

TOCH: Spatio-Temporal Object Correspondence to Hand for Motion Refinement

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Abstract. We present TOCH, a method for refining incorrect 3D hand-object interaction sequences using a data prior. Existing hand trackers, especially those that rely on very few cameras, often produce visually unrealistic results with hand-object intersection or missing contacts. Although correcting such errors requires reasoning about temporal aspects of interaction, most previous work focus on static grasps and contacts. The core of our method are TOCH fields, a novel spatio-temporal representation for modeling correspondences between hands and objects during interaction. The key component is a point-wise object-centric representation which encodes the hand position relative to the object. Leveraging this novel representation, we learn a latent manifold of plausible TOCH fields with a temporal denoising auto-encoder. Experiments demonstrate that TOCH outperforms state-of-the-art (SOTA) 3D hand-object interaction models, which are limited to static grasps and contacts. More importantly, our method produces smooth interactions even before and after contact. Using a single trained TOCH model, we quantitatively and qualitatively demonstrate its usefulness for 1) correcting erroneous reconstruction results from off-the-shelf RGB/RGB-D hand-object reconstruction methods, 2) de-noising, and 3) grasp transfer across objects. We will release our code and trained model on our project page at <http://virtualhumans.mpi-inf.mpg.de/toch/>.

Keywords: hand-object interaction, motion refinement, hand pose estimation

1 Introduction

Tracking hands that interact with objects is an important part of many applications in Virtual and Augmented Reality, gaming, and is required to learn digital humans capable of human-like manipulation tasks. Although there exists a vast amount of literature in tracking hands in isolation, much less work has focused on joint tracking of objects and hands. The high degrees of freedom of the hands, the frequent occlusions, noisy or incomplete observations (*e.g* lack

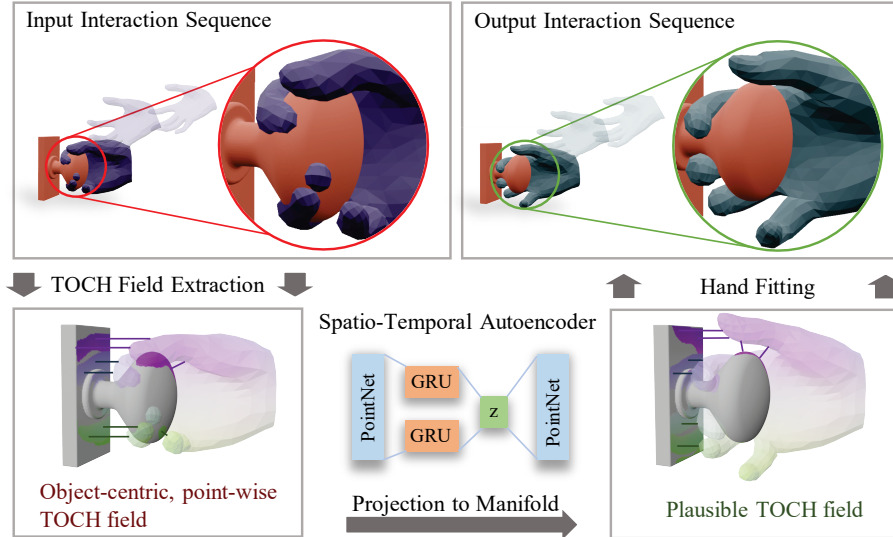


Fig. 1: We propose TOCH, a model for correcting erroneous hand-object interaction sequences. TOCH takes as input a tracking sequence produced by any existing tracker. The hand-object mesh sequence is first converted to a TOCH field, a novel object-centric correspondence representation. The extracted TOCH field is then fed into an auto-encoder, which projects it onto a learned hand motion manifold. Lastly, we obtain the corrected tracking sequence by fitting hands to the reconstructed TOCH field. TOCH is applicable to interaction sequences even before and after contact happens.

of depth channel in RGB images) make the problem heavily ill-posed. We argue that tracking hands interacting with objects requires a powerful prior about common hand interactions conditioned on the object shape.

Modeling hand-object interaction realistically is extremely challenging. Beyond the aforementioned challenges, subtle errors in the estimation have a huge impact on the perceived realism. For example, if the 3D object is floating in the air, grasped in a non-physically plausible way, or the hand and object interpenetrate, the perceived quality will be poor. Unfortunately, such artifacts are common in SOTA hand-tracking methods, and those errors are not well reflected in the typically reported metrics. Researchers have used different heuristics to improve plausibility, such as inter-penetration constraints [25] and smoothness priors [23]. A recent line of work predicts likely static hand poses and grasps for a given object [32,21], but those methods can not directly be used as a prior to fix common tracking and capturing errors. Although there exists work to refine wrong hand-object interactions [56,20], it does not consider motion sequences.

