The Emergence of Complex Bodyguard Behavior Through Multi-Agent Reinforcement Learning

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Abstract

In this paper we are considering a scenario where a team of robot bodyguards are providing physical protection to a VIP in a crowded public space. We show that the problem involves a complex mesh of interactions between the VIP and the robots, between the robots themselves and the robots and the bystanders respectively. We show how recently proposed multi-agent policy gradient reinforcement learning algorithms such as MADDPG can be successfully adapted to learn collaborative robot behaviors that provide protection to the VIP.

1 Introduction

One of the most complex challenges in autonomous robots concerns behaviors that require a complex interaction between robots and humans, as well as between the robots themselves. In particular, learning in these settings is challenging because the learner can not assume that the other robots/agents it is interacting with follow a stable strategy. To keep complexity manageable, most research work in this field is tested on simple problems, such as the cooperative communication or predator-prey, that involve the robot having to interact with only one or two types of other robots/agents.

In this paper we are considering a more complex problem with a practical application. A VIP is navigating a crowded public area. We assume that the bystanders are purposefully moving from landmark to landmark, and use culture-specific crowd navigation protocols [Bölöni *et al.*, 2013] on giving way or asserting their right of way. The goal of a team of robot bodyguards is to physically protect the VIP from assault by appropriately positioning themselves in relation to the current position of the VIP.

The goal of the bodyguards can be stated as a minimization of a metric of the threat to the VIP, a problem made challenging due to the complexity of the environment. The bodyguard robot must adapt its position to the current position of the VIP. Second, the movement must also depend on the movement of the bystanders; if a bystander is heading towards the VIP, the robot needs to position itself to reduce the threat to the VIP. Finally, the robots need to coordinate between each other. This can be achieved either through central planning, explicit communication by exchanging messages or though

implicit communication, by each robot taking actions based on a world view including the other robots.

While it is possible to hand-engineer robot bodyguard behaviors [Bhatia *et al.*, 2016], it is of interest whether such behavior can be learned through reinforcement learning.

2 Problem Formulation

The reward structure of the robotic bodyguard team problem can be modeled as a cooperative Markov game where multiple agents are learning a policy to maximize their rewards. A multi-agent MDP can be defined as a combination of a state space \mathcal{S} , an action space \mathcal{A} , agents $\mathcal{A}_1, \ldots, \mathcal{A}_N$, the transition probabilities that are defined as $\mathcal{T} = \mathcal{S}_1 \times \mathcal{A}_1 \times \ldots \times \mathcal{S}_N \times \mathcal{A}_N$ and the reward function for every agent that is defined as $r_i = \mathcal{R}(\mathcal{S}_i, \mathcal{A}_i)$.

For the sake of simplicity, we are assuming that all the bodyguards have an identical state and action space. We are considering a finite horizon problem where each episode is terminated after T steps.

The environment that provides the rewards is a two-dimensional space, with the usual rules of physical movement, landmarks, line-of-sight and communication. We used the Multi-Agent Particle Environment MPE [Mordatch and Abbeel, 2017] to perform our experiments. MPE is a two-dimensional physically simulated environment that runs in discrete time and continuous state and action space. The environment consists of N agents and M landmarks possessing physical attributes such as location, velocity and mass etc. MPE also allows the agents to communicate via verbal utterances over the communication channel embedded in the environment. The complete observation of the environment is given by

$$o = [x_{1,...N+M}, c_{1,...N}] \in O$$

The state of each agent is the physical state of all the entities in the environment and verbal utterances of all the agents. Formally, the state of each agent is defined as

$$s_i = [x_{j,\dots N+M}, c_{k,\dots N}]$$

where x_j is the observation of the entity j from the prespective of agent i and c_k is the verbal utterance of the agent k.

2.1 Reward Function

[Bhatia *et al.*, 2016] defined a metric that quantifies the threat to the VIP from each crowd member b_i at each timestep t. We

extended the metric to form a reward function defined as

$$\mathcal{R}_{t}\left(\mathcal{B}, VIP, x_{i}\right) = -1 + \prod_{i=1}^{k} \left(1 - TL\left(VIP, b_{i}\right)\right) + \mathcal{D}\left(VIP, x_{i}\right) + p$$

$$(1)$$

where

$$TL(VIP, b_i) = \exp^{-A(Dist(VIP, b_i))/B}$$

and

$$\mathcal{D}(\mathit{VIP}, x_i) = \begin{cases} 0 & m \leq \|x_i - \mathit{VIP}\|_2 \leq d \\ -1 & \text{otherwise} \end{cases}$$

where m is the minimum distance the agents have to maintain at every timestep, d is the safe distance and p is a small penalty to the bodyguard for utterance.

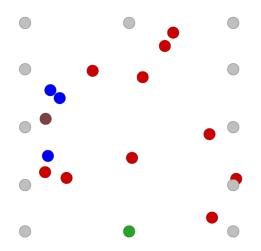


Figure 1: Screenshot showing the emerging collaborative bodyguard behavior. The (brown) VIP aims to reach the green landmark. The (blue) bodyguard robots surround and separate it from the closest bystanders (red). The bystanders navigate among the gray landmarks.

3 Methodology

The bodyguards were trained using multi-agent deep deterministic policy gradients MADDPG [Lowe *et al.*, 2017], a multi-agent extension of the DDPG algorithm described in [Lillicrap *et al.*, 2015]. MADDPG allows agents to have individual policies, but trains them with a centralized Q-function. The gradient $\nabla J(\theta_i)$ of each policy is written as

$$\nabla J\left(\theta_{i}\right) = \mathbb{E}\left[\nabla_{\theta_{i}}\log \pi_{i}\left(a_{i}|s_{i}\right)Q_{i}^{\pi}\left(s_{i}, a_{1}, \dots, a_{N}\right)\right]$$

where $Q_i^{\pi}\left(s_i,a_1,\ldots,a_N\right)$ is a centralized action-value function that takes the actions of all the agents in addition to the state of the agent to estimate the Q-value for agent i. The primary motivation behind MADDPG is that knowing all the actions of other agents makes the environment stationary, even though their policy changes.

4 Experiments

The experiments were conducted in an environment created in MPE, simulating a crowded mall with 12 landmarks representing stores. The VIP is following its own policy of moving towards a goal landmark. 10 bystanders are following their own policy that involve sequentially visiting randomly chosen landmarks. 3 bodyguards were deployed to protect the VIP from physical assault.

For training, the bodyguard agents were trained over 10,000 episodes, each episode being limited to 25 steps using DDPG and MADDPG. After training, performance was measures both empirically (by means of observing the movement of the bodyguards) and by recording the cummulative threat over the episode as defined in [Bhatia *et al.*, 2016]. An example of the achieved behavior is described in Figure 1. As the screenshot shows, the robots learned to surround and move with the VIP, concentrating on the sides where bystanders are closer. Empirical evaluation had shown better performance with MADDPG compared to DDPG.

5 Conclusion

In this paper, we outlined a technique for training a multi robot team of bodyguards that is collaborating towards a common goal of providing physical security to a VIP moving in a crowded environment. We trained the robot behaviors using MADDPG RL, and we observed the emergence of recognizable collaborative bodyguard behavior without any explicit instruction on how to provide security.

References

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