A study on Fault Diagnosis Method of Rolling Bearing Based on Wavelet Packet and Improved BP Neural Network

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Abstract. In this paper, rolling bearing fault diagnosis method is proposed based on wavelet packet threshold de-noising and improved BP neural network. It achieves the goal of signal de-noising by setting the appropriate threshold, and then the denoised signal is decomposed into three layers by wavelet packet. The energy characteristics of the 8 frequency bands are calculated respectively. Levenberg-Marquardt algorithm which is improved the traditional BP neural network to improve the diagnosis efficiency of BP neural network, is proposed. Taking the outer ring fault of rolling bearings as an example, the experimental results show that the wavelet packet threshold de-noising can effectively improve the signal-to-noise ratio. Compared with the traditional BP neural network, the improved BP neural network has better diagnosis efficiency.

1. Introduction
In the industrial production, whether the normal work of the bearing determines the operation of the entire production system, bearing fault will lead to economic losses and even great safety accident of the plane crash. Therefore, it is of great practical significance to study the rapid and effective bearing fault diagnosis technology to ensure the safe and reliable operation of the equipment in order to avoid huge economic losses and to prevent catastrophic accidents. Guo and Deng [1] introduced an improved Empirical Mode Decomposition (EMD) method based on the multi-objective optimization in their paper and is applied to extract the fault feature of rolling bearing with inner and outer race fault. proposed a novel hybrid approach of a random forests classifier for the fault diagnosis in rolling bearings. The approach is tested on simulation and practical bearing vibration signals by considering several fault classes. Li [3] proposed a novel weak signal detection method based on time-delayed feedback monostable stochastic resonance system and adaptive minimum entropy deconvolution to realize the fault diagnosis of rolling bearings. Ren [4] proposed a new feature extraction method for fault diagnosis of rolling bearings under varying speed conditions. Categorized results show that the new approach is capable of handling the bearing fault classification under varying speed conditions. Mishra [5] studied a novel diagnosis scheme based on envelope analysis and wavelet de-noising with
sigmoid function based thresholding to extract the fault related symptoms from noisy vibration signatures of defective ball bearings operating at slow speed.

In this paper, a fault classification algorithm is proposed, which is a new type of wavelet packet and BP neural network. The wavelet packet threshold method is used to denoise, and the denoised signals are decomposed by wavelet packet, and the energy characteristics of each frequency band are calculated, then these feature dates are trained on BP neural network. The traditional BP neural network is improved by Levenberg-Maquardt (LM) algorithm, and the experimental results show that the improved BP neural network has better diagnostic efficiency.

2. Wavelet packet denoising and energy feature extraction

2.1. Wavelet packet threshold denoising
Wavelet packet can decompose the scale factor deeply, and can make the spectrum fine or fine. This also greatly improves the wavelet imperfections. Although the wavelet packet and wavelet analysis methods are approximately the same, wavelet packet has improved the low-frequency signal and high frequency processing method of the upper layer. The wavelet packet de-noising processing steps are as follows:

Select a wavelet base function and the level of decomposition required.
Determine the optimal wavelet packet basis, and calculate the best tree.
Select a suitable threshold and quantify the coefficients.
Wavelet packet reconstruction of signals.

In the above steps, the most important thing is to set the threshold, and the threshold directly affects the quality of the signal denoising process to a certain degree.

2.2. Extracting energy characteristics
After the wavelet packet is decomposed, the frequency of each node signal has different components. In other words, different fault signals are decomposed at different frequencies on each node. This shows that the fault diagnosis of rolling bearings can be used to decompose the energy of each node in the wavelet packet as an indicator. The specific method of extracting energy features is:

![Figure 1. Extraction Process of Wavelet Packet Failure Energy Feature](image)

(1) The signal $f(x)$ is decomposed by $j$ scale wavelet packet, $2^j$ uniform frequency bands are obtained at the $j$ scale, and the denoised signals are decomposed into 3 layers by wavelet packet. Thus, the $8$ frequency band signals from the low frequency to the high frequency are obtained on the third layer;

(2) To improve the time resolution of signal, the signal of frequency band decomposed by wavelet packet containing fault type information is reconstructed;

(3) The energy of the reconstructed signal in each frequency band can be computed as follow

$$E_{j,n} = \int_{R} |f_{j,n}(x)|^2 dx = \sum_{k=1}^{N_j} |d_{j,k}^n|^2, n = 0, 1, ..., 2^j - 1$$ (1)
In the formula, $E$ represents the energy of the $n$ reconstructed wavelet packet node under the $j$ scale; $d$ represents the coefficients sequence of the $n$ reconstructed wavelet packet nodes at the $j$ scale.

(4) The energy of each frequency band signal is normalized. The wavelet packet fault energy feature extraction process is shown in Figure 1.

