A Hybrid Interaction Model for Multi-Agent Reinforcement Learning

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Abstract: The main contribution of this paper is to implement a hybrid method of coordination from the combination of interaction models developed previously. The interaction models are based on the sharing of rewards for learning with multiple agents in order to discover interactively good quality policies. Exchange of rewards among agents, when not occur properly, can cause delays in learning or even cause unexpected behavior, making the cooperation inefficient and converging to a non-satisfactory policy. From these concepts, the hybrid method uses the characteristics of each model, reducing possible conflicts between different policy actions with rewards, improving the coordination of agents in reinforcement learning problems. Experimental results show that the hybrid method can accelerate the convergence, rapidly gaining optimal policies even in large spaces of states, exceeding the results of classical approaches to reinforcement learning.

1 INTRODUCTION

Multi-agent systems in general comprises of adaptive agents that interact with each other in order to conduct a given task. In a multi-agent system, agents need to interact and to coordinate themselves for carrying out tasks (Stone and Veloso, 2000). Coordination between agents can help to avoid problems with redundant solutions, inconsistency of execution, resources wasting and deadlock situations. In this context, coordination models based on learning are capable of solving complex problems involving social and individual behaviors (Zhang and Lesser, 2013).

Besides learning how to coordinate itself, an agent from a multi-agent system must also be able to cooperate to other agents in the system, attempting to solve problems that locally require unknown knowledge or problems that compromise the agent performance to be solved. In this way, sharing agent expertise (usually in terms of *action policies*) becomes essential to converge to a global behavior that satisfies a certain specification or that simply solves a particular problem.

An alternative to share agent's expertise among multi-agents is using specific computational paradigms that maximize performance based on reinforcement parameters (reward or punishment) applied to agents as they interact with the environment. Such paradigms are called *Reinforcement Learning* (RL) (Kaelbling et al., 1996) (Sutton and Barto, 1998).

RL algorithms, such as Q-learning (Watkins and Dayan, 1992), can be used to discover the optimal action policy for a single agent when it repeatedly explores its state-space.

Formally, an action policy can be modeled by a 5-tuple $b=\langle A, S, s^{\circ}, *, \rightarrow \rangle$ that maps states and actions in order to determine, among a set of actions A and a set of states S, which an action $a \in A$ should be performed at a given state $s \in S$. An action policy model has also an initial state $s^{\circ} \in S$, an objective state $s^{*} \in S$, and a transition relation $\rightarrow$ that defines the range of actions possible to be generated from a state. The relation $\rightarrow$ is defined as *memoryless*, i.e., it defines actions taking into account uniquely the current state, which qualifies the approach as a *Markovian Decision Process* (MDP).

A major concern that arises from this action-policy-discovering approach is that it tends to suffer with large state-spaces, due to *state-space explosion* problems. In this case, RL involving multiple agents has shown to be a promising strategy that modular-

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izes the whole problem and locally implements action policies (Ribeiro *et al.*, 2008).

The whole idea behind the implementation of local policies is discovering a global action plan generated by the proper combination of local knowledge of agents. When this approach leads to the best global action plan, the policy Q is said to be optimal (Q^*) and it maximizes the reward received by agents.

The approach investigated in this paper aims to improve the way agents share information with each other. In order to transmit and receive information, agents are required to share a cooperative and coordinated interaction model that eventually leads to improved action policies. So, the kernel for establishing optimized information sharing strategies for multiple agents is the interaction model.

In this paper we introduce a hybrid coordination model for multi-agents using RL techniques. Our approach collects "good" features from individual approaches in the literature and integrates them into a single framework, which can then be used to establish optimized information sharing strategies for multiple agents. Preliminary results compare the performance of the hybrid model with respect to the each particular model that has been used to compose our framework. In general, we have observed a convergence rate among agents substantially better than in the other cases.

The remainder of this paper is organized as follows. In the following section, the state of the art is presented, in which: (i) describes some coordination methods for learning in multi-agent systems; (ii) reviews of the Q-learning algorithm; and (iii) summarizes the interaction models. The details of the proposed method, environmental assessment and numerical results to demonstrate the performance of the method are present in Section 3. Conclusions are drawn in Section 4.

