Wavelet Transform and Neural Networks in Fault Diagnosis of a Motor Rotor

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Abstract: *In the motor fault diagnosis technique, vibration and stator current frequency components of detection are two main means. This article will discuss the signal detection method based on vibration fault. Because the motor vibration signal is a non-stationary random signal, fault signals often contain a lot of time-varying, burst properties of ingredients. The traditional Fourier signal analysis can not effectively extract the motor fault characteristics, but are also likely to be rich in failure information but a weak signal as noise. Therefore, we introduce wavelet packet transforms to extract the fault characteristics of the signal information. Obtained was the result as the neural network input signal, using the L-M neural network optimization method for training, and then used the BP network for fault recognition. This paper uses Matlab software to simulate and confirmed the method of motor fault diagnosis validity and accuracy.*

Key words: fault diagnosis; wavelet transform; neural networks; motor; vibration signal

1 Introduction

With the development of the modern industrialization process, the motor has become a main power equipment in modern industry. It will be harm to production and personal safety if the motor can't work. So it is very necessary to build a mature diagnosis system. The vibration signal of a motor can fully report the running state of motor [1,2]. The vibration signal of a motor often contains large amounts of a time-varying and short-burst ingredient as a non-stationary random signal [3,4], so the traditional signal analysis methods have been unable to extract effectively the fault feature of the motor. Worse, the weak signal with fault information will be filtered as noise. In order to solve the above-mentioned problem, we can let different frequency components of the non-stationary random signal be separated through the wavelet packet transform, which can accurately capture the fault feature from the non-stationary local mutation signal fault feature with fine time-frequency local characteristics and multi-resolution processing. At the same time, we can make fault classification and recognition through the neural network, which makes contributions to the diagnosis field with the strength of adaptive, nonlinear mapping [5] and others.

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2 Motor fault diagnosis methods

The motor fault diagnosis is generally divided into four steps, respectively, signal detection, feature extraction, pattern recognition and diagnosis decision. The first step of the fault diagnosis is to get the initial information from the equipment diagnosed with sensors. This paper studies the motor rotor's vibration in normal, rotor misalignment and bearing rub state and gets some valuable experimental data. After that, we these data can be taken as the input of a neural networks and built the BP neural networks to simulate by using Matlab; then the effective combination and application prospect between wavelet transform and neural networks in fault diagnosis of motor areas can be studied.

3 Wavelet packet analysis and fault feature extraction

3.1 Wavelet transforms analysis [6]

Wavelet is a kind of wave with very short duration which must meet certain admissible conditions. Different from Fourier analysis, the basis of wavelet analysis can be a wavelet function if it meets all the conditions of wavelet basis functions, so it should be based on wavelet admissibility conditions to determine the basic wavelet.

Set $\psi(t) \in L^2(R)$, Fourier transform is $\psi(\omega)$, if $\psi(\omega)$ meets as follows:

$$\int_{-\infty}^{+\infty} \frac{|\psi(\omega)|}{\omega} \mathrm{d}\omega < +\infty \qquad (1)$$

Where $\psi(t)$ is the mother wavelet or basic wavelet. Making certain the following equation can be getten: translations and telescopic for $\psi(t)$

$$\psi_{a\tau}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-\tau}{a}\right) \quad a > 0 \quad \tau \in R \qquad (2)$$

Where $\psi_{a\tau}(t)$ is the continuous wavelet basis function; a is the scale factor and τ is the displacement factor.

Then, the function $f(t)$ of wavelet transform is given as follows:

$$WT_f(a,\tau) \leqslant f(t)$$

$$\psi_{a\,b}(t) \geqslant \frac{1}{\sqrt{a}} \int_R f(t)\, \psi^* \left(\frac{t-b}{a}\right) \mathrm{d}t \qquad (3)$$

