Carnegie Mellon University

MAX-PLANCK-GESELLSCHAFT

Occluded Human Mesh Recovery

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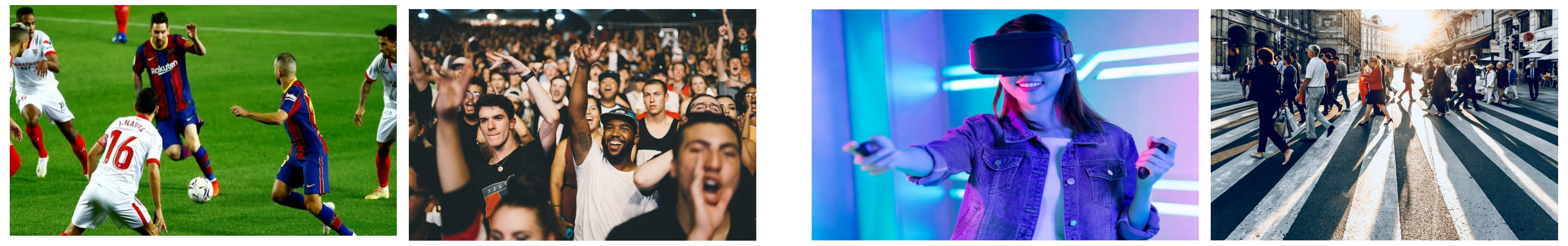
1. Introduction

Goal: Multi-Human Mesh Recovery under severe Occlusion



Sports Social Events Virtual Reality Self-Driving

Contributions:

- We address the limiting *single person assumption* in top-down methods.
- A novel approach to modify any backbone to predict multiple human meshes using parameter-efficient modulation.
- State-of-the-art on occlusion datasets like 3DPW-PC, OCHuman, CrowdPose.

2. Key Challenges

Top-Down Methods:

- ✓ Accurate due to scale invariance.
- ✗ Fails under occlusion and crowding.

Nikos et. al. **Learning to Reconstruct 3D Human Pose and Shape via Model-fitting in the Loop**, ICCV 2019.
Zhang et. al. **3D Human Pose and Shape with Pyramidal Mesh Alignment Feedback Loop**, ICCV 2021.
Kocabas et. al. **Part Attention Regressor for 3D Human Body Estimation**, ICCV 2021.

Bottom-Up Methods:

- ✓ Robust to occlusion.
- ✗ Lacks precise keypoint localization.

Sun et. al. **Monocular, One-stage, Regression of Multiple 3D People**, ICCV, 2021.

Occluded 2D Pose Estimation:

- ✓ Multi-Human 2D pose predictions.
- ✗ Keypoints only! Lacks 3D reasoning.

Li et. al. **CrowdPose Crowded Scenes Pose Estimation and a New Benchmark**, CVPR, 2019.

3. Context Conditioning

Along with the RGB bounding box, OCHMR takes the *context* as input.
We use local and global body-centermaps to represent the input *context*.

