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

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Fig. 1: **LeHome** provides a high-fidelity simulation platform by integrating various household scenarios and objects within the scenarios, especially **deformable** objects.

I. INTRODUCTION

The household scenario is the living space where humans engage in the most frequent and essential daily activities, encompassing diverse tasks such as preparing food, and managing clothing. Unlike those in more structured scenes such as industries, these tasks feature distinct challenges: interactions with diverse, non-standardized objects and adaptation to unstructured, dynamic environments.

However, most prior work [1], [5] has focused on rigid and articulated objects, with limited support for deformable objects. In reality, many household tasks inherently involve deformable items [4], [3] such as garments, food, and sponges. These objects lack fixed shapes and exhibit non-linear deformations that are difficult to model. This presents two fundamental challenges: (i) collecting real-world household data is prohibitively expensive and labor-intensive, as deformable objects' variable states and the inherent complexity of household environments make it difficult to obtain sufficient high-quality data; and (ii) achieving accurate and authentic modeling of deformation is intrinsically hard, since it requires simultaneously capturing complex material properties, nonlinear dynamics, and realistic interactions.

To address these challenges, we propose **LeHome**, a novel household simulation environment. LeHome builds a comprehensive household asset library and categorizes deformable objects into six types—plasmas, granular materials, linear objects, thin shells, volumetric objects, and fluids—while employing multiple physical simulation methods (e.g., PBD, FEM, Dynamic Grids) to ensure physically realistic behaviors. Moreover, an **Action Graph** framework is introduced to model complex manipulation logic, ensuring causal consistency between actions and outcomes and providing a solid physical foundation for high-quality data generation. At the hardware level, LeHome supports mainstream industrial robots (e.g., UR5e, Franka), as well as open-source low-cost platforms (e.g., LeRobot [2], XLeRobot), enabling real-world validation and large-scale deployment in household settings. In addition, LeHome integrates a universal teleoperation data collection scheme, supporting multiple control modes and compatibility across virtual and real scenarios, while leveraging domain randomization to facilitate effective sim-to-real policy transfer.

II. THE LEHOME ENVIRONMENT

LeHome consists of three core components: LeHome Assets, LeHome Engine, and LeHome Benchmark.

