Active Diagnosis by Self-Organization: An Approach by The Immune Network Metaphor

Yoshiteru Ishida
Graduate School of Information Science, Nara Institute of Science and Technology,
Ikoma, Nara, 630-01 Japan
(ishida@is.aist-nara.ac.jp)

Abstract

We propose a concept of active diagnosis that differs from the conventional passive (i.e. event-driven) diagnosis in temporal (diagnosis is carried out by always monitoring normal condition as opposed to identifying faulty only when abnormal condition is detected) sense as well as spatial (diagnosis is carried out by agents distributed in the sensor network) sense. As one way of realizing active diagnosis, we present immunity-based agents approach based on the self creating, monitoring, and maintaining feature of immune systems. We apply the approach to process diagnosis where the agents are defined on the sensor network. Each agent corresponding to sensor or process constraint evaluates a kind of reliability by communicating other agents. System level recognition of sensor/process fault can be attained by continuously and mutually monitoring and maintaining consistency among sensor values and process constraints.

1 Introduction

Diagnosis based on qualitative constraints (expressed by graphically (e.g. [Iri *et al.* 80; Ishida 88]) or logically) have been studied extensively in several communities. One of the important aspect of diagnosis for dynamical systems (such as processing plants) would be that the abnormal state propagate rapidly through many parts, hence results in the pattern (normal/high/low; oscillation; stick etc.) of a large number of sensors (syndrome). The first thing to do may be filtering out unimportant sensor pattern and focusing on the key sensor pattern. We used qualitative reasoning to explain one sensor pattern from the other sensor pattern. In the qualitative diagnosis, by checking the consistency among sensor patterns, the sensor pattern that cannot be explained by the other sensor pattern will be focused, as in [Ishida 88].

There already has been proposed using the consistency monitoring and maintenance in the qualitative constraints among sensor values and process knowledge based on the metaphor of immune system [Ishida 90]. The main point of using the immune system metaphor is using agents (corresponding to immune related cells) that interact mutually, continuously, and dynamically. The immunity-based approach, thereby makes the consistency monitoring and maintenance possible in the dynamic environment where on-line data from sensors arrives dynamically. Another important aspect of the immunity-based approach is that it agrees with the concept of active diagnosis presented in this paper and hence it would be one way of realizing the active diagnosis.

The concept of active diagnosis may be briefly stated as: diagnosis that is attained by actively and continuously monitoring consistency among the current state and normal state for reference. Technologically, active diagnosis may be possible supported by the recent technological development in three fields: active sensing in the sensor technology, active agent in the network technology, and active data base in the data base technology. Diagnostic system may be divided into three subsystems: knowledge data base for diagnosis; sensor system that is interface between diagnostic system and target system for diagnosis; and inference system that diagnose target system based on the knowledge data base and sensor system. Innovation of active sensing, active agent, and active data base can support sensor system, inference system and knowledge data base, respectively.

2 Active Diagnosis and Immunity-Based Approach

Diagnosis, in general, is basically considered an *event-driven* task that is triggered by the event of fault and also it is based on the information in the pattern of abnormal (syndrome). However, as target system becomes information-intensive, the conventional *event-driven* approach may not be sufficient. We propose a concept of active diagnosis as opposed to the conventional passive diagnosis *(event-driven* diagnosis). The concept of active diagnosis is motivated by self-identification process of immune system; by recent argument of pro-activeness as an important element of agents [Wooldridge *et al* 94]; by the concept of *active data base;* and by the recent technological development of active sensing.

Active diagnosis may be characterized by the following requirements:

- Temporal requirement: Self monitoring must be carried out all the time, as opposed to only when some fault is detected.
- Spatial requirement: Monitoring/diagnosis is done by the agents working in a distributed manner in the sensor network.
- Functional requirement: It is biased relatively more to monitoring normal condition rather than to detecting abnormal condition.
- Consistency requirement: Consistency among data must be monitored, similarly to *active data base.* (But not like *active data base,* not only consistency among the knowledge in the knowledge data base for diagnosis but also consistency among the online data from the sensor and the knowledge must be monitored.)

