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Fault Recognition of Rolling Bearings based on EMD and GA-BP Model

Tengxiao Zou[a], Linjun Wang[b], Wenchao Huang[c], Zhouchang Xu[d]

Hubei key Laboratory of Hydroelectric Machinery Design and Maintenance, College of Mechanical and Power Engineering, China Three Gorges University, Yichang, Hubei 443002, P. R. China

[a]1963731883@qq.com, [b]ljwang2006@126.com, [c]451246566 @qq.com,

[d]1941921112 @qq.com

Abstract

For the fault recognition of rolling bearings, a fault recognition method based on Empirical Mode Decomposition (EMD), Genetic Algorithm (GA) and BP neural network is proposed. This model optimizes the initial weight and threshold by the Genetic Algorithm. Moreover, the output error of the training data is the objective function. During the process of fault recognition, the empirical mode decomposition (EMD) energy ratio as the input of the neural network is used to recognize the fault of rolling bearings under different conditions. The results of numerical simulations show that the method is better than the traditional BP neural network in the convergence precision, the recognition rate and the convergence speed.

Keywords

Empirical Mode Decomposition; Genetic Algorithm; BP Neural Network; Rolling Bearings; Fault Recognition.

1. Introduction

Recently, lost of computational methods have been developed to solve the practical engineering problems [1-3], especially in the field of fault diagnosis. Rolling bearings are important parts of large machinery and equipment, which are also very prone to fault. About 30% of many rotating machinery faults are because of rolling bearing failures [4], therefore, effective fault diagnosis and health monitoring of rolling bearings is very important. The vibration signals of rolling bearings have the characteristics of non-linearity and non-stationarity. EMD is a signal processing method proposed by Huang [5], and it has some advantages over wavelet and wavelet packet methods when processing this type of signal because of its good self-adaptability. Therefore, EMD-based methods and improved EMD methods are widely used in fault diagnosis models. With the rapid development of artificial intelligence, fault diagnosis models based on machine learning have become the research object of scholars. [6-7] used EMD combined with spectral kurtosis and Kolmogorov entropy to complete the fault diagnosis of rolling bearings. Wang used the wavelet packet method to decompose the frequency band energy ratio of the fault signal and the time domain characteristics of the fault signal, and the fault recognition of the gearbox was realized by using BP neural network as a classifier [8].

In this paper, we propose a new fault Recognition method based on EMD and GA-BP model for of rolling bearings. This method just uses BP neural network as a classifier and the EMD energy ratio as a feature vector. We use the GA method to construct a GA-BP model by optimizing the initial weight and threshold of the BP neural network. By comparing with the traditional BP neural network,

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we find that it has better performances. Numerical simulations demonstrate the stability and effectivity of the proposed method.

2. Empirical Mode Decomposition

The EMD algorithm can decompose a complex non-stationary signal into the sum of a finite number of basic mode components (Intrinsic Mode Function, IMF) and a residual term, and the IMF must satisfy the following conditions:

(1) The number of local extreme points of the function is the same as the number of zero points or at most one difference during the studied time interval.

(2) The mean of the envelope of the function's local maximum and local minimum points is zero at any time.

The decomposition steps are given as follows:

(1) Find all the maximum and minimum points of the signal $x(t)$ and figure out the upper and lower envelopes, and then find $m_1(t)$, the average of the upper and lower envelopes of the signal. By subtracting the mean m from the original signal, we get the following new signal $h_1(t)$:

$$h_1(t) = x(t) - m_1(t) \tag{1}$$

(2) Check whether $h_1(t)$ satisfies the IMF conditions. If it is satisfied, $h_1(t)$ is the first IMF of $x(t)$ and it is named by $c_1(t)$. If it is not satisfied, then based on $h_1(t)$, step (1) continues until a function satisfies the IMF conditions.

(3) Separating $c_1(t)$ from $x(t)$, we can obtain a new function:

$$r_1(t) = x(t) - c_1(t) \tag{2}$$

Take $r_1(t)$ as the new original signal, and repeat the above steps until the last remainder $r_{n+1}(t)$ is a monotonic function, and then the decomposition terminates. So the signal $x(t)$ can be expressed as:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_{n+1}(t) \tag{3}$$

Suppose one of IMF's energy is E_i, and the sum energy of IMFs is E, and then it can be figured out as:

$$\begin{aligned} E_i &= \int_{-\infty}^{\infty} \left| c_i(t) \right|^2 dt \quad i = 1, 2, \cdots, n \\ E &= \sum_{i=1}^{n} E_i \end{aligned} \tag{4}$$

Then the Energy ratio T can be given as:

$$T = [E_1 / E, E_2 / E. \cdots E_n / E] \tag{5}$$

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3. GA-BP Model

The GA-BP model optimizes the initial weights and thresholds which are randomly generated in the BP neural network by adding a Genetic Algorithm to the traditional BP neural network, so as to improve the convergence precision of the BP neural network.

