Rotating Mechanical Fault Diagnosis of Chaotic Gray Wolf Optimization Neural Network

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Abstract

In order to diagnose the fault of rotating machinery, a new fault diagnosis method based on wavelet packet entropy and chaotic gray wolf optimization neural network is proposed in this paper. First, wavelet packet decomposition is performed on the original signal. Then the energy entropy of each frequency band is calculated to form the fault characteristic vector. Finally, fault diagnosis is realized through the BP neural network optimized by chaotic gray wolf. The experimental results of bearing and gear show that the proposed fault diagnosis method based on wavelet packet entropy and chaotic gray Wolf optimization neural network is feasible for the fault diagnosis of mechanical equipment.

Keywords

Feature Extraction; Wavelet Envelope Entropy; Chaotic Gray Wolf Optimization; Rotating Machinery.

1. Introduction

Many experts developed some advanced methods which are applied to practical engineering problems [1-4]. Rotating mechanical parts are key equipments widely used in modern industrial production. When the rotating machinery fails, periodic vibration signals are generated. Vibration signal contains abundant fault information, but it is very difficult to extract it and distinguish fault types by traditional fault diagnosis methods. Therefore, in order to improve the accuracy of fault diagnosis, people put forward a series of new fault diagnosis methods.

The method of feature extraction of mechanical vibration signal is an important subject. Because the feature extraction process cannot only reduce the data dimension, and reduce the computational complexity, but also the quality of the extracted features will directly affect the accuracy of state recognition. However, traditional feature extraction methods, such as Fourier transform [5, 6], holographic spectrum [7, 8], whose main function is to analyze signals, often fail to meet the quality requirements of information feature extraction. To solve the problem of information feature extraction, Li used local S-transform to extract the maximum singular value of matrix and the proportion of vibration energy, which can effectively extract the fault features [9]. Yuan used EEMD to extract vibration signal features [10]. Ning used wavelet entropy to decompose signals into different frequency bands, and used the entropy to obtain information characteristics of different frequency bands, so as to determine the fault categories [11]. On the basis of fault feature extraction, Huang proposed a new diagnosis method of VMD and MSE based on parameter estimation optimization for bearing fault diagnosis [12]. Chen proposed a fault diagnosis method of rotating machinery, which integrates dimensionless index and information entropy, to realize the recognition of weak bearing fault [13]. These methods can realize the fault identification of rotating machinery to some extent, but they all focus on the improvement of the classification method of diagnosis or the extraction of a certain feature of vibration signal to improve the recognition rate. In order to further improve the recognition rate, it is necessary to extract multiple features of vibration signal as much as possible, and at the same time to ensure that the diagnosis method used can recognize multiple features.

In order to improve the accuracy of rotating machinery fault diagnosis, based on the above research results and methods, this paper proposes a new rotating machinery fault diagnosis method based on wavelet packet entropy and chaos gray wolf optimization neural network. Firstly, the wavelet packet is used to decompose the signal, and then the energy entropy of each frequency band is used to form the eigenvector. Finally, it is input into the trained chaotic gray wolf optimization neural network for recognition.

2. Wavelet packet entropy feature extraction

Information entropy is a measure of the information and uncertainty of a signal. Wavelet packet entropy is a kind of information entropy which combines wavelet packet algorithm with information entropy. In the fault signal of rotating machinery, the information quantity and disorder degree of signal in each frequency band are quite different. Information entropy can be used to evaluate the complexity of each frequency band signal, so this paper uses wavelet packet entropy to extract fault features of rotating machinery. The steps of fault feature extraction are as follows:

(1) The signal is decomposed by 4-layer wavelet packet, and 16 decomposition coefficients are obtained.

(2) According to the coefficients of wavelet packet decomposition, the signal $S_i(i=0,1,2,\cdots,15)$ of each frequency band is reconstructed. The total signal is given as

$$S = S_0 + S_1 + \ldots S_{15} \tag{1}$$

(3) Calculate the energy of each frequency band. The formula is

$$E_i = \int |S_i(t)|^2 \, dt \tag{2}$$

(4) The set of the energy spectrum of the signals in each frequency band is $E=\{E_1, E_2, \cdots, E_n\}$, wavelet packet entropy is given as

$$H = -\sum_{i=1}^{N} P_i \, log P_i \tag{3}$$

In the formula, P_i is the proportion of the energy spectrum value of the *ith* wavelet packet in the whole wavelet packet energy spectrum, where $P_i = E_i / \sum_{i=1}^{n} E_i$.

