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Research Article

Fault Diagnosis of Electromechanical Actuator Based on VMD Multifractal Detrended Fluctuation Analysis and PNN

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Electromechanical actuators (EMAs) are more and more widely used as actuation devices in flight control system of aircrafts and helicopters. The reliability of EMAs is vital because it will cause serious accidents if the malfunction of EMAs occurs, so it is significant to detect and diagnose the fault of EMAs timely. However, EMAs often run under variable conditions in realistic environment, and the vibration signals of EMAs are nonlinear and nonstationary, which make it difficult to effectively achieve fault diagnosis. This paper proposed a fault diagnosis method of electromechanical actuators based on variational mode decomposition (VMD) multifractal detrended fluctuation analysis (MFDFA) and probabilistic neural network (PNN). First, the vibration signals were decomposed by VMD into a number of intrinsic mode functions (IMFs). Second, the multifractal features hidden in IMFs were extracted by using MFDFA, and the generalized Hurst exponents were selected as the feature vectors. Then, the principal component analysis (PCA) was introduced to realize dimension reduction of the extracted feature vectors. Finally, the probabilistic neural network (PNN) was utilized to classify the fault modes. The experimental results show that this method can effectively achieve the fault diagnosis of EMAs even under diffident working conditions. Simultaneously, the diagnosis performance of the proposed method in this paper has an advantage over that of EMD-MFDFA method for feature extraction.

1. Introduction

Although most aircrafts and helicopters still adopt hydraulic actuation systems, electromechanical actuators have increasingly been applied as the key actuators for flight control systems of advanced aircrafts and helicopters in recent years. The main reason is that electromechanical actuator (EMA) has more superiorities in terms of reliability, economy, and other aspects than traditional hydraulic actuator. However, aircrafts and helicopters often perform mission under variable complex environments, and it will cause serious consequences when the faults of EMAs appear. Therefore, fault detection and diagnosis of EMAs in various working conditions play a vital role in the normal operation of aircrafts and helicopters. More and more researches have been done about the function of EMAs, but few are about fault. Consequently, it is very meaningful to carry out the research on fault diagnosis algorithms of EMAs under variable working conditions.

NASA Ames Research Center's researchers conducted failure mode and effect analysis of EMAs through extensive literature investigation, and the main fault modes of EMAs were obtained [1]. The researchers built the flyable electromechanical actuator (FLEA) test-bed, so that the normal data and fault data of EMA can be obtained through a large number of experiments [2]. A method based on neural network was proposed to realize the diagnosis for critical failure modes of EMAs [3]. Narasimhan et al. implemented the degeneration trend prognostics of EMAs by using the Gaussian process regression algorithm [4]. A method based on WPD-STFT time-frequency entropy and PNN was presented by Jing et al., which achieved the accurate diagnosis of EMAs [5]. At present, there are relatively few researches on fault diagnosis methods of EMAs under variable working conditions at home and abroad.

The vibration signal of rotating machinery contains abundant information about the running state of the equipment. And extracting the fault feature which represents the fault information of the equipment is the most important step in fault diagnosis. However, vibration signal generally has the characteristics of nonlinear and nonstationary, and there are external disturbances such as noise, so that extracting features from vibration signal is the key problem for researchers. The commonly used methods for processing vibration signal to extract fault features include short-time Fourier transform (STFT), wavelet transform (WT), empirical mode decomposition (EMD), and local mean decomposition (LMD). STFT can depict signal in both time domain and frequency domain at the same time and can reflect the time-varying characteristics of the signal frequency spectrum. But the window function of STFT is fixed, so it is not suitable to analyze strong time-varying and nonstationary signal [6]. WT can realize the multiresolution analysis of signal, but its resolution in the frequency domain is not adjustable at the same scale, and it needs to preselect the basis function according to the characteristic of the signal [7]. EMD decomposes the signal into a finite number of single-component signals which are called intrinsic mode functions (IMFs). It has great potential for analyzing the nonlinear and nonstationary signal. However, EMD has a series of problems such as end effects, modal confusion, over-envelope and under-envelope, negative frequency, and lacking theoretical basis [8]. LMD is an adaptive time-frequency analysis method which is proposed on the basis of EMD. It can decompose the complex signal into several product functions (PFs). However, LMD also has the problem of end effects, modal confusion, and large amounts of calculation [9]. In addition, fault diagnosis methods based on various multidisciplinary algorithms have been studied in recent years. A rotating machinery fault diagnosis method combining bispectrum and image processing algorithm was proposed, and its validity was proved by experiments of hydraulic pump and centrifugal pump [10]. A method based on narrowband demodulation with frequency shift and spectrum edit was used to achieve the fault diagnosis of gears [11]. Variational mode decomposition (VMD) is a new signal processing method which has a different theoretical framework with EMD [12]. VMD transforms signal decomposition into nonrecursive and variational mode decomposition problem which has theoretical foundation. It shows better noise robustness and can reduce the sampling effect and modal confusion.

Different from time-frequency analysis, fractal analysis can be used to reveal the fractal features of the signal, while fractal features can characterize the different operating states of a complex system. Therefore, fractal features can be utilized as fault features for fault diagnosis. Multifractal analysis can extract fractal features of different local scales, and researchers have applied classical multifractal theory to feature extraction of fault diagnosis in recent years. A method based on wavelet analysis and multifractal spectrum was applied to extract the fault features of hydropower unit [13]. And the multifractal spectrum was combined with PSO-SVM to achieve the fault diagnosis of gearbox [14]. However, the traditional multifractal theory can be easily disturbed by the trend of signal fluctuation and cannot reveal the multifractal characteristics hidden in nonstationary signal accurately. Thus, Liu et al. proposed a method called multifractal detrended fluctuation analysis (MFDFA) combining multifractal (MF) with detrended fluctuation analysis (DFA), which can eliminate the influence of signal fluctuation and can further effectively extract the multifractal characteristics of nonstationary signal. MFDFA has been applied to the field of fault diagnosis for complex system. A method based on MFDFA and local characteristic-scale decomposition-Teager energy operator was proposed to realize the fault diagnosis of rolling bearing [15]. Tang et al. applied MFDFA into the fault diagnosis of nonlinear analog circuit [16].

