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Contents

Application of Negative Selection Algorithm in the Fault Detection and Diagnosis of LRE

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Abstract: To overcome the obstacles existed in the fault detection and diagnosis of liquid rocket engine(LRE) such as the lack of real-time, in-time, and veracity, the negative selection algorithm of artificial immune system was introduced. By constructing the artificial recognition ball (ARB) and adopting the maximum similarity rule, the fault detection and diagnosis were carried out. The experiment was performed with steady state data collected in ground test then. In the multi-dimensional modal space, the fault property was discussed further. Faults surround the normal state in different distance. If the parameters deflect more from the values which were supposed, the fault will be more obvious and it will move away from the normal state in the ARB. Some faults are separable, but some are also lapped over partly. Results show that this method has the function of quickly detection, high rate of correction diagnosis, and powerful ability of discovering the unknown fault. It can be widely applied in the state monitoring and fault diagnosis of LRE.

Keywords: Liquid Rocket Engine; Artificial Immune System; Fault Detection and Diagnosis; Negative Selection Algorithm; Artificial Recognition Ball

1. Introduction

Liquid Rocket Engine(LRE), known as the heart of the spaceflight equipment, is a kind of complicated structural liquid and heat dynamic system running with high tempture, high pressure, strong cauterization and heavy density of energy emitting. So it is sensitive to faults which need to be detected and diagnosed quickly and effectively.

Nowadays, artificial intelligence is widely used to diagnose the fault of the LRE, such as: Neural Network, Expert System and so forth. Neural Network, applied to detect and diagnose the turbo pump fault, has very huge and intricacy structure and needs a relative longer training time. The pattern recognition method relies on a great number of data. While the Expert System is difficult with knowledge express, and its illation relies on the fault mechanism which is the puzzle of the fault diagnosis. The latest years, the fault diagnosis method based on the integration of qualitative and quantitative knowledge has developed rapidly and is quick but ignores the deep-seated relationship in the system.

Artificial immune system(AIS), enlightened by the biology immune system, is one of the artificial intelligence, which simulate the function of the biology system. It has the advantage of noise tolerance, self-organizing, memory and so on. It supplies a new method to solve problems. Basing on the mechanism of lymphoid cell's negative selection, Forrest(1996) supposed the Negative selection Algorithm which could detect the change of a system. So according to the fact of the LRE, the Negative Selection Algorithm was applied.

2. Negative Selection Algorithm

2.1. AIS and Artificial Recognition Ball

In the engineering and science field, artificial immune system(AIS) simulates the mechanism of the human beings' immune system, studies the technology of computing and information disposing and applies the theory in the engineering programme. Timmis said:"AIS, comes from the theory of biology, consults the immune function, mechanism and model and then is used to solve the complicated problems". In according to the theory of immunology based on colony, antibodies exist in the form of colony. The ones with similar functions get structural resemblance. The kindred antibodies have strong affinities with each other also. The ARB, abstracted from the antibodies, is the set of the similarly kind of functional antibodies. Different functional kinds of antibodies are corresponded to different kinds of ARB. The recognition ability of the antibodies to antigen is quantificational measured by the ARB's radius. So Timmis introduced the concept of artificial recognition ball(ARB) with equal radius(Figure 1(a)).

But actrually, the different kinds of antibodies' recongnition ability is discriminating. So the ARBs with different radius were applied in this paper(Figure 1(b)). The stronger the recognition ability, the longer the radius is.

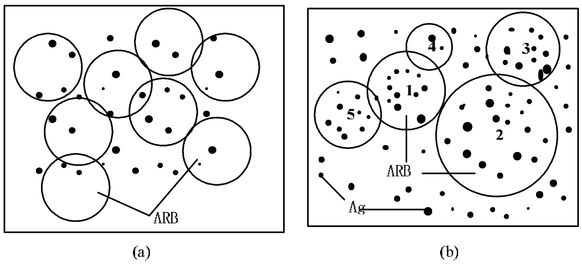

Figure 1. (a)Artificial recognition ball(ARB) presented by Timmis,(b) ARBs with different radius

2.2. Negative Selection Algorithm

Introduced by Forrest, American computer professor, Negative selection algorithm was used to detect the change of the computer circumstance. It came from the mechanism of differences between self and non-self, which conformed to the progress of T-cells' maturation. When the detectors generated randomly, they will be deleted if they detect self, while the others will be reserved as mature detectors to detect the non-self. If the mature detectors are matched with the objects of the system, then the system has got something wrong.

