Reinforcement Learning-based Motion Planning for Robotic Manipulators in Smart Industry

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***Abstract*—The advent of smart industry, propelled by the integration of digital technologies and automation, has revolutionized manufacturing and industrial processes. Robotics and artificial intelligence (AI) are at the forefront of this transformation, driving extensive research into robotic automation and motion planning. Traditional motion planning algorithms, such as artificial potential fields, bio-inspired heuristics, and sampling-based methods, often falter in complex environments due to their high computational demands and tendency to produce non-optimal solutions. Reinforcement learning (RL) has emerged as a powerful alternative, offering real-time adaptation and optimal decision-making in dynamic settings. This paper reviews the inherent limitations of classical motion planning approaches and explores contemporary trends in RL-based methods, with a focus on their application in smart industry. It highlights the advantages of RL in enhancing adaptability, efficiency, and robustness, particularly in high-dimensional and dynamic environments. Key discussions include the integration of RL with traditional techniques, the extension of RL applications across various domains, and the role of sensor-based approaches in improving motion control.**

***Index Terms*—Robotics, Manipulator, Motion Planning, Artificial Intelligence, Reinforcement Learning, Smart Industry**

I. Introduction

Smart industry represents a significant paradigm in manufacturing and industrial processes, driven by the integration of digital technologies and automation. Robotics and artificial intelligence (AI) constitute foundational elements within smart industry, leading to extensive research into robotic automation that leverages diverse data sources [1]. In the field of robotics, motion planning involves the computation and optimization of collision-free and safe trajectories toward target locations within specified environments, with a particular emphasis on enhancing both accuracy and path efficiency [2]. Although various algorithms, including artificial potential fields (APF), bio-inspired heuristic methods, and sampling-based techniques, have been developed for optimization purposes, these approaches often require substantial computational resources and suffer performance degradation in complex environments. This limitation restricts their ability to consistently achieve optimal solutions. In contrast, reinforcement learning (RL) has attracted significant attention due to its capacity for real-time adaptation in complex and dynamic environments, as well as its robustness in discovering globally optimal solutions [3]. This paper offers a concise review of the limitations associated with classical algorithms and explores contemporary research trends in reinforcement learning-based motion planning in smart industry.

II. Motion Planning for Smart Industry

A. Path and trajectory planning

Motion planning is generally categorized into two primary types: path planning and trajectory planning. Path planning focuses on determining the movement direction by generating a path from the initial point to the goal point, without accounting for the dynamic characteristics or motion constraints of the robot. In contrast, trajectory planning involves the execution of movement by defining the path as a function of time, thereby incorporating a temporal dimension. Since path planning does not consider the robot's speed or acceleration during movement, it lacks critical information necessary for effective robot control. Conversely, while trajectory planning accounts for temporal aspects, it does not inherently guarantee a collision-free path. Therefore, both path planning and trajectory planning are essential components of a comprehensive approach to robot motion planning [4].

B. Types of classical motion planning

Classical approaches to motion planning include APF, bio-inspired heuristics, and sampling-based path planning methods. The APF method generates a potential field around the target point and obstacles, making it relatively simple to implement and effective for real-time obstacle avoidance [5]. However, it suffers from the local minimum problem and is ineffective in environments with multiple obstacles. Bio-inspired heuristics encompass methods such as genetic algorithm (GA) and particle swarm optimization (PSO). GA mimics biological evolution to find optimal solutions by applying the principle of survival of the fittest [6]. While GA has a high probability of finding a global optimum, it is computationally intensive. PSO, in contrast, is based on the swarm behavior of birds, where particles adjust their movement direction based on the best solutions identified by both the individual particles and the entire swarm. Although PSO is intuitive and easy to implement, it can converge to a local minimum and is difficult to apply in dynamic environments [7]. Sampling-based path planning methods generate random samples within the configuration space to identify a path, using techniques such as the probabilistic roadmap method (PRM) [8] and rapidly-exploring random trees (RRT) [9]. These methods are advantageous for quickly exploring paths in complex environments, but they often produce paths of lower quality, necessitating further refinement.

III. Reinforcement Learning based Motion Planning

Reinforcement learning optimizes policies through direct interaction with the environment, enabling real-time adaptation and the discovery of optimal solutions in dynamic contexts. Its inherent adaptability, coupled with its capacity to address complex, nonlinear, and unpredictable problems, provides a significant advantage over traditional methods, which often struggle in such scenarios. The robust performance of RL, along with its focus on long-term rewards, makes it particularly well-suited for path planning applications within the smart industry. In smart manufacturing environments, where flexibility, precision, and efficiency are paramount, RL offers significant potential by enabling autonomous systems to adapt in real-time to changing conditions and complex tasks. Recent research shows how RL is being used to improve motion planning and control, supporting the growing demands of smart industry.

