Learning to Coordinate for a Worker-Station Multi-robot System in Planar Coverage Tasks

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Abstract—For massive large-scale tasks, a multi-robot system (MRS) can effectively improve efficiency by utilizing each robot's different capabilities, mobility, and functionality. In this paper, we focus on the multi-robot coverage path planning (mCPP) problem in large-scale planar areas with random dynamic interferers in the environment, where the robots have limited resources. We introduce a worker-station MRS consisting of multiple workers with limited resources for actual work, and one station with enough resources for resource replenishment. We aim to solve the mCPP problem for the worker-station MRS by formulating it as a fully cooperative multi-agent reinforcement learning problem. Then we propose an end-to-end decentralized online planning method, which simultaneously solves coverage planning for workers and rendezvous planning for station. Our method manages to reduce the influence of random dynamic interferers on planning, while the robots can avoid collisions with them. We conduct simulation and real robot experiments, and the comparison results show that our method has competitive performance in solving the mCPP problem for worker-station MRS in metric of task finish time.

I. INTRODUCTION

For massive large-scale tasks in hazardous environments, Multi-Robot System (MRS) dramatically helps to reduce human exposure to potential dangers and improves efficiency effectively. There are various applications of MRS that have come to reality, including search and rescue [1], persistent surveillance [2], planetary exploration [3]. Typically, a robot has only limited working resources, including energy and consumables. For example, most robots are driven by electrical or thermal energy stored in batteries or fuels in advance. While some robots can obtain ambient energy from the environment (e.g., solar energy), the energy transfer is highly dependent on the environmental situation, and the recharging process can sometimes be slow. Thus it can be inefficient for robots in massive long-term tasks. In scenarios like cleaning or agriculture on large-scale fields, the robot has limited consumables like water or chemicals. Therefore, it is essential for robots with large-scale tasks to constantly travel between supply stations and working areas to replenish and work, which is very inefficient for such tasks.

As discussed by Vaughan et al. in [4], the placement of the supply station significantly influences work efficiency for an MRS in the above scenarios. To further improve the efficiency of the MRS, one might consider making the supply station a mobile robot platform. Similar to the Frugal Feeding Problem in [5], the station moves around to serve the working robots. For consistency in this paper, we name such an MRS as the "worker-station" MRS, which is composed of a mobile supply station robot and several working robots. We consider the Multi-robot Coverage Path Planning (mCPP) problem on planar areas for the aforementioned worker-station MRS. As shown in Fig. 1, the workers are equipped with a range device for general area coverage work, and the station is loaded with sufficient resources to provide supplies for workers. The joint objective is to cover a given target area as soon as possible. Solving such a planning problem for the worker-station MRS can be decomposed as below:

1) Coverage planning for each worker to finish general planar coverage work of a given area;
2) Rendezvous planning for the station to service workers in need of replenishment;

In this paper, we mainly focus on solving the mCPP problem for the worker-station MRS on planar areas. There are several challenges to the above problem. First, the joint problem space comprised of the above two planning problems is too large to solve directly and simultaneously. A practical solution is to discretize state and action spaces in mCPP problems [6] and rendezvous planning problems [7], then solve by discrete combinatorial optimization methods separately. However, the system dynamics are hard to model and identify, where each robot has different capabilities and functionality. Thus, such methods can still be infeasible for such complex MRS, even after reducing the problem size. Secondly, planning with dynamic collision avoidance is another challenge for most offline planning methods. One general solution is to combine offline planning with...
local collision avoidance controllers. Nevertheless, such a hierarchical planning scheme would alter the optimal policy that is planned offline without the interference of dynamic obstacles. For complex scheduling tasks like the mCPP problem for worker-station MRS, it will cause conflicts and even deadlocks between robots or planners, and the planning efficiency will get worse as the number of robots grows [8]. To tackle the above challenges, we adopt Deep Reinforcement Learning (DRL) to solve the mCPP problem for worker-station MRS. However, the coordination behaviors of different agents in the worker-station MRS are nontrivial to learn together, and agents often struggle between exploration and exploitation of the coverage task during training. We summarize the main contributions of this paper below:

1) We propose an end-to-end decentralized online planning method to solve the mCPP problem for the worker-station MRS. Our method manages to reduce the influence of random dynamic interferers on planning, while the robots can avoid collisions with them.

