Sensors & Transducers, Vol. 179, Issue 9, September 2014, pp. 128-135

Sensors & Transducers

Research on the Diagnosis of Rotor Coupling Fault Based on Wavelet Packet and Local Fisher Discriminant

Guangbin Wang, Jun Luo, Yilin He, Xiaoyang Du
Hunan Provincial Key Laboratory of Health Maintenance for Mechanical Equipment, Hunan University of Science and Technology, 2 Taoyuan Road Xiangtan 411201, P. R. China
Tel.: +86-0731-58290849-2161, fax: +86-0731-58290849
E-mail: jxxwgb@126.com, luojunhnkjdx@163.com, kuoyelin.21@163.com

Received: 11 June 2014 /Accepted: 29 August 2014 /Published: 30 September 2014

Abstract: this article is for the coupling fault diagnosis of rotor system, and does in-depth analysis of the rotor unbalance and misalignment, and the fault formed by the coupling of these two. Through research, Rotor Coupling was found filled with rich features. In this paper, Wavelet packet de-noising ideas being introduced to the local Fisher discriminant analysis (LFDA), a new method of fault diagnosis based on Wavelet Packet and Local Fisher Discriminant is proposed. The technology of information fusion is applied to the data processing with coupling faults. By comparing and analyzing the algorithms effect of LE, LPP, FDA, LFDA and IOLFA through experiment, it shows that LE and LPP are unable to identify the fault, while FDA, LFDA has better identification, and Wavelet Packet and Local Fisher discriminant has the best effect. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Rotor system, Wavelet packet, Local Fisher discriminant, Coupling fault.

1. Introduction

In rotating machinery, because of its poor manufacturing and assembly or the system being in high-speed and high-load condition, faults are easy to happen such as rotor unbalance, misalignment moderate failure. If not diagnosed timely, it will lead to the second failure like rubbing and foundation loosening, and even trigger multi-coupling faults, which have a significant impact on the normal operation of the machine. What's more, once the failure occurs; it is often not a single one, but a mutual coupling multiple faults. Therefore, analysis of rotor coupling fault diagnosis is particularly important. It shows that rotating machinery fault diagnosis is particularly important. However, the traditional fault diagnosis methods are generally Frequency Analysis, Bispectral Analysis, Wavelet Analysis, Envelopment Analysis, Modal decomposition and fractal geometry etc. These methods have a good effect for single fault identification, but it will encounter many difficulties when they are applied to the coupling fault diagnosis. Frequency domain analysis method such as Frequency Analysis, Envelopment Analysis and Bispectral Analysis always easy to ignore the fault component of weak signal among coupling faults of the uneven strength and hard to find the causality between multiple faults; Wavelet Analysis to extract the characteristic signal by using specific basis functions, single wavelet can only match a failure, therefore it always has one without another when extracting the coupling fault feature and can not be completely accurate fault diagnosis [1]; The fractal dimension as a fault signal measure which could describe the characteristics of the nonlinear system, but dimensional numerical easily affected by the delay time and embedding dimension.

In order to solve these problems, some scholars have put forward new targeted method for fault diagnosis of the coupling. V. Purushotham et al, proposed wavelet analysis and hidden Markov multi-fault diagnosis method for Multiple Fault Diagnosis of rolling bearing of the rotor system [2]; F. Q. Wu et al, put forward making use of support vector machines (SVM) and a full spectrum approach to multiple fault classification of shaft [3]; S. Abbasfon et al, diagnosed multiple faults of rotor-bearing system by taking advantage of support Vector Machine (SVM) and wavelet noise reduction [4]; These theories and methods do not considered overlapping relationship which potential in the low-dimensional manifold of single failure data among coupling faults, but density, direction and dimension of overlapping domains on the manifold all will have a profound effect on the coupling fault diagnosis.

