Inner Attention Modeling for Flexible Teaming of Heterogeneous Multi Robots Using Multi-Agent Reinforcement Learning

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Abstract—With the advantages of member diversity and team scale, heterogeneous multi-robot systems (HMRS) are widely used in complex scenarios, including disaster search and rescue, site surveillance, and traffic control. However, due to the variety of task requirements, it is still challenging to accurately allocate limited team capability to satisfy various task needs effectively. In this paper, a novel adaptive cooperation method, inner attention (innerATT) is developed to flexibly team heterogeneous robots to execute tasks as task needs change. innerATT is designed based on an attention mechanism and a multi-agent actor-critic reinforcement learning algorithm. We briefly validate how the inner attention mechanism can be exploited to enable flexible and robust decision making in guiding cooperation. The results, in two designed scenarios “task variety” and “robot availability variety”, show that innerATT can enable flexible cooperation and reduce resource consumption in search and rescue tasks.

Index Terms—Inner Attention, Multi-Agent Reinforcement Learning, Adaptive cooperation, Heterogeneous Multi-Robot Team.

I. INTRODUCTION

Flexible teaming is necessary for heterogeneous multi-robot system (HMRS) deployments in the real world [1]. First, many robotic applications are inherently distributed over space and time, which could be solved quickly by distributing sub-teams with the same capability to different areas. Flexible teaming can dynamically balance the workload among sub-teams by increasing or decreasing the number of robots in each sub-team [2], [3]. Second, many robotic applications are inherently distributed over functionality, requiring sub-teams with diverse capabilities to operate simultaneously. Flexible teaming can split an HMRS into sub-teams with different functionalities by teaming robots with complementary abilities [4], [5]. Third, in extreme environments such as severe weather, flexible teaming can increase HMRS robustness and reliability by reassigning robot team members to different sub-teams, when robots in a sub-team are broken [6], [7].

Given the task and team varieties, however, flexible teaming is challenging. First, due to the changing requirements of real-world tasks, it is difficult to assess the real-time assistance need in both type and scale for HMRS deployments. Many real-world tasks are inherently distributed in space and time, leading different regions with various tasks requirements. Even for the same working area, the task needs will dynamically change with time. For example, in traffic control situations, the traffic flow is dynamically changing with time and locations. The dynamic nature of task needs, increasing the difficulty of recruiting team members properly in type and scale, can make flexible teaming challenging [2], [8]. Second, real-world factors, such as motor degradation, sensor failure, and robot working status, influence robot availability for HMRS team composition to respond to assistance needs [9], [10]. Faulty...
robots in the robot team may share incorrect information with other members of the team leading the whole team unqualified to the assigned task. The unpredictable nature and negative impacts of these real-world faults limit the number of qualified team members, making it challenging to deploy a qualified robot team with expected capability and team size to satisfy task needs. Third, influenced by both the dynamics in task needs, robot availability, and environment constraints, it is challenging to accurately map robot team capability to task needs \( \Pi \). Assistance needs are dynamic as tasks vary; available robots are with different distances to the requested location; obstacles and weather conditions influence the time and feasibility of robot participation in assistance. All these constraints influence the HMRS team composition as assistance needs require. Ignoring the above varieties in actual situations will negatively influence HMRS performance, and influence the accurate alignment between robot capability and task needs, largely limiting an HMRS’s usage in the real world. Therefore, there is an urgent need to flexibly compose heterogeneous robot teams to satisfy task requirements and effectively utilize robot capabilities optimally.

This paper addresses this need by designing a novel method (innerATT), as shown in Figure 1. By using the inner attention mechanism to pay attention to different available teammates and capture the cooperation-related factors in real-world dynamics, innerATT can flexibly select cooperators and satisfy the dynamic changes in environment and task requirements with minimal efforts. This paper mainly has three contributions:

1) A novel attention supported method (innerATT) based on inner attention mechanism has been designed to guide the flexible cooperation by paying attention to different available teammates and capturing the cooperation-related factors in real-world dynamics.

