The Application of AE Signal in Early Cracked Rotor Fault Diagnosis with PWVD and SVM

Xuejun Li
Hunan Provincial Key Laboratory of Health Maintenance for Mechanical Equipment, Hunan University of Science and Technology, Xiangtan, China
hnkjdxlxj@163.com

Ke Wang, Lingli Jiang
Hunan Provincial Key Laboratory of Health Maintenance for Mechanical Equipment, Hunan University of Science and Technology, Xiangtan, China
wangkekeer@126.com, linlyjiang@163.com

***Abstract*— To further enhance the early diagnose precision and efficiency for rotor crack under condition of strongly noise, AE signals is applied to extract fault feature of early rotor cracks with the advantages of strong anti-noise ability, clear fault feature. Based on the Pseudo Wigner-Ville Distribution (PWVD), the amplitude and frequency as feature vector are extracted from the AE signal in this paper, which are used to diagnose and predict the fault types of different rotor cracks depth by support vector machine (SVM). The experiment is done to verify the proposed method applied to fault diagnosis of cracked rotor.**

***Index Terms*—AE, cracked rotor, fault diagnosis, PWVD, SVM**

I. INTRODUCTION

Fatigue crack is an important rotor fault, which can lead to catastrophic failure if undetected properly and in time. Ref. [1] had presented a review on recent studies and investigations done on cracked rotor. Vibration method is the most widely adopted to diagnose rotor crack fault among the diagnosis methods [2]. However, fault signals collected by vibration sensors are always very weak and annihilation in the background of strong noise interference because of itself principles and accuracy restrictions, there is no or not obvious crack vibration response especially shallow cracks. Therefore, due to the technical bottleneck of traditional vibration method, it is difficult to obtain fault feature of early crack accurately and efficiently on the strong noise background.

Acoustic emission signals have its advantages on early diagnosis of early cracked rotor. Materials and components, are enforced external force to emerge deformation and fracture or the internal stress is exceeded the yield limit and enter the irreversible stage of plastic deformation, will release strain energy by forms of transient elastic wave, which is called acoustic emission. The accuracy of fault diagnosis can be improved by AE signals applied in extracting fault feature of early rotor cracks with the advantages of clear feature frequency, early to predict the crack fault, simple detection device, and strong anti-noise ability. Therefore, the acoustic emission technology has been become one of effective means in monitoring the whole process of crack propagation in present for its real-time and dynamic merit.. Ref. [3] had combined hardware and software to distinguish crack propagation signal based on AE signals collected from high frequency fatigue metal, which taken the relevance of AE signal energy and the cycle times to obtain the forecast result of crack propagation rate. Ref. [4] had adopted multi-parameters method to obtain AE signals of crack initiation in strong noise background and achieved the prediction of crack initiation. Ref. [5] had extracted feature parameters of AE signals from metal fatigue fracture and established the relationship between feature parameters of AE signals and crack growth rate to achieve online inspection of crack. Ref. [6] had identified and diagnosed the gears in normal state, slight crack fault and severe crack fault state using SVM and AE technology.

Fault feature extraction and fault identification are the key technology in the commonly used methods of mechanical fault diagnosis. In the traditional method of fault feature extraction, STFT usually is hard to satisfy the local stationary condition of time window. Wavelet and wavelet packet are strictly divided and energy concentration of wavelet basis which is not easy to construct in the wavelet/wavelet packet method. It is hard for HHT to avoid ending effect in practice. To overcome the impact of cross-interference terms, PWVD can be used for fault feature extraction of cracked rotor. Ref.[7] the transient vibration of a cracked Jeffcott rotor with a switching crack is simulated and time frequency features extracted by Wigner-Ville distribution and Wavelet Transform. Ref. [8] had taken PWVD and multi-resolution analysis to recognize fault noise of engine. Ref. [9] had applied PWVD to diagnose the fault of motor bearing and improved the diagnosis accuracy efficiently. Ref. [10] had combined PWVD with wavelet to realize fault diagnosis of gearbox effectively.

