Kernel Local Fuzzy Clustering Margin Fisher Discriminant Method Faced on Fault Diagnosis

Guangbin Wang
Engineering Research Center of Advanced Mine Equipment
Ministry of Education, Hunan University of Science and Technology
Xiangtan, China
jxxwgb@126.com

Xuejun Li and KuangFang He
Hunan Provincial Key Laboratory of Health Maintenance for Mechanical Equipment, Hunan University of Science and Technology
Xiangtan, China
hnkjdxlxj@163.com, hkf791113@163.com

***Abstract*— In order to better identify the fault of rotor system,one new method based on local fuzzy clustering margin fisher discriminant (LFCMFD) was proposed. For each point on manifold, the farthest point in local neighborhood and the nearest point outside local neighborhood usually constituted the local margin. LFCMFD introduced fuzzy cluster analysis algorithm, eliminated the influence of pseudo-margin points, obtained real local margin, compute with-class scatter and between-class scatte, established local magin fisher discriminant function, found optimal fault diagnosis vector,and then identified the fault class of new testing data by this vector. In order to improve the nonlinear analysis ability of LFCMFD, considering kernel mapping idea, training data with supervision information were mapped to kernel space, constructed kernel fisher discriminant function, LFCMFD algorithm based on kernel method (KLFCMFD)was proposed. The experiment showed, KLFCMFD algorithm had best effect in comparison to other manifold learning algorithm to the rotor fault diagnosis,and fully identify fault class when selecting the appropriate parameters.**

***Index Terms*— fuzzy clustering, local margin, fisher discriminant, kernel mapping, fault diagnosis**

I. INTRODUCTION

The basic problem of fault diagnosis is to find the state of equipment based on the relationship between the fault symptoms and information of equipment operating status, the core is the feature extraction and pattern recognition. Rotor system is the most important part of many large-scale machinery, its fault feature is the abnormal vibration of the rotor. The current study focused primarily on the diagnosis of the non-linear fault. Along with the multi-sensor monitor technology's application, reflected that the device status the information content is getting bigger and bigger, the data dimension is also getting higher and higher, thus causes the efficiency of some failure diagnosis method (for example fuzzy logic, neural network, support vector machines and so on) drops rapidly. In order to solve such so-called “the dimension disaster” question, needs should be carried on the reasonable dimension reduction or the attribute extraction to the data set, and proposes the new solution.

In 2000, Roweis. and Seung simultaneously had published the research papers about the manifold learning in Science [1-2], proposed Isometric feature Mapping (ISOMAP) [1] algorithm and Locally Linear Embedding (LLE) [2] algorithm, and successfully applied them to recognition in the graph and characters. As a starting point, the researchers had launched a variety of algorithms, such as Laplace feature Mapping (LE) [3], Local Tangent Space Alignment (LTSA) [4] and other algorithms[5-6]. The study of manifold learning faced to fault diagnosis for mechanical equipment had just started[7-8], but the problem how to effectively deal with incremental data in manifold learning algorithms hadn’t been resolved, that timely monitoring and on-line diagnosis of equipment status hadn’t been resolved. In 2006, Masashi Sugiyama had proposed Local Fisher Discriminant Analysis (LFDA) algorithm on the basis of Locality Preserving Projection (LPP)[9] and Fisher Discriminant Analysis (FDA) algorithms[10], redefined with-class scatter and between-class scatter by drawing on the supervised learning ideas in LPP, and then built local fisher discriminant function for pattern recognition [11-12]. LFDA seeks for the optimal projection vectors by solving the non-symmetry characteristic equation for dimension reduction and pattern classification, which can not ensure that all vectors are orthogonal and eventually lead to the reconstruction of the data becomes very difficult. At the same time, LFDA is a kind of linear algorithm, therefore it cannot be better to explore non-linear factors generated from the rotor complex vibration. The research fault diagnosis based on LFDA has already begun [13-15].

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In this paper, considering the local margin concept and fuzzy clustering method, Local Margin Fisher Discriminant (LMFD) and Local Fuzzy Clustering Margin Fisher Discriminant (LFCMFD) are proposed. By means of kernel mapping, the LMFD and LFCMFD methods based on kernel are proposed, two linear methods would better treat non-linear signal. The experiment of rotor fault diagnosis shows, the KLMFD and KLFCMFD methods have better effect to other manifold learning algorithm such as FDA、LFDA、LMFD、LFCMFD.

II. THE SEEKING WAY OF LOCAL FUZZY CLUSTERING MARGIN (LFCM)

Local margin is established on the basis of the concept of the border neighborhood. Suppose $x_i \in R^d (i = 1,2\cdots n)$, x_i is be d dimension data sample, then the neighborhood matrix X_i of each x_i is established. The local margin of X_i and $X_j\ (j \neq i)$ may be decided by the nearest point in X_i to x_j and the farest point in X_j to x_i . In manifold learning, k-neighborhood way has often been employed, but it easily brings the pseudo boundary points.

