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Research Article

Rolling Element Bearing Fault Diagnosis Based on Multiscale General Fractal Features

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Nonlinear characteristics are ubiquitous in the vibration signals produced by rolling element bearings. Fractal dimensions are effective tools to illustrate nonlinearity. This paper proposes a new approach based on Multiscale General Fractal Dimensions (MGFDs) to realize fault diagnosis of rolling element bearings, which are robust to the effects of variation in operating conditions. The vibration signals of bearing are analyzed to extract the general fractal dimensions in multiscales, which are in turn utilized to construct a feature space to identify fault pattern. Finally, bearing faults are revealed by pattern recognition. Case studies are carried out to evaluate the validity and accuracy of the approach. It is verified that this approach is effective for fault diagnosis of rolling element bearings under various operating conditions via experiment and data analysis.

1. Introduction

Rolling element bearings are common mechanical parts which are subject to damage. Faulty bearings often cause machine failure and even contribute to the disaster in industry. Therefore, fault diagnosis of rolling element bearing is necessary in condition monitoring of machines. It is critical that fault pattern identification of bearing is performed to prevent machine breakdown and reduce economic loss in early period.

Vibration signal analysis has been used extensively in various bearing condition monitoring techniques and has become one of the most important methods applied for bearing fault diagnostics. The vibration signals generated by faults in bearings have been widely studied. Many studies have developed sound theoretical bases and approaches to diagnose bearing failure [1–3]. Much research focuses on obtaining fault information through time and frequency domain signal processing techniques. It is well known that the impact vibration produced by rolling elements in bearing excites resonances of the surrounding structures. But analysis of the vibration signal is complicated due to the stochastic movement of rolling elements. A method based on envelope spectrum analysis becomes a primary way for bearing fault diagnosis which was stated systematically in [4]. Various faults can be diagnosed through fault characteristic frequencies according to the bearing structure parameters. However, when the bearing rotational speed varies over time, the characteristic frequencies cannot be obtained in frequency domain. Order tracking (OT), which may involve extra computation or auxiliary equipment such as speedometer and tachometer, is used to remove speed fluctuation. The method is complete and complicated, to which many studies are related [5, 6]. And this technique is successful for a wide range of cases.

The specific characteristics of rolling element bearing vibration signal are not periodic, especially under variable speed. It is inappropriate to diagnose fault of rolling element bearing only by adopting traditional diagnosis techniques. Time-frequency domain methods have been adopted to implement bearing fault diagnosis, such as Wigner-Ville distributions (WVD) [7], empirical mode decomposition (EMD) [8], and wavelet transform (WT) [9]. Many kinds of features are extracted to represent the characteristics of vibration signal in different domains, for example, statistics of Root Mean Square (RMS), kurtosis, crest factor, correlation coefficient and spectrum, and independent component analysis (ICA) [10]. Finally, detection of bearing fault can be implemented by intelligent learning methods, such as perceptron, artificial neural network (ANN), or support vector machines (SVM) [11–13]. There are increasing research works that combine traditional time-frequency domain methods and intelligent learning methods for varied conditions of speed and load [14]. This ensemble of methods is developed as advanced hybrid intelligent fault diagnosis for rolling element bearings.

The vibration signals of bearings, especially with faults, often show mutation and nonlinearity [15]. As we know, the vibration signals that are excited by impacts of rolling element present nonstationary characteristics. Moreover, the nonstationary characteristics caused by faults in bearing are often mixed with nonlinear factors due to the complexity of the structure and operating conditions of rolling bearing, such as instantaneous variations in rolling ball movement, changing speed, and various loads. The traditional signal analysis methods based on linear system fail to extract nonlinear features in vibration signal. In order to analyze the nonlinear signals of bearings, a series of advanced techniques have been applied to extract fault features. It has been discovered that nonlinear analysis could provide a great alternative way to extract fault features out of vibration signals. Many nonlinear methods, such as chaos, fractal dimension, Lyapunov exponent, and approximate entropy, have been investigated [16–18]. The results have shown that nonlinear method is an effective way for rolling bearing fault diagnosis.

