

Research Article

Concurrent Fault Diagnosis for Rotating Machinery Based on Vibration Sensors

Qing-Hua Zhang,¹ Qin Hu,^{1,2} Guoxi Sun,¹ Xiaosheng Si,³ and Aisong Qin¹

¹ Guangdong Petrochemical Equipment Fault Diagnosis Key Laboratory, Guangdong University of Petrochemical Technology, Maoming 525000, China

² School of Automation, Guangdong University of Technology, Guangzhou 510006, China

³ Department of Automation, Tsinghua University, Beijing 100084, China

Correspondence should be addressed to Guoxi Sun; 158011382@qq.com

Received 10 January 2013; Accepted 5 April 2013

Academic Editor: Zhangbing Zhou

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Rotating machinery is widely used in modern industry. It is one of the most critical components in a variety of machinery and equipment. Along with the continuous development of science and technology, the structures of rotating machinery become of larger scale, of higher speed, and more complicated, which results in higher probability of concurrent failure in practice. It is important to enable reliable, safe, and efficient operation of large-scale and critical rotating machinery, which requires us to achieve accurate diagnosis of concurrent fault, for example, rolling bearing diagnosis, gearbox diagnosis, and compressor diagnosis. In this paper, to achieve concurrent fault diagnosis for rotating machinery, which cannot be accurately diagnosed by existing methods, we develop an integrated method using artificial immune algorithm and evidential theory.

1. Introduction

For a complex engineering system [1], many fault diagnosis problems involve quantitative data and qualitative information, as well as various types of uncertainties, for example, incompleteness and fuzziness [2]. Conventional analytical models based on pure data, for example, time series analysis models and filter based models, are not always applicable, since it is difficult to obtain a complete set of historical data for developing a perfect mathematical model to simulate a system [3, 4]. Furthermore, due to the fact that human beings hold ultimate responsibility in most situations, the subjective judgment plays an irreplaceable role in making final decision, which may not be always accurate. Thus, it is highly desirable to develop a fault diagnosis that can model and analyze diagnosis problems using uncertain information, which is likely to be incomplete and vague.

The development of methods for handling uncertain information has received considerable attention in the last three decades. Several numerical and symbolic methods have been proposed. Three of the most common frameworks for

representing and reasoning with uncertain knowledge are (i) Bayesian probability theory; (ii) Dempster-Shafer (D-S) theory of evidence; (iii) Fuzzy set theory. Due to the power of the D-S theory in handling uncertainties, so far, it has found many application areas, for example, expert system, uncertainty reasoning.

To avoid the drawbacks of using evidential theory alone to fault diagnosis, for example, its heavy calculation burden due to the exponential “explosion” of the focal elements involved by fault information and data combination [5], in this paper, we present an integrated approach for the concurrent fault diagnosis using artificial immune algorithm [6] and evidential theory [7], aiming to not only improve the diagnosis rate but also increase the reliability of diagnostic conclusion.

This research work has the following theoretical and practical contributions.

- (i) Our method can represent the uncertainty existing in the result of fault diagnosis due to the evidence theory involved.

- (ii) To demonstrate our method, we apply our method to the real test bed of concurrent fault diagnosis for rotating machinery.
- (iii) The results show that our developed method can make accurate judgment for concurrent fault of the rotating machinery which has certain credibility.
- (iv) Regular maintenance of equipment can be scheduled effectively.

The remaining part of this paper is organized as follows. In Section 2, the related work is surveyed and presented. In Section 3, we will describe the experimental conditions and the detailed parameters of the used vibration sensors. Section 4 describes the artificial immune algorithm and dimensionless parameters for fault diagnosis. Our proposed integrated concurrent fault diagnosis method base on the artificial immune algorithm and evidence theory will be given in Section 5. The systematical evaluation in a real test bed for this proposed method is given in Section 6, and Section 7 concludes this paper.

