

3D Human Mesh Modeling and Recovery from RGB and LiDAR



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CVPR
JUNE 3-7, 2026



DENVER
COLORADO

Program

13:30: Understanding Human Parametric Body Mesh Models.

(Romain Brégier)

14:30: 3D Human Mesh Recovery from Images.

(István Sárádi)

15:30: break.

15:45: 3D Human Pose and Shape Estimation from LiDAR Point Clouds.

(Salma Galaaoui)

16:45: end.

Comments

- Resources will be available at:
 - <https://human-mesh-tutorial.github.io/>
- Questions are welcome!

Understanding Parametric 3D Human Body Models



Romain Brégier

Tutorial Goals

- Why modeling the human body?
- Fundamentals of human body modeling for CV.

(Disclaimer: **Anny**)

Definition

- A [human body] model is an **informative** representation of the [human body].
- It should include **only relevant attributes** (for the user).
- It can be used to **describe, explain, predict** these attributes.

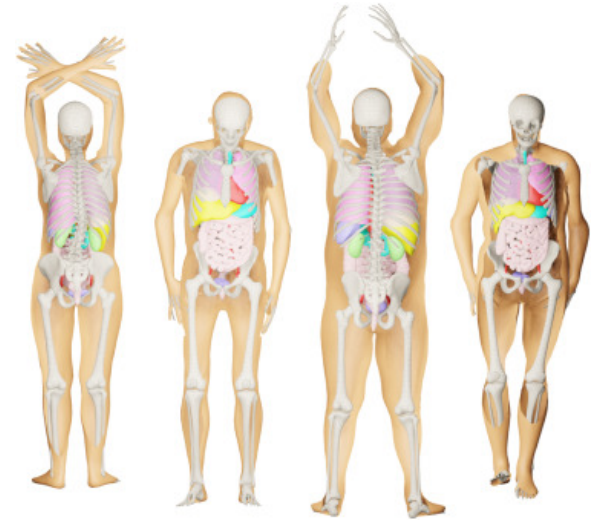
Biomechanics



OpenSim (Seth et al. 2018)

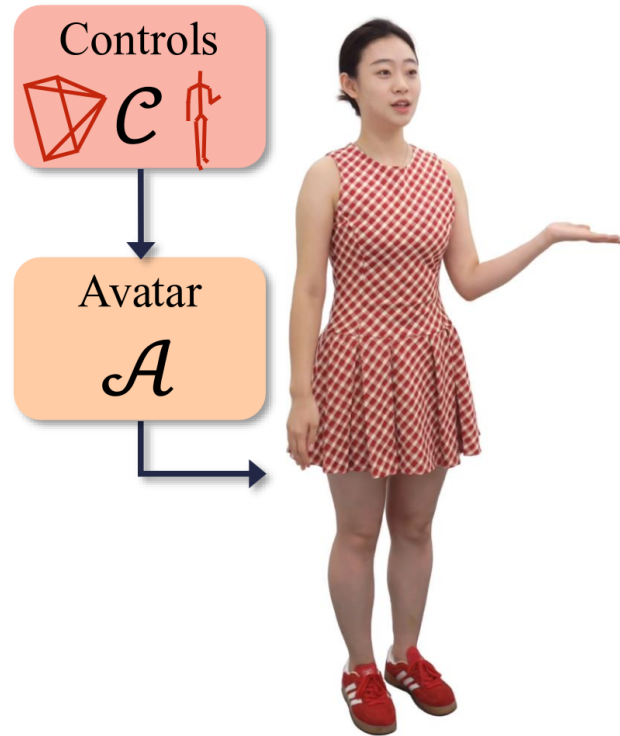


SKEL (Keller et al. 2023)



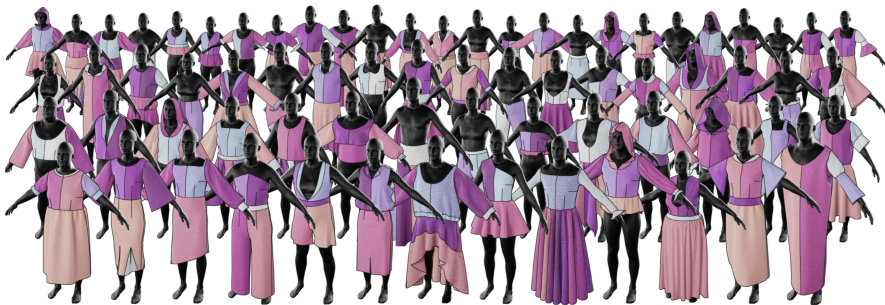
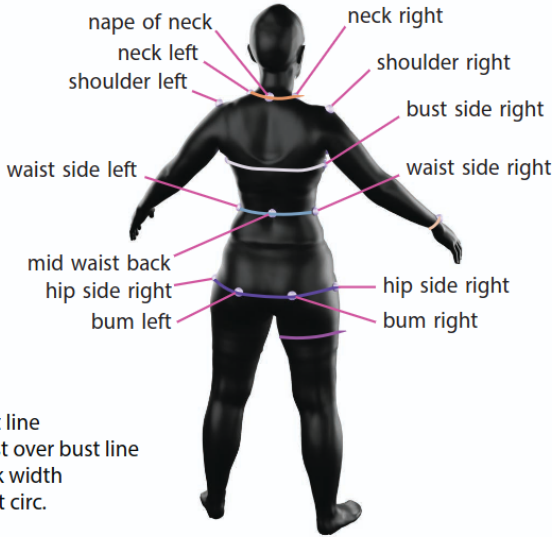
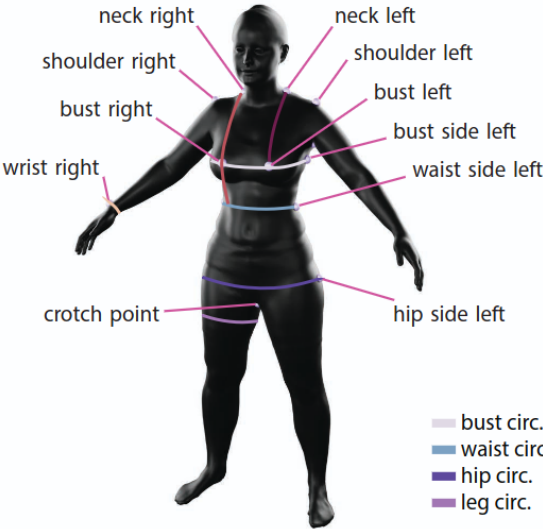
BOSS (Shetty et al. 2023)

Appearance



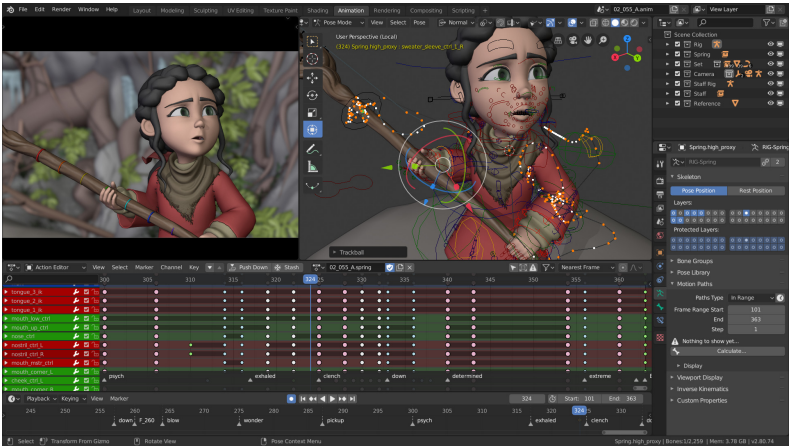
Zielonka et al. EUROGRAPHICS 2026

Body measurements

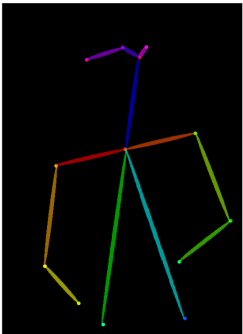


GarmentCodeData (Korosteleva et al. 2024)

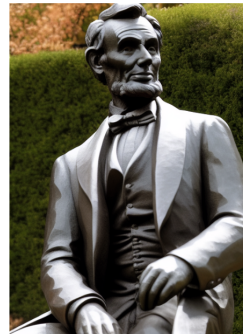
User input



Blender (Spring 2019)



Input human pose



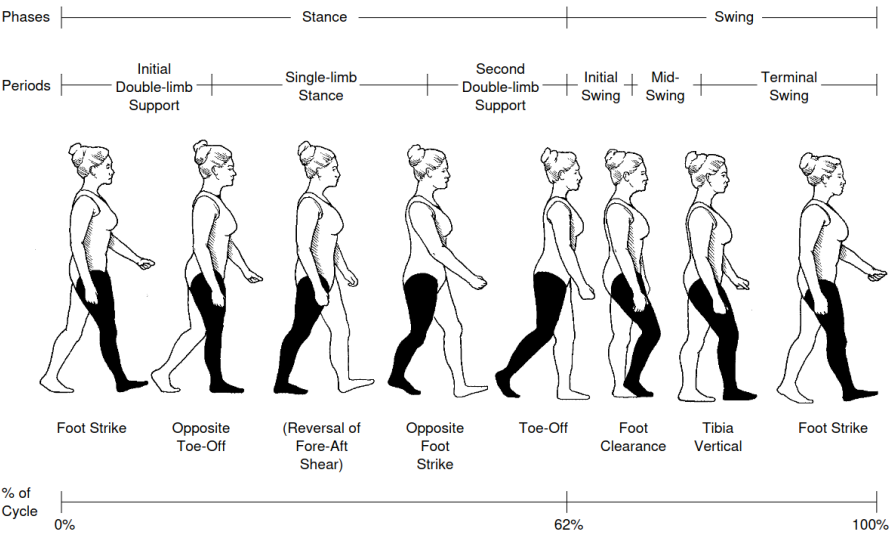
Default

“chef in kitchen”

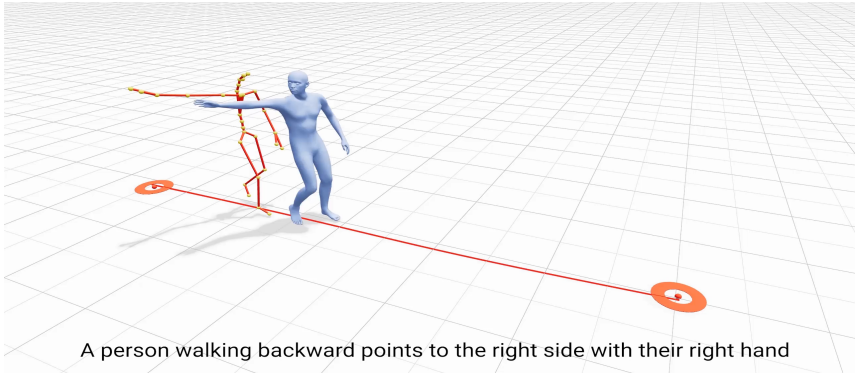
“Lincoln statue”

ControlNet (Zhang et al. ICCV23)

Motion



Chambers et al. 2002

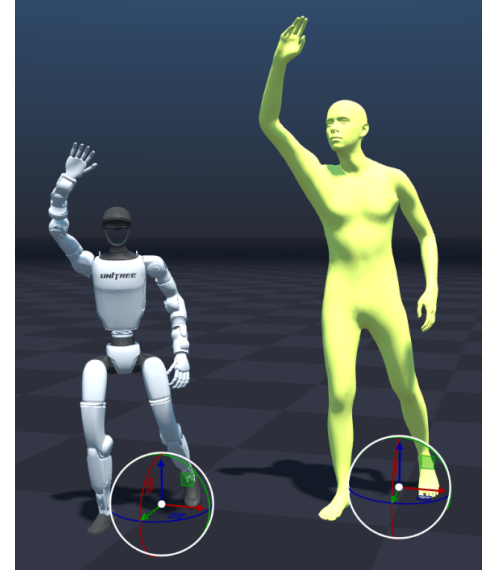


KIMODO (Rempe et al. 2026)

