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Geometry-Guided Progressive NeRF for Generalizable and Efficient Neural Human Rendering

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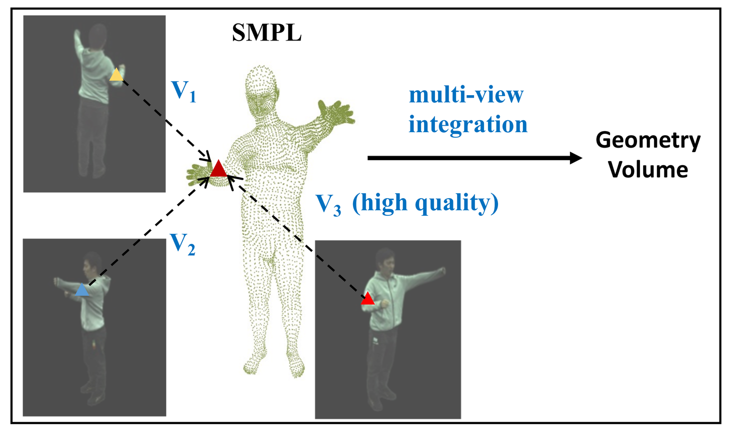
Challenges

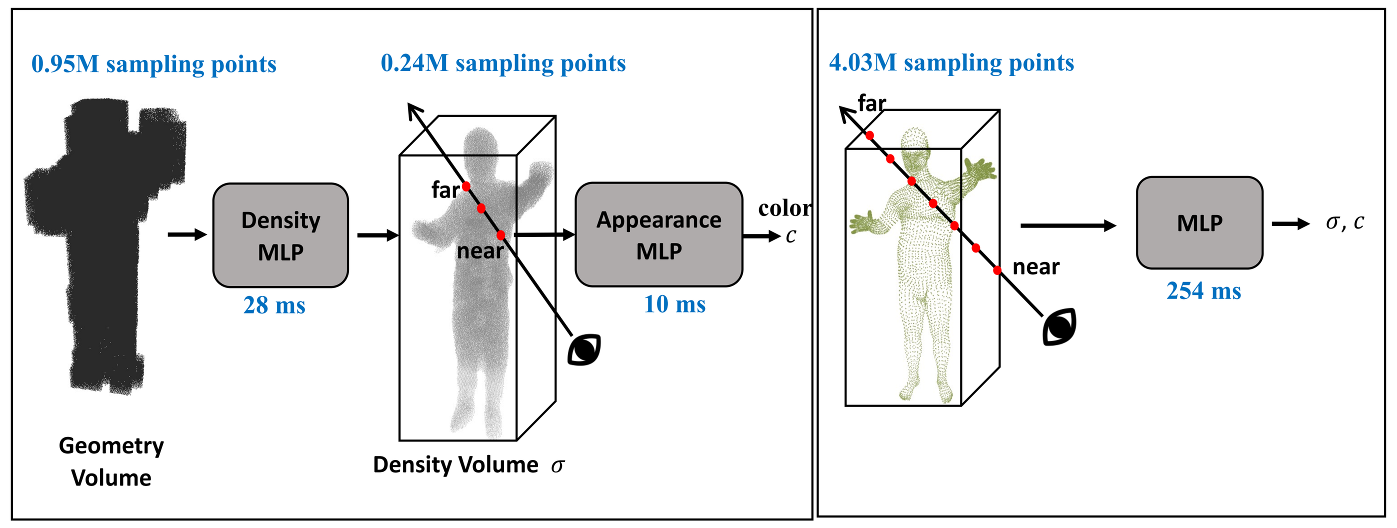
Free-viewpoint human body synthesis with sparse camera views



(a) Geometry-guided image feature integration: V for view.

	Previous	Ours
# Density Points (↓)	4.03M	**0.95M (-76%)**
Density MLP T (↓)	109ms	**28ms (-74%)**
# Color Points (↓)	4.03M	**0.24M (-94%)**
Color MLP T (↓)	145ms	**10ms (-93%)**
Memory (↓)	20.7GB	**9.9GB (-52%)**

