

Understanding Parametric Human Body Models

SCA 2026 - Graduate Summer School

Motivation

Where do we come from?

Where are we now?

Why does this matter?



MSLab

Multimodal Simulation Lab

Where do we come from?

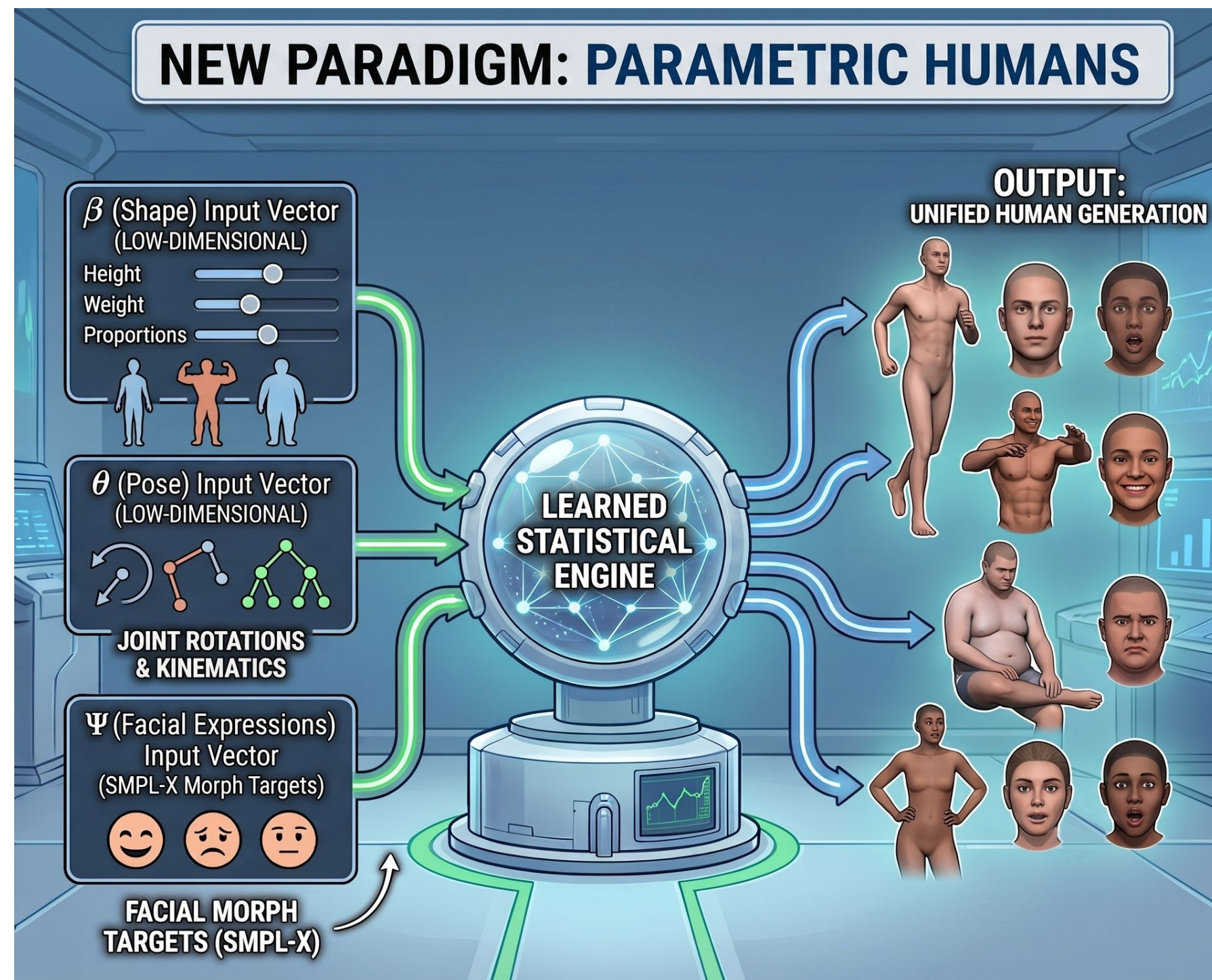


Where are we now?

