Fault Recognition of Rolling Bearing Based on EMD and SOM Neural Network

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***Abstract*—Fault recognition of rolling bearings is the basis of condition-based maintenance. Aiming at the non-stationarity and non-linearity of vibration signals emitted from defective bearings, a fault recognition method is proposed based on Empirical Mode Decomposition (EMD) and Self-Organizing Feature Maps (SOM) neural networks. Vibration signals are decomposed into a collection of IMFs (Intrinsic Mode Functions) by EMD, and then the energy features extracted from IMFs containing fault information are treated as input of SOM neural network. Various bearing health conditions involving different fault types and severity levels are identified by the SOM. Experimental results verified the effectiveness of the proposed method.**

Keywords-EMD; SOM; Rolling bearing; Fault recognition; energy(key words)

I. INTRODUCTION

Rolling bearings are among the core components of rotating machinery. Failures of rolling bearings contribute significantly to the failure of rotating machinery. The health conditions of rolling bearings are associated with the operation safety of the whole mechanical system. Therefore, on-line monitoring and fault diagnosis of rolling bearing conditions has attracted great attention in industry and research communities [1,2]. Accurate identification of bearing conditions is vital to ensure the safe operation of mechanical equipment and avoid catastrophic accidents. Therefore, the need for online detection and intelligent diagnosis of rolling bearings is becoming very urgent [3]. Rolling bearing vibration signals contain abundant information regarding bearing health conditions. The key of fault diagnosis is to extract feature information which can reflect bearing health status from non-stationary vibration signals.

The complex working conditions of bearings, such as non-stationary loads and rotational speeds, as well as non-linear factors (like non-linear stiffness and clearance) in the system, will lead to non-linear and non-stationary vibration signals. Feature extraction can be carried out in time domain, frequency domain or time-frequency domain. Signal processing methods in time domain and frequency domain are difficult to deal with time-varying non-stationary signals [4], while time-frequency analysis like wavelet transform (WT) can achieve this purpose. Unfortunately, WT cannot extract the information reflecting the non-linearity of signals. Empirical mode decomposition (EMD) breaks through the limitation of traditional time-frequency analysis and perform well on non-stationary signals. Compared with traditional time-frequency analysis method, EMD has typical characteristics of self-adaptability, orthogonality and completeness.

In recent years, there is a trend using artificial intelligence technology to automate bearing fault diagnosis. Zhang Long [5] use multi-scale entropy to construct feature vector and Elman neural network to identify seven kinds of bearing conditions. Pi Jun [6] implemented fault diagnosis of aeroengine based on Elman neural network with improved particle swarm optimization, which is used to optimize the weights and thresholds of Elman neural network. Ai Jianliang [7] proposes an aeroengine fault diagnosis method based on adaptive neural network. Jiaojinjin [8] proposes a fault diagnosis model based on immune genetic algorithm optimizing self-organizing mapping neural network. The collected vibration signals of rolling bearings are decomposed into a set of empirical modes. The normalized energies of the intrinsic mode functions (IMFs) containing most fault information serve as feature vectors. The SOM (Self-Organizing Feature Maps) neural network optimized by Immune Genetic Algorithms (IGA) is exploited to identify the fault state. Zhang Qiang [9] extracts the energies of the eight sub-bands from the third layer of wavelet packet decomposition as inputs to SOM neural network for identify the wear state of the pick. SOM neural network has a strong ability of non-linear feature mapping and has a promising performance in rolling bearing fault recognition. However, the input feature vector to SOM neural network has a direct impact on the recognition results.

Based on the above analysis, an intelligent fault identification method for rolling bearings is proposed, which combines the non-linear feature mapping ability of both EMD and SOM neural networks. The method is used to realize online detection and intelligent recognition of rolling bearing fault types and severity levels, which are verified by experiments.

II. EMPIRICAL MODE DECOMPOSITION(EMD)

Empirical mode decomposition (EMD) is the core of Hilbert-Huang transform. It was proposed by Huang [10] in 1998. It breaks through the limitation of traditional time-frequency analysis and has better processing effect for non-stationary signals. Compared with the traditional time-

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frequency analysis method, it has typical characteristics of self-adaptability, orthogonality and completeness. EMD can decompose a signal step by step and produce a series of intrinsic mode functions (IMFs). EMD decomposes the signal into a series of IMFs according to the fluctuation trend of different frequencies of the signal, which have characteristics of notable wave packet with slowly varying.

The process of EMD algorithm is as follows:

(1) Find out all local extremum points in signal $x(t)$.

