IROS HANGZHOU 2025

DexRobot

Generalized Retargeting for Dexterous Manipulation

Anonymous Submission for IROS 2025 Workshop

IROS 2025 Workshop on Dexterous Manipulation

Problem Statement

Dexterous manipulation remains one of robotics' most formidable challenges. A central obstacle is the *retargeting* problem: learning a mapping from human hand trajectories to robot joint commands while bridging the **embodiment gap** between humans and robots. Effective retargeting enables the exploitation of limited human demonstrations, thereby improving sample efficiency and facilitating transfer across tasks and hand morphologies.

Recent work tackles dexterous manipulation from complementary angles but leaves important gaps. **Object-centric** methods [1, 2] learn task-oriented, functional retargeting across many hands and tasks, yet typically train a separate model per demonstration, limiting generalization. **Kinematic-based** methods [3, 4] support diverse hands and trajectories within one model, but their optimization-centric design tends to prioritize pose mimicry over goal completion.

Method Type	Anthropomorphism	Task Fidelity	Real Deploy
Kinematic-based	High	Low	Limited
Object-centric	Low	High	Sim Only
Our Method	**High**	**High**	**Yes**

We present a generic policy framework for anthropomorphic dexterous hand manipulation that bridges the gap between human demonstrations and robotic execution. In contrast to existing methods, our framework learns robust, **goal-directed** manipulation behaviors that **generalize across diverse tasks**, while preserving human-like grasp and motion structure from limited demonstrations to ease teleoperation and transfer.

System Framework

We present a unified Reinforcement Learning based pipeline that learns dexterous teleoperation from offline human–object interaction data and deploys it on real hardware.

