EMD Based on Independent Component Analysis and Its Application in Machinery Fault Diagnosis

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Abstract—**Local rub-impact is the common fault in rotating machinery and results in impact and friction between rotor and stator. The vibration signal due to impact and friction is always non-stationary which includes three components, namely, the rub-impact signal, the background signal and the noise signal. EMD (Empirical mode decomposition) is based upon the local characteristic time scale of signal and could decompose the complicated signal into a number of IMFs (intrinsic mode functions). However, because the weak rub-impact signal is always submerged in the background signal and noise signal. The EMD procedure will generate the components redundancy. In order to solve the problem, a novel method combining with independent component analysis (ICA) and EMD is proposed. ICA is introduced into the EMD procedure, so that the components are orthogonal to each other and the components redundancy can be cut down. In the end, a much better decomposition performances can be obtained. Furthermore, integration of EMD with Hilbert envelope analysis is applied to component instantaneous amplitude in order to obtain envelope spectra from which the mechanical fault can be diagnosed. The analysis results from the rub-impact vibration signals show that the proposed method can be applied to the machinery fault diagnosis effectively.**

Index Terms—**empirical mode decomposition), independent component analysis, Hilbert transform, fault diagnosis, rotating machinery**

I. INTRODUCTION

Rub fault may result in broken machine parts, and lead catastrophic breakdown of the rotating machinery [1]. In order to avoid the occurrence of rub-impact, vibration signal analysis is widely used in rotating machinery condition monitoring and fault diagnosis [2]. Usually, depending on machine operating conditions and severity of defects, the measured vibration signal is always non-stationary and modulated. Furthermore, when the local rub-impact occurs in the rotor system, the vibration signal includes the rub-impact signal, the background signal and the noise signal [3]. The key of the rub-impact fault diagnosis is to extract the rub-impact feature from the vibration signal of the rotor system [4].

Nonlinear and non-stationary signal analysis and processing is one of the most important research areas in information science [5]. A non-stationary signal is usually assumed to be local stationary and its processing is based on the classical theories and techniques for stationary signals. Windowed Fourier transform is a typical example based on such an assumption. Wavelet transform is a time-scale method, which can zoom in or out on the time and frequency scales of a signal adaptively. However, the wavelet basis function must be chosen definitely before it is used, so it cannot be changed adaptively according to the oscillations of the signal at different time. Moreover, an inappropriate wavelet will overwhelm the local characteristic of vibration signal, and lost some useful detail information of original signal. EMD (empirical mode decomposition) is a powerful tool for analyzing the composite, nonlinear and non-stationary signal. EMD is based on the local characteristic time scale of signal and can decompose the complicated signal into a number of IMFs (intrinsic mode functions), each of which is band limited and can represent the features of signal and reserve the local information [6]. However, the decomposition algorithm has some implicit difficulties and the procedures create several drawbacks that originate ''strange'' decompositions [7]. EMD cannot guarantee completeness and orthogonality, and may produce redundant components and affect the accuracy of decompositions.

Independent component analysis (ICA) is a method for finding a linear representation of non-Gaussian so that the components are statistically independent, which is effective in removing components redundancy [8]. In this paper, the ICA is introduced into the EMD procedure to overcome the above limitations, thus the components are orthogonal to each other and components redundancy can be cut down effectively. In the end, the non-stationary

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signal can be decomposed accurately, and a much better decomposition performances can be obtained.

II. EMD And Hilbert Transform

EMD method is developed from the simple assumption that any signal consists of different simple intrinsic modes of oscillations. Any signal can be decomposed into a finite number of IMFs, each of which must satisfy the following definition [6]:

1) In the whole data set, the number of extrema and the number of zero-crossings must either equal or differ at most by one.

2) At any point, the mean value of the envelope defined by local maxima and the envelope defined by the local minima is zero.

An IMF represents a simple oscillatory mode compared with the simple harmonic function. With the definition, any signal $x(t)$ can be decomposed as follows:

1) Identify all the local maxima and local minima, and then connect all these extrema by cubic spline lines to form upper and lower envelopes.

