DIAGNOSIS AND CONTROL FOR MULTI-AGENT SYSTEMS USING IMMUNE NETWORKS

Noriaki Sasaki and Yasuhiko Dote

Muroran Institute of Technology, Department of Computer Science and Systems Engineering,

27-1, Mizumoto-cho, Muroran 050-8585, Japan

Phone: +81 143 46 5432, Fax: +81 143 46 5499

E-mail: dote@csse.muroran-it.ac.jp

Homepage: http://bank.csse.muroran-it.ac.jp/

ABSTRACT

Soft computing (SC) is an evolving collection of methodologies, i.e., fuzzy, neuro, and evolutionary computing. Chaotic computing and immune systems are added later to enhance the soft computing capabilities. The fusion of SC components creates new functions i.e. flexible knowledge representation (symbol and pattern), acquisition and inference. Tractability, machine intelligent quotient, robustness and low cost are also achieved. Among them immune systems are very suitable for control and diagnosis of multi-agent systems (large-scale and complex systems) that interact among human beings, environment and artificial objects corresponding to the usage of complex interactions among antibodies and antigens in the immune systems. Perception and motion are achieved at the same time.

This paper describes novel sensor fault diagnosis for an uninterruptible power supply(UPS) feedback control system and new decision making of a robot in a changeable environment using immune networks and other soft computing methodologies based on cognitive distributed artificial intelligence (CDAI) and reactive distributed AI (RDAI) approaches. Simulation studies show that the proposed methods are feasible and promising for control and diagnosis of large-scale and complex dynamical systems.

NOMENCLEATURE

Nonlinear systems, multi-agent robot, UPS control system, diagnosis, soft computing, immune network, cognitive and reactive distributed artificial intelligence, large-scale and complex systems.

INTRODUCTION

Firstly, this paper proposes a new method of sensor failure detection for a large-scale and complex control systems such as multi-UPS systems operated in parallel using immune networks.

Recently, systems have been increasing in scale and complexity. In such systems, once a certain sensor becomes faulty (abnormal) it often causes a fatal situation since the influence of the failed sensor propagates through the whole system. To prevent the above situation, fault diagnosis techniques have become more and more urgent. Such diagnosis of plant systems, however, are bringing the problems that faulty states are often detected at the propagated points

rather than at the failure origins. Therefore, it is necessary to identify the faulty sensor exactly by integrating the data obtained from the equipped sensors.

To overcome these difficulties, cognitive distributed artificial intelligence (CDAI) approaches and reactive distributed artificial intelligence (RDAI) approaches are now available. Cause consequence tree (CCT) [1][2], signed digraph (SD) [3][4][5] and fuzzy decision tree (FDT) [6][7][8] approaches were reported for CDAI. On the other hand, immune network approaches [9][10][11] were proposed for RDAI. Immunity-based systems were well reviewed by Dasgupta *et al.* [12]. Since the immune network is one of the soft computing methodologies [13], it is well understood to compare it with a neural network [14]. The networks close to Grossberg 's ART and Kohonen's self-organized network are constructed using artificial immune systems [15],[16].

Reactivity is a behavior-based model of activity, as opposed to the symbol manipulation model used in planning. This leads to the notion of cognitive cost, *i.e.*, the complexity of the over architecture needed to achieve a task. Cognitive agents support a complex architecture, which means that their cognitive cost is high. Cognitive agents have internal representation of the world, which must be in enough with the world itself. The process of relating the internal representation and the world is considered as a complex task. On the other hand, reactive agents are simple, easy to understand and do not support internal representation of the world. Thus, their cognitive cost is low and tends to what is called cognitive economy, *i.e.,* the property of being able to perform even complex actions with simple architectures. Because of their complexity, cognitive agents are often considered as self-sufficient: they can work alone or with a few other agents. On the contrary, reactive agents need companionship cannot work isolated, they usually achieve their tasks in groups. Reactive agents are companionship. Reactive agents are situated: they do not take past events into account and cannot foresee the future. Their action is based on what happens now. They try to distinguish situations in the world and world indexes and react accordingly. Thus, reactive agents cannot be foreseen ahead. But, what can be considered as a weakness is one of their strengths because they do not have to revise their world model when perturbations change the world in an unexpected way. Robustness and fault tolerance are two of the main properties of reactive agent systems. A group of reactive agents can complete tasks even when one of them breaks down. The loss of one agent does not prohibit the completion of the whole task, because allocation of roles is achieved locally by perception of the environmental needs. Thus, reactive agent systems are considered as very flexible and adaptive [17].