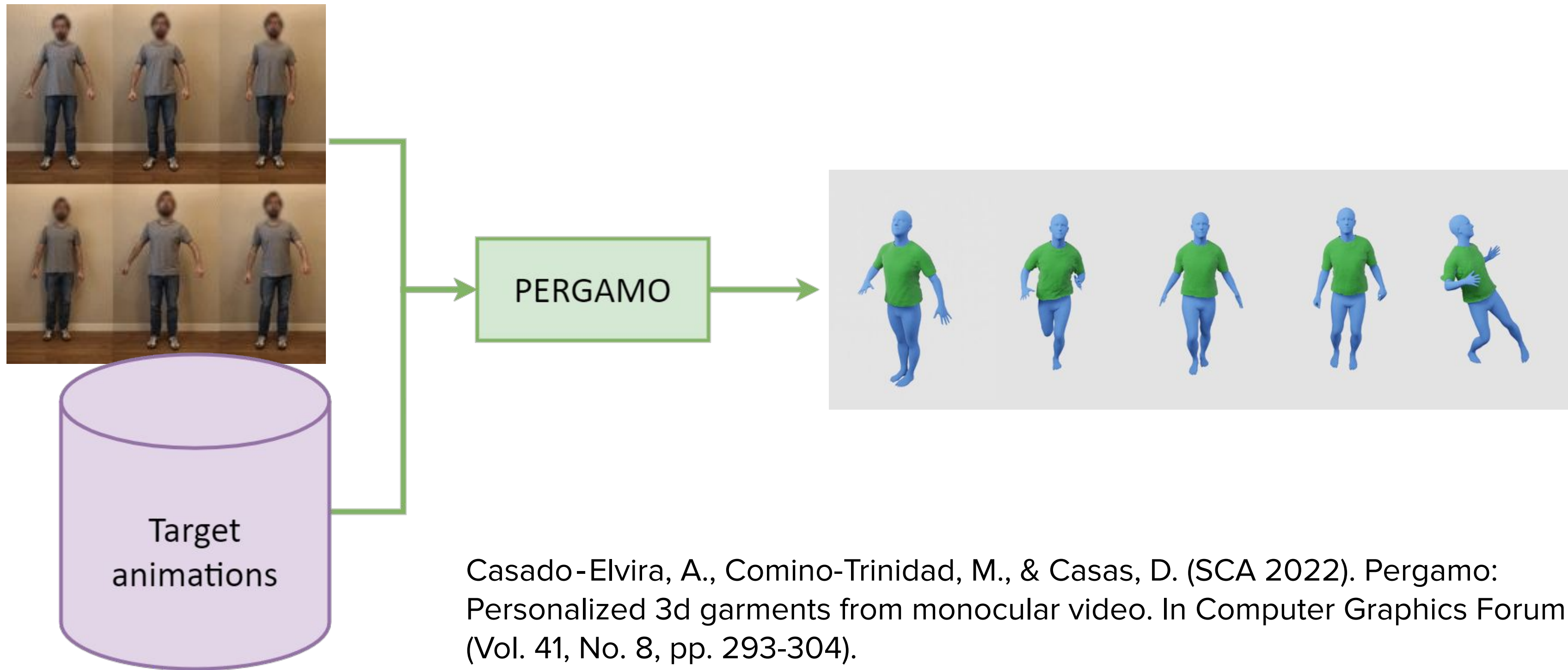


Results Obtained using: Velasquez, H. C., Yiannakidis, A., Shin, S., Becherini, G., Höschle, M., Tesch, J., ... & Black, M. J. (2026). MAMMA: Markerless Accurate Multi-person Motion Acquisition. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 7175-7186).

Where are we now?



Why does this matter?



Casado-Elvira, A., Comino-Trinidad, M., & Casas, D. (SCA 2022). Pergamo: Personalized 3d garments from monocular video. In Computer Graphics Forum (Vol. 41, No. 8, pp. 293-304).

Why does this matter?