(2) The lower envelope and the upper envelope are fitted by cubic spline interpolation for all minimum and maximum points respectively, and all data points are guaranteed to be in the envelope.

(3) Take the average value of the upper and lower envelopes as follows:

$$g_{10} = x(t) - P_{10} \tag{1}$$

Empirical mode decomposition (EMD) decomposes a time series signal into a series of IMFs. Each IMF has the following two characteristics: 1. In the signal, the difference between the number of extreme points and zero points is less than or equal to one; 2. At any time of the signal, the average of extreme points of the upper and lower envelopes is zero, that is, the extreme points of the upper and lower envelopes are symmetrical with respect to the time axis.

(4) Estimate whether g_{10} satisfies the above two characteristics, if g_{10} satisfies the above two characteristics, then g_{10} is the first IMF component of $x(t)$, if not, turn to step 4.

(5) Take g_{10} as the original data, repeat steps 1-3, calculate the average value of upper and lower envelopes p_{11}, then there is $g_{11} = g_{10} - p_{11}$. Judge whether g_{11} satisfies the two characteristics of IMF. If not, continue to cycle the above steps 1-3 to get $g_{1k} = g_{1(k-1)} - p_{1k}$, and obtain all the g_{1k} satisfying the characteristics of IMF, which is recorded as $a_1 = g_{1k}$ and a_1 as the first IMF component of signal $x(t)$.

(6) Separate the obtained a_1 from $x(t)$.

$$y_1 = x(t) - a_1 \tag{2}$$

If y_1 is a monotone function, then the screening ends; if not, take y_1 as the original data, repeat the above 1-4 steps to get the second IMF component y_2 of $x(t)$, and repeat the cycle step n times to get the n IMF components of the signal. as follows.

$$\begin{cases} y_1 = x(t) - a_1 \\ y_2 = y_1 - a_1 \\ \quad \vdots \\ y_n = y_{n-1} - a_n \end{cases} \tag{3}$$

If y_n is a monotone function, or if other loop termination conditions are satisfied, the loop ends. Can get

$$x(t) = \sum_{i=1}^{n} a_i + y_n \tag{4}$$

In the formula y_n is a residual function, indicating the central average trend of the signal.

From the whole process of EMD algorithm, it can be seen that EMD is essentially a process of center tending to be stable. The trend of low-frequency center in the signal is screened out, and the high-frequency component of the signal is retained. When the remaining high-frequency component meets the characteristics of IMF, the screening ends.

III. SOM Neural Network

SOM neural network, also known as Kohonen network, was proposed by Professor T. Kohonen [11] in 1981. SOM is an unsupervised autonomous learning network, which is mainly used to classify the input eigenvectors. SOM is also a competitive neural network. Different from SOM, SOM neural network can study the distribution and topological structure of input vectors. That is to say, each neuron is interrelated with its neighboring neurons. The topological structure is composed of neurons with different excitation states, so it has the characteristics of self-organization. As shown in Figure 1, the SOM output layer is the competition layer, so the SOM model has only two layers of structure: input layer and output layer (competition layer), and the output layer neurons are interconnected to compete with each other for output. The input layer is fully connected with each neuron to form the characteristic topological distribution of the input signal, which can extract the information contained in the input eigenvector very well.

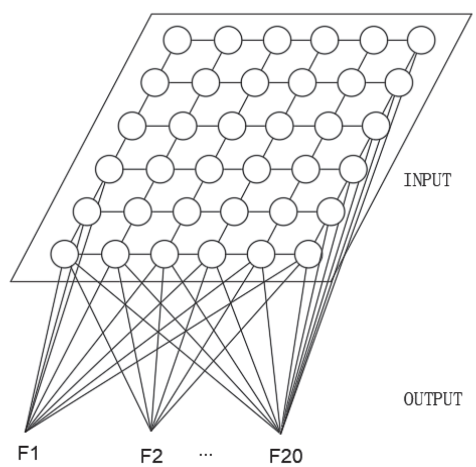

Fig. 1 Structural diagram of SOM model

SOM neural network self-organizing learning process is as follows：

(1) The input eigenvectors are normalized. In order to avoid losing the information contained in the data as much as possible, the first five IMF energy values of each signal are taken as input eigenvectors, and the eigenvectors are normalized to remove the possible singular samples.

$$y = (y_{\max} - y_{\min}) \cdot \frac{f - f_{\min}}{f_{\max} - f_{\min}} + y_{\min} \tag{5}$$

Where f is the original sample value, $f_{\min}$ is the minimum of the sample, $f_{\max}$ is the maximum of the sample, $y_{\min}$ is the minimum of the normalized range, and $y_{\max}$ is the maximum of the normalized range.

