MECHANICAL FAULT RECOGNITION RESEARCH BASED ON LMD-LSSVM

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ABSTRACT
Mechanical fault vibration signals are non-stationary, which causes system instability. The traditional methods are difficult to accurately extract fault information and this paper proposes a local mean decomposition and least squares support vector machine fault identification method. The article introduces waveform matching to solve the original features of signals at the endpoints, using linear interpolation to get local mean and envelope function, then obtain production function PF vector through making use of the local mean decomposition. The energy entropy of PF vector take as identification input vectors. These vectors are respectively inputted BP neural networks, support vector machines, least squares support vector machines to identify faults. Experimental result show that the accuracy of least squares support vector machine with higher classification accuracy has been improved.

Keywords: vibration signals; features extraction; state recognition; local mean decomposition; least squares support vector machines.

RECHERCHE SUR LA RECONNAISSANCE DE LA PANNE MÉCANIQUE BASÉE SUR LMD-LSSVM

RÉSUMÉ
Les signaux de vibration de panne mécanique sont non-stationnaires et entraînent l'instabilité du système, et les méthodes traditionnelles peuvent difficilement extraire les informations de défaillances. Cet article propose un moyen de décomposition locale, et une méthode d'identification basée sur les moindres carrés par une machine à vecteur de support. On introduit la forme d'onde correspondante pour résoudre les caractéristiques des signaux aux extrémités par interpolation linéaire afin d'obtenir la décomposition et la fonction de l'enveloppe, pour ensuite obtenir la fonction de production du vecteur PF, en utilisant la décomposition modale locale. L'entropie d'énergie de vecteur PF prend les vecteurs d'entrée comme identification. Ces vecteurs sont respectivement entrés comme des réseaux neuronaux BP, et la machine à vecteur de support pour l'identification basée sur les moindres carrés pour identifier les défaillances. Les résultats expérimentaux démontrent que l'efficacité de l'identification des moindres carrés par la machine à vecteur de support avait apporté une plus grande exactitude de la classification

Mots-clés : signaux de vibration; extraction des caractéristiques; reconnaissance de l'état; moyen de décomposition locale; identification basée sur les moindres carrés par une machine à vecteur de support.

1. INTRODUCTION

When mechanical fault occurs, vibration signal is a carrier of fault information, so its fault analysis is the first choice to solve the problem of fault. Fault diagnosis usually includes characteristic signal extraction and state identification. Therefore, to improve work efficiency, accurately and effectively conducted state recognition can ensure the safe operation of machinery. Vibration signals often exhibit non-stationary characteristics. Obviously, traditional methods have some limitations on the signal processing due to the impact of noise [1]. Local Mean Decomposition (LMD) as a kind of adaptive non-stationary signal processing method has been widely applied in the field of fault diagnosis. Academics have proposed LMD energy operator demodulation to extract the fault feature [2], the combination of LMD and envelope spectrum analysis [3], LMD-FCM clustering analysis [4], LMD time-frequency analysis method is applied to fault feature extraction [5]. These studies have involved only mechanical fault feature extraction, failed to monitor the fault category. Using the appropriate classifier accurately identify the fault is the key to fault diagnosis.

LMD made use of decomposing signal, however it will be affected by the endpoint effect. The envelope cannot get close near the endpoint leading to increase the LMD decomposition layers, and algorithm also does not convergence, when serious beefed up its border effect, the actual physical meaning of LMD decomposition lose, which influence the accurate fault diagnosis. Therefore, in order to improve the accuracy in LMD decomposition of vibration signal and solve unpredictable movements of the signals at the endpoints appear, the waveform match is used to predict the endpoint value, using linear interpolation to solve moving average smoothing. The simulation of the measured signals shows that the improved local mean decomposition can accurately and effectively extract the fault.

Least Squares Support Vector Machine (LSSVM) has been wide applied as the low training sample requirement [6, 7] 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 [8]. LSSVM makes use of square error in the objective function, and changes the inequality constraints into equality constraints on the basis of SVM [9]. The quadratic optimization problem is transformed into linear equations and training time and classification accuracy increases [10, 11].

