HAMMER: Multi-Level Coordination of Reinforcement Learning Agents via Learned Messaging

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ABSTRACT

Cooperative multi-agent reinforcement learning (MARL) has achieved significant results, most notably by leveraging the representation-learning abilities of deep neural networks. However, large centralized approaches quickly become infeasible as the number of agents scale, and fully decentralized approaches can miss important opportunities for information sharing and coordination. Furthermore, not all agents are equal — in some cases, individual agents may not even have the ability to send communication to other agents or explicitly model other agents. This paper considers the case where there is a single, powerful, *central agent* that can observe the entire observation space, and there are multiple, low-powered, *local agents* that can only receive local observations and cannot communicate with each other. The central agent's job is to learn what message to send to different local agents, based on the global observations, not by centrally solving the entire problem and sending action commands, but by determining what additional information an individual agent should receive so that it can make a better decision. After explaining our MARL algorithm, HAMMER, and where it would be most applicable, we implement it in the cooperative navigation and multi-agent walker domains. Empirical results show that 1) learned communication does indeed improve system performance, 2) results generalize to multiple numbers of agents, and 3) results generalize to different reward structures.

KEYWORDS

Multi-agent Reinforcement Learning, Learning to Communicate, Heterogeneous Agent Learning

1 INTRODUCTION

The field of multi-agent reinforcement learning (MARL) combines ideas from single-agent reinforcement learning (SARL), game theory, and multi-agent systems. Cooperative MARL calls for simultaneous learning and interaction of multiple agents in the same environment to achieve shared goals. Applications like distributed logistics [58], package delivery [40], and disaster rescue [33] are some domains that can naturally be modeled using this framework. However, even cooperative MARL suffers from several complications inherent to multi-agent systems, including non-stationarity [3], a potential need for coordination [3], the curse of dimensionality [42], and global exploration [27].

Multi-agent reasoning has been extensively studied in MARL [27, 32] in both centralized and decentralized settings. While very small systems could be completely centralized, decentralized implementation quickly becomes necessary as the number of agents increase. Decentralization may also become necessary in practice to cope with the exponential growth in the joint observation and action spaces however, it often suffers from synchronization issues [27] and complex teammate modeling [1]. Moreover, independent learners may have to optimize their own, or the global, reward from only their local, private observations [50]. In contrast, centralized approaches can leverage global information and also mitigate non-stationarity through full awareness of all teammates.

Further, communication has been shown to be important, especially in tasks requiring coordination. For instance, agents tend to locate each other or the landmarks more easily using shared information in navigation tasks [11], or communication can influence the final outcomes in group strategy coordination, [13, 57]. There have been significant achievements using explicit communication in video games like StarCraft II [34] as well as in mobile robotic teams [26], smart-grid control [35], and autonomous vehicles [4]. Communication can be in the form of sharing experiences among the agents [59], sharing low-level information like gradient updates via communication channels [7] or sometimes directly advising appropriate actions using a pretrained agent (teacher) [52] or even learning teachers [31, 43].

Inspired by the advantages of centralized learning and communication for synchronization we propose multi-level coordination among intelligent agents via messages learned by a separate agent to ease the localized learning of task-related policies. A single *central agent* is introduced and is designed to learn high-level messages based on complete knowledge of all the local agents in the environment. These messages are communicated to the *independent learners* who are free to use or discard them while learning their local policies to achieve a set of shared goals. By introducing centralization in this manner, the supplemental agent can play the role of a *facilitator* of learning for the rest of the team. Moreover, the independent learners need not be as powerful as required if they must train to communicate or model other agents alongside learning task-specific policies.

A hierarchical approach to MARL is not new — we will contrast with other existing methods in Section 2. However, the main insight of our algorithm is to learn to communicate relevant pieces

of information from a global perspective to help agents with limited capabilities improve their performance. Potential applications include autonomous warehouse management [6] and traffic light control [24], where there can be a centralized monitor. After we introduce our algorithm, HAMMER, we will show results in two very different simulated environments to showcase its generalization. OpenAI's multi-agent cooperative navigation lets agents learn in continuous state space with discrete actions and global team rewards. In contrast, Stanford's multi-agent walker environment has a continuous action space and agents can receive only local rewards.

The main contributions of this paper are to explain a novel and important setting that combines agents with different abilities and knowledge (Section 3), introduce the HAMMER algorithm that addresses this setting (Section 4), and then empirically demonstrate that HAMMER can make significant improvements (Section 6) in two multi-agent domains.

2 BACKGROUND AND RELATED WORK

This section will provide a summary of background concepts necessary to understand the paper and a selection of related work.

2.1 Single Agent Reinforcement Learning

Single-agent reinforcement learning (SARL) can be formalized in terms of Markov Decision Processes (MDPs). An MDP is defined as a tuple $\langle$ S, A, P, R, γ $\rangle$, where S is the set of states, A is the set of available actions for the agent, P: S $\times$ A $\times$ S $\rightarrow$ [0, 1] is the state transition function, R: S $\times$ A $\rightarrow \mathfrak{R}$ is the reward function, and $\gamma \in (0, 1]$ is a discount factor. Actions, selected by a policy π: S $\times$ A $\rightarrow$ [0, 1], are taken and the agent tries to maximize the return, which is the expectation over the sum of discounted future rewards:

$$\mathbf{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \right],$$

where t is the time step.

