A New Interpretable Learning Method for Fault Diagnosis of Rolling Bearings

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***Abstract*— In modern manufacturing processes, requirements for automatic fault diagnosis have been growing increasingly as it plays a vitally important role in the reliability and safety of industrial facilities. Rolling bearing systems represent a critical part in most of the industrial applications. In view of the strong environmental noise in the working environment of rolling bearing, its vibration signals have nonstationary and nonlinear characteristics, and those features are difficult to be extracted. In this article, we proposed a new intelligent fault diagnosis method for rolling bearing with unlabeled data by using the convolutional neural network (CNN) and fuzzy *C*-means (FCM) clustering algorithm. CNN is first utilized to automatically extract features from rolling bearing vibration signals. Then, the principal component analysis (PCA) technique is used to reduce the dimension of the extracted features, and the first two principal components are selected as the fault feature vectors. Finally, the FCM algorithm is introduced to cluster those rolling bearing data in the derived feature space and identify the different fault types of rolling bearing. The results indicate that the newly proposed fault diagnosis method can achieve higher accuracy than other existing results in the literature.**

***Index Terms*— Convolutional neural network (CNN), fault diagnosis, fuzzy *C*-means (FCM), principal component analysis (PCA), rolling bearing.**

I. Introduction

MACHINERY and equipment occupy a very important position in modern society. As one of the most important and common parts of rotating machinery, rolling bearing plays an important role in the whole mechanical system. However, mechanical equipment is often affected by different types of undesirable faults during operation, which causes additional costs and losses in production time [1]. Among them, the mechanical failure caused by the failure of rolling bearing to use normally accounts for about 30% of the total failure. The failure of rolling bearings is caused by a variety of factors, such as incorrect design or installation, acidic liquid corrosion, lack of lubricating oil, and plastic deformation. Fault diagnosis of the rolling bearing by the state monitoring technology has been an attractive research topic in the past two decades. During the operation of the bearing, a pulse vibration signal is generated when the roller passes through the defect at a frequency determined by the bearing speed, the number of rolling bodies, the diameter of rolling bodies, the bearing pitch diameter, and the contact angle of rolling bodies, and the state monitoring technique based on vibration has always been the most common technique in this field. The difficulty of rolling bearing fault diagnosis is that the characteristic signal of rolling bearing is distributed in a wide frequency band, so it is easy to be disturbed by noise [2]. In view of the fact that the vibration signals of rolling bearings have nonstationary and nonlinear features and it is, thus, difficult to extract fault features, how to design effective fault diagnosis methods has become the attractive research focus in recent years.

On the other hand, deep learning (DL) architectures have attracted increasing attention in various fields. Various DL architectures, such as convolutional neural network (CNN) [3], deep belief network (DBN) [4], sparse autoencoder [5], and recurrent neural network [6], are widely used in the field of fault diagnosis of mechanical equipment. Compared with traditional methods, fault diagnosis based on the DL technique has advantages, such as faster and more accurate in diagnosis. Among these DL architectures, the architecture based on CNN has shown the best performance. However, CNN was originally designed for image processing and analysis. In order to apply the powerful processing and analysis capabilities of 2-D-CNN from the image processing area to the field of fault diagnosis, researchers began to convert 1-D vibration signals into 2-D spectrograms and then used 2-D-CNN to analyze the generated 2-D image format of fault data [7], [8]. Recently, several works have applied CNN directly to 1-D signals (see [9]). CNN is a typical supervised learning deep neural network that can extract hidden features from the original data set. At present, most fault diagnosis models based on CNN are classified by CNN directly. In order to make the neural network better perform the prediction function, researchers have combined them with advanced algorithms or statistical methods in other fields. Some classical combinatorial models, such as the combination of neural network and support vector machine [10], neural network and empirical mode decomposition (EMD) method [11], BP neural network and optimal wavelet tree [12], neural network and wavelet transform [13]–[15], neural network, and particle swarm optimization algorithm [16]. Therefore, how to build a comprehensive prediction model to improve the accuracy of

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model prediction has become a challenging work in the field of intelligent fault diagnosis.

Although some DL models have shown powerful functions in classification and regression prediction tasks, these models remain elusive black boxes. This is a key obstacle for the wide application of DL technology and the bottleneck for its further development. It is clear that users will never trust a model that cannot reasonably explain the solution. On the other hand, the fuzzy system is easier to understand in design, and the combination of fuzzy theory and classification algorithm has gradually come into our vision. In the clustering method, the hard c-means process is an outstanding traditional clustering method, which controls each mapping of data set into a cluster. Fuzzy c-means (FCM) evolved from k-means clustering has better classification performance. FCM clustering algorithm is an unsupervised clustering technique and one of the most widely used fuzzy clustering models [17]. The FCM algorithm achieves the fuzzy classification of samples to categories by determining the membership of samples to categories, making the classification results of target data more reasonable.

