

Invertible Neural Skinning



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University of Toronto
Snap Research

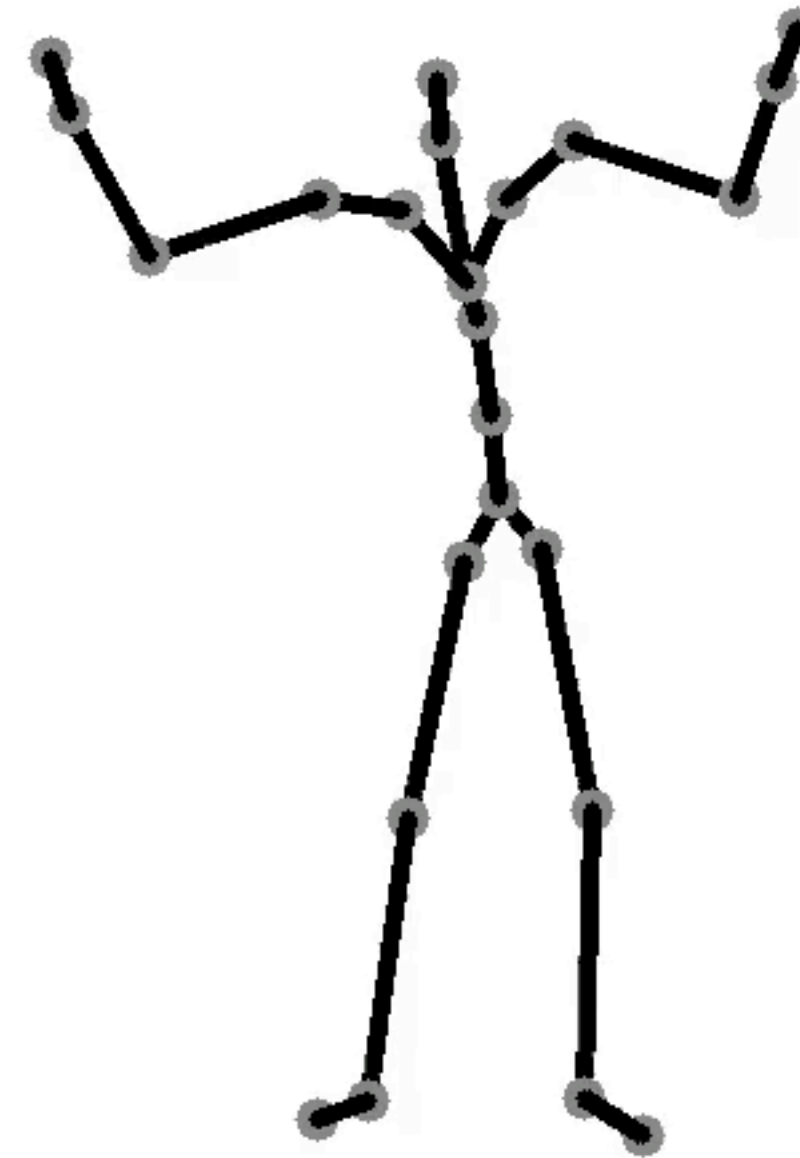


Reposing Task.

Given: Sequence of **3D scans** (meshes) and **SMPL-fitted poses**.



3D scans

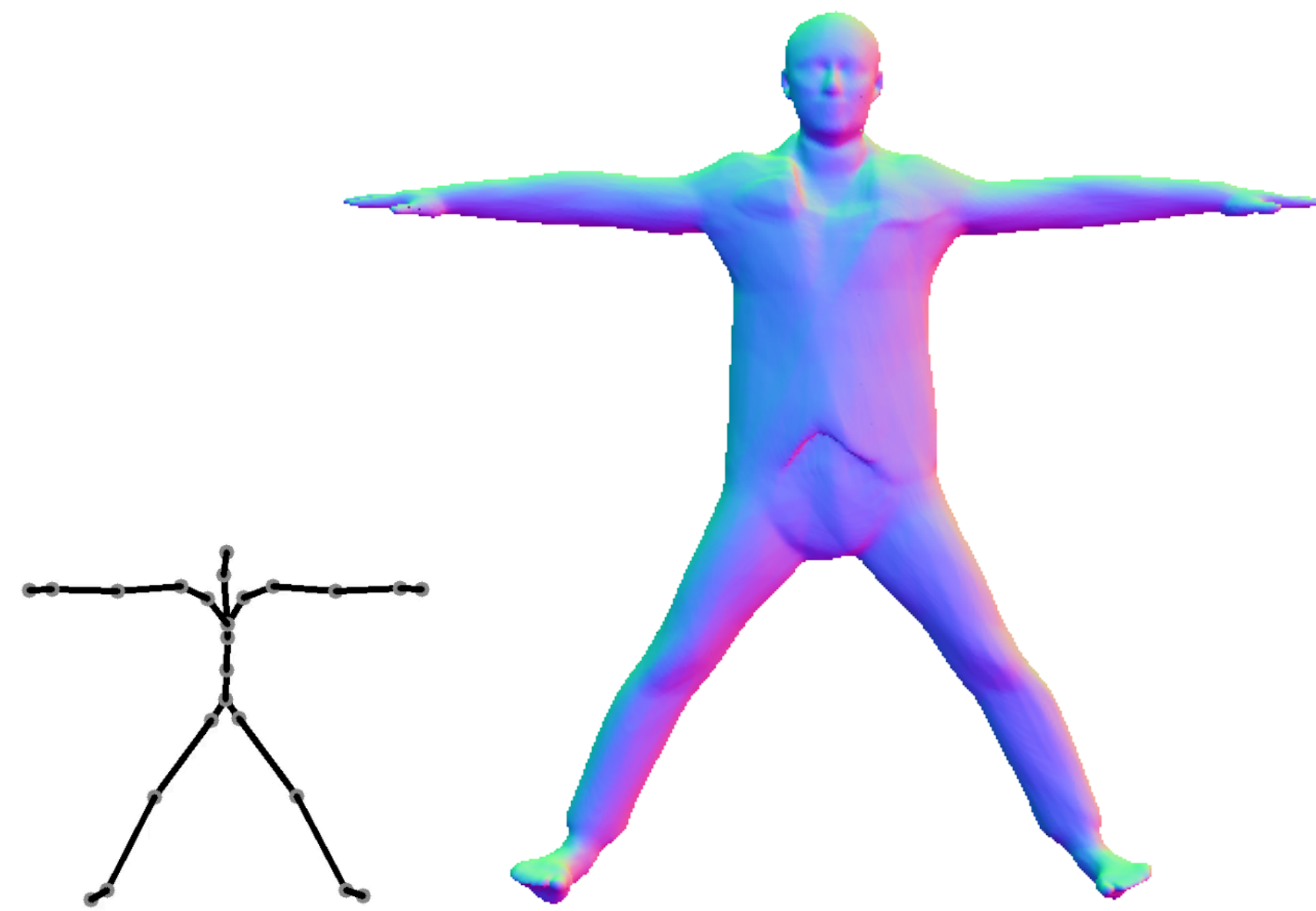


SMPL-fitted poses

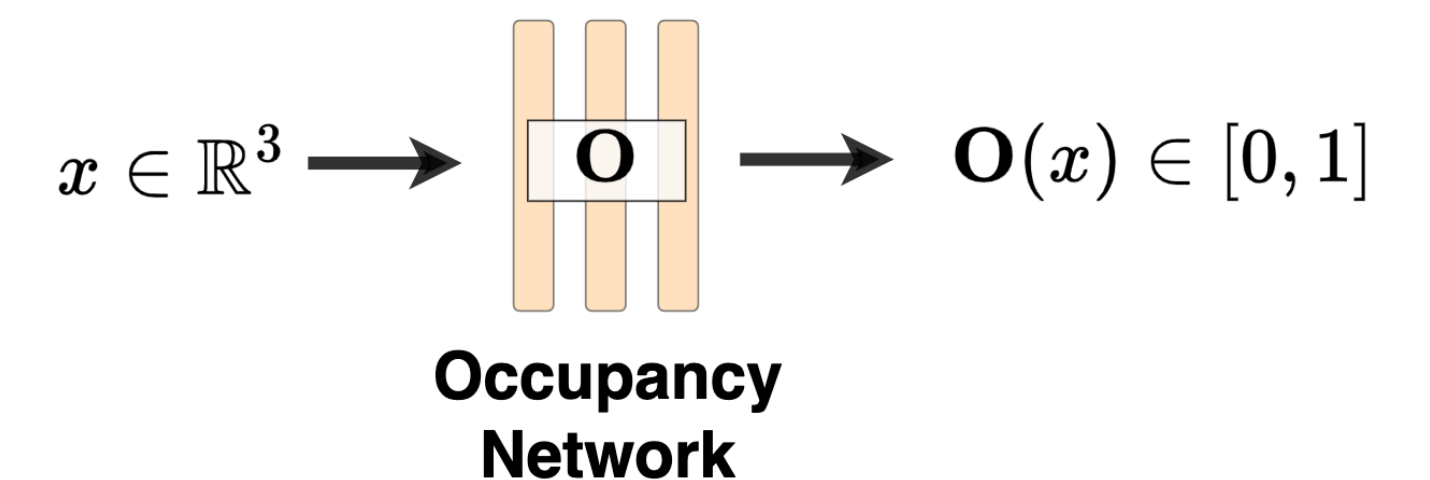
Canonical Space. [Background]

We first define a canonical space where the subject pose is fixed.

And we learn **canonical shape** implicitly using an occupancy network.

