universität freiburg

Policy Learning for Real-time Generative Grasp Synthesis

Sassan Mokhtar

Robot Learning Lab

04 August 2023

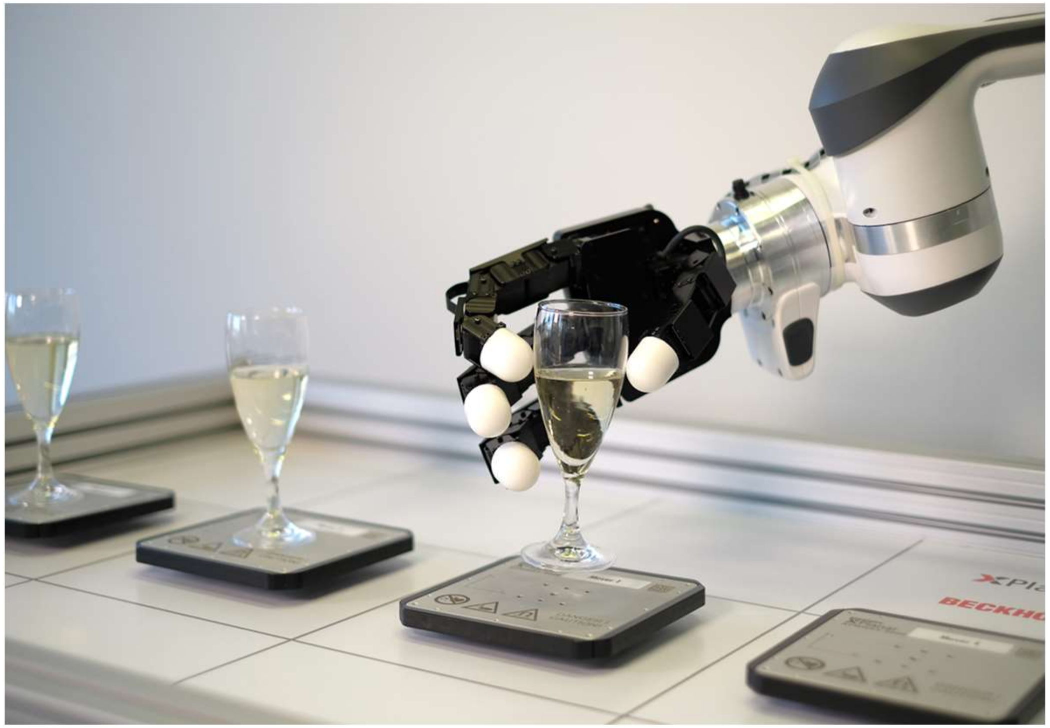
Why Grasping?

GettyImage

ABB

- Fundamental component of robot manipulation
- Many manipulation problems involve grasping
- Wide range of applications

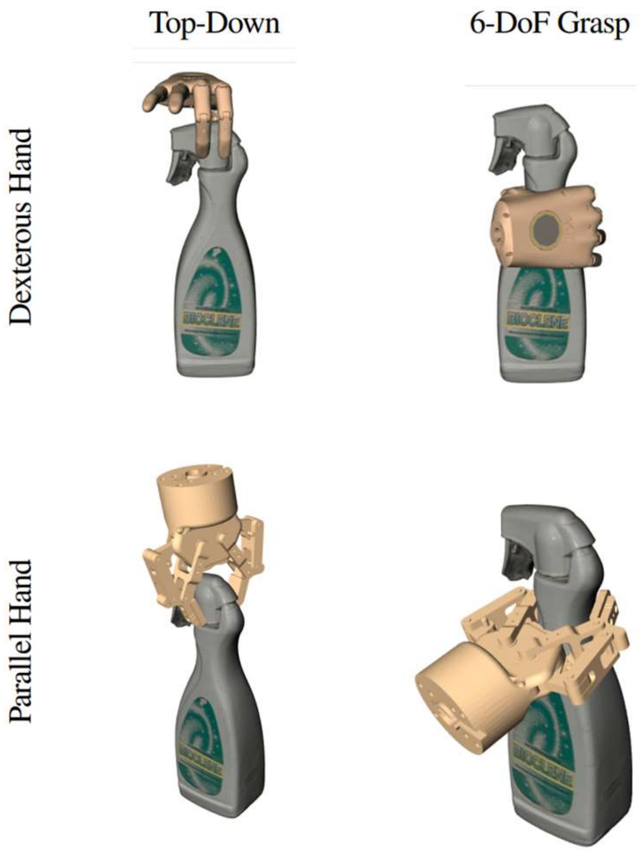
Why Grasping is Challenging?



