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Dynamic Target Navigation based on Multisensor Kalman Filtering and Neighbor Discovery Algorithm

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Abstract: This paper deals with an estimate algorithm which considers optimal control input for dynamic target navigation by using wireless sensor networks and distributed Kalman filter. We propose a novel sensor scheduling algorithm based on a neighbor discovery algorithm for discrete-time linear time-invariant systems. Then we propose an estimate algorithm by sharing predicted estimate values and analyze characteristic of this algorithm. Finally, experimental results show effectiveness of the proposed method in sensor networked feedback systems.

Keywords: Sensor Networks, Distributed control, Multisensor Kalman Filtering, Sensor scheduling, Guidance control

1. INTRODUCTION

Recently wireless sensor networks with the calculation function have attracted more attention, and research of such systems has increased [1, 2]. In these researches, sensor nodes are connected wirelessly and some local estimates are merged into the common estimate by information sharing. It is well known that sensor networks are superior to a observation by a system with single sensor in a fault tolerance, load reduction of operator, collection and application of information etc. Moreover, sensor networks have been applied to control systems such as target tracking systems [3, 4] and also we can construct the guidance control system via a sensor network for traffic control systems, nano-medicines and evacuation guidance. Meanwhile, it is difficult to put the whole system together in sensor scheduling when the number of nodes and structure of the system are changing dynamically [5]. Also, the sensor network might not be able to converge the data of all sensors to a data fusion center because the communications capacity of each sensor has limitation and the system is composed by the large-scale sensor group [6, 7]. Even if all data can be collected, it needs a heavy computation load and communication energy to find the optimal value from among a huge amount of data at short time step. Thus each sensors requires a lot of arithmetic capacity. However, sensor nodes are generally powered and driven by batteries. It is important to utilize the energy efficiently to achieve the energy saving and prolong sensor nodes life. Therefore, to suppress compared number of data and communication electric power, we restrict the number of active sensors at each time step and select a set of sensors for measurement, communication dynamically. In this paper, we consider such sensor scheduling problem as the problem of giving optimal control input by using distributed Kalman filter for the guidance control system via a sensor network by using sensors which are selected from among the sensor group nearby plant.

Distributed Kalman Filter (DKF) in sensor networks has been studied in[8-10]. In these papers, each sensor node calculates the local estimate and an entire system generates the common estimate by information exchange. However, they deal with a sensor network system as a measurement system. Thus, it is difficult to apply to the guidance control that the plant receives arbitrary control inputs. Meanwhile, the sensor scheduling problem cibsuderubg the estimation error variance and communication energy for a feedback control system was proposed in [11]. Each sensor has the communication and observation functions and the control input is applied to the plant by selected sensors. However, the sensor scheduling is carried out in the fusion center by comparing evaluation function. That means, as the number of the sensor grows, the necessary sensor's range of radio communication for scheduling increases. Thus we can not apply these previous methods to this problem directly.

In this paper, by using evaluation function [12] which is influenced by sensor's observation distance, we propose a novel sensor scheduling algorithm which is nearly independent of the aggregate number of sensors in entire network. First of all, we propose the neighbor discovery algorithm that only compares data which is sent by sensors in the neighborhood of the plant, and show the condition that the evaluation function reaches the upper bound value. Then we construct the feedback control system for dynamic target navigation by using the estimation algorithm based on DKF along with this scheduling method. Secondly, we show the proposal DKF's estimation that shares predicted estimate values improves estimate accuracy from the previous DKF's estimation. Moreover, we confirm that not all of sensors have to estimate at every time step. Finally, the effectiveness of the proposal estimation algorithm is verified by the experiments.

2. PROBLEM FORMULATION

2.1 Plant and Sensor Nodes

In this paper, we consider the feedback control system via a sensor network for dynamic target tracking and guidance in Fig.1 . The control objective is to navigate a vehicle from a starting point to any destinations by using multiple sensor information.

