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Improved EEMD Algorithm and Its Application to Fault Diagnosis for Rolling Bearing of Wind Turbine

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Abstract. This paper discusses an improved method for the ensemble empirical mode decomposition (EEMD). To improve the decomposition effect, the mutual information is used to the algorithm. In order to deal with the mode mixing problem, two white noises with opposite signs are added to the original signal. Before the average calculating operation for the intrinsic mode functions (IMFs), the mutual information operation is processed, and the false IMFs are eliminated according to the mutual information threshold. To illustrate the effect of the improved algorithm, the simulated analysis is given in detail, and the analysis results show that the improved algorithm has better decomposition effect than EEMD. As example of application, the improved algorithm has been used to fault diagnosis for the rolling bearing of wind turbine, and the decomposition results are given. The envelope spectrums for different algorithms are presented, and detailed analysis is processed. By comparing the envelope spectrums with the other algorithms, the improved algorithm is proved having the best performance.

Keywords: EEMD, fault diagnosis, mutual information, wind turbine, registration

1 Introduction

Recently years, the wind power has been developed rapidly. But due to the harsh working conditions and the complex construction for wind turbine gearboxes, various faults happen frequently. Gearboxes are the key component for wind turbine, and their working condition will affect the performance of wind turbine. In actual operation, the failure rate for bearings in gearboxes is very high. The statistical data for the failure rate in one year is gathered in Sweden [1], and the data is shown in Table 1. As we can see from Table 1, the faults for bearing are in the majority. So, the study on fault diagnosis for rolling bearing is very important to the reliable operation of wind power.

Table 1. Various faults for wind turbine gearboxes

	Bearing	Gear	Axis	Seal	Lubrication system	The rest
Failure number	41	3	0	8	13	44
Downtime	562	272	0	52	26	230

The vibration signal of bearing in gearboxes is nonlinear and non-stationary signal, and the Hilbert-Huang transform (HHT) is used to analyze it widely [2]. The empirical mode decomposition (EMD) is the core of HHT [3]. EMD was put forward by Huang in 1998. EMD can decompose the nonlinear and non-stationary signal into some intrinsic mode functions (IMFs), and IMFs can show the changing tendency of different components in the original signal. But there are many problems in EMD, and the problems limit its application. One of the problems is the mode mixing [4]. The mode mixing means that the different frequency signals exist in the same IMF, or the same frequency signal is included in some different IMFs. Studies have shown that the mode mixing problem is caused by the intermittency signal or the impulse interference signal. The signal is a series of interval high-frequency signal with small amplitude, and on the other hand, the interference signal can generate some false IMFs. The mode mixing problem leds to the superposition of waveform between two adjacent IMFs, and the factual IMF waveform is indistinguishable. To solve the problem, the ensemble empirical mode decomposition (EEMD) is proposed based on the EMD. Although the decomposition effect is improved in EEMD, the mode mixing problem still exists when the signal-to-noise ratio is low. So, EEMD need to be further improved.

The mutual information was proposed by Shannon, and today, it is an important concept for information theory. It is used to compare the relevant degree for two signals. In this paper, the mutual information is used to improve EEMD. By comparing the relevant with the original signal, the false IMFs are eliminated, and the computation complexity is reduced.

In Wu and Huang [5], EEMD is introduced in detail. Based on EMD, the white gauss noise is added to the original signal, and a series of IMFs are averaged in the process. But many unnecessary IMFs are decomposed because of the asymmetric noise being added to the algorithm, and the decomposition effect need to be improved. In Albert and Nii [6], the correlation coefficient analysis technique is presented, and the seismic signal is analyzed by setting the threshold. But the correlation coefficient analysis can not play its role well in the decomposition process. In Shen, Wang and Zhaozhi [7], Shen introduces the mutual information, and proves that the mutual information is superior to the correlation coefficient in studying the relevance of the variable. But the mutual information is not used to improve the EEMD algorithm.

In this paper, an improved ensemble empirical mode decomposition algorithm (IEEMD) is proposed. The mutual information is applied to the process for calculating IMF, and two opposite signs white noise are added to the signal. By the improved algorithm, the mode mixing problem can be efficiently inhibited, and the false IMFs are reduced greatly.

2 Related algorithm

This section introduces the algorithms that are related to IEEMD.

2.1 Theory of mutual information

The mutual information is used to represent the relevance of the variable, and entropy is used in the derivation process. The entropy of variable X is defined by the formula:

$$H(X) = -\sum_{x \in X} p(x) \bullet \log_2 p(x) \quad \textbf{(1)}$$

Here $p(x)$ is the probability of x occurring. The conditional entropy between two random variables is defined as follow:

$$H(X \mid Y) = -\sum_{x \in X, y \in Y} p(y) \bullet p(x \mid y) \bullet \log_2 p(x \mid y) \quad \textbf{(2)}$$

Here $p(y)$ is the probability of y occurring; $p(x|y)$ is the conditional probability of x occurring on the condition of y occurring. The joint entropy between X and Y is:

$$H(X,Y) = -\sum_{x \in X, y \in Y} p(x,y) \bullet \log_2 p(x,y) \quad \textbf{(3)}$$

Here $p(x, y)$ is the joint probability of x and y occurring at the same time. In general, the relation between the joint entropy and the conditional entropy is:

$$H(X,Y) = H(X \mid Y) + H(Y) \quad \textbf{(4)}$$

The mutual information between X and Y is given as below:

$$I(X,Y) = H(X) - H(X \mid Y) = H(X) + H(Y) - H(X,Y) \quad \textbf{(5)}$$

The next formula is the normalization processing for $I(X, Y)$:

$$I^* = \frac{I(X,Y)}{\sqrt{H(X) \bullet H(Y)}} \quad \textbf{(6)}$$

Where $I^* \in [0,1]$. After the mutual information is obtained, the threshold is needed to be compared with it.

