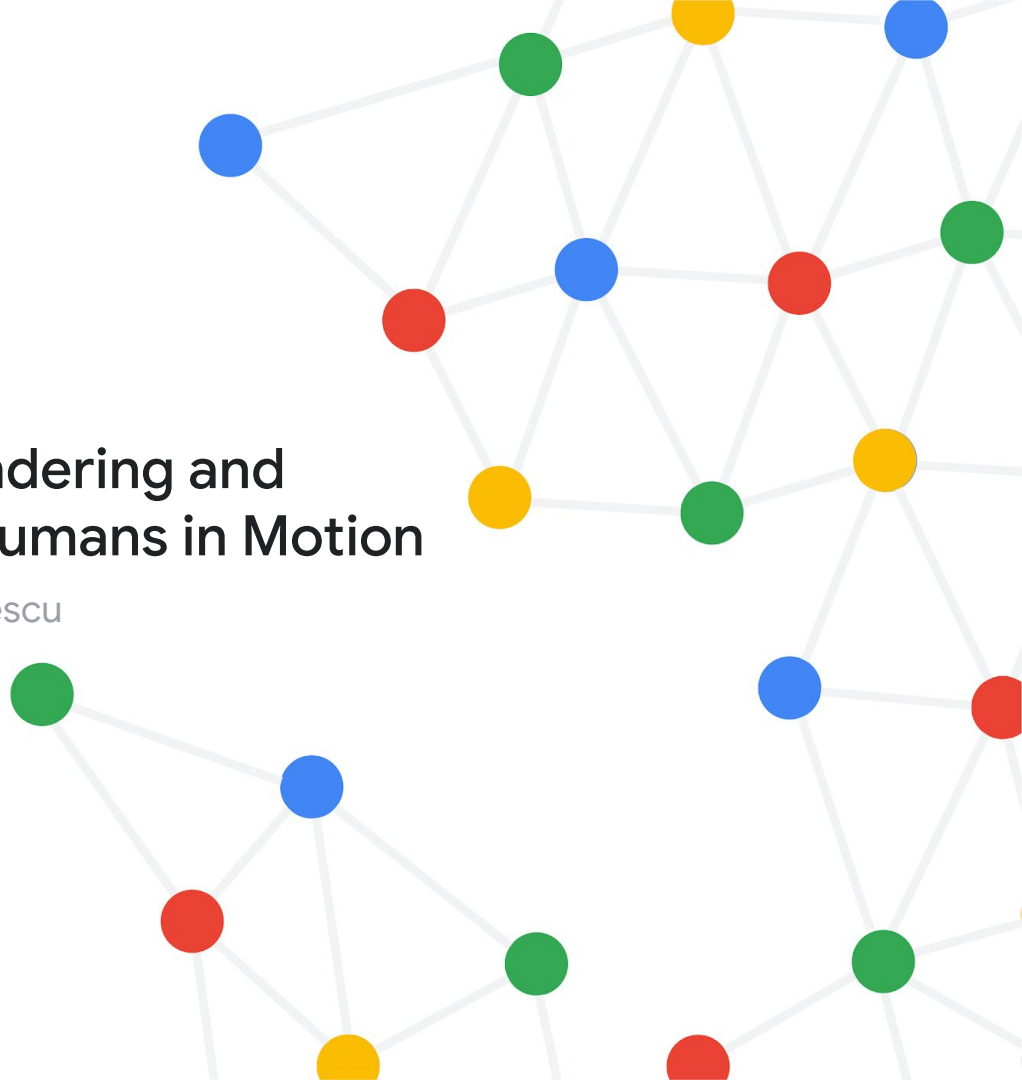
H-NeRF:
Neural Radiance Fields for Rendering and Temporal Reconstruction of Humans in Motion

Hongyi Xu, Thiemo Alldieck, Cristian Sminchisescu



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H-NeRF

Videos with novel views synthesized using H-NeRF

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Neural Radiance Fields

Static Scenes
[Mildenhall et al. 2020]

Human Motion
[Peng et al. 2021]

