Dyna

A Model of Dynamic Human Shape in Motion

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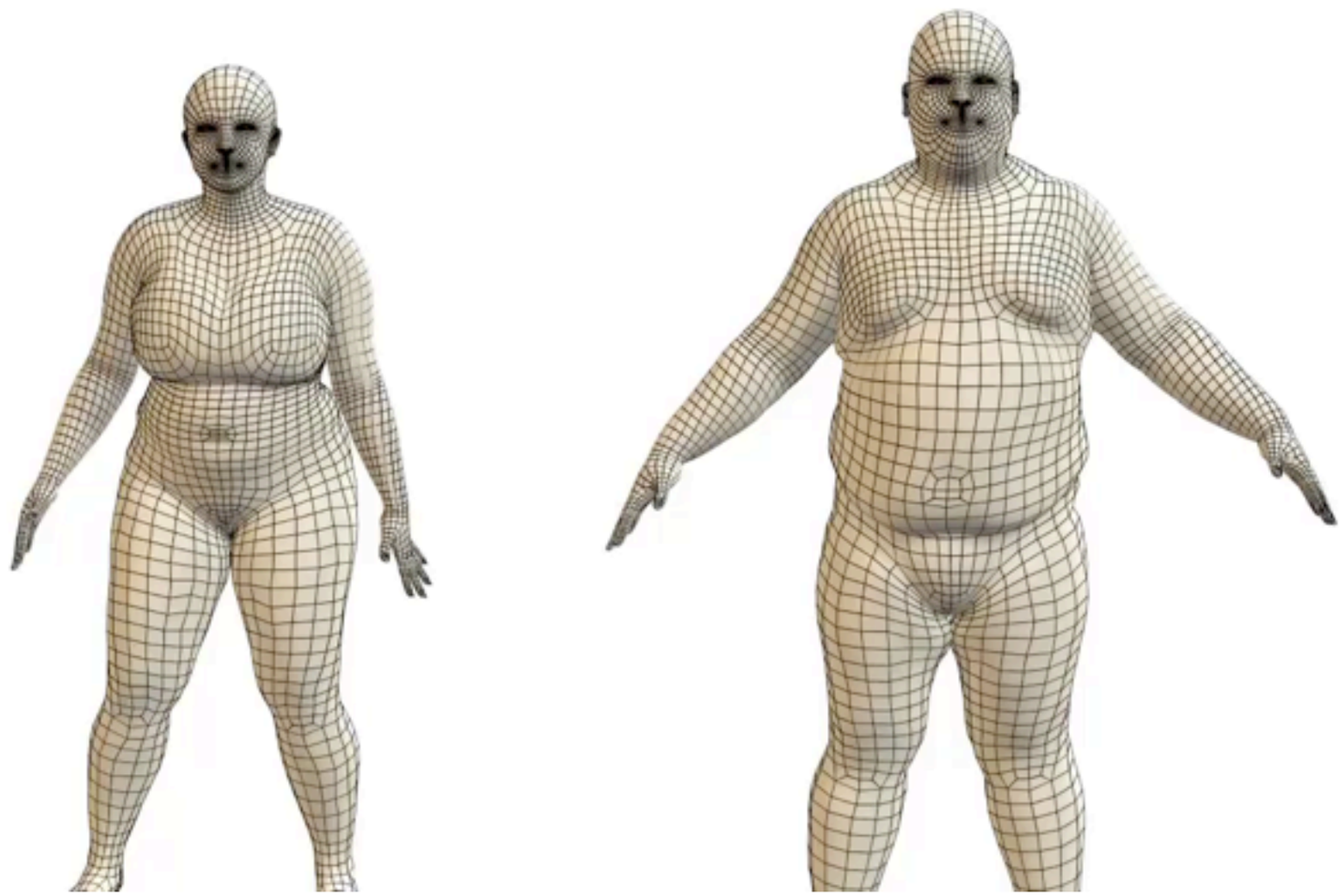
[use of videos and slides by Pons-Moll et al.]

Contribution

Generalizable Model of Soft Tissue Deformation



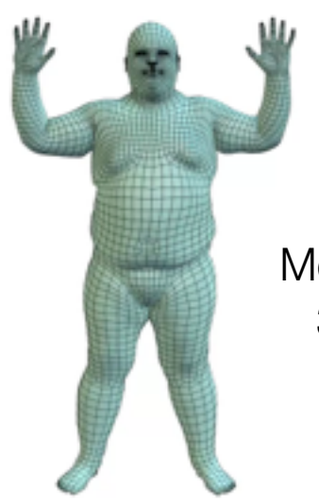
The first **controllable** model of soft tissue deformation
that is **generalizable** to different people,
built from **statistical** analysis of high-resolution 4D data

Human “Jiggle”

4cap

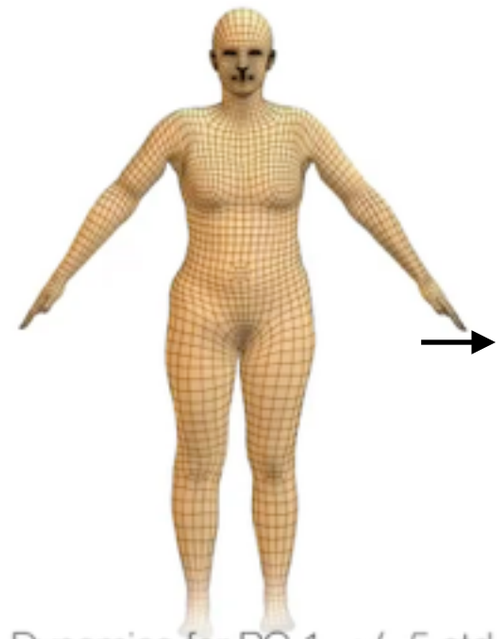
Raw 3D Scans

Mesh Alignment



Mesh Aligned 3D Scans

Dynamic Shape Space



Dynamics for PC 1, +/- 5 std

Input parameters

$$\{\theta_k, \beta_j\}$$

{Pose, Identity}

DYNA

SCAPE
Shape Identity Space
+
Pose Deformation Space

Animation with soft-tissue deformations

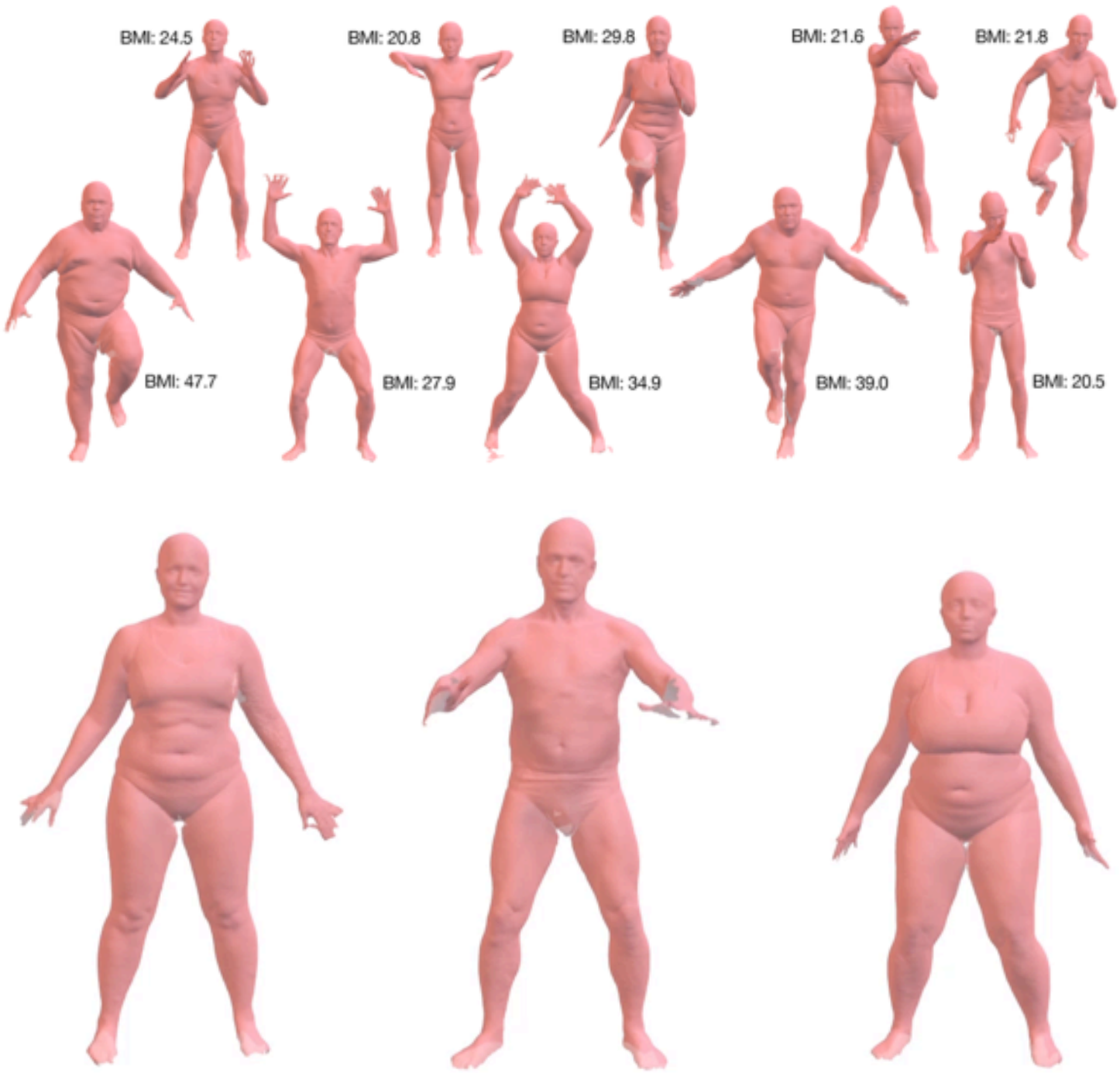
1. High Resolution Data

Capturing Full body 3D Scans at 60 FPS

22 Stereo camera pairs, 34 Speckle Projectors, 22 Color Cameras

Data Collection

Training: 10 subjects (5/5 men/women); Testing: 6 subjects (3/3)



Body Modeling: SCAPE

Transforms a **template mesh** to an **instance mesh**

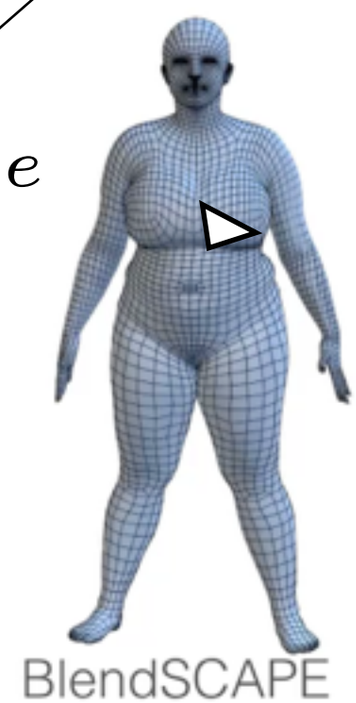
Body shape coefficients of subject *j*

Body pose of subject *j* at time *k*

$$\mathbf{v}_{t,e}(\boldsymbol{\beta}^j, \boldsymbol{\theta}_k^j) \xleftarrow{\text{SCAPE}} \hat{\mathbf{v}}_{t,e}$$

instance triangle edges

template triangle edges in the A pose



Kinematic Chain Rigid Rotations (user defined ownership)

