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ISOMAP AND INTRINSIC MODE FUNCTION FEATURE ENERGY-BASED MULTI-FAULT RECOGNITION METHOD OF ROLLING BEARING

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Abstract. *Aiming at the nonlinear and non-stationary characteristics of vibrations from faulty parts, an approach was proposed to solve the problem by means of Isomap and intrinsic mode function (IMF) energy. The approach firstly conducts empirical mode decomposition to the vibration signals and calculates the energy of each IMF component to form feature vectors. Then Isomap reduces the vector dimensionality, by which bearing conditions can be visually diagnosed. And BP neural network is used to classify fault types. The approach was applied to measured vibration signals from normal condition and outer race, inner race and ball defects of rolling bearing. The results demonstrate that the approach can recognize fault type with high accuracy and high clustering.*
Keywords: Rolling bearing, Fault recognition, Isomap, Intrinsic mode function, Feature energy, BP neural network

1. **Introduction.** The essential of bearing fault diagnosis is conducting a set of procedures of data processing to the vibrations, from which feature information that represents the working condition can be extracted, and performing pattern recognition [1]. In the fault diagnosis field, fault feature extraction is the most important and difficult problem. Feature vectors are composed of some statistics computed from raw observations by mathematics methods. At present, the time domain feature factors, amplitude domain factors and wavelet packet energy are general feature extraction methods [2-4]. However, the composed feature vectors usually contain hundreds of coupling and redundant variables, which is not conducive to pattern recognition. Therefore, dimensionality reduction is needed.

Feature dimensionality reduction is divided to two categories according to the principle, feature selection and feature transformation [5]. Feature selection selects several most weighted variables from the whole feature vector by some way, such as mutual information [6] and Relief-F [7]. The results of feature transformation, however, are not any variables in the feature vector but several new variables. PCA (Principal Component Analysis) [8] and Isomap [9] are representatives of feature transformation. However, PCA simply conducts linear combination to the features that cannot effectively reduce the dimensionality of the nonlinear bearing vibrations. Isomap is a machine learning algorithm based on manifold space. Isomap measures the similarity of every two samples by geodesic in manifold space. And it has an excellent performance in revealing the underlying structure of nonlinear data set.

The paper takes advantage of Isomap in dimensionality reduction and IMF feature energy in feature extraction and proposes a novel fault diagnosis method. Firstly, the principles of Isomap and IMF feature energy are described in Sections 2 and 3, respectively. Then the steps of fault diagnosis are presented in Section 4. Moreover, experiments and result analysis are given in Section 5. Finally conclusions are provided in Section 6.

2. **Principle of Isomap.** Isomap is a global manifold learning method that near points remain nearly and far-away points remain far while reducing the dimensionality [10]. The algorithm takes as input the distances between points in a high-dimensional observation space, and returns as output their coordinates in a low-dimensional embedding that best preserves their intrinsic geodesic distances.

The Isomap algorithm has three steps, which are detailed as follows.

1) Construct neighborhood graph.

Suppose the data set $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_N\}$ is sampled from the m-dimensional input space. Define the graph G over all data points by connecting points i and j if the Euclidean distance $d_X(i,j)$ satisfies the ε or k method. Set edge lengths equal to $d_X(i,j)$.

2) Compute shortest paths.

The geodesic distances between every two point on manifold M are approximately estimated by the shortest paths on neighborhood graph G. Initialize $d_G(i,j)$ as Equation (1).

$$d_G(i,j) = \begin{cases} d_X(i,j), & \text{if } i,\ j \text{ are linked by an edge} \\ \infty, & \text{otherwise} \end{cases} \tag{1}$$

Then find the shortest paths between points as Equation (2).

$$d_G(i,j) = \min\{d_G(i,j), d_G(i,k) + d_G(k,j)\},\ \ k = 1, 2, \cdots, N \tag{2}$$

The matrix of final values $D_G = \{d_G(i,j)\}$ will contain the shortest path distances between all pairs of points in G.

Theoretically geodesic distances are essential in manifold learning algorithm. However, they cannot be computed if the structure of the manifold is unknown. Isomap constructs a neighborhood graph connecting data points to approximate the manifold. Then the geodesic distances are estimated by the shortest paths.

3) Construct d-dimensional embedding.

The embedding from raw data to d-dimension space is performed as Equation (3).

$$(\boldsymbol{y}_i)_p = \sqrt{\lambda_p} v_p^i \tag{3}$$

where $(\boldsymbol{y}_i)_p$ – The p-th component of the d-dimensional coordinate vector; λ_p – The p-th eigenvalue (in decreasing order) of matrix $\tau(D_G)$; v_p^i – The i-th component of the p-th eigenvalue.

