

GHUM & GHUML: **Generative 3D Human Shape** **and Articulated Pose Models**

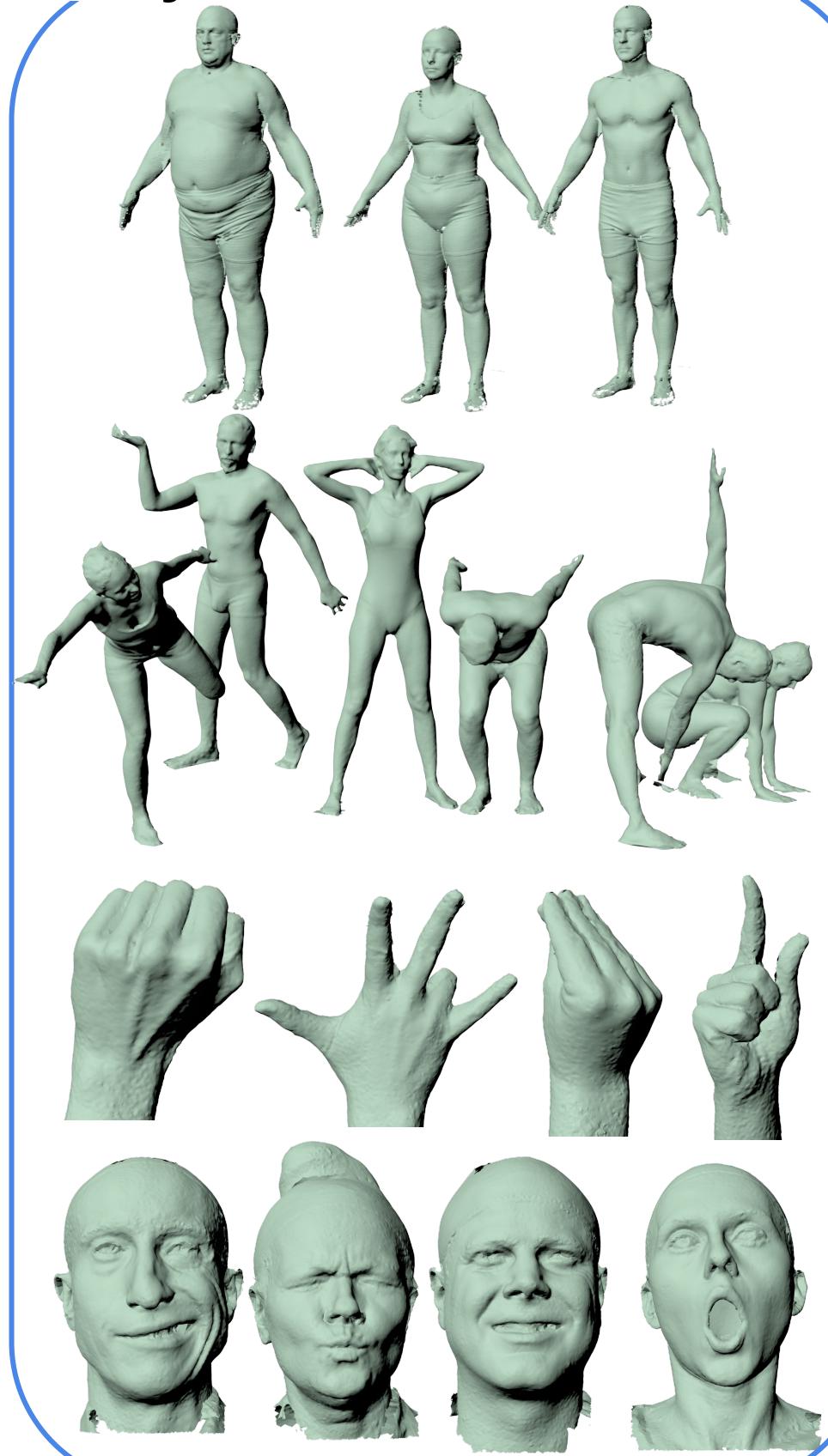
Hongyi Xu, Eduard Gabriel Bazavan, Andrei Zanfir,