In many fault diagnosis results, the accuracy of fault diagnosis based on FCM has been greatly improved, but there still exist some problems, e.g., the original signals cannot always be extracted effectively due to the high dimension of features or data, which may greatly degrade the performance of fault diagnosis. In view of the problem that the features of some original signals cannot be extracted effectively, some researchers have used methods, such as EMD [18], ensemble EMD (EEMD) [19], variational mode decomposition (VMD) [20], and DBN [21] to extract the features of the original signals, and some better results have been achieved. However, it is still impossible to distinguish effectively for some special signals [22].

In this article, a new intelligent fault diagnosis method for machinery is proposed by using the CNN and FCM clustering algorithm. It is very challenging to identify the characteristics of rolling bearings in different states subject to nonstationary and nonlinear noise, and the proposed comprehensive prediction model first uses CNN as an automatic feature extractor, adopt the principal component analysis (PCA) to reduce the dimension of the extracted features, then introduce the FCM clustering algorithm to cluster the data set in the feature space. Finally, the test was carried out through the standard data published by the Bearing Data Center of the Western Reserve University, USA [23]. With the existing fault diagnosis method based on a neural network to classify directly, our classifier does not need a lot of time to train nor does it require a large number of learning samples. Thus, it greatly shortens the time of diagnosis, which can be used for real-time diagnosis. In addition, the clustering performance and identification accuracy are superior to the existing results.

II. Methodology

CNN plays an excellent role in fault diagnosis and has been extensively applied, especially in vibration analysis. However, CNN is still regarded as an unexplainable "black box" that cannot convince users. In order to overcome this weakness,

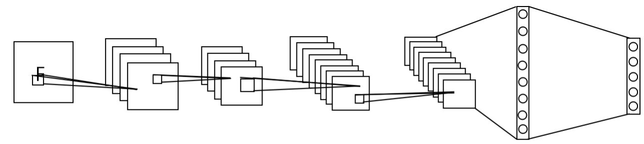

Fig. 1. Structure of CNN.

this article proposes a fault diagnosis model for rolling bearings based on CNN and FCM. By virtue of the powerful feature extraction function of CNN, this model reduces the dimension of extracted features through PCA and then inputs to FCM with clear physical interpretation for classification. First, the theoretical framework of CNN, PCA, and FCM models is introduced, and then, the overall structure of our method is described and discussed technically.

A. Feature Extraction

In recent years, DL has gradually replaced traditional intelligent algorithms as the mainstream, and it has been extensively applied in the areas of speech recognition, image recognition, and data mining. Compared with the traditional feature extraction algorithms, the features extracted through DL are more discriminative, thereby improving the accuracy of classification. However, most fault diagnosis methods apply DL to fault classification or data after signal processing transformation, and the adaptive feature extraction capability of DL is not fully exerted, which limits the further mining of original signals by DL algorithms. In order to give full play to the feature extraction ability of DL, the method proposed in this article uses CNN in DL as a feature extractor and takes the original vibration signal as an input to give full play to CNN's feature extraction capabilities and improve model fault diagnosis capabilities. In 1994, Le Cun and Bengio [24] proposed the CNN model for the first time, inspired by the information received by the human brain. With the in-depth study of CNN, Le Cun and Bengio [24] proposed a LeNet-5 CNN model for character recognition. The CNN model is basically composed of a convolutional layer, pooling layer, and fully connected layer, as shown in Fig. 1. In the subsequent research and practical applications in the literature, CNN plays an excellent role in feature extraction of the original data, and it is widely used in data mining, computer vision, natural language processing, face recognition, and other fields. CNN only perceives the local information and then synthesizes the local information at a higher level to obtain global information. The basic structure of CNN includes two layers: 1) feature extraction layer and 2) feature mapping layer. The convolution layer applies convolution operation to transform the input data, and the convolutional layer is calculated as follows:

$$a_j{}^l = \sum_{i \in M_j} X_i{}^{l-1} * K_{ij}{}^l + b_j{}^l, \quad X_j{}^l = f\left(a_j{}^l\right) \tag{1}$$

where $X_j{}^l$ denotes the activation value of the jth feature map in layer l; M_j is the number of feature maps of this layer; $X_i{}^{l-1}$ is the jth feature map of layer l; $K_{ij}{}^l$ is the weight

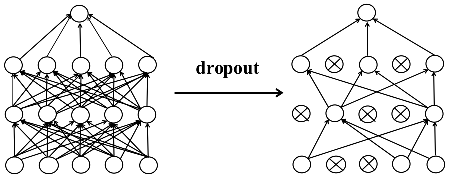

Fig. 2. Neural network model based on the dropout.