The operator τ is defined as Equation (4).

$$\tau(D) = -\frac{1}{2} CSC \tag{4}$$

where S is the matrix of squared distances ($S_{ij} = D_{ij}^2$) and C is the centering matrix ($C_{ij} = \delta_{ij} - 1/N$).

The first MSD (Most Significant Dimension) comes to lie on the first coordinate, the second MSD comes to lie on the second coordinate, and so on.

3. **Principle of IMF Feature Energy.** IMF feature energy is a method of feature extraction based on EMD (Empirical Mode Decomposition). The decomposition is based on the assumption: any complex signal is composed of a set of IMFs. An IMF is a function that satisfies two conditions [11]: (1) in the whole data set, the number of extrema and the number of zero crossings must either equal or differ at most by one; (2) at any point, the mean value of the envelopes defined by the local maxima and minima is zero.

The IMF components of the same order from different signals differ on both frequency components and the energy. Comparing the IMFs of the same order of the normal condition and defect condition, IMF energy of some orders will decrease and that of the others will increase. Therefore, IMF energies could be combined as feature vector to diagnose fault [12].

The numbers of IMFs from different signals are not necessarily equal. Then the first n IMFs are used for feature extraction where n must satisfy one condition that each sample contains at least n IMF components.

The energy of each IMF component is defined as Equation (5).

$$E_j = \int_{-\infty}^{\infty} |c_j(t)|^2 \, \mathrm{dt}, \;\; j = 1, 2, \cdots, n \tag{5}$$

For discrete signal, Equation (5) can be rewritten as Equation (6).

$$E_j = \sum_{i=1}^{N} |c_j(i)|^2 \cdot \Delta t \tag{6}$$

where E_j denotes the energy of the j-th IMF component, $c_j(i)$ is the i-th data point of the j-th IMF component, Δt is the sampling period, and N is the number of discrete points.

The feature vector takes energies of the first n IMFs as its entries. It is designated as

$$\boldsymbol{V} = [E_1, E_2, \cdots, E_n] \tag{7}$$

4. **Steps of Fault Diagnosis.** The proposed approach is detailed as the following chart.

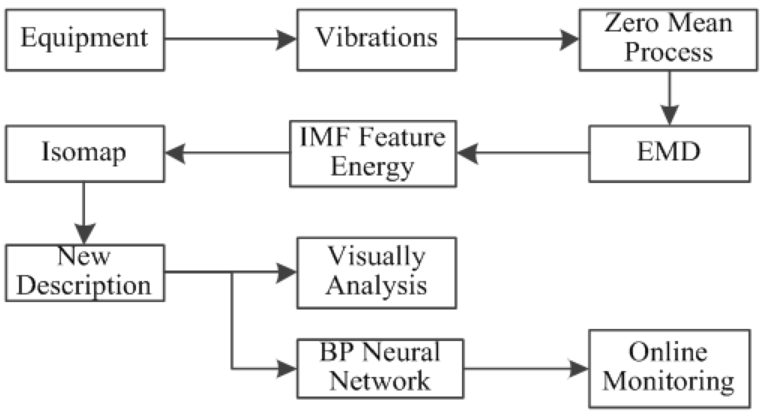

Figure 1. Steps of fault diagnosis

Vibrations are acquired from monitored equipment by sensors. Firstly, perform zero mean process to the vibrations to eliminate the impact of DC component. Secondly, IMFs are obtained from decomposing the signal by EMD, and IMFs feature energy is computed to construct the feature vectors. Thirdly, the dimensionality is reduced by Isomap, so we get new description of vibrations in the new embedding space. Fourthly, the 2-D graph is drawn with the first two MSD to realize visualized analysis on bearing condition intuitively. Lastly, from the analysis, one can easily identify the operating condition of the samples. BP neural network is used to classify faulty type to realize online monitoring.

5. **Experiment and Result.** The vibration signals used in this paper were acquired from MFS-MG test rig which was manufactured by Spectra Quest, Inc. The parameters of test bearings are shown in Table 1.

