Robot Skill Learning for Long-Horizon Assembly Tasks

Introduction

Robotic assembly tasks in modern manufacturing are increasingly complex, requiring robots to handle contact-rich, long-horizon manipulations with high precision and adaptability. Traditional industrial robots are often programmed for a single, rigid assembly sequence which is insufficient for small batches and highly specific productions. Due to the need for advanced learning capabilities and intricate object interactions, closing the gap between conventional programming methods and long-horizon, contact-rich, high-precision assembly remains a significant challenge [1-2]. This project seeks to push the boundaries of robot learning in complex assembly scenarios by developing novel algorithms, ultimately aiming to bridge the simulation-to-reality gap and empower robots with robust contact-rich manipulation skills.

Related Work

To address the limitations of traditional programming in handling contact-rich and long-horizon robotic assembly tasks, numerous recent studies have focused on developing learning-based approaches that enable greater adaptability, precision, and generalization. The following Table 1 summarizes recent methods for robot assembly tasks, presented in order of increasing task complexity: starting with basic operations and hierarchical operations.

Category	Method	Key Idea	Advantages	Limitations
Basic Operations	ProMP Imitation Learning (Zang et al., 2023) [3]	Propose a streamlined imitation learning method under the terse geometric representation to take good advantage of the demonstration data, and then realize the manipulation skill learning of assembly tasks	Achieves higher success than vanilla imitation, with better generalization to new positions	Relies on quality demonstrations and ProMP modeling; the ProMP itself has limited trajectory generalization capability
Basic Operations	SeqPolicy (Modular RL) (Liu et al., 2024) [4]	Divides a multi-peg insertion task into three stages: picking, alignment, insertion. Trains separate deep RL policies for each sub-task and sequences them with a high-level controller	Greatly improves sample efficiency and training convergence by modularizing the task and achieves higher success rates than a single monolithic policy	Not fully end-to-end, the transitions between sub-policies rely on manually defined state conditions
Basic Operations	ScrewMimic (Rahmatizadeh et al., 2024) [5]	A robot learns a bimanual skill (e.g. opening a bottle, rotating a faucet) from a single RGB-D video of a human demonstration.	Outperformed baselines that attempt to imitate directly in joint space, demonstrating that the structured screw-centric approach yields more robust and synchronized bimanual motions	Currently, the policy is learned per object class and limited in generalization if faced with very different objects
Hierarchical Operations	JUICER (Imitation Learning) (Ankile et al., 2024) [6]	Adopt diffusion policy models for expressive action prediction and synthetic trajectory augmentation around critical "bottleneck" states via simulated disassembly/reassembly	Achieves >70% task success with only 10 demos + 100 augmentations + 90 rollout samples; Augmentation improves handling of precision-critical states like insertions	Only validate in simulation envrionment, not yet adapted or tested in real-world setting
Hierarchical Operations	GRT-HL (Yun et al., 2022) [7]	Introduces a hierarchical reinforcement learning framework where the high-level policy generates optimal 3D end-effector trajectories using Gaussian Random Paths (GRP), and the low-level policy learns to execute these trajectories.	Significantly improves sample efficiency by avoiding trajectory exploration in raw action space and generates structurally feasible and optimized trajectories that improve low-level policy stability.	Limits adaptability to dynamic environments and real-world deployment not discussed.

Table 1. Literature Review

In recent studies, reinforcement learning (RL) has demonstrated strong adaptability and advantages in stability and control for long-horizon, contact-rich tasks. However, it requires a large number of interaction samples, is prone to local optima, and heavily depends on accurate environment modeling. In contrast, imitation learning can serve as an effective starting point for RL by accelerating the learning process in the early stages. Therefore, imitation learning can be applied initially to obtain a relatively stable policy, which can then be fine-tuned using RL for precise task execution.