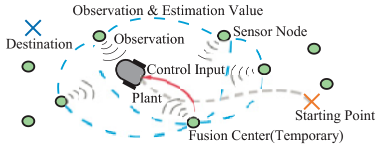

Fig. 1 Sensor Network System

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The control objective can be described as following. This system consists the plant and N sensor nodes $i(i = 1, 2, \ldots, N)$. We assume all sensor nodes can measure the position of the vehicle with sensor noise. The process dynamics of the plant is given by

$$x_{k+1} = Ax_k + Bu_k + w_k \tag{1}$$

where $x_k \in \mathbb{R}^n$, $u_k \in \mathbb{R}^r$, $w_k \in \mathbb{R}^n$ are the state, the control input and the process noise assumed to be zero mean white Gaussian noise respectively. We assume that the control input u_k is given by the following equation and applied from the single sensor node i to the plant. It means the plant takes only one control input from some sensors at each time step.

$$u_k = K\hat{x}^i_{k|k} \tag{2}$$

where $\hat{x}^i_{k|k} \in \mathbb{R}^n$ is the estimate of the single sensor node i and K is the feedback gain. The measurement equation of the sensor node i are given by

$$y^i_k = C^i_k x_k + D^i(x_k)v^i_k \tag{3}$$

where $y^i_k \in \mathbb{R}^{q_i}$, $v^i_k \in \mathbb{R}^p$ are the measurement output of a sensor node i, measurement noise assumed to be zero mean white Gaussian noise respectively. Additionally, $D^i(x_k) \in \mathbb{R}^{m\times p}$ is the state dependent noise which depends on distance between the sensor node i and plant. Now we assume (1) and (3) satisfy following *Assumptions 1-3*.

Assumption 1:

$$\mathrm{E}\left\{\begin{bmatrix} w_k \\ v^i_k \end{bmatrix}\begin{bmatrix} w^T_k & v^{iT}_k \end{bmatrix}\right\} = \begin{bmatrix} W & \mathbf{0} \\ \mathbf{0} & V^i \end{bmatrix} \tag{4}$$

$$E\left\{w_k x^T_0\right\} = E\left\{v_k x^T_0\right\} = \mathbf{0} \tag{5}$$

where W, V^i are the positive semidefinite and positive definite covariance matrix of noises w_k, v^i_k respectively.

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

Assumption 3: The matrix pair (C, A) is detectable, where $C = [C^{1T}_k C^{2T}_k \ldots C^{N'T}_k]^T$ then N' is the total number of active sensors ($0<N'\leq N$).

Assumption 4: Each sensor nodes can communicate to others with a time delay less than a sampling time.

On the assumption that noted above, we deal the guidance control problem of this sensor networked feedback system as sensor scheduling problem. We define this problem as the following optimal problem.

Problem 1: We assume the plant and all sensor nodes satisfy *Assumption 1-4* , and each sensor i has predicted estimate values: predicted state estimate $\hat{x}^i_{k|k-1}$, predicted estimate covariance $P^i_{k|k-1} > 0$. Then each sensor i compute $P^i_{k|k}$. By comparing $P^i_{k|k}$, decide the optimal state estimate $\hat{x}^i_{k+1|k}$ that minimizes following estimation error variance at the plant.

$$\begin{aligned} J &= E\{(x_{k+1} - \hat{x}^i_{k+1|k})^T(x_{k+1} - \hat{x}^i_{k+1|k})\} \\ &= trace(P_{k+1|k}) \end{aligned} \tag{6}$$

To solve *Problem 1*, we discuss an estimation algorithm of sensor node i by using Kalman filter. First, we define the sensor nodes which sent the control input to the plant at time step $k-1$ as $i^f_{k-1} = i^0_k$. It means one of control inputs from $i^f_{k-1}(i \leq N')$ is adopted by the plant at $k-1$. Sensor nodes i^0_k compute predicted estimate values $P^{i^0}_{k|k-1}$, $\hat{x}^{i^0}_{k|k-1}$ at time step $k-1$, then the estimation algorithm is given by following equations which is based on sensor i^0_k's measurement and control input $u^{i^0}_k$. We can see the estimate covariance $P^{i^0}_{k+1|k}$ and the estimate $\hat{x}^{i^0}_{k+1|k}$ is influenced by the state dependent noise $D^{i^0}_k(\hat{x}^{i^0}_{k|k-1})$. Thus, $\hat{x}^{i^0}_{k+1|k}$ is minimum variance estimate for the case of $u^{i^0}_k$'s adoption by the plant.

$$\begin{aligned} \hat{x}^{i^0}_{k+1|k} &= A\hat{x}^{i^0}_{k|k} + Bu^{i^0}_k \\ \hat{x}^{i^0}_{k|k} &= \hat{x}^{i^0}_{k|k-1} + K^{i^0}_k\{y^{i^0}_k - C^{i^0}_k\hat{x}^{i^0}_{k|k-1}\} \end{aligned} \tag{7}$$

$$u^{i^0}_k = K\hat{x}^{i^0}_{k|k} \tag{8}$$

$$K^{i^0}_k = P^{i^0}_{k|k}C^{i^0T}_k(D^{i^0}_k(\hat{x}^{i^0}_{k|k-1})V^{i^0}_k D^{i^0T}_k(\hat{x}^{i^0}_{k|k-1}))^{-1} \tag{9}$$

$$\begin{aligned} P^{i^0}_{k+1|k} &= AP^{i^0}_{k|k}A^T + W_k \\ P^{i^0}_{k|k} &= P^{i^0}_{k|k-1} - K^{i^0}_k C^{i^0}_k P^{i^0}_{k|k-1} \end{aligned} \tag{10}$$

