Application of Fault Phenomenon Vector Distance Discriminance in Woodworking Machinery System Fault Diagnosis

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***Abstract*—Aiming at the problem of diagnosis difficulty caused by too many factors of woodworking machinery system, a kind of diagnosing method based on fault phenomenon was presented. The research on woodworking machinery system fault phenomenon space arrived at conclusion that the emergency of each fault phenomenon subject to 0-1 distribution. Therefore, phenomenon vector corresponding to each fault formed cluster whose accumulation point is expectation of vector. After exclusion of abnormal vectors, the distance discrimination was used to fault diagnosis to establish expert system based on fault phenomenon vector. The confirmed result was return back to fault database so that the system achieve self-learning of real-time diagnosis experiences. Finally, the example on wood-wool working equipment proves that the diagnostic method has characteristics of good real-time, simple operation and high diagnostic accuracy.**

***Index Terms*—woodworking machinery system, distance discrimination, fault phenomenon vector, fault diagnosis**

I. Introduction

The diagnosis of composite fault occurred in woodworking machinery is a difficult challenge at present. It is hard to diagnose the composite fault exactly and comprehensively due to the diversity and influence of faults. The purpose of woodworking machinery fault diagnosis is to identify whether the technical state is normal and determine the nature and site of faults from information related to mechanics running. Its essence is to find a mapping from fault phenomenon space to fault space. In order to accurately find the relationship to maximize extend, many scholars research on increasingly complex woodworking machinery system and presented many fault diagnosis methods based on the idea of expert system. The fault diagnosis of woodworking machinery is artificial neural network, grey model [1, 2] and Support vector machine (SVM). In back propagation artificial neural network (BP-ANN), traditional empirical risk minimization (ERM) is used on training data set to minimize the error. Support vector machine (SVM) based on statistical learning theory is used in many applications of machine learning because of its high accuracy and good generalization capabilities [3, 4].The expert system based on neural network and genetic algorithm has disadvantages of slow convergence speed of training of network or samples, so it is difficult to complete diagnose task that has high real-time requirements [5, 6, 7, 8, 9]. Although Levenberg-Marquardt (L-M) algorithm can overcome the shortcomings, L-M algorithm is a combination of gradient method and Gauss-Newton method. With t he aid of the approximate second derivative, the L-M algorithm is more efficient than t he gradient method. Concerned wit h t he t raining process and accuracy, the L-M algorithm is superior to vary learning rate BP-ANN and SVM [10, 11]. It greatly increased complexity of computation and difficulty of design. Fault diagnosis expert system based on fuzzy theory can describe system fuzzy state, but the key reasoning technology is still at the stage of theoretical study and far away from the application. In contrast, it is simple to design and realize traditional fault diagnosis expert system based on rules. However, expert system based on rules has two bottlenecks of rule making and knowledge acquisition [12,13]To resolve rule making problem with complex strategy solving rule is easy to return to complex algorithms as neural network and genetic algorithm, the problem becomes complex again. Machine learning played good effecting solving problem of knowledge acquisition, while the machine learning strategy is not universal and is prone to induce combination explosion. Through the research on

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probability distribution of fault phenomenon and clustering characteristic of phenomenon group caused by faults, the paper applied the idea of distance discrimination in diagnose strategy. The diagnosis result was feedback to fault database, which provide good solution to solving two problems of traditional expert system based on rules, so that the complexity of system structure and software design difficulty greatly reduced and diagnostic efficiency and engineering practicability greatly enhanced. Finally, Monte Carlo sampling and example of hydraulic excavator proves that the diagnostic method has characteristics of good real-time, simple operation and high diagnostic accuracy. The specific arrangement of the paper is as follows: Section 2 builds mathematical model of fault phenomenon vector; Section 3 determines key techniques of fault phenomenon vector distance discrimination method; Section 4 performs simulation verification of the method taking wood-wool working equipment as example; Section 5 concludes our work.

II. FAULT MODEL ESTABLISHMENT

A. Mathematical Description of Fault Vector Phenomenon

There are many factors led to fault of woodworking machinery system, most of which are not major. Under the influence of many non-essential factors, the phenomenon represented by faults that caused by few major factors appeared random. There are following facts: a fault may lead to simultaneous multiple phenomenons; occurrence of a fault phenomenon may be caused by different fault; multiple possible fault phenomenon caused by a fault is not certain, but statistically law.

