Task Handover Negotiation Protocol for Planned Suspension based on Estimated Chances of Negotiations in Multi-agent Patrolling

Sota Tsuiki, Keisuke Yoneda and Toshiharu Sugawara[a]

Department of Computer Science and Communication Engineering, Waseda University, Tokyo169855, Japan

Keywords: Multi-agent Patrolling Problem, Negotiation, Task Delegation, Coordination, Periodic Inspection, Scheduled Suspension, Timed Patrol.

Abstract: We propose a negotiation method that mitigates performance degradation in the multi-agent cooperative patrolling problem not only during planned suspensions for periodic inspection and replacement, but also during the transition period to the suspension. Recent developments in machine and information technologies have led to the expectation of using multiple intelligent agents to control robots. In particular, cooperation between multiple agents is necessary to process tasks that require complex and diverse capabilities or encompass a large environment. Because robots are machines, they need to be regularly inspected and replaced with new ones to prevent unexpected failures and prolong their lifespans. However, suspending agents for such inspections may cause a rapid performance degradation that cannot be neglected in some applications. Such suspensions are usually planned, and the transition period is known in advance, that is, we know which agents will be suspended and when. Our proposed negotiation method allows agents that are scheduled for suspension to hand over important tasks that should not be neglected to other agents. This mitigates the performance degradation during both the transition and suspension periods. The experimental results show that the performance degradation can be significantly reduced compared to existing methods, especially for security surveillance applications.

1 INTRODUCTION

With the recent development of AI technology, there is a demand for applications that use networked agents, such as intelligent sensors and autonomous robots, to perform dangerous tasks that are impossible for humans to perform or sophisticated and complex tasks on behalf of humans. In particular, the use of multiple cooperative agents is expected in large environments and high-complexity tasks. A problem that abstracts such tasks is the *multi-agent cooperative patrolling problem* (MACPP). In this problem, agents patrol a particular environment simultaneously, and cooperate with and complement one another to accomplish, for example, security surveillance (Chen et al., 2015), environmental monitoring (Rezazadeh and Kia, 2019; Zhou et al., 2020), and cleaning/sweeping in warehouses and public spaces (Altshuler et al., 2011; Wagner et al., 2008; Li et al., 2021).

However, because the agents autonomously determine appropriate actions from their own perspectives, cooperation and coordination between the agents are necessary not only for each individual agent to accomplish its work, but also to avoid actions such as collisions that can prevent other agents from working as well as to ensure overall efficiency by eliminating overlapping redundant work with other agents. However, it is not easy to design and implement cooperative behavior in advance because many factors, such as the temporal and spatial constraints and capabilities of all the agents, must be considered. However, these factors are difficult to understand fully in the design phase. Therefore, an autonomous learning method strategy for efficient cooperative behavior between multiple agents is required in which the capabilities of each individual agent and the other agents, the characteristics of the environment, and the learned behaviors of other cooperative agents are considered. Moreover, if the agents are self-driving robots or machines, it is probable that they will stop for periodic inspections over relatively long cycles that alternate between agents , as well stop over relatively short cycles, such as for recharging. Performance degradation during these suspension periods, especially for

[a] https://orcid.org/0000-0002-9271-4507

a longer cycles that require longer suspension time, must be reduced as much as possible.

There have been several studies on MACPP based on two major approaches for cooperation and coordination between agents. In the first approach, the agents divide the environment into areas of responsibility by themselves explicitly and assign each area to one or a few agents (Ahmadi and Stone, 2006; Elor and Bruckstein, 2009; Kato and Sugawara, 2013; Zhou et al., 2019). For example, Elor and Bruckstein (Elor and Bruckstein, 2009) proposed an area partitioning method to balance the sizes of subareas allocated to individual agents based on the balloon pressure model. However, if a few agents leave the system for inspection, the assignments will need to be recalculated from scratch, and the results for the environmental characteristics learned by the individual agents may become useless.

In the second approach, the agents autonomously select patrol strategies and algorithms according to the environment and the behaviors of the other agents without an explicit division of the environment (Kalra et al., 2005; Elmaliach et al., 2007; Sampaio et al., 2010; Yoneda et al., 2015; Sugiyama et al., 2019; Othmani-Guibourg et al., 2017; Othmani-Guibourg et al., 2018). For example, Yoneda et al. proposed the *adaptive meta-target decision strategy* (AMTDS) in which each agent autonomously decides on an appropriate patrol strategy using reinforcement learning while learning the frequency of visit requests for each location in the environment (Yoneda et al., 2015). Sugiyama et al. proposed *AMTDS with learning of event probabilities to enhance divisional cooperation* (AMTDS/EDC), which is an extension of AMTDS through the addition of a dynamic and lightweight negotiation method to balance the workloads of the agents (Sugiyama et al., 2019). We chose the second approach in the present study because it is more appropriate for addressing the periodic suspension of agents. However, we found that when the number of agents suddenly becomes lower because of periodic suspensions, there is a temporary but considerable decrease in the total performance. The performance degradation cannot be neglected in some critical applications, such as security patrols, to avoid security gaps.

To address this issue, Tsuiki et al. proposed a method called *AMTDS with task handover for scheduled suspension* (AMTDS/TH) to mitigate the overall performance degradation when some agents are suspended for inspection (Tsuiki et al., 2021). In this approach, the negotiation protocol used in AMTDS/EDC is extended and used when agents are in close proximity to one another because of the limitations of Wi-Fi communications. Because the *transition period* for the next suspension of some agents is known in advance, that is, which agents will be stopped and when, the agents that are scheduled for suspension can gradually delegate or hand over some of their tasks to other agents to reduce the performance degradation. It was shown that this method can mitigate the temporary but significant performance degradation due to the planned suspension. However, the number of tasks that are delegated to other agents before the suspension is fixed and cannot be flexibly changed. It is also difficult to determine the appropriate number of tasks to hand over. This led to a large decrease in efficiency before suspension that canceled out the performance improvement during the suspension period.

