ROSE: Reconstructing Objects, Scenes, and Trajectories from Casual Videos for Robotic Manipulation

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Abstract

In this paper, we build a real-to-sim-to-real (Real2Sim2Real) system for robot manipulation policy learning from casual human videos. We propose a new framework, ROSE, that directly leverages casual videos to reconstruct simulator-ready assets, including objects, scenes, and object trajectories, for training manipulation policies with reinforcement learning in the simulation. Unlike existing real-to-sim pipelines that rely on specialized equipment or time-consuming and labor-intensive human annotation, our pipeline is equipment-agnostic and fully automated, facilitating data collection scalability. From casual monocular videos, ROSE enables the direct reconstruction of metric-scale scenes, objects, and object trajectories with physics information in the same gravity-calibrated coordinate for robotic data collection in the simulator. With ROSE, we curate a dataset of simulator-ready scenes from casual videos from our own capture and the Internet, and create a benchmark for real-to-sim evaluation. Across a diverse suite of manipulation tasks, ROSE outperforms the existing baselines, laying the groundwork for scalable robotic data collection and achieving efficient Real2Sim2Real deployment.

1 Introduction

Learning complex manipulation skills from human demonstrations is a long-standing goal in robotics. Casual human videos offer a vast and diverse source of demonstrations, but translating this unstructured visual data into executable robot policies is a significant challenge. Since replicating these scenes in the real world for direct imitation is often impractical or unsafe, a more scalable approach is needed.

This paper develops a real-to-sim-to-real system that bridges this gap, enabling robust policy learning by first reconstructing the essence of a human demonstration within a physically-realistic simulator. Three features need be *simultaneously* present in one *gravity-aligned, metric world frame*: (G) *collidable geometry* for both scene and objects; (P) *physics plausibility* so that contact, scale, and gravity are sensible in simulation (coarse priors over material/density belong here, but exact identification is not the point); and (M) *executable motion*—a time-aligned 6-DoF object trajectory the robot can imitate, replay, or condition on. The minimal sufficient assets that let a robot both plan and act are this G/P/M triad, coherently aligned in world coordinates.

Previous works have explored reconstructing robotics manipulation data from human videos. However, we argue that *four* elements based on the G/P/M triad need to co-occur for turning casual video into robotic data as a scalable data engine—**casual video**, **object trajectory**, **scene**, and **object**. It surfaces where representative methods in Tab. 1 leave gaps. (1) *Being Able to Reconstruct from Casual Video.* Internet-scale demonstrations are predominantly casual (narrow baseline, dynamics).

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Table 1: **Comparison with existing real-to-sim pipelines**. Scene mesh: 3D collision mesh of the scene. Object Mesh: 3D collision mesh of objects. Object Traj.: The 6-DoF pose of objects to be manipulated. Gravity Dir: The gravity direction of the reconstructed scene and objects. Metric Scale: If the reconstructed scene is in metric space (cm). World Coord.: If the reconstructed scene is in the world coordinate. Automation: It is a fully automated pipeline or requires human annotations (*e.g.*, RialTo [57] needs expert human annotation using GUI tools). O: Unknown.

	Characteristics							
Method	Scene Mesh	Object Mesh	Object Traj.	Gravity Dir.	Metric Scale	World Coord.	Automation	**Input / Platform**
RialTo [57]	✓	✓	✓	✓	✓	✓	✗	RGB-Video
Video2Policy [71]	✗	✓	✓	✗	✓	✗	✓	MV-imgs / LiDAR
RL-GSBridge [65]	✗	✓	✗	✗	✗	✓	✗	MV-imgs
SplatSim [46]	✓	✓	✓	✗	✗	✓	✗	RGB-D
ReBot [10]	✗	✗	✓	✗	✓	✓	✓	Video / Mesh
Digital Cousins [7]	O	O	✗	✗	O	✓	✓	Image
Chen et al. [4]	✗	✗	✗	✗	✗	✗	✓	Mesh / Trajectory
URDFormer [5]	✓	✓	✗	✗	✗	✓	✓	MV-imgs
Ditto In the House [19]	✓	✓	✗	✗	✗	✓	O	Image / Interaction
Ours	✓	✓	✓	✓	✓	✓	✓	RGB-Video

