InterMimic: Towards Universal Whole-Body Control for Physics-Based Human-Object Interactions

Sirui Xu[1] Hung Yu Ling[2] Yu-Xiong Wang[1†] Liang-Yan Gui[1†]
[1] University of Illinois Urbana-Champaign [2] Electronic Arts
[†] Equal Advising

https://sirui-xu.github.io/InterMimic

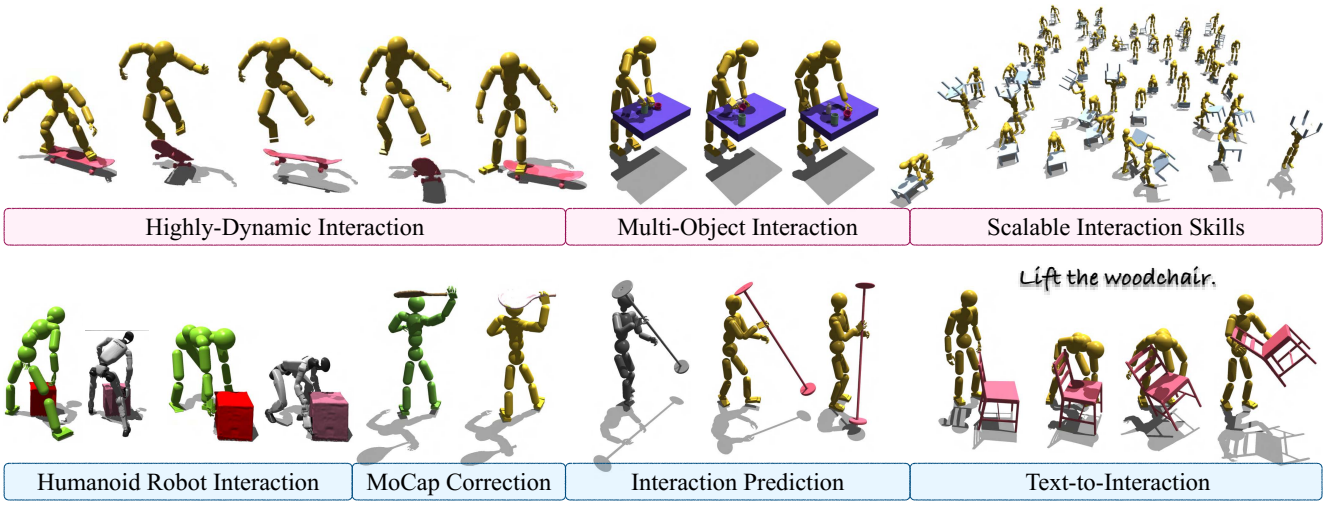


Figure 1. InterMimic enables physically simulated humans to perform interactions with dynamic and diverse objects. It supports highly-dynamic, multi-object interactions and scalable skill learning (**Top**), making it adaptable for versatile downstream applications (**Bottom**): it can translate whole-body loco-manipulation skills to a humanoid robot [24, 81], perfect interaction MoCap data, and bridge kinematic generation, *e.g.*, predicting future interactions from past (InterDiff [101]) or generating interactions given text prompts (InterDreamer [102]).

Abstract

Achieving realistic simulations of humans interacting with a wide range of objects has long been a fundamental goal. Extending physics-based motion imitation to complex human-object interactions (HOIs) is challenging due to intricate human-object coupling, variability in object geometries, and artifacts in motion capture data, such as inaccurate contacts and limited hand detail. We introduce InterMimic, a framework that enables a single policy to robustly learn from hours of imperfect MoCap data covering diverse full-body interactions with dynamic and varied objects. Our key insight is to employ a curriculum strategy – perfect first, then scale up. We first train subject-specific teacher policies to mimic, retarget, and refine motion capture data. Next, we distill these teachers into a student policy, with the teachers acting as online experts providing direct supervision, as well as high-quality references. Notably, we incorporate RL fine-tuning on the student policy to surpass mere demonstration replication and achieve higher-quality solutions. Our experiments demonstrate that InterMimic produces realistic and diverse interactions across multiple HOI datasets. The learned policy generalizes in a zero-shot manner and seamlessly integrates with kinematic generators, elevating the framework from mere imitation to generative modeling of complex human-object interactions.

1. Introduction

Animating human-object interactions is a challenging and time-consuming task even for skilled animators. It requires a deep understanding of physics and meticulous attention to detail to create natural and convincing interactions. While

Motion Capture (MoCap) data provides references, animators often need to correct contact errors caused by sensor limitations and occlusions between humans and objects. However, this process remains unscalable, as refining a single motion demands a delicate balance between preserving the captured data and ensuring its physical plausibility.

Physics-based human motion imitation [38, 63] offers an alternative approach to improving motion fidelity, by training control policies to mimic reference MoCap data within a physics simulator. However, scaling up human-object interaction imitation presents significant challenges: (**i**) *MoCap Imperfection*: Contact artifacts are common, causing expected contacts to fluctuate instead of maintaining consistent zero distance, often due to MoCap limitations or missing hand capture [3, 39]. Accurately imitating MoCap kinematics can result in unrealistic dynamics in simulation. Moreover, HOI datasets often include diverse human shapes, requiring motion retargeting to adapt movements across different human models while preserving interaction dynamics. This retargeting process is imperfect and can introduce new contact artifacts or exacerbate existing ones. (**ii**) *Scaling-up*: Although large-scale motion imitation has been explored in previous works [50, 79, 92, 106], it remains largely underexplored for whole-body interactions involving dynamic and diverse objects.

