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Research Article

A Composite Method of Marine Shafting's Fault Diagnosis by Ship Hull Vibrations Based on EEMD

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The fault diagnosis is always a key issue in the security field of marine propulsion system. There are obvious problems like the unsteady working of sensors, distortion of original data, and ambivalent feature information from marine shafting's vibration or motion. It is therefore critical to develop a more effective method to identify the fault information so that the safety of marine propulsion system can be pre-estimated. Hence, a composite method which is based on the ensemble empirical mode decomposition (EEMD) and coupled with the autocorrelation method (AM), the fast Fourier transform (FFT), is mixed and applied to identify the fault information of marine shafting during its operating by hull vibration. The contrastive analysis of the three methods and fault feature study are then conducted to assess the effectiveness of the proposed method thoroughly and validated by the author previously. The research indicates that the composite method is available to fault diagnosis of marine shafting by hull vibration which coupled the shafting vibration with fault feature.

1. Introduction

As indispensable "links" of ship propulsion torque and thrust transmissions, the ship propulsion shafting system is the key part of a ship. Marine propulsion shafting mainly consists of propeller, intermediate shaft, intermediate bearing, thrust shaft, thrust bearing, stern tube, stern tube bearing and other devices as shown in details in Figure 1. Ship propulsion shafting are affected by some external loads or periodic excitations, such as propeller excitation [1], main engine excitation, wave loads, engine room environmental vibration loads, and so on. During ship navigating, it perhaps happens that the bearings serious wear phenomena derived from the oscillations and whirl of the oil film. The shafting vibration coupled fault information can be transferred constantly to ship hull by the oil film of bearings. The effective extracting fault information is the key work that has drawn much attention of many researchers all around the world. In 2010, Jayaswal P., Verma S. N. et al. [2] investigated the fault diagnosis methods for vibration signals by combining wavelet transform with neural networks and fuzzy logic. In 2016, Khang H. V. et al. [3] used windowed Fourier transform to clearly identify fault characteristic frequencies in time spectrums. Especially, Huang N. E. Reference [4], Zhaohua W. [5], et al. proposed an Empirical Mode Decomposition (EMD) method and ensemble empirical mode decomposition (EEMD), which are now widely used in fault diagnosis. Then the methods were combined and applied to identify the preset bearing failure modes of benches [6], to extract fault features from vibration signals [7], to reduce noise [8] and analyze fault diagnosis of rotating machinery [9] or rolling bearing [10–16]. In 2011, Zhou T. T. [17] proposed a method of partial ensemble empirical mode decomposition (PEEMD) for fault diagnosing of marine shafting for the first time. Then Chen Y [18] and He Y [19] used the envelope analysis method with spectrum kurtosis (SK) to identify marine shafting vibrations. And the above methods certainly are available in fault diagnosing, but the signal is usually limited to vibration sources such as the bearings or shaft, not the hull. Therefore

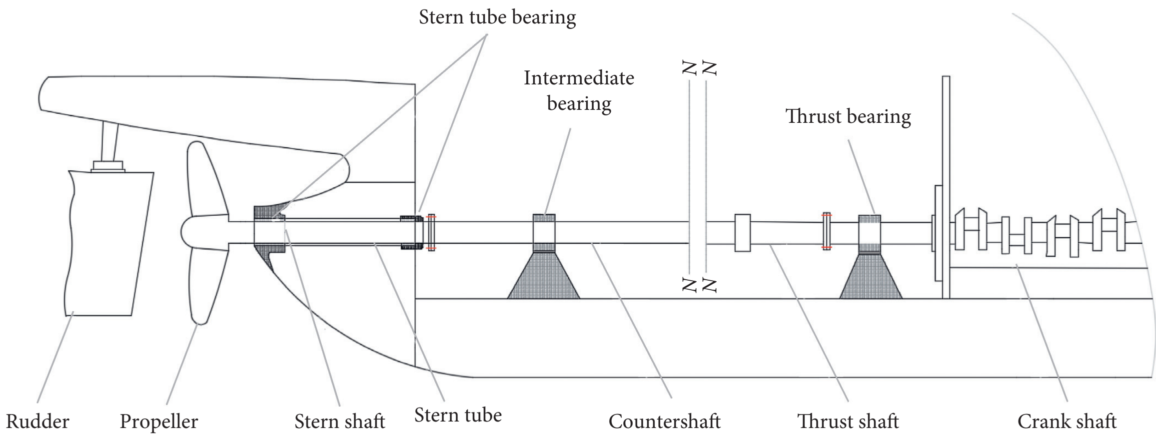


Figure 1: Diagram of marine propulsion shafting.

a Composite method is proposed and applied to identify the marine shafting's fault from the hull vibration, and some simulations and real ship tests are carried out in this paper.

2. Methodology

2.1. Empirical Mode Decomposition. EMD methods can be applied to decompose the signal adaptively to the series of intrinsic mode functions (IMF) of the frequency components which distributes from high frequency to low frequency. Each IMF component contains different characteristic in time domain which can represent the real physical information of the signals. The two IMF conditions need to meet during decomposing process [20]: the number of extreme value is equal to zero value in the original signal, and the up-envelope curve and down-envelope curve is symmetrical to time axis in whole time domain. The decomposing process is shown as follows:

Step 1. The cubic spline curve is adopted to draw the up-envelope curve and down-envelope curve of vibration signal, then the maximum and minimum of them are extracted to calculate the mean m_1. The first IMF component is restructured as follows.

$$h_1 = x(t) - m_1. \quad (1)$$

Here, h_1 is the first IMF component, $x(t)$ is the original vibration signal, m_1 is the mean value of s1 and s2 which are respectively the up-envelope curve and down-envelope curve of the vibration signal drawn by connecting the local maximum point and local minimum point with a cubic spline curve.

Step 2. If h_1 does not meet the IMF conditions, smoothing process will be done and h_1 will be used as the original data as following. h_{12} is the result of repeating the second smoothing process.

$$h_{12} = h_1 - m_{11}. \quad (2)$$

Here, m_{11} is the mean of up-envelope curve and down-envelope curve of h_1. The smoothing step will be done continually until the result meet the IMF conditions. So the h_{1k} can be got finally, which becomes the first IMF component and is denoted by c_1 .

$$c_1 = h_{1k} = h_{1(k-1)} - m_{1(k-1)}, \quad (k > 1 \text{ and } k \in N), \quad (3)$$

where k is the times of repeating smoothing process.

