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Compound fault diagnosis for a rolling bearing using adaptive DTCWPT with higher order spectra

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ABSTRACT
Fault diagnosis plays a vital role in prognostics and health management. Researchers have devoted their efforts in enhancing the accuracy of fault diagnosis. However, diagnosis of compound faults in complex systems is still a challenging task. The problem lies in the coupling of multiple signals, which may conceal the characteristics of compound faults. Taking a rolling bearing as an example, this study aims to boost the accuracy of compound fault diagnosis through a novel feature extraction approach to making the fault characteristics more discriminative. The approach proposes an adaptive dual-tree complex wavelet packet transform (DTCWPT) with higher order spectra analysis. To flexibly and best match the characteristics of the measured vibration signals under analysis, DTCWPT is first adaptively determined by the minimum singular value decomposition entropy. Then, higher order spectra analysis is performed on the decomposed frequency sensitive band for feature extraction and enhancement. The proposed approach is used to analyze experimental signals of a bearing's compound faults and found effective.

KEYWORDS
Adaptive dual-tree complex wavelet packet; compound faults; prognostics and health management; rolling bearing; singular value decomposition

Introduction

Rolling bearings play a significant role in modern industrial equipment (Riera-Guasp, Antonino-Daviu, and Capolino 2015). Compound faults, i.e., more than one type of fault happening at the same time, can occur, and different fault features can be coupled together and hidden in the collected signals (Shao et al. 2018). Sometimes a single fault shows as a compound fault because of the high correlation of the structures (Jiang, Li, and Li 2013a; He et al. 2016). The diagnosis of compound fault is much more difficult than single faults, as different fault types complicate the identification of the fault features. Research on reliable feature extraction of compound fault has been a matter of some urgency since it is closely related to fault diagnosis, failure mechanism and even maintenance strategy in prognostics and health management system (Lin and Kumar 2017). However, diagnosis of compound faults in complex systems is still a challenging task. The problem lies in the coupling of multiple signals through effective feature extraction approaches, which may conceal the characteristics of compound faults.

Several advanced techniques based on wavelet transform and empirical mode decomposition have been used for feature extraction in industrial equipment (Teng et al. 2016; Jedliński and Jonak 2015; Ray et al. 2018; Xia et al. 2019; Gadanayak and Mallick 2019; Mao et al. 2018), including second-generation wavelet packet transform (SGWPT) (Liu et al. 2016; Zhou et al. 2010; Li et al. 2012), ensemble empirical mode decomposition (EEMD) (Li and Hu 2019; Xiang and Zhong 2017; Zheng 2016), etc. These techniques have made great advances in the feature extraction of single faults, but they fail to show a powerful capacity to detect compound fault because shift-variance and frequency aliasing cause the loss of valuable fault information.

Dual-tree complex wavelet packet transform (DTCWPT) (Wang et al. 2020; Shao et al. 2017) and multiwavelet transform (Hong, Liu, and Zuo 2019; Yuan et al. 2017) are enhanced forms of the

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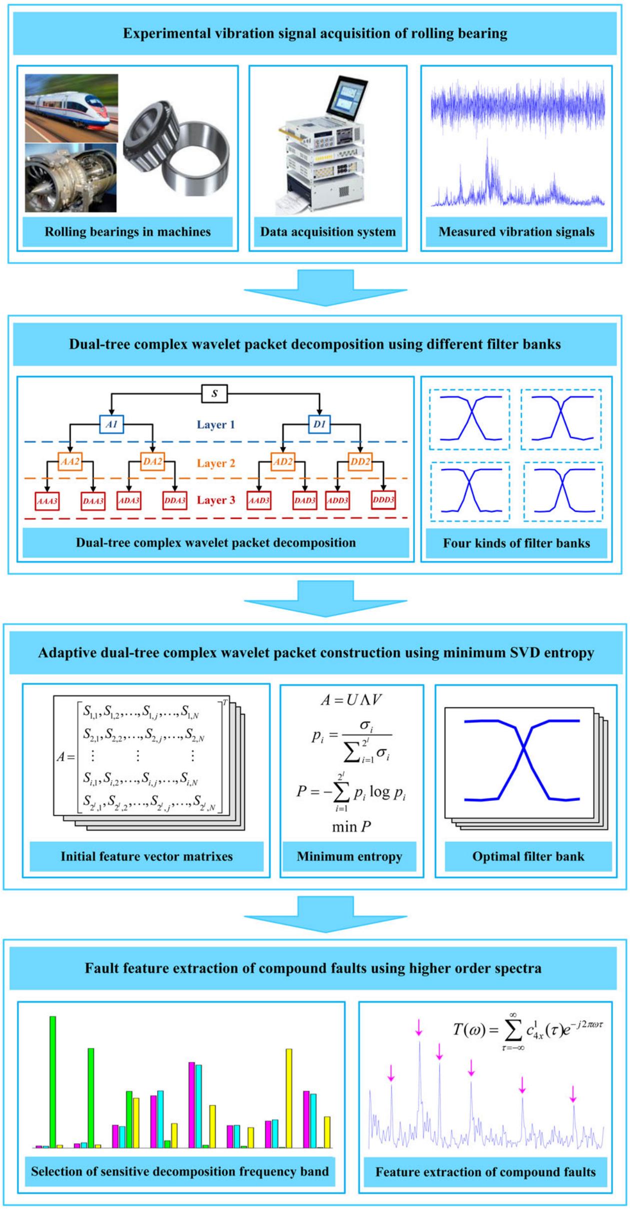

Figure 1. Framework of the proposed approach.

traditional wavelet transform, with the potential to detect the compound fault of a rolling bearing. The multiwavelet transform can match different features of compound fault by utilizing two or more basis functions, while DTCWPT can extract almost all the underlying features of compound fault because of its reduced aliasing and near shift-invariance. Chen et al. (2013) constructed an improved redundant lifting multiwavelet transform to extract two kinds of fault features of a rolling bearing. Wang, He, and Zi (2010) showed the feasibility of the dual-tree complex wavelet transform in detecting compound fault in two cases. However, both techniques have limitations. It is not easy to quickly determine the basic functions of the multiwavelet transform, and the fixed basis functions which are unrelated to the analyzed signals will probably affect the detection of compound fault. To date, four kinds of DTCWPT filter banks have been proposed for feature extraction in mechanical fault diagnosis. In most cases, they perform similarly and can deal with purified or simple vibration signals (Chen et al. 2013). However, when the measured vibration signals are complex and non-stationary, different filter bank probably show different properties. Manually selecting the best filter bank to match the measured signals under analysis usually relies heavily on domain experience. Therefore, the adaptive selection of filter banks for adaptive DTCWPT construction is the first step for preprocessing in feature extraction.