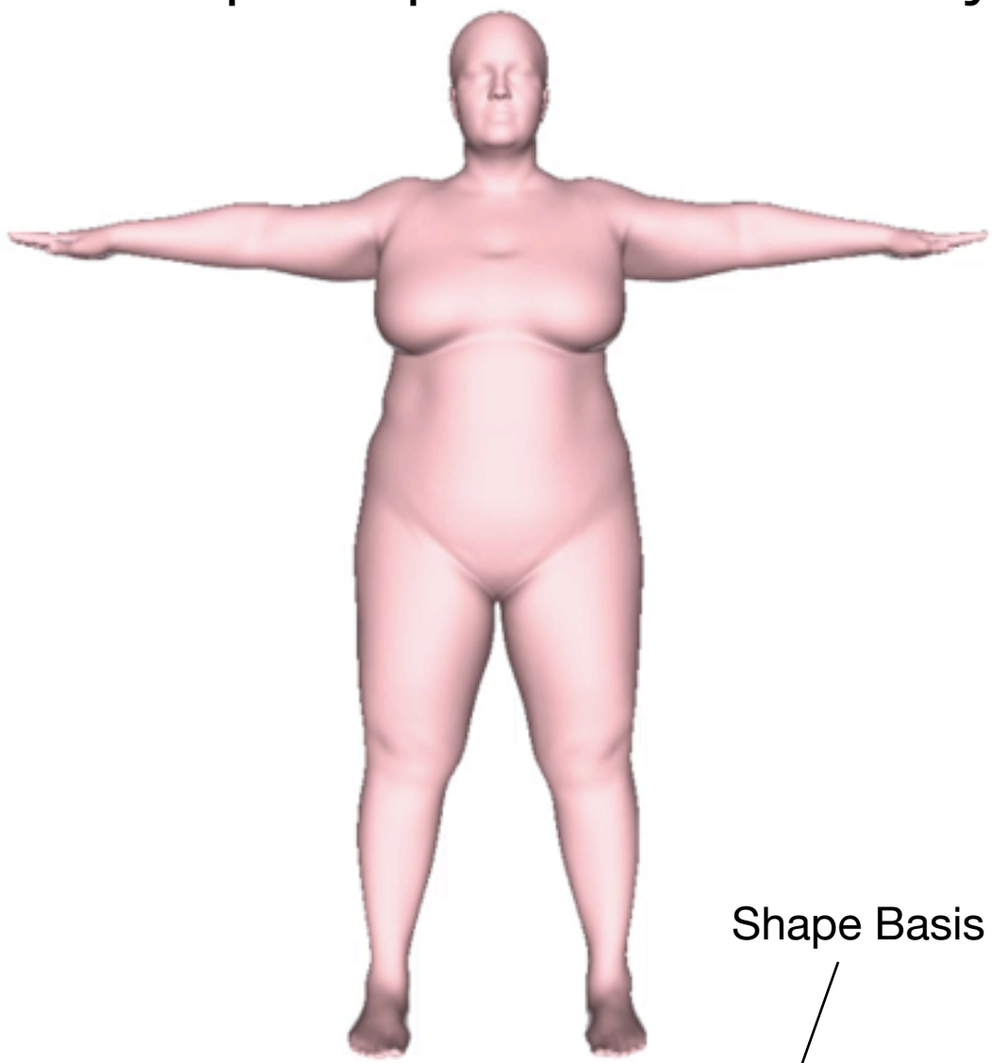
Identity Dependent Deformation (linear function)

Pose Dependent Deformation (linear function)

[Anguelov et al. 2005; Hirshberg et al. 2012]

SCAPE: Shape Identity

The Shape Space of Identity



Shape Basis

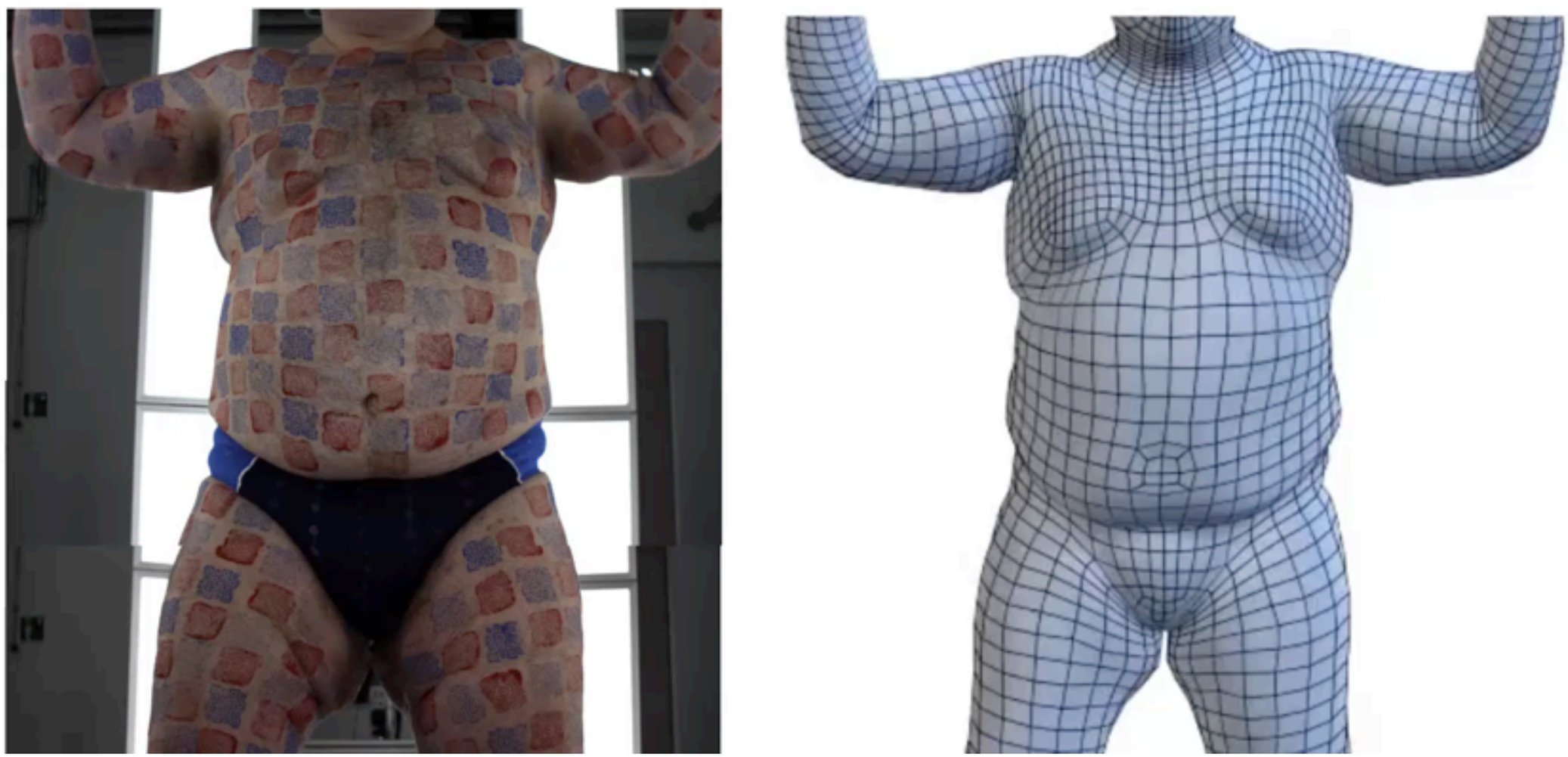
$$\mathbf{S}(\boldsymbol{\beta}) = \boldsymbol{\mu}_{\mathbf{S}} + \sum_{p} \boldsymbol{\beta}_p \mathbf{u}_{\mathbf{S},p}$$

Shape Coefficients

Body Modeling: SCAPE

Transforms a **template mesh** to an **instance mesh**

$$\mathbf{v}_{t,e}(\boldsymbol{\beta}^j, \boldsymbol{\theta}_k^j) = \mathbf{R}^*_{l[t]}(\boldsymbol{\theta}_k^j)\mathbf{S}_t(\boldsymbol{\beta}^j)\mathbf{Q}_t(\boldsymbol{\theta}_k^j)\hat{\mathbf{v}}_{t,e}$$

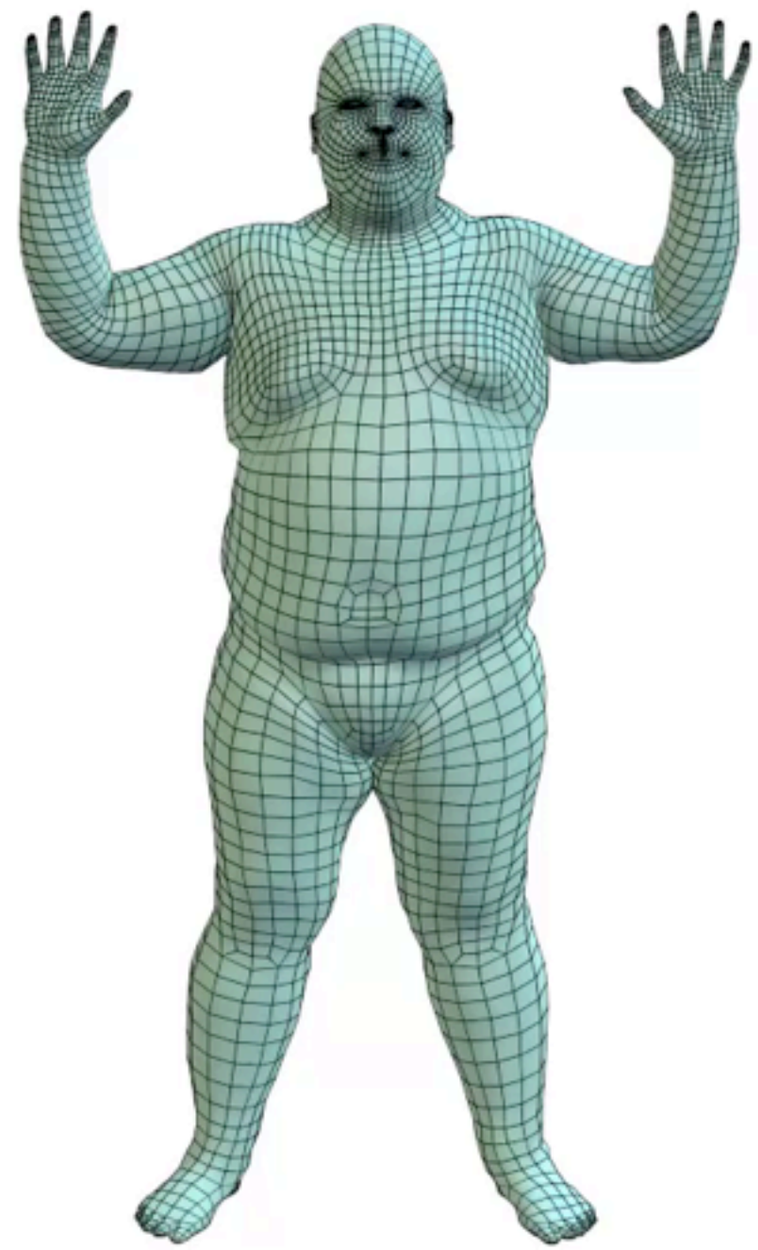


[Anguelov et al. 2005; Hirshberg et al. 2012]