Assume the faults of system are single fault. We can know from statistics that there have *n* types of fault in the running history of system *S*, which forms a fault set $F = \{F_i \mid 1 \le i \le n\}$, where F_i is the *i-th* type fault. We can also know that there are *m* types of fault phenomenon caused by *n* types fault, the set of which is $I = \{I_i \mid 1 \le i \le m\}$.

Define vector $\overrightarrow{D} = (d_1, d_2, \cdots, d_m)$, $d_i \in B = \{0,1\}$, $(1 \le i \le m)$ whose component is a boolean variable to represent a fault phenomenon group, which is called as fault phenomenon vector. Among them, d_i=1 says that the *i-th* phenomenon in set *i* occurs, d_i=0 says it does not occur. As phenomenon caused by a fault constitutes a vector, for the fault F_i, the set constituted by all possible fault phenomenon vectors is exactly a subspace of *m* dimensional boolean space, which is denoted as V_i. For different fault F_i and F_j ($i \ne j$), the constituted subspaces V_i and V_j are not different, but there may be common ground. If V_i and V_j are basically same, and the spatial distribution of fault phenomenon is probably same, the fault V_i and V_j are in a fuzzy set, in other words, it is difficult to distinguish the two faults from the phenomenon. Each dimension of fault phenomenon is subject to 0-1 distribution and respectively has a expectation p_i, then the fault phenomenon vector has a expectation μ . All fault phenomenon vector caused by F_i is the vector family around μ in the space. In other words, the fault phenomenon vector caused by each fault is a natural clustering whose accumulation point is the expectation vector. With the above definition, fault diagnosis becomes such a problem: given a fault phenomenon vector $\overrightarrow{D}$, to determine *i* with a method, so that $\overrightarrow{D} \in V_i$.

B. Establishment of Expert System Model

The whole fault diagnosis system is an expert system. The process of wood-wool working equipment fault diagnosis is shown in Fig. 1. Consists of three main stages flow is as follows:

(a) Retrieving

According to the current fault phenomenon and symptoms of the wood-wool working equipment, retrieve the similar case from a database. If the case is suited to the current fault phenomenon of the equipment

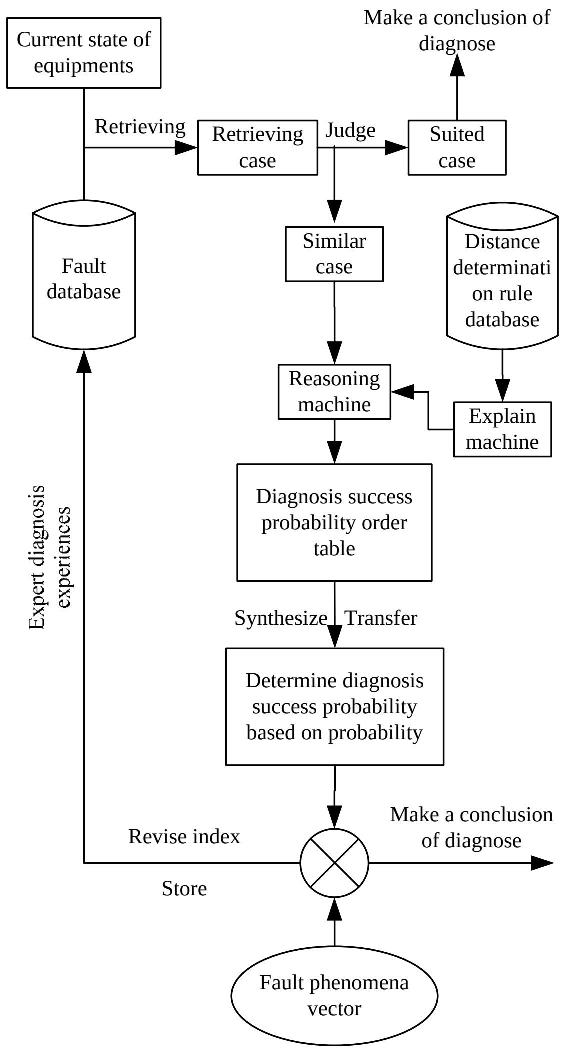

Figure 1. Fault diagnosis expert system model

completely, quote the case directly and make a conclusion.