To make the calculation simple, we use the estimate $\hat{x}_{k|k-1}$ to compute state dependent noise D^i_k in (9). Then the estimate covariance $P^i_{k+1|k}$ satisfies *Property 1*.

Property 1: If the conditions $D^1_k \leq D^2_k$ and $P^1_{k|k-1} \leq P^2_{k|k-1}$ are both satisfied, we obtain $P^1_{k+1|k} \leq P^2_{k+1|k}$ for the case sensor's specification(C, V) is the same.

Proof: By the following inequalities, we can see that, estimate covariance $P^i_{k+1|k}$ becomes a monotonous non-decrease about D^i_k if the each case sensor's specification isn't different.

$$\begin{aligned} & P^2_{k+1|k} - P^1_{k+1|k} \\ &= A\{(I - K^2_k C)(P^2_{k|k-1} - P^1_{k|k-1})(I - K^2_k C)^T \\ &+ 2K^1_k(D^1_k V D^{1T}_k + CP^1_{k|k-1}C^T)K^{1T}_k \\ &+ K^2_k(D^1_k V D^{1T}_k + D^2_k V D^{2T}_k + 2CP^1_{k|k-1}C^T)K^{2T}_k \\ &- (K^2_k + K^1_k)(D^1_k V D^{1T}_k + CP^1_{k|k-1}C^T)(K^2_k + K^1_k)^T\}A^T \\ &\geq A\{(I - K^2_k C)(P^2_{k|k-1} - P^1_{k|k-1})(I - K^2_k C)^T \\ &+ (K^2_k - K^1_k)(D^1_k V D^{1T}_k + CP^1_{k|k-1}C^T)(K^2_k - K^1_k)^T\}A^T \\ &\geq 0 \end{aligned} \tag{11}$$

■

This *Property 1* shows that, when the distance between the sensor and the plant becomes small, $P^i_{k+1|k}$ similarly becomes small, too.

2.2 Neighbor discovery algorithm

When we deal in the large scale system with large quantities of compared data and entail structural dynamic change in the number of active sensors, it is difficult to find the optimal solution for *Problem 1* within 1 time step as occasion demands. Hence we propose the strategy that only compares data which is sent by sensors in the neighborhood of the plant. Then we restrict the comparison range of estimation by using *Property 1*. Now *Problem 1* can be replaced in the following *Problem 2*.

Problem 2: Assume that *Assumptions 1-4* holds. At time step k, each node has predicted estimate values $\hat{x}^{i^0}_{k|k-1}$, $P^{i^0}_{k|k-1} > 0$. Then each sensor i compute $P^i_{k|k}$. By comparing $P^i_{k|k}$ and within r_k radius of the sensor node i^0_k which undertake a temporary fusion center role, decide the optimal state estimate $\hat{x}^i_{k+1|k}$ that minimizes following estimation error variance at the plant. Further,

$dom(r_k)$ is the comparison range of sensor i_k^0 which has r_k radius for comparing J.

$$J = E\{(x_{k+1} - \hat{x}^i_{k+1|k})^T (x_{k+1} - \hat{x}^i_{k+1|k})\}$$
$$i \in dom(r_k) \tag{12}$$

In this *Problem 2*, we distribute fusion center role which is managed by the plant in in *Problem 1* across the sensor i_k^f. Hence, the processing of data fusion and comaparison is treated by i_k^f which vary by the one time step in Fig.2,3.

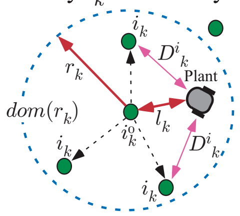

Fig. 2 Neighbor Discovery Algorithm

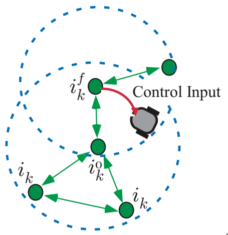

Fig. 3 Selection of i_k^f

2.3 Selection of i_k^f

To select the temporary fusion center i_k^f at time step k, we use a simple rule. When sensor i recieves a data which involve information of J from the other active sensors, sensor i compares J with the data from itself . If J from the other sensors is more smaller than J from i, the sensor i pull out of the selection. Consequently, only the one sensor with the minimum J wins a place in the sensor group which allow two-way communication. However, depending on the situation, it is difficult for all the sensors even in the neighborhood of the plant to allow two-way communication. Therefore, it is not necessarily the case that single sensor i_k^f is chosen by active sensors. We detailed procedure of this selection in section III.