XPlanar

- High-dimensional search space
- Approach the object with no-collision
- Robust Grasps

Top-down vs. 6 DoF Grasps



[1]

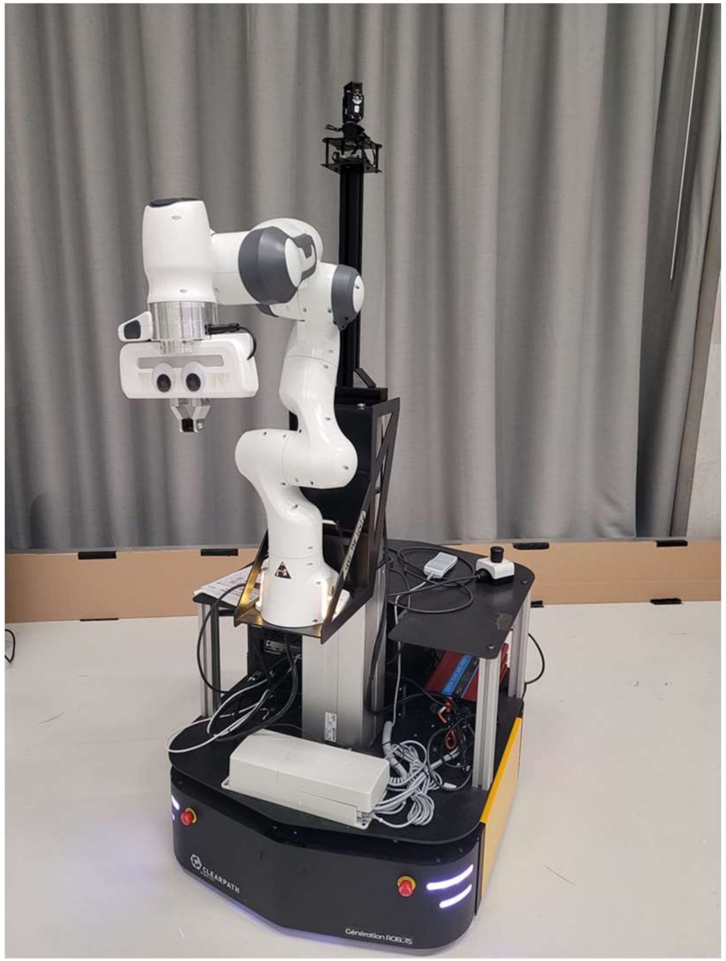
Top-down setting:

+ 4 DoF grasps
+ Simpler to learn
- Not robust in general

Static-Camera vs. Wrist-Camera

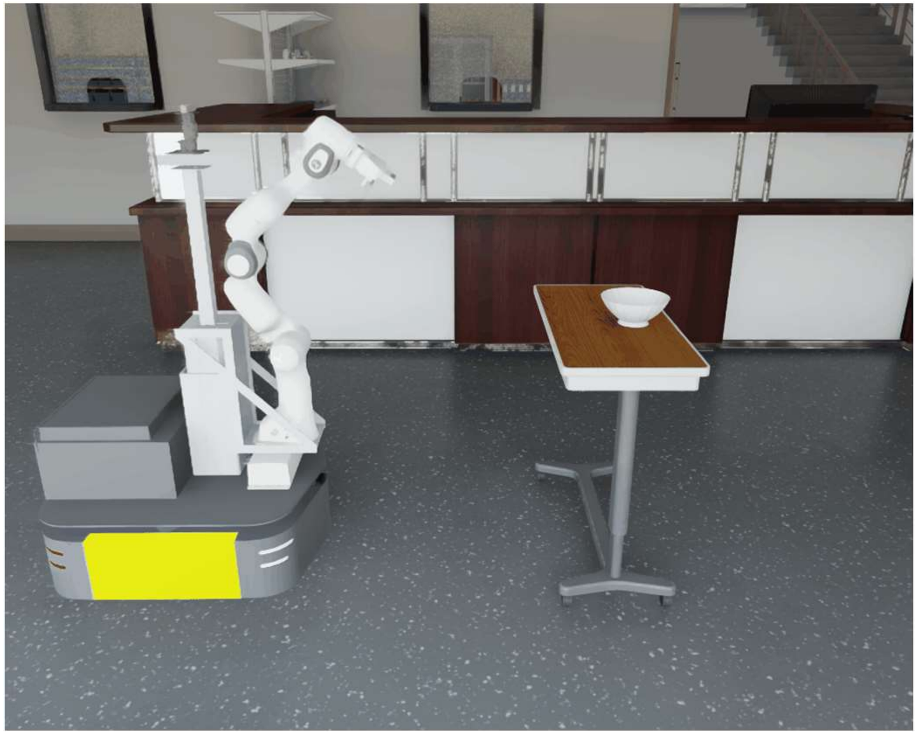
- Most of models are developed for *static-camera* setting
- However, *static-camera* is not realistic for many mobile manipulation settings

Problem Statement



- Grasping for Mobile Manipulation Robots
- The most challenging, but realistic scenario:
  - 6 DoF grasps
  - Only a wrist camera

Contributions



- Design a grasping setup in Issac Sim
- Evaluate the performance of different methods
- Ablation study on the action space and sequence learning

Model-based vs. Learning-based Grasping

- **Model-based Grasping:**
  - Classic Approach
  - Determine grasps based on: contact type, contact model, and grasp wrench space
- **Limitation:**
  - Based on unrealistic and non-generalizable assumptions

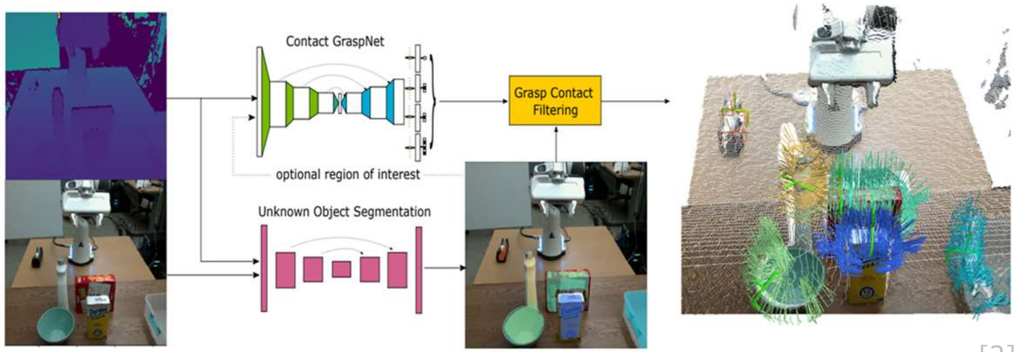
- **Learning-based Grasping:**
  - Modern Approach
  - Leverage data to decrease reliance on assumptions about object's physical properties
  - Utilize computer vision, imitation learning, reinforcement learning, etc.

