Reconstructing Objects along Hand Interaction Timelines in Egocentric Video

Anonymous CVPR submission

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Abstract

We introduce the task of Reconstructing Objects along Hand Interaction Timelines (ROHIT). We first define the Hand Interaction Timeline (HIT) from a rigid object's perspective. In a HIT, an object is first static relative to the scene, then is held in hand following contact, where its pose changes. This is usually followed by a firm grip during use, before it is released to be static again w.r.t. to the scene. We model these pose constraints over the HIT, and propose to propagate the object's pose along the HIT enabling superior reconstruction using our proposed Constrained Optimisation and Propagation (COP) framework. Importantly, we focus on timelines with stable grasps – i.e. where the hand is stably holding an object, effectively maintaining constant contact during use. This allows us to efficiently annotate, study, and evaluate object reconstruction in videos without 3D ground truth.

We evaluate our proposed task, ROHIT, over two egocentric datasets, HOT3D and in-the-wild EPIC-Kitchens. In HOT3D, we curate 1.2K clips of stable grasps. In EPIC-Kitchens, we annotate 2.4K clips of stable grasps including 390 object instances across 9 categories from videos of daily interactions in 141 environments. Without 3D ground truth, we utilise 2D projection error to assess the reconstruction. Quantitatively, COP improves stable grasp reconstruction by $6.2 - 11.3\%$ *and HIT reconstruction by up to* 24.5% *with constrained pose propagation.*

1. Introduction

Accurately reconstructing three-dimensional hand-object interactions is key to unlocking many perception problems, including fine-grained understanding of interactions, but also potential applications in augmented reality, robotic imitation learning and human-machine interactions.

Efforts to reconstruct the object, in-hand, have typically used 3D ground-truth supervision, paired with 3D [4, 50, 65] or 2D input [8, 23, 29, 58, 60]. While such approaches are typically developed to be view-independent, early insights [6, 23, 41] demonstrate that egocentric footage remains significantly challenging, partly due to the considerable occlusion of the object by the hand.

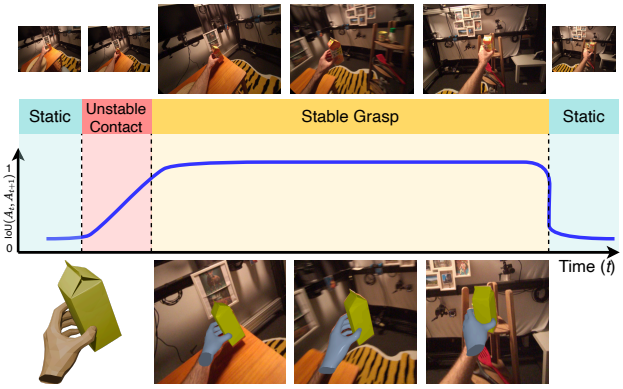

Figure 1. Sample HIT sequence from HOT3D [3] with reconstruction results by our method. We illustrate the three types of temporal segments in hand-object interactions: Static: where the object is static relative to the scene, Unstable Contact: where the hand is firming its grip on the object; and Stable Grasp: where hand is securely holding the object stably, until it is Static again when put down. The plot illustrates the IoU of the in-contact vertices across neighbour frames; for formal definition, refer to Sec. 3.1.

In this work, we particularly focus on egocentric videos, and **for the first time** consider the complete timeline of the interaction – before contact, when in-hand, and after release. We model interactions with *functional intent* – i.e. where the object is operated or moved securely, rather than simply poked or touched. We show that during these functional grasps, the same hand and object vertices remain in contact but the object's pose still changes relative to the hand due to finger and hand articulations.

To estimate the object pose along this timeline, we propose constraints that depend on the type of interaction segment (Static, Unstable Contact or Stable Grasp) as shown in Fig. 1. We propose the Constrained Optimisation and Propagation (COP) framework to optimise the object pose during each interaction segment, then propagate the pose to initialise the next segment. We show sample reconstructions along the HIT in Fig. 2.

To summarise, our contributions are as follows:

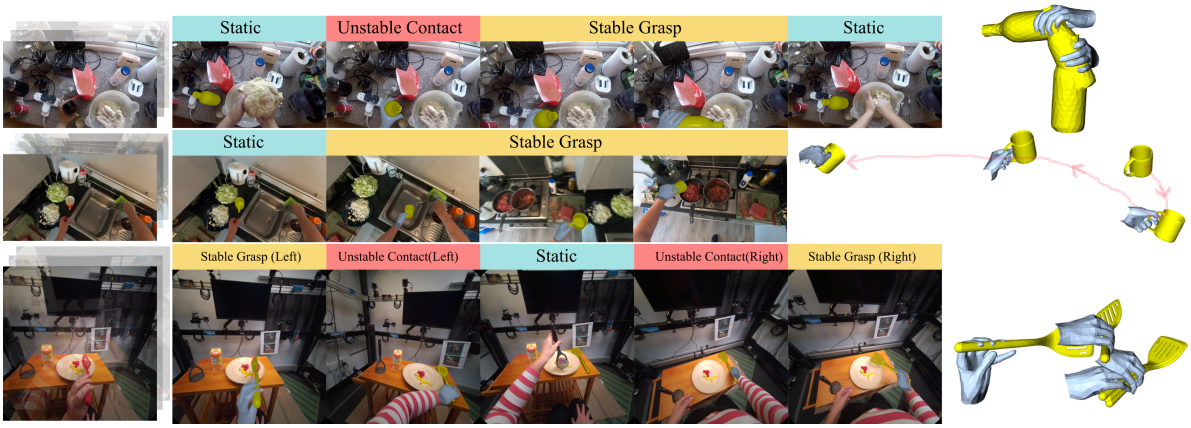

Figure 2. **Qualitative results.** Given a Hand Interaction Timeline (HIT) - with an object in Static, Unstable Contact and Stable Grasp interaction segments, our method, COP, reconstructs hand (blue) and object (yellow) meshes along the HIT. We show input frames (left), projected meshes (middle) and meshes in 3D world coordinate system (right). Rows 1-2 from EPIC-HIT and row 3 from HOT3D-HIT.

