



Eurographics 2009

Interactive Shape Modeling and Deformation

T3: Half-Day Tutorial

Introduction, organization

Speakers

- **Olga Sorkine**

Media Research Lab, VLG

Courant Institute, New York University

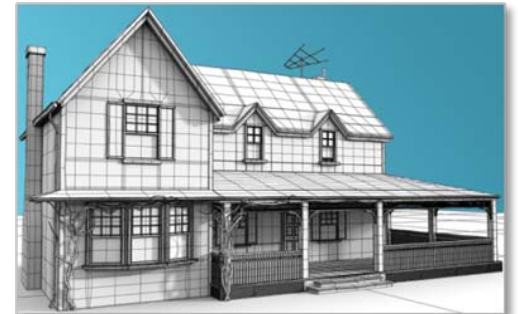
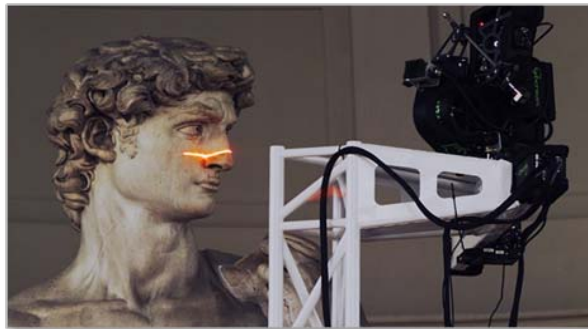
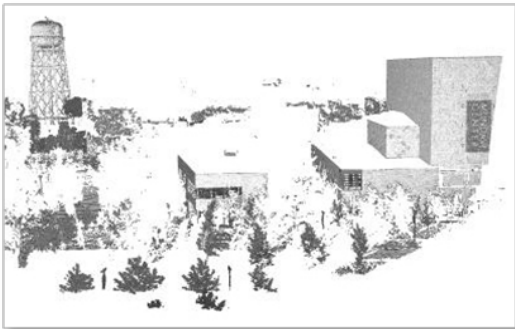
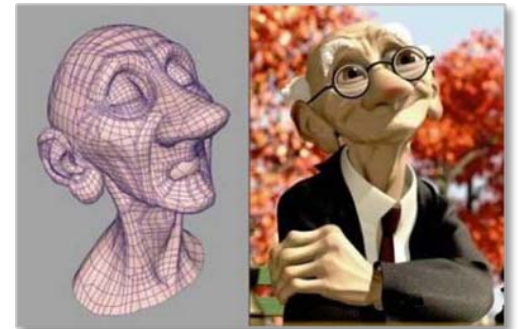
- **Mario Botsch**

Graphics & Geometry Group

Bielefeld University

Shapes and Deformations

- Manually modeled and scanned shape data
- Continuous and discrete shape representations



Shapes and Deformations

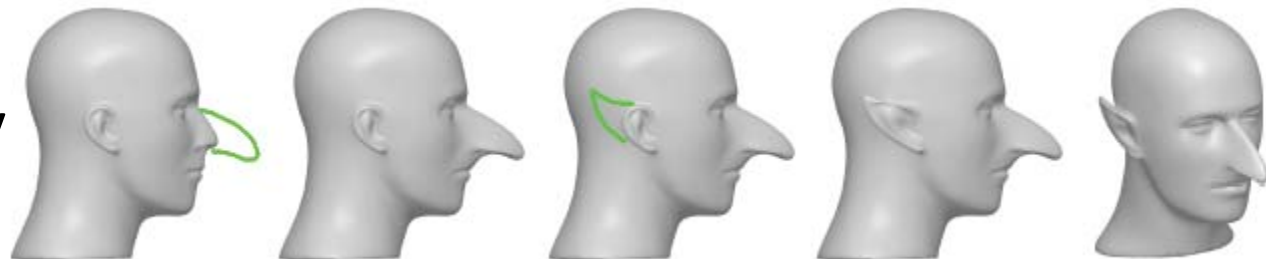
- Why deformations?

- Sculpting, customization
- Character posing, animation







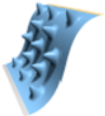



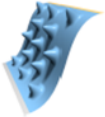



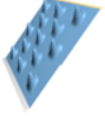



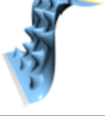



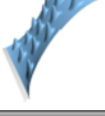



- Criteria?

- Intuitive behavior and interface
- Interactivity



Tutorial Goals

- Present recent research in shape editing
- Discuss practical considerations
 - Flexibility
 - Numerical issues
 - Admissible interfaces
- Comparison, tradeoffs

Approach	Pure Translation	120° bend	135° twist	70° bend
Original model				
Non-linear prism-based modeling [12]				
Thin shells [10] + deformation transfer [14]				
Gradient-based editing [68]				
Implicit Laplacian-based editing [56]				
Rotation invariant coordinates [40]				

Schedule

09:00 – 09:10	Intro (O)
09:10 – 09:25	Shape representations, differential geometry primer (O)
09:25 – 10:05	Linear surface-based deformations (M)
10:05 – 10:30	Linear space deformations (O)
10:30 – 11:00	Break

Schedule (cont'd)

11:00 – 11:10	Summary of linear methods (M)
11:10 – 11:40	Nonlinear surface-based deformations (M)
11:40 – 12:20	Nonlinear space deformations (O)
12:20 – 12:30	Wrap-up (O+M)



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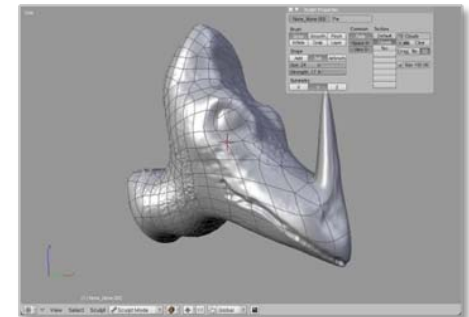
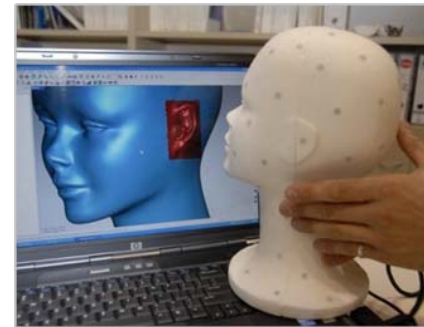
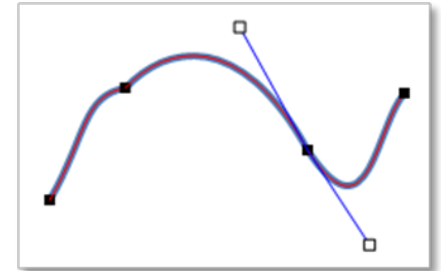
Interactive Shape Modeling and Deformation

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Shape Representations
Differential Geometry Recap

Continuous/analytical surfaces

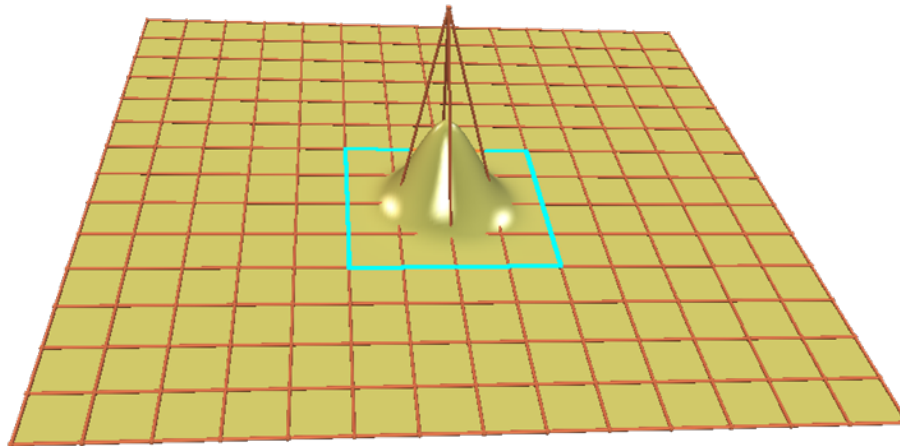
- Tensor product surfaces (e.g. NURBS)
- Subdivision surfaces
- “Editability” is inherent to the representation



Spline Surfaces

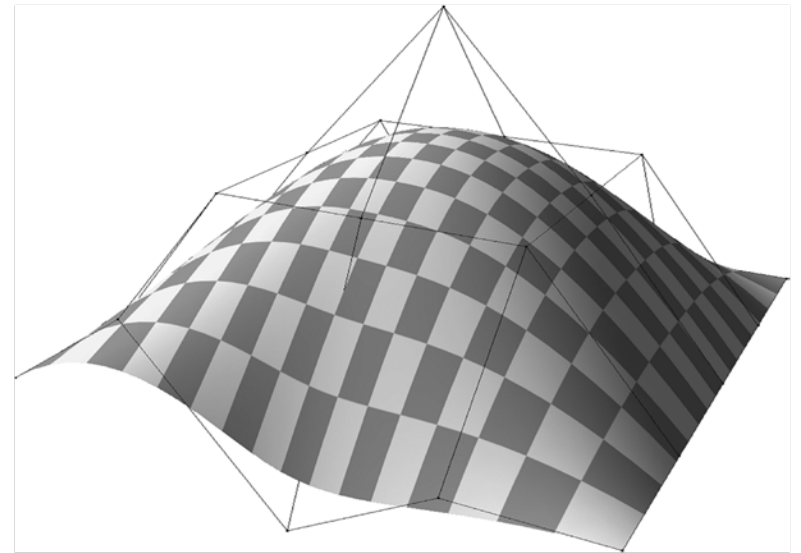
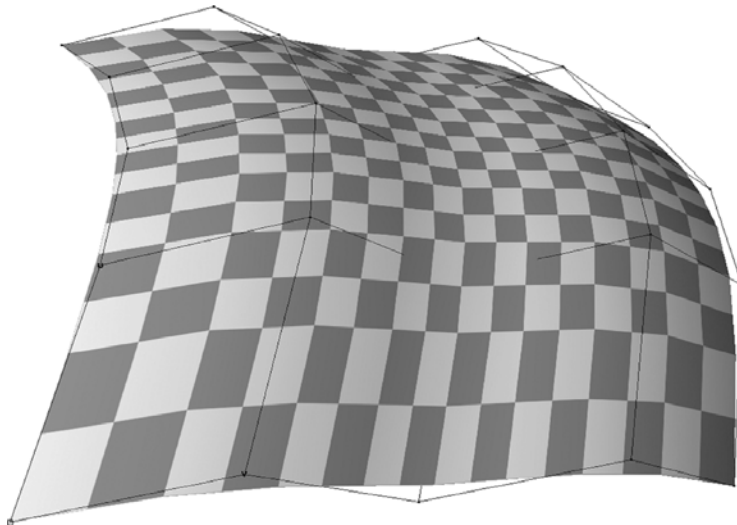
- Tensor product surfaces (“curves of curves”)
 - Rectangular grid of control points

$$\mathbf{p}(u, v) = \sum_{i=0}^k \sum_{j=0}^l \mathbf{p}_{ij} N_i^n(u) N_j^n(v)$$



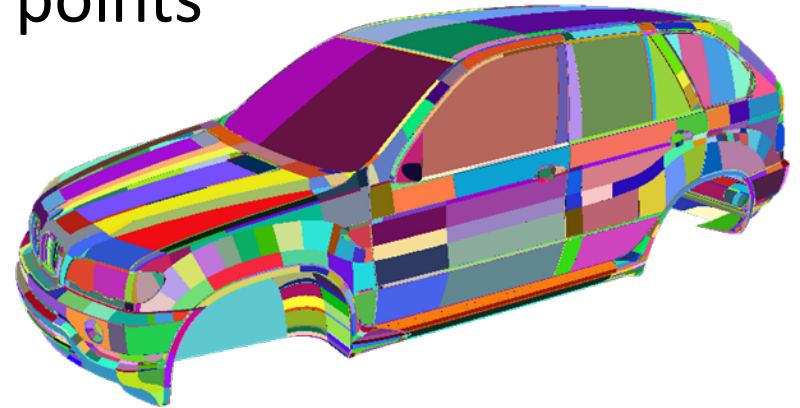
Spline Surfaces

- Tensor product surfaces (“curves of curves”)
 - Rectangular grid of control points
 - Rectangular surface patch



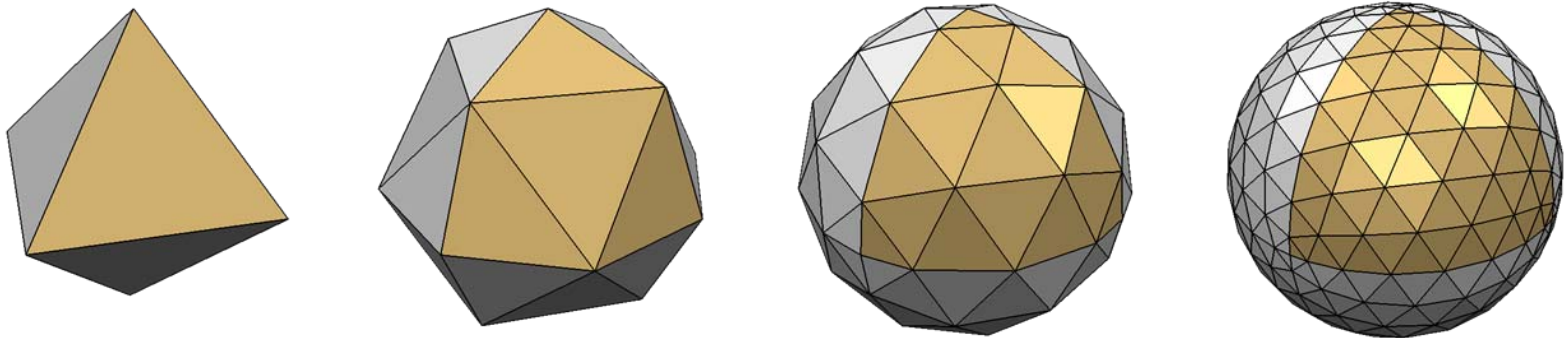
Spline Surfaces

- Tensor product surfaces (“curves of curves”)
 - Rectangular grid of control points
 - Rectangular surface patch
- Problems:
 - Many patches for complex models
 - Smoothness across patch boundaries
 - Trimming for non-rectangular patches



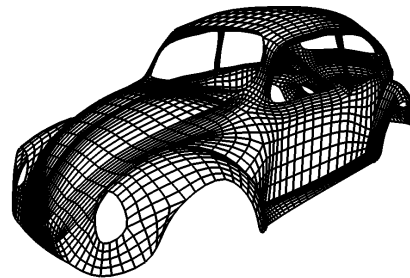
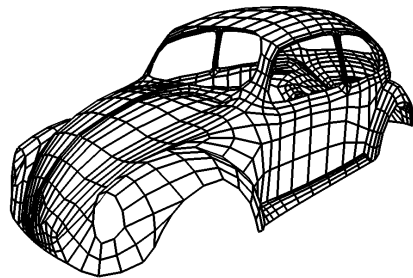
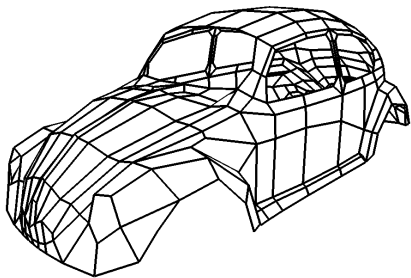
Subdivision Surfaces

- Generalization of spline curves / surfaces
 - Arbitrary control meshes
 - Successive refinement (subdivision)
 - Converges to smooth limit surface
 - Connection between splines and meshes



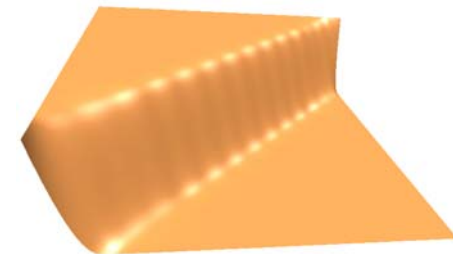
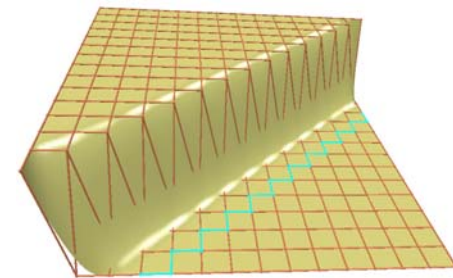
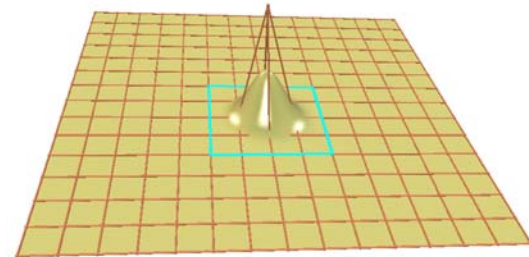
Subdivision Surfaces

- Generalization of spline curves / surfaces
 - Arbitrary control meshes
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 - Converges to smooth limit surface
 - Connection between splines and meshes



Spline & Subdivision Surfaces

- Basis functions are smooth bumps
 - Fixed support
 - Fixed control grid
- Bound to control points
 - Initial patch layout is crucial
 - Requires experts!
- Decouple deformation from surface representation!

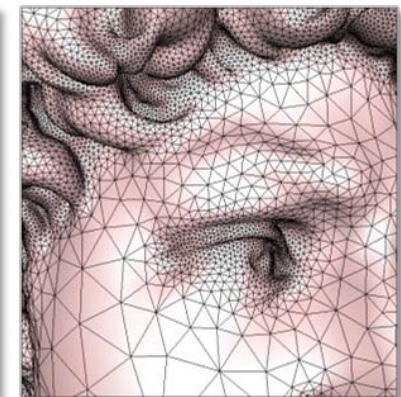
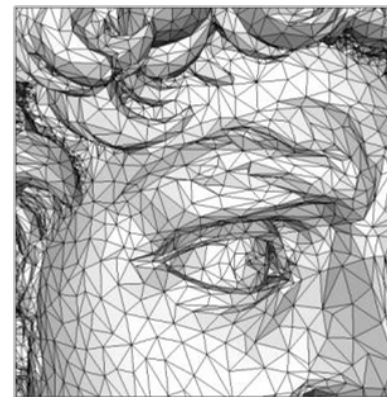
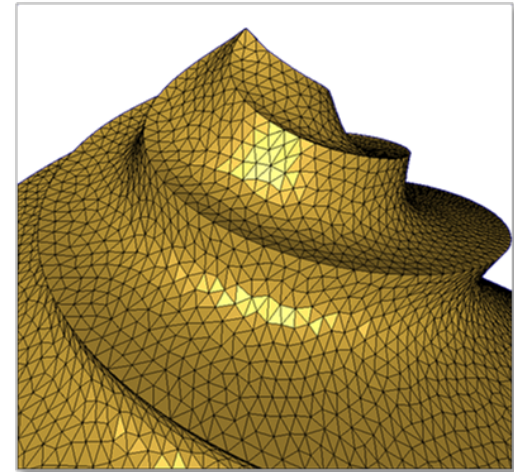


Discrete Surfaces: Point Sets, Meshes

- Flexible
- Suitable for highly detailed scanned data
- No analytic surface
- No inherent “editability”

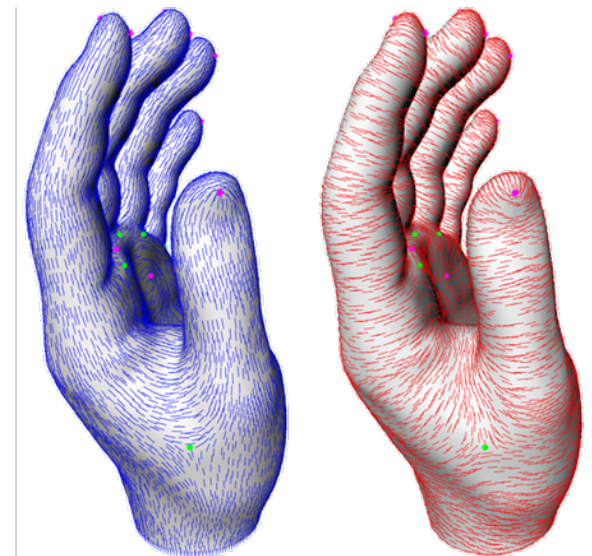
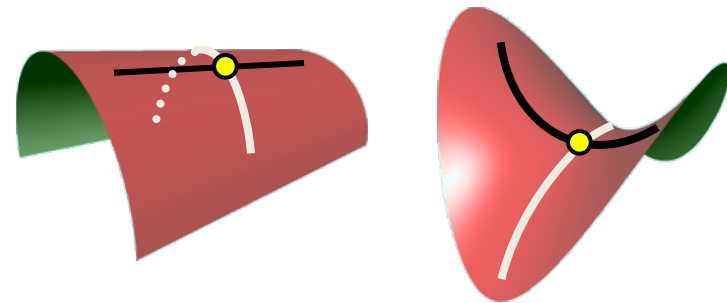


Mesh editing



Differential Geometry

- Tool to analyze shape
- Key notions:
 - Tangents and normals
 - Curvatures
 - Laplace-Beltrami operator



Continuous Case – Parametric

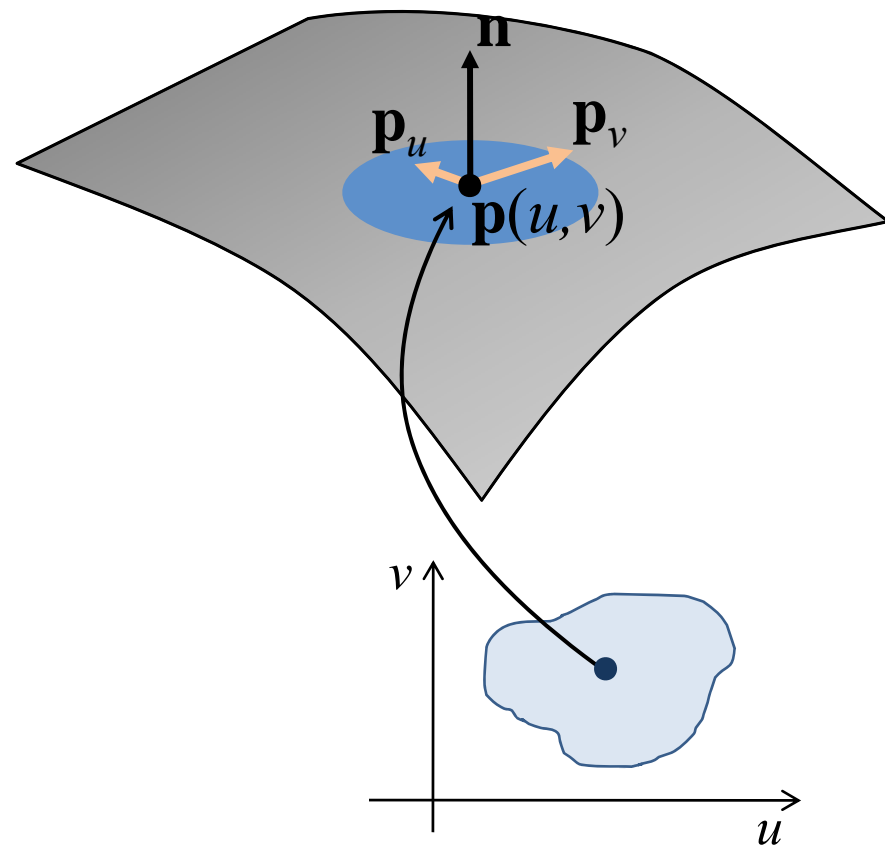
- Local parameterization:

$$\mathbf{p}(u, v) = \begin{pmatrix} x(u, v) \\ y(u, v) \\ z(u, v) \end{pmatrix}, \quad (u, v) \in D \subset \mathbb{R}^2$$

- Tangent plane at point $\mathbf{p}(u, v)$ is spanned by

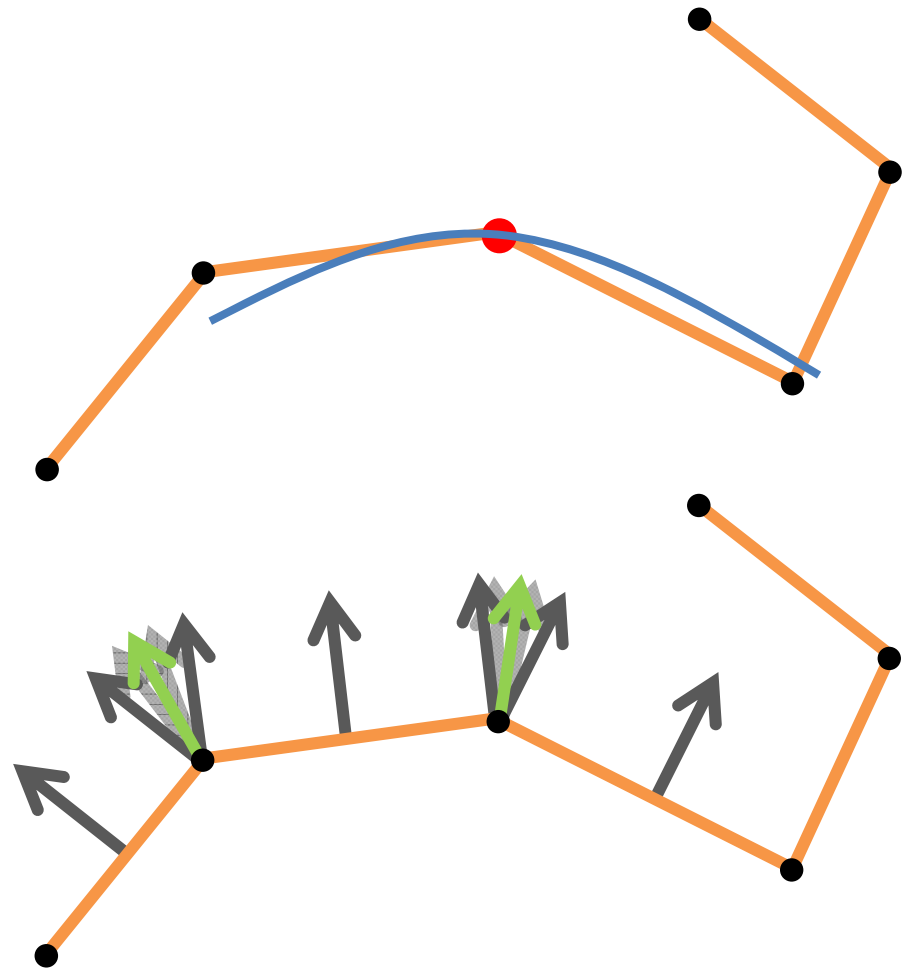
$$\mathbf{p}_u = \frac{\partial \mathbf{p}(u, v)}{\partial u}, \quad \mathbf{p}_v = \frac{\partial \mathbf{p}(u, v)}{\partial v}$$

- Normal: $\mathbf{n}(u, v) = \frac{\mathbf{p}_u \times \mathbf{p}_v}{\|\mathbf{p}_u \times \mathbf{p}_v\|}$

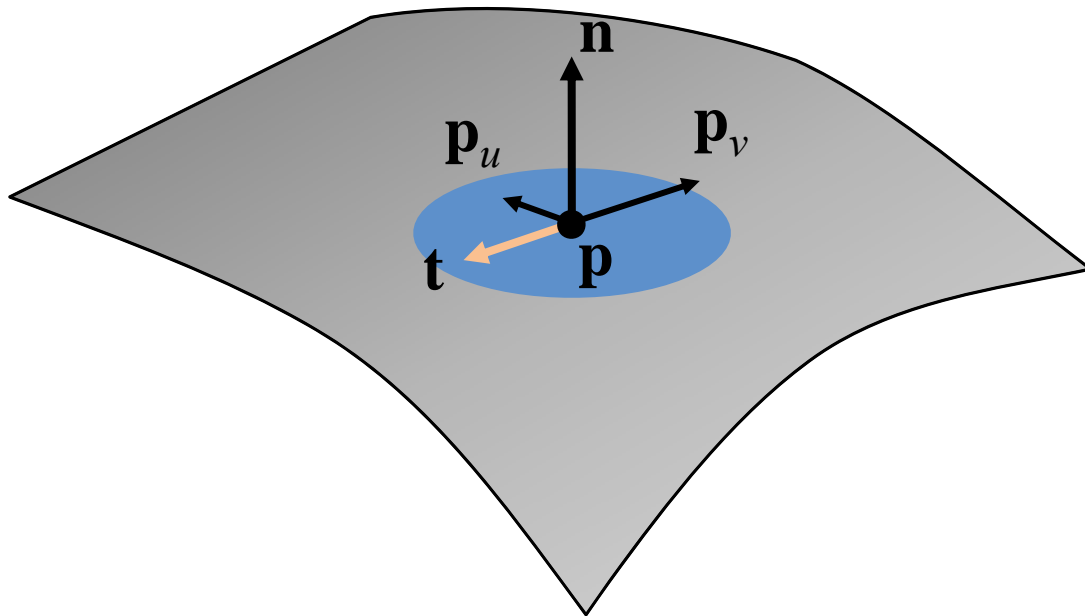


Discrete Case – Piecewise Linear

- No derivatives!
- Strategy 1: locally fit an analytic patch
 - Expensive
- Strategy 2: generalize definitions to discrete case
 - Fast
 - Start from intrinsic notions (non-parametric)



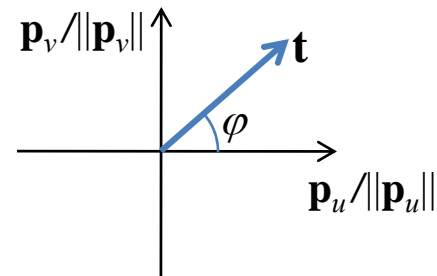
Normal Curvature



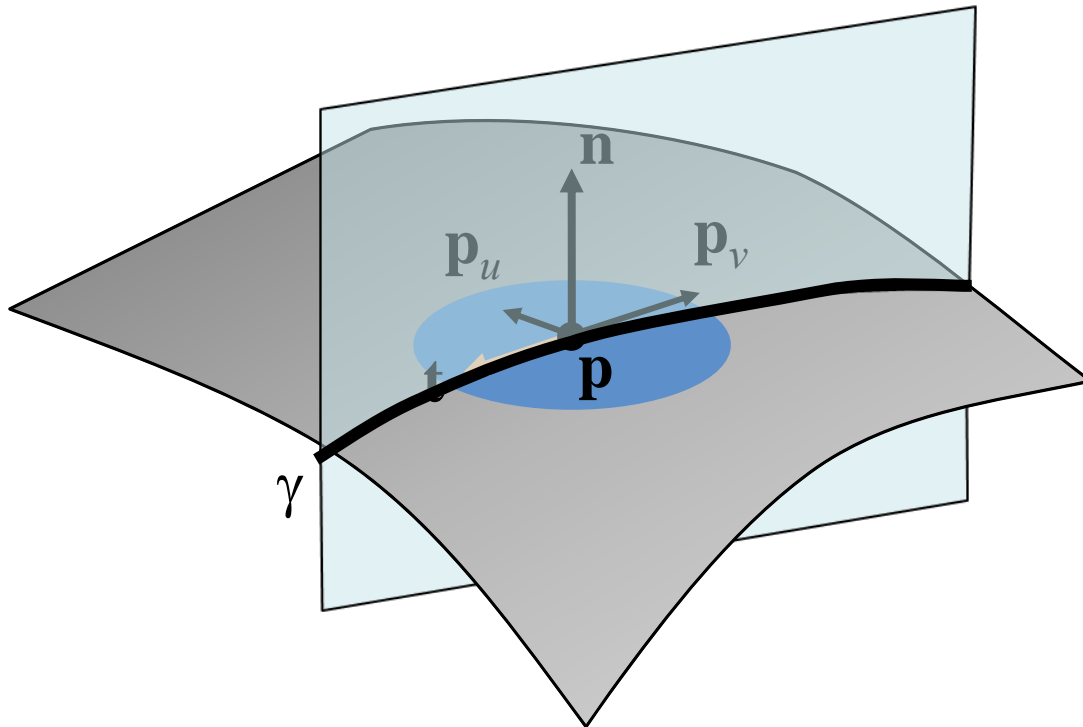
$$\mathbf{n} = \frac{\mathbf{p}_u \times \mathbf{p}_v}{\|\mathbf{p}_u \times \mathbf{p}_v\|}$$

Direction \mathbf{t} in the tangent plane:

$$\mathbf{t} = \cos \varphi \frac{\mathbf{p}_u}{\|\mathbf{p}_u\|} + \sin \varphi \frac{\mathbf{p}_v}{\|\mathbf{p}_v\|}$$



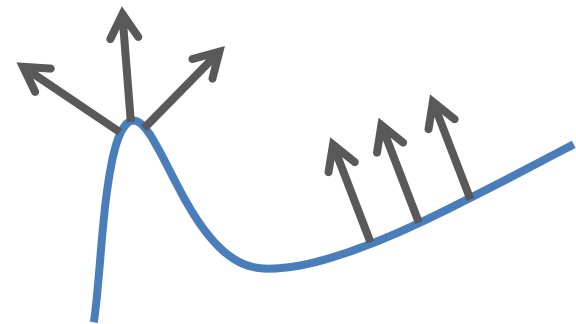
Normal Curvature



The curve γ is the intersection of the surface with the plane through \mathbf{n} and \mathbf{t} .

