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 various objects within the scenarios, especially **deformable** objects.

I. INTRODUCTION

For humans, the household scenario is the living space with the highest frequency of daily activities and the most critical needs. It encompasses a wide variety of essential daily tasks, such as organizing personal belongings, 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 has focused on rigid and articulated objects, with limited support for deformable objects. In reality, many household tasks inherently involve deformable items such as garments, food, and sponges. These objects lack fixed shapes, deform nonlinearly, and have complex physical properties 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 introduce **LeHome**, a novel household simulation environment. It first builds a comprehensive household asset library covering most everyday objects and categorizes deformable objects into six types—plasmas, granular materials, linear objects, thin shells, volumetric objects, and fluids—based on their physical properties and mechanical behaviors. For each category, we adopt suitable simulation methods, including Position-Based Dynamics (PBD), the Finite Element Method (FEM), and Dynamic Grids, to ensure physically faithful behaviors. In addition, we introduce an **Action Graph** framework to model complex manipulation logic, such as a sausage being sliced by a knife, thereby enforcing causal consistency between actions and outcomes and providing a solid physical foundation for generating high-quality training data. At the hardware adaptation level, LeHome supports not only mainstream industrial robots (e.g., UR5e, Franka) but also open-source low-cost robots (e.g., LeRobot, XLeRobot). These low-cost platforms are compact, user-friendly, and easy to maintain, making them more suitable for large-scale deployment in domestic scenarios and offering a critical

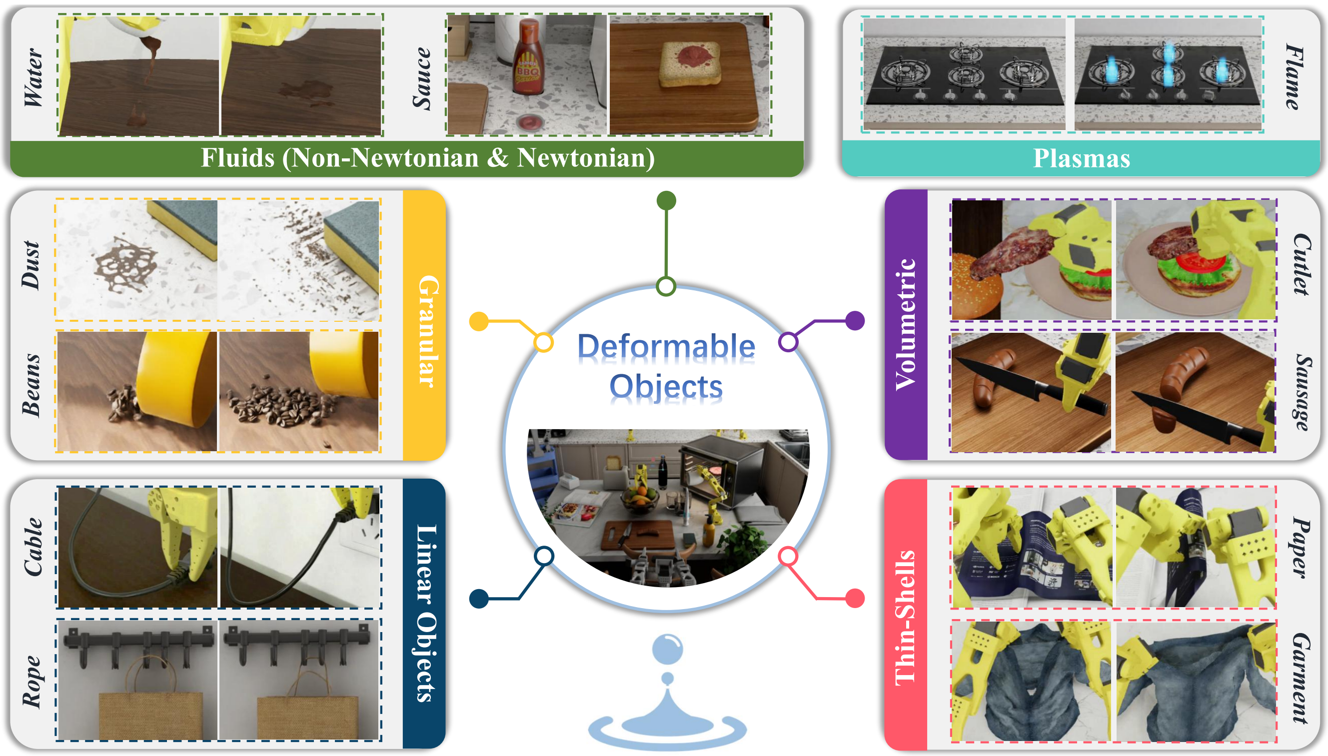

Fig. 2: **Simulated Deformble Objects** of LeHome cover 6 categories with a large number of visually and physically high-fidelity assets for each category.

basis for validating the feasibility and real-world deployment of household robots. Finally, to enhance the environment's practicality and algorithmic support, LeHome integrates a universal teleoperation data collection scheme, providing multiple control options (keyboard, game controller, and Leader-Follower system), compatible with both virtual and real scenarios, and enabling large-scale data collection. This design not only allows simulation data to be seamlessly supplemented with real-robot data but also incorporates domain randomization, effectively supporting the transfer of trained policies to real-world execution.