2) We design a two-stage curriculum learning with an intrinsic curiosity module and soft approximation of the workers’ energy constraints, which successfully guide the training for large-scale coverage tasks.

3) We provide ablation study, simulation, and real robot experimental results. The results show that our method outperforms decomposition-based and graph-based baseline methods in coverage finish time metrics.

II. RELATED WORK

A. Multi-robot Coverage Path Planning

The mCPP problem evolved from the classical Coverage Path Planning (CPP) problem by introducing multiple robots to solve the coverage problem. Most approaches are based on the graph structure, which is proven to be NP-hard [9]. Zheng et al. designed a constant-factor approximation algorithm in polynomial time [10]. Kapoutis et al. uses an area division algorithm to allocate tasks for multiple robots [11]. Apart from graph-based methods, decomposition-based methods also take large parts in the literature [12], [13], which first partition the target area into obstacle-free convex sub-regions for different robots and then apply single robot coverage planning for each robot separately. Most graph-based or decomposition-based mCPP methods do offline planning, and some also require the coverage area to satisfy specific assumptions (e.g., convex-shaped area). In addition, classic offline mCPP methods can be undermined by random dynamic interferers in the environment.

On the other hand, recently, some works have been extending the mCPP problem to various applications with specific constraints, such as geophysical surveys [14], fault-tolerant planning on large-scale outdoor [15]. However, to the best of our knowledge, there are few works on the mCPP problem for the aforementioned worker-station MRS.

B. Worker-Station Multi-robot System

Similar to the worker-station MRS, related works on mobilizing the supply station into an autonomous robot mainly focus on rendezvous planning for station to efficiently recharge the workers in need. For example, Couture et al. [4] only plans for station, while workers are dedicated to delivering goods between fixed source and destination. Similarly, in [16], only rendezvous planning of stations is considered, whereas the workers are programmed to monitor the environment by predefined trajectories persistently. Most of these works consider the workers to be stationary in terms of their motion patterns and state transitions, which reduce the complexity to a solvable level for optimization.

More recently, Yu et al. [17] tried to solve both planning problems for one worker and one station, but it is restricted to node coverage for a given graph. Similarly in Sun et al. [18], the worker is planned to travel between waypoints, while the station is planned to rendezvous to charge the worker. Seyedi et al. [19] planned trajectories for multiple workers and one station with scheduled charging order, which also requires a prior of the environment. Despite the above work managed to plan for both workers and station, it is only applicable on convex target areas with static obstacles, thus is infeasible in an arbitrary target area with dynamic interferers.

III. PROBLEM FORMULATION

In this section, we provide our Multi-agent Reinforcement Learning (MARL) problem formulation of the Multi-robot Coverage Path Planning (mCPP) problem on planar areas, for the worker-station Multi-robot System (MRS) (see Fig. 1). Given target area $\Omega$, the worker-station MRS consists of $m$ workers $W^i$ and $n$ stations $S_j$, where $i = 1, 2, ..., m$ and $j = 1, 2, ..., n$. The goal is to find the optimal policy for each robot in the worker-station MRS, to minimize the coverage task finish time while avoiding collisions with dynamic interferers in the environment.

A. Preliminaries

In this subsection, we first introduce several preliminary concepts and assumptions in the rest of the paper.

1) Worker robot and station robot: we consider both workers and station have limited range of perception and communication: within the perception range, each robot can detect collisions and objects precisely; within the communication range, each robot can receive information from other robots (e.g., the rough global position of other robots). As mentioned previously in the worker-station MRS, workers also have limited energy, while station also have unlimited energy to replenish workers. Note that the coverage work range of worker does not necessarily equal its perception range.