The threshold is very important to mutual information. The correlation of two variables is high when the mutual information between them is bigger than the threshold; rather, the correlation of the variables is low.

There are two types of methods in threshold obtaining. One is using fixed values, and the other is self-study method. The method that using fixed values is simple, and it has a rapid running process. The self-study method can adjust the threshold with the experimental process. The common self-study methods include the Beta-Gamma algorithm [8], the Logistic Regression algorithm [9] and the Score Distribution algorithm [10]. Although the self-study method has high accuracy, the application of the method is limited because of the extensive calculation.

In the IEEMD algorithm, the method of using fixed values is adopted. The method for evaluating the threshold is used according to Albert and Nii [6]. It is given bellows:

$$k = \frac{\max(k_i)}{10 \bullet \max(k_i) - 3}, i = 1, 2, \ldots, n \quad (7)$$

Where k_i is the mutual information between latest decomposed signal and the ith IMF; n is the number of IMFs; $\max(k_i)$ is the biggest mutual information.

In IEEMD, the mutual information between the IMF and latest decomposed signal is evaluated. When the mutual information is bigger than k, the IMF will be retained, or it is eliminated as the false IMF.

2.2 The EMD algorithm

A complicated signal can be decomposed into a set of IMFs by EMD [4]. Supposing the original signal is $S(t)$, the decomposition process of EMD is introduced as follows:

(1) All the extreme points of $S(t)$ are found out.

(2) By cubic spline function, the minimum envelope (denoted with $u(t)$) and the maximum envelope (denoted with $v(t)$) are found out.

(3) The average (denoted with $m(t)$) for $u(t)$ and $v(t)$ is calculated.

(4) The difference value (denoted with $h(t)$) is calculated:

$$h(t) = S(t) - m(t) \quad \textbf{(8)}$$

(5) Repeating the process above until the stop condition is satisfied, and the ith IMF (denoted with $I_i(t)$, i=1,2 ... n) is obtained.

(6) Subtracting the $I_i(t)$ from $S(t)$, and the difference value is assigned to $S(t)$.

Repeating the process above until all the IMFs is worked out.

By the above process, $S(t)$ is decomposed into the sum of a set of IMFs and a residue ($r(t)$).

$$S(t) = \sum_{i=1}^{n} I_i(t) + r(t) \quad \textbf{(9)}$$

2.3 The mode mixing problem of EMD

Generally, the mode mixing problem is easily happened when EMD decomposition is processed. The mode mixing problem is the phenomenon that some great different timescales components exist in one IMF, or the similar timescales components exist in several IMFs. The next example is used to show the mode mixing for EMD decomposition.

Supposing $y(t)$ is a sinusoidal signal:

$$y(t) = \sin(16 \bullet \pi \bullet t) \quad \textbf{(10)}$$

The $e(t)$ is a high-frequency intermittent signal with amplitude value of 0.2, and $Y(t)$ is the signal expressed by next formula.

$$Y(t) = y(t) + e(t) \tag{11}$$

Fig.1 gives the waveforms for $e(t)$ and $Y(t)$. The EMD decomposition results for $Y(t)$ are also shown in Fig.1.

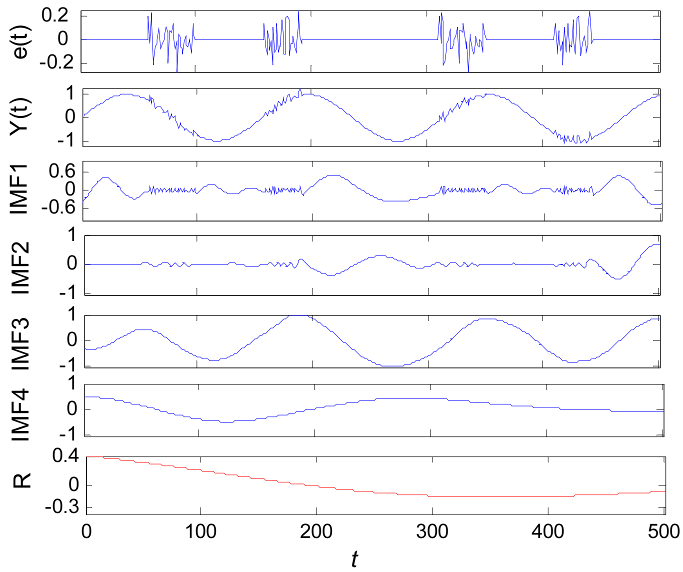

Fig. 1. The mode mixing cased by $e(t)$

From Fig.1 we can see that the IMF1 includes the high-frequency intermittent component and some low-frequency sinusoidal component. In fact, IMF3 should be the decomposition result for $y(t)$. So, the mode mixing is occurred in IMF1, and the subsequent decomposition results are affected. The redundant IMFs are generated, and the endpoint of IMF3 is distorted.