In this paper, we aim to utilize rich yet imperfect motion capture interaction datasets to train a control policy capable of learning diverse motor skills while enhancing the plausibility of these actions by correcting errors, such as inaccurate hand motions and faulty contacts. Our approach is grounded on the key insight of tackling the challenges of *skill perfection* and *skill integration* progressively. We implement a curriculum-based teacher-student distillation framework, where multiple teacher policies focus on imitating and refining small subsets of interactions, and a student policy integrates these skills from the teachers.

Instead of relying on curated data that covers a limited range of actions [4, 51], we employ multiple teacher policies trained on a diverse set of imperfect interaction data and address two key challenges: *retargeting* and *recovering*. First, we unify all training policies to a canonical human model, by embedding HOI retargeting directly into the imitation. This is achieved by reframing the policy learning to optimize both imitation and retargeting objectives. Second, our teacher policies refine interaction motion through learning from it, as accurate contact dynamics enforced by a physics simulator inherently correct inaccuracies in the reference kinematics. To support this, we introduce tailored contact-guided reward and optimize trajectory collection, enabling effective skill imitation despite MoCap errors.

Introducing teacher policies offers several key benefits. By leveraging teacher rollouts, we effectively distill raw MoCap data into refined HOI references with a unified embodiment and enhanced physical fidelity. These refined references guide the subsequent student policy training, reducing the negative impact of errors in the original MoCap data. A major hurdle in scaling motion imitation is the sample inefficiency of Reinforcement Learning (RL), which can lead to prohibitively long training times. Our teacher-student approach mitigates this through a *space-time trade-off*: multiple teacher policies are trained in parallel on smaller, more manageable data subsets, and their expertise is then *distilled* into a single student policy. We begin with demonstration-based distillation to bootstrap PPO [71] updates, reducing reliance on pure trial and error and enabling more effective scaling. As training progresses, the student gradually shifts from heavy demonstration guidance to increased RL updates, ultimately surpassing simple demonstration memorization. This mirrors alignment strategies in Large Language Models (LLMs), where demonstration-based pre-training is refined through RL fine-tuning [56].

To summarize, our contributions are as follows: (**i**) We introduce *InterMimic*, which, to the best of our knowledge, is the *first* framework designed to train physically simulated humans to develop *a wide range of whole-body* motor skills for interacting with *diverse* and *dynamic* objects, extending beyond traditional grasping tasks. (**ii**) We develop a teacher-student training strategy, where teacher policies provide a unified solution to address the challenges of retargeting and refining in HOI imitation. The student distillation introduces a scalable solution by leveraging a space-time trade-off. (**iii**) We demonstrate that our unified framework, *InterMimic*, as illustrated in Figure 1, effectively handles versatile physics-based interaction animation, recovering motions with realistic and physically plausible details. Notably, by combining kinematic generators with *InterMimic*, we enable a physics-based agent to achieve tasks such as interaction prediction and text-to-interaction generation.

2. Related Work

Significant progress has been made in physics-based human interaction animation and control, with advancements in areas such as human-human interactions [45, 90], hand-object interactions [60, 86, 100, 104], human interactions with static scenes [5, 36, 57, 79, 96], and real-world humanoid control for object manipulation [2, 11, 16, 19, 20, 28, 41, 43, 72, 107]. Among these areas, we are the first to achieve universal whole-body loco-manipulation simulation with diverse dynamic objects, beyond pick-and-place and grasping actions – a novel achievement in animation and an idealized reference for real-world humanoid control. Below, we elaborate on recent studies on *whole-body* interaction animation, particularly involving *dynamic objects*.

2.1. Kinematic Interaction Animation

Generating human interactions has been a long-standing topic in animation and computer graphics [15, 37]. Significant advances in character animation have emerged with the advent of deep learning, *e.g.*, including phase-function-based methods [22] that enable object interactions like carrying a box [74] or playing basketball [75]. This is extended to more diverse but static objects approaching [35, 77, 94, 111]. Subsequent efforts [14, 26, 27, 40, 42, 49, 66, 95] integrate object motion into interactions but remain constrained by assuming that interactions occur primarily through the hands. To address this, recent developments [7, 10, 12, 21, 30, 62, 73, 84, 93, 101, 102] introduce interactions in a fashion of whole-body loco-manipulation that engages multiple body parts in contact. However, these methods often suffer from physical inaccuracies, such as floating contacts and penetrations, while they generate only body motion without considering hand dexterity. In this work, we address physical inaccuracies by refining imperfect kinematic generation through physics simulation, with InterDiff [101] and HOI-Diff [62] serving as motion planning for loco-manipulation that bridges high-level decision-making (*e.g.*, text instruction) with low-level execution.

2.2. Physics-based Interaction Animation

Physics-based methods generate motion through motor control policies within a physics simulator, *e.g.*, achieved via deep reinforcement learning to track reference motions [63]. These policies are directly applicable for executing simple interactions, such as punching or striking an object [8, 65, 78, 80]. To achieve more complex interactions, early studies focus on specific scenarios, including notable sports-related [52] examples such as basketball [88], skating [44], soccer [98], tennis [108], table tennis [85], and more proposed in [1]. Research also demonstrates flexibility in more general but simpler box carrying tasks [58, 87, 113]. These advancements are achieved through the integration of multiple control policies [55], the use of adversarial motion priors [13, 18, 64], and imitating diverse kinematic generations [95, 99]. However, these methods train their policies in a *non-scalable* manner, with each policy handling only specific object types or actions. In pursuit of a single, scalable policy to enable multiple interaction skills, existing methods either rely on fixed interaction patterns, such as approaching and grasping objects [4, 51], or extend single-object skills, *e.g.*, interactions involving a basketball [89]. Additionally, they mostly depend on highly curated data from the GRAB dataset [76], which, despite its high quality, primarily features low-dynamic full-body motion and only small-sized objects. More recent datasets [3, 23, 25, 31, 39, 46–48, 53, 97, 103, 109, 110, 112, 114] offer richer full-body interactions with diverse objects but contain noticeable artifacts that challenge existing motion imitation approaches. We process data from OMOMO [39], BEHAVE [3], HODome [109], and IMHD [114] collected in the InterAct [103] dataset, and the multi-object dataset HIMO [53], highlighting InterMimic's *scalability* to diverse interactions and its *robustness* against MoCap artifacts.

