Research Article

Novel Rotating Machinery Structural Faults Signal Adaptive Multiband Filtering and Automatic Diagnosis

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To realize an automatic diagnosis of rotating machinery structure faults, this paper presents a novel fault diagnosis model based on adaptive multiband filter and stacked autoencoders (SAEs). First, to solve the problem where the actual rotating frequency and its harmonics cannot be accurately extracted in engineering applications, an improved adaptive multiband filtering method is designed. This method takes the theoretical rotating frequency as the search center, extracts the maximum within the positive and negative deviation as the actual rotating frequency, and sets a threshold according to the actual value to realize multiband filtering. This method can effectively remove background noise and accurately extract the actual rotating frequency and its harmonics. Second, an unsupervised SAE multiclassification model is established to realize an automatic diagnosis of fault types. This model can automatically extract the in-depth features of the filtered signal and improve the fault classification accuracy. Third, engineering and comparative experiments were carried out to verify the effectiveness and superiority of this model. Results show that the proposed automatic diagnosis model can extract the characteristic components abundantly and accurately recognize rotating machinery structural faults.

1. Introduction

As indispensable equipment in industrial production, rotating machinery plays an important role in the fields of transmission, transportation, precise control, and quantitative production and in ensuring the normal operations of rotating machinery. However, rotating machinery structural faults, such as pedestal looseness, angular misalignment, and static imbalance, often occur especially in a complex working environment. These faults not only produce abnormal vibrations but also lead to the secondary faults of bearings and gears due to the excessive stress generated on peripheral components. Therefore, detecting rotating machinery vibration signals and realizing an automatic diagnosis of structural faults are critical [1, 2].

The key to precisely diagnosing rotating machinery structural faults is to accurately extract the rotating frequency and its harmonics in the vibration signal. However,

given that engineering vibration signals contain a large amount of background noise, improving the signal-to-noise ratio (SNR) of the raw signal is a prerequisite for accurate diagnosis. The commonly used signal filtering methods can be divided into five categories. First, high-pass, low-pass, and band-pass filters have been well applied in engineering signal processing. However, researchers need to fully understand the fault characteristic frequency to accurately set the cutoff frequency for signal filtering. Second, signal decomposition filters, such as empirical mode decomposition (EMD) [3], wavelet transform (WT) [4], and variational mode decomposition (VMD) [5], decomposed the signal into multiple intrinsic mode functions (IMFs) that represent the fault characteristic for reconstructing the signal. Reference [6] used continuous wavelet transform (CWT) and sparse measurement (SM) to detect and characterize the resonance caused by gear faults. In [7], VMD is combined with weighted kurtosis to filter the vibration signal and to

diagnose the fault of low-speed bearings. However, the signal decomposition filter has certain limitations, including breakpoint effects and modal aliasing. Third, spectral kurtosis and its improvement methods [8, 9] identified the best center frequency and bands through spectral kurtosis. Reference [10] used VMD to decompose the vibration signal and extracted the IMF component containing the best fault information based on the weighted kurtosis index. The spectral kurtosis filtering method can help the decomposition algorithm in extracting the best IMF, but this approach cannot work efficiently when a higher impulse is present. Fourth, the stochastic resonance method [11] has introduced new ideas for detecting weak signals in the presence of strong background noise. This method enhances the signal fault characteristics by transforming noise into useful information. Reference [12] has proposed an adaptive stochastic resonance method based on coupled bistable systems and improved its performance in diagnosing faults in rolling bearings, but this approach is particularly sensitive to filter parameters. Fifth, intelligent filtering methods, such as genetic algorithm and particle swarm algorithm filters [13], have been used in [14] (specifically particle swarm optimization) to optimize morphological filtering and subsequently reduced shaft rotation frequency and wheel-track interference. While its use does not require extensive experience, this method is computationally expensive and can easily fall into the local optima.

The multiband filter [15] is specifically designed for filtering the vibration signal of rotating machinery structure faults and only retains the rotating frequency and its harmonics. However, the traditional multiband filter takes the theoretical rotating frequency as the cutoff frequency and is usually unable to extract the actual rotating frequency and its harmonics in engineering applications because of deviations. Therefore, multiband filtering should be improved to accurately realize fault diagnosis.