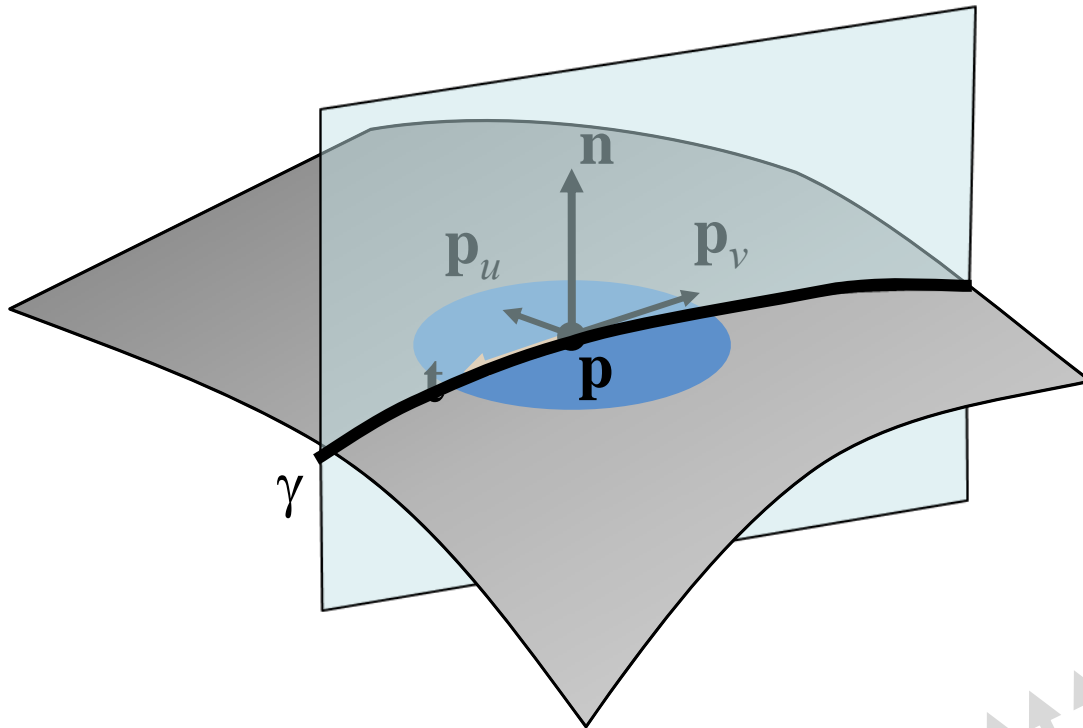
Normal curvature:

$$\kappa_n(\varphi) = \kappa(\gamma(\mathbf{p}))$$



Curvature on a curve: the rate of change in normal

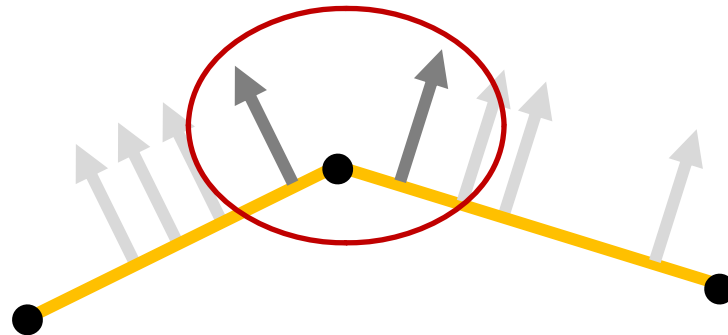
Normal Curvature



The curve γ is the intersection of the surface with the plane through \mathbf{n} and \mathbf{t} .

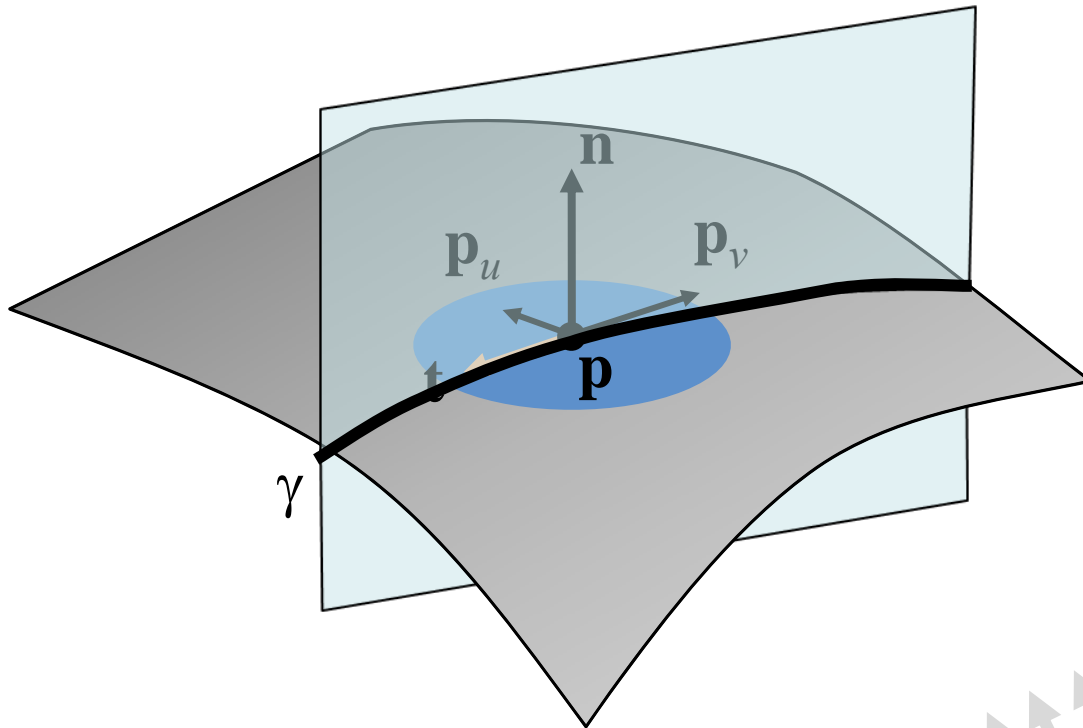
Normal curvature:

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Curvature on a curve: the rate of change in normal

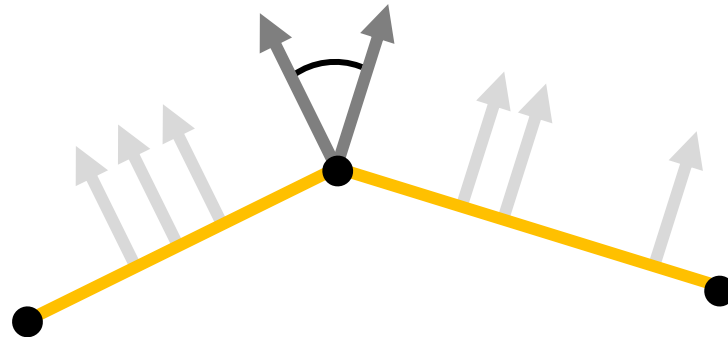
Normal Curvature



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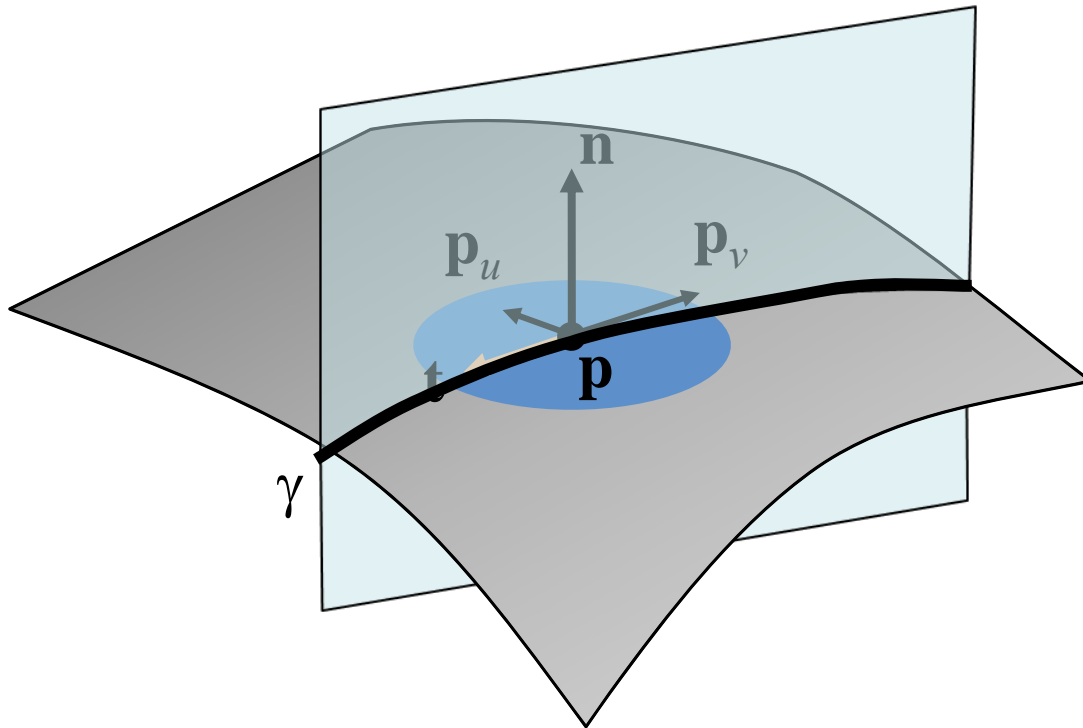
Normal curvature:

$$\kappa_n(\varphi) = \kappa(\gamma(\mathbf{p}))$$



Curvature on a curve: the rate of change in normal

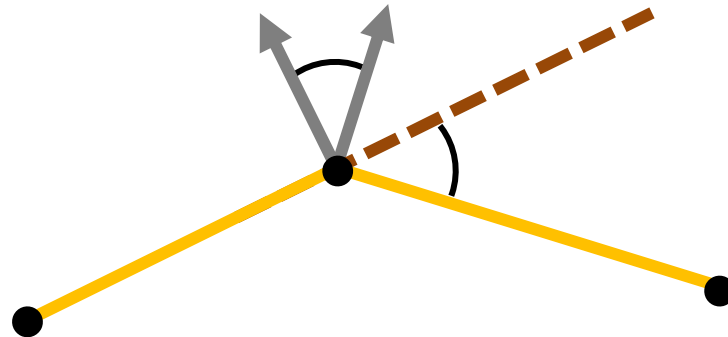
Normal Curvature



The curve γ is the intersection of the surface with the plane through \mathbf{n} and \mathbf{t} .

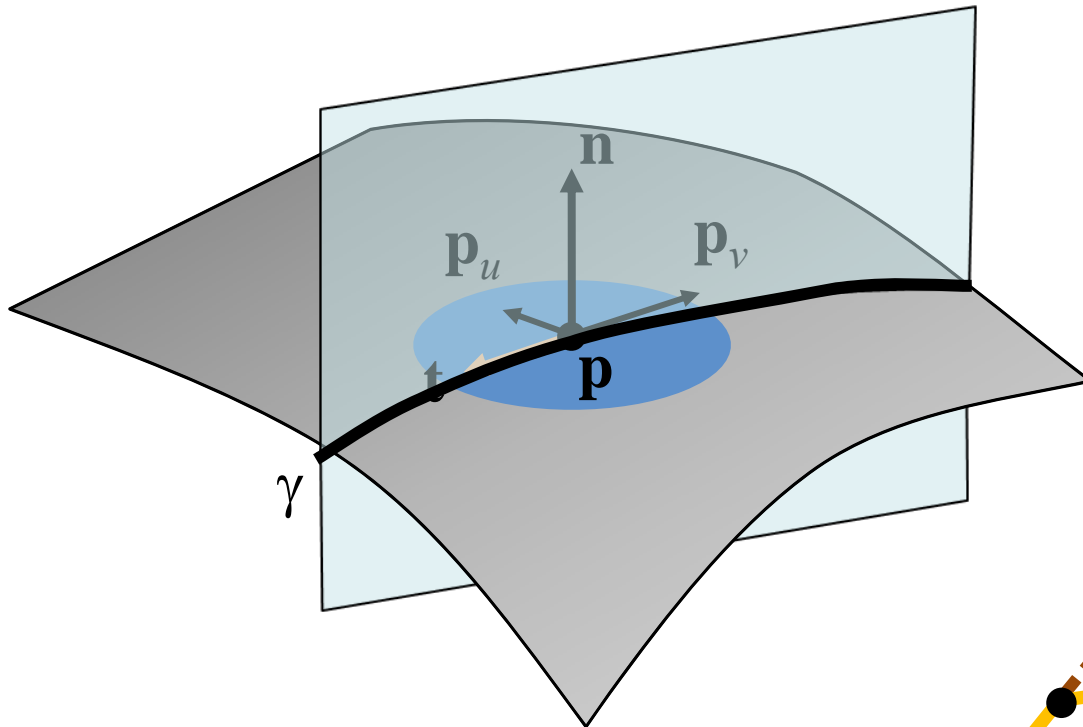
Normal curvature:

$$\kappa_n(\varphi) = \kappa(\gamma(\mathbf{p}))$$



Curvature on a curve: the rate of change in normal

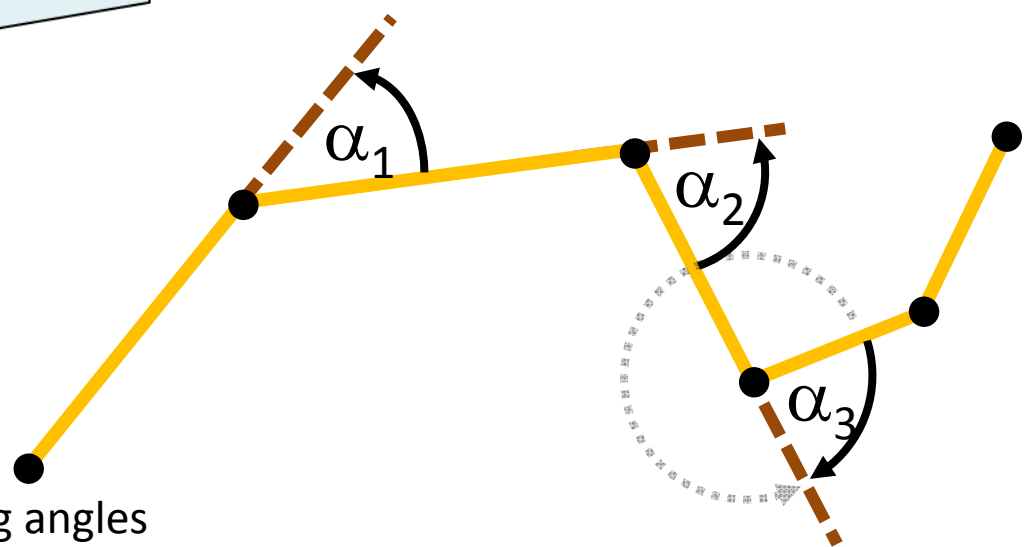
Normal Curvature



The curve γ is the intersection of the surface with the plane through n and t .

Normal curvature:

$$\kappa_n(\varphi) = \kappa(\gamma(p))$$



Discrete curvature: turning angles

Surface Curvatures

- Principal curvatures

- Maximal curvature $\kappa_1 = \kappa_{\max} = \max_{\varphi} \kappa_n(\varphi)$

- Minimal curvature $\kappa_2 = \kappa_{\min} = \min_{\varphi} \kappa_n(\varphi)$

- Mean curvature

$$H = \frac{\kappa_1 + \kappa_2}{2} = \frac{1}{2\pi} \int_0^{2\pi} \kappa_n(\varphi) d\varphi$$

- Gaussian curvature

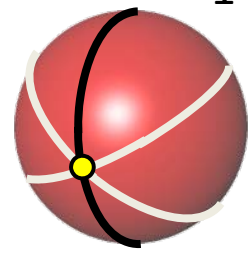
$$K = \kappa_1 \cdot \kappa_2$$

Classification

Local surface shape by curvatures

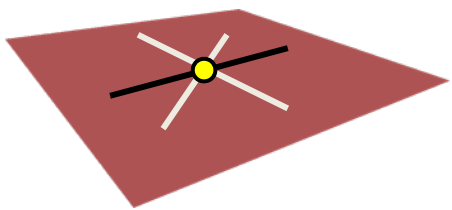
Isotropic:
all directions are
principal directions

$$K > 0, \kappa_1 = \kappa_2$$



spherical (umbilical)

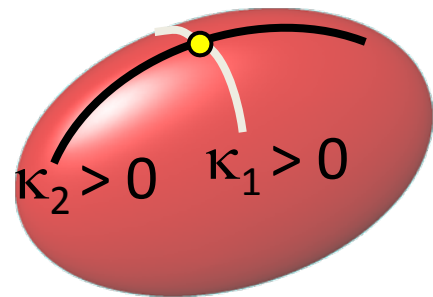
$$K = 0$$



planar

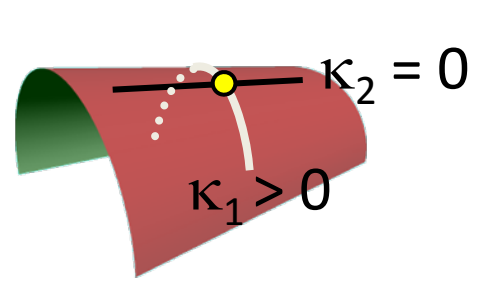
Anisotropic:
2 distinct principal
directions

$$K > 0$$



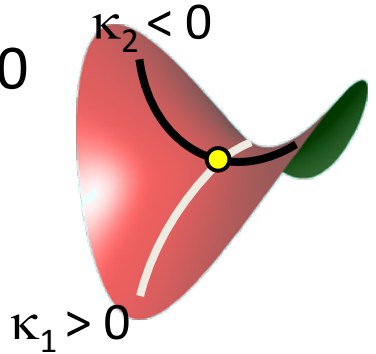
elliptic

$$K = 0$$



parabolic

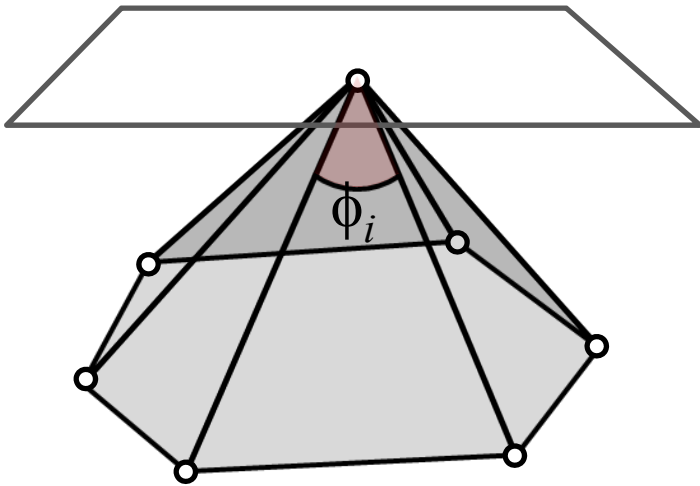
$$K < 0$$



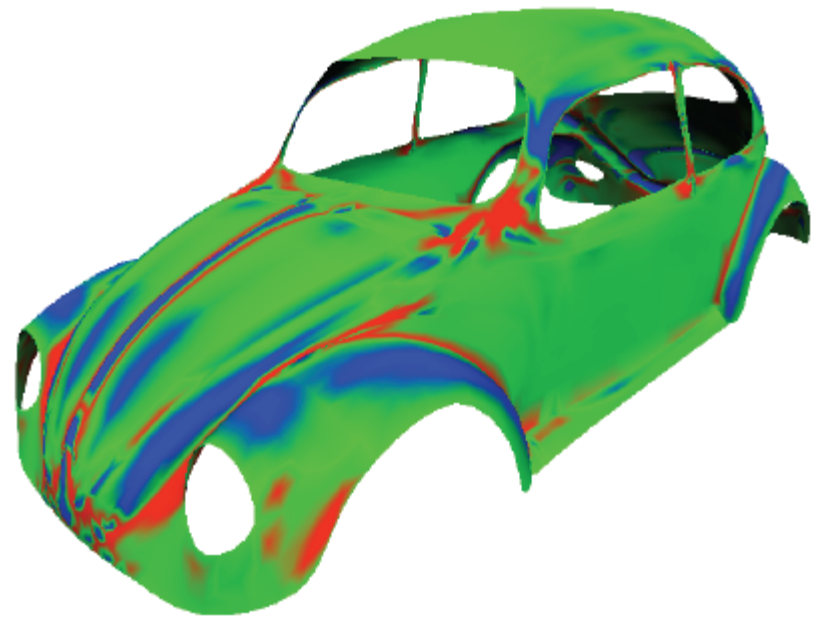
hyperbolic

Discrete Gaussian Curvature

- Angle deficit



$$K = 2\pi - \sum_{i=1}^{|N(\mathbf{v})|} \phi_i$$



Mean Curvature

$$H = \frac{1}{2\pi} \int_0^{2\pi} \kappa(\varphi) d\varphi$$

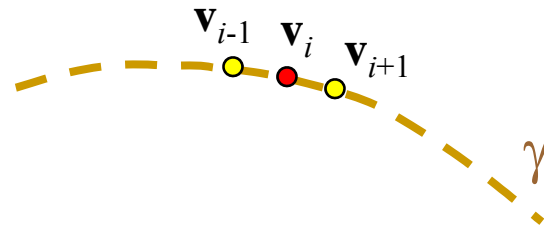
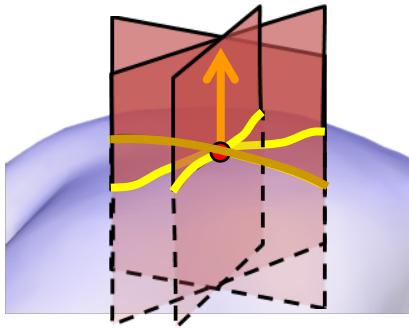
Can define through
the Laplace-Beltrami
operator

$$\Delta_M \mathbf{p} = -H\mathbf{n}$$



Discrete Mean Curvature

- Intuition:



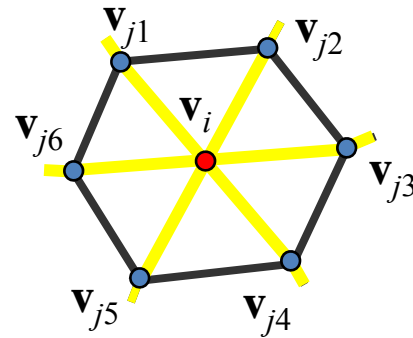
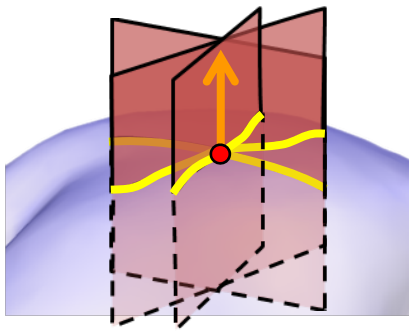
$$H = \frac{1}{2\pi} \int_0^{2\pi} \kappa(\varphi) d\varphi$$

$$\kappa \mathbf{n} = \gamma''$$

$$\gamma'' \approx \frac{1}{t} \left((\mathbf{v}_i - \mathbf{v}_{i-1}) - (\mathbf{v}_{i+1} - \mathbf{v}_i) \right) = -\frac{1}{t} (\mathbf{v}_{i-1} + \mathbf{v}_{i+1} - 2\mathbf{v}_i)$$

Discrete Laplace-Beltrami

- Intuition for uniform discretization

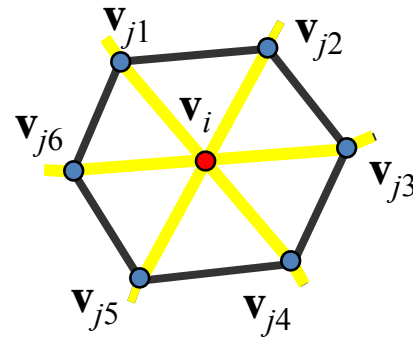
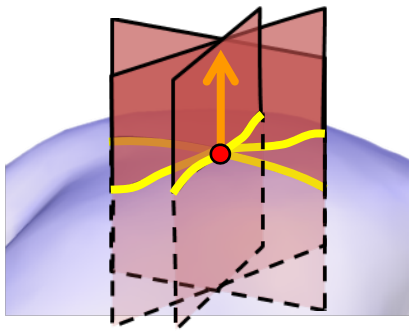


$$H = \frac{1}{2\pi} \int_0^{2\pi} \kappa(\varphi) d\varphi$$

$$\begin{aligned}
 & \mathbf{v}_{j1} + \mathbf{v}_{j4} - 2\mathbf{v}_i \quad + \\
 & \mathbf{v}_{j2} + \mathbf{v}_{j5} - 2\mathbf{v}_i \quad + \\
 & \mathbf{v}_{j3} + \mathbf{v}_{j6} - 2\mathbf{v}_i \quad = \\
 6L(\mathbf{v}_i) &= \sum_{k=1}^6 \mathbf{v}_{jk} - 6\mathbf{v}_i \approx -6H\mathbf{n}
 \end{aligned}$$

Discrete Laplace-Beltrami

- Intuition for uniform discretization



$$H = \frac{1}{2\pi} \int_0^{2\pi} \kappa(\varphi) d\varphi$$

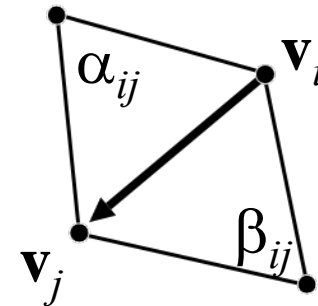
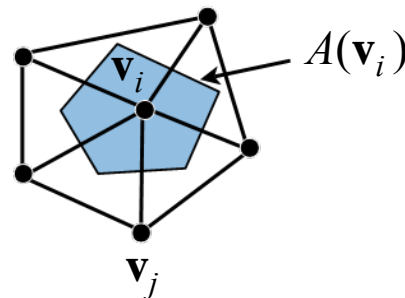
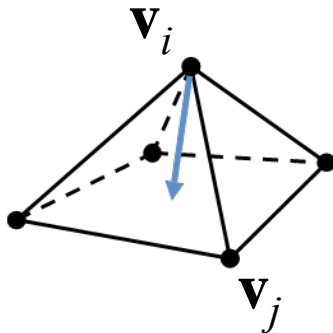
$$\begin{aligned} & \mathbf{v}_{j1} + \mathbf{v}_{j4} - 2\mathbf{v}_i \quad + \\ & \mathbf{v}_{j2} + \mathbf{v}_{j5} - 2\mathbf{v}_i \quad + \\ & \mathbf{v}_{j3} + \mathbf{v}_{j6} - 2\mathbf{v}_i \quad = \end{aligned}$$

$$L(\mathbf{v}_i) = \frac{1}{6} \left(\sum_{k=1}^6 \mathbf{v}_{jk} - 6\mathbf{v}_i \right) \approx -H\mathbf{n}$$

Discrete Laplace-Beltrami

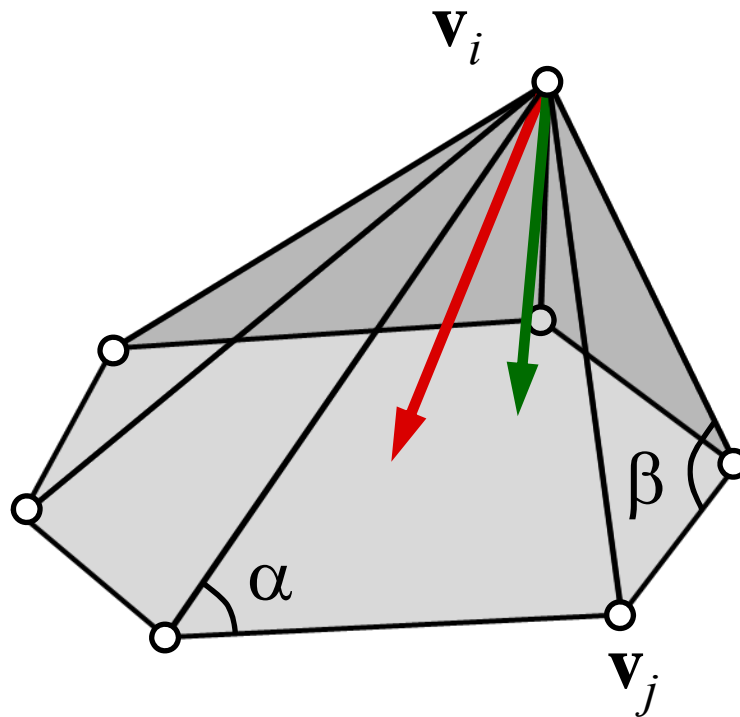
- Cotangent formula – to compensate for triangle shape irregularity

$$L_c(\mathbf{v}_i) = \frac{1}{2A(\mathbf{v}_i)} \sum_{\mathbf{v}_j \in N_1(\mathbf{v}_i)} (\cot \alpha_{ij} + \cot \beta_{ij})(\mathbf{v}_j - \mathbf{v}_i)$$



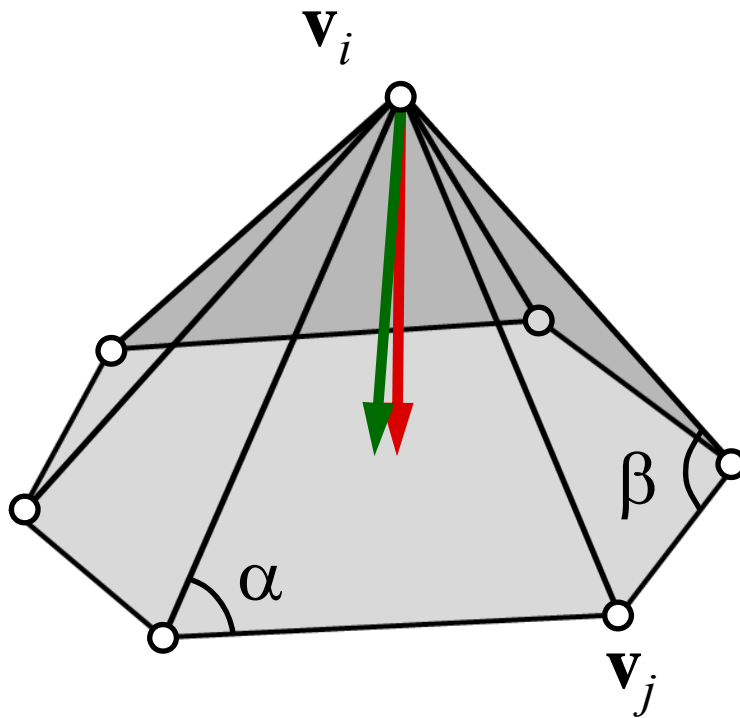
Discrete Laplace-Beltrami

- When the edge lengths are equal, the uniform and the cotangent Laplacians coincide



Discrete Laplace-Beltrami

- When the edge lengths are equal, the uniform and the cotangent Laplacians coincide