Pose/motion transfer

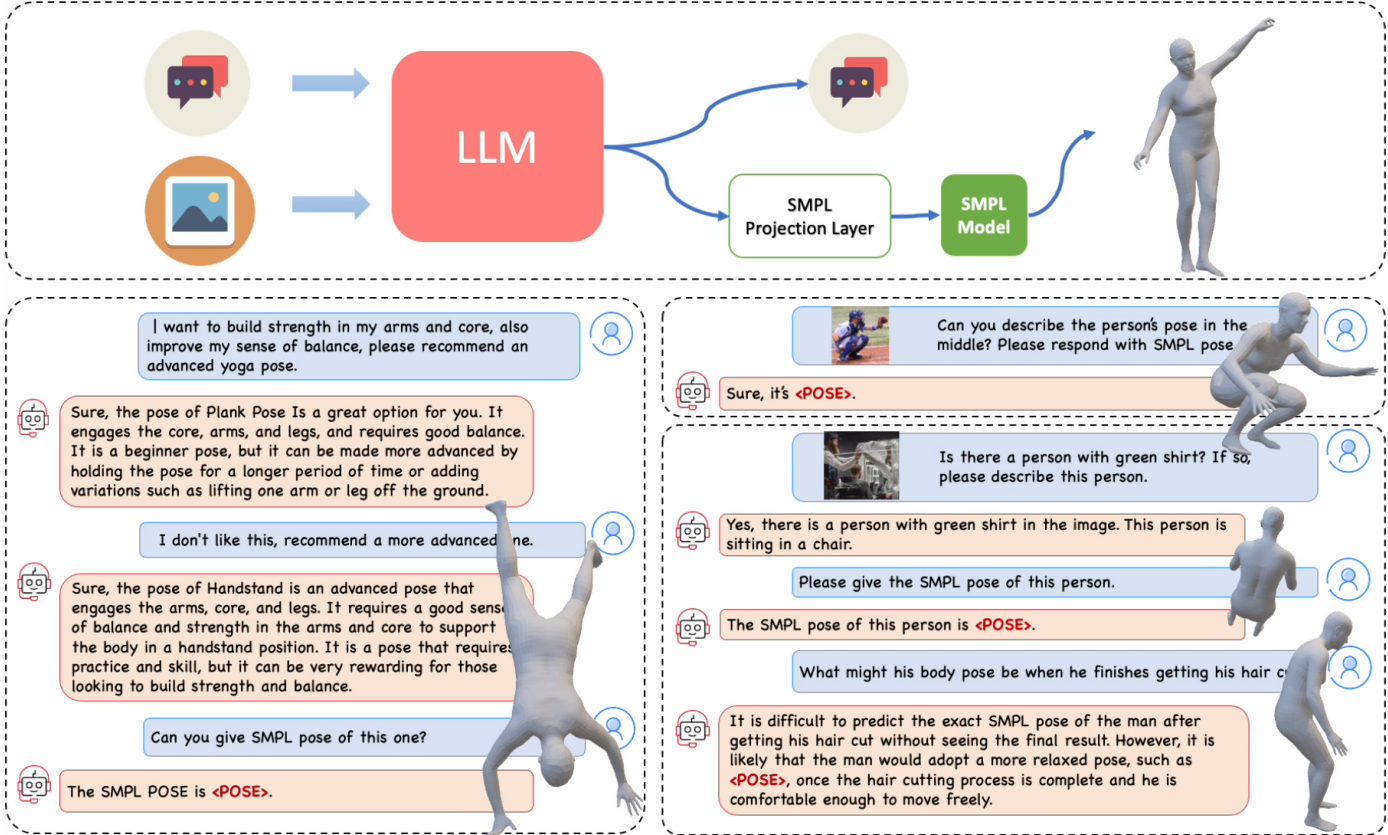


Anny (Brégier et al. 2025)



SOMA retargeter (Nvidia 2026)

Description



Compress information



Predict the unseen



SAM3D Body (Yang et al. 2025)



MultiHMR (Brégier et al. 2025)

Body Model History

A key influence on the field



Gunnar Johansson, Visual Perception for its analysis, Percept

".... the motion of the living body was represented by a few bright spots describing the motions of the main joints.... 10-12 such elements in adequate motion combinations ... evoke a compelling impression of human

David Hogg, 1983



```
class: WALKER
parts:
  partclass: person
  partclass: torso
  weight: 0.05
  [stretch] lift stretch lift
  position: x = 0 y = 45 z = -5 a = 0 b = -5 c = 0 z = 0.35
  partclass: head
  weight: 0.05
  [stretch] lift stretch lift
  position: x = 0 y = 112 z = 0 a = 0 b = 0 c = 0 z = 0.14
  partclass: arm
  weight: 0.05
  [stretch] lift stretch lift
  position: x = 0 y = 112 z = 0 a = 0 b = 0 c = 0 z = 0.14
  partclass: lower-arm
  weight: 0.05
  [stretch] lift stretch lift
  position: x = 0 y = 112 z = 0 a = 0 b = 0 c = 0 z = 0.14
  partclass: lower-arm
  weight: 0.05
  [stretch] lift stretch lift
  position: x = 0 y = 112 z = 0 a = 0 b = 0 c = 0 z = 0.14
```



[Sminchisescu and Triggs '03]



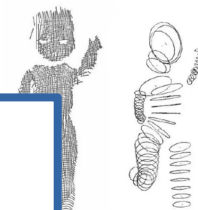
Early body models



[Terzopoulos and Metaxas '93]



[Kakadiaris and Metaxas '00]



evatia & Binford '73

SMPL made Simple

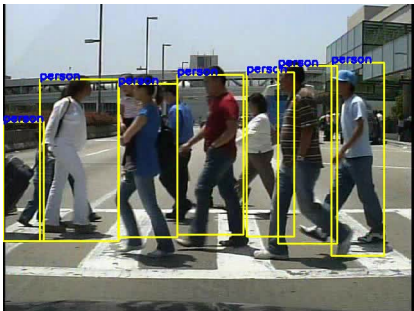
CVPR 2021 Tutorial (June 20, 10:00-18:00 EDT)

Note: even if you missed the tutorial, you will find recordings of all presentations on this site.

Naureen Mahmood, Timo Bolkart, Ahmed A. A. Osman, Joachim Tesch, Dimitrios Tzionas, Michael J. Black

<https://smpl-made-simple.is.tue.mpg.de/>

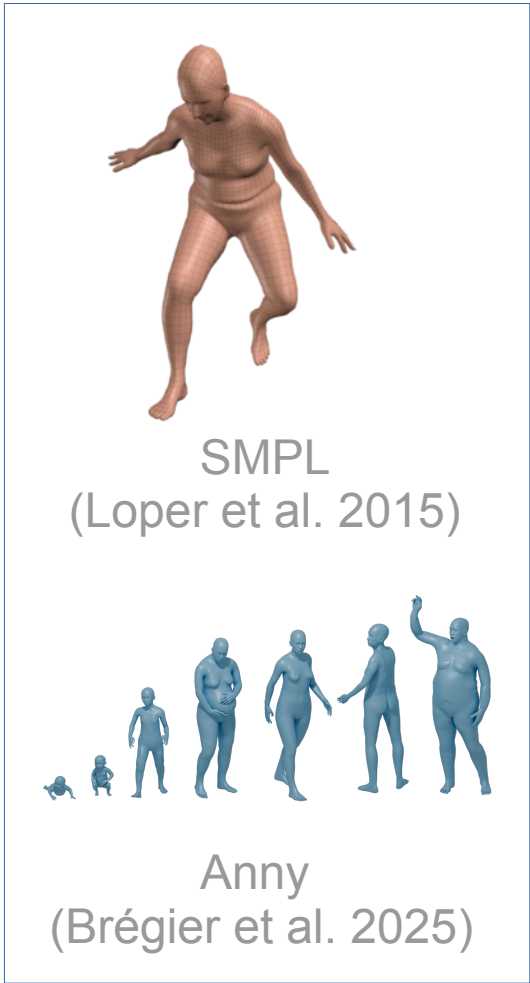
Body Models Spectrum



YOLO
(Redmon et al. CVPR2016)



COCO 17
(Lin et al. 20215)

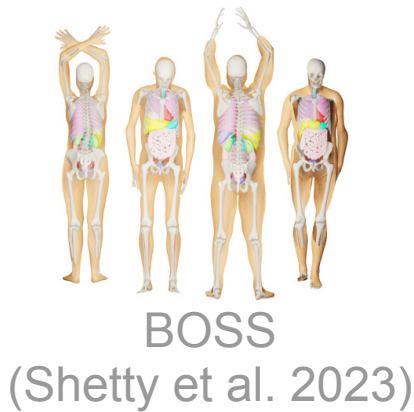


SMPL
(Loper et al. 2015)

Anny
(Brégier et al. 2025)



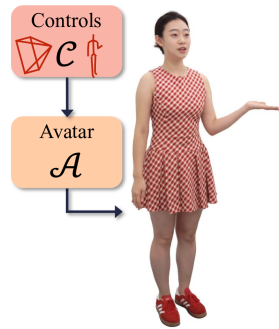
SoftSMPL
(Santesteban et al. 2020)



BOSS
(Shetty et al. 2023)

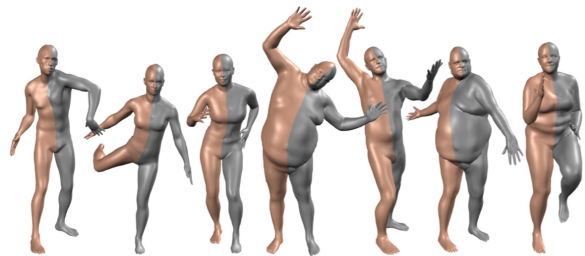


NPMs
(Palafox et al. 2021)



Zielonka et al. 2026

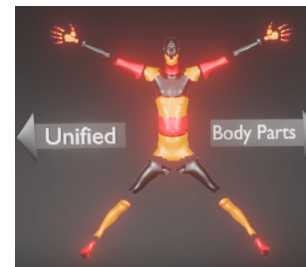
Recent morphable surface body models



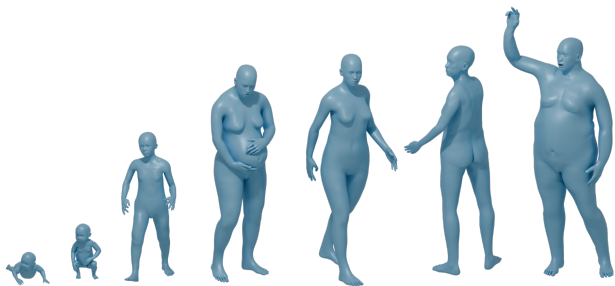
SMPL (Loper et al. 2015)
Frank (Joo et al. 2018)
SMPL-H (Romero et al. 2017)
SMPL-X (Pavlakos et al. 2019)



GHUM (Xu et al. 2020)



STAR (Osman et al. 2020)
SUPR (Osman et al. 2022)



Anny (Brégier et al. 2025)



ATLAS (Park et al. 2025)
MHR (Ferguson et al. 2025)

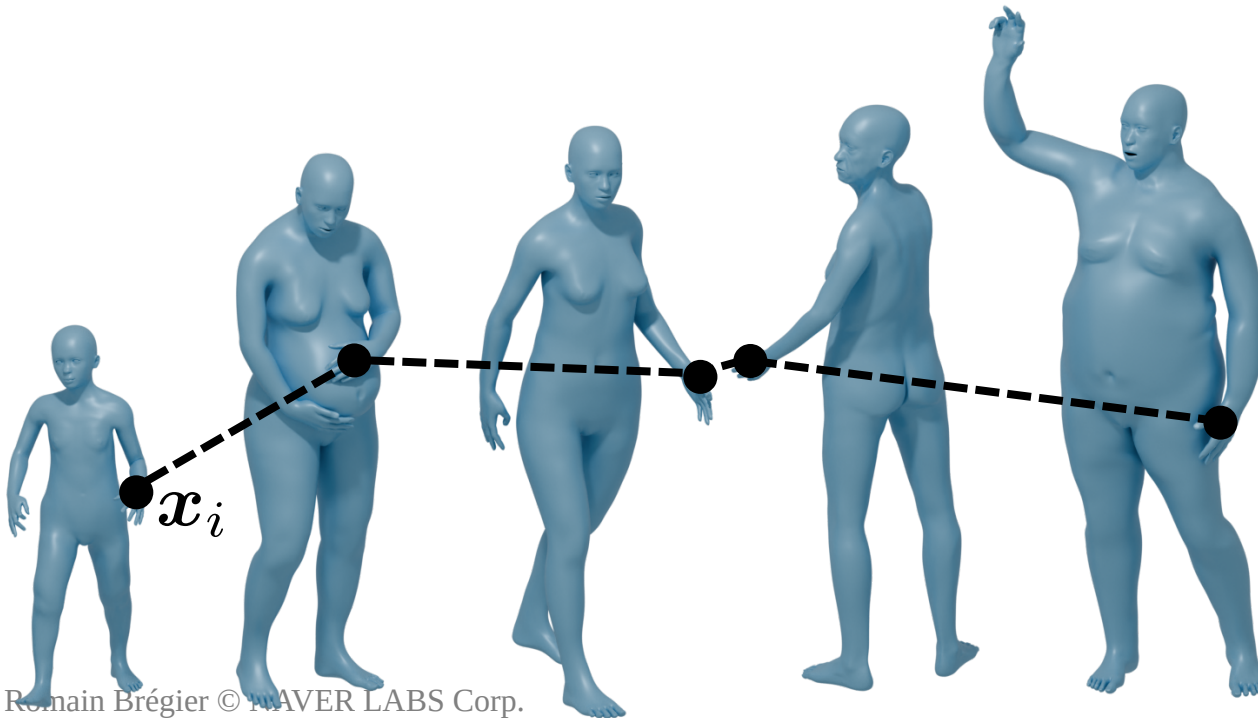


SOMA-shape
SOMA rig (Saito et al. 2026)

