Human and Multi-Agent collaboration in a human-MARL teaming framework

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June 15, 2020

Abstract

Collaborative multi-agent reinforcement learning (MARL) as a specific category of reinforcement learning provides effective results with agents learning from their observations, received rewards, and internal interactions between agents. However, centralized learning methods with a joint global policy in a high dynamic environment present unique challenges in dealing with large amounts of information. This study proposes two innovative solutions to address the complexities of a collaboration between a human and multiple reinforcement learning (RL)-based agents (referred to thereafter as “Human-MARL teaming”) where the goals pursued cannot be achieved by a human alone or agents alone. The first innovation is the introduction of a new open-source MARL framework, called COGMENT, to unite humans and agents in real-time complex dynamic systems and efficiently leverage their interactions as a source of learning. The second innovation is our proposal of a new hybrid MARL method, named Dueling Double Deep Q learning MADDPG (D3-MADDPG) to allow agents to train decentralised policies parallelly in a joint centralised policy. This method can solve the overestimation problem in Q-learning methods of value-based MARL. We demonstrate these innovations by using a designed real-time environment with unmanned aerial vehicles driven by RL agents, collaborating with a human to fight fires. The team of RL agent drones autonomously look for fire seats and the human pilot douses the fires. The results of this study show that the proposed collaborative paradigm and the open-source framework leads to significant reductions in both human effort and exploration costs. Also, the results of the proposed hybrid MARL method shows that it effectively improves the learning process to achieve more reliable Q-values for each action, by decoupling the estimation between state value and advantage value.

1 Introduction

Multi-agent Reinforcement Learning (MARL) employed in various decision-making tasks within multi-agent systems (MAS) has, as of late, resulted in large gains with respect to the scaling of reinforcement learning (RL) in applications such as auto-driving [1], traffic management [2] [3], navigation systems [4] [5] [6], recommender systems [7], and network service/packet delivery [8] [9].

Centralized-based MARL does, however, present unique challenges due to large environment state and action space sizes, as well as reward determination. This complexity, stemming from the difficulties related to dimensionality and
highly-dynamic, continuous environments (considered herein), calls for the running of a large number of MARL based training trials in order to learn about the environment. Decentralised MARL, on the other hand, focuses on individual agents interacting with the environment, while ignoring other agents in order to simplify the training process. While it can reduce observation/action size by ignoring the joint observation/action spaces, it suffers from dramatically changing the transition probabilities and violating the Markov assumption.

Hybrid-based MARL, widely used as of late, considers a decomposition between the training and execution processes, known as centralized training - with decentralized execution (CTDE), that exploits the benefits of both learning methods. Several studies have proposed different hybrid models like counterfactual multi-agent (COMA) policy gradients, multi-agent deep deterministic policy gradient (MADDPG), value decomposition networks (VDN), QMIX, QTRAN, or multi-agent variational exploration (MAVEN), they often suffer from overestimation of the Q-value in value-based RL.

The other approach considered in this study entails the involvement of humans in the training process of RL-based multi-agent systems. While studies have investigated the impact of human feedback and recommended its use to improve the sample efficiency of a single RL agent, as in imitation learning, behavioural cloning (BC), learning from demonstration (LfD), data-set aggregation (DAGGER), generative adversarial imitation learning (GAIL), we could not find any relevant study on human-AI teaming in multi-agent systems. A few studies have investigated the human-AI team concept in single agent systems in which performances of both human and AI agent play a critical role in accomplishing the task of the system. Both human and AI agent, with different expertise levels, should be aware of how to collaborate one another.

The success of RL and multi-agent system (MAS) methods and algorithms in previous years highlights an essential need for scalable simulation platforms and RL frameworks. While different research groups have proposed RL frameworks which can manage different aspects of the agent and environment relationship (OpenAI Gym, MuJoCo, Arcade Learning Environment, RLLib, Horizon, and Dopamine), the lack of a comprehensive human-MARL framework, usable for any type of environment design, and able to facilitate communication between humans and the multi-agent system, prevents researchers from investigating and exploiting human expertise in multi-agent systems.

