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The incipient fault feature enhancement method of the gear box based on the wavelet packet and the minimum entropy deconvolution

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ABSTRACT

The amplitude of the vibration signal in the gearbox of the motor driving system is low, resulting in disturbance and vibration noise effect, especially in the early stage of failure. So, it is difficult to extract the characterization of gearbox fault correctly. A method of incipient fault feature enhancement based on the wavelet packet and the minimum entropy deconvolution (MED) is proposed. Firstly, the vibration signal of the gear box containing the incipient fault is decomposed by the wavelet packet, and the decomposed band is reconstructed to eliminate the noise component which is the initial enhancement of the fault feature. After that the MED is used to filter the reconstructed band blind deconvolution to eliminate the influence of the transmission path, so that the feature components of the fault are enhanced again. The combination of WP and MED weakens the influence of the normal components in the original signal, highlights the impact component of the fault, and fully excavates the hidden fault information in the frequency band after the wavelet packet decomposition. Finally, the experimental results are compared and analysed. The experimental results show that the incipient fault feature extracted by this method improves the accuracy of fault diagnosis.

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Fault diagnosis; systems identification and signal processing; wavelet transforms; theory-methods; time series analysis; systems identification and signal processing

1. Introduction

The gearbox in the motor driving system is an important component of mechanical power transmission, and the failure frequency due to mechanical failure accounted for 60%. Therefore, the problem of gearbox fault is an important factor leading to machine failure. Then, the question of how to extract the fault characteristics of an ordinary functioning gearbox and identify any incipient faults has become a topical issue in the field of fault diagnosis.

In the process of the information extraction from incipient fault features in the gearbox in the motor driving system, scholars at home and abroad have done extensive research and obtained some effective results in fault research methods. Take for example, in order to avoid lack of visual feature extraction and the nonlinear relation in the traditional feature extraction methods, the researchers combined wavelet packet decomposition and high-order cumulant to extract the vibration signal feature. On this basis, through the use of fault classification by means of neural network algorithms, it can accurately and effectively identify the type of faults associated with rolling bearings (Qian & Kang, 2016). Sun, Yang, Chen, Palazoglu, and Feng, (2013) have investigated how discrete wavelet transforms and envelope analysis are combined to construct the characteristic spectrum of

rolling bearing vibration data. As a result of this work, the different working states of rolling bearings are identified by applying spectral cross correlation coefficients (Sun et al., 2013). Sugumaran, Rao, and Ramachandran (2015). introduced the support vector machine (SVM) and the approximate support vector machine (PSVM) into the faults classification, and used the wavelet clusters and a decision tree to determine the optimal wavelet, which increased the classification accuracy (Sugumaran et al., 2015). According to the non-stationary and nonlinear characteristics of fault signals of the gearbox, in a paper by Liu Chunlin, it is shown that the characteristics of gearbox fault signals can be detected by the combination of the multifractal detrended fluctuation fractal (MF-DFA) and SVM. Based on the four multifractal parameters, including the maximum singularity index, the minimum singularity index, the singular spectrum width and the extreme point, the characteristic parameter model of the fault is constructed, and the SVM is used to complete the fault diagnosis and recognition, so in this way good results have been obtained (Liu et al., 2014).

Unfortunately, these algorithms concern mainly obvious fault distinguishing and analysis. With the expanding of the complexity of modern control systems and equipment, the scale of failure is also diversified and

complicated. No matter from what kind of fault it originates, whether it develops on a large scale or from one that breaks out fast, these faults stem from small faults (or an initial incipient fault). Therefore, based on these algorithms, the diagnostic methods for the early discovery of faults need to be established in order to avoid the occurrence of a serious failure.

