Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

On-Line Fault Inference for Large-Scale Event-Driven Systems based on Bayesian Network and Timed Markov Model

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Abstract: This paper presents an on-line fault inference, diagnosis ,and detection strategy for large-scale event-driven controlled systems. First of all, the controlled plant is decomposed into some subsystems, and the global diagnosis is formulated using the Bayesian Network (BN), which represents the causal relationship between the fault and observation in subsystems. The graph structure of the BN is constructed based on the control law adopted in the system. Second, the local diagnoser is developed using the conventional Timed Markov Model, and the local diagnosis results are used to specify the conditional probability assigned to each arc in the BN. By exploiting this decentralized architecture, the computational burden for the diagnosis can be distributed in the subsystems. As the result, the diagnosis for large scale practical system can be realized on-line. Finally, the usefulness of the proposed strategy is verified through some experimental results of an automatic transfer line.

1. INTRODUCTION

Event-driven controlled systems based on the Programmable Logic Controller (PLC) are widely used in many industrial processes. This type of control systems occupies more than eighty percent of the entire existing control systems. Recently, the demands for production facilities are shifting from high speed and highly efficiency to safety and high reliability. In order to meet these requirements, several strategies for fault diagnosis and recovery procedure have been proposed.

In the field of fault diagnosis of discrete-event systems, lots of deterministic approaches have been proposed [1, 2, 3, 4, 6, 7]. These approaches, however, are not applicable to the faults that do not explicitly change the order of the occurrence of events; for example faults in motors embedded in the production line that may reduce the speed of conveyor line. On the other hand, Lunze proposed a stochastic fault diagnosis framework based on system modeling with Timed Markov Model (TMM)[5]. This framework is applicable to the faults that do not affect on the order of the occurrence of events thanks to the stochastic expression of time interval between successive events in the TMM.

However, one of the significant drawbacks of TMM based approach is an explosion of the computational burden which comes from the enormous number of combinations of successive events. This drawback is particularly emphasized when the number of components in the entire system becomes large. In order to overcome the problem, the decentralized approach is highly recommended wherein the diagnosis is performed by each diagnoser together with the communication with other diagnosers.

This paper presents a new decentralized fault diagnosis strategy based on the local/global probabilistic inference. First of all, the controlled plant is decomposed into some subsystems, and the global diagnosis is formulated using the Bayesian Network (BN), which represents the causal relationship between the fault and observation over subsystems. The graph structure of the BN is constructed based on the control law applied to the system. Second, the local diagnoser is developed using the conventional Timed Markov Model (TMM), which was originally developed in [5], and the local diagnosis results are used to specify the conditional probability assigned to each arc in the BN. Finally, the usefulness of the proposed strategy is verified through some experimental results of an automatic transfer line which is widely used in the industrial manufacturing systems.

2. PROBLEM STATEMENT

First, we assume that the controlled system can be divided into n subsystems in consideration of the architecture of the hardware and/or software (see Section 6 for the detail). Furthermore, the output (event) sequence, which corresponds to the series of the ON/OFF of sensors and actuators, can be observed in each subsystem. Then, the event sequence for the k-th subsystem $\mathbf{E}_t^k(t_h)$ is defined as follows:

$$\mathbf{E}_t^k(t_h) = (e_0^k, t_0^k; e_1^k, t_1^k; \ldots; e_H^k, t_H^k)\ , t_H^k \le t_h \tag{1}$$

where e_H^k is the H-th event and t_H^k is the occurrence time of the H-th event in the k-th subsystem. In addition, the κ-th fault in the k-th subsystem is represented by r_κ^k, and a combination of faults for all subsystems is defined as "$\mathbf{r}$–*combination of faults for the entire system*". The set of

