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Fault diagnosis of diesel engine valve clearance under variable operating condition based on soft interval SVM①

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Abstract

The fault detection and diagnosis of diesel engine valve clearance can effectively improve the availability and safety of diesel engine and have extremely important value and significance. Diesel engines generally operate in various stable operating conditions, which have important influence on the fault diagnosis. However, many fault diagnosis methods have been put forward under specific stable operating condition based on vibration signal. As the result of great impact caused by operating conditions, corresponding diagnosis models cannot deal with the fault diagnosis under different operating conditions with required accuracy. In this paper, a fault diagnosis of diesel engine valve clearance under variable operating condition based on soft interval support vector machine (SVM) is proposed. Firstly, the fault features with weak condition sensitivity have been extracted according to the influence analysis of fault on vibration signal. Moreover, soft interval constraint has been applied to SVM algorithm to reduce the random influence of vibration signal on fault features. In addition, different machine learning algorithms based on different feature sets are adopted to conduct the fault diagnosis under different operating conditions for comparison. Experimental results show that the proposed method is applicable for fault diagnosis under variable operating condition with good accuracy.

Key words: diesel engine, fault diagnosis, operating condition, support vector machine (SVM)

0 Introduction

Diesel engine is a kind of core power machinery with excellent power, efficiency and cost performance. It plays an important role in the field of national defense, chemical industry, shipping, nuclear power and so on. However, unexpected faults usually occur as the result of the poor environment, fickle operating conditions and complex structure. Once diesel engine fails, it may not only cause equipment shutdown, directly or indirectly cause economic losses, but also may threaten the personal safety of users or maintenance personnel[1]. Therefore, the condition monitoring and fault diagnosis techniques have attracted more and more attentions and are proved to be valuable. Moreover, the recent achievements of these techniques have been well reviewed and summarized in Ref. [2]. The reported faults mainly include injection faults, faulty oil pressure, knock, piston slap, clearance within cam-distribution system, worn bearings, etc.

The clearance within cam-distribution system, which is used to control the timing of gas intake and exhaust, plays an important role in thermal compensation. However, it tends to increase frequently due to wear of the components or a faulty adjustment during engine overhaul[3]. The abnormal clearance of valve train in adiesel engine will affect the efficiency and may cause performance degradation or deterioration, such as cylinder hitting or valve fracture fault[4]. In order to avoid severe deterioration and economic losses caused by abnormal clearance fault, the research on fault diagnosis of abnormal clearance is of great importance.

The manual detection method cannot meet the requirements of health monitoring of diesel engine, so the real-time monitoring technology is mostly adopted. The common real-time monitoring technologies include key thermal parameters[5], vibration[6], noise[7], cylinder pressure[8], oil[9], and so on. Vibration monitoring

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can use non-invasive sensor to collect high-precision vibration signal data, which has the advantages of simple sensor installation and convenient data acquisition. Therefore, most of the researches on detecting the clearance fault of valve train were conducted based on vibration signal. Simultaneously, the vibration signal measured from cylinder head of diesel engine is highly transient and non-stationary, which makes the detection of abnormal clearance difficult.

At present, many fault detection and diagnosis methods have been put forward based on the vibration signal of cylinder head of diesel engine. Some studies focus on extracting features that can distinguish the faulty condition from healthy condition. In Ref. [10], an impact strength feature was extracted for each valve closing impact by calculating the local root mean square and localizing the impact with adaptive thresholding. In Ref. [11], 16 frequency-domain features were extracted based on the fast Fourier transform (FFT), and then 4 features were obtained by feature dimensionality reduction. The diagnosis model for valve clearance fault was established by combining artificial neural network, support vector machine (SVM) and k-nearest neighbor (KNN). In Ref. [12], the vibration signal was decomposed based on the improved variational mode decomposition (VMD), and the optimal intrinsic mode function was selected for noise reduction. Through the bispectrum analysis of the corresponding reconstructed signal, fault sensitive features are extracted. For the fault diagnosis of valve clearance under variable rotation speed, Ref. [13] conducted adaptive frequency band division and extracted frequency band characteristics based on improved VMD, and finally conducted fault diagnosis in combination with random forest. Moreover, neural network and image classification algorithms have also been applied to the fault detection and diagnosis of valve clearance[14]. Before the image classification algorithms were used, the vibration acceleration signals were usually transferred to time-frequency images by time-frequency transform algorithms, such as wavelet packet transformation.

However, most fault diagnosis methods are put forward without considering the operating conditions. The corresponding diagnosis models cannot deal with the fault diagnosis under different operating conditions with required accuracy. As for operating condition, it contains two aspects: the load that represents the output torque of diesel engine and the rotation speed of crankshaft. During operation of diesel engine, the vibration signal could be affected by the changing operating condition, which will lead to the decrease of fault characteristics' ability to represent fault information. If the influence of operating conditions is not considered in the fault diagnosis method, it can easily lead to misdiagnosis of different operating conditions as faults. Therefore, it is of great practical significance to study a fault diagnosis method that is not affected by operating conditions.

In this paper, a fault diagnosis of diesel engine valve clearance under variable operating condition based on soft interval SVM (SISVM) is proposed. The main contribution of this paper can be summarized as follows.

(1) The fault features with weak condition sensitivity have been extracted according to the influence analysis of fault on vibration signal.

(2) Soft interval constraint has been applied to SVM algorithm to reduce the random influence of vibration signal on fault features.

