Research on Fault Diagnosis Method of Gearbox Based on SA and BP-AdaBoost

Yangyang Zhang¹, Yunxian Jia*, Weiyi Wu¹, Xiaobo Su¹ and Dong Liang¹

¹Army Engineering University, Shijiazhuang, Hebei, 050003, China

Corresponding author’s e-mail: 2108007979@qq.com

Abstract. In order to solve the problems of difficult selection of state feature parameters and poor accuracy of single BP Neural Network in gearbox fault diagnosis, a gearbox fault diagnosis method based on SA and BP-AdaBoost is proposed. Taking the typical fault of a gearbox as the research object, the vibration signal of the typical working state of the gearbox is collected through the preset fault experiment. The time domain statistical parameters with high sensitivity is selected as the feature vectors by the Sensitivity Analysis method. Then these state feature vectors are input into BP-AdaBoost model for training and testing, and their results are compared with those of BPNN model. The results show that the proposed method can quickly and effectively diagnose the fault of gearbox, and is better than BPNN model.

1. Introduction

Gearbox is an important part of vehicle transmission system, mainly composed of gears and bearings. With the extension of operation time, the performance of gearbox gradually deteriorates, and it is one of the mechanical devices with high failure rate because it often works continuously under the harsh environment such as heavy load and high speed[1]. At the same time, due to the important role of gearbox in the transmission device, its health condition will affect the working state of the whole vehicle chassis system. In case of failure, if not handled in time, it will lead to serious consequences[2]. Therefore, the study of gearbox health monitoring and early fault diagnosis is of great significance for the prevention of serious vehicle faults[3].

For the fault diagnosis of modern mechanical equipment, artificial Neural Network is simple, operable and intelligent. Among them, BP Neural Network is the most widely used one[4,5]. Liang Chao et al.[6] used BP Neural Network as classifier for rotor fault diagnosis, Zhang Yingsong et al.[7] established a fault diagnosis model based on BP Neural Network and applied it to the fault diagnosis model of turbofan engine. There are also scholars who use improved BP Neural Network for fault diagnosis of gearbox or gearbox. In reference[8], a fault diagnosis method based on Chaos Quantum Particle Swarm Optimization BP Neural Network is proposed to identify the fault mode of gearbox of wind turbine. In reference[9], the BP Neural Network is improved by using dynamic learning rate, and the gearbox fault diagnosis network model is established. However, the learning algorithm of BP network has a slow convergence speed, and it is easy to fall into the local optimal value, resulting in the low accuracy of diagnosis. The AdaBoost algorithm is introduced into BP Neural Network model to build BP-AdaBoost fault diagnosis model, which can effectively improve the diagnosis accuracy of the original single BP Neural Network.

Based on the above research, this paper proposes a gearbox fault diagnosis method based on sensitivity analysis (SA) and BP-AdaBoost. There are many time-domain statistical parameters of vibration signal, so sa is used to select the time-domain statistical parameters with high sensitivity as the
state eigenvector and reduce the dimension of the state eigenvector. Then these eigenvectors are input into BP-AdaBoost model for training and testing, which can quickly get accurate diagnosis results.

2. SA and BP-AdaBoost

2.1. Sensitivity Analysis
In the process of time-domain analysis, considering that there are many time-domain statistical parameters of vibration signal, many time-domain indexes will greatly increase the calculation time, and some unnecessary parameters will also form interference, which may increase the error. Therefore, it is very important to select the appropriate characteristic parameters to form the fault characteristic vector, which requires that after extracting the time-domain characteristic parameters, these parameters should be further studied. Through sensitivity analysis, the characteristic parameters which can effectively represent the state of gearbox are selected. The calculation formula of sensitivity analysis is:

\[ u = \frac{X_i - X}{X} \]  

(1)

Where \( u \) is the sensitivity, \( X_i \) is the parameter to be analyzed, and \( X \) is the reference parameter. Usually, the time-domain characteristic parameters of normal state are taken as reference parameters, and the time-domain characteristic parameters of fault state are taken as parameters to be analyzed.

2.2. BP-AdaBoost
The main idea of BP-AdaBoost algorithm is: first, each sample is initialized to equal weight, and then iterates \( n \) times with weak classifier. After each iteration, the weight is updated according to the classification result. For the failed samples, a larger weight is given, and more attention is given to the next iteration. Weak classifiers get a sequence of classification functions through multiple iterations. Each classification function will give a certain weight according to the classification error, and finally combine multiple weak classifiers to form a strong classifier with small and stable classification error. The algorithm flow of BP-AdaBoost is shown in Figure 1, and its main steps are as follows.