2 LEARNING IN MULTI-AGENT SYSTEMS

Learning in multi-agent systems, unlike learning in environment with a single agent, assumes that the relevant knowledge is not locally available in a single agent, although it is necessary to coordinate the whole process (Chakraborty and Stone, 2014), (Zhang and Lesser, 2010), (Xuan and Lesser, 2002). One way for an agent to coordinate its actions is by interacting with other agents, changing and evolving their own coordination model.

Coordination by interaction provides the combination of efforts among a group of agents when searching for solutions to global problems (DeLoach and Valenzuela, 2007). A situation of interaction is a set of behaviors resulting from a group of agents that act to satisfy their goals and consider constraints imposed by resources limitations and individual skills. In the literature, learning from interactions composes a preeminent research topic (Ribeiro et al., 2013), (Xinhai and Lunhui, 2009), as well as collective or social learning (Ribeiro et al., 2013), (Ribeiro and Enembreck, 2013).

Learning problems involving RL interaction models depends basically on a structure that enables communication among agents, so that they can share their accumulated rewards, which immediately reinforces the transition system. With this propose, Chapelle *et al.* (2002) propose an interaction model that calculates rewards based on the individual satisfaction of neighboring agents. In this learning process, agents continuously emit a level of personal satisfaction. Differently, Saito and Kobayashi (2016) develop a learning strategy in which agents are able to keep memory about information they have accumulated, so they can reuse them in the future. This method has been tested on colored mazes and reports confirm that it positively impacts on jumpstarts and reduces the total learning cost, compared to the conventional Q-learning method.

Ribeiro and Enembreck (2013) combine theories from different fields to build social structures for state-space search, in terms of how interactions between states occur and how reinforcements are generated. Social measures are used as a heuristic to guide exploration and approximation processes. Experiments show that, identifying different social behavior within the social structure that incorporates patterns of occurrence between explored states helps to improve ant coordination and optimization process.

Usually, it is challenging to integrate different methods into a single improved generic coordination model, especially due to the diversity of the classes of problems and the amount of knowledge necessary from the problem domain. Furthermore, in a multi-agent system, conflicting values for cumulative rewards can be generated, as each agent uses only local learning values (DeLoach and Valenzuela, 2007). Thus, the collective learning assumes that the relevant knowledge occurs when rewards are shared, intensifying the relationship between agents.

2.1 Reinforcement Learning

RL tries to solve problems where an agent receives a return from the environment (rewards or punish-

ments) for its actions. This type of learning has been extensively investigated in the literature (Grze's and Hoey, 2011), (Devlin et al., 2014), (Efthymiadis and Kudenko, 2015), (Tesauro, 1995), (Walsh *et al.*, 2010), (Zhang and Lesser, 2013) in order to approximate solutions to NP-hard problems.

To properly formalize a RL problem, it is essential to first describe how a MDP structure is composed. A MDP is a tuple $\langle S, A, T^{a}_{s,s'}, R^{a}_{s,s'} \rangle$ such that S is a finite set of environmental conditions, that may be composed, for example, by a variable sequence of states $\langle x_1, x_2, \ldots, x_v \rangle$; A is a finite set of actions, where an episode a_n is a sequence of actions $a \in A$ which leads the agent from a state $s_{initial}$ to a state $s_{objective}$, $T^{a}_{s,s'}$ is a transition state relation $T : S \times A \rightarrow [0,1]$, that indicates the probability of an agent to reach a state s' when an action is applied at the state s. Similarly, $R^{a}_{s,s'}$ is a reward function $R : S \times A \rightarrow \Re$ received whenever a transition $T^{a}_{s,s'}$ occurs.

The goal of a RL agent is to learn a policy π: $S \times A$ which maps the current state s into a desired action to maximize the rewards accumulated over the time, describing the agent's behavior (Kaelbling *et al.*, 1996). To achieve optimal policies, the RL algorithm must iteratively explore the state space $S \times A$, updating the accumulated rewards and storing rewards in $Q(s, a)$ (Equation 1).

A well known method that can be used to solve RL problems is called *Q-learning* (Watkins and Dayan, 1992). The basic idea of the method is that the learning algorithm learns an optimal evaluation function for all pair state-action in $S \times A$. The Q function provides a mapping Q: $S \times A \rightarrow V$, where V is the value of expected utility when performing an action a in state s. The function $Q(s,a)$, of the expected reward when choosing the action, is learned through a *trial and error* approach, as described by Equation 1:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[R + (y \times V)] \qquad (1)$$

where $\alpha \in [0,1]$ is the learning rate, R is the reward, or cost resulting from taking action a in state s, y is the discount factor and V is obtained by using the function Q learned by now. A detailed discussion about Q-learning can be found in (Watkins and Dayan, 1992).

