Learning of Activity Cycle Length based on Battery Limitation in Multi-agent Continuous Cooperative Patrol Problems

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Abstract: We propose a learning method that decides the appropriate activity cycle length (ACL) according to environmental characteristics and other agents' behavior in the (multi-agent) continuous cooperative patrol problem. With recent advances in computer and sensor technologies, agents, which are intelligent control programs running on computers and robots, obtain high autonomy so that they can operate in various fields without pre-defined knowledge. However, cooperation/coordination between agents is sophisticated and complicated to implement. We focus on the ACL which is time length from starting patrol to returning to charging base for cooperative patrol when agents like robots have batteries with limited capacity. Long ACL enable agent to visit distant location, but it requires long rest. The basic idea of our method is that if agents have long-life batteries, they can appropriately shorten the ACL by frequently recharging. Appropriate ACL depends on many elements such as environmental size, the number of agents, and workload in an environment. Therefore, we propose a method in which agents autonomously learn the appropriate ACL on the basis of the number of events detected per cycle. We experimentally indicate that our agents are able to learn appropriate ACL depending on established spatial divisional cooperation.

1 INTRODUCTION

With recent developments in technology, we can expect that agents, that are autonomous programs controlling robots and computer systems, often have to collaborate and coordinate with each other to solve complicated and sophisticated problems. However, creating methods for establishing cooperation among multiple agents is challenging due to the difficulty of realizing advanced autonomy and various complex interaction patterns between agents. In particular, it is crucial to estimate others' strategies for cooperation between agents that have their own behavioral strategies and different computational costs. In tackling these issues, the *multi-agent patrol problem* (MAPP) has attracted attention as a good case study on many multi-agent systems because it has essential issues such as autonomy, dispersibility, communication restriction, and scalability, all of which are required to realize intelligent autonomous distributed systems (David and Rui, 2011).

We also extend this problem to the *continuous cooperative patrol problem* (CCPP) in which multiple autonomous agents with limited battery capacities continuously move around in an environment where events occur at a certain probability (Sugiyama and Sugawara, 2017). In the MAPP, all nodes (locations) are visited with the same priority/frequency because the purpose of MAPP is to minimize *idleness* which is the interval of two visits for every node. In comparison, agents in the CCPP are required to visit individual nodes with different visitation requirements, which reflect that events in nodes occur with different probabilities or reflect the importance of nodes. Thus, high visitation requirements indicate, for example, locations that require a high-security level at which no events must be missed in security patrolling applications. Thus, the objective of agents in the CCPP is to minimize the *duration of unawareness* which is the length of time for which agents leave occurred events unaware without visiting the locations.

Thus, because of the importance of these problems, a number of studies have tackled MAPPs and CCPPs in multi-agent system contexts. For example, Cheva (Chevaleyre, 2005) classified various classes of patrolling strategies and compared these strategies. David and Rui (David and Rui, 2011) summarized developments of patrolling methods and indicated issues that must extensively be studied regarding the MAPPs. We (Sugiyama et al., 2016) also proposed

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the learning method, in which agents individually decide where they should work using lightweight communications and using the learning which locations they should visit more frequently than others. They found that the agents with their methods could effectively move around the environment by identifying their responsible areas, i.e., they finally formed a certain cooperation structure based on the division of labors.

Although this method could be used to efficiently patrol an environment to detect events in it, we found that agents have to coordinate their behavior by taking into account the interval of visits. Because we assume that agents are (the control programs of) robots, they often stop operation for battery charging and/or periodic inspections. This interruption in operation may negatively affect patrolling, such as security surveillance. Because temporarily stopping for charging is frequent and inevitable in actual operation, strategic behavior is required to minimize the influence of stopping by taking into account robots' noise and the characteristics of the areas in which they move around. Although a few studies discussed the battery capacity of agents (robots) (Sipahioglu et al., 2010; Jensen et al., 2011; Bentz and Panagou, 2016), the appropriate timing for when to return to charge and when to resume operation for autonomous agents was not clarified in their methods.

A cyclic strategy, in which agents move until the batteries become empty and then charge to make the batteries full in different periodic phases, is one of the simplest ways to minimize the duration of unawareness in the CCPP. In this paper, a sequence of actions from the agent leaving the charging base with a full battery, moving around the environment, returning to the base and completing the charge is called a *round* and the time length of the moving in a round is called *activity cycle length* (ACL). Performance of a cyclic strategy depends on a battery capacity. For example, agents with a small battery capacity cannot cover distant tasks/events, and the cumulative return cost for recharging is high in a large environment due to frequent charging. In contrast, agents with long-life batteries can be expected to move more effectively and cover distant events but they must stop operations for a long time for recharging, resulting in a long duration of unawareness. Therefore, because appropriate ACL may depend on the environmental characteristics and behaviors of other cooperative agents, agents are required to autonomously learn which ACL will lead to better results through actual cooperative behavior from the viewpoint of the entire performance.