GS-based pipelines such as [46, 57, 65] are typically tuned for multi-view, stable captures and are sensitive to dynamics or camera-trajectory violations, which limits robustness under single-take narrow-baseline inputs; several other entries rely on multi-view or controlled capture [4, 5, 7, 10, 19]. (2) *Object trajectory.* A world-aligned 6-DoF object trajectory provides task-resolution signals that planners and policies can directly reuse; video-conditioned control and end-to-end policy learning confirm the value of motion cues [21, 71], while methods emphasizing 3D assets or interaction without exporting an executable, world-frame object trajectory offer less leverage for planning [5, 19, 57]. (3) *Scene.* Object motion is contextual: contact feasibility, clearances, and gravity alignment are defined with respect to the scene; pipelines that do not reconstruct a collidable, metric-scale, gravity-aligned scene (e.g., learning directly from videos without scene geometry [71]) provide limited support for validating contacts or credibly replaying motion. (4) *Object.* Interaction requires an *interactable* object; modern simulators assume well-behaved meshes for stable contact, so policies validated without object geometry risk overfitting to appearance rather than contact-rich behavior. Taken together, partial solutions in Tab. 1 (e.g., scene/object without motion, motion without scene, or assets lacking world/scale/gravity alignment) are valuable components but harder to use as a generalizable engine. Our aim is to deliver *simulator-ready* scene/object meshes and an executable, world-aligned object trajectory from casual video so that downstream planners and policies can both plan and act.

Our thesis is that casual, narrow-baseline videos can be turned into such assets at scale *if* two design choices are made early and enforced end-to-end: first, *unify* camera, metric scale, and gravity so that geometry and motion live in a single world frame throughout; second, treat reconstruction as a high-throughput generator and guard it with a re-rendering consistency gate. We use SSIM with geometric/physical sanity checks to convert long-tail failures into discardable samples before errors cascade. In addition, we treat *physics as plausibility*: we incorporate coarse, category-conditioned priors (e.g., mass estimated by VLM) into the simulation setup to avoid obviously non-physical interactions without over-promising fine identification [34, 47, 62].

Concretely, from a single casual video we (i) recover cameras, metric scale, gravity and physics information; (ii) produce *collidable* scene and object meshes suitable for standard simulators; (iii) estimate an *object-centric 6-DoF trajectory* consistent with that world frame; and (iv) enforce a *post-filtering gate* via differentiable re-rendering and SSIM, complemented by geometric and physical checks. The result is a *simulator-ready* bundle with geometry, physics plausibility and motion produced automatically from casual video.

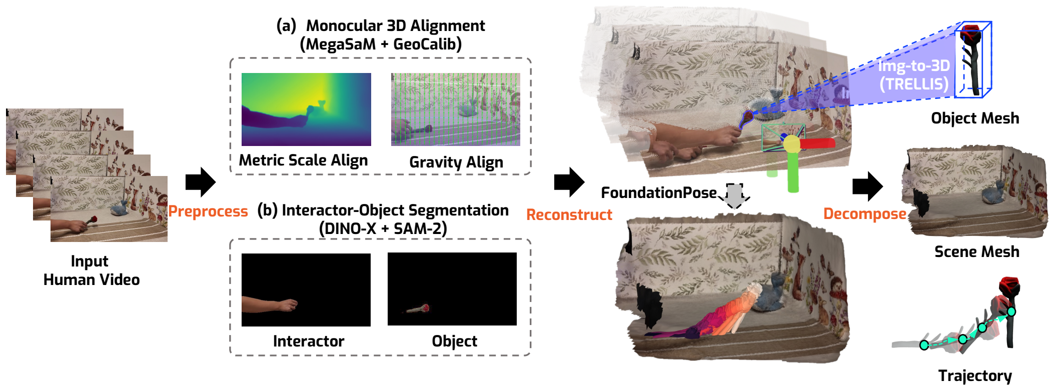

Figure 1: **ROSE Real2Sim pipeline illustration.** (a) We leverage MegaSaM[31] and GeoCalib[58] to reconstruct scene point cloud in the metric-scale and gravity-align world coordinates. (b) We further use SAM-2[48] and DINO-X[49] to detect and track interactor and object mask from videos.

Given only a single RGB camera moving through a real scene, ROSE automatically builds an interactive 3D simulation of that scene, reconstructing the geometry, appearance, and physics information of objects and surfaces. The resulting simulation (a "digital twin" of the scene) can be used to train and evaluate manipulation strategies in a safe and scalable manner. By eliminating much of the manual effort required to create detailed simulated environments, ROSE aims to enable robots to learn and test manipulation policies in faithful virtual replicas of real-world settings, then execute them reliably in the physical world. We collect a large-scale dataset comprising diverse scenes, objects, trajectories, and physically plausible robotic actions for task completion. The dataset includes more than 30 scenes, 50 objects, 600 trajectories, and 3,500 robot action samples.