Step 3. When c_1 is separated from the original signal, the first residual function r_1 is left as equation (4).

$$r_1 = x(t) - c_1. \quad (4)$$

Then the similar smoothing process will be used to get the next residual function until the final residual function is a monotonic function as (4).

$$r_n = r_{n-1} - c_{n-1}, \quad (n > 1, n \in N). \quad (5)$$

Lastly, the signal can be expressed as following function by EMD method.

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

2.2. Ensemble Empirical Mode Decomposition. EMD methods can decompose original signals into a series of intrinsic mode functions (IMF) and a residual component, and which has the adaptability, orthogonality and completeness. Otherwise EMD method still has some theoretical problems like endpoint effecting, mean curve construction, and mode mixing. Hence, EEMD method was composite to curb modal aliasing phenomena. A flow chart of the EEMD method is illustrated in Figure 2, and the details are as follows:

(i) Step 1: add the random Gaussian white no ise $n_i(t)$ to the original vibration signal $x(t)$, so the noise-added signal $x_i(t)$ can be obtained as follows:

$$x_i(t) = x(t) + n_i(t) i = 1, 2, \ldots, M, \quad (7)$$

where the subscript **i** is the serial number, M is the ensemble number.

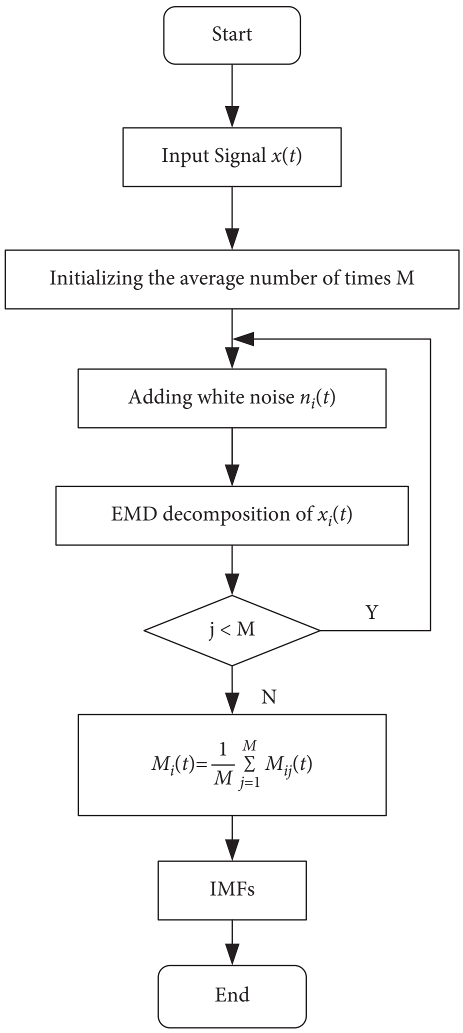


Figure 2: Decomposing process of EEMD.

(ii) Step 2: according to equation (7), the matrix of noise-added signal can be expressed as $[x_1(t), x_2(t), \ldots, x_M(t)]$ $(i = 1, 2, \ldots, M)$,. Then the EMD is adopted to decompose the noise-added signal $x_i(t)\,(i = 1, 2, \ldots, M)$ and the IMF components are obtained which can be described as $\{x_{1,i}(t),\ x_{2,i}(t), \ldots, x_{n,i}(t)\}^T$. So the matrix M with j time of Gaussian white noise can be expressed as equation (8).

$$M = \begin{bmatrix} x_{1,1}(t), & x_{1,2}(t), & \ldots & x_{1,M}(t), \\ x_{2,1}(t), & x_{2,2}(t), & \ldots & x_{2,M}(t), \\ \vdots & \vdots & \vdots & \vdots \\ x_{n,1}(t), & x_{n,2}(t), & \ldots & x_{n,M}(t), \end{bmatrix}. \quad (8)$$

(iii) Step 3: the ensemble means of the corresponding IMF components then is calculated by the equation (9), so the final result of that signal can be obtained more effectively.

$$M_j(t) = \frac{1}{M}\sum_{i=1}^{M} M_{ij}(t), \quad i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, m. \quad (9)$$

2.3. Autocorrelation Method. The autocorrelation functions describe the dependence of the same sample functions of random vibrations between different instantaneous amplitudes. The expressions of the autocorrelation functions of discrete random vibration signals can be derived as follows:

$$R_{xx}(t) = \frac{1}{N}\sum_{i=1}^{N-k} x(i)x(i+k), \quad (k = 0, 1, 2, \ldots), \quad (10)$$

where $R_{xx}(t)$ represents the autocorrelation function, $x(i)$ is the sample function, k is the serial number which belong to the natural number. And the autocorrelation function is described in (10).

$$R_{xx}(k\Delta t) = R_{xx}(\tau). \quad (11)$$

Here, τ is value of the time domain, Δt denotes the interval time of sampling. For the autocorrelation functions, the maximum value is $R_{xx}(0)$ when $\tau = 0$ and the minimum approaches to zero when $\tau \longrightarrow \infty$. So the value of autocorrelation function is limited in the range of zero and $R_{xx}(0)$.

Autocorrelation functions are one of the important parameters of stochastic vibration signal analysis. They also reflect the degrees of smoothness and steepness of a waveform. Therefore, autocorrelation functions are often used to detect periodic vibration components from a random vibration signal contains in the practical engineering project. The autocorrelation functions of periodic components will maintain the original periodic without attenuation and it can be applied to qualitatively analyze the fault features of marine shafting from hull vibration which is also periodic.

