INDIVIDUALIZED CONTROLLED CONTINUOUS COMMUNICATION MODEL FOR MULTIAGENT COOPERATIVE AND COMPETITIVE TASKS

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ABSTRACT

Learning when to communicate and doing that effectively is essential in multi-agent tasks. Recent works show that continuous communication allows efficient training with back-propagation in multiagent scenarios, but have been restricted to fully-cooperative tasks. In this paper, we present Individualized Controlled Continuous Communication Model (IC3Net) which has better training efficiency than simple continuous communication model, and can be applied to semi-cooperative and competitive settings along with the cooperative settings. IC3Net controls continuous communication with a gating mechanism and uses individualized rewards for each agent to gain better performance and scalability while fixing credit assignment issues. Using variety of tasks including StarCraft BroodWars™ explore and combat scenarios, we show that our network yields improved performance and convergence rates than the baselines as the scale increases. Our results convey that IC3Net agents learn when to communicate based on the scenario and profitability.

1 INTRODUCTION

Communication is an essential element of intelligence as it helps in learning from others experience, work better in teams and pass down knowledge. In multi-agent settings, communication allows agents to cooperate towards common goals. Particularly in partially observable environments, when the agents are observing different parts of the environment, they can share information and learnings from their observation through communication.

Recently, there have been a lot of success in the field of reinforcement learning (RL) in playing Atari Games (Mnih et al., 2015) to playing Go (Silver et al., 2016), most of which have been limited to the single agent domain. However, the number of systems and applications having multi-agents have been growing (Lazaridou et al., 2016; Mordatch & Abbeel, 2017); where size can be from a team of robots working in manufacturing plants to a network of self-driving cars. Thus, it is crucial to successfully *scale* RL to multi-agent environments in order to build intelligent systems capable of higher productivity. Furthermore, scenarios other than cooperative, namely semi-cooperative (or mixed) and competitive scenarios have not even been studied as extensively for multi-agent systems.

The mixed scenarios can be compared to most of the real life scenarios as humans are cooperative but not fully-cooperative in nature. Humans work towards their individual goals while cooperating with each other. In competitive scenarios, agents are essentially competing with each other for better rewards. In real life, humans always have an option to communicate but can choose when to actually communicate. For example, in a sports match two teams which can communicate, can choose to not communicate at all (to prevent sharing strategies) or use dishonest signaling (to misdirect opponents) (Lehman et al., 2018) in order to optimize their own reward and handicap opponents; making it important to learn when to communicate.

Teaching agents how to communicate makes it is unnecessary to hand code the communication protocol with expert knowledge (Sukhbaatar et al., 2016)(Kottur et al., 2017). While the content of communication is important, it is also important to know when to communicate either to increase scalability and performance or to increase competitive edge. For example, a prey needs to learn when to communicate to avoid communicating its location with predators.

Sukhbaatar et al. (2016) showed that agents communicating through a continuous vector are easier to train and have a higher information throughput than communication based on discrete symbols. Their

continuous communication is differentiable, so it can be trained efficiently with back-propagation. However, their model assumes full-cooperation between agents and uses average global rewards. This restricts the model from being used in mixed or competitive scenarios as full-cooperation involves sharing hidden states to everyone; exposing everything and leading to poor performance by all agents as shown by our results. Furthermore, the average global reward for all agents makes the credit assignment problem even harder and difficult to scale as agents don't know their individual contributions in mixed or competitive scenarios where they want themselves to succeed before others.

To solve above mentioned issues, we make the following contributions:

1. We propose **Individualized Controlled Continuous Communication Model**, in which each agent is trained with its individualized reward and can be applied to ***any scenario*** whether cooperative or not.
2. We empirically show that based on the given scenario–using the gating mechanism–our model can learn **when to communicate**. The gating mechanism allows agents to block their communication; which is useful in competitive scenarios.
3. We conduct experiments on different scales in three chosen environments including StarCraft and show that IC3Net outperforms the baselines with performance gaps that **increase** with scale. The results show that *individual rewards* converge **faster** and better than *global rewards*.

2 Related work

The simplest approach in multi-agent reinforcement learning (MARL) settings is to use an independent controller for each agent. This was attempted with Q-learning in Tan (1993). However, in practice it performs poorly (Matignon et al., 2012), which we also show in comparison with our model. The major issue with this approach is that due to multiple agents, the stationarity of the environment is lost and naïve application of experience replay doesn't work well.

The nature of interaction between agents can either be cooperative, competitive, or a mix of both. Most algorithms are designed only for a particular nature of interaction, mainly cooperative settings (Omidshafiei et al., 2017; Lauer & Riedmiller, 2000; Matignon et al., 2007), with strategies which indirectly arrive at cooperation via sharing policy parameters (Gupta et al., 2017). These algorithms are generally not applicable in competitive or mixed settings. See Busoniu et al. (2008) for survey of MARL in general and Panait & Luke (2005) for survey of cooperative multi-agent learning.

