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Wavelet correlation feature scale entropy and fuzzy support vector machine approach for aeroengine whole-body vibration fault diagnosis

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Abstract. In order to correctly analyze aeroengine whole-body vibration signals, Wavelet Correlation Feature Scale Entropy (WCFSE) and Fuzzy Support Vector Machine (FSVM) (WCFSE-FSVM) method was proposed by fusing the advantages of the WCFSE method and the FSVM method. The wavelet coefficients were known to be located in high Signal-to-Noise Ratio (S/N or SNR) scales and were obtained by the Wavelet Transform Correlation Filter Method (WTCFM). This method was applied to address the whole-body vibration signals. The WCFSE method was derived from the integration of the information entropy theory and WTCFM, and was applied to extract the WCFSE values of the vibration signals. Among the WCFSE values, the W_{CFSE1} and W_{CFSE2} values on the scale 1 and 2 from the high band of vibration signal were believed to acceptably reflect the vibration feature and were selected to construct the eigenvectors of vibration signals as fault samples to establish the WCFSE-FSVM model. This model was applied to aeroengine whole-body vibration fault diagnosis. Through the diagnoses of four vibration fault modes and the comparison of the analysis results by four methods (SVM, FSVM, WESE-SVM, WCFSE-FSVM), it is shown that the WCFSE-FSVM method is characterized by higher learning ability, higher generalization ability and higher anti-noise ability than other methods in aeroengine whole-vibration fault analysis. Meanwhile, this present study provides a useful insight for the vibration fault diagnosis of complex machinery besides an aeroengine.

Keywords: Wavelet Correlation Feature Scale Entropy (WCFSE), Fuzzy Support Vector Machine (FSVM), aeroengine whole-body vibration, fault diagnosis, WCFSE-FSVM method

1. Introduction

With the increase of the jet thrust, rotating speed, structural dynamic strength and vibration load of aeroengine, more and more vibration faults occur during the operating phases. The vibration fault status is required to be accurately monitored and diagnosed to improve aeroengine security, reliability and lifespan, enhance the aircraft airworthiness and reduce aircraft accidents and maintenance costs. The whole-body vibration fault is one of the faults seriously impacting the aeroengine performance. Excessive vibration phenomenon during the flight operation always increase the abrasion and fatigue damage and even cause the rubbing fault and system damage. The aeroengine

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whole-body vibration fault diagnosis is kept to be one of the focus issues in academic researches and industrial applications [1]. Many vibration fault diagnosis techniques (wavelet (packet) analysis [2–5], information entropy [6–9], Support Vector Machine (SVM) [9–13], etc.) is kept developing since 1980s. Fault diagnosis generally compromises the feature extraction phase and the state recognition phase.

The feature extraction is a big bottleneck and directly affects the accuracy and validity of aeroengine whole-body vibration fault diagnosis because of the existence of nonlinear and unstable weak fault signals with noise or outliers. In fault diagnosis, the extracted feature is required to reflect the system operating condition and to retain high sensitivity against abnormal signal. The wavelet entropy theory proposed in [2,6] based on wavelet analysis technique is demonstrated to be effective in processing vibration signals in general industrial equipment, however, directly employing the wavelet entropy method in aeroengine whole-body vibration fault diagnosis is unreasonable since the fault signals with unclear information and low SNR are always disturbed by noise and outlier. The Wavelet Corrective Feature Scale Entropy (WCFSE) method in [8] is capable to effectively overcome the weakness of wavelet entropy method due to the WCFSE method with the scale wavelet coefficients in scale domain managed to consider the complexity and uncertainty of the system model [4,5,7], which implies the failure characteristic information by selecting effectively the WCFSE values to construct the feature vectors for aeroengine whole-body vibration fault diagnosis.

On the other hand, the state recognition establishes a reliable state classifier by solving the eigenvectors. The Fuzzy SVM (FSVM) applies fuzzy membership function in the SVM method to make sure different samples have different penalty factors (different contributions) by constructing different target functions. Therefore, the weak fault samples with noise and abnormal information may be effectively separated from other samples in [11–16].

