Research Article

An Integrated Fault Diagnosis Method for Rotating Machinery Based on Smoothness Priors Approach Fluctuation Dispersion Entropy and Density Peak Clustering

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In order to fully excavate the fault feature information of rotating machinery and accurately recognize the fault category, a novel fault diagnosis method was proposed, which combines with smoothness priors approach (SPA), fluctuation dispersion entropy (FDE), and density peak clustering (DPC). Firstly, the smoothness priors approach is used to decompose the collected vibration signal of rotating machinery to obtain the trend term and detrend term. Secondly, the fault features of the trend term and detrend term were quantified by fluctuation dispersion entropy to construct eigenvector matrix. Finally, the eigenvector matrix was input into the density peak clustering algorithm for fault recognition and classification. The proposed novel algorithm was applied to the experimental data of the rotating machinery under various working conditions. The experimental results show that our method can precisely identify various fault patterns of rotating machinery. Moreover, our approach can attain higher recognition accuracy than other combination clustering model algorithms involved in this paper.

1. Introduction

Rotating mechanical equipment has been widely used in various large manufacturing systems and important technical equipment, and it has played a significant role in the national economy and industrial development. As the key position of rotating machinery, the running condition of gearbox and rolling bearing will affect the working capability of the total machinery [1]. With the increasing of working time in the complex operating environment, it is easy for rotating machinery to cause faults due to fatigue, which leads to a series of accidents. Consequently, the research on integrated fault diagnosis algorithm is very valuable to assure the normal production of the equipment [2].

Due to the complex operating environment of the transmission system in the rotating machinery, the collected signals are obviously nonstationary and nonlinear [3]. The traditional linear analysis method has some defects in analyzing the above vibration signals. In recent years, entropy is one of the methods to describe the complexity of the vibration signals. It can fully excavate the fault characteristics in nonlinear vibration signals. Therefore, entropy is extensively used in the fault diagnosis and acquired excellent diagnosis results. For example, Dang et al. [4] employed the approximate entropy to the experimental data of the three mechanical vibration signals. The research results found that the approximate entropy can validly evaluate the complexity of vibration signals and accurately identify different fault states. Guan et al. [5] obtained the signal feature information in the rotor system by using sample entropy and input it into the deep belief network, which successfully realized the accurate identification of rotor system faults. Tian et al. [6] applied the permutation entropy to extract the feature information of rolling bearing signals. The results displayed that the permutation entropy can sensitively represent the working characteristics of rolling bearings under various states. However, these methods also have some disadvantages in extracted fault signal feature. The approximate entropy was difficult to match in the calculation process, which was easy to cause deviation of the calculation results.
The calculation speed of the sample entropy was slow for the time series with long data points, and it was easily affected facing the mutation vibration signals. Permutation entropy did not premeditate the connection between signal amplitudes in the calculation process, which was easy to cause the loss of fault message. In order to alleviate the shortcomings of the above methods, Rostaghi and Azami [7] put forward the dispersion entropy (DE) according to the idea of sym- bolic dynamics. This method mapped the data points to multiple categories through the signal amplitude, and the slight change of signal amplitude would not change category labels. Therefore, the dispersion entropy has strong anti-interference ability. It met the requirement of feature extraction of the nonlinear vibration signal. However, the dispersion entropy has poor stability in the face of the time series with large volatility. Azami and Escudero [8] put forward the fluctuation dispersion entropy (FDE) by considering the fluctuation change of signal according to dis- persion entropy. The FDE not only described the irregularity of signal, but also evaluated the dynamic change of signal.

The enrichment of entropy theory provided an effective solution for fault feature extraction of vibration signal. However, the above entropy was limited to the single-scale decomposition of signals. Due to the complexity of collected vibration signals in precision mechanical equipment, it is easy for the dynamic characteristics of single-scale to lose important fault feature information, which have an impact on the reliability of fault diagnosis. Consequently, the complexity of signals under different scales should be analyzed. It was a common decomposition method to multiscale analysis of the collected signal. The wavelet transform was the earliest decomposition method in the problem of multiscale analysis of collected signal. However, the wavelet transform algorithm has the problem that wavelet basis function is too complex. With the continuous research of signal decomposition methods, many adaptive signal decomposition methods have emerged, such as ensemble empirical mode decomposition (EEMD) [9, 10], variational mode decomposition [11, 12], Fourier decom- position [13, 14], symplectic geometry mode decomposition [15, 16], etc. These signal decomposition methods would produce more components in the signal decom- position process. The selection of components was par- ticularly important for fault feature extraction. On the one hand, if too many components were selected, it would cause information redundancy and reduce the calculation efficiency. On the other hand, if too few components were selected, it would not be enough to express the fault characteristic information. Smoothness priors approach could decompose the collected signal into trend item and detrend item [17]. This method effectively reduced the number of decomposed components, which was conducive to the construction feature vectors.

