Rolling Element Bearing Fault Feature Extraction Using EMD-Based Independent Component Analysis

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***Abstract*—This paper introduces a joint bearing fault characteristic frequency detection method using empirical mode decomposition (EMD) and independent component analysis (ICA). Independent component analysis can be used to separate multiple sets of one-dimensional time series into independent time series, which need at least two transducers to obtain more than one set of time series for separation of different sources. To overcome this restriction, preprocessing is needed to construct multiple sets of time series. Empirical mode decomposition has attracted attention in recent years due to its ability to self-adaptively process non-stationary and non-linear signals with multiple intrinsic mode functions being obtained through EMD decomposition. Hence, considering this superiority, this paper employs EMD to transform one set of one-dimensional series into multiple sets of one-dimensional series for pre-processing. After that, independent components (IC) are extracted, which include fault-related signatures in the frequency spectrum. To validate the proposed method, real motor bearing vibration data, including normal bearing data, outer race fault data, and inner race fault data, are used in a case study. The results show that the proposed method can be used for bearing fault extraction.**

Keywords—rolling element bearing; fault feature extraction; empirical mode decomposition; independent component analysis

I. INTRODUCTION

As a common element in mechanical systems, rolling element bearings are widely used in rotating machines, and their failure is a major reason for machine breakdown. An unexpected bearing failure can result in machinery accelerated deterioration and eventually accidents. In order to enhance machine reliability and reduce maintenance cost, bearing condition monitoring becomes an important measure to ensure machine safety. For this reason, a variety of bearing fault detection techniques have been proposed [1, 2].

In condition monitoring of rotating machines with defective bearings, the bearing resonant high frequency gets excited by the impulses arising from the low-frequency bearing local defects (e.g., inner race, outer race, rolling element). A lot of methods, including fast Fourier transform (FFT), the high-frequency resonance technique (HFRT), shock-pulse monitoring (SPM), and wavelet transform (WT), are used to determine the health condition of bearings. FFT alone is not capable of analyzing the frequency content of a defective bearing signal [3]. FFT only provides a global energy-frequency distribution and fails to depict non-stationarity of a signal caused by a local defect. HFRT, which is also called "envelope analysis," is a technique that separates frequencies from vibration signals generated by other elements. The application of HFRT is limited by the use of vibration exciters and controllers [4]. SPM can detect the presence of impulses caused by defects in bearings [5], but it cannot localize a defect in case there exist masking or interference frequencies from other defects (e.g., gearbox) that are similar to the bearing frequencies. As a time-frequency analysis technique, WT was developed recently and is useful for the analysis of transient and non-stationary signatures. The major drawback of WT is that it uses a fixed wavelet function for analysis at certain decomposition levels and does not take into account the signal's characteristics [6].

As a self-adaptive decomposition technique for non-stationary and non-linear signal analysis, empirical mode decomposition (EMD) was proposed by Huang et al. [7]. It is a method that decomposes a time series into a finite number of intrinsic mode functions (IMFs), which represent different oscillatory modes in the data. Recently, research has been conducted on the application and improvement of EMD for mechanical fault diagnosis and condition monitoring. For example, Fan and Zuo [8] applied EMD to decompose signals and used the Hilbert transform to demodulate gearbox fault signals. Li and Ji [9] proposed an improved EMD method for signal feature extraction. Yan and Gao [10] presented an EMD based signal decomposition and feature extraction technique and investigated two criteria, the time-domain energy measure and correlation measure, for the selection of intrinsic mode functions (IMFs).

It should be pointed out that the IMF obtained through EMD decomposition is not completely mono-component under practical engineering circumstances due to complicated vibration signals produced by different machine components. It is reasonable to treat the original IMFs as the linear mixtures of different vibration signals. Based on this assumption, further investigation can be performed by extraction of a major fault source from the IMFs. Therefore, this becomes a blind source separation (BSS) problem for detection of a latent and major fault source. Independent component analysis (ICA) is a

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popular method for solving BSS problems. It transforms multi-channel signals into multiple sets of independent source signals [11]. Therefore, ICA is employed in this paper to extract a latent major fault source.