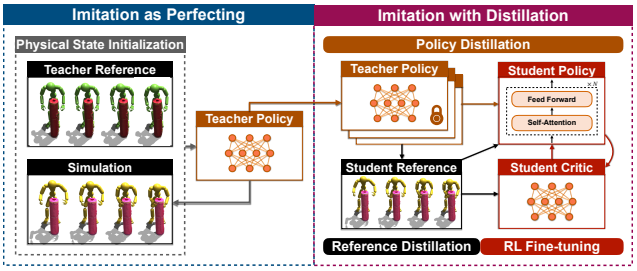


Figure 2. Our two-stage pipeline: (**i**) training each teacher policy (MLP) on a small data subset with initialization corrected via Physical State Initialization (PSI), and (**ii**) freezing the teacher policies to provide refined references for training a student policy (Transformer). The student leverages teacher supervision for effective scaling and is fine-tuned through RL.

3. Methodology

Task Formulation. The goal of human-object interaction (HOI) imitation is to learn a policy π that produces simulated human-object motion $\{\boldsymbol{q}_t\}_{t=1}^{T}$ closely matching a ground-truth reference $\{\hat{\boldsymbol{q}}_t\}_{t=1}^{T}$ derived from large-scale MoCap data. Given the geometries of the human and objects, the policy should also compensate for missing or inaccurate details in the dataset. Each pose $\boldsymbol{q}_t$ has two components: the human pose $\boldsymbol{q}_t^h$ and the object pose $\boldsymbol{q}_t^o$. The human pose is defined as $\boldsymbol{q}_t^h = \{\boldsymbol{\theta}_t^h, \boldsymbol{p}_t^h\}$, where $\boldsymbol{\theta}_t^h \in \mathbb{R}^{52\times3}$ represents the joint rotations, and $\boldsymbol{p}_t^h \in \mathbb{R}^{52\times3}$ specifies the joint positions. Specifically, our human model includes 30 hand joints and 22 joints for the rest of the body, with one root joint's rotation and position specified in global coordinates, whereas the rotations and positions of all other joints are defined relative to their respective parent joints' coordinate systems. The object pose $\boldsymbol{q}_t^o$ is represented as $\{\boldsymbol{\theta}_t^o, \boldsymbol{p}_t^o\}$, where $\boldsymbol{\theta}_t^o \in \mathbb{R}^3$ denotes the object's orientation and $\boldsymbol{p}_t^o \in \mathbb{R}^3$ the position. All simulation states have corresponding ground-truth values, denoted by the hat symbol. For instance, the reference object rotation is $\{\hat{\boldsymbol{\theta}}_t^o\}_{t=1}^{T}$. The environmental setup for the simulation is detailed in Sec. B.

Overview. We formulate interaction imitation as a Markov Decision Process (MDP), defined by states, actions, simulator-provided transition dynamics, and a reward function. Figure 2 illustrates our two-stage framework: (i) training teacher policies $\pi^{(T)}$ on small skill subsets, and (ii) distilling these teachers into a scalable student policy $\pi^{(S)}$ for large-scale skill learning. In Sec. 3.1, we define the states $\boldsymbol{s}_t$

and actions $\boldsymbol{a}_t$, applicable to both teacher $\pi^{(T)}$ and student $\pi^{(S)}$ policies. In Sec. 3.2, we describe how teacher policies are trained via RL, focusing on reward designs that facilitate retargeting, as well as techniques that mitigate the impact of imperfections in the reference data. Sec. 3.3 details the subsequent distillation of teachers into a scalable student policy, leveraging both RL and learning from demonstration.

3.1. Policy Representation

State. The state $\boldsymbol{s}_t$, which serves as input to the policy, comprises two components $\boldsymbol{s}_t = \{\boldsymbol{s}_t^s, \boldsymbol{s}_t^g\}$. The first part, $\boldsymbol{s}_t^s$, contains human proprioception and object observations, expressed as, $\{\{\boldsymbol{\theta}_t^h, \boldsymbol{p}_t^h, \boldsymbol{\omega}_t^h, \boldsymbol{v}_t^h\}, \{\boldsymbol{\theta}_t^o, \boldsymbol{p}_t^o, \boldsymbol{\omega}_t^o, \boldsymbol{v}_t^o\}, \{\boldsymbol{d}_t, \boldsymbol{c}_t\}\}$, where $\{\boldsymbol{\theta}_t^h, \boldsymbol{p}_t^h, \boldsymbol{\omega}_t^h, \boldsymbol{v}_t^h\}$ represent the rotation, position, angular velocity, and velocity of all joints, respectively, while $\{\boldsymbol{\theta}_t^o, \boldsymbol{p}_t^o, \boldsymbol{\omega}_t^o, \boldsymbol{v}_t^o\}$ represent the orientation, location, velocity, and angular velocity of the object, respectively. Motivated by [6], we include object geometry and whole-body haptic sensing from two elements: (**i**) $\boldsymbol{d}_t$, vectors from human joints to their nearest points on each object surface; and (**ii**) $\boldsymbol{c}_t$, contact markers indicating whether the human's rigid body parts experience applied forces; this serves as simplified tactile or force sensing – an important multimodal input in robot manipulation tasks [9]. The goal state $\boldsymbol{s}_t^g = \{\boldsymbol{s}_{t,t+k}^g\}_{k \in K}$ integrates reference poses from the ground truth motion, where $\boldsymbol{s}_{t,t+k}^g$ is defined as,