matrix; ${b_j}^l$ is biased; and "$*$" is the convolution operator. $f(\cdot)$ is the nonlinear activation function, which introduces the nonlinearity into the multilayer neural network. In order to improve the training speed and the network generalization ability, a batch normalization layer is implemented. Next, to increase the training speed of the CNN model and overcome the problem of gradient disappearance, a nonlinear activation function, such as a rectified linear unit (ReLU), is necessary. The ReLU activation function has nonlinear characteristics in the feature extraction process, and the training effect is better. The mathematical expression is

$$f(x) = \max\{0, x\}. \tag{2}$$

A pooling layer is added between the successive convolutional layers, and by reducing the dimension of the feature graph, the number of parameters to be trained for the model is reduced to avoid the occurrence of overfitting. The pooling layer enhances the robustness of feature extraction through the lower sampling factor. Typical pooling operations are divided into mean pooling and max pooling. Pooling reduces the output image by a factor of L in both dimensions by taking a region (Lx $\times$ Ly) and outputting a value that is the mean or maximum of the region. The pooling function is expressed as strict downsampling without filtering: downsample$(\cdot)$, For every ${X_j}^l$, there is

$${S_j}^l = \text{downsample}\left({X_j}^l\right). \tag{3}$$

The number of parameters of the CNN model is huge, and the model is complex. Although it has demonstrated powerful functions, when the experimental data are relatively small, the overfitting phenomenon may occur. In other words, the model can show high accuracy in the training set, but the prediction accuracy is poor in the test set, which will lead to poor prediction performance. In order to avoid the occurrence of overfitting, the dropout regularization method is adopted, and the dropout layer is added after the full connection layer, as shown in Fig. 2. By setting parameters, the neurons in the full connection layer will be deactivated with a certain probability. The experiment proves that dropout is the most effective method to reduce the phenomenon of deep neural network overfitting and improves the generalization ability of CNN so that CNN can perform well in the test set.

B. Feature Dimension Reduction

By the fact that the dimension of feature vector extracted by CNN is usually high, the PCA technique is adopted to reduce the dimension of the eigenvectors. PCA is a dimensionality reduction method often used to reduce the dimensionality of large data sets, and it converts the large variable set to a smaller set that still contains most of the information in the large variable set, which makes machine learning algorithms easier and faster to analyze data without having to deal with irrelevant variables. Assuming that the sample set A is an $q \times p$ matrix, where q represents samples and p represents feature dimensions, x_i is the eigenvector of the ith sample in our original vector space

$$x_i = \left(x_{i1}, x_{i2}, \ldots, x_{ip}\right)$$
$$A = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{q1} & x_{q2} & \cdots & x_{qp} \end{bmatrix}. \tag{4}$$

For the standardized transformation of the data set, the mean value and variance are first obtained

$$\overline{x}_j = \frac{\sum_{i=1}^{q} x_{ij}}{q} \tag{5}$$

$$s_j^2 = \frac{\sum_{i=1}^{q} \left(x_{ij} - \bar{x}_j\right)^2}{q-1} \tag{6}$$

where q is the number of sample sets, x_{ij} is the jth dimension eigenvalue of the ith sample, $\overline{x}_j$ is the mean value on the jth dimension of the original high-dimensional vector space, and s_j^2 is the variance on this component; the standardized data set is

$$\tilde{x}_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}, \quad (i = 1, 2, \ldots, q;\ j = 1, 2, \ldots, p). \tag{7}$$

PCA seeks the projection direction of the maximum variance and sets the projection direction of the maximum variance as the unit column vector of a, and the objective function is

$$\text{argmax}_{\upsilon} = \frac{1}{2} \sum_{i=1}^{q} \frac{1}{q-1} (\tilde{x}_i\, a)^2 \tag{8}$$

where a^{T} is the transpose matrix of a, which satisfies the following constraint conditions:

$$a^{\mathrm{T}} a = 1. \tag{9}$$

Construct the Lagrange multiplier

$$L(\upsilon) = \frac{1}{2} \sum_{i=1}^{q} \frac{1}{q-1} (\tilde{x}_i\, \upsilon)^2 + \lambda\left(1 - a^{\mathrm{T}} a\right) \tag{10}$$

among them

$$\text{Cov} = \sum_{i,j=1}^{q} \frac{1}{q-1} \left(\tilde{x}_i \ \cdot \ \tilde{x}_j^{\mathrm{T}}\right) = \frac{1}{q-1} \tilde{x}^{\mathrm{T}} \cdot \tilde{x}. \tag{11}$$

To solve the characteristic equation $|\text{Cov} - \lambda I_m| = 0$ of the covariance matrix Cov, m characteristic roots are obtained. For each λ_j, $j = 1, 2, \ldots, m$, solve the system of equations $\text{Covb} = \lambda_j b$ and get the unit feature vector b_j.

Construct the dimension reduction transformation matrix

$$U_{ij} = \tilde{x}_i b_j, \quad j = 1, 2, \ldots, m. \tag{12}$$

It is obvious that the variance projected on the direction of the first principal component (the eigenvector with the largest eigenvalue) is the largest, which reflects that the information loss after the extraction of the principal component feature is the smallest [25].