In the early stage of fault recognition, the algorithms commonly used for building classification models include neural networks (NNs) [16], support vector machines (SVMs) [17], and their derivative methods. However, these “shallow structure” requires users to input the feature-extracted data to effectively distinguish different fault types. Deep learning has the advantage of feature self-extraction and can fully describe the actual situation of the input signal and reveal its inherent laws. The most widely used of these algorithms include convolutional neural networks (CNNs) [18], deep belief network (DBN) [19], and stacked autoencoder (SAE) [20]. In [21], the improved SAE is used to achieve feature extraction and dimension reduction for bearing fault diagnosis. In [22], SAE is used to classify the composite material damage types in the presence of strong background noise. Among these methods, SAE is an unsupervised algorithm that can automatically learn features from unlabeled signals and output a better feature description compared with the original input signal. Given the sparseness of SAE, the features are automatically extracted, and the signal dimension is largely reduced.

By synthesizing the above findings, this paper presents an automatic diagnosis method based on adaptive

multiband filter and the SAE multiclassification model. Results of the engineering and comparison experiments prove the effectiveness and accuracy of the proposed automatic diagnosis method. The innovations of this study are summarized as follows:

- (1) In the adaptive multiband filter, a search threshold is designed to accurately extract the actual rotating frequency, and the deflection coefficient is set to ensure that the harmonics are within the optimal extraction range
- (2) The SAE multiclass diagnosis model is built to adaptively extract the deep features of the vibrational signal and to realize an automatic diagnosis of rotating machinery structural faults

The rest of this paper is organized as follows. Section 2 introduces the rotating machinery simplified model and its structure fault features. Section 3 presents the adaptive multiband filter. Section 4 describes the SAE classification model. Section 5 presents the rotating machinery structural faults automatic diagnosis method. Section 6 presents the experimental results. Section 7 concludes the paper.

2. Structural Faults Background

Couplings, connecting shafts, bolts, and support bases are critical mechanical parts of a rotating machinery. When faults appear in these mechanical structures, especially in high-precision equipment, the machinery will be damaged in serious cases. Figure 1(a) shows a simplified model of a rotating machinery, whose common structural faults include coupling looseness, angular misalignment (Figure 1(b)), dynamic load imbalance (Figure 1(c)), static load imbalance (Figure 1(d)), and pedestal looseness.

In the vibration spectrum, those characteristics that represent rotating machinery structure faults are obviously detected in the low frequency (less than 1 kHz). Less than 20 times of the rotating frequency are usually extracted in structural fault diagnosis. Figure 2 shows the spectrum of angular misalignment and pedestal looseness faults. In the structural fault spectrum, shocks occur at the rotating frequency and its harmonics, and the captured impulse obviously differs from that captured for other fault types.

3. Adaptive Multiband Filter

In rotating machinery structure faults, an obvious impulse is detected at the rotating frequency and its harmonic [23]. The traditional multiband filter sets the cutoff frequency based on the theoretical rotating frequency, which usually cannot work well in engineering applications. Therefore, an adaptive multiband filter is designed to extract the actual rotating frequency and its harmonic based on a reasonable setting deviation coefficient. The principle can be expressed as follows.

For the vibration signal $V(v_1, v_2, v_3, \dots, v_n) \sim f(v)$, the following Fourier transform (FFT) is initially applied:

FIGURE 1: Simplified model of rotating machinery and its typical structural faults: (a) simplified model; (b) angular misalignment fault; (c) load dynamic imbalance fault; (d) load static imbalance fault.

FIGURE 2: Vibration spectrum of rotating machinery structure faults: (a) angle misalignment fault; (b) pedestal looseness fault.

$$F(f) = \sum_{i=0}^{n-1} f(v) e^{-j(2\pi/n)ki}, \quad k = 0, 1, 2, \dots, n-1. \quad (1)$$

Afterward, the actual rotating frequency F'_r is computed as

$$F'_r = \max(F_r \pm \beta), \quad (2)$$

where β is the search threshold that is set according to the engineering signal and F_r is the theoretical rotating frequency calculated by the RPM as shown in the following equation:

$$F_r = \frac{\text{RPM}}{60}. \quad (3)$$

The deviation Δf_r between F'_r and F_r can then be calculated as

$$\Delta f_r = |F'_r - F_r|. \quad (4)$$

Afterward, the multiband parameters are set as follows:

$$F'(f) = F(k(F_r \pm \Delta f_r) \pm \delta), \quad (5)$$

where δ is the deflection coefficient that is designed to effectively extract the harmonics components. This coefficient usually ranges from 0 Hz to 3 Hz.