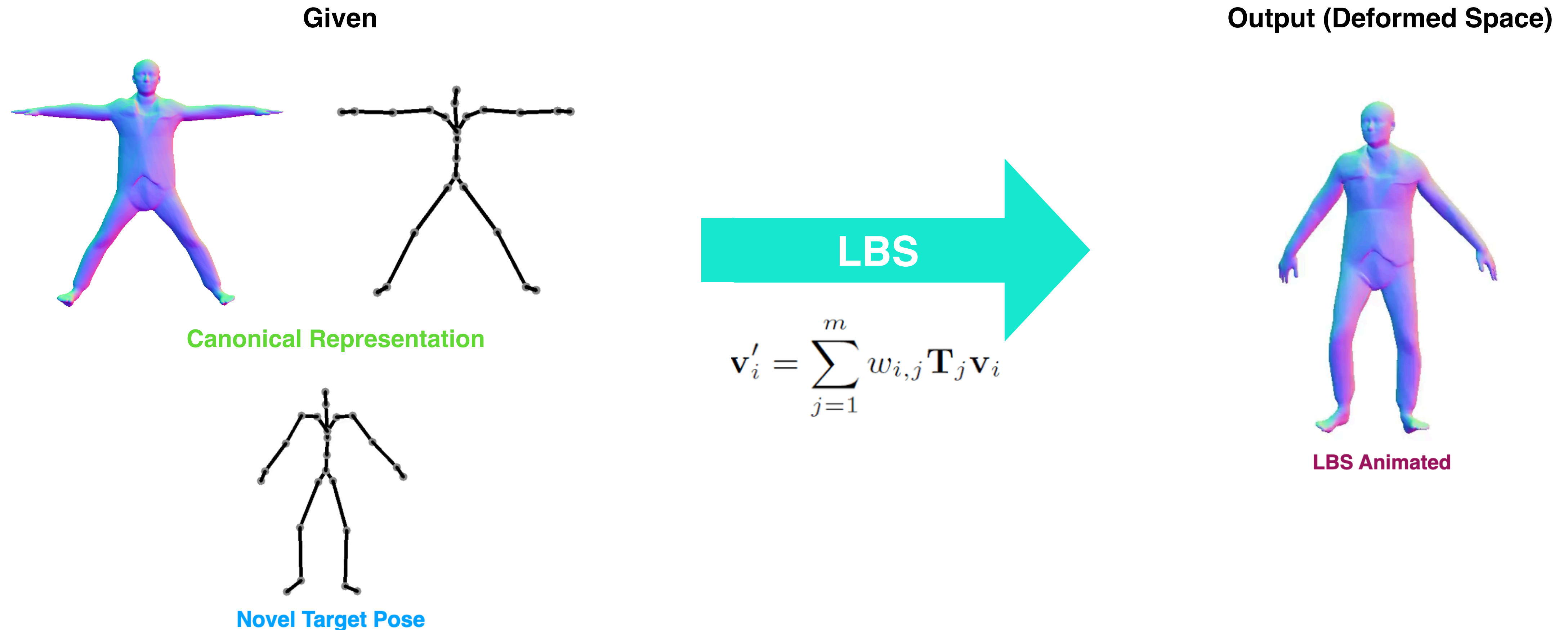


Canonical Representation



Skinning. [Background]

Linear Blend Skinning (LBS) is a way to animate 3D surfaces based on relative bone configurations (canonical to deformed).



Skinning. [Background]

For each point v_i on the surface, we define a set of weights w_{ij} that defines how much the j^{th} bone contributes to its movement.

$$\mathbf{v}'_i = \sum_{j=1}^m \underbrace{w_{i,j} \mathbf{T}_j}_{j^{\text{th}} \text{ bone}} \underbrace{\mathbf{v}_i}_{i^{\text{th}} \text{ point}}$$

Skinning. [Background]

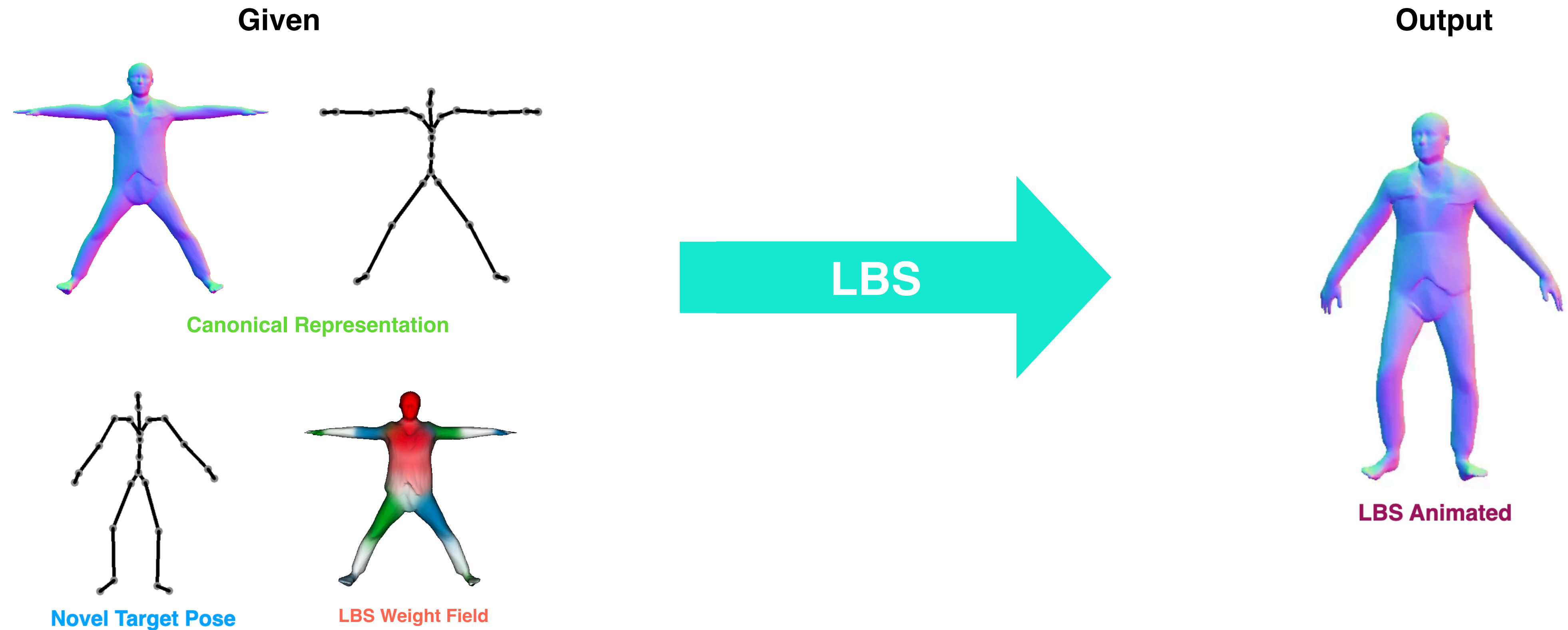
And all weights for an individual point sum to one.

$$\mathbf{v}'_i = \sum_{j=1}^m \underbrace{w_{i,j} \mathbf{T}_j}_{j^{\text{th}} \text{ bone}} \underbrace{\mathbf{v}_i}_{i^{\text{th}} \text{ point}}$$

$$\sum_{j=1}^{|B|} w_{ij} = 1, \forall i$$

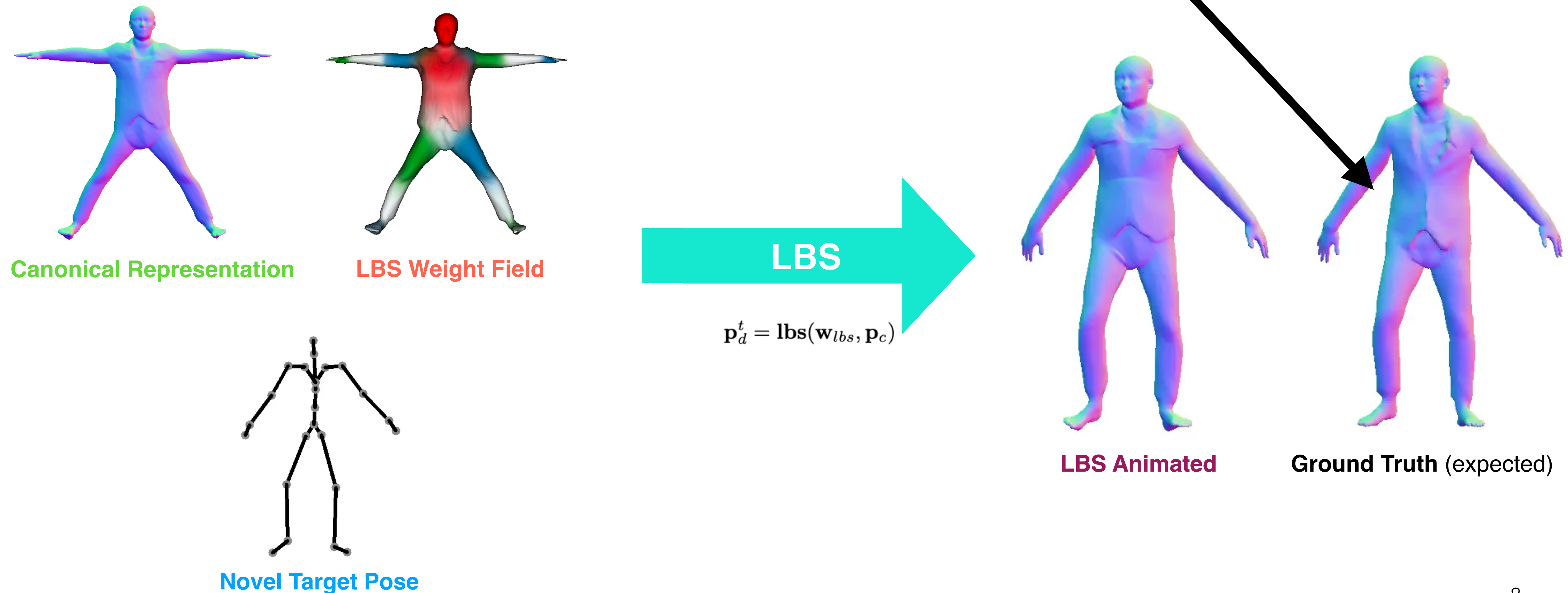
Skinning. [Background]

To use LBS, we learn an extra MLP that predicts LBS weights for every point.