Namely, for the question field $U \in R^l$ which includes the self set $S \subseteq U$ and non-self set $N \subset U$, and $S \cup N = U$, $S \cap N = \varnothing$. The process of detecting is the classification of self and non-self. For the set of detectors(Immune cell, antibody, and so on) $D: D = \{x_1, x_2, \ldots x_i\}$, $x_i \in R^k$, $k \le l, i \in N$, $N = 1,2,3,\ldots$. $f: f(I,x) \to \{p \in R \mid p \ge 0 \wedge p \le 1\}$ is the match function, and $x \in D$, R is the set of real number. e is a match threshold. The classification is completed by Equation (1):

$$match(f,e,I,D) = \begin{cases} I \in N, 1 > f(I,x) \ge 1-e \\ I \in S, 0 < f(I,x) < 1-e \end{cases} \quad \ldots \quad ..(1)$$

In this paper, the negative selection algorithm is coded by real number. The ARBs are used too. The steps of the algorithm are listed as follows:

Step1: define self and non-self as a mustiest of real number of length l over a finite data series, which comes from the object that we wish to protect or monitor.

Setp2: Create the ARBs by the acquired data, then compute the center and the radius of the ARBs;

Step3: Use the Created ARBs to detect the system state, calculate the distance of the state between self and non-self ARBs. If the distance to the center of self ARB is less than the ARB's radius, then the state could be judged as self. Otherwise it is non-self,which means the object got some faults.

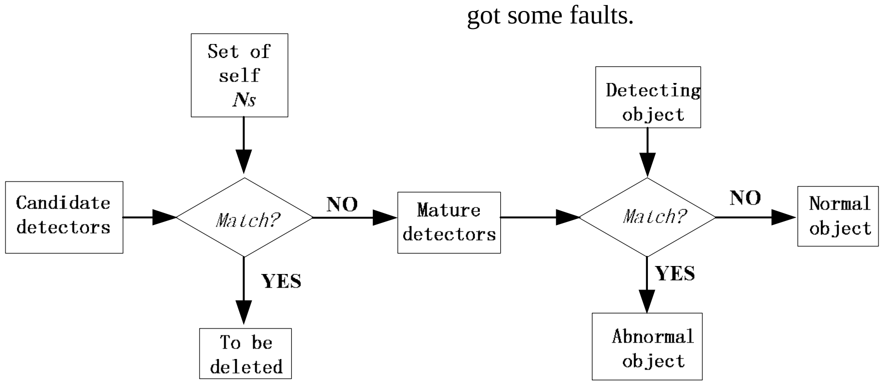

Figure 2. Produce the detectors and the process of abnormal detection

Table 1. Parameters of Monitoring

Serial number	Parameters
1	pressure of enforcing air of the oxidant closet
2	pressure of enforcing air of the fuel
3	flux of oxidant
4	flux of fuel
5	pressure of the exit of oxidant pump
6	pressure of the exit of fuel pump
7	rotate speed of turbine pump
8	pressure of oxidant before spurt
9	pressure of fuel at the offshoot on the main pipeline

Table 2. Fault Mode of the LRE

Mark	Fault Mode

Mode1	increase of the pressure of oxidant closet
Mode2	increase of the pressure of fuel closet
Mode3	increase of both closet
Mode4	decrease of both closet
Mode5	leakage of offshoot of oxidant pipe
Mode6	oxidant start valve obstruct
Mode7	fuel start valve leakage
Mode8	gas leakage of turbine intake