(3) Experimental results confirm that the proposed method can achieve higher accuracy under variable operating condition than other approaches.

The rest of this paper is organized as follows. Section 1 presents the test bench of diesel engine, variable operating conditions and the fault simulation of valve train. Section 2 introduces the fault diagnosis method based on fault features with weak condition sensitivity and soft interval SVM. Section 3 reports the result of fault diagnosis, experimental analysis and the comparison between the proposed method and other traditional methods. Finally, conclusions and prospect are presented in Section 4.

1 Test bench of diesel engine and experiments

1.1 Test bench of diesel engine

The diesel engine numbered TBD234 (produced by Henan Diesel Engine Industry Co. Ltd.) was taken as the research object and the parameters of the diesel engine are shown in Table 1.

Table 1 Parameters of TBD234 diesel engine

Item	Value
Number of cylinders	12
Shape	V-shaped
Firing sequence	B1-A1-B5-A5-B3-A3-B6-A6-B2-A2-B4-A4
Rating speed	2100 rpm
Rating power	485 kW
Normal clearance of intake valve train	0.3 mm
Normal clearance of exhaust valve train	0.5 mm

Acceleration sensors are arranged on the surface of 12 cylinder heads to monitor the vibration information of the diesel engine under the running state, as shown in Fig. 1. The vibration signal of cylinder head contains information of reciprocating, friction, crash of components and gas flow, which can provide data basis for the operating condition recognition of diesel engine. Moreover, an eddy current sensor is arranged on the flywheel connected to the crankshaft to measure the key signal. The key signal can be used for determining the periodic signal. In addition, a hydraulic dynamometer is connected at the output end of the diesel engine to adjust the operating condition.

All the information is collected and processed by the online condition monitoring system (OCMS), and the data is saved to the server through Ethernet transmission. And the sampling frequency of the vibration signal collected by OCMS is 51 200 Hz. The structure diagram of OCMS of diesel engine is shown in Fig. 2.

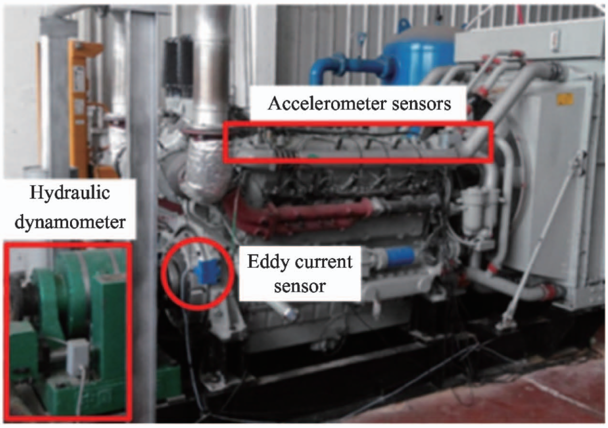


Fig. 1 Test bench of diesel engine

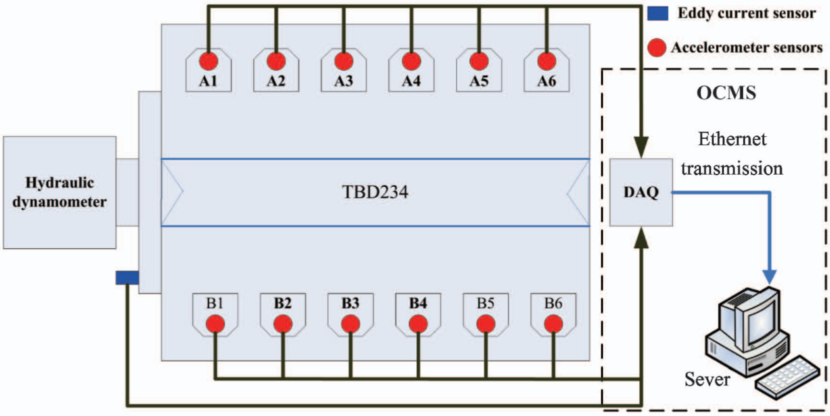


Fig. 2 Structure diagram of OCMS

1.2 Variable operating condition

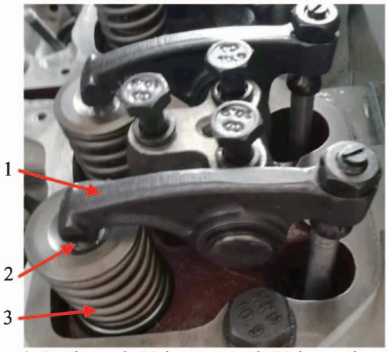
The operating condition of diesel engine is in a state of constant change. According to the performance of the tested diesel engine, several representative operating conditions that are shown in Table 2 can be selected to represent the continuous operating conditions. The *Rev* represents the rotation speed of crank shaft with unit of rpm and the *Load* represents the output torque of diesel engine with unit of N · m. In the related experiments, the operating conditions were adjusted by the hydraulic dynamometer and the corresponding vibration of cylinder head can also be measured and collected.

Table 2 Operating conditions of diesel engine

No.	1	2	3	4	5
Rev/rpm	1500	1500	1500	1800	2100
Load/N · m	700	1000	1300	700	700

1.3 Fault of valve train

A valve train, which is shown in Fig. 3, consists of intake valve and exhaust valve. As shown in the figure, the exhaust valve consists of valve cap, valve spring, and rocker arm, etc. And the valve clearance refers to the clearance between valve cap and rocker.



