An unsupervised learning method for bearing fault diagnosis based on sparse feature extraction

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***Abstract*—Data-driven based methods have shown their strong feature extraction ability in intelligent fault diagnosis. But most methods always need sample labels in network training process, which is undoubtedly increasing the cost of network training. So developing an unsupervised feature learning method without training labels is desirable. In our work, sparse filtering, an effective unsupervised learning method, is presented for bearing fault diagnosis. The fault features are first extracted from frequency spectra of vibration signals by sparse filtering automatically, and ReLU is adopted as activation function for further sparse processing of the features. Then the learned features are input to softmax regression to identify the corresponding fault types. The classification result shows that our method can extract much sparser features and is better than the comparison method.**

Keywords—fault diagnosis; sparse filtering; ReLU; softmax regression

I. INTRODUCTION

Deep neural networks[1] have attracted increasing attention in the field machine learning. They can automatically extract high quality features from the raw signals, but could not work well without tag data. As an alternative to manually designed feature representation, unsupervised learning methods have been widely applied in many image, voice and video applications on extracting good feature representation[2-4]. However, quite a lot of unsupervised learning algorithms are very difficult to implement since they require the adjustment of various parameters. If these parameters are not set correctly, then the learned features are likely to lead to a poor diagnostic accuracy, such as Restricted Boltzmann Machines (RBM)[5], Stacked Autoencoders (SAE)[6], Sparse Encoders[7], Independent Component Analysis (ICA)[8]. For example, there are as many as six parameters in RBM needing to be adjusted.

Ngiam et al.[9] presented an unsupervised learning method which is called sparse filtering, and it ignores the distribution of learning data while only optimizing the sparsity of learning features. At the same time, it performs perfectly on the scale of input dimension and only one feature parameter needs to be adjusted. Therefore, sparse filtering is easy to be adjusted and realized. Meanwhile, in literature [9], sparse filtering is used to carry out image recognition and speech classification, which have produced quite ideal results.

In mechanical fault diagnosis, feature extraction is the focus of the research. Lei et al.[10] used time-domain data collected by the rotating machinery to conduct overlapping sampling, and then input them into sparse filtering model after whitening preprocess to realize intelligent fault diagnosis of the bearing. Wang et al.[11] achieved the visualization operation of feature extraction by combining sparse filtering with t-SNE algorithm. In addition, considering the characteristics of frequency domain signals can show the distribution of discrete frequencies as well as the clearer information of the rotating machinery state. Subsequently, Wang et al.[12] used spectra as input, which not only no need to conduct whitening operation, but also achieved a higher accuracy. Zhang et al.[13] employed time-frequency signal as input and realized gear fault diagnosis. An et al.[14] solved the over-fitting problem of bearing fault diagnosis by removing multi-correlation operation on the weight matrix of sparse filtering. In this paper, sparse filtering is combined with bearing frequency domain data, ReLU is selected as activation function. Then softmax regression is used as the classifier to classify bearing health status according to the learned features.

The content of this paper is arranged as follows: section 2 gives a brief introduction to sparse filtering, and introduces the specific contents of the proposed method in detail; section 3 applies our method to bearing fault diagnosis and verifies the advantages of our method by comparison method; section 4 draws a conclusion.

II. THEORETICAL BACKGROUND

A. Sparse filtering

The structure of sparse filtering network is shown in Fig. 1. Instead of trying to simulate data distribution, it uses $\ell 2$ -norm features to optimize a cost function[9]. It contains three main working principles: population sparsity, lifetime sparsity and high dispersal. The loss function is as follows:

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$$\underset{W}{\text{minimize}}\sum_{i=1}^{M}\|\hat{\boldsymbol{f}}^{i}\|_{1}=\sum_{i=1}^{M}\left\|\frac{\bar{\boldsymbol{f}}^{i}}{\|\bar{\boldsymbol{f}}^{i}\|_{2}}\right\|_{1} \tag{1}$$

where M is the amount of training samples, f_j^i is the learned feature.

