Rotor Crack Detection by Using Multi-vibration Signal from the Basement

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***Abstract*—Rotor crack detection method by using multi-vibration signals gathered at the basements is presented in this paper. The finite element software ANSYS is applied for analyzing the vibration response characteristics of the basement to determine sensor configuration. Feature fusion for time-domain statistics of multiple sensors is performed by using the support vector machine to diagnose the depth of crack rotor fault. Test analysis indicates that this method is fast and accurate to detect rotor crack by fusing the multi-vibration signal of the basement, and also supply a new approach for rotor fault diagnosis.**

***Index Terms*—basement, cracked rotor, fault diagnosis, ANSYS; signal fusion**

I. Introduction

Rotor crack is one of the common faults of the rotating machinery. There are several major incidents caused by rotor crack at home and abroad [1]. Rotor crack is mainly due to the metal fatigue damage caused by alternating thermal stress exceeded the yield limit of materials. The working environment of rotor is usually bad, and the changing mechanical stress and thermal stress frequently applied on rotor easily cause fatigue crack. Therefore, detecting the early rotor crack is significant to prevent catastrophic rotor fracture accident and improve economic efficiency [2].

In order to monitor the rotor, sensors are usually installed those positions near the rotor, e.g. on the bearing seat, on special sensor supporting frames. However, those positions are inconvenient in practical industrial. Rotor fault diagnosis based on signals from the basement can overcome installation problem.

The rotor of rotating machine is mounted into the basement and constitutes rotor-bearing-basement system. Rotor, bearing and the basement have different material property, geometry and movement patterns, and movement pattern of each part is also relatively complex. Through the bearing and bearing pedestal, the fault vibration signal is transmitted from fault rotor to the basement. Taken rotor, bearing and basement as study object, fault signals can be collected from the sensors arranged on the basement.

In recently years, dynamics of cracked rotor is one of the concerned research fields in rotor fault diagnosis all over the word [3-6]. Z.Y.Shang and Q.C.Guo performed dynamic analysis of rotor-bearing system and rotor-support-shock absorption system respectively, established the dynamical models, and analyzed the effects of loose base, rub-impact fault and related factors of the system[5,6]. J.W.Xiang, et al. developed the method of fault diagnosis for cracked rotor using Time-Frequency Analysis and pattern recognition of wavelet and neural network[7-9]. With respect to the finite element modeling and analysis of the cracked rotor-bearing- basement system, Refs.[10-12] have modelled and analyzed of bearing on the rotor system without considering the effect of basement system on rotor system, Ref.[13] have modelled the rotor- bearing-basement system coupling constraints of the bearing side radial which is different with the actual condition.

ANSYS finite element analysis software has the ability to simulate mechine parts with reasonable element, and obtain the deformation of parts under dynamic loads. In this paper takes specifically rotor test rig as a analysis object, the stiffness and damping of cracked rotor and bearing, as well as the impact of the basement, are involved into the cracked rotor-bearing-basement system model, and the vibration characteristics of the basement is analyzed in ANSYS for supplying the layout of basement sensors in fault diagnosis of cracked rotor.

Vibration signals analysis is usually used for fault diagnosis as vibration signals include rich time-domain information of mechanical running condition[14] and is easy to relize online monitoring and diagnosis. However, vibration signals collected at the basement are far away from the vibration source, so the signals carry more interference signals from basement, bearing pedestal, and the others, and the fault feature will be weaker. Thus, there will not be ideal results in a direct signal analysis. The use of multiple sensors can make signals gathering and processing parallelism, and obtain more accurate and comprehensive information. Multi-sensor data fusion has

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the advantages of complementary and fault tolerance of data which can be extended both in spatial and temporal scales[15-17]. It can make full use of multi-sensor resources to get more information and explore the underlying information on the sample data.