$$\begin{aligned} &\{\{\hat{\boldsymbol{\theta}}_{t+k}^h \ominus \boldsymbol{\theta}_t^h, \hat{\boldsymbol{p}}_{t+k}^h - \boldsymbol{p}_t^h\}, \{\hat{\boldsymbol{\theta}}_{t+k}^o \ominus \boldsymbol{\theta}_t^o, \hat{\boldsymbol{p}}_{t+k}^o - \boldsymbol{p}_t^o\}, \\ &\{\hat{\boldsymbol{d}}_{t+k} - \boldsymbol{d}_t, \hat{\boldsymbol{c}}_{t+k} - \boldsymbol{c}_t\}, \{\hat{\boldsymbol{\theta}}_{t+k}^h, \hat{\boldsymbol{p}}_{t+k}^h, \hat{\boldsymbol{\theta}}_{t+k}^o, \hat{\boldsymbol{p}}_{t+k}^o\}\}, \end{aligned} \tag{1}$$

where $\hat{\boldsymbol{\theta}}_{t+k}^h, \hat{\boldsymbol{p}}_{t+k}^h, \hat{\boldsymbol{d}}_{t+k}, \hat{\boldsymbol{c}}_{t+k}$ represent the reference information at time step $t+k$, $\ominus$ denotes the calculation of rotation difference. All continuous elements of $\boldsymbol{s}_t$ are normalized relative to the current direction of view of the human and the position of the root [63].

Given that most MoCap data does not provide reference contact or tactile information, we extract reference contact markers $\hat{\boldsymbol{c}}_{t+k}$ by inferring dynamic information, beyond relying solely on inaccurate contact distances, specifically by analyzing the object's acceleration to detect human-induced forces. To accommodate the variability in contact distances observed in reference motion, we discretize reference contact markers using varying distance thresholds, as illustrated in Fig. 3(**i**). The neutral areas serve as buffer zones, avoiding the penalization or enforcement of strict contact. See Sec. C of supplementary for details.

Action. Our human model has 51 actuated joints, defining an action space of $\boldsymbol{a}_t \in \mathbb{R}^{51\times 3}$. These actions are specified as joint PD targets using the exponential map and are converted into torques applied to each of the human joints.

3.2. Imitation as Perfecting

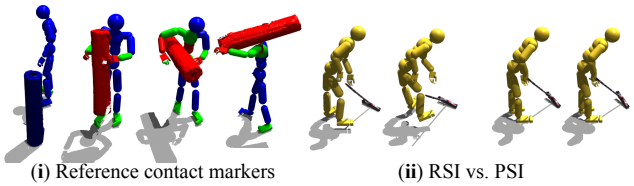
The teacher policy $\pi^{(\mathrm{T})}$ is trained via RL to maximize the expected discounted reward by comparing simulated states against potentially erroneous reference states. The training involves: (**i**) trajectory collection, where we explain how trajectories are initialized and terminated. (**ii**) policy updating, where collected trajectories and their associated rewards are used to refine the policy. In this section, we elaborate on our reward design and how we optimize trajectory collection to mitigate the impact of reference inaccuracies.

Imitation as Retargeting. We tailor teacher policies to each human subject, while all policies share the same base human model. This serves the retargeting purpose by converting HOIs from different human shapes into a unified base shape. Although motion imitation does not necessarily require a unified human model [50, 91], our approach offers two benefits: (i) It enhances integration with kinematic generation methods, which generally perform better on a single, unified shape [17]. (ii) It demonstrates possible integration with real-world humanoid deployment, which requires retargeting to a consistent physical embodiment. In Figure 1, our method translates MoCap data into motor skills on a Unitree G1 [81] with two Inspire hands [24], all without external retargeting in complex contact-rich scenarios. See Sec. F of the supplementary for additional details.

Human [83] or HOI [32] retargeting can be formulated as an optimization problem. Inverse Kinematics (IK) methods, such as those based on quadratic programming [34], demonstrate effectiveness in simplified scenarios but remain underexplored for motions featuring intricate object interactions. RL, by contrast, solves the optimization by maximizing an expected cumulative reward, prompting us to investigate whether RL-driven HOI imitation can be used for HOI retargeting. This extends existing physics-based retargeting approaches, which either omit object interactions [67] or are non-scalable with a single reference [113].

While the kinematics should differ due to the embodiment gap, we argue that the *dynamics* between human and object should remain *invariant*. Thus, we define rewards to include an embodiment-aware component that loosely aligns the simulated kinematics with the reference interaction, and an embodiment-agnostic reward component that encourages dynamics to be close to the reference.

