gSDF: Geometry-Driven Signed Distance Functions for 3D Hand-Object Reconstruction

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Goal

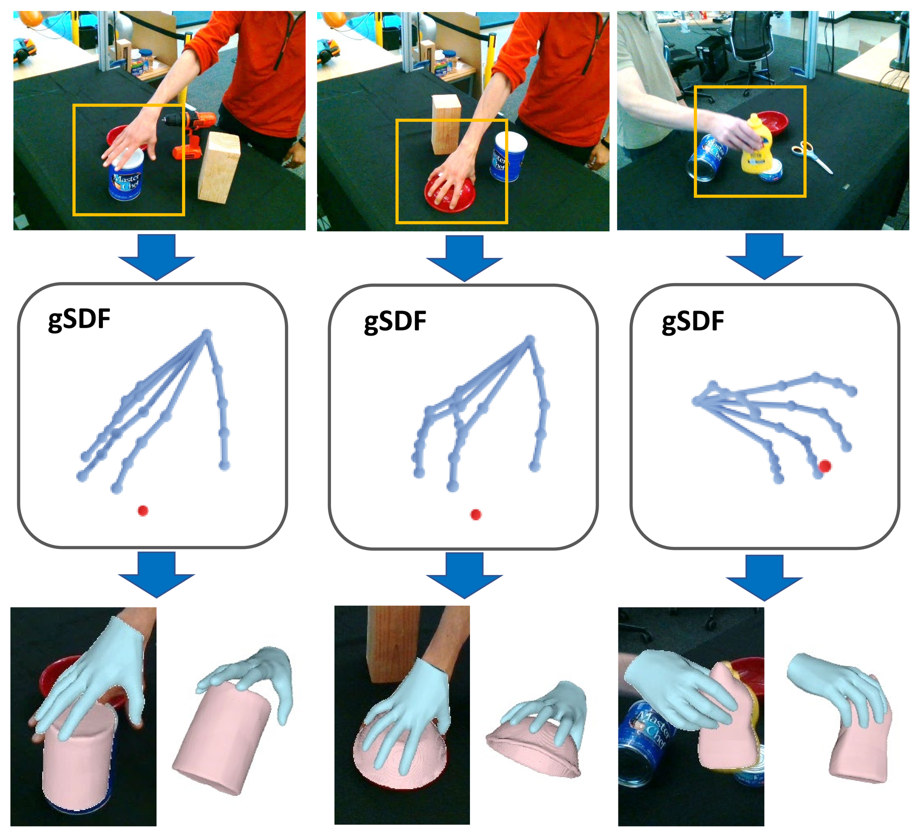
Realistic 3D hand-object reconstruction from **monocular images**.

Contribution

- Align the SDF shape with the underlying **kinematic chains** of pose transformations to simplify the 3D reconstruction.
- Leverage monocular **videos** to alleviate **occlusion and motion blur** issues and improve the performance.

Motivation

- Deep SDFs can generalize to different shape resolutions but lack explicit modeling of the underlying 3D geometry.
- 3D hand-object reconstruction from a single RGB image is intrinsically hard, especially under occlusion or motion blur.



Related work

[1] Y. Hasson, G. Varol, D. Tzionas, I. Kalevatykh, M. Black, I. Laptev, and C. Schmid. Learning joint reconstruction of hands and manipulated objects. *In Proc. CVPR, 2019.*

