

PACKAGING SYSTEMS – TEAM 53

REINFORCEMENT LEARNING FOR ROBOTIC ARMS

TEAM MEMBERS: AINSLEY PHIPPS, ANDREW WATTS, ISIAH COOK, IAN HO

CLIENT MENTOR: ARJUN SUBRAMANIAM

ACADEMIC MENTORS: FREDERICK BERRY, JAMES CONDRON

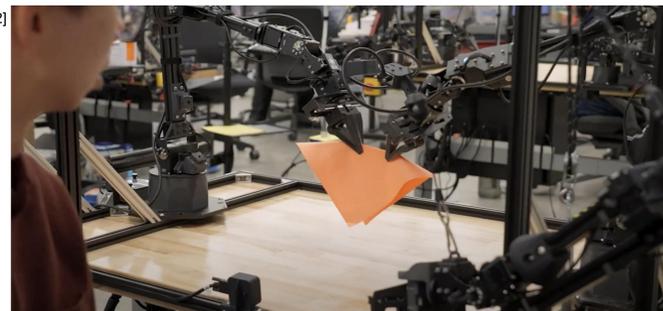
OBJECTIVE

To apply Reinforcement Learning techniques in training Trossen Aloha Stationary Robot Arms to autonomously perform complex, unstructured tasks. This project aims to enhance the adaptability and efficiency of robotic systems in dynamic environments, supporting the company's goal of developing intelligent automation solutions through advanced machine learning methods.

CONCEPTS AND EXPERIMENTATION

This project explores the application of Reinforcement Learning (RL) to train Trossen ALOHA stationary robot arms to autonomously perform unstructured and complex tasks. The primary goal is to develop robotic systems capable of adaptive decision-making in dynamic environments, moving beyond rigid programming to intelligent behavior shaped by experience and feedback.

A dual-computer setup forms the foundation of the control system. A higher processing computer, handles the computational tasks and interacts with a Linux-based laptop, which manages direct control of the robotic arms. These two systems communicate continuously to coordinate learning and execution processes.



Python scripts, adapted from the original ALOHA codebase, are executed through Google Colab to facilitate flexible, cloud-based development and testing. This environment supports rapid iteration and debugging while enabling remote access and collaborative work.

Initial training takes place in a virtual simulation environment, allowing the team to design and test specific manipulation behaviors safely and efficiently. These behaviors include grasping, sorting, and interaction with objects in varied, unpredictable configurations—key elements of unstructured task learning.

Once sufficient performance is achieved in simulation, trained models are transferred to the physical Trossen robot arms. The final phase of experimentation involves real-world testing, where the system's ability to generalize learned behaviors from simulation to hardware is evaluated. This sim-to-real transfer is critical for validating the effectiveness of the training pipeline and ensuring practical deployment.

FINAL DESIGN DESCRIPTION

Episode Data:

A complete set of manually recorded task demonstrations, each stored as an individual episode. These episodes include all relevant motion, timing, and metadata necessary for reproducing and analyzing task behavior.

Training Data:

A curated dataset formatted for model training, derived from the recorded episodes. It includes cleaned and structured input features such as joint angles and positional data, ready for integration into learning pipelines.

Evaluation Data:

A labeled dataset of held-out trials used to measure model performance. Each evaluation run is recorded and stored with consistent formatting to support benchmarking, validation, and future testing.