1. Rocker; 2. Valve cap; 3. Valve spring

Fig. 3 Valve train

Based on the valve clearances of intake valve and exhaust valve, the valve train controls the flow in and out of the combustion chamber. An abnormal valve clearance can lead to improper valve opening and closing, which affects the flow in and out of the combustion chamber. With the passage of time and the extension of the service time, the valve springs may gradually deteriorate and deform, resulting in abnormal valve clearance and decrease in flow control efficiency.

To simulate the fault of valve train, the sizes of valve clearance of the cylinders in column B were set abnormal by thickness measuring ruler. The clearances of inlet valve and exhaust valve of all cylinders in column B are adjusted to complete two comparative experiments and the size configuration of valve clearance is shown in Table 3, in which the statuses corresponding from B_1 to B_6 cylinders represent large increment of intake valve clearance (fault 1), exhaust valve clearance (fault 2), and overall valve clearance (fault 3), small increment of intake valve clearance (fault 4), exhaust valve clearance (fault 5), and overall valve clearance (fault 6) respectively. The comparative experiments are conducted under all above operating conditions.

Table 3 Normal and abnormal valve clearance of cylinders in column B

Number of cylinder	Normal valve		Abnormal valve	
	Intake valve/mm	Exhaust valve/mm	Intake valve/mm	Exhaust valve/mm
B1	0.3	0.5	0.9	0.5
B2	0.4	0.4	0.4	1.1
B3	0.3	0.4	0.9	1.1
B4	0.3	0.5	0.6	0.5
B5	0.3	0.4	0.3	0.8
B6	0.3	0.6	0.4	0.8

Through OCMS, vibration signals of different operating conditions can be measured. The normal and faulty vibration signals under different operating conditions are shown in Fig. 4. The signals in the figure represent two complete cycles, which correspond to 1440 degrees of crankshaft rotating. When fire combustion, closing of intake valve and exhaust valve occurs, it will produce obvious excitation response at the corresponding phase.

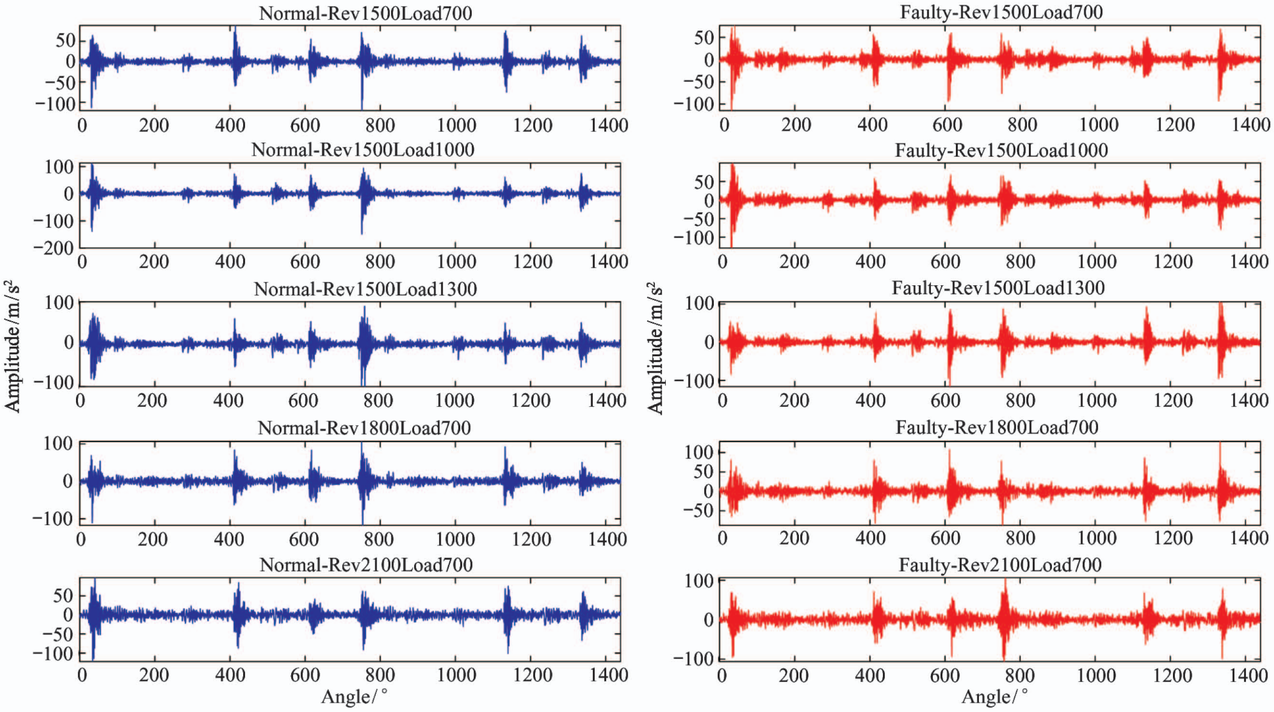


Fig. 4 Normal and fault vibration signals under different operating conditions

It can be seen from Fig. 4 that the similarity of vibration signals not only exists between fault state and health state, but also exists between different operating conditions. In other words, the influence of operating conditions on vibration signals is very similar to that caused by faulty factors. Coupled with the random influence of vibration signals, these similarities not only increase the difficulty of fault diagnosis under stable operating conditions, but also greatly increase the difficulty of fault diagnosis under variable operating conditions. If operating conditions are not considered, other operating conditions may be misdiagnosed as faults.

