Application of EWT AR model and FCM Clustering in Rolling Bearing Fault Diagnosis

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***Abstract*—A fault diagnosis method is proposed, which is based on Empirical Wavelet Transform (EWT), Auto-Regressive (AR) model and Fuzzy C-Mean clustering (FCM) clustering algorithm, in order to solve the problem of fault category is difficult to identify of rolling bearing fault signal. In this method, the original signal of the rolling bearing is decomposed by the EWT, and several AM-FM components are obtained. The AR model is established for each AM-FM component, and the original feature subset is constructed. Then, through the correlation analysis, the four AM-FM components are extremely correlated with the original vibration signal are selected and their AR models are established. Construction of high-dimensional feature subsets based on the auto-regressive parameters of AR model. Finally, using the Locality Preserving Projection (LPP) algorithm to reduce the dimension and enter the low-dimensional feature subset to the FCM clustering, in order to achieve fault diagnosis of bearings. Experiments show that the fault identification method which is proposed in this paper has certain advantages and the fault recognition effect is better.**

Keywords—empirical wavelet transform; AR model; locality preserving projection; fuzzy C-Mean clustering

I. INTRODUCTION

As the core component of rotating machinery, the running state of rolling bearing is directly affecting the use of mechanical equipment. Statistics found that 30 percent causes of failure in the rotating machinery are caused by a bearing failure [1]. Therefore, how to quickly and effectively fault diagnosis of rolling bearings has become a focus in current research.

The feature extraction and fault diagnosis of rolling bearing vibration signal is an important part in the field of rolling bearing fault diagnosis. Due to the vibration signal of rolling bearing is nonlinear and non-stationary, it is difficult to obtain a better result by traditional Fourier transform method. In 1998, N.E.Huang proposed the Empirical Mode Decomposition (EMD), that is a kind of adaptive signal processing method, and this method is not limited by the uncertainty principle, very suitable for nonlinear and non-stationary signal analysis [2]. However, with the in-depth study of EMD method, it is found that there are several problems.

The orthogonality of Intrinsic Mode Function (IMF) cannot be proved by theory.

- It is easy to cause the modes confusion because of the unreasonable convergence condition, the over envelope and the under envelope, which leads to the increase of the order of IMF.
- It takes many iterations to get an actual IMF component, which takes a long time.

For these shortcomings, in 2013, the French scholar Gilles [3] on the basis of wavelet transform and narrow band signal analysis theory, proposes a new adaptive signal processing method, Empirical Wavelet Transform (EWT), it is successfully applied to ECG signal separation and analysis in image noise reduction. Li [2] was successfully applied EWT to mechanical fault diagnosis, proposed a mechanical fault diagnosis method based on EWT, and compared with the traditional EMD method, the results show that the proposed method is superior to the traditional EMD method. In the next few years, scholars have conducted a series of studies on EWT.

The auto-regression parameters of the AR model pool the important information of the state of the system and reflect the sensitivity of the system state change [4]. Therefore, the auto-regression parameters of AR model can be used as the eigenvector to analyze the state change of the system. Due to the AR model is suitable for stationary signals, the AR model can be established for the AM-FM components that are subjected to the smoothing process, and the auto-regression parameters of the AR model can be used to construct the subset of fault features. Since the extracted original feature subset inevitably contains redundant features, it is necessary to reduce the dimension and optimize the extracted original feature subsets.

In the computer science research, the dimension reduction problem has made a series of research progress, typical weight reduction algorithms include Principal Component Analysis (PCA) [5]and Linear Fisher Discriminant (LFD) [6], PCA is a linear projection method for finding the optimal low-dimensional representation of raw data in the least mean square sense, and LFD is through the data between the categories of information, so that the data between the class divergence of the smallest, inter-species divergence of the largest. In addition, Locality Preserving Projection (LPP) [7] is a linear approximation of the nonlinear method Laplacian Eigenmap (LE), it not only solves the shortcomings of traditional linear methods such as PCA, but also can solve the shortcomings of

This project is supported by National Natural Science Foundation of China (Grant No. 51675253).

non-linear difficulty in obtaining new sample projection. It has made some progress in the field of image recognition. Fuzzy C-means clustering (FCM) [8] is one of the most widely used algorithms in fuzzy clustering, it is based on the similarity between data samples, through the iterative optimization of the objective function, the similarity of the sample object is divided into the same class to achieve the classification of data. Thus, as a pattern recognition method, FCM clustering has been widely used in mechanical fault diagnosis.