3. Chaos gray wolf optimization BP neural network

3.1 Chaos gray wolf optimization algorithm

Chaos gray wolf optimization algorithm is a hybrid group optimization algorithm, which combines the advantages of Gray Wolf algorithm and chaos algorithm. Because of the ergodicity of chaos algorithm, the local optimal solution is prevented. The logistic mapping model of chaotic space is a typical chaotic system. The iterative formula is as follows:

$$x^{(k+1)} = \mu x^{(k)}(1 - x^{(k)}) \tag{4}$$

In the formula, $x^{(k+1)}$ is chaos domain; μ is control parameter; when $\mu \in (3.56,4)$ the system is in chaos state.

Gray wolf group is divided into four parts: head wolf α, subordinate wolf β, common wolf γ and other wolves δ. Among them, α, β and γ search and estimate the location of the target. Other wolves use this estimation as a benchmark to calculate the distance between themselves and the target, and finally locate the target. The specific location update formula is:

$$X(t+1) = X_p(t) - A \bullet |C \bullet X_P(t) - x(t)| \tag{5}$$

$$A = 2a \bullet r_1 - a \tag{6}$$

$$C = 2 \bullet r_2 \tag{7}$$

In the above formula, t is the current iteration number; A and C are coefficients; X_p is the target position; X is the gray wolf position; α is the convergence factor; r_1 and r_2 are random numbers in the range of [0,1].

The specific search steps of chaos Gray Wolf algorithm are as follows:

(1) Set the initial number of gray wolf group n, the maximum number of iterations m and the related initial parameters of Gray Wolf algorithm and chaos algorithm. The positions of four kinds of wolves are randomly distributed.

(2) Let the optimal position of all gray wolves be the current objective function value. Eq. (6) and Eq.(7) are used to calculate the coefficients of three kinds of gray wolves, and the positions of α, β and γ are updated according to Eq. (5). The average of three kinds of gray wolf position is the position of the next generation gray wolf. The formula is given by Eq. (8) and Eq. (9):

$$X_1 = X_a - A_1 \bullet |C_1 \bullet X_a \bullet X|, X_2 = X_b - A_2 \bullet |C_2 \bullet X_b \bullet X|, X_3 = X_c - A_3 \bullet |C_3 \bullet X_c \bullet X| \quad (8)$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (9)$$

(3) The first few gray wolves with better target position are selected for chaos optimization, and the steps are given as follows:

(a) Let k = 0, and map the decision variable $x^{(k)}$ to the chaotic variable $cx^{(k)}$ by the following formula:

$$cx^{(k)} = \frac{x^{(k)} - x_{min}}{x_{max} - x_{min}} \quad (10)$$

(b) Using Eq.(4), calculate the next chaotic variable $cx^{(k)}$.

