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Fault-tolerant Sensor Network based on Fault Evaluation Matrix and Compensation for Intermittent Observation

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***Abstract*— This paper deals with a fault-tolerant sensor network configuration problem for a target navigation.**

A sensor network system consists of many sensor nodes and its network connections. Each sensor node can exchange information by wireless communication. A disadvantage of this system's property is that if there is an inaccurate information from a faulty sensor, this information has possibilities to be diffused to other sensors. Therefore, it is important to reduce effects of the inaccurate information by detecting a faulty sensor as possible as we can. And moreover, in feedback control system for navigation, we have to consider a lack of control inputs which happens depending on each sensor's intermittent observation. We propose two estimation methods for constructing a fault tolerant system. Specifically, we propose a fault-evaluation matrix for the fault detection, and we define a novel switching rule for shutting off inaccurate measurement data. Then we also propose a compensation algorithm for the problem of intermittent observation by using an estimated observation value.

I. Introduction

Wireless sensor networks systems have attracted more attention in recent years. This system has been applied to collecting information in a wide range (for example, disaster planning, environmental monitoring, security etc.) by using dynamic network reconfiguration and information exchange between sensor nodes. And also, a sensor network can be applied to state estimation for a moving target [1]–[3]. Moreover, in this paper, we would like to construct a navigation system based on feedback control via a sensor network [4]. Sensor networks are also superior in terms of information integration functions. That is because sensor networks can improve measurement accuracy through the information exchange and sharing. Meanwhile, the disadvantage of this system's property is that if there is an inaccurate information from a faulty sensor [5], this information has possibilities to be diffused to other sensors, and one sensor's fault causes adverse effects on other not faulty sensors' estimation results. Hence, to achieve the navigation based on a state feedback control, we have to dynamically detect the failure occurrence and reduce adverse influence of the sensor fault on the state estimation. And furthermore, in feedback control system, we have to consider a lack of control inputs which is caused on each sensor's intermittent observation [6] and communication failure. Therefore, in parallel with fault detection, we have to compensate for the intermittent observation.

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About a construction of fault-tolerant sensor networks, the fault detection problem of targets which bases on comparison of the sensor measurement is discussed by [7]. But they don't consider the reliability of the sensor itself which observes the target's state. Sensors' fault are considered by [8], but this paper didn't use the fault detection result to reduce the effect of fault signals on estimation. Meanwhile, under the intermittent observation, analysis of state estimation property based on KF is discussed by [9], [10]. However, in those papers, they don't consider the compensation for the missing observation data.

In this paper, we assume such a fault that a random fault signal is mixed into the sensor's measurement value and occur the biased error. At first, we discuss a fault detection problem on sensors measurement by using the observation error covariance. Then, by combining the fault detection result with switching KF in [10], we propose a state estimation algorithm which suppresses the effect of inaccurate observation value against an estimation result. Secondly, by using an imputation method with an estimated observation value, we propose an estimation algorithm for the compensation problem of intermittent observation. Finally we show experimental results to analyze effectiveness of these proposed methods.

In the following section, we first describe the problem formulation, and define the model of the sensor and the plant which is the controlled object. Then we explain about the detail of two fault-tolerant problems which we consider in this paper. Next, we propose and analyze the fault detection switching algorithm and the compensation algorithm for the intermittent observation respectively. Finally we show the experimental setup and outcome of the experiment, and discuss an effectiveness of the proposed methods.

II. PROBLEM FORMULATION

A. Plant and Sensor Nodes

We consider the feedback control system via a sensor network for dynamic target tracking and guidance in Fig.1.

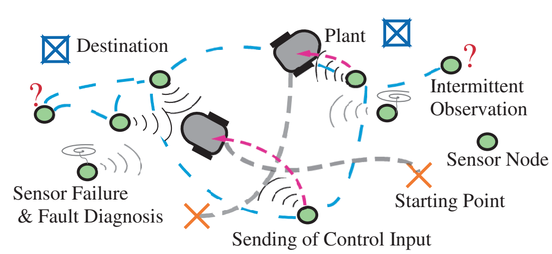

Fig. 1. Problem Formulation

Assume that there exist N_1 plants ($N_1 \geq 1$) and N_2 sensor nodes ($N_2 \geq 2$), each of which is given by following equations (1), (2).

$$x_{k+1}^i = Ax_k^i + Bu_k^i + w_k^i \quad i = 1, \ldots, N_1 \tag{1}$$

where $x_k^i \in \mathbb{R}^n$ is a state of ith plant, $u_k^i \in \mathbb{R}^r$ is a control signal of ith plant, $w_k^i \in \mathbb{R}^n$ is a process noise assumed to be white Gaussian noise with variance $W^i \geq 0$.