William T. Freeman, Rahul Sukthankar, Cristian Sminchisescu

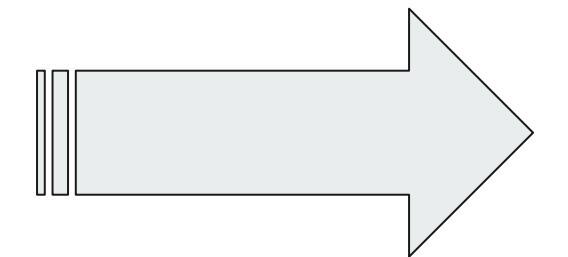
Google Research

GENERATIVE HUMAN MODELING PIPELINE

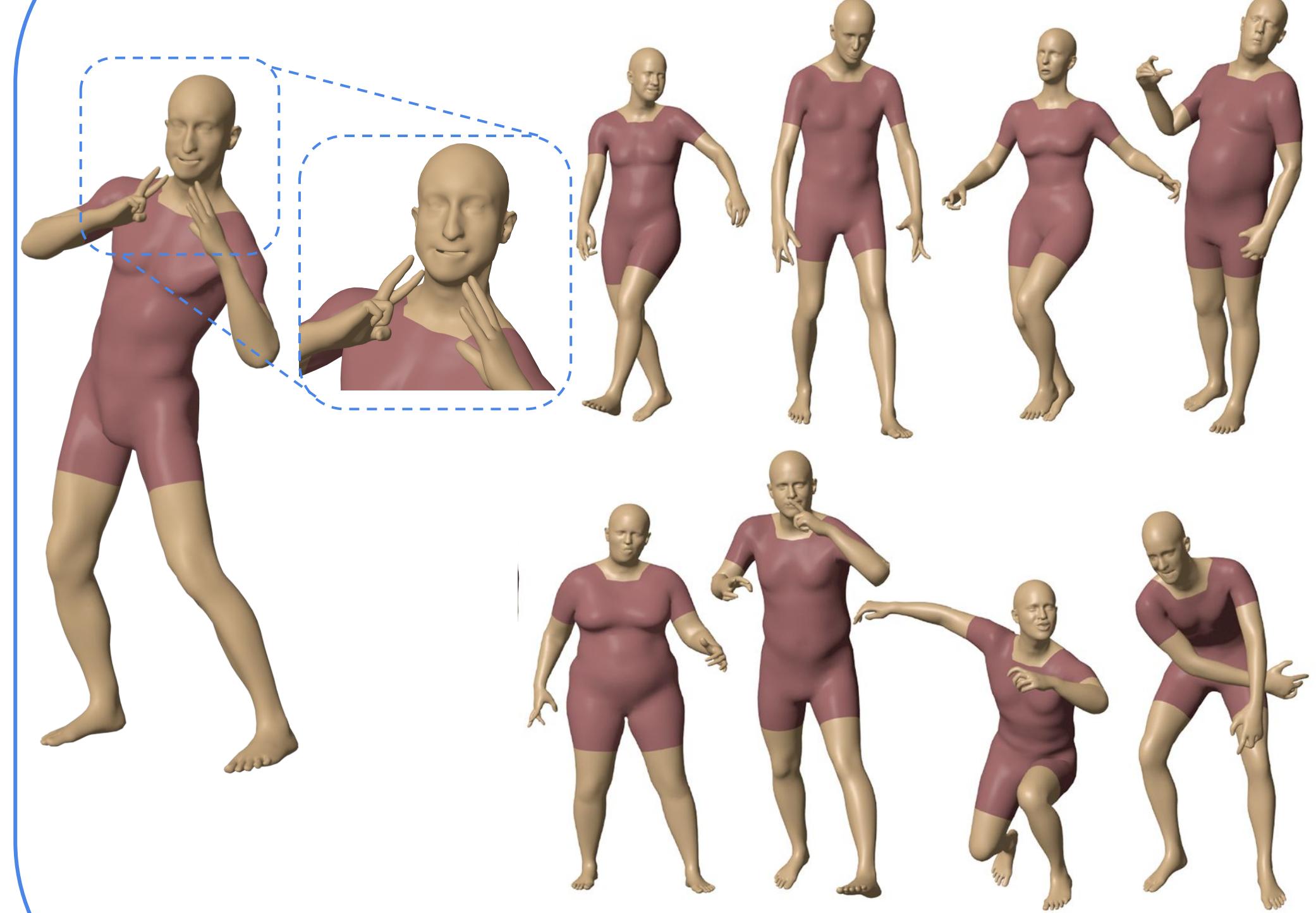
dynamic human scans



end-to-end
deep learning



full-body articulated **generative** human models



Motivation: 3D Human Sensing



F&F
Fitting Room

Dresses | Accessories | Bottoms

Dresses Size 10

Yellow Dress \$15.99
Red Dress \$16.99

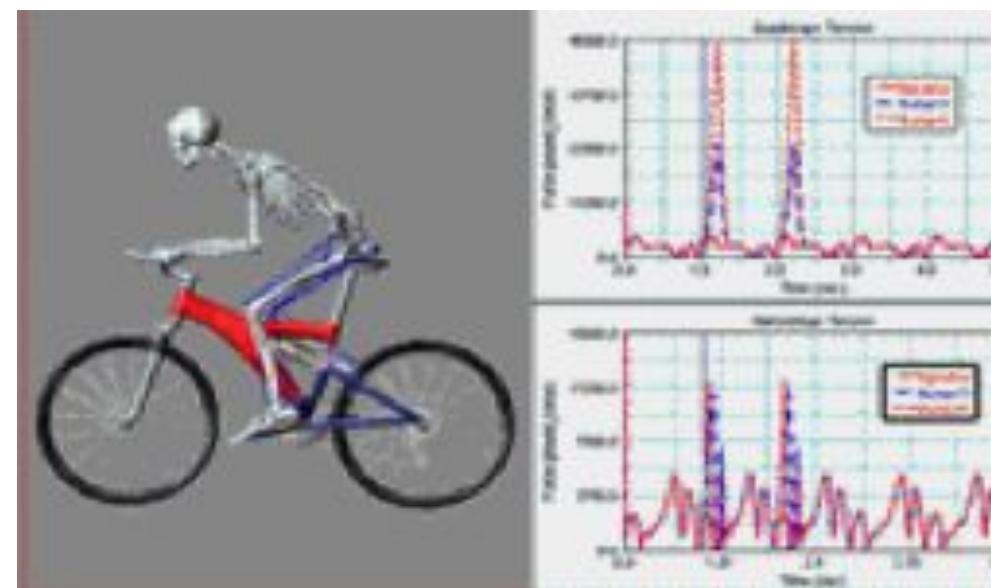
Brown Dress \$21.99
Teal Dress \$16.99

Black Dress \$22.99
Blue Dress \$22.99

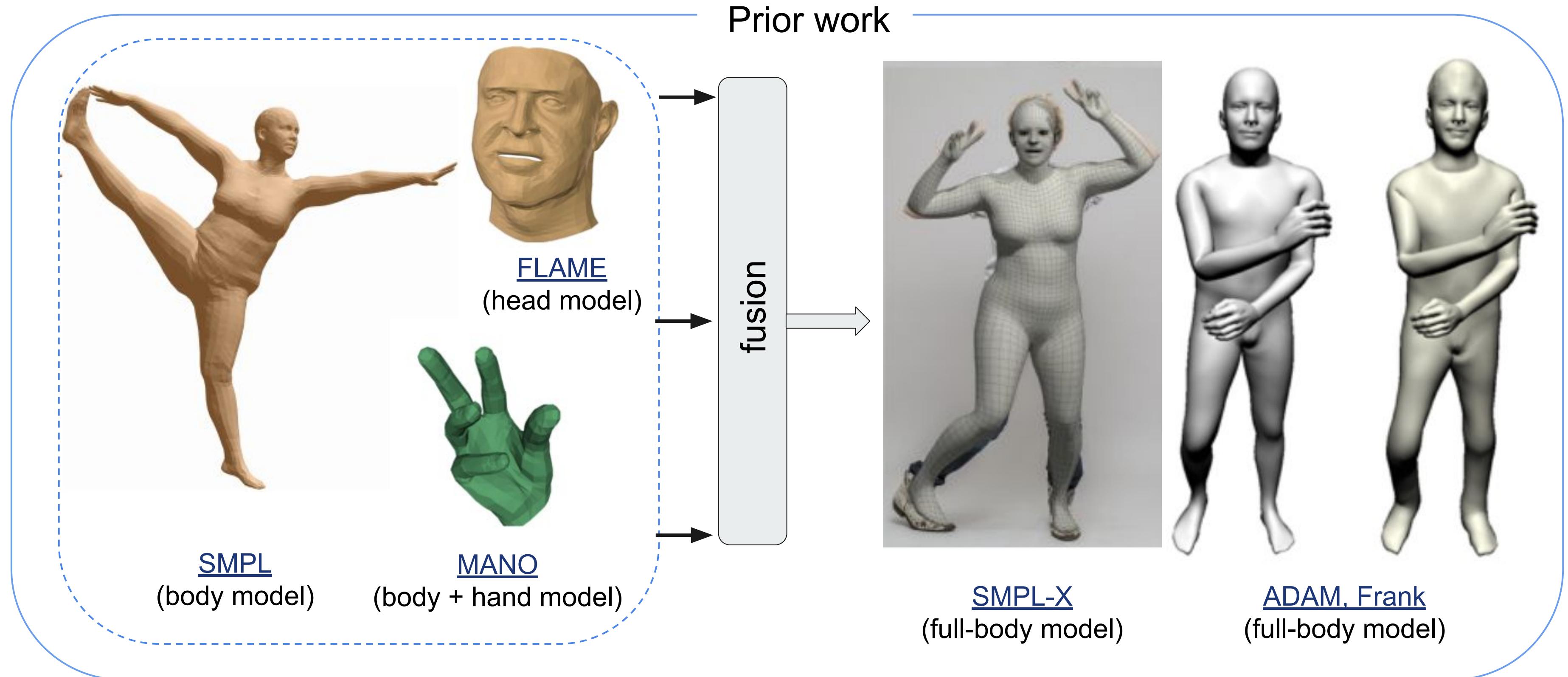
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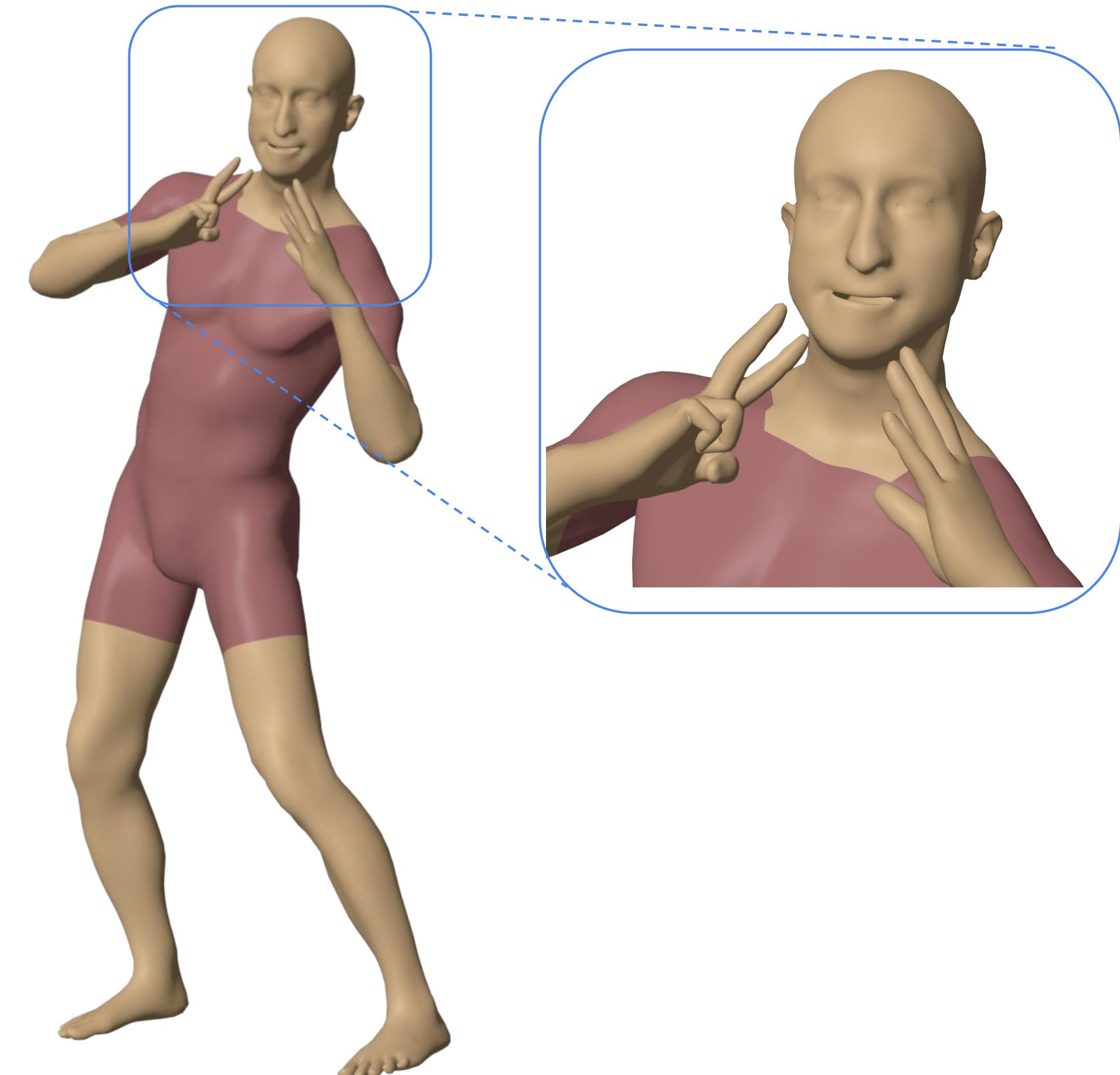


GENERATIVE HUMAN MODELS: PRIOR WORK



TOWARDS FULL-BODY GENERATIVE HUMAN MODEL

- ★ Full-body generative human model
- ★ All model components trained in a single consistent learning loop



END-TO-END TRAINING PIPELINE

Trainable modules:

- █ body shape VAE
- █ expression VAE
- █ pose-space deformation
- █ joint centers predictor
- █ skinning weights

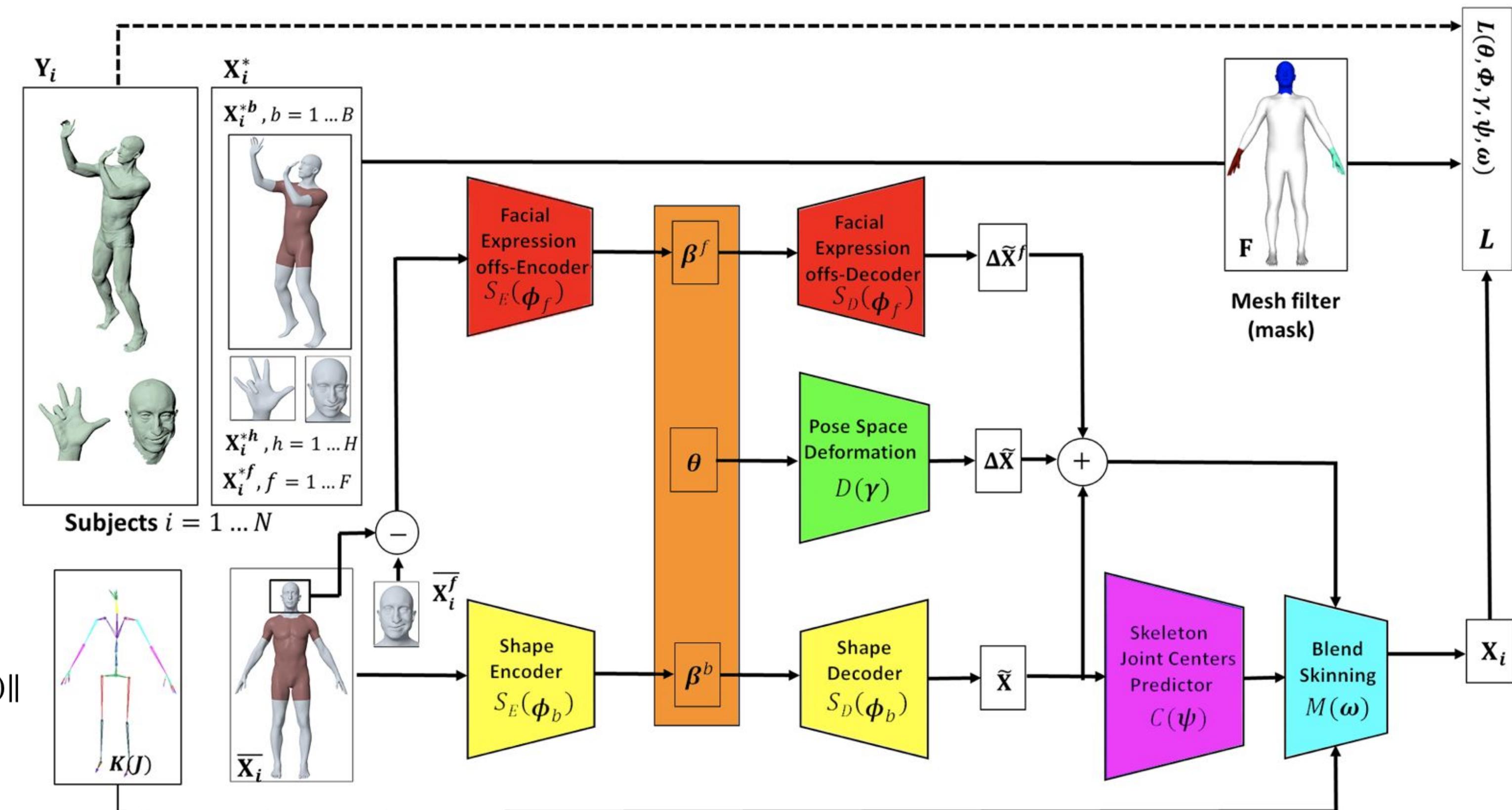
Model parameters:

- █ latent codes: β^b, β^f
- pose: θ

Losses:

masked reconstruction loss

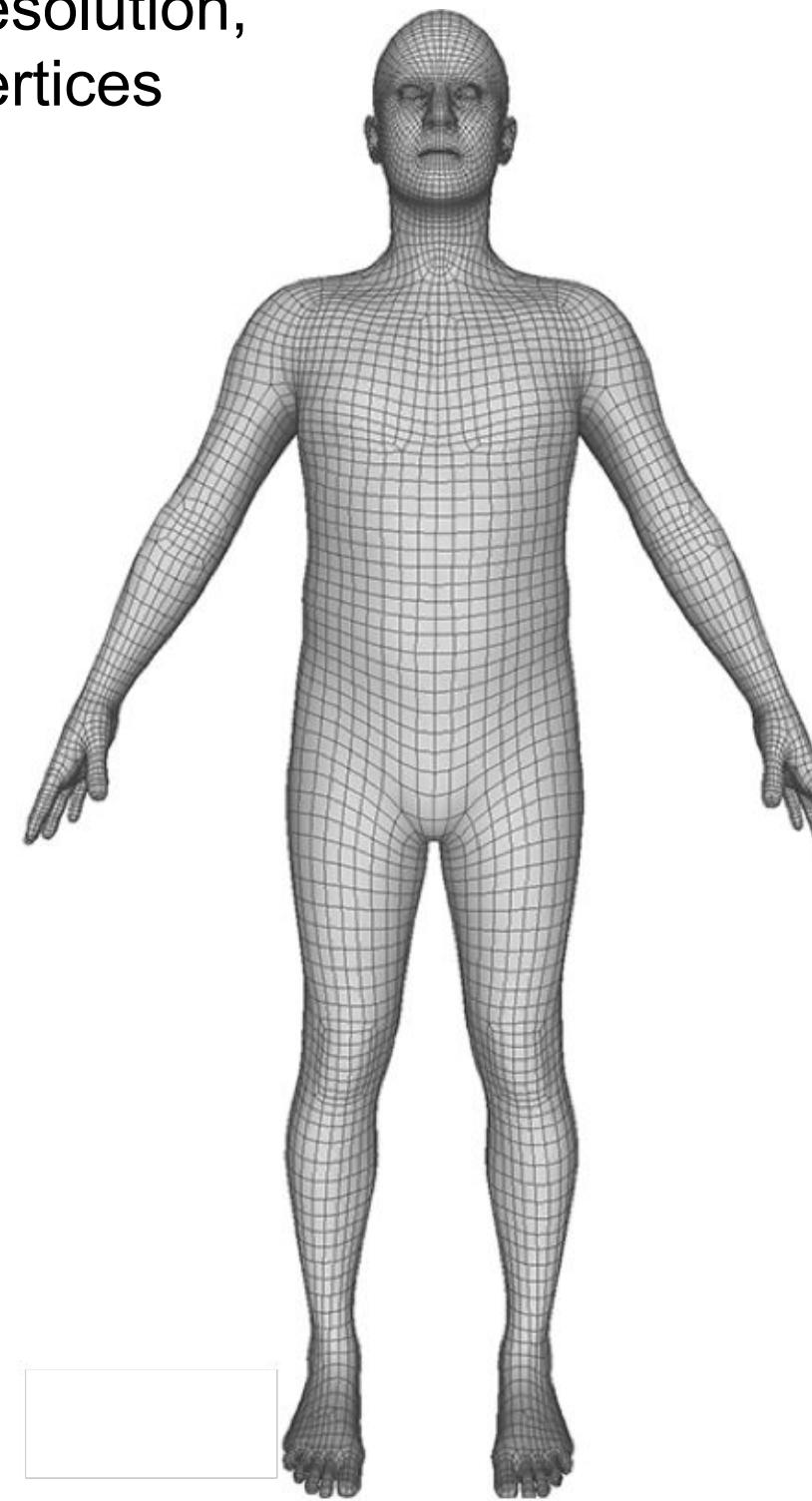
$$\frac{1}{N} \sum_i^N \| F_i(X_i^* - X_i(\beta^b, \beta^f, \theta)) \| + \text{parameters regularizers}$$



GHUM AND GHUML(ite): TEMPLATES

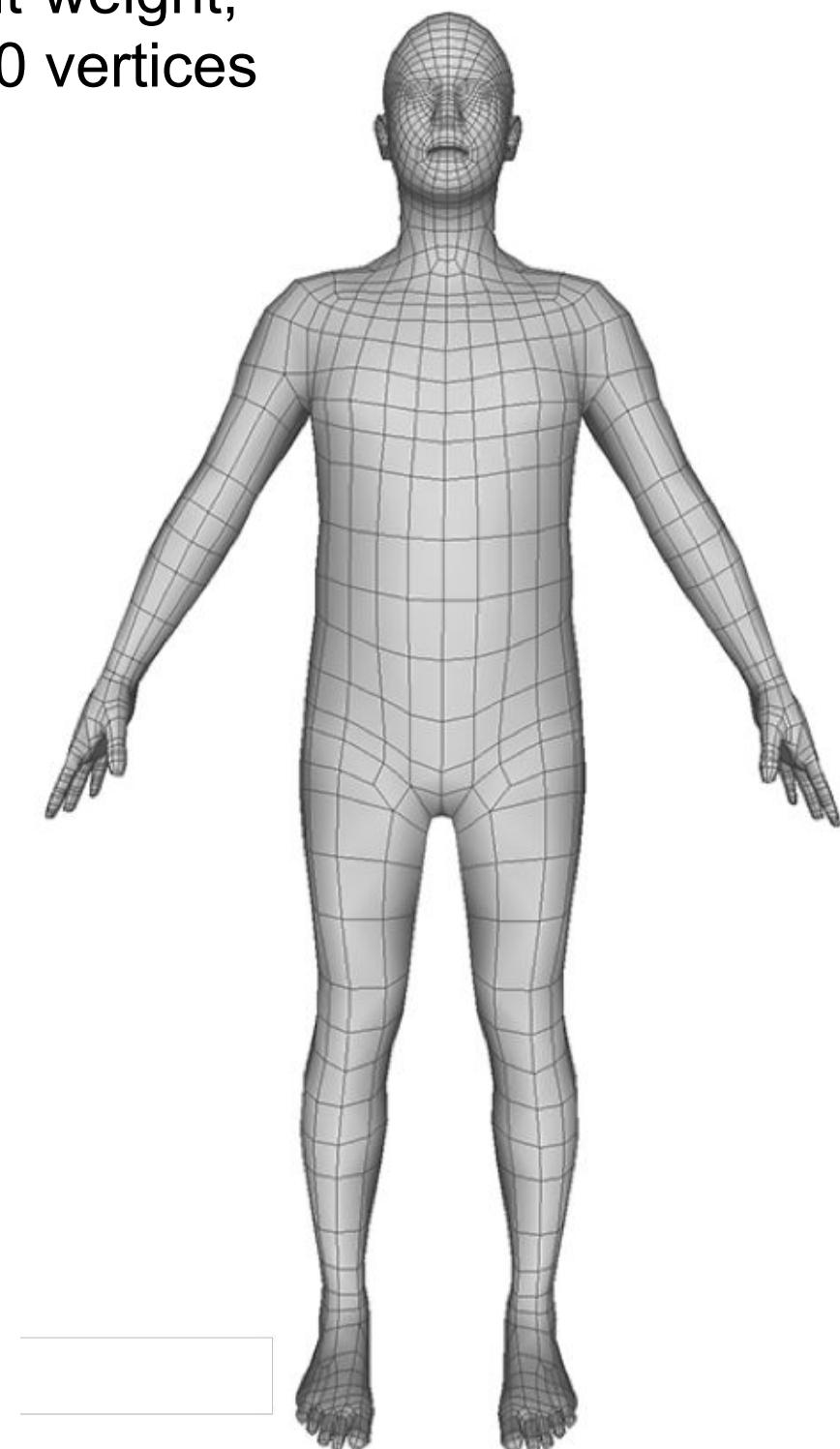
GHUM:

moderate-resolution,
10168 vertices



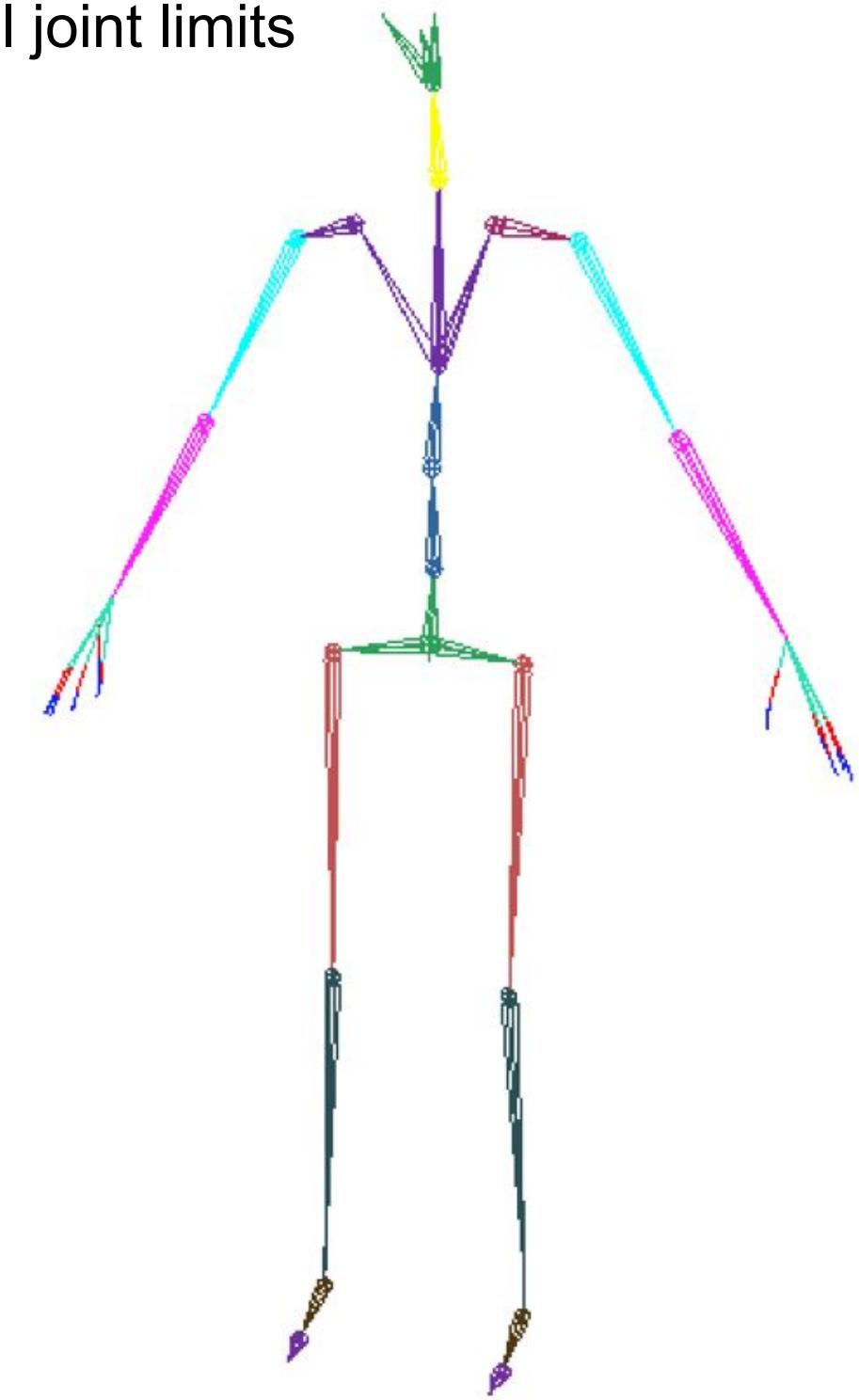
GHUML(-ite):