The *Problem 2* is solved by each sensor node i in the neighborhood of the plant. We call this comparison method for scheduling sensors a neighbor discovery algorithm. In *Problem 1*, it is required that each sensor i is able to obtain estimation from all sensors and sends control input and J to the plant. However, such a problem setting is not realistic from the viewpoint of the communication restriction and power consumption [1].

2.4 Predicted Estimate Value Sharing Algorithm

Even when two or more sensors and estimators are used in the same time step (ex. DKF), each KF only uses the predicted estimate value which was calculated by itself at previous time step respectively. Thereafter, we call this method that each estimator only leverages independent predicted estimate $P^i_{k|k-1}, \hat{x}^i_{k|k-1}$ as predicted estimate value update algorithm in this paper (Fig.4). In the fault of this algorithm, regardless of sensor's state (active for observation and transmission / inactive for save energy), all sensors in whole network have to update the estimate value without interruption.

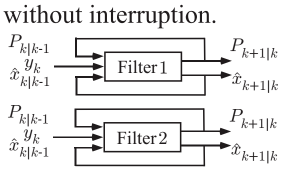

Fig. 4 Predicted Estimate Value Update Algorithm

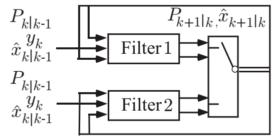

Fig. 5 Predicted Estimate Value Sharing Algorithm

Then we propose the algorithm that each sensors shares the optimal value as predicted estimate value from among the value estimated at previous time step $k-1$ by comparing J. This is called predicted estimate value sharing algorithm (Fig.5). In this algorithm, each sensors i_{k-1}^f that transmitted the control input at previous time $k-1$ step offers the predicted estimate value $P^{i^0}_{k|k-1}, \hat{x}^{i^0}_{k|k-1}$ at present time k. Thus only sensors which recieve the predicted estimate value from i_{k-1}^f can get on estimation at time step k. In this process of estimation, i_{k-1}^f need to have specific predicted estimate value $P^{i^0}_{k|k-1}, \hat{x}^{i^0}_{k|k-1}$ but the other sensors need not necessarily have specific predicted estimate. When we use this method in combination with neighbor discovery algorithm, only active sensors in the neighborhood of the plant may always estimate at each time step, we can reduce the computational cost in a large-scale system. Then these predicted estimate value update algorithm and predicted estimate value sharing algorithm satisfy the following *Theorem1*.

Assumption 5: For each sensors i, we define state dependent noise D_k^i which is computed by predicted estimate value update algorithm and $D_k^{i^0}$ which is computed by predicted estimate value sharing algorithm respectively. Then we assume these noise satisfy $D_k^i \fallingdotseq D_k^{i^0}$.

Theorem 1: At time step k, we define estimate covariance $P^{update}_{k+1|k}$ which is computed by predicted estimate value update algorithm and $P^{share}_{k+1|k}$ which is computed by predicted estimate value sharing algorithm respectively in each sensors i. Assume that *Assumption 5* holds. Then $P^{update}_{k+1|k}$ and $P^{share}_{k+1|k}$ satisfy the following.

$$P^{update}_{k+1|k} \geq P^{share}_{k+1|k} \tag{13}$$

Proof: We define specific predicted estimate value $P^i_{k|k-1}$ which is calcurated by the predicted estimate value update algorithm and $P^{i^0}_{k|k-1}$ which is computed by predicted estimate value sharing algorithm respectively in each sensors i. Additionally, $\mathcal{P}^{i^0}_{k|k-1}$ is the set of the predicted estimate value which is collected by sensor i at time step k. Then we can see $P^{i^0}_{k|k-1}, P^i_{k|k-1} \in \mathcal{P}^{i^0}_{k|k-1}$ and $P^{i^0}_{k|k-1} = \min \mathcal{P}^{i^0}_{k|k-1}$. Therefore, the algebraic relation $P^{i^0}_{k|k-1} \leq P^i_{k|k-1}$ is satisfied. Hence, under the assumption $D_k^i \fallingdotseq D_k^{i^0}$, we can see $P^{update}_{k+1|k} \geq P^{share}_{k+1|k}$ by using a similar way in equation 11. ■

3. DKF-BASED ESTIMATION

In this section, we describes the estimation algorithm based on DKF to solve the *Problem 2*.