2 Fault diagnosis considering variable operating condition

The main purpose of this work is to develop a method for detecting and diagnosing abnormal valve clearance under different operating conditions. The fault diagnosis method considering variable operating condition includes three aspects: extraction of fault features with weak condition sensibility, feature correlation processing and fault diagnosis based on soft interval SVM.

2.1 Extraction of fault features with weak condition sensibility

According to the structure and working principle of the valve train, with the increase of valve clearance, the opening time of the valve will be relatively delayed, while the closing time of the valve will be relatively advanced. The opening and closing times of the valve have changed, while the timing system controlling the valve action still runs normally according to the original law, which will lead to a significant increase in the valve action acceleration when the valve is opened and closed, and the larger the valve clearance, the longer the valve dislocation time. Therefore, when the valve clearance increases abnormally, it will lead to intensified valve impact and the corresponding impact energy will increase. And the characteristics of impact energy corresponding to valve closing can be extracted to characterize the differential information of valve clearance. As the vibration signal has strong transient and non-stationary characteristics, single fault feature make it difficult to diagnose faults perfectly. Therefore, different energy characteristics will be combined and used for fault diagnosis. For a whole-period angular domain vibration signal, the following energy-related features can be extracted.

2.1.1 Energy characteristics in frequency domain

As the valve gap becomes abnormally large, the sitting impact of the valve closing increases, and the absolute energy of the periodic signal also becomes stronger. Compared with time-domain energy characteristics that are easily affected by operating conditions, the frequency-domain energy characteristics are more stable and robust to operating conditions. By fast Fourier transform, the time domain signal can be transformed into the sum of multiple periodic functions and shows the amplitude and phase change with frequency. The definition of energy characteristics in the frequency domain is shown in Eq. (1).

$$F_1 = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{1}$$

where, y_i represents the amplitude of ith point in frequency spectrum.

In order to compare the different influence of fault and operating condition on this feature, frequency domain energy feature extraction was carried out for vibration signals in different operating conditions under normal and fault status of B1 cylinder, and the results are shown in Fig. 5.

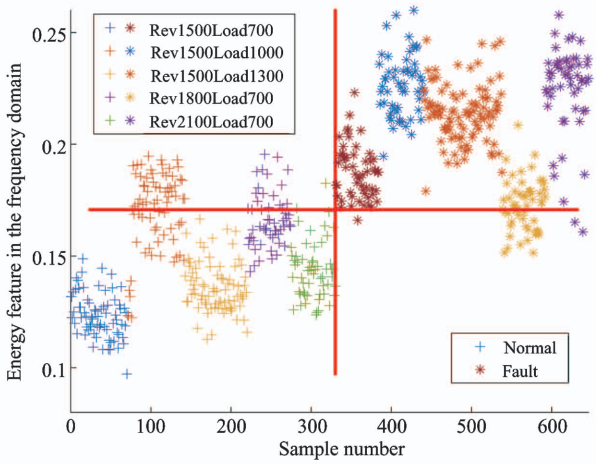


Fig. 5 Frequency domain energy feature of normal and fault vibration signals under different operating conditions

It can be seen from Fig. 5 that the energy characteristics in the frequency domain can provide a basis for the fault diagnosis of abnormal valve clearance under variable operating conditions to a certain extent, although the feature is not ideal.

2.1.2 Distribution variation characteristics of spectrum

The increase of impact energy of valve closing not only changes the energy of specific frequency band, but also affects the spectrum distribution of vibration signal. The intensification of impact leads to the increase of excitation response, which will correspondingly change the frequency aggregation and dispersion[15], the related features are shown in Eqs(2) – (8).

$$a = \frac{\sum_{i=1}^{n} (f_i y_i)}{\sum_{i=1}^{n} y_i} \tag{2}$$

$$F_2 = \frac{\sum_{i=1}^{n} [y_i - F_1]^2}{n - 1} \tag{3}$$

$$F_3 = \sqrt{\frac{1}{n}\sum_{i=1}^{n} [(f_i - a)^2 y_i]} \tag{4}$$

$$F_4 = \frac{\sum_{i=1}^{n} [(f_i - a)^3 y_i]}{n(F_3)^3} \tag{6}$$

$$F_5 = \frac{\sum_{i=1}^{n} [(f_i - a)^4 y_i]}{n(F_3)^4} \tag{7}$$

$$F_6 = \frac{\sum_{i=1}^{n} [\sqrt{f_i - a} y_i]}{n\sqrt{F_3}} \tag{8}$$

where, y_i and f_i represent the amplitude and frequency of ith point in frequency spectrum respectively.

In order to compare the different influence of fault and operating condition on these features, the features extracted from vibration signals in different operating conditions under normal and fault conditions are shown in Fig. 6.