2. Related Work

Previous researchers have conducted considerable effort on rotating machinery diagnostics and developed a variety of diagnosis methods. In [11], a fault diagnosis system based on the wavelet transform and artificial immune system is presented, in which the wavelet transform is used to analyze nonstable signals and obtain their eigenvectors, and the artificial immune algorithm is also proposed to conduct self-nonsel analysis based on these eigenvectors. The system is successfully applied to vehicle fault diagnosis with good results. In [12], a new hybrid approach based on conventional fuzzy soft clustering and artificial immune systems for sensor multiple faults is proposed, which can require no prior knowledge, or the system behavior, and no learning processes are required. This new approach uses the fuzzy clustering c-means algorithm firstly to generate a single fuser for the input sensor signals. Then a fault detector was generated based on the artificial immune systems. In [13], support vector machine (SVM) is a classification method, but some parameters in SVM are selected by man's experience. Aydin et al. used a multiobjective artificial immune algorithm (AIA) to optimize the parameters of SVM. The fault diagnosis of induction motors and anomaly detection problems shows that the SVM optimised by AIA can give higher recognition accuracy than the normal SVM. In [14], Wang et al. proposed the improved immune algorithm based on Discrete Particle Swarm Optimization (DPSO) technique to solve the problem that exists in fault diagnosis. This approach can improve the mutation mechanism and enhance the immune algorithms performance. Simulation results show that the new scheduling algorithm can deal with the uncertainty situation and be suitable for multifaults diagnosis. In [15], a composite fault diagnosis approach was proposed, combining the real-valued negative selection (RNS) algorithm with the support vector machine. In the new method, the difficult problem of lacking training samples was solved by using the

new method in the conventional classification algorithm. In [16], Wanjun et al. proposed a fuzzy-immunity mixed fault diagnosis method. This method can resolve quantitatively diagnosis for gun-launched missile fault in the lack of prior knowledge. In [17], the authors propose two model-based fault detection and isolation schemes for robot manipulators using soft computing techniques, as an integrator of Neural Network and Fuzzy Logic. The first scheme isolates faults by passing residual signals through a neural network. The second scheme isolates faults by modelling faulty robot models for defined faults and combining these models as a generalized observers scheme structure. In [18], the authors present an integrated fault diagnostics model based on the Genetic Algorithm and Artificial Neural Network for identifying shifts in component performance and sensor faults. The diagnostics model uses response surfaces for computing objective functions to increase the exploration potential of the search space while easing the computational burden firstly. Then a nested neural network is used with genetic algorithm. The nested neural network functions as a filter to reduce the number of fault classes to be explored by the genetic algorithm. In [19], the authors present an integrated neural fuzzy approach for transformer fault diagnosis, which formulates the modeling problem of higher dimensions into lower dimensions. Then, the fuzzy rule base is designed by applying the subtractive clustering method which is very good at handling the noisy input data. The simulation result shows that the method possesses superior performance in identifying the transformer fault type. In [20], the authors make use of advantages of the neural network and the fault tree to construct the fault diagnosis system. The fault tree with an intuitive, logical, and strong features for a simple structure determines the source of the problem, but for accessing to complex and uncertain domain knowledge, and neural networks technology has to learn the characteristics of self-association and can just make up the shortcomings of the model fault tree diagnosis. The authors take control box faults of a certain digital control system as an example to simulate. The training results show that the method can be more accurate and quick to make fault diagnosis. In [21], the author proposed a new method based on support vector machine with genetic algorithm to fault diagnosis of a power transformer. In this method, the genetic algorithm is used to select appropriate free parameters of support vector machine. The simulation result indicates that the proposed method can achieve higher diagnostic accuracy. In [22], the authors proposed a fault diagnosis method based on kernel principal component analysis (KPCA) and support vector machines (SVM). Firstly initial feature vectors of motor vibration signal were mapped into higher-dimensional space with kernel function. Then the PCA method was used to analyze the data in the high-dimensional space to extract the nonlinear features which is used as training sample of SVM fault classifier. Lastly, the rotor fault is identified using the trained classifier. Research results showed that the method can identify motor rotor fault efficiently and fulfill fault classification accurately. In [23], the researcher demonstrated the ability of genetic programming to discover automatically the different bearing conditions. The genetic programming

(GP) can generate new features from the original dataset without prior knowledge of the probabilistic distribution. The created features are then used as the inputs to a neural classifier for the identification of six bearing conditions. In [24], the authors presented a fault diagnostic method based on a real-encoded hybrid genetic algorithm evolving a wavelet neural network (WNN). The main drawbacks of a back propagation algorithm of wavelet neural network (WNN) are that the optimal procedure is easily stacked into the local minima and cases that strictly demand initial value. A real-encoded hybrid genetic algorithm evolving a WNN can be used to optimize the structure and the parameters of WNN instead of humans in the same training process. A number of examples were further given to show that the method proposed has good classifying capability for single- and multiple-fault samples of power transformers as well as high fault diagnostic accuracy. In [25], a fault diagnosis method is proposed based on adaptive neurofuzzy inference system (ANFIS) in combination with classification and regression tree (CART), which is used as a feature selection procedure to select pertinent features from data set. The crisp rules obtained from the decision tree are then converted to fuzzy if-then rules. The hybrid of back-propagation and least squares algorithm are utilized to tune the parameters of the membership functions. Research results show that the CART-ANFIS model has potential for fault diagnosis of induction motors. In [26], the authors presented a study on the application of particle swarm optimization (PSO) combined with artificial neural networks (ANNs) and support vector machines (SVMs) for bearing fault detection in machines. The classifier parameters, for example, the number of nodes in the hidden layer for ANNs and the kernel parameters for SVMs, are selected along with input features using PSO algorithms. In [27], Dong et al. applied neural network and Dempster-Shafer theory (D-S) to rotor in turbine generator set to diagnose multiple faults. The D-S reasoning theory is used to do fusion decision making based on the diagnosis result.