In practical application, signal analysis and deal with through computer, the signal $f(t)$ must be into discrete time sequence. On the continuous wavelet transform, the scale factor and displacement factor that is continuous must be discrete, so we get the DWT discrete wavelet transform. Making the power series discrete for the scale factor, let $a = a_0^j, a_0 > 0, j \in Z$, are the discrete displacement factor, get $\tau = k a_0^j \tau_0$, in the equation, a_o and τ_0 is greater than zero real constants, j and k as integers, then the discrete wavelet basis function is:

$$\psi_{a_0^j k\tau_0}(t) = a_0^{\frac{-j}{2}} \psi(a_0^{-j} t - k\tau_0) \qquad (4)$$

Usually taking the constant $a_0 = 2, \tau_0 = 1$, the wavelet basis function is simplified as follows:

$$\psi_{2^j k}(t) = 2^{\frac{-j}{2}} \psi(2^{-j} t - k) \qquad (5)$$

The giving function $f(t)$ discrete wavelet transform can be expressed as follows:

$$WT_f(j,k) \leqslant f(t)$$

$$\psi_{j\,k}(t) \geqslant 2^{\frac{-m}{2}} \int_R f(t)\, \psi^* (2^{-m} t - k)\, \mathrm{d}t \qquad (6)$$

3.2 Wavelet packet to extract the fault characteristic signal

The wavelet packet analysis can not only be decomposed on the scale space or the low-frequency part, but also be decomposed on the wavelet space or the high-frequency part decomposition, so it has been widely used with great advantages. Wavelet packet decomposition of the original signal can be decomposed into different frequency bands in the projection, for those within the frequency band of the signal analysis is called the frequency analysis technique [7]. Wavelet packet analysis can be divided into levels and frequency bands more according to the analysis of signal characteristics and adaptive selection of the appropriate frequency band, so that it is matched with the signal spectrum, thereby improving the time-frequency resolution so that the fault features extraction are in refinement of the band. The three-layer wavelet packet decomposition are described in the process of decomposition of the wavelet packet. Figure 1 shows the schematic diagram of three-layer wavelet packet transform. Schematic diagram of three-layer wavelet packet transform is shown in Figure 1.

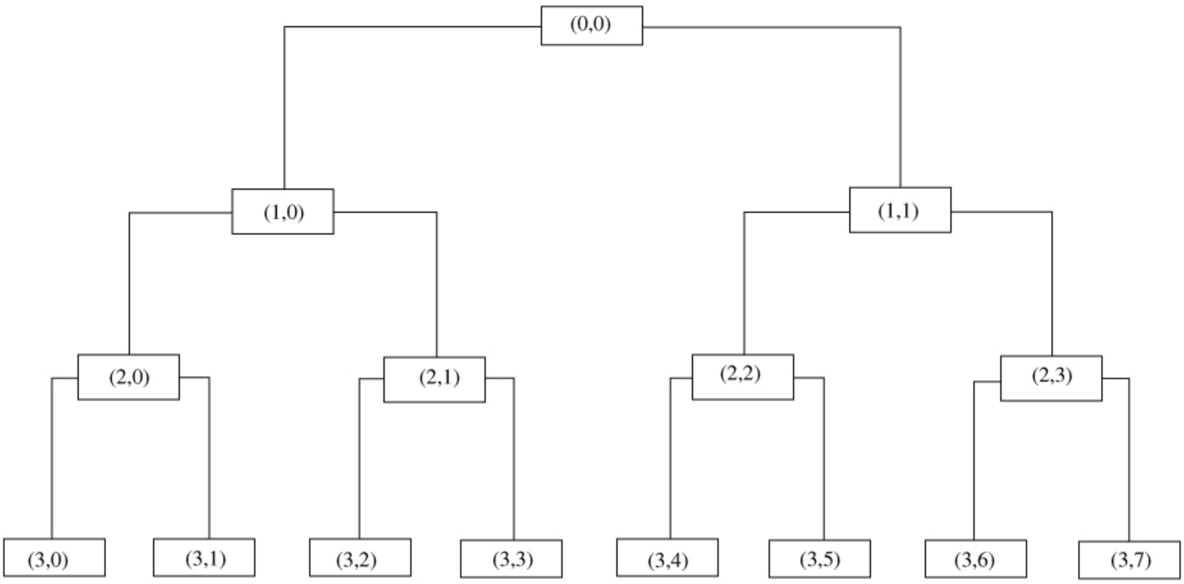

Figure 1 Schematic diagram of three-layer wavelet packet transform

Graph (0, 0) is a representation of the original signal S, (1, 0) representing the wavelet packet decomposition low frequency coefficient of the first layer, (1, 1) representing the wavelet packet decomposition of the first layer of high frequency coefficient, (3, 0) representing the zeroth node coefficient, the other analogy.

