Rolling Bearing Diagnosis Based on LMD and Neural Network

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Abstract

Inner ring pitting, the outer indentation and rolling element wear are typical faults of rolling bearing. In order to diagnose these faults rapidly and accurately, the paper proposes a novel diagnosis method of rolling bearing based on the energy characteristics of PF component and neural network by the vibration signal of local mean decomposition(Local mean decomposition, LMD). The vibration signal is decomposed into several PF components by the local mean decomposition, the calculated energy characteristics of the PF component are inputted to the neural network to identify the type of rolling bearing faults. At the same time, the genetic algorithm is introduced to optimize the structure parameters of neural network, which improves diagnostic rate and accuracy of faults. The results show that this method has a higher diagnosis and recognition rate for the typical faults of rolling bearing.

Keywords: *Rolling bearing, LMD, Genetic algorithms, Neural network, Fault diagnosis.*

1. Introduction

Rolling bearing is a critical part of the transmission gear. Failures like inner ring pitting, outer ring creasing and rolling elements wear, etc. can be resulted from wear, fatigue, corrosion, overload and so on, while the equipment is operating. The measured vibration acceleration signal of the roller bearing is a kind of typical non-stationary signal which reflects weak energy of status information, this will bring some trouble to fault diagnose because of its. Therefore, knowing how to extract fault information characters from non-stationary vibration signals is very important for Fault Diagnosis of Rolling Bearings. Up to now, the main approaches to process non-stationary signal include Wigner Distribution, short-time Fourier transform, wavelet transform, EMD and LMD, etc. But all of them have their own limitation. For example, cross terms appear when analysis multicomponent signal by using Wigner Distribution, the time-frequency window of short-time Fourier transform is fixed; although the time-frequency window of wavelet transform is variable, but it is also mechanical lattice type division of time-frequency plane, the same as Fourier transform, so essentially, it's not a kind of self-adaptive signal process approach;

Problems like over envelope, owe envelop, mode confusion, end effect, IMF criterion and no fast algorithm, etc. and the unexplainable negative frequency will be produced by using Hilbert transform to get analytic signal and compute instantaneous frequency. Recently, a new approach of self-adaptive time-frequency analysis which is called Lockalmean decomposition (LMD) is proposed by Jonathan S.Smith. LMD represent a complicated multicomponent signal as the sum of several production functions (PF). Each PF component is the product of one envelope signal and one pure FM signal, and the complete time-frequency distribution (TFD) of original signal is combination of instantaneous amplitudes and instantaneous frequencies of all PF components, the characteristic information of original signal can be achieved more precisely and effectively, so LMD is an ideal method to process multicomponent AM and FM signal, to extract energy of PF component as characteristic.

This paper presents an approach of combining neural network with energy characteristic of PF component extracted by using LMD to diagnose faulty rolling bearing. First, decompose the vibration signal by LMD to get energy characteristic of PF component as the input of neural network, and optimize the neural network structure parameters by applying genetic algorithm to improve the faults recognition speed and accuracy. Comparing the diagnostic result of rolling bearing work in well condition, work with inner ring pitting, work with outer ring indentation and work with rolling body wear, it shows the approach of combining neural network with energy characteristic of PF component proposed by this paper has the advantages of faster diagnosis speed and higher accuracy, and at the same time, it shows this method is available for classic fault diagnosis of bearings in gearboxes.

2. LMD method

Essentially, LMD is a kind of method that isolates pure FM signal and envelop signal from original signal, next for loop processes PF components (these components have physical significance) which are products of the pure FM signal and envelop signal until all PF components are extracted, then we can get the time-frequency distribution of the original signal. The original signal $x(t)$ is the sum of all the PF components and, that is:

$$x(t)=\sum_{p=1}^{k} PF_p(t)+u_k(t) \tag{1}$$

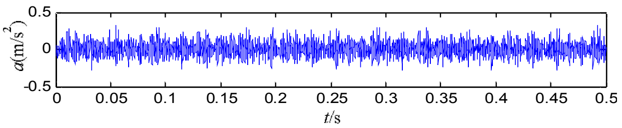

Fig. 1 Vibration signal of a rolling bearing with inner race fault

Fig. 1 shows the vibration acceleration signal of a rolling bearing with inner ring fault. The result of decomposing the signal using LMD method is shown in Fig. 2, the complicated multiple-component AM and FM signal have been decomposed to simple component AM and FM signal. The different characteristic components can be reflected by the relationship between the PF components and the corresponding components of the signal.

