ICRA 2025 Workshop on
Learning Meets Model-Based Methods
for Contact-Rich Manipulation

Stop Merging, Start Separating:
Why Merging Learning and Modeling Won't Solve Manipulation but Separating the General From the Specific Will

Vito Mengers*[,1,2,3] Alexander Koenig *[,1,3] Xing Li*[,1,2,3] Adrian Sieler[1,3] Aravind Battaje[1,2,3] Oliver Brock[1,2,3]

[1] Robotics and Biology Laboratory, Technische Universität Berlin [2] Science of Intelligence, Research Cluster of Excellence, Berlin [3] Robotics Institute Germany (RIG)

* Equal contributions.

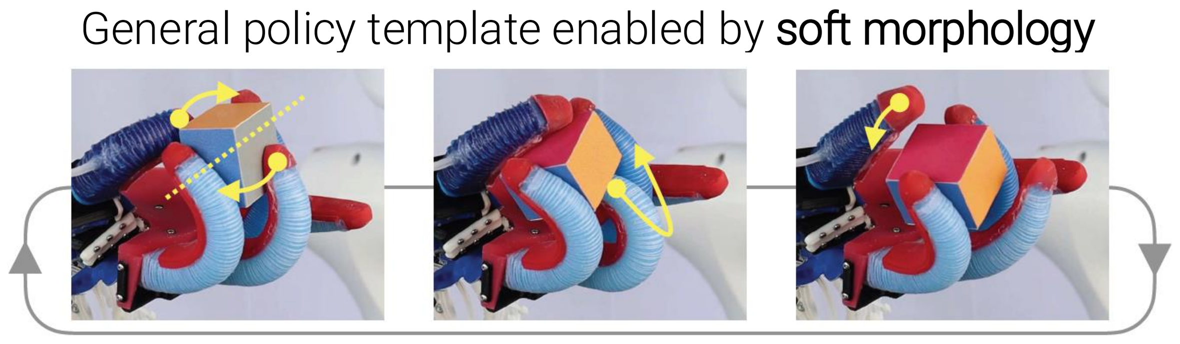
Two-Stage Policy Creation

1. **General Policy Template**
   Captures reusable, task-invariant structure
2. **Instance Completion**
   Performed during the task execution via interaction, sensing, or compliance

