LeHome: A Simulation Environment for Deformable Object Manipulation in Household Scenarios

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***Abstract*—Household environments are among the most common yet challenging domains for robotics, where manipulating deformable objects is especially difficult due to varied shapes, complex dynamics, diverse materials, and the lack of reliable deformable-object support in existing simulators. We introduce LeHome, a comprehensive simulation environment for deformable object manipulation in household scenarios. LeHome covers a wide spectrum of deformable objects, such as garments and food, offering high-fidelity dynamics and realistic interactions that existing simulators struggle to reproduce. It further supports multiple robotic embodiments with an emphasis on low-cost robots, enabling end-to-end evaluation of household tasks on resource-constrained hardware. By bridging realistic deformable-object simulation and practical robotic platforms, LeHome provides a scalable testbed for advancing household robotics. Webpage: lehome-web.github.io/**

I. INTRODUCTION

The household is the living space with the highest frequency of daily human activities, encompassing essential tasks such as organizing belongings, preparing food, and managing clothing. Unlike more structured scenes such as industrial settings, these tasks involve diverse, non-standardized objects and unstructured, dynamic environments.

Household scenarios have thus attracted increasing attention, spanning both simulated household platforms [10] and robotic policies for household tasks [15, 5].

However, a key mismatch remains between current benchmarks and real-world needs: most existing methods target rigid and articulated objects, while many household tasks inherently involve deformable objects (*e.g.*, garments and food) that lack fixed shapes and deform nonlinearly under applied forces. Building large-scale, realistic datasets for such objects remains a major challenge for two reasons: (i) collecting real-world data is prohibitively expensive and labor-intensive given their variable states and the complexity of household environments; and (ii) modeling deformation is intrinsically hard, requiring complex material properties, nonlinear dynamics, and realistic interactions to be captured simultaneously.

We present **LeHome**, a household simulation environment for high-fidelity manipulation of diverse deformable objects. LeHome provides an asset library spanning liquids, gaseous fluids, granular objects, linear objects, thin shells, and volumetric objects, modeled with appropriate engines including Position-Based Dynamics (PBD), Finite Element Method (FEM), and Eulerian Fluid Simulation to balance physical realism and task coverage. To enable complex manipulation mechanisms, such as cutting a sausage into multiple pieces, LeHome further introduces the **Action Graph**, a graphical logical model that enforces causal consistency between actions and outcomes, aligning the simulation with real-world dynamics.

LeHome extends robot support from commonly used industrial manipulators to open-source low-cost platforms. As low-cost robots are more compact, easier to deploy, and cheaper to maintain, LeHome places particular emphasis on them, lowering the hardware and deployment barrier and enabling scalable, repeatable validation of core household-robot functionalities.

Finally, LeHome integrates diverse teleoperation methods compatible with both virtual and real scenarios, allowing simulation datasets to be seamlessly supplemented with real-world demonstrations under the same pipeline. We further apply domain randomization during trajectory replay to automatically generate more diverse data. Real-robot evaluations confirm that LeHome supports effective sim-to-real transfer for deformable object manipulation, with domain randomization mitigating distribution shift for more robust real-world deployment.

II. RELATED WORK

Simulation in household scenarios. Existing platforms either support relatively constrained manipulation scenes [3] or extend to more diverse scenarios with limited visual fidelity [6]. Recent work improves realism [7], yet high-fidelity interaction with deformable objects (*e.g.*, garments, food) remains challenging despite their ubiquity in households.

Deformable object manipulation. Prior works specialize in cloth [13], soft materials, fluids, and food [14], or linear and thin-shell objects [12]. However, most remain confined to a single category and cannot capture multi-modal interactions (*e.g.*, cloth with furniture, sausages with knives), which LeHome unifies within furnished household scenarios.