In the process of EMD, the signal envelopes need to be obtained by connecting extreme points. But when the high-frequency intermittent disturbance signal is added, the calculating process for extreme points is affected. The final envelopes are inevitably reflected by the intermittent disturbance signal, and that leds to the mode mixing phenomenon of EMD decomposition.

2.4 The EEMD algorithm

To deal with the mode mixing problem of EMD, the EEMD is proposed in recent years. The noise assisted analyzing method can restrain the mode mixing caused by the EMD method. By applying noise assisted analyzing method in EMD, EEMD is put forward. The simplified steps of EEMD are described as follows. Refer to [11] for more detailed information.

(1) Adding white noise signals (denoted with $n_i(t)$, i=1,2, ... , n) into the original signal $S(t)$;

(2) Decomposing the original signal by EMD algorithm and a sequence of IMFs are obtained;

(3) Repeating steps (1) and (2), and different white noise signals are added for each time.

(4) Averaging the corresponding IMFs of all sequences to eliminate the influence of Gaussian white noise and the final decomposition result is obtained.

Fig.2 shows the implementation process of EEMD.

When the amplitude for interrupt signal is small, the EEMD is effective. But when the signal-to-noise ratio is low, the mode mixing problem still cannot be eliminated. Also, because the asymmetric noise is added to the algorithm, many false IMFs are decomposed. So, the EEMD algorithm needs to be improved.

3 The IEEMD algorithm and simulation analysis

In this section, the IEEMD algorithm and its simulation analysis are introduced.

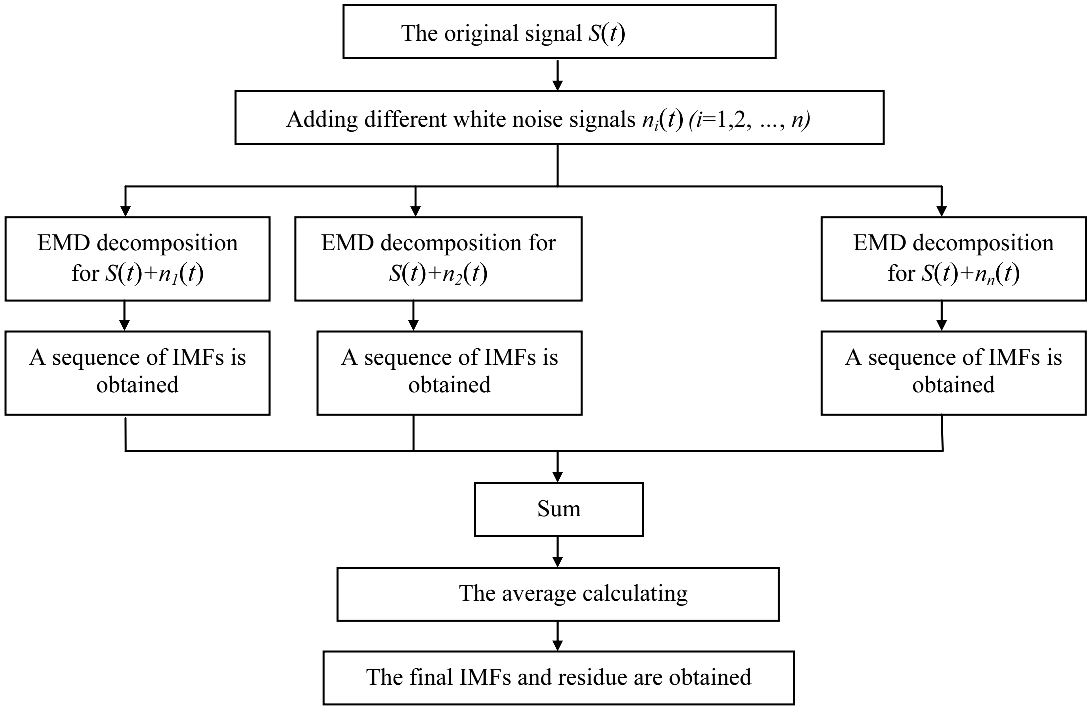

Fig. 2. The flow chart for EEMD

3.1 The IEEMD algorithm

The mutual information is used to IEEMD. To the non-stationary signal $S(t)$, the IEEMD is illustrated as below:

(1) Adding the white noise signal (mean is 0) $n_i(t)$ and $-n_i(t)$ to the $S(t)$.

$$S_i^+(t) = S(t) + a_i \bullet n_i(t) \tag{12}$$

$$S_i^-(t) = S(t) - a_i \bullet n_i(t) \tag{13}$$

Where a_i is the amplitude of $n_i(t)$ $(i=1,2,\ldots, k)$, k is the number of $n_i(t)$.

