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Fault Diagnosis of Sensors based on Empirical Mode Decomposition and Neural Network

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ABSTRACT

In the paper, fault information of multiple sensors is decomposed into the sum of multiple intrinsic modal functions by the method of empirical mode decomposition, the lapping and invalid features in samples is removed after decomposition, and the energy entropy matrix containing the main information is extracted to construct fault characteristics. The neural network fault diagnosis model is established through training. Finally, according to the line number of the maximum value in the network output, the fault type of the sample is diagnosed. The simulation results show that the fault feature extraction is effective, the fault diagnosis accuracy is high.

1. Introduction

With the rapid development of industrial production, the industrial process has the characteristics of large scale, many variables and high complexity. Therefore, it is necessary to effectively extract sensor feature information for real-time process monitoring. Because of the load change, rigidity change, mechanical vibration and other factors in the external environment, the acquired sensor information inevitably contains a lot of transient non-stationary signals. But the traditional Fourier transform and wavelet transform analysis methods are based on the assumption that the sensor signal is stationary or piecewise stationary, so it is impossible to carry out a comprehensive and stationary signals accurately, which is the key to effective process monitoring and fault diagnosis.

With the development of artificial intelligence technology, a large number of new technologies have been applied to fault monitoring and diagnosis of complex industrial processes. Empirical Mode Decomposition (EMD) is adaptive and can deal with non-linear and non-stationary signals[4-5]. EMD is a time-frequency analysis method proposed by N.E. Huang in 1998.The non-stationary and non-linear original signal can be decomposed into the sum of several stationary intrinsic mode functions (IMFs). Several IMFs containing the main fault main information can be extracted and the corresponding energy matrices can be obtained. These matrices can be used as the eigenvector matrices of the original signal. The calculation methods of energy matrix and singular value matrix are given in reference [7], and they are combined with extreme learning machine for fault diagnosis of motor bearings. By extracting vibration signals of gearbox as state parameters, a fault diagnosis model of Gearbox Based on BP neural network is established in literature [8]. By extracting characteristic parameters of signals that have occurred faults and collecting a large amount of information data as known samples, the neural network is trained and applied to the diagnosis of unknown faults in gearbox in literature [9] .Literature [10] extracts fault features by wavelet analysis and combines with improved BP neural network to diagnose rolling bearing fault.

In this paper, the sensor data are decomposed by EMD, and the initial eigenvector matrix is formed by IMF components. Because the energy matrix of the same order IMF decomposed from different kinds of signals is obviously different, the energy matrix is used as the input of the neural network as the eigenvector, the sensor fault is used as the output of the network, and the weights of each layer are adjusted by the continuous self-training of the BP neural network to obtain the mapping relationship between the final input and output, and the fault diagnosis model based on EMD and neural network is established.

2. Empirical Mode Decomposition(EMD)

EMD is a self-adaptive signal processing method. In essence, it is a stationary processing of time series. It can decompose

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non-stationary and non-linear signals into the sum of a finite number of IMFs. The IMF must meet the following two conditions,

(1) For a data sequence, the number of extreme points and zero-crossing points must be equal or at most one difference.

(2) At any point, the average value of the upper envelope consisting of local maximum points and the lower envelope consisting of local minimum points is 0.

The EMD decomposition steps are as follows:

(1) All maximum and minimum points of the analyzed signal are obtained, and the upper and lower envelopes are formed by fitting all maximum and minimum points with cubic spline curve respectively.

