An Immune Network Approach to Sensor-Network with Self-Organization for Sensor and Process Faults *

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Key Words - Failure diagnosis; sensor network; sensor faults; process faults; immune nets; self-organization; simulation

Abstract

The self-organizing diagnosis has been studied by applying the idea of autonomous and decentralized systems extracted from the concept of immune network. The model implements network-level recognition by connecting information from local recognition units by dynamical evaluation chain. The model has been further elaborated for engineering concerns of identifying not only sensor faults but process faults. The sensor faults will be identified by evaluating reliability of data from sensor, while the process faults will be identified by evaluating that of constraints that must be satisfied among these data. We have demonstrated that the extended sensor network will work against both sensor faults and process faults by an illustrative example.

1 Introduction

1.1 Immune network as autonomous decentralized system

Massively parallel and distributed model has been proposed and studied based on neural network metaphor but elaborated for pattern recognition task as found in backpropagation networks [1]. These models mainly focus on learning capability which is made possible by using pattern distributed over parameters such as connection weights. In contrast to supervised learning in backpropagation networks, competetive leaning that allows unsupervised learning (thus closer to self-organization in this sense) has also been studied (e.g. [2]). Further elaboration on the competetive learning has been studied in self-organizing topological feature maps (e.g. [3]) where best-matching cell not noly activate itself but its topographical neighbors. This mechanism projects input data on the network where features embedded in the data are reflected in the activation pattern in the network.

Autonomous decentralized system (e.g. [4, 5]) is a concept extracted not only from self-organizing biological systems but also from self-organizing economic structure of free market, organization of nations, development of enterprises etc. The essence of autonomous decentralized systems (as opposed to central processing systems) is that they consists of autonomous agents, to whom most of decisions are left to their disrection. Autonomous agents (not necessarily homogeneous), hence should have a high intelligence. These autonmous agents form a kind of field (called autonomous field) that implicitly restrict their behavior. A familiar example taken from recent topics may be INTERNET, which develops with the

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free hand of each site but restricted so that each site at least must follow a certain protocols to be connected with the rest of INTERNET. Another significant feature of autonomous decentralized systems is that its structure is dynamic and hence cannot be designed or specified beforehand. In this sense, the design specification may be embedded in autonomous agents and autonomous field formed by them. It must be left to dynamic developmental process of the autonomous field.

We have suggested [6, 8] that another typical example taken from biological systems is immune networks, where intelligent agents (recognizing units consisting of B-cells and T-cells of specific type) communicate dynamically as opposed to communicate with hard-wired link in neural networks.

The motivation of this work is to elaborate the immune network as one model of autonomous decentralized systems towards an information processing paradigm. More specifically, the objective of this paper is to elaborate the network model extracted some features of immune network for applying it to self-organizing diagnosis.

1.2 Informational features of immune systems

Mathematical models of immune systems have been studied in mathematical immunology [9, 10]. However, most of them tried to explain quantitative aspect of immunological phenomena. Recently, some [11, 12, 13] tries to extract information processing mechanism from the immune systems for the application to information processing systems. In this paper, rather than building a detailed mathematical model of immune systems, an attempt has been made to explore the information processing principle in immune system focusing on the information processing capabilities, such as pattern recognition and learning, as done in neural network models.

Studies to establish immune net information models by investigating the features of information processing done there, and by reflecting these features into the models were performed. The features of information processing done by immune systems may be summed up as follows:

- Memory: Huge amount of patterns are memorized and distinguished.
- Recognition: System level recognition may be attained by recognition chain in unit level (idiotypic network).
- Learning: Pattern recognition capability is acquired by learning (not by copying through generations but acquired in one generation).
- Diversity: Diversity needed for discrimination of huge amount of patterns is generated by genetic recombination.

We have developed an immune algorithm [14] that uses recognition, learning, diversity similar to immune systems. In this paper, we focus on memory and recognition from the network hypothesis (see next subsection).

Other than these two models, acquiring diversity by combinatorial generation may potentially give insight to building new information models, since most of the current models depend upon copying for storage and transfer of information.