Low-cost robots. Mainstream industrial robots (*e.g.*, Franka, UR) are reliable but costly and bulky for household use, motivating low-cost open-source platforms such as Aloha [16]. LeHome adopts the LeRobot series (LeRobot [2], LeKiwi [9],

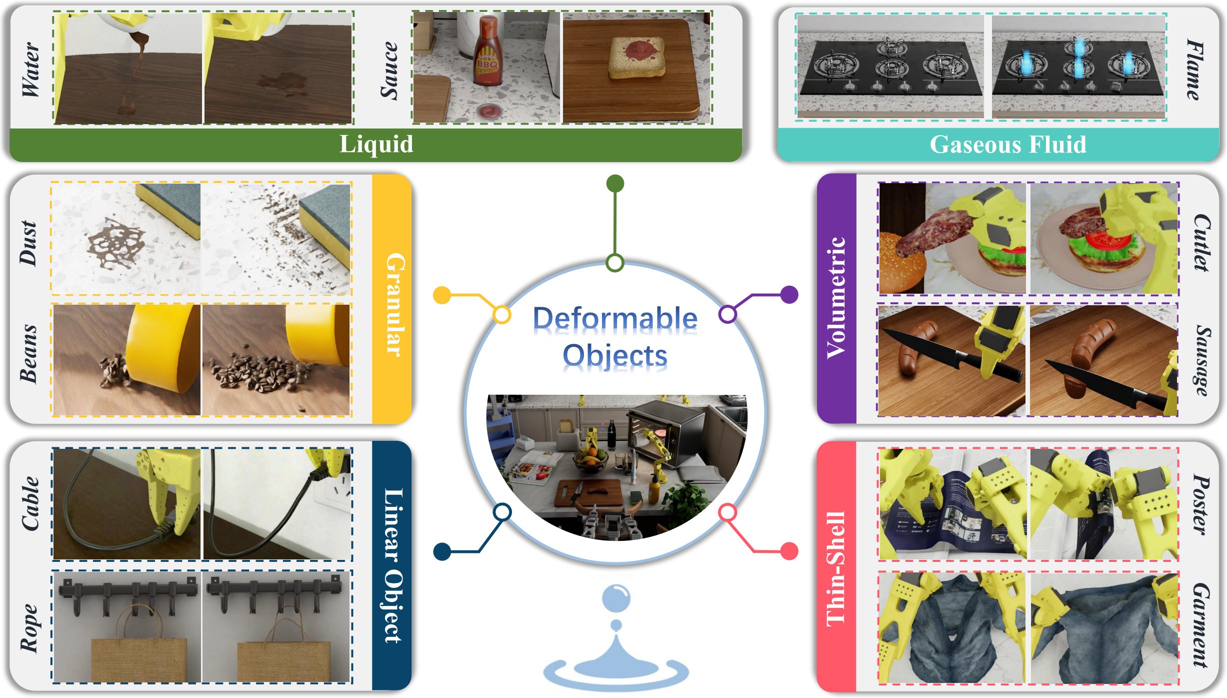

Fig. 1: **Simulated Deformable Objects** cover six categories with visually and physically high-fidelity assets for each category.

XLeRobot [11]), which further reduces cost and integrates community manipulation algorithms, offering a path toward large-scale household deployment.

III. ENVIRONMENT

A. Overview

LeHome is a household simulation environment for manipulation research, emphasizing deformable objects. It comprises three tightly connected components: **LeHome Assets** (realistic scenes, diverse objects, and multiple robot embodiments), **LeHome Engine** (the computational core integrating physics simulation and interaction mechanisms), and **LeHome Benchmark** (representative tasks with teleoperation data collection).

B. Assets, Physics, and Mechanisms

Beyond rigid and articulated objects, LeHome provides deformable assets with physics models chosen by their mechanical characteristics (Fig. 1). We group them into six categories:

1) **Liquid** (*e.g.*, water): near-constant volume without a fixed shape, simulated with PBD for efficient contact-rich motion.
2) **Gaseous Fluid** (*e.g.*, flame): compressible and volume-changing, simulated via Omniverse Flow on a sparse voxel grid.
3) **Granular Object** (*e.g.*, beans): collision-dominated particles, with fine granules handled by PBD and coarse ones approximated as rigid bodies.
4) **Linear Object** (*e.g.*, rope): slender, bending-dominated geometry, modeled by a multi-rigid-body chain or FEM.
5) **Thin Shell** (*e.g.*, garment): thin planar geometry with bending and stretching, simulated with PBD or FEM depending on deformation complexity.
6) **Volumetric Object** (*e.g.*, sausage): continuous solids simulated with FEM for elastic or elastoplastic behavior.