2) Energy Capacity and Rendezvous Recharge: denote the energy capacity for worker $W^i$ as a constant $c_i$. Suppose the current energy left for $W^i$ at time $t$ is $e^i_t$, then current percentage of remained energy $p^i_t$ is defined as: $p^i_t = \frac{e^i_t}{c_i} \in [0, 1]$. A worker $W^i$ is said to be “exhausted” if $p^i_t$ is lower than a threshold $p'$, otherwise it is said to be “normal”. Also, since we mainly focus on the planning problem at a higher level in this paper, the local rendezvous of workers and station is simplified by comparing with a position threshold $\epsilon$. We assume a worker can be replenished by any station, then the
discharge and recharge for each worker $W^i$ is determined by comparing $\varepsilon$ with the euclidean distance between the global positions of $x^W_i$ and $x^S^j$ for worker $W^i$ and station $S^j$:

$$e^i_t = \begin{cases} \max \{0, e^i_{t-1} - e_{\text{discharge}}\}, & \|x^W_i - x^S^j\| > \varepsilon \\ \min \{e^i, e^i_{t-1} + e_{\text{charge}}\}, & \|x^W_i - x^S^j\| \leq \varepsilon \end{cases}$$

(1)

3) Coverage Task and Synchronized Coverage Area: coverage by workers is only carried out when worker has energy left. Once a worker starts to recharge, it would be released from station $S$ if and only if it is fully recharged (i.e., $p^i_t = 1$). Denote the coverage area of each worker $W^i$ at time $t$ as $C^i_t$. Here we assume the overall covered area $C_t$ at time $t$ can be updated and synchronized among all agents during the task. The update and synchronization of $C_t$ can be implemented by mutual information exchange for robots within the communication range: $C_t = \bigcup_{i=0}^{\mu} \bigcup_{n=1}^{\nu} C^i_t$.

Fig. 2: Model the coverage task by uniform sampling

For a released worker $W^i$ with energy left (i.e., $p^i_t > 0$), the coverage area $C^i_t$ at time $t$ is determined by uniformly sampling as depicted in Fig. 2: given the sampling resolution $m_{\text{rasterization}}$, the coverage area $C^i_t$ is approximated by uniformly sampling the coordinates within the shape boundaries of the target coverage area $\Omega$ (i.e., rasterization). Then, the coverage area is represented by a set of coordinates in planar space. Thus, the union operations on coverage areas $C_t$ turn into set union operations, which is computationally tractable using a hash-set compared with area union operations.

B. Multi-agent Reinforcement Learning

We first introduce the Decentralized Partially Observable Markov Decision Process (Dec-POMDP) [20] denoted by $(\mathcal{R}, \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{O}, r, b)$, where $\mathcal{R}$ is the set of agents, $\mathcal{S}$ is the joint state space, $\mathcal{A}$ is the joint action space, $\mathcal{P}$ is the state-transition model, $\mathcal{O}$ is joint observation space, $r$ is the shared reward function and $b$ is the initial state distribution. With a shared reward function $r$, we can formulate the MARL problem by single-agent reinforcement learning objective [21]:

$$\max_{\pi} \mathbb{E} \left[ \sum_{t \leq T, s_t = b} \gamma^t r(s_t, a_t, s_{t+1}) \mid a_t^i \sim \pi(\cdot \mid o_t^i) \right]$$

(2)

where $\pi$ is the policy and $\gamma$ is reward discount factor, $s_t \in \mathcal{S}$ and $a_t \in \mathcal{A}$ are the joint state and action of agents at time $t$ respectively. Given the initial state of agents $s_0$ and the observation $o_t^i$ at time $t$, the action $a_t^i$ is sampled from the policy $\pi$. The goal is to maximize the expected discounted reward within a time horizon of $T$. Note that Eq. 2 can be adopted for agents with different observations or functionalities (each corresponds to a different policy), as long as they share a common reward function.