The essence of intelligent fault diagnosis was pattern recognition. Pattern clustering could accurately distinguish fault types. References [18, 19] used support vector machine to realize bearing fault type identification. However, the SVM method can only deal with labeled data points. Most of the collected time series in practical equipment are unlabeled. The clustering method could realize the effective classification of unlabeled time series. According to different theoretical basis, the clustering algorithm could be divided into partition clustering method [20, 21], hierarchy clustering method [22, 23], grid clustering method [24, 25], and density clustering method [26, 27]. The partition clustering algorithm was easily affected by the initial clustering center. When the hierarchical clustering algorithm faced high-di- mensional data sets, the clustering results would fall into local optimization. The clustering quality of the grid clus- tering algorithm depended on the size of grid. Rodriguez and Laio [28] proposed clustering by fast search and found density peaks in 2014, which was called density peaks clustering (DPC) for short. The DPC algorithm could adaptively decide the number of clusters, and it could carry out adaptive clustering in the face of any size data sets.

In conclusion, in view of the problems of lack of self-adaptability in the selection of feature vectors and lower fault diagnosis accuracy in the existing fault diagnosis algorithms based on fault signals, a novel fault diagnosis algorithm was put forward, combined with smoothness priors approach, fluctuation dispersion entropy, and density peak clustering. The main work of this paper is summarized as follows:

1. Compared with the conventional signal decompo- sition algorithms, the collected vibration signals were decomposed into the trend term and detrend term by the SPA algorithm. The SPA method successfully reduced the number of components after decom- position. This method described all the fault feature of the collected vibration signals in two scales, and it avoided the redundancy of feature selection.

2. By using the advantages of good stability and strong noise resistance of the FDE, the FDE of trend term and detrend term was calculated as the fault feature vector. It not only was strong fault description ability, but also improved the stability of fault feature extraction.

3. The advantage of the DPC algorithm was that it did not set cluster number in advance. The SPA-FDE- DPC methods were applied to rotating machinery fault identification, which effectively improved the accuracy of fault recognition.

The rest of this paper is constructed as follows. Section 2 presents the essential theories of the SPA, FDE, and DPC methods. Section 3 discusses the selection of the relevant parameters. In Section 4, the effectiveness of the proposed approach is proven by using the experimental data of roat- ing machinery. In addition, contrastive analysis between the various algorithms is executed in Section 4. Finally, some conclusions are summarized in Section 5.

2. Methodologies

2.1. Smoothness Priors Approach. The SPA method was first applied to human ECG signal processing. The calculation process of the SPA is relatively simple. The trend term and detrend term of the original signal can be quickly
decomposed by selecting single parameter. The SPA algorithm presumes that the original signal $X$ consists of two parts:

$$X = X_0 + X_1,$$  \hspace{1cm} (1)

where $X_0$ is a trend term, $X_1$ is a detrend term, and it could be represented as

$$X_i = H\theta + \nu,$$  \hspace{1cm} (2)

where $H \in R_{M \times N}$ is the observation array, $R$ expresses the real number field, $M$ expresses the number of sample rows, $N$ expresses the sample attribute, $\nu \in R_{N \times 1}$ is the observation deviation, and $\theta \in R_{N \times 1}$ is the regression coefficient; the algorithm was changed into an optimum seeking method to calculate the regression coefficient $\theta$; therefore $X_i = H\theta$ could calculate the trend term in the original vibration signal. We usually use the least square algorithm to calculate the parameters. The SPA algorithm employs the differential parameters $\|D_d (H\theta)\|$ to the simplified calculation process and optimizes it to assure that $H\theta$ filters out the trend term of the original vibration signal:

$$\hat{\theta}_I = \arg \min \theta \{ \| H\theta - X \|^2 + \lambda^2 \| D_d (H\theta) \|^2 \},$$  \hspace{1cm} (3)

where $\lambda$ expresses the positive regularization parameter, and $D_d$ expresses the order of the differential calculation matrix. Through derivation and calculation, the formula of $D_d$ is as follows:

$$D_d = \begin{bmatrix} \frac{d(X_{1d})}{dX_1} & \cdots & \frac{d(X_{Nd})}{dX_N} \\ \vdots & \ddots & \vdots \\ \frac{d(X_{1d})}{dX_1} & \cdots & \frac{d(X_{Nd})}{dX_N} \end{bmatrix},$$  \hspace{1cm} (4)