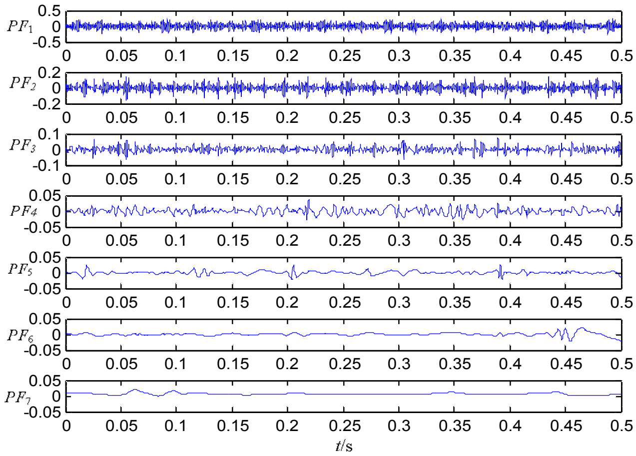

Fig. 2 LMD decomposition result of the vibration signal of the rolling bearing with inner ring fault

Using LMD method to decompose the signals from 4 different kinds of rolling bearings: proper one, one with inner ring pitting, one with outer ring indentation and one with rolling element abrasion. Then compute the energy of each in the top 7 layers after decomposing as the characteristic vector, the results shown in the following table 1:

Table 1 Character vector of normal, inner race pitting, rolling body abrasion and outer race indentation

	PF1	***PF2***	***PF3***	***PF4***	***PF5***	***PF6***	***PF7***
Normal bearing	0.128	0.382	0.212	0.125	0.107	0.234	0.129
Inner ring pitting	0.292	0.300	0.114	0.047	0.013	0.016	0.029
Rolling element wear	0.070	0.045	0.052	0.058	0.017	0.006	0.005
Outer ring indentation	0.083	0.126	0.086	0.033	0.007	0.056	0.065

As shown in the table above, the energy characters of PF components derived from different faults by using LMD method are different, therefore, LMD is an effective way to decompose signal, and the energy characters of PF components can be input into the neural network.

3. The Fault Diagnosis Model based on optimized Neural Network

3.1 The model structure of Neural Network (NN)

BP network has the merits such as parallel processing and distributed storage, and it is one of the most widely used Neural Network (NN) [8, 9] in practical application. The common structure of BP network is constituted of input layer, hidden layer and output layer, with each layers connected by a weighting value.

(1) The number of input-layer nodes

The selection of input layers node has a direct bearing on the whole structure and the output of the network. The number of nodes should not too many and not too few. The whole network structure will be no viable in the area of fault recognition with fewer nodes. On the other hand, more nodes will increase the complex of network which will cause in network running slowly. In this paper, through LMD decomposing, the four types of fault signals including normal bearing, inner ring pitting, rolling element wear and outer ring indentation will respectively choose the energy of each layer as the characteristic vectors from the earliest seven layers PF1, PF2, PF3, PF4, PF5, PF6 and PF7. Therefore, the number of output layer nodes is m =7, namely (x1, x2……… x7,).

(2) The number of hidden-layer nodes
Select three layers as the BP network model. There is not a unified formula in choosing the number of hidden-layer nodes at present, so it can choose an empirical formula to decide the number of hidden layer nodes by the experiences of forefathers. The formula as follow:

$$T = 2m + 1 \qquad (2)$$

T is the number of hidden layer nodes; m is the number of input layer nodes. As a result, T =15.

(3) The number of output-layer nodes
Identify the four kinds of fault signals, “The inner ring pitting”, “The outer indentation”, “The rolling element wear” and “Normal bearing”. Since the ideal output result could be identified directly according to the fault signals, the output-layer nodes are four types of fault signals (y1, y2, y3, y4). This paper uses binary encoding format as fault outputs. The type of output sample can be judged by the corresponding category which has a maximum node within the real network output. The desired outputs are shown in table 2 below.

