FAULT DIAGNOSIS OF BEARINGS BASED ON WPD AND RBF NEURAL NETWORKS

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Conventional signal processing techniques usually result in false information when they are applied to the ship mechanical fault signals, because the ship mechanical faults by nature are non-stationary and transient events. Wavelet Packet Decomposition (WPD) is a time–frequency domain technique that can be applied to non-stationary process perfectly. RBF neural network behave better than BP neural network in approximation ability, classification ability and learning speed. A new fault diagnosis method based on WPD method and RBF neural network is presented. With the method, the rolling element bearings vibration signals are decomposed into several frequency bands from high to low with WPD, trained and configured networks with the energy characteristics of frequency bands are used to detect the novelties or anomalies of faulty signals. The proposed method is applied to the fault diagnosis of rolling element bearings, and the entire 80 test results could correctly identify the bearing faults. The results show that the combination of WPD and RBF neural networks could reliably separate different fault conditions.

1. Introduction

Condition monitoring of rotating machinery is important in terms of system maintenance and process automation. Rolling element bearing failures are one of the foremost causes of failures in rotating machinery [1]. The vibration signal is the most widely used for fault monitoring and diagnosis [2]. Fault signal is usually non-stationary; therefor, the traditional Fourier transform signal analysis methods might not be applicable [3]. Wavelet packet decomposition has a strong feature extraction ability, which can analyse signals simultaneously in the time domain and frequency domain, and distinguish signal and noise in the mutant part effectively, in order to achieve bearing fault feature extraction [4-5].

In this paper, a new technique for localized bearing fault diagnosis is developed using the wavelet transform and RBF neural networks. In this method, experimental vibration signals for normal and faulty bearings are decomposed into different frequency bands ranging from high-to-low by Wavelet packet decomposition. Then a feature vector is defined using the energy of each frequency band. By using selected segments from the available experimental data, typical sample feature vectors are generated for both normal bearings and bearings with different types of faults under different load conditions. Then different pattern classification methods have been studied in the decision making stage, including the RBF neural networks system, which is believed to be most suitable for complex situations due to its adaptability and the capability of the network to realize a non-linear approximation.
2. Wavelet Packet Decomposition

Wavelet packet decomposition is now becoming a competent tool for signal analysis. Compared with the normal wavelet analysis, it has special abilities to attain higher discrimination by analysing the higher frequency domains of a signal [5]. The frequency domains separated by the wavelet packet can be easily selected and classified according to the characteristics of the analysed signal. So the wavelet packet is more appropriate than wavelet in signal analysis and has much wider applications such as signal and image compression, de-noising and speech coding.

Wavelet packet decomposition uses a pair of low pass and high pass filters to divide a space; this corresponds to splitting the frequency content of a signal into approximately a low-frequency and a high-frequency component. Wavelet decomposition leaves the high-frequency part alone and keeps splitting the low-frequency part. In wavelet packet decomposition, we can choose to split the high-frequency part also into a low-frequency part and a high-frequency part. Thus, in general, wavelet packet decomposition divides the frequency space into various parts and allows better frequency localization of signals.

As shown in Fig. 1, the wavelet packet decomposition can be viewed as a tree. The root of the tree is the original data set. The next level of the tree is the result of one step of the wavelet transform. Subsequent levels in the tree are constructed by recursively applying the wavelet transform step to the low and high pass filter results from the previous wavelet transform step. Then when the decomposition process is achieved the energy in the different spectrum bands can be calculated.

![Wavelet packet decomposition tree](image)

Figure 1. Wavelet packet decomposition tree.

3. Diagnosis approach for roller bearings based on WPD and ANN

It is assumed that the fault vibration signal of a roller bearing has been decomposed with third level WPD into 8 sub-bands S30, S31,..., S37. Energy of each sub-band can be computed by the following equation:

\[
E_{3i} = \int |S_{3i}(t)|^2 dt = \sum_{j=1}^{n} |x_{i,j}|^2
\]  

(1)

Where \(x_{i,j}\) is the reconstruction signal of the jth node in the ith sub-band.

The energy of each sub-band is normalized with the total energy \(E\), which was expressed as:

\[
E = \sqrt{\sum_{i=0}^{7} |E_{3i}|^2}.
\]  

(2)
The normalized energy is:

$$S_i = \frac{E_{3i}}{E}$$

(3)

Feature vector = \( (S_0, S_1, \cdots, S_7) \).