The solution in formula (4) is

$$\hat{\theta}_I = \left( H^T H + \lambda^2 H^T D_d^T D_d H \right)^{-1} H^T X,$$  \hspace{1cm} (5)

The observation matrix $H$ could be received by studying the feature of the original data series $X$. For the sake of calculation, $H$ employs the unit matrix $I \in R^{N \times N}$. When the order of the matrix $D_d$ is set to 2, the trend item can be easy to calculate. Therefore, the order of the matrix $D_d$ is set to 2, and it can be presented as

$$D_2 = \begin{bmatrix} 1 & -2 & 1 & \cdots & 0 \\ 0 & 1 & -2 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & 1 & -2 & 1 \end{bmatrix}.$$  \hspace{1cm} (6)

After eliminating the trend item $X_n$ the detrend component $X_i$ can be further calculated as

$$\hat{X}_i = X - H\hat{\theta}_I = \left[ I - \left( I + \lambda^2 D_d^T D_d \right)^{-1} \right] Z = UZ,$$  \hspace{1cm} (7)

where $U = \left( I - \left( I + \lambda^2 D_d^T D_d \right)^{-1} \right)$, and there is $\hat{X}_i = UZ$.

In formula (7), the matrix $U$ is equal to a high-pass filter. The frequency feature can be received by conducting Fourier transform of the matrix $U$.

2.2. Fluctuation Dispersion Entropy. The FDE is a novel algorithm to describe the complex features of the collected signals and the dynamic change of signal fluctuation. The FDE values of the collected signals of length $N$: $X = \{x_1, x_2, \cdots, x_N\}$ were expressed as follows:

**Step 1.** The normal distribution function was used to map the times series $X$ to $Y = \{y(1), y(2), \cdots, y(N)\}$

$$y(j) = \frac{1}{\delta \sqrt{2\pi}} \int_{-\infty}^{x(j)} e^{-(t-\mu)^2/2\sigma^2} dt,$$  \hspace{1cm} (8)

where $\delta$ expresses the standard deviation of the $X$, and $\mu$ expresses the mean of the $X$.

**Step 2.** Using linear distribution map each $y(j)$ to an integer value from 1 to $c$

$$z(j) = \text{Int}(c \times y(j) + 0.5),$$  \hspace{1cm} (9)

where $c$ expresses an integer value, and $\text{Int}$ expresses the rounding function.

**Step 3.** For classification sequence $Z = \{z(1), z(2), \cdots, z(N)\}$, with embedding dimension $m$ and time delay $\tau$, the embedding vector $Z_{\text{md},c} = \{Z_{\text{md},c}(1), Z_{\text{md},c}(2), \cdots, Z_{\text{md},c}(N-(m-1)d)\}$ was expressed as

$$Z_{\text{md},c}(1) = \{z(1), z(1 + d), \cdots, z(1 + (m-1)d)\},$$

$$Z_{\text{md},c}(2) = \{z(2), z(2 + d), \cdots, z(2 + (m-1)d)\},$$

$$\vdots$$

$$Z_{\text{md},c}(N-(m-1)d) = \{z(N-(m-1)d), z(N-(m-2)d), \cdots, z(N)\}.$$  \hspace{1cm} (10)
Step 4. Compute the difference between neighbor elements in the embedded vector \( Z^{m,d,c} = \{\overline{Z}^{m,d,c}(1), \ldots, \overline{Z}^{m,d,c}(N - (m - 1)d)\} \) to obtain \( F^{m,d,c} \). \( F^{m,d,c} \) was defined as

\[
\begin{align*}
F^{m,d,c}(1) &= \{z(1 + d) - z(1) + c, \ldots, z((m - 1)d) - z(1 + (m - 2)d) + c\}, \\
F^{m,d,c}(2) &= \{z(2 + d) - z(2) + c, \ldots, z((m - 1)d) - z(2 + (m - 2)d) + c\}, \\
&\vdots \\
F^{m,d,c}(N - (m - 1)d) &= \{z(N - (m - 2)d) - z((N - m - 1)d) + c, \ldots, z(N) - z(N - (m - 2)d) + c\}.
\end{align*}
\]

