A Study of Fault Diagnostic based on Artifcial Immune Systems

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***Abstract*—Artificial Immune technology, a resource limited artificial immune classifier system,has performed well on elementary classification tasks. This paper presents one form of mapping Artificial Immune Systems (AIS) into Learning Classifier Systems for fault diagnosis. We propose a novel ideal to apply semantics in immune models. Similar to Learning Classifier Systems, a better understanding of AIS can be obtained when they are analysed under the perspective of complex Semantic system. One of the goals here is to determine complementary features of both systems (Semantic systemand AIS), aiming at providing a novel mapping conception for fault diagnosis. Our motivation comes from the use of a semantic structure for diagnosis of mine hoist based AIS.**

***Index Terms*—fault diagnosis; semantic structure; Artificial Immune Systems; System modelling;**

I. INTRODUCTION

The problem of detecting faults in complex real plants is strategically important for its various implications, e.g. avoiding major plant breakdowns and catastrophes, safety problems, fast and appropriate response to emergency situations and plant maintenance. Hoists are vital systems in mine industrial applications. Therefore, fault diagnosis of the mine hoist has been the subject extensive research. Fault detection is in general a very difficult, yet important task for mine hoist. Due to the broad scope of the process fault diagnosis problem and the difficulties in its real-time solution, many analytical-based techniques [1, 2] have been proposed during the past several years for the fault detection of technical plants.

Recently, with the development of artificial intelligence, Computational Intelligence (CI) methods, Neural Networks (NN), Fuzzy Logic (FL),Evolutionary Algorithms (EA), etc., more and more fault diagnostic approaches have emerged as new techniques for fault diagnostic systems [3,4]. The immune system, a kind of information processing system with specific features of recognition, self-organizing, memory, adaptation, and learning, has been adopted by a growing number of researchers to simulate the interactions between various components or the overall behaviors based on an immunology viewpoint [5–7]. In the study of [8], a nonlinear system identification scheme with satisfactory robustness and efficiency was developed employing the features of the artificial immune system. Then an immune model-based fault diagnosis methodology including the residual generation, residual filtering, fault alarm concentration (FAC), and artificial immune regulation (AIR) was developed to diagnose system failures in [9].It has been shown that artificial immune system (AIS) [10-11]provides various feasible approaches in engineering applications .

In this investigation, an semantic-centered artificial immune-model-based fault diagnosis methodology（SAIM）was developed to diagnose system failures, and semantic -valued negative selection algorithms in particular, is considered. The paper is organized as follows. In Section 2 gives a detailed re-description of the fault diagnosis model in semantics. In Section 3 semantic-centered immune model scheme is presented as a highly simplified representation of some of the mechanisms of AIS. Section 4 describes the learning algorithm of SAIM for fault diagnosis design. Case studies and results by SAIM are simulated and applied to intelligent fault diagnosis in mine hoist in Sections 5, while the conclusions of the study are summarized in Section 6

II. SYSTEM MODELLING

Industrial processes are usually characterized by nonlinear, time-varying behaviour, and multiple-input/ multiple-output situations, rendering the attractiveness of modelling techniques obvious. A system that includes the capability of detecting and diagnosing faults is called the ‘fault diagnosis system’ [12].Such a system has to perform two tasks, namely fault detection and fault isolation. The purpose of the former is to recognize that a fault has occurred in the system. The latter has the purpose of locating the fault. The desirable characteristics one would like the diagnostics system to possess are quick detection and diagnosis, isolability, robustness, novelty identifiability, classification error estimate,

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adaptability, explanation facility, modeling requirements, storage and computational requirements and multiple fault identifiability.

Comparatively, different techniques for linear system identification, control and monitoring are readily available. However, when the system operating range becomes wider, the linearized model is no longer able to represent the dynamic behaviour of the system. One solution is to use nonlinear methods such that nonlinear observers with analytical approach [12] and geometric approach [13] which require a perfect knowledge of nonlinear system. In practice, process industries as mining, are characterized by complex processes which often operate in multiple operating regimes. It is often difficult to obtain nonlinear models that accurately describe plants in all regimes. Also, considerable effort is required for development of nonlinear models. An attractive alternative to nonlinear technique is to use a semantics model strategy.