Parametric surface model

Body landmarks consistent across poses and identities

$$\mathbf{X} = (\mathbf{x}_i \in \mathbb{R}^3)_{i=1\dots V}$$



$$\mathbf{X} = f(\boldsymbol{\beta}, \boldsymbol{\theta})$$

$\boldsymbol{\beta}$ Body shape

$\boldsymbol{\theta}$ Pose

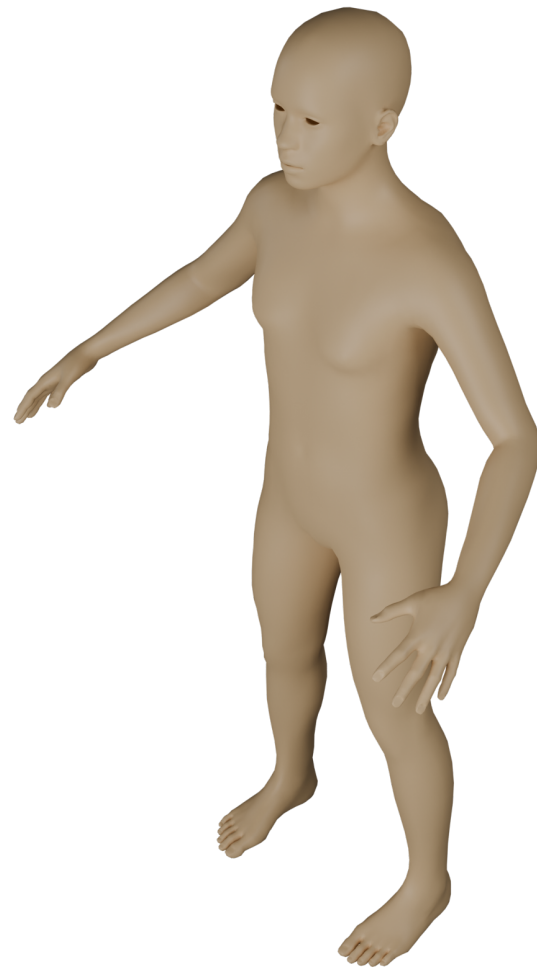
SCAPE (Anguelov et al. 2005)

Rigid body pose

$$\mathbf{x}_{\mathcal{W}} = \mathbf{T}_{body} \mathbf{x}_{body}$$

$$\mathbf{T}_{body} = \begin{pmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}_{3 \times 1} & 1 \end{pmatrix} \in SE(3)$$

$\mathbf{x}_{body}$ coordinates *wrt.* the *body*
 $\mathbf{x}_{\mathcal{W}}$ absolute coordinates



Composed body

$$\mathbf{x}_{\mathcal{W}} = \mathbf{T}_{\mathcal{B}} \mathbf{x}_{\mathcal{B}}$$

$\mathbf{x}_{\mathcal{B}}$ coordinates *wrt.* the part $\mathcal{B}$

$\mathbf{T}_{\mathcal{B}}$ body part pose

$\mathbf{x}_{\mathcal{W}}$ absolute coordinates

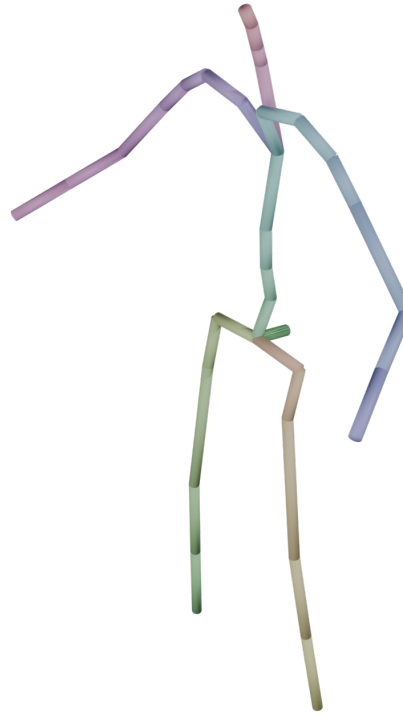


Skeletal animation

Forward kinematics:

$$\mathbf{T}_{bone} = \mathbf{T}_{parent} \mathbf{T}_{bone}^{local}$$

$$\mathbf{T}_{bone}^{local} = \begin{pmatrix} \mathbf{R} & \mathbf{0}_{3 \times 1} \\ \mathbf{0}_{1 \times 3} & 1 \end{pmatrix}$$



Linear Blend Skinning



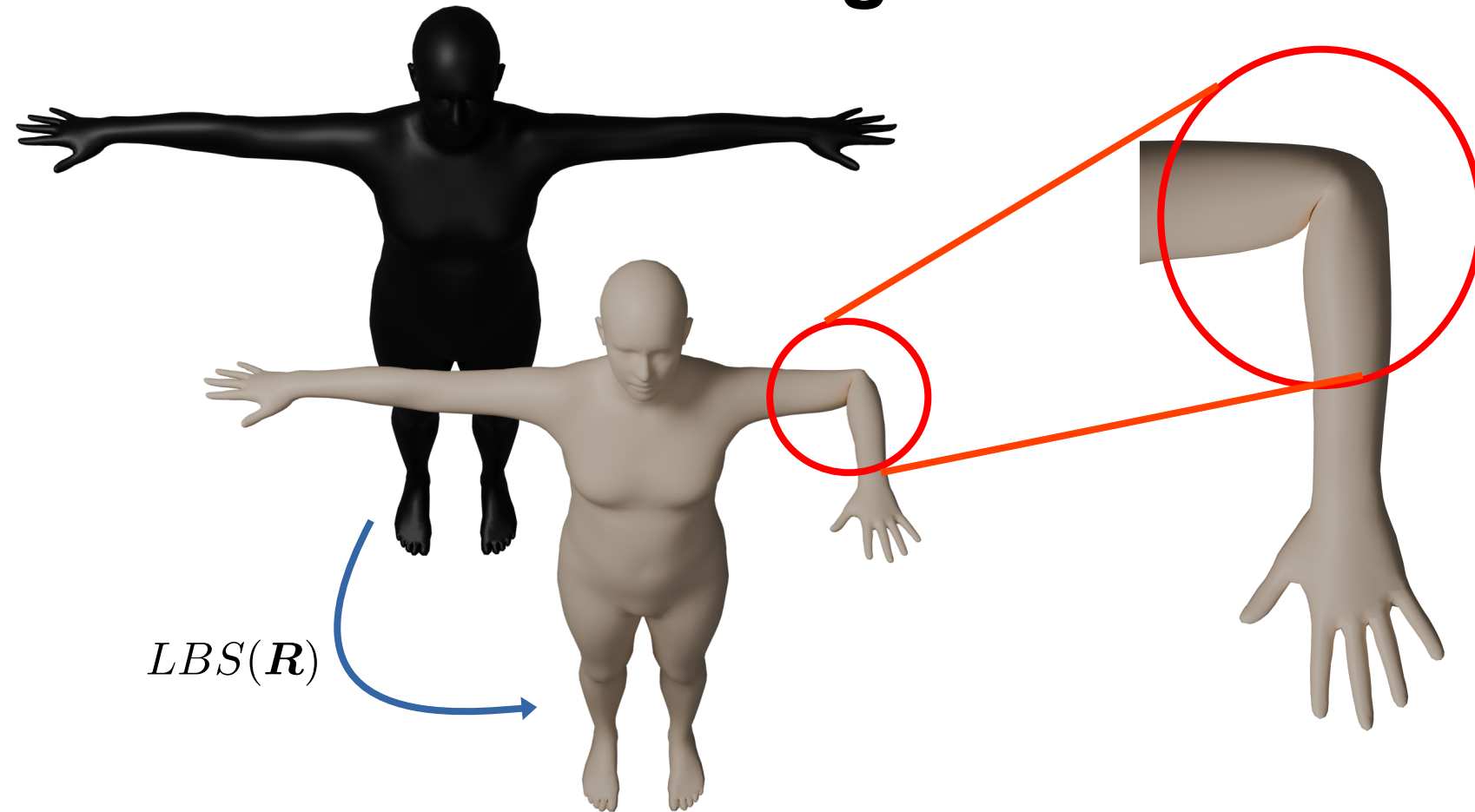
$$x_{\mathcal{W}} = T_{\mathcal{B}}x_{\mathcal{B}}$$



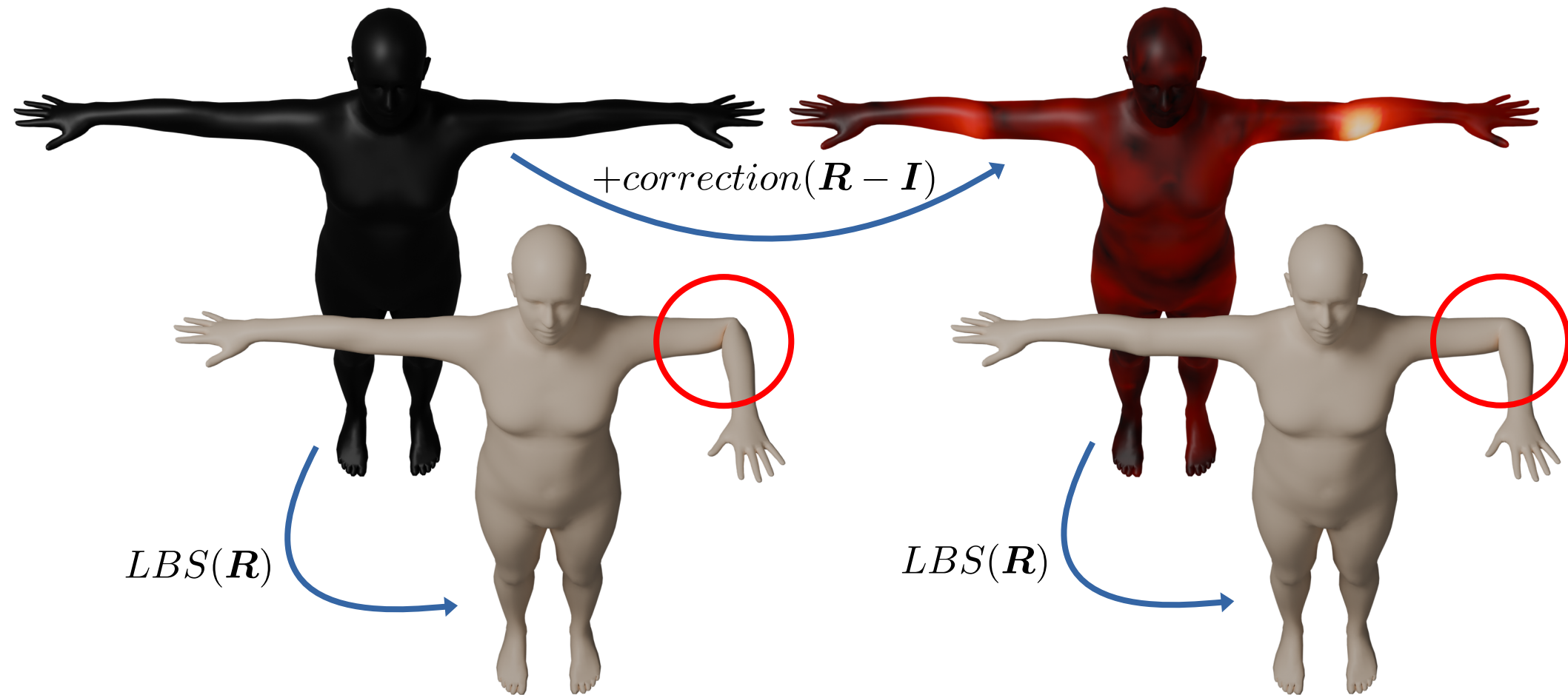
$$x_{\mathcal{W}} = \sum_{\mathcal{B}} w_{\mathcal{B}} T_{\mathcal{B}} x_{\mathcal{B}}$$