The inverse Fourier transform (IFFT) is eventually used for the extracted signal, and the adaptive multiband filter is completed.

$$f'(v) = \frac{1}{n} \sum_{i=0}^{n-1} F(f) e^{j(2\pi/n)ki}, \quad k = 0, 1, 2, \dots, n-1. \quad (6)$$

Figure 3 shows the framework of the traditional multiband filter and adaptive multiband filter. In the raw spectrum, there is a deviation Δf_r between the actual rotating frequency F'_r and the theoretical rotating frequency F_r . The traditional multiband filter cannot effectively extract harmonic components (after $2F'_r$) when the deviation reaches a certain value. However, the adaptive multiband filter can accurately extract the rotating frequency and its harmonics.

4. SAE Classification Model

SAE is an unsupervised neural network based on deep learning that usually comprises multiple autoencoders stacked in series. The feedback of the output data is realized via the back-propagation algorithm [24, 25]. SAE can automatically extract the in-depth characteristics of the input signal in order for the output to achieve a better signal reproduction. Figure 4 shows the typical autoencoder (AE) structure, which contains an encoder represented by $\mathbf{h} = f(\mathbf{x})$ and a reconstructed decoder represented by $\mathbf{y} = g(\mathbf{h})$. The input signal $\mathbf{x} = (x_1, x_2, x_3, \dots, x_n)$ is mapped to the output $\mathbf{y} = (y_1, y_2, y_3, \dots, y_n)$ through the hidden layer $\mathbf{h} = (h_1, h_2, h_3, \dots, h_m)$, where $m < n$.

The AE specific principle is defined as follows.

First, the signal $\mathbf{x} = (x_1, x_2, x_3, \dots, x_n)$ is inputted into the AE model, and the hidden layer $\mathbf{h} = (h_1, h_2, h_3, \dots, h_m)$ can be expressed as

$$\mathbf{h} = f(\omega_h \mathbf{x} + \mathbf{b}_h). \quad (7)$$

Second, the hidden layer $\mathbf{h}$ is mapped to the original high-dimensional space, and the reconstructed output data $\mathbf{y} = (y_1, y_2, y_3, \dots, y_n)$ are obtained as

$$\mathbf{y} = g(\omega_y \mathbf{h} + \mathbf{b}_y), \quad (8)$$

where ω_h and ω_y are the weight matrices and $\mathbf{b}_h$ and $\mathbf{b}_y$ are the bias terms. ω_h and $\mathbf{b}_h$ work for the input and hidden layers, respectively, whereas ω_y and $\mathbf{b}_y$ work for the hidden and output layers, respectively. Both $f(\mathbf{x})$ and $g(\mathbf{h})$ are activation functions called Sigmoid that can be computed as

$$f(\mathbf{x}) = \frac{1}{1 + e^{-\mathbf{x}}}. \quad (9)$$

The parameters are updated constantly until the reconstruction error $e(\mathbf{x}, \mathbf{y})$ reaches the minimum value.

The SAE classification model is stacked by multiple autoencoders in series [26], which means that the hidden layer of the previous autoencoder is used as the input layer of the next autoencoder as shown in Figure 5. The adaptive multiband filtered spectrum is used as the input data of the first encoder, and $h(N)$ represents the N_{th} hidden layer information.

FIGURE 3: The framework of the adaptive multiband filter and traditional multiband filter.

FIGURE 4: Principle of autoencoder.

5. Rotating Machinery Structural Faults Automatic Diagnosis Method

This paper proposes a method for automatically diagnosing rotating machinery structural faults based on an adaptive multiband filter and the SAE classification model. The detailed diagnosis process is shown in Figure 6, and the specific diagnosis steps are described as follows:

Step 1: Acquire the vibration signal by using the accelerometer under the normal state of the rotating machinery

Step 2: Acquire the vibration signals under different structural faults, and the sampling frequency and sampling time are the same as those under the normal state

Step 3: Filter the vibration signals using the adaptive multiband filter and extract the rotating frequency and

FIGURE 5: The principle of the SAE classification model.

FIGURE 6: The automatic diagnosis process of rotating machinery structural faults.

its harmonic components (less than 20 times of the rotating frequency)

Step 4: Divide the samples into training and testing samples

Step 5: Build and train a SAE classification model based on training samples

Step 6: Input the test samples to diagnose the rotating machinery structural fault types

Table 1 shows the detailed algorithm steps of the rotating machinery structural faults automatic diagnosis.

6. Experimental Verification

6.1. Experiment Platform. To verify the effectiveness of the proposed method, the experimental platform shown in Figure 7 is used for acquiring vibration signals. This experimental platform mainly includes shafts, support

TABLE 1: Rotating machinery automatic diagnosis algorithm.

