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Based on the LMD - KPCA - LSSVM Mechanical Fault Diagnosis Research

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Abstract **– In order to extract fault, based on nonlinear feature extraction capability of kernel principal component analysis(KPCA) and good classification performance of least squares support vector machine (LSSVM), local mean decomposition (LMD) and KPCA-LSSVM mechanical fault diagnosis algorithm is proposed. When a device failure occurs, a variety of statistical parameters of vibration signals contain a wealth of state characteristics that is a relevant and redundant, which will reduce the generalization ability and the recognition accuracy of the classifier. A series of production function PF component of the signal obtained by LMD, using KPCA to remove redundant features of sample data which include the vibration signal sequence domain characteristic parameters and timing AR parameters, as well as energy entropy PF component. To extract the nonlinear principle component in the input data space, and then fault classification using LSSVM. Experimental results show that, PF energy entropy characteristics are better than temporal characteristics and timing parameters of AR parameters, and KPCA-LSSVM classification model with respect to the direct use of LSSVM has better classification accuracy.**

Keywords **– Vibration Signal, Local Mean Decomposition, Kernel Principle Component Analysis, Least Squares Support Vector Machine, Fault Diagnosis.**

I. Introduction

With the development of modern industrial technology, machinery and equipment are often more complicated, automated, high-speed and intelligent. The running state of the equipment monitoring and accurate fault diagnosis has become an essential step. Machinery in the event of a failure, the vibration signal will exhibit nonlinear and non-stationary, state laws of various signal characteristic parameters reflecting the characteristics are not the same, and there are correlation and redundancy, this will reduce the generalization ability and the precision of recognition classifier. So the reasonable choice of characteristic parameters and classifier is of great significance to detect the fault [1].

Feature extraction is through the exchange of input features, new features can appear regularly in the new coordinate space, so as to eliminate the redundant and noisy data. The KPCA kernel function is introduced so that the input vectors are mapped to a high-dimensional feature space, thus which has better reparability, and in the high dimension space the mapping data are analyzed by linear principal component, nonlinear principal components of original feature parameters is obtained, so it has good ability to extract nonlinear features[2]-[4]. LSSVM as the training sample requirement is low and has the wide application [4]-[5], to solve the practical problem of the neural network, fuzzy logic and Bayesian network reasoning method in less training data samples, nonlinear and high dimensions [6].

At present, many scholars have researched the characteristic parameters of single in the mechanical fault classification [7]-[12], but some statistical parameters of vibration signal contains a rich state characteristic, analyze time domain features and temporal AR models of vibration signal, as well as energy entropy of local mean decomposition parameters through principal component, and the main component of the input are classified by LSSVM. The experimental results show that the method can effectively extract nonlinear features and accurate fault classification.

II. Algorithm Model

A. Local mean decomposition

No stationary signal with the statistical properties of the time dependent on the time and frequency domain analysis is able to get the characteristic of time domain and frequency domain signals. In recent years, local mean decomposition (LMD) proposed by Smith can effectively analyze mechanical vibration fault signal [9]-[11]. Local mean decomposition is not limited to the Fourier transform, according to the characteristics of vibration signal, adaptive band selection to optimize the resolution, accurate analysis of the signal information effectively, also won't appear negative frequency generated by Hilbert transform, adaptive analysis of nonlinear and unsteady signals caused by mechanical failure.

Local mean decomposition signal are made up of an envelope signal and a pure FM signal, the single component of the PF obtained by multiplying the decomposition envelope signal and a pure FM signal, LMD process the next iteration to after PF separation, until the balance signal is a monotonic function, calculate every single component PF instantaneous frequency and instantaneous amplitude, the instantaneous amplitude is the PF corresponding envelope function, instantaneous frequency come from their corresponding pure frequency modulation function. For a given arbitrary signal $x(t)$, after k loops for a series of PF component and a allowance signal $u_k(t)$ refer to "(1)".