The sensor was piezoelectric accelerometer made by PCB (Type 608A11). The DAQ card was NI 9234. Data acquisition system was programmed by LabVIEW. A 5 kg load

TABLE 1. Parameters of test bearings

Brg. No.	No. of R. E.	R. E. Dia. (in)	Pitch Dia. (in)	BPFO	BPFI	BSF
ER-12K	8	0.3125	1.318	3.048	4.95	1.992

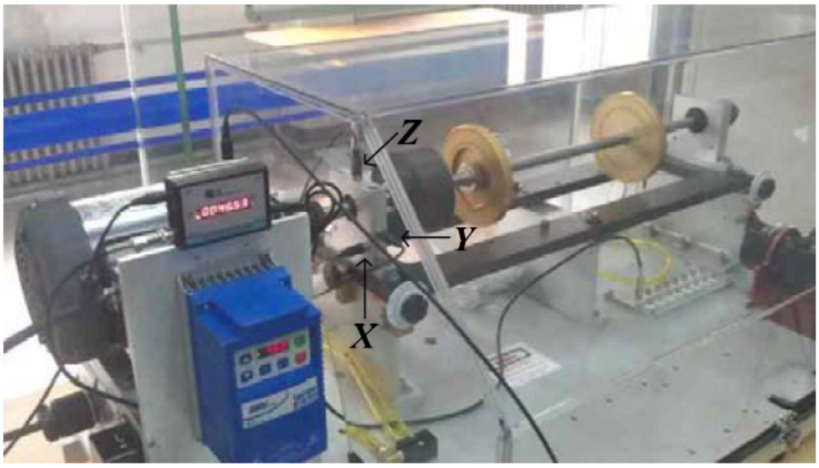

FIGURE 2. Experimental setup for vibration signal acquisition

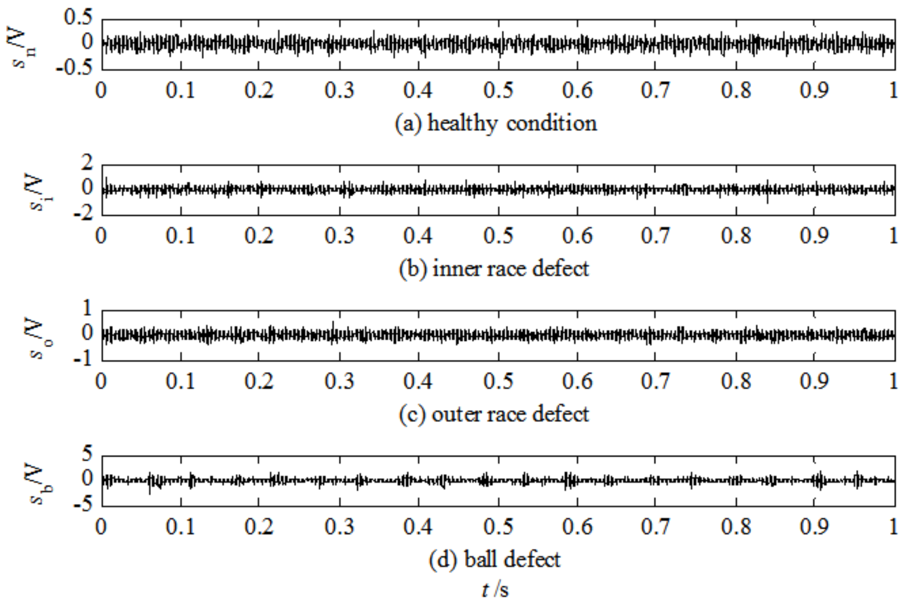

FIGURE 3. Time domain waveforms for each condition

was placed on the right of the tested bearing by 20 cm to enhance the radial vibration. The vibration data was acquired from direction Z. Figure 2 shows the experimental setup.

The shaft speed was set to 1500 rpm. The sampling frequency was set to 12.8 kHz. The working conditions include inner ring, outer ring and ball defects and healthy condition. Each condition contains 50 samples. Each sample contains 12800 data points. Figure 3 shows the time domain waveforms for each condition.

EMD decomposed 200 measured samples and the results show that the number of IMFs derived from each sample is between 11 and 13. Figure 4 shows a decomposition result of a sample in healthy condition. As illustrated in Figure 4, there are 11 IMFs and a residue.

The feature vector was constructed with the energies of the first 10 IMFs. Combine the 200 feature vectors to form the 200-by-10 feature matrix. Table 2 shows the changes of data structure.