After an adaptive DTCWPT has been constructed to match a vibration signal's characteristics, the next step in feature extraction is signal postprocessing. Unlike the power spectrum, higher order spectra can provide both amplitude and phase information for the analyzed signal (Gelman, Petrunin, and Komoda 2010). In addition, higher order spectra can suppress heavy background noise and thus indicate the nonlinear behavior of complex systems (Kovach and Howard 2019; Marnerides, Pezaros, and Hutchison 2018; Yunusa-Kaltungo, Sinha, and Nembhard 2015; Zhou et al. 2012; Hickey et al. 2009; Nikias and Mendel 1993). These unique characteristics make higher order spectra analysis more advantageous for the feature extraction and enhancement of bearing faults than traditional methods, such as fast Fourier transform (FFT) spectrum analysis or Hilbert transform demodulation spectrum analysis.

In this paper, a novel approach called adaptive DTCWPT with higher order spectra is proposed to detect compound fault in a rolling bearing. First, DTCWPT is used to preprocess the measured vibration signals and accurately extract the underlying fault characteristic information; the best filter bank is then adaptively selected using the minimum singular value decomposition (SVD) entropy. Next, higher order spectra analysis is performed on the decomposed frequency sensitive band for feature extraction and enhancement. Finally, the proposed approach is used to analyze the experimental signals of bearing compound fault. The results confirm that the proposed approach is more effective than other approaches.

The remainder of this paper is mainly organized as follows. Second section describes the proposed approach. Third section applies the proposed approach to extract the features of compound fault. Finally, fourth section offers a conclusion.

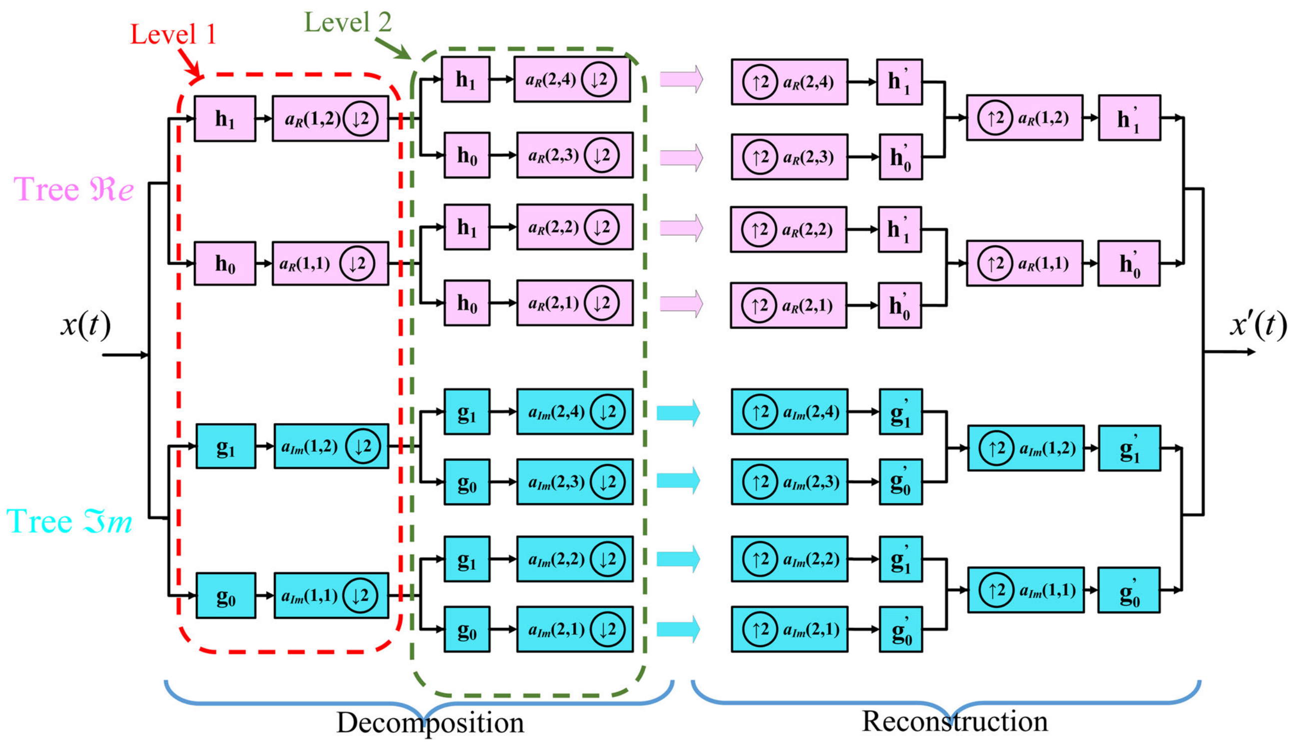

Figure 2. Decomposition and reconstruction process of a two-level DTCWPT.

Proposed approach

The framework of the proposed approach is shown in Figure 1 and summarized as follows.

Step 1: Collect the experimental signals of bearing compound fault using a data acquisition system.
Step 2: Use four kinds of DTCWPT filter banks to decompose the analyzed vibration signals successively and obtain the four corresponding original feature vector matrixes.
Step 3: Calculate the SVD entropy value of each original feature vector matrix successively; select the filter bank corresponding to the minimum SVD entropy as the optimal filter bank.
Step 4: Calculate the normalized energy distribution of the decomposed frequency bands using the optimal filter bank and select the frequency sensitive band for further analysis.
Step 5: Apply higher order spectra analysis to the decomposed frequency sensitive band for feature extraction and enhancement of compound fault.

Four filter banks

DTCWPT can achieve signal decomposition and reconstruction through two parallel manifestations of the discrete wavelet transform (Tree $\Re e$ and Tree $\Im m$) (Selesnick, Baraniuk, and Kingsbury 2005; Yu et al. 2016; Qu, Zhang, and Gong 2016), as shown in Figure 2. Both satisfy the perfect reconstruction condition; each of the trees contains a set of low-pass ($\mathbf{h_0}$ and $\mathbf{g_0}$) and high-pass filters ($\mathbf{h_1}$ and $\mathbf{g_1}$).

