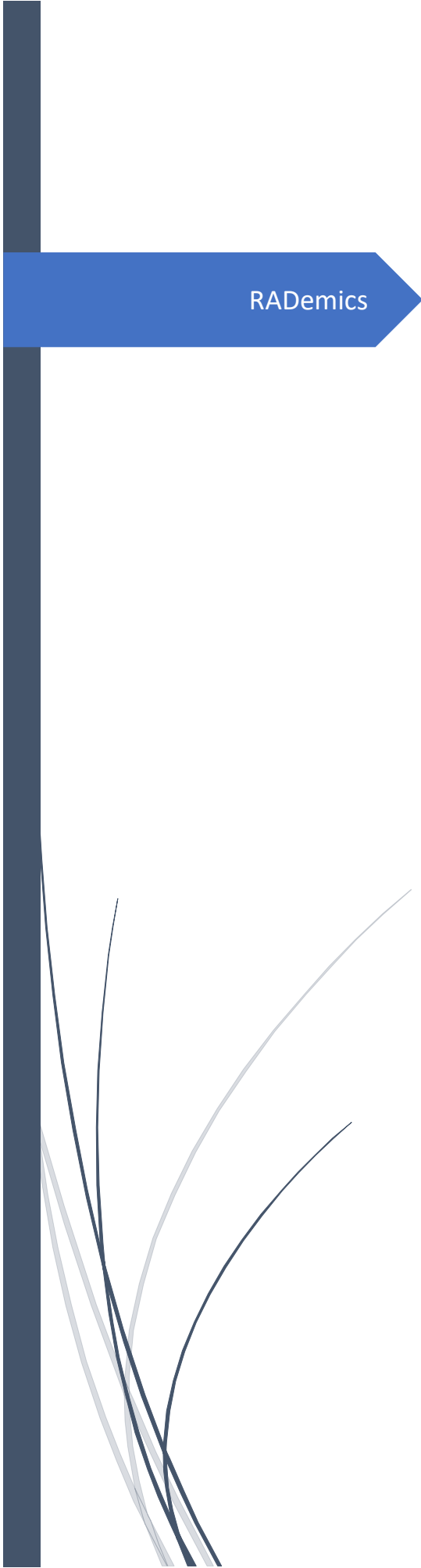




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Deep Q-Network Architectures for Task Planning and Control in Autonomous Robotic Systems

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Abstract

This chapter explores the integration of Deep Q-Network (DQN) architectures for task planning and control in autonomous robotic systems. Focusing on the synergy between high-level planning and low-level control, it delves into the role of reinforcement learning in enhancing task execution and decision-making. The chapter discusses various aspects of autonomous systems, including task allocation, coordination, and real-time adaptation. A key highlight was the application of hybrid control strategies, combining deep learning models with traditional control methods to address the challenges of dynamic environments. Special attention was given to the scalability and flexibility of multi-agent systems, enabling collaborative task execution among multiple robots. Human-robot collaboration was examined, emphasizing the integration of human feedback into robotic task planning. This comprehensive analysis presents innovative solutions for optimizing autonomous systems in industries such as manufacturing, healthcare, and logistics, advancing the potential of robotics in real-world applications.

Keywords:

Deep Q-Network, Task Planning, Autonomous Systems, Hybrid Control, Multi-Agent Systems, Human-Robot Collaboration.

Introduction

The rapid advancements in robotics and artificial intelligence have significantly transformed the landscape of autonomous systems [1]. Autonomous robotic systems are designed to perform tasks with minimal human intervention, making them increasingly integral to industries such as manufacturing, logistics, healthcare, and even exploration [2-4]. Task planning and control are fundamental aspects of these systems, as dictate how robots perceive their environment, plan actions, and execute tasks efficiently [5,6]. The need for precise control and adaptive task planning mechanisms becomes even more critical as the complexity of tasks and environmental dynamics increases [7]. Deep Q-Network (DQN) architectures, a class of reinforcement learning models, have emerged as powerful tools to address these challenges [8,9]. By combining deep learning with Q-learning, DQNs enable robots to learn optimal actions from experience, making them highly effective in complex, unpredictable settings [10-14].

One of the key advantages of DQN architectures was their ability to handle the exploration-exploitation trade-off, which was central to reinforcement learning [15]. In task planning, robots must balance exploring new actions that could lead to better outcomes with exploiting known actions that have already proven effective [16,17]. DQNs enable robots to continuously improve their decision-making capabilities over time by learning from interactions with the environment [18]. This dynamic learning process was essential in environments that are too complex or uncertain for traditional rule-based systems [19,20]. By using DQNs, robots can autonomously adapt to changes in their environment, enhancing their efficiency and autonomy in completing tasks [21]. The integration of such architectures has revolutionized the way robots are programmed to handle a variety of tasks, from simple actions to highly complex decision-making scenarios [22,23].

Hybrid control approaches, which combine high-level planning with low-level control, represent another significant advancement in autonomous robotic systems [24]. While high-level planning involves strategic decision-making based on task objectives, low-level control focuses on the precise execution of actions in real-time [25]. The challenge lies in coordinating these two levels to ensure that robots perform tasks efficiently without deviating from the intended goals. DQN architectures, with their ability to optimize actions through reinforcement learning, offer a unique advantage in this area. By providing continuous feedback loops between planning and execution, DQNs enable robots to adjust their actions based on real-time data, improving both task performance and adaptability. This synergy between high-level planning and low-level control was crucial for enabling robots to function effectively in dynamic, real-world environments.