2.4. Method Developing. In fact, the fault signals of marine shafting system are characterized with periodicity and can easily be overwhelmed by strong background noise, so it is difficult to identify fault information accurately in measured signals. The composite method combines the ensemble empirical mode decomposition (EEMD) innovatively, the autocorrelation method (AM), and the fast Fourier transform (FFT), which is abbreviated as EEAF. The EEAF has displayed good adaptability, orthogonality, and completeness in our research. In its analysis process, the measured signals are first decomposed by the EEMD method and the original signals with some strong background noise are decomposed to a series of IMF components. That also improves effectively the ratio of signal-to-noise for the periodic components. Then, autocorrelation analysis is done for obtaining the autocorrelation function of each IMF component, which is applied to determine the periodicity of IMF components. Finally, the frequencies and amplitudes of the periodic signals can be effectively extracted from the IMF components with periodic signals by filtering, excluding and spectrum analysis. The process of EEAF is shown in Figure 3 and is divided into the following steps.

(i) Step 1: the decomposing of the measured original signal by EEMD is performed, which is presented in Chapter 2.2 previously. And the IMF components are obtained.

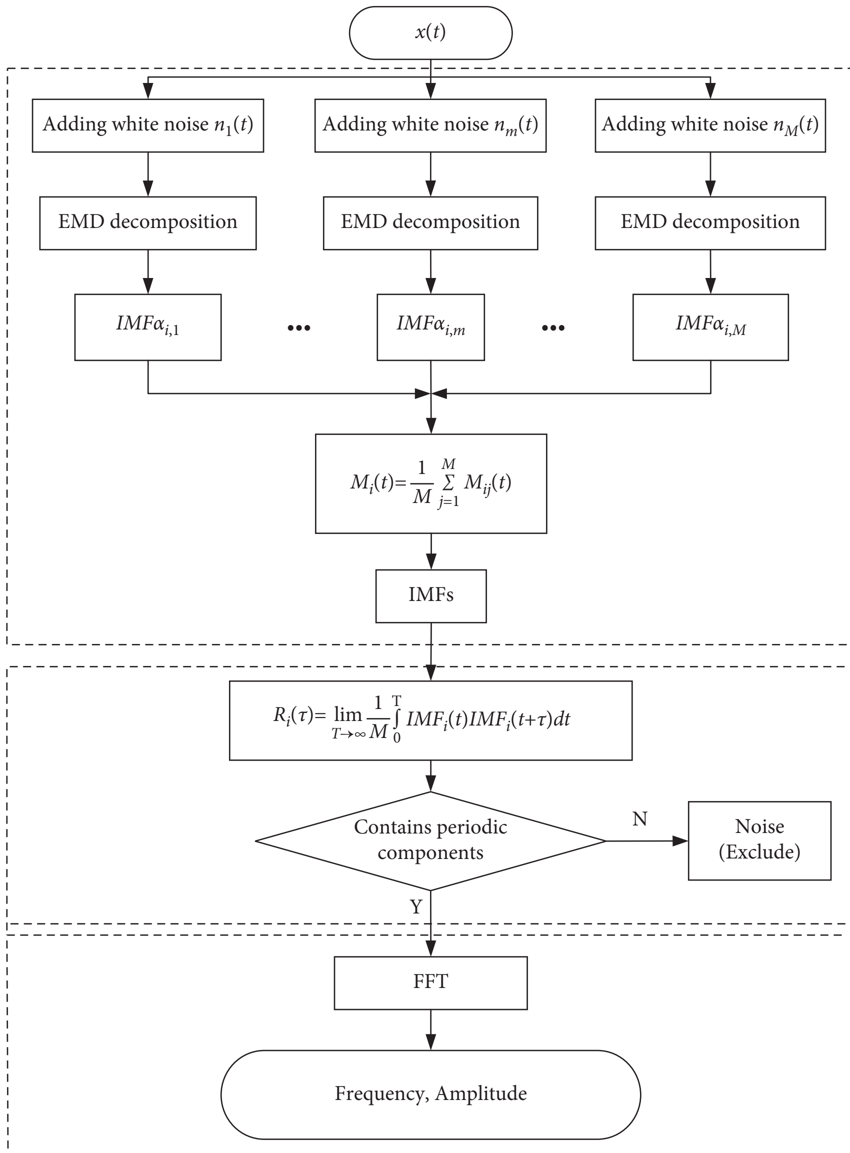


Figure 3: Decomposing process of the EEAF.

(ii) Step 2: to construct the autocorrelation function $R_i(\tau)$ of the IMF components as equation (12).

$$R_i(\tau) = \lim_{T\longrightarrow\infty} \frac{1}{T}\int_0^T x_i(t)x_i(t+\tau)dt , \tag{12}$$

where T is the period time of IMF component. For discrete signals, (11) can be transformed into the following:

$$R_i(n\Delta t) = \frac{\sum_{i=0}^{N-n} x_i(t_i)x(t_i+n\Delta t)}{N-n}, \tag{13}$$

where N represents the length of the related data, n denotes the number of delays, i is the time serial number; τ indicates the delay timed. The $R_i(n\Delta t)$ can be used to eliminate the random disturbance noise with aperiodic features, and identify the IMF components with periodic features.

(iii) Step 3: the IMF components with periodicity are extracted by FFT analysis. The periodic component characteristic quantities in the IMF components such as frequencies and amplitudes, can be obtained.

3. Numerical Verification

The followed case is done to verify the EEAF method. The designated signal is composed of the periodic components and random environmental noise, which can be expressed as the following equation.

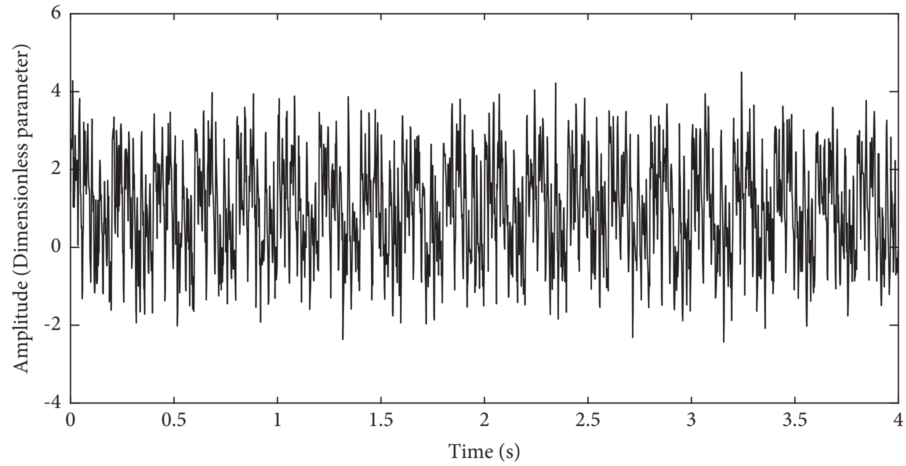


FIGURE 4: The waveform of the designated signal in time domain.