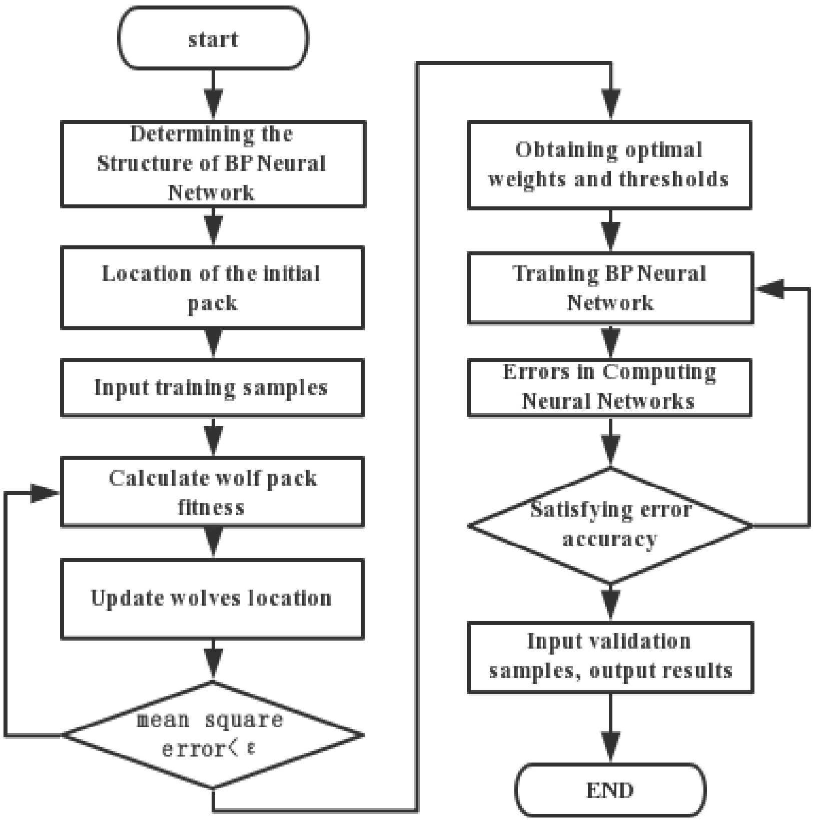

Fig. 1 Flow chart of chaos particle swarm optimization neural network

(c) According to the following formula, the chaotic variables $cx^{(k+1)}$ are converted into decision variables $x^{(k+1)}$ which is given as follows:

$$x^{(k+1)} = x_{min} + cx^{(k+1)}(x_{max} - x_{min}) \tag{11}$$

(d) The decision variable x is taken as a new solution and evaluated.

(e) If the new solution is better than the original solution or the predefined maximum number of iterations arrives, the new solution will be output as the result of chaos local search, otherwise, $k = k + l$ will return to step (b) to continue.

(4) Let the remaining gray wolves redistribute randomly, and compare the new position of each gray wolf with its optimal value. If the former is better than the latter, the new position will be updated to the optimal position.

(5) When the maximum number of iterations m of gray wolf group is reached, the result is output. Otherwise, return to step (2).

3.2 Parameter optimization based on chaos Gray Wolf algorithm

(1) Parameter coding: BP neural network, assuming that its input layer is a, its hidden layer is b, and its output layer is c. The dimension D of the optimization parameter can be expressed as:

$$D = (a \times b) + (b \times c) + b + c \tag{12}$$

(2) Initialization: randomly distribute the positions of three kinds of gray wolves, their dimension is d dimension, and set the initial objective function value of three kinds of gray wolves as infinite.

(3) Fitness evaluation: network optimization is to find a group of optimal parameters, with the least mean square error of output samples. We select the following fitness function:

$$f = \frac{1}{N}\sum_{j=1}^{C}\sum_{i=1}^{N}\left(y_{ji}^{d} - y_{ji}\right)^2 \tag{13}$$

(4) In the formula: n is the total number of training samples; C is the number of output neurons of the network; y_{ji}^{d} is the ideal output; y_{ji} is the actual output.

(5) Termination condition: the maximum number of iterations or a certain accuracy of the group is reached, and the current optimal position is recorded, otherwise, the third step is returned. The specific steps of chaos particle swarm optimization neural network are shown in Fig. 1.

4. Application examples

4.1 The extraction of feature vector

The experimental device consists of motor, torque sensor, power tester and electronic controller. 6205-2RS type deep groove ball bearing is used in the test object. The number of rolling elements is 9; the diameter of rolling elements is 7.94004mm; the contact angle is 65 °; the outer diameter of bearing is 52mm; the inner diameter is 25mm; the thickness is 15mm; the signal sampling frequency is 12kHz; the motor speed is 1750r / min. The signal types of bearings are normal, inner ring fault, outer ring fault and rolling element fault. Take 50 groups of data for each fault, a total of 200 groups of data. A set of signals is taken into the second section, and a set of data is used to get 16 eigenvalues. The module of the fault gear of the gearbox is 2; the number of teeth is 75; the material is S45C; the signal sampling frequency is 5120Hz; the speed of the fault gear is 880r / min. The fault types of gears are normal, fracture, pitting and wear. Take 26 groups of data for each fault type, 104 groups in total. In the same way, 16 eigenvalues are obtained from a set of data. In order to illustrate the effect of feature extraction, 16 characteristic values of four signal types of bearing and gear are used. They are shown in Figs. 2-3.

Fig. 2 shows 16 characteristic values of normal, inner ring fault, outer ring fault and rolling element fault from top to bottom. From Fig. 2, it can be seen that the 16 characteristic values of normal and inner ring are obviously different from that of outer ring fault and rolling element fault. The eigenvectors of outer ring fault and rolling element fault are similar, but there are differences in each value. Fig. 3 shows 16 characteristic values of normal, fracture, pitting and wear from top to bottom. The 16 eigenvalues of the four fault types are obviously different. The difference of these different eigenvalues can provide the basis for the classification of fault diagnosis.

