Rolling Bearing Fault Classification Based on Stacked Denoising Auto Encoders

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Abstract. Aiming at the characteristics of large capacity and diversity of rolling bearing fault data, an intelligent rolling bearing fault diagnosis method based on stacked denoising auto encoders was proposed. Firstly, Principal Component Analysis was used to reduce the dimension of the original data, and the redundant information is deleted. Then, three de-noising auto-encoders are created to train the bearing data. Then, a stack de-noising auto-encoder with three hidden layers is stacked with the trained DAE for reverse optimization. Finally, the features are input into soft-max classifier to realize rolling bearing fault diagnosis. The experimental results show that SDAE network can extract fault features effectively, and it is better than back propagation neural network in generalization and fault classification accuracy.

Keywords: Rolling bearing, stacked denoising auto coder, fault classification, feature extraction.

1. Introduction

Rolling bearing plays an extremely important role in modern industry, its normal operation will not only have a significant impact on social and economic development, if the fault can’t be detected in time, it will also pose a serious threat to the personal safety of employees. Therefore, the rolling bearing fault diagnosis is of far-reaching significance. At present, the difficulty of rolling bearing fault diagnosis is that it is difficult to extract effective fault features from massive data, resulting in low diagnostic accuracy.

Li [1] used BP neural network to learn meaningful and dissimilar features from different scale signals, to improve the accuracy of fault diagnosis. Zhou [2] first decomposes the early fault free features and similar failure samples of bearings by using wavelet packet energy entropy, extracts energy value as the original feature, then establishes radial basis (RBF) neural network to diagnostice rolling bearing faults. All of the above methods can obtain high accuracy of fault diagnosis, but the artificial experience is needed to determine the network structure, so the accurate model can’t be obtained. Moreover, the accuracy of the above method is low when dealing with a large number of actual signals, and the algorithm speed is low; when the data dimension is particularly large, it is particularly difficult to train an effective model. From the perspective of deep learning, these algorithms are shallow learning methods.
Deep learning uses deep network to extract Abstract high-dimensional features of complex data. Because of its strong nonlinear fitting ability, it is gradually applied to various fields, especially in the field of pattern recognition and fault diagnosis. As a method to realize unsupervised learning [3], the essential features of data can be extracted from a large number of high-dimensional data, and good results have been achieved in prediction and classification problems. In 2006, Hinton [4] first proposed the method and model training process of building deep neural network, increasing the number of hidden layers of automatic encoder to form deep auto encoder, which is of great significance for the development of deep neural network. At present, deep neural network has shown its superior performance in image classification [5], speech recognition [6], fault diagnosis and other fields.

To sum up, in order to improve the accuracy of fault diagnosis, this paper uses stacked noise reduction auto encoder deep neural network to extract features of rolling bearing data, and makes full use of deep neural network to mine deep information of data, so as to establish an effective rolling bearing fault diagnosis network.

2. Principle of stack noise reduction auto coding

2.1. Auto Encoder

Auto encoder (AE) [7] is an auto supervised learning algorithm, which shows its superior performance in processing high-dimensional complex data. The network structure is shown in Figure 1. The number of input layer nodes of automatic encoder is larger than that of hidden layer, and the features can be learned by unsupervised learning method by minimizing reconstruction error. The principle is as follows:

\[ h_{w,b}(x) = f_{\theta}(x^n) = s(Wx^n + b) \]  \hspace{1cm} (1)

Where: \( s \) is the activation function; \( \theta \) is the parameter matrix of the coding network; \( W \) is the weight matrix; \( b \) is the bias coefficient.

Next, the hidden layer vector is reconstructed by decoding function, the obtained \( x^n \) is as follows:

\[ \hat{x} = g_{\theta'}(h_{w,b}(x)) = s(W' h_{w,b}(x) + b') \]  \hspace{1cm} (2)

Where: \( \theta' \) is the parameter matrix of decoding network; \( W' \) is the weight matrix from hidden layer to output layer; \( b' \) is the bias coefficient.
Finally, an error loss function is constructed for network training:

\[
J(W,b) = \frac{1}{m} \sum_{i=1}^{m} \left( \frac{1}{2} \| x - \hat{x} \|^2 \right) + \frac{\lambda}{2} \sum_{i=1}^{m} \sum_{j=1}^{n-i} \| W^{(i)} \|^2
\]

(3)

Where: \( n_i \) is the number of network layers constructed, \( s_i \) is the number of units of layer \( L \); \( \lambda \) is the weight attenuation coefficient; \( m \) is the number of samples.

2.2. Denoising auto encoder

The essence of AE reconstruction strategy is that it only depends on learning from the original data, but it can’t guarantee the error. In order to improve the network performance, Vincent et al. [8] proposed de noising auto encoder (DAE) network. On the basis of AE, DAE adds noise to the input layer data (input layer node is set to zero randomly), which can effectively prevent the over fitting problem, and make the whole encoder network have stronger robustness and better extract the essential characteristics of fault data.

