International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 2 Issue 10 ǁ October 2014 ǁ PP.31-37

Study Of The Fault Diagnosis Based On Wavelet And Fuzzy Neural Network For The Motor

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Abstract: *In the fault diagnosis of the motor, the vibration signals can fully reflect the status of the motor. In this paper, on the basis of wavelet packet fault feature extraction, a new approach for motor fault diagnosis based on wavelet packet analysis and fuzzy RBF neural network was presented.The method gains the energy of characteristic channel of bearing failure vibration signals of asynchronous motor, which adopts the technology of wavelet packet analysis. It also composes the characteristics of the vector as input of fuzzy RBF neural network, used to diagnose the induction motor bearing failures. The method overcomes the slow convergence, a long training time, local minimum problems when using BP neural network. Experimental results shows that using fuzzy RBF neural network can improve the accuracy of the motor fault diagnosis.*

Keywords: *motor; fault diagnosis; wavelet packet analysis; fuzzy RBF neural network*

I. I. INTRODUCTION

With the development of science and technology, electrical equipment has become the main driving force in the modern industry. The process of production will be forced to suspend if the electrical equipment broken down, which causes huge economic losses. Since the structure of the motor and other factors like the environment and the load, the motor signal contains a lot of noise, the noise will make the useful signal are not recognized. When the signal contains more distortion and useful information, the traditional fourier analysis rules is powerless. Therefore, the wavelet packet analysis method can deal with non-stationary signals, which has been increasing widely used[1].

Literature[2] uses BP neural network to diagnostic motor fault, but due to non-stationary signals resulting in diagnostic errors. Literature[3]and[4] use wavelet packet combine with BP neural network to diagnose motor fault, but BP neural network is easy to fall into local minima. Literature[5]and [6] use the wavelet packet and RBF neural network, and this method has high requires for data demanding. This article gives the motor fault diagnosis based on wavelet packet analysis and fuzzy RBF neural network, using the wavelet package's weak signal changes and sudden changes in good analytical to process the signal. Then extract signal energy and feature vectors, which takes the feature vector as the input vector of fuzzy RBF neural network, and also trains network to achieve fault diagnosis requirements. The method can effectively diagnose motor failure by measurement.

II. PROBLEM DESCRIPTION

Steps for fault diagnosis of motor bearing are signal detection, feature extraction, detection, diagnosis and decision.

When the bearing failed at some point, this point contacts with the surrounding will generate an impulse and lead to a change of frequency for the bearing. Differences arising out of failure frequency varies, from vibration signal in frequency and energy will produce a corresponding change. Wavelet packets analysis can be effective for signal time-frequency decomposition, multi-level division band, further decomposes high frequency parts of the multiresolution analysis is not subdivided deeply and according to the characteristics of the signal being analyzed, adaptively select the appropriate frequency band to match the signal spectrum, thus increasing the time-frequency resolution.

Where $g_j^n(t) \in u_j^n$, g_j^n can be expressed as

$$g_j^n(t) = \sum_l d_l^{j,n}(2^j t - 1)$$

Wavelet packet decomposition is broken $g_{j+1}^n(t)$ down into $g_j^{2n}(t)$ and $g_j^{2n+1}(t)$,wavelet packets decomposition algorithm is

$$d_l^{j+1,2n} = \sum_k h_{k-2l} d_k^{j,n}$$

$$d_l^{j+1,2n+1} = \sum_k g_{k-2l} d_k^{j,n}$$

Wavelet package reconstruction algorithm is

$$d_l^{j,n} = \sum_k [h_{l-2k} d_k^{j+1,2n} + g_{l-2k} d_k^{j+1,2n+1}]$$

As shown in Fig.1, with three layers of wavelet packets decomposition as an example of wavelet packets decomposition processes. Signal S is decomposed into low frequency signal $A1$ and high frequency $D1$ signal, $A1$ and $D1$ continue to be divided into more detailed low frequency and high frequency sections and decomposing. Signals use wavelet packet decomposition and reconstruction can provide the input signal of the RBF neural network.