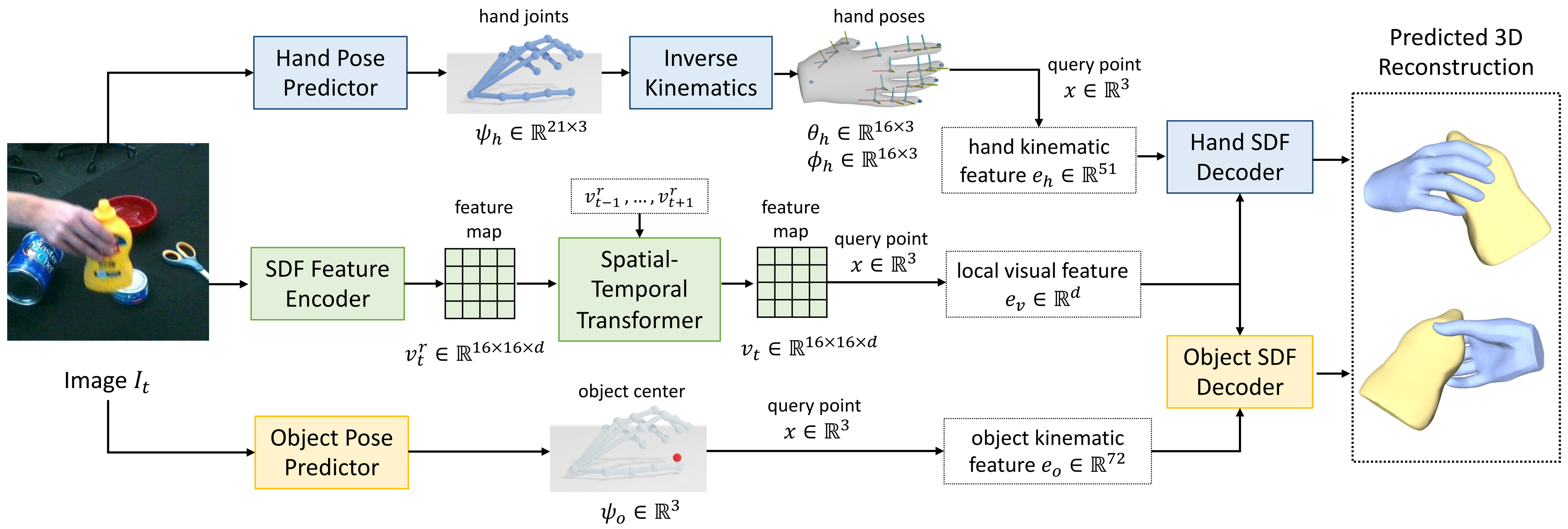
[2] K. Karunratanakul, J. Yang, Y. Zhang, M. Black, K. Muandet, and Siyu Tang. Grasping Field: Learning Implicit Representations for Human Grasps, *In Proc. 3DV, 2020.*

[3] Y. Ye, A. Gupta, and S. Tulsiani. What's in your hands? 3D Reconstruction of Generic Objects in Hands. *In Proc. CVPR, 2022.*

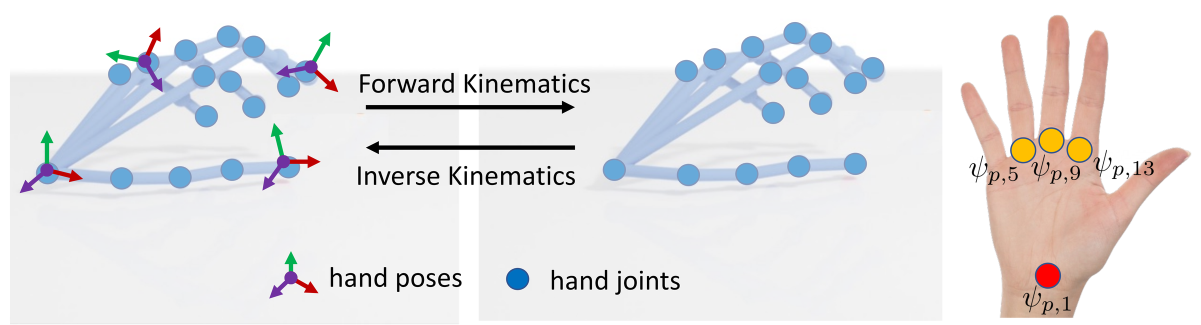
[4] Z. Chen, Y. Hasson, C. Schmid, I. Laptev. AlignSDF: Pose-Aligned Signed Distance Fields for Hand-Object Reconstruction. *In Proc. ECCV, 2022.*

Approach

We formulate the joint hand-object 3D reconstruction task as a multi-task learning framework.



