Deep Reinforcement Learning for Robotic Grasping with Tactile Sensor Feedback

Bahador Beigomi, Zheng H. Zhu
Department of Mechanical Engineering, York University, Toronto, Canada
Baha2r@yorku.ca, Gzhu@yorku.ca

ABSTRACT

Deep Reinforcement Learning (DRL) has exhibited remarkable proficiency in enabling robots to execute complex tasks, such as object grasping using tactile sensor feedback. Traditional robotic grasping methods, dependent on handcrafted algorithms and heuristics, frequently face difficulties in coping with the intricacy and variability inherent in real-world situations. In contrast, DRL can derive robust grasping policies directly from data, removing the necessity for explicit modeling or feature engineering.

In this research, we introduce an innovative and unique approach to robotic grasping, specifically addressing the challenges of grasping free-floating targets in zero gravity environments. These challenges include controlling contact force between objects, where excessive force could result in pushing the target away or damaging the gripper. Our method employs deep reinforcement learning for automated feature design, which streamlines the problem, allowing the robot to learn grasping strategies through trial and error. We utilize the Soft Actor Critic (SAC) algorithm, a cutting-edge off-policy reinforcement learning technique, to optimize the gripper's performance.

To enable effective learning, we devise a shaped reward function that incorporates three-fingered hand poses from grasping demonstrations for various objects into the early stages of the training episodes. This shaped reward allows the agent to acquire efficient grasping policies. Our method is trained entirely in simulation using the Pybullet environment, thus eliminating the need for prior knowledge or demonstrations. We showcase our approach with a three-finger Robotiq gripper, designed to approach, pursue, and ultimately grasp a floating object in zero gravity.

Despite the potential of DRL in robotic grasping, several challenges remain, including the high dimensionality of sensor data, extensive action spaces, and balancing exploration and exploitation during learning. Our method tackles these challenges through strategic learning techniques and efficient computation. By training the agent in simulation, it can develop a robust and versatile grasping policy applicable to a wide range of real-world scenarios, such as grasping floating objects in unstructured environments or objects with uncertain positions and orientations.

Our proposed approach demonstrates its capacity to enhance the performance of grasping tasks across various applications, spanning from manufacturing and assembly lines to logistics, rescue, and exploration missions. The key contributions of this paper include the novel application of the SAC algorithm, the development of a shaped reward function for efficient learning, and the adaptation of our method to the distinct challenges of grasping in zero gravity environments, distinguishing it from conventional deep reinforcement learning methods.