

Research Article

Research on Rolling Bearing Fault Diagnosis Based on Volterra Kernel Identification and KPCA

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A rolling bearing fault diagnosis method based on the Volterra series and kernel principal component analysis (KPCA) is proposed. In the proposed method, first, the improved genetic algorithm (IGA) is used to identify the Volterra series model of the bearing in four states: normal, rolling element fault, inner ring fault, and outer ring fault. The Volterra time-domain kernel is used as the feature vector for kernel principal component analysis to classify and identify the faults. The feasibility of the fault diagnosis method of the Volterra level and kernel principal component analysis is verified by the experimental results.

1. Introduction

Rolling bearings are widely used in various fields of national economy and national defense industry as they are called “the joints of industry.” As the rolling relationship between its main components makes it the most vulnerable component in machinery, therefore, the fault diagnosis study of rolling bearings is very important. The failure diagnosis technique is essentially a process of failure mode identification, commonly known as a method of finding fault classification [1–5]. Fault diagnosis technology has been developed since the middle of last century. It has formed an interdisciplinary and comprehensive technology that integrates many fields such as advanced sensing technology, artificial intelligence algorithms based on big data, and signal processing technology. Using the data obtained from the testing equipment and analyzed by the relevant intelligent algorithm, fault diagnosis is carried out to diagnose the fault status of the machinery and equipment in order to find the location where the fault appears, so as to repair the fault problem, achieve the purpose of eliminating the hidden danger of the fault, and lay the foundation for providing good maintenance decisions for the machinery

and equipment. The verification of fault diagnosis based on vibration analysis can achieve both online and offline monitoring, which is more effective for early fault diagnosis, high efficiency of diagnosis, accurate fault localization, and thus reliable diagnosis results, making it widely used in many fields [6–8]. The prerequisite for rolling bearing fault diagnosis is to obtain the vibration signal with fault information, mainly by using vibration sensors to measure the working status information of the bearing, analyze the key indicators such as the amplitude of the periodic pulse generated by the bearing fault vibration signal, the frequency, and the characteristic frequency of the fault, to determine the location where the bearing fault occurs, and analyze the degree of the bearing fault. Through the sensors installed inside the bearing housing or box, the vibration fault signal of the bearing is collected using a data acquisition card (DSP) or the NI board, and then the vibration data are analyzed by computer software processing to diagnose the nature and type of the fault [9, 10].

The nonlinear fault diagnosis method based on the Volterra level is a typical nonparametric model estimation method. The failure of rolling bearings usually exhibits nonlinear characteristics, and the Volterra level model can

visually express the dynamic behavior of nonlinear systems. The input and output signals of the nonlinear system are used to model the system and to discriminate whether the system is in a fault state based on the changes in the Volterra kernel. Research on fault diagnosis based on the Volterra level theory has yielded some valuable results. Mumolo et al. [11] described page sequences in the truncated form of Volterra frequency domain kernels, which can be used for fault prediction. Tan and Sepehri [12] used a second-order Volterra frequency domain model to describe a nonlinear hydraulic transmission system and used a multiorder recursive estimation algorithm to determine the parameters in the model, and the simulation and experiments proved that the method can correctly identify the different operating states of the system. Tang et al. [13] used a genetic algorithm to identify the Volterra time-domain kernel, through the mean square value of the first three orders of the time-domain kernel and the number of cusps of the second-order kernel surface map and effectively identified the difference between the bumper fault and the normal state of the rotor-bearing system. Jiang et al. [14] used a recursive least squares algorithm to identify the first three orders of the Volterra time-domain kernel of a nonlinear system and experimentally verified with a normal state and a cracked rotor, and the results demonstrated that the method can accurately determine the changes in the system. Li et al. [15] introduced the quantum particle swarm optimization-based algorithm into the Volterra model identification of rotating machinery, using the first third-order GIRF as the feature vector for classification and identification using the SVM, and the experimental results showed that the method can correctly distinguish the fault states of rotating machinery.

