Humans can selectively focus on different information based on different tasks requirements, other people’s abilities and availability. Therefore, they can adapt quickly to a completely different and complex environments. If, like people, robot could obtain the same abilities, then it would greatly increase their adaptability to new and unexpected situations. Recent efforts in Heterogeneous Multi Robots Teaming have try to achieve this ability, such as the methods based on communication and multi-modal information fusion strategies. However, these methods will not only suffer from the exponential explosion problem with the increase of robots number but also need huge computational resources. To that end, we introduce an inner attention actor-critic method that replicates aspects of human flexibly cooperation. By bringing attention mechanism on computer vision, natural language process into the realm of multi-robot cooperation, our attention method is able to dynamically select which robots to attend to. In order to test the effectiveness of our proposed method, several simulation experiments have been designed. And the results show that inner attention mechanism can enable flexible cooperation and lower resources consuming in rescuing tasks.

**Keywords** Multi-Agent Reinforcement Learning, Dynamic cooperation, Multi-robot teaming, Attention, Low resource consuming

### 1 Introduction

The heterogeneous multi robots team have gained great interests in the last decades because of its several foreseen benefits compared to single robot team such as the increased ability to increase reliability, resolve tasks complexity, increase performance and simplicity robot’s design [1,3]. It could be widely used in household, industrial and society applications or situations that are too dangerous for human beings. Such as, in natural disaster search-and-rescue tasks [4,6], larger area can be searched and more victims can be rescued efficiently by using a heterogeneous multi robots team; In city traffic condition control field [7,9], it will be much more easy and cheap to deployment a huge number of robots team to monitor the whole city’s traffic conditions by using small and simple robots; What’s more, in complex tasks situations [10,12], the heterogeneous multi robots team has also been used to resolve task complexity by allocating different kind robots with different part tasks.

Eventhough the applications of heterogeneous multi robots team has witnessed significant progress, effective deployments and cooperation of heterogeneous robots team are still challenging. The followings are some factors that will make tasks more challenging. First, Given the discrepancy between simulation and the real environment in terms of dynamics and perception, such simulation-to-reality transfer is hindered [13,15]. For example, real-world constrains such as obstacle distribution, terrain conditions, and system reliability, can also cause unexpected issues to undermine
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Figure 1: An illustration of the human inspired inner attention using the developed IAAC model. By using the inner attention mechanism, the UAV can selectively based on other robots to make decisions and flexibly participate to different tasks.

robot team’s performance [15][21]. Second, robots’ different capability, availability and dynamically changing status, making the application challenging in balancing the efficiency of tasks executions and the effectiveness of utilizing the robot capabilities [16][18]. In order to fulfill the flexible cooperation in complex and challenging environments, the robots must have the ability to deal with huge amount of unexpected situations and flexibly cooperate with each other based on the selectively chosen information. For example, in order to rescue the trapped victims in flood disaster, the robot should learn how to choose which robots to cooperate with by taking its own situation, other robots’ availability and capability into consideration. What’s more, real-world faults, such as motor degradation and sensor failure, can make some robots unreliable by sharing incorrect information and degrade the robots team’s performances.

To solve these challenges, an inner attention supported adaptive cooperation (IAAC) method, as shown in Figure 1, has been developed in this paper, by imitating human’s attention mechanism. The assumption behind IAAC is that if the robots are trained able to dynamically select which robots to attend to and cooperate with, they can be flexible enough to deal with the unknown dynamical situations. In this research, we mainly have three contributions:

1. a novel attention supported method for formulating a general concern-involved cooperation mechanism for general heterogeneous robots teaming, to guide the flexible cooperation with the considerations of robot capability, availability limitations.
2. a theoretical analysis for the robustness of multi-robot flexible cooperation has been developed, to prove that our proposed method is robust enough to deal with unexpected situations like sensor failure.
3. a deep reinforcement learning based simulation framework has been introduced for evaluating robot teaming effectiveness, efficiency and robustness.

2 Related Work

Heterogeneous multi robots team has been investigated in the robotics field to successfully accomplish complex tasks coming from our dynamic and unpredictable world. A number of researches exist which aim to show the utility of using human-designed heuristic strategies in multi robots teaming to increase their performance [22][24]. However, these pre-designed cooperation methods should take all the details and situations into account and will perform poorly especially for partial observation task. There are also many works still required human intervention to achieve complex tasks [25][27]. When a huge amount of robots need to be deployed, it will need lots of well-trained human operators
Figure 2: The architecture of IAAC. The inner attention mechanism determines the attention weight between each agent based on the inputs of agents' observations, and actions. Calculating $Q(o,a)$ with attention for robot $i$. Each agent encodes its observations and actions, sends it to the inner attention mechanism, and receives a weighted sum of other agents' encodings.