Parametric Human Models

The SMPL Model

The SMPL Model: Step by Step

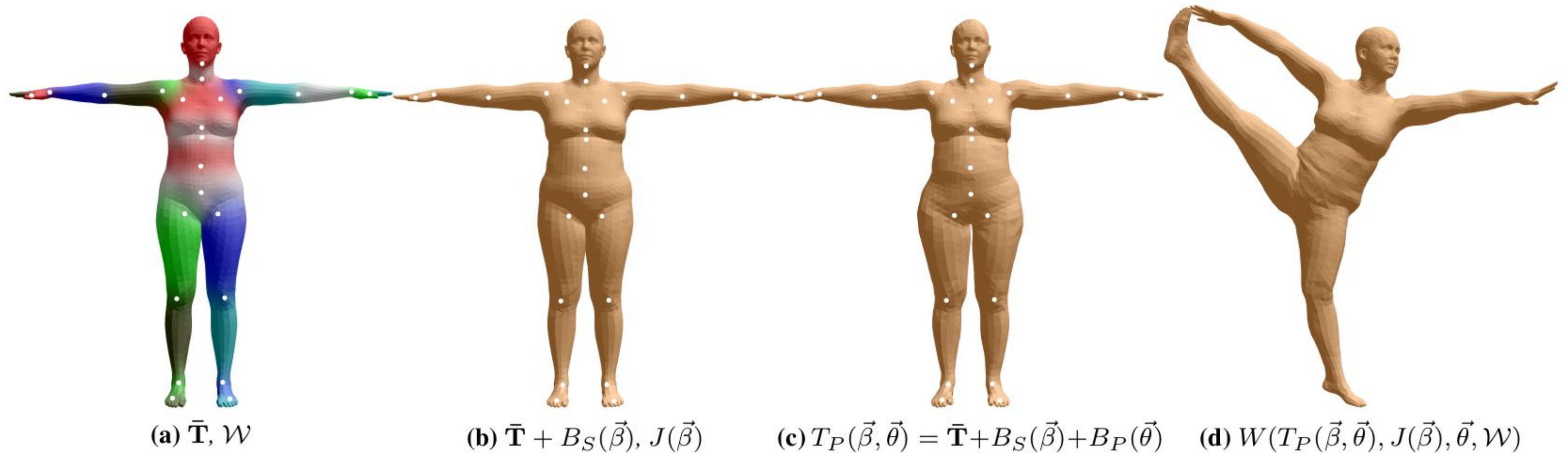
Shifting to SMPLX



MSLab

Multimodal Simulation Lab

The SMPL Model



Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J. (2015). SMPL: a skinned multi-person linear model. ACM Transactions on Graphics (TOG), 34(6), 1-16.

The SMPL Model: Step by Step

T (Template Mesh):

The zero-pose, neutral rest mesh representing the mean human body shape, consisting of 6,890 vertices for SMPL and expanded to 10,475 vertices for SMPL-X.



(a) $\bar{\mathbf{T}}, \mathcal{W}$

Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J. (2015). SMPL: a skinned multi-person linear model. ACM Transactions on Graphics (TOG), 34(6), 1-16.

The SMPL Model: Step by Step

T (Template Mesh):

The zero-pose, neutral rest mesh representing the mean human body shape, consisting of 6,890 vertices for SMPL and expanded to 10,475 vertices for SMPL-X.

```
1 import bpy
2 import numpy as np
3
4 # Path to your extracted SMPL-X model file (e.g., SMPLX_NEUTRAL.npz)
5 model_path = "/home/marcct/Documents/SMPL/SMPLX/SMPLX_NEUTRAL_2020.npz"
6 data = np.load(model_path, allow_pickle=True)
7
8 # Variable names matching mathematical SMPL notation
9 T_bar = data['v_template'] # \bar{T} : Base rest template vertices
10 F = data['f'] # F : Face topology indices
11 W = data['weights'] # \mathcal{W} : Linear blend skinning weights matrix
12 kintree = data['kintree_table'][0] # Kinematic tree parent indices for hierarchy
```



(a) $\bar{T}$, $\mathcal{W}$

Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J. (2015). SMPL: a skinned multi-person linear model. ACM Transactions on Graphics (TOG), 34(6), 1-16.

The SMPL Model: Step by Step

W (Skinning Blend Weights):

A fixed matrix computed offline by minimizing the error between a deformed template and thousands of multi-pose 3D scans (from datasets like MPI D-FAUST) to find the optimal surface influence for each joint.



(a) $\bar{\mathbf{T}}, \mathcal{W}$

Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J. (2015). SMPL: a skinned multi-person linear model. ACM Transactions on Graphics (TOG), 34(6), 1-16.