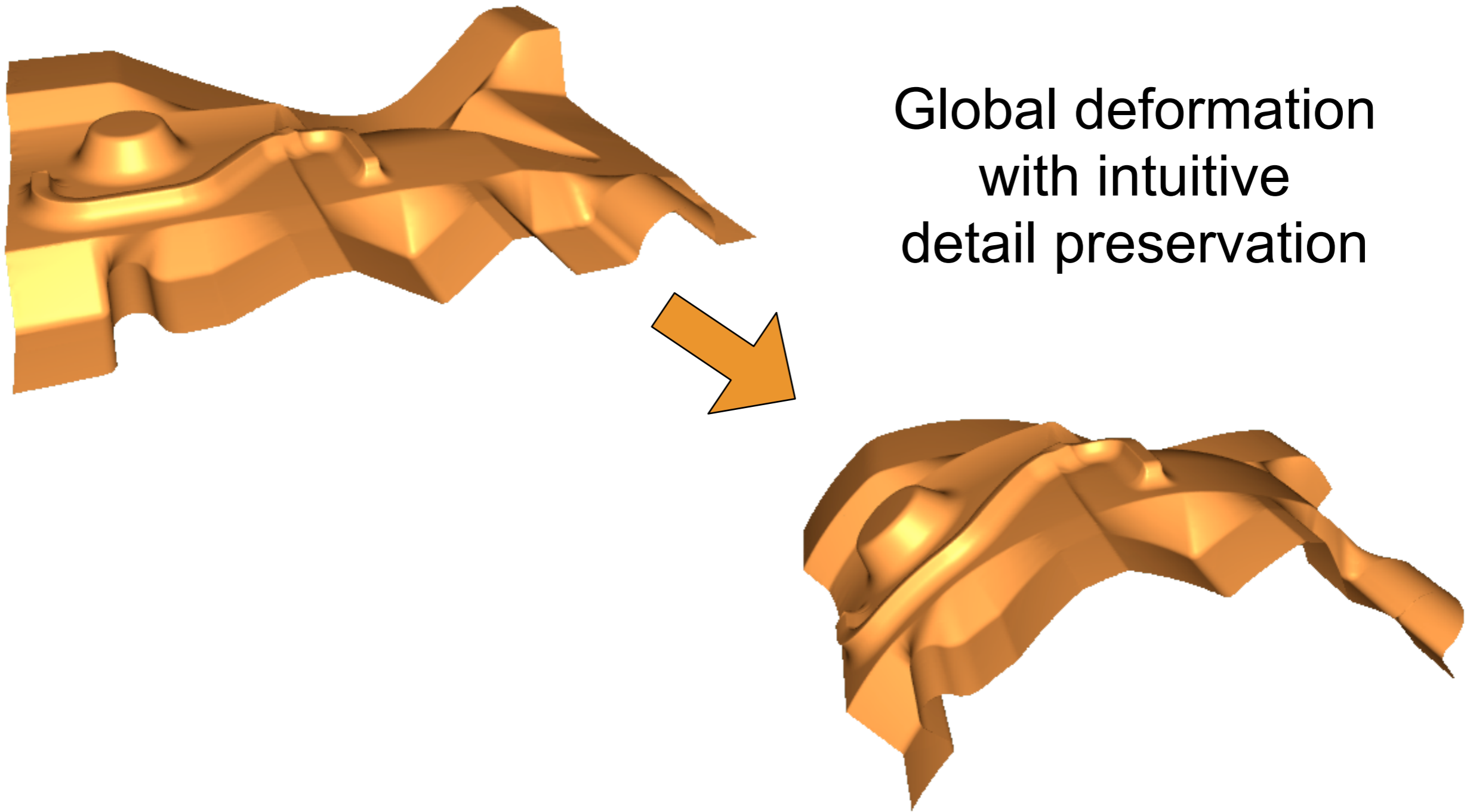


Linear Surface-Based Deformation

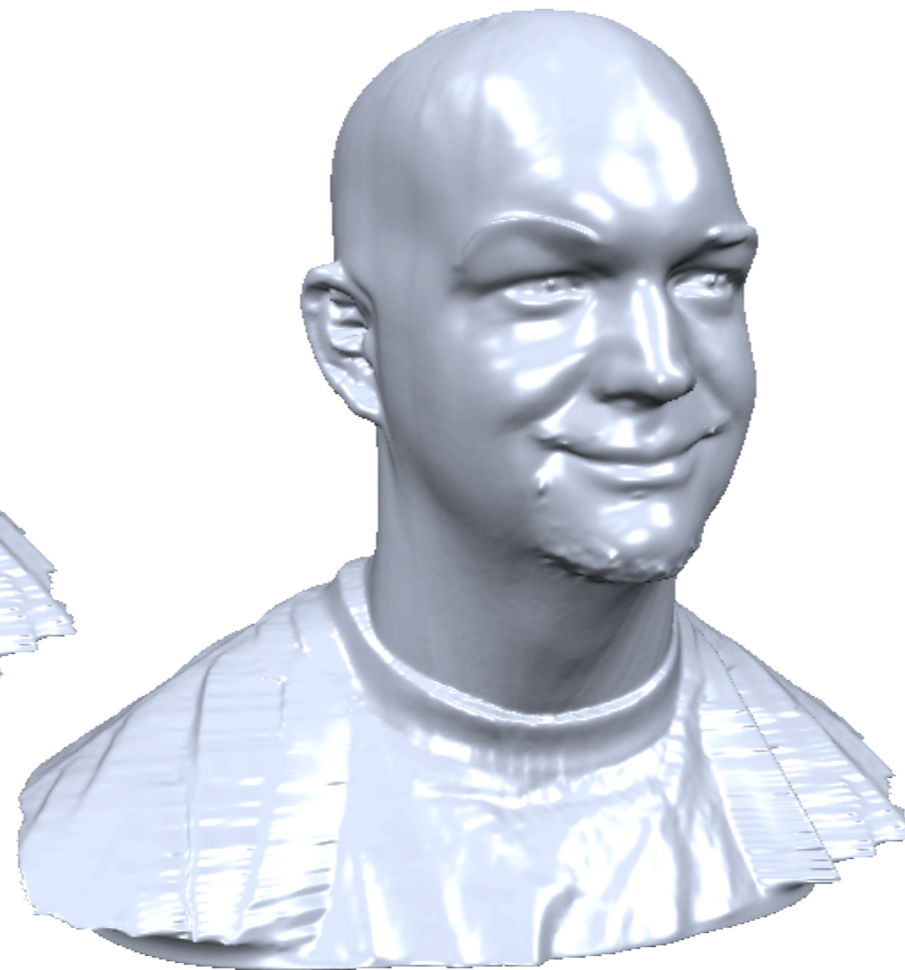
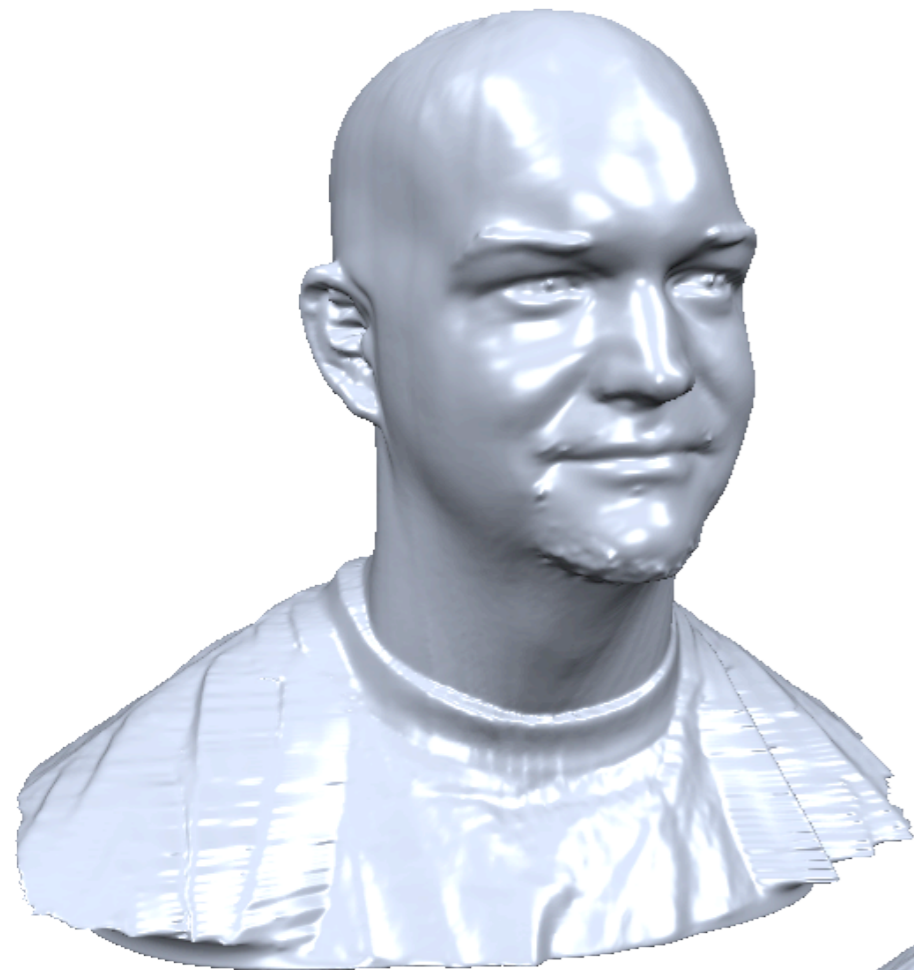
Prof. Dr. Mario Botsch

Computer Graphics & Geometry Processing
Bielefeld University

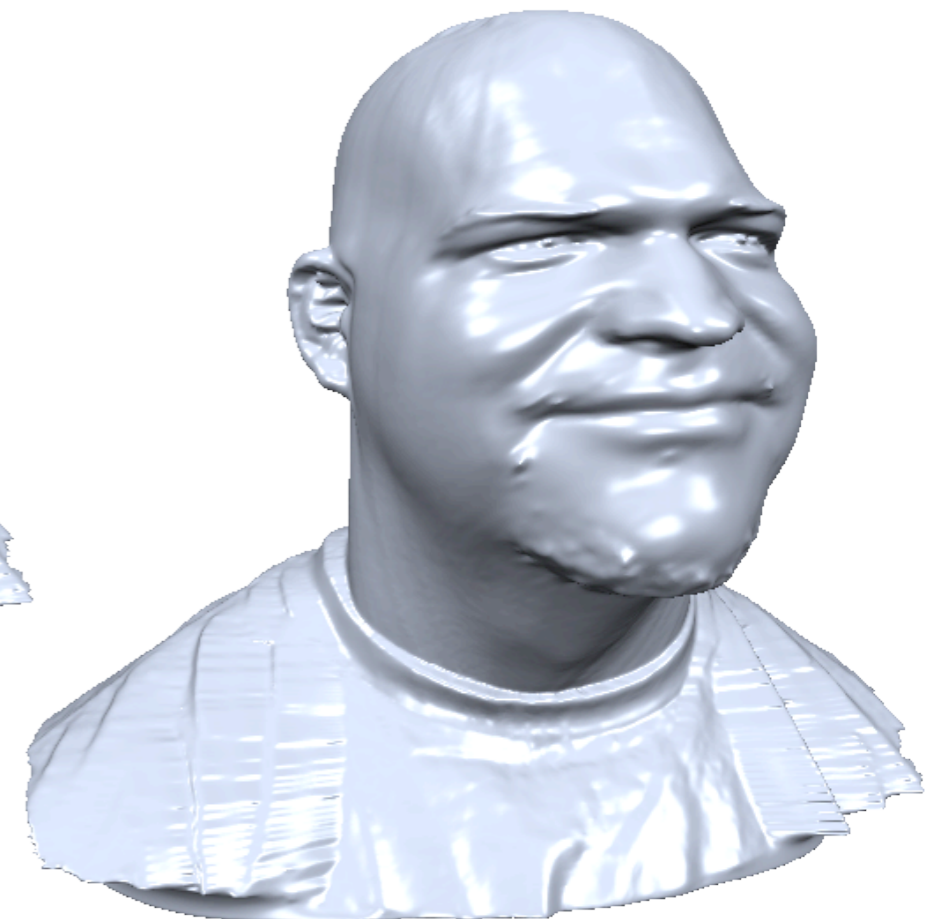
Mesh Deformation



Mesh Deformation



Local & global
deformations

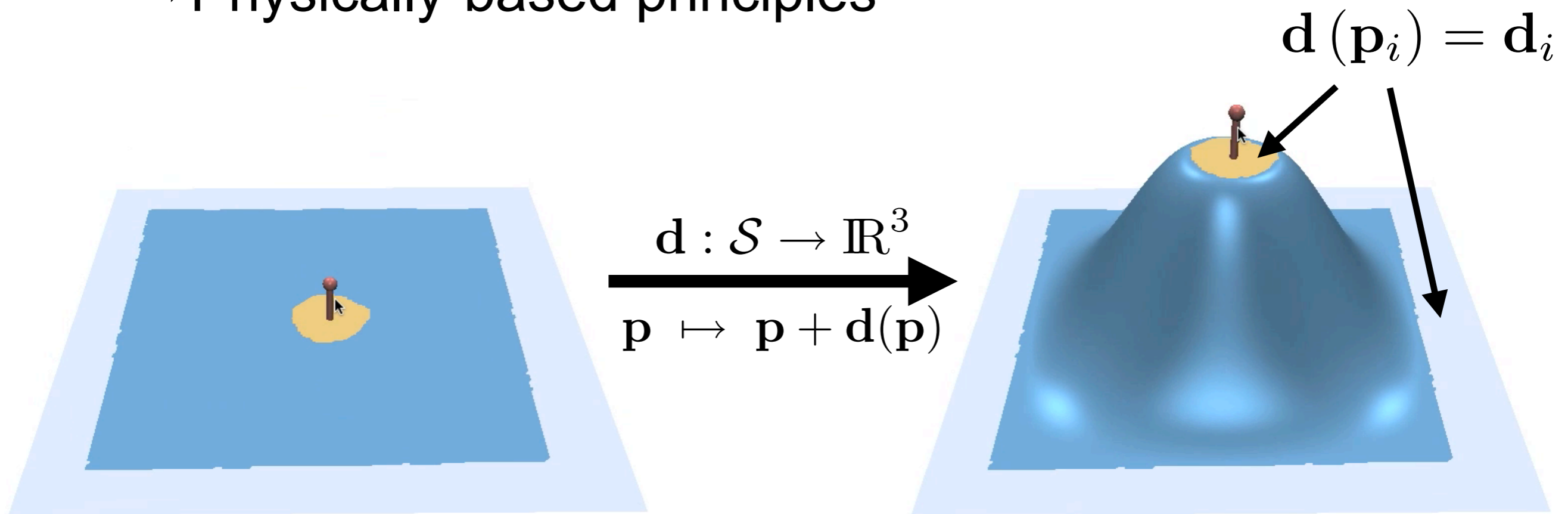


Linear Surface-Based Deformation

- **Shell-Based Deformation**
- Multiresolution Deformation
- Differential Coordinates

Modeling Metaphor

- Mesh deformation by displacement function \mathbf{d}
 - Interpolate prescribed constraints
 - Smooth, intuitive deformation
 - ➔ Physically-based principles



Shell Deformation Energy

- **Stretching**

- Change of local distances
- Captured by 1st fundamental form

$$\int_{\Omega} k_s \|\mathbf{I} - \bar{\mathbf{I}}\|^2$$

$$\mathbf{I} = \begin{bmatrix} \mathbf{x}_u^T \mathbf{x}_u & \mathbf{x}_u^T \mathbf{x}_v \\ \mathbf{x}_v^T \mathbf{x}_u & \mathbf{x}_v^T \mathbf{x}_v \end{bmatrix}$$

- **Bending**

- Change of local curvature
- Captured by 2nd fundamental form

$$\int_{\Omega} k_b \|\mathbf{II} - \bar{\mathbf{II}}\|^2$$

$$\mathbf{II} = \begin{bmatrix} \mathbf{x}_{uu}^T \mathbf{n} & \mathbf{x}_{uv}^T \mathbf{n} \\ \mathbf{x}_{vu}^T \mathbf{n} & \mathbf{x}_{vv}^T \mathbf{n} \end{bmatrix}$$

- **Stretching & bending is sufficient**

- Differential geometry: “1st and 2nd fundamental forms determine a surface up to rigid motion.”

Physically-Based Deformation

- Nonlinear stretching & bending energies

$$\int_{\Omega} k_s \underbrace{\|\mathbf{I} - \mathbf{I}'\|^2}_{\text{stretching}} + k_b \underbrace{\|\mathbf{II} - \mathbf{II}'\|^2}_{\text{bending}} \, dudv$$

- Linearize terms \rightarrow Quadratic energy

$$\int_{\Omega} k_s \underbrace{\left(\|\mathbf{d}_u\|^2 + \|\mathbf{d}_v\|^2 \right)}_{\text{stretching}} + k_b \underbrace{\left(\|\mathbf{d}_{uu}\|^2 + 2 \|\mathbf{d}_{uv}\|^2 + \|\mathbf{d}_{vv}\|^2 \right)}_{\text{bending}} \, dudv$$

Physically-Based Deformation

- Minimize linearized bending energy

$$E(\mathbf{d}) = \int_{\mathcal{S}} \|\mathbf{d}_{uu}\|^2 + 2 \|\mathbf{d}_{uv}\|^2 + \|\mathbf{d}_{vv}\|^2 \, dudv \rightarrow \min$$

$f(x) \rightarrow \min$

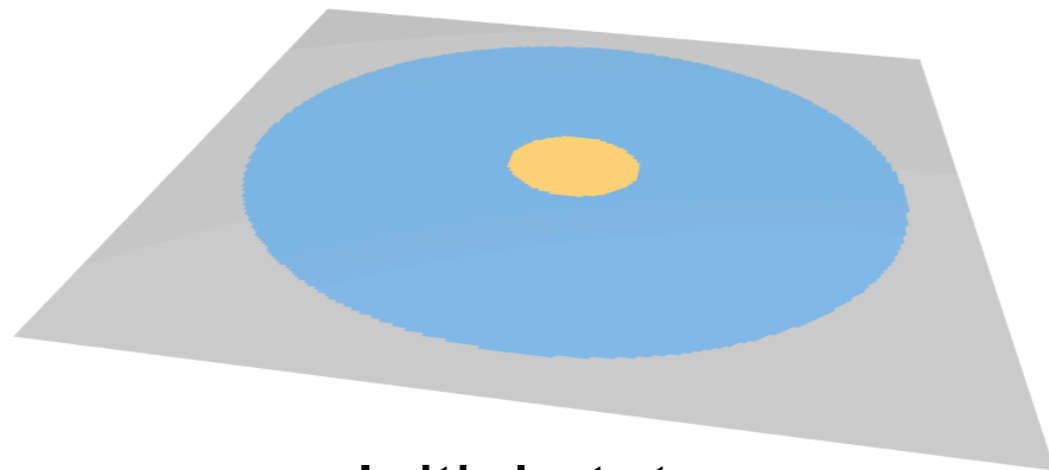
- Variational calculus \rightarrow Euler-Lagrange PDE

$$\Delta^2 \mathbf{d} := \mathbf{d}_{uuuu} + 2\mathbf{d}_{uuvv} + \mathbf{d}_{vvvv} = 0$$

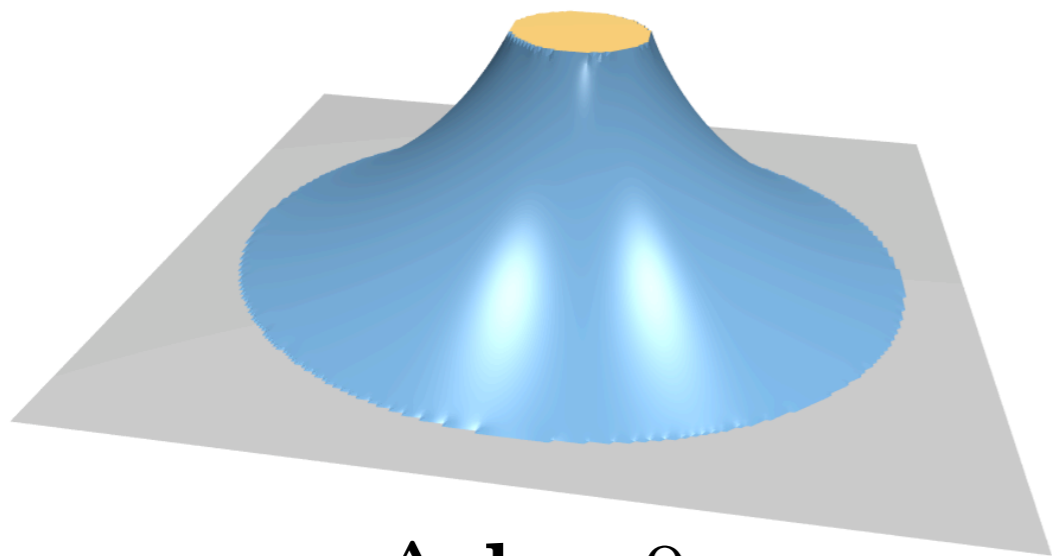
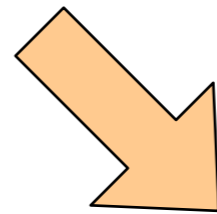
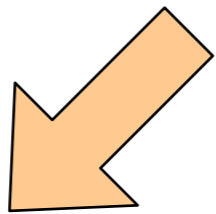
$f'(x) = 0$

\rightarrow “Best” deformation that satisfies constraints

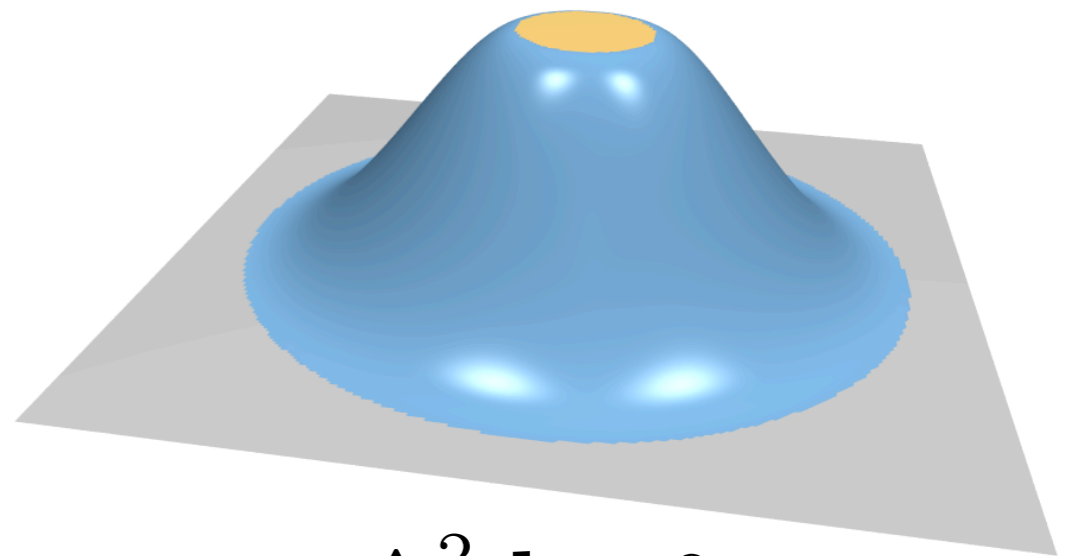
Deformation Energies



Initial state



$\Delta d = 0$
(Membrane)



$\Delta^2 d = 0$
(Thin plate)

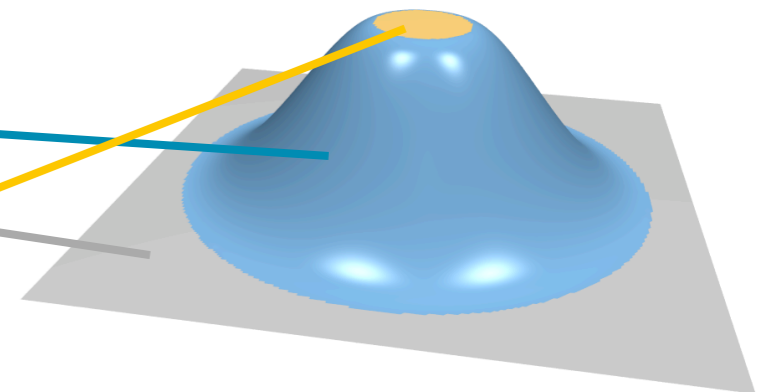
PDE Discretization

- Euler-Lagrange PDE

$$\Delta^2 \mathbf{d} = 0$$

$$\mathbf{d} = 0$$

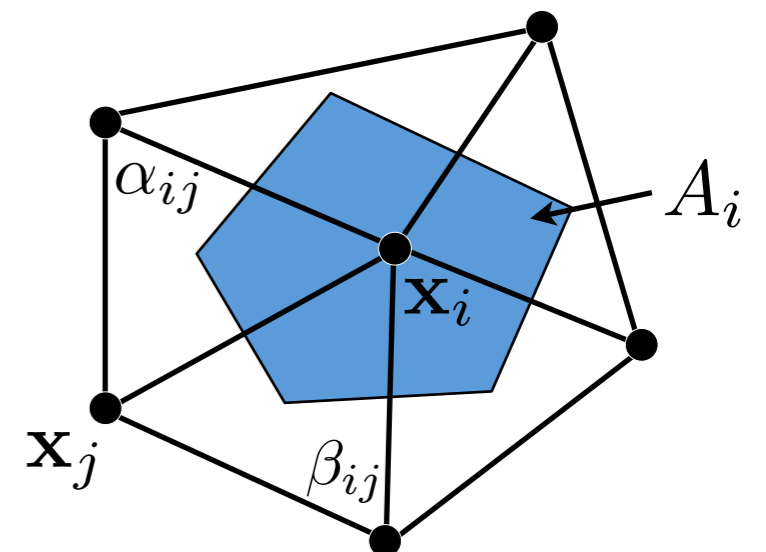
$$\mathbf{d} = \delta \mathbf{h}$$



- Laplace discretization

$$\Delta \mathbf{d}_i = \frac{1}{2A_i} \sum_{j \in \mathcal{N}_i} (\cot \alpha_{ij} + \cot \beta_{ij}) (\mathbf{d}_j - \mathbf{d}_i)$$

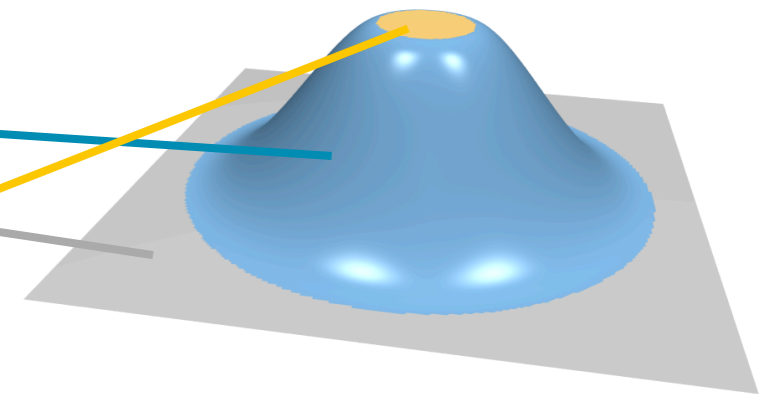
$$\Delta^2 \mathbf{d}_i = \Delta(\Delta \mathbf{d}_i)$$



Linear System

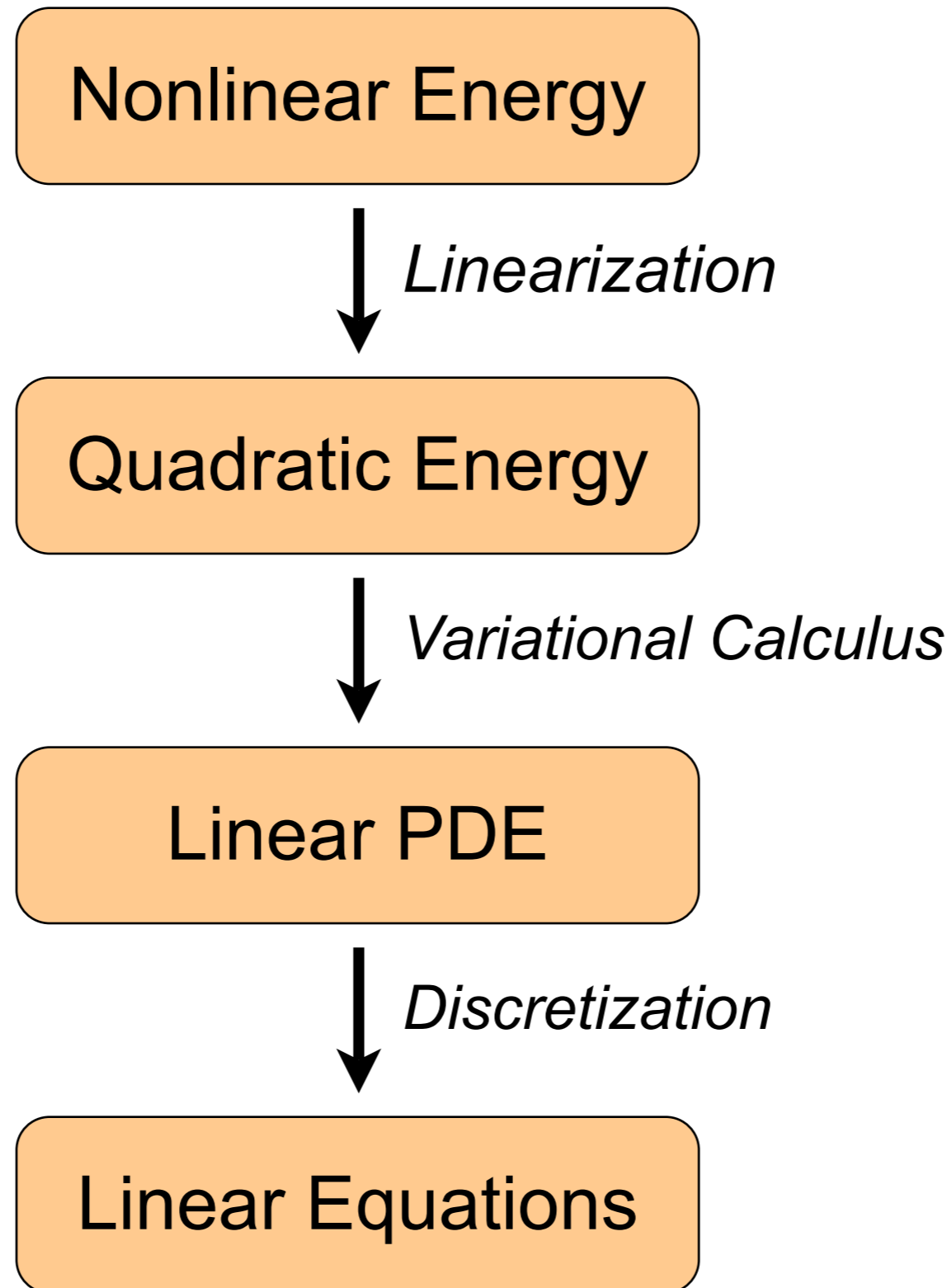
- Sparse linear system (19 nz/row)

$$\begin{pmatrix} & \Delta^2 & \\ \mathbf{0} & \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{I} \end{pmatrix} \begin{pmatrix} \vdots \\ \mathbf{d}_i \\ \vdots \end{pmatrix} = \begin{pmatrix} \mathbf{0} \\ \mathbf{0} \\ \delta \mathbf{h}_i \end{pmatrix}$$

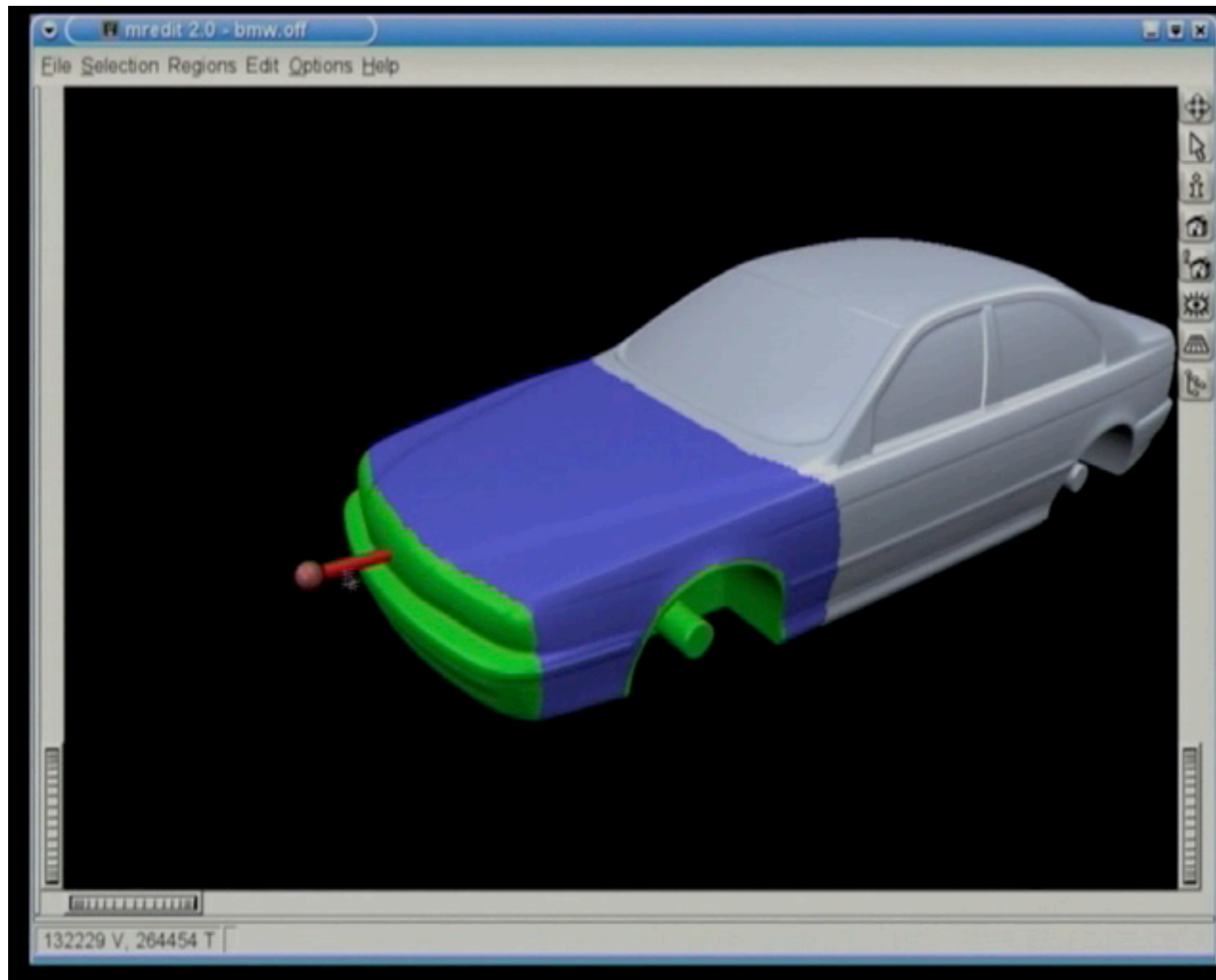


- Turn into symmetric positive definite system
- Solve this system *each frame*
 - Use efficient linear solvers !!!
 - Sparse Cholesky factorization
 - **See course notes for details**

