Research Article

Gear Fault Diagnosis Based on Empirical Mode Decomposition and 1.5 Dimension Spectrum

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Aiming at the nonlinear and nonstationary feature of mechanical fault vibration signal, a new fault diagnosis method, which is based on a combination of empirical mode decomposition (EMD) and 1.5 dimension spectrum, is proposed. Firstly, the vibration signal is decomposed by EMD and the correlation coefficient between each intrinsic mode function and original signal is calculated. Then these intrinsic mode function components, which have a big correlation coefficient, are selected to estimate its 1.5 dimension spectrum. And this method uses 1.5 dimension spectrum of each intrinsic mode function to reconstruct its power spectrum. And these power spectrums are summed to obtain the primary power spectrum of gear fault signal. Finally, the information feature of fault is extracted from the reconstructed 1.5 dimension spectrum. A model to reconstruct 1.5 dimension spectrum is established, and the principle and steps of the method are presented. Some simulated and measured gear fault signals have been processed to demonstrate the effectiveness of new method. The result shows that this method can greatly inhibit the interference of Gauss noise to raise the SNR and recognize the secondary phase coupling feature of the signal. The proposed method has a good real-time performance and provides an effective method to determine the early crack fault of gear root.

1. Introduction

A common method for extracting the mechanical fault is assuming that vibration signals are stable with Gaussian distribution [1–3]. But the real measured signals often are nonstationary and non-Gaussian distribution. In particular, in the event of failure, signal is easy to be affected by the Gaussian noise. The gear fault signal is a typical nonlinear and nonstationary signal [3]. The machinery system usually produces sum and difference frequency components when the failure occurs. This is a nonlinear coupling phenomenon. In power spectrum, it is presented as the sum and the difference of frequency side bands [4, 5]. For this nonlinear phenomenon, it is difficult to solve the problem fundamentally by the traditional power spectrum analysis and processing method [5]. In theory, the Gauss noise and the non-Gaussian colored noise can be completely inhibited and the phase information of the nonlinear system can be maintained by High-order cumulants (HOC) [6, 7]. Nonlinear coupling feature can be effectively detected by HOC, which provides a reliable and effective tool for the extraction of fault features.

But the HOC have high computational complexity and cost a great deal of time. As a special case of HOC, the 1.5 dimension spectrum provides an alternative because it not only retains the advantages of HOC but also has low computational complexity [8, 9]. Empirical mode decomposition (EMD) is a new adaptive decomposition method, and the decomposed components can reconstruct the original signal, which laid a foundation for further signal processing [10]. Based on the combination of EMD and 1.5 dimension spectrum, a fault feature extraction method is proposed in this paper. And it is applied in the gearbox fault diagnosis to explore its ability of fault feature detection.

2. Empirical Mode Decomposition Method

Empirical mode decomposition (EMD) is also called Huang transform, which can effectively separate various frequency components of the signal from the time curve in the form of intrinsic mode function (IMF) [10]. And the original signal can be reconstructed by decomposed component. This

method, which has been researched widely, is very suitable for nonlinear and nonstationary signal processing. IMF satisfies two conditions [10, 11]. (1) In the entire sequence, the number of extrema (maxima plus minima) and the number of zero-crossing points is equal or differs by one. (2) At any time, the mean value of the envelope, as defined by the local maxima and the local minima, is zero. EMD is a process of cyclic decomposition; the specific steps can be described as follows: For a given signal $x(t)$, locate all the local extrema. Then fit all the extrema on the curve to construct the two envelopes $u_0(t)$ and $v_0(t)$. The mean of the upper and lower envelopes $m_0(t)$ is calculated as

$$m_0(t) = \frac{1}{2} (u_0(t) + v_0(t)). \quad (1)$$

After $x(t)$ subtracts $m_0(t)$, the remaining part is obtained as

$$h_1(t) = x(t) - m_0(t). \quad (2)$$

Ideally, $h_1(t)$ should be an IMF. If $h_1(t)$ cannot meet the condition of LMF, taking $h_1(t)$ as the original signal, the corresponding upper envelope $u_1(t)$ and lower envelope $v_1(t)$ of $h_1(t)$ are calculated and the same interpolation scheme is reiterated to the remainder. Consider

$$\begin{aligned} m_1(t) &= \frac{1}{2} (u_1(t) + v_1(t)), \\ h_2(t) &= h_1(t) - m_1(t), \\ &\vdots \\ m_{k-1}(t) &= \frac{1}{2} (u_{k-1}(t) + v_{k-1}(t)), \\ h_k(t) &= h_{k-1}(t) - m_{k-1}(t). \end{aligned} \quad (3)$$