It can be seen from Fig. 6 that the distribution variation characteristics of spectrum have low sensitivity to

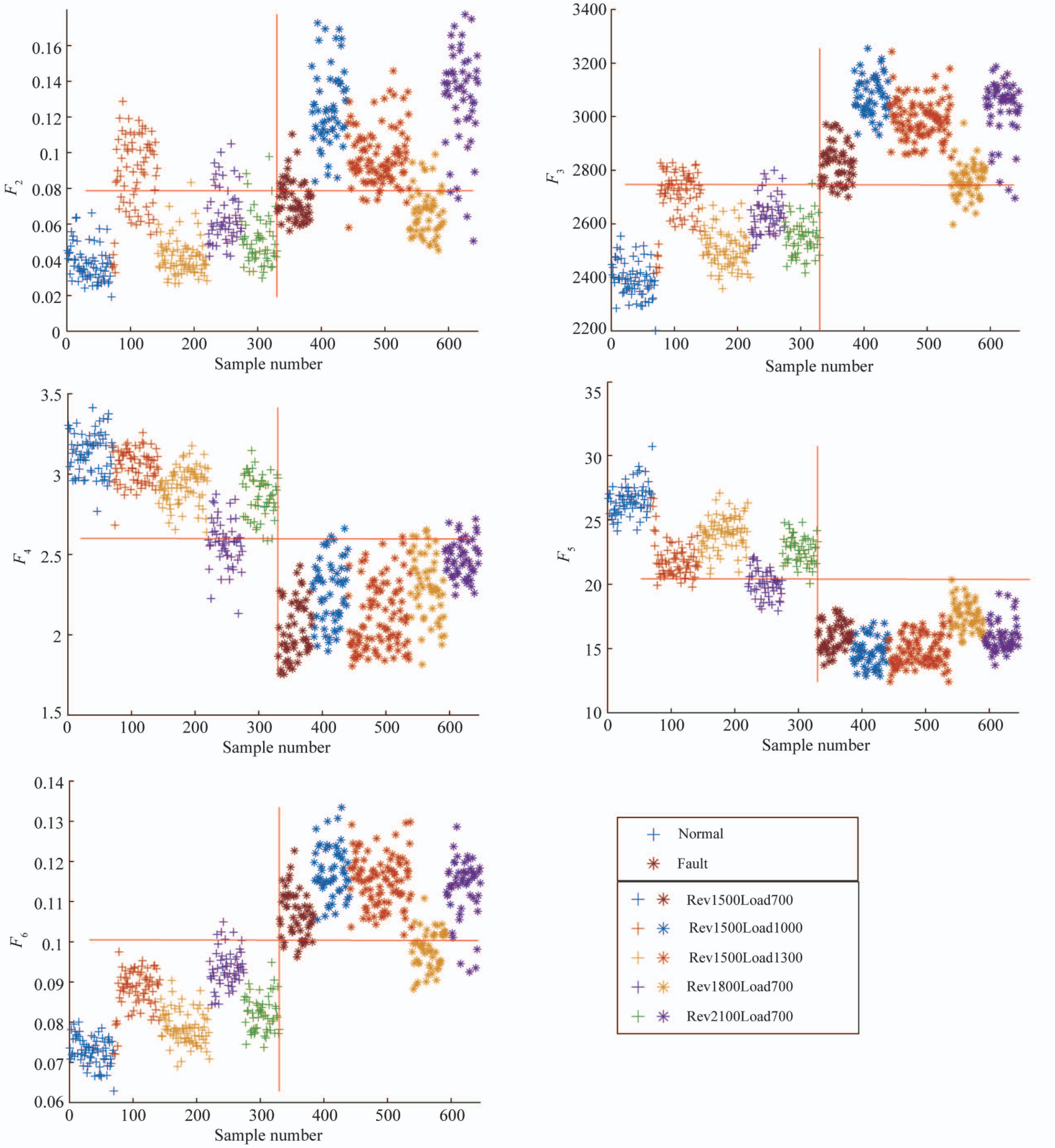


Fig. 6 Features of vibration signals in different operating conditions under normal and fault status

operating conditions and high sensitivity to faults. Because a single feature cannot completely distinguish the normal and fault states under different operating conditions, it is necessary to integrate multiple features for fault diagnosis.

2.2 Feature correlation processing

All the above features are extracted from the same signal to represent the same type of information. Although the expression of features is different, with the increase of the number of features, the possibility of repeated expression of information also increases. As the number of features increases, the correlation between the different features increases. In order to quantify the degree of linear correlation between different features, Pearson correlation coefficient is used. The Pearson correlation coefficient is defined in Eqs(9) - (10).

$$Cov(X_i, X_j) = E\{[X_i - E(X_i)], [X_j - E(X_j)]\} \tag{9}$$

$$r(X_i, X_j) = \frac{Cov(X_i, X_j)}{(D(X_i)D(X_j))} \tag{10}$$

where, $E(X_i)$ and $E(X_j)$ represent the expectation of X_i and X_j respectively, $D(X_i)$ and $D(X_j)$ represent the standard deviation of X_i and X_j respectively, and Pearson correlation coefficient r varies from -1 to 1. As can be seen from the above confusion matrix in Fig. 7, there is a high degree of correlation between the different features.

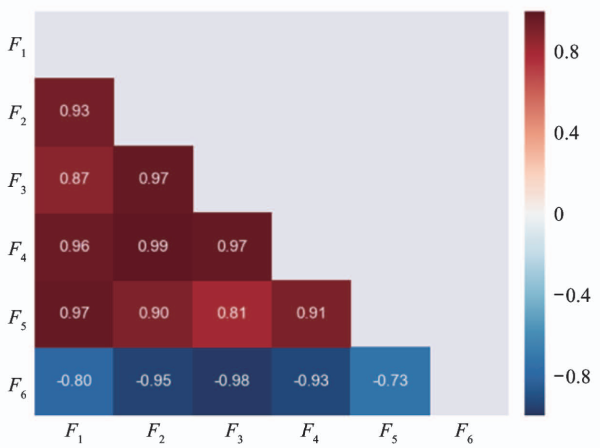


Fig. 7 Pearson correlation coefficients of features

Principal component analysis (PCA)[16] can transform the correlated feature combinations into several linearly independent synthetic variables by means of orthogonal transformation, so as to achieve feature dimension reduction. Therefore, PCA can be carried out on the above feature combinations, and the first three principal components with information proportion of 99.9% can be selected to represent all the features.