In this paper, we extend the method proposed in (Sugiyama et al., 2016) to learn appropriate ACL in the CCPP model in order to adapt other agents' cooperative strategies (including their ACL) and the characteristics of the areas in which individual agents mainly move around. In this method, we assume that agents have long-life batteries and they can adaptively decide their ACL by returning/restarting regardless of their remaining battery capacities, because it is easy to shorten ACL. Of course, they must not run out of battery during operations. The features of our method is that, like the method in (Sugiyama et al., 2016), it does not require tight communication and deep inference for cooperation, meaning that frequent message exchange and the sophisticated reasoning of others' internal intentions are not used; this makes our method efficient and lightweight, and thereby, our method is applicable to dynamic environments. We experimentally indicate that agents with our method are able to identify appropriate ACL. Furthermore, we found that agents established a spatial division of labor, as in (Sugiyama et al., 2016); thus, agents individually identify where they should move around as the nodes they are responsible for. This enables agents to decide ACL differently and appropriately for their own specific situations.

2 RELATED WORK

Various approaches, especially approaches based on reinforcement learning for the MAPP and CCPP, are examined so far. David and Rui (David and Rui, 2011) summarized the development of patrolling methods. They stated that non-adaptive solutions such as methods based on the traveling salesman problem often outperform other solutions in many cases except in large or dynamic environments. To adapt to these environments, they insisted that agents must have high autonomy. Machado et al. (Machado et al., 2003) evaluated reactive agents and cognitive agents that have different depths to analyze patrol graphs and investigated the characteristics of these agents. In actual patrol problems, because cognitive agents have greater perception, they can do more sophisticated operations due to recent developments in technology. Santana et al. (Santana et al., 2004) modeled a patrolling task as a reinforcement learning problem and proposed adaptive strategies for autonomous agents. Then, they showed that their strategies were not always the best but were superior in most of the experiments.

The CCPP assumes a dynamic environment in which events occur with certain probabilities and the duration of unawareness is considered instead of idleness as in the MAPP. Ahmadi and Stone (Ahmadi and

Stone, 2006), by assuming that events to be found were generated stochastically, proposed agents that learn the probability of events and adjust their area of responsibility to minimize the average required time to detect events. Chen and Yum (Chen and Yum, 2010) modeled a patrolling environment with a nonliner security level function in the context of a security problem. In this model, agents have to visit each node with a different frequency according to the values of the function. Pasqualetti et al. (Pasqualetti et al., 2012) studied a patrol problem in which all nodes have different priorities, but their model was a simple cyclic graph with a small number of nodes. Popescu et al. (Popescu et al., 2016) proposed a patrolling method for a wireless sensor network in which agents collect saved data from sensors with limited storage independently. Agents in this model decide the priorities of nodes to visit on the basis of the accumulated amount of data and data generation rate.

Sugiyama et al. (Sugiyama et al., 2016) proposed a method called the *adaptive meta-target decision strategy with learning of dirt accumulation probabilities* (AMTDS/LD) by combining the learning of a target decision strategy in the planning process and the learning of the importance of each location for cleaning tasks. Agents with AMTDS/LD indirectly cooperate with other agents by learning the importance of nodes, which is partly taken into account reflects the visiting frequencies of other agents. They also extended their method by introducing simple negotiation to enhance the division of labor in a bottom-up manner (Sugiyama and Sugawara, 2017). However, they did not discuss the intervals of visits, which is another key issue of the CCPP. In the CCPP, agents with limited capacity batteries have to stop their operation to recharge, so agents have to coordinate with each other by adjusting timings of starting and recharging for appropriate visiting patterns.

Other researchers also take into account battery capacity in the multi-robot patrol problem. Jensen et al. (Jensen et al., 2011) presented strategies for replacing robots that have almost empty batteries with other robots that have fully charged ones to keep coverage and minimize interruptions for sustainable patrol. Bentz and Panagou (Bentz and Panagou, 2016) proposed an energy-aware global coverage technique that shifts distributions of effort networks according to the degree of an agent's energy constraints. Sipahioglu et al. (Sipahioglu et al., 2010) proposed a path planning method that covers an environment by considering energy capacity in multi-robot applications. This method partitions a complete coverage route into subroutes and assigns them to robots by considering the energy capacities of the robots. These methods are mainly focused on how to divide work areas for cooperative activities. However, they do not focus on controlling the phases of ACL on the basis of the battery capacity. Therefore, we propose a learning method that decides the appropriate activity duration depending on the characteristics of the tasks of agents for more effective cooperation.

3 MODEL

3.1 Environment

The environment in which agents patrol is described by graph $G = (V, E)$, which can be embedded into a two-dimensional plane with a metric, where $V = \{v_1, \dots v_m\}$ is a set of nodes, so node $v \in V$ has coordinates $v = (x_v, y_v)$. An agent, an event, and an obstacle can exist on node v. E is a set of edges. An edge connecting v_i and v_j is expressed by $e_{i,j} \in E$. Agents can move one of their neighbor nodes along an edge. An environment may have obstacles, R_o ($\subset V$). Agents cannot move to and events do not occur on the nodes in R_o.