which is expensive and time consuming. In last decades, some researchers have attempted to combine the strengths of deep reinforcement learning mechanism with the control policies for robotics applications \cite{28-30}. Multi Agent Reinforcement Learning has been proved to be effective for enabling sophisticated and hard-to-design behaviors of robot individuals \cite{31-35}. Even though it has been used in robotics research, multi-agent reinforcement learning are still far from being generically applicable to dynamic environments with complex tasks. For example, \cite{36-40} formulated swarm systems as a special case of the decentralized control and used an actor-critic deep reinforcement learning approach to control a group of cooperative agents, but it can only be used in homogeneous robots situation; In \cite{41-45}, distributed task allocation where agents can request help from cooperating neighbors have been proposed, but it also may not be able to deal with heterogeneous agents. \cite{46-48} are the approach to address heterogeneous multi-agent learning in urban traffic control. However, the proposed deep reinforcement learning approach learns ineffectively in complex traffic conditions. As for the attention mechanism which has been widely used in computer vision, natural language process and text classification fields \cite{68-70}. In \cite{49-52} attention mechanism has been used to cooperate effectively by precisely obtaining necessary communications from other agents. However, in order to calculate whether the communication is necessary for each pair of agents, agent’s local observation and the trajectory will all be needed, which is inefficient. The IAAC presented in this paper can dynamically select which agents to pay attention to by using an inner attention mechanism. The intuition behind our idea comes from the fact that, in many real-world environments, it is beneficial for agents to know which other agents it should pay attention to. Therefore, IAAC has the ability to deal with heterogeneous multi robots teaming in dynamic situations. Besides, by utilizing attention to select relevant information for estimating critics, our method do not need huge communications between agent pairs, which is more efficient.
There have been many efforts in dealing with the possibility that a few robots will break during multi robots cooperation. In [53–57] passive healing strategies has been used to increase the resilience of multi robots system. Although this method is able to increase the tolerance of faulty robots, the passive healing strategies usually require relatively high swarm connectivity and specification of tolerable speed values which may be difficult to specify in advance. In [58–60] a multi-sensors fusion approach has been proposed to maintain the integrity and the continuity of the robots’ localization. Although this approach can increase the fault tolerance ability of multi robots system, the multi-sensors fusion method also need a fault detect and execute unit which is computational expensive. Besides, to the best of our knowledge, there have been relatively few attempts to develop methods that are both effective for flexible cooperation and robust to the possible unexpected real-world factors. With the inner attention mechanism, our proposed method IAAC can train each robot to be flexible enough to adapt its behavior based on the dynamic environment and robust enough to handle the real-world failures such as robot broken and sensor failure.

At last, in the multi robots cooperation system, most of works have focused on how to develop a cooperation strategy that can accomplish complex tasks efficiently. However, few of them have pay attention to the other factors such as resources consume. Eventhough, multi robots teams with different cooperation strategies can rescue same amount of victims in the same period of time, they will consume different resources such as fuel or electrical power. [61–65] proposed an exploration strategy taking information gain and distance cost into account. [63] proposed a novel method controlling each robot based on a utility function that takes information gain and distance cost into consideration. Eventhough these methods can improve the multi-robot exploration in terms of map quality, exploration time and information gain, they only evaluated on homogeneous robots. In this paper, our proposed method IAAC will be applied to heterogeneous multi-robot team under the resources consume constrains.

### 3 Inner Attention Supported Adaptive Cooperation

The cooperation flexibility, robustness to sensor failures and resources consuming efficiency of existing multi-robot teaming methods are hard to satisfy the requirements of real-world applications. Therefore, it is meaningful to improve multi-robot team’s cooperation flexibility, robustness to sensor failures and resources consuming efficiency. In this section, we introduce our IAAC method from the following aspects: prerequisite notation and formulation, inner attention mechanism and theoretical analysis.

#### 3.1 Dynamic Teaming Modeling Using Multi-Agent Actor Critics

To model complex and dynamic relations in heterogeneous robot teaming, multi-agent actor-critic deep reinforcement learning algorithm extended from Markov Decision Process has been used, which has been proved to be effective in guiding multi-agent cooperation [35] [66] [67]. Multi-agent deep reinforcement learning is defined by the number of agents, $N$; state space, $S$; a set of actions for all agents, $A = \{A_1, \ldots, A_N\}$; transition probability function over next possible states, $T: S \times A_1 \times \ldots \times A_N \to P(S)$; a set of observations for all agents, $O = \{O_1, \ldots, O_N\}$; and reward function for each agent $R_i : S \times A_1 \times \ldots \times A_N \to R$. We will consider the application scenario of multi-agent cooperation as a fully observable environment in which we assume that each agent $i$ can receive observation, $O_i$, which contains accurate positions and statuses of other agents. A robots action selections include exchanging location information, sharing and allocating task goal, maintaining connectivity, etc. By using reinforcement learning for guiding the cooperation, each robot learns an individual policy function, $\pi_i : O_i \to P(A_i)$ which is a probability distribution on potential cooperation actions. The goal of multi-agent reinforcement learning is aim to learn an optimal cooperation strategy for each agent which can maximize their expected discounted returns,

$$J_i(\pi_i) = E_{a_1 \sim \pi_1, \ldots, a_N \sim \pi_N; s \sim T} \left[ \sum_{t=0}^{\infty} \gamma^t r_t(s_t, a_{1t}, \ldots, a_Nt) \right] \quad (1)$$

where $\gamma \in [0, 1]$ is the discount factor that determines how much the policy favors immediate reward over long-term gain.