A fault diagnosis method for EMA based on VMD-MFDFA and PNN is proposed in this paper. Firstly, the vibration signal of the accelerometer is collected. After preprocessing the vibration signal, a series of IMFs are obtained by using the VMD. Then, the multifractal features of IMFs are calculated by MFDFA, and the fault feature vectors are acquired by reducing the dimension with PCA. Finally, PNN model is trained to classify the fault modes.

2. Feature Extraction Method Based on VMD and MFDFA

The vibration signal of the EMA has the characteristics of nonlinear, nonstationary, and strong time-varying. In this paper, the vibration signal is decomposed by VMD, and the feature vectors are extracted by MFDFA to characterize the operating state of the EMA.

2.1. A Description of Variational Mode Decomposition (VMD). The VMD algorithm can obtain the optimal solution of the constrained variational problem and determine different central frequencies and bandwidths through iteration. The intrinsic mode functions (IMFs) of different frequencies are obtained by nonrecursive decomposition [17]. The implementation of VMD is divided into two parts: the construction of variational problem and the solution of variational problem [18].

The first part is the construction of variational problem. This time-frequency analysis method assumes that the multicomponent signal f consisted of k intrinsic mode functions u_k with limited bandwidth, and the central frequency of each intrinsic mode function corresponds to ω_k.

The analytic signal of each intrinsic mode function is obtained by Hilbert demodulation as the following formula:

$$\left(\delta(t) + \frac{j}{\pi t}\right) u_k(t). \tag{1}$$

A central frequency is estimated as $e^{-j\omega_k t}$ for each analytic signal, and the frequency spectrum of each IMF is modulated to the fundamental frequency band:

$$\left[\left(\delta(t) + \frac{j}{\pi t}\right) u_k(t)\right] e^{-j\omega_k t}. \tag{2}$$

The square norm L^2 of the above analytic signal gradient is calculated, and the bandwidth of each IMF is estimated.

Then, the constrained variational problem is obtained as the following formula:

$$\min_{\{u_k\}\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\}$$
$$\text{s.t.} \quad \sum_k u_k(t) = f, \tag{3}$$

where $\{u_k\} = \{u_1, \ldots, u_k\}$ represents one of the k intrinsic mode functions obtained by decomposition and $\{\omega_k\} = \{\omega_1, \ldots, \omega_k\}$ represents the central frequency of each intrinsic mode function.

The second part is the solution of variational problem. In order to obtain the optimal solution of the variational model, Lagrange multiplication operator $\lambda(t)$ and quadratic penalty factor α need to be introduced to change the constrained variational problem into nonconstrained variational problem. The transformed Lagrange expression is

$$L(\{u_k\}, \{\omega_k\}, \lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_k u_k \right\|_2^2 + \left\langle \lambda(t) - \sum_k u_k(t) \right\rangle. \tag{4}$$

The saddle point of formula (4) is obtained through iteratively updating u_k^{n+1}, ω_k^{n+1}, and λ^{n+1} by using the alternate direction method of multipliers (ADMM).

The update method of u_k^{n+1} is

$$u_k^{n+1}(\omega) = \frac{f(\omega) - \sum_{i \neq k} u_i(\omega) + (\lambda(\omega)/2)}{1 + 2\alpha(\omega - \omega_k)^2}. \tag{5}$$

The update method of ω_k^{n+1} is

$$\omega_k^{\;n+1} = \frac{\int_0^\infty \omega |u_k(\omega)|^2 d\omega}{\int_0^\infty |u_k(\omega)|^2 d\omega}. \tag{6}$$

The update method of λ^{n+1} is

$$\lambda^{n+1}(\omega) = \lambda^n(\omega) + \tau \left[f(\omega) - \sum_k u_k^{n+1}(\omega) \right]. \tag{7}$$

The real part after the Fourier transform of $\{u_k^{n+1}(\omega)\}$ combining formula (5) and formula (6) is the intrinsic mode functions $\{u_k(\omega)\}$.

The specific steps of VMD can be described as follows [19]:

(1) Initialize $\{u_k^1\}$, $\{\omega_k^1\}$, $\{\lambda^1\}$, and n.

(2) Set $n = n + 1$ and begin the circulation.

(3) Update u_k and ω_k according to formula (5) and formula (6).

(4) Set $K = K + 1$, and repeat step (3) until $K = k$.

(5) Update λ according to formula (7).

(6) Repeat step (3) to step (5), until iteration stop condition $\sum_k \|u_k^{n+1} - u_k^n\|_2^2 / \|u_k^n\|_2^2 < e$ is reached.

In the process of decomposition by VMD, the central frequency and bandwidth of each IMF are constantly updated to realize the adaptive decomposition of signal.

2.2. A Description of Multifractal Detrended Fluctuation Analysis (MFDFA). Multifractal detrended fluctuation analysis can effectively eliminate the effect of signal fluctuation trend and can accurately extract the implied multifractal features of nonlinear signal [20].

The steps of MFDFA can be described as follows [21]:

(1) For time series x_k, construct cumulative deviation $Y(i)$ of the sequence to the mean:

$$Y(i) \equiv \sum_{k=1}^{i} |x_k - \langle x \rangle|, \quad i = 1, \ldots, N,$$
$$\langle x \rangle = \frac{1}{N} \sum_{k=1}^{N} x_k. \tag{8}$$

(2) The new sequence $Y(i)$ is divided into nonoverlapping m subsequences with a fixed scale s:

$$m = \text{int}\left(\frac{N}{s}\right). \tag{9}$$

Then, the sequence is divided into m segments by the same scale from the reverse direction of the sequence, and 2 m subsequences can be obtained.