light-weight,
3190 vertices



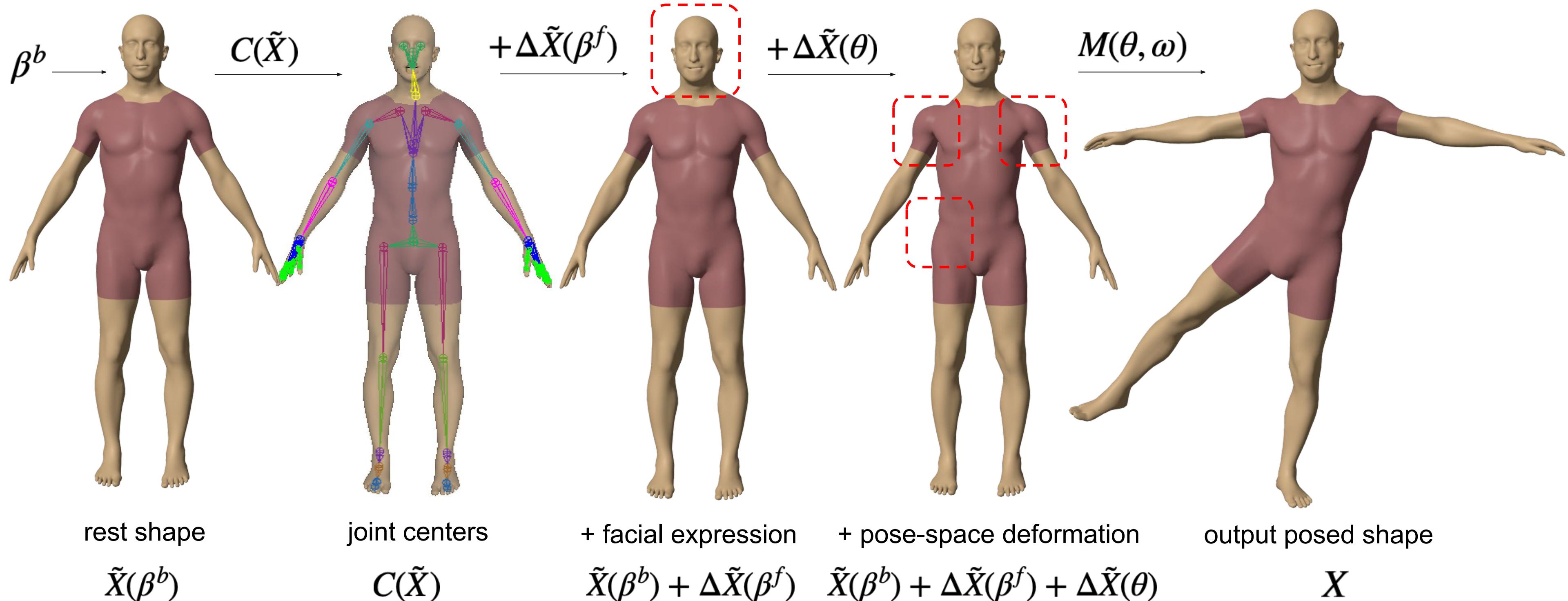
Shared skeleton:

minimal parameterized,
anatomical joint limits



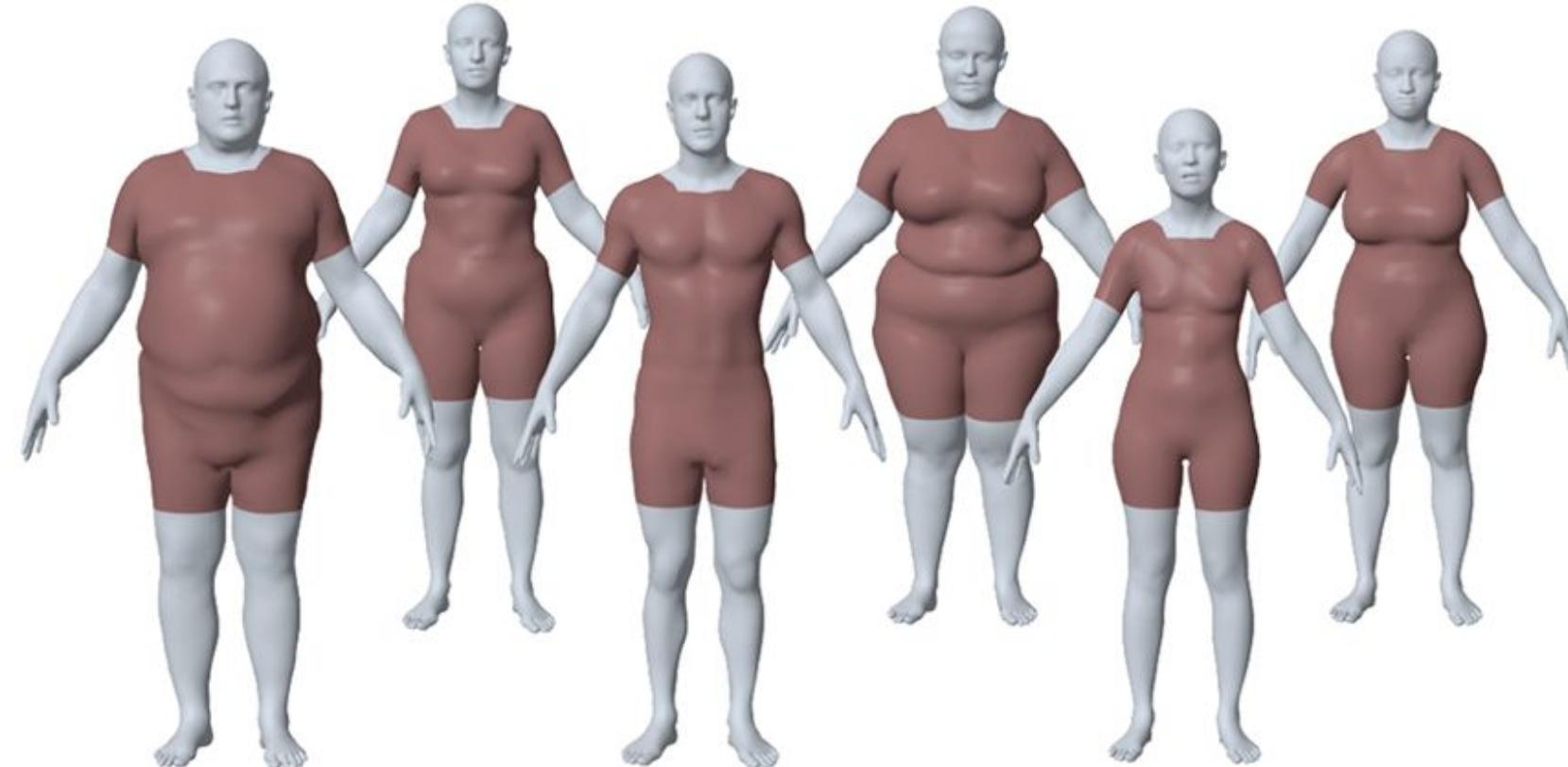
GHUM AND GHUML(ite): MODEL FORMULATION

$$X(\beta^b, \beta^f, \theta) = M(\tilde{X}(\beta^b), \Delta\tilde{X}(\beta^f), \theta, \Delta\tilde{X}(\theta), C(\tilde{X}), \omega)$$



REGISTRATION TO GHS3D + CAESAR

4.3K subjects, 60K high-resolution dynamic human scans, including close-up head and hand scans.



