Tool-as-Interface: Learning Robot Tool Use from Human Play through Imitation Learning

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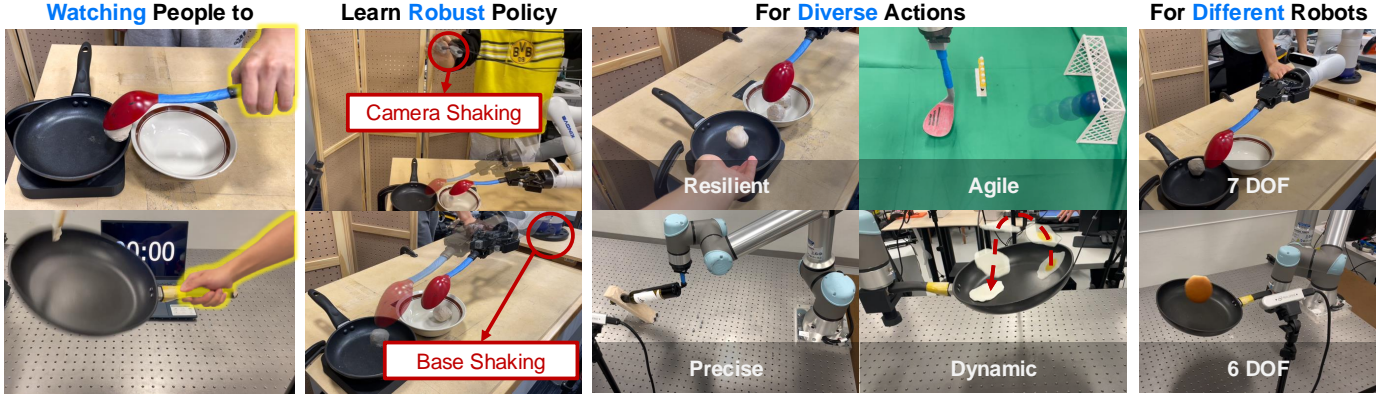https://tool-as-interface.github.io

Fig. 1: **Tool-as-Interface.** We propose a scalable data collection and policy learning framework designed to transfer diverse, intuitive, and natural human play into effective visuomotor policies. The framework enables robots to learn robust policies that can operate effectively under challenging conditions, such as base and camera movement, and achieve high performance on a variety of complex manipulation tasks.

Abstract—Tool use is critical for enabling robots to perform complex real-world tasks, and leveraging human tool-use data can be instrumental for teaching robots. However, existing data collection methods like teleoperation are slow, prone to control delays, and unsuitable for dynamic tasks. In contrast, human play—where humans directly perform tasks with tools—offers natural, unstructured interactions that are both efficient and easy to collect. Building on the insight that humans and robots can share the same tools, we propose a framework to transfer tool-use knowledge from human play to robots. Using two RGB cameras, our method generates 3D reconstruction, applies Gaussian splatting for novel view augmentation, employs segmentation models to extract embodiment-agnostic observations, and leverages task-space tool-action representations to train visuomotor policies. We validate our approach on diverse real-world tasks, including meatball scooping, pan flipping, wine bottle balancing, and other complex tasks. Our method achieves a 71% higher average success rate compared to diffusion policies trained with teleoperation data and reduces data collection time by 77%, with some tasks solvable only by our framework. Compared to hand-held gripper, UMI [13], our method cuts data collection time by 41%. Additionally, our method bridges the embodiment gap, improves robustness to variations in camera viewpoints and robot configurations, and generalizes effectively across objects and spatial setups.

I. INTRODUCTION

Tool use is essential to how humans interact with and transform their environment [56, 35]. For instance, humans use a pan to fry food and flip it, ensuring even cooking on both sides. Despite its significance, tool use beyond parallel jaw grippers remains underexplored in robotics, with research primarily focused on simpler tasks like grasping and pick-and-place operations [5, 40, 9, 31, 30]. In this paper, we focus on cost-effective data collection and efficient training of robot policies to rapidly acquire tool-use skills.

Imitation learning provides a promising pathway for robots to acquire tool-use skills by directly learning from human demonstrations [18, 22, 23, 25]. The paradigm excels in handling diverse tool-use tasks, as it bypasses the need for task-specific programming by relying solely on human demonstrations. However, its full potential hinges on addressing key challenges in collecting high-quality training data. Various teleoperation systems [28, 48, 7, 17, 25, 44, 70, 57, 34, 55, 39, 8] and hand-held grippers [54, 16, 46, 41, 37] have been developed to facilitate the collection of high-quality data. Teleoperation methods, such as kinematic replication and hand or body retargeting, show great potential [71, 19, 63, 52, 42]. However, their reliance on direct access to robot hardware limits both practicality and scalability. Hand-held grippers [49, 13] offer an alternative by enabling demonstrations in diverse environments. While they reduce dependency on robotic systems, their high costs and the technical expertise required for tasks like 3D printing and assembly restrict their accessibility to a specialized group of users.