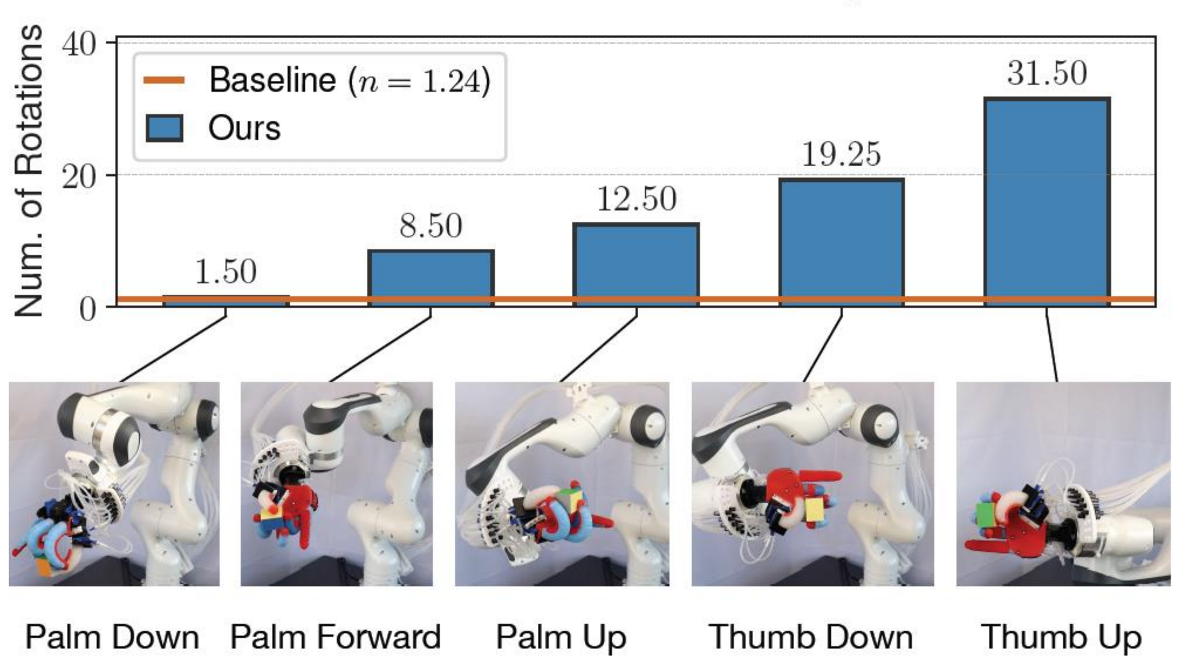
In-Hand Manipulation

1. **General Policy Template**
   Sequence of local actuation primitives
2. **Instance Completion**
   Soft morphology of compliant hands

General policy template enabled by **soft morphology**



Generalization after **instance completion**



Experimental Results

We built the RBO Hand 3 with a dexterous and compliant morphology. The above figure shows that a general policy for object rotation transfers to different wrist orientations of a robotic arm. We achieve up to an order of magnitude more object rotations than the current state of the art.

Our previous work (Bhatt et al. RSS, 2021) showed that the hand's soft morphology adapts general policy templates to more problem instances (e.g., different object geometries, poses and execution speeds).

Bhatt, A., Sieler, A., Puhlmann, S., & Brock, O. (2021). Surprisingly robust in-hand manipulation: An empirical study. Robotics: Science and Systems

Learning from Demonstration

1. **General Policy Template**
   Sequence of Environmental Constraint Exploitations
2. **Instance Completion**
   Adaptive compliant controller and human corrections

General policy template enabled by
Environmental Constraints (ECs)

Generalization after **instance completion**

Experimental Results

We achieve 90% success on long-horizon, contact-rich tasks using only one demonstration per task. The policy extracts from a single demonstration generalizes to various object placements and geometric models.

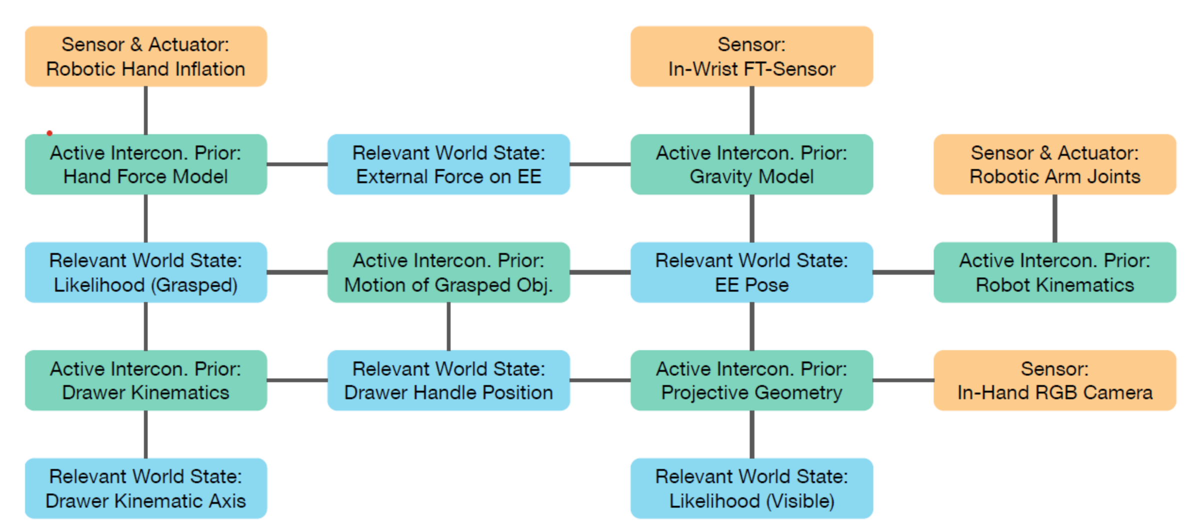
Li, Xing, and Oliver Brock. "Learning from demonstration based on environmental constraints." IEEE Robotics and Automation Letters 7.4 (2022): 10938-10945.