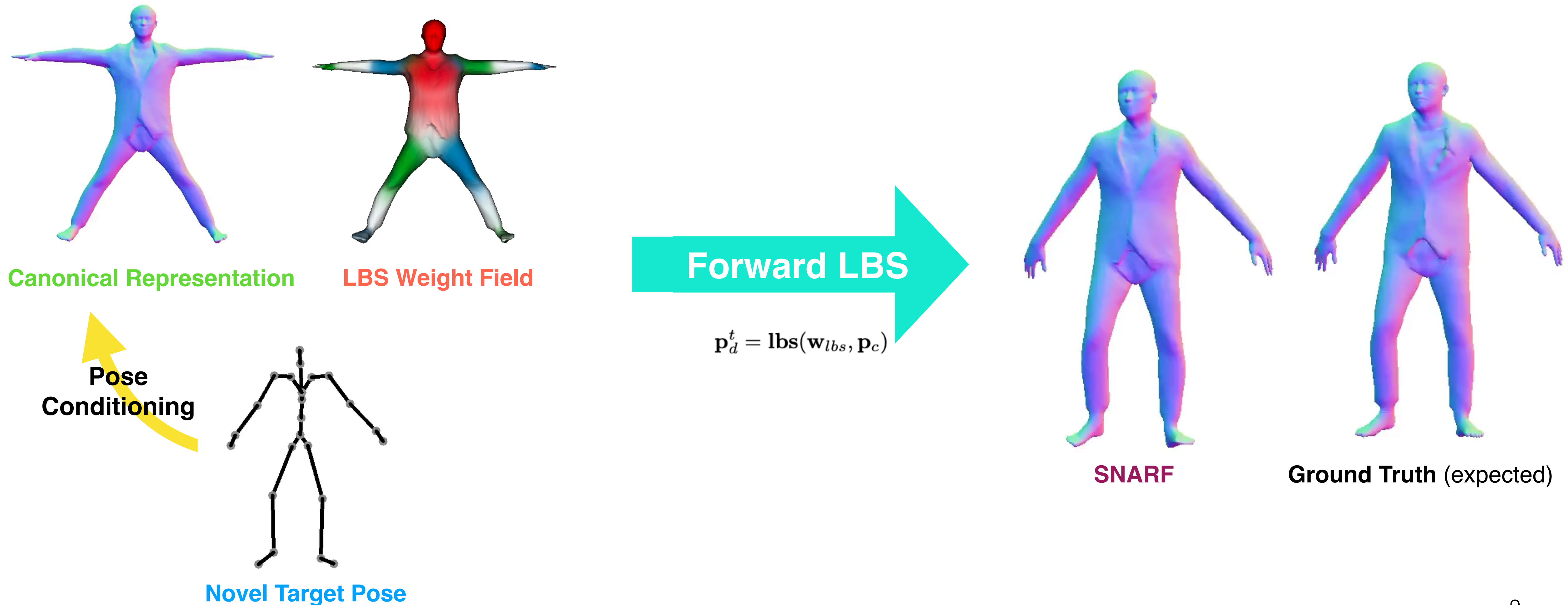
LBS Shortcomings. [Background]

But LBS **cannot capture non-linear deformations** of clothes and body tissue well.



Fixing LBS. [Background]

To overcome this, prior works (eg. SNARF) **condition** canonical representation **on target pose**.



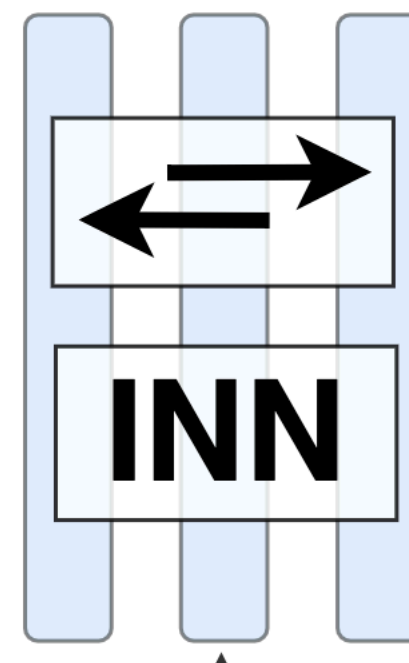
Drawbacks of pose-conditioned canonical space.

- **For each new pose**, we have to **extract a new mesh** first and then animate it. [**expensive operation**]
- The **same subject has different meshes** (vertices, faces) for different poses. [**no correspondences**]



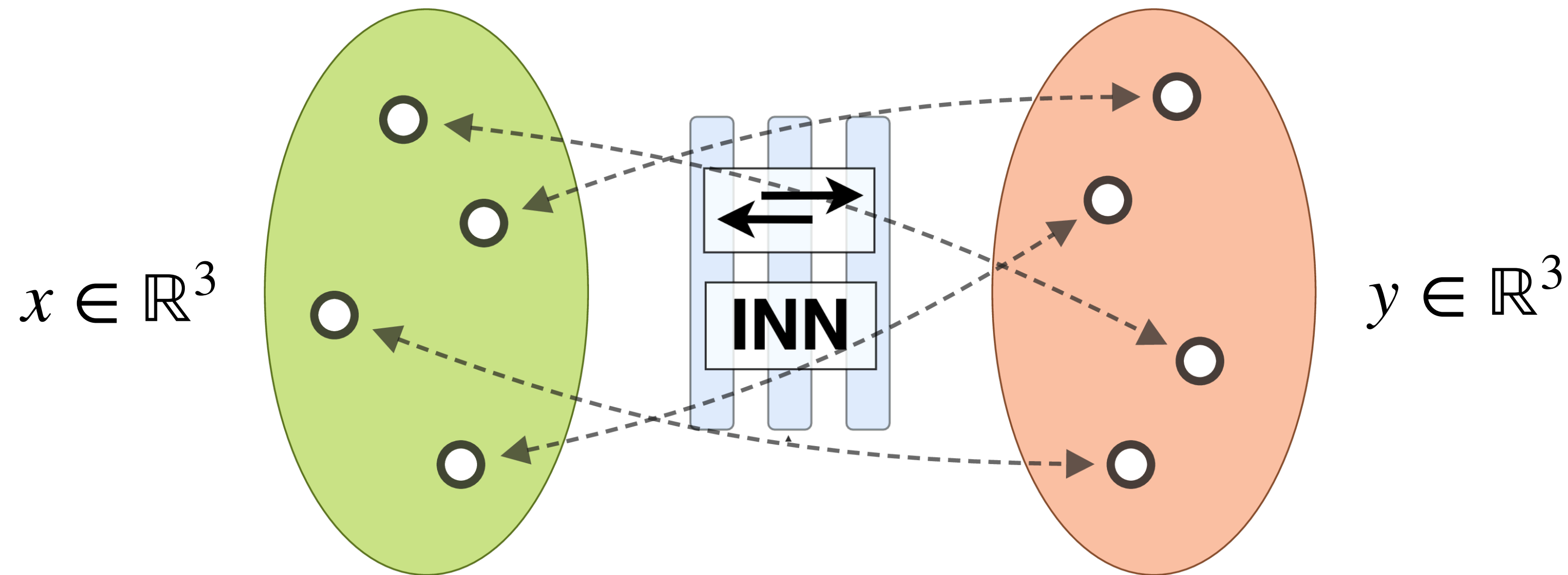
Invertible Neural Skinning [Approach]

Our core contribution is the use of **Invertible Neural Network (INN)** in the reposing pipeline.



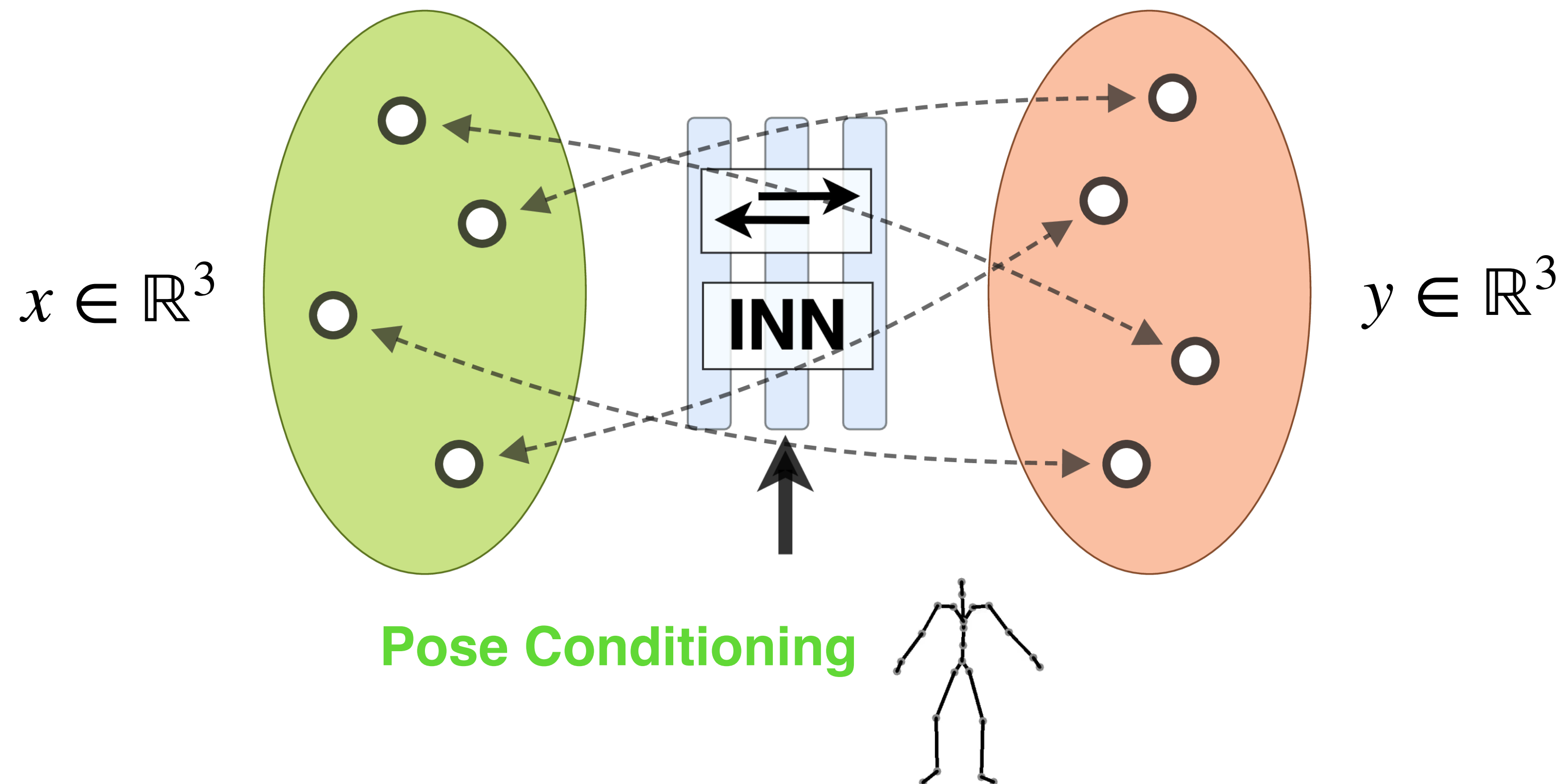
Invertible Neural Skinning [Approach]

An **Invertible Neural Network (INN)** defines a bijective mapping between its input and output spaces.