3.1 BP Neural Network

BP neural network is a multi-layer feedforward neural network which is trained by the error back-propagation algorithm, and it is also one of the most widely used neural networks. In the process of forward information transmission, and the error between the actual output and the ideal output are compared. If the error exceeds a preset value, the error is propagated back to adjust the weight and threshold of the network to reduce the error [9].

BP neural network is composed of input layer, hidden layer and output layer. The number of nodes of input layer and output layer is determined by the dimension of input and output, respectively. For the hidden layer, it is calculated by the following empirical formulas:

$$\begin{aligned} &l = \sqrt{m+n} + \alpha \qquad \alpha \in [0,10] \\ &l = 2m+1 \\ &l = \log_2 n \\ &0.02m < l < 4m \end{aligned} \tag{6}$$

where l is the number of nodes in the hidden layer, and m and n are the number of nodes in the input layer and the number of nodes in the output layer respectively.

3.2 Genetic Algorithm

Genetic algorithm is a global adaptive search algorithm [10], this algorithm generates a population at first randomly, that is, a chromosome, which continuously evolves under the guidance of the fitness function. After genetic operations such as select, cross and mutation, the chromosome with the best fitness can be obtained. There are several key concepts:

(1) Fitness

The function of fitness is to guide the evolution direction of the algorithm. Assuming that the objective function is $f(x)$. The fitness function is defined as:

$$Fit(x) = F(f(x)) \tag{7}$$

(2) Select

Select operation refers to the selection of chromosomes with better fitness in each generation for operation according to a certain strategy. Common selection strategies include roulette selection, sort selection, elite selection, etc.

(3) Cross

Cross operation simulates the behavior of crossover and exchange of homologous chromosomes during the sexual reproduction. The same position between different chromosomes is cut off, and then the information is exchanged to form a new chromosome. The cross probability P_c is usually controlled between 0.4 and 0.9 to ensure the diversity of the population.

(4) Mutation

Mutation operation refers to the deviation of chromosomes in the process of replication to produce new chromosomes. The emergence of mutation behavior reduces the possibility of the algorithm

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falling into a local optimum, and the mutation probability P_m is controlled in the range of between 0.01 and 0.1 to maintain population diversity.

3.3 The Establishment of GA-BP Model

Because the initial weights and thresholds of the BP neural network are randomly generated, the idea of the GA-BP model is used to treat the initial weights and thresholds as genes, combine them into one chromosome. We use the error between the actual output and ideal output of the training data as a fitness function to guide the evolution direction of chromosomes. The steps are given as follows.

(1) Define the topology of the BP neural network, including the number of network layers and the number of nodes in each layer

(2) Initialize the population; Produce a certain number of chromosomes.

(3) Define the fitness function to guide population evolution, and then perform genetic operations.

(4) Stop the evolution when the conditions to stop the evolution are satisfied.

4. Example Analysis

4.1 Data Setting

The experimental data used the rolling bearing experimental data published by Case Western Reserve University. Under a load 0~3 hp of the motor, the experiment simulates four different working conditions of rolling bearings including normal, ball, inner ring and outer ring fault, and there are three different depth with each one fault. The data used in this paper is the vibration signal collected by the acceleration sensor on the bearing end of the drive end. The motor load is 2hp, the sampling frequency is 12kHz, and the fault depth is 0.18mm. The data setting is shown in Table 1.

Table 1. The Data setting

Fault type	Training data	Test data	Fault Depth Label
Normal (N)	30	20	1(0.18mm)
Ball (B1)	30	20	
Inner ring (I1)	30	20	
Outer ring (O1)	30	20	

4.2 The Establishment of Eigenvector

First, the signal is segmented with 2048 points as a unit. Each signal takes 50 segments. For them, 30 groups are used as training data and 20 groups are used as test data. There are 120 training data and 80 test data in total. Then we use the EMD method to process each group of signals and find the energy ratio of the IMF. Because the energy is mainly concentrated in the first 5th order IMF, and the first 5th order IMF energy ratio is taken to construct the feature vector. One of each condition's IMF energy ratio is shown in Figure 1.