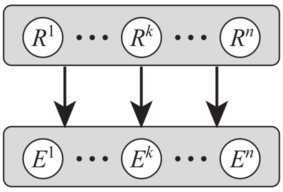


Fig. 1. Bipartite Bayesian Network for fault diagnosis

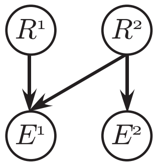


Fig. 2. Example of Bayesian Network

r–*combination of faults for the entire system*, $\mathcal{R}$ is defined by

$$\mathcal{R} = \{\mathbf{r} = (r^1, r^2, \cdots, r^n) | r^k \in \{r^k_1, r^k_2, \cdots, r^k_{f_k}\}\} \quad (2)$$

where f_k is the number of faults of k-th subsystem which includes normal (non-faulty) situation. This paper deals with the following diagnosis problem:

$$\text{Given : output sequence} \quad \mathbf{E}^1_t(t_h), \cdots, \mathbf{E}^n_t(t_h)$$
$$\text{Find : fault} \quad \mathbf{r} \in \mathcal{R}$$

3. GLOBAL DIAGNOSIS BASED ON BAYESIAN NETWORK

Bayesian Network (BN) is a probabilistic inference network which expresses qualitative causal relations between some random variables by a graph structure together with the conditional probability assigned to each arc [8].

In this section, the proposed global diagnosis method is explained. First, two types of random variables are defined. The first one is R^k which takes r^k_κ ($\kappa \in \{1, \cdots, f_k\}$) as a realization. The second one is the E^k which takes the observed event sequence as a realization. In the BN, the causal relationship between these random variables are defined using a graph structure wherein each node corresponds to each random variable. For the purpose of the fault diagnosis, we restrict the structure of the BN in the bipartite graph. One subset consists of the set of R^ks, and the other subset consists of the set of E^ks (Fig. 1). We also assume that there are no causal relationship between nodes in the same subset. The development of an appropriate graph structure must be made by considering the physical and logical interactions between subsystems. In Section 6, some algorithms are introduced to construct the graph structure of the BN based on the control law applied to the system. The fault diagnosis can be realized by calculating the occurrence probability of each fault conditioned by the observed event sequence:

$$P(R^k = r^k_i | E^1 = \boldsymbol{E}^1_t(t_h), \cdots, E^n = \boldsymbol{E}^n_t(t_h)).$$

Figure 2 shows the example of the BN for fault diagnosis. The occurrence probability of the fault in the subsystem 1 can be systematically calculated as follows: First, the joint probability distribution (JPD) is uniquely decided based on the graph structure.

$$P(R^1, R^2, E^1, E^2) = P(R^1)P(E^1|R^1, R^2)P(R^2)P(E^2|R^2). \quad (3)$$

Then, the occurrence probability of the fault in the subsystem 1 is calculated by marginalizing the JPD. For example, the fault occurrence probability of the fault r^1_α in the subsystem 1 is calculated as follows:

$$\begin{aligned} &P(R^1 = r^1_\alpha | E^1 = \mathbf{E}^1_t(t_h), E^2 = \mathbf{E}^2_t(t_h)) \\ &= \frac{1}{Z}\Big\{P(R^1 = r^1_\alpha)\sum_{R^2} P(E^1 = \mathbf{E}^1_t(t_h) | R^1 = r^1_\alpha, R^2) \\ &\quad \times P(R^2)P(E^2 = \mathbf{E}^2_t(t_h)|R^2)\Big\} \end{aligned} \quad (4)$$

where Z is normalized term and is represented as (5).

$$\begin{aligned} Z = &\sum_{R^1} P(R^1) \sum_{R^2} P(E^1 = \mathbf{E}^1_t(t_h)|R^1, R^2) \\ &\times P(R^2)P(E^2 = \mathbf{E}^2_t(t_h)|R^2). \end{aligned} \quad (5)$$

In (4), the term $P(E^1 = \mathbf{E}^1_t(t_h)|R^1 = r^1_\alpha, R^2)$ represents the conditional probabilities assigned to the corresponding arc. This conditional probability can be calculated using the local diagnosis results and the Bayesian estimation (see section 5.1 for detail). Also, the prior probabilities (for example $P(R^1 = r^1_\alpha)$ in (4) are supposed to be given in advance.

