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Fault Pattern Recognition of Rolling Bearing Based on Wavelet Packet Decomposition and BP Network

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Abstract

According to energy frequency distribution differences of bearing vibration signal in different failure modes, a rolling bearing fault pattern recognition technique is proposed by integrating the orthogonal wavelet packet decomposition and BP neural network. The orthogonal three layer wavelet packet decomposition for rolling bearing vibration signal is carried out to get the third layer wavelet packet decomposition coefficients from low frequency to high frequency, and then the different frequency band signals are reconstructed respectively to extract energy features by means of wavelet packet decomposition coefficients. Using the energy feature vector of different frequency band as the model input of the BP neural network，60 sets of samples data are trained to obtain the pattern recognition network model for different bearing fault, then 40 sets of test data are used to verify the BP network model to discriminate the type of rolling bearings fault. The experimental results show that the proposed method in this paper can identify the fault of rolling bearings more accurately.

Keywords: Rolling Bearing Failure; Wavelet Packet Decomposition; BP Neural Network; Pattern Recognition

1 INTRODUCTION

As one of the most common components in all kinds of mechanical equipment, the operating condition of rolling bearing directly affects performance and safety of mechanical equipment, thus to carry out the study of rolling bearing fault diagnosis technology has great significance for equipment security and economic benefits. The traditional method is mostly to make spectrum analysis of vibration signal for rolling bearing fault detection, but in many cases, such as early of failure or low-speed rotation, vibration signal containing fault feature is very weak and often overwhelmed by the surrounding non-fault characteristic signals, so that we can not effectively detect hidden faults [1,2]. Therefore, it is important for mechanical equipment fault diagnosis to accurately extract failure information from rolling bearing vibration signal. The wavelet analysis is localized analysis method of time-frequency domain, by stretching shift operation it enable signal to be made multi-scale thinning, namely, it achieve frequency subdivision at low frequencies and achieve time subdivision at high frequencies. Ultimately, the wavelet analysis can automatically adapt to the requirements of time-frequency signal analysis [3.4]. As a network system to mimic human brain information processing mechanism, artificial neural network can complete the function such as learning, memory, recognition and reasoning. It consists of a large number of interconnected nonlinear highly parallel processing units, and has simple mathematical ability to simulate some basic characteristics of human mind. It is a powerful tool for dealing with nonlinear problems where BP neural network plays an important role in fault diagnosis [5,6]. Meanwhile, Compared with the normal wavelet analysis, the wavelet packet decomposition has special abilities to attain higher discrimination by analyzing the higher frequency domains of a signal, then the

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method of combining wavelet packet decomposition with neural network enables us to effectively realize fault diagnosis and pattern recognition.

2 WAVELET PACKET DECOMPOSITION AND RECONSTRUCTION

Wavelet packet decomposition enables us to make orthogonal decomposition for the signal in the entire frequency band. The basic idea of wavelet packet algorithm is to achieve even or odd part from the first decomposition results of high-frequency and low-frequency by the arithmetic of extracting one from two. During next decomposition, not only the low frequency part of signal is decomposed, the high frequency portion will also be decomposed, so that both in the low frequency band and in the high-frequency bands the decomposition signal have the same time-frequency resolution rate [3-5]. This spatial decomposition can always be repeated down, the signal is decomposed into different adjacent frequency bands, with the increase of decomposition level, the frequency band is divided more thinly. When the signal is decomposed into the j-layer, the amount of data for each frequency band is half of the former data signal. Furthermore, the more the layer of decomposition is down, the lower is temporal resolution of the signal on each frequency band .Therefore, in order to improve the resolution, we can take the following signal reconstruction methods .To observe the time-domain waveform signal on a frequency band, then keep the data in this frequency band, the data segment is set to zero on other frequencies, then use the reconstruction formula to reconstruct the signal of every layer, so the amount of signal data obtained will increase double by subsequent reconstruction of each layer. After j th layer signal reconstruction, the temporal signal resolution can be increased to the original size of signal on the frequency band. This method can also be used to reconstruct the signals on several different frequency bands together [7,8]. If the signal on all frequency bands is together reconstructed, we can reconstruct the original signal.