Methodology

The proposed methodology comprises five core components: (1) Learning from Human Demonstrations, (2) Skill Decomposition, (3) Robust Policy Generation, (4) Hierarchical Learning, and (5) Sim-to-Real Transfer. The first four stages are developed and rigorously evaluated in simulation using the ISSAC platform. The final stage, Sim-to-Real Transfer, focuses on deploying the learned policies to real robotic hardware in real-world assembly scenarios. The workflow of the Methodology is demonstrated in Figure 1.

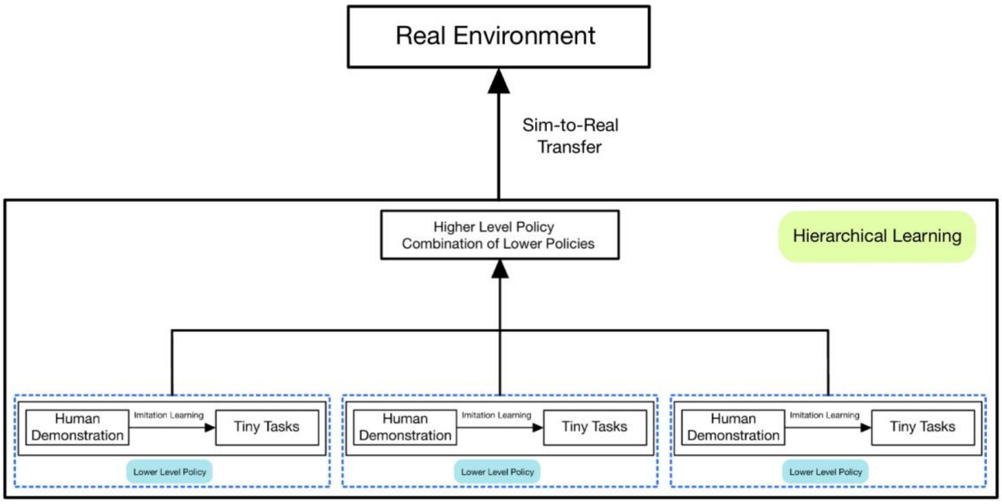

Figure 1. Workflow of Robot Skill Learning for Long-Horizon Assembly Tasks

(1) Learning from Human Demonstrations

Demonstration-Based Imitation Learning can be used to combine with RL to accelerate training speed and accuracy [8], especially Behaviour Learning, is a better solution for operation of RL such as assembling here. Nowadays, imitation learning has emerged as one of the most efficient methods for robots to acquire new skills, which can work as flexible and scalable solutions for robot learning [9-10].

(2) Skill Decomposition

The robot skills can be divided into several tiny tasks, such as Grasping, Alignment, Insertion and Tightening. Then the specific assembly will consist of several tiny tasks. For different assembly tasks, tiny tasks can be integrate together, instead of learning policy for each workpiece.

(3) Robust Policy Generation

A robust policy ensures that the assembly process is resilient to variations in the size, shape, roughness, and position of the workpiece.

(4) Hierarchical Learning

To enable robots to adapt during the assembly process, Hierarchical Reinforcement Learning (HRL) can be used to decompose long-term reinforcement learning tasks into hierarchical sub-tasks [11]. For the assembly tasks, the HRL could be designed as two stages:

- High level policy: the order and combination of low level policy(e.g. Grasping, Alignment, Insertion and Tightening)
- Low level policy: specific operation parameter, such as the force of grasping, the angle of robotic arm to tighten, which can be learned by imitation learning

(5) Sim-to-Real Transfer for Robotics

In the transferring process from simulation to the real world, it is crucial to enhance contact-rich manipulation for real-world applications. This is achieved by recording multimodal sensor data and evaluating the interaction dynamics between the robotic arm and the workpiece. Based on these observations, system parameters are fine-tuned to improve precision, stability, and adaptability in physical environments.

Expected Outcomes

This project will develop a hierarchical learning framework that integrates imitation learning and reinforcement learning to enable contact-rich, long-horizon robotic assembly. It is expected to generate modular and transferable skills, bridge the gap between simulation and the real world, and achieve performance comparable to state-of-the-art methods in complex assembly scenarios.

References

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