4. LOCAL DIAGNOSIS BASED ON TMM

4.1 Timed Markov model

For the local diagnosis, the relationship between two successive events observed in the corresponding subsystem are represented by means of a Timed Markov Model (TMM). The TMM is one of the Markov model wherein the state transition probabilities depend on time. In other words, state transition probabilities vary according to the time interval between two successive events. In the following, representation of the event driven system based on the TMM is briefly described [5].

First of all, the set of fault random variables which are connected to the random variable E^k in the BN is defined and denoted by $R^{k_1}, R^{k_2}, \cdots, R^{k_{m_k}}$ where m_k is the number of the fault random variables (for example, R^1, R^2 for E^1, and R^2 for E^2 in Fig.2). Then, a combination of these realizations is defined as "$\mathbf{r}^k$*–combination of faults for the k-th subsystem*". Furthermore, the set of these is denoted by

$$\mathcal{R}^k = \{\mathbf{r}^k = (r^{k_1}, r^{k_2}, \cdots, r^{k_{m_k}}) | r^k \in \{r^k_1, r^k_2, \cdots, r^k_{f_k}\}. \quad (6)$$

Roughly speaking, $\mathbf{r}^k$ consists of the realization of the faults which affect on the measurement of the k-th subsystem E^k. For example, in Fig. 2, $\mathbf{r}^1 = (r^1, r^2)$, and $\mathbf{r}^2 = (r^2)$. Based on definition of the $\mathbf{r}^k$, the following two functions are defined to specify the stochastic characteristics in the TMM.

Definition 1. $f_{e^k_{H+1}e^k_H}(\mathbf{r}^k, \tau)$ represents a probability density function for the time interval τ under the situation that the fault $\mathbf{r}^k$ exists. Note that τ is a time interval between two successive events e^k_{H+1} and e^k_H in the k-th subsystem.

Definition 2. $F_{e^k_H}(\mathbf{r}^k, t_h)$ represents a probability distribution function at the sampling time t_h that the event e^k_{H+1} does not occur within $t_h - t^k_H$ after the event e^k_H has

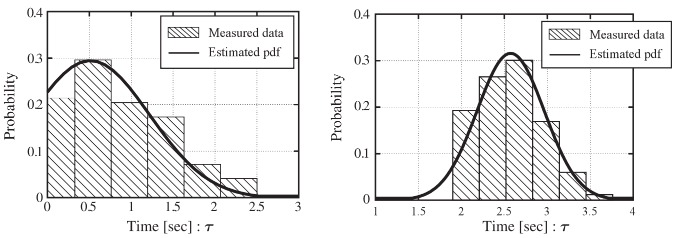


Fig. 3. Example of measured data and estimated probability density function $f_{e^k_{H+1}e^k_H}(\mathbf{r}^k, \tau)$

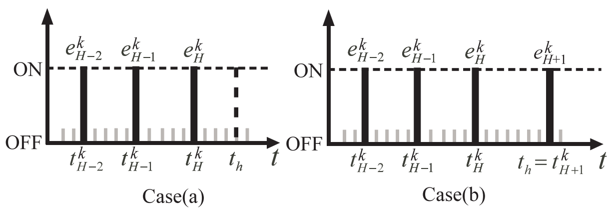


Fig. 4. Time and events in the cases (a) and (b)

occurred at t^k_H under the situation that the fault $\mathbf{r}^k$ exists. $F_{e^k_H}(\mathbf{r}^k, \tau^k)$ is represented as follows:

$$F_{e^k_{H+1}e^k_H}(\mathbf{r}^k, t_h) = \int_0^{t_h - t^k_H} f_{e^k_{H+1}e^k_H}(\mathbf{r}^k, t)dt, \tag{7}$$

$$F_{e^k_H}(\mathbf{r}^k, t_h) = 1 - \sum_{e^k_{H+1} \in \mathcal{E}^k} F_{e^k_{H+1}e^k_H}(\mathbf{r}^k, t_h) \tag{8}$$

where $\mathcal{E}^k$ is the set of events that occur in the k-th subsystem.