The purpose of this research is to propose a method using an EMD-based independent component analysis technique for rolling element bearing fault feature extraction. The rest of the paper is organized as follows. Section 2 gives a brief introduction of empirical mode decomposition and independent component analysis techniques. Section 3 presents our proposed method for the bearing fault feature extraction. In section 4, a case study utilizing real motor bearing vibration data is presented to validate the proposed method. Conclusions are summarized in section 5.

II. Theoretical Background

A. Empirical Mode Decomposition

Empirical mode decomposition is a method to decompose non-linear, multi-component signals into a series of zero-mean AM-FM components that are called intrinsic mode functions. It was developed based on the assumption that any signal consists of different simple intrinsic modes of oscillations. According to the definition of IMF [7], two conditions should be satisfied: 1) the number of extrema and zero crossings may differ by no more than one; 2) the local mean is zero.

As discussed in [12], EMD is defined by the algorithm and does not have an analytical formulation. Given a signal $x(t)$, the algorithm of EMD can be summarized as below [7, 12]:

1) Find all the local extrema of $x(t)$.

2) Connect all the local maxima of the signal using a cubic spline line. The connected line is called the upper envelope $e_{\max}(t)$. Similarly, find the lower envelope $e_{\min}(t)$ with the local minima.

3) Calculate the mean of the upper and lower envelopes $m(t)$, and the detail $h_i(t)$ can be obtained as follows:

$$m(t) = (e_{\min}(t) + e_{\max}(t))/2 \tag{1}$$

$$h_i(t) = x(t) - m(t) \tag{2}$$

4) Check whether $h_i(t)$ is an IMF. If $h_i(t)$ is not an IMF, repeat the loop on $h_i(t)$. If $h_i(t)$ is an IMF, then set $c_1(t) = h_i(t)$.

5) Separate $c_1(t)$ from $x(t)$, and a residual $r_1(t)$ can be given as

$$r_1(t) = x(t) - c_1(t) \tag{3}$$

6) Treat the residual $r_1(t)$ as the original signal and iterate steps (1)–(5) $n-1$ times. As a result, n IMFs can be obtained, as follows:

$$\begin{aligned} r_2(t) &= r_1(t) - c_2(t) \\ &\cdots \\ r_n(t) &= r_{n-1}(t) - c_n(t) \end{aligned} \tag{4}$$

The decomposition process does not stop until the residual $r_n(t)$ becomes a monotonic function or a constant from which no more IMF can be extracted. Then the EMD is completed, and the original signal $x(t)$ is decomposed as:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{5}$$

B. Independent Component Analysis

Assume that there are n linear mixtures, $x_1(t)$, $x_2(t)$, …, $x_n(t)$, measured by n transducers and n independent source signals $s_1(t)$, $s_2(t)$, …, $s_n(t)$. Then each linear mixture can be expressed as [13]:

$$x_j(t) = a_{j1}s_1 + a_{j2}s_2 + \cdots a_{jn}s_n,\ j = 1,2,\ldots n \tag{6}$$

Eq. (6) can be written as:

$$\mathbf{X} = \mathbf{AS} \tag{7}$$

Here, $\mathbf{X} = [x_1(t), x_2(t), \ldots, x_n(t)]^T$, $\mathbf{S} = [s_1(t), s_2(t), \ldots, s_n(t)]^T$, and $\mathbf{A}$ is the square matrix with elements a_{ij}, where $i = 1,2,\ldots n$ and $j = 1,2,\ldots,n$. The model in (7) is called independent component analysis, or the ICA model.

Generally, these independent source components are latent variables and cannot be measured directly. Therefore, only the vector $\mathbf{X}$ is observed, and both the matrix $\mathbf{A}$ and the vector $\mathbf{S}$ are estimated through $\mathbf{X}$. If the matrix $\mathbf{A}$ and the vector $\mathbf{X}$ are available, the inverse of $\mathbf{A}$, namely $\mathbf{W}$, and the vector $\mathbf{S}$ can be computed by:

$$\mathbf{W} = \mathbf{A}^{-1} \tag{8}$$

$$\mathbf{S} = \mathbf{WX} \tag{9}$$

The Central Limit Theorem shows that the distribution of the sum of a large number of independent random variables tends to be a Gaussian distribution. Thus, any variables of $\mathbf{X}$ must have a distribution that is closer to Gaussian than that of any variable of $\mathbf{S}$ because each variable of $\mathbf{X}$ is formed by the mixture of all variables of **X**. Non-Gaussianity is useful to obtain independent components. There are many different methods for measuring non-Gaussianity discussed in [13]. This paper employs the FastICA based on the fixed-point iteration scheme to find a maximum of the non-Gaussianity [14].