Fault components in vibration signals are low and of small amplitude in the beginning, it gives rise to system disturbance and noise masking characteristics, which are not easy to detect. Based on these diagnostic features, the small fault can be divided into slowly changing small faults and mutating small faults. In this way, the classification framework for detecting minor faults can be put forward (Liu et al., 2014). In the case put forward by Fafa Chen, the early detection of faults in the gearbox is very weak (Chen, Tang, & Yao, 2013). The incipient fault fusion diagnosis model of the gearbox is constructed by combining the DSMT theory with wavelet neural network. DSMT theory has overcome the limitations of the traditional DST evidence theory by making use of the wavelet neural network, which has realized the reliable allocation of multi-source evidence, and so the model has achieved a better effect. Suiyi Chen et al. (2013) present the method based on the time domain and frequency domain that kurtosis wavelet energy feature extraction and combined with an early discriminative weighted probabilistic neural network. According to the advantages of kurtosis statistics in the impact load feature extraction of diagnostic information, the advantage of wavelet packet decomposition in the frequency domain signal acquisition is preserved. It has the advantage of taking into account the problem of noise pollution. The discriminative weight method is introduced in the probabilistic neural network and finally succeeds in the early diagnosis of a faulty gearbox (Chen, Zhou, & Yi, 2012). By means of the introduction of high sensitivity to the incipient fault entropy in comprehensive divergence and two assessments, in paper by Harmouche, Delpha, and Diallo (2015) the amplitude of the incipient fault can be estimated in the multivariable process, and so the incipient fault detection model in a noisy environment is constructed. On this basis, through the fault noise ratio, the analytical model of the divergence of Gauss noise is deduced, thus completing the estimation of the fault amplitude theory, and in this way showing the effectiveness of the method. The method mentioned by Youren Wang is based on the experience of the wavelet transform energy aggregation (EA-EWT) model of fault diagnosis, and the use of the maximum kurtosis-envelope spectrum entropy criterion for sensitive component screening and the minimum entropy deconvolution (MED) of signals, which were selected for noise reduction, Hilbert envelope analysis of denoised

signal so as to achieve early diagnosis of fault (Wang, Chen, Sun, Sun, & Huang, 2017). The method proposed in Zhao, Huang, and Qin (2015) is a combination of wavelet transform and empirical mode decomposition to extract incipient fault features while using multiple components of signal decomposition and kurtosis of frequency components to automatically select the envelope spectrum extraction, and it has achieved good results.

Although the incipient fault diagnosis method in different fields has achieved good results. In the actual work environment, the vibration signal of the gear box is passed through the box to the surface of the box, which will weaken the impact of the early fault of the weak gear. So, this paper proposes the wavelet packet and the MED combined method to extract the incipient fault feature of the gearbox in the motor driving system.

2. Background of theory

2.1. Wavelet packet decomposition

Wavelet packet decomposition is an extension of wavelet analysis; the basic idea is to make the vibration signal information concentrated. It will be the bands of multi-level division; the multi-resolution analysis is further decomposed into low-frequency bands and high-frequency bands, and according to the analysis of the characteristics of the signal by adaptive selection of the corresponding frequency band which matched with the signal spectrum so as to improve the time–frequency resolution (Deng & Tang, 2017; Sun, Liu, Xingung, & Bo, 2017; Zhao et al., 2016).

The vibration signal $x(n)$ of the gearbox in the motor driving system is decomposed into small packets, and the essence of the decomposition is to let the signal pass through filters (h_k and g_k) with different center frequencies but the same bandwidth. The two samples are sampled at the same time, and the signal is decomposed into two parts, the high frequency and the low frequency (Deng & Tang, 2017). Each time the data are decomposed, the data in each frequency band are reduced by half, and the data quantity is compressed.

It is assumed that the frequency band width Δf of wavelet packet decomposition, the decomposition layer number j and the sampling frequency f_s satisfy the relation:

$$\Delta f = f_s / (2 * 2^j) \quad (1)$$

After wavelet packet decomposition, the amplitude, energy, mean, variance and kurtosis of the vibration signal in each frequency band can be selected as characteristic parameters. In this paper, energy is selected as the characteristic parameter of the signal.