(3) Fit the polynomial trend of each subsequence by using the least square method, and calculate the variance as follows:

$$F^2(s, v) \equiv \frac{1}{s} \sum_{i=1}^{s} \{ Y[(v-1)s + i] - y_v(i) \}^2, \quad v = 1, 2, \ldots, m,$$
$$F^2(s, v) \equiv \frac{1}{s} \sum_{i=1}^{s} \{ Y[N - (v-m)s + i] - y_v(i) \}^2,$$
$$v = m+1, m+2, \ldots, 2m, \tag{10}$$

where $y_v(i)$ is the fitting polynomial of the v subsequence.

(4) Calculate the mean value of the q-order fluctuation function:

$$F_q(s) \equiv \left\{ \frac{1}{2m} \sum_{v=1}^{2m} \left[F^2(s, v) \right]^{q/2} \right\}^{1/q}, \tag{11}$$

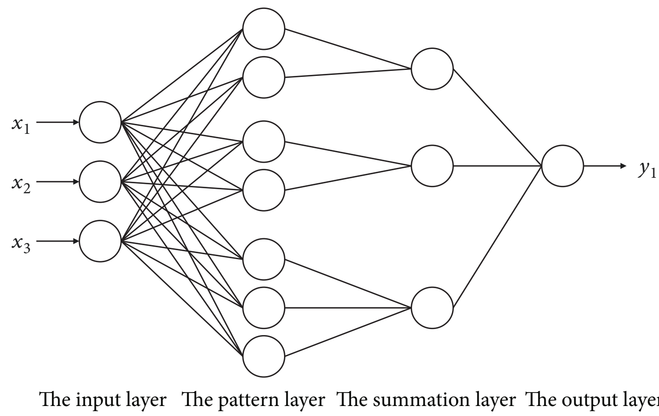

Figure 1: Basic structure of probabilistic neural network.

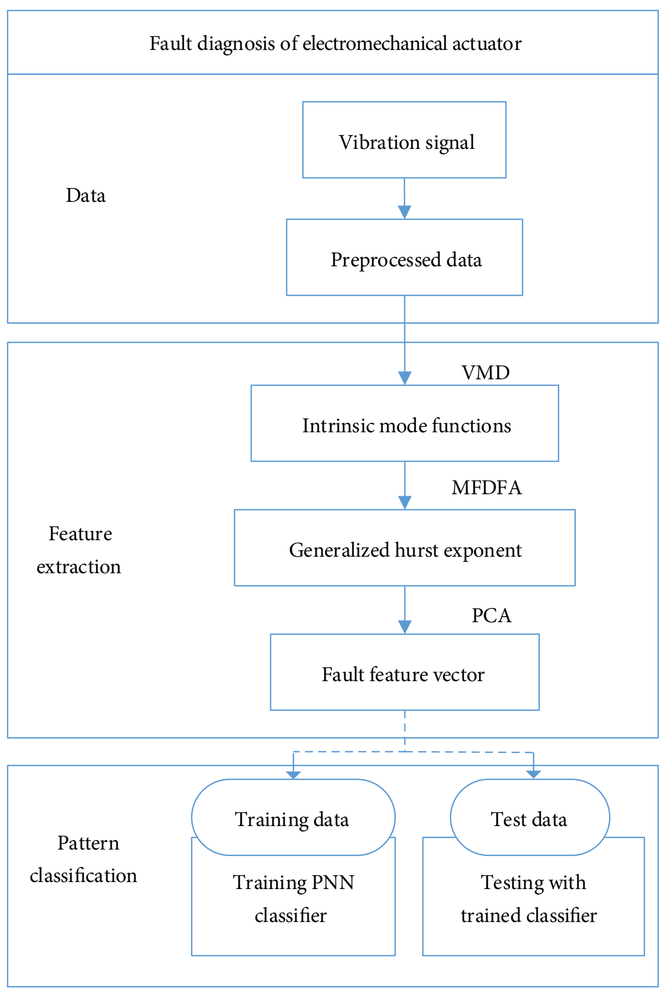

Figure 2: The fault diagnosis procedure of EMA.

where different values of q represent different degrees of fluctuation. And when $q = 2$, MFDFA degenerates to DFA.

(5) Change the length of the subsequence s and repeat steps (2) to (4).

(6) $F_q(s)$ is the function of the length of the subsequence s and the fractal order q and has the following power-law relation with the scale s:

$$F_q(s) \sim s^{H(q)}, \tag{12}$$

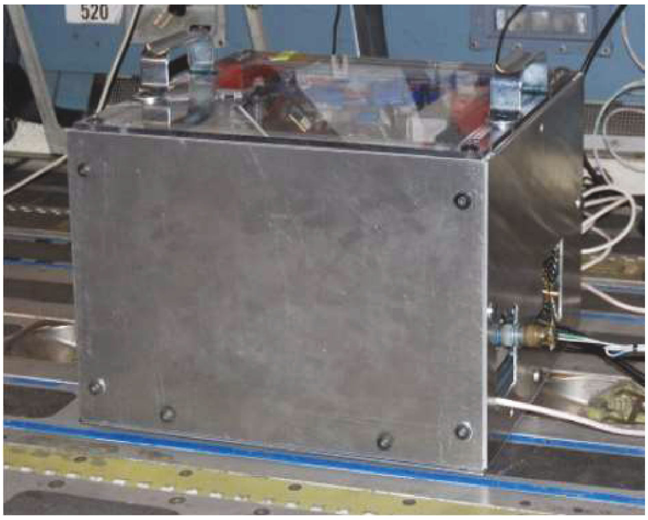

Figure 3: The FLEA test-bed.

where $F_q(s)$ is the mean value of q-order fluctuation function and H_q is the generalized Hurst exponent.