$\bar{\boldsymbol{f}}_j = \boldsymbol{f}_j / \|\boldsymbol{f}_j\|_2$ normalizes the feature row by $\ell 2$ -norm, and $\hat{\boldsymbol{f}}^i = \bar{\boldsymbol{f}}^i / \|\bar{\boldsymbol{f}}^i\|_2$ also normalizes the feature column by the same way. At last, all the features are mapped on the unit $\ell 2$ -norm ball.

For sparse filtering, the nonlinear feature is calculated by using an activation function. In our experiment, ReLU is employed as the activation function, and the structure is shown in Fig. 2:

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

The nonlinear characteristics obtained are:

$$f_j^i = \mathrm{ReLU}\left(\boldsymbol{W}_j^T \boldsymbol{x}^i\right) \tag{3}$$

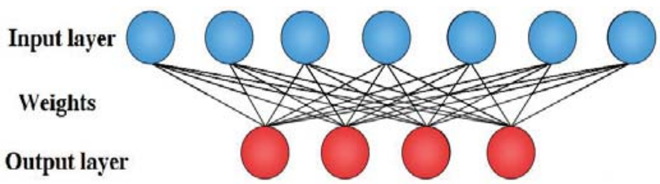


Fig. 1 Structure of sparse filtering.

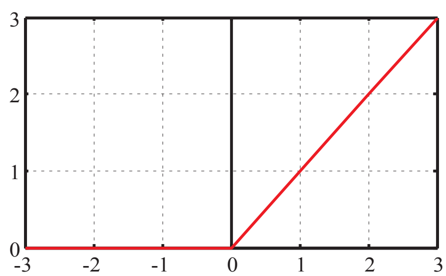


Fig. 2 Structure of ReLU.

B. Proposed framework

The method framework is displayed in Fig. 3. Firstly, the frequency spectra of seven bearing health conditions are collected and composed $\{\boldsymbol{x}^i, l^i\}_{i=1}^{M}$, where $\boldsymbol{x}^j \in \Re^{N_{in}\times 1}$ is the ith sample including N_{in} time domain vibration points, $\boldsymbol{l}^i$ is the condition label of $\boldsymbol{x}^i$, M is the sample amount of the dataset. Then the dataset is combined into a matrix form $\boldsymbol{T} \in \Re^{N_{in}\times M}$, and input to sparse filtering model for training $\boldsymbol{W}$. At last, $\boldsymbol{W}$ is used to map the samples to $\boldsymbol{f}^i \in \Re^{N_{out}\times 1}$. In fault classification stage, $\{\boldsymbol{f}^i\}_{i=1}^{M}$ are combined with label $\{l^i\}_{i=1}^{M}$ to train softmax regression, and the rest samples are used for testing.

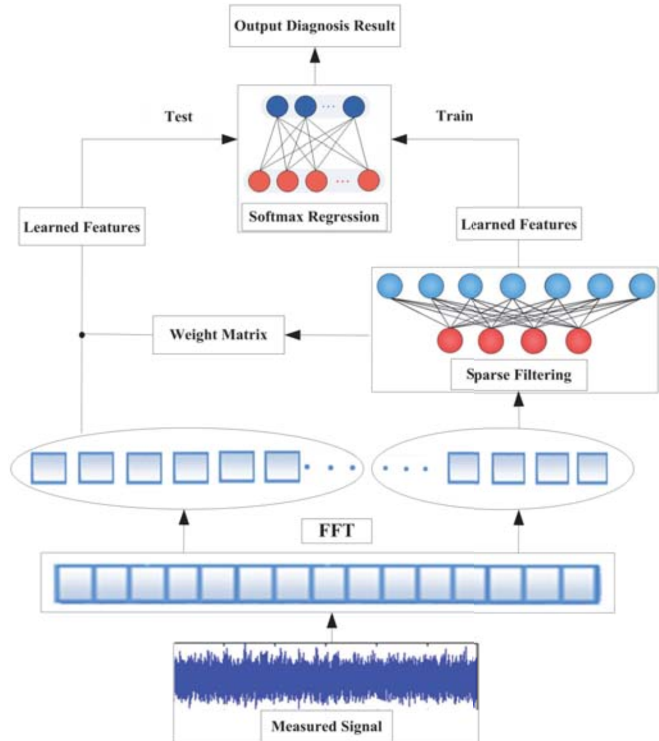


Fig. 3 Flowchart of our method.