Node $v \in V$ has the *event occurrence probability value* $p(v)$ $(0 \leq p(v) \leq 1)$, and it indicates that an event occurs on v with probability $p(v)$. The number of unaware events without processing on v at time t is expressed by $L_t(v)$, where $L_t(v)$ is a non-negative integer. $L_t(v)$ is updated on the basis of $p(v)$ every tick by

$$L_t(v) \leftarrow \begin{cases} L_{t-1}(v) + 1 & \text{(if an event occurs)} \\ L_{t-1}(v) & \text{(otherwise).} \end{cases} \quad (1)$$

$L_t(v)$ become 0 when an agent visits v. Discrete time with units called *tick* is used in this model. In one tick, events occur on nodes, agents decide their target node, agents move to neighbor nodes, and agents process events.

3.2 Agent

Before we describe the agent model, we explain that one assumption which we introduce to simplify our problem. In this study, we assume that agents always get their own and others' locations. An environment with this assumption can be realized, for example, by equipping agents with indicators, such as infrared emission and reflection devices. We believe that this is a reasonable assumption because technology for sensors and positioning systems are being rapidly developed. However, we do not assume that agents can get others' internal information such as the adopted strategy and the selected target node because reasoning by using/estimating others' internal information seems complicated. Because we want to focus on the period of cyclic behavior for better cooperative work, we do not consider this costly reasoning.

Let $A = \{1, \ldots, n\}$ be a set of agents. When agents obtain $p(v)$ in advance, they can use $p(v)$ for their patrol. However, in actual patrol problems, $p(v)$ is usually unknown. Moreover, the appropriate frequency to visit depends not only on $p(v)$ but also on the frequencies of other agents' visits.

Therefore, agents have to learn priorities to visit nodes through their actual patrols. Agent i has the *degree of importance* (simply, *importance* after this) $p^i(v)$ for all nodes in an environment, and it reflects both $p(v)$ and other agents' behavior. When i visits node v at t and detects events $L_t(v)$, i updates $p^i(v)$, as

$$p^i(v) \leftarrow (1-\beta)p^i(v) + \beta\frac{L_t(v)}{I_t^i(v)}, \tag{2}$$

where $I_t^i(v)$ is the elapsed time from t_{visit}^v which is the time of the last visit to v and calculated as

$$I_t^i(v) = t - t_{visit}^v. \tag{3}$$

β $(0 < \beta \leq 1)$ is the learning rate.

3.2.1 Target Decision and Path Generation Strategy

Agents repeatedly generate paths to move through a *planning process*. The planning usually consists of two subprocesses: *target decision* and *path generation* for patrol. Agent i first decides the next target node $v_{tar}^i \in V$ by using the target decision process and then generates the appropriate path from the current node to v_{tar}^i by using the path generation process. Because our purpose is to extend the AMTDS/LD and to compare our proposed method with AMTDS/LD, we briefly explain it. Agent i with AMTDS/LD simultaneously learns the appropriate strategy s in S_{plan} and $p^i(v)$ with Formula (2), where S_{plan} is the set of target decision strategies described below. The policy for selecting the target decision strategy from S_{plan} is adjusted based on Q-learning with the ε-greedy learning strategy. Thus, i updates the Q-value of the selecting $s \in S_{plan}$ on the basis of the sum of detected events until i arrives at v_{tar}^i, which is the target decided by s. The details of Q-learning for this policy and AMTDS/LD are outside the scope of this paper; please refer to (Sugiyama et al., 2016).

We will explain the elements of S_{plan}, i.e., the target decision strategies used in AMTDS/LD.

Random Selection (R).
Agent i randomly selects v_{tar}^i among all nodes V.

Probabilistic Greedy Selection (PGS).
Agent i selects v_{tar}^i in which i estimates the value of unaware events $EL_t^i(v)$ at time t using $p^i(v)$ and elapsed time from last visit $I_t^i(v)$ by

$$EL_t^i(v) = p^i(v) \cdot I_t^i(v). \tag{4}$$

Then, i selects v_{tar}^i randomly from the N_g highest nodes in V according to the values of $EL_t^i(v)$, where N_g is a positive integer.

Prioritizing Unvisited Interval (PI).
Agent i selects v_{tar}^i randomly from the N_i highest nodes according to the value of interval $I_t^i(v)$ for $v \in V$, where N_i is a positive integer. Agents with this strategy are likely to prioritize nodes that have not been visited recently.

Balanced Neighbor-Preferential Selection (BNPS).
Agent i estimates if many unaware events may exist near nodes by using the learned threshold value, and i selects v_{tar}^i from such nodes. Otherwise, i selects v_{tar}^i by using the PGS. The details are described elsewhere (Yoneda et al., 2013).

Note that we can also regard AMTDS, AMTDS/LD, and our proposed method as target decision strategies.

We use the *gradual path generation* (GPG) method as the path generation strategy in this research (Yoneda et al., 2013). Agent i with the GPG first calculates the shortest path from current node to v_{tar}^i and then regenerates a path to v_{tar}^i by adding nodes nearby the shortest path and whose values of $EL_t^i(v)$ are identified as high. We do not explain the GPG method in detail because it is beyond the scope of this paper, but it is also described elsewhere (Yoneda et al., 2013).