$$x(t)=\sum_{p=1}^{k} PF_P(t)+u_k(t) \tag{1}$$

PF components are decomposed by LMD often focus on most prominent, the most important information of the original signal [8]. By information entropy theory to PF components for its energy entropy, make the system of the disorder degree of a certain measure is given. Assuming the LMD method is adapted to a PF component resulting from the original signal is decomposed the corresponding energy respectively $E_1, E_2, \cdots, E_n$. Energy forms a kind of automatic division of the frequency domain; the energy entropy is defined for each PF component as follow.

$$H_i = -\sum_{j=1}^{N} p_i(j)\log p_i(j) \qquad (2)$$

N is the original signal length, $p_i = E_i / E$ represent the proportion of the first PF component of energy in the total energy, the energy of the PF is defined as $E_i = \int_{-\infty}^{+\infty} |C_i(t)|^2 dt$.

B. Kernel principle component

Kernel principal component analysis (KPCA) as a nonlinear generalization of PCA, the basic idea is using nonlinear transformation to map sample data in a high-dimensional feature space, using PCA in the new space for feature extraction. Suppose there are n samples $x_1, x_2, \cdots, x_n \in R^m$, the input samples are mapped to high dimensional feature space of F by nonlinear transform, covariance matrix $\varphi(x_i)$ is defined as follow.

$$C^F = \frac{1}{n}\sum_{i=1}^{n} \varphi(x_i)\varphi(x_i)^T \qquad (3)$$

The characteristic value and vector is obtained by formula 4.The characteristic value $\lambda \geq 0$, V is the feature vector.

$$\lambda V = C^F V \qquad (4)$$

Feature vector V in the new space can be represented linearly use $\varphi(x_i)$.

$$V = \sum_{i=1}^{N} \alpha_i \varphi(x_i) \qquad (5)$$

Defining the nuclear matrix K

$$K = \langle \varphi(x_i)\varphi(x_j) \rangle \qquad (6)$$

The equation (3)(5)(6) combine the equation (4), converting Eigenvector V to eigenvectors of the nuclear matrix.

$$n\lambda\alpha = K\alpha \qquad (7)$$

The corresponding feature vectors of λ_k is α_k, the projection of samples $\varphi(x_i)$ in the V_k direction of the F space is the K nonlinear principal component $h_k(x)$.

$$h_k(x) = \sum_{i=1}^{n} \alpha_i^k K(x_i, x) \qquad (8)$$

C. Least Squares Support Vector Machine

Least Squares Support Vector Machine (LSSVM) make the use of square error in the objective function, and make the inequality constraints into equality constraints on the basis of SVM, the quadratic optimization problem is transformed into linear equations, the training time and classification accuracy has increased. The basic principles are described below.

Set the input sample x is n-dimensional vector, the output samples is y, samples are expressed in the form $\{(x_i, y_i)\}$, $i = 1,2\ldots,n$ the nonlinear mapping function can map the input samples in the high dimensional feature space refer to “(9)”

$$y = f(x, w) = \mathrm{sgn}[W^T \phi(X) + \beta] \qquad (9)$$

Optimization objective function refer to “(10)”

$$\min_{w,\beta\xi} = J(W, \beta, \xi) = \frac{1}{2}W^T W + \frac{1}{2}C\sum_{i=1}^{N}\xi_i^2 \qquad (10)$$

w is the weight, β the offset vector , C is the regularization factor, ξ_i is the error vector. Constraints refer to “(11)”

$$y_i[W^T \phi(x_i) + \beta] = 1 - \xi_i \; i = 1,2\ldots,n \qquad (11)$$

To make the constrained optimization problem into unconstrained optimization problems introduced Lagrange multiplier α_i, as shown refer to “(12)”

$$L(W, \beta, \xi_i; \alpha_i) = J(W, \xi_i) - \sum_{i=1}^{n} \alpha_i \{ y_i [W^T \phi(x_i) + \beta] - 1 + \xi_i \} \qquad (12)$$