(2) The average value of upper and lower envelopes is m_1, the first screening subtracts the original signal x(t) from m_1 to get $h_1(t)$,

$$h_1(t) = x(t) - m_1 \quad (1)$$

(3) In the second screening, $h_1(t)$ obtained from the first screening is used as the new original signal, and the average value of the upper and lower envelopes of $h_1(t)$ is m_2.

$$h_2(t) = h_1(t) - m_2 \quad (2)$$

(4) In the second screening, the decomposed $h_2(t)$ is used as the original signal . By analogy, the kth screening is performed until the kth screening is the intrinsic mode function.

$$h_k(t) = h_{k-1}(t) - m_k \quad (3)$$

(5)Order $c_1=h_k(t)$,c_1 is the first IMF decomposed from the original signal x(t), and the data sequence $r_1(t)$ with the highest frequency component removed is x(t).

$$r_1(t) = x(t) - c_1 \quad (4)$$

(6) The second IMF component of x(t) can be obtained by repeating the steps (1) and (2) above. Thus, n IMFs satisfying the conditions are obtained.

$$\begin{cases} r_2(t) = r_1(t) - c_2 \\ r_3(t) = r_2(t) - c_3 \\ \vdots \\ r_n(t) = r_{n-1}(t) - c_n \end{cases} \quad (5)$$

Until $r_n(t)$ becomes a monotone function, that is to say that it contains at most one pole and cannot be extracted from IMF. In order to ensure the physical significance of each screening IMF, the standard deviation S_d calculated according to formula (6) must satisfy the condition of more than 0.1.

$$S_d = \sum_{t=0}^{T} \frac{[h_{k-1}(t) - h_k(t)]^2}{h_{k-1}^2(t)} \quad (6)$$

After the above decomposition, the original signal x(t) can be expressed as

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \quad (7)$$

Where $c_i(t)$ is the decomposed IMF and $r_n(t)$ is the residual function.

The n energy values obtained by EMD method can be calculated by formula (8).

$$E_i = \int_{-\infty}^{+\infty} |c_i(t)|^2 dt \quad i = 1, 2, \cdots, n \quad (8)$$

The energy value is normalized according to formula (8) to form an energy matrix.

$$E_i = \frac{E_i}{\sum_{i=1}^{n} E_i} \quad i = 1, 2, \cdots, n \quad (9)$$

$$E = [E_1 \; E_2 \; \cdots \; E_n] \quad (10)$$

3. Neural network

Artificial neural network (ANN) is actually an active network composed of a simple computational processing unit (i.e. neurons) and a network topology, which can describe almost any nonlinear system.

3.1 BP neural network

BP neural network is a multi-layer feedforward network with hidden layers. The learning process of BP neural network includes two stages: forward and backward propagation. In the process of forward propagation, the input information is processed layer by layer from the input layer to the output layer, and the state of each layer of neurons only affects the next layer. If the desired output is not obtained in the output layer, then it will switch to counter propagation that the error signal will be transferred back to the original connection path, and the error signal will be minimized by modifying the weights of neurons in each layer.

The good self-learning ability and classification ability of neural networks are closely related to the structure of neural networks. If there are n neurons in the input layer as input signals, the input signals can be decided whether to be normalized and the way to be normalized according to their values and data types. The selection of the number of nodes in the hidden layer is of great significance to the output layer results, which can be determined according to the following formula:

$$n_1 = \sqrt{n+m} + \alpha \quad (11)$$

Where,n_1 is the number of hidden layers. n is the number of input units. m is the number of output unit. α is the constant between [1,10]. The number of output layers is determined by the fault type, and its value is generally between [0,1].

3.2 Calculation steps of BP neural network learning algorithm

（1）Initialize the network weight W

（2）Take samples one by one from the training sample set, input information into the network, and calculate the output of each layer node by the network. There are N processing units in each layer. For the p-th training sample (p=1,2,3...) the input sum of unit j is denoted as a_{pj}, and the output is denoted as o_{pj},

$$a_{pj} = \sum_{i=1}^{N} W_{ij} o_{pi} \tag{12}$$

$$o_{pj} = f\left(a_{pj}\right) = \frac{1}{1+e^{-a_{pj}}} \tag{13}$$

(3) Calculate the network error, that is, the error between the actual output and the expected output of the network,

$$E_p = \frac{1}{2}\sum_j \left(d_{pj} - o_{pj}\right)^2 \tag{14}$$

$$E = \sum_p E_p \tag{15}$$

Where, d_{pj} is the expected output of the p^th^ input mode output unit j

(4) Calculate the training error.