2) The mean of upper and lower envelope value is designated as $m_1(t)$, and the difference between the signal $x(t)$ and $m_1(t)$ is the first component, $h_1(t)$, i.e.

$$x(t) - m_1(t) = h_1(t). \tag{1}$$

If $h_1(t)$ is an IMF, take it as the first component of $x(t)$. If $h_1(t)$ is not an IMF, take it as the original signal and repeat the steps until $h_{1k}(t)$ is an IMF, and designate it $h_{1k}(t)$ as $c_1(t)$.

$$c_1(t) = h_{1k}(t). \tag{2}$$

3) Separate $c_1(t)$ from $x(t)$ by

$$r_1(t) = x(t) - h_1(t). \tag{3}$$

*4)*Treat residue $r_1(t)$ as the original signal and repeat the procedure to extract all possible IMFs. The decomposition process can be stopped, when residue (i.e. $r_n(t)$) becomes a monotonic function, from which no more IMFs can be extracted. The original signal can be represented as,

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t). \tag{4}$$

Thus, we can achieve a decomposition of the signal into IMFs $c_1(t)$, $c_2(t)$, . . . , $c_n(t)$, and a residue $r_n(t)$, which is the mean trend of $x(t)$. The IMFs include different frequency bands ranging from high to low. The frequency components contained in each frequency band are different and change with the variation of signal $x(t)$.

For each IMF $c_i(t)$ in (4), we can always have its Hilbert transform as,

$$H[c_i(t)] = \frac{1}{p}\int_{-\infty}^{+\infty} \frac{x(t)}{t-t} dt. \tag{5}$$

With this definition, we can have an analytic signal as,

$$x_i(t) = c_i(t) + jH_i(t) = \mathrm{a_i}(t)e^{jj_i(t)}. \tag{6}$$

where

$$a_i(t) = \sqrt{c_i^{\,2}(t) + H^2[c_i(t)]}. \tag{7}$$

$$j_i(t) = \arctan\frac{H[c_i(t)]}{c_i(t)}. \tag{8}$$

From (8), we can have the instantaneous frequency as:

$$w_i(t) = \frac{j_i(t)}{2p}. \tag{9}$$

After performing the Hilbert transform to each IMF component, the original signal can be expressed as the real part (RP) in the following form,

$$x(t) = RP\sum_{i=1}^{n} \mathrm{a_i}(t)e^{jj_i(t)}. \tag{10}$$

III. Independent Component Analysis

Independent component analysis(ICA) is very closely related to the method called blind source separation(BSS). The main purpose of ICA is to find a linear representation of non-Gaussian data so that the components are statistically independent. Consider n sources s_1, s_2,…, s_n, which are statistically independent, m measurements from sensors x_1, x_2,…, x_m, which are represented as a linear combination of sources s_i as follows,

$$x = As. \tag{11}$$

where A and s are unknown and x is known. A is the mixing matrix; The source vector $s = [s_1, s_2, ..., s_n]^T$; The observed vector $x = [x_1, x_2, ..., x_m]^T$.

Our aim is to seek a demixing matrix which recovers the source vector s from the observed vector x. The elements of y are estimates of the observed vector x which can be used to represent the observed vector x as follows,

$$y = Wx = WAs. \tag{12}$$

where W is the demixing matrix.

ICA is a two-step process. First step is to choose a principle, based on which a cost function is obtained. Next, a suitable method for optimizing the cost function needs to be adopted. One of the best methods is the FastICA algorithm, which uses the negentropy as the cost function to estimate s_i. Entropy is a measure of the average uncertainty in a random variable. A Gaussian variable has the maximum entropy among all random variables with equal variance. For random vector y, the negentropy is defined as [9].

$$J(y) = H(y_{gauss}) - H(y). \tag{13}$$

Where y_{gauss} is a Gaussian random vector with the same covariance as y. Hence, negentropy of a Gaussian random vector is the difference of entropy with the corresponding Gaussian random vector. To estimate negentropy efficiently, a simpler approximation of negentropy as follows is used,

$$J(y) \approx c\{E[G(y)] - E[G(y_{gauss})]\}^2. \tag{14}$$

Where y is assumed to be of zero mean and unit variance; G is any non-quadratic function; c is a constant.

Using a fixed-point iteration scheme to find directions in which the negentropy is maximized, the demixing matrix W can be achieved [10].

IV ICA-EMD METHOD

The EMD method can decompose a given signal into a finite number of IMFs that admit well-behaved Hilbert transforms. The necessary conditions for the basis to represent non-stationary time series are complete and orthogonal, but the orthogonality is not guaranteed theoretically. By virtue of the decomposition, the components should all be locally orthogonal to each other, for each component is obtained from the difference between the signal $x(t)$ and its local mean $\overline{x(t)}$ through the maximal and minimal envelopes; therefore,

$$\overline{(x(t) - \overline{x(t)}) \cdot \overline{x(t)}} = 0. \tag{15}$$

Nevertheless, equation (15) is not strictly true, because the mean is computed via the envelopes, hence it is not the true mean for nonlinear and non-stationary signal analysis. Furthermore, because the weak rub-impact signal is always submerged in the background and noise signals in practice engineering, EMD cannot guarantee completeness and orthogonality, and may produce redundant components.