Let $\psi_h(t)$ and $\psi_g(t)$ represent wavelet functions, with $\phi_h(t)$ and $\phi_g(t)$ the respective scaling functions. Then, the complex wavelet transform can be expressed by (Wang, He, and Zi 2010)

$$\begin{cases} \psi^C(t) = \psi_h(t) + i\psi_g(t) \\ \phi^C(t) = \phi_h(t) + i\phi_g(t) \end{cases} \quad [1]$$

where $\psi_h(t)$ is real and even, and $i\psi_g(t)$ is imaginary and odd. The two real and imaginary parts are selected in such a way that they form a Hilbert transform pair:

$$\psi_g(t) = H[\psi_h(t)] = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{\psi_h(t-\tau)}{\tau} d\tau \quad [2]$$

where $H[\cdot]$ is a Hilbert transform operator.
The excellent properties of DTCWPT can be attributed to the well-designed filter banks. The low-pass filters in one tree provide an approximate half-sample delay of the low-pass filters in the other tree, thus confirming the sampling points of Tree $\Re e$ always stay in the middle of Tree $\Im m$. The time–domain and frequency–domain relationships of the low-pass filters can be written as follows (Wang, He, and Zi 2010; Qu, Zhang, and Gong 2016):

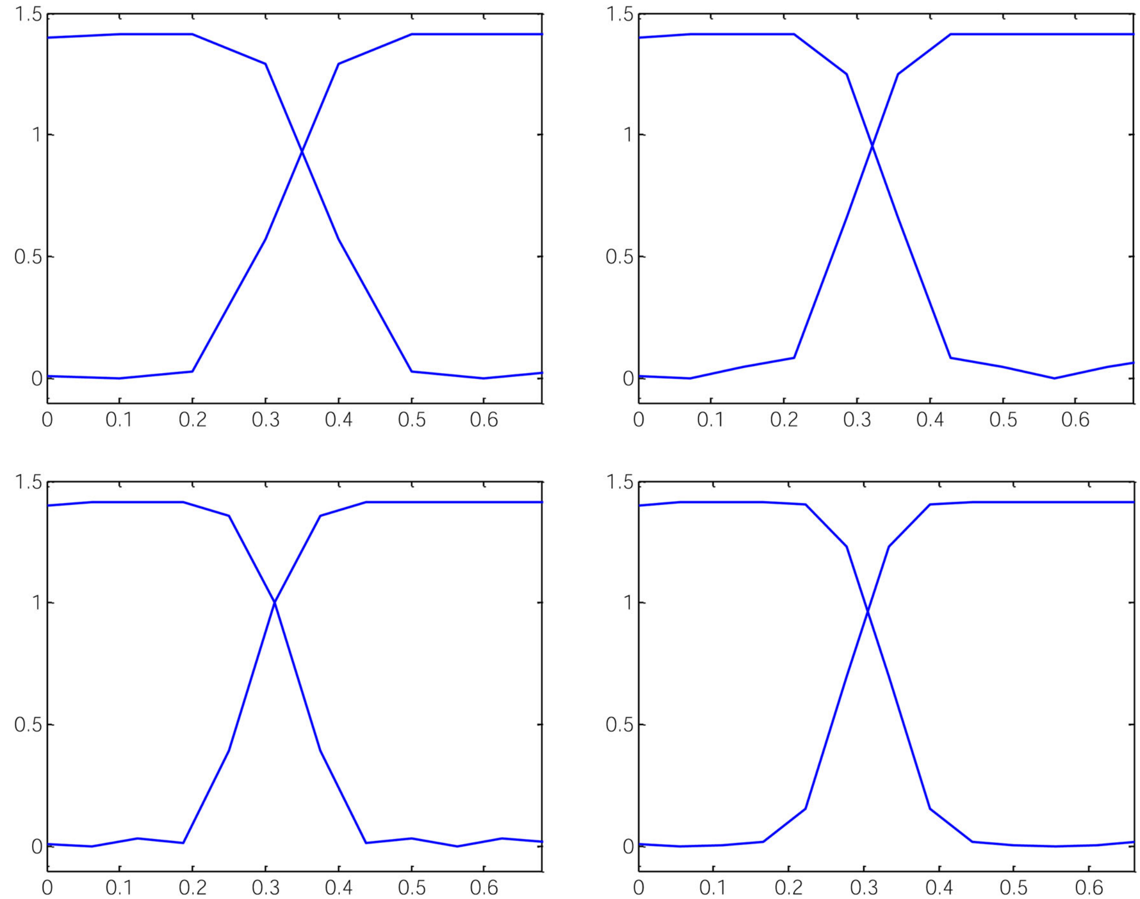

Figure 3. Four kinds of DTCWPT filter banks: (a) Filter bank A, (b) Filter bank B, (c) Filter bank C, (d) Filter bank D.

$$g_0(n) \approx h_0(n - 0.5) \qquad [3]$$

$$G_0(e^{j\omega}) \approx e^{-j0.5\omega} H_0(e^{j\omega}) \qquad [4]$$

where n refers to the time shift. The Q-shift filter design method is generally used to satisfy the half-sample delayed requirement (Wang, He, and Zi 2010). The outstanding symmetry provided by the Q-shift method facilitates the feature extraction of mechanical vibration signals. At present, four kinds of DTCWPT filter banks designed using the Q-shift method have been developed: Filter bank A (10-order Q-shift filter), Filter bank B (14-order Q-shift filter), Filter bank C (16-order Q-shift filter), and Filter bank D (18-order Q-shift filter), as shown in Figure 3. It is worth noting that each filter bank displays its own properties when matching the characteristics of vibration signals.

Adaptive DTCWPT construction

Singular values can reveal the intrinsic feature of a given vector matrix, and they have been applied in machinery fault diagnosis because of their high reliability, sensitivity, and signal to noise ratio (Zhang et al. 2016; Zhao and Ye 2016; Qiu et al. 2006). By performing SVD on the feature vector matrix designed with the decomposed frequency bands, SVD entropy can be easily calculated to effectively describe the changes and singularities among the analyzed signals (Jiang, Xia, and Wang 2013b; Banerjee and Pal 2014). Specifically, the energy distribution of the collected vibration signal of health bearing is more random and uniform compared with faulty bearing, leading to a larger SVD entropy value. Moreover, different fault characteristics show different entropy values, and smaller entropy values represent stronger fault characteristics. Thus, this paper adopts the minimum SVD entropy principle to adaptively select the optimal DTCWPT filter bank for the analyzed signals.