(b) Modifying

It takes fault phenomenon vector as input and to reason with explained distance discrimination rules and past fault data. The reasoning machine issued a diagnostic probability order table of diagnosis result according to discrimination analysis rules, where the fault with maximum probability is the preferred result, and others are options by decreasing order of probability. If the case is not matched completely, The diagnostic probability order table will be available to maintenance personnel for reference of further confirm, use the Distance determination rule database, parts fault characteristic and actions record [16] etc. to Reasoning, adjust, rewrite, match and synthesize the case which has been retrieved according to the current fault phenomenon of equipment.

(c) Storing

Make the corrected case in keeping with the diagnosis of the current fault phenomenon, and make a conclusion. At the same time, the confirmed result will be fed back to fault database for record to prepare for the next diagnostic reference.

The distance discrimination was used to fault diagnosis to establish expert system based on fault phenomenon vector. The core of fault diagnosis is that it can memorize/store the former fault, its environments and the process accurately, furthermore, it uses the past diagnosis experience, process and methods to complete the current diagnosis through analogy and association while diagnosing. Therefore, fault diagnosis based on fault phenomenon vector is a kind of methods realized through analogy [17, 18], and its design mode is to utilize the past designed case directly instead of the summary of design experience.

III. Key Techniques

A. Rule-Based Diagnostic Expert Systems

In the rule-based systems, knowledge is represented in the form of production rules. A rule describes the action that should be taken if a symptom is observed. The empirical association between premises and conclusions in the knowledge base is their main characteristic. These associations describe cause-effect relationships to determine logical event chains that were used to represent the propagation of complex phenomena. The general architecture of these systems includes domain independent components such as the rule representation, the inference engine and the explanation system. Basic structure of a classical rule-based expert system is shown in Fig. 2.

Expert diagnosis experiences suitably formatted consists the basis for the classical expert system approach. Fault diagnosis requires domain specific knowledge formatted in a suitable knowledge representation scheme and an appropriate interface for the human-computer dialogue. In this system the possible symptoms of faults are presented to the user in a screen where the user can click the specific symptom in order to start a searching process for the cause of the fault. Additional information about checking or measurements is used as input that, in combination with stored knowledge in the knowledge base guide to a conclusion [19, 20, 21, 23].

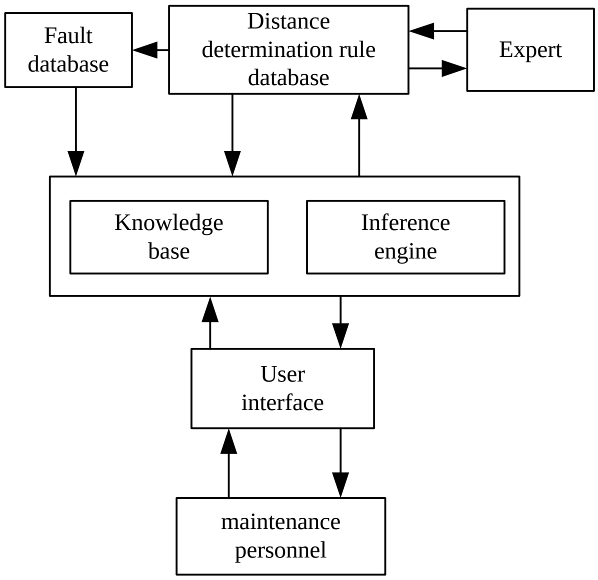

Figure 2. Basic structure of a rule-based expert system.

B. Reasoning Rules Formulation

The formulation of rules needs to resolve problem of fault data table design. Table 1 is the designed fault data table of F_1, where each line represents a fault phenomenon vector.

Using the above method, we can build fault data table for each F_i. Each fault phenomenon obeys standard 0-1 distribution, the value of which is shown in (1). The expectation of each phenomenon is p_{ij}, where i represent that the phenomenon is caused by the i-th fault; j

TABLE I.
Data Table of F_1

	Phenomenon						
	Number	I_1	I_2	I_3	I_4	···	I_m
F_1	1	1	0	0	1	···	1
	2	1	0	1	0	···	0
	3	0	0	1	1	···	0
	4	1	0	1	0	···	0
	5	1	0	1	1	···	0
	6	1	0	1	0	···	0
	7	1	0	1	1	···	0
	8	0	0	0	1	···	0
	9	1	0	0	0	···	0
	10	1	1	1	0	···	0
	···	···	···	···	···	···	···
Total	1000	913	11	946	583	···	50

represents that this phenomenon is the *j-th* phenomenon in the set; N is the sample data amount of this fault; I_{ijt} represents that the *t-th* fault phenomenon vector of fault i is caused by the *j-th* component.