To address these limitations, we turn to human play — a natural, intuitive method through which humans interact with their environment during everyday activities without relying on external devices or specialized setups. Human play refers to the natural process in which humans use their hands to operate tools and interact with and manipulate the environment freely. Unlike controlled demonstrations that require expensive

hardware or meticulous preparation, human play involves the spontaneous use of tools to interact with the environment. Human play is an accessible, scalable, and cost-effective approach to data collection, requiring no prior knowledge or technical expertise, such as 3D printing or assembly, from participants. However, existing methods struggle to fully harness the potential of human play. Key challenges include the embodiment gap and the reliance on single-view data, which limits the insights that can be drawn from human play data [51, 3, 33, 4, 53, 36, 47].

Our framework addresses these challenges by leveraging the observation that humans and robots can share the same tools. We propose a novel approach that utilizes human play data to train robust and adaptable robot policies for diverse tool-use tasks (Figure 1). Our method minimizes reliance on expensive hardware, making data collection more scalable and accessible to non-experts. By capturing 3D information using two RGB cameras and generating 3D reconstructions, our method enables view-invariant policy learning through novel view augmentation. To facilitate direct policy transfer from human play to robotic systems, we employ a segmentation model to filter out embodiment-specific information. Additionally, we leverage task-space tool-action representations to ensure robustness to variations in robot base configurations.

Our contributions are as follows:

1) We propose a novel framework that leverages two-view human play data to enable scalable, intuitive, and cost-effective data collection for training robot policies on complex tool-use tasks.
2) We validate the effectiveness of our approach across a range of challenging real-world tool-use tasks, including nail hammering, meatball scooping, pan flipping, wine bottle balancing, and soccer ball kicking. Our method achieves a 71% improvement in success rate and reduces data collection time by 77% compared to diffusion policies trained on SpaceMouse [14] or Gello [63] data, with some tasks solvable only by our method. Our method also outperforms handheld grippers like UMI [13], reducing collection time by 41%.
3) We provide an extensive analysis of our method's robustness under varying conditions, including changes in camera poses, robot base movements, and human-induced perturbations. Additionally, we conduct ablation studies to evaluate the effects of different design choices on policy performance, including embodiment segmentation, random cropping, and novel view augmentation.

II. RELATED WORKS

A. Data Collection for Robot Learning

High-quality data is essential for training robots to learn and generalize across tasks. Simulation data has been widely used for its cost-effectiveness and scalability [72, 38, 24, 69], but the gap between simulation and real-world performance remains a persistent challenge. To overcome this, many researchers have turned to real-world teleoperated demonstrations, which offer more reliable transferability by minimizing the domain gap between training and testing environments [73, 11, 12, 48, 62]. Advancements in leader-follower devices, like ALOHA [71, 19] and GELLO [63], have simplified robot demonstration data collection but remain tied to specific robot platforms. More recently, portable tools such as hand-held grippers, e.g., UMI [13] and LEGATO [49], have emerged as a promising alternative for in-the-wild data collection. Yet, their high cost and the need for custom robot modifications continue to limit widespread adoption. Tool-based policy representations have emerged as an effective way to collect data for robot learning. MimicTouch uses tactile-based tools for contact-rich manipulation [67], while ScrewMimic models bimanual tasks as constrained screw motions for learning from human videos [2]. However, tactile methods require extra hardware, and the screw motion assumption may not hold. Another line of work by Wen et al. [59] aims to learn category-level representations from a single demo to transfer pose trajectories across similar objects [59], but assumes a static target (e.g., battery slot), limiting real-world applicability in real-world tasks where the spatial configuration of objects may change. Unlike these methods, our method only requires natural human data, without assuming access to tactile sensors or requiring constrained screw motion models, making it significantly more cost-effective, scalable, and accessible.