Our work can be considered as an all-scenario extension of Sukhbaatar et al. (2016)'s CommNet for collaboration among multiple agents using continuous communication; usable only in cooperative settings as stated in their work and shown by our experiments. Due to continuous communication, the controller can be learned via backpropagation. However, this model is restricted to fully cooperative tasks as hidden states are fully communicated to others which exposes everything about agent. On the other hand, due to global reward for all agents, CommNet also suffers from credit assignment issue.

The Multi-Agent Deep Deterministic Policy Gradient (MADDPG) model presented by Lowe et al. (2017) also tries to achieve similar goals. However, they differ in the way of providing the coordination signal. In their case, there is no direct communication among agents (actors with different policy per agent), instead a different centralized critic per agent – which can access the actions of all the agents – provides the signal. Concurrently, a similar model using centralized critic and decentralized actors with additional counterfactual reward, COMA by Foerster et al. (2017) was proposed to tackle the challenge of multiagent credit assignment by letting agents know their individual contributions.

Vertex Attention Interaction Networks (VAIN) (Hoshen, 2017) also models multi-agent communication through the use of Interaction Networks (Battaglia et al., 2016) with attention mechanism (Bahdanau et al., 2014) for predictive modelling using supervised settings. The work by Foerster et al. (2016b) also learns a communication protocol where agents communicate in a discrete manner through their actions. This contrasts with our model where multiple continuous communication cycles can be used at each time step to decide the actions of all agents. Furthermore, our approach is amenable to dynamic number of agents. Peng et al. (2017) also attempts to solve micromanagement tasks in StarCraft using communication. However, they have non-symmetric addition of agents in communication channel and are restricted to only cooperative scenarios.

In contrast, a lot of work has focused on understanding agents' communication content; mostly in discrete settings with two agents (Wang et al., 2016; Havrylov & Titov, 2017; Kottur et al., 2017;

Lazaridou et al., 2016; Lee et al., 2017). Lazaridou et al. (2016) showed that given two neural network agents and a referential game, the agents learn to coordinate. Havrylov & Titov (2017) extended this by grounding communication protocol to a symbols's sequence while Kottur et al. (2017) showed that this language can be made more human-like by placing certain restrictions. Lee et al. (2017) demonstrated that agents speaking different languages can learn to translate in referential games.

3 MODEL

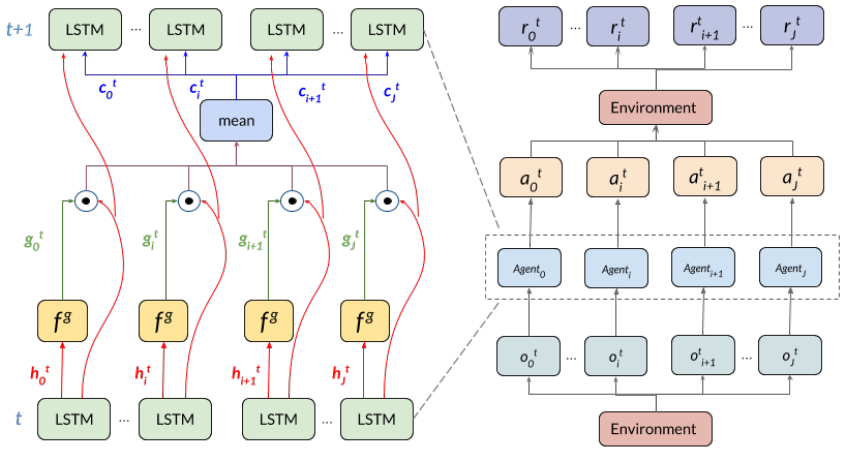


Figure 1: An overview of IC3Net. (Left) In-depth view of a single communication step. LSTM gets hidden state, h_t and cell state, s_t (not shown) from previous time-step. Hidden state h_t is passed to Communication-Action module f_g for a communication binary action g_t. Finally, communication vector c_t is calculated by averaging hidden states of other active agents gated by their communication action ac_t and is passed through a linear transformation C before fed to LSTM along with the observation. (Right) High-level view of IC3Net which optimizes individual rewards r^t for each agent based on observation o^t.

In this section, we introduce our model **Individualized Controlled Continuous Communication Model (IC3Net)** as shown in Figure 1 to work in multi-agent cooperative, competitive and mixed settings where agents learn what to communicate as well as when to communicate.

First, let us describe an independent controller model where each agent is controlled by an individual LSTM. For the j-th agent, its policy takes the form of:

$$\begin{aligned} h_j^{t+1}, s_j^{t+1} &= LSTM(e(o_j^t), h_j^t, s_j^t) \\ a_j^t &= \pi(h_j^t), \end{aligned}$$

where o_j^t is the observation of the j-th agent at time t, $e(\cdot)$ is an encoder function parameterized by a fully-connected neural network and π is an agent's action policy. Also, h_j^t and s_j^t are the hidden and cell states of the LSTM. We use the same LSTM model for all agents, sharing their parameters. This way, the model is invariant to permutations of the agents.