Embodiment-Aware Reward. When the human and object are far apart, retargeting should prioritize capturing rotational motion, whereas when they are close, accurate position tracking becomes crucial for achieving contact. To reflect this, we define the weights $\boldsymbol{w}_d$ that are inversely proportional to the distances between joints and the object [113]. The reward thus includes cost functions for joint position $E_p^h = \langle \boldsymbol{\Delta}_p^h, \boldsymbol{w}_d \rangle$, rotation $E_\theta^h = \langle \boldsymbol{\Delta}_\theta^h, \mathbf{1} - \boldsymbol{w}_d \rangle$, and interaction tracking $E_d = \langle \boldsymbol{\Delta}_d, \boldsymbol{w}_d \rangle$, where $\langle \cdot, \cdot \rangle$ is the inner product, $\boldsymbol{\Delta}_p^h[i] = \|\hat{\boldsymbol{p}}^h[i] - \boldsymbol{p}^h[i]\|$, $\boldsymbol{\Delta}_\theta^h[i] =$



(i) Reference contact markers (ii) RSI vs. PSI

Figure 3. (i) Visualization of reference contact markers that accommodate varied contact distances: red to promote contact, green for neutral areas where contact is neither promoted nor penalized, and blue to penalize contact. (ii) Initializing the rollout with reference (RSI) or reference corrected via simulation (PSI).

$\|\hat{\boldsymbol{\theta}}^h[i] \ominus \boldsymbol{\theta}^h[i]\|$, and $\boldsymbol{\Delta}_d[i] = \|\hat{\boldsymbol{d}}[i] - \boldsymbol{d}[i]\|$ represent the displacement for the variables defined in Sec. 3.1 with timestep t omitted. The formulation of $\boldsymbol{w}_d$ is provided in Sec. D of supplementary. The reward to be maximized can be formulated as $\exp(-\lambda E)$ for each cost function E with a specific hyperparameter λ. Details can be found in Sec. D.

Embodiment-Agnostic Reward. The reward includes components for object tracking and contact tracking. The object tracking cost is defined for position $E_p^o = \|\hat{\boldsymbol{p}}^o - \boldsymbol{p}^o\|$ and rotation $E_\theta^o = \|\hat{\boldsymbol{\theta}}^o - \boldsymbol{\theta}^o\|$, with all values normalized to the human's current position and direction. The contact tracking reward comprises two cost functions: body contact promotion E_b^c and penalty E_p^c, both aligning the simulated contact $\boldsymbol{c}$ with reference markers $\hat{\boldsymbol{c}}$, as shown in Figure 3. We define three contact levels – promotion, penalty, and neutral – to accommodate potential inaccuracies in reference contact distances. The detailed formulation can be found in Sec. D of the supplementary. Since the physics engine does not differentiate between object, ground, and self-contact, we adopt two strategies: **(i)** we model foot-ground contact promotion and penalty. This ensures proper foot lifting during cyclic walking and mitigates foot hobbling. **(ii)** We allow self-collision to avoid self-contact promotion but to promote object interaction. This poses minimal risk as the policy is guided by MoCap reference, which, although lacking perfect contact accuracy, rarely shows self-penetration. For humanoid robots with embodiments that differ from the MoCap reference and require real-world applicability, we disable self-collision, as discussed in Sec. F.

We introduce energy consumption rewards [105] to penalize large human or object jitters, with a proposed contact energy penalizing abrupt contact to promote compliant interactions. See Sec. D of supplementary for more details.

Hand Interaction Discovery. We use data with average or flattened hand poses [3, 39], which makes accurate object manipulation imitation challenging. To address this, we activate a reference contact marker for any hand part when a *fingertip* or *palm* is near an object. Given tasks that do not demand high dexterity, employing a contact-promoting reward with this marker enables policies to develop effective hand interaction strategies, leveraging the exploratory nature of RL. Additionally, we constrain the range of motion (RoM) of the hands to ensure natural movement. See Sec. D and Sec. B of the supplementary for further details.

Policy Learning. Following [63], the control policy π is trained using PPO [71] with the policy gradient $L(\psi) = \mathbb{E}_t[\min(r_t(\psi)A_t, \text{clip}(r_t(\psi), 1-\epsilon, 1+\epsilon)A_t)$. ψ are the parameters of π and $r_t(\psi)$ quantifies the difference in action likelihoods between updated and old policies. ϵ is a small constant, and A_t is the advantage estimate given by the generalized advantage estimator GAE(λ) [70].

Physical State Initialization. Learning later-phase motion can be essential for policies to achieve high rewards during earlier phases, compared to incrementally learning from the starting phase. Thus, Reference State Initialization (RSI) [63] sets the current pose $\boldsymbol{q}_t$ to a reference pose $\hat{\boldsymbol{q}}_t$ at a random timestep t, for initializing the rollout. However, initializing with the imperfect reference can introduce *critical artifacts*, such as contact floating or incorrect hand motion, leading to unrecoverable failures, *e.g.*, object falling, as depicted in Figure 3(ii). These issues render many initializations ineffective, limiting training on certain interaction phases since successful rollouts may not reach them before the maximum length. The problem is exacerbated by the use of prioritized sampling [79, 91], which favors high-failure-rate initializations.

To address the need for higher-quality reference initialization, we propose *Physical State Initialization* (PSI). As illustrated in Figure 2, PSI begins by creating an initialization buffer that stores reference states from MoCap and simulation states from prior rollouts. For each new rollout, an initial state is randomly selected from this buffer, which increases the likelihood of starting from advantageous positions. Once a rollout is completed, trajectories are evaluated based on their expected discounted rewards; those above a certain threshold are added to the buffer using a first-in-first-out (FIFO) strategy, while older or lower-quality trajectories are discarded. This selective reintroduction of high-value states for initialization helps maintain stable policy updates. We apply PSI in a sparse manner to ensure training efficiency. As shown in Figure 3(ii), PSI can collect trajectories for policy update that RSI does not effectively utilize. Further details are provided in Sec. E of the supplementary.