(2) Network initialization. Set network parameters, such as the number of nodes in the output competition layer is set to 10 x 10 = 100, the learning rate in the classification stage is 0.9, the structure function of the topology is hexagonal, and the distance function is Euclidean. The learning steps in the classification stage are divided into 10, 30, 50, 100, 200, 500 and 1000.

(3) Input eigenvector. Five IMF energy values are input to the input layer.

(4) Calculate the distance. The Euclidean distance between each neuron and the input vector is calculated. The Euclidean distance between the first neuron and the input vector is as follows:

$$d_i = \|X - W_i\| \tag{6}$$

(5) Weight updates. Correct the connection weights of each neuron to its adjacent neurons.

$$\Delta W_{ij} = \omega_{ij}(t+1) - \omega_{ij}(t) = \eta(t)(x_i - \omega_{ij}(t)) \tag{7}$$

As the number of steps increases, η gradually decreases to 0.

$$\eta(t) = 0.2(1 - \frac{t}{10000}) \tag{8}$$

(6) Check whether the requirements are met. If the requirement is met, the algorithm is terminated, otherwise step 3 is returned for the next round of learning.

IV. EXPERIMENTAL ANALYSIS

A. Rolling Bearing Test Bench

Rolling bearing data are from the bearing data center of Case Western Reserve university in the United States, The test bench, as shown in Figure 2, consists of a three-phase induction motor with a power of 1.49 kW on the left, a torsion sensor in the middle and a dynamometer on the right. The vibration data is connected to the magnetic base of the housing through an acceleration sensor, and the accelerometer is installed at the driving end of the motor housing and at the 12 o'clock position of the fan end. Digital data is collected through 12,000 samples per second and 48,000 samples per second. The test bearing is installed in the drive end of the left motor on the right side to support the motor shaft. The fault is implanted into the test bearing by Electric Discharge Machining. Four types of bearing health state, including normal bearing, roller fault, inner ring fault and outer ring fault, are simulated in the experiment. Each type of fault can be divided into different fault degrees include mild failure and severe failure, there are seven different bearing conditions.

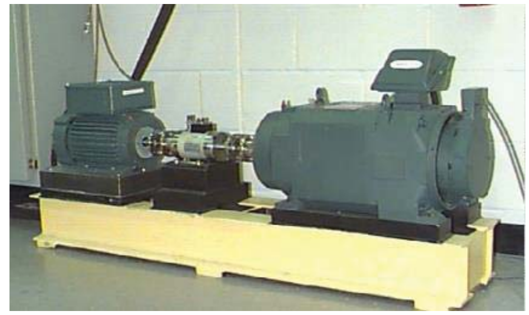

Fig.2 Physical drawings of rolling bearing failure test bench

Table I shows the specific type and degree of bearing health status studied in this paper. The degree of failure is expressed by the size of fault diameter and fault depth. During the experiment, the sampling frequency of data is 12 000 Hz, the speed of motor is 1797 r/min, the length of each sample is 2 000, and the number of bearing samples in each state is 60. Fig. 3 shows the time-domain waveform of a signal of seven bearing states. The vibration of normal bearing is more stable than that of fault-grabbing state. The impact caused by the fault can be clearly seen in both inner ring fault and outer ring fault.

TABLE I EXPERIMENTAL DATA OF ROLLING BEARING FAILURE STATUS

Bearing Conditions	Fault Size/mm	Samples Number	Conditions Number
Normal	0	60	G1
Ball fault	0.1778×0.2794	60	G2
	0.5334×0.2794	60	G3
Inner fault	0.1778×0.2794	60	G4
	0.5334×0.2794	60	G5
Outer fault	0.1778×0.2794	60	G6
	0.5334×0.2794	60	G7