Wavelet packet signal reconstruction is based on the interference and noise frequency band of signal reconstruction. As long as the signal decomposition characteristics of signal and noise is decomposed into different frequency bands, we remove the interfering noise reconstruction signal [8]. Following is the wavelet packet feature vector construction process [9]:

1) For signal $f(t) \in L^2(R)$ the wavelet packet coefficients can be obtained as follows:

$$S^k_{j\,n}(t) \leqslant f(t) \tag{7}$$

Where $S^k_{j\,n}(t)$ $(k = 1, 2, \cdots, m)$ is the nodes (j, i) corresponding to the wavelet packet coefficient, K node (j, i) is the on the coefficient of the number, n is the j layer wavelet packet nodes $(n = 0, 1, \cdots, 2^{j-1})$, integer j and i, respectively, scale and the transformation factor.

2) Set the original signal $f^k_{0\,0}(t)$ decomposed into $f^k_{j\,n}(t)$ $(n = 0, 1 \cdots, 2^{j-1})$, where j is the number of a wavelet packet, n is the j layer wavelet packet nodes, then the wavelet packet node n signal can be represented as $f^k_{j\,n}(t)$ at time $[t_1, t_2]$ internal energy, can be expressed as follows:

$$e_{j\,n} = \int_{t_1}^{t_2} | f^k_{j\,n}(t) |^2 \mathrm{d}t = \sum_{k=1}^{m} | x^k_{j\,n} |^2 \tag{8}$$

3) Normalization: the signal of three layer wavelet packet decomposition ($j = 3$; $n = 0, 1, \cdots, 7$; $k = 1, 2, \cdots, m$), then the feature vector $T_a = [e_0, e_1, \cdots, e_{2j-1}]^{\mathrm{T}}$;

4) Because total energy is larger after the wavelet

transform of e_{jn}, e_{jn} is not conducive to pattern classification as follows:

$$E_{j\ i} = \frac{e_{jn}}{\sum_{j=0}^{7} e_{jn}} \quad (9)$$

To construct the feature vector, when $j = 3$, $T = [E_{30}, E_{31}, E_{32}, E_{33}, E_{34}, E_{35}, E_{36}, E_{37}]$ in the simulation analysis gives the fault feature extraction of specific data as the neural network training and test data.

4 Neural networks and fault recognition

4.1 BP neural network

A neural network in modern neuroscience research is presented on the basis of the simulation of the human brain by the large number of certain characteristics of artificial neurons composed of parallel and distributed network storage, with knowledge and experience in making available features. Based on the BP neural network algorithm is the most widely used models belonging to the feedforward network, also known as the error back propagation algorithm network and includes an input layer, hidden layer and output layer. It is through the back-propagation learning rule to adjust the network weights and threshold value of the network and the minimum square error. Including the forward propagation and propagation, in the forward propagation of learning samples into the input layer, hidden layer to output the operation back layer, if the output layer did not achieve the desired results, then the calculation of output layer error changes value, then into the error back propagation stage, the error signal along the original connection from the input layer and output layer returns layer by layer to adjust the connection weights, for the minimum error.

This paper uses the motor as the diagnosis object, while the fault reason and no clear linear relationship between the state is not conducive to an accurate mathematical model to describe, the motor can be the fault data as a sample feature vector is input to the neural network and the given desired output. The neural network, by modifying the neuron weights training, reaches the permitted error range after cessation of training; it can be an other fault feature vector as input into the trained neural network, thus realizing the fault identification.