Suppose the farest point x_{c1} and the minor farest point x_{c2} in the same class of x_i, we belive that x_{c1} is the pseudo boundary point of x_i when $dis(x_i, x_{c1}) - dis(x_i, x_{c2}) \rangle\rangle d$, it should be replaced by x_{c2} . If the neighbor points of x_i uniformly distributed in the local space, we believe no pseudo boundary point. Meanwhile, let cluster centers two which one is x_{i1} and other is x_{i2} . Suppose the distance d_{i1} between x_i and x_{i1}, the distance d_{i2} between x_i and x_{i2}, then $\max\ (d_{i1}/d_{i2},\ \ d_{i2}/d_{i1}) \to 1$

The basic steps to search local fuzzy clustering margin are as follows. At first, select the number of neighbors and construct local neighborhood graph, then run the c-mean clustering in the local subspace of x_i and obtain two cluster center x_{i1} and x_{i2} ,calculate the distance d_{i1} between x_{i1} and x_i , d_{12} between x_{i2} and x_i respectively, if the larger value of d_{i1}/d_{i2} and d_{i2}/d_{i1} close to 1, the farest with-class point x_q and the closest the between-class point x_p in the different class from x_i construct the local margin point pairs. Otherwise, repeat construct a new local neighborhood by removing the furthest point to x_i in the same class from the original local neighborhood, when $\max(d_{i1}/d_{i2}, d_{i2}/d_{i1})$ converges to 1,the furthest point is the real local margin.

III. LOCAL MARGIN FISHER DISCRIMINANT (LMFD) AND LOCAL FUZZY CLUSTERING MARGIN FISHER DISCRIMINANT (LFCMFD)

In LFDA, the with-class and between-class divergence were solved based on all point pairs of the local neighborhood point of x_i ,but in LMFD, the with-class and between-class divergence were solved based on the local margin point paris of x_i, computation is greatly reduced.

Here, the weight vector of edge in the local neighborhood graph is determined by the way of cold kernel, if this point is real local margin point and $\overline{A} = 1$, otherwise $\overline{A} = 0$. Thus local margin with-class and between-class divergence $\hat{S}^w$ 、 $\hat{S}^b$ may be defined as follows:

$$\hat{S}^w = \sum_{i=1}^{n} (x_i - x_p)(x_i - x_p)^T \tag{1}$$

$$\hat{S}^b = \sum_{i=1}^{n} (x_i - x_q)(x_i - x_q)^T \tag{2}$$

Suppose y_i 、 y_p 、 y_q are the low-dimensional mapping of x_i 、 x_p and x_q , then $y_i = W^T x_i$; $y_p = W^T x_p$, $y_q = W^T x_q$, The optimal projection vector W may be obtained by solving to Eq.4

$$\begin{aligned}
&\max \frac{\sum_{i=1}^{n} (y_i - y_p)(y_i - y_p)^T}{\sum_{i=1}^{n} (y_i - y_q)(y_i - y_q)^T} \\
&= \max \frac{\sum_{i=1}^{n} (W^T x_i - W^T x_p)(W^T x_i - W^T x_p)^T}{\sum_{i=1}^{n} (W^T x_i - W^T x_q)(W^T x_i - W^T x_q)^T} \\
&= \max \frac{\sum_{i=1}^{n} W^T [(x_i - x_p)(x_i - x_p)^T] W}{\sum_{i=1}^{n} W^T [(x_i - x_q)(x_i - x_q)^T] W} \\
&= \max \frac{W^T \hat{S}^b W}{W^T \hat{S}^w W}
\end{aligned} \tag{3}$$

If the vector $\alpha \in R^d$ is the basis projection vector, the optimal question on Eq.3 can be expressed by solving to Eq.4.

$$f(\alpha)=\alpha_m^T\hat{S}^b\alpha_m/(\alpha_m^T\hat{S}^w\alpha_m) \tag{4}$$

The transformation matrix *T* is made of the eigenvectors corresponds to m largest eigenvalue of $\hat{S}^w\alpha=\lambda\hat{S}^b\alpha$. The linear dimension reduction and pattern recognition can be performed by *T*. The basic steps of fault diagnosis by LMFD algorithm are as follows:

Step 1. Select the number of local neighbors, find the local margin point pairs.

Step 2. Calculate $\hat{S}^w$ 、 $\hat{S}^b$ according to Eq.1 and Eq.2,obtain local fisher discriminant function $f(\alpha)$.

Step 3. obtain the optimal mapping matrix $T=[\alpha_1,\alpha_2,\cdots\alpha_m]$ by solving the eigenvectors corresponds to the maximum eigenvalues of $\hat{S}^w\alpha=\lambda\hat{S}^b\alpha$.

Step 4. Suppose the training and test sample matrix are X and Z, calculate the low-dimensional coordinates Y of training samples X by $Y=T^TX$, identify the c-mean cluster center of each class. Calculate n the low-dimensional coordinates of testing samples by T^TZ, we can obtain diagnosis class of equipment by the nearest neighbor classifier.

The difference between LFCMFD method and LMFD method lies in the diffrent method of finding the local margin in step 1. The method of former is fuzzy C-means clustering, but the latter directly use the with-class farthest point and between-class closest point to obtain the local margin. Then build local margin fisher criterion, find the projection vectors to achieve the fault diagnosis on machinery and equipment.

