ISSN: 2414-1895 DOI: 10.6919/ICJE.201908_5(9).0024

Research on Fault Diagnosis of Rolling Bearing Based on SOM Neural Network

Xiaoqiang Yao[1, a], Gang Tang[1, b] and Xiong Hu[1, c]

[1]Shanghai Maritime University, Shanghai 201306, China.

[a]xiaoqiangshmtu@163.com, [b]gangtang@shmtu.edu.cn, [c]huxiong@shmtu.edu.cn

Abstract

In order to solve the problems of rolling bearing fault diagnosis and complex nonlinear pattern classification, according to the non-stationary and nonlinear characteristics of rolling bearing vibration signals, by analyzing the influence of bearing vibration signal training sample set, feature extraction methods and other factors on bearing fault diagnosis, a state clustering analysis method based on Self-Organizing Maps neural network is designed. In this method, five fault features of rolling bearings are extracted, and SOM neural network is used for training to obtain a bearing state discrimination model. Finally, the trained model is used to identify the fault types of rolling bearings. The verification of actual bearing fault data shows that the fault diagnosis method based on SOM neural network can accurately and effectively identify the fault of rolling bearing, and the accuracy rate is as high as 100%.

Keywords

Rolling bearing, fault diagnosis, SOM neural network, feature extraction.

1. Introduction

Bearing, as one of the key components of most electric and power drives, is the main device that leads to rotating machine failures, which indirectly leads to about 41% of machine failures [1]. Therefore, effective fault diagnosis of bearings is very important to maintain the safe and normal operation of electric and power drives. However, it is not easy to diagnose the faults of bearings. Its essence is a pattern recognition problem. In order to recognize the state of bearings more accurately, effective feature extraction and more accurate classification of bearing vibration acceleration signals are needed [2].

At present, the bearing fault diagnosis methods applied in engineering mainly include time domain analysis and frequency domain analysis. The time domain method mainly identifies the bearing state by monitoring some statistical parameter variation rules of the bearing [3], such as AR (autoregressive) model parameter estimation, etc. The frequency domain method diagnoses the state of the bearing by using fast Fourier transform (FFT) to detect frequency components related to faults in the vibration spectrum [4]. However, these methods need to know the frequency of bearing faults in order to accurately identify bearing faults and carry out severity evaluation, and the diagnosis results are subjective to some extent. With the rapid development of in-depth learning, intelligent algorithms are widely used in fault diagnosis of machinery and equipment.

Self-organizing map (SOM) neural network is an intelligent algorithm widely used in the field of equipment fault diagnosis in recent years. With the deepening of research, the accuracy of SOM neural network in equipment fault diagnosis is also getting higher and higher. E Germen et al. [5] use SOM neural network to diagnose the faults of induction motors, which can not only evaluate the possible differences between the failed motors and healthy motors, but also provide a model to define

ISSN: 2414-1895 DOI: 10.6919/ICJE.201908_5(9).0024

the types of faults, and identify the faults of the same type of bearing damage caused by misalignment or roller defects in the adjacent areas of the training network. SOM neural network is an unsupervised self-learning algorithm with simple structure, strong self-organization and self-learning ability, and has the functions of distributed storage, parallel processing, global collective application and lateral association of information [4].

In this paper, SOM neural network is applied to cluster analysis of bearing states. By extracting the effective features of bearing vibration acceleration signals, SOM network is used to cluster these features effectively, quickly and adaptively, and to identify bearing states more accurately, which provides certain basis for bearing maintenance.

2. SOM Neural Network Clustering Principle and Steps

2.1 SOM Neural Network Clustering Principle

SOM neural network is a kind of unsupervised learning network, which has the function of simulating the self-organizing feature mapping of human brain nerve. By actively finding the rules and essential attributes of sample data, SOM neural network can self-organize and adaptively change the connection weights between networks. The network structure comprises an input layer and a competition layer, wherein the input layer corresponds to a high-dimensional input vector; the competition layer consists of ordered nodes on a two-dimensional grid; and the input vector and the output node are connected through weight vectors [6] [7]. The basic structure is shown in fig. 1.