Ishida [9] studied the mutual recognition feature of the immune network model for fault diagnosis. In his implementation, fault tolerance was attained by mutual recognition of interconnected units in the studied plant, *i.e.,* system level recognition was achieved by unit level recognition. However, this approach is steady state analysis and is not applicable to dynamical systems.

Kayama *et al.* devised a sensor fault detection scheme for a complex and large-scale feedback system using immune networks using Kohonen feature maps and fuzzy inference. In their work the sensors were considered as antibodies connected with each other. Each sensor watched another sensor's output and informed its abnormality by fuzzy decision making from learning vector quantizations from other sensors. The scheme presented by Kayama *et al.* cannot be applied to dynamical systems [10].

Ishiguro *et al.* [11] applied the immune network model to online fault-diagnosis of plant systems. To

apply the immune network to plant fault diagnosis, following assumption were made.

1) The number of failure origins is one;

2) Failure states propagate through branches without exceptions; and

3) No feedback loop exists in the future propagation.

Therefore their method is not directly applicable to feedback control systems.

In this paper feedback systems are decomposed into decision tree structure that has only the forward passes with branches using fuzzy decision tree concept [6] based on knowledge obtained by simulations. The presented system uses a fast fuzzy neural network with general parameter (GP) learning [19]. Then, the sensors are assumed as antibodies in our immune network. Each antibody receives the stimulation and suppression from the adjacent antibodies and also from

itself by calculating failure rate with the fast fuzzy neural network [19], and the dispassion. The density (concentration) of each antibody, called as failure origin ratio, is calculated by nonlinear differential equation driven by the received signals presented by Farmer *et al.* The sensor that shows the highest failure origin ratio is considered as failed sensor.

Secondly, the same decision making process described above by calculating concentration rate of each antibody in the immune system, a surviving robot in the environment where predators, obstacles, and foods exist, is proposed [21].

This paper is organized as follows. Section I describes sensor fault diagnosis using immune networks. Decision making of a robot interacting changeable environment is given in Section II and Last Section concludes this paper.

I. SENSOR FAULT DIAGNOSIS USING IMMUNE NETWORKS

A. Sensor Fault Diagnosis for UPS Control System

Ishiguro *et al.* applied immune network in fault diagnosis in a plant [11], and used following assumptions.

• The number of failure origins is one,

• Failure states propagate through branches without exceptions, and

• No feedback loop exists in the future propagation.

The variables that reflect the state of the sensors, called as *failure origin ratios*, are normalized between 1 and 0. If the failure origin ratio of a certain sensor increases, the possibility of failure origin of the sensor increases or otherwise decreases. The failure origin ratio corresponds to the concentration of antibodies in the immune network and varies by its stimulation and suppression and that of adjacent sensors on both sides.

The magnitude of the suppression and stimulation vary based on the failure origin ratio of the adjacent sensors. When the fast fuzzy neural network [19] detects the faulty state of the sensor i, it increases the failure origin ratio x_i. The failure origin ratio x_{i-1} of the adjacent sensor $i-1$ on source side is increased by stimulation of the sensor i. In this case the failure origin ratio x_{i+1} of the sensor $i+1$ is decreased by the suppression of the sensor i. On the other hand, the fast fuzzy neural network detects the fault-free state of sensor i and suppresses (decreases) the failure origin ratio x_i. From the above consideration, the failure origin ratio x_i is calculated as follows.

$$\frac{dx_i}{dt} = \{b(x_{i+1}) - d(x_{i-1}) + s_i - k\}x_i \qquad (1)$$

$$x_i = \frac{1}{1 + \exp\{a(x_i - \mathbf{a})\}} \qquad (2)$$

where k and $\mathbf{a}$ are positive constants, a is a negative constant, b and d are the stimulation and