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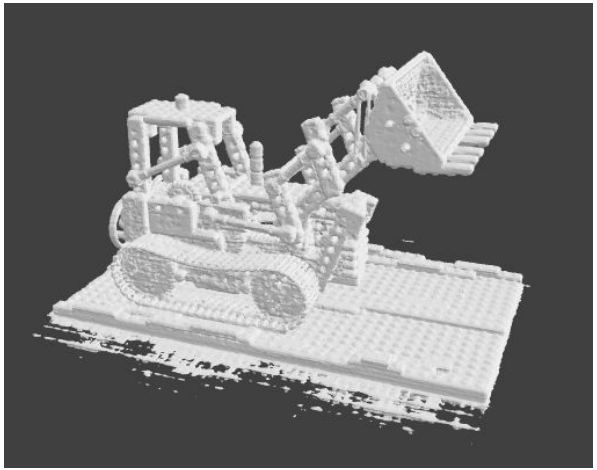
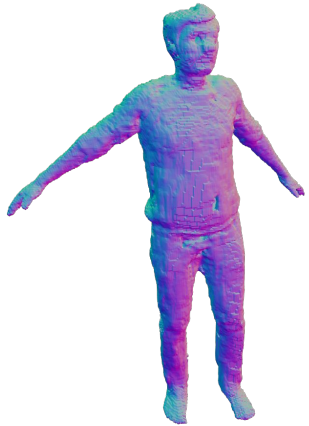
Limitations of Neural Radiance Fields





Neural rendering does not generalize well for viewpoints far from the training set

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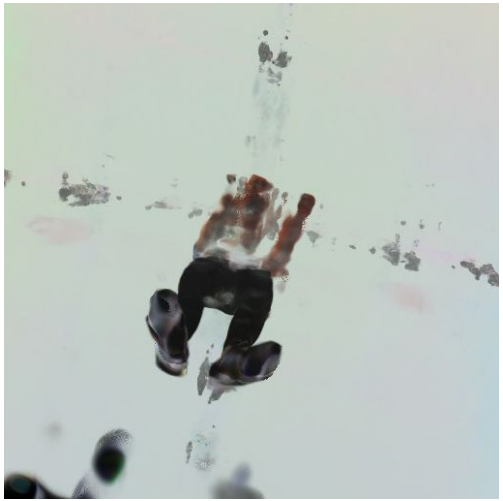
Limitations of Neural Radiance Fields



Neural rendering does not generalize well for viewpoints far from the training set, and for deformable and articulated structures

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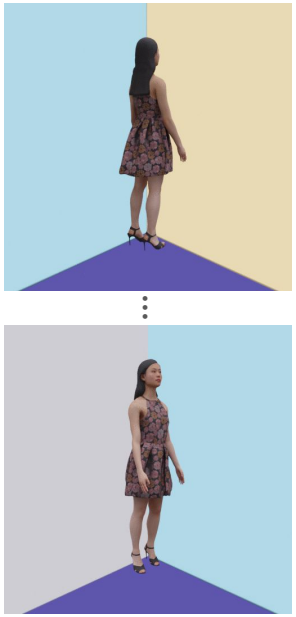
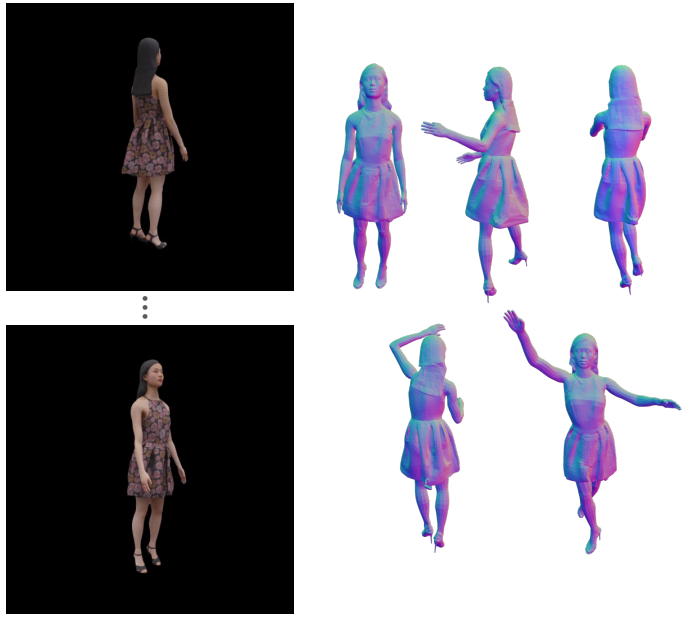
H-NeRF