3. Engineering Application

3.1. Compute Process

1) Express of self and non-self

Based on the testing data, the simulating calculation was aimed at some fixed type of liquid rocket engine. Parameters and fault modes are listed in Table 1 and Table 2. In Table 1, parameter 1th and 2th has only one detecting point respectively, while others have 4 detecting points. All data came from these detecting points were listed ordinal together, then became a vector of 30 dimension. Eight common fault modes are selected to validate whether this method is useful and advanced. The condition of the LRE could be fixed by the 30 dimensional vector. Just as follows:

$\vec{X}_i = \{x_1, x_2, ...x_n\}_i, n = 30, i \in N$, N is the total amount of the known state data, n is the amount of the detecting points. The fault mode is figured as Y_j , $j = 1, 2, ...m$, $m = 8$. So Y_j is the set of similar states' data.

Self, figured as C , is defined as normal state. All faults are non-self and figured as $\overline{C}$. Therefore, non-self is built up by the m quantitiative known fault modes and the unknowns. Namely: $\overline{C} \supseteq \{Y_1, Y_2, ..., Y_m, ...\}$. The definition of self and non-self is used to monitor LRE and detect the faults.

2) The artificial recognition ball(ARB)

The kind and recognition ability of ARB depends on its location in the fault space and its radius. Each fault mode(including the normal state one) is corresponded with an ARB. The center of the ARB is figured as $\vec{Y}_i$, $i = 0, 1, ..., m, ...$, when i equals 0, it is the normal state. And $r_i, i = 0, 1, ..., m, ...$ is the ARB's radius. The Euclid distance is used to denote the similarity of the data.

$$d(\vec{X}_i, \vec{X}_j) = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2}, i, j = 0, 1, ...N \quad (2)$$

The smaller the $d(\vec{X}_i, \vec{X}_j)$, the more similar the state $\vec{X}_i$ and $\vec{X}_j$. The probability of the two belonging to part of the same fault mode is higher. For the known fault modes, the center of each ARB, $\vec{Y}_i = \{y_1, y_2, ..., y_n\}, n = 30$, is calculated by the average of the known data of each fault mode.

$$\vec{Y}_i = \frac{\sum_{k=1}^{h} \vec{X}_{ik}}{h}, \quad h \in N \quad (3)$$

$\vec{X}_{ik}$ is one of the data vectors of the fault mode Y_i , and h is the amount of the fault state data. For one fault mode, the distance of state data to the center could be calculated by Equation (4):

$$\overline{d}_i = \frac{\sum_{k=1}^{h} d(\vec{X}_{ik}, \vec{Y}_i)}{h} \quad (4)$$

Then, the radius

$$r_i = a \times \overline{d}_i \times [1 + \frac{h - Sum(d(\vec{X}_{ik}, \vec{Y}_i) < \overline{d}_i)}{Sum(d(\vec{X}_{ik}, \vec{Y}_i) < \overline{d}_i)}] \quad (5)$$

$a > 0$, h is the total amount of the mode i . $Sum(d(\vec{X}_{ik}, \vec{Y}_i) < \overline{d}_i)$ is the amount of the state vectors whose distance to the center is smaller than the average distance of the mode i . a is an alterable parameter, which could be changed if necessary. Its value will discussed in the result.

It could be recognised that the radius of the ARB depends on the density of the fault data(Equation(5)). Because it is not reasonable that the data whose $d(X_{ik}, Y_i) > \overline{d}_i$ will not be contained in the range of the ARB when the radius equals the avarage distance $\overline{d}_i$. Therefore,

$$q_i = \frac{h - Sum(d(\vec{X}_{ik}, \vec{Y}_i) < \overline{d}_i)}{Sum(d(\vec{X}_{ik}, \vec{Y}_i) < \overline{d}_i)}, i = 0, 1, ...m, ... \quad (6)$$

And $q_i > 0$, which is value of modification. The more dispersive the data, the bigger the q_i . The less dispersive,

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the smaller the q_i, and the radius is closer to the avarage diatance.