C. Fault Identification

FCM integrates the essence of fuzzy theory and is an effective algorithm to realize automatic data classification. This algorithm is widely used in image segmentation and pattern recognition areas and has high accuracy and clear physical interpretation. Therefore, the FCM algorithm is selected as the main algorithm for fault classification and identification of rolling bearing. Compared with k-means hard clustering, FCM provides more flexible clustering results. Aiming at minimizing the Euclidean distance and the weighted sum of fuzzy membership of all data points and each clustering center, FCM constantly modifies the clustering center and classification matrix to meet the termination criteria and clusters data samples with similar characteristics into one class [26], [27].

FCM is a process of iteratively calculating membership u_{pq} and clustering center ρ_q until they reach the optimal, which is to minimize the objective function J_m [28], [29]. For a single sample, the membership of each clustering center is 1. The specific steps of FCM are as follows.

1) Determine the number of clustering centers ρ and fuzzy coefficient $\sigma = 2$, and initialize the clustering centers and membership matrix.
2) Calculate the clustering centers $\gamma = [\rho_q]$ according to the following equation:

$$\rho_q = \frac{\sum_{p=1}^{\mu} u_{pq}^{\sigma} x_p}{\sum_{p=1}^{\mu} u_{pq}^{\sigma}} \tag{13}$$

where σ is the fuzzy coefficient; p and q are the class labels; p is the pth sample; x is a sample with d dimensions; and u_{pq} represents the membership of sample x_p belonging to class q. ρ_q is the center of the q cluster and also has d dimensions.
3) The Euclidean distance between the sample point and the clustering center is calculated to update the membership u_{pq}

$$u_{pq} = \frac{1}{\sum_{\upsilon=1}^{\gamma} \left(\frac{\|x_p - \rho_q\|}{\|x_p - \rho_\upsilon\|} \right)^{\frac{2}{\sigma - 1}}} \tag{14}$$

where $\|*\|$ could be any metric that represents distance.
4) Compute the objective function J_m

$$J_m = \sum_{p=1}^{\mu} \sum_{q=1}^{\gamma} u_{pq}^{\sigma} \|x_p - \rho_q\|^2, \quad 1 \le \sigma \le \infty. \tag{15}$$

5) Determine whether the iteration termination condition is satisfied

$$\max\left\{ \left| u_{pq}^{(\upsilon+1)} - u_{pq}^{(\upsilon)} \right| \right\} < \varepsilon \tag{16}$$

where υ is the number of iterations steps and ε is the error threshold.

Stop the iteration if the termination condition is met; otherwise, return to Step 2 to continue the iteration.

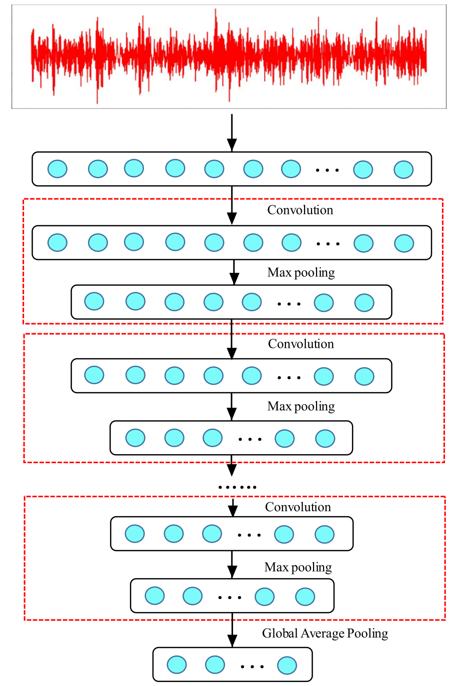

Fig. 3. Structure of the proposed network of CNN.

The above expression means that, if the iteration continues, the membership degree will only change slightly; in this scenario, the optimal solution has been found. This process converges to the local minimum or saddle point of the target J_m.

D. Model Design

In this section, the implementation of our proposed fault diagnosis approach is introduced.

The model is composed of three parts: feature extraction, dimension reduction, and fault classification. In the feature extraction segment, as shown in Fig. 3, the CNN model consists of five standard convolution layers, and a global average pooling layer, a batch normalization layer, and a maxpooling layer follow each standard convolution layer. The parameters of the proposed model are represented in Table I. In the CNN method, the convolution kernel is used to describe the local characteristics of the data, and the parameters of each convolution kernel are determined by the backpropagation (BP) algorithm, so as to automatically extract the characteristics of the data. BP refers to the calculation of the error value between the network output value and the real value by the loss function and then the BP of the error value. At present, the most widely used loss function of CNN is the categorical cross-entropy loss function. In order to train CNN to fit the proposed model, using the Adam optimization algorithm minimizes the categorical cross-entropy, whose formula is

$$E = -\frac{1}{\sigma} \sum_{\alpha=1}^{\sigma} [y_\alpha \ln t_\alpha + (1 - y_\alpha) \ln(1 - t_\alpha)] \tag{17}$$

TABLE I
PARAMETERS OF THE CNN NETWORK

Network	Layer Size	Number
Convolutional layer 1	64×1	16
MaxPooling 1	2×1	16
Convolutional layer 2	3×1	32
MaxPooling 2	2×1	32
Convolutional layer 3	3×1	64
MaxPooling 3	2×1	64
Convolutional layer 4	3×1	64
MaxPooling 4	2×1	64
Convolutional layer 5	3×1	64
MaxPooling 5	2×1	64
Global Average Pooling	-	-

