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Fault Diagnosis Based on Wavelet Genetic Neural Network for Motor

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Abstract

In the motor fault diagnosis technology, vibration signals can fully reflect the motor operation conditions. In this paper, a linear motor fault diagnosis method based on wavelet packet and neural network was presented. The improved neural network system was designed with variable hidden layer neurons. The network chose different numerical values depending on different situations to reach the requirements that improving diagnostic accuracy and shortening the diagnosis time. The linear motor's normal and two common faults vibration signals were analyzed and the vibration signals energy characteristics were extracted through wavelet packet, then identified fault through neural network. The experimental results show that this method can effectively improve the motor fault diagnosis accuracy.

Keywords*: wavelet packet, fault diagnosis, genetic neural network, vibration signals*

1. Introduction

The motor works as the main power equipment of modern industries, and its role is self-evident [1-3]. As the motor's structural characteristics, installation environment, load conditions and other factors, the motor's signals often contain a lot of noise. Sometimes the noise will make the useful signals unrecognized [4]. Sometimes traditional Fourier analysis method can not meet the requirements. Especially, when more useful information in the signal is distorted, the Fourier analysis is powerless. Wavelet analysis has enjoyed increasingly and widely use with its unique advantages on processing non-stationary signals [5].

Reference [6] proposed feature extraction method for motor's fault signal based on optimal wavelet basis. This method identifies the optimal wavelet basis for specific motor fault signal but didn't diagnose specifically the faults. Reference [7] proposed feature extraction method for motor's inter-turn short circuit based on wavelet packet. It diagnosed inter-turn short circuit fault according to the contradistinction of band's energy feature.

In this paper, wavelet db6 which has high adaptability for the faults signals is combined with BP neural network. A method of wavelet and neural network system with Genetic Algorithms to optimize the weights and thresholds, variable hidden layer neurons is introduced at the same time. So that accuracy of the diagnosis and performances of time are improved. Analyze normal signal and two fault signals of linear motor with wavelet packet's good analytical performance of signal's slight change and mutation. Extract feature vectors of signal energy. The feature vectors are used as neural network's input vectors. Train the network to reach the requirements of fault diagnosis. According to the test, this method can diagnose the fault effectively.

2. Research Method

Multi-resolution analysis can be an effective time-frequency decomposition of signals. But because of its scaling function changes based on binary, it has a higher frequency resolution in the low frequency band, while in the high frequency band frequency resolution is poor and the signal's frequency band is divided at index equal intervals. Wavelet packet analysis provides a more meticulous method of analysis for the signal. By dividing the frequency band into multi-levels, the high-frequency part which is not broken down by multi-resolution

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analysis can be further decomposed. And adaptively select the frequency band according to the characteristics of the signal. Make it match with the signal spectrum and increase the time-frequency resolution. Therefore wavelet packet analysis has wider practical value.

In the multi-resolution analysis, shows that multi-resolution analysis divides the square-integrable space into orthogonal sum of all subspaces, of which is the wavelet subspace of wavelet function. Subdivide the wavelet subspaces according to binary form and so improve the frequency resolution. Scale subspace and wavelet subspace are characterized by a new subspace. Therefore, we have:

$$\begin{cases} U_j^0 = V_j \\ U_j^1 = W_j \end{cases} \tag{1}$$

Then $V_{j-1} = V_j \oplus W_j$, the orthogonal decomposition of the space $L^2(R)$, can be unified as $U_{j-1}^0 = U_j^0 \oplus U_j^1$ by U_j^n. Define the subspace U_j^n as closure space of the function $u_n(x)$, U_j^{2n} is the closure space of the function $u_{2n}(x)$, let $u_n(x)$ satisfy the following two-scale equations:

$$\begin{cases} u_{2n}(x) = \sum_{k \in Z} h_k u_n(2x-k) \\ u_{2n+1}(x) = \sum_{k \in Z} g_k u_n(2x-k) \end{cases} \tag{2}$$