Based on the above analysis, the method of combining EWT method, AR model and FCM clustering is put forward to the fault diagnosis of rolling bearing, and the effectiveness of the method is verified by experiments.

The rest of this paper is organized as follows. Section II describes the basic principles of EWT, LPP, and FCM clustering, Section III presents the experiment process. Section IV discusses the experimental results, and Section V concludes this paper.

II. BASIC DEFINITION

A. Empirical Wavelet Transform

EWT is a new adaptive signal processing method in recent years, that core idea is to adaptive divide the Fourier spectrum of the signal, constructing a set of wavelet filters suitable for the signal to be processed, to extract the AM-FM component with a tightly supported Fourier spectrum, and ultimately get a meaningful instantaneous frequency and instantaneous amplitude, and then get Hilbert spectrum.

Suppose that the Fourier support $[0, \pi]$ is divided into N consecutive parts $\Lambda_n=[\omega_{n-1},\omega_n](\omega_0=0,\omega_N=\pi)$, where ω_n denotes the boundary between the parts, and the value is chosen as the minimum between the two maximum values of the signal Fourier spectrum. As shown in Fig.1, a transition period (the shaded portion in Fig. 1) with a width $T_n=2\tau_n$ is defined with each ω_n as the center.

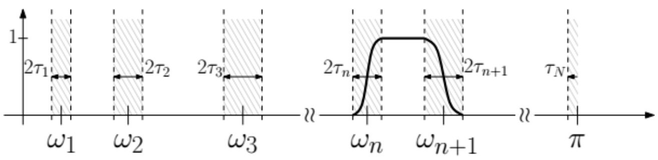


Fig.1. Partitioning of the Fourier axis.

On the basis of determining Λ_n, the empirical wavelet is defined as a bandpass filter on each Λ_n, the empirical wavelet is constructed according to the construction method of Littlewood-Paley and Meyer wavelet [9]. The empirical wavelet function $\hat{\psi}(\omega)$ and the empirical scale function $\hat{\varphi}(\omega)$ are defined as [3]:

$$\hat{\psi}_n(\omega)=\begin{cases}1\,; |\omega|\le(1-\gamma)\omega_n\\ \cos\{\frac{\pi}{2}\beta[\frac{1}{2\gamma\omega_n}(|\omega|-(1-\gamma)\omega_n)]\}; \\ \qquad (1-\gamma)\omega_n\le|\omega|\le(1+\gamma)\omega_n\\ 0\,; \textit{others}\end{cases} \tag{1}$$

$$\hat{\varphi}_n(\omega)=\begin{cases}1\,; |\omega|\le(1-\gamma)\omega_n\\ \cos\{\frac{\pi}{2}\beta[\frac{1}{2\gamma\omega_n}(|\omega|-(1-\gamma)\omega_n)]\}; \\ \qquad (1-\gamma)\omega_n\le|\omega|\le(1+\gamma)\omega_n\\ 0\,; \textit{others}\end{cases} \tag{2}$$

where:

$$\beta(x)=x^4(35-84x+70x^2-20x^3)$$

$$\tau_n=\gamma\omega_n$$

$$\gamma<\min_n\left(\frac{\omega_{n+1}-\omega_n}{\omega_{n+1}+\omega_n}\right)$$

The key to Fourier segmentation is determine N. In addition to 0 with π, you need to find N-1 boundary. In the literature [3],the threshold value $M_i\,(i=1,2,\cdots,k)$ in the frequency domain is calculated in the order of decreasing order, that is, $M_1\ge M_2\ge\cdots\ge M_k$ and normalized to [0,1]. It is necessary that M_k be greater than the threshold $M_{k+\alpha}(M_1\text{-}M_m)$, where α is the relative amplitude ratio and the value is between [0,1]. α is determined, then N is the number of maximum points larger than the threshold value, so it is preferable that ω_n is N-1 boundary corresponding to the first N maximum values of the threshold value.

The original signal reconstruction formula is defined as:

$$\begin{aligned}f(t)&=W_f(0,t)*\phi_1(t)+\sum_{n=1}^{N}W_f(n,t)*\psi_n(t)\\ &=F^{-1}\left[\hat{W}_f(n,\omega)\hat{\phi}_1(\omega)+\sum_{n=1}^{N}\hat{W}_f(n,\omega)\hat{\psi}_n(\omega)\right]\end{aligned} \tag{3}$$

where $\hat{W}_f(0,\omega),\hat{W}_f(n,\omega)$ is $W_f(0,t),W_f(n,t)$ Fourier transform of weighting coefficient.

