Risk Management System based on Uncertainty Estimation by Multi-Agent

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***Abstract*— The purpose of this paper is to create risk management system that multi-agent patrols for maintaining security. We consider that maintaining security is equal to relieving uncertainty. Therefore, we formulate uncertainty of places needed to maintain security by the entropy in an information theory. We call these places "check point i(i=1,2,···,n)". Agents patrol and observe check point's condition value with updating patrol schedule on the basis of estimating uncertainty of check points in real time. We propose the method "Earliest Deadline First Scheduling with Adaptive Risk Estimation(EDFRE)" to relieve uncertainty. Then we compare the proposaled method with simpleEDF(Earliest Deadline First) scheduling. The result indicated that our proposal method was effective for dynamic situation.**

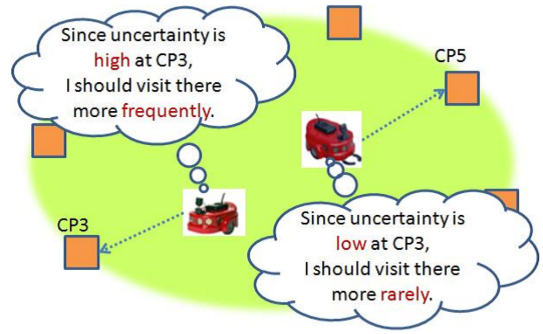


Fig. 1. Optimized patrol scheduling

I. Introduction

An environment where human and robots move in is always full of uncertainty. When moving in an environment like this, it becomes necessary to know how to move while decreasing its uncertainty. Generally, it is called " Risk Management " the dicrease of its uncertainty and the consideration of the handling of actualized risk, for example natural disasters. In our work, we define the former as " Risk Management " and discuss it. As an example of such Risk Management, we can mention the observation and patrol by police or guard. This work have the intention of always knowing the status of observation points or keeping it prediction horizon. In other words, their intention is to discrease the risk of observational uncertainty. For automatizing this action by robots, our paper treats a patrol scheduling problem considering uncertainty risk of observational points. Each agent keeps patrolling and sensing a condition value at observational points(check point:CP) in the environment. We propose a model that each CP(ith CP:CPi)'s uncertainty risk about the condition value is becames zero right after sensing by agent and increases with time after sensing by agent. We propose entropy of Gaussian distribution changing with time as an indicador of uncertainty risk changing with time(details in next section). And this uncertainty risk is defined as a risk of the system. Agents need to evaluate the uncertainty risk about CPi and decide a patrol interval according to the acceptable risk about CPi. If CPi's uncertainty is estimated high, rate of increase of entropy would be fast. So, agent needs to patrol and sense frequently the CPi. On the other hand, if CPi's uncertainty is estimated low, rate of increase of entropy would be slow. So, agent is allowed to patrol and sense rarely the CPi. Additionally, it is expected that excessive patrol to low uncertainty CP is inhibited for saving observational resources. In this way, while agents adjust a patrol interval to CPi adaptive uncertainty level, agents optimize the patrol scheduling with satisfying permissible range of uncertainty risk of system(Fig.1). This is our purpose.

Agents do not know CPi's uncertainty level(rate of increase of entropy). This paper proposes an algorithm that CPi's uncertainty level is estimated and updated by observation by agents. It is realized that the patrol scheduling method balances the valiable uncertainty risk with observational resources by updating optimized ideal patrol interval to CPi. The patrol scheduling problem we treat considers uncertainty risk of CP to be classified into two classes. One is multiple Traveling Saleseman Problem with Time Window(mTSPTW)[1]. The other is the realtime scheduling problem[4]. mTSPTW is a benchmark problem of combination optimization algorithm and have a convergent solution[2][3]. However, the problem we treat does not have a convergent solution, since patrol scheduling is always updated. So, these are alike but essentially different problems. On the other hand, the realtime scheduling is entirely used to task scheduling of CPU[5]. The scheduling is executed by feeding parameters (start time, cost, deadline and cycle time) by user. Recently this is actively used to task scheduling of robots[9]. There are RM(Rate Monotonic)[6][7],DM(Deadline Monotonic) and EDF(Earliest Deadline First)[8] scheduling as major algorithms. In past task scheduling of robots, the parameters of the task is given from the outside and is already-known[10]. When applying it to the present study, the outside is an initial value that the person gives and the task scheduling based on the initial estimation of uncertainty given by the person. The person's estimation might be appropriate to some degree. However, accuracy cannot be garanteed if uncertainty factors increase. The present study proposes adding adaptive Risk Estimation function to update the patrol interval automatically to the EDF scheduling(EDFRE). The EDF scheduling is the scheduling method for paying attention to deadline. Since we should consider the patrol interval is defined as the tolerance by the observation uncertainty risk of increase with time, we improve the EDF scheduling. The research of the patrol problem considering the observation uncertainty risk is scarce so far. The attempt of self-generating the patrol interval from the observational uncertainty risk estimation by robot is unparalleled.