To maximize this expectation, one class of RL algorithms aim to learn a Q-value (state-action) function and the Bellman optimality equation for the same can be defined as

$$Q^*(s \in S, a \in A) = \sum_{s' \in S} P(s, a, s') \left[R(s, a, s') + \gamma \max_{a' \in A} Q^*(s', a') \right]$$

It provably converges to the optimal function Q^* under certain conditions. It has also become popular to use non-linear function approximators to scale to huge state spaces — like in DQN [28].

In another popular choice for solving RL tasks — policy gradients — the parameters of the policy θ are directly updated to maximize an objective $\mathbf{J}(\theta)$ by moving in the direction of $\nabla \mathbf{J}(\theta)$. However, policy gradient methods can exhibit high variance gradient estimates, are sensitive to the selection of step-size, progress slowly, and sometimes encounter catastrophic drops in performance. The situation becomes worse in the case of multi-agent systems where, often, rewards for each agent are altered by interactions of other agents in the environment. In our work, we focus on Proximal Policy Optimization (PPO) [39], which reduces these challenges, while also being relatively easy to implement. Its objective function, well-suited for updates using stochastic gradient descent, can be defined as follows:

$$L^{CLIP}(\theta) = \mathbf{E}_t \left[min(r_t(\theta)A_t, clip(r_t(\theta), 1 - \epsilon, 1 + \epsilon)A_t) \right],$$

where r_t is the ratio of probability under the new and old policies respectively, A_t is the estimated advantage at time t and ϵ is a hyperparameter.

2.2 Multi-Agent Reinforcement Learning

SARL can be generalized to competitive, cooperative, or mixed multi-agent settings. We focus on the fully cooperative multi-agent setting, which can described as a generalization of MDPs to stochastic games (SGs). An SG for n local agents, and an additional centralized agent in our case, can be defined as the tuple $\langle S, U, O_1, \ldots, O_n, A_1, \ldots, A_n, P, R, \gamma \rangle$ where S is the set of all configurations of environment states for all agents, U is the set of all actions for the central agent, $O_1, \ldots, O_n$ represent the observations of each local agent, $A_1, \ldots, A_n$ correspond to the set of actions available to each local agent and P is the state transition function. γ is the discount factor. In case all the agents have the same common goal, i.e., they aim to maximize the same expected sum, the SG becomes fully cooperative.

The state transitions in a multi-agent case are as a result of the joint action of all the agents U $\times A_1 \times \cdots \times A_n$. The policies join together to form a joint policy h: S $\times$ U $\times$ $\mathbf{A}$. There can be two reward structures possible for the agents. First, they could share a common team reward signal, $R : S \times A \rightarrow \mathfrak{R}$, which can be defined as function of the state s $\in$ S and the agents joint action A: $A_1 \times ... \times A_n$. In the case of such shared rewards, agents aim to directly maximize the returns for the team. Second, each agent might receive its own reward $R_i : O_i \times A_i \rightarrow \mathfrak{R}$. Such localized rewards mean that agents each maximize their own total expected discounted return r = $\sum_{t=0}^{\infty} \gamma^t r^t$.

2.3 Relevant Prior Work

Recent works in both SARL and MARL have employed deep learning methods especially to tackle the high dimensionality of the observation and action spaces [9, 23, 28, 34, 49].

Several works in the past have taken the advantage of hierarchical approaches to MARL. The MAXQ algorithm was designed to provide for a hierarchical break-down of the reinforcement learning problem by decomposing the value function for the main problem into a set of value functions for the sub-problems [5]. Tang et al. [51] used temporal abstraction to let agents learn high-level coordination and independent skills at different temporal scales together. Kumar et al. [16] presented another framework benefiting from temporal abstractions to achieve coordination among agents with reduced communication complexities. These works show positive results with the idea of combining centralized and decentralized approaches in different manners and are therefore closely related to our work. Vezhnevets et al. [55] introduce Feudal networks in hierarchical reinforcement learning and employ a Manager-Worker framework. However, there are some key differences. In their case, the manager directly interacts with the environment to receive the team reward and accordingly distributes it among the workers (analogous to setting their goals), unlike in our work where the

central agent interacts indirectly and receives the same reward as is earned by the local agents. In our work, the central agent is only allowed to influence the actions of independent learners rather than set their goals explicitly. Also, they partly pretrain their workers before introducing the manager into the scene. In contrast, our results show that when the central agent and the independent learners simultaneously learn, they achieve better performance.

Some works have developed architectures that use centralized learning but ensure decentralized execution. COMA [9] used a centralized critic to estimate the Q-function along with a counterfactual advantage for the decentralized actors in MARL. VDN [47] architecture trained individual agents by learning to decompose the team value functions into agent-wise value functions in a centralized manner. QMIX [36] employs a mixing network to factor the joint action-value into a monotonic non-linear combination of individual value functions for each agent. Another work, MADDPG [25], extends deep deterministic policy gradients (DDPG) [23] to MARL. They learn a centralized critic for each agent and continuous policies for the actors and also allow explicit communication among agents. Even though the works mentioned here work in a similar setting and allow for using extra globally accessible information like in our work, they mainly aim at decentralized execution which applies to domains where global view is unavailable. In contrast, we target domains where a global view is accessible to a single agent, even during execution.

