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Rolling Bearing Fault Diagnosis with Hilbert Spectrum Based on EEMD

LU Jinming + and Meng Fanlin
School of Energy Source and Power Eng., Jiangsu University of Science and Technology, Zhenjiang, China

Abstract. A new time-frequency distribution to detect bearing inner race fault is proposed here, which is based on HHT and EEMD. The intrinsic mode functions generated by EEMD can alleviate the problem of mode mixing and its Hilbert spectrum has more focusing force in time-frequency distribution. The characteristic frequencies of a rolling bearing with inner-race fault were found in the instantaneous energy density of Hilbert spectrum. Compared with other time-frequency distribution, this method can show the fault characteristic frequencies more clearly and has less calculation expensive.

Keywords: component; rolling bearing; fault diagnosis; HHT; ensemble empirical mode decomposition (EEMD); instantaneous energy density.

1. Introduction

When a rolling bearing element strikes a localized defect, a very short impulse occurs and excites the resonance of the structure. Therefore, the vibration signature of the damaged bearing consists of exponentially decaying sinusoid having the structure resonance frequency. The duration of the impulse is extremely short compared with the interval between impulses, and so its energy is distributed at a very low level over a wide range of frequency and hence, can be easily masked by noise and low-frequency effects. The periodicity and amplitude of the impulses are governed by the bearing operating speed, location of the defect, geometry of the bearing, and the type of the bearing load.

The rolling elements experience some slippage as the rolling elements enter and leave the bearing load zone. As a consequence, the occurrence of the impacts never reproduce exactly at the same position from one cycle to another, moreover, when the position of the defect is moving with respect to the load distribution of the bearing, the series of impulses is modulated in amplitude. All these make the bearing defects very difficult to detect by conventional FFT-spectrum analysis which assumes that the analyzed signal to be strictly periodic.

One of the methods to overcome the modulation problem is envelope demodulation techniques. The inconvenience of the envelope demodulation techniques is that the most suitable pass-band must be identified before the demodulation takes place [1].

The wavelet transform and the ensemble empirical mode decomposition provides powerful multi-resolution analysis in both time and frequency domain and thereby becomes a favored tool to extract the transitory features of non-stationary vibration signals produced by the faulty bearing [2]. The wavelet transform is not a self-adaptive method for the appropriate wavelet base function must be selected at first.

EMD is a self-adaptive signal processing method that can be applied to non-linear and non-stationary process perfectly. But it still leaves some annoying difficulties unresolved. One of the major drawbacks of the original EMD is the frequent appearance of mode mixing, which is defined as a single Intrinsic Mode Function (IMF) either consisting of signals of widely disparate scales, or a signal of a similar scale residing

+ Corresponding author.
E-mail address: Ljm280ljm@163.com.

in different IMF components. Mode mixing is often a consequence of signal intermittency. As discussed by Huang et al., the intermittence could not only cause serious aliasing in the time-frequency distribution, but also make the physical meaning of individual IMF unclear [3].

The Ensemble EMD (EEMD), a new noise-assisted data analysis (NADA) method proposed by Z. H. Wu and N. E. Huang [4], defines the true IMF components as the mean of an ensemble of trials, can clearly separate the scale naturally without any a priori subjective criterion selection, and can eliminate the problem of mode mixing automatically [5].

2. EEMD and Instantaneous Energy Density Spectrum

The added white noise would populate the whole time-frequency space uniformly with the constituting components of different scales. When signal is added to this uniformly distributed white background, the bits of signal of different scales are automatically projected onto proper scales of reference established by the white noise in the background. Each individual trial may produce very noisy results, for each of the noise-added decompositions consists of the signal and the added white noise. Since the noise in each trial is different in separate trials, it is canceled out in the ensemble mean of enough trials. The ensemble mean is treated as the true answer [6].