Invertible Neural Skinning [Approach]

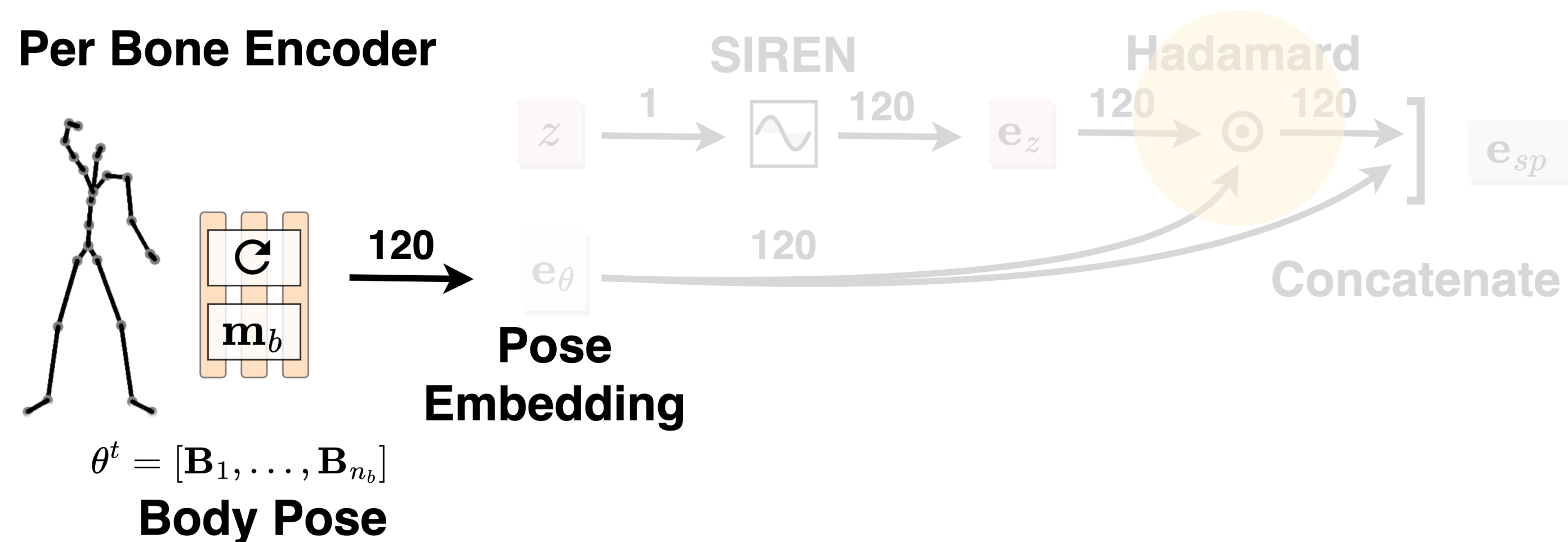
We introduce **Pose-conditioned INN (PIN)** to handle non-linear deformations, such as those of clothes.



Bone Pose Encoder. [Approach]

Our second contribution is the bone pose encoder.

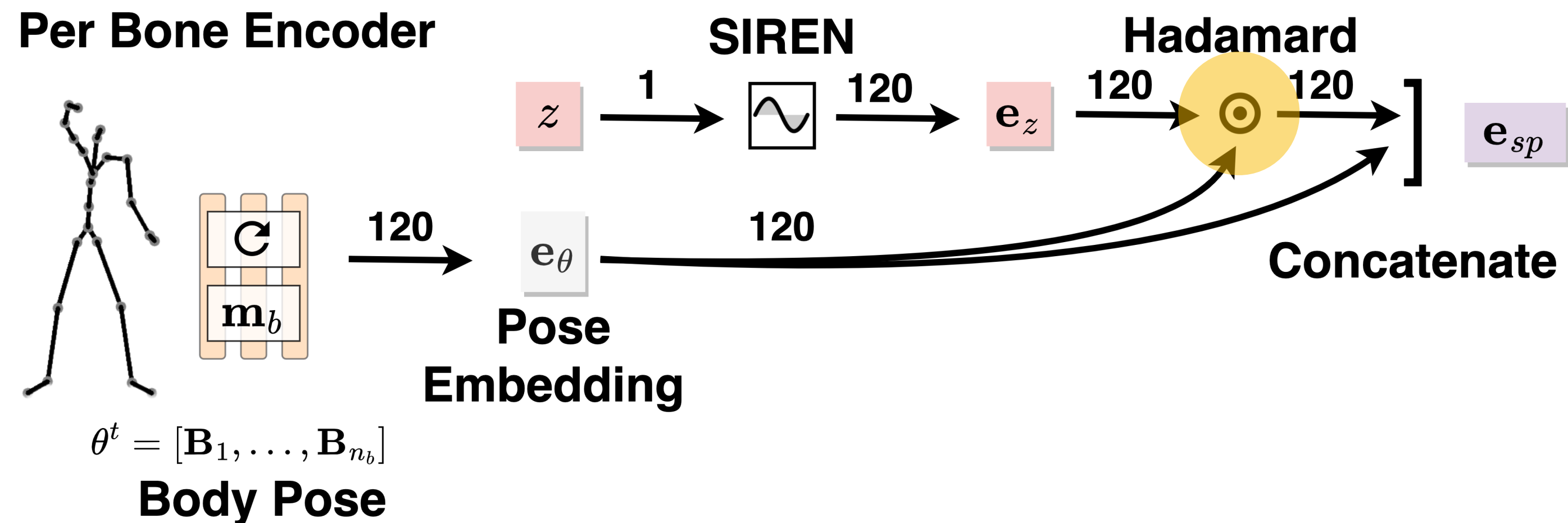
We encode each bone pose (rotation and translation) separately, and concatenate them.



Bone Pose Encoder. [Approach]

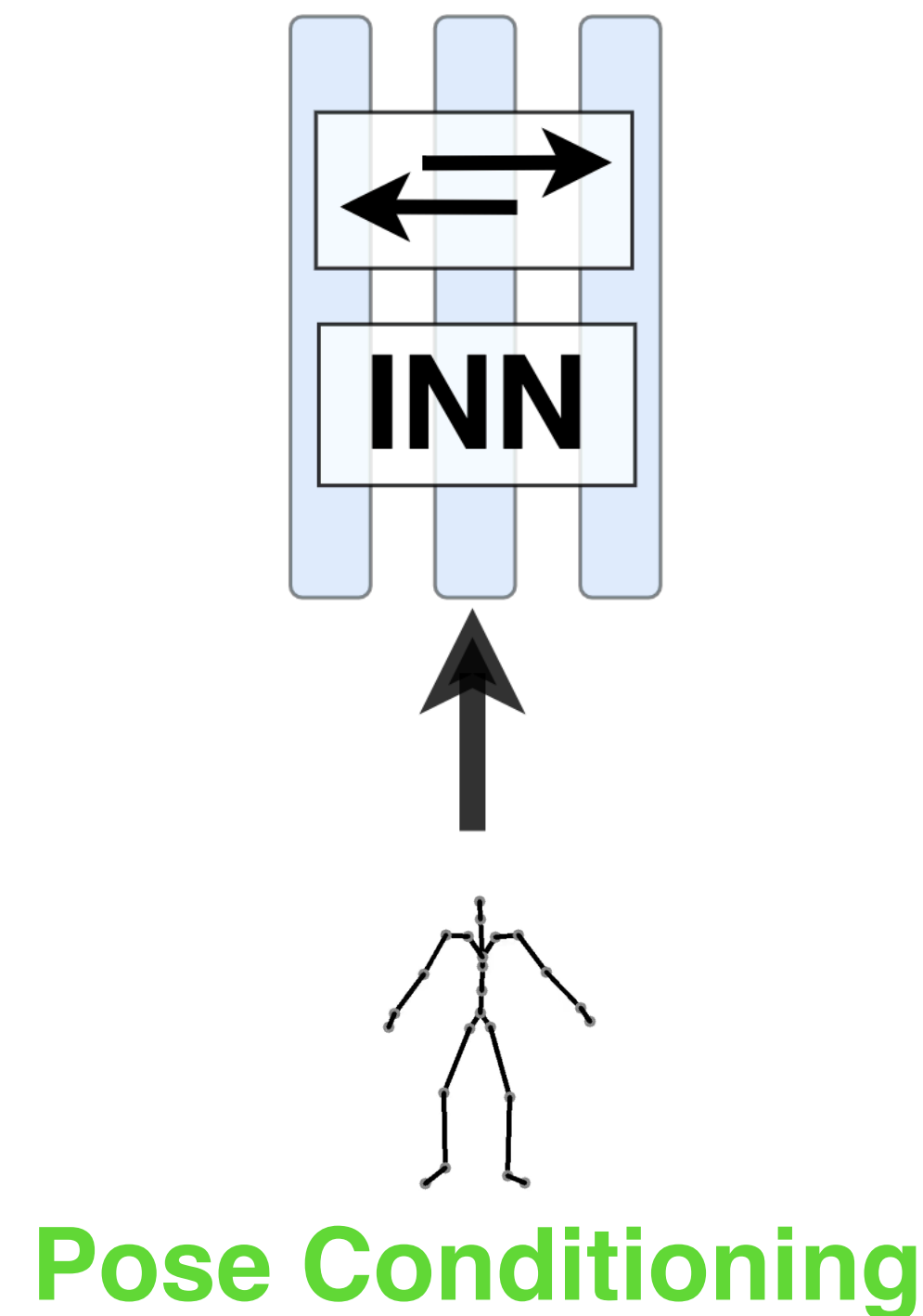
We take a dot product of this pose embedding with the spatial embedding.