$w_{\mathcal{B}}$ skinning weight wrt. $\mathcal{B}$

Linear Blend skinning artifacts



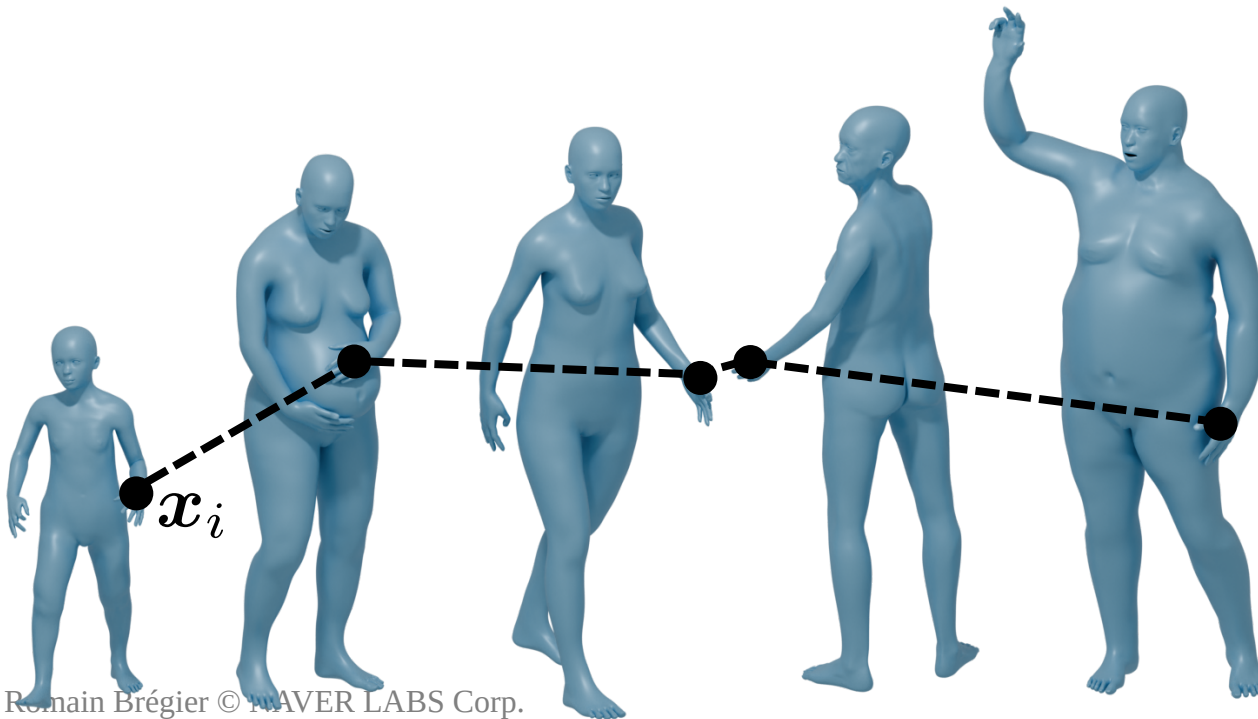
SMPL: Pose corrective deformations



Parametric surface model

Body landmarks consistent across poses and identities

$$\mathbf{X} = (\mathbf{x}_i \in \mathbb{R}^3)_{i=1\dots V}$$



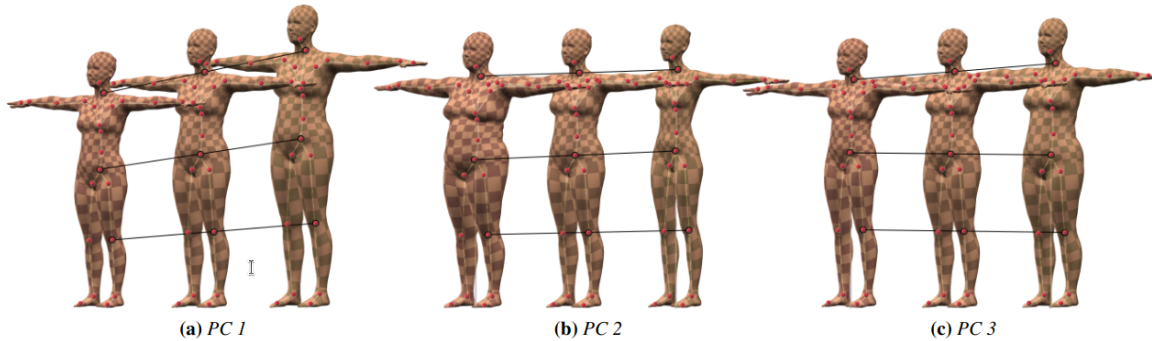
$$\mathbf{X} = f(\boldsymbol{\beta}, \boldsymbol{\theta})$$

$\boldsymbol{\beta}$ Body shape

$\boldsymbol{\theta}$ Pose

SCAPE (Anguelov et al. 2005)

Identity modeling



SMPL (Loper et al. 2015)

SMPL/SMPL-H/SMPL-X/SOMA

Linear deformations (blendshapes)

$$\mathbf{X} = \mathbf{X}_0 + \sum_i \beta_i \mathbf{B}_i$$

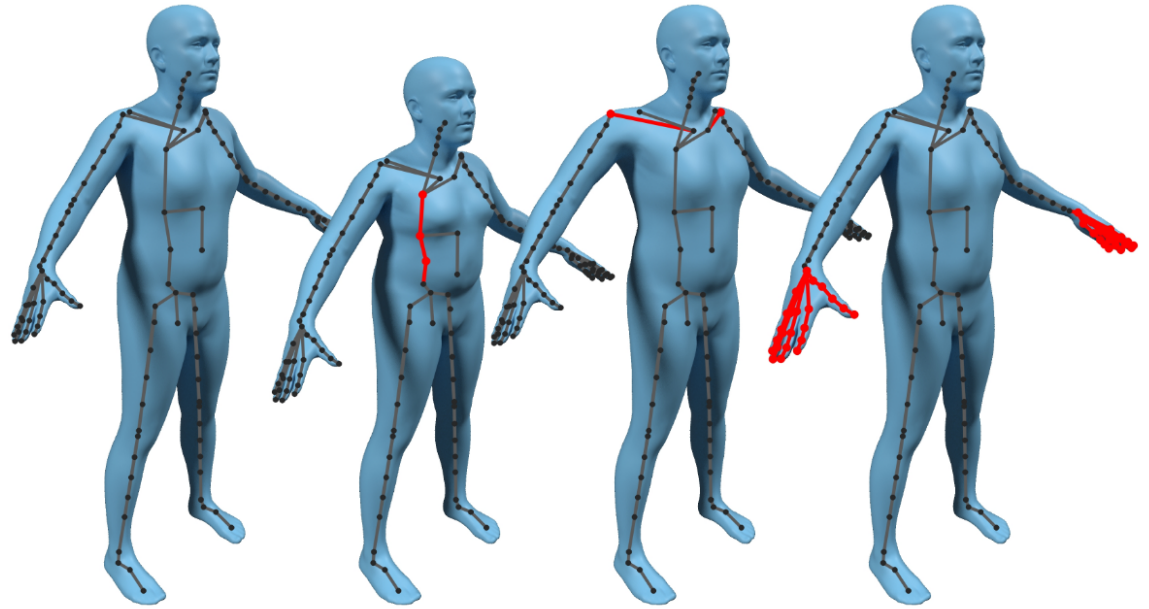
GHUM (Xu et al. 2020): nonlinear deformations

$$\mathbf{X} = \text{Decoder}(\boldsymbol{\beta})$$

ATLAS/MHR: skeletal deformations

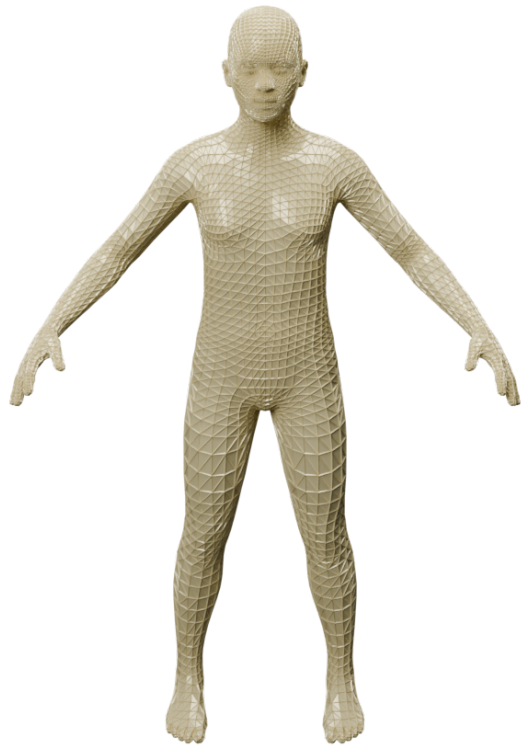
$$\mathbf{T}_{bone}^{local} = \begin{pmatrix} \mathbf{A} & \mathbf{0}_{3 \times 1} \\ \mathbf{0}_{1 \times 3} & 1 \end{pmatrix}$$

$$\mathbf{A} = \mathbf{R} \begin{pmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & s_z \end{pmatrix}$$



ATLAS (Park et al. 2025)

Statistical shape modeling



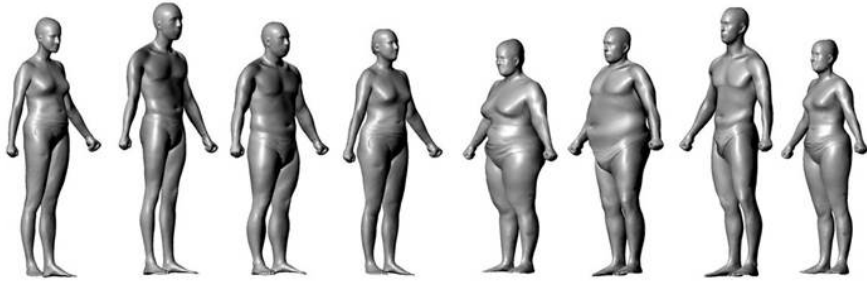
Template mesh

Fitting

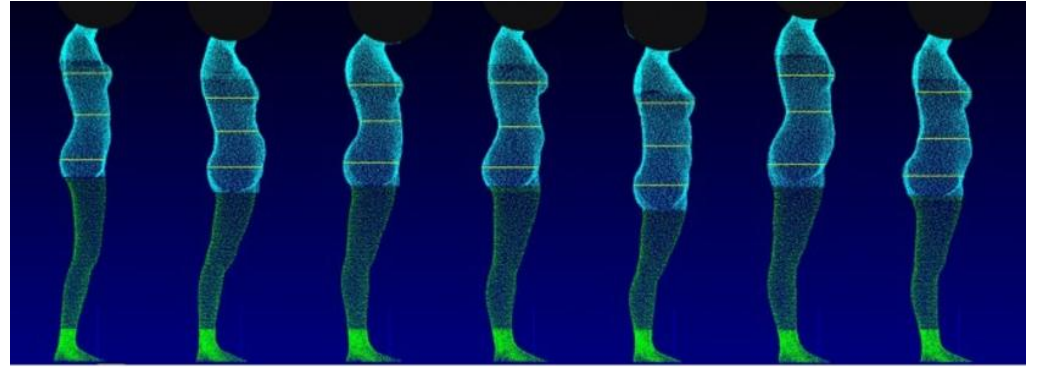


3D scans
(ATLAS)

3D Body Scan datasets



CAESAR (~3.8k subjects)



SizeUSA (~10k subjects)

+ other proprietary datasets

3D scans training sets

Model	# scans*	# body identities
SMPL	3,800	1,800
STAR	14,000	1,800
GHUM	60,000	4 300
SUPR	1,200,000	15,000
ATLAS	600,000	15,000
MHR	26,000	7,110
SOMA-Shape	9,629	9,629
Anny	N.A.	N.A.