The simulation was developed to evaluate the proposed method. First, the performance of proposed method(EDFRE) was checked. Next, it was simulated on the condition of increasing uncertainty of initial estimated uncertainty one by one. Finally simpleEDF, which is the ooptimum patrol interval for initial estimated uncertainty, was given as comparison with the proposed method, showing that the proposed method is excellent in adaptability to uncertainty of initial estimated uncertainty.

II. Modeling of Risk Management Problem

A. Abstract of Risk Management Problem

In the present study, it is defined that agents keep patrolling some observational points in the environment(Fig.2) to decrease the observational uncertainty risk as " Risk Management ". Each agent keeps patrolling, sensing a condition value of CP. We propose a model that CPi's uncertainty risk about the condition value becames zero right after sensing by agent and increases with time after sensing by agent. We propose entropy of Gaussian distribution changing with time as an indicator of uncertainty risk changing with time. And this uncertainty risk is defined as the risk of system. Agents need to evaluate the uncertainty risk about CPi and decide a patrol interval according to the acceptable risk about CPi. The state variable that changes stochastically for a fixed time is set as the condition value of CP. The state variable has a probabilistic swinging. Therefore, the model in which the existence probability distribution extends with time was proposed. It is synonymous with the rise of the probability, the state variable exceed the threshold, that the observation uncertainty risk has risen. Therefore, always keeping the state variable inside a safe level(the threshold) becomes a concrete purpose of agents.

B. Modeling of observation point having uncertainty

First of all, state variable x_i is defined as the condition value of CPi of the environment. x_i has threshold x_{th}. It is equal to exceeding of $\mid x_i \mid x_{th}$ that CPi deviates from the safety standard. Agents assume it to be dangerous. x_i is changed by every fixed time $d\tau$. x_i at time τ_i is made $x_i(\tau_i)$, and x_i at $\tau_i + d\tau$ is made $x_i(\tau_i + d\tau)$ and the conversion equation from $x_i(\tau_i)$ to $x_i(\tau_i + d\tau)$ is made as follows:

$$x_i(0) = 0 \quad (1)$$

$$x_i(\tau_i + d\tau) = x_i(\tau_i) + B_i \quad (2)$$

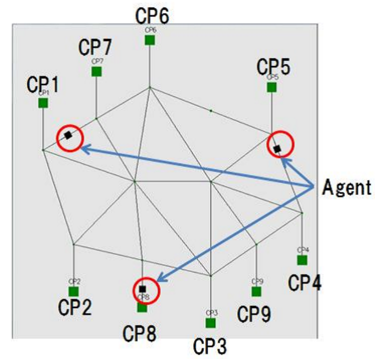


Fig. 2. Patrol map of Check Point

TABLE I
Definition of parameters

x_i	condition value of CPi
x_{th}	threshhold of condition variable of CP
y_{in}	nth observation value of CPi
τ_{in}	observation interval whe y_{in} was gotten
z_{in}	converted value from y_{in} and τ_{in}
σ_0	uncertainty of initial estimated uncertainty
σ_i	uncertainty of CPi
$\hat{\sigma}_{i0}$	initial estimated uncertainty of CPi
$\hat{\sigma}_i$	estimated uncertainty of CPi by Agent
τ_i	elapsed time of CPi after last observation by Agent
H_i	risk of observational uncertainty of CPi
H_{th}	threshhold of risk of observational uncertainty
$\Delta\tau_i$	ideal observational interval of CPi
$\Delta\tau_i^*$	real observational interval of CPi