Aim at the poor generability in the common practical sensor installation in rotor fault diagnosis, the fault diagnosis of multi-sensors signal fusion based on the basement is proposed. This paper takes the basement as monitoring object on the base of the integrated test rig, analyzes the basement vibration characteristics of cracked rotor test rig supported by bearing in the actual operation situation by ANSYS, and obtains the optimal layout of multi-sensor on the basement. Support vector machine is applied for feature fusion of time-domain statistics of multi-sensors vibration signal for cracked rotor fault diagnosis.

II. VIBRATION CHARACTERISTICS ANALYSIS OF THE BASEMENT

ANSYS is a commercial finite element analysis software with the capability to analyze a wide range of different problems, e.g. elasticity, fluid flow, heat transfer, and electro-magnetism. [18-19]. ANSYS has direct interface with majority CAD softwares, such as Pro/E, UG, and AutoCAD. ANSYS can run under a variety of environments, e.g. IRIX, Solaris, and Windows NT. In this paper, the geometry model is established in Pro/E, and imported to ANSYS. The detailed rotor test rig is modeled with considering the stiffness and damping of cracked rotor, bearing, and basement constituted as a cracked rotor- bearing- basement system, and the vibration characteristics of the basement is analyzed for sensor configuration in fault diagnosis of cracked rotor.

A. Experimental platform

The Spectra Quest's sliding bearing rotor test rig of the United States is taken as the experiment platform. The test rig can simulate normal mechanical equipment failures for fault diagnosis research. Fig.1 is the physical map of rotor test rig.

Table.1 is the dimension parameters of the rotor test rig, Table.2 is the material properties parameters of the rotor test rig. Circulating oil supply system in the right of the rig provides oil lubrication. The rotor is driven by a motor, and can obtain the speed from 0-6000 rpm by adjusting output voltage of regulator manually.

B. Finite element modeling of cracked rotor test rig

Geometrical model is built in Pro/E, and a crack is modeled with depth of 3mm and width of 0.1mm in the middle of the rotor. The export model is in IGES format from Pro/E, and then imported into ANSYS. Figure.2 is the geometrical model of the rotor test rig.

The solid element Solid95 is used for rotor, quality element Mass21 is used for the rotor center of mass, Matrix27 element is used to define sliding bearing. Each sliding bearing can be simulated by two Matrix27, one uses for the stiffness matrix, another for damping matrix. Oil film force of sliding bearing applied on the rotor can be simplified and simulated with eight oil film force coefficients of sliding bearing. Each component is

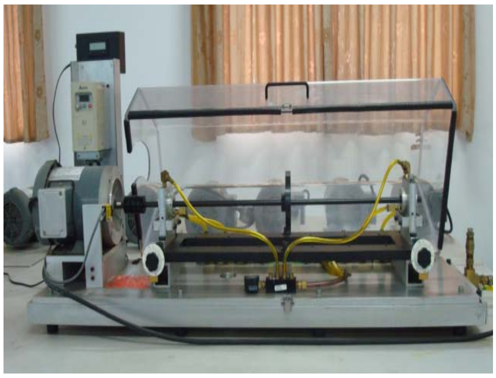


Figure 1. The rotor test rig

TABLE I.
THE DIMENSION PARAMETERS OF ROTOR TEST RIG (UNITS: MM)

name	size	name	size
Basement(l)	850	Turnable(d)	126
Basemen(w)	222	Turnable(w)	16
Rotor(l)	850	Bearing pedestal (l)	146
Rotor(d)	13	Bearing pedestal (w)	17
Sliding bearing(id)	13	Bearing pedestal (h)	117
Sliding bearing(od)	16	Sliding bearing(w)	9

L: long; w: wide; d: diameter; h: height; id: inside diameter; od: outside diameter.

TABLE II.
THE MATERIAL PROPERTIES PARAMETERS OF THE ROTOR TEST RIG.