To improve the precision of aeroengine whole-body vibration fault diagnosis, the Wavelet Corrective Feature Scale Entropy and Fuzzy Support Vector Machine (WCFSE-FSVM) method is proposed to extract the fault features based on the WCFSE method and to build the fault diagnosis model based on the FSVM method.

2. The WCFSE method for feature extraction

In this section, the WCFSE method for fault diagnosis is detailed based on the Wavelet Transform Correlation Filter Method (WTCFM).

2.1. The WCFSE method

Information entropy was first proposed to measure information. Assuming that the status of an uncertain system is denoted by a random variable X within finite values, where the probability of x_j is $p_j = p\{X = x_j\}$ $(j = 1, 2, \cdots, l)$ and $\sum_{j=1}^{l} p_j = 1$, so the information quantity I_j of x_j and the information entropy $H(X)$ of X in [6–8] are

$$\begin{aligned} I_j &= -\log P_j \\ H(X) &= -\sum_{j=1}^{l} p_j \log p_j \end{aligned} \tag{1}$$

where $p_j \log p_j = 0$ when $p_j = 0$.

For rotor system, the information entropy H denotes the information measure of the vibration signal under a given condition, i.e., the H measures the uncertainties of rotor vibration. The method is able to be applied to reasonably estimate the complexity of random signal of the vibration system. The information entropy value H with disordered level of a signal shows positive variation [6]. The WTCFM processes a vibration signal $x(t)$ [4,5,8] and accurately extract the important signal features by the correlative operation of wavelet transformed coefficients in each scale. The method is reported to be robust for extracting weak fault information in [7]. The wavelet coefficients $D_j = \{d_j(k), k = 1, 2, \cdots, N; j = 1, 2, \cdots, m\}$ of high SNR in scales and the scale coefficient C_m are expanded. The

$\{D_j, (j = 1, 2, \cdots m, m+1)\}$ is regarded to be a repartition of signal $x(t)$. Hence, according to the information theory, the measurement p_{jk} of D_j may be defined by.

$$p_{jk} = d_{F(j)}(k) \Bigg/ \sum_{k=1}^{N} d_{F(j)}(k) \tag{2}$$

where $d_{F(j)}(k)$ is the Fourier transformation of $d_j(k)$. The WCFSE value of D_j is

$$W_{CFSEj} = -\sum_{k=1}^{N} P_{jk} \log P_{jk} \tag{3}$$

2.2. *Extracting the WCFSEs of whole-body vibration fault signal*

As is shown in the Eq. (3), the W_{CFSEj} expresses the uniformity of energy distributing and the complexity of the scale j in vibration signal, so the fault features of vibration signals are able to be quantized by the information entropy. The WCFSE values vary with the high frequency vibration signal distribution that come from aeroengine fault occurrence. The monitor and diagnosis of vibration status are accomplished by changing the WCFSE values on each scale. The features of vibration signals of the whole-body faults are extracted according to the WCFSE method. The specific steps are

- Get wavelet coefficients of each scale based on the discrete wavelet transformation of the vibration signals.
- Decompose the wavelet coefficients into five layers to avoid the distortion of the characteristic signals during wavelet correlation filtering based on the WTCFM and achieve the higher SNR scale wavelet domains.
- Calculate the WCFSE values by the Eq. (2) and Eq. (3). The fifth layer WCFSE value is such a small low-frequency gradient signal that the W_{CFSE6} can be ignored. A feature vector $\boldsymbol{F} = [W_{CFSE1}, W_{CFSE2}, \cdots, W_{CFSE5}]$ is constructed by utilizing the entropy values. To avoid the WCFSE values to be overestimated leading to a difficult analysis, the eigenvector may be normalized.

$$W = \left(\sum_{j=1}^{5} |W_{CFSEj}|^2 \right)^{1/2} \tag{4}$$

The vector $\boldsymbol{F}$ is rewritten as:

$$\boldsymbol{F} = \left[\frac{W_{CFSE1}}{W}, \frac{W_{CFSE2}}{W}, \cdots, \frac{W_{CFSE5}}{W} \right] \tag{5}$$

The W_{CFSE1} and W_{CFSE2} contain main information and majorly reflect the fault feature in high frequency band for aeroengine whole-body vibration. Thus, the W_{CFSE1} and W_{CFSE2} are regarded as the characteristic parameters to construct fault feature vectors Eq. (6) and to judge the vibration condition.