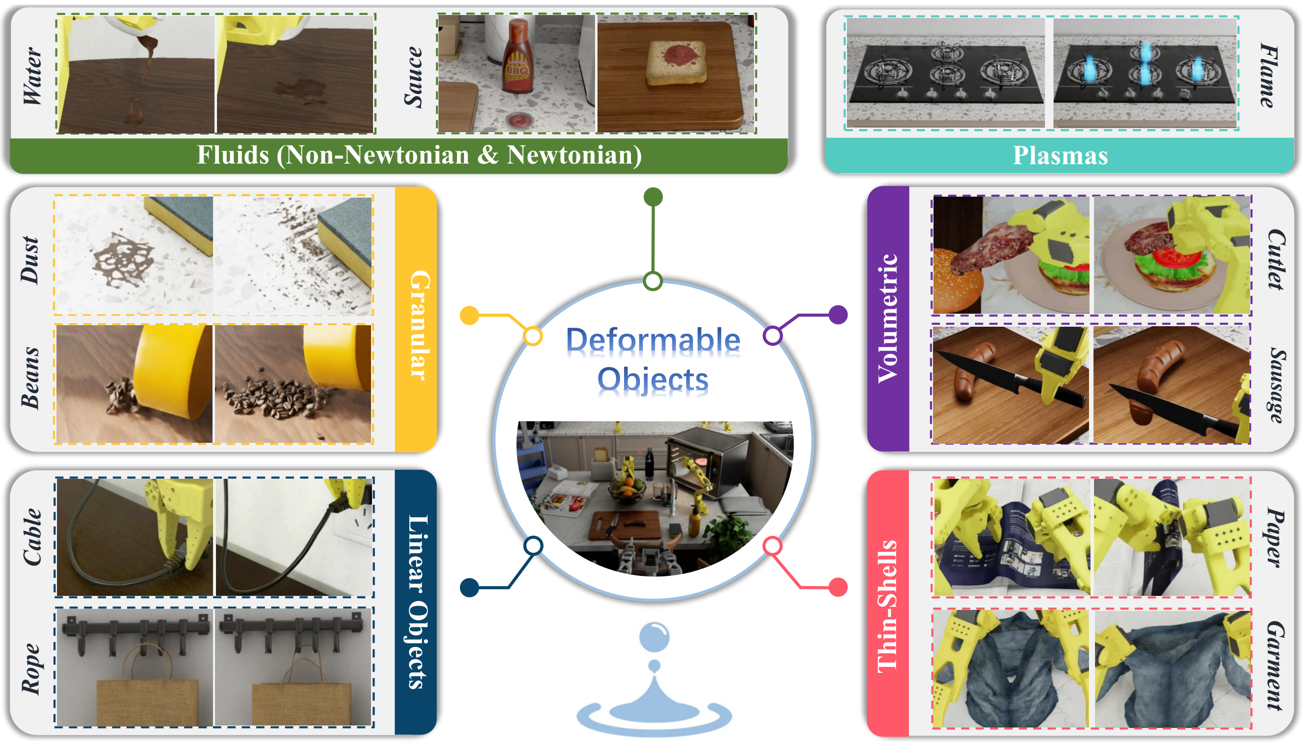

Fig. 2: **Simulated Deformable Objects** of LeHome cover 6 categories with a large number of visually and physically high-fidelity assets for each category.

A. *Assets and Physics*

Beyond standard rigid and articulated objects, LeHome provides a diverse set of deformable assets, categorized into six classes to ensure accurate physical modeling and targeted methodological support as shown in Fig. 2:

- Plasmas: Ionized particles governed by electromagnetic forces (e.g., Flame).
- Granular: Discrete aggregates dominated by inter-particle forces (e.g., Dust, Beans).
- Linear Objects: Characterized by high tensile strength and bending deformation (e.g., Cable, Rope).
- Thin-Shells: Planar geometries with anisotropic properties (e.g., Paper, Garment).
- Volumetric Objects: Continuum bodies with elastic and plastic behaviors (e.g., Sausage, Cutlet).
- Fluids: Continuously deforming matter with no fixed shape (e.g., Water, Juice).

To accurately simulate these categories, LeHome employs a variety of physics methods. Position-Based Dynamics (PBD) is used for large-scale thin-shells, fluids, and linear objects. The Finite Element Method (FEM) is applied to volumetric objects and small-scale thin-shells to finely characterize local stress-strain relationships. For plasmas and granular materials, a Dynamic Grid method is used to efficiently capture the flow-like phenomena.

B. *Action Graph Mechanism*

Previous simulators struggle to model fine-grained physical interactions like cutting or state transitions, failing to replicate real-world "cause-and-effect" details. To overcome this, LeHome introduces Action Graph, a graphical logic modeling technology for high-fidelity dynamic interactions.

The Action Graph is an event-driven system composed of three key components: i) Nodes: Basic logical units, including On-Trigger, Computation, and State Update nodes. ii) Connections: Directed edges that define dependencies and data flow between nodes. iii) Execution Logic: An event-driven mechanism that activates relevant node chains only when a trigger event occurs, ensuring efficiency.

For instance, in the sausage-cutting task (Fig. 3): i) An On-Trigger Node detects the collision between the knife and the sausage. ii) This triggers a Computation Node that performs real-time geometric mesh segmentation based on the cutting plane. iii) A State Update Node is synchronously activated to create new objects (the split halves) and update their physical properties and textures. This mechanism ensures smooth, realistic, and physically consistent interactions.

C. *Low-Cost Robots and Teleoperation*

To promote the large-scale adoption of household robots, LeHome offers comprehensive support for low-cost and compact robot platforms, featuring the full LeRobot series (LeRobot, xLeRobot, LeKiwi) alongside mainstream industrial robots (Franka, UR5e). To facilitate efficient collection of manipulation data, LeHome integrates a versatile teleoperation framework (Fig. 4), which comprises: i) Accessible Controls: Keyboard and game controller interfaces for 6-DoF end-effector control, balancing ease of use and functionality. ii) Master–Follower System: A high-fidelity setup where a physical master arm directly drives its virtual counterpart,