Step 5. \( F^{m,d,c}(j) = \{z(j + d) - z(j) + c, \ldots, z((m + 1)d) - z(j + (m - 2)d) + c\} \) was allotted to the dispersion pattern \( \pi_{n_1}^{v_1} \wedge \ldots \wedge v_{(m-2)} \) where \( v_0 = z(j + d) - z(j) + c \), \( v_1 = z(j + d) - z(j) + c, \ldots, v_{(m-2)} = z((j + 1)d) - z(j + (m - 2)d) + c \). The number of probable dispersion modes that could be allocated to each embedded vector \( Z^{m,d,c} \) was equivalent to \((2c - 1)^{(m-1)}\). For each probable dispersion mode \( \pi_{n_1}^{v_1} \wedge \ldots \wedge v_{(m-2)} \), its relative frequency value \( p(\pi_{n_1}^{v_1} \wedge \ldots \wedge v_{(m-2)}) \) was expressed by

\[
p(\pi_{n_1}^{v_1} \wedge \ldots \wedge v_{(m-2)}) = \frac{\text{number}\left\{j\mid j \leq N - (m - 1)d, \overline{F}^{m,d,c}(j) \text{ has type} \pi_{n_1}^{v_1} \wedge \ldots \wedge v_{(m-2)} \right\}}{N - (m - 1)d}.
\]

Using some simulation signals to compare the capability of the FDE and DE, the constructed simulation signals \( y_1, y_2, \) and \( y_3 \) could be expressed as follows:

\[
\begin{align*}
x_1 &= 0.6 \cos(60\pi t), \quad 0 \leq t \leq 1, \\
x_2 &= 0.8 \cos(300\pi t), \quad 0.3 \leq t \leq 0.7, \\
y_1 &= x_1 + x_2, \\
y_2 &= x_1 + 3x_2, \\
y_3 &= x_1 + x_2 + 1.4,
\end{align*}
\]

where the signal sampling frequency was set to 2 kHz. It could receive the sensitivities of the two different algorithms to the signals oscillation amplitude by calculating the FDE and DE values of the \( y_1, y_2, \) and \( y_3 \). The FDE and DE values of the three constructed simulation signals are displayed in Table 1.

| Signal | FDE | DE |
|--------|-----|----|
| \( y_1 \) | 0.3 | 0.2 |
| \( y_2 \) | 0.4 | 0.3 |
| \( y_3 \) | 0.5 | 0.4 |

These three constructed simulation signals have different amplitude values. It could be found from Table 1 that the similar DE values were calculated for these three dissimilar simulation signals, and the FDE values were different. It could be proved that the DE algorithm did not consider the impact of the signal amplitude in the calculation process and could not accurately discriminate signal types with large amplitude values differences. The FDE algorithm could better measure signals complexity.

2.3. Density Peak Clustering. The main innovation of the DPC algorithm is to obtain the optimal clustering center only through the density and distance between data samples. The core of the algorithm is the selection of clustering centers: (a) The cluster centers were surrounded by adjacent data points with lower local densities. (b) They are at a relatively large distance from any points with higher local density. The detailed calculation steps of the DPC algorithm are as follows:

Step 1. Computing local density. Suppose that the original data point sets with enough labeled samples \( D_n = \{(x_{i}^{\prime}, y_{i}^{\prime})\}_{i=1}^{N} \), where \( x_{i}^{\prime} \) expresses the sample points \( i \) in the original data sets, \( y_{i}^{\prime} \) represents the sample label, and \( N_i \) expresses the number of sample points. The density \( \rho_{i} \) of the data points \( x_{i} \) was computed as

\[
\rho_{i} = \sum_{j} \chi(d_{ij} - d),
\]

where \( d_{ij} \) expresses the distance between \( x_{i} \) and \( x_{j} \), and \( d \) represents cut-off distance. \( \chi(d) \) expresses a function defined by

\[
\chi(d) = \begin{cases} 
1, & d < 0, \\
0, & d \geq 0,
\end{cases}
\]
Table 1: The FDE and DE values of the three constructed simulation signals.

| Algorithm | \( y_1 \) | \( y_2 \) | \( y_3 \) |
|-----------|----------|----------|----------|
| FDE       | 0.1664   | 0.1226   | 0.1479   |
| DE        | 0.4784   | 0.4784   | 0.4784   |

where \( \rho_i \) expresses the local density of \( x_i \), and the value of \( \rho_i \) is equivalent to the number of data points that are closer than \( d_i \) to data point \( x_i \).