$$F = [W_{CFSE1}, W_{CFSE2}] \tag{6}$$

3. FSVM diagnosis method

3.1. *FSVM diagnosis method*

Comparing with the SVM, the training samples of the FSVM embody a membership term besides the sample value and category code (class number). Assuming that a training sample set is $(((\boldsymbol{x}_1, y_1, \mu(\boldsymbol{x}_1)), \cdots, (\boldsymbol{x}_n, y_n, \mu(\boldsymbol{x}_n)))$, where $x_i \in \boldsymbol{R}^N$ is the i th sample feature (value), $y_i \in \{-1, 1\}$ is category number and $\mu(\boldsymbol{x}_i) \in (0, 1]$ is membership, the mapping relationship φ is defined as mapping the training samples from the original model space $\boldsymbol{R}^N$ to high dimensional feature space $\boldsymbol{Z}$, symbolized by $z = \varphi(\mathbf{x})$. From the fuzzy membership theory, $\mu(\boldsymbol{x}_i)$ indicates the credibility of the sample $\boldsymbol{x}_i$ belonging to y_i. The ξ_i is the error of the objective function of the FSVM, and $\mu(\boldsymbol{x}_i)\xi_i$ is the weight error. The optimal objective function [4,5] is

$$\Phi(\omega, \xi) = \frac{1}{2}\|\omega\|^2 + C(\sum_{i=1}^{n} \mu(\boldsymbol{x}_i)\xi_i)$$
$$s.t. \quad \begin{cases} y_i\left[(\omega^T \cdot z_i) + b\right] - 1 + \xi_i \geqslant 0 \\ \xi_i \geqslant 0 \\ i = 1, 2, \cdots, n \end{cases} \tag{7}$$

where the constant C is a penalty factor, the ω is the weight of linear classification function y_i. The discriminated functions of x_i is

$$f(\boldsymbol{x}) = \operatorname{sgn}\left(\sum_{\boldsymbol{x}_i} \alpha_i y_i K(\boldsymbol{x}_i, \boldsymbol{x}) + b\right) \tag{8}$$

where $K(\boldsymbol{x}_i, \boldsymbol{x})$ is a kernel function, the purpose of which is to convert the complex inner production in high-dimensional feature space into a simple computational function in a low-dimensional model space.

From Eq. (7), the influence of ξ_i obviously become weak when $\mu(\boldsymbol{x}_i)$ decreases, which leads to the corresponding $\boldsymbol{x}_i$ unimportant. The penalty factor C is fuzzed in order to make different samples featured with different penalty factors, so that the negative impacts of exception samples with noise or outliers are highly reduced and even eliminated, on the other hand, the dominated samples of normal support vectors on the optimal classification surface are retained. The fuzzy membership design is a key technique in designing the FSVM. To design the appropriate fuzzy membership, the present study employs the membership function proposed in [12] to process the aeroengine whole-body vibration signal, since the membership function building technique in [12] considers not only the relationship between the samples of the given class and their class center, but also the relationship amongst the various samples to distinguish the support vectors from the exception samples with noises.

3.2. Mathematical model of FSVM diagnosis method

The aeroengine whole-body vibration fault diagnosis is a multiclass signal process problem which requires establishing a multiclass FSVM classifier. The methods of constructing a multi-class classifier in [10,16] contains one against all (1-a-a) method, one to one (1-a-1) method, directed a cyclic graph SVM (DAGSVM) method, etc., In this paper, the FSVM multi-classifier is designed based on the 1-a-a method. For this purpose, a set of training samples is assumed

$$(((\boldsymbol{x}_1, y_1, \mu(\boldsymbol{x}_1)), \cdots, (\boldsymbol{x}_n, y_n, \mu(\boldsymbol{x}_n)))$$

where $\boldsymbol{x}_i \in \boldsymbol{R}^N$ and $y_i \in \{1, 2, \cdots, k\}$ and $0 \leqslant \mu(\boldsymbol{x}_i) \leqslant 1$.