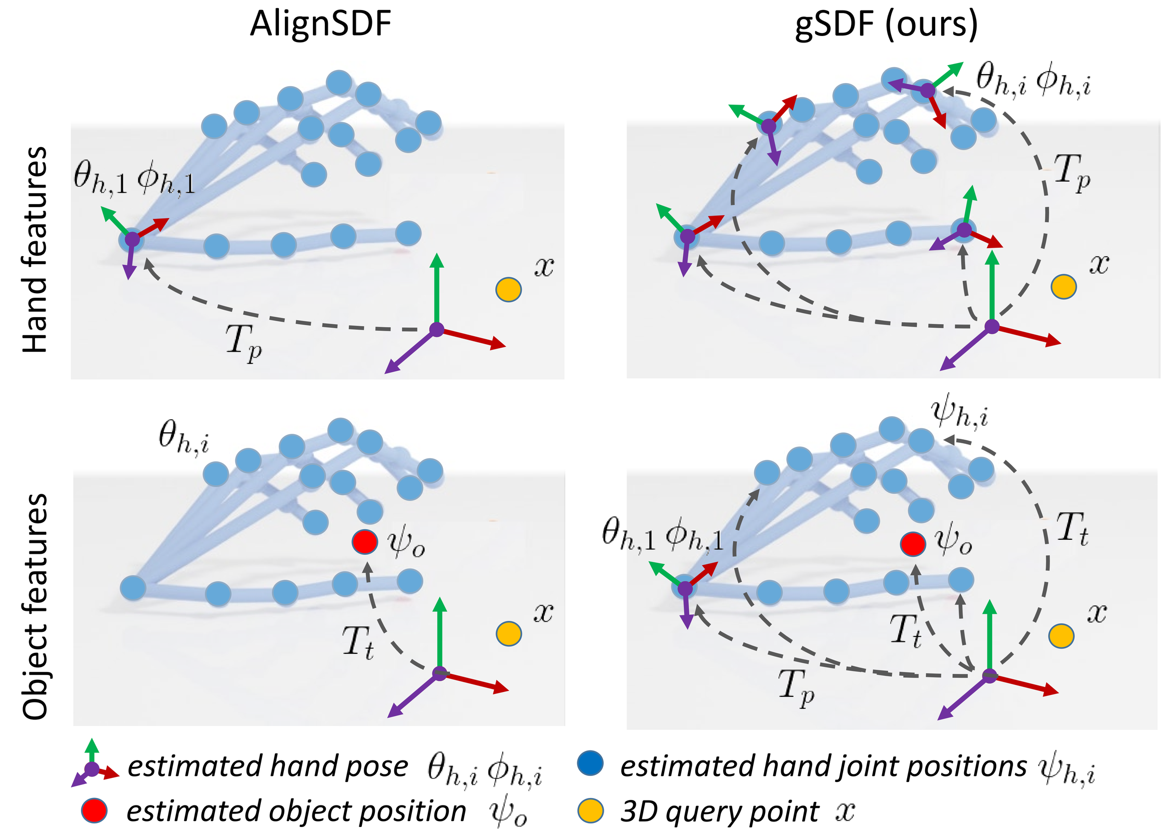
Pose Estimation



(a) Hand Kinematics (b) Hand Joints

- As shown in (b), since deep CNNs is good at detecting interested points, we first use neural networks to predict 3D hand joint locations from single-view images.
- As shown in (a), we use inverse kinematics to recover the pose transformations for each hand bone.

