

APPENDIX

A. Dataset Structure

Each demonstration in our dataset is stored as a time-aligned trajectory $D = \{(\mathbf{o}_t, \mathbf{a}_t)\}_{t=1}^T$. At each time step, the observation contains multi-view camera images, robot proprioception, and a language instruction:

$$\begin{aligned}\mathbf{o}_t &= \{o_{\text{cam},t}, o_{\text{prop},t}, o_{l,t}\}, \\ o_{\text{cam},t} &= \{I_t^{\text{front}}, I_t^{\text{wrist1}}, I_t^{\text{left/wrist2}}\}, \\ o_{\text{prop},t} &= \{q_{\text{arm},t}, q_{\text{hand/gripper},t}\}.\end{aligned}\quad (1)$$

Here, the superscript identifies the camera view. For the Tube Transfer (XHand) task, only the front and wrist1 views, $(I_t^{\text{front}}, I_t^{\text{wrist1}})$, are included to match the real-robot setup. The proprioceptive vector $q_{\text{arm},t}$ contains the manipulator joint positions, while $q_{\text{hand/gripper},t}$ contains the joint positions of the end-effector hand or gripper. The latter is an articulated hand in dexterous setups and a gripper in simpler setups. The term $o_{l,t}$ denotes the language instruction associated with the trajectory. The corresponding action at time step t is stored as

$$\mathbf{a}_t = [\text{pos}_{\text{ee},t}, \text{quat}_{\text{ee},t}, q_{\text{hand/gripper},t}], \quad (2)$$

where $\text{pos}_{\text{ee},t} \in \mathbb{R}^3$ is the end-effector position, $\text{quat}_{\text{ee},t} \in \mathbb{R}^4$ is a unit quaternion representing the end-effector orientation, and $q_{\text{hand/gripper},t} \in \mathbb{R}^{n_{\text{hand/gripper}}}$ is the hand- or gripper-joint position vector. For dual-arm tasks, the action contains the concatenated commands for both arms:

$$\mathbf{a}_{\text{dual},t} = \mathbf{a}_{1,t} \oplus \mathbf{a}_{2,t}. \quad (3)$$

B. Visualization and Language Instruction of AutoBio+ Tasks

Table I presents the visualization information and language instructions for the fourteen AutoBio+ tasks.

C. Randomization Settings of AutoBio+ Tasks

At the beginning of each episode, AutoBio+ randomizes both the task scene and the robot initialization. Scene randomization covers object poses, discrete slot assignments, and, where applicable, visual appearance. Robot randomization perturbs the initial joint configuration within task-specific ranges. Table II reports the sampling rules and reset ranges used for each task.

D. Evaluation Infrastructure

AutoBio+ provides a unified evaluation infrastructure built around domain randomization, task-specific success checking, and model-independent policy communication. At each episode reset, AutoBio+ applies domain randomization to the robot’s initial joint configuration and the object poses. Each task is equipped with a task-specific success-checking function that determines completion from the simulator state. AutoBio+ and the policy runtime are decoupled via a ZeroMQ [1] observation–action interface, allowing policies to run in independent Python environments with different versions and dependencies. The simulator serializes the current visual observations, proprioceptive state, and language

prompt to an external inference process and receives action chunks in return. Consequently, a model can be evaluated from a separate process, machine, or software environment without being integrated into the simulator’s dependency stack.

The thread mechanism in AutoBio+ is inherited from AutoBio [2]. We ported its original MuJoCo implementation to mlab, enabling large-scale parallel simulation from CPU to GPU while preserving the mechanism’s behavior.

E. Training Details

All evaluated models are fine-tuned. For the simulated-task evaluation, each model is trained for 30,000 optimization steps on a single NVIDIA H200 GPU. The batch size for $\pi_{0.5}$ is 32.

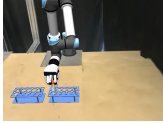
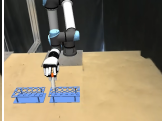
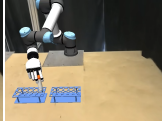
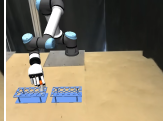
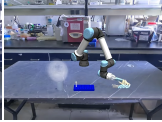
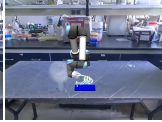
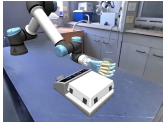
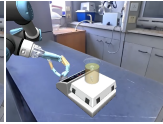
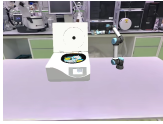
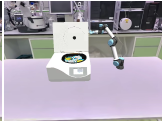
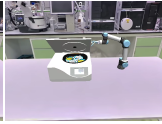
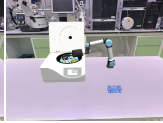
For the real-world Transfer Tube (XHand) experiment, we train the $\pi_{0.5}$ model on 100 real-world demonstrations. The training uses the same 30-step action horizon as the simulated $\pi_{0.5}$ experiments. We train for 30,000 optimization steps on a single GPU with a batch size of 32. The peak learning rate is 5×10^{-5} with a 3,333-step warmup; the optimizer uses AdamW with $\beta_1 = 0.9$, $\beta_2 = 0.95$, weight decay 10^{-10} , and gradient-norm clipping at 1.0.