B_i shows the Brownian motion and is a probabilistic swinging according to Gaussian distribution. This Gaussian distribution has a variance σ_i each CP have especialy. Eq.(2) becomes it above as follows if it shows in the stochastic differential equation:

$$dx_i = dB_i \quad (3)$$

In solving, it becomes Gaussian distribution changing with time. The above is shown by the equation:

$$p(x_i) = \frac{1}{\sqrt{2\pi}\sigma_i\tau_i} \exp\left\{-\frac{x_i^2}{2(\sigma_i\tau_i)^2}\right\} \quad (4)$$

As a result, a probabilistic swinging joins the condition value of CP and it becomes the model that the existence probability distribution extends with time.

C. Setting of function of Agent and estimated model of check point

1) Function of Agent: The moving speed is the same for all agents and the map of the field is assumed to be known. Moreover, the specified communication between agents is not done and the exchange of information uses the blackboard model. Agents can observe the condition value x_i of CPi by visiting CPi. Also agents can adjust the condition value to $x_i(0)$ and the observational uncertainty risk to 0 (make $\tau_i = 0$). Agents estimate and update $\hat{\sigma}_i$ in the CP estimation model shown by the next paragraph from an observational data. Also, agents can know when x_i exceeds x_{th} and the estimation of the uncertainty is changed along with it. Under such a condition, agents estimate the observational risk H of CPi based on estimated uncertainty of CPi $\hat{\sigma}_i$ from the observation for the condition value of CPi not to exceed the threshold. Therefore, agents update the patrol scheduling in real time and do the risk management. Also, each agent executes the algorithm individually.

2) Estimated model of check point: The Gaussian distribution changing with time is applied to the estimation model of CP. The Gaussian distribution changing with time have a temporary variance $(\hat{\sigma}_i\tau_i)^2$. It is given by multiplying elapsed time of CPi τ_i from the observation by agent at the end by the estimated uncertainty of CPi $\hat{\sigma}_i$. In a word, τ_i rises, $(\hat{\sigma}_i\tau_i)^2$ rises, and the probability for the condition value x_i to exceed the threshold rises with it. Therefore, $\hat{\sigma}_i$ is an estimation increase rate of the probability for $\mid x_i \mid$ to exceed x_{th}. In addition, because agent makes $\tau_i = 0$ at the same time as visiting and observing CPi, become $(\sigma_i\tau_i)^2 = 0$. In addition, the condition value will return to initial value $x_i(0)$ as a result. An important parameter in the present study is the uncertainty σ_i. But the initial value $x_i(0)$ is not so important. So, it is not an excessive assumption making $x_i(0) = 0$ of eq.(2) for the simplification of the calculation. The above is shown by the equation:

$$\hat{p}(x_i) = \frac{1}{\sqrt{2\pi}\hat{\sigma}_i\tau_i}\exp\left\{-\frac{x_i^2}{2(\hat{\sigma}_i\tau_i)^2}\right\} \quad (5)$$

In this way, x_i is estimated to be a random variable according to $N(0, (\hat{\sigma}_i\tau_i)^2)$. Also, initial estimated uncertainty is defined as $\hat{\sigma}_{i0}$. $\hat{\sigma}_{i0}$ is decided stochastically by Gaussian distribution having uncertainty of initial estimated uncertainty σ_0 as variance(eq.(6)). If $\sigma_0 = 0$, it would become $\hat{\sigma}_{i0} = \sigma_i$. But the probability, that $\mid \sigma_i - \hat{\sigma}_{i0} \mid$ grows, rises as σ_0 grows.

$$p(\hat{\sigma}_{i0}) = \frac{1}{\sqrt{2\pi}\sigma_0}\exp\left\{-\frac{(\hat{\sigma}_{i0} - \sigma_i)^2}{2\sigma_0^2}\right\} \quad (6)$$

In addition, in the present study, the observation uncertainty risk is formulated by the entropy in the information theory. Entropy H_i is calculated for eq.(5):

$$\begin{aligned} H_i &= -\int_{-\infty}^{\infty}\hat{p}(x_i)\log\hat{p}(x_i)dx \\ &= \log\sqrt{2\pi e}\hat{\sigma}_i\tau_i \quad (7) \end{aligned}$$