**Step 2.** Compute the minimum distance. Based on the principle of the clustering center, it was important to compute the minimum distance \( \delta_i \), which was estimated by the minimum distance between the \( x_i \) and any other point whose local density was higher than that of point \( x_i \):

\[
\delta_i = \min \left\{ d_{ij} \right\}.
\]  

(17)

Facing the data points which have the highest local density, it usually merely let

\[
\sigma_i = \max \left\{ d_{ij} \right\}.
\]  

(18)

**Step 3.** Decide the cluster centers. When all \( \rho_i \) and \( \delta_i \) are computed, it can draw a two-dimensional decision graph. There will be some misjudgment that the cluster centers are decided only through \( \rho_i \) and \( \delta_i \). Therefore, a new method was proposed by the value of \( y_i \) sorted in decreasing order. The calculation method of each \( y_i \) is

\[
y_i = \rho_i \times \delta_i.
\]  

(19)

The external index \( F \)-measure and the internal index silhouette are usually used to assess the clustering results of the DPC method. The definitions of silhouette and \( F \)-measure indicators are as follows.

(a) Silhouette evaluation index:

\[
\text{Sil}(t) = \frac{[z(t) - y(t)]}{\max\{y(t), z(t)\}}
\]  

(20)

In formula (20), \( y(i) \) expresses the average distance of the \( x_i \) to other sample points in the same cluster as \( i \). \( z(i) \) represents the minimum average distance from \( x_i \) to points in a different cluster of which \( x_i \) is not the same member.

(b) \( F \)-measure evaluation index:

\[
F = \frac{2 \times (\text{Recall} \times \text{Precision})}{(\text{Recall} + \text{Precision})}
\]  

\[
\text{Precision} = \frac{TP}{TP + FP}
\]  

(21)

\[
\text{Recall} = \frac{TP}{(TP + FN)}
\]

where \( TP \) is the true positive expressing the number of pair data points having the same categories labels belonging to the same cluster center, \( FP \) is the false positive expressing the number of pair data points having different categories labels belonging to the same cluster center, and \( FN \) is the false negative expressing the number of pair data points having the same categories labels belonging to different cluster center.

3. Parameters Selection of the Fluctuation Dispersion Entropy

During the computing process of the FDE approach, four parameters need to be set in advance: data length \( N \), classes \( c \), embedding dimension \( m \), and time delay \( d \). In order to discuss the performance of various parameters on the FDE entropy results, the FDE values of an actual bearing vibration signal under different parameters are calculated and compared.

Firstly, the effect of the embedding dimension \( m \) on the calculation process of the FDE value is studied. Reference [29] suggests that the better results can be obtained when the embedding dimension \( m \) is set to 2 or 3. The FDE values of vibration signals under various embedding dimensions \( m \) are displayed in Figure 1. By surveying Figure 1, it can be found that the increasing of the \( m \) will lead to the worse stability of the FDE value. However, when the \( m \) is too small, the probability pattern of the reconstructed sequence is less, which will lead to the inability to accurately evaluate the dynamic change of the signal amplitude. When \( m = 3 \), the stability of the FDE reaches the optimal values. So this paper chooses \( m = 3 \).

Secondly, the influence of the classes \( c \) on the FDE value is studied. Reference [30] suggests that the value range of the classes \( c \) is \([4, 8]\). Figure 2 shows the effects of different data lengths \( N \) and classes \( c \) on the FDE values. By observing Figure 2, the FDE changes greatly with the increase of the classes \( c \). However, if the classes \( c \) value is too small, the two data points with difference amplitude may be allocated to the same categories. When \( c = 6 \), the change trend of the FDE value is relatively flat. Therefore this paper sets \( c = 6 \).

Thirdly, the effect of the data length \( N \) on the calculation process of the FDE value is analyzed. The FDE values of vibration signals with different data length \( N \) under different classes \( c \) are shown in Figure 3. With the increasing of \( c \), the data length has little impact on the calculation process of the FDE values when the data length \( N \) is greater than 2048. When \( c = 6 \), the difference of the FDE values of the \( N = 2048 \), \( N = 4096 \), \( N = 8192 \) is less than 0.01. When the \( N \) is greater than 2048, the FDE value tends to be stable. So this paper chooses \( N = 2048 \).