III. EXPERIMENTAL VERIFICATION

A. Data description

A specially designed bearing fault diagnosis test bed is used for vibration signal acquisition. The structure of the test bed is shown in Fig. 4. The experimental equipment mainly includes: motor, coupling, gearbox and bearing seat, etc. The motor has a speed of 1500 r/min and a planetary gearbox speed ratio of 1:3, so the output speed is 4500 r/min. A sensor is mounted on the surface of the bearing seat with 12.8 kHz sampling frequency. Seven different bearing health conditions were designed: normal condition (NC), 3 inner race faults (0.2mm/0.6mm/1.2mm), which were named as IF1, IF2, IF3; 3 outer race faults (0.2mm/0.6mm/1.2mm), which were named as OF1, OF2, OF3. 400 data points were collected for each sample, 200 samples were collected for each type, so 1,400 samples were collected. 200 Fourier coefficients per sample are obtained by FFT. Details of each type of bearing fault signal are shown in Fig. 5.

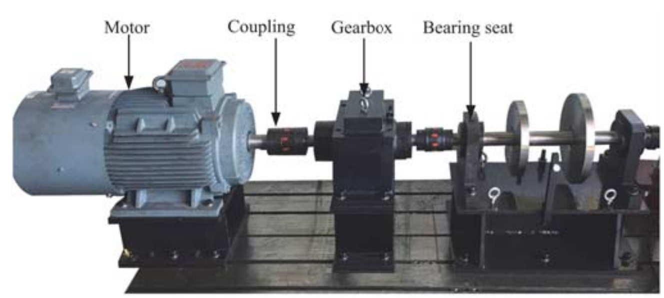


Fig. 4 Bench of bearing fault.

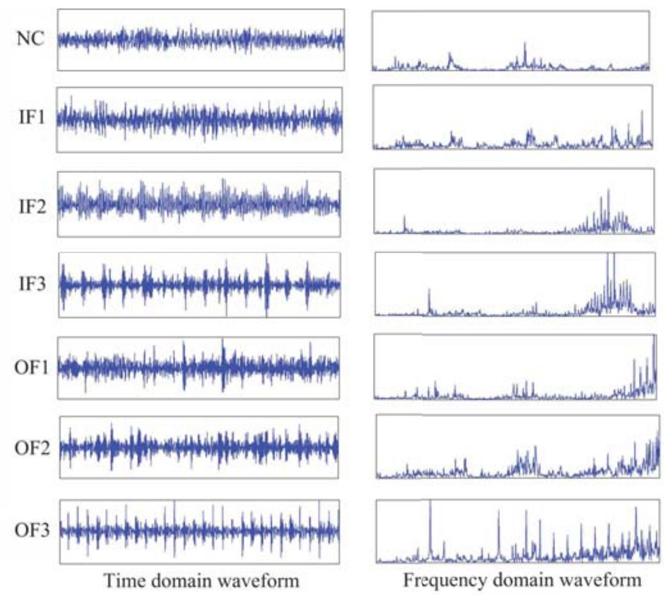


Fig. 5 Bearing fault signal characteristics.

B. *Diagnosis result*

Firstly, we randomly select 10% samples for the training process of sparse filtering. N_{in} is equal to the dimension of Fourier coefficients, and N_{out} is equal to N_{in}. After $\boldsymbol{W}$ is trained, then we use it to map out the learned features. Finally, all the feature vectors are input to softmax classifier to obtain diagnosis accuracy.