The vibration signal of the rolling bearing exhibits nonlinear characteristics, the nonlinear characteristics are more obvious when it fails, and with the development of the faults, the nonlinearity of the system will gradually increase. There are few fault diagnosis methods based on the Volterra time-domain kernel. This paper focuses on Volterra time-domain kernel identification based on intelligent algorithms and combines feature extraction classification methods, which are applied to the fault diagnosis of rolling bearings. First, an accurate and reliable Volterra kernel identification method needs to be found, and many identification methods have been proposed, including the classical least squares algorithm and the least mean square algorithm but the identification accuracy is not high and the noise immunity is poor [16–19]. Therefore, in this paper, the improved genetic algorithm (IGA) will be used to identify Volterra time-

domain kernels and the Volterra kernel chromosomes are encoded with real numbers instead of binary, with adaptive chromosome structure, and adaptive search range, introducing restart strategy, which improves the identification accuracy and makes the algorithm better local convergence and facilitates the population to find the global optimal solution. The IGA can adjust the model structure according to the degree of correlation between the Volterra kernel and the system output to eliminate interfering terms and obtain a simplified Volterra time-domain model of the system.

Kernel principal component analysis (KPCA) technology can reduce the dimensionality of the dataset and increase the interpretability of the data. Simultaneously, it can retain most of the data features in the data. Map input data from a low-dimensional space to a high-dimensional feature space through nonlinear mapping, the PCA method, which is mainly used in the field of linear analysis, are extended to the field of nonlinear analysis, and linear principal element analysis is performed on the obtained mapped data [20, 21].

Based on the abovementioned method, this article proposes a KPCA fault identification method based on an improved genetic algorithm for Volterra time-domain kernel identification. This method first obtains the Volterra time-domain kernel, which is identified by an improved genetic algorithm and combined with KPCA. Then, the KPCA method is used to extract its features, and finally, the system faults are classified and identified. The experimental results demonstrate the effectiveness of this method.

2. IGA-Based Identification of Volterra Kernels

For a nonlinear system, $u(k)$ and $y(k)$ are the system inputs and outputs, correspondingly, represented as the following third-order Volterra series:

$$\begin{aligned}
 y(k) = & \sum_{\tau_1=0}^{M-1} h_1(\tau_1)u(k-\tau_1) \\
 & + \sum_{\tau_1=0}^{M-1} \sum_{\tau_2=0}^{M-1} h_2(\tau_1, \tau_2)u(k-\tau_1)u(k-\tau_2) \\
 & + \sum_{\tau_1=0}^{M-1} \sum_{\tau_2=0}^{M-1} \sum_{\tau_3=0}^{M-1} h_3(\tau_1, \tau_2, \tau_3)u(k-\tau_1)u(k-\tau_2)u(k-\tau_3).
 \end{aligned} \tag{1}$$

Formally, $M \in \mathbb{N}$ is the memory length. $h_n(\tau_1, \dots, \tau_n)$ denotes the n th-order Volterra time-domain kernel of the nonlinear system.

The input matrix \mathbf{P} of the system with the kernel vector \mathbf{H} and the output vector \mathbf{Y} are defined, respectively, as follows:

$$\mathbf{P}(k) = \left[u(k), \dots, u(k - (M - 1)); u^2(k), \dots, u(k)u(k - (M - 1)), u^2(k - 1), \dots, u^2(k - (M - 1)); u^3(k), \dots, u^3(k - (M - 1)) \right]^T, \quad (2)$$

$$\mathbf{H} = [h_1(0), \dots, h_1(M - 1); h_2(0, 0), \dots, h_2(0, M - 1), h_2(1, 1), \dots, h_2(M - 1, M - 1); h_3(0, 0, 0), \dots, h_3(M - 1, M - 1, M - 1)]^T \quad (3)$$

$$\mathbf{Y} = [y(k), y(k + 1), \dots, y(k - (M - 1))] \quad (4)$$

Then, the input-output relationship of the nonlinear system can be expressed as follows:

$$\mathbf{Y} = \mathbf{PH} + \mathbf{e}. \quad (5)$$

Here, $\mathbf{Y} \in R^L$ is the output vector (L is the data length), $\mathbf{P} \in R^{L \times R}$ is the input matrix, $\mathbf{H} \in R^R$ is the nonlinear system Volterra kernel vector (R is the kernel vector length), and N is the system nonlinearity. According to equation (2), the nonlinear system identification based on the Volterra level model is essentially solving the nonlinear system Volterra kernel vector \mathbf{H} with the known system input and output data, and the goal is to minimize the error term \mathbf{e} .