2 Related Work

2.1 Sim-to-Real RL Policy Transfer

Training robot policies with RL in simulation, followed by a sim-to-real (Sim2Real) policy transfer, has become one of the most successful robot learning strategies in wide applications, such as locomotion [18, 25, 26, 32, 55], loco-manipulation [11, 12, 17, 51], dexterous manipulation [16, 45], *etc*. One advantage of such Sim2Real RL training lies in the low-cost, safe, and more potential in improving generalization through domain / dynamic randosmizations [41, 56], making it a widely adopted alternative to collecting real-world data that is typically time-consuming and labor-intensive. However, such a low-cost and safe simulation training alternative may bring a Sim2Real gap that makes it hard for the Sim2Real policy transfer. To address this issue, a lot of works have been proposed to mitigate the gap, *e.g.*, curriculum learning of Sim2Real constraints [18, 27, 33, 52], teacher-student distillation of privileged information like object states or environment extrinsics [25, 27, 43], 3D awareness [15, 23, 39, 54, 72], and perception augmentation / randomization [1, 2, 6, 9, 35, 50].

2.2 Real-to-Sim Dynamic Scene and Object Transfer

Recently, a lot of efforts in 3D vision have been devoted to creating simulated twins of the real-world scenes / objects from 2D videos [22, 30, 38], which is critical in enriching operating environments when training robot policies in simulation. Generally, transferring real-world scene videos to the 3D simulation that is useful for robot learning involves three key components: i) 3D scene geometry, ii) 3D object geometry, and iii) object dynamics, which requires two key techniques as follows.

Dynamic 3D Scene Reconstruction from 2D focuses on recovering the appearance and geometry of scenes from 2D images or videos. Earlier methods [28, 30, 59, 64, 70] typically rely on dense multiview capture and require significant computational resources to reconstruct dynamic scenes, often using NeRF-based [37] or 3D Gaussian Splatting [24] representations that evolve over time. More recently, with advances in deep multiview stereo [29, 61] and monocular depth estimation [42, 69], a new line of work has emerged that better captures the geometry of dynamic scenes from casual inputs. Notably, approaches such as MegaSaM [31], MonST3R [73], and CUT3R [60] demonstrate robust and efficient dynamic 3D reconstruction from casually captured monocular videos. These methods mark a significant step towards scalable, large-scale scene reconstruction and asset creation for downstream applications like robotics.

3D Object Dynamics from 2D provides the object-level kinematic dynamics encoded as object spatial translation and orientation in 3D, offering valuable priors that help both traditional motion planning methods and learning-based approaches. To capture such object dynamics, various object representations have been used as the policy tracking goal. For example, Bharadhwaj et al. [2] propose to use object and hand segmentation as proxy information, followed by a segmentation image conditioned policy that achieves better generalization.

Meanwhile, some works utilize the point-level flow map of objects or images as the point tracking objective and achieve great progress [3, 8, 13, 67]. Different from relying on such proxy representations, our approach directly collects 6DoF trajectories through pose estimation [63], offering a scalable and efficient solution for acquiring high-quality motion data. Notably, a concurrent work, Video2Policy [71], also proposes to use 6DoF object trajectories as object dynamics. However, Video2Policy only reconstructs the object states and places objects on the same canonical tabletop in a specific robot frame. In contrast, our approach transfers both the dynamic scenes and the objects in the world coordinate, where the world frame reconstruction helps SLAM-based scene reconstruction [31].

3 ROSE:Reconstructing Object, Scene, and Trajectory

3.1 Object Reconstruction

Object Grounding. As shown in Fig. 1, given a target object label from user input or LLM inference, we scan the video frame-by-frame until the object is first detected by DINO-X [49]. The detected bounding box is passed to SAM 2 [48] to obtain the initial target object mask $\mathbf{M}^{\text{init}}$. SAM 2 then propagates this mask through the remainder of the sequence, yielding per-frame object masks $\{\mathbf{M}_t\}_{t=1}^{N}$.

Object Mesh Reconstruction. Using the segmented masks, we leverage TRELLIS [66] to reconstruct the 3D object mesh $\mathcal{M}^{\text{obj}}$, which provides 3D reconstruction pipelines from both single image and multiview images. Since most manipulation videos are filmed from a single viewpoint, we select the initial mask $\mathbf{M}^{\text{init}}$ to reconstruct $\mathcal{M}^{\text{obj}}$. For highly occluded or feature unclear situation, we would use masks from multiple non-occuluded views to reconstruct.