The SMPL Model: Step by Step

W (Skinning Blend Weights):

A fixed matrix computed offline by minimizing the error between a deformed template and thousands of multi-pose 3D scans (from datasets like MPI D-FAUST) to find the optimal surface influence for each joint.

```
1 import bpy
2 import numpy as np
3
4 # Path to your extracted SMPL-X model file (e.g., SMPLX_NEUTRAL.npz)
5 model_path = "/home/marcct/Documents/SMPL/SMPLX/SMPLX_NEUTRAL_2020.npz"
6 data = np.load(model_path, allow_pickle=True)
7
8 # Variable names matching mathematical SMPL notation
9 T_bar = data['v_template'] # \bar{T} : Base rest template vertices
10 F = data['f'] # F : Face topology indices
11 W = data['weights'] # \mathcal{W} : Linear blend skinning weights matrix
12 kintree = data['kintree_table'][0] # Kinematic tree parent indices for hierarchy
```



(a) $\bar{T}$, $\mathcal{W}$

Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J. (2015). SMPL: a skinned multi-person linear model. ACM Transactions on Graphics (TOG), 34(6), 1-16.

The SMPL Model: Step by Step

Bs (Shape Blendshapes):

A fixed displacement matrix calculated via Principal Component Analysis (PCA) on thousands of aligned 3D body scans from the CAESAR dataset to capture major structural identity variations like height and weight.

10 Betas (The Research Default)

300 Betas (The Full Spectrum)



$$(b) \bar{T} + B_S(\vec{\beta}), J(\vec{\beta})$$

Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J. (2015). SMPL: a skinned multi-person linear model. ACM Transactions on Graphics (TOG), 34(6), 1-16.

The SMPL Model: Step by Step

Bs (Shape Blendshapes):

A fixed displacement matrix calculated via Principal Component Analysis (PCA) on thousands of aligned 3D body scans from the CAESAR dataset to capture major structural identity variations like height and weight.

10 Betas (The Research Default)

300 Betas (The Full Spectrum)

```
8 # Variable names matching mathematical SMPL notation
9 T_bar = data['v_template']          # \bar{T} : Base rest template vertices
10 W = data['weights']                 # \mathcal{W} : Linear blend skinning weights matrix
11 kintree = data['kintree_table'][0]  # Kinematic tree parent indices for hierarchy
12 F = data['f']                       # F : Face topology indices
13
14 # Change these values to test different body shapes/identities
15 Betas = np.array([1.5, -0.8, 2.0, 0.5, -1.2, 0.3, -0.5, 1.1, -0.2, 0.7])
16
17 # Extract the shape blendshapes matrix B_S
18 B_s = data['shapedirs'][:, :, :10]
19
```



$$(b) \bar{T} + B_S(\vec{\beta}), J(\vec{\beta})$$

Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J. (2015). SMPL: a skinned multi-person linear model. ACM Transactions on Graphics (TOG), 34(6), 1-16.

The SMPL Model: Step by Step

$J(\beta)$ (Joints of Beta):

Represents the rest-pose world coordinates of the body's skeletal joints, mathematically calculated by multiplying a learned joint regressor matrix against the shape-deformed rest template mesh.



(b) $\bar{T} + B_S(\vec{\beta}), J(\vec{\beta})$

Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J. (2015). SMPL: a skinned multi-person linear model. ACM Transactions on Graphics (TOG), 34(6), 1-16.

The SMPL Model: Step by Step

$J(\beta)$ (Joints of Beta):

Represents the rest-pose world coordinates of the body's skeletal joints, mathematically calculated by multiplying a learned joint regressor matrix against the shape-deformed rest template mesh.

```
17 # Extract the shape blendshapes matrix B_S
18 B_s = data['shapedirs'][:, :, :10]
19
20 # Decode \beta into Template mesh displacements via dot product
21 v_displacements = np.dot(B_s, Betas)
22 T_shaped = T_bar + v_displacements
23
24 # Compute joint locations J from the base template using the regressor matrix \mathcal{J}
25 J_regressor = data['J_regressor']
26 if hasattr(J_regressor, 'toarray'):
27     J_regressor = J_regressor.toarray()
28 J = np.dot(J_regressor, T_shaped) # J(\beta) in rest pose where shape coefficients \beta
```