multi-subject dataset



multi-body-pose dataset

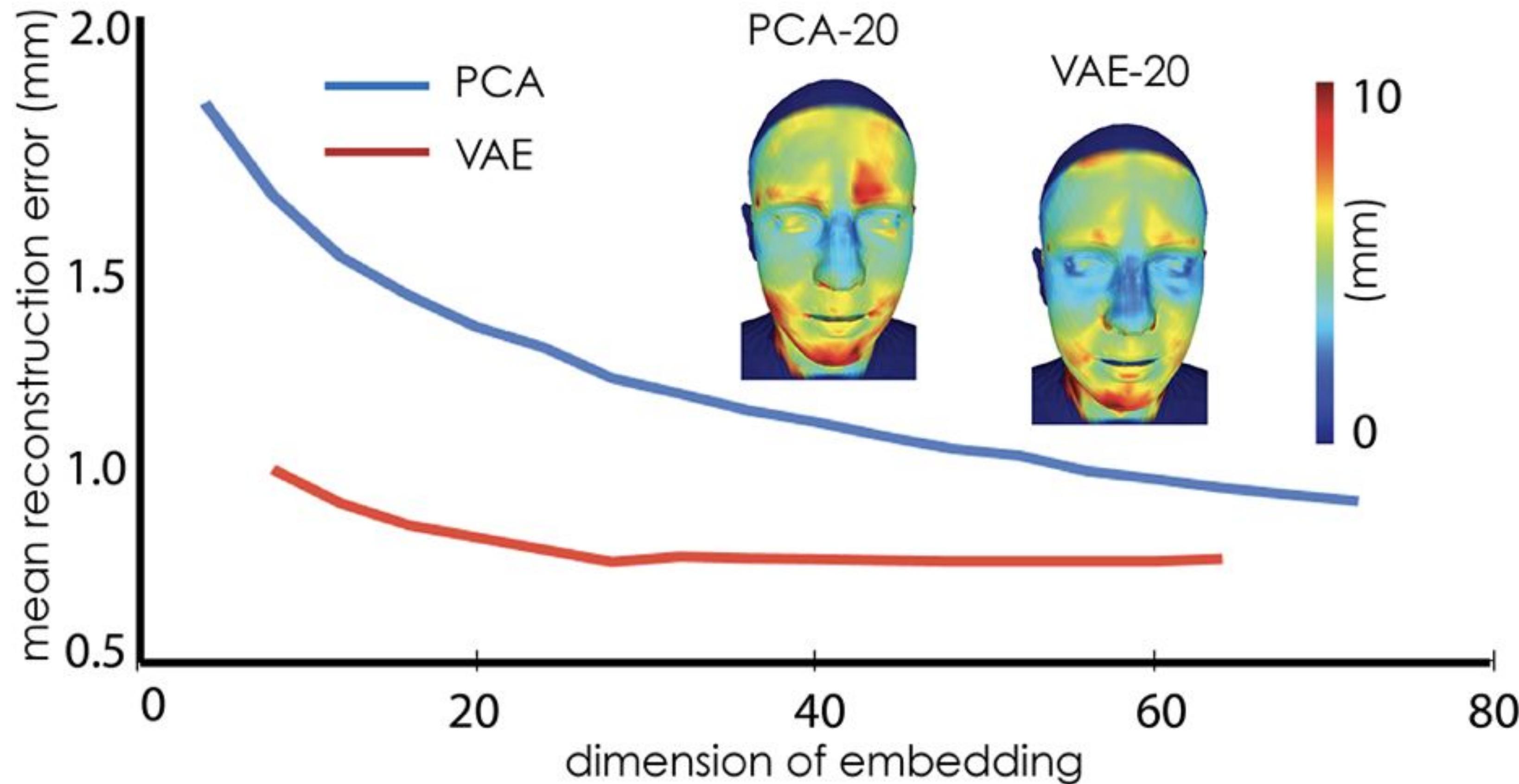


multi-expression dataset

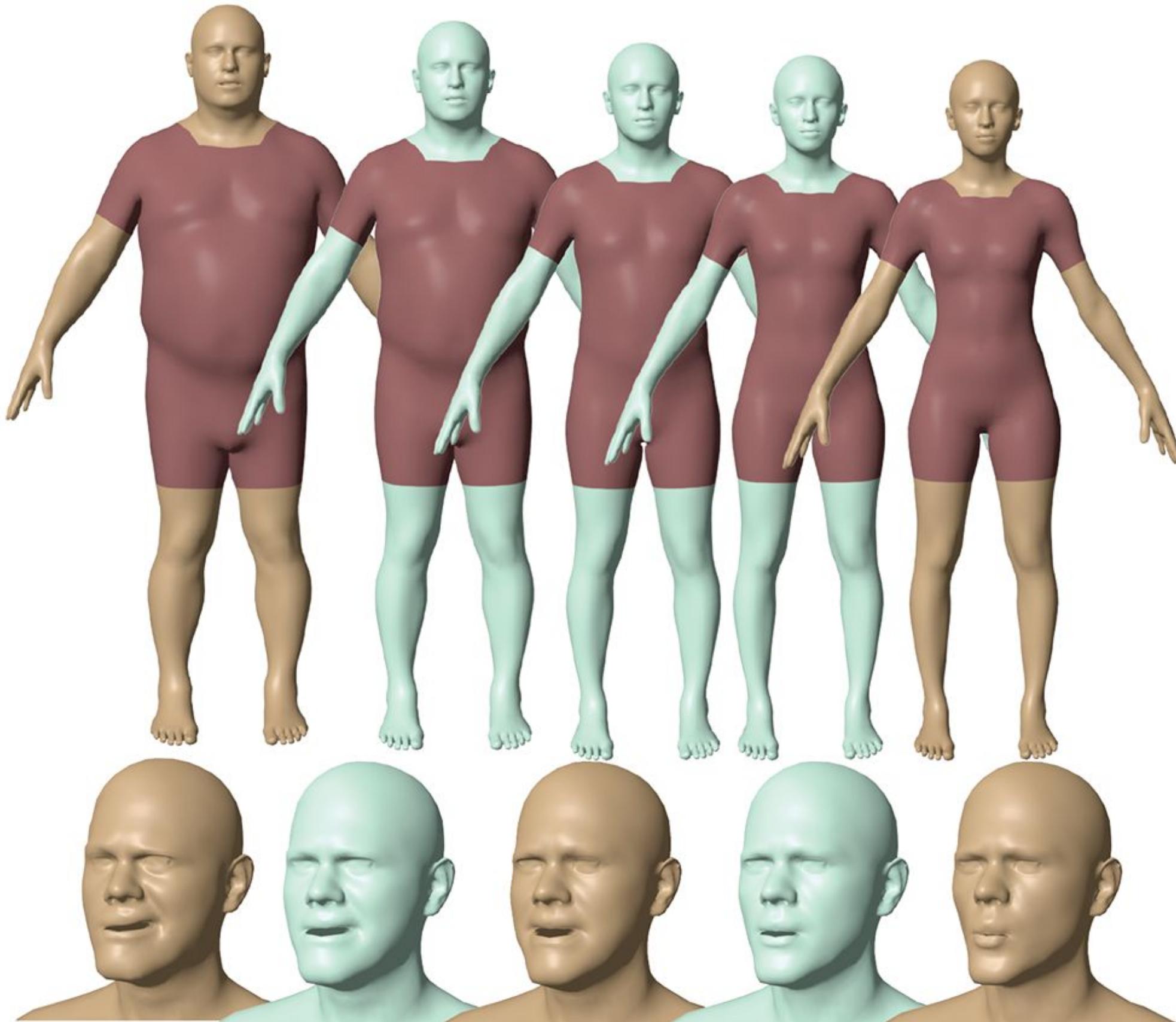


multi-hand-pose dataset

VARIATIONAL SHAPE AND EXPRESSION AUTOENCODER

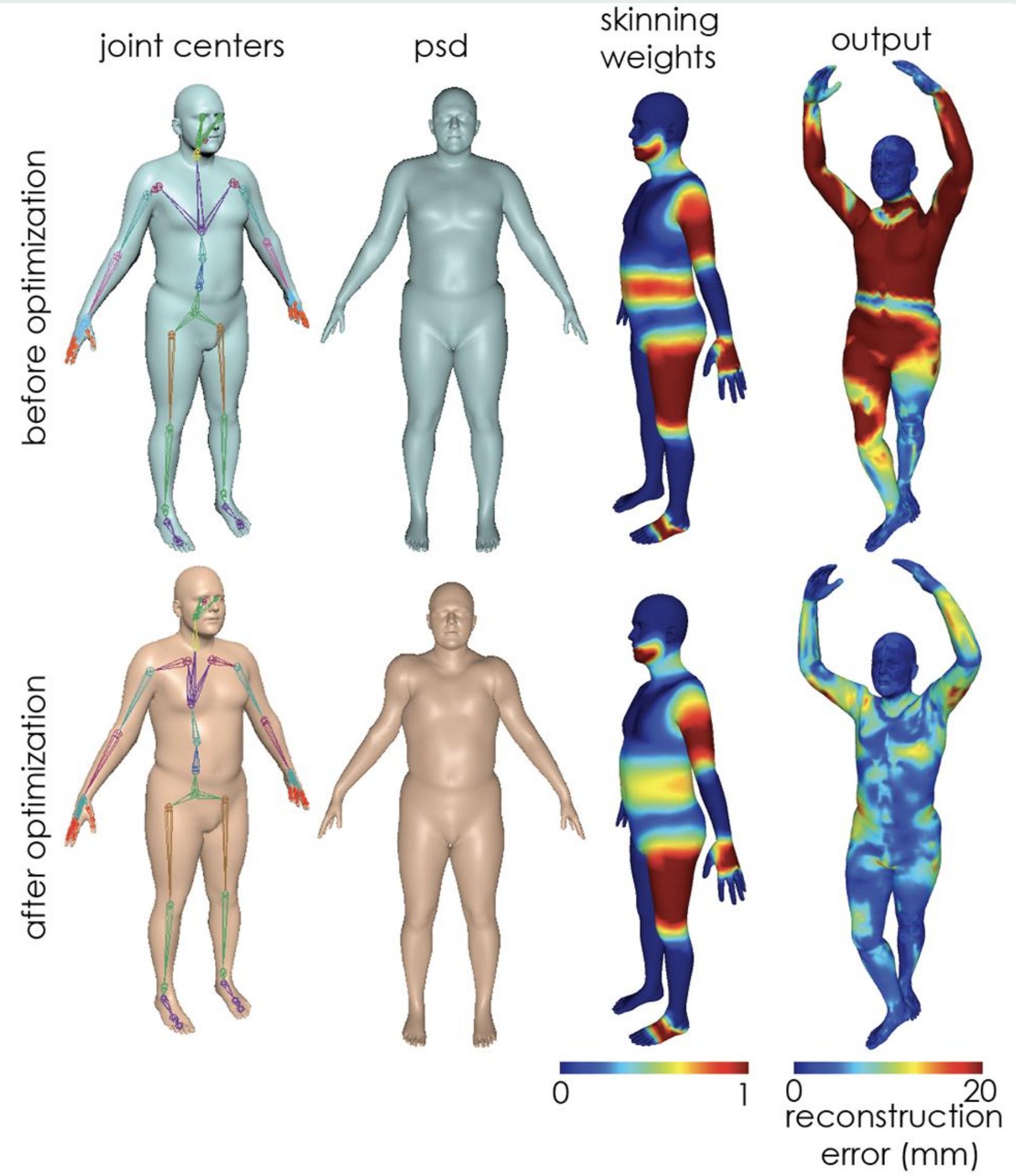
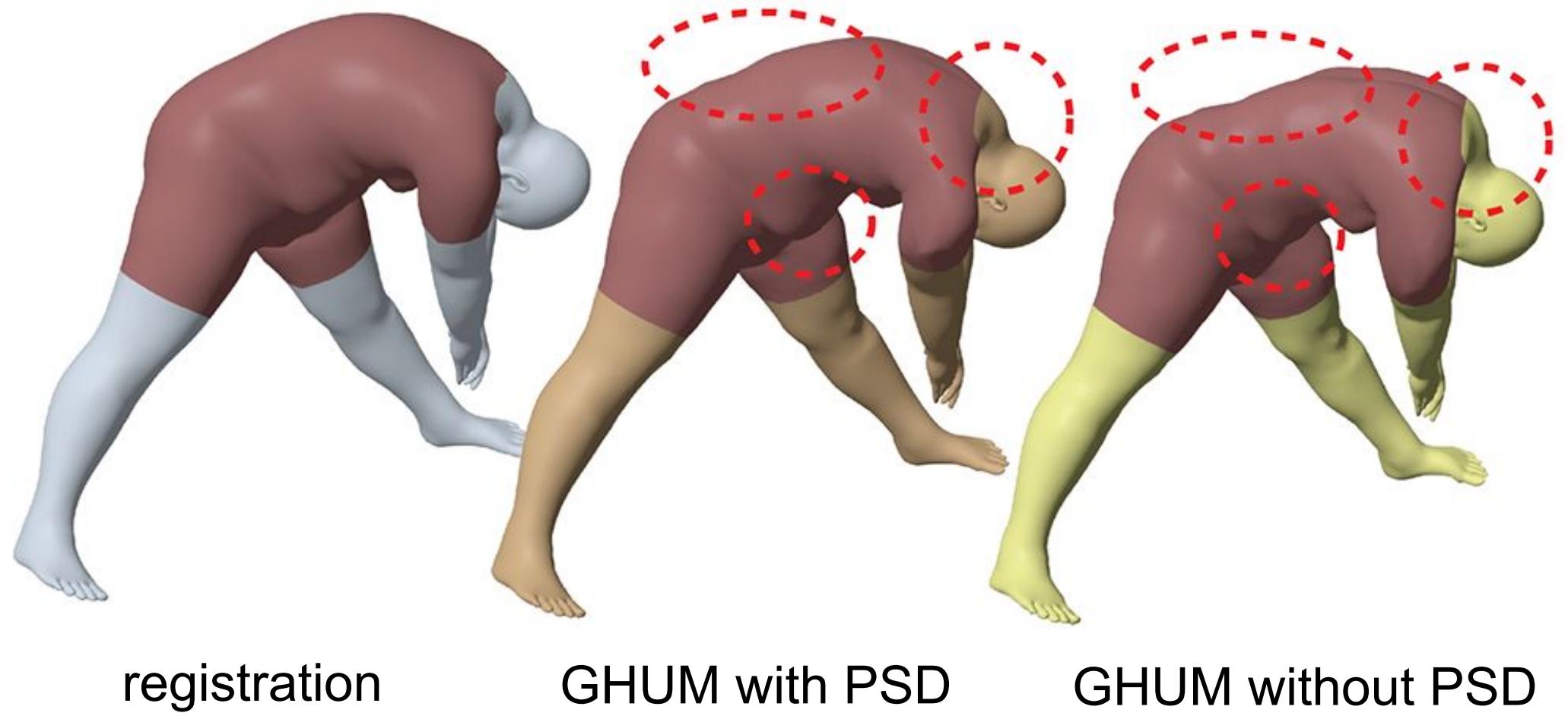


LATENT SPACE INTERPOLATION



(brown: samples; green: interpolation)

