



GitHub

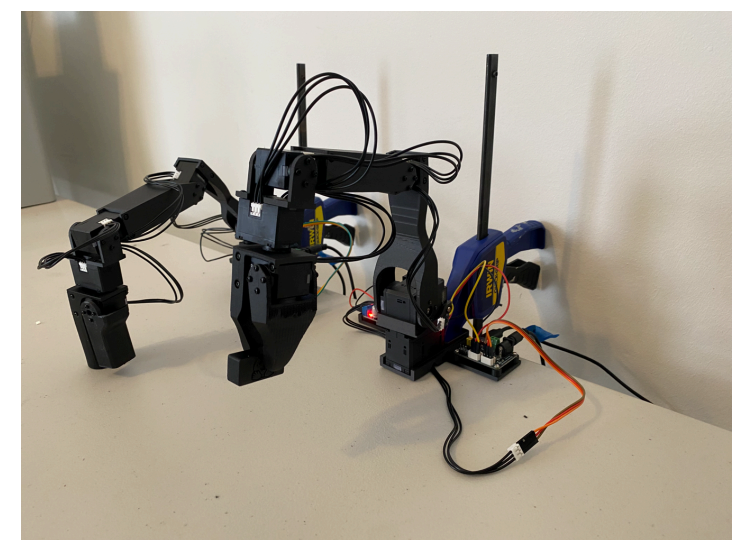


Syncere AI

Motivation

How can we train a robot manipulator to be compliant and safe?

- Robots must react in real time to disturbances
- External force sensors are expensive (Franka arm costs \$10k+). Koch LeRobot is an open source 5-DOF robotic arm for around \$200



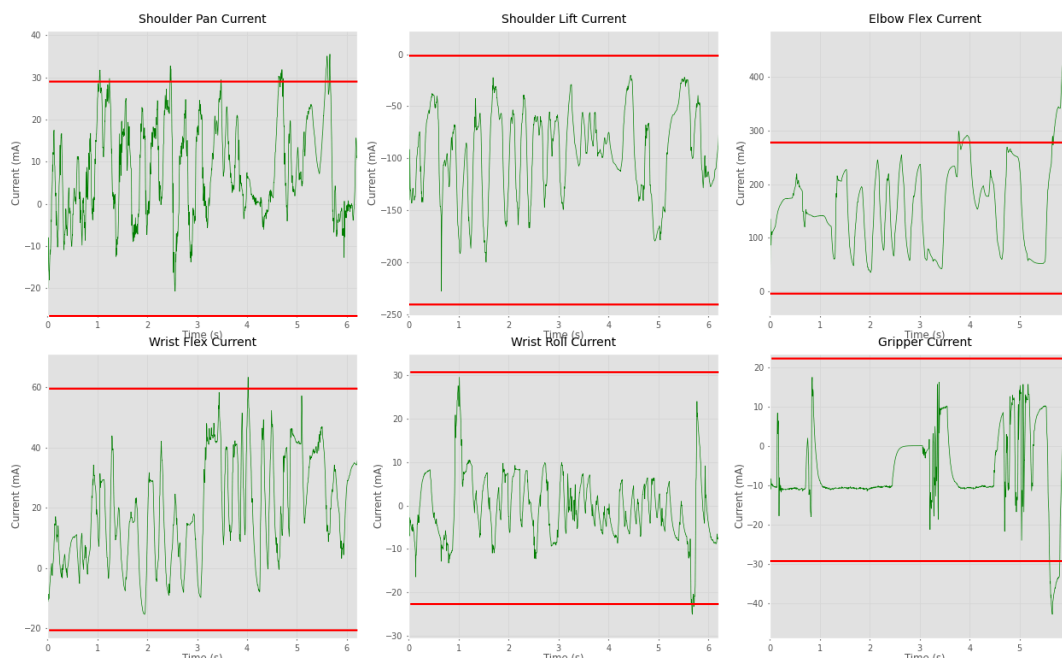
Koch arm V1.1



Koch playing chess

Contributions

- CLARA, an end-to-end compliant control pipeline, combining SOTA U-Net diffusion model and impedance controller trained in RL.
- Bilateral teleoperation to provide operator force feedback by reading follower arm's current to detect contact.



