Bearing Fault Diagnosis Based on BP Neural Network and Transfer Learning

Ningbo Zhang*, Yawei Li, Xingbo Yang and Junhao Zhang

College of mechanical and electrical engineering, Zhengzhou University of light industry, Zhengzhou 450002, Henan, China

*Corresponding author e-mail: 331902010062@zzuli.edu.cn

Abstract. Rolling bearing is widely used in rotating machinery, which is one of the most prone to failure of industrial parts. In order to obtain the running state of rolling bearing timely and accurately, this paper uses Fourier transform to preprocess the data; based on the transfer component analysis to narrow the difference between the labeled data and the unlabeled data distribution, it is convenient to extract the feature information; BP neural network algorithm is used to build the network model, and then the data is tested, so as to realize the detection of bearing fault state and diagnosis. The experimental results show that the transfer learning based on principal component analysis can calibrate the features of unlabeled data well, and BP neural network can identify the fault types of rolling bearing well.

Keywords: Fault Diagnosis, Transfer Learning, BP Neural Network, Rolling Bearing

1. Introduction
Rotating machinery is a significant part of modern mechanical equipment. Whether it is the rolling mill, steam turbine in the industrial production, or the internal combustion engine and aeroengine in the life and traffic, if the rotating mechanism fails, it is easy to cause the whole operation process paralysis and part of the equipment damage, resulting in economic losses and even threat to life safety. As a hinge part of large rotating machinery, rolling bearing has the characteristics of heavy load, fast speed and so on. It is one of the most prone to failure of industrial parts [1]. Most of the faults are caused by bearing failure. Therefore, it is particularly vital to diagnose the motion state of the bearing, so as to ensure the safety of production and avoid unnecessary economic losses.

The title of this paper comes from the competition of intelligent manufacturing innovation and optimization. In this paper, the principles of Fourier transform, BP neural network and transfer component analysis based on transfer learning are introduced. After that, the data is processed and the network model is constructed. Finally, the model is trained and tested. Experiments show that the network model is simple, practical, easy to operate, and has a certain help for later scholars.

2. Fourier Transform Principle
Engineering signals are generally aperiodic, and aperiodic function \( f(x, y) \) can be regarded as
function \( f_T(x) \) of period \( T \to \infty \). The larger \( T \) is, the closer \( f_T(x) \) is to \( f(x) \) and \( f(x) \) satisfies the Dirichlet condition. The Fourier transform condition is expressed as

\[
F(\omega) = \int_{-\infty}^{+\infty} f(t) e^{-j\omega t} \, dt
\]  

(1)

\( j = \sqrt{-1} \), At present, there are many discrete forms in time domain and frequency domain. The time domain signal is replaced by the frequency domain signal of Fourier transform, namely discrete Fourier transform. The discrete Fourier transform can be expressed as

\[
X(k) = \sum_{n=0}^{N-1} x(n) e^{-\frac{2\pi jkn}{N}}
\]  

(2)

\( k = 0, 1, 2, \cdots N-1 \), \( x(n) \) is the sampling value obtained from the \( n \)th acquisition of signal \( x(t) \). Direct calculation of \( N \)-point discrete Fourier transform requires \( N^2 \) complex operations [2]. It has been found that the use of its symmetry, periodicity and reducibility, such as mixed basis, split basis, time-domain extraction, frequency-domain extraction, time-frequency extraction, vector basis and vector split basis to explore a variety of called fast Fourier transform.

3. Principle of BP Neural Network

In 1985, American scientists such as de Rumelhart and J L MC Clelland put forward the concept of neural network, which has been widely used and developed since then [3-4]. The emergence of neural network makes the iterative process pass forward and the error propagate backward. BP neural network can contain a large number of input-output relations, and the network model is simple. It has become a widely used neural network system. The basic structure of BP neural network consists of input layer, hidden layer and output layer. Each layer of neural network is connected by countless neurons (including a certain connection weight), and there are no interconnected neurons in the layer. The neural flow process of BP neural network mainly includes two neural learning processes: forward and backward. After the transfer input of the hidden layer, if the expectation of the sample output is not consistent with the reality, then it turns to back propagation, and the system adjusts the connection weights of each layer to reduce the error until it meets the accuracy requirements [5].

