Research Summary

Presenter: Tianyi Xiang
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Research summary structure

1. Quick introduction

2. Previous research

3. Future plans

1. Quick portfolio

Education:

- **Undergraduate school – Xi’an Jiaotong Liverpool university; Rank 1**
  BEng Mechatronics and Robotic System

- **Graduate school – Yale University**
  MS Mechanical engineering & Material Science

  - **Grab Lab – Supervisors: Prof. Aaron Dollar**
  - **Social Robotics Lab – Supervisors : Prof. Brian Scassellati**

Tianyi Xiang

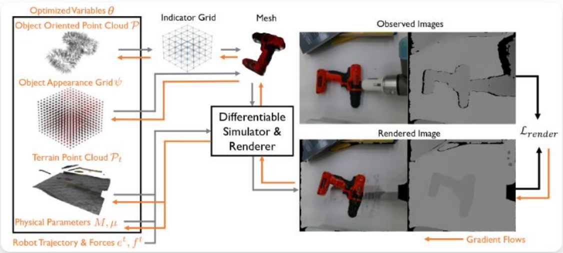
1. Quick portfolio

Research interest:

- Intersection of physics-based modeling and machine learning
- Perception & Motion planning
- Optimization
- Mechanics (trivial)

Publications:

1. CASE 2024; first author
2. ICAC 2024; first author
3. RA-L 2024 (submitted); second author

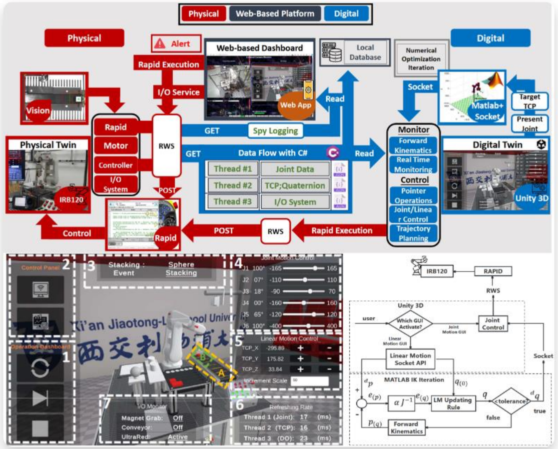


"Real-to-Sim via End-to-End Differentiable Simulation and Rendering"

Yifan Zhu, **Tianyi Xiang**, Aaron Dollar, Zherong Pan

IEEE Robotics and Automation Letters (RA-L 2024), Manuscript submitted for publication.

PDF

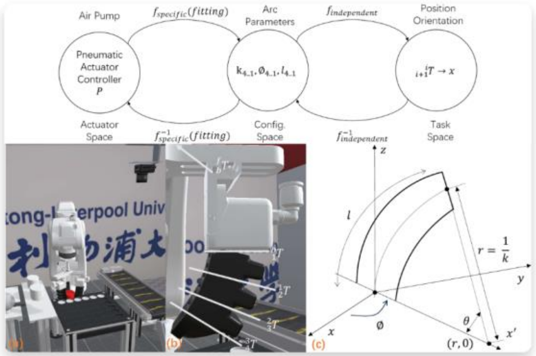


"Development of a Simple and Novel Digital Twin Framework for Industrial Robots in Intelligent Robotics Manufacturing"

Tianyi Xiang, Borui Li, Xiaonan Pan, Quan Zhang

20th International Conference on Automation Science and Engineering (CASE 2024).

PDF



"A Novel Approach to Grasping Control of Soft Robotic Grippers based on Digital Twin"

Tianyi Xiang, Borui Li, Quan Zhang, March Leach, Enggee Lim

29th International Conference on Automation and Computing (ICAC 2024).

PDF

2. Common research gaps of robots in uncertain worlds

Common problem: robots lack an <u>identification</u> of <u>physical world models</u>

Manipulable object: <u>perfect 3D mesh, mass of inertia, and friction.</u>
Collision models (ground, walls): <u>3D mesh and friction.</u>

Physics properties
of sponge and plate?

Contact rich manipulation: washing dishes

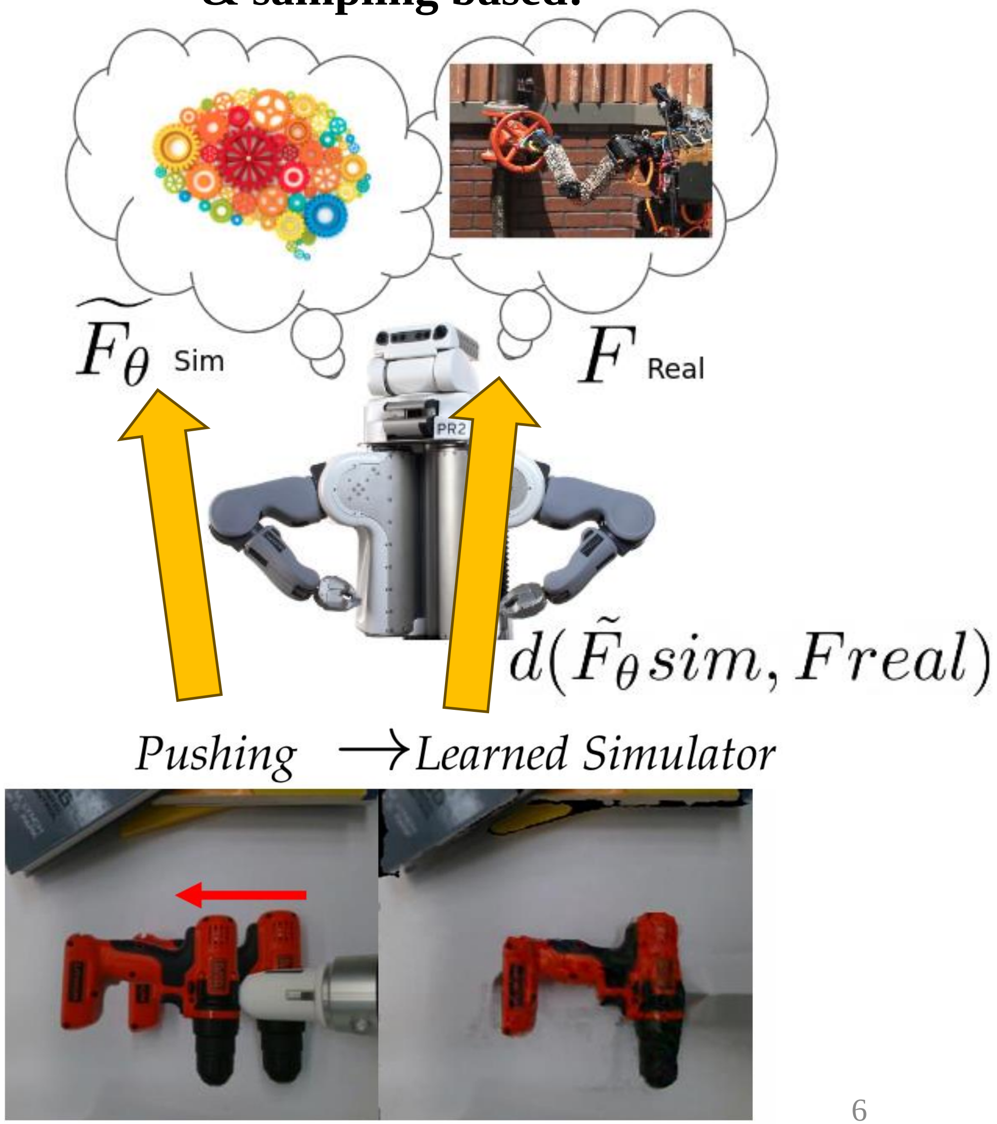
3. Solution & Research interest

Solution & Research interest:
Physics-Informed Machine Learning in Robotics

Especially, I focus on
differentiable simulator

Advantage: Extract physics models, e.g. perfect 3D mesh, mass of inertia, friction.

Optimization based ML
& sampling based!



Previous Researches

Private Repository now:

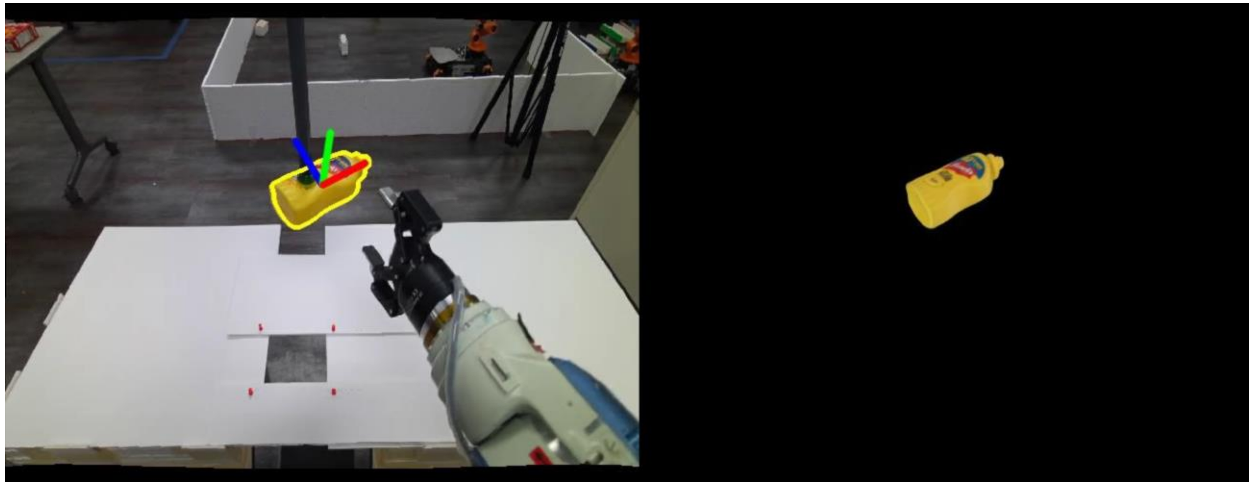
- Later maybe open-source!

End-to-End system identification via differentiable simulation and rendering

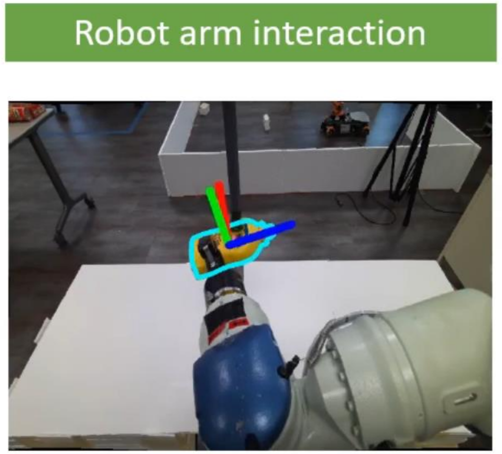
[1] Y. Zhu, **T. Xiang**, A. Dollar, and Z. Pan, "Real-to-Sim via End-to-End Differentiable Simulation and Rendering". RA-L 2024