Then the feature vector was used for ANN training and fault diagnosing.

In the present system, a recognition method for rolling bearings fault condition using RBF neural networks is examined to evaluate the effectiveness of the proposed system. RBF neural network behave better than BP neural network in approximation ability, classification ability and learning speed. The RBF neural network has a feedforward architecture with an input layer, a hidden layer, and an output layer. RBF networks belong to the category of kernel networks [6]. Each hidden node (unit) computes a kernel function on input data, and the output layer achieves a weighted summation of the kernel functions. Each node is characterized by two important associated parameters: 1) its center and 2) the width of the radial function. A hidden node provides the highest output value when the input vector is close to its center and this output value decreases as the distance from the center increases. Finally, use the data which completes training of the network classification. Then, input the test model in order. The network may export the test result. The diagnosis process of rolling element bearings was showed below in the figure 2.

![Diagram](image)

**Figure 2.** The diagnosis process of bearings based on WPD and RBFNN.

4. **Application**

The ball bearing test data for normal and faulty bearings was provided by Case Western Reserve University Bearing Data Center [7]. Experiments were conducted using a 2 hp Reliance Electric motor, and acceleration data was measured at locations near to and remote from the motor bearings.

As shown in Figure 3 above, the test stand consists of a 2 hp motor (left), a torque transducer/encoder (center), a dynamometer (right), and control electronics (not shown). The test bearings support the motor shaft. Motor bearings were seeded with faults using electro-discharge machining (EDM). Faults ranging from 0.007 inches in diameter to 0.040 inches in diameter were introduced separately at the inner raceway, rolling element (i.e. ball) and outer raceway. Faulted bearings were
reinstalled into the test motor and vibration data was recorded for motor loads of 0 to 3 horsepower (motor speeds of 1797 to 1720 RPM).

Figure 3. Schematic diagram of the bearing testing setup.

Vibration data was collected using accelerometers, which were attached to the housing with magnetic bases. Accelerometers were placed at the 12 o’clock position at both the drive end and fan end of the motor housing. During some experiments, an accelerometer was attached to the motor supporting base plate as well.

The data of drive end accelerometer data was used for experimental verification. The drive end bearing is 6205-2RS deep groove ball bearing. The key parameters of the bearing are: bearing diameter: 39.04mm; ball diameter: 7.94 mm; number of balls: 9; rotational speed of bearing: 1750rpm.

Figure 4. Inner-race defect.

Outer-race defects are revealed at the Ball-Passing Frequency Outer-race BPFO [8]:

$$BPFO \text{ (in Hz)} = \frac{n}{2} f_r \left(1 + \frac{d}{D} \cos \beta \right) = 104.56 \text{Hz}$$

Inner-race defects are revealed at the Ball-Passing Frequency Inner-race BPFI:

$$BPFI \text{ (in Hz)} = \frac{n}{2} f_r \left(1 - \frac{d}{D} \cos \beta \right) = 157.94 \text{Hz}$$
Rolling element defects are revealed at the Ball-Passing Frequency Roller BPFR or the Ball Spin Frequency BSF:

$$\text{BPFR or BSF (in Hz)} = \frac{D}{d} f_r \left[ 1 - \left( \frac{d}{D \cos \beta} \right)^2 \right] = 137.48 \text{Hz}$$

In this experiment, the sampling frequency of vibration signal is 12000Hz; the filtering frequency was chose 400Hz combined with the bearing fault characteristic frequency. The three layer wavelet packet was selected for data decomposition and reconstruction, and then the character vector was constructed by the energy of each frequency band. The third layer frequency band domains are: 0 ~ 25Hz; 25 ~ 50Hz; 50 ~ 75Hz; 75 ~ 100Hz; 100 ~ 125Hz; 125 ~ 150Hz; 150 ~ 175Hz; 175 ~ 200Hz.

The wavelet packet decomposition was used for analysis the vibration signal of Normal bearing running condition, Inner-race defect, Rolling element defect, and Outer-race defect. The Figure 4 shows the decomposition result of Inner-race defect condition, the 8 signals under the origin signal are the third level wavelet packet decomposition results. And Figure 5 shows the energy character vector of the four conditions.