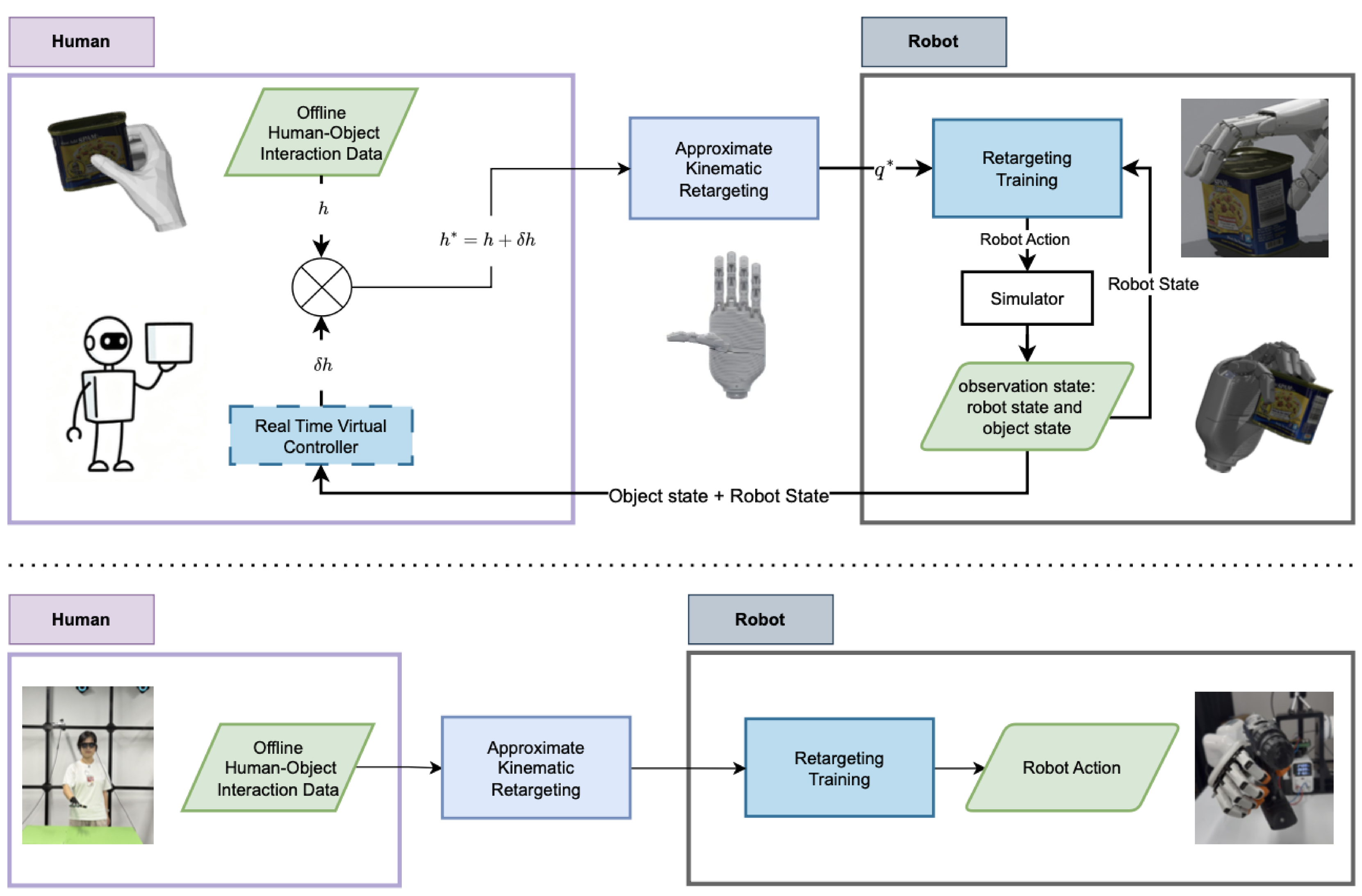

Figure 1. Our hierarchical RL framework introduces a three-layer training pipeline: (1) *Real-Time Virtual Operator*: outputs a correction δh to the offline human data h, aims to mimic a human operator in teleoperation. (2) *Approximate Kinematic Retargeting*: an NN-based retargeting policy trained on kinematic retargeting data, maps each corrected human demo $h^* = h + \delta h$ to robot joint targets q^*, which serve as a baseline. (3) *Retargeting Training*: outputs robot actions according to q^*, aiming to mimic human motion and complete the task.

Key Contributions

1. Unified Retargeting Across Tasks and Learning Paradigms

- A single framework applicable to both teleoperation and dataset-driven learning.
- Generalizes across diverse manipulation tasks and datasets while simultaneously achieving *task fidelity* and *anthropomorphism*.

2. Virtual-Operator–Driven Training Pipeline

- Introduces a virtual operator that simulates human teleoperation with a learnable policy, enabling realistic and adaptive robot control.