A. AIS Infrastructure

Computational models and problem solving approaches inspired from the Biological Immune System (BIS) are called AIS [14,15].The study and design of artificial immune systems (AIS) is a relatively new area of research that tries to build computational systems that are inspired by the natural immune system (NIS). AIS are a relatively new area of research with a diversity of applications such as data mining, computer security and robotics.

In the *immune network theory*, originally proposed by Jerne [16], antibodies are capable of recognising not only antigens, but also other antibodies. As antibodies can recognise and be recognised by other antibodies, this interaction forms a network of communication (interaction) within the immune system. Artificial immune systems (AIS) are composed of computational intelligence methodologies, inspired by the natural immune system for the solution of real-world problems.

According to [17,18], AIS can be designed three main parts:First a *representation scheme*; then a set of *mechanisms to evaluate* individuals each other; and some *adaptation procedures*. There are also many similarities between the AIS framework discussed and some basic design principles of other biologically inspired techniques, such as neural networks and evolutionary algorithms. Therefore, though there might be slight differences among the many frameworks for modelling complex fault diagnosis systems, it is possible to stress a set of basic components in a representation scheme or some evaluation mechanisms.

After identifying basics for immune system, and having briefly discussed the fundamentals of artificial immune systems, we will first map AIS into the framework for fault diagnosis for mine hoist. In the following section we will map artificial immune systems into learning classifier systems in fault diagnosis.

A fault diagnosis for mine hoist based semantic search utility was developed with the AIS infrastructure embedded in it. With the development of the Semantic Web [19-22] research about ontology is playing a central role as a source of shared and exchanged information over the Semantic Web. This paper ontologically analyzes the fault process. For mine hoist fault knowledge, we found a lot of fault attributes including: fault classification, fault causes, symptoms, diagnosis, measures, prevention, etc.

B. System modelling in faulty case

Model-based fault detection is based on the generation of a discrepancy between the measured and estimated process behaviours using a model.

Definition 1. Given a set $\inf o^n$ as n-dimensional discrete data set, Characteristics of model under $\inf o^n$ is $\mathrm{Re}\,l^n(A_1, A_2, \cdots, A_n)$, $AttriSe(\mathrm{Re}\,l^n) = \{A_1, A_2, \cdots, A_n\}$ is Attribute Set of $\mathrm{Re}\,l^n$, $Dom(A_j)$ is Attribute domain, where $j = 1, 2, \cdots, n$.

Definition 2. A system is defined as a dual sequence $(AttriSe(\mathrm{Re}\,l^n), \mathrm{Re}\,l^n)$, $AttriSe(\mathrm{Re}\,l^n)$ denotes the logic description of the symptoms of the system components at various layers, It is a non-empty finite set of first-order statements. And system constituted by a group of components, which are expressed as $\mathrm{Re}\,l^n$

Definition 3. Given a set $t = (V_{A_1}, V_{A_2}, \cdots, V_{A_n}) \in \mathrm{Re\,l^n}$,where $A_j \in AttriSe(\mathrm{Re}\,l^n)$, $V_{A_j} \in Dom(A_j),\ j = 1, 2, \cdots, n$. We assume that E is an expression, the number of variables of E is recorded as $arity(E)$. For example, expression: $q:"A \vee A \wedge (B \vee \neg C)"$, then $arity(q) = 3$. Each attribute corresponds to only one-dimensional, and attributes are data-related, dimension is analysis-related. $|W|$ denotes the number of elements in W, $|Dom(A_i)|$ is the number of elements in $Dom(A_i)$ $i = 1, 2, \cdots, n$

Definition 4. For given models A_1, A_2 ,we define $A \prec_{\mathrm{ab}} A_2$ if $A_1|\mathrm{ab}| \subset A_2|\mathrm{ab}|$, where $A|\mathrm{ab}|$ denotes the fault components included in model A

Definition 5. Diagnosis problem of mine hoist system can be described with a five-duple as $< D, A, C, M, A^* >$,where $C \subseteq D \times A = \{C_1, C_2, \cdots, C_L\}$ is the causal relation mapping from D to A, $M \subseteq A \times D = \{M_1, M_2, \cdots, M_L\}$ is the causal relation mapping from A to D. $\{Ci = < d_k^{\,i}, a_j^{\,i} > | \, d_k^{\,i} \in D_i, a_j^{\,i} \in A_j, i = 1, 2, \ldots, L\}$ describes the causal relationship mapping from faults to symptoms of all layers. $< d_k^{\,i}, a_j^{\,i} >$ denotes that emergence of the k-fault $d_k^{\,i}$ in the i-hierarchy components may lead to the j-symptom $a_j^{\,i}$ in the same hierarchy. So we can express