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Fault recognition methods in machinery and equipment mainly have statistical pattern recognition method and artificial neural network (ANN). Statistical pattern recognition is the basic method of mode recognition on the basis of traditional statistical, and the algorithm is reasonable under the premise of sufficient number of samples. It is not appropriate to adopt the corresponding classification algorithm when the training sample data is small. ANN does not require pre-given discriminate function, and it can automatically form decision-making areas through its own learning mechanism. Ref. [11] had proposed a novel method by combining modal analysis of cracked rotor system and artificial neural network, the result show that the trained ANN models have good performance to identify the crack location and depth, single crack and dual cracks, with higher accuracy and efficiency. However, the neural network built on empirical nonlinear model is lack of a unified framework of mathematical theory, therefore, the model structure and parameters will change with the initial value and human factors. At the same time, neural networks and statistical pattern recognition methods have the same problem: the number of samples must be enough.

SVM is a special machine learning theory in the case of small samples. It has strong theoretical basement that can overcome the defects of traditional classification and solve the practical problems with small sample, nonlinear, high dimension and local minimum points. Ref. [12]had combined SVM with wavelet packet to achieve early fault diagnosis for rolling bearing. Ref. [13] had established fault diagnosis model on the basis of the analysis of SVM multi-classification algorithm and feature vectors for rolling bearing.

PWVD is introduced to extract time-frequency feature parameters of AE signals, combining with SVM to construct fault classifier for predicting and diagnosing faults of different rotor crack depth.

II. DIAGNOSIS PRINCIPLE

A. Pseudo Wigner-Ville Distribution

For signal x , its Wigner-Ville Distribution is expressed by:

$$W_x(t,v)=\int_{-\infty}^{\infty} x\left[t+\frac{\tau}{2}\right]x^*\left[t-\frac{\tau}{2}\right]e^{-j2\pi v\tau}d\tau \tag{1}$$

Where, τ is the variable of time different.

It is assumed that a signal is the sum of two signals:

$$x(t)=x_1(t)+x_2(t) \tag{2}$$

Then:

$$W(t,v)=W_{11}(t,v)+W_{22}(t,v)+2\operatorname{Re}(t,v) \tag{3}$$

Where, W is the Wigner distribution of x , W_{11} is the Wigner distribution of x_1 , W_{22} is the Wigner distribution of x_2 , W_{12} is the cross terms Wigner distribution of the signal x_1 and x_2 .

From the Equation (3), the Wigner distribution of two signals is not the sum of Wigner distribution of each signal, and it is difficult to explain Wigner distribution and determine by the fault information because of the cross terms $2\operatorname{Re}\{W_{12}(t,v)\}$. When the signal has multiple frequency components, the cross interference is inevitable due to the inherent bilinear structure of Wigner distribution.

Considering the unique cross-term interference of WVD (mostly caused by noises and multi-component), finiteness of actual integration and the concerned signal characteristics, it can obtain the effect of localization by adding window function which is similar with STFT. This distribution is called Pseudo Wigner-Ville Distribution (PWVD) and expressed as follow:

$$W_{PS}(t,\omega)=\int h(\tau)s^*(t-\frac{\tau}{2})s(t+\frac{\tau}{2})e^{-j\omega\tau}d\tau \tag{4}$$

Where, $h(\tau)$ is the window function of the peak value at moment of $\tau=0$. As the selectivity characteristic of window function, PWVD can compress the interference effect of cross term to some extent. Usually, because the window function has the effective of low-pass, the frequency of windowed treatment are smooth equivalent with WVD [14-16]. PWVD is nonlinear quadratic transformation and can describe the energy density and strength of signals in different time and frequency, which has characteristic of good accumulation of energy, higher time-frequency resolution and time-frequency edge. Therefore, it can be used as vigorous tool for AE signal feature extraction with the advantages of suppress noise jamming and crosstalk interference.

B. Support Vector Machine

The SVM is a new machine learning method based on statistical learning theory in fault classification methods [17-18]. It can solve many practical problems with the characteristics of the small sample, nonlinear, and high dimensional pattern recognition, it also can overcome the shortcomings of the learning method of neural network, such as difficult to determine the network structure, slow convergence, local minimum, over learning, less learning and large data samples need for training.

SVM can find the best compromise between the model complexity and learning ability based on limited sample of information, and obtain the best generalization ability.

