

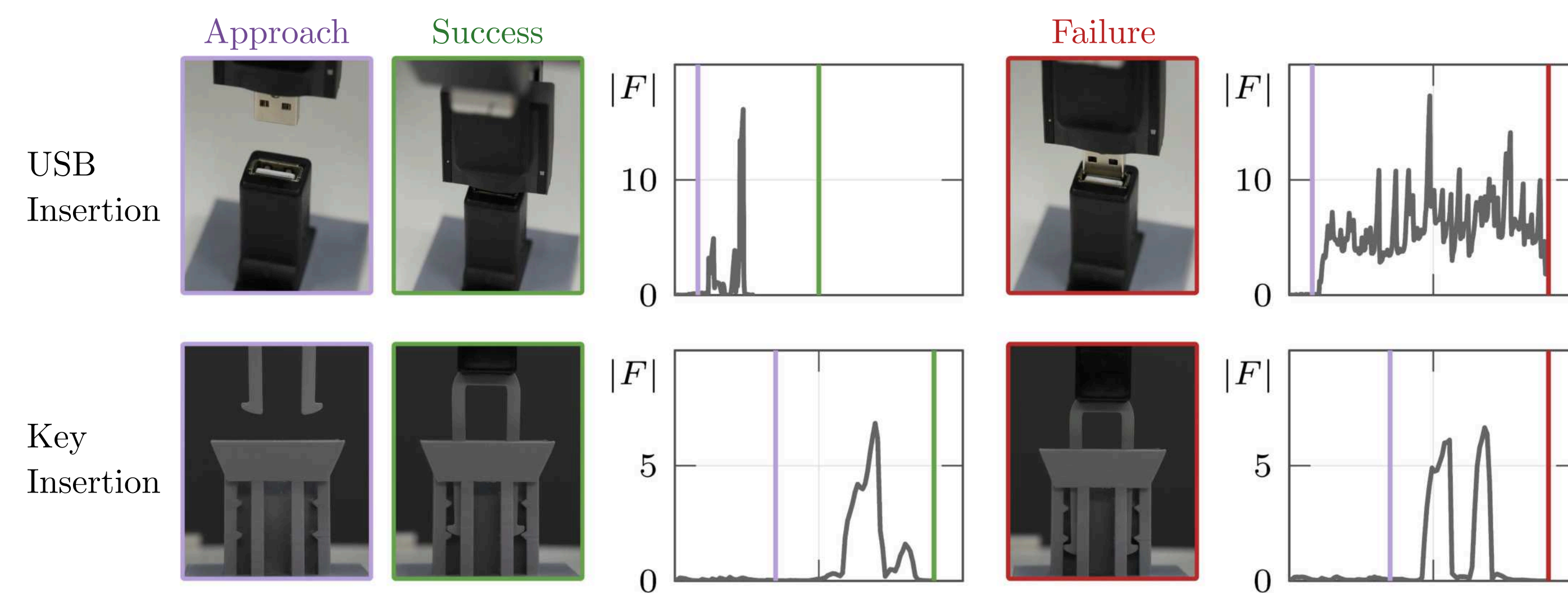
Force-Aware Residual Reinforcement Learning for Contact-Rich Manipulation

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Why do VLAs struggle with contact-rich manipulation?

