



HumMorph: Generalized Dynamic Human Neural Fields from Few Views

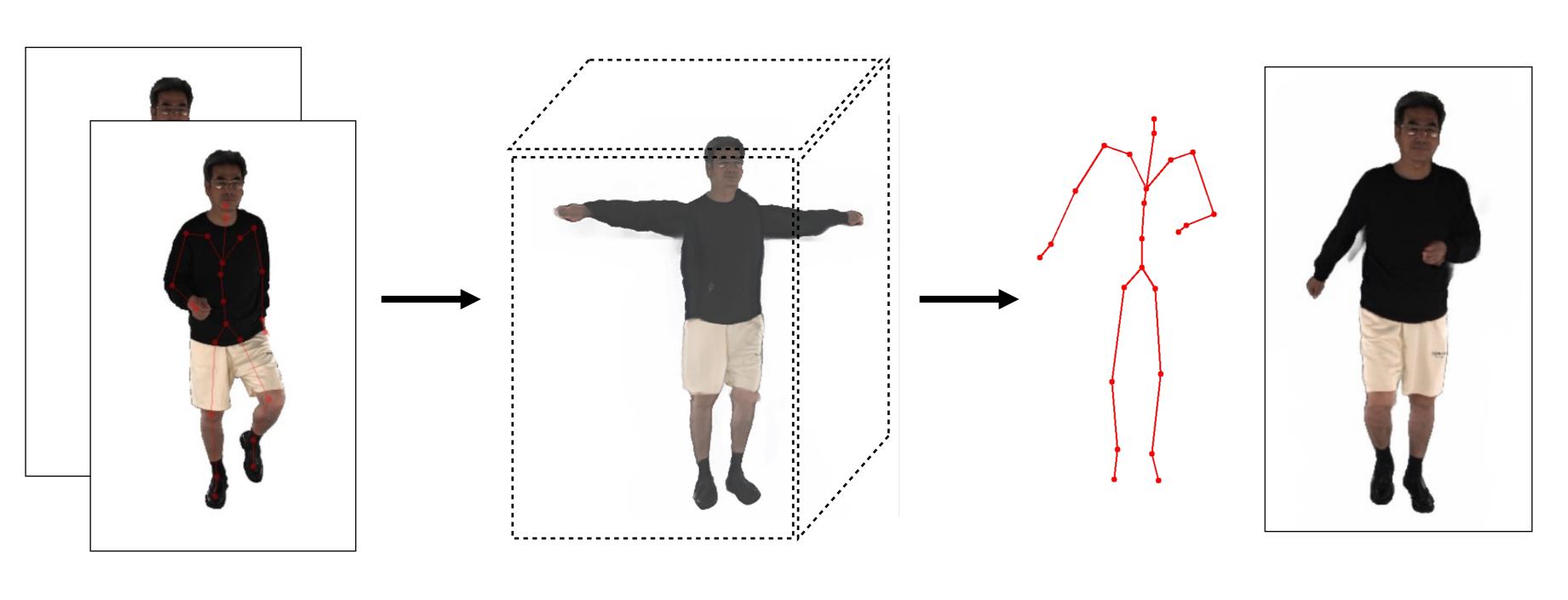


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Input: skeleton shape.

Introduction

Task: Given a few observed frames of a subject in motion, synthesize their dynamic 3D model that can be animated to a given target pose and rendered from an arbitrary viewpoint.



Input: a few monocular views with pose parameters

Estimate: subject NeRF model in canonical pose

Input: target pose parameters

Output: render in target pose

Why *HumMorph*?

Subject-specific approaches

Require test-time optimization

Need extensive observations

(typically ca. 30 frames)

Other generalized approaches



Assume accurate body shape and pose parameters (impractical)