The basic idea of SVM can be described in Fig.1. Solid point and hollow point represent two samples respectively. H is classification line, H_1 and H_2 are passing each type sample which is nearest to H , both of them are paralleling with H , the distance between them is called classification interval. It is supposed that the training sample set is (x_i,y_i) , where: $i=1,2,\cdots,n.$ x is the input vector, $x\in R^d$. i is the number of samples. y is the category of input vectors. For classification problem of the two types, $y\in(+1,-1)$. The general form of linear discriminate function in D-dimensional space is

$g(x) = w \cdot x + b$, classification plane equation is expressed as follow:

$$w \cdot x + b = 0 \tag{5}$$

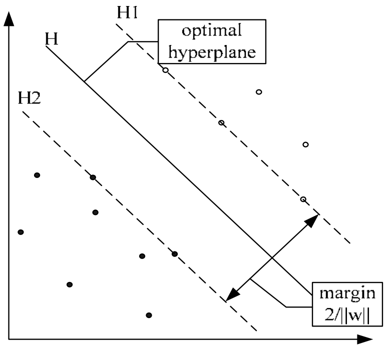


Figure.1 Diagram of SVM.

Discriminant function will be normalized, so that all samples are meeting $|g(x)| \ge 1$, that is the samples nearest to classification plane, $|g(x)| \ge 1$. therefore, the classification interval is $2/\|w\|$, the maximum interval is equivalent to make $\|w\|^2$ become the minimum. To correctly classify all samples using classification line that is also to make it satisfy the follow constraints:

$$y_i\left[(w \cdot x_i) + b\right] - 1 \ge 0, \ i = 1, \cdots, n \tag{6}$$

Considering that some training samples are inseparable linear, Vapnik had introduced non-negative slack variables into SVM to relax the constraints of equation(5), it can be expressed as follow:

$$y_i[(w \cdot x_i) + b] \ge 1 - \xi_i, \ \xi \ge 0, \ i = 1, \cdots, n \tag{7}$$

Obviously, when the division is wrong, $\xi_i > 0$. Thus, we hope get the smaller $\sum_i \xi_i$ as far as possible when seeking the classification plane. Therefore, the original objective function is to get the minimum of $\|w\|^2/2$ will transfer to find the minimum of $\|w\|^2/2 + C(\sum_i \xi_i)$ (where, $C > 0$, is an adjustable constant and can be used for controlling the degree of punishment to wrong sub-samples). This is a quadratic programming problem. To solve the dual problem, the optimal classification decision function can be expressed by:

$$f(x) = \mathrm{sgn}\left[\sum_{i=1}^{n} \alpha_i y_i K(x_i \cdot x) + b\right] \tag{8}$$

Where K is the kernel function. sgn is the sign function. n is the number of training samples.

For the linear problem, K is the dot product of two vectors. For nonlinear problem, the core idea of SVM is the introduction of nonlinear mapping ϕ that is to construct the optimal separating plane by mapping the input vectors into a high dimensional space. Currently, the widely used kernel functions are polynomial kernel function, radial basis function kernel function and Sigmoid function.

The standard SVM is used for solving the binary classification problems [18-21]. The multi-classification problem should be solved in field of fault diagnosis. Now, some more fruitful multi-classification SVM are proposed, including one-to-one, one-to-rest and directed acyclic graph.

In this paper, Matlab7.1 is used to analysis the data and RBF is chosen as the kernel function. The parameters (c, γ) of RBF are chosen by net search and cross validation. Multi-class classifications of one-to-rest are used to construct multi-fault classifiers for recognizing different crack depth of fault rotor.

III. Rotor Crack Experiment

A. Test Conditions

The basic principle of AE detecting for rotor crack is that AE signals sent from crack propagation will transmit around in the form of elastic wave, which will be picked up by AE sensors placed on the bearing surface and be changed into electrical signal after passing the coupling agent. Through the pre-amplifier, the electrical signals will be put into the AE equipment, and then, after the process of zoom, A/D conversion and data acquisition, data export, signal analysis, and finally data will be displayed. the process of AE testing is shown in Fig.2

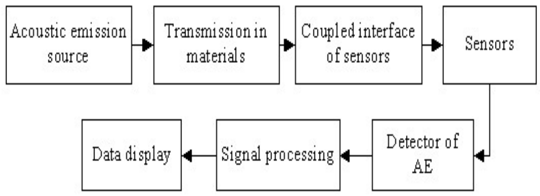


Figure.2 Schematic of acoustic emission testing.