The empirical mode $f_k(t)$ is defined as follows:

$$f_0(t)=W_f(0,t)*\phi_1(t) \tag{4}$$

$$f_k(t)=W_f(k,t)*\psi_k(t) \tag{5}$$

Hilbert transform is obtained by performing Hilbert transform on each empirical modal function.

B. Locality Preserving Projection

The basic idea of the LPP algorithm is to find a projection matrix for two points that are close to each other in the high-dimensional spatial data set under the condition that the local structure of the data is kept constant so that the two points of the high-dimensional space are close the projection coordinates on the low-dimensional space are also close.

The set of high-dimensional data sets is n d-dimensional vector $\boldsymbol{X} = \{x_1, x_2, ..., x_n\}$, the sensitive feature set of low-dimensional embedded space is n r-dimensional vector $\boldsymbol{Y} = \{y_1, y_2, ..., y_n\}$ ($R << d$), the projection matrix is $\boldsymbol{A}$. $y_i = \boldsymbol{A}^T x_i$, where the projection matrix $\boldsymbol{A}$ can be obtained by minimizing the objective function shown in equation (6):

$$J = \sum_{i=1}^{n}\sum_{j=1}^{n}\left\| y_i - y_j \right\|^2 S_{ij} \tag{6}$$

where S_{ij} is an element of the weight matrix $\boldsymbol{S}$.

$$S_{ij} = \begin{cases} \exp\left(-\dfrac{\left\| x_i - x_j \right\|^2}{\sigma} \right), & when\ x_i\ is\ connected\ to\ x_j \\ 0, & others \end{cases} \tag{7}$$

where σ is the thermonuclear width, $\sigma > 0$.

The projection matrix $\boldsymbol{A}$ is calculated by using equation (8).

$$\begin{aligned} A_{\text{opt}} &= \arg\min\left(\sum_{i=1}^{n}\sum_{j=1}^{n}\left\| A^T x_i - A^T x_j \right\|^2 S_{ij} \right) \\ &= \arg\min(A^T XLX^T A) \end{aligned} \tag{8}$$

Define the Lagrange function as:

$$g(a,\lambda) = a^T XLX^T a + \lambda\left(1 - a^T XDX^T a\right) \tag{9}$$

where λ is a Lagrange multiplier, Partial derivative

$$\frac{\partial g}{\partial a} = 0 \tag{10}$$

$\boldsymbol{D}$ is a diagonal element value of n×n diagonal matrix,

$\boldsymbol{L}=\boldsymbol{D}-\boldsymbol{S}$ is a Laplace matrix.Introduce the constraint

$\boldsymbol{YDY^T} = \boldsymbol{I}$, therefor:

$$A^T XDX^T A = I \tag{11}$$

Thus the LPP algorithm becomes an eigenvalue problem:

$$XLX^T A = \lambda XDX^T A \tag{12}$$

Then the eigenvectors corresponding to the former r least nonzero eigenvalues constitute the projection matrix.

$$\boldsymbol{A}=[a_1, a_2, a_3, \cdots, a_r] \tag{13}$$

C. Fuzzy C-Mean Clustering

Fuzzy C-mean clustering is the most classical one in the clustering algorithm based on objective function. By optimizing the traditional hard-clustering algorithm, the iterative optimization classification of the data samples is realized by the objective function based on the square of error.

Set to clustered sample collection $\boldsymbol{X}=\{x_1,x_2,\cdots,x_n\}$, fuzzy classification matrix $\boldsymbol{U}=(u_{ij})_{K\times n}$, where K is the number of cluster centers, N is the number of samples, u_{ij} indicates that jth sample to be divided belongs to ith category. $1\le i\le K$, $1\le j\le n$.

Define the objective function of FCM as:

$$J(U,V) = \sum_{j=1}^{n}\sum_{i=1}^{K} u_{ij}^m d_{ij} \tag{14}$$

where m is a fuzzy weighting index, usually set 2.

FCM clustering is essentially an iterative process that satisfies the classification matrix $\boldsymbol{U}$ and the clustering center $\boldsymbol{V}$, which minimizes the objective function $\boldsymbol{J}$ $(\boldsymbol{U},\boldsymbol{V})$. Proceed as follows:

- Determine the number of clustering centers K, fuzzy weight index m, initial membership degree classification matrix $\boldsymbol{U}=(u_{ij})_{K\times n}$.
- Calculate the cluster center

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \tag{15}$$

- Calculate the distance from the data point x_j to the cluster center v_i.

$$d_{ij} = \left\| x_j - v_i \right\| = (x_j - v_i)^T (x_j - v_i) \tag{16}$$

- Update membership classification matrix

$$u_{ij} = \frac{1}{\sum_{l=1}^{K} (d_{ij} / d_{lj})^{\frac{2}{m}-1}} \tag{17}$$

up to $\left\| U^l - U^{l-1} \right\| < \mathcal{E}$ and $\mathcal{E}$ is given accuracy.