3.2 Scene Reconstruction

Scene Point Cloud Reconstruction. For every video frame $\mathbf{I}_t$, MegaSaM [31] provides the camera intrinsics $\mathbf{K}_t$, the camera pose $\mathbf{G}_t = [\mathbf{R}_t|\mathbf{t}_t]$, and a relative depth map $\mathbf{D}_t^{\text{rel}}$. We feed $\mathbf{I}_t$ to UniDepth [42] to obtain an absolute depth estimate $\mathbf{D}_t^{\text{abs}}$. A global scale factor $\hat{\alpha}$ and offset $\hat{\beta}$ align $\mathbf{D}_t^{\text{rel}}$ to metric depth $\mathbf{D}_t^{\text{align}}$. Each pixel is back-projected using $\mathbf{K}_t$, $\mathbf{G}_t$ and $\mathbf{D}_t^{\text{align}}$ to obtain its corresponding 3D point, which we accumulate into a raw scene point cloud $\mathcal{P}$. Then we apply GeoCalib [58] onto the first frame and obtain a gravity-align transformation $\mathbf{P}^{\text{gravity}}$. Then we apply $\mathbf{P}^{\text{gravity}}$ to each of the following frame to ensure the scene is under the gravity-aligned coordinate.

Scene Mesh Reconstruction. The sparse, hole-ridden point cloud $\mathcal{P}$ yielded by the previous stage is first densified with Neural Kernel Surface Reconstruction (NKSR) [20]; its *detail* hyper-parameter is tuned to close gaps while preserving fine geometry. To satisfy simulator requirements, namely orientability, 2-manifoldness, and self-intersection freedom, we subsequently apply an Alpha Wrapping procedure [44], producing a watertight, validity-guaranteed surface. Finally, color is restored by a point-to-vertex transfer: each mesh vertex inherits the distance-weighted average RGB of its three nearest neighbors in the processed point cloud, yielding a textured, simulation-ready scene mesh $\mathcal{M}^{\text{scene}}$.

3.3 Trajectory Reconstruction

Improved Foundation Pose. Given a set of segmentation masks $\{\mathbf{M}_t\}_{t=1}^{N}$, we employ Foundation-Pose [63] in a model-based setting to estimate the object's 6-DoF pose $\mathbf{P}^{\text{obj}}$. The estimator takes as input the RGB image $\mathbf{I}$, the reconstructed object mesh $\mathcal{M}^{\text{obj}}$ from Sec. 3.1, the camera intrinsics matrix $\mathbf{K}$, and the aligned depth map $\mathbf{D}^{\text{align}}$ from Sec. 3.2. Since FoundationPose assumes metric consistency between depth and mesh, we introduce a scale-alignment procedure.

Specifically, we backproject pixels (u, v) inside $\mathbf{M}^{\text{init}}$ to 3D points $\mathbf{p}(u, v) \in \mathbb{R}^3$ in camera coordinates using $\mathbf{D}^{\text{align}}$ and $\mathbf{K}$. We then compute the maximum pairwise distance among these points,

$$\mathbf{d}^{\text{image}} = \max_{(u_1,v_1),(u_2,v_2)\in\mathbf{M}^{\text{init}}} \|\mathbf{p}(u_1, v_1) - \mathbf{p}(u_2, v_2)\| \tag{1}$$

For the mesh, we compute the maximum vertex-to-vertex distance $\mathbf{d}^{\text{mesh}}$,

$$\mathbf{d}^{\text{mesh}} = \max_{\mathbf{x}_a,\mathbf{x}_b\in\mathcal{M}^{\text{obj}}} \|\mathbf{x}_a - \mathbf{x}_b\|. \tag{2}$$

These yield an initial scale estimate $\rho_0 = \mathbf{d}^{\text{image}}/\mathbf{d}^{\text{mesh}}$.

To account for noise in depth, intrinsics, and occlusions, we refine the scale by a discrete search

$$\rho \in \left[\rho_0/\alpha,\ \rho_0\alpha\right] \quad \text{with step size } s.$$

For each candidate scale ρ, we scale the mesh $\mathcal{M}^{\text{obj}}$, run FoundationPose to obtain the pose $\mathbf{P}^{\text{obj}}(\rho)$, render the corresponding silhouette $\hat{\mathbf{M}}(\rho)$, and select the ρ^* that minimizes the IoU loss with the ground-truth mask $\mathbf{M}^{\text{init}}$:

$$L_{\text{IoU}}(\rho) = 1 - \frac{\sum_{i\in\Omega} \hat{m}_i(\rho)\, m_i}{\sum_{i\in\Omega}\left(\hat{m}_i(\rho) + m_i - \hat{m}_i(\rho)\, m_i\right)}. \tag{3}$$

Here Ω denotes the image domain, $m_i \in \{0, 1\}$ is the ground-truth mask value, and $\hat{m}_i(\rho) \in [0, 1]$ is the rendered mask value at pixel i. We take the final pose as $\mathbf{P}^{\text{obj}} = \mathbf{P}^{\text{obj}}(\rho^*)$ and use it to initialize pose tracking, yielding poses for subsequent frames.