TABLE II
PARAMETERS OF ROLLING BEARING SKF6205

Ball diameter	Inside diameter	Outside diameter	Pitch diameter
7.94mm	25mm	52mm	39.04mm

where σ is the number of samples of this category; t is the predicted value; and y is the true value, where the learning rate is set to 0.001. The ReLU is used as the nonlinear activation function of each convolution layer to improve the convergence rate of the model. The trained CNN model is used to extract the features of rolling bearing vibration signals, and the obtained feature vector matrix was subjected to PCA dimensionality reduction operation (the first two PCs were regarded as the input of FCM for fault diagnosis) and input into FCM to obtain the final classification result. However, the membership matrix U obtained using the FCM clustering algorithm is not suitable as the basis for the final classification. In order to make the classification results more clear, this article uses the maximum membership method to harden U. In the maximum membership method, the maximum membership value of each row in U is set to 1, and the other terms of the row are set to 0. From the U_{hard} obtained by this method, the classification of the samples can be seen intuitively.

Compared with other fault diagnosis models, this model can effectively extract the characteristics of vibration signals of rolling bearings and use FCM for fault diagnosis, which is more interpretable and can achieve fault diagnosis of rolling bearing more accurately and quickly, which will be validated in the experiment part.

III. EXPERIMENT AND RESULT ANALYSIS

A. Experimental Data Set

In order to verify the effectiveness of the method proposed in this article, the experimental data of the bearing data center of the Western Reserve University are used to verify the experiment [23], and the experimental platform is shown in Fig. 4. The test object is the drive end bearing SKF6205-2RSJEM type deep groove ball bearing in Fig. 5, and the parameters are shown in Table II.

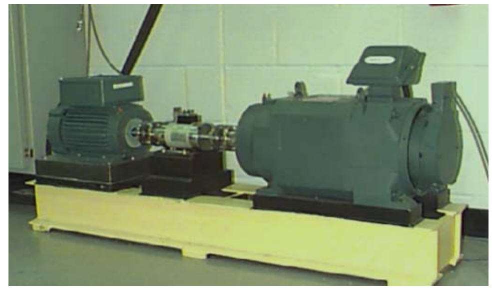

Fig. 4. Bearing test platform.

Fig. 5. SKF6205—2RSJEM deep groove ball bearings.

TABLE III
ROLLER BEARINGS EXPERIMENTAL DATA

Datasets	Fault type	The number of samples
A/B/C/D	NR	60/60/60/60
	BF1	60/60/60/60
	BF2	60/60/60/60
	BF3	60/60/60/60
	IRF1	60/60/60/60
	IRF2	60/60/60/60
	IRF3	60/60/60/60
	ORF1	60/60/60/60
	ORF2	60/60/60/60
	ORF3	60/60/60/60

In this experiment, an acceleration sensor is placed above the bearing seat at the drive end of the motor, and the fixed sensor position remains unchanged. The processed faulty bearings are installed in the test motor to achieve the collection of vibration acceleration signals of different faulty bearings. The sampling frequency is 12 000 Hz, and the load is 735 W. Among them, the motor loads include load 0 (1797 rpm), load 1 (1772 rpm), load 2 (1750 rpm), and load 3 (1730 rpm). Table III shows the working conditions. In Table III, normal data (NR) and three faults inner race fault (IRF), outer race fault (ORF), and ball fault (BF) with fault diameters of 0.18 (1), 0.36 (2), and 0.54 mm (3 hp) are employed in this article. A, B, C, and D represent four data sets; each data set contains rolling bearing data in ten different states. Each type of failure data set has 60 samples and contains 2048 sampling points, so different data sets A, B, C, and D have a total of 600 samples. The time-domain figure of the various original