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the cause and effect relationship mapping from symptoms of Low-layer components A_{i+1} to fault set D_i in upper layer components as $M_i = < a_l^{i+1}, d_k^{\ i} > | \, d_k^{\ i} \in D_i, a_l^{i+1} \in A_{i+1}, i = 1, 2, \ldots, L\}$, $< a_l^{i+1}, d_k^{\ i} >$ means that l- symptom a_l^{i+1} of i+1-layer components may result from k-fault $d_k^{\ i}$ in the i- layer components. i- layer , A_i denotes the symptom set of i-layer. Figure 1 describes the two types of causal relationship.

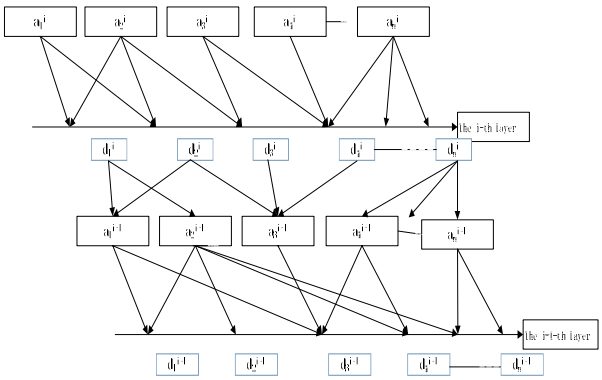

Figure 1. Two-causal mappingrelationship

Definition 6. For $a_j^{\ i} \in A_i$,we define fault mapping as,for $a_j^{\ i+1} \in A_{i+1}$, we can define fault mapping as $D(a_j^{\ i+1}) = \{d_k^{\ i} \mid < a_k^{\ i+1}, d_k^{\ i} > \in M_i\}$. We define symptoms mapping in the same way:

$\{A(d_k^{\ i}) = \{a_l^{\ i} \mid < d_k^{\ i}, a_l^{\ i} > \in C_i\}$,

$\{A(d_k^{\ i+1}) = \{a_l^{\ i+1} \mid < a_l^{\ i+1}, d_k^{\ i} > \in M_i\}$.

C. *The immune-based symbiotic semantics*

AIS can be defined as an abstract computational system for solving complex computational or engineering problems. The concepts of AIS are inspired by ideas, processes, and components extracted from the immune system. In AIS, antibodies/antigens are represented in a simplified manner by vectors of parameters $AttriSe(\mathrm{Re}\,l^L) = \{A_1, A_2, \cdots, A_L\}$,the L attributes can be regarded as a point in an L-dimensional search - space. AIS are applied by coding systems in terms of strings and operating on them in the relevant space.

Definition 7. Each antibody has an affinity threshold as indicated by the enclosing circles around these antibodies. Antigens located within these circles are considered to belong to the nonself set ($V_N = (V_{N1}, V_{N2}, \cdots, V_{Nn}), 0 \le Vs_i \le 1, i = 1, 2, \cdots, n$) and are then identified as anomalies,while antigens outside the circles are regarded as members of the self set ($Vs = (Vs_1, Vs_2, \cdots, Vs_n), 0 \le Vs_i \le 1, i = 1, 2, \cdots, n$).

Definition 8. In L-dimensional space, $B = (ab_1, ab_2, \cdots, ab_l), i = 1, 2, \cdots, l$ denotes antibody vector, and $D = \{B_1, B_2, \cdots, B_n\}, j = 1, 2, \cdots, n$ denotes state detectors.

There are many ways to generate detectors in the nonself set. For example, detectors can be generated randomly and then tested to see if they fit into the self set or not , the process can be repeated until the desired number of detectors has been generated. One of the problems of random generation is the difficulty of generating acceptable detectors. The computational cost grows exponentially with the size of the self sets. Other approaches more closely modelling natural immune systems include the use of clonal selection and somatic hypermutation or similar methods of deriving detectors from the self sets. In this paper, random generation of detectors or antibodies was used, since the systems considered were relatively small.