![Figure 4](image_url1)

(a) Normal running condition
(b) Inner-race defect
(c) Rolling element defect
(d) Outer-race defect

**Figure 5.** „a… Results of a healthy bearing using wavelet packet analysis „b… Results of outer-race defect using wavelet packet analysis „c… Results of inner-race defect using wavelet packet analysis „d… Results of rolling element defect in a wavelet packet analysis.

In this application, 80 samples were selected for training, including 20 normal running samples, 60 samples of failures, and 80 samples for testing (20 in each case). The diagnosis results of RBF neural network were shown below in table 1 and table 2 (only the first five diagnosis results of each fault condition were shown here).
Table 1. Diagnosis results of RBF neural network.

<table>
<thead>
<tr>
<th>Number</th>
<th>Normal bearing running</th>
<th>Number</th>
<th>Rolling element defect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.0184 -0.0148 0.0429</td>
<td>6</td>
<td>1.0775 -0.1239 0.0502</td>
</tr>
<tr>
<td>2</td>
<td>0.0349 0.0858 -0.0746</td>
<td>7</td>
<td>0.9405 0.0197 0.0014</td>
</tr>
<tr>
<td>3</td>
<td>0.0214 0.0503 -0.0228</td>
<td>8</td>
<td>1.0664 -0.0935 0.0708</td>
</tr>
<tr>
<td>4</td>
<td>0.0043 -0.0028 0.0255</td>
<td>9</td>
<td>1.0282 -0.0675 0.0675</td>
</tr>
<tr>
<td>5</td>
<td>-0.0582 -0.0488 0.0983</td>
<td>10</td>
<td>1.0850 -0.1521 0.1059</td>
</tr>
</tbody>
</table>

Table 2. Diagnosis results of RBF neural network.

<table>
<thead>
<tr>
<th>Number</th>
<th>Rolling element defect</th>
<th>Number</th>
<th>Outer-race defect</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>-0.0138 1.0595 -0.1512</td>
<td>16</td>
<td>-0.0119 0.1126 0.9092</td>
</tr>
<tr>
<td>12</td>
<td>-0.0033 1.0573 -0.0650</td>
<td>17</td>
<td>-0.0258 0.0524 0.9992</td>
</tr>
<tr>
<td>13</td>
<td>-0.0001 1.0294 -0.1544</td>
<td>18</td>
<td>0.0040 -0.0080 0.9686</td>
</tr>
<tr>
<td>14</td>
<td>-0.0059 0.9738 0.0357</td>
<td>19</td>
<td>0.0150 0.0062 0.9872</td>
</tr>
<tr>
<td>15</td>
<td>-0.0060 1.0316 -0.0990</td>
<td>20</td>
<td>0.0004 0.1165 0.8824</td>
</tr>
</tbody>
</table>

Neural network output status: 0 0 0 representatives Normal bearing running condition; 1 0 0 representatives motor bearing Inner-race defect; 0 1 0 representatives the Rolling element defect of motor bearing; 0 0 1 representatives motor bearing Outer-race defect.

The 80 test results showed that the fault diagnosis accuracy of rolling bearings reached 100%. So it is indicated that the fault diagnosis method combined WPD with RBFNN is effective.

5. Conclusion

In this paper, a new method based on wavelet packet decomposition and RBF neural network for bearing fault diagnosis is proposed. Wavelet packet decomposition method is used to extract appropriate features from the monitoring signals, and diagnosis model is built using RBF neural network. This type of decomposition allowed getting deeper into the signal features by adjusting both the time and the frequency scales. These energy features are then used to model the fault behaviour of the component by learning the parameters of the corresponding RBFNN models. The diagnosis results also show that RBFNN is a good candidate for future development work because of its non-linear approximation capability and adaptability. It is expected that using wavelet packet decomposition and RBF neural network, it may be possible to identify the variety faults of rolling bearings.

REFERENCES


6 K. Z. Mao. RBF Neural Network Center Selection Based on Fisher Ratio Class Separability Measure. *IEEE TRANSACTIONS ON NEURAL NETWORKS*, VOL. 13, NO. 5, SEPTEMBER 2002

7 http://www.eecs.case.edu/laboratory/bearing/download_fan.htm