1.3 The concept of immune network and its implications

Theory of immune network proposed by Jerne [16] provides the network view that B-cells are mutually and dynamically connected by antigen antibody interaction. Not only antigen but also antibody generated by B-cells will act as an angigen against the other B-cells, thus presupposing *internal image* of the antigen. Both antigen and its internal image activate the same specific type of B-cell. This network view would implicitly suggest that the immune memory is somehow embedded in the network; when disturbed by antigen, the network in an equilibrium will move to other equilibrium point, thus memorized the encounter with the antigen. The character of the network theory is that it placed an importantce on (1) the homogeneous network conncected by antigen antibody interaction, and (2) the existence of internal images for antigens.

After the proposal of immune network (idiotypic network) theory by Jerne, systems approach have been made extensively to characterize immune response by dynamical models [17, 9]. These dynamical models essentially describe population dynamics of antigen, antibody, and specific immune related cells in a similar manner to the models describing population dynamics of species in mathematical ecology.

Although the systems approach may explain some immunological phenomena by associating characteristics of immune response with interactions among antigen, antibody and B-cells, fundamental problems such as mechanism of immune memory still remained; whether the memory can be attributed to local cells (long-lived cell) or to the network of cells.

Theory of immune network by Jerne is not much mentioned recently in immunology after more practical view of interleukin network (which is complex network involving not only B-cells but T-cells, MHC molecules; not only antibody but interleukin that do not correspond to specific antigen) becomes dominant. Nevertheless, it may give an important insight for information processing to attain an intelligent diagnostic system capable of self organizing diagnosis.

Our model, first motivated by immune network concept though, has been elaborated for engineering use rather than simulating or modeling immune systems. Thus, there is no intention of asserting that our model reflects any phenomena actually happen in immune networks. However, features of immune systems we have tried to use may be summarized as follows;

- Recognition of non-self (faults in processing plants in our application) is done by distributed units which dynamically interacts with each other in parallel.

- Distributed units carry redundant information. (Sensor values carry the redundant information in our application.)

- Each unit reacts based only on its own knowledge (i.e. it refers to its own state to judge its consistency with others), but this local information processing connected by evaluation chain leads to emergent behaviour: identification of the identity. (Each sensor judges other sensors by checking the consistency with its own value.)

- Memory is realized as stable equilibrium points of the dynamical network. Recognition of the network is done by changing the state of the network from one stable equilibrium to another one by disturbances on the network. (Diagnosis is done by obtaining the stable equilibrium points where change of consistency pattern is considered to be disturbance.)

In this paper, we implemented these features in our application of sensor netwrok. However, we do not persue the parallelism between our model and immune systems any more.

1.4 Immune network approach to measurement

The problem of integrating distributed sensors with fault tolerance concerns [18] and different types of sensors for intelligence [19] have been studied extensively with the progress of device technology such as intelligent sensors and their integrating techniques. Although the study of sensor fusion rather focused on integrating different types of sensors, our approach is aimed to enhance the processing done in autonomous sensors using redundant information shared by many sensors, and to support self-organization of the sensor networks.

The sensor network, we proposed, is designed especially to work in dynamical and noisy environments found in industrial processing plants [15]. The motivation of developing sensor network is not only practical reason of using redundant information in sensors of instrumentation system, but a little more ambitious one; we try to develop biological instrumentation system inspired by immune systems. As a result, it is possible to distribute the knowledge of normal functioning process into all the sensors and the relation among sensors. Thus, the sensor network is robust in the sense that it would work even with faulty sensors. It is also flexible in the sense that it can represent knowledge of relative relation among sensor values as opposed to represent reference values specified by pemissble maximum and minimum.