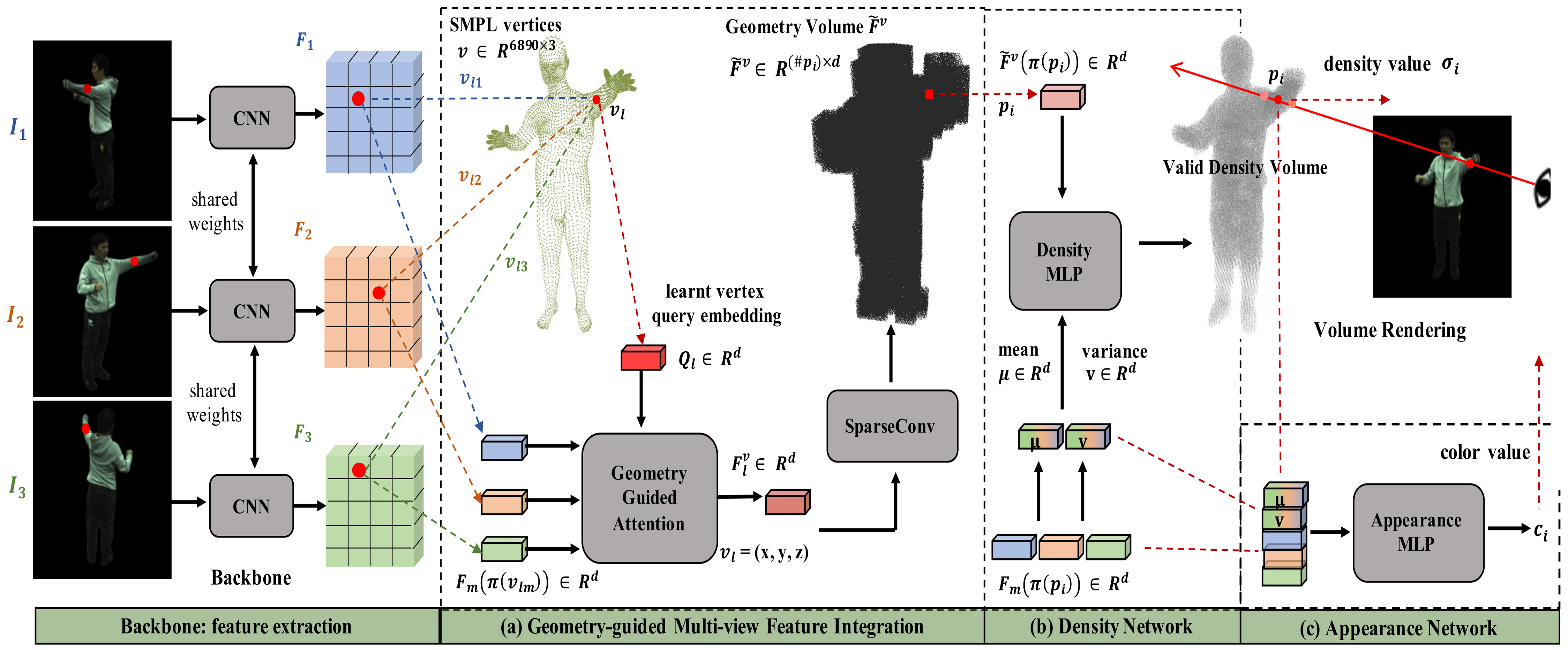
(c) Efficiency Comparison



(b) Rendering pipeline: our efficient geometry-guided progressive pipeline (left) vs. previous (right).
The amount of sampling points and forward time in blue are measured on the same data and model parameters.

- The human body is highly non-rigid and commonly has self-occlusions over body parts, which may lead to ambiguous results
- High computational and memory cost of NeRF-based methods severely hinder human synthesis with accurate details in high-resolution.

Solutions



- Propose a novel geometry-guided progressive NeRF (GP-NeRF) for generalizable and efficient human body rendering, which reduces the computational cost of rendering significantly and also gains higher generalization capacity simply based on the single-frame sparse views.
- Propose an effective geometry-guided multi-view feature integration approach, where we let each view compensate the low-quality occluded information for other views with the guidance of the geometry prior.