This ensures that deformations in INN only occur when the pose-embedding is non-zero.



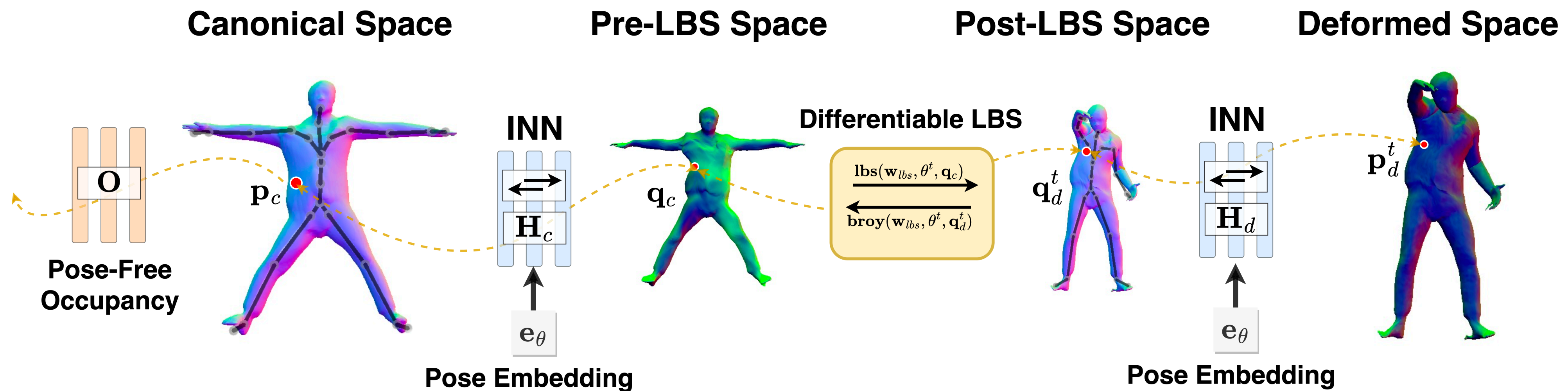
Pose-conditioned INN. [Approach]

Using bone pose encoder we build Pose-conditioned INN, and use it to model non-linear deformations.



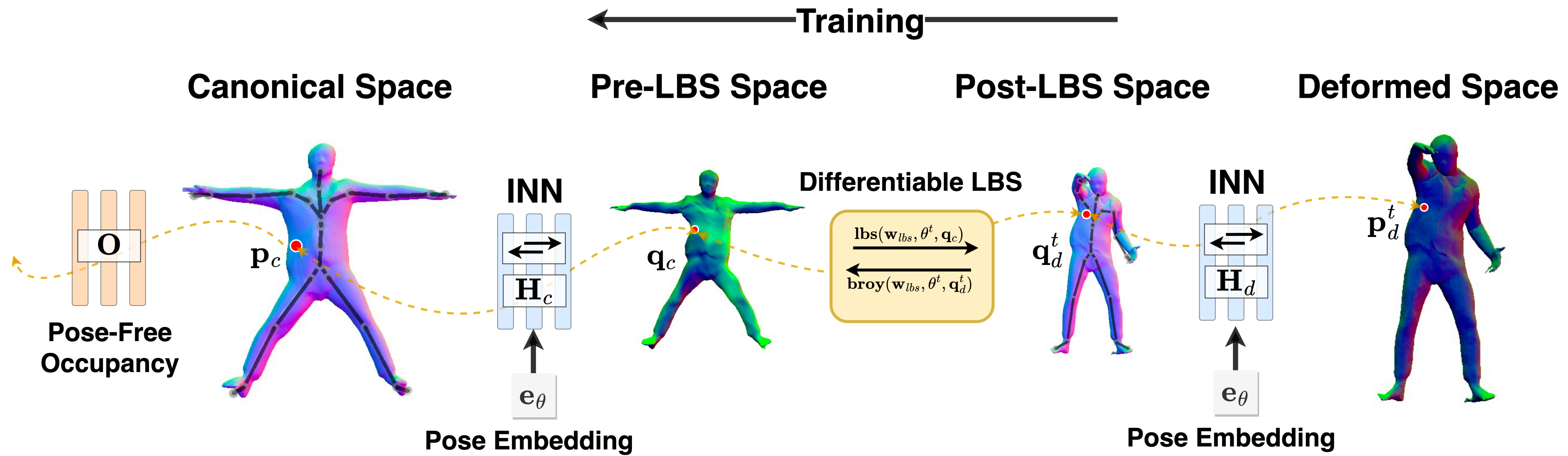
Invertible Neural Skinning [Overall]

We chain **two PINs** around an **LBS** block to build final reposing pipeline.



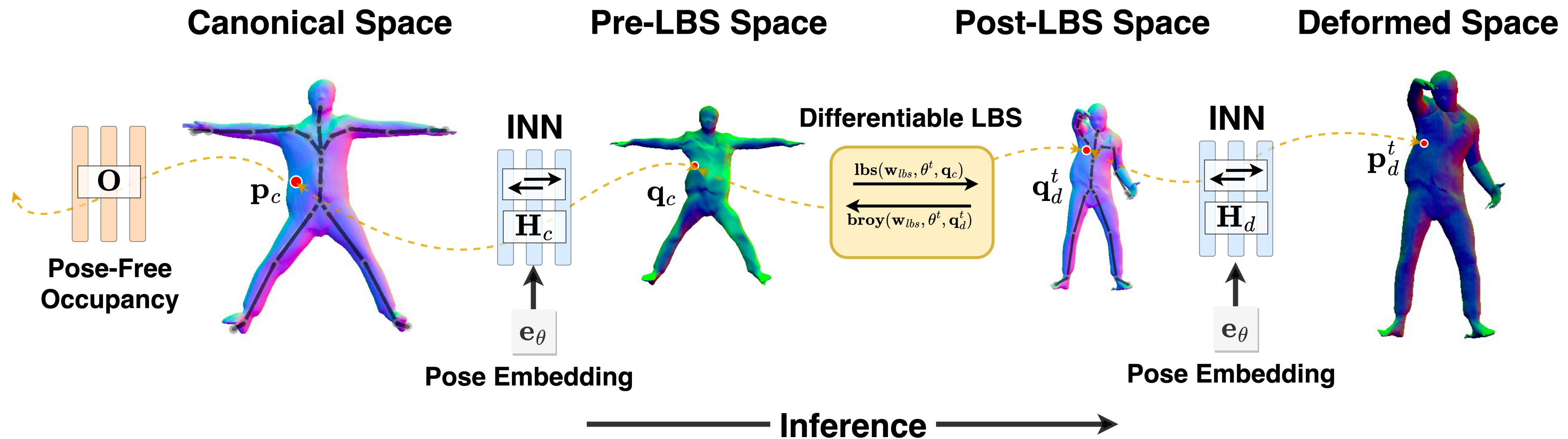
Invertible Neural Skinning [Overall]

Training: Sample points in the deformed space, and train our network to predict its occupancy [0/1], use BCE loss.



Invertible Neural Skinning [Overall]

Inference: First extract a mesh in canonical space only once, and repose it using learned LBS and PINs.



Metrics.

Bounding Box IoU: How many **points sampled uniformly** in space have correct occupancy?

Surface IoU: How many **points sampled around the ground truth surface** have correct occupancy?

Results.

We match/outperform previous methods, and baselines on both metrics on CAPE (clothed human dataset).

Subject	Clothing	IoU Surface					IoU Bounding Box				
		AVG-LBS	FIRST-LBS	SNARF	SNARF-NC	INS (ours)	AVG-LBS	FIRST-LBS	SNARF	SNARF-NC	INS (ours)
Average		65.01%	57.41%	<u>72.24%</u>	66.89%	73.13%	65.12%	57.5%	<u>72.17%</u>	66.78%	73.19%

Results.

INS does not require mesh extraction at each step, so it is an **order of magnitude faster** than baseline.