Therefore, in this study, we integrate a novel negotiation method with conventional AMTDS/TH to estimate the number of tasks that should be delegated to other agents during the transition period. The decrease in performance is thereby mitigated not only during the planned suspension period but also during the preceding transition period. We then conducted experiments for the two MACPP applications of cleaning/sweeping and security surveillance, and evaluated the proposed method by comparing its performance with those of the previous AMTDS/TH method and other conventional methods.

2 RELATED WORK

Many studies to enable cooperative and coordinated behavior between multiple agents to execute an MACPP instance efficiently and effectively have been conducted. As mentioned in the previous section, there are two major approaches for agent coordination in MACPPs. The first approach involves the division of the environment into distinct subareas that one or a few agents are in charge of autonomously so that the agents can work cooperatively with high efficiency while avoiding conflicts and redundant work (Ahmadi and Stone, 2006; Elor and Bruckstein, 2009; Kato and Sugawara, 2013; Zhou et al., 2019; Xie et al., 2020). For example, Ahmadi and Stone proposed a method to partition the areas of responsibility through negotiations in an environment in which the frequency of events is possibly non-uniform, as in our case, and the agents should visit the locations with different frequencies. Hence, the area is partitioned by the agents to balance their visiting frequency (Ahmadi and Stone, 2006). Elor and Bruckstein proposed a method to divide the environment into areas of responsibility for individual agents by equalizing their expansion force. This method was inspired by the pressure model of a balloon (Elor and Bruckstein, 2009).

The second approach is to autonomously decide on an appropriate patrol strategy based on the surrounding environment and the state of the agents without explicitly dividing the environment in advance (Kalra et al., 2005; Elmaliach et al., 2007; Sampaio et al., 2010; Yoneda et al., 2015; Sugiyama et al., 2019). For example, Elmaliach et al. proposed a method in which the patrol paths in the environment are generated and assigned to individual agents (Elmaliach et al., 2007). Sugiyama et al. proposed a negotiation protocol to balance the workload between agents by exchanging information about the locations that should be visited frequently (Sugiyama et al., 2019). We chose the second approach because efficiency may be negatively impacted in the first approach when no agents are assigned to certain areas. However, even in the second approach, the previous studies have not considered temporal suspension. Planned suspensions can result in significant performance degradation. In particular, Sugiyama et al. reported that sudden stoppages considerable reduce efficiency (Sugiyama et al., 2019).

Some recent studies have used learning algorithms to enable multiple agents to patrol an environment in a cooperative manner (Zhou et al., 2019; Xie et al., 2020). For example, Zhou et al. formulated the patrolling problem as a Bayes-adaptive transition-decoupled partially observable Markov decision process and introduced a decentralized online learning algorithm using the Monte Carlo tree search method (Zhou et al., 2019). Xie et al. used particle swarm optimization (PSO) to find reasonable patrol paths by partitioning the environment (Xie et al., 2020). Othmani-Guibourg et al. proposed the learning of distributed multi-agent patrol strategies using a *long short-term memory* (LSTM) network which is embedded in each agent and trained using data generated in a simulated environment. The network then navigates the agent in the environment to be patrolled by determining its next movement (Othmani-Guibourg et al., 2018). However, these studies also did not consider the significant deterioration that results when periodic suspensions cause sudden changes in the environment, which includes the other agents.

There are a number of studies on planned suspension/stoppages in multi-agent frameworks. Panteleev et al. and Ghita et al. proposed methods to produce plans for the periodic maintenance/inspection and repair of technical equipment using a multi-agent simulation environment (Panteleev et al., 2014; Ghita et al., 2018). These studies differ from ours in that their aim is to develop work plans that account for planned leaves to reduce the workload of staff managing technical equipment. In other research fields, for example, Gavranis and Kozanidis developed an algorithm for the flight maintenance problem (FMP problem) (Gavranis and Kozanidis, 2015). Seif and Andrew extended this algorithm to solve the operation and maintenance planning problem, which is a generalized version of the FMP problem (Seif and Andrew, 2018). Moradi and Shadrokh proposed a robust trust-based scheduling system that uses a heuristic algorithm for efficient resource allocation to ensure the reliability of the system for scheduling maintenance activities during planned shutdowns with unknown activity durations (Moradi and Shadrokh, 2019). However, to the best of our knowledge, these methods require centralized control, and there is no study so far on methods for autonomous agents to prepare for the planned suspension by themselves.

3 MACPP MODEL

The MACPP model and issues addressed in this study are the same as those in the conventional studies (Sugiyama et al., 2019; Tsuiki et al., 2021), and are described in detail below.

3.1 Environment

The environment patrolled by the agents is represented by a graph, $G = (V, E)$, embedded in a two-dimensional Euclidean space, where $V = \{v_1, \dots, v_n\}$ is the set of nodes corresponding to locations in the environment, and E is the set of edges $e_{i,j}$ connecting nodes v_i and v_j in V. An agent, an *event*, and an obstacle can exist at node $v \in V$. Note that the events in this study can vary depending on the application; for example, in a security surveillance application, the number of events in a location corresponds to the alert level at the location, and the accumulation of events represents an increase in the alert level. In other examples, an event in a cleaning application corresponds to the accumulation of a piece of dirt at a location and the task is to vacuum the accumulated dirt up; in an egg collection application, an event is the laying of an egg on a certain area of the ground in a free-range farm, and the task is to collect the laid eggs (Li et al., 2021).

The length of all the edges can be assumed to be one without the loss of generality by adding dummy nodes as needed. Let $d(v_i, v_j)$ be the shortest distance between v_i and v_j (i.e., the minimum number of edges between two nodes), and $m(v_i, v_j)$ be the Euclidean distance. We introduce a discrete time with the unit of a time step and assume that an agent can move to a neighboring node and process the tasks on the current node in a time step.

