Multi-agent Coordination using Reinforcement Learning with a Relay Agent

Wiem Zemzem and Moncef Tagina
COSMOS Laboratory, National School of Computer Science, University of Manouba, Tunis, Tunisia

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Abstract: This paper focuses on distributed reinforcement learning in cooperative multi-agent systems, where several simultaneously and independently acting agents have to perform a common foraging task. To do that, a novel cooperative action selection strategy and a new kind of agents, called "relay agent", are proposed. The conducted simulation tests indicate that our proposals improve coordination between learners and are extremely efficient in terms of cooperation in large, unknown and stationary environments.

1 INTRODUCTION

Reinforcement learning (RL) negotiates the problem of how an agent can learn by interacting with its environment and observing the results of these interactions. It is an important technique for automatic learning in uncertain environments. Though it has been applied to many domains widely, the multiagent case has not been investigated thoroughly. This is due to the difficulty of applying the theory of the single-agent RL to the multi-agent case and it becomes much harder when dealing with more complex problems, like cooperative learning in distributed systems (Partalas et al., 2008). It's the main focus of the current paper: we aim to coordinate a group of autonomous agents in order to perform a cooperative foraging task in a distributed manner.

Many existing works dealing with distributed cooperative systems use independent learners (ILs). These learners are called independent since they learn independently from each other without taking into account the behaviors of the other agents (Torrey and Taylor, 2012). They hence bring the benefit of a state space size independent of the number of agents but suffers from the lack of multi-agent coordination. A direct communication between ILs is, therefore, useful in order to ensure knowledge sharing and transfer among them.

As examples, the policy averaging (PA) method (Tan, 1997) and the experience counting (EC) method (Cunningham and Cao, 2012) are proposed as sharing strategies that are adopted by all agents in the environment. Results show that these sharing methods expedite learning and outperform independent learning methods. However, they assume that each agent knows how many other agents are in the environment and has enough memory to store the information learned by each of them. In real situations where agents are robots and take on a physical form, these assumptions may prove to be unrealistic. In addition to that, at each learning iteration, all state/action pairs are evaluated and updated after querying other agents for their entire Qtables and, at the end of each step, all agents will have the same stored data. Again, these updates and information exchange are computationally intensive, especially in the case of a large number of agents and/or a large size of the environment.

Another method, called D-DCM-MultiQ (Guo and Meng, 2010), seems to be more interesting than these latter. By this approach, each agent stores a simple QTable, like a single-agent system, and at each learning step, it only updates the current experimented state/action pair using its own information in addition to those of its local neighbors. The multi-agent cooperation is then ensured with a little amount of stored and exchanged data. However, this method suffers from some limitations, namely the non-continuous spread of the goal's reward causing the blockage of learning and even the no completion of the assigned task. Our previous work, presented in (Zemzem and Tagina, 2015), deals with the same problem but in non stationary environments. The proposed approach sort previous knowledge according to the moment of its last modifications and uses the

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information of the next state instead of the current one, which increases the amount of stored information and needs additional calculations. Using our previous approach, a satisfactory result was approved in the case of dynamic environments. However, a simpler and less costly approach can be adopted when dealing with only stationary environments: this is the objective of the current paper.

Several propositions have been made in the present manuscript in order to overcome the shortcomings of the D-DCM-MultiQ method and improve multi-agent learning in large, stationary and unknown environments. The main contributions of this paper are presented in the following points:

- In order to overcome the limitations of the D-DCM-MultiQ method, the action selection strategy is not only based on the own information of the learner, but also on the information of its neighbors which increases the efficiency of the choice. In this regard, a new cooperative action selection strategy is proposed and evaluated. This proposed method is derived from the ε-greedy policy (Coggan, 2004). Using this latter, no memorization of exploration specific data is required, which makes it particularly interesting for very large or even continuous state-spaces.
- As the communication between agents is local, an agent can trap between two states (one state inside the communication range of the neighboring agent and another state outside its communication range). To this end, a second form of agent, called "relay agent", is designed to ameliorate the cooperation between learning agents by storing all learners' information. When choosing the next action to perform, each learning agent should especially exploit the relay's backups if it is within its neighborhood.
- To ensure an efficient learning regardless of the environment size and the communication range, the relay agent must move randomly during the whole learning phase in order to cover different regions of the environment over time and ensure the resolution of bottleneck situations in a timely manner.
- A particular update of the relay's knowledge is suggested in order to optimize the size of the stored data; for each state/action pair, the relay agent stores only the most promising value of all neighbors' information related to this pair, instead of saving all learners' information. As a result, the relay retains a single Qvalue for each state/action pair, like a learning agent.