The proposed EEMD is developed as follows:

(1). Normalize the zero mean data $x(t)$, $x(t)/\sigma_x$, σ_x is the standard deviation of data. adding noise $\pm k \cdot n(t)$ to the data, $n(t)$ is a normalized white noise, k is the ratio of the standard deviation of the added noise and that of $x(t)$, and it was proposed to be 0.2 by Z. H. Wu and N. E. Huang [5].

$$X_1(t) = x(t)/\sigma_x + k \cdot n(t) \tag{1}$$

$$X_2(t) = x(t)/\sigma_x - k \cdot n(t) \tag{2}$$

(2). Decompose the data with added white noise into IMFs;

$$X_1(t) = \sum_{j=1}^{m} c_{1,j} + r_{1,m} \tag{3}$$

$$X_2(t) = \sum_{j=1}^{m} c_{2,j} + r_{2,m} \tag{4}$$

(3). Repeat step 1 and step 2 again and again, but with different white noise series each time;

$$X_{1,i}(t) = x(t) + k \cdot n_i(t) \tag{5}$$

$$X_{2,i}(t) = x(t) - k \cdot n_i(t) \tag{6}$$

$$X_{1,i}(t) = \sum_{j=1}^{m} c_{1,i,j} + r_{1,i,m} \tag{7}$$

$$X_{2,i}(t) = \sum_{j=1}^{m} c_{2,i,j} - r_{2,i,m} \tag{8}$$

(4). Repeat N times, obtain the (ensemble) means of corresponding IMFs of the decompositions as the final result.

$$c_j = \frac{1}{2 \times N} \sum_{i=1}^{N} (c_{1,i,j} + c_{2,i,j}) \tag{9}$$

$$r_m = \frac{1}{2 \times N} \sum_{i=1}^{N} (r_{1,i,m} + r_{2,i,m}) \tag{10}$$

the final result is

$$X(t)=\sigma_x(\sum_{j=1}^{m}c_j+r_m) \tag{11}$$

The Hilbert transform of IMFs is defined in the following equation, which is the convolution of signal $c_i(t)$ with $1/t$ and emphasize the local properties of $c_i(t)$.

$$\hat{c}_i(t)=\frac{1}{\pi}\int_{-\infty}^{\infty}\frac{c_i(\tau)}{t-\tau}d\tau \tag{12}$$

Combining $c_i(t)$ and $\hat{c}_i(t)$, we can obtain the analytic signal $z_i(t)$:

$$z_i(t)=c_i(t)+j\hat{c}_i(t)=a_i(t)e^{j\varphi_i(t)} \tag{13}$$

$$a_i(t)=\sqrt{c_i^2(t)+\hat{c}_i^2(t)} \tag{14}$$

$$\varphi_i(t)=\arctan\frac{\hat{c}_i(t)}{c_i(t)} \tag{15}$$

Where $a_i(t)$ is the instantaneous amplitude of $c_i(t)$, which reflects how the energy of $c_i(t)$ varies with time t and $\varphi_i(t)$ is the instantaneous phase of $c_i(t)$.

The instantaneous frequency $f_i(t)$ is given as

$$f_i(t)=\frac{1}{2\pi}\omega_i(t)=\frac{1}{2\pi}\times\frac{d\varphi_i(t)}{dt} \tag{16}$$

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

$$\begin{aligned}x(t)&=RP\sum_{i=1}^{n}a_i(t)e^{j\varphi_i(t)}\\&=RP\sum_{i=1}^{n}a_i(t)e^{j\int\omega_i(t)dt}\end{aligned} \tag{17}$$

Here we left out the residue on purpose for it is either a monotonic function or a constant. Eq.(17) gives both amplitude and frequency of each component as functions of time. This frequency-time distribution of the amplitude is designated as the Hilbert spectrum

$$H(\omega,t)=RP\sum_{i=1}^{n}a_i(t)e^{j\int\omega_i(t)dt} \tag{18}$$

Hilbert spectrum express the instantaneous amplitude (energy)-instantaneous frequency-time distribution, and have much more physical meaning than other time-frequency distribution.