Input: monocular or
sparse multi-view videos

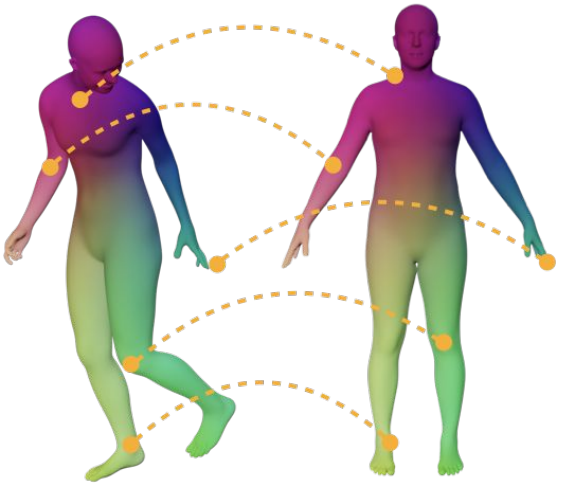
Neural radiance field



Output: rendering and temporal
reconstruction of a human in motion

Implicit 3D Body Model (imGHUM) for shape and appearance regularization

1. Rich geometric prior for occupancy



2. Semantic mapping function to integrate appearance over time into a common coordinate system

The implicit body model is an important building block of H-NeRF

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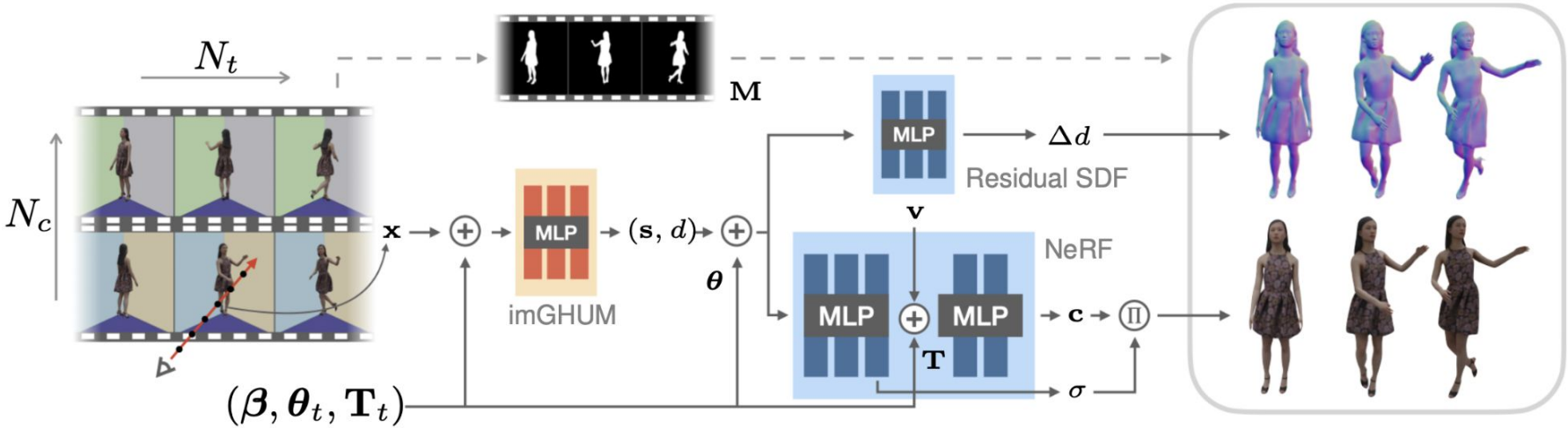
Overview