3.4 Post Filtering System

To ensure our pipeline maintains a high level of quality we run each result through a filtering system. In order to holistically evaluate the quality of our results, we combine our reconstructed scene, object, trajectory, and camera poses and render them into a reconstructed video to compare with the original video. This formulation enables our filtering system to remove results which may have malformed object meshes, incorrectly textured scenes, or inaccuracies in trajectory and pose reconstruction as well as filter based on the accumulated error from each of these potential sources over time.

To ensure there is temporally consistent accuracy between our pipeline's reconstruction and original video, our filtering system places the object back into the scene following the reconstructed trajectory from each time step of our pipeline's result. For each object position we render a frame from the corresponding reconstructed camera pose. Upon rendering each of the reconstructed frames, f^{recon}, we compute the SSIM with each of the video's original frames, f^{gt}. We average across all the frames and finally filter results based on an established threshold from previous success and failure cases.

$$\text{SSIM}_{\text{avg}} = \frac{1}{N}\sum_{t=1}^{N} \text{SSIM}(f_t^{\text{recon}}, f_t^{\text{gt}}) \tag{4}$$

$$\text{success} = \begin{cases} 1, & \text{if SSIM}_{\text{avg}} > \text{SSIM}_{\text{thresh}} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

With this filtering system, our pipeline gains the capability to reconstruct scenes from large numbers of casual videos, offering scalability while ensuring that reconstruction quality is maintained.

3.5 Robot Action Collection

Building on the object trajectories reconstructed by the pipeline described above, we further explain how we collect robotic action data to enable the object to follow the trajectory and complete the task. With the reconstructed scene and object, we first load them into the simulator. Given the object's motion, our goal is to control the robot to interact appropriately with the object and guide it along the desired trajectory. We primarily utilize two baseline approaches for diverse robotic action collection: motion planning-based and reinforcement learning-based methods.

Motion Planning. For the motion planning-based algorithm, we first predict an appropriate grasping pose for the object. Once a stable grasp is achieved, the robot follows the object's trajectory using end-effector control based on cuRobo[53]. If the object remains stable and the trajectory is successfully followed, a data sample is considered successfully collected. For this method, we only consider the parallel-jaw gripper setting. In detail, we use GSNet [40] to predict grasp poses based on the point cloud generated in the simulation. After executing a planned trajectory to successfully grasp the object, the robot then follows the trajectory obtained from our vision pipeline to collect valid data.

Reinforcement Learning. Although the motion planning-based method is efficient and easy to implement, it is not sufficient for all scenarios. For example, when using high-dimensional robotic hands, as opposed to simple parallel-jaw grippers, predicting an appropriate grasping pose becomes significantly more challenging. In such cases, reinforcement learning (RL) allows the robot to explore and learn effective grasping strategies to complete the task.

Our RL baseline consists of two stages: object grasping and object manipulation. In the first stage, we design a reward function composed of three terms: a reaching reward r_{reach}, a grasping reward r_{grasp}. In the second stage, we follow the object trajectory generated by our previous pipeline to complete the task. To achieve this, we use CuRobo to control the end-effector and track the trajectory accurately.

It is also worth noting that we explored an end-to-end RL approach without the two-stage setting. While we carefully designed a reward function for trajectory following, we found that it was difficult for the policy to accurately replicate the generated motion, particularly in cases involving complex rotations. This limitation arises from the inherent nature of RL: since learning relies heavily on exploration, it is challenging for a policy to acquire precise trajectory-following behavior, especially when the robot is simultaneously required to grasp and manipulate the object.

3.6 Sim-to-real Transfer

With action data collected, we further train a model for sim-to-real transfer. A key advantage of our vision pipeline is its ability to generate high-quality, simulation-ready scene and object meshes, along with corresponding object trajectories. This enables fast and accurate robotic data collection in simulation. Using this data, we can leverage a high-quality renderer to produce realistic visual datasets. This allows us to train a vision-based robotic model capable of directly transferring to real-world scenarios.

4 Experiments

4.1 Experiment Setup

Our model is able to collect robotic data from diverse datasets from various sources, including outdoor, indoor environments. We benchmarked our real-to-sim method in RoboVerse[14] simulation environment and validated it in both simulation and real-world settings using the Franka arm and Unitree G1 humanoid robots.

4.2 Benchmark Construction

We construct a new benchmark to evaluate the fidelity of real-to-sim-to-real pipeline scene reconstructions from casual monocular videos as shown in Tab. 2. Because existing metrics treat scene layout, object shape, and motion separately, our benchmark fuses them into one holistic evaluation. It provides five simulated environments with full ground-truth geometry, appearance, and trajectories, plus a casually captured video that serves as the pipeline's input. Evaluation uses four metrics: per-frame Chamfer distance between scene point clouds, Chamfer distance for object geometry, and APE/RPE (translation and rotation) for object trajectories. Scores are averaged across frames to yield stable measures. Together, these metrics reveal how well a method recovers both the static environment and the dynamics of the objects within it.