$$\begin{cases} s = s_1 + s_2 + s_3 + s_4 + s_5 + s_0, \\ s_1 = 0.6\ \sin(10\pi t), \\ s_2 = 0.6\ \sin(30\pi t), \\ s_3 = 0.8\ \sin(60\pi t), \\ s_4 = \sin(100\pi t), \\ s_5 = 0.6\ \sin(200\pi t), \end{cases} \tag{14}$$

where s_0 is the random Gaussian white noise, s_1, s_2, s_3, s_4 and s_5 are five different periodic functions. The random Gaussian white noise has an amplitude standard deviation of 0.2, and the ensemble number is set as $M = 100$. So the waveform of the designated signal is shown in Figure 4.

Through the EEMD method, the modes and residual components are extracted and shown in Figure 5. The designated signal has been decomposed to nine IMF components and one residual component. Then select the IMF component with periodic feature to avoid confusion, the autocorrelation analysis of nine IMF components are conducted. The results are shown in Figure 6. In Figure 6, the autocorrelation functions of IMF1, IMF2, IMF3, IMF4, and IMF5 are periodic obviously, and they have retained the original periodicity without attenuation. Subsequently, they are retained and used for the further analysis. However, the autocorrelation function waveforms of the remaining components have obvious periodicity, but disordered. The effect of Gaussian white noise plays a main factor of the result, and it should be eliminated.

Finally, the five IMF components with periodicity, IMF1, IMF2, IMF3, IMF4, and IMF5, are transformed by the fast Fourier transform. The feature quantities of IMF component such as frequency and amplitude are extracted. The frequency domain of the five IMF components is presented in Figure 7, in which the preset frequencies (100 Hz, 50 Hz, 30 Hz, 15 Hz and 5 Hz) are successfully recognized. Furthermore, the amplitudes corresponding to the five frequencies are obtained, those are 0.62162, 0.986, 0.7856, 0.5932, and 0.5829 respectively. To compare the data of Table 1, the extracted frequencies are exactly the same as the preset frequencies, but there are little changes in amplitude observed with the values for both within a 3% error range because of the slight confusion. In summary, the EEAF method is available to extract the periodic component with fault feature through the case study.

4. Test and Discussion

In actual ship, the complexity of the hull vibrations are much greater than that of the analog signals. The test is done in a 64000DWT bulk carrier, whose total length is 199.90 m, the length between perpendicular lines is 194.5 m, the molded width is 32.26 m, and the molded depth is 18.50 m. In addition, its design draft, deadweight and design speed are 11.30 m, 63,800 ton, 15.60 knot respectively. During sea trial of this ship, the temperature of the stern bearings rises rapidly to 87°C, and a high temperature alarm is raised (Note: the alarm value is set at 60°C). So the abnormal wear of the stern bearings occurs. For analyzing the reason of the fault, the test is done. In the test of hull vibration, test datum of eight steady operating conditions (33.0 r/min, 41.1 r/min, 42.0 r/min, 49.1 r/min, 50.0 r/min, 51.0 r/min, 55.1 r/min, and 56.0 r/min) are collected in consequence. The sampling frequency of the measuring instrument is set at 512 Hz, and the sampling time is 60 seconds. The eight sensors of vibration are arranged on the tail seal plate and the stiffening plates on both sides, as illustrated in Figure 8. No.3 sensor and No.4 sensors are used to gather the longitudinal vibrations of hull, No.7 sensor and No.10 sensors are applied to collect the transverse vibrations of hull, other sensors are for hull's vertical vibrations.

4.1. Vertical Vibration. In the current study, the vertical vibration test data of the hull stern structure are collected by four vibration sensors, namely the No. 5, 6, 8, and 9 observation points, as shown in Figure 9. The four sensors of hull vertical vibration are symmetrically arranged on the stiffening plates of two hull sides. So the vibration data