From the above survey over the related works, we can observe that there is a continuing trend to develop a fusion method (which can fully utilize the advantages of multiple methods) for the concurrent fault diagnosis, due in part to the complexity of concurrent failures and uncertainty in its diagnosed results. This naturally leads to our primary objective of this paper, that is, to achieve concurrent fault diagnosis for rotating machinery, which cannot be accurately diagnosed by the current methods.

3. Experimental Conditions and Basis

3.1. The Studied Rotating Machinery. In this research work, a motor-gearbox-magnetic powder brake test device has been developed by our research lab (Guangdong province Petrochemical Equipment Fault Diagnosis Key Laboratory, Guangdong University of Petrochemical Technology, China), as shown in Figure 1, which consists of three major parts as (1) motor, (2) magnetic powder brake, and (3) transducer. Two sensors are used to gather sensory data from the rotating

TABLE 1: The main components of the studied rotating machinery.

Equipment	Motor	Magnetic powder brake	Transducer
Model	Senlima YP	CZ-2	Anchuan-VS606V7
Parameters	Power 1.5 Kw; rated voltage 380 V; reference frequency 50 Hz	Rated torque 20 N·m; exciting current 0.6 A; allowable sliding power 1.6 Kw	Three phase; rated voltage 400 V; power 1.5 Kw

TABLE 2: The characteristics of the vibration sensor.

Measurement range	Collection functions
Acceleration: 0.1~199.9 m/s ² Single peak value (0-P)	The range of frequencies: the minimum frequency:10 Hz; the maximum frequency: 100~10 KHz with adjusting continuously
Velocity: 0.01~19.99 cm/s Virtual value (rms) Displacement: 0.001~1.999 mm	Dynamic range: 72 dB The stop band of decay rate: 72 dB/oct
Peak-peak values (P-P)	the acquisition parameters: vibration acceleration, vibration velocity, and vibration displacement
The minimum frequency: 10 Hz	Antialiasing low-pass filter: 100~10 KHz with continuous variable
The maximum frequency: acceleration 10 Hz, velocity 1 Hz, and displacement 1 KHz	
The measure precision: plus-minus 5% plus-minus two words	

machinery. The detailed parameters for each unit are given in Table 1.

3.2. The Used Sensory Data Collection System. In Figure 2, we can see the used vibration sensor and machinery health collector in this research work. The sensor can gather three types of information: (1) vibration acceleration, (2) vibration velocity, and (3) vibration displacement. The detailed feature description about the used sensor is given in Table 2.

3.3. Used Variable in This Paper. The used variable in this paper is listed in Table 3.

4. Artificial Immune Algorithm and Dimensionless Parameters

Based on biological immune system through antigen recognition, immune response, and clone selection process to judge their "own" or "nonself" substances (Figure 3 shows the concept of self and nonself space), to maintain and protect a



FIGURE 1: The developed real test bed.

TABLE 3: The used variable in this paper.

Variable	Definition
$p(x)$	The probability density function from the observed vibration signal's amplitude
x	The vibration amplitude
S_f	Waveform index
I_f	Impulse index
CL_f	Margin index
C_f	Peak index
K_v	Kurtosis index
X_{rms}	A dimension parameter named as root of mean square(RMS)
m_{ij}	The sensitivity of the i th kind of nondimensional index detector to the j th kind of failure
g_{ij}	The effective information preserved in the total feature information of a dimensionless index to generate a mature immune detector
d_{ij}	The diagnosis capability factor of the kind of i th dimensionless index immune detector to the kind of j th fault

stable internal environment, Forrest and Hofmeyr proposed a negative selection algorithm in [28] to detect patterns.