C. Worker-Station MRS Coverage Task Formulation

As introduced previously, the worker-station MRS consists of two types of agents with different functionality: the workers are responsible for coverage work with limited energy, whereas the station is responsible for replenishing workers with unlimited energy. Thus following Eq. 2, we define the agents $R = \{W^i\}_{i=1}^{m} \bigcup \{S^j\}_{j=1}^{n}$ as the set of stations and workers, and $\mathcal{A} = \{a^i\}_{i=1}^{m+n}$ are the actions of workers and stations sequentially. We define policy $\pi_\theta$ and policy $\pi_\phi$ for stations and workers respectively, and a shared reward function $r$ for both agents. Then, we can formalize the mCPP problem for worker-station MRS as a fully cooperative MARL problem [22]:

$$\pi_\theta^*, \pi_\phi^* = \arg \max_{\pi_\theta, \pi_\phi} \mathbb{E} \left[ \sum_{t \leq \min(T, T_{\\text{finish}})} \gamma^t r(s_t, a_t, s_{t+1}) \right]$$

(3)

where $a_t^i \sim \pi_\theta(\cdot \mid o_t^i)$, $i = 1, 2, ..., m$ are the actions of workers, and $a_t^j \sim \pi_\phi(\cdot \mid o_t^j)$, $j = m+1, m+2, ..., m+n$ are the actions of stations. Note that the planning horizon $T$ is replaced by the minimum of the original time horizon $T$ and the coverage task finish time $T_{\text{finish}}$.

In order to finish the cooperative coverage task as soon as possible, with collision avoidance and rendezvous to recharge, we define the shared reward function $r$ as below:

$$r = \sum_{i=0}^{k} (^i r)^i + \sum_{i=0}^{k} (^i r)^i + r_{\text{collision}} + r_{\text{time}}$$

(4)

The first component $(^i r)^i$ is the covering reward for $i$-th worker, which is the only positive term to guide the coverage planning of workers. The second component $(^i r)^i$ is a penalty term added when a worker’s energy is close to its energy capacity, which guides the rendezvous planning of station. The details of the first two reward components are elaborated in Sec. IV. The third component $r_{\text{collision}}$ is a constant collision penalty whenever a collision occurs, which guides the agents for dynamic collision avoidance. The last component $r_{\text{time}}$ is a constant time penalty in each time step whenever the coverage task has not finished, which helps to find more time-efficient planning policies.

Since the total coverage reward of the coverage area $\Omega$ is a constant (i.e., only new covered area provide rewards), and the other three penalty terms would stop accumulating once the coverage task finishes, only a time-optimal coverage and rendezvous planning policy with collision avoidance can reach the optimal task performance. Therefore, by designing and selecting appropriate rewards for the above components in Eq. 3, we can apply MARL algorithms to train the agents for the worker-station MRS coverage task to coordinate with each other for theoretical optimal performance.

IV. Deep Reinforcement Learning Approach

In this section, we introduce key components of our DRL-based planning method. We follow the paradigm of centralized training and decentralized execution (CTDE) [23], which has been widely used in MARL for Dec-POMDP
modeled robot learning problems [24], [25]. The training and planning phases are elaborated in Sec. IV-A. In Fig. 4, we summarize our end-to-end planning pipeline. For an ego agent (worker or station), the perception-range and communication-range observations described in Sec. IV-B are encoded into feature vectors by a convolution neural network. Then, they are stacked upon zero-range observation, constituting the final observation vector $\hat{o}_t^i$ in latent space. The policy network $\pi_\theta$ for worker and $\pi_\phi$ for station are both Multi-layer Perceptron (MLP) modules, each of which takes $\hat{o}_t^i$ for the $i$-th agent at time $t$ and output its action $a_t^i$. The action $a_t^i$ is then converted to velocity commands as mentioned in Sec. IV-C, which solves both rendezvous planning for station and coverage planning for workers.