B. Cross-Embodiment Policy Learning

Cross-embodiment policy learning enables robots to transfer policies across embodiments, such as those with different kinematic structures [21, 45, 66]. Prior work has explored conditioning policies on embodiment representations using multi-embodiment datasets [15, 58, 68, 10, 20, 45, 1], but these approaches often face challenges in effectively leveraging human play data. Recent approaches utilize human play, such as estimating point flow from human video [61] or generating latent plan or high-level plans from human data [32, 57]. However, their dependence on robot data for low-level control limits scalability when robot data is expensive or difficult to collect. Additionally, prior works highlight the importance of masking human and robot embodiments for visual consistency [3, 27]. However, Bahl et al. [3] relies on predefined motion primitives, while Kareer et al. [27] still requires robot data with human data as augmentation. Our approach adopts a similar masking idea but enables robots to learn freely, even agile motions from human videos, without any robot data. Another line of work tokenizes observation inputs and action outputs into a unified transformer network, enabling generalized policy learning across embodiments [50, 65]. However, these methods require large models and extensive datasets, making them resource-intensive and time-consuming to train, and lack the capability for direct policy transfer between embodiments. Overall, reliance on robot-specific hardware and data restricts scalability and accessibility. In contrast, our method leverages natural human play, eliminating the need for robot data as a training source.
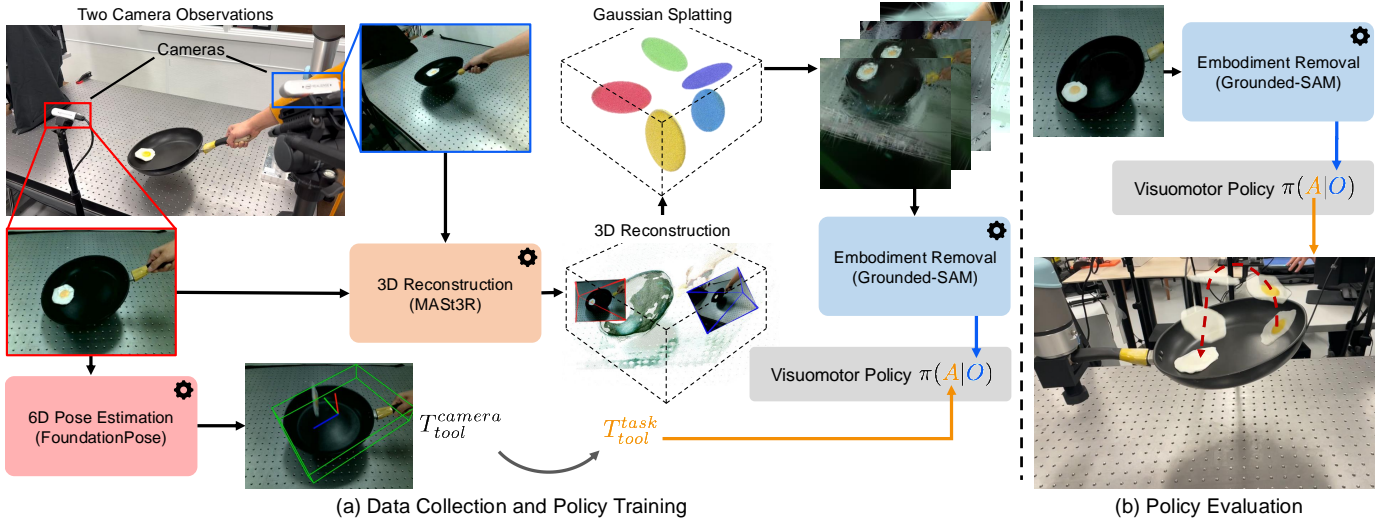
Fig. 2: **Policy Design.** Human play data was collected using two RGB cameras and processed through the foundation model MASt3R [29] to generate 3D reconstructions. Using 3D Gaussian splatting, we sampled novel views to augment the dataset. The human hand (embodiment) was segmented out from the images to create embodiment-agnostic observations, which serve as inputs to the policy. To label actions for policy training, a pose estimation model (FoundationPose [60] in this work) was used to extract the tool's pose in the camera frame, $T_{\text{tool}}^{\text{camera}}$. A coordinate transformation was then applied to compute the tool's pose in the task space, $T_{\text{tool}}^{\text{task}}$. Finally, a diffusion policy was implemented as the visuomotor policy to enable effective learning and execution.

III. PROBLEM STATEMENT

We formulate the robotic manipulation task as a Markov Decision Process, where the goal is to learn a policy $\pi : \mathcal{O}^r \to \mathcal{A}$ that enables a robot to perform a given task. The robot's observation space, $\mathcal{O}^r$, consists of a single-view RGB image $I^r \in \mathbb{R}^{128 \times 128 \times 3}$ and proprioception data $x^r \in SE(3)$. To train the policy, we use an imitation dataset composed of N human play, denoted as $D = \{(O_0^h, O_1^h, \dots)\}_{n=1}^N$. Each human play observation $\mathcal{O}^h$ consists of two RGB images captured from different viewpoints: $\mathcal{O}^h = \{I^{v1}, I^{v2}\}$, where $I^{vi} \in \mathbb{R}^{480 \times 640 \times 3}$. We preprocess the dataset to get the action by using a 6D pose estimation and tracking model, resulting in $D = \{(O_0^h, a_0, O_1^h, a_1, \dots)\}_{n=1}^N$, where each action $a \in SE(3)$.

