Proficiency Constrained Multi-Agent Reinforcement Learning for Environment-Adaptive Multi UAV-UGV Teaming

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Abstract—A mixed aerial and ground robot team, which includes both unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs), is widely used for disaster rescue, social security, precision agriculture, and military missions. However, team capability and corresponding configuration vary since robots have different motion speeds, perceiving ranges, reaching areas, and resilient capabilities to the dynamic environment. Due to heterogeneous robots inside a team and the resilient capabilities of robots, it is challenging to perform a task with an optimal balance between reasonable task allocations and maximum utilization of robot capability. To address this challenge for effective mixed ground and aerial teaming, this paper developed a novel teaming method, proficiency aware multi-agent deep reinforcement learning (Mix-RL), to guide ground and aerial cooperation by considering the best alignments between robot capabilities, task requirements, and environment conditions. Mix-RL largely exploits robot capabilities while being aware of the adaption of robot capabilities to task requirements and environment conditions. Mix-RL's effectiveness in guiding mixed teaming was validated with the task "social security for criminal vehicle tracking".

I. INTRODUCTION

Diversity of robot function and team size enables a mixed aerial-ground robot system, including both Unmanned Aerial Vehicle (UAV) and Unmanned Ground Vehicle (UGV), to perform complex tasks with large area coverage and environment dynamics. In the context of natural disaster search-and-aid tasks [10], [13], [14], [15], a larger area can be searched, and more victims can be located and rescued efficiently by using a heterogeneous aerial-ground team. In the agriculture field [16], [17], [18], the team with heterogeneous aerial-ground robots has been proved a powerful tool to accomplish supervising and farming tasks; In [19], [20], [21], heterogeneous aerial-ground teams have been used to reduce task complexity by assigning sub-tasks to different robots. For example, while a UAV locates victims who require medical treatment, the UAV cannot assist the victim directly. Therefore, the nearest UGV is requested to deliver medical supplies to complete the task.

Complex and dynamic conditions pose challenges for establishing efficient aerial-ground robot teams. First, robots are generally designed for specific conditions and tasks, while the real-world tasks are dynamic and complex so it is more difficult to deploy and scale [25], [26], [27]. Secondly, real-world factors such as motor degradation and sensor failure make the actions of faulty robots unpredictable and therefore decrease the cooperation effectiveness [28], [29], [30]. Thirdly, the diversity of capabilities of individual robots makes it challenging to design an algorithm to integrate all the capabilities on one aerial-ground robot team [3], [24]. However, ignoring the heterogeneous robot capabilities will limit the potential of mixed aerial-ground teaming in real-world applications. Therefore, there is an urgent need to develop a methodology to maximize the advantage and simplify the controlling of mixed aerial and ground robot teams.

To address this challenge, this paper proposed a proficiency aware multi-agent deep reinforcement learning method (Mix-RL) to formulate robot proficiency. As shown in Fig. 1 using the Mix-RL, an aerial-ground robot team can flexibly deploy strategies to complete tasks in dynamic environments based on the awareness of the robot teammates’ capabilities. The main contributions of this research are as follows:

(1) A proficiency aware multi-agent actor-critic method has been proposed to exploit the potential of a mixed aerial-ground team by optimizing the team configuration.

(2) A reinforcement learning-based mixed aerial-ground robot cooperation framework has been developed to dynamically design strategies for tasks based on robot capabilities, task requirements, and environment conditions.

II. RELATED WORK

Prior work investigated mixed teaming of heterogeneous robots. To complete searching and rescuing tasks, [4], [21], [8], systems for UAVs and UGVs collaboration were designed to allocate specific tasks to different team members. However, their studies are unsuitable for real-time applications in unexpected situations. These methods have
a burdensome hierarchical controlling structure that requires transmitting information to a central decision maker to generate strategies. In this paper, each team member understands the proficiency of individual members and directly request help from others. We provided a more efficient cooperation mechanism using a decentralized control strategy with proficiency awareness. A decentralized mixed cooperation scheme was investigated [5], [22] where the drone and the human operator provided guidance to UGVs for navigating among obstacles. [23] investigated the synergistic integration of aerial and ground vehicles, which showed complementary capabilities. However, the study did not explore the in-process changes of proficiency, making it difficult to allocate the tasks to suitable teammates according to real-time conditions. Our paper utilized the actor-critic learning algorithm, which allows each member to criticize the behaviors of its teammates and learn to self-correct in a real-time manner.

There are applications that leverage the flexibility of multi-robot teams to perform tasks in human-hostile environments [6], [7]. The multi-robot tasks in these applications were dynamic and cooperative. However, the applications only involved uniformed robot types and were limited by prior knowledge of the working map. Some researches also investigated mixed robot team for navigating, tracking or searching tasks with centralized controlling architecture [5], [8]. However, the robot control in these research was either limited in inter-teammate awareness or heavily dependent on human attention. Given that, the proficiency-aware mixed cooperative method in our paper presented a more efficient and flexible way for multi-robot systems to work in a complex and dynamic environment.