The main goal of this paper is to effectively involve humans in multi-agent collaborative systems to achieve "human-MARL teaming". The proposed solution is divided into two main components: (1) leveraging the "human-MARL teaming framework", specifically, using COGMENT to handle collaboration between human and multiple RL-based agents in different environments. Using COGMENT, we present a new method for online human-agent interaction employing different simulated environments and simulators. (2) Reduce the overestimation of the Q-value component of hybrid-based MARL by proposing Dueling Double Deep Q learning MADDPG (D3-MADDPG). We validate the proposed human-MARL teaming method and framework using a designed simulator deployed through Cogment. This simulation, called “Flames”, revolves around a team made of a human helicopter pilot and several Unmanned Aerial Vehicles (UAVs) fighting forest fires together. The MARL environment consists of this team of RL agent drones that autonomously scout for fires and the human pilot who then douses the flames.

The remainder of the paper is organized as follows: Section 2 presents an overview of other related works. Section 3 describes the background methods of this study. Section 4 deals with the proposed methods and the contributions of this paper. Section 5 deals with the experimental and detailed analysis of the results followed by a discussion of the performance obtained. Finally, Section 6 concludes this paper by summarizing the results achieved.

## 2 Related Works

Having an agent learn behavior from only an environmental reward, the key concept behind RL, is particularly difficult in complex environments due to their high dimensionality and associated task complexity. The union of humans and RL agents in the training loop, exploiting human knowledge and experience by way of Imitation Learning (IL) is a promising solution yielding improved data efficiency and robust policies. In a typical implementation of IL, which is presented as Behavioural Cloning (BC) or Learning from Demonstration (LfD), the goal is to train a classifier-based model to predict the human’s actions. However, the statistical learning assumption relies on ignoring the relationship between the current and the next states during the execution. Data-set Aggregation (DAGGER) and Generative Adversarial IL (GAIL) introduce new approaches for incorporating human experience. These studies have proposed iterative algorithms for an online learning approach for training a stationary deterministic policy. Note however that in DAGGER, the information from the states may not be intuitive and in GAIL, there is a drawback due to a requirement for a large number of interactions during the training.

While this kind of human-AI collaboration, specifically dealing with human feedback to improve the RL agent performance, has been widely investigated in numerous studies, our research has failed to discover any existing studies...
that consider human and RL-based multi-agent teaming. The main focus of this study is "human-MARL teaming", specifically the mode of human-AI collaboration where humans and RL-based agents accomplish tasks together in a multi-agent system. Therefore the objective cannot be achieved by just a lone human or agent, and the responsibilities in the environment are partitioned and/or shared between humans and agents. We have found limited studies covering "human-AI teams" which refer to supervised single-agent single-human teams in classifier’s recommendation systems [29] [40].

Traditionally, the training mechanism in MARL algorithms has been assigned to each agent separately. This approach is referred to decentralized or distributed learning. A decentralized learning architecture can reduce the difficulty of the learning process and the complexity of the calculations [41] [42] [43]. [14] has proposed a distributed deep loop Q network (DDRQN), which solves the problem of multi-agent communication and cooperation that can be observed in the state portion. Often, value-based RL algorithms are challenged by inherently non-stationary environments, while policy gradient methods suffer from a variance that increases significantly as the number of agents grows.

[43] has proposed a multi-focus attention network (MANet) method that can simulate human spatial extraction ability. However, in a large-scale multi-agent environment, it is difficult for agents to differentiate between valuable information that assists in decision making and globally shared information. To tackle this difficulty, [44] has proposed an attentional communication model that learns when communication is needed and how to integrate shared information for the decision making. [14] proposed an actor-critic method called COMA policy gradients, where a centralized critic was used to estimate the Q-function, and decentralized actors were used to optimize the agent policies. [15] has presented a variation of actor-critic methods named MADDPG that considers action policies of other agents to successfully maximize the global reward. It had also been introduced a training method to mix the agents’ policies that lessens over-fitting and leads to more robust multi-agent policies.

Several studies and research groups [30] [31] [32] [33] [34] [35] have designed and released various RL frameworks. However, our research failed to reveal existing frameworks that actually facilitate "human-MARL teaming". The essential needs in a human-MARL teaming that existing RL frameworks cannot provide, are: 1) client (human) interface: current frameworks generally provide no significant way of interfacing client services to the environments; 2) tech-stack agnosticity: most frameworks remain focused on their respective tech-stacks, preventing the formation of an efficient learning system using multiple applications developed on different tech verticals; 3) inter-actor communication: Communication between agents during trials is either non-existent or handled inefficiently in these frameworks.