suppression from the adjacent sensors, s_i represent the stimulation and suppression calculated by the fast fuzzy neural network [19], and k denotes the dispassion factor to ensure the global stability of the immune network. The described system is illustrated in Fig. 1.
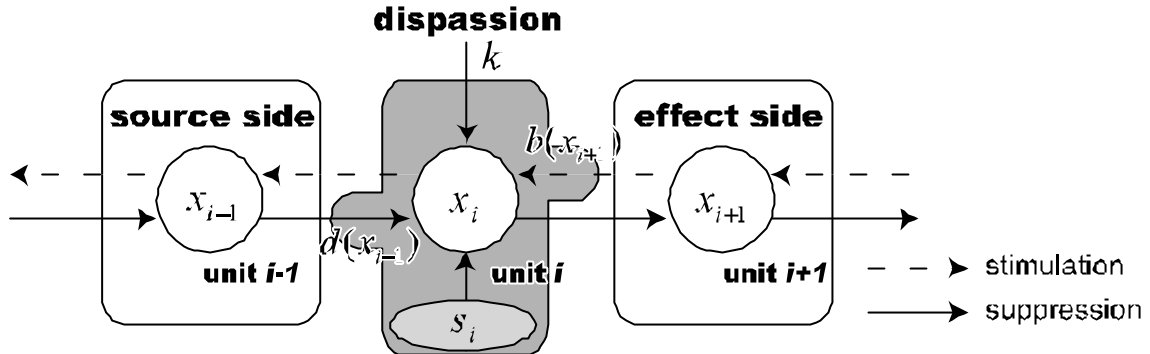

Fig. 1. Concentration of antibody.

In this paper, feedback systems are decomposed into decision tree structure which has only the forward passes with branches using fuzzy decision tree concept [6] based on knowledge obtained by simulations, as shown in Fig. 2, which is automatically achieved by our developed fast fuzzy neural network with general parameter (GP) learning [19].

Fig. 2. Decomposition of systems into tree structure.
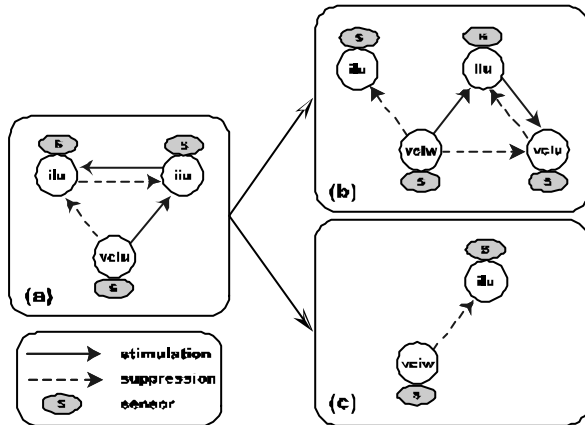
B. Simulation Results

The UPS system used in our research is shown in Fig. 3. For simplicity, we consider four sensors, that is, an inverter line current (iiu), a load line current (ilu), a load u-phase voltage ($vciu$), and a load w-phase voltage ($vciw$).