Fractal dimensions are widely used in nonlinearity analysis because it can quantitatively characterize nonlinear behavior. The correlation dimension is used to reveal the fault feature of rotating machinery in [19]. The combination of box-counting dimension, information dimension, and correlation dimension is applied to realize bearing fault diagnosis in [20]. Wavelet packet fractal technology is also utilized to diagnose rotating machinery in [21]. Even so, many fractal dimensions are sensitive to a flurry of factors besides bearing faults. It was proposed that the nonlinear feature of correlation dimension is related to the length of signal, the embedded dimension, the time delay, and so on in the bearing fault diagnosis experiment [22]. Moreover, in practical applications, how to decide the threshold of the nonlinear features is quite a problem. Multiscale fractal dimension can describe local nonlinear feature in different scales. To address these problems, multiscale nonlinear features were introduced for bearing fault diagnosis [23, 24]. This paper combines nonlinear analysis and intelligent diagnostics to implement bearing fault diagnosis. Specifically, a whole methodology based on Multiscale General Fractal Dimensions (MGFDs) of vibration signal and pattern recognition method is proposed. General fractal dimension is defined and utilized to reveal the approximation and detail of vibration signal in different scales. Then a feature space is constructed through MGFDs. Finally, intelligent pattern recognition method is utilized to implement classification of fault pattern in the feature space.

The rest of this paper is organized as follows. In the second section, the definition of general fractal dimension is introduced. The principle and methodology of multiscale general fractal dimensions are addressed. In the third section, the vibration signals of rolling element bearings under different conditions are collected and analyzed. The experimental parameters are optimized according to the effectiveness of the methodology. The feasibility and reliability of the methodology for different bearing faults in various conditions are also proven in this section. In the fourth section, the conclusions are presented in closing.

2. Principle and Methodology

2.1. Preliminaries on Fractal Dimension. Theoretical fractals are infinitely self-similar, iterated locally and globally which are not easily described in traditional Euclidean geometric language. Fractals are not limited to nonlinear geometric patterns but can also describe processes in time. So fractal properties in the vibration time series can be suggested because of its nonstationary and nonlinear characteristics.

Fractal patterns are characterized by fractal dimension that is a ratio providing a statistical index of complexity. Fractal dimension can describe the changing of pattern with scale at which it is measured. But in reality, fractal characteristics only exist in a certain scale. Fractal dimensions in different scale can be estimated, respectively.

There are many types of definition of fractal dimension and several methods available to estimate fractal dimension, such as box-counting dimension, correlation dimension, and information dimension. The fractal dimension method is essentially a sequence of approximation associated with decreasing scale that is a geometric factor of simple figure forming the approximation [25]. Here, a general fractal dimension based on the time series cover is introduced to approximate the signal in time domain. This kind of fractal dimension concentrates on the changing pattern of time series.

2.2. Principle of General Fractal Dimension. In order to investigate fractal dimension of vibration signal in time domain, a two-dimensional graph can be made for vibration time series by way of the sample time as X-coordinate and the signal amplitude as Y-coordinate. According to the principle of fractal dimension, there is

$$M_\delta(S) \sim c\delta^D \quad \text{at } \delta \longrightarrow 0, \tag{1}$$

where $M_\delta(S)$ is approximation area of the sampled signal trajectory S, δ is the scale, and D is fractal dimension of the trajectory. Based on the principle of cover fractal dimension, the fractal dimension of sampled vibration signal can be calculated by minimal cover of series ichnography.

Suppose $y = f(t)$ is signal function in domain of closed time interval $[a, b]$; the domain is divided into m sections of δ, the division is $\omega_m = [a = t_0 < t_1 < \cdots < t_m = b]$, and $\delta = (b - a)/m$. To cover these m $(m = 1, 2, \ldots)$ sections, every minimal cover of each section is a rectangle of which the length is δ and the height is $A_i(\delta)$ that is the difference between maximal value and minimal value of the signal in section $[t_{i-1}, t_i]$ $(i = 1, 2, \ldots, m)$. The minimal cover of the time series of closed interval $[a, b]$ is

$$M(\delta) = \sum_{i=1}^{m} M_i(\delta) = \sum_{i=1}^{m} A_i(\delta)\,\delta. \quad (2)$$