IV. KERNEL LOCAL MARGIN FISHER DISCRIMINANT (KLMFD) AND KERNEL LOCAL FUZZY CLUSTERING MARGIN FISHER DISCRIMINANT (KLFCMFD)

The LMFD and LFCMFD methods are linear, the effect of fault recognition to non-linear signal generated from the complex vibration of rotor is limited, the introduction of kernel method can solve this question.

First, the nonlinear vibration signal are mapped to kernel space F by kernel function ϕ and obtain kernel matrix K. Assume that the projection vectors of x_i 、 x_p and x_q are $\varphi(x_i)$ 、 $\varphi(x_p)$ and $\varphi(x_q)$, then S^w and S^b can be computed by Eq.5 and Eq.6.

$$S^w=\sum_{i=1}^{n}(\varphi(x_i)-\varphi(x_p))(\varphi(x_i)-\varphi(x_p))^T \tag{5}$$

$$S^b=\sum_{i=1}^{n}(\varphi(x_i)-\varphi(x_1))(\varphi(x_i)-\varphi(x_q))^T \tag{6}$$

The kernel matrix K can be expressed as:

$$K=\{k_{ij}\}=\{\varphi(x_i)\bullet\varphi(x_j)\}=\{\varphi(x_i)\varphi(x_j)^T\} \tag{7}$$

In Eq.7,

$$\begin{aligned}&[\varphi(x_i)-\varphi(x_p)][\varphi(x_i)-\varphi(x_p)]^T\\&=\varphi(x_i)\varphi(x_i)^T+\varphi(x_p)\varphi(x_p)^T-2\varphi(x_i)\varphi(x_p)^T\\&=k_{ii}+k_{pp}-2k_{ip}\end{aligned} \tag{8}$$

So S^w and S^b can be expressed by the kernel matrix k_{ij} as:

$$S^w=\sum_{i=1}^{n}[k_{ii}+k_{pp}-2k_{ip}] \tag{9}$$

$$S^b=\sum_{i=1}^{n}[k_{ii}+k_{qq}-2k_{iq}] \tag{10}$$

The fisher discriminant function of LMFD and LFCMFC based is:

$$f(\alpha)=\alpha_m^TS^b\alpha_m/(\alpha_m^TS^w\alpha_m) \tag{11}$$

The transformation matrix T_K is made of the eigenvectors corresponds to m largest eigenvalue of $S^w\alpha=\lambda S^b\alpha$ .So $T_K=[\alpha_1,\alpha_2,\cdots\alpha_m]$.

TO data samples x_i, its' low-dimension projection vectors z_i of KLFCMFD and KLMFD are:

$$z_i^r=\sum_{j=1}^{n}\alpha_j^rK_{ij}\qquad r=1,2,\cdots m \tag{12}$$

z_i^r means the r-th element of vector z_i. The basic steps of fault diagnosis by LMFD algorithm are as follows:

Step 1. Select the number of local neighbors, find the local margin point pairs.

Step 2. Select kernel function ϕ,mapping train sample to kernel space,obtain kernel matrix K by Eq.7.

Step 3. Calculate S^w 、 S^b according to Eq.9 and Eq.10, obtain local fisher discriminant function $f(\alpha)$.

Step 4. obtain the optimal mapping matrix

$T_K = [\alpha_1, \alpha_2, \cdots \alpha_m]$ by solving the eigenvectors corresponds to the maximum eigenvalues of $S^w \alpha = \lambda S^b \alpha$.

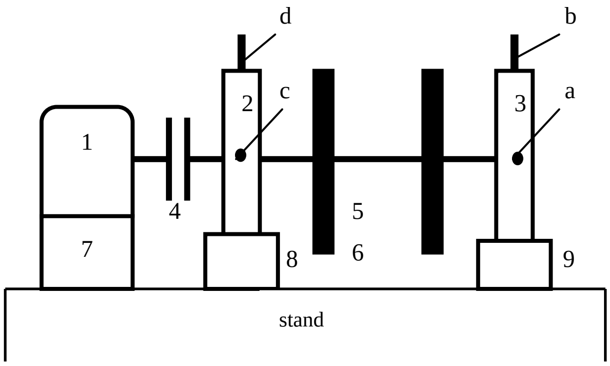
Step 5. Suppose the kernel matrix of the training and test sample are K_X and K_Y, obtain the low-dimensional coordinates Z_X and Z_Y by Eq.12. First, find the cluster center of each fault in Z_X, we can obtain diagnosis class of Z_Y by the nearest neighbor classifier.

The difference between KLFCMFD method and KLMFD method lies in the former using fuzzy C-means clustering to find local real margin.

V. EXPERIMENT FOR ROTOR FAULT DIAGNOSIS

A. Experimental equipment

In order to verify diagnosis effect of these algorithms, experiment had been operated on QPZZ-II rotor experimental stand. We had completed test experiment in three fault status including normal system, inner ring crack fault of bearing and loose fault of base.