Learning-based Models

- **Grasp-pose Estimation:**
  - Based on Computer Vision techniques
  - Find the static grasp synthesis in the robot's initial pose
- **Limitation:**
  - Reactive Scenes
  - Accuracy in mobile manipulation setting

- **Policy Learning:**
  - Imitation Learning, Reinforcement Learning
  - The model decides at each step of the trajectory
  - **Idea**: Dynamic selection of grasp points might improves performance over initial static selection

Baseline: Contact-GraspNet

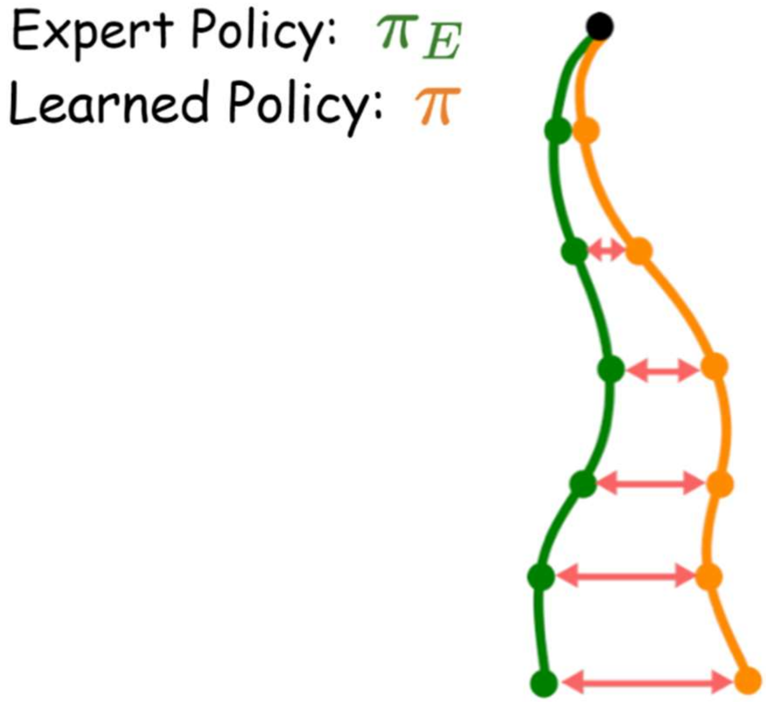


[2]

- **Novelty**: Obtain non top-down grasps in 4 DoF formulation

- Static selection of grasp synthesis
- Treat 3D points of the recorded point-cloud as potential grasp contacts
- Mask collected point-cloud to reduce number of points
- To propose the rotation and grasp width for refined 3D points

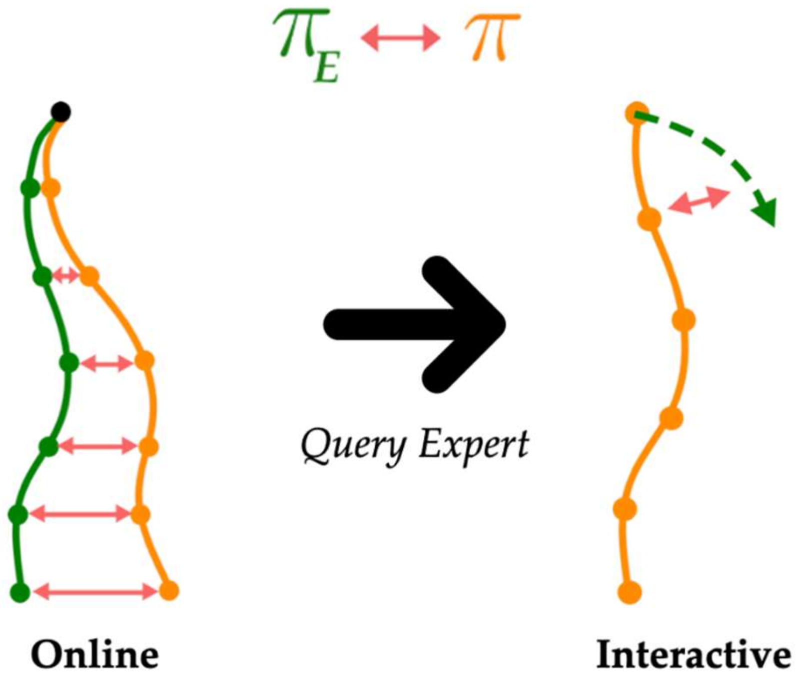
Behavior Cloning



- **Goal**: To find a policy that imitates the expert policy by leveraging set of demonstrations