Derivation Steps

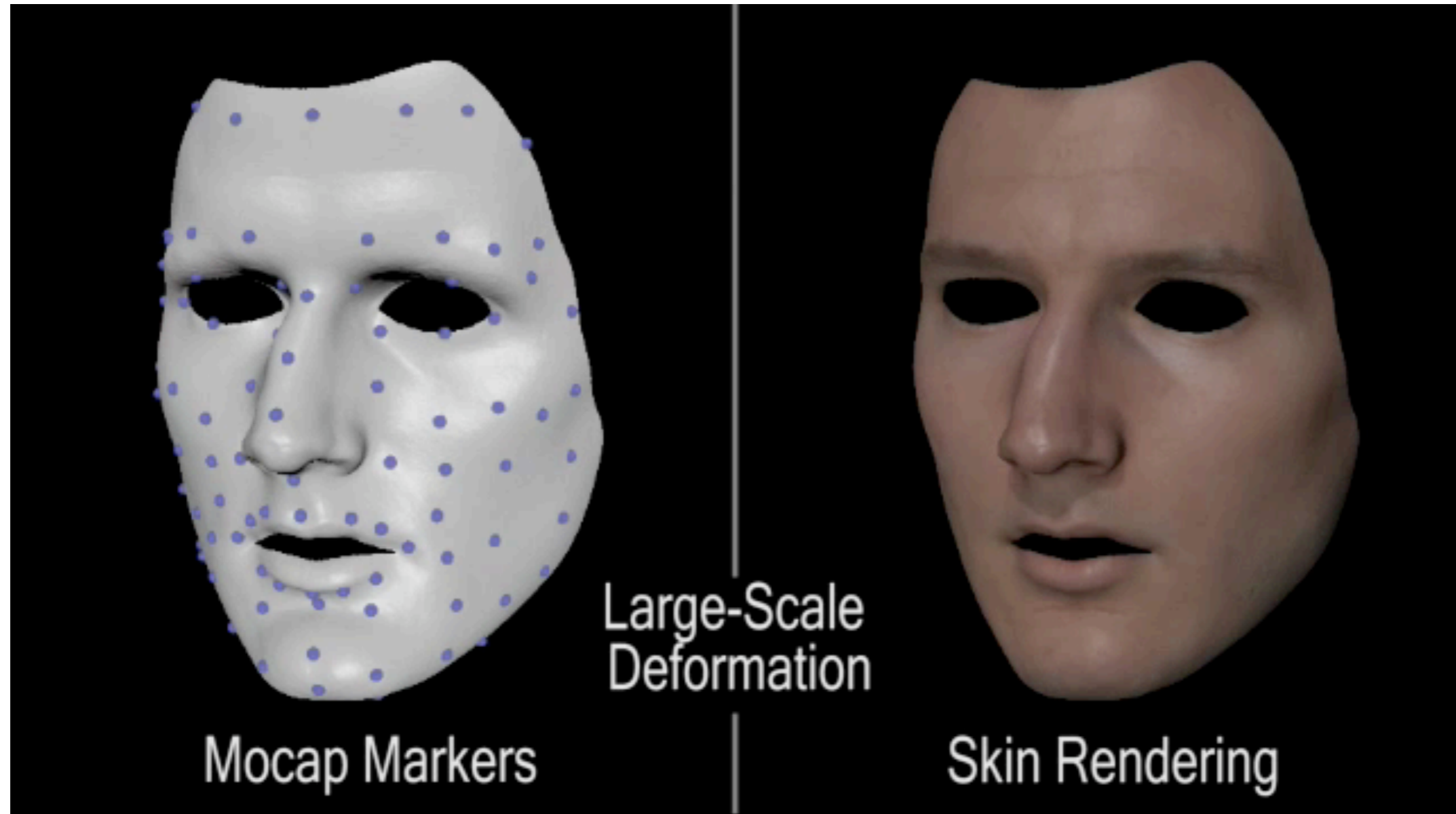


CAD-Like Deformation



[Botsch & Kobbelt, SIGGRAPH 04]

Face Animation



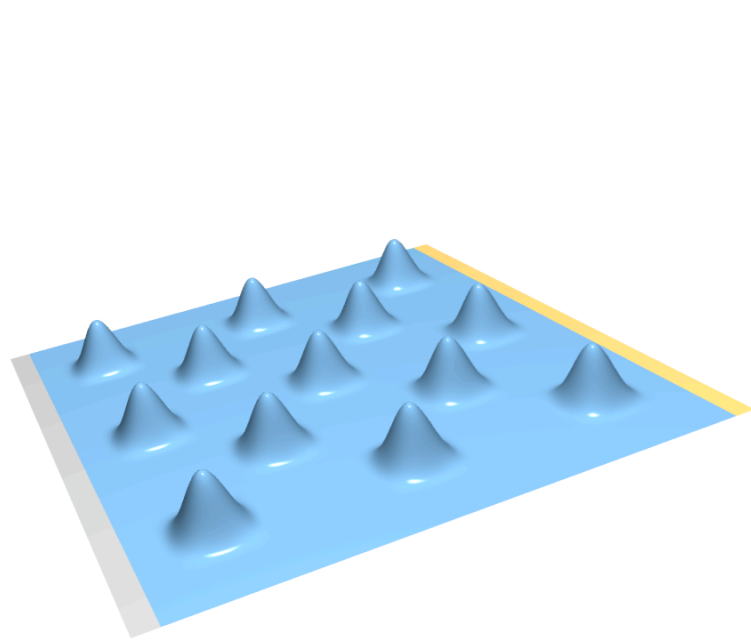
[Bickel et al, SCA 08]

Linear Surface-Based Deformation

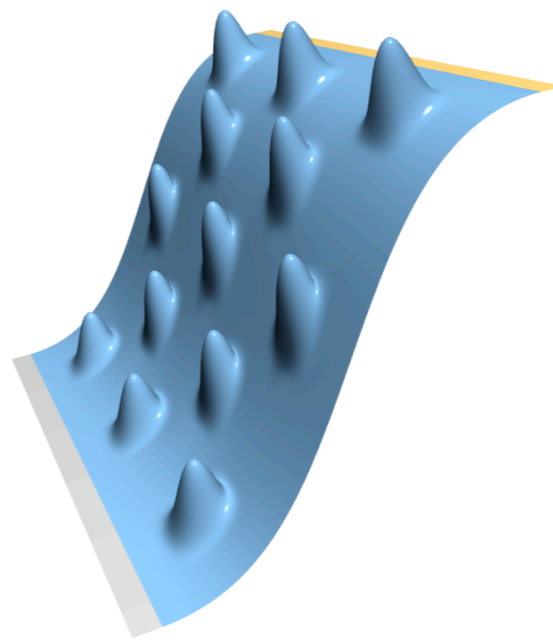
- Shell-Based Deformation
- **Multiresolution Deformation**
- Differential Coordinates

Multiresolution Modeling

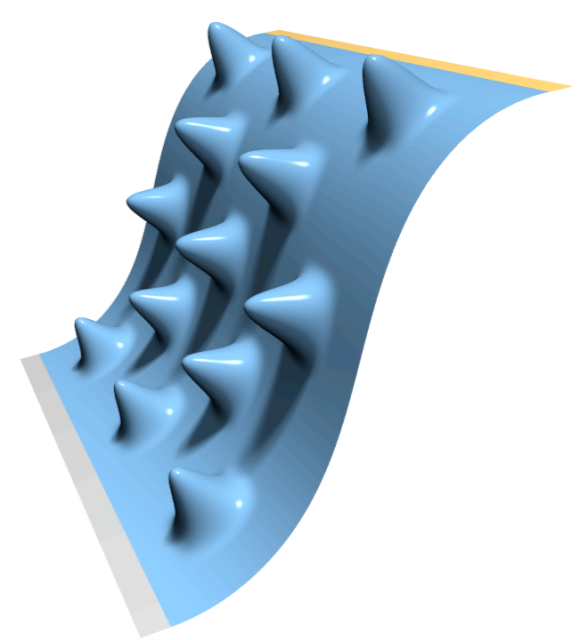
- Even pure translations induce local rotations!
 - ➔ Inherently non-linear coupling
- Alternative approach
 - Linear deformation + multi-scale decomposition...



Original

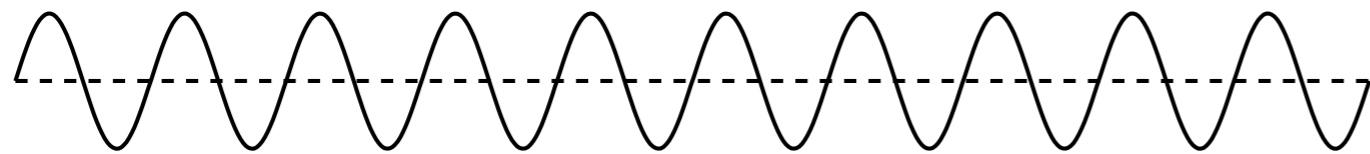


Linear



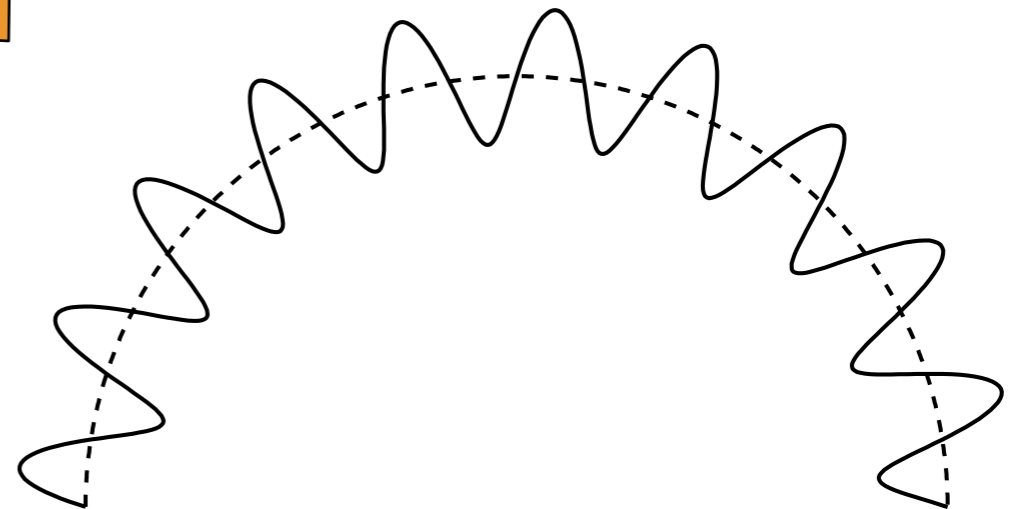
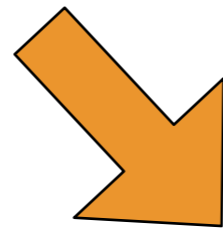
Nonlinear

Multiresolution Editing



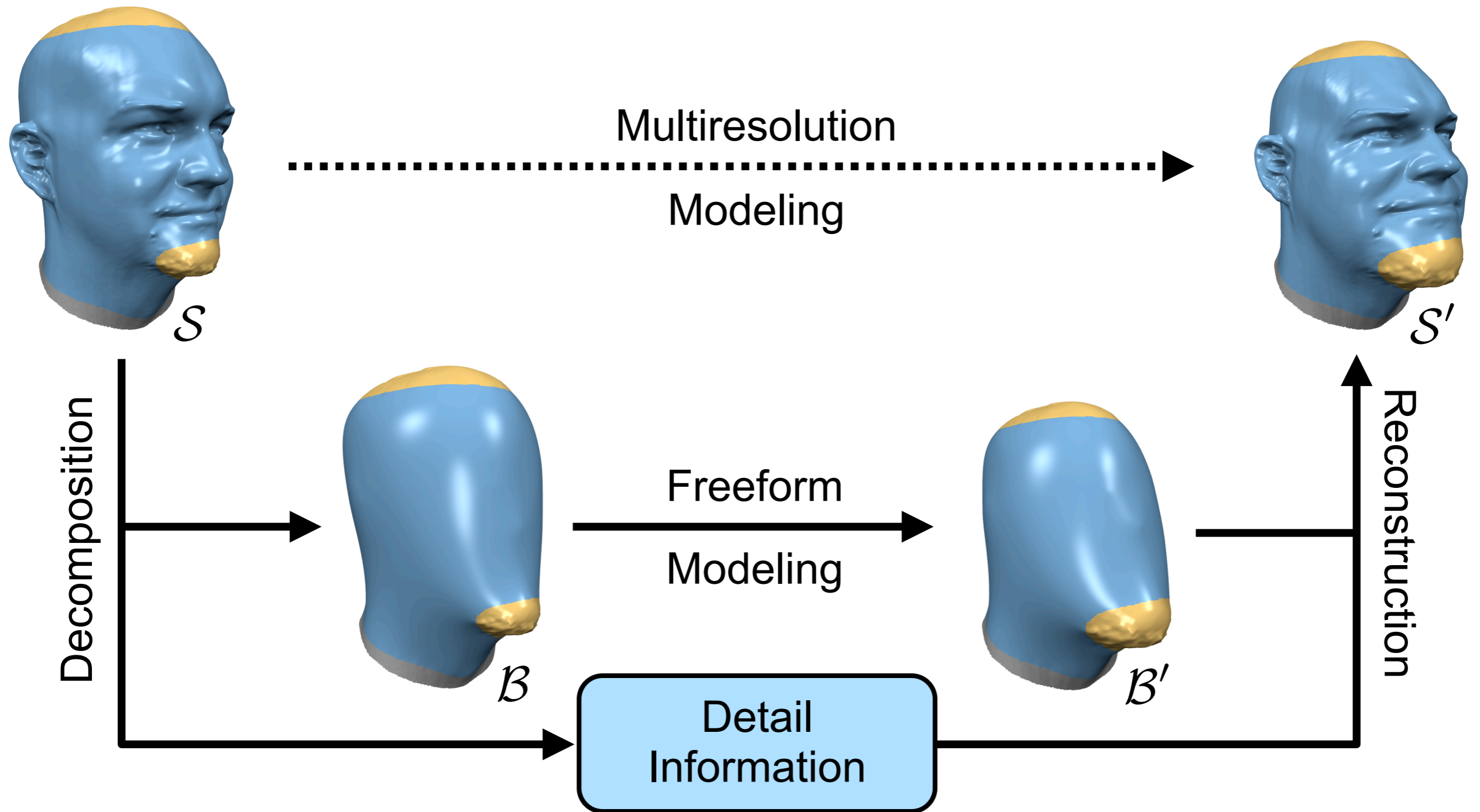
Frequency decomposition

Change low
frequencies

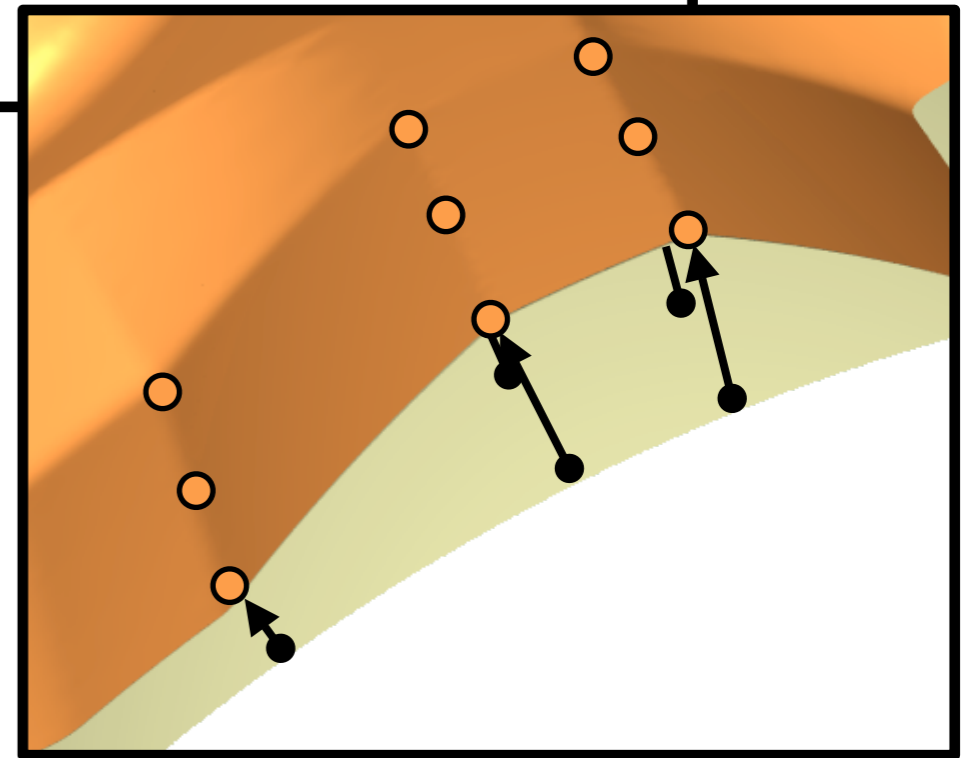
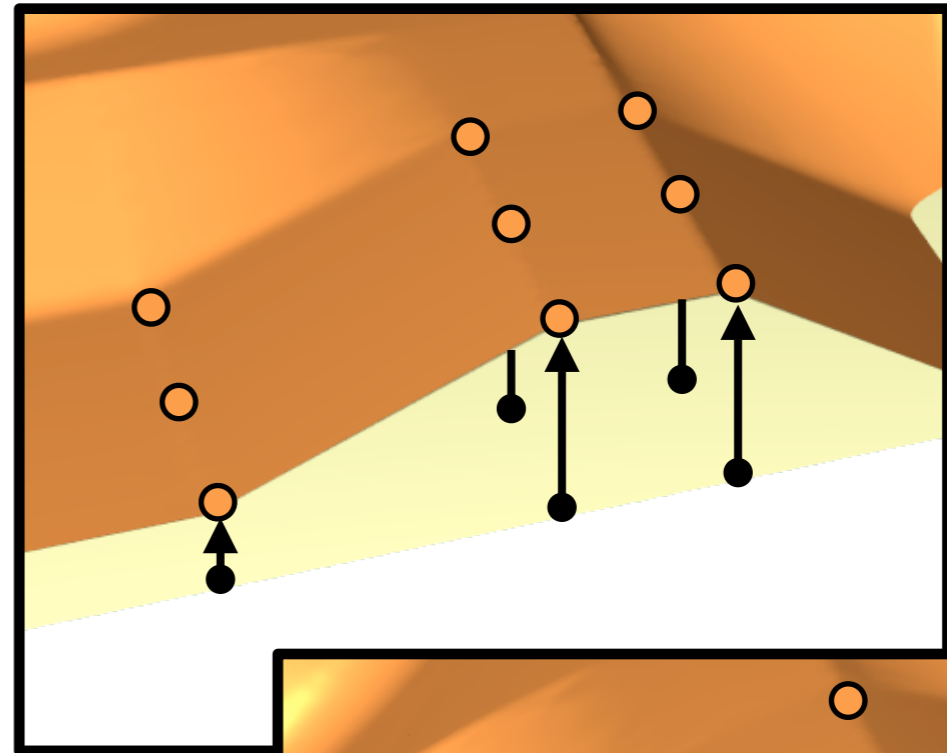
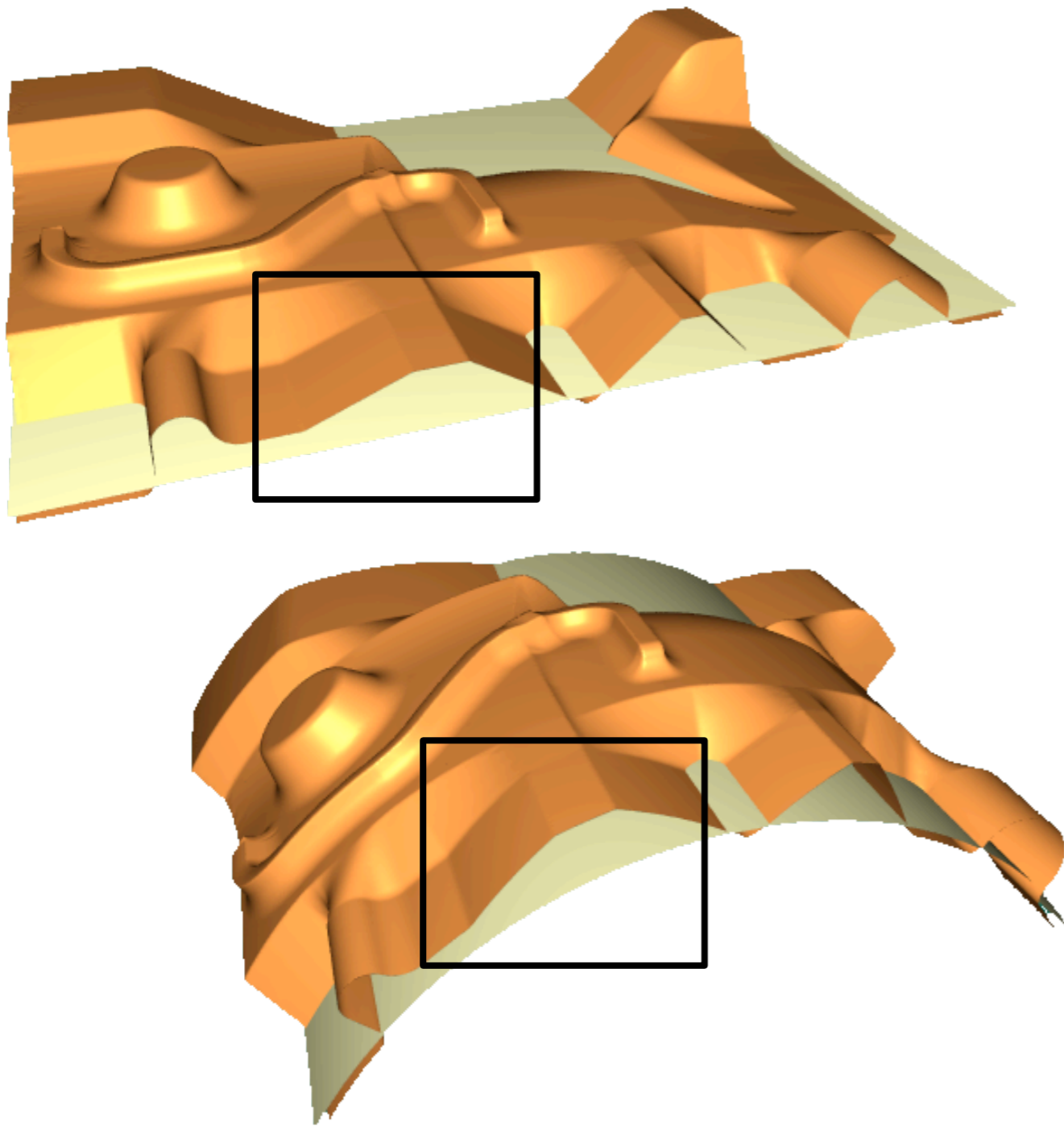


Add high frequency details,
stored in local frames

Multiresolution Editing

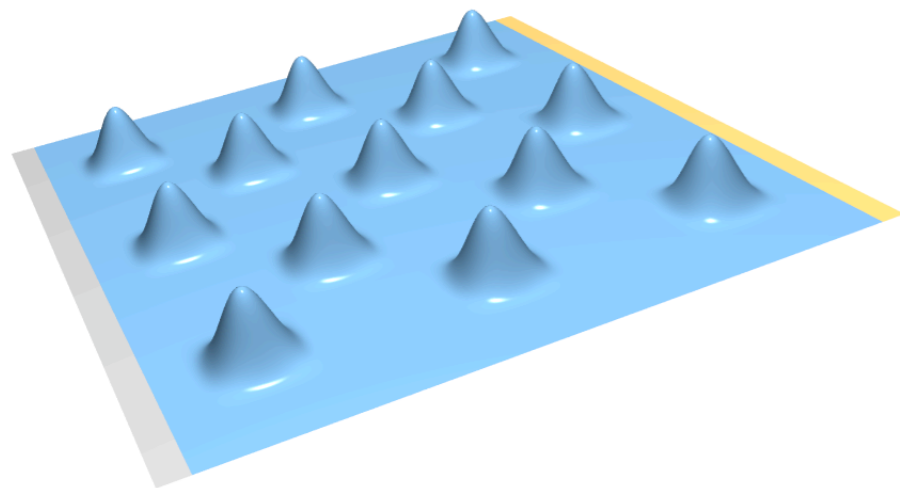


Normal Displacements

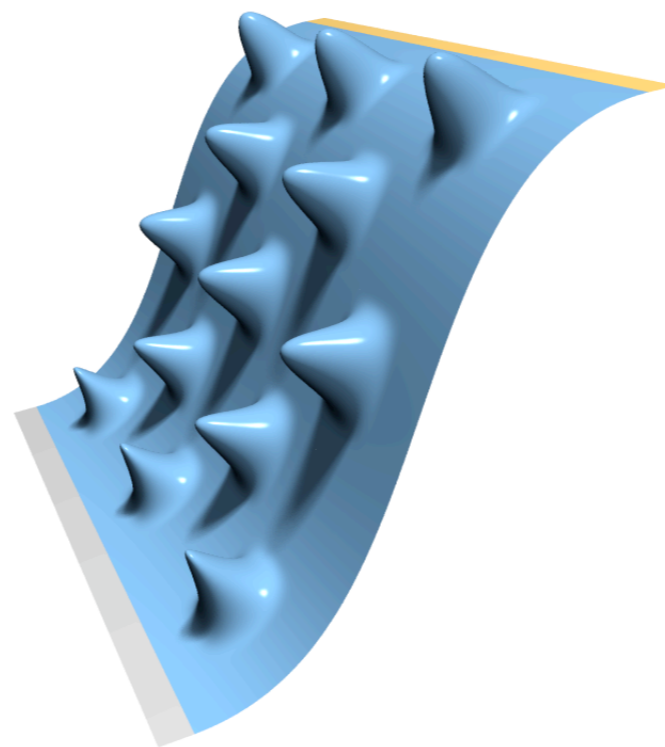


Limitations

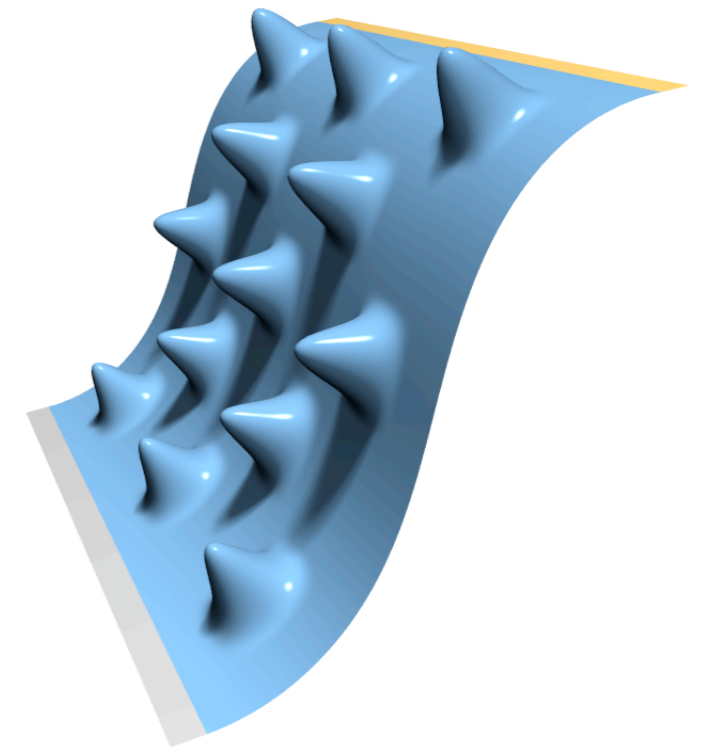
- Neighboring displacements are not coupled
 - Surface bending changes their angle
 - Leads to volume changes or self-intersections



Original



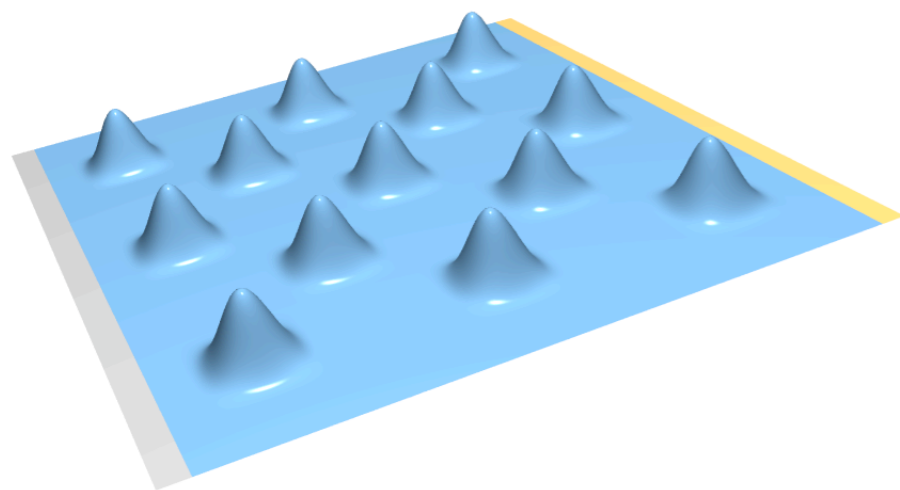
Normal Displ.



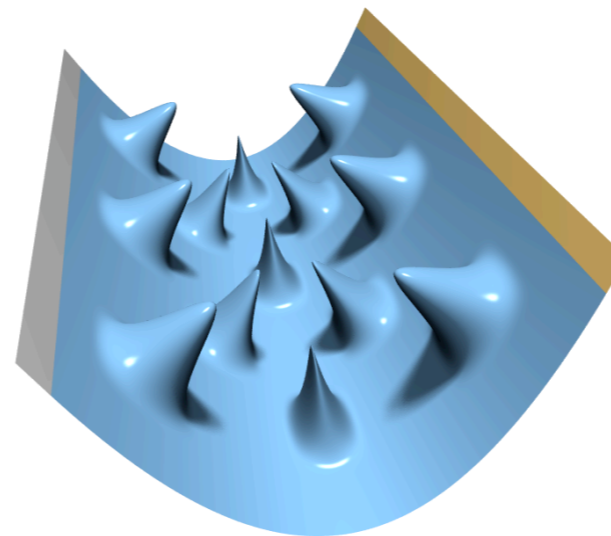
Nonlinear

Limitations

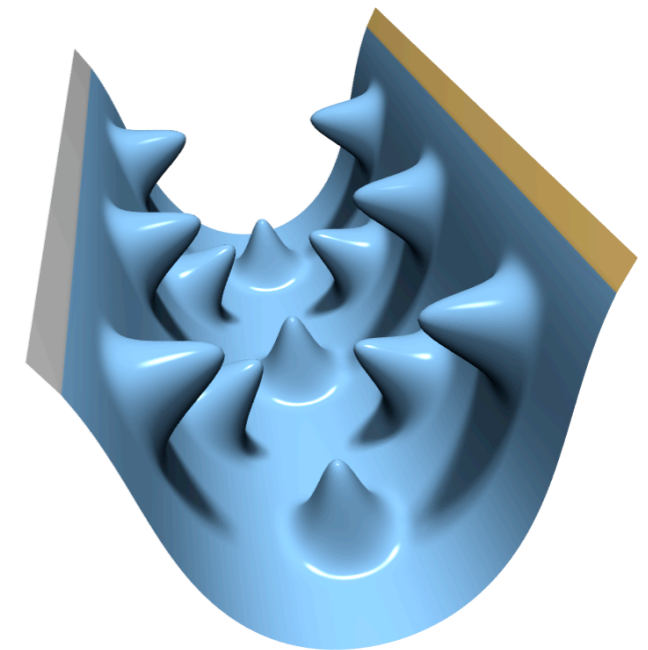
- Neighboring displacements are not coupled
 - Surface bending changes their angle
 - Leads to volume changes or self-intersections



Original



Normal Displ.