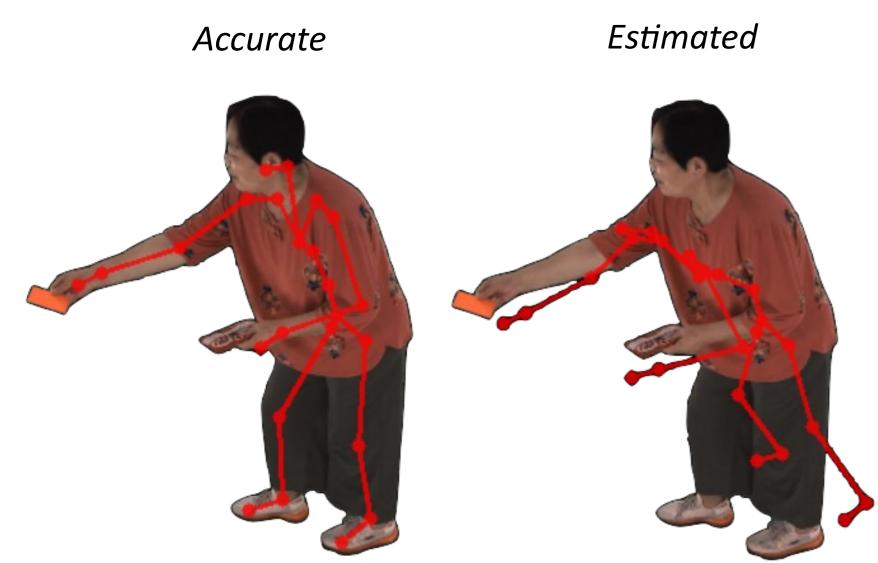
HumMorph (ours)

Uses only feed-forward passes during inference Requires less observed views (1 - 4)
Learns a prior, inpaints unobserved details



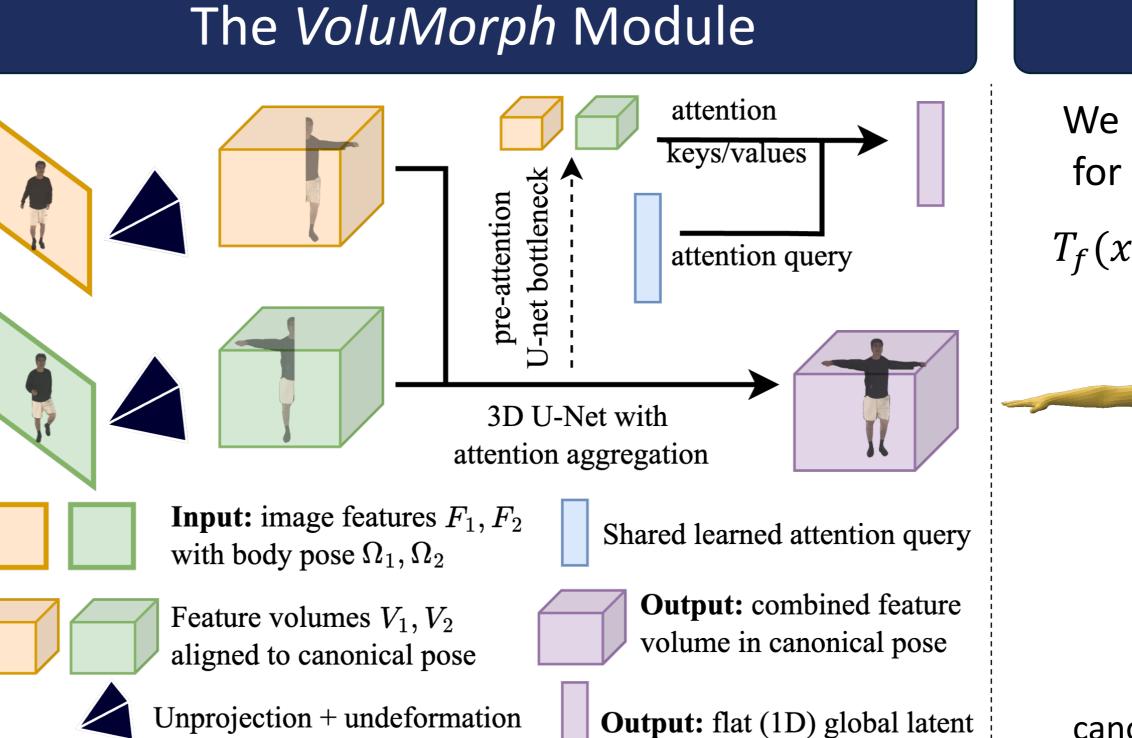
Significantly more robust to errors in the noisy parameters

Estimated Body Shape and Pose



- The accurate body shape and pose parameters are typically estimated from multi-view camera setups.
- They should be directly estimated from the input views instead.
- ► Fig. on the left: frames with skeleton annotated in red using accurate (left) and estimated (right) body shape and pose parameters. Parameters estimated using HybrIK (Li et al., CVPR '21).