In 2000, the journal Science published three papers [5-7] which made manifold learning algorithm as a starting point, and greatly drove the development of machine learning, data mining techniques. Classic manifold learning algorithm includes ISOMAP [8], Locally Linear Embedding (LLE) [9], Laplacian Eigenmaps (LE) [8, 9], Learning Technology Systems Architecture (LTSA) [10, 11] etc. The foundation of the supervised manifold learning and semi-supervised manifold learning pave the road for manifold learning to be directly applied to pattern recognition. But as the classic manifold learning algorithm are processed in batch, if new data point is to be learned, we need to break the data structure of the original data points and calculate the whole algorithm again, which is not only of low efficiency but also inapplicable to fault diagnosis. This is because fault diagnosis is based on a number of known classes of training data to identify particular devices with a relatively constant recognition model, and then use this model directly to test the new data. Mechanical equipment fault diagnosis requires high timeliness in discovery and algorithm, which the classic manifold learning algorithm is obviously unable to meet the need. Locality Preserving Projections (LPP) [12] algorithm proposed a characteristic linear mapping for the Laplacian operator, which brings about a new way for solving this problem. While Local Fisher Discriminant Analysis (LFDA) [13, 14] which synthesized the Locality Preserving Projections (LPP) and of Fisher Discriminant Analysis (FDA), introduce Category supervision information into LLP, and constructs the local Fisher discriminant function for pattern recognition, and clear all obstacles for the use of manifold learning methods for fault diagnosis.

In this paper, the wavelet packet de-noising idea is introduced into the LFDA. The technology of information fusion is adopted. By comparing and analyzing the algorithms effect of LE, LPP, FDA, LFDA and IOLFA through experiment, it shows that LE and LPP are unable to identify the fault, while FDA, LFDA has better identification, and Wavelet Packet and Local Fisher discriminant has the best effect.

2. Local Fisher Discriminant Analysis Algorithm

Assume that Data sample matrix of $n \quad m$ dimension is $X = [\mathrm{x}_1, \mathrm{x}_2, L\, X_n] = [X_1, X_2, L\, X_c]$. X_{i} shows n_j sample sets of class i. Assume that scatter matrix of classes within, between classes and overall respectively represented are represented respectively by S^w, S^b and S^m, as are shown in formula 1, 2, 3.

The transformation of type 1 and 2 can be obtained scatter matrix of classes within and between classes, such as type 4 and 5:

$$S^W = \frac{1}{n}\sum_{j=1}^{c}\sum_{X_i \in X_J}(x_i - \mu_j)(x_i - \mu_j)^T , \tag{1}$$

$$S^b = \frac{1}{n}\sum_{j=1}^{c} n_j(\mu_j - \mu)(\mu_j - \mu)^T , \tag{2}$$

$$S^m = \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)(X_i - \mu)^T = S^W + S^b , \tag{3}$$

$$S^w = \frac{1}{2}\sum_{i,j=1}^{n} W_{i,j}^W (X_i - X_j)(X_i - X_j)^T , \tag{4}$$

$$S^b = \frac{1}{2}\sum_{i,j=1}^{n}\left(\frac{1}{n} - W_{i,j}^b\right)(X_i - X_j)(X_i - X_j)^T , \tag{5}$$

and

$$\overline{A}_{i,j}^w = \begin{cases} W_{i,j}/n_c & y_i, y_j \in c \\ 0 & y_i \in c, y_j \in c \end{cases}, \tag{6}$$

$$\overline{A}_{i,j}^b = \begin{cases} W_{i,j}(1/n - 1/n_c) & y_i, y_j \in c \\ 1/n & y_i \in c, y_j \notin c \end{cases}, \tag{7}$$

$$W_{i,j} = \exp\left(-\frac{\| X_i - X_j \|^2}{\sigma_i \sigma_j}\right), \tag{8}$$

$$\sigma_i = \| X_i - X_J^K \| \, (K = 7) , \tag{9}$$

where $W_{i,j}$ represents the degree of neighbor relations between any two points in the data space.

Larger $W_{i,j}$ means that the neighbor relationship between two sample data points is closer, while smaller $W_{i,j}$ means that the neighbor relationship between two sample data points is farther. The projection rules of LFDA algorithm can be represented as:

$$T_{LFDA} = \arg\max_{T \in R^{m \times n}} tr\left((T^T S^b T)(T^T S^W T)^{-1}\right), \quad (10)$$

Namely we can just solve the optimal solution of matrix equation (10), which equals to solving the maximum eigenvalues corresponding eigenvectors of equation $S^W \phi = \lambda S^b \phi$.

3. Fault Signal Noise Reduction Method Based on Wavelet Packet

Commonly, a variety of wavelet packets basis can be applied to the wavelet packet decomposition of the fault signal.

