A New Signal Classification Method Based on EEMD and FCM and Its Application in Bearing Fault Diagnosis

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Abstract. In order to diagnose nonlinear and non-stationary fault signals in bearings, a new method is presented based on the ensemble empirical decomposition (EEMD) and the fuzzy c-means (FCM) clustering algorithm. At first, the bearing fault signals were decomposed using EEMD and the intrinsic mode functions (IMF) were produced. Second the energy ratios of these IMFs were computed and taken as the characteristic parameters for the FCM clustering algorithm. Then the FCM clustering method was conducted to classify the bearing fault signals into different classes. Finally, on the basis of the preceding classification results, we diagnosed a bearing fault through taking its distances between different cluster centers as the criteria. Experiments showed that the bearing fault signal classification results conformed to actualities well. The new signal classification method can be effectively utilized in bearing fault diagnosis.

Introduction

Rolling bearings are the critical parts of rotating machinery. Therefore, it is of great significance to find a method for precisely and automatically diagnosing the faults occurring in the bearings. Signal classification plays an important role in bearing fault diagnosis. For the purpose of classifying signals, the fuzzy c-means (FCM) clustering algorithm is an efficient method based on minimization of a criterion function. For classifying signal data using FCM, a feature space generally needs to be established. The commonly used one is the energy spectrum because emitted signals from different systems often have distinctive energy distribution in the frequency domain. In order to obtain the energy spectrum, the signals need to be decomposed first. Wu and Huang developed a noise-assisted data analysis method called ensemble empirical mode decomposition (EEMD) [1]. EEMD will be used in this paper to decompose nonlinear and non-stationary bearing fault signals because it is an adaptive time-frequency signal processing method since it is based on the local characteristic time scales of the signal and can decompose the signal into intrinsic mode functions (IMF) that are determined by the signal itself.

Methods

Ensemble empirical mode decomposition (EEMD). The procedures of EEMD are as follows:

1. For an given original signal $x(t)$, add a random white noise signal $n_j(t)$ to $x(t)$:

$$x_j(t) = x(t) + n_j(t), \quad j = 1, 2, \cdots, M \ . \tag{1}$$

where $x_j(t)$ is the noise-added signal and M is the total number of trails.

2. Decompose $x_j(t)$ into a series of IMFs c_{ij} using EMD as the following:

$$x_j(t) = \sum_{i=1}^{N_j} c_{ij} + r_{N_j} \ . \tag{2}$$

where c_{ij} represents the *i*th IMF of the *j*th trial, r_{N_j} denotes the residue of *j*th trial and N_j is the number of the IMFs in the jth trial.

3. If $j < M$, then repeat step 1 and step 2, and add different random white noise signals each time.
4. Obtain $I = \min(N_1, N_2, \cdots, N_M)$ and compute the ensemble means of corresponding IMFs of the decompositions as the final result:

$$c_i = \left(\sum_{j=1}^{M} c_{ij}\right) \Big/ M, \quad i = 1, 2, \cdots, I . \tag{3}$$

5. Report the ensemble mean $c_i \left(i = 1, 2, \cdots, I\right)$ as the final IMFs.

Fuzzy c-means (FCM) clustering algorithm. The fuzzy c-means clustering algorithm was presented by Bezdek in 1981 [2], which is a kind of c-means algorithm using membership to describe the degree that every sample belongs to each cluster. In order to minimizing the object function J , FCM clustering algorithm divides samples into fuzzy groups, and gets cluster centers of each data set. Fuzzy c-means clustering algorithm is the process of continuously adapting cluster centers and the membership matrix by iteration and its main procedures are as the following:

1. Initialize the membership matrix U using stochastic number between 0 and1, and the value of the center of each cluster, set the category number c , and the iteration stop threshold ε .
2. Modify the membership matrix.
3. Modify each cluster center value.
4. If the difference between two continuous J is less than the threshold ε : $\left|J_m(t) - J_{m+1}(t)\right| < \varepsilon$, stop the iteration and output the membership matrix and the cluster center value by loop, otherwise return to step 2 and go on running iteration of the circulation.

As a result, one of the best membership matrix and the corresponding cluster center value of the matrix can be obtained, which determine the optimal cluster for the original samples.

Energy ratios. As for the IMFs of the original signal obtained by using the EEMD method, the procedures to calculate their energy ratios are as the following:

1. Compute the energy E_i of each IMF c_i :

$$E_i = \sum_{t=1}^{N} \left|c_i(t)\right|^2 . \tag{4}$$

where N is the data length of the original signal.

2. Construct the feature vector E with $E_i (i = 1, \cdots, c)$ as its elements:

$$E = \left[E_1, E_2, \cdots, E_c\right]. \tag{5}$$

3. Normalize E to obtain the energy ratios of IMFs:

$$R = \left[r_1, r_2, \cdots, r_c\right], \quad r_i = E_i \Big/ \left(\sum_{i=1}^{c} E_i\right). \tag{6}$$

Then R is the final feature vector, and the energy ratios r_i can be used as characteristic parameters for the FCM clustering algorithm.