In this work, we propose TOCH, a data-driven method for refining noisy 3D hand-object interaction sequences. In contrast to previous work in interaction modeling, TOCH does not only consider static interactions but can also be ap-

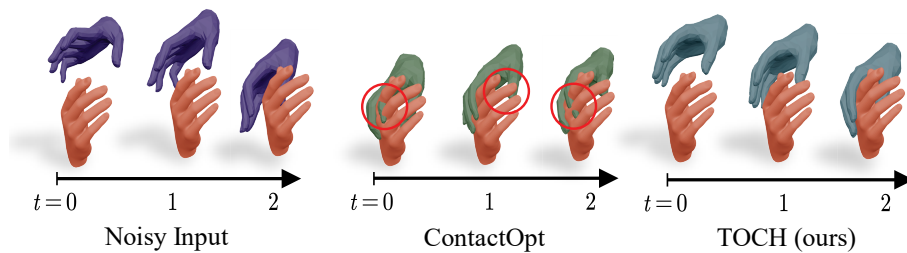


Fig. 2: Example refinement of an interaction sequence. Left: a noisy sequence of a hand approaching and grasping another static hand. Middle: ContactOpt [20] always snaps the hand into grasping posture regardless of its position relative to the object, as it is not designed for sequences. Right: TOCH preserves the relative hand-object arrangement during interaction while refining the final grasp.

plied to sequences without introducing snapping artifacts. The whole approach is outlined in Figure 1. Our key insight is that estimating point-wise, spatio-temporal object-hand correspondences are crucial for realism, and sufficient to constrain the high-dimensional hand poses. Thus, the point-wise correspondences between object and hand are encoded in a novel spatio-temporal representation called *TOCH field*, which takes the object geometry and the configuration of the hand with respect to the object into account. We then learn the manifold of plausible TOCH fields from the recently released MoCap dataset of hand-object interactions [56] using an auto-encoder and apply it to correcting noisy observations. In contrast to conventional binary contacts [9,20], TOCH fields also encode the position of hand parts that are not directly in contact with the object, making TOCH applicable to whole interaction sequences, see Figure 2. TOCH has further useful properties for practical application:

- As demonstrated by our experiments, TOCH can effectively project implausible hand motions to the learned object-centric hand motion manifold and produce visually correct interaction sequences that outperform previous static approaches.
- By virtue of the rotation and translation invariance of the TOCH field representation, it only requires a small amount of data to learn a manifold of plausible interactions.
- Since TOCH does not depend on a specific sensor (RGB image, depth map, IMUs), its integration with trackers is flexible.
- Our method is superior to the current SOTA (ContactOpt [20]), while being an order of magnitude faster.

2 Related Work

2.1 Hand and Object Reconstruction

Hand Reconstruction and Tracking. Reconstructing 3D hand surfaces from RGB or depth observations is a well-studied problem [28]. Existing work can gen-

erally be classified into two paradigms: discriminative approaches [18,12,71,41,7] directly estimate hand shape and pose parameters from the observation, while generative approaches [55,57,59] iteratively optimize a parametric hand model so that its projection matches the observation. Recently, more challenging settings such as reconstructing two interacting hands [64,44,53] are also explored. These work ignore the presence of objects and are hence less reliable in interaction-intensive scenarios.

Joint Hand and Object Reconstruction. Jointly reconstructing hand and object in interaction [46,3,61,54,65,66,48] has received much attention. Owing to the increasing amount of hand-object interaction datasets with annotations [26,22,9,17,73,36], deep neural networks are often used to estimate an initial hypothesis for hand and object poses, which are then jointly optimized to meet certain interaction constraints [26,23,13,24,11]. Most work in this direction improve contact realism by encouraging a small hand-to-object distance and penalizing inter-penetrating vertices [30,3]. However, these simple approach often yield implausible interaction and do not take the whole motion sequence into account. In contrast, our method alleviates both shortcomings through a object-centric, temporal representation that also considers frames in which hand and object are not in direct contact.

2.2 Hand Contact and Grasp

Grasp Synthesis Synthesizing novel hand grasp given an object is a popular research direction in robotics [52]. Traditional approaches either optimize for force-closure condition [15] or sample and rank grasp candidates based on learned features [6]. There are also hybrid approaches that combine the merits of both [42,37]. Recently, a number of neural network-based models are proposed for this task [25,56,14,72,29]. In particular, Karunratanakul *et al.* [32,31] represent the hand-object proximity as an implicit function. Taking inspiration from this, we represent the hand relative to the object by a set of signed distance values distributed on the object surface.

Object Manipulation Synthesis. Compared with static grasp synthesis, generating dexterous manipulation of objects is a more difficult problem since it additionally requires dynamic hand and object interaction to be modeled. This task is usually approached by optimizing hand poses to satisfy a range of contact force constraints [39,63,43,70]. Hand motions generated by these work are physically plausible but lack natural variations. Zhang *et al.* [67] utilized various hand-object spatial representations to learn object manipulation from data. An IK solver is used to avoid inter-penetration. We took a different approach and solely use an object-centric spatio-temporal representation, which is shown to be less prone to interaction artifacts.