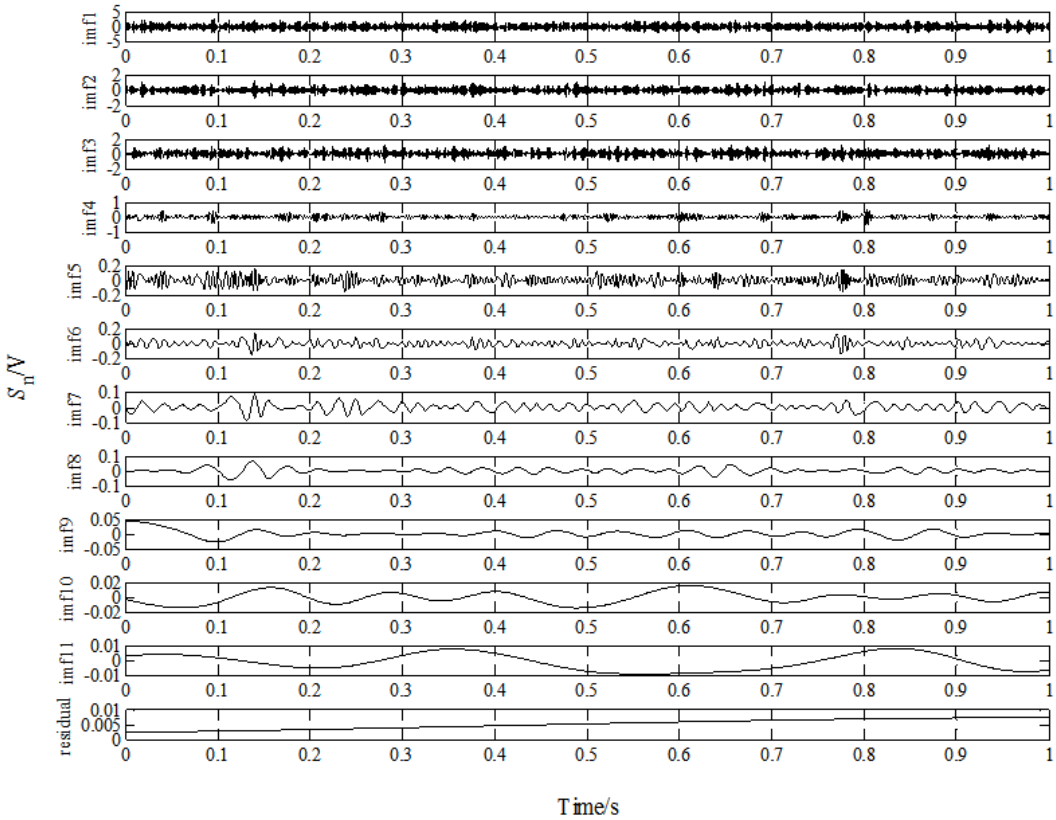

FIGURE 4. Decomposition result of a sample in healthy condition

TABLE 2. Changes of data structure

data process	matrix structure	explanation
raw data set	200×12800	2-D, rows are samples and columns are data points
EMD	$200 \times n \times 12800$	3-D, samples, number of IMFs, data points respectively
IMF energy	$200 \times n$	2-D, rows are samples and columns are feature variables
reduction	$200 \times d$	2-D, rows are samples and columns are new variables