Fault diagnosis criteria. Given a rolling bearing fault signal $y(t), t = 1, \cdots, N$, the fault criteria to diagnose which kind of fault it belongs to are Euclidian distances $d_i (i = 1, 2, \cdots, \mathrm{c})$ between the different cluster centers $c_i (i = 1, 2, \cdots, \mathrm{c})$ and it as the following:

$$d_i = \left\|c_i - y\right\| = \left(\sum_{t=1}^{N} \left(c_i(t) - y(t)\right)^2\right)^{1/2} . \tag{7}$$

If $d_m (1 \le m \le c)$ is the smallest among all these distances, $y(t)$ will be diagnosed as the mth kind of bearing fault.

The principle of the new method

The procedures of our new method can be summarized in the flowchart as shown in Fig. 1.

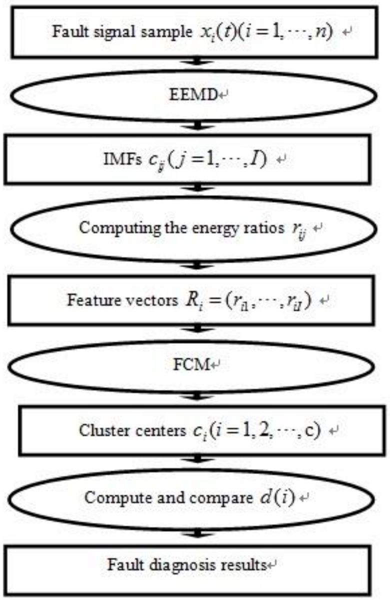

Fig. 1 The processing procedures of the new method

Experiment results and analysis

Classification results of fault signal sample. The fault signal samples corresponding to different bearing parameters are listed in Table 1 [3].

Table 1: 12K Drive end bearing fault data

Motor load	Motor speed	Inner Race	Ball	Outer Race
0	1797	IR007_0	B007_0	OR007@6_0
1	1772	IR007_0	B007_1	OR007@6_1
2	1750	IR007_0	B007_2	OR007@6_2

Table 2: Energy ratios of IMFs

Sample	IMF1	IMF2	IMF3	IMF4	IMF5
IR007_0	0.8046	0.1445	0.0439	0.0042	0.0020
IR007_1	0.8095	0.1409	0.0387	0.0071	0.0021
IR007_2	0.7932	0.1423	0.0562	0.0060	0.0019
B007_0	0.9246	0.0308	0.0341	0.0053	0.0048
B007_1	0.9397	0.0254	0.0201	0.0114	0.0027
B007_2	0.9409	0.0289	0.0200	0.0059	0.0037
OR007@6_0	0.9810	0.0109	0.0048	0.0020	0.0006
OR007@6_1	0.9762	0.0139	0.0061	0.0025	0.0009
OR007@6_2	0.9767	0.0152	0.0059	0.0016	0.0003

Table 3: Membership matrix

Sample	First class	Second class	Third class
IR007_0	0.0003	0.0005	0.9991
IR007_1	0.0024	0.0039	0.9937
IR007_2	0.0034	0.0054	0.9912
B007_0	0.0513	0.9413	0.0074
B007_1	0.0325	0.9657	0.0019
B007_2	0.0294	0.9690	0.0016
OR007@6_0	0.9939	0.0058	0.0003
OR007@6_1	0.9983	0.0016	0.0001

OR007@6_2	0.9976	0.0022	0.0001

It can be seen from Table 2 that the energy of rolling bearing fault signal samples mainly focus on high frequency, so only the energy ratios of the first five IMFs obtained from the EEMD method are taken as the characteristic parameters for the FCM clustering algorithm.

Table 3 shows the membership matrix that result from the FCM algorithm. The membership matrix indicates that the fault signal samples can be classified into three categories, which coincides with the fact as shown in Table 1: The signal data results from Inner Race fault, Ball fault and Outer Race fault of the bearing, respectively.

Fault signal diagnosis. In order to diagnose the rolling bearing signal OR007@3_0 belongs to which type of fault, the Euclidian distances between different cluster centers shown in Table 4 and it are calculated and displayed in Table 5.

Table 4: Cluster centers

Type	IMF1	IMF2	IMF3	IMF4	IMF5
First Class	0.9779	0.0134	0.0056	0.0020	0.0006
Second Class	0.9352	0.0283	0.0246	0.0075	0.0037
Third Class	0.8025	0.1426	0.0462	0.0058	0.0020

From Table 5, we can notice that the distance between the cluster center of the third class signal samples and OR007@3_0 is the smallest. So it is diagnosed as the third kind of bearing fault (Outer Race fault) signal according to the fault diagnosis criteria. In fact, OR007@3_0 comes from the experiment with outer raceway faults located at 3 o'clock (orthogonal to the load zone) and the third class signal samples were collected from the experiments conducted with outer raceway faults located at 6 o'clock (directly in the load zone). Actually, both of them are resulted from the Outer Raceway bearing fault. Therefore our new method has diagnosed the bearing fault successfully.

Table 5: Distance between OR007@3_0 and cluster centers

Distance	First Class	Second Class	Third Class
OR007@3_0	0.2317	0.0603	0.0109

Conclusions

A new signal classification method based on EEMD and FCM is proposed in this paper and it has been applied well to bearing fault diagnosis. The new method combines the merits of EEMD and FCM, so it is an adaptive method and fits to classify the nonlinear and non-stationary bearing fault signals. The experiments show that the classification results of the fault bearing samples consist highly with the actual fact. And the new method has succeeded in diagnosing another bearing signal as the outer raceway fault. Consequently, the new method is an efficient method for classifying nonlinear and non-stationary signals and can be used to diagnose bearing faults effectively.

Acknowledgements

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