To illustrate our approach of sensor network, we use the metaphor of weighing. There are roughly two methods of weighing objects: one is using scale that requires a sophisticated central processing mechanism that maps weight to the number; another is using balance that uses many types of balance weights and compare the weight of the target object with some set of balance weights. The former is often accurate and efficient, once the mechanism of mapping is devised. However, the latter method of object-against-object offers a distributed and robust way of weighing. The network view of immune systems can be understood with this metaphor; regarding many types of balance weights as recognizing agent (immune related cells such as B-cell and T-cell that react only with specific antigen) and action of weighing by balance as recognition by paratope and epitope with spatial complementality. The result of recognition is used to activate other recognizing agent, similarly to the fact that the result of balance is used to determine more appropriate balance weight against the target object. This object-against-object weighing is more robust, since the weighing mechanism is a simple comparison and that information is distributed into many balance weights. Although this metaphor is rough, it seems to reflect many important informational features of immune netwrok. It may be more appropriate to consider the immune network more sophisticated than the simple balance weighing system in the following points:

1. Each agent has not only information but a recognizing mechanism itself. (Each recognizing agent is comparable with a balance weight equipped with balance rather than only balance weight.)

2. Recognizing agent activated by an encounter with the antigen will reproduce its clone

to enhance the ability of elimination of the antigen. (Balance weights, when used, can self reproduce the balance weights of the same type.)

3. The reproduction above will be performed with mutation to increase the affinity with the antigen. (Balance weight, when used, can reproduce not only the same type, but slightly different types, hence enhancing precision in weighing.)

We will persue this object-against-object measurement, and applied it to adaptive intelligent diagnosis. However, we do not persue the adaptive change of the population of specific agent mentioned 2 and 3 above. We have implemented immune algorithm which uses 2, 3 and diversity generation by genetic recombination elsewhere[14].

2 Diagnostic model by self-organization

Fig. 1 shows the evaluation chain of five units. Each unit tries to identify the identity (self/non-self for immune systems, faulty/normal for diagnosis) other units. State variable (r_i and its normalization R_i) indicating the identity of units are assigned to each unit. Dynamical system is constructed by associating the time derivative of the state variable with state variables of other units connected by the evaluation chain.

A possible association corresponding to the evaluation chain would be the following dynamical system (this is the model 3 stated later):

$$\begin{aligned}
dr_1(t)/dt &= -4R_4 - r_1(t) \\
dr_2(t)/dt &= -4R_4 - 4R_5 - r_2(t) \\
dr_3(t)/dt &= -4R_4 - 4R_5 - r_3(t) \\
dr_4(t)/dt &= -4R_1 - 4R_2 - 4R_3 - r_4(t) \\
dr_5(t)/dt &= -4R_2 - 4R_3 - r_5(t)
\end{aligned}$$

When the units 4 and 5 are faulty, we have the test result as shown in Fig. 1.

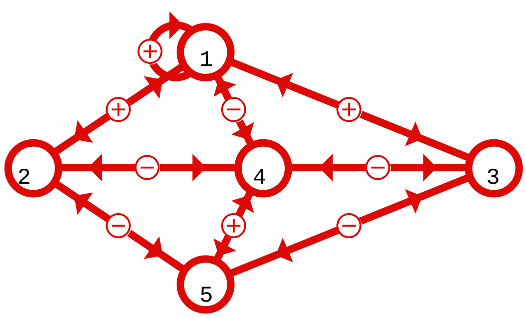

Figure 1: An example of evaluation chain

Simple voting at each unit does not work, since three units 2, 3 and 5 are all evaluated as faulty by two other units and hence cannot be ranked in terms of the possibility of faulty.

Self-diagnosable system [20] consists of a set of units $U = \{u_i\} i = 1..n$ each of which has capability of testing other units and being tested by others as well. e_{ij} indicates the test on the unit u_j done by the unit u_i. Thus, the test outcome T_{ij} of the test e_{ij} is defined:

$$T_{ij} = \begin{cases} -1 & \text{if a testing unit } u_i \text{ is normal and a tested unit } u_j \text{ is faulty.} \\ 1 & \text{if both units } u_i \text{ and } u_j \text{ are normal.} \\ -1/1 & \text{if a testing unit } u_i \text{ is faulty.} \\ 0 & \text{if there is no test from unit } u_i \text{ to unit } u_j. \end{cases}$$

The continuous value R_i between 0 and 1, indicating faulty and normal of the unit respectively, is assigned to each unit. We call the value R_i calculated by the diagnostic models the reliability measure.is actually faulty.