IC3Net extends this independent controller model by allowing agents to communicate their internal state, gated by a discrete action. The policy of the j-th agent in a IC3Net is given by

$$\begin{aligned} g_j^{t+1} &= f^g(h_j^t) \\ h_j^{t+1}, s_j^{t+1} &= LSTM(e(o_j^t) + c_j^t, h_j^t, s_j^t) \\ c_j^{t+1} &= \frac{1}{J-1} C \sum_{j' \neq j} h_{j'}^{t+1} \odot g_{j'}^{t+1} \\ a_j^t &= \pi(h_j^t), \end{aligned}$$

where c_j^t is the communication vector for the j-th agent, C is a linear transformation matrix for transforming gated average hidden state to a communication tensor, J is the number of alive agents currently present in the system and $f^g(.)$ is a simple network containing a soft-max layer for 2 actions

(communicate or not) on top of a linear layer with non-linearity. The binary action g_j^t specifies whether agent j wants to communicate with others, and act as a gating function when calculating the communication vector. Note that the gating action for next time-step is calculated at current time-step. We train both the action policy π and the gating function f^g with REINFORCE (Williams, 1992).

In Sukhbaatar et al. (2016), individual networks controlling agents were interconnected, and they as a whole were considered as a single big neural network. This single big network controller approach required a definition of an unified loss function during training, thus making it impossible to train agents with different rewards.

In this work, however, we move away from the single big network controller approach. Instead, we consider multiple big networks with shared parameters each controlling a single agent separately. Each big network consists of multiple LSTM networks, each processing an observation of a single agent. However, only one of the LSTMs need to output an action because the big network is only controlling a single agent. Although this view has a little effect on the implementation (we can still use a single big network in practice), it allows us to train each agent to maximize its *individual* reward instead of a single global reward. This has two benefits: (i) it allows the model to be applied to both cooperative and competitive scenarios, (ii) it also helps resolve the credit assignment issue faced by many multi-agent (Sukhbaatar et al., 2016; Foerster et al., 2016a) algorithms while improving performance with scalability and is coherent with the findings in Chang et al. (2003).

4 Experiments[1]

We study our network in multi-agent cooperative, mixed and competitive scenarios to understand its workings. We perform experiments to answer following questions:

1. Can our network learn the gating mechanism to communicate only when needed according to the given scenario? Essentially, is it possible to learn *when to communicate*?
2. Does our network using individual rewards scales better and faster than the baselines? This would clarify, whether or not, *individual rewards* perform better than *global rewards* in multi-agent communication based settings.

We first *analyze* gating action's (g_t) working. Later, we train our network in three chosen environments with variations in difficulty and coordination to ensure scalability and performance.

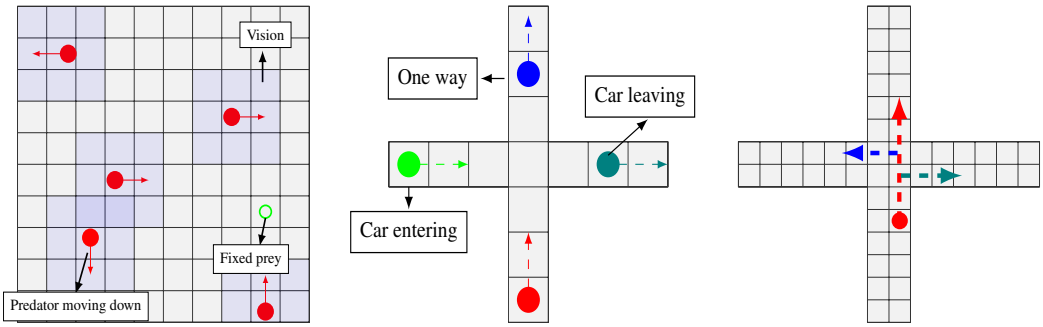


Figure 2: **Environments**. **(Left)** 10×10 version of predator-prey task where 5 predators(red circles) with limited vision of size 1 (blue region) try to catch a randomly initialized fixed prey (green circle). **(Center and Right)** Easy and medium versions of traffic junction task where cars have to cross the the whole path minimizing collisions using two actions, gas and $brake$ respectively. Agents have zero vision and can only observe their own location. **(Right)** In medium version, chances of collision are increased due to more possible routes and increased number of cars.

4.1 Environments

We consider three environments for our analysis and experiments. (i) a predator-prey environment (**PP**) where predators with limited vision look for a prey on a square grid. (ii) a traffic junction environment (**TJ**) similar to Sukhbaatar et al. (2016) where agents with limited vision must learn

[1]The code will be available at https://github.com/IC3Net/IC3Net.

to communicate in order to avoid collisions. (iii) StarCraft BroodWars[2] (**SC**) explore and combat tasks which test control on multiple agents in various scenarios where agent needs to understand and decouple observations for ***multiple opposing units***.

4.1.1 PREDATOR PREY

In this task, we have n predators (agents) with limited vision trying to find a stationary prey. Once a predator reaches a prey, it stays there and always gets a positive reward, until end of episode (rest of the predators reach prey, or maximum number of steps). In case of zero vision, agents don't have a direct way of knowing prey's location unless they jump on it.

We design three cooperation settings (competitive, mixed and cooperative) for this task with different reward structures to test our network. See Appendix 6.2 for details on grid, reward structure, observation and action space. There is no loss or benefit from communicating in mixed scenario. In competitive setting, agents get lower rewards if other agents reach the prey and in cooperative setting, reward increases as more agents reach the prey. We compare with baselines using mixed settings in subsection 4.3.2 while explicitly learning and analyzing gating action's working in subsection 4.2.