- **Step 1**: data selection and network initialization. Select \( m \) group training samples from the sample space and initialize the sample weight \( D(i) = 1/m \). According to the dimension of sample input and output, the structure of neural network is determined, and the weight and threshold of BP Neural Network are initialized.
- **Step 2**: weak classifier prediction. When the first \( t \) weak classifier is trained, the BP Neural Network is trained with training data and the output of the training result is predicted. The prediction sequence \( g(t) \) and the sum of prediction errors \( e_t \) are obtained.
3. Experimental verification

In order to verify the effectiveness of the proposed method, a group of experiments are set up to verify the real experimental data. The vibration analysis and fault diagnosis experiment platform system of QPZZ-Ⅱ rotating machinery is adopted in the experiment. The gearbox used in the experiment is mainly composed of a pair of meshing gears. According to the common failure modes of gearbox, this experiment simulates four operation states of gearbox, namely pitting, wear, tooth breakage and normal state. During the experiment, the acceleration monitoring data in the Y direction of the load side of the gearbox input shaft are collected by the acceleration sensor, the sampling frequency is 5120 Hz, and 150 groups of sample data are collected for each state.

In order to extract fault information more comprehensively, this paper selects 14 commonly used time-domain statistical parameters, which are: mean value, root mean square value, square root amplitude, absolute mean amplitude, mean square value, maximum value, minimum value, peak-peak value, waveform index, peak value index, pulse index, margin index, skew index and kurtosis index.

The above characteristic parameters are numerous, which will inevitably produce interference or overlap, and the 14 dimensional data sample will increase the calculation amount, so the effective solution is to carry out sensitivity analysis. Sensitivity analysis is conducted for 14 characteristic parameters of each state, and the analysis results are shown in Figure 2.

It can be seen from the above figure that the first, fifth and 13th characteristic parameters are highly sensitive, and there are great differences between different fault modes, so the recognition ability of different states of gearbox is better. Therefore, three characteristic parameters, namely mean value (P1), mean square value (P2) and skew index (P3), are selected as the characteristic parameters of gearbox state. The state characteristic parameters of 150 groups of sample data in each state are calculated to obtain 150 state eigenvectors in each state. Some state eigenvectors are shown in Table 1.
Figure 2. Sensitivity analysis of characteristic parameters

Table 1. State eigenvector

|       | P1     | P2     | P3     |
|-------|--------|--------|--------|
| Type 1| 0.0486 | 19.5797| -0.0803|
|       | 0.0308 | 17.3548| -0.0769|
|       | 0.0280 | 18.4701| -0.0687|
|       | 0.0327 | 11.3584| -0.1667|
| Type 2| 0.0425 | 12.5395| 0.0692  |
|       | 0.0395 | 13.0963| -0.1683|
|       | 0.1104 | 383.1858| -0.0336|
| Type 3| 0.0486 | 392.4404| 0.0070  |
|       | 0.0890 | 409.6765| 0.0050  |
|       | 0.0659 | 40.6511 | -0.1370 |
| Type 4| 0.0153 | 37.7756 | -0.0523 |
|       | -0.0038| 36.5522 | -0.1858 |

The BP-AdaBoost fault diagnosis model is established, and in the 160 groups of state eigenvectors of each state, 100 groups are randomly selected as training samples, and the rest 50 groups are selected as test samples. Input the training samples into the model in turn to train them. After the training, input the test samples to get the gearbox fault diagnosis results, as shown in Table 2.

Table 2. Test results

| Type  | 50 | 50 | 50 | 50 | Total accuracy rate |
|-------|----|----|----|----|---------------------|
| Test samples | 49 | 48 | 47 | 50 | 97% |
| Accuracy quantity | 100% | 96.67% | 95% | 100% |

From the test results, it can be seen that the method proposed in this paper can accurately identify the operation state of the gearbox, and the total accuracy reaches 97%. In order to further verify the superiority of the proposed method, three groups of comparative experiments are carried out below, and the experimental results are summarized as shown in Table 3.

Table 3. Comparison of test results

|       | BPNN | BP-AdaBoost | SA & BP-AdaBoost |
|-------|------|-------------|------------------|


| Total number of test samples | 200 | 200 | 200 |
|-----------------------------|-----|-----|-----|
| Accuracy quantity           | 173 | 186 | 194 |
| Accuracy rate               | 86.5% | 93% | 97% |
| Running time                | 1.713 s | 3.436 s | 2.097 s |

Obviously, AdaBoost integrated learning method can effectively enhance the fault diagnosis ability of BPNN, and the accuracy of BP-AdaBoost fault diagnosis model is higher than BPNN. SA method can significantly reduce the dimension of data, reduce the calculation time, and improve the accuracy.

4. Conclusions
This paper presents a fault diagnosis method of gearbox based on SA and BP-AdaBoost. The results of experiment and simulation show that Sensitivity Analysis (SA) method can extract the feature parameters with high sensitivity and reduce the dimension of data. The state feature vector composed of three feature parameters can represent the key and useful fault information. BP-AdaBoost method can use the state feature vector to diagnose the fault mode of gearbox quickly and accurately, which has certain value in engineering practice reference significance and application value.

Acknowledgments
This work was supported by National Natural Science Foundation of China (71871220),

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