- **Main Limitation**: *Distribution mismatch* in states under the expert policy and the learned policy

Behavior Cloning with Feedback



- Pre-train the model using vanilla behavior cloning
- Aggregating dataset, while learned policy is exploring
- Ground-truth actions, act as feedback for the learned policy
- Expected to be more robust

Action space Candidates

- *Euler Angle pose*: (3D position, 3D orientation)
  - \+ Intuitive, simple
  - \- Gimbal lock, numerical instability
- *Transformation matrix* (SE3)
  - \+ Numerically stable
  - \- Higher dimension (12, instead of 6)
- *Twist*: (3D position, 3D orientation)
  - \+ Numerically stable, low dimensional
  - \- Sensitive to “dt”

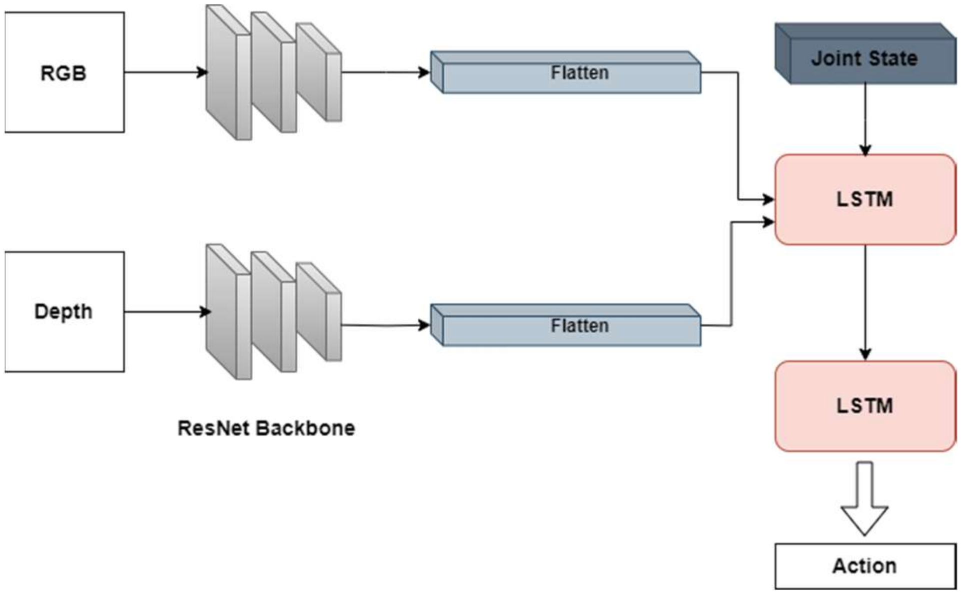
Other Components

- **State Space:**
  - RGB-D images
  - Joint positions

- **Expert Policy:**
  - ACRONYM dataset
  - Custom controller, based on inverse Kinematics

- **Sequence Learning:**
  - *The entire trajectory*:
    - \+ Uniform LSTM mode for training and validation
    - \- Difficulty for batch learning
    - \- High memory costs
  - *Subset of trajectory*:
    - \+ Simple batch-learning
    - \- Inconsistency in LSTM modes

Network Architecture



Components:

- *ResNet Backbone*: Process images to determine state
- *Joint State*: Additional source for determining state
- *LSTM*: To include history