According to Karush Kuhn Tucher (KKT) conditions :

$$\begin{cases} \frac{\partial L}{\partial W} = 0 \to W = \sum_{i=1}^{N} \alpha_i y_i \phi(x_i) \\ \frac{\partial L}{\partial \beta} = 0 \to \sum_{i=1}^{N} \alpha_i y_i = 0 \\ \frac{\partial L}{\partial \xi_i} = 0 \to \alpha_i = C\xi_i \\ \frac{\partial L}{\partial \alpha_i} = 0 \to y_i[W^T \phi(x_i) + \beta] - 1 + \xi_i = 0 \end{cases} \qquad (13)$$

Remove the error vector ξ_i and weight vector w :

$$\begin{bmatrix} 0 & y^T \\ y & ZZ^T + C^{-1}I \end{bmatrix} \begin{bmatrix} \beta \\ \overline{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ 1N \end{bmatrix} \qquad (14)$$

$Z = [\phi(x_1), \ldots, \phi(x_N)]^T$, $1_N = [1, \ldots, 1]^T$, $\overline{\xi} = [\xi 1, \ldots, \xi_N]^T$, $\overline{\alpha} = [\alpha 1, \ldots \alpha_N]^T$. ZZ^T Product operation is instead of kernel function $k(x_i, y_i)$ that meets the conditions of Mercer. The classification decision function is:

$$f(x) = \mathrm{sgn}[\sum_{i=1}^{N} \alpha_i y_i K(x_i, y_i) + \beta] \qquad (15)$$

III. Experimental Result

This paper analyze 6205-2RSJEM SKF deep groove ball bearing from Case Western Reserve University in American [13]. Use EDM technology layout on the bearing fault, which is 0.007 inch in diameter. The normal state, the bearing inner ring fault, ball fault, outer race fault four states each 118 groups of experimental data analysis. Among them, four states were randomly selected from each group of 18 data as training samples, each state of 100 groups of data remaining as a test sample. Time domain analysis of characteristic parameters of the sample as shown in Table 1, only list for each state in which 2 sample parameters. The parameters of AR model contains the information state important characteristics of the system, the final prediction error criterion (FPE criterion) in determining order number, order number of different bearing vibration signal sequence obtained by different, the minimum order is 26 order, the main state of the system is determined by a few order of the AR parameter, as unified order, listed the first 8 order parameters as shown in Table 2, parameter lists only two samples. The different frequency bands PF component of the signals obtained by Local mean decomposition, energy entropy characterize depict the bearing vibration signal changing with the frequency distribution. Energy entropy of the PF components is in table 3.

Table 1: The time domain signal sequence characteristic parameters

Fault type	time domain signal sequence characteristic parameters					
	Mean value	Standard deviation	Skewne	Kurtosis	Margin factor	Impact factor
Normal state	0.0124	0.0750	-0.1630	2.7563	4.1304	3.5334
	0.0116	0.0695	-0.1074	3.1848	5.7953	4.8901
Inner race fault	0.0158	0.2929	0.0765	5.2451	9.3585	6.5381
	0.0153	0.2839	0.0812	5.2232	9.2226	6.4064
Ball fault	0.0158	0.1369	0.0151	2.9336	5.1658	4.3754
	0.0157	0.1305	0.0079	2.8429	5.0237	4.1659
Outer race fault	0.0341	0.6452	0.0727	7.9988	10.4212	7.4926
	0.0345	0.6959	0.1153	7.3559	11.8502	8.3994

Table 2: AR model parameters of the signal sequence

Fault type	AR model parameters							
	AR1	AR2	AR3	AR4	AR5	AR6	AR7	AR8
Normal state	-1.6204	0.9008	-0.2498	0.2589	-0.3475	0.4287	-0.4003	0.1859
	-1.5681	0.7655	-0.1335	0.1776	-0.2926	0.3527	-0.2895	0.1626
Inner race fault	-0.7322	1.5254	-1.4183	1.6176	-1.3790	1.6541	-1.3891	1.6136
	-0.6096	1.3005	-1.0221	1.0902	-0.6697	0.9328	-0.4958	0.741
Ball fault	-0.8834	1.4582	-1.6283	0.9985	-0.9257	0.8559	-0.4993	0.6754
	-0.8526	1.3606	-1.5012	0.7979	-0.7167	0.6378	-0.2280	0.4126
Outer race fault	-0.0505	1.2720	-0.7370	0.2951	-0.7481	0.5664	-0.4954	1.1912
	-0.1795	1.3613	-0.9905	0.6162	-1.0541	0.9290	-0.8848	1.5135

