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Mechanical Fault Diagnose of Diesel Engine Based on HOC and SVM

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Abstract—For the non-stationary feature of diesel engine vibration signals, a fault diagnosis method is proposed using EMD(Empirical Mode Decomposition),HOC(Higher Order Cumulants) and SVM(Support Vector Machine). The energy of IMFs(Intrinsic Mode functions) decomposed by EMD and higher order cumulants of the signals form feature vectors, and SVM is used as a fault feature classifier to diagnose fault. Compared with other methods, the result shows that combined method of EMD and HOC can describe the essential characteristics of the signals more effectively, and SVM is superior to neutral network because of high classification precision and strong generalization ability for small samples.

Keywords-Higher Order Cumulants; Support Vector Machine; Empirical Mode Decomposition; Fault Diagnose

1. Introduction

The vibration signals on the engine surface include much useful information about working status of engine and its parts. It's a very complicated system composed of many parts, and strongly affected by noise, moreover the vibration signals often show non-stationary, so it's difficult to extract fault feature. The number of samples is limited because of huge lost of engine arising from failure occurrence, this restricts traditional pattern recognition methods which need large scales of faults samples such as neutral network. The technique of HOC and SVM provides new ideas to solve the problems.

HOC method is an overhead subject in the fields of signal processing in the world in recent years [1]. It is widely used in various problems those need to consider the non-Gaussian, non-mini-mum Phase, color noise and non-linear or cycling stability, and it can not only suppress Gaussian color noise but also sometimes reduce the non-Gaussian color noise automatically, so it provides a reliable fault diagnosis method for the engine. EMD is proposed as a method to analyze time-frequency signal by Huang in 1998, which suits for non-stationary signal processing [2]. The combination of the two methods can extract the fault features of engines effectively.

Statistical Learning Theory based on the principle of minimizing the structural risk aims at settling the question of machinery study with limited samples. The purpose of SLT is to get the optimization with limited samples, and the experimental risk and believe range are considered too. SVM is developed from Statistical Learning Theory as a classification method, the basic idea of which is to select the smallest structural risk, and address the contradiction between learning ability and generalization ability of learning machine. It overcomes the flaw of traditional pattern recognition methods required a large number of samples, and suits for small samples of engine fault diagnosis.

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Therefore, a engine fault diagnosis method based on EMD, HOC and SVM is putted in this article. The fault feature vector extracted by the combination of EMD and HOC is as the input of SVM classifier, and identify the type of engine crankshaft bearing fault.

2. Empircal Mode Decomposition

EMD is a generally nonlinear, non-stationary data processing method developed by Huang et al.(1998) . The basic principle of EMD is to decompose a time series into a sum of oscillatory functions, namely, intrinsic mode functions (IMFs). In the EMD, the IMFs must satisfy the following two requirements:

(1) The functions have the same numbers of extrema(sum of maxima and minima) and zero-crossing or differ at the most by one.

(2) The functions are symmetric with respect to local zero mean.

With these two requirements, some meaningful IMFs can be well defined. Otherwise, if one blindly applied the technique to any data series, the EMD may result in a few meaningless harmonics. Usually, an IMF represents a simple oscillatory mode, compared with the simple harmonic function. In practice, the EMD process of a signal can be describe as follows:

(1) Identify all the maxima and minima of time series $x(t)$.

(2) Generate its upper and lower envelopes, $e_{\min}(t)$ and $e_{\max}(t)$, with cubic spline interpolation.

(3) Calculate the point-by-point mean($m(t)$)from upper and lower envelopes:

$$m(t) = (e_{\min}(t) + e_{\max}(t))/2 \tag{1}$$

(4) Extract the mean from the time series and define the difference of $x(t)$ and $m(t)$ as $d(t)$:

$$d(t) = x(t) - m(t) \tag{2}$$

(5) *Check the properties of* $d(t)$*:*

(a) If it is an IMF,denote $d(t)$ as ith IMF and replace $x(t)$ with the residual $r(t) = x(t) - d(t)$. The ith IMF is often denoted as $c_i(t)$ and the i is called its index;

(b) If is not, replace $x(t)$ with $d(t)$;

(6) Repeat step1)-5) until the residual satisfies some stopping criterion.

One stop criterion proposed by Huang et al.(2003a) for extracting an IMF is: iterating predefined times after the residue satisfies the restriction that the number of zero-crossings and extrema do not differ by more than one and the whole sifting process can be stopped by any of the following predetermined criteria: either when the component $c_i(t)$ or the residue $r(t)$ becomes so small that it is less than the predetermined value of a substantial consequence, or when the residue $r(t)$ becomes a monotonic function from which no more IMFs can be extracted. The total number of IMFs is limited to $\log_2 N$, where N is the length of data series. The original time series can be expressed as the sum of some IMFs and a residue:

$$x(t) = \sum_{j=1}^{N} c_j(t) + r(t) \tag{3}$$

where N is the number of IMFs, and $r(t)$ means the final residue [3].