According to the actual situation, we can select the best one of these wavelet packet bases [15], known as the optimal basis, which is the standard of entropy, and can be selected from the optimal solution of the tree function. The definition of wavelet packet function can be expressed by the following mathematical relationship.

Among them, $g(k) = (-1)^k h(1-k)$ that is to say, the $g(k)$ and $h(k)$ is orthogonal to each other; the wavelet function: $y_1(t) = \varphi(t)$ Scaling function: $y_0(t) = \varphi(t)$

$$\begin{cases} y_{2n}(t) = \sqrt{2}\sum_{k \in z} h(k) u_n(2t-k) \\ y_{2n+1}(t) = \sqrt{2}\sum_{k \in z} g(k) u_n(2t-k) \end{cases}, \quad (11)$$

Sequence consisting of formula 11 $\{y_n(t) \mid n \in z^+\}$ is an orthogonal wavelet packet of basis function, set n a non-negative number, then

$$y_{i+1}^n = y_{j+1}^{2n} \oplus y_{j+1}^{2n+1} \quad j \in z, \quad (12)$$

Suppose $g_j^n(t) \in U_j^n$, $g_j^n(t) = \sum_t d_I^{j,m} u_m(2^j t - 1)$. So $\{d_l^{j,2m}\}$ and $\{d_l^{i.2m+1}\}$ can be obtained form the $\{d_l^{i+1,m}\}$, and the decomposition and reconstruction Wavelet packet can be expressed as formula 13 and 14:

$$\begin{cases} d_I^{j,2m} = \sum_k a_{k-2I} d_k^{j+1,m} \\ d_I^{j,2m+1} = \sum_k b_{k-2I} d_k^{j+1,m} \end{cases}, \quad (13)$$

$$d_I^{j+1,m} = \sum_k (h_{k-2I} d_k^{j,2m} + g_{k-2I} d_k^{j,2m+1}), \quad (14)$$

4. Rotor Fault Diagnosis Method Based on Wavelet Packet and LFDA

Based on the above several classic manifold learning algorithms, LFDA algorithm introduced the orthogonal iteration idea to ensure projection base vector orthogonal with each other, which brings gospel to discrimination of complex data. However, this method of the correct recognition rate is unstable in high-dimensional complex and a small amount of vibration signal processing and mapping data, which cannot classify the data rightly. The paper will make the best use of the advantage of Wavelet that multi-fault signals can be decomposed according to needs, combine LFDA algorithm and propose a new intelligent diagnosis method of coupling fault based on wavelet packet and LFDA. The steps of the method are as follows:

Step 1. Decompose the acquired coupling fault signal in the wavelet packet, then choose a wavelet and determine the number of layers which need to be broken down, and then decompose the fault signal by wavelet packet.

Step 2. Determine the optimal wavelet packet basis according to needs and calculate best tree (This step can be selected according to specific needs).

Step 3. Select an appropriate threshold to quantize all the wavelet packet coefficients.

Step 4. According to lowest level quantization coefficients and decomposed coefficient of wavelet packet, reconstruct the fault signal, and take the reconstructed data as sample data.

Step 5. Select the local neighborhood of sample data to construct neighborhood graph. If two points belong to the same neighborhood, then draw connections, else not.

Step 6. Solve the divergence between the classes $W_{i,j}$ and internal $W_{i,j}$, the degree of neighbor relationship $W_{i,j}$ between any two points in data space.

Step 7. Solve the projection matrix T_m, and solve the equation $S^w \phi = \lambda S^b \phi$ to get feature equation vector of the largest eigenvalues.

Step 8. Reduce the dimension of the sample space to find cluster centers, classify the projection of the training data, and finally realize the fault diagnosis.

5. Rotor Fault Diagnosis Test

5.1 Rotor Fault Diagnosis Test System

To verify the effect of the rotor fault diagnosis method based on wavelet packet and LFDA, we conducted imbalance, misalignment and imbalance-misalignment coupling faults experiments in Spectra Quest's rotor test rig. The experimental apparatus and measuring points are shown in Fig. 1. Two rolling bearings are mounted in an axial, radial and the six vertical Sensor. Rotor vibration signal is acquired by using PULSE acquisition system, at an sampling frequency 8192 Hz (set speed 10 Hz, 20 Hz, 30 Hz and 40 Hz). The required imbalance fault simulation experiment is simulated by installing the bolt threaded hole in the middle of the disk of the rotor system. 36 threaded holes are arranged on the turntable, on which can be installed a 5.596 g bolt. The two knobs around the plinth (as shown in Fig. 1 of partial enlargement) can be adjusted to control the relative position of the bearing housing at both ends of the axial and radial, while the coupling fault simulation is to set the needed research coupling fault type in the laboratory bench at the same time.