III. ROBOT PROFICIENCY AWARE MIXED COOPERATION AND COMPETITION

In this section, a proficiency-aware multi-agent deep reinforcement learning algorithm was proposed to support heterogeneous robot cooperation, which is derived from [11]. The algorithm utilizes a framework of centralized training with decentralized execution, which eases the training process in a non-stationary environment; this model also integrated with a proficiency-aware mechanism, which exploits the advantage of the resilient capabilities of robot to facilitate robot teaming in different environments.

A. Multi-Agent Deep Reinforcement Learning

Preliminaries. Considering a multi-robot cooperation and competition problem in which the robots have shared and conflicting goals. The problem with N robots typically consists of a sequential set of states S modelling the positions and the conditions of the robots, a set of robot actions A₁, A₂, ..., A_N constricting all the safe movements according to the specific physical features of robots, and a set of observations O₁, O₂, ..., O_N for each robot. Each robot decides how to take action according to the policy π_θ(a_i|o_i), where policy parameters are denoted by θ = {θ₁, ..., θ_N}. By adopting the policy, robots reach new states described by the state transition function T : S × A₁ × A₂ × ... × A_N → S. Upon reaching the new state, each robot receives a reward r_i : S × A_i → R. Restricted by perceiving ability of robot and real world limitations, each robot obtains a distinctive local observation o_i : S → O_i. This paper considers a case of two multi-robot teams with different objectives and receiving varied even adversarial rewards. Each robot aims at maximizing its own expected aggregate objective,

\[ J(θ_i) = E_{s,a,s′,o_i ∼ π_i}[R_i] \]  

(1)

where discounted reward \( R_i = \sum_{t=0}^{TME} γ^t r_{i,t} \) and discount factor \( γ \in [0, 1] \).

Multi-Robot Actor-Critic Learning. Robots are given the actions \( a = (a_1, ..., a_N) \) and the observations \( s = (O_1, O_2, ..., O_N) \) of the robots of both teams to perceive the world. Once the robots are equipped with extra information, the world can be seen as fully known and be treated as stationary despite the changing of policies. Then the gradient of (1) with deterministic policies can be written as:

\[ \nabla_θ J(θ_i) = \mathbb{E}_{s,a,s′,o_i ∼ π_i[\nabla_θ \log \pi_i(a_i|o_i)Q_i^\pi(s,a)|a_i=μ(o_i)]} \]  

(2)

where \( Q_i^\pi(s, a_1, ..., a_N) \) is the extra information for the robots at training time, which includes the observations of all the robots and selected state information \( s = (o_1, ..., o_N, s_1, ..., s_N) \). The team’s awareness to exploit the most capable robots in cooperation can be cultivated through updating the policy along (2) to minimize the regression loss:

\[ L(θ_i) = \mathbb{E}_{s,a,r,a′}[\{Q_i^\mu(s, a) - y\}^2] \]  

where \( y = r_i + γ Q_i^\mu(s′, a′)|a′=μ(o_j) \)  

(3)

B. Proficiency Awareness Modeling for Mixed Teaming

Selecting robots with proper capabilities to perform tasks in a complex environment assures task success. This paper defines the environment as \( E_T = \{e_1, e_2, \ldots \} \), where \( T \) is the assigned task, and \( e \) is the environmental condition such as lawn or forest. Considering the differences in capabilities of robots, this paper defines the capabilities of robot \( i \) as \( A_i : \{A_i^c = (a_i^c, a_i^c', \ldots), e \in E_T \} \), where \( a_i \) is the capability of robot \( i \) such as velocity or observation range. \( A_i \) means robot \( i \) has different capabilities such as velocity and observation range for different environmental conditions such as lawn or forest. The proficiency \( f_p(E, T, A) \) is defined as:

\[ f_p(E, T, A) = \prod_{e \in E_T} f_p(e, A_e^c), e \in E_T, i \in N \]  

(4)

if \( \forall e \in E_T \) and \( \forall i \in N, f_p(E, T, A) > \xi \), the mixed teaming is with proficiency. \( N \) is the number of robots in the team. \( f_p \) is the measurement of efficiency of a team of robots with different capabilities \( A_i^c \) performing a task in different environment conditions, such as \( e_1 \) and \( e_2 \). \( \xi \) is a predefined efficiency threshold. If one UAV and one UGV - the capabilities are denoted as \( A_1, A_2 \) respectively - are selected to perform the task together, then \( f_p(E, T, A) = f_p(e_1, A_1^c, A_2^c) \times f_p(e_2, A_2^c, A_2^c) > \xi \), the mixed teaming is with proficiency.