3.1 Neighbor discovery algorithm based on DKF

In this algorithm, only sensors in the neighborhood of the plant observe and estimate the plant's state by using the predicted estimate value sharing algorithm. Thereafter, we call this algorithm DKF-neighbor discovery strategy. First of all, we define the following assumption about the communication of the sensor.

Assumption 6:

1. Each sensors range of radio communication is longer than 1 step movement distance of the plant.
2. Each sensors doesn't move at least when they observe and estimate the plant.
3. Each sensors can make out the position of the other sensors by receiving data.

We propose the following estimate algorithm for the sensor network under *Assumption 6*.

DKF-neighbor discovery strategy

1. Each sensors $i_{k-1}^f = i_k^0$ sends the control input to the plant at time step $k-1$.
2. At time step k, i_k^0 calculates $P^{i^0}_{k+1|k}, \hat{x}^{i^0}_{k|k}$ respectively by using KF. i_k^0 sends information $P^{i^0}_{k|k-1}$, $P^{i^0}_{k|k}$, $P^{i^0}_{k+1|k}$, $\hat{x}^{i^0}_{k|k-1}$and $\hat{x}^{i^0}_{k|k}$ to the other active sensors existing within a radius r_k from i_k^0.
3. Each sensors i_k which receives information from i_k^0 begins observing and capturing y_k^i. Then i_k calculates $P^i_{k+1|k}, \hat{x}^i_{k|k}$ respectively by using information from i_k^0 and DKF.
4. i_k transmits $\hat{x}^i_{k|k-1}, P^i_{k|k-1}, \hat{x}^i_{k|k}, P^i_{k|k}, P^i_{k+1|k}$ within r_{k1} radius and recieve data from the other i_k. Thus i_k compares estimate covariance with neighborhood active sensors. It means that each sensors stand in sensor groups among sensors which can comunicate each other and select the temporary fusion center i_k^f in line with selection method of i_k^f previously described.
5. As a result, the sensor i_k^f which has the minimum estimate covariance is selected among the each sensors group.
6. Each sensors i_k^f computes and updates $\hat{x}^i_{k|k}$, $P^i_{k|k}$, $\hat{x}^i_{k+1|k}$ and $P^i_{k+1|k}$ by using DKF and information from the other sensors in the sensor group.
7. i_k^f transmits control input u_k^i and $P^i_{k+1|k}$ to the plant.
8. When i_k^0 can not recognize the control input from i_k^f, i_k^0 transmits control input and $P^{i^0}_{k+1|k}$ to prevent no control input reaching the plant.
9. At time step $k+1$, each sensors i_k^f works as i^0_{k+1}.

The communication distance r_k of each sensors i_k depend on the distance l_k between i_k and the plant. To compute r_k, we use $\hat{x}^{i^0}_{k|k-1}$ which is estimated by i^f_{k-1} in this paper.

$$r_{max} \geq r_k = \delta l_k, \quad \delta > 1 \tag{14}$$

The communication radius is longer than the moving distance of the plant by (14) and shorter than the upper bound $r_{max} \geq r_k$ which is each sensor's maximum range of radio communication. Moreover, when i_k receives information from two or more i_k^0 , i_k selects sensor i_k^{0*} which has the minimum evaluation function J . Then i_k sets $r_{k1} = r_k^*$ to hold the communication with i_k^{0*} . As an application of this method, we enable sensors which are in the neighborhood of the plant but cannot allow two-way communication with i^f_{k-1} to start estimation by using multi-hop communication and predicted estimate value sharing algorithm at process 4 . Then, when all sensors share same predicted estimate value by repeating predicted estimate value sharing algorithm , the relation $P^1_{k|k-1} = P^2_{k|k-1}$ and *Property 1* are always satisfied.