The above procedure is repeated till $h_k(t)$ conforms to the properties of IMFs described previously. $h_k(t)$ is the first IMF of original signal $x(t)$, called $C_1(t)$. Then the first $C_1(t)$ is subtracted by $x(t)$ to get the residue $r_1(t)$. Consider

$$\begin{aligned} C_1(t) &= h_k(t), \\ r_1(t) &= x(t) - C_1(t). \end{aligned} \quad (4)$$

The residue $r_1(t)$, which contains longer-period components, is treated as new data and subjected to the same sifting process as described above. This procedure can be repeated to obtain all the subsequent $r_j(t)$ ($j = 1, 2, \dots, n$). Consider

$$\begin{aligned} r_1(t) - C_2(t) &= r_2(t), \\ &\vdots \\ r_{n-1}(t) - C_n(t) &= r_n(t). \end{aligned} \quad (5)$$

At the end of the decomposition, $x(t)$ is represented as the sum of n IMFs and a residue $r_n(t)$:

$$x(t) = \sum_{i=1}^n C_i + r_n. \quad (6)$$

In order to verify the reconfigurable property of EMD, a simulated signal is processed. Firstly, the original signal is decomposed with EMD method, and then the obtained IMFs are summed to reconstruct signal. Figure 1 shows the error between the reconstructed signal and the original signal. From these diagrams, it can be seen that the error is small between the reconstructed signal and the original signal. The amplitude of error and that of signal are different in 15 orders of magnitude. The error is computer calculation error and can be negligible. Being visible, the original signal can be reconstructed using the decomposed component, with almost no energy loss [10, 12], which provides a new way for noise suppression.

3. Higher Order Statistics and Higher Order Spectrum

Higher order statistics is a mathematical tool which is used to describe the higher order (second-order or above) statistical feature of a random process [6, 13]. Being similar to the power spectrum of Fourier transform of autocorrelation function, multidimension Fourier transform of higher order cumulant is defined as higher order spectrum (or multispectrum) [14, 15].

For a random variable $x(t)$, the joint cumulant for the order number $r = k_1 + k_2 + \dots + k_n$ is defined as

$$\begin{aligned} c_{k_1, k_2, \dots, k_n} &= (-j) \frac{\partial^r \psi(\omega_1, \omega_2, \dots, \omega_n)}{\partial \omega_1^{k_1} \partial \omega_2^{k_2} \dots \partial \omega_n^{k_n}} \Big|_{\omega_1=\omega_2=\dots=\omega_n=0} \\ &= (-j) \frac{\partial^r \Phi(\omega_1, \omega_2, \dots, \omega_n)}{\partial \omega_1^{k_1} \partial \omega_2^{k_2} \dots \partial \omega_n^{k_n}} \Big|_{\omega_1=\omega_2=\dots=\omega_n=0}. \end{aligned} \quad (7)$$

Here, $\Phi(\omega_1, \omega_2, \dots, \omega_n) = E\{\exp[j(\omega_1 x_1 + \omega_2 x_2 + \dots + \omega_n x_n)]\}$.

If $x(t)$ is k order stationary process of zero mean, k order accumulation of this process is defined as

$$\begin{aligned} c_{kx}(\tau_1, \tau_2, \dots, \tau_n) \\ = \text{cum}(x(t), x(t + \tau_1), \dots, x(t + \tau_{k-1})). \end{aligned} \quad (8)$$

Here, $\text{cum}(g(x))$ is the united accumulation.