The improved genetic algorithm used to identify the Volterra time-domain kernel in this paper can adaptively adjust the model structure compared with the GA, together with the use of the restart strategy and search range optimization, resulting in a better local search capability and identification accuracy of the algorithm. The Volterra time-domain kernel identification process based on the improved genetic algorithm is shown in Figure 1.

The Volterra system identification method based on an improved genetic algorithm ensures a faster search process and convergence speed compared to the traditional gradient-based method. The new approach is improved from the traditional genetic algorithm-based method in the following aspects.

- (1) It uses real numbers instead of binary to encode Volterra nuclear chromosomes. The advantages of using real-time encoding in Volterra level recognition include reducing the encoding and decoding time and avoiding the ‘‘Hamming cliff’’ phenomenon caused by binary encoding.
- (2) Adaptive chromosome structure: Chromosomes in this paper, namely, the kernel vectors of the Volterra model, are continuously removed in iterations except for items that have no significant effect on the system output, allowing the algorithm to find the optimal chromosome structure and improve the discrimination accuracy.
- (3) The adaptive search range is defined as the upper and lower bounds of the gene. During the iterative process, the adaptation reaches a threshold and continuously narrows the search range for better local convergence of the algorithm.

- (4) An elitist genetic algorithm based on a restart strategy was introduced. Genetic algorithms are likely to fall into a local optimum and be in an evolutionary stagnation state during the iteration of finding the best. Restarting the population according to appropriate rules expands the solution space of the population and facilitates the population to find the global optimal solution.

Volterra levels suffer from the ‘‘dimensional catastrophe’’ problem, resulting in an enormous number of high-order kernels, with a small percentage of key kernels contributing to the output and a sparse distribution in the overall structure. Thus, we wanted to find a way to determine the structure of the Volterra hierarchy, excluding irrelevant kernels in it that are less correlated with the output.

In the modified genetic algorithm-based Volterra time-domain kernel identification process, every chromosome will be matched with an equal-length binary code, indicating the nature of the corresponding kernel in this way, with $\mathbf{1}$ representing the critical kernel and $\mathbf{0}$ the irrelevant kernel. To prevent the real critical kernels from being rejected, all kernels of the chromosome were coded as $\mathbf{1}$ at the beginning of the iteration. Obviously, the algorithm iterates to a certain number of generations to obtain a better solution set. In this algorithm, the irrelevant kernel rejection procedure is initiated when the fitness value of the optimal chromosome in the population is higher than a preset threshold, that is, the highest adapted chromosome is examined when each iteration is completed, and the decision of whether to remove the candidate gene depends on the degree of correlation between the model output and the actual output of the system after the candidate gene reduction. Assuming that the system input has L points, the correlation level from the model output to the system output for the removal of candidate g is given by the following equation:

$$\rho(g) = \frac{\text{Cov}(\mathbf{Y}, \mathbf{Y}_{ng})}{\sqrt{\text{var}(\mathbf{Y})\text{var}(\mathbf{Y}_{ng})}}, \quad (6)$$

where Cov is the covariance, $\widehat{\mathbf{Y}} = \sum_{i=1, i \neq g}^R \mathbf{P}(i) \times \widehat{\mathbf{H}}(i)$ is the output of the model after removing the candidate g , $\widehat{\mathbf{H}}(i)$ represents the i -th gene value of $\widehat{\mathbf{H}}$, $\mathbf{p}(i)$ stands for the i -th column of the input matrix \mathbf{P} , and var is the mean squared error function, which tests all correlation coefficients $\rho(i)$, $i = 1, \dots, R$ and removes the candidate genes that do not exceed the threshold value according to the threshold