We first assign the value between 0 and 1 (the initial value of the reliability measure) to each unit. Then we calculate the reliability measures R_i by the following dynamical model.

$$dr_i(t)/dt = \sum_{e_{ji} \in T^i} T_{ji} R_j + \sum_{e_{ij} \in T_i} T_{ij} R_j - \frac{1}{2} \sum_{e_{ij} \in T_i} (T_{ij} + 1) \tag{1}$$

$R_i(t) = \frac{1}{1+\exp(-r_i(t))}$

where T_i is a set of all the tests done by the unit u_i, and T^i is a set of all the tests on the unit u_i.

Let $J_i(T, R)$ denote the right hand side of the equation 1.

and $T^*_{ij} = T_{ij} + T_{ji}$.

We have already provided the model when the test done by even reliable unit is no reliable[7]. The test outcome, then, is defined as:

$$T_{ij} = \begin{cases} 1 & \text{if both a testing unit } u_i \text{ and a tested unit } u_j \text{ is normal.} \\ -1/1 & \text{if either a testing unit } u_i \text{ or a tested unit } u_j \text{ is faulty .} \\ 0 & \text{if there is no test from unit } u_i \text{ to unit } u_j. \end{cases}$$

In that case, the evaluation function $J_i(T, R)$ of the above diagnostic model should be modified to:

$$dr_i(t)/dt = \sum_{e_{ji} \in T^i} (T_{ji} - 1) R_j(t) + \sum_{e_{ij} \in T_i} (T_{ij} - 1) R_j(t) \tag{2}$$

$R_i(t) = \frac{1}{1+\exp(-r_i(t))}$

With the incomplete tests, consistent diagnosis is such reliability measure vector that if $R_i = 1$ then R_j must be 0 only when $T_{ij} = -1$. For a consistent diagnosis $\mathbf{R}co = (Rco_1, \ldots, Rco_n)$, $Rco_i = 1(0)$ implies that $\sum_{j \neq i} T^+_{ij} R_j \geq 0 (\leq 0)$ by the definition of consistent diagnosis.

We have further modified the model so that it keeps the information of ambiguous state of sensor reliability measure [7].

$$dr_i(t)/dt = \sum_j T^+_{ji} R_j(t) - r_i(t) \tag{3}$$

In this system, there are equilibrium points satisfying that $r_i(t) = \sum_j T^+_{ji} R_j(t)$. Thus, R_i monotonically reflects the value of $\sum_j T^+_{ji} R_j(t)$. If $\sum_j T^+_{ji} R_j(t)$ is close to 0, then R_i is close to 0.5. We will discuss the extention of this model in this paper.

3 Application to Fault Diagnosis: A Sensor Network

from sensors As a possible application of these models, self-detecting sensory network for processing plants has been proposed. When the sensor s_i and s_j are related as $s_j = M^+(s_i)$ where M^+ is a such function that value interval I_k of s_i correspond to the value interval J_k of s_j . In process diagnosis for example, temperature, pressure, and flow measured independently often have such interrelation, and hence interval correspondence between e.g. high temperature and high pressure is attained. Composing a unit u_i which will produce test outcome T_{ij} by the sensory data of s_i and s_j

$$T_{ij} = \begin{cases} 1 & s_j \in J_k \text{ when } s_i \in I_k \\ -1 & \text{otherwise} \end{cases}$$

It should be noted that the evaluation above between units i and j is asymmetric, since the the constraint for caluculating I_k from s_i and that for caluculating J_k from s_j are not necessarily same. However, in process diagnosis where the constraints used are often balance equation, the constraints are common for i and j, hence the evaluation is symmetric (see exmaple below). If the process value calculated from other process value is not pinpoint, and only plausible interval is obtained, then we must say that the test here is incomplete. In that case, the model with incomplete test should be adopted. As we will see in the next example, we must also adopt the model with incomplete test in the case when test is done by inequality.

Consider an example of a heat exchanger of the condenser type. Two flows i.e. the flow of the shell side and flow of the tube side exchange heat. Steam enters from the inlet of the shell side, then it is condensed, and finally being cooled by the flow of the tube side. The flowing object of the tube side then come out being heated by the flow of the shell side.

Now, we consider the inequalities among temperatures of these two flows.