Quantitative Results

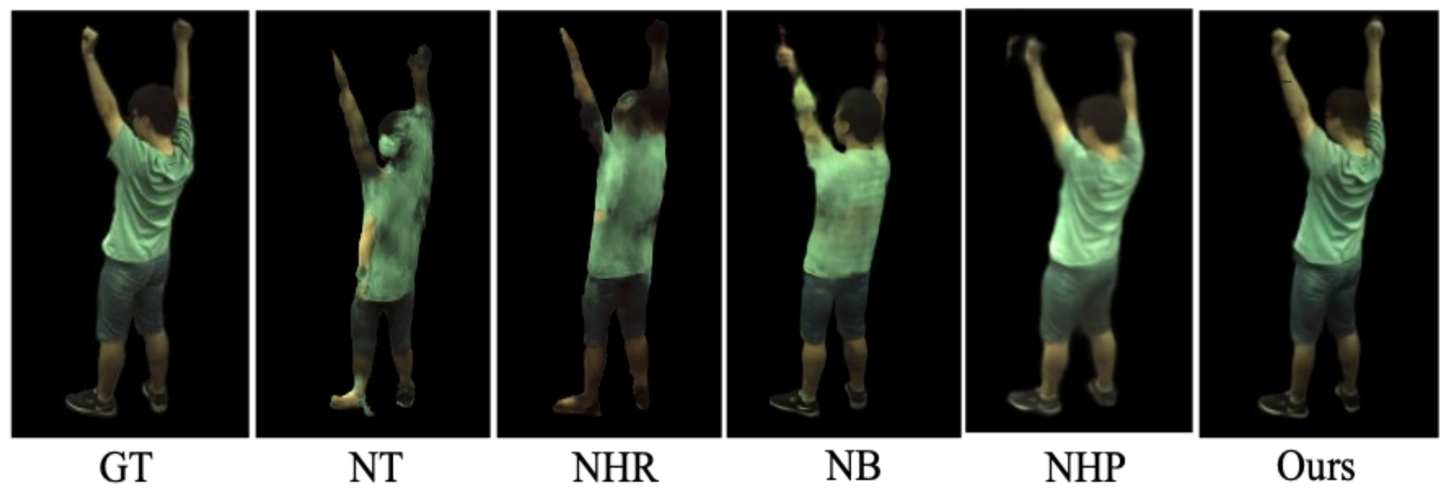
Method	Dataset Train	Dataset Test	Per-scene training	Unseen Pose	Unseen Body	Results PSNR (↑)	Results SSIM (↑)
Performance on training frames							
NT [37]	ZJU-7	ZJU-7	✓	✗	✗	23.86	0.896
NHR [39]	ZJU-7	ZJU-7	✓	✗	✗	23.95	0.897
NB [28]	ZJU-7	ZJU-7	✓	✗	✗	28.51	**0.947**
NHP [12]	ZJU-7	ZJU-7	✗	✗	✗	28.73	0.936
GP-NeRF (Ours)	ZJU-7	ZJU-7	✗	✗	✗	**28.91**	0.944
Performance on unseen frames from training data							
NV [19]	ZJU-7	ZJU-7	✓	✓	✗	22.00	0.818
NT [37]	ZJU-7	ZJU-7	✓	✓	✗	22.28	0.872
NHR [39]	ZJU-7	ZJU-7	✓	✓	✗	22.31	0.871
NB [28]	ZJU-7	ZJU-7	✓	✓	✗	23.79	0.887
NHP [12]	ZJU-7	ZJU-7	✗	✓	✗	26.94	0.929
GP-NeRF (Ours)	ZJU-7	ZJU-7	✗	✓	✗	**27.92**	**0.934**
Performance on test frames from test data							
NV [19]	ZJU-3	ZJU-3	✓	✓	✗	20.84	0.827
NT [37]	ZJU-3	ZJU-3	✓	✓	✗	21.92	0.873
NHR [39]	ZJU-3	ZJU-3	✓	✓	✗	22.03	0.875
NB [28]	ZJU-3	ZJU-3	✓	✓	✗	22.88	0.880
PVA [30]	ZJU-7	ZJU-3	✗	✓	✓	23.15	0.866
Pixel-NeRF [41]	ZJU-7	ZJU-3	✗	✓	✓	23.17	0.869
NHP [12]	ZJU-7	ZJU-3	✗	✓	✓	24.75	0.906
GP-NeRF (Ours)	ZJU-7	ZJU-3	✗	✓	✓	**25.96**	**0.921**
Generalization performance across datasets							
NHP [12]	AIST	ZJU-3	✗	✓	✓	17.05	0.771
GP-NeRF (Ours)	THUman-7	ZJU-3	✗	✓	✓	24.74	0.907
GP-NeRF (Ours)	THUman-all	ZJU-3	✗	✓	✓	**25.60**	**0.917**