Optimized Skinning

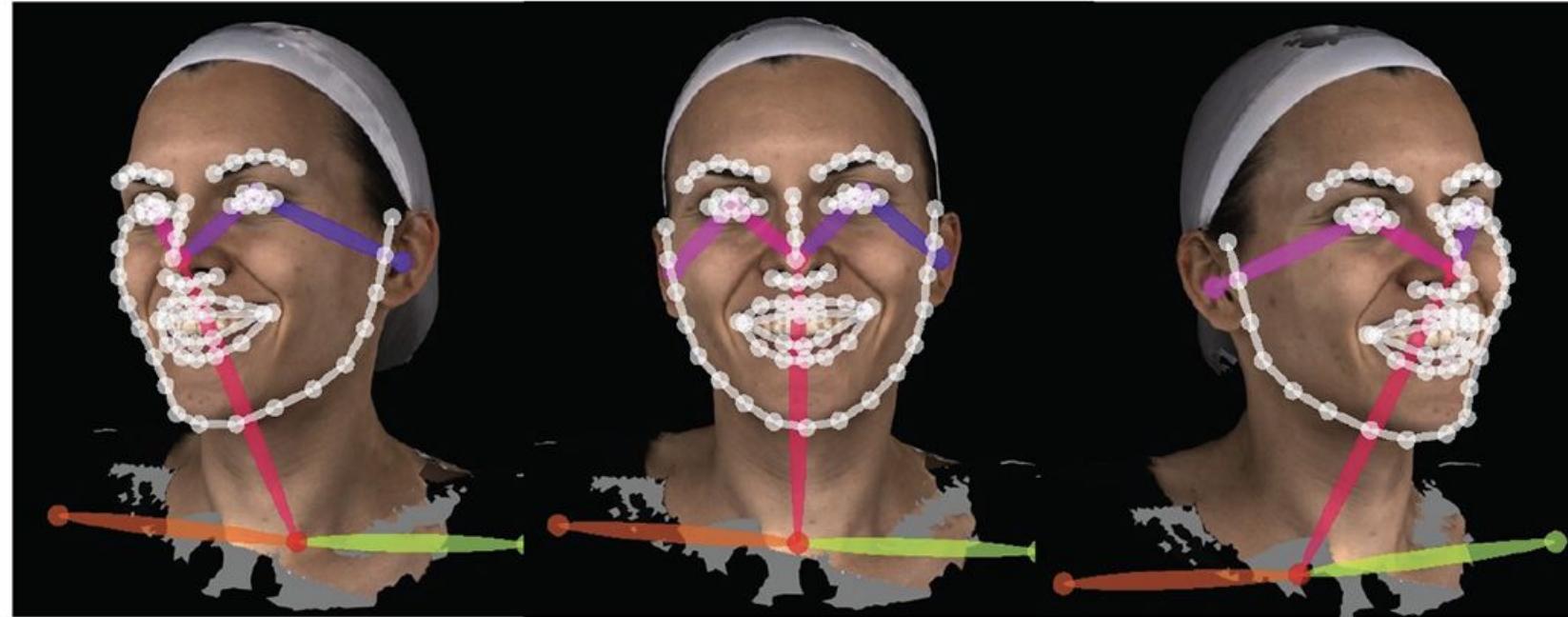


AUTOMATIC 3D LANDMARKS DETECTION

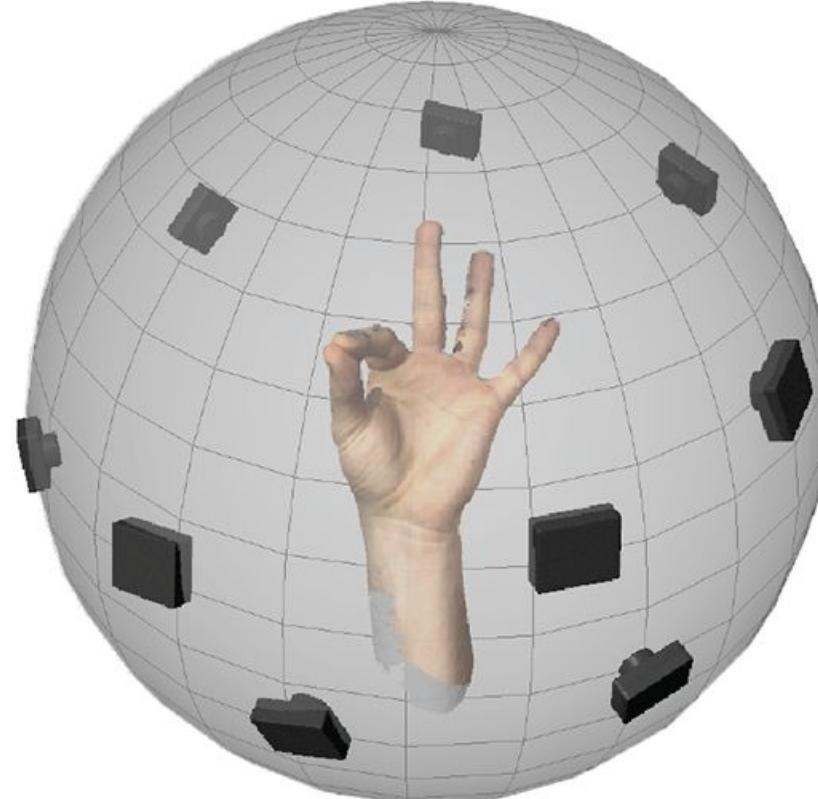
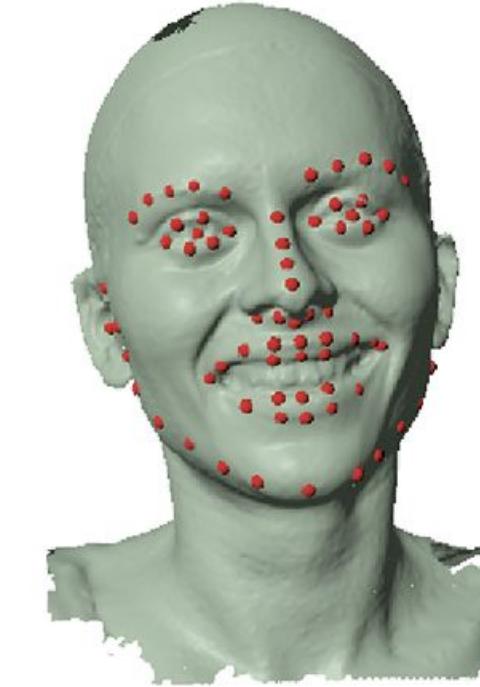
Mutiview renderings



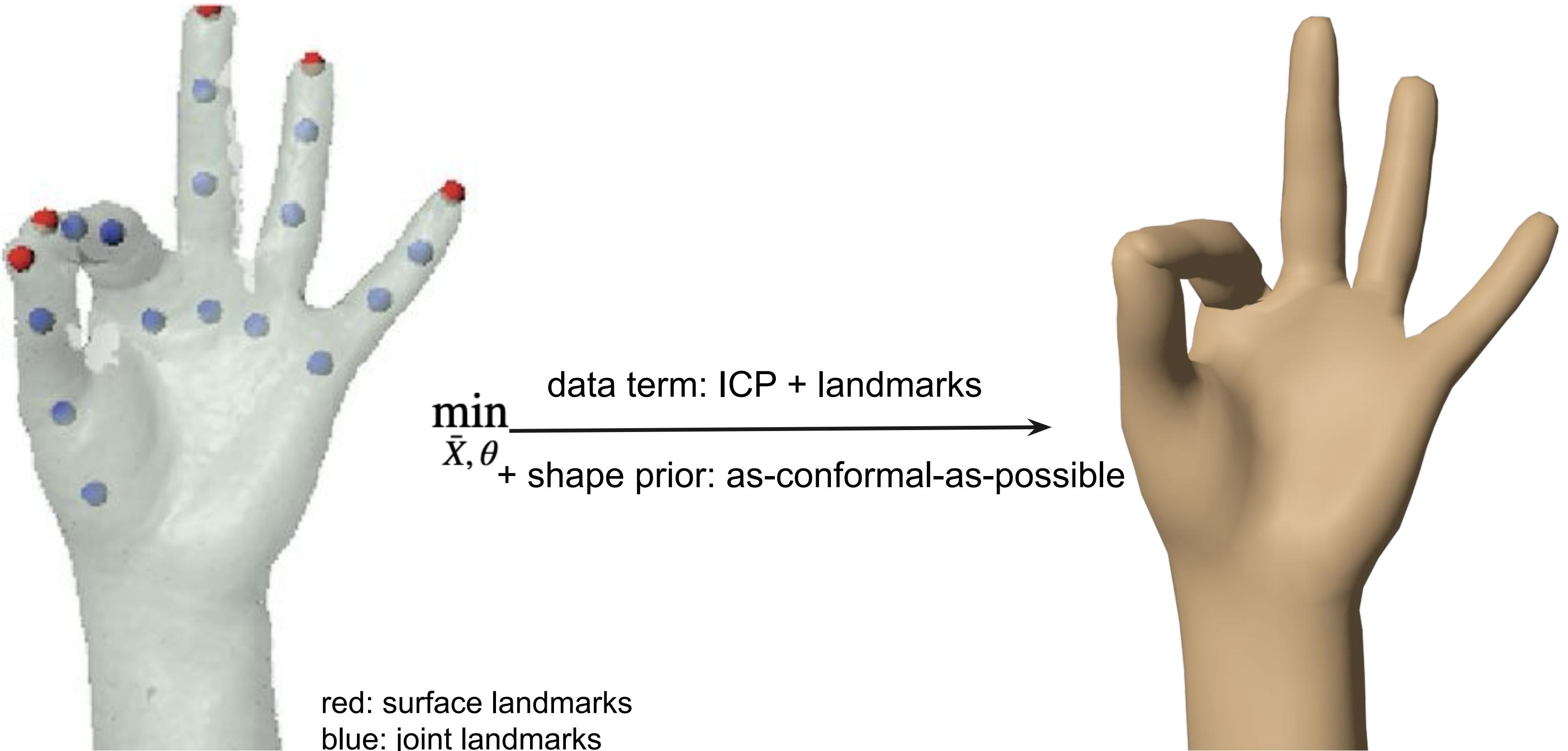
2D landmarks detection



3D landmarks triangulation



ARTICULATED AS-CONFORMAL-AS-POSSIBLE REGISTRATION



FULL-BODY SHAPE ESTIMATION

We estimate full-body shape at A pose by fusing body scan with close-up head and hand scans



close-up
head & hand scan



shape with
close-up scans



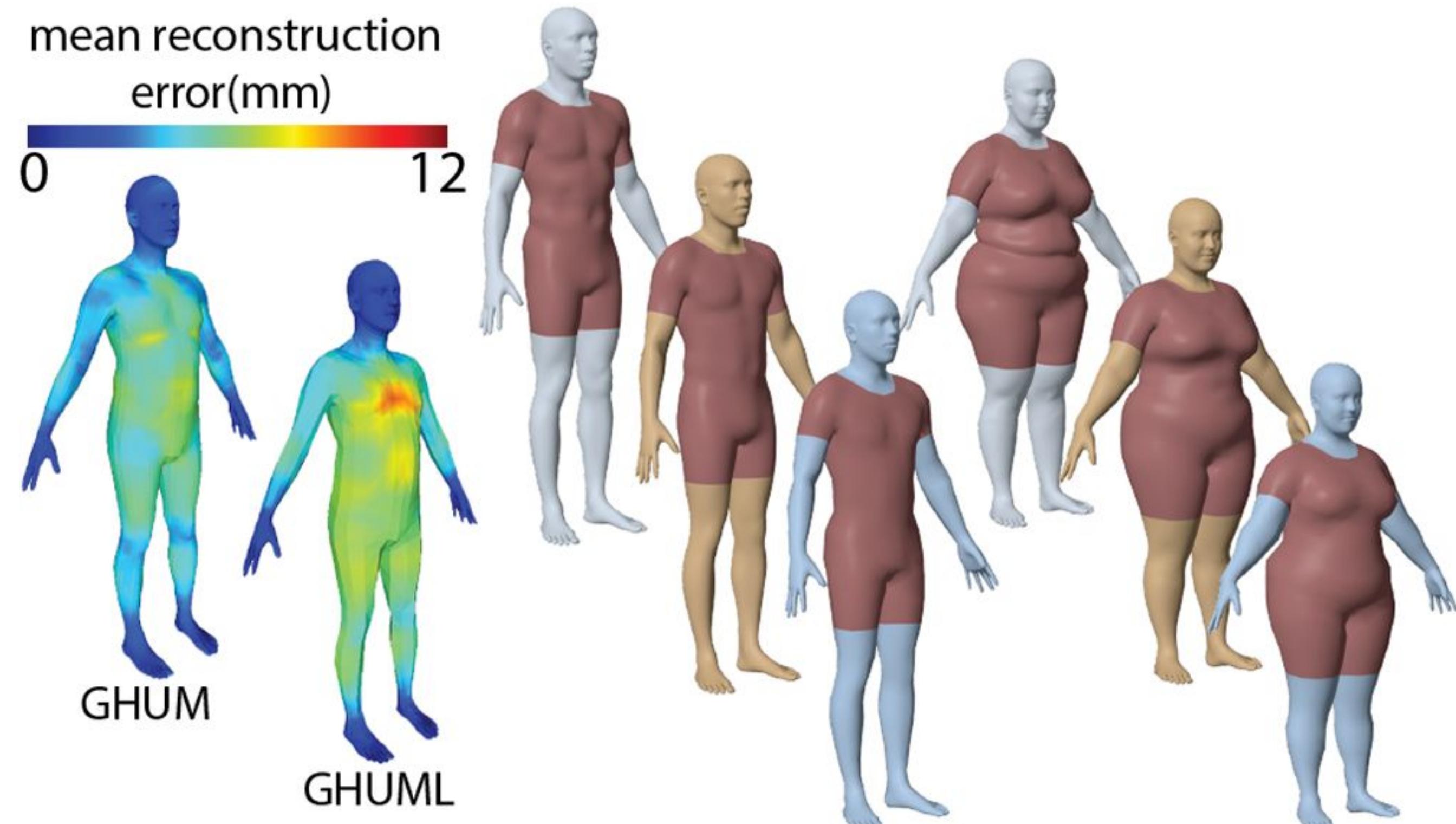
shape without
close-up scans

EVALUATION: CAESAR RECONSTRUCTION

mean vertex reconstruction
error to registrations:

GHUM 2.81 mm

GHUML 3.27 mm

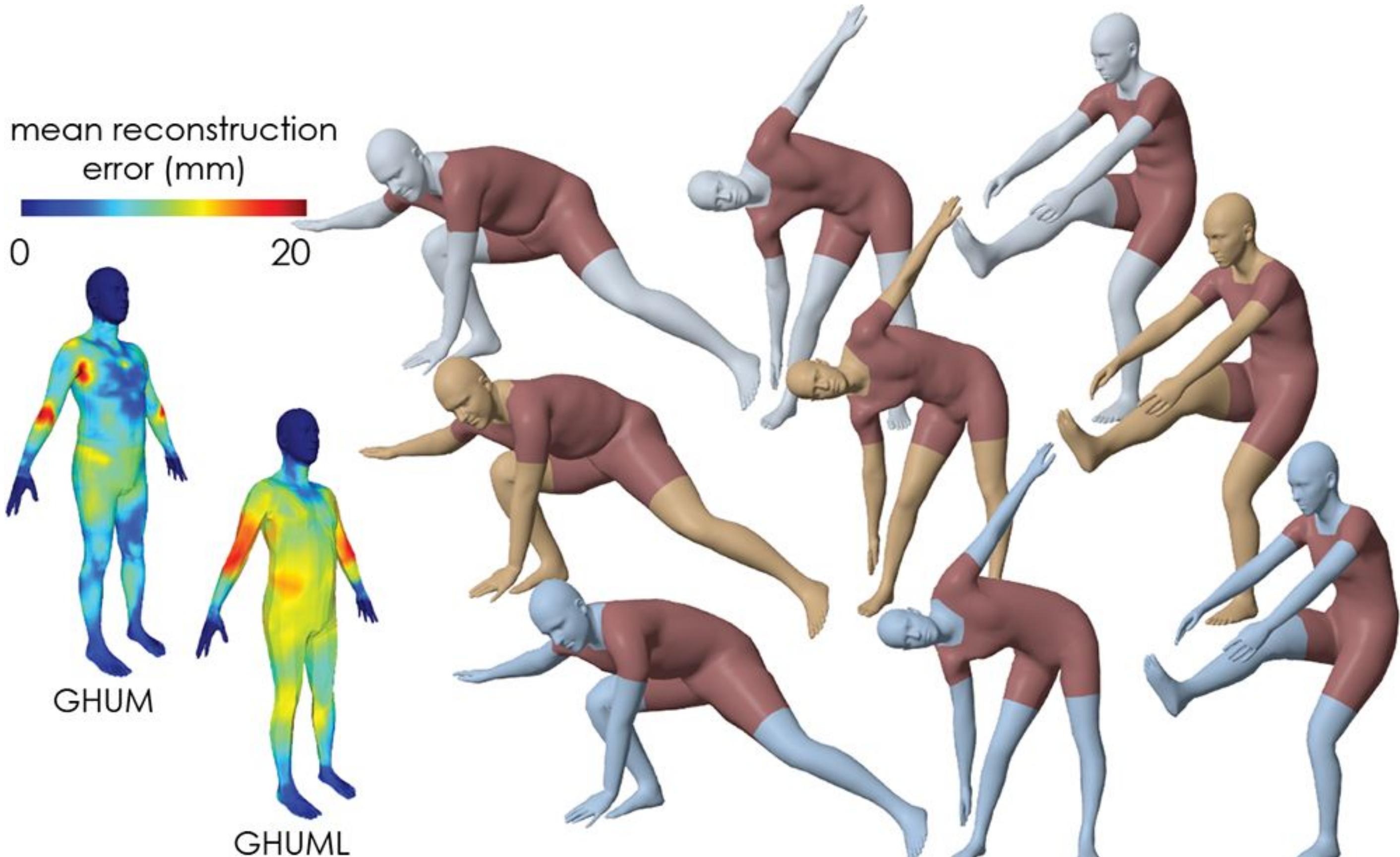


EVALUATION: GHS3D BODY RECONSTRUCTION

mean vertex reconstruction
error to registrations:

GHUM 5.21 mm

GHUML 6.32 mm



EVALUATION: GHS3D HAND RECONSTRUCTION

mean vertex reconstruction
error to registrations:

GHUM 2.22 mm

GHUML 2.81 mm



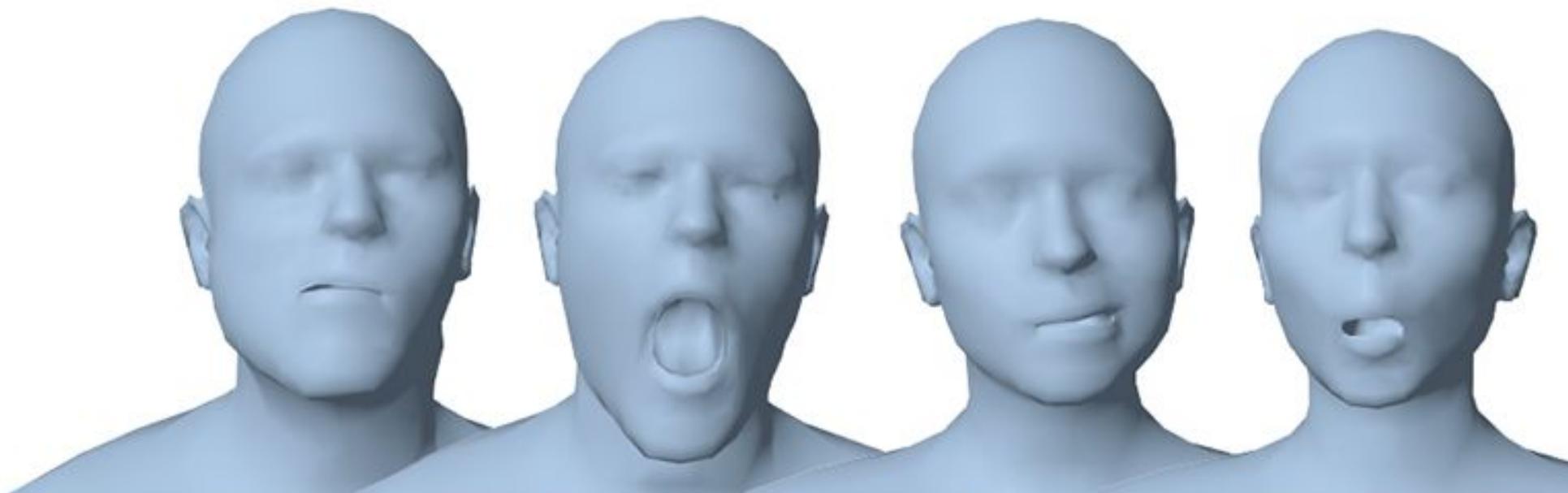
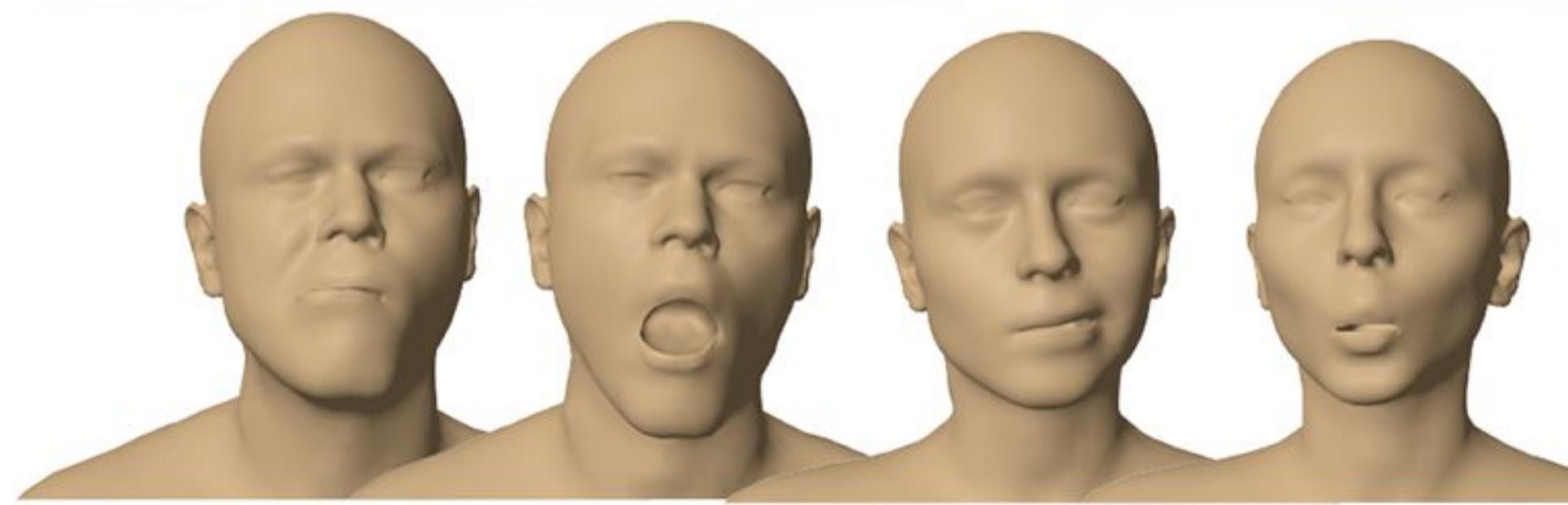
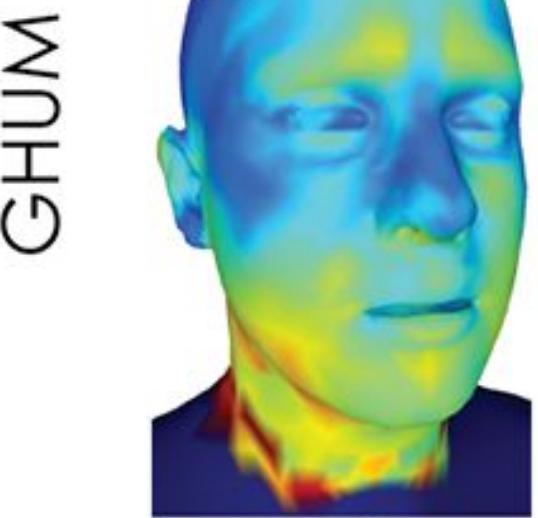
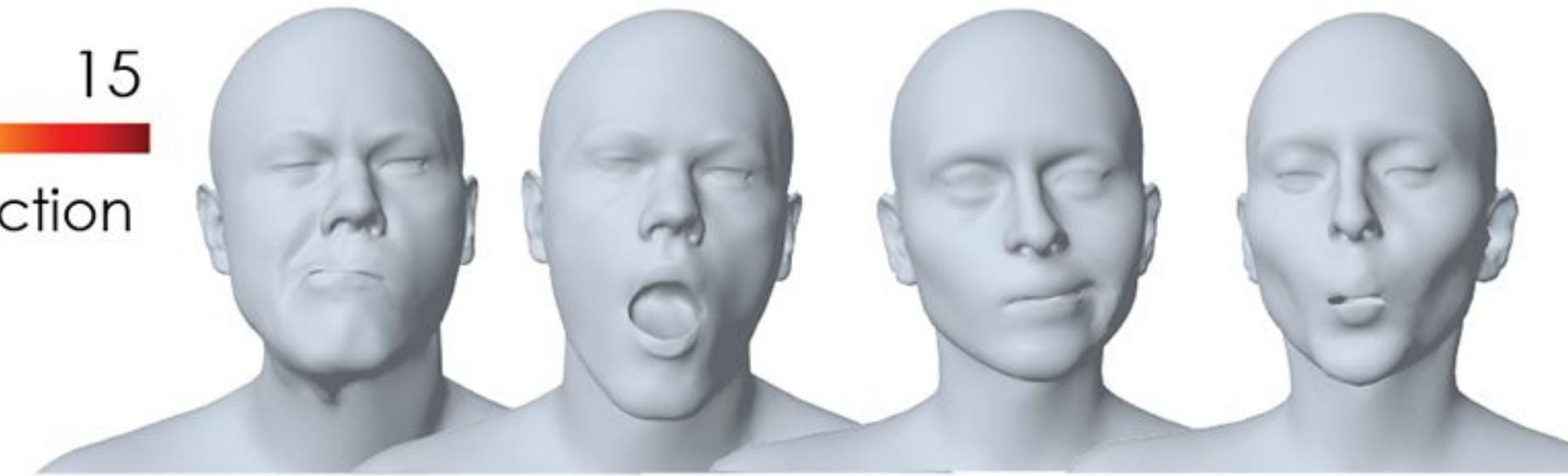
EVALUATION: GHS3D HEAD RECONSTRUCTION