3.2.2 Battery Setting

Agent i has a battery with a limited capacity, so it must periodically return to its charging base $v_{base}^i \in V$ to charge its battery for continuous patrolling. The battery specifications of agent i are denoted by $(B_{max}^i, B_{drain}^i, k_{charge}^i)$, where $B_{max}^i (> 0)$ is the maximal capacity of the battery, $B_{drain}^i (> 0)$ is the amount of battery consumption per one tick, and $k_{charge}^i (> 0)$ is the time taken to charge one battery at charging base v_{base}^i. The remaining amount of the battery of agent i at time t is expressed in $b^i(t) (0 \leq b^i(t) \leq B_{max}^i)$.

Agents in this model must go back to v_{base}^i before $b^i(t)$ becomes 0 as shown below. Agent i calculates the *potential*, $\mathcal{P}(v)$, for all nodes in advance. $\mathcal{P}(v)$ is the minimal amount of battery consumption necessary to return from node v to v_{base}^i and is calculated as

$$\mathcal{P}(v) = d(v, v_{base}^i) \times B_{drain}^i, \tag{5}$$

where $d(v_k, v_l)$ is the shortest path length from node v_k to node v_l. After agent i decides v^i_{tar} on the basis of the target decision strategy, i judges whether i can arrive at v^i_{tar} before i moves to v^i_{tar} using with

$$b^i_t \geq \mathcal{P}(v^i_{tar}) + d(v^i_t, v^i_{tar}) \times B^i_{drain}, \tag{6}$$

where $v^i_t \in V$ is current node of agent i at time t. If this inequation does not hold, i changes v^i_{tar} as

$$v^i_{tar} \leftarrow v^i_{base}, \tag{7}$$

and immediately returns to v^i_{base}. Agents recharge batteries at charging bases until they are full and then restart patrol.

Our purpose is to appropriately decide ACL depending on the characteristics of their working environments, the recognition of the importances of all locations and the behavior of other agents. Because agents can return to the charging base earlier, it is easy to shorten ACL if they have long-life batteries.

3.3 Performance Measure and Requirement of CCPP

The requirement of the CCPP is to minimize The number of unaware events, $L_t(v)$, by visiting important nodes without being aware of event occurrences. For example, in cleaning tasks, agents should vacuum accumulated dirt as soon as possible without leaving it and keep the amount of dirt low. Therefore, we define a performance measure when agents adopted strategy $s \in S_{plan}$, $D_{t_s,t_e}(s)$, for the interval from t_s to t_e to evaluate our method.

$$D_{t_s,t_e}(s) = \sum_{v \in V} \sum_{t=t_s+1}^{t_e} L_t(v), \tag{8}$$

where $t_s < t_e$. $D_{t_s,t_e}(s)$ is the cumulative unaware duration in $(t_s, t_e]$, so a smaller D_{t_s,t_e} indicates better system performance.

We can also consider another performance measure. For example, in security patrol applications, agents should keep the maximal number of $L_t(v)$ as low as possible, because a high value for $L_t(v)$ indicates significant danger. This measure is defined by

$$U_{t_s,t_e}(s) = \max_{v \in V, t_s < t \leq t_e} L_t(v). \tag{9}$$

Therefore, agents in the CCPP are required to lower one of the performance measures, $D_{t_s,t_e}(s)$ or $U_{t_s,t_e}(s)$, depending on the type of application.

4 PROPOSED METHOD

In this section, we describe our method in which agents learn the appropriate ACL to improve performance. We named our method, which is an extension of AMTDS/LD (Sugiyama et al., 2016), *AMTDS with cycle learning* (AMTDS/CL). Agent i has ACL as s^i_c ($0 < s^i_c \leq \lfloor B^i_{max}/B^i_{drain} \rfloor$) (we normalize the value in (B^i_{max}, B^i_{drain}) so that $B^i_{drain} = 1$ here after). Agent i with AMTDS/CL regards its battery capacity B^i_{max} as s^i_c and then uses the battery control algorithm in Sec. 3.2.2. The length of ACL is a trade-off because a longer ACL enables agents to act for a long time, but agents also require a long charging time. In our method, agent i selects s^i_c from a set of possible ACLs, $S^i_c = \{s_{c1}, s_{c2}, \dots\}$, where $\max_{s \in S^i_c}(s) = B^i_{max}$. For simplicity, $s \in S^i_c$ is a divisor of B^i_{max}.

The process of learning the appropriate ACL consists of two learning subprocesses. The purpose of the first subprocess is to decide the initial Q-values for all possible ACLs in S^i_c because the initial Q-values offset the performance of Q-learning and, in general, their appropriate values are dependent on the environment. In this subprocess, agents calculate the average number of detected events per one tick while active as follows. First, i selects an ACL from S^i_c at random and starts patrol. Then, when i returns to the base to charge, it calculates e^i_1 by using

$$e^i_1 = E^i_1 / t^i_{travel1}, \tag{10}$$

where E^i_1 is the number of detected events in the first round and $t^i_{travel1}$ is time length when agent i move in the first round.