2.3 Fault diagnosis of diesel engine valve clearance based on soft interval SVM

Considering the random characteristics of the vibration signal, although the fault feature combination can describe the state information of the valve mechanism well, it is not guaranteed that the fault feature can make the training samples completely linearly separable in the feature space. Therefore, in order to avoid the overfitting of the fault diagnosis model to realize the classification of the training samples, the support vector machine based on soft interval is introduced to allow individual training samples to be unconstrained. The generalization ability of the fault diagnosis model can be improved by easing the constraint.

SVM maps the data samples to the high-dimensional feature space through the nonlinear kernel function to find a hyperplane in the feature space that can maximize the sum of the distance between the two heterogeneous support vectors and the hyperplane based on the training set.

Assuming $D = \{(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \cdots, (\boldsymbol{x}_i, y_i), \cdots, (\boldsymbol{x}_n, y_n)\}$, $\boldsymbol{x}_i \in \boldsymbol{R}^d$, $y_i \in \{+1, -1\}$, D is the training set, and n samples are both independent dimensional vectors which submit to the same distribution. Meanwhile, the normal vector $\boldsymbol{W} = (w_1, w_2, \cdots, w_d)$ represents the direction of the hyperplane $\boldsymbol{W}^{\mathrm{T}}\boldsymbol{x} + b = 0$ and the displacement term b represents the distance from the hyperplane to the origin. It is the optimal hyperplane to separate samples correctly under the condition of the largest class interval. The solution of the optimal separation plane can be transformed into the following objective function and constraint conditions.

$$\begin{aligned} &\min_{\boldsymbol{w}, b} \quad \frac{1}{2} \| \boldsymbol{w} \|^2 \\ &\text{s.t.} \quad y_i(\boldsymbol{w}^{\mathrm{T}} x_i + b) \geqslant 1 \end{aligned} \tag{11}$$

When some samples are allowed to fail to meet the constraints in SVM model training, it can be realized by introducing penalty factor $C(C>0)$ into the optimization target function, which is shown in Eq. (12).

$$\begin{aligned} &\min_{\boldsymbol{w}, b} \quad \frac{1}{2} \| \boldsymbol{w} \|^2 + C \sum_{i=1}^{n} \xi_i \\ &\text{s.t.} \quad \begin{cases} \xi_i \geqslant 0 \\ y_i(\boldsymbol{w}^{\mathrm{T}} x_i + b) \geqslant 1 - \xi_i \end{cases} \end{aligned} \tag{12}$$

The optimization model is a convex quadratic programming problem, which can be solved efficiently by the dual form of the model obtained by Lagrange multiplier method.

Obviously, the value of the penalty factor is closely related to the requirement of satisfying the constraint. When the penalty factor goes to infinity, it means that all samples are required to satisfy the constraint conditions, while when the penalty factor takes an appropriate value, some samples are allowed to not satisfy the constraint. In the actual training process of the model, the fewer samples that do not meet the constraints, the better the performance of the model; otherwise, the stability of the obtained separation hyperplane will become worse, resulting in a significant decline in the differentiation ability of the model. Therefore, the value of the penalty factor should not be too small.

Taking the vibration data of large increment of exhaust valve clearance (fault 1) as example, the penalty factor C was analyzed as an independent variable with value [1:10:10000]. According to the fault diagnosis based on soft interval SVM, the irregular parabolic curve of accuracy changing with C can be obtained and shown in Fig. 8.

It can be seen from Fig. 8 that the value of penalty factor ranges from 1681 to 2281, the accuracy can be maximized. Therefore, the penalty factor can be designed to be 2000 in this paper.

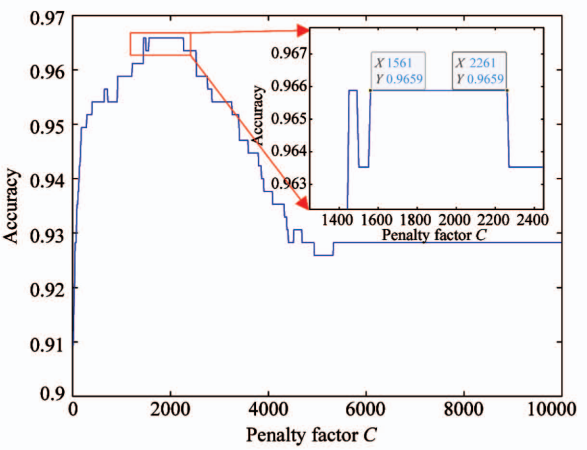


Fig. 8 Sensitivity analysis of penalty factor

2.4 Process of fault diagnosis method considering variable operating condition

The process of fault diagnosis method considering variable operating condition can be divided into 5 parts.

(1) Data acquisition. Vibration data of diesel engine is the basis of fault diagnosis and can be collected by the OCMS.

(2) Signal preprocessing. Signal preprocessing is an important step to improve the quality of data, which affects the subsequent signal analysis. The most important process is the signal interception of the whole cycle and the resampling in angular domain according to the key signal.

(3) Feature extraction. The fault features with weak condition sensibility are extracted to represent the key information of vibration signal.

(4) Feature correlation processing. The fault features with correlations need to be processed by PCA.