There has been considerable progress in learning by communication in cooperative settings involving partially observable environments. Reinforced Inter-Agent Learning (RIAL) and Differentiable Inter-Agent Learning (DIAL) proposed in [7] use neural networks to output communication messages in addition to agent's Q-values. RIAL used shared parameters to learn a single policy whereas DIAL used gradient sharing during learning and communication actions during execution. Both methods use discrete communication channels. On the other hand, CommNet [46], used continuous vectors, enabled multiple communication cycles per time step and the agents were allowed to freely enter and exit the environment. Lazaridou et al. [19] and Mordatch et al. [30] trained the agents to develop an emergent language for communication. Furthermore, standard techniques used in deep learning like dropout [45] have inspired works like [15], where messages of other agents are dropped out during learning to work well even in conditions with only limited communication feasible. In all these works, however, the goal is to learn inter-agent communication alongside local policies that suffer from the bottleneck of simultaneously achieving effective communication and global collaboration [41]. They also face difficulty in extracting essential and high-quality information for exchange among agents [41]. Further, unlike HAMMER, these works expect more sophisticated agents available in the environment in terms of communication capabilities or the ability to run complex algorithms to model other agents present — which might not always be feasible.

One of the popular ways of independent learning is by emergent behaviours [21, 22, 49] wherein each agent learns its own private policy and assumes all other agents to be a part of the environment. This methodology disregards the underlying assumptions of single-agent reinforcement learning, particularly the Markov property. Although this may achieve good results [27], it may also fail due to non-stationarity [18, 54]. Self-play can be a useful concept in such cases [2, 44, 53], but it is still susceptible to failures by forgetting past knowledge [17, 20, 37]. Gupta et al. [12] extend three SARL algorithms, Deep Q Network (DQN) [29], Deep Deterministic Policy Gradient (DDPG) [23], and Trust Region Policy Optimization (TRPO) [38], to cooperative multi-agent settings.

3 SETTING

This section details a novel setting in which multiple agents — the central agent and the independent learners — with different capabilities and knowledge are combined (see Figure 1). The HAMMER algorithm is designed for this type of cooperative multi-agent environment.

Consider a warehouse setting where lots of small, simple, robots fetch and stock items on shelves, as well as bring them to packing stations. If the local agents could communicate among themselves, they could run a distributed reasoning algorithm, but this would require more sophisticated robots and algorithms. Or, if the observations and actions could be centralized, one very powerful agent could determine the joint action of all the agents, but this would not scale well and would require a very powerful agent. Section 6 will make this more concrete with two multi-agent tasks. Now, assume an additional central agent in the team, which can have a global perspective, unlike the local agents, who have only local observations. Further, the central agent is more powerful — not only does it have access to more information, but it can also communicate messages to all local agents. The local agents can only blindly transmit their observations and actions to the central agent and receive messages in return. Like this, the local agents can simply rely on the communicated messages to get briefed about the other agents in the environment and make informed decisions (actions) accordingly. Consequently, the central agent must learn to encapsulate the available information in its, possibly large, inputs into smaller vectors (messages) to facilitate the learning of the independent learners.

Having described an overview of the setting, we can now have a closer look at the inputs, outputs, and roles of the agents in the heterogeneous system. The centralized agent receives a global observation $s \in S$ on every time step and outputs a unique message (equivalently, executes an action), $u_i \in U$, to each of the local agents, where i is the agent identifier. Its global observation s is the union of all the local observations $o_i \in O_i$ and actions of the independent learners $a_i \in A_i$ — can either be obtained from the environment or transmitted to it by the local agents at every time step. u_i encodes a message vector that a local agent can use to make better decisions. Local agents receive a partial observation o_i, and a private message u_i from the central agent. Based on o_i and u_i, at each time step, all n local agents will choose their actions simultaneously, forming a joint action $(A_1\times, \ldots, \times A_n)$ and causing a change in the environment state according to the state transition function P.

Upon changing the dynamics of the environment, a reward $r \in R$ — which could be team-based or localized — is sent back to local agents, using which they must learn how to act. If the messages from the central agent were not useful, local agents could learn to ignore such messages. Every time the central agent communicates a message u_i to a local learner, it receives the same reward as is

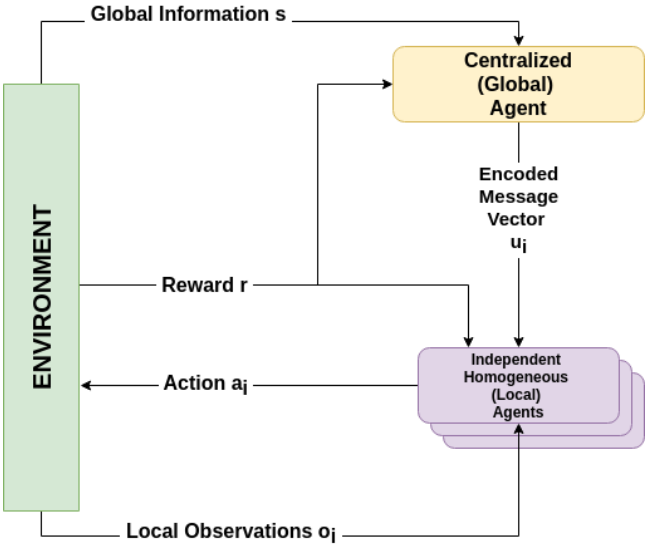

Figure 1: Our cooperative MARL setting: a single global agent sends messages to help multiple independent local agents act in an environment

obtained by that local agent on performing an action a_i in the environment. In other words, the central agent does not directly interact with the environment to get feedback, instead, it learns to output useful messages by looking at how the independent agents performed in the environment using the messages it communicated to them. In domains with localized rewards for agents, the central agent gets a tangible reward for its messages, whereas, in other cases that have team rewards, it needs to learn using comparatively abstract feedback. In Section 6 we show that HAMMER generalizes to both the reward structures.