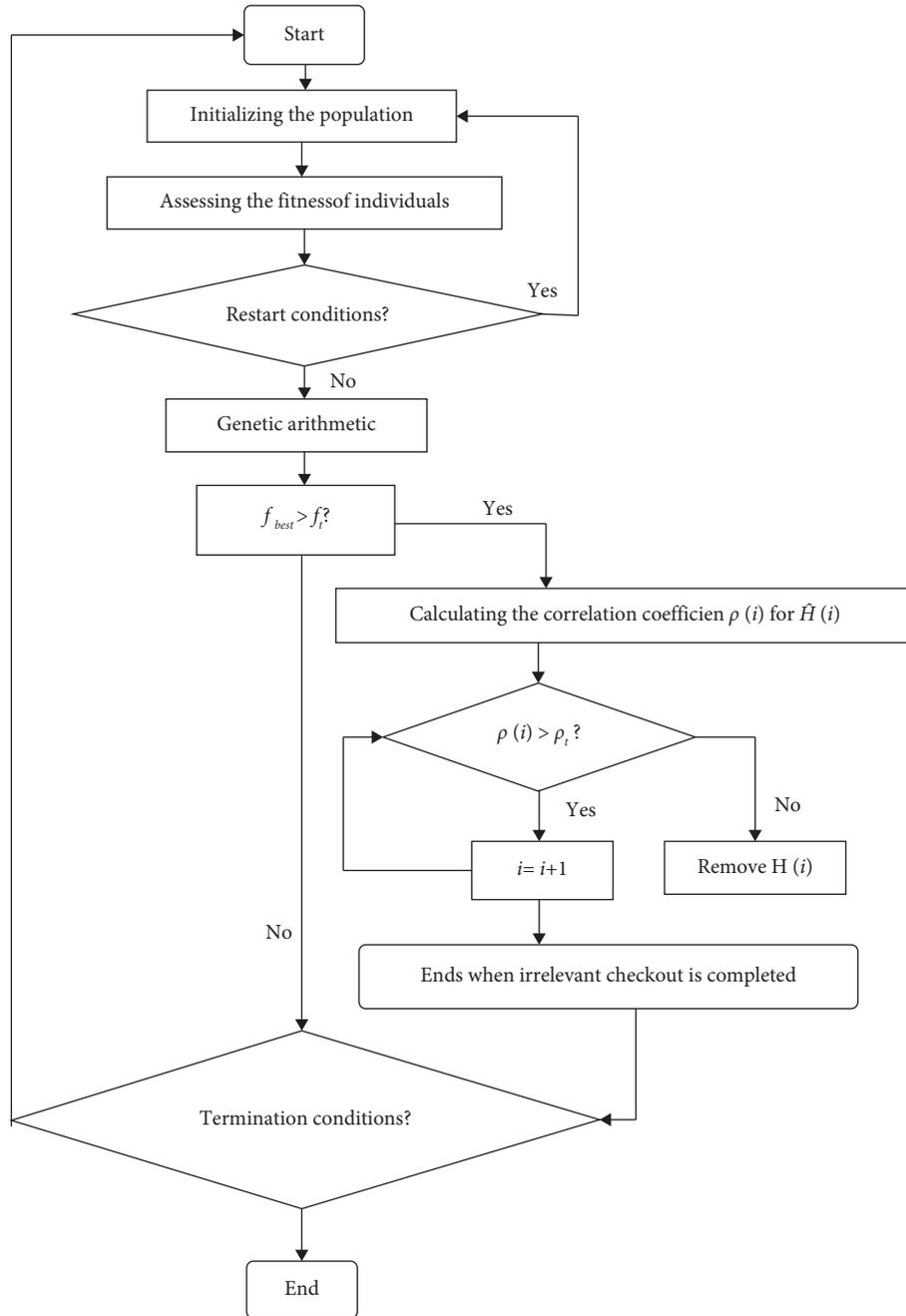


FIGURE 1: IGA-based Volterra time-domain kernel identification process.

value ρ_t set in advance. Similarly, the corresponding columns of the input matrix are removed to reduce the computational effort. By continually removing irrelevant kernels in this way in iterations, a concise and accurate model can be constructed. Similarly, the corresponding columns of the input matrix were deleted to reduce the computational effort. This way, by continuously removing irrelevant kernels in iterations, a succinct and detailed model can be constructed. The tuning of the model structure may stop when there are no remaining irrelevant kernels that can exceed a predetermined threshold. The process of removing irrelevant nuclei is shown in Figure 1. It is worth noting that

the abovementioned operation is performed when the fitness of the best chromosome meets a predetermined value and the number of iterations reaches a specific number. The purpose is to prevent critical nuclei from being removed when the population is still unstable early in the iteration.

3. Kernel Principal Component Analysis Method

Kernel principal component analysis (KPCA) technology can reduce the dimensionality of the dataset and increase the interpretability of the data. Simultaneously, it can retain

most of the data features in the data. Specifically, it is a nonlinear mapping of the input space into a high-dimensional feature space and converting it into a linear problem in the high-dimensional space. The problem is then implemented in the high-dimensional space [22–24].