2) A theoretical analysis for the robustness of multi-robot flexible cooperation has been proved to show that the negative impact of real-world disturbances can be reduced by using the inner attention mechanism.

3) A deep reinforcement learning-based simulation framework was developed to evaluate the flexible teaming of heterogeneous multi robots under real-world disturbances.

II. INNER ATTENTION SUPPORTED ADAPTIVE COOPERATION

The innerATT helps a robot in a team to selectively pay different attention to different robots by using the inner attention mechanism. As shown in Figure 1, given the inputs of all robot’s status and observations, innerATT automatically determines the amount of attention paid to different robots.

A. Robot Inner Attention for Team Adaptability Modeling

The basic robot teaming framework is supported by a multi-agent actor-critic deep reinforcement learning (MAAC) algorithm, which is defined by the number of robots, \( N \); state space, \( S \); a set of actions for all robots, \( A = \{A_1,...A_N\} \); transition probability function over the next possible states, \( T: S \times A_1 \times ... \times A_N \rightarrow P(S) \); a set of observations for all robots, \( O = \{O_1,...O_N\} \); and reward function for each robot \( R_i: S \times A_1 \times ... \times A_N \rightarrow R \). By using extended actor-critic reinforcement learning for guiding the cooperation, each robot learns an individual policy function, \( \pi: O_i \rightarrow P(A) \), which is a probability distribution on potential cooperation actions. The goal of multi-agent reinforcement learning is to learn an optimal cooperation strategy for each robot which can maximize their expected discounted returns:

\[
J_i(\pi_i) = E_{\omega, \sigma, s \sim T} \left[ \sum_{t=0}^{\infty} \gamma^t r_{it}(s_t, a_{1t}, ..., a_{Nt}) \right]
\]  

where * represent \( \{1, ..., N\} \); \( \gamma \in [0, 1] \) is the discount factor that determines the degree to which the policy favors immediate reward over long-term gain.

In the extended actor-critic framework consisting of centralized training with decentralized execution, to calculate the Q-value function \( Q_i(o, a) \) for the robot \( i \), the critic receives the observations, \( o = (o_1, ..., o_N) \), and actions, \( a = (a_1, ..., a_N) \), for all robots, which will take redundant information into account. Therefore, each robot should pay more attention to task-relevant information based on task requirements and robot availability. To do that, the inner attention mechanism has been used as a complementary part of the extended actor-critic framework. Intuitively, with the innerATT, the robots can selectively cooperate with proper team members to flexibly satisfy dynamic task needs with limited team sources.

To generate the attention weights, the embedded information is fed into the innerATT to get the Q-value function \( Q_i(o; a) \) for the robot \( i \), which is a function:

\[
Q_i(o; a) = w^T \sigma(w^1, <e_i, x_i>)
\]  

where \( \sigma \) is rectified linear units (ReLU), \( w^1 \) and \( w^2 \) are the parameters of critics. The inner attention mechanism has shared query \( w_q \), key \( w_k \), and value \( w_v \) matrices. Each robot’s embedding \( e_i \) can be linearly transformed into \( q_i, k_i, \) and \( v_i \) separately. The contribution from other robots, \( x_i \), is a weighted sum of other robots value:

\[
x_i = \sum_{j \neq i} \alpha_{ij} v_j = \sum_{j \neq i} \alpha_{ij} \sigma(v_j)
\]  

the attention weight \( \alpha_{ij} \) compares the similarity between \( k_j \) and \( q_i \), and the similarity value can be obtained from a softmax function:

\[
\alpha_{ij} = \frac{S_{ij}}{\sum_{k=1}^{N} S_{ik}} = \frac{e_j w_k^T w_q e_i}{\sum_{k=1}^{N} e_k w_k^T w_q e_i}
\]  

To better analyze the effectiveness of the innerATT method, a baseline method without the inner attention mechanism has also been designed. In the baseline method, the attention weights \( \alpha \) are simply fixed to \( \frac{1}{N-1} \). Given that only the values of attention weights are changed to a fixed value, both innerATT and baseline methods are implemented with an approximately equal number of parameters.
B. Theoretical analysis of innerATT’s robustness

