Proposal of ROB599 final project

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***Abstract*— Group project proposal that requesting for three people to do final project together in reproducing ACT alogrithm in real world environment**

I. Project Ideas

The main objective of this project is to complete long-horizon manipulation tasks using affordable robotic hardware through imitation learning. Generally, we plan to use the Koch robotic arm [1] to build a teleoperation system for data collection. The collected data will be used to train a model with Action Chunking Transformers [2] . As this is a final project, we intend to start with the Lerobot [3] codebase, which provides many useful tools to facilitate our work.

A. Koch Robotic Arm

The Koch robotic arm is an affordable, dual-arm system designed by Alexander Koch, featuring a leader arm and a follower arm, each costing approximately $250. Figure **??** illustrates the experimental setup, including 3 cameras from different angles. During data collection, the leader arm is manually operated, and its joint angles are mirrored by the follower arm for real-time teleoperation, enabling efficient data gathering. After training, the learned model can be deployed on the follower arm to perform manipulation tasks autonomously.

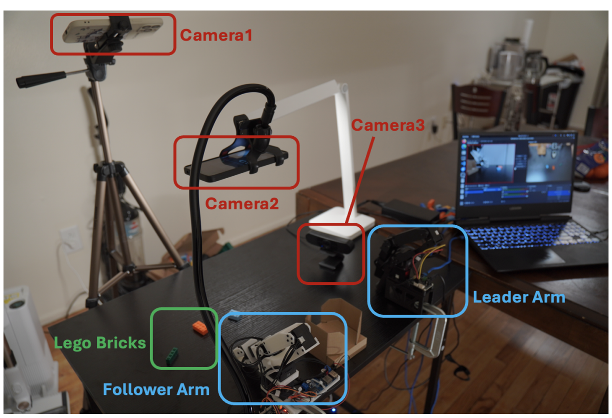

Fig. 1. Experimental Setup

B. Action Chunking with Transformers

Action Chunking with Transformers (ACT) is an imitation learning algorithm designed to address challenges in fine-grained, bimanual manipulation tasks. ACT learns a generative model over action sequences, enabling robots to perform precise, closed-loop behaviors, which are essential for complex manipulation tasks.

C. Lerobot

Lerobot is an open-source project developed by Hugging Face to support research in reinforcement learning for robotics. It offers tools, models, and simulations for training and testing RL algorithms on real-world robotic platforms. Lerobot's modular structure allows for flexible integration with various types of robots, making it an ideal choice for experimenting with novel RL and imitation learning algorithms in realistic scenarios.

II. Experiment Design

In this section, we outline the experimental setup to evaluate the long-horizon performance of the Action Chunking with Transformers (ACT) on a pick-and-place task. The objective is to test the algorithm's ability to handle extended sequences of actions with varying levels of complexity in object arrangement.

A. Task Setup

The task involves picking up and placing multiple LEGO building blocks arranged on a table. We will vary the scene in terms of the arrangement and spacing of the blocks to simulate different levels of difficulty. The robotic arm, equipped with the ACT, will attempt to pick up and place each block in a designated location. This setup will allow us to measure the algorithm's performance across different configurations and task complexities.

B. Experimental Conditions

The experiments will be conducted under three primary conditions as shown in Figure 2:

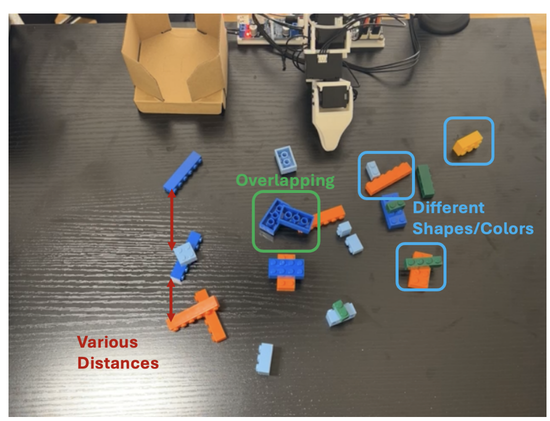

Fig. 2. An Example of Data House Layout

- **Block Overlap:** This condition tests the performance of the ACT when LEGO blocks are partially overlapping. Scenarios will include both non-overlapping and overlapping arrangements to understand the algorithm's handling of occluded or partially accessible objects.
- **Distance Between Blocks:** We will vary the distance between blocks in the scene. Configurations with closer blocks will challenge the algorithm to differentiate between neighboring objects, while wider spacing will test its ability to efficiently navigate and move across the workspace.
- **Variation in Block Types:** We will introduce blocks of different colors, shapes, and sizes to evaluate the algorithm's adaptability to diverse objects within the same environment. This variation will assess how well the ACT can generalize to different object characteristics in the pick-and-place task.

C. Evaluation Metrics

The following metrics will be used to evaluate the performance of the ACT:

- **Success Rate:** Defined as the ratio of successfully grasped and placed blocks to the total number of blocks in each trial. This metric will measure the algorithm's ability to complete the task accurately.
- **Completion Time:** The total time taken to finish the task in each condition, from the start of the sequence to the successful placement of the final block. This metric will provide insight into the efficiency of the ACT algorithm under varying conditions.

D. Experimental Procedure

For each experimental condition, the robot will perform five trials, with each trial consisting of a different random arrangement of blocks within the specified condition parameters. At the start of each trial, the position and configuration of blocks will be randomized within the defined constraints (e.g., distance, overlap, and variation). After each trial, the robot's performance will be recorded and averaged across all trials in each condition to obtain a comprehensive understanding of its strengths and limitations.

By examining the results across these conditions, we aim to determine how well the ACT algorithm performs in complex, long-horizon pick-and-place tasks and identify key factors influencing its performance.

III. Reason for Three-Person Team

Our decision to have a three-person team for this project is driven by the scope and demands of the tasks involved:

- Assembling the robot from scratch and performing extensive calibrations to ensure precise movements.
- Collecting our own data in a real-world environment, which requires substantial time and effort to capture and prepare accurately.
- Conducting experiments and training multiple policies to evaluate the ACT algorithm, necessitating dedicated time and resources.

These tasks collectively require a significant amount of hands-on work, making a three-person team essential for effectively managing responsibilities and ensuring the project's success.

References

[1] J. Moss, "Koch v1.1 robot arm," https://github.com/jess-moss/koch-v1-1, 2024, accessed: 2024-11-04.

[2] T. Z. Zhao, V. Kumar, S. Levine, and C. Finn, "Learning fine-grained bimanual manipulation with low-cost hardware," *arXiv preprint arXiv:2304.13705*, 2023.

[3] R. Cadene, S. Alibert, A. Soare, Q. Gallouedec, A. Zouitine, and T. Wolf, "Lerobot: State-of-the-art machine learning for real-world robotics in pytorch," https://github.com/huggingface/lerobot, 2024.