The rest of the paper is organized as follows. Problem statement is described in Section 2. In Section 3, the D-DCM-Multi-Q approach is presented and briefly reviewed. Section 4 is dedicated to present our suggestions for improvement. Several experiences are conducted in Section 5 showing the efficiency of our proposals. Some concluding remarks and future works are discussed in Section 6.

2 PROBLEM STATEMENT

The learning problem is a cooperative foraging task in a large, stationary and two-dimensional discrete environment. As in (Guo and Meng, 2010) and (Zemzem and Tagina, 2015), agents can perform four actions: "left", "right", "up" and "down" and their decisions are only based on the interaction with the environment as well as the interaction with local neighbors. It is assumed that all agents are initially in the nest, and each agent can locate itself using its on-board sensors such as encoders and can detect the target or obstacles using sonar sensors. Each agent has limited onboard communication range and can share its state information with its neighbors that are within its communication range.

The foraging task may be abstractly viewed as a sequence of two alternating tasks for each agent:

- Start from the nest and reach the food source (Foraging Phase). In this case, the learning method is applied.
- Start from the food source, laden with food, and reach the nest (Ferrying Phase). Every time one agent finds the food source, it will wait for other agents to reach the target (Waiting Phase). Once all the agents find the food source, they start a collective transport phase. As agents must follow the same path, they select the shortest path among all agents' foraging paths (Zemzem and Tagina, 2015).

To provide agents with distributed RL, we use a model close to Markov Decision Processes (MDPs). It is a tuple of (n, S, A, T, R), where n is the number of agent's neighbors. S is a set of states which is defined as $S = [s_1, .., s_m]$, where m is the number of states each of which is identified by the coordinates (x, y). A is a set of actions available to an agent which is defined as $A = [a_1, .., a_p]$. $R : S \times A \longrightarrow r$ is the reward function for an agent and T is a state transition function (T is a probability distribution over S) (Bruno C. Da Silva, Eduardo W. Basso, Ana L. C. Bazzan, 2006).

3 A REVIEW OF THE D-DCM-MultiQ METHOD

D-DCM-MultiQ is a distributed reinforcement learning method for multi-agent cooperation (Guo and Meng, 2010). To update its Q-value at a state s_i, the i^{th} agent uses its own Q-value at that state as well as the Q-values of its neighboring agents at the next state s'_i (see Eq.1).

$$Q_{k+1,i}(s_i,a_i) = (1-\alpha_k)\,Q_{k,i}(s_i,a_i) + \alpha_k * \left(R_{k,i}(s_i,a_i) + \frac{\gamma}{N}\sum_{j=1}^{N} max_{a_j} Q_{k,j}\left(s'_i,a_j\right)\right) \quad (1)$$

As noted in (Guo and Meng, 2010), $Q_{k+1,i}(s_i,a_i)$ represents the new Q-value of the i^{th} agent after executing action a_i at state s_i and receiving the immediate reward $R_{k,i}(s_i,a_i)$. α is the learning rate, γ is the decaying factor and N is the neighbors' number of the i^{th} agent.

As to the action selection strategy, the Boltzmann policy (Coggan, 2004) was applied in (Guo and Meng, 2010). At any state s, action a is selected according to the following probability:

$$\frac{e^{\frac{Q(s,a)}{T}}}{\sum_a e^{\frac{Q(s,a)}{T}}} \quad (2)$$

where T, called temperature, decreases over time according to the rule of $T = \frac{T0}{b+1}$. b is the number of tasks being finished by an agent.