Then, relationship between two successive events observed in the subsystem can be described by specifying the probability density functions. Figure 3 is examples of the probability density function $f_{e^k_{H+1}e^k_H}(\mathbf{r}^k, \tau)$ which can be estimated based on the operating data of the objective system [9]. These functions play essential role in the TMM based diagnosis, and must be identified in advance.

4.2 Local diagnosis method

The goal of the local diagnosis is to find the following fault occurrence probability based on the observation only of the k-th subsystem:

$$p^k_M(\mathbf{r}^k, t_h) \equiv P(R^{k_1} = r^{k_1}_{\kappa_1}, \cdots, R^{k_m} = r^{k_m}_{\kappa_m} | E^k = \mathbf{E}^k_t(t_h)). \tag{9}$$

Equation (9) represents an occurrence probability of the $\mathbf{r}^k$ conditioned by the observation in the k-th subsystem $\mathbf{E}^k_t(t_h)$. For the calculation of (9), the recursive algorithm has been developed in [5]. First, the following two cases must be distinguished:

Case(a): There is no event at time t_h.
Case(b): The $(H+1)$-th event e^k_{H+1} occurs at time t_h.

Figure 4 shows relations between time and events in the cases of (a) and (b). The diagnosis begins with no information on the existence of the fault, i.e. the initial probabilities are given by

$$p^k_M(\mathbf{r}^k, 0) = \frac{1}{n_{\mathcal{R}^k}} \tag{10}$$

where $n_{\mathcal{R}^k}$ denotes the number of realizations in $\mathcal{R}^k$ and is calculated as $n_{\mathcal{R}^k} = \prod_{i=1}^{m_k} f_{k_i}$. Next, an auxiliary function $p^k_a(\mathbf{r}^k, t_h)$ is calculated as follows:
Case(a) : No event is observed at time t_h

$$p^k_a(\mathbf{r}^k, t_h) = F_{e^k_H}(\mathbf{r}^k, t_h) p^k_M(\mathbf{r}^k, t^k_H). \tag{11}$$

Case(b) : The $(H+1)$-th event e^k_{H+1} occurs at time t_h

$$p^k_a(\mathbf{r}^k, t_h) = f_{e^k_{H+1}e^k_H}(\mathbf{r}^k, t^k_{H+1} - t^k_H) p^k_M(\mathbf{r}^k, t^k_H). \tag{12}$$

The fault occurrence probability given by (9) is updated by

$$p^k_M(\mathbf{r}^k, t_h) = \frac{p^k_a(\mathbf{r}^k, t_h)}{\sum_{\mathbf{r}^k \in \mathcal{R}^k} p^k_a(\mathbf{r}^k, t_h)}. \tag{13}$$

5. OVERALL DIAGNOSIS PROCEDURE

5.1 Calculation of conditional probability in the BN

In the global diagnosis, the calculation of the conditional probability was the key computation (see (4) as an example). The conditional probabilities assigned to each arc (appearing in the marginalized JPD) in the BN can be calculated using (9) and Bayes theorem as follows:

$$P(E^k = \mathbf{E}^k_t(t_h) | R^{k_1} = r^{k_1}_{\kappa_1}, \cdots, R^{k_m} = r^{k_m}_{\kappa_m}) = \frac{p^k_M(\mathbf{r}^k, t_h) P(E^k = \mathbf{E}^k_t(t_h))}{P(R^{k_1} = r^{k_1}_{\kappa_1}, \cdots, R^{k_m} = r^{k_m}_{\kappa_m})} \tag{14}$$

where the prior probability $P(R^{k_1} = r^{k_1}_{\kappa_1}, \cdots, R^{k_m} = r^{k_m}_{\kappa_m})$ is given in advance. Note that the probability $P(E^k = \mathbf{E}^k_t(t_h))$ is not required to be calculated in advance because it is canceled out in (4). This equation implies that the global diagnosis can be executed by integrating results of the local diagnosis.