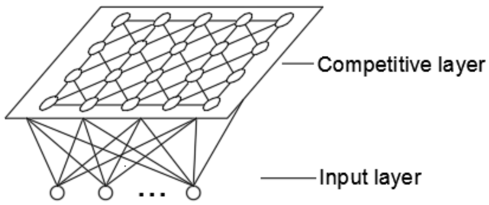

Fig. 1 SOM Neural Network Topology

2.2 SOM Neural Network Clustering Steps

SOM neural network selectively responds to the sample data of the input layer, and automatically configures similar sample data nearby on the network according to the similarity between the input sample data. The learning steps are as follows [8] [9].

2.1.1 Initialization and normalization of weights

Initialization of weights is such that the initial position of the weights and the distribution area of the input samples sufficiently overlap. By selecting part of the data from the vibration intensity data of the bearing as a training sample for the SOM neural network, then randomly selected m input sample from all training sample sets as initial weights and normalized.

$$\hat{w}_{ji} = \frac{w_{ji}}{\|w_{ji}\|}, (1 \le i \le m) \tag{1}$$

where, w_{ji} is the initial weight, $\|w_{ji}\|$ is the Euclidean norm of the weight vector and $\hat{w}_{ji}$ is the normalized weight.

2.1.2 Training sample normalization

$$X = \frac{\hat{X}}{\|\hat{X}\|} = \left(\frac{x_1}{\sqrt{\sum_{j=1}^{n} x_j^2}}, \cdots, \frac{x_n}{\sqrt{\sum_{j=1}^{n} x_j^2}}\right)^T \tag{2}$$

where, $\hat{X}$ is the training sample, $\|\hat{X}\|$ is the Euclidean norm of the training sample vector and x_j is the j characteristic component value of the training sample vector.

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2.1.3 Get winning neurons

The normalized vibration intensity sample data of the bearing is put into the input layer of the SOM network, the Euclidean distance of the training sample data and the weight vector is calculated, and the neuron with the smallest distance is defined as the winning neuron d_j.

$$d_j = \|X - W_j\| = \sqrt{\sum_{i=1}^{m}(x_i(t) - \omega_{ji}(t))^2} \tag{3}$$

where, d_j is Euclidean distance between training sample data and weight vector, and weight vector winning neuron is $d_k = \min(d_j)$.

2.1.4 Defining a winning neighborhood

The winning neighborhood determines the weight adjustment domain at time t with the winning neuron j^* as the center. The initial neighborhood $N_{j*}(0)$ is larger, and $N_{j*}(t)$ gradually shrinks with the training time. The size of the winning neighborhood is expressed by the radius of the neighborhood.

$$r(t) = C_1 e^{-B_1 t/T} \tag{4}$$

where, C_1 is a constant greater than zero related to the number of nodes in the output layer, B_1 is a constant greater than one and T is the preset maximum number of times of training.

2.1.5 Adjustment weight

Adjust the weights of all neurons in the winning neighborhood.

$$w_{ij}(t+1) = w_{ij}(t) + \eta(t,N)[x_i^p - w_{ij}(t)],(i = 1,2,\cdots,n,\ j \in N_{j\cdot}(t)) \tag{5}$$

where, $W_{ij}(t+1)$ is the adjusted weight, $\eta(t,N)$ is a function of the training time t and the topological distance N between neurons in the neighborhood.

2.1.6 Training requirements

The $\eta(t)$ is the functional value of the topological distance between the j neuron and the winning neuron after training, $\eta_{\min}$ is the set minimum topology distance function value. If $\eta(t) < \eta_{\min}$, the network training is ended. Otherwise, come back 2.2.2 to continue.

