

BodyMap: What is it?

DensePose:

1. Correspondences only for the unclothed body
2. Learned on sparse, hard to annotate data
3. Discrete
4. No hands/hair

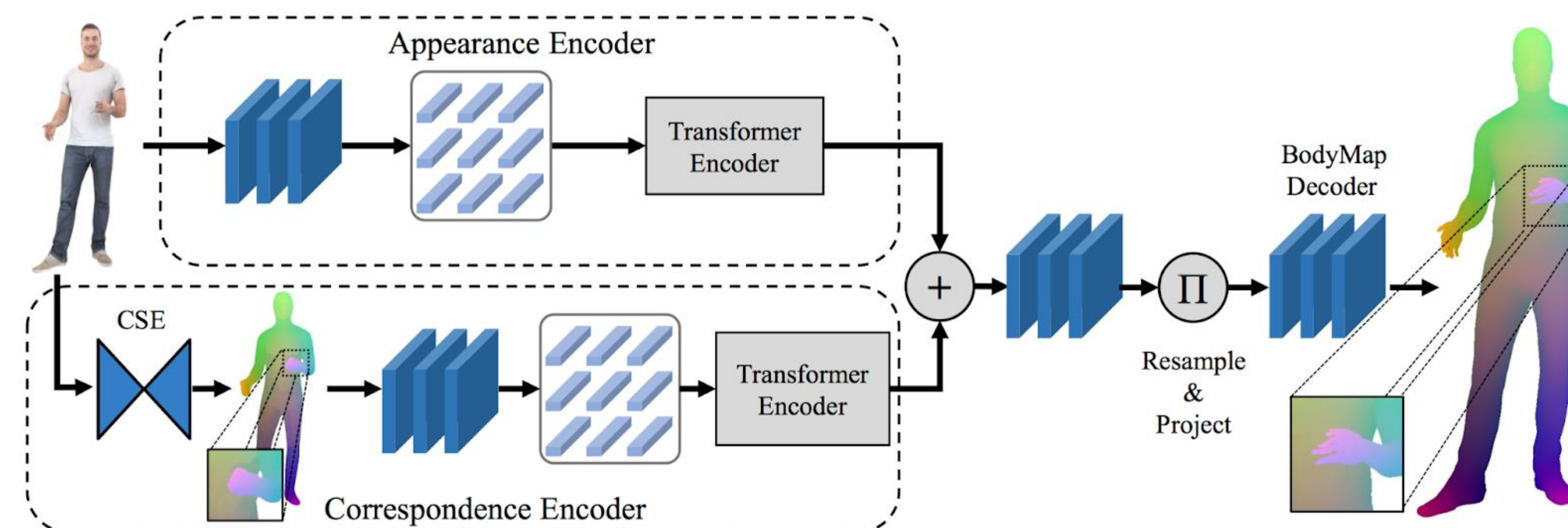


BodyMap

1. Correspondences for the clothed body
2. Learned on synthetic data
3. Continuous
4. Accurately captures hands/hair

BodyMap: Architecture

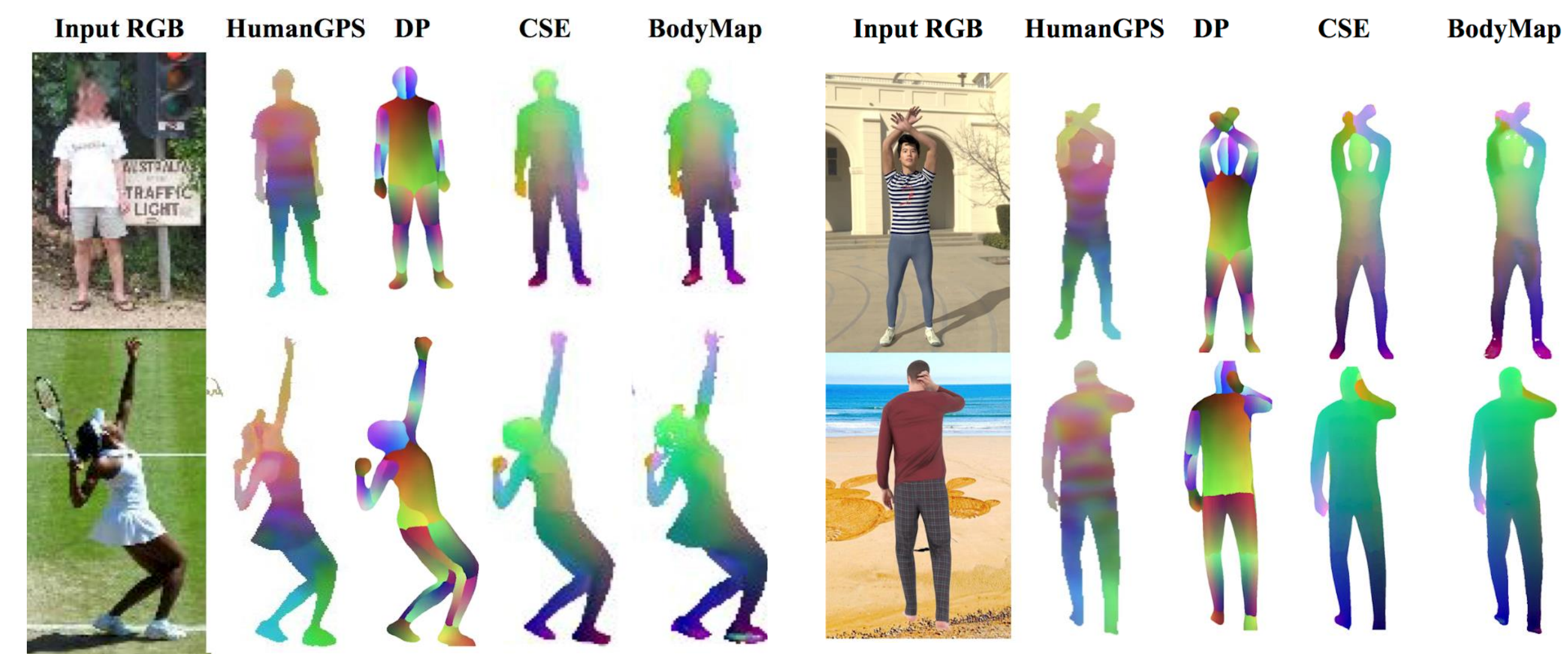
Given an RGB image of a human we (a) extract its CSE [1] estimate, (b) feed the RGB and CSE images to their respective encoders (ViT [2]) and (c) feed both representations to a decoder that generates the final result.