We create three levels for this environment – as mentioned in Appendix 6.2 – to compare our network's performance with increasing number of agents and grid size. 10×10 grid version with 5 agents is shown in Fig. 2 (left). All agents are randomly placed in the grid at start of an episode.

4.1.2 TRAFFIC JUNCTION

Following Sukhbaatar et al. (2016), we test our model on the traffic junction task as it is a good proxy for testing whether communication is working. This task also helps in supporting our claim that IC3Net provides good performance and faster convergence in fully-cooperative scenarios similar to mixed ones. In the traffic junction, cars enter a junction from all entry points with a probability p_{arr}. The maximum number of cars at any given time in the junction is limited. Cars can take two actions at each time-step, gas and $brake$ respectively. The task has three difficulty levels (see Fig. 2) which vary in the number of possible routes, entry points and junctions. We make this task harder by always setting vision to zero in all the three difficulty levels to ensure that task is not solvable without communication. See Appendix 6.3 for details on reward structure, observation and training.

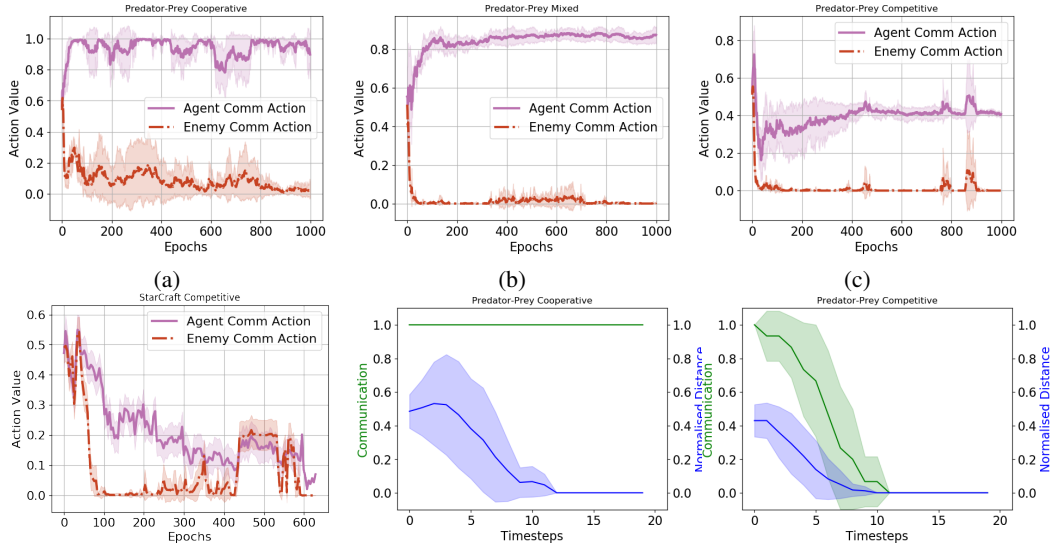
4.1.3 STARCRAFT: BROODWARS

To fully understand the scalability of our architecture in more realistic and complex scenarios, we test it on StarCraft combat and exploration micro-management tasks in partially observable settings. StarCraft is a challenging environment for RL because it has a large observation-action space, many different unit types and stochasticity. We train our network on Combat and Explore task. The task's difficulty can be altered by changing the number of our units, enemy units and the map size.

By default, the game has macro-actions which allow a player to directly target an enemy unit which makes player's unit find the best possible path using the game's in-built path-finding system, move towards the target and attack when it is in a range. However, we make the task harder by (i) removing macro-actions making exploration harder (ii) limiting vision making environment partially observable(iii) unlike previous works (Wender & Watson, 2012; Ontanón et al., 2013; Usunier et al., 2016; Peng et al., 2017), initializing enemy and our units at random locations in a fixed size square on the map, which makes it challenging to find enemy units. Refer to Appendix 6.4 for reward, action and observation details. We consider two types of tasks in StarCraft:

Explore: In this task, we have n agents trying to explore the map and find an enemy unit. This is a direct scale-up of the PP but with more realistic and stochastic situations. To complete the task, agents must be within a particular range of enemy unit called *explore vision*. Once an agent is within *explore vision* of enemy unit, we $noop$ further actions. The reward structure is same as the PP with an only difference being that an agent needs to be within the *explore vision* range of the enemy unit instead of being on same location to get a non-negative reward. We use *medic* units which doesn't attack enemy units to simulate our explore task without any of kind of combat happening.

[2]StarCraft is a trademark or registered trademark of Blizzard Entertainment, Inc., in the U.S. and/or other countries. Nothing in this paper should not be construed as approval, endorsement, or sponsorship by Blizzard Entertainment, Inc



(a) (b) (c)

(d) (e) g_t vs Timesteps, Cooperative (f) g_t vs Timesteps, Competitive

Figure 3: **Learning Gating Action**: Plots show gating action g_t for predators and prey averaged over each epoch in PP. In cooperative setting **(a, e)** agent almost always communicate to increase their own reward. In **(b)** mixed setting and **(c)** competitive setting, predators only communicate when necessary and profitable. As is evident from **(d)**, they stop communicating once they reach prey. In all cases, prey almost never communicates with predators as it is not profitable for it. Similarly, in competitive scenario **(d)** for SC, team agents learn to communicate only when necessary due to the division of reward when near enemy, while enemy agent learns not to communicate as in PP.