The clustering evaluation index uses the classification coefficient (PC) and the classification entropy (CE) to determine the effect of clustering.

PC:

$$V_{pc} = \frac{1}{n}\sum_{j=1}^{n}\sum_{i=1}^{K} u_{ij}^2 \tag{18}$$

The closer the value of V_{pc} is to 1, the clustering effect is better.

CE:

$$V_{ce} = -\frac{1}{n}\sum_{j=1}^{n}\sum_{i=1}^{K} u_{ij} \ln u_{ij} \tag{19}$$

The closer the value of V_{ce} is to 0, the clustering effect is better.

III. EXPERIMENT PROCESS

This paper presents a fault diagnosis method combining EWT, AR model and fuzzy C-means clustering. Firstly, the original vibration signal is decomposed by EWT to obtain multiple AM-FM components. Second, the AR model is established by choosing the four AM-FM components which are most relevant to the original vibration signal through the correlation selection. The high-dimensional feature subset is constructed by the most regression parameter of the AR model. Since the high-dimensional feature subset inevitably contains irrelevant the LPP algorithm is used to reduce the dimension. Finally, the low-dimensional feature subset is input into the FCM clustering algorithm, and the pattern recognition is carried out. Specific steps are as follows:

Step1 : The original vibration signal is subjected to EWT to obtain a number of AM-FM components.

Step2 : A number of AM-FM components were analyzed for correlation, the formula for calculating the correlation coefficient is defined as:

$$\rho_{f,f_k} = \left| \frac{E[(f_k(t)-\mu_{f_k})(f(t)-\mu_f)]}{\sigma_{fk}\sigma_f} \right| \tag{20}$$

where $f(t)$, $f_k(t)$ is the original signal after EWT and the modal components, E is a mathematical expectation. μ_f , σ_f , μ_{f_k} , σ_{f_k} is $f(t)$, $f_k(t)$ corresponding to the time domain mean and standard deviation.

Step3 : The AR model of four AM-FM components closest to the original vibration signal is established, and the auto-correlation parameter is used to construct the high-dimensional feature subset.

Step4 : The dimension of the high-dimensional feature is reduced by LPP algorithm.

Step5 : The low-dimensional feature subset is reduced as the input of FCM clustering algorithm, and clustering evaluation index is used to determine the clustering effect.

IV. EXPERIMENT ANALYSIS

In order to illustrate the effectiveness of the proposed method, this method is applied to experimental data analysis. The experimental data for this study are from rolling bearing data is the Electrical Engineering Laboratory at Case Western Reserve University [10]. Bearing models for the SKF 6205-2RS deep groove ball bearings. Motor power is about 1494W, speed of 1730 r/min, the use of EDM technology in the bearing layout of a single point of failure, fault diameter of 0.1778mm, the depth of 0.2974mm. In the case of sampling frequency of 12kHz, Rolling Element Fault (REF), Inner Race Fault (IRF), Outer Race Fault (ORF) and Normal (NORM) 4 states of the vibration signal each 50 groups, the data length is 2048.The original vibration information of the four states is shown in Fig.2.