By using EMD, $S_i^+(t)$ and $S_i^-(t)$ are decomposed respectively, and the jth IMF sequence is obtained. The IMF sequences are $\{I_{ij}^+(t)\}$ and $\{I_{ij}^-(t)\}$. The mutual information between $I_{ij}^+(t)$ and $S_i^+(t)$, and the mutual information between $I_{ij}^-(t)$ and $S_i^-(t)$ are computed respectively. If the mutual information values are less than threshold, the relevant IMFs are eliminated. What type of the IMFs is retained can be determined by the value of threshold.

(2) Averaging the retained IMFs by the following formula and the jth IMF is obtained:

$$I_j(t) = \left(\frac{1}{N+}\sum_{i=1}^{N+} I_{ij}^+(t) + \frac{1}{N-}\sum_{i=1}^{N-} I_{ij}^-(t)\right) \Big/ 2 \tag{14}$$

Here $N+$ and $N-$ represent the number of retained IMFs respectively.

(3) The remainder signal is computed by following formula:

$$r(t) = S(t) - \sum_{j=1}^{n} I_j(t) \tag{15}$$

Here, n is the number of IMFs that have been obtained. $I_j(t)$ is the jth IMF.

(4) If the termination condition cannot be satisfied, the next step will be continued.

(5) Regarding $r(t)$ as the new original signal, namely, $r(t)$ is assigned to $S(t)$, and the process returns (1) to continue.

Repeat the procedures above until all IMFs are decomposed.

Fig.3 shows the implementation process of IEEMD.

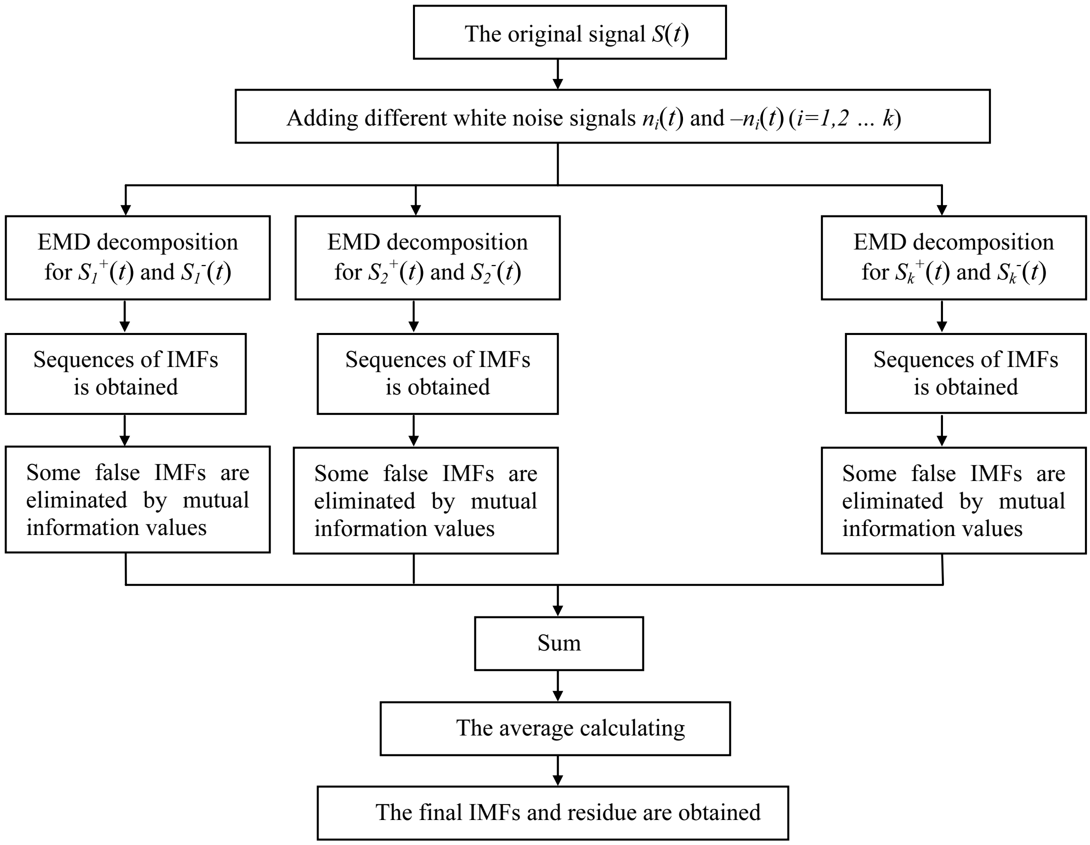

Fig. 3. The flow chart for IEEMD

As can be seen from above procedures, comparing with EEMD (in EEMD, only one white noise signal is added), two white noise signals which are of opposite sign are added to original signal. That will offset some noise influence by the IEEMD process. The decomposition effect will be more perfect, and the reconstruction error caused by white noise will be reduced [12]. But that makes the decomposition process become complex, and some false IMFs will be produced. So, before step (2), the mutual information is introduced to the algorithm. Some IMFs whose mutual information is less than the threshold are eliminated, and the next step will have less false IMFs. That will make the decomposition results reflected more characteristics of original signal, and some nose is also eliminated. So, by the above improved procedures, the final decomposition error for each IMF is reduced, and the reconstruction error caused by the white noise is decreased either. The decomposition process can be more perfect.