According to basic idea of Mattat algorithm [3], the algorithm of wavelet packet decomposition and reconstruction is given below. The wavelet packet decomposition algorithm is expressed as

$$c_{j-1,k} = \sum_{m=-\infty}^{+\infty} \hat{h}_{m-2k} c_{j,m} \tag{1}$$

$$d_{j-1,k} = \sum_{m=-\infty}^{\infty} \hat{g}_{m-2k} c_{j,m} \tag{2}$$

where $\hat{h}_k, \hat{g}_k$ denotes the conjugate coefficient of orthogonal filters. $c_{j,k}$, $d_{j,k}$ respectively represents scale coefficient and wavelet coefficient. So the wavelet packet reconstruction algorithm is expressed as

$$c_{j,k} = \sum_{m=-\infty}^{+\infty} h_{k-2m} c_{j-1,\mathrm{m}} + \sum_{m=-\infty}^{+\infty} g_{k-2m} d_{j-1,\mathrm{m}} \tag{3}$$

where h_k, g_k are the coefficients of orthogonal filters.

The above formulas are used to get signal components on some frequency bands or several frequency bands, then to extract the signal characteristics [6-8]. In engineering practice, the decomposition coefficients is obtained by threshold value process or statistical process to highlight the characteristics coefficient and to reduce the noise components, then the coefficients are chosen to make signal reconstruction for extraction of signal characteristic. In this paper, considering bearing vibration state is close correspondence to characteristic values and non-characteristic values, the extraction method is selected that the signal is directly reconstructed after selecting decomposition.

3 TEST SYSTEM AND FAULT FEATURE EXTRACTION

3.1 Test System

As shown in Fig. 1, the rolling bearing bench is employed to simulate the working condition of bearing, where a 6307 rolling bearing is installed in the drive end of the bench, a flexible shaft couplings equipped with rotating turntable is driven by a three-phase induction motor, the motor speed is 1750 r/min. To handle different types of bearing failure modes, the experiment tests run four times, the sampling rate is 12 kHz, the sampling number is 1024. During the 10 tests in the simulation test bench, 10 sets of data are acquired in each test (totally 100 sets of data in the whole test). The first 60 sets of data are used to train the BP neural network and build the network model; the other 40 sets of data are taken to check the feasibility of the neural network model.

FIG.1 ROTATING TEST PLATFORM SYSTEM

3.2 Signal Feature Extraction

The rolling bearing fault vibration signal is measured by sensor and sampled by A/D, then the original signal of bearing failure is obtained. The original acquisition signal diagram of ball faults is shown in Fig. 2. According to the proposed wavelet algorithm, the sampled fault signal is decomposed into three layers wavelet packet. By using the wavelet decomposition and reconstruction, 8 band signals are shown in Fig. 3.