Thus, active diagnosis may require more resources for computation and communication than the conventional passive diagnosis. Active diagnosis may be implemented based on the three technologies developed independently; active sensing for the instrumentation system of target system, active data base for the knowledge data base of diagnosis, and active agents on the sensor network. The technology of active sensing can be used for the temporal and functional requirement of active diagnosis; that of active agents for the spatial and functional requirement; and that of active data base for the consistency requirement. There may be many ways to realize the above active diagnosis. One way would be the immunity-based approach. Immune system is considered the self-identification process that continuously monitor self, discriminate self/non-self, and maintain identity materially [Tauber 94]. This essence of immune system agrees with the concept of *active diagnosis* that extends diagnosis from the event-driven task. Immune network (idiotypic network) theory was proposed by Jerne [Jerne 73], Further, learning model based on the idea of immune network has been studied [Farmer *et a*l. 86]. Learning model based on the neural network has been studied extensively (e.g. [Hopfield 82; Cohen & Grossberg 83]). Features of immune network we have tried to use may be summarized as follows.

- Recognition is done by distributed agents which dynamically interacts with each other in parallel. The agents carry redundant information.
- Each agent reacts based only on its own knowledge.
- 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 by disturbances on the network.

3 Dynamic Interaction Among Agents

Figure 1 shows the evaluation chain of five agents. Each agent tries to identify the identity (faulty/normal for diagnosis) other agents. State variable (r_i and its normalization R_i) indicating the identity of agents are assigned to each agent. Dynamical system is constructed by associating the time derivative of the state variable with state variables of other agents connected by the evaluation chain.

The continuous value R_i between 0 and 1, indicating faulty and normal of the agent respectively, is assigned to each agent. We call the value R_i calculated by the diagnostic models the reliability measure to distinguish it from probabilistic concept of reliability.

When the agents 4 and 5 are faulty, we have the test result as shown in Figure 1. A possible association corresponding to the evaluation chain would be the following dynamical system:

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

The concept of self-diagnosable model consisting of agents capable of testing other units is not new [Preparata *et al.* 67]. Simple voting at each agent does not work, since three agents 2, 3 and 5 are all evaluated as faulty by two other agents and hence cannot be ranked in terms of the possibility of faulty. The significant feature of our model is that it can correctly diagnose the above case when the agents 4 and 5 are faulty by dynamically and continuously propagating evaluation through agents. The bottom line is that propagating and sharing information really counts, although instantaneous and local voting does not work.

We first assign the value between 0 and 1 (the initial value of the reliability measure) to each agent. Then, the reliability measures R_i follows by the next dynamical model.

$$dr_i(t)/dt = \sum_j T^+_{ji} R_j(t) - r_i(t) \qquad (1)$$

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

$$T^+_{ij} = \begin{cases} T_{ij} + T_{ji} - 2 & \text{tests i to j and j to i exist.} \\ T_{ij} + T_{ji} - 1 & \text{one of the tests i to j or j to i exists.} \\ 0 & \text{neither test i to j nor j to i exists.} \end{cases}$$

and T_{ij} in this model is as follows:

$$T_{ij} = \begin{cases} 1 & \text{i and j are normal.} \\ -1/1 & \text{i or j is faulty .} \\ 0 & \text{test from i to j does not exist.} \end{cases}$$

This model is the modified version of *black and white model* [Ishida 90; Ishida & Mizessyn 92] so that it keeps the information of ambiguous state of sensor reliability measure (the model (1) called *gray model*).

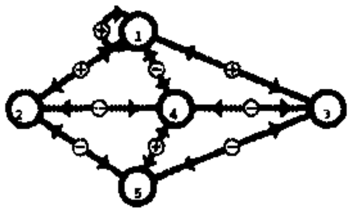

Figure 1: An example of evaluation chain

4 Agents on the Sensor Network

In this section, we relate the agents (that interact based on the dynamics presented in the previous section) to the sensor network for the application to process diagnosis. Agents will be elaborated gradually from a simple one for sensor diagnosis to a complex one for process diagnosis for the convenience of presentation.