Actor Critic Policy gradient algorithm is a learning process to solve reinforcement learning problems, which targets at modeling and optimizing the policy directly. To maximally improve team performance given current status of all robots, a robots policy is updated by encouraging updating along the gradient:

$$\nabla_{\theta} J(\pi_\theta) = \nabla_{\theta} \log(\pi_\theta(a_t | s_t)) Q_\psi(s_t; a_t) \quad (2)$$

Where $\theta$ denotes the parameters for the policy, $Q$ is an approximation function of the expected discounted returns

$$Q_\psi(s_t; a_t) = E\left[ \sum_{t'=t}^{\infty} \gamma^{t'-t} r_{t'}(s_{t'}, a_{t'}) \right] \quad (3)$$
it can ameliorate policy gradient methods’ high variance issue by replacing the original return term in the policy gradient estimator. For each cooperation step, the action value $Q$ for the robot $i$ needs to observe its neighbors status $o$ and actions $a$ and learned by off-policy temporal-difference learning by minimizing the regression loss:

$$L_Q(\psi) = E_{(s,a,r,s') \sim D}[(Q_\psi(s,a) - y)^2]$$

where $y = r(s,a) + \gamma E_{a' \sim \pi(s')}[Q_\bar{\psi}(s',a')]$, $Q_\bar{\psi}$ is the target $Q$-value function, which is simply an exponential moving average of the past $Q$-functions. $D$ is the experience replay buffer, which stores the previous robot cooperation experience to further reduce the loss. $\psi$ and $\bar{\psi}$ denote the parameters for the target critics and critics, respectively.

In our multi-agent cooperation scenarios, naive application of actor critic reinforcement learning methods naturally encounter some limitations, such as non-stationary of the environment from the perspective of individual agents. Since each agents policy is changing as training progresses, and the environment becomes non-stationary from the perspective of any individual agent. This presents learning stability challenges and prevents the straightforward use of past experience replay, which is crucial for stabilizing policy gradient methods. Therefore, we will use an extended actor-critic framework consisting of centralized training with decentralized execution, allowing the policies to use extra information to ease training, so long as this information is not used at test time. More concretely, in the gradient of the expected return for agent $i$, the $Q_{\pi_i}(s; a_1, ..., a_N)$ is calculated centrally with a global objective of improving the whole teams performance on executing the task that takes the actions of all agents as input, in addition to the agents’ statuses $x$, and outputs the $Q$-value for agent $i$. In the simplest case, $x$ could consist of the observations of all agents, $x = (o_1, ..., o_N)$, however we could also include additional state information if available. Given that each robot may have different cooperation requirements, different teammates available, and limited perceiving capability, each robot distributively implements cooperation policy. This centrally-learn and distributively-use manner will support a flexible teaming for heterogeneous robots, such that the cooperators and cooperation actions will be adjusted dynamically.

### 3.2 Robot Inner Attention for Team Adaptability Modeling

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 agent $i$, the critic receives the observations, $o = (o_1, ..., o_N)$, and actions, $a = (a_1, ..., a_N)$, for all agents, which will take lots of redundancy information into account. In addition, the action space will also increase exponentially with the number of agents. Given that in reality applications, each robot will have different cooperation requirements, different teammates available, and limited perceiving capability. Therefore, in order to improve agents’ cooperation flexibility, we should train the critic for each agent with the ability of selectively paying attention to other agents. That is, each agent is aware of which agents it should pay attention to rather than simply take all agents into consideration at every step.

The inner attention mechanism functions in a manner similar to the differentiable key-value memory methods. Intuitively, in agents decision-making process, the goal of our method is to selectively paying attention to other agents. The shared critic receives the observations, actions and statues from all agents and generates $Q$-values for each agent. The contribution of other agents statues is evaluated by multiple attention heads by generating different attention weights for different agents. This paradigm was chosen, in contrast to other attention-based approaches, as it doesn’t make any assumptions about the temporal or spatial locality of the inputs, as opposed to approaches taken in the natural language processing and computer vision fields. With the inner attention mechanism the agents can have flexible cooperation abilities, then they can be more robust to the unexpected real-world failures and will consume lesser resources when rescuing the same amount victims.

In details, the embedding function $g_i$ is a two layer multiple layer perception (MLP) which takes agents’ observations and actions as input. Then the embedded information are feeded into the inner attention mechanism to get the $Q$-value function $Q_i(o; a)$ for the agent $i$, which is a function of agent is embeddings, as well as other agents contributions:

$$Q_i(o; a) = w^2 \sigma(\langle w^1, e_i, x_i \rangle)$$

where $\sigma$ is rectified linear units (ReLU), $w^1$ and $w^2$ are the parameters of critics. Similar to the query-key system, the inner attention mechanism also have shared query $(w_q)$, key $(w_k)$ and value $(w_v)$ matrix. Each agent’s embedding $e_i$ can be linearly transformed into $q_i$, $k_i$ and $v_i$ separately. The contribution from other agents, $x_i$, is a weighted sum of other agents 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 then passes the similarity value into a softmax function:

$$\alpha_{ij} = \frac{e_j w_k^j w_q e_i}{\sum_{k=1}^N e_k w_k^j w_q e_i}$$
The matching is then scaled by the dimensionality of these two matrices to prevent vanishing gradients. In our experiments, we will use \( P \) set of key-value parameters \((w^p_i, w^p_j, w^P_{ij})_{j=1}^P\), which gives rise to an aggregated contribution from all other agents to the agent \( i \) and we simply concatenate the contributions from all set parameters as a single vector. Note that the matrix for extracting queries, keys, and values are shared across all agents, which encourages a common embedding space. The sharing of critic parameters between agents is possible, because multi-agent value-function approximation is, essentially, a multi-task regression problem.