$$\mu_i^* = (p_{ij})_{j=1,2,\cdots,m} = (\frac{\sum_{t=1}^{N} I_{ijt}}{N})_{j=1,2,\cdots,m} \quad (1)$$

The variance is as (2):

$$r_i = (S_{ij}^2)_{j=1,2,\cdots,m} = (\frac{1}{N-1}\sum_{t=1}^{N}(I_{ijt} - p_{ij})^2)_{j=1,2,\cdots,m} \quad (2)$$

Covariance between different phenomenons is as (3):

$$\sum_i = [\sigma_{iuv}]_{u\times v=m\times m} = [\sum_{k=1}^{N} I_{iuk} I_{ivk} P(I_{iuk}, I_{ivk})]_{u\times v=m\times m} \quad (3)$$

Where, $P(I_{iuk}, I_{ivk})$ is the joint probability of two fault phenomenon, which has only four cases as (4):

$$P(I_{iuk}, I_{ivk}) = \begin{cases} P(0,0) \\ P(0,1) \\ P(1,0) \\ P(1,1) \end{cases} \quad (4)$$

The research on woodworking machinery system fault phenomenon space arrived at conclusion that the emergency of each fault phenomenon subject to 0-1 independent and has the same distributions, That denoted as I_{i1}, I_{i2}, ... , I_{in}. With finite expected value $\mu_i^* = E(I_{ij})$ and finite variance $\sigma_i^2 = D(I_{ij})$.

Let $S_n = I_{i1} + I_{i2} + \ldots + I_{in}$.

We know $D(S_n) = n\sigma_i^2$, $D(\frac{S_n}{n}) = \frac{\sigma_i^2}{n}$ Also we know that $E(\frac{S_n}{n}) = \mu^*$.

We know from the large number law，by chebyshev's inequality, then for any $\varepsilon > 0$, as (5):

$$P\left(\left|\frac{S_n}{n}\right| - \mu_i^* \ge \varepsilon\right) \le \frac{\sigma_i^2}{n\varepsilon^2}. \quad (5)$$

Thus, for fixed ε as (6):

$$P\left(\left|\frac{S_n}{n}\right| - \mu_i^*\right) \ge \varepsilon \to 0 \quad (6)$$

As $n \to \infty$. Equivalently as (7):

$$P\left(\left|\frac{S_n}{n}\right| - \mu_i^*\right) < \varepsilon \to 1. \quad (7)$$

That when the number of sample goes to infinity, the expectation limit of samples is equal to that of the overall is shown in (5-7) and sample variance is equal to that of overall, the covariance of sample is equal to that of overall [22].

As Table 1 shows, the expectation of I_1 caused by F_1 is equal to p_{11}=913/1000 =0.913. Furthermore, the expectation fault phenomenon vector of fault F_i is μ_i^*, which is the accumulation point according to probability distribution in the space of all fault phenomenon caused by F_i. The discrimination analysis idea indicates that when perform distance discrimination of all μ_i^* and fault phenomenon vector to be diagnosed, then the fault phenomenon vector is possible belong to the *x-th* space. That is the probability that it caused by the *x-th* is the largest. In this way, the order result from little to large will led to sort of diagnose probability descending. The distance here can be Euclidean distance as (8), or be Mahalanobis distance as (9):

$$Dis_i = \left\|\mu - \mu_i^*\right\| = \sum_{j=1}^{\infty}(d_j - p_{ij}) \quad (8)$$

$$Dis_i(x,G) = \sqrt{(\overrightarrow{D} - \mu_i^{*T})\sum_i^{-1}(\overrightarrow{D} - \mu_i^*)} \quad (9)$$

Where, $\sum_i^{-1}$ is the inverse matrix of covariance matrix.

The Euclidean distance is intuitive, while the Mahalanobis distance needs to compare and discriminate the standard overall phenomenon caused by each fault, so to as reflect reality. In the practical application, Mahalanobis distance needs to know the inverse matrix of covariance matrix among all phenomenon, which involve inverse operation, so it ie relatively complex.