1.motor 2,3 bearing 4.coupler 5,6.rotor 7,8,9.base a,b c d.sensor
Figure 1. Experiment equipment and distribution of measuring point

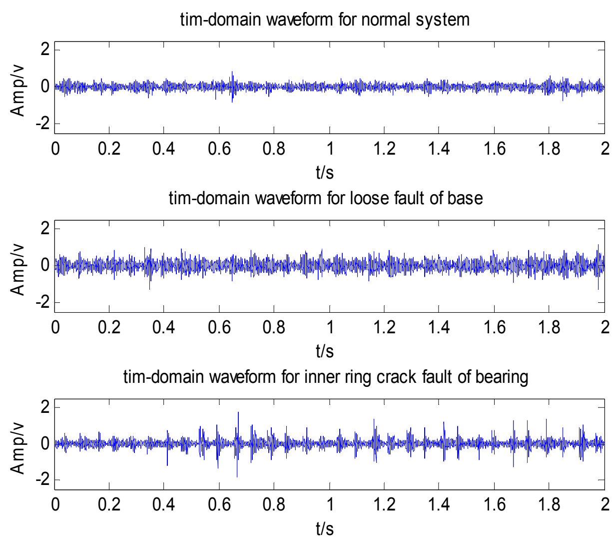


Figure 2. Time domain waveform of three fault status

Measuring point is shown in Fig.1. L1~L4 are four piezoelectric accelerometers ,which were installed on the rolling bearing base in vertical and horizontal direction, the vibration signal was gotten by using the DEWE-201 data acquisition system, sampling frequency was 5000HZ, each fault signal had be sampled in the nine different condition, such as different speed of 10HZ、20HZ and 30HZ, different load of no load, large load and small load. Figure 2 shows time domain waveform of three fault status sampled by sensor L1 in the speed of 20HZ and no load.

B. Characteristic fusion of multi-sensor signal data

In the experiment, the rotor vibration characteristic is often different in the horizontal and vertical directions. They are also different for vibration amplitude, frequency and change of frequency on different fault types. At the same time, the distance between measuring point and fault source has also impact on signal strength. In order to better determine fault class. In the experiment we syncretize the signals of four vibration acceleration sensor.

In accordance with the three levels of data abstraction, information fusion method can be divided into data-level fusion, feature-level fusion and decision-level fusion. In this study, using feature-level fusion, we selected 8 time-domain characteristics (variance, skewness, kurtosis, RMS, peak index, wave index, pulse index, margin index) to each sensor, then four sensors had 32 characteristics, constituted 32-dimensional data , and sensor characteristics order followed a, b, c, d. 288 samples had been obtained in experiment,we picked up 48 samples as training samples and other 48 samples as test samples in each fault class data.

C. Analysis of experimental result

Fig.3 is experimental result of fault pattern recognition for training data by respectively using five methods, such as LMFD, LFCMFD, KLMFD and KLFCMFD, the sign * is on behalf of normal status, the sign O is on behalf of base loose fault, the sign + is on behalf of bearing inner ring fault. As can be seen, using LMFD and LFCMFD, it is easy to recognize normal and fault state, but not effective to distinguish two kinds of different fault. Using KLMFD and KLFCMFD, it is better to distinguish three different status.Here, kernel parameter σ is 0.03, the number of neighbor is 33.

After getting the optimal projection vectors to achieve the best classification results, using the vector, we had completed the experiment of fault diagnosis for 144 training samples and 144 test samples.

For LFMD and LFCMFD, the correct recognition rate is relevant with the number of neighbor, while for KLFMD and KLFCMFD, the correct recognition rate is not only relevant with the number of neighbor, but also relevant with kernel function and kernel parameter. where, function select gauss kernel, parameter is σ. The experimental result is as shown in Fig.4, Fig.5 and Fig.6.

