



Introduction

- Background: 3D hand mesh reconstruction from monocular images is a crucial yet challenging task, as hands are often severely occluded by objects.
- Motivation: Previous works often have disregarded essential 2D hand pose information, which contains hand prior knowledge that is strongly correlated with occluded regions.
- Contributions: We propose a novel 3D hand mesh reconstruction network HandGCAT, that can fully exploit hand prior as compensation information to enhance occluded region features. experimental results show that our method achieves state-of-the-art performance on 3D hand mesh benchmarks that contain severe occlusions.

Performance **Results on HO3D Datasets**

Method	PA-MPJPE \downarrow	PA-MPJPE AUC \uparrow	$PA\text{-}MPVPE\downarrow$	PA-MPVPE AUC \uparrow
I2L-MeshNet [32] (CVPR'20)	1.12	0.775	1.39	0.722
Hasson et al. [33] (CVPR'20)	1.10	0.780	1.12	0.777
Hampali et al. [34] (CVPR'20)	1.07	0.788	1.06	0.790
METRO [29] (CVPR'21)	1.04	0.792	1.11	0.779
Liu et al. [35] (CVPR'21)	0.99	0.803	0.95	0.810
I2UV-HandNet [2] (ICCV'21)	0.99	0.804	1.01	0.799
ArtiBoost [36] (CVPR'22)	1.14	0.773	1.09	0.782
Keypoint Trans. [14] (CVPR'22)	1.08	0.786	-	-
MobRecon [37] (CVPR'22)	0.92	-	0.94	-
HandOccNet [20] (CVPR'22)	0.91	0.819	0.88	0.819
HandGCAT (Ours)	0.87	0.826	0.87	0.827

COMPARISON WITH STATE OF THE ART METHODS ON HOSD VS.						
Method	PA-MPJPE \downarrow	PA-MPJPE AUC \uparrow	PA-MPVPE ↓	PA-MPVPE AUC \uparrow	F@5	
ArtiBoost [36] (CVPR'22)	1.08	0.785	1.04	0.792	0.50	
Keypoint Trans. [14] (CVPR'22)	1.09	0.785	-	-	-	
HandOccNet [20] (CVPR'22)	1.07	0.786	1.04	0.791	0.47	
HandGCAT (Ours)	0.93	0.814	0.91	0.818	0.55	

Results on DexYCB Dataset

TABLE III				
COMPARISON WITH SOTA ON DEXYCB DATASET.				

Method	MPIPE	PA-MPIPE
Spurr et al. [40] (ECCV'20)	17.34	6.83
METRO [29] (CVPR'21)	15.24	6.99
Liu et al. [35] (CVPR'21)	15.28	6.58
HandOccNet [20] (CVPR'22)	14.04	5.80
HandGCAT (Ours)	13.76	5.60



HandGCAT: Occlusion-Robust 3D Hand Mesh Reconstruction from Monocular Images

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Method



Overview of the Proposed Method

The proposed HandGCAT consists of backbone, KGC, CAT, and regressor. Resnet-50 with FPN extracts image feature F_I . pose. CAT fuses F_P into F_I and thus imagines occluded regions.

• KGC captures hand prior knowledge F_P using GCNs from the 2D • Finally, the regressor reconstructs the 3D hand mesh.

Ablation Study

TABLE IV COMPARISON OF MODELS WITH VARIOUS KGC ARCHITECTURES ON HO3D v2.

KGC architectures	PA-MPJPE ↓	PA-MPVPE ↓	F@5 ↑	F@15 ↓
MLP	0.93	0.93	0.547	0.959
1-layer GCN	0.92	0.92	0.546	0.961
2-layer GCNs	0.90	0.89	0.570	0.961
3-layer GCNs	0.89	0.88	0.573	0.963
4-layer GCNs	0.87	0.87	0.584	0.963
5-layer GCNs	0.89	0.88	0.579	0.962

TABLE V COMPARISON OF MODELS WITH VARIOUS CAT ARCHITECTURES ON HO3D v2.

CAT architectures	PA-MPJPE ↓	PA-MPVPE \downarrow	F@5 ↑	F@15 ↑
Two Transformers	0.90	0.90	0.563	0.962
Single CAT block	0.89	0.88	0.574	0.962
Two CAT blocks	0.87	0.87	0.584	0.963
Three CAT blocks	0.88	0.87	0.583	0.963

Extensive

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