To simply explain whether inner attention mechanism works, the output of the Q-value neural network with inner attention mechanism, when the input is \( x \), can be written as:

\[
f(x) = w^T \sigma(w^T x), \quad x = <e_i, x_i> \tag{5}
\]

the robots can be more robust to other robots’ failure or a broken sensor [12]. Consider that a small perturbation is added to a particular robot \( j \)’s embedding, such that \( e_j \) is changed to \( e_j + \Delta e \) while all the other robots’ embeddings remain unchanged. How much will this perturbation affect the attention weights \( \alpha_{ij} \)? For a particular \( i (i \neq j) \), the

\[
S_{ij} = e_j w_i^T w_q e_i \tag{6}
\]

is only changed by one term since:

\[
S'_{ij} = \begin{cases} 
S_{ij} + \Delta ew_i^T w_q e_i, & \text{if } (i \neq j), \\
S_{ij}, & \text{otherwise.}
\end{cases} \tag{7}
\]

where \( S'_{ij} \) denotes the value after the perturbation. Therefore, with the perturbed input, each set of \( \{S_{ij}\}_{j=1}^n \) will only have one term being changed. For the perturbation part, assume \( \|\Delta e\| \leq \delta_1 \) and \( \|e_i\| \leq \delta_2 \), then the expected value:

\[
E[S'_{ij} - S_{ij}] \leq \|w_q\| \|w_k\| \delta_1 \delta_2 \tag{8}
\]

Then, the probability results can be obtained by using Markov inequality:

\[
P(|S'_{ij} - S_{ij}| \geq \varepsilon) \leq \frac{\|w_q\| \|w_k\| \delta_1 \delta_2}{\varepsilon} \tag{9}
\]

Therefore, as the norm of \( w_q, w_k \) are not too large (usually regularized by \( L_2 \) during training), there will be a significant amount of \( i \) such that \( S'_{ij} \) is perturbed negligibly. Therefore, with the inner attention mechanism, innerATT method is more robust to a broken robot or sensor failure.

III. Experiment Settings

To validate innerATT’s effectiveness in improving HMRS adaptability, a cooperative environment with two typical scenarios “task variety” and “robot availability variety” were designed. These two scenarios frequently occur and generally represent the deployment dynamics of HMRS in the real world. Therefore, by validating innerATT effectiveness in these two scenarios, we hope to get a general conclusion on the efficacy of (innerATT) in improving HMRS adaptability.

The environment, in Figure 2, was implemented based on the open-source multi-agent particle environment (MPE) framework [13]. The size of the artificial environment was set to \( 2 \times 2 \). The parameters of robots, shown in Table I, were set according to real-world robots. In this environment, there are two victims and four rescuing robots. For the rescuing robots, two of them are food delivery robots providing living supplies such as food and water, and one of them is a safety guidance robot providing victims with useful information about the location of safer places. The remaining robots are medical assistance robots, which are mainly used to provide medical treatments to heavily injured victims. As for the victims, one of them is heavily injured, requiring both food and medical assistance for survival, defined as “Task 1”; while another victim who is trapped but in good health will need food delivery as well as safety guidance for moving to a safer place, defined as “Task 2”. As for the typical “task variety” scenario, food delivery robots are needed in both kinds of tasks. Therefore the food delivery robots should flexibly adapt to different tasks and satisfy different task requirements. As for the “robot availability variety” scenario, the medical assistance robot or safety guidance robot’s motors could be broken due to mechanical failures, which will have negative impacts on food delivery robots’ cooperator availability. Therefore, this scenario can be used to evaluate food delivery robots’ robustness to real-world disturbances.