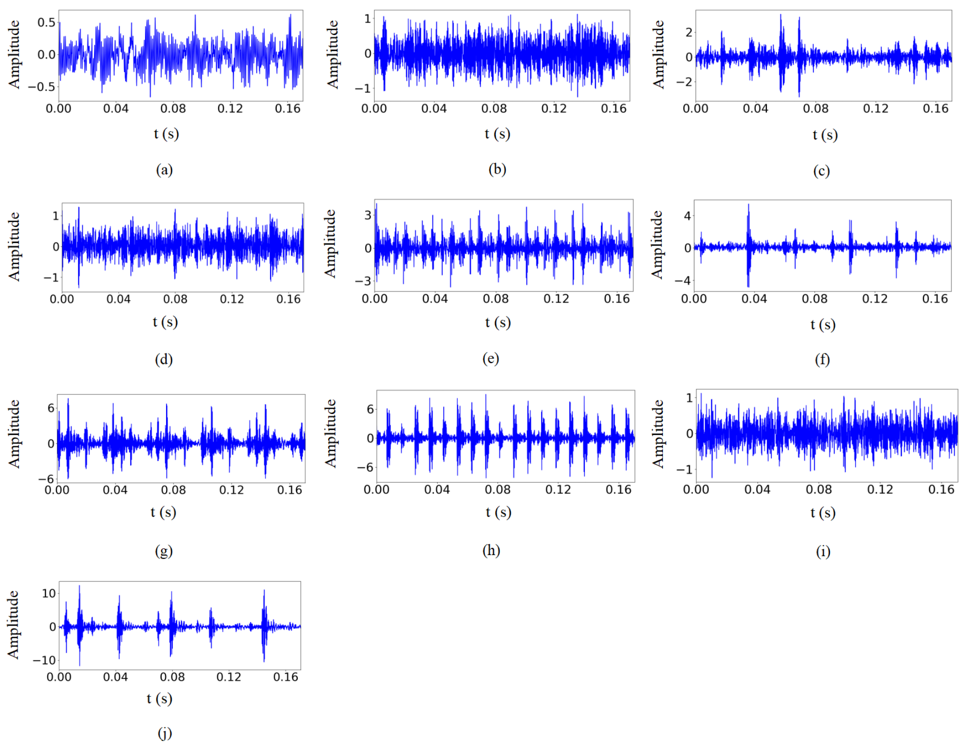

Fig. 6. Time-domain waveforms for each working condition. (a) NR. (b) BF1. (c) BF2. (d) BF3. (e) IRF1. (f) IRF2. (g) IRF3. (h) ORF1. (i) ORF2. (j) ORF3.

vibration signals is shown in Fig. 6. The method of comparison with the EEMD-SVD-FCM model is used for analysis [19].

B. Procedures of Our Method

For the rolling bearing fault diagnosis method using CNN-based feature extraction and FCM clustering, vibration signal of rolling bearing under different state is collected as a data set. Then, the pretrained CNN model is used for feature extraction of the 1-D vibration signal of the rolling bearing. Through the CNN model, the vibration signal characteristics of rolling bearings in different states can be extracted effectively. On the basis of the trained CNN model, the clustering analysis is carried out for the data sets of ten different states of rolling bearings. Specific operation steps are as follows.

1) Collect vibration signals of rolling bearings in different states as a data set, preprocess the collected vibration signals appropriately, and train and test the model as original signals.
2) The original signal is divided into known fault samples and fault samples to be tested, input into the trained CNN model, extract its features, and use PCA to reduce the dimension of the extracted features.
3) The clustering center and membership matrix of the FCM model are updated by the feature set of known fault samples. When the objective function J_m meets the iteration termination condition, it stops updating and outputs clustering center and the hardened membership matrix.
4) According to the clustering center and membership matrix of the known fault samples, the fault samples to be tested are identified to determine which type of known fault samples they belong to. The specific identification steps are as follows: the membership matrix of the known fault samples and the fault samples to be tested is merged to form a matrix of $(N+1)$ rows and ten columns. If all elements in line $N+1$ of the membership matrix after hardening are the same as all elements in line m $(1 \le m \le N)$, it indicates that the fault sample to be identified belongs to the same category as the mth known fault sample. As shown in the following matrix, all elements in the last row are the same as all elements in the first row, indicating that the fault category of the sample to be tested is the same as the known fault sample in the first row

$$\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

C. Comparison Studies

In order to further verify the superiority of the proposed method, it is compared with the method based on EEMD feature extraction and FCM clustering. In this article, data set A is used as a known fault sample, and the CNN-PCA-FCM

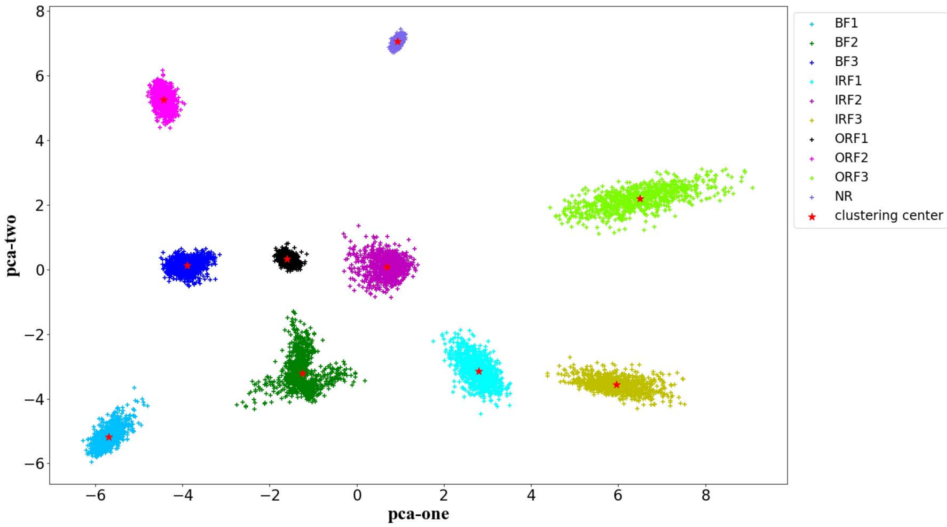

Fig. 7. CNN-PCA-FCM clustering result.