Research gap of classical computer vision

Foundation Pose CVPR 2024 **(Highlight)**



BundleSDF CVPR 2023

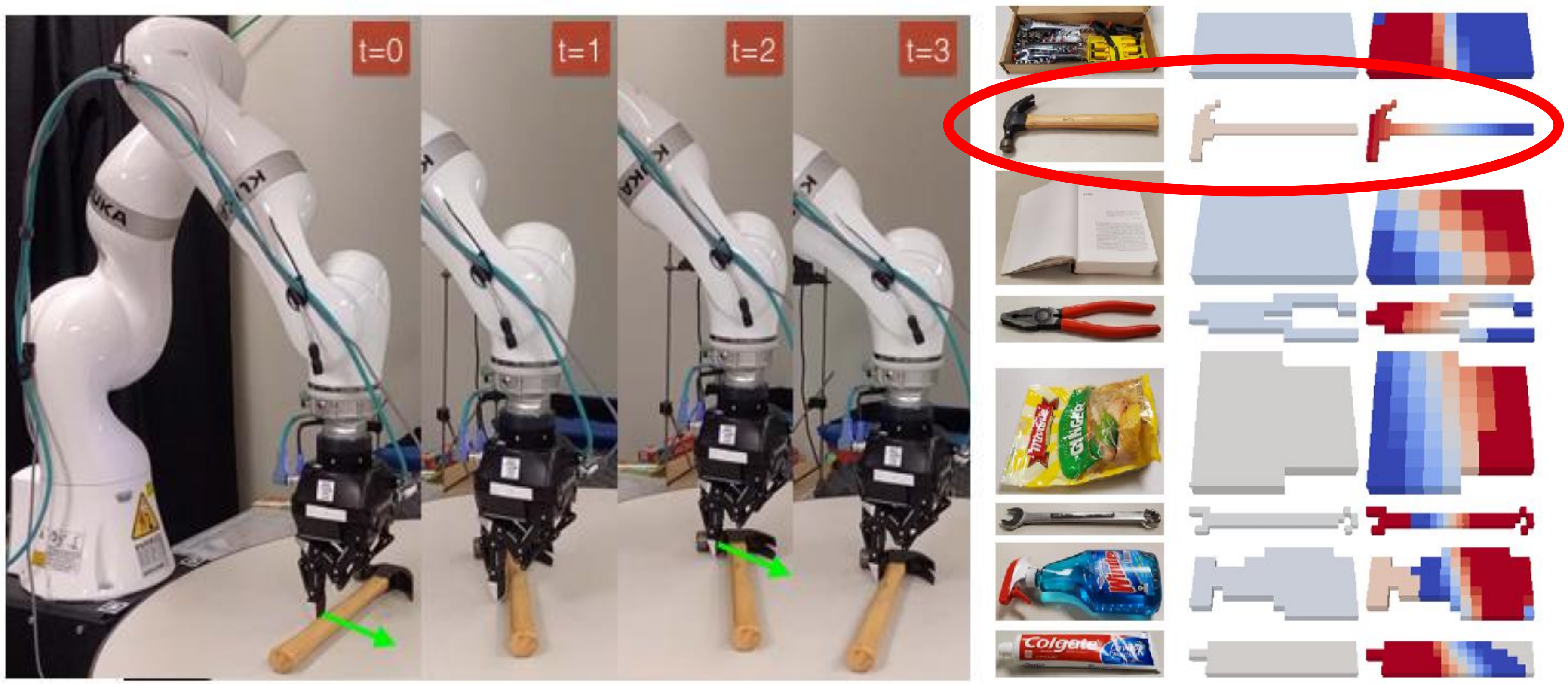


Drawback:

1. **3D Mesh is not completed.**
2. **Physical properties are missing, e.g. inertia, mass, friction.**

which are significant for contact rich manipulation.

Research gap of prior differentiable simulation

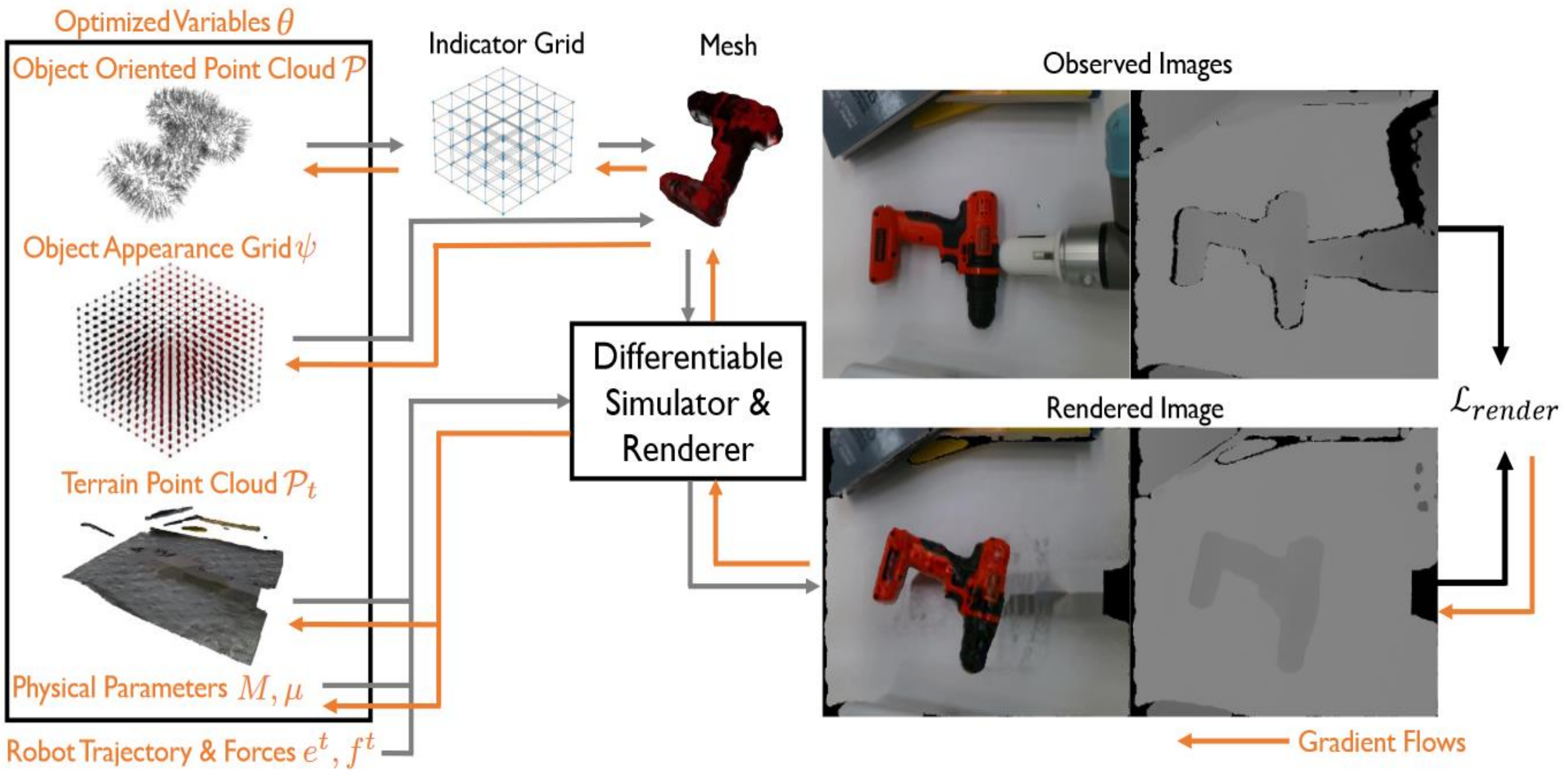


3D shapes are pre-known and well defined at beginning!

[1] "Learning to Slide Unknown Objects with Differentiable Physics Simulations," RSS 2020

Assumption: pre-known shapes and appearances of the objects

System identification: differentiable simulation and rendering



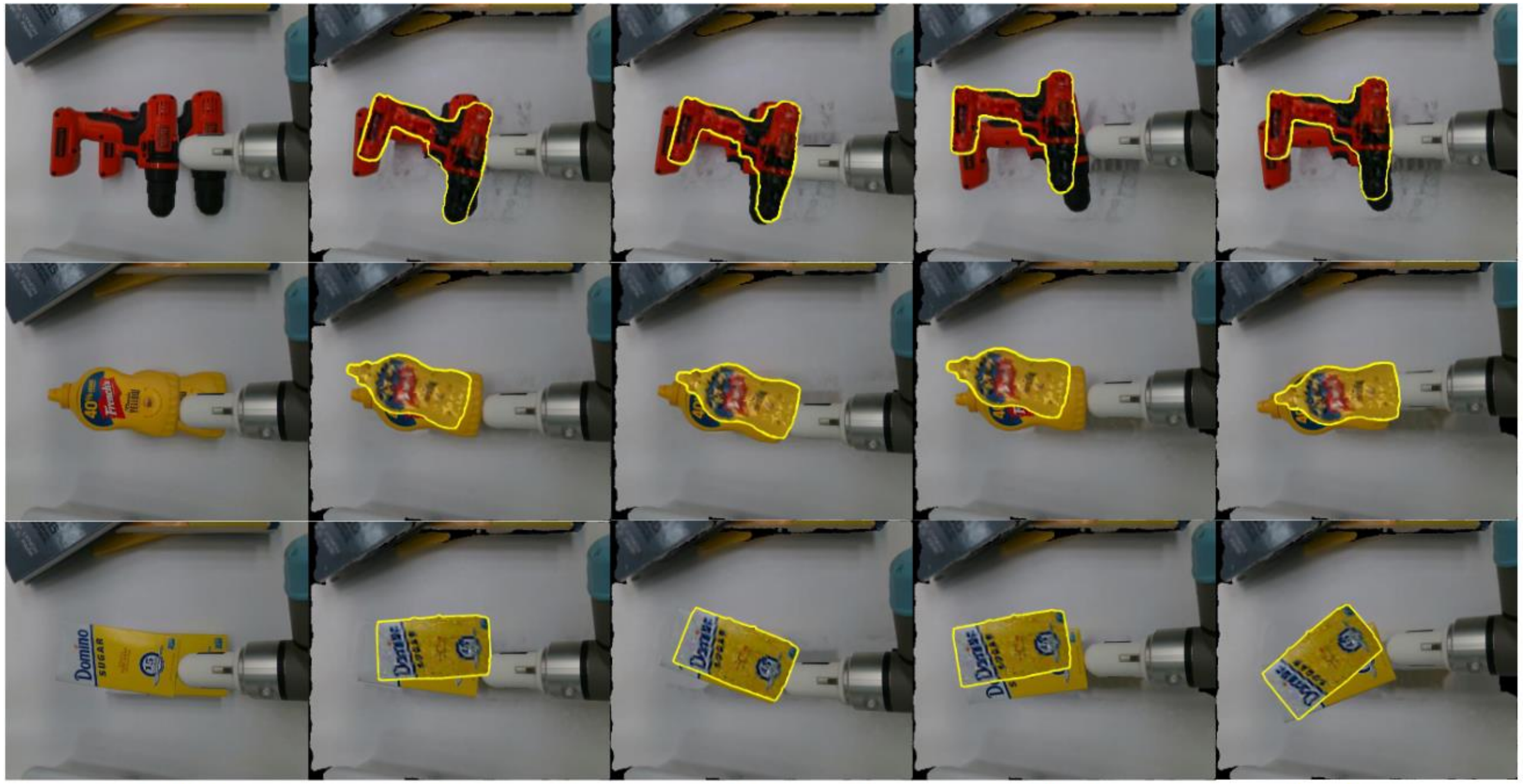
Y. Zhu, **<u>T. Xiang</u>**, A. Dollar, and Z. Pan, "Real-to-Sim via End-to-End Differentiable Simulation and Rendering". RA-L 2024 submitted

Results

Object	Novel View Synthesis: MSE ↓	SSIM ↑	PSNR ↑	Train Dynamics Error: Unilateral Chamfer (mm)	Pos. (mm)	Rot. (°)	μ	Test Dynamics Error: Unilateral Chamfer (mm)	Pos. (mm)	Rot. (°)
Box	0.00312	0.950	25.1	1.99	12.2	0.749	0.107	3.50	11.6	23.3
Drill	0.00413	0.942	24.0	4.91	15.1	3.85	0.0970	8.21	12.3	12.7

TABLE I

NOVEL VIEW SYNTHESIS AND DYNAMICS PREDICTION ERRORS FOR THE SIMULATED EXPERIMENTS



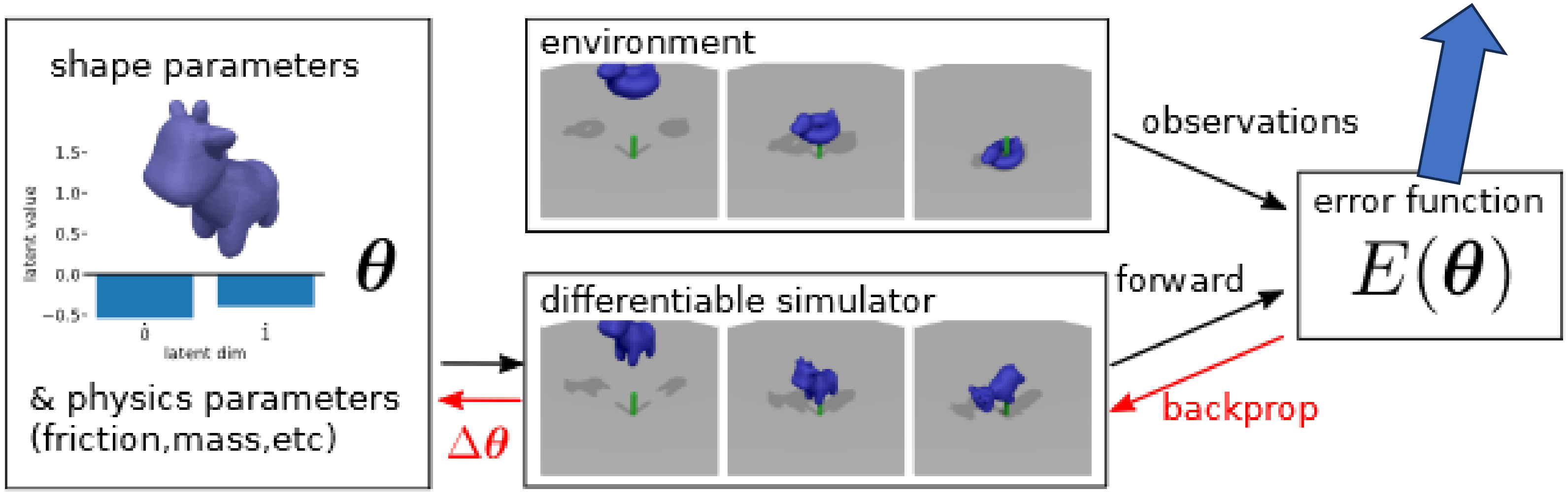
Train Push | Train Trajectory | Test Trajectory 1 | Test Trajectory 2 | Test Trajectory 3

Fig. 8. Train and test results of the physical experiments. Each row shows the results from an object. The columns from left to right are: 1) the robot's push to collect the training data, 2) the optimized object position at the end of the train trajectory, and 3)-5) those at the end of the three different test trajectories. The predicted object poses with the optimized θ highlighted with a yellow silhouette are overlaid with the ground-truth object and robot, and the background rendered from the optimized simulator. [Best viewed in color.]