- We propose the task of Reconstructing Objects along Hand Interaction Timelines (**ROHIT**) to reconstruct 3D poses, for rigid known objects, in egocentric videos.
- We propose the Constrained Optimisation and Propagation (**COP**) framework that optimises the object pose for various interaction segment types.
- We curate hand interaction timelines from the egocentric HOT3D dataset, to evaluate our method with 3D ground truth. We refer to this as **HOT3D-HIT** dataset.
- We label $2.4K$ stable grasps clips from EPIC-Kitchens, along with 96 HIT, which we call the **EPIC-HIT** dataset.
- We evaluate COP on both datasets and show $6.2 - 11.3\%$ improvement in stable grasp reconstruction and up to 24.5% gain in HIT reconstruction with propagation.

2. Related Works

Here we discuss work on hand pose estimation, object pose estimation and joint hand-object reconstruction. For comparison of hand object reconstruction datasets, see Tab. 1.

3D Hand Pose Estimation. Estimating 3D hand pose from images has been proposed for both free hands and hands in-interactions. FrankMocap [47] is a commonly used CNN-based model in many hand-object reconstruction methods [6, 23, 41, 60, 61]. METRO [34] proposes to use a transformer on top of the CNN feature for regression. WildHands [45] addresses the perspective distortion for egocentric hand pose estimation. Recently, fully transformer-based methods [15, 33, 42, 43, 67] train on scaled training data with higher network capacity, they achieve superior performance. The transformer based HaMeR [42] has been recently used as guidance for full body estimation task [63] to show its usefulness. In this work, our in-the-wild pipeline also uses HaMeR [42] due to its robust performance.

3D Object Pose Estimation. A full review of works on estimating 3D objects pose from single image is out of our scope. Here, we focus on relevance for hand-object interaction scenarios. To estimate 3D object pose, several works [7, 20, 39, 40, 53] assume a known object shape template and estimate 6-DoF pose by fitting it to 2D image features (e.g. masks or keypoints), using either 2D-3D [7, 40] or 3D-3D correspondences [20, 39, 53]. Other methods [19, 57] estimate object pose and shape jointly, however, at the cost of geometric fidelity. While effective, these works typically assume unoccluded objects.

3D Hand-Object Reconstruction. Methods are grouped into two categories. The first category, known-CAD methods, assumes that object CAD models are given and fits 3D shapes into 2D observations. These can further be classified into data-driven [1, 10, 27, 32, 35, 36, 52, 54, 58, 59] or optimisation-based [6, 23, 41] methods. Data-driven methods learn to jointly reconstruct hands and objects from seen object examples, whereas optimisation-based methods address the reconstruction by directly fitting to 2D signals. RHO [6] is the first optimisation based single-frame method. The optimisation-based methods [6, 23, 41] share the same pipeline where hand/object is first independently optimised, followed by joint optimisation with physical constraint terms. In particular, HOMan [23] is a generalisation of the single-frame method that incorporates temporal knowledge through the smoothness of mesh vertices over time and the propagation of object pose initialisation.

The second category, CAD-agnostic methods, estimates the object pose without using explicit CAD models. Many CAD-agnostic methods [8, 9, 22, 29, 44, 60, 62, 64] learn object shape priors, or retrieve from (generative-)object pools [2, 28, 38]. The other line of methods [17, 21, 26, 55] uses neural networks to fit the underlying object shape from multiple views. We experimentally show that CAD-agnostic methods are incapable of generalising to in-the-wild egocentric videos.

Our method belongs to the first category, adopting a simplified assumption needed for the challenges of in-the-wild

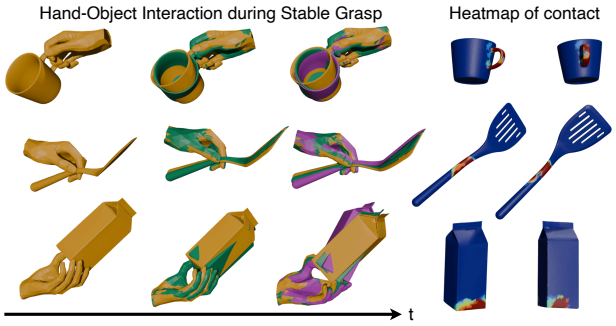

Figure 3. **Stable Grasp Intuition.** Three samples from HOT3D. In each row, we align the hand coordinate system for three frames from one stable grasp. Left: finger articulations and object pose vary over time. Right: contact area (shown as a heat map of objects vertices in contact with the hand) remains consistent.

reconstruction. This also allows us to focus on HIT reconstruction, which has not been attempted before. Different from all previous optimisation-based methods, we examine the object's relative motion through various segments and reconstruct it throughout the HIT.