Figure 1 shows the raw training losses for the 12 simulated tasks and the real-world Transfer Tube (XHand) experiment.

REFERENCES

- [1] P. Hintjens, *ZeroMQ: Messaging for Many Applications*. O’Reilly Media, 2013.
- [2] Z. Lan, Y. Jiang, R. Wang, X. Xie, R. Zhang, Y. Zhu, P. Li, T. Yang, T. Chen, H. Gao, X. Yang, X. Li, H. Zhang, Y. Mu, and P. Luo, “AutoBio: A simulation and benchmark for robotic automation in digital biology laboratory,” in *International Conference on Learning Representations*, 2026.

TABLE I
VISUALIZATION AND LANGUAGE INSTRUCTION OF THE FOURTEEN AUTOBIO+ TASKS.

Task	Gaussian Background	Visualization				Language Instruction
Attach Pipette Tip	Fume Hood					Attach the pipette tip with the Shadow hand.
Aspirate with Pipette	Fume Hood					Pick up the pipette and move it directly above the cryovial to perform the pipetting operation.
Transfer Tube (XHand)	Real Tube-Rack Scene					Pick up the centrifuge tube and move it to the other rack, row [row], col [column].
Manipulate Tweezers	Lab Bench					Pick up the tweezers, move them to the cryovial, grasp it with the tweezers, and place it into the fogging liquid nitrogen flask.
Heat & Stir Agar Solution	Lab Bench					Place the beaker on the heating plate, turn the knob on, then return the knob to its home position with the Wuji hand.
Close Centrifuge Lid	Centrifuge Station					Close the centrifuge lid with the Wuji hand.
Load Centrifuge	Centrifuge Station					Insert the tube into the centrifuge slot symmetrically opposite the already placed tube with the Shadow hand.
Tighten Tube Cap	Autolab Enclosure					Dual-Aloha arms screwing on centrifuge tube cap: one grasps the tube from the rack and then grips the tube while the other twists the cap.
Transfer Tube (Shadow)	Autolab Enclosure					Insert the tube into rack row [row], column [column] with the Shadow hand.
Ignite Bunsen Burner	Heating and Mixing Station					Rotate the Bunsen burner's silver ring to turn it on, then rotate the yellow ring to increase the flame temperature.
Loosen Tube Cap	Autolab Enclosure					dual-Shadow unscrewing centrifuge tube cap: one stabilizes tube while the other twists cap

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TABLE I
VISUALIZATION AND LANGUAGE INSTRUCTION OF THE FOURTEEN AUTOBIO+ TASKS (CONTINUED).

Task	Gaussian Background	Visualization	Language Instruction
Open Thermal Cyclor Lid	Reagent Cabinet		Open the thermal cyclor with the XHand.
Close Thermal Cyclor Lid	Reagent Cabinet		Close the thermal cyclor with the XHand.
Operate Mixer Panel	Heating and Mixing Station		Set the mixer to [time] seconds, [temperature] degrees Celsius, and [speed] RPM with the XHand.

TABLE II
TASK-SPECIFIC RANDOMIZATION SETTINGS FOR THE FOURTEEN AUTOBIO+ TASKS.

Task	Object / visual randomization	Robot reset ranges (rad.)
Attach Pipette Tip	Tip slot sampled from the 6×4 tip-box grid.	UR5e: $[-0.20, 0.20]$.
Aspirate with Pipette	Cryovial slot sampled from the 5×12 rack grid.	UR5e: $[-1.89, 2.76]$; Shadow: $[-0.95, 1.12]$.
Transfer Tube	XHand: source tube slot sampled from the 5×2 rack. Shadow: target row $\in \{0, \dots, 4\}$ and column $\in \{0, 1\}$ sampled; tube pose follows the selected slot.	UR5e (XHand): $[-0.20, 0.30]$; UR5e (Shadow): $[-1.89, 2.07]$; Shadow: $[-0.95, 1.12]$.
Manipulate Tweezers	Tweezers $dx, dy \sim U(-0.025, 0.025)$ m and yaw $\sim U(-0.10, 0.10)$ rad; tube slot sampled.	Wuji: $[-0.12, 0.12]$.
Heat & Stir Agar Solution	Plate: $dx \sim U(-0.02, 0.02)$, $dy \sim U(0, 0.02)$ m; beaker: $dx \sim U(-0.02, 0.02)$, $dy \sim U(-0.02, 0)$ m.	UR5e: $[-0.10, 0.10]$.
Close Centrifuge Lid	Centrifuge $dx, dy \sim U(-0.025, 0.025)$ m.	UR5e: $[-0.10, 0.10]$.
Load Centrifuge	Target slot sampled from the 5×2 safe-slot set; tube pose follows the selected slot.	UR5e: $[-1.19, 1.07]$; Shadow: $[-0.95, 1.12]$.
Tighten Tube Cap	Cap $dx, dy \sim U(-0.01, 0.01)$ m; rack slot sampled.	Aloha: $[-0.05, 0.08]$.
Ignite Bunsen Burner	Burner $dx \sim U(-0.07, 0.07)$, $dy \sim U(-0.055, 0.055)$ m; flame appearance randomized.	UR5e: $[-0.08, 0.08]$; XHand: $[-0.05, 0.05]$.
Loosen Tube Cap	Cap $dx, dy \sim U(-0.01, 0.01)$ m; rack slot sampled.	Shadow: $[-0.95, 1.12]$.
Open Thermal Cyclor Lid	–	–
Close Thermal Cyclor Lid	Cyclor $dx \sim U(-0.08, 0)$ m.	UR5e: $[-0.16, 0.16]$.
Operate Mixer Panel	–	UR5e: $[-0.20, 0.30]$.

