm. The data signal is reconstructed based on kurtosis value and correlation coefficient. The reconstructed signal is further processed by wavelet algorithm. Each experimental result is thoroughly analyzed. The envelope spectrum analysis shows that this method can detect fault information effectively and quickly.

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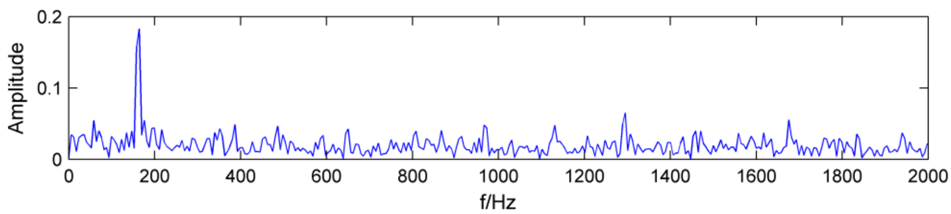

Fig. 7. The envelope spectrum of the final reconstructed signal

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