III. SEMANTIC-CENTRIC DIAGNOSTIC MODEL BASED ON AIS

In order to carry out a precise diagnosis by identifying system behavior which deviated from the “normative” phenomenon, how to establish a model system to reflect the semantic system is a key factor for fault diagnosis. At the same time, we should make use of existing mature tools as far as possible to get the compiling model.

Definition 8.Attribute set $X \subset AttriSe(\mathrm{Re}\,l^n)$, $Y \subset AttriSe(\mathrm{Re}\,l^n)$, $X \ne \varnothing, Y \ne \varnothing, X \cap Y \ne \varnothing$ .Assuming P and Q are propositional formula consisting of 1 order atomic predicates which well-defined by Logic operations $\wedge, \vee, \neg$ and the symbols of attributes in X and Y. We call the expression $R: "P \to Q"$ as meta-rules on $\inf o^n$, which is marked as R_m, and $\{R_m\}$ is a set of meta-rules. Then $W = X \cup Y$ is the set of meta-rules on $\inf o^n$ .If $r_m, r_m' \in \{R_m\}$, and attributes set of meta-rules are the same, we can said that r_m and are in the same tribe. Compared with the traditional rules, the definition 8. increase the logic operator "or" and "non-" to get a stronger expressing ability.

Definition 9 Giving the rule $R_m: "P \to Q"$, for all atomic predicate formula in the expression, we can constitute expression $"P_i \to Q_i"$ called R_i In accordance with corresponding attribute values given by t, then R_i is an instance of meta-rules for R_m on $\inf o^n$ .Where $t_f = \prod_s \left(V_{A_1}, V_{A_2}, \cdots, V_{A_n}\right)$ is characteristic element group of R_i ,that is t_f can uniquely identify an instance of R_m

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on $\inf o^n$. $Ins\tan ce(R_m, \inf o^n)$ is instance set of R_m on $\inf o^n$

A. Structural immune network learning

A fault diagnosis based semantic search utility was developed with the AIS infrastructure embedded in it. A high level view of the utility is shown in Figure 2

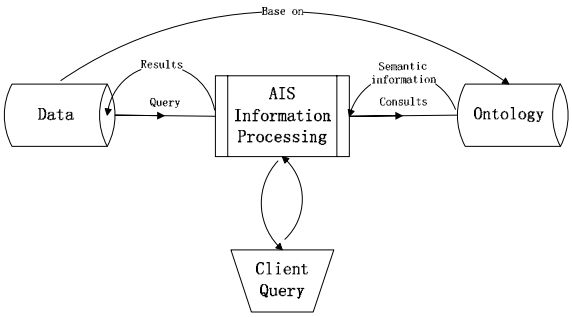

Figure 2. A fault diagnosis based semantic search utility with AIS.

In our AIS we regard the normal behaviors as self and abnormal behaviors as non-self. Antibodies are semantic queries and antigens are a collection of the system behaviors.

B. Semantic Shape-Space

Immune cell and antibody are very important for AIS. In general, antigen is corresponding to the problem to be solved and antibody to the solution for it. Therefore antigens need to be constructed according to the characteristics of instances of tuples R_i ,which are expressed as the following form: $A_1(\mathrm{sys}_1,\mathrm{pos}_1), A_2(\mathrm{sys}_2,\mathrm{pos}_2),\cdots,A_k(\mathrm{sys}_k,\mathrm{pos}_k)$,where $A_j \in AttriSe(\mathrm{Re}\,l^n)$, $V_{A_j} \in Dom(A_j),\ j=1,2,\cdots,n$, sys denotes the symptoms, pos identificate the location of the symptoms. Antigen-encoding sequence of the above example can be encoded as follows:

TABLE I. ANTIGEN CODING

A_1	sys_1	pos_1	A_2	sys_2	pos_2	A_3	sys_3	pos_3	$\cdots$

In the same form of knowledge representation, a lymphocyte is expressed as a rule, $type \cdot head \# literal \# negative \cdot negative \cdot positive$