Finally, the influence of the time delay \( d \) on the FDE values was discussed. When \( c = 2–10 \), the relationship between time delay \( d \) and the FDE values is displayed in Figure 4. By observing Figure 4, the FDE values change greatly with the increase of the time delay \( d \). When \( d > 1 \), some frequency information may be lost, which will affect the accuracy of the FDE values. Therefore this paper sets \( d = 1 \).
4. Experimental Process and Analysis

4.1. The Fault Diagnosis Method. The intelligent fault diagnosis algorithm, which combines SPA, FDE, and DPC clustering, has the following feature. The SPA method reduces the number of components after decomposition and avoids the redundancy of the feature selection. Besides, the FDE eigenvector has good stability and strong noise resistance. Finally, the eigenvectors with high sensitivity are input into the DPC method for cluster recognition. The flowchart of the integrated fault diagnosis algorithm based on SPA-FDE-DPC is displayed in Figure 5. The detailed steps of the approach are as follows:

Step 1. Collect original signals of the rotating machinery under various work states with sensors.

Step 2. The original signals under various work states are decomposed into the trend term and detrend term by SPA algorithm.

Step 3. Calculate the FDE of the trend term and detrend term of the signals in different conditions, and construct the eigenvector matrix.

Step 4. The eigenvector matrix is input into the DPC clustering method for cluster recognition. The clustering evaluation index is used to quantitatively assess the clustering performance of the proposed algorithm.

4.2. Case Study 1: Rolling Bearing Fault Diagnosis

4.2.1. Rolling Bearing Experimental Data. In order to verify the effectiveness, the proposed scheme was employed to the experimental datasets shared by Case Western Reserve University (CWRU) Bearing Data Center [31]. Using the collected vibration data by the sensor at the motor driving end, the experimental conditions were set as follows: the sample frequency was 12 kHz; the motor speed was...
1772 rpm. Consider the normal signal (NR), inner race fault signal (IRF), ball fault signal (BF), and outer race fault signal (ORF), where IRF, BF, and ORF were selected for two various diameters (0.007 and 0.021 mils), and finally a total of 7 states were selected. Each condition included 50 samples with a length of 2048 points. The details of the data used in the experiment are listed in Table 2. Figure 6 displays the time-domain waveform of the collected vibration signals under various states, from which it can be seen that these collected signals are obviously nonstationary and nonlinear characteristics, and it is difficult to distinguish these signals directly.

4.2.2. Rolling Bearing Fault Identification. Firstly, taking the BF07 as an example, the collected vibration signal is decomposed by SPA to acquire the trend term and detrend term, and the decomposition results are displayed in Figure 7. By observing Figure 7, it can be found that the trend term retains the basic feature of the decomposition signal, and the distinction between the trend term and the detrend term is obvious. The rationality of multiscale decomposition of signal is effectively shown by the SPA algorithm.

In order to compare with other algorithms, the collected signal of the BF07 is also decomposed by ensemble empirical mode decomposition (EEMD). After EEMD decomposition, 11 IMF components and 1 trend item are acquired, and the number of components acquired is much larger than the SPA method. The first six IMF components are selected for display in Figure 8. It is generally considered that the first two components retain the core fault information of vibration signal, and the eigenvalues of the first two components are calculated as eigenvectors. However, after EEMD decomposition, the correlation coefficient of IMF1 and IMF2 is 0.958, while after SPA decomposition, the correlation coefficient of trend term and detrend term is 0.091. It shows that the discrimination between IMF1 and IMF2 component is small, and there will be some difficulties in subsequent feature extraction.

Then, calculating the FDE values of trend term and detrend term to obtain 7 groups 2 × 50 FDE eigenvectors, the average value is displayed in Table 3. By observing Table 3, it can be found that the FDE values of trend item and detrend item of various bearing signals have good discrimination. It proves that the complexity of the signals under various working states are different. Therefore, selecting the FDE of trend term and detrend term as the eigenvector can fully describe the fault characteristic information of different signal states.

Finally, all the 2 × 350 groups of the FDE values are input into the DPC algorithm, and Figure 9 displays the clustering results. The decision graph produced by the SPA-FDE-DPC algorithm is displayed in Figure 9(a). The red round solid data points express the cluster centers in the decision graph. It can be found that the number of the clusters is seven, which is equivalent to the actual number of fault types. The specific clustering results of the proposed scheme are displayed in Figure 9(b). It can be found that the seven states of the rolling bearing are obviously separated. The seven data samples are clustered near their respective cluster centers according to the fault type, and the distance between each cluster center is far. The data points of the same fault type are closely distributed, and there is no cross aliasing between different fault types. It shows that the proposed algorithm has better fault classification performance in the diagnosis of different bearing fault types.