Appendix: basic principle: Differentiable simulator, DiffSDFsim

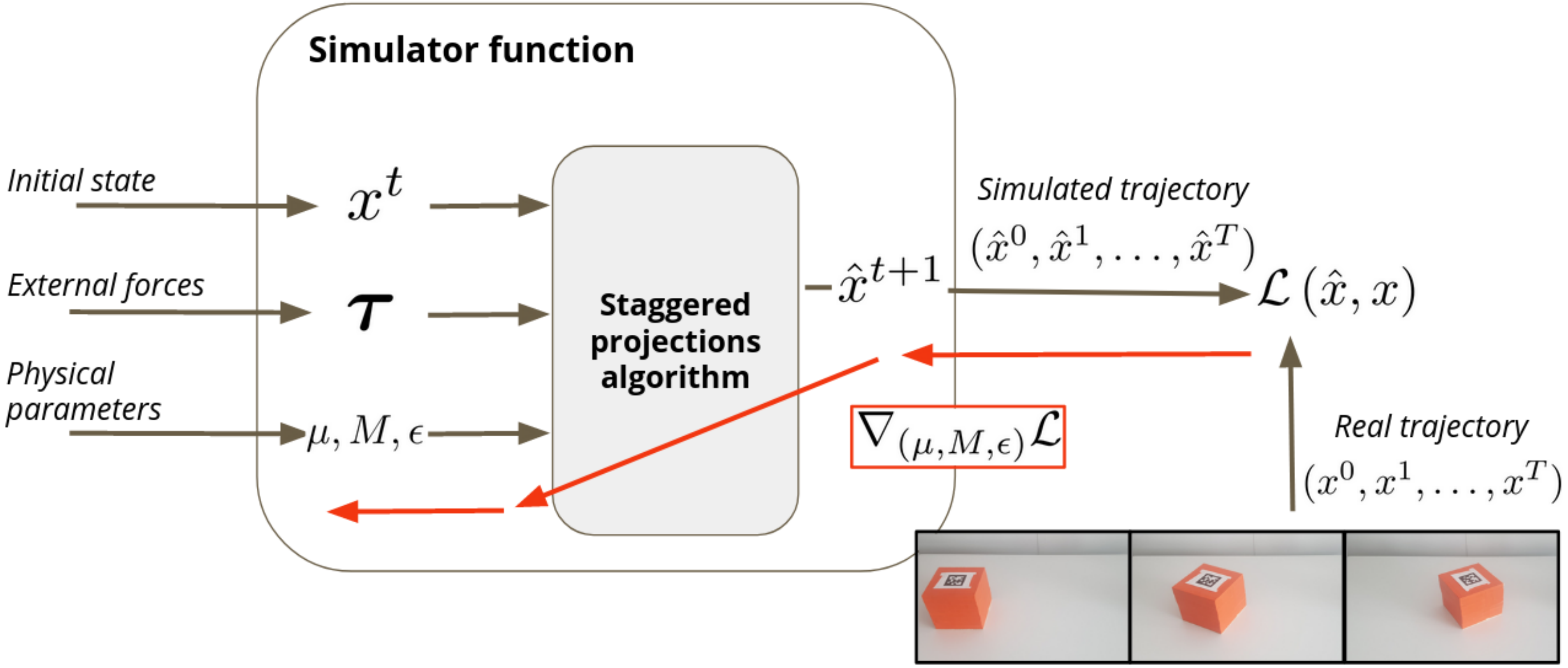
Error differentiate at rendered images.

3D reconstruction



M. Strecke and J. Stueckler, “DiffSDFSim: Differentiable Rigid-Body Dynamics With Implicit Shapes,” in *2021 International Conference on 3D Vision (3DV)*, Dec. 2021, pp. 96–105. doi: [10.1109/3DV53792.2021.00020](10.1109/3DV53792.2021.00020).

Appendix: Differentiable simulator basic principle



M. Strecke and J. Stueckler, "DiffSDFSim: Differentiable Rigid-Body Dynamics With Implicit Shapes," in *2021 International Conference on 3D Vision (3DV)*, Dec. 2021, pp. 96–105. doi: 10.1109/3DV53792.2021.00020.

Active project: Simulator and robotics interactive action for object segmentation

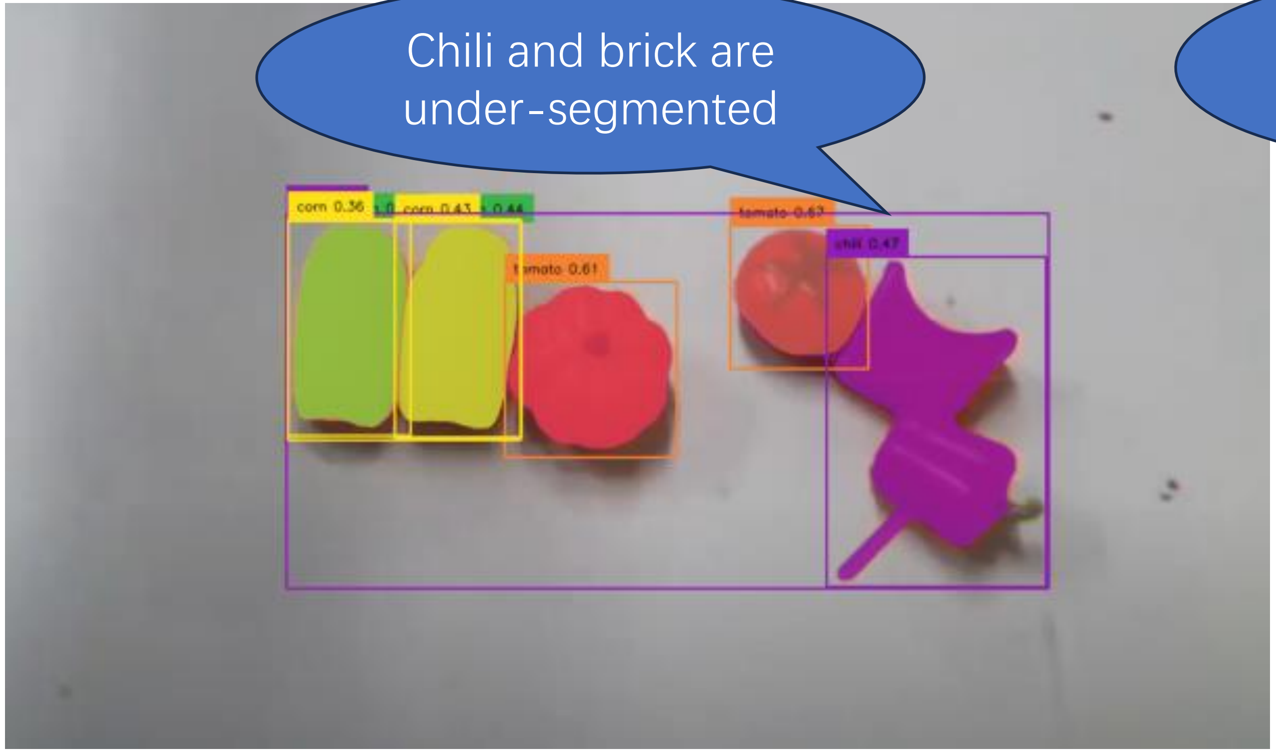
SAM mask generation and simulator aided segmentation correction

Research gap: over-segmentation and under-segmentation of SAM

Segmentation Anything Model (SAM) results:

under-segmentation

Chili and brick are under-segmented



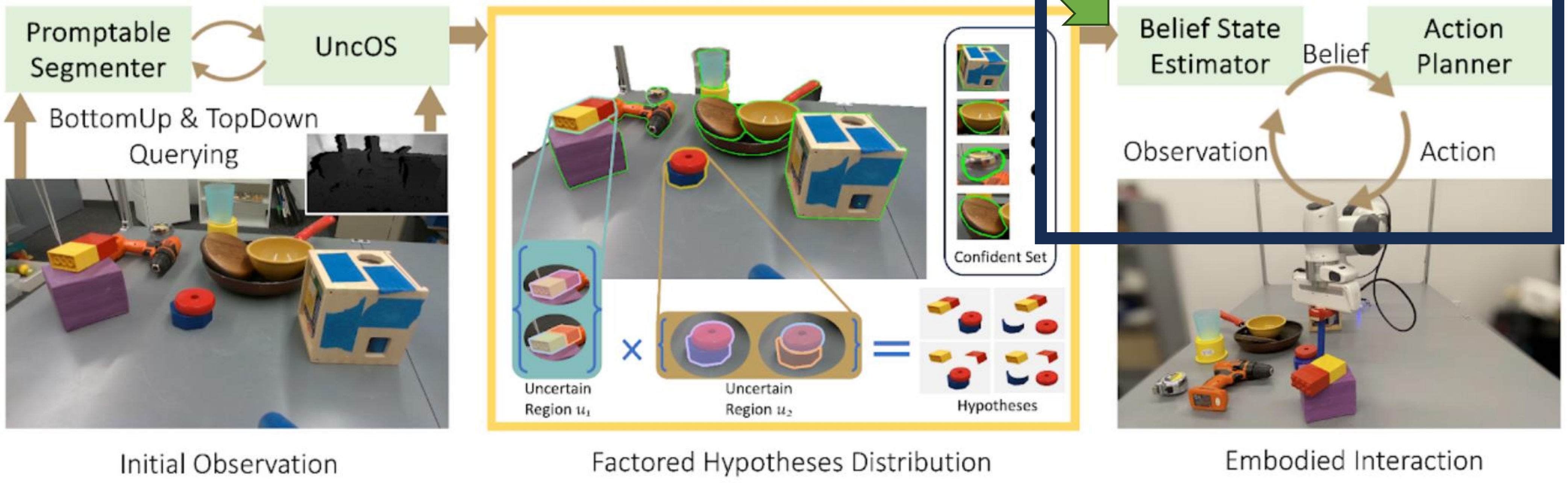
over-segmentation

Frog’s back is over-segmented

Research gap of robot interactive action segmentation works

Criticism of Ransac for belief update

Solution: use simulator, calculate error at rendered image



Research gap: Good at under-segmentation but doesn't work at all at over-segmentation

[1]X. Fang, L. P. Kaelbling, and T. Lozano-Pérez, "Embodied Uncertainty-Aware Object Segmentation," Aug. 08, 2024, *arXiv*: arXiv:2408.04760. IROS 2024. doi: 10.48550/arXiv.2408.04760.

Opensource!

- Perception pipeline: GitHub Code
- Motion Planning Pipeline: GitHub Code

Liquid Manipulation

liquid manipulation framework based on category-level pose, shape estimation and a pouring action optimizer.