3. The ROHIT Task

3.1. What is a Hand Interaction Timeline?

A Hand Interaction Timeline (HIT) for a given object is a video sequence that focuses on the hand interacting with one object to either use or move that object. From the object's perspective, the HIT can be divided into many contiguous segments of three types:

- Static: before/after a hand interaction, the object is typically supported by a surface and is thus static relative to the scene/world.
- Stable Grasp: the hand grasps the object firmly, allowing functional usage and secure movement (details below).
- Unstable Contact: the object is neither Static nor in Stable Grasp, *e.g.* when a grip is being formed on the object.

As in Fig 2, the HIT can involve many temporal segments (e.g. Static → Unstable Contact → Stable Grasp → Unstable Contact → Stable Grasp → Static). Our task is to reconstruct the hand-object interaction along the full HIT.

The term Stable Grasp has been previously used in human grasp analysis [5, 12, 18]. While definitions vary, they centre around the object being "held securely with one hand, irrespective of the hand orientation" [18]. Intuitively, this means that *the same hand and object vertices remain in contact for the grasp duration*.

Formally, for any pair of frames i and j within the Stable Grasp, we use S_i and S_j to denote the in-contact area on the object surface, and intersection-over-union $\text{IOU}(S_i, S_j)$ between in-contact areas. Following above intuition, the duration of the stable grasp is defined as:

$$[l^*, r^*] = \underset{l,r}{\text{argmax}}\,(r - l) \quad \text{s.t. } \text{IOU}(S_i, S_j) > \tau \quad \forall l \leq i < j \leq r \tag{1}$$

where τ specifies the minimum IOU threshold. The $\text{argmax}\,(r - l)$ implies the duration of the stable grasp. Importantly, while there is a *consistent contact area*, the hand orientation and finger articulations/poses vary during the stable grasp. This allows the object pose to vary relative to the hand – see Fig. 3.

Similarly if $S_i = \emptyset$, the object is not in contact with the hand and is thus assumed Static. If $S_i \neq \emptyset$ but $\text{IOU}(S_i, S_j) \leq \tau$, the object is in an Unstable Contact.

3.2. ROHIT task and Notations

ROHIT aims to jointly estimate the object poses over hand interaction alone one Hand Interaction Timeline (HIT). This allows reconstructing 3D mesh of the hand and the object, per frame. We assume the knowledge of object category CAD model, as well as the hand-side (left/right) associated with each segment. We also assume the temporal boundaries within the HIT, *i.e.* the start/end of each segment. Note that the assumption of hand side and in-hand segment boundary is implicit in **all prior works** that assume the hand is already grasping the object. These annotations expect the durations (start-end) of the hand grasps as input.

Following prior works [6, 23, 41], we use MANO [46] to represent the **hand mesh**, which takes as input the per-frame finger articulation vector $\theta^n \in \mathbb{R}^{45}$ and outputs the hand mesh with vertices $V_h^n = \text{MANO}(\theta^n) \in \mathbb{R}^{778\times3}$ in the *hand coordinate system*. When unavailable, we utilise an off-the-shelf method [42] to obtain finger articulations for each frame θ^n. Additionally, we utilise the hand-to-camera ($h2c$) pose T_{h2c}^n, which determines the hand wrist orientation and position. T_{h2c}^n is used to transform meshes from the hand coordinate system to the *camera coordinate system* for each frame.

For the **object mesh**, $V_o \in \mathbb{R}^{|V_o|\times3}$ denotes the known object vertices in the *object coordinate system*. We denote the object-to-hand ($o2h$) poses T_{o2h}^n and the object scale $s \in \mathbb{R}$, which transform the object vertices to $V_{o:h}^n$ in the *hand coordinate system* for each frame. Given the hand-to-camera pose T_{h2c}^n, the object mesh in the camera coordinate is represented as

$$V_{o:c}^n = T_{h2c}^n\,(T_{o2h}^n(s * V_o)) \tag{2}$$

Lastly, to reconstruct the HIT in world coordinates, we use the world-to-camera pose T_{w2c}^n. In Static segments (Sec. 4.1) this allows us to represent the object mesh in the camera coordinate as