In this paper, Q-learning is used to generate and evaluate partial and global action policies. By applying Q-learning it is possible to find a policy to an agent. However, if similar agents interact into the same environment, each agent has its own MDP, and optimal global behavior can not be set by local analysis. Thus, in an environment formed by several agents, the goal is to select the actions of each MDP at time t, so that the total expected rewards for all agents is maximized.

2.2 Reinforcement Learning with Multiple Shared Rewards

In RL algorithms with multiple shared rewards, agents can produce a refined set of behaviors obtained from the executed actions. Some behaviors (*e.g.*, a global action policy) are shared by agents through a partial policy action (Q_i). Usually, such policies contain partial information (learning values) about the environment (E), but communicate with a central structure to share rewards in an integrated way in order to maximize the sum of the partial rewards obtained during the learning process. When policies $Q_1,\ldots,Q_x$ are integrated, it is possible to make a new policy $\partial = \{Q_1,\ldots,Q_x\}$, where $\partial(s,a)$ is a table that denotes the best rewards acquired by agents during the learning process.

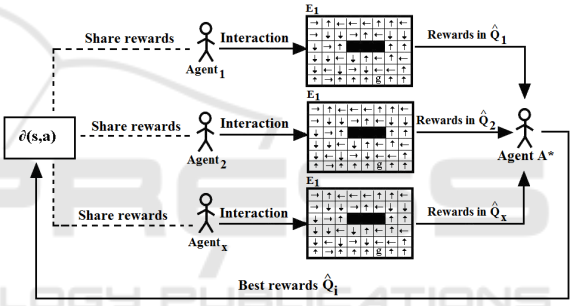


Figure 1: Learning with shared rewards (Ribeiro *et al.*, 2008).

Figure 1 shows how agents exchange information during learning. When the agent A* receives rewards from other agents $Agent_i$, the following process occurs: when $Agent_i$ reaches the goal state g from a state $s \neq g$ with a lower-cost way, the agent uses a model to share such rewards with other agents. The learning values of a partial policy $\hat{Q}_i$ can be used to upgrade the overall policy $\partial(s,a)$, further interfering in how other agents update their knowledge and interact with the environment.

Figure 1 also shows the function that shares such rewards. This task can be accomplished in three ways (summarized in subsection 2.2.1), all internally using Q-learning. The best rewards from each agent are sent to $\partial(s,a)$, forming a new policy with the best rewards acquired by agents $Agent_i = \{i_1,\ldots i_x\}$, which can be socialized with other agents. A cost function (Equation 2) is used to estimate $\partial(s,a)$, which calculates the cost of an episode (path from an initial state s to the goal g) in a given policy.

$$cost(s,g) = \sum_{s \in S}^{g} 0.1 + \sum_{s \in S}^{g} st(S) \quad (2)$$

The discovery of this path is performed with the A* algorithm which produces a generative model for managing policies that maximize the expected amount of reward, *i.e.*, optimal policies, according to the methodology presented in (Ribeiro *et al.*, 2006).

The cooperative RL algorithm, the other algorithms, and the elements formalizing the RL models are detailed in (Ribeiro *et al.*, 2008). Figure 2 summarizes the learning process with the models in an activity diagram that uses the algorithms proposed in (Ribeiro *et al.*, 2008).

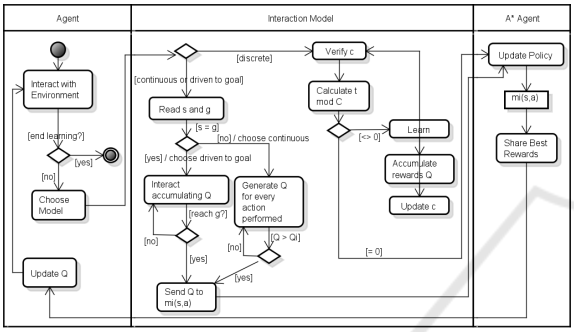


Figure 2: The learning process activity diagram with the interaction models.

2.2.1 Interaction Models

In this subsection, we summarize the models presented in (Ribeiro *et al.*, 2008).