1. $T_{hi} > T_{ho}$
2. $T_{lo} > T_{li}$
3. $T_{hi} > T_{li}$
4. $T_{ho} > T_{lo}$

where
T_{hi}: temperature at inlet of shell side,
T_{ho}: temperature at outlet of shell side,

T_{li}: temperature at inlet of tube side,
T_{ho}: temperature at outlet of tube side.

Using these relation among sensors, sensor network will be constructed. For example, when the relation (1) $T_{hi} > T_{ho}$ does not hold, then either T_{hi} or T_{ho} can be faulty. This means that the sensors measuring valuesT_{hi}, T_{ho} are testing each other through this relation. The tests done by these inequalities are incomplete, for even if the tested sensor is faulty it will not be recognized unless the tested sensor value fails to satisfy the inequality. Thus, the model under incomplete test should be used for this case.

Fig. 2 shows sensor network of these four sensors.

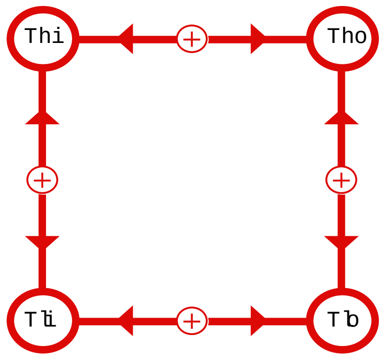

Figure 2: Diagram of sensor network in a heat exchanger

We have applied the above approach to industrial processing plants such as a process including firing section of a cement process with twenty thermometers and a blast furnace of a steel process with about five hundred thermometers [7, 8].

Fig. 3 shows a sensor network generated by the Sensor Net Generator for the preheating process of a cement plant. Twenty-two sensors (thermometers) are involved. In constructing the sensor net, not only process knowledge but the experimental knowledge among sensor values is used to obtain enough relations for diagnosis.

4 Extension of the Sensor Network

4.1 Process fault diagnosis by evaluating reliability of the constraints

In order to extend the sensor network so that it can diagnose process fault as well, we have discussed two methods: (1) simply preparing the unit corresponding to the process fault, and (2) introduction of vertual sensor composed of multiple sensors elsewhere [15]. In this paper, we propose another natural extension based on the insight that the knowledge of normal process is embedded in the constraints among sensors. Thus, when process faults occurs, it ammount to violation of the constraints. In fact, when process fault occurs, reliability measures of many sensors related to the constraints become low simultaneously. Fig. 4 illustrates the situation when process fault occurs.

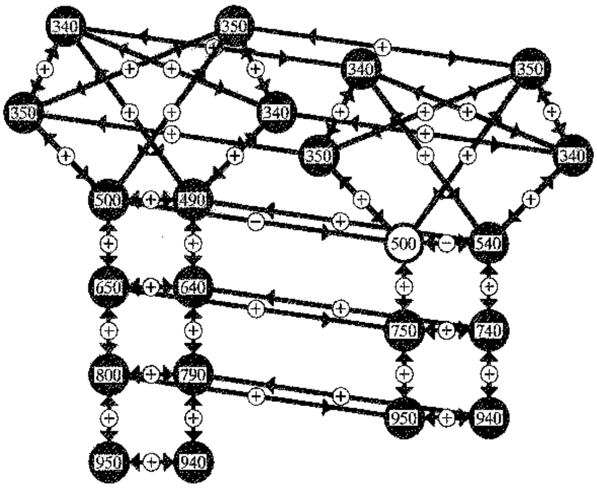

Figure 3: An Example of a Session of Sensor Network for a Cement Process

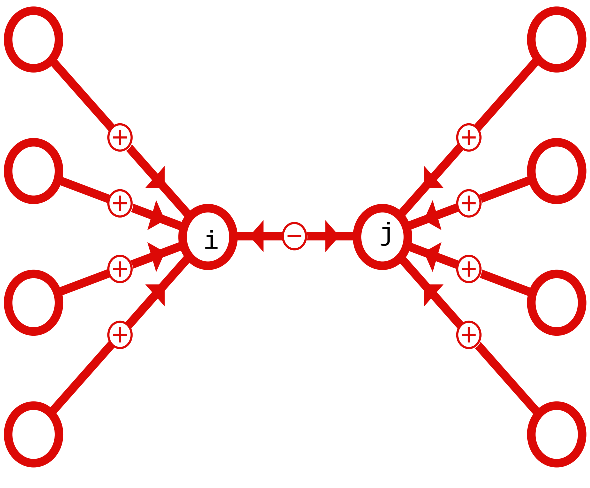

Figure 4: Situation when process fault occurs

Therefore, one natural way of detecting process fault by sensor net is to introduce reliability measure for testing relation. Let $R_{T_{ji}}$ denote the reliability measure of the test T_{ji}. Then the dynamical model 3 becomes as follows:

$$dr_i(t)/dt = \sum_j T_{ji}^{+} R_j(t) R_{T_{ji}} - r_i(t) \tag{4}$$

$$dr_{T_{ji}}(t)/dt = T_{ji}^{+} R_j(t) R_i(t) - r_{T_{ji}}(t) \tag{5}$$

$$R_i(t) = \frac{1}{1+\exp(-r_i(t))}$$

$$R_{T_{ji}}(t) = \frac{1}{1+\exp(-r_{T_{ji}}(t))}$$

The equation 4 is a modification naturally resulted by considering the effect of the reliability measure of the test T_{ji}. The change rate of the unit i; $dr_i(t)/dt$ should reflect all the opinions of other units weighted not only with the reliability of these other units but with those of their testing.

The equation 5 comes from the fact that the testing relation is considered to be unreliable only when $T_{ji}, R_j(t)$ and $R_i(t)$ are contradictory; $T_{ji} = -1, R_j(t) = 1$ and $R_i(t) = 1$.

4.2 Sensor net for multiple testings

Constraints among process variables may be expressed by the vector equation: $\mathbf{f}(\mathbf{y}^*, t) = 0$ where $\mathbf{y}^*$ is the true values of process variables. The testing results for multiple testing can be defined as:

$$T_k \equiv \begin{cases} 1 & \text{if } |f_k(\mathbf{y}(t), t)| \leq \epsilon_k \\ -1 & \text{if } |f_k(\mathbf{y}(t), t)| > \epsilon_k \end{cases} \tag{6}$$

where $\mathbf{y}$ is the measured values (i.e. sensor values). Let $S = \{s_1, \cdots, s_n\}$ be set of all the sensors and let S_k be the subset involved in the constraint f_k. When there are more than three variables in f_k, the model 4 and 5 can be modified as follows:

$$dr_i(t)/dt = \sum_{k, s_i \in S_k} \{T_k^{+} R_{T_k}(t) \prod_{\substack{j, s_j \in S_k \\ j \neq i}} R_j(t)\} - r_i(t) \tag{7}$$

$$dr_{T_k}(t)/dt = \frac{1}{2}(T_k^{+} - 1) \prod_{i, s_i \in S_k} R_i(t) - r_{T_{ji}}(t) \tag{8}$$

$$R_{T_k}(t) = \frac{2}{1+\exp(-r_{T_k}(t))}$$

where $T_k^{+} \equiv n_k T_k, n_k \equiv |S_k|$: the number of the sensor involved in the constraint f_k.

As an illustrative example, consider the process of keeping the level and temperature in a tank as shown in the left of Fig. 5. The right of Fig. 5 shows the sensor network of this process consisting of eight sensors and eight tests among the sensors.

The model of this sensor network follows:

$$
\begin{aligned}
dr_{F_O}(t)/dt &= R_L(t)R_{T_0}(t) + R_{F_I}(t)R_{T_7}(t) + R_L(t)R_{F_I}(t)R_{T_1}(t) - r_{F_O}(t) \\
dr_{F_I}(t)/dt &= R_{F_O}(t)R_{T_7}(t) + R_L(t)R_{F_O}(t)R_{T_1}(t) + R_{F_H}(t)R_{F_C}(t)R_{T_6}(t) - r_{F_I}(t) \\
dr_L(t)/dt &= R_{F_O}(t)R_{T_0}(t) + R_{F_I}(t)R_{F_O}(t)R_{T_1}(t) + R_{V_H}(t)R_T(t)R_{T_2} + R_{V_C}(t)R_T(t)R_{T_3}(t) - r_L(t) \\
dr_{F_H}(t)/dt &= R_{V_H}(t)R_{T_4}(t) + R_{F_I}(t)R_{F_C}(t)R_{T_6}(t) - r_{F_H}(t) \\
dr_{F_C}(t)/dt &= R_{V_C}(t)R_{T_5}(t) + R_{F_I}(t)R_{F_H}(t)R_{T_6}(t) - r_{F_C}(t) \\
dr_{V_H}(t)/dt &= R_{F_H}(t)R_{T_4}(t) + R_L(t)R_T(t)R_{T_2}(t) - r_{V_H}(t) \\
dr_T(t)/dt &= R_{V_H}(t)R_L(t)R_{T_2} + R_{V_C}(t)R_L(t)R_{T_3}(t) - r_T(t) \\
dr_{V_C}(t)/dt &= R_{F_C}(t)R_{T_5}(t) + R_T(t)R_L(t)R_{T_3}(t) - r_{V_C}(t) \\
dr_{T_0}(t)/dt &= \frac{1}{2}(T_0 - 1)R_{F_O}(t)R_L(t) - r_{T_O}(t) \\
dr_{T_1}(t)/dt &= \frac{1}{2}(T_1 - 1)R_{F_O}(t)R_{F_I}(t)R_L(t) - r_{T_1}(t) \\
dr_{T_2}(t)/dt &= \frac{1}{2}(T_2 - 1)R_T(t)R_{V_H}(t)R_L(t) - r_{T_2}(t) \\
dr_{T_3}(t)/dt &= \frac{1}{2}(T_3 - 1)R_T(t)R_{V_C}(t)R_L(t) - r_{T_3}(t) \\
dr_{T_4}(t)/dt &= \frac{1}{2}(T_4 - 1)R_{F_H}(t)R_{V_H}(t) - r_{T_4}(t) \\
dr_{T_5}(t)/dt &= \frac{1}{2}(T_5 - 1)R_{F_C}(t)R_{V_C}(t) - r_{T_5}(t) \\
dr_{T_6}(t)/dt &= \frac{1}{2}(T_6 - 1)R_{F_H}(t)R_{F_C}(t)R_{F_I}(t) - r_{T_6}(t)
\end{aligned}
$$

Fig. 6 shows the time evolution of the reliability measures of sensors and those of testing relations when there is a leakage in the pipe between F_I and F_H or between F_I and F_C. In this case, the constraint $F_I = F_H + F_C$(i.e. the testing relation T_6) will be violated.

It can be seen that although there is some decrease of the reliability measure of the sensor F_H, there is significant decrease of the reliability measure of the testing relation T_6. Thus, the process fault will be known. Fig. 7 shows the time evolution of the reliability measures of sensors and those of testing relations when the sensor F_H is faulty. Again, although there is some decrease of the reliability measure of tests related to the faulty sensor F_H, there is significant decrease of the reliability measure of the faulty sensor F_H. Thus, sensor fault can be concluded without difficulty.

5 Conclusion

One of the important information processing done by immune systems is the cooperative recognition by mutually connected units which lead to emergent recognition capability.

We developed a dynamic network architecture based on this idea of evaluation chain found in immune (idiotypic) netwrok. The dynamic network model is elaborated as sensor network that can diagnose not only sensor fault by evaluating reliability of data from sensors but also process fault by evaluating reliability of constraints among data. The sensor network dynamically reacts on the online data from sensors. It can self-identify the faulty sensor and

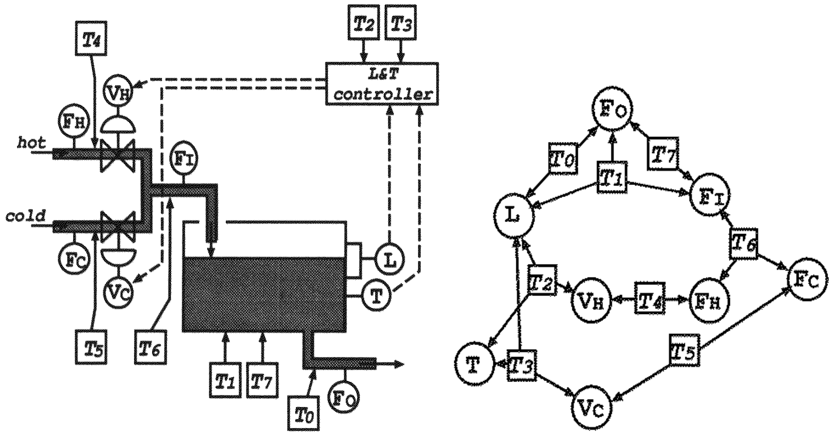

Figure 5: Tank with level and temperature controlled(left) and its sensor net(right)