For a node $\forall v \in V$, we denote the *event occurrence probability* at v as $p(v)$ $(0 \le p(v) \le 1)$ at every time step. At time step t, the number of accumulated events $L_t(v)$ on node v is updated as

$$L_t(v) = \begin{cases} L_{t-1}(v) + 1 & \text{(if an event occurs)} \\ L_{t-1}(v) & \text{(otherwise, i.e., with} \\ & \text{probability } 1 - p(v)\text{).} \end{cases}$$

When an agent arrives at v, all events on v are processed and eliminated by executing the corresponding tasks, and $L_t(v)$ is set to 0.

3.2 Agents and Their Behaviors

Let $A = \{1, \ldots, n\}$ be a set of n agents. Agent $i \in A$ has a finite capacity battery and must return to its charging base before the battery level reaches zero. Agent i assigns an importance $p^i(v)$ to each node $\forall v \in V$. $p^i(v)$ is the predicted probability of event occurrence inferred from the number of events executed by the agent itself $(0 \le p^i(v) \le 1)$. Note that because $p^i(v)$ is the probability predicted by each individual agent, it can differ between agents, even for the same node v. The calculation of $p^i(v)$ is described in Section 3.3.

Although i cannot directly access the value of $L(v)$, it can estimate the number of events $EL^i_t(v)$ accumulated at node v at time t using the predicted $p^i(v)$ through

$$EL^i_t(v) = p^i(v) \times (t - t^v_{vis}),$$

where t^v_{vis} is the time when node v is most recently visited by an agent, and t^v_{vis} is assumed to be shared with all the agents.

The agent i decides its actions as follows: First, it determines the next target node v^i_{tar} through a *target decision strategy* (TDS), generates a path to v^i_{tar} using the path generation strategy, and moves to it along the path. When i arrives at v^i_{tar}, it determines the next target node and thereafter repeats the cycle of path generation and movement described above. However, i returns to the charging base when its remaining battery capacity is low. Agent i uses the AMTDS (Yoneda et al., 2015) to select its TDS. AMTDS is a meta-strategic method for selecting an appropriate TDS from a set of basic TDSs by Q-learning based on $EL^i_t(v)$ and the expected rewards based on the number of events executed per time step . In the experiments below, the TDSs are the four simple basic strategies of *random selection*, *probabilistic greedy selection*, *prioritization of unvisited interval sections*, and *balanced neighbor-preferential selection*.

After the next target node v^i_{tar} is determined, the agent uses *gradual path generation* (GPG) (Yoneda et al., 2015) to generate a path. i generates the shortest path to v^i_{tar} using a simple path-finding algorithm (such as A*-search). If there is a node that has a high value of $EL^i_t(v)$ in the vicinity of the generated shortest path, i adds a detour to that node to the path. The details of the four TDSs, the GPG, and the method of returning to the charging base are beyond the scope of this paper; please refer to (Yoneda et al., 2015) for more details.

3.3 Learning and Exchange of Importance Values of Nodes

The importance values of the nodes and the negotiation to delegate tasks/nodes, which were introduced in AMTDS/EDC (Sugiyama et al., 2019), are the central concepts in our proposed method. The importance value of node $\forall v$ is initialized as $p^i(v) = 0$. When agent i executes the task in node v at time t, $p^i(v)$ is updated regardless of the number of events accumulated in v as

$$p^i(v) = (1 - \alpha)p^i(v) + \alpha \frac{1}{t - t^v_{vis}},$$

where α $(0 < \alpha \le 1)$ is the learning rate for the importance value.

To further promote load balancing and coordination between the agents and increase robustness against environmental changes, the agents exchange importance values through negotiation among themselves. This means that i delegates to or is delegated to by other agents so that the agents in the system can patrol intensively. When $m(v^i, v^j) < d_{co}$ for $i, j \in A$, where the parameter $d_{co} (> 0)$ specifies the *communication range* between the agents, i and j are in communication range and can negotiate with each other. Moreover, to suppress excessive communication, we introduce the *minimum communication interval* $B (> 0)$ between i and j, that is, i and j store the last time they negotiated with each other, $T^{i,j}_{lst}$, and do not negotiate with each other until $T^{i,j}_{lst} + B$.

Agent i has its *responsible node set* $V^i_R \subset V$, which is the set of N^i_R (> 0) nodes with the highest importance values. The initial values are set to $V^i_R = V$ and $N^i_R = |V|$. V^i_R and N^i_R are updated when i returns to the charging base. The agents use two types of negotiation (negotiation for balancing task workloads and negotiation for exchanging responsibility) between themselves to update $p^i(v)$, V^i_R, and N^i_R. For more details on the two types of negotiations and how $p^i(v)$, V^i_R, and N^i_R are updated, please refer to (Sugiyama et al., 2019).

3.4 Evaluation Metrics

We evaluate the system using two types of metrics depending on the expected applications. The first is the *total number of time steps in which the events are left unprocessed*. For example, in a cleaning or egg collection application, the number of unprocessed events (pieces of dirt not sucked up by the vacuum cleaner or uncollected eggs) remaining in the environment and the amount of time they are left unprocessed should be minimized. D_{t_s,t_e} between time t_s and t_e ($t_s < t_e$) is defined as

$$D_{t_s,t_e} = \sum_{v \in V} \sum_{t=t_s+1}^{t_e} L_t(v).$$

A smaller value of D_{t_s,t_e} indicates a more efficient patrol.

The second metric is the *maximum number of unprocessed events* for all the nodes. For example, in a timed security patrol, no single point should be left unmonitored. Therefore, all agents must maintain the maximum number of unprocessed events (i.e., time left unmonitored) across all nodes so that the predefined alert level is not exceeded . This metric U_{t_s,t_e} between time t_s and t_e ($t_s < t_e$) is defined as

$$U_{t_s,t_e} = \max_{v \in V, t_s \le t \le t_e} L_t(v).$$

A smaller value of U_{t_s,t_e} also indicates a more efficient patrol. Hereafter, for the sake of simplicity, D_{t_s,t_e} and U_{t_s,t_e} are denoted as $D(s)$ and $U(s)$, respectively, and t_s and t_e are omitted if their values are obvious. Our goal is to maintain $D(s)$ and $U(s)$ low even when a number of agents are stopped for scheduled suspensions.