Define variance $A(\delta)$ as

$$A(\delta) = \sum_{i=1}^{m} A_i(\delta). \quad (3)$$

According to the definition of time series fractal dimension, set D_μ as minimal cover dimension:

$$M(\delta) = A(\delta)\,\delta \sim \delta^{D_\mu}. \quad (4)$$

As we know

$$\langle A(\delta)\rangle = \frac{1}{m}\sum_{i=1}^{m} A_i(\delta), \quad (5)$$

where $\langle\ \rangle$ denotes the average within the time domain, because $m * \delta$ is equal to the length of time series so $m^{-1} \sim \delta$, and there is

$$\langle A(\delta)\rangle \sim \delta^{D_\mu}. \quad (6)$$

With m increasing, the scale factor δ is decreasing. An approximation of vibration time series in decreasing scale is made by this way. For the signal time series when $\delta \to 0$

$$\langle |f(t+\delta) - f(t)| \rangle \sim \langle A(\delta)\rangle. \quad (7)$$

So

$$\langle |f(t+\delta) - f(t)| \rangle \sim \delta^{D_\mu}, \quad (8)$$

where D_μ is a kind of general fractal dimension of the sampled time series. It denotes statistical property and fractal property of the time series. D_μ can be calculated as

$$D_\mu = \lim_{\delta \to 0} \frac{\ln(\langle A(\delta)\rangle)}{\ln(\delta)}. \quad (9)$$

If same fractal characteristics exist in all the scales, a straight line in the graph of $\ln(\langle A(\delta)\rangle) \sim \ln(\delta)$ can be fitted by least square method, and the slope of this line gives us an approximate estimation of fractal dimension. It can represent the change of vibration time series pattern. The time series minimum covering method can be completely independent from affine scaling of signal amplitude range. The general fractal dimension method is robust to variations in operating conditions.

2.3. Methodology of Multiscale Fractal Dimensions. For real-world signals with fractal structures, a single global fractal dimension at all scales is impossible. The practical fractal dimension of signal is also dependent on the used scale. Hence, a single noninteger number is not enough to represent entire complexity of a signal. In order to solve this deficiency in characterization of the signal, multiscale fractal dimensions methodology is developed. Unlike global fractal dimension estimated by the slope of log-log curve, the multiscale fractal dimension scheme estimates local fractal dimensions along the scales [26].

For the scales $\delta_1, \delta_2, \ldots, \delta_m$ ranking from small to large, the local fractal dimension is estimated by calculating the slope of a line segment fitted by least squares over the adjacent scales in $\ln(\langle A(\delta)\rangle) \sim \ln(\delta)$ plane. In this way, MGFDs can describe a signal by a series of fractal dimensions along the scales. The computation process is listed as follows.

(1) A section of accelerometer data are collected for computing. Here, a section of time series including L $(L = 2^{13})$ sampled points is truncated for each evaluation in the experiments.

(2) The value of $\ln(\langle A(\delta)\rangle)$ and $\ln(\delta)$ with increasing scale δ is computed, where $\delta = L/2^m$ $(m = 1, 2, \ldots, 13)$.

(3) The series of local fractal dimensions are estimated through the adjacent points on $\ln(\langle A(\delta)\rangle) \sim \ln(\delta)$ plane. A series of MGFDs are obtained by this way.

(4) A fractal feature space is constructed through MGFDs as the input of pattern recognition to identify fault patterns.

Here, the most popular intelligent methods of K-nearest neighbor classifier (KNNC), back-propagation neural networks (BPNNs), and least squares support vector machines (LS-SVMs) are selected as pattern recognition for training and testing [27–29]. Among these three classifiers, the KNNC algorithm predicts the test sample's category according to the K training samples which are the nearest neighbors to the test sample, and judge it to the category which has the largest category probability. BPNNs are constructed by three layers of neurons: input layer, hidden layer, and output layer. BPNNs are able to represent any functional relationship between input and output if there are enough neurons in the hidden layers. LS-SVMs are a class of kernel-based learning methods, which are a set of related supervised learning methods that analyze data and recognize patterns. In the experiments, $K = 3$ is set for KNNC. The number of input neurons equals the dimension of feature space, the output neurons equal the type of bearing faults, and the hidden layer units are set to 3 in three levels of BPNNs. And the kernel function of LS-SVMs is 2nd order polynomial kernel as

$$K(x, x_i) = \left(1 + \frac{x_i^T x}{c}\right)^d, \quad (10)$$

where polynomial degree $d = 2$.