4.1. Negative Selection Algorithm. The basic idea of the negative selection algorithm is to produce a set of change detectors, which can detect changes in what is considered normal behavior of a system. The algorithm consists of two stages: Generating Detector Set stage and Training Detector Set stage. The Generating Detector Set stage caters for the generation of change detectors. Briefly, the procedure proposed the following: (1) define self data; (2) generate a candidate detector randomly; and (3) match each candidate detector with self data; if it matches; delete it, if not, add it to detector set. Subsequently, system is monitored for changes using the detectors generated in Generating Detector Set stage; if any detector ever matches the input data, then an abnormal is known to have occurred. Otherwise, the system is normal, as shown in Figure 4.



FIGURE 2: In this machinery health collector, two vibration sensors are associated. The gathered sensory data will be stored in the data collector first and then exported to computer.

In this paper, we first introduce this algorithm to detect the type of a fault in rotating machinery by constructing an immune detector based on the vibration signal analysis.

4.2. Dimensionless Parameters. Based on the probability density function $p(x)$ from the observed vibration signal, we obtained the dimension parameters such as the mean, the average amplitude, the root of mean square (RMS) value, slope, and kurtosis. These parameters have the sensitivity of equipment failure, but if we directly use them for fault detection, because of changing working conditions, such as speed, load, and equipment sensitivity, these dimension parameters also change over time. This means that these parameters are difficult to improve the diagnostic accuracy when used directly. To solve this problem, we introduce dimensionless parameters in the following [29].

Dimensionless parameters are the ratio of two-dimension parameters, defined as follows:

$$\zeta_x = \frac{\left[\int_{-\infty}^{+\infty} |x|^l p(x) dx \right]^{1/l}}{\left[\int_{-\infty}^{+\infty} |x|^m p(x) dx \right]^{1/m}}, \quad (1)$$

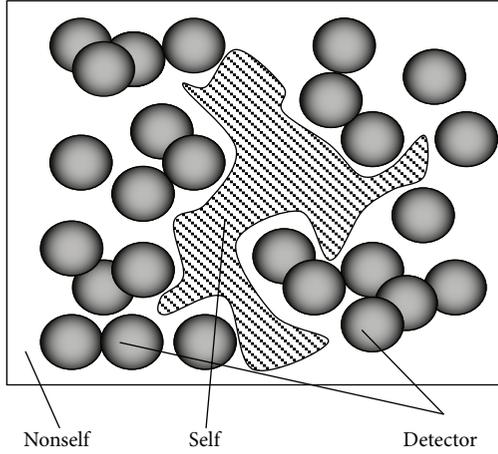


FIGURE 3: The figure illustrates the concept of self, nonself, and detector in a feature space.

where x denotes the vibration amplitude, and $p(x)$ denotes the probability density function of vibration amplitude.

In the practice, the following dimensionless parameters are frequently used and it is found that they behave well for rotating machinery fault diagnosis, specifically,

- (i) if $l = 2, m = 1$, have waveform index S_f ,
- (ii) if $l \rightarrow \infty, m = 1$, have impulse index I_f ,
- (iii) if $l \rightarrow \infty, m = 1/2$, have margin index CL_f ,
- (iv) if $l \rightarrow \infty, m = 2$, have peak index C_f ,
- (v) kurtosis index $K_v = \beta/X_{rms}^4$. In the formula, β is a dimension parameter named kurtosis, which is defined as $\beta = \int_{-\infty}^{\infty} x^4 p(x) dx$. X_{rms} is a dimension parameter named as RMS, defined as $X_{rms} = \sqrt{\int_{-\infty}^{\infty} x^2 p(x) dx}$.

Based on $p(x)$ and the vibration signals, the five nondimensional parameters defined above can be directly used to detect the anomaly in the vibration signal in real time and implemented easily. It is also found that these parameters are sensitive enough to the fault and thus can reflect the fault condition and are not interfered with the absolute level of vibration signals. In addition, the dimensionless parameters are stable with respect to the load, conditions, and speed of equipment so that the relationship between the working conditions of the machine and these parameters is not significant. This unique feature is very useful for fault diagnosis since they can capture the anomaly only in the observed signals.

In order to facilitate us to introduce the integration diagnosis method, some definitions used in this paper are as follows.

Definition 1. we define m_{ij} as the fault sensitive index of the i th kind of nondimensional index detector to the j th kind of failure, with $m_{ij} \leq 1, i = 1, 2, \dots, l, j = 1, 2, \dots, n$. The ratio m_{ij} measures the values for the ratio of the maximum

nondimensional failure index value and the minimum size of the index under normal conditions. The smaller the ratio is, the less sensitive the index is to the fault.