Discrete Model: The agents share learning in a predefined cycle interactions *c*. Cooperation in the discrete model occurs as follows: the agent accumulates rewards obtained from its actions during the learning cycle. At the end of the cycle, each agent sends the values of $\hat{Q}_i$ to *∂(s,a)*. The agent share its reward if and only if it improves the efficiency of the other agents at the same state.

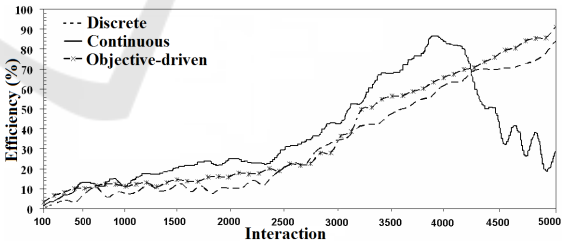
Continuous Model: The agents cooperate at every transaction $T^{a}_{s,s'}$. Cooperation in the continuous model occurs as follows: if $s \neq g$, then every action performed by the agent generates a reward value, which is the sum of the accumulated reinforcements for all players in action *a* in state *s*. The goal is to accumulate the greatest rewards in $\hat{Q}_i$ that can be shared at each iteration.

Objective-driven Model: Unlike the discrete model, cooperation occurs when the agent reaches the goal state, *i.e.*, $s = g$. In this case, the agent interacts accumulating reward values. It is necessary because in this model the agent shares his rewards only when the state goal is reached. When the agent reaches the goal state, the rewards value is sent to *∂(s,a)*. If the state reward value improves the overall efficiency, then the agents share such rewards. It shows that even sharing unsatisfactory rewards (due to of lack interaction), the agent is able to adapt his behavior without damaging the global convergence.

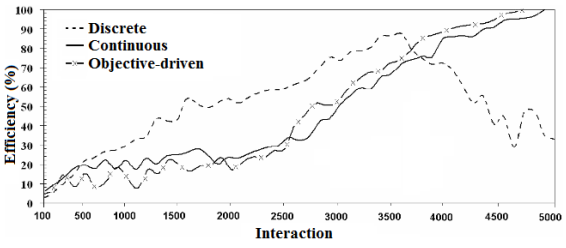
3 HYBRID COOPERATION MODEL

In RL based on shared rewards, is usual to discover intermediate action policies that are not appropriate to achieve a certain goal. In fact, the knowledge exchange among agents may lead to intermediate action plans that do not immediately fit to the agent's convergence. As each agent constantly updates its own learning, it becomes necessary that all agents are aware of all updates happening and of the reward from each agent.

Using the previously presented approaches for agent's coordination based on shared rewards, there is no guarantees that the action plans will converge sometime. It can happen that policies with initially mistaken states and values are improved by rewards informed by other intermediate policies, improving the *∂(s,a)* function. However, the opposite is also possible, *i.e.*, initially interesting policies, with high level rewards, may become less interesting to be chosen during a given policy, as states previously producing successful hits and errors.



A. **400** states and **5** agents



B. **400** states and **10** agents

Figure 3: Coordination models (Ribeiro *et al.*, 2008).

In order to overcome this inconvenience (local

maximum), we develop in this paper a hybrid method for multi-agents coordination. This approach emerges from the discrete, continuous and objective-driven models previously presented. By analyzing results collected from those models, we claim that the behavior of $\partial(s,a)$ changes as a function of number of interactions of the algorithms, the quantity of episodes involved in the problem and the cardinality of the set of agents that have been used. Figure 3 supports our claim by comparing coordination models immerse in a 400-states environment.

The proposed hybrid method capture the best features from each individual interaction model, at every interaction of the coordination. The discovery of new action policies is done without delaying the learning process, reducing the probability of conflicts among actions from different policies.

Technically, the hybrid method can be summarized as follows: at every interaction of *Q*-learning, the agent's performance is collected from each interaction model. This composes what we call a *learning table* named *HM-∂(s,a)* (Hybrid Method). When the model update condition is reached, the agent starts its learning process using the best performance calculated from the learning tables in the interaction models. The learning is then transferred to *HM-∂(s,a)*. Therefore, the function *HM-∂(s,a)* will always comprise the best rewards obtained from the discrete, continuous and objective-driven models.

```
   Algorithm for the Hybrid Method
M:discrete-D,  continuous-C,  objective-O
//models
   Qi: QM_D, QM_C, QM_O //learning tables
1   For each instance of Qi ∈ M do
2      If QM_D *> QM_C and
3         QM_D *> QM_O then
4            HM-∂(s,a) ← QM_D
5      else if
6           QM_C *> QM_D and
7           QM_C *> QM_O then
8              HM-∂(s,a) ← QM_C
9      else
10             HM-∂(s,a) ← QM_O
11     end if
12  end for
13  Return (HM-∂(s,a))
```

Algorithm 1: Hybrid Method Algorithm.