OpenAI Gym [30], one of the most popular toolkits for developing and evaluating RL algorithms, acts as a perfect bridge between academia and industry. However, OpenAI Gym is not a framework and does not directly support efficient learning system using multiple applications developed on different tech verticals; 3) inter-actor communication: Communication between agents during trials is either non-existent or handled inefficiently in these frameworks. However, our research failed to reveal existing frameworks that actually facilitate "human-MARL teaming". The essential needs in a human-MARL teaming that existing RL frameworks cannot provide, are: 1) client (human) interface: current frameworks generally provide no significant way of interfacing client services to the environments; 2) tech-stack agnosticity: most frameworks remain focused on their respective tech-stacks, preventing the formation of an efficient learning system using multiple applications developed on different tech verticals; 3) inter-actor communication: Communication between agents during trials is either non-existent or handled inefficiently in these frameworks. However, our research failed to reveal existing frameworks that actually facilitate "human-MARL teaming". The essential needs in a human-MARL teaming that existing RL frameworks cannot provide, are: 1) client (human) interface: current frameworks generally provide no significant way of interfacing client services to the environments; 2) tech-stack agnosticity: most frameworks remain focused on their respective tech-stacks, preventing the formation of an efficient learning system using multiple applications developed on different tech verticals; 3) inter-actor communication: Communication between agents during trials is either non-existent or handled inefficiently in these frameworks.

### 3 Background

The Decentralized-Partially Observable Markov Decision Process (Dec-POMDP) is a suitable choice for modeling a multi-agent sequential decision making problem. The objective of a Dec-POMDP model is to find the best policy \( \pi \) for each agent when multiple agents at time \( t \) use the partial observations \( z \in Z \) from the observation function \( O(s, a) : S \times A \rightarrow Z \) on the system state to decide individual actions in order to achieve a common goal [45]. The tuple \( T =< S, U, P, r, Z, O, n, \lambda > \) represents memorization of each event in a Markov Decision Process (MDP). \( s \in S, a \in A \) and \( u^n \in U \) present the state of the environment, agent, and action taken by agents, respectively. The state transition probability is presented by \( P(s' | s, u) : S \times U \times S \rightarrow [0, 1] \), where, \( u \in U \equiv U^n \) describes the joint action. The agents share the same reward function \( r(s, u) : S \times U \rightarrow \mathbb{R} \) and discount factor \( \gamma \in [0, 1] \) [46].

A joint policy \( \pi \) with a joint value function \( Q^\pi(s, u) : S \times U \rightarrow \mathbb{R} \) is considered, where \( R_t = \sum_{i=0}^{\infty} \gamma^i r_{t+i} \), \( \pi^n(u^n | r^n) : T \times U \rightarrow [0, 1] \), and \( r^n \in T \equiv (Z \times U)^4 \) presents discounted return, stochastic policy, and action-observation history for each agent, respectively.

Deep Q-learning consists of a multi-layer Deep Q-learning neural network (DQN) in which \( Q(s, \theta) \) updates \( \theta \), the parameters of the network by observing the next state \( s' \) after taking an action \( u^n \in U \) in state \( s \) and receiving an immediate reward \( r \). When updating the parameters of \( \theta \), the error is minimized by:

\[
\Delta(\theta) = \sum_{i=1}^{m} \left[ \left( r + \gamma max_{u'} Q(s', u'; \theta') - Q(s, u; \theta) \right)^2 \right]
\] (1)
where \( m \) and \( \theta' \) represent the sampling batch and parameters of the target network, respectively. This equation shows that a greedy policy is calculated by \( \max_u Q(s', u; \theta') \) and \( Q(s, u; \theta) \). The max operator uses the same values to both select and evaluate an action, and it may lead to overestimation of value estimates [21]. To reduce the overestimation in DQN, [21] introduced double Q-learning (DDQ-learning) with decomposing the max operation of \( \max_u Q(s', u) \) into action selection and action evaluation, separately. To minimize the error, we use:

\[
\Delta(\theta)_{DDQN} = \sum_{i=1}^{m} [((r + \gamma Q(s', \arg\max \theta Q(s', u'; \theta')) - Q(s, u; \theta))^2]
\]  