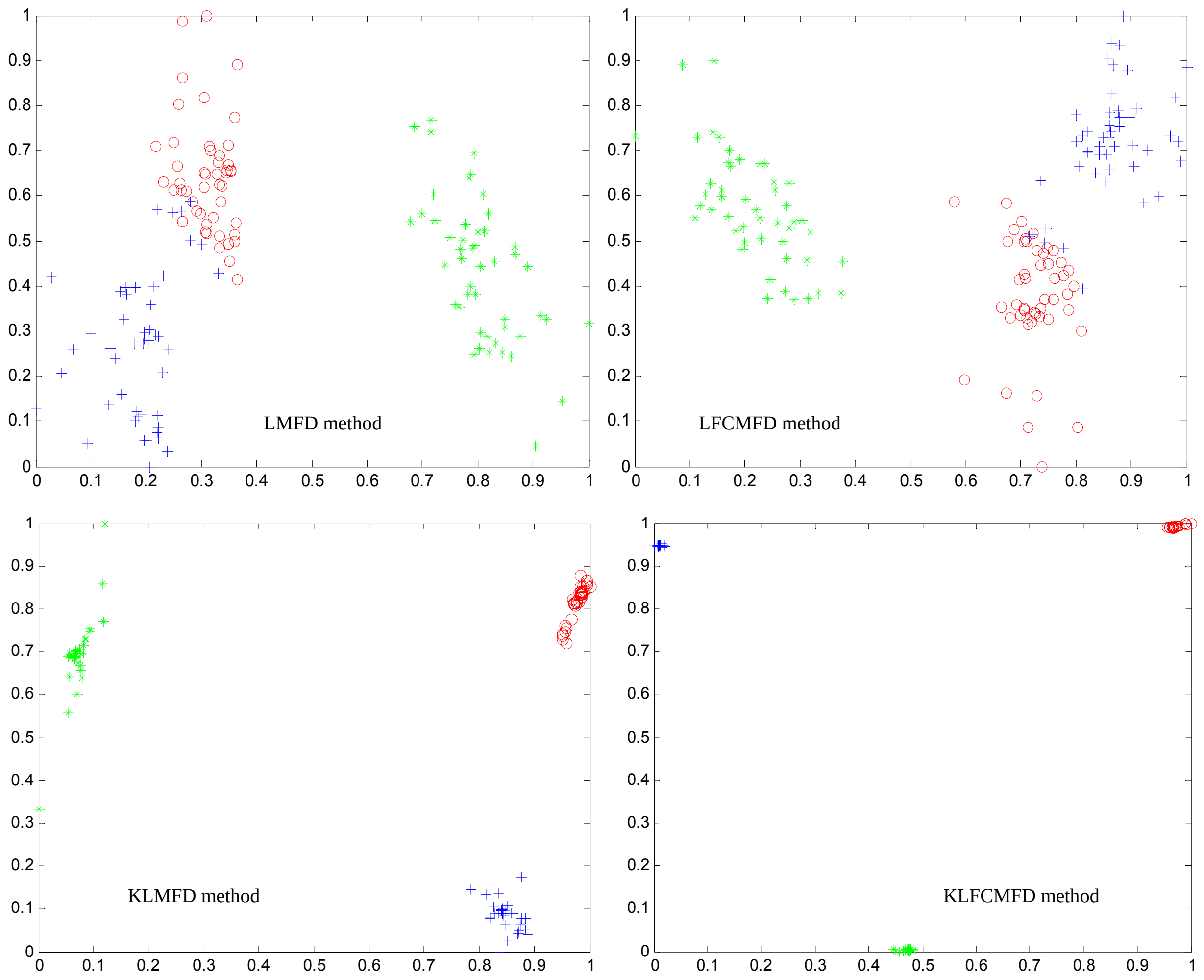


Figure 3. Fault pattern recognition's reuslt of four methods(LMFD、LFCFD、KLMFD、KLFCMFD)

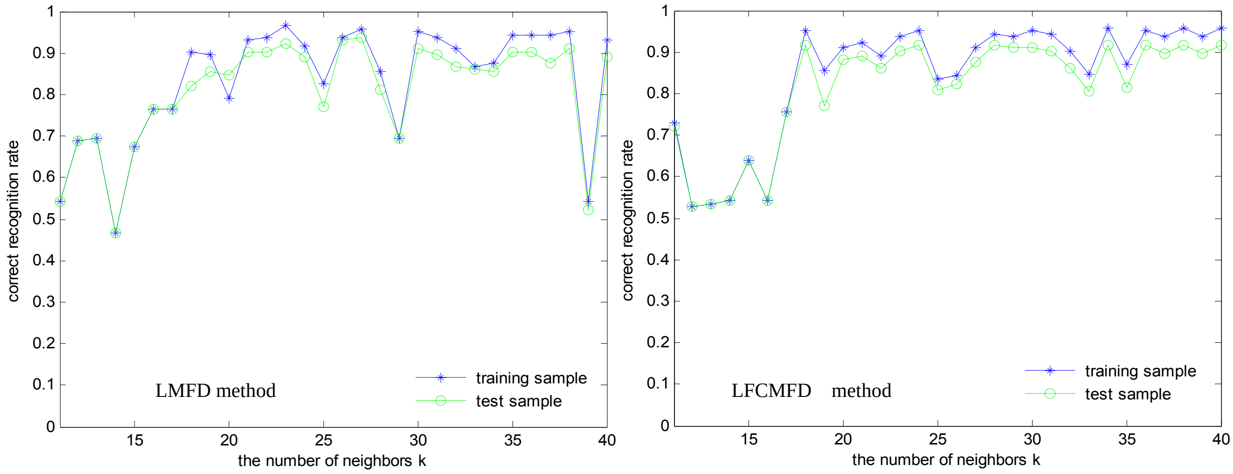
As can be seen from Fig.4, for the two linear methods, both the training sample and the test samples, the correct recognition rate can not reach 100% whatever the number k of neighbors select . When k is greater than 18, the correct recognition rate may be more than 80% except individual points . Because of the interference of pseudo margin point, it sometimes appears that recognition rate suddenly reduce when using LMFD method, however, LFCMFD method adopts fuzzy clustering method, it can effectively reduce the interference of pseudo margin point and achieve stable fault recognition effect

In Fig.5, for KLMFD method, we can find that the number of neighbors k is slight influence to the result of fault diagnosis, which is different from linear method. But Gaussian kernel parameters σ has very big effect to the result of fault diagnosis. For test samples, along with the increase of σ, the correct recognition rate of will be reduce. Highest correct recognition of the test sample may reach 100% when $\sigma = 0.02$, and only correct recognition of some points reduce. When $\sigma = 0.04$, highest correct recognition rate of the test sample may reach 95.83%. When $\sigma = 0.06$, highest correct recognition rate of the test sample reduce to 92.36%, correct recognition of some points reduce to 80%. On the whole, no matter the training sample or testing samples, the correct recognition rate appear sudden decrease, this is the result of interference with pseudo margin points.