$$y_k^{ji} = C_k^{ji} x_k^i + D_k^{ji} v_k^j + F_k^j g_k^j \quad j = 1, \ldots, N_2 \tag{2}$$

where $y_k^{ji} \in \mathbb{R}^m$ is a measurement output of jth sensor node, $v_k^j \in \mathbb{R}^p$ is a measurement noise assumed to be white Gaussian noise with variance $V^j \geq 0$ respectively. We assume each sensor j can observe only one plant's state x_k^i in every time step. Additionally, $D_k^{ji} := D^j(x_k^i) \in \mathbb{R}^{m \times p}$ is a state dependent function([11]) which depends on distance between the jth sensor node and ith plant, and $F_k^j \in \mathbb{R}^{m \times n}$, $g_k^j \in \mathbb{R}^n$ is a random failure signal generated by malfunction of the sensor. If it becomes $F_k^j g_k^j > 0$, the jth sensor becomes faulty by having a bias on the measurement output y_k^{ji}. Now we assume (1) and (2) satisfy following assumptions 1-3.

Assumption 1:

i) $E\{v_k^j v_s^{jT}\} = E\{w_k^i w_s^{iT}\} = 0 \ (k \neq s)$
ii) $E\{v_k^j w_k^{iT}\} = 0$, $E\{g_k^j w_k^{iT}\} = 0$, $E\{g_k^j v_k^{jT}\} = 0$
iii) $E\{x_0^i w_k^{iT}\} = 0$, $E\{x_0^i v_k^{jT}\} = 0$, $E\{x_0^i g_k^{jT}\} = 0$
iv) $E\{w_k^i w_k^{iT}\} = W_k^i > 0$, $E\{v_k^j v_k^{jT}\} = V_k^j > 0$, $E\{[g_k^j - E(g_k^j)][g_k^{jT} - E(g_k^j)]\} = G_k^j \geq 0$

Assumption 2: $(A, W^{\frac{1}{2}})$ is reachable.

Assumption 3: (C_k^j, A) is detectable.

where x_0^i is a initial state of the ith plant. This system uses the following state feedback as a control input.

$$u_k^i = L\hat{x}_{k|k}^{ji} \tag{3}$$

where $\hat{x}_{k|k}^{ji} \in \mathbb{R}^n$ is an estimate of the ith plant computed by the sensor node j, and $L \in \mathbb{R}^{r \times n}$ is a feedback gain that had been previously calculated by solving the LQG control problem.

B. Definition of Fault Tolerance Problems

In this paper, we define two types of fault tolerance problems as follows

Problem 1: Under the assumptions 1-3 are held, and the output of each sensor is given by equation (2) at time step k, then detect the sensor which satisfied $F_k^j g_k^j > 0$ and find the state estimation algorithm to minimize the effect of sensor failure by excluding the observation of the faulty sensor.

Problem 2: Under the assumptions 1, 2 are held, and the jth sensor's output y_k^{ji} becomes intermittent, then estimate an observation $\hat{y}_k^{ji}$ to satisfy the assumption 3 and find the state estimation algorithm to reduce the effect of intermittent observation.

The Problem 1 assumes a case that jth sensor has a less accurate observation output in time step k. And the Problem 2 assumes a case that there is no jth sensor observation output in time step k. In next section, we propose estimation algorithms based on KF to solve the Problem 1 and 2 respectively.

III. Fault Detection & Compensation for Intermittent Observation

A. Fault-Detection Switching

To solve the Problem 1 on dynamically, first we propose a Fault-Evaluation matrix M_k^{ji} to detect the failure signal $F_k^j g_k^j$ in equation (2).

When we consider estimation process in time step k, we define sensor nodes which sent the control signal to the plant at previous time step $k-1$ as $j_{k-1}^f = j_k^0$. Assume that $P_{k|k-1}^{j^0 i}$, $\hat{x}_{k|k-1}^{j^0 i}$ are predicted estimate values computed by j_k^0 in time step $k-1$, then the estimation algorithm of the sensor j_k^0 can be written as by following equations.

$$\begin{aligned} \hat{x}_{k+1|k}^{j^0 i} &= A\hat{x}_{k|k}^{j^0 i} + Bu_k^{j^0 i} \\ \hat{x}_{k|k}^{j^0 i} &= \hat{x}_{k|k-1}^{j^0 i} + \gamma_k^{j^0 i} K_k^{j^0 i} \{\tilde{y}_k^{j^0 i}\} \\ \tilde{y}_k^{j^0 i} &= y_k^{j^0 i} - C_k^{j^0 i} \hat{x}_{k|k-1}^{j^0 i} \end{aligned} \tag{4}$$

$$\begin{aligned} P_{k+1|k}^{j^0 i} &= AP_{k|k}^{j^0 i} A^T + W_k \\ P_{k|k}^{j^0 i} &= P_{k|k-1}^{j^0 i} - \gamma_k^{j^0 i} K_k^{j^0 i} C_k^{j^0 i} P_{k|k-1}^{j^0 i} \end{aligned} \tag{5}$$

$$\begin{aligned} K_k^{j^0 i} &= P_{k|k-1}^{j^0 i} C_k^{j^0 iT} \{S_k^{j^0 i}\}^{-1} \\ S_k^{j^0 i} &= cov(\tilde{y}_k^{j^0 i}) \end{aligned} \tag{6}$$