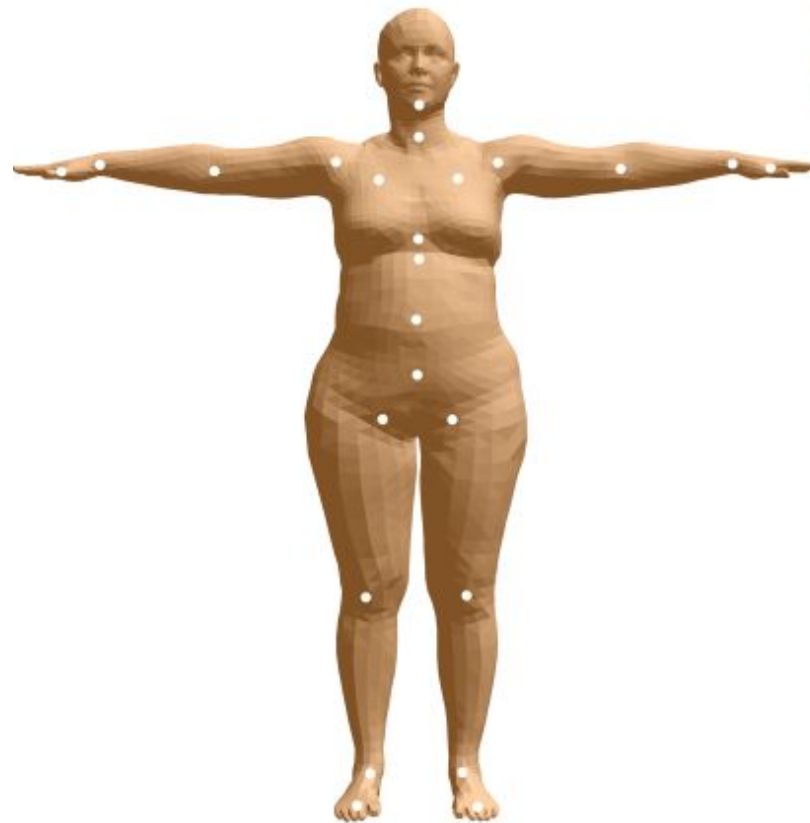
(b) $\bar{T} + B_S(\vec{\beta}), J(\vec{\beta})$

Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J. (2015). SMPL: a skinned multi-person linear model. ACM Transactions on Graphics (TOG), 34(6), 1-16.

The SMPL Model: Step by Step

Bp (Pose Blendshapes):

An optimized matrix of 3D vertex displacements multiplied linearly by the 207 elements of the joints' relative 3 x 3 rotation matrices (9 x 23 joints) to counteract linear skinning artifacts and preserve muscle volume during bending.



$$(c) T_P(\vec{\beta}, \vec{\theta}) = \bar{\mathbf{T}} + B_S(\vec{\beta}) + B_P(\vec{\theta})$$

Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J. (2015). SMPL: a skinned multi-person linear model. ACM Transactions on Graphics (TOG), 34(6), 1-16.

The SMPL Model: Step by Step

Bp (Pose Blendshapes):

An optimized matrix of 3D vertex displacements multiplied linearly by the 207 elements of the joints' relative 3 x 3 rotation matrices (9 x 23 joints) to counteract linear skinning artifacts and preserve muscle volume during bending.

```
37 # Extract the pose blendshapes matrix B_P to calculate volume corrections
38 B_p = data['posedirs']
39
40 # Dynamically determine the number of pose-driven joints from the tensor shape
41 NumJoints = B_p.shape[2] // 9
42
43 # Initialize the pose vector array for all joints including the root
44 Thetas = np.zeros((NumJoints + 1, 3))
45
46 # Apply a rotation to the right hip which is joint index 2 in the standard hierarchy
47 Thetas[0] = np.array([0, -np.pi/2, 0])
48 Thetas[1] = np.array([-np.pi/2, 0.0, 0.0])
```



$$(c) T_P(\vec{\beta}, \vec{\theta}) = \bar{\mathbf{T}} + B_S(\vec{\beta}) + B_P(\vec{\theta})$$

Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J. (2015). SMPL: a skinned multi-person linear model. ACM Transactions on Graphics (TOG), 34(6), 1-16.

Shifting to SMPLX

1. Main Body Core (Indices 0 to 21)

These 22 joints are almost identical to the original SMPL model. They control the major skeletal posture.

2. Facial Expressive Joints (Indices 22 to 24)

SMPL-X introduces three joints directly to the head structure to drive facial articulation alongside the expression blendshapes:

3. Left Hand & Fingers (Indices 25 to 39)

The hands are modeled using 15 joints, tracking 3 deformation pivot points for each of the 5 fingers (Thumb, Index, Middle, Ring, Pinky).