According to Eq.1, the experiences of neighboring agents is incorporated into the Q-value of the i^{th} agent through a weighted linear combination of their state values. So, each agent can learn from the previous experiences of its neighbors. However, these incorporation isn't always advantageous. In the contrary, the following problems can occur when applying the D-DCM-MultiQ method:

- Impossible cooperation in the case of obstacle avoidance scenario: If an agent A_1 hits an obstacle and gets a penalty, it saves this experience into its state value. When the same scenario occurs to another agent A_2 and agent A_1 is within its neighborhood, A_2 can't profit from the previous experience of its neighbor to avoid that obstacle since the multi-agent cooperation is only available when updating a state-action pair (s,a). However, according to the RL concept, this update is only occurring after experiencing the action a in the state s. A_2 could take advantage of prior knowledge of its neighbor A_1 if the cooperation was incorporated in the choice of the next action to perform, but this was not the case of the Boltzmann policy.
- Blockage of learning: By exploiting the knowledge of its neighbors when updating each state/ action pair, an agent can spread promising information (related to the food source) to intermediate states even before detecting the target. This will lead to a non-continuous spread of the goal's reward from the food source to the nest area. The agent can then trap between two intermediate states because only its own information is used when choosing the next action to perform. As the Boltzmann temperature decreases, the exploration rate also decreases and the opportunity to reach the target becomes increasingly difficult. This blockage is indeed due to an insufficient coordination between agents. Increasing exploration can solve these situations but prevents the system from constantly taking the best solution after convergence.

In the next section, we will present our suggestions to overcome these impasses, especially the proposition of a cooperative action selection strategy and the introduction of a new form of agent, called "relay agent", to improve the information exchange between learners.

4 OUR PROPOSALS FOR IMPROVING MULTI-AGENT COORDINATION

When using the Qvalues of all existing agents in the neighborhood, some of these values may be not promising before the convergence of the learning algorithm. For a better backward propagation of the goal's reward, a useful update of the Qvalue can be obtained by using only the information of the agent having the highest Qvalue in the next state. In this case, equation (1) becomes:

$$Q_{k+1,i}(s_i,a_i) = (1-\alpha_k)\,Q_{k,i}(s_i,a_i) + \alpha_k * \left(R_{k,i}(s_i,a_i) + \gamma max_{a'}(max_j\, Q_{k,j}\left(s'_i,a'\right))\right) \quad (3)$$

where agent j refers to agent i or one of its neighbors.

4.1 First Proposal: A Cooperative Action Selection Strategy

To ensure that each agent gets the most out of its neighborhood information, one possible solution is to exploit this information in the action choice in addition to when updating the state/action values. Thus, each agent chooses the next action to perform based on its own information as well as the information of its neighbors.

As a result, a new cooperative action selection strategy, called CG-LRVS (Cooperative Greedy policy based on Least Recently Visited States), is proposed. It's defined by Eq.4.

$$action_{CG-LRVS} = \begin{cases} argmax_a Q^*(s,a) & \text{with probability } \varepsilon \\ argmax_a Q^*(s,a) \text{ and leading to the least recently visited state} & \text{with probability } (1-\varepsilon) \end{cases} \quad (4)$$

where

$$|Q^*(s,a)| = max_{rob}|Q_{rob}(s,a)| \quad (5)$$

and rob refers to each agent in the communication range, including the agent itself.

For each pair (s,a), $max_{rob}|Q_{rob}(s,a)|$ refers to the largest absolute value of $Q(s,a)$ of all agents in the neighborhood. Once the agent selects the most reliable Qvalue of each available action in the current state s $(Q^*(s,a_1),...,Q^*(s,a_p))$ by using the absolute value and exploiting the information of all its neighborhood, it then applies the Boltzmann policy to select an action among all available ones.

The absolute value is particularly considered in order to determine the action leading to an obstacle that has already been tested by at least one agent. Thereby, this obstacle can be avoided without being really experimented, which makes possible the cooperation in the case of obstacle avoidance scenarios. The following scenario is presented for further explanation:

Consider that a penalty of -90 is received by an agent if it hits an obstacle and (s_i,a_i) is a state/action pair leading to a collision. At time step t, an agent R_1 is in the state s_i and has a neighboring agent R_2; If the transition (s_i,a_i) is already experimented by R_1 ($Q_{R1}(s_i,a_i) = -90$) and not yet by $R_2(Q_{R2}(s_i,a_i) = 0)$. Without using absolute values, $max_a(Q_{R1}(s_i,a_i), Q_{R2}(s_i,a_i)) = max_a(-90,0) = 0$. As a result, R_1 can choose the action a_i and make a bad decision in spite of its previous knowledge. On the contrary, by using the absolute value, $max_{rob}(|Q_{R1}(s_i,a_i)|,|Q_{R2}(s_i,a_i)|)$= $max_{rob}(|-90|,|0|) = 90$. R_1 will consider that the transition (s_i,a_i) has a value of -90 ($Q^*((s_i,a_i) = -90)$. The probability assigned to this transition, using the Boltzmann policy, will be lower than some other transitions (s_i,b). Consequently, R_1 will avoid this obstacle and chooses a more trusted action in that state.