To show the superiority of our method, we use a commonly used absolute value function in literature [11] as the activation function for comparison, so its feature calculation formula is as follows:

$$f_j^i = \left| \boldsymbol{W}_j^T \boldsymbol{x}^i \right| \tag{4}$$

The experiment is carried out 20 trials and the test accuracies of the two methods are shown in Fig. 6. The average testing accuracies of the two methods are 99.72% and 97.65%, respectively. It shows that our method is completely superior to comparison method. Then, we use t-SNE[16] to visualize the dimensionality reduction results of the high-dimensional features obtained by the two methods. The 2D results obtained by the 15th trial are displayed in Fig. 7. It is easy to find from Fig. 7(a) that the mapping features of different fault types are perfectly separated, and the same fault type samples are gathered together. In contrast, the dimensionality reduction result of the comparison method shown in Fig. 7(b) are relatively poor, and almost all fault types have some samples that are not completely clustered together. By contrastive analysis, it can be concluded that our method is the best choice in exploring the bearing data feature types.

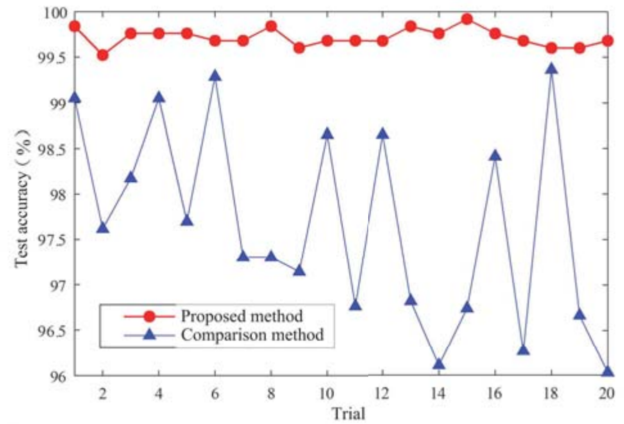
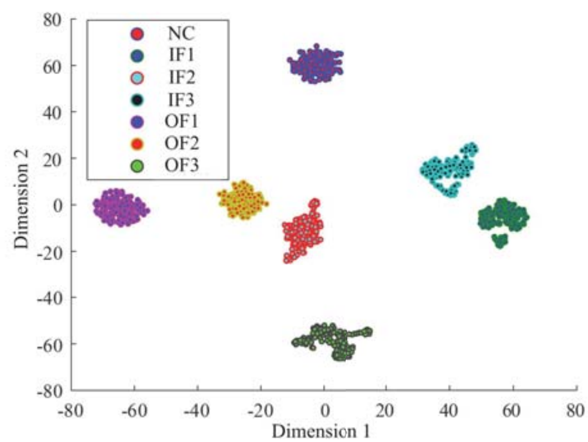
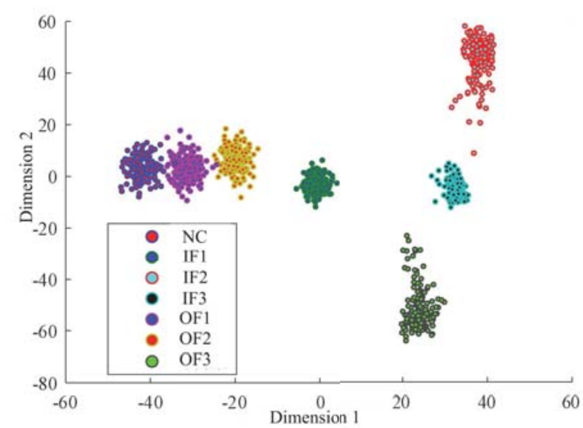


Fig. 6 Comparison of test accuracies.



(a) Proposed method



(b) Comparison method

Fig. 7 Comparison of dimension reduction results.