4 THE HAMMER ALGORITHM

This section introduces HAMMER, the *Heterogeneous Agents Mastering Messaging to Enhance Reinforcement learning* algorithm, designed for the cooperative MARL setting discussed above.

There are multiple local and independent agents in an environment given tasks. Depending on the domain, they may take discrete or continuous actions to interact with the environment. As also stated before, we introduce a single central agent into the environment. This agent is relatively powerful and is capable of 1) obtaining a global view of all the other agents present in an environment and 2) transmitting messages to them. It learns a separate policy and aims to support the local team by communicating short messages to them. It is designed to use both a global or local reward structure. Hence, local agents' private observations will now have additional messages sent to them by the central agent and they can choose to use or discard it while learning their policies.

As described by Algorithm 1, in every iteration, the centralized agent receives the union of private observations of all local agents along with their previous actions (line 3). It encodes its input and outputs an individual message vector for each agent (line 7). These

Algorithm 1: HAMMER

1 **Initialize** Actor-Critic Network for the central agent (CA), Actor-Critic Network for independent (shared parameters) agents (IA), and two experience replay memory buffers (B and B') ;
2 **for** *episode e = 1 to TOTAL_EPISODES* **do**
3 Fetch combined initial random observations $s = [o_1, ..., o_i]$ from environment (o_i is agent i's local observation);
4 *Input:* Concat (s, a'_1, ..., a'_i) $\rightarrow$ CA (a'_i is previous action of agent i, or 0 on the first time step);
5 **for** *time step t = 1 to TOTAL_STEPS* **do**
6 **for** *each agent* n_i **do**
7 *Output*: message vector $u_i \leftarrow$ CA, for agent n_i;
8 *Input:* Concat ($o_i \in s$, u_i) $\rightarrow$ IA ;
9 *Output*: local action $a_i \leftarrow$ IA ;
10 **end**
11 Perform sampled actions in environment and get next set of observations s' and rewards r_i for each agent ;
12 Add experiences in B and B' for CA and IA respectively;
13 **if** *update interval reached* **then**
14 Sample random minibatch b $\in$ B and b' $\in$ B';
15 Train CA on b and IA on b' using stochastic policy gradients ;
16 **end**
17 **end**
18 **end**

messages from the central agent are sent to the independent learners, augmenting their private partial observations obtained from the environment (line 8). Then, they output an action (line 9) affecting the environment (line 11). Reward for the joint action performed in the environment is returned (line 11) and is utilized as feedback by all the agents to adjust their parameters and learn private policies (lines 14—15)

The independent learners follow the formerly proposed idea of having a single network with shared parameters for each of them, allowing a single policy to be learned with experiences from all the agents simultaneously [8, 12]. Parameter sharing has been successfully applied in several other multi-agent deep reinforcement learning works [10, 34, 36, 46, 48]. Learning this way makes it centralized, however, execution can be decentralized by making a copy of the policy and using them individually in each of the agents. Furthermore, often in cooperative multi-agent settings, concurrent learning does not scale up to the number of agents and can make the environment dynamics non-stationary, hence difficult to learn [12]. In this implementation of HAMMER, a single policy is learned for the local agents via the centralized learning, decentralized execution setting.

Note that while we focus on parameter sharing for independent agents and using PPO methods for learning the policies, HAMMER can be implemented with other MADRL algorithms. Moreover,

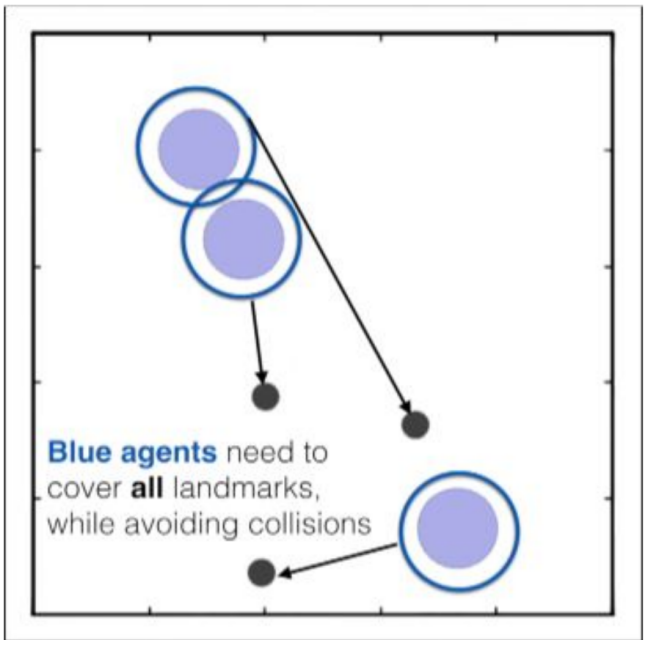

Figure 2: The cooperative navigation environment is composed of blue agents and black (stationary) landmarks the agents must cover, while avoiding collisions.

even though we test with a single central agent in this paper, it is entirely possible that multiple central agents could even better assist independent learners.