3. Improved BP-NN theory based on LM algorithm

The LM algorithm uses the approximate second derivative information, which is a combination of the descending gradient algorithm and the Gaussian Newton algorithm. It has the local characteristics of the Newton method, that is, an ideal search direction can be found in the vicinity of the optimal value. In addition, there is a global characteristic of the gradient method, that is, a few steps in the beginning of the iteration of the faster decline. Therefore, the algorithm is faster than the gradient descent algorithm, and is more stable [6,7]. The iterative expression of the LM algorithm is shown in equation (2).

$$x(k + 1) = x(k) + \Delta x$$  \hspace{2cm} (2)

In which \(\Delta x = -(J^T(x)J(x) + \mu I)^{-1}J^T(x)e(x), \quad J(x) = \begin{bmatrix} \frac{\partial e_i(x)}{\partial x_1} & \frac{\partial e_i(x)}{\partial x_2} & \cdots & \frac{\partial e_i(x)}{\partial x_n} \\ \frac{\partial e_i(x)}{\partial x_1} & \frac{\partial e_i(x)}{\partial x_2} & \cdots & \frac{\partial e_i(x)}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial e_i(x)}{\partial x_1} & \frac{\partial e_i(x)}{\partial x_2} & \cdots & \frac{\partial e_i(x)}{\partial x_n} \end{bmatrix}$$

Where \(x(k)\) is the vector of weights and threshold values constituting the \(k\)-th iteration, \(e_i(x)\) is the error of the \(i\)-th network node, \(I\) is a unit matrix; \(J(x)\) is the Jacobian matrix, \(\mu\) is a more adaptive adjustment coefficient of zero.

$$x(k + 1) = x(k) - (J^T(x)J(x) + \mu I)^{-1}J^T(x)e(x)$$  \hspace{2cm} (3)

When \(\mu \to 0, \mu I \approx 0, \Delta x = -(J^T(x)J(x))^{-1}J^T(x)e(x).\) The equation (2) becomes the formula (3) which is the Gaussian Newton algorithm.

When \(\mu \to \infty, J^T(x)J(x) \approx \mu I, J^T(x)J(x)\) is negligible, At this point, the LM algorithm is reduced to a gradient descent method.

Thus, the LM algorithm can realize the combination of the Gauss Newton method and the gradient descent method by adjusting adaptively the value. The practice result shows that the LM algorithm is several times or even hundreds of times faster than the descending gradient method. At the same time, \((J^T(x)J(x) + \mu I)^{-1}\) is positive definite in LM algorithm, that is, \(\Delta x\) always exists solution, and for Gaussian Newton method \(J^T(x)J(x)\) is not necessarily full rank. It can be seen, LM algorithm is better than Gauss Newton method [6].

4. Result and analysis

In order to test effectively the diagnosis method proposed in this paper, we adopt the experimental fault table as shown in figure 2. The test bench mainly has an AC variable frequency motor (power 0.55KW), several sensors (acceleration sensors 4, laser speed meter 1), five gears (three large gears, two small gears), several bearings, gearbox, speed controller and so on. Various faults can be simulated quickly by adjusting the mounting position of the mechanical parts and the organic
combination of the components. The mechanical parts of the system includes defective bearings (outer ring defects, inner ring defects, ball defects), as well as computer and signal conditioner (not shown) and other equipment.

Taking the fault of rolling bearing outer ring as an example, the wavelet packet threshold denoising method is used to denoise the collected signals, as shown in figure 3. It is easy to see that the signal-to-noise ratios of the fault signals are obviously improved after de-noising. Then, the denoised signals are decomposed into three layers by wavelet packet. The energy characteristics of each frequency band are calculated by formula (1), as shown in figure 4. As can be seen from Figure 4, it can be found that the energy of the fault free signal is mainly concentrated in the first frequency band, while the energy characteristic of the fault signal is mainly concentrated in the second frequency band, which can be used as a preliminary judgment of the fault characteristics.

The calculated energy characteristics are taken as input vectors of BP neural network, and 200 sets of data are used for network training, then with 20 sets of test data for diagnostic tests, test results show that the data of the 18 groups of diagnosis is successful and the diagnosis success rate is 90%. Taking a group of successful test data as an example, Figure 5 shows the traditional BP neural network and improved BP Neural Network with LM algorithm, respectively. The transfer function of the output layer and the hidden layer of the BP neural network are set as purelin and logsig functions, respectively. The minimum mean square error is set to $10^{-8}$, and the training steps are 1000. The diagnosis results show that the traditional BP neural network needs to train 91 steps to complete the fault diagnosis, and the improved BP neural network of LM algorithm needs only 42 steps to finish the fault diagnosis. Obviously, it can be seen that the improved BP neural network with LM algorithm has higher diagnosis efficiency than the traditional BP neural network.

![Figure 2. Experiment platform](image)

![Figure 3. Comparison of noise before and after the fault of bearing outer race](image)
Figure 4. Energy spectrum of three layer decomposition: (a) normal signals, (b) fault signals of bearing outer race

5. Conclusion
Bearing failure is a common kind of fault in rotating machinery and equipment, real-time monitoring and successful diagnosis of the fault type is very necessary. In this paper, a new method is proposed based on wavelet packet threshold denoising, and BP neural network is improved by LM algorithm. The method is applied to the outer ring fault of rolling bearing. The experimental results show that the fault diagnosis method has good denoising effects and high diagnostic accuracy. In addition, improved BP Neural Network with LM Algorithm is better than traditional BP neural network.

Figure 5. Training process of traditional BP neural network and improved BP neural network based on LM algorithm

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