Definition 2. we define g_{ij} as the effective information preserved in the total feature information of a dimensionless index to generate a mature immune detector, with $g_{ij} \leq 1, i = 1, 2, \dots, l, j = 1, 2, \dots, n$. The quantity g_{ij} measures the ratio of the amount of the lost value and the useful fault information. The more the lost value is, the smaller the quantity g_{ij} is.

Definition 3. we defined d_{ij} as the diagnosis capability factor of the kind of i th dimensionless index immune detector to the kind of j th fault, with $d_{ij} \leq 1, i = 1, 2, \dots, l, j = 1, 2, \dots, n$. The quantity d_{ij} can be calculated as follows,

$$d_{ij} = \frac{m_{ij}g_{ij}}{\sum_{k=1}^l m_{kj}g_{kj}}, \quad i = 1, 2, \dots, l, j = 1, 2, \dots, n. \quad (2)$$

5. The Integration of Artificial Immune and Evidential Theory

The method developed by Zhang [30] improved the negative selection algorithm and made use of the above five nondimensional parameters to generate the five immunity detectors. These detectors were further used to diagnose the fault of rotating machinery. We can obtain the range of each dimensionless parameter in different fault mode. It is found in the experimental results that the ranges of some nondimensional parameters for different values of fault modes will duplicate or even cross with each other. Making the target dimensionless parameter immune detector with each fault mode is unique and does not cross with those of other dimensionless characteristics. In practice, it is usual to reduce these value ranges to achieve an accurate fault diagnosis. The detector with such desired properties is named mature immune detector.

5.1. The Evidence Theory for Fault Diagnosis. The evidence theory developed by Dempster [31] was extended and refined by Shafer [32]. The evidence theory is related to Bayesian probability theory in the sense that they both can update subjective beliefs given new evidence. The major difference between the two theories is that the evidence theory is capable of combining evidence and dealing with ignorance in the evidence combination process. Specifically, it can distinguish the events such as “do not know,” “uncertainty,” and other important concepts on cognition. The basic concepts and definitions of the evidence theory relevant to this paper are briefly described as follows.

Let $\Theta = \{F_1, \dots, F_n\}$ be a collectively exhaustive and mutually exclusive set of hypotheses, called the frame of discernment. A basic probability assignment (BPA) is a function $m : 2^\Theta \rightarrow [0, 1]$, called a mass function and satisfying

$$m(\emptyset) = 0, \quad 0 \leq m(A) \leq 1, \quad \sum_{A \subseteq \Theta} m(A) = 1, \quad (3)$$

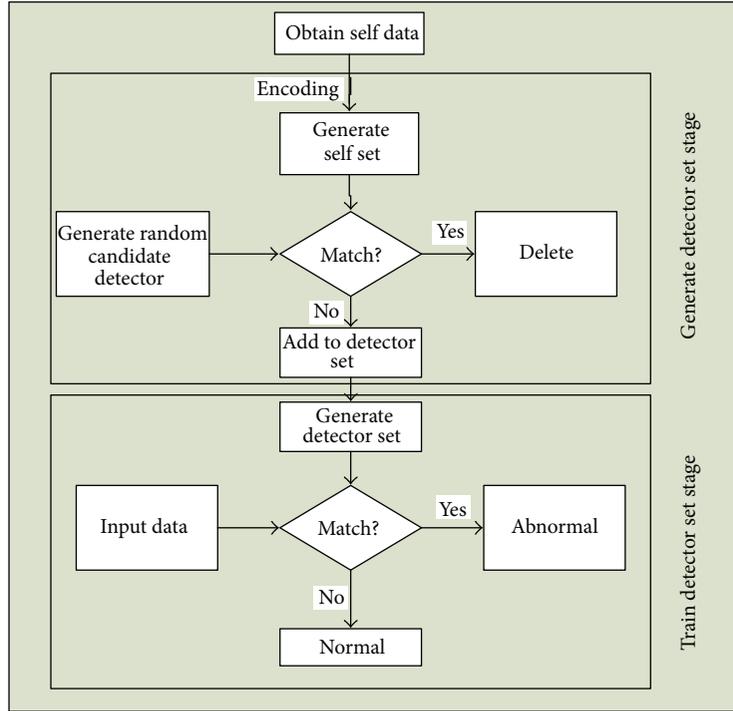


FIGURE 4: Negative selection algorithm.

where \emptyset is an empty set, A is any subset of Θ , and 2^Θ is the power set of Θ , which consists of all the subsets of Θ , that is, $2^\Theta = \{\emptyset, \{F_1\}, \dots, \{F_N\}, \{F_1, F_2\}, \dots, \{F_1, F_N\}, \dots, \Theta\}$. The assigned probability (also called probability mass) $m(A)$ measures the belief exactly assigned to A and represents how strongly the evidence supports A . All assigned probabilities sum to unity and there is no belief in the empty set \emptyset . The probability assigned to Θ , that is, $m(\Theta)$, is called the degree of ignorance. Each subset $A \subseteq \Theta$ such that $m(A) > 0$ is called a focal element of m . All the related focal elements are collectively called the body of evidence.

