In 2005, Chu [3] applied the envelope analysis to the signals of bearing faults. He used the envelop analysis to demodulate the signals at a constant rotation speed and conducted qualitative analysis for different bearing faults with the extracted features of fast Fourier transform (FFT) spectra. In 2007, Yu et al. [4] combined the EMD method and envelope analysis to extract the faulted features of the IMF components. In their spectrum analysis results, significant peaks are observed at the characteristic frequencies of bearing fault. The spectral magnitude at the corresponding characteristic frequencies was used as the features, and then the support vector machine (SVM) was employed to identify the bearing defects effectively.

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1. Introduction

The Hilbert–Huang transform (HHT) was proposed by Huang et al. in 1998 [1]. According to the signal characteristics, the HHT method is able to decompose the signal into a number of intrinsic mode functions (IMFs) adaptively through the empirical mode decomposition (EMD) process. There exists only one frequency value in an IMF at any moment in temporal scale and thus the concept of instantaneous frequency can help to construct the time–frequency distribution as well as the marginal spectra. Furthermore, Wu and Huang [2] proposed the ensemble EMD (EEMD) method, a noise-assisted data analysis approach, to eliminate the influence of the intermittent signal and to resolve the mode mixing problem. Therefore, the true IMFs can provide more significant physical meanings while the analysis procedure.

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Wu and Huang [5] proposed the post-processing approach to facilitate the EEMD method in 2009. This process resolves the mode-mixing drawback and the
non-IMF problem concurrently, and thus it will be easier to identify the faulted signature in a specific IMF.

In 2014, Pan and Tsao [6] used the time–frequency analysis method to decide which IMFs should be selected through the EMD process, so that the features of multi-fault in bearing can be observed.

SVM has been used for classification purpose for many years. Madzarov et al. [7] provided the review and comparison of different SVM algorithms. Yang et al. [8] investigated the intelligent bearing fault diagnostics through the HHT approach as well as the SVM method. Additionally, Seryasat et al. [9] employed the HHT method and a multi-classification SVM algorithm to diagnose the bearing faults.

Even though the studies of bearing fault diagnosis have been explored for decades, advances and novelty of the related research are still conducted during these years because of the improvement of signal processing techniques as well as the development of intelligent machines. Zhang et al. [10] proposed a new roller-bearing defect diagnosis approach through using the wavelet analysis and particle swarm optimization technique. The various computation schemes of entropy in the information theory were also employed extensively to analyze the vibration signals for machine faults diagnostics [11,12].

In order to advance the state-of-art of bearing fault diagnosis, both the envelope analysis and relative period spectrum method were used for diagnosing the single and double defects on the bearing components. The analysis results demonstrate that the proposed approach is feasible to accurately diagnose the single and double defects on the inner and outer races of the bearing.

2. Vibration Analysis Method

2.1. Hilbert–Huang Transform

The HHT is an adaptive time–frequency analysis method. The EMD process of HHT is capable of decomposing the signal into several IMFs which are the signal components of different frequency range. Assume that a complicated signal \( X(t) \) is composed of a number of mono-oscillating components, therefore the EMD process can be formulated as

\[
X(t) = \sum_{j=1}^{m} C_j(t) + r(t)
\]

where \( C_j(t) \) represents the \( j \)-th IMF and \( r(t) \) is the signal trend which is a constant or monotonic function.

The IMFs are obtained through the sifting process of EMD method and the cubic spline fitting is used to determine the signal envelope. Therefore, the stoppage criteria of EMD are applied to set the iteration number of sifting process. Two stoppage criteria are recommended for the EMD process:

1. Standard deviation (SD):

   The literature [1] pointed out that the SD value between the results of consecutive sifting processes is suggested to be 0.2–0.3. If the SD value is lower, the computation efforts will be higher and it may determine the IMF signal of constant amplitude. The possible amplitude modulation phenomenon of IMF may not be observed.

2. The iteration ends when the number of local extrema of the extracted signal component and the number of zero-crossings of the extracted signal component are the same or different at most by one in the sifting process.

2.2. Envelope Analysis

When the bearing components have defects, the cyclic impact vibration can occur under the operating period. It is normally observed that the vibration signal of high frequencies reveals the phenomenon of low-frequency amplitude modulation (AM). Mathematically, the AM phenomenon can be formulated by the multiplication of a high-frequency carrier signal and a low-frequency envelope. Since the envelope of the vibration measurements contains the crucial information with regard to the bearing defects, the envelope analysis means as well as the demodulation technique are the important methods for the extraction of the signal features. Therefore, the envelope analysis is a commonly used method in fault diagnosis of rotating machinery.