Where $g_k = (-1)^k h_{1-k}$, the two coefficients also have an orthogonal relationship. When n=0, by the above formula, we have:

$$\begin{cases} u_0(x) = \sum_{k \in Z} h_k u_0(2x-k) \\ u_1(x) = \sum_{k \in Z} g_k u_0(2x-k) \end{cases} \tag{3}$$

Equation (3) is the two-scale equation of scaling function $u_0(x)$ and wavelet function $u_1(x)$. By Equation (2) and Equation (3), space decomposition can be obtained as follows:

$$U_{j-1}^n = U_j^{2n} \oplus U_j^{2n+1} \tag{4}$$

A sequence $\{u_n(x)\}$ constructed by Eq. 2 and Eq. 3 is called wavelet packet determined by basis function $\varphi(x) = u_0(x)$.

Wavelet packet decomposition algorithm: we get $\{d_l^{j,2n}\}$ and $\{d_l^{j,2n+1}\}$ by $\{d_l^{j-1,n}\}$, where d is wavelet packet coefficient.

$$\begin{cases} d_l^{j,2n} = \sum_k h_{k-2l} d_l^{j-1,n} \\ d_l^{j,2n+1} = \sum_k g_{k-2l} d_l^{j-1,n} \end{cases} \tag{5}$$

By the inverse of the above formulae, the wavelet packet reconstruction algorithm is:

$$d_l^{j-1,n} = \sum_k \left(h_{l-2k} d_l^{j,2n} + g_{l-2k} d_k^{j,2n+2} \right) \tag{6}$$

Wavelet analysis is essentially decomposed the signal into approximate parts of low-frequency and detail parts of high-frequency, and then only to the low frequency part for the second decomposition, while the high frequency part without decomposition. And so on, we can get the coefficients of wavelet decomposition. The wavelet packet analysis is not only to the low frequency part of the decomposition, but also to the secondary decomposition of high frequency part. It is shown in Figure 1, with three layers of wavelet packet decomposition as an example shows the process of wavelet packet decomposition. After S is decomposed into low frequency A1 and high frequency D1, A1 and D1 will be decomposed into more detailed, low frequency, high frequency components, and can be continuously decomposed down.

In Figure 1, A is an exploded outline signal of the low-frequency, D is the exploded detail signal of the high frequency. The numbers behind indicate the layer numbers of wavelet packet decomposition.

The decomposition has the following relationship:

S=AAA3+DAA3+ADA3+DDA3+AAD3+DAD3+ADD3+DDD3

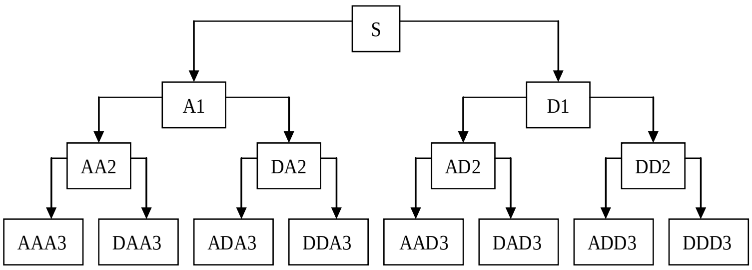

Figure 1. Wavelet Packet Decomposition

The signal energy feature vector which got from wavelet packet decomposition and reconstruction can provide a sample for BP neural network. So that wavelet can combine with neural network. BP Network is an error back-propagation network. In the forward propagation, Input information is handled from the input layer to the hidden layer, and then is passed to the output layer. If you cannot get the desired output in the output layer, then turn to back-propagation, return the difference between the actual output value and the expected value along the original connecting channels. The error reaches the allowable range by modifying the connection weights of neurons between layers. Network training is completed.