ScazLab

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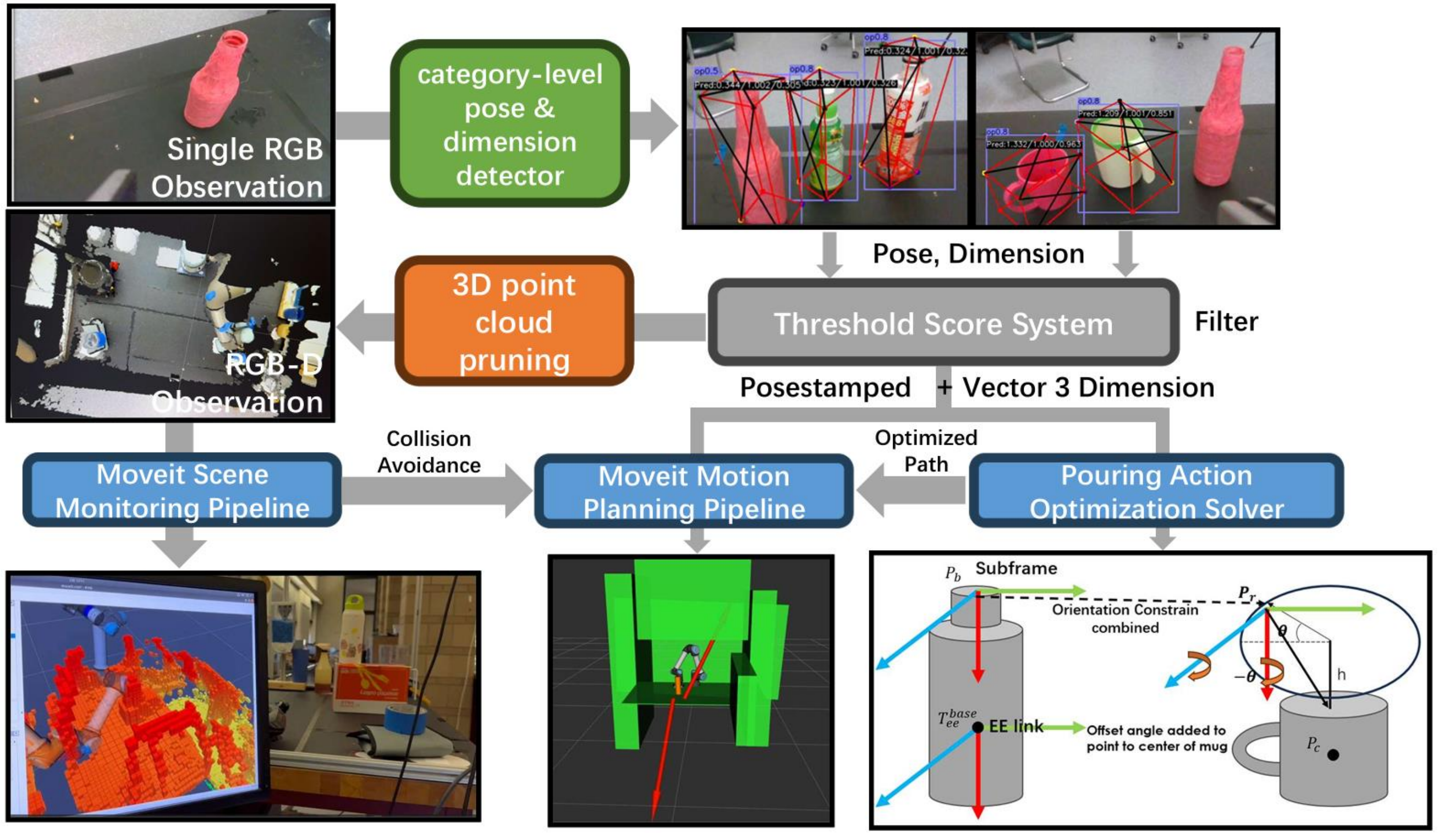
Research gap & overview framework

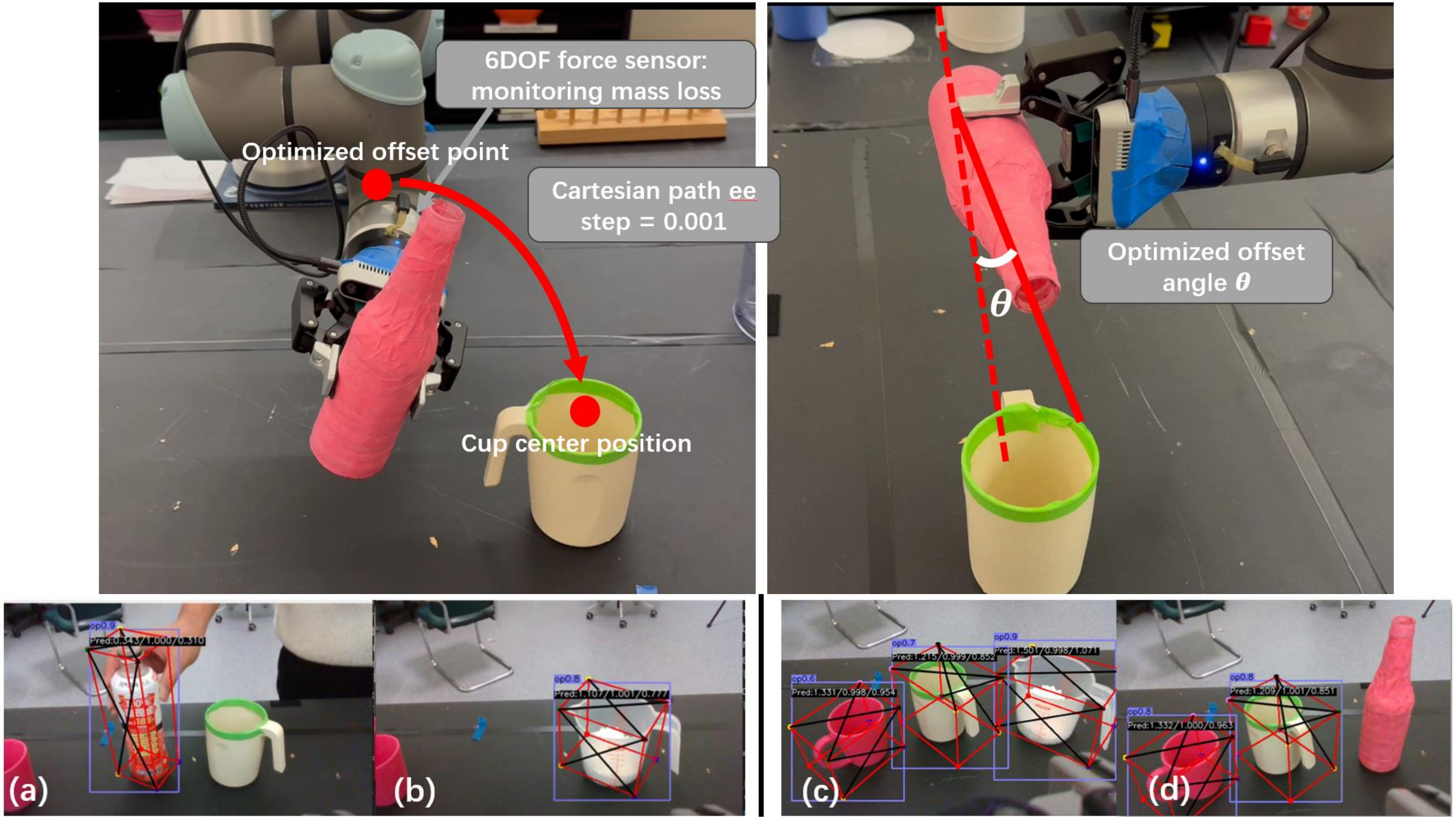
Research gap:

<u>Generalizability + optimization</u>

<u>Unseen cups & bottles with shapes and patterns in uncertain scene</u>, incorporating with **<u>optimization trajectory with constrain</u>**.



Result



6DOF force sensor: monitoring mass loss
Optimized offset point
Cartesian path ee step = 0.001
Cup center position
Optimized offset angle θ
θ
(a)
(b)
(c)
(d)

Opensource!

➢ Unity & MATLAB: Tianyi20/DT_IRB120

Efficient real-time teleoperation for industrial robots

[1]**T. Xiang**, B. Li, X. Pan, and Q. Zhang, "Development of a Simple and Novel Digital Twin Framework for Industrial Robots in Intelligent Robotics Manufacturing," in *2024 IEEE 20th International Conference on Automation Science and Engineering (CASE)*, Aug. 2024, pp. 4187–4193. doi: 10.1109/CASE59546.2024.10711459.

Research gap: teleoperation for industrial robots

Collaborative robots

Industrial robots

Communication when teleoperation doesn’t work well at industrial robot, cause the CPU is always low cost.