The configuration of the fast fuzzy neural network with GP learning is shown in Fig. 4. The number of delay elements is set to 10. The number of Gaussian functions is 3 for ilu and iiu and is 2 for $vciw$ and $vciu$. In Eq. 1, s_i is 0 for normal state and is 0.4 for abnormal state. The centers of Gaussian functions were uniformly distributed over the whole range. The applied overlapping factor is 0.2.
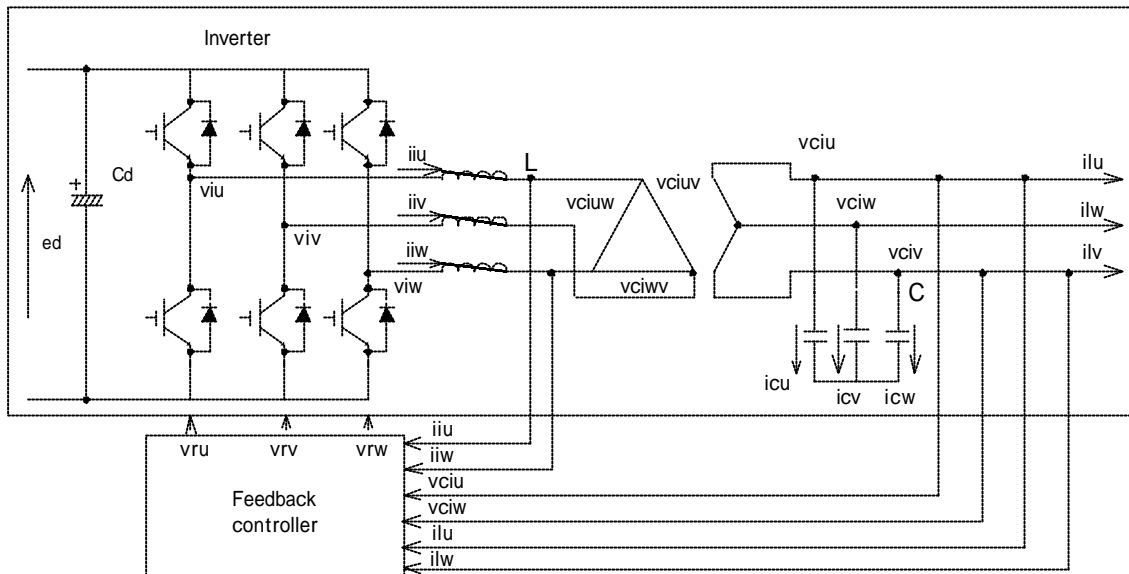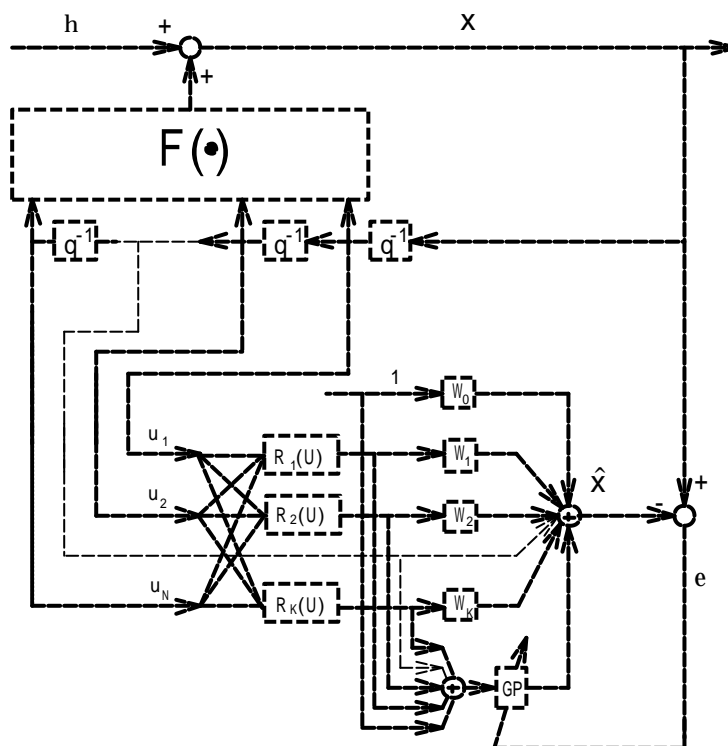
Fig. 3. UPS control system

Fig. 4. Fast fuzzy neural network.

The stimulation and suppression (see Eq. 1) are shown in Fig. 5, where k is 0.1, a is 3.3, and a is 0.5. These parameters are empirically tuned.