2.3. Relative Period Spectrum

The analysis procedure using the relative period spectrum is stated as follows:

![Figure 1. Picture of bearing test rig; (1) motor drive; (2) motor; (3) shaft; (4) bearing housing; (5) data acquisition card; (6) accelerometer.](image-url)
(1) Find the local maximum of the original signal \( Y(t) \) and determine the \( n \) local temporal points \( t_i \) corresponding to the \( n \) maxima.

(2) Determine the interval \( d_i \) between the two consecutive local temporal points corresponding to the \( n \) maxima, that is

\[
d_i = t_{i+1} - t_i, \quad i = 1, 2, \ldots n - 1.
\]

(3) Given a target period \( P_t \) and then calculate the temporal ratio \( p_i \) of \( d_i \) to the target period, that is

\[
p_i = d_i / P_t, \quad i = 1, 2, \ldots n - 1.
\]

**Figure 2.** Envelop spectrum of composed signal (first 3 IMFs): normal bearing.

**Figure 3.** Envelop spectrum of composed signal (first 3 IMFs): inner race defect.
The occurrence rate is then defined to be the ratio of the occurrence number at \( s_k \) to the total occurrence number. The relative period spectrum is thus expressed as the occurrence rate distribution for each \( s_k \).

Since the major features of bearing faults are related to the shaft rotating speed, the target period \( P_t \) is set as the shaft rotating period in this study. \( S \) is selected as 0–1 and \( z \) is 0.005.

Figure 4. Envelop spectrum of composed signal (first 3 IMFs): roller defect.

Figure 5. Envelop spectrum of composed signal (first 3 IMFs): single outer race defect.

(4) Select the coverage \( S \) and the increment interval \( z \). The series \( s_k \) is then defined as

\[
s_k = z \times k, \quad k = 0, 1, \ldots, S/z.
\]

(5) When the value of \( p_i \) is between \( s_k \pm 0.5z \), then the number of the occurrence of \( p_i \) counts to \( s_k \). The occurrence rate is then defined to be the
sets of bearings. The defects were produced artificially on the inner/outer race and roller through the electric discharge machining technology, and then one of the bearings was replaced by the defective bearing to simulate the running conditions of defective bearings. The accelerometer was installed on the bearing housing to measure the

3. Experimental Verification and Analysis Results

3.1. Experimental Setup

As shown in Figure 1, the test rig of bearing consisted of a shaft that was driven by the motor and supported by two sets of bearings. The defects were produced artificially on the inner/outer race and roller through the electric discharge machining technology, and then one of the bearings was replaced by the defective bearing to simulate the running conditions of defective bearings. The accelerometer was installed on the bearing housing to measure the
defect on bearing outer race, (5) double defects on bearing outer race with circumferential interval of 45°, (6) double defects on bearing outer race with circumferential interval of 90°, (7) double defects on bearing outer race with circumferential interval of 135°, and (8) double defects on bearing outer race with circumferential interval of 180°.

The rotating speed in this experiment was set to 444 and 592 rpm for the running conditions of the eight classes of vibrating acceleration. The vibration signals were recorded through the data acquisition device. In this experiment, the sampling rate of the data acquisition device was set to 6.4 kHz. Each measured signal set contains 32,000 data points.

There were eight classes of bearing faults in this experiment, including (1) normal bearing, (2) defect on bearing roller, (3) single defect on bearing inner race, (4) single defect on bearing outer race, (5) double defects on bearing outer race with circumferential interval of 45°, (6) double defects on bearing outer race with circumferential interval of 90°, (7) double defects on bearing outer race with circumferential interval of 135°, and (8) double defects on bearing outer race with circumferential interval of 180°. The rotating speed in this experiment was set to 444 and 592 rpm for the running conditions of the eight classes of
Table 1. Diagnosis result of first round classification.

| True class | Normal | Inner race defect | Outer race defect | Roller defect | Accuracy (%) |
|------------|--------|-------------------|-------------------|---------------|--------------|
| 444 rpm    | Normal | 20                | 0                 | 0             | 100          |
|            | Inner race defect | 0                | 20                | 0             | 100          |
|            | Outer race defect | 0                | 0                 | 100           | 100          |
|            | Roller defect    | 3                 | 0                 | 0             | 85           |
| 592 rpm    | Normal | 20                | 0                 | 0             | 100          |
|            | Inner race defect | 0                | 20                | 0             | 100          |
|            | Outer race defect | 0                | 0                 | 96            | 96           |
|            | Roller defect    | 2                 | 0                 | 0             | 90           |

Figure 10. Mean relative period spectrum: single outer race defect.

Figure 11. Mean relative period spectrum: double outer race defects with 45° interval.
the signal components of high frequencies are composed for envelope analysis. With this process, the amplitude modulation phenomenon due to impact between the defective components can be analyzed. Figure 2–5 illustrate the envelope spectra of the composed signals (first three IMFs) for the different classes of single bearing defect under the shaft rotating speed of 444 rpm. It can be observed that the different classes of single bearing defect have obvious spectral distributions. Furthermore,

bearing faults, respectively. A total of 800 sets of vibration measurement, consisting of fifty data-sets for each class, were recorded in this study.