Agents repeat this subprocess and they randomly selects an ACL in each rounds. We also denote E^i_k and e^i_k as the number of detected events and the average of the detected events per tick in the k-th round. Agent i continues this process for the initial T_{init} ticks, where T_{init} is a positive integer. Then, at the end of the first subprocess, i calculates e_i, which is the average of the values of $e^i_1, e^i_2, \dots$ obtained by Formula (10) during the first subprocess. The e_i will be set to the initial Q-value of s_c, $Q^i(s_c)(\forall s_c \in S^i_c)$, in the second subprocess.

If agent i finds that the current time t is larger than T_{init}, it enters the second learning subprocess. Before i starts to patrol from its charging base, i decides s_c with probability $1 - \varepsilon$ as

$$s_c \leftarrow \arg\max_{s'_c \in S_c} Q^i(s'_c); \tag{11}$$

Otherwise, i randomly selects s_c from S_c. When there is a tie break in Eq. 11, agents select one of the candidates at random.

We assume that i will continuously use the selected s_c for several times without updating Q-value. In the CCPP, it is better for agents to visit individual nodes, especially important nodes, in shorter intervals when their battery levels are high. However,

Table 1: Parameters.

Model	Parameter	Value
PGS	N_g	5
PI	N_i	5
AMTDS/LD	β	0.05
	ε	0.05
AMTDS/LC	γ	0.05
	ε	0.05
	T_{init}	100,000

when agents visit nodes so frequently, they may find smaller number of events; therefore, the Q-values of the short ACLs tend to be small, even if i visit the important nodes where i must find events as many as possible and keep the number of unaware events low. This means that if agents update $Q^i(s_c)$ every short round, they cannot correctly evaluate the ACL. Therefore, we introduce the parameter $C^i_{s_c}$ to make their activity time identical regardless of the value of s_c; this achieves fair learning results. When agent i decides its ACL with Formula (11), i calculates $C^i_{s_c}$ by

$$C^i_{s_c} = B^i_{max}/s_c. \tag{12}$$

After that, i selects the s_c in $C^i_{s_c}$ rounds continuously without updating Q-value.

After i finishes $C^i_{s_c}$ rounds patrol using the selected s_c, i updates $Q^i(s_c)$;

$$Q^i(s_c) \leftarrow (1-\gamma)Q^i(s_c) + \gamma \frac{\sum_{k=k_0-C^i_{s_c}+1}^{k_0} E^i_k}{C^i_{s_c}}, \tag{13}$$

where k_0 indicates the number of the most recent round. Note that the first learning subprocess is dedicated to calculating the initial Q-values and i never updates $Q^i(s_c)$. The calculation of initial Q-values is mandatory for the fast convergence of Q-learning.

5 EXPERIMENTS AND DISCUSSION

We evaluated our method in two experiments. First, we investigated whether agents with our method learn the appropriate ACL, by comparing the results of our learning method with those of the AMTDS/LD with a fixed ACL. Note that, in this experiment, all agents had a charging base in the same location. In the second experiment, we investigated the difference in learned ACLs when the agents' charging bases were located at different locations. Therefore, they were likely to be affected by the characteristics of the local areas nearby the charging bases.

5.1 Experimental Setting

We constructed two simulated large environments, called "Office A" and "Office B", for agents to patrol as shown in Fig. 1. These environments consisted of six rooms (labeled *Rooms 0-5*), a corridor, and a number of nodes where events occurred frequently. We set $p(v)$ for $v \in V$ as

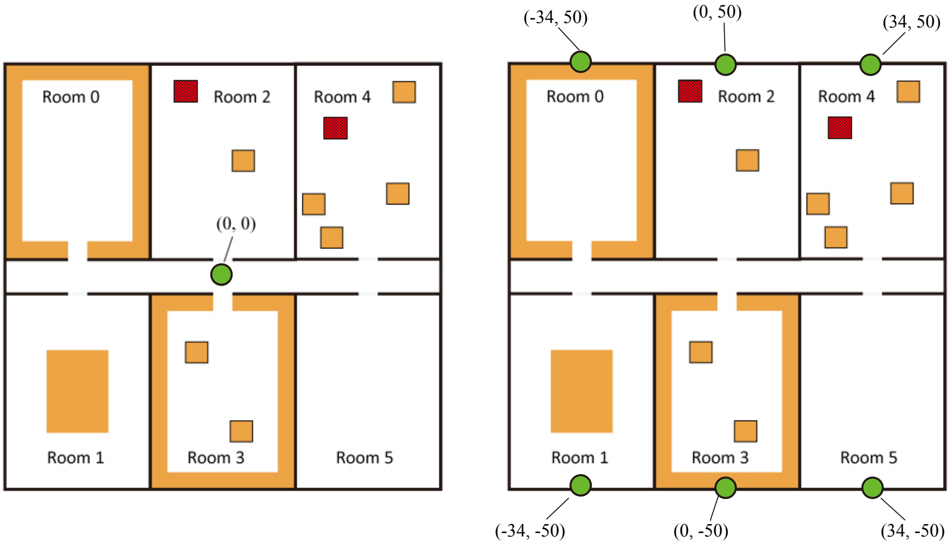
$$p(v) = \begin{cases} 10^{-3} \text{ if } v \text{ was in a red region,} \\ 10^{-4} \text{ if } v \text{ was in an orange region, and} \\ 10^{-6} \text{ otherwise,} \end{cases} \tag{14}$$

and the colored regions are shown in Fig. 1. The green circles in these environments are charging bases. In Office A, all agents had charging bases in the same location. In Office B, we divided agents into six groups, and the charging bases of each group were assigned to one of six rooms differently. Each room had charging bases in Office B, but agents had to return to their own assigned charging bases. The environments are represented by a 101×101 2-dimensional grid graph with several obstacles (walls). We set the length of edges between nodes to one.