Given a measured vibration signal S, the signal is decomposed into l levels. The decomposed 2^l frequency band signals are denoted as $S_i = [S_{i,1}, S_{i,2}, \ldots, S_{i,j}, \ldots, S_{i,N}]^T$ $(i = 1, 2, \ldots, 2^l;\ j = 1, 2, \ldots, N)$, where $S_{i,j}$ is the jth data point in the ith band signal at level l, and N is the data length of each band signal. $S_1, S_2, \ldots, S_{2^l}$ form the original feature vector matrix $A = [S_1 \quad S_2 \ \ldots \ S_{2^l}]$, whose size is $N \times 2^l$. Based on the SVD theory, matrix A can be decomposed as follows:

$$A = U\Lambda V \qquad [5]$$

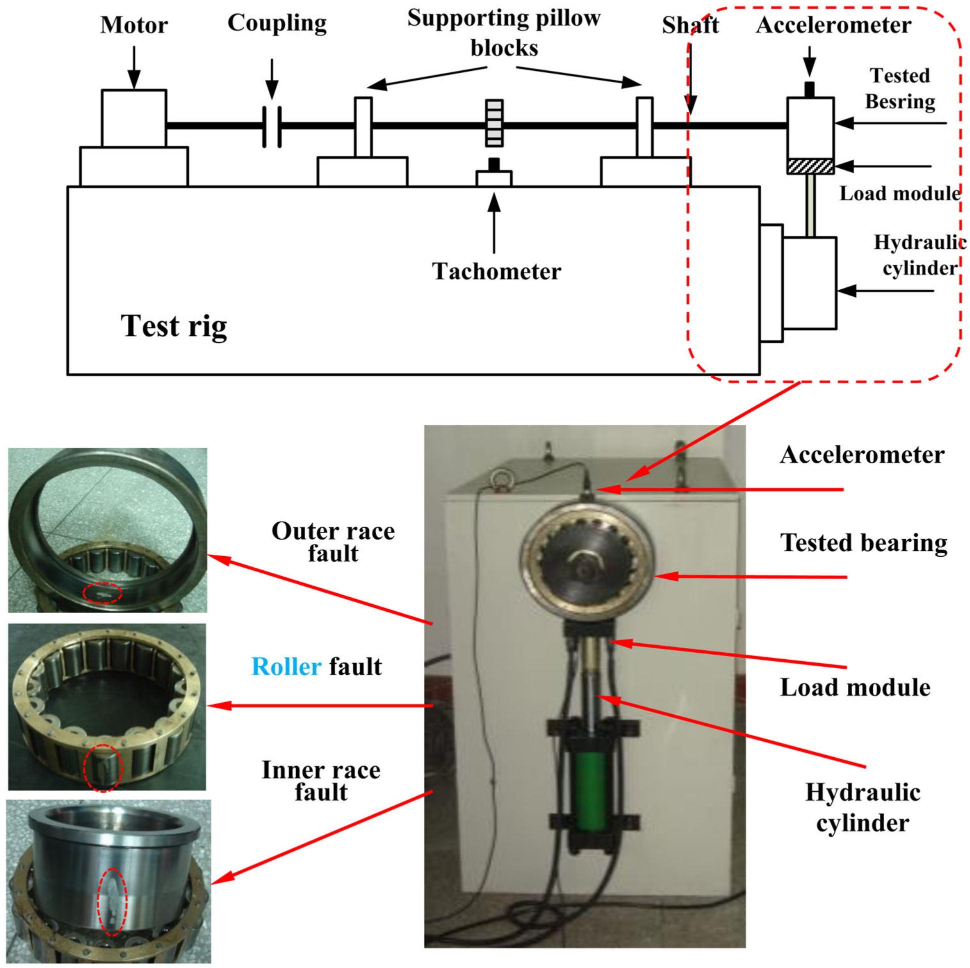

Figure 4. Experimental setup for compound fault of bearing.

where U and V are both orthogonal matrixes, whose sizes are $N \times N$ and $2^l \times 2^l$, respectively, and Λ is a $N \times 2^l$ diagonal matrix. The diagonal elements σ_i $(i = 1, 2, \ldots, 2^l)$ of matrix Λ are the singular values of the original feature vector matrix A. Based on SVD theory and information entropy theory, SVD entropy is defined as

$$p_i = \frac{\sigma_i}{\sum_{i=1}^{2^l} \sigma_i} \quad [6]$$

$$P = -\sum_{i=1}^{2^l} p_i \log p_i \quad [7]$$

where p_i is the normalization factor of the singular value σ_i, and P is the SVD entropy value.

Feature extraction and enhancement using higher order spectra

Higher order spectra are the spectral representations of higher order cumulants of an analyzed signal; they have been widely used in many different applications, including pattern recognition, nonlinear system identification, machinery fault diagnosis, etc. At present, two kinds of higher order spectra analysis methods have been considered for feature extraction of rotating machinery: bispectrum (diagonal slice spectrum of the third-order cumulant) and trispectrum (diagonal slice spectrum of the fourth-order cumulant) (Collis, White, and Hammond 1998). The bispectrum can effectively eliminate heavy background noise and extract more quadratic nonlinear coupling characteristics hidden in the signal than Hilbert transform demodulation spectrum analysis. The trispectrum method is a further development of bispectrum analysis; it overcomes the latter's inability to capture the cubic coupling information of many complex signals, such as the measured vibration signals of compound fault (Mccormick 1999).

In this paper, the trispectrum method is used on the frequency sensitive band decomposed by the adaptive DTCWPT for post-processing; then, the characteristic frequency components hidden in the vibration signal are extracted and enhanced.

Table 1. Parameters of the tested bearing in the experiments.

Parameter	Value
Bearing type	552732QT
Inner race diameter	160 mm
Outer race diameter	290 mm
Pitch diameter (D)	225mm
Roller diameter (d)	34 mm
Roller number (Z)	17
Contact angle (α)	0°

Let $x(t)$ be the vibration signal measured from the rolling bearing. Then, the fourth-order cumulant of $x(t)$ can be defined as (Collis, White, and Hammond 1998)

$$\begin{aligned} c_{4x}(\tau_1,\tau_2,\tau_3) &= cum\{x(n),x(n+\tau_1),x(n+\tau_2),x(n+\tau_3)\} \\ &= E[x(n)x(n+\tau_1)x(n+\tau_2)x(n+\tau_3)] \\ &\quad - R_x(\tau_1)R_x(\tau_2-\tau_3) \\ &\quad - R_x(\tau_2)R_x(\tau_3-\tau_1) - R_x(\tau_3)R_x(\tau_1-\tau_2) \end{aligned} \quad [8]$$

with

$$R_x(\tau_i) = E[x(n)x(n+\tau_i)] \ (i=1,2,3) \quad [9]$$

where $cum\{\cdot\}$ denotes the cumulant operator, $E[\cdot]$ denotes the expectation operator, and τ_i $(1,2,3)$ are the delays.