These category-specific physics models capture continuous deformation and contact, but household manipulation also requires discrete causal changes, such as state transitions or cutting an object into separate pieces. As shown in Fig. 2, LeHome bridges physics and task logic with the **Action Graph**, an "event-response" model that decomposes action triggering, state transition, and physical computation into controllable modules. It contains **Attributes** for typed state and metadata, **Nodes** for trigger, computation, and update units, and **Connections** for data and logic flow.

C. Robots and Data

We provide a suite of low-cost LeRobot-family embodiments (LeRobot, LeKiwi, XLeRobot) covering single, bimanual, and mobile-manipulation configurations, lowering the deployment barrier for home-robot applications. To collect demonstration data, we support multiple teleoperation methods (Fig. 3): keyboard/joystick joint-space commands as a low-cost modality, a leader-follower system for intuitive joint-synchronized control, and, for mobile robots, hybrid control combining arm synchronization with keyboard/joystick base locomotion.

To further increase data without extra teleoperation cost, we apply domain randomization with trajectory replay. Per

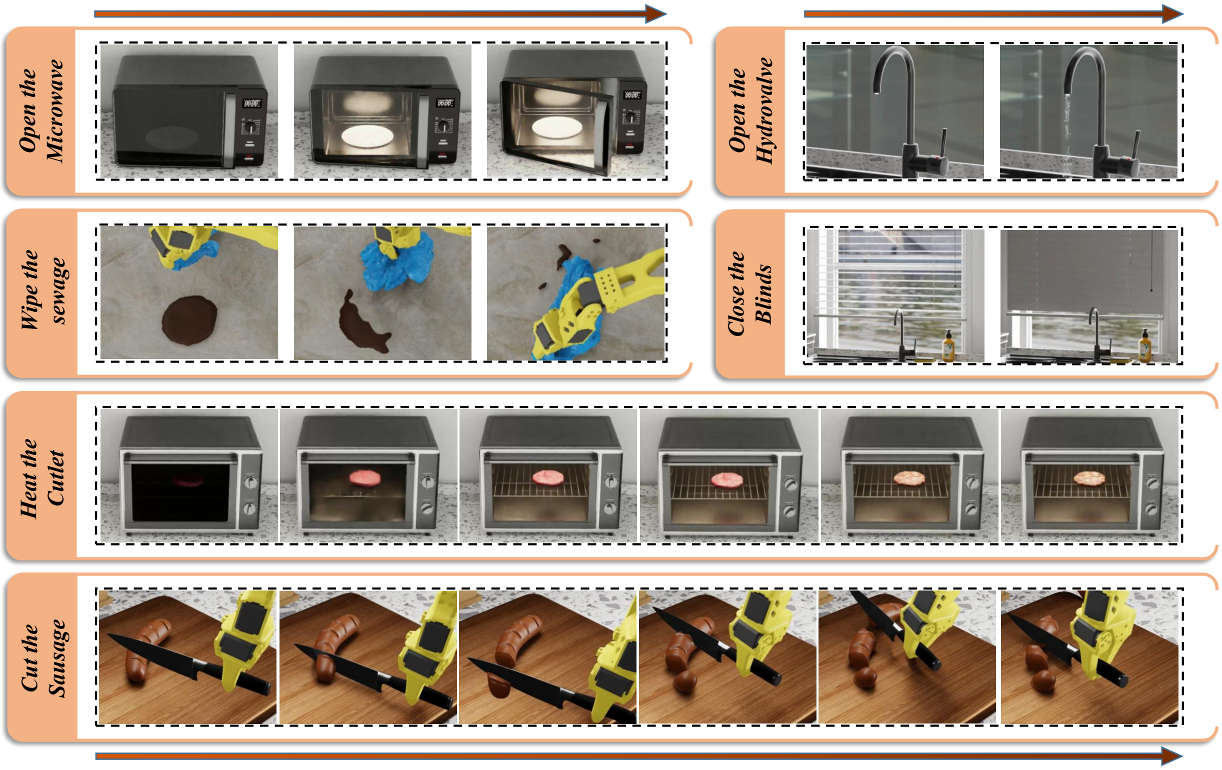

Fig. 2: **Diverse Manipulation Mechanisms.** LeHome models causal relationships of manipulation through the action graph, ensuring the simulation results align with real-world causal relationships and providing high-fidelity interactions.

episode, four factors are randomized while preserving physical dynamics: **initialization position**, **lighting**, **background texture**, and **material appearance**. Recorded trajectories are then replayed under randomized appearance with object positions fixed, and filtered by task-specific success detectors. This mitigates the sim-to-real gap and improves robustness at minimal cost.