The above equations (4)-(6) are based on the switching KF estimation algorithm proposed in the paper [10], and these state estimation process are switched dynamically by the switching parameter $\gamma_k^{j^0 i} \in \mathbb{R}^1$. If $\gamma_k^{j^0 i} = 1$, the above estimation algorithm works as a standard KF, and if $\gamma_k^{j^0 i} = 0$, the obtained estimation results at time step k are independent of the sensor j^0's observation. In the paper [10], $\gamma_k^{j^0 i}$ was switched in random order by stochastic variable, Hence it is not the problem of determining the reliability of the sensor observations. Thus, in this paper, we propose a novel switching rule by using the Fault-Evaluation matrix to establish an estimation algorithm which depends on the results of sensor fault detection. When the sensor j^0 observes the i th plant at time step k, to determine the reliability of this observation, we define the Fault-evaluation matrix M_k^{ji} as following.

Fault-Evaluation Matrix

$$\begin{aligned} M_k^{j^0 i} :=& S_k^{j^0 i} - C_k^{j^0 i} P_{k|k-1}^{j^0 i} C_k^{j^0 iT} - \hat{D}_k^{j^0 i} \hat{V}_k^{j^0 i} \hat{D}_k^{j^0 iT} \\ =& D_k^{j^0 i} V_k^{j^0 i} D_k^{j^0 iT} - \hat{D}_k^{j^0 i} \hat{V}_k^{j^0 i} \hat{D}_k^{j^0 iT} + F_k^{j^0} G_k^{j^0} F_k^{j^0 T} \\ &+ E\{C_k^{j^0 i} \eta^{j^0 i} (g_k^{j^0 T} F_k^{j^0 T} - E[g_k^{j^0 T} F_k^{j^0 T}]) \\ &- E[C_k^{j^0 i} \eta^{j^0 i}](g_k^{j^0 T} F_k^{j^0 T} - E[g_k^{j^0 T} F_k^{j^0 T}])\} \\ &+ E\{F_k^{j^0} g_k^{j^0} (\eta^{j^0 iT} C_k^{j^0 iT} - E[\eta^{j^0 iT} C_k^{j^0 iT}]) \\ &- E[F_k^{j^0} g_k^{j^0}](\eta^{j^0 iT} C_k^{j^0 iT} - E[\eta^{j^0 iT} C_k^{j^0 iT}])\} \end{aligned} \tag{7}$$

where $\eta^{j^0 i} := x_k^i - \hat{x}_{k|k-1}^{j^0 i}$is an estimate error of the sensor j^0, $\hat{D}_k^{j^0 i} := D_k^{j^0 i}(\hat{x}_{k|k-1}^{j^0 i})$ is a estimation of the state dependent function. And $\hat{V}_k^{j^0 i}$ is a covariance of an estimated noise $\hat{v}_k^{j^0 i}$ which is assumed to be white Gaussian noise.

Excluding the measurement noise covariance and its estimated value, the equation (7) is consist of failure signal's covariance and correlations with other parameters and $F_k^j g_k^j$. If there is not sensor fault($F_k^j g_k^j = 0$), the estimate error covariance in (5) converges to a finite value under the assumption 1-3. Then convergence of $x_k^i - \hat{x}_{k|k-1}^{j^0 i}$ means a convergence of $D_k^{j^0 i} V_k^{j^0 i} D_k^{j^0 iT} - \hat{D}_k^{j^0 i} \hat{V}_k^{j^0 i} \hat{D}_k^{j^0 iT}$, where each state dependent function $D_k^{j^0 i}$, $\hat{D}_k^{j^0 i}$ is based on x_k^i, $\hat{x}_{k|k-1}^{j^0 i}$ respectively. On the other hand, if there is a sensor fault, the value of $M_k^{j^0 i}$ is changed depending on the presence of $F_k^{j^0} G_k^{j^0} F_k^{j^0 T}$. We detect dynamically the failure signal $F_k^j g_k^j$ in sensor j_k^0 by using this Fault-Evaluation matrix $M_k^{j^0 i}$. And furthermore, based on this detection result, the obtained estimation results at time step k become independent of the sensor j^0's observation. Here, in order to suppress the reference of observed value $y_k^{j^0 i}$ including the failure, we propose the switching-rule for $\gamma_k^{j^0 i}$ as follows.

