Future Research Trends by Integrating Deep Reinforcement Learning, Robotics and Game Theory

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1. Introduction †

This paper deals with fusion of deep reinforcement learning, robotics and game theory, with the goal to identify possible future research trends by integrating these three techniques.

Deep reinforcement learning that combines reinforcement learning and deep learning has drawn much attentions since deep reinforcement learning based algorithm beated world champions at the game of Go [1] as well as playing numerous Atari video games [2].

Robotics [4] is an interdisciplinary branch of engineering and science that includes mechanical engineering, electronic engineering, information engineering, computer science, and others. A robot usually is the target of robotics.

Game theory is always known for the famous example prisoner's dilemma. In 1950s, John Nash developed a criterion for mutual consistency of players' strategies, known as *Nash equilibrium* [3].

The aforementioned three techniques seems independent. Actually, they have common subject, objective, and application, and it is expected to strengthen the effect of these three techniques by integrating them in a common framework. To the best our knowledge, it is the first time to consider these three techniques at the same time in this paper. The main contributions are summarized as follows.

- We identify the common points of deep reinforcement learning, robotics and game theory after brief introduction of these three theories.
- We provide possible future research directions by integrating deep reinforcement learning, robotics and game theory .

2. Basic Concept Introduction

In this sections, core concepts of deep reinforcement learning, robotics and game theory are introduced in details.

Deep Reinforcement Learning: Reinforcement learning (RL) [5] is concerned with how agents ought to take actions in an environment so as to maximize some notion of cumulative reward (see Fig. 1). The actions are taken according to the current states of the agent, by estimated long term reward based on the past experiences. However,

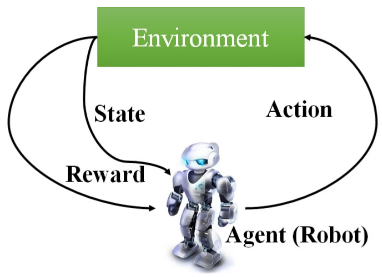

Fig. 1 Reinforcement learning model.

sometimes, it is impossible for the agents to get enough experiences for too many states to estimate the long term reward. Then deep learning is utilized to estimate the long term reward from limited experience when the number of states is large.

Robotics: Robotics deals with the design, construction, operation, and use of robots, as well as computer systems for their control, sensory feedback, and information processing [4]. There are many types of robots; they are used in many different environments and for many different uses. Robots that use artificial intelligence interact with their environment on their own without a control source, and can determine reactions to objects and problems they encounter using their preexisting programming. Please refer to Fig. 2 for the architecture of a robot.

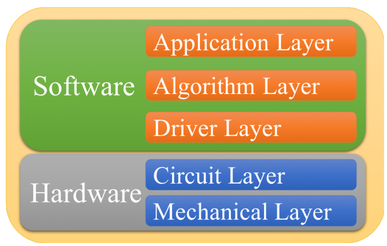

Fig. 2 Architecture of a robot.

Game Theory: Game theory is from decision making studies, it concentrates on the mathematical models among rational intelligent decision makers who have interact with each other to achieve their objectives [3]. A game in

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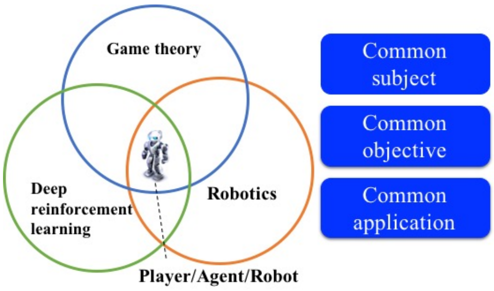

Fig. 3 The common point of reinforcement learning, game and robotics.

strategic form has the following three elements:

- the set of players I, where I is a finite set.
- the pure-strategy space S_i for each player $i, i \in I$.
- and the payoff function u_i that gives player i's utility $u_i(s)$ for each profile $s = (s_1, ..., s_I)$ of strategies.

A Nash equilibrium is a profile of strategies such that each player's strategy is an optimal response to the other players' strategies [3]. In Nash equilibrium, payoff of each player is maximized.

3. Common Points of Deep Reinforcement Learning, Robotics, and Game Theory

Some common points can be analyzed as follows based on the basic concepts introduced in section 2 (see Fig. 3).

- *Common subject*: Agent is the central subject of deep reinforcement learning, while the subjects of robotics and game theory are robot and player, respectively. As shown in Fig. 3, agent, robot and player can be acted by the same one. Here, agent/robot/player is defined as *subject* in this paper.
- *Common objective*: The objective of agent in deep reinforcement learning is to maximize/minimize some notion of cumulative reward, while the objective of robot can be maximize/minimize some metrics for a task and the objective of player in a game is to maximize his/her payoff. Their objective can be the same for some applications.
- *Common application*: For some applications, deep reinforcement learning, robotics and game theory can be applied from different aspects, with the same goal. For example, a mobile robot, can be acted a player in a game to compete with other mobile robot for communication resource, while at the same time, the mobile robot can also be acted as an agent in deep reinforcement learning for maximizing its cumulative reward over a period of time.

Furthermore, robotics and deep reinforcement learning may generate data for data analytics. The results of data analytics help the robotics and deep reinforcement learning agent to improve themselves (see Fig. 4).

4. Future Research Directions

Some interesting future research directions can be identified based on the aforementioned introduction and analysis.

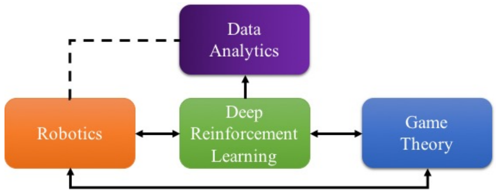

Fig. 4 Relationship among deep reinforcement learning, robotics, game theory and data analytics.

Energy minimization and resource allocation in autonomous systems: Autonomous systems such as autonomous driving system that integrating many technologies like sensor fusion, control theory and engineering, localization, telecommunication have drawn much attentions in recent years. In such a kind of system, the autonomous car is kind of robot that can be seen as the agent of the deep reinforcement learning, who tries to minimize cumulative energy in a dynamic and unknown environment, and when communicates with roadside unit (RSU), the autonomous car is acted as player tries to maximize its payoff by competing for communication resources with other cars.

Navigation in multiple mobile robot system: In a multiple mobile robot system, how to navigate in an unknown indoor environment is quite challenging. Real time information gotten from the unknown environment should be fused and form an indoor map for navigation when there are obstacles like people, table and so on. The mobile robot can be seen as the agent in deep reinforcement learning tries to minimize the time to the destination place, while the limited computation and storage resources make the mobile robot as a player to play a game competing for the mobile edge computing (MEC) computation and storage resource in one hand. On the other hand, many different mobile robots in different places can share their sensor information by playing a cooperative game, which help the mobile robot to improve their navigation performance.

5. Conclusions

We have tried to integrate deep reinforcement learning, robotics and game theory together to identify some new research directions for solving some new challenging problems, after the analysis of some common points. It is expected the contents in this paper can inspire researchers in related research fields.

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