In conclusion, the BP neural network structural is (7, 15, 4), Wij is the weight and bi is the threshold with input layer and hidden layer respectively, Wjk is the weight and bk is the threshold with hidden layer and output layer respectively, i =1,2……7, j =1,2……15, k =1,2,3,4, Fig. 3 is the three-layer model.

Table 2: Desired output of Bearing

Bearing Type	***Desired output vector***
Normal bearing	(1 0 0 0)
Inner ring pitting	(0 1 0 0)
Rolling element wear	(0 0 1 0)
Outer indentation	(0 0 0 1)

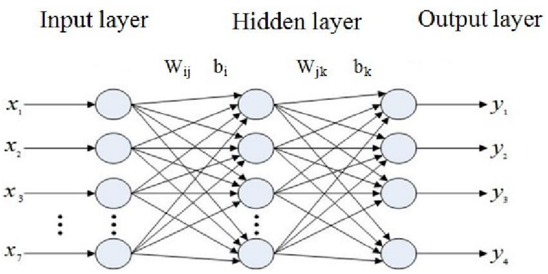

Fig. 3 The three-layer model of the BP neural network structural

3.2 Genetic algorithm optimizing BP neural network (GA-BP)

BP network Genetic algorithm is a kind of global search method algorithm based on the reference the natural selection biology evolution process and the mechanism of nature genetics [10, 11]. By simulating the process of natural evolution to search for the optimum solution, regard the argument of solving problems as gene, transform the problem parameters which need to be optimized into the coded string, and make a suitable selection with coded string by fitness function and a series of genetic manipulation, to retain the individual which has the highest fitness. Apply GA to the optimization of BP neural network structural parameters. Specific steps are as follows:

According to BP, construct the initial population by setting each parameter of GA and encoding, sequencing and building chromosomes with network Wij and bi;
Apply the inverse of E which is the BP error sum of squares as the individual fitness function, evaluate the quality of link weight and threshold, abandon the lower adaptive value of weight and threshold and retain the higher weight and threshold, select the individual which has a higher adaptive value pass on to the next generation. The function of network error sum of squares is

$$E = \sum_{k}^{p} (T_k - Z_k) \qquad (3)$$

The fitness function is as follow,

$$F(k) = 1/E \qquad (4)$$

T_k is the desired output, and Z_k is the actual output of network, k =1,2,3,4;

Judge E, the biggest of fitness of individual in the populations, whether satisfied with the accuracy requirements. If the accuracy requirements are met, continue the evolutionary process. Otherwise, implement the fourth step, until the condition is met;

The genetic operators include choice, crossover and mutation can be utilized to optimize the current population, produce the next generation and then turn to the step 2;

Output the initial weight and threshold of BP;

Calculate the error of output and estimate whether satisfied with the accuracy requirements. If the condition is met, then end the practice. Otherwise, continue to fix the BP weight and threshold until the accuracy requirements are met.

4. PF Component and Neural Network Optimization in the Application of Rolling Bearings

In order to verify the effectiveness of the fault diagnosis method based on PF energy characteristics and neural network optimization that proposed in this paper, we conducted the experiments at integrated fault simulation experiment platform of Spectra Quest's company, use the SCX-1000 data acquisition system to collect data, adopted QTH8-YD65 piezoelectric acceleration sensor which is mounted on the horizontal and vertical directions of the rolling bearing pedestal's both ends to measure the vibration signals. We simulated the four fault states of normal bearing, inner ring pitting, outer ring indentation, rolling element wear. For the acquired signal, first using LMD to decompose the original signal, then take the energy of each layer after decomposing as the input of the neural network optimization, last output four diagnostic results of normal bearing, inner race corrosive pitting, outer race indentation, rolling element wear. The fault diagnosis model based on the PF energy characteristics and neural network optimization is shown in Figure 4.