By this methodology, MGFDs are estimated on the signal amplitude-time plane. They describe quantitatively nonlinear features of vibration signal through minimum covers that represent transformation of the vibration signal contour in different scales. We do not need to take into account the influence of the embedded dimension, time delay, signal shift, and so forth. The only parameters that need to be considered

Figure 1: Bearing components with faults.

in computation are the length of signal and division of scales. Real-time calculation can be performed in the engineering field. So MGFDs can reveal the approximate and detailed essence of vibration signal in different scales, which are seldom interfered with by external condition, for example, the variation of rotating speed and noise. The detailed verification of this methodology via experiments is described in the next section.

3. Experiments and Discussion

3.1. Experiments of Different Bearing Faults. A series of vibration signals of rolling element bearings with different faults were acquired from a rolling element bearing test rig. In the experiments, the rolling bearings were NSK-6000 deep groove ball bearings. A single point fault was introduced to the test bearings, respectively, by electrodischarge machining with fault diameters of 0.3 mm, 0.6 mm, and 1.0 mm. The rolling element bearing components with faults are shown in Figure 1. Four data sets of normal condition, ball fault, inner race fault, and outer race fault were sampled from the experimental system with a sampling frequency of 12 kHz. The motor rotating speed was set to 1500 rpm at first.

The vibration signals and the envelope power spectrums of different bearings are shown in Figure 2. The envelope spectrum of the normal bearing is relatively flat in (a). The inner race fault characteristic frequency of 154.5 Hz and the outer race fault characteristic frequency of 104 Hz can be distinguished easily from the envelope spectrum in (b) and (c). The ball fault characteristic frequency of 137 Hz in (d) is not clear because of the more random motion of the balls.

The multiscale general fractal dimensions of these four types of bearings calculated by the presented MGFDs method are shown in Figure 3. There are obvious distinctions among the four types of bearings along the scale δ. The normal bearing displays the largest fractal dimension in small scales and decreases smoothly. The fractal dimensions of inner race faulty bearing and outer race faulty bearing rise in different middle scales. The fractal dimension of the ball faulty bearing fluctuates in large scales. The vibration signals of different types of bearings show diverse fractal dimensions in different scales which provide a way to diagnose the faults in bearing.

3.2. Experiments under Variable Speed. The vibration signal under increasing rotational speed from 500 rpm to 3500 rpm is shown in Figure 4. The characteristic frequency cannot be extracted from the envelope spectrum, but the shapes of multiscale general fractal dimensions do not change much with variation of shaft rotating speed as shown in Figure 5. MGFDs of vibration signals sampled under variable rotating speeds, for example, varying from 500 rpm to 3000 rpm, and varying from 500 rpm to 3500 rpm, 1000 rpm, 1500 rpm, 2000 rpm, 2500 rpm, 3000 rpm, and 3500 rpm, are shown in Figure 5. The legend label of 500–3000 means outer race faulty bearing with speed varying from 500 rpm to 3000 rpm, and N500–3000 means normal bearing with speed varying from 500 rpm to 3000 rpm, and so on. The fold lines represent the multiscale fractal dimensions, among which the blue ones are normal bearings and the red ones are outer race faulty bearings. The vibration signals of bearings in the same state under different speeds show almost similar multiscale fractal dimensions in Figure 5.

3.3. Experiments with White Noise. When different levels of white noise are added to the vibration signal, MGFDs of normal bearing and inner faulty bearing are shown in Figure 6. The legend label of IS0 means inner race faulty bearing signal without noise, IS2 means inner race faulty bearing signal with added white noise with SNR = 2, NS0 means normal bearing signal without noise, and NS2 means normal bearing signal with added white noise with SNR = 2, and so on. The fold lines represent the multiscale general fractal dimensions, among which the blue ones are the normal bearings signal with white noise and the red ones are the inner race faulty bearings signal with white noise. Figure 6 shows that MGFDs are almost robust to the white noise with SNR ranging up to 2.