Suppose the dataset $X = \{x_1, x_2, \dots, x_n\} \in R^m$ has n samples, and each sample $x_i (i = 1, 2, \dots, n)$ is m -dimensional, then

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \quad (7)$$

$$= [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_m]^T,$$

where

$$\mathbf{x}_i = (x_{1i}, x_{2i}, \dots, x_{mi})^T, i = 1, 2, \dots, m. \quad (8)$$

KPCA is to analyze the m variables x_1, x_2, \dots, x_m in the original data to form m new orthogonal variables, namely,

$$\begin{cases} \mathbf{F}_1 = w_{11}x_1 + w_{21}x_2 + \cdots + w_{m1}x_m, \\ \mathbf{F}_2 = w_{12}x_1 + w_{22}x_2 + \cdots + w_{m2}x_m, \\ \cdots \\ \mathbf{F}_m = w_{1m}x_1 + w_{2m}x_2 + \cdots + w_{mm}x_m, \end{cases} \quad (9)$$

which is abbreviated as follows:

$$\mathbf{F}_i = w_{1i}x_1 + w_{2i}x_2 + \cdots + w_{mi}x_m, i = 1, 2, \dots, m. \quad (10)$$

Among them, \mathbf{X}_i is an n -dimensional vector, and \mathbf{F}_i is also an n -dimensional vector. The coefficient W_{ij} in formula (10) needs to meet the following conditions:

- (1) F_i is not correlated with $F_j (i \neq j; i, j = 1, 2, \dots, m)$;
- (2) The variance of \mathbf{F}_1 is greater than the variance of \mathbf{F}_2 is greater than the variance of \mathbf{F}_3 , and so on;
- (3) $w_{k1}^2 + w_{k2}^2 + \cdots + w_{km}^2 = 1, i = 1, 2, \dots, m$.

When W_{ij} satisfies the abovementioned conditions, neither of the new parameters is inter-related and the variance diminishes sequentially. The transformation matrix \mathbf{W} composed of coefficients is expressed as follows:

$$\mathbf{W} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1m} \\ w_{21} & w_{22} & \cdots & w_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nm} \end{bmatrix}, \quad (11)$$

which makes

$$\begin{aligned} \mathbf{F} &= [\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_m] \\ &= \mathbf{W}^T \mathbf{X}. \end{aligned} \quad (12)$$

Nonlinear features can be extracted from the mapped data in the high-dimensional space by principal component analysis using kernel function mapping. It analyzes the data samples and critical features of the data are retrieved,

denoting these data samples as batches of new orthogonal variables. These variables are called principal components, which are linear functions of the variables in the original dataset, and they continuously maximize the variance. Projection between principal components after finding the first few principal components can better classify and identify the data.

Based on the fault diagnosis method of Volterra time-domain kernel principal component analysis, the Volterra time-domain kernel in different states is used as a sample set, conducting a kernel principal component analysis of them to realize the classification and identification of nonlinear systems. The basic steps are as follows:

- (1) Preprocessing the input and output signals of known state;
- (2) The Volterra time-domain kernel is identified by the IGA algorithm. The Volterra kernel identified by the data sample of the known state is used as the training sample matrix $X_N \times M_1$ (N is the length of the kernel, and M_1 is the number of samples) and part of it is used as the test matrix $\tilde{X}_{N \times M_2}$;
- (3) Calculate the sample mean and standardize the sample matrix \mathbf{X} to obtain the matrix $\bar{\mathbf{X}}$;
- (4) $\mathbf{V} = (1/M_1)\bar{\mathbf{X}}\bar{\mathbf{X}}^T$ is constructed as the covariance matrix of the sample matrix;
- (5) Find the eigenvalue λ_i and eigenvector W_i of the covariance matrix \mathbf{V} , and arrange the eigenvalues $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_R$ in the descending order from large to small, and the corresponding eigenvectors are $\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_n$;
- (6) The first k principal components of the matrix \mathbf{X} are obtained by using the formula, and the contribution rate to the system accounts for 85% or more, usually the first three principal components;
- (7) Make the first principal component diagram of the sample matrix; then, make the projection diagram of the first and second principal components. Projection plots show the 2nd principal component and the 3rd component. The principal components of different states will be distributed in different positions in the figure;
- (8) Calculate the principal components of the test matrix, make a principal component diagram and a projection diagram, and compare it with the graphics obtained in step (7), and then the operating status of the test data can be judged and the preliminary fault identification can be completed.