The class-radius is assumed to be $r = \max\limits_{\boldsymbol{x}_i} \|\boldsymbol{x}_i - \bar{x}\|$, the training samples are classified based on the 1-a-a method, the k classifiers are trained through one sample $\boldsymbol{x}_i$ owning one fuzzy membership $\mu(\mathbf{x}_i)$ in training process. When the l th class is separated from the rest samples, the central point and class radius of the l th class are respectively x_+ and r_+, while the rest samples are treated as the other class, the central point and class radius of which are expressed by x_- and r_-, the $\mu(\boldsymbol{x}_i)$ is

$$\mu(\boldsymbol{x}_i) = \begin{cases} 1 - \|x_+ - \boldsymbol{x}_i\| / (r_+ + \delta) & y_i = l \\ 1 - \|x_- - \boldsymbol{x}_i\| / (r_- + \delta) & y_i \neq l \end{cases} \tag{9}$$

where the δ is a sufficiently small value to avoid $\mu(\boldsymbol{x}_i) = 0$.

The FSVM training process is carried out to acquire all the two-classifiers. Then the k two-classifiers are obtained

$$f(\boldsymbol{x}) = \omega_i \times \boldsymbol{x} + b_i = \sum_{\boldsymbol{x}_i} \alpha_i y_i K(\boldsymbol{x}_i, \boldsymbol{x}) + b \quad i = 1, 2, \cdots, k \tag{10}$$

Therefore, a new sample x is diagnosed to affiliate to the class number by

$$class(\boldsymbol{x}) = \arg\max\{f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \cdots f_k(\boldsymbol{x})\} \tag{11}$$

Table 1
Measuring point locations for aeroengine whole-body vibration

Section	Location	Measuring points
1-1	Through the pivots before fan	1-Measure horizontal vibration velocity
		2-Measure vertical vibration velocity
2-2	Through intermediary casing	3-Measure horizontal vibration velocity
		4-Measure vertical vibration velocity
3-3	Through LPT pivots	5-Measure horizontal vibration velocity
		6-Measure vertical vibration velocity
4-4	External accessories casing	7-Measure horizontal vibration acceleration
		8-Measure vertical vibration acceleration
5-5	Reducer	9-Measure horizontal vibration acceleration

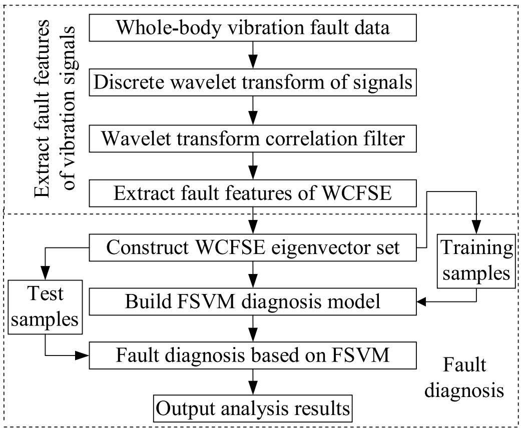

Fig. 1. Aeroengine whole-body vibration fault diagnosis model based on WCFSE-FSVM.

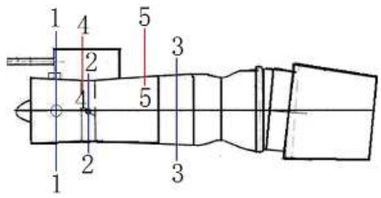

Fig. 2. Schematic illustration of aeroengine type location.

4. Integrated fault diagnosis model based on WCFSE-FSVM

The fault diagnosis model based on WCFSE-FSVM is shown in Fig. 1 which includes the feature extraction and the fault diagnosis (state identification). The characteristic parameters of aeroengine whole-body vibration fault signal are extracted by using the WTCFM. The WCFSE values reflecting the failure state were obtained based on the information entropy theory. The WCFSE values full reflecting fault features are selected to build the eigenvector set as the fault diagnosis samples (the input samples) of the FSVM model. In the fault diagnosis, some samples are taken as the training samples to establish the FSVM fault diagnosis model, while the other samples are regarded as the test samples to verify the FSVM model through aeroengine whole-body vibration fault diagnosis.