As can be seen from Fig.6, the KLFCMFD method is as KLMFD method, the number of neighbors k has little effect to correct recognition rate of the sample, but gaussian kernel parameter σ has very big effect. Along with the increase of σ, the correct recognition rate of test sample will be reduced constantly, and change rule is consistent with KLMFD, but the range of change greatly reduce.

Now, we compare the change scope of the correct recognition in two kernel methods when kernel parameter changes, the number of neighbors k =12 ~ 40. Form Tab.1, we can see that the change scope of the correct recognition rate obtained by KLFCMFD method is less than the rate obtained by KLMFD. It shows that fuzzy clustering margin search method has a very good effect in reduce false margin point interference, and improve the average level of fault identification accuracy.

For the training sample, using LFCMFD and KLFCMFD , the highest diagnostic accuracy rate achieve 95.83% and 100% respectively. For the testing sample, both the highest diagnostic accuracy rate also can achieve 91.67 and 100% respectively. From the perspective of each method's computational complexity, LFDA algorithm has more than the four local margin fault diagnosis methods proposed in this paper. Especially, when fault class and the quantity diagnostic data increase, the require of timely and stability of algorithm increase, KLFCMFD algorithm will have greater advantages in diagnosis effect and efficiency.



Figurer 4. The change of the correct recognition rate with *k* in LMFD and LFCMFDmethods