2. Mesh Alignment

Bring all 3D scans for all subjects *j* and times *k* into correspondence

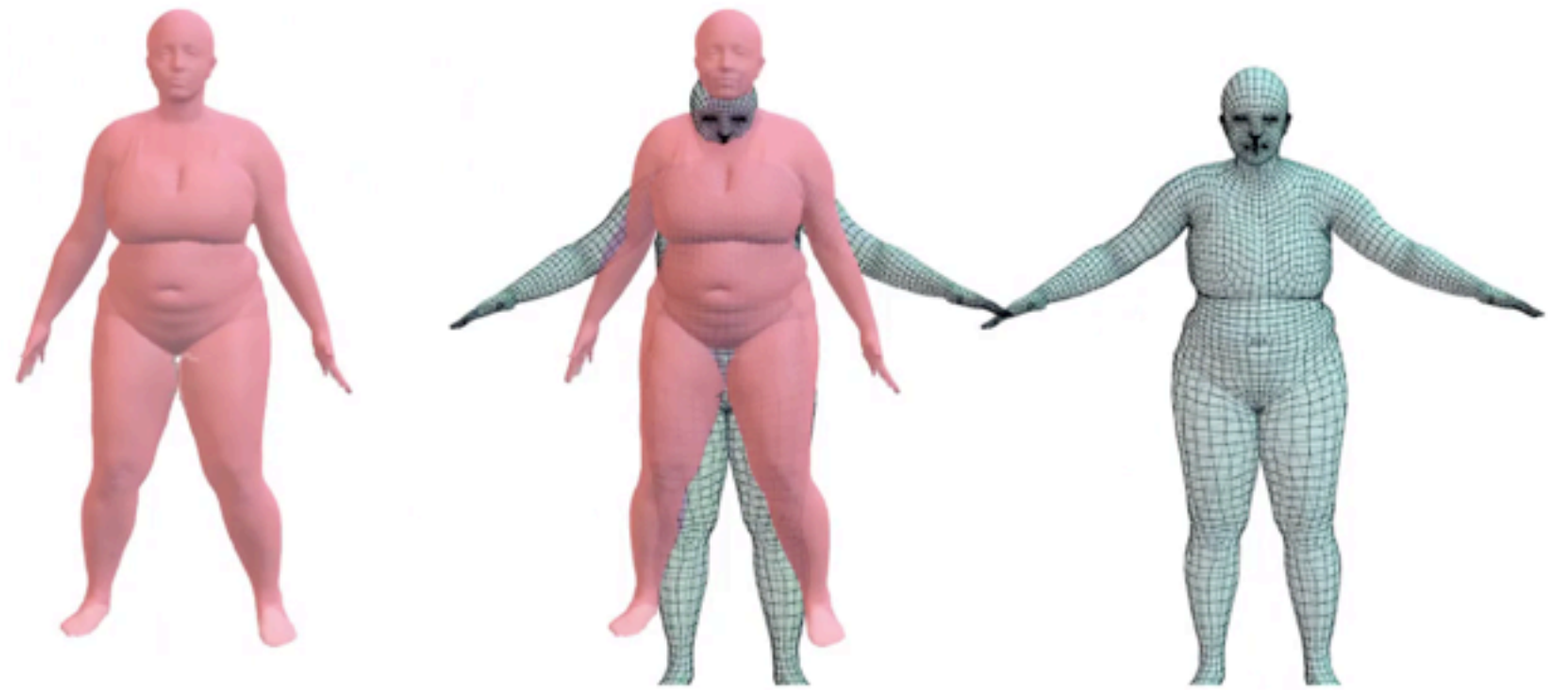
4D scan



Aligned mesh

2. Mesh Alignment

Bring all 3D scans for all subjects *j* and times *k* into correspondence



Raw Scan | Fitting process | Alignment

Cost Function

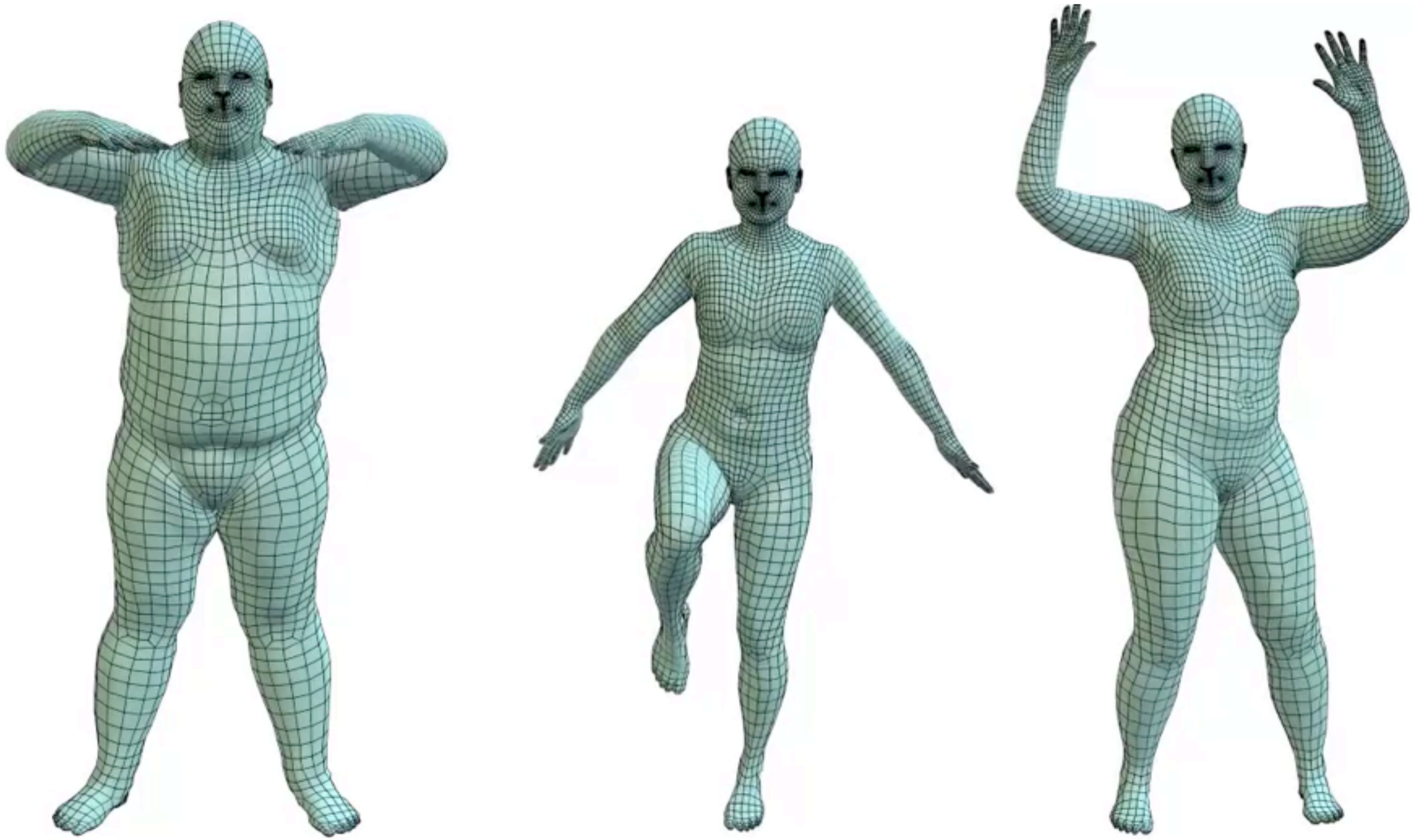
$$E(\mathcal{M}_k^j, \boldsymbol{\theta}_k^j; \mathcal{S}_k^j) = w_g \underline{E_g} + w_c \underline{E_c}$$

Data Term
(Distance to scan)

$$E_g(\mathcal{M}; \mathcal{S}) = \sum_{x_s \in S} \rho(\min_{x_m \in \mathcal{M}} \|x_m - x_s\|)$$

"Prior" Term
(Distance to Blendscape)

$$E_c(\mathcal{M}_k^j, \boldsymbol{\theta}_k^j) = \sum_{t,e} w_t \|\mathcal{M}_{t,e,k}^j - \mathbf{v}_{t,e}(\boldsymbol{\theta}_k^j)\|_F^2$$