A. DRL Training and Planning Phases

We follow the paradigm of CTDE to train the policy network of each agent in Eq. 3, then deploy the corresponding policy networks on robots for planning. During training, the state of the whole system and observations of all other agents are needed for better training performance in simulation. During planning, each agent receives only its zero-range, perception-range, and communication-range observations as described in Sec. IV-B, then output the best action according to the corresponding trained policy network. We unfold the details in CTDE in the following two parts.

1) Centralized training phase: for training algorithm, we use the multi-agent actor-critic algorithm MA-POCA [26] to train the policy networks for workers and stations. During training, a centralized critic network is trained to estimate the value of the current system state, including the whole system and observations of all agents. Note that states and observations of the whole system are only needed during training and can be easily accessed in simulations. According to [27], such a centralized critic network would greatly help the training of the actor network (i.e., policy network).

![Fig. 3: Two-stage curriculum learning for mCPP problem of worker-station MRS: (a) Stage-I: one station with single worker; (b) Stage-II: multiple stations with multiple workers.](image)

For better policy exploration of the coordination behaviors towards the coverage task during training, we adopt the Intrinsic Curiosity Module (ICM) [28]. In short, the ICM trains a self-supervised inverse dynamic model that predicts the consequences of an agent’s actions, and uses that prediction error as an intrinsic reward to guide the agent’s exploration during training. In considerations of training performance, we designed a two-stage curriculum learning [29] evolving from single worker into multiple workers, which guides workers and station for better policies during training.

As shown in Fig. 3-(a), stage-I is designed to make it easier for both worker and station to focus on learning some basic behaviors, such as the ability of collision avoidance with static obstacles and dynamic interferers. For worker, the “cover and replenish” behavior is learnt when the remained energy of worker is at a low level. For station, the behavior of finding and following exhausted worker is learnt. Once training of stage-I is converged, we can then extend the worker and station to multiple ones, and adapt the pre-trained policy networks to train for final policies (see Fig. 3-(b)).

2) Decentralized execution phase: unlike the centralized training phase, each agent only needs its own observation during the decentralized planning phase. Specifically speaking, each agent only takes its own observation as introduced in IV-B, and outputs optimal action by its observation and the corresponding policy network $\pi_\phi$ and $\pi_\theta$.

B. Observation Space

For both worker and station, the observation $\hat{o}_t^i$ of the $i$-th ego agent at time $t$ consists of following three types: 1) zero-range observation $(\hat{o}^i_t)$ includes its own basic information; 2) perception-range observation $(p^i_t)$ contains precise local information within its perception range; 3) communication-range observation $(c^i_t)$ includes rough global information within its communication range. A demonstration of observation is shown in the ego agent observation block in Fig. 4.

| perception-range | communication-range |
|------------------|---------------------|
| worker obstacle  | worker station      |
| worker worker(normal) | worker(exhausted) |
| station obstacle | station station     |
| station worker(normal) | station worker(exhausted) |

TABLE I: Encoded objects in perception-range and communication-range observations for ego agents in the worker-station MRS.

Here we elaborate on each type of observation for an ego agent. For both workers and stations, $(\hat{o}^i_t)$ includes global position and local velocity, which are then stacked vertically as 1-D zero-range observation. Note that when the $i$-th agent is worker, the percentage of remaining energy $p^i_t$ is also included in $(\hat{o}^i_t)$. Both $(p^i_t)$ and $(c^i_t)$ are encoded as images with object positions (see Fig. 4), which are translated and rotated with the $i$-th ego agent. The encoded objects in $(p^i_t)$ and $(c^i_t)$ are listed in Tab. I. For $(p^i_t)$, it is a $20 \times 20$ image with $n_p$ channels (i.e., the number of encoded objects) and $n_{perc}$ grid resolution (i.e., length per pixel). For $(c^i_t)$, it is a $30 \times 30$ image with $n_c$ channels and $n_{comm}$ grid resolution.