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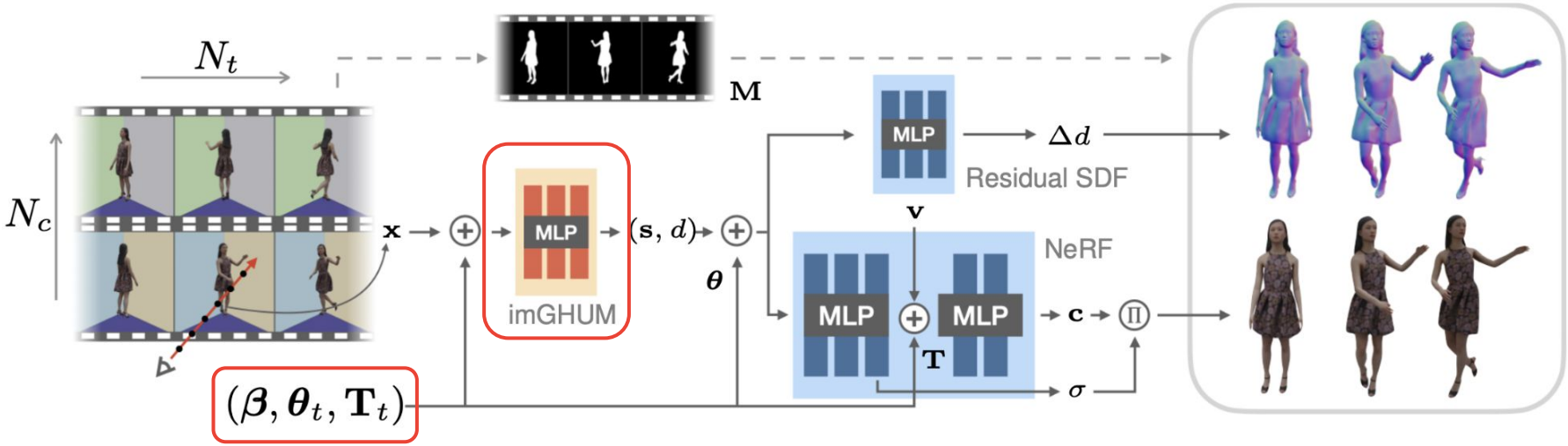
Overview



The implicit SDF-based body model imGHUM serves as a geometric prior and common reference frame

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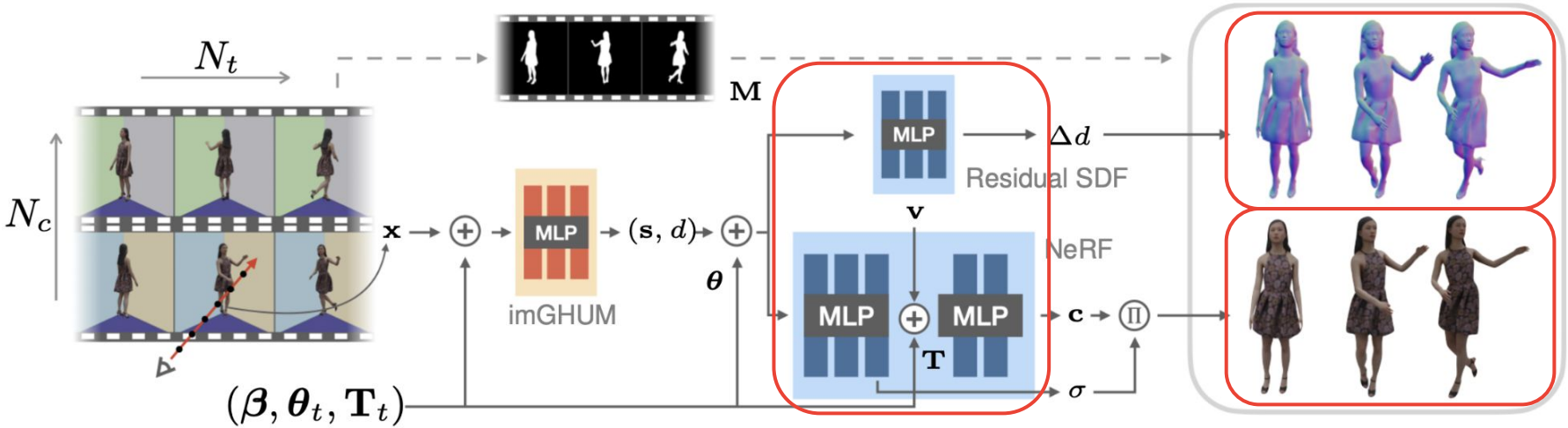
Overview