In the process of IEEMD, two parameters need to be determined. The parameters are the amplitude of white noise signal and the total number for white noise signals that will be added to the process. The decomposition effect can be given by the following formula:

$$e = \varepsilon / \sqrt{M} \tag{16}$$

Here e is the difference value between the original signal and the sum of all IMFs. The ε is the amplitude of white noise signal and M is the total number for white noise signals that will be added.

The smaller the e, the better the decomposition effect is. The e can become small by decreasing ε or increasing M. But when ε is too smaller, the effect for adding white noise signal will be disappear. Similarly, when M is too bigger, the running time of IEEMD will be longer. For now, there is not theoretical foundation to determine ε and M [12]. Usually, the value of ε is between 0.01 and 0.5, and the value of M is 100 or 200. In this paper ε=0.2, M=100.

3.2 Simulation analysis

In the simulation analysis, the intermittent noise and the pulse interference signal are respectively added to the original signal, and the simulations are processed respectively.

The next signal is used to simulation process.

$$x(t) = x_1(t) + x_2(t) \quad \textbf{(17)}$$

Here $x_1(t)$=8*sin(60*pi *t+pi/12); $x_2(t)$=4*sin(120*pi *t+pi/2); t=0:1/1250:0.4.

An intermittent noise signal $n(t)$ is added to $x(t)$. The $n(t)$, $x(t)$ and the final mixed signal are shown in Fig.4. The mutual information threshold is 0.21.

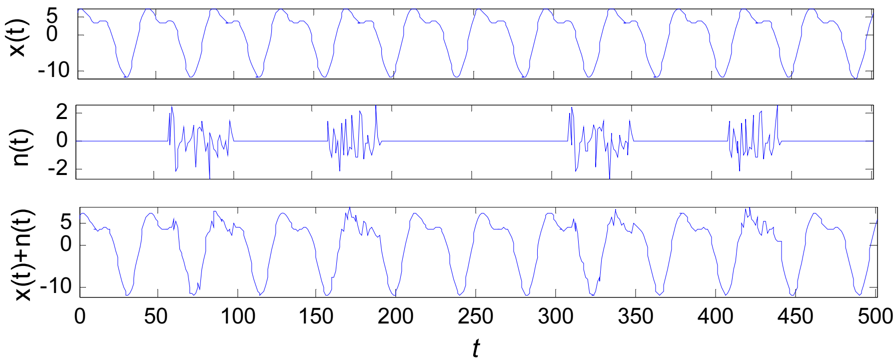

Fig. 4. Curve of signal with intermittent noise

To the signal $x(t)$+$n(t)$, the EMD, EEMD and IEEMD are processed respectively, and the decomposition results are respectively shown by Fig.5, Fig.6 and Fig.7. From the figures, we can see that seven IMFs and a residue are decomposed by EMD and EEMD, and five IMFs and a residue are decomposed by IEEMD.

Fig.5 is the decomposition results by EMD. From Fig. 5 we can find that the mode mixing problem is happened. The high-frequency component and low-frequency component are mixed in IMF1 of Fig.5. The high-frequency component reflects the intermittent noise signal $n(t)$, and the low-frequency component reflects the signal $x(t)$. The mode mixing affects the subsequent decomposition process badly, and the original signal cannot be decomposed correctly.

Fig.6 is the decomposition results by EEMD. We can see the IMF3 and IMF4 can respectively reflect the $x_2(t)$ and $x_1(t)$ of original signal. IMF1 can reflect the intermittent noise signal $n(t)$. But from the IMF2 we can find that there still exists slight mode mixing. That affect the subsequent IMFs, and there are obvious deformation at the endpoints of IMF3 and IMF4. Also, there are too much false IMFs in Fig. 6, and the reason is that the asymmetric noise is added to the original signal in EEMD algorithm.