3) the precept of detection and diagnosis

For the condition $\vec{I} \in U$, it need to be estimated whether it is normal or not firstly. If $d(\vec{I},\vec{Y}_0) < r_0$, then $\vec{I} \in C$. But if $\vec{I} \in \overline{C}$, then it must be judged which fault it is.

For the condition $\vec{I} \in U$, if $T \subset X$, $T = \{\vec{t}_1, \vec{t}_2, \dots \vec{t}_p\}$, p is the amount of the known state data. Mark:

$$d = 1 - \frac{\min\limits_{i=1,2,\dots,p} \{d(\vec{I},\vec{t}_i)\}}{r_i} \qquad (7)$$

(1)If $\vec{t}_i \in Y_j$, When $l \le d < 1$, then $\vec{I} \in Y_j$, $j = 1, 2, \dots, m$. The l is a parameter ralated to the congeneric similarity. This method conforms to the way of human beings' cognizance that if two things represent some enough similar characters then they are congeneric. The d is used to estimate the similarity. It is affected by the distance of the state vector and the corresponding ARB's radius. In this paper, to relieve the compution, $l = 0.95$.

(2)If $0 \le \min\limits_{i=1,2,\dots,p} \{d(\vec{I},\vec{Y}_i)\} < r_i$, then $\vec{I} \in Y_i$, $i = 0, 1, \dots, m$.

(3)If the mode of the state can not be fixed by rule (1)and (2), then a new ARB denoting a new fault mode need to be created. The center locates at $\vec{I}$, and the radius equals $\min\limits_{i=1,2,\dots,p} \{d(\vec{I},\vec{t}_i)\} - d$. Put this new fault mode in the data storeroom, in order to make the fault storeroom more perfect.

3.2. Simulation Result

According to the known fault data, the simulation was carried out by programming on Visual C++ 6.0. The detecting results are showed in Figure 4 and Figure 5.

For the ordinary faults or those arosed by little or a bit big parameter changing, this method is effective and of high exactness. The detecting result is greatly affected by ARBs' radius(Figure 5). The longer the radius, the bigger the ability of fault-tolerance and the ratio of detecting will decrease. While on the opposite position, the ratio of miscarrage of justice will increase. So, it seems to have an optimized radius to make the method more effective. Then arpha(a) is used to optimize the raidius and control the simulation process according to the truth. When $a = 1$, the ratio of exactness of testing sample and training sample are both high. So in this paper, $a = 1$.

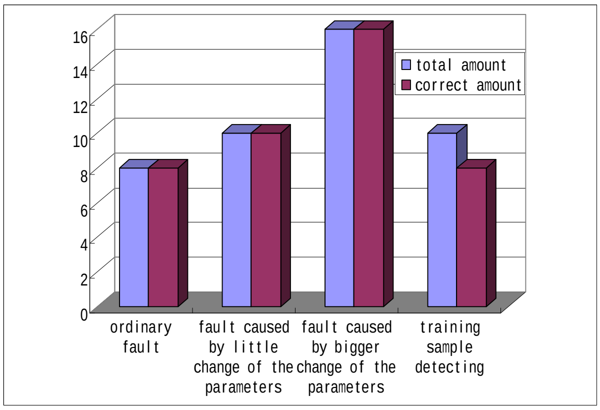

Figure 4. Result of fault detecting

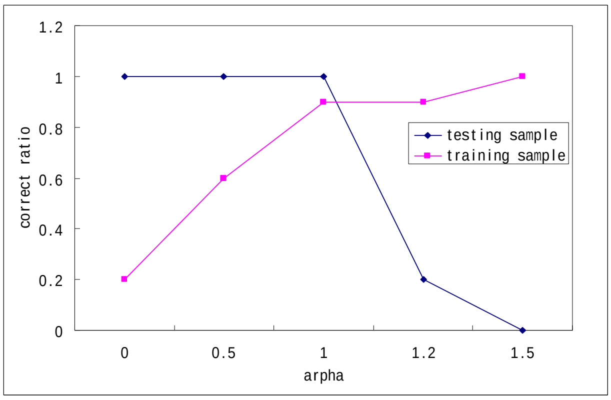

Figure 5. Affect cause by the radius of ARB, arpha is the ratio ,a regulable parameter

The diagnosis results are showed in Table 4 to Table 9, and the normal ARB's radius is 0.127825.(data are standardized). When the degree of a fault increase with parameters changing bigger, the distance of its ARB to normal state increase too. Namely, the more visible the fault, the more removed its ARB to the normal state.