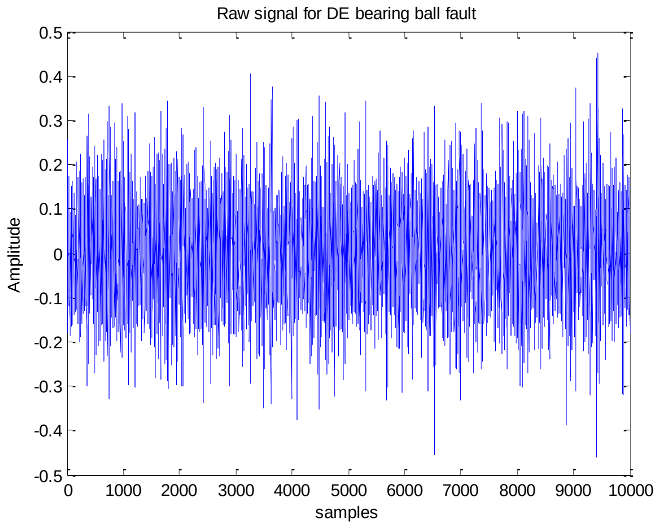

FIG.2 RAW SIGNAL FOR DE BEARING BALL FAULT

FIG.3 THE 3RD WPD SIGNALS FOR BEARING BALL FAULT

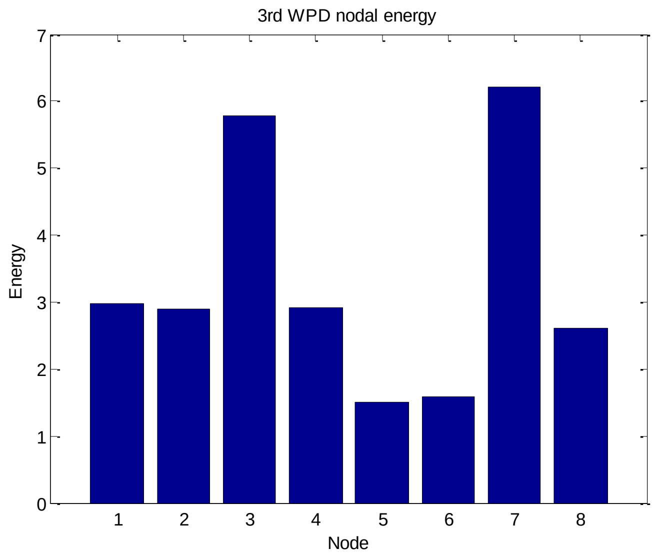

FIG.4 THE 3RD WPD NODAL ENERGY FOR BEARING BALL FAULT

From Fig. 3, it is observed that the amplitude oscillation of the time-domain waveform is relatively small in the normal operation of bearing, hence it can be concluded that the noise elimination is solved by adjusting the high-frequency coefficients from layers wavelet decomposition to reconstruct the signal. It is intuitively shown the important role of the wavelet decomposition and reconstruction in signal de-noising. Thus, the accuracy of neural network pattern recognition is improved by applying the signal.

The reconstructed signal in each band is extracted, and the node energy E_{3j} is given:

$$E_{3j} = \int \left| s_{3j}(t) \right|^2 dt = \sum_{k=1}^{n} \left| x_{jk} \right|^2 \tag{4}$$

where $x_{jk}(j=0,1,\cdots,7,k=1,2,\cdots,\mathrm{n})$ denotes the magnitude of n discrete points in the reconstructed signal s_{3j} [7,8],and the 3rd WPD nodal energy for bearing inner ring fault are shown in Fig. 4. In order to improve the clustering of the feature vectors, and make it better discrete distribution to Facilitate network input and recognition processing, the feature vectors need to be normalized to become the normalized feature vectors $C_{3j}=[c_{30},c_{31},\cdots,c_{37}]$, the range of each element c_{3j} in the feature vectors is between 0 and 1. For the energy feature vector series $E_{3j}=[e_{30},e_{31},\cdots,e_{37}]$ of different bands, the normalization method is given in (5), the normalized data is shown in Table 1, and:

$$c_{3j} = \frac{e_{3j} - \max(E_{3j})}{\max(E_{3j}) - \min(E_{3j})} \tag{5}$$

TABLE 1 THE NORMALIZED PROCESSING FEATURE VECTORS

Node No.	Normal	Inner	Outer	Ball
c_{30}	1.0000	0.0675	0.2310	1.0000
c_{31}	0.6280	0.0349	0.2154	0.4796
c_{32}	0.1434	1.0000	0.8662	0.9920
c_{33}	0.3741	0.0690	0.2124	0.2857
c_{34}	0	0.0054	0	0
c_{35}	0.0347	0	0.0058	0.0042
c_{36}	0.0202	0.6694	1.0000	0.6098
c_{37}	0.0690	0.0428	0.1153	0.0347

4 THE PATTERN RECOGNITION OF BP NEURAL NETWORK

4.1 BP Network Model

BP neural network (Back Propagation Neural Network) is a multilayer forward neural network with one-way transmission. The structure of BP model is shown in Fig. 5. BP network contains input layer, output layer and one or more hidden layers，without the coupled node in the same layer network, in addition, every node is a single neurons[9.10]. Because of decoupled node in the layer node, each layer neuron only has one input from the previous layer of neurons, and the output of each layer neuron only affects the output of layer neuron. The differentiable functions are usually selected as the activation function of the neurons, e.g. Sigmoid type function. In fact, BP neural network algorithm is the error back propagation learning algorithm, which is also known as gradient algorithm. It utilizes the methods of mean square error and gradient descent to realize the modification to the connection weight of network, and hence the desired learning performance of BP network can be highly efficiency satisfied.

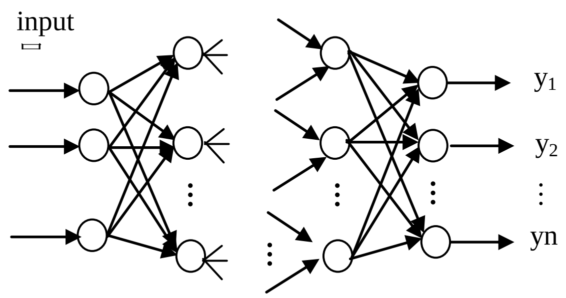

FIG.5 THE BASIC STRUCTURE OF BP NEURAL NETWORK

The activation function of the network is selected as S-Sigmoid function. From the characteristic of S-type function and the satisfactory results, we consider any initial weight value at (-1,1). With the specific condition and the previous experience, fault signal recognition learning rate is generally chosen as 0.01. In this experiment, the learning rate is taken as 0.01. On the other hand, it has no uniform standard formula to determine the number of hidden layer nodes at the present time. To appropriately choose the number of hidden layer nodes, an empirical formula proposed in the previous works is given as follows:

$$T = 2m + 1 \tag{6}$$

To determine the structure of BP network, four characteristic parameters of rolling bearing fault are selected as input, the number of input layer nodes is 8, the number of hidden layer nodes is 17, the number of output layer nodes is 4. The feature vectors from the wavelet decomposition is used to train the BP network, which make BP network to keep the desired structures.