III. THE PROPOSED METHOD FOR ROLLING ELEMENT BEARING FAULT DIAGNOSIS

A. *Bearing Fault Characteristic Frequencies*

Generally, rolling element bearings consist of inner race, outer race, rolling elements and cage. When a defect occurs on the surface of certain part of the bearing, the corresponding fault characteristic frequency gets excited. In order to detect the location of the defect, it is necessary to identify the existence of fault characteristic frequency. The formulae for the various characteristic frequencies are as follows [1]:

Ball pass frequency, outer race:

$$BPFO = f_{rO} = \frac{nf_r}{2}(1 - \frac{d}{D}\cos\beta) \tag{10}$$

Ball pass frequency, inner race:

$$BPFI = f_{rI} = \frac{nf_r}{2}(1 + \frac{d}{D}\cos\beta) \tag{11}$$

Ball spin frequency:

$$BSF = f_{rR} = \frac{Df_r}{2d}[1 - (\frac{d}{D}\cos\beta)^2] \tag{12}$$

Fundamental train frequency:

$$FTF = f_{rC} = \frac{f_r}{2}(1 - \frac{d}{D}\cos\beta) \tag{13}$$

Here, d, D, n, β, f_r are the rolling element diameter (mm), the pitch diameter (mm), the number of rolling elements, the contact angle (°), and the rotating frequency of the bearing shaft (Hz), respectively.

B. *The EMD Based ICA Method For Bearing Feature Extraction*

Assume a piece of bearing vibration signal $x(t)$ is obtained by a signal transducer. When there exists a local defect on certain part of the bearing, the recorded signal presents a modulation phenomenon caused by the resonant vibration stimulated by a bearing defect. The corresponding fault characteristic frequency and its harmonics become dominant over the entire frequency domain after demodulation. Hilbert transform can be used to demodulate the signal and the envelope signal is obtained and denoted as $y(t)$.

By applying EMD decomposition on the envelope signal $y(t)$, n IMFs $c_1(t), c_2(t), \ldots c_n(t)$ are obtained. Among all IMFs, those containing fault-related signatures are useful for bearing fault detection. According to [10], it is reasonable to construct a selection criterion based on the frequency energy of IMF. Therefore, all IMFs are mapped into the frequency domain by the Fourier transform and their absolute values are given by:

$$ES_i(f) = \left| \int_{-\infty}^{+\infty} c_i(t) e^{-2\pi i f t} dt \right|, \quad i = 1,2,\ldots,n \tag{14}$$

Frequency spectrum energy proportion is calculated as:

$$ESS_i = \sum_f (ES_i(f))^2, \quad i = 1,2,\ldots,n \tag{15}$$

$$I_i = \frac{ESS_i}{\sum_i ESS_i}, \quad i = 1,2,\ldots,n \tag{16}$$

According to (16), the IMFs with the m largest I_i values are selected for further construction of the matrix **X** in the ICA model, and these IMFs are denoted as $c_{(1)}(t), c_{(2)}(t), \ldots, c_{(m)}(t)$. That is, $\mathbf{X} = [c_{(1)}(t), c_{(2)}(t), \ldots, c_{(m)}(t)]^T$.

In ICA analysis, two preprocessing steps are suggested according to [13]. One is centering and the other is whitening. After two preprocessing steps, FastICA is implemented for the identification of a latent fault source, and the procedure of the FastICA is described as follows [14]:

1. Choose an initial weight vector $\mathbf{W}_k$ randomly, and let $k = 0$.

2. Calculate $\mathbf{W}_k^+ = E\{\tilde{\mathbf{X}} g(\mathbf{W}_k^T \tilde{\mathbf{X}})\} - E\{g'(\mathbf{W}_k^T \tilde{\mathbf{X}})\}\mathbf{W}_k$.