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Experimental Setup

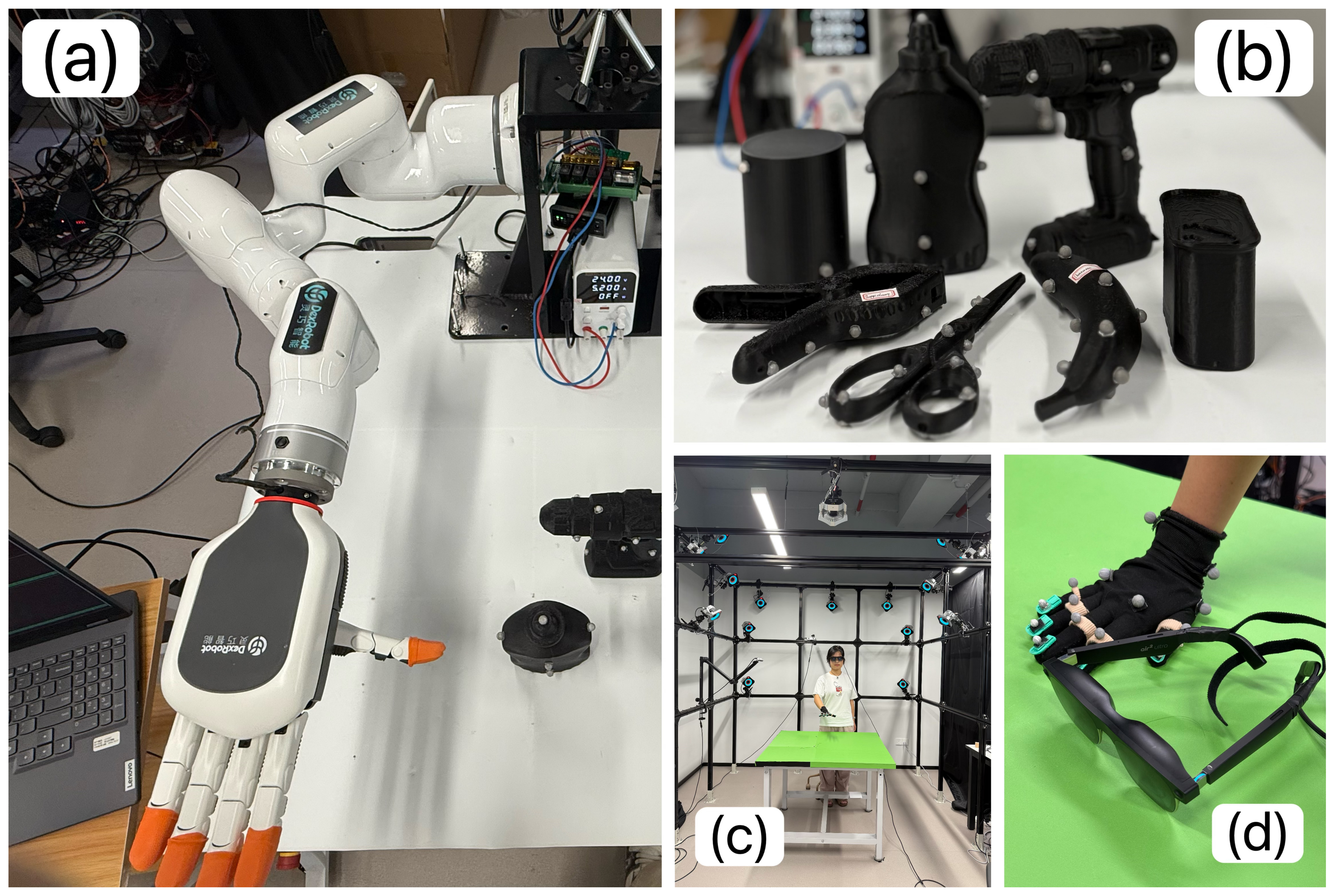


Figure 2: Teleoperation setup: (a) End-effector: **DexHand021**, Robot-arm: JAKA Mini, (b) 3-D printed YCB objects, (c) Motion-capture system: ChingMu mocap, and (d) Stereo RGB-D camera: ZED Mini.