According to eq.(7), it is understood that H_i depends on $\hat{\sigma}_i$, that shows the uncertainty, and increases with time. Moreover, when the threshold of the condition value is defined x_{th}, agents judge that estimated existence probability of x_{th} over 0.1% is dangerous. The user can set this estimated existence probability of x_{th}. When the temporary variance $(\hat{\sigma}_i\tau_i)^2$ is replaced by σ_{th}^2 when this estimated existence probability of x_{th} is 0.1%,

$$\begin{aligned} \sigma_{th} &= \hat{\sigma}_i\tau_i \quad (8) \\ H_i &= \log\sqrt{2\pi e}\sigma_{th}. \quad (9) \end{aligned}$$

It becomes synonymous with the estimated existence probability of x_{th} 0.1%. H_i at this time becomes threshold H_{th} of the observational uncertainty risk.

III. EDF Scheduling with Adaptive Risk Estimation(EDFRE)

A. Abstract of EDFRE

The proposed EDFRE consists greatly of three parts. One is an estimation algorithm of the uncertainty of CPi that uses Bayesian estimation from the observational data of CPi. The second formulates the observational uncertainty risk of CPi from the estimated uncertainty by using entropy and is a decision algorithm of the ideal patrol interval of CPi based on it. The third is a patrol scheduling algorithm that uses EDF based on the ideal patrol interval. The behavior model of agent that mounts EDFRE is shown in Fig.3.

B. Method to estimate uncertainty

Agents estimate and update $\hat{\sigma}_i$ in the above-mentioned CPi estimated model by online Bayesian estimation[11], [12], [13], [14]. First, to do Bayesian estimation, the observational data is standardized. y_{in} according to $N(0, (\hat{\sigma}_i\tau_{in})^2)$ is converted into z_{in} according to $N(0, (\hat{\sigma}_i)^2)$ by using y_{in}(an nth observed value x_i of CPi) and τ_{in}(τ_i when an nth observed value x_i of CPi is obtained):

$$y'_{in} = \frac{y_{in}}{\sigma_i\tau_{in}} \quad (10)$$

Moreover, z_{in} similarly output from $N(0, \hat{\sigma}_i^2)$(the Gaussian distribution at $\tau_i = 1$) is standardized:

$$z'_{in} = \frac{z_{in}}{\sigma_i} \quad (11)$$

When $z'_{in} = y'_{in}$,

$$z_{in} = \frac{y_{in}}{\tau_{in}}. \quad (12)$$

This is assumed to be an observational data, and Bayesian estimation is done. Bayesian estimation theorem is shown by the following equation when a population parameter is θ and a data is x:

$$p(\theta|x) = \frac{l(\theta|x)\,p(\theta)}{k} \quad (13)$$

$p(\theta|x)$ is a posteriori distribution. $l(\theta|x)$ is a likelihood. The likelihood is the value that shows plausibility that guesses what the precondition was from the observational data. $p(\theta)$ is a prior distribution. k is a constant because the integration value of the numerator becomes one($k = \int(numerator)d\theta$). In the present study, $\theta = \hat{\sigma}_{in}^2$ and $x = z_{in}$. First, the likelihood is decided. Since the estimated model of CP is the Gaussian distribution,

$$l(\hat{\sigma}_{in}^2|z_{in}) = (2\pi\hat{\sigma}_{in}^2)^{-\frac{1}{2}}\exp\left\{-\frac{z_{in}^2}{2\hat{\sigma}_{in}^2}\right\}. \quad (14)$$

Next, the prior distribution is decided. First time uses the natural conjugate prior distribution and the following uses posteriori distribution $p(\hat{\sigma}_{i(n-1)}^2|z_{i(n-1)})$ obtained from the last estimation(eq.(16)):

$$\begin{aligned} p(\hat{\sigma}_{in}^2) &= p(\hat{\sigma}_{i(n-1)}^2|z_{i(n-1)}) \\ &= \frac{1}{k}(\hat{\sigma}_{i(n-1)}^2)^{\frac{-\nu_{i(n-1)}}{2}-1}\exp\left\{\frac{-\lambda_{i(n-1)}}{2\hat{\sigma}_{i(n-1)}^2}\right\} \quad (15) \end{aligned}$$