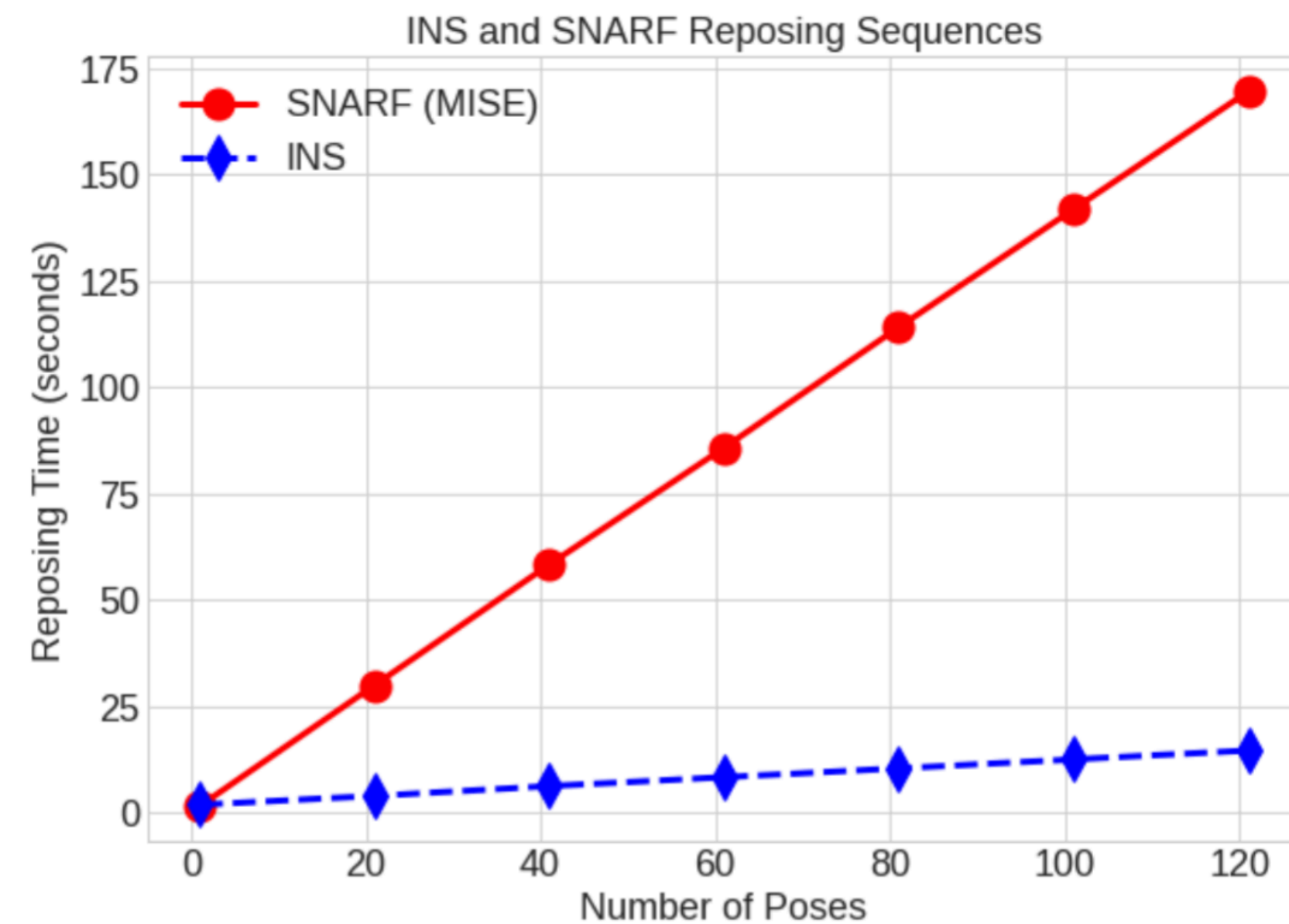


Figure 5. **Reposing time comparison between INS and SNARF**
We show the time taken by SNARF vs INS for reposing a mesh extracted at 128^3 resolution across 125 different target poses. INS performs reposing an order of magnitude faster than SNARF.

Ablation Study.

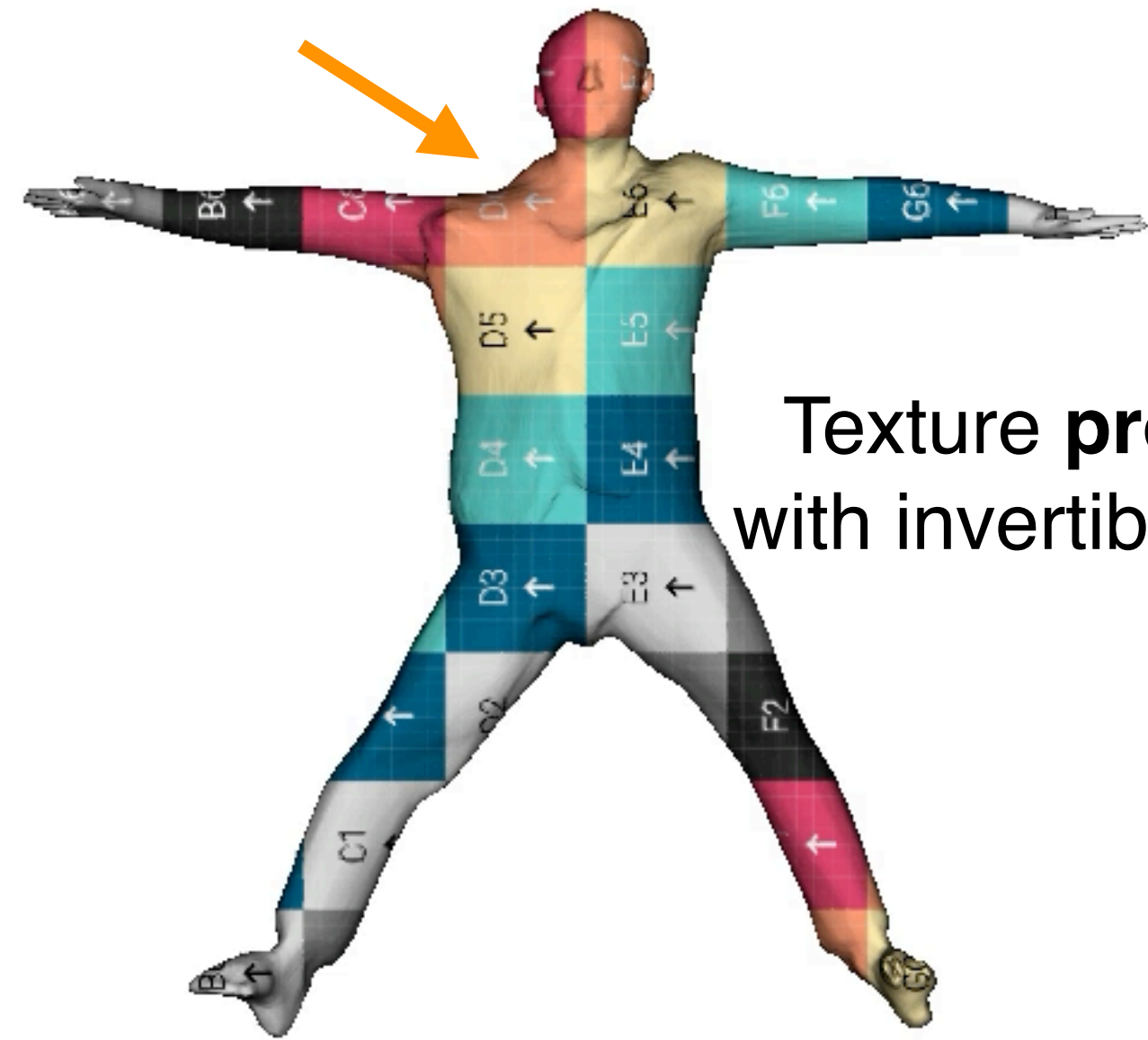
Not using bone-pose multiplication, leads to a huge drop in performance.

#	Ablation	IoU Surface (%)	IoU Bounding Box(%)
1	INS(vanilla)	72.83	72.69
2	w/o Pose Mul.	61.94 _{-10.89}	62.00 _{-10.69}
3	w/o SIREN	69.67 _{-3.16}	69.57 _{-3.12}
4	w/o Rotation	71.91 _{-0.92}	71.87 _{-0.82}
5	w/o \mathbf{H}_d	72.66 _{-0.17}	72.58 _{-0.11}
6	w/o \mathbf{H}_c	67.89 _{-4.94}	67.81 _{-4.88}
7	w/o LBS	40.79 _{-32.04}	40.65 _{-32.04}

Table 3. **Ablation Table.** We perform an ablation study of INS

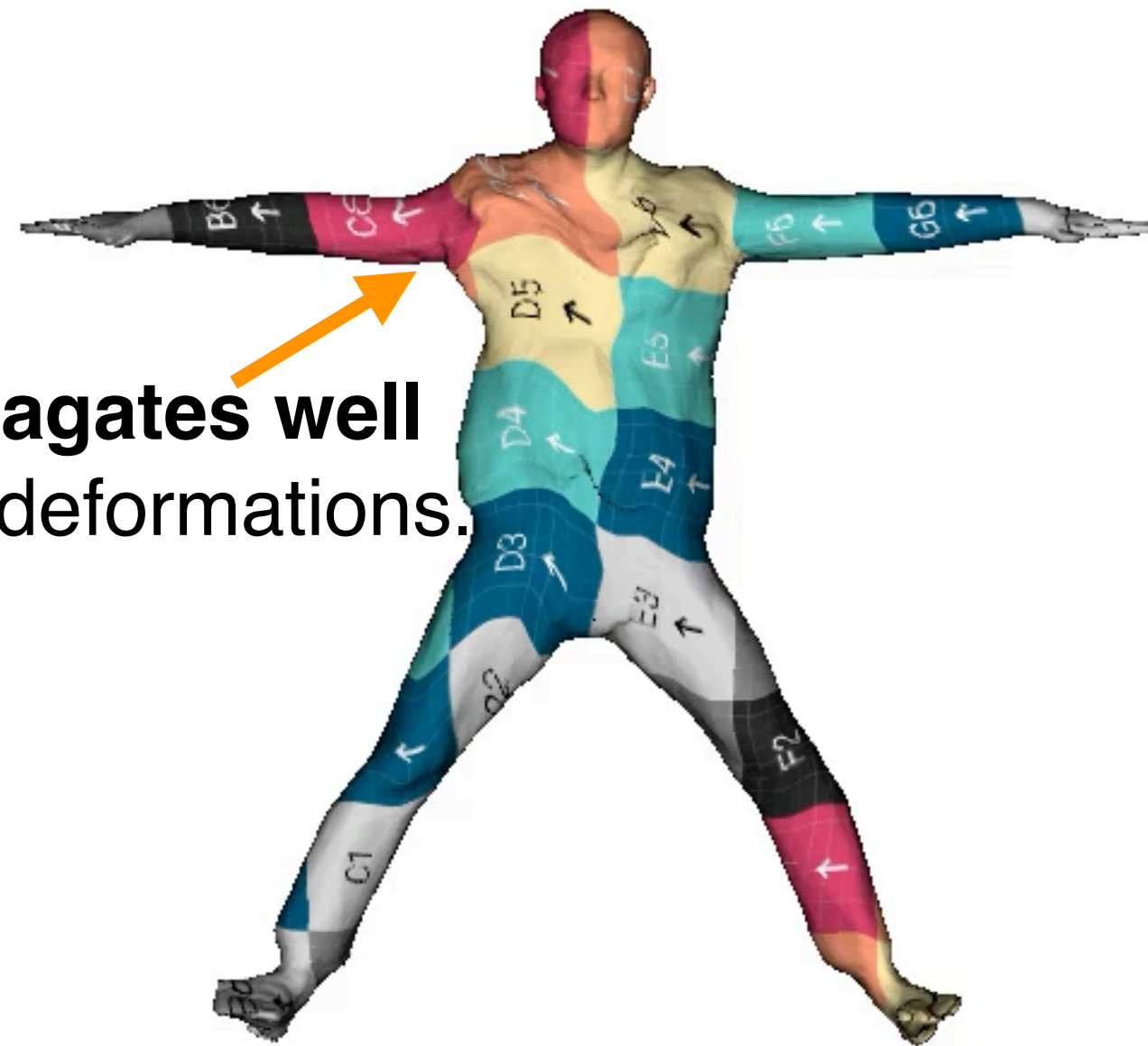
Qualitative Results [INS].