Contact Refinement. Recently, some work focus on refining hand and object contact [56,62,20]. Both [62] and [20] propose to first estimate the potential contact region on the object and then fit the hand to match the predicted contact. However, limited by the proposed contact representation, they can only model

hand and object *in stable grasp*. While we share a similar goal, our work can also deal with the case where the hand is *close to* but not in contact with the object, as a result of our novel hand-object correspondence representation. Hence our method can be used to refine a tracking sequence.

2.3 Pose and Motion Prior

It has been observed that most human activities lie on low-dimensional manifolds [16,60]. Therefore natural motion patterns can be found by applying learned data priors. A pose or motion prior can facilitate a range of tasks including pose estimation from images or videos [5,2,40], motion interpolation [38], motion capture [68], and motion synthesis [27,1,10]. Early attempts in capturing pose and motion priors mostly use simple statistical models such as PCA [47], Gaussian Mixture Model [5] and Gaussian Process Dynamical Model [60]. With the advent of deep generative models [33,19], recent work rely on auto-encoders [49,34] and adversarial discriminators [69,35] to faithfully capture the motion distribution.

Compared to body motion prior, there are less work devoted to hand motion prior. Ng *et al.* [45] learned a prior of conversational hand gestures conditioned on body motion. Our work bears the most similarity to [21], where an object-dependent hand pose prior was learned to foster tracking. Hamer *et al.* [21] proposed to map hand parts into local object coordinates and learn the object-dependent distribution with a Parzen density estimator. The prior is learned on a few objects and subsequently transferred to objects from the same class by geometric warping. Hence it cannot truly capture the complex correlation between hand gesture and object geometry.

3 Method

In this section, we describe our method for spatio-temporal refinement of hand pose sequences during interaction with an object. We begin by introducing the problem and outline our approach. Let $\mathbf{H} = (\mathbf{H}^i)_{1 \leq i \leq T}$ with $\mathbf{H}^i \in \mathbb{R}^{K \times 3}$ denote a sequence of vertices that describe hand meshes over the course of an interaction over T frames. We only deal with sequences containing a single hand and a single rigid object mesh, whose vertices we denote as $\mathbf{O} \in \mathbb{R}^{L \times 3}$. We assume the object shape to be known. Since we care about hand motion relative to the object, in the following we express the hands in object local space, and the object coordinates remain fixed over the sequence. The per-frame hand vertices \mathbf{H}^i in object space are produced by a parametric hand model MANO [51] using linear blend skinning:

$$\mathbf{H}^i = \text{LBS}(\mathbf{Y}; \boldsymbol{\beta}, \boldsymbol{\theta}^i) + \mathbf{t}_H^i. \quad (1)$$

where the parameters $\{\boldsymbol{\beta}^i, \boldsymbol{\theta}^i, \mathbf{t}^i\}$ denote shape, pose and translation w.r.t. template hand mesh \mathbf{Y} , respectively.

Observing the hand-object motion through RGB or depth sensors, a hand tracker yields an estimated hand motion sequence $\tilde{\mathbf{H}} = (\tilde{\mathbf{H}}^i)_{1 \leq i \leq T}$. The goal

of our method is to improve the perceptual realism of this potentially noisy estimate using prior information learned from training data.

Concept. We observe that during hand-object interactions, the hand motion is heavily constrained by the object shape with which the hand interacts. Therefore, noisy hand-object interaction is a deviation from a low-dimensional manifold of valid hand motions, conditioned on the object. We formulate our goal as learning a mapping to maximize the posterior $p(\mathbf{H}|\tilde{\mathbf{H}}, \mathbf{O})$ of the real motion \mathbf{H} given the noisy observation $\tilde{\mathbf{H}}$ and the object with which the hand interacts. This amounts to finding an appropriate sequence of MANO parameters, which is done in three steps (see Figure 1): **1**) The initial estimate of a hand motion sequence is encoded with a TOCH field, our object-centric, point-wise correspondence representation (Section 3.1). **2**) The TOCH fields are projected to a learned low-dimensional manifold using a temporal denoising auto-encoder (Section 3.2). **3**) A sequence of corrected hand meshes is obtained from the processed TOCH fields (Section 3.3).

3.1 TOCH Fields

Naively training an auto-encoder on hand meshes is problematic, because the model could ignore the conditioning object and learn a plain hand motion prior. Moreover, if we include the object into the formulation, the model would need to learn manifolds for all joint rigid transformation of hand and object, which leads to high problem complexity [32]. Thus, we represent the hand as a TOCH field \mathbf{F} , which is a spatio-temporal object-centric representation that makes our approach invariant to joint hand and object rotation and translation.

TOCH Field Representation. For an initial estimation $\tilde{\mathbf{H}}$ of the hand mesh and the given object mesh \mathbf{O} , we define the TOCH field as a collection of point-wise vectors on a set $\{\mathbf{o}_i\}_{i=1}^N$ of N points, sampled from the object surface:

$$\mathbf{F}(\tilde{\mathbf{H}}, \mathbf{O}) = \{(c_i, d_i, \mathbf{y}_i)\}_{i=1}^N, \quad (2)$$

where $c_i \in \{0, 1\}$ is a binary flag indicating whether the i -th sampled object point has a corresponding point on the hand surface, $d_i \in \mathbb{R}$ is the signed distance between the object point and its corresponding hand point, and $\mathbf{y}_i \in \mathbb{R}^3$ are the coordinates of the corresponding hand point on the un-posed canonical MANO template mesh. Note that \mathbf{y}_i is a 3D location on the hand surface embedded in \mathbb{R}^3 , encoding the correspondence similar to [4,58].