The training error of the output layer and the hidden layer is iterated according to the following formula,

$$\sigma_{pj} = \begin{cases} f'(a_{pj})(d_{pj} - o_{pj}) & (output\ layer) \\ f'(a_{pj})\sum_k \sigma_{pk} W_{pj} & (hidden\ layer) \end{cases} \tag{16}$$

(5) Weight adjustment

From the output layer to the first hidden layer, the weights of each connection of the network are adjusted according to the weight correction formula according to certain principles to reduce the error, weight correction formula,

$$W_{ij}\left(t+1\right) = W_{ij}(t) + \eta \sigma_{pj} o_{pi} \tag{17}$$

Where, η is the learning factor

(6) Repeat the above steps for each sample in the training sample set until the error of the entire training sample set meets the requirements.

4. Simulation experiment

4.1 Sensor fault diagnosis data

There are 6 sensors, and the probability of failure of each sensor is the same. When all sensors are normal, the sample data is matrix X. When the sensor works normally, its data matrix is

$$X = GT + e \tag{18}$$

$$T = [t_1 \ t_2 \ t_3]^T$$

where $t_i (i=1,2,3)$ is a random matrix with mean 0 and variance 1,0.64 and 0.36, noise matrix $e = [e_1 \ e_2 \ \cdots \ e_5 \ e_6]^T$, among them, $e_i (i=1,2,\cdots,5,6)$ is a random matrix with mean 0, variance 0.2 and normal distributed, G is the mixed matrix, randomly selected as

$$G = \begin{bmatrix} -0.1681 & 0.2870 & -0.2835 \\ 0.4354 & 0.3812 & 0.1455 \\ 0.0247 & -0.0235 & 0.4096 \\ -0.1173 & -0.1763 & 0.4382 \\ 0.0825 & 0.1398, & 0.3204 \\ -0.3825 & 0.1250 & 0.4836 \end{bmatrix}$$

Assuming that the i^th^ sensor fails, the sample can be expressed as

$$X' = X + \alpha_i \beta_i \tag{19}$$

Where, α_i is the fault amplitude of the i^th^ sensor, and the magnitude of the fault amplitude obeys the normal distribution [2,5]. β_n represents the sensor serial number of the fault, i.e. the fault direction, as shown below,

$$\beta_n = \left[\underset{i-1}{0\cdots0} \quad \underset{i}{1} \quad \underset{m-i}{0\cdots0} \right]^T$$

The position of element 1 is determined by the serial number of the failed sensor. In each mode, 100 groups of data are selected, and a total of 700 samples are used to train the neural network, the data of some training samples are shown in table 1.

There are a total of 700 samples in table 1, and there are 7 modes, i.e. normal, sensor no. 1 fault, sensor no. 2 fault, sensor no. 3 fault, sensor no. 4 fault, sensor no. 5 fault, sensor no. 6 fault and sensor no. 7 fault. The expected output matrix of the neural network is constructed by matching the fault of each sample with the output node of the neural network, this is shown in table 2. In table 2, 1 to 700 represent the sample number, and the row number of value 1 is the fault type of the sample. Since the fault type of each sample is unique, there is only one value 1 in each column, and the rest is 0.

Tab.1 Part training sample data

Fault type	Sample number	Sensor 1 data	Sensor 2 data	Sensor 3 data	Sensor 4 data	Sensor 5 data	Sensor 6 data
Normal	1	0.2807	-0.8615	0.3414	0.6297	-0.3917	1.3683
	…	…	…	…	…	…	…
	100	-0.3842	0.0272	-0.3080	-0.1794	-0.0273	-0.3614
Sensor 1 fault	101	3.8622	-0.8615	0.3414	0.6297	-0.3917	1.3683
	…	…	…	…	…	…	…
	200	4.0409	0.0272	-0.3080	-0.1794	-0.0273	-0.3614
Sensor 2 fault	201	0.2807	3.8665	0.3414	0.6297	-0.3917	1.3683
	…	…	…	…	…	…	…
	300	-0.3842	3.0139	-0.3080	-0.1794	-0.0273	-0.3614