Framework of Digital Twin System

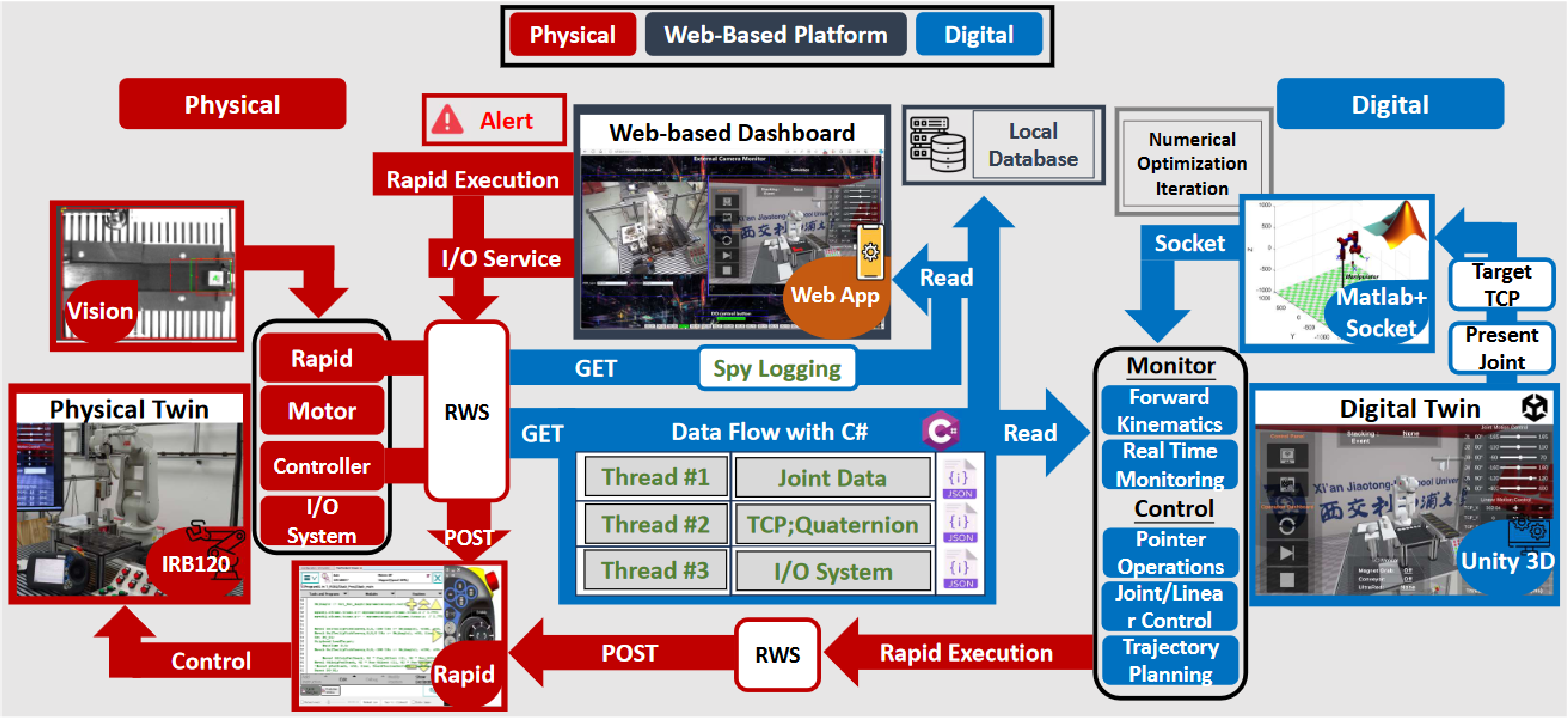
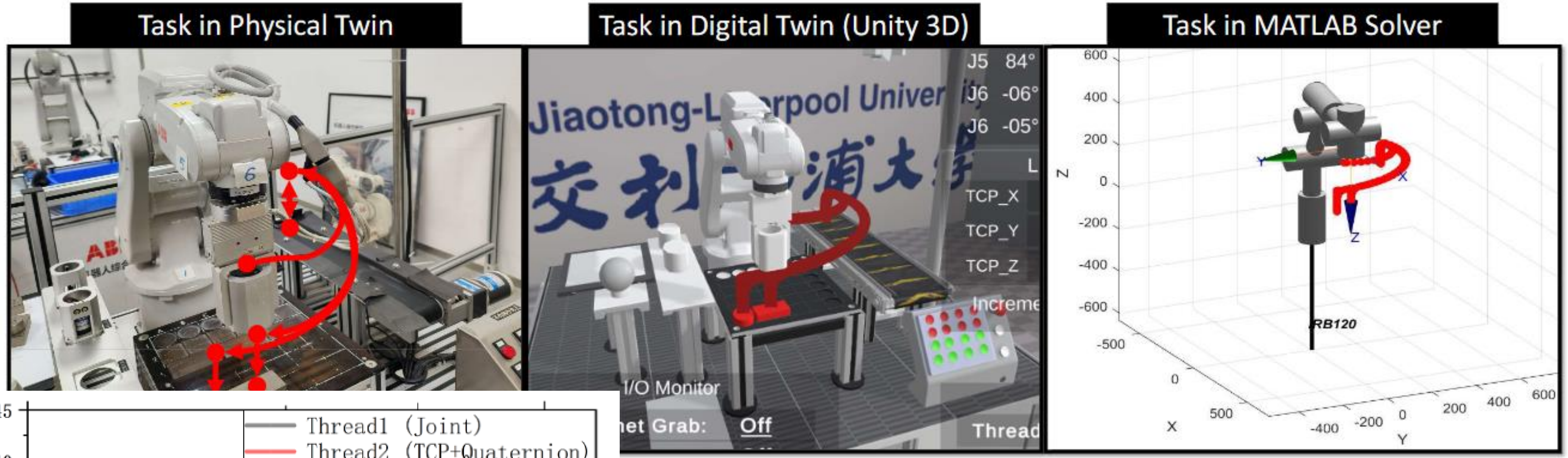
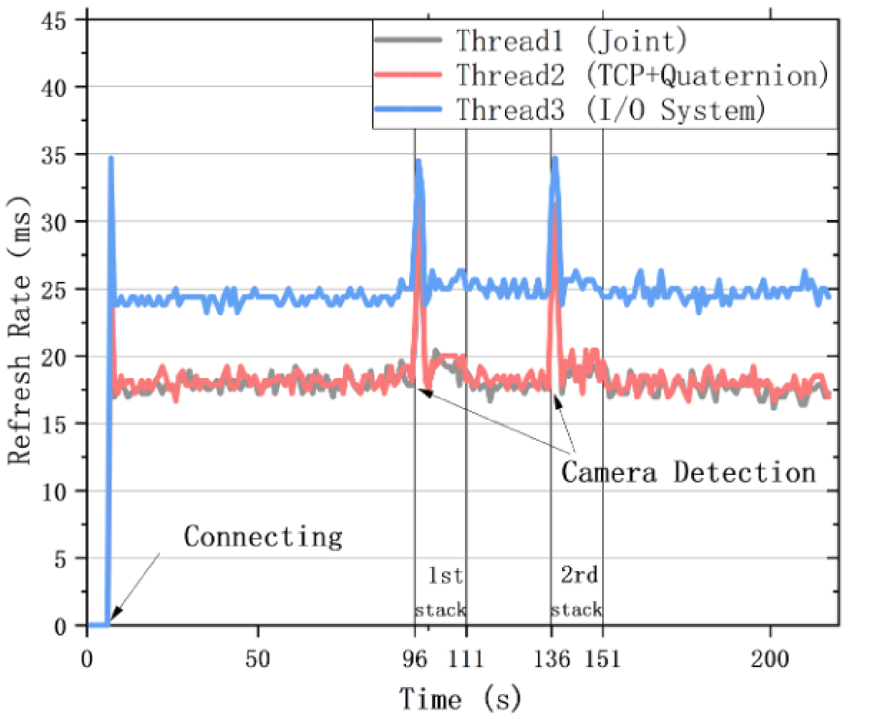


Fig. 2: The Framework of the Proposed Digital Twin System for the Stacking Robot Workstation

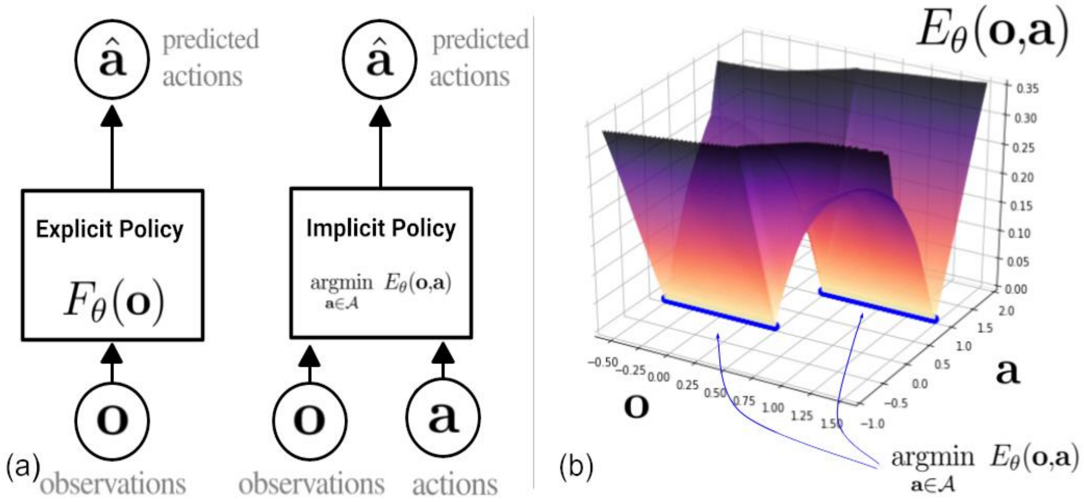
Result & Evaluation

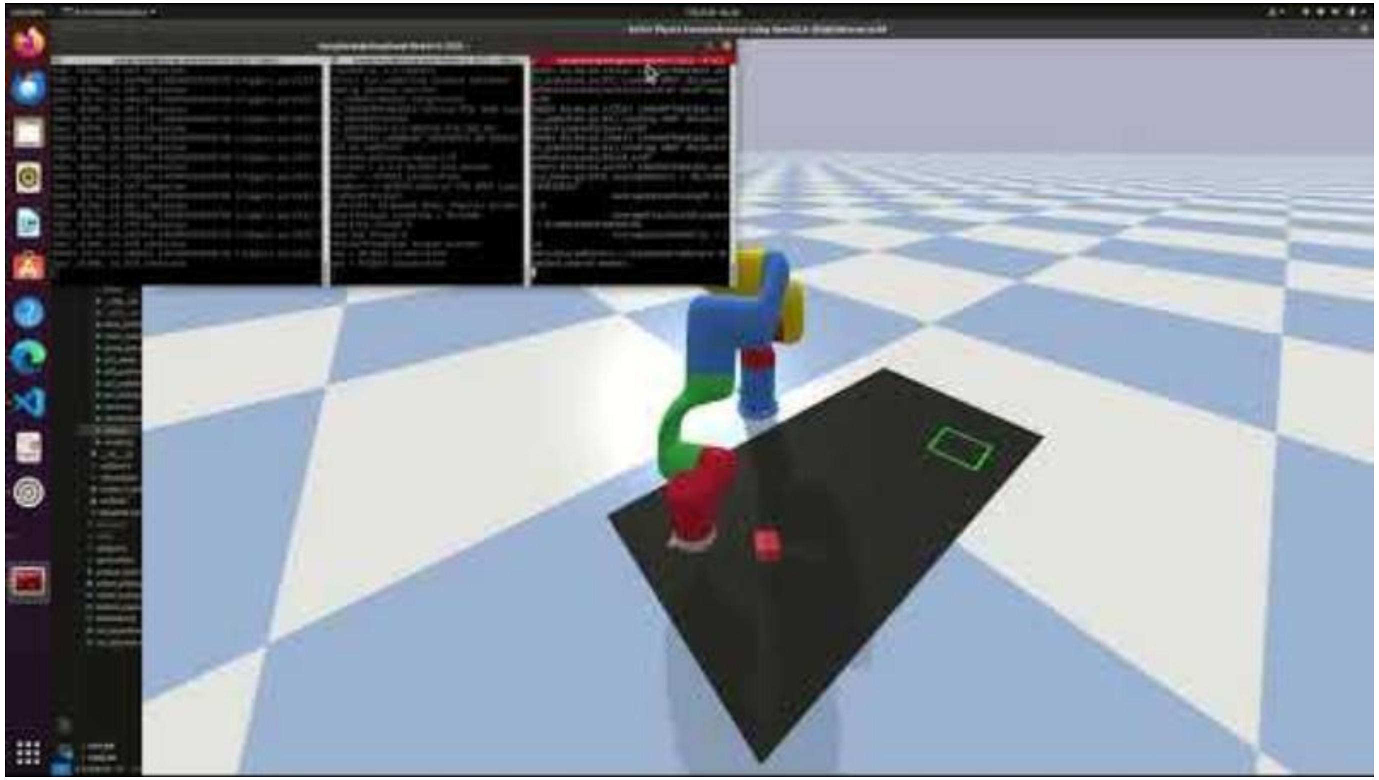




- ➢ **Refresh rate ~ 17ms**
- ➢ **Better real-time performance at teleoperation**

Followed Imitation Learning





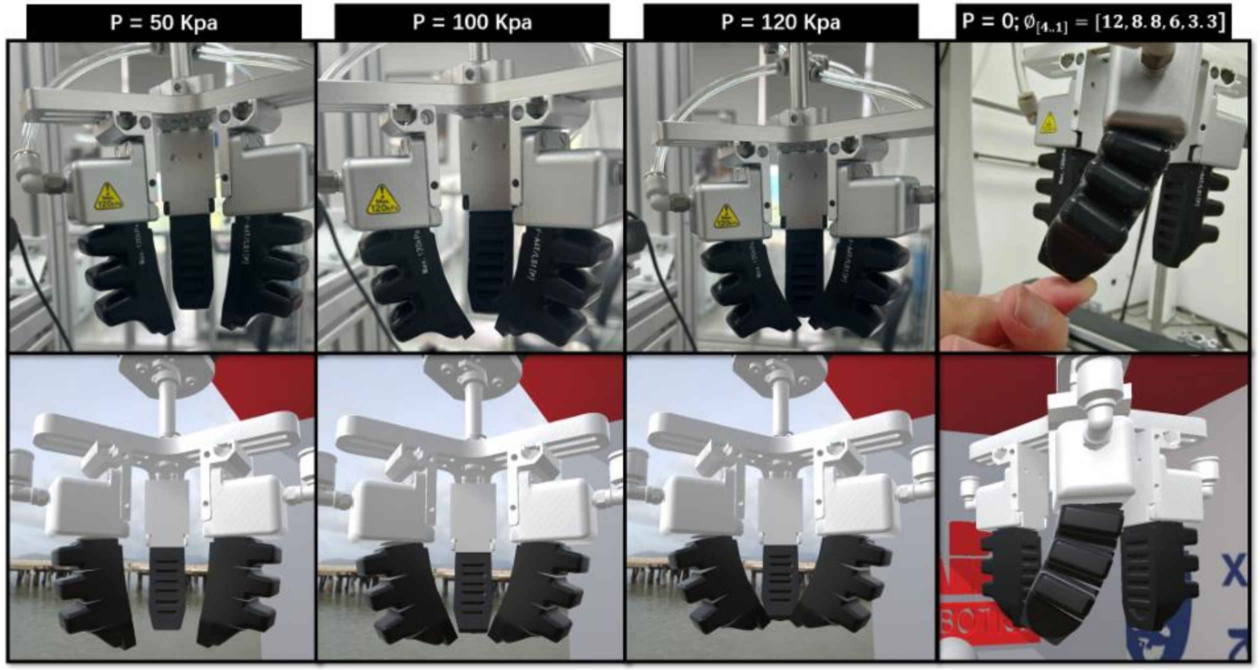
[1]P. Florence *et al.*, “Implicit Behavioral Cloning,” Sep. 01, 2021, *arXiv*: arXiv:2109.00137. doi: 10.48550/arXiv.2109.00137.