4.2.3. Methods Comparison and Analysis. In order to explain the superiority of the proposed approach, this paper compares the signal decomposition and feature extraction method. The extracted feature vectors by SPA + DE, EEMD + FDE, and EEMD + DE are, respectively, input into the DPC clustering, and Figures 10–12 display the clustering results:

(1) By analysis in Figures 9–12, it can be found that SPA + FDE/DE has better clustering effect than EEMD + FDE/DE. This is because there is noise in the feature vector extracted by EEMD + FDE/DE. The first two components decomposed by EEMD are selected as feature vectors, which do not fully reflect all fault feature information of vibration signal. The correlation coefficients of the first two components after EEMD decomposition are large, resulting in small difference of feature vectors, so the effect of fault clustering is poor.

(2) Observing Figures 9 and 10, it can be found that SPA + DE has poor clustering effect and many wrong classification points. This shows that FDE is more accurate than DE in expressing the characteristic information of fault signal.

The clustering results of four fault diagnosis methods are evaluated by silhouette and F-measure, and Table 4 displays specific quantitative evaluation results. It can be found that the fault accuracy of the SPA + FDE + DPC method reaches 100%. Moreover, the silhouette and F-measure index of the proposed approach have the highest value in these compared methods. It reveals that the proposed approach has optimal fault diagnosis effect compared with the compared integrated methods.

4.3. Case Study 2: Gearbox Fault Diagnosis

4.3.1. Gearbox Experimental Data. To demonstrate the validity of the proposed approach in the gearbox fault classification, the dataset was taken from the experimental platform QPZZ-II by Jiangsu Qingpeng Diagnosis Engineering Co., Ltd [32]. The working conditions were set as follows: the signal sample frequency was 5.12 kHz; the motor speed was 880 rpm. In the experiment, a total of five working
Table 2: The details of the datasets for rolling bearing experiment.

| Signal type         | Labels | Fault diameters (mils) | Number of sample | Data length |
|---------------------|--------|------------------------|------------------|-------------|
| Normal              | NR     | 0                      | 50               | 2048        |
| Inner race fault    | IRF07  | 7                      | 50               | 2048        |
|                     | IRF21  | 21                     | 50               | 2048        |
| Ball fault          | BF07   | 7                      | 50               | 2048        |
|                     | BF21   | 21                     | 50               | 2048        |
| Outer race fault    | ORF07  | 7                      | 50               | 2048        |
|                     | ORF21  | 21                     | 50               | 2048        |

Figure 6: Time-domain vibration signals for rolling bearing under various working states: (a) NR; (b) IRF07; (c) BF07; (d) ORF07; (e) IRF21; (f) BF21; (g) ORF21.

Figure 7: The SPA decomposition results of the BF07: (a) BF07; (b) trend terms; (c) detrend terms.
Figure 8: The first six IMF components of EEMD for the BF07 signal: (a) IMF1; (b) IMF2; (c) IMF3; (d) IMF4; (e) IMF5; (f) IMF6.

Table 3: The FDE of the trend and detrend of the rolling bearing under various states.

| Signal type | Trend  | Detrend |
|-------------|--------|---------|
| NR          | 0.654  | 0.269   |
| IRF07       | 0.774  | 0.386   |
| BF07        | 0.791  | 0.343   |
| ORF07       | 0.716  | 0.416   |
| IRF21       | 0.736  | 0.335   |
| BF21        | 0.816  | 0.326   |
| ORF21       | 0.635  | 0.325   |

Figure 9: The clustering result of the rolling bearing by using the SPA-FDE-DPC: (a) decision graph and (b) clustering result.
Statues were considered involving the normal condition (NC), gear pitting (GP), gear breaking (GB), pinion wear (PW), and gear pitting compound pinion wear (GP + PW). Due to the limited length of the collected sample data, a gliding sample window with a length of 2048 and a moving step of 1024 is employed. Each condition includes 50 samples with a length of 2048 data points. Table 5 displays the experimental sample description of the gearbox. The vibration signal waveform of the gearbox under various states is displayed in Figure 13. By observing Figure 13, the gearbox fault condition cannot be distinguished because their amplitude features are similar.

4.3.2. Gearbox Fault Identification. The collected vibration signal of the gearbox is analyzed by the same processing method. Firstly, use the SPA method to decompose the vibration signal under various states to obtain the trend term and detrend term. Secondly, calculate the FDE of trend and detrend term to obtain 5 groups $2 \times 50$ FDE eigenvectors, and the average values are displayed in Table 6. By observing Table 6, it can be found that the extract feature vectors are different, and it can effectively distinguish different fault states.