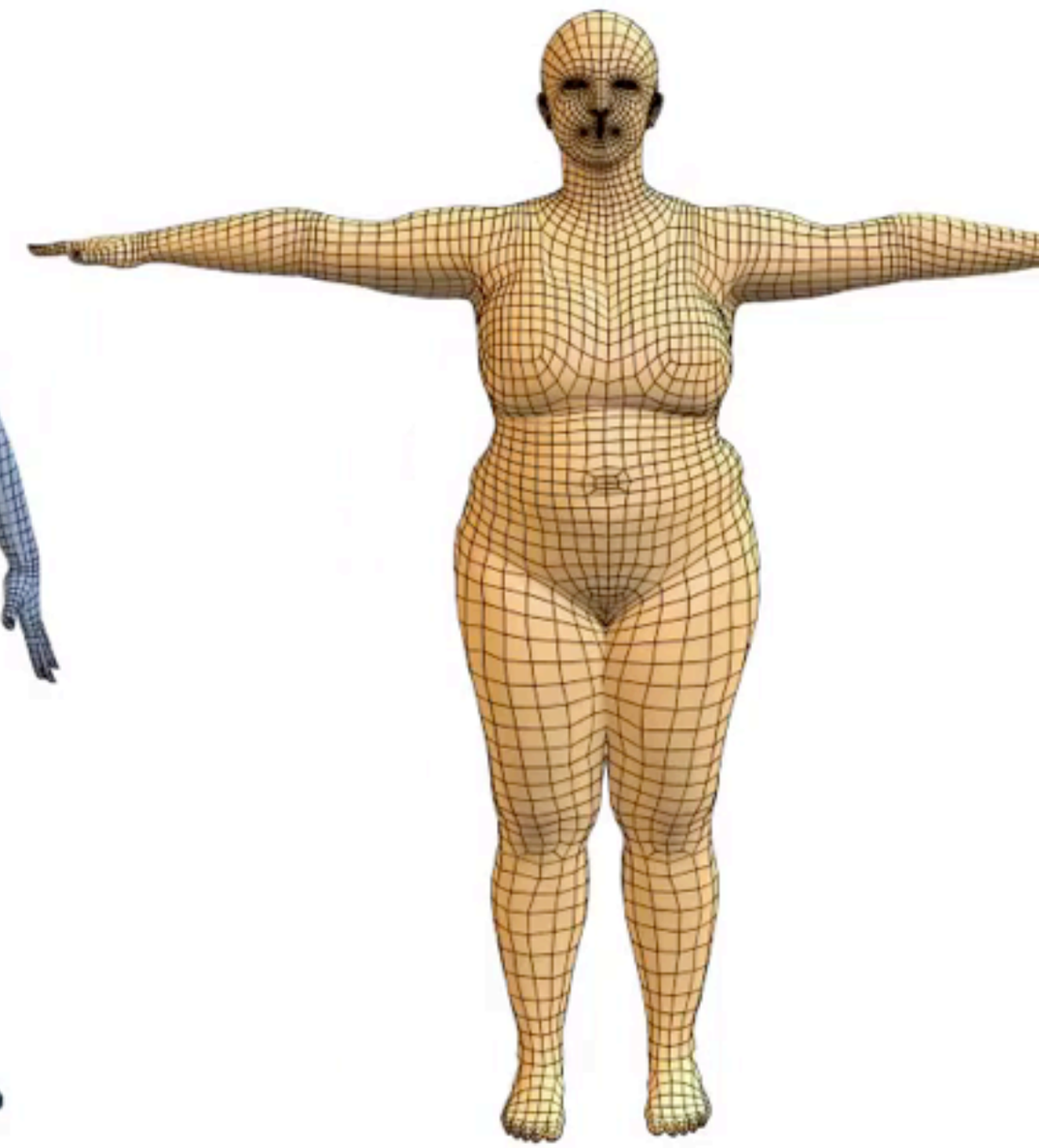
~70,000 aligned meshes

40,000 for training available for research at

http://dyna.is.tue.mpg.de

Alignment

BlendSCAPE



Residuals

3. Dynamic Shape Space

Total Nonrigid Deformation of the Body

Identity Shape Coefficients

Identity Shape Basis

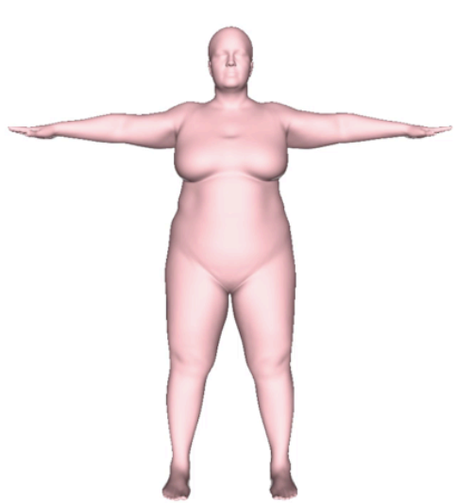
Dynamic Shape Coefficients

Dynamic Shape Basis

$$\mathbf{T}(\boldsymbol{\beta}, \boldsymbol{\delta}_k) = \boldsymbol{\mu}_{\mathbf{S}} + \sum_p \boldsymbol{\beta}_p \mathbf{u}_{\mathbf{S},p} + \boldsymbol{\mu}_{\mathbf{D}} + \sum_p \boldsymbol{\delta}_{k,p} \mathbf{u}_{\mathbf{D},p}$$

Identity shape

$\mathbf{S}(\boldsymbol{\beta})$



Dynamic shape

$\mathbf{D}(\boldsymbol{\delta}_k)$

SCAPE

[Anguelov et al. 2005; Hirshberg et al. 2012]

$$\mathbf{v}_{t,e}(\boldsymbol{\beta}^j, \boldsymbol{\theta}_k^j) = \mathbf{R}^*_{l[t]}(\boldsymbol{\theta}_k^j)\underbrace{\mathbf{S}_t(\boldsymbol{\beta}^j)}_{\text{Identity shape}}\mathbf{Q}_t(\boldsymbol{\theta}_k^j)\hat{\mathbf{v}}_{t,e}$$

VS

DYNA

[Pons-Moll et al. 2015]

$$\begin{aligned}\mathbf{v}_{t,e}(\boldsymbol{\beta}, \boldsymbol{\theta}_k, \boldsymbol{\delta}_k) &= \mathbf{R}^*_{l[t]}(\boldsymbol{\theta}_k)\mathbf{T}_t(\boldsymbol{\beta}, \boldsymbol{\delta}_k)\mathbf{Q}_t(\boldsymbol{\theta}_k)\hat{\mathbf{v}}_{t,e} \\ &= \mathbf{R}^*_{l[t],k}(\boldsymbol{\theta}_k)(\underbrace{\mathbf{S}_t(\boldsymbol{\beta}) + \mathbf{D}_t(\boldsymbol{\delta}_k)}_{\text{Identity shape + soft-tissue deformation}})\mathbf{Q}_t(\boldsymbol{\theta}_k)\hat{\mathbf{v}}_{t,e}\end{aligned}$$

3. DYNA Model

2nd Order Autoregressive Model for δ

Angular Velocity/ Acceleration of Pose

History of dynamic coefficients

$$\mathbf{x}_k = \{\dot{\boldsymbol{\theta}}_k, \ddot{\boldsymbol{\theta}}_k, \boldsymbol{v}_k, \boldsymbol{a}_k, \hat{\dot{\boldsymbol{\delta}}}_{k-1}, \hat{\ddot{\boldsymbol{\delta}}}_{k-2}\} \in \mathcal{X}$$

Velocity/Acceleration of Root

Dynamic coefficients are a linear function:

$$\boldsymbol{\delta}_k^j = \sum_{n=1}^{4} \mathbf{B}_n^j \underline{\mathbf{x}_k}[n] + \sum_{l=1}^{M} \mathrm{diag}(\mathbf{a}_l) \underline{\hat{\boldsymbol{\delta}}_{k-l}^j} + \mathbf{b}^j$$

velocity and accel. of limbs and root

Previous estimated dynamic coefficients

3. DYNA Model

Training

$$\boldsymbol{\delta}_k^j = \sum_{n=1}^{4} \mathbf{B}_n^j \underline{\mathbf{x}_k}[n] \; + \sum_{l=1}^{M} \mathrm{diag}(\mathbf{a}_l) \underline{\hat{\boldsymbol{\delta}}_{k-l}^j} + \mathbf{b}^j$$

$$\mathbf{p}^j \;=\; \{\mathbf{b}^j, \{\mathbf{B}_n^j\}_{n=1}^4, \{\mathbf{a}_l^j\}_{l=1}^M\}$$

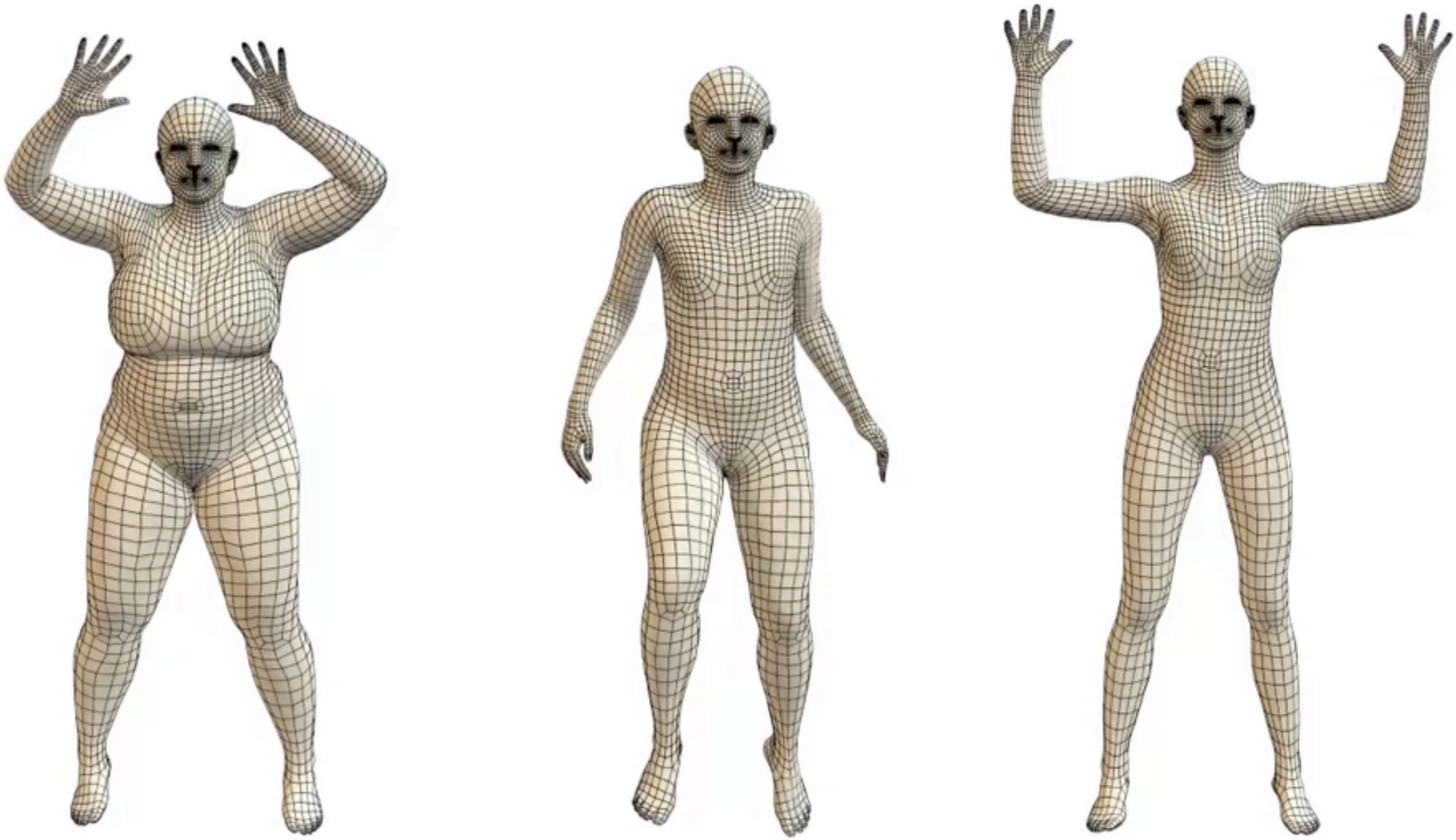
$$\delta_k^j \xleftarrow{\quad g(\cdot) \quad}$$

$$\mathbf{x}_k \;=\; \{\dot{\boldsymbol{\theta}}_k, \ddot{\boldsymbol{\theta}}_k, \boldsymbol{v}_k, \boldsymbol{a}_k, \hat{\dot{\boldsymbol{\delta}}}_{k-1}, \hat{\ddot{\boldsymbol{\delta}}}_{k-2}\} \in \mathcal{X}$$

$$\mathcal{R}_w(\mathbf{p}^j; \mathcal{D}) \quad = \quad \sum_{i=1}^{N_{\mathrm{subj}}} \sum_{k=1}^{|\mathcal{D}^i|} \frac{1}{|\mathcal{D}^i|} \|\underline{w_i}(\boldsymbol{\delta}_k^i - g_i(\mathbf{x}_k^i; \mathbf{p}^j)\|^2$$