Algorithm 1 presents the integration of discrete, continuous and objective-driven interaction models. As it can be observed, for every learning cycle, the agent performance is compared with respect to the interaction models that have been used (by the operator '*>' over the three learning tables). When a given model returns a superior performance with respect to the model that has been compared, this learning is transferred to *HM-∂(s,a)*, which represents the current action policy of the Hybrid Method. The next section presents a simulation environment to assess the efficiency of the proposed model.

3.1 Experimental Results

In order to assess the proposed approach, we present a simulation environment composed by a state-space representing a traffic structure over which agents (drivers) try to find a route.

The structure has an initial state (s_{init}), an objective state (g) and a set of actions $A = \{\uparrow$ *(forward),* $\rightarrow$ *(right),* $\downarrow$ *(back),* $\leftarrow$ *(left)}*. A state s is a pair *(X,Y)* in which the element define the position on the axis X and Y, respectively. A status function $st : S \rightarrow ST$ maps traffic situations (rewards) to states, such that *ST = {–0,1 (free route); –0,2 (a bit stuck); –0,3 (stuck or unknown); –0,4 (heavily stuck); –1 (blocked); 1,0 (g)}*.

For this scenario, agents simulates available routes for drivers. The global goal is elaborate an action policy (combination that maps states and actions) that can determine the best route connecting s_{init} to g. The global action policy is defined by determining step by step which action $a \in A$ should be performed at each state $s \in S$. After every moving of the agent (transition/ interaction) from a state s to a state s', it knows whether or not its action has been positive, as it recognizes the set of rewards shared by the other models. The rewards for a given transition $T^{a}_{s,s'}$ is denoted by *st(s')*.

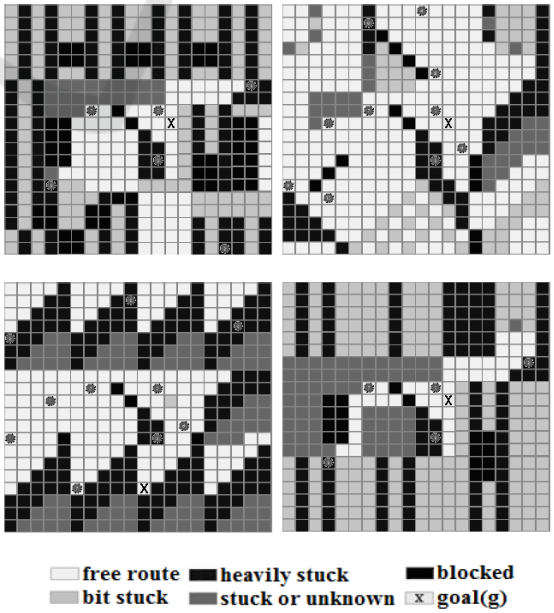


Figure 4: Simulated scenarios. The agents have a visual field depth of 1.

Figure 4 presents some scenarios that have been used for simulations. They have been arbitrarily generated, aiming to reproduce situations as closely as possible to real world situations. The agents are randomly positioned into the state-space. When an agent reaches the goal state, this agent is randomly positioned into others state s, until the stopping criterion is satisfied (interactions numbers).

3.2 Comparative Analysis

The results illustrated in this section compares the Hybrid Method to the individual performances obtained as in the Discrete, Continuous and Objective-driven interaction models.

The parameters that have been used in the Hybrid Method are the same as those used for the individual models: discount fator (y) of 0.99 and learning rate (α) of 0.2 (Ribeiro *et al.*, 2008).

Experiments have been conducted on environments ranging from 100 (10 × 10) to 400 (20 × 20) states. For the sake of clarity, however, in this paper we concentrate them on the largest state-space. The results that follow compare the Hybrid Method to the other methods using 3, 5 and 10 agents, in an environment composed by 100, 250 and 400 states.