This paper presents a series of production function (PF) components by using LMD, then uses energy entropy as the input vector of the recognizer. LSSVM accurately identify the fault. In order to reflect unique advantages of the squares support vector machines in small sample pattern recognition problems, the paper make comparison to neural networks and support vector machines. Experimental results show that the proposed method can be successfully applied to mechanical fault diagnosis.

2. ALGORITHM MODEL

2.1. Local Mean Decomposition

Local mean decomposition signal are made up of an envelope signal and a pure frequency modulation(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 after PF separation, until the balance signal is a monotonic function, calculate every single component PF's 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 any given signal, the basic process is described by the following decomposition:

1. In the decomposition process of LMD we need to extract the extreme points of the original signal. Smith [12] believed that this is an endpoint extreme point, and in fact cannot predict the trend signals at the endpoints. The endpoints may not be extreme points of the signal and then spurious components will end gradually inward, polluting the entire signal sequence. Therefore we need to obtain the actual

signal endpoint's possible changes. In this paper, the waveform matching mirror extension method can reflect the internal law and extreme size of the signal. Suppose a signal $x(t)$ and take the left endpoint as example: $s(0)$ is labeled as the first endpoint, $s_1(t_1)$ is labeled as the first maximum value and $s_2(t)$ is labeled as the first minimum, composing the three points of a waveform. This moves to the right per 1 unit, each step will appear as a certain waveform. In order to find the most similar waveform, define the error as

$$e(t) = \frac{s1(t_1) * s2(t_3) - s2(t_2) * s1(t_4)}{s1(t_1) - s2(t_2)} \tag{1}$$

After completing all waveform movements, each step will cause an error $e(t)$. Calculate the minimum error value as matching value of the waveform endpoint and estimate the right endpoints using the same method. According to this principle, the endpoint value of the signal is obtained.

2. Extract the signal $x(t)$ all local extreme points. Calculate the local mean $m_{11}(t)$ and the envelope $a_{11}(t)$. Principle is as follows, assuming that all the local extreme value point of the original signal $x(t)$ is $n_{ij}(l_M)$, $m = 1, 2, \ldots, M$, l_M represent a total of extreme value point, the subscript i is the position of PF, foot mark j is the cycle-index. The local mean function $m_{ij}(t)$ and envelope function $a_{ij}(t)$ are obtained as

$$\begin{cases} m_{ij}(t) = \frac{n_{ij}(l_M) + n_{ij}(l_{M+1})}{2} \\ a_{ij}(t) = \frac{|n_{ij}(l_M) - n_{ij}(l_{M+1})|}{2} \end{cases} \tag{2}$$

The local mean function and envelope function is obtained by a line connecting two points and the moving average smoothing. Smith used mean of local third longest span as a moving average span [12]. Contrary to Smith, in [13] the authors used the shortest span directly as a moving average through thousands of studies, if it is the longest span will cause missing details characteristics of the signal, but the shortest span is not able to successfully terminate the iteration, some small fluctuations cause an infinite loop, at the same time, it affect the results of the decomposition speed and identification accuracy of signals. In order to avoid excessive smoothing effect, linear interpolation acquire local minimum and maximum value of the signal, upper and lower envelope and of the signal and linear interpolation operation respectively, the new local mean and envelope function is

$$\begin{cases} m(t) = (E_{\max}(t) + E_{\min}(t))/2 \\ a(t) = |E_{\max}(t) - E_{\min}(t))|/2 \end{cases} \tag{3}$$

3. The separate local mean function $m_{11}(t)$ from a given signal as

$$h_{11}(t) = x(t) - m_{11}(t) \tag{4}$$

The first subscript represents the request of the first signal; the second subscript represents the first iteration of the first signal.