C. Design of Learning Strategy

When the system is built, we should summarize expert diagnosis experience and input. The automatic learning in system running process can add conformed fault phenomenon vector into fault database. The sort according to probability from large to little will cause misdiagnosis, which means it may be wrong to take the fault at the most front as diagnosis result. The discrimination may cause mistakes, which is the fact that can not mastered by people. If the empirical data is very rich, the possibility of misdiagnosis will be very small. As to mistakes, the system will be the second diagnosis, which is ranked second in the probability of failure as a diagnostic output, and so on.

The storage form affects the problem solving efficiency, whereas regulation and evaluation affect the problem solving accuracy. The matching degree of the fault and fault phenomenon can be expressed as (10):

$$D_s(c,c') = 1 - \sqrt{\sum_{i=1}^{n} W_i (X_i - Y_i)^2 / n} \quad (10)$$

Where D_s is the matching degree of fault c and fault phenomenon c' ; W_i is the weight of characteristic parameter i; n is the number of all symptoms; X_i and

Y_i are respectively the initial character or the conclusion credibility of fault *c* and fault phenomenon c'.

If $D_s = 1$, it indicates that the fault and fault phenomenon are most suited, namely matched completely; if $D_s = 0$, the fault and fault phenomenon are completely different [19].

Experience data is not all valid. According to expert experience, the fault phenomenon vector that is obviously not corresponding to fault phenomenon correspond to a fault, which is identified as abnormal. The abnormal should not be discarded directly, but added into database after marking. The reason is that if the abnormal after a major problem in direct disposal will cause the system to continue to drop later, the system will be committing a serious error. When conducting distance discrimination, these abnormal data should be excluded to avoid affect of small probability abnormal on discrimination analysis. If this abnormal occurs frequently afterwards, the frequency of abnormal will naturally large. According to the abnormal determination formula (11), it will not still in the scope of abnormal.

$$\frac{\left\|\vec{D} - \mu_i^*\right\|}{\left\|D^*\right\|} \geq \alpha\%, D^* = (1,1,\cdots,1)_m \tag{11}$$

Where, α is the abnormal discrimination index that can be controlled.

D. Diagnose Algorithm Design

Diagnosis algorithm flow is as follows:

Step 1: Input fault phenomenon to be diagnosed $D_x = (d_1, d_2, \cdots, d_n)$.

Step 2: For all fault F_i, $i = 1,2,\cdots,n$.

(a) Compute expectation vector μ_i of F_i with (1);

(b) As to all fault phenomenon vector of F_i, to conduct abnormal discrimination with (11);

(c)Using all abnormal vectors, re-compute expectation μ_i^* of F_i.

Step 3: As far as to be diagnosed vector D_x, compute European (or Mahalanobis) distance D_{isi} of each fault with (8) or (9).

Step 4: Order D_{isi} from small to large to obtain diagnose probability order table $\begin{pmatrix} P_{i_k} \\ i_k \end{pmatrix}_n$.

Step 5: The maintenance personnel confirm faults according to probability from small to large.

Step 6: The confirm result is fed back to fault data table.

The diagnose probability order table $\begin{pmatrix} P_{i_k} \\ i_k \end{pmatrix}_n$ means the probability P_{i_k} of fault whose number is i_k sorted in the *k-th* position of the table. As to the diagnosis result, if it is caused by the i_1*-th* fault, it indicates that the first diagnosis is successful. If it is caused by the i_2*-th* fault, then the first diagnosis is failure and second diagnosis is successful. And so on.

IV. Model Simulation

A. Simulation Algorithm Design

The simulation algorithm is based on the above diagnosis algorithm. The standard to measure its efficiency is diagnostic success rate DFR_k of the *k-th* diagnosis and accumulative success rate $\overline{DFR_k}$, the definition of which is shown in (12) and (13).

$$DFR_k = n_k / M \tag{12}$$

Where, n_k is the frequency of vector to be diagnosed after *k* times diagnosis; *M* is the total time of diagnosis.

$$\overline{DFR_k} = \sum_{i=1}^{k} n_i \Big/ M \tag{13}$$

Where, $\overline{DFR_k}$ is the percentage that fault be diagnosed after *k* times of diagnosis. Obviously, *k*=1 is the fault detection rate. *k*=2 is the probability that isolate fault to two elements, and so on.

The simulation algorithm is as follows:

Step 1: As to all faults $i = 1,2,\cdots,n$, use Monte Carlo method to sample according to fault phenomenon vector. Each fault generates *N* groups of sample data.

