A novel deep feature fusion method for fault diagnosis of planetary gearbox

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1. Introduction

The accuracy of planetary gearbox fault diagnosis and recognition, especially the automatic and accurate identification of composite faults, is still a major challenge for rotating machinery fault diagnosis. In this paper, an intelligent fault diagnosis method for planetary gearbox based on deep feature fusion of multi-channel autoencoder is proposed. Firstly, there is a disadvantage of insufficient feature extraction ability and poor stability for a single deep learning model. In this paper, a multi-channel deep feature extraction structure is constructed by parallel combination of autoencoder with different characteristics. Secondly, a feature combination strategy is designed for the deep features extracted by multi-channel deep feature extraction structure, which ensures that the fusion features have better robustness and representation. Finally, in order to verify the feasibility and correctness of the method, the proposed method and other fault diagnosis methods will be applied to compare the vibration signals of the planetary gearbox. The results show that the proposed method overcomes the shortcomings of single deep neural network with low precision, poor stability and low generalization performance, which are more effective than traditional methods and other standard deep learning methods.

2. The proposed method

Based on the autoencoder, this paper proposes a novel intelligent fault diagnosis method based on fusion of deep features. The method is mainly divided into three parts as follows: multi-channel feature extraction structure construction, feature fusion strategy design and the general process of the method implementation.

Due to the simplicity of the single deep neural network structure, the diagnosis results show low stability and poor generalization ability when identifying planetary gearbox failures. In order to overcome the limitations of the single network model and improve the stability and generalization ability of the fault diagnosis model, this paper proposes a multi-channel autoencoder model for extracting features. The multi-channel autoencoder model is shown in Fig.1. It shows the layer-by-layer learning process of the original data by the multi-channel autoencoder.

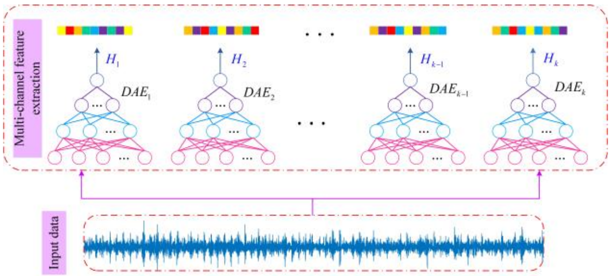

Fig.1 This is a multi-channel autoencoder feature extraction structure

This paper designs a simple new feature fusion strategy for weight distribution. Different weights are assigned according to the contribution rate of each feature, which can effectively avoid the fused features from containing too much redundant information and retain the deep features of the original signal. This combination strategy mainly includes the following two points: (1) Different weights are assigned according to the exact values corresponding to each model. (2) Calculate the fused features based on the weight size. A detailed description of the designed feature fusion strategy is as follows.

Step 1: The training sample $\mathbf{X}=[\mathbf{x}_1,\mathbf{x}_2,...,\mathbf{x}_n]$ and the training label $\mathbf{Y}=[\mathbf{y}_1,\mathbf{y}_2,...,\mathbf{y}_n]$ are input into the deep AE, the deep DAE, the deep SAE, and the deep CAE model for feature extraction, and the corresponding accuracy rates Acc_i are calculated. Where is the $\mathbf{x}_i$ sample data, and $\mathbf{y}_i$ is the label data corresponding to $\mathbf{x}_i$.

Step 2: Assign different fusion weights to **H**$_1$, **H**$_2$, **H**$_3$, and **H**$_4$ respectively. Where **H**$_1$, **H**$_2$, **H**$_3$, and **H**$_4$ are deep features corresponding to deep AE, deep DAE, deep SAE, and deep CAE, respectively.

$$w_i=\frac{Acc_i}{\sum_1^4 Acc_i} \tag{1}$$

Where w_i has $w_1+w_2+w_3+w_4=1$.

Step 3: Calculate the deep features **H** after fusion based on the fusion weights

$$\mathbf{H}=\sum_1^4 w_i\mathbf{H}_i \tag{2}$$

After the above three steps, the deep fusion feature is used as the input of the Softmax classifier.