Table 3: Local mean decomposition of different frequency band energy entropy

Fault type	PF energy entropy					
	PF1	PF2	PF3	PF4	PF5	PF6
Normal state	0.2845	0.3496	0.3640	0.2380	0.0994	0.1171
	0.2435	0.3642	0.3553	0.2500	0.0848	0.1130
Inner race fault	0.3655	0.2604	0.2052	0.1550	0.2576	0.2475
	0.3633	0.2840	0.2115	0.3179	0.2139	0.1081
Ball fault	0.1854	0.2009	0.1294	0.1285	0.0584	0.1195
	0.1874	0.2418	0.2679	0.1710	0.0454	0.1508
Outer race fault	0.0146	0.0104	0.1098	0.3639	0.3524	0.3653
	0.1224	0.0161	0.1209	0.3290	0.3675	0.3197

From table 1 to table 3 lists the feature library, different fault states of each characteristic parameter have different values, in order to characterize the bearing state, because of the redundancy and correlations between the characteristic parameters, KPCA extracting nonlinear principal component input LSSVM to identify fault. Research shows that, when , the extraction of principal components can ensure the main information of original state. LSSVM classifier using RBF kernel function, in order to minimize misclassification rate, using L - a fold and the grid search method to optimize the regularization parameter C and kernel parameter, make for clinical samples in KPCA feature subspace projection component input into the training well, parameter optimization of classifier, so as to realize the fault classification of equipment. Fig.1 shows three characteristics of the inner ring fault, the graph shows that PF energy entropy and the AR parameters in the two main components when the classification accuracy reached the optimal, time domain parameter is reached its optimum, three principal component classification accuracy rate were 97.50%, 97.50%, 95.50%, and the cumulative variance contribution rates were 85.26%, 97.58%, 85.25%.Fig.2 shows the three characteristics of ball fault, the PF energy entropy and the AR parameters when the number is two achieve the optimal accuracy of 98.50% and 98.00%, the time domain feature parameters have three principal achieved 89.50% accuracy, the cumulative variance contribution rates were 90.68%, 97.70%, 87.16%.Fig.3 represents the outer ring fault ,PF energy entropy and the AR parameters when the number is two achieve the optimal accuracy of 98.00% and 97.00%, the time domain characteristic parameters in the main components are three when reached the optimal classification accuracy of 84.50%, the cumulative variance contribution rates were 91.01%, 87.05%, 85.49%.In short, if reduce principal component number, due to the characteristics of information loss reduces the classification accuracy rate, increase the number of principal component, the data noise impact, also lead to the deterioration of classification performance. Through KPCA feature set dimension reduction, especially the AR parameters from 26 dimension reduced to 2 dimension can achieve high accuracy, improve the classification accuracy at the same time, to avoid the redundant and irrelevant features, reduce the computational complexity of classifier.