(5) Fault diagnosis. Based on the processed fault features and soft interval SVM, the fault diagnosis under different operating conditions can be performed.

The flow chart of fault diagnosis under different operating conditions is shown in Fig. 9.

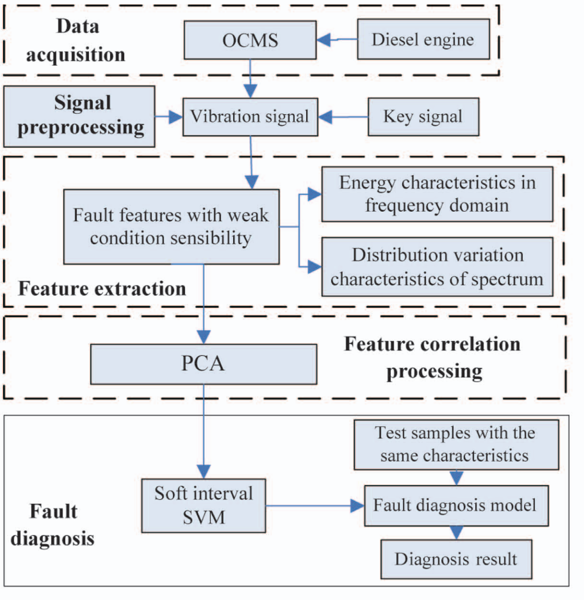


Fig. 9 Flow chart of fault diagnosis under different operating conditions

3 Experiments

According to the process shown in Fig. 9, the applicability of the proposed method is verified by the normal and fault vibration data of valve train under different operating conditions. Based on the same vibration data, the proposed method is compared with the traditional method to verify its effectiveness and accuracy.

3.1 Fault diagnosis under different operating conditions

To verify the applicability of the proposed method, the normal and fault data of valve train were measured under different operating conditions and shown in Table 4. In the table, $N1$ and $N2$ represent the number of training samples and test samples respectively.

Based on vibration signal, condition monitoring system of diesel engine needs to be capable of identifying whether the diesel engine is in normal or fault state. Therefore, when abnormal valve clearance occurs, the monitoring system can timely warn of failure.

Table 4 Division of experimental data

Rev		1500 /rpm	1500 /rpm	1500 /rpm	1800 /rpm	2100 /rpm
Load		700 /N·m	1000 /N·m	1300 /N·m	700 /N·m	700 /N·m
Normal	*N*1	70	72	78	54	56
	*N*2	30	30	30	30	30
Fault1	*N*1	54	56	98	54	54
	*N*2	30	30	30	30	30
Fault2	*N*1	54	56	98	54	54
	*N*2	30	30	30	30	30
Fault3	*N*1	54	56	98	54	54
	*N*2	30	30	30	30	30
Fault4	*N*1	54	56	98	54	54
	*N*2	30	30	30	30	30
Fault5	*N*1	54	56	98	54	54
	*N*2	30	30	30	30	30
Fault6	*N*1	54	56	98	54	54
	*N*2	30	30	30	30	30

The 1050 groups of feature data in the testing set were input to the soft interval SVM model for pattern recognition, among which 150 groups were feature data in normal state and the remaining 900 groups were feature data in abnormal state. The comparison of classification results of PCA correlation processing and initial features are shown in Table 5.

Table 5 Comparison of the classification result

Correlation processing	Accuracy of normal state	Accuracy of fault state	Average accuracy
PCA ($n=3$)	0.9333 (140/150)	0.9533 (858/900)	0.9505 (998/1050)
Initial features ($n=6$)	0.9133 (137/150)	0.9478 (853/900)	0.9429 (990/1050)

The above result shows that PCA can reduce the redundancy between different features while retaining important information and keeping the accuracy basically unchanged.

The applicability of fault diagnosis method under different operating conditions is very important to the status monitoring of diesel engine, and the confusion matrix of result is shown in Table 6.

The method can ensure that the average accuracy is more than 90% under different operating conditions, and can give an accurate alarm when the valve clearance turns abnormal.

Table 6 Confusion matrix

Rev	*Load*	Status	Classification result: Normal	Classification result: Fault	Accuracy
1500 /rpm	700 /N·m	Normal	29	1	0.9667
		Fault	6	174	
1500 /rpm	1000 /N·m	Normal	30	0	0.9667
		Fault	7	169	
1500 /rpm	1300 /N·m	Normal	29	1	0.9619
		Fault	7	173	
1800 /rpm	700 /N·m	Normal	28	2	0.9286
		Fault	13	167	
2100 /rpm	700 /N·m	Normal	24	6	0.9048
		Fault	14	166	

3.2 Comparative analysis of different methods based on different feature sets

It is well known that different features have different adaptability to learning algorithm, so different machine learning methods are selected for comparison and discussion. The soft interval SVM was compared with the following learning methods: random forest (RF), KNN, naive Bayes (NB), linear discriminant analysis (LDA), and SVM[17-18]. At the same time, the fault features with weak condition sensibility (Set A with 3 features), multi-domain feature set[15] (Set B with 39 features) and the low dimensional multi-domain feature set based on PCA (Set C with 3 features) are both used to conduct the fault diagnosis under different operating conditions. The results are shown in Fig. 10.