Sensor 3 fault	301	0.2807	-0.8615	3.1614	0.6297	-0.3917	1.3683
	…	…	…	…	…	…	…
	400	-0.3842	0.0272	3.2729	-0.1794	-0.0273	-0.3614
Sensor 4 fault	401	0.2807	-0.8615	0.3414	3.4715	-0.3917	1.3683
	…	…	…	…	…	…	…
	500	-0.3842	0.0272	-0.3080	3.1218	-0.0273	-0.3614
Sensor 5 fault	501	0.2807	-0.8615	0.3414	0.6297	3.4298	1.3683
	…	…	…	…	…	…	…
	600	-0.3842	0.0272	-0.3080	-0.1794	4.5016	-0.3614
Sensor 6 fault	601	0.2807	-0.8615	0.3414	0.6297	-0.3917	5.9736
	…	…	…	…	…	…	…
	700	-0.3842	0.0272	-0.3080	-0.1794	-0.0273	3.5986

Tab.2 Fault types of samples and the corresponding output of neuron network nodes

Serial	Fault type	Expect output																				
		1	…	100	101	…	200	201	…	300	301	…	400	401	…	500	501	…	600	601	…	700
1	No fault	**1**	…	**1**	0	…	0	0	…	0	0	…	0	0	…	0	0	…	0	0	…	0
2	Sensor 1 fault	0	…	0	**1**	…	**1**	0	…	0	0	…	0	0	…	0	0	…	0	0	…	0
3	Sensor 2 fault	0	…	0	0	…	0	**1**	…	**1**	0	…	0	0	…	0	0	…	0	0	…	0
4	Sensor 3 fault	0	…	0	0	…	0	0	…	0	**1**	…	**1**	0	…	0	0	…	0	0	…	0
5	Sensor 4 fault	0	…	0	0	…	0	0	…	0	0	…	0	**1**	…	**1**	0	…	0	0	…	0
6	Sensor 5 fault	0	…	0	0	…	0	0	…	0	0	…	0	0	…	0	**1**	…	**1**	0	…	0
7	Sensor 6 fault	0	…	0	0	…	0	0	…	0	0	…	0	0	…	0	0	…	0	**1**	…	**1**

4.2 Sensor fault diagnosis based on EMD and neural network

The fault diagnosis process based on EMD and neural network can be divided into offline modeling stage and online monitoring stage, the overall fault diagnosis flow chart is shown in Fig.1.

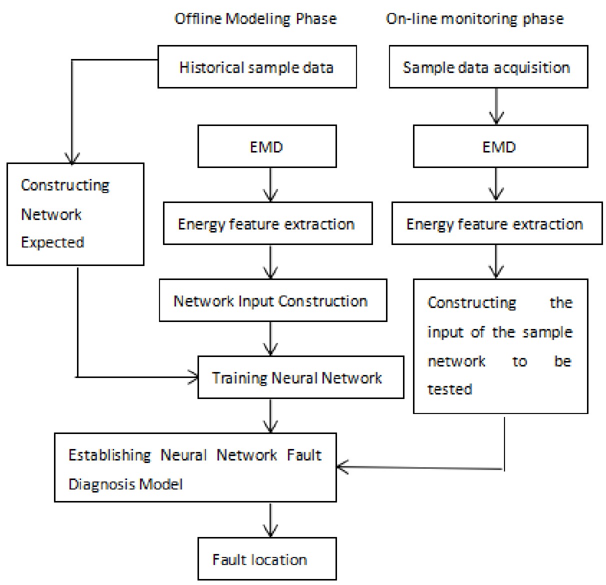


Fig.1 Fault diagnosis flow chart based on EMD

The specific steps are as follows:

Step 1: EMD decomposition of historical sample data

The sample data of different fault types of each sensor in table 1 are decomposed by EMD, respectively. The time domain waveform of NO. 1 sensor in normal state is shown in Fig.2. EMD decomposed into 6 IMF components, as shown in Fig.3.