Finally, all the $2 \times 250$ groups of the eigenvectors are input into the DPC algorithm, and Figure 14 displays the clustering results. From the decision diagram in
Figure 12: The clustering result of the rolling bearing by using the EEMD-DE-DPC: (a) decision graph and (b) clustering result.

Table 4: The evaluation indexes of the rolling bearing under various fault diagnosis methods.

| Fault diagnosis methods    | Accuracy (%) | Silhouette | F-measure |
|----------------------------|--------------|------------|-----------|
| SPA + FDE + DPC            | 100          | 0.992      | 1         |
| SPA + DE + DPC            | 95.43        | 0.724      | 0.862     |
| EEMD + FDE + DPC          | 91.14        | 0.618      | 0.731     |
| EEMD + DE + DPC           | 86           | 0.476      | 0.677     |

Table 5: Experimental sample description of the gearbox.

| Signal type                          | Labels  | Number of sample | Data length |
|--------------------------------------|---------|------------------|-------------|
| Normal condition                     | NC      | 50               | 2048        |
| Gear pitting                         | GP      | 50               | 2048        |
| Gear breaking                        | GB      | 50               | 2048        |
| Pinion wear                          | PW      | 50               | 2048        |
| Gear pitting compound pinion wear    | GP + PW | 50               | 2048        |

Figure 13: Continued.
Figure 14(a), it can be found that the gearbox fault types are five. By surveying Figure 14(b), it can be found that the sample data of the gearbox are divided into five fault types, and there is no aliasing phenomenon among them.

4.3.3. Methods Comparison and Analysis. Similar to case study 1, this paper conducts some contrast experiments to demonstrate the superiority of the proposed approach in the gearbox compared to the SPA + DE + DPC, EEMD + FDE + DPC, and EEMD + DE + DPC. The clustering results are shown in Figures 15–17:

1) By analysis of Figures 14–17, it can be found that the sample data of SPA + FDE/DE has good aggregation. This is because more components are obtained by EEMD decomposition of the collected signal. Moreover, the time-domain characteristics of the first two components after EEMD decomposition are too similar; the difference of feature vectors is small.

2) Observing Figures 14 and 15 it can be found that the SPA + FDE has no wrong classification points. This shows that FDE has stronger ability to obtain fault characteristic information of signal.

| Signal type | Trend  | Detrend |
|-------------|--------|---------|
| NC          | 0.853  | 0.505   |
| GP          | 0.772  | 0.523   |
| GB          | 0.743  | 0.522   |
| PW          | 0.673  | 0.504   |
| GP + PW     | 0.703  | 0.532   |

Table 6: The FDE of trend and detrend of the gearbox under various states.
Figure 15: The clustering result of the gearbox by using the SPA-DE-DPC: (a) decision graph and (b) clustering result.

Figure 16: The clustering result of the gearbox by using the EEMD-FDE-DPC: (a) decision graph and (b) clustering result.
The clustering index is used to evaluate the four diagnosis methods, and Table 7 displays the calculation results. It can be found from Table 7 that SPA+FDE+DPC has the highest fault accuracy compared with the other three integrated methods. The silhouette and F-measure value of the proposed method are close to 1.

5. Conclusions
In order to overcome the defects of traditional fault feature extraction methods, this paper presents a novel fault diagnosis algorithm of SPA-FDE-DPC, which can accurately identify the fault types. The effectiveness and feasibility of the proposed approach are confirmed by the experimental data of the rolling bearing and gearbox. This paper can summarize the following conclusions:

1. The SPA algorithm is a novel signal processing approach, which avoids the data redundancy and interference caused by too many eigenvectors in the traditional signal decomposition methods.
2. The FDE is a new type of entropy, which is more stable than DE and more appropriate for feature extraction.
3. The proposed approach is used for the experimental data of the rolling bearing and gearbox under various working states; the SPA-FDE-DPC method can effectively identify fault type. Comparing with the other three combination algorithms, the proposed approach has better separation and higher recognition rate in the fault diagnosis.

Data Availability
The rolling bearing data used in the manuscript can be downloaded from the open-source database: https://engineering.case.edu/bearingdatacenter/download-data-file. The gear data used in the manuscript can be downloaded from the open-source database: https://download.csdn.net/download/wdddongcheng/11151037.

Conflicts of Interest
The authors declare that there are no conflicts of interest regarding the publication of this paper.

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