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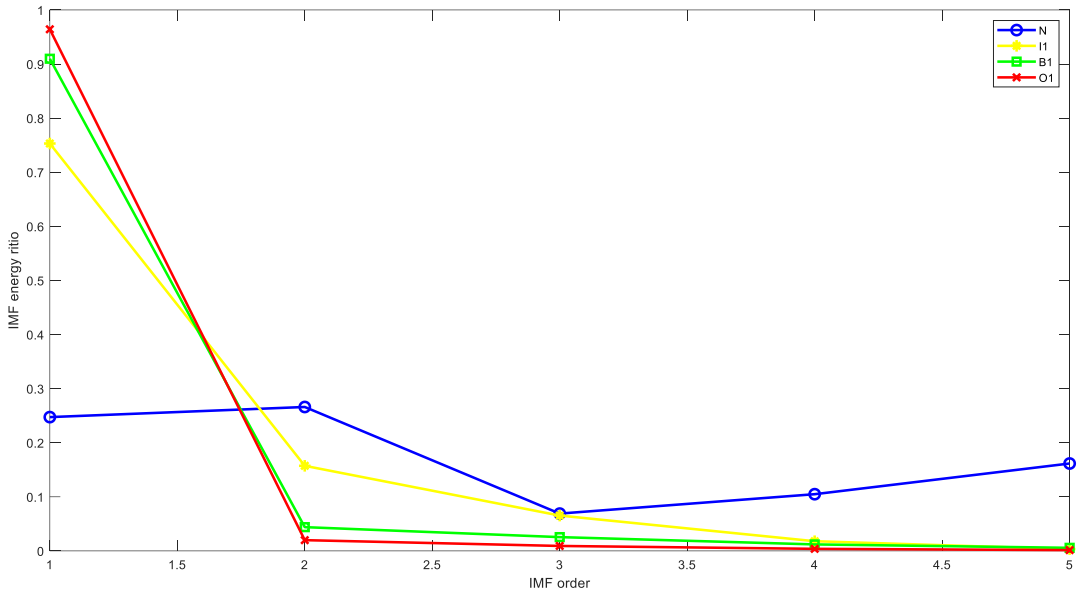

Figure 1. The IMF energy ratio of 4 conditions

4.3 Fault Diagnosis based on GA-BP Model

We use a classic three-layer BP neural network in this paper. We have 5 nodes in the input layer according to the dimension of the eigenvector. The number of nodes in the output layer is determined according to the fault type. The number of nodes in the hidden layer is 9 by Eq. (6). In addition, the ideal output of different operating conditions is defined, where the normal is [1,0,0,0], the ball fault is [0,1,0,0], and the inner ring fault is [0,0,1,0]. The outer ring fault is [0, 0, 0, 1].

The parameters of the genetic algorithm are given as: the initial population is 50, the maximum number of iterations is 80, and the selection strategy is the roulette method. Pc and Pm are 0.85 and 0.1, respectively. We input 120 sets of training data into the GA-BP model to train and save the network. Then 80 sets of test data are input into the trained model for the test. The results of 5 experiments are given as follows. Table 2 shows the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), the recognition rate, and the average convergence speed of the five experiments of the two models. The convergence speed refers to the number of iterations in the convergence of the BP neural network, and Figure 5 shows the best-performing fitness curve in 5 experiments of GA.

Table 2. The average value of the evaluation indicator of BP and GA-BP

Model	RMSE	MAE	Accuracy	Convergence speed
BP	0.1412	0.0453	0.9825	24
GA-BP	0.0395	0.0111	0.9975	15.4