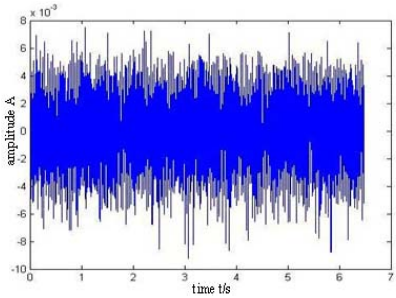
The Spectra Quest's comprehensive fault simulate test rig of the United States is taken as the experiment platform. The test bed can simulate common mechanical equipment fault for analysis. The SWAES full waveform acoustic emission monitoring instrument of Danish and Beijing ShengHua's data acquisition system are used for software and hardware system of AE detection. The AE testing physical configuration is as shown in Fig.3.

To simulate crack propagation, four experimental shafts with the same material model have been prefabricated. The size is 16mm × 53mm, the materials used for 1Cr18Ni9Ti. One is normal and other are cracked rotors, the crack are formed by wire-cut method and fatigue test equipment. The crack depth is 3mm、5mm、8mm respectively, the width is 0.12mm, the location of shaft crack is in the central shaft near the turntable.

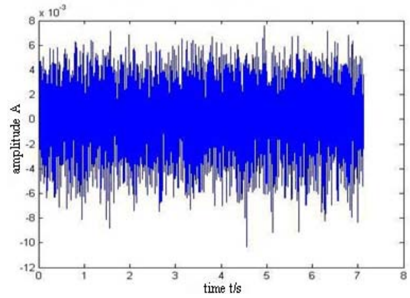
Figure.3 Acquisition system of AE signal.

In the experiment, under the same condition (constant speed is 1800 r/min and load is 2.5kg), vibration signal and AE signals of four rotors are collected, respectively. The time domain waveforms diagram were described after being pretreated. As shown in Fig. 4 and Fig. 5:

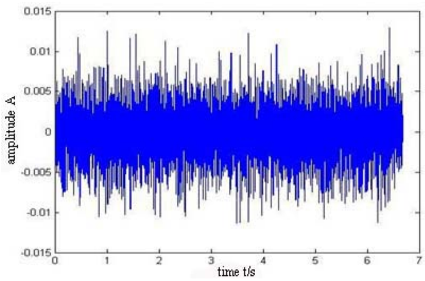
The Figure 4 is the vibration signal time-domain graph at the speed of 1800r/min, it can be seen that the vibration signal of the normal rotor and crack rotor are no obvious differences. The Fig.5 is the AE signal time-domain graph, it can be seen that the signal amplitude is low, especially 3mm cracked rotor. With the deepness of the crack, the signal amplitude has increased



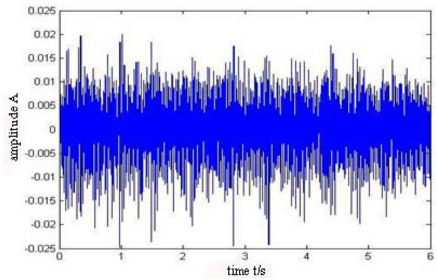
a) Normal rotor



b) 3mm crack depth

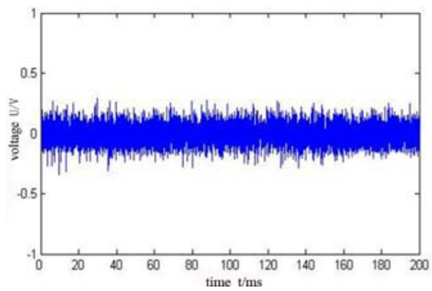


c) 5mm crack depth

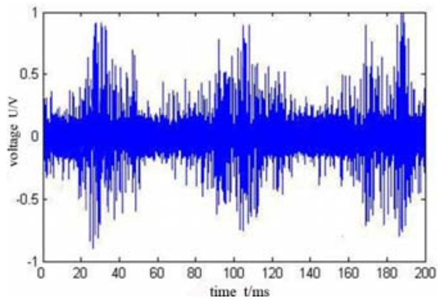


d) 8mm crack depth

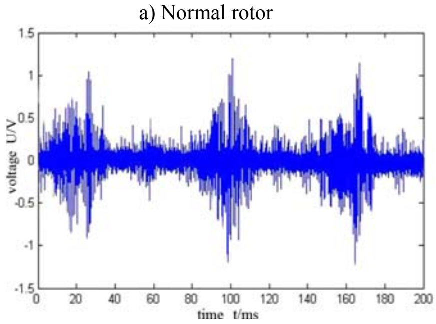
Figure.4 Time domain map of vibration signal at 1800r/min



