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REAL TIME DECISION MAKING USING REINFORCEMENT LEARNING IN AUTONOMOUS ROBOTICS

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Abstract

Autonomous robotic systems increasingly operate in dynamic, uncertain, and safety-critical environments where intelligent real-time decision making plays a decisive role in ensuring reliable and efficient task execution. Conventional control approaches often exhibit limited adaptability when environmental conditions change rapidly, creating the need for learning-based frameworks capable of continuous improvement through experience. Reinforcement Learning (RL) has emerged as a powerful paradigm for enabling autonomous robots to learn optimal decision policies by interacting with their surroundings and maximizing long-term cumulative rewards. Recent advances in Deep Reinforcement Learning (DRL) have further strengthened robotic perception, motion planning, autonomous navigation, manipulation, and cooperative multi-agent coordination by integrating deep neural networks with sequential decision-making models.The chapter presents a comprehensive review of real-time decision making using reinforcement learning in autonomous robotics, covering fundamental RL concepts, policy optimization strategies, deep reinforcement learning algorithms, robot perception, environment understanding, motion planning, dynamic obstacle detection, continuous learning, and multi-agent reinforcement learning. Critical aspects of safety-aware learning, simulation-to-real-world transfer, policy adaptation, and scalable deployment are examined to provide a holistic understanding of intelligent robotic systems. Practical applications across industrial automation, healthcare, warehouse logistics, autonomous vehicles, unmanned aerial systems, agriculture, and swarm robotics demonstrate the growing impact of reinforcement learning in solving complex real-world problems. Emerging research directions, including explainable reinforcement learning, edge artificial intelligence, digital twins, federated learning, and foundation models, are also discussed to highlight future opportunities for developing robust, adaptive, and trustworthy autonomous robotic systems. The chapter provides a structured reference for researchers, academicians, and practitioners seeking to understand recent developments and future trends in reinforcement learning-driven autonomous robotics.

Keywords: Reinforcement Learning, Deep Reinforcement Learning, Autonomous Robotics, Real-Time Decision Making, Multi-Agent Reinforcement Learning, Robot Perception

Introduction

Autonomous robotics has emerged as one of the most influential research domains within artificial intelligence, driven by rapid advances in sensing technologies, computational intelligence, embedded systems, and machine learning algorithms [1]. Modern robotic systems perform increasingly sophisticated tasks that extend far beyond traditional industrial automation, supporting applications in healthcare, intelligent transportation, precision agriculture, warehouse logistics, disaster response, defense, and space exploration [2]. Such applications require robotic platforms capable of perceiving complex environments, interpreting large volumes of sensory information, and making intelligent decisions within stringent time constraints [3]. Conventional control approaches, designed primarily for structured and predictable environments, often struggle to maintain reliable performance when operating conditions become uncertain or continuously changing. Dynamic obstacles, incomplete environmental knowledge, sensor noise, and unpredictable external disturbances introduce significant challenges that demand adaptive decision-making capabilities [4]. As robotic systems evolve toward higher levels of autonomy, the integration of learning-based intelligence has become essential for achieving robust, efficient, and context-aware operation across diverse real-world environments [5].

The increasing complexity of autonomous robotic applications has elevated real-time decision making to a central research challenge in intelligent robotics. Every autonomous robot continuously receives information from multiple sensing modalities, including cameras, LiDAR, radar, inertial measurement units, ultrasonic sensors, and depth perception devices [6]. This heterogeneous sensory information must be processed rapidly to construct an accurate representation of the surrounding environment before selecting appropriate actions [7]. Delays in perception or decision generation can reduce navigation efficiency, increase energy consumption, compromise operational safety, and negatively affect mission success [8]. Industrial robots require immediate responses to changes on production lines, autonomous vehicles must react instantly to moving pedestrians and traffic conditions, and healthcare robots demand precise adaptive behavior while interacting with patients [9]. These operational requirements highlight the necessity for intelligent decision-making frameworks capable of learning from experience while continuously adapting to changing environmental conditions. Efficient real-time decision making therefore represents a fundamental requirement for the successful deployment of autonomous robotic systems [10].

Reinforcement Learning (RL) has become one of the most promising computational paradigms for addressing sequential decision-making problems encountered in autonomous robotics [11]. Unlike supervised learning approaches that rely on labeled training data, reinforcement learning enables robotic agents to acquire optimal decision policies through continuous interaction with their environment [12]. An intelligent agent observes environmental states, executes actions, receives evaluative rewards, and gradually improves its policy by maximizing cumulative long-term returns [13]. Such a learning process enables robots to discover effective behavioral strategies without requiring manually programmed responses for every possible situation. Reinforcement learning naturally aligns with robotic applications involving navigation, manipulation, path planning, obstacle avoidance, task scheduling, and autonomous exploration because each decision directly influences future environmental states and mission outcomes [14]. Continuous policy refinement allows robotic systems to adapt to previously unseen scenarios while maintaining operational efficiency under uncertain conditions, making reinforcement learning a highly suitable approach for intelligent autonomous decision making [15].