Performance Degradation Assessment and Fault Diagnosis of Bearing Based on EMD and PCA-SOM

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Abstract. Bearings are used in a wide variety of rotating machineries, and bearing vibration signals are non-stationary signals. According to the non-stationary characteristics of bearing vibration signals, a bearing performance degradation assessment and fault diagnosis method based on empirical mode decomposition (EMD) and PCA-SOM is proposed in this paper. Firstly, vibration signals are decomposed into a finite number of intrinsic mode functions (IMFs), and EMD energy feature vector, which is composed of all the IMF energy, is obtained; then, principal component analysis (PCA) is introduced in to reduce the dimension of feature vectors; finally, the reduced feature vectors are chosen as input vectors of SOM neural network for performance degradation and fault diagnosis. The analysis results from bearings with different fault diameters and fault patterns show that the proposed method is able to assess the degradation of bearing suitably, and achieve fault recognition rate of over 95% for various bearing fault patterns.

1. Introduction

Bearing is one of the most important element in rotary machine; to a great degree, its performance influences the whole machine's performance. To prevent unexpected bearing failure that might cause costly downtime, even casualties, performance degradation assessment and diagnosis of it has received considerable attention for many years.

A variety of bearing performance degradation assessment and diagnosis researches have been conducted, and these studies mainly focus on three aspects: signal analysis, overlap or distance calculation and pattern recognition. Recently, wavelet-based methods have been widely used for assessment and diagnosis of bearing [1]. However, the wavelet transform still has some inevitable deficiencies, including interference terms, border distortion and energy leakage, all of which will generate a lot of small undesirable spikes all over the frequency scales and make the results confused [2]. And then, empirical mode decomposition (EMD), was demonstrated to be superior to wavelet analysis in many applications [2, 3]. EMD is based on the local characteristic time scales of a signal and could decompose the complicated signal into a number of IMFs. Frequency components contained in each IMF not only relate to the sampling frequency, but also change with the signal itself. The performance degradation of bearing is always assessed by calculating the overlap or distance between the real-time features and the baseline features in feature space, Qiu and Lee introduces enhanced and robust prognostic methods for bearing including a wavelet filter based method for fault identification and Self Organizing Map (SOM) based method for performance degradation assessment [4], but distortion occurs when the high-dimensional data is mapped into low-dimensional data by using SOM, meanwhile, training SOM network with high-dimensional data is a time-consuming process. Fault diagnosis can be seen as a problem of pattern recognition and various intelligent methods have been applied [5]. However, many classification algorithms, such as RBF and SVM, is not suitable for performance degradation assessment.

In order to solve the above-mentioned problems, a method which combines EMD and PCA-SOM is proposed in this paper.

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2. Methodology

Performance degradation assessment and fault diagnosis of bearing based on EMD and PCA-SOM is shown in Figure 1. The method is composed of two parts: performance degradation assessment and fault diagnosis. The result of performance degradation assessment is quantitatively indicated by confidence value (CV), following Lee (1996), ranging from 0 to 1 (which indicates unacceptable and normal performance, respectively) over time. Once the CV of bearing decreases to 0.8, which indicates the occurrence of degradation, the diagnosis algorithm is activated and used to classify faults of bearing. For performance degradation assessment, the original vibration signal is decomposed by EMD and some IMF components are obtained firstly, then, as the IMF energy of different vibration signals illustrate the energy of acceleration vibration signal in different frequency bands, and will change when bearing fault occurs, the energy feature vectors are obtained by calculating the energy of each IMF component; secondly, PCA is introduced in to reduce the dimensions of energy feature vectors; finally, the first SOM neural network, which is trained with normal bearing data, is used to assess the performance degradation of bearing. For fault diagnosis, in order to identify the fault pattern of bearing, another SOM neural network, which is trained and labeled with data of different fault pattern (normal, inner race defect, ball defect, outer race defect), served as a fault classifier and the reduced feature vectors are taken as neural network input vectors, by observing the sample position in SOM hits figure, the fault pattern of bearing can be determined.