3. Data description

In this experiment, the data of the planetary gearbox was collected by the test rig. The test rig consists of a 3-horsepower 3-phase motor, a 2-stage planetary gearbox, a 2-stage fixed-shaft gearbox supported by rolling bearings, a bearing load and a programmable magnetic brake. In this experiment, six working conditions were considered, including the normal working conditions of the planetary gearbox, the gear wheel crack failure condition, the gear broken tooth failure condition and three composite fault conditions.

4. Experimental verification

In order to verify the effectiveness and advancement of the method, the traditional BPNN, SVM and RF fault diagnosis methods are used to verify the same data set. Similarly, the standard deep DAE, standard deep CAE, standard deep SAE, standard deep AE, DBN, and CNN models were used to diagnose the planetary gearbox. To ensure the reliability of the experimental results of this method, this paper conducted ten experiments on the data set of the planetary gearbox. The average training accuracy and average test accuracy of this method and BPNN, SVM and RF fault diagnosis methods are shown in Table 1.

It can be concluded from Table 1 that the method has higher training accuracy (98.096%) and lower standard deviation (0.2665) than other methods. The diagnostic result of the method for the test sample is 97.220% much higher than BPNN, RF, SVM, standard deep DAE, standard deep SAE, standard deep CAE, standard deep AE and CNN models input as FFT data. Among them, their test accuracy is 54.296%, 65.519%, 65.535%, 92.264%, 94.106%, 94.180%, 93.402%, and 91.358%, respectively. After feature extraction, the test accuracy of BPNN, RF, and SVM increased to 84.074%, 90.402%, and 89.389%, respectively. Although the accuracy of fault identification in these methods is greatly improved, it cannot be compared with this method.

5. Conclusions

This paper proposes a deep feature fusion method for fault diagnosis of rotating machinery. Firstly, to improve the feature learning ability, a multi-channel feature extraction structure is composed of four different deep autoencoders. Secondly, the principal component analysis is used to fuse the deep features of the learning, which further eliminates the redundant information of the features and improves the quality of the features. Finally, the merged deep features are input to the Softmax classifier for fault diagnosis. The effectiveness of the method is verified by experimental data from a planetary gearbox. The diagnosis results of these data show that the proposed method has better robustness and effectiveness in feature extraction and fault identification than traditional intelligent fault methods. Compared with other standard deep learning models, this method overcomes the shortcomings of single deep neural network model with low precision, poor stability and low generalization performance.

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Table 1 Diagnostic results of different methods in 10 experiments.

Methods	Average accuracy (%) ± standard deviation	
	Training samples	Testing samples
Method 1	98.096% ± 0.2665	97.220% ± 0.1663
Method 2	86.579% ± 1.4554	84.074% ± 1.3482
Method 3	56.937% ± 7.9295	54.296% ± 7.9106
Method 4	91.866% ± 0.8630	90.402% ± 1.3115
Method 5	68.508% ± 1.1042	65.519% ± 1.8644
Method 6	91.651% ± 0.6052	89.389% ± 0.7682
Method 7	67.506% ± 0.4679	65.535% ± 1.1093
Method 8	95.303% ± 0.6366	92.264% ± 0.6752
Method 9	96.017% ± 0.3497	94.106% ± 0.8992
Method 10	96.089% ± 0.8294	94.180% ± 0.7920
Method 11	96.615% ± 0.6644	93.402% ± 0.7240
Method 12	94.550% ± 0.5896	91.358% ± 0.8039

Remarks: Method 1-The proposed method; Method 2-BPNN with 28 features; Method 3-BPNN with FFT data; Method 4-RF with 28 features; Method 5-RF with FFT data; Method 6-SVM with 28 features; Method 7-SVM with FFT data; Method 8-deep DAE with FFT data; Method 9-deep SAE with FFT data; Method 10-deep CAE with FFT data; Method 11-deep AE with FFT data; Method 12-CNN with FFT data.