As multi-hidden layers network is high accuracy but overly complex, that makes the training time increased. In this paper, design and use a single hidden layer neural network with variable hidden layer neurons and optimized by Genetic Algorithms. The ability that network obtains information from the training is concerned about the number of nodes on the hidden layer. The more nodes the hidden layer has, the stronger the ability to access information, and vice versa. If the number of nodes in the hidden layer is too many, the complexity of training will increase and some noncoherent factors will appear and affect the entire network, then cause excessive anastomosis. So the design of hidden layer must consider multiple factors.

In this paper, firstly determine the range of the number of neurons based on experience formula, and then determine the number of neurons in the hidden layer by comparing the error ratio.The empirical formulae are:

$$\begin{aligned} &l=\log_2 m \\ &l=2m+1 \\ &l=\sqrt{m+n}+a \\ &l=\sqrt{0.43mn+0.12n^2+2.54m+0.77n+0.86} \end{aligned} \tag{7}$$

Where is the number of neurons in the input layer, is the number of neurons in the output layer, is the number of neurons in the hidden layer, the range of is 1~10.

The energy of vibration signal is changed. The main component of the vibration signal is the nonstationary vibration signal, noise and low frequency interference when away from the force of the pulse. Signal energy is small. The energy of the vibration signal is relatively large when near the force of the pulse. So you can use the changed energy of each frequency band to extract the fault features. The energy of bands can be obtained by wavelet packet decomposition coefficients. Specific steps are as follows.

Table 1. Frequency Range

Signal	Frequency range
S0	0~0.125f
S1	0.125f~0.250f
S2	0.250f~0.375f
S3	0.375f~0.500f
S4	0.500f~0.625f
S5	0.625f~0.750f
S6	0.750f~0.875f
S7	0.875f~1f

Use the vibration signal which is decomposed into three layers by wavelet db6 to reconstruct the wavelet packet decomposition coefficients. Extract signals of each frequency band. If the frequency range of original signal is 0~f, the decomposed signals of each layer is Sj(j=0,1, …,7). The frequency range is shown in Table 1.

Reconstruct the wavelet packet coefficients. Strike the total energy of each frequency band signal. Let the total energy of each band signal as Ej, the amplitude of the reconstructed signal Sj at each discrete point is represented by x_{jk} , we have:

$$E'_j = \sum_{k=1}^{n} \left| x_{jk} \right|^2 \tag{8}$$

Construct feature vector with elements which are energy of each band. Feature vector is constructed as follows:

$$T = \left[E'_0, E'_1, E'_2, E'_3, E'_4, E'_5, E'_6, E'_7 \right] \tag{9}$$

Since is a larger value when the energy is larger, the above feature vector is normalized in order to reduce the amount of calculations, and then represented by:

$$T = \left[E_0, E_1, E_2, E_3, E_4, E_5, E_6, E_7 \right] \tag{10}$$

$$E_j = \frac{E'_j}{\sqrt{\sum_{j=0}^{7} \left| E'_j \right|^2}} \tag{11}$$

In this paper, the diagnostic object is the faults of linear motor. Collect linear motor's fault signal of mover misalignment and bearing outer race fault. Use the feature vector obtained above as a sample input for neural network and set the expected output. Training will complete when the error reaches the allowable range. Then the test sample will be entered into neural network to identify faults. Neural network design method is as follows:

Energy eigenvectors which come from the motor status signal treated by wavelet packet decomposition and reconstruction are used as input training samples. Set the desired output. The number of neurons in the output layer is 3. When the output is (1,0,0), it indicates normal condition. The output (0,1,0) indicates mover misalignment. The output (0,0,1) indicates bearing outer race fault.

The neural network is a three-tier network consisting of input layer, hidden layer and output layer. Since each input feature vector contains eight elements, the number of neurons in the input layer is 8. Compare the errors when nodes are different. Select node 17.

Use Matlab to write the BP neural network program and train the neural network. Adjust the network parameters according to the situation. If the results of the training meet the requirements, the test samples could be entered for diagnosis. If the results don't meet the requirements, then increase training samples and repeat training until the output meet the requirements.