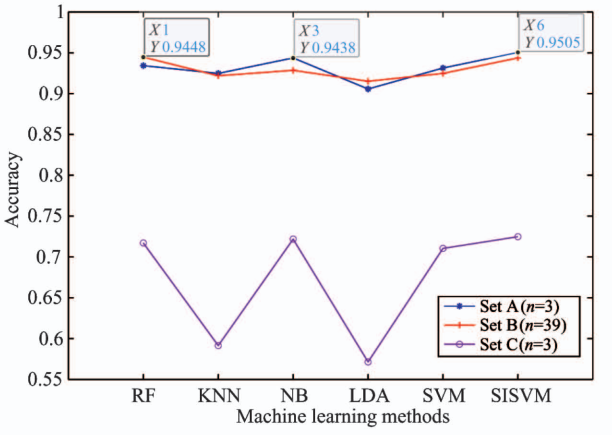


Fig. 10 The accuracies under different methods based on different feature sets

Through comparative analysis of the above results, the following conclusions can be drawn.

(1) Although many other features are added into the multi-domain feature set, the effect is weak. If PCA is used for dimensionality reduction, the important in-

formation for fault diagnosis will be easily filtered out.

(2) The fault features with weak condition sensibility are applicable for fault diagnosis considering variable operating condition with good accuracy by combining a classification algorithm.

The above results prove the effectiveness and superiority of the proposed method in this paper.

4 Conclusion

In this paper, an effective approach has been proposed for the fault diagnosis under different operating conditions. The proposed method is capable of monitoring and diagnosing the fault considering variable operating condition based on the vibration signal of cylinder head. The fault features with weak condition sensibility are extracted to explore the state information of vibration signal firstly. Subsequently, PCA is taken to deal with the correlation and redundancy between features. Moreover, soft interval constraint has been applied to SVM algorithm to reduce the randomness influence of vibration signal on fault features. Finally, experimental data are used to verify the effectiveness of the method, and the experimental results prove that the selected fault features are indeed ideal for fault diagnosis under different operating conditions with higher accuracy and less features than other methods.

References

[1] Mao Z W. Research on Typical Fault Diagnosis and Unstable Condition Monitoring and Evaluation for Piston Engine[D]. Beijing: College of Mechanical and Electrical Engineering, Beijing University of Chemical Technology, 2017 (In Chinese)

[2] Delvecchio S, Bonfiglio P, Pompoli F. Vibro-acoustic condition monitoring of internal combustion engines: a critical review of existing techniques[J]. *Mechanical Systems Signal Processing*, 2018, 99: 661-683

[3] Ftoutou E, Chouchane M, Besbès N. Internal combustion engine valve clearance fault classification using multivariate analysis of variance and discriminant analysis [J]. *Transactions of Institute of Measurement and Control*, 2012, 34:566-577

[4] Witek L. Failure and hermos-mechanical stress analysis of the exhaust valve of diesel engine[J]. *Engineering Failure Analysis*, 2016, 66: 154-165

[5] Tang G G, Fu X L, Shao G S, et al. Application of improved grey model in prediction of thermal parameters for diesel engine[J]. *Ship and Boat*, 2018, 5: 39-46

[6] Liu Y. Research on Fault Diagnosis for Fule System and Valve Train of Diesel Engine Based on Vibration Analysis [D]. Tianjin: College of Mechanical Engineering, Tianjin University, 2016

[7] Figlus T, Lišˇcák Š, Wilk A, et al. Condition monitoring of engine timing system by using wavelet packet decomposition of a acoustic signal[J]. *Journal of Mechanical Science and Technology*, 2014, 28(5): 1663-1671

[8] D'Ambrosio S, Ferrari A, Galleani L. In-cylinder pressure-based direct techniques and time frequency analysis for combustion diagnostics in IC engines [J]. *Energy Conversion and Management*, 2015, 99: 299-312

[9] Wu T H, Wu H K, Du Y, et al. Progress and trend of sensor technology for on-line oil monitoring[J]. *Science China Technological Sciences*, 2013, 56: 2914-2926

[10] Flett J, Bone G M. Fault detection and diagnosis of diesel engine valve trains[J]. *Mechanical Systems Signal Processing*, 2016, 72: 316-327

[11] Jafarian K, Mobin M, Jafari-Marandi R, et al. Misfire and valve clearance faults detection in the combustion engines based on a multi-sensor vibration signal monitoring [J]. *Measurement*, 2018, 128:527-536

[12] Bi X Y, Cao S Q, Zhang D M. Diesel engine valve clearance fault diagnosis based on improved variational mode decomposition and bispectrum[J]. *Energies*, 2019, 12 (4): 661

[13] Zhao N Y, Mao Z W, Wei D H, et al. Fault diagnosis of diesel engine valve clearance based on variational mode decomposition and random forest[J]. *Applied Sciences*, 2020, 10(3):1124

[14] Mu W J, Shi L S, Cai Y P, et al. Diesel engine fault diagnosis based on the global and local features fusion of time-frequency image [J]. *Journal of Vibration and Shock*, 2018, 37(10): 14-19

[15] Yan X A, Jia M P. A novel optimized SVM classification algorithm with multi-domain feature and its application to fault diagnosis of rolling bearing[J]. *Neurocomputing*, 2018, 313: 47-64

[16] Wei W, Tao G, Heng Y. Study on metal oxide varister fault diagnosis based on principal component analysis and BP neural network[J]. *Insulators and Surge Arresters*, 2019 (6):20-25

[17] Li H. Statistical Learning Method[M]. Beijing: Tsinghua University Press, 2012 (In Chinese)

[18] Zhou Z H. Machine Learning[M]. Beijing: Tsinghua University Press, 2016 (In Chinese)

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