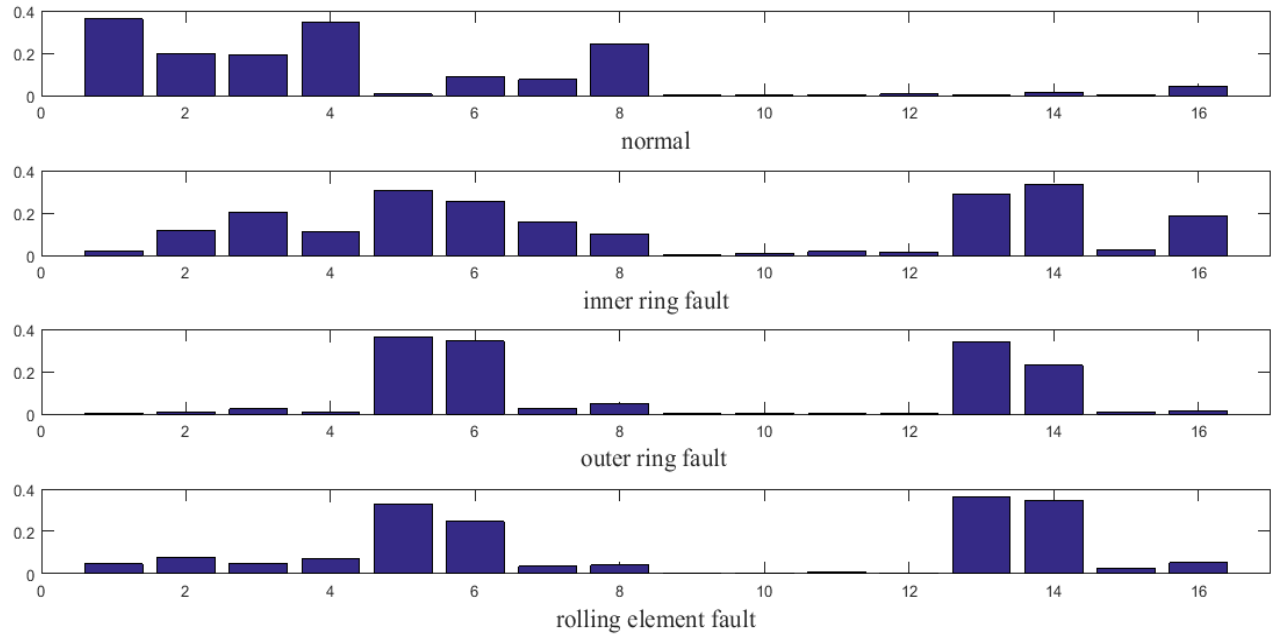

Fig. 2 The extraction of bearing feature

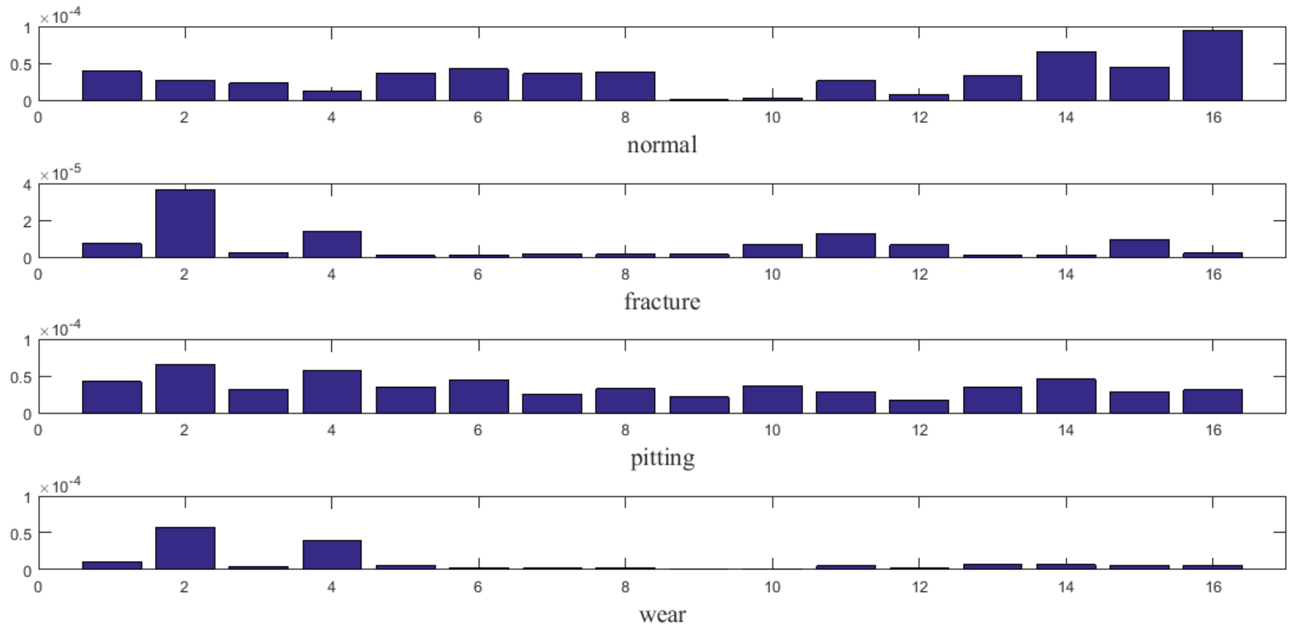

Fig. 3 The extraction of gear feature

4.2 The chaos gray wolf neural network

Through the above method, we get 200 groups of data for bearing, and each group of data has 16 dimensions. The eigenvector is 16 dimension, and the number of nodes in the input layer is 16. There are four types of fault signals in this paper, so the output layer node can be determined as 4. By setting different hidden layer nodes to train the chaos gray wolf neural network, the hidden layer node can be determined as 12. Table 1 shows the number of training samples, validation samples and theoretical fault codes set in this paper for various bearing fault diagnosis. 180 sets of data are input into the chaos gray wolf neural network as the training data, and then 20 sets of verification data are used for verification, and the results are shown in Table 2.

Table 1. The sample number of bearings and corresponding codes

Fault type	Training sample	Validation sample	Trouble code
Normal	45	5	1000
Inner ring	45	5	0100
Outer ring	45	5	0010
Rolling body	45	5	0001

Table 2. Output eigenvectors of bearings and corresponding codes