3. Higher Order Cumulants

3.1 The definition of moment function and cumulants

Cumulants can be generated by the characteristic function of random variable, if $X = [x_1, x_2, \ldots, x_n]^T$ is a random vector with joint probability density function, its first characteristic function is defined as

$$\Phi(\omega_1, \ldots, \omega_n) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} f(x_1, \cdots, x_n) e^{j(\omega_1 x_1 + \cdots + \omega_n x_n)} dx_1 \cdots dx_n \tag{4}$$

The second characteristic function is defined as the logarithm of the first characteristic function.

$$\psi(\omega_1, \cdots \omega_n) = \ln[\varphi(\omega_1, \cdots \omega_n)] \tag{5}$$

$\{x(n)\}$ is the k-order zero-mean stationary random process, then the k-order moment of the process is defined as the k-order derivative of the first characteristic function at the origin:

$$m_{kx}(\tau_1, \cdots, \tau_{k-1}) = E[x(n), x(n+\tau_1), \cdots, x(n+\tau_{k-1})] \tag{6}$$

K-order cumulants is defined as the k-order derivative of the second characteristic function for the random process at the origin, which expresses as follows.

$$c_{kx}(\tau_1, \tau_2, \cdots, \tau_{k-1}) = cum[x(n), x(n+\tau_1), \cdots, x(n+\tau_{k-1})] \tag{7}$$

For a zero-mean stationary random process $x(t)$, its second-order and fourth-order cumulants respectively are c_{2x} and c_{4x} [4].

$$c_{2x}(\tau) = E\{x(t)x(t+\tau)\} = m_2(\tau) \tag{8}$$

$$\begin{aligned} c_{4x}(\tau_1,\tau_2,\tau_3) &= E\{x(t)x(t+\tau_1)x(t+\tau_2)x(t+\tau_3)\} \\ &= c_{2x}(\tau_1)c_{2x}(\tau_2-\tau_3) - c_{3x}(\tau_2)c_{2x}(\tau_3-\tau_1) = c_{2x}(\tau_3)c_{2x}(\tau_1-\tau_2) \end{aligned} \tag{9}$$

3.2 The Higher Order Cumulants of Gaussian Process

$X = [x_1, x_2, \cdots x_n]^T$ is n-dimensional Gaussian random vector, the vector's mean is $\mu = [\mu_1, \cdots, \mu_n]^T$, the covariance matrix is $\sum_{n\times n}$, then the second characteristic function is as follows.

$$\psi(\omega) = \ln(\varphi(\omega)) = j\mu^T\omega - \frac{1}{2}\omega^T \Sigma \omega \tag{10}$$

Since $\psi(\omega)$ is a quadratic polynomial on the variable ω_i, more than third order derivative of $\psi(\omega)$ on variable ω_i equal to zero. Extended to the Gaussian random process, more than two order cumulants is zero [5]. Therefore, the higher order cumulants are blind to the Gaussian random process, which shows advantages as follows.

(a) Detect amplitude information of signals effectively, and provide phase information of signals, also it's used for non-minimum phase systems and signal recognition;

(b) It can suppress Gaussian noise and improve the performance of signal parameter estimation.

(c) Extract the extent of deviation from Gaussian distribution for random process, and use for signal classification.

(d) Detect and depict the nonlinear characteristics of the signal or identify the nonlinear degree of the system.

4. The Engine Fault Diagnosis Method Based on Emd,Hoc and Svm

4.1 Feature Extraction

Usually engine vibration signals are non-stationary, most of which are influenced by the noise. EMD separates modes in accordance with the characteristic time scales. Because there is no fixed priori base, the decomposition is adaptive. EMD is suitable for nonlinear and non-stationary signal analysis due to the variable instantaneous amplitudes and frequencies. And higher order cumulants can reduce the impact of Gaussian color noise on the signal effectively. We can extract the fault features of vibration signals by combining them. The process consists of following steps:

(1) Decompose the signal by EMD, select the first 5 IMF components contained the main fault information.