3.4. Classification of Multiscale General Fractal Dimensions. In this section, the ability of MGFDs to distinguish different bearing conditions in varied speed is evaluated. The experiments of four types of bearings, for example, normal bearing, inner race faulty bearing, outer race faulty bearing, and ball faulty bearing under six different rotating speeds of 1000 rpm, 1500 rpm, 2000 rpm, 2500 rpm, 3000 rpm, and 3500 rpm, were implemented, respectively. Ten vibration signal samples containing 8192 points were selected from each experiment. Thus, there were sixty samples for each

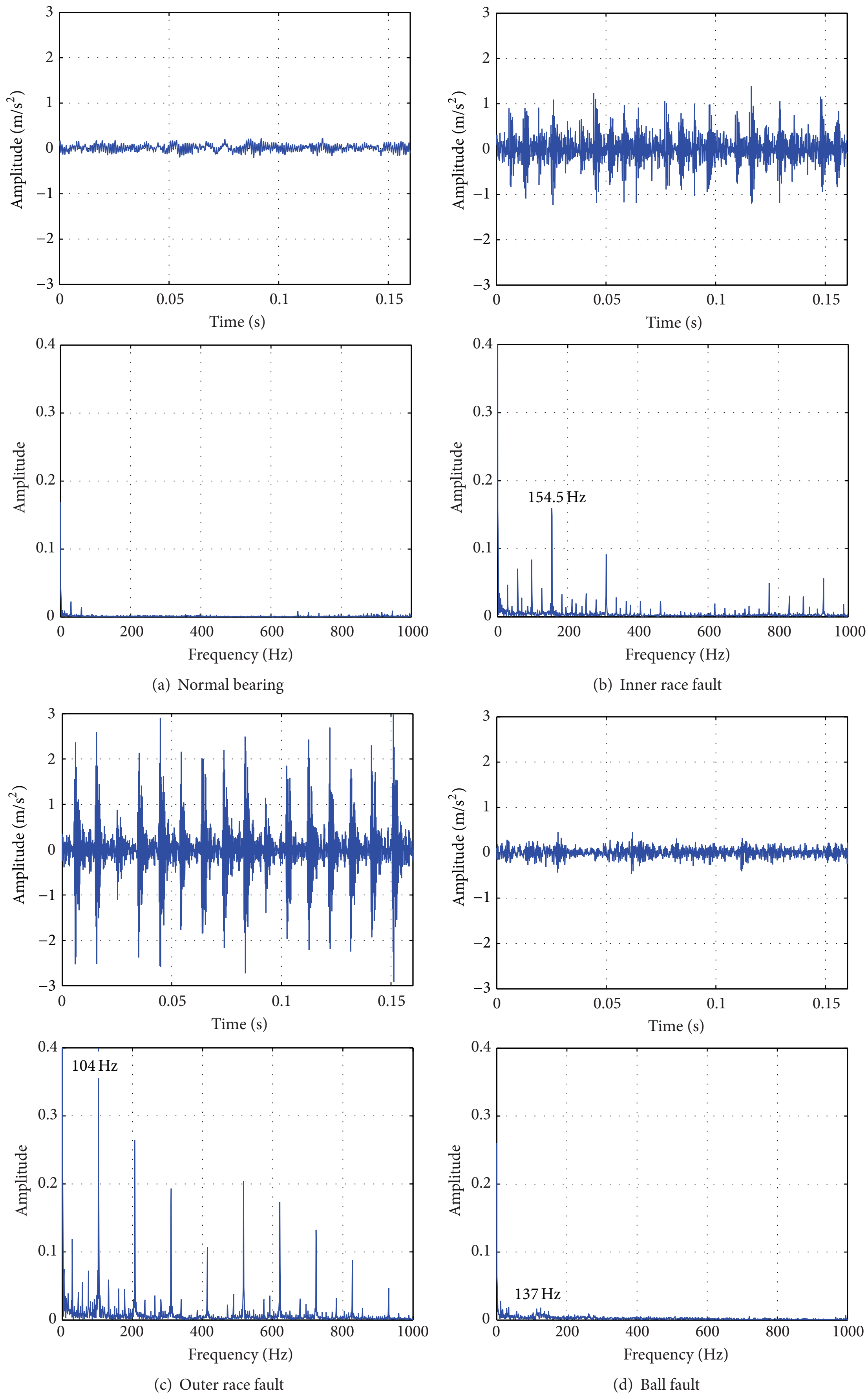

FIGURE 2: Vibration signal and envelope power spectrum of different bearings.