4 PROPOSED METHOD

In this study, we propose an extension of AMTDS/TH (Tsuiki et al., 2021) called *AMTDS with task handover for scheduled suspension based on the estimated chance of encounters* (AMTDS/THE) to reduce performance degradation during the periods of task handover and planned suspension. Specifically, because agents can only negotiate between themselves when they encounter each other, that is, when their distance is shorter than d_{co}, the agents memorize the number of times that they have negotiated from the (re)start time. The agents that are scheduling their planned suspension estimate the number of possible negotiation opportunities until the suspension using these data and determine the number of nodes that should be delegated to other agents during the transition period. This reduces the efficiency loss not only during the planned suspension but also during the transition period before the planned suspension.

4.1 Estimation of Encounters until Planned Suspension

To estimate the number of possible negotiations until the planned suspension time, agent i counts the number of encounters for negotiation $N^i_{en}(t)$ between the current time t and the most recent start time or return time from inspection. Note that the agents do not negotiate with one another until B time steps have passed since the last negotiation. The agents also do not consider the content or quantity of the negotiation or the agents that they have negotiated with.

The next planned suspension S for periodic inspection or replacement is given in advance as a tuple $S = (A_S,\ T_{sp},\ T_{rs},\ D_{tp})$, where $A_S (\subset A)$ is the set of agents that will be suspended from the start time of the suspension T_{sp} to the return time from the suspension T_{rs}. Parameter D_{tp} is the length of the transition period; thus, the scheduled suspension is announced to all agents at $T_{sp} - D_{tp}$. When S is announced at t, agent i estimates the number of opportunities for negotiation $N^i_{ng}(t)$ until T_{sp} as

$$N^i_{ng}(t) = N^i_{en}(t) \times \frac{T_{sp} - t}{t - T_{st}} \times \frac{|A_S|}{|A| - 1},$$

where T_{st} is the time at which i initializes $N^i_{en}(t)$ and starts to count it. Therefore, $T_{sp} - t$ is the time remaining until the planned suspension is reached. Note that $N^i_{ng}(t)$ is an estimated value and therefore usually differs from those of other agents which may be working in different areas.

4.2 Negotiation for Handover during Transition Period

When both agents i and j are in A_S or in $A \setminus A_S$, they negotiate with each other by using the negotiation protocol proposed in (Sugiyama et al., 2019) to enhance workload balance and activity coordination among agents. Otherwise, when $i \in A_S$ and $j \in A \setminus A_S$, they perform a negotiation for unidirectional task delegation to increase the number of nodes that j is responsible for by transferring some of the importance values from i to j. This implies that i indirectly delegates some tasks in its important nodes to j.

First, agent $i \in A_S$ selects the top $e^i_g (> 0)$ nodes with the highest importance values from V^i_R. Then, the selected nodes are transferred from i to j at a fixed ratio of $p^i(v)$. The importance values of the se-

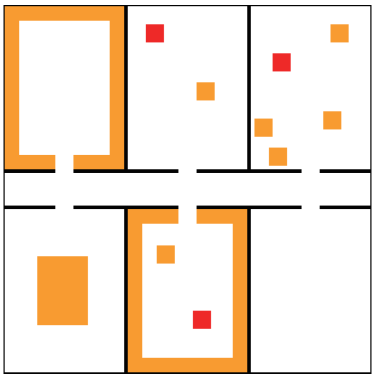


Figure 1: Experimental environment.

lected nodes for i and j are updated using the following equations:

$$p^j(v) \leftarrow p^j(v) + p^i(v) \times \delta_c$$
$$p^i(v) \leftarrow p^i(v) \times (1 - \delta_c),$$

where $\delta_c (0 < \delta_c < 1)$ is the *ratio of importance value passed*. This means that agent i does not completely forget the delegated nodes, but rather induces j to expand its work scope. Thus, j may not visit these nodes frequently, and i will also visit the nodes that it has delegated.

The number of nodes e^i_g that agent i transfers to another agent is determined using $N^i_{ng}(t)$ by the following formula:

$$e^i_g = \left\lfloor \frac{N^i_R}{\max(1, N^i_{ng}(t))} \right\rfloor, \tag{1}$$

where $N^i_R > 0$ is the upper limit of the nodes to be delegated and is updated in both i and j as

$$N^i_R \leftarrow N^i_R - e_g$$
$$N^j_R \leftarrow \min(|V|, N^j_R + e_g).$$

The max in the denominator in Eq. (1) prevents division by zero. Note that after the importance values are updated, the sets of responsible nodes, V^i_R and V^j_R, are updated when i and j return to their charging bases.

5 EXPERIMENTS

5.1 Experimental Setting

We conducted experiments to compare the proposed AMTDS/THE method with the conventional AMTDS/EDC and AMTDS/TH methods to demonstrate that AMTDS/THE can mitigate performance degradation both due to the task handover from the suspended agents during the transition period and due to the suspension of the agents for inspection. In this experiment, we used $D(s)$ for the cleaning application and $U(s)$ for the timed security patrol application and introduced different lengths of the transition period leading up to the suspension to show that the proposed method is effective in various applications of the MACPP.