3. Let $\mathbf{W}_k = \mathbf{W}_k^+ / \left\| \mathbf{W}_k^+ \right\|$.

4. If not converged, go back to step 2. That is to say, if $\mathbf{W}_k$ and $\mathbf{W}_{k-1}$ are not in the same direction, go back to step 2.

In this algorithm, $E(\bullet)$ denotes the expectation operation; $\tilde{\mathbf{X}}$ is the vector of **X** after the centering and whitening steps; and $g(\bullet)$ is the derivative of the nonquadratic function G used in the measuring of the non-Gaussianity of the ICA modeling [13].

Assume that the obtained independent components are expressed as $\mathbf{S} = [IC_1(t), IC_2(t), \ldots IC_m(t)]^T$. In order to select the optimal IC that can distinguish the bearing fault characteristic frequency from other frequencies, a new index is proposed here to choose the best IC among all variables of **S**.

When a bearing fault happens, its corresponding characteristic frequency and harmonics appear in the frequency spectrum. Therefore, the index should reflect the contribution of both the characteristic frequency and its harmonics, and it is defined as:

$$IES_i(f) = \left| \int_{-\infty}^{+\infty} IC_i(t) e^{-2\pi i f t} dt \right|, \quad i = 1, 2, \ldots, m \qquad (17)$$

$$ICI_i = IES_i(f^*) \times IES_i(2f^*) \times \cdots \times IES_i(kf^*), \quad i = 1, 2, \ldots, m \qquad (18)$$

where f^* represents the bearing fault characteristic frequency, and k is the harmonic order. The normalization form of the index is given as:

$$C_i = \frac{ICI_i}{\sum_i ICI_i}, \quad i = 1, 2, \ldots, m \qquad (19)$$

Based on (19), the IC with the largest C_i is regarded as the most useful independent component among all available ICs.

IV. Experimental Validation

A. Description of Experiment

In this section, the real motor bearing data collected with a sampling frequency of 12 kHz by an accelerometer placed at the drive end of the motor housing were used for the validation of the proposed method [15]. The bearing was running with a speed of 1772 rpm, which corresponds to the bearing shaft rotating speed, f_r = 29.53 Hz. Single point defects were introduced into the normal bearings using electro-discharge machining with a fault diameter of 0.007 inches and a fault depth of 0.0011 inches. Three pieces of vibration signals with a length of 12,000 sampling points were collected, including the normal bearing vibration signal, the signal with the outer race defect, and the signal with the inner race defect. The corresponding fault characteristic frequencies are calculated as f_{rI} = 160.02 Hz and f_{rO} = 105.93 Hz, respectively. The time-domain plots of the raw vibration signals are shown in Fig. 1.

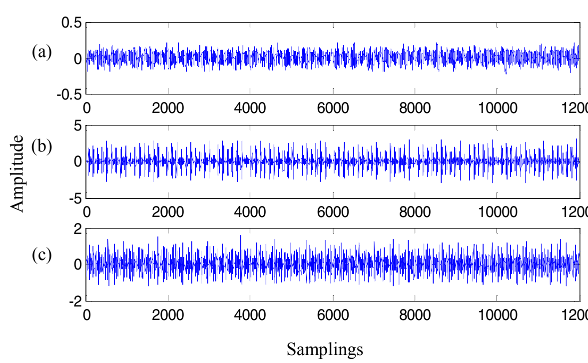

Figure 1. Raw vibration signals: (a) the normal bearing signal; (b) the signal wih outer race defect; (c) the signal with inner race defect.

B. Validation Results

In the process of signal analysis, the Hilbert transform is employed firstly to demodulate the raw signal and get the envelope signal. Through EMD decomposition, IMFs are obtained. Fig. 2 shows the IMFs extracted from the normal bearing vibration signal, and no fault-related characteristic frequencies can be observed from the frequency spectra of the IMFs.