Efficient teleoperation with underactuated flexible gripper and industrial robots

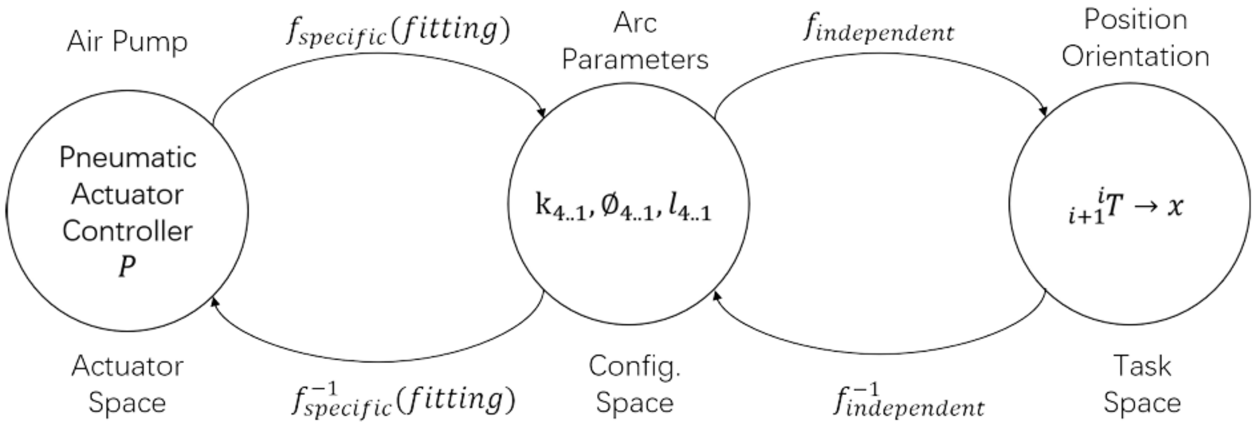
[1]**T. Xiang**, B. Li, Q. Zhang, M. Leach, and E. Lim, "A Novel Approach to Grasping Control of Soft Robotic Grippers based on Digital Twin," in *2024 29th International Conference on Automation and Computing (ICAC)*, Aug. 2024, pp. 1–6. doi: 10.1109/ICAC61394.2024.10718822.

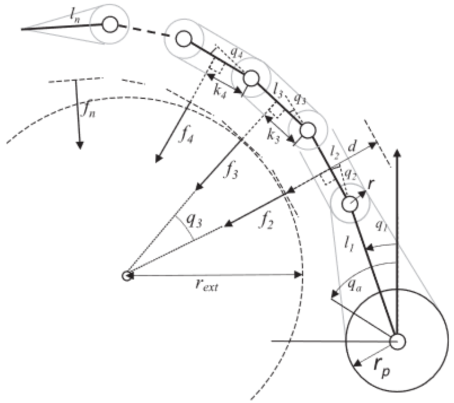
Research gap & Result

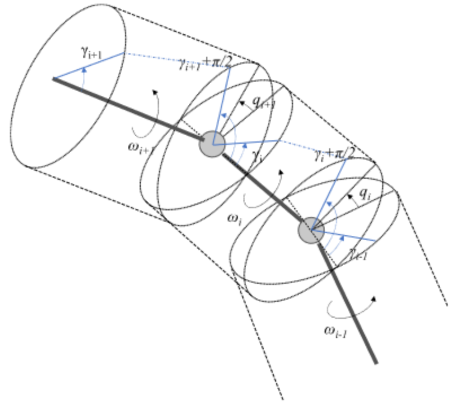
- Research gap: **<u>Efficient teleoperation with pneumatics flexible gripper in industrial robots.</u>**
- Result: Extremely efficient communication rate when teleoperation, around 17 ms.



Method: piecewise constant curvature kinematics







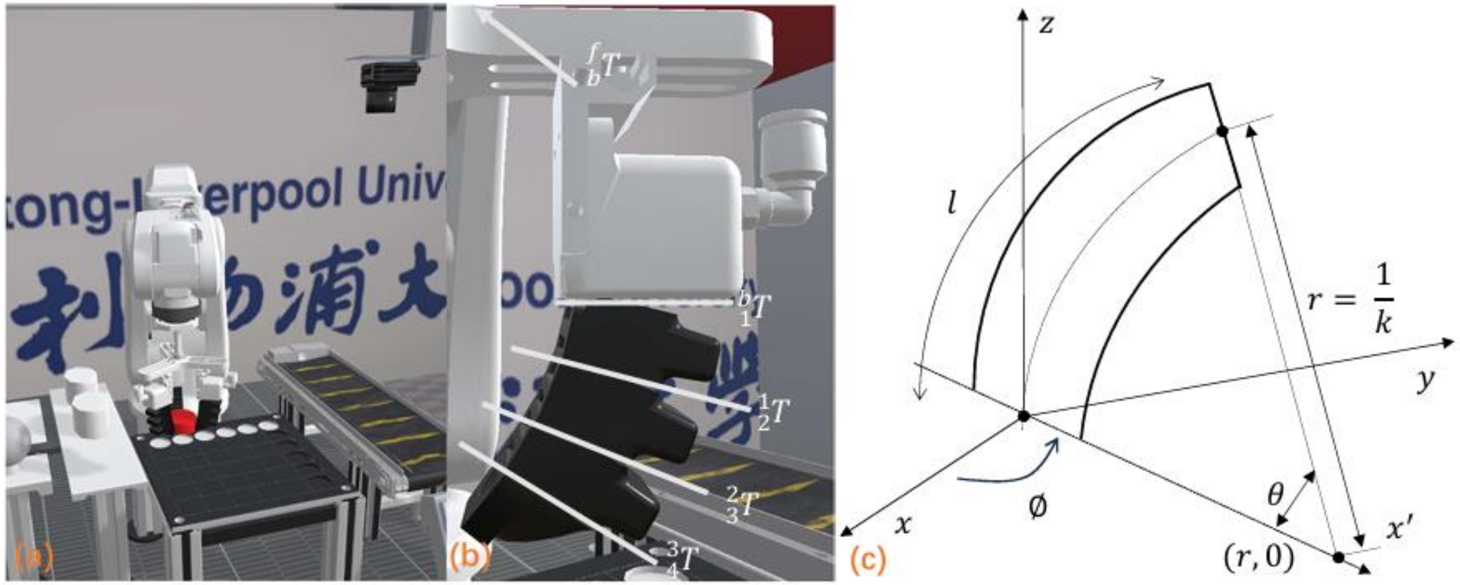
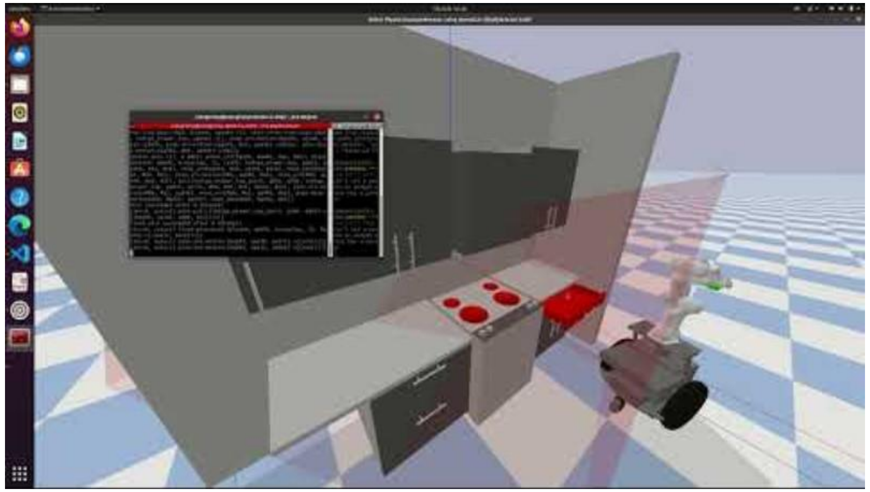


Fig. 4: Four Piecewise Robot Independant Mapping Soft Gripper: (a): Flexible gripper with robot working screenshot (b): Assembled Together Four-piece Soft gripper constant curvature model with four homogeneous transformation matrix T in Unity 3D; (b): Arc Configuration Space for only One piece soft gripper when angle ϕ rotates the arc to new x' axis.

Some miscellaneous research projects

Some miscellaneous research projects

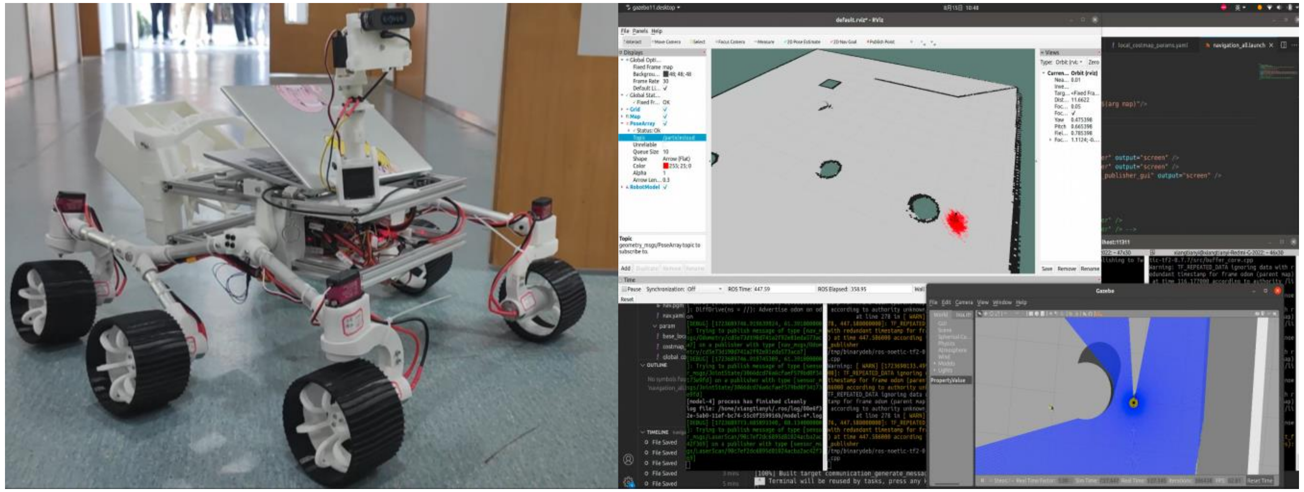
Task planning: PDDL-stream task and motion planning (TAMP)



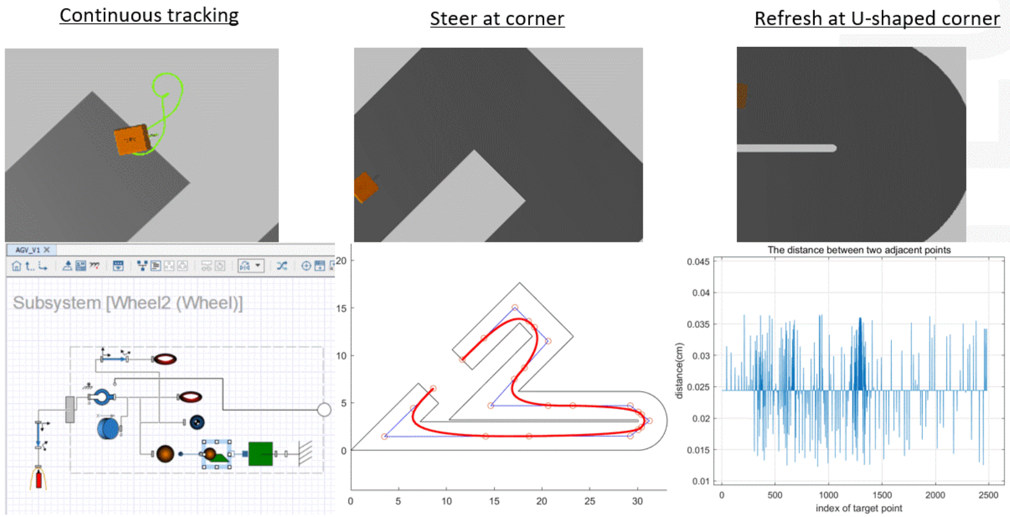
Criticism: However, PDDL itself is only an open-loop planner.

[1]C. R. Garrett, T. Lozano-Pérez, and L. P. Kaelbling, "PDDLStream: Integrating Symbolic Planners and Blackbox Samplers via Optimistic Adaptive Planning," Mar. 23, 2020, *arXiv*: arXiv:1802.08705. doi: 10.48550/arXiv.1802.08705.