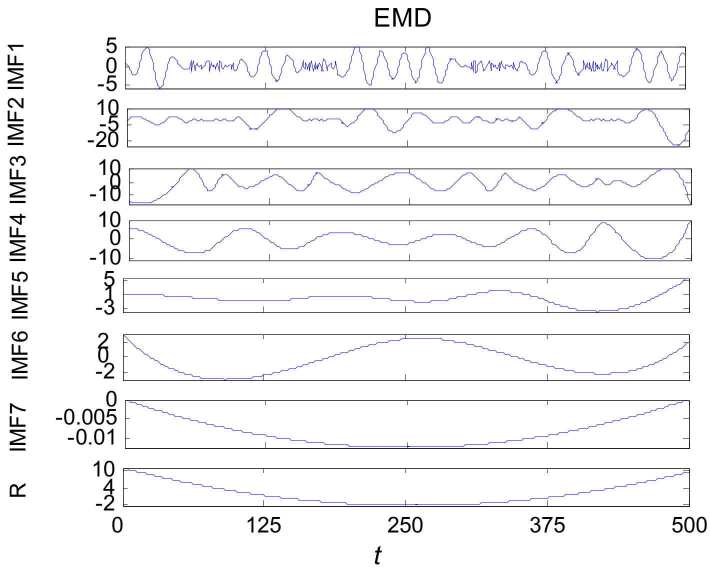

Fig. 5. Curve of EMD decomposition results

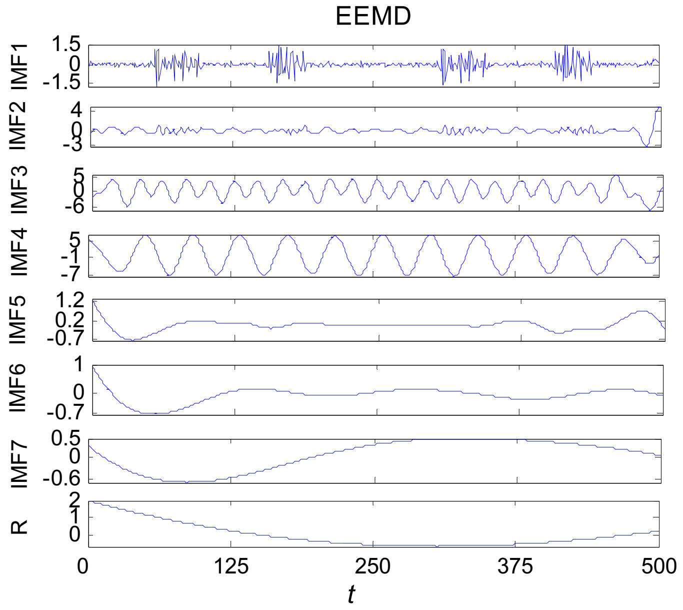

Fig. 6. Curve of EEMD decomposition results

Fig.7 is the decomposition results by IEEMD. From Fig.7 we can see that mode mixing is eliminated effectively. The IMF1 reflects the intermittent noise signal $n(t)$; IMF3, IMF4 respectively reflect $x_2(t)$, $x_1(t)$ of original signal. From the curves of IMFs, we find the amplitude of IMF2 becomes small compare with Fig.6. The deformation at the endpoints of IMF3 and IMF4 is eliminated. Also, the amplitude for IMF3 and IMF4 decomposed by IEEMD in Fig. 7 is more closely to original signal, and the final decomposition number in Fig.7 is also less than the number decomposed in Fig.6. That is because the mutual information is used to eliminate the false component, and some nose is also eliminated. This fully demonstrates that IEEMD has better decomposition effect than EEMD for the signal with intermittent noise.

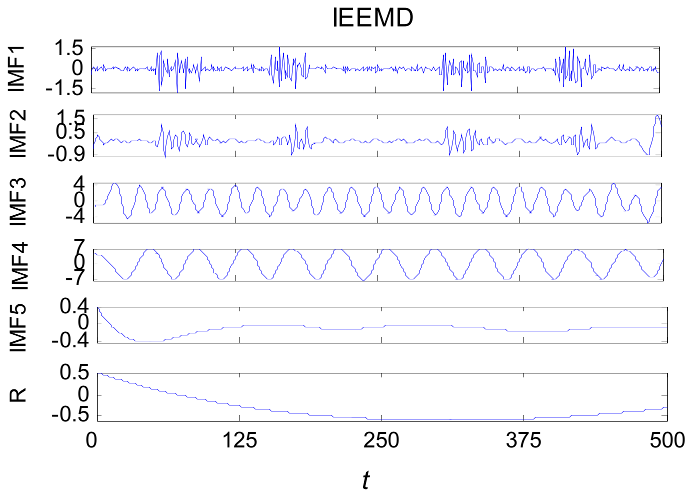

Fig. 7. Curve of IEEMD decomposition results

The next formula is used to the simulation for signal with pulse interference component.

$$f(t) = 8 \bullet \sin(60 \bullet \pi \bullet t + \pi / 12) \tag{18}$$

Where t=0:1/1250:0.4. A pulse interference signal $k(t)$ is added to $f(t)$. The $k(t)$ and the mixed signal $f(t)+k(t)$ are shown in Fig.8.

To the signal $f(t)+k(t)$, the EEMD and IEEMD are processed respectively, and the decomposition results are given by Fig.9 and Fig.10 respectively.