Context

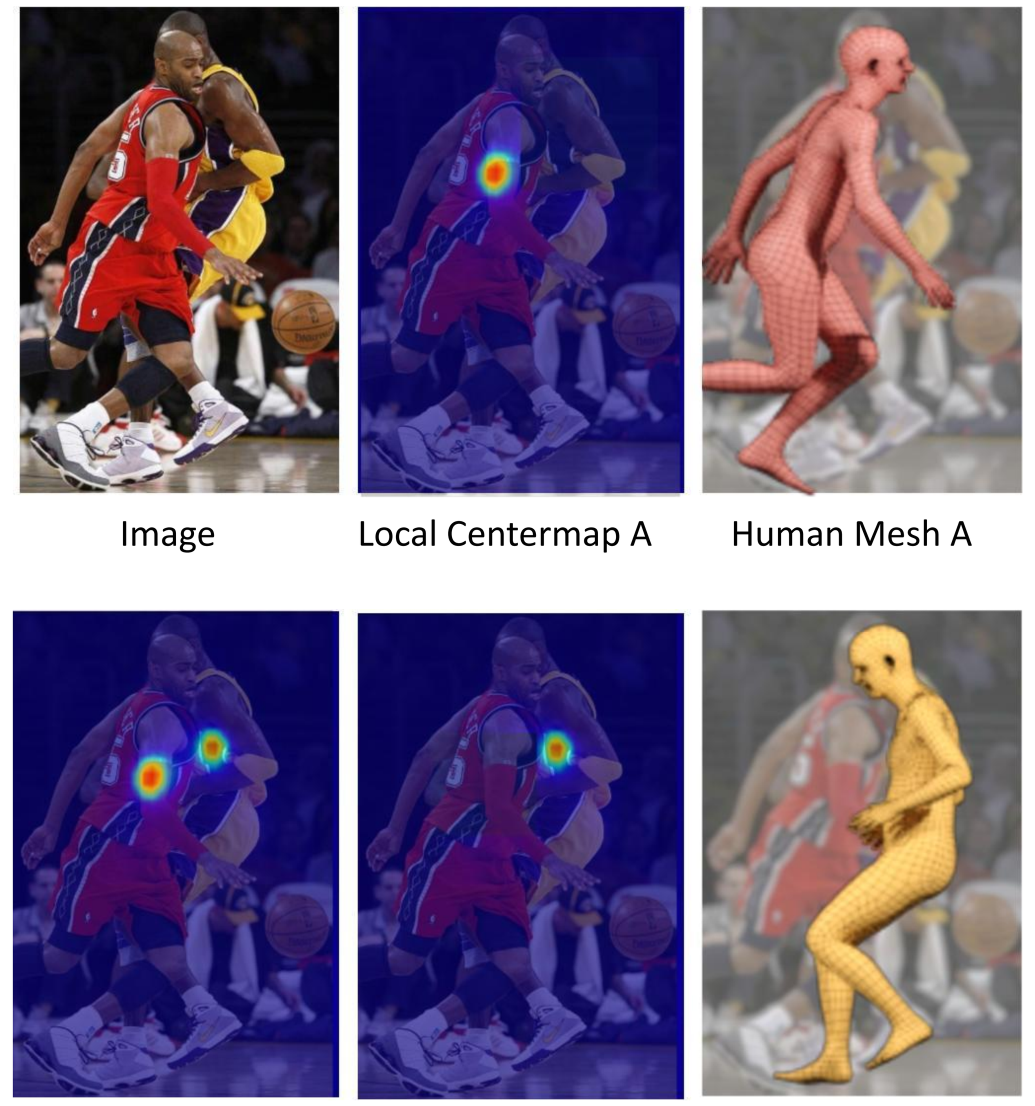
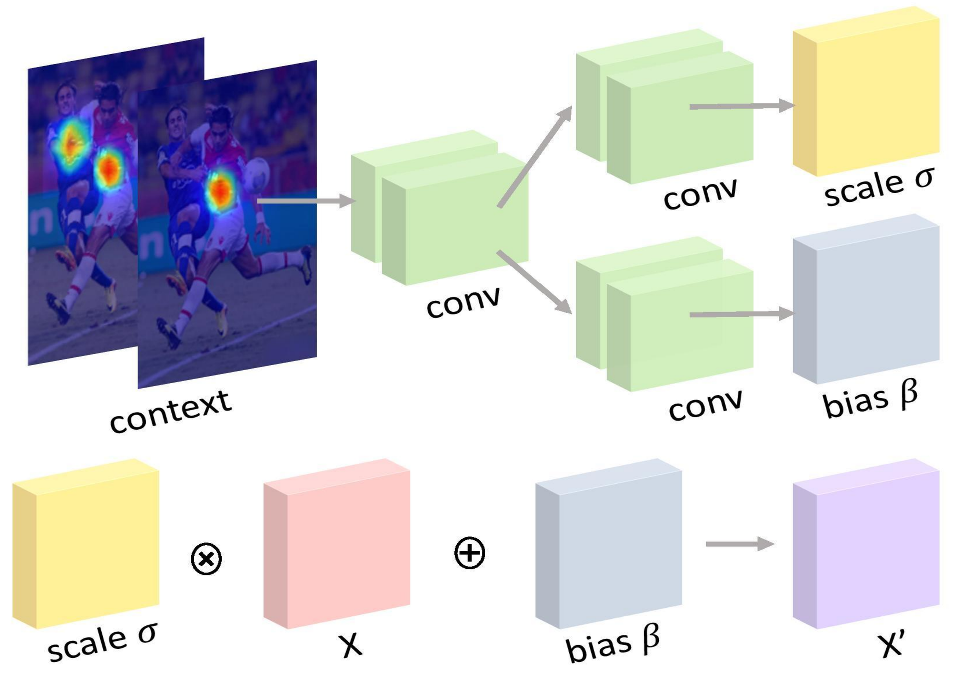