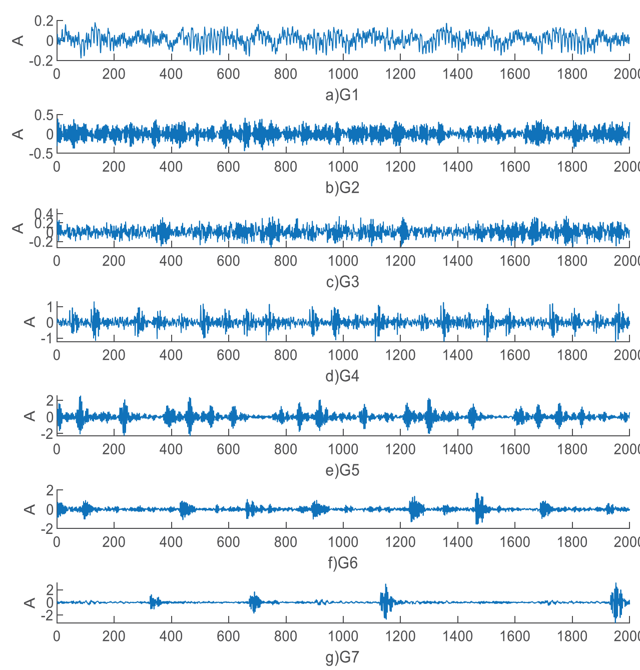

Fig. 3 Time Domain Signal Diagrams of Seven Kinds of Bearing States

B. EMD Extracts State Features

EMD is used to extract the features of the seven bearing states mentioned above. EMD decomposition of the signal can obtain several IMF components. The square value of the IMF is used as the IMF energy, the energy of the first several components are only greater, because there is less information missing. In order to preserve the energy information in the signal as much as possible and reduce the dimension of the data, the first five IMF components are selected and the energy values of each component are calculated. The energy values are input into SOM neural network as eigenvectors to identify rolling bearing faults. Fig. 4 shows the first five IMF components obtained by EMD decomposition under normal conditions. Fig. 5 is the average energy of the first five IMF components in seven bearing states.

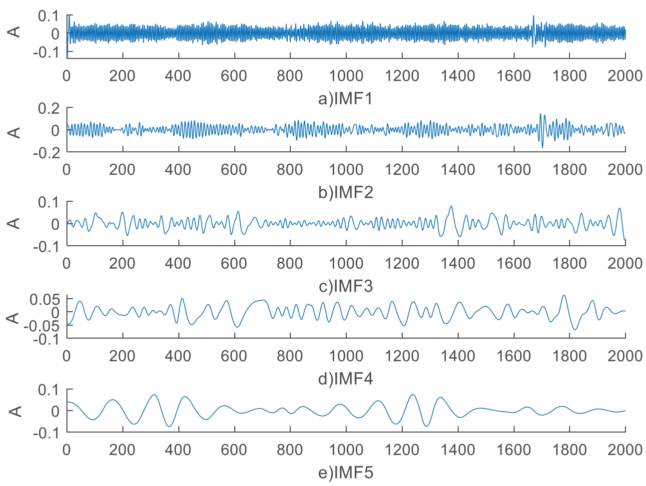

Fig. 4 The first five IMF components of bearings in normal state

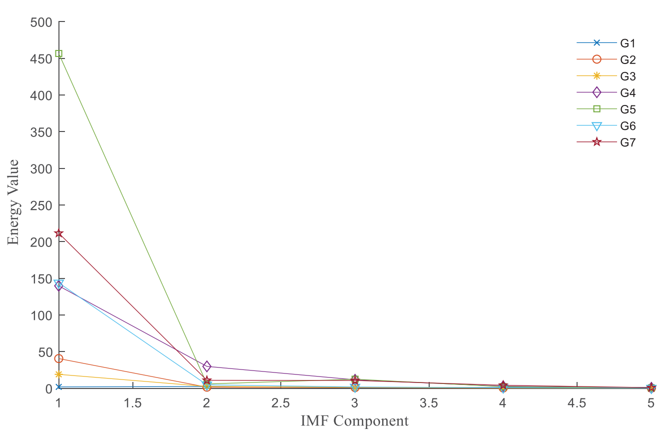

Fig. 5 Energy of seven fault state signals for rolling bearings

C. Establishment and Training of SOM Neural Network

The establishment of SOM neural network requires the setting of relevant initial network parameters. Five IMF energy values are taken as input eigenvectors, five nodes in the input layer and 10 *10=100 neurons in the output layer. In the classification stage, the learning rate is 0.9, in the tuning stage, the learning rate is 0.02. In the tuning stage, the neighborhood distance is 1, the structure function is hexagonal topological structure, and the distance function is Euclidean distance. In the classification stage, the learning step is gradually increased to 10, 30, 50, 100, 200, 500 and 1000, so as to select the most suitable step for training..