Our objective is to train a robot to perform the same task as demonstrated in the human dataset while overcoming the embodiment differences. We assume that the tool is rigid, the tool and the end effector are rigidly attached during deployment, and the transformation between the tool and the end effector is estimated once before deployment. Our approach aims to allows the robot generalize task execution across embodiments while retaining the core skills demonstrated by humans.

IV. OUR ROBOT POLICY LEARNING FRAMEWORK

Our framework enables the direct transfer of human play data into deployable robot policies. It is designed to fulfill the following key objectives:

- **Support for Dynamic and High-Precision Tasks:** Human play, with its inherent fluidity, enables the execution of highly dynamic tasks. Examples include flipping an egg in a pan or performing other actions that require swift, accurate, and natural motions — challenges that are often difficult to address with traditional teleoperation systems or handheld grippers.

- **Robustness:** The framework ensures robust performance under dynamic conditions, enabling reliable task execution even with moving or shaking cameras. While broader deployment on mobile platforms such as quadrupeds or humanoids remains an open challenge, our design and experimental results suggest strong potential for generalization to dynamic environments.

- **Generalization Across Robotic Embodiments and Object Categories:** The framework demonstrates broad generalizability, validated on robotic platforms such as the UR5e and Kinova Gen3. It extends its capabilities to manipulate a wide range of object categories, showcasing its adaptability to various tasks, setups, and environments.

- **Affordability and Accessibility:** The framework requires only two monocular RGB cameras, such as smartphones, webcams, or RealSense cameras. With approximately 7.14 billion smartphones worldwide — covering around 90% of the global population — this setup is accessible to almost anyone [26]. By relying solely on RGB cameras, the framework eliminates the need for designing, printing, or manufacturing additional hardware during the data collection, ensuring a cost-effective and inclusive solution.

- **Intuitive and Natural Interaction:** Users can interact naturally, without the need for specialized equipment or additional tools. Using their bare hands and common tools, participants can intuitively perform a variety of tasks. Our approach removes technical barriers associated with 3D printing and other hardware setups, fostering a seamless, user-friendly experience for data collection.

The following sections outline the framework's design (Figure 2), its underlying principles, and logistical considerations for development and deployment.

A. Tool Usage for Data Collection and Manipulation

Humans naturally and intuitively use tools for everyday tasks such as cooking, eating, cleaning, and interacting with the world. Tools act as extensions of human actions, enabling diverse interaction with objects. The natural relationship between tools and objects provides an ideal interface for training robots to mimic human actions using tools, with minimal gap between human and robot tool usage. While grasping and pick-and-place tasks have been extensively studied in previous works, our work focuses on enabling robots to use the same tools humans commonly employ to interact with their environment effectively with the following benefits:

- **Minimized Embodiment Gap:** Abstracting actions to the tool pose reduces morphological dependency, enabling policies to generalize across embodiments.
- **Scalable Data Collection:** Simplifies the data collection process by eliminating the need for costly robot-specific demonstrations, making our method more accessible.

During data collection, humans can naturally use tools with their hands without requiring additional devices. For robot deployment, the tool can be attached to the robot in two ways:

- **Rigid Grasping:** Grasping or picking, which has been extensively studied in prior works, is demonstrated in our Kinova Gen3 robot experiments and involves the robot securely grasping the tool.
- **Customized Fast Tool Changer:** Designed for versatility, the tool changer is compatible with any robot that uses the ISO 9409-1-50-4-M6 flange, as demonstrated in our UR5e experiments.

B. Embodiment-Agnostic Perception

To encourage cross-embodiment transfer, we adopt a strategy that reduces the perception gap between the training and deployment phases. During training, human play data is collected, featuring human hands interacting with tools and objects. In deployment, robots execute the learned tasks. As showcased in our experiments, the visual differences between human hands and robotic end-effectors can introduce discrepancies that hinder generalization. To address this, we employ Grounded-SAM [43] to segment and mask out the embodiments in each phase. During training, human hands are masked, while during deployment, the robotic embodiments are masked, which ensures that the remaining parts of the scene in both training and testing phases appear visually similar. By aligning perception across embodiments, the framework mitigates distractions caused by embodiment-specific features, enabling better generalization to human-to-robot policy transfer.