Double Dueling Deep Q learning (D3Q-learning), is an extension of DDQ-learning, which represents separated evaluators for the state value \( V(S) \) and the action advantage \( A(S) \) functions. This helps us to generalize learning process across actions without changing the baseline RL algorithm [22]. Also, by decomposing the estimation, the D3Q-learning can prioritize the state without having to learn the effect of each action at each state, as it is presented in the equation below:

\[
Q(S, u, \theta, \alpha, \beta) = V(s; \theta, \beta) + (A(s, u; \alpha) - \frac{1}{\|A\|} \sum A(s, u'; \alpha))
\]

where, \( \alpha, \beta \) presents the parameters of the two streams of fully-connected layers.

MADDPG is a MARL algorithm based on policy gradient method [15] without a differentiable model assumption for the environment dynamics or particular communication structure between agents. It utilizes CTDE to extend the Actor-Critic of DDPG method. It defines a scenario with \( N \) agents who present their policies by \( \mu = (\mu_1, ..., \mu_n) \), and parameters by \( \theta = (\theta_1, ..., \theta_n) \). The expected return gradient is presented by \( J(\theta_i) = E[R_t] \) for the agent \( i \) can be reformulate as:

\[
\nabla_{\theta_i} J(\mu_i) = E_{x,a,u} \left[ \nabla_{\theta_i} \mu_i Q_1^\mu(X, a_1, ..., a_N) | | a_i = \mu_i(\alpha_i) \right]
\]

where, \( Q^\mu_i(X, a_1, ..., a_N) \) is a centralized function that takes as input the actions of all agents, \( a_1, ..., a_N \), and outputs the Q-value for agent \( i \). The parameters of the policy network are updated using the policy gradient from Equation [4] by an optimizer. The loss function is as follows:

\[
\zeta(\theta) = E_{x,a,r,u'} [Q_1^\mu(X, a_1, ..., a_N) - y]^2
\]

where \( y \) represents the target Q value calculated by the Bellman equation, and \( y \) can be written as:

\[
y = r_i + \gamma Q_1^\mu(X, a_1, ..., a_N) | | a_i = \mu_i(\alpha_i)
\]

where, \( \mu' = (\mu_0', ..., \mu_N') \) represents the policy of all agents in the new states, \( Q^\mu_1 \) is the Q value output from the target network in the Critic, and \( \lambda \) is a discount factor.

4 Methods

4.1 COGMENT

This study addresses the development and demonstration of human-MARL teaming using our designed unique framework, called COGMENT (See Figure [1]). COGMENT RL framework plays an important role in enabling cooperative, assistive, and competitive interaction between humans and RL for this study and is therefore briefly discussed here. The current version of COGMENT was developed by the AI Redefined team and released as an open source framework to accelerate human-MARL teaming. COGMENT’s architecture is composed of and focused on three main elements: environment, actors, and the orchestrator. Each element is discussed in the following paragraphs.

Environment: The environment is the set of rules defining how a trial evolves over time for any given use-case. It can be a simple environment dealing with a single-agent, a single-human, a few simple rules/parameters, or it can be considerably complex with multiple distinct actors (agents and humans), multi-observation/action spaces and complex rules/parameters driving the dynamics of the environment.

Actors: In the COGMENT framework, actors can be defined as either human or agent. They receive observations/send actions from/to the environment and send feedback, and/or provide recommendations to other actors. In the case of human actors, front end interface clients (a web client or mobile application) are used to interact with the user(s).

Orchestrator: The Orchestrator is the nexus of the whole system as it manages the communications, synchronization, and the combining of rewards from multiple sources. It includes a host of other optional features such as generating
offline datasets, performance metrics, analytics, simple project bootstrapping, etc. The Orchestrator offers multiple options that address shortcomings in currently available RL frameworks, as well as addressing active or passive training and multi or single agent systems.