Where type is the type of rules, head is the head of the atomic rules. # literals are the number of literals in rules. #negative is the number of negative literals in rules, positive is the positive literals in rules. To take hydraulic system fault as an example, Type is abnormity（Hydraulic System）, head is loss（hydraulic pressure station）, and then lymphocyte phenotype is as follows:

$$ab(\mathrm{pos}_1)\ \ \mathrm{B}(\mathrm{b}):\ A_1(\mathrm{sys}_1,\mathrm{pos}_1)\wedge A_2(\mathrm{sys}_2,\mathrm{pos}_2)\wedge\cdots$$
$$\wedge(\neg A_{k+1}(\mathrm{sys}_{k+1},\mathrm{pos}_{k+1}))\cdots\wedge(\neg A_m(\mathrm{sys}_m,\mathrm{pos}_m)))$$

Where m, K is a constant, denote the maximum number of atoms in rules. literals appear in Rules can be determined from the above predicate. The number of parameters in predicates may are different slightly, here we simplify described as two parameters.

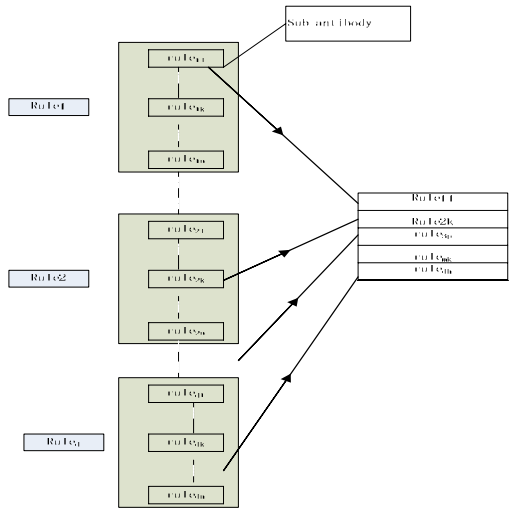

Figure 3. The structure of antibody.

Definition 10. Antibody is a 3-tuple, $F=(f_1, f_2)$ comes from the immune cell that produces this antibody. $S=(S_1,S_2)$ is a 2-tuple, where S_1 and S_2 are the substitution formulas for those in S respectively by attribute values of record in relation instance. $I=(P_1,P_2,P_3,P_t)$ stores information about affinity. where $p1$, $p2$, $p3$ and pt are the support number of S_1 , S_2 , $S_1 \wedge S_2$ and the total number of records who were tested respectively.

IV. FAULT DIAGNOSIS BASED ON SIM-PSO

This section presents a proposed classification based diagnosis method combined with immunity strategy with similarity measure of semantics and PSO for an enhanced classification performance. Information fault diagnosis based on semanic immunity with PSO is a process of obtaining the optimal compound feature and detecting different faults with higher reliability and robustness.

A. semantic-Valued Negative Selection (SNS) Algorithm

The negative selection algorithm is based on the principles of self-nonself discrimination in the immune system. This negative selection algorithm can be summarized as follows.

Define self as a collection of elements in a feature space , a collection that needs to be monitored. Then generate a set of *detectors*, each of which fails to match any string in *Self*.

Definition 11. Each antibody has an affinity threshold as indicated by the enclosing circles around these antibodies. Antigens located within these circles are

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considered to belong to the nonself set ($V_N = (V_{N1}, V_{N2}, \cdots, V_{Nn}), 0 \le Vs_i \le 1, i = 1, 2, \cdots, n$) and are then identified as anomalies,while antigens outside the circles are regarded as members of the self set ($Vs = (Vs_1, Vs_2, \cdots, Vs_n), 0 \le Vs_i \le 1, i = 1, 2, \cdots, n$).

Definition 12. In L-dimensional space, $B = (ab_1, ab_2, \cdots, ab_l), i = 1, 2, \cdots, l$ denotes antibody vector, and $D = \{B_1, B_2, \cdots, B_n\}, j = 1, 2, \cdots, n$ denotes state detectors.

We adopted a semantic-valued NS (SNS) algorithm, which tries to alleviate the limitations previously mentioned, while using the structure of the higher-level representation to speed up the detector generation process.

B. Self set and normal / abnormal state recognition

The first step of constructing self set Vs is to initialize normal antigen data set, that is to gather signals in normal status, then analysis and extract the unitary features. Self-purification should be performed in initializing normal antigen data set. The way is to calculate the affinity between antigens, and delete the antigens whose affinity greater than the purification threshold, then the rest antigens make up of self set Vs .