3.2 Estimation algorithm based on DKF with predicted estimate value sharing algorithm

Now, the sensor group that received $P^{i^0}_{k|k-1}$, $P^{i^0}_{k|k}$, $P^{i^0}_{k+1|k}$, $\hat{x}^{i^0}_{k|k-1}$and $\hat{x}^{i^0}_{k|k}$from i^f_{k-1} is assumed to be $i_k \in 1, \ldots, n$. Each i_k estimates as follows by using observation data y_k^i and $P^i_{k+1|k}$, $\hat{x}^i_{k|k}$, $P^i_{k|k}$, $\hat{x}^i_{k|k-1}$, $P^i_{k|k-1}$ which are sent by the other active sensors $j_k \in i_k$.

$$\begin{aligned} \hat{x}^i_{k+1|k} &= A\hat{x}^i_{k|k} + Bu^i_k \\ \hat{x}^i_k &= \hat{x}^{i^0}_{k|k-1} + K^i_k\{y^i_k - C^i_k\hat{x}^{i^0}_{k|k-1}\} \end{aligned} \tag{15}$$

$$K^i_k = P^i_k C^{iT}_k (D^i_k(\hat{x}^i_{k|k}) V^i_k D^{iT}_k(\hat{x}^i_{k|k}))^{-1} \tag{16}$$

$$\begin{aligned} (P^i_k)^{-1} = &(P^{i^0}_{k|k-1})^{-1} \\ &+ C^{iT}_k (D^i_k(\hat{x}^i_{k|k}) V^i_k D^{iT}_k(\hat{x}^i_{k|k}))^{-1} C^i_k \end{aligned} \tag{17}$$

$$P^i_{k|k} = [(P^i_k)^{-1} + \sum_{j=0}^{n}\{(P^j_{k|k})^{-1} - (P^j_{k|k-1})^{-1}\}]^{-1} \tag{18}$$

$$P^i_{k+1|k} = AP^i_{k|k}A^T + W_k \tag{19}$$

$$\begin{aligned} \hat{x}^i_{k|k} = P^i_{k|k}[&(P^i_k)^{-1}\hat{x}^i_k + \sum_{j=0}^{n}\{(P^j_{k|k})^{-1}\hat{x}^j_{k|k} \\ &- (P^j_{k|k-1})^{-1}\hat{x}^j_{k|k-1}\}] \end{aligned} \tag{20}$$

Above estimation algorithm for target guidance is based on the algorithm for target tracking in [13]. Furthermore, our proposed algorithm considers the effect of state dependent noises and responds to predicted estimate value sharing algorithm. First, according to DKF-neighbor discovery strategy, each sensors i_k estimates the plant's state by using y^i_k and information from i^0_k in (15), (17). Next, each i_k exchanges estimation result mutually among the other active sensors j_k. Thus i_k compares estimate covariance with j_k and chooses the sensor i^f_k which has the minimum estimate covariance. When i_k select itself as i^f_k which is a candidate target and become the temporary fusion center, i_k updates estimation by using estimation results of j_k in (18), (20)and compute the control input. By using these estimation comparison and sharing, we can prevent entire i_k from transmitting the control input to the plant. However, as explained in previous section, the control input cannot also be uniquely decided because it is not necessarily the case that single sensor i^f_k is chosen. Hence, in this case, the plant needs to select the optimal value by comparing corresponding $P^i_{k+1|k}$ from among two or more than two control inputs. Therefore, we can see the control input which minimize the evaluation function J and the solution of *Problem 2* as the following.

$$\begin{aligned} u_k &= K\hat{x}^j_{k|k} \\ \hat{x}^j_{k|k} &= \min trace(P^j_{k+1|k}) \end{aligned} \tag{21}$$

The above-mentioned estimation algorithm which bases on DKF satisfies the following propositions.

Property 1: The estimation error covariance matrix which is calculated by DKF and using predicted estimate value sharing algorithm is smaller than the matrix which is calculated by KF , for the case these estimation is based on the same predicted estimate value.

Proof: (17), (18) are the estimation error covariance matrixes of the sensor i_k calculated respectively by KF and DKF. (18) is computed by adding information (22) to (17) from other sensors j_k.

$$\sum_{j=0}^{n} C_k^{jT} D_k^j(\hat{x}_{k|k}^j) V_k^j D_k^{jT}(\hat{x}_{k|k}^j) C_k^j \geq 0 \tag{22}$$

Hence $P_k^i \geq P_{k|k}^i$ is satisfied. Therefore, $AP_k^i A^T + W_k \geq AP_{k|k}^i A^T + W_k$ is also shown. It means that when we use the estimation error covariance which is computed by DKF and the estimation from other sensors, the estimate result is more accurate than the estimate result which is computed by KF. ■

Property 2: In *Problem 2*, when we assume that *Assumption 6* holds, upper bound $trace\ P_{k+1|k}^{i^0}$ of the evaluation function J is given by the control input in (8).