Serial number	Fault type	Output results of fault characteristics				Trouble code
1	Normal	1.0000017	-1.6020e-05	-4.0588e-05	4.0166e-05	1000
2	Normal	1.0000419	-8.8345e-06	-3.1611e-05	2.2885e-05	1000
3	Normal	1.0000195	-1.9912e-05	-3.4205e-05	1.2369e-05	1000
4	Normal	0.9999980	-6.2827e-06	8.7425e-05	-6.3198e-05	1000
5	Normal	1.0000219	-1.3622e-05	-3.3162e-05	1.6415e-05	1000
6	Inner ring	6.8313e-06	1.0000078	-6.9947e-05	5.6582e-05	0100
7	Inner ring	2.6987e-05	0.9999953	0.0003038	-0.0003239	0100
8	Inner ring	-0.0001320	0.9999904	-0.0001070	0.0001746	0100
9	Inner ring	2.4784e-05	0.9999988	0.0001847	-0.0001803	0100
10	Inner ring	-4.1629e-05	1.00000007	-0.0001476	0.0001736	0100
11	Outer ring	0.0007758	5.9102e-05	0.9991097	0.0003167	0010
12	Outer ring	-0.0001644	-1.6704e-05	1.0003240	-0.0002021	0010
13	Outer ring	0.0001470	2.2221e-05	0.9997170	0.0001887	0010
14	Outer ring	-6.5723e-05	-1.0938e-05	1.0001228	-9.0235e-05	0010
15	Outer ring	-7.1773e-06	-6.8657e-06	0.9999841	1.3373e-05	0010
16	Rolling body	-0.0001274	4.2532e-07	0.0003760	0.9997085	0001
17	Rolling body	-2.9548e-05	-2.7760e-05	0.0009216	0.9990863	0001
18	Rolling body	-3.6036e-05	7.3727e-06	0.0004288	0.9996072	0001
19	Rolling body	0.0001887	3.2056e-06	0.0001005	0.9997822	0001
20	Rolling body	-0.0002311	-6.0290e-05	0.0014892	0.9986578	0001