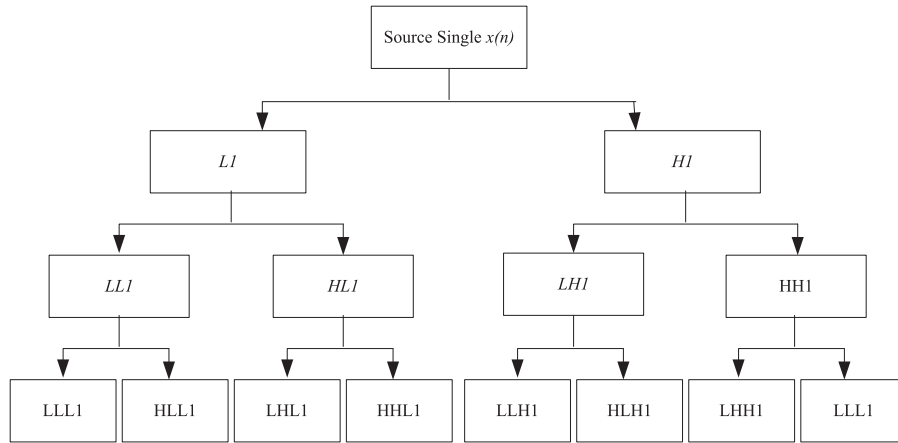


Figure 1. Decomposition tree structure.

The sampling signal is decomposed by wavelet packet. After decomposition, the low frequency part L and high-frequency part H are obtained. Considering the length of data and the order of wavelet, the data is decomposed into three layers, the high frequency information of the sampled data is reflected. Therefore, the number of wavelet packet decomposition layers is 3, and the signal characteristics of 8 frequency components from low frequency to high frequency are extracted respectively. The decomposition structure is shown in Figure 1.

2.2. Wavelet packet reconstruction

Let S represent the original signal and (i, j) represent the first i layer and the j node in the wavelet packet decomposition tree. Of which $i = 0, 1, 2, \dots, N; j = 0, 1, 2, \dots, 2^N - 1$, N is the decomposition layer number, and the wavelet packet decomposition coefficients are reconstructed to extract the signal of each frequency band:

$$S = \sum_{j=0}^{2^N-1} S_j \tag{2}$$

Among them, S_j represents the reconstructed signal in each frequency band and N is the decomposition layer number.

Suppose that the minimum frequency is 0 and the highest frequency is h in the original signal S . The frequency range may be evenly divided into 8 parts. If every frequency component were represented by the symbol $S_j (j = 0, 1, 2, \dots, 7)$, the frequency range obtained is shown in Table 1.

2.3. The minimum entropy deconvolution

The MED was first proposed by Wiggins in 1978 and was first applied to the extraction of seismic wave reflection

Table 1. Frequency range represented by frequency components.

Signal	S_0	S_1	...	S_7
Frequency range	$0-0.125 h$	$0.125 h-0.25 h$...	$0.875 h-h$

parameters (Yao et al., 2017). The basic principle of this method is to use the minimum entropy to enhance the impulse component, thus suppressing the noise and enhancing the impulse component of the filtered signal (Zhang et al., 2017). The termination condition of the calculation is the maximum kurtosis.

$$y(n) = h(n) \times S(n) + e(n) \tag{3}$$

In which, $S(n)$ is the signal in each band after the reconstruction of the wavelet packet, $e(n)$ is the noise, $h(n)$ is the transfer function and $y(n)$ is the mixed signal (Zhang et al., 2017).

The entropy of the signal becomes larger because of the influence of noise. Therefore, we need to find an optimal inverse filter $g(n)$, so that $y(n)$ can recover all the characteristic information of $S(n)$ (Zhang et al., 2017) as follows:

$$s(n) = g(n) \times y(n) = \sum_{k=1}^K g(n)y(n - k) \tag{4}$$

In which k is the length of the inverse filter.