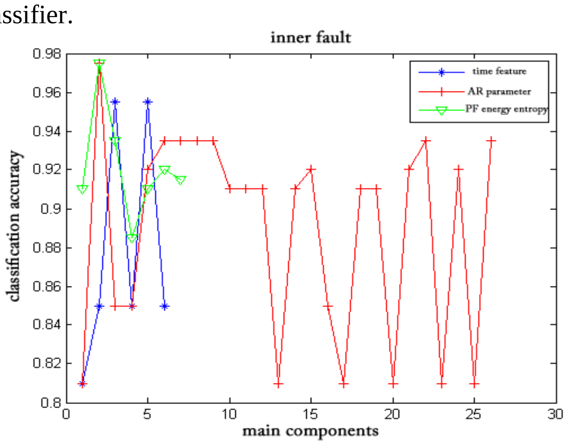

Fig.1. Inner race fault KPCA number of principal components

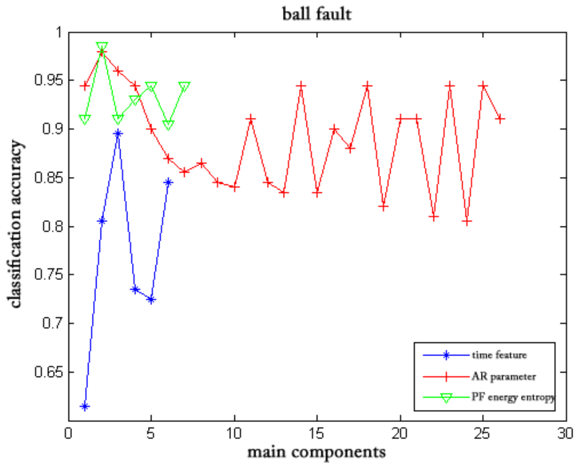

Fig.2. Ball fault KPCA number of principal components

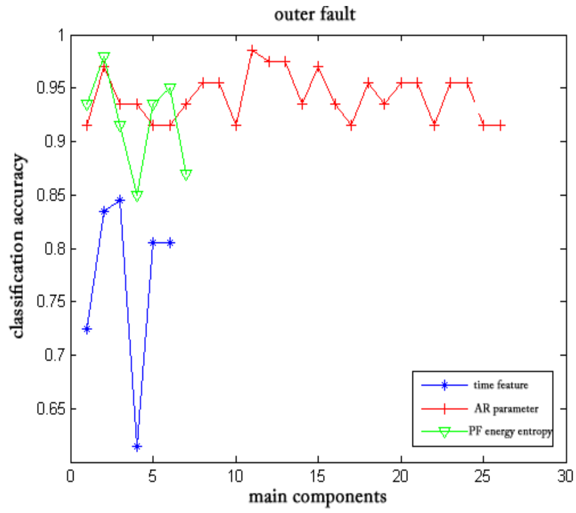

Fig.3. Outer race fault KPCA number of principal components

Table 4: Classification results compare between LSSVM and KPCA-LSSVM

Parameters	Classification method	Dime-nsion	Fault state			Accuracy
			Inner fault	Ball fault	Outer fault	
Time domain	LSSVM	6	85.00%	83.00%	80.50%	82.83%
	KPCA-LSSVM	3	95.50%	89.50%	84.50%	89.83%
AR parameters	LSSVM	26	93.50%	91.00%	91.50%	92.00%
	KPCA-LSSVM	2	97.50%	98.00%	97.00%	97.50%
PF energy entropy	LSSVM	7	92.00%	91.50%	87.50%	90.33%
	KPCA-LSSVM	2	97.50%	98.50%	98.00%	98.00%

In order to verify the influence of kernel principal component analysis on the classification accuracy rate, table 4 lists the results of three kinds of classification of bearing fault, according to the results of KPCA-LSSVM showed that the local mean decomposition PF energy entropy with respect to the AR parameters and time domain characteristic parameters are extracted directly from the original signal, the PF component more accurately portray the fault state of the bearing vibration signal, PF component has good characterization about the vibration signal energy along with the change of frequency, describe the characteristic information of different scale, can be directly used as good input characteristic parameters identification. And through the KPCA the original feature set is mapped to a feature space of new, based on the inhibition of data correlation and redundancy, reducing the dimension of the feature set, can avoid the influence of noise in data, to obtain more classification information, improve performance of classifiers, while reducing the computational complexity and improving fault classification accuracy obviously, its performance is better than directly using LSSVM method

IV. Conclusions

A bearing fault classification model in KPCA combined with LSSVM is given; the actual data simulation results show that the KPCA-LSSVM classification model performance was better than directly using LSSVM classification model, complete data samples is relatively small when a fault in a bearing, there is correlation between data. Therefore, the kernel principal component analysis for reducing noise, feature extraction of main element contains the main information of fault classification, and then use the LSSVM. In addition, the characteristic parameters of decomposition of PF energy entropy obtained by local mean are better than that of direct extraction of signal sequence, can be used as the input feature subset.

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