Interaction Early Termination. Early Termination (ET) [63] is commonly used in motion imitation, ending an episode when a body part makes unplanned ground contact or when the character deviates significantly from the reference [50], thus stopping the policy from overvaluing invalid transitions. However, additional conditions should be considered for human-object interactions. We propose *Interaction Early Termination* (IET), which supplements ET with three extra checks: **(i)** Object points deviate from their references by more than 0.5 m on average. **(ii)** Weighted av-

erage distances between the character's joints and the object surface exceed 0.5 m from the reference. (**iii**) Any required body-object contact is lost for over 10 consecutive frames. Full conditions are detailed in Sec. E of the supplementary.

3.3. Imitation with Distillation

As shown in Figure 2, after training the teacher policies on data from each subject (Sec. 3.2), we aggregate them to train a student policy $\pi^{(\mathrm{S})}$ to master all skills. As outlined in Algorithm 1, the combined teacher policies, denoted by $\pi^{(\mathrm{T})}$ for brevity, serves dual roles by providing state-action trajectories $(\boldsymbol{s}^{(\mathrm{T})}, \boldsymbol{a}^{(\mathrm{T})})$: (**i**) the state $\boldsymbol{s}^{(\mathrm{T})}$ for reference distillation, and (**ii**) the action $\boldsymbol{a}^{(\mathrm{T})}$ for policy distillation.

Reference Distillation. Noisy MoCap data can hinder policy learning, especially at larger scales. In contrast, teacher policies trained on smaller-scale data effectively address these issues by correcting contact artifacts, refining hand placements, and recovering missing details (see Figures 1 and 5). To fully leverage teacher policies, we use their rollouts as references for defining the student policy's goal state and reward functions, distinguishing our approach from distillation based on only action output.

Policy Distillation. We apply distillation on action outputs, which we view as crucial for scaling policies to large datasets. In essence, we trade space for time: teacher policies are trained in parallel on smaller data subsets, allowing the student policy to scale through distillation. Following Algorithm 1, we begin with Behavior Cloning (BC) [29] and use RL fine-tuning to go beyond demonstration memorization, an approach common in LLM alignment [56]. We integrate BC into online policy updates with a staged schedule: we start with DAgger [69] and gradually transition to PPO. Throughout, the critic is continuously trained with the reward from Sec. 3.2. This RL fine-tuning phase is crucial as teacher policies may behave differently when performing similar skills, and simple BC can lead to suboptimal "averaging" behavior, where RL fine-tuning helps the student converge on optimal solutions.

Algorithm 1 Distillation with RL Fine-tuning

Input: A composite policy $\pi^{(\mathrm{T})}$ integrated from individual teacher policies, student policy parameters $\boldsymbol{\psi}$, student value function parameters $\boldsymbol{\phi}$, schedule hyperparameter β for DAgger, horizon length H for PPO
for $t = 0, 1, 2, \ldots$ **do**
  for h from 1 to H **do**
    Sample a variable $u \sim \mathrm{Uniform}(0, 1)$
    Collect $\boldsymbol{s}^{(\mathrm{T})}, \boldsymbol{a}^{(\mathrm{T})}$ from teacher $\pi^{(\mathrm{T})}$
    Obtain the refined reference from $\boldsymbol{s}^{(\mathrm{T})}$ to define $\boldsymbol{s}^{(\mathrm{S})}$ and $r(\cdot)$, obtain $\boldsymbol{a}^{(\mathrm{S})}$ from $\pi^{(\mathrm{S})}_{\boldsymbol{\phi}}(\boldsymbol{a}^{(\mathrm{S})}|\boldsymbol{s}^{(\mathrm{S})})$.
    if $u \leq \frac{t}{\beta}$ **then** ▷ Use the teacher
      Given $\boldsymbol{s}^{(\mathrm{S})}$, execute $\boldsymbol{a}^{(\mathrm{S})}$, observe $\boldsymbol{s}'^{(\mathrm{S})}, r$
    else ▷ Use the student
      Given $\boldsymbol{s}^{(\mathrm{S})}$, execute $\boldsymbol{a}^{(\mathrm{T})}$, observe $\boldsymbol{s}'^{(\mathrm{S})}, r$
    end if
    Store the transition $(\boldsymbol{s}^{(\mathrm{S})}, \boldsymbol{s}'^{(\mathrm{S})}, \boldsymbol{a}^{(\mathrm{S})}, \boldsymbol{a}^{(\mathrm{T})}, r)$
  end for
  Update $\boldsymbol{\phi}$ with TD(λ)
  Compute PPO objective: $L(\psi)$
  Compute $J(\psi) = \|\boldsymbol{a}^{(\mathrm{S})} - \boldsymbol{a}^{(\mathrm{T})}\|$
  Compute the weight: $w = \min(\frac{t}{\beta}, 1)$
  Update ψ by gradient: $\nabla_{\psi}(wL(\psi) + (1-w)J(\psi))$
end for

3.4. Architecture

We set the keyframe indices K (Sec. 3.1, Eq. 1) to $\{1, 16\}$ for the teacher policies and $\{1, 2, 4, 16\}$ for the student policy. The broader observation window for the student policy helps it better distinguish different skills with larger-scale data. Teacher policies employ MLPs, common in physics-based animation [63], while the student policy handles higher-dimensional observations, for which MLPs are less effective. Thus, we use a transformer [82] architecture for sequential modeling [79], as shown in Figure 2.

4. Experiments

We evaluate teacher policies on their ability to imitate imperfect HOI references, and assess the entire teacher-student framework for scalability to large-scale data and zero-shot generalization across various scenarios. Additional experiments are provided in Sec. G of supplementary.