Finding correspondences. As we model whole interaction sequences, including frames in which the hand and the object are not in contact, we cannot simply define the correspondences as points that lie within a certain distance to each other. Instead, we generalize the notion of contact by diffusing the object mesh into \mathbb{R}^3 . We cast rays from the object surface along its normal directions, as outlined in Figure 1. The object normal vectors are obtained from the given object mesh. The correspondence to an object point is obtained as the first intersection with the hand mesh. If there is no intersection, or the first intersection is not

Algorithm 1: Finding object-hand correspondences

Input: Hand mesh \mathbf{H} , object mesh \mathbf{O} , uniformly sampled object points and normals $\{\mathbf{o}_i, \mathbf{n}_i\}_{i=1}^N$

Output: Binary correspondence indicators $\{c_i\}_{i=1}^N$

for $i = 1$ **to** N **do**

$c_i \leftarrow 0;$
if \mathbf{o}_i inside \mathbf{H} $s \leftarrow -1$ else $s \leftarrow 1$;
$\mathbf{r}_1 \leftarrow \text{ray}(\mathbf{o}_i, s\mathbf{n}_i);$
$\mathbf{p}_1 \leftarrow \text{ray_mesh_intersection}(\mathbf{r}_1, \mathbf{H});$
if $\mathbf{p}_1 \neq \emptyset$
$\mathbf{r}_2 \leftarrow \text{ray}(\mathbf{o}_i + \epsilon s\mathbf{n}_i, s\mathbf{n}_i);$
$\mathbf{p}_2 \leftarrow \text{ray_mesh_intersection}(\mathbf{r}_2, \mathbf{O});$
if $\mathbf{p}_2 = \emptyset$ or $\ \mathbf{o}_i - \mathbf{p}_1\ < \ \mathbf{o}_i - \mathbf{p}_2\ $
$c_i \leftarrow 1;$

the hand, this object point has no correspondence. If the object point is inside the hand, which might happen in case of noisy observations, we search for correspondences along the negative normal direction. The detailed procedure for determining correspondences is listed in Algorithm 1.

Representation properties. The described TOCH field representation has the following advantages. **1)** It is naturally invariant to joint rotation and translation of object and hand, which reduces required model complexity. **2)** By specifying the distance between corresponding points, TOCH fields enable a subsequent auto-encoder to reason about point-wise proximity of hand and object. This helps to correct various artifacts, *e.g.* inter-penetration can be simply detected by finding object vertices with a negative correspondence distance. **3)** From surface normal directions of object points and the corresponding distances, a TOCH field can be seen as an encoding of the partial hand point cloud from the perspective of the object surface. We can explicitly derive that point cloud from the TOCH field and use it to infer hand pose and shape by fitting the hand model to the point cloud (c.f. Section 3.3).

3.2 Temporal Denoising Auto-encoder

To project a given TOCH field, we use a temporal denoising auto-encoder, consisting of an encoder $g_{\text{enc}} : (\hat{\mathbf{F}}_i)_{1 \leq i \leq T} \mapsto \mathbf{z}$, which maps a sequence of noisy TOCH fields (concatenated with the coordinates and normals of each object point) to a latent representation \mathbf{z} , and a decoder $g_{\text{dec}} : \mathbf{z} \mapsto (\hat{\mathbf{F}}_i)_{1 \leq i \leq T}$, which computes the corrected TOCH fields $\hat{\mathbf{F}}$ from the latent code. As the input and output TOCH fields consist of vectors attached to points, a PointNet-like [50] architecture is used to implement g_{enc} and g_{dec} . The point features in each frame are first processed by consecutive PointNet blocks to extract frame-wise features. These features are then fed into a bidirectional GRU layer to capture temporal motion patterns. The decoder network again concatenates the encoded frame-wise features with coordinates and normals of the object points and produces

denoised TOCH fields $(\hat{\mathbf{F}}_i)_{1 \leq i \leq T}$. The network is trained by minimizing

$$\mathcal{L}(\hat{\mathbf{F}}, \mathbf{F}) = \sum_{i=1}^T \sum_{j=1}^N c_j^i \left(\|\hat{\mathbf{y}}_j^i - \mathbf{y}_j^i\|_2^2 + w_{ij} (\hat{d}_j^i - d_j^i)^2 \right) - \text{BCE}(\hat{c}_j^i, c_j^i), \quad (3)$$