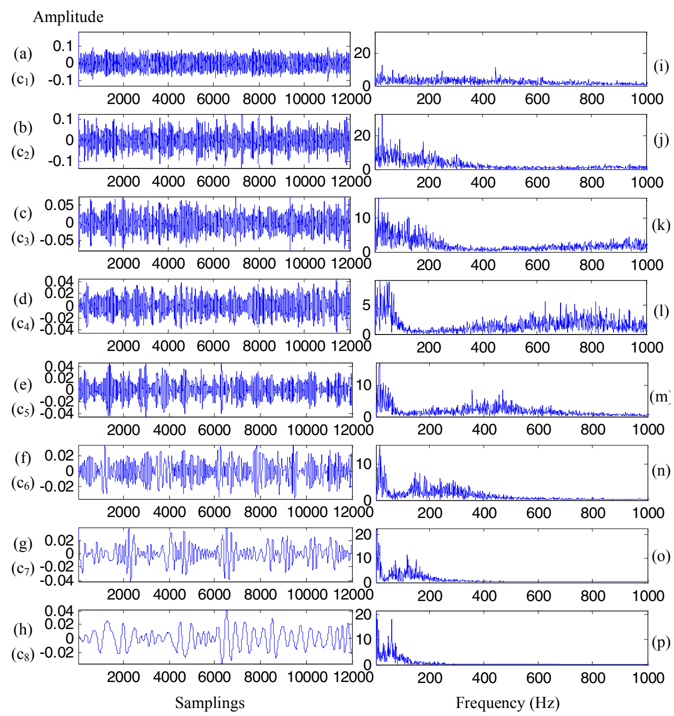

Figure 2. IMFs extracted from the normal bearing vibration signal together with their corresponding frequency spectra.

Fig. 3 shows the IMFs extracted from the vibration signal of a bearing with an outer race defect and their frequency spectra. The BPFO f_{rO} and its harmonics can be observed from the results. Based on the energy percentage of IMFs calculated using (14)–(16), the IMFs C1–C8 are selected as the input of ICA. Eight independent components are gained with ICA and their frequency spectra are plotted in Fig. 4. A comparison of Fig. 3 and Fig. 4 shows that EMD-based ICA obtained better results because it can identify more fault-related signatures. According to the selection criterion defined by (17)–(19), IC_5 is the optimal component that includes the f_{rO} and the eight harmonic components.

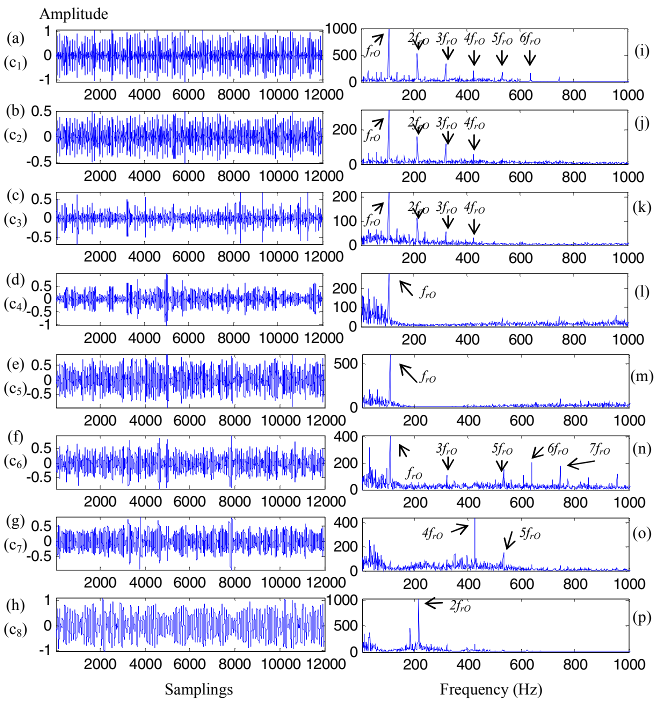

Figure 3. IMFs extracted from an outer race defect vibration signal, together with their corresponding frequency spectra.

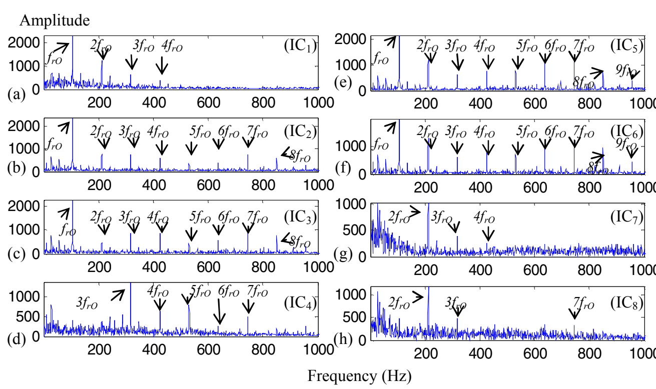

Figure 4. Frequency spectra of ICs extracted from an outer race defect vibration signal using the proposed method.