TABLE IV
COMPARISON RESULTS OF TWO CLUSTERING EFFECTS

Model	Dataset	PC	CE
EEMD-SVD-FCM [19]	A	0.832	0.332
CNN-PCA-FCM	A	0.913	0.185

model and the EEMD-SVD-FCM model [19] are trained, respectively. In addition, the standard clustering center and membership matrix obtained from data set A are adopted to perform fault diagnosis for data sets B, C, and D.

First, the CNN-based feature extraction and FCM clustering methods mentioned in this article are used for verification, including the following two consecutive stages.

1) Input the extracted rolling bearing data into the trained CNN model; the known fault sample data and the fault sample data to be identified are feature extracted; and the extracted features are subject to PCA dimensional-reduction operation. The eigenvector matrix X_1 composed of the eigenvectors of ten states of the rolling bearing is shown in the following. It can be seen that the feature vectors of each fault can be effectively distinguished

$$X_1 = \begin{bmatrix} -1.7627 & 3.8869 & -0.3758 & -2.3487 & 1.5355 \\ 0.0782 & 2.9407 & -1.5263 & -3.4634 & 3.3237 \\ -4.6509 & 6.1193 & -0.3858 & 0.6110 & -2.3673 \\ 1.2705 & -4.6123 & -0.4790 & -5.3682 & 2.7425 \\ 4.8231 & 0.5126 & 7.3043 & -2.4319 & -4.3973 \\ 6.5775 & 0.4797 & -5.8158 & 3.0874 & -2.5528 \\ 2.0200 & -0.1679 & 3.3813 & 6.1739 & 5.6962 \\ -6.4627 & -4.5779 & 0.1408 & 1.8258 & -1.7377 \\ -0.2401 & -3.3569 & -0.0782 & -1.0493 & -0.1554 \\ -2.6363 & -0.5623 & -0.8032 & 1.9346 & -1.5159 \end{bmatrix}.$$

2) The feature set of known fault samples is input into the FCM model. Since there are ten types of known fault samples, the number of clustering centers is set to 10, and the iteration termination error is $\varepsilon = 0.0001$. The FCM clustering algorithm is used to cluster eigenvector matrix to obtain clustering centers and membership matrix. In order to increase the visualization effect, the known failure sample data are increased to 600 groups, and the image shown in Fig. 7 is obtained. The red five-pointed star in the figure is the clustering center. It can be seen that each type of sample point closely surrounds the clustering center, which can effectively distinguish different faults. Then, we classify the fault samples to be tested, and the accuracy rate can reach to 100%

$$X_2 = \begin{bmatrix} 21.0792 & 5.1034 & 4.5956 & 2.2294 & 1.7220 \\ 30.3176 & 7.5939 & 6.7632 & 4.7863 & 2.3595 \\ 16.8549 & 4.5143 & 3.9445 & 1.5886 & 1.1038 \\ 38.9590 & 15.4329 & 9.2452 & 3.8851 & 2.7347 \\ 31.5331 & 8.1702 & 7.4361 & 4.5018 & 2.7318 \\ 68.4619 & 14.4076 & 11.2001 & 6.1101 & 3.2710 \\ 80.3059 & 11.5944 & 9.5193 & 4.9993 & 2.8735 \\ 14.9807 & 5.2968 & 4.3178 & 2.4615 & 1.8029 \\ 57.8322 & 18.1139 & 14.2047 & 6.1728 & 3.3535 \\ 7.8486 & 6.2913 & 3.7587 & 3.4911 & 2.9291 \end{bmatrix}.$$

EEMD feature extraction and FCM clustering are used to repeat the above steps, and the results will be compared with the proposed method. The EEMD-SVD-FCM model decomposing the vibration signal of the rolling bearing by the EEMD method and n intrinsic mode functions (IMFs) $i_1, i_2, \ldots, i_n$ are obtained. The n IMF components are combined into the initial eigenvector matrix $A = [i_1, i_2, \ldots, i_n]^{\mathrm{T}}$. The singular value decomposition (SVD) of matrix A is carried out to obtain the singular value $\delta = [\delta_1, \delta_2, \ldots, \delta_n]$, which is taken as the eigenvector matrix of the rolling bearing. Since the fault vibration signal characteristics of the rolling bearing are mainly concentrated on the first few IMF components, the first five IMF components are selected for feature extraction in this article. The eigenvector matrix X_2 composed of the