Now, we describe our reward functions which encourage the agents to cooperate in dynamic environments. In the learning process, we will give the corresponding reward based on their behaviour. At the time step \( t \), the agent obtains its own observation \( o_t \) and the contribution from other agents \( x_t \). The agent is likely to execute the action with highest reward. To describe the reward function accurately, we first illustrate our expectations for the agents in the cooperation tasks. Each agent is expected to avoid collisions with other agents and obstacles in the environment, cooperate with other agents to rescue victims. In other words, the tasks we encourage agents to do are rewarded positively, while behavior we wish the agents to avoid is rewarded negatively. So at the time step \( t \), each agent seeks a policy \( \pi(a_t \mid o_t, x_t) \) that could reach the expected goals. Reward function \( R_t \) for each robot is as follows:

\[
R_t = \text{Rewards} + \text{Collisions} + \text{Steps}
\]

Here, \( R_t \) is the combination of three aspects: rewards from interacting with the environment, collision with other robots or walls and steps cost for rescuing per victim.

\[
\text{Rewards} = -\min_{j \in C} \text{Dist}(agent_i, \text{victim}_j)
\]

which represent that the agent’s expected action is to rescue the closest victim, cooperate with proper candidates and \( C \) is a set of victims and robots that need \( agent_i \) to rescue and cooperate separately according to expected cooperation.

\[
\text{Collisions} = \begin{cases} 
-5 \times \sum_{\text{wall} \in \text{Walls}} \mathbb{I}(\text{agent}_i, \text{wall}) \\
-1 \times \sum_{j \neq i} \mathbb{I}(\text{agent}_i, \text{agent}_j)
\end{cases}
\]

implies that the agent should avoid collision with obstacles and \( \mathbb{I}(\ast) \) is the indication function indicating whether \( \text{agent}_i \) is collide with wall, other agents or not. \( \text{Steps} \) is used to take resources consume into account, which means the average steps needed to rescue one victim. Given that the expected goals are represented by reward functions, the inner attention mechanism can facilitate the training process by maintain the property on flatness of minima and the exist of good sharp of minima. Besides, when the inner attention mechanism is used, the number of linear regions reduces leading to a simpler loss landscape, yet the approximation error remains small. This leads to lower sample complexity for achieving a desired prediction error. Therefore, the inner attention mechanism can facilitate the learning process and make the agents to learn expected goals more easier.

### 3.3 Theoretical analysis

In order to simply explain whether inner attention mechanism works, we simply consider a two-layer ReLU neural network with inner attention mechanism, which is the same as the latter part of our critic neural network. The weights of the first layer can be denoted as \( w^1 \), the weights of the second layer as \( w^2 \), and the ReLU function is represented by \( \sigma(\ast) \). Then the output of the two layer neural network, when the input is \( x \), can be written as:

\[
f(x) = w^2T \sigma(w^1, x), x = <e_i, x_i>
\]

Here, we simply proof that when inner attention mechanism is used, the number of linear regions reduces leading to lower sample complexity for achieving a desired prediction error.

According to [71], first, assume the sparsity of the attention weights is \( \|\alpha\|_0 = s_0 \), we know all the inputs \( e_i \) of the neural network with corresponding attention weight \( \alpha_i = 0 \), will be inactive. Therefore, we can omit all these inactive inputs. And assume the size of hidden layer \( n_1 > s_0 \). Then we can split \( n_1 \) units into \( s_0 \) groups, with \( \lfloor \frac{n_1}{s_0} \rfloor \) number of units in each group. That means, \( s_0 \) different groups can represent as \( s_0 \) active inputs. In every group, for example in \( j \)th group, we can assign \( q = \lfloor \frac{n_1}{s_0} \rfloor \) and choose the neural network layer’s parameters for \( i = 1, 2, ..., q \) as:

\[
\begin{align*}
\ h_1(e) &= \max(0, w_j e) \\
\ h_2(e) &= \max(0, 2w_j e - 1) \\
& \vdots \\
\ h_q(e) &= \max(0, 2w_j e - (q - 1))
\end{align*}
\]
here we denote $w_j$ to be a vector with $j_{th}$ entry’s value equal to 1 and all other entries are assigned to 0. And in the second layer, we assign $w^2 = (w_3; \ldots; w_3)$, where $w_3 = (1; -1; 1; \ldots; (-1)^{q+1})$ is a well designed vector, corresponding to $h_1$ to $h_q$ in each group. Then the designed network has $q$ linear regions inside each group, giving by the intervals:

$$(-\infty, 0], [0, 1], [1, 2], \ldots, (q - 1, \infty)$$

Each of these intervals has a subset that is mapped by $w_3 h(z)$ onto the interval $(0, 1)$. Therefore the total number of linear regions is lower bounded by $\left\lfloor \frac{q}{\frac{d}{2}} \right\rfloor$. Therefore the number of linear regions has been bounded and lead to a simpler neural network landscape. Then we can improve data efficiency by adapting the inner attention mechanism. That means, we can achieve a desired prediction error with fewer training samples.