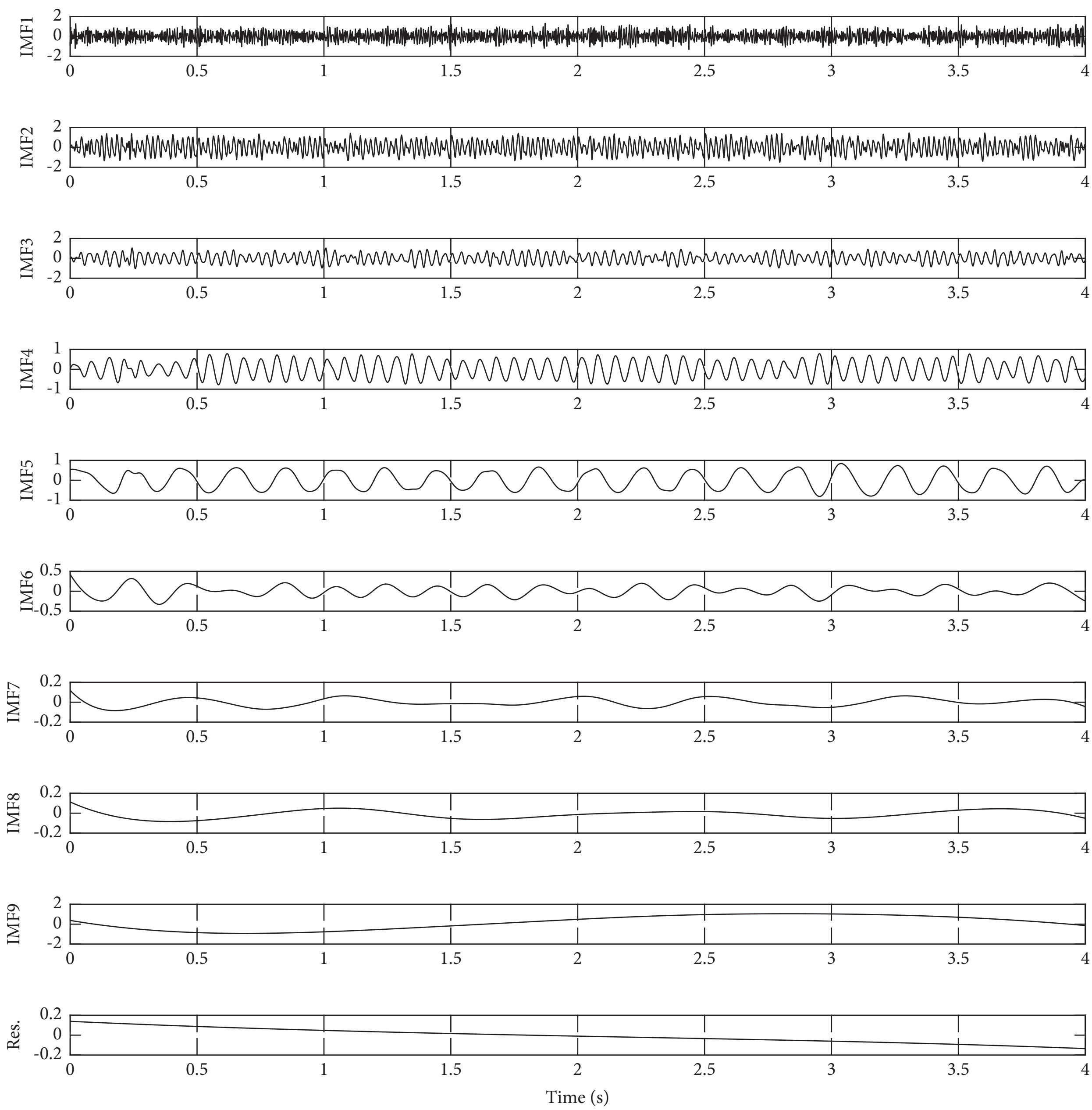


Figure 5: Waveforms of IMF components and residual components.

of the No. 5 and No. 6 are analyzed through the EEAF method. The main quantities coupled in the hull vertical vibrations with periodicity are obtained, as detailed in Table 2. The data show that there are slight differences in the frequencies of the vibration data collected from the two measuring points. However, the deviations are less than 5%. Furthermore the data of Table 2 are used to draw the curves of frequency and amplitude in Figure 9. In Figure 9(a), the frequencies of hull vertical vibrations are distributed mainly in 5th order line and 2nd order trend line. The amplitudes of hull vertical vibrations are shown in Figure 9(b), and the amplitudes of the 5th order vibration signals present a trend of increasing, decreasing and then increasing again. The phenomena happens in some ships with misalignments of marine propulsion shafting. That is to say, the amplitude of hull vertical vibration in 5th order increases with the increase of the shaft speed. Therefore, it indicates that the propulsion shafting of this ship is misaligned.

4.2. Longitudinal Vibration. The data from the sensors of No. 3 and No. 4 are the signals of hull longitudinal vibration. Similar to the aforementioned processes, an EEAF method is

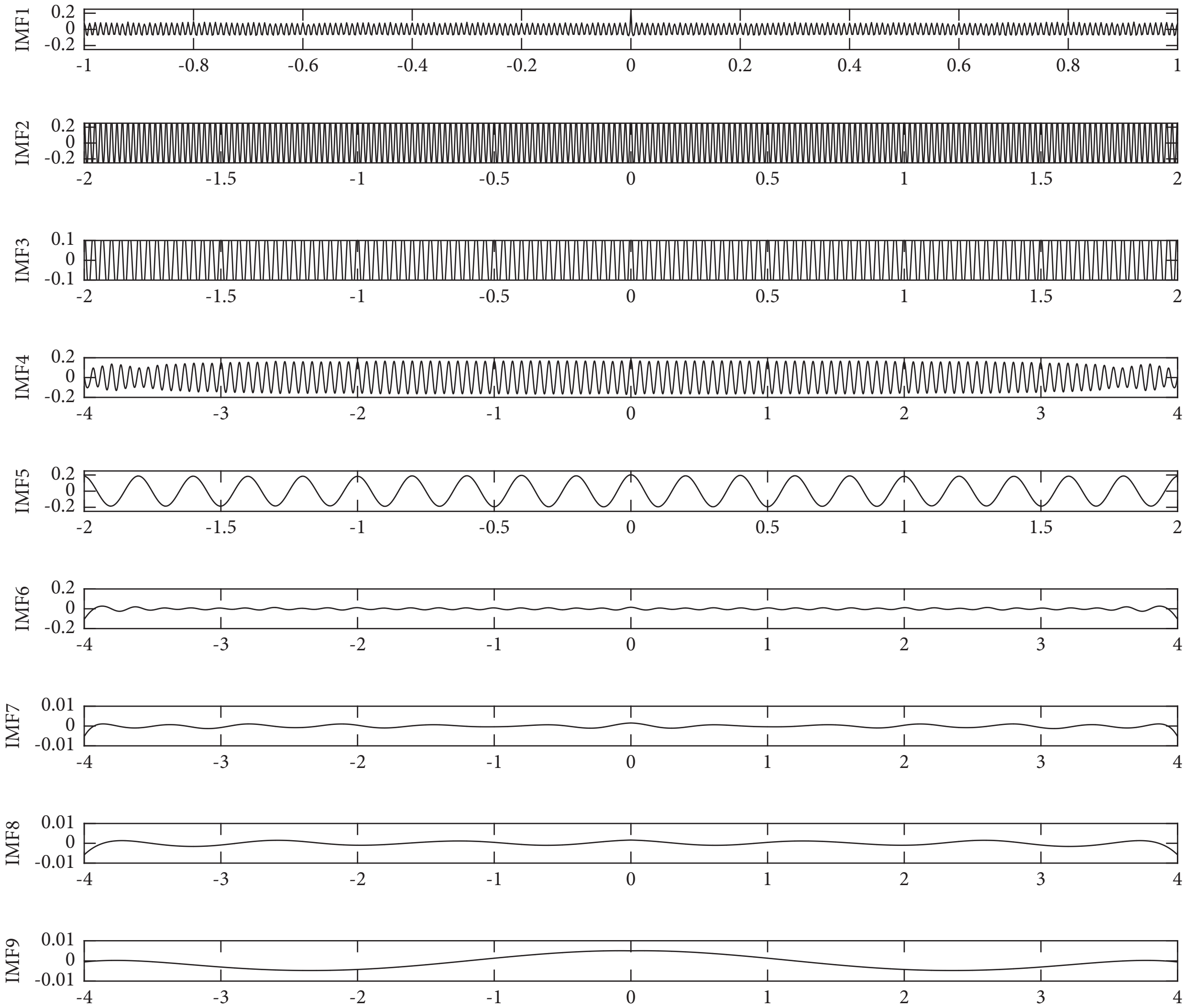


Figure 6: Autocorrelation functions of all IMF components.