Fault-Detection Switching

$$\gamma_k^{j^0 i} := \begin{cases} 1 & \text{if } \mathcal{M}_{min} \leq \text{trace} M_k^{j^0 i} \leq \mathcal{M}_{max} \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

where $\mathcal{M}_{min}$, $\mathcal{M}_{max}$ are the thresholds for determining the magnitude of acceptable fault. In this paper, we have pre-set these thresholds offline. But if there exists fault detection result at previous time step $k-1$, we can also choose $\mathcal{M}_{min}$, $\mathcal{M}_{max}$ dynamically by referring $M_{k-1}^{j^0 i}$. Then the Fault-evaluation matrix and the switching-rule satisfy following properties.

Property 1: When we can assume that the ith plant's state x_k^i and estimate $\hat{x}_{k|k-1}^{j^0 i}$ are both uncorrelated with the sensor's failure signal $g_k^{j^0}$, the inequality $M_k^1 \leq M_k^2$ is satisfied under the relation $F_k^1 G_k^{j^0} F_k^{1T} \leq F_k^2 G_k^{j^0} F_k^{2T}$.

Proof: The estimation result was uncorrelated with effect of failure signal at previous time step by using our proposed fault detection, thus we can assume x_k^i, $\hat{x}_{k|k-1}^{j^0 i}$ is independent of $g_k^{j^0}$. If this deuncorrelation is held, the equation (7) is simplified as (9). In the equation (9), $F_k^{j^0} G_k^{j^0} F_k^{j^0 T} \geq 0$ is the only parameter which depends on the sensor fault. Hence magnitude relation of the Fault-evaluation matrices is equivalent to the magnitude relation of failure signals.

$$\begin{aligned} M_k^{j^0 i} &= S_k^{j^0 i} - C_k^{j^0 i} P_{k|k-1}^{j^0 i} C_k^{j^0 iT} - \hat{D}_k^{j^0 i} \hat{V}_k^{j^0 i} \hat{D}_k^{j^0 iT} \\ &= D_k^{j^0 i} V_k^{j^0 i} D_k^{j^0 iT} - \hat{D}_k^{j^0 i} \hat{V}_k^{j^0 i} \hat{D}_k^{j^0 iT} \\ &+ F_k^{j^0} G_k^{j^0} F_k^{j^0 T} \end{aligned} \quad (9)$$

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Property 2: When the sensor j_k^0 has a sensor fault in the observation, the estimation error covariance in equation (5) is larger than the covariance in equation (10) and an inequality $\bar{P}_{k|k}^{j^0 i} \leq P_{k|k}^{j^0 i}$ is satisfied.

$$\bar{P}_{k|k}^{j^0 i} = P_{k|k-1}^{j^0 i} - K_k^{j^0 i} C_k^{j^0 i} P_{k|k-1}^{j^0 i} \quad (10)$$

Proof: When we use the switching KF and the switching parameter satisfies $\gamma_k^{j^0 i} = 0$ by fault detection, we can see the relation $P_{k|k}^{j^0 i} = P_{k|k-1}^{j^0 i}$ by 5). In this case, the estimation error covariance becomes monotone increasing over time. Then if the failure signal in j_k^0 continues to obstruct a measurement, $P_{k+1|k}^{j^0 i}$ becomes divergence as $k \to \infty$. In contrast, the case using a standard KF and holding the assumption 3, the estimation algorithm satisfies $\bar{P}_{k|k}^{j^0 i} < P_{k|k-1}^{j^0 i}$. Therefore, even if $F_k^j g_k^j$ continues to obstruct, the estimation error covariance becomes finite over time.

$$\begin{aligned} y_k^{j^0 i} &= C_k^{j^0 i} x_k^i + D_k^{j^0 i} v_k^{j^0} + F_k^{j^0} g_k^{j^0} \\ &\fallingdotseq F_k^{j^0} g_k^{j^0} \; (F_k^{j^0} g_k^{j^0} \gg C_k^{j^0 i} x_k^i + D_k^{j^0 i} v_k^{j^0}) \end{aligned} \quad (11)$$

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B. Compensation for Intermittent Observation

In the previous section, we proposed the estimation algorithm with dynamic fault detection by using Fault-evaluation matrix and excluding faulty sensor. Our next attention is compensation for estimation result for the case there is no sensor observation available. Such compensation problem can be expressed as the Problem 2 described above. Under a setting of the Problem 2, if we use standard KF for the sensor j^0, the estimation result is not updated, hence $P_{k|k}^{j^0 i} = P_{k|k-1}^{j^0 i}$. Against this method, to solve the Problem 2, we propose the following estimation algorithm.