Fig. 2 is time-domain waveform of three types of faults under 30 Hz in speed and without load. Fig. 3 is frequency domain after Fourier transform.

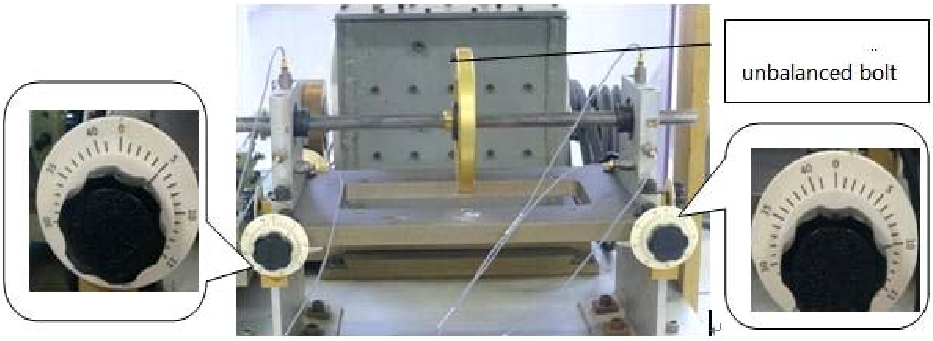

Fig. 1. Fault simulation of imbalance and misalignment in rotor system.

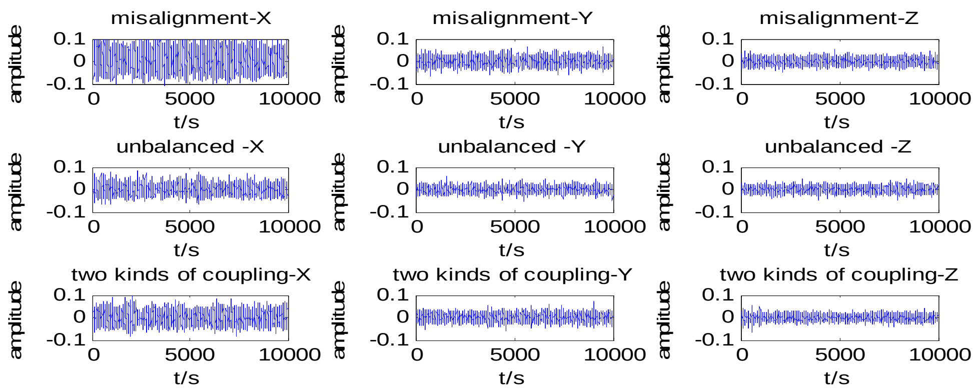

Fig. 2. Time domain characteristic figure of the rotor.

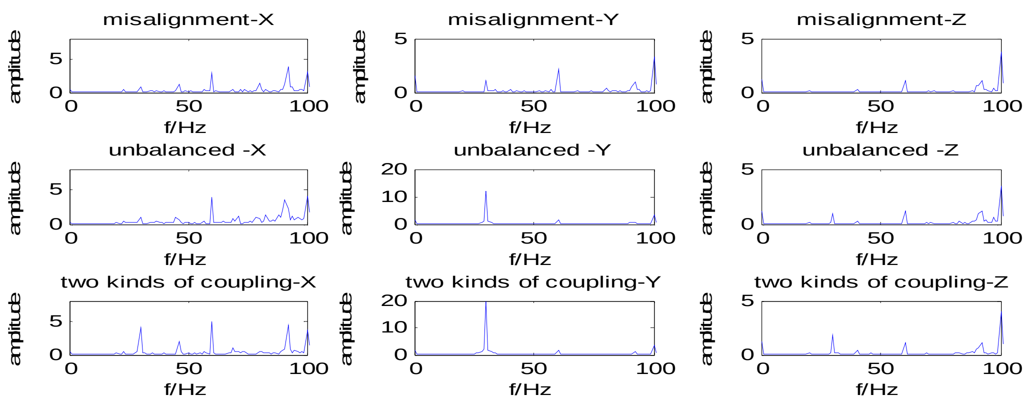

Fig. 3. Frequency domain characteristic figure of the rotor with faults.