The same scenario will take place if this transition is already experimented by R_2 ($Q_{R2}(s_i,a_i) = -90$) and not yet by $R_1(Q_{R1}(s_i,a_i) = 0)$: By exploiting the knowledge of R_2, R_1 will avoid the obstacle without the need to experiment it before.

Finally, as explained in our previous work (Zemzem and Tagina, 2015), exploiting least recently visited states accelerates learning since it encourages the agent to visit new and distant areas. This exploitation is possible using a new table $Anc : S \mapsto \mathbb{N}$ storing the last visit of each visited state. $Anc(s) = t$ means that the last visit of the state s was occurred at the learning iteration t. Each agent i saves one table Anc and updates it as follows:
For each pair $(s,a) \in S \times A$: $Anc(s,a) = Anc_j(s,a)$, where j refers to the same agent or one of its neighbors having the largest value of $Anc(s,a)$ (see Eq.6).

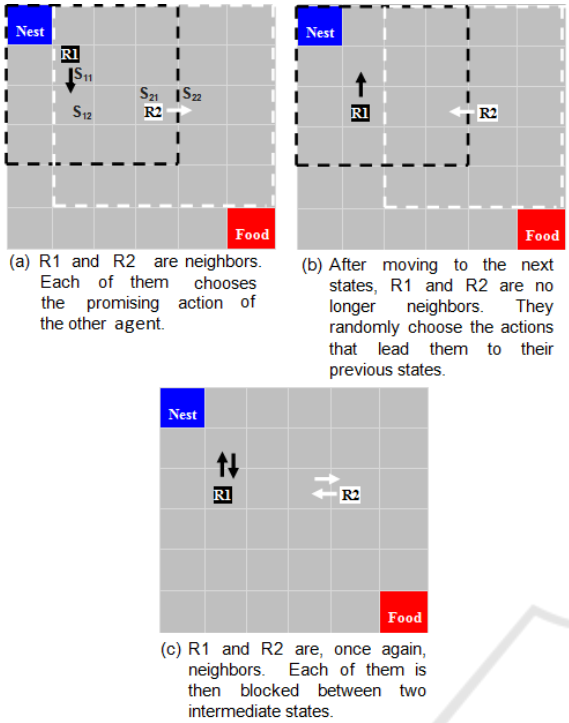
$$j = argmax_{agent}(Anc_{agent_i}(s,a), Anc_{neighbor_{i_1}}(s,a), ..., Anc_{neighbor_{i_n}}(s,a)) \quad (6)$$

4.2 Limits of Cooperative Action Selection Strategies

Because of the limited communication range, each agent can't take advantage of promising information of another agent unless it is within its neighborhood. As a result, even by using cooperative action selection strategy, the blockage still occur in the limits of the communication range and can't be solved if the other agent is waiting at the food source. Other blocking situations can occur during intermediate episodes (not the first one) after the propagation of the goal's reward to several non-consecutive states. In that case, all learning agents can trap between intermediate states before reaching the target and remain at this situation since no other agent can help them. Fig. 1 illustrates this scenario. In this example, the communication range is set to 3.

4.3 Second Proposal: Adding a "Relay" Agent

Our objective is to solve the problem of blockage while maintaining the same properties of the D-DCM-MultiQ approach namely, a model-free method and a



(a) R1 and R2 are neighbors. Each of them chooses the promising action of the other agent.

(b) After moving to the next states, R1 and R2 are no longer neighbors. They randomly choose the actions that lead them to their previous states.

(c) R1 and R2 are, once again, neighbors. Each of them is then blocked between two intermediate states.