Estimation Algorithm with Compensation

$$\begin{aligned} P_{k|k}^{j^0 i} &:= \{(P_{k|k-1}^{j^0 i})^{-1} \\ &+ \alpha_k^{-2} C_k^{j^0 iT} (\hat{D}^{j^0 i} \hat{V}_k^{j^0 i} \hat{D}^{j^0 iT})^{-1} C_k^{j^0 i}\}^{-1} \end{aligned} \quad (12)$$

$$\begin{aligned} K_k^{j^0 i} &:= P_{k|k-1}^{j^0 i} C_k^{j^0 iT} \\ &\times \{C_k^{j^0 i} P_{k|k-1}^{j^0 i} C_k^{j^0 iT} + \alpha_k^2 \hat{D}^{j^0 i} \hat{V}_k^{j^0 i} \hat{D}^{j^0 iT}\}^{-1} \end{aligned} \quad (13)$$

The equation (12) shows compensation by estimation $\hat{D}_k^{j^0 i} \hat{V}_k^{j^0 i} \hat{D}_k^{j^0 iT}$ for missing observation noise covariance $D^{j^0 i} V_k^{j^0 i} D^{j^0 iT}$, and equation (14) shows a state estimated value corresponding to the covariance in equation (12).

$$\hat{x}_{k|k}^{j^0 i} = \hat{x}_{k|k-1}^{j^0 i} + K_k^{j^0 i} (\tilde{\hat{y}}_k^{j^0 i} + l_k^{j^0 i}) \quad (14)$$

$$\begin{aligned} \hat{y}_k^{j^0 i} &= C_k^{j^0 i} \hat{x}_{k|k-1}^{j^0 i} + \hat{D}_k^{j^0 i} \hat{v}_k^{j^0 i} , \\ \tilde{\hat{y}}_k^{j^0 i} &= C_k^{j^0 i} x_k^i - \hat{y}_k^{j^0 i} \end{aligned} \quad (15)$$

$$l_k^{j^0 i} = (1+\alpha_k) \hat{D}^{j^0 i} \hat{v}_k^{j^0 i} - E\{C_k^{j^0 i} (x_k^i - \hat{x}_{k|k-1}^{j^0 i})\} \quad (16)$$

The equation (14) shows update of the state estimated value $\hat{x}^{j^0 i}_{k|k-1}$ by estimated measurement output $\hat{y}^{j^0 i}_{k}$ and $\alpha_k \in \mathbb{R}^1$ in (16) is a monotonically increasing function over time.

$$\alpha_k = \epsilon \alpha_{k-1} \ , \ \epsilon > 1 \tag{17}$$

Then the estimate error covariance in (12) satisfies following theorem 1.

Theorem 1: When sensor j^0_k can't get any measurement output y^0_k at time step k, $P^{j^0 i}_{k|k}$ and $P^{j^0 i}_{k|k-1}$ satisfy inequality relation $P^{j^0 i}_{k|k} \leq P^{j^0 i}_{k|k-1}$, where $P^{j^0 i}_{k|k}$ which is computed by proposed compensation method, $P^{j^0 i}_{k|k-1}$ which has not been updated since the previous time $k-1$. Additionally, $P^{j^0 i}_{k|k} = P^{j^0 i}_{k|k-1}$ is held under the persistent lack of observations.

Proof: We can easily see the $P^{j^0 i}_{k|k} \leq P^{j^0 i}_{k|k-1}$ because there is a constraint about noise $\hat{D}^{j^0 i}_k \hat{V}^{j^0 i}_k \hat{D}^{j^0 iT}_k > 0$ in (12). But if the persistent lack of observations occurs, we get the relation $\alpha \rightarrow \infty$ over the time. And because the second term in (12) converges to zero, as a result, the estimation error covariance $P^{j^0 i}_{k|k}$ is equal to $P^{j^0 i}_{k|k-1}$.

Next, we would like to describe about the derivation of the estimate value of observational error $C^{j^0 i}_k x^i_k - \hat{y}^{j^0 i}_k$in (14). At first, we need to compute $\pm(\tilde{\hat{y}}^{j^0 i}_k - E[\tilde{\hat{y}}^{j^0 i}_k])$ by using the equation (18).

$$\begin{aligned} cov(\tilde{\hat{y}}^{j^0 i}_k) &= C^{j^0 i}_k P^{j^0 i}_{k|k-1} C^{j^0 iT}_k + \hat{D}^{j^0 i}_k \hat{V}^{j^0 i}_k \hat{D}^{j^0 iT}_k \\ &= E\{(\tilde{\hat{y}}^{j^0 i}_k - E[\tilde{\hat{y}}^{j^0 i}_k])(\tilde{\hat{y}}^{j^0 i}_k - E[\tilde{\hat{y}}^{j^0 i}_k])^T\} \end{aligned} \tag{18}$$

Then, to compute an estimate value which is nearly equal to the true observational error $\tilde{y}^{j^0 i}_k$, we define the parameter β_k as following (20).