Kinematic Features

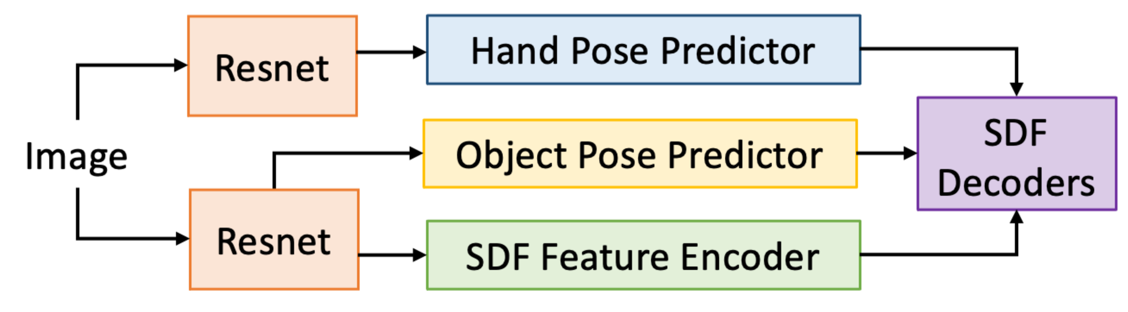


- For hand kinematic features, compared with a recent work [4], we use full kinematic chains of pose transformations.
- For object kinematic features, instead of only considering the object translation as in [4], we additionally consider relative positions between the query point *x* and each hand joint.

Visual Feature

- We use the spatial and temporary transformer to aggregate features from multiple frames.
- Then, we project the query point *x* onto the plane of the feature map and obtain the refined local feature for the shape reconstruction.

Network Architecture



- Our model consists of hand pose predictor, object pose predictor, SDF feature encoder and SDF decoders.
- We use two backbones to handle the task of 3D shape reconstructions and the task of pose predictions separately.
- We observe that our model can achieve the best performance when the object pose predictor and SDF feature encoder shares the same backbone.

Results

We validate the method by conducting experiments on ObMan and DexYCB benchmarks. We employ metrics including Chamfer Distance (CD) and F-score (FS) to evaluate the quality of results.

Quantitative Comparison on ObMan

Methods	$CD_h \downarrow$	$FS_h@1 \uparrow$	$FS_h@5 \uparrow$	$CD_o \downarrow$	$FS_o@5 \uparrow$	$FS_o@10 \uparrow$	$E_h \downarrow$	$E_o \downarrow$
Hasson *et al.* [1]	0.415	0.138	0.751	3.60	0.359	0.590	1.13	-
Karunratanakul *et al.* [2]	0.261	-	-	6.80	-	-	-	-
Ye *et al.* [3]	-	-	-	-	0.420	0.630	-	-
Chen *et al.* [4]	0.136	0.302	0.913	3.38	0.404	0.636	1.27	**3.29**
gSDF (Ours)	**0.112**	**0.332**	**0.935**	**3.14**	**0.438**	**0.660**	**0.93**	3.43

Quantitative Comparison on DexYCB

Methods	$CD_h \downarrow$	$FS_h@1 \uparrow$	$FS_h@5 \uparrow$	$CD_o \downarrow$	$FS_o@5 \uparrow$	$FS_o@10 \uparrow$	$E_h \downarrow$	$E_o \downarrow$
Hasson *et al.* [1]	0.537	0.115	0.647	1.94	0.383	0.642	1.67	-
Karunratanakul *et al.* [2]	0.364	0.154	0.764	2.06	0.392	0.660	-	-
Chen *et al.* [4]	0.358	0.162	0.767	1.83	0.410	0.679	1.58	**1.78**
Chen *et al.* [4] [1†]	0.344	0.167	0.776	1.81	0.413	0.687	1.57	1.93
gSDF (Ours)	**0.302**	**0.177**	**0.801**	**1.55**	**0.437**	**0.709**	**1.44**	1.96

Qualitative Results