5. Aeroengine whole-body vibration fault diagnosis

5.1. *Select aeroengine vibration testing points and SVM parameters*

In this paper, an aeroengine fixed on test rig has been chosen. The five typical cross sections and the nine vertical and horizontal points in aeroengine are regarded as the measuring points as shown in Table 1 and Fig. 2. Vibration data are the test rig data and derived from an aeroengine research unit of China. The data (167 groups) of four vibration modes (normal and three fault modes, i.e., rotor imbalance, rotor-to-stator rub and rig looseness) are extracted and each one contains nine measuring points of vibration signals. The data set respectively are divided into 53, 34, 41 and 39 groups for four modes, respectively. The Radial Basis Function (RBF) $k(x,y) = \exp\left(-\frac{\|x-y\|^2}{2\delta}\right)$ in [6,9] is taken as the FSVM kernel function. δ in the RBF and C in the Eq. (7) are respectively 4 and 287.

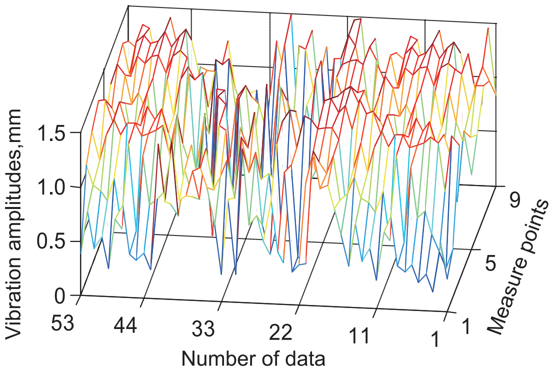

Fig. 3. 3-D graphics of the vibration signals for rotor normal.

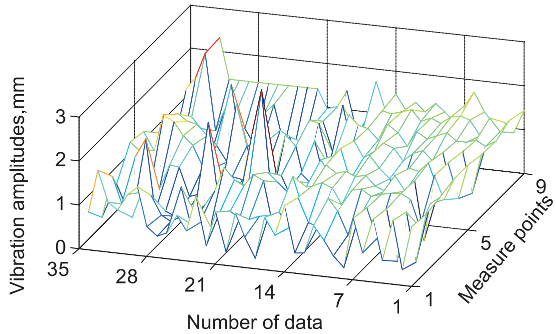

Fig. 4. 3-D graphics of the vibration signals for rotor imbalance.

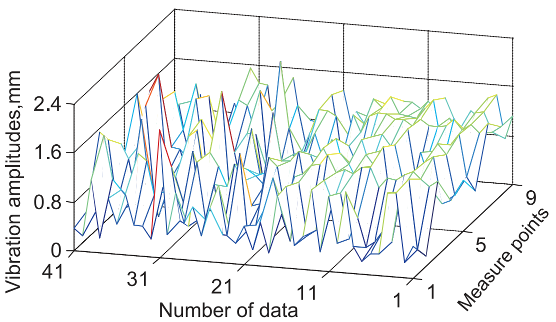

Fig. 5. 3-D graphics of the vibration signals for rotor-to-stator rub.

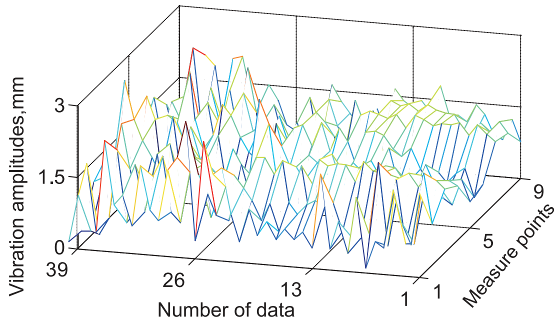

Fig. 6. 3-D graphics of the vibration signals for looseness.

5.2. *Build feature vector set*

Through selecting the raw data, the graphic models of the vibration signals four vibration modes (normal and three fault modes-rotor imbalance, rotor-to-stator rub and rig looseness), the data number of which are respectively 53 groups, 34 groups, 41groups and 39 groups, are shown in Figs 3–6. The three-dimensional (3-D) diagram is comprised of measure point, number of data and vibration amplitude.