Assuming that the higher order accumulation $c_{kx}(\tau_1, \dots, \tau_{k-1})$ is absolutely summable,

$$\sum_{\tau_1=-\infty}^{+\infty} \dots \sum_{\tau_{k-1}=-\infty}^{+\infty} |c_{kx}(\tau_1, \dots, \tau_{k-1})| < \infty; \quad (9)$$

then K order cumulative spectrum is defined as $k - 1$ dimension Fourier transform of k order cumulant:

$$\begin{aligned} s_{kx}(\omega_1, \dots, \omega_{k-1}) \\ = \sum_{\tau_1=-\infty}^{+\infty} \dots \sum_{\tau_{k-1}=-\infty}^{+\infty} c_{kx}(\tau_1, \dots, \tau_{k-1}) \exp \left\{ -j \sum_{i=1}^{k-1} \omega_i \tau_i \right\}. \end{aligned} \quad (10)$$

Traditionally, higher order cumulant spectrum is called higher order spectrum or multispectrum; the most common

FIGURE 1: Error between the reconstructed signal and original signal. (a) Original signal. (b) EMD decomposition of original signal. (c) Reconstructed signal. (d) Error.

high order spectrum is three-order spectrum (known as double spectrum). Consider

$$B_x(\omega_1, \omega_2) = \sum_{\tau_1=-\infty}^{+\infty} \cdots \sum_{\tau_2=-\infty}^{+\infty} c_{3x}(\tau_1, \tau_2) e^{-j(\omega_1 \tau_1 + \omega_2 \tau_2)}. \quad (11)$$

4. 1.5 Dimension Spectrum

For a random variable $x(t)$, the diagonal slice of its three-order cumulant $c_{3x}(\tau_1, \tau_2)$ (τ_1, τ_2 is time delay) is denoted as

$c_{3x}(\tau, \tau)$. Then the Fourier transform of this diagonal slice is defined as 1.5 dimension power spectrum of $x(t)$ [8, 16]:

$$\begin{aligned} C_{3x}(\omega) &= \sum_{\tau=-\infty}^{+\infty} c_{3x}(\tau, \tau) e^{-j\omega\tau}, \\ C_{3x}(\omega) &= \int_{-\infty}^{+\infty} c_{3x}(\tau, \tau) e^{-j\omega\tau} d\tau \\ &= \int_{-\infty}^{+\infty} \left[\int_{-\infty}^{+\infty} x(t) x^2(t + \tau) dt \right] e^{-j\omega\tau} d\tau. \end{aligned} \quad (12)$$

1.5 dimension spectrum holds several excellent characteristics and provides a convenient way for the signal processing [9].

(a) Supposing $x(t)$ is n -order real harmonic signal which has zero mean and its fundamental frequency is ω_0 , when $|\omega_m| < |\omega_l|$, the following expression was established:

$$\begin{aligned} C(\omega_m) &> C(\omega_l), \\ \omega_m &= m\omega_0, \quad m = \pm 1, \pm 2, \dots, \pm n, \\ \omega_l &= l\omega_0, \quad l = \pm 1, \pm 2, \dots, \pm n. \end{aligned} \quad (13)$$

The properties show that the fundamental frequency component of signal is strengthened when the 1.5 dimension spectrum is used to analyze harmonic signal. It provides a good method to extract the fundamental frequency component of the signal.

(b) In case that $n(t)$ is Gauss white noise with zero mean, its 1.5 dimension spectrum can be established as $C(\omega) = 0$. The property indicates that the 1.5 dimension spectrum can effectively restrain the Gauss white noise.

(c) Assuming that $x(t)$ is harmonic signal, ω_1 , ω_2 , and ω_3 are the three harmonic components, and $\omega_1 > \omega_2 > \omega_3$. If $\omega_1 \neq \omega_2 + \omega_3$, which means that frequency does not meet the coupling relationship, the following expression can be obtained:

$$\begin{aligned} C(\omega_1) &= 0, \\ C(\omega_2) &= 0, \\ C(\omega_3) &= 0. \end{aligned} \quad (14)$$

If $\omega_1 = \omega_2 + \omega_3$, which means that frequency meets the coupling relationship, the following must be determined:

$$\begin{aligned} C(\omega_1) &\neq 0, \\ C(\omega_2) &\neq 0, \\ C(\omega_3) &\neq 0. \end{aligned} \quad (15)$$

The property suggests that three coupling harmonic terms can be extracted by 1.5 dimension spectrum and the harmonic term, which does not meet coupling relationship, can be eliminated.