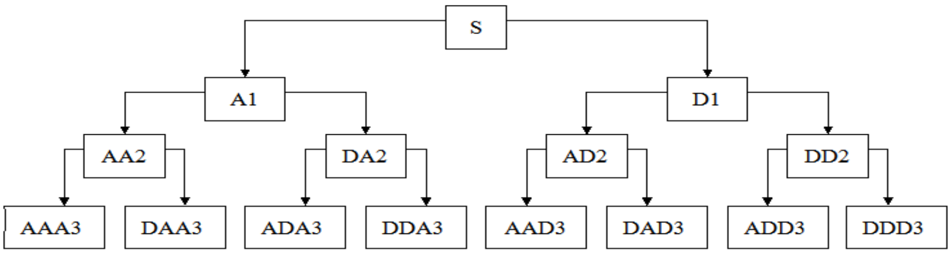


Fig.1 wavelet packet decomposition

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

The feature vectors are input to the fuzzy neural network that have been normalized after obtaining by wavelet packet analysis. The fuzzy neural network absorbs the benefits of fuzzy logic, neural networktechnology, expert's knowledge and experience, through self-learning to increase the decision-making ability of the system. So use motor fault diagnosis based on fuzzy RBF neural network.

III. MAIN CONTENTS

Extent of bearing failure can be seen as a vague concept. Choose large, medium and small three fuzzy subsets to fuzzy the extraction of fault energy, and its normal membership function is as follows,

$$y_1 = \begin{cases} 1 - e^{-\frac{(x-c)^2}{\sigma^2}} & x > c \\ 0 & x \le c \end{cases}$$

$$y_2 = e^{-\frac{(x-c)^2}{\sigma^2}} \qquad 0 < x < +\infty$$

$$y_3 = \begin{cases} 1 - e^{-\frac{(x-c)^2}{\sigma^2}} & x \le c \\ 0 & x > c \end{cases}$$

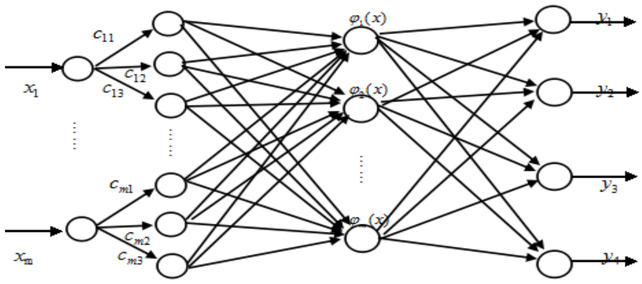
Where y_1 、 y_2 、 y_3 are large, medium and small three fuzzy subset's membership, x is the fault feature, c is average value of the fault feature in the training samples, σ is the variance of the fault feature in the training samples.

Training of RBF neural networks can be classified into unsupervised learning and supervised learning. The unsupervised learning determines the weights between the input and the hidden layers, and the supervised learning determines the weights between the hidden and the output layers.

The structure of fuzzy RBF neural network is shown in Fig.2. The input layer is the first, which receives a feature vector after the wavelet packet decomposition and sent the input vector directly to the next layer.The fuzzy layer is the second, which fuzzy the input vector. Each input layer node corresponding to three fuzzy layer nodes, and the fuzzy layer has 24 neurons that will enter data into different membership of fuzzy subset and output to the hidden layer. The hidden layer is the third, which is the maps from the input to the output of fuzzy value. The output layer is the fourth, the output is:

$$y_k = \sum_{k=1}^{p} w_{jk} \varphi_p \qquad j = 1,2,3 \cdots n$$

Where y_k is the output of the kth unit of the output's layer, w_{jk} is the weights from the hidden layer's the jth element to the output layer's the kth element. p is the number of output layer nodes.



input layer fuzzy layer hidden layer output layer

Fig.2 The structure of the fuzzy RBF neural network

The steps of using the wavelet packet analysis to extract the feature energy of the fault signal.