The normal/abnormal state recognition is essentially using reverse selection algorithm to identify whether the equipment condition is in gear. For the antigens to be detected, should calculate the affinity of each pair. It is normal when the affinity is less than the corresponding threshold. Otherwise, such that each fails to match any element in Vs , it's in fault.

C. Generating detectors based on SIM-PSO

To diagnose faults, a novel SIM-PSO scheme is proposed to partition test-antigens to patterns corresponding to different system faulty situations. The spirit of pattern recognition and clustering techniques finds the classification of features from the symptoms and generates well-defined subgroups. However, the feature selection procedure generally relies on a criterion function and a search strategy. The former is used to decide whether a feature subset is better than another, while the latter determines feature subset candidates.

The reverse selection algorithm inspirited by the reverse selection theory, its main characteristic is that it does not require prior knowledge. But it has some limitations as well. The reverse selection algorithm can only find whether there are changes in self set. It does not know what kind of fault had happened with this method. In this paper , a dynamic immune algorithm is adopted to generate memory antibody set for each fault pattern. It can classify the tested data set by calculating the affinity between the antigens to be tested and every memory antibody in all memory antibody sets. The generation of the memory antibody detectors for each fault pattern is in the process of self-learning and self-adaptive. The steps of algorithm are as follows: Initialization; Affinity calculation;Velocity and position update; Inhibit selection;Training antibody representation.;Inhibition in memory antibody set; Terminate condition.

Memory cells disposed by the above arithmetic cloud obviously characterise the fault conditions. So make the memory cell set as candidates of the initial solution set, to search dynamicly the optimize solution space by PSO. (see Fig4.)

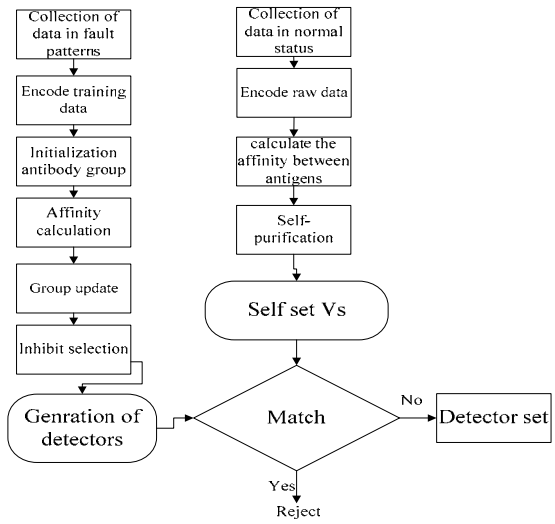

Figure 4. Detector generation scheme

D. Process monitoring

Once the set of detectors was in place, the process could be monitored. In the algorithm, all initial antibodies are genegrated random for the first response. Once again, partial initial antibodies are genegrated random and partial genegrated from memory cells for the later response.By this way,antibodies from memory cells have a higher fitness with multiformity.So the approach is clearly accelerated the searching speed.

Memory antibody sets identify the faults by calculating the affinity between the tantigens to be tested and antibodies in each memory antibody sets respectively(see Fig9.). If the mean affinity larger than the threshold, then consider it match with the certain memory antibody set for the particular fault pattern. The subjection ratio that antigens to a particular fault pattern can be calculated as follows:

$$\delta_i = C_i / N_i \quad (1)$$

Where C_i is the number of antibodies matched with antigen for some faulr pattern; N_i is the total number of antibodies in the detector. Take maximal δ_i corresponding detector as the determinant classification. If the value of δ are same for different detectors, then estimate it is a multi-fault.

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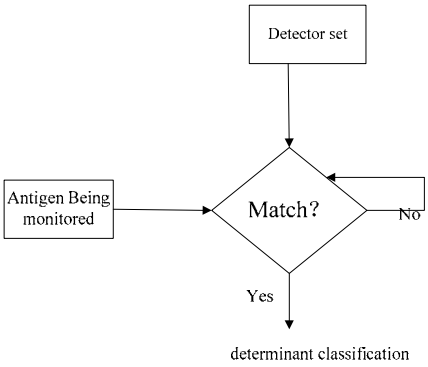

Figure 5. Application of the detectors to monitoring

E. Fault classification mechanism

The main task in fault diagnosis is to classify the test-antigen into a number of distinguishable patterns corresponding to different faulty situations . If the pattern of the symptoms of different faults is identical, it can easily diagnose the underlying faults.