If x_k is a monofractal time series, H_q is a constant, and if x_k is a multifractal time series, H_q is the function of order q. The different order corresponds to the different generalized Hurst exponent.

The generalized Hurst exponent can describe the influence of the past time series on the present and the later time series, and the influences are different under different states of system.

Therefore, the generalized Hurst exponent can be used as the feature vector to describe the multifractal characteristics of the system and can characterize the different states of the system.

3. Fault Classification Based on PNN

The theoretical basis of probabilistic neural network (PNN) is Bayesian minimum risk criterion. PNN directly considers the probability characteristics of the sample space and takes the typical samples of the sample space as the nodes of the hidden layer. There is no need for training anymore once PNN is determined, and it is only necessary to append samples according to actual problems [22]. PNN has the advantages of short training time and global optimization and has great performance for classification.

The network structure of PNN is shown in Figure 1, which consists of the input layer, the pattern layer, the summation layer, and the output layer [23].

The input layer receives the values from the training data and transmits feature vectors to the network, and the number of neurons is equal to the dimension of the sample vectors.

The pattern layer calculates the matching regulation between the feature vectors and the different modes of the training data, and the number of neurons is equal to the

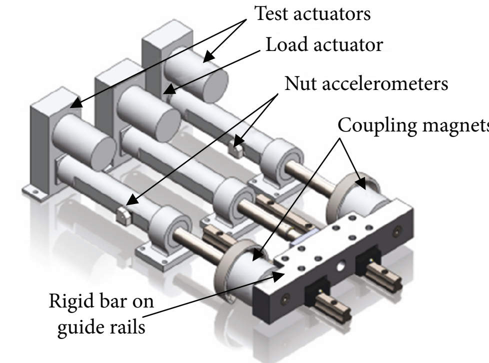

Figure 4: The model of FLEA test-bed.

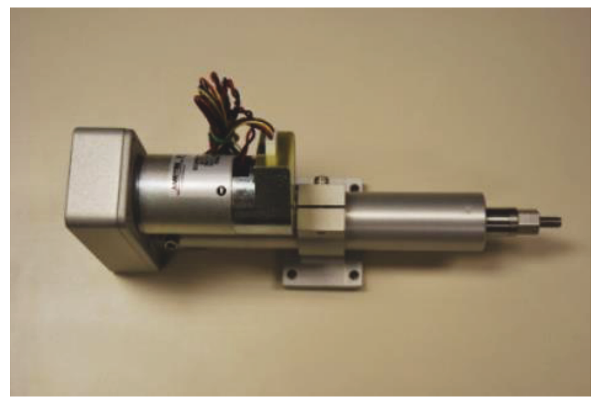

Figure 5: The EMA in the FLEA test-bed.

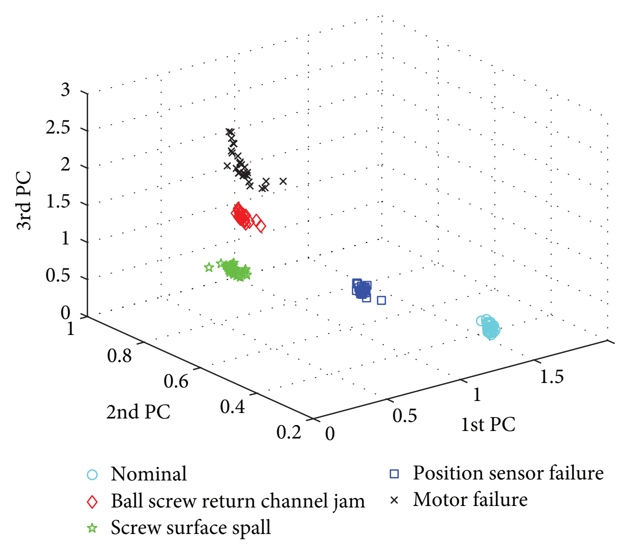

Figure 6: Clustering result of the fault features under condition 1.

sum of the training samples. The output of each unit of this layer is

$$f(X, W_i) = \exp\left[-\frac{(X - W_i)^T (X - W_i)}{2\delta^2}\right], \tag{13}$$

Table 1: The description of five working conditions.

Condition name	Position profile	Parameters	Load profile (load is in lbs)	Max. velocity (m/s)	Comments
Condition 1	Sine sweep	80 mm, 0.0625 Hz, 0.5 Hz	Constant at 0	0.08	Parameters represent amplitude and initial and final frequencies
Condition 2	Trapezoidal	40 mm, 22 s (1 + 1-second motion, 10 + 10-second hold)	Constant at −10	0.04	Parameters represent amplitude and time period of trapezoidal wave
Condition 3	Trapezoidal		Constant at 0	0.04	
Condition 4	Trapezoidal	40 mm, 21 s (0.5 + 0.5-second motion, 10 + 10-second hold)	Constant at 0	0.08	
Condition 5	Trapezoidal		Constant at 10	0.08	

where W_i is the weight of the input layer to the pattern layer and δ is the smoothing factor.

The summation layer adds the probability that each group of neurons belongs to a pattern and calculates the estimated probability density function of this pattern. A fault mode has only one summation layer neuron.

The output layer puts the mode with the greatest probability in the summation layer as the output. The output of a neuron with maximum probability is 1, and the output of other neurons is 0. The number of neurons in the output layer is equal to the number of the modes.

4. Fault Diagnosis Scheme of EMA Based on VMD-MFDFA and PNN

This paper presents a fault diagnosis method based on VMD-MFDFA and PNN for EMA, and the procedure of diagnosis scheme is shown in Figure 2.

(1) Decompose the vibration signals of EMA into a series of IMFs by utilizing VMD.

(2) Calculate the generalized Hurst exponents of IMFs as feature vectors by using MFDFA.

(3) Reduce the dimension of the feature vectors to obtain the final fault features by utilizing PCA.