where \mathbf{F} denotes the groundtruth TOCH fields and $\text{BCE}(\hat{c}_j^i, c_j^i)$ is the binary cross entropy between output and target correspondence indicators. Note that we only compute the first two parts of the loss on TOCH field elements with $c_j^i = 1$, i.e. object points that have a corresponding hand point. We use a weighted loss on the distances \hat{d}_j^i . The weights are defined as

$$w_{ij} = \frac{\exp(-\|d_j^i\|)}{\sum_{k=1}^{N_i} \exp(-\|d_k^i\|)} N_i, \quad (4)$$

where $N_i = \sum_{j=1}^N c_j^i$. Intuitively this weighting scheme encourages the network to pay more attention to regions of close interaction, where a slight error could have huge impact on contact realism. Multiplying by the sum of correspondence ensures equal influence of all points in the sequence (instead of equal influence of all frames). For further details about the architecture, we refer to the supplemental materials.

3.3 Hand Motion Reconstruction

After projecting the noisy TOCH fields of input tracking sequence to the manifold learned by the auto-encoder, we need to recover the hand motion from the processed TOCH fields. The TOCH field is not fully differentiable w.r.t. the hand parameters, as changing correspondences would involve discontinuous function steps. Thus, we cannot directly optimize the hand pose parameters to produce the target TOCH field. Instead, we decompose the optimization into two steps. We first use the denoised TOCH fields to locate hand points corresponding to the object points. We then optimize the MANO model to find hands that best fit these points, which is a differentiable formulation.

Formally, given denoised TOCH fields $\mathbf{F}^i(\mathbf{H}, \mathbf{O}) = \{(c_j^i, d_j^i, \mathbf{y}_j^i)\}_{j=1}^N$ for frames $i \in \{1, \dots, T\}$ on points $\{\mathbf{o}_j\}_{j=1}^N$, we first produce the partial point clouds $\hat{\mathbf{Y}}^i$ of the hand as seen from the object’s perspective:

$$\hat{\mathbf{y}}_j^i = \mathbf{o}_j + d_j^i \mathbf{n}_j^i. \quad (5)$$

Then, we fit MANO to those partial point clouds by minimizing:

$$\mathcal{L}(\boldsymbol{\beta}, \boldsymbol{\theta}, \mathbf{t}_H) = \sum_{i=1}^T \mathcal{L}_{\text{corr}}(\boldsymbol{\beta}, \boldsymbol{\theta}^i, \mathbf{t}_H) + \mathcal{L}_{\text{reg}}(\boldsymbol{\beta}, \boldsymbol{\theta}) \quad (6)$$

The first term of Equation 6 is the hand-object correspondence loss

$$\mathcal{L}_{\text{corr}}(\boldsymbol{\beta}, \boldsymbol{\theta}^i, \mathbf{t}_H) = \sum_{j=1}^N c_j^i \left\| \hat{\mathbf{y}}_j^i - (\text{LBS}(\text{Proj}_{\mathbf{Y}}(\mathbf{y}_j^i); \boldsymbol{\beta}, \boldsymbol{\theta}^i) + \mathbf{t}_H) \right\|^2, \quad (7)$$

where LBS is the linear blend skinning function in Equation 1 and $\text{Proj}_{\mathbf{Y}}(\cdot)$ projects a point to the nearest point on the template hand surface. This loss term ensures that the deformed template hand point corresponding to \mathbf{o}_i is at a predetermined position derived from the TOCH field.

The last term of (6) regularizes shape and pose parameters of MANO,

$$\mathcal{L}_{\text{reg}}(\boldsymbol{\beta}, \boldsymbol{\theta}) = w_1 \|\boldsymbol{\beta}\|^2 + w_2 \sum_{i=1}^T \|\boldsymbol{\theta}^i\|^2 + w_3 \sum_{i=1}^{T-1} \|\boldsymbol{\theta}^{i-1} - \boldsymbol{\theta}^i\|^2 + w_4 \sum_{i=2}^{T-1} \sum_{k=1}^J \|\ddot{\mathbf{p}}_k^i\| \quad (8)$$

where $\ddot{\mathbf{p}}_k^i$ is the acceleration of hand joint k in frame i approximated by central difference. Besides regularizing the norm of MANO parameters, we additionally enforce temporal smoothness of hand poses. This is necessary because term (7) only constrains those parts of a hand with object correspondences. Per-frame fitting of TOCH fields can lead to multiple plausible solutions, which can only be disambiguated by considering neighbouring frames. Since (6) is highly non-convex, we optimize it in two stages. In the first stage, we freeze the shape and pose parameters, and only optimize hand orientation and translation. We then jointly optimize all the variables in the second stage. See supplemental materials for further details.

4 Experiments

In this section, we evaluate the presented method on synthetic and real datasets of hand/object interaction. The goal of our experiments is to verify that TOCH is able to produce *realistic interactions on motion sequences* (Section 4.3), *outperforms previous static approaches* in several metrics (Section 4.4), and derives a *meaningful representation* for hand object interaction (Section 4.5). Before presenting the results, we introduce the used datasets in Section 4.1 and the evaluated metrics in Section 4.2.