Step 2: Extract a fault *x* using random method and then extract a fault phenomenon vector D_x.

Step 3: To diagnose with diagnosis algorithm and present probability order table $\begin{pmatrix} P_{i_k} \\ i_k \end{pmatrix}_n$.

Step 4: Repeat Step 2 and Step 3 *M* times.

Step 5: For $k = 1,2,\cdots,n$, statistical n_k. Compute DFR_k and $\overline{DFR_k}$, then output.

B. Simulation Result Analysis

As to *MQ3130*-type wood-wool working equipment system, there are total 7 typical faults: rolling bearing fault、eccentric disk fault、the gear and rack fault、tool change Spindle fault、crank-connecting rod mechanical fault、work piece installation fault and feed drive structures fault. That denoted as $I_1, I_2, \cdots, I_7$. The distribution parameter of system fault and corresponding phenomenon is shown in Table 2.

Design fault database with the method of Table 2 and conduct simulation, where the distance discrimination use Euclidean distance. M=1000, N=1000. The abnormal discrimination index $\alpha = 30$. Each fault samples to generate 1000 vectors and extract 1000 samples for simulation. The output result is shown in Table 3 and Table 4.

TABLE II.
DISTRIBUTION PARAMETER OF SYSTEM PARAMETER AND CORRESPONDING PHENOMENON

	F_1	F_2	F_3	F_4	F_5	F_6	F_7
I_1	0.5	0.60	0.89	0.88	0.01	0.53	0.01
I_2	0.95	0.80	0.95	0.06	0.01	0.90	0.02
I_3	0.8	0.50	0.96	0.01	0.96	0.9	0.4
I_4	0.1	0.02	0.01	0.96	0.01	0.08	0.98
I_5	0.2	0.02	0.9	0.07	0.89	0.3	0.05
I_6	0.01	0.35	0.01	0.8	0.03	0.00	0.3
I_7	0.9	0.90	0.01	0.02	0.92	0.93	0.02
I_8	0.3	0.40	0.00	0.98	0.01	0.33	0.05
I_9	0.7	0.01	0.01	0.99	0.01	0.68	0.8
I_{10}	0.3	0.01	0.01	0.02	0.88	0.25	0.01

Results of Table 3 show that the number of abnormal of each fault is little, which is consistent with actual situation. In Table 4, one time fault detection rate is as high as 0.852. The three times accumulative diagnosis success rate is up to 0.979 when k=3, which means the probability that isolate fault to three elements can up to 0.979. The reason is vector distribution parameters of F_4 and F_5 is very close. From the above definition we can know that these three faults can be regarded as a fuzzy group. At the moment, we can regard them as a fault, so one time fault detection rate is up to 0.979. The data result analysis indicates that this kind of diagnosis method based fault phenomenon vector discrimination is effective.

TABLE III.
NUMBER OF EXCLUDED ABNORMAL.

Fault number	F_1	F_2	F_3	F_4	F_5	F_6	F_7
Number of abnormal	1	0	0	25	23	2	1

TABLE IV.
DIAGNOSIS SIMULATION RESULT

The *k-th* diagnosis	Diagnosis success probability	Misdiagnosis probability	Cumulative success rate
1	0.852	0.148	0.852
2	0.097	0.051	0.949
3	0.030	0.021	0.979
4	0.012	0.009	0.991
5	0.009	0.000	1.000
6	0.000	0.000	1.000
7	0.000	0.000	1.000

V. CONCLUSION

The paper presented a kind of woodworking machinery system diagnosis method based on fault phenomenon vector discrimination analysis. Starting from the clustering characteristics of fault phenomenon vector, conduct reasoning rule design based on the idea of discrimination analysis idea. The expert system model was built using determination and exclusion of abnormal. Finally, simulation illustration of *MQ3130*-type wood-wool working equipment proves that the diagnostic method has characteristics of good real-time, simple operation and high diagnostic accuracy.

However, the technique is a new branch of artificial intelligence, so systemic fruits are still not abundant, theories are still not mature, and the research and application are still in the exploring stage. If we apply it in machinery fault diagnosis system, the techniques of fault phenomenon vector and fault, retrieving and matching, self-study method, etc. would need further improved. With the increasing complication of the equipment and systems, fault diagnosis based on fault phenomenon vector will become an effective method in the fault diagnosis realm.

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