In the training of denoising auto coding network, the random operator maps the damaged sample \( x \) to the original data \( x \) through the function \( g_\theta(f_\theta(\cdot)) \), where \( f_\theta \) is the coding function and \( g_\theta \) is the decoding function.

The model structure of DAE is shown in Figure 2.

![Figure 2 Structure of DAE model](image)

2.3. Stacked denoising auto encoders

The idea of Stacked denoising auto encoders (SDAE) is to stack multiple DAEs to form a deep network architecture. The number of DAEs depends on the actual demand. The basic principle is to train the network, so that the reduced signal contains the essential features of the fault, and the interference part of the high-dimensional signal is removed. Finally, the trained features are used for classification and recognition.

The structure of SDAE is shown in Figure 3.

![Figure 3 SDAE model structure](image)

2.4. Fine tuning stack denoising auto encoders

After completing the SDAE network pre training, the gradient descent algorithm [9] is applied to update the weights. The specific process is as follows.
For each node $i$ of output layer $l_n$, the residual formula is as follows:

$$
\delta_{i}^{(n)} = \frac{\partial}{\partial z_{i}^{(n)}} \frac{1}{2} \| y - h_{w,b}(x) \|^2 = -(y_i - a_i^{(n)}) \| f'(z_i^{(n)}) \|
$$  \hspace{1cm} (4)

For hidden layer $l = n_l - 1, n_l - 2, \ldots, 2$, the residual expression is as follows:

$$
\delta_{i}^{(l)} = (\sum_{j=1}^{m} W_{x_{i}j}^{(l)} \delta_{j}^{(l+1)}) + \beta(-\frac{\rho}{\rho_j} + \frac{1-\rho}{1-\rho_j}) f'(z_i^{(l)})
$$  \hspace{1cm} (5)

$$
f'(z_i^{(l)}) = \eta_i^{(l)}(1-\eta_i^{(l)})
$$  \hspace{1cm} (6)

In equation (6), $i$ and $j$ represent the $i$-th node of hidden layer $l$ and the $j$-th node of hidden layer $l+1$ respectively, $\rho_j$ represents the average activation value of the $j$-th node.

(3) The partial derivative of loss function to $W, b$ is obtained:

$$
\left\{ \begin{array}{l}
\frac{\partial}{\partial W_{x_{i}j}^{(l)}} C(W, b; x, y) = a_i^{(l)} \delta_{j}^{(l+1)} \\
\frac{\partial^2}{\partial b_{i}^{(l)}} C(W, b; x, y) = \delta_{i}^{(l+1)} 
\end{array} \right.
$$  \hspace{1cm} (7)

Where, $C(W, b; x, y)$ is the mean square error function of input and output.

(4) The parameters are updated as follows:

$$
\left\{ \begin{array}{l}
W_{x_{i}j}^{(l)} = W_{x_{i}j}^{(l)} - \eta \frac{\partial}{\partial W_{x_{i}j}^{(l)}} C(W, b) \\
b_{i}^{(l)} = b_{i}^{(l)} - \eta \frac{\partial}{\partial b_{i}^{(l)}} C(W, b)
\end{array} \right.
$$  \hspace{1cm} (8)

Where $\eta$ is the learning rate.

3. Fault classification of rolling bearing based on SDAE

3.1. Network construction

The stacked SDAE only has feature extraction function, but not fault classification function. In this paper, the soft Max classifier is added to the last output layer, and the SDAE network is trained by using the labeled training set data, then the SDAE network with bearing fault diagnosis ability can be obtained.

3.2. SDAE training process

The rolling bearing fault diagnosis training based on SDAE is divided into six steps, and the flow chart is shown in Figure 4.

1. Obtain all kinds of vibration signals and label them, and divide them into training set and test set.
2. Initialize SDAE network parameters and determine SDAE network structure. The noise figure of denoising auto coding is set as 0.1, the learning rate is 1, and the number of training is 100;
(3) The first layer of DAE is trained, and its hidden layer is used as the input layer of the next DAE. The next layer of DAE is trained until all the n-layer DAEs are trained;
(4) The trained multi-layer DAE networks are stacked to form a deep SDAE network, and the soft Max classifier is added to the top layer of SDAE.
(5) Use test data and data tags to fine tune the whole network;
(6) After the training, the structure of SDAE network was adjusted again according to the diagnostic accuracy.