4. Principles of Migration Component Analysis

TCA maps data from different sources to a regenerated Hilbert space by constructing kernel function, which effectively reduces the difference of data distribution in different domains [6-9]. TCA is based on the maximum mean difference (MMD) to complete the spatial mapping of two domains. Assuming that the original space is \( x \), the source domain data with features and the target domain data without features are \( D_s = \{X_s, Y_s\} \), \( D_t = \{X_t, Y_t\} \), respectively. The marginal distribution is \( P(X_s) \) and \( P(X_t) \), and the conditional distribution is \( P(Y_s/X_s) \) and \( P(Y_t/X_t) \). In practical application, \( P(X_s) \neq P(X_t) \) and \( P(Y_s/X_s) \neq P(Y_t/X_t) \) are caused by environmental factors. Suppose there is a mapping function \( \phi \) satisfying \( P(\phi(X_s)) = P(\phi(X_t)) \). TCA thinks that when the edge distribution of two domains is the same, the conditional distribution is also the same.

5. Specific Implementation Steps

5.1 Data Preprocessing

The source domain data with feature tags and the source domain data without feature tags are
transformed by Fourier transform. Then, the part of positive frequency domain is selected for normalization, and the amplitude range is [0,1].

5.2 Feature Extraction
According to TCA theory, the data of source domain and target domain are mapped to the similar feature space to decrease the distribution difference between target data and source domain data[10]. For the data after Fourier transform, calculate the column average value, and then arrange it in the order from large to small. In order to reduce the calculation time and improve the efficiency, the first 100 data are selected and the index values are recorded respectively. This set of data is combined to form a new training set.

5.3 Building Network Model
The model consists of three parts: input layer, output layer and hidden layer. The input layer is the characteristic signal that needs to be input, the output layer is the output result signal of the demand, and the hidden layer is the key part of the network model. Based on MATLAB software platform, this paper establishes a BP neural network model. It mainly includes the determination of nodes, the selection of functions, the setting of errors and the determination of learning rate [11].

5.3.1 Input and Output of Network. The network input is a new training set for feature extraction. As the output node of fault diagnosis, the fault diagnosis type of bearing should be judged directly from the output results. The five states of the bearing correspond to five network outputs, so they are set as follows: rolling element fault (1,0,0,0); inner and outer ring fault (0,1,0,0); normal (0,0,1,0,0); inner ring fault (0,0,0,1,0); outer ring fault (0,0,0,0,1).

5.3.2 Network parameters. The number of hidden layer neurons is $n_2$, the number of input neurons is $n_1$, and there is an approximate relationship, $n_2 = 2n_1 + 1$. The input dimension of the network is 7, the output dimension is 5, and the number of hidden layer nodes is 15. The training frequency is 100, the training goal is 0.00001, and the learning rate is 0.01 [12].

5.4 Training and Testing of Network Model

5.4.1 Network training. After the neural network model and training parameters are determined, the following Matlab code is used to create the training bearing fault diagnosis BP network. Where P is the training matrix after Fourier transform and normalization, and T is the output objective matrix.

```matlab
Net = newff(P,T,[15]);
net.trainParam.epochs = 100;
net.trainParam.goal = 1e-5;
net.trainParam.lr = 0.01;
[net,tr] = train(net,P,T);
```

The Simulink model is called by the SIM function, and the accuracy of the training set is 98.4%; then the verification set of known bearing fault state is input into the network for verification, and the results show that the accuracy of the verification set is 100%. It can be seen that the network performance is very good and meets the requirements. The trained neural network model is the identification network for bearing fault diagnosis.

5.4.2 Network test. The preprocessed test set data is input into the neural network. The test consequence show that the accuracy of normal bearing test is 100%, the accuracy of rolling element fault is 95.63%, the accuracy of inner ring fault is 98.65%, the accuracy of outer ring fault is 97.83%,
and the accuracy of inner and outer ring fault is 96.31%.

6. Concluding Remarks

According to the theory of transfer component analysis, this paper uses function to reduce the distribution difference between the source domain data with feature tag and the target domain data without feature tag. Fourier transform of vibration signal can accurately reflect the fault characteristic information. Based on BP neural network, the inner ring, outer ring, inner and outer ring and rolling element faults of rolling bearing are identified. Compared with other diagnosis methods, this method can judge the fault type more accurately, and the operation is simple and easy to realize.

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