Second, in order to analysis the flatness properties of minima, we consider a minimum $\theta = (w^1; w^2; w_q; w_k; w_v)$ satisfying that $w^* \neq 0$ for $* = 1; 2; q; k; v$. For any $\varepsilon > 0$, $C(L; \theta; \varepsilon)$ has an infinite volume, and for any $M > 0$, we can find a stationary point such that the largest eigenvalue of $\nabla^2 L(\theta)$ is larger than $M$. In order to analysis that, here we define an $\beta$ scale transformation such that:

$$T_\beta : (w^1, w^2) \rightarrow (\beta w^1, \beta w^2)$$

All and the value, query and value matrices remain the same. Then we know the jacobian determinant for $T_\beta = \beta^{pd-1}d$. Since $pd_1 d \leq d$, as we assign $\beta \rightarrow \infty$, such that the jacobian determinant goes to infinity, and the volume of $C(L; \theta; \varepsilon)$ goes to infinity. For the Hessian matrix, we still assume a positive diagonal element $\delta > 0$ in $w^1$. Similarly we have the Frobenius norm:

$$\nabla^2 L(T_\beta(\theta)) = \begin{bmatrix} \beta^{-1} I & 0 & 0 \\ 0 & \beta I & 0 \\ 0 & 0 & I \end{bmatrix} \nabla^2 L(\theta) \begin{bmatrix} \beta^{-1} I & 0 & 0 \\ 0 & \beta I & 0 \\ 0 & 0 & I \end{bmatrix}$$

is lower bounded by $\beta^{-2} \delta$. When we choose sufficient small $\beta$, we have the biggest eigenvalue of $\nabla^2 L_\beta(\theta)$ is larger than any constant $M$. Therefore there exists a stationary point such that the operator norm for Hessian is arbitrary large [72].

What’s more, by using the inner attention mechanism, the agents can also be more robust to other agents’ failure or sensor broken [73]. Consider that a small perturbation is added to a particular agent $j$’s embedding, such that $e_j$ is changed to $e_j + \Delta e$ while all the other agent’s embedding remain unchanged. We then study how much this perturbation will affect the attention weights $a_{ij}$. For a particular $i(i \neq j)$, the

$$S_{ij} = e_j w^T_k w_q e_i$$

is only changed by one term since:

$$S'_{ij} = \begin{cases} S_{ij} + \Delta e w^T_k w_q e_i, & \text{if } (i \neq j), \\ S_{ij}, & \text{otherwise}. \end{cases}$$

where we use $S'_{ij}$ to denote the value after the perturbation. Therefore, with the perturbed input, each set of $\{S_{ij}\}_{i,j=1}^N$ will only have one term being changed. Furthermore, the changed term in equation is the inner product between $e_i$ and a fixed vector $\Delta e w^T_k w_q$; although this could be large for some particular $e_i$ in the similar direction of $\Delta e w^T_k w_q$, if the embeddings $\{e_i\}_{i=1}^N$ are scattered enough over the space, the inner products cannot be large for all $\{e_i\}_{i=1}^N$. Therefore, the change to the next layer will be sparse. For instance, we can prove the sparsity under some distributional assumptions on $\{e_i\}$:

For the perturbation part, the expected value $E[S'_{ij} - S_{ij}] = E[\Delta e_i]$, where $z = \Delta e w^T_k w_q$ is a fixed vector. Assume $\|\Delta e\| \leq \delta$ and $\{e_i\}_{i=1}^N$ are $d$-dimensional vectors uniformly distributed on the unit sphere. Then it is easy to derive:

$$\|z\| \leq \|w_q\| \|w_k\| \delta$$

(18)

To bound this expectation, we first try to bound $b_1 = E[|e_i| I_1]$, where $I_1 = [1; 0; \ldots; 0]$. Due to the rotation invariance we can obtain:

$$b_1 = b_2 = \ldots = b_d$$

(19)

given that $\sum_i \|b_i\|^2 = 1$:

$$\|b_1\| = \|b_2\| = \ldots = \|b_d\| = \frac{1}{\sqrt{d}}$$

(20)

This implies $E[|z e_i| \leq \|w_q\| \|w_k\| \delta / \sqrt{d}]$. Using Markov inequality, we can then find the probability results $P(|S'_{ij} - S_{ij}| \geq \varepsilon) \leq \|w_q\| \|w_k\| \delta / \varepsilon \sqrt{d}$. 


Figure 3: Simulated environment illustration. In the flood disaster, there are trapped victims with different injury levels. For the victims with low injury level (Task1), they need rescuing robots providing useful information to guide them to safer places; while the victims with high injury level (Task2) will another kind robots providing them with emergency medicine immediately. The main robots team should figure out how to split into different sub-teams that can rescue these victims effectively and efficiently.

Therefore, as the norm of $w_q; w_k$ are not too large (usually regularized by $L_2$ during training) and the dimension $d$ is large enough, there will be a significant amount of $i$ such that $S'_{ij}$ is perturbed negligibly. In contrast, embeddings from RNN-based models are relatively more sensitive to perturbation of one robot’s embedding, as shown below. Similar to the previous case, we assume an embedding sequence $\{e_1, e_2, ..., e_N\}$, and an embedding $e_j$ is perturbed by $\Delta e$. For the vanilla RNN model, the embeddings are sequentially computed as $z_i = \sigma(Ae_i + Bz_{i-1})$. If $e_j$ is perturbed, then all the $\{z_i\}_{i=1}^{N}$ will be altered. Therefore, the sensor failure and robot broken can more easily influence all the embeddings.

4 Evaluation

In this section, we will first introduce our experimental settings. Second, we will show the training performance compared with the baseline method, and the corresponding analyze. Then, we will analysis robots’ dynamic cooperation and robustness. Finally, we also analysis the efficiency of our proposed method in the resources consume.