4.1 Agents for sensor self-diagnosis

In process diagnosis, it is often the case that measurements such as temperature, pressure, flows, measured independently are related with each other. In other words, some of these measurements are redundant. Using the dependencies, many relations among sensors can be constructed. In the sensor network proposed in this section, each agent (corresponding to sensor) evaluates other agents using these relations, rather than just measuring the process values [ishida & Mizessyn 92].

In our approach, the agents of the network naturally correspond to the sensors (processes originated at sensors), and the relations are obtained from simple process knowledge. These relations between the values of the sensors have the following form:
Value of Variable A > Value of Variable B
From such a relation, we can build a link between the sensor monitoring the value A and that monitoring the value B, and say that agents of the previous sensors can evaluate with each other.

Figure 2 shows the sensor network of these twenty-two sensors. Sensors connected by bi-directional arc have mutually evaluating via above relations. Figure 3 shows a sensor diagnosis system for the preheating process of a cement plant. More relations (arcs) among sensor values, higher diagnostic performance is obtained. In constructing the sensor net, not only process knowledge but the experimental knowledge among sensor values is used to obtain enough relations for diagnosis. Further, in our implementation of sensor net builder, not only inequalities but equations with many funcitons can be used for the relations. In other application to a blast furnace of steal plant, about five hundred sensors (thermometers) are involved. By setting the relation more sensitive, the sensor net is known to be useful not only diagnosis but also monitoring global conditon of furnace.

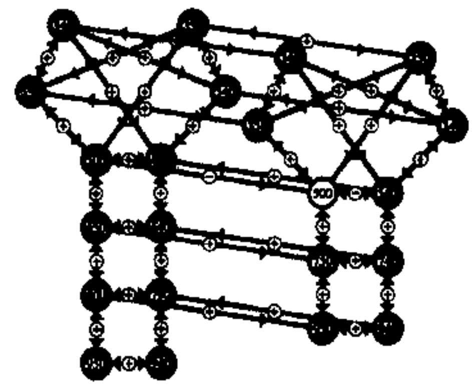

Figure 2: An Example of the Sensor Network for a Cement Process

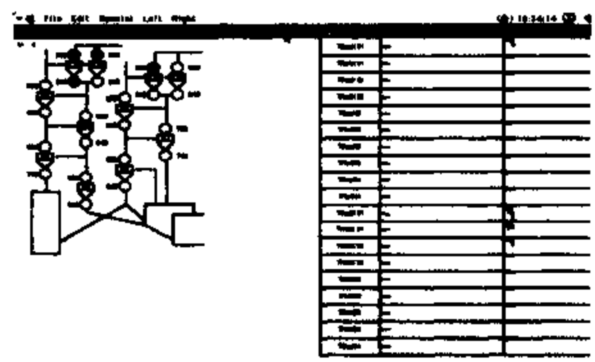

Figure 3: A Session of Sensor Network of the Cement Plant

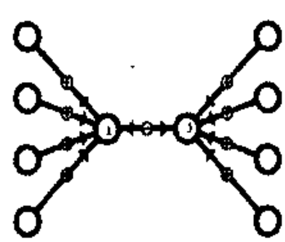

Figure 4: Situation when process fault occurs

4.2 Agents for process diagnosis

In this section, we review 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 amount to violation of the constraints. In fact, when process fault occurs, reliability measures of many sensors related to the constraints become low simultaneously [2]. In other words, when sensor values do not satisfy the constraint among these values, then it would imply that sensors or process corresponding to the constraint may be faulty. Figure 4 illustrates the situation when process fault corresponding to the constraint between the sensor i and j occurs. In the sensor net, when sensors are faulty few agents corresponding to the faulty sensors show low reliability measure. However, when process fault occurs, many agents show low reliability measure simultaneously, since process fault amounts to the violation of constraints among sensors.

