Adaptive Robotic Grasping with Replay Tail Memory Enhancement

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***Abstract*— Robotic grasping faces catastrophic forgetting as knowledge of manipulated objects fades when handling new items. This paper introduces "replay tail," a memory technique using an RGBD camera to capture tabletop scenes, convert observations to 3D point clouds, and generate vertically projected heightmaps. Building on deep Q-learning combining deep neural networks and reinforcement learning, replay tail replays recent heightmap experiences to maintain adaptation. By emphasizing recent interactions during memory replay, grasping policies continuously recalibrate, preventing performance degradation despite emerging novelty. Experiments with 2000 simulated automated grasping attempts show 89% average success rates using replay tail versus 86% otherwise. These highlights replay tail's potential to enable real-world deployment by mitigating catastrophic forgetting through consolidated recent memories.**

Keywords—Robotic grasping, Memory replay, Replay tail, Catastrophic forgetting, RGBD camera, Heightmaps, Deep Q-learning.

I. Introduction

Robotic grasping, a crucial and intricate skill, has been a longstanding challenge in robotics research for over half a century [1]. Traditional methods require a detailed understanding of the structure, position, and orientation of an object in order to determine the optimal grasping strategy. By contrast, analytical approaches rely on geometric information using the physical dimensions and shapes of objects to guide the grasping process.

Recent data-driven techniques [2] have shown significant promise for robotic grasping using machines and deep neural networks to directly map visual observations to the grasp parameters. However, these approaches often depend on large, labeled datasets, making the data collection process time- and power-intensive. The development of adaptable and generalizable systems for robotic grasping has been further advanced through research into real-time grasp force selection policies [3] and the design of flexible grasp tools [4] that can handle a variety of objects. Additionally, the exploration of object characteristics such as center of mass and mass determination [5] plays a crucial role in enhancing the precision of robot grasping mechanisms.

Recent research has adopted an end-to-end deep learning approach directly from RGB images to determine position and orientation. For instance, Pinto and Gupta [6] trained a convolutional neural network (CNN) on over 50k attempts to predict grasp success from RGB images in a self-supervised manner. Mahler et al. [7] proposed GQ-CNN, a CNN-based model that rates grasp candidates on synthetic point clouds using an analytic grasping metric. Levine et al. [8] collected over 800k grasp attempts on 14 robots to train a deep visuomotor policy end-to-end, from monocular images to motion commands.

Deep reinforcement learning (DRL) offers an appealing framework for acquiring dexterous grasping skills through pure self-supervised interactions using reward signals instead of manual oversight [9]. Quillen et al. [10] compared various deep reinforcement learning techniques for vision-based grasping in simulation, including DQN, DDPG, and TRPO. Breyer et al. [11] evaluated different input modalities like depth, segmentation, and simulation vs. reality for deep reinforcement learning of grasping. However, a fundamental limitation hampering the real-world deployment of these learning-driven systems is their tendency to experience catastrophic forgetting [12]. Older knowledge of previously manipulated items tends to fade as new objects are encountered and information is encoded in the network weights. This significant domain shift degrades the grasping performance when novel objects must be handled alongside the existing objects.

Our work closely aligns with the research conducted by Zeng et al. [13], in which the synergies between pushing and grasping were learned through Deep Q-learning. They demonstrated an effective grasping performance on a pile of objects by sequencing actions that combined pushing and grasping. However, in grasping, he did not consider the possibility of introducing novel objects during training. In contrast, a specialized memory replay technique called "replay tail" was used to preferentially replay recent experiences, maintain adaptation by emphasizing recent interactions during memory replay, and allow grasp policies to continue calibrating dynamic environments.

In our approach, a simulated environment was designed to represent cluttered tabletop scenes with eight diverse items. A simulated RGB-D camera provides input point cloud data, based on which multiple height map representations are generated through slicing, projection, and an 16-way rotation. Specialized feature extraction via DenseNet [14] converts