ICA is a method for finding a linear representation of non-Gaussian data so that the components are statistically independent, which is effective in removing redundancy. To overcome the above limitations, the theory of ICA was introduced into the EMD procedure and a novel method combining EMD and ICA is proposed, which can improve the decomposition algorithm, thus the components are orthogonal to each other and the decomposition redundancy can be cut down. Then the signal components can be expressed accurately and the weak impulsive feature can be extracted from original signals. The ICA- EMD method follows four operations:

1) Decompose the measured signal X by using the EMD method, and obtain the first component IMF1.

2) Let IMF1 and X be the input to the FastICA algorithm, after performing ICA procedure, we can obtain two independent components which are ICA1 and ICA2 respectively.

3) Because the high frequency component was decomposed firstly, the higher frequency ICA component among the two ICA components can be regarded as IMF1 component, let the other ICA component be a new measured signal X1.

4) Repeat the above processes and obtain the other orders IMFs.

V ICA-EMD METHOD

In order to verify the validity of the proposed method, the local rub-impact fault occurs only in one position was conducted on a rotor test rig. The radial displacement vibration signal with local rub-impact fault picked up by the displacement sensor is shown in Fig.1. The rotating frequency is 47 Hz and the sampling frequency is 2560 Hz. The FFT spectrum of the rub-impact vibration signal is shown in Fig.2. It can be demonstrated from Fig. 2 that the dominant frequency components of the rub-impact signal are the rotating frequency 47 Hz and its 2×. However, the higher frequency components with rub-impact information are submerged in the stronger background signal.

The rub-impact vibration signal shown in Fig.1 is decomposed by EMD method and 4 IMF components are obtained shown as Fig.3. It can be seen from the IMF components listed in Fig.3 that there was no amplitude-modulated characteristic. Because the decomposition redundancies appear when performing the EMD method to the rub-impact vibration signal shown in Fig. 1, the signal components cannot be expressed accurately. So in the EMD procedure the decomposition redundancies carries great subjectivity that would bring inaccurate diagnosis result, whereas the ICA-EMD method can overcome the limitation which occurs in the EMD procedure.

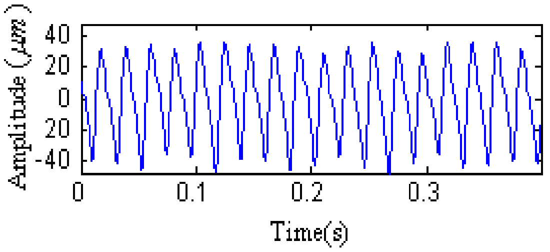

Figure 1. The radial displacement vibration signal of the rotor system with local rub-impact vibration fault.

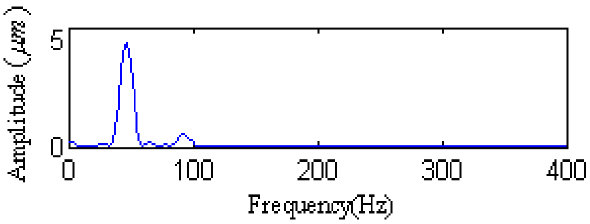

Figure 2. FFT spectrum of rub-impact Signal.

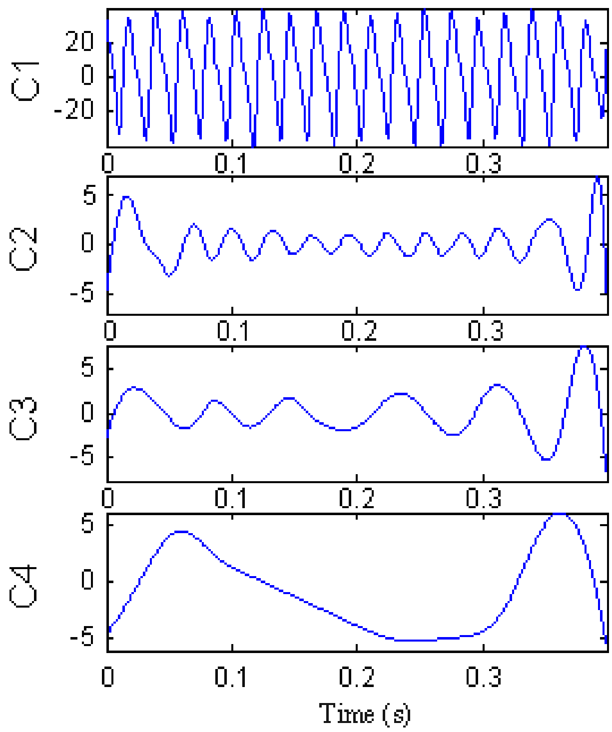

Figure 3. Decomposition result of the rub-impact signal by using EMD.