(4) Classify the fault modes by using PNN.

5. Case Study

In order to verify the effectiveness of the fault diagnosis method proposed in this paper, we have conducted experiments by using the data from the FLEA test-bed of NASA database. The FLEA test-bed is shown in Figures 3 and 4, and the EMA in the test-bed is shown in Figure 5. The fault diagnosis experiments have been carried out in the following five states: the normal state, ball screw return channel jam, screw surface spall, motor failure, and position sensor failure. The vibration signals were acquired from the FLEA test-bed with a sampling frequency of 20 kHz for 30 seconds. And the data of each state has been divided into 29 groups (20,000 sampling points per group) to analyze conveniently. Moreover, for the sake of validating the adaptability to variable working conditions of the proposed method, the experiments have been carried out under five different conditions.

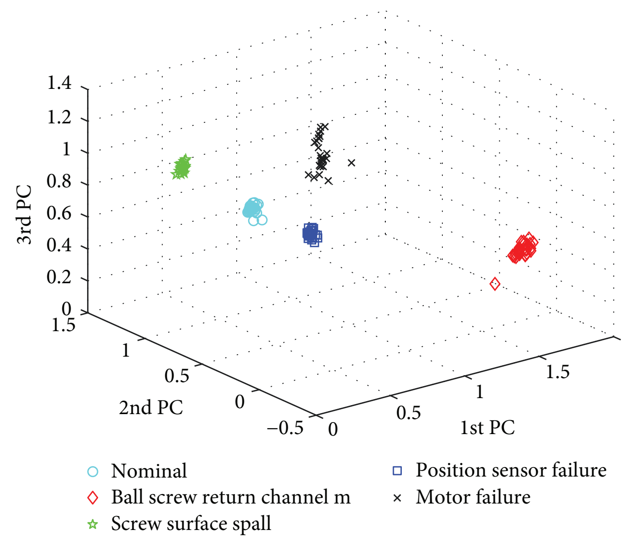

Figure 7: Clustering result of the fault features under condition 2.

5.1. Fault Feature Extraction Based on VMD and MFDFA. First, the collected raw vibration signals are preprocessed by normalizing.

Second, the preprocessed signals are decomposed by VMD. The VMD method needs to predetermine the number of modes k before decomposing signal. However, there will be modes with the same central frequency when the number of decomposition mode is more than 3. Therefore, the preprocessed signals are decomposed into three IMFs by using VMD in this paper.

Then, the MFDFA is applied to extract the multifractal features of decomposed IMFs. The generalized Hurst exponents are selected as fault features with the order $q = [-5, 0, 5]$. And in order to improve the accuracy of fault diagnosis, the 9-dimensional generalized Hurst exponents are reduced to 3-dimensional fault feature vectors by using PCA.

The clustering result of the final fault feature vectors is shown in Figure 6, which shows that the feature vectors acquired by the proposed method in this paper can characterize the state of EMA.

5.1.1. Fault Feature Extraction under Different Conditions. In practical application, EMA usually runs under variable working conditions, so it is of great significance to diagnose

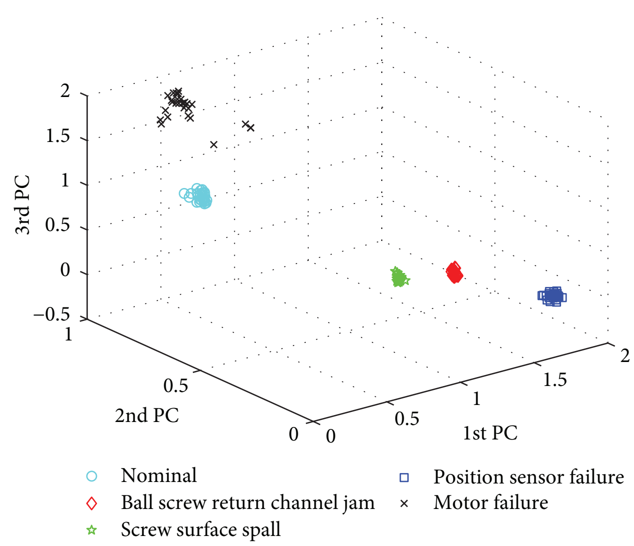

FIGURE 8: Clustering result of the fault features under condition 3.

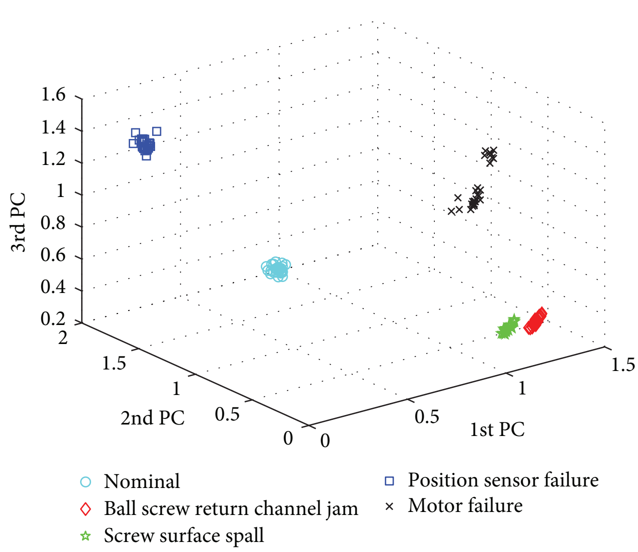

FIGURE 9: Clustering result of the fault features under condition 4.

accurately under different conditions. In order to prove the adaptability of the method to working conditions, the experiments are conducted under five different conditions as shown in Table 1.

The vibration signals of EMA are collected under the five working conditions, and the fault features are extracted by utilizing VMD-MFDFA-PCA method. Figures 7–10 show the clustering results of fault feature vectors under four conditions except condition 1.