Nonlinear

Limitations

- Neighboring displacements are not coupled
 - Surface bending changes their angle
 - Leads to volume changes or self-intersections
 - **See course notes for some other techniques...**
- Multiresolution hierarchy difficult to compute
 - Complex topology
 - Complex geometry
 - Might require more hierarchy levels

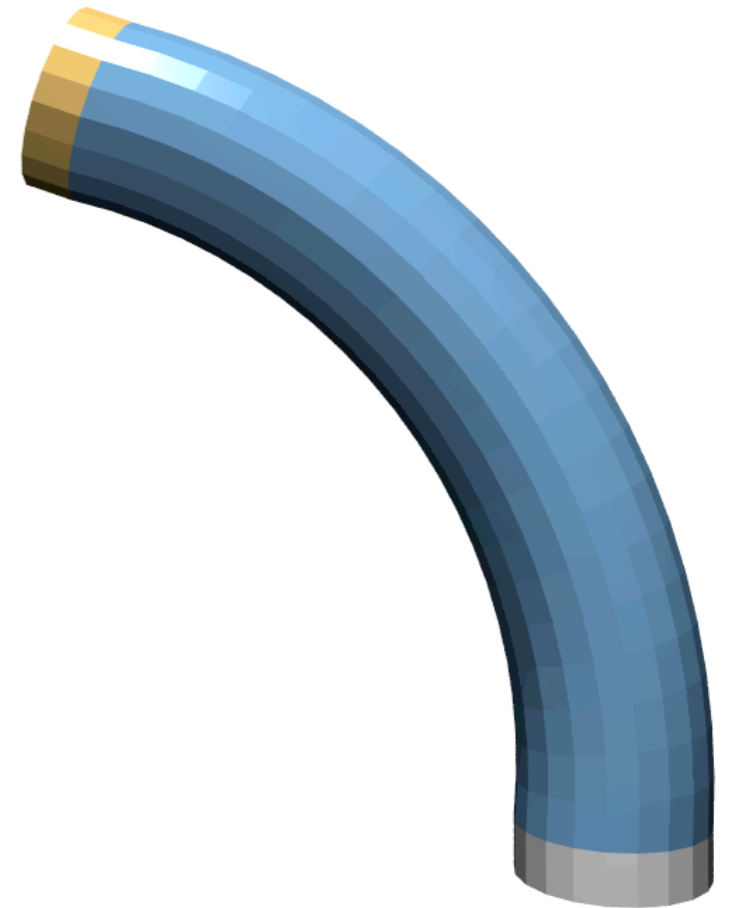
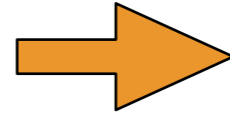
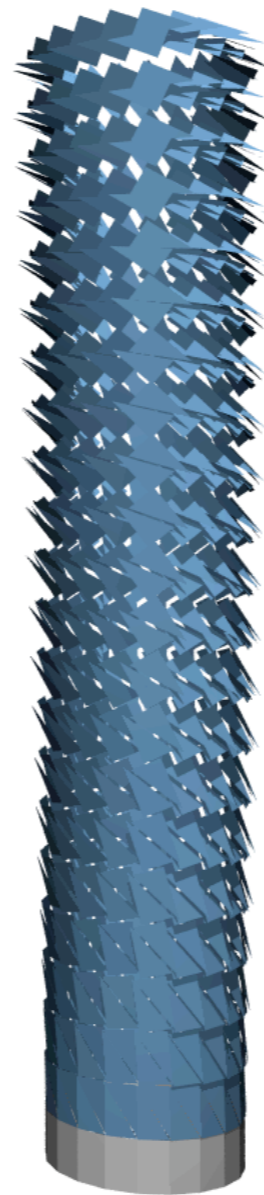
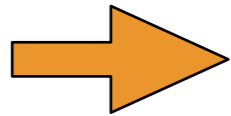
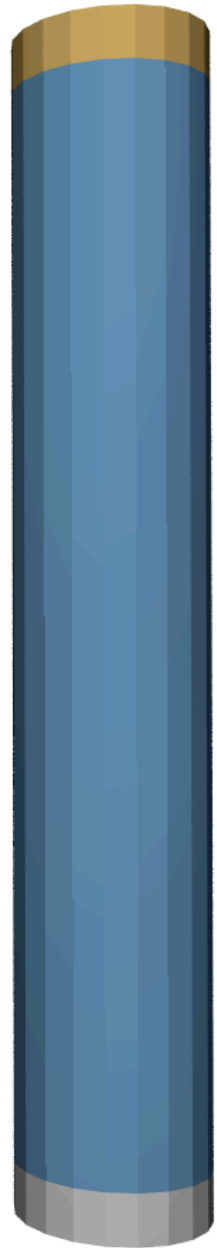
Linear Surface-Based Deformation

- Shell-Based Deformation
- Multiresolution Deformation
- **Differential Coordinates**

Differential Coordinates

1. Manipulate *differential coordinates* instead of *spatial* coordinates
 - Gradients, Laplacians, local frames
 - Intuition: Close connection to surface normal
2. Find mesh with desired differential coords
 - Cannot be solved exactly
 - Formulate as energy minimization

Differential Coordinates



Original

Rotated Diff-Coords

Reconstructed Mesh

Differential Coordinates

- **Which differential coordinate δ_i ?**
 - Gradients
 - Laplacians
 - ...
- **How to get local transformations $T_i(\delta_i)$?**
 - Smooth propagation
 - Implicit optimization
 - ...

Gradient-Based Editing

- Manipulate gradient of a function (e.g. a surface)

$$\mathbf{g} = \nabla \mathbf{f} \quad \mathbf{g} \mapsto \mathbf{T}(\mathbf{g})$$

- Find function \mathbf{f}' whose gradient is (close to) \mathbf{g}'

$$\mathbf{f}' = \operatorname{argmin}_{\mathbf{f}} \int_{\Omega} \|\nabla \mathbf{f} - \mathbf{T}(\mathbf{g})\|^2 \, dudv$$

- Variational calculus \rightarrow Euler-Lagrange PDE

$$\Delta \mathbf{f}' = \operatorname{div} \mathbf{T}(\mathbf{g})$$

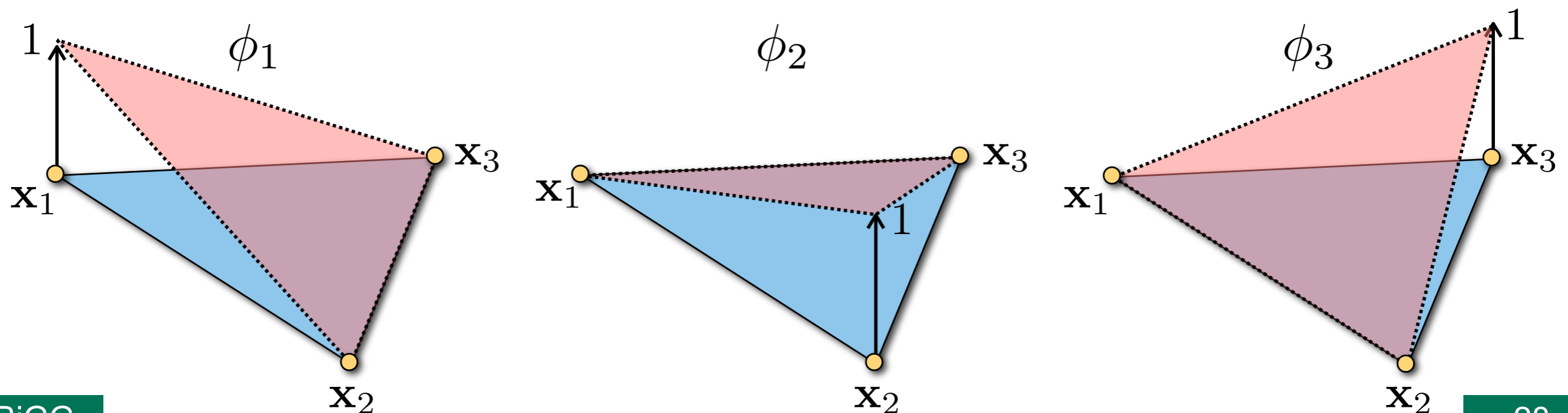
Gradient-Based Editing

- Consider piecewise linear **coordinate function**

$$\mathbf{p}(u, v) = \sum_{v_i} \mathbf{p}_i \cdot \phi_i(u, v)$$

- Its gradient is

$$\nabla \mathbf{p}(u, v) = \sum_{v_i} \mathbf{p}_i \cdot \nabla \phi_i(u, v)$$



Gradient-Based Editing

- Consider piecewise linear ***coordinate function***

$$\mathbf{p}(u, v) = \sum_{v_i} \mathbf{p}_i \cdot \phi_i(u, v)$$

- Its gradient is

$$\nabla \mathbf{p}(u, v) = \sum_{v_i} \mathbf{p}_i \cdot \nabla \phi_i(u, v)$$

- It is constant per triangle

$$\nabla \mathbf{p}|_{f_j} =: \mathbf{g}_j \in \mathbb{R}^{3 \times 3}$$

Gradient-Based Editing

- Gradient of coordinate function \mathbf{p}

$$\begin{pmatrix} \mathbf{g}_1 \\ \vdots \\ \mathbf{g}_F \end{pmatrix} = \underbrace{\mathbf{G}}_{(3F \times V)} \begin{pmatrix} \mathbf{p}_1^T \\ \vdots \\ \mathbf{p}_V^T \end{pmatrix}$$

- Manipulate per-face gradients

$$\mathbf{g}_j \mapsto \mathbf{T}_j(\mathbf{g}_j)$$

Gradient-Based Editing

- Reconstruct mesh from new gradients
 - Overdetermined ($3F \times V$) system
 - Weighted least squares system
- ➔ Linear Poisson system $\Delta \mathbf{p}' = \text{div } \mathbf{T}(\mathbf{g})$

$$\underbrace{\mathbf{G}^T \mathbf{D} \mathbf{G}}_{\text{div } \nabla = \Delta} \cdot \begin{pmatrix} \mathbf{p}'_1{}^T \\ \vdots \\ \mathbf{p}'_V{}^T \end{pmatrix} = \underbrace{\mathbf{G}^T \mathbf{D}}_{\text{div}} \cdot \begin{pmatrix} \mathbf{T}_1(\mathbf{g}_1) \\ \vdots \\ \mathbf{T}_F(\mathbf{g}_F) \end{pmatrix}$$

Laplacian-Based Editing

- Manipulate Laplacians field of a surface

$$\mathbf{l} = \Delta(\mathbf{p}) \quad , \quad \mathbf{l} \mapsto \mathbf{T}(\mathbf{l})$$

- Find surface whose Laplacian is (close to) δ'

$$\mathbf{p}' = \operatorname{argmin}_{\mathbf{p}} \int_{\Omega} \|\Delta \mathbf{p} - \mathbf{T}(\mathbf{l})\|^2 \, dudv$$

- Variational calculus yields Euler-Lagrange PDE

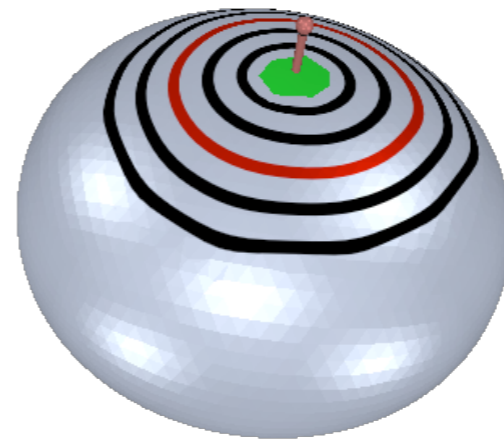
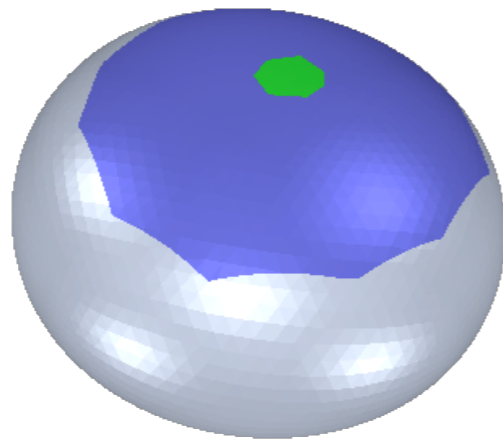
$$\Delta^2 \mathbf{p}' = \Delta \mathbf{T}(\mathbf{l})$$

Differential Coordinates

- Which differential coordinate δ_i ?
 - Gradients
 - Laplacians
 - ...
- **How to get local transformations $\mathbf{T}_i(\delta_i)$?**
 - Smooth propagation
 - Implicit optimization
 - ...

Smooth Propagation

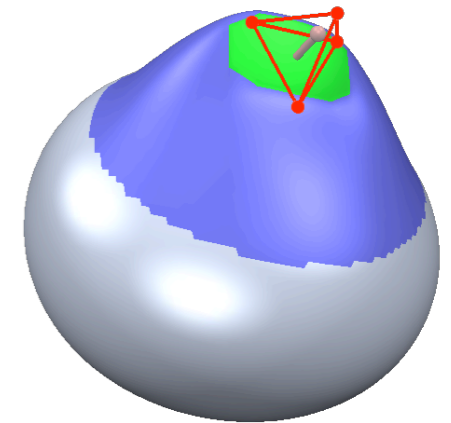
1. Compute handle's deformation gradient
2. Extract rotation and scale/shear components
3. Propagate damped rotations over ROI



Deformation Gradient

- Handle has been transformed affinely

$$\mathbf{T}(\mathbf{x}) = \mathbf{A}\mathbf{x} + \mathbf{t}$$



- Deformation gradient is

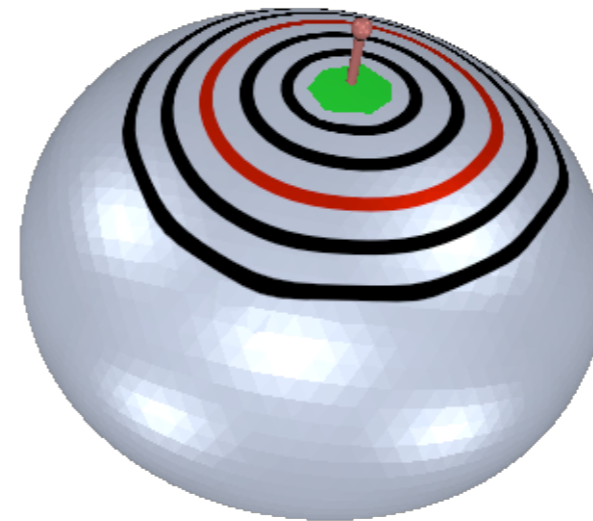
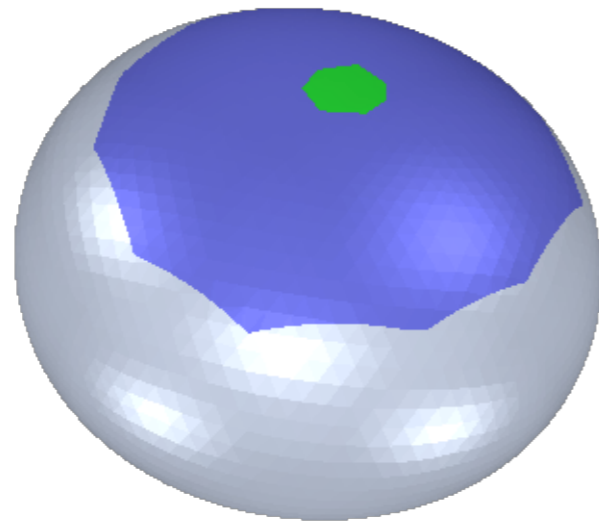
$$\nabla \mathbf{T}(\mathbf{x}) = \mathbf{A}$$

- Extract rotation \mathbf{R} and scale/shear \mathbf{S}

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T \quad \Rightarrow \quad \mathbf{R} = \mathbf{U}\mathbf{V}^T, \quad \mathbf{S} = \mathbf{V}\mathbf{\Sigma}\mathbf{V}^T$$

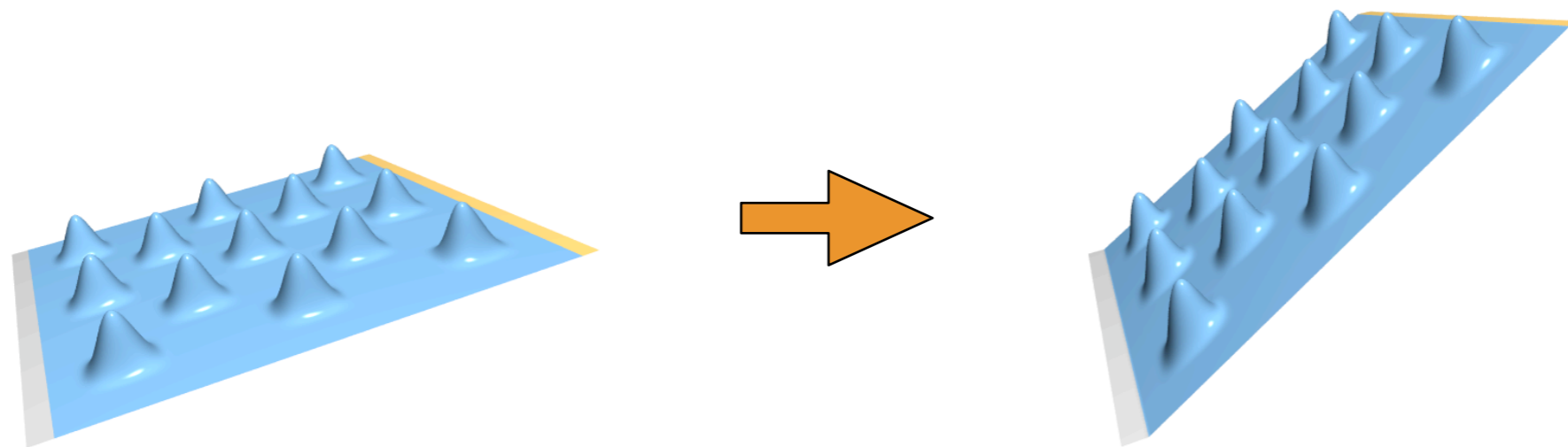
Smooth Propagation

- Construct smooth scalar field $[0,1]$
 - $s(\mathbf{x})=1$: Full deformation (handle)
 - $s(\mathbf{x})=0$: No deformation (fixed part)
 - $s(\mathbf{x})\in(0,1)$: Damp handle transformation (in between)



Limitations

- Differential coordinates work well for **rotations**
 - Represented by deformation gradient
- **Translations** don't change deformation gradient
 - Translations don't change differential coordinates
 - “*Translation insensitivity*”



Implicit Optimization

- Optimize for positions \mathbf{p}_i' & transformations \mathbf{T}_i

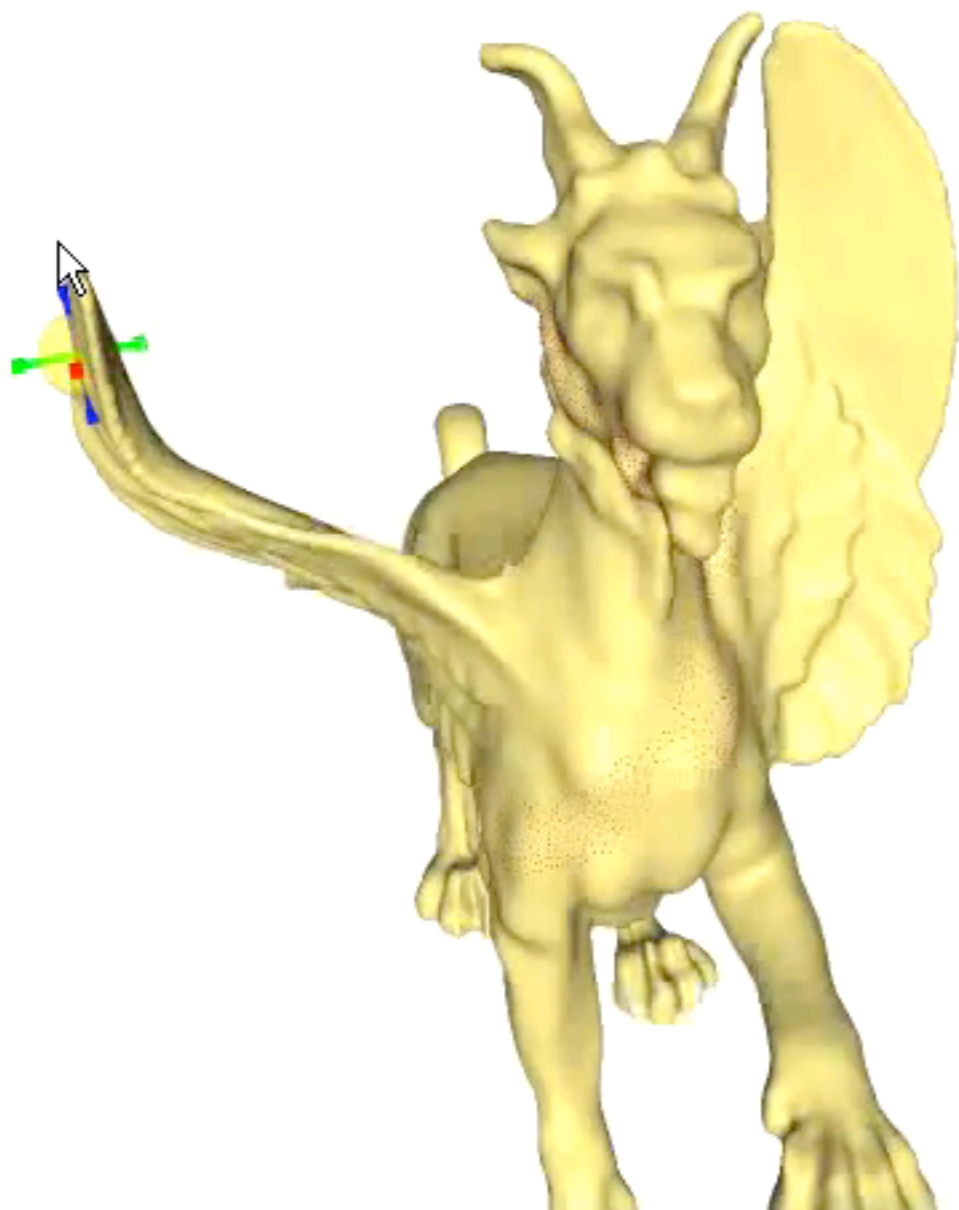
$$\Delta^2 \begin{pmatrix} \vdots \\ \mathbf{p}'_i \\ \vdots \end{pmatrix} = \begin{pmatrix} \vdots \\ \Delta \mathbf{T}_i(\mathbf{l}_i) \\ \vdots \end{pmatrix} \iff \mathbf{T}_i(\mathbf{p}_i - \mathbf{p}_j) = \mathbf{p}'_i - \mathbf{p}'_j$$

- Linearize rotation/scale \rightarrow one linear system

$$\mathbf{T}_i = \begin{pmatrix} s & -r_3 & r_2 \\ r_3 & s & -r_1 \\ -r_2 & r_1 & s \end{pmatrix}$$

Laplacian Surface Editing

Enter filename:



+
 +

Editing -

ROI -

Edit params

Free ring radius
Fixed ring radius
Handle radius

ROI selection type

Euclidean radius
 Geodesic radius

Edit Mode
 Render anchors

System data -

+

Matrix size:

+

+

+
 +

Connection to Shells?

- Neglect local transformations \mathbf{T}_i for a moment...

$$\int \|\Delta \mathbf{p}' - \mathbf{l}\|^2 \rightarrow \min \longrightarrow \Delta^2 \mathbf{p}' = \Delta \mathbf{l}$$

- Basic formulations equivalent!
- Differ in detail preservation
 - Rotation of Laplacians
 - Multi-scale decomposition

$$\begin{array}{l} \mathbf{p}' = \mathbf{p} + \mathbf{d} \\ \mathbf{l} = \Delta \mathbf{p} \end{array}$$

$$\Delta^2 (\mathbf{p} + \mathbf{d}) = \Delta^2 \mathbf{p}$$

$$\int \|\mathbf{d}_{uu}\|^2 + 2 \|\mathbf{d}_{uv}\|^2 + \|\mathbf{d}_{vv}\|^2 \rightarrow \min \longleftarrow \Delta^2 \mathbf{d} = 0$$

Linear Surface-Based Deformation

- Shell-Based Deformation
- Multiresolution Deformation
- Differential Coordinates



Eurographics 2009

Interactive Shape Modeling and Deformation

T3: Half-Day Tutorial

Linear Space Deformations

Space Deformation

- Displacement function defined on the ambient space

$$\mathbf{d} : \mathbb{R}^3 \rightarrow \mathbb{R}^3$$

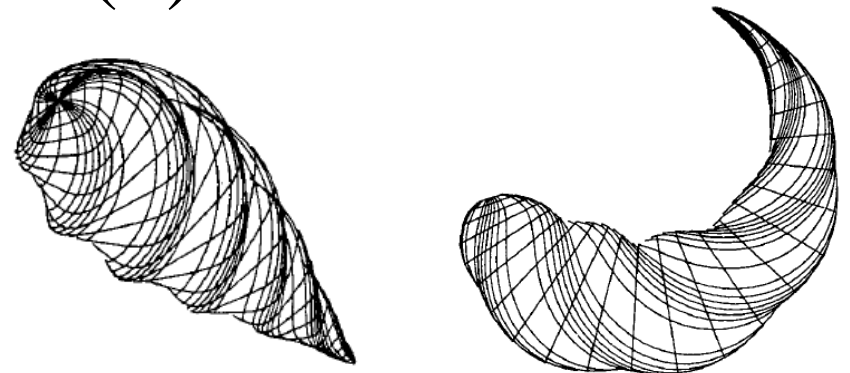
- Evaluate the function on the points of the shape embedded in the space

$$\mathbf{x}' = \mathbf{x} + \mathbf{d}(\mathbf{x})$$

Twist warp

Global and local deformation of solids

[A. Barr, SIGGRAPH 84]

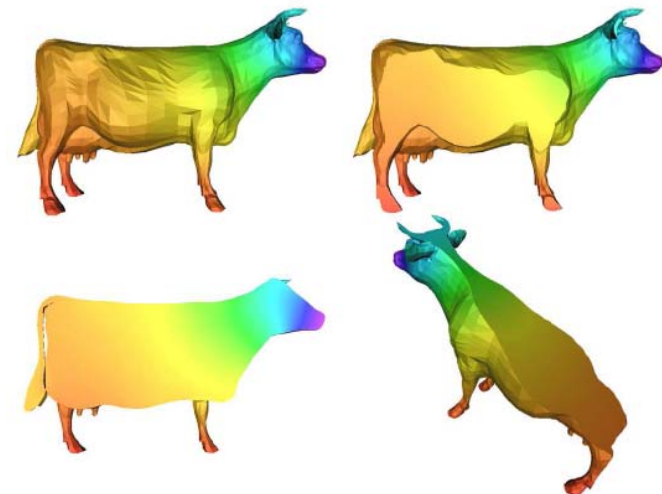


Freeform Deformations

- Control object
- User defines displacements \mathbf{d}_i for each element of the control object
- Displacements are interpolated to the entire space using basis functions $B_i(\mathbf{x}) : \mathbb{R}^3 \rightarrow \mathbb{R}$

$$\mathbf{d}(\mathbf{x}) = \sum_{i=1}^k \mathbf{d}_i B_i(\mathbf{x})$$

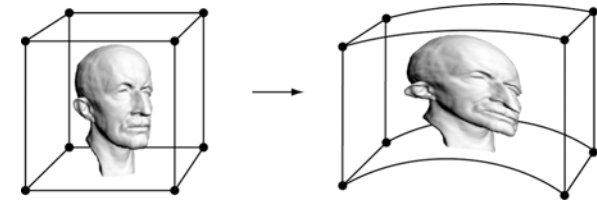
- Basis functions should be smooth for aesthetic results



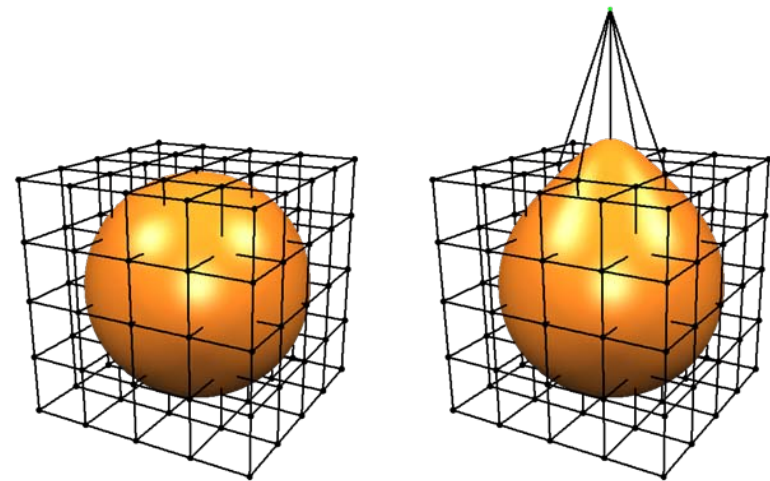
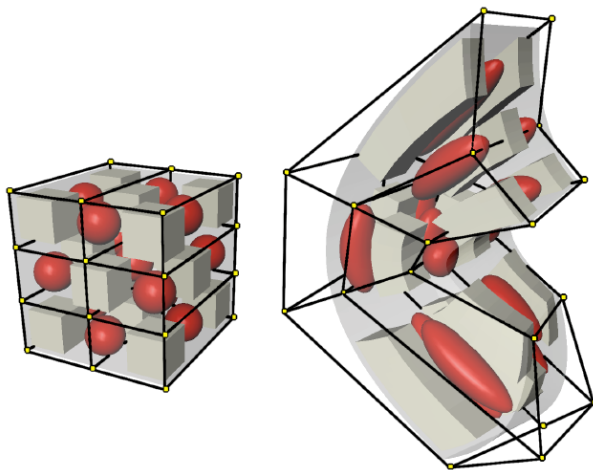
Trivariate Tensor Product Bases

[Sederberg and Parry 86]

- Control object = lattice
- Basis functions $B_i(\mathbf{x})$ are trivariate tensor-product splines:

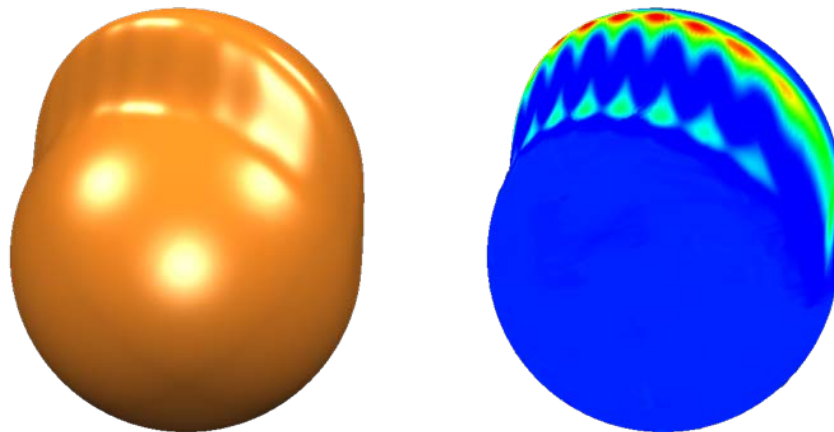


$$\mathbf{d}(x, y, z) = \sum_{i=0}^l \sum_{j=0}^m \sum_{k=0}^n \mathbf{d}_{ijk} N_i(x) N_j(y) N_k(z)$$