$$V_{o:c}^n = T_{w2c}^n(T_{o2w}^n(s * V_o)) \tag{3}$$

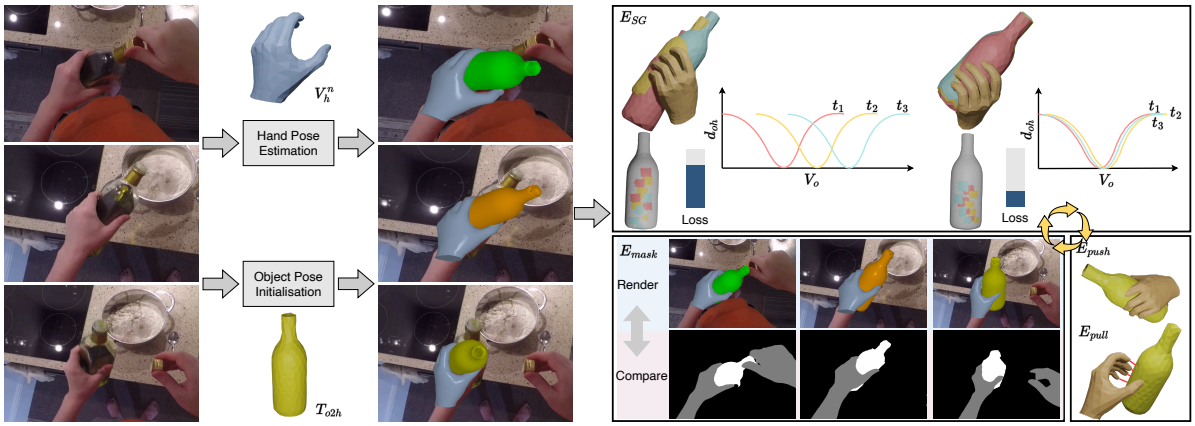

Figure 4. **Optimising the Stable Grasp segment**. We show three frames within one stable grasp. We utilise HaMeR [42] to reconstruct the hand mesh in-the-wild. We initialise T^n_{o2h} to one T_{o2h}, but keep the diverse finger articulations from the hand pose estimates. During optimisation, we measure the distance between each hand vertex and object vertices V_o. In the left plot, we show that the contact area $d_{oh} \approx 0$ differs over time (visualised on the gray bottle). The novel loss, E_{SG}, minimises the variation of distance between the hand and object vertices over time, by adjusting the object's pose relative to the hand. As E_{SG} is minimised, the contact area is aligned (see updated plot). Additional losses are used to regularise the optimisation: E_{mask} renders the reconstruction and compares it against estimated object masks while E_{push} and E_{pull} respectively ensure the object is not penetrated by or away from the hand.

where T^n_{o2w} is object-to-world pose. In Stable Grasp and Unstable Contact segments, the hand-to-world pose T^n_{h2w}, obtained via $T^n_{h2w} = (T^n_{w2c})^{-1} \times T^n_{h2c}$, is used to convert between the hand coordinate and the world coordinate,

$$T^n_{o2w} \underset{T^n_{h2w}}{\overset{(T^n_{h2w})^{-1}}{\rightleftharpoons}} T^n_{o2h} \tag{4}$$

The world-to-camera pose $T^n_{w2c} = (T^n_{c2w})^{-1}$ is provided from egocentric datasets [3, 51] or can be estimated [48].

4. Constrained Optimisation and Propagation

We propose the Constrained Optimisation and Propagation (COP) framework to reconstruct hand-object mesh pairs along the HIT. Our proposal stems from the understanding of the various constraints governing the changing in-contact vertices of the object along the HIT (Fig 1). To accommodate variable length segments, we always use N sampled frames per segment. Once each segment is optimised, using specific constraints, the pose is propagated to initialise the next segment – as object poses have to remain temporally smooth. We first explain the constrained optimisation for each type of segment.

4.1. Optimising a Static Segment

While the object appears moving in the camera due to head motion in an egocentric video, during the Static segment, the object is stationary in the world coordinate system.

Static Constraint. When the object is static, the object-to-world pose T_{o2w} remains fixed across all N frames in the segment, $T_{o2w} = T^n_{o2w}$. We use Eq. (3) to get the object mesh in camera coordinate $V^n_{o:c}$, and optimise T_{o2w} and the scale s using the *render-and-compare* loss.

Render-and-Compare Loss (E_{mask})**:** This loss focuses on estimating a reconstruction that best matches the 2D projections of object masks throughout the sequence. We measure the error via sum of pixel differences:

$$E^n_{mask} = |\mathcal{C}^n_o \otimes (\mathcal{M}^n_o - \Pi(V^n_{o:c}))|^2_2 \tag{5}$$

where $\mathcal{M}^n_o$ is the object mask which we use for supervision and $\Pi(\cdot)$ is the differentiable projection function [30]. $\mathcal{C}^n_o$ is the occlusion-aware mask as in [23, 66] which only computes the error within regions of the object that are not occluded, set to 1 for the object and the background, and 0 for the hand. This masking avoids penalising the missing parts of the object due to hand occlusion.

4.2. Optimising a Stable Grasp Segment

In a stable grasp, the object's pose is controlled by the in-hand contact vertices. We thus optimise the object relative pose w.r.t. the hand, *i.e.* T^n_{o2h}. This is different from optimising the object w.r.t. to the camera [23, 41]. We use Eq. (2) to get the object mesh in camera coordinate frame $V^n_{o:c}$, and optimise T^n_{o2h} and s.

Stable Grasp Constraint. Following the formal definition from 3.1, we use the stable contact area as our constraint to optimise this segment type. Recall that the object pose relative to the hand can change as long as the vertices in contact with the hand remain stable. We introduce a new loss E_{SG} to model this constraint.

Stable Grasp Loss (E_{SG})**:** First, we limit this to the hand vertices that are typically in contact with objects – these are the five fingertips (see supp. for visualisation). More formally, let's denote this subset of hand vertices as $V_F \subset V_h$. For each object vertex $v_o \in V_o$, we calculate the distance

d_{oh} to each $v_h \in V_F$. We then minimize the average variation of this distance across all pairs of frames n and m:

$$E_{SG} = \sum_{v_o \in V_o} \sum_{v_h \in V_F} \sum_{n=1}^{N} \sum_{m=1}^{N} |d_{oh}^n - d_{oh}^m|_1 \quad (6)$$

$$d_{oh}^n := |v_o^n - v_h^n|_2^2 \quad (7)$$

where v_h refers to one hand vertex, with v_h^n representing its location at frame n; similarly, v_o and v_o^n denote the object vertex and its frame-specific location, respectively.

Note that we assume a rigid object, so we can only minimise E_{SG} by updating its overall pose – i.e. translating and rotating the object relative to the hand. As E_{SG} is minimised, the object's pose is optimised so as to minimise the difference between d_{oh}^n and d_{oh}^m for all pairs of frames. Optimising for this distance is the same as aligning the contact area – *i.e.* if two frames have the same hand-object vertex distance, then the contact area will undoubtedly be aligned.