It can be seen from the figures that the proposed method can accurately extract the fault features of EMA under different conditions and can adapt to the variable working conditions in the practical environment.

5.1.2. Comparison between the Proposed Method with EMD-MFDFA for Feature Extraction. In order to verify the excellent performance of the feature extraction method proposed

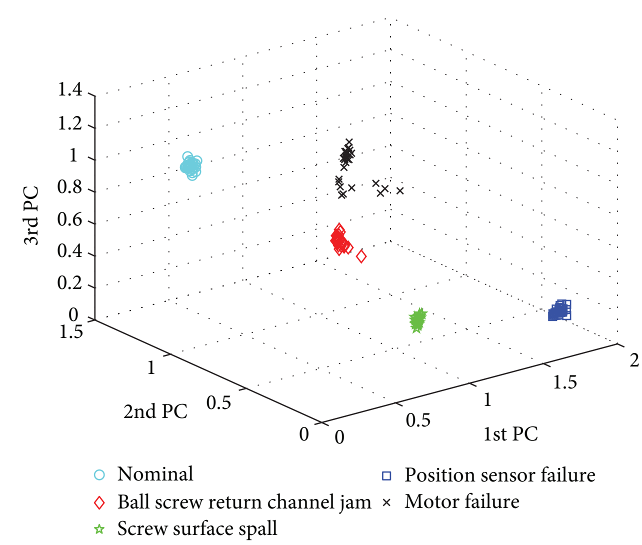

FIGURE 10: Clustering result of the fault features under condition 5.

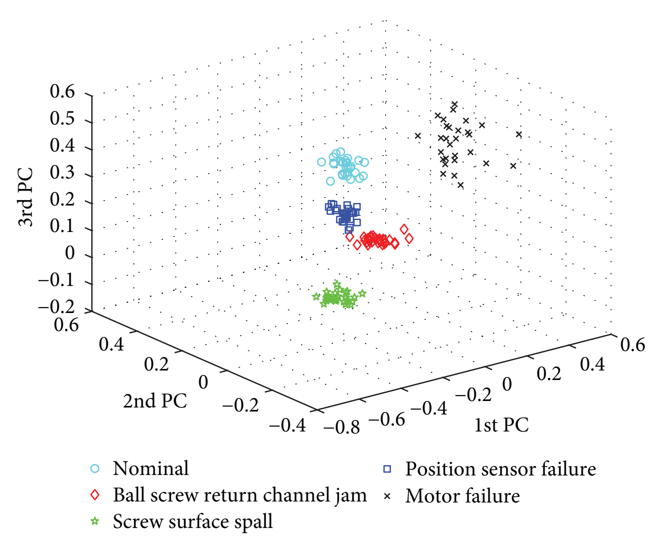

FIGURE 11: Clustering result of the fault features with EMD-MFDFA under condition 1.

in this paper, the method based on EMD-MFDFA is applied to extract the fault feature vectors of EMA for comparison. This method combines the widely used empirical mode decomposition time-frequency analysis method with the MFDFA to extract the fault features of EMA.

Firstly, the original vibration signal is preprocessed and then decomposed by EMD into a series of IMFs with frequencies from high to low. Secondly, the first three IMFs containing the main fault information are selected. Then, the 9-dimensional generalized Hurst exponents are extracted by using MFDFA with the parameter $q = [-5, 0, 5]$. Finally, the PCA is applied to reduce the dimension of the 9-dimensional features to obtain a 3-dimensional generalized Hurst exponents as the ultimate fault feature vectors. The clustering result is shown in Figures 11–15.

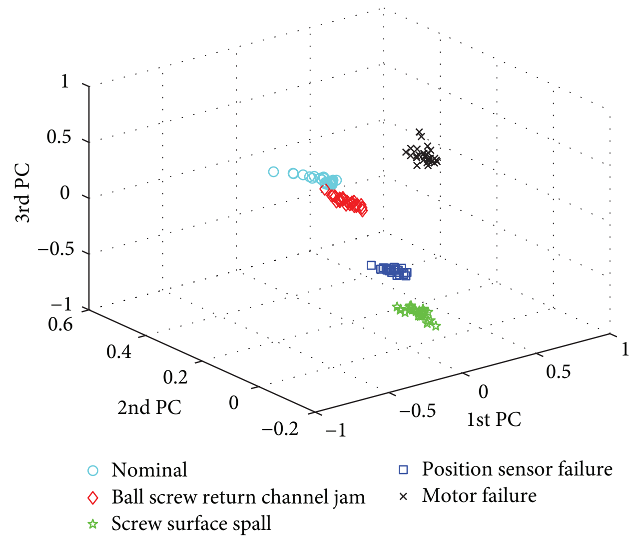

FIGURE 12: Clustering result of the fault features with EMD-MFDFA under condition 2.

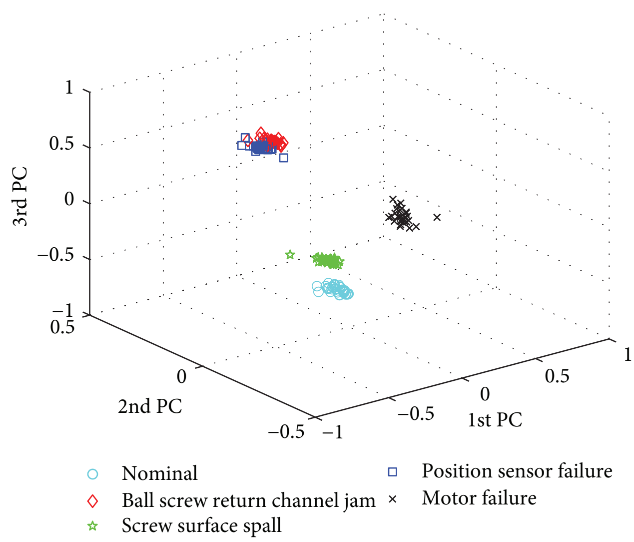

FIGURE 13: Clustering result of the fault features with EMD-MFDFA under condition 3.