4.2 Algorithem of BP neural networks

A BP neural network is for design fault identification, identification of the running state of the motor. The first step, with the wavelet packet decomposition to extract the motor state signal feature vectors as input samples is as follows:

$$T = [E_{30}, E_{31}, E_{32}, E_{33}, E_{34}, E_{35}, E_{36}, E_{37}] \quad (10)$$

Corresponding to a given desired output to X_{id}, two output neuron nodes, neuronal output (0,1) that the rotor (1,0), said rotor misalignment, (1,1) of said bearing rub. The second step, according to the Kolmogorov theorem to determine the three layer network structure, the input layer, hidden layer and output layer neurons nodes were N, $2N+1$ and M, where $N = 8$, $M = 2$. The middle layer neurons select an S type tangent function as the activation function of neurons in the output layer and selection of the S logarithm function as the activation function. The third step, preparing process of BP neural network training, until the training results can meet the requirements, selection of new test samples as training after the input of the neural network is a network performance testing. The process flow is as follows [10].

BP neural network algorithm is shown Figure 2.

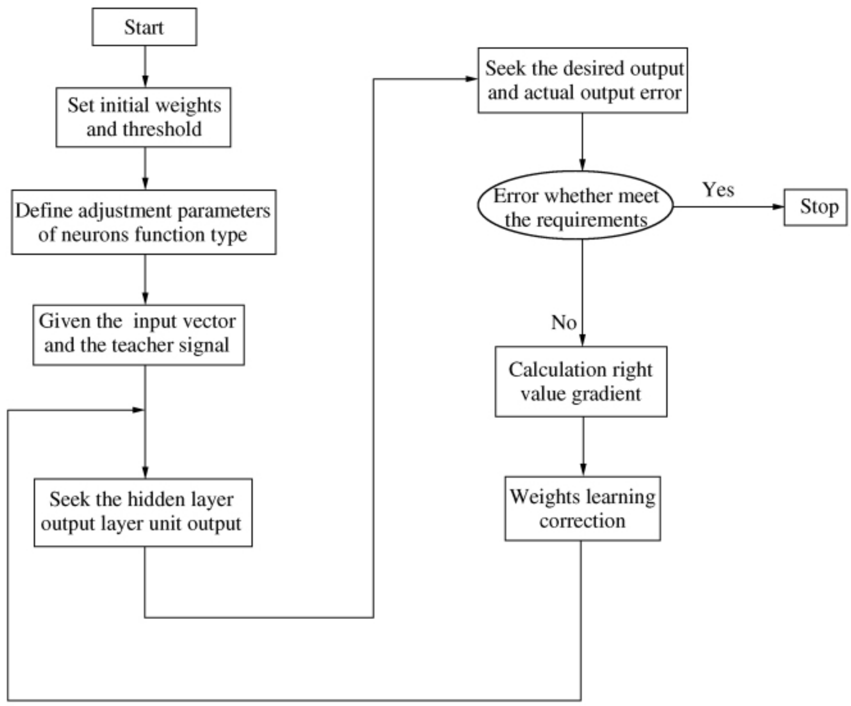

Figure 2 BP neural network algorithm

5 Matlab software simulations

Using an acceleration sensor to collect the motor original vibration signal, six groups of sample data are in the following diagram. The sample signal is shown Figure 3.