According to the WCFSEM method thought, the vibration signals and eigenvectors of four modes are analyzed and extracted. The process is as follows:

– Extract the vibration signal features for each group data of nine measuring points to get the wavelet coefficients in scale domains with high SNR (5-layer of wavelet decomposition).
– Calculate the WCFSE eigenvectors of each scale domain by the Eq. (1) to the Eq. (3).

$$\boldsymbol{F} = [W_{CFSE1}, W_{CFSE2}, \cdots, W_{CFSE5}] \tag{12}$$

– Select the W_{CFSE1} and W_{CFSE2} that fully reflect fault feature from Scale 1 and Scale 2 as the characteristic parameters to build the eigenvector like the Eq. (6)

$$\boldsymbol{F}' = [W_{CFSE1}, W_{CFSE2}] \tag{13}$$

– In the data of nine measuring points in each group, $\boldsymbol{F}'$ of every point is arranged in sequence to construct the vibration eigenvector $\boldsymbol{T}$ of every group data

$$\boldsymbol{T} = (\boldsymbol{F}'_1, \boldsymbol{F}'_2, \cdots, \boldsymbol{F}'_9) = (T_1, T_2, \cdots, T_{18}) \tag{14}$$

According to this method, 167 feature vectors of four fault modes are calculated as the diagnosis samples of FSVM model. Every eigenvector has 18 eigenvalues which are the WCFSE values. Hence, the eigenvectors of four typical modes of aeroengine whole-body vibration are gained in Table 2 (four vectors are listed only because of little space).

Table 2
Part feature vectors based on WCFSE values under different models

Measuring point number	Feature of measuring point F'	WCFSE values	T	WCFSE eigenvector of four fault modes Normal	Imbalance	Rubbing	Looseness
1	F'_1	W_{CFSE1}	T_1	6.11	18.86	23.93	29.05
		W_{CFSE2}	T_2	5.85	17.26	19.89	30.70
2	F'_2	W_{CFSE1}	T_3	24.41	24.80	34.81	37.23
		W_{CFSE2}	T_4	23.75	22.09	31.76	33.50
3	F'_3	W_{CFSE1}	T_5	6.51	14.57	25.60	30.59
		W_{CFSE2}	T_6	6.12	12.39	20.30	27.88
4	F'_4	W_{CFSE1}	T_7	8.57	15.85	30.78	39.23
		W_{CFSE2}	T_8	7.56	16.10	32.15	35.71
5	F'_5	W_{CFSE1}	T_9	50.32	20.62	22.37	24.46
		W_{CFSE2}	T_{10}	42.39	19.10	16.39	22.80
6	F'_6	W_{CFSE1}	T_{11}	23.46	19.98	17.51	17.84
		W_{CFSE2}	T_{12}	22.87	16.39	14.29	12.76
7	F'_7	W_{CFSE1}	T_{13}	7.70	11.09	17.51	17.84
		W_{CFSE2}	T_{14}	6.75	9.13	16.83	15.37
8	F'_8	W_{CFSE1}	T_{15}	7.66	16.51	25.75	29.64
		W_{CFSE2}	T_{16}	6.88	15.23	19.83	18.92
9	F'_9	W_{CFSE1}	T_{17}	83.92	115.64	112.39	220.63
		W_{CFSE2}	T_{18}	76.32	109.28	102.57	238.31

Table 3
Diagnosis results of four methods (SVM, FSVM, WESE-SVM and WCFSE-FSVM)

Fault modes	Sample number	SVM		FSVM		WESE-SVM		WCFSE-FSVM	
		Correct	Accuracy	Correct	Accuracy	Correct	Accuracy	Correct	Accuracy
Normal	43	39	90.70%	40	93.02%	42	97.67%	41	95.35%
Imbalance	24	20	83.33%	22	91.67%	22	91.67%	22	91.67%
Rubbing	31	26	83.87%	28	90.32%	27	87.10%	29	93.55%
looseness	29	25	86.21%	26	89.66%	26	89.66%	28	96.55%
Total/mean	127	110	86.61%	116	91.34%	117	92.13%	120	94.49%

5.3. *Fault diagnosis and analysis*

As is shown in the Table 2, the W_{CFSE1} s and W_{CFSE2} s of nine measuring points of aeroengine whole-body vibration constitute the feature vectors $\{\boldsymbol{T}\}$. These feature vectors were used for the fault diagnose for aeroengine whole-body vibration. The 10 feature vectors of each model were looked as the training samples to establish FSVM model. And then these samples were employed to test the validity of FSVM model established again. The result shows that the fault diagnosis accuracy is 100%, which states the fact that the FSVM model possesses good learning ability.