Similarly, the vibration signal of the bearing with an inner race defect is analyzed and the results are given in Fig. 5 and Fig. 6. Fig. 5 shows the IMFs and their spectra obtained from the vibration signal of the bearing with an inner race defect, and the BPFI f_{rI} and its harmonics can be identified. Through ICA analysis, more fault signatures can be observed from the spectra of the IC components (Fig. 6). Therefore, the proposed method has good capability for fault feature extraction. Based on the selection criterion defined by (17)–(19), IC_2 is the optimal component that contains most fault-related signatures.

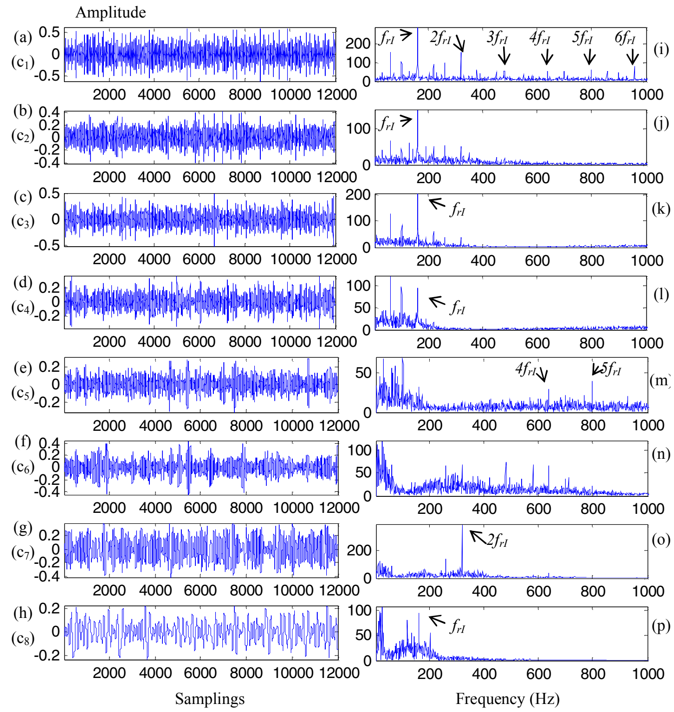

Figure 5. IMFs extracted from an inner race defect vibration signal, together with their corresponding frequency spectra.

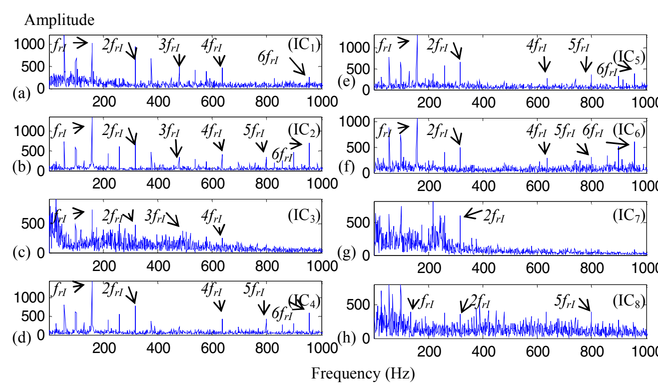

Figure 6. Freuqency spectra of ICs extracted from an inner race defect vibration signal using the proposed method.

V. CONCLUSIONS

Rolling element bearing failure is one of the major reasons for machine breakdown, and many bearing fault detection methods have been investigated in the past decades. This paper introduces a bearing fault feature extraction method using empirical mode decomposition based ICA analysis. The EMD is employed to decompose the time domain signal into several IMFs, and the ICA is applied to extract the latent major fault source from the IMFs.

A case study on the vibration signals of the motor bearings was conducted, and the analysis demonstrated that the proposed method can identify the fault signatures. From the EMD-based ICA analysis in this paper, an optimal independent component can be selected, which includes various fault-related signatures.

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