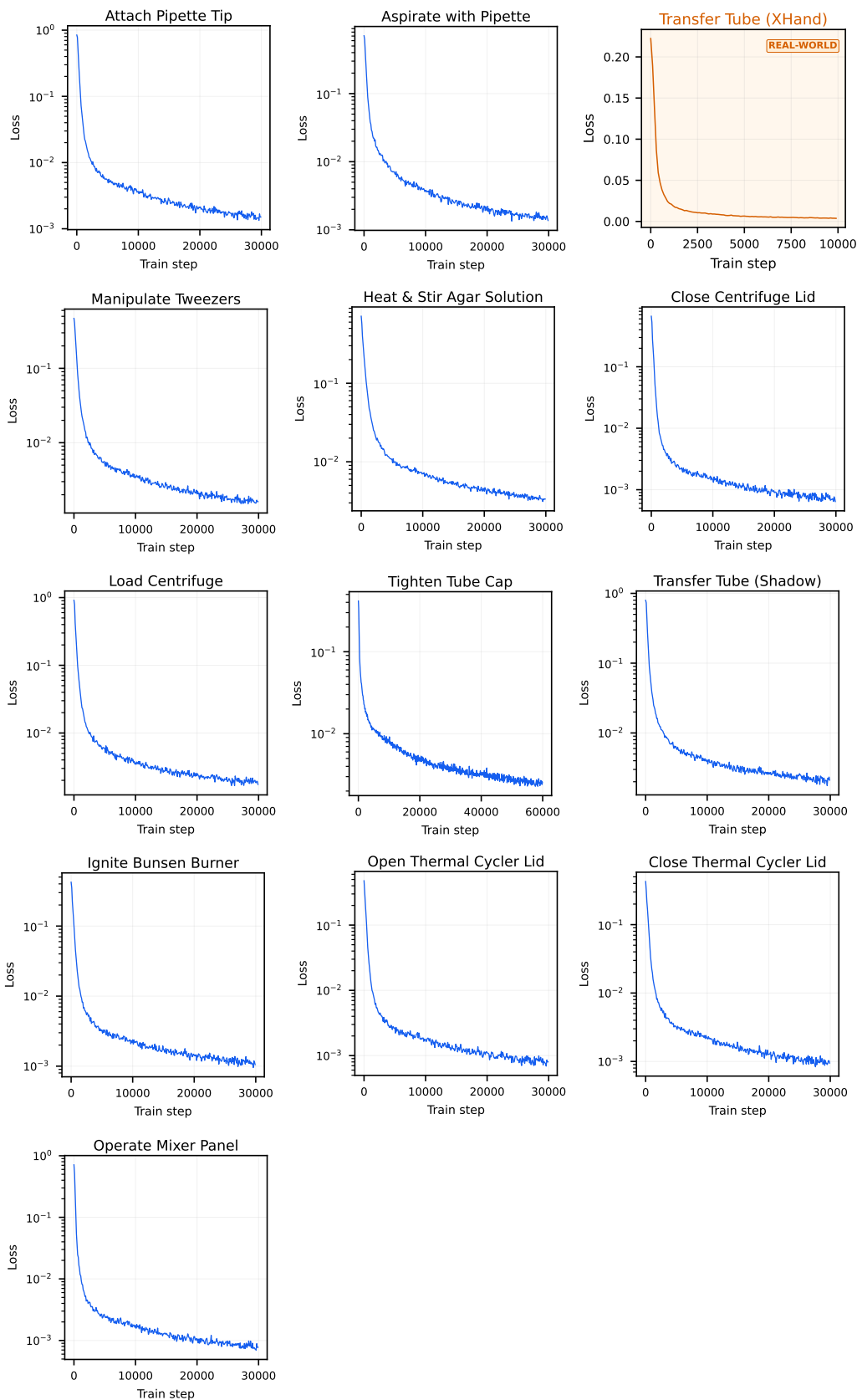


Fig. 1. Raw training loss curves for 13 tasks. The orange panel denotes $\pi_{0.5}$ training on real-world data for Transfer Tube (XHand), whereas the blue panels denote $\pi_{0.5}$ training on simulated task data.