(2) Calculate the energy of each IMF component.

$$E_i = \int_{-\infty}^{+\infty} |c_i|^2 dt \quad i = 1,2,...,5 \tag{11}$$

(3) Construct the feature vector T with the element of energy.

$$T = [E_1, E_2, \cdots, E_5] \tag{12}$$

(4) Normalize the vectors.

$$E = [\sum_{i=1}^{5} |E_i|^2]^{\frac{1}{2}} \tag{13}$$

$$T' = [E_1/E, E_2/E, \ldots, E_5/E] \tag{14}$$

(5) The five feature elements extracted by EMD can not fully describe the essential characteristics of vibration signals, so it is necessary to introduce new feature elements. Higher order cumulants can handle the intrinsic properties of non-Gaussian and Gaussian Processes. Experimental results show that the second-order and fourth-order cumulants of vibration signals can be used as new feature elements. So add them to the previous five feature elements and form seven new feature vectors.

4.2 Pattern Recognition Based on SVM

The central idea of SVM is to adjust the discriminant function, use the classified information of boundary sample points fully, and form classification hyperplane to achieve classification between the two kinds of samples, the hyperplane with the largest margin will show the best generalization. Given a set of training data $\{(x_i, y_i)\}$ $x_i \in R^d$, where x_i is an input vector in R_d and y_i is the class label associated with x_i , for $i = 1, 2, 3...n$ .If the points which lie on the hyperplane satisfy $y_i[(\omega \cdot x_i)+b]-1 \ge 0, i=1,2,\cdots n$,all samples can be separated correctly. The margin is $2/\|\omega\|$ obviously. Thus we can find the optimal plane which gives the maximum margin by minimizing $\|\omega\|^2$ [7].

The method of calculating extreme values by Lagrange function is used to obtain the optimal plane. Thus by calculating the extreme value of a quadratic function with constraint of inequality and replacing an inner product by the kernel function $K(x, y)$ in feature space of nonlinear transformation, we can get the optimal classification function:

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{n} \alpha_i^* y_i K(x_i, x) + b^* \right) \tag{15}$$

where $K(x, y)$ should satisfy Mercer's condition [8], determine the type of samples by judging the sign of $f(x)$ at last. Specific steps of the algorithm in this paper are as follows.

1) Select the appropriate kernel function. Common kernel functions are linear kernel function, polynomial kernel function, radial basis kernel function and Sigmoid kernel function, because radial basis function can map non-linear data transforming into high- dimensional space, it is chosen in this paper.

2) Select the suitable penalty C and RBF parameter g through the cross validation repeatedly.

3) Select the appropriate multiple classifier. Common classification algorithms are "One against Rest", "One against One, "Error Correcting Output Code," and so on. Because the types of engine crankshaft bearing failure and training samples are limited, which is suitable for "one against one "algorithm, it's used in this paper.

4) Input the training samples to SVM and according the selected parameters to train them. Then input the test sample to well-trained SVM model for pattern recognition.

5. Application of Fault Diagnosis Real

5.1 Signal Acquisition

The experiment was done on a diesel whose type is Cummins 6Bt 5.9. The matching clearances between the crank shaft neck and the fourth bearing for the third cylinder are 0.08 mm (normal condition); 0.20 mm(light fault); and 0.40 mm(severe fault) in turn. The locations of the vibration sensors are the bottom left of the third cylinder, which is on the crankshaft bearing considered as the best test location. The datum acquirer monitor engine's rotary speed at any moment and record signal immediately when engine's rotary speed gets to the value that has been preset [8]. The sample frequency is 12800 Hz, the sample points are 8192，The preset value of the starting rotary speeds for the unstable signal acquirer is1800 r/min. Get 18 sets of data which correspond to 3states respectively.

5.2 Signal Processing

First, decompose the signal by EMD. Time domain waveform and some IMF components decomposed by EMD of the first group data when the crankshaft bearing is on severe fault are displayed in figure 1.

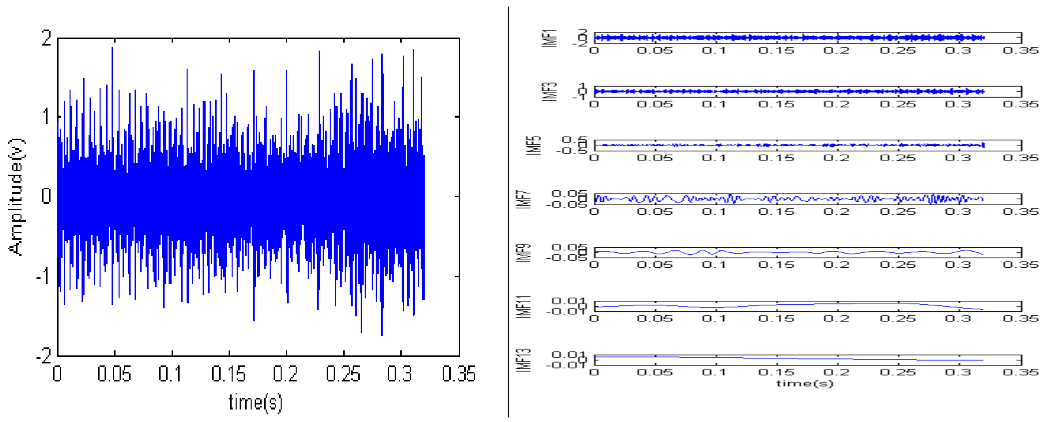

Fig.1 the signal on severe fault and some IMFs decomposed by EMD

According to equation (11) (12) (13) (14) calculate the energy of IMFs and normalize them, then calculate the second-order and fourth-order cumulants to form feature vectors. Then get 18 sets of feature vectors, select the previous six sets as training samples, another 12 sets as test samples, which is listed in table Ⅰ.