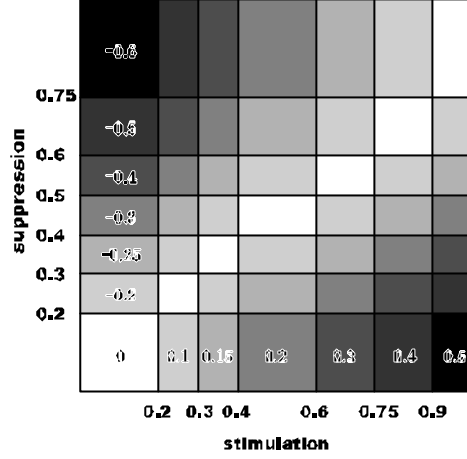The result of sensor fault detection is shown in Fig. 6.
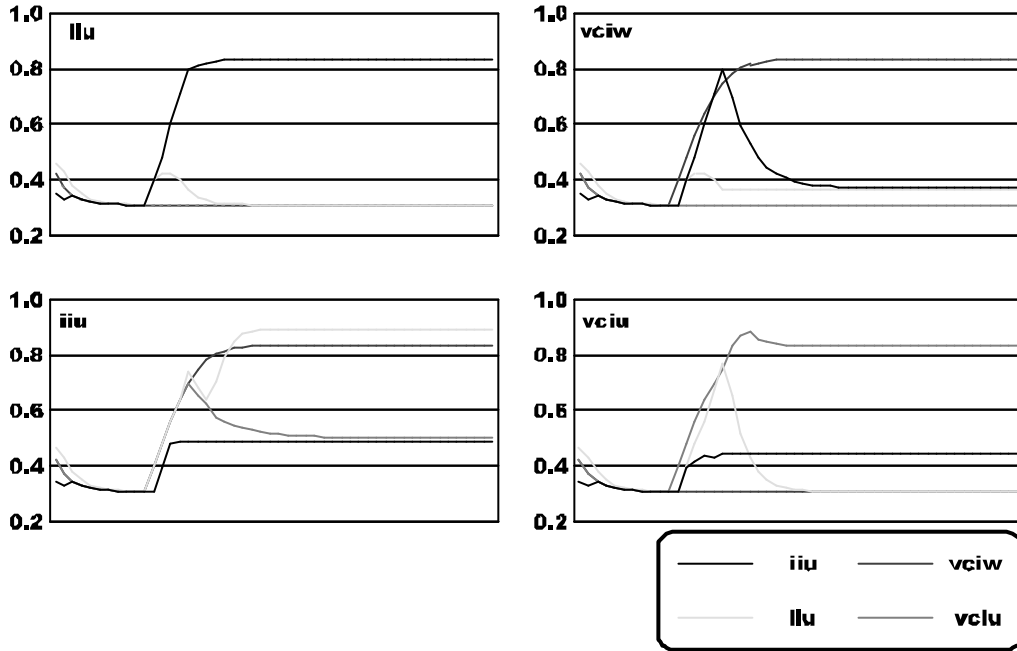
Fig. 5. Ratio of stimulation and suppression.

Fig. 6. Result of sensor failure detection.

II. SURVIVING ROBOT IN A CHANGEABLE ENVIRONMENT [21]

A. A surviving robot in a changeable environment using decision making by immune networks

An artificial decision making robot 'immunoid' by interactions among antibodies in artificial immune networks is considered. In this simulated environment, there are following three kinds of objects: (1) predator, (2) obstacles, and (3) food. It is assumed that pre-specified quantity of initial energy is given to the immunoid at the beginning of each simulation. For quantitative evaluation, the following assumptions are made.

1. If the immunoid moves, it consumes energy E_m

2. If the immunoid is captured by a predator, it consumes energy E_p

3. If the immunoid collides with an obstacle, it losses energy E_o

4. If the immunoid picks up food once, it obtains energy E_i

The predators attack the immunoid if they detect the immunoid within the pre-specified detectable range.

Therefore, in order to survive as long as possible, the immunoid must select a competence module (antidody) suitable for the current situation (antigen). The immunoid are equipped with external and internal detectors. External detectors can sense eight directions as shown in Fig. 7. Each can detect the distance to the objects by three degrees, near, mid, and far. The internal detector senses the current energy level.
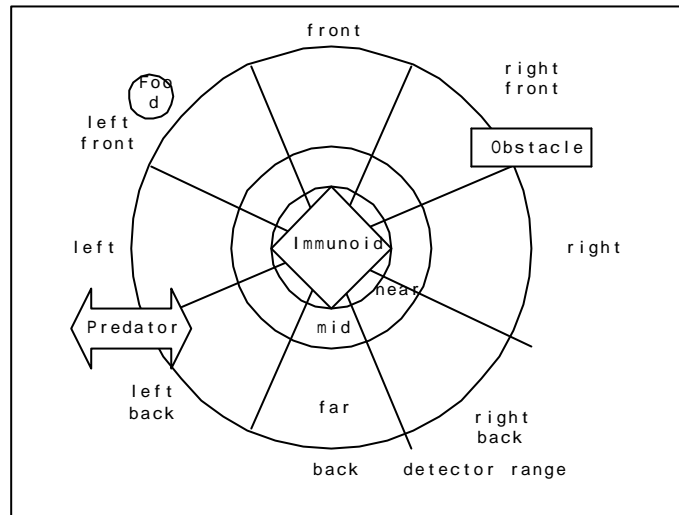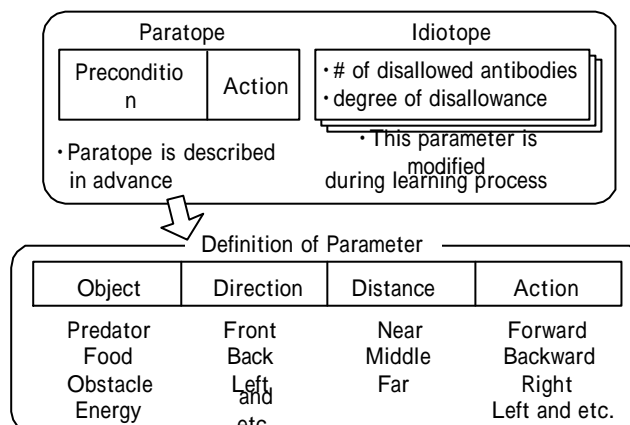