Therefore, one natural way of detecting process fault by sensor net is to introduce agent and reliability measure for testing relation. (Another avenue may be using virtual sensors that would virtually monitor events and state which are not directly measured by the real sensors [ishida & Tokimasa]) Let RT_{IJ} denote the reliability measure of the test T_{ji}. Then the dynamical model (1) becomes as follows:

$$dr_i(t)/dt = \sum_j T_{ji}^{+} R_j(t) R_{T_{ji}} - r_i(t) \qquad (2)$$

$$dr_{T_{ji}}(t)/dt = T_{ji}^{+} R_j(t) R_i(t) - r_{T_{ji}}(t) \qquad (3)$$

The equation 2 is a modification naturally resulted by considering the effect of the reliability measure of the test T_{ji}. The change rate of the agent i; $dr_i(t)/dt$ should reflect all the opinions of other agents weighted not only with the reliability of these other agents but with those of their evaluations. The equation 3 comes from the fact that the evaluating relation is considered unreliable only when $T_{ji}, R_j(t)$ and $R_i(t)$ are contradictory; $T_{ji} = -1, R_j(t) = 1$ and $R_i(t) = 1$.

4.3 Agents with 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 relations (constraints) can be defined as:

$$T_k \equiv \begin{cases} 1 & \text{if } |f_k(\mathbf{y}(t), t)| \le \epsilon_k \\ -1 & \text{if } |f_k(\mathbf{y}(t), t)| > \epsilon_k \end{cases} \qquad (4)$$

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 2 and 3 can be modified as follows:

$$dr_i(t)/dt = \sum_{k, s_i \in S_k} \{T_k^{+} R_{T_k}(t) \prod_{\substack{j, s_j \in S_k \\ j \neq i}} R_j(t)\} - r_i(t) \quad (5)$$

$$dr_{T_k}(t)/dt = \frac{1}{2}(T_k^{+} - 1) \prod_{i, s_i \in S_k} R_i(t) - r_{T_{ji}}(t) \qquad (6)$$

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 Figure 5. The right of Figure 5 shows the sensor network of this process consisting of eight sensors and eight relations among the sensors. The model of this sensor network follows:

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

Figure 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 there is a significant decrease of the reliability measure of the testing relation T_6. Thus, the process fault will be known.

5 Related Work and Discussions

The continuous monitoring and maitaining consistency among agents by dynamic interactions may be comparable to the probabilistic reasoning [Pearl 86; Pearl 87] discussed in AI community. The main difference of the

[1] This is somewhat similar to the immune response where activation is propagated through huge amount of immune related cells when antigen is presented to the immune system.

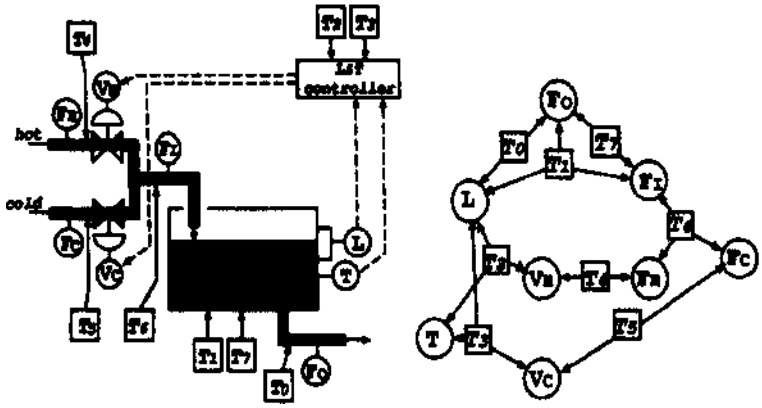

Figure 5: Tank with level and temperature controlled(left) and its sensor net(right)