Figure 4 visualises this loss by considering three timestamps for the hand and bottle (t_1, t_2, t_3). We consider a single hand vertex and plot the distance to all object vertices over time. Before optimising the E_{SG} loss, the distances to bottle vertices changes over time – visualised through the d_{oh} coloured curves (left graph). After optimising for E_{SG}, the plots are better aligned (right graph). We visualise the contact area on the bottle before/after minimising E_{SG}.

In addition to this newly introduced loss, we also use E_{mask}, introduced in Eq 5, as in the Static segment enforces the reconstruction to match the observation of the object in the images. We also use two standard physical heuristic losses E_{push} and E_{pull} to ensure contact and avoid mesh penetration between the hand and the object.

Push (E_{push}) and Pull (E_{pull}) Loss : Motivated by previous works [6, 23, 41, 58], E_{push} pushes the object out of the penetrating region against the hand while the balancing loss E_{pull} pulls the object to touch the hand. For calculations of E_{push} and E_{pull}, refer to the supp.

Combining the four losses, the objective function for the Stable Grasp segment becomes:

$$E(\{T_{o2h}^n\}, s) = \lambda_1 E_{SG} + \sum_{n=1}^{N} (E_{mask}^n + \lambda_2 E_{push}^n + \lambda_2 E_{pull}^n) \quad (8)$$

where λ_1 is the weight for E_{SG} and λ_2 is the weight for E_{push}^n and E_{pull}^n and s is the object scale.

The stable grasp optimisation is overviewed in Fig. 4. E_{SG} is key to optimising a Stable Grasp as it optimises jointly across frames. Note that prior work [23] does add temporal smoothing over time, which we experimentally show to be insufficient for accurate optimisation.

4.3. Optimising an Unstable Contact Segment

When the object is beyond the stable grasp, but still in the hand, we only make assumption on the contact with the hand. We thus utilise E_{mask}, E_{push}, E_{pull} losses *without* the stable grasp assumption, *i.e.* set $\lambda_1 = 0$ in Eq. (8).

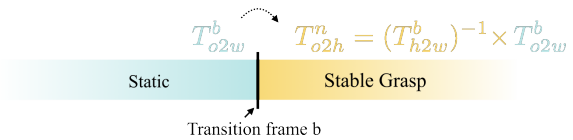

Figure 5. Sample propagation (e.g. from Static to Stable Grasp).

4.4. Pose Propagation in COP

When we optimise along the HIT, each segment is optimised in order. Figure 5 illustrates an example propagation from Static to Stable Grasp segment. Once the segment is optimised, we obtain the object-to-world pose at the last frame, b, which is the transitioning pose to the next segment T_{o2w}^b. Intuitively, the object-to-world pose should be consistent at the transition frame b. Where needed, Eq. (4) is utilised to convert from the hand coordinate into the world coordinate, or back from the world to the hand coordinate.

The optimal pose at b is passed to the next consecutive segment as an additional initialisation. Propagating the object-to-world pose at the transition is key to our proposed propagation. Notice that both the pose of the object and its scale are used to initialise the next segment. We propagate between **all consecutive segments** regardless of the type, *e.g.* Stable Grasp → Static or Static → Unstable Contact.

Each initialisation, including the propagated one, is optimised independently based on the constrained losses for the segment type (Sec 4.1-4.3). We select the pose with the minimum E_{mask} as our method's prediction. This is again passed to the next segment in the HIT, and so on.

5. Experiments

5.1. Dataset

With the definition of HIT and Stable Grasp in Sec. 3.1, we annotate timelines from unscripted egocentric videos. In HOT3D [3], we automatically annotate HITs from the 3D ground truth – we refer to these sequences as **HOT3D-HIT**. Object masks are provided by the ground truth. In EPIC-KITCHENS [13], we manually annotate HIT segments for 9 rigid and commonly used object categories (plate, bowl, bottle, cup, mug, can, pan, saucepan, glass). Corresponding object masks are available from the VISOR dataset [14]. We refer to this datasets as **EPIC-HIT**.

We compare against existing datasets in hand-object reconstruction in Tab. 1 (full table in supp.). For HOT3D, we automatically extract 1,239 stable grasps and extend them to 113 HITs covering 3,288 segments (w/ 872 Static and 1177 Unstable Contact). For EPIC-KITCHENS, we labelled 2,431 video clips of Stable Grasp from 141 distinct videos in 31 kitchens. We additionally manually label 96

Table 1. **Dataset Comparison**. Here we compare various characteristics and labels provided by various datasets. We also show statistics of Stable Grasp and HIT (when available). †: subjects in the released train/val set

Dataset	Year	Characteristics			Labels			Stable Grasps' Stats					HIT's Stats			
		In-the-wild	Funct. Intent	Ego	Pose GT	Stable Grasp	HIT	#Env	#Sub	#Cat	#Inst	#Seq	Avg. Duration	#frames	Avg. Seg. Per HIT	#Seq
HOI4D [37]	2022	✗	✓	✓	3D	✗	✗	610	9	20	800	5,000	-	-	-	-
ARCTIC [16]	2023	✗	✓	✓	3D	✗	✗	1	9†	11	11	339	-	-	-	-
HOGraspNet [11]	2024	✗	✗	✓	3D	✓	✗	1	99	30	30	~3861	-	-	-	-
HOT3D [3]	2024	✗	✓	✓	3D	✗	✗	4	19	33	33	295	-	-	-	-
HOT3D-HIT (ours)	2025	✗	✓	✓	3D	✓	✓	4	9	22	22	1,239	121.1s	410,650	29.1	113
MOW [6, 41]	2021	✓	✓	✗	✗	✗	✗	500	500	121	500	500	-	-	-	-
EPIC-HIT (ours)	2025	✓	✓	✓	2D Mask	✓	✓	141	31	9	~390	2,431	13.8s	79,736	2.8	96