COGMENT uses general-purpose Remote Procedure Calls (gRPC) to handle the communications between the different elements of the system. gRPC is a high-tech framework that can be utilized in any environment, efficiently as a micro-server, to connect services. In addition to load balancing, it communicates to and across the Orchestrator with plug-in support for tracing, health checking and authentication. Its use is cardinal to distributed computing, enabling remote connection of devices, mobile applications and browsers (usually the clients used by the users) through backend services. Heuristic and/or RL agents can communicate with clients (used by humans), other agents, and the environment through gRPC. Agents can be containerized using docker allowing the deployment of agents on different and/or machines in a distributed fashion.

COGMENT supports all agent types (heuristic, RL-based, IL-based, learning or non-learning, neural-network based, graph-based, etc.) including heterogeneous agents. COGMENT comes bundled with SDKs which support the development of agents, clients, and environments in multiple software languages. COGMENT includes a host of other optional features such as generating offline datasets, performance metrics, analytics, simple project bootstrapping, etc. and enables very large scale distributed deployment of projects.

4.2 Proposed MARL algorithm: D3-MADDPG

This study proposes a new MARL algorithm to leverage the benefits of both centralised and decentralized MARL algorithms. Inspired by MADDPG [15], this study proposes D3-MADDPG, by modifying the network of MADDPG, and replacing the Q-learning algorithm with Double Dueling Deep Q learning (D3Q-learning). We aim to explicitly reduce the overestimation of Q-learning through a simple change in the target value, as presented in Figure 2. Specifically, Eq. 6 is replaced by $y = r + \gamma Q(s, \text{argmax}_u Q(s, u))$, the value-based part of D3Q-learning (Eq. 3). We replace the Q value that represents the value of choosing a specific action at a given state, and not the V value that represents the value of the given state regardless of the action taken.

The policy network in the Actor block (See Figure 2) selects an action according to the observation of the current agent, and the action is used to step the environment and generate the new state and rewards. From the saved samples in the
Figure 3: Experimental human-MARL teaming environment, Flames: (a) Smoke fog at the beginning of the trial, (b) Smoke fog dissipating, (c) Environment situation under the smoke fog, (d) An example of the Flames at the middle of the trial

experience replay buffer, random collected samples are sent to the target network in the Actor. The new actions output from the target network in the Actor are passed to the target network in the Critic. The target network in the Critic obtains the new states from the samples and the actions passed by the Actor and outputs the D3Q-learning values of the new states. The target D3Q values can be calculated using the reward values obtained from the samples and the D3Q values of new states output by the target network in the Critic.

The evaluation network in the Critic outputs the estimated centralized D3Q-learning values after it receives the sampled states and actions. In the Critic, the mean squares of the differences between the estimated centralized D3Q values and the target D3Q values are used as the loss value to train the evaluation network and update its parameters. Based on the estimated centralized D3Q values, the strategy gradient can be calculated to train and update the policy network in the Actor. The parameters of the target networks are updated by superposing the parameters of the policy network or the evaluation network and the parameters of the target network proportionally.

5 Experimental results

We have designed an environment called “Flames”, where Unmanned Aerial Vehicles (UAVs) and a human helicopter pilot team up to fight forest fires together. In this MARL environment the roles in the team are divided between the RL agent drones that autonomously scout for fires and the human pilot who then douses the flames. We have selected this use-case because monitoring and controlling forest fires is an interesting application for aerial robotics can pose serious challenges for firefighters, especially considering the potential for loss of life. An interesting challenge for this study is to use RL agent drones distributed as a multi-agent system and help the human firefighter pilot to extinguish or contain the fire(s). The goal for the human pilot is to fly over the fires, discharge water, and thereby douse the flames. The MARL drones are capable of monitoring a non-static target or tracking a moving target, and discover the location of the fire(s).

As Figure 3a presents, at the beginning of the trial, the whole environment is covered by smog or fog and the pilot cannot see fire locations. However, drones can dissipate smog/fog by moving in the environment (See Figure 3b). Figure 3c shows the hidden part of the environment by removing the smog/fog layer. Figure 3d demonstrates the environment midway through a trial. For a forest fire fighting scene, we define four types of non-static objects; tree zone, on-fire zone, charred zone, and doused zone. These objects are represented by the colours; green, red, dark brown, and light brown, respectively. While the drone’s actions are driven by RL algorithms, we have considered three modes for the pilot, namely, human pilot, auto-pilot, and dual mode. In the human pilot mode, the human user controls the helicopter with the aid of a mouse, tracing trajectories on the screen by dragging the cursor to the desired location. The auto-pilot mode implements automatic control of the helicopter; and the dual mode combines the two other modes by letting the users assume control of the helicopter at their discretion, defaulting to auto-pilot when they are not interacting.