Combat: We test an agent's capability to execute a complex task of combat in StarCraft which require coordination between teammates, exploration of a terrain, understanding of enemy units and formalism of complex strategies. We specifically test a team of n agents trying to find and kill a team of m enemies in a partially observable environment similar to the explore task. The agents, with their limited vision, must find the enemy units and kill all of them to score a win.

4.2 Analysis of the Gating Mechanism

We analyze working of gating action (g_t) in IC3Net by using cooperative, competitive and mixed settings in Predator-Prey (4.1.1) and StarCraft explore tasks (4.1.3). However, this time the enemy unit (prey) is trained along with the predators and shares parameters with them. All of its actions are *noop*; hence essentially making it stationary. The enemy gets a *positive reward* equivalent to r_{time} = 0.05 per timestep until no predator/medic is near or captures it; after that it gets a reward of 0.

Fig. 3 shows values (averaged per epoch) of predators' gating action for communication among themselves and enemy's gating action for its communication with predators in all scenarios. We test on 5×5 map size for PP and 50×50 for SC. We evaluate with similar competitive and cooperative settings in StarCraft's explore task and found similar plots (3(d)). We can deduce following observations:

- In all the three cases, the prey learns not to communicate. If prey communicates, predators will reach faster and it stops getting reward once an agent comes near or on top of it.
- In cooperative setting, the predators are openly communicating with the gating action value close to 1. While the prey starts to communicate with the predators in the start, it eventually learns not to communicate; so as not to share its location. We believe as everyone is communicating in this setting, it takes more training time to adjust weights for the prey. Our preliminary tests suggest that in cooperative settings, it is beneficial to fix gating action to 1.0 as communication is almost always needed. It also helps in faster training by skipping training of the gating action.
- In the mixed setting, agents don't always communicate, which we believe fits with mixed scenarios where there is no benefit or loss by communicating. As from the start agents are not fully-cooperative, the prey is easily able to learn not to communicate as the weights are adjusted towards non-cooperation.
- Predators rarely communicate in case of the competitive setting. Note that, this environment is not fully-adversarial as predators can explore faster if they communicate which eventually

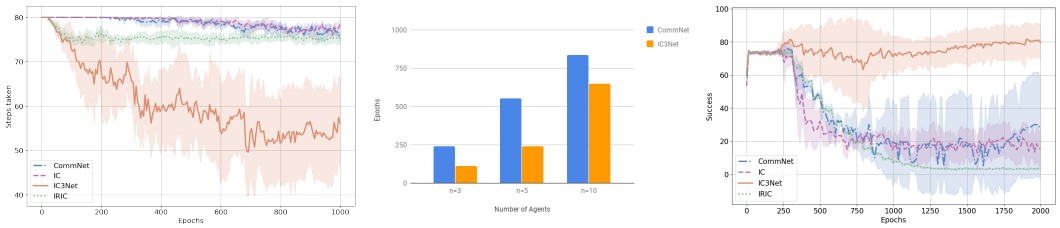


Figure 4: Plots for PP and TJ task. **(Left)** Average steps taken to complete an episode in 20×20 grid. **(Center)** IC3Net converges faster than CommNet as the number of predators (agents) increase in Predator-Prey environment. **(Right)** Success % in medium TJ task trained with curriculum. Performance and convergence of IC3Net is superior than baselines.

leads to overall higher rewards. Moreover, we also observe that in this setting, the agents only communicate while it's profitable for them, i.e. before reaching the prey (3 (f)) as communicating afterwards can impact their future rewards.

- Using experiments in this section, one can empirically decide that agents can learn to communicate when it is profitable; thus allowing same network to be used in all settings.

4.3 Scalability and Generalization Experiments

In this section, we look at bigger versions of our environments to understand scalability and generalization aspects of IC3Net

4.3.1 Baselines

For **training details**, refer to Appendix 6.1. We compare IC3Net with **baselines** specified below in all scenarios.

Individual Reward Independent Controller (IRIC): In this controller, model is applied individually to all of the agents' observations to produce the action to be taken. Essentially, this can be seen as IC3Net without any communication between agents; but with individualized reward for each agent. Note that no communication makes gating action (g_t) *ineffective*.

Independent Controller (IC - IC3Net w/o Comm and IR): Like IRIC except the agents are trained with a global average reward instead of individual rewards. This will help us understand the credit assignment issue prevalent in CommNet.

CommNet: Introduced in Sukhbaatar et al. (2016), CommNet allows communication between agents over a channel where an agent is provided with the average of hidden state representations of other agents as a communication signal. Like IC3Net, CommNet also uses continuous signals to communicate between the agents. Thus, CommNet can be considered as IC3Net without both the gating action (g_t) and individualized rewards.