**Head motion =
joints (jaw, eyelids, neck) articulation +
facial expressions**

mean vertex reconstruction
error to registrations:

GHUM 2.96 mm

GHUML 3.82 mm



GHUM VS SMPL



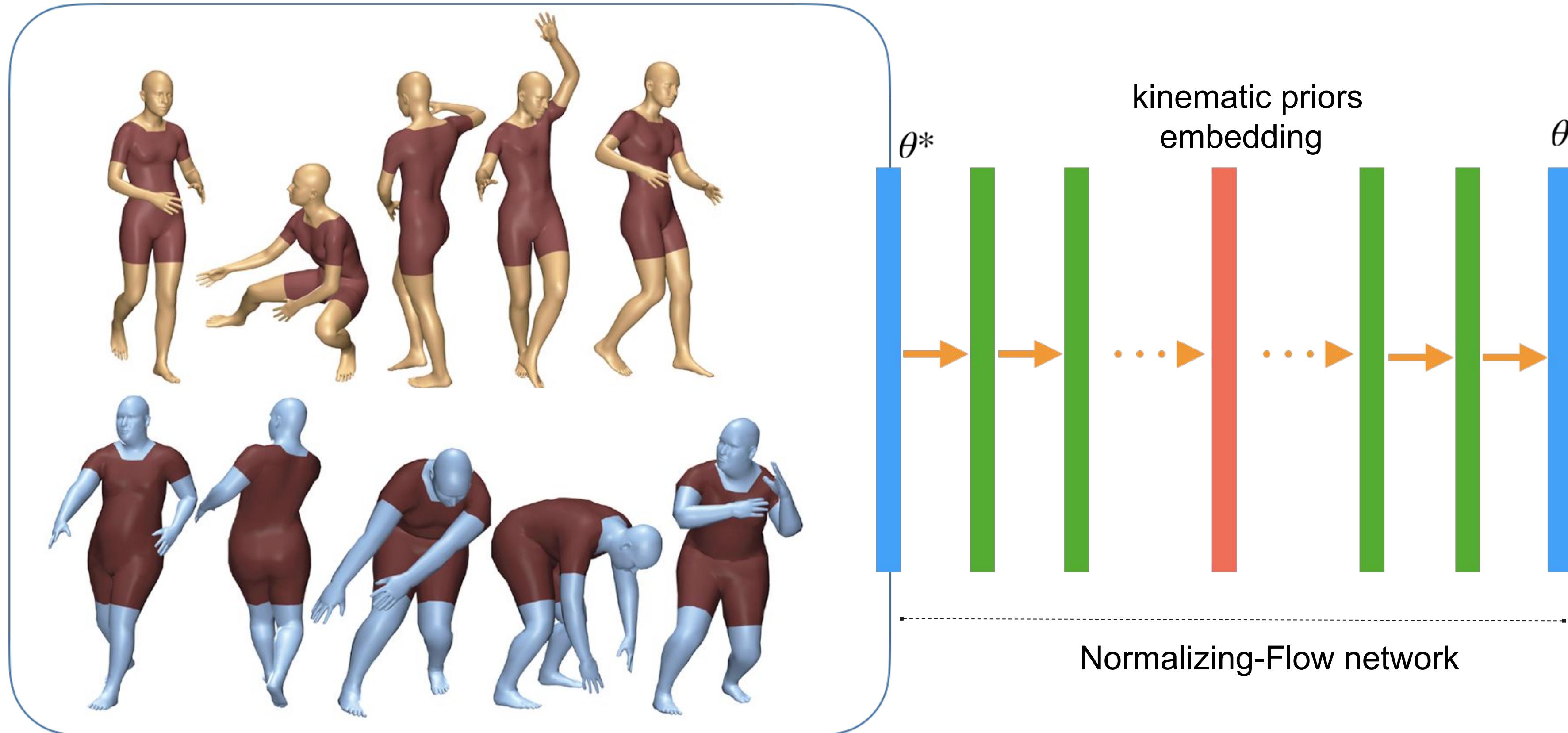
- GHUM is close (or slightly better) to SMPL in skinning visual quality
- Vertex point-to-plane error (body-only)

GHUM: 4.23 mm

SMPL: 4.96 mm

MOTION RETARGETING AND KINEMATIC PRIORS

We retarget our models to **2.8M** CMU and **2.2M** Human36M motion capture frames.

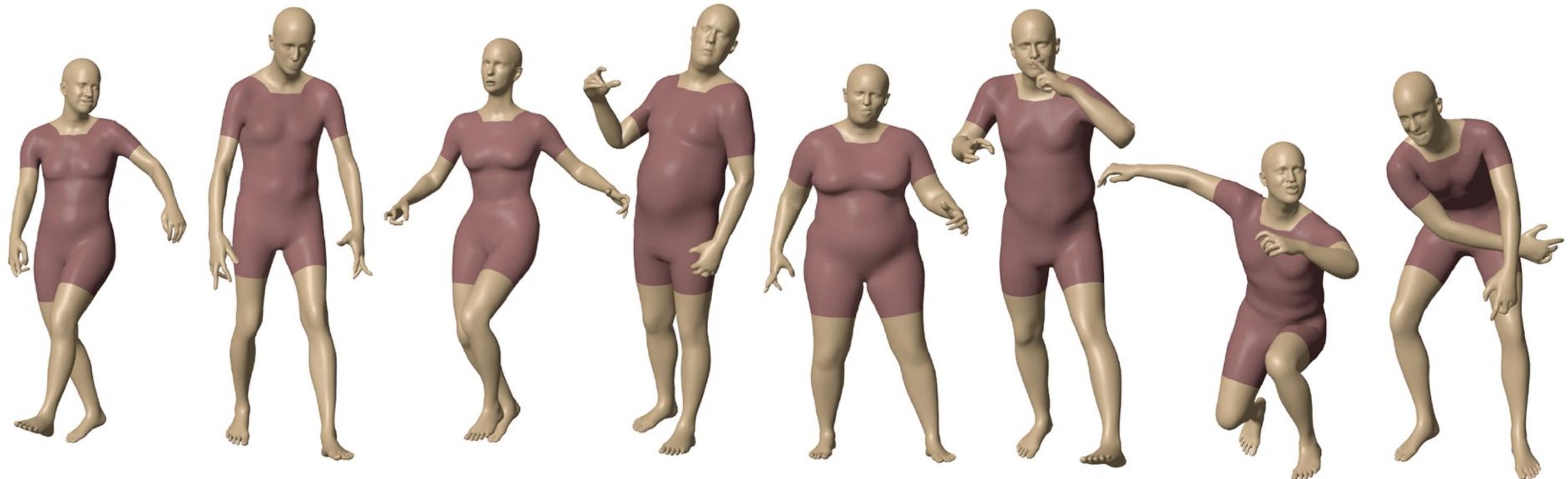


FULL-BODY RECONSTRUCTION IN MONOCULAR IMAGES



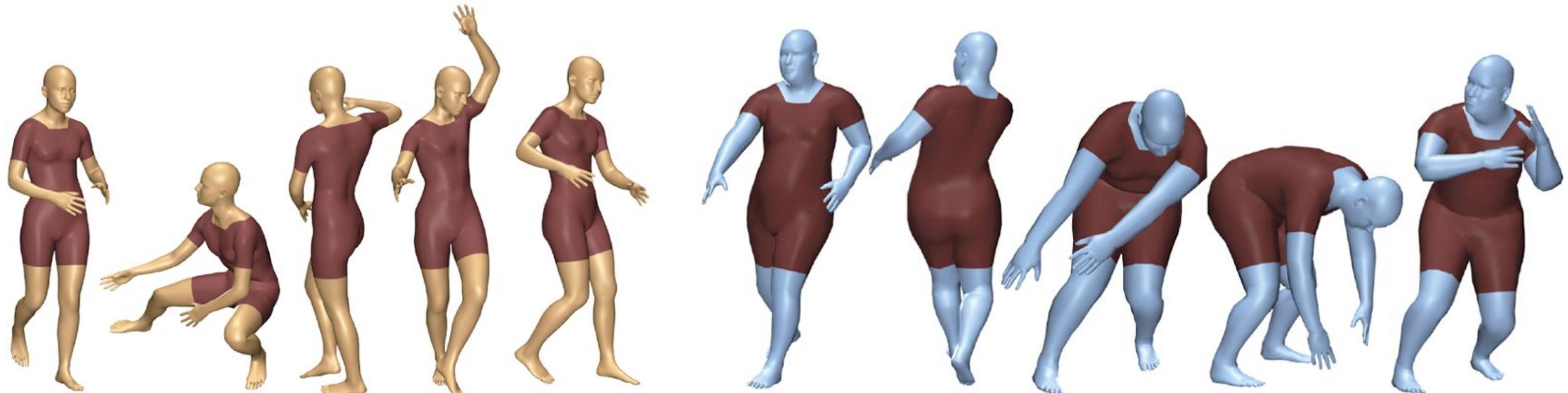
CONCLUSION

- An end-to-end generative, articulated 3D human shape learning pipeline.
- GHUM & GHUML: two high-quality full-body generative human models, available for research (<https://github.com/google-research/google-research/ghum>).



Thank You

Website: <https://github.com/google-research/google-research/ghum>



Google Research