A. RL-based performance enhancements

Reinforcement learning has been the focus of numerous studies aimed at advancing robot motion planning and control due to its potential in enhancing the adaptability and performance of industrial robots in complex and dynamic environments. R. Meyes et al. introduced an RL-based approach that enables robots to autonomously learn and adapt to complex tasks, such as welding and cutting, without pre-programmed instructions [10]. The method was validated using a wire loop game, where the RL agent successfully learned to control the robot through real-time feedback, demonstrating the ability to generalize to new configurations. This approach reduces computational costs and enhances flexibility and robustness, improving the resilience of industrial robots in manufacturing. P. Chen et al. propose an RL-based method using the soft actor-critic (SAC) algorithm and prioritized experience replay (PER) to improve dynamic obstacle avoidance and real-time path planning [11]. The SAC algorithm's entropy-based exploration strategy helps avoid local optima, ensuring more effective learning in unpredictable environments. J. Weber and M. Schmidt describe a method using the deep deterministic policy gradient (DDPG) algorithm to enhance inverse kinematics and motion planning for industrial robot manipulators [12]. The integration of a novel state space representation with a tailored reward function allows the DDPG agent to precisely control the robot's tool, even under challenging conditions with arbitrary start and target positions.

B. Integrate with existing methods

Deep reinforcement learning(DRL) is increasingly being used to address the limitations of traditional methods, offering new ways to enhance flexibility, adaptability, and performance in scenarios where classical approaches fall short. B. Sangiovanni and M. Piastra describe a hybrid control methodology that integrates classical motion planning algorithms with DRL for robot path planning and obstacle avoidance [13]. Their method enhances traditional techniques by incorporating a DRL-based approach that activates when the robot encounters dynamic obstacles, allowing it to adjust its path dynamically. This hybrid system combines the reliability of classical methods with the adaptability of DRL, providing a robust solution for complex environments while reducing the computational burden of real-time planning. Similarly, Li et al. propose a hybrid framework that integrates traditional path planning with DRL [14]. This framework leverages the exploratory capabilities of traditional planners alongside the exploitation strengths of DRL, making it well-suited for complex and dynamic industrial environments. By using a DRL algorithm with Tsallis entropy-based automatic adjustment, the method optimizes both path planning and inverse kinematics for redundant robot manipulators, achieving energy-efficient and adaptive solutions in real-time industrial applications.

C. Extend application

Reinforcement learning in robot motion control is driving the expansion of its applications across various fields, enabling more precise, adaptive, and efficient solutions for complex and dynamic tasks. Z. Li and C. Su describe an approach that enhances RL for robot manipulation and grasping tasks using dynamical movement primitives (DMPs) in a humanoid-like mobile manipulator [15]. By integrating RL with DMPs, the method effectively addresses challenges in vision feedback, manipulation dynamics, and external perturbations, making it suitable for both high-level operational space planning and low-level joint control. This integration allows the robot to perform complex tasks like grasping in uncertain environments, extending RL's applicability in robotics by improving redundancy resolution, trajectory optimization, and real-time adaptability. In space operations, where adaptability and precision are critical, the EfficientLPT algorithm combines RL with prior policy guidance to handle tasks with high dimensionality and dynamic coupling [16]. This method balances exploration and exploitation through a novel reward function, enhancing convergence and planning accuracy while enabling robots to autonomously adapt to dynamic environments. J. Zhong et al. present a hybrid algorithm that combines DRL with inverse kinematics for collision-free path planning in welding manipulators [17]. The method leverages DRL for navigating high-dimensional spaces and inverse kinematics for efficiently guiding the manipulator, improving learning speed, robustness, and reducing computational load, making it ideal for precision-driven industrial tasks in confined or dynamic settings.

D. Sensor based approach

Sensor-based approaches are increasingly being used to enhance reinforcement learning-based motion control, enabling robots to adapt more effectively to dynamic and uncertain environments. Z. Liu et al. propose a deep reinforcement learning-based hybrid visual servoing (DRL-HVS) controller for autonomous robotic assembly tasks. By integrating position-based visual servoing and image-based visual servoing, the method addresses challenges such as field of view constraints, image local minima, and obstacle collisions. The DRL-HVS controller, trained using the DDPG algorithm in a simulated environment, can be quickly deployed in real-world systems.

An adaptive exploration strategy (AES) further improves training efficiency by dynamically adjusting exploration noise. T. Bhuiyan et al. propose a DRL approach for industrial robot path planning using distance sensors for real-time obstacle detection. Virtual laser sensors provide 360-degree obstacle detection, enabling the DRL agent to adjust its path as obstacles appear. Trained using the proximal policy optimization (PPO) algorithm in randomized 3D environments, the DRL agent outperforms traditional planners by generating shorter, faster paths and handling dynamic obstacles more effectively, making it ideal for precision-driven industrial applications.

IV. Conclusions

The integration of reinforcement learning into motion planning has shown significant promise in advancing industrial robotics, particularly within smart industry. While traditional approaches can be effective, they often struggle with the computational complexity and adaptability required in dynamic and unpredictable environments. In contrast, RL offers flexible and robust solutions, enabling real-time adaptation and optimization in complex scenarios. This paper has reviewed the limitations of classical algorithms and highlighted how RL is enhancing performance, integrating with existing methods, extending its application to new domains, and incorporating sensor-based approaches. The integration of RL into robot motion planning marks a significant step toward achieving the flexibility, precision, and efficiency required by smart industry, positioning RL as a central technology in the future of autonomous systems within complex industrial landscapes.

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