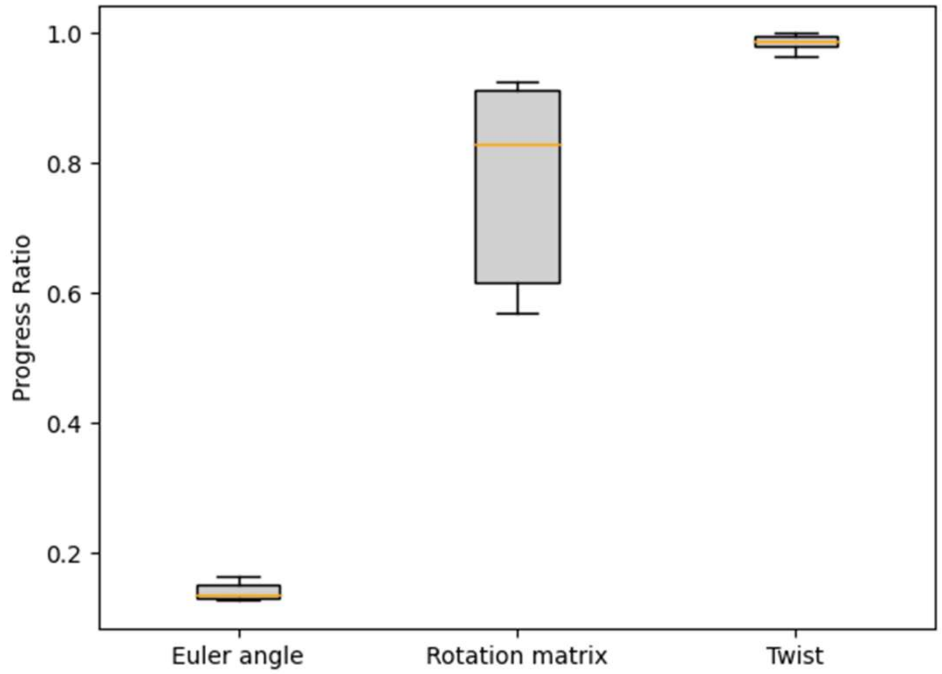
Evaluations

- **Ablation Studies:**
  - *Action Spaces*
  - *Sequence Learning*
- **Metrics:**
  - *Success Rate*: Rate of successful grasps
  - *Progress Ratio*: Progress ratio towards grasp pose
- **Scenarios**:
  - *1-object scenario*: Picking a bowl in random places
  - *10-object scenario*: Picking 10 different objects in random places

Ablation experiments: Action Spaces

1-Object Experiment

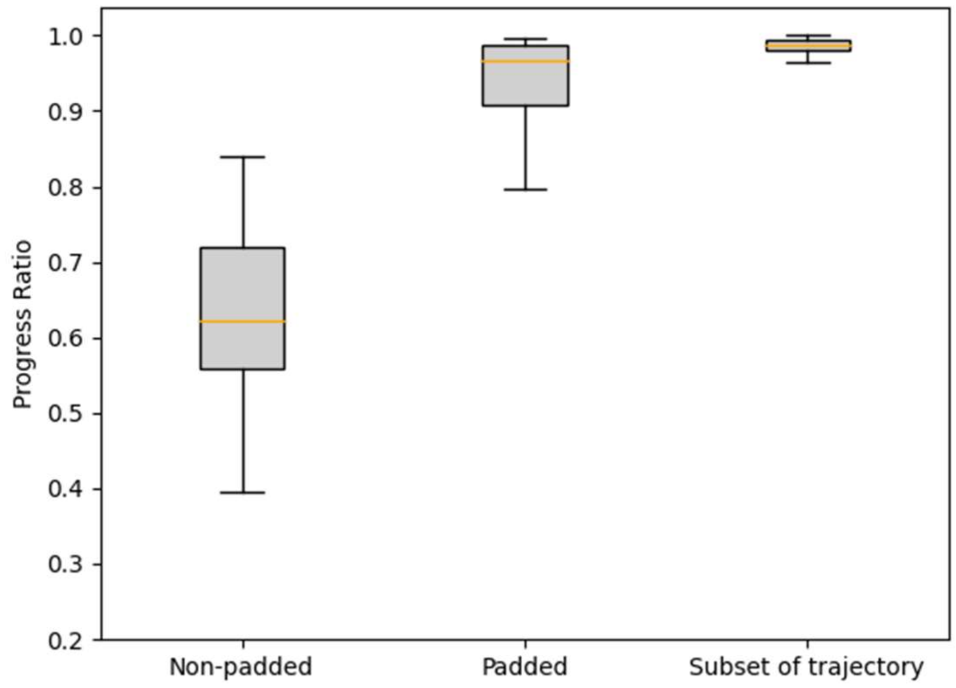
	Progress towards grasp pose	Success ratio
Euler angle	0.12	0.0
Rotation matrix	0.82	0.0
Twist	**0.98**	**0.81**