C. Action Space

We define the action space as a 2d continuous vector space consisting of linear and angular velocities. Given the max linear velocity $v^i_{max}$ and max angular velocity $\omega^i_{max}$ of the $i$-th robot, the sampled action $a_t^i$ is scaled by multiplying $v^i_{max}$ or $\omega^i_{max}$ to give the desired velocity commands.

D. Reward Design

As mentioned in Eq. 4, the shared reward $r$ for all agents consists of four components. Here we only elaborate on the
first two terms since the last two are simply penalty constants as introduced previously. Recall that the first component \((r^c)^i\) is the covering reward for i-th worker at each time \(t\), where positive rewards are given when a new area is covered. Once the coverage work is completed, the training episode will terminate with a completion reward \(r_{\text{finish}}\):

\[
(r^c)^i = \begin{cases} 
    r_{\text{finish}}, & \Omega = \bigcup_{t'=0}^t \bigcup_{i=1}^n C^i_{t'}, \\
    r_{\text{cover}} \times (|C^i_t| - |C^i_{t-1}|), & \text{otherwise} \end{cases}
\] (5)

The second component \((r^r)^i\) is a soft approximation modeling on the hard constraint of worker’s capacity. For worker \(W^i\), it allows \(p^i_t\) to be less than zero during training, which let \(W^i\) still be able to move when \(p^i_t \leq 0\) (i.e., no energy left). More specifically, such a soft approximation uses a truncated exponential function for \((r^r)^i\) as below:

\[
(r^r)^i = \begin{cases} 
    -1 \times \min\{1, \exp\left(p^i_t - p^c\right)\}, & p^i_t < p^c \\
    0, & \text{otherwise} \end{cases}
\] (6)

where \(p^c\) is the threshold indicating whether the worker is exhausted. Such design results from practical considerations: 1) direct modeling such hard constraint during training makes worker struggles to learn the “cover and replenish” behavior when energy is exhausted; 2) the truncated exponential penalty approximation with a relatively large derivative around \(p^c\) makes worker aware of its exhausted status when \(p^i_t\) approaches \(p^c\). Note that the energy capacity hard constraint of worker is only modeled as a soft constraint during training; it is still a hard constraint (i.e., workers cannot move once \(p^i_t \leq 0\)) during planning.

V. EXPERIMENTS & RESULTS

A. Implementation Details

Since we mainly focus on strategy-level planning problems in this paper, we use Unity and ML-Agents toolkit [30] to build the environment and system. The dynamic interferers are modeled in a loop to first move in a constant speed and a random direction within a given period, and then rotate with a random angle. Such a loop for interferers repeats until the coverage task finishes. Also, worker can only be replenished when it is exhausted (i.e., \(p^i_t < p^c\)) and near the station.

B. Simulation Results

We modeled three simulation scenes in Unity to conduct simulation experiments, including ablation study and the coverage task performance comparison. As in Fig. 5-(a)

![Fig. 5: Modeled simulation scenes in Unity. The target coverage areas are bounded within the grey obstacle areas.](image)

| test-case name | star | corridor | cuhksz-1 | cuhksz-2 |
|----------------|------|----------|----------|----------|
| target area size | 30×30 | 120×50 | 180×60 | 180×60 |
| worker cover radius | 4 | 4 | 2 | 2 |
| # of workers | 2 | 3 | 3 | 6 |
| # of stations | 1 | 1 | 1 | 2 |
| # of interferers | 1 | 6 | 6 | 6 |

TABLE II: Design details of simulation test-cases.

and (b), two irregularly shaped scenes are used in simulation experiments, where robots of the worker-station MRS are initialized in the initial position. In addition, we modeled the CUHKSZ campus for coverage work in Fig. 5-(c), where...
the buildings are considered static obstacles. Fig. 6 shows the motion trajectories of the worker-station using our planning method in simulation test-cases. Based on the three modeled scenes, we designed four test-cases described in Tab. II. Note that in cuhksz-2 test-case, only the left-bottom group of robots is included for the coverage work.