The traditional neural network fault diagnosis system chooses the feature vectors from the wavelet decomposition as sample input for neural network, and obtains the output to judge the final result. Obviously, the output data of network can't be completely the absolute of expectation, i.e. 0 or 1. To increase the diagnostic capability, the interval criterion is introduced. For one of failure modes in rolling bearing, all failure modes are used as binary representation, the expected output is 0 or 1, thus, it need to revalue the output results. For a output result, it needs to choose a discrimination interval, then compare the simulation data with the discrimination interval, and judge the data to 0 or 1, if the simulation result is less than 0.1 or more than 0.9 (e.g. 0.0238, 0.926), it is concluded that the result is 0 or 1, otherwise, the simulation results have meaningless. While the simulation data is closer to 0 or 1, the accuracy rate of pattern recognition is higher; whereas the discrimination interval is smaller, the accuracy rate of pattern recognition is lower. The specific operating condition is given as follows: normal bearing (1,000), ball fault (0100), inner fault (0010), outer of the ring fault (0001).

4.2 Training and Testing of the Network Model

When the initial model of network is obtained, the neural network is trained by the training sample input. Let 60 sets of data from the first 6 tests use to network training. In order to improve the reliability and credibility of pattern recognition in testing, the valid output is the maximum value of the four elements in output vector and more than 0.9.The vector position of maximum element need to match the number of bearing mode, otherwise, the output is not invalid. Finally, let the rest 40 sets of data to check feasibility of network and take the interval criterion for output data.

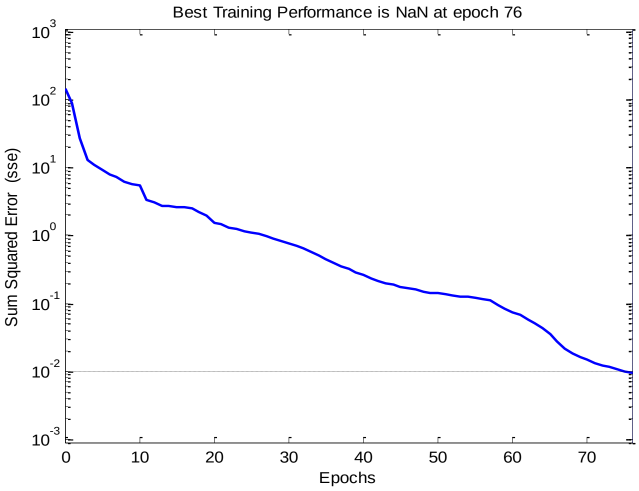

FIG. 6 BP TRAIN ERROR CURVE FOR THE INNER RING FAULT

Feature vectors of fault signals are extracted via wavelet decomposition, which are taken for training the BP neural network. By selecting one of the typical failure modes, the error trajectory is trained. BP neural network training error curve on the inner ring fault is shown in Fig. 6, it is seen that the convergence rate of BP network is fast during 76 steps, which satisfies the desired performance. To verify the effectiveness of the trained network model, the rest 40 sets of data are tested to the network performance. With the above trained BP neural network, it is three sets of data false or invalid results, the total accuracy rate is 92.5%, the specific fault recognition rate is shown in Table 2. Compared the diagnosis results of neural network and the actual results, it is obviously that the recognition rate for is relatively high. The results illustrate that the wavelet decomposition to extract feature vectors of the fault signal is practical.

TABLE 2 BP NEURAL NETWORK FOR A GIVEN TEST FAILURE

Sample type	samples	False number	Recognition rate	Overall recognition rate
Normal	10	0	100%	92.5%
Linner ring	10	0	100%	
Outer ring	10	2	80%	
Ball	10	1	90%	

5 CONCLUSION

In this paper, a rolling bearing fault pattern recognition method based the orthogonal wavelet packet decomposition and BP neural network is developed. To eliminating the noise of the original signal, wavelet decomposition and reconstruction for extracting energy feature vectors are used, the normalized feature vectors is better for training the neural network model. Experimental results show that rolling bearing fault pattern recognition based on wavelet packet decomposition and reconstruction to extract energy feature vectors as sample input for BP neural network has a high recognition accuracy. Therefore, machinery fault diagnosis method based on wavelet decomposition and reconstruction of BP neural network is feasible.

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