Instantaneous energy density is expressed as

$$IE(t)=\int_{\omega}H^2(\omega,t)dt \tag{19}$$

Obviously, $IE(t)$ is the function of time, it represented the energy rising and dropping. Instantaneous energy density spectrum is the power spectral density (PSD) of $IE(t)$

3. Application in inner race fault of rolling bearing

The fault platform of rotating machine consists of a driving electromotor, rolling bearings, gear box, shaft, eccentricity turn plate and a magnetic powder arrester. The set can simulate different fault in every velocity. The type of sensor is B&K4638, electric charge amplifier type is B&K2635, signal analysis instrument is

CF5220. The rotating speed is measured by magnetoelectricity sensor and the vibration is measured by piezoelectricity sensor.

There are 13 balls in the 36.5mm diameter rolling bearing, each ball's diameter is 7mm. On the inner race of this bearing a defect is made, showed as Fig.1.

Fig.1: A rolling bearing with inner-race fault

A pair of meshing gear, the bigger gear with 75 teeth and the pinion with 55 teeth. On the one tooth face a pitting fault is made, showed as Fig.3.

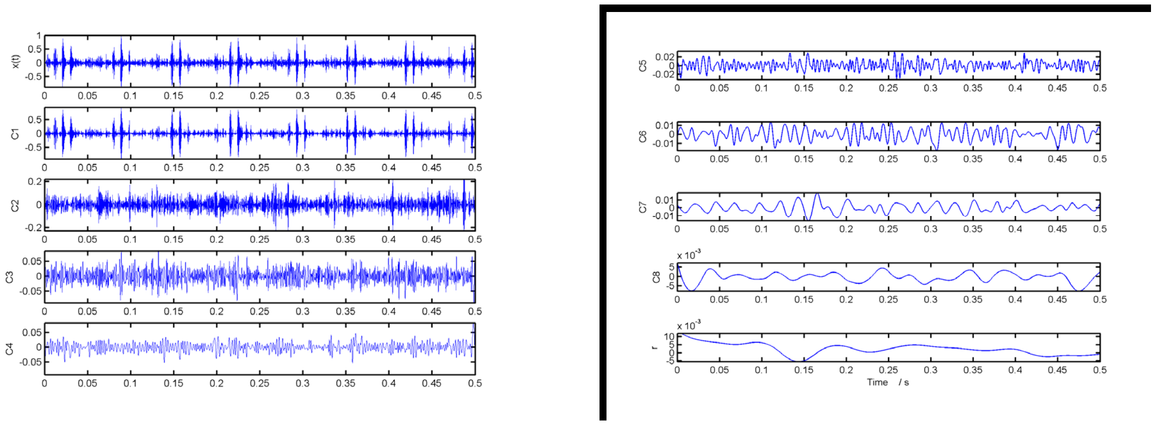

Fig. 2: IMFs by EEMD of vibration signal on a rolling bearing with inner-race fault

Fig.2 showed the IMFs c1~c8 and the residue r of vibration signal $x(t)$ on a rolling bearing with inner-race fault gained by EEMD. Fig.3 showed its Hilbert spectrum. Fig.4 showed its Instantaneous energy density.