5.2 diagnosis procedure

The procedure of the proposed decentralized diagnosis is depicted in Fig. 5. First of all, observe the event sequence in each subsystem. Second, perform the local diagnosis in each subsystem based on the observed event sequence and calculate the conditional probabilities in the BN using (14). Then, calculate the fault occurrence probabilities by means of the BN (global diagnosis). Finally, select the greatest probability among all fault candidates in each subsystem. The diagnosis result for the k-th subsystem is the fault r^k_i that satisfies the following equation in the case that the fault candidates for the k-th subsystem are $\{r^k_1, \cdots, r^k_{f_k}\}$.

Diagnosis Result for the k-th subsystem

$$= \arg\max_{r^k_i} \Big(P(R^k = r^k_1 | E^1 = \mathbf{E}^1_t(t_h), \cdots, E^n = \mathbf{E}^n_t(t_h)), \cdots, P(R^k = r^k_{f_k} | E^1 = \mathbf{E}^1_t(t_h), \cdots, E^n = \mathbf{E}^n_t(t_h)) \Big). \tag{15}$$

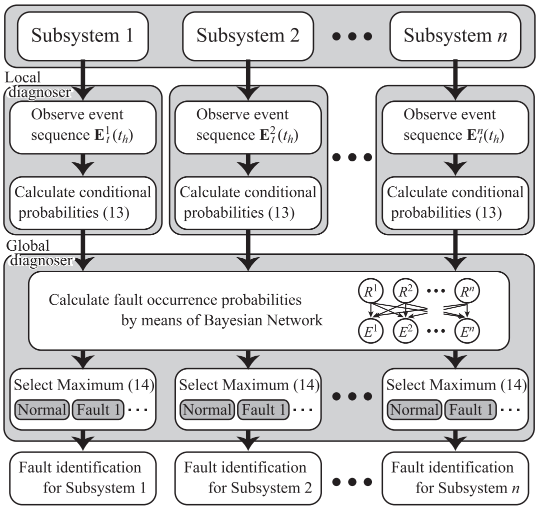


Fig. 5. Procedure of the decentralized fault diagnosis

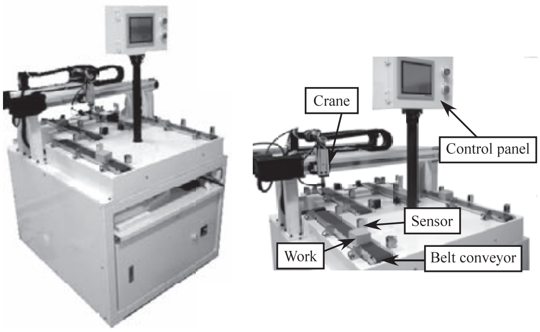


Fig. 6. Prototype of automatic transfer line

6. CONSTRUCTION OF GRAPH STRUCTURE

In this section, the graph structure of the BN is constructed based on the control law implemented on the logic controller. The construction process is explained step by step with an example.

The total system is supposed to be given by three tuples:

$$G = \{S, A, C\} \tag{16}$$

where S is the set of sensors, A is the set of actuators, and C is the set of control laws. Then, the overall system is divided into subsystems

$$G^k = \{S^k, A^k, C^k\},\ G = G^1 \cup G^2 \cup \cdots \cup G^n, \tag{17}$$

where A^k is a set of actuators of k-th subsystem, C^k is a set of control laws which activates A^k. S^k is a set of sensors which are included in the k-th subsystem.

Figure 6 shows an automatic transfer line used for experiment. Figure 7 shows the illustrative diagram of Fig. 6. This system transfers works to the unload station by means of four belt-conveyors (L1, L2, L3, L4: their length are 50cm) and two cranes (C1, C2). Sensors (S1 to S12) are installed at the beginning, end and center of each conveyor, and the sensor S13 is installed at the unload station. The events are observed when the work crosses the sensors, and are superimposed in Fig. 7. This transfer line system is decomposed into the six subsystems (Lane1, Lane2, Crane1, Lane3, Lane4, Crane2) as shown in Fig. 7.