System Breakdown

A full package of project documentation, including detailed notes, copied command references, and a comprehensive walkthrough of our setup. This guide offers insights, troubleshooting tips, and advice for navigating and improving the system in future work.

```
Training ☆ ☁
PRO File Edit View Insert Runtime Tools Help
Q Commands + Code + Text
[ ] lcd /content/act_training_evaluation/act
python3 /content/act_training_evaluation/act/imitate_episodes.py \
--task_name aloha_can_move \
--cplt_dir /content/cplt_dir \
--policy_class ACT \
--kl_weight 10 \
--chunk_size 100 \
--hidden_dim 512 \
--batch_size 8 \
--dim_feedforward 3200 \
--num_epochs 2000 \
--lr 1e-5 \
--seed 0
Traceback (most recent call last):
  File "/content/act_training_evaluation/act/imitate_episodes.py", line 14, in <module>
    import torch
  File "/usr/local/lib/python3.11/dist-packages/torch/__init__.py", line 405, in <module>
    from torch._C import * # noqa: F403
  File "/usr/local/lib/python3.11/dist-packages/torch/_C.py", line 216, in <module>
    from frozen importlib._bootstrap*
KeyboardInterrupt
^C
[ ] import os
import shutil
from sklearn.model_selection import train_test_split
# Define source and destination directories
src_dir = "/content/drive/MyDrive/Aloha/aloha_can_move"
train_dir = "/content/aloha_can_move/train"
val_dir = "/content/aloha_can_move/val"
# Create destination directories if they don't exist
os.makedirs(train_dir, exist_ok=True)
os.makedirs(val_dir, exist_ok=True)
# Get list of all .hdf5 files in the source directory
all_files = [f for f in os.listdir(src_dir) if f.endswith(".hdf5")]
# Split into training and validation sets (80/20)
train_files, val_files = train_test_split(all_files, test_size=0.2, random_state=42)
```

TROSSEN ALOHA WORKSTATION



Leader Arms: Manually operated by the user, these serve as the main input for training. Movements are mirrored by the follower arms, enabling intuitive task demonstration and data collection.

Follower Arms: These arms replicate leader movements in real time, supporting imitation learning and task playback for training models to perform physical actions accurately.

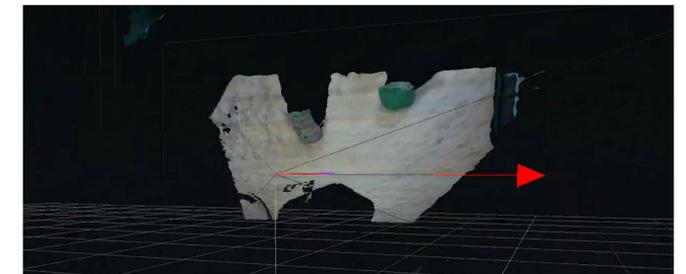
Intel RealSense Cameras: Intel RealSense depth cameras provide 3D vision and spatial awareness for object detection, scene understanding, and improving robotic interaction accuracy.



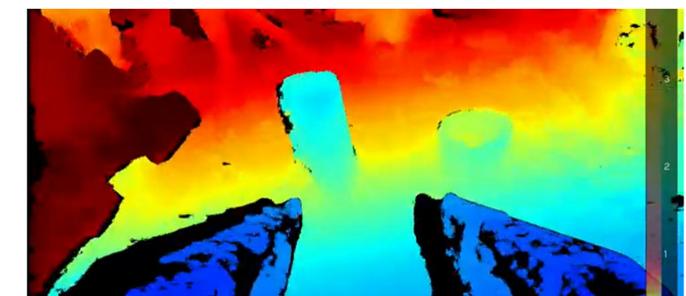
Polytechnic Institute

This project is a collaboration between Purdue Polytechnic students and Packaging Systems, utilizing Trossen Robotics' ALOHA workstation. All hardware and software developments are based on company-owned property. For more details, please contact the project team or refer to documentation provided by Purdue Polytechnic and Packaging Systems.

VIRTUAL ENVIRONMENT VIEW



DISTANCE VIEW



CONCLUSION AND RECOMMENDATIONS

This project shows how robots can learn complex tasks through trial and error using Reinforcement Learning. A strong start—like recording over 200 task examples—helps build a solid foundation for training. It's also important to get comfortable with the software tools early on. Testing throughout the process helps catch issues before they grow. Changing computers or systems can take more time than expected, and writing code often requires patience and persistence. Small adjustments can make a big difference in performance. Overall, careful planning, steady progress, and flexibility are key to developing smart, reliable robotic systems.

[1] Robotics (n.d.). Trossen Robotics ALOHA Stationary V2.0. <https://robotics.cs.purdue.edu/trossen-robotics-internal-manipulation-aloha.html>
[2] EIN Presswire. (2024, March 26). Trossen Robotics ALOHA Stationary Featured in Google DeepMind's Gemini robotics research. <https://www.einpresswire.com/article/794594113>