4.3.2 Results

Table 1: (Left) **Predator Prey**: Avg. number of steps taken to complete the episode in three different environment sizes in mixed settings. IC3Net completes the episode faster than the baselines by finding the prey. (Right) Traffic Junction: Success rate on various difficulty levels with zero vision for all. IC3Net provides better performance than baselines consistently especially as the scale increases.

	Predatory-Prey (Avg. Steps)				**Traffic Junction (Success %)**		
Model	**5x5, n=3**	**10x10, n=5**	**20x20, n=10**	**Model**	**Easy**	**Medium**	**Hard**
IRIC	16.5± 0.1	28.1± 0.2	75.0± 1.4	IRIC	29.8± 0.7	3.4± 0.5	35.0± 0.6
IC	16.4± 0.49	28.0± 0.74	77.4± 0.8	IC	30.2± 0.4	3.4± 0.5	47.0± 2.9
CommNet	9.1± 0.1	13.1± 0.01	76.5± 1.3	CommNet	93.0± 4.2	54.3± 14.2	50.2± 3.5
IC3Net	**8.9± 0.02**	**13.0± 0.02**	**52.4± 3.4**	IC3Net	**93.0± 3.7**	**89.3± 2.5**	**72.4± 9.6**

Predator Prey: Table 1 (left) shows average steps taken by the models to complete an episode i.e. find the prey in mixed setting. IC3Net reaches prey faster than the baselines as we increase the number of agents as well as the size of the maze. In 20×20 version, the gap in average steps is almost

24 steps, which is a substantial improvement over baselines. Figure 4 (right) shows the scalability graph for IC3Net and CommNet which supports the claim that with the increasing number of agents, IC3Net converges faster at a better optimum than CommNet. Through these results on the PP task, we can see that compared to IC3Net, CommNet doesn't work well in mixed scenarios. Finally, Figure 4 (left) shows the training plot of 20×20 grid with 10 agents trying to find a prey. The plot clearly shows the faster performance improvement of IC3Net in contrast to CommNet which takes long time to achieve a minor jump. We also find same pattern of the gating action values as in 4.2.

Traffic Junction: Table 1 (right) shows the success ratio for traffic junction. We fixed the gating action to 1 for TJ as discussed in 4.2. With zero vision, it is not possible to perform well without communication as evident by the results of IRIC and IC. Interestingly, IC performs better than IRIC in the hard case, as we believe without communication, the global reward in TJ acts as a better indicator of the overall performance. On the other hand, with communication and better knowledge of others, the global reward training face a credit assignment issue which is alleviated by IC3Net as evident by its superior performance compared to CommNet. In Sukhbaatar et al. (2016), well-performing agents in the medium and hard versions had vision > 0. With zero vision, IC3Net is to CommNet and IRIC with a performance gap greater than 30%. This verifies that individualized rewards in IC3Net help achieve a better or similar performance than CommNet in fully-cooperative tasks with communication due to a better credit assignment.

Table 2: StarCraft: Win Ratio and average number of steps taken to complete episodes for explore and combat tasks. IC3Net beats the baselines with huge margin in case of exploration tasks, while it is as good as CommNet in case of 10 Marines vs 3 Zealots combat task.

	IRIC		IC		CommNet		IC3Net	
StarCraft task	**Win %**	**Steps**	**Win %**	**Steps**	**Win %**	**Steps**	**Win %**	**Steps**
Explore-10Medic 50×50	35.4± 1.7	52.7± 0.6	18.0± 1.63	55.5± 0.4	9.2± 3.12	58.4± 0.5	**64.2± 17.7**	**41.2± 8.4**
Explore-10Medic 75×75	9.0± 4.2	58.6± 0.9	1.0± 0.2	59.1± 0.4	2.1± 0.3	59.9± 0.1	**17.0± 15.2**	**57.2± 3.5**
Combat-10Mv3Ze 50×50	74.6± 5.1	35.0± 0.8	51.8± 3.0	48.6± 0.4	88.0± 7.2	33.3± 1.2	87.4± 1.0	33.6± 0.2

StarCraft: Table 2 displays win % and the average number of steps taken to complete an episode in StarCraft explore and combat tasks. We specifically test on (i) Explore task: 10 medics finding 1 enemy medic on 50×50 cell grid (ii) On 75×75 cell grid (iii) Combat task: 10 Marines vs 3 Zealots on 50 x 50 cell grid. Maximum steps in an episode are set to 60. The results on the explore task are similar to Predator-Prey as IC3Net outperforms the baselines. Moving to a bigger map size, we still see the performance gap even though performance drops for all the models.

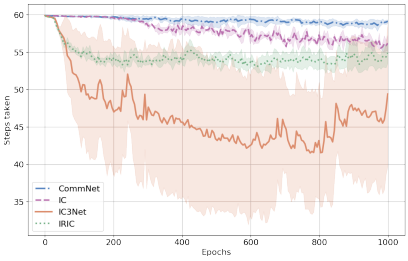


Figure 5: Average steps taken to complete an episode StarCraft Explore-10Medic 50×50 tasks (right).