Datasets for training: HO3D, Arctic, DexYCB, **DexCanvas**

Results

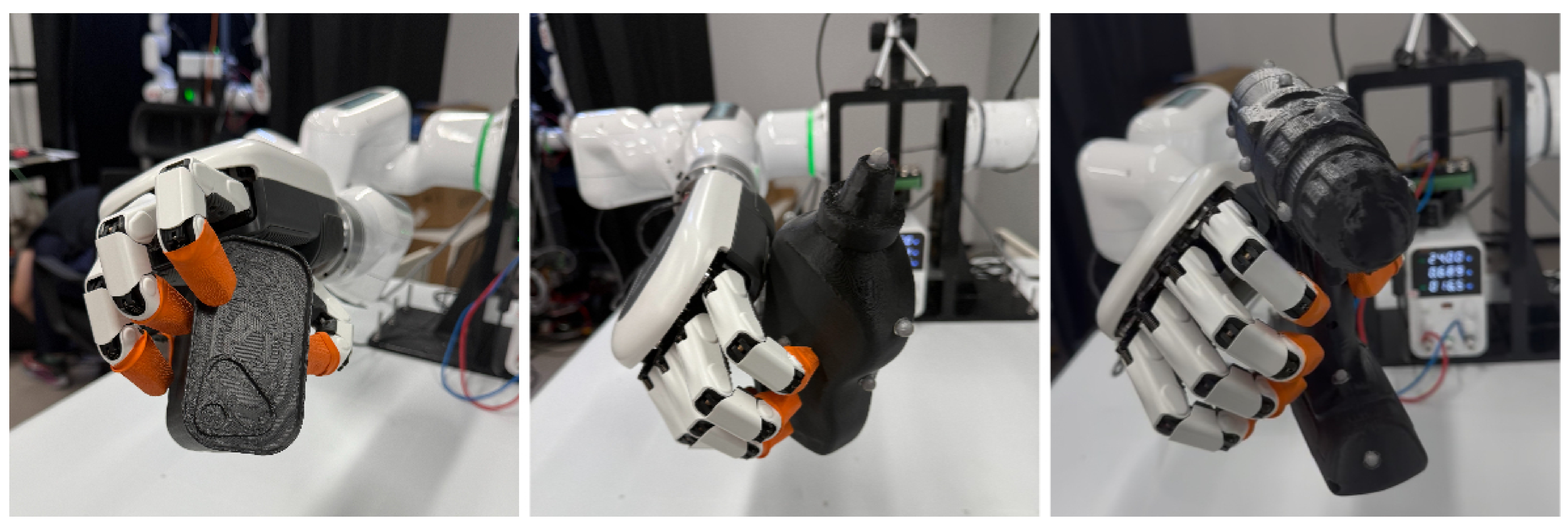
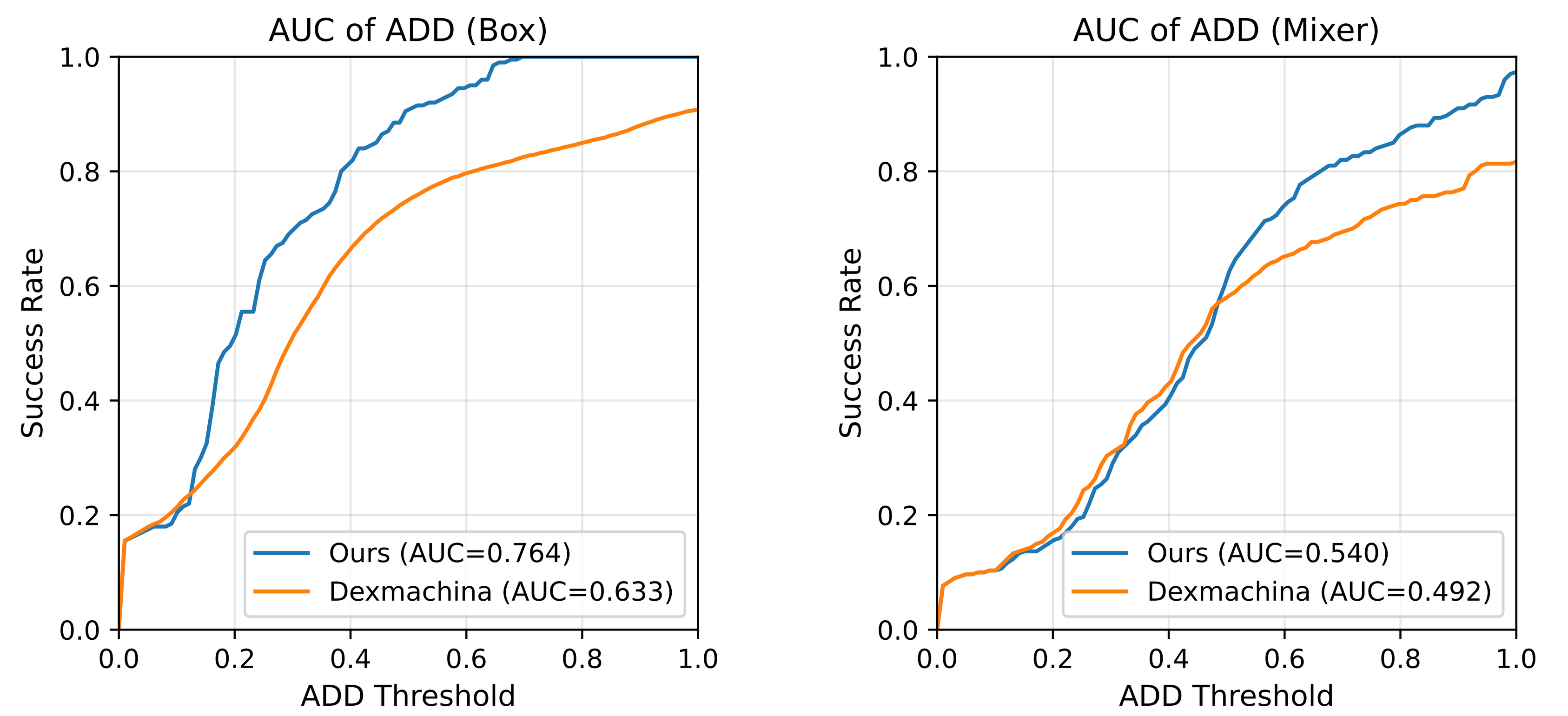


Figure 3: Three grasp regimes under teleoperation: (i) power (whole-hand force closure), (ii) enveloping (full-wrap stabilization), (iii) tool-handle (axis-aligned for manipulation).



(a) Caption A

(b) Caption B

Figure 4. We evaluated our model across multiple tasks using the Area Under the Curve of Average Distance (ADD–AUC) [2]. For each frame t, we compute ADD_t. For thresholds $\tau \in [0, 1]$, a frame is a success if $\mathrm{ADD}_t \le \tau$; at each τ, the sequence-level success rate is the fraction of successful frames. Sweeping τ yields the accuracy–threshold curve, and its area (AUC) is the final score.

Conclusions

Impact: First system to successfully bridge the gap between human demonstrations and robotic execution with virtual controller control.

Future Work: Extension to bimanual manipulation, tactile sensing integration, and transfer to non-anthropomorphic hands.

References