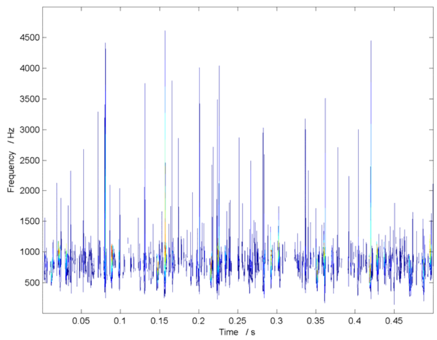

Fig. 3: Hilbert spectrum of vibration signal

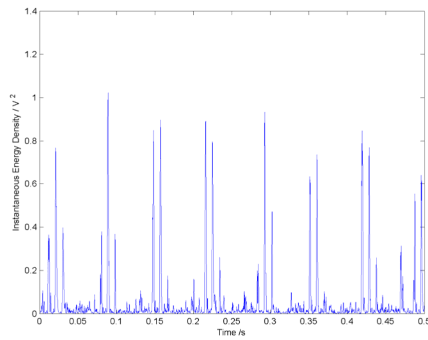

Fig. 4: Instantaneous energy density

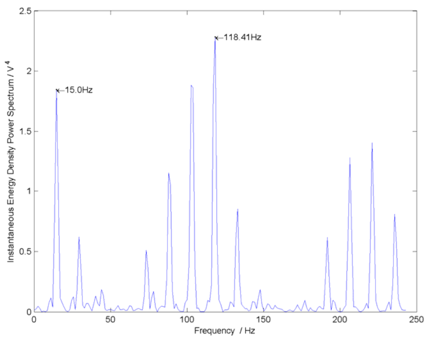

Fig. 5: Instantaneous energy density spectrum of vibration signal

Fig.5 showed the instantaneous energy density spectrum of vibration signal on a rolling bearing with inner-race fault, the shaft rotating frequency 15.0Hz and the fault characteristics frequency 117.8Hz, is very close to the theoretical result 116.1Hz, the error is caused by frequency resolving power. The wedding frequencies are also found in the Fig.5 and it demonstrates the modulation between the shaft rotating frequency and the fault characteristics frequency.

Fig.6 showed the Choi-Williams time-frequency distribution of the vibration signal. Fig.7 showed its instantaneous energy density spectrum. Compared with HHT time-frequency distribution based EEMD, the CWD has the almost same effect, but has much more calculation expenses.

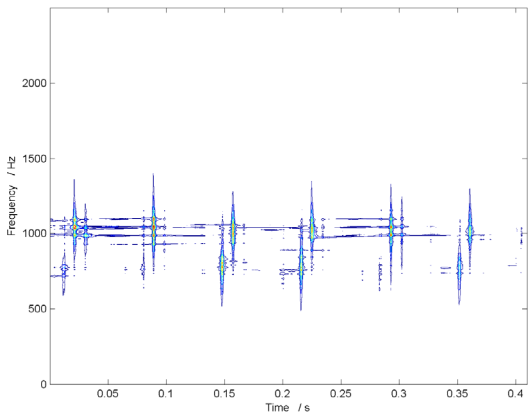

Fig. 6: The Choi-Williams time-frequency distribution (CWD)

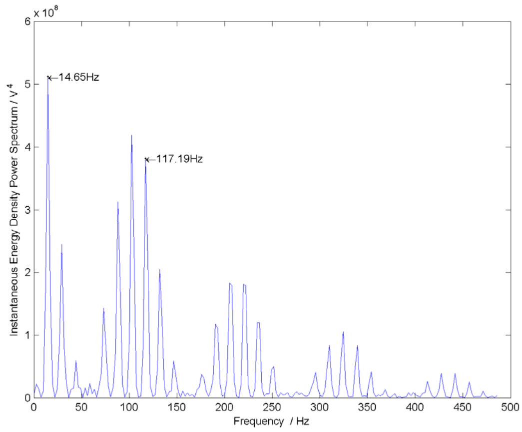

Fig.7: Instantaneous energy density spectrum of CWD

4. Conclusion

Mode mixing is one of the major drawbacks of the original EMD, and it makes difficult to extract the fault feature from its Hilbert spectrum. With noise-assisted, the EEMD method can eliminate the problem of mode mixing automatically to gain the approximating IMFs. The Hilbert spectrum of this IMFs expressed the real time-frequency distribution of the signal.

The shaft rotating speed frequency, the fault characteristics frequency (FCF), the harmonic FCF and its webbing frequency can be found in the instantaneous energy density spectrum of vibration signal on a rolling bearing with inner-race fault.

The effectiveness of this method was demonstrated by analysis the vibration signals of a rolling bearing with inner-race fault. Compared with other time-frequency distribution, this method can show the fault characteristic frequencies more clearly and has less calculation expensive.

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