On the combat task, IC3Net performs comparably well to CommNet as the global reward on winning is huge and shifts the weight toward task being fully-cooperative. To confirm that 10 marines vs 3 Zealots is hard to win, we run an experiment on reverse scenario where our agents control 3 Zealots initialized separately and enemies are 10 marines initialized together. We find that both IRIC and IC3Net reach a success percentage of 100% easily. We find that even in this case, IC3Net converges faster than IRIC.

5 Conclusions and Future Work

In this work, we introduced IC3Net which aims to solve multi-agent tasks in various cooperation settings by learning when to communicate. Its continuous communication enables efficient training by backpropagation, while the discrete gating trained by reinforcement learning along with individual rewards allows it be used even in all scenarios and on larger scale.

Through our experiments, we show that IC3Net performs well in cooperative, mixed or competitive settings and learns to communicate only when necessary. Further, we show that agents learn to stop communication in competitive cases. We show scalability of our network by further experiments. In future, we would like to explore possibility of having multi-channel communication where agents can decide on which channel they want to put their information similar to communication groups but dynamic. It would be interesting to provide agents a choice of whether to listen to communication from a channel or not.

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6 APPENDIX

6.1 TRAINING DETAILS

We set the hidden layer size to 128 units and we use LSTM (Hochreiter & Schmidhuber, 1997) with recurrence for all of the baselines and IC3Net. We use RMSProp (Tieleman & Hinton, 2012) with initial learning rate as a tuned hyper-parameter. All of the models use skip-connections (He et al., 2016). The training is distributed over 16 cores and each core runs a mini-batch till total episodes steps are 500 or more. We do 10 weight updates per epoch. We run predator-prey, StarCraft experiments for 1000 epochs, traffic junction experiment for 2000 epochs and report the final results. In mixed case, we report the mean score of all agents, while in cooperative case we report any agent's score as they are same. We implement our model using PyTorch and environments using Gym (Brockman et al., 2016).We use REINFORCE (Williams, 1992) to train our setup. We conduct 5 runs on each of the tasks to compile our results. The training time for different tasks varies; StarCraft tasks usually takes more than a day (depends on number of agents and enemies), while predator-prey and traffic junction tasks complete under 12 hours.

6.2 DETAILS OF PREDATOR PREY

In all the three settings, cooperative, competitive and mixed, a predator agent gets a constant time-step penalty $r_{explore} = -0.05$, until it reaches the prey. This makes sure that agent doesn't slack in finding the prey. In the mixed setting, once an agent reaches the prey, the agent always gets a positive reward r_{prey} = 0.05 which doesn't depend on the number of agents on prey. . Similarly, in the cooperative setting, an agent gets a positive reward of $r_{coop} = r_{prey} * n$, and in the competitive setting, an agent gets a positive reward of $r_{comp} = r_{prey} / n$ after it reaches the prey, where n is the number of agents on the prey. The total reward at time t for an agent i can be written as:

$$r_i^{pp}(t) = \delta_i * r_{explore} + (1 - \delta_i) * n_t^{\lambda} * r_{prey} * |\lambda|$$

where δ_i denotes whether agent i has found the prey or not, n_t is number of agents on prey at time-step t and λ is -1, 0 and 1 in the competitive, mixed and cooperative scenarios respectively. Maximum episode steps are set to 20, 40 and 80 for 5×5, 10×10 and 20×20 grids respectively. The number of predators are 5, 10 and 20 in 5×5, 10×10 and 20×20 grids respectively. Each predator can take one of the five basic movement actions i.e. $up, down, left, right$ or $stay$. Predator, prey and all locations on grid are considered unique classes in vocabulary and are represented as one-hot binary vectors. Observation obs, at each point will be the sum of all one-hot binary vectors of location, predators and prey present at that point. With vision of 1, observation of each agent have dimension $3^2 \times |obs|$.

6.3 DETAILS OF TRAFFIC JUNCTION

Traffic junction's observation vocabulary has one-hot vectors for all locations in the grid and car class. Each agent observes its previous action, route identifier and a vector specifying sum of one-hot vectors for all classes present at that agent's location. Collision occurs when two cars are on same location. We set maximum number of steps to 20, 40 and 60 in easy, medium and hard difficulty respectively. Similar to Sukhbaatar et al. (2016), we provide a negative reward r_{coll} = -10 on collision. To cut off traffic jams, we provide a negative reward $\tau_i r_{time}$ = -0.01 τ_i where τ_i is time spent by the agent in the junction at time-step t. Reward for ith agent which is having C_i^t collisions at time-step t can be written as:

$$r_i^{tj}(t) = r_{coll} C_i^t + r_{time} \tau_i$$

We utilized curriculum learning Bengio et al. (2009) to make the training process easier. The p_{arrive} is kept at the $start$ value till the first 250 epochs and is then linearly increased till the end value

during the course from 250th to 1250th epoch. The $start$ and end values of p_{arrive} for different difficulty levels are indicated in Table 3. Finally, training continues for another 750 epochs. The learning rate is fixed at 0.003 throughout. We also implemented three difficulty variations of the game explained as follows.

Table 3: Traffic Junction: Variations in different traffic junction difficulty levels. T refers to True as in the difficulty level has 2-way roads and F refers to False as in the difficulty level has 1-way roads.