Method Overview Output: NeRF in target pose Ω_q query at x_c global feature $f_{\rm glob}$ final motion weights Wglobal triplane features in canonical pose VoluMorph module linked by deformation $x_c = T_b(x_p, \Omega_g; \mathcal{I})$ voxel feature $f_{ m vox}$ feature volume V VoluMorph module in canonical pose ' \neg query at $u^{(t)}$ (w/o global feat.) final feature f $u^{(t)}:$ find corresp. point project to image heuristic motion weights canonical space NeRF in pose Ω_t using T_f plane of I_t $\sigma(x_c; \mathcal{I})$, $\mathbf{c}(x_c; \mathcal{I})$ with shared bias pixel-aligned



Input: 2D featuremaps F_t

for observed images I_t with poses Ω_t

We use **linear blend skinning** for body deformations T_f, T_b $T_f(x_c, \Omega) = x_p \quad T_b(x_p, \Omega) \approx x_c$

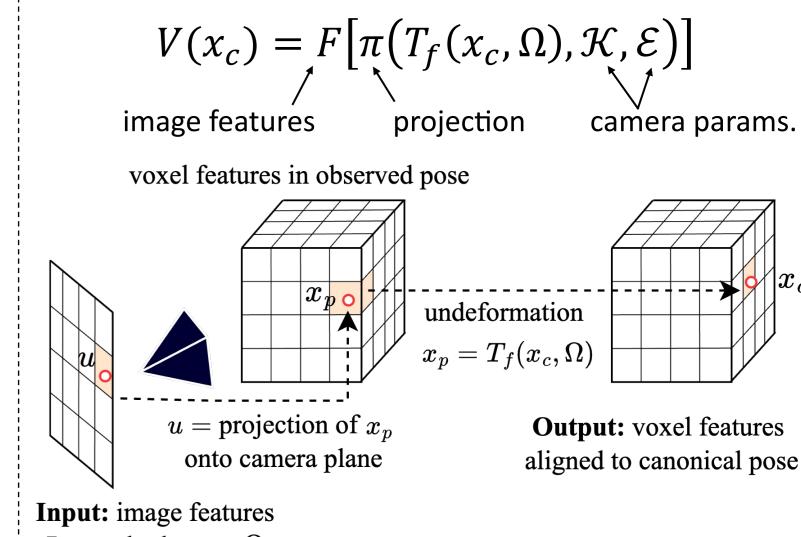
body pose Ω

Deformations

features $f_{
m pix}^{(t)}$

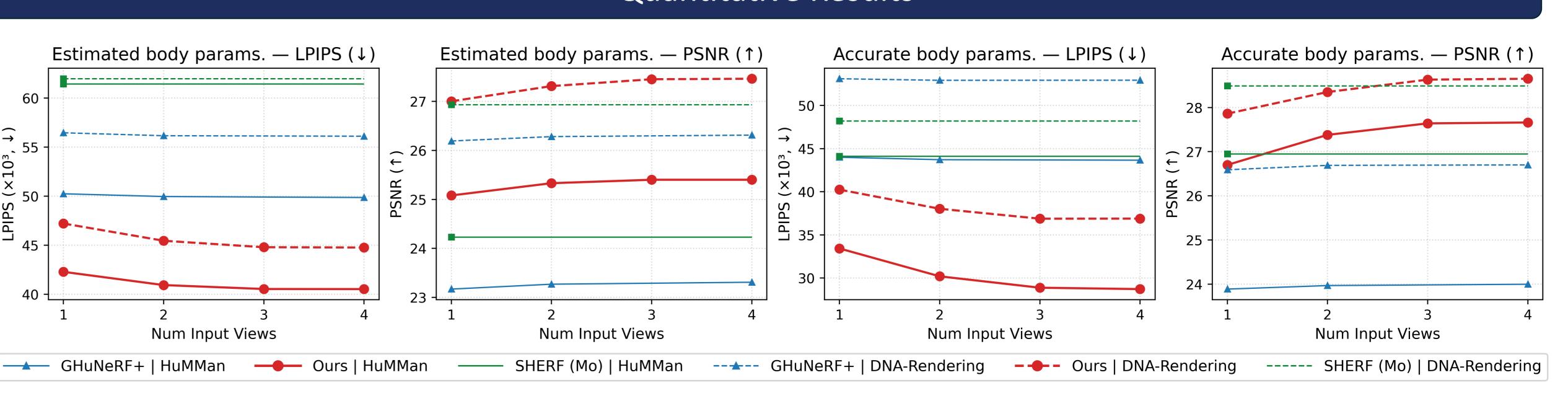
Unprojection + Undeformation

The aligned feature volume V at voxel position x_c is