C. View Augmentation

We use cameras for data collection due to their availability. With approximately 7.14 billion smartphones equipped with cameras, our approach can scale effectively [26]. However, using data from a single camera introduces challenges such as a lack of 3D perception and sensitivity to camera pose.

a) 3D Reconstruction: To address these issues, we use MASt3R [29], an image-matching model that reconstructs accurate 3D environments from two RGB images. This eliminates the need for additional depth sensors, which are less common and consume more power compared to RGB sensors. We use two cameras to capture demonstration data. Then MASt3R processes the images to reconstruct a 3D point cloud without requiring camera extrinsics or intrinsics, and globally align point maps within a multi-view 3D reconstruction framework. The process results in high-quality 3D representations.

b) Data Augmentation: Using 3D Gaussian splatting, we model the scene and synthesize novel viewpoints from human play data, which effectively augments the dataset, generating additional perspectives even if the training data was captured from only two views. These synthetic viewpoints provide the robot with a multi-angle understanding of the scene, allowing the policy to be trained on a more diverse and comprehensive set of visual inputs. Additionally, we apply random cropping to the images for data augmentation before feeding them into the policy network, following the approach from diffusion policy [11, 12]. Random cropping further improves the method's robustness, enabling the policy to generalize better to variations in visual inputs.

D. Action Representation for Tool Manipulation

To support general tool usage, we propose a task-frame, tool-centric action representation denoted as $T_{\text{tool}}^{\text{task}}$. This representation focuses on the tool being manipulated, independent of human or robot morphology or camera pose. A visual depiction of the coordinate systems is provided in Figure 3.

Using a 6D pose estimation model (e.g., Foundation-Pose [60]), we determine the tool's pose in the camera frame, $T_{\text{tool}}^{\text{camera}}$. To make the policy robust to camera and base movement, we transform this into the task frame:

$$T_{\text{tool}}^{\text{task}} = T_{\text{camera}}^{\text{task}} T_{\text{tool}}^{\text{camera}},$$

where $T_{\text{camera}}^{\text{task}}$ represents the transformation from the camera to the task frame.

E. Training and Deploying Robot Policies

We use diffusion policy [11] as our policy representation to predict $T_{\text{tool}}^{\text{task}}$, trained using the ACCESS system [6]. During deployment, for stationary robots, the task frame aligns with the base frame. For robots with moving base, base movement is compensated using $T_{\text{task}}^{\text{base}}$. The final end-effector pose in the robot base frame, used as the control command for the robot controller, is computed as:

$$T_{\text{eef}}^{\text{base}} = T_{\text{task}}^{\text{base}} T_{\text{tool}}^{\text{task}} T_{\text{eef}}^{\text{tool}},$$

where $T_{\text{eef}}^{\text{tool}}$ is the fixed transformation between the tool and the robot end-effector.

V. POLICY EVALUATIONS

Our experimental evaluations aim to assess the effectiveness of our framework for deploying robot policy learning across three key dimensions:

TABLE I: **Benchmark Attributes of Real-World Tasks.** These benchmarks evaluate the precision, adaptability, and capability of our framework to address tasks requiring high precision, handling extreme dynamics, utilizing extrinsic dexterity, performing in contact-rich scenarios, and overcoming gravity.

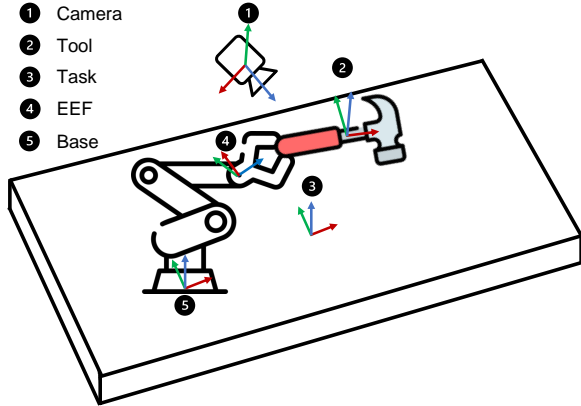| Benchmark	High-Precision	Extreme Dynamics	Using Extrinsic Dexterity	Contact-Rich	Overcoming Gravity
Task 1: Nail Hammering	✔	‒	‒	‒	‒
Task 2: Meatball Scooping	✔	‒	✔	✔	‒
Task 3: Pan Flipping (Egg, Bun, Patty)	‒	✔	✔	✔	✔
Task 4: Wine Balancing	✔	‒	✔	✔	✔
Task 5: Soccer Ball Kicking	‒	‒	‒	✔	‒

Fig. 3: **Coordinate System Diagram.** This diagram illustrates the Camera frame, Tool frame, Task space frame, End-Effector (EEF) frame, and Base frame. We use $T_{\text{tool}}^{\text{task}}$ as the action representation for the visuomotor policy output.