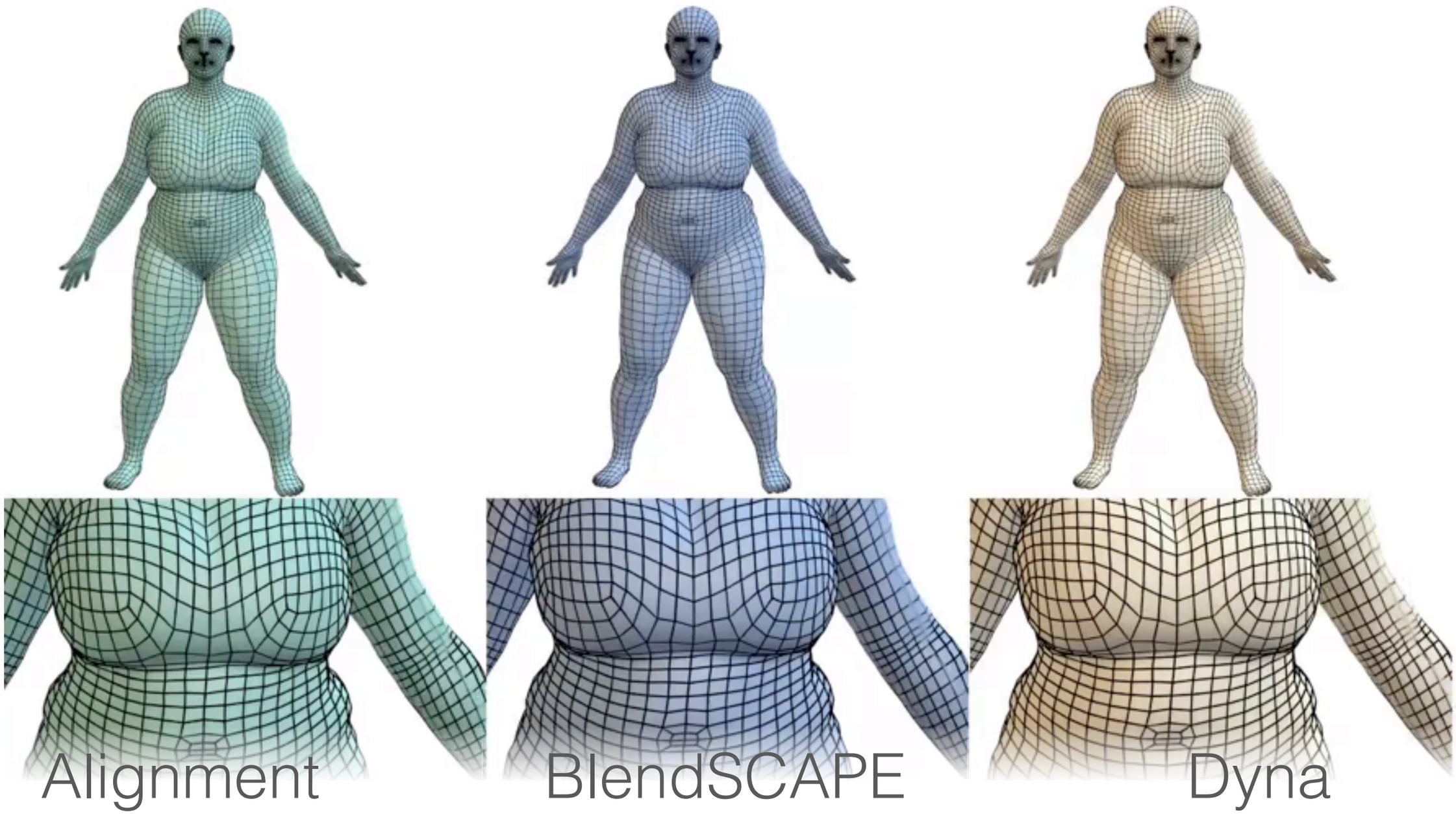
weight to bias to subject specific data

Dyna Model Results



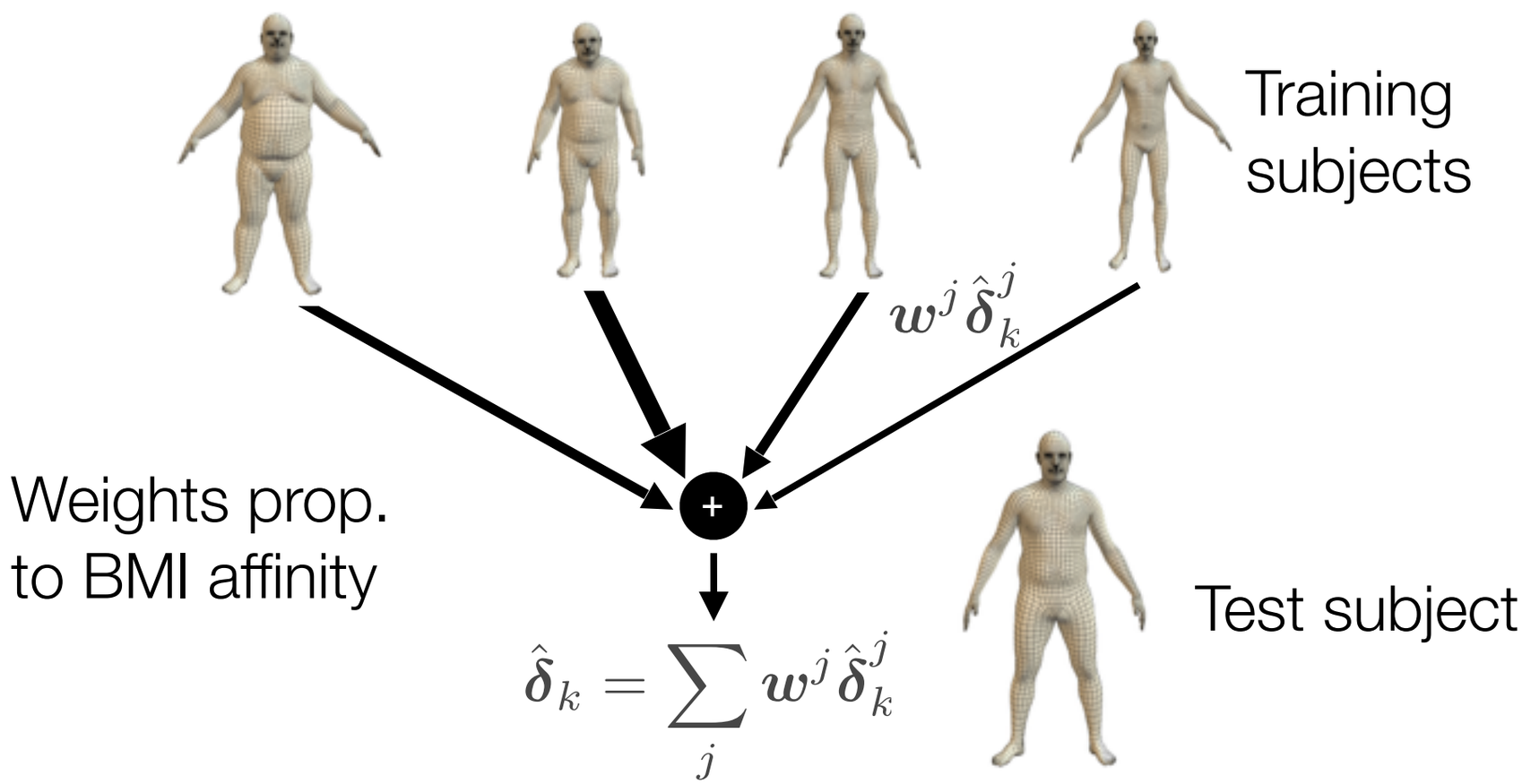
Dyna Model Results

“Stunt double” mode



Dyna Model Results

Subject specific dynamics



Dyna Model Results

Contribution 4: Animator control

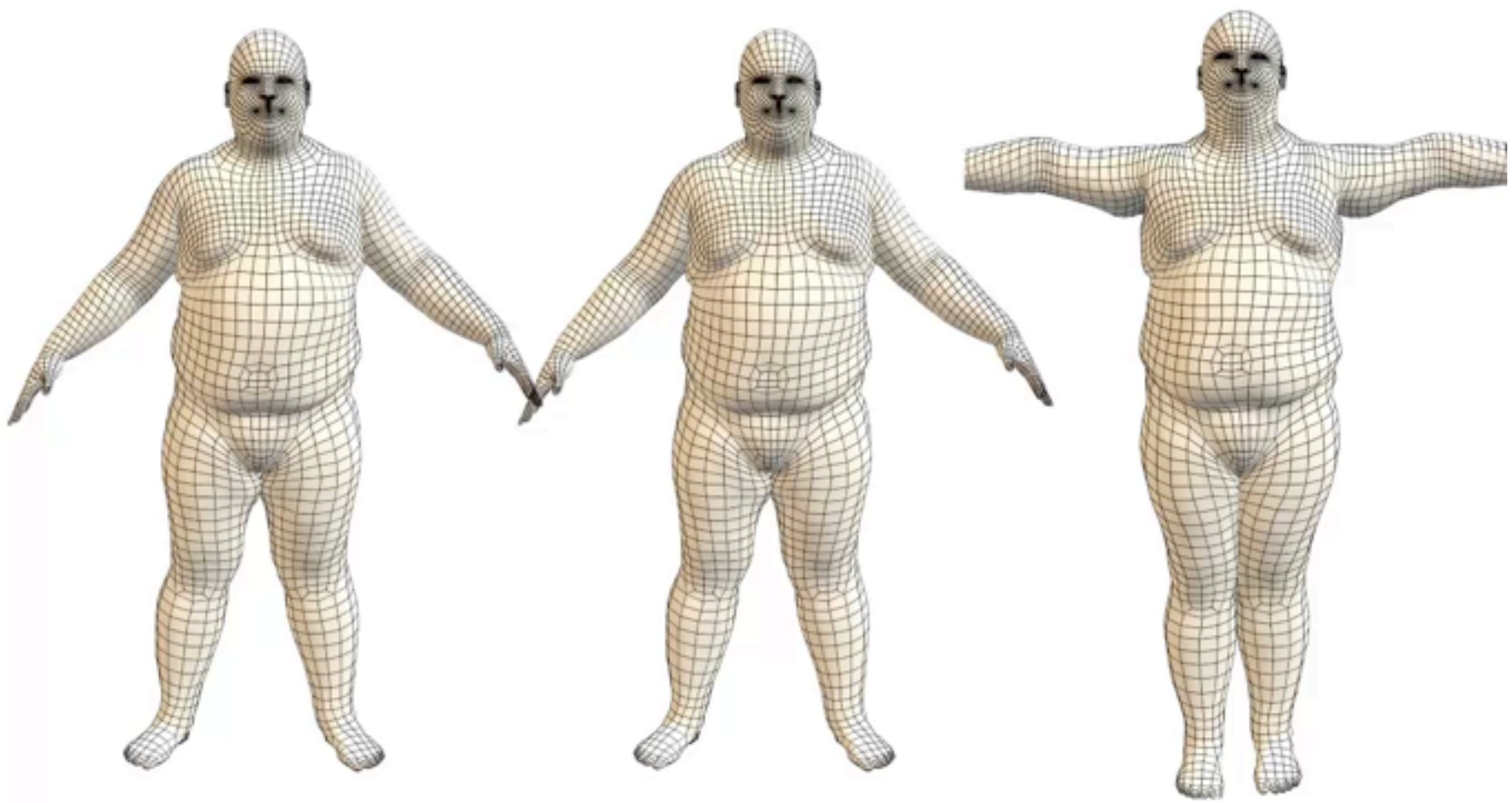
- Animators want to produce artistic effects
  - Weight editing
  - Retarget
  - Exaggerate
  - Local editing