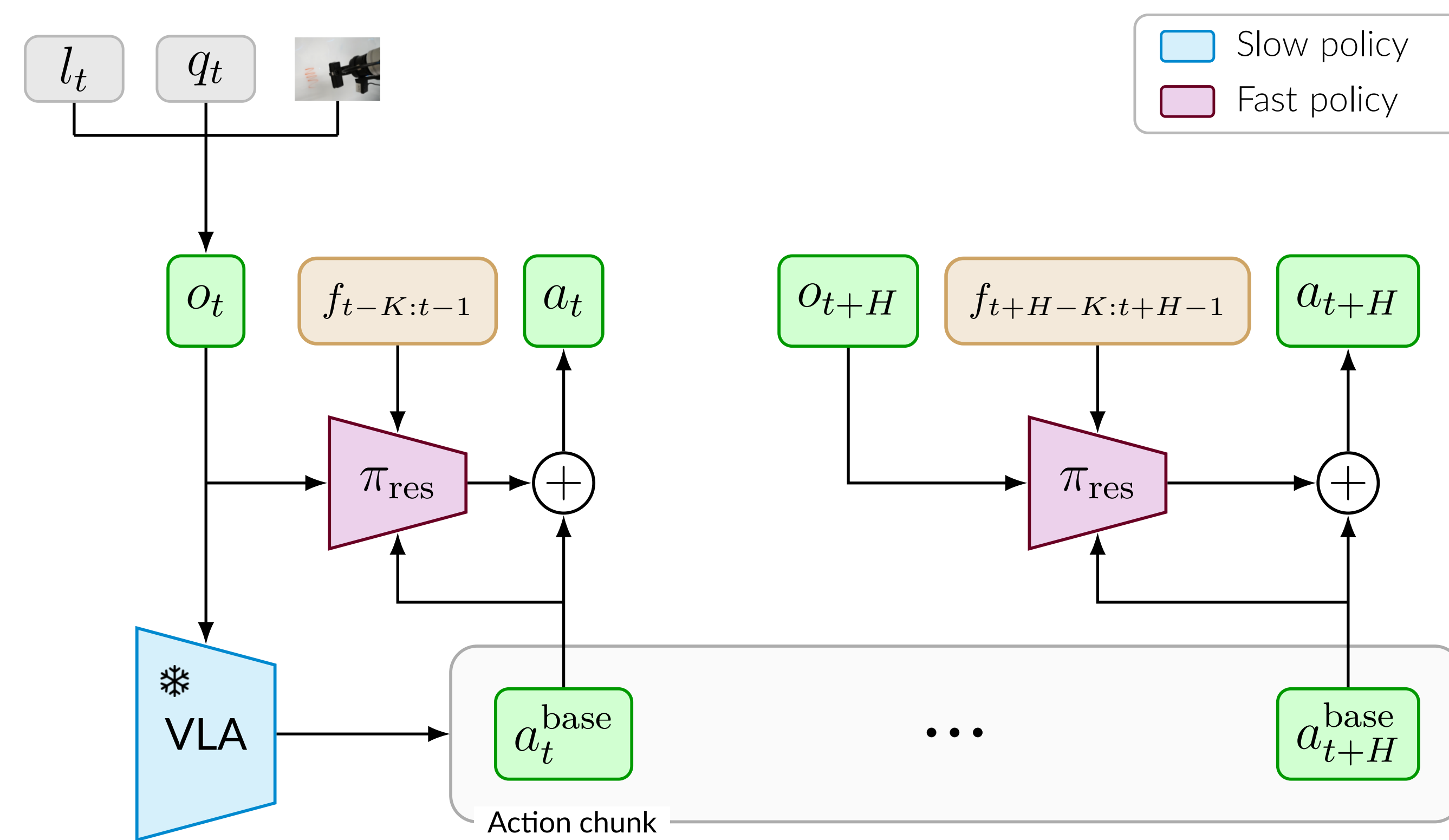
Success in contact-rich tasks depends on rapidly changing contact forces that are difficult to infer from vision alone.