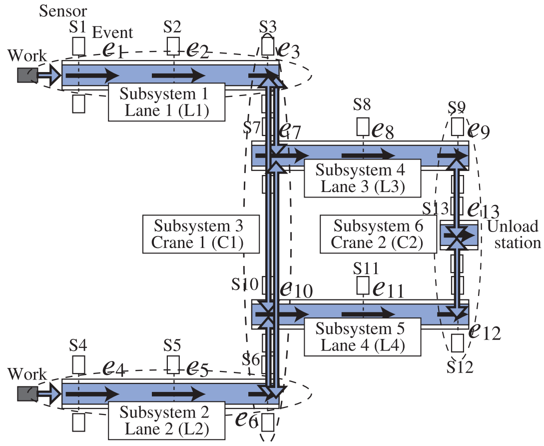


Fig. 7. Diagram of transfer line and definition of events

Table 1. Set of events in each subsystem

Lane1	$\mathcal{E}^1 = \{e_1, e_2, e_3\}$	Lane2	$\mathcal{E}^2 = \{e_4, e_5, e_6\}$
Crane1	$\mathcal{E}^3 = \{e_3, e_6, e_7, e_{10}\}$	Lane3	$\mathcal{E}^4 = \{e_7, e_8, e_9\}$
Lane4	$\mathcal{E}^5 = \{e_{10}, e_{11}, e_{12}\}$	Crane2	$\mathcal{E}^6 = \{e_9, e_{12}, e_{13}\}$

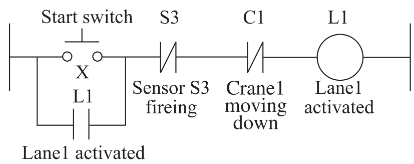


Fig. 8. Ladder logic of control law C^1

The set of events observed in each subsystem is specified in Table 1.

The implemented control low is summarized as follows:

- Each lane is interlocked with its terminal sensor (S3, S6, S9, and S12), and stops when the terminal sensor is fired.
- The lane continues to behave in the absence of the interlock.
- Crane1 and Crane2 transfer a work from Lane1 to Lane3 and from Lane2 to Lane4, respectively.
- The crane transfers a work to the other lane when the destination lane halts by the interlock

This control low can be described in the form of a ladder logic [10]. For example, Fig. 8 shows a ladder logic of C^1 wherein the operating condition of the Lane1 is expressed as $\mathrm{L1} = (\mathrm{X} \vee \mathrm{L1}) \wedge \overline{\mathrm{S3}} \wedge \overline{\mathrm{C1}}$. Based on representation as ladder logic, the causal relationships between sensors and actuators are expressed by a sensor actuator dependency (SAD) graph by the following algorithm:

Algorithm 1: Construction of SAD graph

Step 1 For all $k = 1, \cdots, n$, allocate the set of sensors S^k on the left side and the actuator A^k on the right side.

Step 2 For all $k = 1, \cdots, n$, draw a dashed arrow from A^k to S^h when the controller C^h includes the operating condition of A^k.

Step 3 For all $k = 1, \cdots, n$, draw a solid arrow from S^h to A^k when C^k includes the sensor $s^h \in S^h$ as the starting or halting condition of A^k,