Difficulty	P-arrive Start	P-arrive End	N-total	Arrival Points	Routes per Entry Point	Two-Way	Junctions	Dimension
Easy	0.1	0.3	5	2	1	F	1	7×7
Medium	0.05	0.2	10	4	3	T	1	14×14
Hard	0.02	0.05	20	8	7	T	4	18×18

The easy version is a junction of two one-way roads on a 7×7 grid. There are two arrival points, each with two possible routes and with a N_{total} value of 5.

The medium version consists of two connected junctions of two-way roads in 14×14 as shown in Figure 2 (right). There are 4 arrival points and 3 different routes for each arrival point and have $N_{total} = 20$.

The harder version consists of four connected junctions of two-way roads in 18×18 as shown in Figure 6. There are 8 arrival points and 7 different routes for each arrival point and have $N_{total} = 20$.

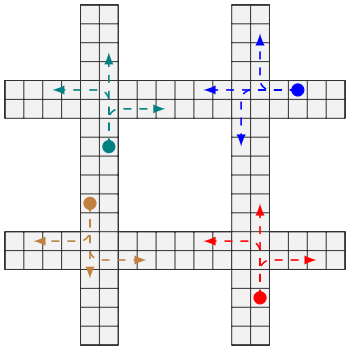

Figure 6: Hard difficulty level of traffic junction task with four connected junctions, eight entry points and at each entry point there are 7 possible routes increasing chances of collision.

6.4 StarCraft Details

6.4.1 Observation and Actions

Explore: Observation for each agent is *(absolute x, absolute y)* and enemy's *(relative x, relative y, visible)* where *visible*, *relative x* and *relative y* are 0 when enemy is not in *explore vision*. Agents have 9 actions to choose from which includes 8 basic directions and one stay action.

Combat: Agent observes its own *(absolute x, absolute y, healthpoints + shield, weapon cooldown, previous action)* and *(relative x, relative y, visible, healthpoints + shield, weapon cooldown)* for each of the enemies. *relative x* and *relative y* are only observed when enemy is visible which is corresponded by *visible* flag. All of the observations are normalized to be in between (0, 1). Agent has to choose from 9 + m actions which include 9 basic actions and 1 action for attacking each of the m agents. Attack actions only work when the enemy is within the $sight$ range of the agent, otherwise it is a $noop$. In combat, we don't compare with prior work on StarCraft because our environment setting is much harder, restrictive, new and different, thus, not directly comparable.

6.4.2 Combat Reward

To avoid slack in finding the enemy team, we provide a negative reward r_{time} = -0.01 at each timestep when the agent is not involved in a combat. At each timestep, an agent gets as reward the difference between (i) its normalized health in current and previous timestep (ii) normalized health at previous

timestep and current timestep for each of the enemies it has attacked till now. At the end of the episode, terminal reward for each agents consists of (i) all its remaining health * 3 as negative reward (ii) 5 * m + all its remaining health * 3 as positive reward if agents win (iii) normalized remaining health * 3 for all of the alive enemies as negative reward on lose. In this task, the group of enemies is initialized together randomly in one half of the map and our agents are initialized separately in other half which makes task even harder, thus requiring communication. For an automatic way of individualizing rewards, please refer to Foerster et al. (2017).

6.4.3 EXAMPLE SEQUENCE OF STATES IN COOPERATIVE EXPLORE MODE

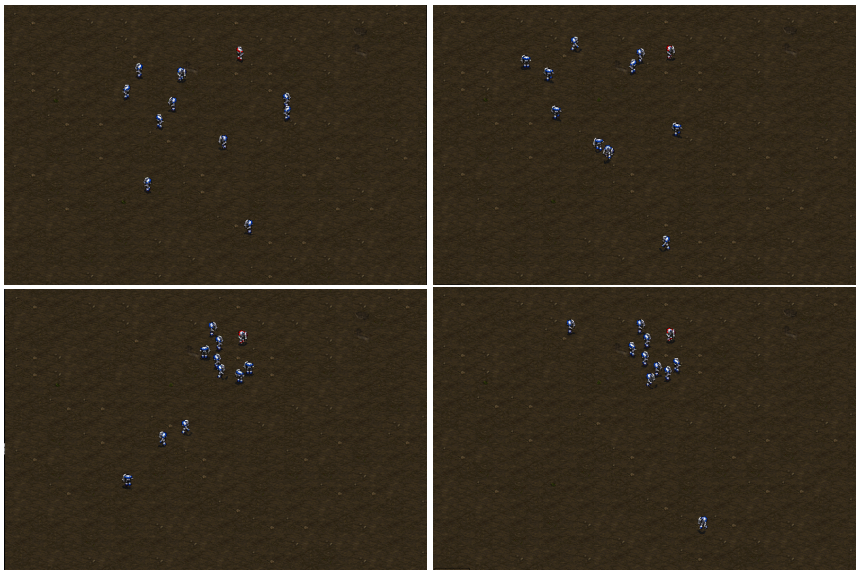

Figure 7: State sequence in SC Cooperative Explore. We can see how agents which are randomly initialized communicate to reach the enemy faster. Once, some agents are near the prey and other reach very fast due to communication