TABLE I TEST AND TRAINING SAMPLES FOR SVM

Types Of Samples	**NO**	**The Energy Of the Front 5 IMF Components**					**Cumulants**		**Fault Level**
		X1	X2	X3	X4	X5	X6	X7	y
Training Samples	1	0.9595	0.2698	0.0739	0.0300	0.0155	0.52	0.23	normal
	2	0.9495	0.2942	0.1034	0.0297	0.0173	0.57	0.15	normal
	3	0.9707	0.2179	0.0977	0.0242	0.0100	0.15	0.05	light
	4	0.9777	0.1870	0.0908	0.0284	0.0113	0.15	0.04	light
	5	0.9447	0.2981	0.1316	0.0333	0.0146	0.14	0.011	severe
	6	0.9451	0.3009	0.1206	0.0375	0.0149	0.15	0.028	severe
Test Samples	7	0.9696	0.2298	0.0782	0.0225	0.0214	0.48	0.27	normal
	8	0.9604	0.2637	0.0839	0.0272	0.0177	0.58	0.16	normal
	9	0.9541	0.2859	0.0804	0.0356	0.0167	0.56	0.11	normal
	10	0.9675	0.2402	0.0676	0.0341	0.0209	0.59	0.28	normal
	11	0.9767	0.1957	0.0845	0.0257	0.0086	0.15	0.034	light
	12	0.9549	0.2726	0.1120	0.0276	0.0221	0.17	0.034	light
	13	0.9739	0.2117	0.0793	0.0186	0.0089	0.174	0.06	light
	14	0.9547	0.2843	0.0785	0.0373	0.0100	0.19	0.07	light
	15	0.9318	0.3363	0.1253	0.0523	0.0154	0.17	0.035	severe
	16	0.9370	0.3075	0.1579	0.0445	0.0223	0.21	0.026	severe
	17	0.9354	0.3197	0.1420	0.0487	0.0158	0.16	0.023	severe
	18	0.9541	0.2725	0.1199	0.0272	0.0165	0.18	0.028	severe

The number of the failure modes is three, moreover the present investigation employs “one against one” classification pattern, Thus the number of two-class SVMs is easy to derived: $3\times(3-1)/2=3$ .Using training samples, SVM are trained, and well-trained model of classifier is obtained. Through cross validation we choose the penalty C=100, and parameter of RBF $\gamma=1/2\sigma^2=1.3$ as the best parameters. Then input 18 sets of data together to the SVM model, get the accuracy of the results by assessing the test data at last.

In order to compare the performance of classifiers, the combination of EMD, HOC and BP neural network for fault diagnosis is used; while in order to illustrate the action of HOC in feature extraction, use EMD to extract fault feature only, namely put the energy of the prior 5 IMF components as characteristic value to form feature vectors, and input them to classifiers. Under the same scale test and train the samples, get the classification results shown in Table Ⅱ.

TABLE II THE CONTRAST OF RECOGNITION ACCURACY BY 4 METHODS

Fault Level	**EMD+BP**	**EMD+HOC+BP**	**EMD+SVM**	**EMD+HOC+SVM**
Normal	5/6	6/6	5/6	6/6
Light	5/6	5/6	5/6	6/6
Severe	6/6	6/6	6/6	6/6

Can obtain from table Ⅱ, the feature vectors obtained by EMD can not fully describe the failure characteristics of the signal. BP neural network is easy to fall into local minimum, and sensitive to the training parameters, moreover it can not recognize the engine failure in the case of limited samples effectively. The approach of adding higher order cumulants to feature vectors and using SVM for pattern recognition gets good results.

6. Conclusions

(1) The combination of EMD and HOC as the preprocessor to extract fault feature has higher recognition accuracy than EMD solely, the feature vectors of the signal extracted by the former can show the essential characteristics of each fault better.

(2) The final decision of SVM is only from a small number of support vectors, which is less affected by feature dimensions of the inputting samples. It has advantages of high classification precision and strong generalization performance for small samples, the experimental result shows that it is superior to BP neural network.

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