To allow for a simple comparison with conventional methods, the experimental environment was the same as that used in (Sugiyama et al., 2019) and (Tsuiki et al., 2021). This environment $G = (V, E)$ is a two-dimensional 101×101 grid structure comprising six rooms and a central corridor, as shown in Fig. 1. The node $v \in V$ is located on the coordinates (x_v, y_v), where $-50 \leq x_v, y_v \leq 50$. The black lines indicate the walls. For node $\forall v \in V$ in the environment, the event occurrence probability of node $p(v)$ in Fig. 1 is set as follows:

$$p(v) = \begin{cases} 10^{-3} & \text{(if } v \text{ is in a red region)} \\ 10^{-4} & \text{(if } v \text{ is in an orange region)} \\ 10^{-6} & \text{(otherwise, i.e., in a while region)} \end{cases}$$

based on the colors of the nodes. Events are more likely to occur in the nodes with deeper colors.

The number of agents is 20 ($|A| = 20$), and the charging base v^i_{base} of all the agents is placed at $(0, 0)$, the center of the environment. It is also possible to place a charging base at a different location for each agent. Agent i leaves v^i_{base} when its battery is full, patrols the environment according to its own strategy, and returns to v^i_{base} before its battery level reaches zero. The agents perform this action cycle repeatedly. We set the battery capacity of each agent to 900, and assume that the battery decreases by one per time step. Therefore, the battery is exhausted in 900 time steps. The time required to increase the charge in the battery by one unit is 3 time steps. This means that it takes 2700 time steps for the battery capacity to reach full capacity from a totally discharged state. For this reason, we set the data collection interval $t_e - t_s$ for the evaluation indices $D(s)$ and $U(s)$ to 3600, because the maximum number of time steps in the charge and movement cycle is 3600. The values for the battery were set with reference to an actual cleaning robot.[1]

The length of each experimental run was set to 3,500,000 time steps. The experimental results shown below are the average values of 20 runs. A set comprising half of the agents from A was randomly selected in each trial and denoted as A_1. We define

[1]It was assumed that one time step corresponds to approximately 4 seconds, the moving speed is approximately 0.25 m/s, the maximum continuous operational time is approximately 1 hour, and the maximum charging time is approximately 3 hours.

Table 1: Experimental parameters.

Description	Parameter	Value
Number of agents	$\lvert A \rvert$	20
Communication range	d_{co}	5
Minimum communication interval	B	10800
Ratio of importance values passed	δ_c	0.5
Data collection interval	$t_e - t_s$	3600
Learning rate for importance value	α	0.1

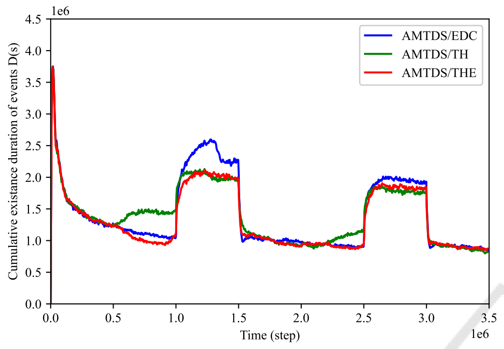


Figure 2: Variation of $D(s)$ over time.

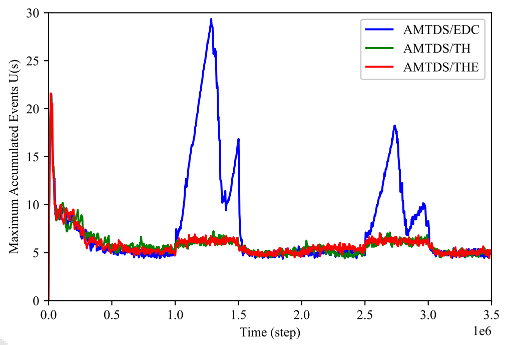


Figure 3: Variation of $U(s)$ over time.

$A_2 = A \setminus A_1$. We set two planned suspensions, S_1 and S_2, in each run by assuming that the next inspections are scheduled for a few days or weeks and performed two experiments with different suspension schedules. Recall that the planned suspension is represented by $(A_S,\ T_{sp},\ T_{rs},\ D_{tp})$. In Experiment 1 (Exp. 1), the planned suspensions are represented as

$$S_1 = (A_1,\ 1{,}000{,}000,\ 1{,}500{,}000,\ 500{,}000),$$
$$S_2 = (A_2,\ 2{,}500{,}000,\ 3{,}000{,}000,\ 500{,}000),$$

and in Experiment 2 (Exp. 2) as

$$S_1 = (A_1,\ 1{,}000{,}000,\ 1{,}500{,}000,\ D_{tp}),$$
$$S_2 = (A_2,\ 2{,}500{,}000,\ 3{,}000{,}000,\ D_{tp}),$$

where we set $D_{tp} = 100{,}000$ and $20{,}000$. As mentioned above, 3600 time steps correspond to approximately four hours in our simulated environment; therefore, the transition periods of $D_{tp} = 500{,}000$, $100{,}000$, and $20{,}000$ correspond to approximately three weeks, 4.5 days, and one day, respectively. The number of agents to be suspended in each planned suspension was 10, which is half of the total number of agents. Although it is unlikely that half of the agents will be stopped in actual operations, the experiments were performed with extreme settings to confirm the effectiveness of the proposed method.

5.2 Performance Comparison

We plot the results for the evaluation metric $D(s)$ for the cleaning-type application and $U(s)$ for the security patrol for the proposed AMTDS/THE method and the conventional AMTDS/EDC and AMTDS/TH methods in Fig. 2 and Fig. 3. The following two observations can be made from the figures:

First, compared to the conventional AMTDS/EDC method, in which task delegation is not performed before the planned suspension, the large performance degradation during the planned suspension, especially the sharp and significant deterioration of $U(s)$, are reduced in the proposed AMTDS/THE and AMTDS/TH methods. Comparing between AMTDS/THE and AMTDS/EDC, the peak value of $U(s)$ in AMTDS/THE was reduced by approximately 76.5% compared to AMTDS/EDC during the first planned suspension and by approximately 61.4% during the second suspension. For the cleaning problem, the sum of $D(s)$ was improved by approximately 14.3% for the first suspension and by approximately 5.68% for the second. Note that there was no significant difference in performance degradation during the planned suspension between AMTDS/THE and AMTDS/TH, as shown in Figs. 2 and 3, respectively. This is because agents scheduled for planned suspension could effectively delegate a portion of their nodes to agents not scheduled for the next planned suspension; thus, they continued to cover the entire area, which prevented a large performance deterioration.