Method	#r (M) (↓)	#$\mathbf{p}^d$ (M) (↓)	#$\mathbf{p}^c$ (M) (↓)	Time (ms) (↓)	Mem (GB) (↓)
NHP [10]	0.063	4.03	4.03	1160	14.20
NHR [34]	0.063	4.03	4.03	636	10.20
NB [24]	0.063	4.03	4.03	611	21.80
GP-NeRF† 3×	0.063 (-0.0%)	4.03 (-0.0%)	4.03 (-0.0%)	589 (-3.6%)	14.53 (-33.3%)
GP-NeRF† 2×	0.063 (-0.0%)	4.03 (-0.0%)	4.03 (-0.0%)	567 (-7.2%)	20.74 (-4.9%)
GP-NeRF 2×	**0.039 (-38.1%)**	**0.95 (-76.4%)**	**0.24 (-94.0%)**	243 (-60.2%)	**9.88 (-54.7%)**
GP-NeRF 1×	**0.039 (-38.1%)**	**0.95 (-76.4%)**	**0.24 (-94.0%)**	**175 (-71.4%)**	14.25 (-34.6%)

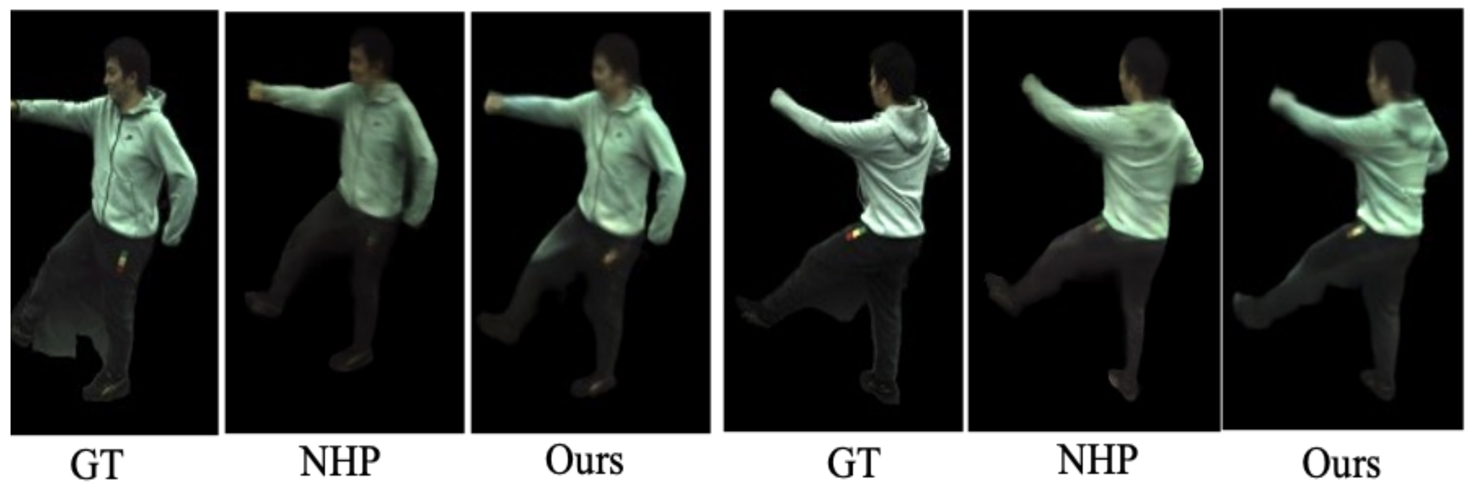
Method	T^d-MLP (ms) (↓)	T^d-total (ms) (↓)	T^c-MLP (ms) (↓)	T^c-total (ms) (↓)	PSNR (↑)
GP-NeRF† 2×	108.58	226.56	145.38	146.39	26.56
GP-NeRF 2×	28.08 (-74.1%)	83.65 (-63.1%)	10.02 (-93.1%)	11.4 (-92.2%)	**26.67 (+0.4%)**
GP-NeRF 1×	**23.55 (-78.3%)**	**74.07 (-67.3%)**	**9.50 (-93.5%)**	**10.27 (-93.0%)**	**26.67 (+0.4%)**

- Our GP-NeRF has achieved state-of-the-art performance on the ZJU-MoCap dataset, taking only 175ms on RTX 3090 and reducing time for rendering per image by over 70.