Comparisons with SOTA

DensePose-COCO

Method	AP	AP_{50}	AP_{75}	AR	AR_{50}	AR_{75}
AMA-net [6]	64.1	91.4	72.9	71.6	94.7	79.8
DensePose [3]	66.4	92.9	77.9	71.9	95.5	82.6
DensePose-DeepLab [3]	51.8	83.7	56.3	61.1	88.9	66.4
SimPose-Rendppl. [5]	57.3	88.4	67.3	66.4	95.1	77.8
SimPose-SMPL [5]	56.2	87.9	65.3	65.2	95.1	75.2
CSE [1]	67.0	93.8	78.6	72.8	96.4	83.7
CSE-DeepLab [1]	68.0	94.1	80.0	74.3	97.1	85.5
BodyMap RGB-only	71.0	94.3	83.3	75.2	94.3	86.1
BodyMap	75.2	95.8	89.7	79.8	97.3	89.7



Qualitative Results

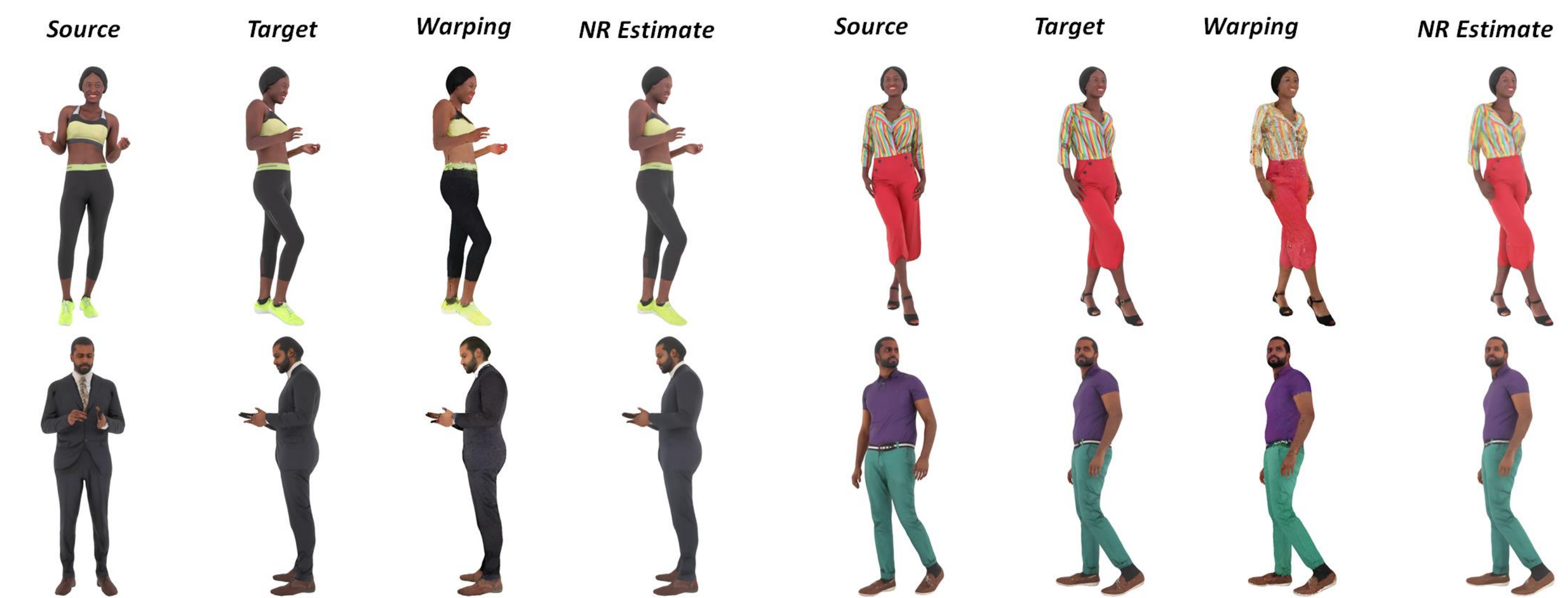


Applications

Cloth Swapping



Novel View Rendering



Layered Correspondences for Clothed Humans



- [1] Continuous Surface Embeddings, NeurIPS 2020
 [2] Vision Transformers for Dense Prediction ICCV 2021
 [3] DensePose: Dense human pose estimation in the wild CVPR 2018
 [4] HumanGPS: Geodesic PreServing Feature for Dense Human Correspondences, CVPR 2021
 [5] Simpose: Effectively learning densepose and surface normals of people from simulated data ECCV 2020
 [6] Adaptive multi-path aggregation for human densepose estimation in the wild, ACM MM 2019