Second, these figures also show that the performance degradation during the transition period until the planned suspension was significantly reduced in

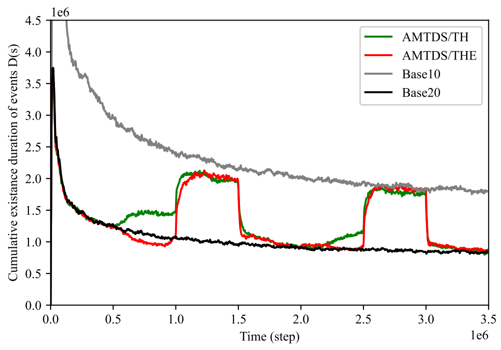


Figure 4: Performance comparison ($D(s)$).

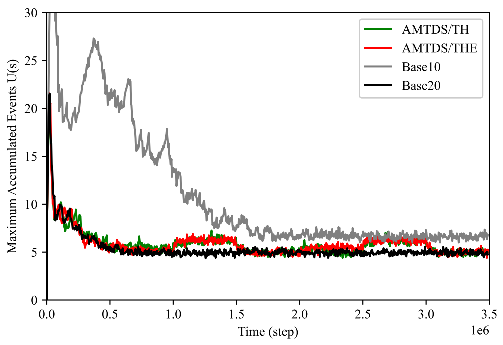


Figure 5: Performance comparison ($U(s)$).

AMTDS/THE compared to AMTDS/TH, especially for $D(s)$, although AMTDS/TH also delegated nodes during the transition period. A detailed numerical analysis showed that AMTDS/THE reduced the total $D(s)$ during the transition period by approximately 26.0% for the first transition period and by approximately 9.00% for the second transition period compared to AMTDS/TH. Comparing the performance of AMTDS/TH and AMTDS/EDC, the efficiency improvement during the planned suspension obtained with AMTDS/TH was offset by the efficiency loss during the transition period. Meanwhile, there was no significant difference in $U(s)$ during the transition period between AMTDS/THE and AMTDS/TH, and neither method caused a significant decrease in efficiency.

In general, the workload of the agents during the transition period is likely to become unbalanced and result in degraded performance because of task handover for delegation. In AMTDS/THE, this negative effect was prevented because the important nodes that were deemed necessary to be always covered were gradually and evenly handed over using the accurately estimated number of negotiation opportunities until the beginning of the suspension period. In contrast, because the number of negotiation opportunities were not accurately estimated in AMTDS/TH, a large number of nodes were delegated at an early stage. Therefore, the agents that were delegated many nodes could not process all of them . This caused the efficiency to be degraded before the suspension.

5.3 Performance Analysis

Although the sudden loss of efficiency due to the planned suspension was found to be mitigated in AMTDS/THE, we would like to verify whether the resulting efficiency was adequate. Because there were only 10 running agents during the planned suspension period, we compared the efficiency with that of the case in which the MACPP instances were executed with 10 agents from the beginning without planned suspensions. We also examined the efficiency when all 20 agents were running at all times with no planned suspension. The results are shown in Figs. 4 and 5. Note that the labels “Base10” and “Base20” in these figures represent the results for the cases of 10 agents and 20 agents, respectively.

These figures show some interesting results. First, in the performance results during the two planned suspensions, both of the metrics, $D(s)$ and $U(s)$, were as low as or lower than the case of 10 agents with no planned suspensions at all (i.e., “Base10”). This indicates that the proposed method not only mitigated performance degradation during the planned suspensions, but prevented it completely. Second, the values of $D(s)$ and $U(s)$ were greatly improved compared to the Base10 case when AMTDS/THE or AMTDS/TH was adopted, especially during the first planned suspension period. This may be because it took more time for the agents to learn, especially for $U(s)$, when there were only 10 agents compared to when there were 20 agents, because there were fewer opportunities for interactions between the agents for learning. Hence, the learning stabilized faster when the number of agents was 20. It is therefore better to run a large number of agents (e.g., 20) in the earlier stages and then to reduce the number of agents using the proposed method to speed up the learning convergence, even when the final number of agents is 10.

Furthermore, the metric $D(s)$ during the transition period of the first planned suspension (Fig. 4) indicates that AMTDS/THE exhibited better efficiency than the case in which 20 agents worked constantly (“Base20”). We can see from the curve for Base20 in Fig. 4 that the learning had not yet converged, even during the transition period of the first planned suspension. We believe that the joint work at the important nodes was increased through information sharing in the proposed AMTDS/THE when the agents informed other agents of the important nodes they had learned so far, albeit unilaterally.

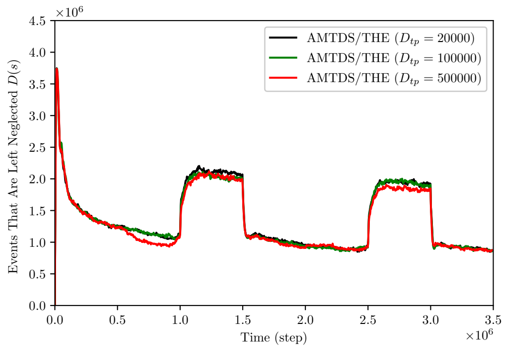


Figure 6: $D(s)$ at different transition periods (D_{tp}).