After the immune model has been generated, monitoring is followed by an on-line comparison between system behavior and model output(fitness). The model is created on a healthy plant, so any mismatch leads to suspicions concerning the presence of faults.

Based on the immune system mechanisms , take each sample in the known fault pattern as an antibody, samples to be classified as antigens, then the fault diagnosis issue is a process of antibodies identifying antigens. Not all the antibodies are detectors, only those antibodies with the affinity to antigen greater than the affinity threshold can be selected.

The specific steps followed in this investigation are summarized below:

1)Take the to-be-classified sample as antigen,genegrate self set by training simple in normal mode, according to the known failure mode samples, genegrate nonself sets as fault detectors by training simple in different system faulty situations. Then calculate the kernel affinity of the antigen representated with each antibody in self set. First identify whether the antigen match with self-set, then discriminate the normal/abnormal state according to reverse selection algorithm.

2) Calculate the kernel affinity of the antigen discriminated as abnormal with each antibody in detectors in different system faulty situations. Then judge whether it match with the fault pattern according to threshold.

3) If matched with more than one detectors, then calculate the subjection ratio to find the classification.

4) If the antigen discriminated as abnormal mismatch with any detectors, the diagnosis system will automatically record the antigen, and brought it to the experts. If confirmed as a new antigen, add it in the training antibody set A to achieve the overall evolution for the memory antibody library. When this kind of antigen appear again, the system will make the right identification.

5) It is impossible for the training samples to cover all symptoms in normal/abnormal conditions, so the self set and detectors should Self-evolve when the antigen representated confirmed as a new antigen.

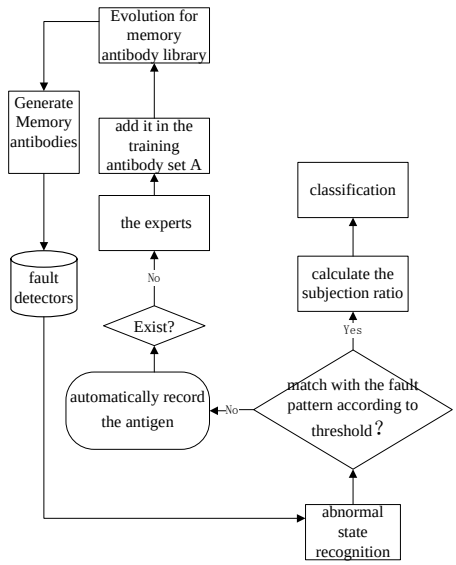

Figure 6. Process of the immune system mechanisms

V. ONLINE SEMANTICS FAULT DIAGNOSIS SUBSYSTEM

The ontology of faults discussed thus far suggests us the necessity of creating a reasoning system and describing a model which can deal with wider scope of faults.

As occurrence of fault in mine hoist usually is associated with the mechanism itself, the production environment and maintenance and many other aspects, it will result in incomplete information impacting on the final diagnosis if considerate individually any subsystem. We consider information integration of different systems to share information between systems based on the domain ontology for mine hoist fault diagnosis have set up.

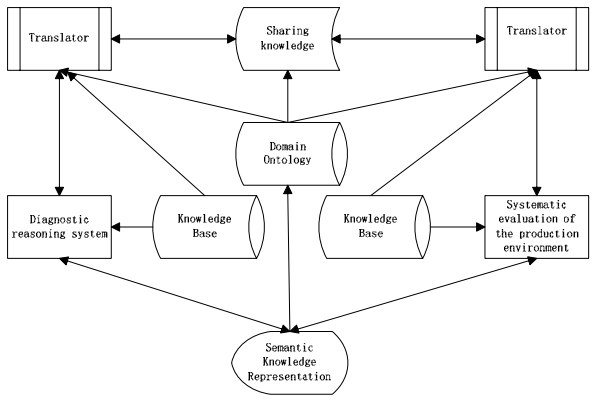

Figure 7. Fault diagnosis system based on semantic AIS

A. Brake system fault

It is directly related to the safe operation of hoist for braking system running good or bad. Therefore, in order to ensure that the braking system be in a safe and reliable operation, in addition to choice reasonable state parameters in the design of the calculation, The key