4.1 Experiment Settings

We construct an environment that test various capabilities of our approach IAAC. We investigate in three main directions. First, we study our proposed method’s ability of flexibly adapting to the dynamic environments. We hypothesize that our method with inner attention mechanism can cooperate dynamically according to different cooperation requirements and different teammates available. To this end, we implement a cooperative environment, with two different kind tasks which should be accomplished by different kind robots’ cooperation. As such, we can evaluate our approaches ability to dynamically cooperation based on dynamic environments.
The environment in Figure 3 is implemented in the MPE (multi-agent particle environment) framework [66]. A simple multi-agent particle world with a continuous observation and discrete action space, along with some basic simulated physics. We found this MPE framework useful for creating experiment environments consisting of multi-agent, complex environments and diverse interactions among agents, while keeping the control and perception problems very simple. In our designed environment, we use discrete action spaces and basic physics engine to control agent’s movements, which makes the environment very similar to our real world since agents momentum incorporates have been taken into account. The size of artificial environment is 2 X 2, which can satisfy the amount of agents needed to test our method, but not too large to cause inadequate exploration problem. The experimental environment has continuous action space, so the agent can move to anywhere on the map determined by its velocity and acceleration parameters. Each agent can sense the environment information and has a communication range covering the whole environment. And the goal for the whole system is to search and rescue as many victims as possible during one episode.

To be concrete, the environment involves 6 total agents, 2 of which are victims with different injury level and 4 of which are robots. Each robot should cooperate with each other to rescue different injury level victims. For the robots, 2 of them provide living supplies such as food and water, 1 of which can provide victims with useful information for example the locations of the safer places, etc. and the rest robot is mainly used to provide heavily injured victims with medicine treatments. As for the victims, one is heavily injured and needs living supplies and medicine treatments by different kind robots’ cooperation; while for the other victims who is in a good health condition will need living supplies and useful information guiding him to a safer place. All robots are able to see each others positions with respect to their own. In addition to the rewards received when one victim is successfully rescued, robots are additionally penalized for colliding with each other. As such, the task contains a mixture of individual rewards and requires different modes of attention which depend on tasks, environment conditions, and robot abilities. In order to analysis the properties of our inner attention mechanism, we will compare it with the baseline mode. In this model, we use uniform attention by fixing the attention weight $\alpha$ to be $\frac{1}{(N-1)}$. This restriction prevents the model from focusing its attention on specific agents. Given that we only change the attention weights to fixed, all the models are implemented with approximate equal total number of parameters.

As for our training procedure, we use an off-policy, extended actor-critic method for maximum entropy reinforcement learning in the training progress of 25,000 episodes. There are 12 threads to process training data in parallel and a replay buffer to store experience tuples of $(o_t, a_t, r_t, o_{t+1})$ for each time step. The environment gets reset every episode of 100 steps. The policy network and the attention critic network get updated 4 times after the first episode. In detail, we sample 1024 tuples from the replay buffer and update the parameters of the Q-function loss and the policy objective through policy gradients. Adam optimizer is used and the learning rate is set as 0.001. We use a discount factor $\gamma$ of 0.99. The embedded information uses a hidden dimension of 128, and 4 attention heads are used in our attention critics. The performance of each approach is assessed by the average rewards per episode and the average steps consumed for rescuing one victim.

As shown in Figure 4, in the Figure 4(left), our proposed method with inner attention mechanism is competitive when compared to uniform attention weights method, that means these two methods can rescue the same number victims during the same time. However, in Figure 4(right), our proposed method with inner attention mechanism is more efficiency when compared to uniform attention weights method, that means our proposed method will take less steps when rescue the same number victims as the uniform attention weights method. In the next subsections, by analyzing in details, we investigate our proposed method in three main directions: First, we study the ability of adapting to task varieties. Secondly, we also want to evaluate agents’ robustness, especially when there are robot failure in the team. This scenario is analogous to real-life tasks such as the sensor failure or broken. To this end, we adjust this task environment by randomly fix broken agent’s status, position and actions to zero. And finally, in the real-life multi robots cooperation system, we need pay attention not only to develop a cooperation strategy that can accomplish complex tasks efficiently but also to the other factors such as resources consuming, distance cost, etc. Therefore, we also analysis the efficiency of our proposed method in the resources consume (moving steps needed) for rescuing per victim.

Table 1: The configurations of robots

| Type   | Speed$_{max}$ | Mass | Ability                      |
|--------|---------------|------|------------------------------|
| $UAV_1$ | 1.0           | 1.0  | Providing food and water     |
| $UAV_2$ | 1.5           | 0.5  | Providing medical staff       |
| $UAV_3$ | 1.5           | 0.5  | Providing information about safer places |
Figure 4: (Left) Average Rewards on multi robots cooperation. (Right) Average Rewards taking resources consume (moving steps) into consideration on multi robots cooperation. Our model IAAC can rescue more victims by consuming the same amount resources.

Figure 5: If the robots have been trained with flexible cooperation ability, in the idea cases, after infinite times of experiments, the UAV1 and UAV2 should have equal probability to participate in task1 or task2.