4. Right Hand & Fingers (Indices 40 to 54)

This region perfectly mirrors the left hand with another 15 joints:

Pavlakos, G., Choutas, V., Ghorbani, N., Bolkart, T., Osman, A. A., Tzionas, D., & Black, M. J. (2019). Expressive body capture: 3d hands, face, and body from a single image. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 10975-10985).

Shifting to SMPLX

Basic SMPL

```
output = model(  
    betas=torch.zeros(batch_size, 10),  
    global_orient=torch.zeros(batch_size, 3),  
    body_pose=torch.zeros(batch_size, 63),  
    transl=torch.zeros(batch_size, 3)  
)
```

(There could be up to 300 betas and 100 expression parameters)

SMPLX

```
output = model(  
    betas=torch.zeros(batch_size, 10),  
    global_orient=torch.zeros(batch_size, 3),  
    body_pose=torch.zeros(batch_size, 63),  
    left_hand_pose=torch.zeros(batch_size, 45),  
    right_hand_pose=torch.zeros(batch_size, 45),  
    jaw_pose=torch.zeros(batch_size, 3),  
    lefteye_pose=torch.zeros(batch_size, 3),  
    righteye_pose=torch.zeros(batch_size, 3),  
    expression=torch.zeros(batch_size, 10),  
    transl=torch.zeros(batch_size, 3)  
)
```

Pavlakos, G., Choutas, V., Ghorbani, N., Bolkart, T., Osman, A. A., Tzionas, D., & Black, M. J. (2019). Expressive body capture: 3d hands, face, and body from a single image. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 10975-10985).

Shifting to SMPLX

$B_E(\psi)$ (Expression Blendshapes):

An optimized matrix of 3D vertex displacements multiplied linearly by the 100 elements of the ψ expression parameters to produce rich facial expressions.



Pavlakos, G., Choutas, V., Ghorbani, N., Bolkart, T., Osman, A. A., Tzionas, D., & Black, M. J. (2019). Expressive body capture: 3d hands, face, and body from a single image. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 10975-10985).

Shifting to SMPLX

$B_E(\psi)$ (Expression Blendshapes):

An optimized matrix of 3D vertex displacements multiplied linearly by the 100 elements of the ψ expression parameters to produce rich facial expressions.

```
37 # Define an array for 10 facial expression parameters (Psi)
38 Psi = np.array([8, -0.5, 1.2, 0.0, -0.3, 0.9, 0.1, -0.4, 0.5, -0.2])
39
40 # Extract the expression blendshapes matrix B_E from dimensions 300 to 310
41 B_e = data['shapedirs'][:, :, 300:310]
42
43 # Decode \psi into facial expression displacements
44 v_expr_displacements = np.dot(B_e, Psi)
45
46 # Combine base template, body shape, and facial expression displacements
47 T_shaped = T_shaped + v_expr_displacements
```

Pavlakos, G., Choutas, V., Ghorbani, N., Bolkart, T., Osman, A. A., Tzionas, D., & Black, M. J. (2019). Expressive body capture: 3d hands, face, and body from a single image. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 10975-10985).