Ablation experiments: Sequence Learning

1-Object Experiment

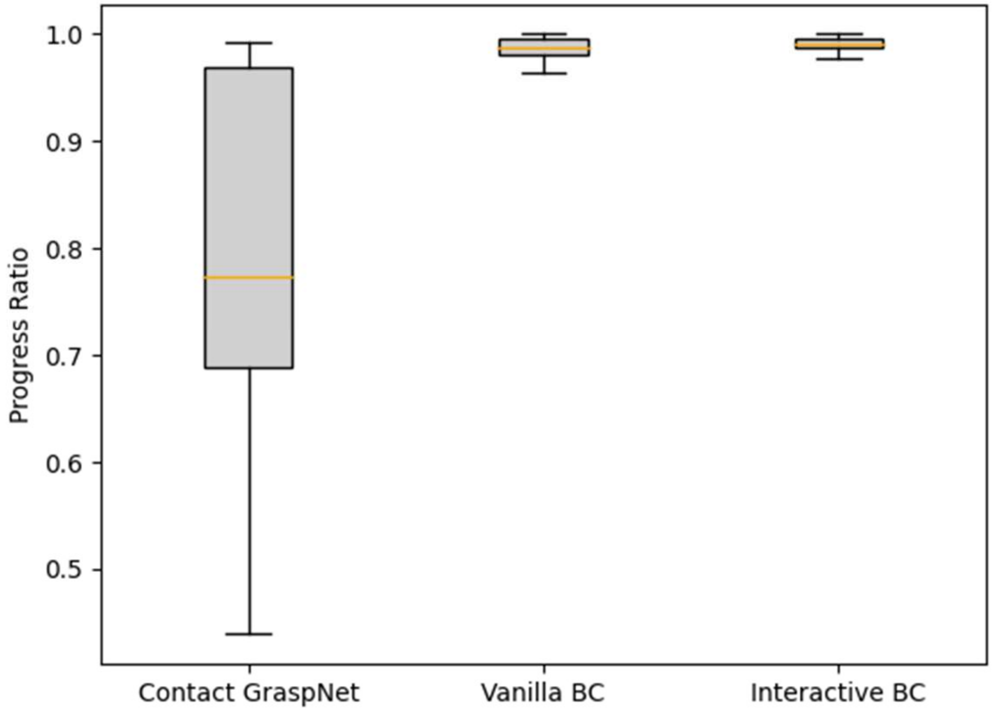
	Progress towards grasp pose	Success ratio
Entire trajectory(non-padded)	0.62	0.0
Entire trajectory(padded)	0.94	0.52
Subset of trajectory (25 steps)	**0.98**	**0.81**