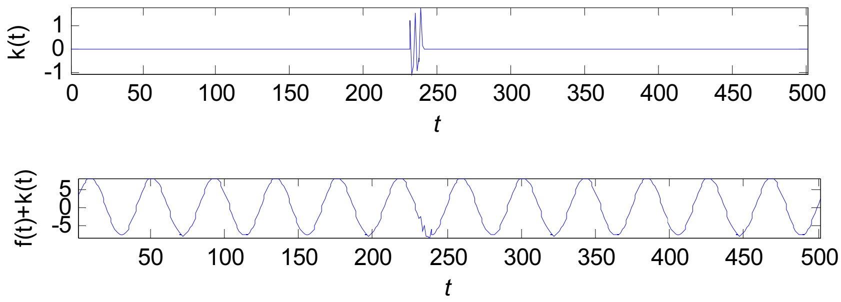

Fig. 8. The curve of signal with pulse interference

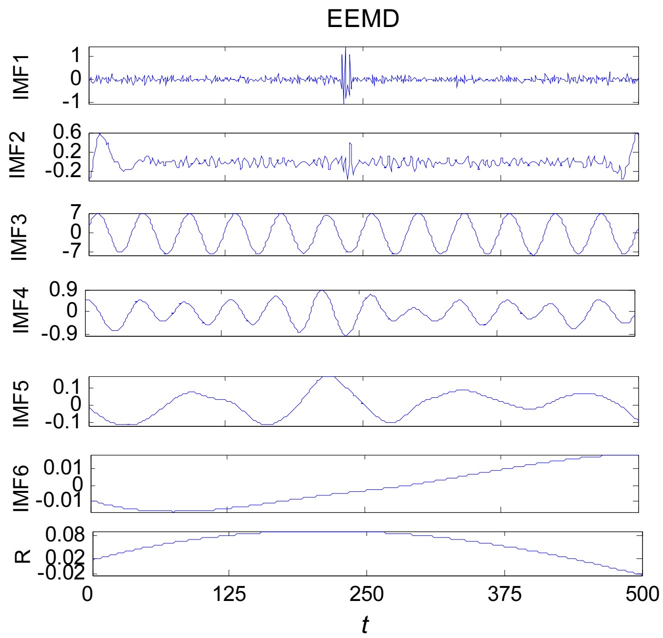

Fig. 9. Results of EEMD decomposition

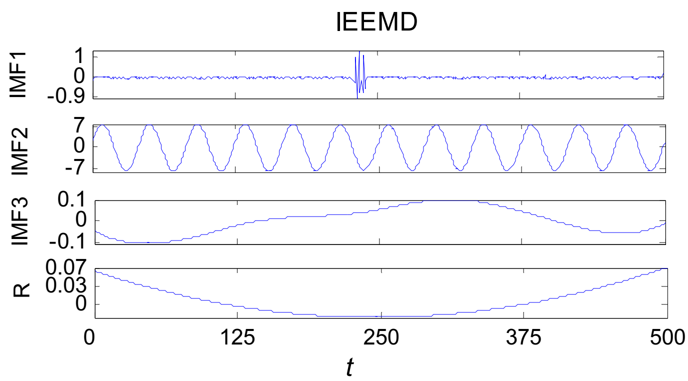

Fig. 10. Results of IEEMD decomposition

From Fig.9 and Fig.10 we can see that both algorithms have inhibitory effect on the mode mixing. The sine signal can be decomposed out from the mixed signal by EEMD and IEEMD. The IMF3 in Fig.9 and the IMF2 in Fig.10 correspond to the sine function $f(t)$. But the decomposition effect of IEEMD is obviously better than that of EEMD. There are six IMFs in Fig.9, and too much false components are decomposed by EEMD. In Fig.10, only one redundant component is decomposed, and the residue closes to zero. The sine function and the pulse interference component are perfectly decomposed by IEEMD.

4 Application study

If the wind turbine gearboxes have the fault of fatigue flaking, the impulse signal is generated when the rolling elements passing the fault in the process of rotation [13], and the vibration signal has specific characteristics [14-15]. So, the type of fault can be obtained by analyzing the vibration signal.

To verify the effectiveness of IEEMD, the bearing outer ring fault data is used to the experiment. The experimental data comes from the data centre of Case Western Reserve University. Bearing designation is SKF 6205-2RS, and rotational frequency is 1797r/min. The more detailed information about the experiment condition can be obtained by [16]. The vibration signal is collected by acceleration sensor, and the sample frequency is 12KH. According to the calculation from theory formula, the characteristic frequency for bearing outer ring fault is 107.3 Hz.

Fig.11 shows the IMF1- IMF6 decomposed by IEEMD. From the figure, we know that the mode mixing is restrained effectively. To present the superiority of IEEMD, the envelope spectrum analysis is processed to the decomposition for EMD, EEMD and IEEMD respectively. By studying the envelope spectrums, we can see that all the first two IMFs envelope spectrums can present the fault frequency spectrum obviously, and the superiority of IEEMD can not be embodied clearly. But to IMF3 and IMF4, the difference can be embodied clearly. For each algorithm, Fig.12 shows the envelope spectrums of IMF3 and IMF4.