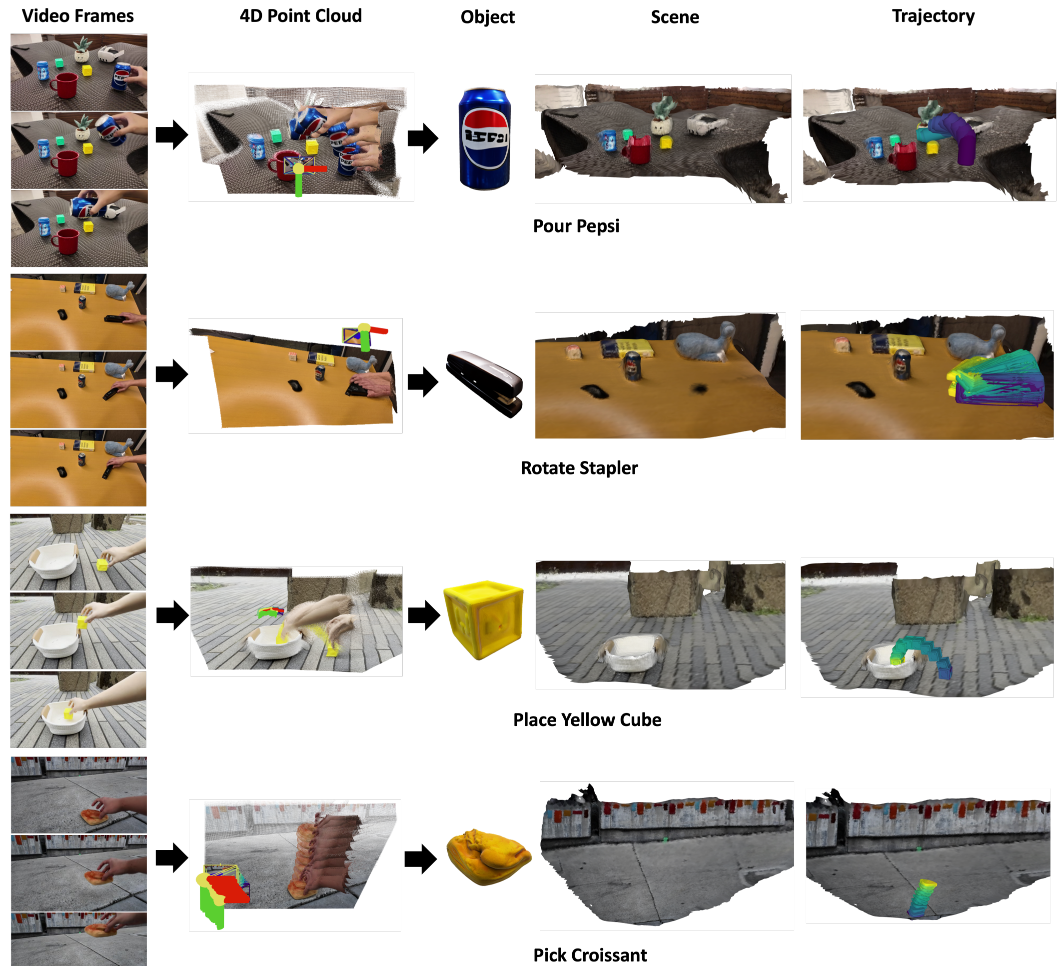

Figure 2: **Qualitative ROSE Real2Sim results.**

Task	Avg. Scene Chamfer Dist.	Object Chamfer Dist.	Translation APE	Rotation RPE	Translation RPE
Unstack	0.6211	0.02158	0.003242	3.724	0.001649
Place	0.6945	0.01060	0.02629	3.804	0.02269
Lift	0.6696	0.02786	0.02208	9.065	0.004374
Push	0.7513	0.01516	0.01086	4.229	0.002170
Rotate	0.6513	0.01394	0.008418	3.508	0.003301
Average	0.6776	0.01782	0.01418	4.866	0.006837

Table 2: **Benchmark comparison across tasks.** ROSE's performance metrics from our benchmark. Avg. Chamfer distance is computed for scene reconstructions, while object metrics include Chamfer distance, Absolute Pose Error (APE), and Relative Pose Error (RPE).