We co-train a neural radiance field and a signed distance function to enable high fidelity in **both** view synthesis **and** 3D reconstruction

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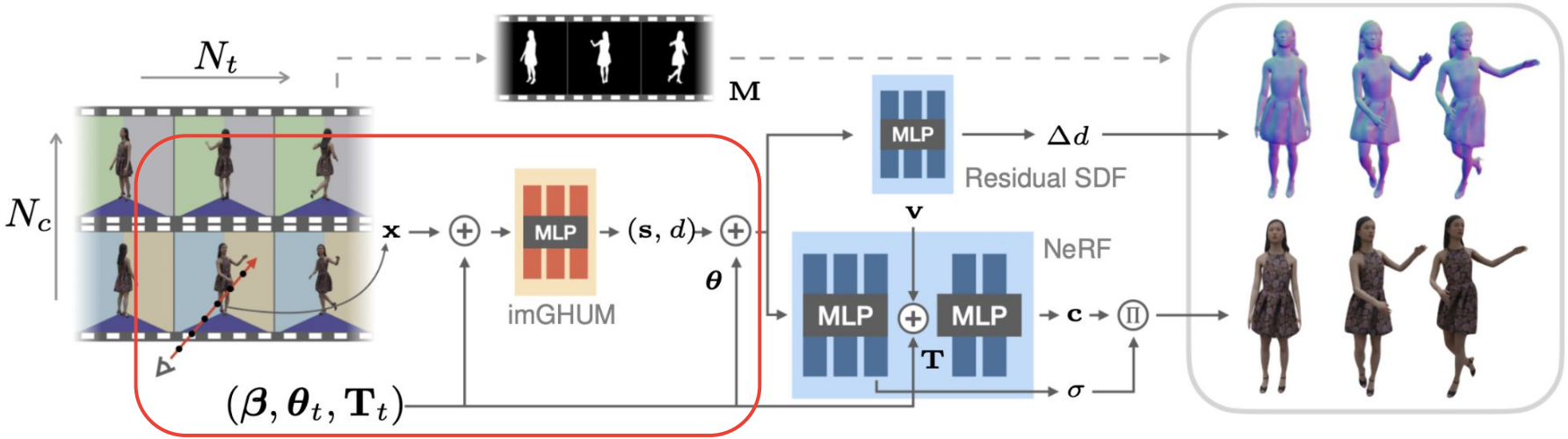
Overview



At test time, the subject can be animated with different motions, or even synthesized with extrapolated shape, by varying imGHUM's generative parameters