$$\begin{aligned} & cov\{\tilde{y}^{j^0 i}_k - (\tilde{\hat{y}}^{j^0 i}_k - E[\tilde{\hat{y}}^{j^0 i}_k] + \beta_k)\} \\ = \ & cov\{D^{j^0 i} v^{j^0 i}_k + \hat{D}^{j^0 i}_k \hat{v}^{j^0 i}_k + E[\tilde{\hat{y}}^{j^0 i}_k] - \beta_k\} \end{aligned} \tag{19}$$

$$\beta_k : \ = \ (1+\alpha_k)\hat{D}^{j^0 i} \hat{v}^{j^0 i}_k + E[C^{j^0 i}_k \hat{x}^{j^0 i}_{k|k-1} - \hat{y}^{j^0 i}_k] \tag{20}$$

The parameter β_k depends on α_k, and we can adjust reliability of estimated measurement noise covariance by this parameter tuning. By using the result of (18) and (20), we can choose the estimate value of observational error as the equation (21). And (21) shows that the estimate value of observational error is consist of the estimate value of observation and the average estimated error.

$$\begin{aligned} & \tilde{\hat{y}}^{j^0 i}_k - E[\tilde{\hat{y}}^{j^0 i}_k] + \beta_k \\ = \ & \tilde{\hat{y}}^{j^0 i}_k + (1+\alpha_k)\hat{D}^{j^0 i} \hat{v}^{j^0 i}_k - E[C^{j^0 i}_k \eta^{j^0 i}] \\ = \ & \tilde{\hat{y}}^{j^0 i}_k + l^{j^0 i}_k \end{aligned} \tag{21}$$

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C. Neighbor Discovery Algorithm

Next, we would like to explain about sensor scheduling algorithm. Usually, there is limitations of sensor's communication distance and constraints of electric power consumption. Hence, to navigate each plant dynamically by feedback control and also to cut power consumption, we have to choose sensors which are appropriate for sending control input to each target. In this paper, we propose Neighbor Discovery algorithm to achieve efficient sensor scheduling and restructuring of network in [12], [13]. When we use Neighbor Discovery algorithm for targets state estimation and scheduling sensors , whole process can be described as following.

Sensor Scheduling by Neighbor Discovery Algorithm

i) At time step k, we define the sensor j^0_k, and assume that j^0_k sent control input to the ith plant in the previous time step $k-1$.
ii) j^0_k runs the fault detection based on Fault-evaluation matrix $M^{j^0 i}_k$, and estimate the state of ith plant by using switching KF in (5).
iii) j^0_k sends the estimation result $P^{j^0 i}_{k|k-1}$, $P^{j^0 i}_{k|k}$, $P^{j^0 i}_{k+1|k}$, $\hat{x}^{j^0 i}_{k|k-1}$, $\hat{x}^{j^0 i}_{k|k}$ to other sensor j_k within the radius $r^{j^0}_k$ (refer Fig. 2).
iv) Each sensor j^n_k which received information from j^0_k selects one target by comparing $P^{j^0 i}_{k|k-1}$. Then, if j^n_k selects ith plant as target, j^n_k gets measurement output $y^{j^n i}_k$.
v) j^n_k runs fault detection, state estimation and sends or receives information $\hat{x}^{j^n i}_{k|k-1}$, $P^{j^n i}_{k|k-1}$, $\hat{x}^{j^n i}_{k|k}$, $P^{ji}_{k|k}$, $P^{j^n i}_{k+1|k}$ in the vicinity of j^n_k.
vi) By comparing $P^{j^n i}_{k+1|k}$, each j^n_k selects j^*_k as the sensor with optimal estimation accuracy in the information sharing group.
vii) j^*_k sends the control input $u^{j^* i}_k$ and $P^{j^* i}_{k+1|k}$ to the plant.
viii) If the ith plant can't receive the control input, estimates itself based on compensation for intermittent observation in (12).
ix) We redefine the sensor j^*_k as j^0_{k+1}, and repeat whole process in the next time step (refer Fig. 3).

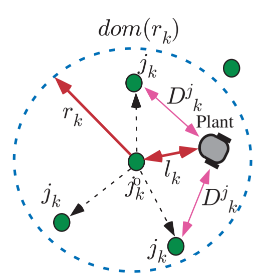

Fig. 2. Neighbor Discovery Strategy

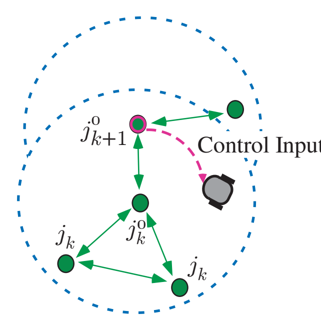

Fig. 3. Network Update

This algorithm works as guidance control by selecting optimal control input which minimize the estimated error covariance $P^{j^* i}_{k+1|k} = \min_j \mathcal{P}$, where $\mathcal{P}$ is the set of each sensor's $\{P^{j^n i}_{k+1|k}$ $(\{P^{j^1 i}_{k+1|k}, P^{j^2 i}_{k+1|k}, \ldots, \{P^{j^n i}_{k+1|k}\} \in \mathcal{P})$. Each $\{P^{j^n i}_{k+1|k}$ is computed by sensors which exist near the ith plant. In this paper, we proposed the estimation algorithm only based on each sensor's KF . But if we are allowed to use DKF based on information exchange between sensors, it becomes possible to assist a fault sensor's estimation by sharing correct observation data with other sensors. The communication distance $r_k^{j^0}$ of each sensor j_k^0 depends on the estimated distance d_k^{ji} between j_k^0 and the ith plant.