It can be seen that scatter points of fault feature vectors by using feature extraction method based on EMD-MFDFA are relatively close, so that it is hard to clearly classify the fault modes. And it can also be proved that the method proposed in this paper has better performance for fault feature extraction.

5.2. Fault Classification Based on PNN. The PNN classifier model is trained to identify the fault modes of EMA under different working conditions. In each working condition, the 3-dimensional fault feature vectors of each fault mode are taken as the input of PNN, and the fault category labels are taken as the output of PNN. The first 15 sets of data of each fault mode are used as training data, and the training data is used to train the PNN classifier. Then, the fault labels

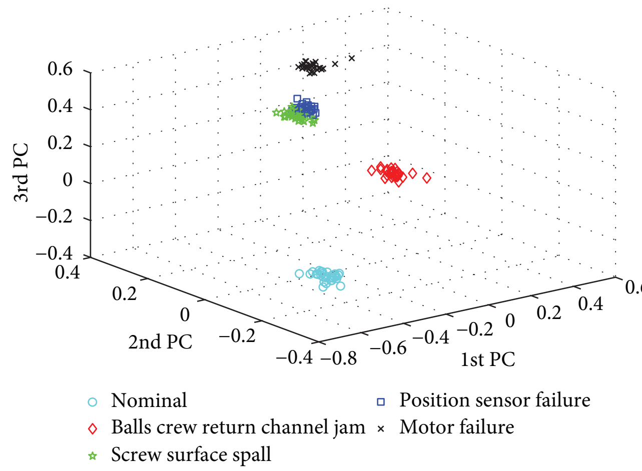

FIGURE 14: Clustering result of the fault features with EMD-MFDFA under condition 4.

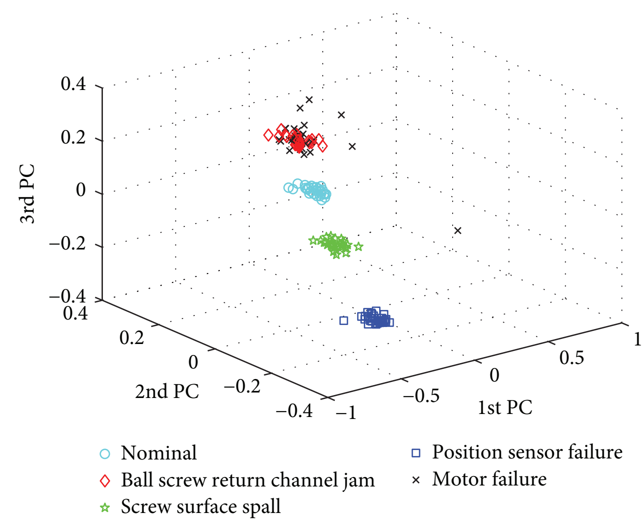

FIGURE 15: Clustering result of the fault features with EMD-MFDFA under condition 5.

of the last 14 sets of testing data are identified by the trained PNN classifier, and the final fault diagnosis result is obtained.

In the trained PNN classification model, 3 nodes in the input layer are determined according to the dimension of the feature vectors, 75 nodes in the pattern layer are determined according to the number of training samples, and 5 nodes in the summation layer and the output layer are determined according to the number of categories of the fault modes. And the smoothing factor of PNN is set to 1.0. The failure modes of the test samples correspond to the normal state, ball screw return channel jam, screw surface spall, position sensor failure, and motor failure, respectively, when the output of PNN is 1, 2, 3, 4, and 5.

The test results under five conditions are shown in Figures 16–20.

It can be seen from the figures that the diagnostic fault labels of the test samples are in high agreement with the

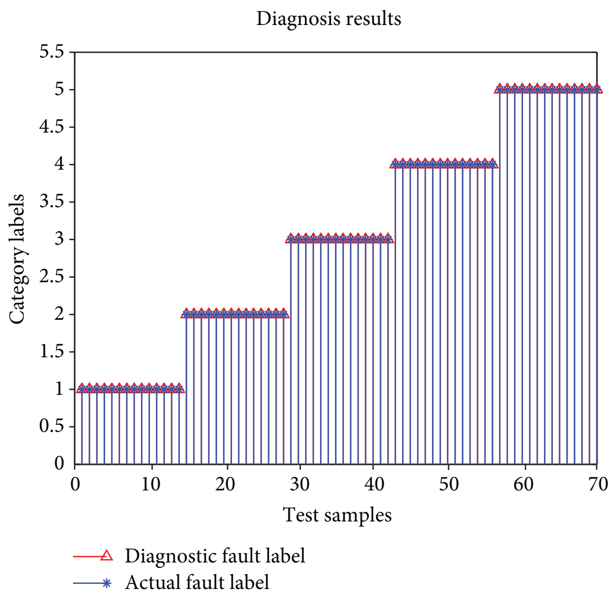

FIGURE 16: Classification result under condition 1.

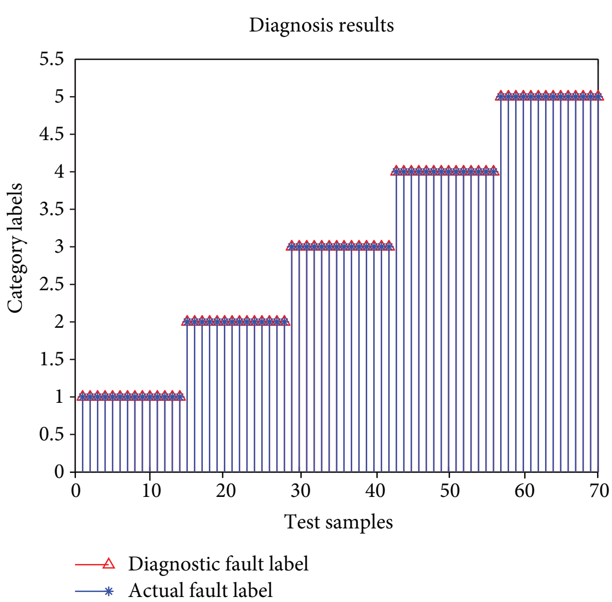

FIGURE 17: Classification result under condition 2.