* not apple-to-apple comparison

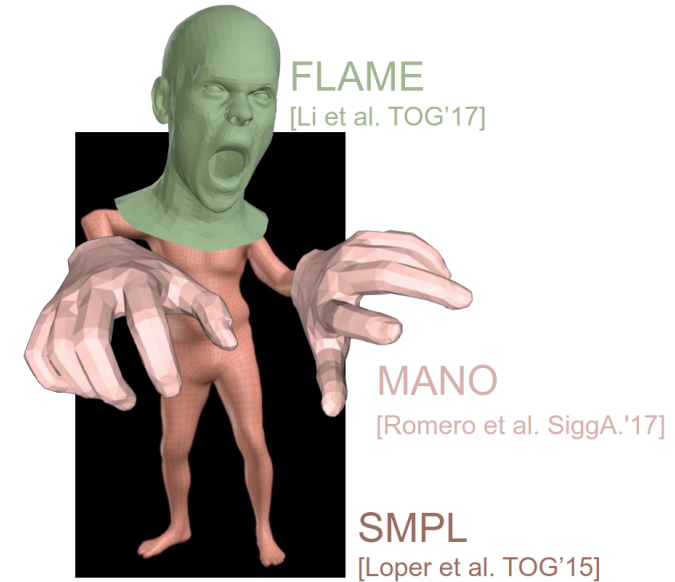
Hands and facial expression

Model stitching

SMPL-H (Romero et al. 2017) = SMPL + MANO

Frank (Joo et al. 2018) = SMPL + FaceWarehouse

SMPL-X (Pavlakos et al. 2019) = SMPL + MANO + FLAME



[Courtesy of G. Pons Moll]

Joint learning

GHUM (Xu et al. 2020)

SUPR (Osman et al. 2022)

(can be split in independent parts)

ATLAS (Park et al. 2025)

MHR (Ferguson et al. 2025)

Shape modeling evaluation



Scan



Fit



Fitting Error



Statistical shape modeling

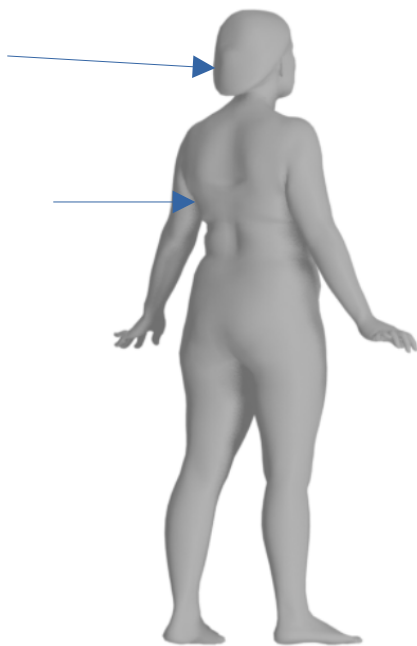
Pros:

- Learned from actual data
- Models in-distribution data very well

Cons:

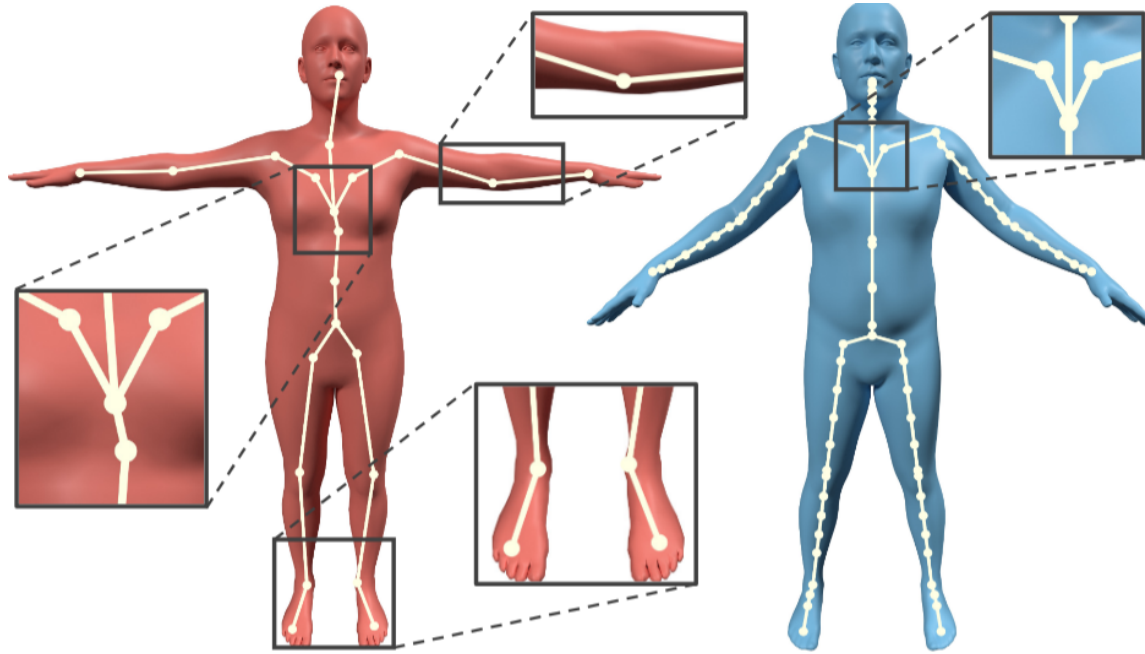
- Distribution biases
 - North America and Europe adults
 - “Only” 15k identities
 - Can over-fit

Statistical shape modeling “over-fitting”



SMPL-X fit (300 shape components)

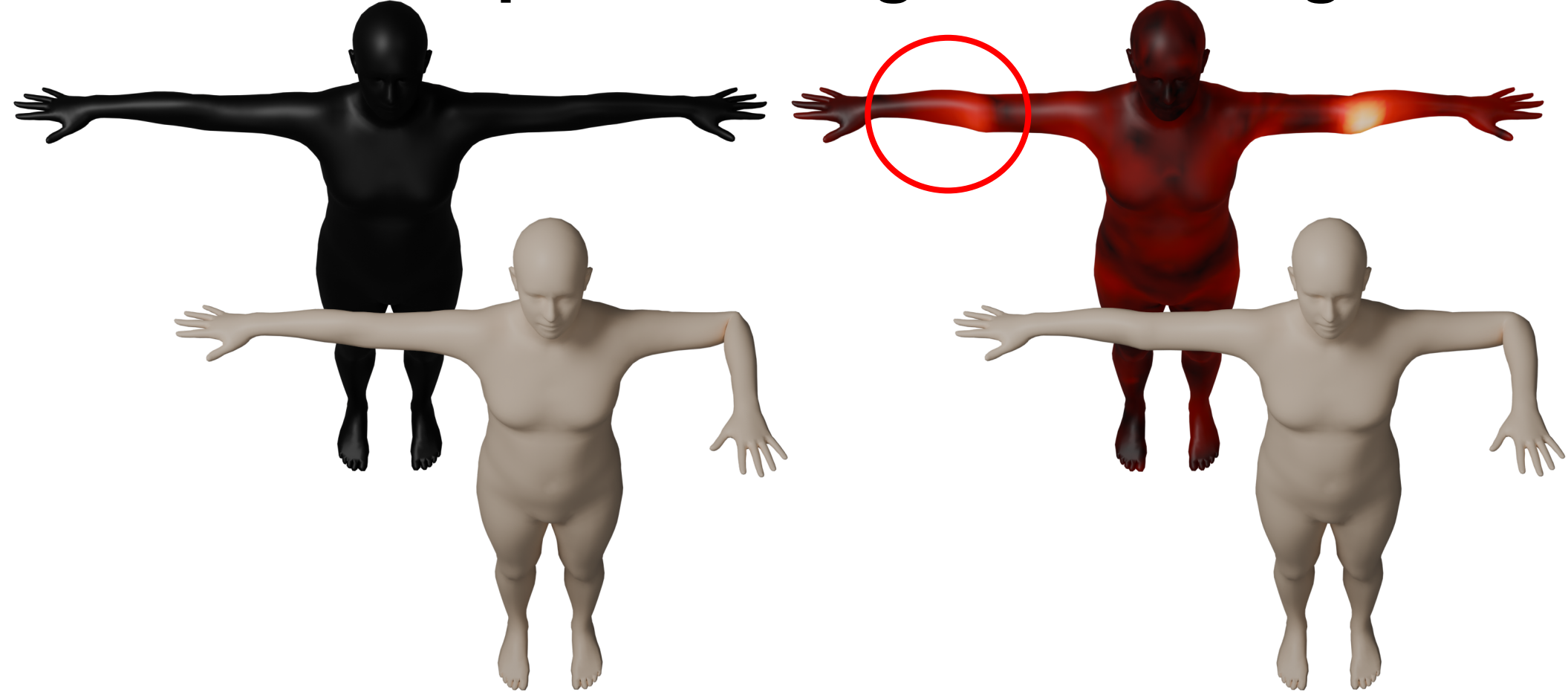
Statistical shape modeling “over-fitting”



SMPL-X

ATLAS

Statistical shape modeling “over-fitting”