- **Capabilities:** What skills can our framework enable robots to acquire, and how robust are the policies under challenging conditions like a moving camera or base?
- **Effectiveness:** How well does our framework achieve its objectives outlined in Section IV? Can it support reliable and scalable policy learning for complex tasks while streamlining data collection for highly dynamic, contact-rich, or dexterous scenarios?
- **Policy Execution Efficiency:** How efficiently do the trained policies execute tasks? Does our framework enable smoother and more natural motion trajectories? Can it achieve faster and more fluid task completion compared to baseline methods?

To evaluate our framework for learning from direct human play, we developed a set of real-world robotic task domains using two embodiments: Kinova Gen3 and UR5e. These tasks are designed to test various aspects of policy capabilities, efficiency and effectiveness. Table I summarizes the key characteristics of these tasks. Visual input for the policies is provided by two RealSense D415 cameras. We describe the tasks in detail, highlighting their challenges and the specific capabilities we aim to test.

Baselines: The primary focus of this work is to demonstrate the effectiveness and efficiency of learning directly from human play without relying on robot-generated data. We compare our approach against two baselines: a diffusion policy trained on robot demonstrations, and UMI [13], a hand-held gripper-based data collection method. The robot demonstration dataset is collected using either a SpaceMouse or Gello interface

TABLE II: **Task Success Rates and Completion Times.** Success rates are the number of successful trials out of total episodes, and average completion times are based on successful trials. "DP" refers to the diffusion policy trained on teleoperation data. "Not Feasible" tasks denote cases where teleoperation failed due to extreme dynamics, precision, or reactivity demands. Our method consistently achieves higher success rates and shorter completion times.

Task	Method	Success Rate	Time (s)
Hammer Nailing	DP	0/13	-
	Ours	**13/13**	**11.0**
Meatball Scooping	DP	5/12	42.0
	Ours	**10/12**	**12.4**
Pan Flipping - Egg	DP	Not Feasible	-
	Ours	**12/12**	**1.5**
Pan Flipping - Burger Bun	DP	Not Feasible	-
	Ours	**9/12**	**1.9**
Pan Flipping - Meat Patty	DP	Not Feasible	-
	Ours	**10/12**	**2.3**
Wine Balancing	DP	Not Feasible	-
	Ours	**8/10**	**30.9**
Soccer Ball Kicking	DP	Not Feasible	-
	Ours	**6/10**	**2.0**

under the same data collection time. Additionally, we perform ablation studies to analyze the impact of key components, such as random cropping of images before policy training, novel view synthesis-based data augmentation, and the effects of embodiment segmentation. To further illustrate the advantages of our approach, we compare trajectory rollouts for a meatball-scooping episode, highlighting how our method is more sample-efficient and less prone to distribution shifts by eliminating excessive waypoints.

Evaluation Metrics: During testing, we introduce two types of variations: (1) randomizing the initial spatial configurations of objects in each task to assess policy generalization, and (2) varying camera positions to evaluate the robustness of policies to different viewpoints. All methods, including the baseline and ablation variants, are tested under the same conditions. Performance is evaluated using two metrics: success rate, which measures the proportion of successfully completed task trials and reflects policy effectiveness, and task completion time, which captures the average duration to complete tasks and reflects policy efficiency.

VI. EXPERIMENT RESULTS

In our experiments, we demonstrate that our framework is both effective and efficient for training robots with advanced
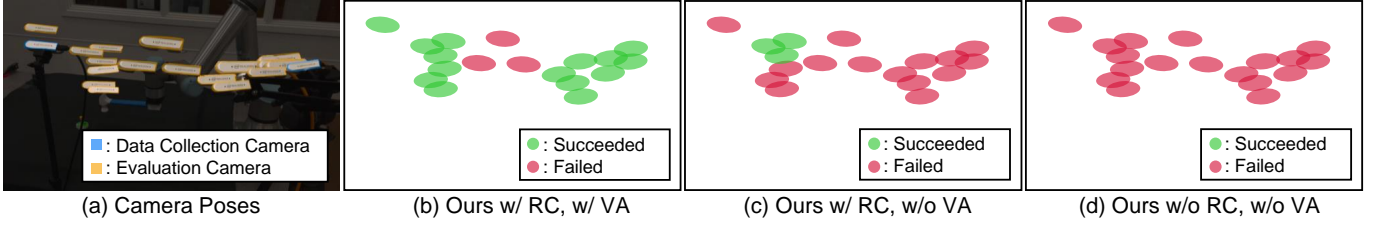
Fig. 4: **Policy Testing Across Camera Poses in Nail Hammering.** (a) Camera poses for data collection and evaluation. (b-d) Performance ranges for methods trained with/without random cropping (RC) and view augmentation (VA).