Proof: In our proposal method, each sensors i_{k-1}^f which sent the control input to the plant at previous time step $k-1$ send predicted estimate value to other sensors i_k then i_k begin observation and estimation at time step k. In the process of the information exchange with i_{k-1}^f, i_k whose estimate result $P_{k+1|k}^i$ satisfies $P_{k+1|k}^{i^0} < P_{k+1|k}^i$ is passed over i_k^f which transmit control input at time step k. Therefore, the upper bound value of J is given from one of the sensors i_{k-1}^f. ■

Boundedness of estimate error covariance matrix

When the state dependent noise $D_k^{i^0}$ monotonically non-decreases at time step k, the estimation error covariance $P_{k+1|k}^{i^0}$ that i_{k-1}^f monotonically non-decreases similarly.

$$\begin{aligned} & P_{k+1|k}^{i^0} - P_{k|k-1}^{i^0} \\ & \geq A\{(I - K_k^{i^0} C^{i^0})(P_{k|k-1}^{i^0} - P_{k-1|k-2}^{i^0})(I - K_k^{i^0} C^{i^0})^T \\ & + (K_k^{i^0} - K_{k-1}^{i^0})(D_{k-1}^{i^0} V D_{k-1}^{i^0 T} + C^{i^0} P_{k-1|k-2}^{i^0} C^{i^0 T}) \\ & (\ K_k^{i^0} - K_{k-1}^{i^0})^T\} A^T \\ & \geq 0 \end{aligned} \tag{23}$$

We can see $P_{k|k-1}^{i^0} \geq P_{k-1|k-2}^{i^0}$ from the relation $D_{k-1}^{i^0} \geq D_{k-2}^{i^0}$ in the same way *proof 2.1* Then, if communication radius r_k and $D_k^{i^0}$ are finite values, the affect of $D_k^{i^0}$ in estimation error covariance becomes smaller according to the passage of time. Thus we define the feedback gain L from *Assumption 3*. For the case each estimations are based on the same initial value, and if $A' := A - LC^{i^0}$ is an asymptotically stable, estimation error covariance $P(K)$ computed by Kalman gain K becomes smaller than $P(L)$ which is based on L[14]. Now, we define renewing time as $k=0$ when $D_k^{i^0}$ becomes upper bound D.

$$\begin{aligned} P_{k|k-1}(L) = & A'^k P_0 (A'^T)^k \\ & + \sum_{t=0}^{k-1} A'^t [W + LDVD^T L^T](A'^T)^t \end{aligned} \tag{24}$$

The right side of (24) is settled in $k \to \infty$ and we can see the following inequality.

$$P_{k|k-1}(K) \leq P_{k|k-1}(L) < \infty \tag{25}$$

Therefore, if $D_k^{i^0}$ is a finite value , and even a monotonous non-decrease, $P_{k+1|k}^{i^0}$ reaches the upper threshold with the passage of time $k \to \infty$.

4. EXPERIMENTAL VERIFICATIONS

In this section, a effectiveness of the proposal estimation algorithm is evaluated by experiment. In this experiment, each measurement output is calculated from the image of a CCD camera mounted above the vehicle as shown in Fig.6. The video signals are acquired by a frame grabber board PicPort-color and image processing software HALCON generate nine measurements. Consequently, nine sensor nodes and measurement noises exist in the computer. We employ DS1104 (dSPACE Inc.) as a real-time calculating environment for an estimation and sensor scheduling.

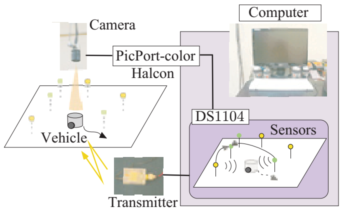

Fig. 6 Experimental setup

The experiment was carried out on a two-wheeled vehicle as the plant. Now two-wheeled vehicle has a non-holonomic constraint. However two-wheeled vehicle can be defined following framework via virtual structure for feedback linearization[15].

$$A = \begin{bmatrix} 1 & 0 & T_s & 0 \\ 0 & 1 & 0 & T_s \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},\ B = \begin{bmatrix} \frac{T_s^2}{2} & 0 \\ 0 & \frac{T_s^2}{2} \\ T_s & 0 \\ 0 & T_s \end{bmatrix} \tag{26}$$

where T_s=0.1 and x_0=[2.0 1.0 0 0 $]^T$ are the sampling time and the initial state respectively. In this verification, we use nine sensor nodes. Then each sensor node has the following measurement equation and the position of sensor $S_k^i = (\mathcal{X}_k^i, \mathcal{Y}_k^i)$ is shown in (28) respectively.