IV. EXPERIMENT

We evaluate LeHome along two axes: whether its high-fidelity simulation supports policy learning across diverse household tasks, and whether training in LeHome facilitates effective sim-to-real transfer.

A. Tasks and Baselines

We select six representative tasks spanning multiple rooms: **Fold Garment** and **Fling Garment** (bedroom), **Assemble Burger** and **Cut Sausage** (kitchen), **Pour Coffee** (living room), and **Wipe Surface** (bathroom), covering single-arm and bimanual manipulation, tool use, and rigid, deformable, food, and fluid interactions. On these tasks, we compare four representative policies under a unified imitation-learning setup: two RGB-only baselines, **Diffusion Policy (DP)** [4] and **ACT** [16], and two language-conditioned VLAs, **Pi0** [1] and **SmolVLA** [8].

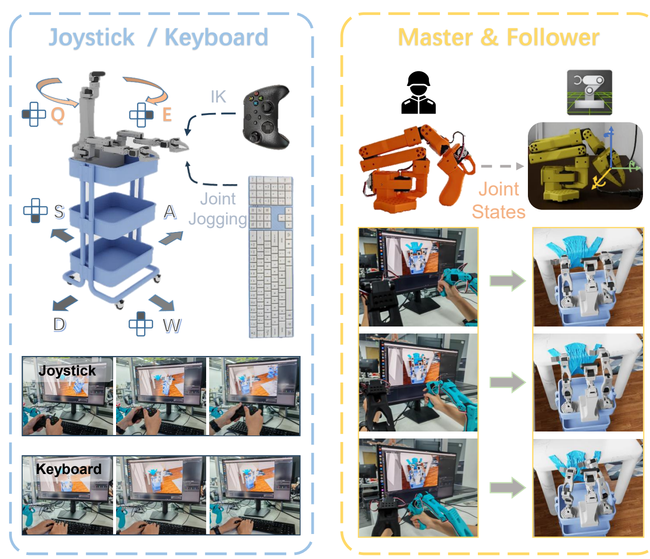

Fig. 3: **Teleoperation Methods.** (Left) We use Joystick and Keyboard to teleoperate XLeRobot, and (Right) Leader-Follower Teleoperation for LeRobot.

B. Results

Table I reports simulation success rates with 50 demonstrations per task and 100 evaluation trials. Different policies excel on different tasks, while Fling Garment remains difficult

TABLE I: **Results of Simulation Evaluation.**

Task	ACT	DP	SmolVLA	Pi0
Fold Garment	45.0%	30.0%	70.0%	44.0%
Assemble Burger	78.0%	35.0%	40.0%	39.0%
Fling Garment	25.0%	20.0%	36.0%	14.0%
Cut Sausage	77.0%	93.0%	90.0%	75.0%
Pour Coffee	80.0%	30.0%	40.0%	40.0%
Wipe Surface	60.0%	30.0%	60.0%	60.0%

for all methods (14–36%), highlighting the challenge of large-deformation garment manipulation.

For real-world transfer, we compare dual-arm LeRobot under **Real** (10 real demonstrations) and Sim+Real **Co-Training** (LeHome demonstrations plus the same real data). **Co-Training** improves average success from about 15% to 50%, suggesting that domain-randomized simulation data improves data efficiency and robustness in low-data settings.

V. CONCLUSIONS

We present LeHome, a household simulation environment for manipulating deformable objects in everyday home scenarios. LeHome provides physically grounded deformable assets for realistic household tasks. It further introduces Action-Graph-based interaction mechanisms to model causal effects. By deploying tasks on low-cost LeRobot-family platforms through an end-to-end data pipeline, LeHome lowers the barrier to training and validating household manipulation algorithms on practical robotic embodiments.

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