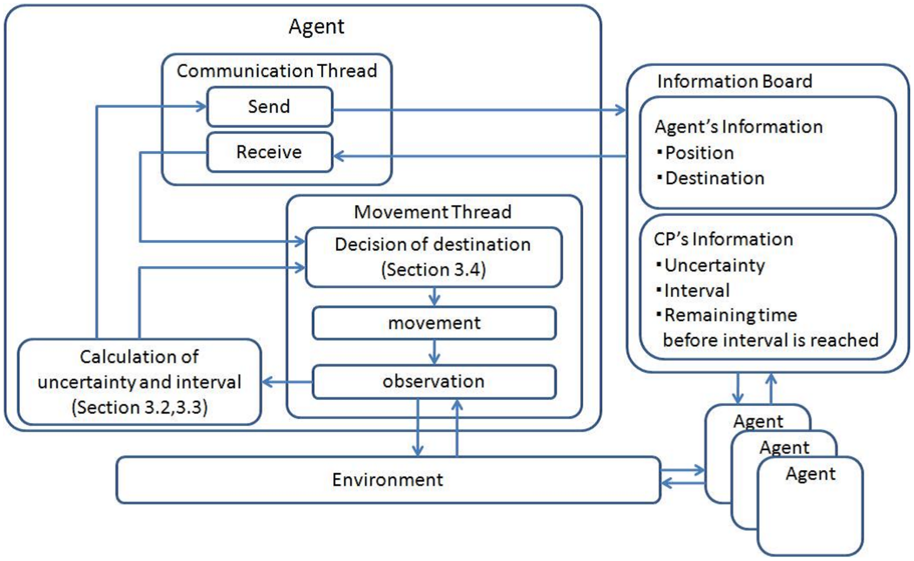


Fig. 3. Behavior model of agent

where $\nu_{i(n-1)} = n-1$, $\lambda_{i(n-1)} = \sum_{k=1}^{n-1} z_{ik}^2$. When eq.(14) (15) is substituted for eq.(13),

$$p(\hat{\sigma}_{in}^2|z_{in}) = \frac{l(\hat{\sigma}_{in}^2|z_{in})p(\hat{\sigma}_{in}^2)}{k} = \frac{1}{k}(\hat{\sigma}_{in}^2)^{-\frac{\nu_{in}}{2}-1}\exp\left\{-\frac{\lambda_{in}}{2\hat{\sigma}_{in}^2}\right\}. \quad (16)$$

where $\nu_{in} = \nu_{i(n-1)} + 1$, $\lambda_{in} = \lambda_{i(n-1)} + z_{in}^2$. In this way, the posteriori distribution of $\hat{\sigma}_{in}^2$ becomes the reverse-Kay square distribution $\chi^{-2}(\nu_{in}, \lambda_{in})$. Average of this distribution $\frac{\lambda_{in}}{\nu_{in}-2}$ is assumed to be a point-estimate value of $\hat{\sigma}_i^2$, and update $\hat{\sigma}_i^2$ and the estimated model of CPi.

C. Method to decide ideal patrol interval

Entropy H_i is calculated for the Gaussian distribution of CPi $N(0, (\hat{\sigma}_{in}\tau_{in})^2)$ obtained in the foregoing paragraph.By eq.(7),

$$H_i = \log\sqrt{2\pi e}\hat{\sigma}_i\tau_i. \quad (17)$$

Moreover, the entropy of a Gaussian distribution $N(0, \sigma_{th}^2)$ whose existence probability of x_{th} is 0.1% becomes threshold H_{th} of the observational uncertainty risk:

$$H_{th} = \log\sqrt{2\pi e}\sigma_{th} \quad (18)$$

From the above, a time $\Delta\tau_i$ to the excess of H_{th} by H_i can be calcuated. This becomes an ideal patrol interval of CPi. H_{th} is substituted at the left of eq.(17). And, in addition, both sides are assumed to be multipliers of Napier's const e:

$$e^{H_{th}} = 1 + \sqrt{2\pi e}\hat{\sigma}_i\Delta\tau_i \quad (19)$$

$$\Delta\tau_i = \frac{e^{H_{th}} - 1}{\sqrt{2\pi e}\hat{\sigma}_i} \quad (20)$$

Here, $+1$ at the right of eq.(19) is a measure to make $H_{th} > 0$. This $\Delta\tau_i$ becomes the ideal patrol interval and $\Delta\tau_i - \tau_i$ becomes the remainder time to the ideal patrol interval. The patrol scheduling is decided by using these for EDF.