Fig.7. Simulated environment.

Fig.8. Representations of antibodies.

The immunoid moves in the eight directions The detected current situation and prepared competence modules work as antigens and antibodies, respectively. To make an immunoid (antibody) select a suitable antibody against the current antigen, the way of description of antibodies is highly important. Moreover, it is noticed that the immunogical arbitration mechanis m selects an antibody in bottom up manner by communicating among the antibodies. To realize the above requirements the description of antibodies are defined as follows. The identity of a specific antibody is generally determined by the structure of its paratope and idiotope. Fig. 8 depicts the representation of antibodies.

As shown in this figure 8, a pair of precondition action to paratope, the number of disallowed antibodies and the degree of disallowance to idiotope are respectively assigned. In addition, the structure of

paratope is divided into four portions: objects, direction, distance, and action.

For adequate selection of antibodies, one state variable called concentration is assigned to each antibody. The selection of antibodies is simply carried out in a winner-take all fashion. Namely, only one antibody is allowed to activate and act correspondingly to the world if its concentration is the largest. The concentration of the antibody is influenced by the stimulation and suppression from other antibodies, the stimulation from antigen, and the dissipation factor (i.e. natural death). The concentration of i-th antibody, which is denoted by a_i, is calculated by (3) and (4) gives the rate of interaction among antigens and antibodies.

$$dA_i(t)/dt = \left\{ \left(\mathbf{a} \sum_{j=1}^{N} m_{ji} a_j(t) / \sum_{j=1}^{N} m_{ji} \right) - \left(\mathbf{a} \sum_{k=1}^{N} m_{ik} a_k(t) / \sum_{k=1}^{N} m_{ik} \right) + \mathbf{b} m_i - k_i \right\} a_i(t) \quad (3)$$

$$a_i(t+1) = 1/(1 + \exp(0.5 - A_i(t))) \quad (4)$$

where N is the number of antibodies, and m_i denotes matching ratio between antibody i and antigen, m_{ij} denotes degree of disallowance of antibody j for antibody i. The first and second terms of right hand side denote the stimulation and suppression from other antibodies, respectively. The third term represents the stimulation from antigen, and the forth term the natural death.

B. Simulation results (All simulations are carried out in our laboratory).

100 simulations are carried out with

No. of predators= 5; No. of obstacles= 5; No. of foods= 10; and No. of antibodies= 91 for a medium-size multi-agent system.

Average lifetime:

1. Immunoid's random walk: 313.14
2. Without interactions among antibodies: 564.86
3. With interactions among antibodies: 621.46

No. of collides against predators and obstacles and obtaining foods:

S. No.	Predators	Predators	Foods
1	19.91	1.84	0.54
2	9.04	5.92	4.27
3	7.84	5.23	5.02

The proposed method is clearly the best.

This approach is promising for decision-making in autonomous mobile robots (one of multi-agent robots). However, two disadvantages exist. One is how to cope with environmental changes. The other is how to design agents. It is required in the future to devise some real-time reinforcement learning. In these simulation studies, designs of agents are much improved.

III. CONCLUSIONS

Among soft computing methodologies immune networks are suitable to construct reactive distributed artificial intelligence. This paper proposed one of the promising methods for diagnosis and control of large-scale and complex systems (multi-agent systems) using immune networks and other soft computing methodologies. In order to make these systems be optimized and evolve evolutionary computation [20] will be introduced for future research.

REFERENCES

[1] B. Frogner, *et al. "*Methodology, conceptual design, and capabilities of a disturbance analysis system," *SCI Report,* 1978.

[2] L. Felkel, "Analytical methods and performance evaluation of the STAR application in the Grafenehe in field nuclear power plant," *IAEE specialist meeting on NPPCI,* 1979.