2.1. EMD energy feature vector

The EMD method is developed from the simple assumption that any signal consists of different simple intrinsic modes of oscillations. Each signal could be decomposed into a number of intrinsic mode functions (IMFs), an IMF represents a simple oscillatory mode compared with the simple harmonic function.

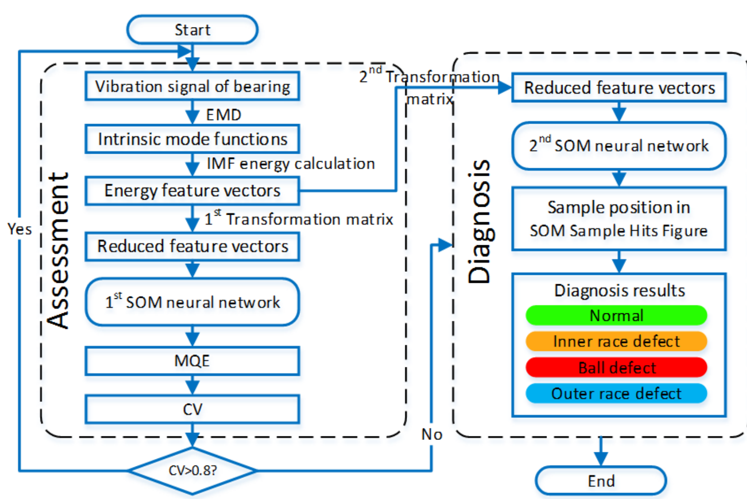

Figure 1. Performance degradation assessment and fault diagnosis based on EMD and PCA-SOM.

While the bearing with different faults is operating, the corresponding resonance frequency components are produced in the vibration signals, and the energy of fault vibration signal changes with the frequency distribution. To illustrate this change case as mentioned above, the energy of each IMF is calculated.

If n IMFs and a residual r_n are obtained from the vibration signals $x_i(t)$ and the energy of the n IMFs is $E_{i1}, E_{i2}, ..., E_{in}$, respectively. E_i is the 2-norm of $\left[E_{i1}, E_{i2}, ..., E_{in}\right]$,

$$E_i = \sqrt{E_{i1}^2 + E_{i2}^2 + ... + E_{in}^2} \tag{1}$$

Then, the EMD energy feature vector are defined as

$$F_i = \left[E_{i1} / E_i, E_{i2} / E_i, \cdots, E_{in} / E_i \right] \tag{2}$$

2.2. Principal component analysis

PCA is a kind of multivariable analysis method. By using variable transform, correlated variables are changed into uncorrelated new variables, which is useful to data analysis. So it is used in multi-dimension analysis widely. The general method of PCA is described in reference [6]. The PCA is now widely used for lowing redundancy and realizing reduction of data to enhance the analysis efficiency.

In this paper, the EMD feature vectors are transformed to reduced feature vectors with transformation matrix. It is worthy to note that the transformation matrix in performance degradation assessment and the transformation matrix in fault diagnosis are different matrices. As is shown in Figure 2, the 1st transformation matrix is used to reduce the dimension of feature space which is composed of feature vectors of normal bearing, while the other one consist of feature vectors of all fault patterns (normal, inner race defect, ball defect, outer race defect).