3. Bearing Acceleration Signal and Feature Extraction

In order to verify the effectiveness of SOM neural network for bearing fault diagnosis, rolling bearing data collected by the Electrical Engineering Laboratory of Case Western Reserve University in the United States were used. The experimental platform includes a 2 horsepower motor (left), a torque sensor (middle), a power meter (right) and electronic control equipment, as shown in fig. 2.

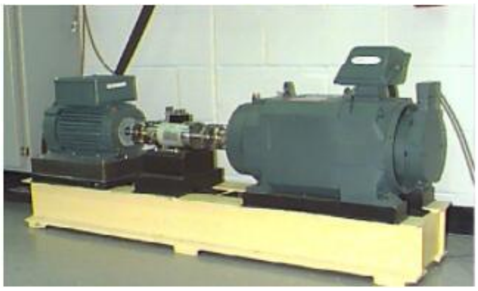

Fig. 2 Fault bearing test platform

The bearing model is SKF6205 deep groove ball bearing, the bearing rotation speed is 1797 r/min, single point damage is done by EDM, the damage diameter is 0.007 inch (i.e. 0.1778mm), the sampling frequency is 12kHz, the acceleration vibration signals of the drive end of the bearing in normal state, inner race fault, rolling body fault and outer race fault (the damage points are at centered

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@3:00, centered @6:00 and centered @12:00 respectively) are collected, and the sample length of each set of data is 32768. The time domain diagram of the vibration signal is shown in fig. 2, where: (a) is the normal signal of the bearing; (b) is the bearing inner race fault signal; (c) is the bearing roller fault signal; (d) It is a bearing outer race fault signal. The upper picture shows the outer race fault at centered @3:00, the middle picture shows the outer race fault at centered @6:00, and the lower picture shows the outer race fault at centered @12:00.