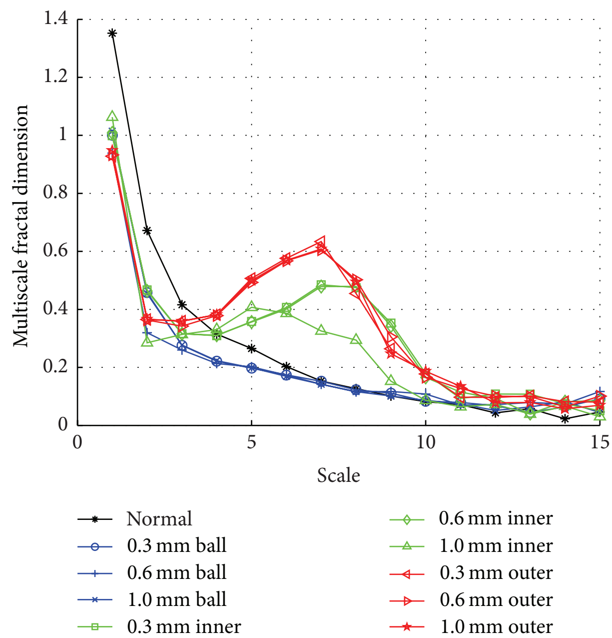

Figure 3: Multiscale general fractal dimensions of different bearings.

type of bearing. 240 samples were collected for training and testing of pattern recognition in total. For each type of bearing, thirty samples were randomly selected for training and remaining thirty samples are used for testing. Twelve scale general fractal dimensions were computed from each sample as the input feature vector for pattern recognition. Hence, a training dataset with dimension 120 × 12 and a testing dataset with the same dimension were obtained. *K*NNC, BPNNs, and LS-SVMs were employed to classify the four types of bearings under variable speeds. In order to get a more accurate evaluation, the processes of random selection, training, and testing were repeated 100 times. Finally, average testing classification error rates were chosen as the evaluation standards.

For comparison, the methods based on wavelet packet (WP) and empirical mode decomposition (EMD) were used to classify the same datasets. In wavelet packet decomposition, the discrete Meyer wavelet was utilized to decompose the vibration signal into vectors of coefficients. The WP decomposition was applied up to wavelet packet level of $J = 3$. So $2^J = 8$ vectors $C_{J,k}(i)$ were produced in the Jth level, where $k = 0, 1, \ldots, 2^J - 1$ and $i = 1, \ldots, I$. Each vector contained approximately $I = N_t/2^J$ coefficients that implicated the information in a specific frequency band of the signal. Here the statistical features, for example, kurtosis, skewness, and standard deviation, were calculated from each wavelet coefficient vector [30, 31]. Therefore, 24 features can be calculated for each sample as the input feature vector of pattern recognition based on statistical analysis and wavelet packet decomposition.

In empirical mode decomposition, each vibration signal can be decomposed into a number of Intrinsic Mode Functions (IMFs) [32, 33]. Thus, we can achieve a decomposition of signal into n-empirical modes and a residue r_n. The coefficients of IMFs $C_1, \ldots, C_n$ include different frequency bands ranging from high to low. The frequency components contained in each frequency band are different and they change with the variation of original signal. Normalized energies of IMFs E_i/E_T constitute the input feature vectors for pattern recognition, where E_i $(i = 1, \ldots, n)$ is the energy of each IMF and E_T is the total energy of the signal. Here, the EMD level was set as $n = 14$. So, 14 features could be calculated for each sample based on EMD. Finally the processes of random selection, training, and testing were repeated 100 times to evaluate effectiveness of these methods in the same way.

Table 1: The classification error rates of pattern recognition.

	*K*NNC	BPNN	SVM
MGFDs	0.54%	4.34%	0.30%
Energies of EMD	1.67%	9.08%	8.04%
Statistics of WP	6.25%	7.62%	11.6%

The average testing classification error rates of MGFDs, the normalized IMF energies of EMD, and the WP-statistic features using three classifiers on four bearing datasets under varied speed are given in Table 1. The average classification error rates in the table show clearly that MGFDs are always outperforming the other methods by using different classifiers on four bearing datasets. It reveals the capability of MGFDs to distinguish bearing fault under varied speed.

3.5. Optimization of MGFDs. As we discussed above, the result of MGFDs could be affected by several external factors, for example, bearing rotational speed, noise, selection of the scales of MGFDs, and the length of the samples. It has been verified that MGFDs were robust to varied speed and external white noise. Here the effect of scale and length of samples are evaluated.

The figures of MGFDs (Figures 3, 5, and 6) show that the distinctions among MGFDs at small scales are significant, while the distinctions become blurred when the scale becomes larger and all MGFDs tend to zero. This is due to the average minimum cover of signal remaining unchanged when the scale becomes large enough. In order to implement real-time computation and accuracy of this methodology, the size of scales and the length of samples can be determined according to the testing classification error rates of pattern recognition.