Dyna

Exaggeration

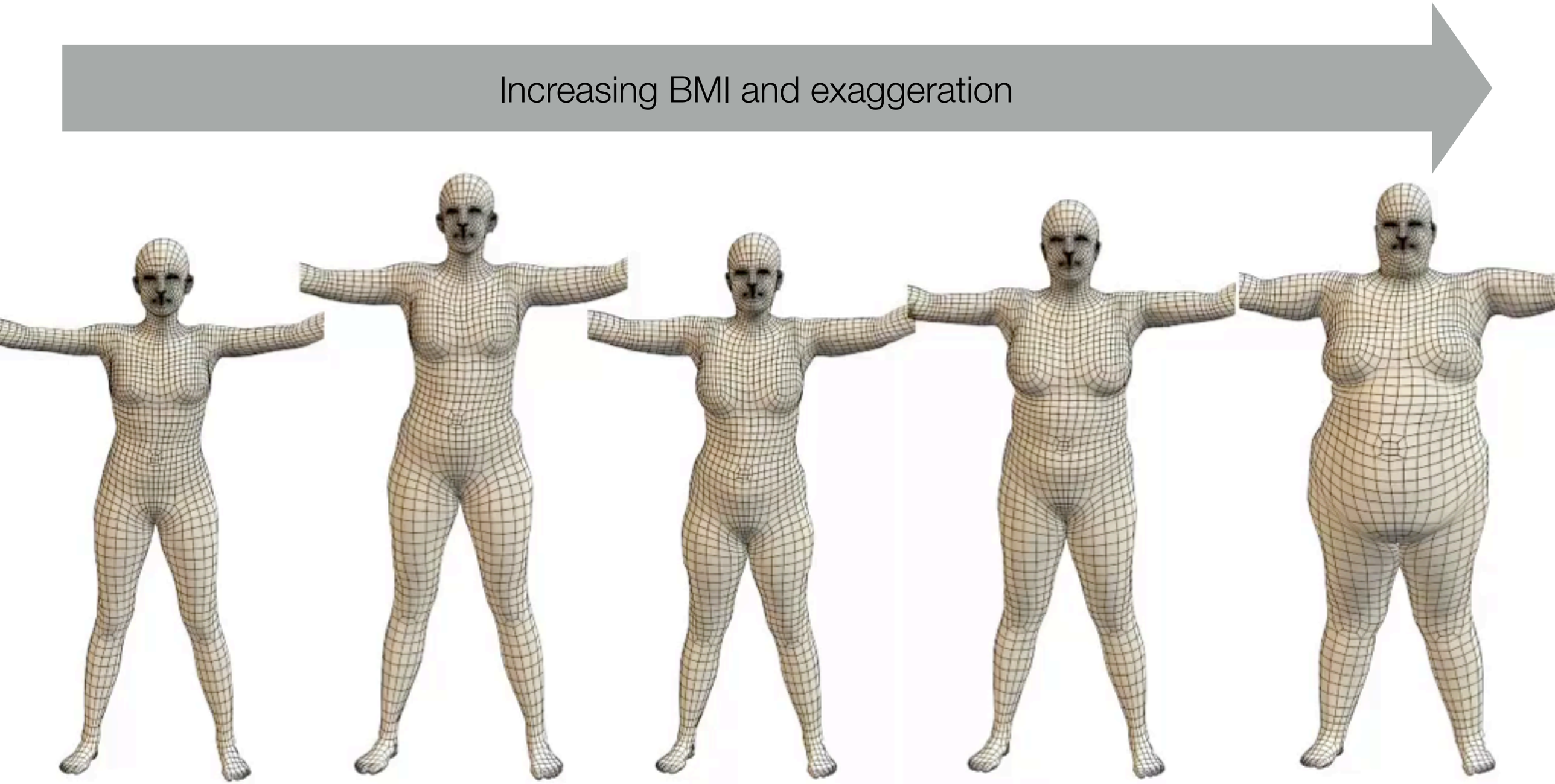
Scale factor

$$\mathbf{T}(\boldsymbol{\beta}, \boldsymbol{\delta}_k) = \boldsymbol{\mu}_{\mathbf{S}} + \sum_p \boldsymbol{\beta}_p \mathbf{u}_{\mathbf{S},p} + \boldsymbol{\mu}_{\mathbf{D}} + \boxed{s} \sum_p \boldsymbol{\delta}_{k,p} \mathbf{u}_{\mathbf{D},p}$$



Original | Exaggerated | Exaggeration unposed

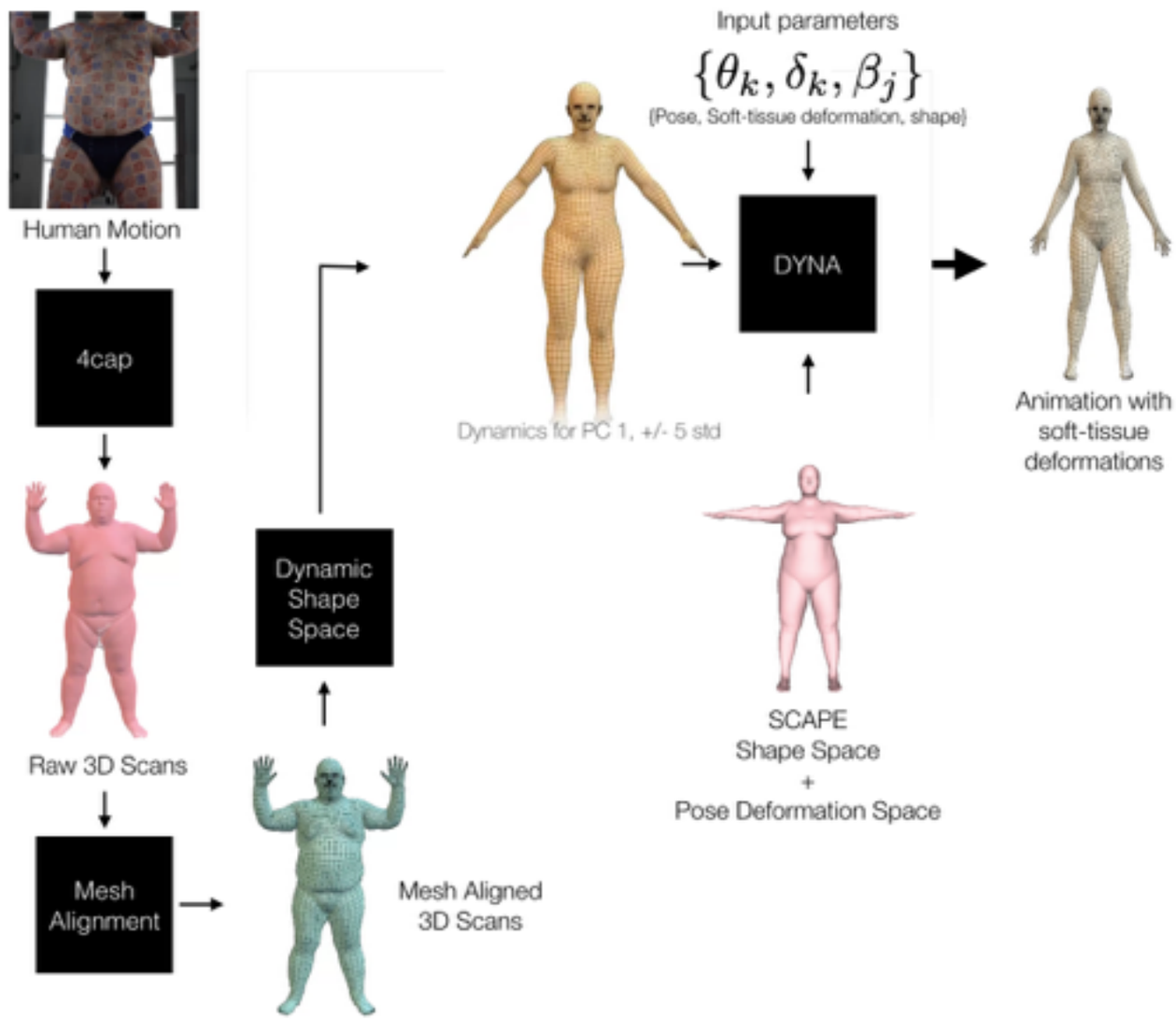
Deformations depend on body shape



Static bodies from CAESAR dataset

Summary of Contributions

Generalizable Model of Soft Tissue Motion



1. **Data Capture:** Custom 4D scanning system
2. **Mesh Alignment:** Automated alignment of thousands of dynamic scans
3. **Dyna Model:** Dyna is a model of "how we jiggle" that generalizes to novel shapes and motions
4. **Animator control:** Artistic effects can be easily achieved using Dyna

The first **controllable** model of soft tissue deformation that is **generalizable** to different people, built from **statistical** analysis of high-resolution 4D data

Dyna
Pros and Cons

Pros

- Realistic
- Fast (prediction cost negligible)
- Easy to use and control
- Generalizes to new people and motions

Cons

- Does not generalize to external forces
- Minimal quantitative validation
- Factorization of pose and identity compromised in model?
- Does not handle multiple scales of deformation