4.1 Datasets

GRAB. We train TOCH on GRAB [56], a MoCap dataset for whole-body grasping of objects. GRAB contains interaction sequences with 51 objects from [8]. Following the recommended split, we pre-select 10 objects for evaluation and testing, and train with the rest sequences. Since we are only interested in frames where interaction is about to take place, we filter out frames where the hand wrist is more than 15 cm away from the object. Due to symmetry of the two hands, we choose to anchor correspondences to the right hand. Frames involving left hands are flipped to increase the amount of training data.

HO-3D. HO-3D is a dataset of hand-object video sequences captured by RGB-D cameras. It provides frame-wise annotations for 3D hand poses and 6D object poses, which are obtained from a novel joint optimization procedure. As shown in [20], the groundtruth annotations in HO-3D is not accurate enough, so we only

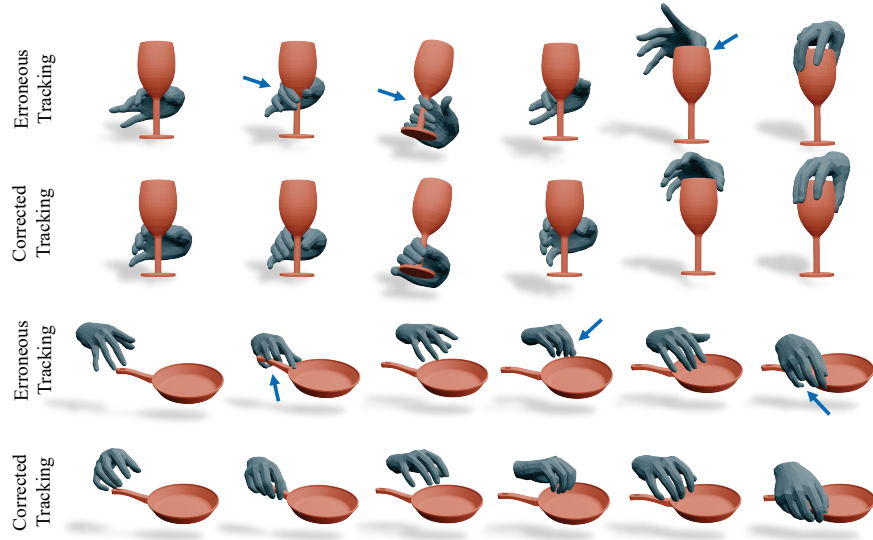


Fig. 3: Qualitative results on two synthetic hand-object interaction sequences that suffer from inter-penetration and non-smooth hand motion. The results after TOCH refinement show correct contact and are much more visually plausible. Note that TOCH only applies minor changes in hand poses but the perceived realism is largely enhanced. Please watch the supplemental video for animated results.

use it for evaluating RGB-based hand estimators. There are several versions for HO-3D. We evaluate on its first official release for fair comparison with baselines.

4.2 Metrics

Mean Per-Joint Position Error (MPJPE). We report the average Euclidean distance between refined and groundtruth 3D hand joints. This metric measures the accuracy of hand poses. Since the reliability of pose annotations varies across datasets, this metric should be jointly assessed with other perceptual metrics.

Mean Per-Vertex Position Error (MPVPE). This metric represents the average Euclidean distance between refined and groundtruth 3D meshes where groundtruth is available. It takes into account the hand’s shape and pose.

Solid Intersection Volume (IV). We measure the degree of hand-object interpenetration by voxelizing hand and object meshes and reporting the volume of voxels occupied by both. Solely considering this metric can be misleading since it does not account for hovering artifacts, where the object is not in effective contact with the hand.

Contact IoU (C-IoU). This metric assesses the Intersection-over-Union between the groundtruth contact map and the predicted contact map. The contact

GRAB-Type → Noise →	GRAB-T (0.1)	GRAB-T (0.2)	GRAB-R (0.03)	GRAB-R (0.05)	GRAB-B (0.1 & 0.03)
MPJPE (mm) ↓	15.96 → 9.93	31.9 → 12.3	4.58 → 9.58	7.53 → 9.12	17.3 → 10.3
MPVPE (mm) ↓	16.0 → 11.8	31.9 → 13.9	6.30 → 11.5	10.3 → 11.0	18.3 → 12.1
IV (cm ³) ↓	2.48 → 1.79	2.40 → 2.50	1.88 → 1.52	1.78 → 1.35	2.20 → 1.78
C-IoU (%) ↑	3.56 → 29.2	2.15 → 16.7	11.4 → 26.6	5.06 → 24.4	1.76 → 26.6

Table 1: We quantitatively evaluate TOCH on multiple perturbed GRAB test sets with different types and magnitude of noise. The numbers inside the parentheses indicate standard deviation of the sampled Gaussian noise. Although pose accuracy is not always improved, TOCH significantly boosts interaction realism for all noise levels, which is demonstrated by the increase in contact IoU and reduction in hand-object inter-penetration.