used to analyze the test data and the main parameters of the extracted information from periodic longitudinal vibration are obtained, as detailed in Table 3.

In Figure 10(a), the frequencies are mainly distributed in the 5th order trend line. As shown in Figure 10(b), the amplitudes increase with the increasing of the shaft speed until the tail bearing failure occurs. The corresponding peak speed of the 5th order curve is observed to be extremely close to the resonance speed of this marine shaft torsional vibration and longitudinal vibration.

4.3. Transverse Vibration. The transverse vibrations of hull come from the sensors of No. 7 and No. 8 in Figure 8. Through the EEAF method, the transverse vibrations of the hull are extracted and the main data filled in Table 4.

Figure 11 shows the characteristics of the periodic components in the hull longitudinal vibration under the different operating conditions which are presented in Table 4. As shown in Figure 11(a), the extracted frequencies are mainly distributed on the line of the 5th order vibration. Similar to the aforementioned processes, the amplitudes of

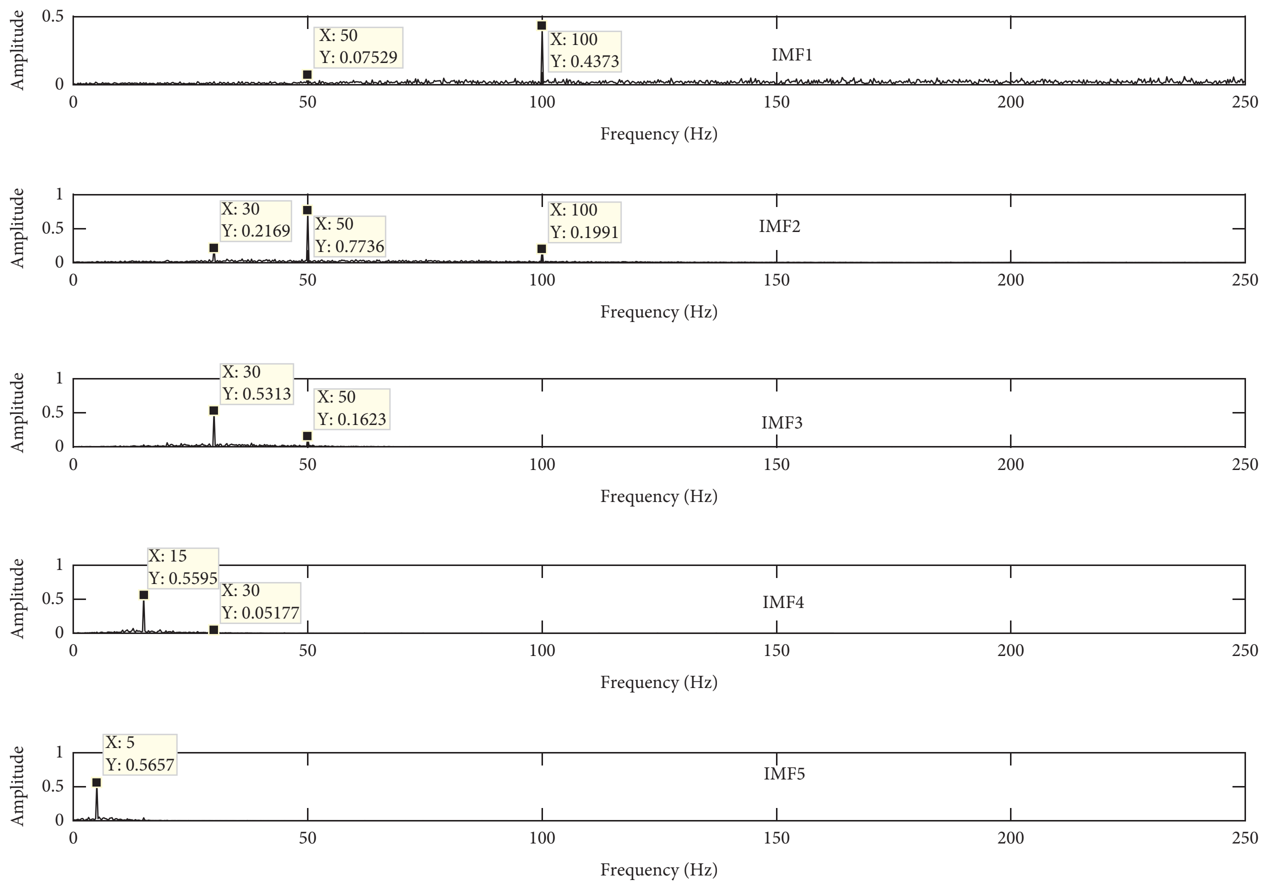


Figure 7: Frequency spectrum of IMF_1, IMF_2, IMF_3, IMF_4, and IMF_5.

Table 1: Main datum of EEAF method and designated signal.