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factor is the implementation of on-line monitoring and diagnosis. For the state of the braking system.

a) poor following of brake: The good and bad following of brake directly affect the quality of braking performance. If the brake lag, it is easy to lead speeding, over-roll or brake accidents. Brake lag is usually caused by the following reasons.

b) brake shoe clearance is too large. If the brake shoe clearance is too large, it is Inevitable to lead brake lag. So the brake shoe clearance must always be real-time monitoring.

c) Air moving time of disc brake is too long. For disc brakes, air moving time should be no more than 0.5 s. Main reasons lead to Air moving should be: spring fatigue failure; large resistance within gates; large circuit resistance of hydraulic system; large brake clearance. If the air moving for too long, it will also lead to brake lag, which would cause serious consequences.

d) The system, if mixed with a small amount of air , will be lead to brake lag. Because of the compressibility of air is 1000 times more than liquid. If the system is mixed with a small amount of air, it will seriously affect the transmission of liquid pressure. Thus it should carry out regular checks of the residual gas in systems. the source of this fault in the system can not be monitored in our experimental conditions .

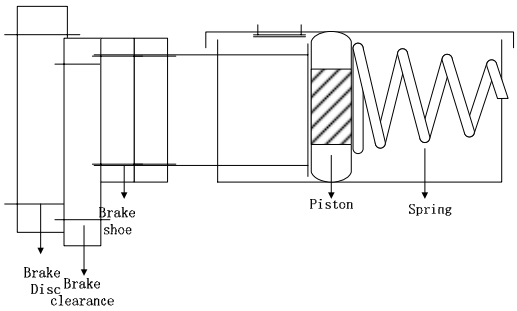

Figure 8. Structure of brake disc

We monitored the following parameters to realize the diagnosis: the maximum oil pressure, oil pressure of gate opening, residual pressure, and oil pressure affixed to gate., the maximum spring force, the spring force when the gate opening, the spring force affixed of the gate, the minimum spring force, as well as brake shoe station. By this parameters, the braking torque, air moving time, the braking resistance of the fuel tank, residual pressure can be the sized.

1) When the maximum value of F2 is less than the minimum designed high-value of the hydraulic system , then a hydraulic system failure occurs， that means the loss of hydraulic pressure .

2) When the F2 too much deviate from the normal residual pressure, it will result in both cases, when the F2 is greater than the maximum deviation, then the braking torque will be too small, fault is classified as residual pressure is too high; when the F2 is smaller than the minimum deviation in the negative, the brake torque at this time there will be too large, failure is classified as low residual pressure.

Example given above is converted to the form of predicates that can be described as: pressure (hydraulic， hydraulic System) ， Power（spring， arrester brake）

B. *Description of test simulation process*

In the above-mentioned modeling system based on AIS, We achieved a fault diagnosis subsystem for mine hoist with AIS based on semantic (SAIS) in the model of our existing platform.

In order to support this model-based diagnostic techniques,we increased an object, a diagnostic agent in the container .The diagnostic agents call the results of the parameters data and semantic information to determine the "facts" or "observation." to make the appropriate diagnosis . At the same time, we add a diagnostic interface to the original component interface for the component of "implementation". The diagnostic agents get fault reasoning based on the observed facts and the description of the existing system. In the event of failure, agents make assumptions in accordance with the rules of a certain fault .

In this paper, our ontology is shown in formal languages. and concentrate enumeration of possible fault-hypotheses with interactive control of the search space. An investigation on verification of fault-hypotheses and detection of symptoms remains as future work.

VI. CONCLUSION

One of our main aims of this paper is to present concepts of fault diagnosis. In this paper, our ontology is shown in formal languages. And concentrate enumeration of possible fault-hypotheses with interactive control of the search space.

In this paper, the elements of fault diagnosis method based on AIS are discussed, and put forward a novel "semantics" centric fault diagnosis method. For model-based diagnostic methods, we constructed the compiling method to describe the complex semantic model. This method not only has a strong expression of the scope of semantic, and can use the theorem has been proved to solve a very small diagnosis. This makes the model proposed in this paper can be very easy to use in the real system. This model compiling method, will become a very promising diagnostic technology for the distribution of the semantic component of the fault diagnosis system.

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