5.2. The Characteristics of the Fusion of Multi-sensor Signals

In the fault diagnosis experiments, the vibration characteristics of the same kind of failure are differently in the axial, radial and vertical varies respectively, while different fault types are different in these three directions in terms of vibration amplitude, vibration velocity and vibration rate. For the rotor system, the distance between sensor measurement points and the fault source will also affect the test signal strength and signal to noise ratio (SNR). To better identify the fault type, we first integrate the signal fusion of the six vibration acceleration sensor.

The experiment uses data-level integration to constitute the vector indexes which can represent the fault features. Then 11 time-domain parameters were extracted out respectively from the sample data of these four states [16], which can constitute the original feature space. The 11 time-domain parameters are: mean, mean square, peak, skewness, kurtosis, root mean square value, pulse index, the absolute mean, peak indicators, waveform factor. Each sample vector has a total of 66 $(11\times 6=66)$ eigenvalues, constituting 66 dimensional sample data.

5.3. The Analysis of Fault Diagnosis Result

The 144 groups of data were selected at the rotational speed of 10 Hz, 20 Hz and 30 Hz (Four kinds of fault, a total $(4\times 36=144)$). The data was divided into training data and test data. Take 120 groups of data as the training sample, and then take 6 groups of misalignment fault data at the speed of 20 Hz, and 6 groups of unbalanced-misalignment coupling fault data at the speed 20 Hz as a test sample.

Training samples are estimated at dimension. Correlation dimension is estimated to be 0; neighboring field is estimated to be 1; GMST is estimated to be 2; the maximum likelihood is estimate to 15. Therefore, in this paper the signal intrinsic dimension selected is 2. Then each group of 66-dimensional data samples is simplified to two-dimensional and finally normalized to reduction results.

Fig. 4~9 represent the result of feature extraction and pattern recognition of the 4 fault training data, which is gained from the Fourier transform before the signal went through bandpass filter noise cancellation on LE, LPP, FDA, LFDA, IOLFDA and Wavelet packet and LFDA six kinds of algorithm. In the figure, the horizontal and vertical coordinates represent the component 1 and 2 of main characteristics; green '*' indicates normal state; red 'O' indicates misalignment fault; blue '+' indicates unbalance fault, black '★' says the imbalance – misalignment coupling faults.

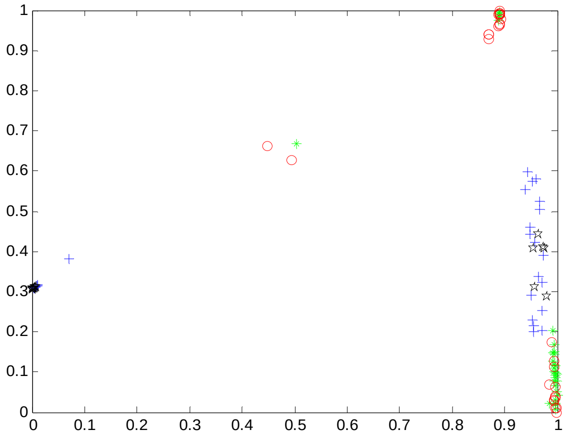

Fig. 4. Fault recognition results of LE.

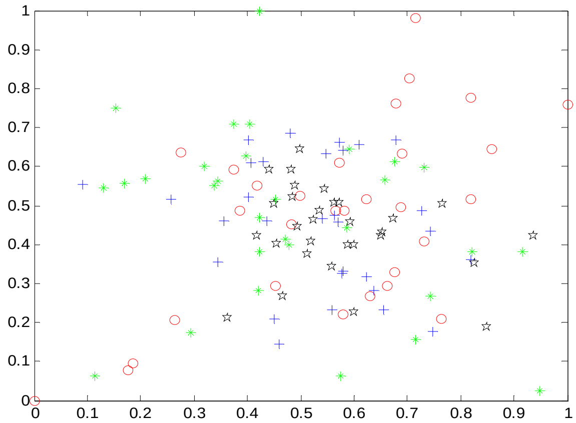

Fig. 5. Fault recognition results of LPP.