4. Demodulate the separated signals $h_{11}(t)$ as

$$s_{11}(t) = h_{11}(t)/a_{11}(t). \tag{5}$$

In the ideal time, the demodulated $s_{11}(t)$ should be pure FM signal, which meet the local envelope $a_{12}(t) = 1$. If the $s_{11}(t)$ does not meet this condition, $s_{11}(t)$ is regarded as a given signal repeating steps 3) and 4), until $s_{11}(t)$ become pure frequency modulation signal, i.e. $-1 \leq s_{11}(t) \leq 1$, the local envelope function $a_{1(n+1)}$ satisfy $a_{1(n+1)}(t) = 1$.

5. The envelope of signal PF obtained by multiplying all local envelope $a(t) = a_{11}(t)a_{12}(t)\ldots, a_{1n}(t) = \Pi_{q=1}^{n} a_{1q}(t)$. The first single component PF is

$$PF_1(t) = a_1(t)s_{1n}(t) \tag{6}$$

6. A new signal $u_1(t)$ separates $\mathrm{PF}_1(t)$ from $x(t)$ as

$$u_1(t) = x(t) - PF_1(t) \tag{7}$$

7. The signal $x(t)$ is decomposed into k single components PF and a monotonic function $u_k(t)$ after k cycles until $u_k(t)$ is a monotonic function through repeating steps 1 to 6 as follows:

$$x(t) = \sum_{p=1}^{k} PF_P(t) + u_k(t) \tag{8}$$

2.2. Least Squares Support Vector Machine

Set the input sample x is n-dimensional vector. The output sample is y and 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 as

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

Then optimize the objective function as

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

where w is the weight, β the offset vector, C is the regularization factor, xi_i is the error vector. The constraints are given as

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

To transform the constrained optimization problem into an unconstrained optimization problem, we introduce the Lagrange multiplier α_i:

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

According to Karush–Kuhn–Tucker (KKT) conditions

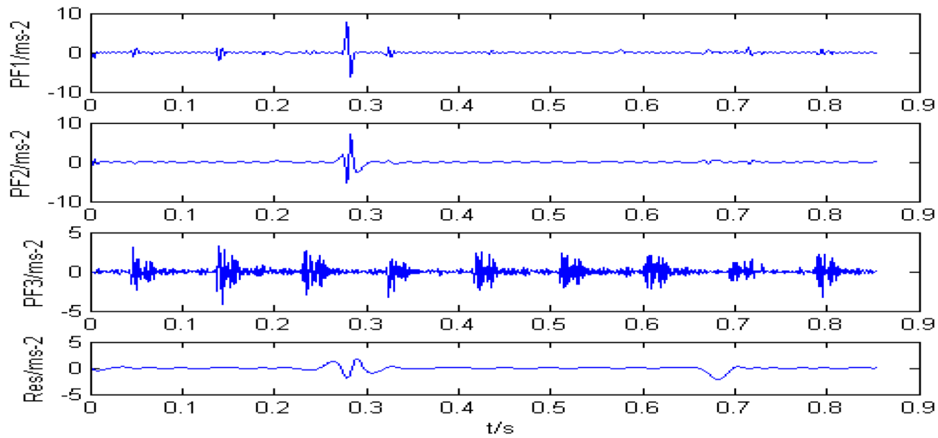
$$\begin{cases} \frac{\partial L}{\partial W} = 0 \to W = \sum_{i=1}^{N} \ \alpha_i y_i \phi(x_i) \\ \frac{\partial L}{\partial \beta} = 0 \to \sum_{i=1}^{N} \ \alpha_i y_i = 0 \\ \frac{\partial L}{\partial \xi_i} = 0 \to \alpha_i = C\xi_i \\ \frac{\partial L}{\partial \alpha_i} = 0 \to y_i[W^T \phi(x_i)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