By comparing the sample fault output code in Table 2 with the training code in Table 1, the running state of the bearing can be obtained. The output results of the fourth group of fault characteristics are: 0.999980, - 6.2827e-06, 8.7425e-05, - 6.3198e-05. Among them, - 6.2827e-06, 8.7425e-05 and - 6.3198e-05 are all close to 0, while 0.999980 is close to 1. The fault output code is [1000], which is the same as the normal code in Table 1; The output results of the 18th group of fault characteristics are: - 3.6036e-05, 7.3727e-06, 0.0004288, 0.9996072, of which -3.6036e-05, 7.3727e-06, 0.0004288 are all close to 0, and 0.9996072 is close to 1, and the fault output code is [0001], which is the same as the generation code of rolling element fault in table 1. Therefore, it can be concluded that when the working state of the bearing is unknown, the extracted eigenvector can be input into the trained chaotic gray wolf neural network, and the outer ring fault can be judged as long as the fault output code is [0010]. In the same way, other faults can also be identified according to the output code. Comparing 20 groups of test sample fault codes with the codes shown in Table 2, the fault diagnosis results in Table 3 can be obtained.

Table 3. The comparison of output results of bearing test samples

Fault type	Validation sample	Correct sample	Accuracy rate
Normal	5	5	100%
Inner ring5	5	5	100%
Outer ring	5	5	100%
Rolling body	5	5	100%

From Table 3, it can be clearly seen that the accuracy of chaos gray wolf neural network reaches 100 for all fault types set in this paper.

Through the above method, there are 104 groups of data for gears. Two groups of different types of signals are selected, eight groups are used as verification data, and the other 96 groups are used as the training data. Table 4 shows the corresponding values of training samples, verification samples and theoretical fault codes set for various gear fault diagnosis. The input layer is 16 and the output layer is 4. By setting different hidden layer nodes to train chaos gray wolf neural network, the hidden layer nodes are 10. the verification data is input into the trained chaotic gray wolf neural network, and the results are shown in Table 5.

Table 4. The sample number of gears and corresponding codes

Fault type	Training sample	Validation sample	Trouble code
Normal	24	2	1000
Fracture	24	2	0100
Pitting	24	2	0010
Wear	24	2	0001

Table 5. Gear output eigenvectors and corresponding codes

Serial number	Fault type	Output results of fault characteristics				Trouble code
1	Normal	1.00000000	-3.6849e-11	-5.4417e-10	-1.4463e-10	1000
2	Normal	1.00000000	-3.6849e-11	-5.4417e-10	-1.4463e-10	1000
3	Fracture	-1.5344e-10	1.0000000001	2.3078e-09	-1.0838e-09	0100
4	Fracture	-1.5344e-10	1.0000000001	2.3078e-09	-1.0838e-09	0100
5	Pitting	-1.1123e-10	5.9250e-10	1.000000004	-1.7702e-09	0010
6	Pitting	-1.1123e-10	5.9250e-10	1.000000004	-1.7702e-09	0010
7	Wear	1.8879e-09	-2.5080e-10	-6.2767e-09	1.000000001	0001
8	Wear	1.8879e-09	-2.5080e-10	-6.2767e-09	1.000000001	0001

The correct fault code can be obtained by comparing the output code of the test sample in Table 5 with the training code in Table 4. The feasibility of the proposed method is proved again.

In order to highlight the advantages of this method, the diagnosis method of chaos gray wolf neural network is compared with the recognition method without optimization. The data used in the experiment are the number of training samples and validation samples set in Table 1 and Table 4. The discrimination results of each diagnosis model for the same data are shown in Table 6 and 7.

Table 6. Bearing faults recognition rates of different diagnostic models

Model	Accuracy rate	mean square error	Average absolute error
Chaos gray wolf neural network	100	1.0855e-07	1.6776e-04
Gray wolf neural network	95	0.0196573	0.0266312
BP neural network	55	0.5203314	0.6170175

Table 7. Gear fault recognition rates of different diagnostic models

Model	Accuracy rate	mean square error	Average absolute error
Chaos gray wolf neural network	100	4.5816e-18	1.3143e-09
Gray wolf neural network	100	1.2423e-17	2.6618e-09
BP neural network	37.5	0.7035452	0.6341281

It can be seen from Table 6 that the mean square error and mean absolute error of chaos gray wolf neural network are smaller than those of other neural networks, and the recognition accuracy is higher.