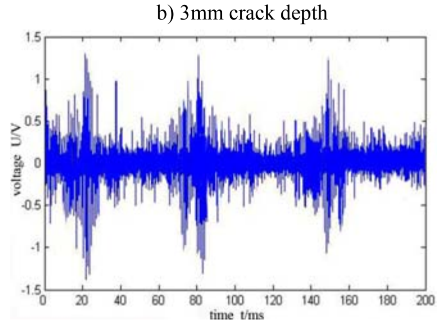
a) Normal rotor



b) 3mm crack depth



c) 5mm crack depth



d) 8mm crack depth

Figure.5 Time domain diagrams of acoustic emission signal at 1800r/min trend. Time-domain signals of normal rotor are flat relatively and lower about 0.3V. While clear pulses of AE signal can be seen in crack rotor signal graph. Therefore, AE testing method is easier to identify early crack fault than vibration detection.

B. fault feature extraction

WVD of AE signals of 3mm crack rotor at 1800r/min are calculated after being pretreated. From Fig.6, fault feature of crack AE signals can not identify effectively because of the existence of serious cross term interference and noise.

In this regard, PWVD of above signal is calculated after being windowed，which is shown in Fig.7.

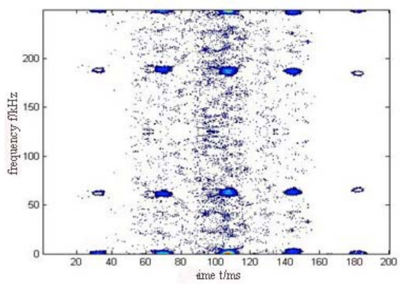
The time-frequency distribution diagrams of WVD and PWVD are compared, it can be seen from figure 6 that cross-term interference and noise are eliminated obviously, fault feature of AE signals are highlighted. The AE event occurred at 32ms, 107ms and 182ms, time interval is 75ms, and the frequency range is low of 60-65 kHz, indicating that a slow expansion of the crack has occurred

Figure.8 and Figure.9 are the contour maps and three-dimensional maps of 3mm crack rotor at the speed of 36oor/min and 45oor/min respectively.

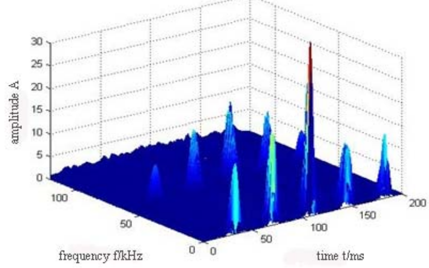
TABLE1.
FEATURES OF AE SIGNAL OF DIFFERENT CRACK DEPTH

Crack depth /mm	Speed /(r·min^{-1})	Amplitude /V	Frequency /kHz	Cycle /ms
3mm	1800	0.85~0.95	50~75	75
5mm	1800	1.0~1.3	65~85	72
8mm	1800	1.3~1.5	50~70、80~100	64

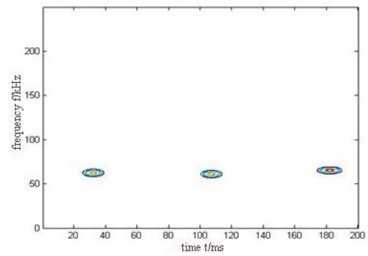
The results show that PWVD has higher time-frequency resolution, its contour map and three dimensional maps precisely described the number, intensity, and time of pulses, AE events and other information of AE signal of crack rotor, which achieved a precise diagnosis of early crack fault. Although there are some cross interference terms in high speed, but it does not affect the recognition of fault feature because the fault feature is still obvious.



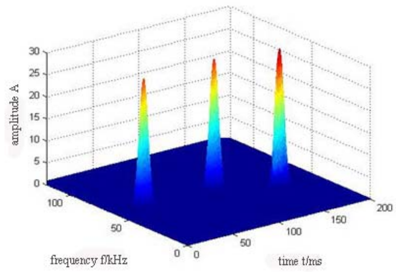
a) contour map.



b) Three-dimensional map.
Figure.6 Wigner-Vill distribution of AE signal



a) contour map.



b) Three-dimensional map.
Figure.7 Pseudo Wigner-Vill distribution of AE signal

PWVD of AE signals of the four rotors are calculated successively. According to the experimental data, AE signal features of crack rotor of different depth are obtained as shown in Table 1. Those feature parameters can be used as the object of feature extraction.