When the fault shock signal is restored, the aim of the inverse filter is to restore the S_j to the maximum part feature and the related information state making the entropy minimum and the expression is as follows:

$$\frac{\partial g(n)}{\partial g(k)} = y(n - k) \tag{5}$$

The norm of the sequence $\hat{x}(n)$ obtained after deconvolution by formula (4) is used to measure the value of

entropy. The expression is as follows:

$$Q_2^4(g(n)) = \frac{\sum_{i=1}^N S^4(i)}{\left[\sum_{i=1}^N S^2(i)\right]^2} \quad (6)$$

When the norm $Q_2^4(\bullet)$ of sequence $\hat{x}(n)$ in formula (6) is the largest, the value of inverse filtering is optimal. The expression is as follows:

$$\frac{\partial Q_2^4(g(n))}{\partial g(n)} = 0 \quad (7)$$

The joint formula (5) can be obtained:

$$\begin{aligned} & \frac{\sum_{n=1}^N S^2(n)}{\sum_{n=1}^N S^4(n)} \sum_{n=1}^N S^3(n)y(n-k) \\ &= \sum_{p=1}^K g(p) \sum_{n=1}^N y(n-k)y(n-p) \end{aligned} \quad (8)$$

Formula (8) can be written in the form of a matrix as follows:

$$f = Ag \quad (9)$$

In which, A is the auto-correlation matrix of $y(n)$, $f = (f(k))^T$, $f(k)$ can be expressed as

$$f(k) = a \sum_{n=1}^N S^3(n)y(n-k) \quad (10)$$

$$a = \frac{\sum_{n=1}^N S^2(n)}{\sum_{n=1}^N S^4(n)} \quad (11)$$

Formula (9) obtains the inverse filtering matrix after iteration as follows:

$$g = A^{-1}f \quad (12)$$

2.4. The wavelet packet energy eigenvalue extraction

When the gear fails, the signal energy of each node will change obviously, so the energy characteristic vector can be constructed by the frequency band energy spectrum. The signal energy of each frequency band can be calculated, as shown in Equation (13).

$$E_j = \int |S_j|^2 dt = \sum_{k=1}^m |x_{jk}|^2 \quad (13)$$

Among them, x_{jk} ($j = 0, 1, 2, \dots, 7; k = 0, 1, \dots, m$) represents the magnitude of the discrete points of the reconstructed signal S_j . Where m is the sampling point of the work cycle, and then construct the feature vector. In order to eliminate the influence of different factors, the feature

vector selection of M bands was normalized, as shown in formula (14).

$$E_j = \left(\sum_{j=1}^m |E_j|^2 \right)^{1/2} \quad (14)$$

$$\vec{d} = [E_1, E_2, \dots, E_m]^n \quad (15)$$

Thus, it can be seen that the vibration signal is decomposed by wavelet packet, and after wavelet packet reconstruction, the energy is calculated in a different frequency spectrum as the characteristic parameter of gearbox fault. Finally, the feature vector is regarded as the fault features of the gear box in the motor driving system.

3. Framework and algorithm for incipient fault characteristics extracting of the gear box in the motor driving system by the combination of WP and MED

Based on the above theoretical analysis, the algorithm based on the wavelet packet and MED for extracting the incipient failure of the gearbox is as follows:

- Step1 : the original signal is the input signal of the wavelet packet. The specific steps are as follows: Through the analysis of the data and the comparison of the processing results, it is found that the wavelet-based Daubechies with three decomposition layers is the best. So, 3 layers of wavelet packets are decomposed, and 8 frequency bands from low frequency to high frequency are extracted. After the signal is reconstructed by formula (2), the signals of 8 frequency bands are obtained.
- Step2 : By using MED, the impulse components can be enhanced, and the noise can be suppressed so that the impulse components of micro-faults can be enhanced. Firstly, an optimal inverse filter $g(n)$ is found to recover the characteristic information of the reconstructed signal in the frequency band. Then, the entropy value is measured by the deconvolution sequence. Finally, an optimal inverse filter is obtained when the sequence norm in formula (6) is a maximum. The feature is enhanced. For the 8 frequency bands, MED is used to enhance the fault characteristics.
- Step3 : For the enhanced 8 band signals, the energy of the 8 bands is calculated using the formulas (13)–(15) as the eigenvalue of the fault.
- Step4 : The fault eigenvalues are classified by SVM.

The basic framework is shown in Figure 2.