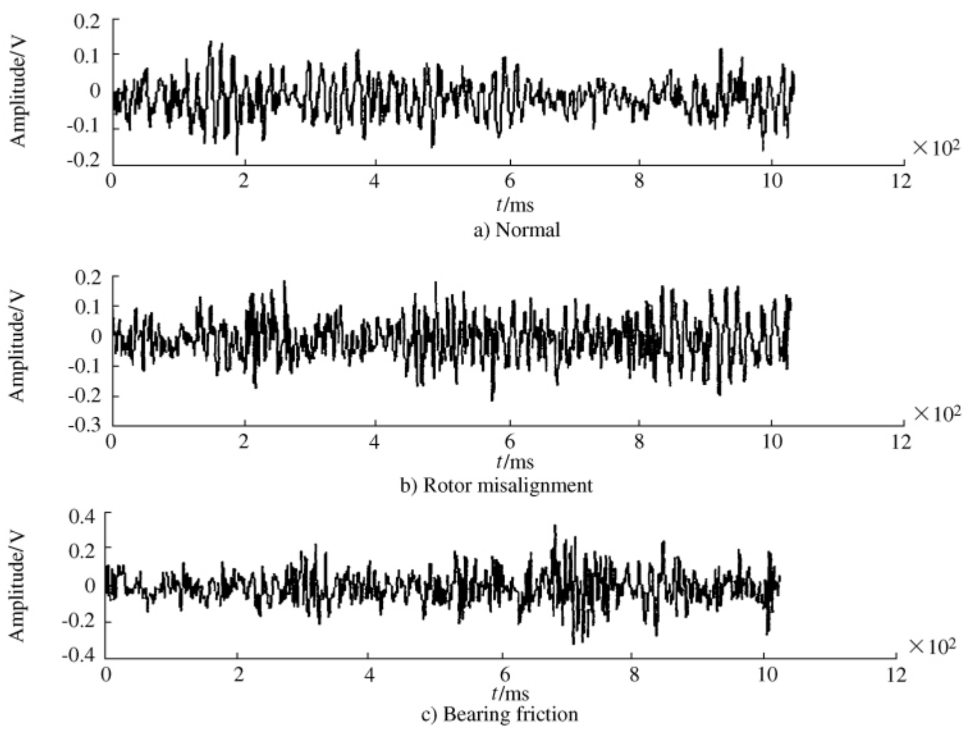

Figure 3 The sample signals

The signal after A/D conversion and discrete process, according to the feature signal extraction steps written using the matlab wavelet packet signal analysis procedure, the sample signal feature extraction, to get samples of the six groups of feature vector signals is in the Table 1.

Table 1 The Eigen vector of sample signals

Signal feature vector	E_0	E_1	E_2	E_3	E_4	E_5	E_6	E_7	Motor states
T_1	0. 781 8	0. 257 6	0. 284 3	0. 238 3	0. 274 2	0. 155 2	0. 167 4	0. 179 8	Normal
T_2	0. 811 2	0. 242 6	0. 301 1	0. 252 7	0. 263 4	0. 161 0	0. 172 4	0. 167 1	Normal
T_3	0. 154 1	0. 979 2	0. 312 4	0. 225 7	0. 127 3	0. 067 9	0. 086 4	0. 177 4	Rotor misalignment
T_4	0. 154 6	0. 998 9	0. 307 8	0. 215 6	0. 131 6	0. 081 3	0. 085 9	0. 182 2	Rotor misalignment
T_5	0. 170 6	0. 107 9	0. 934 7	0. 204 2	0. 252 9	0. 205 2	0. 071 7	0. 140 5	Bearing friction
T_6	0. 167 9	0. 123 1	0. 899 7	0. 203 7	0. 267 8	0. 207 0	0. 081 0	0. 139 7	Bearing friction

According to the BP neural network design process, Matlab prepared using a BP network program, the input signal and the desired output sample feature vectors to neural network training, after training desired output and the actual output are in the Table 2.

Table 2 The anticipant output and practical output

Desired output	Actual output	Motor state
0 1	0. 022 6 0. 889 4	Normal
0 1	0. 022 7 0. 998 7	Normal
1 0	0. 886 3 0. 001 5	Rotor misalignment
1 0	0. 8903 0. 001 3	Rotor misalignment
1 1	0. 9834 0. 970 8	Bearing friction
1 1	0. 9813 0. 993 8	Bearing friction

In the range of allowable error, desired output and the actual output is basically consistent, indicating that the network is composed of a fault state recognizer training success. Then the same acceleration sensor to collect the other three groups test signal, through A/D conversion and the discretization of the test signal as shown below, is used for training neural network performance testing. The testing signals is shown Figure 4.

Using the wavelet packet to the test signal analyzed, the extracted feature vectors are as shown in the Table 3.