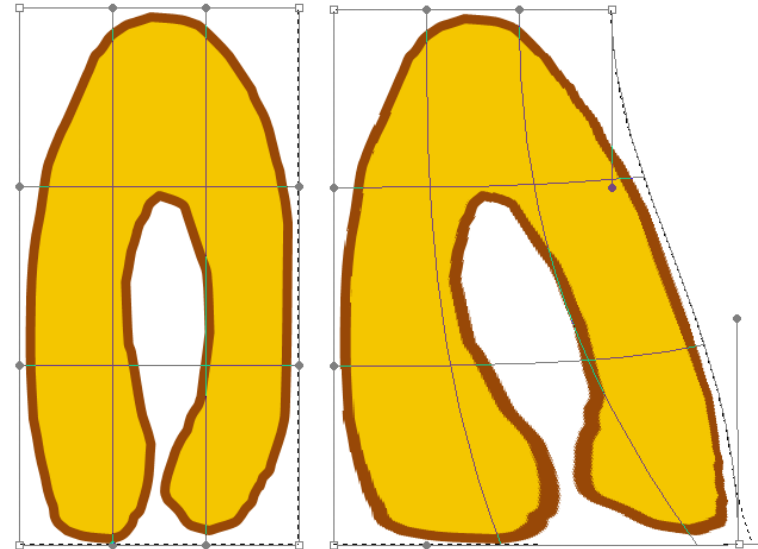
Trivariate Tensor Product Bases

- Similar to the surface case
 - Aliasing artifacts
- Interpolate deformation constraints?
 - Only in least squares sense



Lattice as Control Object

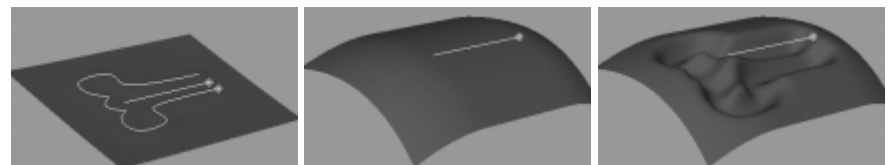
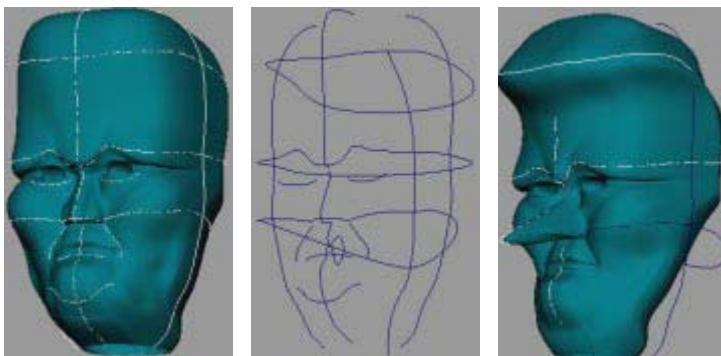
- Difficult to manipulate
- The control object is not related to the shape of the edited object
- Part of the shape in close Euclidean distance always deform similarly, even if geodesically far



Wires

[Singh and Fiume 98]

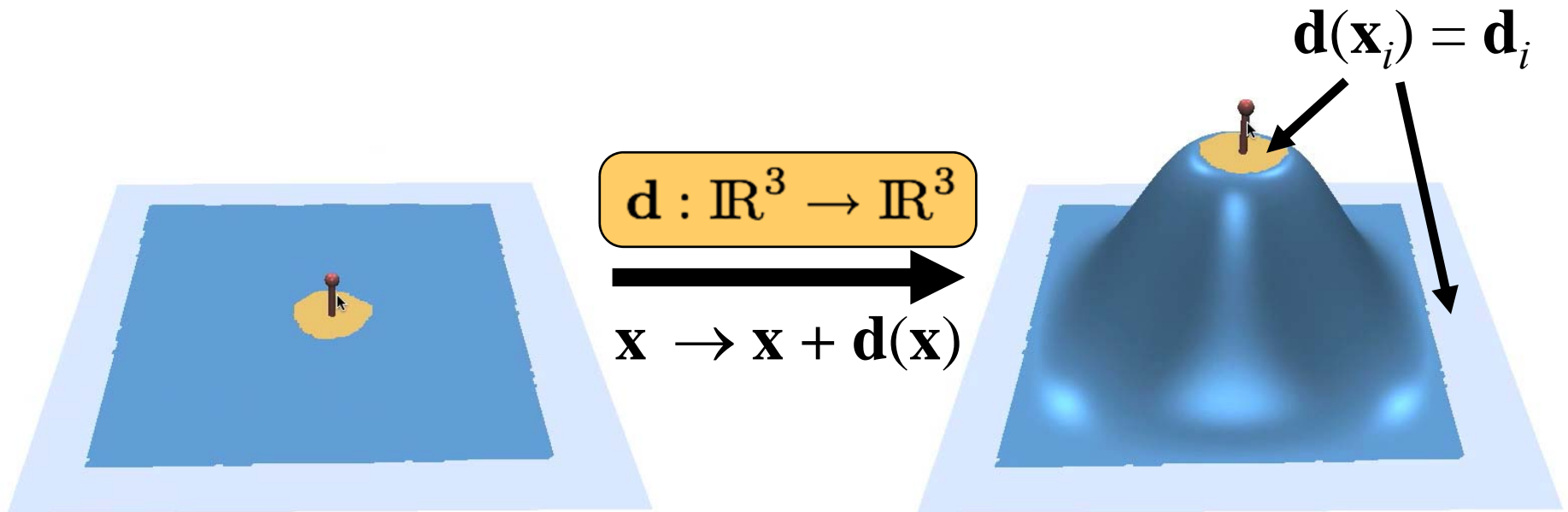
- Control objects are arbitrary space curves
- Can place curves along meaningful features of the edited object
- Smooth deformations around the curve with decreasing influence



Handle Metaphor

[RBF, Botsch and Kobbelt 05]

- Wish list for the displacement function $\mathbf{d}(\mathbf{x})$:
 - Interpolate prescribed constraints
 - Smooth, intuitive deformation



Volumetric Energy Minimization

[RBF, Botsch and Kobbelt 05]

- Minimize similar energies to surface case

$$\int_{\mathcal{R}^3} \left\| \mathbf{d}_{xx} \right\|^2 + \left\| \mathbf{d}_{xy} \right\|^2 + \dots + \left\| \mathbf{d}_{zz} \right\|^2 dx dy dz \rightarrow \min$$

- But displacements function lives in 3D...
 - Need a volumetric space tessellation?
 - No, same functionality provided by RBFs!

Radial Basis Functions

[RBF, Botsch and Kobbelt 05]

- Represent deformation by RBFs

$$\mathbf{d}(\mathbf{x}) = \sum_j \mathbf{w}_j \cdot \varphi(\|\mathbf{c}_j - \mathbf{x}\|) + \mathbf{p}(\mathbf{x})$$

- Triharmonic basis function $\varphi(r) = r^3$
 - C^2 boundary constraints
 - Highly smooth / fair interpolation

$$\int_{\mathbb{R}^3} \|\mathbf{d}_{xxx}\|^2 + \|\mathbf{d}_{xyy}\|^2 + \dots + \|\mathbf{d}_{zzz}\|^2 dx dy dz \rightarrow \min$$

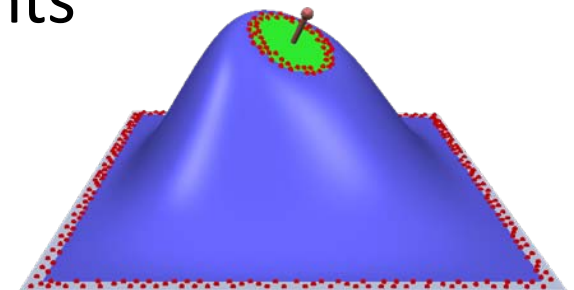
RBF Fitting

[RBF, Botsch and Kobbelt 05]

- Represent deformation by RBFs

$$\mathbf{d}(\mathbf{x}) = \sum_j \mathbf{w}_j \cdot \varphi(\|\mathbf{c}_j - \mathbf{x}\|) + \mathbf{p}(\mathbf{x})$$

- RBF fitting
 - Interpolate displacement constraints
 - Solve linear system for \mathbf{w}_j and \mathbf{p}



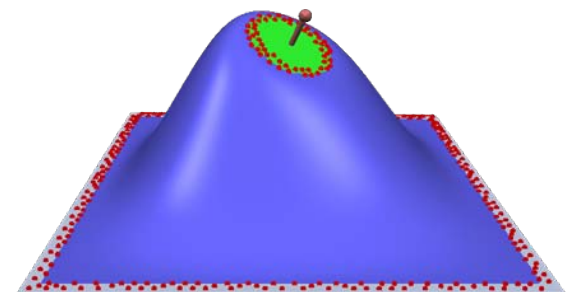
RBF Fitting

[RBF, Botsch and Kobbelt 05]

- Represent deformation by RBFs

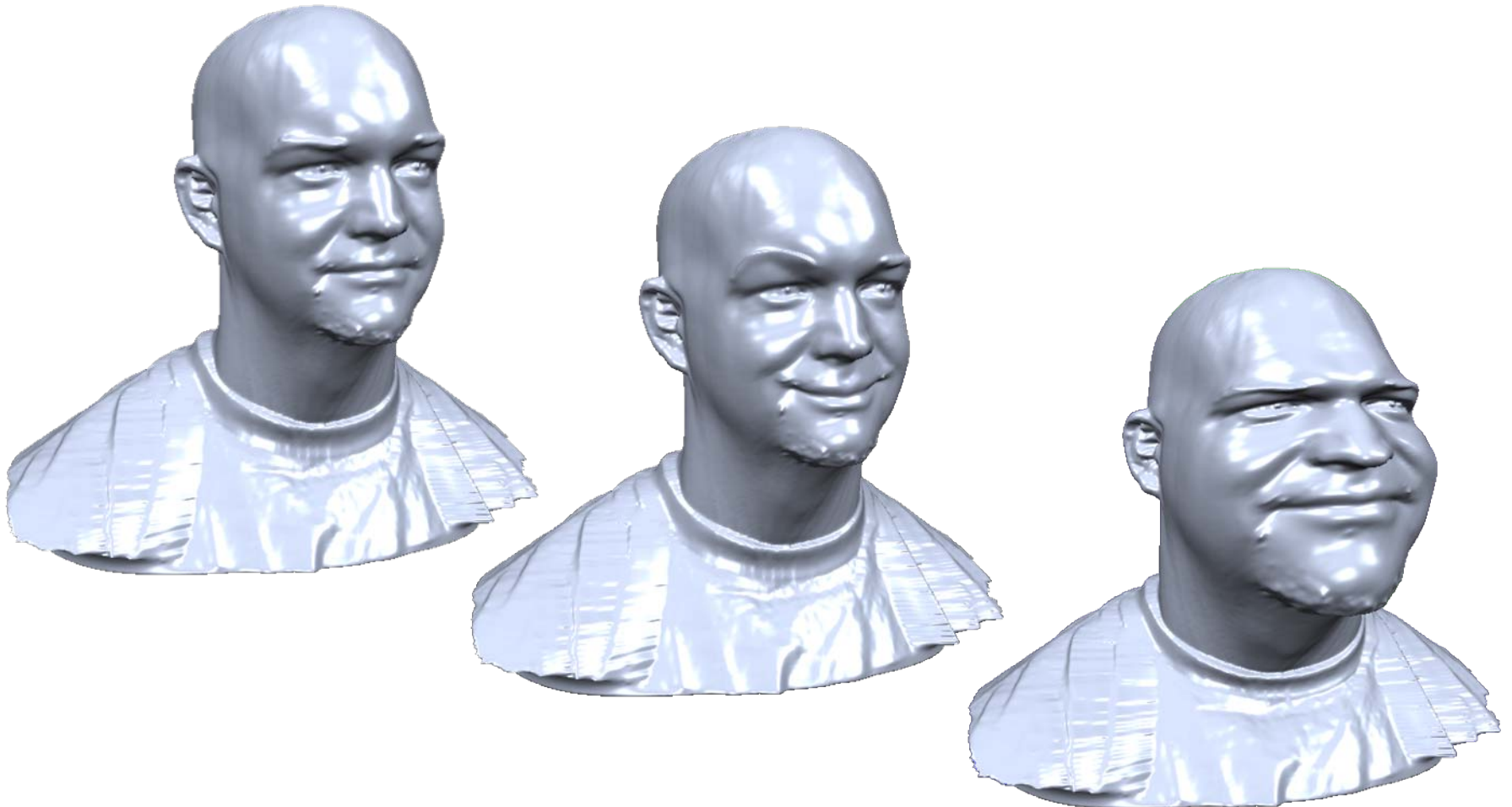
$$\mathbf{d}(\mathbf{x}) = \sum_j \mathbf{w}_j \cdot \varphi(\|\mathbf{c}_j - \mathbf{x}\|) + \mathbf{p}(\mathbf{x})$$

- RBF evaluation
 - Function \mathbf{d} transforms points
 - Jacobian $\nabla \mathbf{d}$ transforms normals
 - Precompute basis functions
 - Evaluate on the GPU!



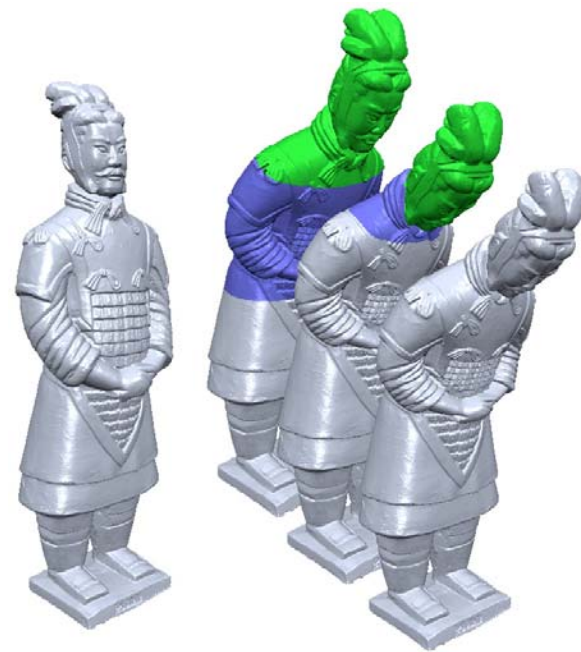
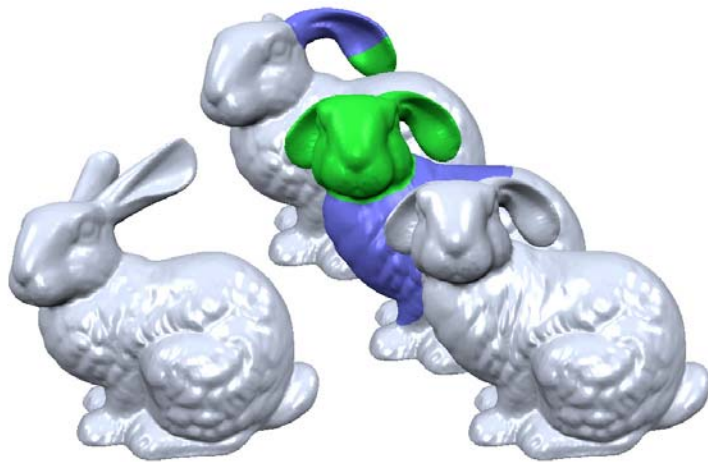
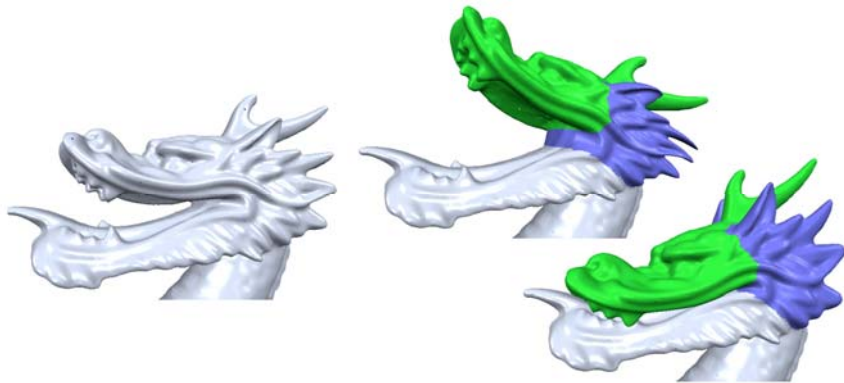
Local & Global Deformations

[RBF, Botsch and Kobbelt 05]



Local & Global Deformations

[RBF, Botsch and Kobbelt 05]

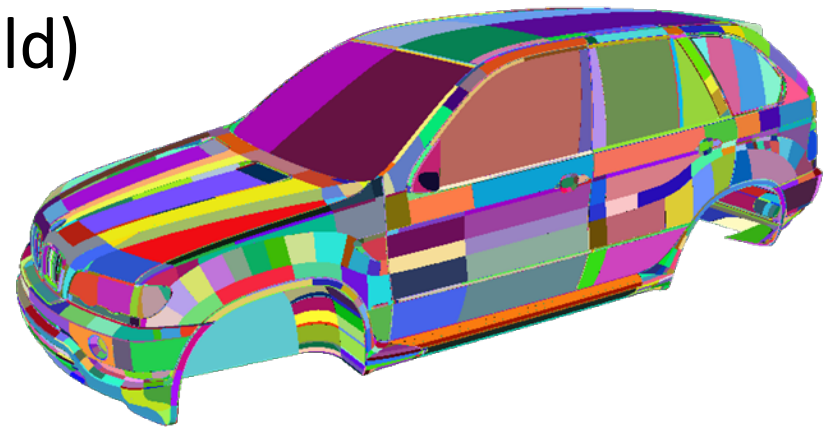


1M vertices
movie

Space Deformations

Summary so far

- Handle arbitrary input
 - Meshes (also non-manifold)
 - Point sets
 - Polygonal soups
 - ...



- Complexity mainly depends on the control object, not the surface

- 3M triangles
- 10k components
- Not oriented
- Not manifold

Space Deformations

Summary so far

- Handle arbitrary input
 - Meshes (also non-manifold)
 - Point sets
 - Polygonal soups
 - ...



$$\mathbf{F}(x, y, z) = (F(x, y, z), G(x, y, z), H(x, y, z))$$

then the Jacobian is the determinant

$$Jac(\mathbf{F}) = \begin{vmatrix} \frac{\partial F}{\partial x} & \frac{\partial F}{\partial y} & \frac{\partial F}{\partial z} \\ \frac{\partial G}{\partial x} & \frac{\partial G}{\partial y} & \frac{\partial G}{\partial z} \\ \frac{\partial H}{\partial x} & \frac{\partial H}{\partial y} & \frac{\partial H}{\partial z} \end{vmatrix}$$

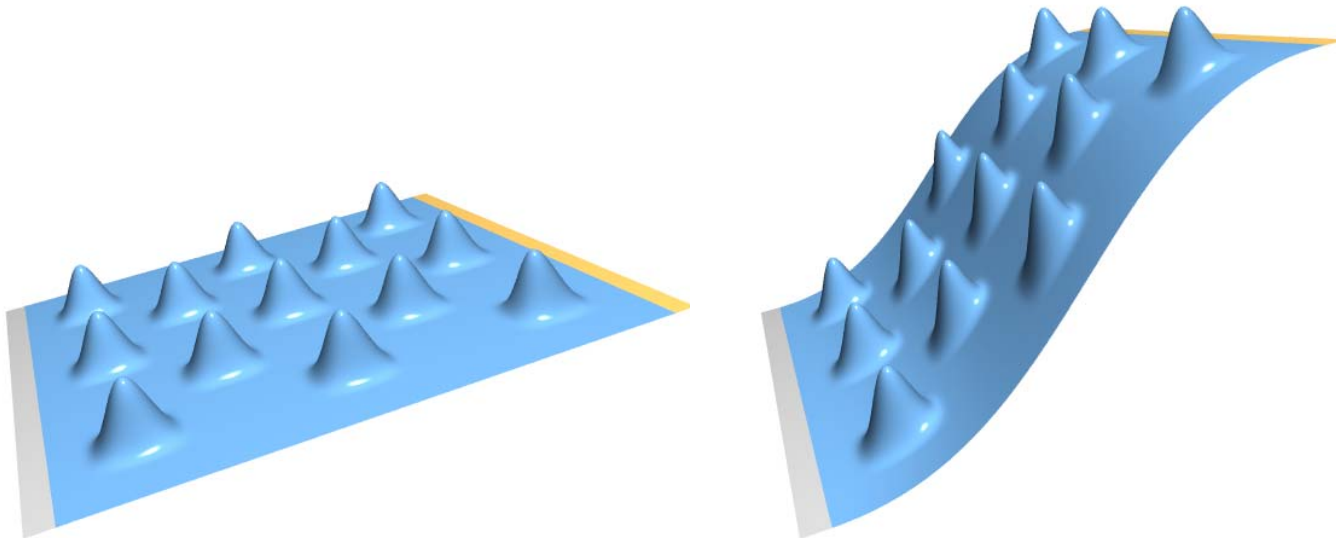
- Easier to analyze: functions on Euclidean domain

- Volume preservation: $|\text{Jacobian}| = 1$

Space Deformations

Summary so far

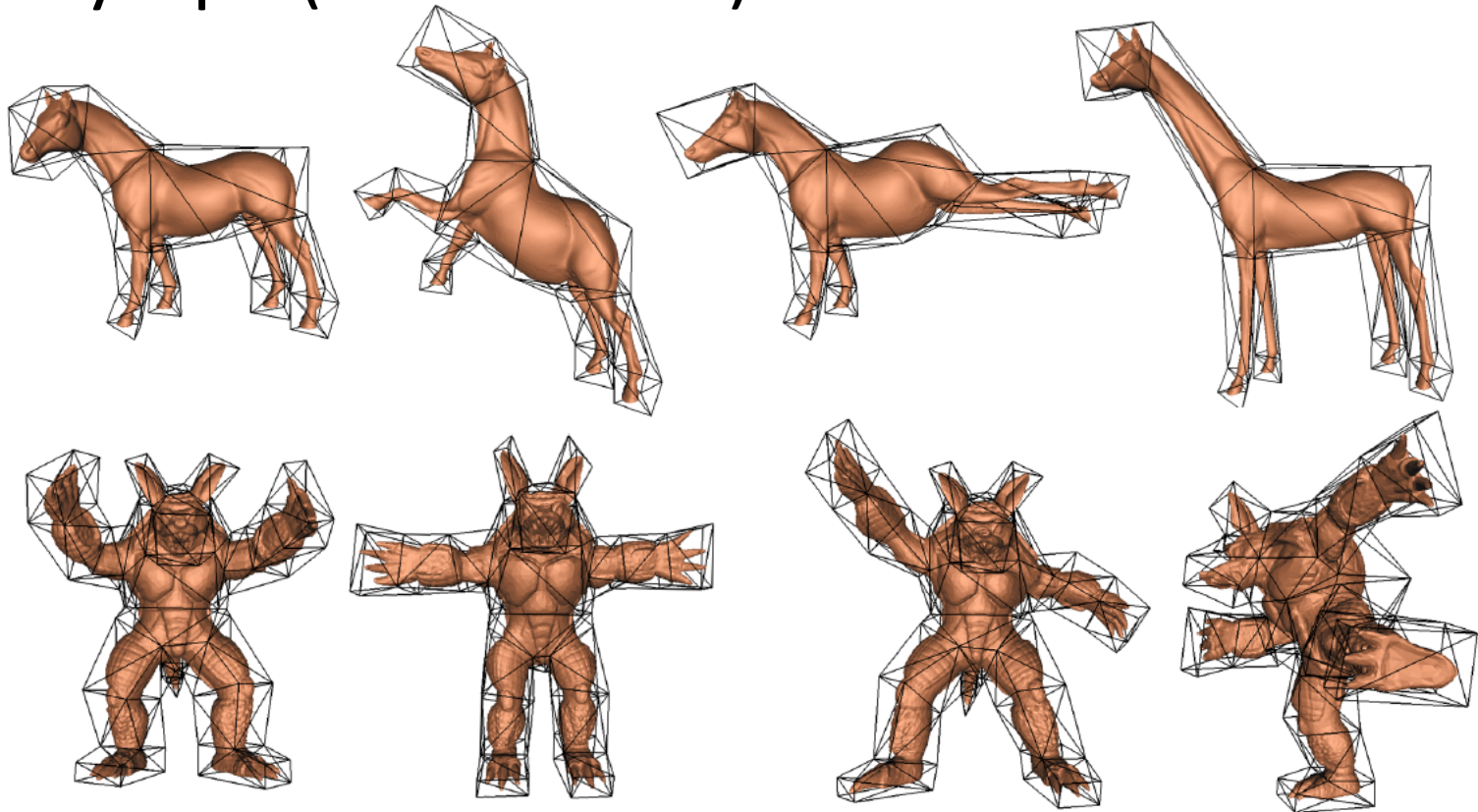
- The deformation is only loosely aware of the shape that is being edited
- Small Euclidean distance \rightarrow similar deformation
- Local surface detail may be distorted



Cage-based Deformations

[Ju et al. 2005]

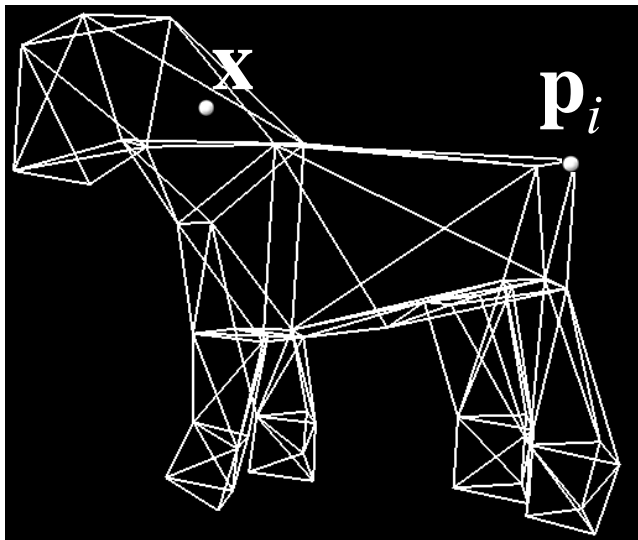
- Cage = crude version of the input shape
- Polytope (not a lattice)



Cage-based Deformations

[Ju et al. 2005]

- Cage = crude version of the input shape
- Polytope (not a lattice)
- Each point \mathbf{x} in space is represented w.r.t. to the cage elements using coordinate functions

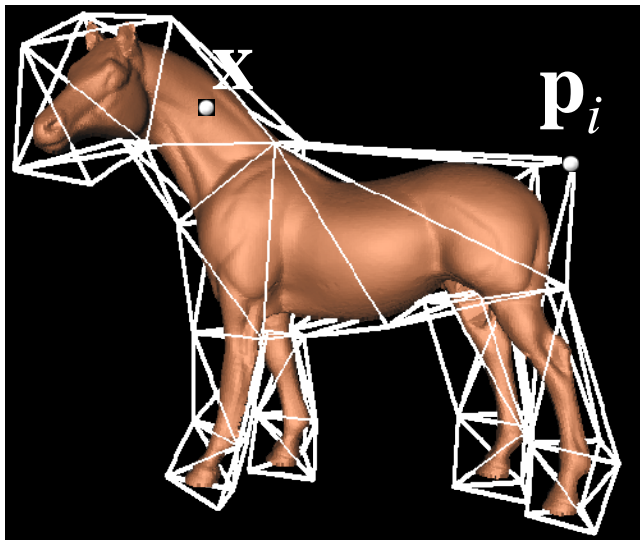


$$\mathbf{x} = \sum_{i=1}^k w_i(\mathbf{x}) \mathbf{p}_i$$

Cage-based Deformations

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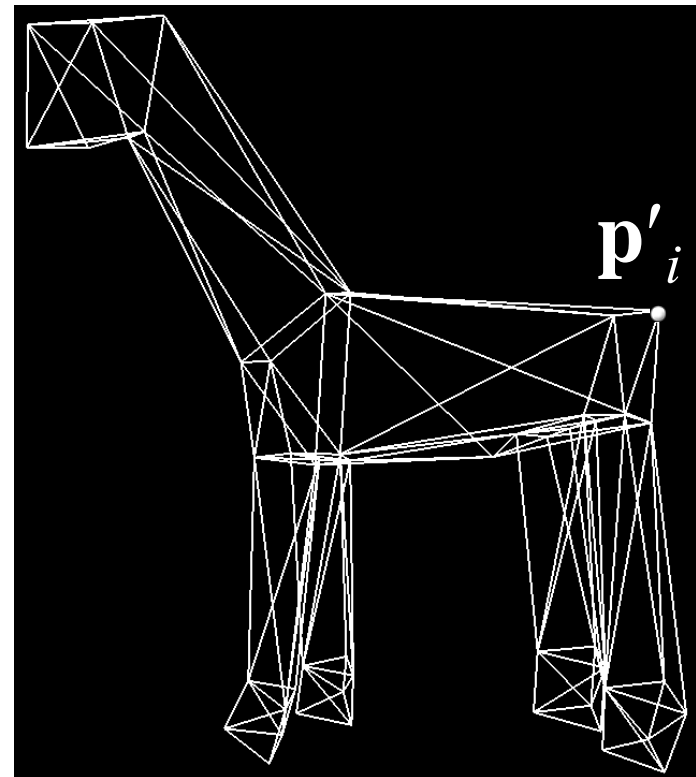
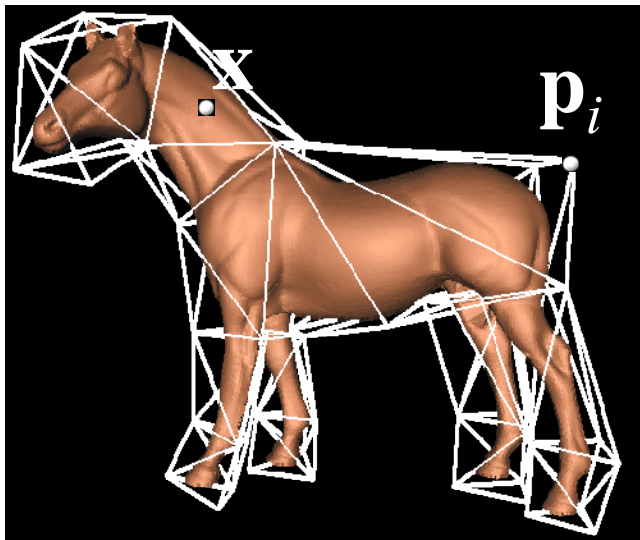


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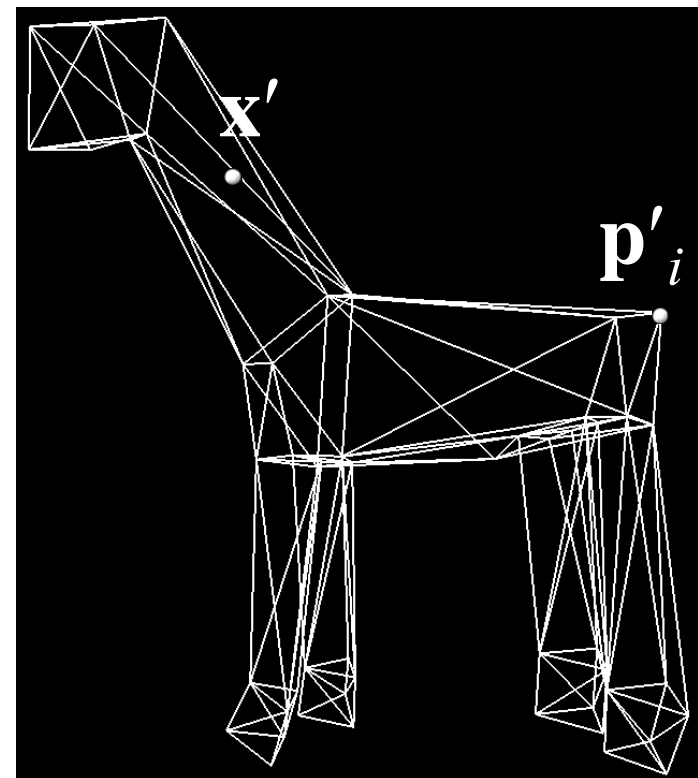
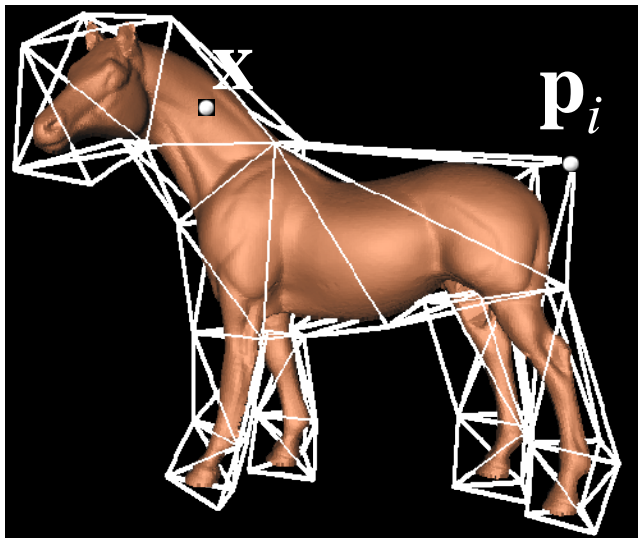