$$r_{max} \geq r_k^{j^0} = \delta d_k^{ji}, \quad \delta > 1 \tag{22}$$

Equation (22) shows that the communication radius $r_k^{j^0}$ is longer than the distance d_k^{ji} and smaller than the upper bound r_{max}.

IV. Verification by Experiment

In this section, we would like to show the effectiveness of our proposal algorithms. First, we describe the experimental environment of the verification as in Fig.4.

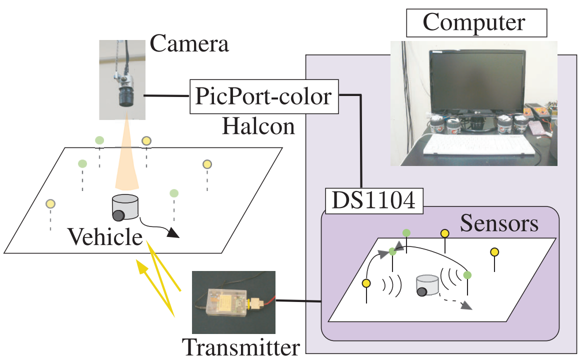

Fig. 4. Experimental System

We used a two-wheeled vehicle as the controlled target plant($N_1 = 1$). The two-wheeled vehicle has a nonholonomic constraint. However this vehicle can be defined as following framework like as (1) via virtual structure for feedback linearization [13], [14]. Assuming that the state of the plant is described as $\boldsymbol{x}_k = [\, x_k \ y_k \ \dot{x}_k \ \dot{y}_k \,]^T$, then A and B are given by the following.

$$A = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, B = \begin{bmatrix} \frac{T^2}{2} & 0 \\ 0 & \frac{T^2}{2} \\ T & 0 \\ 0 & T \end{bmatrix} \tag{23}$$

where, $T = 0.1[s]$ is the sampling time, and the covariance of process noise is assumed to $Q = 1 \times 10^{-3} I_4$. In this experiment, we used nine sensor nodes ($N_2 = 9$) to observe and navigate the target plant. Each sensor was placed on the 2D field and the position X-Y coordinate of each sensor was the following $\zeta^j = (\mathcal{X}^j, \mathcal{Y}^j)$.

$$\begin{aligned} \zeta^1 &= (0,0),\ \zeta^2 = (0,0.5),\ \zeta^3 = (0,1.0) \\ \zeta^4 &= (1.0,0),\ \zeta^5 = (1.0,0.5),\ \zeta^6 = (1.0,1.0) \\ \zeta^7 &= (2.0,0),\ \zeta^8 = (2.0,0.5),\ \zeta^9 = (2.0,1.0) \end{aligned} \tag{24}$$

Additionally, the covariance matrixes of measurement noises V^j and measurement matrixes C_k^{ji} are assumed to be as the following, respectively.

$$C_k^{ji} = \begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix},\ (j = 1, \ldots, 9) \tag{25}$$

$$V^j = diag\{0.8, 1.4, 0.0045, 0.0045\} \tag{26}$$

Each measurement output is calculated from the image of a CCD camera which was mounted above the vehicle as shown in Fig.4. The video signals are acquired by a frame grabber board PicPort-color, then the image processing software HALCON generates nine measurements. Consequently, virtual nine sensor nodes and measurement noises have been presented on the computer [14]. We employ DS1104 (dSPACE Inc.) as a real-time calculating environment for an estimation and sensor scheduling. We set up model parameters of the state dependent function $D_k^{ji} := D^j(x_k^i)$ in the following assumption 4.

Assumption 4: The state dependent function $D_k^{ji} := D^j(x_k^i)$ can be expressed as the following.

$$D_k^{ji} = \begin{bmatrix} 0.1+2\| x_k^i - \mathcal{X}^j \| & 0 & 0 & 0 \\ 0 & 0.1+2\| y_k^i - \mathcal{Y}^j \| & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{27}$$

A. Fault-Detection Switching

We show experimental results for verification of our two proposed algorithms. Here, maximal communication radius $r_{max} = 1.0$ is a communication constraint. We set up the initial state of the target plant as $x_0 = [1.4 \ 0.7 \ 0 \ 0]^T$ and the initial estimation error covariance matrix as $P_0 = 0.1 \times I$. First, Fig.5 shows the trajectory of the target moving to the desired value $(x, y) = (0, 0)$. Each Fig.7, 8 shows an effect of the fault signal (Fig.6) against the sensor 1's estimation. The sensor 1 observed the target's movement and we added a fault signal to this sensor's measurement output. We can see that the fault-evaluation matrix fluctuated based on the occurrence of the fault signal by Fig.7. Further more by using the result of this fault-detection switching, the sensor reflected deteriorations of measurement accuracy in estimate accuracy as in Fig.8.