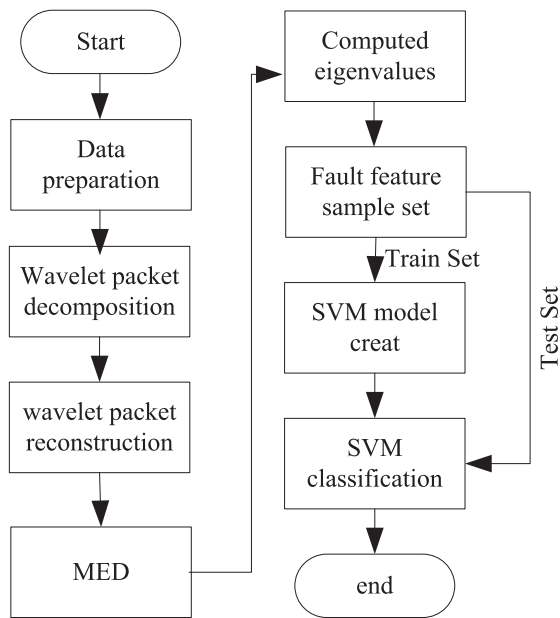


Figure 2. Basic framework for fault identification.

4. Experimental simulations

4.1. Background introduction

The data collected in this paper come from the multistage centrifugal fan fault diagnosis unit, which is made up of the variable-speed drive motor, bearing, gearbox, shaft, heavy turntable, speed regulator and so on. The motor power of the device is 0.75 kW. The multistage centrifugal fan fault diagnosis unit is shown in Figure 3.

The fault diagnosis unit of the multistage centrifugal fan is made up of gear, bearing and transmission shaft. The gear fault accounts for most of the mechanical faults. The sampling frequency of the sampled data is $f = 5120$ Hz. The gear speed is 880 r/min. The normal gear and two types of gear fault are shown in Figure 4.

4.2. Feature extraction

In order to verify the validity of the feature extraction method for incipient faults, the source data of the normal



Figure 3. The multistage centrifugal fan fault diagnosis unit.

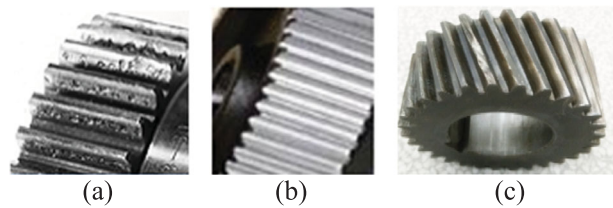


Figure 4. Fault type. (a) Pitting, (b) normal and (c) abrasion.

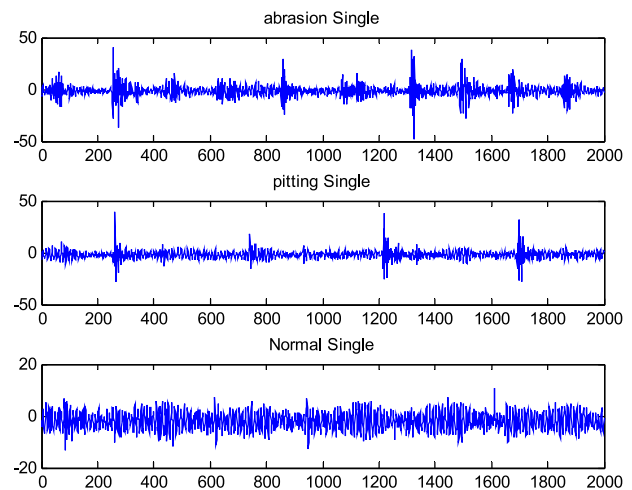


Figure 5. Source signal.

signal of the gear, the pitting signal and the abrasion signal are taken as the source. Figure 5 is a vibration source signal in three states of the gear box.

When the wavelet packet is decomposed, the sampling frequency of the sampled data is $f = 5120$ Hz, the number of decomposition layers is 3 and the small wave base is Daubechies. The signal characteristics of the 3rd layers and 8 frequency components are extracted. The energy spectrum of each band for abrasion single in the 3rd layer is shown in Figure 6.