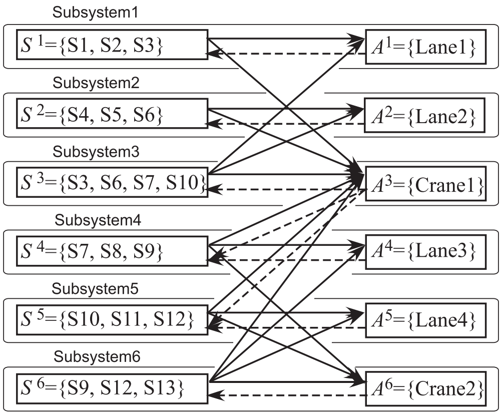


Fig. 9. Sensor actuator dependency (SAD) graph

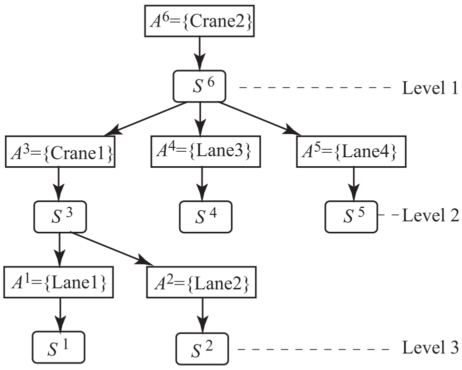


Fig. 10. Dependency tree for Crane2 (Subsystem 6)

The SAD graph is constructed as Fig. 9 from the ladder logic. In the next step, a dependency tree (DT) is produced from the SAD graph by the following algorithm:

Algorithm 2: Construction of DT

Step 1 Set $k = 1$.
Step 2 Set $l = 1$.
Step 3 Allocate S^h under A^k and set the level of S^h to be l if S^h is connected to A^k by a dashed arrow in the SAD graph and has not appeared in the level less than l.
Step 4 Allocate A^m under S^h in level l if A^m is connected to S^h by a solid arrow in the SAD graph and has not appeared in the level less than l.
Step 5 Go to Step 6 if no actuator exists in Step 4, else go to Step 3 with $l = l + 1$.
Step 6 End the algorithm if $k = n$, else go to Step 2 with $k = k + 1$.

The DT is produced as Fig. 10 from Fig. 9. In the last step, the structure of BN is produced from the DT by the following algorithm:

Algorithm 3: Construction of graph structure of BN

Step 1 For all $k = 1, \cdots, n$, allocate the nodes of the random variable R^k and E^k on the upper side and the lower side, respectively.
Step 2 For all $k = 1, \cdots, n$, draw an arrow from R^k to E^h for all h where S^h is included in the level 1 to L of A^k's DT.

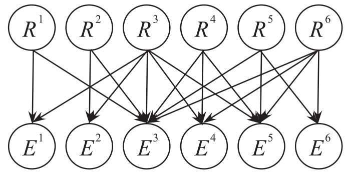
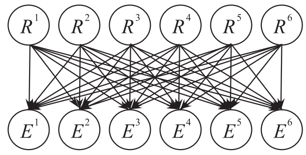


Fig. 11. Graph structure 1



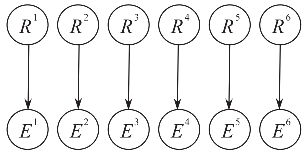


Fig. 12. Graph structure 2 Fig. 13. Graph structure 3

Table 2. Candidates of faulty condition

Symbol	Detail of fault
r_1^1	Lane1 is normal
r_1^2	Lane2 is normal
r_2^2	Speed of the belt-conveyor L1 is reduced
r_1^3	Crane1 is normal
r_2^3	Speed of the crane C1 is reduced
r_1^4	Lane3 is normal
r_1^5	Lane4 is normal
r_2^5	Speed of the belt-conveyor L2 is reduced
r_1^6	Crane2 is normal
r_2^6	Speed of the crane C2 is reduced

In this algorithm, parameter L is a threshold to take into consider the causal relationship between the subsystems into the graph structure of the BN. Figure 11 is the resultant graph structure when $L = 2$. Note that this graph structure is specified to diagnose faults in the actuators because the DTs which is used to construct the graph structure start from the actuators. In order to diagnose faults in the sensors, another graph structure needs to be constructed from DTs which start from the sensors. The DT starting from a sensor is easily constructed by modifying Algorithm 2.