5.4 Effect of Transition Period Length

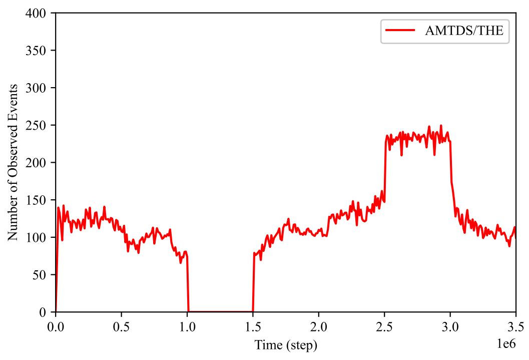
In Exp. 2, we verified whether AMTDS/THE was effective even when the transition period until the next planned suspension was shortened by setting $D_{tp} = 100,000$ or $20,000$. Because we set $B = 10800$, the number of opportunities for negotiations between each pair of agents was at most 8–10 when $D_{tp} = 100,000$ and 1-3 when $D_{tp} = 20,000$; however, considering the contingency of encounters, the actual opportunities for negotiation were lower than these numbers. The results for $D(s)$ obtained using AMTDS/THE are plotted in Fig. 6, along with the results when $D_{tp} = 500,000$ in Exp. 1. Note that we do not show the results for $U(s)$ because the results were the same as those when $D_{tp} = 500,000$.

Figure 6 indicates that even when the transition periods were shortened to $D_{tp} = 100,000$ and $20,000$ time steps, the performance degradation during the transition period and the planned suspension was still reduced in AMTDS/THE. Although there was a very slight decrease in efficiency (i.e., $D(s)$ has increased) during the suspension period, the decrease was negligible. Meanwhile, when the transition period was 500,000, the learning was accelerated in AMTDS/THE, but $D_{tp} = 100,000$ and $20,000$ were too short to positively affect the learning efficiency. If B is set to a smaller value, the agents will have more opportunities for negotiation, and the learning efficiency will be improved even if the transition period is short. However, this involves a trade-off in that it also increases unnecessary communication. This issue will be the subject of future research.

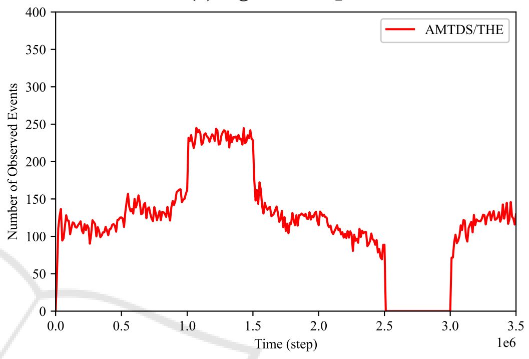
5.5 Discussion

To determine if the nodes were actually delegated, we investigated the number of events that were processed by agents in A_1 and A_2 over time. The results for a randomly selected experimental run of Exp. 1 are plotted in Fig. 7). Note that the agents in A_1 stopped during the first suspension period (Fig. 7a), and the agents in A_2 stopped in the second one (Fig. 7b). The figure indicates that, even during the transition period, agents that were going to be suspended in the next suspension period processed a considerable number of events, although their workload gradually decreased. Immediately after they stopped, the events to be processed were quickly transferred to other agents. We can also see that the agents that returned from suspension quickly increased the amount of task processed by using the learning results before the suspension, and at the same time, the agents that have not been suspended reduced their workload.

As mentioned before, we believe that this was made possible by the sharing of important nodes with other agents through the proposed negotiation method in which the agents did not transfer the nodes with events for processing directly but only transferred the ratio δ_c of their importance values. We set $\delta_c = 0.5$ in our experiments. If agent i directly transfers the locations, the agent j that is receiving them may already be overloaded or some of the received locations may be far from the area usually covered by j; hence, it is often not easy for j to complement i for such delegated nodes.



(a) Agents in A_1



(b) Agents in A_2

Figure 7: Number of events observed by agents.

Table 2: Ratio of difference between the actual and estimated number of negotiations (%).

Method	Mean	Max	Min
AMTDS/TH	91.6	92.0	91.2
AMTDS/THE	7.7	15.2	1.7

In contrast, because $\delta_c = 0.5$, agent *i* did not completely forget the locations it has delegated but revisited them at certain intervals, albeit at a lower frequency in AMTDS/THE. If a large number of events remained, *i* would then understand that the delegated agent *j* was in a situation in which it could not work adequately; therefore, *i* increased its importance value again. These nodes were then delegated by *i* to other agents during subsequent negotiations. Through the repeated occurrence of this process, the overloaded conditions were reduced and inappropriate delegations remedied. This led to an improvement in efficiency before the planned suspension.

Finally, we investigated whether the agents in AMTDS/THE could estimate the number of future negotiation opportunities until the next suspension period. We calculated the ratio of the difference between the estimated and actual numbers of negotiation opportunities in AMTDS/TH and AMTDS/THE. The mean maximum and minimum ratios of the differences are listed in Table 2. The results show that the agents in AMTDS/THE could estimate the number of negotiation opportunities accurately, but the agents in AMTDS/TH could not and underestimated. In general, it is not easy to estimate the number of future negotiation opportunities owing to contingencies. The number of future negotiation opportunities is also affected by the value of *B*, which may prevent agents from negotiating with one another. Thus, it seems that AMTDS/TH was designed to promote active node delegation by estimating a smaller number of opportunities for negotiation. However, this resulted in considerable performance degradation in the transition period owing to some agents becoming overloaded because of overly hasty delegation.

6 CONCLUSION

In this paper, we proposed a method called AMTDS/THE to mitigate the temporary but rapid performance degradation caused by planned suspension in the MACPP. In AMTDS/THE, the agents to be suspended delegate an important part of their tasks/nodes to other agents during the transition period to prepare for suspension and prevent performance degradation during the planned suspension period, especially in the security patrol problem. Furthermore, AMTDS/THE can also prevent performance degradation during the transition period. This improvement is attributed to the introduction of a mechanism for agents to accurately estimate the number of remaining opportunities for negotiation with other agents until the next planned suspension. The mechanism also enables agents to decide on the number of nodes to be delegated based on the number of estimated opportunities.