Remove the error vector ξ_i and weight vector w

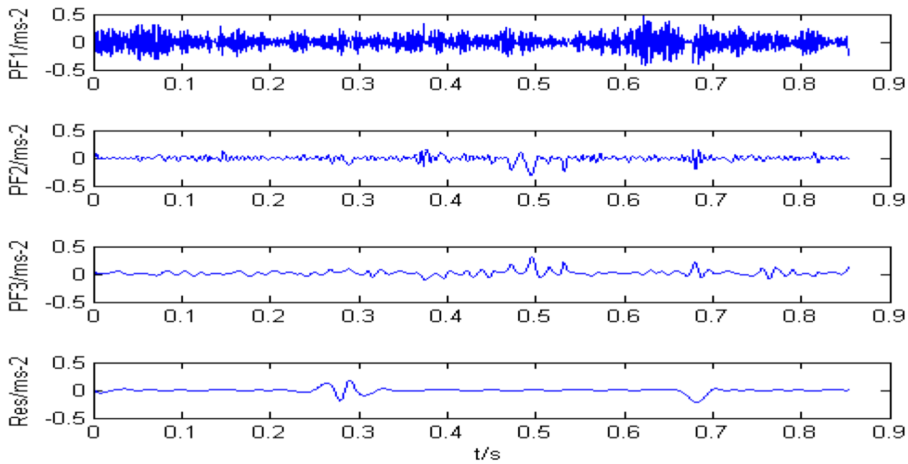
$$\begin{bmatrix} 0 & y^T \\ y & ZZ^T + C^{-1} I \end{bmatrix} \begin{bmatrix} \beta \\ \bar{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ 1N \end{bmatrix}. \tag{14}$$

$Z = [\phi(x_1), \ldots, \phi(x_N)]^T, 1_N = [1, \ldots, 1]^T, \bar{\xi} = [\xi_1, \ldots, \xi_N]^T, \bar{\alpha} = [\alpha_1, \ldots, \alpha_N]^T$. 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

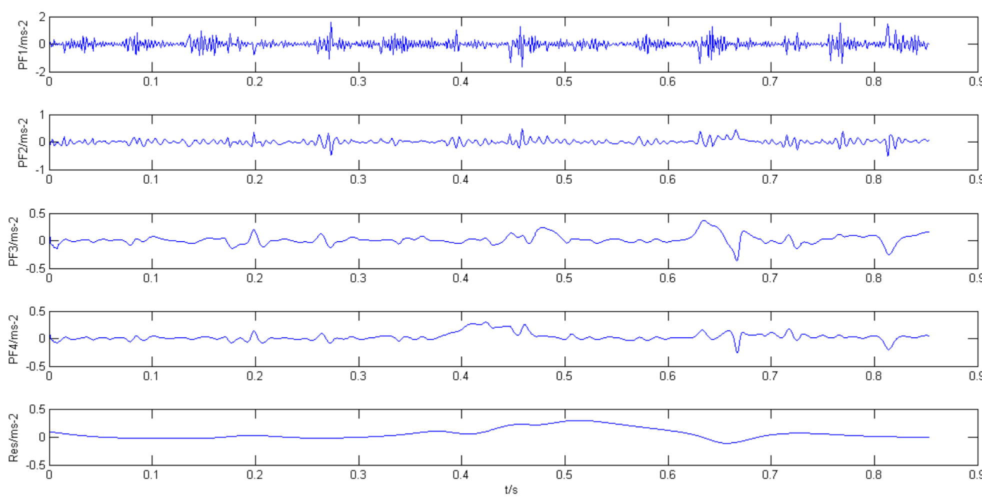
$$f(x) = \text{ sgn } \left[\sum_{i=1}^{N} \alpha_i y_i K(x_i, y_i) + \beta \right] \tag{15}$$



(a) Waveforms of outer ring fault



(b) Waveforms of ball bearing fault



(c) Waveforms of inner ring fault

Fig. 1. LMD decompose waveforms.

Table 1. The energy of the bearing fault.