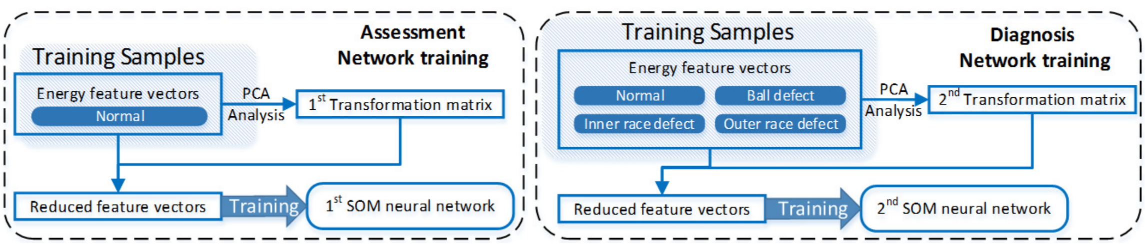

Figure 2. PCA analysis and SOM neural network training.

2.3. SOM neural network

SOM neural network structure is composed by input layer and competitive layer. Input layer is a one-dimensional vector, and competition level is a two-dimensional planar array. SOM neural network is used to assess the performance degradation and classify the fault pattern of bearings in this paper.

For performance degradation assessment, SOM is trained with vibration signals form normal bearing (see Figure 1). For each input feature vector, a best match unit (BMU) can be found in the SOM. The distance between the input data feature vector and the weight vector of the BMU, which can be defined as minimum quantization error (MQE) [4], actually indicates how far away the input data feature vector deviates from the feature vector of normal bearing. Hence, the degradation trend can be visualized by the trend of the MQE. As the MQE increases, the extent of the degradation becomes severer. A threshold can be set as the maximum MQE that can be expected and the degradation extent can be normalized by converting the MQE into CV, in which MQE increases while the CV decreases.

For fault diagnosis, cluster-then-label method is employed. SOM provides a way of representing multidimensional feature space in a one or two-dimensional space while preserving the topological properties of input feature space, so the feature vectors of same fault pattern cluster together in the two-dimensional space, which can be observed in SOM sample hits figure. SOM is trained with reduced feature vectors from all the fault patterns (see Figure 2), then, we identify the clusters of each input vector, each cluster is marked with a single color, which, in turn, allows the prediction of the label of every cluster.

3. Experiment results

The data used in the application experiment comes from the bearing data center [7], which provides access to ball bearing test data for normal and faulty bearings. In the experiment, three common types of fault of bearing were set respectively: inner race defect, ball defect and outer race defect. To verify the assessment method, single point faults were introduced to the test bearings using electro-discharge machining with fault diameters of 7 mils, 14mils and 21mils (1 mil=0.01 inches). The motor speed is 1750r/min, and the sampling rate is 120 KHz.

For performance degradation assessment, 100 feature vectors, which are extracted form 100K vibration signal data, are used to train the 1st SOM neural network, and 80 sets of data are used to validate the algorithm, as is shown in Table 1. One point should pointed out that one EMD energy feature vector is extracted from 1000 samples of vibration signal.

Table 1. Test feature vectors

Test feature vectors for performance degradation assessment				
Pattern	Normal	7mils fault	14mils fault	21mils fault
Sample size	20 feature vectors	20 feature vectors	20 feature vectors	20 feature vectors
No.	1-20	21-40	41-60	61-80
Test feature vectors for fault diagnosis				
Pattern	Normal	Inner race defect	Ball defect	Out race defect
Sample size	20 feature vectors	20 feature vectors	20 feature vectors	20 feature vectors

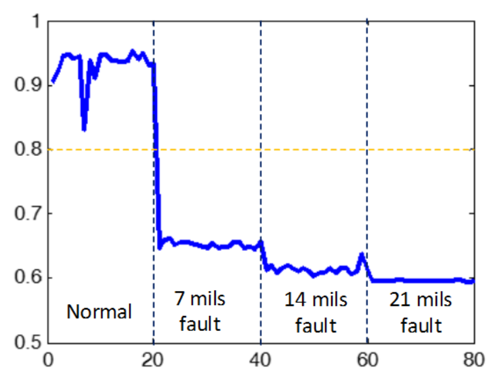

Figure 3. CV of different bearings.