Adaptive multiband filter and SAE automatic diagnosis algorithm	
Input: original signal of different fault $V = \{v_1, v_2, \dots, v_N\}$.	
(1) Adaptive multiband filtering	
For $i = 1: N$	
(1) $V_i(t)$ FFT $V_i(f)$	
(2) $F_r = \max(F_r \pm \beta)$, $F_r = \text{RPM}/60$	
(3) $\Delta f_r = F_r' - F_r $	
(4) $V_i'(f) = V_i(k(F_r \pm \Delta f_r) \pm \delta)$	
End	
(2) SAE diagnosis model	
(1) $X_i'(f) = V_i'(f) = (x_1, x_2, x_3, \dots, x_n)$,	
$Y \in \{[1, 0, \dots, 0], [0, 1, \dots, 0], \dots, [0, 0, \dots, 1]\}$	
(2) $X'(f) \rightarrow (X'_{\text{train}}(f), X'_{\text{test}}(f))$,	
$Y \rightarrow (Y_{\text{train}}(f), Y_{\text{test}}(f))$	
(3) for $i = 1$: epochs	
$(X'_{\text{train}}(f), Y_{\text{train}})$ SAE Training SAE _{diag}	
End $\rightarrow$	
(4) $(X'_{\text{test}}(f), Y_{\text{test}})$ SAE _{diag} Y_{diag}	
Output: accuracy rate of test samples.

FIGURE 7: Rotating machinery experimental platform.

elements, couplings, counterweight plates, attachment bolts, bearings, and bearing bases.

Figure 8 shows the rotating machinery structural faults, including angle misalignment (AM), coupling looseness (CL), dynamic imbalance (DI), pedestal looseness (PL), and static imbalance (SI), for the experiment. The laser alignment instrument is used in the angular misalignment experiment to set the coupling misalignment angle. Meanwhile, weights are added in one of the counterweight plates in the dynamic imbalance experiment and in two counterweight plates in the static imbalanced experiment. For the coupling and pedestal looseness experiments, the bolts are all loose.

6.2. Performance Evaluations. To evaluate the effect of the proposed automatic diagnosis method, a rotating machinery structure faults experiment is carried out under 1800 RPM. The accelerometer is used to acquire the vibration signals, and Table 2 presents specific information.

Figure 9 shows the raw vibration signals (in red) and their spectrums (in blue) under normal states and the five fault states. In the vibration signal, given that the background noise floods the impact of the structural fault, distinguishing the rotating machinery status is impossible. In the spectra, although the characteristics at the rotating frequency and its harmonics differ across six states, the background noise still affects the fault diagnosis.

The diagnosis accuracy rates of the raw vibration signal and its original spectrum are compared based on the SAE classification model. Table 3 shows 3 hidden layers (layer 1 to layer 3) in the SAE model. The other specific parameters are described as follows.

The diagnosis results are presented in Figure 10. The diagnosis accuracy rate is recorded 10 times to avoid contingency. Figure 10 shows that the diagnosis accuracy rate of the raw signal is low and that the average accuracy rate is only 15.83%. Although the accuracy rate of the spectrum increased significantly with an average value of 91.83%, this rate cannot meet the ideal requirements in engineering applications.

Therefore, to improve fault diagnosis accuracy, the signal should be filtered before inputting into the SAE classification model. Figure 11 shows the spectrum filtered by the adaptive multiband filter. Compared with the original spectrum shown in Figure 9, the background noise was removed effectively, and the rotating frequency and its harmonic components were accurately extracted.

As shown in Table 4, the spectrums under the normal and structural faults states were divided into train and test samples. Figure 12 shows that the SAE diagnosis accuracy rate is 100%, thereby confirming that the proposed method can accurately diagnose faults.

6.3. Diagnosis Result under Different RPMs. To verify the accuracy of the proposed method at different RPMs, experiments were performed under 700, 900, and 1100 RPM. Figure 13 shows the original spectrum and adaptive multiband filtered spectrum. Compared with the original spectrum, the background noise in the filtered spectrum was removed, and the actual rotating frequency and its harmonics were accurately extracted.

Figure 14 shows the diagnostic accuracy rate of the adaptive multiband filtered spectrum and original spectrum under different RPMs. In these experiments, to avoid contingency of identification, the final diagnosis accuracy rates were computed as the average of 10 measurements. For the adaptive multiband filtered diagnosis, the accuracy rates recorded under 700 RPM and 900 RPM were 98.49% and 99.16%, respectively, whereas those recorded under 1100 RPM and 1800 RPM were both 100%. The variance among the measurements was relatively smaller than those captured in the original spectrum, thereby further confirming the effectiveness of the proposed automatic diagnosis method.