Datasets. We use the following datasets from InterAct [103]: OMOMO [39], BEHAVE [3], HODome [109], IMHD [114], and HIMO [53]. OMOMO, containing 15 objects and approximately 10 hours of data, is our primary dataset for evaluating the full teacher-student distillation framework for its scale. We train 17 teacher policies, one per subject, with subject 14 reserved as the test set and the remaining data used for training the student policy. A small portion of data is discarded after teacher imitation due to severe MoCap errors that could not be corrected (see Sec. F and Sec. H of the supplementary). Additional datasets are used to evaluate teacher policies in various MoCap scenarios with different error levels and interaction types. We focus on highly dynamic motions (Figure 1) and interactions involving multiple body parts (Figure 4), while excluding scenarios such as carrying a bag with a strap, since the simulator [54] used lacks full support for soft bodies.

Metrics. We use the following metrics: (**i**) *Success Rate* is defined as the proportion of references that the policy successfully imitates at least once, averaged across all references, while (**ii**) *Duration* is the time (in seconds) that the imitation is maintained without triggering the interaction early termination conditions introduced in Sec. 3.2. (**iii**)

Figure 4. Qualitative comparison between PhysHOI [88] (top), the reference motion (middle) from the BEHAVE [3] dataset, and the interaction refined by our teacher trained on it (bottom). InterMimic faithfully imitates the interactions involving multiple body parts while correcting errors in the original reference.

Human Tracking Error (E_h) measures the per-joint position error (cm) between the simulated and reference human (excluding hand joints for BEHAVE [3] and OMOMO [39] due to inaccuracy). (**iv**) *Object Tracking Error* (E_o) measures the per-point position error (cm) between the simulated and reference object. Both errors are averaged over the duration of the imitation in the best-performing trial.

Baselines. To facilitate fair comparisons, we downgrade our method for teacher policy evaluation to imitate either a single MoCap clip (Figure 4) or multiple clips with a single object (Table 1), enabling direct comparison with PhysHOI [88] and SkillMimic [89] (Sec. 4.1 and 4.2). Due to the lack of established baselines for large-scale HOI imitation, we adapt the following variants for comparison with our student policy (Sec. 4.3): (**i**) **PPO** [71] trains an imitation policy from scratch, following [63]. We experiment with both versions, with and without *reference distillation*; (**ii**) **DAgger** [69] distills the student without RL fine-tuning, a process we refer to as *policy distillation*.

Implementation Details. The control policies operate at 30 Hz and are trained using the *Isaac Gym* simulator [54]. Teacher policies are implemented as MLPs with hidden layers of sizes 1024, 1024, and 512. The student policy is implemented as a three-layer Transformer encoder with 4 heads, a hidden size of 256, and a feed-forward layer of 512. The critics are also modeled as MLPs with the same architecture as the teacher policies. To integrate the student policy with kinematic generators, including text-to-HOI [62] and future interaction prediction [101], we train these models using reference data distilled by the teacher policies from the OMOMO [39] dataset, following the same train-test split as the student policy training. For the text-to-HOI model, we train it to generate 10 seconds of motion and use 24 generated samples for evaluation, while for future interaction prediction, the model generates 25 future frames given 10 past frames and we use 60 generated samples for evaluation. See Sec. F of the supplementary.

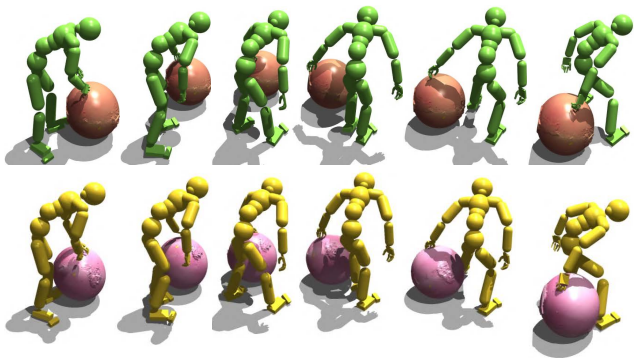


Figure 5. We recover plausible object rotations (bottom) that are challenging for motion capture due to the equivariant geometries of objects, which result in the object sliding on the ground (top).

Method	Time$^{\uparrow}$	$E_h{}^{\downarrow}$	$E_o{}^{\downarrow}$
SkillMimic [89]	12.2	7.2	13.4
InterMimic (**Ours**) w/o IET	40.3	6.7	9.9
InterMimic (**Ours**) w/o PSI	36.1	6.6	10.2
InterMimic (**Ours**)	**42.6**	**6.4**	**9.2**

Table 1. Quantitative comparison between the teacher policy from InterMimic and SkillMimic [89] to imitate data extracted from the BEHAVE [3] dataset involving a single subject interacting with yogamat. We ablate our proposed approach by removing interaction early termination and physical state initialization.

4.1. Quantitative Evaluation

Table 1 shows that the baseline struggles with MoCap imperfections, *e.g.*, incorrect hand positioning, and thus results in clearly shorter tracking durations. In contrast, our method maintains reference tracking for longer durations and produces interactions that closely match the reference. Table 2 shows that our method consistently outperforms baselines in both training data imitation and out-of-distribution generalization, including interactions from the test set and from kinematic generations. We discuss the effectiveness of specific design choices in Sec. 4.3.