4.2 Adapting to Task Varieties

In order to analysis our proposed method’s adapting ability to task varieties, in our simulated environment we have designed two different kind of tasks: in the first task, besides living supplies, victim is heavily injured and needs medicine treatments; while in the second task the victim who is in a good health condition will need useful information to guide him to a safer place. That means the robots providing living supplies should learn to dynamically cooperate with other robots providing medicine treatment or useful information based on different tasks (victim’s injury level) and other robot’s availability. For example, in order to rescue a victim who are heavily injured, the robot which provide medicine treatment should cooperate with the closest robot that provides living supplies rather than the robot far away from it only if the closest robot isn’t occupied by other rescuing tasks.
Table 2: UAVs participate rate compare

| Inner Attention | Agent0 | Agent1 | $\chi^2$ | Without Attention | Agent0 | Agent1 | $\chi^2$ |
|-----------------|--------|--------|----------|-------------------|--------|--------|----------|
| $Task_1$        | 0.526  | 0.474  | 0.32     | 3.84              | 0.903  | 0.097  | 80.64    |
| $Task_2$        | 0.441  | 0.559  | 1.77     | 3.84              | 0.085  | 0.915  | 81.39    |

Figure 6: Attention entropy for each head over the course of training for the four agents in the multi robot cooperation environment. A lower entropy value indicates that the head is basing on specific agents to make decisions.

As shown in Figure 5, if the robots can flexibly cooperate with other agents based on dynamic environment, in the ideal case after infinite times of simulation, the number of robot providing living supplies cooperates with robot providing medicine treatment should be equal to that of cooperating with robots providing useful information. In order to quantitatively measure robots’ flexibility, we will calculate the rate of robots’ cooperation with each other in 80 episodes by the following formulation:

$$rate_{ij} = \frac{Num_{ij}}{\sum_{k=1}^{N} Num_{ik}}$$  \hspace{1cm} (21)

Where, $\sum_{k=1}^{N} Num_{ik}$ is the total number of victims rescued by robot i; $Num_{ij}$ is the total number of victims rescued by the cooperation of robot i and robot j. In Table 2 we compare the cooperation rates collected from the model trained by our approach and the baseline method. We show that the robots trained by our method with inner attention mechanism are more flexible than those trained by the baseline model. As suspected, the baseline model’s critics use all information non-selectively, while our approach with inner attention mechanism can learn which robots to pay more attention through the inner attention mechanism and compress that information into a constant-sized vector. Thus, our approach is more flexible and sensitive to the dynamically changing environments. Besides that, in Figure 6, we also demonstrate the effect of the attention head on the robot during the training process, we test the entropy of the attention weights for each robot for each of the four attention heads that we use in the rescue task. A lower entropy value indicates that the head is focusing on specific agents, with an entropy of 0 indicating attention focused on one agent. In the rescue task for agents 0, 1, 2 and 3, we plot the attention entropy for each agent. Since victims appear randomly in the training process and the position of each agent is different, each agent faces various situations and needs to cooperate with other agents reasonably based on the dynamic environments. In addition, each of the four
attention heads uses a separate set of parameters to determine an aggregated contribution from all other agents, which means each agent tends to be influenced differently by other agents.

Even though the cooperation rate of different robots can represent the flexibility of multi-robot cooperation. However, it can not explain the quality of these flexible corporations, that is these metric can not evaluate whether these corporations are reasonable or not. Therefore, we need other metrics to evaluate the quality of agents cooperation. In order to do that, we need to figure out what is the ideal cooperation for multi-agent cooperation tasks. Just as mentioned above, the ideal cooperation should take complex conditions into account, such as teammate availability, cooperating with proper kind agents and dynamic situations. In order to simplify the complex ideal cooperation in multi-agent search and rescue tasks, in this work we have defined the ideal cooperation by two simple rules:

1. one robot can only cooperate with proper kind robots.
2. one robot should rescue its closest victim only if it isn’t occupied by other tasks.

In Figure 7, we have figure out three situations for awkward cooperation, which aren’t consist with human’s intuition and all the awkward trajectory path has been illustrated by red dashed arrow lines. In situation 1, even though \textit{agent}_0 and \textit{agent}_1 are all closer to \textit{victim}_0, \textit{agent}_2 should choose to cooperate with \textit{agent}_0 and rescue \textit{victim}_0. Because \textit{agent}_0 is closer to \textit{victim}_0 than \textit{agent}_1. However, even though \textit{agent}_0 is also closer to \textit{victim}_1 than \textit{agent}_1, since that \textit{agent}_0 is already cooperating with \textit{agent}_2, \textit{agent}_3 can only cooperate with \textit{agent}_1 and rescue \textit{victim}_2. The awkward trajectory paths shown in Figure 7 aren’t satisfy with the above description. In situation 2, that is a very easy case, in which \textit{agent}_0 is much closer to \textit{victim}_0 and \textit{agent}_1 is much closer to \textit{victim}_1. Therefore, \textit{agent}_2 should choose to cooperate with \textit{agent}_0 and \textit{agent}_3 will cooperate with \textit{agent}_1. In situation 3, this situation is a little similar to situation 1, except that both \textit{agent}_0 and \textit{agent}_1 are both closer to \textit{victim}_1, therefore the agents’ optimal path is similar to situation 1. In all these situations, even though the robots can cooperate with each other and rescue victims, their cooperation strategy is not optimal which will result in consuming more resources. In order to quantitatively measure robots’ cooperation quality, we have count the number of agent’s cooperation cases that are consist with the human’s intuition and the number of agent’s cooperation cases that are not consist with human’s intuition. As shown in Table 3, For the method with inner attention mechanism, after 20 episodes the rates of \textit{agent}_0’s awkward cooperation in \textit{task}_1 and \textit{task}_2 are 0.85(17/20) and 0.85(17/20). \textit{Agent}_1’s awkward cooperation rates in \textit{task}_1 and \textit{task}_2 are 0.9/(18/20) and 0.85(17/20) separately. As for the results for the baseline model without attention mechanism, after 20 episodes the rates of \textit{agent}_0’s awkward cooperation in \textit{task}_1 and \textit{task}_2 are 0.55(11/20) and 0.55(11/20). \textit{Agent}_1’s awkward cooperation rates in \textit{task}_1 and \textit{task}_2 are 0.65/(13/20) and 0.5(10/20) separately. Therefore, our approach can have more meaning corporations based on the dynamically changing environments compared with the baseline method.
Table 3: Awkward cooperation rate