Figure 4 presents the results of the comparison between vanilla MADDPG and D3-MADDPG through the related heat-maps. We also show, on the same scale, the empirical evaluation made to test whether overestimation appears in practice. As can be seen, the vanilla MADDPG shows a huge overestimation when dealing with a high number of agents or a large action space in a MARL setup. The proposed D3-MADDPG is able to reduce auto-correlation between action selection and action evaluation which, in turn, results in a significant reduction of the overestimation of the action value, regardless of the number of agents or action space size.
To analyse the human-MARL teaming concept, compatibility of the environment with the Cogment framework, and effectiveness of the proposed D3-MADDPG algorithm, we implemented different centralized and decentralized MARL algorithms for the drones, specifically, DQN, D3QN, MADDPG and D3-MADDPG. We investigated the impact the number of drones aiding the pilot had on the results and analysed the effect of the various pilot modes and their impact on human involvement in relation with the performance in achieving the goals set for this project (see Figure 5).

To demonstrate the importance of the number of drones on the overall performance, we varied their number using a range of 3 to 6 drones. As expected, increasing the number of drones dramatically improved the amount of, and speed at which the fire locations were revealed. As shown in Figures 5a to 5d, increasing the number of drones from 3 to 6 improves the final score by approximately 20%, regardless of the MARL method used.

Factoring in different human involvement levels via the use of the human-piloted, auto-piloted, and dual modes (see Figures 5a through 5d), shows that the human-piloted mode doesn’t perform as well as the two other modes, regardless of the algorithm type or number of drones. We hypothesize that a primary reason for the lesser performance of the human pilot could be due to the latency of human reactions compared to auto-pilot mode. The figures also show that human pilots have a large standard deviation compared to the two other modes due to the raw difference in human performance from one trial to another, which can be attributed to the varying focus of the human pilot. While autopilot mode outperforms human pilot mode by roughly 10 to 20 employing different algorithms and numbers of drones, dual mode shows a slight improvement in performance over the autopilot mode. The standard deviation of dual mode is high compared to the autopilot mode due to the greater human latency and attention factors.

Comparison between two decentralised algorithms (see Figures 5a and 5b), shows that D3QN agents outperform DQN agents about 12 for different pilot modes when the number of drones is more than 5. Comparison between two hybrid learning algorithms (CTDE) (see Figures 5c and 5d), shows that the proposed D3-MADDPG algorithm can increase the performance of Human-MARL teaming by about 6 in both autopilot and dual modes when the number of drones is more than 4.

6 Conclusion

In order to address the context of “Human-MARL teaming”, where neither a human nor multiple RL-based agents can achieve goals without working together, we presented in this study two innovative solutions. The first is a new open-source MARL framework called COGMENT, able to efficiently couple humans and agents in real-time complex dynamic systems where their interactions in a shared environment are leveraged for learning. The second is a new MARL method named D3-MADDPG allowing agents to train decentralised policies parallely in a joint centralised policy. This solved the overestimation problem posed by traditional Q-Learning methods. In order to demonstrate those innovations, we designed a real-time environment involving autonomous UAVs driven by RL agents, and a helicopter piloted by a human user. UAVs and the helicopter had to collaborate in order to find and fight forest fires; the UAVs were tasked with scouting the location of the fire(s), while the helicopter’s role was to extinguish them. The results of this study on a collaborative paradigm showed that the use of the new framework COGMENT led to significant reductions in both the human effort needed and the exploration costs. The use of D3-MADDPG showed significant improvements in the learning process, thanks to reduction of overestimation in value function achieved by decoupling the estimation processes of state value and advantage value.
Figure 5: Experimental results on Flames with different numbers of drones: (a) DQN, (b) D3QN, (c) MADDPG, and (d) D3-MADDPG.

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