DIY mars Rover & ROS SLAM navigation



AGV with PLC control simulation



Future research plans

Overview of research plans

(1): How to infer world models for **various** types of physics phenomena, like **different material properties,** introducing various constrains.

(3): After the system identification, how to implement a **real-to-sim-to-real** method as **downstream control**?

(3): Before the system identification, how to design **upstream task planning** to inform **when and where** to inform our system identification?

(4): How to build **better hardware** while considering sensing, perception, control, and hardware?

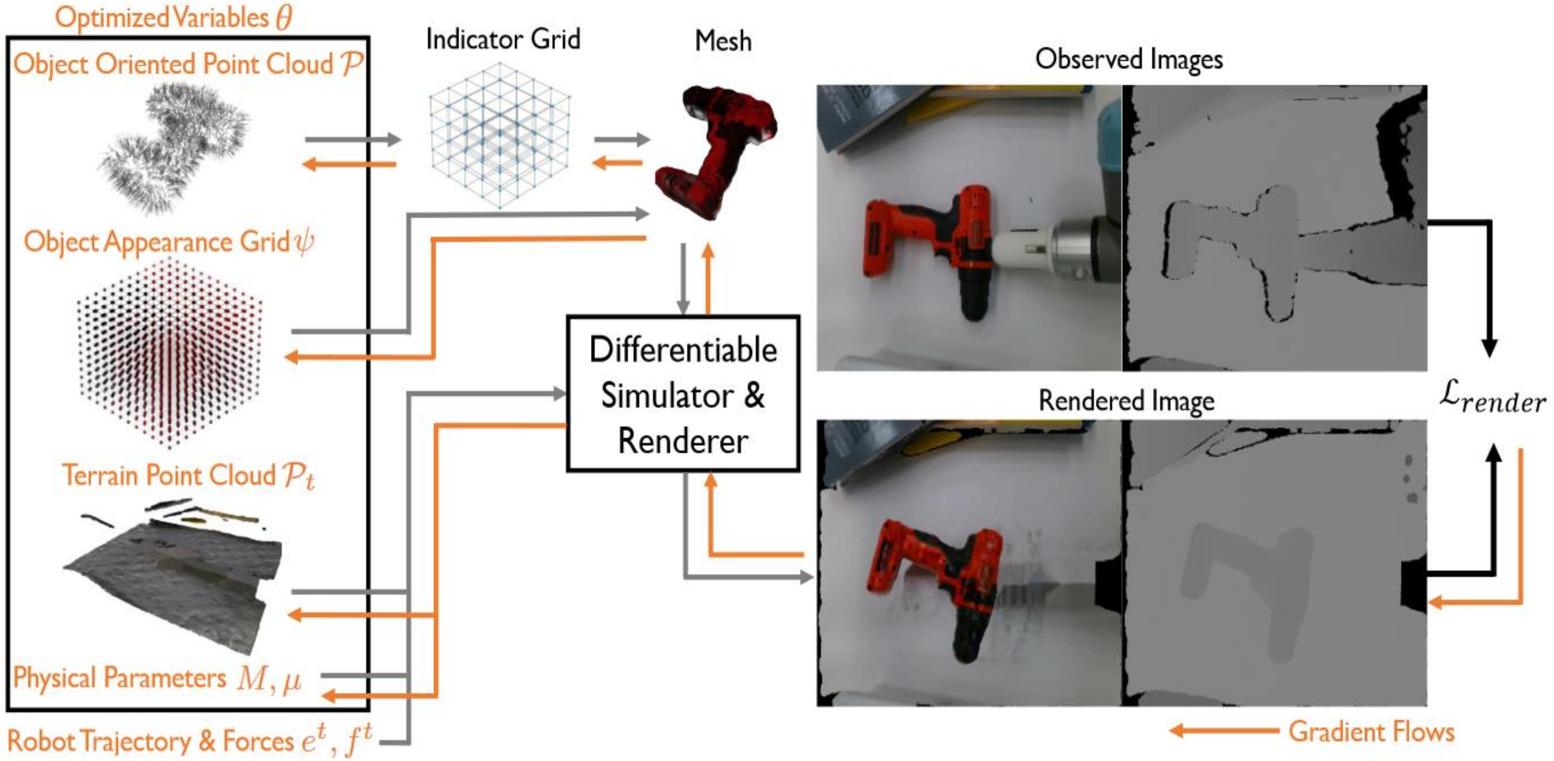
1. System identification for (1) **flexible & (2) articulated & (3) multiple bodies**

How to combine extra physics constraints for different objects categories? Especially, dealing with flexible bodies?

Research gap: system identification for (1) flexible body

BundleSDF CVPR 2023

Our work: RA-L 2024

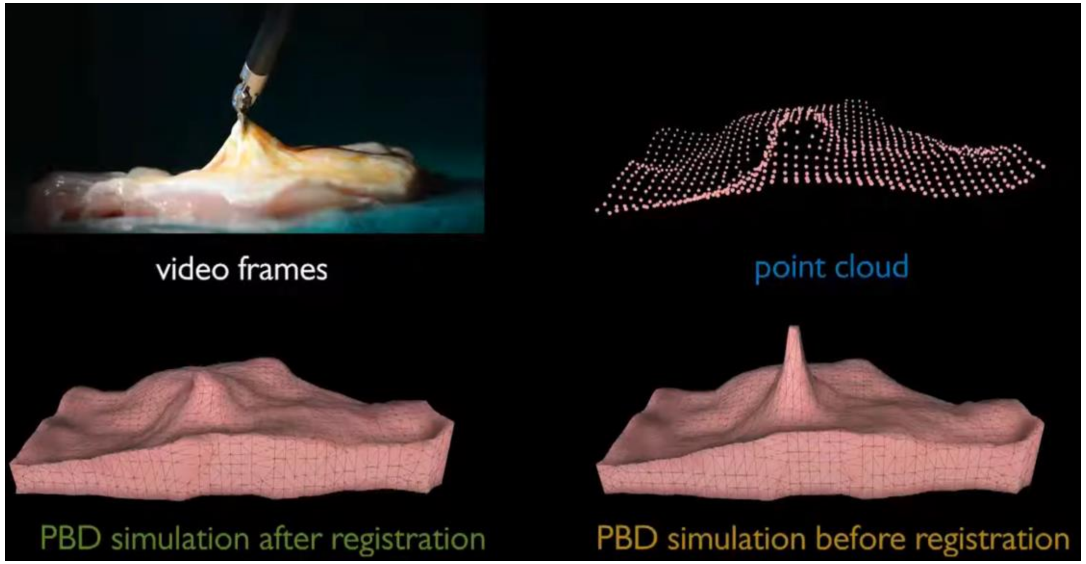


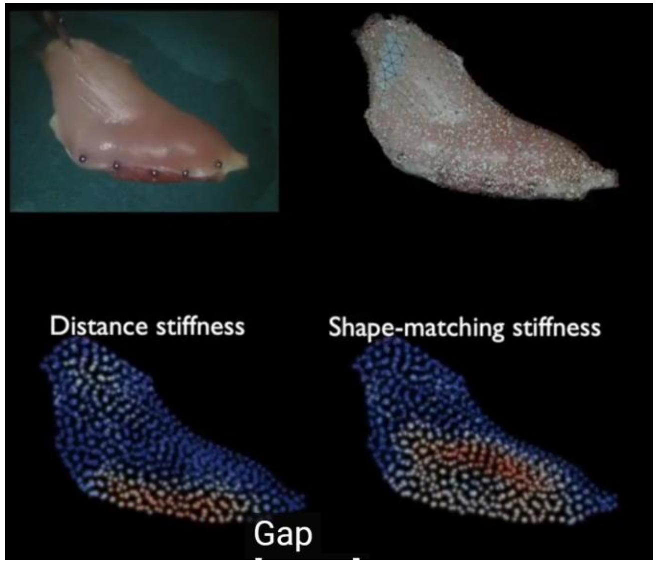
Problem: infer flexible material properties, e.g. 3D mesh, mass-of-inertia, friction

Research gap: physical properties for soft tissue in surgical robots

Real-to-Sim Registration of Deformable Soft Tissue with Position-Based Dynamics for Surgical Robot Autonomy, *ICRA 2021*

Real-to-Sim Deformable Object Manipulation: Optimizing Physics Models with Residual Mappings for Robotic Surgery, *ICRA 2024*





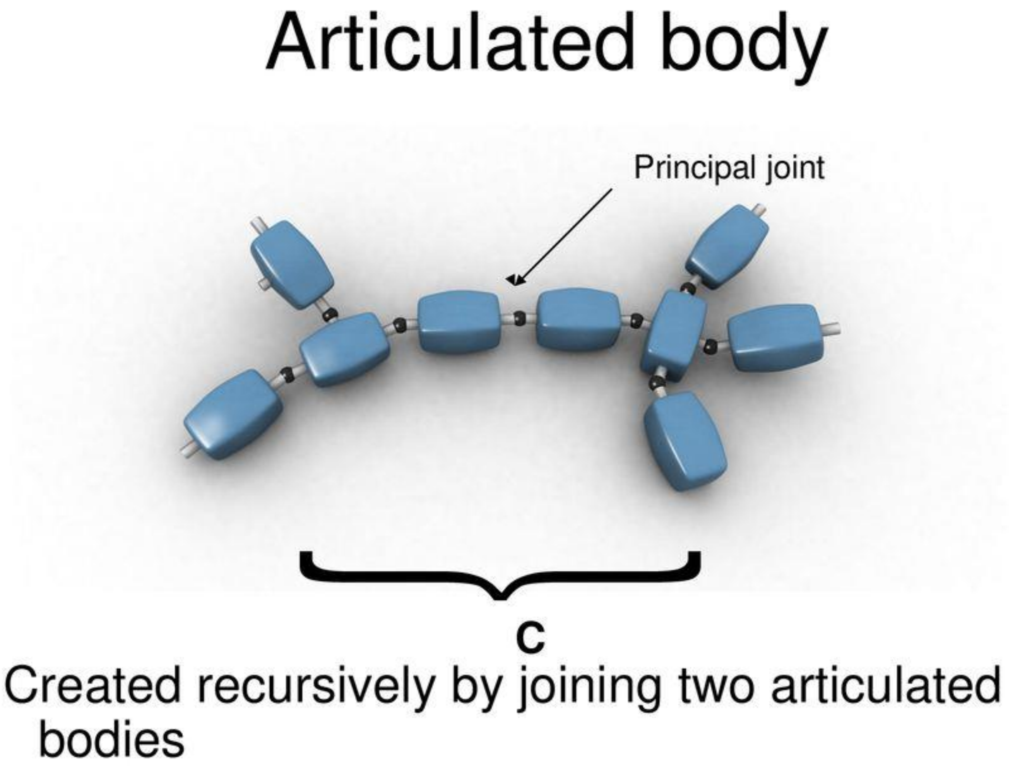
Common Drawbacks:

(1) Initial **3D shapes and patterns** are well-defined and pre-given.

(2) The model used is **positional static**. It cannot deal with dynamic online changes.

(3) Some properties are missing to be optimized: Young's modulus, strain, stress, friction..