5 TASKS AND IMPLEMENTATION DETAILS

This section details two multi-agent environments that we use to evaluate HAMMER. In addition to releasing our code after acceptance, we fully detail our approach so that results are replicable.

5.1 Cooperative Navigation

Cooperative navigation is one of the Multi-Agent Particle Environments [25]. It is a two-dimensional cooperative multi-agent task with a continuous observation space and a discrete action space consisting of n movable agents and n fixed landmarks. Figure 2 shows the case for $n = 3$. Agents occupy physical space (i.e., are not point masses), perform physical actions in the environment, and have the same action and observation spaces. The agents must learn to cover all the landmarks while avoiding collisions, without explicit communication. The global reward signal, seen by all agents, is based on the proximity of any agent to each landmark and the agents are penalized on colliding with each other. The team reward can be defined by the equation:

$$R = [\sum_{n=1,l=1}^{N,L} min(dist(a_n, l))] - c,$$

where N is the number of agents and L is the number of landmarks in the environment. The function *dist()* calculates the distance in terms of the agent's and landmark's (x_i, y_i) position in the environment. c is the number of collisions among the agents and is subtracted as a penalty of -1 for each time two agents collide. The action is discrete, corresponding to moving in the four cardinal directions or remaining motionless. Each agent has a fixed reference frame and its observation can include the relative positions of other agents and landmarks if they are within the frame. Note that the local observations do not convey the velocity (movement direction) of other agents. Consistent with past work, the initial positions of all the agents and the landmark locations are randomized at the start of each episode, and the episode ends after 25 time steps.

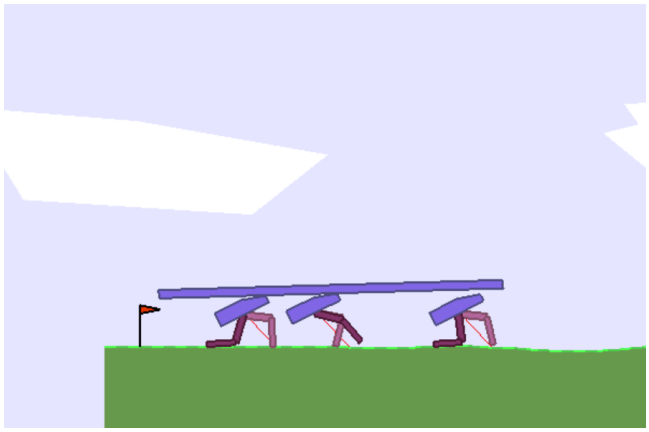

Figure 3: In the multi-agent walker environment, multiple robots work together to act in continuous action spaces to transport a package over varying terrain to a destination without falling.

To test HAMMER, we modify this task so that a centralized agent receives the union of local agents' observations and has access to all their actions at every time step. To test HAMMER's scalability, we also change the number of agents and landmarks in the environment. We are most interested in this environment because of the motivating robotic warehouse example.

5.2 Multi-Agent Walker

Multi-agent walker is a more complex, continuous control benchmark locomotion task [12]. A package is placed on top of n pairs of robot legs which can be controlled. The agents must learn to move the package as far as possible to the right towards a destination, without dropping it. The package is large enough (it stretches across all of the walkers) that agents must cooperate. The environment demands high inter-agent coordination for them to successfully navigate a complex terrain while keeping the package balanced. This environment supports both team and individual rewards, but we focus on the latter case to be less similar to the cooperative navigation task. Each walker is given a reward of -100 if it falls and all walkers receive a reward of -100 if the package falls. Throughout the episode, each walker is given an additional reward of +1 for every step taken. However, there is no supplemental reward for reaching the destination. By default, the episode ends if any walker falls, the package falls, after 500 time steps, or if the package successfully reaches the destination. Each agent receives 32 real-valued numbers, representing information about noisy Lidar

measurements of the terrain and displacement information related to the neighbouring agents. The action space is a 4-dimensional continuous vector, representing the torques in the walker's two joints of both legs. Figure 3 is an illustration of the environment with $n = 3$ agents.

Similar to the Cooperative Navigation domain, we tweaked this environment so that the local agents in it can transmit all their private observations and local actions to a central agent. This environment was chosen primarily to test our approach in the continuous action domain and in cases where individual agents receive their own local rewards instead of global team rewards, but it is also significantly more challenging than the cooperative navigation domain.

5.3 Implementation Details

In both domains, two networks were used — one for the central agent and the second for the independent agents. The parameters were shared for independent agents. PPO used policy gradients to train all the networks. For the actor and critic networks of both central and individual agents, 2 fully-connected multi-layer perceptron layers were used to process the input layer and to produce the output from the hidden state. The central agent's actor network outputs a vector of floating points scaled to $[-1, 1]$ and is consistent across domains. A tanh activation function was used everywhere, with the exception of the local agent's output. Local agents in cooperative navigation used a softmax over the output, corresponding to the probability of executing each of the five discrete actions. Local agents in the multi-agent walker task used 4-output nodes, each of which modeled a multivariate Gaussian distribution over torques.