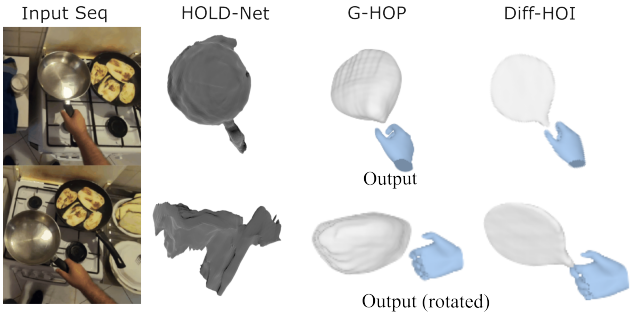

Figure 6. **Reconstruction based approach** [17, 61, 62] fail for in-the-wild egocentric videos. See supp. for more examples.

HITs, covering 296 segments (135 Static, 106 Stable Grasp, and 28 Unstable Contact). Details in supp.

5.2. Implementation Details

Following HOMan [23], we sparsely and linearly sample 30 frames from each segment for optimisation and evaluation. For each object, we use 10 rotation initialisations and 1 global translation to initialise T_{o2h}, following [23]. The error E_{mask} is defined in pixels whilst E_{SG}, E_{push} and E_{pull} are defined in 3D space (metres). We use the camera's focal length f as a scaling factor: $\lambda_f = f * \texttt{render_size}$. We use $\texttt{render_size} = 256$ and set $\lambda_1 = \lambda_f$ and $\lambda_2 = 0.1 * \lambda_f$ (Eq 8). The optimisation takes on average 30s on a RTX 4090 for one 30-frame segment. Please refer to the supp. for additional implementation details.

5.3. Baselines and Quantitative Metrics

We focus on baselines that are able to reconstruct object poses in the hand, using a predefined CAD model. Since COP does not require training, we do not compare with data-driven methods [16, 35, 35, 58, 59]. We compare to:

- **HOMan** [23]—A common CAD-based baseline that progressively optimises the object pose relative to the hand. HOMan implements temporal smoothing and uses E_{pull} and E_{push}. Similar to our method, we use VISOR [14] masks for fair comparison.
- **Rigid** [49]—assumes that objects are not allowed any motion within grasp, minimising overall rotation and translation of the object relative to the hand.
- **Dynamic**—A variation of COP without the stable grasp constraint ($\lambda_1 = 0$).

We note that RHOV [41] is a relevant baseline but no code is available to be used as a baseline. CAD-agnostic methods [17, 44, 56, 60, 61] fail catastrophically on our datasets (see Fig. 6) making them unsuitable as baselines.

We use two standard metrics for evaluation with/without 3D ground truth, suitable for all segment types:

Average Distance (ADD) is the standard metric for methods with 3D ground truth. Following [11, 24, 31, 57], we measure the distance of corresponding vertices between GT and predicted object vertices, and average it over vertices and frames. ADD is 1 for a sequence if average distance is less than 10% of the object's diameter, and 0 otherwise. In symmetric CAD models, we calculate the minimal average distance among the valid symmetric transformations [25].

Intersection-over-Union (IOU). We use IOU as a proxy of pose accuracy when 3D GT is *not* available. We measure IOU between ground truth mask and rendered mask for the object in camera view. We report average IOU across all frames. In case of occlusion with other components, only the non-occluded area of the rendered projection is used.

We also propose variations of these standard metrics that particularly measure the Stable Grasp in HIT:

Average Stable Contact Area at ADD Success (SCA-ADD). When a pose is considered correct for a sequence, *i.e.* average distance is within 10% of the object's diameter and thus ADD is 1, we measure the stable contact area across the sequence, defined as the average IOU of in contact area between all pairs of frames (Sec. 3.1). SCA-ADD is set to 0 when ADD is 0 (average distance below threshold). We average SCA-ADD over all examples. We use this metric to showcase our ability to reconstruct stable grasps.

Average Stable Contact Area at high IOU (SCA-IOU). We analogously report SCA when IOU is more than certain thresholds. We use 80% as threshold on HOT3D, and report both 80% and 60% on EPIC. SCA-IOU is set to 0 when IOU is below the threshold. We report average SCA-IOU.

IOU vs. SCA-IOU. Note that IOU and SCA-IOU can be contradictory. A method can maximise IOU by individually fitting to each mask, resulting in a lower SCA-IOU. Using both metrics allows us to understand the performance of different baselines versus our proposed COP.

Table 2. **Results on Stable Grasp in HOT3D-HIT.** Green for best and yellow for second best. COP† is COP w/o propagation.