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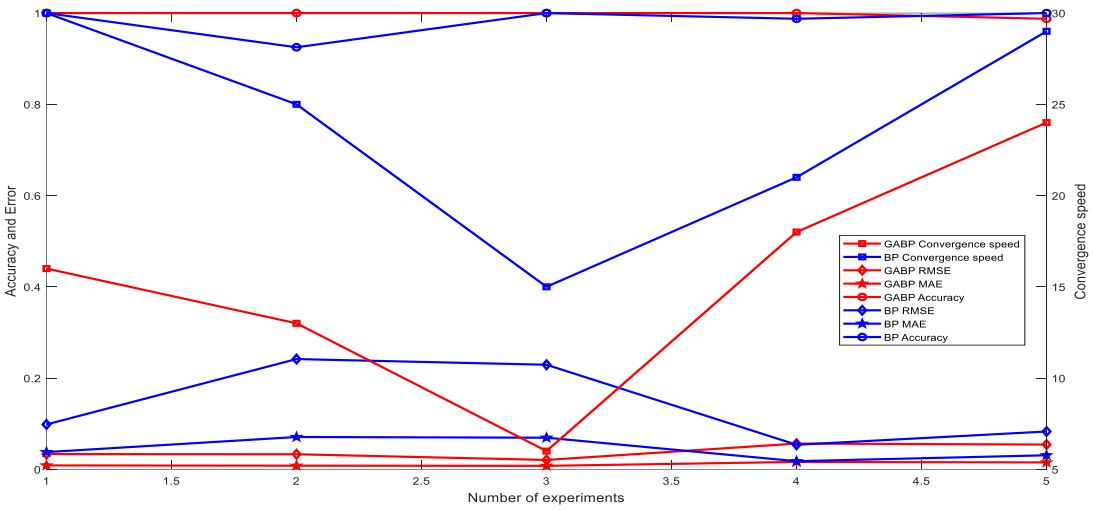

Figure 2. The evaluation index values curve

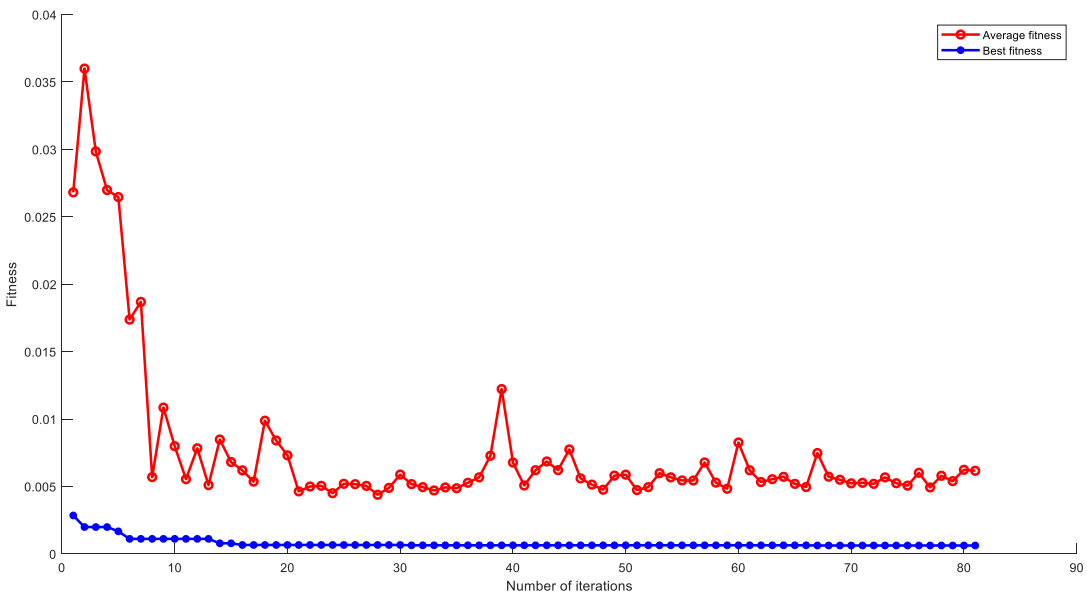

Figure 3. Fitness curve

As can be seen from Table 2, the recognition rate of two models are very well. However, compared to the BP model, the GA-BP model has lower RMSE and MAE, and also converges faster. As can be seen from Figure 2, the recognition rate of the GA-BP model is more stable, and the performance is the best in the third experiment. The fitness curve of the GA in the third experiment is shown in Figure 3. It can be seen that the algorithm can converge faster and reaches a minimum value after about 12 iterations.

5. Conclusion

This paper proposes a fault identification method based on EMD and GA-BP method, and applies this method to the identification problem of rolling bearings. The following conclusions can be drawn through numerical results:

(1) Using EMD and BP neural network to recognize the faults of rolling bearings can get the high recognition rate of diagnosis.

(2) Using GA method to optimize the initial weight and threshold of the BP neural network, and make the BP neural network improve the convergence precision, the convergence speed and the recognition rate.

(3) The proposed method can effectively recognize different types of faults of rolling bearings and accurately classify them, and it can provide an effective means for the health monitoring of rolling bearings.

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