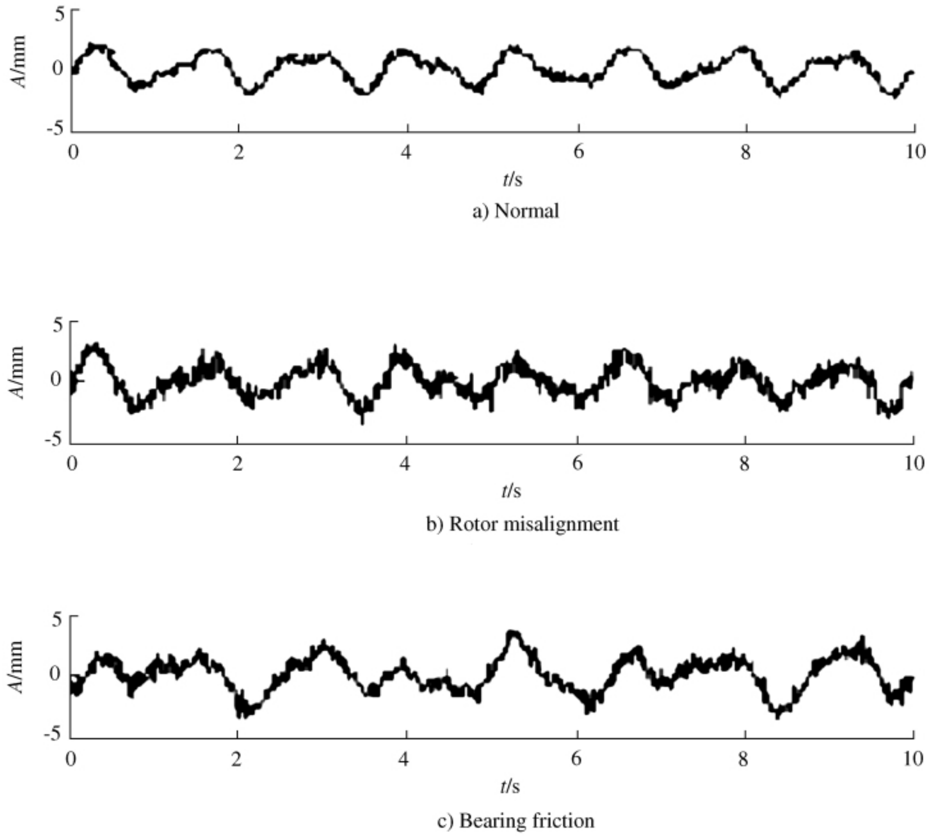

Figure 4 The testing signals

Table 3 The Eigen vector of testing signals

Signal feature vector	E_0	E_1	E_2	E_3	E_4	E_5	E_6	E_7	Motor state
T_1^*	0.801 8	0.268 6	0.297 6	0.239 3	0.274 3	0.166 2	0.167 4	0.189 1	Normal
T_2^*	0.166 1	0.998 9	0.212 5	0.225 4	0.137 1	0.068 2	0.087 4	0.168 1	Rotor misalignment
T_3^*	0.171 6	0.107 4	0.956 4	0.205 3	0.252 7	0.216 3	0.073 5	0.146 2	Bearing friction

The test group 3 vector is input to a neural network fault analysis, the test results are as shown in the Table 4.

Table 4 The testing output

Test output		Motor state
0.056 7	0.929 7	Normal
0.950 8	0.001 1	Rotor misalignment
0.978 6	0.897 6	Bearing friction

The test results are consistent with the signal corresponding to the state and demonstrate the use of wavelet packet analysis can effectively extract the fault feature vector, and by the trained BP neural network can make accurate diagnosis of motor faults.

6 Conclusions

In this paper, the wavelet packet analysis and BP neural network are combined for motor fault diagnosis. The method can be effectively used for motor fault diagnosis based on wavelet packet analysis. To over-come the FFT analysis signal of fault signal in weak and singular signal components difficult to extract fault, a further training method of RBF neural network by fault identification is given. Experimental results show that the accuracy and efficiency of the proposed method can be the actual application of the motor fault diagnosis system research application. Thus the motor maintenance and repair work can provide timely information and save manpower and funds.

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Brief Biographies

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