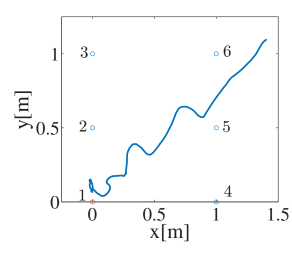

Fig. 5. Vehicle's Trajectory

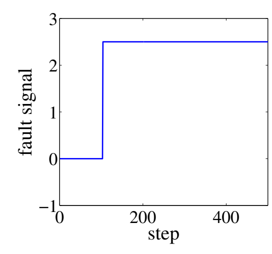

Fig. 6. Fault Signal in Sensor 1

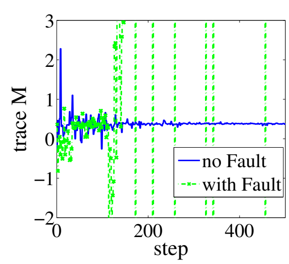

Fig. 7. Trace M for Sensor 1

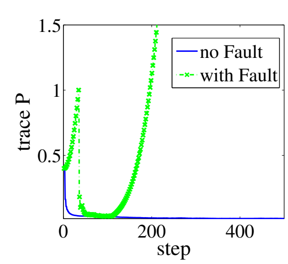

Fig. 8. Trace P for Sensor 1

B. Compensation for Intermittent Observation

Next, we show the result of the estimation algorithm with compensation. We set to occur an intermittent observations after 200 steps from the start of each sensor observation as in Fig.9. We have been reconfigured the initial state of the target as $x_0 = [1.5\ 1.0\ 0\ 0]^T$.

Fig.10 shows a comparison of the estimate error covariance. Each line means the estimate accuracy of our proposed method and conventional method respectively, and we can see that proposed compensation method by (12) maintained more low covariance value than conventional method which chose $P^{j^0 i}_{k|k} = P^{j^0 i}_{k|k-1}$.

Fig.11 and Fig.12 show a comparison of target's actual trajectories and estimated trajectories, respectively. The — line means the behaviour of the target which was based on the control input with the compensation, and the $--$ line means the behaviour which was based on the control input without compensation. By these results, we can confirm that the target converged more closer to the desired value $(x, y) = (0, 0)$ when the compensation had been performed.

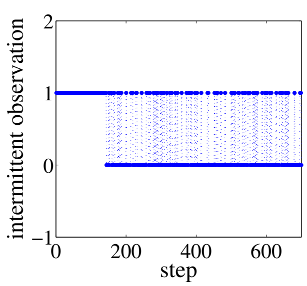

Fig. 9. Observation Corruption

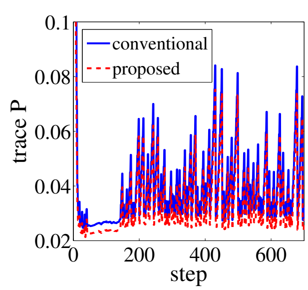

Fig. 10. Trace P for Vehicle

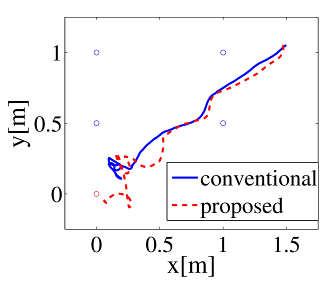

Fig. 11. Vehicle's Trajectory

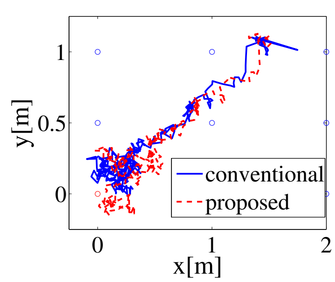

Fig. 12. Trajectory of Estimation

V. Conclusion

In this paper, first, we proposed an estimation algorithm based on fault-detection switching. To detect fault signals, we defined a Fault-evaluation matrix, then combined the fault detection result with switching KF. We showed that each sensor can suppresses the effect of inaccurate observation value against the estimation result. Consequently, sensors were able to reflect deteriorations of measurement accuracy in estimate accuracy.

Secondly, we discussed about the compensation problem, and to maintain a low covariance value under intermittent observation, we proposed an estimation algorithm based on an imputation method by using an estimated observation value.

Finally we showed experimental results to analyze effectiveness of these proposed methods.

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