Material name	E /MPa	μ	ρ/kgm^{-3}	parts
Aluminums-alloy	70000	0.35	2700	Basement, bearing pedestal
copper	130000	0.35	8200	Sliding bearing
steel	210000	0.3	7800	Rotor, turntable

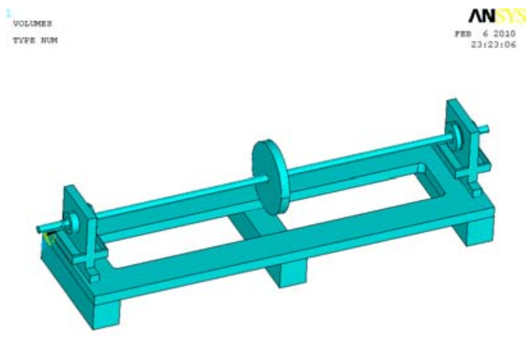


Figure 2. The geometric model of the rotor test rig column.

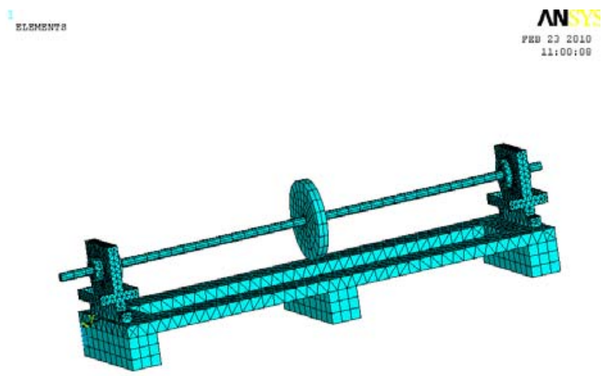


Figure 3. The finite elements model of cracked rotor test rig.

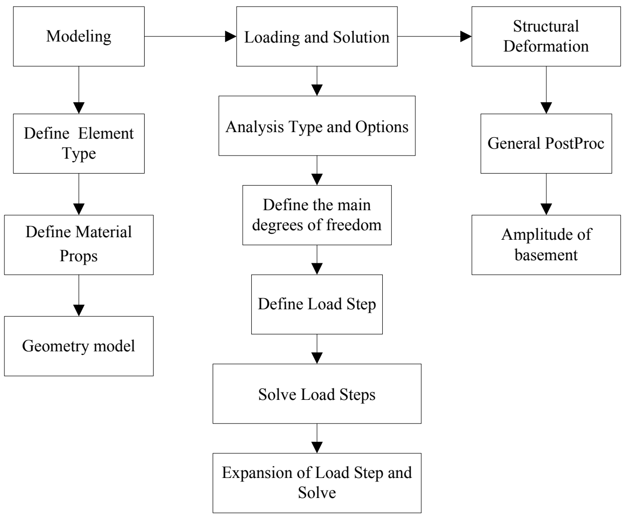


Figure.4 The basic steps of transient analysis

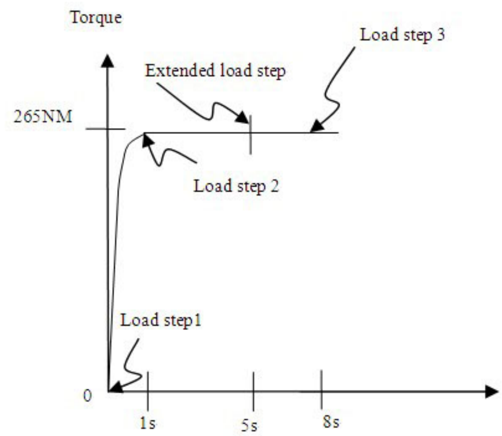
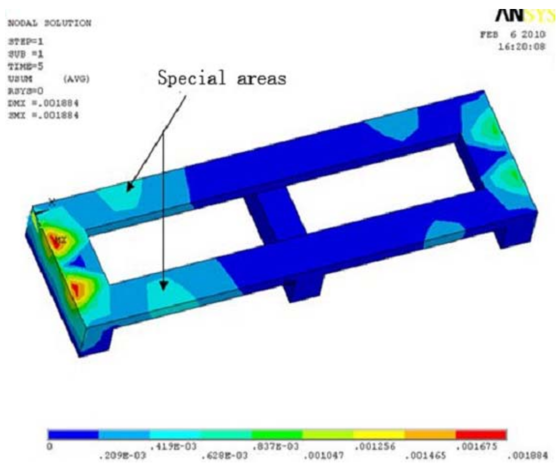


Figure 5. The torque-time curve



Fiure 6. The equivalent displacement map of the basement

assigned with material parameter, the model is meshed with scanning and local mesh. Finer element of rotor and bearing pedestal is obtained.