4.3 Data Generation Time and Qualitative Results

With post filtering system we are able to reconstruct scenes from casual videos while maintaining the quality of our results. We present qualitative results on Fig. 2, demonstrating how our pipeline reconstructs geometrically accurate scene, object and object trajectory from casual videos to enable policy training. Additionally we compare the runtime of our pipeline against the runtime of the leading baseline which can be seen in Tab. 3. ROSE reconstructs environments and trajectory data around **8x faster** than the baseline on while remaining accuracy on geometry.

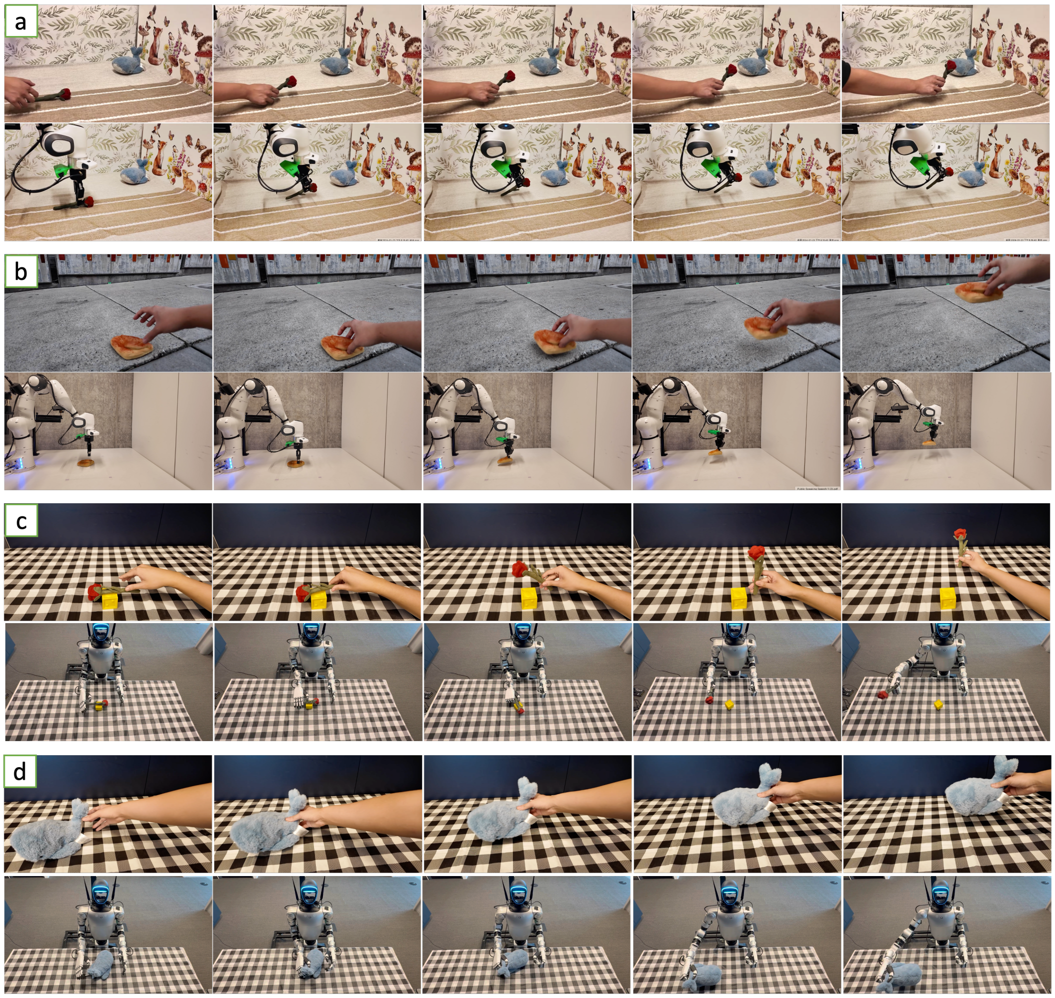

Figure 3: **Qualitative ROSE real-world results.**

Task Name	ROSE (Ours)		Improved V2P	
	Recon Time ↓	SSIM ↑	Recon Time ↓	SSIM ↑
Triangle Move Mouse	**8m46s**	**0.803**	72m39s	0.746
Circle Move Mouse	**8m28s**	**0.789**	71m45s	0.734
Flip Magic Cube	**7m57s**	**0.718**	70m37s	0.598
Rotate Stapler	**8m39s**	**0.715**	83m01s	0.582
Pour Pepsi	**9m22s**	**0.713**	77m58s	0.632

Table 3: **Pipeline Runtime and Reconstruction Quality.** Comparison of ROSE and Video2Policy (V2P) with 3DGS-based scene reconstruction runtimes and SSIM values.