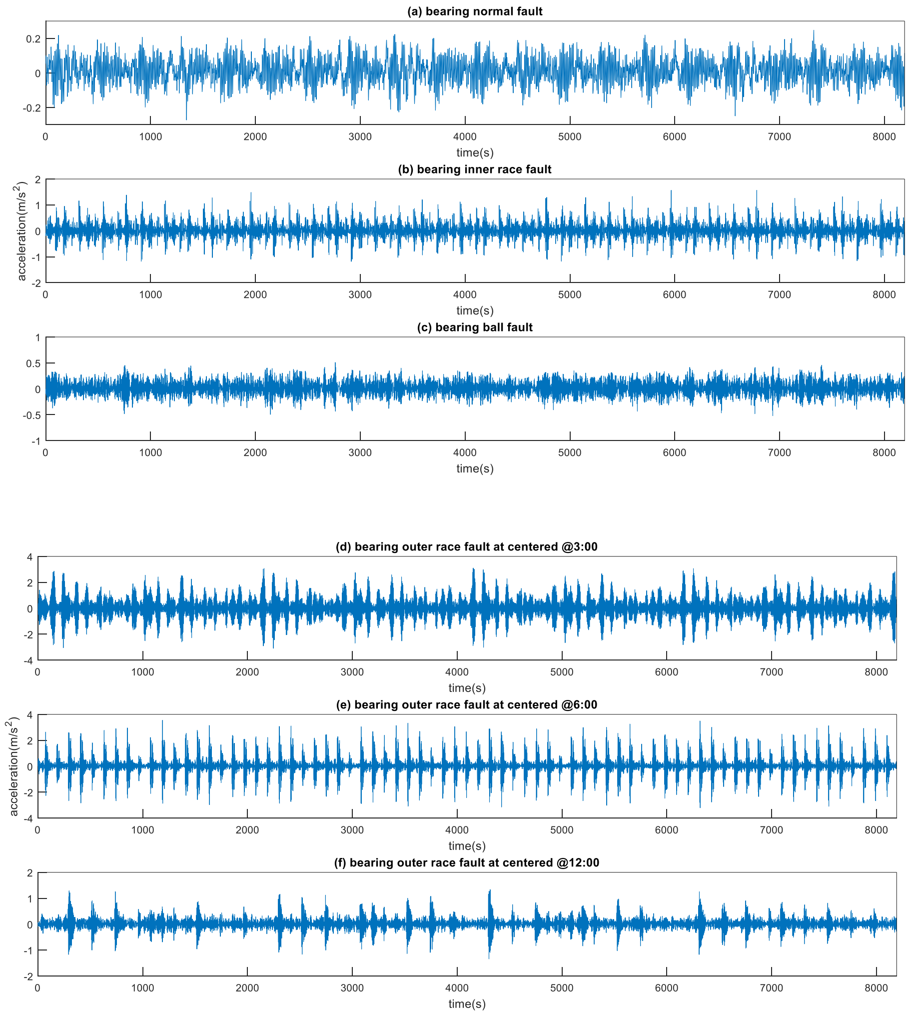

Fig. 3 Time Domain Diagram of Normal and Fault Bearing Vibration Signals

As can be seen from fig. 3, the time domain signal of the bearing is relatively smooth when it is normal, and there is no obvious vibration impact. When the bearing fails, the amplitude of the vibration signal is several times that of the normal vibration signal, reflecting that the energy of the failure signal is large and the impact is obvious. The fault signals of bearing outer race at centered @3:00, centered @6:00 and centered @12:00 are modulated by low-frequency signals with constant period and frequency and large amplitude.

3.1 Feature Extraction

The average value of the signal describes the average change of the signal with time and represents the static part or DC component of the signal. The mean square value reflects the fluctuation of the signal relative to zero value and represents the energy or power of the signal in diagnosis, which is of great significance. RMS is a widely used parameter. For vibration speed, RMS corresponds to vibration energy [10]; Skewness index describes the degree to which the signal distribution deviates from the normal distribution, and is sensitive to the state change of the bearing. When the rolling bearing has a local fault, the impact vibration signal caused by the fault obviously deviates from the

ISSN: 2414-1895 DOI: 10.6919/ICJE.201908_5(9).0024

normal distribution. Kurtosis index is a non-dimensional parameter to describe the peak degree of waveform. When the signal approximately obeys normal distribution, its kurtosis value is about 3, while when the signal has more impact components, the kurtosis value increases obviously.

In this paper, the five most important characteristic indexes of rolling bearing vibration acceleration signal are extracted, including three dimensional characteristic indexes and two dimensionless characteristic indexes, namely, mean value μ_x, standard deviation σ_x, effective value X_{RMS}, skewness index K_1 and kurtosis index K_2. See Formulas (6)-(10) for details.

$$\mu_x = \frac{\sum_{i=1}^{N} x(t_i)}{N} \tag{6}$$

$$\sigma_x = \frac{\sum_{i=1}^{N} (x(t_i) - \mu_x)}{N} \tag{7}$$

$$X_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x^2(t_i)} \tag{8}$$

$$K_1 = \sqrt{\frac{1}{6N}}\sum_{i=1}^{N} (\frac{x(t_i) - \mu_x}{\sigma_x})^3 \tag{9}$$

$$K_2 = \sqrt{\frac{N}{24}}\left[\sum_{i=1}^{N} (\frac{x(t_i) - \mu_x}{\sigma_x})^4 - 3\right] \tag{10}$$

where, $x(t_i)$ is the bearing vibration acceleration signal, μ_x is the mean value of the bearing vibration acceleration signal, σ_x is the standard deviation of the bearing acceleration signal, and N is the number of collected signal samples.

4. Case Analysis

The vibration acceleration signal of the rolling bearing is taken as a sample feature set of 6144×5 dimension extracted according to equations (6)-(10) as a fault feature, and some feature data are shown in table 1. Among them, class number 1 represents bearing normal state, 2 represents bearing inner race fault, 3 represents bearing ball fault, 4 represents bearing outer race fault at centered @3:00, 5 represents bearing outer race fault at centered @6:00, and 6 represents bearing outer race fault at centered @12:00.