C. Vibration analysis of the basement

Transient dynamic analysis is also called time history analysis, and used to identify structural response under the time-varying loads. Its input data are the load varying with time, output data are time-varying displacement, stress, and strain. Figure.4 is the basic steps of transient analysis.

According to the formula $T = 9550 P/n$; where, P is the power, n is the speed. The power of load motor is 500W, Under the speed of 30 r/min, then T=265.28 N·m. Transient analysis are selected in solver type of the ANSYS; Reduced method is used to determine the transient response in change loads with time. Shown in Figure.5 is the torque-time curve of the rotor test bed from start to the stable operation.

The vibration direction of the upper and lower are defined as the main degree of freedom, the load step is set as 0.5s; The test bed is fixed by constraining all direction of the bottom of the rotor test bed and all the axial direction of the rotor, the rotor will not appear to axial slide. After the solution of the initial load step, the second load step will be calculated for imposing torque to the shaft.

A independent node is generated in a suitable location of center line of the rotor; a quality unit MASS21 will be generate in the node in order to transfer torque; using the command Cerig to build rigid structure between the independent node and the actual torque node; the torque apply in the quality unit MASS21. After the load step second, changing the end time of load, and not loading , the load step third will be calculated; finally, the frequency of the extended load time are set as 5s, to calculate and analyze the extended load step.

By applying the torque of the actual speed on the finite element model of test rig, transient analysis is performed to obtain the response status of the basement.

After programming ANSYS, time Hist postproc can export the corresponding nodal displacement, stress, and strain. Vibration signal is mainly measureed by vibration amplitude, so the displacement of the corresponding node is analyzed. Fig.6 is equivalent displacement map of the basement structure.

From Fig.6, the closer is the position from the bearing pedestal; the larger is the vibration amplitude. Some special areas between the two bearing pedestal have larger vibration amplitude marked in Fig.6. These areas are a relatively good position to install the sensor. Therefore, two sensors are placed near the bottom of the left bearing seat (No.1-2); two sensors are placed on the special areas (No.3-4). There are some designed places for sensor installation near bearing seat in the test rig, so Sensor 5 (No.5) is placed on the place of left bearing seat as comparison and reference places.

III. MULTI-SENSOR SIGNAL FUSION BASED ON SVM

A. The Basic Concepts of Support Vector Machine

SVM is a new machine learning method based on statistical learning theory and structural risk minimization[20-22]. 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[23-24].The basic idea of SVM can be described in Fig.7.

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:

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

Discriminant function will be normalized, so that all

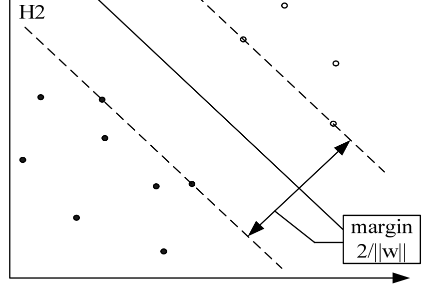


Figure.7 Diagram of SVM.

samples are meeting $|g(x)| \geq 1$, that is the samples nearest to classification plane, $|g(x)| \geq 1$. 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:

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

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:

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

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:

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

Where sgn is the sign function; C is the penalty factor; a^* is the support vector; x_i is the Lagrange multiplier; K is the kernel function, If the K is appearing as inner product in linear separable case, it is also named linear kernel function. Otherwise, it can be expressed as radial kernel function, polynomial kernel function and Sigmoid kernel function.

The standard SVM is used for solving the binary classification problems. However the multi-classification problem should be solved in field of fault diagnosis. Now, some more fruitful multi-classification SVM are proposed [25], including one by one, one by more and directed acyclic graph. The one by one way of the multi-classification method mainly introduces in this paper.