[3] T. Umeda, K. Kuriyama, E. O'shima, and H. Matsuyama, "A graphical approach to cause and effect analysis of chemical processing systems," *Chemical Engineering Science,* vol. 35, pp. 2379-2388, 1990.

[4] M. Iri, K. Aoki, E. O'shima, and H. Matsuyama, "A graphical approach to the problem of locating the origin of the system failure," *Journal of the Operations Research Society of Japan,* vol. 23, no. 4, pp. 295-312, 1980.

[5] M. Iri, K. Aoki, E. O'shima, and H. Matsuyama, "An algorithm for diagnosis of system failures in the chemical process," *Computer & Chemical Engineering,* vol. 3, pp. 489-493, 1979.

[6] D. Fuessel and R. Isermann, "Hierarchical motor diagnosis utilizing structural knowledge and a self-learning neuro-fuzzy scheme," *IEEE Trans. on Industrial Electronics,* vol. 47, no. 5, pp. 1070-1077, 2000.

[7] M. Kubat, "Decision trees can initialize redial-basis function networks," *IEEE Trans. on Neural Networks,* vol. 9, no. 5, pp. 813-821, 1998.

[8] E. C. C. Tsang, X. Z. Wang, and D. S. Yeung, "Improving learning accuracy of fuzzy decision trees by hybrid neural networks," *IEEE Trans. on Fuzzy Systems,* vol. 8, no. 5, pp. 601-614, 2000.

[9] Y. Ishida, "An immune network model and its applications to process diagnosis," *Systems and Computers in Japan,* vol. 24, no. 6, pp. 38-45, 1993.

[10] M. Kayama, Y. Sugita, Y. Morooka, and S. Fukuoka, "Distributed diagnosis system combining the immune network and learning vector quantization," in *Proc. of the IEEE Int.l Conf. on Industrial Electronics*, Orland, FL, pp. 1531-1536, 1995.

[11] A. Ishiguro, Y. Watanabe, and Y. Uchikawa, "Fault diagnosis of plant systems using immune networks," in *Proc. of the IEEE Int. Conf. on Multisensor Fusion and Integration for Intelligent Systems, Las Vegas,* pp. 34-42, 1994.

[12] D. Dasgupta and N. Attoh-Okine, "Immunity-based systems: A Survey," *in Proc. of the IEEE SMC,* Orland, FL, pp. 369-374, 1997.

[13] Y. Dote, S. J. Ovaska, T. Furuhashi, and Y. Suzuki. (Eds.), *The Special Issue on Industrial Innovation Using Soft Computing, Proceedings of the IEEE,* September, 2001.

[14] D. Dasgupta, "Artificial neural networks and artificial immune systems: Similarities and differences," in *Proc. of the IEEE SMC,* Orland, FL, pp. 873-878, 1999.

[15] T.Yamagchi, M.Tou, K.Ishizuka and K.Awano, "Adaptive Multi-Valued Immune Network and Its Applications",JEE Transactions C, vol.121, no.11,pp1748-1754,2001.(in Japanese)

[16] L.N.De Castro and F.J.Von Zuben, " Immune and Neural Network Models: Theoretical and Empirical Comparisons", International Journal of Computational Intelligence and Applications, vol.1, no.3, p239-237,September 2001.

[17] G. M. P. O' Hare and N. R. Jennings (Eds.), *Foundations of Distributed Artificial Intelligence,* New York, NY: John Wiley & Suns Inc., 1996.

[18] N. K. Jerne, *Towards a network theory of the immune system, annual immunology,* 125C, pp. 373-389, 1974.

[19] D. F. Akhmetov, Y. Dote, and S. J. Ovaska, "Fuzzy neural network with general parameter adaptation of nonlinear time series," *IEEE Trans. on Neural Networks,* vol. 16, no.1, pp. 148-152, 2001.

[20] D. B. Fogel, *Evolutionary Computation - Towards a New Philosophy of Machine Intelligence,* Piscataway, NJ, IEEE Press, 2000.

[21] A. Ishiguro, Y. Shirai, T. Kondo, and Y. Uchikawa, "Immunoid: An Architecture for behavior

arbitration based on the immune networks," in *Proc. of the Int. Conf. on Intelligent Robotics and Systems,* Osaka, Japan, pp. 1730-1738, 1996.