4. Experimental Research

The basic idea of KPCA feature extraction based on the Volterra time-domain kernel is as follows: first, using the improved genetic algorithm, identify the first three orders of the Volterra time-domain model with four states of rolling bearing normal, outer ring fault, inner ring fault, and rolling

body fault; then, use the KPCA method to classify the first three orders of the Volterra kernel to achieve state classification and fault identification.

Rolling bearing vibration data were obtained from the Case Western Reserve University Bearing Data Center, and the experimental rig was arranged as shown in Figure 2, consisting of an electric motor with horsepower 2 (left), torque transducer (center), power test meter (right), and electronic controls (not shown in the figure). The experimental platform is to test the bearings supporting the motor, where the bearing failure condition is arranged by EDM technology for a single point of failure. For the bearing failure diameter setting, there are four types, i.e., 0.007 inch, 0.014 inch, 0.021 inch, and 0.028 inch, and the simulated bearing operating condition has four different load cases, namely, the load of 0hp, 1hp, 2hp, and 3hp. The bearing fault condition was introduced by using an electric spark discharge to introduce a single point of failure. The acceleration sensors were arranged at the drive end, the base, along with the fan end, and the vibration signals reflecting the bearing status were collected by the acceleration sensors. Data acquisition was done using a 16-channel DAT recorder. The collected vibration signals are subject to random errors and noise interference caused by external factors; so, the vibration signals are noise reduced using the harmonic wavelet filtering method. Table 1 shows the details of the relevant bearings and the frequency of failures. The sampling frequency of the digital signal is 12 kHz, and the bearing fault data at the drive end are also collected at a sampling rate of 48 kHz. Bearing fault locations are mainly distributed in three locations, i.e., rolling body, inner ring, and outer ring. Taking the drive end bearing as an example, the motor horsepower and speed and the size of the fault are shown in Table 2. Specific information about the experimental platform setup as well as the fault setup is available on the Case Western Reserve Bearing Experiment Center website [25].

Hereby, 30 sets of data are collected for four different states of rolling bearing normal, outer ring failure, inner ring failure, and rolling element failure. According to the Volterra level theory, the data collected at the drive side are used as the input signal, and the data collected at the fan side are used as the output signal. Assuming that the model order is 3 and the first three-order memory lengths are 10, 4, and 3, the lengths of the first three-order kernel vectors $\mathbf{h}_1(\bullet)$, $\mathbf{h}_2(\bullet)$, and $\mathbf{h}_3(\bullet)$ are 10, 10, and 10, respectively, which means the length of the Volterra kernel vector \mathbf{H} is 30. Among them,

$$\begin{aligned} \mathbf{h}_1 &= [h_1(0), h_1(1), \dots, h_1(9)], \\ \mathbf{h}_2 &= [h_2(0,0), h_2(0,1), \dots, h_2(3,3)], \\ \mathbf{h}_3 &= [h_3(0,0,0), h_3(0,0,1), \dots, h_3(2,2,2)], \\ \mathbf{H} &= [\mathbf{h}_1, \mathbf{h}_2, \mathbf{h}_3]. \end{aligned} \quad (13)$$

Following the first three orders of Volterra time-domain kernels of the nonlinear system obtained by the IGA method, KPCA is used, and the Volterra kernels obtained from the identification of 20 sets of signals for each state are



FIGURE 2: Rolling bearing test bench.

used as the training data, and then the Volterra kernels of another 10 sets of signals are used as the test data for fault identification.

First, the linear component $\mathbf{h}_1(\bullet)$ of the Volterra time-domain kernel is taken for the kernel principal component analysis, where the graph \ast represents the normal state, \diamond represents the rolling body fault, \triangleleft represents the outer ring fault, and $+$ represents the inner ring fault. The sample numbers represent the principal components of the test data for each of the four conditions of the rolling bearing.

As can be seen from Figure 3, when only the Volterra linear kernel is considered for principal component analysis, only the normal states are successfully separated on the first principal component distribution obtained by KPCA, with the data from the other states still mixed together. The normal state and the inner ring fault have their clustering centers, but it is impossible to distinguish the rolling body from the outer ring fault data; on the projection maps of the 1st and 3rd principal components, the clustering centers of the normal data are not obvious, and the data of the other three states are mixed and scattered; so, the recognition effect is poor.