$$\begin{aligned} & C_k^1 = [1\,1\,0\,0], C_k^2 = [1\,1\,1\,1], C_k^3 = [1\,1\,0\,0] \\ & C_k^4 = [1\,1\,1\,1], C_k^5 = [1\,1\,0\,0], C_k^6 = [1\,1\,1\,1] \\ & C_k^7 = [1\,1\,0\,0], C_k^8 = [1\,1\,1\,1], C_k^9 = [1\,1\,1\,1] \end{aligned} \tag{27}$$

$$\begin{aligned} & S_1 = (0,0),\ S_2 = (0,0.5),\ S_3 = (0,1.0) \\ & S_4 = (1.0,0),\ S_5 = (1.0,0.5),\ S_6 = (1.0,1.0) \\ & S_7 = (2.0,0),\ S_8 = (2.0,0.5),\ S_9 = (2.0,1.0) \end{aligned} \tag{28}$$

Additionally, the covariance matrices of noises W and V^i are assumed to be as the following, respectively.

$$W = 1 \times 10^{-3} I_4 \tag{29}$$

$$V^i \quad = \quad diag\{0.8, 1.4, 0.0045, 0.0045\} \tag{30}$$

Thus we design the feedback gain K by LQG control and we assume the state dependent noise $D_k^i(\boldsymbol{x}_k)$ in the form following.

$$D_k^i(\boldsymbol{x}_k)=\begin{bmatrix} 0.1+\parallel x_k-\mathcal{X}_k^i\parallel & 0 & 0 & 0\\ 0 & 0.1+\parallel y_k-\mathcal{Y}_k^i\parallel & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 1\end{bmatrix} \quad (31)$$

In this case, we set the initial state of the plant as $x_0 = [1.5\ 1\ 0\ 0]^T$ and the initial estimation error covariance matrix was set as $P_0 = 0.1 \times I$. Moreover, we assume each sensor's maximum range of radio communication $r_{max} = 1.5$ with $\delta = 2$. The experimental results are shown in Fig. 7-10. Fig.7 is a comparison between true value of vehicle's trajectory $\hat{x}_{k|k}$ and estimate value of them at each time step. We can see the vehicle reached the desired value $(x, y) = (0, 0)$ by using state feedback control and the control input from sensors in the same way as the simulation result in Fig.7.

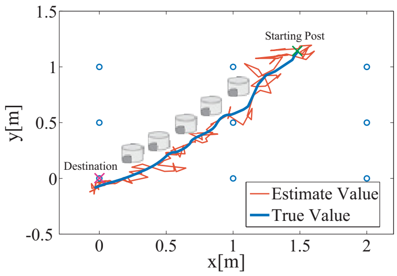

Fig. 7 Vehicle's Trajectory (Experiment)

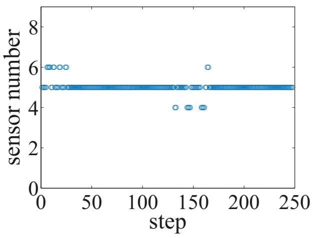

Fig. 8 Selection at Sensor5 (Experiment)

Fig.8 shows the selection of the predicted estimate values which was sent by other sensors to sensor 5. This result shows that the sensor 5 can estimate by using optimal predicted estimate value which is based on predicted estimate value sharing algorithm. Fig.9 shows the switching of the control input at the plant. This result is not fed back to the sensor network side. However, the vehicle reached the nearby desired value even if each sensors cannot completely understand which control input was selected by the plant.

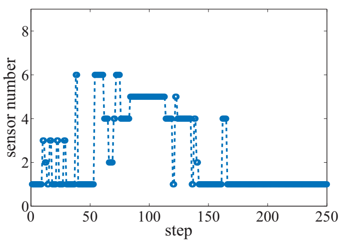

Fig. 9 Switching of Sensors (Experiment)

Fig.10 is a comparison between the minimum evaluation function which is based on the proposal method and previous method respectively. As shown in Fig.10, the estimation error covariance which bases on our proposal method is smaller than the estimation error covariance which bases on previous method.

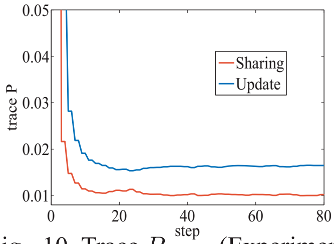

Fig. 10 Trace $P_{k|k-1}$(Experiment)

5. CONCLUSION

In this paper, we proposed estimate algorithm as DKF-neighbor discovery strategy which is based on DKF that combined neighbor discovery and predicted estimate value sharing algorithms. Finally, we evaluated the effectiveness of this algorithm by the experiments. Then we designed the feedback control system via a sensor network by using these algorithms.

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