1.5 dimension spectrum is a special case of the higher order spectrum. It has the ability to suppress Gauss noise and symmetrical distributed noise and has the minimum amount of computation which is similar to the amount of Fourier power spectrum in the high order spectrum [9]. The fundamental frequency component of harmonic signal can be strengthened and the nonquadratic phase coupling harmonic components can be eliminated by the 1.5 dimension spectrum. Quadratic phase coupling is a kind of nonlinear phase coupling way. For three components c_1 , c_2 , and c_3 (frequency of each component is f_1 , f_2 , and f_3 , resp.; phase of each component is φ_1 , φ_2 , and φ_3 correspondingly), if $f_3 = f_1 + f_2$ and $\varphi_3 = \varphi_1 + \varphi_2$, then component c_3 is caused by the quadratic phase coupling of c_1 and c_2 . When mechanical system failure occurs, the strong nonlinear feature is shown and quadratic

phase coupling is generated by system. Traditional power spectrum inhibits all phase information. So it cannot be used to identify the quadratic phase coupling characteristic of mechanical fault signal. Bispectrum, which can be used to check the characteristics of quadratic phase coupling, retains the phase information of non-Gauss process. But the amount of computation of bispectrum is large and its estimation precision is low. In contrast, the analysis performance of bispectrum for quadratic phase coupling can be retained and the Gauss noise in signal can be inhibited completely by the 1.5 dimension spectrum [16].

5. Methods and Steps

Figure 2 illustrates the algorithm flow chart of fault diagnosis based on EMD-1.5 dimension spectrum. According to the above principle, the fault diagnosis method can be described as follows:

- (1) In order to eliminate the interference of cross-term which is introduced by different frequency components, the fault signal $x(t)$ is decomposed by EMD to obtain a series of IMF components as $c_1, c_2, \dots, c_n$.
- (2) The correlation analysis is applied between the obtained IMF and the original signal, and then the pseudocomponent with small correlation coefficient is eliminated.
- (3) The 1.5 dimension spectrum is calculated from the selected IMF components.
- (4) The 1.5 dimension spectrum of each order of IMF is added up to get the 1.5 dimension spectrum of original signal.
- (5) Finally the diagnostic results are obtained from the reconstructed 1.5 dimension spectrum.

6. Simulated Signal Analysis

The effectiveness of the fault diagnosis method based on EMD decomposition and 1.5 dimension spectrum will be verified by analyzing the simulated signal. Simulated signal is described as follows:

$$\begin{aligned} x(t) &= \left[\cos\left(35 * 2 * \pi * t + \frac{\pi}{3}\right) \right. \\ &\quad \left. + \cos\left(75 * 2 * \pi * t + \frac{\pi}{6}\right) \right]^2 \\ &\quad + \cos\left(160 * 2 * \pi * t + \frac{\pi}{4}\right). \end{aligned} \quad (16)$$

The sampling frequency is 1 kHz; the length of data is 1000 points. The simulated signal time-domain waveforms are shown in Figure 3. According to Euler formula, the above simulated signal can be launched into the sum of some cosine signals as 70 Hz, 110 Hz, 40 Hz, 150 Hz, and 160 Hz. Figure 4 shows the spectrum of simulated signal from Fourier transform.

Figure 5 shows the results of the EMD decomposition of the simulated signal and the corresponding power spectrums

FIGURE 2: Algorithm flow chart of fault diagnosis based on EMD-1.5 dimension spectrum.

FIGURE 3: Time series of simulated signal.

FIGURE 4: Fourier spectrum of simulated signal.

of the obtained IMFs. From the power spectrum of each IMF component, it can be seen that the decomposition process is carried out from high frequency to low frequency, which illustrates that EMD has the characteristics of multiresolution analysis. The components “imf₁”~“imf₅” are the dominant components, and “Residual” is the remaining amount or a weak item because its amplitude is 1/200 of original signal. Thus, the EMD is an adaptive process of decomposition from high frequency to low frequency.