As for the training procedure, the extended actor-critic method for maximum entropy reinforcement learning was used in the training progress of 25,000 episodes. There were 12 threads to process training data in parallel and a replay buffer to store experience tuples \( (o_t, a_t, r_t, o_{t+1}) \) for each time step. The environment got reset every episode of 100 steps. The policy network and the attention critic network were

| Type                | Speed (m/s) | Mass (kg) | Ability          |
|---------------------|-------------|-----------|------------------|
| Food Delivery       | 1.0         | 1.0       | Food             |
| Safety Guidance     | 1.5         | 0.5       | Information      |
| Medical Assistance  | 1.5         | 0.5       | Medicine         |

Fig. 2. Simulated environment illustration. In the flood disaster, there are trapped victims with different injury levels. For the victims with high injury level (Task 1), they need rescuing robots providing them with food, water, and emergency medical treatment; While for the victims with low injury level (Task 2), they will need other kinds rescuing robots providing food, water, and useful information to guide them to safer places. The main robots team is expected to split into different sub-teams that can rescue these victims effectively.
updated four times after each episode. In detail, sampling 1024 tuples from the replay buffer and updating the parameters of the Q-function and the policy objective through policy gradients. Adam optimizer was used, and the initial learning rate was set as 0.001 and the discount factor $\gamma$ of 0.99. The embedded information function used a hidden dimension of 128, and four attention heads were used in the inner attention mechanism.

IV. RESULTS

A. Adapting to Task Varieties

In the typical "task variety" scenario, robots’ flexibility, the cooperation rate between food delivery robots and other rescuing robots, was calculated in a period of time (80 episodes) by using the following formulation:

$$\text{rate}_{ij} = \frac{\sum_{k=1}^{N} \text{Num}_{ik}}{\sum_{k=1}^{N} \text{Num}_{ik}}$$

(10)

where, $\sum_{k=1}^{N} \text{Num}_{ik}$ is the total number of victims rescued by robot $i$; $\text{Num}_{ij}$ is the total number of victims rescued by the cooperation of robot $i$ and robot $j$. The results are shown in Table II, in Task 1, the cooperation rates of food delivery robots trained by innerATT are 0.52 and 0.48 respectively, which is similar to uniform distribution with 95% confidence; while the cooperation rates of food delivery robots trained by baseline method are 0.90 and 0.10, which doesn’t have enough evidence to prove that it is similar to the uniform distribution. Similar results have been shown for task 2, that the robots trained by innerATT are more flexible than those trained by the baseline method. As suspected, the baseline model’s critics use all information non-selectively, while innerATT can learn which robots to pay more attention through the inner attention mechanism. Thus, innerATT method is more flexible and sensitive to dynamically change tasks. Besides that, Figure 3 demonstrates the effect of the attention head on the robot during the training process by showing the entropy of the attention weights for each robot. From the results shown in Figure 3, the entropy of all robot attention heads is continually decreasing to 1.02 around, which indicates that innerATT can train the robots to selectively pay attention to a specific team member through the inner attention mechanism.

To further prove that the inner attention mechanism is beneficial to robot’s flexible adaptation to different tasks, the relationship between robot behavior and their inner attention weights was analyzed to illustrate attention supports in adjusting robot behaviors for flexible teaming. Figure 4 (A) is an illustration of a specific scenario occurring during the experiment. In the pre-stage, food delivery 1 robot is firstly cooperating with medical assistance robot to rescue the heavily injured victim (Task 1). At this moment, food delivery 1 robot needs to pay more attention to medical assistance robot. After finishing Task 1, in the middle-stage and post-stage, it will change to cooperate with a safety guidance robot to rescue the trapped victim in good health (Task 2). At this time, food delivery 1 robot needs to pay more attention to safety guidance robot. Figure 4 (B) is the curves of food delivery 1 robot’s total attention weights over the other three robots. In the pre-stage, the curve of total attention weights paid on medical assistance robot has the highest values, which supports the food delivery 1 robot to selectively cooperate with medical assistance robot. In the middle-stage and post-stage, the curves of total attention weights paid on medical assistance robot and safety guidance robot are decreasing and increasing separately, which supports food delivery 1 robot to transfer its attention from medical assistance robot to safety guidance robot. Therefore, the inner attention mechanism can support robot flexible teaming behaviors to different tasks. Figure 4 (C) are the curves of food delivery 1 robot’s attention weights, generated by each attention head, over other rescuing robots.