Table 1 Training Sample Feature Set and Classification Number

sample number	mean value	standard deviation	valid value	skewness index	kurtosis index class label	class label
1	0.0155	0.0013	0.0390	-0.4491	19.9159	1
2	0.0176	0.0017	0.0451	0.7401	34.8536	1
3	0.0361	0.0013	0.0484	0.7297	12.1882	1
4	0.0310	0.0015	0.0483	0.4352	14.1371	1
5	0.1507	0.1071	0.3268	0.7104	74.2915	2
6	0.2026	0.0698	0.2636	0.6388	30.9196	2
7	0.1472	0.0506	0.2252	-1.2140	43.8519	2

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8	0.3173	0.1537	0.3916	1.7192	155.1381	2
9	0.1294	0.0255	0.1598	0.3685	78.0208	3
10	0.1171	0.0206	0.1442	0.7776	53.8621	3
11	0.1167	0.0237	0.1546	0.3675	91.3311	3
12	0.1371	0.0262	0.1620	-0.3699	79.6503	3
13	0.4639	0.7999	0.8943	0.7321	155.2895	4
14	0.4153	0.6075	0.7777	0.6427	107.4891	4
15	1.5218	0.5888	0.7652	0.7421	75.3017	4
16	0.3082	0.5593	0.7467	0.3923	92.5258	4
17	0.2332	0.9256	0.9622	-0.1357	112.8688	5
18	0.1301	1.1563	1.0758	0.5709	115.5247	5
19	0.1709	1.6913	1.3006	0.4273	158.2284	5
20	0.1843	0.8048	0.8972	-0.0687	61.5617	5
21	0.0703	0.0110	0.1056	1.6280	202.9827	6
22	0.1916	0.0150	0.1221	-1.3261	145.9551	6
23	0.1120	0.0132	0.1156	-1.2336	169.8541	6
24	0.4008	0.0092	0.0986	1.4691	73.1334	6

70% of the vibration acceleration signal characteristics of rolling bearings are taken as training sets and 30% as test sets, which are simulated by MATLAB R2017. Input the training sample set of dimension into SOM network, and set the competition layer as grid type with 200 training times. The best map is obtained after the training, and the output result is shown in fig. 4. Then the test sample set of dimension is input into SOM network, after 200 times of training, the prediction category of corresponding bearing sample is obtained, and the prediction category is compared with the real category of bearing to obtain the prediction accuracy of SOM neural network.

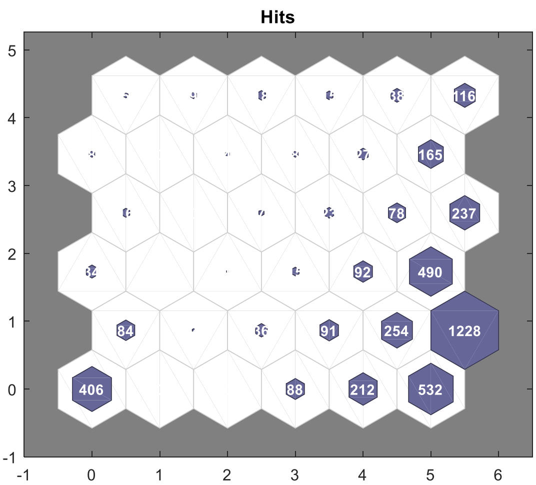

Fig. 4 Statistical chart of winning neurons

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As can be seen from fig. 4, the blue hexagon represents the winning neuron after the SOM network training is completed, the number in the neuron represents the number of its classified input vectors, and the white hexagon represents the neuron that did not win the chance of winning in the training process, and is always in an inhibitory state, i.e. "dead" neuron. Therefore, neurons 2, 3, 8, 14, 15, 20, 21, 25, 26, 27, 31, 32, 34 in the competition layer are "dead" neurons. By comparing the real state of the bearing with the number of the winning neuron, the corresponding relationship between the bearing state and the winning neuron can be obtained, as shown in Table 2.