Calculating the correlation coefficients between each IMF and the original signal, respectively (in other words, the correlation coefficient between “imf₁” and the original signal is calculated, and then the correlation coefficient between “imf₂” and the original signal is calculated, and so on), they are 0.761, 0.753, 0.624, 0.617, 0.178, and 0.162. It can be seen that “imf₁”~“imf₄” have much larger correlation coefficient than the following two components. Their value is not in the same order of magnitude. Thus, the components after “imf₄” can be deduced as the false component. In the analysis of

original signal, the 1.5 dimension spectrum of “imf₁”~“imf₄” is calculated. And 1.5 dimension spectrum of original signal can be obtained after superposition. Figure 6 shows the 1.5 dimension spectrum of simulated signal.

Figure 4 is compared with Figure 6. In the Fourier spectrum shown in Figure 4, the frequency components of the simulated signal, respectively, 40 Hz, 70 Hz, 110 Hz, 150 Hz, and 160 Hz, can be detected. Gauss white noise exists throughout the frequency band, and its amplitude is large. In the 1.5 dimension spectrum shown in Figure 6, the frequency components which meet nonlinear coupling relationship are 40 Hz, 70 Hz, 110 Hz, and 150 Hz. The frequency component 160 Hz, which is not in the coupling, is eliminated. This also verifies the property of the 1.5 dimension spectrum discussed above.

In order to further verify the ability of suppressing of Gauss white noise, Figure 7 shows the 1.5 dimension spectrum and Fourier spectrum of noised signals which are from different SNR: 10 dB, 0 dB, and -10 dB. In the three situations of SNR, even though in the case of SNR = 0 dB, the 1.5 dimension spectrum can still accurately extract the peak value of 4 components. The spectrum line is relatively smooth, the frequency components are pure, and the peak feature is clear after noise reduction. After adding the noise with SNR = -10 dB, which is a strong interference, the peak values of 40 Hz and 110 Hz frequency components are still clearly presented. Comparing the Fourier spectrum with the 1.5 dimension spectrum of simulated signal, it can be drawn that the signal extraction ability of Fourier spectrum is weaker under the condition of above three kinds of noise. In particular, when SNR = -10 dB, the peak of Fourier spectrum of useful signal is almost submerged by that of noise. Thus it can be seen that 1.5 dimension spectrum can effectively remove the Gauss noise and reduce effect of noise and has a better effect than Fourier spectrum.

Table 1 compares the running time of Fourier spectrum, 1.5 dimension spectrum, and bispectrum under different SNR circumstances. Spectrum estimation processions of three kinds of method are similar. In Table 1, the speed of spectrum estimation based on Fourier transform is the fastest in the case of same data length and SNR. Although the speed of the 1.5 dimension spectrum is slower than that of the Fourier method, the computation time is significantly shorter than that of the bispectrum. The efficiency has been improved by almost 3 times of magnitude. The running time of the bispectrum is increased from 1.86 s to 3.87 s when the SNR

FIGURE 5: EMD decomposition and spectrum of IMFs of simulated signal.

FIGURE 6: EMD-1.5 dimension spectrum of simulated signal.

is decreased from 20 dB to -20 dB. Meanwhile the running time of the 1.5 dimension spectrum is only increased from 0.542 s to 0.968 s, and the increase is small.

From the above simulation experiments, we come to a conclusion that the 1.5 dimension spectrum can effectively extract the nonlinear coupling features of the signal while restraining the Gauss white noise and it is faster than other higher order spectrum. 1.5 dimension spectrum is suitable for the real-time feature extraction of fault signal under mass data and low SNR condition.

TABLE 1: Run-time comparison of three methods under different SNR conditions.

Sampling points	SNR/dB	Running time/s		
		Fourier spectrum	1.5 dimension spectrum	Bispectrum
1024	-20	0.819	0.968	3.87
	-10	0.736	0.975	2.93
	0	0.489	0.761	2.07
	10	0.314	0.653	1.97
	20	0.205	0.542	1.86

7. Measured Signal

In order to further verify the effectiveness of the proposed method in the fault feature extraction of gears, the gear with gear tooth crack fault is tested and analyzed. A comprehensive fault simulation test bench is used to do gear fault diagnosis test. The test bench is composed of motor, a mechanical transmission device, sensor, the hardware circuit, computer, and related software. Figure 8 shows the test bench. The number of teeth of driving wheel is $Z_1 = 10$ and motor speed is $f_{r1} = 720$ rpm. The number of teeth of driven wheel

FIGURE 7: EMD-1.5 dimension spectrum (left) and Fourier spectrum (right) of simulated signal with different SNR. (a) SNR = 10 dB. (b) SNR = 0 dB. (c) SNR = -10 dB.