B. Adapting to Robot Availability

In addition to robot flexible teaming, robustness to real-world disturbances is important in HMRS. If the robots cannot flexibly adapt to real-world disturbances, such as some robots are broken in the robot team or the faults caused by sensor failures, then there may be undesirable and uncontrollable effects on other teammates. What’s more, broken robots may share incorrect information with other members of the team leading to incorrect behaviors of cooperation.
With the inner attention mechanism, the HMRS team is more robust to sensor failure or broken units, which has been theoretically proved in the method section: Theoretical analysis of innerATTs robustness. To practically measure the robustness of innerATT, the typical robot failure issue “motor broken” is simulated. Then food delivery robots’ cooperation rates are calculated to estimate their robustness to the “motor broken” disturbance. In the ideal cases, if the food delivery robots are robust enough, they will have an equal chance to participate in Task 1 or Task 2. That means food delivery robots will not be influenced by faulty robots. As Table III shows, considering Task 1 when safety guidance robot is broken, the cooperation rates of food delivery robots trained by innerATT are 0.54 and 0.46 respectively, which is similar to
uniform distribution with 95% confidence; while the cooperation rates of food delivery robots trained by baseline method are 0.91 and 0.09, which means the food delivery robots have been significantly influenced by the broken robot. Similarly, as for Task 2 when the medical assistance robot is broken, similar results are observed. Therefore, the robots trained by innerATT are more robust to robot failure than those trained by the baseline method.

To further prove that the inner attention mechanism is beneficial to robot robustness to real-world factors, similar to Figure 4, the relationship between robot behavior and their inner attention weights was analyzed to illustrate attention supports in adjusting robot behaviors for increasing robot resilience. From the curves of medical assistance robot’s total attention weights over the other three robots in Figure 5, similar results can be obtained that the inner attention mechanism can increase robot robustness to real-world robot failures by adjusting robot behaviors for increasing robot resilience.

V. CONCLUSION AND FUTURE WORK

This paper designs a novel inner attention model, innerATT, allowing multi heterogeneous robots to cooperate flexibility by paying attention to their capability differences. innerATT improves the robustness and efficiency of heterogeneous robot deployments over sensor and robot failures. Two types of scenarios - "task variety" and "robot availability variety" - were designed to evaluate the effectiveness of innerATT method. Comparisons were made between innerATT and the baseline method (multi-agent actor-critic reinforcement learning method without inner attention mechanism) in guiding robot teaming. With the inner attention, robots can cooperate more flexibly, maintain stability, and rescue more victims while consuming fewer resources. The robots are encouraged to cooperate with capable robots and discouraged from cooperating with incapable ones to adapt to real-world tasks. The simulation results demonstrate the feasibility of using this innerATT model for guiding flexible teaming of heterogeneous robots with varying task needs, providing theoretical support for real-world flexible teaming of heterogeneous robot deployments.

In this work, our primary focus is validating the feasibility of using attention for flexibly composing a heterogeneous robot team. Noted that the simulated environment is different from the real-world environment; the robots’ capabilities are different from real-world robots. To implement this model for real-world robot teaming, appropriate robot modeling and environmental features will need to be considered to re-train and implement this model. In addition, large training data about real-world needs to be provided to ensure the optimal performance of the model.

In the future, novel inner attention-based methods considering real-world features will be designed to deploy heterogeneous multi-robot teams effectively. Moreover, the research of robot behavior understanding and human trust modeling will be an option to improve the performance of HMRS in the real world. Future research also could focus on the scalability of heterogeneous robot teaming, expanding the current task scenarios to broader ones, including more dynamic and diverse tasks.

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**TABLE III**

| Task | UAVs participate rate when one robot is broken |
|------|---------------------------------------------|
|      | food delivery1 | food delivery2 | $\chi^2(\alpha = 0.05)$  |
| Task1 | innerATT       | 0.54           | 0.46           | 0.51 < 3.84 |
| Task1 | Baseline      | 0.91           | 0.09           | 74.6 > 3.84 |
| Task2 | innerATT      | 0.49           | 0.51           | 0.01 < 3.84 |
| Task2 | Baseline      | 0.07           | 0.93           | 76.9 > 3.84 |