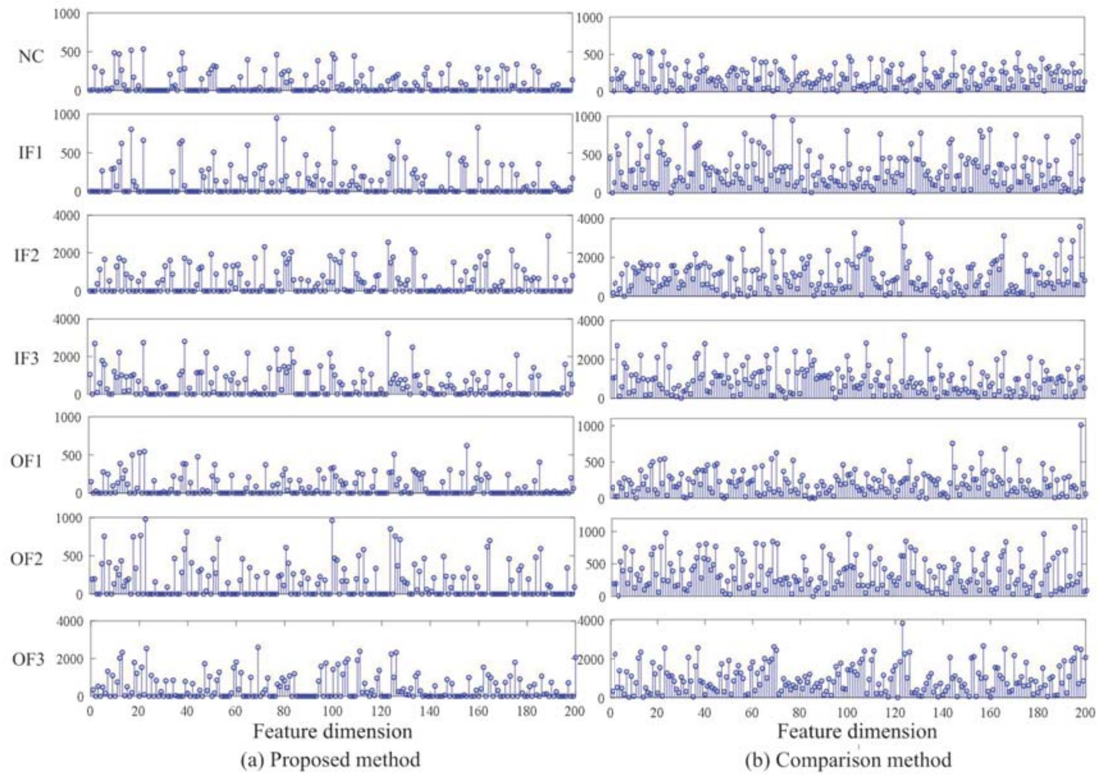


Fig. 8 Comparison of high dimensional feature vectors.

C. Sparse feature representation

To further show the ability of the activation function ReLU in sparse feature extraction, the high-dimensional feature vectors learned by the two methods through the sparse filtering model are presented in the form of Fig. 8. The feature amplitudes of the two methods are almost the same, and the extracted features of our method are much sparser than those of the comparison method, which is mainly manifested in the presence of many zero values in the high-dimensional feature vectors of the proposed method, while the feature values in comparison method are almost all positive values, and the feature peaks are relatively dense. Thus it shows the sparsity of the feature vectors learned by our method. According to ReLU function structure as shown in Fig. 2, the negative terms in learning features are all set to zero, while non-negative terms remain unchanged, so the learned features are becoming further sparse. However, the absolute value function in the comparison method is to take the absolute value of all negative values in the learned features. Although it can also obtain a high accuracy, the features are not sparse, and the test accuracy is significantly lower than the proposed method.

IV. CONCLUSION

In this paper, an unsupervised feature extraction method is proposed and applied to bearing fault diagnosis. Firstly, sparse filtering is adopted to adaptively learn sparse features from the spectra of signals, and ReLU is selected as the activation function. Then, the learned features are input into softmax for classification. Through the bearing fault experiment validation, our method has shown quite strong ability on bearing fault feature identify. Meanwhile, by comparative analysis with the absolute value function, the proposed method has shown its superiority in diagnosis accuracy, dimension reduction performance and sparse feature extraction. Therefore, the proposed method can realize bearing intelligent fault diagnosis in an unsupervised way.

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