In the interest of experiment time, we limit trials to 30,000 episodes in cooperative navigation and 10,000 in multi-agent walker. We set $\gamma = 0.95$ in all our experiments. After having tried six learning rates in PPO $\{0.01, 0.001, 0.002, 0.005, 3 \times 10^{-4}, 1 \times 10^{-2}\}$, we found 3×10^{-4} to be the best for the centralized agent and 1×10^{-2} to be the best for independent agents in both domains. Training batch sizes were tuned to 2000 and 4000 respectively for the central and independent agents in both domains. Five independent trials with different random seeds were run on for both environments for establishing statistical significance. The clip parameter for PPO was set to 0.2. Empirically, we found that messages lengths of 4 and 8 performed well in the navigation and multi-agent walker tasks, respectively.

6 RESULTS

This section describes the experiments conducted to test HAMMER's potential of encapsulating and communicating learned messages, speeding up independent learning and scalability, on the two environments — cooperative navigation and multi-agent walker — whose details are described in the previous section. All the curves are averaged over five independent trials (except the ablative study of comparing the performance of HAMMER with different message lengths — where three independent trials were conducted).

6.1 Cooperative Navigation Results

We investigated in detail the learning of independent learners in the cooperative navigation environment under different situations.

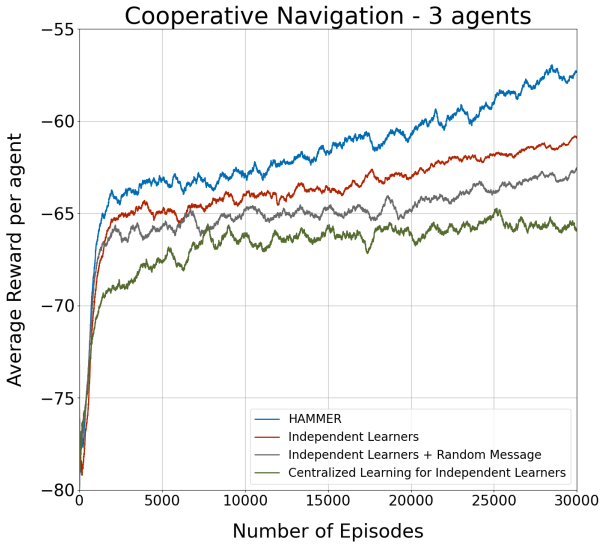

Figure 4: HAMMER agents outperform independent PPO learners in cooperative navigation. Using a similar framework as HAMMER, but providing the local agents with random messages, causes degraded performance (as expected). HAMMER also significantly outperforms centrally learned policy for independent agents.

Learning curves used for evaluation are plots of the average reward per local agent as a function of episodes. Moreover, to smooth the curves for readability, a rolling mean with a window size of 500 episodes was used for each of the cases.

First, we let the local agents learn independently, without any aid from other sources. The corresponding curve (red), as shown in Figure 4, can also act as our baseline to evaluate learning curves obtained when the learners are equipped with additional messages. As described earlier, the experimental setup is consistent with earlier work [12].

Second, we used a central agent to learn messages, as described by HAMMER, and communicated them to the local learners to see if the learning improved. HAMMER performed significantly better than the previous case over a training period of 30,000 episodes, as can be seen in Figure 4. From this experiment, we can claim that results show: (1) HAMMER agents were able to learn much faster as compared to independent local agents, and (2) the success implies that the central agent was able to successfully learn to produce useful smaller messages. (Recall that the total global observation vector has 18 real-valued numbers, and our message uses only 4.)

To help evaluate the communication quality, random messages of the same length were generated and communicated to the independent agents to see if the central agent was indeed learning relevant or useful messages. As expected, random messages induce a larger observation space with meaningless values and degrade the performance of independent learners (see Figure 4). This also supports the claim that the central agent is learning much better messages to communicate (rather than sending random values) as

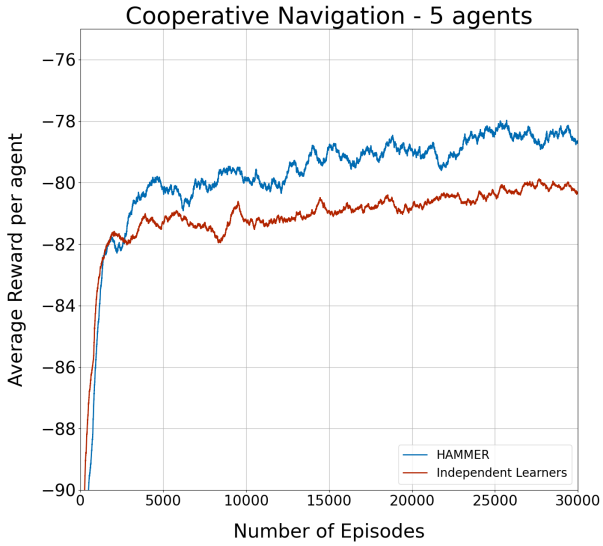

Figure 5: Graphs show the performance of 5 local agents in the cooperative navigation task. y-axis shows the average rewards earned per agent. HAMMER outperforms independent learners in case of larger number of agents too. This suggests that HAMMER is scalable.