Table 2 Distribution of Winning Neurons in Training Set and Test Set

bearing condition	winning neuron in training set	test set winning neuron
bearing normal state	24, 30, 35, 36	24, 30, 36
bearing inner race fault	28, 29	29
bearing ball fault	4, 5, 9, 16	4, 5, 9
bearing outer race fault at centered @3:00	10, 11, 13, 17, 19, 22, 33	10, 11, 13, 17
bearing outer race fault at centered @6:00	1, 7, 12, 18, 23	1, 7, 12, 18
bearing outer race fault at centered @12:00	6	6

As can be seen from Table 2, the winning neurons corresponding to the normal state of the bearing are numbered 24, 30, 35 and 36. The winning neurons corresponding to the inner race fault are numbered 28 and 29. The winning neuron number corresponding to the rolling body fault is 4, 5, 9 and 16; the number of winning neurons corresponding to the bearing outer race fault at centered @3:00 are 10, 11, 13, 17, 19, 22 and 33. The winning neuron numbers corresponding to the bearing outer race fault at centered @6:00 are 1, 7, 12, 18 and 23; the winning neuron number corresponding to the bearing outer race fault at centered @12:00 is 6. The training set winning neurons and the test set winning neurons are drawn in the same graph, as shown in fig. 5. From the graph, it can be seen that the winning neuron numbers corresponding to the samples in the test set are all in the training set winning neuron number set, and the fault identification accuracy rate is as high as 100%.

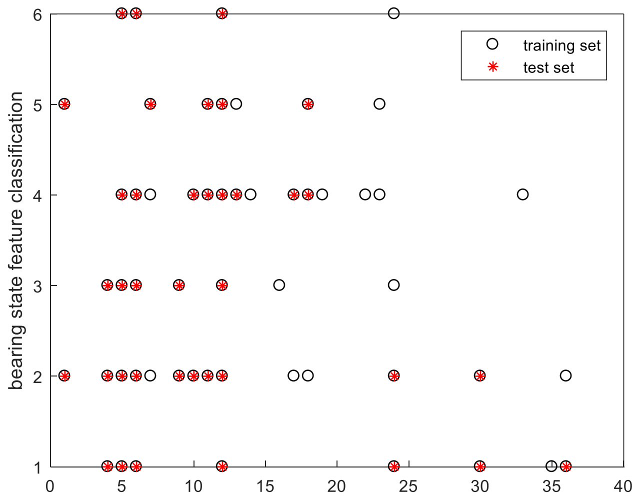

Fig. 5 Classification Results Based on SOM Neural Network

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5. Conclusion

In this paper, vibration acceleration signals of rolling bearings in normal state and fault state are selected. By extracting fault features of vibration signals, training sets and test sets of fault feature signals are established. SOM neural network is used to carry out self-organized learning on training sample sets and predict data types in test sample sets, so as to achieve the purpose of bearing fault diagnosis and state monitoring. The experimental results show that SOM neural network can accurately identify the working state of rolling bearings, provide certain basis for equipment maintenance, and reduce economic losses caused by bearing damage. As the sample data of this rolling bearing training is small, the bearing state discrimination model obtained through SOM neural network training is not accurate. When the vibration signal database collected is large enough, a more accurate relationship between bearing state and vibration signal can be established.

Acknowledgements

This work was supported in part by the National Natural Science Foundation of China under Grant 31300783, in part by the China Postdoctoral Science Foundation under Grant 2014M561458, in part by the Doctoral Fund of the Ministry of Education Jointly Funded Project under Grant 20123121120004, in part by the Shanghai Maritime University Research Project under Grant 20130474, in part by the Shanghai Top Academic Discipline Project Management Science and Engineering, and in part by the High-Tech Research and Development Program of China under Grant 2013A2041106.

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