Parameters	SN				
	1	2	3	4	5
Setting frequency	100 Hz	50 Hz	30 Hz	15 Hz	5Hz
Extracting frequency	100 Hz	50 Hz	30 Hz	15 Hz	5Hz
Error	0	0	0	0	0
Setting amplitude	0.6	1	0.8	0.6	0.6
Extracting amplitude	0.6162	0.986	0.7856	0.5932	0.5829
Error	2.7%	1.4%	1.8%	1.133%	2.85%

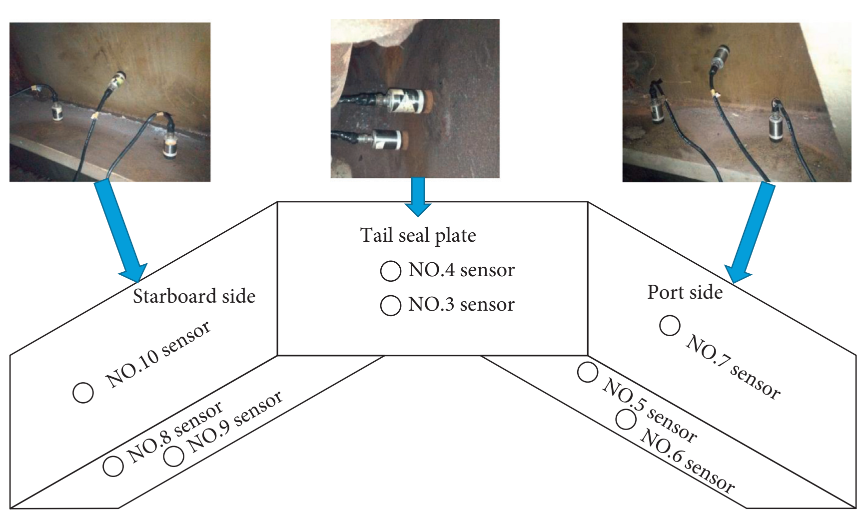


Figure 8: Arrangement of sensors during hull vibration test.

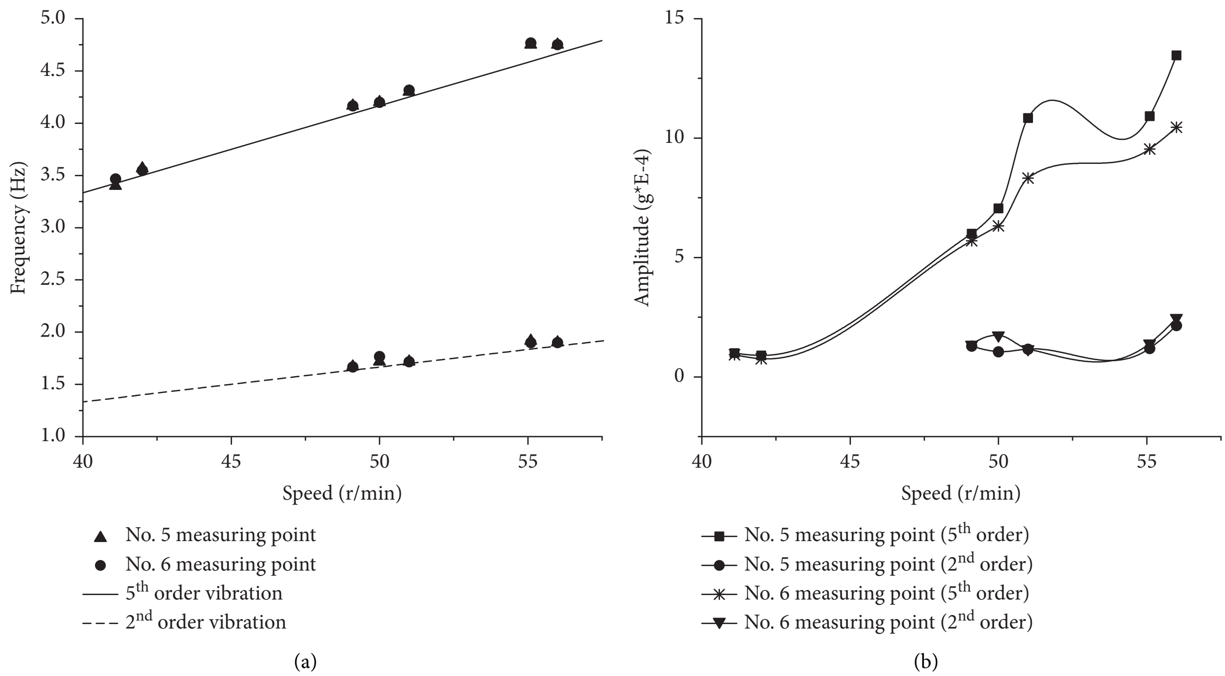


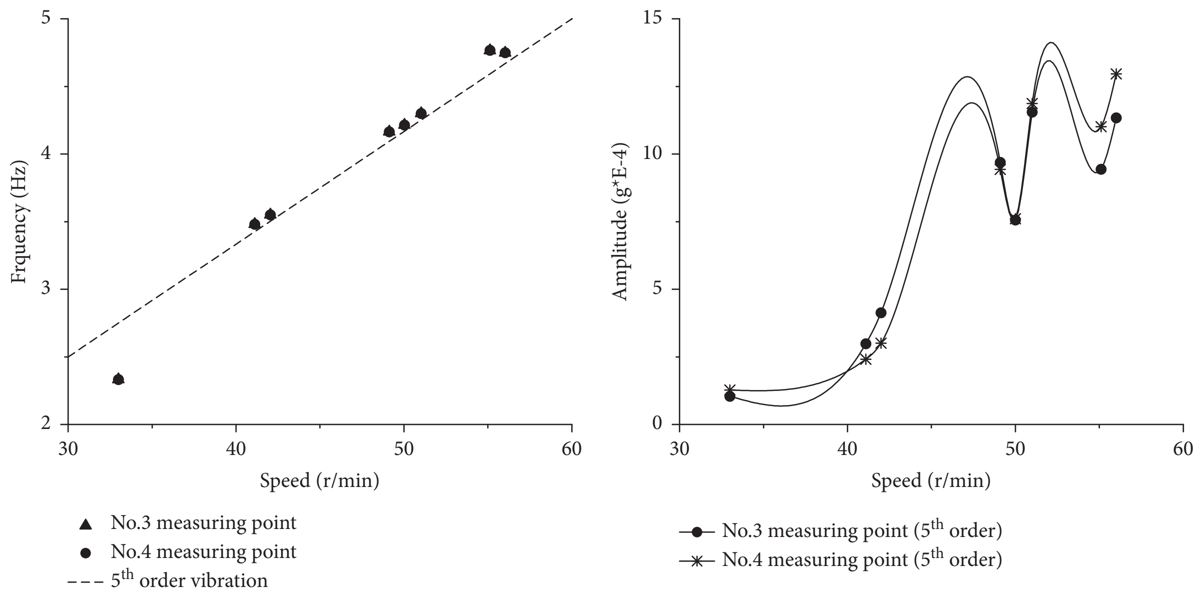
Figure 9: Main parameters of hull vertical vibrations. (a) Frequency (b) Amplitude.