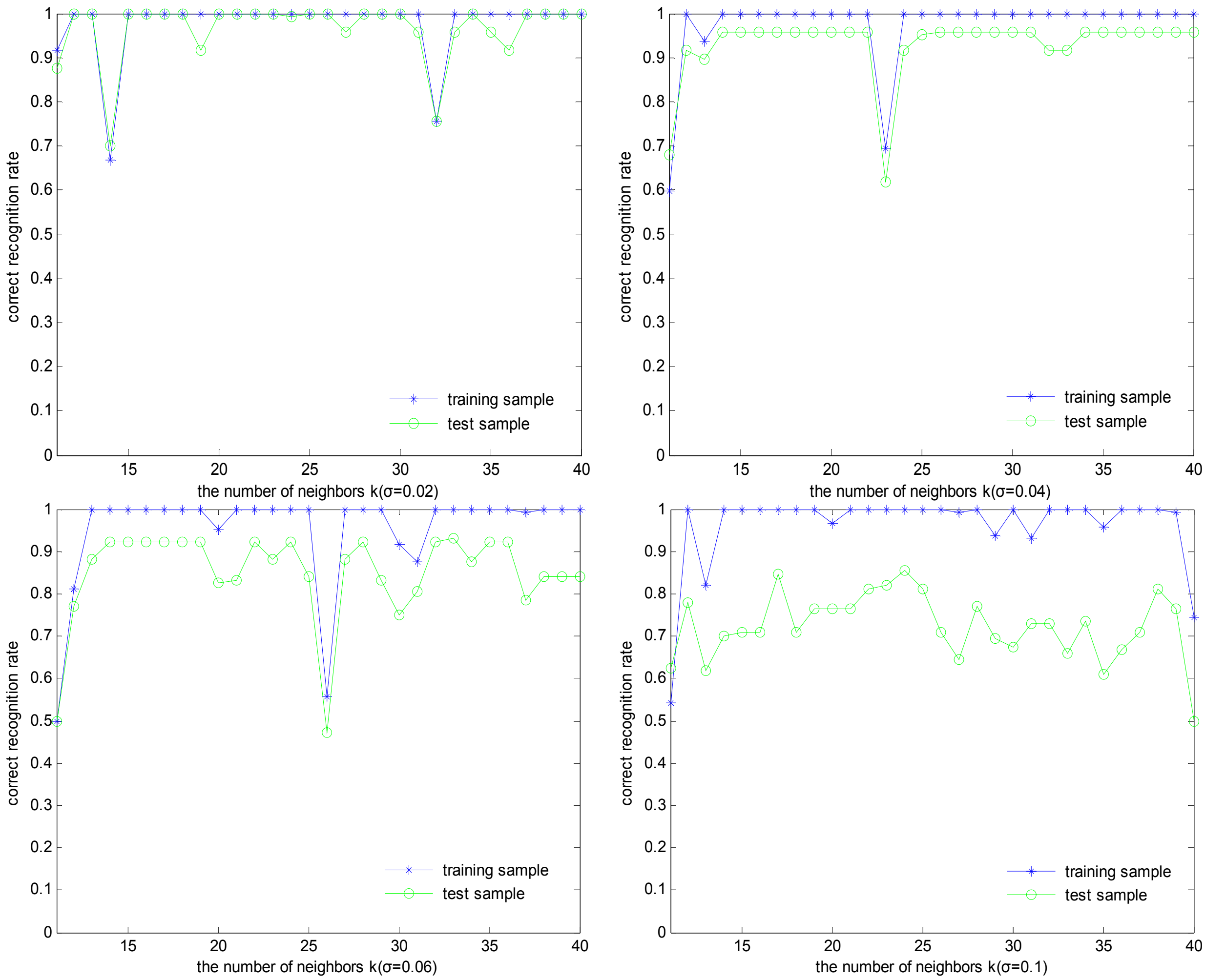


Fig.5 The change of the correct recognition rate with *k* and σ in KLMFD method

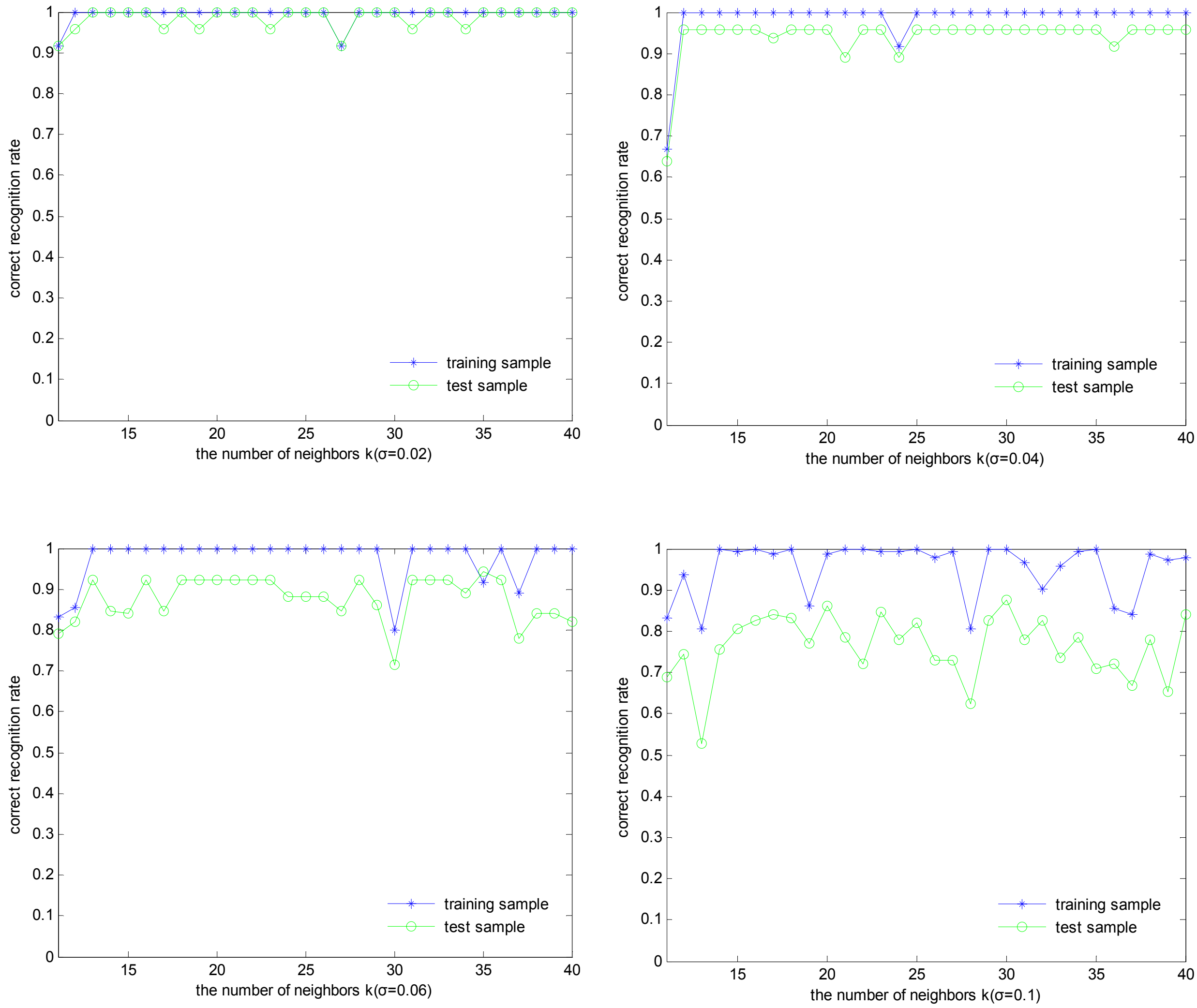


Fig.6 The change of correct recognition rate with k and σ in KLFCMFD method

TABLE Ⅰ.
THE CHANGE OF THE CORRECT RECOGNITION RATE IN KLMFD AND KLFCMFD

Kernel parameter	The correct recognition rate to all samples in KLMFD			The correct recognition rate to all samples in KLFCMFD		
	highest	lowest	change scope	highest	lowest	change scope
σ =0.02	100%	66.67%	33.33%	100%	91.67%	8.33%
σ =0.04	100%	69.64%	30.36%	100%	88.89%	11.11%
σ =0.06	100%	55.56%	44.44%	100%	71.53%	28.47%
σ =0.10	100%	50%	50%	100%	52.78%	47.22%

VI. CONCLUSION

In this paper, we have studied the concepts of the margin and local margin, given the local margin definition by choosing the farthest similar data points and the recent heterogeneous data points of each point as the local margin, proposed local margin fisher discriminant fualt diagnosis method. In order to eliminate the interference of the pseudo margin points which appeared in determining local margin by using k adjacent method, seeking method based on fuzzy cluster analysis was found, proposed local fuzzy clustering margin fisher discriminant fualt diagnosis method. In the two methods, after finding local margin and local fuzzy clustering magin, compute with-class scatter and between-class scatte, constructe fisher discriminant function, find optimal fault diagnosis vector, and then identify the fault type of new testing data by this vector.