Texture applied *only* to the fixed canonical frame.



INS (canonical space)

Texture propagates well with invertible deformations.



INS deformations by H_c

Texture **does not overflow** across different regions.

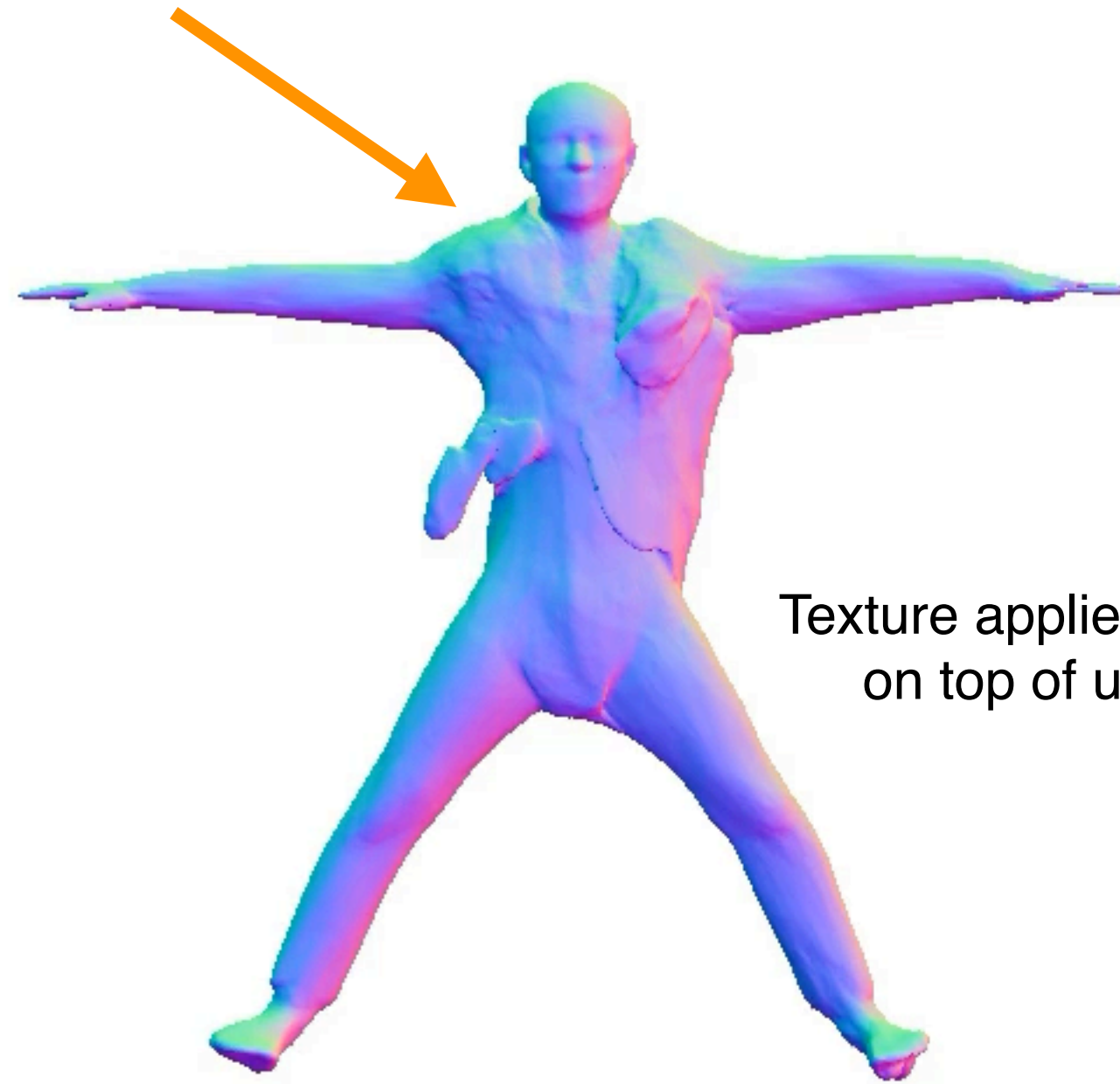


INS (final output)

Texture Propagation using INS — Fast and Consistent

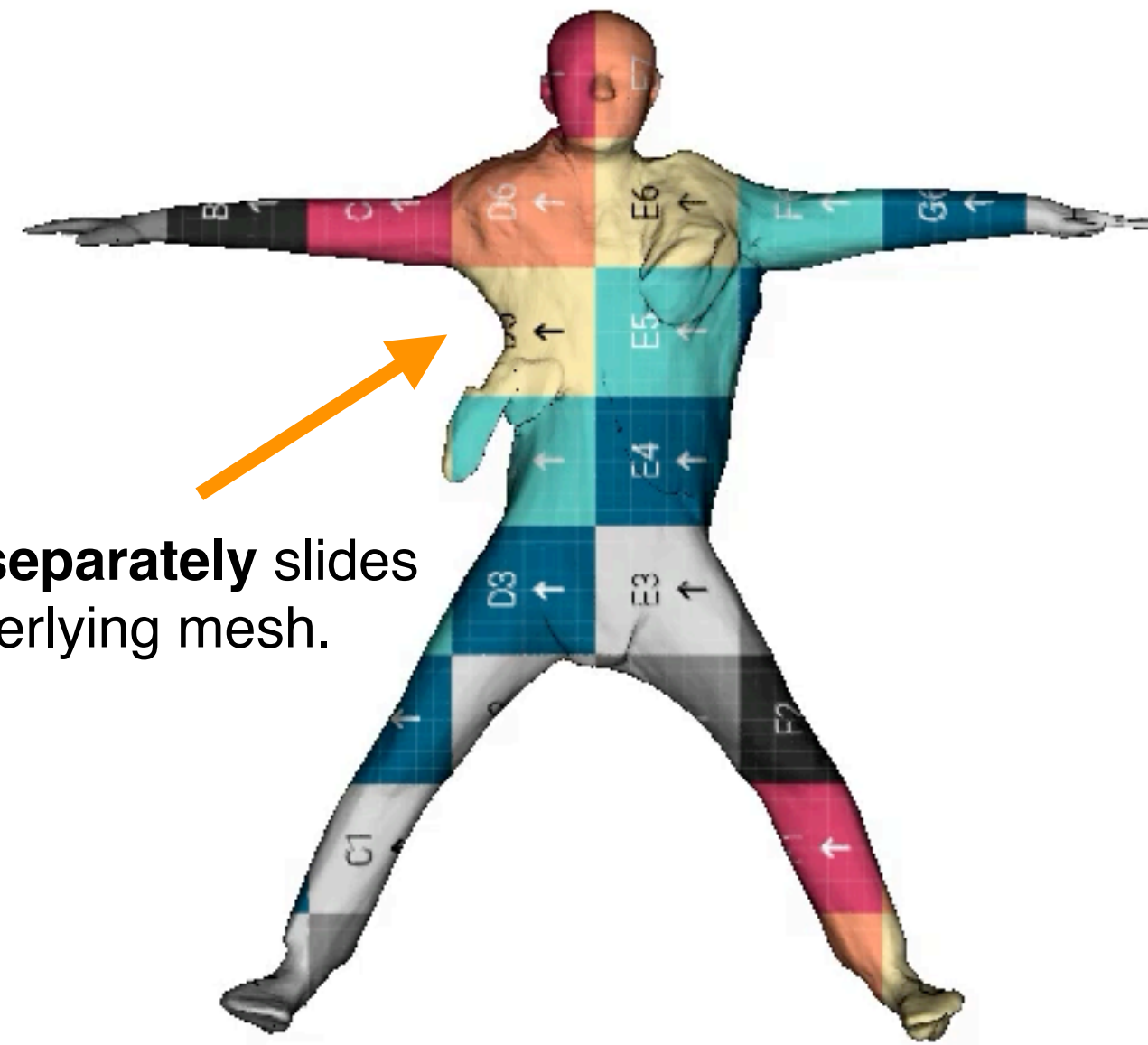
Qualitative Results [SNARF].