C. Fault diagnosis analysis of rotor crack.

Fault diagnoses of SVM are based on feature vector of fault signals for fault diagnosis and pattern recognition. Means of two parameters (amplitude, frequency) are extracted from the result of PWVD method of AE signal as sample of feature vector.

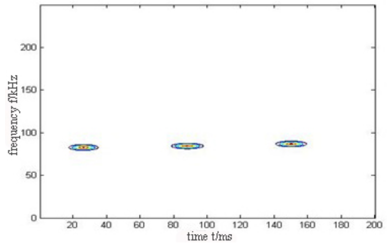
Sample data are set as table 2. There are 200 sample data in total, which can be divided into four kinds equally by no crack、3mm crack rotor、5mm crack rotor and 8mm crack rotor, of which have 50 groups with 30 groups used for training and the remaining for testing.

According to classification, four fault classifiers are constructed; the logic diagram is shown in Fig.10.

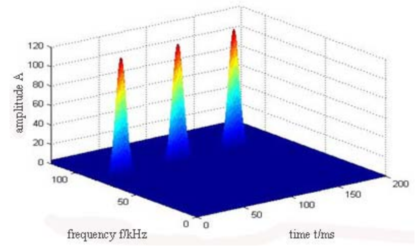
TABLE2.
DESCRIBES THE SAMPLE DATA

Crack depth	Training samples	Testing samples	Total samples
normal	30	20	50
3mm	30	20	50
5mm	30	20	50
8mm	30	20	50
total	120	80	200

The optimal classification function f1(x)-f4(x) are established by importing the indicator of training sample x into VSM1~VSM4 for judging the testing samples. Firstly, the feature vector is inputted into SVM1, if y =

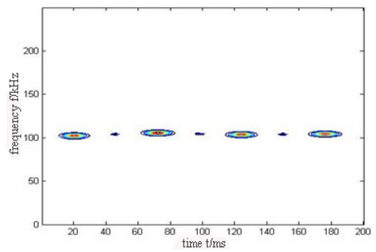


a) contour map.

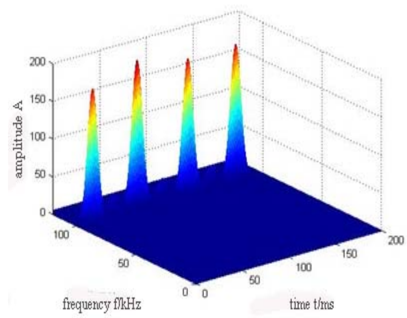


b) Three-dimensional map.

Figure.8 PWVD of shaft of crack 3mm depth at 3600r/min



a) contour map.



b) Three-dimensional map.

Figure.9 PWVD of shaft of crack 3mm depth at 4500r/min

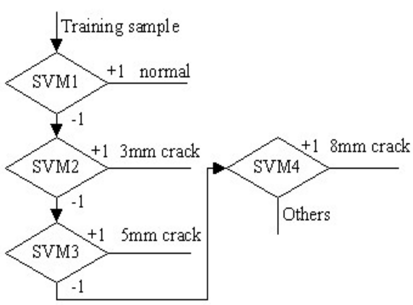


Figure.10 Multi-fault classifier of support vector machine

+1, it can be judged as normal rotor, else is fault rotor. The crack depth is discerned by analyzing the output results of SVM2-SVM4. The specific classified effects of testing samples shown in Fig.11 to Fig.14, which are normal and fault classification, 3mm crack and other classification, 5mm crack and other classification, 8mm crack and other classification. In the figures, the red plus sign means " +1", the blue diamonds is "-1".

From the Fig.11 to Fig.14, the numbers of SVM are 3、4、4 and 3, the rates of total samples are 15%、20%、20% and 15%, the training correct rates are 100%、90%、95% and 100%， classification results are ideal. The experiment result shows that the rationality of selected parameters and the effectiveness of constructed classifiers, which proves the superiority of SVM in fault classification.

