

Machine Learning Attentive Implicit Representation of Interacting Two-Hand Shapes

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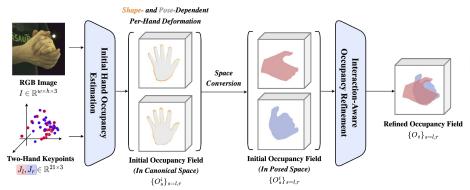


Motivation & Challenges

- 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 canonical space, and
 - 2) Interaction-aware two-hand occupancy refinement in posed space.



Initial Per-Hand Occupancy Estimation

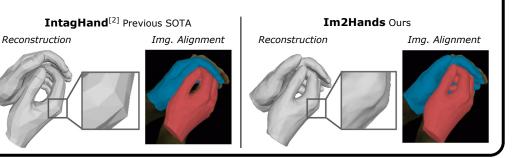
$$\mathcal{I}(x \mid I, J) = \max_{b=1, \dots, B} \{ \bar{\mathcal{H}}_b(\mathbf{T}_b x, f_b^{\phi}, f_x^{\phi}, f_b^{\omega}) \}$$

- $\bar{\mathcal{H}}_b$: Part occupancy network for bone b
- T_bx: Canonicalized query point for bone b
- f_h^{ϕ} , f_h^{ω} : Per-bone shape and pose features
- f_{x}^{ϕ} : Per-query shape (query-image attention) feature



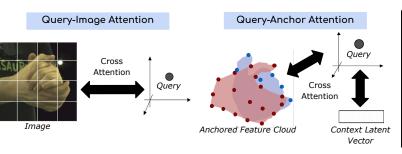
We propose Im2Hands (Implicit Two Hands), the first neural implicit representation for two interacting hands.

- Learns resolution-free two-hand geometries with high hand-hand and hand-image coherency
- Does not require dense vertex correspondences or MANO^[1] parameter annotations for training
- Achieves 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 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.



We also proposed an optional keypoint refinement module for image-based reconstruction scenario.

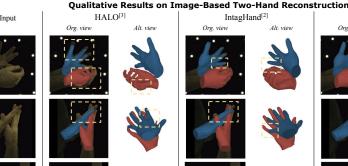
Please check the paper for more details.

Experiments

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

Using Image and Keypoint Inputs IoU (%) ↑ CD (mm) ↓ Two-Hand-Shape-Pose[5] \mathcal{I}, \mathcal{L} 54.8 IntagHand \mathcal{I}, \mathcal{L} 67.0 3.88 HALO^{[3} \mathcal{J} 74.7 2.62 HALO*[3] \mathcal{I}, \mathcal{J} 75.8 2.51 Im2Hands (Ours) \mathcal{I}, \mathcal{J} 77.8

Using Image Inputs Only (+ Predicted Keypoints)		
Method	IoU (%) ↑	CD (mm)↓
Two-Hand-Shape-Pose ^[5]	48.4	6.09
IntagHand ^[2]	59.0	4.69
DIGIT ^[6] + HALO ^[3]	45.1	7.64
IntagHand ^[2] + HALO ^[3]	53.8	5.38
DIGIT ^[6] + Im2Hands (Ours)	59.4	4.75
IntagHand ^[2] + Im2Hands (Ours)	62.1	4.35





 We also show generalization test results on RGB2Hands^[6] and EgoHands[7] datasets.



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- K. Karunratanakul et al. A skeleton-driven neural occupancy representation for articulated hands. In 3DV, 2021.
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