Associated with each BPA are a belief measure (Bel) and a plausibility measure (Pl) which are both functions: $2^\Theta \rightarrow [0, 1]$, defined by the following equations, respectively:

$$\text{Bel}(A) = \sum_{F \subseteq A} m(F), \quad (4)$$

$$\text{Pl}(A) = \sum_{A \cap F \neq \emptyset, F \subseteq \Theta} m(F) = 1 - \text{Bel}(\neg A),$$

where A and B are subsets of Θ . $\text{Bel}(A)$ represents the exact support to A , that is, the belief of the hypothesis A being true; $\text{Pl}(A)$ represents the possible support to A , that is, the total amount of belief that could be potentially placed in A . $[\text{Bel}(A), \text{Pl}(A)]$ constitutes the interval of support to A and can be seen as the lower and the upper bounds of the probability to which A is supported. The two functions can be connected by the following equation:

$$\text{Pl}(A) = 1 - \text{Bel}(\neg A), \quad (5)$$

where $\neg A$ denotes the complement of A . The difference between the belief and the plausibility of a set A describes the ignorance of the assessment for the set A [32].

Since $m(A)$, $\text{Bel}(A)$, and $\text{Pl}(A)$ are in one-to-one correspondence, they can be seen as three facets of the same piece of information. There are several other functions such as commonality function and doubt function, which can also be used to represent evidence. They all represent the same information and provide flexibility in a variety of reasoning applications.

The kernel of the evidence theory is the Dempster's rule of combination by which the evidence from different sources is combined. The rule assumes that the information sources are independent and use the orthogonal sum to combine multiple belief structures $m = m_1 \oplus m_2 \oplus \dots \oplus m_n$, where \oplus represents the operator of combination. With two belief structures m_1 and m_2 , the Dempster's rule of combination is defined as follows:

$$m_1 \oplus m_2(C) = \begin{cases} 0, & C = \emptyset, \\ \frac{\sum_{A \cap B = C} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \emptyset} m_1(A) m_2(B)}, & C \neq \emptyset, \end{cases} \quad (6)$$

where A and B are both focal elements and $[m_1 \oplus m_2](C)$ itself is a BPA. The denominator, $1 - \sum_{A \cap B = \emptyset} m_1(A) m_2(B)$, is called the normalization factor, and $\sum_{A \cap B = \emptyset} m_1(A) m_2(B)$ is called the degree of conflict, which measures the conflict between the pieces of evidence. Several researchers have investigated the combination rules of evidence theory and fuzzy sets. Note that the crude application of the D-S theory and the combination rule can lead to irrational conclusions in the aggregation of multiple pieces of evidence in conflict.

TABLE 4: The specific integrated diagnostic process.

Step 1	We first measure vibration signals of a variety of failure modes in rotating machinery through a large number of experiments and generate seven mature immune detectors corresponding to seven nondimensional parameters by the artificial immune system.
Step 2	Based on the results obtained from Step 1, we can obtain the index ranges of different faults and calculate the fault features (such as m_{ij} , g_{ij} , and d_{ij}).
Step 3	We can measure the non-dimensional index to determine the probability of different faults by the mature immune detector. For example, after obtaining a set of experimental data, we use waveform index to determine the fault, and kurtosis index to determine the fault j and then we can empirically calculate the basic probability assignment by the cumulative number of experiment results.
Step 4	When we get the diagnosis probability of various indices to different faults by the cumulative proportion of the total number of experiments, we define the diagnosis probability of various indices to different faults as basic probability assignment functions and use evidential theory to aggregate these data.
Step 5	We assume the greatest credibility as a final diagnostic result. That is, the fault is the one with the greatest credibility in the aggregated results.

TABLE 5: The range of each nondimensional parameter.