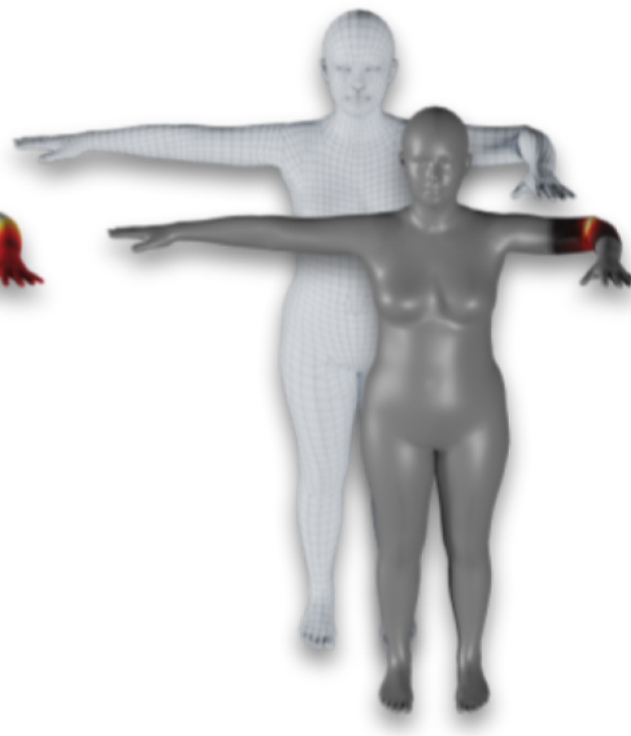


STAR: sparse local corrections

SMPL

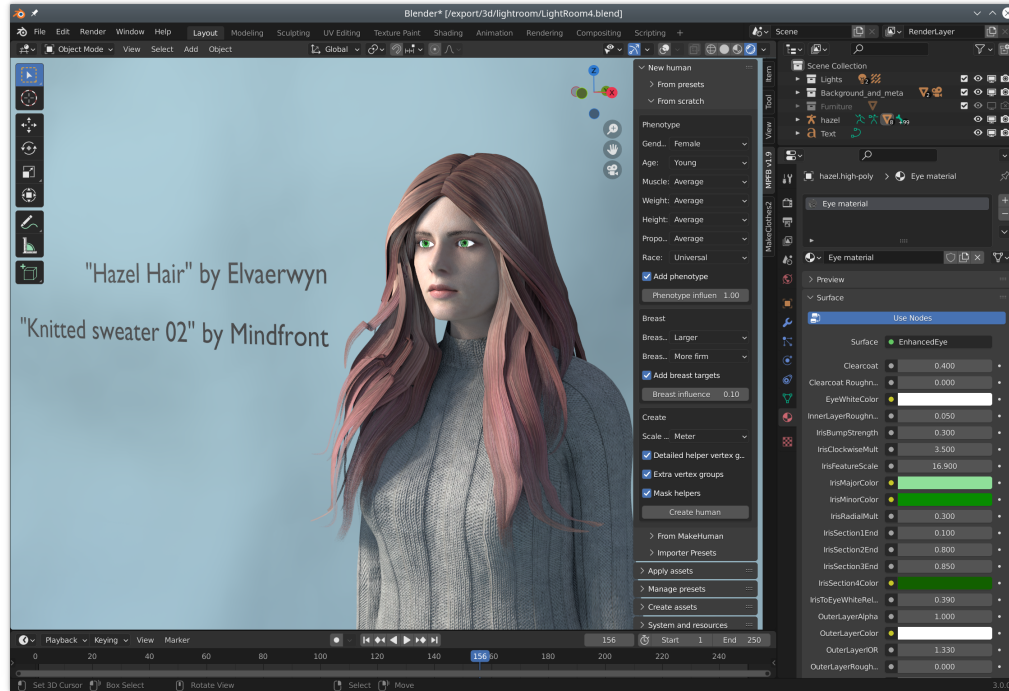


STAR

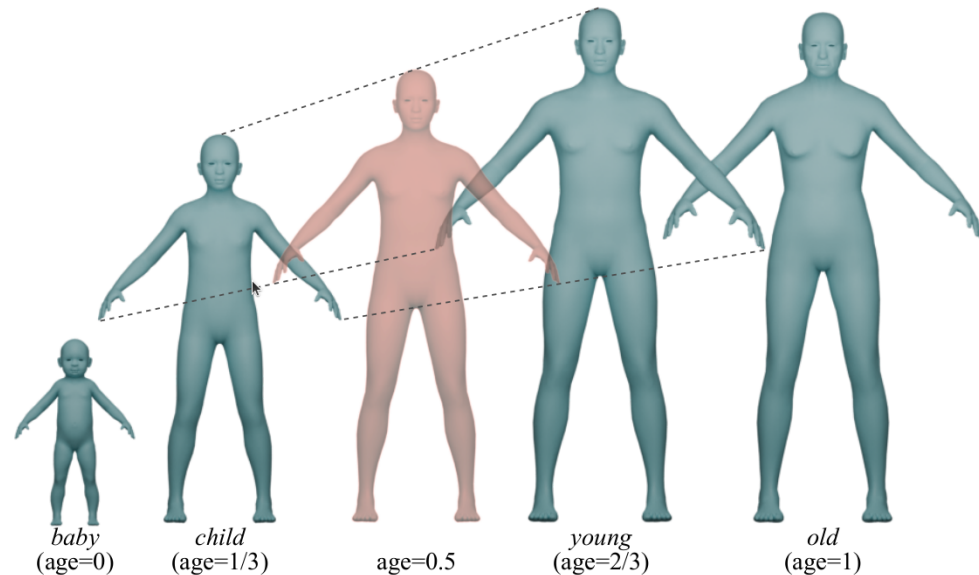


STAR (Osman et al. ECCV2020)

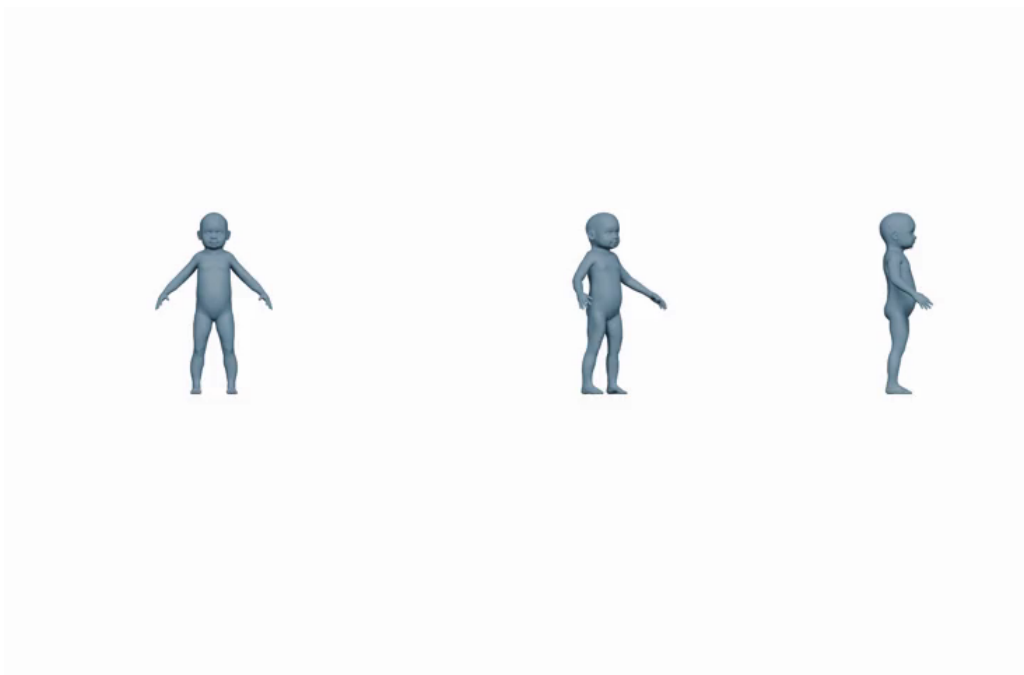
Anny: artist-based shape modeling



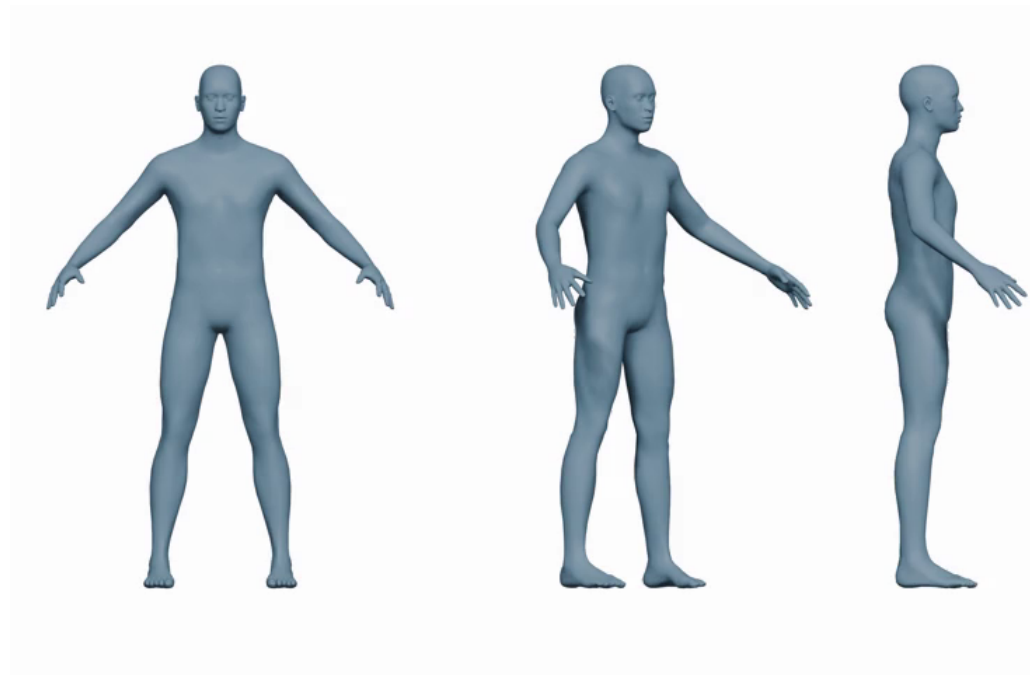
MPFB (2026)



Aenny artist-defined semantic parameters

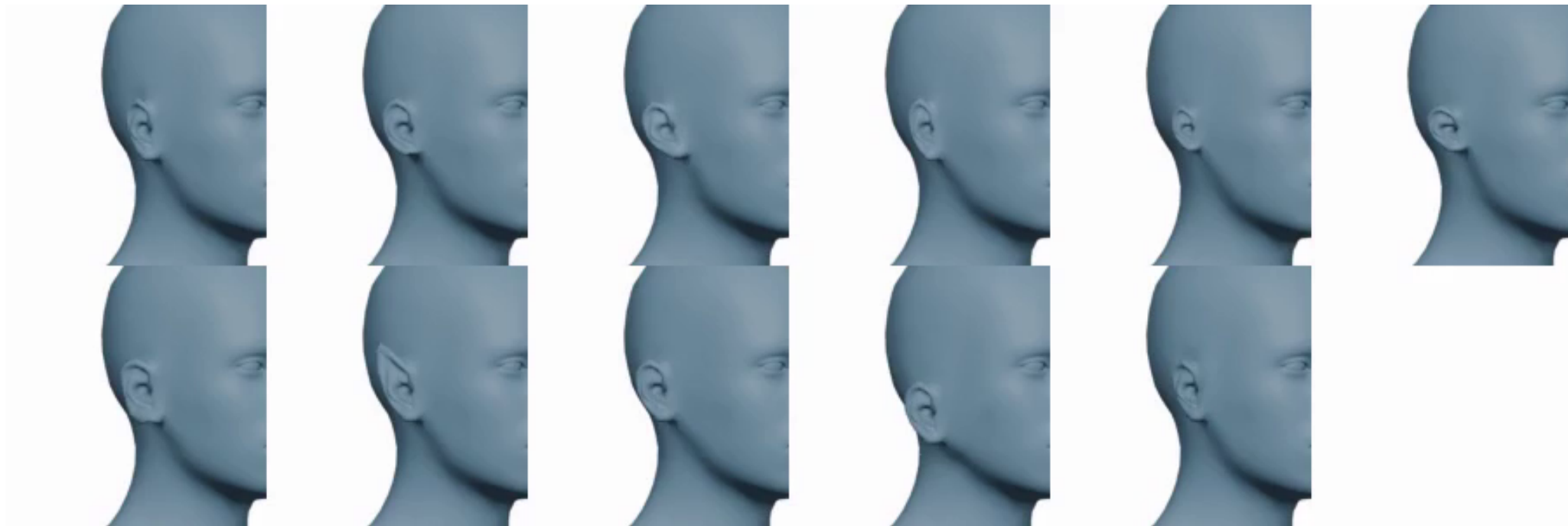


“age”



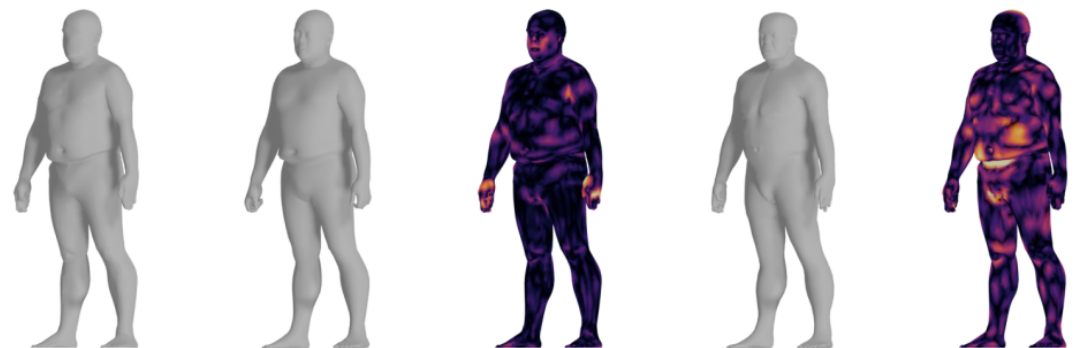
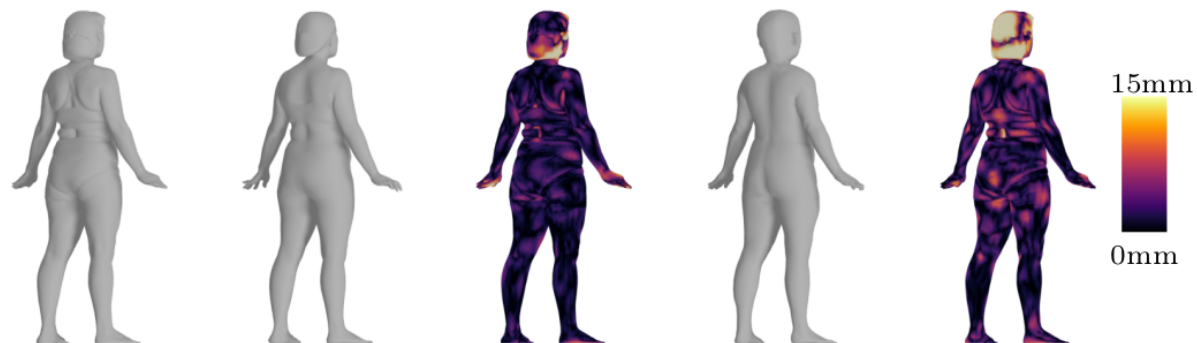
“gender”