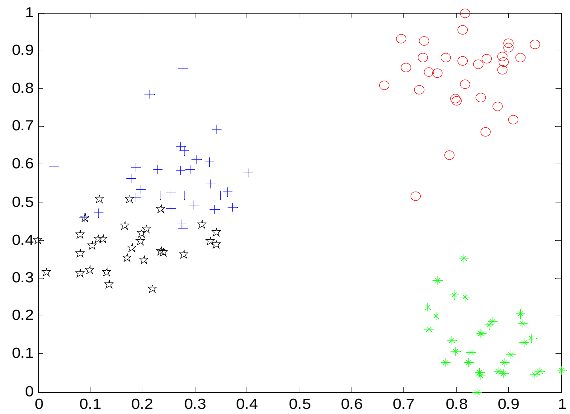

Fig. 6. Fault recognition results of FDA.

It can be seen in the figure that:

1) LE and LPP algorithm cannot identify the types of studied faults at all, while FDA and LFDA algorithm can fully identify normal and fault data and two types of single fault, but they cannot effectively identify imbalances and imbalances – misalignment coupling faults.

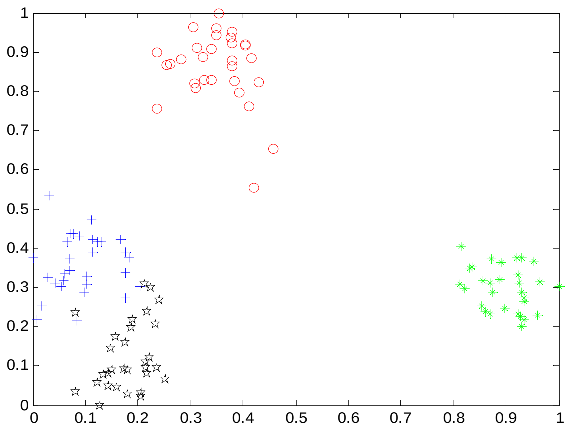

Fig. 7. Fault recognition results of LFDA.

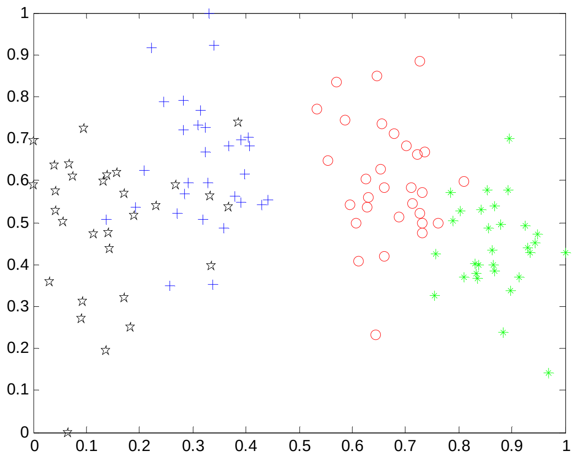

Fig. 8. Fault recognition results of IOLFDA.

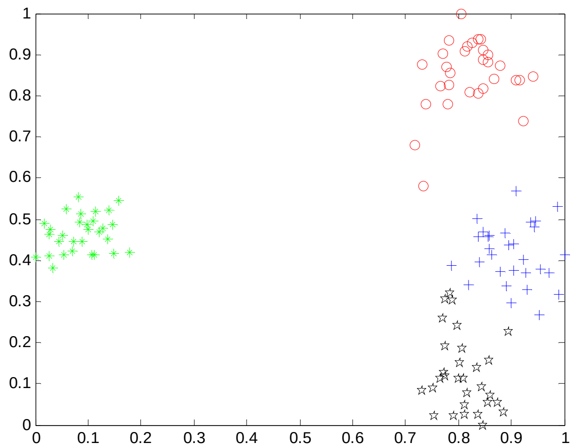

Fig. 9. Results of wavelet packet and LFDA.

2) IOLFDA algorithm preferably identify normal and fault data and two types of single fault, but the effect is not as good as that of FDA and LFDA algorithm, and it can't identify a single fault and failure data of coupling.

3) Wavelet packet and LFDA algorithm can not only recognize the difference between a single failure of the normal data, but also fully distinguish two single fault data and the data of single fault and coupling faults.