Fault type	S_f	C_f	I_f	CL_f	K_v	N_1	N_2
Normal	1.215~1.227	0.917~0.931	1.213~1.232	1.135~1.186	2.205~2.297	3.463~3.809	1.467~1.727
Grinding teeth	1.242~1.257	1.320~1.341	1.923~1.962	1.657~1.676	2.776~2.872	6.326~6.829	0.974~1.182
Inside and outside ring grinding	1.257~1.287	1.223~1.320	1.849~1.923	1.562~1.657	2.515~2.776	4.906~6.289	5.062~5.542
Concurrent fault	1.287~1.357	1.007~1.220	1.465~1.849	1.252~1.562	2.045~2.205	3.058~3.455	8.162~8.504

The evidence theory is applied to the fault diagnosis through the synthesis of information to get some basic probability assignment functions. After obtaining these basic probability assignment functions, the D-S combination rule can be used to aggregate them to get a final judgment with certain belief degrees in the focal elements. This final judgment can characterize the uncertainty in fault diagnosis and thus is useful to avoid the false alarm in final decision.

5.2. An Integrated Concurrent Fault Diagnosis Method Using Artificial Immune Algorithm and Evidence Theory. In the following section, we will present an integrated method using artificial immune algorithm and evidential theory for fault diagnosis.

Considering the existing dimensionless parameters is insensitive to the change of working condition, so it is applicable to fault diagnosis technology, yet it is not very satisfactory for concurrent fault diagnosis in rotating machinery, and the number of the conventional dimensionless parameters is few. In order to overcome the disadvantages of conventional dimensionless parameters in rotating machinery fault classification, building new dimensionless parameter, which especially possesses the features of integrated diagnosis, is of great significance to improve capability of diagnosing fault and analyzing fault characteristics. A new method based on genetic programming is proposed to construct the new dimensionless parameters [33]. According to this method, simple dimensionless parameters are combined and new dimensionless parameters are formed, then fitness function is adopted to measure the performance of new generated

indexes. With this method, two new dimensionless parameters having better classification ability than that of existing ones are obtained for fault diagnosis of rotating machinery. These two new dimensionless parameters are as follows:

$$(i) N_1 = K_v^2 + C_f^2 - CL_f I_f;$$

$$(ii) N_2 = (S_f K_v + I_f - C_f CL_f)(S_f I_f - C_f^2).$$

In our paper, we use these two parameters with five previous parameters to detect the fault. The specific integrated diagnostic process is summarized in Table 4.

The above integrated approach can be illustrated by Figure 5. We assign different weight coefficients to seven dimensionless indexes before aggregation using the evidence theory. This is based on the fact that each index has different diagnosis capability and sensitivity for different faults. Such technology via assigning weights for each index can improve the reliability of diagnosis results and avoid possible incorrect conclusion resulted by the evidence conflict. Many scholars have adopted this idea to improve the combination methods of evidence theory. The details can be found in these literatures and thus we do not touch them here to save the space.

6. A Case Study (See Figure 6)

Using our testing equipment, the experimental data are measured as shown in Table 5.

From the range of the indexes which are listed in Table 5, we can calculate m_{ij} , g_{ij} , and d_{ij} using our developed approach in Section 4.2. We do not list these indexes due

TABLE 6: The obtained basic probability assignment functions from seven indexes.

Fault type	Value of weighting						
	S_f	C_f	I_f	CL_f	K_v	N_1	N_2
Grinding teeth	0.41	0.32	0.39	0.4	0.14	0.19	0.11
Inside and outside ring grinding	0.23	0.35	0.22	0.28	0.45	0.58	0.34
Concurrent fault	0.36	0.33	0.39	0.32	0.41	0.23	0.55

TABLE 7: The final results of our integrated approach.

	Grinding teeth	Inside and outside the ring grinding	Concurrent fault	Diagnosis
M_2	0.4	0.24	0.36	Grinding teeth
M_3	0.44	0.16	0.4	Grinding teeth
M_4	0.51	0.12	0.37	Grinding teeth
M_5	0.13	0.11	0.76	Concurrent fault
M_6	0.1	0.23	0.67	Concurrent fault
M_7	0.02	0.17	0.81	Concurrent fault