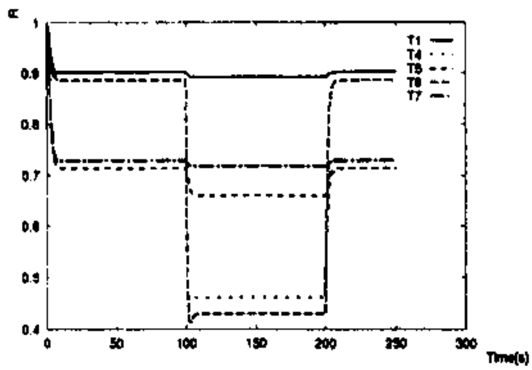

Figure 6: Time evolution of the reliability measures when there is a leakage in the pipe between F_l and F_H or between F_l and F_c

approach from the probabilistic reasoning is that it is for evaluating the reliability of the agent where each agent is capable of evaluating other agents, as opposed to evaluating simple event. It is possible to describe the event dependency of the reliability of agents by Bayesian network, however, the network would be cyclic hence preventing the usual probabilistic approach. Since the model can be simulated by a continuous differential equation, the method fits in the dynamic environment such as processing plants where the target system can be described by a differential equation. One demerit of our method is that we do not consider the axioms of probability. In fact, dynamics of reliability of each agent depends on the reliabilities of other adjacent agents, and unreliability does not appear in the dynamics. The dynamics of both reliability and unreliability of agents satisfying the constraint that their sum must be one would be a complicated differential equation. Another interesting problem is to recast the probabilistic reasoning on Bayesian network to the continuous differential equations, which would make simulation as well as stability analysis easier.

Data reconciliation studied in the control theory community also focus on finding a consistent interpretation among data from senosrs. *Data reconciliation* has been extensively studied for estimating the state of process filtering out noise by the state estimate methods [Toja & Biegler 91; Liebman *et al.* 92]. However, when there are gross errors such as process/sensor faults, the techniques does not apply, since the constraints used for estimation changes due to these gross errors. Some researches have been made for modifying the data reconciliation so that it will work even when gross errors may exist [Toja &. Biegler 91; Narasimhan & Harikumar 93a]. Extension of the immunity-based agent approach for process diagnosis so that it will work with measurement error by incorporating the data reconciliation has been proposed [Ishida & Tokimasa 96].

The characteristic of the approach to process diagnosis is that it admits only relative relation between process values without referring (although possible) to the absolute value of the process values. One merit is that the approach does not suffer from the shifting of all the process values (which occurs depending on the load to the process or the change of environment such as seasonal change), since the method only focuses on the consistency among sensor values and the process knowledge. Further, the change of some knowledge (embodiedy by agents) does not propagate to the other parts, since the relation among process values are rather independent from each other. When the model is implemented in a distributed processing environment, the evaluation of the reliability measure can be done in a fully distributed and autonomous manner in the sensor network.

The main difficulty of the approach discussed in this paper is to find enough relations between agents. Generally speaking, such relations could be obtained from physical theories (mass or heat balances, thermodynamical principles, etc.), mathematics (the value of a flow is always a positive value, a ratio is comprised between 0 and 1, ...), or by experimentations. More the sensors values are redundant, more there are testing relations. The performance of the diagnosis depends on the quality of the relations involved; the diagnosability depends on the number of distinct relations, and the reliability of the diagnosis depends on the reliability of the relations involved.

So far we have discussed under the assumption that interactions among agents are determined beforehand. In the future, more adaptive and flexible system should be aimed where these interactions are generated by the active agents themselves.

6 Conclusion

We have proposed active diagnosis as a new diagnostic paradigm which may be realizable using the recent development of active sensing, active data base and active agents. We extracted an immunity-based agent approach from self identifying/defining/maintaining feature of immune systems. Since the nature of immune system agrees with the concept of active diagnosis well, we point out that the approach would be one candidate for realizing an active diagnosis. As an immunity-based agent approach, on-line sensor-based diagnosis for process plant has been discussed by defining agent on the sensor network.

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