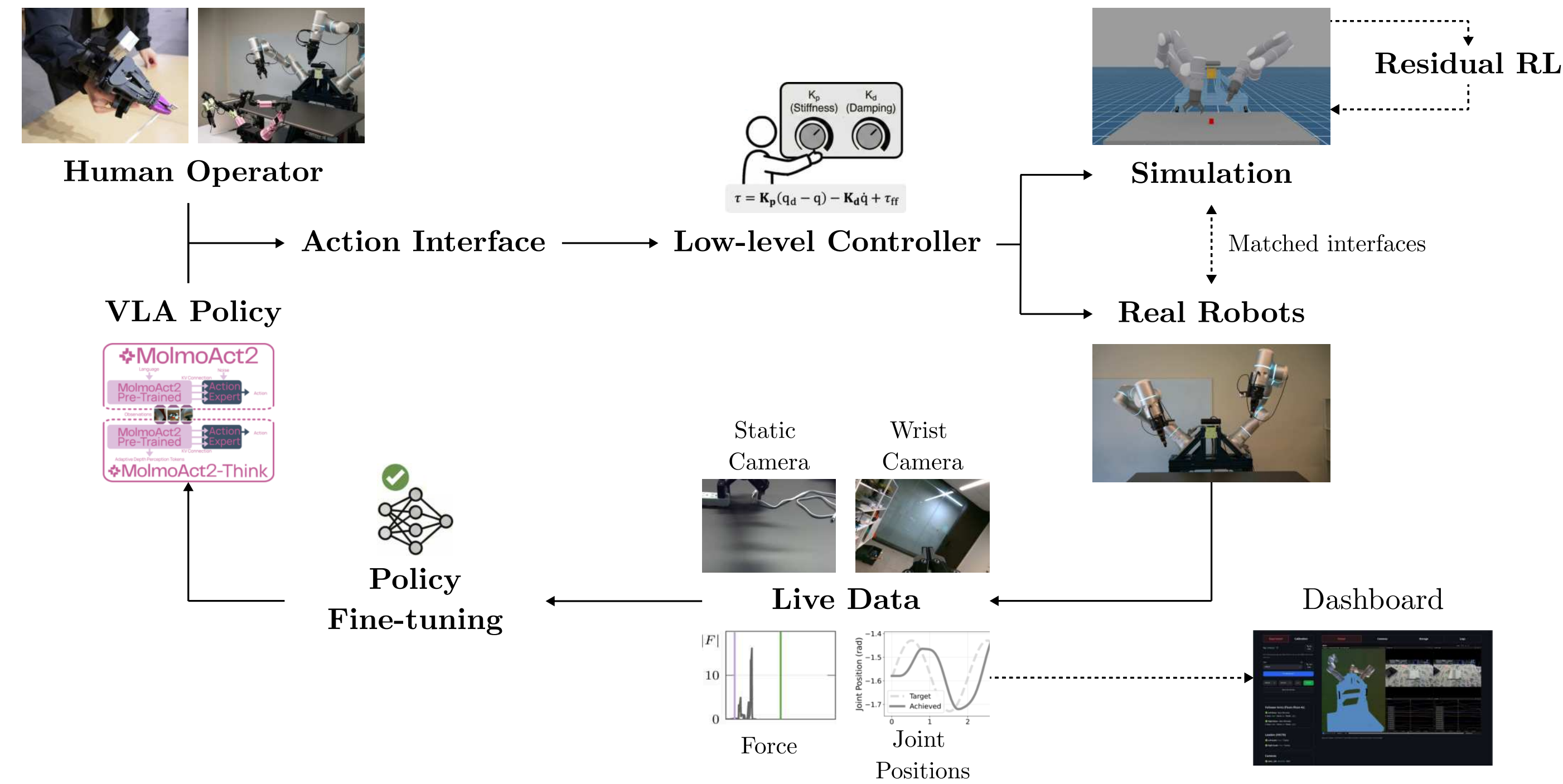
Successful and failed executions can look visually similar while producing substantially different force profiles. [1]

Our initial approach

Our initial hypothesis is that a fast, force-aware residual policy can refine the action chunks proposed by a slower VLA. We will investigate whether this improves contact-sensitive manipulation.