D. Method to decide patrol scheduling

Agents want to patrol so that H_i should not exceed H_{th} and to suppress total moved distance to the minimum. Efficiency is expected to be optimized because the agent does not move until H_i approaches H_{th}, which reduces moved distance and, therefore, excessive observations. The decision method of the time that stands by is described. When a number of CPs is n_c and a number of agents is n_a, a number of CPs that one agent will bear is defined as $c = n_c/n_a$. The travel time between CP that is the longest is defined as t_{max}. $t_{i,rest}$ is defined as follows:

$$t_{i,rest} = \Delta\tau_i - ct_{max} \quad (21)$$

Agents will stand by when $t_{i,rest}$ is positive. The flow of EDFRE that integrates the above-mentioned three algorithms is shown.

(1) visiting to CPi
(2) obtaining the condition value and reseting the condition value and the risk
(3) estimating and updating uncertainty of CPi
(4) sorting CPs other agents will not go to in ascending order of $\Delta\tau_i - \tau_i$
(5) searching the closest agent to CP in the order
(6) when I am the nearest to CPi, next destination is decided CPi
(7) standing by until becoming $t_{i,rest} < 0$, and moving
(8) return to (1)

IV. Simulation

A. Purpose

Two kinds of simulations are done. The condition of simulation 1 is fixing uncertainty of initial estimated uncertainty σ_0 and changing the number of agents. The purpose of simulation 1 is to confirm that the proposed method works effectively and to discover the best number of agents to the given condition(field, threshold and σ_0). The condition

TABLE II

UNCERTAINTY σ_i FOR EACH CHECK POINT

	CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8	CP9
σ_i	4.3	1.5	2.5	2	3.8	1	4	2	1.5

of simulation 2 is changing uncertainty of initial estimated uncertainty σ_0 and fixing the number of agents. The simulation 2 is done by EDFRE and simpleEDF respectively, and compared. The purpose of simulation 2 is to confirm that EDFRE is excelling in adaptability to uncertainty of initial estimated uncertainty.

B. Simulation 1

1) Condition of simulation 1: The setting of σ_i does in TableII and $\sigma_0 = 1.0$. Threshold x_{th} of the condition value x_i is defined as $x_{th} = 33$. This 33 is a value of existence probability 0.1% in $N(0, 10.5^2)$. The threshold of the risk(entropy) can be obtained here:

$$\begin{aligned} H_{th} &= \log \sqrt{2\pi e}\sigma_{th} \\ &= \log(\sqrt{2\pi e} \times 10.5) \\ &\simeq 3.8 \end{aligned} \tag{22}$$

The simulation 1 is executed until $t = 500$ in the above conditions. It is done ten times by fixing $n_c = 9$ and changing n_a from 2 to 8 about each value. The estimated uncertainty $\hat{\sigma}_i$ and actual patrol interval $\Delta\tau_i^*$ is plotted for the time axis and the correlation between $\hat{\sigma}_i$ and $\Delta\tau_i^*$ is confirmed. Moreover, n_m(frequency for x_i to exceed x_{th}) and d(sum total of moved distance of all agents) is obtained, evaluation function D is made as follows:

$$D = 500n_c t - 10000n_m - 300n_a t - 0.75d \tag{23}$$

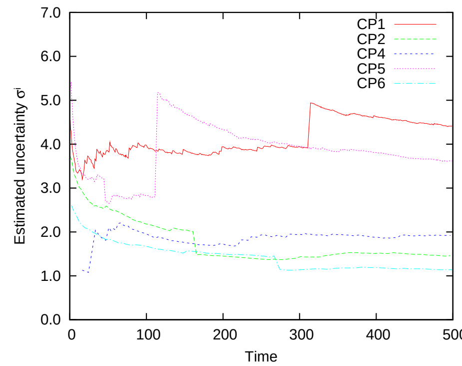
This average and standard deviation are made a bar chart and the change according to the number of agents is confirmed.