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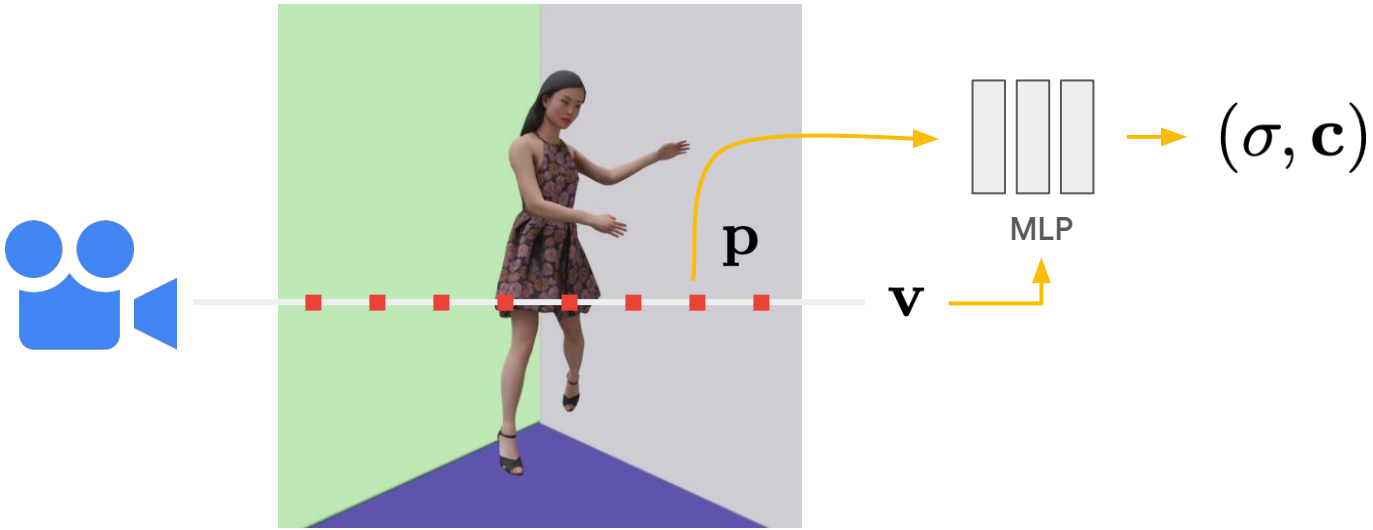
NeRF Formulation



The rendering component of our method builds upon the original NeRF formulation, and is trained using only image observations

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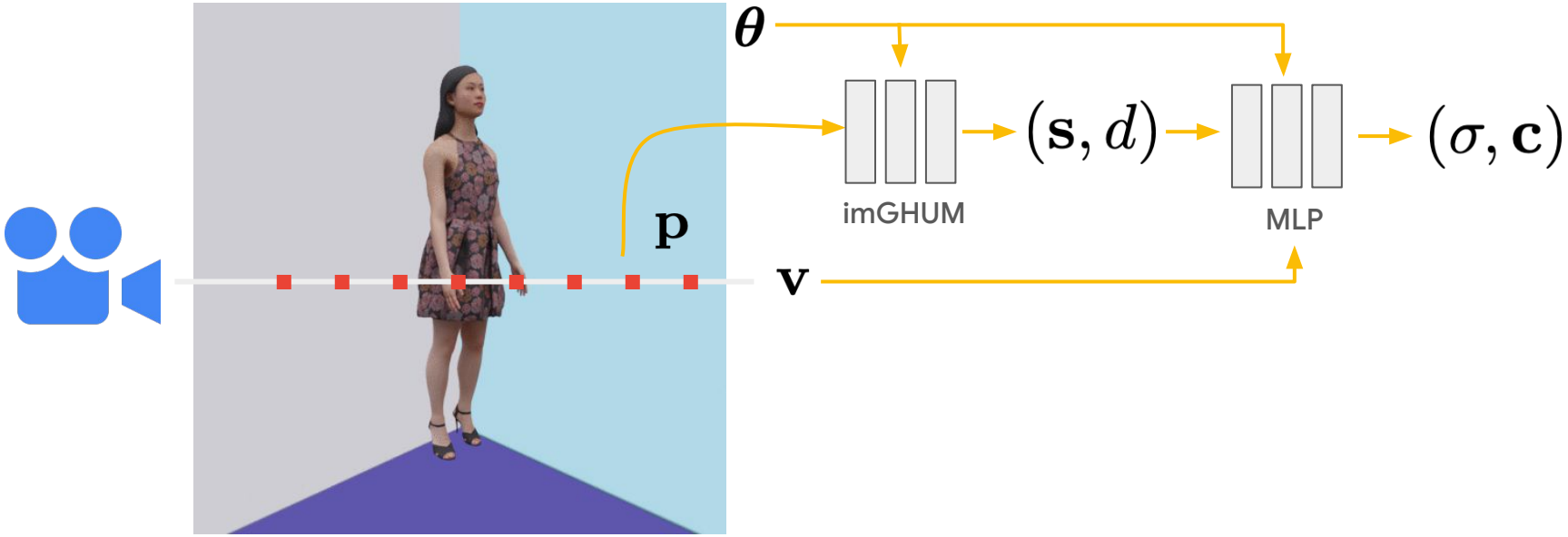
Dynamic NeRF Formulation