The number m of MGFDs from 1 to 12 corresponding to the scale $\delta = L/2^m$ was chosen for assessment. For each choice of m, the processes of training and testing were repeated for 100 times. Then the average classification error rates were obtained for determining the size of scale and the length of samples. The results of average classification error rates are shown in Figure 7. It can be observed that when $m \geq 10$, the average classification error rates of three classifiers are under 1%. If the size of the scale is too large, the accuracy of classification could decline because of too much distracting information. Therefore, the size can be set

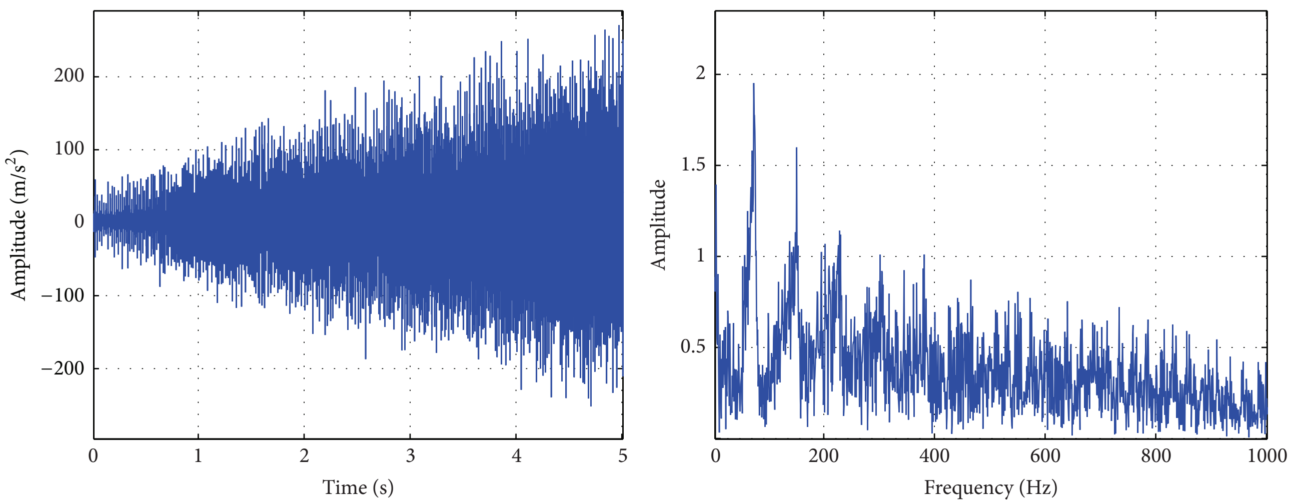

FIGURE 4: Vibration signal and envelope power spectrum under variable speed.

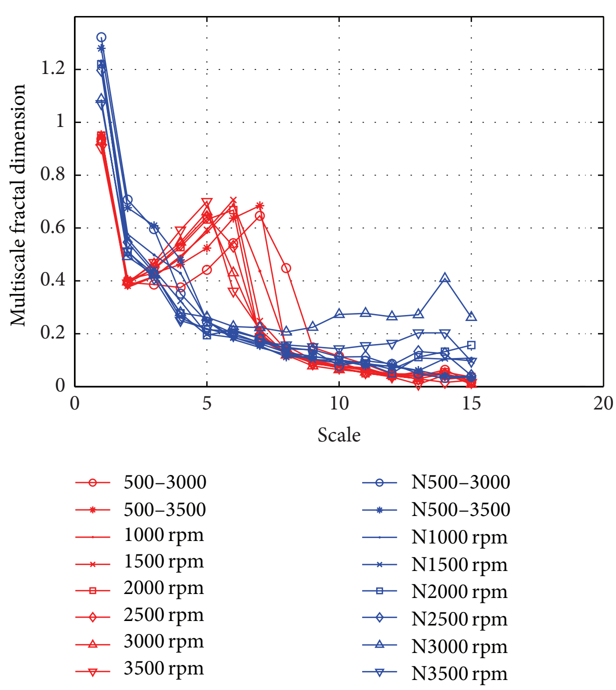

FIGURE 5: Multiscale general fractal dimensions under variable speed.