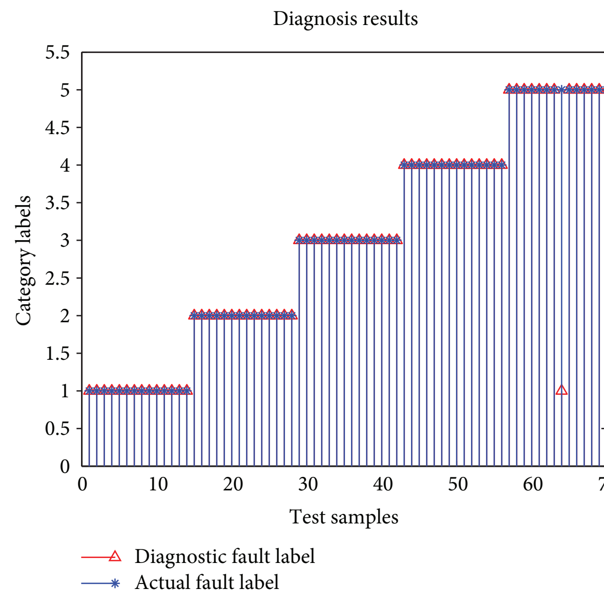

FIGURE 18: Classification result under condition 3.

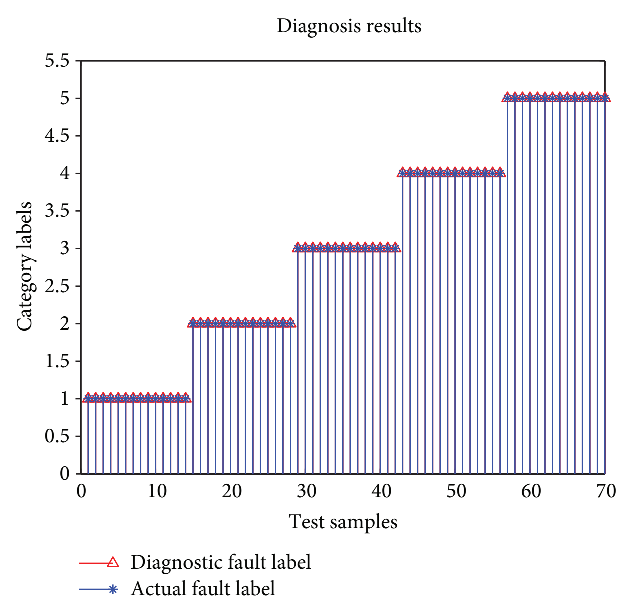

FIGURE 19: Classification result under condition 4.

actual fault labels. The diagnosis accuracy of condition 1 is 100%, the diagnosis accuracy of condition 2 is 100%, the diagnosis accuracy of condition 3 is 98.67%, the diagnosis accuracy of condition 4 is 100%, and the diagnosis accuracy of condition 5 is 100%. The diagnosis results indicate that the method proposed in this paper can accurately diagnose EMA and has great diagnostic performance.

6. Conclusion

EMA is more and more widely applied in the flight control system of aircrafts and helicopters, and it is of great importance to diagnose the fault of EMA in time for the safety of aircrafts and helicopters. Thus, it is very meaningful to research the fault diagnosis of EMA. A fault diagnosis method based on VMD-MFDFA-PNN for EMA is presented in this study. Firstly, VMD is applied to decompose the vibration signal of EMA into the IMFs which contain the fault information. Secondly, the generalized Hurst exponents of IMFs are calculated as the fault features by MFDFA. Then, the PCA is utilized to reduce the dimension of the generalized Hurst exponents. Finally, the PNN model is trained to classify the fault modes. The results show that the method proposed in this paper can extract the features sensitive to the fault of EMA and can conduct accurate fault diagnosis under different working conditions. The great performance

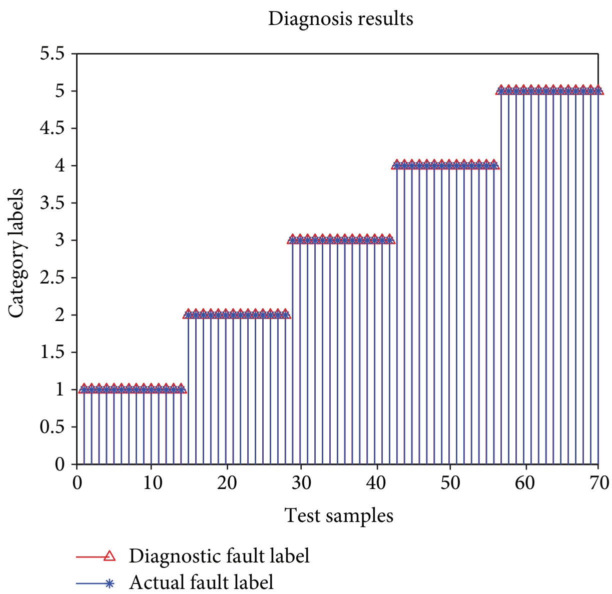

Figure 20: Classification result under condition 5.

of the proposed method is further validated by comparing with EMD-MFDFA-PCA.

However, the computational complexity of the proposed algorithm is relatively large. Therefore, in the case of limited computer resources, the calculation speed will be slightly slower. Future work will concentrate on two aspects. The first one is the study on improving the computational efficiency of the method proposed in this paper for the occasions with high real-time requirements. The second one is the study on health assessment and degeneration trend prognostics of EMA.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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