3.2. Vibration Signal Analysis and Feature Extraction

The vibration measurements were first decomposed into a number of IMFs through the EMD method, and then

Figure 12. Mean relative period spectrum: double outer race defects with 90° interval.

Figure 13. Mean relative period spectrum: double outer race defects with 135° interval.
that the proposed approach is capable of diagnosing the different types of single bearing defect accurately.

Since the spectral distributions of the different classes of double bearing defects cannot reveal the obvious distinguishability, the proposed method of relative period spectrum was employed for diagnosing the different classes of double bearing defects. The local maximum of the envelope signal that was extracted in the first round of classification was determined to form the envelope of the second layer. By repeating the same steps, the envelope of the fourth layer was obtained. The calculation of the relative period spectrum was applied for the envelope signals in the four layers. Figure 10–14 show the mean relative period spectra of the single/double bearing defects with circumferential interval of 45°, 90°, 135°, and 180°, respectively. It can be observed that the distinguishability among the different classes of double outer race defects was enhanced, and thus the features extracted from the

Figure 6–9 illustrate the envelope spectra of the composed signals (first three IMFs) for the different classes of double bearing defects under the shaft rotating speed of 444 rpm. It is also noted that the spectral distributions in Figure 6–9 have the same peaks at 7.4 Hz (shaft rotating frequency) apparently and present similar manners without obvious distinguishability.

The peak magnitude at the FFT-based spectrum of the envelope signals were extracted as the faulted features. The extracted features of 30 data-sets among the 50 data-sets were randomly selected for the SVM model training and the remaining 20 data-sets were used for testing. In the first round of classification, the extracted features of FFT-based spectrum were utilized to diagnose the different types of single bearing defect, including the normal bearing, inner race defect, single outer race defect, and roller defect. Table 1 shows the diagnosis result of different defective types in the first round of classification. The result demonstrates that the proposed approach is capable of diagnosing the different types of single bearing defect accurately.

Since the spectral distributions of the different classes of double bearing defects cannot reveal the obvious distinguishability, the proposed method of relative period spectrum was employed for diagnosing the different classes of double bearing defects. The local maximum of the envelope signal that was extracted in the first round of classification was determined to form the envelope of the second layer. By repeating the same steps, the envelope of the fourth layer was obtained. The calculation of the relative period spectrum was applied for the envelope signals in the four layers. Figure 10–14 show the mean relative period spectra of the single/double bearing defects with circumferential interval of 45°, 90°, 135°, and 180°, respectively. It can be observed that the distinguishability among the different classes of double outer race defects was enhanced, and thus the features extracted from the

Table 2. Diagnosis result of second round classification.

| True class | 444 rpm | 592 rpm |
|------------|---------|---------|
| 45° Single defect | 17 | 19 |
| 90° Single defect | 0 | 0 |
| 135° Single defect | 0 | 0 |
| 180° Single defect | 2 | 0 |

Figure 14. Mean relative period spectrum: double outer race defects with 180° interval.
relative period spectra are definitely beneficial for the diagnosis of double outer race defects.

In order to diagnose the classes of double outer race defects, the data-sets that were classified into the outer race defect were collected for the further diagnosis. In the second round of classification, the distributions of the mean relative period spectra were extracted as the features for diagnosing the different classes of double outer race defects. The procedure of model training and signal feature testing was the same as that in the first round of classification. Table 2 shows the diagnosis result in the second round of classification. The result validated the feasibility of the proposed relative period spectrum for accurately diagnosing the double outer race defects with different circumferential intervals.

4. Conclusion

In this research, the EMD signal separation means combining the FFT-based spectrum analysis in frequency domain and the relative period spectrum method in time domain were employed to diagnose the faulted bearing with single and double defects. In the first round of classification, the features that were extracted from the FFT-based spectra were capable of diagnosing the different classes of bearing faults, including normal bearing, bearing with inner race, roller and outer race defects. In the second round of classification, the classes of double defects on the outer race can be diagnosed accurately using the features of proposed relative period spectrum method. With the two rounds of classification, the diagnostic results demonstrated the effectiveness of the proposed approach for diagnosing the different classes of single and double defects on the bearing with the overall accuracy of 95%.

Nomenclature

| Symbol | Description |
|--------|-------------|
| $X(t)$ | Complicated signal |
| $Y(t)$ | Original time series |
| $C_j(t)$ | IMF component |
| $r(t)$ | Signal trend |
| $d_i$ | Interval between two consecutive temporal points corresponding to local maxima |
| $P_t$ | Target period |
| $p_i$ | Relative period ratio |
| $S$ | Coverage |
| $z$ | Increment interval |

Author Contribution

This research was carried out independently by the authors.

Disclosure Statement

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