In order to better identify the fault of rotor system, considering kernel mapping, we proposed fault diagnosis method local margin and local fuzzy clustering margin fisher discriminant based on kernel, realized the algorithm's change from linear to non-linear. The experiment of rotor fault diagnosis shows, the four methods such as LMFD, LFCMFD, KLMFD 和 KLFCMFD have been different degrees level to fault diagnosis of machinery and equipment, but the stability of KLFCMFD and LFCMFD are better than LMFD and KLMFD, KLFCMFD has the best pattern recognition and diagnosis capacity.

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REFERENCES

[1] .H.Sebastian Seung, and Daniel D.Lee, "The manifold ways of perception", *Science*, vol.290, pp.2268- 2269, December 2000.

[2] Sam T.Roweis, and Lawrence K.Saul, "Nonlinear dimen sionality reduction by locally linear embedding", *Science*, vol. 290, pp.2323- 2226, December 2000.

[3] M.Belkin, and P.Niyogi, "Laplacian eigenmaps for dimen sionality reduction and data representation" , *Science*, vol. 290, pp.2323- 2226, December 2000.

[4] Z. Zhenyue, and Z. Hongyuan, "Principal manioflds and nonlinear dimension reduction via Tangent Space Alignmnet", *SIAM Journal on Scientific Computing*, vol. 26, pp.313-338, January 2005.

[5] K.Olga, O.Oleg, and Matti Pietikäinen, "Supervised locally linear embedding algorithm for pattern recognition", *Pattern Recognition and Image Analysis*, vol.2652, pp.386-394, December 2003.

[6] M.Belkin, and P.Niyogi, "Semi-Supervised learn- ing on riemannian manifolds", *Maching Learning*, vol.56, pp.209-239, January 2004.

[7] Y. jianhong, X. jinwu, Y. debin, and Li min, "Noise reduction method for nonlinear time series based on principal manifold learning and its application to fault diagnosis", *Chinese Journal of Mechanical Engineering*, Chinese, vol.45, pp.154-158, August 2006.

[8] J. quansheng, J. minping, H. jianzhong, and X. feiyun, "Method of fault pattern recognition based on laplacian eigenmaps", *Journal of System Simulation*, Chinese, vol.20, pp.5710-5713, October 2008.

[9] H. Xiaofei and P.Niyogi. "Locality preserving projections", *Advances in Neural Information Processing Systems 16, cambrifge*, June 2004.

[10] .W.guangbin, L.yilun, Z.xianqiong, "fault diagnosis of rolling bearings based on LLE_KFDA', *Materials Science Forum*, vol. 626-627, pp. 529-534, September 2009

[11] S.Masashi, "Local fisher discriminant analysis for aupervised dimensionality reduction", *Proceedings of 23rd International Conference on Machine Learning*, pp.905-912 June 2006.

[12] S.Masashi, S.Roweis, "Dimensionality reduction of multimodal labeled data by local fisher discriminant analysis", *Machine Learning Re-search*, vol.8, pp.1027-1061, 2007

[13] W.guangbin, H.liangpei, K.yuhua, "Fault diagnosis based on kernel schur-orthogonal local fisher discriminant", *chinese journal of scientific instrument*, Chinese , vol.31, pp.1005- 1009, May 2010

[14] .W.guangbin, H.liangpei, K.yuquan, "Rotor Fault Diagnosis Based on Orthogonal Iteration Local Fisher Discriminant", *Journal of Vibratiion, Measurement and Diagnosis*, Chinese, vol.30, pp.500- 503, October 2010

[15] W.guangbin, H.liangpei, "An improved noise reduction algorithm based on manifold learning and its application to signal noise reduction" , *Applied Mechanics and Materials*, vol.26-28, pp.653-656, September 2010

Guangbin Wang, male, born in December 1974 in LinZhou city of Henan province, obtained PHD in 2010 from Central South University, research field are manifold learning and equipment's fault diagnosis.

He has been working at Hunan University of Science and Technology since 1999, mainly engaged in student management, teaching and scientific research. His works have, "Fault diagnosis based on kernel schur-orthogonal local fisher discriminant", Chinese journal of scientific instrument(2010),"Rotor Fault Diagnosis Based on Orthogonal Iteration Local Fisher Discriminant" Journal of Vibratiion, Measurement and Diagnosis(2010);"A improved noise reduction algorithm based on manifold learning and its application to signal noise reduction" , Applied Mechanics and Materials(2010).His research interest are nonlinear signal processing and equipment's condition monitoring and fault diagnosis.

Dr. Wang is a member of Hunan Province instrument ation Institute. In recent years, he presided 2 provincial research projects, obtained two provincial academic awards, published more than 20 academic papers.

Xuejun Li, male, born in 1969.He is currently a professor in Key Laboratory of Health Maintenance for Mechanical Equipment of Hunan Province, Hunan Science and Technology University, China. He obtained his PhD degree in2003.His research interests include mechanical dynamics, failure diagnose, dynamic test and signal dealing, equipment maintenance technology.

Kuanfang He, male, born in 1979. He received Ph. D from South China University of Technology in 209. He is currently working at Hunan University of Science and Technology, China. His research interests include dynamic monitoring and control for electromechanical systems.