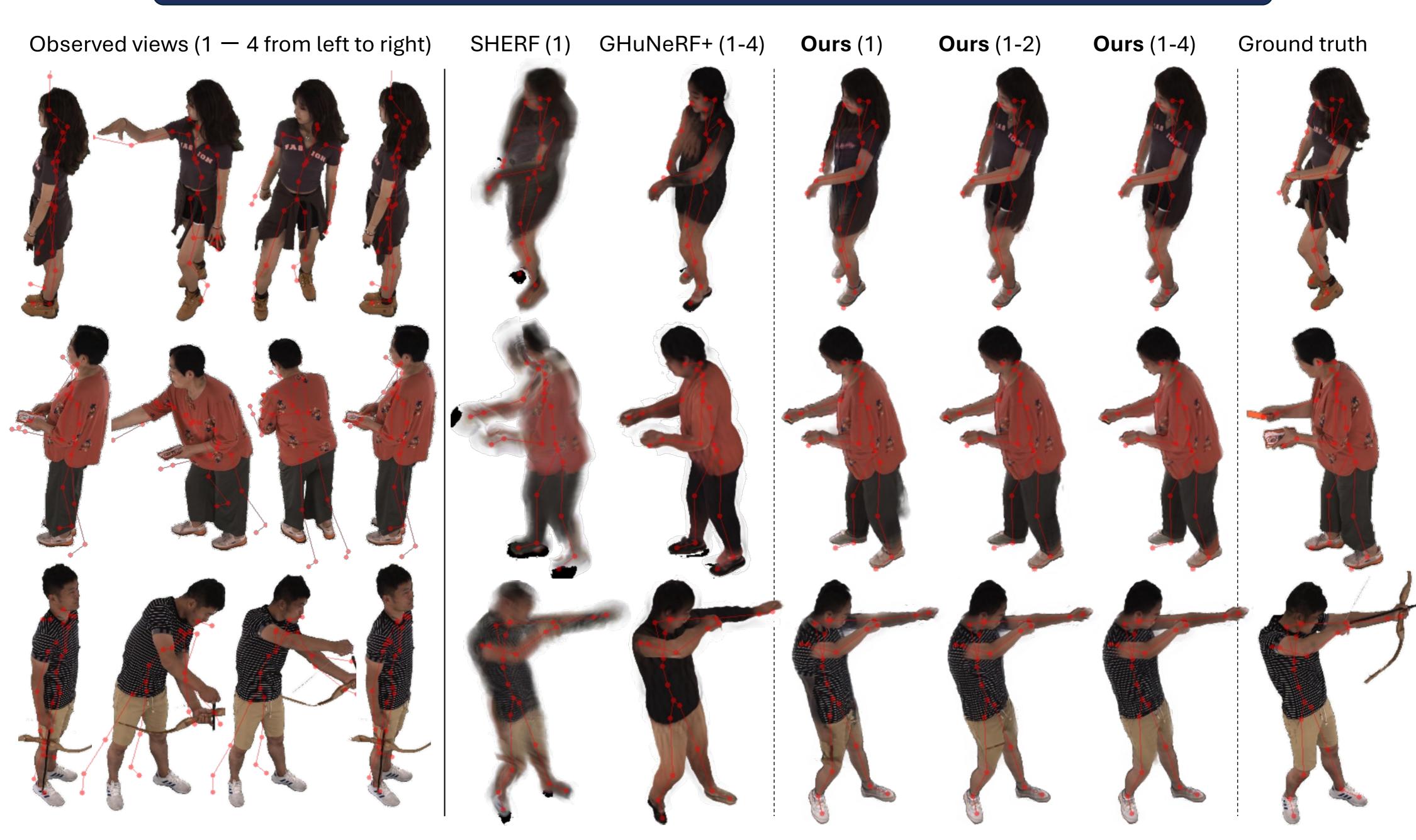


Quantitative Results

canonical pose

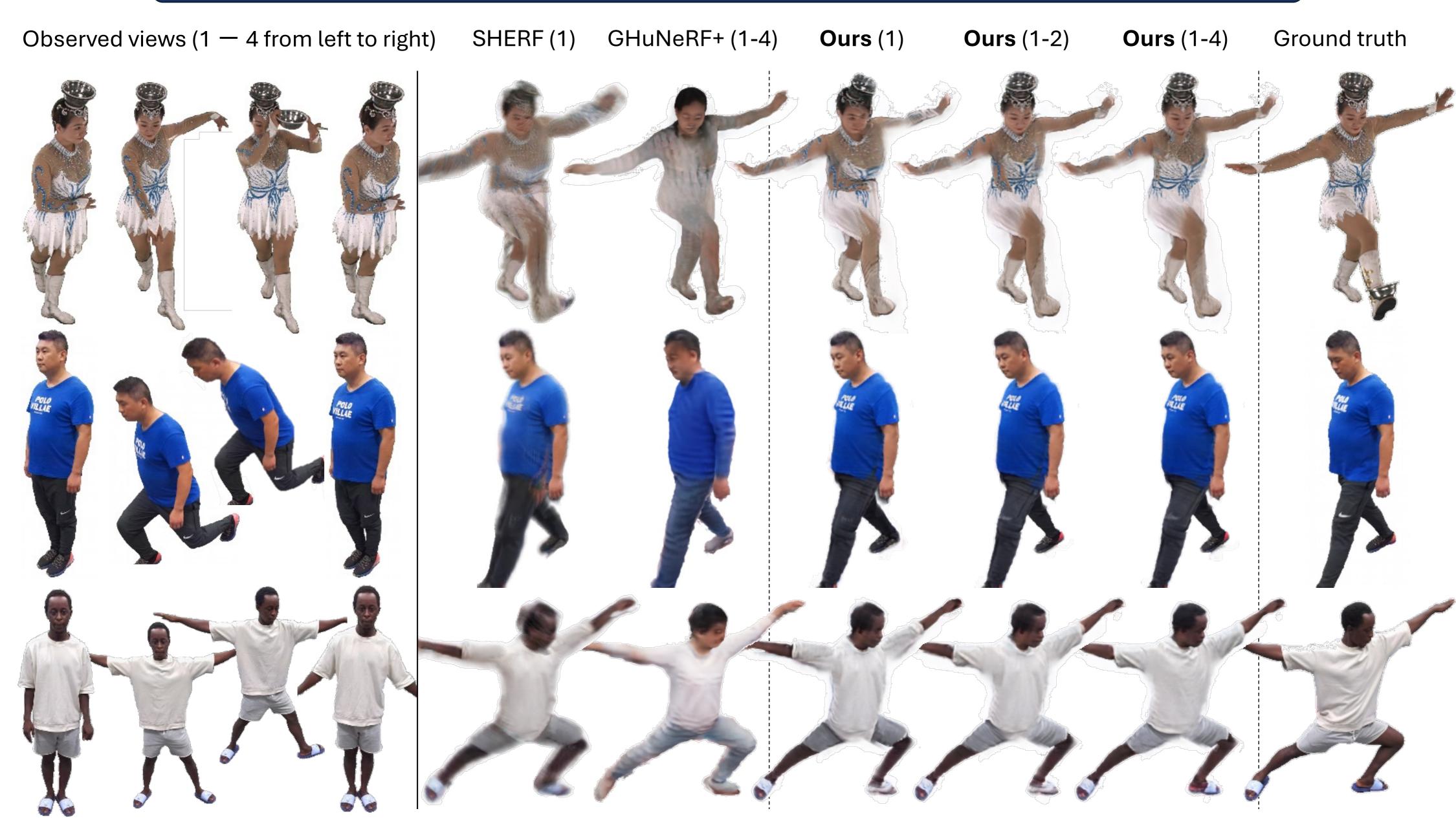


Results with **Estimated** Pose Parameters



Numbers in parentheses indicate the range of observed views. SHERF only accepts a single input view. Poses estimated using HybrlK directly from input views (shown in red).

Results with **Accurate** Pose Parameters



Numbers in parentheses indicate the range of observed views. SHERF only accepts a single input view.

The accurate poses are provided by the datasets.