FIGURE 8: Comprehensive fault simulation test bench.

FIGURE 9: Time series of measured signal.

gear is $Z_2 = 15$, module is $m = 2$ mm, rotating frequency of gear axis is $f_{r2} = 480$ rpm, meshing frequency is $f_z = 120$ Hz, and sampling frequency is 1 kHz. A gear with defects has been considered and a small crack to one gear has been added. In the gear, a small groove, with 0.1 mm width and 3 mm depth, is processed to simulate tooth crack. Figure 9 shows the time-domain waveform of the gearbox vibration signal. It can be seen that the periodic impulse signals are almost drowned in the strong background noise, and the

time-domain waveform is very complex. Figure 10 illustrates the corresponding Fourier spectrum of the signal. In the spectrum, the specific features of the signal are difficult to be distinguished, so it is difficult to extract the fault signal.

The fault signal is decomposed by EMD method. The IMF components and their corresponding power spectrum are shown in Figure 11. In the figure, it can be seen that the

FIGURE 10: Fourier spectrum of measured signal.

FIGURE 11: EMD decomposition and spectrum of IMFs of measured signal.

FIGURE 12: EMD-1.5 dimension spectrum of measured signal.

FIGURE 13: Partial enlarged drawing of EMD-1.5 dimension spectrum of measured signal (80 Hz–200 Hz).

signal is decomposed into 9 layers from high frequency to low frequency. The correlation coefficients between each component and the signal are calculated: they are 0.711, 0.704, 0.484, 0.701, 0.714, 0.632, 0.556, and 0.521. The IMF component, whose correlation coefficient is more than 0.5, is chosen to calculate 1.5 dimension spectrum. After superposition, the spectrums of fault signal are shown in Figure 12. In order to observe the meshing frequency and its edge frequency band, Figure 12 is amplified locally. Figures 14 and 13 show the spectrum line of the part frequency range.

In Figure 12, it can be clearly seen that there are obvious spectrum lines in 8 Hz, 16 Hz, 24 Hz, and 32 Hz, which are very close to the calculated output rotational frequency (8 Hz) and its harmonic frequency. In Figure 13, it is clear that there is a clear spectrum line at 120 Hz, and the meshing frequency (120 Hz) is very close to the theoretical value. There are obvious spectrum lines in 104 Hz, 112 Hz, 120 Hz, 128 Hz, and 136 Hz. The distance between these frequencies is very close to the output shaft rotating frequency, which illustrates that the meshing frequency is modulated by the rotating frequency. In Figure 14, it is clear that there are obvious spectrum lines in 224 Hz, 232 Hz, 240 Hz, 248 Hz, and 256 Hz. The distance between these frequencies is also very close to the output shaft rotating frequency in theory. 240 Hz is very close to the two doubling frequency (240 Hz) of the meshing frequency calculated in theory, which shows that the two doubling frequency of the meshing frequency is modulated by the rotating frequency. The same feature is also generated at the 360 Hz frequency point. From above

FIGURE 14: Partial enlarged drawing of EMD-1.5 dimension spectrum of measured signal (200 Hz–300 Hz).

result, we come to a conclusion that the output shaft gears have faults, which meet the actual fault conditions.

8. Conclusion

Combining the advantage of empirical mode decomposition and 1.5 dimension spectrum, a united mechanical fault diagnosis method is proposed. Simulated and measured signal analysis shows that EMD decomposition is a complete adaptive decomposition process for signal. And the decomposed IMF can be used to reconstruct the original signal, which lays the foundation for the selection of IMF with high correlation degree. 1.5 dimension spectrum is a special case of the high order spectrum. It has the ability to suppress Gauss noise and symmetrical distributed noise and has the minimum amount of computation which is similar to the amount of power spectrum. The analysis performance of bispectrum for quadratic phase coupling can be retained by 1.5 dimension spectrum. Based on empirical mode decomposition and 1.5 dimension spectrum, the nonlinear coupling characteristics can be extracted and the Gauss white noise can be effectively suppressed by the proposed method; EMD-1.5 dimension spectrum method provides the conditions for accurately extracting fault feature information.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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