Figure 1: Failings of the first proposal.

local communication range. To this end, we propose to use a ”relay” agent storing the Qvalues functions of all learning agents. Whenever a learning agent is in the neighborhood of the relay agent, it transmits its new function values to this relay agent. Thus, the relay updates its old knowledge. Conversely, when choosing the next action to perform, each learning agent exploits, in preference, the information of the relay if it is in its neighborhood. Otherwise, it uses the knowledge of the neighboring learners. In the worst case, if the neighborhood is empty, the agent uses only its own function values Q. Thus, by adding a ”relay” agent, a learning agent can take advantage of promising information from another agent not necessarily in its communication range. The same procedure is applied when updating the table Q and the table Anc (in Eq. 3 and Eq6, j refers to the relay else neighboring learners and in the worst case to the agent itself).

By this way, the blockage will be solved only in the area inside the communication range of the relay. As the relay's communication is also limited, fixing the relay in a specific position is not promising; a learning agent may be trapped between several states that are not all covered by the relay nor by other learners. A better alternative is that, at each learning step, the relay moves randomly and communicates with its neighboring learners to update its stored information. Using a moving relay, the blockage will be solved whatever the size of the environment, the communication range and the number of learning agents. This will be further explained in the experimental Section.

To avoid the storage of the Qtables of all learners, a reduction in the size of the relay's information is possible by retaining a single Qvalue for each state/action pair, like a learning agent. For each pair $(s,a) \in S \times A$, the update of Q by the relay is then as follows: $Q(s,a) = Q_j(s,a)$, where j refers to the relay or one of the neighboring learners having the largest absolute value of $Q(s,a)$ (see Eq. 7).

$$j = argmax_r(|Q_{relay}(s,a)|, |Q_{neighbor_1}(s,a)|, ..., |Q_{neighbor_n}(s,a)|) \quad (7)$$

4.4 Algorithms' Summary

Fig. 2 describes the learning procedure. Compared to D-DCM-MultiQ, the novelty is in using the CG-LRVS policy (Eq.4) for the action choice, the update of the Q-value using only the information of the agent having the highest Q-value in the next state (Eq. 3), in addition to a slight modification in the execution of learning steps so that the learner uses the same neighboring information to update the last experienced state/action pair as well as to choose the next action to perform.

```
Initialization
{
   For (agent i=1,..., N)
    {
     Initialize agent's position;
     For (state s=1,..., M)
        {
         Initialize Q(s, a) and Anc(s) to be zero;
        }
    }
}
For (agent i=1,...,N)
{
    Select action according to eq.4;
}
While (TRUE)
{
   For (agent i=1,...,N)
    {
     Execute action;
     Reward(i)=getReward();
    }
   For (agent i=1,...,N)
    {
     Update Anc(s): Anc(s)← t;
     Update Q(s,a) according to eq.3;
     If (TRUE)
       {
       Select action according to eq.4;
       }
    }
}
```

Figure 2: The pseudo code of the learner's behavior.

The relay agent doesn't use a learning approach. Fig. 3 describes how it acts at each learning step.

```
Initialization
{
    Initialize relay's position;
    Initialize Q(s, a) and Anc(s) to be zero;
}
While (TRUE)
{
    Select a random action;
    Execute action;
    Update Q and Anc as described earlier;
}
```

Figure 3: The pseudo code of the relay's behavior.

5 EXPERIMENTS AND ANALYSIS

In this Section, we will evaluate the impact of our proposals on distributed multi-agent decision-making. As described earlier, the testing scenario is a cooperative foraging task with a static target. We aim to evaluate the performance of our learning method in a wide unknown environment. While the experiences done in (Guo and Meng, 2010) are restricted to a 10×10 grid world, several experiences will be conducted in what follows with varying the environment size, the limit of the communication and the number of learning agents. The largest tested environnement contains 61×61 cells. It is then more than 37 times larger than the environment which is considered in (Guo and Meng, 2010).

The testing environment is simulated using Simbad, a Java 3d robot simulator (Hugues and Bredeche, 2006). A 30×30 grid world is shown in Fig. 4. The cell, called the nest, is the starting position. A ball, situated at the bottom right corner, refers to the food. The maze is surrounded by walls and contains obstacles.