4) Fig. 6~9 show that unbalanced-misalignment coupling faults projection data was next to projection data of unbalanced fault, but far from misalignment fault projection data. The reason is that the imbalance misalignment coupling faults show up unbalanced fault characteristics.

The fault recognition correction rate is not only related to the embedding dimension, but also related to the neighboring numbers. The selected embedding dimension in this article is 2-dimensional, then most faults are only associated with the choice of neighboring numbers. Fig. 10, Fig. 11 represent the fault recognition correct rate and the number of neighbors graph of local Fisher discriminant algorithm and iterative orthogonal local Fisher discriminant algorithm respectively, among which fault recognition rate of training samples is shown in blue, and the test sample is shown in green. It can be found in the figure:

1) The fault recognition correct rate changed as the neighboring number varied.

2) When the number of neighboring is between 26 and 30, fault recognition rate of the LFDA algorithm reached the maximum value, then training sample identification rate is 99.17 % to LFDA, and test data is 88.9 %; but training sample identification rate is 89.17 % to IOLFDA, while test data is 66.7 %.

3) Wavelet packet algorithm and LFDA has a higher recognition rate than IOLFDA algorithm, the correct recognition rate of which is above 0.6. While Wavelet packet with LFDA algorithm changed greatly with the number of neighboring numbers. The highest fault recognition rate of other algorithms is shown in Table 1, among which the slash indicates the correct recognition of the algorithm rate is less than 50 %, which fails to identify the fault.

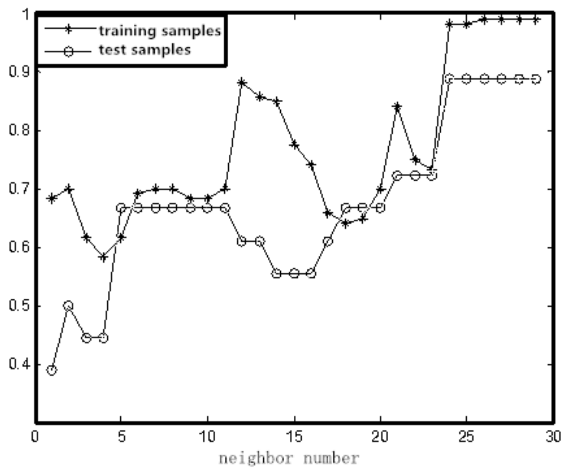

Fig. 10. Wavelet packet and LFDA recognition rate with the neighbor number of variation.

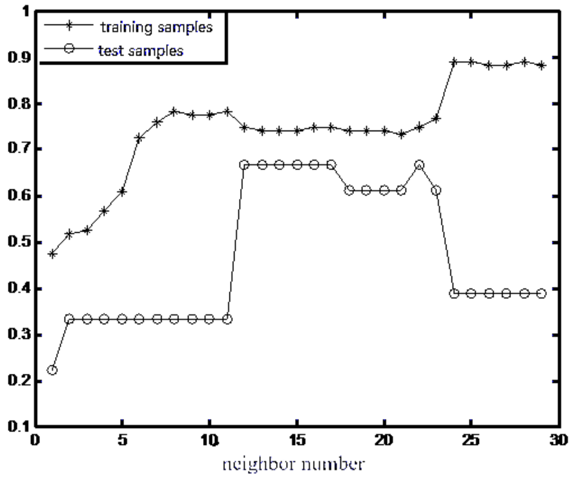

Fig. 11. IOLFDA recognition rate with the neighbor number of variation.

Table 1. Highest recognition rate of the four algorithms.

Data sample	The most correct recognition rate (%)					
	LE	LPP	FDA	LFDA	IOLFDA	Wavelet packet and LFDA
Training samples	/	/	93.3	95.83	89.17	99.17
Test samples	/	/	54.2	77.8	66.7	88.9

6. Conclusions

This paper gave a research on the rotor system unbalance, misalignment and imbalance-misalignment fault features. Analysis showed: 1) The rotor system failures have different Failure Characteristics in different directions. 2) Unbalanced fault occurs mainly in the vertical 1 frequency doubling. 3) With unbalanced-misalignment coupling faults, both in the vertical and radial exhibit to 1 frequency doubling, especially obvious in the vertical direction, while in the axial direction with 1 frequency doubling, 2 frequency doubling and 3 frequency doubling all exist, which is 3-frequency-doubling-oriented. This paper proposes a fault diagnosis method based on wavelet packet and LFDA algorithm. By comparing and analyzing the algorithms effect of LE, LPP, FDA, LFDA and IOLFA through experiment, it shows that Wavelet Packet and Local Fisher Discriminant Analysis (LFDA) have the best effect. They can not only recognize the difference between a single fault and the normal, but also distinguish imbalance, misalignment fault and coupling faults completely.