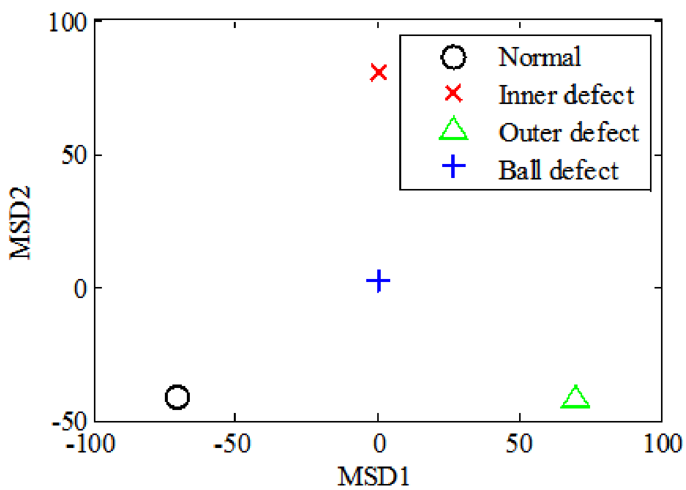

FIGURE 5. Result based on Isomap

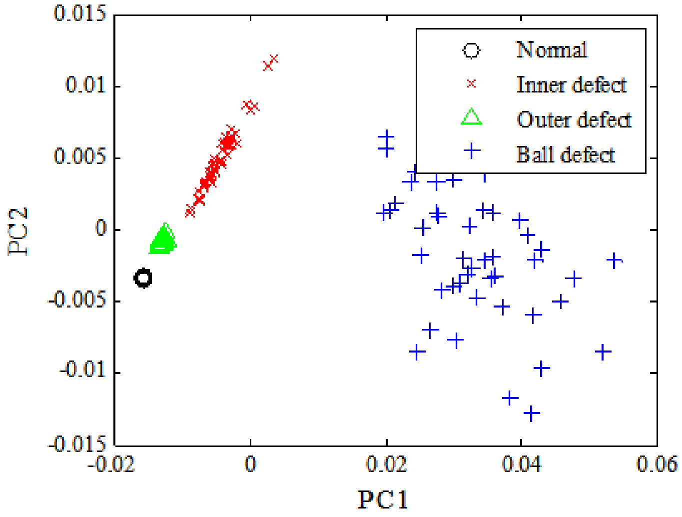

FIGURE 6. Result based on PCA

Two methods were used to reduce the dimensionality, i.e., Isomap (Figure 5) and PCA (Figure 6). Draw a 2-D graph with the first two MSD so we can find the bearing operating condition by eye which satisfies human cognition habit. As seen from Figure 5, the sample points representing four different conditions were excellently separated from each other with a high clustering. Therefore, the proposed method based on Isomap is effective to bearing fault diagnosis. Figure 6 shows a less clustering in the diagnosis result, especially the points denoting ball defect scatter widely. The reason is that each ball spins while revolving around the shaft and IMF energies fluctuate. Therefore, the approach based on Isomap outperforms that based on PCA.

Isomap algorithm exhibits high clustering in fault diagnosis as shown in Figure 5. The direct reason is that the coordinate values of samples are equal or hardly differ. Then the coordinates are computed as Equation (3) so the values depend on shortest paths matrix $\boldsymbol{D}$. Therefore, the high clustering derives from the Isomap algorithm principle.

In engineering practice, it is inefficient to examine the diagnosis result by eye, so a classifier is necessary to identify fault types to realize online monitoring. The traditional SVM (Support Vector Machine) only can solve binary classification problems. However, BP neural network is good at multi category classification problems [13]. So it is the classifier in this paper. To each condition, select 35 samples as the training set and the other 15 samples as testing set. The input layer contains 2 neurons: the hidden layer 8

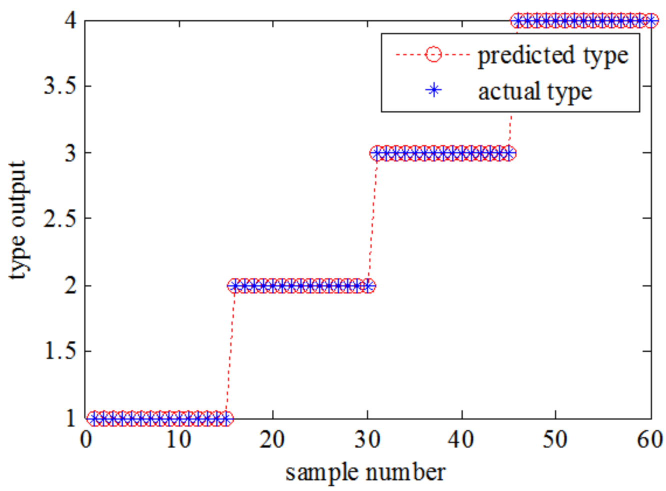

FIGURE 7. Classification result by BP neural network

neurons and the output layer 4 neurons. Hyperbolic tangent S function is the activation function. Performance is evaluated by mean square error and the maximum iterations are limited to 100.

Here the output label 1 denotes the healthy condition; label 2 denotes inner defect condition, label 3 denotes outer defect condition and label 4 denotes ball defect condition. The right ratio of classification result by BP neural network is 100% (Figure 7). It shows that the proposed method can accurately recognize the bearing fault types.

6. **Conclusions.** This paper proposed an approach based on Isomap and IMF energy to solve the problem that the bearing vibrations are non-stationary and nonlinear. The proposed method takes advantage of Isomap in dimensionality reduction and IMF feature energy in feature extraction. Experimental results show that Isomap can fully preserve the intrinsic structure of data set, discovering nonlinear information and extract the sensitive features. Combining Isomap and IMF energy can visually diagnose the fault type which satisfies human cognition habit. Combined with BP neural network it can accurately output the type label which is beneficial to online monitoring. In the future, this proposed method could be improved in some aspects, such as signal decomposition, fault types classification.

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