Let $\tau_1=\tau_2=\tau_3=\tau$ be the diagonal slice spectrum of the fourth-order cumulant, which can be calculated as follows:

$$c_{4x}^1(\tau) = E\left[x(n)x^3(n+\tau)\right] - 3R_x(\tau)R_x(0) \quad [10]$$

The trispectrum $T(\omega)$ is the Fourier transform of $c_{4x}^1(\tau)$, defined as

$$T(\omega) = \sum_{\tau=-\infty}^{\infty} c_{4x}^1(\tau)e^{-j2\pi\omega\tau} \quad [11]$$

The trispectrum method is used to analyze the frequency sensitive band for feature extraction. The selection of the decomposition frequency sensitive band is based on the normalized energy distribution, which can be calculated as follows:

$$E_i = \frac{E(S_i)}{\sum_{i=1}^{2^l} E(S_i)} \quad [12]$$

$$E(S_i) = \sum_{j=1}^{N} \left|S_{i,j}\right|^2 \quad [13]$$

where $E(S_i)$ represents the vibration energy of the ith decomposition band signal.

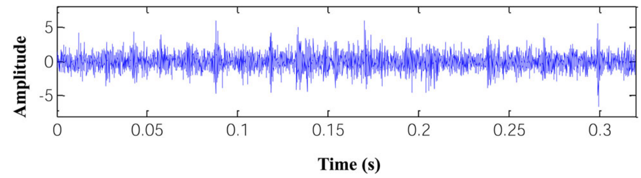

Figure 5. Measured vibration signal of tested bearing.

Compound fault diagnosis of rolling bearing

Experimental setup for compound bearing fault

In the next step, the proposed approach is used to diagnose the compound fault of a rolling bearing. Figure 4 shows the experimental test rig. The vibration signals measured from the tested bearing with compound fault are used for analysis. Rub faults using an electric discharge occur in three locations: inner race, outer race, and roller. The sampling frequency f_s is 12.8 kHz under 9800 N radial load, and the rotating speed is about 549 rpm.

When a defect occurs on a certain part of the bearing, this creates a fault characteristic frequency where vibration energy increases. Three kinds of fault characteristic frequencies can be calculated by

$$f_i = \frac{Z}{2}\left(1 + \frac{d\cos\alpha}{D}\right)f_r \quad [14]$$

$$f_o = \frac{Z}{2}\left(1 - \frac{d\cos\alpha}{D}\right)f_r \quad [15]$$

$$f_b = \frac{D}{2d}\left[1 - \left(\frac{d}{D}\right)^2 \cos^2\alpha\right]f_r \quad [16]$$

where f_r is rotating frequency, D is pitch diameter, d is rolling element diameter, Z is number of rolling elements, and α is contact angle. f_i, f_o, and f_b represent fault characteristic frequencies of the inner race, outer race, and roller, respectively.

More parameters of the tested bearing are listed in Table 1. Three kinds of fault characteristic frequencies can be calculated using Eqs. [14] to [16]; i.e., $f_i =$ 89.53 Hz, $f_o = 66.02$ Hz, and $f_b = 29.59$ Hz. Figure 5 shows the measured vibration signal of the tested bearing. Note that the periodic impulse component is too weak to be detected. The FFT spectrum of the vibration signal is shown in Figure 6. As the figure indicates, the frequency components are complex and abundant, and the required characteristic frequencies cannot be extracted.

Results

For comparative purposes, three other methods, i.e., EEMD, SGWPT and multiwavelet packet transform

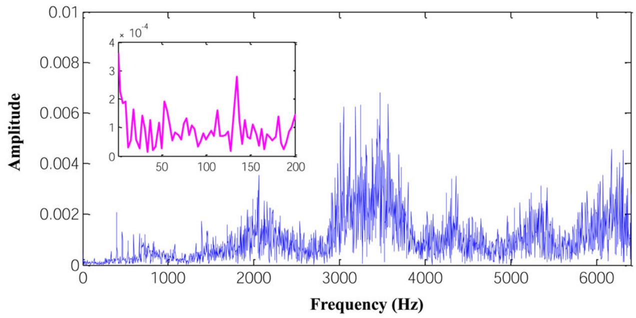

Figure 6. FFT spectrum of measured bearing vibration signal.

Table 2. Four sets of contrastive experiments.

Experiments	Purposes
Experiment 1	Validate the effectiveness of the proposed method in detecting compound fault
Experiment 2	Validate the superiority of DTCWPT
Experiment 3	Validate the feasibility of the adaptive strategy using the minimum SVD entropy
Experiment 4	Investigate the performance of two kinds of higher order spectra analysis techniques

(MulWPT), are also used. It should be pointed out that the postprocessing technique of these three methods is Hilbert transform demodulation spectrum analysis. In order to fully compare the performance of the proposed approach with the three other approaches, four sets of contrastive experiments are designed, and more details are available in Table 2.

Table 3 lists the SVD entropy values of the four types of DTCWPT filter banks in Experiment 1. Based on these values, filter bank D is selected as the optimal filter bank to adaptively match the analyzed signal characteristics. Figure 7 shows the normalized energy distribution of the decomposed frequency bands in Experiment 1; in which the largest vibration energy occurs is selected as the fault frequency sensitive band. Figure 8 gives the analyzed results of the four approaches in Experiment 1. Based on the researchers' experimental experience, the main parameters of the four approaches are described as follows:

- DTCWPT: the decomposition level is set to 3, and filter bank D selected as the filter bank according to minimum SVD entropy. The length of the analyzed signal is given as $N = 8192$, and then the resolution ratio is $\Delta f = f_s/N = 1.5625$ Hz.
- EEMD: the standard deviation of Gaussian white noise is set to 0.02, and the first 8 intrinsic mode functions (IMFs) containing main energy and information are chosen for signal analysis. To improve computing efficiency, the signal length is 4096.
- SGWPT: the length of the analyzed signal is 4096, the decomposition level is set to 3; the predicting coefficient is [0.0117 − 0.0977 0.5859 0.5859 − 0.0977 0.0117], and the update coefficient is [0.0059 − 0.0488 0.2930 0.2930 − 0.0488 0.0059]. To improve computing efficiency, the signal length is 4096.
- MulWPT: the length of the analyzed signal is 4096, Geronimo Hardin Massopust multiwavelet (Sun et al. 2014) is selected, and the decomposition level is set to 3. To improve computing efficiency, the signal length is 4096.

Table 3. Corresponding SVD entropy values for the four kinds of DTCWPT filter banks.