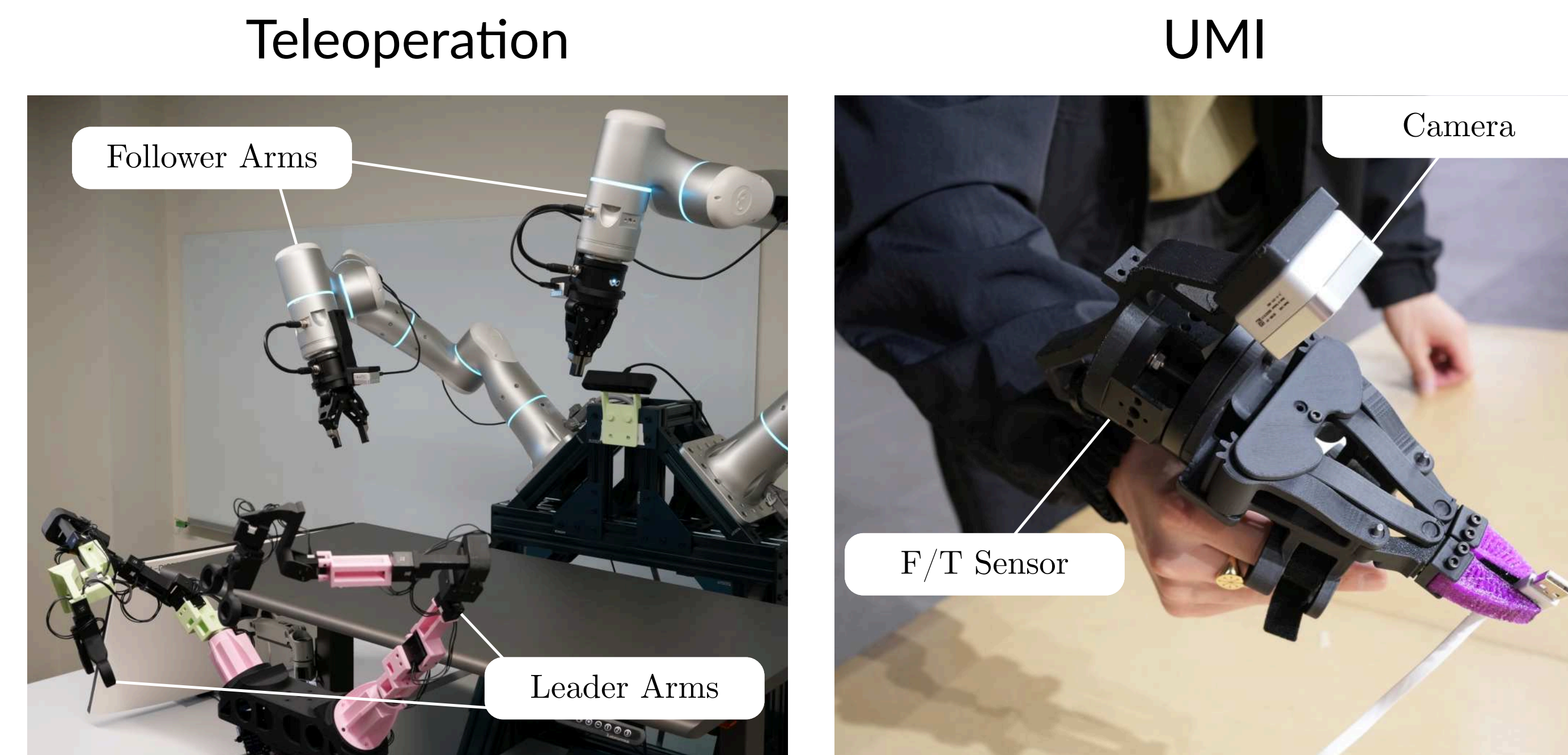
End-to-end experimental system



Visual elements adapted from Demystifying When and Why VLAs Fail [1], Tune to Learn [2], and MolmoAct2 [3].

Data collection and teleoperation

We use two complementary interfaces to collect human demonstrations.



Leader-follower control for demonstrations directly on the robot.

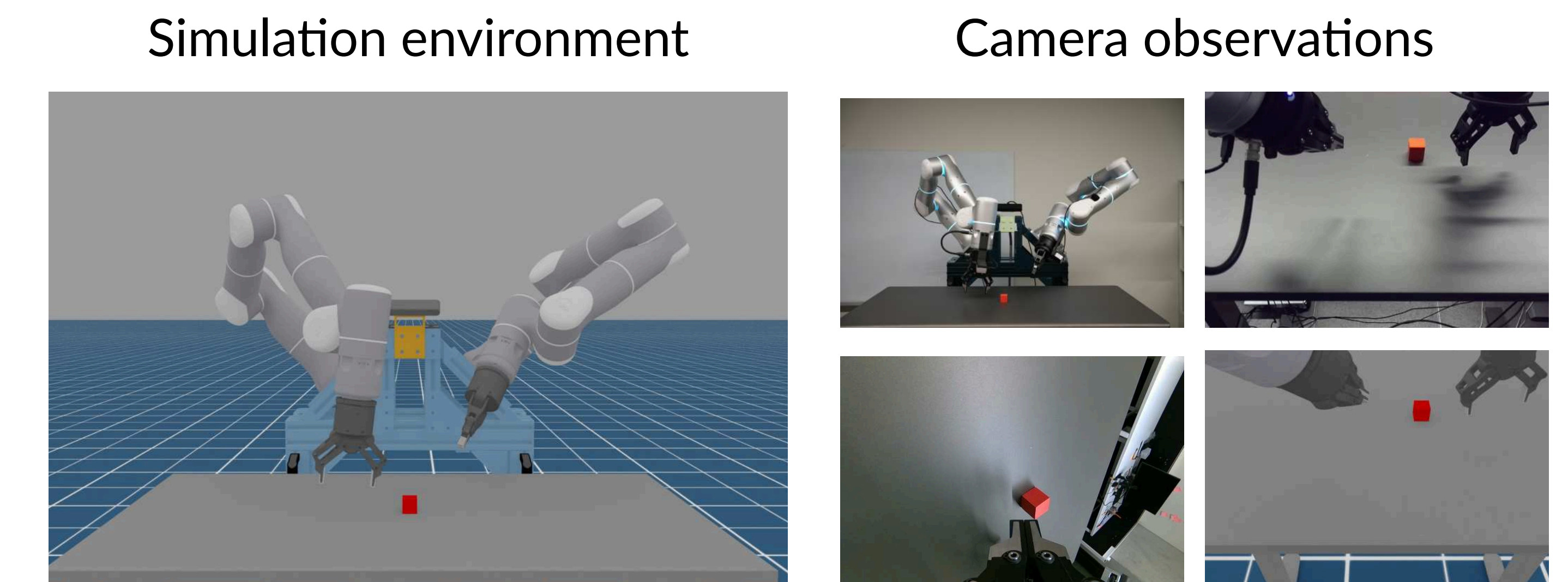
- Matched kinematics
- Gravity compensation
- Force feedback
- 500 Hz control; 100 Hz force sensing