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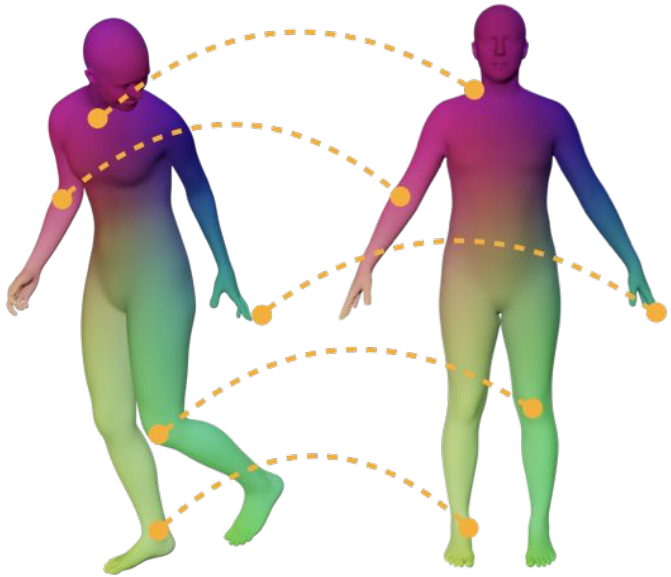
imGHUM as Spatial Warping Function



imGHUM returns distance and semantics that map every point in space into a common reference frame

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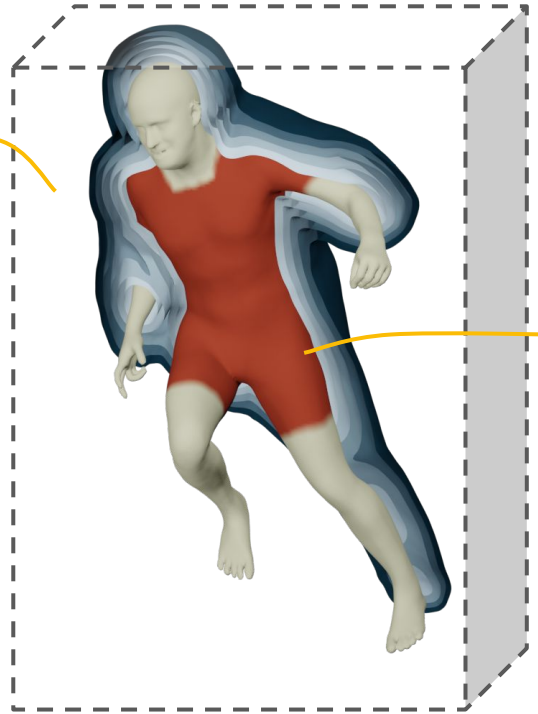
imGHUM as Geometric Prior

We expect the occupancy of the reconstructed subject to be inside imGHUM's relaxed bounding box.



We expect high NeRF density inside the imGHUM body estimate.

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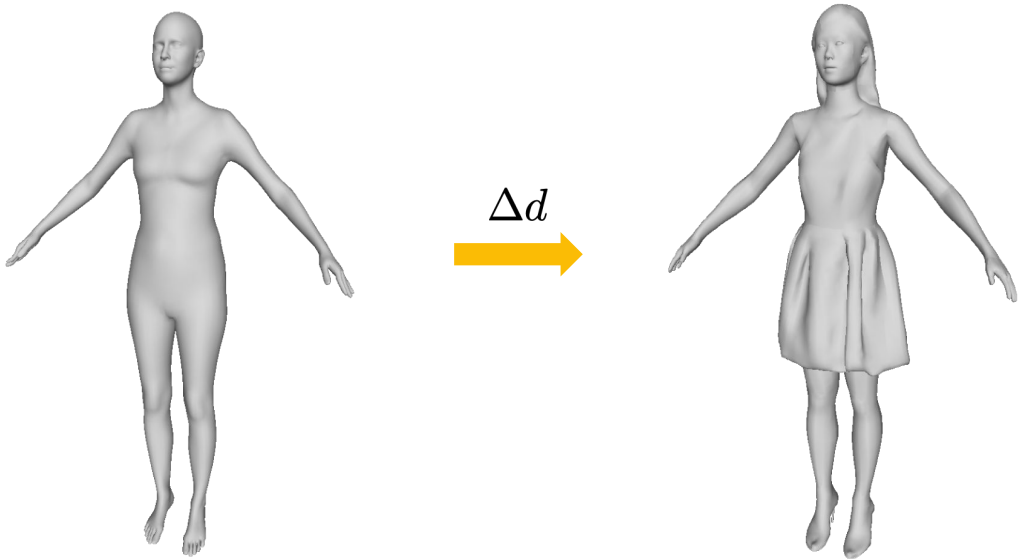
Residual SDF