Every frame (mesh) in canonical space has different topology



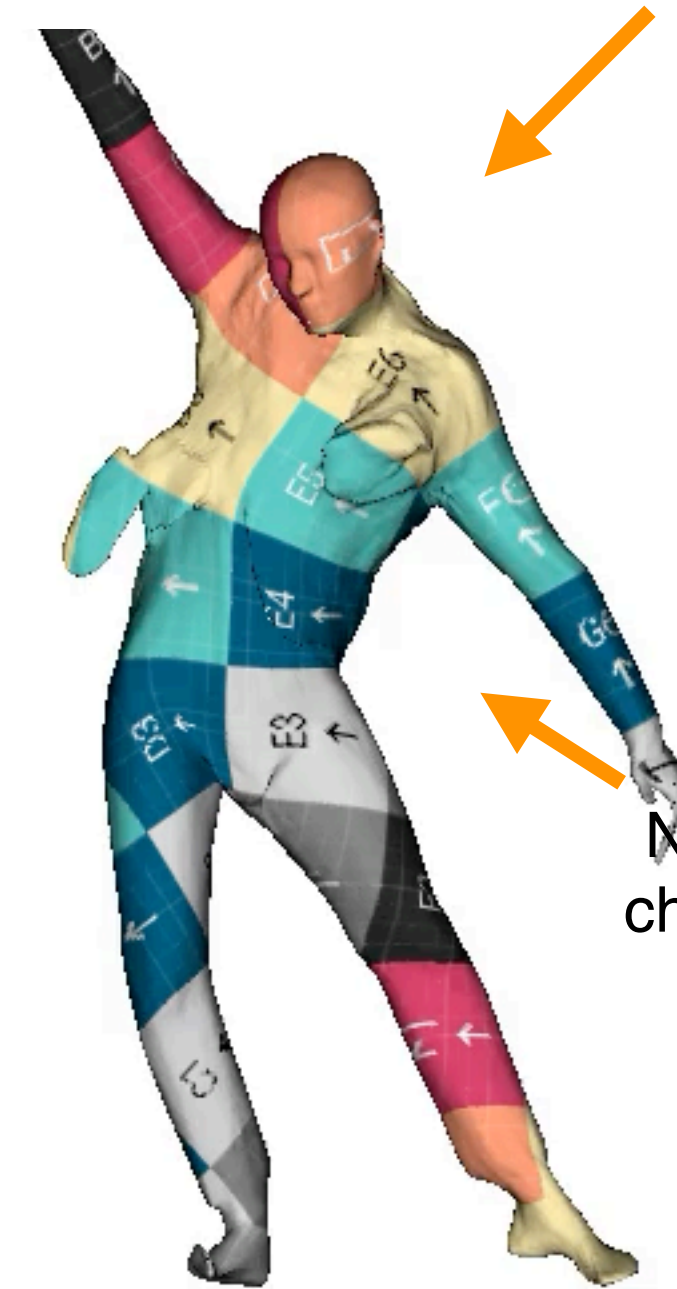
SNARF (canonical space)

Texture applied **separately** slides on top of underlying mesh.



Per-frame Texturing (canonical)

Causes **jittery artifacts** as frames have inconsistent textures.

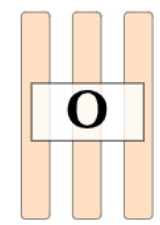


Notice the blazer outline changing colors (E3—E4)

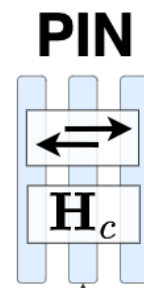
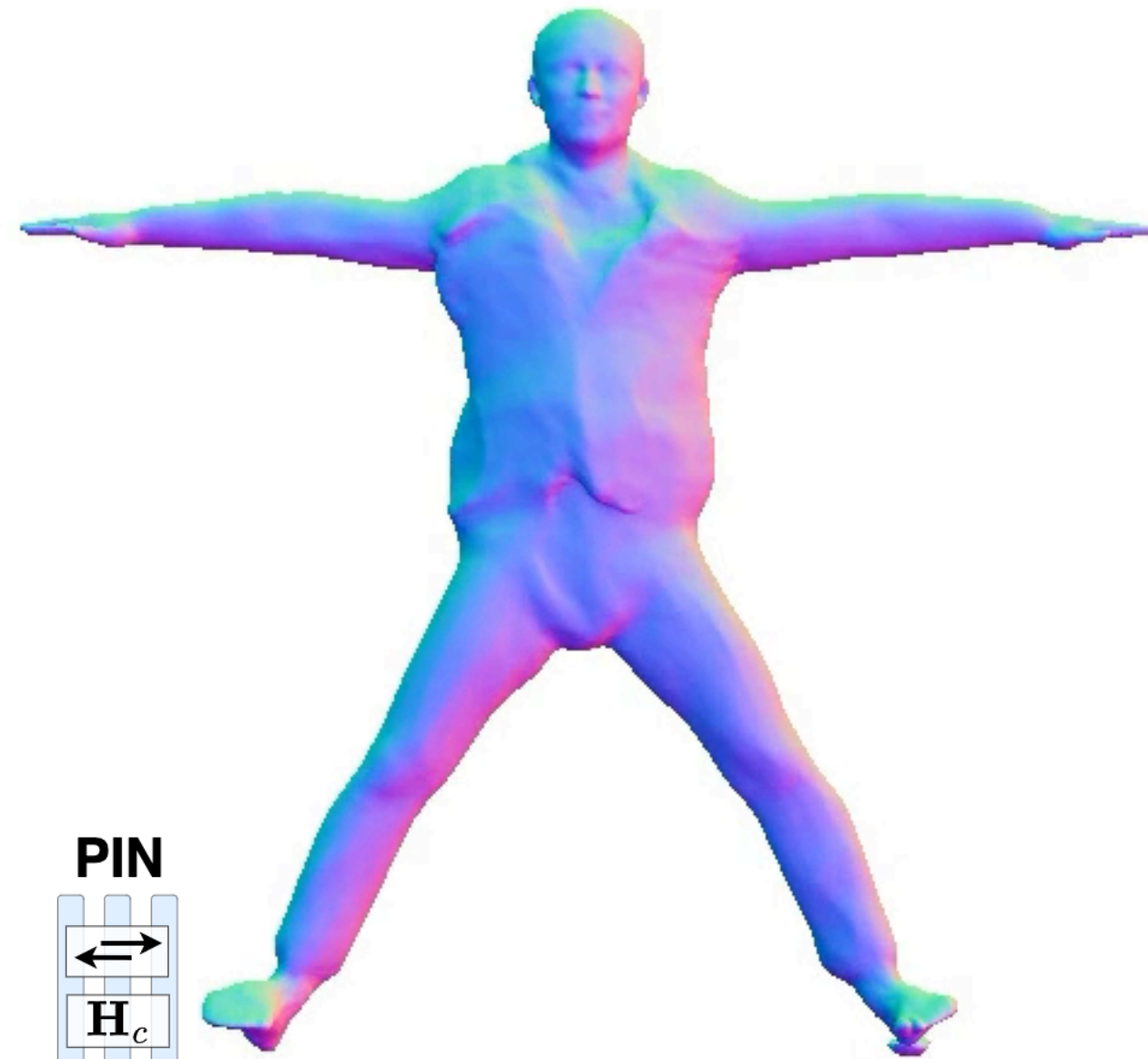
SNARF (jittery output)

Texture Propagation in SNARF — Slow and Jittery

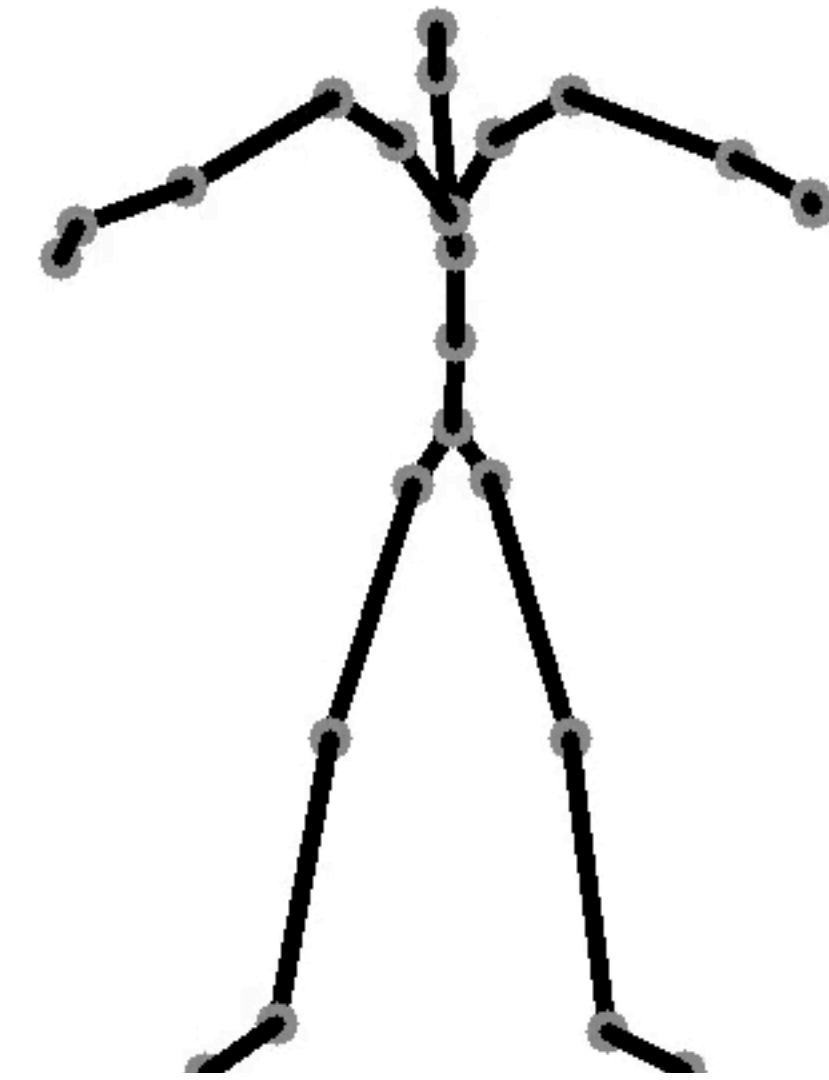
Pose-varying INS deformations.



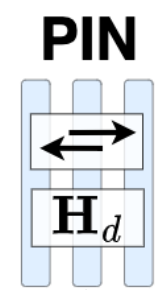
Pose Free Canonical Space



Pose deformations by \mathbf{H}_c



Target / Animation Pose



Pose deformations by \mathbf{H}_d



Ground Truth



INS output

Invertible Neural Skinning (Summary)

- an end-to-end **learnable** reposing technique,
- **preserves correspondences** across poses,
- more **accurate** and captures **pose-varying effects**,
- an **order of magnitude faster** than state-of-the-art.

Thanks!

Visit our poster on Thursday morning at CVPR.