1) Ablation Study: to validate the effects on training performance brought by our curriculum learning design and ICM, we conducted ablation study in the corridor test-case. We also trained a centralized policy with PPO [31] to validate the benefits of the CTDE decentralization paradigm. In short, the PPO agent takes the observation of object-positions encoded images, which should cover the whole coverage area with high resolution as in the perception-range observation. Therefore, it is much larger than the image observations for each ego agent in CTDE. With the same visual encoder in Fig. 4, the feature vectors are fed into MLP of the same size to output the joint actions that are distributed to each robot. It is evident in Fig. 7 that a centralized policy using PPO failed in our problem. Such a failure is largely due to: 1) the training difficulties on a much larger network (about 1.5e6 parameters with centralized PPO, 0.1e6 parameters for both worker and station policies with CTDE); 2) and the lack of cooperation between agents with centralized PPO.

We now compare the results within the CTDE paradigm. For two-stage curriculum learning, as shown in Fig. 7, when training from scratch without curriculum, agents in the worker-station MRS struggle at a locally optimal policy and cannot finish the coverage task. When initializing from Stage-I, it provides basic policy networks for both worker and station, which vastly improves the sample efficiency and guides the training procedure. As for ICM, we first initialize policy networks from pre-trained Stage-I curriculum learning. As shown in Fig. 7-(b), the task finish time $T_{\text{finish}}$ shows that agents trained with ICM are better than agents trained without it, which reflects the reward gap between two training curves (green and black) in Fig. 7-(a). Such reward gap results from the earlier finish of the coverage task, which eliminates more accumulating time penalty $T_{\text{time}}$.

2) Decomposition-based and Graph-based Baselines: to evaluate the coverage task performance, we modified graph-based and decomposition-based mCPP methods to several heuristic baseline methods on discretized state space. In addition, since these offline centralized mCPP baseline methods have no dynamic collision avoidance ability with interferers, we adopt a wait-and-move policy for all baseline methods.

Mobile-BCD: for decomposition-based baseline method, we follow the Boustedphoned Cellular Decomposition (BCD) algorithm [32] and adopts it as the so-called mobile-BCD for our problem. We briefly describe the procedure: 1) the map is initially decomposed into cells via BCD; 2) in each cell, back-and-forth trajectories on the uncovered area are generated and evenly distributed to workers; 3) the stations always move to the nearest exhausted worker to replenish it.

Static-MSTC*: for graph-based mCPP baseline methods, we first modify the state-of-the-art mCPP algorithm MSTC* [33] into a static stations version, namely static-MSTC*. In order to account for the continuous energy capacity of workers in our problem setting, the critical modification in static-MSTC* is the constraint approximation from the node-based energy capacity constraint in the original MSTC* to the travel time-based constraint as in Eq. 1.

Mobile-MSTC*: based on the static-MSTC* method, we further mobilize the stations and design the mobile-MSTC* baseline as follows: 1) the target area is first decomposed into sub-regions via k-means clustering; 2) depth-first-search is applied to plan for the stations loaded with workers, to travel to the center of next uncovered sub-region; 3) at each sub-region, the workers cover the area via the static-MSTC* baseline method. Note that the $k$ value in the $k$-means clustering algorithm is chosen according to the capacity $c$ to make partitions suitable for efficient planning.

3) Coverage Task Performance: we compared the coverage task finish time $T_{\text{finish}}$ among our method and the above baseline methods on all the test-cases in Tab. II. The smaller $T_{\text{finish}}$ is, the better the planning strategy for the mCPP problem is. Note that to adopt the mobile-MSTC* baseline method, we decompose the CUHKSZ map into two

![Fig. 6: motion trajectories of worker-station MRS using our method.](image)

![Fig. 7: Ablation study of two-stage curriculum learning. Intrinsic Curiosity Module (ICM) and centralized PPO in corridor test-case.](image)
equal-sized areas, and each area runs the mobile-MSTC* baseline separately to finish the coverage work.

