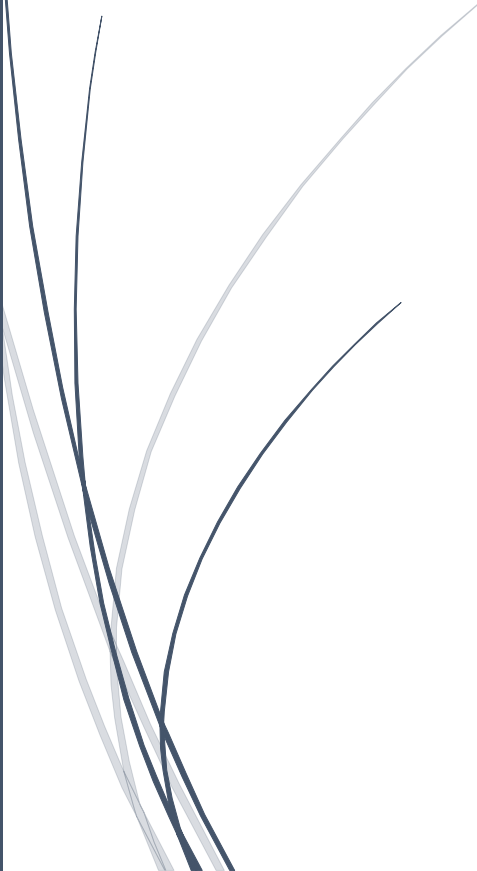


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INTEGRATION OF REINFORCEMENT LEARNING WITH SENSOR DATA IN SMART ROBOTICS

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INTEGRATION OF REINFORCEMENT LEARNING WITH SENSOR DATA IN SMART ROBOTICS

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Abstract

Smart robotics has advanced significantly with the integration of reinforcement learning and sensor technologies, enabling robots to perform tasks with greater intelligence, adaptability, and autonomy. Reinforcement learning allows robots to learn optimal actions through interaction with the environment, while sensors provide real-time information required for perception, navigation, object detection, and decision-making. The combination of these technologies improves the ability of robots to operate efficiently in dynamic and uncertain environments across various application domains. This chapter presents the fundamental concepts of smart robotics, reinforcement learning, and robotic sensor technologies, followed by an overview of sensor data processing, sensor fusion, and deep reinforcement learning techniques. The discussion explains how reinforcement learning utilizes sensor information to support autonomous navigation, adaptive control, and real-time decision-making. Simulation environments, digital twins, sim-to-real transfer learning, edge intelligence, cloud robotics, and performance evaluation methods are also discussed to highlight recent developments in intelligent robotic systems. Practical applications in industrial automation, healthcare, agriculture, logistics, search-and-rescue, and service robotics demonstrate the effectiveness of integrating reinforcement learning with sensor data. The chapter concludes by discussing current challenges and future research directions for developing reliable, efficient, and intelligent autonomous robotic systems.

Keywords: Reinforcement Learning, Smart Robotics, Sensor Fusion, Deep Reinforcement Learning, Autonomous Robots, Edge Intelligence.

Introduction

The rapid advancement of artificial intelligence has transformed the design and functionality of modern robotic systems, enabling autonomous operation in environments that demand continuous adaptation and intelligent decision-making [1]. Traditional robotic systems primarily rely on predefined rules, fixed control algorithms, and manually programmed behaviors, which perform effectively in structured environments but exhibit limited flexibility when operating under dynamic and uncertain conditions [2]. The increasing complexity of industrial automation, healthcare services, logistics, agriculture, disaster management, and autonomous transportation has created a growing demand for robots capable of learning from experience and responding

intelligently to changing situations [3]. Reinforcement learning has emerged as an effective machine learning paradigm that enables robots to acquire optimal behaviors through continuous interaction with their surroundings. Instead of depending entirely on handcrafted control strategies, reinforcement learning allows robotic systems to improve performance based on environmental feedback [4]. This learning capability supports autonomous navigation, object manipulation, motion planning, and adaptive decision-making, making reinforcement learning a key technology in the development of next-generation smart robotics [5].

The effectiveness of reinforcement learning largely depends on the quality of environmental information available to the learning agent [6]. Modern robotic platforms incorporate a wide range of sensing technologies that continuously collect information about both the surrounding environment and the internal state of the robot. Vision sensors capture visual information for object recognition and scene understanding, while LiDAR and radar provide accurate distance measurements and three-dimensional mapping capabilities [7]. Inertial measurement units monitor orientation and motion, whereas tactile sensors, force–torque sensors, ultrasonic sensors, and proximity sensors provide valuable information for interaction with objects and surrounding obstacles [8]. These heterogeneous sensors generate large volumes of data that require efficient processing before meaningful decisions can be made. The integration of multimodal sensor data enables robots to develop a comprehensive understanding of complex environments, reducing uncertainty and improving perception accuracy [9]. Reliable sensor information therefore serves as the foundation for intelligent reinforcement learning algorithms that support autonomous robotic behavior [10].

Recent developments in deep learning have significantly enhanced the capability of reinforcement learning to process high-dimensional sensor observations and solve complex robotic control problems [11]. Deep reinforcement learning combines neural networks with reinforcement learning algorithms, allowing robots to learn directly from raw sensor inputs without extensive manual feature engineering [12]. This advancement has improved robotic performance in applications such as autonomous navigation, robotic manipulation, warehouse automation, collaborative manufacturing, healthcare assistance, agricultural monitoring, and intelligent service robots [13]. Sensor fusion techniques further strengthen learning performance by combining complementary information from multiple sensing devices into unified environmental representations [14]. Such integrated perception improves localization accuracy, obstacle detection, trajectory planning, and adaptive motion control under uncertain operating conditions. Digital twin technology, simulation environments, edge computing, and cloud robotics have also contributed to accelerated training and reliable deployment by providing efficient platforms for policy optimization and large-scale data processing before implementation on physical robotic systems [15].