TABLE V
RESULTS OF CLASSIFICATION ACCURACY I

Model	Dataset	Test accuracy(%)										Total (%)
		NR	BF1	BF2	BF3	IRF1	IRF2	IRF3	ORF1	ORF2	ORF3	
EEMD-SVD-FCM	B	96.7	66.7	100	90	100	100	100	100	91.7	96.7	94.17
	C	100	100	23.3	100	100	100	100	100	81.7	86.7	89.17
	D	100	71.7	100	76.7	100	100	100	100	100	40	88.83
CNN-PCA-FCM	B	100	100	100	100	96.6	100	100	100	100	98.3	99.5
	C	100	100	100	100	100	100	100	100	100	100	100
	D	100	100	100	93.3	100	100	100	100	100	100	99.3

eigenvectors of ten states of the rolling bearing is shown above. It can be seen that the eigenvectors of the second row [30.3176 7.5939 6.7632 4.7863 2.3595] and the fifth row [31.5331 8.1702 7.4361 4.5018 2.7318] of the eigenvector matrix are very similar; the third row [16.8549 4.5143 3.9445 1.5886 1.1038] and the eighth row [14.9807 5.2968 4.3178 2.4615 1.8029] of the eigenvector matrix are also very similar; and the features extracted from different fault data are not distinguished effectively, which will affect the subsequent search of the standard clustering center.

The two indicators, partition coefficient (PC) and classification entropy (CE), are used to evaluate the clustering effect of the EEMD-SVD-FCM model [19] and the CNN-PCA-FCM model in our work. When the PC value is close to 1 and the CE value is close to 0, the clustering effect is better, and PC and CE are defined [30] as

$$\mathrm{PC} = \frac{1}{\mu}\sum_{p=1}^{\rho}\sum_{q=1}^{\mu}\left(u_{pq}\right)^2 \tag{18}$$

$$\mathrm{CE} = -\frac{1}{\mu}\sum_{p=1}^{\rho}\sum_{q=1}^{\mu}u_{pq}\log\left(u_{pq}\right) \tag{19}$$

where u_{pq} denotes the membership value of the qth point in the pth cluster.

Data set A is used to evaluate the clustering effect of the EEMD-SVD-FCM model and the CNN-PCA-FCM model, and the comparison results of its clustering effect are shown in Table IV. It can be seen that the PC value of the CNN-PCA-FCM is 8% points higher than that of the EEMD-SVD-FCM model, and the CE value is closer to 0.

In order to prove that CNN can extract signals effectively, we use classification accuracy to compare the CNN-PCA-FCM model and the EEMD-SVD-FCM model. Using the standard clustering center and membership matrix obtained from data set A, fault diagnosis is carried out on data sets B, C, and D of other load conditions. The corresponding clustering accuracy is shown in Table V. As can be seen from Table V, the classification accuracy of the CNN-PCA-FCM model is higher than that of the EEMD-SVD-FCM model with the same diagnostic problem and diagnostic data, up to 100%. Taking 60 test samples as an example, it follows from Table VI that the CNN-PCA-FCM model saves much more time compared with the EEMD-SVD-FCM model.

To further illustrate the advantages of the CNN model proposed in this article, we use two schemes to change the structure of CNN to form a new CNN model, and we also use data sets B, C, and D to compare with the CNN model in this article. We denote Convolutional layer1 + MaxPooling1 as layer1, Convolutional layer2 + MaxPooling2 as layer2, Convolutional layer3 + MaxPooling3 as layer3, Convolutional layer4 + MaxPooling4 as layer4, and Convolutional layer5 + MaxPooling5 as layer5. Since the parameters of layer3, layer4, and layer5 of the CNN model are the same, the specific scheme is given as follows: scheme1: layer1 + layer2 + layer3; scheme2: layer1 + layer2 + layer3 + layer4. The comparison results are shown in Table VII, and the advantages of the CNN model in this article are further illustrated by the comparison with the scheme1 and scheme2.

TABLE VI
RESULTS OF CLASSIFICATION TIME

Model	CNN+PCA+FCM	EEMD+SVD+FCM
Time	5.17s	1142.33s

TABLE VII
RESULTS OF CLASSIFICATION ACCURACY II

	Dataset	Model		
		CNN+PCA+FCM	Scheme1	Scheme2
Test accuracy(%)	B	99.5	98.5	100
	C	100	90	89.83
	D	99.3	80	79

By comparing the feature vector matrix, clustering effect, diagnosis accuracy, and diagnosis time, the proposed method can effectively extract the characteristics of the rolling bearing vibration signal, and to distinguish the clustering effect and the diagnosis time, the identification accuracy is superior to the EEMD-SVD-FCM model.

IV. CONCLUSION

In this article, we proposed an approach for fault diagnosis using CNN and FCM clustering algorithm. In this work, CNN is used to automatically extract features from rolling bearing vibration signals, and then, PCA is used to reduce the dimension of the extracted features. Finally, fault diagnosis has been achieved via clustering those rolling bearing data in the derived feature space using the FCM algorithm. The experimental data from the bearing data center of Western Reserve University are tested, and the performance is compared with the method based on EEMD, which proves the effectiveness of the method proposed in this article. More specifically, our method takes less time for the diagnosis and can also effectively identify the fault types that are difficult to distinguish by the EEMD. In future work, the signal preprocessing method can be further studied to improve the performance of the current method.

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