Table I shows that there are 60 samples for each bearing condition. 60 samples are divided into training set and testing set, of which 40 are training samples and the rest 20 are to be tested.The training results are shown in Fig. 6. When the training steps are 10, the SOM neural network classifies the data preliminarily. The different fault degrees of rolling element failures can not be well distinguished, and the different fault degrees of outer ring failures can not be completely distinguished.With the increase of training steps, when the training steps reach 100, the recognition accuracy has been greatly improved. When the steps increase to 200, seven kinds of bearing failure states can be completely distinguished. Continuing to increase training steps found that there was no better training effect, not only the training time was longer, but also no more practical significance. Therefore, the training steps of 200 were selected for training, which could meet the clustering requirements well.

TABLE II CLUSTERING RESULTS OF ASYNCHRONOUS SIZE

Training Step	Condition Labels						
	G1	G2	G3	G4	G5	G6	G7
10	100	20	50	91	1	7	41
30	10	1	3	80	91	31	95
50	51	9	6	60	6	99	33
100	1	61	52	98	20	93	60
200	31	81	52	20	80	94	77
500	91	1	32	98	20	4	96
1000	100	65	48	9	21	83	27

Table II shows that when the training steps are 200 steps, the corresponding winning neurons of normal bearing, rolling body slight fault, rolling body serious fault, inner ring slight fault, inner ring serious fault, outer ring slight fault and serious fault are 31, 81, 52, 20, 80, 94, 77, respectively.

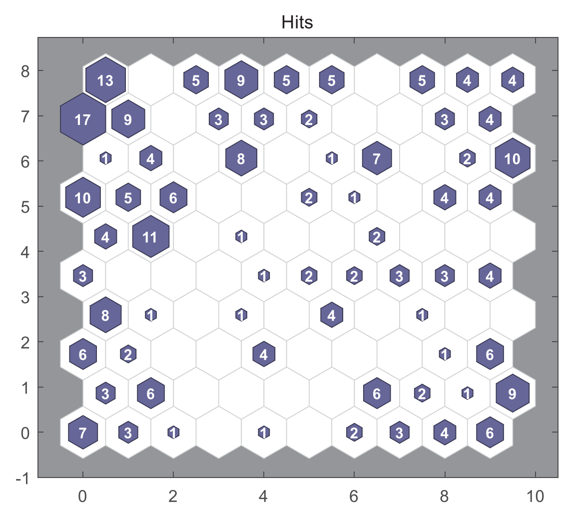

Fig.6 Clustering results of SOM neural network

Fig 6 is the corresponding hexagonal topology. The positions of neurons in seven bearing states are given. The results of seven kinds of bearing state clustering correspond to the winning neurons in Fig. 6, but the results of all the test data input to SOM neural network may correspond to any of the 100 neurons. At this time, the weighted distance graph of neurons is needed to assist in judging the bearing failure state. A region of neurons radiated from the winning neurons of each bearing state can represent the corresponding bearing state, and seven bearing states can be clearly distinguished in the topological structure.

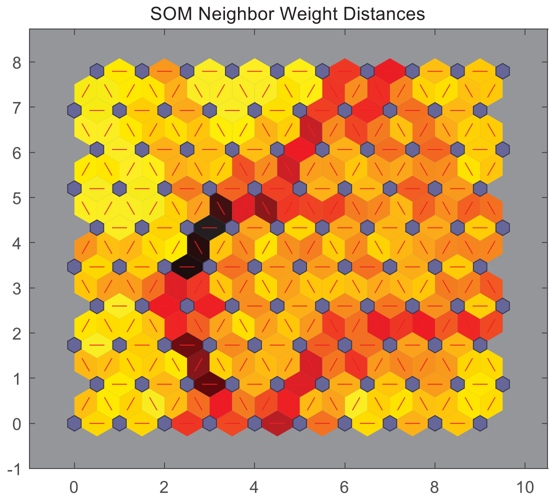

Figure 7 Distance between adjacent neurons

Figure 7 is a weight distance map between adjacent neurons. Light blue hexagons represent 100 neurons and straight lines represent the weight connections between neurons. The color of each diamond is filled from yellow to black, the darker color means the farther weight distance between two neurons. It shows that there is a big gap between the bearing failure states of the two neurons. The distance between neurons can be used for bearing failure states and make auxiliary judgment.

Fig 7 shows the corresponding relationship between the seven bearing States and the corresponding area neuron numbers as shown in Fig. 8. There is a clear distinction between fault neurons and non-fault neurons, and fault neurons have competitive victory neurons corresponding to each fault state to represent the fault state type. According to the distance from each fault state competitive victory neuron, other neurons assisting in judging bearing fault state are determined. The corresponding neuron numbers of seven bearing fault states are defined as Table III. Show.

