Research on rolling bearing fault diagnosis of high-speed train

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Abstract. The rolling bearing is the main vulnerable component of a rotating machinery on high-speed train, which is very important to the safe operation of high-speed train. Based on the fundamental analysis of the causes of rolling bearing faults on high-speed trains, the feasibility of wavelet packet analysis and BP neural network in rolling bearing fault diagnosis of high-speed trains is discussed. In this paper, wavelet packet is used to denoise data and extract features, then the training BP neural network is used to diagnose and analyze the characteristic data accurately, and the diagnosis results are obtained. By comparing the training results, the number of wavelet packet decomposition is determined, and the accuracy of BP neural network diagnosis is improved. In this paper, the analysis is carried out by using the bearing data of American electrical laboratory “Case Western Reserve University”, an efficient and fast method for rolling bearing diagnosis is presented, which can be applied to real-time fault diagnosis and monitoring of rolling bearing faults for high speed train.

1. Introduction

High speed trains are faced with complex working environments such as heavy load, high speed and long continuous operation, some of the key parts are easy to go wrong, if not promptly found these faults or defects will cause a series of chain reaction, leading to the high speed train unsafely operation, will eventually endanger the entire high-speed railway network security operations[1].

As a key component of high-speed train, rolling bearing of high-speed train is prone to mechanical damage under the condition of long time, high speed and heavy load, which affects the operation safety of high-speed train. Axle box bearings of China's high speed trains mainly rely on imports, localization hasn't been realized yet, and many of the relevant standards of China's railway transportation system mainly refer to foreign countries[2]. Because of the high speed, the working environment of the rolling bearing is worse, Its monitoring difficulty is multiplied by ordinary trains[3]. Until today, the train accidents occur frequently because of the failure of the key components of the train. According to the statistics of China's railway system in recent years, there are more or less mechanical defects or injuries in the axle box bearings of domestic trains, especially for high-speed trains. Chinese train and key parts basically rely on fixed maintenance or overhaul period for off-line testing, however, it can only detect the damaged parts, it is difficult to detect the parts which are about to fail and can not be early warning of the train. Even though most of the trains are equipped with real-time monitoring systems and alarm devices, most of them are difficult to detect [4] in small initial faults.

In recent years, China's railway system has paid more and more attention to the localization and state detection of the rolling bearings of the train. At present, most of the monitoring technology of axle box bearings in China is axle temperature detection, and more and more intelligent monitoring system [5] is applied on some "Shaoshan" and "harmony" locomotives. In order to improve the
efficiency of the train operation and reduce the economic losses in China's railway system, combined with the fault feature extraction of train rolling bearing, a wavelet-BP neural network diagnostic model is proposed in this paper, and a high-speed motor bearing is selected as a specific research object to conduct a comprehensive verification.

2. Fault diagnosis data source of rolling bearing for high speed train
The source of data used in this paper is the bearing data of the Case Western Reserve University electrical laboratory. The rolling bearing test stand was set up in the laboratory, and the rolling bearing fault of stable speed was set artificially by the way of EDM. The motor used in the experiment is 2 horsepower SKF 6205-2RS JEM deep groove ball bearing Reliance motor. The test platform consists of a motor (left), torque sensor / encoder (Center), dynamometer (right) and electronic control equipment. The diameter of the tested bearing was 175μm, 350μm, 525μm, 700μm, 1000μm. The whole acceleration sensor is fixed on the shell of the top of the driving bearing of the induction motor, and the data type is Matlab format. The data content is the initial vibration signal of the normal rolling bear and the initial vibration signal data of the inner and outer race faults.