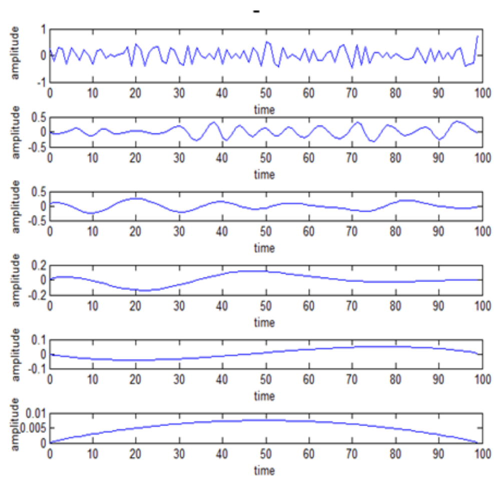


Fig. 2 The time domain waveform of normal state of sensor 1

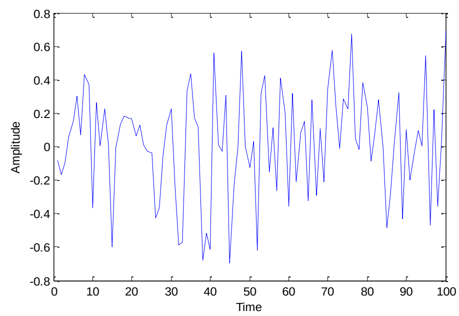


Fig.3 EMD result of sensor 1

The energy entropy with a large proportion in the energy matrix contains much information, and the sum of the first six energy entropy is close to 1, so only the first six IMF are selected for analysis.

Step 2: energy entropy fault feature extraction

Fault feature extraction is the basis of constructing training sample set and test sample set. The energy entropy of each IMF component is calculated according to equations (8) and (9). The data of 700*6 in table 1 are compressed to 42*5, and overlapping or invalid features are removed to construct a feature space with a lower dimension. The energy entropy of each IMF component is shown in table 3.

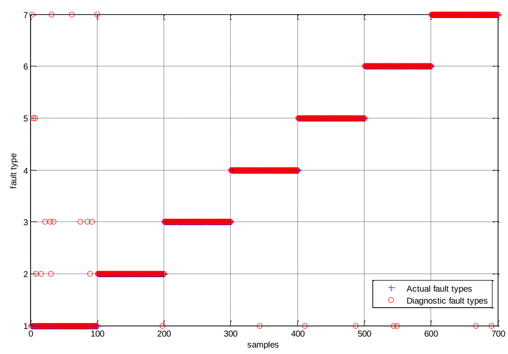
Tab.3 Energy entropy fault characteristics

Fault type	Sensor number	Energy entropy				
		E1	E2	E3	E4	E5
normal	1	0.5812	0.1662	0.1132	0.1170	0.0159
	2	0.6261	0.2345	0.0784	0.0194	0.0344
	3	0.6365	0.1952	0.1005	0.0214	0.0119
	4	0.6155	0.2729	0.0647	0.0282	0.0000
	5	0.5174	0.1760	0.2191	0.0600	0.0028
	6	0.5565	0.2124	0.0324	0.0516	0.0875
Sensor 1 fault	1	0.0175	0.0067	0.0177	0.0260	0.1580
	…	…	…	…	…	…
	6	0.5565	0.2124	0.0324	0.0516	0.0875
Sensor2 fault	1	0.5743	0.1643	0.1118	0.1156	0.0157
	2	0.0335	0.0094	0.0103	0.0259	0.1597
	…	…	…	…	…	…
	6	0.5565	0.2124	0.0324	0.0516	0.0875
Sensor 3 fault	1	0.5743	0.1643	0.1118	0.1156	0.0157
	…	…	…	…	…	…
	3	0.0175	0.0047	0.0049	0.0479	0.1988
	…	…	…	…	…	…
	6	0.5565	0.2124	0.0324	0.0516	0.0875
Sensor 4 fault	1	0.5743	0.1643	0.1118	0.1156	0.0157
	…	…	…	…	…	…
	4	0.0210	0.0037	0.0134	0.0203	0.1754
	…	…	…	…	…	…
	6	0.5565	0.2124	0.0324	0.0516	0.0875
Sensor 5 fault	1	0.5743	0.1643	0.1118	0.1156	0.0157
	…	…	…	…	…	…
	5	0.0159	0.0070	0.0261	0.0202	0.1541
	6	0.5557	0.2121	0.0323	0.0515	0.0873
Sensor 6 fault	1	0.5723	0.1637	0.1114	0.1152	0.0156
	…	…	…	…	…	…
	6	0.0161	0.0055	0.0542	0.2233	0.7008