In actual applications, it is necessary to shorten the transition period before the planned suspension. For this reason, we would like to improve the method so that the agents can autonomously decide the timing of the planned suspension.

ACKNOWLEDGEMENTS

This work was partly supported by JSPS KAKENHI Grant Numbers 17KT0044 and 20H04245.

REFERENCES

Ahmadi, M. and Stone, P. (2006). A multi-robot system for continuous area sweeping tasks. In *Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006.*, pages 1724–1729. IEEE.

Altshuler, Y., Yanovski, V., Wagner, I. A., and Bruckstein, A. M. (2011). Multi-agent cooperative cleaning of expanding domains. *The International Journal of Robotics Research*, 30(8):1037–1071.

Chen, S., Wu, F., Shen, L., Chen, J., and Ramchurn, S. D. (2015). Multi-agent patrolling under uncertainty and threats. *PLOS ONE*, 10(6):1–19.

Elmaliach, Y., Agmon, N., and Kaminka, G. A. (2007). Multi-robot area patrol under frequency constraints. In *Proceedings 2007 IEEE International Conference on Robotics and Automation*, pages 385–390.

Elor, Y. and Bruckstein, A. M. (2009). Multi-a(ge)nt graph patrolling and partitioning. In *2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology*, volume 2, pages 52–57.

Gavranis, A. and Kozanidis, G. (2015). An exact solution algorithm for maximizing the fleet availability of a unit of aircraft subject to flight and maintenance requirements. *European Journal of Operational Research*, 242(2):631–643.

Ghita, B., Agnès, L., and Xavier, D. (2018). Scheduling of production and maintenance activities using multi-agent systems. In *2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA)*, volume 1, pages 508–515. IEEE.

Kalra, N., Ferguson, D., and Stentz, A. (2005). Hoplites: A market-based framework for planned tight coordination in multirobot teams. In *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*, pages 1170–1177.

Kato, C. and Sugawara, T. (2013). Decentralized area partitioning for a cooperative cleaning task. In Boella, G., Elkind, E., Savarimuthu, B. T. R., Dignum, F., and Purvis, M. K., editors, *PRIMA 2013: Principles and Practice of Multi-Agent Systems*, pages 470–477, Berlin, Heidelberg. Springer Berlin Heidelberg.

Li, G., Chesser, G. D., Huang, Y., Zhao, Y., and Purswell, J. L. (2021). Development and optimization of a deep-learning-based egg-collecting robot. *Transactions of the American Society of Agricultural and Biological Engineers*, 64(5):1659–1669.

Moradi, H. and Shadrokh, S. (2019). A robust reliability-based scheduling for the maintenance activities during planned shutdown under uncertainty of activity duration. *Computers & Chemical Engineering*, 130:106562.

Othmani-Guibourg, M., El Fallah-Seghrouchni, A., and Farges, J.-L. (2018). Path generation with LSTM recurrent neural networks in the context of the multi-agent patrolling. In *2018 IEEE 30th International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 430–437.

Othmani-Guibourg, M., Fallah-Seghrouchni, A. E., Farges, J.-L., and Potop-Butucaru, M. (2017). Multi-agent patrolling in dynamic environments. In *2017 IEEE International Conference on Agents (ICA)*, pages 72–77.

Panteleev, V., Kizim, A., Kamaev, V., and Shabalina, O. (2014). Developing a model of multi-agent system of a process of a tech inspection and equipment repair. In *Joint Conference on Knowledge-Based Software Engineering*, pages 457–465. Springer.

Rezazadeh, N. and Kia, S. S. (2019). A sub-modular receding horizon approach to persistent monitoring for a group of mobile agents over an urban area. *IFAC-PapersOnLine*, 52(20):217–222. 8th IFAC Workshop on Distributed Estimation and Control in Networked Systems NECSYS 2019.

Sampaio, P. A., Ramalho, G., and Tedesco, P. (2010). The gravitational strategy for the timed patrolling. In *2010 22nd IEEE International Conference on Tools with Artificial Intelligence*, volume 1, pages 113–120.

Seif, J. and Andrew, J. Y. (2018). An extensive operations and maintenance planning problem with an efficient solution method. *Computers & Operations Research*, 95:151–162.

Sugiyama, A., Sea, V., and Sugawara, T. (2019). Emergence of divisional cooperation with negotiation and re-learning and evaluation of flexibility in continuous cooperative patrol problem. *Knowledge and Information Systems*, 60(3):1587–1609.

Tsuiki, S., Yoneda, K., and Sugawara, T. (2021). Reducing efficiency degradation due to scheduled agent suspensions by task handover in multi-agent cooperative patrol problems. In *The International FLAIRS Conference Proceedings*, volume 34.

Wagner, I. A., Altshuler, Y., Yanovski, V., and Bruckstein, A. M. (2008). Cooperative cleaners: A study in ant robotics. *The International Journal of Robotics Research*, 27(1):127–151.

Xie, J., Zhou, R., Luo, J., Peng, Y., Liu, Y., Xie, S., and Pu, H. (2020). Hybrid partition-based patrolling scheme for maritime area patrol with multiple cooperative unmanned surface vehicles. *Journal of Marine Science and Engineering*, 8(11).

Yoneda, K., Sugiyama, A., Kato, C., and Sugawara, T. (2015). Learning and relearning of target decision strategies in continuous coordinated cleaning tasks with shallow coordination1. *Web Intelligence*, 13(4):279–294.

Zhou, X., Wang, W., Wang, T., Lei, Y., and Zhong, F. (2019). Bayesian reinforcement learning for multi-robot decentralized patrolling in uncertain environments. *IEEE Transactions on Vehicular Technology*, 68(12):11691–11703.

Zhou, X., Wang, W., Wang, T., Li, M., and Zhong, F. (2020). Online planning for multiagent situational information gathering in the Markov environment. *IEEE Systems Journal*, 14(2):1798–1809.