Probabilistic Neural Network Motor Bearing Fault Diagnosis Based on Improved Feature Extraction

Fanchao Min\textsuperscript{1st, a}, Jingyu Xue\textsuperscript{2nd, b}, Fengying Ma\textsuperscript{3rd, c}\textsuperscript{*}

Qilu University of Technology, Jinan, Shandong, China
\textsuperscript{a}e-mail: Min\textunderscore FC@163.com, \textsuperscript{b}e-mail: daoxiang.mo@163.com, \textsuperscript{c}Corresponding author: mafengy@163.com

Abstract—According to the fault characteristics of the rolling bearing in the motor, Db6 wavelet is used to decompose the waveform data, and the feature vector extraction method is improved. The probabilistic neural network is used to diagnose the fault category of the rolling bearing of the motor, and compared with the traditional feature extraction method. Experiments show that the accuracy of the method proposed in this paper reaches 98%, and it has a very broad application prospect in fault diagnosis in actual industrial production.

1. INTRODUCTION
Motors play a pivotal role in industrial production. The stability and reliability of their operation are directly related to industrial safety production and economic benefits. The inspection and fault diagnosis section provides reliable guarantees for the normal operation of the motors. However, motor bearings are prone to faults on the inner ring, rolling elements, and outer ring. If the faulty bearing is not detected and running under load, it may cause serious safety accidents. Therefore, the motor bearing fault diagnosis method with high recognition accuracy and low false alarm rate has become a research hotspot at home and abroad [1]. Although traditional diagnosis methods such as shock pulse method and resonance demodulation method greatly improve the diagnosis accuracy, they still require manual assistance, which makes it difficult to achieve accurate diagnosis in complex environments. Therefore, it is very necessary to use intelligent methods to perform state detection and fault diagnosis of rolling bearings [2]. As a widely used intelligent method, neural network has the advantages of strong nonlinear mapping ability, self-learning, self-organization and self-adaptation, which is very suitable for the fault diagnosis of rolling bearing.

2. THE OVERALL STRUCTURE
In this paper, wavelet packet decomposition and PNN are combined to diagnose the faults of rolling bearings. The diagnosis process is shown in Figure 1. In this paper, wavelet packet decomposition is used to extract the effective features of the vibration signal, and the feature vector is optimized, and then the fault state of the rolling bearing is identified by PNN.
2.1 Principle of wavelet packet analysis
The motor generates vibration signals during operation. When the equipment fails due to external or inherent defects, it will have an impact on the bearing. This impact will generate vibration. The vibration will cause the motor to change its working state and cause signal deviation. When the equipment fails, the vibration response of different positions is different. The different characteristic values will be produced. This article divides the motor faults into inner ring faults, outer ring faults and shaft body faults.

Wavelet transform is a signal time-scale analysis method. It has the characteristics of multi-resolution analysis and has the ability to characterize the local characteristics of the signal in the time and frequency domains. It has high frequency resolution in the low frequency part, high time resolution and low frequency resolution in the high frequency part, and the use of continuous wavelet transform for dynamic system fault detection and diagnosis has good results [3-5]. Wavelet packet analysis can provide a more refined analysis method for the signal, divide the frequency band into multiple levels, divide the frequency band into multiple levels, and further decompose the high-frequency part that is not subdivided in the multi-resolution analysis. It can be analyzed according to the characteristics of the signal, adaptively select the corresponding frequency band to match the signal spectrum, thereby improving the time-frequency resolution [6].

This paper uses wavelet packet to decompose the collected motor vibration signal in three layers, and then divide the collected signal into 8 frequency bands, and then according to the energy distribution after decomposition, the front signal is showing the kind of components (inner ring, outer ring, rolling). The typical characteristic frequency of the failure, so as to determine the type and severity of the failure of the rolling bearing. After the vibration signal is decomposed by the wavelet packet, the energy distribution on the different orthogonal wavelet packet space at a certain level, like the fault characteristic frequency spectrum of the rolling bearing, reflects the essential characteristics of the running condition of the rolling bearing. The wavelet packet decomposition process is shown in Figure 2.
Multi-resolution analysis has a good time-frequency decomposition effect, but the low frequency and high frequency bands have the disadvantages of poor time resolution and frequency resolution respectively. Compared with multi-resolution analysis, wavelet packet analysis can perform multi-layer decomposition on all frequency bands of the signal, and subdivide the neglected high-frequency parts. Wavelet packets are more widely used in practice because of their adaptive selection of frequency band matching between the measured signal and the corresponding spectrum [7, 8].

Wavelet packet analysis can be expressed as follows:

Define subspace \( U_n \) as the closed space of function \( U_n(t) \), and \( U_n(t) \) is the closed space of \( U_{2n}(t) \), and make \( U_n(t) \) satisfy the following two-scale equation:

\[
U_{2n}(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} h(k) U_n(2t - k)
\]

\[
U_{2n+1}(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} g(k) U_n(2t - k)
\]

\[
U_0(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} h(k) U_0(2t - k)
\]

\[
U_1(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} g(k) U_0(2t - k)
\]

The sequence \( \{ u_n(t) \} \) (where \( n \in \mathbb{Z} \)) constructed by formula (1) (2) is called an orthogonal wavelet packet determined by the basis function \( u_0(t) = (t) \). When \( n=0 \), it is the case of (3) (4).