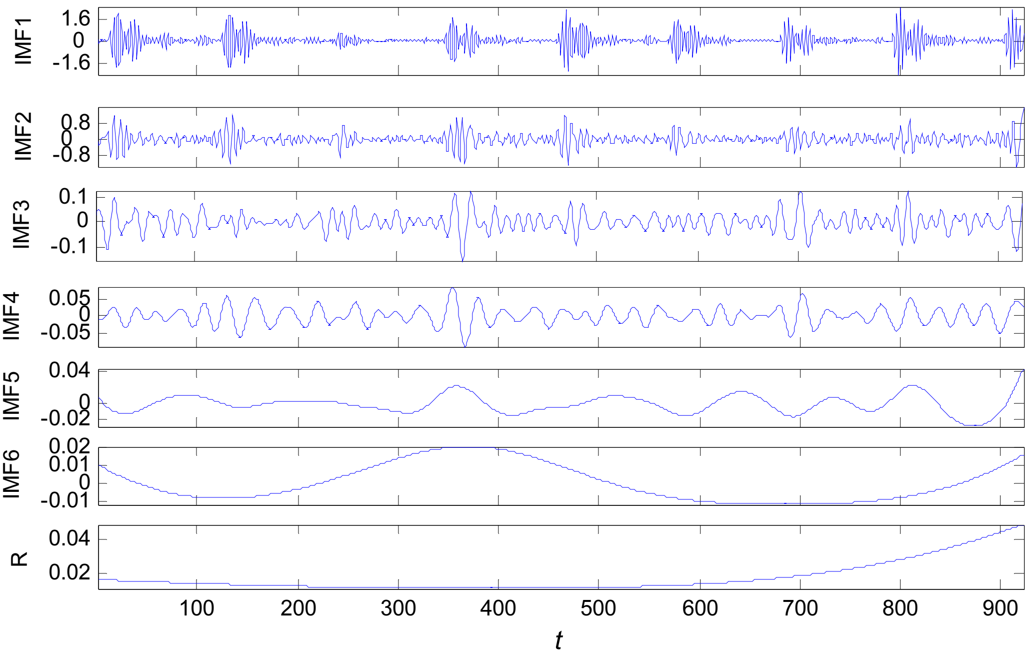

Fig. 11. The decomposition results of IEEMD

To the envelope spectrums of IMF3 in Fig.12, all of the spectrums can recognize the fault frequency spectrum, and the spectrum for second harmonic frequency can also be shown clearly. But the IEEMD spectrum for second harmonic frequency can be shown by the maximal amplitude.

To the envelope spectrums of IMF4 for Fig.12, there is not obvious fault frequency spectrum in EMD's result, and the spectrum for second harmonic frequency can not be shown in EEMD's result. But the spectrum for fault frequency and the spectrum for second harmonic frequency can both be presented clearly in IEEMD's result. So, we can draw the conclusion that the IEEMD is superior to the other algorithms.

5 Conclusions

An improved algorithm (IEEMD) is studied in this paper. In order to solve the mode mixing problem, two white noise signals which are of opposite sign are added to original signal. The mutual information is

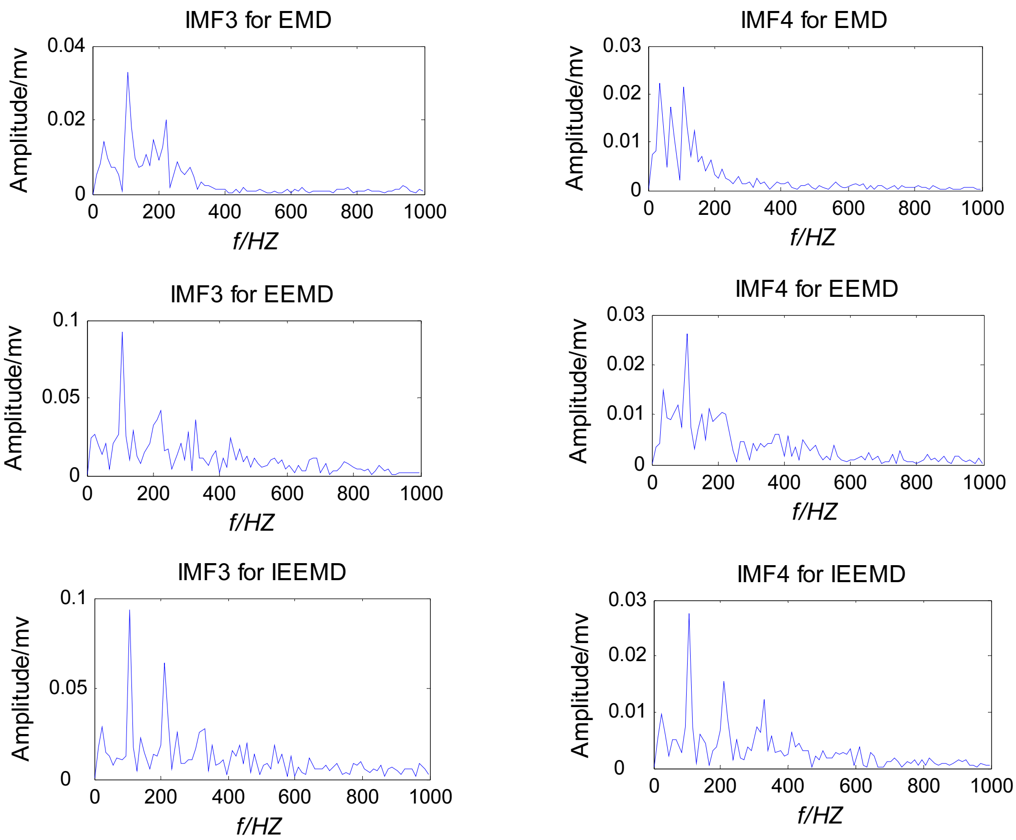

Fig. 12. The envelope spectrums of IMF3 and IMF4

introduced to the IEEMD algorithm so as to obtain the better decomposition effect. Based on the mutual information, before the overall average operation, the false IMFs whose mutual information is less than threshold are eliminated. The noise by decomposition process is reduced effectively. The simulation analysis is given in detail, and the results prove that IEEMD is superior to EEMD. The application study has shown that the IEEMD has better performance.

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