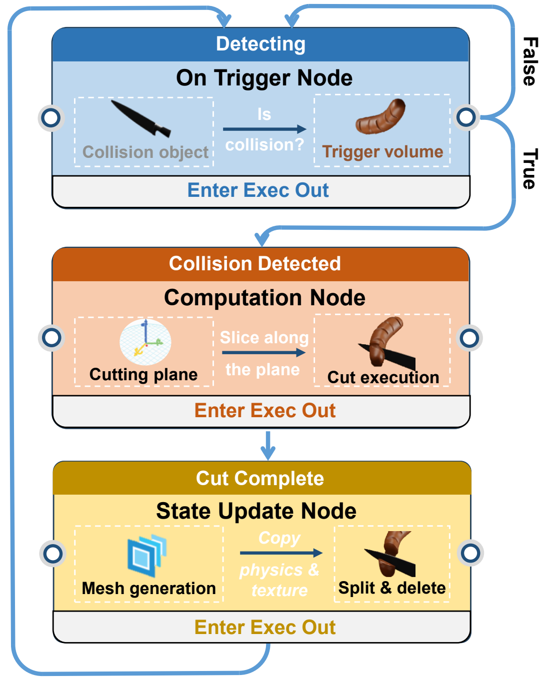

Fig. 3: Example **Action Graph Workflow** on sausage cutting, which consists of an On-Trigger Node, a Computation Node, and a State Update Node.

enabling precise expert demonstrations, particularly for complex bimanual manipulation tasks.

LeHome meets real-time data collection requirements on a single workstation equipped with an Intel i7-12700 CPU, 64 GB RAM, and an NVIDIA RTX 4090 GPU, with memory usage maintained around 12 GB.

III. EXPERIMENTS

We conducted experiments to demonstrate that LeHome can (1) provide a platform to support policy learning algorithms for various household tasks, and (2) generate data that facilitates policy execution in the real world. We selected six representative tasks, including Fold Garment, Cut Sausage, Assemble Burger, and Wipe Surface, which cover bimanual manipulation, tool use, and interactions with deformable objects, fluids, and rigid bodies.

In simulation experiments, we adopted ACT, Diffusion Policy, SmolVLA and Pi0 as our baselines. For each task, 50 teleoperated demonstrations were collected for training. The results show that all algorithms were successfully trained and evaluated. For example, in tasks such as Fold Garment and Assemble Burger, methods like ACT and SmolVLA achieved success rates above 60%, indicating that the simulated environment supports various types of policy learning effectively. To further assess the visual and physical fidelity of LeHome, we conducted sim-to-real experiments comparing two training regimes: Real-Only (using 10 real-world demonstrations) and Few-shot (pre-trained in simulation with domain randomization and fine-tuned on the 10 real demos). The results show that policies augmented with LeHome's simulated data achieved substantially higher real-world success rates—for instance, ACT improved from 10–20% to 40–70%, and SmolVLA from 10–20% to 40–60%. These findings demonstrate that LeHome's high-fidelity simulation effectively bridges the sim-to-real gap and enhances policy generalization in real-world environments.

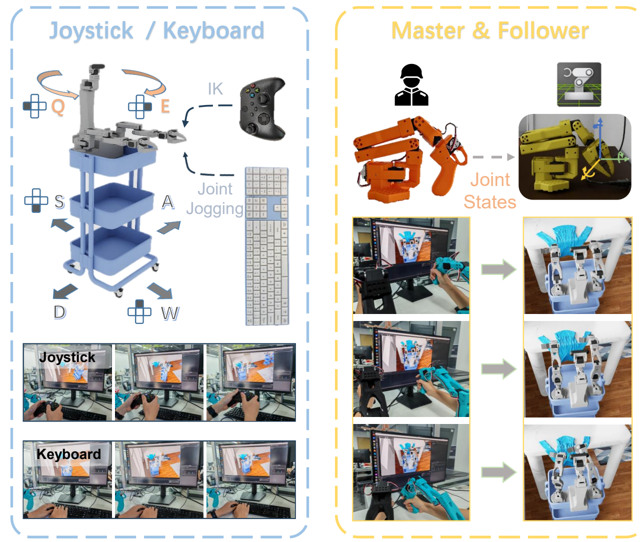

Fig. 4: **Teleoperation Methods.** (Left) We integrate Joystick and Keyboard to teleoperate XLeRobot, and (Right) Leader-Follower Teleoperation for LeRobot.

IV. CONCLUSION

We presented LeHome, a comprehensive simulation environment and benchmark for manipulating deformable objects in household scenarios. LeHome provides a diverse suite of physically grounded deformable assets, a novel Action Graph mechanism for realistic interactions, and end-to-end support for low-cost robotic platforms. Our experiments confirm that LeHome is a valuable testbed for policy learning and that its high-fidelity simulation data can significantly improve real-world task performance. We believe LeHome will provide a critical foundation for advancing the large-scale deployment of robots in household environments.

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