Next, the first three orders of Volterra kernels were used as feature vectors for kernel principal component analysis, and the principal components with a contribution rate greater than 85% in the first three orders were selected for classification; the obtained results are shown in Figure 4. Although the four states of the rolling bearing cannot be well distinguished by the first principal element, the clustering center of each state is prominently shown on the projection maps of the first and second principal elements and the first and third principal elements, and its interclass scatter is larger than the intraclass scatter, and the state identification effect is better.

The experiments abovementioned show that when using only the linear Volterra kernel as the feature vector for kernel principal component analysis, the effect of classification and identification is not very satisfactory and cannot distinguish between outer ring faults and rolling body faults. When the first third-order Volterra time-domain kernel is used as the feature vectors for kernel principal component analysis, all four operating states can be clearly distinguished, with satisfactory classification and identification results. It can be seen that the Volterra time-domain kernels contains rich fault information, and the different states of the nonlinear system can be effectively distinguished using the first three orders of the Volterra

TABLE 1: Bearing details and failure frequency.

Bearing types	Fault locations	Inner ring passing frequency (Hz)	Outer ring passing frequency (Hz)	Cage passing frequency (Hz)	Rolling body passing frequency (Hz)
SKF 6205-2RS JEM	Drive side	5.415	3.585	0.3983	2.375
SKF 6203-2RS JEM	Fan end	4.947	3.053	0.3816	1.994

TABLE 2: Data and working conditions.

Data	Motor load (HP)	Motor speed (rpm)	Fault sizes (in)
Drive side 0	0	1797	0.007
Drive side 1	1	1772	0.014
Drive side 2	2	1750	0.021
Drive side 3	3	1720	0.028

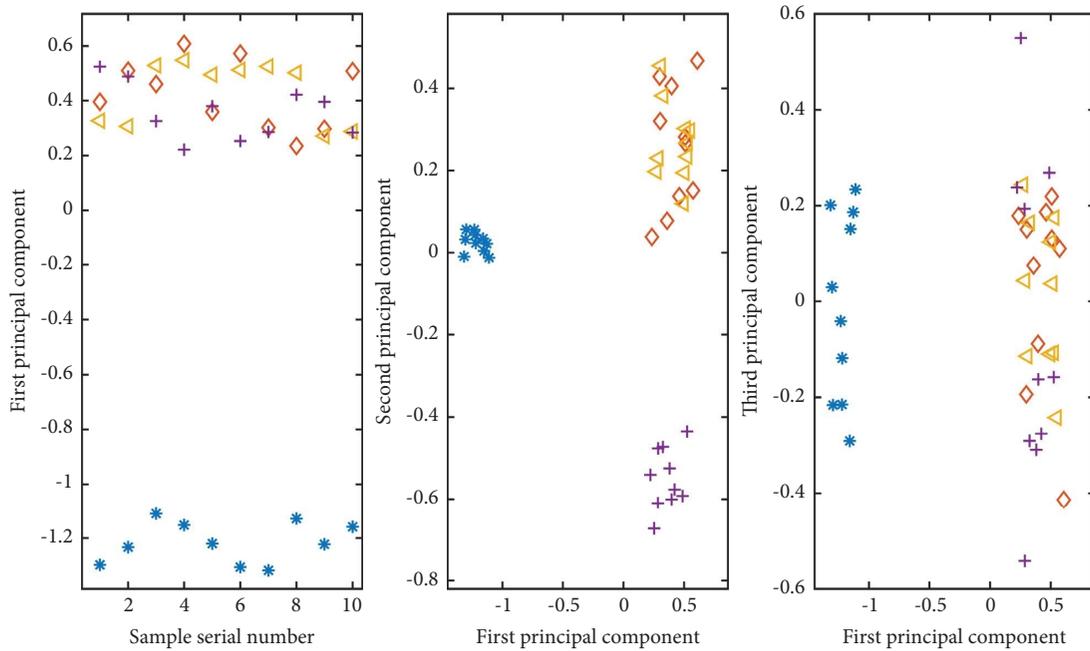


FIGURE 3: Identification results of kernel principal component analysis with first-order kernels only.

kernels. Experimental results show that the kernel principal component analysis method has good classification ability and the kernel principal component analysis fault identification method based on the Volterra time-domain kernel is effective.