To extract the rub-impact signal, the ICA-EMD method was applied to detect the rub-impact vibration signal shown in Fig.1. Firstly, the vibration signal is denoised by using lifting wavelet, then is decomposed by the ICA-EMD method. The decomposition result is shown in Fig.4. It can be seen from Fig.4 that the component C1 has the obvious amplitude-modulated characteristics. The Hilbert envelope analysis is then applied to the component C1 in order to obtain the envelop spectra of the component C1 which is shown in Fig.5. From Fig.5 it can be seen that in the envelop spectrums of the component C1 there is the obvious spectrum line at the rotating frequency 47 Hz, which is produced by the periodic impact between the rotor and the stator. Hence, the component C1 including the rub-impact information is just the rub-impact characteristic signal. The other components C2 and C3 are the background signal related to the rotating frequency, the frequencies included in the components C3 and C2 are the rotating frequency and its double, which coincides with the FFT spectrum shown in Fig.2, while the residue C4 is the noise signal with lower frequency component. Therefore, by using the ICA-EMD method, the rub-impact signal, the background signal and the noise signal can be separated from the vibration signal of the rotor system with local rub-impact fault, thus the rub-impact information in the high frequency band can be extracted from the strong background signal effectively, and the fault feature of the rub-impact vibration signal can be obtained.

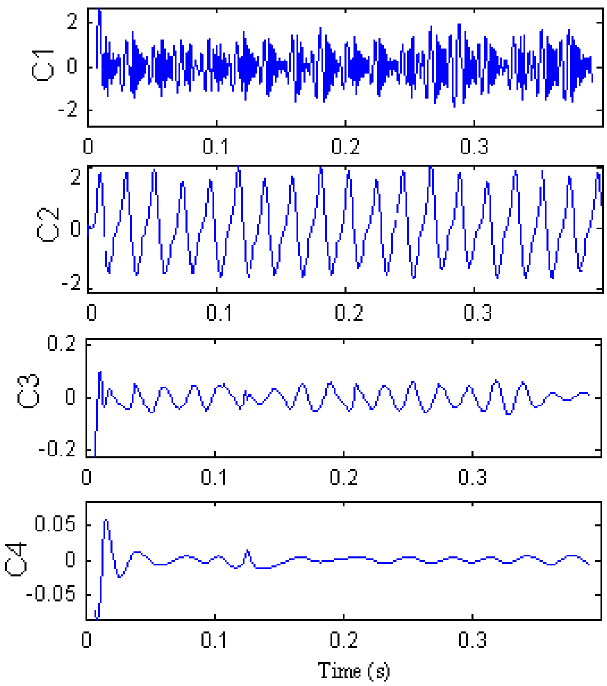

Figure 4. Decomposition result of the rub-impact signal by using ICA-EMD.

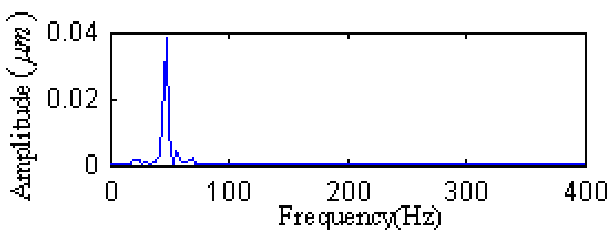

Figure 5. Hilbert envelope spectrum of the component C1.

In this experiment, we utilize the EMD method and the ICA-EMD method to decompose the rub-impact signal respectively. Fig. 3 and 4 are the decomposition results respectively. We consider the first IMF which represents the main features of the vibration signal. From the results, we can find that the decomposition performance obtained by using the ICA-EMD method is much better than that of the straightforward EMD method. Compared with the straightforward EMD procedure, the ICA-EMD method can eliminate components redundancy and obtain a much better decomposition performance, so the signal components can be expressed accurately. The rub-impact information in the high frequency band can be extracted from the strong background signal effectively by using the ICA-EMD method. Therefore, the fault feature of the vibration signal can be obtained efficiently.

VI. Discussion

EMD as a data driven alternative approach to the analysis of non-stationary signals appears some drawbacks. Because the rub-impact signal is weak, it is very difficult to separate the rub-impact signal from the vibration signal including noise and background signal by using the straightforward EMD method. Here we proposed solutions for the problem of components redundancy in order to obtain an algorithm with better performances. The proposed method can remove the components redundancy in EMD method and improve the quality of decomposition. Compare to the straightforward EMD, the ICA-EMD method can obtain a much better decomposition performance, and the amplitude-modulated characteristic information of the rub-impact signal can be extracted from the measured vibration signal. Experimental analysis results show that the proposed method can be applied to the feature extraction of the rotor systems with local rub-impact fault effectively.

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