Method	HO-3D		
	MPJPE (mm) ↓	MPVPE (mm) ↓	IV (cm ³) ↓
Hasson <i>et al.</i>	11.4	11.4	9.26
RefineNet	11.6	11.5	8.11
ContactOpt	9.47	9.45	5.71
TOCH (ours)	9.32	9.28	4.66

Table 2: Quantitative evaluation on HO-3D compared to Hasson *et al.* [23], RefineNet [56] and ContactOpt [20]. We follow the official evaluation protocol of HO-3D and report hand joint and mesh errors after Procrustes alignment. TOCH outperforms all the baselines in terms of pose error and interaction quality.

map is obtained from the binary hand-object correspondence by thresholding the correspondence distance within ± 2 mm. We only report this metric on GRAB.

4.3 Refining Synthetic Tracking Error

In order to use TOCH in real settings, it would be ideal to train the model on the predictions of existing hand trackers. However, this requires large amount of images/depth sequences paired with accurate hand and object annotations, which is currently not available. Moreover, targeting a specific tracker might lead to overfitting to tracker-specific errors, which is undesirable for generalization.

We observe that hand errors can be decomposed into inaccurate global translation and inaccurate joint rotations, and the inaccuracies produced by most state-of-the-art trackers are small. Therefore, we propose to synthesize tracking errors by manually perturbing the groundtruth hand poses of the GRAB dataset. To this end, we apply three different types of perturbation to GRAB: translation-dominant perturbation (abbreviated GRAB-T in the table) applies an additive noise to hand translation \mathbf{t}_H only, pose-dominant perturbation (abbreviated GRAB-R) applies an additive noise to hand pose θ only, and balanced perturbation (abbreviated GRAB-B) uses a combination of both. We only train

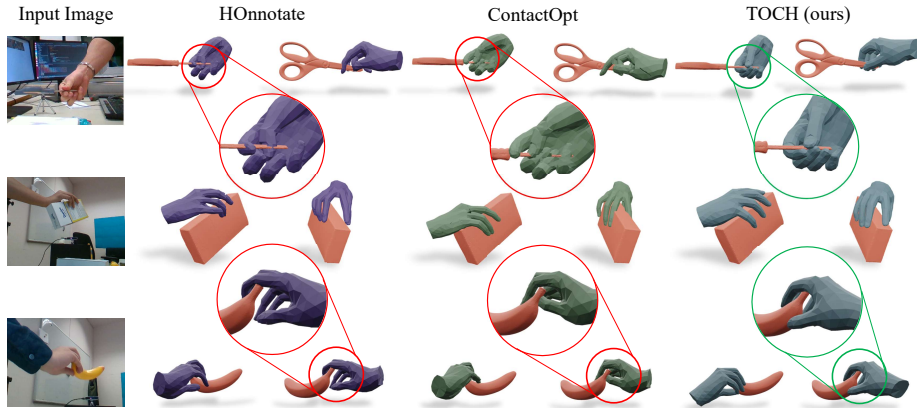


Fig. 4: Qualitative comparison with HOnnotate and ContactOpt. Each sample reconstruction is visualized in two views, the image-aligned view and a side view. We can clearly see hand-object inter-penetrations for HOnnotate and ContactOpt, while our reconstructions are more visually realistic, even though we don’t use any inter-penetration loss in hand fitting.

on the last type while evaluate on all three. The quantitative results are shown in Table 1 and qualitative results are presented in Figure 3.

We can make the following observations. First, TOCH is most effective for correcting translation-dominant perturbations of the hand. For pose-dominant perturbations where the vertex and joint errors are already very small, the resulting hands after TOCH refinement exhibit larger errors. This is because TOCH aims to improve interaction quality of a tracking sequence, which can hardly be reflected by distance based metrics such as MPJPE and MPVPE. We argue that more important metrics for interaction are intersection volume and contact IoU. As an example, the perturbation of GRAB-R (0.03) only induces a tiny joint position error of 0.03 mm, while it results in a significant 88.6% drop in contact IoU. This validates our observation that any slight change in pose has a notable impact on physical plausibility of interaction. TOCH effectively reduces hand-object intersection as well as boosts the contact IoU even when the noise of testing data is higher than that of training data.

4.4 Refining RGB(D)-based Hand Estimators

To evaluate how well TOCH generalizes to refine real tracking errors, we test TOCH on state-of-the-art models for joint hand-object estimation from image or depth sequences. We first report comparisons with the RGB-based hand pose estimator [23], and two grasp refinement methods RefineNet [56] and ContactOpt [20] in Table 2. Hasson *et al.* [23] predict hand meshes from images, while RefineNet and ContactOpt have no knowledge about visual observations and directly refine hands based on 3D inputs. In order to ensure a fair comparison, we only compare on static frames with contact between hands and objects, as

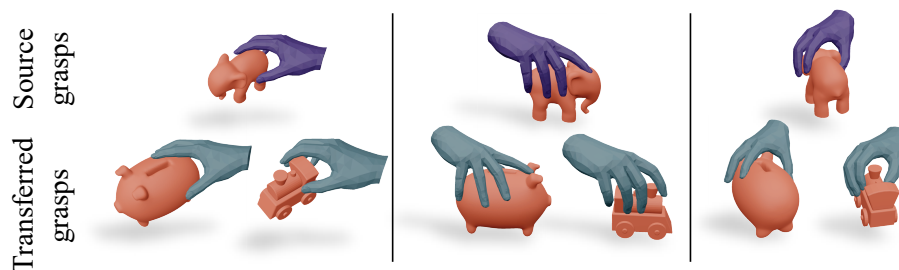


Fig. 5: Transferring grasping poses across objects of different geometry. The top row shows three different source grasps which are subsequently transferred to two target objects in the bottom row. The hand poses are adjusted according to shape of target objects while preserving overall contacts.