Other Applications

Dimensionality Reduction

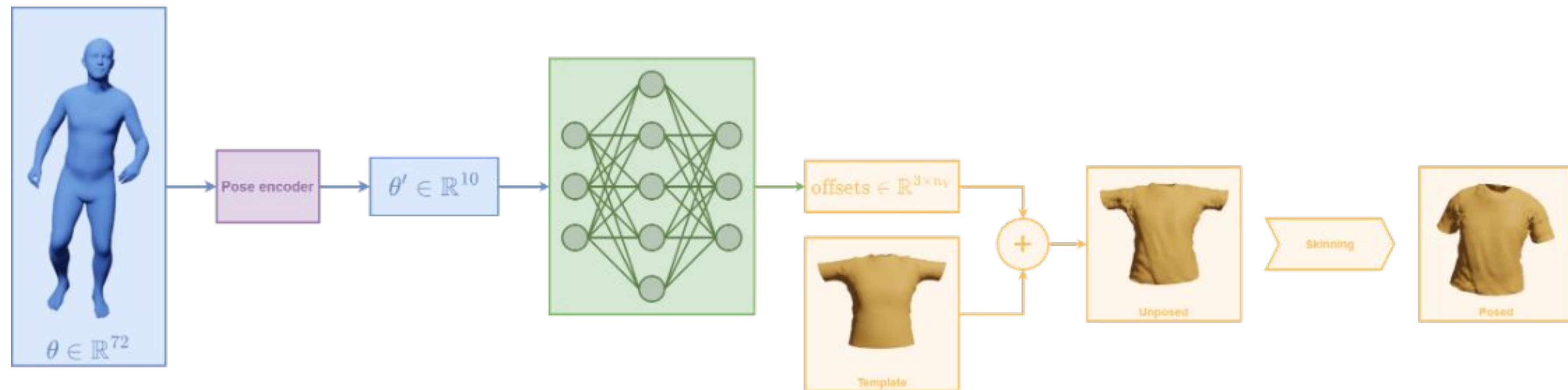
Texturing



MSLab

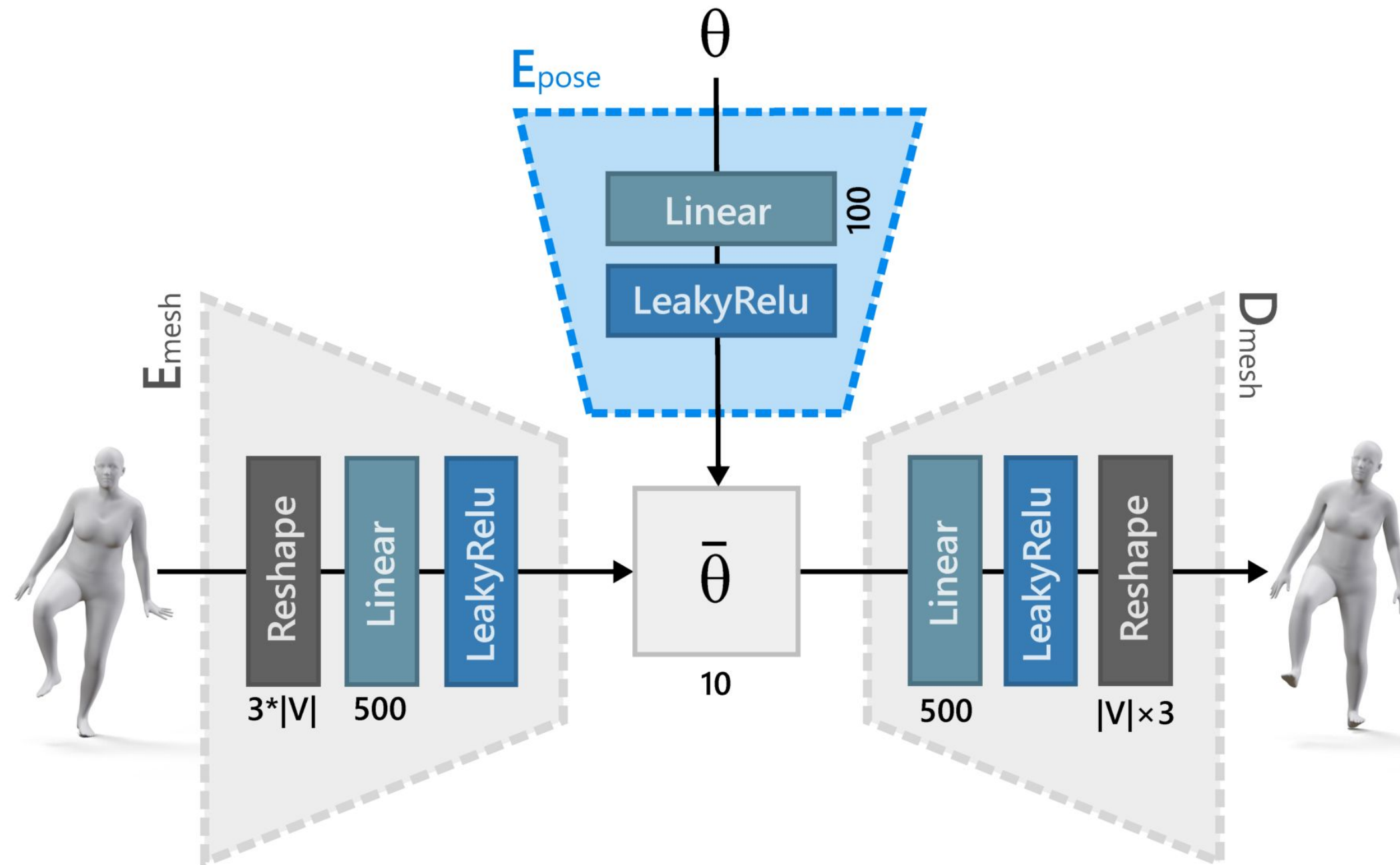
Multimodal Simulation Lab

Dimensionality Reduction



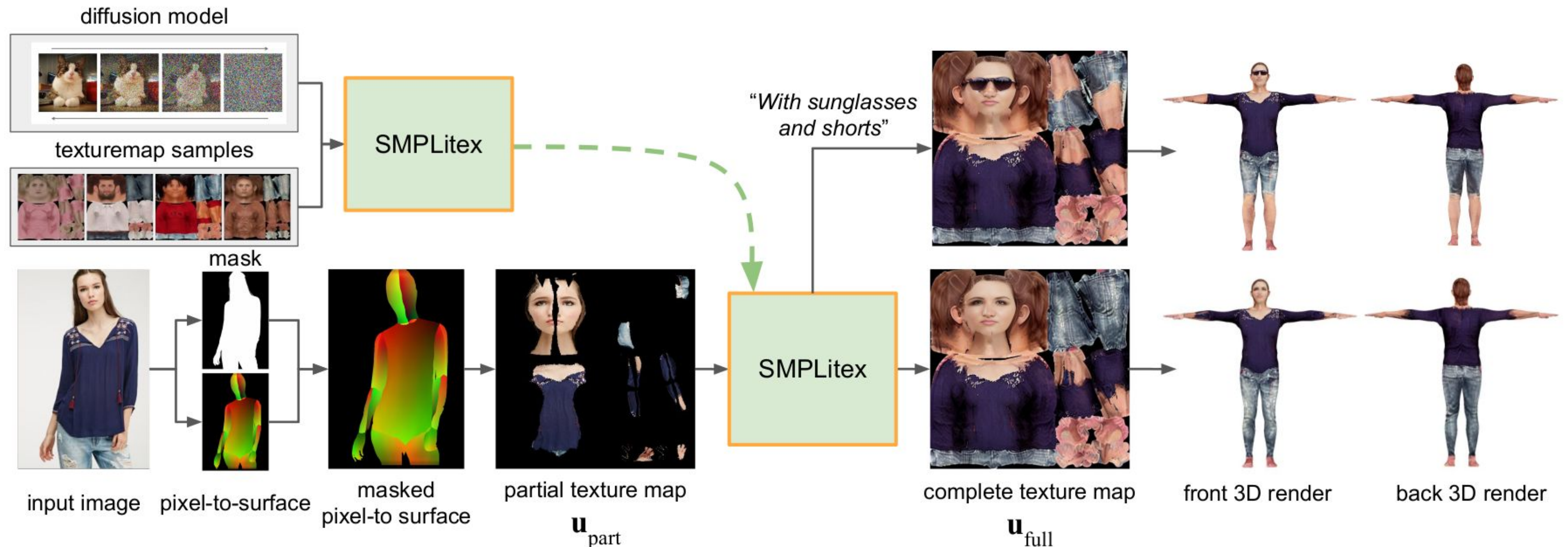
Santesteban, I., Garces, E., Otaduy, M. A., & Casas, D. (2020, May). SoftSMPL: data-driven modeling of nonlinear soft-tissue dynamics for parametric humans. In Computer Graphics Forum (Vol. 39, No. 2, pp. 65-75).

Dimensionality Reduction



Santesteban, I., Garces, E., Otaduy, M. A., & Casas, D. (2020, May). SoftSMPL: data-driven modeling of nonlinear soft-tissue dynamics for parametric humans. In Computer Graphics Forum (Vol. 39, No. 2, pp. 65-75).

Generative Textures for Avatars



Casas, D., & Comino-Trinidad, M. (2023). SMPLitex: A Generative Model and Dataset for 3D Human Texture Estimation from Single Image.

Generative Textures for Avatars



"Futuristic astronaut"



"Angela Merkel, shirt"

[The SMPLitex Dataset](#)

Thanks!

Q & A



MSLab

Multimodal Simulation Lab



These slides are provided under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International ([CC-BY-NC-ND 4.0](https://creativecommons.org/licenses/by-nc-nd/4.0/)) license, with the exception of figures, diagrams, and images extracted from scientific publications. For these specific third-party materials, please refer to the original publications to verify their copyright status and licensing terms. The inclusion of these third-party elements in this presentation does not imply an extension of the CC-BY-NC-ND license to them.