**Test-cases star, corridor, cuhksz-2:** we first compare static-MSTC* with mobile-MSTC* and mobile-BCD. In test-cases star and corridor, the performance of mobile-MSTC* and mobile-BCD is nearly the same as static-MSTC*. In test-case cuhksz-2, the mobile-MSTC* and mobile-BCD manage to improve task performance by mobilizing the station and planning for station and workers separately. However, there remains vast space for coverage task performance improvement; the mobile-station and mobile-BCD baselines that separately plan for stations and workers with dynamic interferers still perform inefficiently.

We now compare our method with baseline methods. In general, the comparison results on the three test-cases show that our planning method can generate good coordination behaviors of coverage planning and rendezvous planning for workers and station, which leads to a better performance in metrics of $t_{\text{finish}}$ after around $0.5e7$ to $1.5e7$ training steps. Compared with the mobile-MSTC* baseline in test-cases corridor and cuhksz-2 with larger target areas, our method unlocks more benefits by mobilizing the station and utilizing the mobility of each robot in the MRS. Interestingly, when an exhausted worker leaves the perception or communication range of station, the rendezvous for recharge is still possible, as stations would explore to search exhausted workers.

![Fig. 8: Comparisons of the coverage task finish time.](image)

C. Real Robot Performance

As complementary to the simulated environments, we also conduct hardware experiments of our method on real robots. As shown in Fig. 9, we tested our method in Star scene, of which we made a replica in the real world. The worker-station MRS consists of two workers (black differential-driven wheeled robots) and one station (yellow skid-steer wheeled robot), the dynamic interferer is a quadrupeled robot. The workers are considered replenished once its distance to the station is smaller than a threshold. We use the PID controller for velocity commands of all robots, with a motion capture system providing their global position information.

![Fig. 9: Real robot demonstration of our planning method.](image)

Fig. 9-(a) depicts the worker-station MRS with our method, where the station is moving towards worker #2 to replenish it and worker #1 is executing coverage work. Fig. 9-(b) is a comparison of the coverage area between simulation and real robot, the blue area is covered by workers and the green area is the motion range of station, the whole coverage task in the real world took 140 seconds.

D. Discussions

To the best of our knowledge, there is no existing online and simultaneous planning method for the worker-station MRS. Therefore, our choice of the baseline methods is naive heuristics-based planning approaches, which also need extensive research to reach optimal performance with fine-tuned hyperparameters. There are several limitations of our DRL-based planning method. First, when there is only a comparably small number of workers with a small cover radius, the unregulated trajectories of workers with continuous action space would leave more uncovered gaps needed for revisiting. Second, since our method mainly focuses on strategy-level planning for workers and station towards the coverage task, we use a relatively simple controller for the generated velocity actions to control real robots, which could cause a performance gap between simulation and reality.
VI. CONCLUSIONS & FUTURE WORK

In this paper, we introduce the worker-station Multi-robot System (MRS) to solve the Multi-robot Coverage Path Planning (mCPP) problem, which can be generalized to various applications in the real world. We provide a fully cooperative multi-agent reinforcement learning formulation of the above problem, and propose an end-to-end decentralized online planning method based on Deep Reinforcement Learning. Our method simultaneously plans for workers and station to work together and utilize the mobility of each robot toward the coverage task. We conduct ablation study, simulation and real robot experiments and demonstrations. The experimental results show that our method is more efficient in planning for workers and station, and our method can better utilize the mobility of each robot compared with the mobile-station baseline method. For future work, there are two directions to further improve the coverage task performance based on our method. First, by regulating the trajectories with the graph-based mCPP method, there would be fewer missing gaps after workers covered an area. However, it might potentially raise the time for random dynamic collision avoidance. Second, by explicitly pre-allocating or negotiating which exhausted workers should the stations be responsible for, the stations can be more efficient to replenish specific workers.

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