Fault	Energy		
	PF1	PF2	PF3
Outer fault	0.4971	0.0915	0.0022
	0.4622	0.0901	0.0047
	0.4839	0.0958	0.0082
	0.4601	0.0948	0.0087
	0.4789	0.0939	0.0064
Inner fault	0.3272	0.0995	0.0021
	0.3626	0.0931	0.0017
	0.3803	0.0956	0.0032
	0.3301	0.0918	0.0007
	0.3769	0.0919	0.0004
Ball fault	0.1098	0.0105	0.0096
	0.1025	0.0112	0.0072
	0.1034	0.0153	0.0022
	0.0813	0.0185	0.0075
	0.0898	0.0192	0.0046

3. SIMULATIONS AND DISCUSSION

In this paper we select 6205-2RSJEM SKF deep groove ball bearing drive end bearing of Washington Case Western Reserve University for analysis. The experimental platform consist of 2 horsepower motor (1 HP = 746 W), torque sensors, power meter and electronic control equipment. The bearing is arranged 0.007 inch bearing failure using EDM. The sampling frequency of the signal is 12 kHz, the sampling points is 1024, the engine speed 1797 r/min. Select 100 groups of data for each of three states under the fault of the bearing inner race, outer race fault, ball bearing for experimental analysis. The random 70 groups of data under the three states is the training sample, the rest of each 30 groups of data as test samples among them.

3.1. LMD Decomposition Results

Figures 1(a–c) respectively represent waveforms of the outer fault, ball bearing fault and inner fault by local mean decomposition. When the bearing in the event of fault, the energy concentrated in the high frequency part, so select the first three components of the proposed energy PF value as an input sample.

3.2. The Energy of PF

This paper uses the energy characteristics of PF components as feature vectors, enter LSSVM identify the fault. The experimental procedure is as follows:

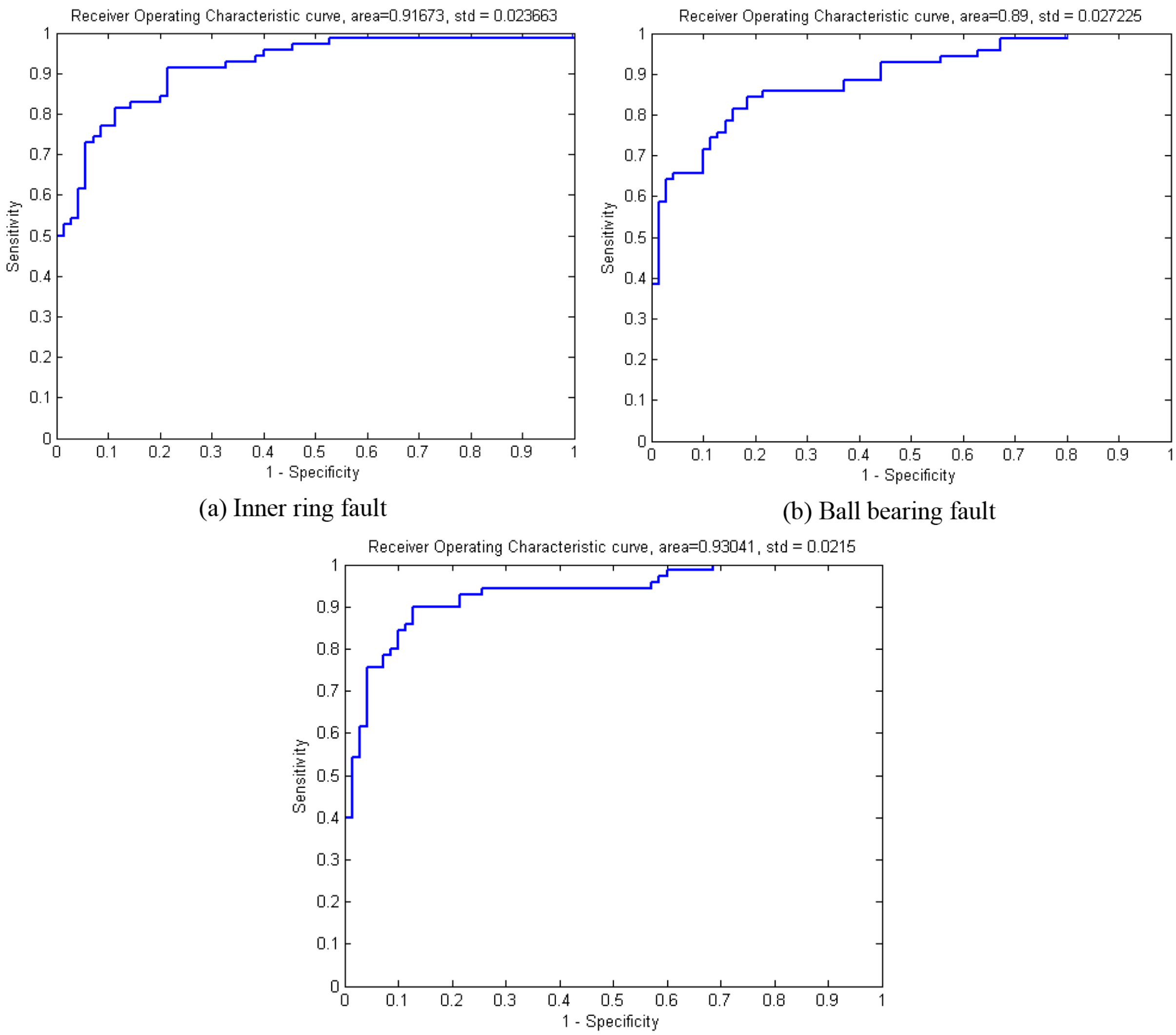
1. The collected vibration signal is LMD decomposed into different numbers of PF component. Select the PF component that contains the main fault information.

