Dyna
A Model of Dynamic Human Shape in Motion

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[use of videos and slides by Pons-Moll et al.]
The first **controllable** model of soft tissue deformation that is **generalizable** to different people, built from **statistical** analysis of high-resolution 4D data.
Animation with soft-tissue deformations

Human "Jiggle"

4cap

Mesh Aligned 3D Scans

Mesh Alignment

Raw 3D Scans

Dynamic Shape Space

Dynamics for PC 1, +/- 5 std

SCAPE
Shape Identity Space
+ Pose Deformation Space

Input parameters
\{θ_k, β_j\}

{Pose, Identity}

DYNA

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 $k$
- Instance triangle edges

\[ \mathbf{v}_{t,e}(\boldsymbol{\beta}^j, \boldsymbol{\theta}^j_k) \]

SCAPE

- Kinematic Chain
- Rigid Rotations
  (user defined ownership)
- Identity Dependent Deformation
  (linear function)
- Pose Dependent Deformation
  (linear function)

\[ \hat{\mathbf{v}}_{t,e} \]

template triangle edges in the A pose

[Anguelov et al. 2005; Hirshberg et al. 2012]
SCAPE: Shape Identity

The Shape Space of Identity

\[ S(\beta) = \mu_s + \sum_p \beta_p u_{s,p} \]
Body Modeling: SCAPE

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

\[ \mathbf{v}_{t,e}(\beta^j, \theta_k^j) = R^*_l[t](\theta_k^j)S_t(\beta^j)Q_t(\theta_k^j)\hat{\mathbf{v}}_{t,e} \]

[Anguelov et al. 2005; Hirshberg et al. 2012]
2. Mesh Alignment

Bring all 3D scans for all subjects $j$ and times $k$ into correspondence.
2. Mesh Alignment

Bring all 3D scans for all subjects \( j \) and times \( k \) into correspondence.

Cost Function

\[
E(\mathcal{M}^j_k, \theta^j_k; S^j_k) = w_g E_g + w_c E_c
\]

Data Term (Distance to scan)

\[
E_g(\mathcal{M}; S) = \sum_{x_s \in S} \rho \left( \min_{x_m \in \mathcal{M}} \|x_m - x_s\| \right)
\]

“Prior” Term (Distance to Blendshape)

\[
E_c(\mathcal{M}^j_k, \theta^j_k) = \sum_{t,e} w_t \|\mathcal{M}^j_{t,e,k} - \mathbf{v}_{t,e}(\theta^j_k)\|^2_F
\]
~70,000 aligned meshes
40,000 for training available for research at
http://dyna.is.tue.mpg.de
3. Dynamic Shape Space

Total Nonrigid Deformation of the Body

\[
T(\beta, \delta_k) = \mu_S + \sum_p \beta_p u_{S,p} + \mu_D + \sum_p \delta_{k,p} u_{D,p}
\]

Identity shape \( S(\beta) \)

Dynamic shape \( D(\delta_k) \)
SCAPE
[Anguelov et al. 2005; Hirshberg et al. 2012]
\[
v_{t,e}(\beta^j, \theta^j_k) = R_{l[t]}^*(\theta^j_k) S_t(\beta^j) Q_t(\theta^j_k) \hat{v}_{t,e}
\]
Identity shape

VS

DYNA
[Pons-Moll et al. 2015]
\[
v_{t,e}(\beta, \theta_k, \delta_k) = R_{l[t]}^*(\theta_k) T_t(\beta, \delta_k) Q_t(\theta_k) \hat{v}_{t,e}
\]
\[
= R_{l[t],k}^*(\theta_k)(S_t(\beta) + D_t(\delta_k)) Q_t(\theta_k) \hat{v}_{t,e}
\]
Identity shape + soft-tissue deformation
3. DYNA Model

2nd Order Autoregressive Model for $\delta$

Angular Velocity/ Acceleration of Pose
History of dynamic coefficients

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

Velocity/Acceleration of Root

Dynamic coefficients are a linear function:

$$\delta_k^j = \sum_{n=1}^{4} B_n^j \mathbf{x}_k[n] + \sum_{l=1}^{M} \text{diag}(\mathbf{a}_l) \delta_{k-l}^j + \mathbf{b}^j$$

velocity and accel. of limbs and root
Previous estimated dynamic coefficients
3. DYNA Model

Training

\[
\delta_k^j = \sum_{n=1}^{4} B_n^j x_k[n] + \sum_{l=1}^{M} \text{diag}(a_l)\delta_{k-l}^j + b^j
\]

\[
p^j = \{b^j, \{B_n^j\}_{n=1}^{4}, \{a_l^j\}_{l=1}^{M}\}
\]

\[
\delta_k^j \rightarrow g(\cdot) \rightarrow x_k = \{\theta_k, \theta_k, v_k, a_k, \delta_k-1, \delta_k-2\} \in \chi
\]

\[
\mathcal{R}_w(p^j; \mathcal{D}) = \sum_{i=1}^{N_{\text{subj}}} \sum_{k=1}^{|\mathcal{D}_i|} \frac{1}{|\mathcal{D}_i|} \| w_i (\delta_k^i - g_i(x_k^i; p^j)) \|^2
\]

weight to bias to subject specific data
Dyna Model Results
Dyna Model Results

“Stunt double” mode

Alignment
BlendSCAPE
Dyna
Dyna Model Results

Subject specific dynamics

Weights prop. to BMI affinity

\[ \hat{\delta}_k = \sum_j w^j \hat{\delta}^j \]

Training subjects

Test subject
Dyna Model Results

Contribution 4: Animator control

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

\[ T(\beta, \delta_k) = \mu_S + \sum_p \beta_p u_{S,p} + \mu_D + s \sum_p \delta_{k,p} u_{D,p} \]

Original
Exaggerated
Exaggeration unposed
Deformations depend on body shape

Increasing BMI and exaggeration

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
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
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 $\rightarrow$ 4cap $\rightarrow$ Raw 3D Scans $\rightarrow$ Mesh Alignment $\rightarrow$ Dynamic Shape Space $\rightarrow$ Mesh Aligned 3D Scans

Input parameters: $\{\theta_k, \delta_k, \beta_j\}$

{Pose, Soft-tissue deformation, shape}

Dynamics for PC 1, +/- 5 std $\rightarrow$ DYNA $\rightarrow$ Animation with soft-tissue deformations

SCAPE Shape Space + Pose Deformation Space
Dyna
Weight Editing

-30 Kg
Original
+30 Kg
\[ T(\beta, \delta_k) = \mu_D + \sum_p \delta_{k,p} u_{D,p} \]

Identity shape

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

Requires data
Minimal generalizability
Requires general design
Fast
Deals with missing data
Deals with uncertainty

Physical

Requires data
Generalizes well
Requires specific design
Slow
Missing data?
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