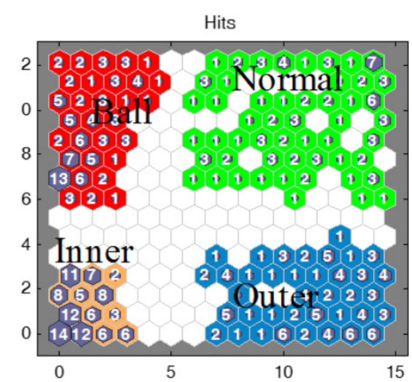

Figure 4. SOM samples with training data sets.

For fault diagnosis, 400 feature vectors, consist of 100 feature vectors of normal bearing and 300 feature vectors of fault bearing (including inner race defect, ball defect and outer race defect), are used to train the 2nd SOM neural network. After SOM neural network training and clustering, each cluster is marked with a single color (normal-green, inner race defect-yellow, ball defect-red, outer race defect-blue), and is shown in Figure 4. After that, 80 sets of data are used to test the SOM neural network for fault diagnosis (see Table 1).

The results of performance degradation assessment of bearings are shown in Figure 3. The CVs of the first 20 samples, collected from the vibration signals of normal bearing, are highly above 0.8, the predetermined failure threshold, which indicate stable performance. While the other CVs are below the threshold, and the CVs decrease when fault diameters increase. These test results indicate that the CV can reflect the performance degradation of bearing well.

Figure 5 shows the results of fault diagnosis. The first figure is test with vibration signals of normal bearing, the green area represents normal states, which is labeled by using training samples, in this test, 19 test data sets fall in the green area and 1 sample fall out of the area; the second figure is test with vibration signals of bearing with inner race defect, all of 20 test data sets fall in the yellow area; the third figure is test with vibration signals of bearing with ball defect, and 1 sample fall out of red area; the fourth figure is test with signals form bearing with outer race defect and all the test data sets fall in the labeled blue area. So there are 2 tests of misjudgement of fault diagnosis out of 80 tests, and the corresponding accuracy is 97.5%.

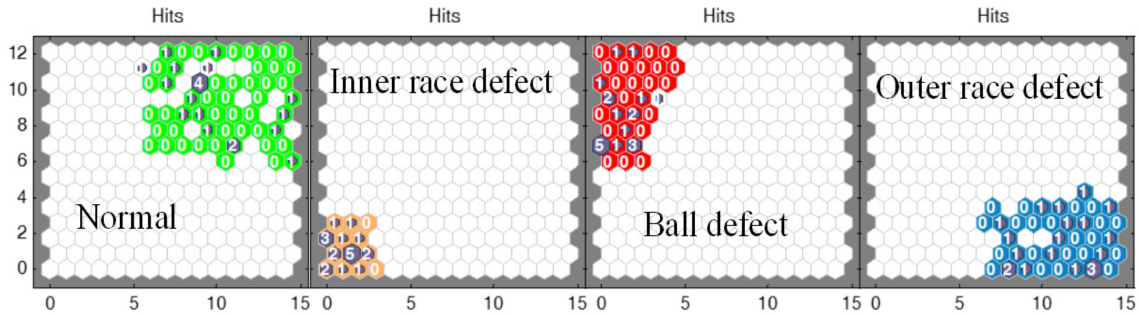

Figure 5. SOM sample hits.

4. Conclusion

In this work we have presented a method to performance degradation assessment and fault diagnosis of bearing by means of EMD and PCA-SOM. The advantage of this methodology relies in the efficient synergy between the well-known advantages of SOM unsupervised learning and the feature extraction tools based on EMD, allowing to discover relationships between fault-related features, also, PCA is introduced to reduce the dimension of feature vectors, which makes the assessment and diagnosis more accurate. An experiment is conducted to demonstrate the possibility and effectiveness of the proposed approach. Furthermore, the concept of quantitative diagnosis, which is based on the MQE to every fault pattern, will be presented and studied.

Acknowledgements

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