The fault ARBs surround around the noraml state in the multi-demension space(Figure 5). Some faults are sensitive to the changing parameters, then they will have a longer radius(as: Mode8). For the fixed diagnosis method, the faults could be separated and both superposed partly. The states in the superposed areas could be diagnosed as different modes, which shows that some different faults could cause same change of the parameters. This is why some faults are difficult to be diagnosed. Some fault will put up another fault's charactors during the faults whose parameters' changing affects each other greatly. But when the fault became serious, they could be separated soon.

Table 3. Distance between faults and the normal state when the faults increased by parameter changing bigger

Parameter changing	0.02	0.06	0.10	0.16	0.20
Mode1	0.136423	0.137168	0.138444	0.141342	0.143924
Mode2	0.137811	0.141787	0.146736	0.155817	0.162817
Mode3	0.137988	0.14635	0.14875	0.16029	0.1693
Mode4	0.134932	0.133648	0.134173	0.138298	0.143132
Parameter changing	0.02	0.06	0.10	0.12	0.14
Mode6	0.137082	0.14119	0.153292	0.148647	0.142532
Parameter changing	0.10	0.30	0.50	0.60	0.70
Mode5	0.138165	0.147268	0.158511	0.164177	0.169718
Mode7	0.133915	0.1305	0.128515	0.127936	0.127676
Mode8	0.119364	0.342221	0.91105	0.69195	0.7846

Table 4 Distance between the centre of the fault modes and normal state

	Distance to the normal state	ARB's radius
Normal state (Mode0)		0.127825
Mode1	0.139996	0.0255326
Mode2	0.151802	0.0177411
Mode3	0.15516	0.0177411
Mode4	0.136112	0.019124
Mode5	0.16106	0.0385692
Mode6	0.148239	0.0318421
Mode7	0.128142	0.019124
Mode8	0.644305	0.398956

Table 5 Distance of a fault mode between the another

distance	Mode2	Mode3	Mode4	Mode5	Mode6	Mode7	Mode8
Mode1	0.0518361	0.0425543	0.0736546	0.108123	0.0530702	0.0508228	0.680894
Mode2	0	0.0295684	0.0915005	0.091006	0.0723117	0.0832397	0.691117
Mode3		0	0.10481	0.117339	0.076907	0.0882757	0.691438
Mode4			0	0.064282	0.0614759	0.0318734	0.673393
Mode5				0	0.0906294	0.0881856	0.689898
Mode6					0	0.0553519	0.705565
Mode7						0	0.664926
Mode8							0

Table 6. Results of diagnosis

Simulation order	1	2	3
Mode1	Mode1	Mode1	Mode1
Mode2	Mode1	Mode2	Mode2
Mode3	Mode1	Mode1	Mode3
Mode4	Mode1	Mode4	Mode4
Mode5	Mode4	Mode5	Mode5
Mode6	Mode1	Mode1	Mode6
Mode7	Mode1	Mode7	Mode7
Mode8	Mode0	Mode7	Mode8

Table 7. Results of diagnosis with the "Red-line" detection

Simulation order	1	2	3
Mode1	Mode1	Mode 1	Mode 1
Mode2	Mode 2	Mode 2	Mode2
Mode3	Mode 3	Mode 3	Mode 3
Mode4	Mode 4	Mode 4	Mode 4
Mode5	Mode 5	Mode 5	Mode 5
Mode6	Mode 6	Mode 6	Mode 6
Mode7	Mode 7	Mode 7	Mode 7
Mode8	Mode 8	Mode7	Mode 8