4.2. Qualitative Evaluation

Figure 4 shows a representative sequence from the experiment in Table 1, illustrating how our teacher policy corrects interactions that PhysHOI [88] fails to track robustly – our method effectively withstands and corrects incorrect hand positioning and floating contacts in the reference. Beyond obvious errors, our method also rectifies the rotation of symmetric objects that MoCap inaccurately depicts as slid-

PPO	Reference Distillation	Policy Distillation	Architecture	OMOMO-Train [39]				OMOMO [39]-Test				OMOMO [39]-Test (w ×10)				HOI-Diff [62]				InterDiff [101]			
				Succ.↑	Time↑	E_h↓	E_o↓	Succ.↑	Time↑	E_h↓	E_o↓	Succ.↑	Time↑	E_h↓	E_o↓	Succ.↑	Time↑	E_h↓	E_o↓	Succ.↑	Time↑	E_h↓	E_o↓
✓	×	×	MLP	23.9	101.6	7.2	15.6	9.6	85.3	7.5	16.2	3.9	71.2	7.5	17.9	0.0	0.0	-	-	6.7	11.7	**6.2**	16.4
×	✓	✓		54.5	139.9	7.1	11.0	54.3	140.2	7.1	**11.2**	15.5	91.7	9.3	13.7	4.2	84.8	10.1	**9.7**	65.0	27.4	7.5	13.4
✓	✓	×		71.7	152.8	8.9	12.7	91.6	173.7	8.5	13.2	45.8	127.6	9.1	14.9	8.3	**130.9**	10.1	13.8	73.3	28.9	6.9	14.4
✓	✓	✓		**90.7**	**168.0**	**5.5**	**9.7**	95.5	173.9	**5.4**	11.9	**62.6**	**140.9**	**6.6**	14.5	**12.5**	121.4	8.6	12.1	75.0	29.1	**6.2**	13.5
✓	✓	✓	Transformer	88.8	167.0	6.0	10.2	**98.1**	**176.5**	5.9	11.3	56.8	134.7	**6.6**	**13.2**	**12.5**	119.0	**8.5**	12.6	**76.7**	**29.3**	6.4	**13.3**

Table 2. Quantitative evaluation of large-scale interaction imitation using OMOMO [39], kinematic generations from HOI-Diff [62], and InterDiff [101]. Additionally, we evaluate on test set when objects with weights ten times greater than those used during training.

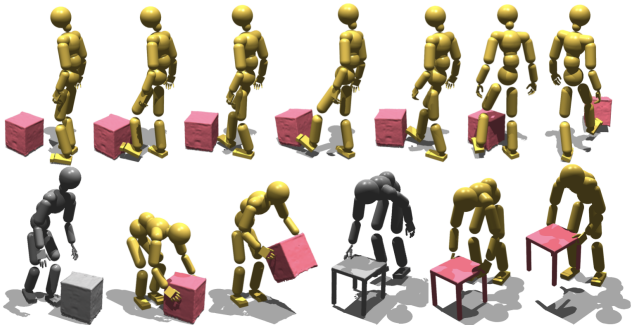


Figure 6. Zero-shot integration with a text-to-HOI model HOI-Diff [62] (**Top**), using 'Kick the large box' as the prompt, and an interaction prediction model InterDiff [101] (**Bottom**), where gray meshes are past states and colored illustrate future generations.

ing along the ground, shown in Figure 5. Figure 6 presents additional examples that complement Figure 1, demonstrating how our approach integrates with kinematic generators for future interaction prediction and text-to-interaction synthesis. This zero-shot generalization extends to novel objects unseen during training (Figure 7), highlighting the effectiveness of our object geometry and contact-encoded representation, as well as the large-scale training.

4.3. Ablation Study

Effectiveness of PSI and IET. We conduct an ablation study, as demonstrated in Table 1, comparing the full approach to "Ours w/o PSI". The results validate that Physical State Initialization (PSI) is effective by mitigating inaccuracies in the motion capture data. We also observe reduced effectiveness without our interaction early termination, as training often spends rollouts on irrelevant periods.

Effectiveness of Reference Distillation. Compared to directly scaling imitation from MoCap with potential imperfections (line 1 in Table 2), using references refined by the teacher policy (line 3) achieves consistently better performance on all metrics. The improvement is even more pronounced on the test set, where, without reference distillation, the policy struggles with unseen shapes, while retargeting by reference distillation eliminates the difficulty.

Effectiveness of Joint PPO and DAgger Updates. As shown in Table 2, training a policy from scratch (line 3) or relying solely on policy distillation (DAgger, line 2) fails to

Figure 7. Zero-shot generalization of our student policy on novel objects from BEHAVE [3] and HODome [109].

achieve optimal performance. While supervised skill learning lays the groundwork, additional PPO fine-tuning is crucial for resolving conflicts among teacher policies. This is important because our subject-based clustering may not effectively distinguish between different interaction patterns, and ambiguity arises when multiple teachers produce different actions for similar motions.

Effectiveness of Transformer for Policy Learning. From Table 2, we see that using a Transformer policy (line 5) outperforms MLP-based approaches, particularly on the test set and out-of-distribution cases generated by the kinematic model. We attribute this to the Transformer's inductive bias in sequential modeling and its capacity to incorporate longer-term observations, enabling it to handle complex spatio-temporal dependencies more effectively.

5. Conclusion

In this work, we introduce a framework for synthesizing realistic human-object interactions that are both physically grounded and generalizable. Unlike previous methods, our approach leverages a rich repository of imperfect MoCap data to facilitate the learning of various interaction skills across a wide variety of objects. To address inaccuracies in the MoCap data, we propose contact-guided rewards and optimize trajectory collection, enabling teacher policies to recover missing physical details in the original data. These teacher policies are used to train student policies within a distillation framework that combines policy distillation and reference distillation, thus enabling efficient skill scaling. Our approach shows zero-shot generalizability, which effectively bridges the gap between imitation and generative capabilities by integrating with kinematic generation. We believe that this framework can be adapted for whole-body loco-manipulation for real-world robots, enabling them to handle objects with human-like dexterity and nuance.

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