As shown in Figure 6, the energy extracted through WP-MED is more obvious than WP.

4.3. SVM fault identification

In order to verify the rationality and effectiveness of the algorithm for extracting the incipient fault features of gears, the SVM is used to identify faults. The acceleration vibration signal of the gear is collected and two kinds of fault types of gear are analysed. Fifteen groups of samples are selected as the training data and 11 sets of samples are used as test data for each type of gear box. The gear fault is shown in Table 2, and the classification results are shown in Figures 7 and 8.

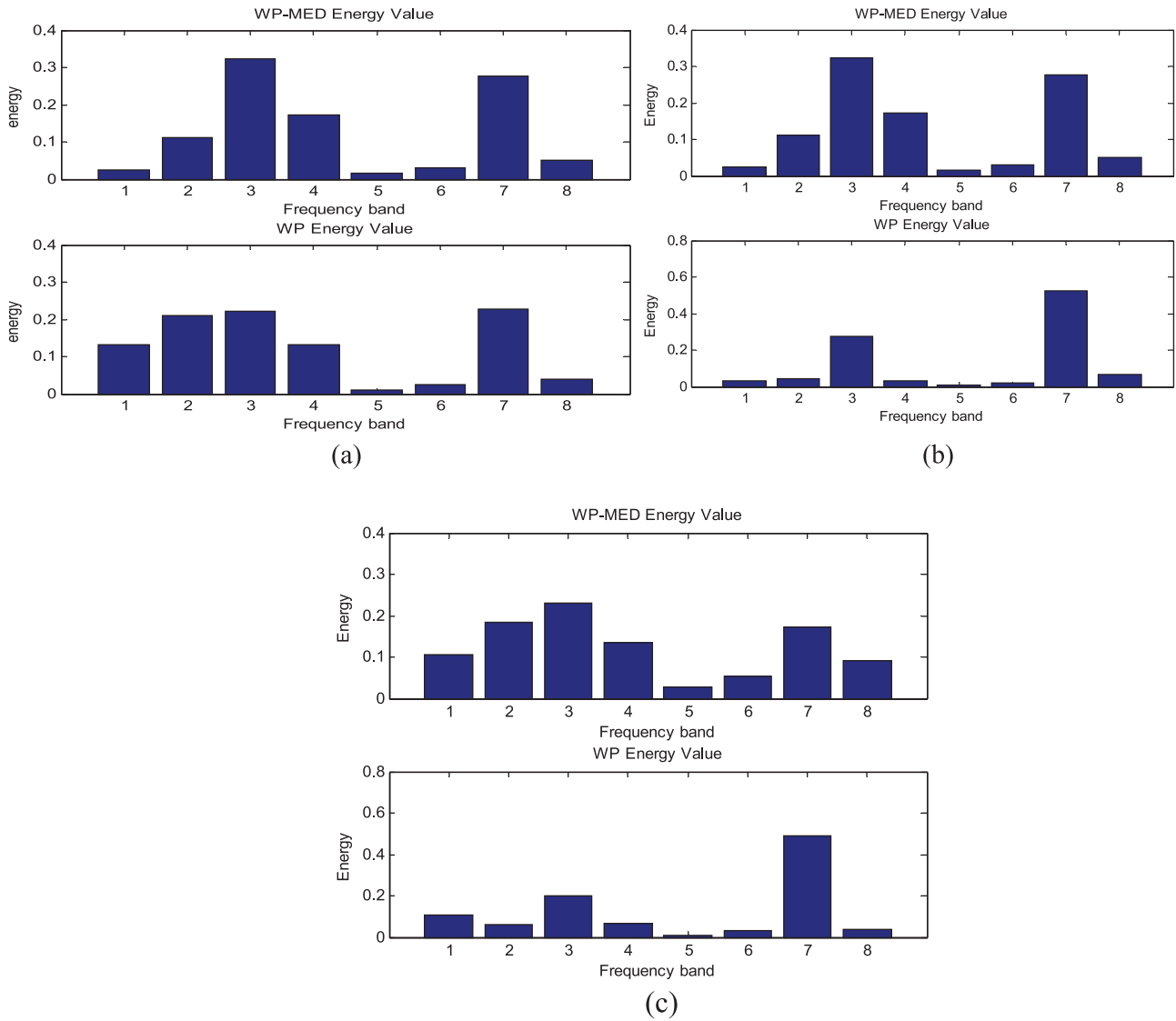


Figure 6. The fault energy feature. (a) The fault of pitting energy feature. (b) The fault of abrasion energy feature. (c) The fault of normal energy feature.

Table 2. The fault type.

Fault type	Speed (r/min)	Load
Abrasion single	880	0
Pitting single	880	0
Normal single	880	0

As shown in Figures 7 and 8, label 1 represents the pitting signal, label 2 represents the abrasion signal and label 3 represents the normal signal. Figure 7 is the wavelet packet energy extraction of the feature input and the SVM classifier identifies 91.4% of the fault. In Figure 8, we first use MED to enhance the fault impact