Four filter banks	Order of filter bank	SVD entropy value
Filter bank A	10	0.5859
Filter bank B	14	0.5061
Filter bank C	16	0.5422
Filter bank D	**18**	**0.4794 (minimum)**

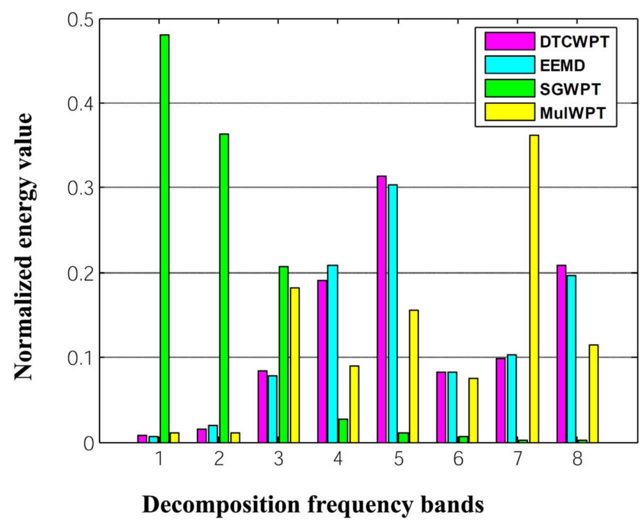

Figure 7. Normalized energy distribution of decomposition frequency bands using various methods.

In Experiment 2, DTCWPT, EEMD, SGWPT, and MulWPT are first adopted to preprocess the vibration signal, and then the higher order spectra (trispectrum) technique is used to analyze the corresponding decomposition frequency sensitive bands. Figure 9 provides the comparative results for Experiment 2.

To validate the validity of the proposed adaptive strategy, the performance of the four kinds of filter banks is compared in Experiment 3, as shown in Figure 10. From Figure 10, Filter bank A can only extract inner race and outer race characteristic frequencies and f_i and f_o. Filter bank B, filter bank C, and filter bank D can extract all of the characteristic frequencies.

Experiment 4 investigates the performance of two kinds of higher order spectra analysis techniques (i.e., bispectrum and trispectrum) for feature extraction

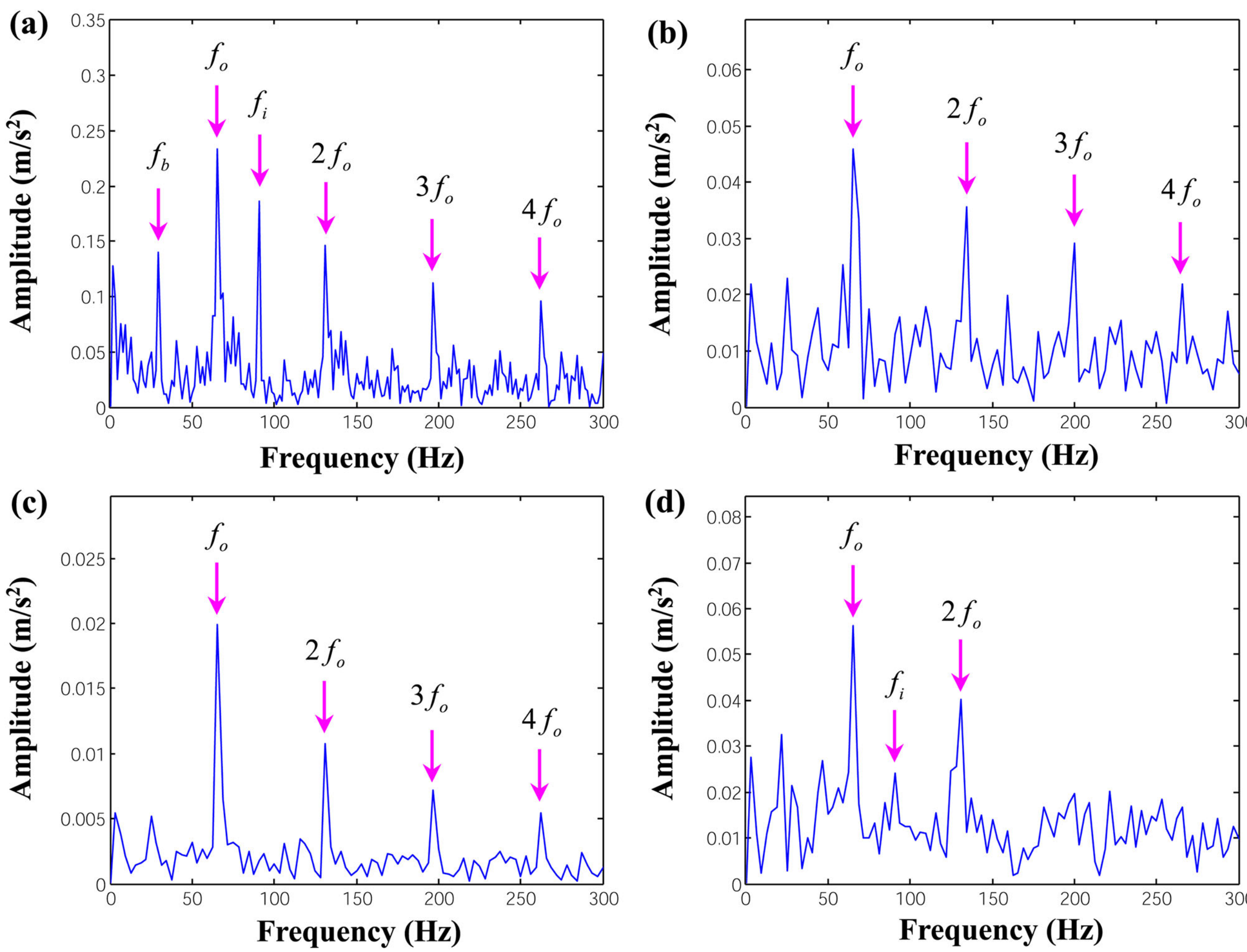

Figure 8. Results of the four approaches in Experiment 1: (a) proposed approach, (b) EEMD with Hilbert transform demodulation spectrum, (c) SGWPT with Hilbert transform demodulation spectrum, (d) MulWPT with Hilbert transform demodulation spectrum.

and enhancement of compound fault, as shown in Figure 11. The two higher order spectra analysis techniques both can extract all of the characteristic frequencies.

Discussions

Through the comparison results in Figure 8 in Experiment 1, it can be found that all of the characteristic frequencies are well-extracted using the proposed approach, moreover, double frequency $2f_o$, triple frequency $3f_o$, quadruple frequency $4f_o$ of outer race are obtained as well. Specifically, the extracted frequency values of f_b, f_o, and f_i shown in Figure 8 are 29.69, 65.63, and 90.63 Hz, respectively. The errors between the extracted frequencies and theoretical frequencies are all smaller than the resolution ratio of 1.5625 Hz. Despite EEMD with Hilbert transform demodulation spectrum and SGWPT with Hilbert transform demodulation spectrum can extract f_o, $2f_o$, $3f_o$, and $4f_o$ of outer race, they both fail to extract roller and inner race characteristic frequencies. MulWPT with Hilbert transform demodulation spectrum can only extract roller and outer race characteristic frequencies f_i and f_o. Although the signal length for each comparative method is set to 4096 to improve computing efficiency, repeated experiments have been actually carried out under other lengths, and the results are quite similar.