3. Results and Analysis

Firstly the collected vibration signals of linear motor are decomposed and reconstructed by wavelet packet. Use Matlab to write wavelet packet signal handler. Energy features are extracted after the decomposition and reconstruction of the sample signals. Reconstructed signals of each band are shown in Figure 2, Figure 3 and Figure 4, 6 groups of eigenvectors are shown in Table 2.

Table 2. Eigenvector

Signal eigenvectors	E0	E1	E2	E3	E4	E5	E6	E7	Work status
T1	0.7403	0.2202	0.2431	0.2349	0.2186	0.2336	0.2186	0.2207	Normal
T2	0.7687	0.2321	0.2236	0.2126	0.2351	0.2270	0.2232	0.2283	Normal
T3	0.3424	0.6425	0.2225	0.2591	0.2149	0.2245	0.2690	0.2132	Mover misalignment
T4	0.3466	0.6480	0.2229	0.2505	0.2737	0.2240	0.2067	0.1965	Mover misalignment
T5	0.2268	0.4270	0.2849	0.5909	0.2257	0.2070	0.1988	0.2821	Outer ring fault
T6	0.1907	0.4524	0.2631	0.6627	0.1900	0.2186	0.2212	0.2383	Outer ring fault

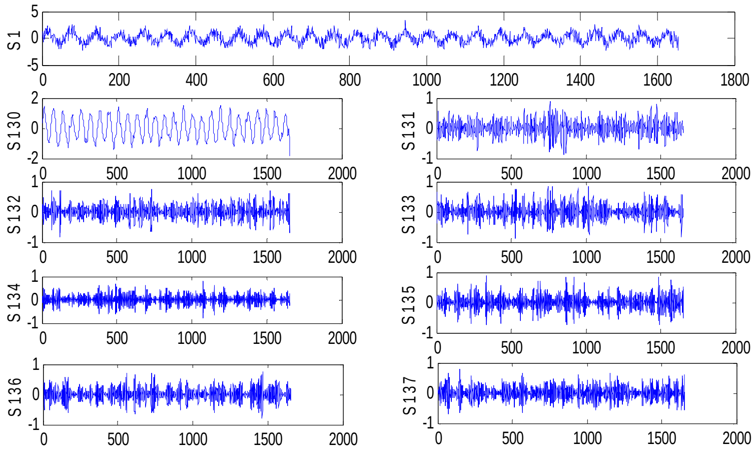

Figure 2. Normal Signal

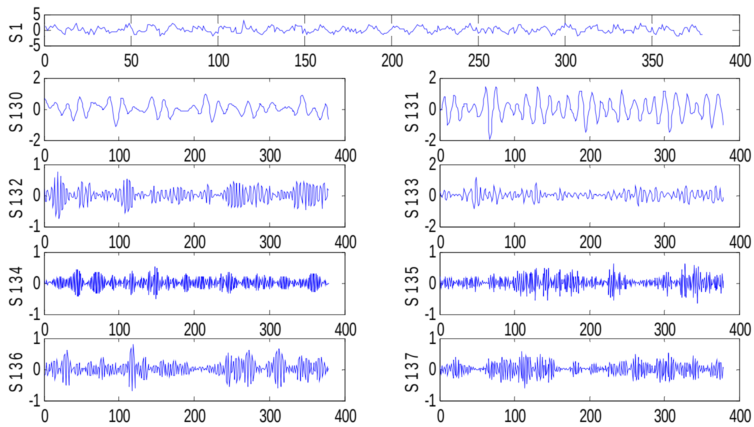

Figure 3. Mover Misalignment

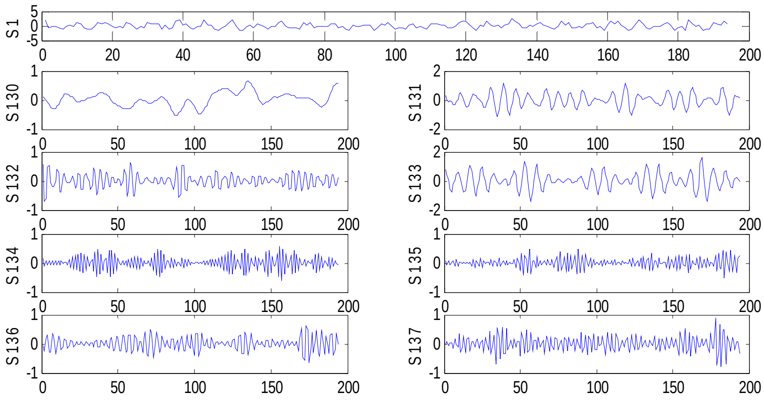

Figure 4. Outer Ring Fault

Use Matlab to write the BP neural network program, the desired output and the resulting feature vectors which are used as training samples are entered into the neural network. Train the network with variable hidden layer neurons. The comparison of the actual output and the desired output is shown in Table 3.

Table 3. The Actual Output and The Desired Output

The desired output			The actual output			Motor status
1	0	0	0.9846	0.0062	0.0057	Normal
1	0	0	0.9813	0.0079	0.0067	Normal
0	1	0	0.0341	0.8393	0.0298	Mover misalignment
0	1	0	0.0287	0.8528	0.0277	Mover misalignment
0	0	1	0.0067	0.0051	0.9936	Outer ring fault
0	0	1	0.0048	0.0038	0.9869	Outer ring fault

Analysis the other three groups of test signals with Wavelet Packet Decomposition, the normal signal, mover misalignment signal and outer ring fault signal are shown in Figure 5, Figure 6 and Figure 7.