Features of the four operating states of the rolling bearing were extracted by kernel principal component analysis. Under the new operating conditions, the same kernel identification and kernel principal component analysis for the unknown signals were carried out and

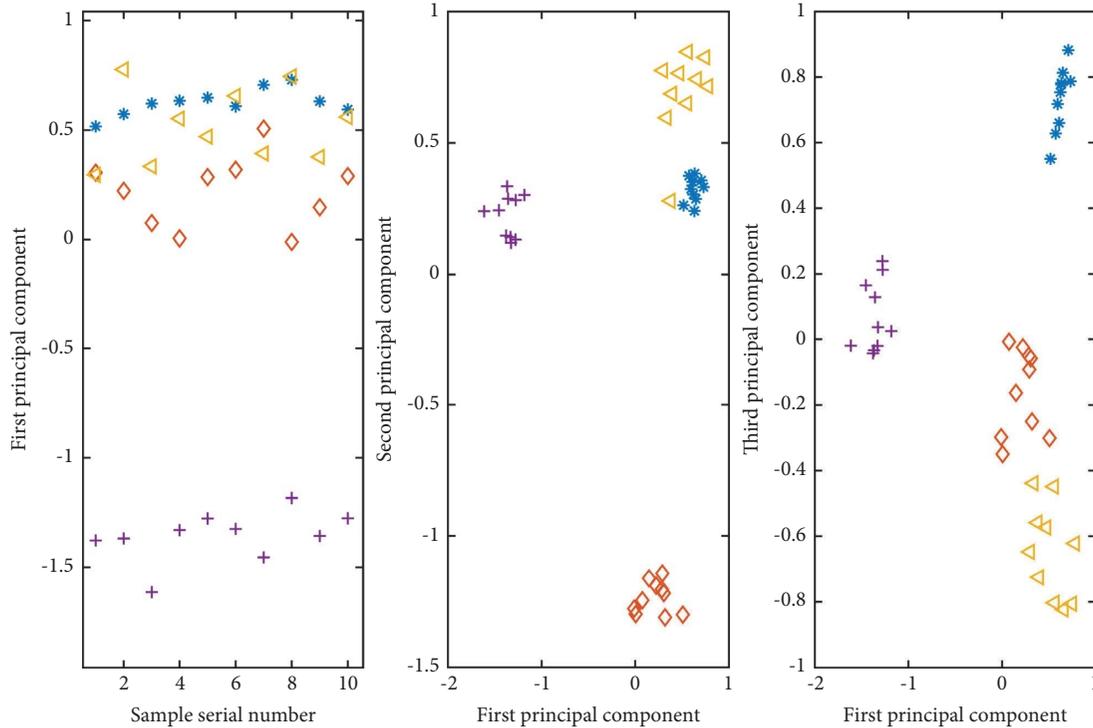


FIGURE 4: Identification results of kernel principal component analysis with the first third-order kernel.

then compared with the four known normal or fault features to determine the type of fault.

5. Conclusion

When the system fails, its internal transmission characteristics will change and the nonlinear characteristics are obvious. The Volterra time-domain kernel contains rich fault information and could capture the intrinsic characteristics of nonlinear systems. Taking the Volterra time-domain kernel as a feature vector, feature extraction and fault identification can be performed. The kernel principal component analysis method can project high-dimensional data to low-dimensional, increase the interpretability of the data while retaining most of the data features in the original data, and make the data classification clearer. The Volterra kernel of the four states identified by the proposed IGA algorithm is used as the first three-order principal components of the feature vector (the contribution rate greater than 85%), and the fault classification and identification is performed through the analysis of the first three principal components, and the four states of rolling bearing normal, rolling body fault, inner ring fault, and outer ring fault are clearly identified, which shows that the use of the first three-order Volterra kernel can effectively distinguish the different states of the system and the fault identification method of nuclear principal component analysis based on the Volterra time-domain kernel is effective.

Data Availability

Rolling bearing vibration data were obtained from the Case Western Reserve University Bearing Data Center. Case

Western Reserve University Bearing Data Center website: <https://engineering.case.edu/bearingdatacenter/welcome>.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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