Category	SCA-IOU				ADD				SCA-ADD			
	HOMan [23]	Rigid [49]	Dynamic	COP†	HOMan [23]	Rigid [23]	Dynamic	COP†	HOMan [23]	Rigid [49]	Dynamic	COP†
bottle_bbq	23.1	39.2	34.2	43.5	4.9	30.5	52.4	57.3	3.8	16.9	21.0	26.7
bottle_mustard	15.2	16.8	23.2	32.3	0.0	12.5	37.5	37.5	0.0	5.9	14.9	18.3
bottle_ranch	16.8	33.3	32.9	40.4	9.1	31.8	50.0	56.8	5.9	17.4	19.6	25.4
bowl	39.4	53.4	32.8	48.7	36.5	84.9	84.9	89.7	23.3	44.8	28.5	43.7
can_parmesan	29.1	44.8	32.8	43.5	0.0	19.0	27.0	30.2	0.0	9.0	10.4	14.7
can_soup	32.4	50.3	37.1	50.6	3.0	14.1	21.2	26.3	2.5	6.7	7.6	13.8
can_tomato_sauce	36.2	46.3	33.2	45.8	2.0	2.9	9.8	9.8	1.6	1.1	3.2	4.2
carton_milk	24.9	27.5	29.8	38.3	0.0	35.3	17.6	29.4	0.0	15.8	6.0	14.5
carton_oj	5.5	35.0	25.6	39.3	0.0	31.2	43.8	43.8	0.0	16.2	14.4	20.6
cellphone	49.3	8.3	17.6	23.0	42.3	9.6	23.1	25.0	31.6	6.7	8.5	14.0
coffee_pot	27.1	42.4	35.5	43.7	18.4	57.1	71.4	75.5	15.3	29.1	28.1	35.2
dino_toy	24.8	15.9	38.6	40.5	33.3	66.7	72.2	77.8	24.8	32.7	34.5	39.7
food_vegetables	43.0	41.6	40.7	48.9	9.5	23.8	33.3	23.8	8.4	14.1	18.7	13.2
keyboard	37.6	31.8	21.9	31.4	60.9	84.1	92.8	91.3	35.6	29.4	19.8	28.1
mouse	48.3	59.3	44.5	56.3	18.6	39.5	67.4	72.1	13.8	28.9	34.1	43.8
mug_white	15.2	33.1	30.9	42.4	11.1	28.9	37.8	57.8	8.1	15.9	17.5	28.9
plate_bamboo	36.6	56.3	33.6	55.1	35.6	81.4	89.8	93.2	24.4	50.0	30.5	50.5
potato_masher	2.2	5.3	17.7	26.5	4.9	50.5	47.6	29.4	2.9	28.3	15.4	25.2
puzzle_toy	37.1	46.4	32.1	44.8	24.4	54.9	51.2	64.6	17.9	29.2	19.1	31.7
spatula_red	1.3	14.6	26.7	35.4	4.8	50.8	76.2	85.7	3.3	33.0	24.6	35.4
whiteboard_eraser	23.0	42.6	36.0	42.1	20.0	80.0	100.0	100.0	9.9	37.8	36.0	42.1
whiteboard_marker	30.4	49.2	37.4		0.0	100.0	66.7	45.7	0.0	71.2	27.3	35.4
Average	27.8	37.4	30.8	**42.0**	16.8	43.0	51.9	**58.1**	11.5	22.9	18.4	**26.8**

Table 3. **Results on Stable Grasp in EPIC-HIT.** Green for best and yellow shows the second best. COP† is COP w/o propagation.

Category	IOU				SCA@0.8				SCA@0.6			
	HOMan [23]	Rigid [49]	Dynamic	COP†	HOMan [23]	Rigid [49]	Dynamic	COP†	HOMan [23]	Rigid [49]	Dynamic	COP†
bottle	56.6	66.0	75.5	72.2	3.5	16.4	21.8	29.6	5.7	51.9	36.6	56.3
bowl	54.2	52.9	57.9	55.1	1.0	10.5	9.3	11.9	1.6	28.2	19.7	32.0
can	47.5	49.8	55.2	53.6	3.5	12.7	13.0	16.5	5.3	24.1	19.4	28.1
cup	56.9	61.4	67.5	66.1	5.5	12.4	16.5	20.0	7.8	43.2	38.9	49.7
glass	55.4	57.6	65.2	63.1	3.0	10.0	14.8	15.9	4.2	36.3	30.1	40.9
mug	59.4	58.1	63.8	62.1	3.9	6.5	6.3	9.2	6.6	36.3	29.6	42.5
pan	48.3	45.8	48.9	42.4	0.5	4.5	4.3	3.5	1.9	18.6	12.8	15.1
plate	61.1	61.5	68.1	65.3	1.0	15.5	17.6	22.5	1.6	39.3	30.1	46.4
saucepan	51.1	53.1	57.5	54.4	0.4	3.1	5.4	5.3	2.4	32.7	25.7	31.1
Average	54.8	55.8	**61.7**	58.2	1.9	10.6	12.2	**15.0**	3.3	33.4	25.2	**36.5**

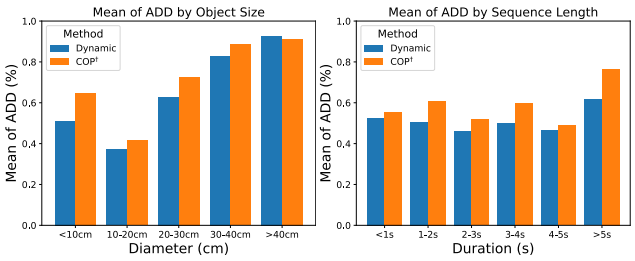

Figure 7. Improvement of COP over Dynamic method for different object sizes (left) and Stable Grasp lengths (right).

5.4. Results and Ablation

Stable Grasp in HOT3D-HIT. We first study the reconstruction of Stable Grasp segments. To ensure fair comparison, here COP does not employ propagation. Table 2 contains per-category results for Stable Grasp in HOT3D-HIT. On average, COP improves ADD from 51.9% with the dynamic assumption to 58.1% within the Stable Grasp, and improves SCA-ADD from 22.9% with the rigid assumption to 26.8%. Categories like "potato_masher" significantly improve in ADD score (+16.5%). The baseline 'Rigid' has high SCA-ADD, but ADD is significantly lower than COP. HOMan [23] performs badly on most categories as the contact is not maintained through its iterative optimisation.