The mean square error and mean absolute error of gray wolf neural network are smaller than those of BP neural network, and the recognition accuracy is higher. Table 7 also shows this situation, but the recognition accuracy is higher than that of the bearing, because the frequency band distribution of the gear original data is obvious, and the fault features extracted by wavelet packet entropy are obvious. Based on this, the superiority of the proposed method is shown.

5. Conclusion

In this paper, a new method for fault diagnosis for rotating machinery is proposed. The proposed method uses wavelet packet to decompose the signals, and then extracts the feature vectors through energy entropy. Finally, the chaotic particle swarm optimization neural network is used to identify.

(1) The proposed method can effectively extract the fault feature information and classify the fault types.

(2) In the fault signal processing of different rotating machinery, the fault type code which corresponds to the verification sample can be obtained, and the recognition rate of fault type is 100%.

(3) Under the same data set, the optimized neural network is better than the unoptimized neural network.

In this paper, although the proposed method is used to diagnose the faults of rotating machinery, and it is not our ultimate goal. In the future, we will study the fault characteristics of rotating machinery system and integrate other diagnosis methods to realize the diagnosis of mixed fault types of mechanical system.

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References

[1] L.J. Wang, Y.X. Xie, Z.J. Wu, Y.X. Du, K.D. He, A new fast convergent iteration regularization method, Engineering with Computers 35 (2019) 127–138.

[2] L.J. Wang, L. Xu, Y.X. Xie, Y.X. Du, X. Han, A new hybrid conjugate gradient method for dynamic force reconstruction, Advances in Mechanical Engineering 11 (1) (2019) 1–21.

[3] L.J. Wang, J.W. Liu, Y.X. Xie, Y.T. Gu, A new regularization method for the dynamic load identification of stochastic structures, Computers and Mathematics with Applications 76 (2018) 741–759.

[4] L.J. Wang, Y.X. Xie, Q.C. Deng, The dynamic behaviors of a new impulsive predator prey model with impulsive control at different fixed moments, Kybernetika 54 (2018) 522-541.

[5] Y.Y. Jin, Partial Discharge Feature Extraction Based on Synchronous Extrusion Fourier Transform and Multiscale Dispersion Entropy, Wuhan University of Science and Technology, 2019. (In Chinese)

[6] T. Jia, Facial expression recognition based on multi-level fractional Fourier domain feature fusion, Zhengzhou University, 2013. (In Chinese)

[7] H.C. Xiang, Fault diagnosis of rolling bearing based on full vector spectrum, Kunming University of Science And Technology 2018. (In Chinese)

[8] X.W. Du, G.R. Wen, C. Jiang, Y.H. Liao, A Fault Feature Extraction Method for Rotor Start-Up or Slowdown Process Based on Fractional Fourier Transform and Holospectrum, Journal of Vibration, Mcasurcmcnt & Diagnosis 36 (2016) 729-733+812. (In Chinese)

[9] W.Y. Li, H. Heng, L.H. Zhao, L. Han, Shoe Wear Fault Diagnosis of Axial Piston Pump Based on Local s Transform and Extreme Learning Machine, Chinese Hydraulics & Pneumatics 12 (2019) 15-21. (In Chinese)

[10] B. Yuan, J.H. Yu, Y.X. Zhou, Fault diagnosis of hydraulic pump based on eemd-svm, Lifting the transport machinery 20 (2019) 90-95. (In Chinese)

[11] J.Z. Lin, H.S. Ou, W.Y. Feng, Y.D. Wang, Research of Empty Diagnosis for Wood Based on Wavelet Entropy and BP Neural Network, Instrumentation Technology 46 (2017) 16-19. (In Chinese)

[12] D.Y. Huang, L.Y. Ke, M.T. Lin, G.X. Shun, A New Fault Diagnosis Approach for Bearing based on Multi-scale Entropy of the Optimized VMD, Control and Deci 4 (2019) 1-8. (In Chinese)

[13] R.X. Chen, H.N. Wu, Y.F. Han, L. Zhao, Z.Y. Wu, L.L. Chen, Rotating machinery fault diagnosis under different rotating speeds based on fusion of non-dimensional index and information entropy, Journal of Vibration and Shock 38 (2019) 219-227. (In Chinese)