Li, Xing, Manuel Baum, and Oliver Brock. "Augmentation enables one-shot generalization in learning from demonstration for contact-rich manipulation." (2023) IEEE/RSJ IROS

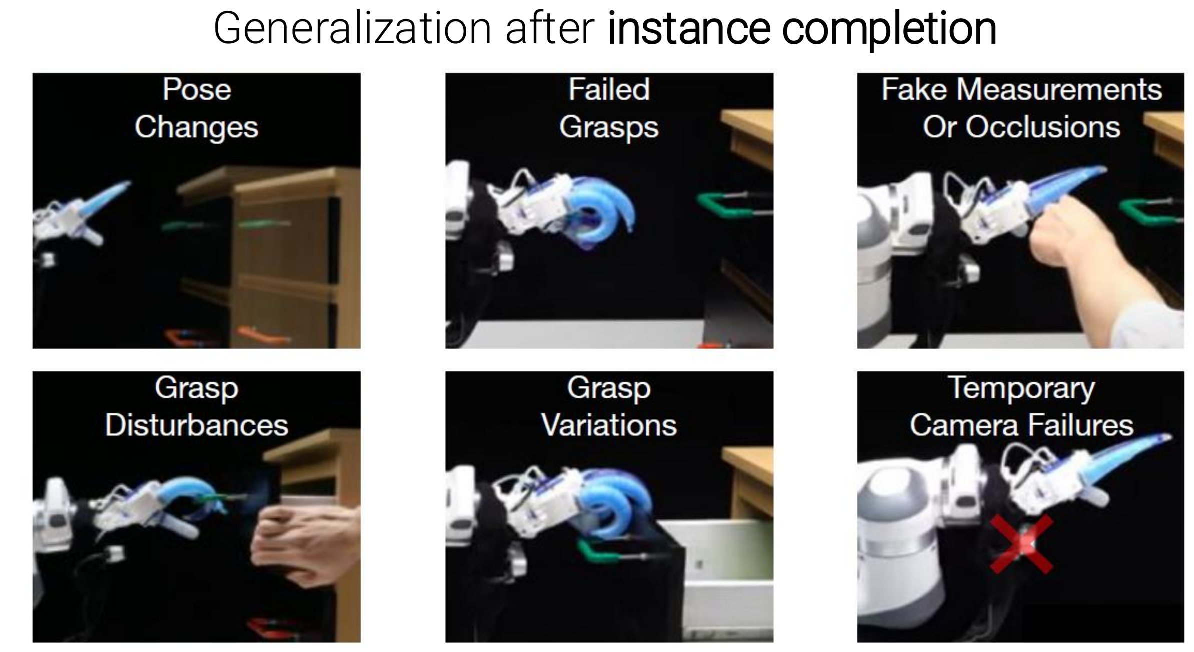
Active Interconnections

1. **General Policy Template**
   A dynamic network of estimators linked by active interconnections
2. **Instance Completion**
   Actions derived from gradients of the network, continuously refined through sensory feedback

General policy template enabled by **persistent regularities**



Generalization after **instance completion**



Experimental Results

In a drawer-opening task, using a wrist-mounted RGB camera and a force-torque sensor, our approach results in successful executions despite high degree of disturbance and uncertainty (Mengers & Brock. ICRA 2025). This form of behavior generation does not resort to planning or explicitly-coded recovery behaviors.

Mengers, Vito, and Oliver Brock. "No Plan but Everything Under Control: Robustly Solving Sequential Tasks with Dynamically Composed Gradient Descent." (2025) IEEE ICRA

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