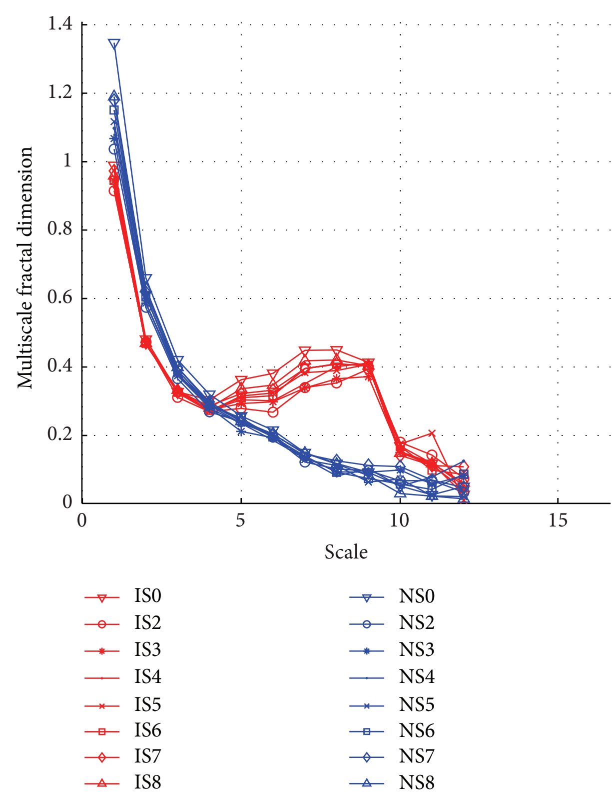

FIGURE 6: Multiscale general fractal dimensions with different SNR white noise.

to $\delta = L/2^m$ $(m = 1, 2, \ldots, 10)$ and the length of samples can be set to $L = 2^{12}$.

4. Conclusions

In this paper, a novel rolling element bearing fault diagnosis approach based on multiscale fractal features of vibration signal was presented. This approach combined fractal theory and intelligent pattern recognition methods to implement bearing fault diagnosis. The methodology was proposed to classify different types of rolling element bearings under different operating conditions.

Multiscale General Fractal Dimensions (MGFDs) were defined to illustrate the fractal feature of rolling element bearing vibration signal at first. The vibration signals demonstrated different fractal structures when different deficiencies developed in rolling element bearing. MGFDs could provide

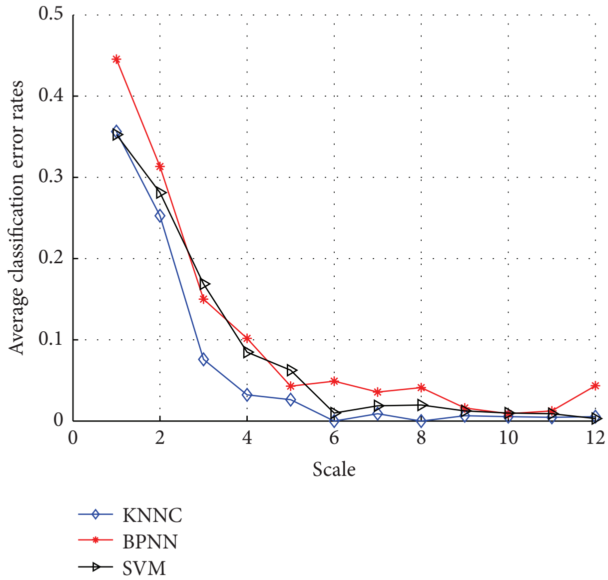

Figure 7: Diagram of average classification error rate versus scale.

a lot of discriminative information which revealed the change of vibration signal pattern with the scale. Through theoretical analysis and experimental verification, the approach could accurately classify the rolling element bearing states, for example, ball fault, inner race fault, outer race fault, and normal state under varied operating conditions. MGFDs were robust to variation of the rotational speed and external white noise in the experiments.

The performance of MGFDs and other methods, such as EMD and WPD, were evaluated by using three classifiers of *K*NNC, BPNNs, and LS-SVMs in comparative experiments. It has been observed that MGFDs outperformed other approaches in varied operating conditions. Lastly, the size of scales and length of samples were optimized through testing classification error rates that ensured the reliability and effectiveness of this approach. It has been demonstrated that MGFDs were capable of revealing fault of rolling element bearings accurately and could be generalized for fault diagnosis of other rotating machines in the future.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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