For all performed experiments, the Q-value of each agent is setup to be zero initially. The exploration rate is defined as $\varepsilon = 0.5$. γ and α are defined as 0.9 for all agents. The neighborhood range is set at $\frac{Grid\_Width}{3}$ for each agent. This means that two agents can communicate when the distance between them is less than $\frac{Grid\_Width}{3}$ cells (using the Manhattan distance). It is assumed that agents can localize themselves within the grid map but they don't know where the target and obstacles are. The action set for each agent are defined as "up", "right", "down" and "left". Since it is a grid-based environment, we define the actual position of the agent as its state variable. We assume that every grid is large enough to contain several agents at the same time. These parameter settings and assumptions are used in (Guo and Meng, 2010) to evaluate the D-DCM-MultiQ algorithm. Note that all conducted experiences in the rest of the paper contain only one relay which moves randomly and the size of the multi-agent system corresponds to the number of learning agents.

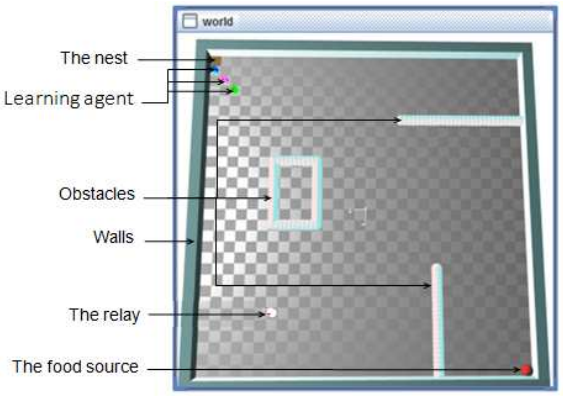


Figure 4: A 30×30 grid world.

Finally, as we deal with a large state space, several experiences have been made while varying the goal's reward and the best reward distribution is then adopted. It is defined as follows: $r = 0$ for regular actions, $r = -90$ for actions resulting collision with obstacles and $r = 18000$ for actions leading to the food source.

5.1 Result 1: The Impact of Cooperative Action Selection on the Learning Performance

In this Section, the proposed CG-LRVS policy (Eq. 4) is evaluated. For that, two systems of three learning agents are compared with varying the number and nature of agents that cooperate when selecting actions in each system:

- 1^{st} system using a cooperative action selection procedure (the agent exploits the relay's information if it's within its neighborhood else all others neighboring learners' information and in the worst case, only its own information) and a cooperative update of Q (Eq. 3).
- 2^{nd} system using a cooperative update of Q (Eq. 3) but without a cooperative action selection procedure (the agent uses only its own information). As described earlier, a minimum of cooperation in the action selection policy must be satisfied in order to avoid blocking situations and allow the completion of the foraging task. For that, we keep only one situation of cooperation between agents: it's when the relay and the learner are in the same cell.

As shown in Fig. 5-a, learning is accelerated through cooperative decisions. By exploiting more knowledge in the choice of the next action to perform,

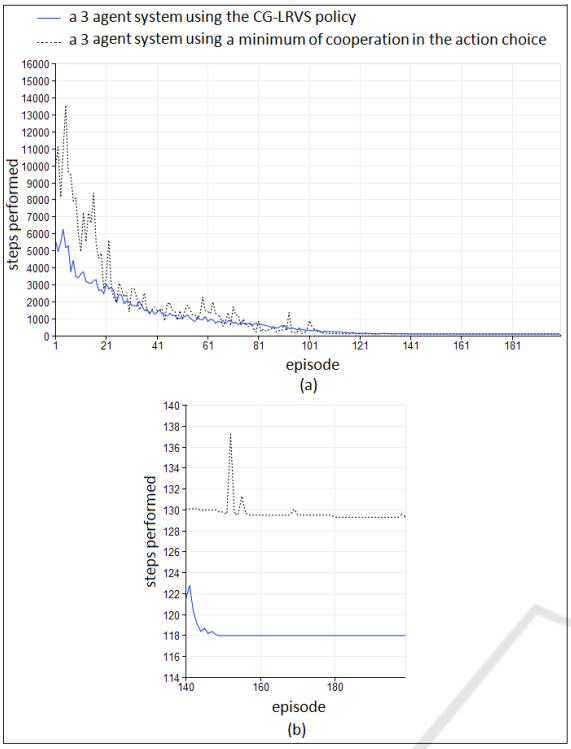


Figure 5: The average number of time steps needed on each episode over time, with varying the level of cooperation during the selection of actions (average of thirty experiences).

the chance to detect the food source at the earliest possible opportunity is increased and the length of learning episodes is therefore reduced. Moreover, comparing the learning curves in Fig. 5-b, the constructed path is less efficient when decreasing the cooperation level between agents: the agent doesn't benefit from other neighbors' knowledge to optimize its own path. That's why the agents' trajectories are often different and haven't the same length.