It can be observed from Figure 9 in Experiment 2 that DTCWPT can retain all the fault information, which is more effective than EEMD, SGWPT, and MulWPT. In addition, through the comparison results between Figure 9 and Figure 8 in Experiment 1, higher order spectra (trispectrum) analysis is more effective than Hilbert transform demodulation spectrum analysis. For example, EEMD with higher order spectra and SGWPT with higher order spectra can extract both the inner race and outer race characteristic frequency.

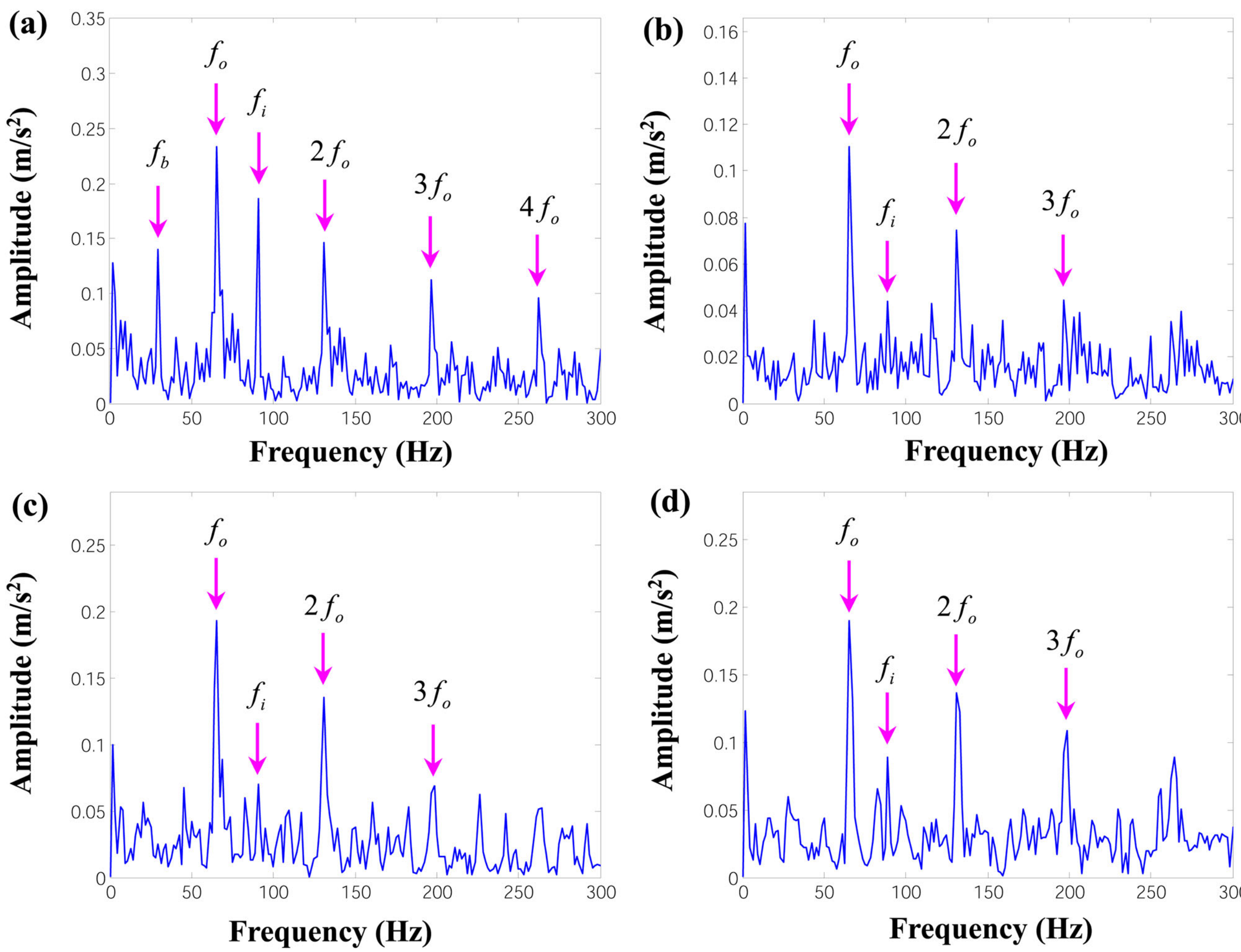

Figure 9. Comparative results for Experiment 2: (a) DTCWPT with higher order spectra (proposed approach), (b) EEMD with higher order spectra, (c) SGWPT with higher order spectra, (d) MulWPT with higher order spectra.

Experiment 3 aims to compare the four kinds of DTCWPT filter banks. As shown in Figure 10, despite filter bank B and filter bank C can extract all of the characteristic frequencies, compared with filter bank D, the extracted fault characteristics are slightly weaker. Furthermore, we can conclude that: (1) each filter bank has its own properties to match the analyzed vibration signal; (2) the proposed adaptive strategy based on the minimum SVD entropy is effective to select the optimal filter bank.

Figure 11 shows the comparison results in Experiment 4, the two higher order spectra analysis techniques (trispectrum and bispectrum) both can extract all of the characteristic frequencies. It seems to be concluded that trispectrum is better than bispectrum in this case study; however, their performance difference is quite small. More cases are suggested so as to fully investigate their performance.

As a summary, the proposed approach is more effective for feature extraction of compound fault than the other approaches. The superiority comes from two aspects as follows. (1) Adaptive DTCWPT constructed with minimum SVD entropy can well match the analyzed vibration signals to extract all the underlying features due to reduced aliasing and near shift-invariance. (2) Higher order spectra can suppress heavy background noise to enhance the extracted features.