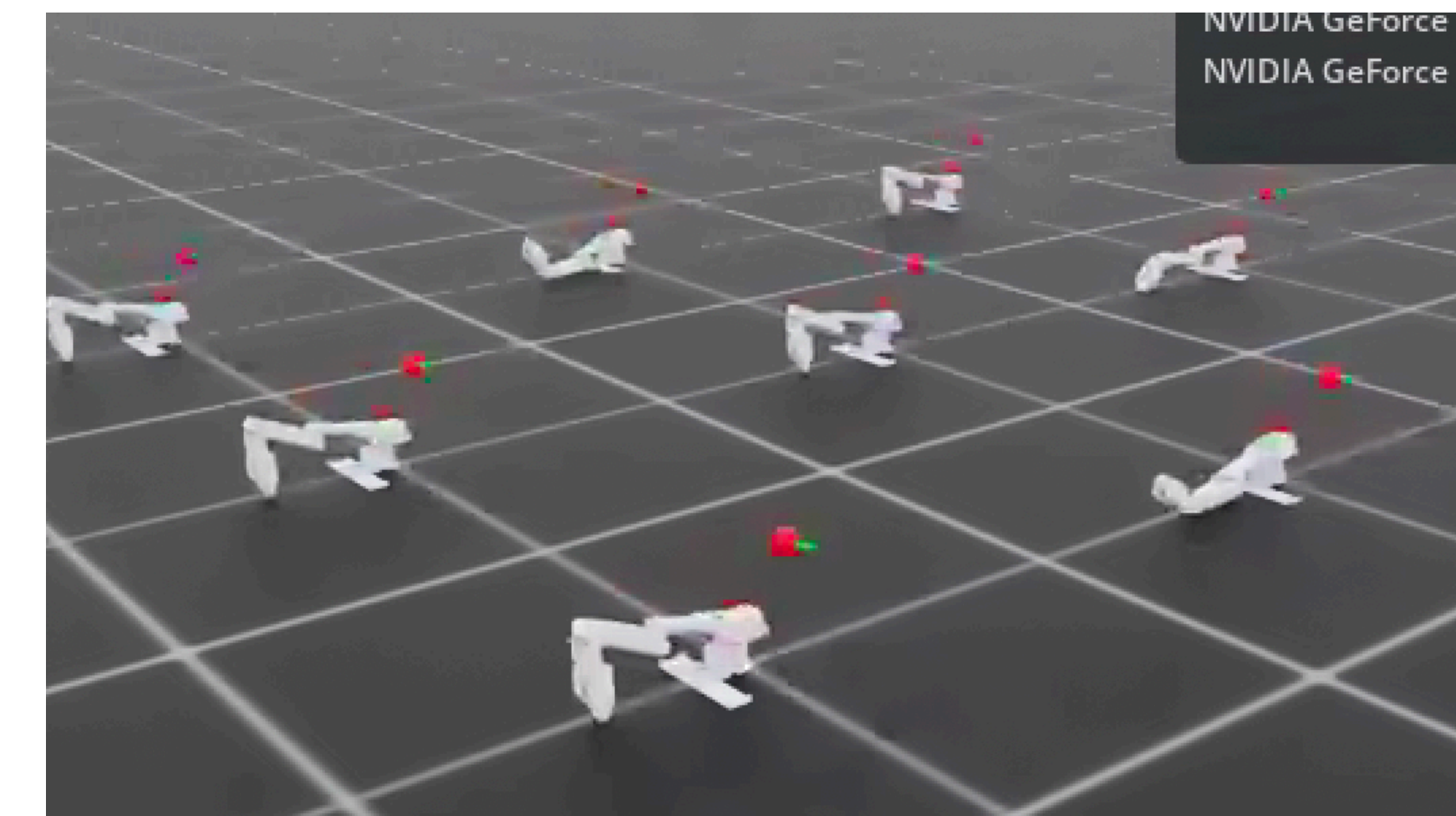
—: Free movement max threshold

—: Real time current reading

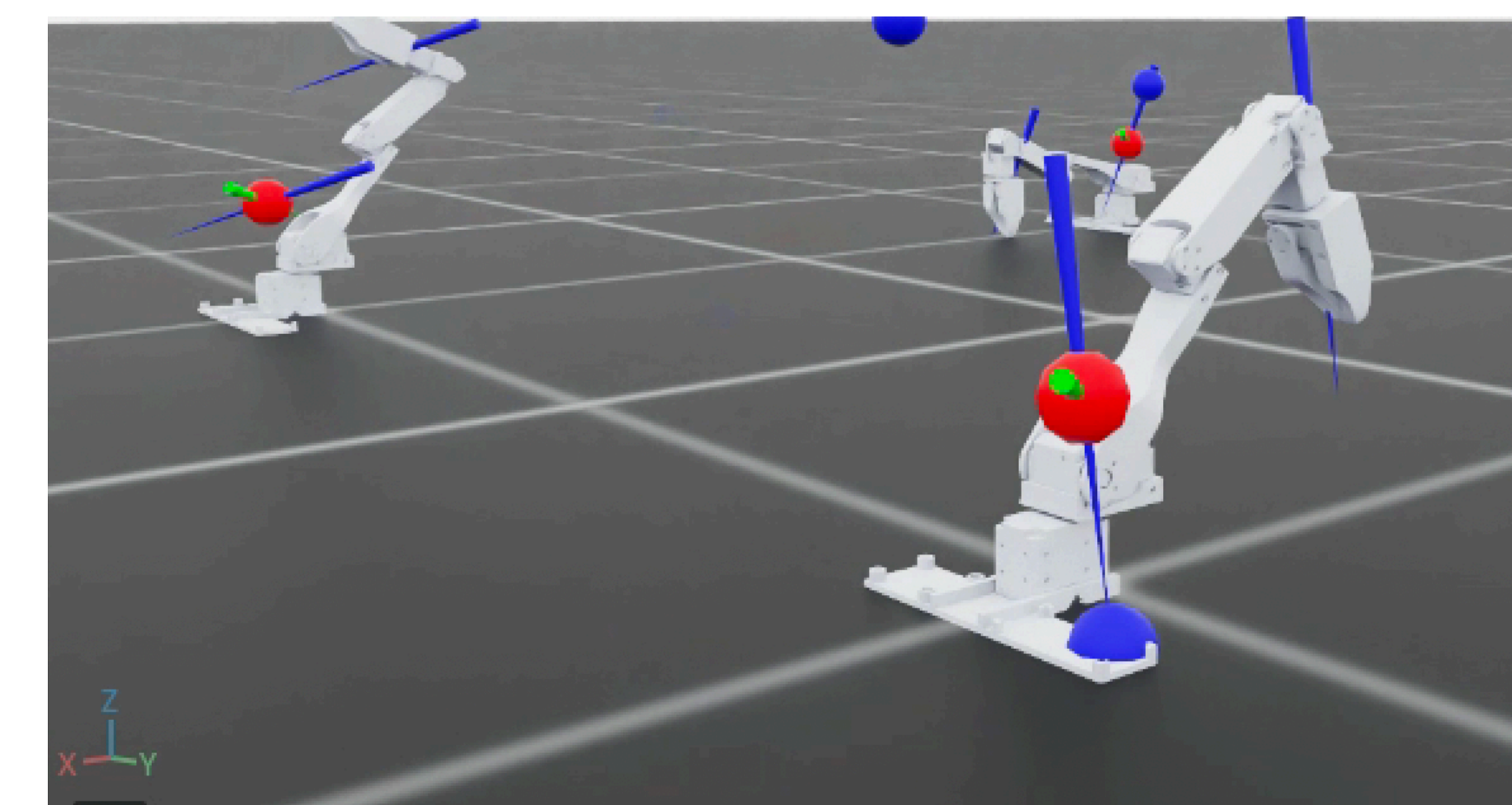
RL Training

Training the impedance controller with curriculum learning in NVIDIA's Isaac Lab

Stage 1: Position only



Stage 2: Sample external force



Reward function:

$$Reward^{(t)} = -w_1 \|\mathbf{x}_{curr}^{(t)} - \mathbf{x}_{target}^{(t)}\|_2 + w_2 \left[1 - \tanh \left(\frac{\|\mathbf{x}_{curr}^{(t)} - \mathbf{x}_{target}^{(t)}\|_2}{\sigma} \right) \right] - w_3 \cdot 2 \arccos \left(\left| \langle \mathbf{q}_{curr}^{(t)}, \mathbf{q}_{target}^{(t)} \rangle \right| \right) - w_4 \|\mathbf{u}^{(t)} - \mathbf{u}^{(t-1)}\|_2$$