①Do the three wavelet packet decomposition to the collected signals, and obtained eight wavelet packet decomposition coefficients of the third layer from low frequency to high frequency: $(X_{30}, X_{31}, X_{32}, X_{33}, X_{34}, X_{35}, X_{36}, X_{37})$

②Reconstruction of the wavelet packet decomposition coefficients, extracting each frequency range of the signal: (S_{30}, S_{31}, S_{32}, S_{33}, S_{34}, S_{35}, S_{36}, S_{37})

The total signal： $S = S_{30} + S_{31} + S_{32} + S_{33} + S_{34} + S_{35} + S_{36} + S_{37}$

Table.1 three layer decomposition of wavelet packet frequency range

signal	frequency range
S_0	0~0.125 f
S_1	0.125 f ~0.25 f
S_2	0.25 f ~0.375 f
S_3	0.375 f ~0.5 f
S_4	0.5 f ~0.625 f
S_5	0.625 f ~0.75 f
S_6	0.75 f ~0.875 f
S_7	0.875 f ~ f

Calculate the total energy of each band,the output signal $S_{3j}\,(j = 0,1\cdots 7)$ of each band that corresponds to the energy signal is: $E_{3j}\,(j = 0,1\cdots 7)$

The total energy is: $E_j^{'} = \sum_{k=1}^{n} \left| x_{jk} \right|^2$

③Construct the characteristic vector T , $T = [E_0, E_1, E_2, E_3, E_4, E_5, E_6, E_7]$

Since E_j is biger, normalized to T , assume that $E = \left(\sum_{j=0}^{7} E_j \right)^{1/2}$, after the normalization, the characteristic vector is: $T^{'} = \left[E_{30}/E, E_{31}/E, \cdots E_{37}/E \right]$

According to this article, the date which is used to analysis comes from the Case Western Reserve university provides in the network. Gather the asynchronous machine four condition’s signals as normal, rolling element fault,outer ring fault and inner ring fault, after wave packet decomposition restructuring, the characteristic vector which various frequency bands signal energy constitutes takes the sample characteristic vector input the fuzzy neural network.

Assigns expects output as Table.2.

Table.2 the meaning of each output unit

unit1	unit2	unit3	unit4	meaning
1	0	0	0	normal
0	1	0	0	inner ring fault
0	0	1	0	outer ring fault
0	0	0	1	cage fault

IV. MATLAB SIMULATION EXAMPLES

First of all, do the wavelet packet decomposition and reconstruction to the vibration signals of induction motor that collected. Write the signal wavelet packet processing program in matlab, and do the wavelet packet decomposition and reconstruction and energy feature extraction to the simple signals, then get the restructuring signal characteristic vector of the various frequency bands as follows.