7. APPLICATION TO AUTOMATIC TRANSFER LINE

In this section, the proposed diagnosis procedure is applied to the automatic transfer line depicted in Fig. 7. The diagnosis procedure is executed by means of three graph structures. Graph structure 1 depicted in Fig. 11 is derived by using the algorithm described in Section 6. Graph structure 2 depicted in Fig. 12 considers full connection, in other words, $L = \infty$. Graph structure 3 depicted in Fig. 13 considers the case that the fault in each subsystem influence only on the corresponding subsystem.

7.1 Candidates of fault

In this paper, we consider the candidates of fault in each subsystem specified in Table 2. For the lane, the "normal" implies the case that the speed of the belt-conveyor is between 7.8cm/sec and 8.6cm/sec, and the "Speed of the belt-conveyor is reduced" implies the case that the speed of the belt-conveyor goes down between 7.0cm/sec and 7.8cm/sec. Faults r_2^2 and r_2^5 may come from a fatigue of the actuator. For the crane, the "Speed of the crane is reduced" implies the case that it takes more 0.2 sec than the "normal" condition to transfer a work to the destination lane. Thus, $1 \times 2 \times 2 \times 1 \times 2 \times 2 = 16$ faulty cases are investigated for the entire system including cases that some faults occur simultaneously in some subsystems.

7.2 Experimental conditions

Experimental conditions are specified as follows:

- Works are provided to the Lane1 and Lane2 alternately with almost constant intervals (about 2 sec).
- Works do not exist in the system at time $t_h = 0$.
- The experiment is finished if ten works are transferred to the unload station.
- A sampling time for observation of events is 0.1 sec.

Under these experimental conditions, the event sequences are collected. The probability density functions (PDFs) for every combination of two successive events in each subsystem are estimated before fault diagnoses. In this paper, the PDFs are estimated through fifty trials per each faulty case in advance.

7.3 Results of fault diagnosis

We have performed the experiments ten times for each faulty case, i.e., the total number of the trials is $10 \times 16 = 160$. The statistics of the diagnosis results are listed in Table 3. In Table 3, the "Success Rate" means the rate that the all diagnosis results coincide with the actual fault situation, the "Wrong Diagnosis Rate" means the rate that at least one of the subsystems had wrong diagnosis result, and the "Undetection Rate" means the rate that the diagnosis result was "normal" in spite of existence of the fault.

The success rate of the graph structure 1 and 2 are both increased compared with the structure 3. This reason is considered that the causal relationships between the subsystems are ignored in the structure 3. The structure 2 is better than the structure 1 from viewpoint of the success rate, however, the number of the PDFs of the structure 1 is almost half of that of the structure 2. Because the number of the PDFs is concerned with the computational burden for the realtime inference, the structure 1 can be realized with less computational burden than the structure 2. The computing time in Table 3 is the resultant time of diagnosing 150.5 second data, and which was obtained from the maximum computing time of the local diagnosers and the computing time of the global diagnoser. The level threshold L of Algorithm 3 should be selected from the both viewpoint of the success rate and the computational burden.

Table 3. Comparison of diagnosis results among graph structure: Computing time for diagnosing 150.5sec data

Graph structure	Success	Wrong	Undetected	Number of PDFs	Computing time
1	91.3%	8.1%	0.6%	482	21.0sec
2	94.4%	3.8%	1.9%	976	51.7sec
3	86.3%	7.5%	6.3%	104	1.8sec

8. CONCLUSIONS

This paper has presented a new decentralized fault diagnosis strategy for the event-driven controlled systems. First of all, the controlled plant was decomposed into some subsystems, and the global diagnosis was formulated using the Bayesian Network (BN), which represents the causal relationship between the fault and observation between subsystems. The graph structure of the BN was constructed based on the control law applied to the system. Second, the local diagnoser was developed using the conventional Timed Markov Model (TMM), and the local diagnosis results were used to specify the conditional probability assigned to each arc in the BN. By exploiting the decentralized diagnosis architecture, the computational burden for the diagnosis can be distributed to the subsystems. As the result, large scale diagnosis problems in the practical situation can be solved. Finally, the usefulness of the proposed strategy has been verified through some experimental results of an automatic transfer line.

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