- If a force is sampled, the equilibrium distance computed by Hooke's law is added to target position

Important considerations

- Constrained orientation sampling due to Koch's limited range of movement
- Domain randomization, observation & action noise, random action delays to overcome sim-to-real gap
- Using Weight and Biases (wandb) to visualize training results

Training Procedure

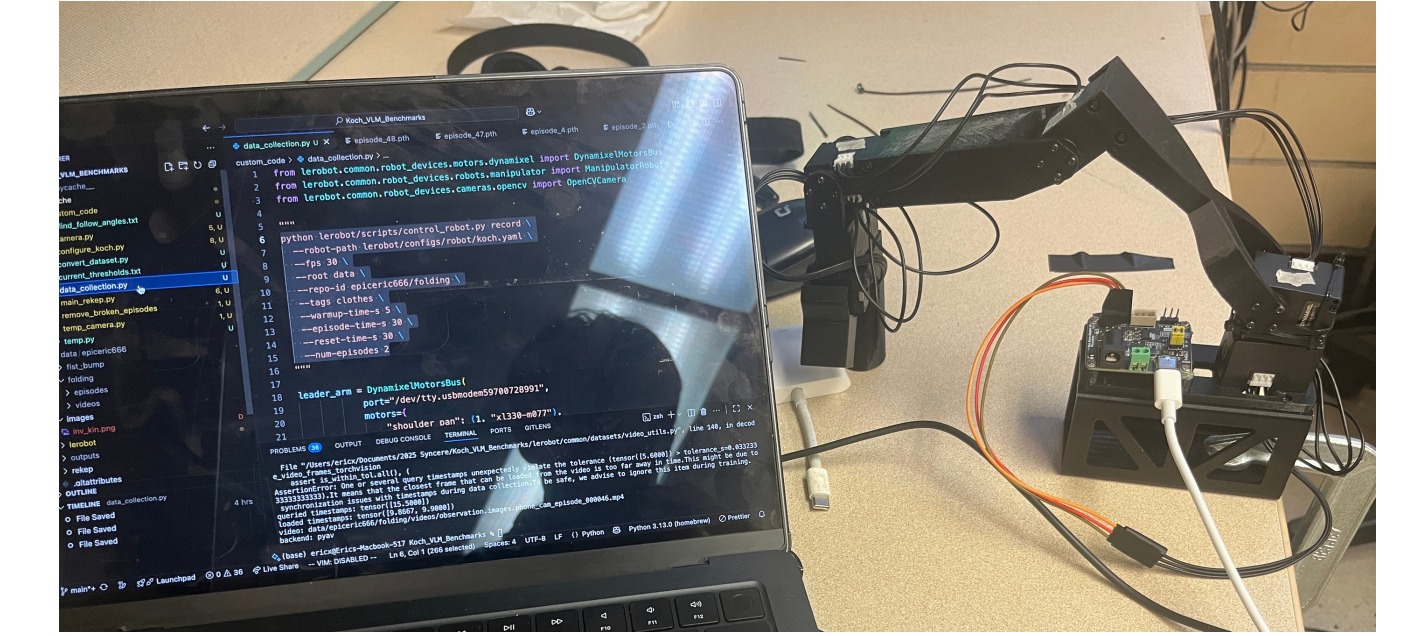
- Proximal Policy Optimization (PPO) with RSL-RL
- 3000 episodes on 2 NVIDIA 3070 GPUs