We deployed 20 agents in the environments. We assumed that agents did not know $p^i(v)$ in advance, so we initially set $p^i(v)$ as 0. Agents started their patrols from the assigned v^i_{base} and periodically returned to v^i_{base} to recharge before their batteries became empty. We set the actual battery specifications of all agents as $(B^i_{max}, B^i_{drain}, k^i_{charge}) = (2700, 1, 3)$ and set S_c to $S_c = \{300, 900, 2700\}$. When agents selected s_c to be 2700, the patrol cycle length was maximum (10,800 ticks), whose breakdown consists of the active time (2700 ticks) and the charging time (8100 ticks). Therefore, for the target decision strategy s we measured $D_{t_s,t_e}(s)$ and $U_{t_s,t_e}(s)$ every 14,400 ticks, which was longer than the maximum cycle length. In experiments below, we set AMTDS/LD or AMTDS/CL to s. The parameter values used in the model are listed in Table 1.

5.2 Comparison of Fixed Activity Cycle

In the first experiment, we compared the performance results of four types of agents that used AMTDS/LD with one of the fixed ACLs, s_c = 300, 900, or 2700 with those by the agents with AMTDS/CL in Office A as shown in Fig. 1(a). Hereinafter, AMTDS/LD with fixed ACL s_c is denoted as AMTDS/LD(s_c). The experimental results shown below are the average values of ten independent experimental runs. Figure 2 plots the performance, $D(s)$, and Fig. 3 plots the performance of $U(s)$ over time. Note that the smaller $D(s)$



(a) Office A (b) Office B

Figure 1: Environments.

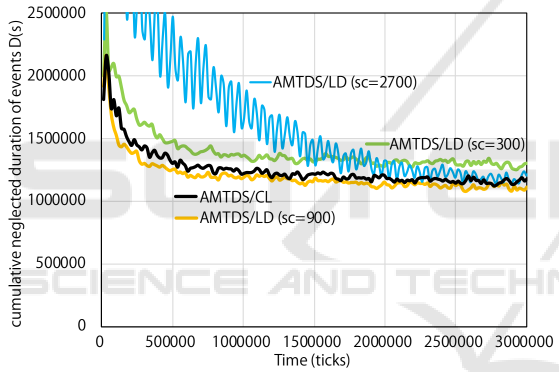


Figure 2: Improvement in $D(s)$ over time in Office A.

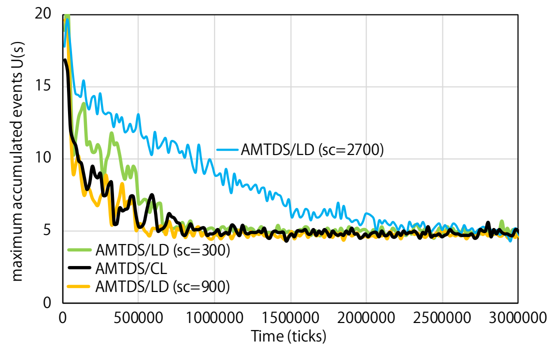


Figure 3: Improvement in $U(s)$ over time in Office A.

and $U(s)$ are better.

Both figures indicate that agents with AMTDS/LD(900) were the most efficient, and the agents with AMTDS/CL exhibited almost the same efficiency as that with AMTDS/LD(900). The efficiency of the agents with AMTDS/LD(2700) was the worst and seemed unstable at first, but it gradually improved over time. Because AMTDS/LD(2700) requires quite a long time to recharge, the number of patrolling agents were unstably fluctuated. However, the phases of their periodic cycles gradually shifted naturally and finally disappeared. In contrast, the converged performance of the agents with AMTDS/LD(300) was always worse than the others. This is because the ACL was too short to cover the entire environment, especially areas distant from the charging bases, and the agents in charge of distant area had to return very frequently to the charging bases. We can say that, in this particular experimental environment, the ACL of 900 seemed the best. However, this depends on the environmental characteristics and we cannot decide the appropriate ACL in advance. In comparison, the agents with the proposed AMTDS/CL can adaptively select ACLs by themselves without such a prior decision.

Figure 4 indicates the number of agents that selected $\forall s_c \in S^i_c$ with AMTDS/CL over time. Note that we plotted in this figure the values every 10,000 ticks from 200,000 ticks; because agents started from deciding the initial Q-values until 100,000 ticks and then entered the learning of ACL from 100,000 ticks, the learning results in the first 200,000 were unstable. We can see from this figure that many agents selected 900 ticks for s_c since AMTDS/LD(900) exhibited the best performance in this environment and this was consistent with the results when agents have the fixed ACL.