Anny: artist-defined semantic parameters



ear shape parameters

3D scan fitting



Scan

SMPL-X (300 components)

Anny (164 components)



Scan

SMPL-X+A (301 components)

Anny (164 components)

Anny: Artist-based shape modeling

Pros:

- No 3D scans required
 - Cost
 - Privacy
- Parameter semantics
 - (“age”, “height”, “ear shape”,...)
- Good fitting quality
- Diversity
 - Children, elders, very tall individuals

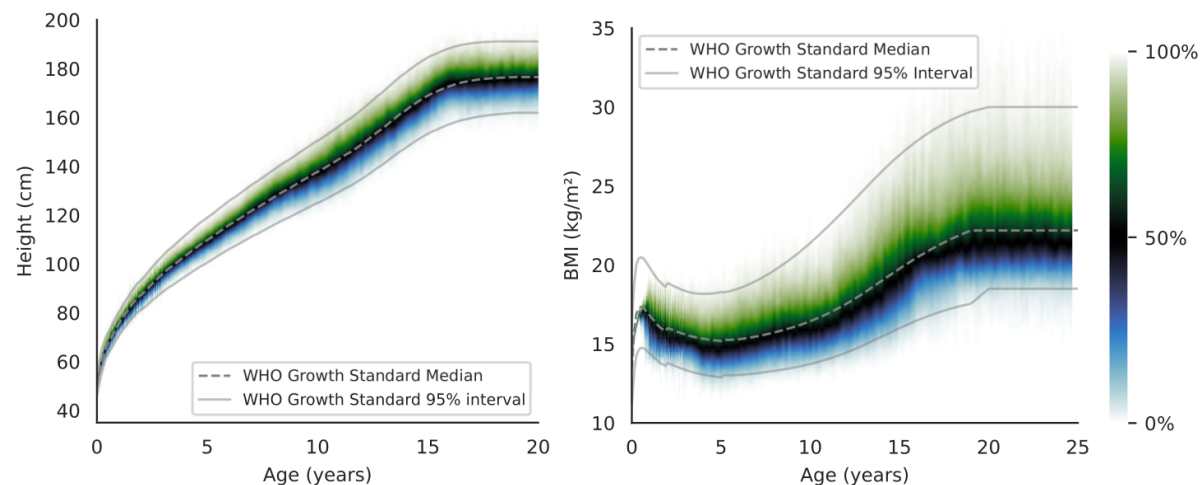
Neutral

- Explicit biases: artistic stereotypes

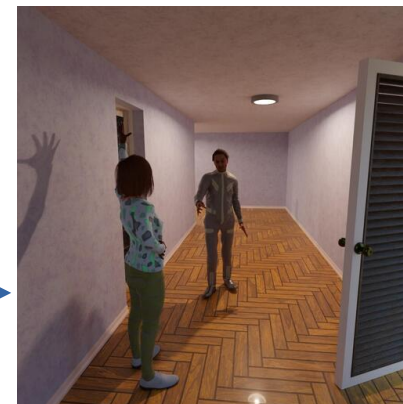
Cons:

- Less precise modeling (fat, body skin folds)
- Uncalibrated distribution

Anny: Height/BMI calibration



WHO growth standards



Anny-One
Synthetic shapes dataset

HMR training

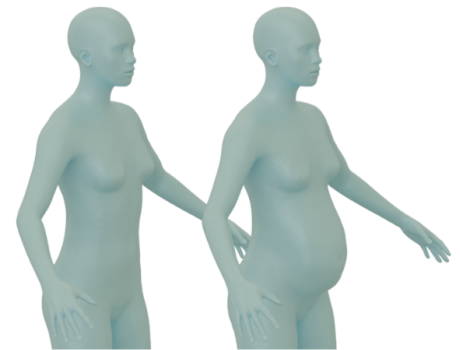
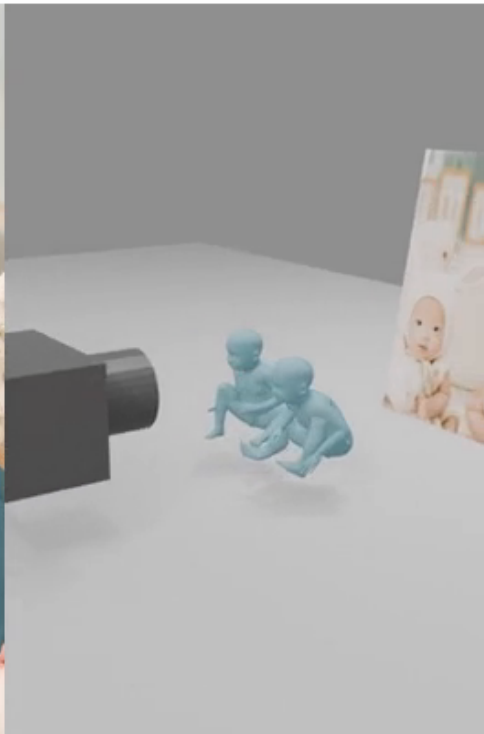


Diversity

Image

Anny-Fit

Side view



stomach-pregnant

Anny-Fit

(Bravo Sánchez et al. CVPR2026 Findings)

Fundamental limitations (all models)



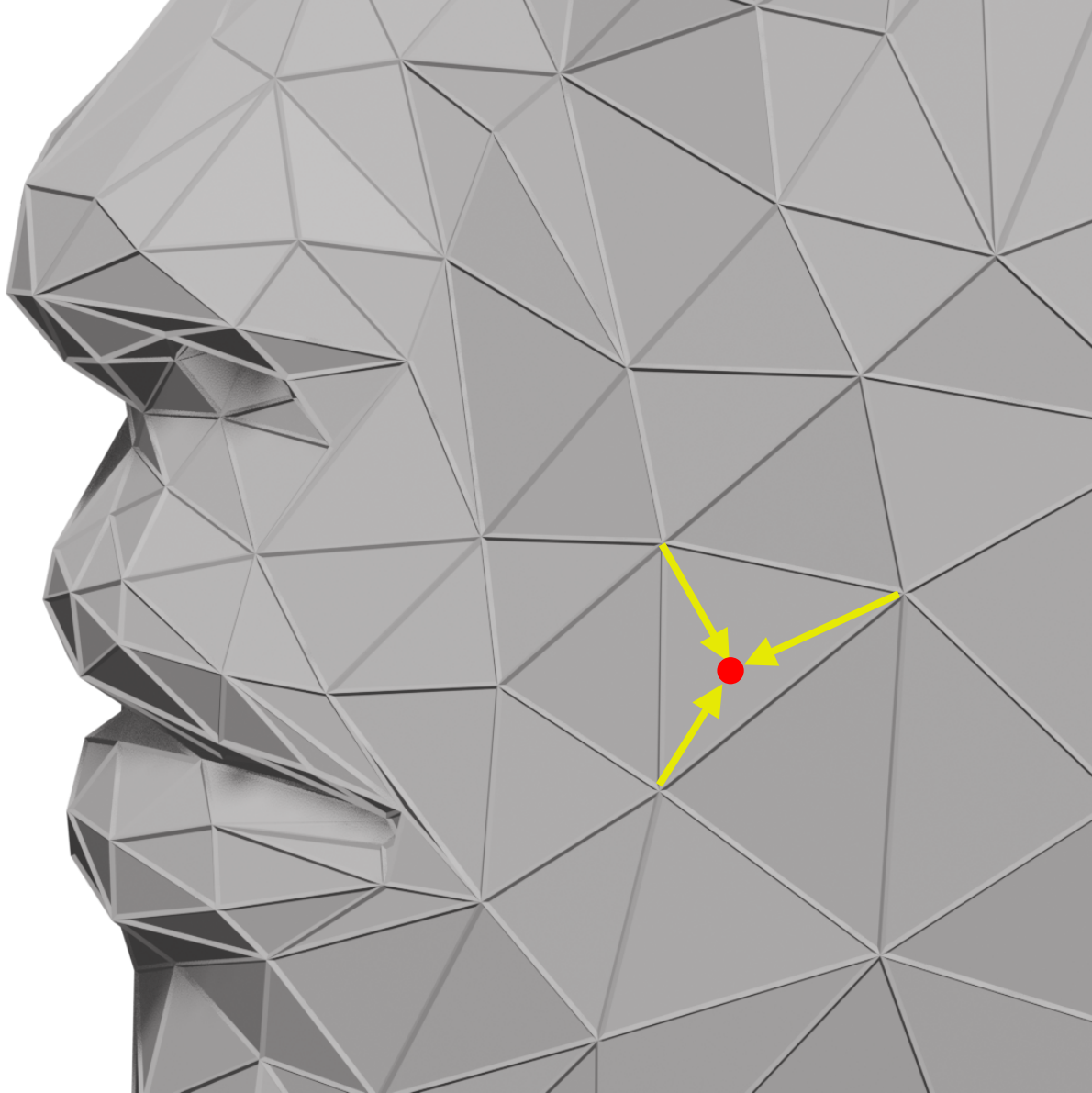
Which body model should you use?

**“The nice thing about standards is that there are so many to choose from.”
(Andrew S. Tanenbaum.)**

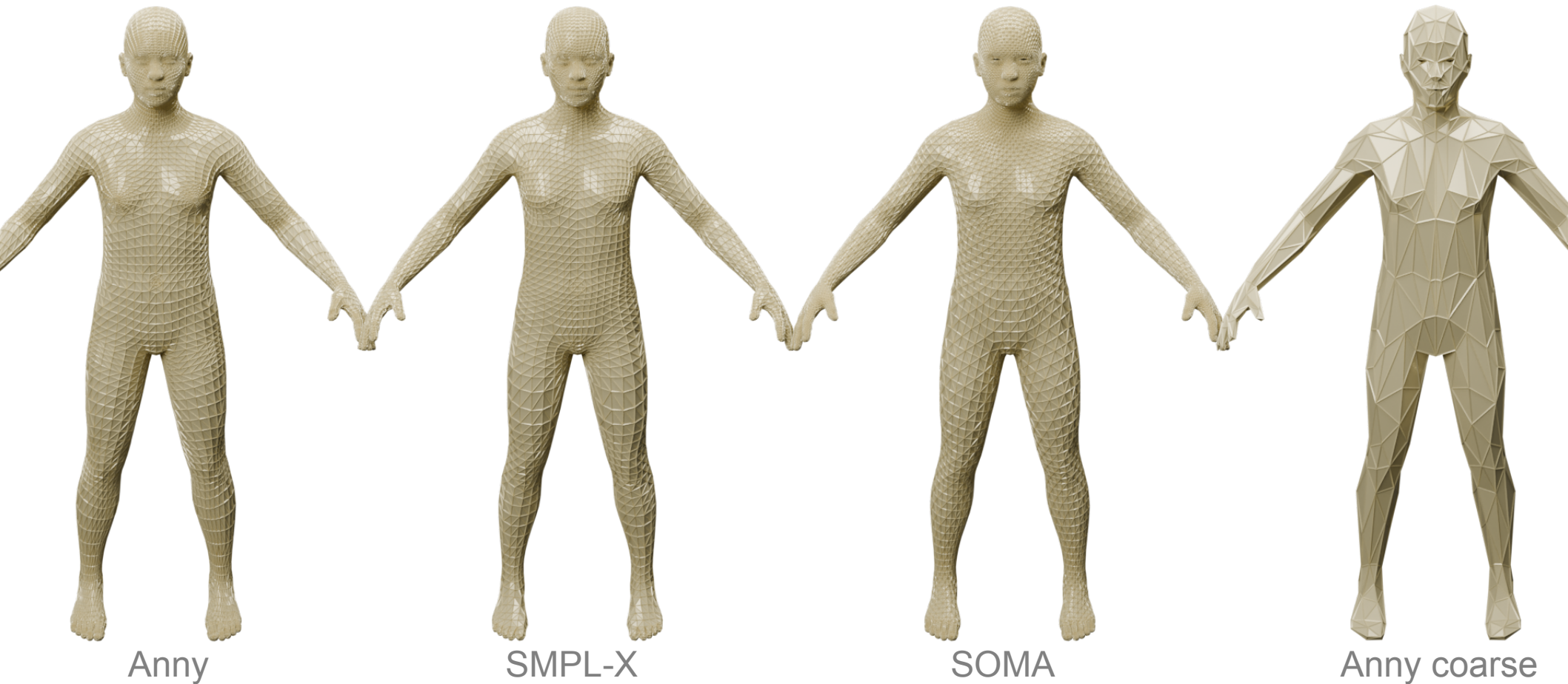
Conversions between models are possible.