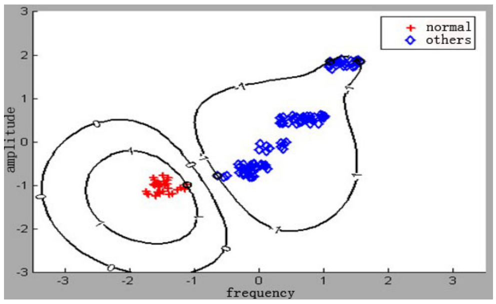


Figure.11 SVM1-normal and fault classification

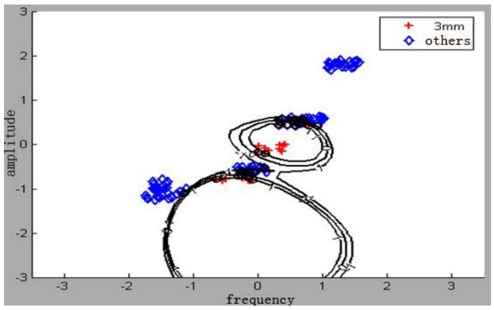


Figure.12 SVM2-3mm and other classification

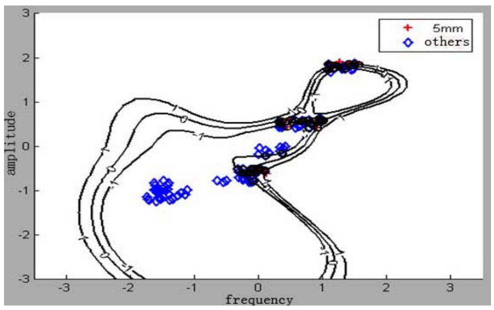


Figure.13 SVM3-5mm and other classification

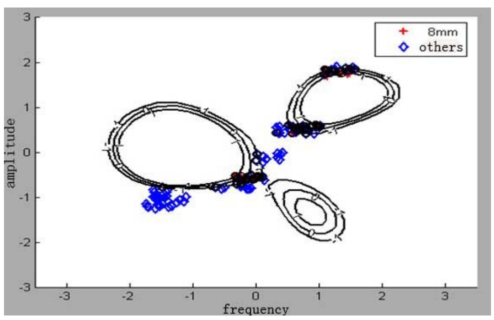


Figure.14 SVM4-8mm and other classification

IV. CONCLUSIONS

Aiming at inaccurately and inefficiently fault feature of early crack by the vibration method in the environment of strong noise, this paper has adopted method of combining PWVD with SVM to do time-domain feature extraction and fault recognition for AE signal for cracked rotor. Acoustic emission technique was used to monitor the condition of rotor crack and diagnose fault for crack rotor, which has advantages of obvious feature frequency and early prediction time of fault. SVM is used for constructing multi-fault classifier, which can recognize different crack depth on fault rotor effectually. The method of combining PWVD with SVM has deepened the studies on characteristics of AE signal, and possesses extremely important significance in promoting the development of fault diagnosis technology.

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Xuejun Li , male, born in September, 1969, in Xiang-tan city of Hunan province, received master degree in 1996 and PHD in 2003 from Central South University and Post-doctoral degree from Tsinghua University in 2009, research field are Health maintenance and control technology and equipment.

He is currently a professor and laboratory director in Key Laboratory of Health Maintenance for Mechanical Equipment of Hunan Province, Hunan Science and Technology University, China, mainly engaged in student management, teaching, scientific research. His other works are “Health maintenance rotary his book Theory and Technology”(Beijing, Mechanical Industry Press, December 2004), “Wavelet Function Suitable for Fault Feature Extraction of Acoustic Emission Signal”, Chinese Journal of Mechanical Engineering(2008). His research interests include mechanical dynamics, failure diagnose, dynamic test and signal dealing, equipment maintenance technology.

Prof. Li is the secretary general of Instrument and Control Society of Hunan Province, in recent years; He is presiding more than 30 research projects, obtained 5 identification results of the international advanced level and applied 12 patents, published more than 60 academic papers.

Ke Wang, male, born in 1985. He is a graduate candidate in Key Laboratory of Health Maintenance for Mechanical Equipment of Hunan Province, Hunan Science and Technology University, China, mainly research direction is mechanical fault diagnosis and equipment health maintenance technology.

Lingli Jiang, female, born in 1981. She received MSc from Hunan University of Science and Technology in 2007. She is currently a PhD candidate in Central South University. Her main research directions is mechanical fault intelligent diagnosis.