FIGURE 8: Rotating machinery structural faults experiments: (a) angular misalignment; (b) coupling looseness; (c) dynamic imbalance; (d) pedestal looseness; (e) static imbalance.

TABLE 2: Experimental conditions and parameters.

Parameter	Values
RPM	1800
Rotation frequency	30 Hz
Sampling frequency	5000 Hz
Sampling points	25600

FIGURE 9: The vibration signal (in red) and spectrum (in blue).

TABLE 3: SAE classification model parameters.

Types	Values	Parameters	
		Activation function	Learning rate
Hidden layer 1	100	Sigmoid	0.9
Hidden layer 2	50	Sigmoid	0.8
Hidden layer 3	20	Sigmoid	0.8

FIGURE 10: SAE diagnosis results of raw vibration signal and its spectrum.

FIGURE 11: The filtered spectrum by adaptive multiband filter.

TABLE 4: SAE automatic diagnosis parameters.

Types	Train samples	Test samples	Sample label
N	40	10	1
AM	40	10	2
CL	40	10	3
DI	40	10	4
PL	40	10	5
SI	40	10	6

FIGURE 12: SAE diagnosis results.

6.4. Comparison Experiments

6.4.1. Comparison of Different Filtering Methods. To verify the effectiveness of adaptive multiband filtering methods, the raw vibration signal was filtered by low-pass and multiband filters for comparison. Table 5 shows the parameter settings of the three filters.

Figure 15 shows the original spectrum and the three filtered spectra. In the original spectrum, the actual rotating frequency was 32.26 Hz, which deviates from the theoretical rotating frequency (30 Hz) by 2.26 Hz. Meanwhile, in the low-pass filtered spectrum, the noise is still obvious, which affects the rotating frequency and its harmonic extraction. In the traditional multiband filtered spectrum, the harmonic components cannot be accurately extracted after the second harmonic. The adaptive multiband filter can accurately extract the rotating frequency and its harmonic components.

Figure 16 shows the 10 SAE multiclassification model diagnosis results captured for the original spectrum and the three filtered spectra. The average accuracy rates of the low-pass and multiband filters were 86% and 89.67%, respectively, both below 90%, thereby proving that the adaptive

multiband filter can effectively remove background noise, accurately extract the rotating frequency and its harmonics characteristic components, and greatly improve the rotating machinery structural fault automatic diagnosis accuracy rate.

6.4.2. Comparison of Different Classification Models. In the classification model comparison, the BP neural network, radial basis function (RBF) neural network, and extreme learning machine (ELM) neural network were used to establish automatic diagnosis models. Figure 17 presents the results. Among the three classification models, SAE obtained the highest diagnostic accuracy rate and the smallest variance for the 10 measurements, thereby indicating that the SAE multiclassification model has the best stability among all compared models. Meanwhile, among the four classification models, the accuracy rate of adaptive multiband filtered spectrum was significantly improved compared with that of the original spectrum, and all of these models obtained accuracy rates of greater than 98.5%. Therefore, the proposed automatic diagnosis method is further proven to be effective.

(a)

FIGURE 13: Continued.

(b)

FIGURE 13: Continued.

FIGURE 13: The original and adaptive multiband filtered spectrum: (a) 700 RPM; (b) 900 RPM; (c) 1100 RPM.

FIGURE 14: Diagnosis results at different RPMs.

TABLE 5: Filters related parameter.

Filter	Parameters
Low pass	Cutoff frequency 1000 Hz
Multiband	Deflection coefficient 3 Hz
Adaptive multiband	Deflection coefficient 3 Hz

FIGURE 15: Comparison of multiband filter and adaptive multiband filter.

FIGURE 16: Comparison of different filters.

FIGURE 17: Comparison of the corresponding diagnosis results of different classification models.

7. Conclusion

This study proposed a method for automatically diagnosing rotating machinery structure faults based on an adaptive multiband filter and the SAE multiclassification model. The engineering experiments and comparisons prove that

- (1) Compared with traditional multiband filtering, the proposed method, which was improved by setting reasonable search thresholds and deviations, can accurately extract the actual rotating frequency and its harmonic in engineering experiments
- (2) By establishing the SAE multiclassification model, the fault diagnosis accuracy of the proposed method increased to 100%
- (3) The comparison with different filtering methods and classification models further validated the effectiveness of the proposed automatic diagnosis method

Data Availability

The raw/processed data required cannot be shared at this time as the data also form part of an ongoing study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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