Cage-based Deformations

[Ju et al. 2005]

- Cage = crude version of the input shape
- Polytope (not a lattice)

$$\mathbf{x}' = \sum_{i=1}^k w_i(\mathbf{x}) \mathbf{p}'_i$$

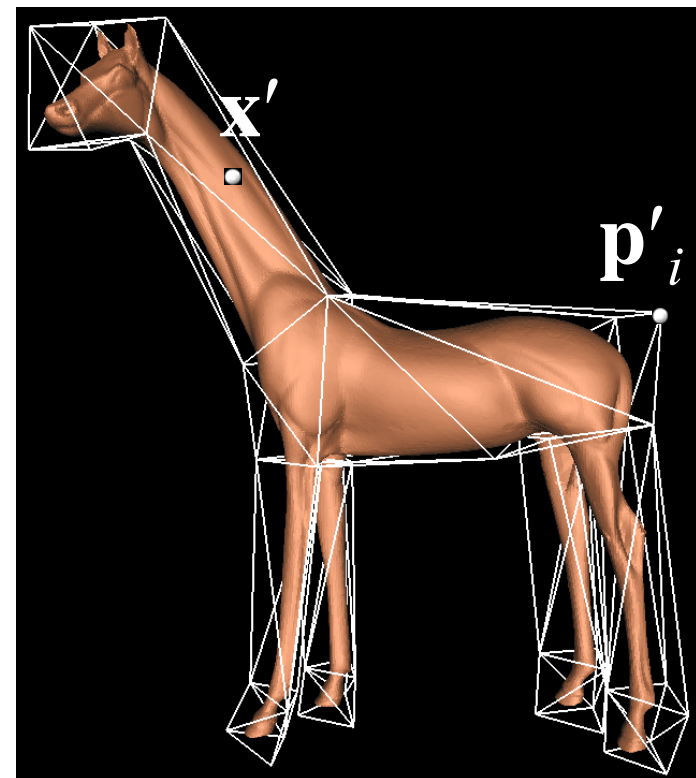
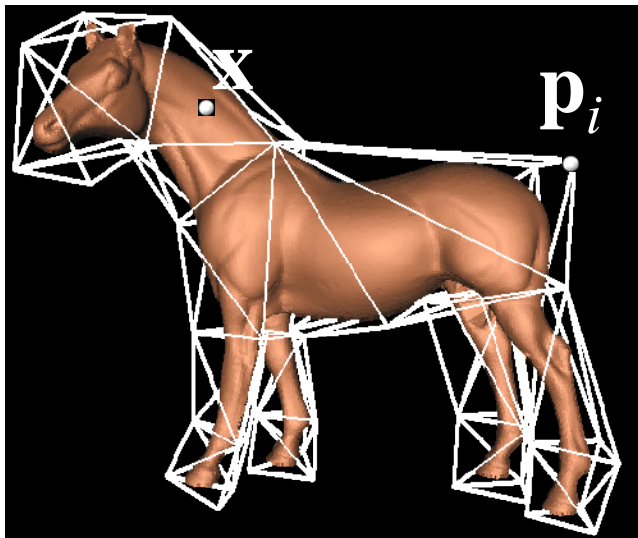


Cage-based Deformations

[Ju et al. 2005]

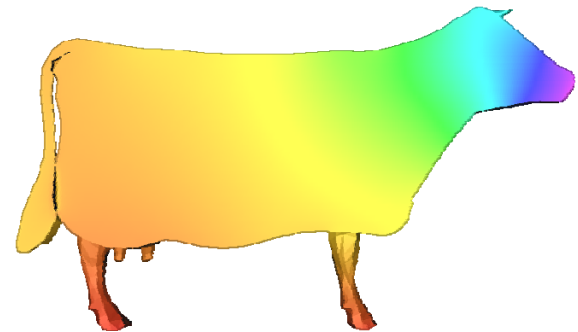
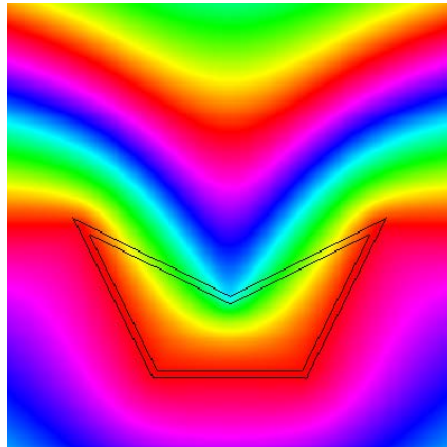
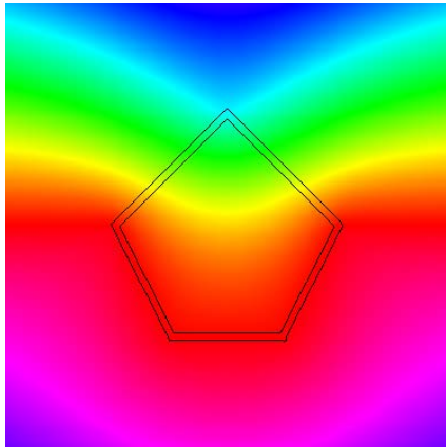
- Cage = crude version of the input shape
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$$\mathbf{x}' = \sum_{i=1}^k w_i(\mathbf{x}) \mathbf{p}'_i$$



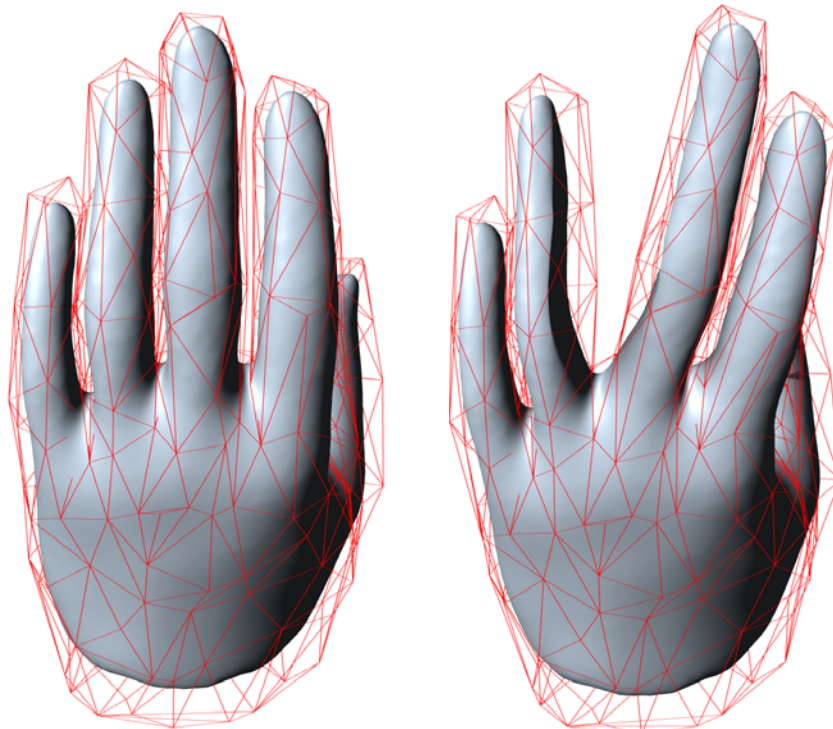
Coordinate Functions

- Mean-value coordinates (Floater, Ju et al. 2005)
 - Generalization of barycentric coordinates
 - Closed-form solution for $w_i(\mathbf{x})$



Coordinate Functions

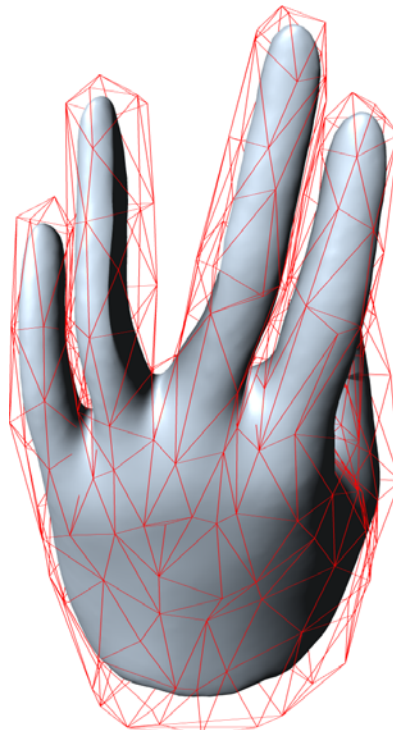
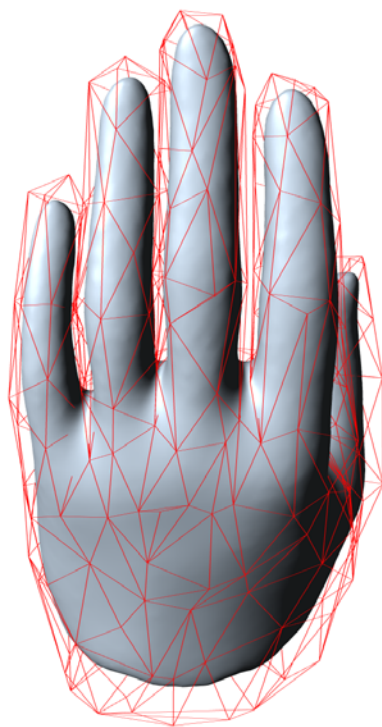
- Mean-value coordinates (Floater, Ju et al. 2005)
 - Not necessarily positive on non-convex domains



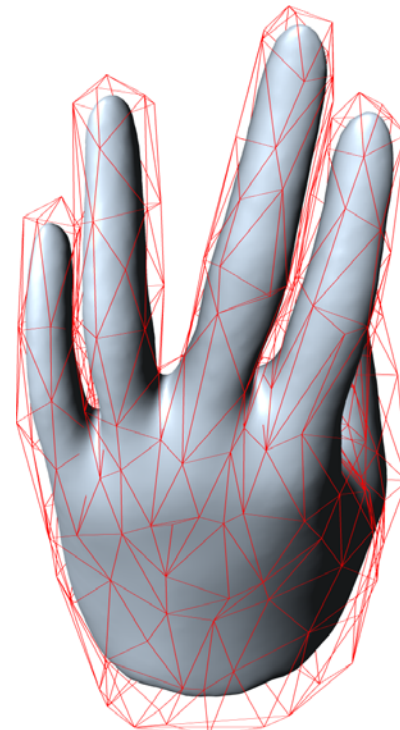
MVC

Coordinate Functions

- PMVC (Lipman et al. 2007) – ensures positivity, but no longer closed-form and only C^0



MVC



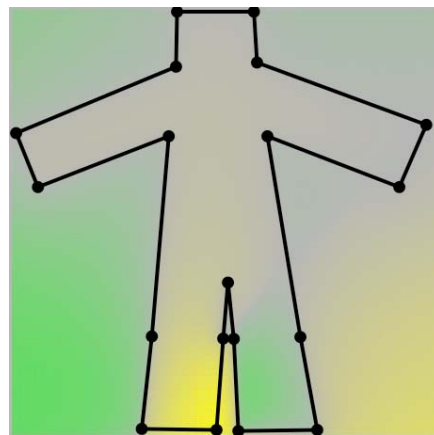
PMVC

Coordinate Functions

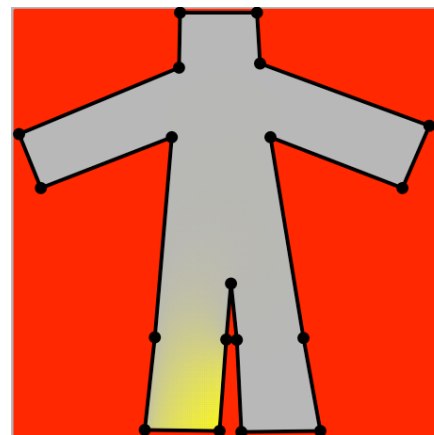
- Harmonic coordinates (Joshi et al. 2007)
 - Harmonic functions $h_i(\mathbf{x})$ for each cage vertex \mathbf{p}_i
 - Solve

$$\Delta h = 0$$

subject to: h_i linear on the boundary s.t. $h_i(\mathbf{p}_i) = \delta_{ij}$



MVC



HC

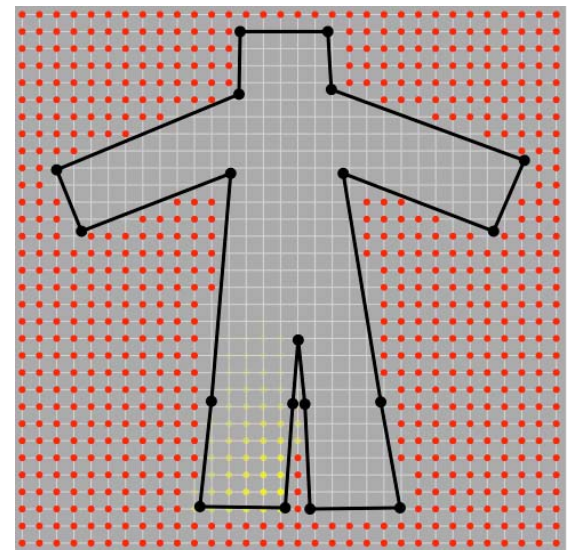
Coordinate Functions

- Harmonic coordinates (Joshi et al. 2007)
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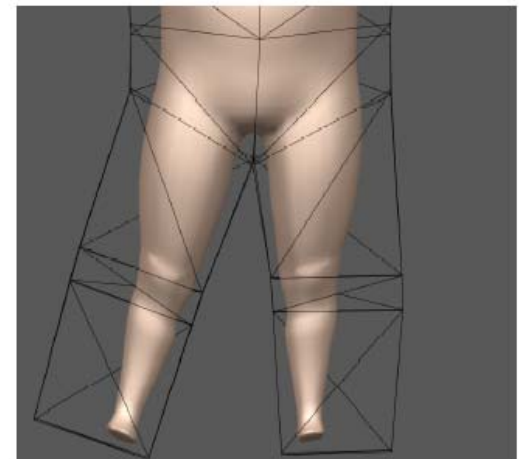
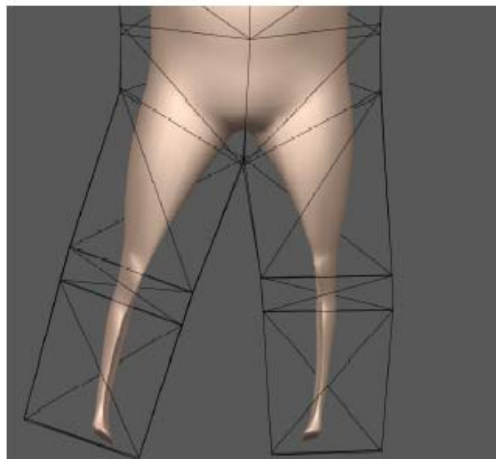
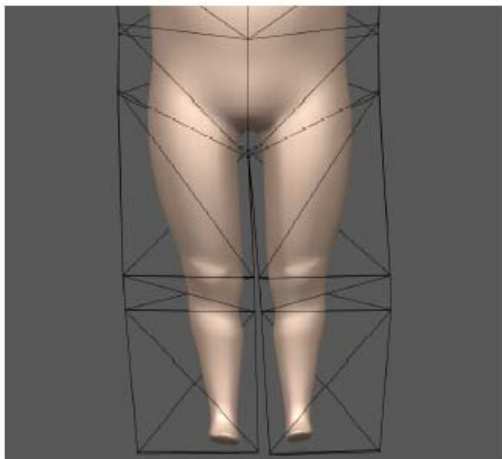
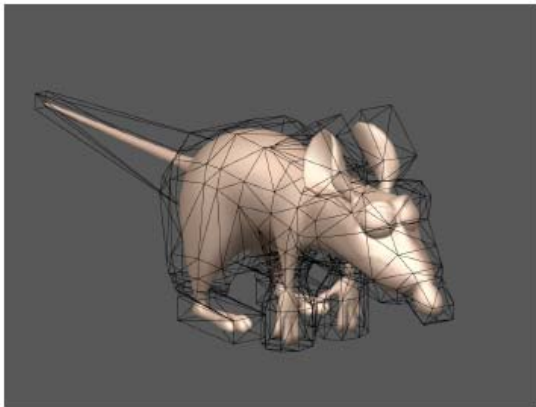
subject to: h_i linear on the boundary s.t. $h_i(\mathbf{p}_i) = \delta_{ij}$

- Volumetric Laplace equation
- Discretization, no closed-form



Coordinate Functions

- Harmonic coordinates (Joshi et al. 2007)

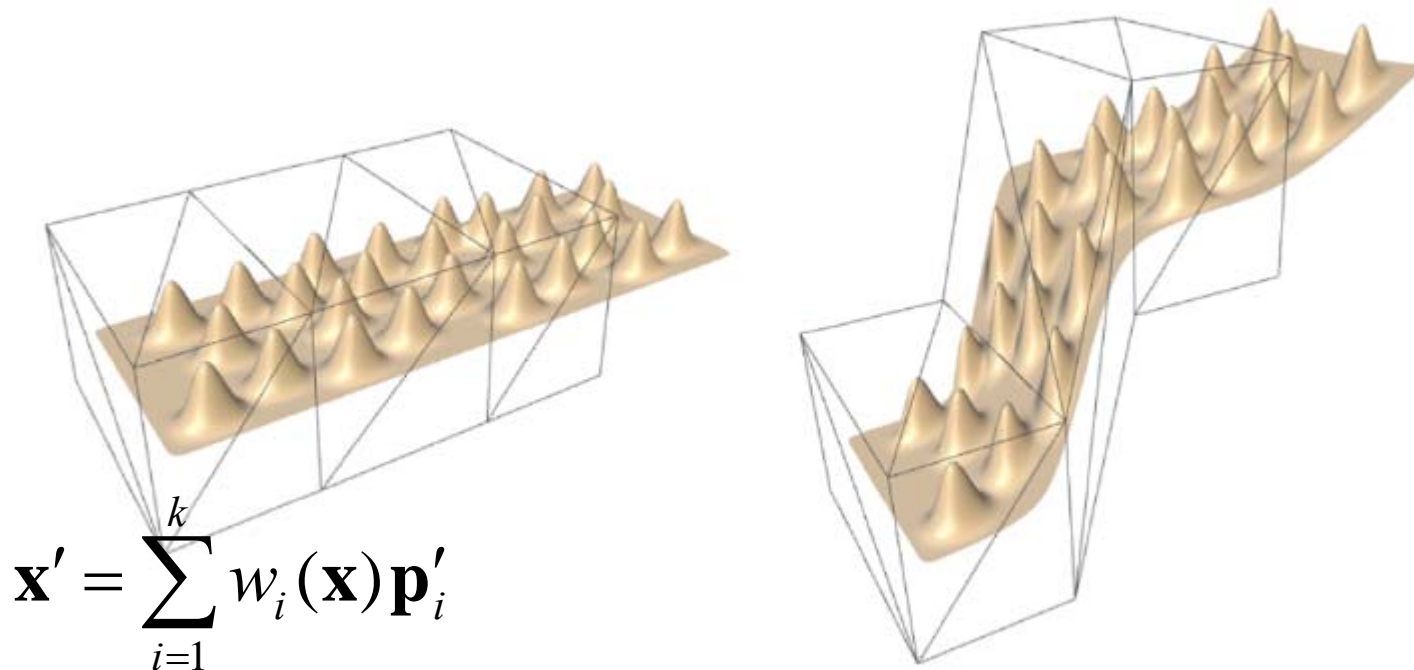


MVC

HC

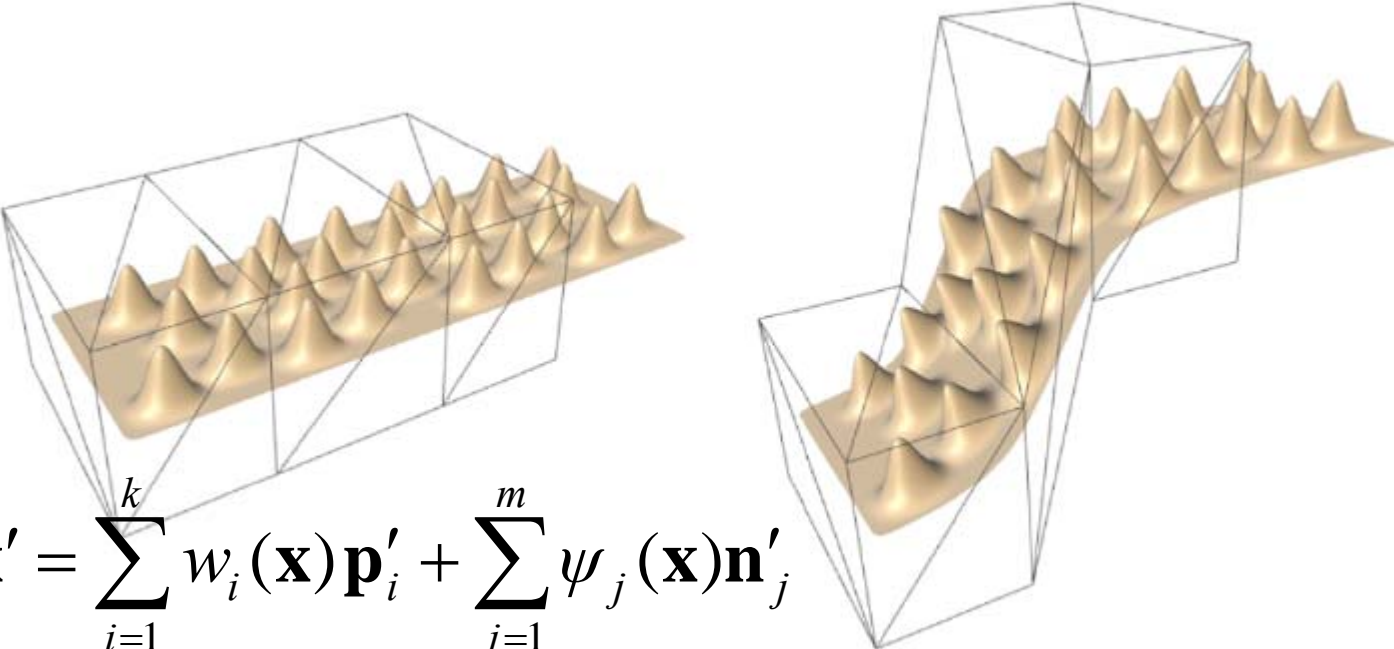
Coordinate Functions

- Green coordinates (Lipman et al. 2008)
- Observation: previous vertex-based basis functions always lead to affine-invariance!



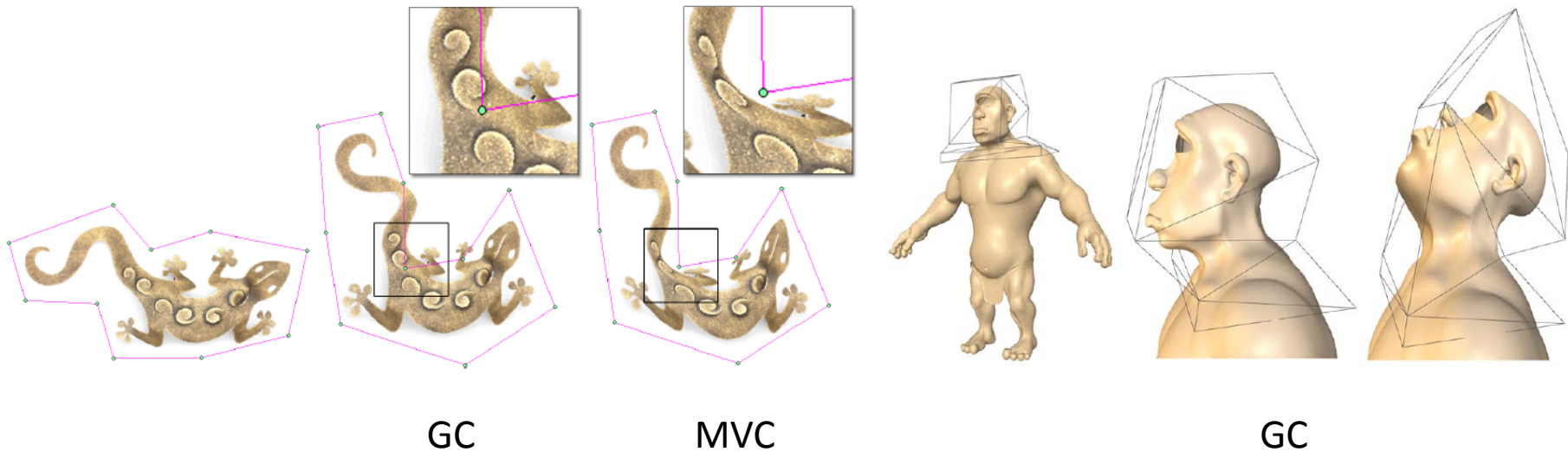
Coordinate Functions

- Green coordinates (Lipman et al. 2008)
- Correction: Make the coordinates depend on the cage faces as well


$$\mathbf{x}' = \sum_{i=1}^k w_i(\mathbf{x}) \mathbf{p}'_i + \sum_{j=1}^m \psi_j(\mathbf{x}) \mathbf{n}'_j$$

Coordinate Functions

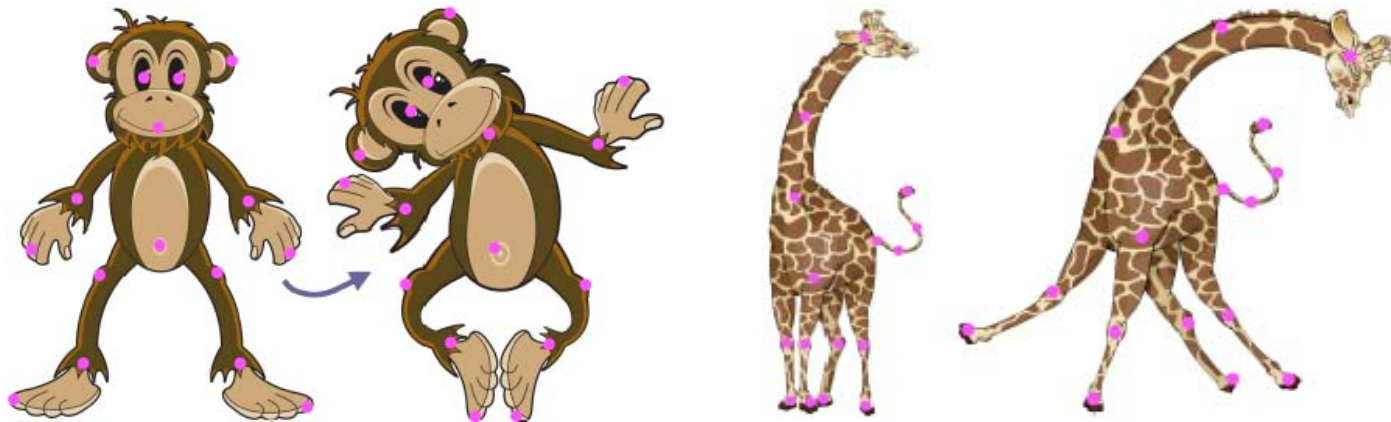
- Green coordinates (Lipman et al. 2008)
- Closed-form solution
- Conformal in 2D, quasi-conformal in 3D



Coordinate Functions

- Green coordinates (Lipman et al. 2008)
- Closed-form solution
- Conformal in 2D, quasi-conformal in 3D

Alternative interpretation in 2D via holomorphic functions and extension to point handles : **Weber et al. Eurographics 2009**



Coffee/Tea Break

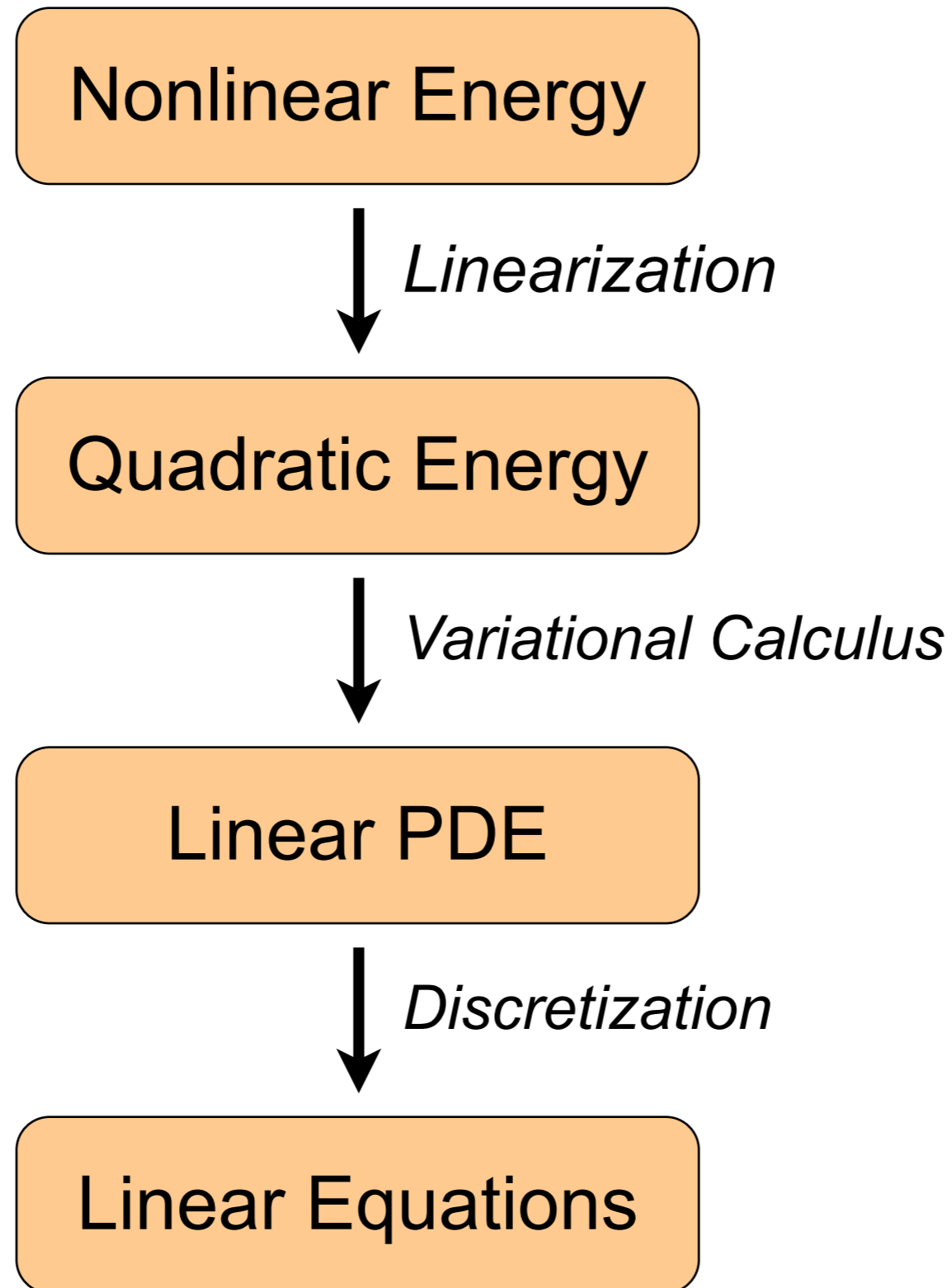
Resume at 11:00

Summary of Linear Methods

Prof. Dr. Mario Botsch

Computer Graphics & Geometry Processing
Bielefeld University

Linear Approaches



Linear Approaches

- Resulting linear systems

- Shell-based $\Delta^2 \mathbf{d} = \mathbf{0}$
- Gradient-based $\Delta \mathbf{p} = \nabla \cdot \mathbf{T}(\mathbf{g})$
- Laplacian-based $\Delta^2 \mathbf{p} = \Delta \mathbf{T}(\mathbf{1})$

- Properties

- Highly sparse
- Symmetric, positive definite (*SPD*)
- Solve for new RHS each frame!