SIGGRAPH Review Form

Questions

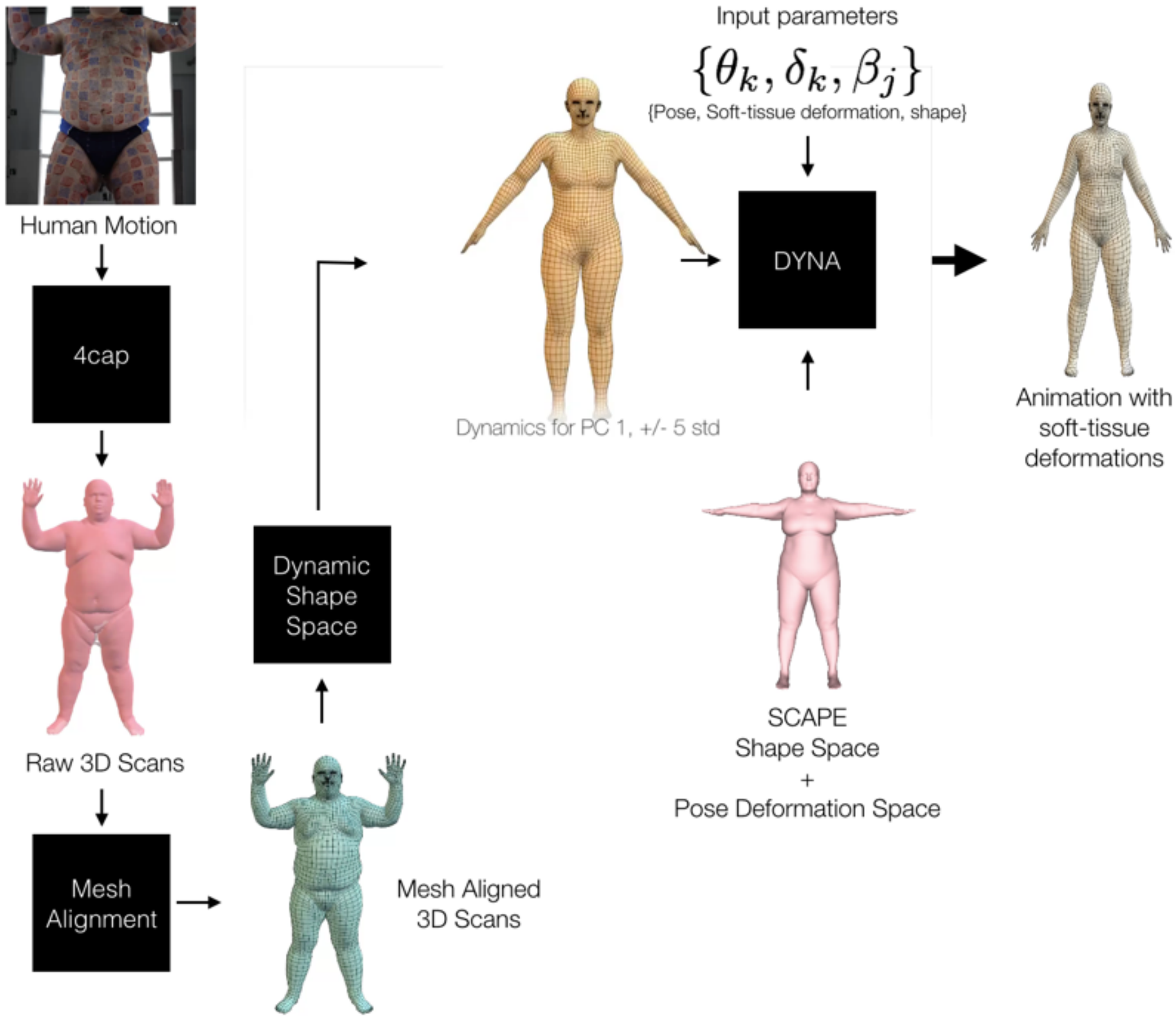
Clarity of Exposition: Generally well-written (has a few typos)

Quality of References: Good separation into physics-based vs statistical models. Reasonable coverage of papers.

Reproducibility: Details of optimization are given. Requires knowledge of SCAPE.

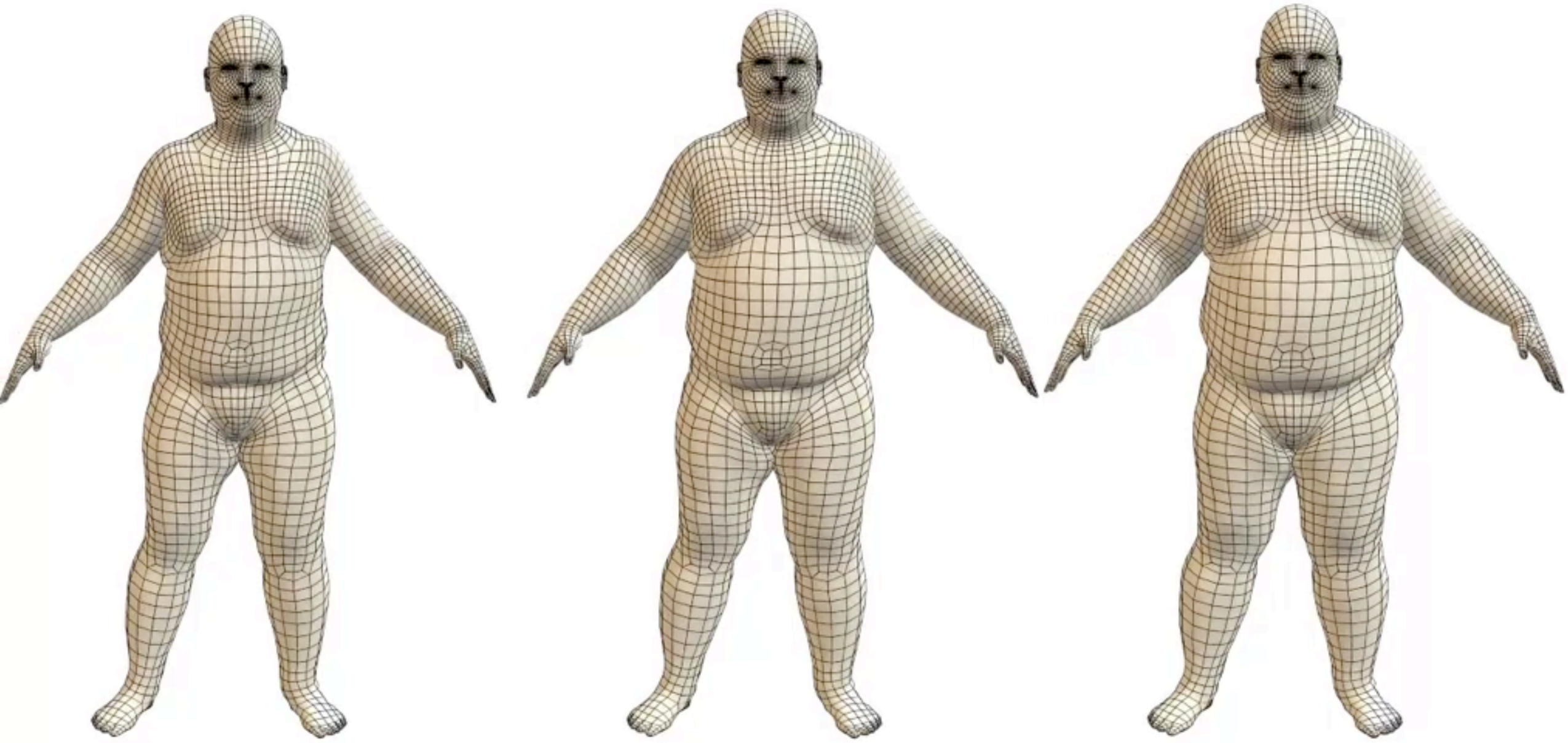
Rating: ~4.0

Explanation of Rating: Clear contributions with limited quantitative evaluation


Human Motion
4cap
Raw 3D Scans
Mesh Alignment
Mesh Aligned 3D Scans
Dynamic Shape Space
Dynamics for PC 1, +/- 5 std
Input parameters
$\{\theta_k, \delta_k, \beta_j\}$
{Pose, Soft-tissue deformation, shape}
DYNA
Animation with soft-tissue deformations
SCAPE Shape Space + Pose Deformation Space