Obtain all kinds of vibration signals and label them
Start
Divide training set and test set
Set the number of SDAE hidden layer, network structure, learning rate and other parameters
The t-th self coding network is trained and its output is taken as the input of the next layer network, and then the (t-1)-th self coding network is trained
Fine tune the entire SDAE network
Input test data and calculate diagnostic accuracy
The error meets the expected accuracy
N
Y
Complete SDAE network training
Diagnosis results

Figure. 4 Network training flow charts

4. Rolling bearing fault simulation test
In order to verify the diagnosis effect of deep neural network based on stacking noise reduction and auto coding for rolling bearing fault, and its superior performance for large sample and large capacity fault data processing, two simulation experiments are designed in this section. The first simulation experiment mainly compares the influence of SDAE with 2, 3 and 4 hidden layers on the accuracy of fault diagnosis, and selects the optimal deep network structure. In the second simulation experiment, BPNN and RBFNN are used for fault diagnosis, and the advantages of SDAE deep network for bearing fault diagnosis are verified by comparison.

4.1. Data preprocessed
The open data center of the University of Kessler [10]. Firstly, the classification tag is transformed into SDAE processing structure, the first type is [1 0 0 0 0 0 0 0 0 0], the second type is [0 1 0 0 0 0 0 0 0 0]. Because the feature data dimension is too high, each sample corresponds to 5120 features, it is difficult to extract effective data features, so the second data processing is carried out. Principal
Component analysis (PCA) is used to reduce the dimension of sample data, and the first 100 dimensions data is taken as the feature after dimension reduction. The processed data sets are randomly divided into 700 training sets and 300 test sets.

4.2. Test scheme and analysis
Considering the influence of the number of hidden layers of SDAE network on the diagnosis accuracy, 2, 3 and 4 layers of SDAE network are constructed, and the frequency domain fault data is analyzed by SDAE network. The classification accuracy is shown in Figure 5.

![Figure 5 Network diagnosis results at different depths](image1)

![Figure 6 Confusion matrix](image2)

Figure 5 shows the effect of stacked noise reduction auto coding network structure on training times and error. It can be seen from Figure 5 that the accuracy of SDAE with two hidden layers is about 80% after 100 times of training, that of SDAE with four hidden layers is about 85% after training, and that of SDAE with three hidden layers is more than 90% after 100 times of training, which fully proves that SDAE network with three hidden layers has the advantage of processing large sample data SDAE network with three hidden layers is selected to study.

As shown in Figure 6, the horizontal axis of the confusion matrix represents the predicted value, the vertical axis represents the real value, the diagonal line represents the classification accuracy of each type of fault in SDAE network, and the non-diagonal line represents the classification error rate. BF indicates rolling element fault, if indicates inner ring fault, of indicates outer ring fault, NC indicates normal state.

As can be seen from Figure 6, when the actual category is B007, the proportion of misclassification to OR07 is 2%, and when the actual category is OR14, the proportion of misclassification to IR14 is 4%. The overall classification accuracy of the whole test set reaches 98.4%, which fully verifies that the network proposed in this paper has a good classification effect on bearing fault diagnosis.

4.3. Comparison with traditional intelligent methods
In order to verify the effectiveness of the above-mentioned network for rolling bearing fault diagnosis, it is compared with the traditional BPNN. Moreover, in order to reflect the advantages of SDAE network more obviously, the hidden layer of BPNN is increased to three layers, and the same BPNN structure as SDAE network structure is constructed, that is, the BPNN model is 100-50-30-20-10. The simulation results show that the accuracy of BPNN training set and test set is 91.125% and 91.037%, which further verifies the advantages and effectiveness of SDAE network for processing bearing fault data.

In order to compare the experimental results, RBFNN was introduced, the accuracy rate of training set was 93.354%, and the accuracy of test set was 92.964%. The accuracy rate of fault diagnosis was better than BPNN, but the diagnostic performance was inferior to that of SDAE deep neural network.
As shown in Table 1, the accuracy of fault diagnosis of 3-layer SDAE network is better than other networks in training set and test set, which fully verifies the effectiveness of the method proposed in this paper.

Table 1 Comparison of fault diagnosis accuracy of BP, 2-layer SDAE, 3-layer SDAE and 4-layer SDAE

| Network      | Training set accuracy rate (%) | Test set accuracy (%) |
|--------------|-------------------------------|-----------------------|
| BP           | 0.91125                       | 0.91037               |
| RBF          | 0.93354                       | 0.92964               |
| 2-layer SDAE | 0.86068                       | 0.84786               |
| 3-layer SDAE | 0.98018                       | 0.97821               |
| 4-layer SDAE | 0.91211                       | 0.90132               |

5. Conclusions
Aiming at the characteristics of large capacity and diversity of rolling bearing data, this paper proposes a rolling bearing fault diagnosis method based on SDAE. The effectiveness of SDAE network is verified by processing bearing fault data. Compared with RBFNN and BPNN with the same network structure, SDAE network has great advantages in fault feature extraction, operation speed and convergence accuracy. It is suitable for accurate fault diagnosis of rolling bearing and fully proves the excellent performance of SDAE network.

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