2) Result: From Fig.4, the correlation between $\hat{\sigma}_i$ and $\Delta\tau_i^*$ is confirmed. $\Delta\tau_i^*$ is short for CPi that $\hat{\sigma}_i$ is high. Oppositely $\Delta\tau_i^*$ is long for CPi that $\hat{\sigma}_i$ is low. Therefore, it can be confirmed that the proposed algorithm functions effectively.

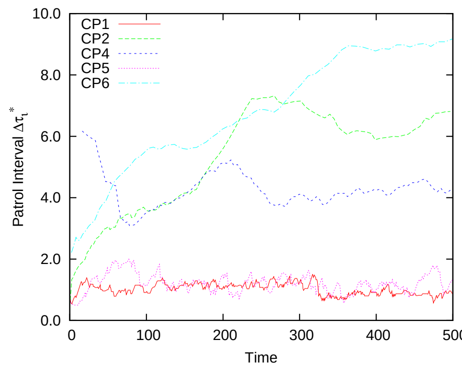
From Fig.5, it is understood that D is the highest when $n_a = 3$. When $n_a = 2$, the risk management is not success since the number of agents are insufficient. When $n_a \geq 4$, D decreases since the number of agents is tedious. It was able to be discovered that $n_a = 3$ was the most suitable in this condition.

C. Simulation 2

1) Condition of simulation 2: The simulation 2 is executed until $t = 500$ in the same conditions of x_{th} and σ_i with simulation 1. Also, $n_c = 9$, $n_a = 3$. It is done ten times by changing σ_0 from 0 to 2 about each value at intervals of 0.1 by using EDFRE and simpleEDF respectively. Performance P is given by the next equation, and the average and standard deviation are plotted. In simpleEDF, $\hat{\sigma}_{i0}$ is given to random



(a)Transition of estimated uncertainty



(b)Transition of patrol interval

Fig. 4. Correlation between estimated variance and patrol interval

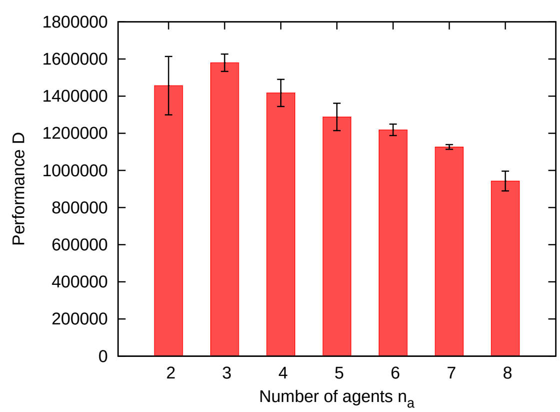


Fig. 5. Optimal number of agents in 9 CPs and $\sigma_0 = 1.0$

variable by σ_0 and the patrol scheduling is done based on it. Moreover, since CPi is clustered in three groups based on the initial condition, the best patrol scheduling is led in the conditions($n_a = 3$, $n_c = 9$ and $\hat{\sigma}_{i0}$). The change in performance P by the change in uncertainty of initial estimated uncertainty is compared between EDFRE and the optimum solution at $\hat{\sigma}_{i0}$ by simpleEDF. The moving speed of agent is defined as $v(= 160)$. The interval when CP changes the condition value is defined as $d\tau(= 0.25)$. In this time,

$$P = \frac{100}{P_{max}} \cdot \frac{tvn_a}{d\left(1 + \exp\left\{n_m - \frac{tn_c}{1000d\tau}\right\}\right)} \tag{24}$$

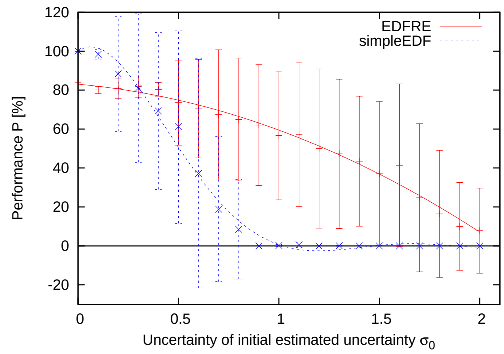


Fig. 6. Comparison between EDFRE and simpleEDF

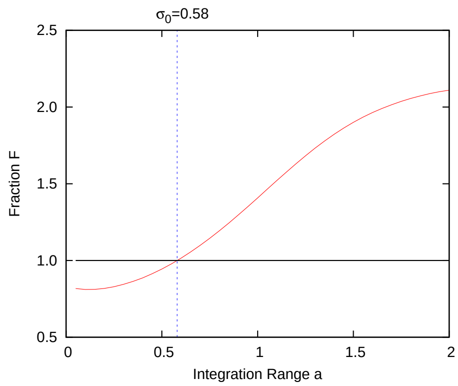


Fig. 7. Performance ratio curve F(a)