It is supposed that the total number of categories is k, the principle of one by one is to construct the classifier of two types as many as possible, every classifier is only used for training 2 types samples among the k and the result is to construct $k(k-1)/2$ classifiers totally. The voting method of the test samples is adopted for deciding the categorization. However, the number of classifiers is increasing dramatically with increase of the number of k, that leads to the decision speed are very slow.

B. Multi-sensor fusion models

Fault diagnosis of cracked rotor applying the multi-sensor signal fusion technology, which can make

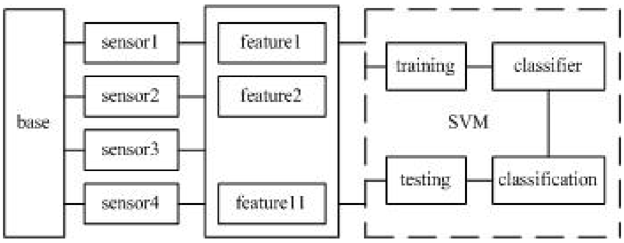


Figure 8. Model of multi-sensor information fusion.

full use of resources of multiple sensors and improve the accuracy and reliability of diagnosis. The signals collected from the basement's 4 sensors take fusion by SVM. The same feature extracted from 4 sensors is selected to compose a 4-dimensional feature vector for pattern recognition. The model of signal fusion is expressed as follow in figure 8.

The SVM fault diagnosis method is based on features of fault signal for fault diagnosis and pattern recognition. The statistical parameters of vibration signal in time-domain are directly taken as features and without the conversion of the collected signal which can effectively avoid related errors in the process of second conversion for it is simple and intuitive. The 11 normal time-domain statistics are taken as features and the multi-sensor signal fusion based on SVM is taken for different fault recognition to cracked rotor in this paper. The normal time domain statistical parameters are expressed as follows in table Ш.

TABLE IV

NORMAL TIME-DOMAIN STATISTICS

Feature	Equation
Mean	$\bar{x} = \sum \lvert x_i \rvert / n$
Peak	$x_{rms} = (\sum_{i=1}^{n} x_i^2 / n)^{1/2}$
RMS	$x_{rms} = (\sum_{i=1}^{n} x_i^2 / n)^{1/2}$

TABLE V.

THE DIAGNOSIS OF MULTI-SENSOR DATA FUSION

Serial number	features	Accuracy of all test samples (%)
1	Mean	98.67
2	RMS	99.67
3	Root	97.33
4	Standard deviation	98.67
5	Peak	85.33
6	Skewness	58.00
7	kurtosis	71.00
8	Shape factor	72.33
9	Crest factor	69.33
10	Impulse factor	64.00
11	Margin factor	64.67

IV. EXPERIMENT OF CRACK ROTOR FAULT DIAGNOSIS

A. *Analysis of multi-sensor signal fusion based on the basement.*

The test system composed of DEWE-16 channels high-precision test system of Dewetron (Austria) and PCB603C01 acceleration sensors (USA) is chosen in the experiment. Under the rotor speed of 30 rev/sec, sampling frequency is set as 10KHz. The vibration signals collected from basement's 4 sensors in the cases of normal, 3mm and 5mm cracked rotor.

All of states, 100 set intercepted signals collected from the basement's sensor are intercepted for pattern recognition using SVM. One kind of features is chosen each time. One 4-dimensional array is composed of 4 sensors signals. 50 sets of data are used for model training and the other 50 sets of data for testing. Considering there are many time-domain statistical parameters and the features of performed by each parameter are different, 11 common time-domain statistical parameters are selected to analyze and compare with each other successively under the same condition to obtain the optimal time-domain features in pattern recognition of cracked rotor. The SVM calculation is used LibSVM-mat-2.9 developed by Lin Chih-Jen and others. The radial basis function is selected, and the penalty factor C and kernel function parameter g are optically selected by the methods of web search and cross-vibration. The multi-class discriminate selects one by one to distinguish two samples. In the m-class training samples, m(m-1)/2 SVM classifiers are constructed and the voting results of the testing samples can be decided the categorization. The results are expressed as follows in Table V:

It is clearly known that, selecting appropriate features and using multi-sensor signal fusion technology based on the basement can effectively diagnose cracked rotor from Tab.4.