Data Collection

Setup

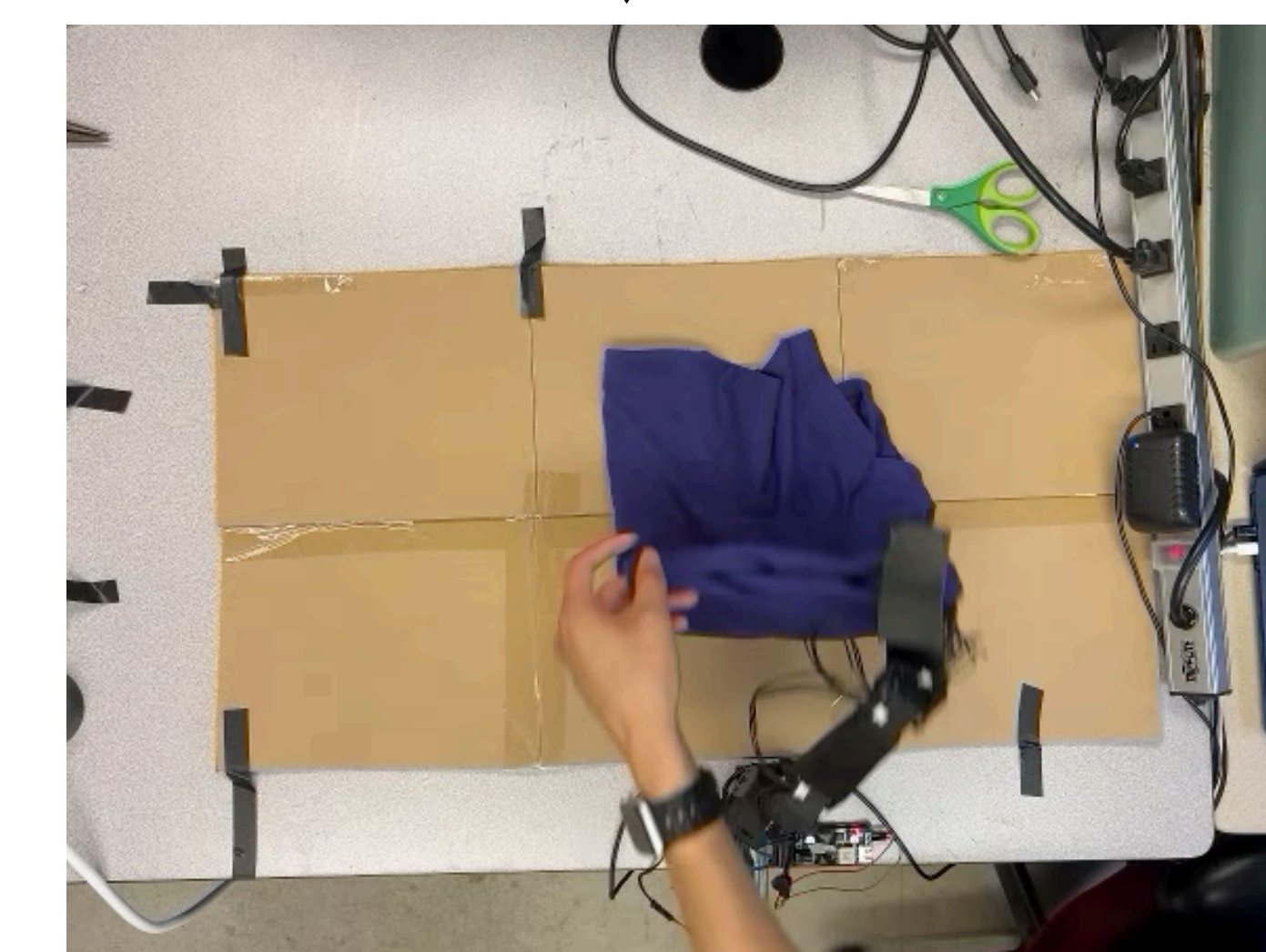


Follower arm performing task

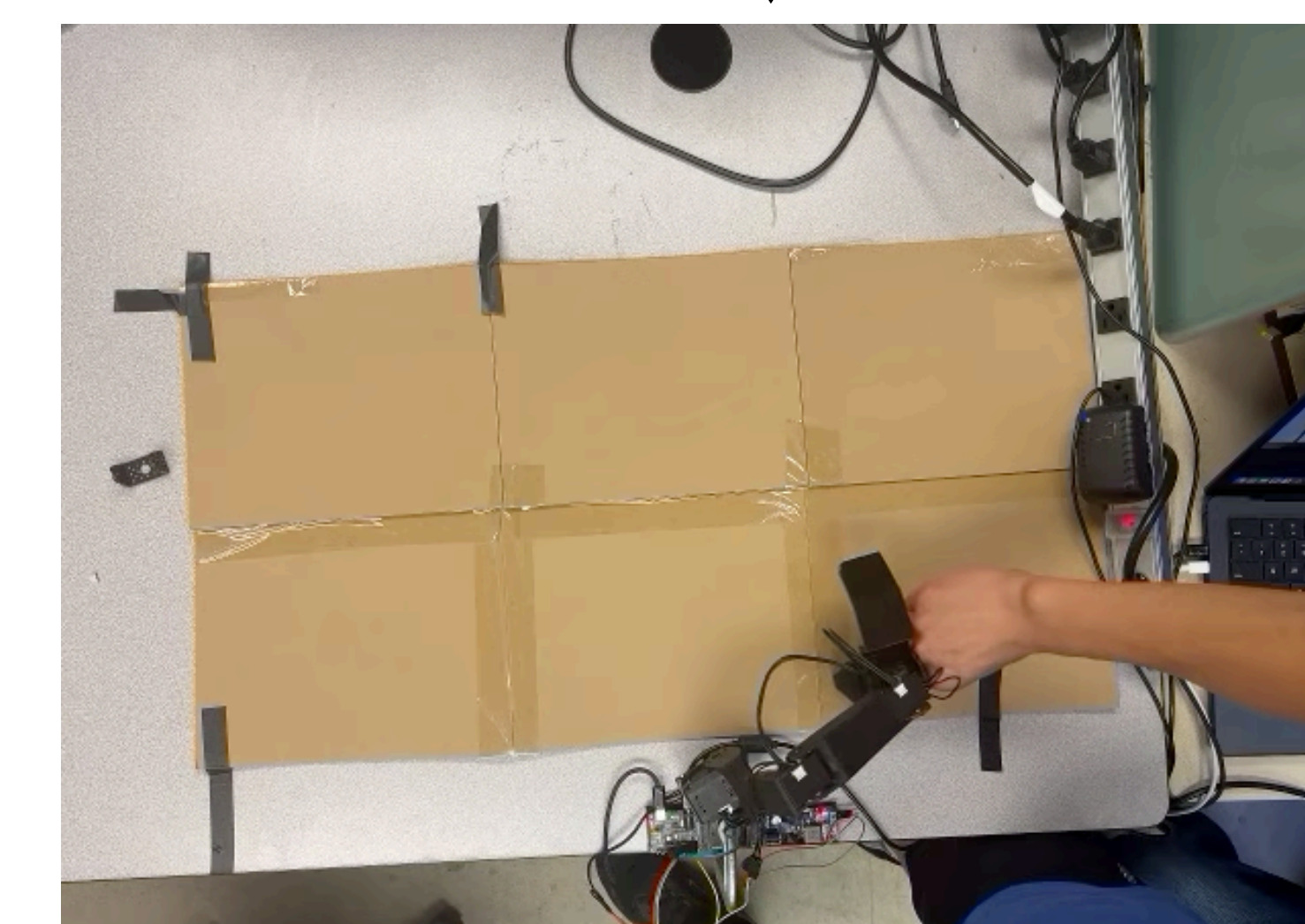


Leader arm & computer providing input

Two main tasks