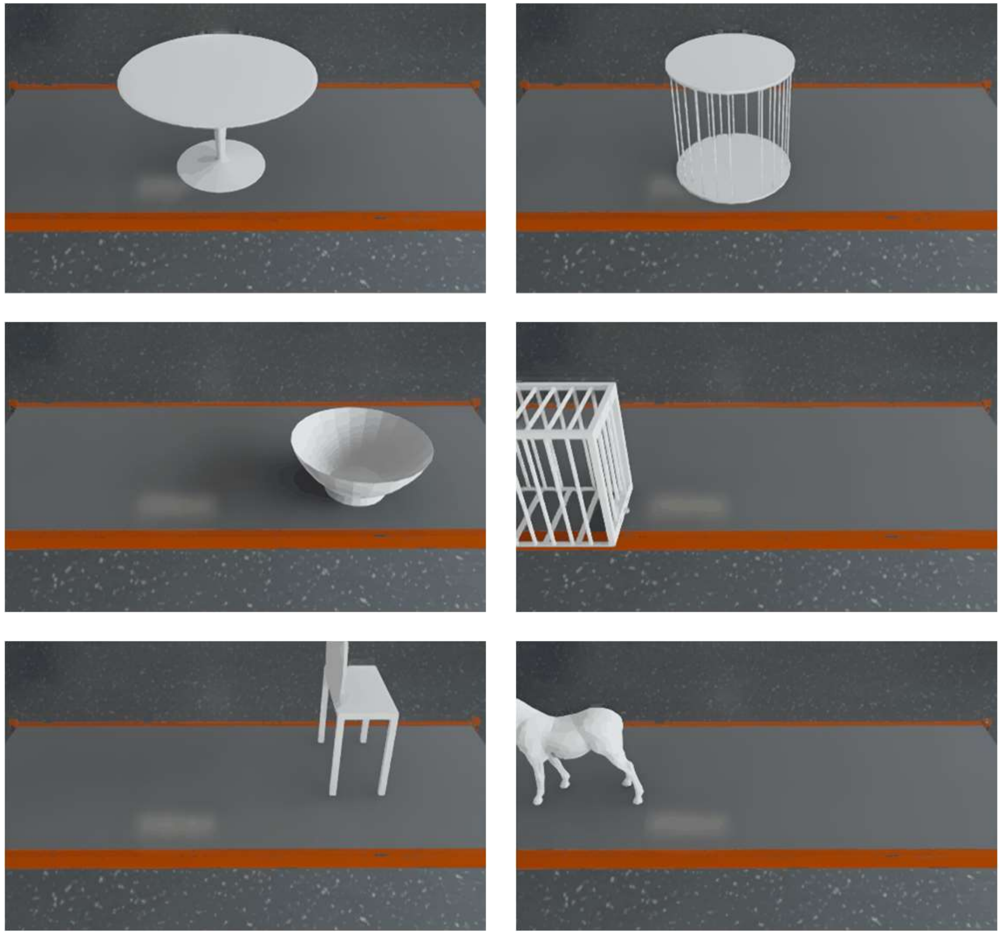
Results

1-Object Experiment

	Progress towards grasp pose	Success ratio
Contact GraspNet	0.81	0.0
Vanilla Behavior Cloning	0.98	0.81
Interactive Behavior Cloning	**0.99**	**0.90**



Limitation



10-Object scenario:

- Prolonged training period of 250,000 steps and the collection of over 3000 trajectories (approximately 6 days of training)

- The policy network learned to approach the object, but did not achieve successful grasping.

Conclusion and Future Work

Conclusion:

- Realistic scenario design for mobile manipulation robot grasping
- Grasp-pose estimation baseline underperformed
- Interactive behavior cloning outperformed in single object grasping
- In more complex tasks, successful grasping was unachievable in reasonable time

Future work:

- Adjust the training process to enhance efficiency
- Develop a Hybrid model of grasp pose estimation and policy learning method

References

1. Newbury, Rhys, et al. "Deep learning approaches to grasp synthesis: A review" *2023 IEEE Transactions on Robotics. 2023*

2. SunderSundermeyer, Martin, et al. "Contact-graspnet: Efficient 6-dof grasp generation in cluttered scenes" *2021 IEEE International Conference on Robotics and Automation (ICRA). 2021*

3. Chisari , Eugenio, et al. “Correct me if i am wrong: Interactive learning for robotic manipulation” *2022 IEEE Robotics and Automation Letters. 2022*

4. Mandlekar, Ajay, et al. “What matters in learning from offline human demonstrations for robot manipulation” *2021 arXiv preprint arXiv:2108.03298. 2021*