2. Calculate the energy of major component of PF E_i.

$$E_i = \int_{-\infty}^{\infty} |C_i(t)|^2 \, \mathrm{d}t \tag{16}$$

3. The energy entropy Obtained 2 composes of feature vector T and feature vector normalization.

$$T' = [E_1/E, E_2/E, \ldots, E_n/E] \tag{17}$$



(a) Inner ring fault

(b) Ball bearing fault

(c) Outer ring fault

Fig. 2. The Receiver Operating Characteristic (ROC) curve.

$$E = \left(\sum_{i=1}^{n} |E_i|^2 \right)^{1/2} \tag{18}$$

4. Enter the training and testing samples into LSSVM using the kernel function RBF to identify faults.

Calculate the energy vector as an input sample in bearing three states. Follow the steps described to get the fault input vector. Table 1 lists the actual output results of the 15 groups of data.

3.3. Fault Identification Results

The energy vector was randomly selected 70 sets of data for each fault, compare to the normal data respectively, input LSSVM the three types of fault data. In order to get higher recognition accuracy, using L-a fold and the grid search method to optimize the regularization parameter c and kernel parameter ϕ, the three curves show that LSSVM recognizer has good classification performance as Figs. 2(a–c). After two

Table 2. Bearing fault classification performance comparison of three models.

Network model	Fault state	Test samples	Correct number	Accuracy	Comprehensive accuracy
BP	inner	30	22	73.33%	67.78%
	outer	30	19	63.33%	
	ball	30	20	66.67%	
SVM	inner	30	25	83.33%	75.55%
	outer	30	22	73.33%	
	ball	30	21	70.00%	
LSSVM	inner	30	26	86.67%	84.45%
	outer	30	26	86.67%	
	ball	30	24	80.00%	

iterations, the initial value of inner ring fault is $c = 0.00816101$, $\phi = 0.409761$, $c = 0.19655$, $\phi = 4.1045$ is the new parameter. Ball fault from $c = 0.00432003, \phi = 0.450535$ to $c = 1.25908$, $\phi = 20.1365$. For outer ring fault $c = 0.32752$, $\phi = 0.15714$ only two iterations, $c = 10.0382$, $\phi = 53.044$.