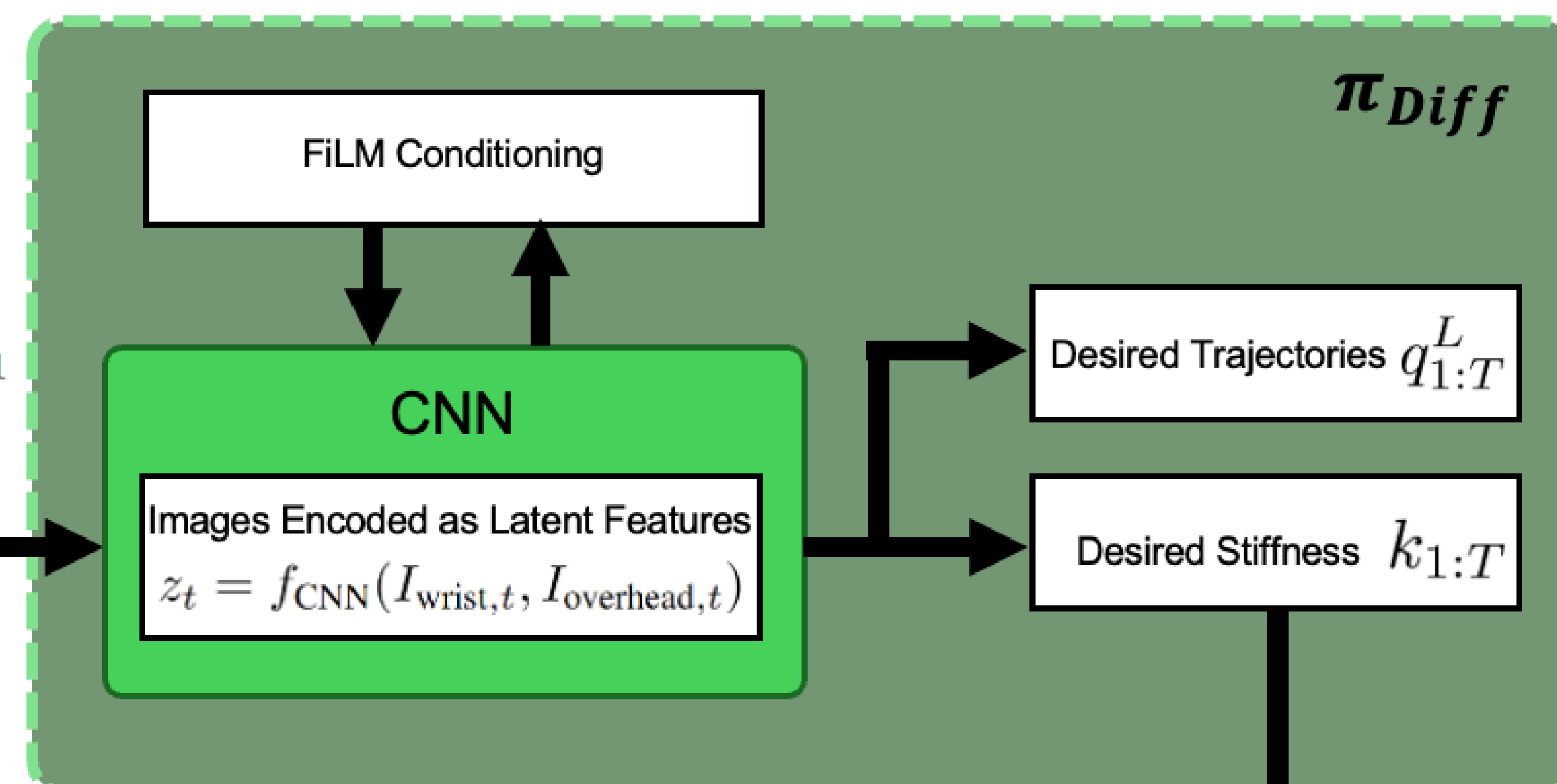
Shirt folding



Fist bump

Pipeline

Diffusion-Based Planning



π_{RL}

The policy is trained to approximate the compliant displacement law