II. THE LEHOME ENVIRONMENT

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

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 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 the 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:

- Nodes: Basic logical units, including On-Trigger, Computation, and State Update nodes.
- Connections: Directed edges that define dependencies and data flow between nodes.
- 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), the process is modeled as follows: 1) An On-Trigger Node detects the

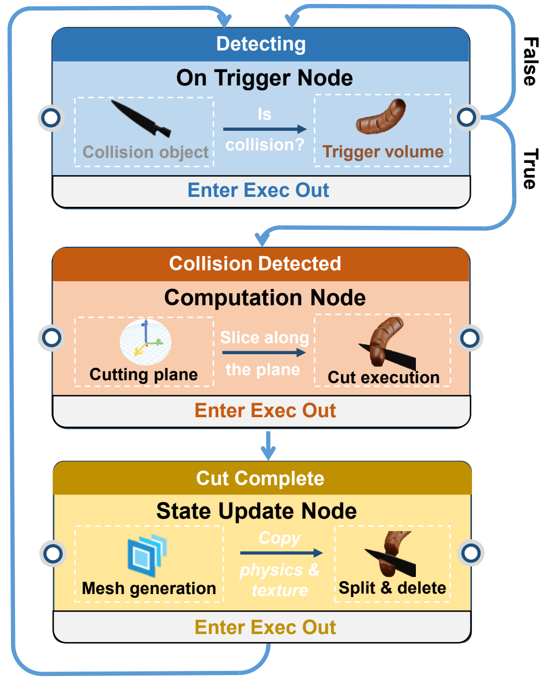

Fig. 3: Example **Action Graph Workflow** on sausage cutting, which consists of an On-Trigger Node, a Computation Node, and a State Update Node.

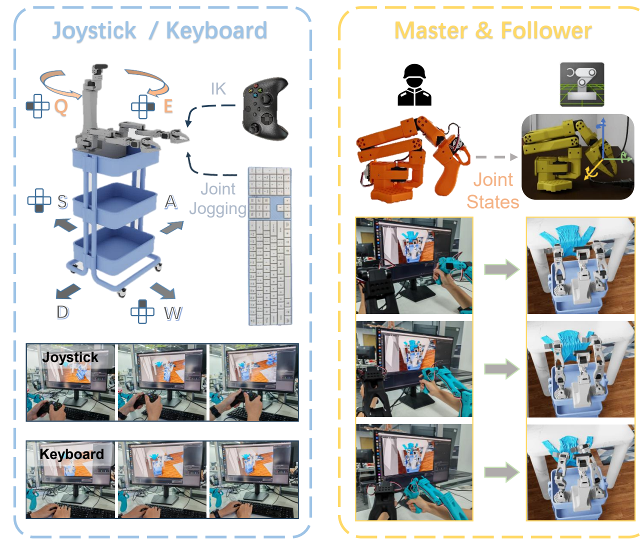

Fig. 4: **Teleoperation Methods.** (Left) We integrate Joystick and Keyboard to teleoperate XLeRobot, and (Right) Leader-Follower Teleoperation for LeRobot.

collision between the knife and the sausage. 2) This triggers a Computation Node that performs real-time geometric mesh segmentation based on the cutting plane. 3) A State Update Node is synchronously activated to create new objects (the split halves) and update their physical properties and textures. This mechanism ensures that complex interactions are continuous, natural, and physically compliant.

C. Low-Cost Robots and Teleoperation

To promote the large-scale adoption of household robots, LeHome provides extensive support for low-cost, miniaturized robot platforms, featuring the complete LeRobot series (LeRobot, XLeRobot, LeKiwi) in addition to mainstream industrial robots (Franka, UR5e). To facilitate the collection of manipulation data, LeHome implements a diverse and efficient teleoperation framework (Fig. 4). This includes:

- Accessible Controls: Keyboard and game controller options for 6-DoF end-effector control, offering a balance between accessibility and functionality.
- Master & Follower System: A high-fidelity ”real-to-sim” leader-follower system where an operator manipulates a physical master arm to provide direct kinematic control of its virtual counterpart. This method is invaluable for collecting nuanced expert demonstrations, especially for complex bimanual tasks.

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.

For evaluation, we used representative imitation learning (ACT, Diffusion Policy) and vision-language action (SmolVLA, Pi0) baselines. In simulation experiments, we collected 50 teleoperated demonstrations for each task for training. The results, shown in Table II of the original paper, indicate that all algorithms could be successfully trained and evaluated, confirming that LeHome is a robust testbed for diverse policy learning frameworks across challenging household scenarios.

To evaluate the visual and physical fidelity of LeHome, we conducted sim-to-real experiments. We compared policies trained under two regimes: ”Real-Only” (using 10 real-world demonstrations) and ”Few-shot (Hybrid)” (pre-trained in simulation with domain randomization and fine-tuned on the 10 real demos). As shown in Table III of the original paper, for tasks like Fold Garment, Assemble Burger, and Wipe Surface, policies augmented with LeHome’s simulation data achieved significantly higher success rates in the real world. This demonstrates that the high-fidelity simulation in LeHome effectively bridges the sim-to-real gap.

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.