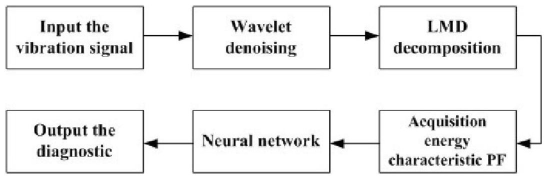

Fig. 4 The fault diagnosis model based on the PF energy characteristics and neural network optimization

Because the useful information in the layer would be less along with the LMD decomposition, to reduce the complexity of computing, we took the decomposing PF of previous 7 layers, extracted 50 samples in each fault, composed the 200*7 sample set. The characteristic parameters we obtained are presented in Table 3:

Table 3 Part of the characteristic parameter's values

SAMPLE	*PF1*	*PF2*	*PF3*	*PF4*	*PF5*	*PF6*	*PF7*
x1	*0.12849*	*0.38254*	*0.21228*	*0.12538*	*0.10799*	*0.23454*	*0.12971*
x2	*0.1422*	*0.2847*	*0.32626*	*0.38693*	*0.41058*	*0.021541*	*0.041392*
x3	*0.29246*	*0.30039*	*0.04763*	*0.013058*	*0.016375*	*0.016375*	*0.029089*
x4	*0.41113*	*0.17747*	*0.12231*	*0.064193*	*0.020069*	*0.021797*	*0.0014103*
x5	*0.070903*	*0.044931*	*0.052882*	*0.058284*	*0.017178*	*0.0065585*	*0.005993*
x6	*0.070992*	*0.094987*	*0.13547*	*0.055548*	*0.0156*	*0.0020125*	*0.00022*
x7	*0.08323*	*0.1262*	*0.086161*	*0.033388*	*0.0076132*	*0.056062*	*0.065736*
x8	*0.14744*	*0.14172*	*0.12501*	*0.05144*	*0.026*	*0.0046917*	*0.0019385*

BP neural network training is built on the basis of large quantity of fault signal samples, this article set 40 samples of each fault as the training sample, the other 10 samples as the test sample. For the same fault sample, we use BP neural network after optimization and BP neural network to conduct the fault diagnostic identification. The results are shown in Table 4:

Table 4 Part of antifriction bearing identification results of BP and GA-BP algorithm

Signal type	*algorithm*	*Output of the network*				*Target output*
Normal	*GA-BP*	1.0024	-0.00067	-0.00048	-0.0021	1 0 0 0
	BP	1.0000	-0.000132	0.013277	-0.0132	
Inner ring pitting	*GA-BP*	0.01317	0.9807	0.02232	-0.0213	0 1 0 0
	BP	0.11752	0.97026	-0.0196	-0.06822	
Rolling element wear	*GA-BP*	0.005102	-0.00089	1.0042	-0.00916	0 0 1 0
	BP	-0.000133	-0.000378	0.85117	0.14879	

Outer indentation	*GA-BP*	-0.000435	0.009101	-0.00345	0.99361	0 0 0 1
	BP	0.00338	-0.00489	-0.09911	1.1006	

The accuracy rate of GA-BP and BP algorithm is shown in Table 5:

Table 5 Bearing fault diagnosis testing result

Bearing type	***algorithm***	***Test sample size***	***Diagnosis result***		***The accuracy rate of diagnosis***
			correct	***error***	
Normal	*GA-BP*	10	10	0	100%
	BP		9	1	90%
Inner ring pitting	*GA-BP*	10	9	1	90%
	BP		9	1	90%
Rolling element wear	*GA-BP*	10	7	3	70%
	BP		5	5	50%
Outer indentation	*GA-BP*	10	8	2	80%
	BP		7	3	70%
Total	*GA-BP*	40	34	6	85%
	BP		30	10	75%

It can be seen from the table, the precision and accuracy rate of BP neural network are improved after optimization. It has been proved that BP neural network after optimization can be used in the application of antifriction bearing identification.

As can be seen from the above comprehensive comparison, through optimizing BP neural network's structural parameters, we not only improved the efficiency of network training significantly, but also greatly improved the accuracy rate of BP neural network used in antifriction bearing fault identification, provided a practical and feasible method for antifriction bearing fault identification.

5. Conclusion

LMD is an adaptive signal decomposition method, it can decompose the complicated multi-component as the aggregation of the finite instantaneous frequency PF component which has the physical meaning. We separately extracted the PF component energy characteristics of normal bearing, inner ring pitting, rolling element wear, outer ring indentation, the result indicate that characteristic value extracted by the LMD method has a significant difference.

Experiment simulation proved that the bearing fault diagnosis method of genetic algorithm optimized BP neural network improved the accuracy and failure rate compared with the fault diagnosis method of BP neural network.

The proposed fault diagnosis method based on PF energy characteristic and optimized neural network, provide a new method to achieve the high efficiency and high precision in antifriction bearing fault diagnosis

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