Observe that in Figures 5-11 the Hybrid Method has shown to be more efficient with respect to the individual performance achieved by the other models. In general, it has shown to be superior at any interaction phase, which substantially reduces the number of interactions necessary to find out a proper action policy.

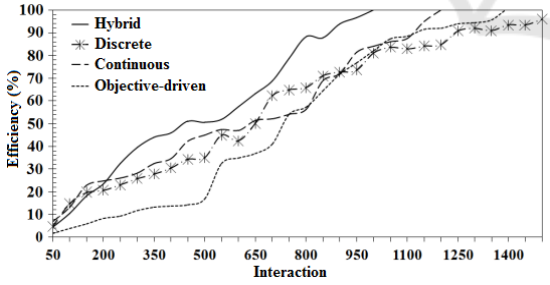


Figure 5: **100** states and **3** agents.

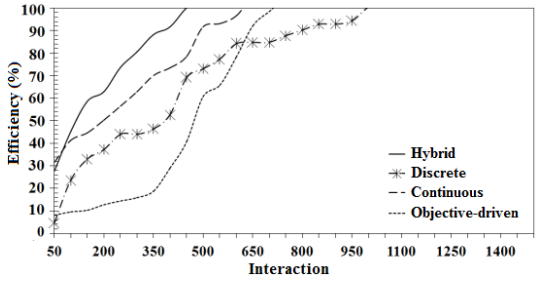


Figure 6: **100** states and **10** agents.

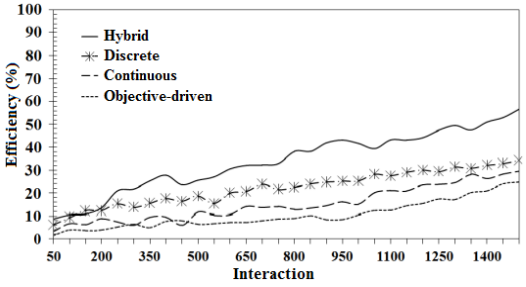


Figure 7: **250** states and **3** agents.

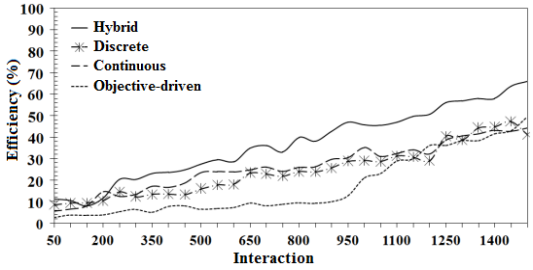


Figure 8: **250** states and **5** agents.

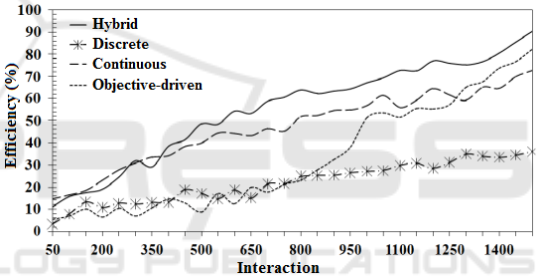


Figure 9: **250** states and **10** agents.

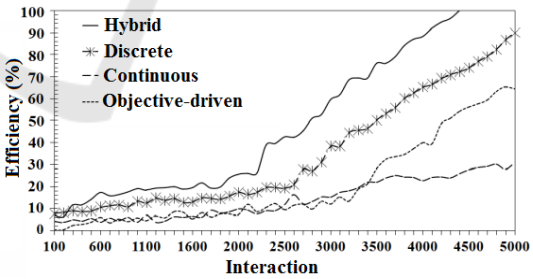


Figure 10: **400** states and **3** agents.

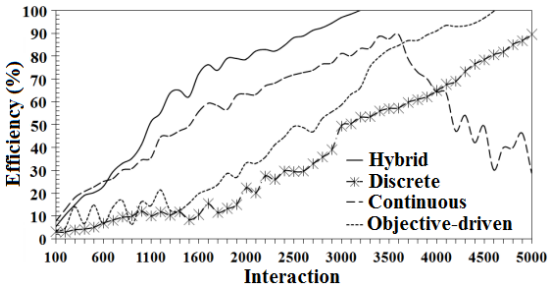


Figure 11: **400** states and **10** agents.