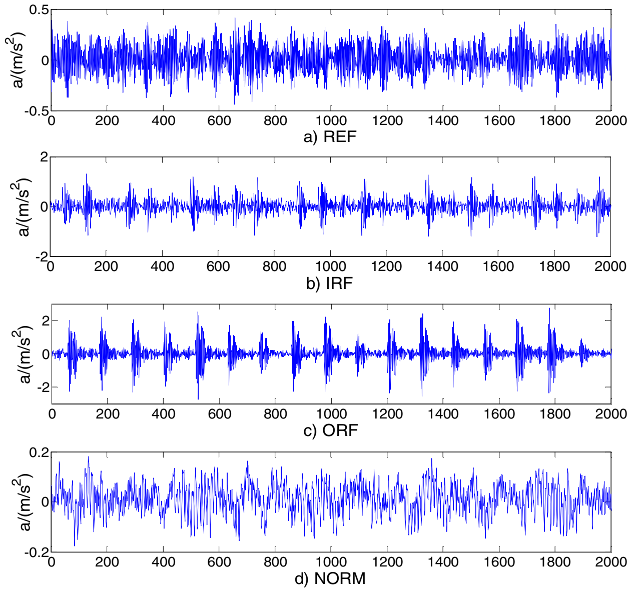
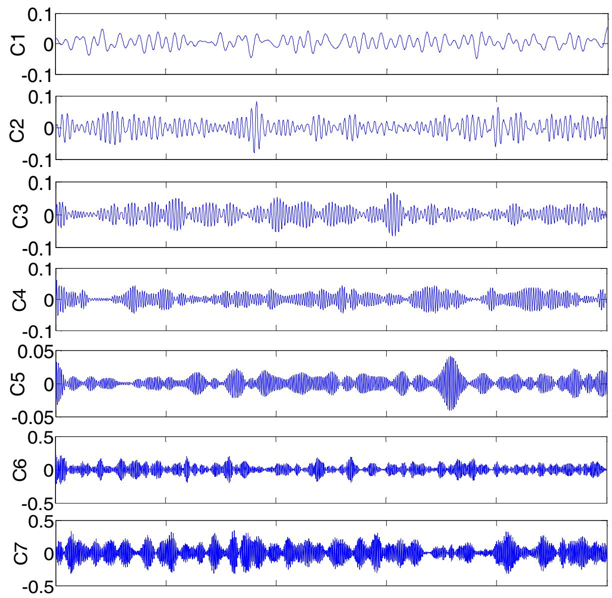


Fig.2. The time domain waveform of the four different types signals.

In this paper, we randomly select the rolling element fault signal for analysis. The AM-FM component of the original vibration after EWT decomposition is shown in Fig.3. The correlation coefficient is calculated by the equation (20), and the AR model is established by selecting the four AM-FM components most correlated with the original vibration signal according to the correlation coefficient. The high-dimensional feature subsets are constructed by the auto-regressive parameters of the AR model, the methods used to determine the order of the AR model are: the Final Prediction Error (FPE) method and Akaike's Information Criterion (AIC) theory. According to the FPE criterion, the AR model is determined to be 8, and the auto-correlation parameter is calculated by the improved covariance method, so that the dimension of the original feature subset is 32 dimensions.



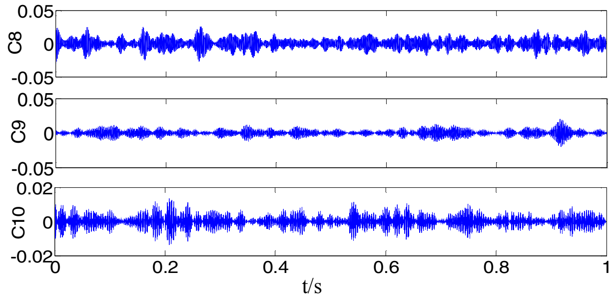


Fig.3. Rolling element failure EWT processing results.

The original feature subset is reduced dimension by using the LPP algorithm. The dimensionality d of the dimension reduction is calculated by the maximum likelihood estimation method, and the nearest neighbor parameter k is taken as 8.

In order to verify the superiority of EWT method, EMD method and EEMD method are used to decompose the original vibration signal. For EEMD method, two parameters need to be set, embedded dimension and Gaussian white noise standard deviation. In this paper, the embedding dimension set 100, and the standard deviation of Gaussian white noise is 0.2 times of the standard deviation of the original signal. Because the EMD method and EEMD method decomposition of the main fault information are concentrated in the previous few components, so select the first four components to establish the AR model, and self-regression parameters constitute a high-dimensional feature subset dimensionality.

The low-dimensional feature subsets obtained by dimensionality reduction of the three methods are input into the FCM clustering, and the Fig.4, Fig.5 and Fig.6 is obtained. In the process of analysis, the number of clustering centers K=4, ε=0.0001.

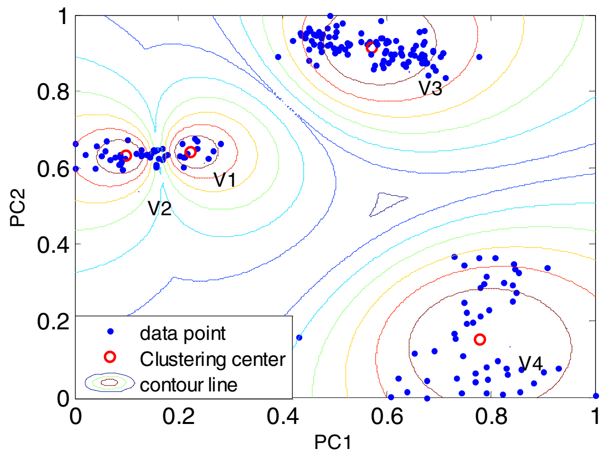


Fig.4. The 2D clustering contour diagram of EMD.