Conclusions

Diagnosis of compound faults in complex systems is still a challenging task due to the coupling of multiple signals, which may conceal the characteristics of compound faults. Taking a rolling bearing as an example, this study aims to boost the accuracy of compound fault diagnosis through a novel feature extraction approach to making the fault characteristics more discriminative through developing a novel approach of feature extraction based on adaptive DTCWPT with higher order spectra. In this approach, the advantages of DTCWPT, SVD entropy, and higher order spectra are fully combined. Specifically, DTCWPT is introduced to preprocess the measured vibration signals and its best filter bank is adaptively selected using the

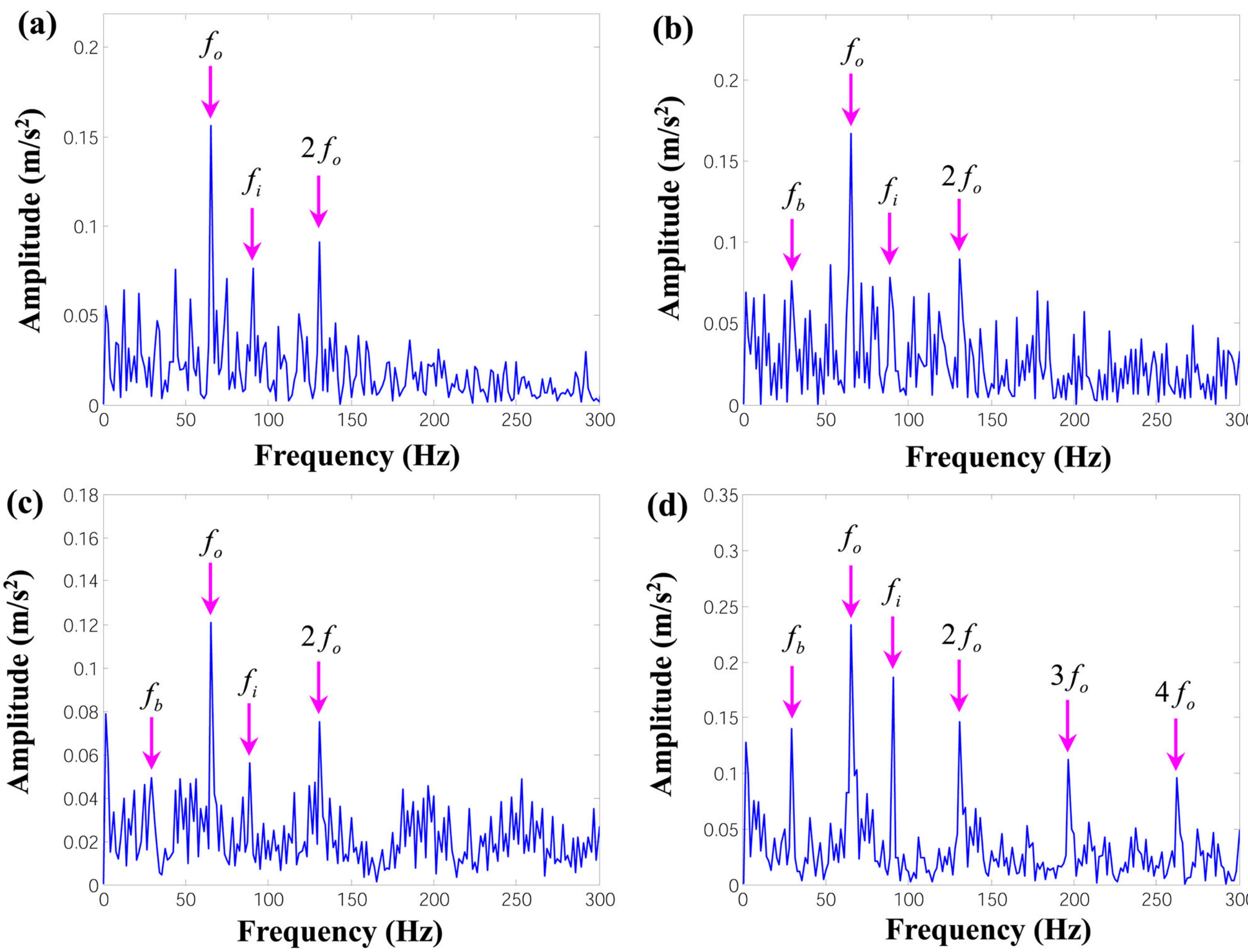

Figure 10. Comparison of performance of the four kinds of DTCWPT filter banks in Experiment 3: (a) Filter bank A, (b) Filter bank B, (c) Filter bank C, (d) Filter bank D (adaptively selected using minimum SVD entropy).

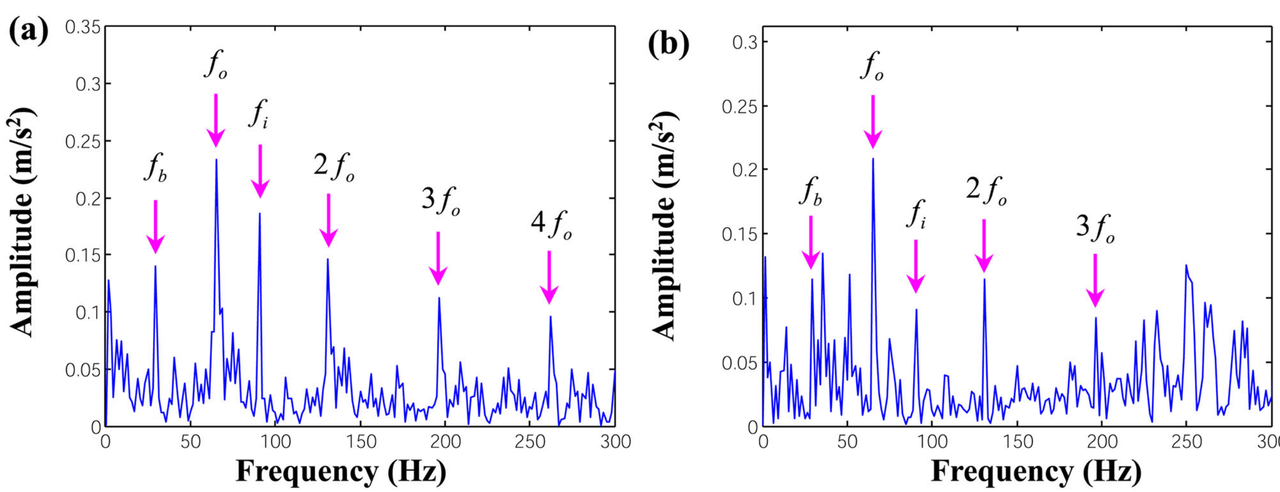

Figure 11. Comparison of two kinds of higher order spectra in Experiment 4: (a) adaptive DTCWPT with trispectrum (proposed), (b) adaptive DTCWPT with bispectrum.

minimum SVD entropy. Higher order spectra analysis is used for feature extraction and enhancement.

The performance of the proposed approach is tested with the experimental signals of roller bearing's compound fault. Despite the proposed approach focuses on the combination of three existing techniques, the application result in compound fault diagnosis is satisfactory. In addition, we carry out many comparisons to demonstrate the superiority of the proposed approach. In the future, we plan to design new DTCWPT filter banks.

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