4.4 Robotic Dataset Collection

Leveraging our scene, object, and trajectory reconstruction results, along with our robotic data collection pipeline, we construct a robotic manipulation dataset from monocular video. In the end, we collect **3.5k** valid robotic datasets with diverse task settings and environment variation.

Simulation Environment Setup. Based on RoboVerse [14], we develop a pipeline for generating simulation environments. We use a standardized configuration file to process scene layouts and object meshes. After loading the target robot into the simulation, we perform unit tests to ensure proper setup and collision-free initialization. We then follow the data collection pipelines to gather robotic manipulation data.

Manipulation Benchmark in Simulation. We establish a simulation benchmark to evaluate the performance of different robotic data collection methods. Specifically, we compare our proposed motion-planning-based approach and a two-stage reinforcement learning (RL) method against an end-to-end RL baseline. Our results show that the motion planning-based and two-stage RL methods perform differently across various settings—each demonstrating strengths in different scenarios. Comparing with strong baselines, including the concurrent work Video2Policy [**?**], Our method achieves the best performance on three out of four tasks as well as on the average score as shown in Tab. 4.

Method	PickPepsi	StackBlock	PlaceBowl	MoveTriangle	Average
End-to-End RL	**1.00**	0.00	**1.00**	0.00	0.50
Video2Policy [71]	0.00	0.00	0.40	0.00	0.10
Ours (Motion Planning)	0.80	**1.00**	0.40	0.80	0.75
Ours (Two-stage RL)	**1.00**	0.60	**1.00**	**1.00**	**0.90**

Table 4: **Task completion rate in simulation.**

4.5 Sim-to-Real Transfer

To validate the usefulness of our collected data, we conduct experiments to demonstrate the effectiveness of both the dataset and the trained policy.

Zero-shot Robotic Manipulation and Data Collection. We evaluate our collected robotic data and data collection pipeline in real-world settings. Specifically, we deploy the motion-planning-based method as shown at c and d row in Fig 3 in a physical environment to assess its capability for zero-shot data collection and task execution using only a single demonstration. We test the data collection system across 13 different scenarios, achieving success in 11 of them—resulting in an **84.6%** success. The failure is primarily due to incorrect grasp poses and joint limit violations during motion planning.

Policy Sim-to-Real Transfer. We further train an RGB-based policy in simulation and demonstrate that, using the assets generated by our real-to-sim pipeline, the action data collected in simulation, and high-quality rendering based on RoboVerse [14], the resulting policy can zero-shot generalize to the real world.

5 Conclusion

We presente ROSE, an end-to-end, equipment-agnostic Real2Sim pipeline that lifts casual monocular videos into simulator-ready assets: metric-scale, gravity-aligned scene reconstructions, watertight textured meshes that meet simulator validity constraints, and consistent 6-DoF object trajectories in a unified world frame. The system combines robust geometric recovery with a post-hoc filtering stage that enforces temporal consistency, yielding assets that can be consumed directly by both motion-planning and learning-based controllers. On top of this vision stack, we standardized the handoff to robotics—curating a benchmark that evaluates scene, object, and trajectory fidelity jointly, and building data-collection routines that translate demonstrations into scalable simulation rollouts.

Empirically, ROSE recovers geometry and dynamics with strong fidelity across diverse manipulation tasks and outperforms prior Real2Sim baselines in simulation, while also enabling zero-shot transfer on real robots. Together with the curated assets and 3D reconstructions, these results indicate that high-quality manipulation data can be collected from casual videos at scale, reducing manual environment authoring and separating risky exploration from the real world. We view ROSE as a step toward video-driven Real2Sim2Real at population scal, where casual videos become a training substrate for policies. It standardizes the interface between perception, asset creation, and policy learning, and opens a path to richer, safer, and more diverse robotic data collection.

6 Limitations

Our current scope is restricted to rigid scenes and objects. Articulation, deformable materials, and fluid-like dynamics are not modeled, and we do not yet reason about contact compliance or material parameters beyond simple frictional settings. The object mesh is typically reconstructed from limited viewpoints; under severe occlusion, low texture, specularity, or translucency, geometry and pose tracking may degrade. As with any monocular pipeline, metric scale and intrinsics are estimated rather than measured, making ROSE susceptible to residual scale or gravity misalignment in challenging conditions.

On the control side, our data-collection stack emphasizes parallel-jaw grasping and a two-stage policy structure; purely end-to-end trajectory following proved fragile for complex rotations, and we do not yet leverage force/tactile feedback. Extending ROSE to articulated and deformable objects, multi-object interactions, richer physics priors, tactile sensing, broader robot platforms, and physically informed filtering is an important next step toward making casual videos a dependable substrate for policy learning at scale.

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