Here, $-tn_c/1000\Delta t$ in eq.(24) is a frequency for x_i to exceed x_{th} that corresponds to 0.1% at $t = 500$.

2) Result: In Fig.6, the approximation curve to EDFRE is defined as y_1 and the approximation curve to simpleEDF is defined as y_2. The performance P has fallen on y_1 by rising of uncertainty of the initial estimated uncertainty σ_0. This shows that the mistake increases as the time, that approach to correct estimation, increases. Also, since $y_1 = y_2$ is solved, it is understood that y_1 and y_2 intersect at $\sigma_0 = 0.321$. Therefore, it was shown that EDFRE was more effective when $\sigma_0 \geq 0.321$ though the optimum scheduling in $\hat{\sigma}i0$ by simpleEDF was effective when $\sigma_0 \leq 0.321$. Moreover, by seeing ratio $F(a)$ of values $(A(a)_1, A(a)_2)$ in which each approximation curve is integrated within the range of $0 \leq \sigma_0 \leq a$, the evaluations of expectation performance of the proposal method to uncertain initial values are compared:

$$F(a) = \frac{A(a)_1}{A(a)_2} = \frac{\int_0^a y_1 d\sigma_0}{\int_0^a y_2 d\sigma_0} \qquad (25)$$

From Fig.7, it was understood to become $F = 1$ at $\sigma_0 = 0.58$. Moreover, it was shown that EDFRE was 2.1 times more effective than simpleEDF in the range of $0 \leq \sigma_0 \leq 2$. We confirmed that EDFRE was excelling in adaptability to uncertainty initial estimated uncertainty.

V. Conclusion

In the present study, the patrol to reduce the observational uncertainty risk to observation points with uncertainty was assumed to be risk management. It is a purpose to develop the system to which the autonomous robot group where each one has the decision-making mechanism automatically does it. Then, in the beginning, we modeled check point that existed in the environment with uncertainty. Next, the estimated model of check point was constructed. Moreover, we proposed the algorithm to which it was estimated and updated by online Bayesian estimation by the observation. Next, the allowable limit of the observational uncertainty risk formulated by entropy was set and the ideal patrol interval was decided. Finally, we proposed EDFRE to which the patrol scheduling was in real time updated by using EDF based on the ideal patrol interval by self-generating. As resalt, we succeeded in the risk management in the condition having uncertainty of initial estimated uncertainty and the effectiveness of the proposed method was shown. By comparing between EDFRE and the optimum solution at $\hat{\sigma}_{i0}$, we showed that EDFRE was excelling in adaptability to uncertainty of initial estimated uncertainty.

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Risk Management System based on Uncertainty Estimation by Multi-Agent

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An environment where human and robots move in is always full of uncertainty. Generally, it is called "Risk Management" the dicrease of its uncertainty and the consideration of the handling of actualized risk, our paper treats a patrol scheduling problem considering uncertainty risk of observational points. Each agent keeps patrolling and sensing a condition value at check point:CP in the environment. We propose a model that each CP(ith CP:CPi)'s uncertainty risk about the condition value is becames zero right after sensing by agent and increases with time after sensing by agent. We propose entropy of Gaussian distribution changing with time as an indicador of uncertainty risk changing with time. Agents need to evaluate the uncertainty risk about CPi and decide a patrol interval according to the acceptable risk about CPi. While agents adjust a patrol interval to CPi adaptive uncertainty level, agents optimize the patrol scheduling with satisfying permissible range of uncertainty risk of system. Therefore, the present study proposes adding adaptive Risk Estimation function to update the patrol interval automatically to the EDF scheduling(EDFRE). A simulation was developed to evaluate the proposed method. We showed that the proposed method is excellent in adaptability to uncertainty of initial estimated uncertainty.