Acknowledgements

Financial support from National Natural Science Foundation of China (51175170), The Industrial Cultivation Program of Scientific and Technological Achievements in Higher Educational Institutions of Hunan Province (10CY008), Aid program for science and technology innovative research team in higher educational institutions of Hunan province, are gratefully acknowledged.

References

[1]. Wang Xiao-Dong, He Zheng-Jia, Adaptive construction of multiwavelet and research on composite fault diagnosis of rolling bearing, *Journal of Vibration Engineering*, Vol. 23, Issue 8, 2010, pp. 438-443.

[2]. V. Purushotham, S. Narayanana, A. N. Suryanajrayana, et al, Multi-fault diagnosis of rolling bearing elements using wavelet analysis and hidden Markov model based fault recognition, *Journal of NDT&E International*, Vol. 38, Issue 8, 2005, pp. 654-664.

[3]. F. Q. Wu, G. Meng, Compound rub malfunctions feature extraction based on full-spectrum cascade analysis and SVM, *Journal of Mechanical Systems and Signal Processing*, Vol. 20, Issue 8, 2006, pp. 2007-2021.

[4]. S. Abbasfon, A. Rafsanjani, A. Farshidianfar, et al, Rolling element bearing multi-fault classification based on wavelet noising and support vector machine, *Journal of Mechanical Systems and Signal Processing*, Vol. 21, Issue 7, 2007, pp. 2933-2945.

[5]. J. B. Tenenbaum, V. Silva, J. C. Langford, A global geometric gramework for nonlinear dimensionality reduction, *Science*, Vol. 290, No. 5500, 2000, pp. 2319-2323.

[6]. H. S. Seung, D. L. Daniel, The manifold ways of perception, *Science*, Vol. 290, No. 5500, 2000, pp. 2268-2269.

[7]. S. Roweis, L. Saul, Nonlinear dimensionality reduction by locally linear embedding, *Science*, Vol. 290, No. 5500, 2000, pp. 2323-2326.

[8]. M. Belkin, P. Niyogi, Laplacian Eigenmaps for dimensionality reduction and data representation, *Neural Computation*, Vol. 15, Issue 6, 2003, pp. 1373-1396.

[9]. M. Belkin, P. Niyogi, Laplacian Eigenmaps and spectral techniques for embedding and clustering, in *Proceedings of the Advances in Neural Information Processing Systems*, Whistler, Canada, 2002, pp. 1-7.

[10]. Z. Y. Zhang, H. Y. Zha, Nonlinear dimension reduction via local tangent space alignment, *IDEAL*, Hong Kong, China, 2003.

[11]. Z. Y. Zhang, H. Y. Zha, Principal manifolds and nonlinear dimension reduction via local tangent space alignment, *Scientific Computing*, Vol. 26, Issue 1, 2005, pp. 313-318.

[12]. W. Min, K. Lu, X. He, Locality preserving projection, *Pattern Recognition*, Vol. 37, Issue 4, 2004, pp. 781-788.

[13]. S. Masashi, Local Fisher discriminant analysis for supervised dimensionality reduction, in *Proceedings of 23rd International Conference on Machine Learning*, 2006, pp. 905-912.

[14]. S. Masashi, Dimensionality reduction of multimodal labeled data by local Fisher discriminant analysis, *Machine Learning Research*, Vol. 8, Issue 5, 2007, pp. 1027-1061.

[15]. Ge Zhexue, Chen Zhongsheng, Matlab time-frequency analysis technology and its application, *The People's Posts and Telecommunications Press*, Beijing, 2006, pp. 1061-1072.

[16]. Chen Guo, Introduction to aircraft detection and diagnosis techniques, *China Civil Aviation Publisher*, Beijing, 2007.