Research gap: system identification for (2) articulated bodies



Research gap: system identification for (3) multiple bodies

Potential Solution: introduce various constrains

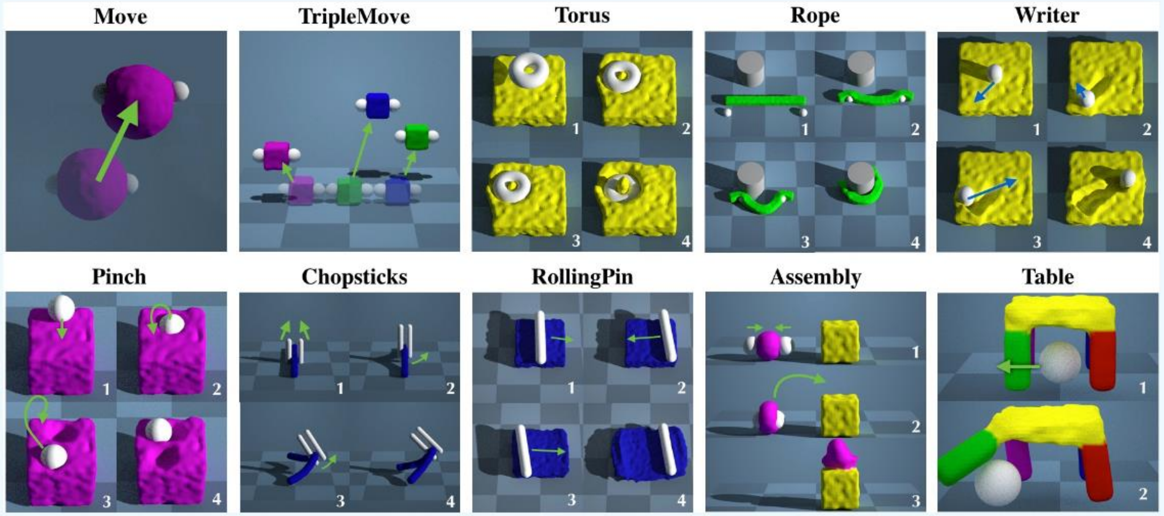
DaxBench: Benchmarking Deformable Object Manipulation with Differentiable Physics

Website DaxBench | Paper ArXiv | Source Code

DaXBench is a differentiable simulation framework for deformable object manipulation. While existing work often focuses on a specific type of deformable objects, DaXBench supports fluid, rope, cloth, etc ; it provides a general-purpose benchmark to evaluate widely different DOM methods, including planning, imitation learning, and reinforcement learning. DaXBench combines recent advances in deformable object simulation with JAX, a high-performance computational framework. All DOM tasks in DaXBench are wrapped with the OpenAI Gym API for easy integration with DOM algorithms.

PlasticineLab: A Soft-Body Manipulation Benchmark with Differentiable Physics

Website PlasticineLab | Paper ArXiv | Source Code

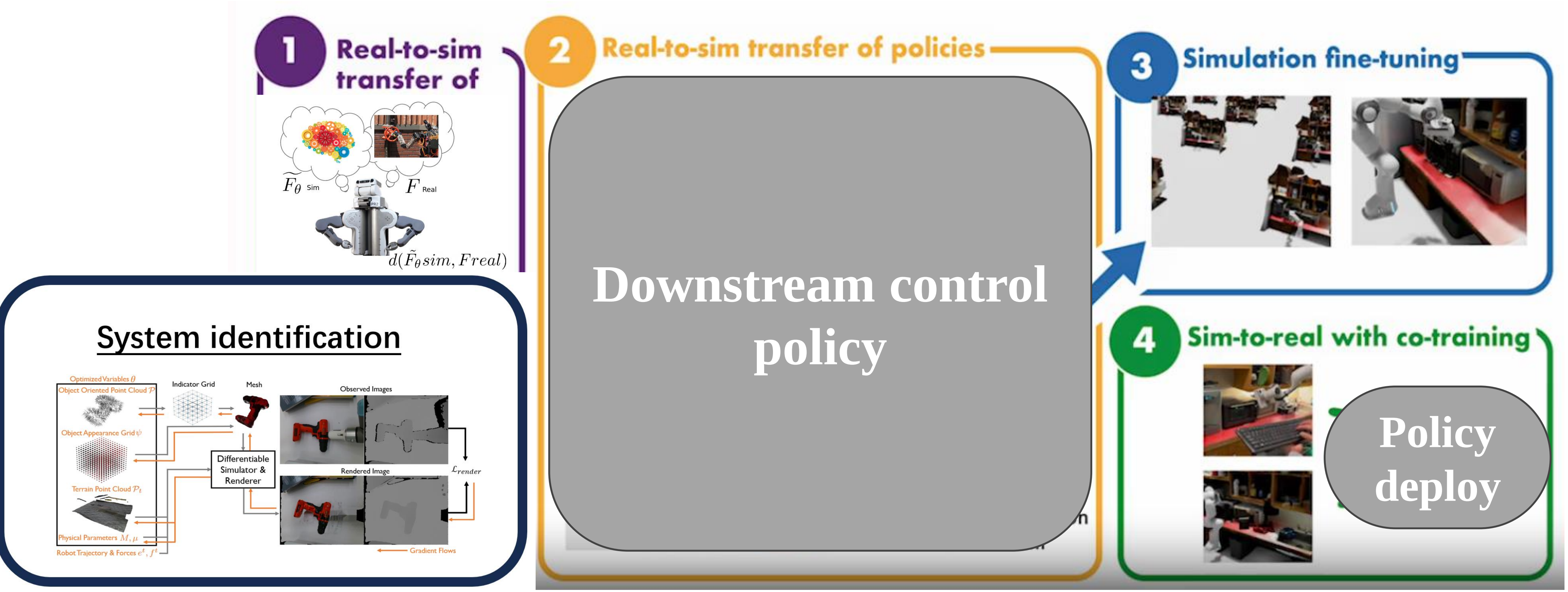


PlasticineLab is a differentiable physics benchmark including a diverse collection of soft body manipulation tasks. In each task, the agent uses manipulators to deform the plasticine into a desired configuration. The underlying physics engine supports differentiable elastic and plastic deformation using the DiffTaichi system, posing many underexplored challenges to robotic agents. We evaluate several existing RL methods and gradient-based methods on this benchmark.

2. **Downstream control: real-to-sim-to-real** with world model prediction

After predicting the world model, how to train robots to work in that environment?

2. Research gap: Real-to-sim-to-real with system identification

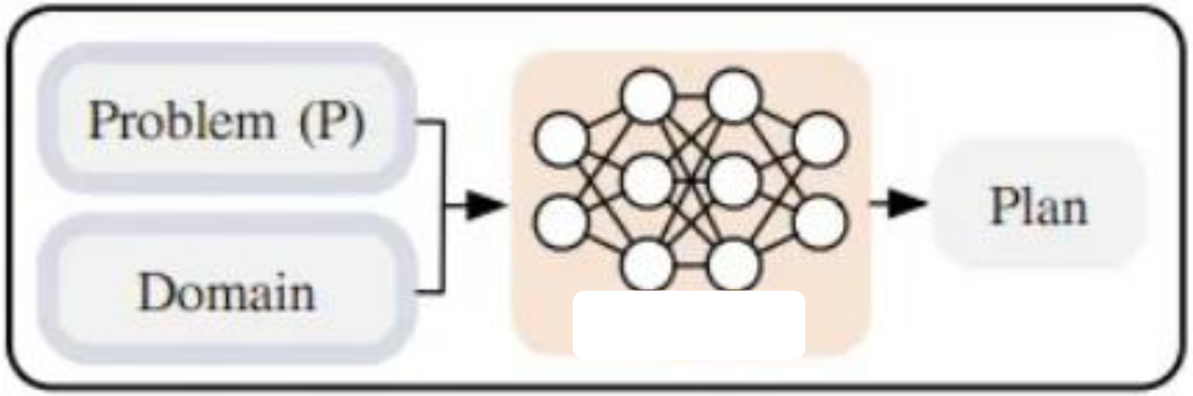


3. **<u>Upstream task planning</u>**: **<u>where and when</u>** to inform our world model prediction?

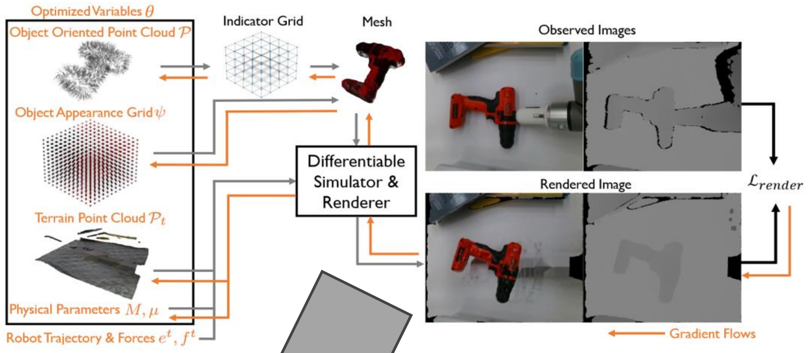
When being placed in the wild, when and where should robots to invoke the world model prediction method?

2. Research gap: upstream task planning for system identification

Upstream task planning



System identification



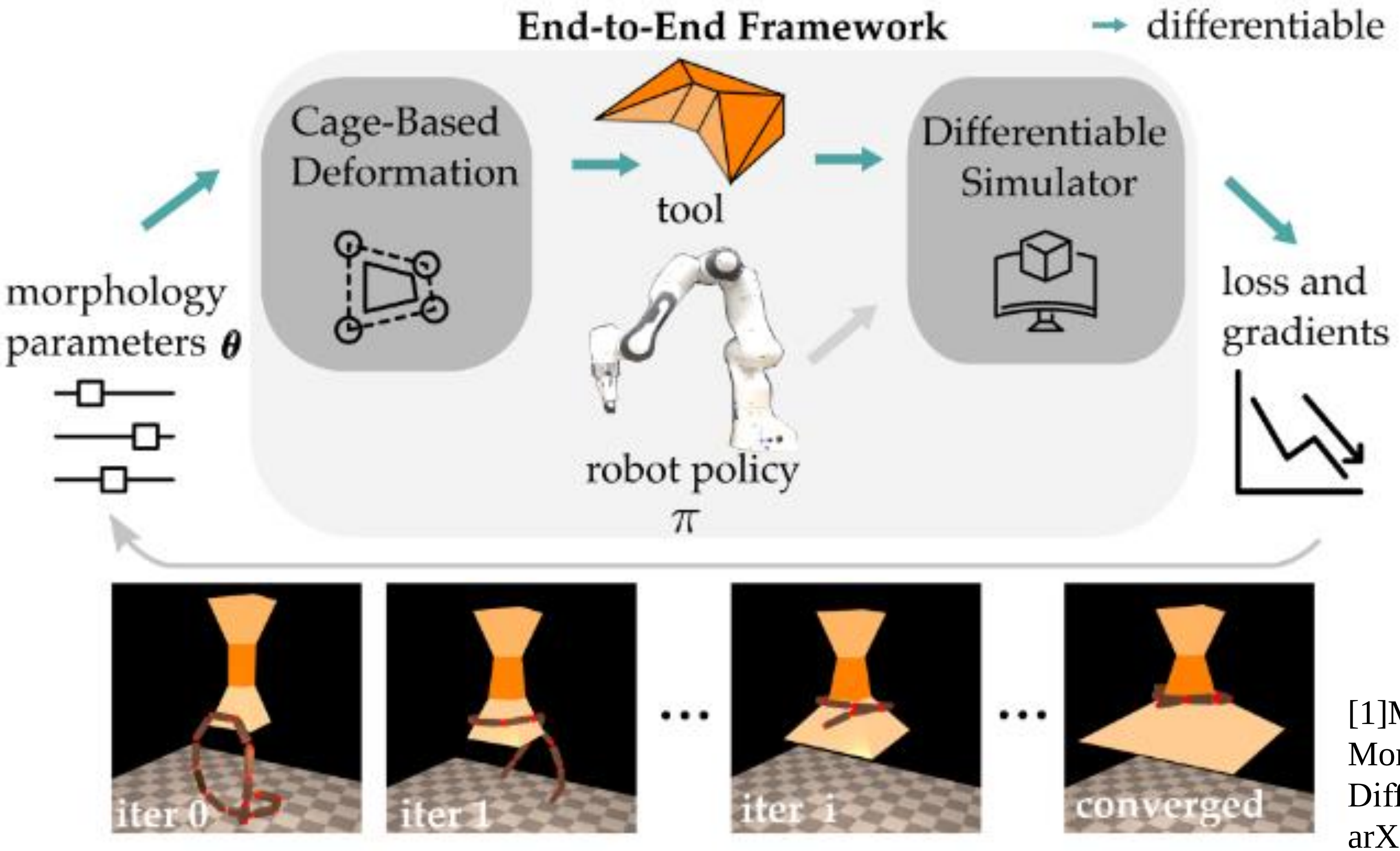
Downstream control of task

4. Morphological Optimization: **Co-Design Mechanism** with Sensing, Perception, and Control.

How to build better hardware while considering sensing, perception, control, and hardware?

4. Research gap: physics design and control are always separated

Solution: co-optimization of both morphology and control.



End-to-End morphology optimization pipeline: optimize tool morphology parameters

[1]M. Li, R. Antonova, D. Sadigh, and J. Bohg, "Learning Tool Morphology for Contact-Rich Manipulation Tasks with Differentiable Simulation," Nov. 04, 2022, *arXiv*: arXiv:2211.02201. doi: 10.48550/arXiv.2211.02201.

The End

Thank you for listening.

Any questions?