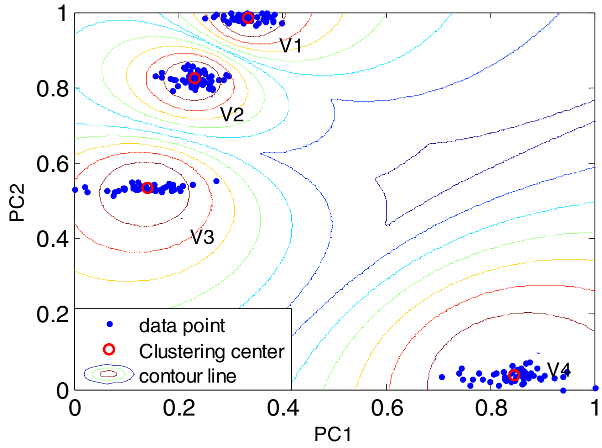


Fig.5. The 2D clustering contour diagram of EEMD.

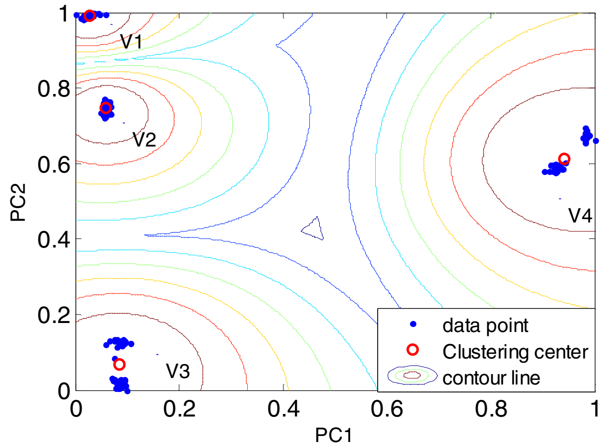


Fig.6. The 2D clustering contour diagram of EWT.

Analysis of Fig.3, Fig.4 and Fig.5 shows that, EWT than EMD, EEMD have obvious advantages. The 200 groups of samples were processed around the four cluster centers around the distribution, there is no obvious cross-aliasing between the data distributed around different cluster centers, and a data sample of the same fault type signal is distributed at the same cluster center. After FCM clustering, all data samples are distributed to different clustering centers according to the type of fault due to the similarity of the same type of signal samples. The clustering effect of three methods was tested by PC and CE. The results are shown in TABLE.I.

TABLE I . Evaluation of Clustering Effect of Different Methods

Different Methods	**Clustering Evaluation Index**	
	PC	***CE***
EMD	0.8210	0.3722
EEMD	0.9407	0.1416
EWT	0.9865	0.0441

As can be seen from TABLE.I, compare the other two methods, EWT has the best clustering effect. After the reduced dimension, the PC value of EWT is the largest, PC=0.9865, most close to 1. Meanwhile, CE value is the smallest, CE=0.0441, most close to 0. Because the EWT method not only does not exist modal aliasing, but also have good adaptability to signal. The PC value of the EMD method is minimal, because its exist modal aliasing, signal decomposition is not ideal. Although EEMD method adding Gaussian white noise, better inhibit the modal aliasing, it has a certain advantage over the EMD method, modal aliasing is not completely eliminated. Compared with the EWT method, it has a poor clustering effect.

V. CONCLUSION

In this paper, due to rolling bearing fault signal has non-linear, non-stationary characteristics, lead to fault category is difficult to identify, and a fault diagnosis method is proposed. EWT is a new adaptive signal processing method which has emerged in recent years. This method has the characteristics of simple calculation, fast calculation and complete theoretical basis. On this basis, this paper has presented the method of combining EWT method, AR model and FCM clustering and applies it to the fault diagnosis of rolling bearing. Experiments show that EWT and AR models proposed in this paper have obvious advantages in feature extraction, through LPP dimensionality reduction, input to FCM has achieved good clustering effect, can distinguish the different states of the bearings well, and there is no overlap between the fault classes. It is an effective method for adaptive fault information extraction and classification.

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