TABLE III: **Task success rates comparing our method with the hand-held gripper-based method on Nail Hammering.**

Method	Demo Duration & Count	Success Rate
UMI [13]	∼180 seconds (25 demos)	0/13
UMI	∼720 seconds (100 demos)	**13/13**
Ours	∼180 seconds (40 demos)	**13/13**

capabilities. Furthermore, leveraging human play data enables robots to perform smoother movements and acquire skills that are challenging or even impossible to achieve with robot-generated data.

A. Capabilities and Effectiveness

Table II presents the results of our real-world robot tasks, showing that our framework consistently outperforms baseline methods by achieving significantly higher success rates across all evaluated scenarios. We further compare our method with a stronger hand-held gripper baseline, UMI [13], as shown in Table III. In our default setup, SLAM-based mapping failed due to low environmental texture. To address this limitation, we added a textured background to support reliable mapping for UMI. For the nail hammering task, we evaluated UMI using 25 demonstrations (matching our collection time) and 100 demonstrations (to assess its ideal performance). UMI failed all 13 trials with 25 demonstrations but succeeded in all 13 trials with 100. UMI could not be applied to the wine balancing task due to contact-induced tool displacement, nor to the pan flipping task due to tool inertial slippage. In the soccer kicking task, large and fast motions made it nearly impossible to localize the demonstration trajectory within the initial map.

B. Policy Execution Efficiency

Our framework demonstrates exceptional efficiency in task execution, achieving faster task completion times and producing smoother action motions compared to baseline methods, as shown in Table II. The efficiency is largely attributed to the nature of human play data, which captures the fluidity and speed of real-world human activities, resulting in smoother and more natural trajectories in the training dataset. In contrast, previous approaches relying on teleoperated data often suffer from significantly slower speeds and less natural motions, limiting their effectiveness in dynamic scenarios. By leveraging the realistic dynamics of human play, our framework not only accelerates task execution but also enhances motion quality, making it better suited for real-world applications.

C. Benefits of Tool-Based Action Representation in Task Space

We observed that using the tool in the camera frame as the action representation allows the policy to perform comparably to prior works when the camera is stationary. However, the success rate drops to zero when the camera is moving. Tracking the camera pose in real time during motion is non-trivial, leading to incorrect calculations of the end-effector position in the base frame. When the base moves, policies relying on the tool in the base frame fail entirely, achieving zero success. These failures occur because such policies assume a fixed relative transformation between the base and the workspace, an assumption invalidated by base motion. In contrast, representing actions using the tool in task space enables the policy to remain effective under base perturbations. Our approach demonstrates robust performance when camera poses vary, when the base moves, and even during simultaneous shaking of the camera and base.

D. Effects of Random Cropping and View Augmentation

Our experiments show that random cropping (RC) and view augmentation (VA) enhance policy robustness to diverse camera poses. Training with RC improves resilience to minor camera perturbations, such as small movements or shaking, while VA extends robustness by exposing the model to a broader range of camera configurations during training. We evaluated these techniques on the nail hammering task and present the results in Figure 4, comparing three models: one trained with both RC and VA, one with RC only, and one without either technique. The combined use of RC and VA significantly expands the working range of camera configurations, including those with substantial deviations from the original viewpoint. The robustness arises from the model's exposure to a diverse set of camera poses during training.

E. Generalization

Object Generalization: Our method generalizes effectively to different objects in pan flipping tasks, including a toy egg, a 3D-printed meat patty, and a real burger bun. With only 13 demonstrations, the policy succeeds by leveraging a simple but effective strategy: tilting the pan to slide the object into a corner, then flicking the pan to propel and flip the object. Our manipulation approach for pan flipping enables robust generalization across diverse object types.

Tool Generalization: To assess the generalization ability of our policy across different tools, we conducted a pan-flipping experiment using a burger bun and five pans: large, medium, small, tiny, and square. For each pan, we collected 12 trials

Fig. 5: **Robustness to Camera and Base Movement.** (a) Camera Pose Robustness: The policy demonstrated the ability to handle camera shaking across three tasks—meatball scooping, nail hammering, and pan flipping. The first row shows the camera view, while the second row provides a scene overview with the shaking motion. (b) Robot Base Robustness: The policy successfully compensated for base shaking, even when the shaking frequency exceeded the robot's control frequency. (c) Chicken Head Stabilization: At lower base movement frequencies, the end effector displayed a stabilization effect similar to a chicken's steady head. (d) Combined Robustness: The policy maintained task performance under simultaneous camera and base shaking.