Additionally, we investigated the characteristics of agents that selected 300 and 2700 as their ACL. Fig-

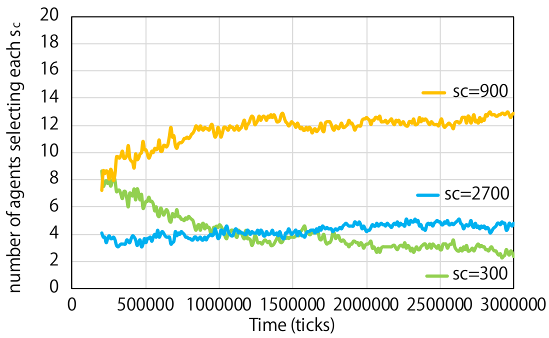


Figure 4: Number of agents selecting each s_c over time in Office A.

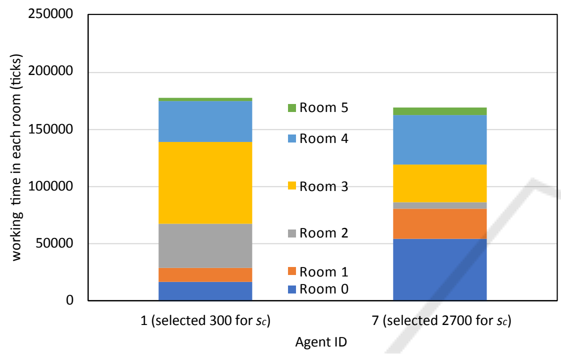


Figure 5: Working time in each Room of agent 1 and agent 7 in last 1,000,000 ticks in Office A.

ure 5 shows the working time of agents whose IDs were 1 and 7, i.e., how long they spent in each room during the last 1,000,000 ticks. Note that Agent 1 selected 300 and Agent 7 selected 2700 for their ACLs at last, though 900 was usually the best as the ACL in the environment. We also note that the data shown in Fig. 5 is one result selected from the experimental trials, but we found that a similar tendency could be observed in other trials. Agent 1 more often patrolled Room 2 and Room 3 than Agent 7. Room 2 and Room 3 were near the charging base, Room 2 had specific regions in which events frequently occurred, and many nodes in Room 3 also had a higher $p^i(v)$. Therefore, Agent 1 could find many events in Room 2 and Room 3; thus, patrolling with a short ACL was better from the viewpoint of Agent 1 to keep the number of unaware events low.

Meanwhile, Agent 7 frequently patrolled many rooms, some of which were distant from the charging base. We confirmed that, unlike Agent 1, Agent 7 had a high value of $p^i(v)$ in more and farther nodes, so Agent 7 selected a long ACL to move around in a large area. This analysis indicates that, from a global viewpoint, agents with a short s_c and long s_c complementarity covered different areas. That is because some agents with AMTDS/CL did not select 900 for

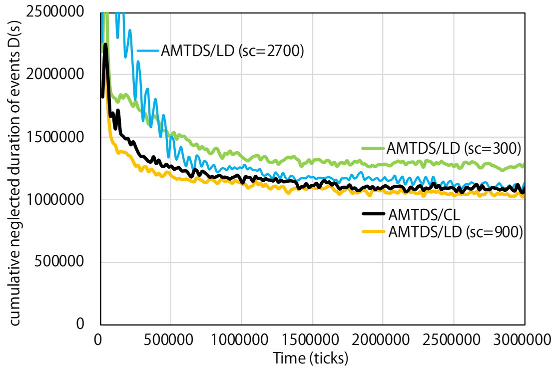


Figure 6: Improvement in $D(s)$ over time in Office B.

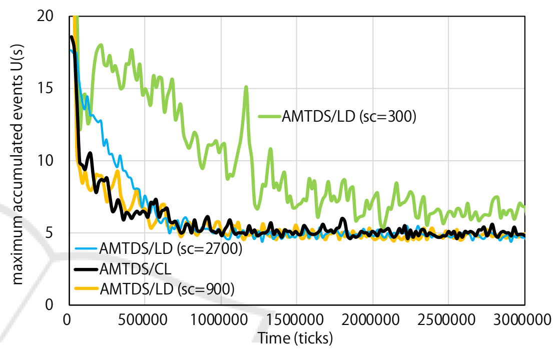


Figure 7: Improvement in $U(s)$ over time in Office B.

s_c and deterioration of efficiency was not occurred, although AMTDS/LD(900) was best efficiency. These results showed that agents with our method learned the appropriate ACL s_c without prior knowledge on the environments, and actually, agents decided ACLs on the basis of their learned $p^i(v)$ and working area. We believe that such diversity in agent strategies also enhances the response capabilities to environmental changes as well as the improvement in the efficiency.