5.2 Result 2: The Impact of Modifying the Size of the Environment, the Number of Learning Agents and the Communication Range on the Learning Performance

It is of interest to understand the impact of modifying the size of the environment, the number of learning agents as well as the range of communication on our proposed learning method. Specifically, we intend to determine how the learning performance evolves in addition to how the communication frequency is affected.

To do that, several experiments are carried out with varying the aforementioned elements. In each experiment, results are calculated over 30 runs. The reward is defined as $\{-90, 0, 18000\}$.

The communication frequency measures how often information are transferred from one agent to another. For each agent (relay and learner), the communication frequency (resp. Com-Freq-Relay and Com-Freq-Learner) increases by 1 communication unit after receiving information from another agent. The communication frequency of the entire system (Com-Freq-System) is calculated by summing up the communication frequency of all its agents.

We note that the communication frequency is only recorded during the foraging phase. From the beginning of learning, the relay moves randomly and exchanges information with its neighboring learners. Once the food source is reached by all learners and the ferrying phase is started. Learning agents no longer communicate with the relay. This latter remains motionless and stops communicating with its neighbors until it is interrogated by one learning agent, which means the beginning of a new foraging phase.

5.2.1 Learning Performance

Table. 1 records the conducted experiments, the number of episodes and the average number of time steps required for the convergence of the system in each studied case.

It can be seen that, regardless of the size of the environment and the limit of the communication, the number of episodes and time steps needed before finding the optimal solution is decreased by increasing the number of agents. Learning is also accelerated by increasing the communication range; In the case of the 30×30 grid world and with the same number of agents, learning is expedited by raising the value of the communication range. The same holds true for the 61×61 grid world.

5.2.2 Impact of Increasing the Communication Range on the Communication Frequency

In this section, we aim to study the impact of increasing the communication range on the communication frequency. For that, two systems of several agents are tested:

- In the 1^{st} system, a 30×30 grid world is considered with varying the communication range from 5 to 10. The results are shown in Fig. 6.
- In the 2^{nd} system, a 61×61 grid world is considered with varying the communication range from 10 to 20. The results are shown in Fig. 7.

After increasing the communication range (to 10 in the 1^{st} system and to 20 in the 2^{nd} one), we note

Table 1: This caption has one line so it is centered.

Marge Communication	Grid Size	Number of learning agents	Episodes necessary for convergence	Average number of time steps needed for convergence (Mean values/Standard error)
5	10×10	2	24	3858.533 ± 88.33
		4	14	2392.566 ± 60.611
		8	8	1446.666 ± 41.632
	30×30	2	246	270440.566 ± 4141.963
		4	158	208745.233 ± 3597.89
		8	102	155556.566 ± 3473.187
		12	74	122650.233 ± 2753.296
10	30×30	2	189	215807.9 ± 3796.626
		4	94	133714.566 ± 2745.421
		8	54	79230.833 ± 1648.466
		12	35	59355.966 ± 1352.006
	61×61	2	468	$3.995 \cdot 10^6 \pm 22891.716$
		8	208	$2.314 \cdot 10^6 \pm 18597.436$
		20	108	$1.38 \cdot 10^6 \pm 13473.187$
		40	71	$0.898 \cdot 10^6 \pm 10298.942$

that, in both cases, the difference between Com-Freq-Relay and Com-Freq-learner becomes much greater and that Com-Freq-Relay increases significantly by extending the number of agents, contrary to Com-Freq-learner which increases much smaller in the 1^{st} system (Fig. 6-a and Fig. 6-b) and even decreases in the 2^{nd} one (Fig. 7-a and Fig. 7-b).