| Bearing    | Fault Location | Diameter | Depth | Bearing Manufacturer |
|------------|----------------|----------|-------|----------------------|
| Drive End  | Inner Raceway  | .007     | .011  | SKF                  |
| Drive End  | Inner Raceway  | .014     | .011  | SKF                  |
| Drive End  | Inner Raceway  | .021     | .011  | SKF                  |
| Drive End  | Inner Raceway  | .028     | .050  | NTN                  |
| Drive End  | Outer Raceway  | .007     | .011  | SKF                  |
| Drive End  | Outer Raceway  | .014     | .011  | SKF                  |
| Drive End  | Outer Raceway  | .021     | .011  | SKF                  |
| Drive End  | Outer Raceway  | .040     | .050  | NTN                  |
| Drive End  | Ball           | .007     | .011  | SKF                  |
| Drive End  | Ball           | .014     | .011  | SKF                  |
| Drive End  | Ball           | .021     | .011  | SKF                  |
| Drive End  | Ball           | .028     | .150  | NTN                  |
| Fan End    | Inner Raceway  | .007     | .011  | SKF                  |
| Fan End    | Inner Raceway  | .014     | .011  | SKF                  |
| Fan End    | Inner Raceway  | .021     | .011  | SKF                  |
| Fan End    | Outer Raceway  | .007     | .011  | SKF                  |
| Fan End    | Outer Raceway  | .014     | .011  | SKF                  |
| Fan End    | Outer Raceway  | .021     | .011  | SKF                  |
| Fan End    | Ball           | .007     | .011  | SKF                  |
| Fan End    | Ball           | .014     | .011  | SKF                  |
| Fan End    | Ball           | .021     | .011  | SKF                  |

This paper uses four kinds of data, such as normal bearing data, inner race fault data, outer race fault data and rolling body fault data, which are used to analyze, process and diagnose faults through Matlab software. The experimental fault specification is shown as table 1. The sampling rate of the data is 12kHz, For normal bearings, data are collected at the single point drive end and fan end defects. The motor load is 2 HP, and the speed is 1750r/min.

3. Data processing of rolling bearing for high speed train based on wavelet packet decomposition
In this paper, the wavelet packet analysis method is used to diagnose and analyze the rolling bearing of high speed motor, so that the fault analysis method of rolling bearing of high-speed train is obtained.

A set of approximate coefficients and a set of detail coefficients can be obtained by wavelet packet structure, which can be used to achieve feature extraction later. In this case, it provides a richer analytical method: in a one-dimensional case, it produces a complete two fork tree, and in two-
dimensional case, it produces a complete four fork tree. With the increase of resolution, wavelet packet has better quality, which can be analyzed and refined in the amplification part. Wavelet packet analysis has a certain adaptability, and it can select the corresponding frequency to improve the resolution.

\[(0, 0)\]
\[(1, 0)\]
\[(2, 0)\]
\[(3, 0)\]
\[(1, 1)\]
\[(2, 1)\]
\[(3, 1)\]
\[(2, 2)\]
\[(3, 2)\]
\[(2, 3)\]
\[(3, 3)\]
\[(3, 4)\]
\[(3, 5)\]
\[(3, 6)\]
\[(3, 7)\]

Figure 1 Three layer decomposition tree structure of wavelet packet

In the tree of three layer decomposition of wavelet packet, as shown in Figure 1, (a, b) represents the node, “a” denotes the number of layers, and “b” represents the position corresponding to each node of each layer. In addition to the original signal, each node represents a decomposed set of feature information vectors, including high frequency features and low frequency features. In addition to the bottom layer, each node in the middle layer is divided into two nodes by the upper layer, so the number of the lower nodes is two times of the upper node number.

In this paper, the Matlab software is used to de-noising the experimental data by wavelet packet analysis. The motor speed is 1750r/min, and the sampling rate is 12kHz. In order to display the characteristics of signal data conveniently, this paper uses the db1 wavelet to analyze the 6000 data before the experiment.

Taking Inner race fault of rolling bearing as example.

The Time domain waveform of inner race fault is shown as Figure 2(a); the frequency domain waveform of inner race fault is shown as Figure 2(b); the wavelet packet decomposition of inner race fault is shown as Figure 2(c).

Figure 2 (a) Time domain waveform of inner race fault

Figure 2 (b) Frequency domain waveform of inner race fault
Figure 2 (c) Wavelet packet decomposition denoising waveform of inner race fault

The data features are compared to the three layer wavelet packet de-noising signal, respectively. In order to facilitate the training of BP neural network, this paper selects the data obtained from the three layer wavelet packet decomposition to carry out the input training.

The output samples of the BP neural network with three layers of wavelet packet decomposition are as follows:

- Normal bearing: [1 0 0 0]
- Inner race fault: [0 1 0 0]
- Outer race fault: [0 0 1 0]
- Rolling element fault: [0 0 0 1]

The three layer wavelet packet decomposition scheme is adopted, and the result shows that the decomposition layer meets the expected requirements. The momentum BP neural network uses 8 hidden neurons, the standard BP neural network uses 12 hidden neurons, the number of the neurons in the hidden layer is confirmed by an empirical formula and experiment one by one, referring to the speed and accuracy of convergence.