When the motor fails, the fault signal is included in the entire frequency map. Certain frequencies of the signal spectrum are significantly enhanced and weakened in other frequencies. Therefore, different faults can be diagnosed by calculating the characteristic value of the spectrum signal.

2.2 Improved eigenvalue extraction method

The Db6 wavelet function is used as the wavelet basis for feature extraction of the fault signal. The feature extraction process:

(1) Over-sampling of the vibration data output when the motor fails, and Db6 wavelet packet decomposition to obtain 8 frequency bands. That is, the reconstructed signal of the eight frequency bands from S0 to S7 is expressed as

\[
S=\{S_0,S_1,S_2,S_3,S_4,S_5,S_6,S_7\}
\]

(2) Find the total energy of the 8 frequency bands. Suppose the signal energy corresponding to \( S_i \) is \( E_i \), and find the square of its energy norm
\[ E_i^2 = \left( \sum_{i=1}^{n} |x_i|^2 \right)^2 \]  

(6)

3. Find the probability of the node that is the energy ratio

\[ H_i = \text{sum}(E_i^2) \]  

(7)

\[ X_i = \frac{(E_i)^2}{H_i} \]  

(8)

4. Construct the energy feature vector M of each frequency band, namely

\[ M = [X_0, X_1, X_2, X_3, X_4, X_5, X_6, X_7] \]  

(9)

5. Preprocess the obtained vector

\[ N = \frac{\text{Ln}(M) - \mu}{\sigma} \]  

(10)

Where \( \mu \) is the mean value of the original data, and \( \sigma \) is the standard deviation of the original data. The energy feature vector N is used as the input element of the probabilistic neural network classifier, and the fault of the motor is diagnosed through the classifier.

2.3 Probabilistic Neural Network (PNN)

Neural network is an artificial intelligence algorithm proposed based on biological principles. It simulates the transmission mode of biological neurons and is simplifying. The process of motor fault diagnosis is a process of pattern recognition. Compared with traditional pattern recognition methods, artificial neural networks can realize arbitrarily complex discriminative surfaces and have stronger adaptability [9].

This paper uses a four-layer neural network structure as shown in Figure 3:

![PNN network structure](image)

The first layer is the input layer, which is used to receive the value of the training sample. This article uses the feature vector obtained by wavelet packet decomposition as input and transmits the data to the hidden layer (second layer). The number of neurons is similar to the dimension of input vector. The second hidden layer is the base layer. Each neuron node in the hidden layer has a center. The distance between the input vector and the center is calculated, and a scalar value is returned at the end. The third layer is the summation layer, which is responsible for connecting the pattern layers of each category. The fourth layer is the output layer, which is responsible for outputting the highest score in the summation layer [10].

Compared with the traditional BP neural network, the probabilistic neural network has simple training, fast convergence speed, and is suitable for real-time data processing. Its hidden layer adopts the non-linear mapping function of secondary radial basis. This method considers the interleaving of samples of different types of patterns. It has strong fault tolerance and real-time online detection, which is more suitable for industrial production applications.
3. ANALYSIS OF EXPERIMENTAL RESULTS

The rolling bearing data of this experiment comes from the Bearing Data Center of Western Reserve University. The bearing model used is 6205-2RS JEM SKF deep groove ball bearing, torque sensor and coupling and other auxiliary equipment. Four types of faults are simulated, including normal, inner ring fault, outer ring fault, and rolling element fault. The vibration data of each working condition is collected by an acceleration sensor, which is installed on the surface of the experimental device. The sampling frequency is 12 KHz, and the motor speed is 1797 rpm. Experiment one uses 350 sets of data (including four types of faults), of which 300 sets are training samples, and the remaining 50 sets are test samples. The four types of fault data feature extraction vectors are shown in Figure 4.

![Figure 4 Four types of feature data extraction](image)

The training samples obtained after the traditional wavelet packet decomposition and the training samples reached after the improved feature extraction are learned by the PNN neural network, and the test samples are tested. The results are shown in Figures 5-6.

![Figure 5 PNN output after traditional feature extraction](image)
Through the comparison of the above figures, it can be obtained: the fault diagnosis method using the improved feature extraction method combined with the probabilistic neural network, compared with the traditional results after wavelet packet decomposition, the method proposed in this paper has high accuracy and no false negative rate. As long as the training sample data is sufficient, the probabilistic neural network can converge to the Bayesian classifier. The probabilistic neural network allows to increase and decrease the training set, predict the results more accurately, and does not require long-term training, and the four types of fault diagnosis are accurate the rate can reach 98%.

4. SUMMARY
Fault diagnosis of motor rolling bearing is urgently needed in modern industrial production. The improved feature extraction and Probabilistic Neural Network (PNN) methods proposed in this paper for rolling bearing fault diagnosis have been verified by experiments. They have a good recognition effect, and the fault detection is rapid, the corresponding time is short. PNN can be applied to real-time online detection, which is conducive to industrial production. The experimental results show that the output results after the improved feature value extraction and traditional methods have significant improvements in diagnostic accuracy and false negative rate; the feature value extraction method proposed in this paper is applicable to a variety of feature extraction methods. Since the production site or maintenance plant has a large amount of offline data, the original data will be diversified and complicated due to the different types of equipment and data monitoring sensors. Therefore, the direction of the next research is how to better introduce the successful experience of traditional bearing fault diagnosis, such as the introduction of temperature, acceleration, and acoustic transmitter signals at the same time.

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