For experiments on environments with 100 states, the number of interactions has been reduced in average 22.8% when using 3 agents; 26.7% with 5 agents; and 41.1% using 10 agents. For environments with 250 states, the method reduces the number of interactions in 21.1% with 3 agents; 21.9% with 5 agents; and 32.7% for 10 agents. For environments with 400 states, the number of interactions has been reduced in 17,4% with 3 agents; 22,9% with 5 agents; and 29,1% for 10 agents. Table 1 summarizes the improvements of the Hybrid Method compared to the best method among the other models.

Table 1: Overall comparative analysis.

State-space	Number of agents		
	3	5	10
100	16.5%	68.7%	36.9%
250	49.4%	30.9%	32.6%
400	44.2%	41.1%	38.2%

The overall improvement achieved by the Hybrid Method, considering all tested number of agents and state-spaces, reaches the order of 40%.

4 CONCLUSIONS AND DISCUSSIONS

This article designs a hybrid method to improve coordination in multi-agent systems from the combination of interaction models presented in a previous work. In sequential decision problems an agent interacts repeatedly in the environment and tries to optimize its performance based on the rewards received. Thus, it is difficult to determine the best actions in each situation because a specific decision may have a prolonged effect, due to the influence on future actions. The proposed hybrid method is able to take the agent to an acceleration in the convergence of their action policy, overcoming the particularities found in the interaction models presented in (Ribeiro *et al.*, 2008). The political of these models may have different characteristics in environments with different configurations, causing the agent fails to converge at certain cycles of learning. Thus, the hybrid method of coordination uses the best features of interaction models (summarized in Subsection 2.3.1). The hybrid method policies outweigh the policy of each model, assisting in the exchange of best rewards to form a good overall action policy. This is possible because the hybrid method can estimate the best rewards acquired through learning, discovering an arrangement with the best ribs found in partial action policies for each model.

Accumulate rewards generated by different action policies is an alternative to support an adaptive agent in search of good action policies. Experiments with the hybrid method show that even with a higher computational cost, the results are satisfactory, since the approach improves convergence in terms of the Q-learning algorithm standard. The complexity introduced using n agents is around $O(n \times m)$, which is equal to $O(m)$ since n is a small constant and $O(m)$ is the complexity of the RL algorithm used as baseline.

Despite the satisfactory results, additional experiments are needed to answer some open questions. For example, the use of algorithms with different paradigms could be used to explore the states with the highest congestion regions? We observed that in these regions the rewards of states are smaller. A reinforcement learning algorithms system with different paradigms was proposed in (Ribeiro and Enembreck, 2013), where the results seem to be encouraging. It is intended also use different methods of learning to analyze situations such as: (i) explore the most distant states the goal, where exploration is less intense and; (ii) use a heuristic function, which a priori could accelerate the convergence of algorithms, where a heuristic policy indicate the choice of the action taken and, therefore, limit the agent of the search space. It is intended to further evaluate the method in dynamic environments and with greater variations states.

4.1 Real-world Applications

The hybrid model proposed in this paper has been tested in scenarios in which it was possible to control all the environmental variables. In many real-world problems, you cannot always control the factors that affect the system, such as external variables to the environment. With the promising results of the hybrid model presented in this article, we started to adapt this model to a real case to support the daily decisions of the poultry farmer. In this problem, the agent of the system is used to generate action policies, in order to control the set of factors in the daily activities, such as food-meat conversion, amount of food to be consumed, time to rest, weight gain, comfort temperature, water and energy to be consumed, etc. The main role of the agent is to perform a set of actions to consider aspects such as productivity and profitability without compromising bird welfare. Initial results show that, for the decision-taking process in poultry farming, our model is sound, advantageous and can substantially improve the agent ac-

tions in comparison with equivalent decision when taken by a human specialist. In the moment, we are evaluating the performance of the agent when handling specific management situations; checking the performance of the algorithm to process variations of scenario; and changing the set of attributes used to generate the rules, which can make them less susceptible to influence. Such statements are objects of study for future research.

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REFERENCES

Chakraborty, D. and Stone, P. (2014). Multiagent learning in the presence of memory-bounded agents. *Autonomous Agents and Multi-Agent Systems*, 28(2):182–213.

Chapelle, J., Simonin, O., and Ferber, J. (2002). How situated agents can learn to cooperate by monitoring their neighbors' satisfaction. *ECAI*, 2:68–78.