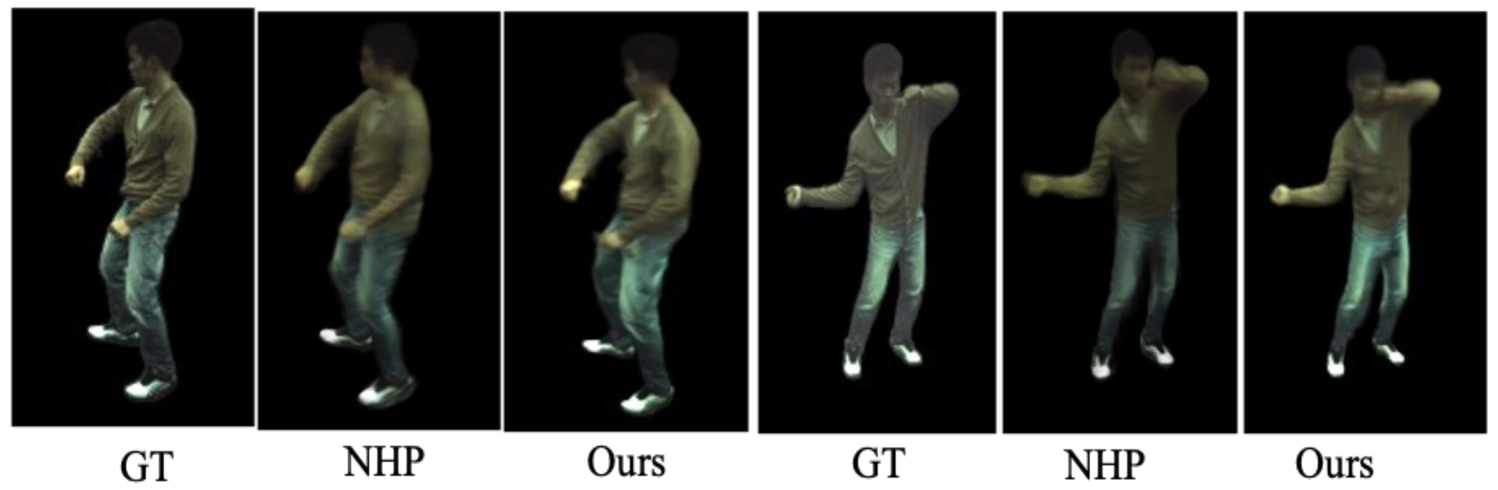
Qualitative Results



(a) Seen dataset, seen body, unseen pose



(c) Seen dataset, unseen body (human #2)

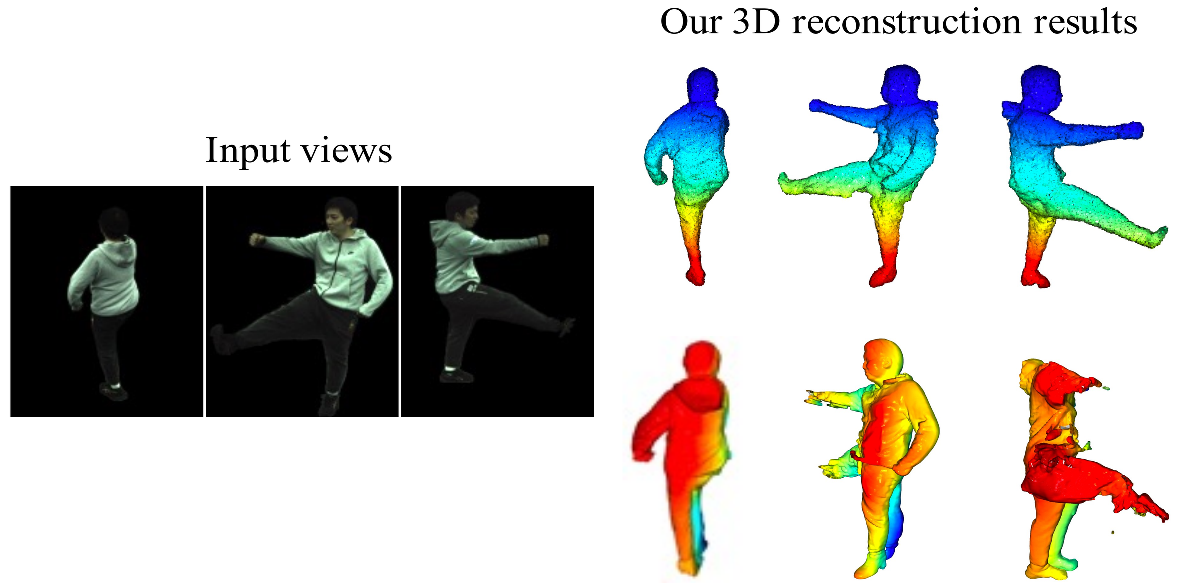


(b) Seen dataset, unseen body (human #1)

(d) Seen dataset, unseen body on THUman dataset
(for each image pair, GT in the left, our results in the right)

Reconstructed 3D Results

(a) Seen human body



(b) Unseen human body

- Ours can stick to the normal human body geometry better than methods without geometry priors and can reconstruct more accurate lighting conditions.
- Our synthesis can reconstruct very close human body shape and clothes details like hoods and folds on unseen human bodies.