|               | $Agent_0$ | $Agent_1$ | Without Attention | $Agent_0$ | $Agent_1$ |
|---------------|-----------|-----------|-------------------|-----------|-----------|
| $Task_1$      | 0.15      | 0.10      | $Task_1$          | 0.45      | 0.35      |
| $Task_2$      | 0.15      | 0.15      | $Task_2$          | 0.45      | 0.5       |

Figure 8: The robots will choose the trajectories which are more efficient in resources consume (black color, fewer moving steps) rather than trajectories that are not efficient (red color, more moving steps).

Besides, in order to quantitatively prove that our proposed method with inner attention mechanism is much more efficient than the baseline model (shown in Figure 8), we have calculated the average trajectory distance needed to rescue per victim by the following formulation:

$$\overline{Distance_T} = \frac{Distance^{T}_{Total}}{Victims^{T}_{Total}}$$  \hspace{1cm} (22)

where $\overline{Distance_T}$ is the average distance costed to rescuing one victim during time $T$, $Distance^{T}_{Total}$ is the total distance calculated by summing all agents trajectory length in a period of time $T$, and $Victims^{T}_{Total}$ is the total number of rescued victims during time $T$. As Figure 9 shows, after 25,000 episodes’ training, the model trained by inner attention mechanism is much lower-cost consuming than the model trained without attention mechanism. When $T = (25, 50, 75, 100, 125, 150)$ episodes, the average distance for attention model is less than the non-attention model. For example, the average distance cost for the inner attention model is 0.09 lower when compared with the model without inner attention mechanism. However, after 5,000 episodes’ training, the model without attention mechanism is much efficient that the model trained with attention. That’s because the attention mechanism has increase the complexity of the Deep Neural Network’s framework. So the method without attention mechanism can learning faster than the inner attention model and can rescue more victims during the same time. But with the training process, the efficiency of rescuing victims is both increase for all method. Since the average distance needed for rescuing one victim is much less from 5,000 episode to 25,000 episode. In conclusion, we can say that our approach can is more efficient in resources consumes compared with the baseline method.
Figure 9: Average moving steps per episode. With training process, all methods can become more efficient in resources consuming. And after finishing the training process, IAAC method is more efficient than the baseline method.

Figure 10: Robustness: the faulty robot UAV4 will have no influence on other robots’ flexible teaming.

4.3 Adapting to Robot Availability

As shown in Figure 10, in addition to robots’ flexible awkward cooperation, if the robots can learn to pay different attention to robots selectively, the robots teaming will be more robust to sensor failure or robot broken. Since the other
normal robots can dynamically choose which robot to cooperate with based on different situations. Besides that, in the method section, we also proved mathematically that the perturbation of one robot’s failure can in fact only have sparse affect to the attention scores when the input embedding are scattered enough in the space. When some robots are broken in a team, the faults caused by sensor failures may have undesirable and uncontrollable effects on other teammates. In addition, broken robots may share incorrect information with other members of the team leading to incorrect behaviors of cooperation. In order to measure the robustness of our proposed method, we assume agent 3 is broken in our simulated environment and all its status are fixed to zeros. Then we will calculate different robots’ cooperation rate with each other. In the idea cases, if the robots is robust enough, agent 0 and agent 1 will have equal chance to participate into task 1 and task 2. That means each robot can flexibly choose which robot to cooperate with based on its own local situations and won’t be influenced by other faulty factors. As Table 4 shows, considering task 1 when agent 3 is broken, the robots trained with inner attention mechanism have the equal chance to cooperate with agent 2 and provide living supplies for the victims. However, the robots trained without attention mechanism will be affected by the broken agent 3. Similarly, as for task 2 when agent 2 is broken, the same results are observed. Therefore, we conclude that our approach can is more robust to sensors failure or robot broken compared with the baseline method.

5 Conclusion and Future Work

We presented a inner attention mechanism method (IAAC) to help a multi-robot team to flexible teaming. This allows the multi-robot team to cooperate flexibility, improve its robustness over sensor failure and lower the resources consumed to rescue one victim. The key idea is to utilize inner attention mechanism to select meaningful information between related agents for estimating critics. Three types of evaluations adapting to task varieties, adapting to robot availability and lower cost for rescuing victims are simulated and clearly show the inner attention mechanism model is better than the model without attention. With inner attention mechanism, the robots can cooperate with each other more flexible, maintain stable under some real-world faculties and rescue more victims by consuming less resources. The robots are encouraged to cooperate with proper robots selectively and discouraged from depending on broken or faulty robots. In doing so the negative influence caused by misleading information is largely reduced and robots can cooperate properly. The simulation results for the three evaluations demonstrate the effectiveness of inner attention mechanism in increasing the flexibility of robots’ cooperation. In the future research, we will focus on increasing the number of agents and further highlight the advantage of cooperation ability in multi-agent reinforcement learning systems.

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