Table 2: Main datum of hull vertical vibrations.

Speed	Point			
	No. 5		No. 6	
	Frequency (Hz)	Amplitude (g•10^{-4})	Frequency (Hz)	Amplitude (g•10^{-4})
33 r/min	—	—	—	—
41.1 r/min	3.400	0.9989	3.467	0.9301
42 r/min	3.567	0.8932	3.550	0.756
49.1 r/min	1.670	1.297	1.667	1.355
	4.167	5.994	4.167	5.696
50.0 r/min	1.717	1.060	1.767	1.743
	4.200	7.055	4.200	6.325
51.0 r/min	1.717	1.168	1.717	1.161
	4.300	10.840	4.317	8.326
55.1 r/min	1.917	1.196	1.900	1.399
	4.750	10.920	4.767	9.544
56.0 r/min	1.900	2.157	1.900	2.474
	4.750	13.460	4.750	10.450

Table 3: Main data of hull longitudinal vibrations.

Speed	Point			
	No. 3		No. 4	
	Frequency (Hz)	Amplitude (g•10^{-4})	Frequency (Hz)	Amplitude (g•10^{-4})
33 r/min	2.333	1.044	2.333	1.276
41.1 r/min	3.483	2.988	3.483	2.411
42 r/min	3.550	4.136	3.55	3.008
49.1 r/min	4.167	9.697	4.167	9.435
50.0 r/min	4.217	7.567	4.217	7.608
50.0 r/min	4.300	11.550	4.300	11.87
55.1 r/min	4.767	9.442	4.767	11.01
56.0 r/min	4.750	11.340	4.750	12.96

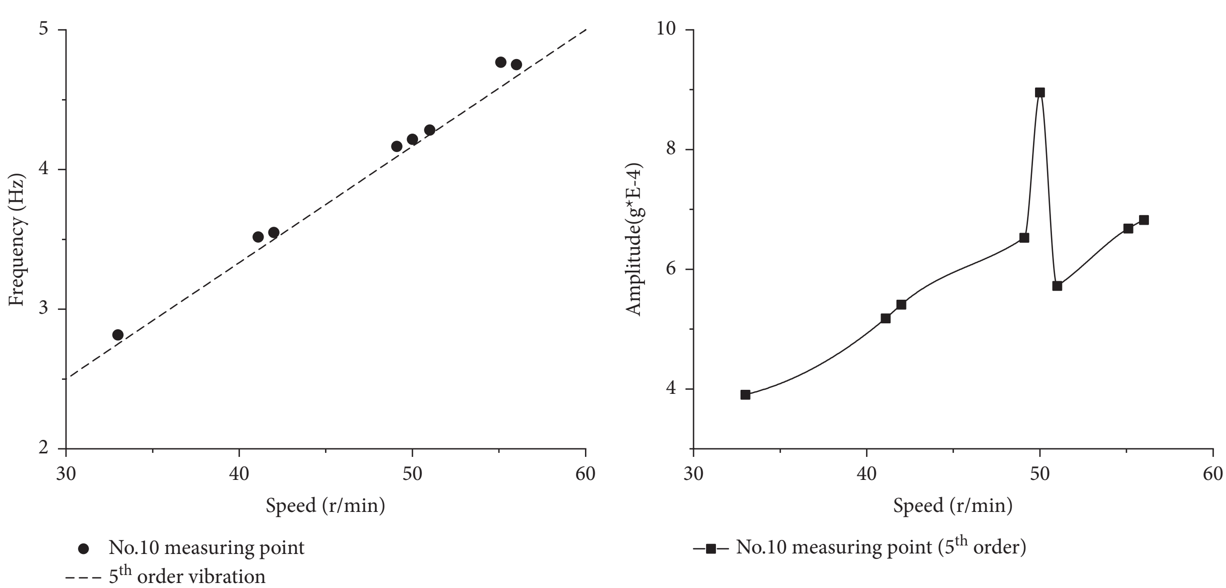


(a) (b)

Figure 10: Main parameters of hull longitudinal vibrations. (a) Frequency (b) Amplitude.

Table 4: Main data of Hull Transverse Vibrations.

Speed	Point No. 10 measuring point	
	Frequency (Hz)	Amplitude (g•10^{-4})
33 r/min	2.817	3.904
41.1 r/min	3.517	5.179
42 r/min	3.550	5.407
49.1 r/min	4.167	6.524
50.0 r/min	4.217	8.956
50.0 r/min	4.283	5.721
55.1 r/min	4.767	6.681
56.0 r/min	4.750	6.823



(a) (b)

Figure 11: Main parameters of hull transverse vibrations. (a) frequency (b) amplitude.

these frequencies in the 5th harmonics increase firstly and then decrease with the increase of the shaft speed. When the tail bearings are in fault, the amplitudes are observed to increase once again.

5. Conclusions

In this study, a novel method of extracting periodic fault information of marine propulsion shafting by the hull vibrations is proposed, which is referred to as the EEAF method. Through the numerical verification, test and discussion, the EEAF method is available to extract the useful frequencies and amplitudes connected with marine shafting's fault. In addition, this method has alleviated the modal aliasing problems successfully, and can decompose and extract the periodic feature quantities which characterize the fault features of marine shafting from the measured signals more accurately. The fault features extracted from the hull vibrations are similar with the phenomena of marine shafting misalignment. So the fault information obtained by EEAF method from hull vibrations can be used to pre-estimate the operating condition of marine shafting qualitatively. However, there should be more experiments and tests to develop the effectiveness and quantitative of the fault diagnosis of the EEAF method.

Data Availability

The test data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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