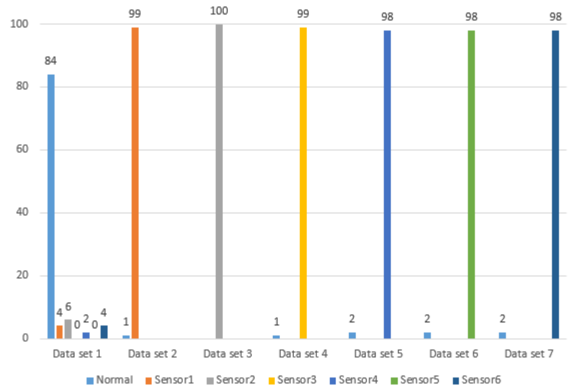
Step 3: Establishment of neural network fault diagnosis Model

Using neural network to diagnose faults, a neural network model is established, which is to determine the number of nodes in the input layer, the hidden layer and the output layer of the network. Because there are six sensors and seven fault types in the sample data in Table 1, the number of nodes in the input layer and output layer of the neural network is 6 and 7. The number of nodes in the hidden layer is 8 according to formula (11). If the sample data are not decomposed by EMD, the data in Table 1 are normalized by min-max method [11]. The processed data are trained to get the neural network model of fault diagnosis.

If the data samples are decomposed by EMD, the energy entropy characteristics of various types of faults in Table 3 are arranged in a row, and the 6*35 matrix is formed to train the neural network, and the neural model of fault diagnosis is obtained.

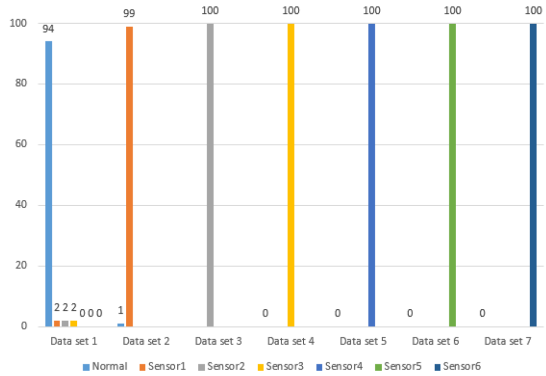


(a) Simulation diagram



(a) bar chart

Fig.4 simulation diagram and bar chart of neural network fault diagnosis

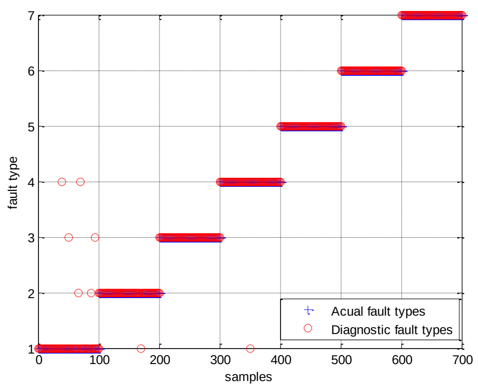


(b) bar chart

Fig.5 Simulation diagram and bar chart of Neural network fault based EMD

Step 4: Fault diagnosis of the sample to be tested

Formula (17) and Formula (18) are used to generate the samples to be tested and input the trained neural network model to diagnose the faults. The line number of the maximum value in the network output is the fault type of the samples to be tested. Fig. 4 is the simulation and histogram of the fault diagnosis results of the neural network. Fig. 5 is a simulation and histogram based on EMD and neural network fault diagnosis results.