Image Local Centermap A Human Mesh A
Global Centermap Local Centermap B Human Mesh B

CoNorm Block

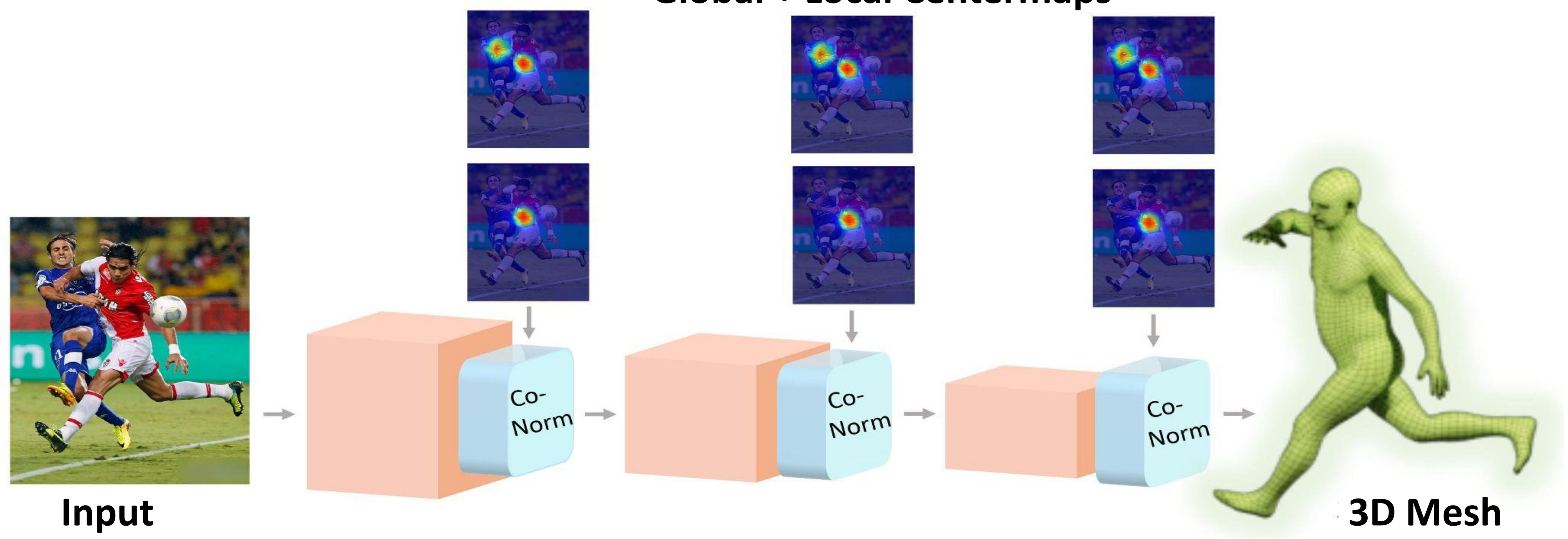


Losses

Interpenetration Loss Depth-ordering Loss

4. Architecture

Any top-down architecture can be made robust to occlusion!
Just start by inserting CoNorm blocks across the backbone.



Comparison to State-of-the-Art

Occluded Datasets

Method	3DPW-PC (↓)	OCHuman (↑)	CrowdPose (↑)
SPIN	132.7	11.1	14.8
PyMaF	126.7	14.3	17.4
ROMP	119.7	15.6	18.9
OCHMR	**117.5** (-2.2)	**24.8** (+6.8)	**21.4** (+2.5)
SPIN (gt bb)	128.4	16.9	17.2
OCHMR (gt bb)	**112.2** (-16.2)	**37.7** (+20.8)	**23.6** (+6.4)

General Datasets

Method	3DPW (↓)	COCO (↑)
SPIN	94.7	11.3
CRMH	105.9	12.6
PyMaF	92.8	13.8
ROMP	91.3	14.7
OCHMR	**89.7** (-1.6)	**15.3** (+0.6)

Qualitative Results