DeLoach, S. and Valenzuela, J. (2007). An agent environment interaction model. In Padgham, L. and Zambonelli, F., editors, *Agent-Oriented Software Engineering VII*, volume 4405 of *Lecture Notes in Computer Science*, pages 1–18. Springer Berlin Heidelberg.

Devlin, S., Yliniemi, L., Kudenko, D., and Tumer, K. (2014). Potential-based difference rewards for multiagent reinforcement learning. In *Proceedings of the 2014 International Conference on Autonomous Agents and Multi-agent Systems*, AAMAS '14, pages 165–172, Richland, SC. International Foundation for Autonomous Agents and Multiagent Systems.

Efthymiadis, K. and Kudenko, D. (2015). Knowledge revision for reinforcement learning with abstract mdps. In *Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems*, AAMAS '15, pages 763–770, Richland, SC. International Foundation for Autonomous Agents and Multiagent Systems.

Grze's, M. and Hoey, J. (2011). Efficient planning in rmax. In *The 10th International Conference on Autonomous Agents and Multiagent Systems - Volume 3*, AAMAS '11, pages 963–970, Richland, SC. International Foundation for Autonomous Agents and Multiagent Systems.

Kaelbling, L. P., Littman, M. L., and Moore, A. P. (1996). Reinforcement learning: A survey. *Journal of Artificial Intelligence Research*, 4:237–285.

Ribeiro, R., Borges, A., and Enembreck, F. (2008). Interaction models for multiagent reinforcement learning. In *Computational Intelligence for Modelling Control Automation, 2008 International Conference on*, pages 464–469.

Ribeiro, R. and Enembreck, F. (2013). A sociologically inspired heuristic for optimization algorithms: A case study on ant systems. *Expert Systems with Applications*, 40(5):1814 – 1826.

Ribeiro, R., Enembreck, F., and Koerich, A. (2006). A hybrid learning strategy for discovery of policies of action. In Sichman, J., Coelho, H., and Rezende, S., editors, *Advances in Artificial Intelligence - IBERAMIASBIA 2006*, volume 4140 of *Lecture Notes in Computer Science*, pages 268–277. Springer Berlin Heidelberg.

Ribeiro, R., Ronszcka, A. F., Barbosa, M. A. C., Favarim, F., and Enembreck, F. (2013). Updating strategies of policies for coordinating agent swarm in dynamic environments. In Hammoudi, S., Maciaszek, L. A., Cordeiro, J., and Dietz, J. L. G., editors, *ICEIS (1)*, pages 345–356. SciTePress.

Saito, M. and Kobayashi, I. (2016). A study on efficient transfer learning for reinforcement learning using sparse coding. *Automation and Control Engineering*, 4(4):324 – 330.

Stone, P. and Veloso, M. (2000). Multiagent systems: A survey from a machine learning perspective. *Autonomous Robots*, 8(3):345–383.

Sutton, R. S. and Barto, A. G. (1998). *Reinforcement Learning : An Introduction*. MIT Press. Tesauro, G. (1995). Temporal difference learning and tdgammon. *Commun. ACM*, 38(3):58–68.

Walsh, T. J., Goschin, S., and Littman, M. L. (2010). Integrating sample-based planning and model-based reinforcement learning. In Fox, M. and Poole, D., editors, *AAAI*. AAAI Press.

Watkins, C. J. C. H. and Dayan, P. (1992). Q-learning. *Machine Learning*, 8(3):272–292.

Xinhai, X. and Lunhui, X. (2009). Traffic signal control agent interaction model based on game theory and reinforcement learning. In *Computer Science-Technology and Applications, 2009. IFCSTA '09. International Forum on*, volume 1, pages 164–168.

Xuan, P. and Lesser, V. (2002). Multi-Agent Policies: From Centralized Ones to Decentralized Ones. *Proceedings of the 1st International Joint Conference on Autonomous Agents and Multiagent Systems*, Part 3:1098–1105.

Zhang, C. and Lesser, V. (2010). Multi-Agent Learning with Policy Prediction. In *Proceedings of the 24th AAAI Conference on Artificial Intelligence*, pages 927–934, Atlanta.

Zhang, C. and Lesser, V. (2013). Coordinating Multi-Agent Reinforcement Learning with Limited Communication. In Ito, J. and Gini, S., editors, *Proceedings of the 12th International Conference on Autonomous Agents and Multiagent Systems*, pages 1101–1108, St. Paul, MN. IFAAMAS.