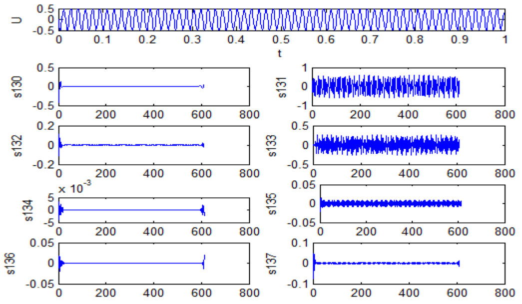


Fig.3 normal signals

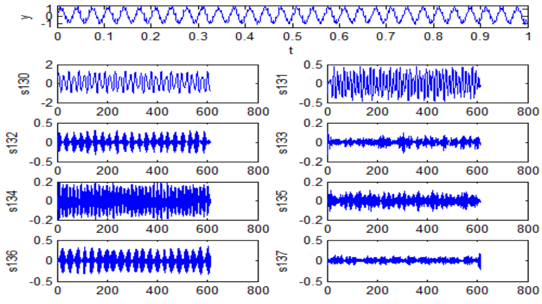


Fig.4 inner ring fault signals

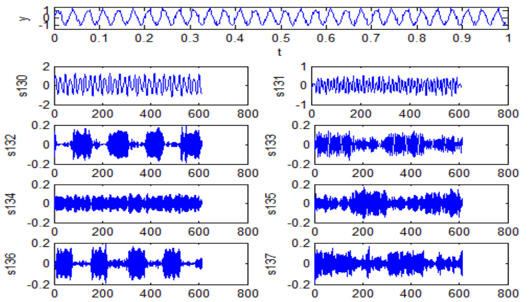


Fig.5 outer ring fault signals

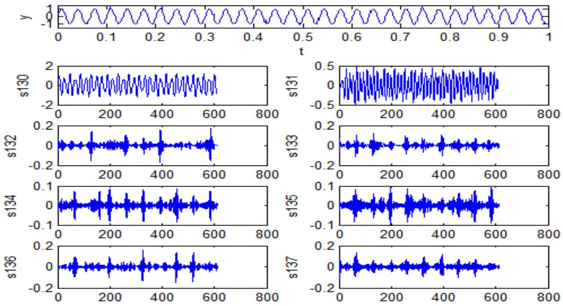


Fig.6 cage fault signals

Table.3 characteristic vector

signal characteristic vector	E0	E1	E2	E3	E4	E5	E6	E7	work state
T1	0.0773	0.9196	0.0226	0.3839	0.0010	0.0152	0.0053	0.0144	normal
T2	0.1562	0.9094	0.0450	0.3815	0.0170	0.0154	0.0097	0.0270	normal
T3	0.8995	0.3222	0.1452	0.0396	0.1492	0.0617	0.1831	0.0690	inner ring fault
T4	0.8921	0.3198	0.1671	0.0412	0.1490	0.0643	0.2029	0.0685	inner ring fault
T5	0.9162	0.3401	0.0905	0.0832	0.0862	0.0861	0.0833	0.0892	outer ring fault
T6	0.9117	0.3442	0.1037	0.0877	0.0829	0.0868	0.0937	0.0930	outer ring fault
T7	0.9399	0.3283	0.0400	0.0352	0.0357	0.0384	0.0429	0.0364	cage fault
T8	0.9346	0.3369	0.0477	0.0463	0.0443	0.0465	0.0485	0.0466	cage fault

Extract of fault characteristic vector and carries on normalized processing to compose a group of characteristic vector as a set of eigenvectors of the fuzzy RBF neural network's input. Extract data as training samples of the trained neural network under the four conditions of the motor, and the four groups of data as the test sample for testing the trained neural network. Training samples are not listed one by one. Test samples are shown in Table.4.

Table.4 test characteristic vector

motor state	test samples		
normal	0.1562	0.9094	0.3815
	0.0970		
inner ring fault	0.8921	0.3198	0.0412
	0.2029		
outer ring fault	0.9162	0.3442	0.0877
	0.0937		
cage fault	0.9399	0.3283	0.0352
	0.0485		

Using the matlab program to programming, and train the fuzzy RBF neural network with the training samples. Bring the test samples into the training RBF neural network and fuzzy RBF neural network for testing. The output based on RBF neural network as shown in Table.5, and the output based on fuzzy RBF neural network as shown in Table.6.

Table.5 test output

test output				motor state
0.865	0.115	0.084	0.096	normal
0.092	0.892	0.106	0.076	inner ring fault
0.132	0.095	0.916	0.078	outer ring fault
0.153	0.099	0.148	0.811	cage fault

Table.6 test output

test output				motor state
0.925	0.082	0.039	0.015	normal
0.037	0.962	0.052	0.026	inner ring fault
0.042	0.026	0.929	0.053	outer ring fault
0.078	0.028	0.039	0.923	cage fault

From above, contrast Table.2 with Table.5 and Table.6. The test results correspond to the actual signal states shows it is possible to extract the fault feature extraction of fault signal based on wavelet packet, and diagnose fault with the fuzzy RBF neural network. Compare the two sets of test output using RBF neural network and fuzzy RBF neural network, which shows that fuzzy RBF neural networks can more accurately detect the motor fault.

V. CONCLUSION

Vibration exists in all running processing of motors. When the motor is internal malfunction, energy and amplitude of motor vibration signal will also change, and the characteristics of vibration signals caused by different faults are also different. In this paper, fault diagnosis based on wavelet packet and fuzzy RBF neural network combine, which does the signal feature extraction by using the wavelet packet analysis method, and then uses fuzzy RBF neural network to recognize the state. The results show the accuracy and feasibility of this method.

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