Considering the situation with multiple robots (\( R_o \)), this paper defines the awareness of proficiency as the robot set
that the robot who has a greater capability to the specific environment has a larger probability to be chosen to perform the task. The awareness of proficiency is denoted as:

\[
P(\sum r^*_o) = \forall \sum r_o \in R_o : f_p(\mathbb{E}, T, \mathbb{A} \sum r^*_o) \geq f_p(\mathbb{E}, T, \mathbb{A} \sum r_o)
\] (5)

Overall, the increase in \(P(\sum r^*_o)\) means the robot team has a better awareness of proficiency and performs the assigned task with more efficiency based on this awareness.

The overall reward in the training process of Reinforcement Learning, \(Reward_i\), includes two separate reward functions: objective reward function and proficiency reward functions.

\[
Reward_i = R_{i,\text{objective}} + R_{i,\text{position}}
\] (6)

Robots’ awareness of proficiency is introduced by the proficiency reward function, \(R_{i,\text{position}}\), which is modeled by robot motion constraints and observations.

\[
R_{i,\text{position}} = \beta \text{Velocity}_i(s) + \gamma \text{Observation}_i(s)
\] (7)

\(\beta\) and \(\gamma\) are the balance weights. The proficiency reward function indicates robot has varied capability when it is in different regions of the environment. The differences in capability between robots, including mobility and real-time observation range, determine their different \(R_{i,\text{position}}\) for every state. For example, a robot will have a negative \(\text{Velocity}_i(s)\) while it is in an incapable state \(s\). On the other hand, objective reward function \(R_{i,\text{objective}}\) describes the distance between robots and its target position measures how well a robot fulfills its objective.

### IV. Evaluation

The effectiveness of mixed cooperation and competition for robot teaming could be reflected through effective behaviors of mixed UAV-UGV teams in a task under dynamic environments. In this section, we evaluated mixed UAV-UGV behaviors with a surveillance task under the simulation environment of Kent State University Student Center, University Library and Risman Plaza. The environment was simulated with CRAImrs simulation platform.

The performance of the Mix-RL method was compared with the original multi-agent actor-critic algorithm to show the improvement in the task reward, success rate of task, appropriate involvement of individual robots.

#### A. Experiment Environment Settings

This paper used three different kinds of vehicles in the experiment. Firefly has a redundant 6-rotor propulsion system that is very robust and guarantees a stable flight, as shown in Figure 2b [1]. In our experiment, Firefly has a wide range of perception but moves slower than Iris. Iris is a quad-copter, shown in Figure 2c. It is not as stable as Firefly, but it can fly faster [2]. Iris moves fast but has a relatively small range of perception. Husky is a ground robotic platform, shown in Figure 2a. Its max speed is 1.0 m/s.
TABLE I: Parameters of UAV and UGV

| Type    | $V_{max}$ (m/s) | Acceleration ($m/s^2$) | Radius (m) |
|---------|-----------------|------------------------|------------|
| Firefly | 5.0             | 1.0                    | 30         |
| Iris    | 7.0             | 2.0                    | 30         |
| Husky   | 1.0             | 0.1                    | 15         |

Fig. 4: Learning curves of mixed robot cooperation with and without proficiency awareness. We trained for 20,000 episodes with both methods. The plots report the mean episode rewards during the training and the error bars are calculated with 95% confidence interval over 5 runs.

Proficiency Awareness. The performance of multi-robot with proficiency awareness was demonstrated by if the deployment of robots adapts to the dynamic environment given the differences in robot’s mobility, flexibility and observation range. During the testing phase, situations were observed in open area where police UAVs chase the criminal robot. Because: 1) UGV have a lower average speed compared with UAVs; 2) There are plenty of police UAVs for one ground target. Therefore, the high involvement of police UAV in the task contributes to a successful capture. In contrast, without using the proficiency-aware method, results show that the robot team failed to cooperate, which means the lack of participation of capable robots in the task is the main reason for multi-robot cooperation failures.

Cooperation Effectiveness. The mix-RL model can improve the proficiency of multi-robot cooperation. Here we adopted task success rates to measure the effectiveness and reliability of multi-robot cooperation. The algorithm with proficiency awareness maintained a high task success rate. The task success rate of robot team with-awareness in Task Plaza was 89.60%, while the task success rate of robot team without-awareness was 55.20%. Besides, as shown in Figure 4, the mean reward of training episodes with proficiency-aware setting was 71.29. However, The mean reward of training episodes without proficiency-aware setting was –16.33. Therefore, the mix-RL model can improve the efficiency of cooperative and competitive aerial-ground robot teaming in different scenarios.

V. CONCLUSION

This paper proposed a proficiency-aware actor-critic method (mix-RL), which improved the success rate and efficiency of cooperative and competitive aerial-ground robot teaming. We deployed a heterogeneous UAV-UGV team to perform tasks in ground target tracking scenarios. The effectiveness of mix-RL in improving task success rates is presented to validate the feasibility of deploying this method for guiding the flexible teaming of mixed aerial-ground robot in dynamic environments. In the robot function-adaptive situation, with proficiency-aware setting, the robot team could generate appropriate teaming engagement to leverage the different capabilities of individual robots. In the future, one important research can be the scalability of the method with a larger number of heterogeneous robots and targets.

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