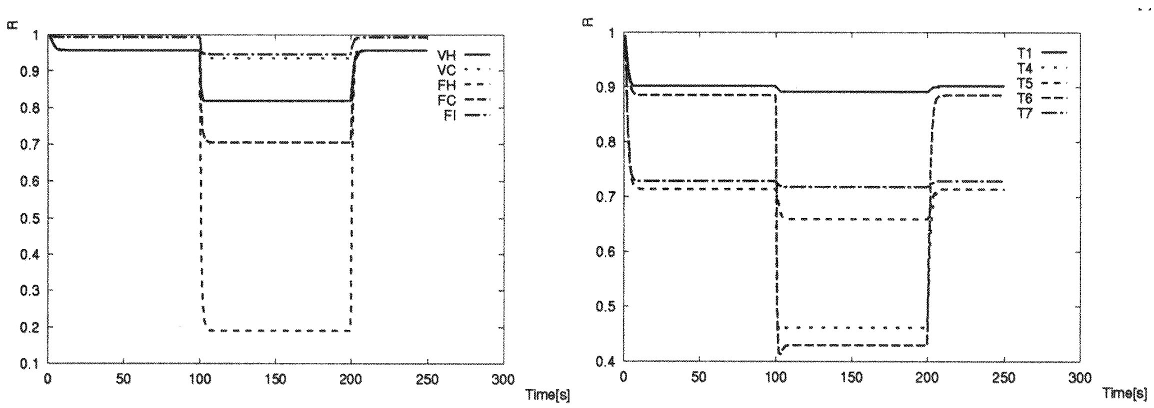

Figure 6: Time evolution of the reliability measures when there is a leakage in the pipe between F_I and F_H or between F_I and F_C

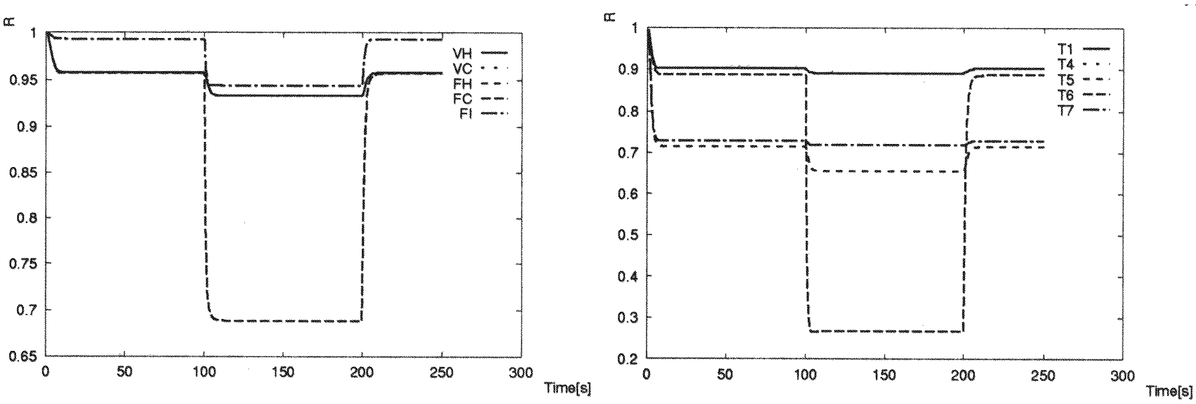

Figure 7: Time evolution of the reliability measures when the sensor F_H is faulty

faulty constraint by moving from an equilibrium to the other equilibrium reacting on the change of data and hence change on the relation among data.

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