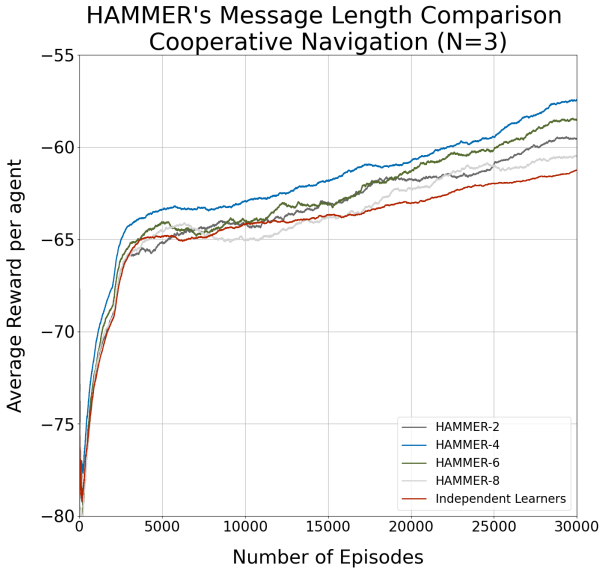

Figure 6: HAMMER-n, in the figure, corresponds to using a message length of n for HAMMER. Plots show that the length of the learned message influences the performance of HAMMER on cooperative navigation, but that even poorly-tuned message lengths still allow HAMMER to perform at least as well as independent PPO agents. (This graph is smoothed using a larger moving average window — 2000 episodes — for readability.)

it outperforms the independent learning of agents provided with random messages.

To confirm that the central agent is not simply forwarding a compressed version of the global information vector to all the agents, we let the independent agents learn in a fully centralized manner, using a joint observation space. The performance drops drastically in this case (Figure 4). This suggests that the central agent in HAMMER is learning to encapsulate only partial but relevant information as messages and communicates them to facilitate the learning of local agents. Complete information would have become too overwhelming for the localized agents to learn how to act and hence slowed the progress, as is clear by the curve (green) shown in Figure 4. It has been shown that this approach does not perform well in domains like pursuit, water world and multi-agent walker earlier [12]. We confirm the same in the cooperative navigation environment for N=3 agents as well.

To test scalability, we also tried N=5. The average reward per agent obtained within the training remains lesser than in the case of N=3. However, HAMMER still outperforms independent learning (see Figure 5). This suggests scalability of HAMMER to a larger number of agents. Empirically, we found that when increasing the number of agents from three to five, performance improved when the length of the central agent's messages was increased from four to eight. We speculate that with larger information made accessible to the central agent, a broader bandwidth for encapsulating it was required by HAMMER.

The final ablation study compared the performance with messages of lengths $\{2, 4, 6, 8\}$ when $n = 3$ in cooperative navigation. As expected, messages that were too small (which likely could not include enough information to be useful) or too large (which likely increased the agent's state space too much) performed worse (see figure 6). However, it is interesting to notice that changing the message lengths was not hurting the performance of the independent learners like in the case when random messages were being fed (Figure 4). We speculate here that the central agent attempted to extract and encapsulate relevant messages out of the global knowledge but in cases with lesser capacity, was only partially successful. If the messages would have been close to random values, they would have harmed the learning of independent agents (Figure 4). In the case of larger messages, they would have included extra information along with the relevant pieces, but being large, would have masked the private observations of the local agents, hence slowing their progress.

In summary, HAMMER successfully summarizes relevant global knowledge into small messages to individual learners that outperforms other cases — (1) unaided independent learning, (2) independent agents supplied with random messages, and (3) fully centralized training of independent agents. Moreover, HAMMER scales to a larger number of agents in the environment.

6.2 Multi-Agent Walker Results

This section shows that HAMMER also works in a multi-agent task with continuous control and individual rewards. Figure 7 shows that HAMMER performs substantially better than unaided independent

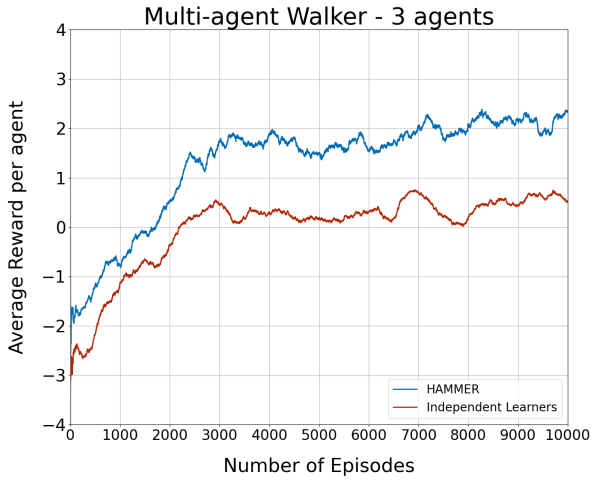

Figure 7: HAMMER significantly improves the performance over independent local agents in the multi-agent walker task.