$$q_t^* = q_t^L + K_t^{-1} f_{ext,t}$$

$$K_t = \text{diag}(k_{t,1}, \dots, k_{t,6})$$

Compliant Trajectories q_t

Compliant Desired Joint Target q_t^L

Stiffness k_t

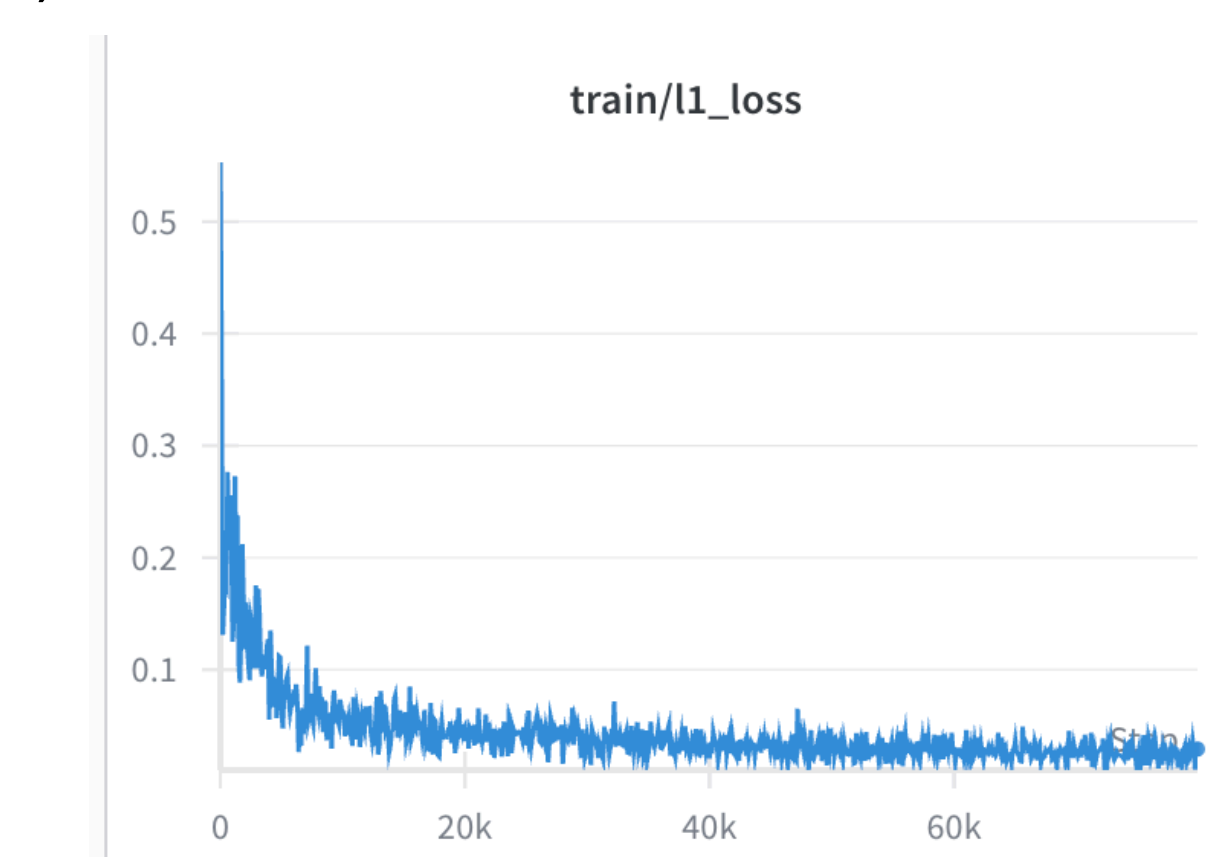
External Torques $f_{ext,t}$

RL for Compliance

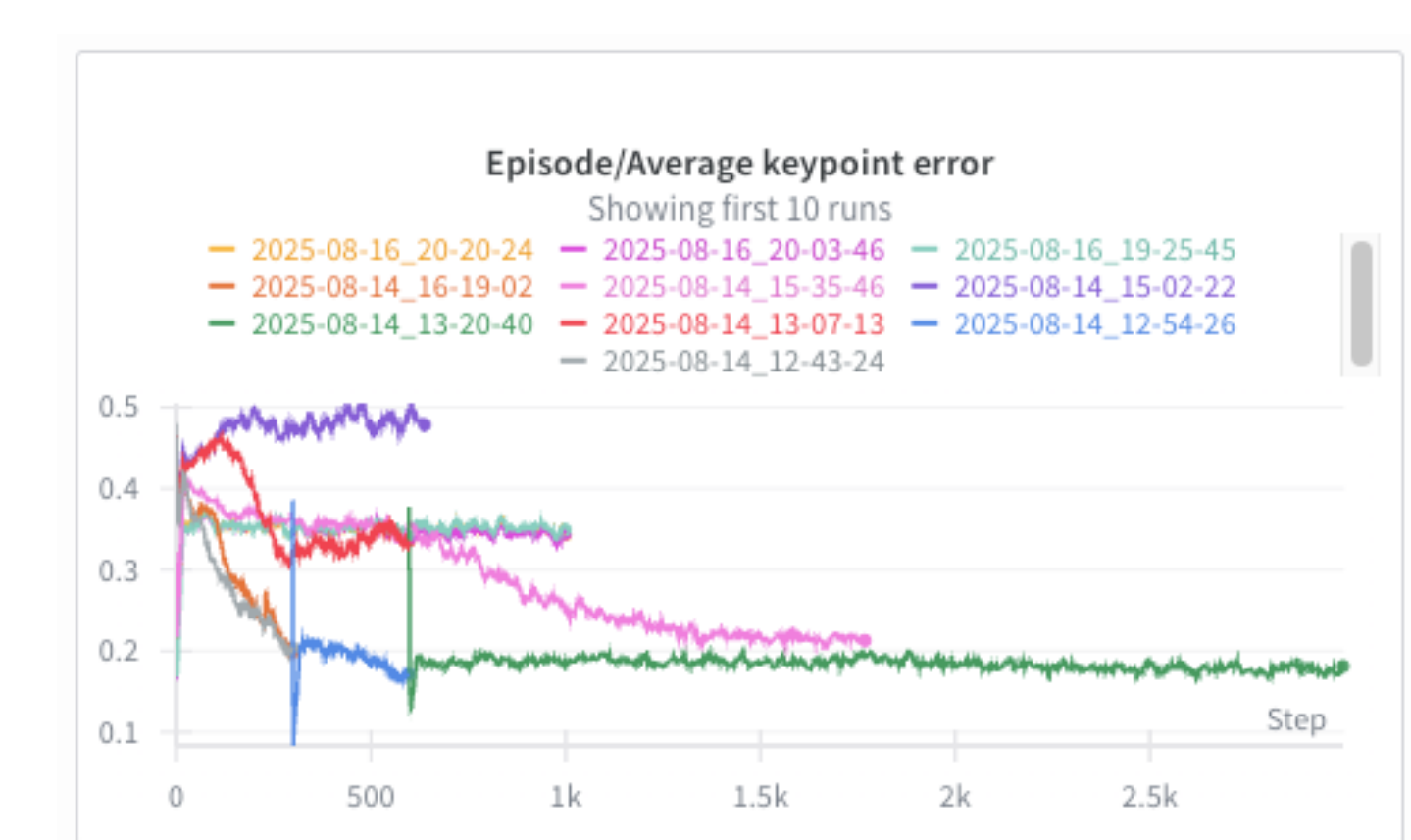
Executable joint commands $u_t = \pi_{RL}(q_t, q_t^L, k_t, f_{ext,t})$