component and then extract energy from the wavelet packet as the feature input, and the SVM classifier identifies 97.4% of the fault. Experimental results show that using WP-MED to enhance fault characteristics is effective.

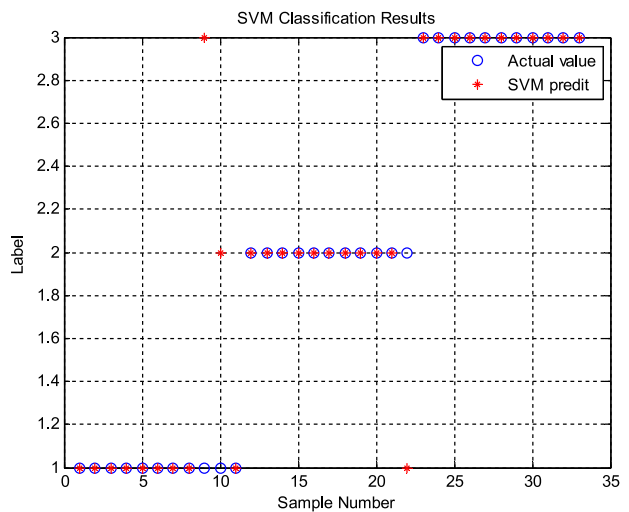


Figure 7. WP-SVM classification result.

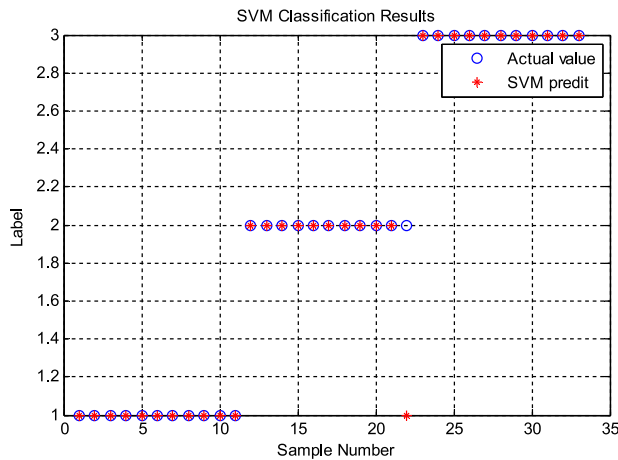


Figure 8. WP-MED SVM classification result.

5. Summary

In this paper, to identify the incipient fault of the gear box in a motor driving system, the feature enhancement method based on the combination of MP and MED is proposed. The wavelet packet decomposition is used to extract frequency band energy (no scale index) as the incipient fault feature of the gear. In order to highlight the impact component of the fault, the MED is used to enhance the fault impact component of the frequency band reconstructed by the wavelet packet, and then the energy of each frequency band is extracted as a barrier feature. The experiment results show that the method proposed in this paper can effectively extract the early fault features of gears, and improve the classification accuracy.

Disclosure statement

No potential conflict of interest was reported by the authors.

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