with varying initial configurations and reported the success rates (Fig. 7). The policy was trained on demonstrations using the large, medium, and square pans, and evaluated on all five. Results indicate that our method exhibits some generalization across both pan sizes and shapes (circular vs. square). High success rates were observed with the large and medium pans. However, performance declined on smaller pans, likely due to their limited surface area. The square pan also showed lower success rates, as its shallow edges allowed the bun to slide out during flipping.
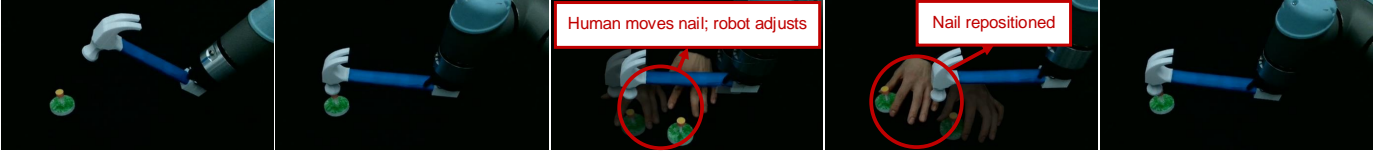
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F. Robustness

Camera Pose Robustness: We evaluated the policy's ability to handle camera pose variations by introducing camera shaking in three tasks: meatball scooping, nail hammering, and pan flipping (egg), as shown in Figure 5(a). The first row shows the camera view, while the second row shows the scene overview

(a) Nail Tracking

Human moves nail; robot adjusts

Nail repositioned

(b) Multiple Meatball Scooping

Human tosses another meatball

Human throws a third meatball

(c) Adaptive Egg Flipping

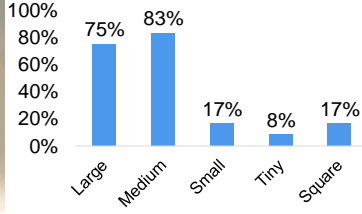Human flips egg back

Fig. 6: **Human Perturbation Robustness.** This figure showcases the robot's ability to handle human-induced perturbations across three tasks: (1) In nail hammering, the robot successfully followed a manually moved nail; (2) In meatball scooping, it located and scooped meatballs even when additional ones were thrown into the pan mid-task; and (3) In egg flipping, the robot consistently flipped the egg back after human intervention repositioned it. These results highlight the policy's robustness to unpredictable human perturbations.

(a) Different Pans Used   (b) Success Rate

Fig. 7: **Tool Generalization** (a) The tested pans. (b) Success rate across 12 testing trials.

and the shaking motion. Despite the disturbances, the policy successfully completed all tasks. This robustness stems from random cropping during training, which allows the policy to adapt to partially cropped inputs and minor visual changes.

Robot Base Robustness: To evaluate robustness to base movement, we manually shook the robot base during task execution (Figure 5(b)). When the shaking frequency exceeded the control frequency, the end effector oscillated with the base. However, the task-space action design enabled the robot to compensate for these movements and maintain task success. Additionally, as shown in Figure 5(d), the policy remained effective even when both camera and base shaking were applied simultaneously.

Chicken Head Stabilization: At lower frequencies of base movement, where the shaking was slower than the robot's control frequency, the end effector exhibited a stabilization effect similar to a chicken's head remaining steady [64], as shown in Figure 5(c). The behavior highlights the robot's ability to maintain precise control during mild perturbations.

Human Perturbation Robustness: We further tested the policy's resilience to human-induced perturbations across three tasks, as shown in Figure 6. In the nail hammering task, the robot successfully tracked and followed a manually moved nail by a human. During meatball scooping, the robot located

and scooped meatballs, even when additional meatballs were thrown into the pan mid-task. For egg flipping, the robot consistently flipped the egg back each time a human intervened and returned the egg to different initial positions. These results underscore the policy's robustness in maintaining reliable performance under real-time human interactions.

VII. CONCLUSION

In this work, we presented a novel framework for human-to-robot imitation learning that leverages human play data to bridge the embodiment gap and enables robust policy training for diverse tool-use tasks. Unlike traditional data collection methods, which are often costly, hardware-dependent, and require technical expertise, our framework democratizes data collection by removing the need for specialized equipment or prior knowledge. Our approach makes data collection more accessible and scalable, empowering broader adoption in robotic learning. We validated our framework across a range of challenging tasks, including nail hammering, meatball scooping, pan flipping with various objects, wine bottle balancing, and soccer ball kicking. The results demonstrate the framework's superior performance, robustness to variations in camera poses and base movements, and adaptability to different embodiments, such as 6-DOF and 7-DOF robots. By enhancing accessibility, scalability, and reliability, our work lays a strong foundation for advancing robotic manipulation in complex, real-world scenarios.

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