5.3 Adaptation to Environmental Characteristics

In the second experiment, we also evaluated the four types of agents in a slightly different environment where there were six charging bases for each room, named "Office B", as shown in Fig. 1(b). A charging base in Room n is denoted by $v_{base\text{-}n}$. We set Agents 0, 1, 2, and 3 to $v_{base\text{-}0}$, Agents 4, 5, and 6 to $v_{base\text{-}1}$, Agents 7, 8, and 9 to $v_{base\text{-}2}$, Agents 10, 11, 12, and 13 to $v_{base\text{-}3}$, Agents 14, 15, and 16 to $v_{base\text{-}4}$, and Agents 17, 18, and 19 to $v_{base\text{-}5}$. The improvement $D(s)$ is plotted in Fig. 6, and $U(s)$ over time in Office B is plotted in Fig. 7.

We can confirm that the efficiency of AMTDS/CL and AMTDS/LD(900) was almost identical from

Table 2: Number of agents selecting each s_c described by their charging bases at 3,000,000 tick in Office B.

	Location of charging base					
	Room 0	Room 1	Room 2	Room 3	Room 4	Room 5
s_c=300	1.2	0.3	0.2	1.7	0.0	0.0
s_c=900	2.1	1.7	2.3	2.2	2.1	1.0
s_c=2700	0.7	1.0	0.5	0.1	0.9	2.0

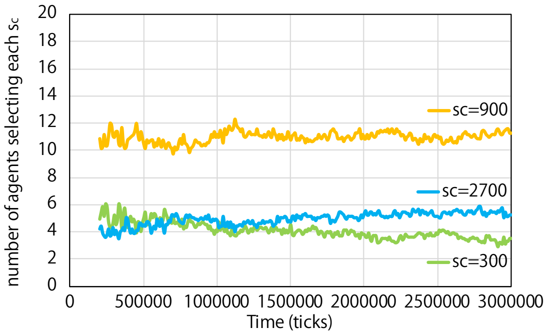


Figure 8: Number of agents selecting each s_c over time in Office B.

these figures. If we carefully compare Fig. 6 with Fig. 2, the converged performances of all methods were almost identical in both performances. However, the convergence of the AMTDS/LD(2700) in Fig. 6 seemed faster, and the performance also seemed stabler than those of AMTDS/LD(2700) in Fig. 2. In Office B, the charging bases were distributed, so the patrol patterns of individual agents differed even if agents had the same length of ACL. Figure 7 indicates that agents with AMTDS/LD(300) were the worst, which differed from the results of the first experiment (see Fig. 3). This indicates that the performance, $U(s)$, also depended on the distance between the charging bases and the work locations. In the second experiment, the areas individual agents visited were distinct, so nodes were covered by a smaller number of agents than in Office A.

The number of agents that selected each s_c for AMTDS/CL as shown in Fig. 8, was similar characteristic to Fig. 4. In this experiment, we were interested in the differences in ACL learned on the basis of the locations of agents' charging bases. Table 2 lists the average number of agents that selected $s_c \in S_c^i$ for AMTDS/CL for each charging base location. This table shows that 900 was mainly selected as the value of s_c by many agents, but we can observe different characteristics according to agents' base locations. We already knew that 900 was appropriate for this environment; thereby, we focused on and analyzed the agents that selected other ACLs. Agents whose charging base was in Room 5 obviously learned that the long ACLs were better. Because they could find only a few events near their base (Room 5 did not have a node with a high $p(v)$), they had to explore nodes farther away to help other agents. Relatively more agents whose bases were in Rooms 0 and 3 selected 300 as their ACL. In these rooms, there were many nodes with a high $p(v)$ as shown in Fig. 1. Thus, these agents could find many events near their bases. By selecting the shorter ACLs, they could reduce the cost of moving to other rooms and focused on specific nodes in the local rooms. In addition, they could visit nearby nodes at an appropriate and shorter frequency by improving the accuracy of the estimated $p^i(v)$ for the specific nodes.

When we carefully observed the experimental runs, we found that agents whose base was in Room 5 selected 900 as their ACL at first, but after that, they gradually changed to 2700. We can explain this change as follows. At first, they selected 900 since it seemed more appropriate than others. However, after other agents whose bases were in other rooms focused on nodes near their base and improved their patrol performance. In contrast, there were no nodes with high importance values $p^i(v)$ in Room 5, and agents whose base was Room 5 had to visit more of the other rooms to find events. This suggests indirect communication through learning the importance value. Therefore, agents could perform well by learning the ACLs to improve the entire system performance in a real-time manner, and this learning of the length was thanks to the results of the learning of importance $p^i(v)$.

6 CONCLUSION

We proposed an autonomous method for learning the activity cycle length, which is how long individual agents act to work in collaborative environments. This method reflects the activities of other collaborative agents, which are also learning mutually to contribute to the entire performance. We experimentally showed that agents with our method, AMTDS/CL, performed effectively comparable with the same efficiency as the best case with a fixed ACL, without giving any prior knowledge on the best ACL and the environmental characteristics in advance. We also analyzed the relationships between the selected ACL and agents' behaviors. Nodes were covered with a number of agents with different frequencies, phases, and periods; this resulted in effective covering of the environment only through lightweight communication with others. We also proposed a strategy in which agents select the appropriate activity cycle length from among fixed possible activity cycles because we think that agents have to consider complexity to estimate the environmental workload.

Our future work is to find an activity control strategy in which agents estimate a workload with high accuracy and flexibility to control their activity while taking into account their remaining energy.

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