Vertex interpolation

$$\mathbf{x}^{target} = \sum_i w_i \mathbf{x}_i^{src}$$



Topologies / Level of Details

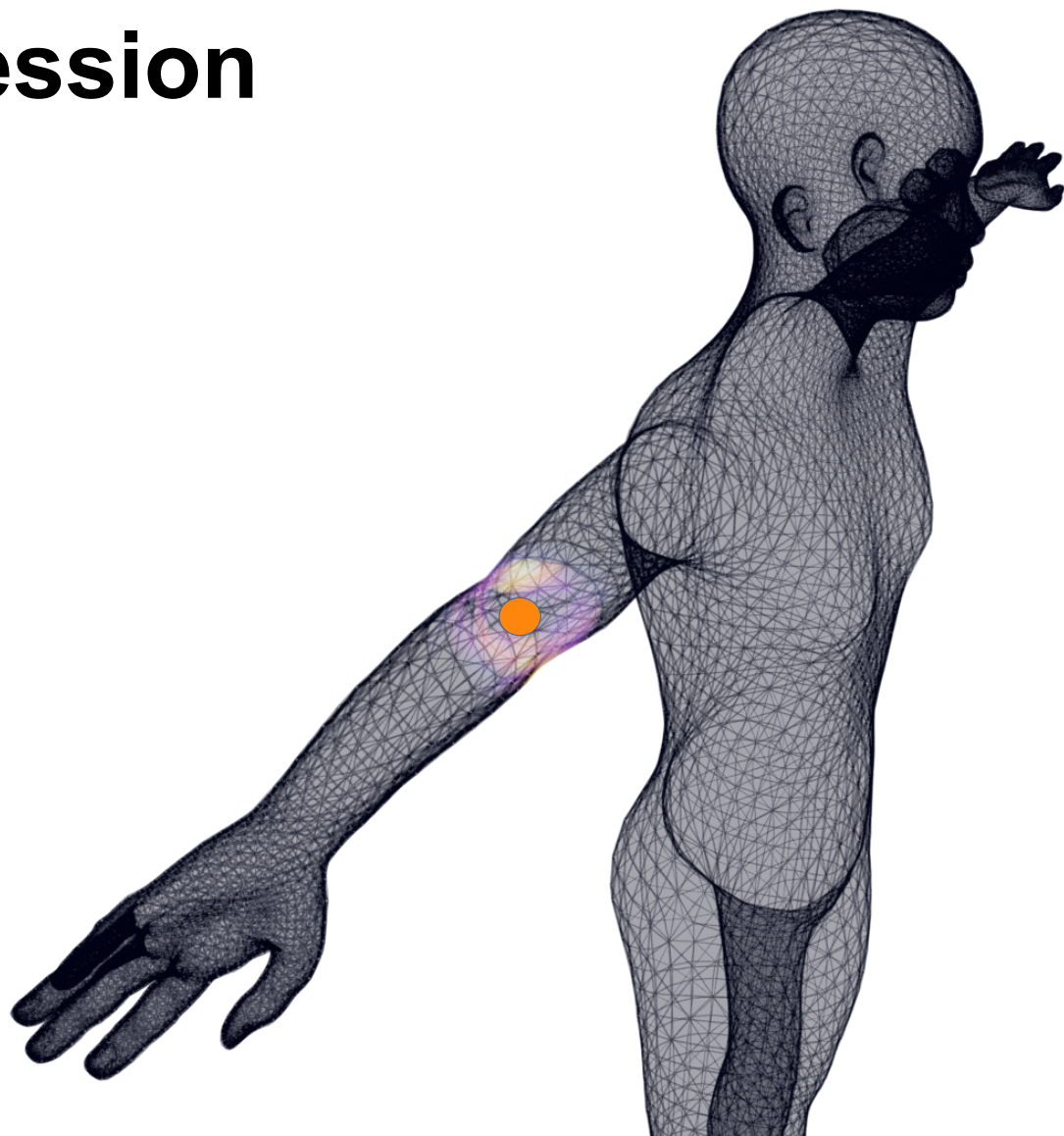


Joint location regression

$$\mathbf{t}^{bone} = \sum_i w_i \mathbf{x}_i^{ref}$$

Used by:
SMPL
SMPL-X

...
SOMA (Saito et al. 2026)

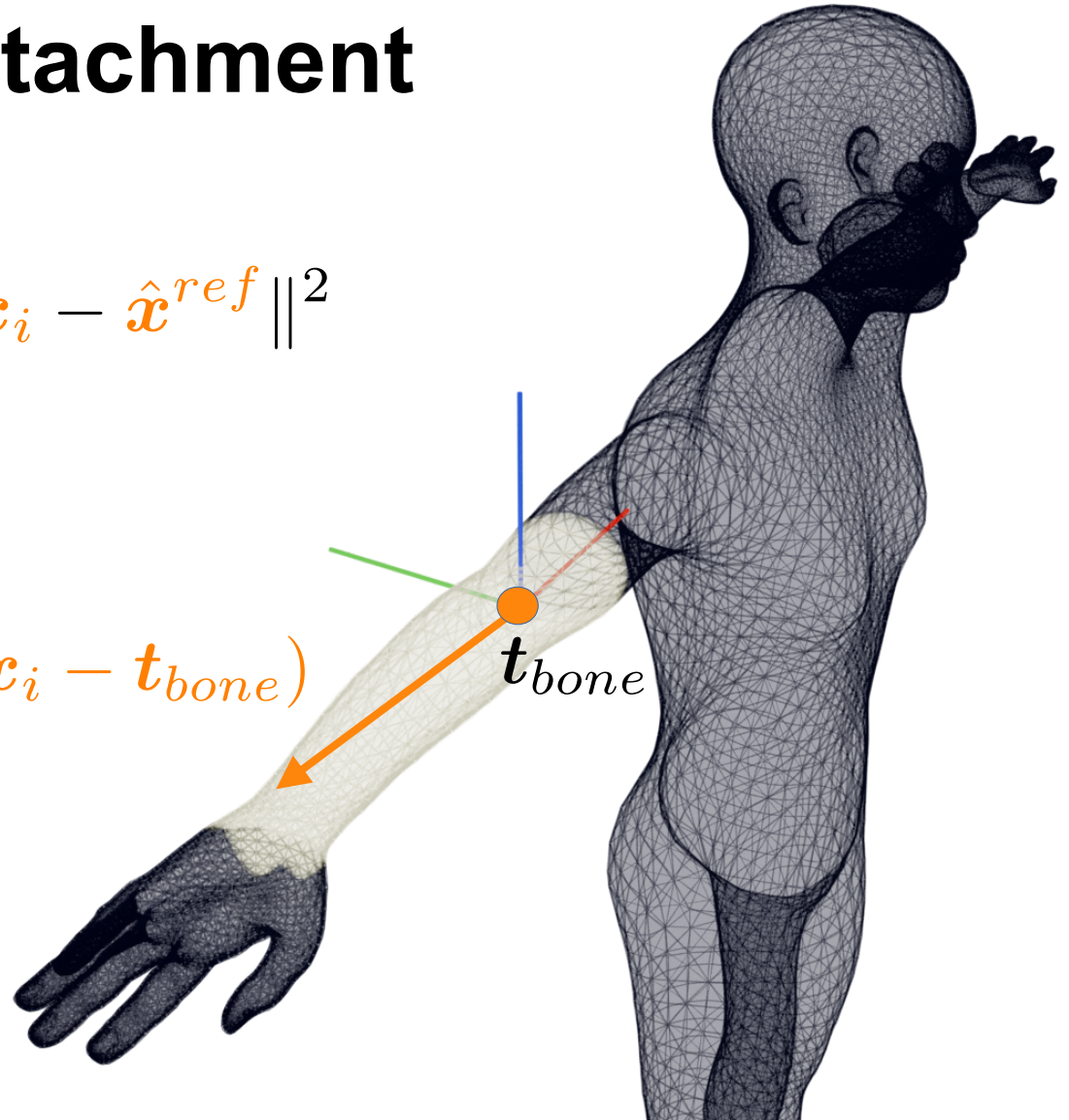


Bone orientation attachment

$$R_{bone} = \arg \min_R \sum_i w_i \|R \hat{x}_i - \hat{x}^{ref}\|^2$$

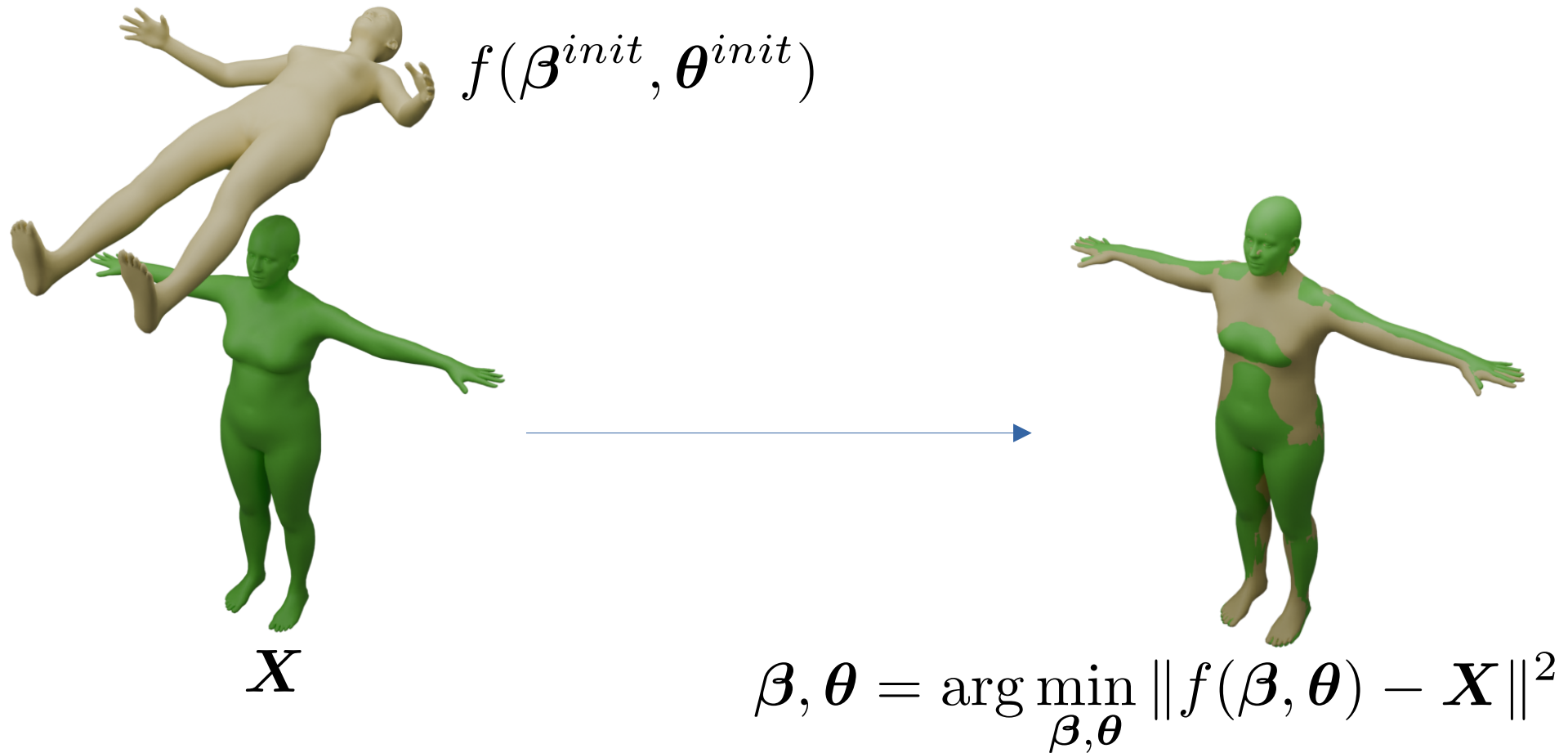
closed form solution

with $\hat{x}_i = (x_i - t_{bone})$



SOMA (Saito et al. 2026)

Parameters Fitting



“all models are wrong, but some are useful.”

George Box

De-facto **historical standards:**

SMPL
SMPL-X

Later refinements:

GHUM, STAR, SUPR, ATLAS

Application-specific:

OSSO, SKEL, BOSS,
SMIL, ...

Free alternatives:

Anny
MHR
SOMA rig