Method	MPJPE (mm) ↓	IV (cm ³) ↓	C-IoU (%) ↑
Hand-centric baseline	11.2	2.03	18.9
TOCH (No Corr.)	11.6	1.55	25.8
TOCH (Full model)	10.3	1.78	26.6

Table 3: Comparison with baselines on GRAB-B (0.1 & 0.03). We show that TOCH achieves the lowest hand joint error compared to using a hand-centric architecture and ablating dense hand-object correspondence. Although TOCH without dense correspondence presents a lower intersection volume, it’s due to the artifacts that hand hovers above the object instead of making contact in some test cases. As shown by Contact IoU, TOCH recovers the highest percentage of contact regions among all three methods.

both previous methods are not designed for motion sequences or frames without contact. Groundtruth object meshes are assumed to be given for all the methods. TOCH achieves the best score for all three metrics on HO-3D. In particular, it reduces the mesh intersection volume, indicating an improved interaction quality. We additionally evaluate TOCH on HONotate [22], a state-of-the-art RGB-D tracker which is used to annotate the groundtruth for HO-3D. Figure 4 shows some of its failure cases and how these errors are corrected by TOCH.

4.5 Analysis and Ablation Studies

Grasp transfer. In order to demonstrate the wide-applicability of our learned features, we utilize the pre-trained TOCH auto-encoder for grasp transfer although it was not trained for this task. The goal is to transfer grasping sequences from one object to another object while maintaining plausible contacts. Specifically, given a source hand motion sequence and a source object, we extract the TOCH fields and encode them with our learned encoder network. We then simply decode using the target object – we perform a point-wise concatenation of

the latent vectors with point clouds of the target object, and reconstruct TOCH fields with the decoder. This way we can transfer the TOCH fields from the source object to the target object. Qualitative examples are shown in Figure 5.

Object-centric representation. To show the importance of the object-centric representation, we train a baseline model which directly takes noisy hand joint sequences $\{\tilde{\mathbf{j}}^i\}_{i=1}^T$ as input and naively condition it on the object motion sequence $\{\mathbf{O}^i\}_{i=1}^T$. See Table 3 for a quantitative comparison with TOCH. We can observe that although the hand-centric baseline makes small errors in joint positions, the resulting motion is less physically plausible, as reflected by its higher interpenetration and lower contact IoU.

Semantic correspondence. We argue that explicit reasoning about semantic correspondence to shand helps TOCH better model hand-object interactions. To show this, we train another baseline model in the same manner as in Section 3, except that we adopt a simpler representation $\mathbf{F}(\mathbf{H}, \mathbf{O}) = \{(c_i, d_i)\}_{i=1}^N$, where we keep the binary indicator and signed distance without specifying which hand point is in correspondence. The loss term (7) accordingly changes from mean squared error to Chamfer distance. We can see from Table 3 that the baseline model gives worse results in recovering groundtruth contact.

Complexity and running time. The main overhead incurred by TOCH field is in computing ray-triangle intersections, the complexity of which depends on the number of sampled object points, number of hand and object triangles, and the specific hand-object arrangement. As an illustration, it takes around 2s per frame to compute the TOCH field on 2000 sampled object points for an object mesh with 48k vertices and 96k triangles on Intel Xeon CPU. One potential way to reduce computing time is to simplify the object mesh before testing intersections. We also expect further performance boost when using GPU-optimized routines. In hand-fitting stage, TOCH is significantly faster than ContactOpt since the hand-object distance can be minimized with mean squared error loss once correspondences are known while ContactOpt relies on nearest neighbour query to recompute the contact map at every iteration. Fitting TOCH to a sequence runs at approximately 1 fps on average while it takes ContactOpt over a minute to fit a single frame.

5 Conclusion

In this paper, we introduced TOCH, a spatio-temporal model of hand-object interactions. Our method encodes the hand with TOCH fields, an effective novel object-centric correspondence representation which captures the spatio-temporal configurations of hand and object even before and after contact occurs. TOCH reasons about hand-object configurations beyond plain contacts, and is naturally invariant to rotation and translation. Experiments demonstrate that TOCH outperforms previous methods on the task of 3D hand-object refinement, while being an order of magnitude faster than the second best performing method (ContactOpt). In future work, we plan to extend TOCH to model more general human-scene interactions.

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