The FSVM model was used to classify (distinguish) the residual 127 feature vectors which contained the weak and exceptional signals therein. The results are shown in Table 3. From the Table 3, it is verified that the model has good generalization ability.

In order to highlight the feasibility and effectiveness of the WCFSE-FSVM method proposed, the method was compared separately with other fault diagnosis method (SVM in [10], FSVM proposed in [12], wavelet energy spectrum entropy SVM (WESE-SVM) in [6]) based on the same data and computing environment. The testing results reveal that these diagnostic models are equally good learning ability since all testing accuracies are 100% based on the same training samples. The diagnosis results of four methods are shown in Table 3.

As shown in the Table 3, the diagnostic accuracy (94.49%) of the WCFSE-FSVM method is significantly higher than that (87.40%) of SVM method. It is explained that the SVM diagnostic effect is no ideal by directly diagnosing the original data of vibration signal because these data contains the weak signals, noise and exceptional samples, which affect seriously the classification results. In addition, it is indicated that the diagnostic precisions of the FSVM method and the WESE-SVM method is respectively 91.34% and 92.13%, which are inferior to that of WCFSE-FSVM diagnosis method. The reason is that the FSVM fault diagnosis method does not do well in handling the

Table 4
Diagnosis results of four methods for anti-noise ability

Fault mode	SVM	FSVM	WESE-SVM	WCFSE-FSVM
Total accuracy (%)	83.46	89.76	89.76	93.70
Total reducing accuracy (%)	3.15	1.58	2.37	0.79

weak vibration signal samples although is good at dealing with the samples with noise and outliers, moreover, the WESE-SVM is not of capacity to well process the fault with noise and outliers in spite of dealing commendably with the weak signals. Thus, the conclusions are suffice to show that the WCFSE-FSVM diagnostic model is more effective than other models because the WCFSE-FSVM method has higher generalization ability due to be good at conquering the weak signals, the noise and exceptional samples.

In order to verify the WCFSE-FSVM diagnostic model's anti-noise ability, 127 groups of input data (testing samples) are overlaid by the noise signal, the mean and variance of which are respectively 2 and 5. These samples were treated as the diagnostic samples of four fault diagnostic models. Through the anti-noise ability analyses, the results are shown in Table 4.

From the Table 4, the accuracy of the WCFSE-FSVM fault diagnosis method is 93.70% and accordingly reduced at 0.79% to no noise disturbing. Its anti-noise ability is significantly better than the other three methods (SVM, FSVM and WESE-SVM), the precisions of which decline respectively at 3.15%, 1.58% and 2.37%. It is obvious that the diagnostic system based on WCFSE-FSVM method is most effective in diagnosing the samples with noise and is verified to be feasible and effective for aeroengine whole-body vibration fault diagnosis.

6. Conclusion

The objective of the effort is proposed the WCFSE-FSVM method to address the samples with noise, exceptional and weak signals for aeroengine whole-body vibration fault diagnosis. Some conclusions are

(1) The WCFSE-FSVM method is advanced by fusing the WCFSE theory and FSVM; meanwhile, the mathematical model is established and applied in aeroengine whole-body vibration fault diagnosis.
(2) As shown from diagnosing the fault samples which are the feature vectors consistent composed of the WCFSE values of aeroengine whole-body vibration signals, the fault diagnosis accuracy 94.49% of the WCFSE-FSVM method is higher than those of other methods (SVM, FSVM and WESE-SVM) and verifies the effectiveness and feasibility of the WCFSE-FSVM method which has good learning ability, generalization ability.
(3) Through the anti-noise verification, it is demonstrated that the WCFSE-FSVM method possesses good anti-noise ability and fault tolerate capability because the precision of the WCFSE-FSVM method is superior to those of other methods.

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