According to Fig. 6-b, we can see that in the case of a 30×30 grid world, the increase of Com-freq-learner is much smaller with Com-range=10 than that with Com-range=5. Moreover, when the number of learning agents exceeds 7, Com-Freq-Learner using Com-range=10 is less than that using Com-range=5.

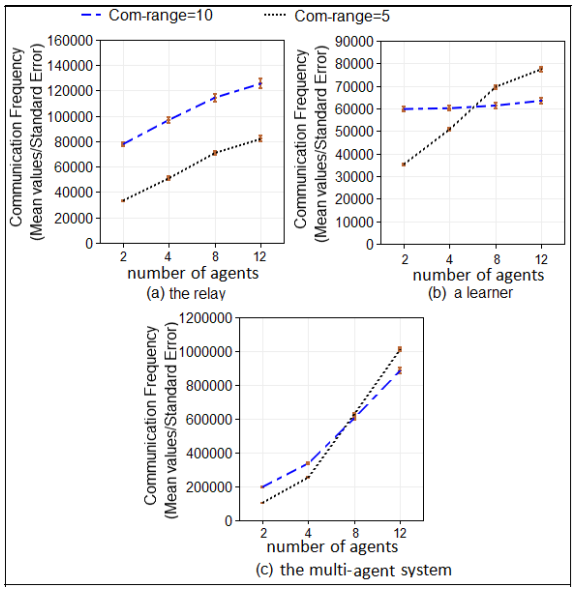


Figure 6: The impact of increasing the range of communication in the communication frequency (average of thirty experiences in a 30×30 grid world).

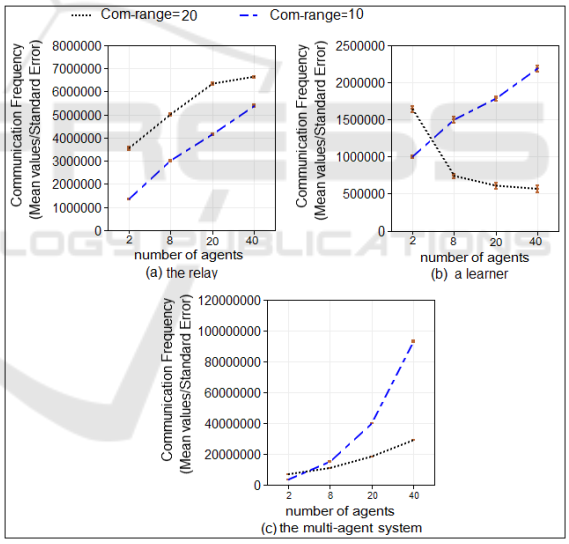


Figure 7: The impact of increasing the communication range in the communication frequency (average of thirty experiences in a 61×61 grid world).

As a result, the communication frequency of the entire system is also decreased while the learning is accelerated. Fig. 6-c illustrates this result; if number-of-agents>7:

Com-Freq-Sys(Com-range=10)$<$Com-Freq-Sys(Com-range=5)

The same holds true for the 61×61 grid world. According to Fig. 7, we can see that with Com-range=20, Com-Freq-Learner decreases by increasing the number of learners. This is because the commu-

nication with the relay is more favored which makes the cooperation more efficient. As a result, when the number of learning agents exceeds 4, the communication frequency of the entire system is also decreased while the learning is speeded up.

This justifies again why our method outperforms those storing all agents' Qtables by each learner, as EC (Cunningham and Cao, 2012) and PA (Tan, 1997). Using these latter methods, each learning agent communicates with all its neighbors which will always lead to the increase of Com-Freq-Sys. The gain made by our proposed method is not limited to the communication frequency but other savings in memory and computation are also ensured due to the decrease of information saved and updated by each learner.

6 CONCLUSION AND FUTURE WORKS

In this paper, a new distributed RL method for cooperative multi-agent systems is proposed. Its is based on a cooperative action selection policy and a relay agent that accelerate learning and ensure a good multi-agent coordination. However, to ensure an effective sharing of information, this method ignores collisions between agents. We expect to further improve our work by eliminating this restrictive assumption and trying more complex scenarios. Possible test cases include stochastic mazes (rather than deterministic mazes), several targets, as well as continuous state spaces. Real-world applications are usually characterized by these complex elements.

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