In order to reflect the superiority of the proposed algorithm, the PF component input BP neural network, standard support vector machines to identify the fault, performance comparison shown in Table 2. Select the number of samples tested is less than the training sample, using the same input samples were entered in the model, we know LSSVM can effectively identify faults, each state recognition accuracy is higher than other two kinds of recognizer, the recognition accuracy achieve 84.45%.

4. CONCLUSIONS

In this paper we combine the energy entropy of production function component by decomposed in local mean with least squares support vector for mechanical fault recognition to solve the low BP neural network generalization capabilities and standard SVM training while increasing the number of samples time slows down, least squares support vector machines can more accurately identify the fault. The article introduces waveform matching to solve the original features of signals at the endpoints, using linear interpolation to get local mean and envelope function. Experimental results show that the algorithm provided can be used in the identification of mechanical fault, thus providing the basis for the ability to guarantee the normal operation of machinery, real-time monitoring of machinery running.

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REFERENCES

1. Cao, C.F., Yang, S.X. and Yang, J.X., "Vibration mode extraction method based on the characterristics of white noise", *Journal of Mechanical Engineering*, Vol. 46, No. 3, pp. 65–70, 2010.
2. Chen, B.J., He, Z.J., Chen, X.F. and Zi, Y.Y., "Locomotive fault diagnosis based on local mean decomposition demoddulating approach", *Journal of Xi'an Jiao Tong University*, Vol. 44, No. 5, pp. 40–44, 2010.
3. Li, Z.N., Liu, W.B. and Xiao, Y.X., "Guanhua wu. fault diagnosis method of rolling bearing based on local mean decomposition envelope spectrum and support vector machine", *Journal of Mechanical Design and Manufacturing*, Vol. 11, No. 5, pp. 170–173, 2011.
4. Zhang, S.Q., Sun, G.X. and Li, L., "Study on mechanical fault diagnosis method based on LMD approximate entropy and fuzzy C-means clustering", *Chinese Journal of Scientific Instrument*, Vol. 34, No. 3, pp. 714–720, 2013.

5. Wang, Y.X. and He, Z.J., "Several key issues of local mean decomposition method used in mechanical fault diagnosis", *Journal of Vibration and Shock*, Vol. 31, No. 9, pp. 10–12, 2012.
6. Liang, X., "Nonlinear feature extraction and LSSVM application in the chemical process faults diagnosis", *Journal of Computer Applications*, Vol. 30, No. 1, pp. 236–239, 2010.
7. Tang, C.X. and Yang, C.H., "Weihua gui, hongqiu zhu. based on KPCA-LSSVM silicon-manganese alloy smelting slag basicity prediction research process", *Chinese Journal of Scientific Instrument*, Vol. 31, No. 3, pp. 689–693, 2010.
8. Wang, X.B., "Application of neural network path optimization in fault diagnosis", *Chengdu, University of Electronic Science and Technology*, pp. 10–12, 2012.
9. Wen, T.X. and Wang, J.J., "Fault diagnosis of rolling element bearing based on wavelet package and LSSVM", *Journal of Computer Simulation*, Vol. 29, No. 6, pp. 202–205, 2012.
10. Gopalakrishnan, K. and Kim, S., "Support vector machines approach to HMA stiffness prediction", *Journal of Engineering Mechanics*, Vol. 137, No. 2, pp. 138–146, 2011.
11. Liu, L.M., Wang, A.N. and Sha, M., "Multi-class classification methods of cost-conscious LS-SVM for fault diagnosis of blast furnace", *Journal of Iron and Steel Research International*, Vol. 18, No. 10. pp. 17–23, 33, 2011.
12. Smith, J.S., "The local mean decomposition and its application to EEG perception data", *Journal of the Royal Society Interface*, Vol. 2, No. 5, pp. 443–454, 2005.
13. Ren, D.Q., "Rotating machinery fault feature extraction method and system research based on local mean decomposition", *Zhejiang, University of Zhejiang*, pp. 45–47, 2008.