About the features, for examples mean, RMS, root and standard deviation, all have higher rate of recognition on the rotor fault diagnosis, which can be selected as features in the process of crack fault diagnosis based on SVM. Though the recognition rate of a very few features have reached more than 80% among the skewness, kurtosis, shape factor, crest factor, impulse factor and margin factor, the overall level is less than 70%. Thus, there are not suitable for selected features of fault diagnosis of cracked rotor.

B. *Comparison and analysis.*

The 100 sets data are intercepted among the vibration signals collected from single-sensor of bearing seat which

TABLE VI.
THE DIAGNOSIS OF SINGLE SENSOR ON BEARING PEDESTAL

features	Test accuracy of single-sensor (%)			
	normal	3mm crack	5mm crack	All test samples
4 kinds of features	90	30	98	72.67

have strong power for feature extraction, and 4 kinds of time-domain features (mean, RMS, root and standard deviation) which have higher recognition rate are selected to compose a 4-dimensional feature vector. The 50 sets of the data are used for model training and the other 50 sets of data for testing and then the recognition rate of the single sensor can be obtained.

According to the Tab.V and Tab.VI, it can conclude that the diagnostic effect of multi-sensor signal fusion based on the basement (Up to 99.67%) is significantly better than traditional single-sensor based on bearing seat (72.67%).

The 11 kinds of time-domain statistics are taken as features, to diagnosis for multi-sensor signal fusion based on the basement on the rotor's different condition (normal, 3mm crack and 5mm crack). The diagnosis comparison chart is expressed as follows:

The recognition rate of 11 kinds are shown in the Fig.9, Some features, such as mean, RMS, root and standard deviation, have higher recognition rate, and it can prove the mentioned conclusion above: selecting appropriate features and using multi-sensor signal fusion technology can effectively diagnose cracked rotor. Fault recognition rate of the 3mm crack is lower than the other two cases. When a weak fault feature is the early stage of crack, fault identification of 3mm crack is relatively low, thus, we should pay more attention on this situation.

V. CONCLUSIONS

In this paper, the optimal sensors installation location on the basement is obtained by vibration characteristics analysis. The pattern recognition for rotor crack fault based on SVM is developed. The 11 normal used non-dimensional statistical parameters of time-domain signal are taken as features to study fault recognition rate of different features. The results are mainly shown as follows.

1. Finite element software is used for analyzing the vibration characteristics of the basement to obtain the optimal sensor installation location, which provides guidance for signal acquisition in fault diagnosis.

2. Some statistical parameters such as mean, RMS, root, and standard deviation have high fault recognition rate by using SVM to diagnosis for crack rotor, and they can be used as the reference pattern recognition and selected as feature vectors.

3. Compared with traditional bearing-pedestal single sensor pattern recognition, multi-sensor signal fusion method based on SVM with signals from basement of rotor system, has higher recognition rate and better performance for early crack fault.

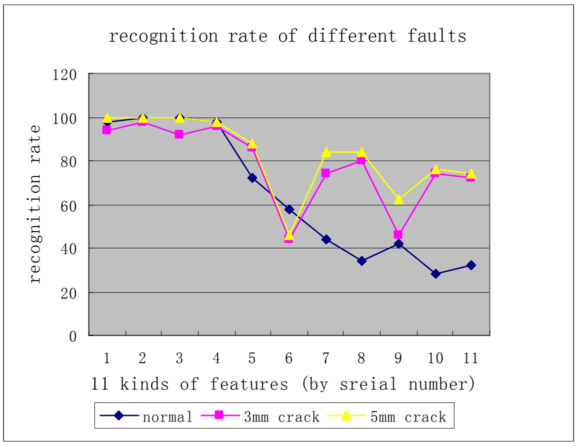


Figure.9. Diagnosis comparison chart.

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