Results

1) CLARA

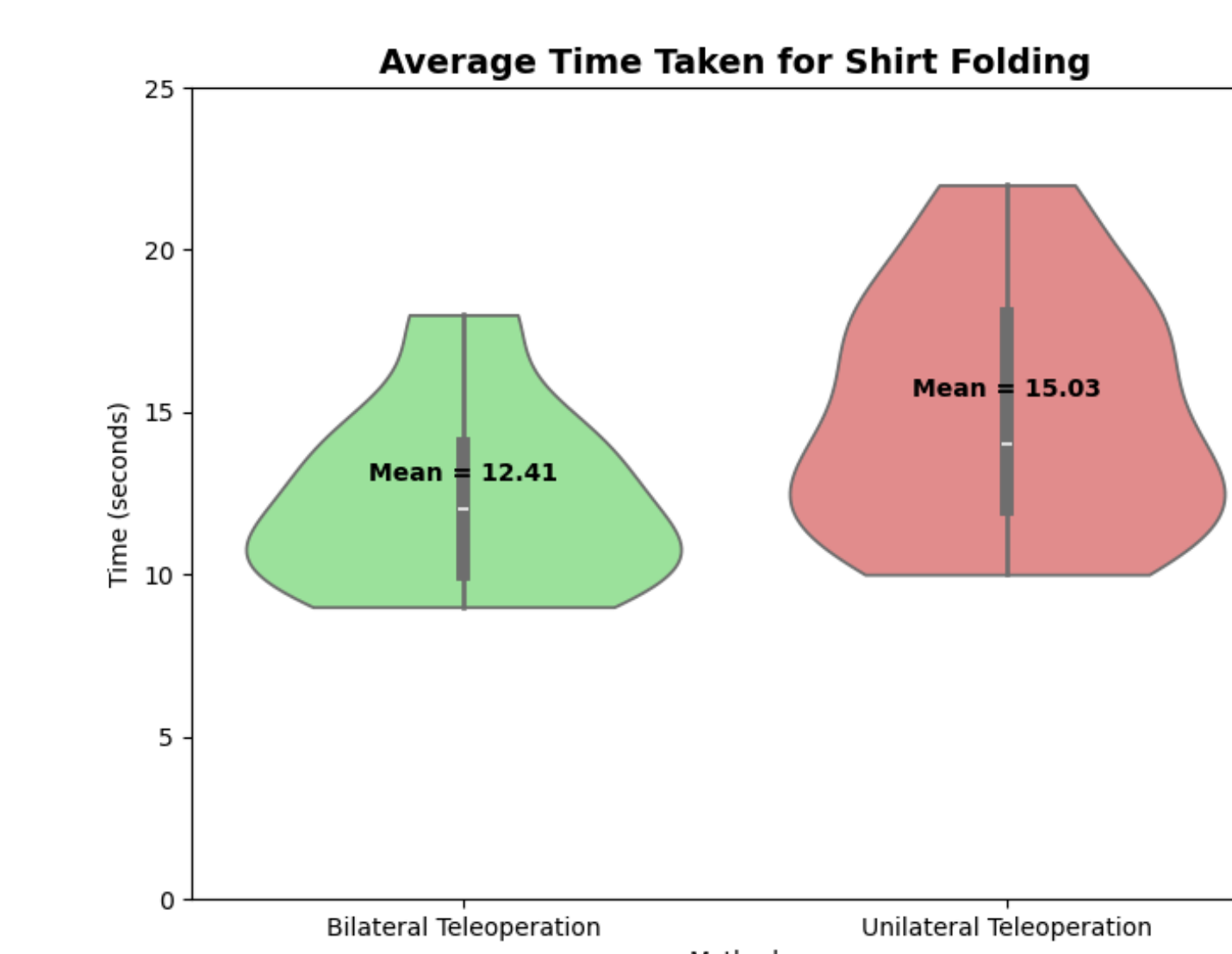


Diffusion loss plot



RL target error plot across runs

2) Bilateral teleoperation



Comparison violin plot

- Ideal diffusion loss curve
- RL decreases slowly and plateaus at around 10cm

- Data split across 50 episodes of training
- Decreased teleoperation time by 17%
- Saved time compounds over large training process
- User rates safer and more intuitive