In Fig. 7, we investigate the impact of Stable Grasp sequence length and different object sizes. COP consistently outperforms Dynamic, only dropping slightly for large objects in HOT3D. Moreover, COP performs significantly better for smaller objects and on long sequences.

Stable Grasp in EPIC-HIT. Table 3 contains analogous per-category results for Stable Grasp in EPIC-HIT. COP outperforms baselines on the SCA metric. Dynamic performs well on IOU, as it fits to each mask individually but *does not* maintain a stable grasp indicated by the lower SCA metric. Rigid achieves best SCA results on the "pan" category only – indicating the functional hold of the pan does not allow finger articulations. Figure 8 shows reconstruction results of COP on Stable Grasp in EPIC-HIT.

HIT in HOT3D-HIT. In Tab. 4, we show quantitative results on the full timelines (HIT) reconstruction on HOT3D-HIT. Improvements can be seen across the board – ADD in Stable Grasp segments is improved by 12.2% and Static segments benefits also, improving by 14.5%. This highlights that COP with propagation improves the reconstruc-

Figure 8. **Qualitative Results on Stable Grasp in EPIC-HIT** (2 examples/category): projected reconstruction results and reconstruction in rotated views. Bottom: failure cases due to wrong hand pose (left) and extreme occlusion (right).

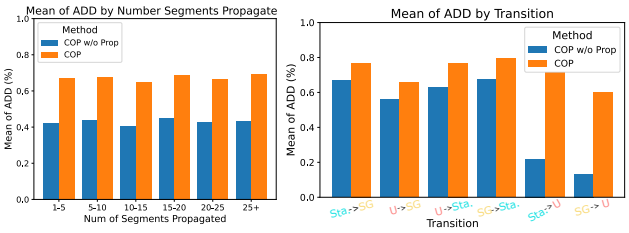

Figure 9. Impact of propagation on segment count and types.

tion across all segment types.

Figure 9 summarises the impact of propagation on HITs with different segment count and types. Improvement is consistent across counts. Notably, transition to Unstable Contact shows significant improvement in ADD.

HIT in EPIC-HIT. In Tab. 5 we report analogous results on EPIC-HIT. COP again shows consistent improvements over all metrics across different types of segments. We show qualitative results for HIT reconstruction in Fig. 2.

Ablation on the constraint in Eq. (6). Recall that in E_{SG}, we first index every object vertex $v_o \in V_o$, compute its distance to each finger tips vertex, then constrain the variation over all pairs of frames. In Tab. 6, we ablate two variants, aiming to maximise the stable contact area: i) select the nearest object vertex v_o^* corresponds to each $v_h \in V_F$, instead of selecting all object vertices V_o; ii) select N consecutive frames to constrain d_{oh}. The results show that our constraint performs the best.

Ablation on the weights in Eq. (8). In Tab. 7, we ablate the weights λ_1 and λ_2 introduced in the loss function Eq. (8). The results suggest that E_{SG} is important while the physical heuristics E_{pull} and E_{push} are also necessary. Dynamic is equivalent to $\lambda_1 = 0$ and $\lambda_2 = 0.1$.

Additional Results. In supp., we (i) ablate the robustness to noise in the segment boundaries along the HIT; (ii) report results on stable grasp segments from the ARCTIC dataset [16] with matching conclusions; and (iii) show further examples of failure of CAD-Agnostic methods on in-the-wild recordings.

Table 4. Results on HOT3D-HIT

Method	Stable Grasp		Static	Unstable Contact
	ADD	SCA-ADD	ADD	ADD
COP *w/o Propagation*	58.1	26.8	64.7	17.3
COP	**70.3**	**34.1**	**79.2**	**67.1**

Table 5. Results on EPIC-HIT

Method	Stable Grasp		Static	Unstable Contact
	IOU	SCA@0.8	IOU	IOU
COP *w/o Propagation*	68.0	23.8	65.8	74.3
COP	**69.2**	**25.5**	**68.3**	**79.0**

Table 6. Ablation on the Stable Grasp Loss E_{SG} variants on HOT3D. We show improvement over the Dynamic Baseline

Obj. Vert. Selection	Frames Selection	ADD	SCA-ADD
V_o	N^2 pairs	58.1 (+6.2)	26.8
v_o^*	N^2 pairs	52.9 (+1.0)	21.3
V_o	N consecutive	54.2 (+2.3)	22.5
Dynamic Baseline		51.9 (+0.0)	18.4

Table 7. **Ablation on the loss weights.** Chosen λ_1 and λ_2 in blue

λ_1	λ_2	ADD	SCA-ADD
0	0.1	51.9	18.4
1	0	54.8	25.0
1	0.1	58.1	26.8
10	0.1	51.5	26.6

6. Conclusion

We proposed the Reconstructing Objects along Hand Interaction Timelines (ROHIT) task – which aims to reconstruct an object along time including when the object is static in the scene, in an stable or unstable grasp. To tackle the task, we propose the Constrained Optimisation and Propagation (COP) framework which builds around Stable Grasp and propagates poses across segments for superior reconstruction. We propose HOT3D-HIT (with 3D ground truth) and EPIC-HIT (in-the-wild) datasets to evaluate COP. We highlight the efficacy of stable grasp and pose propagation on both datasets. By reconstructing full timelines, we hope to encourage future works to quantitatively evaluate timeline reconstruction methods in-the-wild.

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