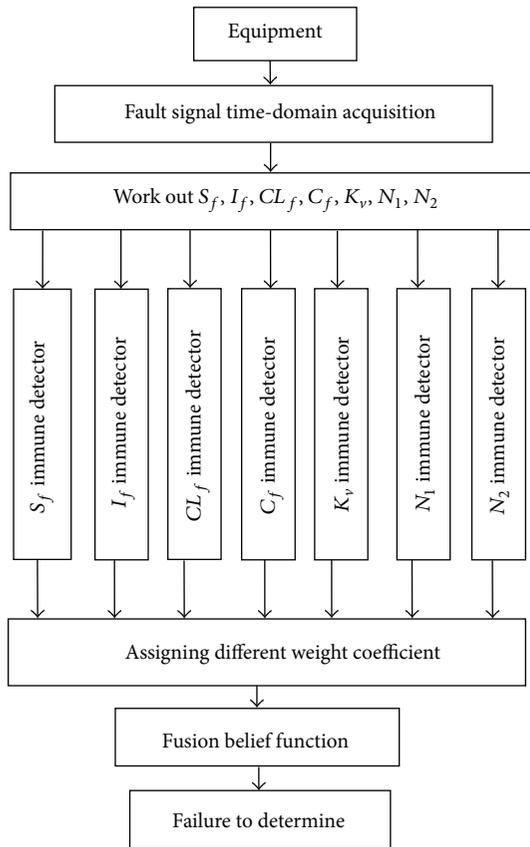


FIGURE 5: Schematic of the developed diagnosis approach.

to the limited space. Based on these data, we choose d_{ij} as the relative weighting factor and then calculate the diagnosis probability of each index to different faults as basic probability assignment function. The normalized results which were calculated by our approach are shown in Table 6.

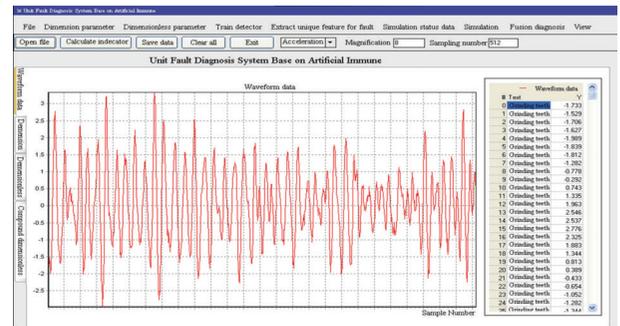


FIGURE 6: Waveform of the acceleration under grinding fault.

Based on the basic probability assignment functions summarized in Table 6, we then use evidential theory to fuse the data. The final aggregated results are shown in Table 7.

In Table 7, M_2 represents the fusion values of the first two normalized distribution of weight data in Table 6. The M_3 represents the fusion values of the first three normalized distributions of weight data, and so on. Finally, after aggregating all these seven basic probability assignment functions, we can find that the concurrent fault will occur with credibility 0.81, and thus we have enough evidence to claim that the concurrent fault occurs and actually this result matches the right fault result occurring in our experimental case. This demonstrates the implementation and effectiveness of our integrated approach for the concurrent fault.

7. Discussion

To achieve concurrent fault diagnosis for rotating machinery, which cannot be accurately diagnosed by the current methods, we develop an integrated method using artificial immune algorithm and evidential theory to solve this problem. Our developed method can take advantages of artificial

TABLE 8: The comparison of three methods in fault diagnosis.

Method	Strengths	Weaknesses
AIS [8, 9]	AIS can deal with the problem that the solution of fault diagnosis is lack of fault samples; the reasonable antibody set could be obtained from normal specimens using this algorithm.	This algorithm needs relatively large antibody set to ensure a higher detection rate, which leads to taking long time to generate detector and detect faults. In addition, the threshold value of the joint stress between antigen and antibody and the self radius is currently not well resolved. The designed threshold value has limitations for different faults
Evidence theory [10]	D-S evidence theory has a strong ability of dealing with uncertain information, which can effectively improve the credibility of diagnosis and reduce diagnostic uncertainty.	In the case of serious conflicting evidence, the result using the D-S evidence theory to fuse information directly does not agree with practice situation. The method of determining the reliability of evidence needs to be studied.
An integrated method using AIS and evidence theory presented in this paper	The integrated diagnostic technology uses more types of dimensionless immune detectors and decision-making systems of the evidence theory to detect fault; the excellent detector can be derived through multi-information fusion technology.	There is a subjective, human element when assigning a weight to dimensionless immune detector. We need experience to deal with the weight.

immune algorithm and evidential theory and thus has ability to diagnose the fault in a quick and effective manner. In particular, our method can represent the uncertainty existing in the result of fault diagnosis due to the evidence theory involved. In order to demonstrate our method, we apply our method to the case of concurrent fault diagnosis for rotating machinery. The results show that our developed method can make accurate judgments for concurrent fault of the rotating machinery under consideration, and the diagnosis result has certain credibility. Finally, we carried on some comparison with other algorithms in Table 8.

Acknowledgments

This work was partially supported by the NSFC under Grant 61174113 and the Natural Science Fund of Guangdong Province under Grant S2011020002735.

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