We co-learn a residual SDF to the (fixed) imGHUM model to be able to represent hair and clothing

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Results

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Novel View Synthesis

Ground truth H-NeRF

Ground truth H-NeRF

Training views

Test views (45° from training)

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Geometric Reconstruction

Each pair:
Ground truth (left) Ours (right)

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Comparison with SoTA

Ground truth

Ours

NeuralBody
[Peng et al. 2021]

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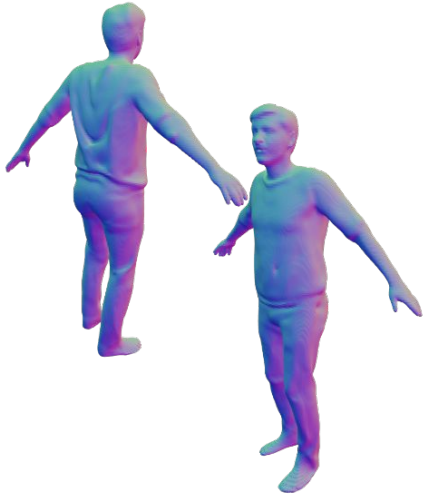
Comparison with SoTA

Ground-Truth



Ours

NeuralBody
[Peng et al. 2021]

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Rendering new Motions

Training sequence

Training sequence

Synthesized **unseen motions** rendered using **testing** camera **views**

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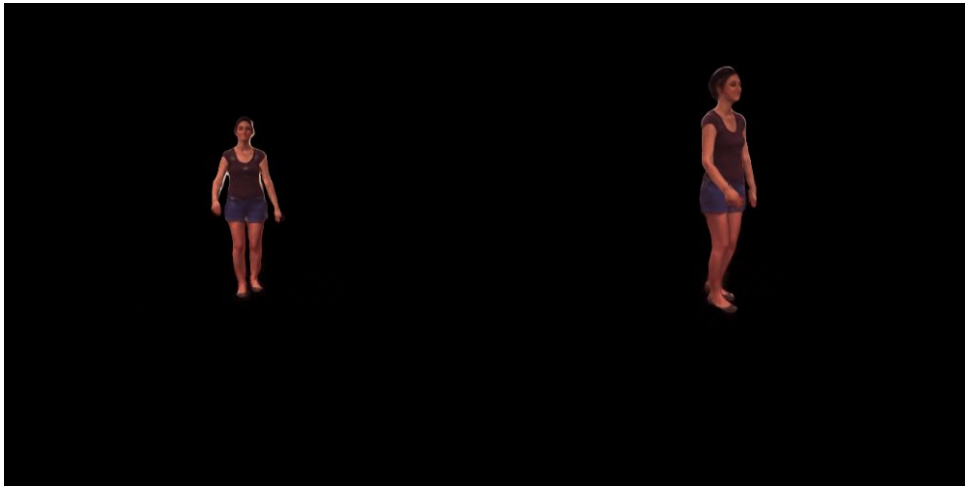
Rendering new Motions based on Sparse Real-World Training Images

PeopleSnapshot (trained on 1 camera)



Human 3.6M (trained on 4 cameras)

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Statistical Body Shape Editing

Two subjects rendered with statistically modified body shapes,
both lower and higher BMI w.r.t. photographed (center)

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Generalization

Novel view synthesis and geometric reconstruction
with a novel shape and a novel pose sequence

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Thank You

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