Portable interface [4] for collecting demonstrations without the robot.

- Camera-equipped gripper
- Onboard force/torque sensor
- Robot-matched gripper geometry

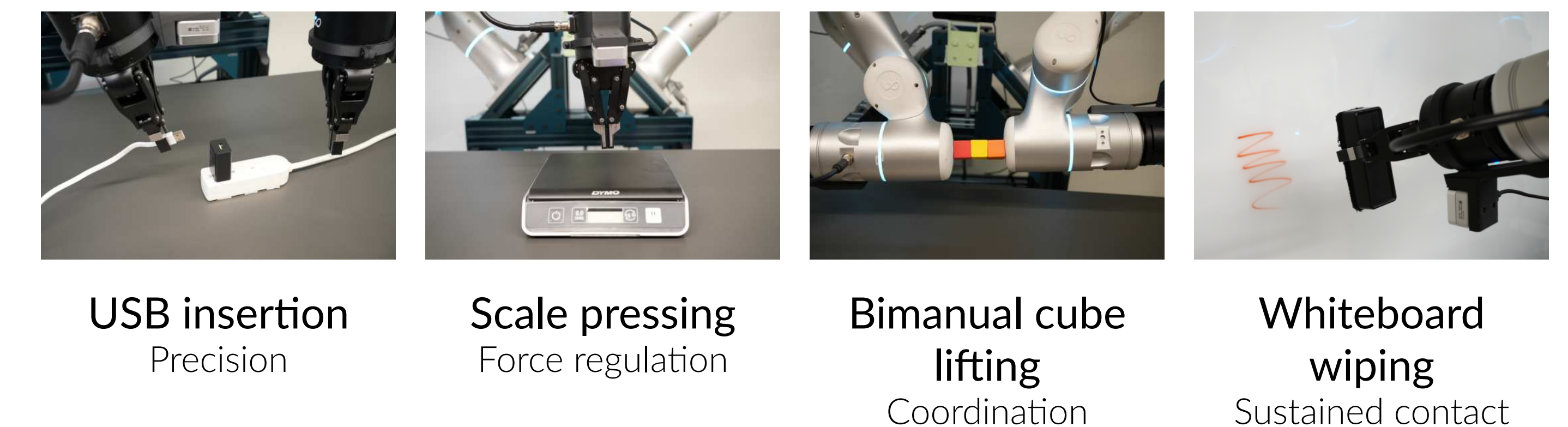
Simulation and real-world infrastructure

Matched simulated and physical setups share common control and observation interfaces.



Planned evaluation tasks

We target four manipulation tasks where success depends on precise contact interaction and force awareness.



Next steps: Collect demonstrations and fine-tune a VLA to establish baseline performance across all four tasks.

References

- [1] C. Pares-Morlans, N. Kuhn, I. Liu, A. Longhini, and J. Bohg, "Demystifying When and Why VLAs Fail in Contact-Rich Tasks and How to Fix Them," *arXiv preprint arXiv:2608.01402*, 2026.
- [2] A. Bronars, Y. Park, and P. Agrawal, "Tune to Learn: How Controller Gains Shape Robot Policy Learning," *arXiv preprint arXiv:2604.02523*, 2026.
- [3] H. Fang et al., "MolmoAct2: Action Reasoning Models for Real-World Deployment," *arXiv preprint arXiv:2605.02881*, 2026.
- [4] C. Chi et al., "Universal Manipulation Interface: In-the-Wild Robot Teaching Without In-the-Wild Robots," *arXiv preprint arXiv:2402.10329*, 2024.