Table 8. Results of diagnosis for an un-known fault

Simulation order	1	2	3	4	5	6	7
Mode	Mode1	Mode1	Mode1	Mode9	Mode9	Mode9	Mode9

Table 9. Consumed time of fault detection and diagnosis

Simulation order	1	2	3	4	5
Consumed time of detection	0.015	0.015	0.015	0.015	0.015
Consumed time of diagnosis	0.016	0.031	0.047	0.015	0.016

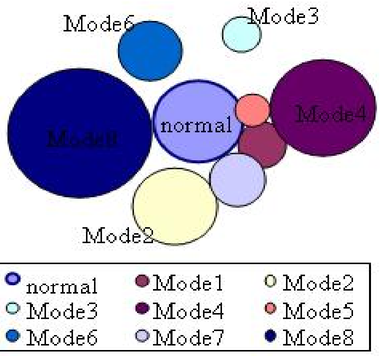

Figure 5. fault ARBs are around the normal state

This method is also not very good at deal with the sup-perposed states singlely(Table 6). So the Red Line me-thod are used as an assistant . The results are showed in Table 7.

When the method confronts some unknown states which are not able to be diagnosed, then a new ARB will be created, which means the system took place a new fault(Table 8).

The average consumed time of fault detecting is 0.015 second, while the average consumed diagnosis time is 0.02 second(Table 9). It is quick enough to the sampling time, and coule be used as on-line monitor method.

Conclusions

In this paper, the negative selection algorithm of artifical immune system was applied in the fault diagnosis of the liquid rocket engine. It is a quick and useful method which could meet the need of fault on-line monitor. Combined with Red Line fault detection method, it is exact to diagnose the fault. When there are some new unkown fault taking place, they will be detect quickly. This is a typical character of this method. And it could be widely used on missile in the future. How to diagnose the unkown fault was not studied, which is the next task of the research.

References

[1] Forrest S, Perelson A, Cherukuri R. Self-nonself discrimination in a computer. In: Proceedings of 1994 IEEE Computer Society Symposium on Research in Security and Privacy. Los Almitos, CA, USA: IEEE Computer Society ,1994: 202-212.

[2] Timmis J, Neal M, Hunt J. An artificial immune system for data analysis. Biosystem,2000,55(1-3):143~150.

[3] Timmis J, Neal M. A resource limited artificial immune system for data analysis. Knowledge-Based-System, 2001(14): 121-130.

[4] F. Gonzalez, D. Dasgupta, and R. Kozma. Combining negative selection and classification techniques for anomaly detection. In D. B. Fogel, M.A.El-Sharkawi, X.Yao, G.Greenwood, H.Iba, P.Marrow, and M.Shackleton, editors, Proceedings of the 2002 Congress on Evolutionary Computation CEC2002,USA, May 2002 IEEE Press, 2002: 705-710.

[5] YU Da-ren, WANG Jian-bo, WANG Guang-xiong. Leak fault identification of rocket engine using self-organizing feature map net work. Journal of Propulsion Technology, Feb. 2001 Vol.22 No.1: 47-49.

[6] Yang Erfu, Zhang Zheng-peng, Cui Ding-jun, Liu Guo-qiu. Recognizing the Fault Patterns of Liquid Rocket Engine by Neural Networks, Missiles and Space Vehicles,1995 Vol.1:19-28.

[7] ZHANG Wei, ZHANG Yu-xiang, HUANG Xian-xiang. Multi-fault diagnosis for turbo-pump based on neural net work. Journal of Propulsion Technology, Feb. 2003 Vol.24 No.1:17-21.

[8] Huang Min-chao, Wu Jian-jun, Zhu Heng –wei, Wang Ke-hang. Vibration Detection of Liquid Rocket Engine Based on Fuzzy Neural Networks.Journal of Vibration Engineering, Vol. 10, No.2 Jun. 1997: 119-224.