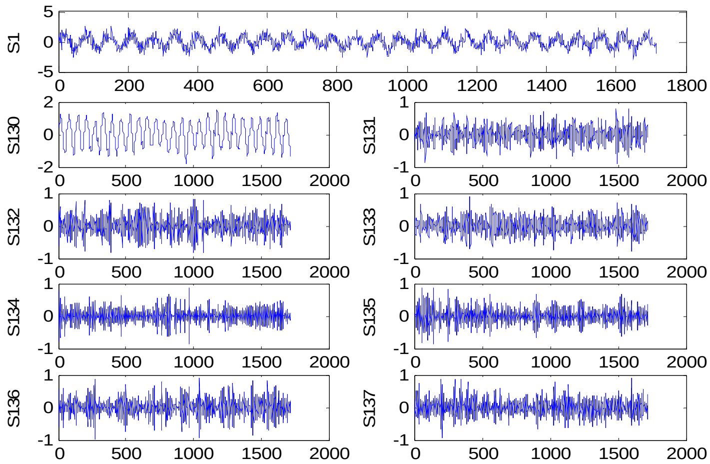

Figure 5. Normal Signal of the Test Group

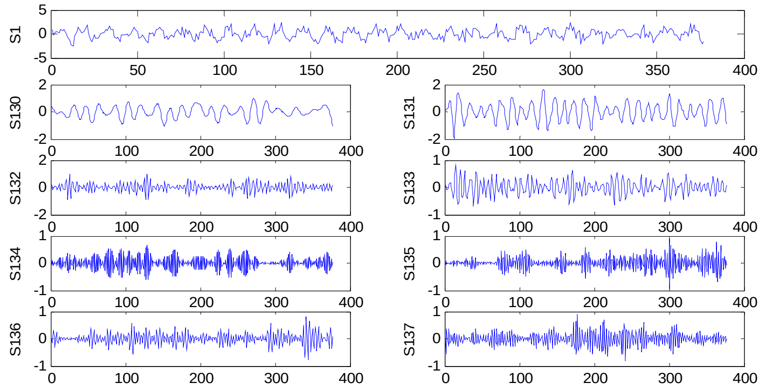

Figure 6. Mover Misalignment of the Test Group

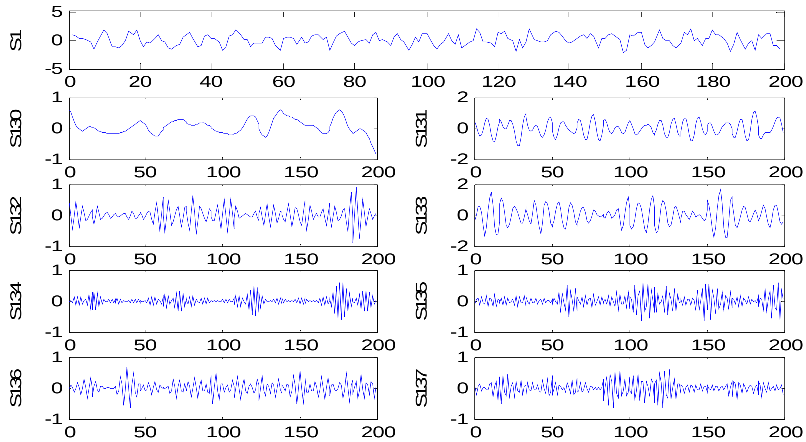

Figure 7. Outer Ring Fault of the Test Group

The test eigenvectors are shown in Table 4. Input the three groups of eigenvectors to the trained neural network. The output of test is shown in Table 5.

Table 4. The Test Eigenvectors

Signal eigenvectors	E0	E1	E2	E3	E4	E5	E6	E7	Motor status
T'1	0.7514	0.2220	0.2256	0.2439	0.2466	0.2562	0.2458	0.2290	Normal
T'2	0.4128	0.6532	0.2726	0.2520	0.2566	0.2501	0.1941	0.2385	Mover misalignment
T'3	0.2408	0.4574	0.2517	0.6167	0.1865	0.2460	0.2133	0.2254	Outer ring fault

Table 5. The Test Output

Test output			Motor status
0.9557	0.0046	0.0051	Normal
0.0306	0.9311	0.0298	Mover misalignment
0.0113	0.0062	0.9874	Outer ring fault

The 6 groups of training samples are entered into the neural network with variable hidden layer neurons and optimized by Genetic Algorithm. Train the network, The output is shown in Table 6.

Table 6. The Output of The Optimized Network

The desired output			The actual output			Motor status
1	0	0	0.9994	0.0003	0.0023	Normal
1	0	0	0.9994	0.0003	0.0024	Normal
0	1	0	0.0024	0.9993	0.0014	Mover misalignment
0	1	0	0.0020	0.9994	0.0014	Mover misalignment
0	0	1	0.0034	0.0004	0.9979	Outer ring fault
0	0	1	0.0031	0.0004	0.9979	Outer ring fault

As can be seen from the Table that the system is more stable, the diagnosis accuracy is further improved. Enter the test samples to the optimize network. The actual outputs are shown in Table 7.

Table 7. The Test Output of The Optimized Network

Test output			Motor status
1.0000	0.0015	0.0001	Normal
0.0003	0.9963	0.0009	Mover misalignment
0.0002	0.0035	0.9982	Outer ring fault

The results show that using the neural network which has variable hidden layer neurons and optimized by Genetic Algorithms to extract fault signal feature and diagnose fault effectively. Its stability and accuracy can meet the engineering needs.

4. Conclusion

Vibration phenomenon is prevalent in the machinery and equipment during operation. Linear motor will have different vibration when in different operating states. When the motor has internal faults or parts defect, the energy and amplitude of the vibration signal will change. Different faults cause different characteristics of the vibration signal. In this paper, a linear motor fault diagnosis method based on wavelet packet and neural network was presented. Extract the signal feature with wavelet packet which is sensitive to mutation and slight change in the signal. Then identify faults by neural network system with variable neurons in the hidden layer and optimized by Genetic Algorithms. The results show the correctness and feasibility of the proposed method.

Provide a statement that what is expected, as stated in the "Introduction" chapter can ultimately result in "Results and Discussion" chapter, so there is compatibility. Moreover, it can also be added the prospect of the development of research results and application prospects of further studies into the next (based on result and discussion).

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