Dyna

Weight Editing

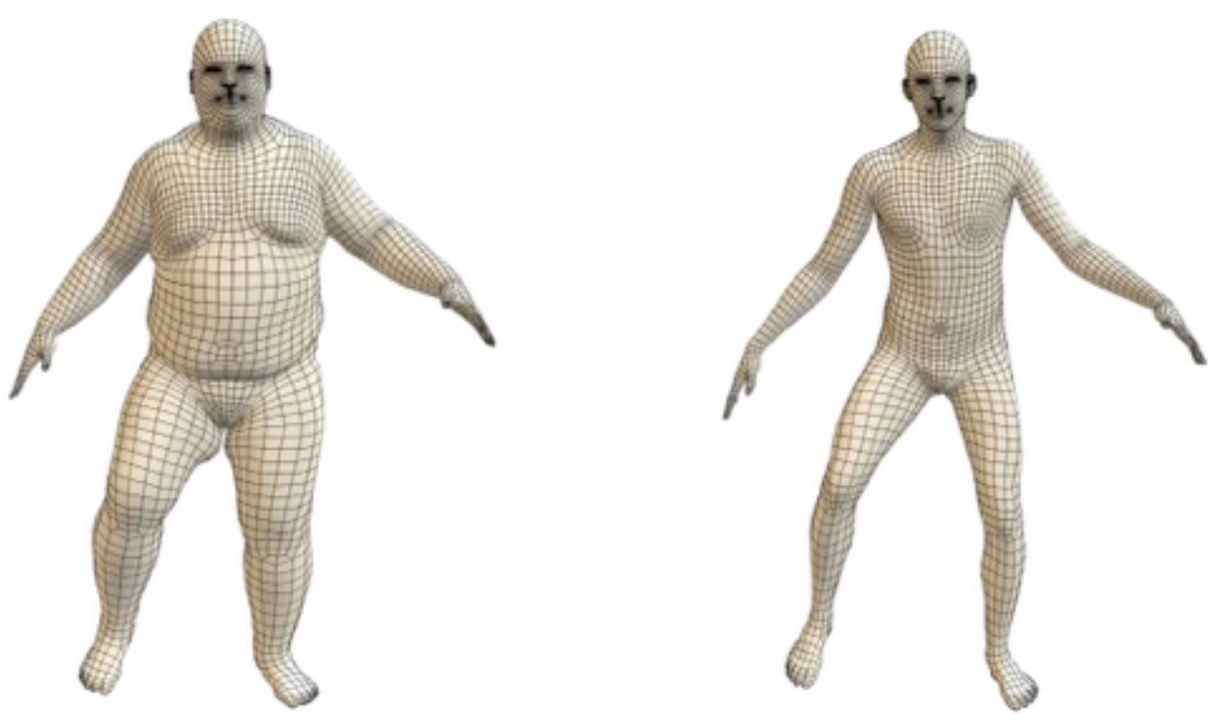


-30 Kg | Original | +30 Kg

Dyna

Retargeting

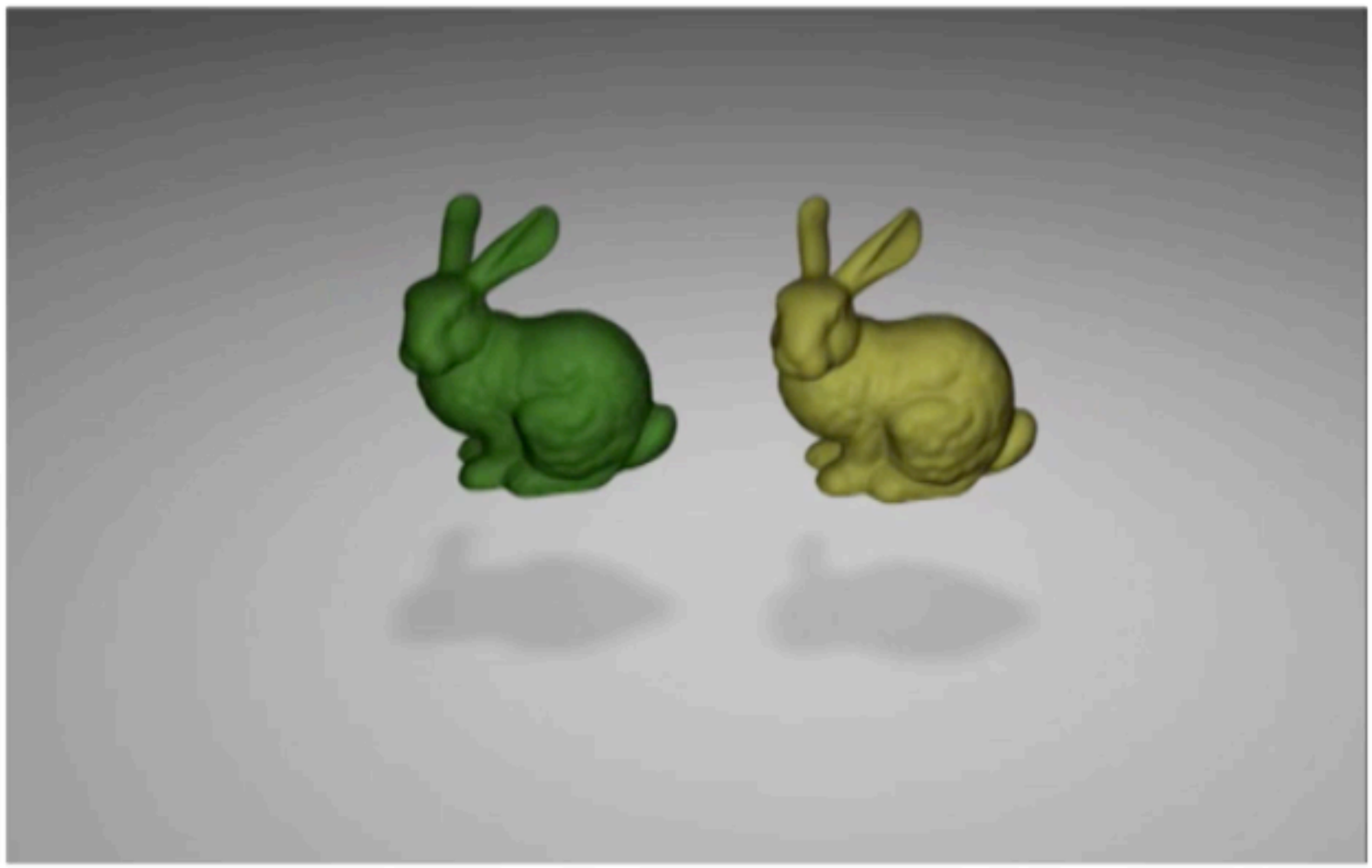
$$\mathbf{T}(\boldsymbol{\beta}, \boldsymbol{\delta}_k) = \underbrace{\quad}_{\text{Identity shape}} + \underbrace{\boldsymbol{\mu}_{\mathbf{D}} + \sum_p \boldsymbol{\delta}_{k,p} \mathbf{u}_{\mathbf{D},p}}_{\text{Dynamic shape}}$$



Original

Retargeted subject

Physical simulation of materials



Levin et al., 2011

Physical simulation of humanoids

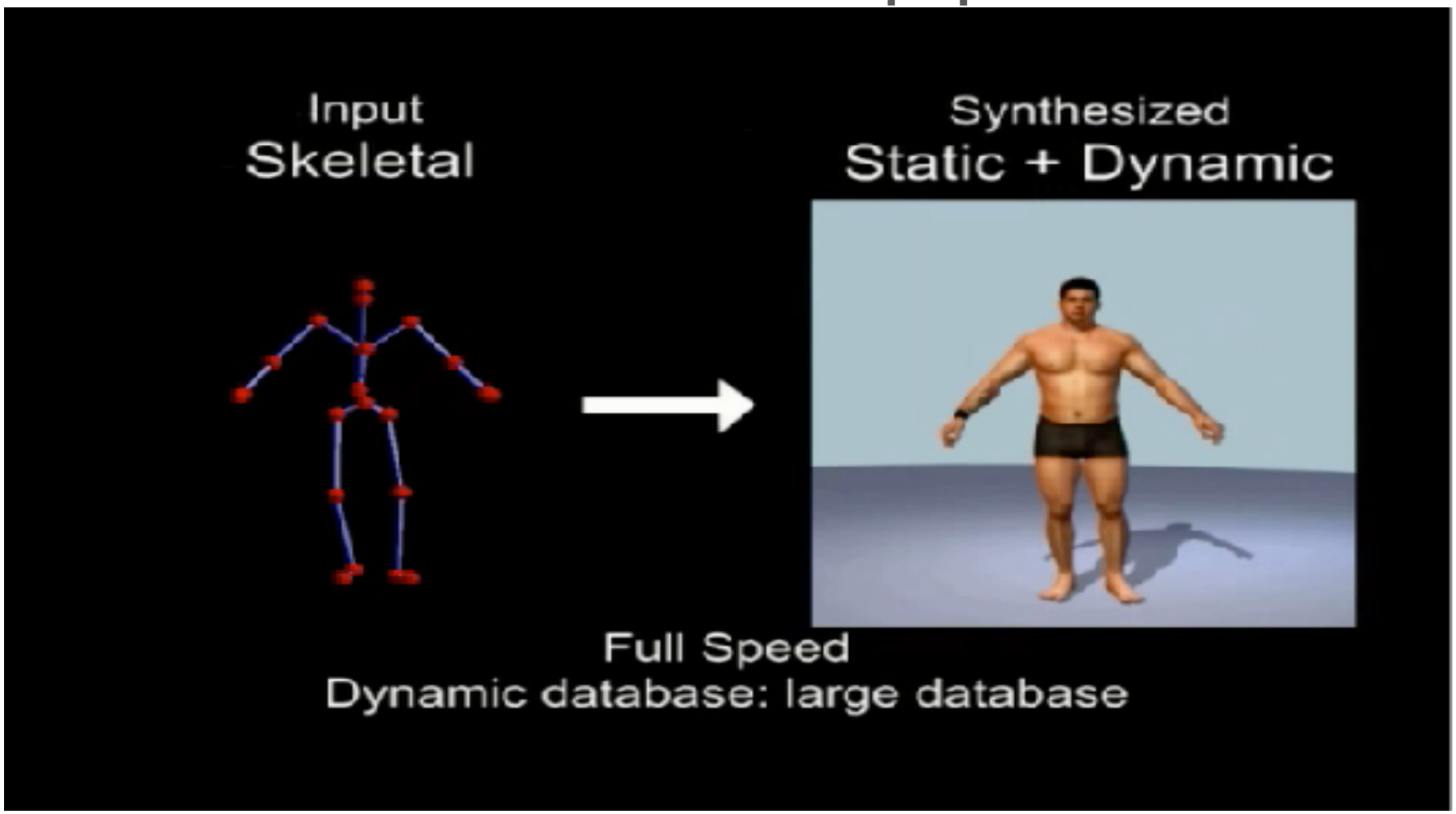
James and Pai, 2002

Physical simulation approach

- Chadwick et al. 1989
- Capell et al. 2002
- Larboulette et al. 2005
- Maurel et al. 1998
- Aubel and Thalmann 2001
- Fan et al. 2014
- Lee et al. 2009
- James and Pai 2002
- Hahn et al. 2012
- Scheepers et al. 1997
- Sifakis et al. 2005
- Teran et al. 2005
- Terzopoulous and Waters 1990
- Pratscher et al. 2005
- Li and Kry 2014
- Kim and James 2012

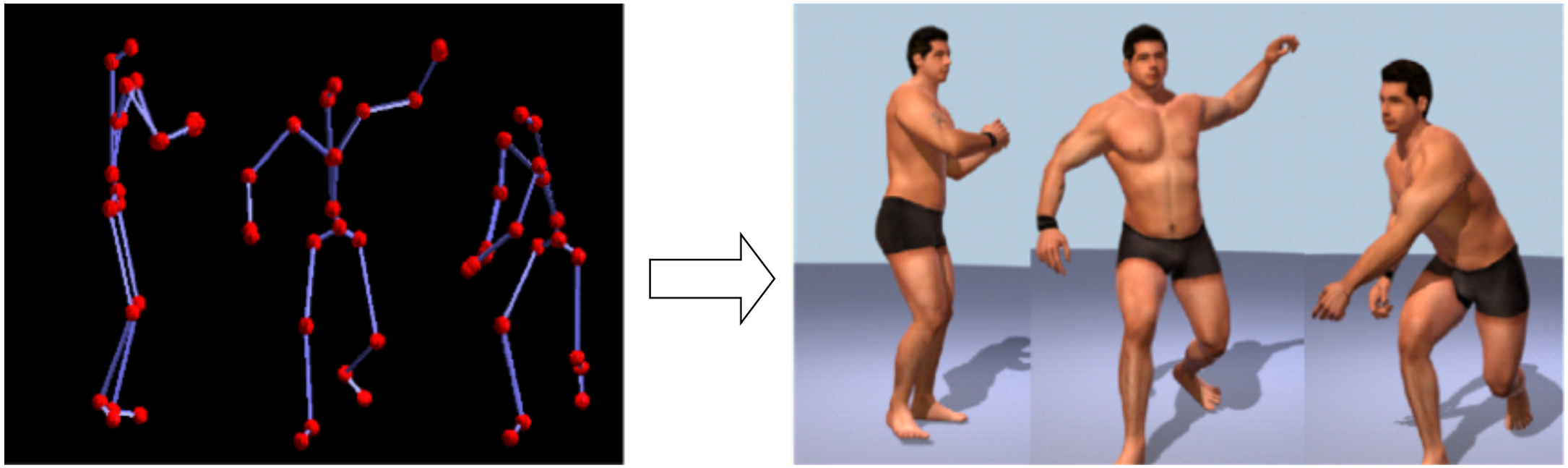
Statistical	Physical
Requires data	Requires data
Minimal generalizability	Generalizes well
Requires general design	Requires specific design
Fast	Slow
Deals with missing data	Missing data?
Deals with uncertainty	

Data driven approach



Park and Hodgins [2008] *subject specific* model. Built using ~400 markers, driven using ~40-50

Data driven approach



- Park and Hodgins [2008] built a *subject specific* model from ~300-400 markers, and then drive meshes from fewer