TABLE III NUMBER OF NEURONS CORRESPONDING TO FAULT STATE AND SAMPLE CLASSIFICATION

Fault Category	Numbers Of Neuron Representation
G1	31，1，2，3，11，12，21，22，32，41
G2	81，71，82，91，92
G3	52，51，61，62，63，72
G4	20，7，8，9，10，17，18，19，29，30
G5	80，69，70，79，89，90，98，99，100
G6	94，74，84，85，86，93，95，96
G7	77，5，25，34，35，36，37，38，46，47，48，49，50，54，55，57，66，67，76

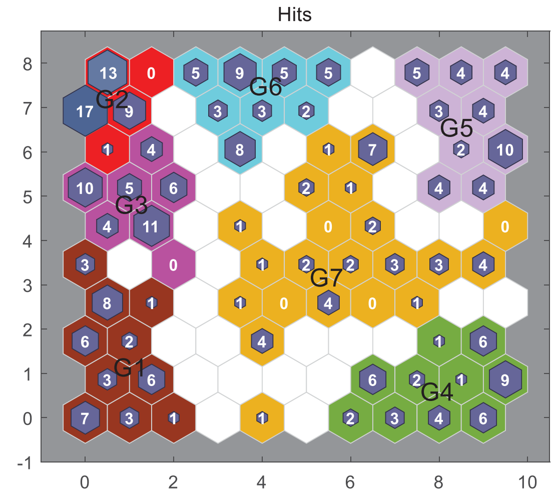

Fig.8 Sample Classification of Training Data Set

D. *Test result*

As shown in Table I, rolling bearings are divided into seven different fault states, each of which has 60 samples and a total of 420 samples. Forty groups of training data are selected for each failure state, and the remaining 20 groups are used as test data to form a training set containing 40*7=280 groups of data and a test set containing 20*7=140 groups of data. Five IMF energies of each group of data are extracted as eigenvectors. The training data are normalized into the SOM neural network for training, and the test data are input into the SOM neural network model to identify the fault state. The recognition results show that 139 out of 140 test samples can accurately identify the bearing fault state. Only one sample has an error in recognition. The severe rolling fault is identified as a slight rolling fault. The error may be due to signal acquisition. The noise interference of time-set system results in 99.29% fault recognition rate of test samples.

Thirty-five groups of test results were randomly selected from 140 groups of test data. The actual prediction classification, expected classification and error classification of test samples were shown in Figure 8.

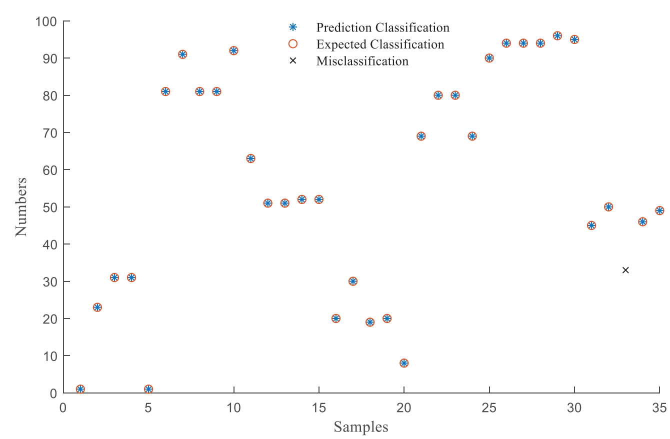

Fig.9 Clustering results

V. Conclusions

The first five IMF energies of the vibration signal are extracted by EMD, and they are used as feature vectors to realize the intelligent recognition of rolling bearing fault conditions by using SOM neural network unsupervised self-organizing learning. In the experiment, seven kinds of bearing fault conditions of four fault types were collected, IMF energy of vibration signal was obtained by EMD, and pattern recognition of seven fault states was realized by SOM neural network. The results show that SOM neural network can accurately identify seven kinds of bearings fault conditions

(1) The acceleration sensor is used to collect the rolling bearing signals of different fault types and different fault degrees. The EMD is used to extract the extracted signals to obtain the energy values of the five IMFs. The energy value of the obtained IMF is gradually reduced with the decomposition of the signal.

(2) A fault identification model based on EMD and SOM neural network rolling bearing is proposed. The experimental results show that the fault identification model has an accuracy of 99.29% for seven fault state samples, which provides an effective method for online fault detection of rolling bearings.

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