4. Research on rolling bearing fault diagnosis of high speed train based on Neural Network

The standard BP network algorithm uses the SDBP algorithm, the convergence speed of the algorithm is slow, it is easy to cause a local minimum point, and in the process of learning BP neural network, the effect is not stable. Aiming at the shortcomings of BP neural network, the improved momentum BP neural network algorithm is introduced, a new coefficient is joined in the gradient descent algorithm, that is Momentum coefficient $\eta$ ($0<\eta<1$) $^6$. The momentum BP neural algorithm will feed back to the forward work correction error in the process of working error feedback, and generate a correction, when the correction error is too large, the next revision of the system will produce a correction of the opposite sign of the previous correction to correct the accuracy. When the last correction is too small, the revised value of the next system will be the same as the symbol of the previous revision, in order to speed up the correction of the system error $^7$. The correction speed of the whole algorithm is greatly accelerated by the constant feedback of the correction and the adaptation of the revised quantity. Therefore, in the process of using the momentum BP algorithm, there will be relatively stable learning results even using a large learning speed.

The test data of the algorithm is the data matrix of all kinds of fault rolling bearings and normal rolling bearings, the test data matrix is shown as Table 2. After wavelet analysis and normalization, it is convenient to recognize and improve the recognition accuracy $^8$.

| Test data matrix |
|------------------|
| Normal bearing   | Inner race fault | Outer race fault | Rolling element fault |
| 0.0103           | 0.0148           | 0.0177           | 0.0441                |
| 0.0697           | 0.0238           | 0.1269           | 0.0419                |
| 0.0727           | 0.0453           | 0.0476           | 0.0032                |


The calculation results of momentum BP neural network is shown as Figure 3.

![Graph showing performance of momentum BP neural network](image)

**Figure 3 Calculation results of momentum BP neural network**

The actual output of the algorithm is:

\[
Y = \begin{bmatrix}
0.7685 & 0.0126 & 0.0332 & 0.1438 \\
0.2312 & 0.9864 & 0.1034 & 0.0604 \\
0.2356 & 0.0543 & 0.5784 & 0.0021 \\
0.0044 & 0.0375 & 0.0598 & 0.9861
\end{bmatrix}
\]

The corresponding results are:

\[
y = \begin{cases}
\text{Normal bearing} \\
\text{Inner race fault} \\
\text{Outer race fault} \\
\text{Rolling element fault}
\end{cases}
\]

The input sample P of this experiment is all the data in Table 4, the target vector T is the [1,0] matrix corresponding to the input vector, and the test vector T_test is randomly extracted and classified by wavelet processing in each fault mode. The actual output of the experiment is compared with the ideal output of the target. It can be seen that it has a certain approximation, and a certain recognition diagnostic effect can be basically achieved. In addition to using the code to perform the arithmetic operation of the momentum BP neural network, the Matlab can also be used to carry out the
operation with the Neural Net Fitting APP. However, the parameter adjustment of the Matlab's neural network toolbox is limited, and it is not convenient to adjust the precision of the target.

5. Conclusion
This paper analyzes and diagnoses the bearing data of the American electrical laboratory “Case Western Reserve University”, an efficient and rapid diagnosis method for rolling bearings is expected to be obtained, which is applied in high-speed train real-time diagnosis of rolling bearing fault monitoring. Based on the fundamental analysis of the causes of the rolling bearing failures of high-speed trains, the measures and methods for preventing faults can be put forward theoretically, so as to reduce the failure frequency of high-speed trains. The wavelet packet is used to de noise and feature extraction for data analysis. At last, the diagnosis results are obtained by using the training BP neural network to diagnose and analyze the accurate data. By comparing the number of layers of wavelet packet decomposition, the accuracy of BP neural network diagnosis is improved. By using BP neural network, the input vectors obtained from the three level wavelet packet decomposition and the input vectors obtained by the four wavelet packet decomposition are trained. It is concluded that using three layers of wavelet packet decomposition to carry out BP neural network training is the best.

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