

lm2Hands: Learning Attentive Implicit Representation of Interacting Two-Hand Shapes

Jihyun Lee, Minhyuk Sung, Honggyu Choi, Tae-Kyun Kim

Motivation & Challenges

- Existing two-hand reconstruction methods model hands with low-resolution meshes with a fixed MANO^[1] topology (|V| = 778).
- Neural implicit representation can model continuous shapes. It is also known to reconstruct shapes that are well-aligned to the input images.
- → However, implicitly modeling complex articulations and interaction contexts between two hands is highly challenging.

Method

- We propose two novel attention-based modules designed for:
- 1) Initial per-hand occupancy estimation in the canonical space, and
- 2) Interaction-aware two-hand occupancy refinement in the original space.



$$\mathcal{I}(x \mid I, J) = \max_{b=1, \dots, B} \{ \bar{\mathcal{H}}_b(\mathbf{T}_b x, \frac{f_b^{\phi}, f_x^{\phi}}{f_b^{\phi}, f_b^{\omega}}) \}$$

- $\overline{\mathcal{H}}_{h}$: Part occupancy network for bone b
- $\mathbf{T}_{b}x$: Canonicalized query point for bone **b**
- $f_{b}^{\phi}, f_{b}^{\omega}$: Per-bone shape and pose features^[3]
- \int_{r}^{ϕ} : Per-query shape (query-image attention) feature

Overview

- We propose Im2Hands (Implicit Two Hands), the first neural implicit representation for two interacting hands.
- Learns resolution-free two-hand geometries with high hand-to-hand and hand-to-image coherence
- Does not require vertex-wise shape correspondences or MANO^[1] parameter annotations for training
- Achieves the state-of-the-art accuracy on two-hand reconstruction



Two-Hand Occupancy Refinement

- To encode the initial geometry of two hands, we represent them as anchored feature cloud (i.e. feature vectors of the points evaluated to be on surface by our initial occupancy network).
- We then apply cross-attention between (1) a query, (2) anchored features, and (3) a context latent vector to estimate the refined occupancy.



Using Image and Keypoint Inputs

Method	Inputs	$ $ IoU (%) \uparrow $ $ CI	O (mm) ↓	Method	IoU (%) ↑	CD (mm)↓
Two-Hand-Shape-Pose ^[5] IntagHand ^[2]	\mathcal{I}, \mathcal{L} \mathcal{I}, \mathcal{L}	54.8 67.0	5.51 3.88	Two-Hand-Shape-Pose ^[5] IntagHand ^[2]	48.4 59.0	6.09 4.69
HALO ^[3]	\mathcal{J}	74.7	2.62	DIGIT ^[6] + HALO ^[3] IntagHand ^[2] + HALO ^[3]	45.1	7.64
HALO* ^[3]	\mathcal{I},\mathcal{J}	75.8	2.51	DIGIT ^[6] + Im2Hands (Ours)	59.4	4.75
Im2Hands (Ours)	\mathcal{I},\mathcal{J}	77.8	2.30	IntagHand ^[2] + Im2Hands (Ours)	62.1	4.35

Qualitative Results on Image-Based Two-Hand Reconstruction







EaoHands^[8] datasets.





References

[1] J. Romero et al. Embodied hands: Modeling and capturing hands and bodies together. TOG, 2017. 2] M. Li et al. Interacting attention graph for single image two-hand reconstruction. In CVPR, 2022.] K. Karunratanakul et al. A skeleton-driven neural occupancy representation for articulated hands. In 3DV, 2021 [4] G. Moon et al. Interhand2.6m: A dataset and baseline for 3d interacting hand pose estimation from a single rgb image. In ECCV, 2020. [5] B. Zhang et al. Interacting two-hand 3d pose and shape reconstruction from single color image. In ICCV, 2021. [6] Z. Fan et al. Learning to disambiguate strongly interacting hands via probabilistic per-pixel part segmentation. In 3DV, 2021. [7] J. Wang et al. Rob2hands: Real-time tracking of 3d hand interactions from monocular rob video, TOG, 2020. [8] S. Bambach et al. Lending a hand: Detecting hands and recognizing activities in complex egocentric interactions. In ICCV, 2015.



Experiments

Im2Hands achieves SOTA reconstruction results on InterHand2.6M^[4].

Using Image Inputs Only (+ Predicted Keypoints)



We also show generalization test results on RGB2Hands^[7] and

Reconstruction