(a) simulation diagram

In order to further analyze the feasibility of sensor fault diagnosis method based on empirical mode decomposition and neural network, the contribution graph analysis method is used to diagnose the sample data in Table 1.Contribution graph analysis method [12,13] is a commonly used fault diagnosis method. By calculating the contribution value of each variable of the sample to the monitoring statistics, a histogram is made for comparative analysis. The variable with large contribution is considered to be more likely to cause the occurrence of faults. The results of fault diagnosis are shown in Table 4. In Table 4, NN, RBC and EMDNN represent fault diagnosis based on neural network method, contribution graph analysis method and empirical mode decomposition and neural network method respectively. Each fault type has 100 samples to be tested.

From Table 4, it can be seen that the correct rate of fault diagnosis based on neural network for normal data and sensor 1 is low, and the average correct rate of fault diagnosis is 96.57%. Although the RBC algorithm has a high diagnostic accuracy for normal data, when sensor 1 and sensor 3 fail, the diagnostic accuracy is directly reduced to less than 80%, and the average diagnostic accuracy is 89.43%.The average correct rate of fault diagnosis based on EMDNN is 99%, which is higher than that based on NN and RBC.

Tab.4 comparison of fault diagnosis results of different fault diagnosis methods

Fault type	Diagnosis method	Fault diagnosis result of test sample							
		Normal	Sensor 1 fault	Sensor 2 fault	Sensor 3 fault	Sensor 4 fault	Sensor 5 fault	Sensor 6 fault	Fault diagnosis accuracy
Normal	NN	84	4	6	0	2	0	4	84%
	RBC	99	0	0	1	0	0	0	99%
	EMD	94	2	2	2	0	0	0	94%
Sensor 1 fault	NN	1	99	0	0	0	0	0	99%
	RBC	0	86	0	0	0	0	14	86%
	EMD	1	99	0	0	0	0	0	99%
Sensor 2 fault	NN	0	0	100	0	0	0	0	100%
	RBC	0	0	76	22	0	2	0	76%
	EMD	0	0	100	0	0	0	0	100%
Sensor 3	NN	1	0	0	99	0	0	0	99%
	RBC	0	0	21	77	0	2	0	77%

fault	EMD	0	0	0	100	0	0	0	100%
Sensor 4 fault	NN	2	0	0	0	98	0	0	98%
	RBC	0	0	0	0	100	0	0	100%
	EMD	0	0	0	0	100	0	0	100%
Sensor 5 fault	NN	2	0	0	0	0	98	0	98%
	RBC	0	0	1	0	0	99	0	99%
	EMD	0	0	0	0	0	100	0	100%
Sensor 6 fault	NN	2	0	0	0	0	0	98	98%
	RBC	0	11	0	0	0	0	89	89%
	EMD	0	0	0	0	0	0	100	100%

5. Conclusion

In this paper, sensor fault diagnosis based on EMD and neural network is studied. Firstly, EMD decomposition algorithm is used to remove the overlapping and invalid features from the huge sample data, extract the fault features of energy entropy effectively, and construct a lower dimension feature space. Secondly, according to the fault characteristics and types of sensors, the number of nodes in input layer, hidden layer and output layer of the neural network is determined, and the fault diagnosis model of the neural network is established by training the neural network with limited fault samples. Finally, the tested samples are input into the trained neural network fault model. The line number of the maximum value in the network output is the fault type of the tested samples, and the fault diagnosis is completed. The fault feature extraction method is effective and the fault diagnosis accuracy is high. The simulation example shows that the method is feasible and effective.

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