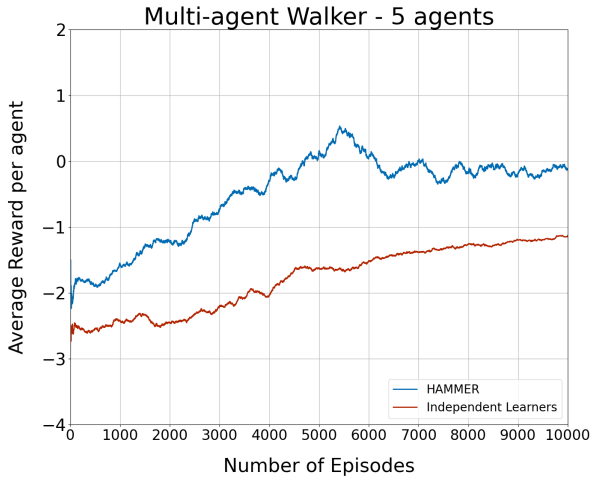

Figure 8: HAMMER outperforms independent local agents when increasing from 3 to 5 local agents in multi-agent walker.

local agents. Like in the cooperative navigation task, results here are averaged over five independent trials, with an additional 500-episode moving window to increase readability. Additional results in Figure 8 confirm that HAMMER outperforms independent learning in the case of 5 walkers. In the case of N=3 walkers, we used a message length of 8 for the central agent, whereas an increased length of 10 showed a better performance for the N=5 walkers scenario. We did not include this result as Gupta et al. [12] already show that independent learners outperform a centralized policy in the multi-agent walker domain.

HAMMER performing better in a domain like Multi-Agent Walker confirms the generalization of the approach to continuous action spaces and different reward structures. Positive results in increasing the number of agents further supports the claim of HAMMER being scalable.

Results comparing the average performances and their standard errors of HAMMER and independent learning (IL) are shown in Table 1. The results for the two domains in this section show that (1) heterogeneous agents successfully learn messaging and enable multi-level coordination among the independent agents to enhance reinforcement learning using HAMMER approach, (2) HAMMER scales to more number of agents, (3) the approach works well in both discrete and continuous action spaces, and (4) the approach performed well with both individual rewards and global team rewards.

Table 1: The average Performances and standard errors in different settings show that HAMMER does outperform independent learning (IL) agents, but that in some cases the differences are unlikely to be statistically significant.

Environment	Agents	HAMMER	IL
Cooperative Navigation	N=3	-61.52 ± 12.63	-63.94 ± 4.69
	N=5	-79.67 ± 8.58	-82.94 ± 4.30
Multi-agent Walker	N=3	1.35 ± 0.59	-0.29 ± 2.16
	N=5	-0.48 ± 0.95	-2.08 ± 0.42

7 CONCLUSION

This paper presented HAMMER, an approach used to achieve multi-level coordination among heterogeneous agents by learning useful messages from a global view of the environment or the multi-agent system. Using HAMMER, we addressed challenges like non-stationarity and inefficient coordination among agents in MARL by introducing a powerful all-seeing central agent in addition to the independent learners in the environment. Our results in two domains, the cooperative navigation and multi-agent walker, showed that HAMMER can be generalized to discrete and continuous action spaces with both global team rewards and localized personal rewards. HAMMER also proved to be scalable by outperforming unaided independent learners in cases with more agents in both the domains. We believe that the key reasons for the success of HAMMER were two-fold. First, we leveraged additional global information like global states, actions and rewards in the system. Second, centralizing observations has its own benefits, including helping to bypass problems like non-stationarity in multi-agent systems and avoiding getting stuck in local optima [14, 56]. Several works, related to ours (discussed earlier) demand extremely powerful agents in the environment — ones that can transmit to other agents and/or are capable of modeling other agents in the system. This might not always be feasible, motivating HAMMER. Only one central agent needs to be powerful while the independent learners can be simple agents interacting with the environment based on their private local observations augmented with learned messages.Warehouse management and traffic lights management are good settings that could fit these assumptions well.

8 FUTURE WORK

There are several directions for future work from here. First, both the domains used in this work involved low-dimensional observation spaces and seem to offer substantial global coverage on combining local observations. HAMMER's results in multi-agent settings with tighter coupling and further complex interactions involved among agents such as in autonomous driving in SMARTS [60] or heterogeneous multi-agent battles in StarCraft [34] could help better appreciate the significance of the method. Second, more complex hierarchies could be used, such as by making several central agents available in the system. Third, in this work, we performed an initial analysis of message vectors communicated by HAMMER. But additional work remains to better understand if and how HAMMER tailors messages for the local agents using its global observation. It would also be interesting to further study how RL learns to encode information in messages and try to understand what the encoding means. Fourth, the maximum number of agents tested for in this work is 5 and even though both the chosen domains were complex multi-agent test-beds, we believe it would be useful to conduct further experiments to justify HAMMER's scalability. Fifth, even though we emphasize why empirical comparisons with techniques like COMA, VDN, Q-MIX, and MADDPG are not relevant, considering that their goals and that of HAMMER are closely related, we could include them as empirical comparisons. Sixth, in our setting, communication is free — future work could consider the case where it was costly and attempt to trade off the number of messages sent with the learning speed of HAMMER. Seventh, we explicitly did not allow inter-agent communication among the local learners. If local agents had the ability to communicate small amounts of data to each other, would a centralized agent still be able to provide a significant improvement?

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