Linear SPD Solvers

- **Dense Cholesky factorization**
 - Cubic complexity
 - High memory consumption (doesn't exploit sparsity)
- **Iterative conjugate gradients**
 - Quadratic complexity
 - Need sophisticated preconditioning
- **Multigrid solvers**
 - Linear complexity
 - But rather complicated to develop (and to use)
- **Sparse Cholesky factorization**
 - Linear complexity
 - Easy to use

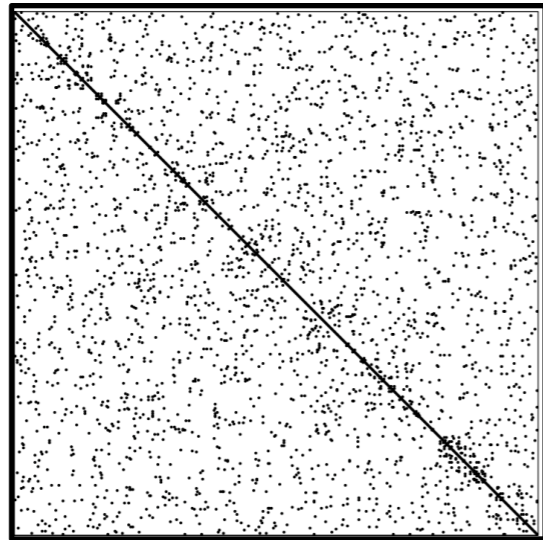
Dense Cholesky Factorization

$$\text{Solve } \mathbf{Ax} = \mathbf{b}$$

1. Cholesky factorization $\mathbf{A} = \mathbf{LL}^T$
2. Solve system $\mathbf{y} = \mathbf{L}^{-1}\mathbf{b}, \quad \mathbf{x} = \mathbf{L}^{-T}\mathbf{y}$

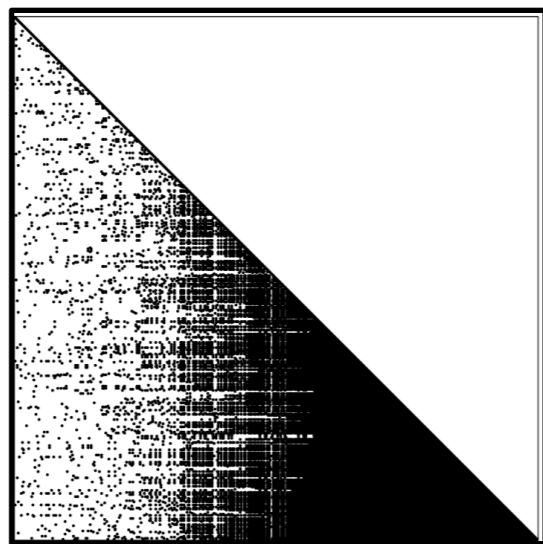
Dense Cholesky Factorization

$A=LL^T$
500×500 matrix
3500 non-zeros



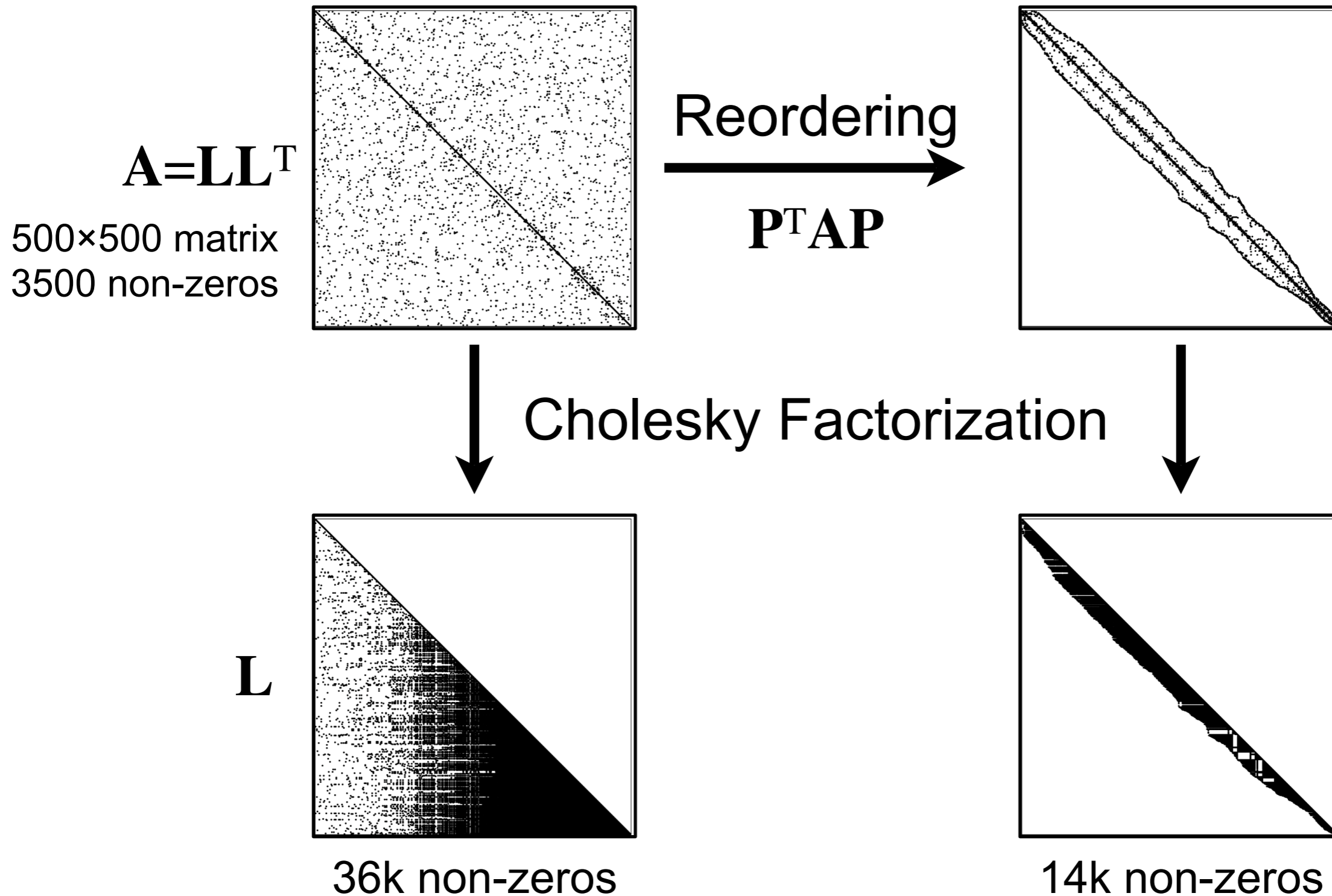
Cholesky Factorization

L

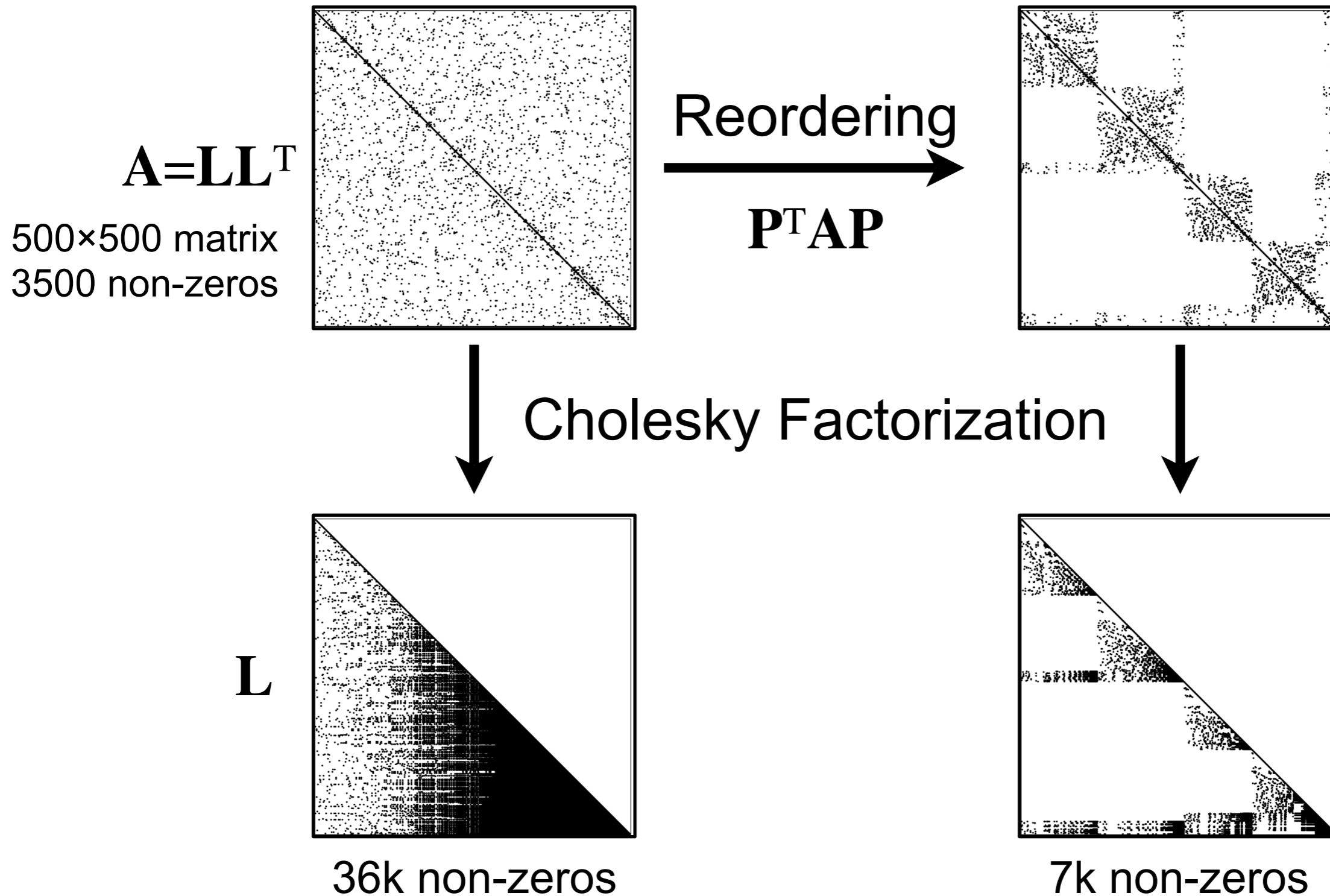


36k non-zeros

Sparse Cholesky Factorization



Sparse Cholesky Factorization



Sparse Cholesky Solver

$$\text{Solve } \mathbf{Ax} = \mathbf{b}$$

Pre-computation

1. Matrix re-ordering $\tilde{\mathbf{A}} = \mathbf{P}^T \mathbf{A} \mathbf{P}$

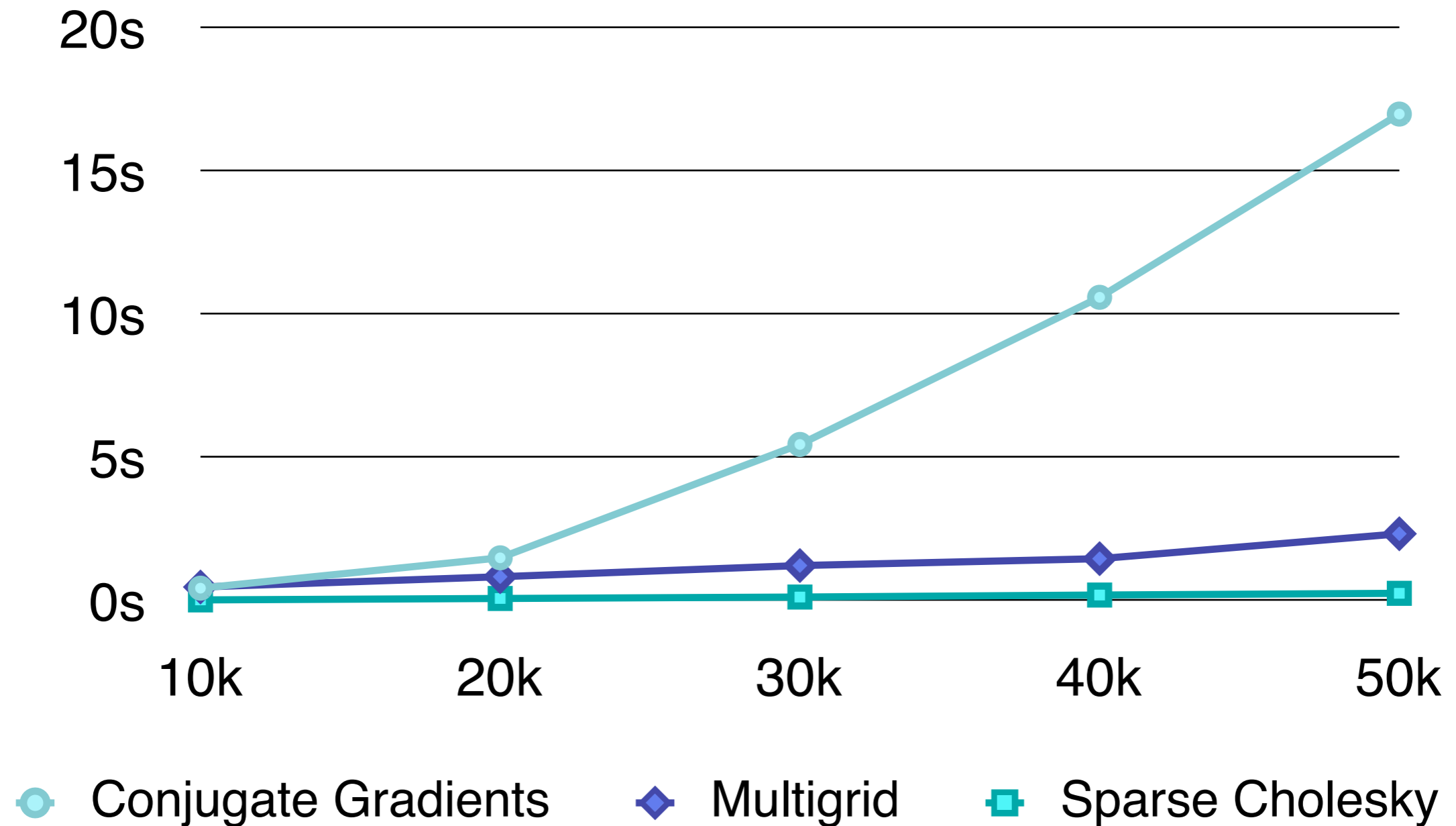
2. Cholesky factorization $\tilde{\mathbf{A}} = \mathbf{L} \mathbf{L}^T$

3. Solve system $\mathbf{y} = \mathbf{L}^{-1} \mathbf{P}^T \mathbf{b}, \quad \mathbf{x} = \mathbf{P} \mathbf{L}^{-T} \mathbf{y}$

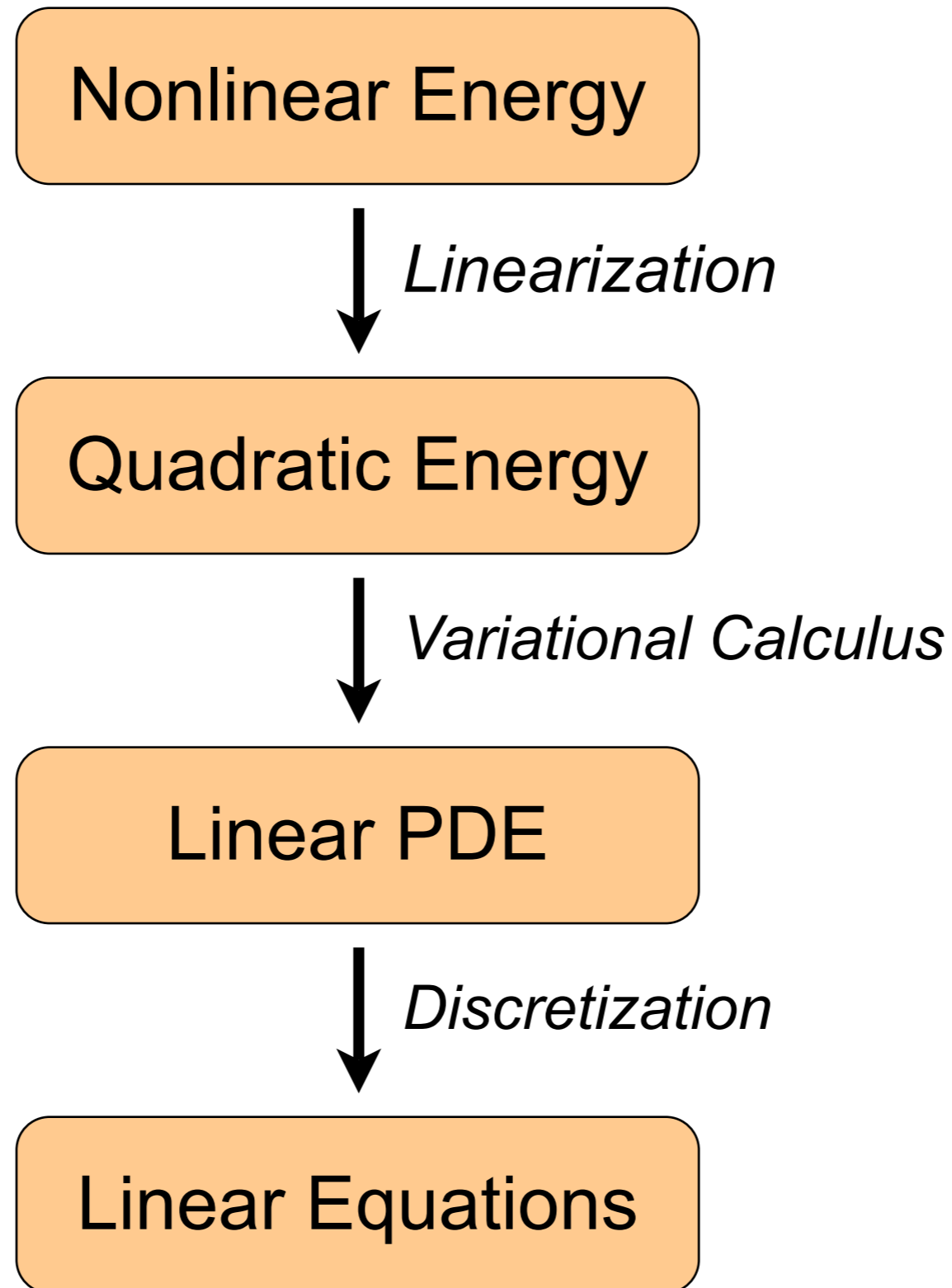
Per-frame computation

Bi-Laplace Systems

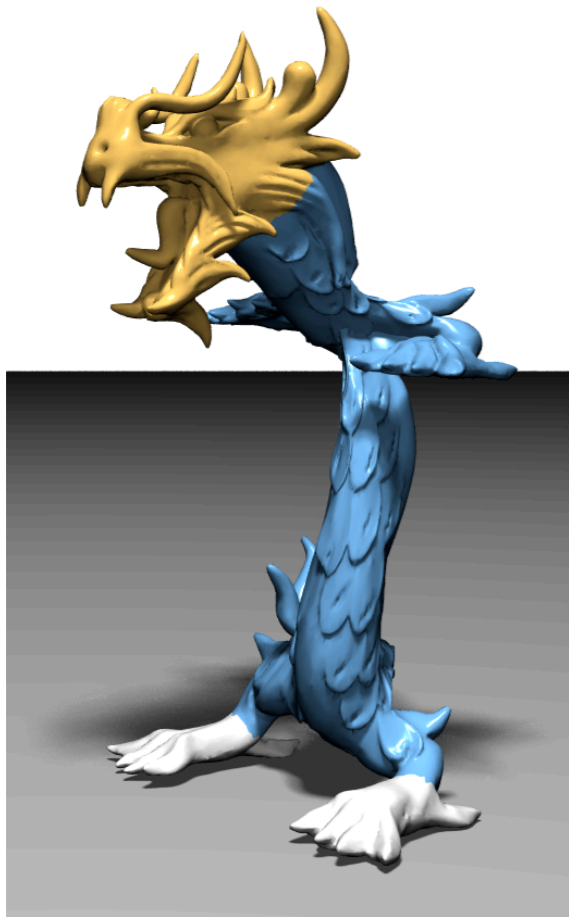
3 Solutions (per frame costs)



Linear Approaches



Linear vs. Nonlinear



Shell

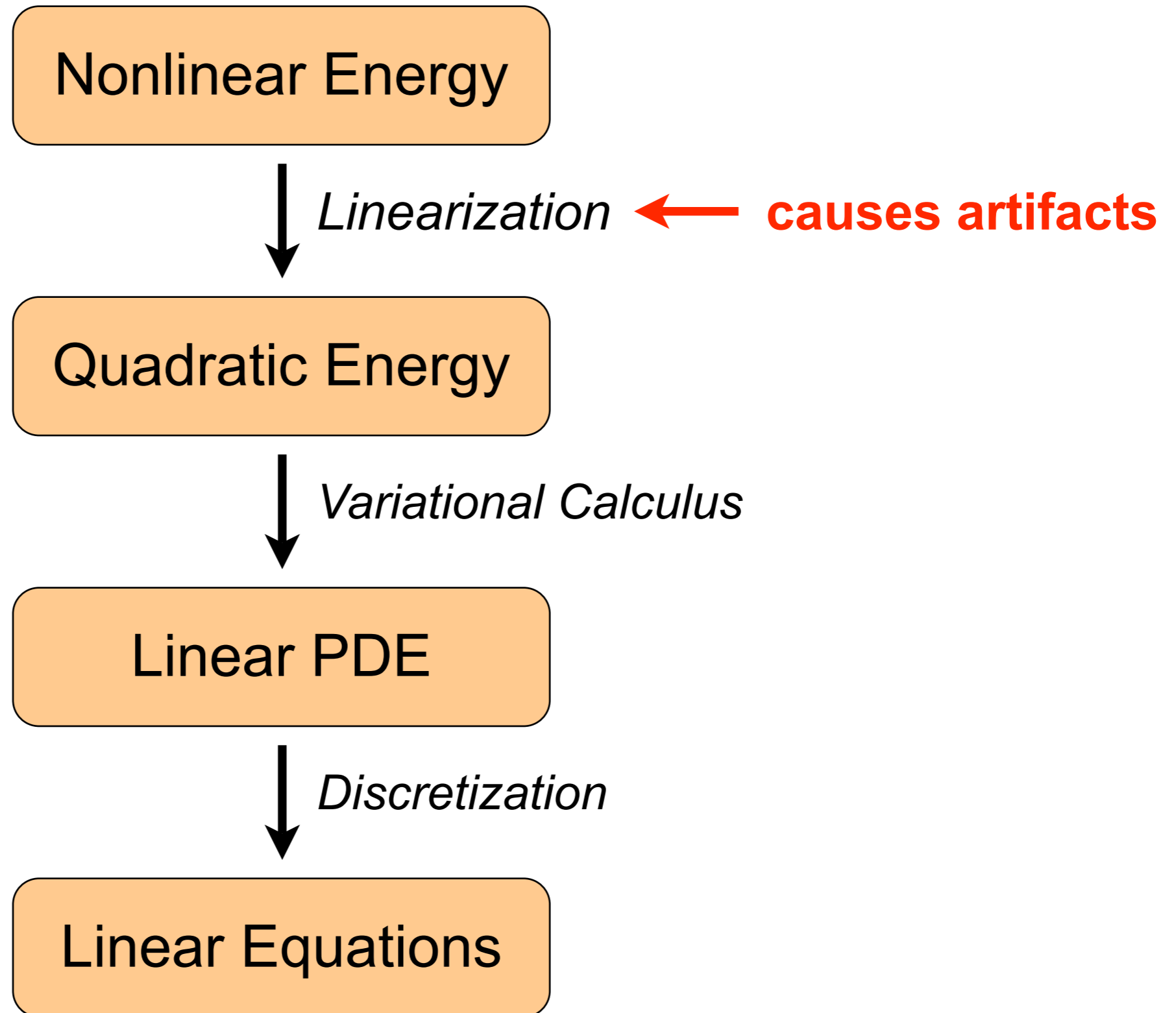


Gradient



Nonlinear

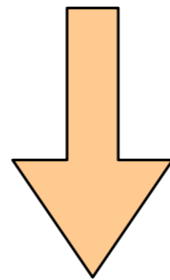
Linear Approaches



Linearizations / Simplifications

- **Shell-based deformation**

$$\int_{\Omega} k_s \|\mathbf{I} - \mathbf{I}'\|^2 + k_b \|\mathbf{\Pi} - \mathbf{\Pi}'\|^2 \, dudv$$

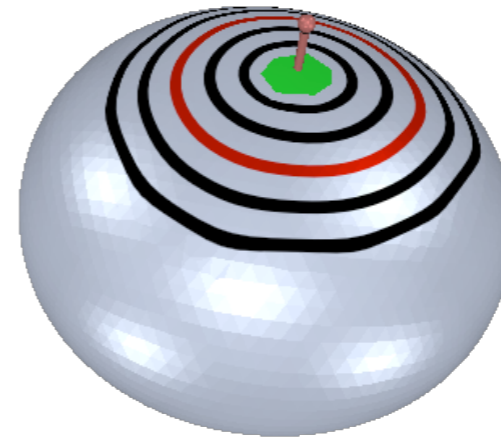
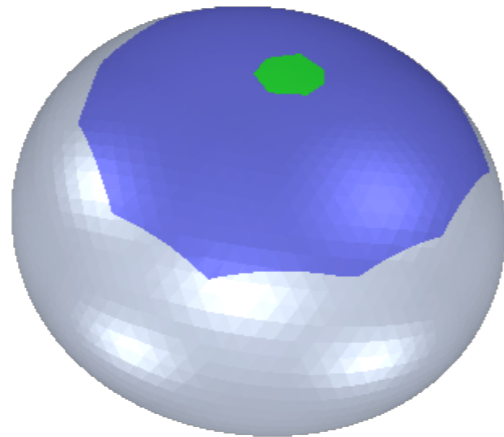


$$\int_{\Omega} k_s \left(\|\mathbf{d}_u\|^2 + \|\mathbf{d}_v\|^2 \right) + k_b \left(\|\mathbf{d}_{uu}\|^2 + 2 \|\mathbf{d}_{uv}\|^2 + \|\mathbf{d}_{vv}\|^2 \right) \, dudv$$

Linearizations / Simplifications

- **Gradient-based editing**

$$\nabla T(\mathbf{x}) = \mathbf{A}$$



Linearizations / Simplifications

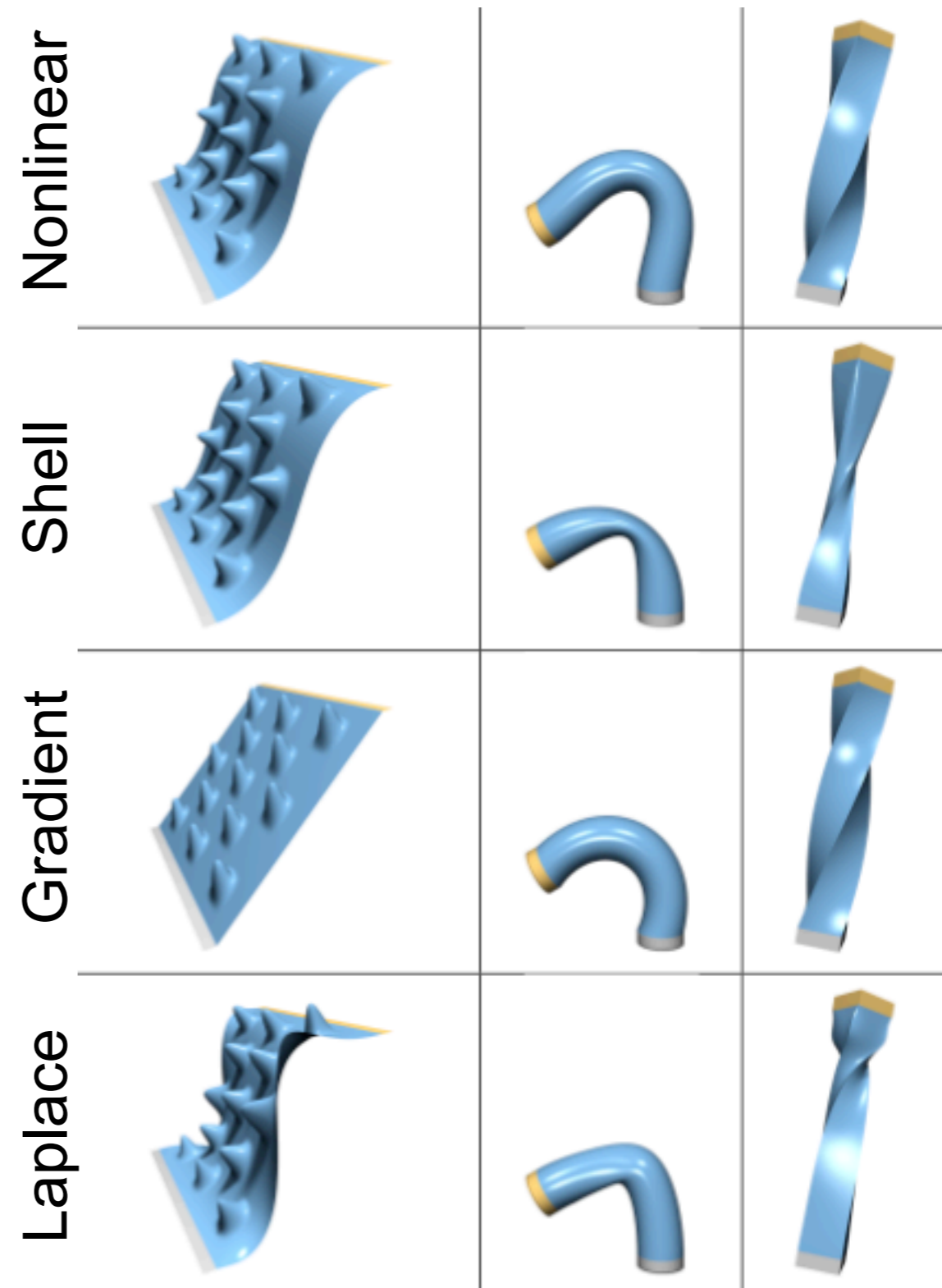
- **Laplacian surface editing**

$$\mathbf{R}\mathbf{x} \approx \mathbf{x} + (\mathbf{r} \times \mathbf{x}) = \begin{pmatrix} 1 & -r_3 & r_2 \\ r_3 & 1 & -r_1 \\ -r_2 & r_1 & 1 \end{pmatrix} \mathbf{x}$$

$$\mathbf{T}_i = \begin{pmatrix} s & -r_3 & r_2 \\ r_3 & s & -r_1 \\ -r_2 & r_1 & s \end{pmatrix}$$

Linear vs. Nonlinear

- Analyze existing methods
 - Some work for translations
 - Some work for rotations
 - No method works for both



Linear vs. Nonlinear

- Linear approaches
 - Solve linear system each frame
 - Small deformations
 - Dense constraints
- Nonlinear approaches
 - Solve nonlinear problem each frame
 - Large deformations
 - Sparse constraints



Nonlinear Surface-Based Deformation

Prof. Dr. Mario Botsch

Computer Graphics & Geometry Processing
Bielefeld University

Nonlinear Surface Deformation

- **Nonlinear Optimization**
- Shell-Based Deformation
- (Differential Coordinates)

Nonlinear Minimization

- Given a nonlinear deformation energy

$$E(\mathbf{d}) = E(\mathbf{d}_1, \dots, \mathbf{d}_n)$$

find the displacement $\mathbf{d}(\mathbf{x})$ that minimizes $E(\mathbf{d})$, while satisfying the modeling constraints.

- Typically $E(\mathbf{d})$ stays the same, but the modeling constraints change each frame.

Gradient Descent

- Start with initial guess \mathbf{d}_0
- Iterate until convergence
 - Find descent direction $\mathbf{h} = -\nabla E(\mathbf{d})$
 - Find step size λ
 - Update $\mathbf{d} = \mathbf{d} + \lambda \mathbf{h}$
- Properties
 - + Easy to implement, guaranteed convergence
 - Slow convergence

Newton's Method

- Start with initial guess \mathbf{d}_0
- Iterate until convergence
 - Find descent direction as $\mathbf{H}(\mathbf{d}) \mathbf{h} = -\nabla E(\mathbf{d})$
 - Find step size λ
 - Update $\mathbf{d} = \mathbf{d} + \lambda \mathbf{h}$
- Properties
 - + Fast convergence if close to minimum
 - Needs pos. def. \mathbf{H} , needs 2nd derivatives for \mathbf{H}

Nonlinear Least Squares

Given a nonlinear vector-valued error function

$$\mathbf{e}(\mathbf{d}_1, \dots, \mathbf{d}_n) = \begin{pmatrix} e_1(\mathbf{d}_1, \dots, \mathbf{d}_n) \\ \vdots \\ e_m(\mathbf{d}_1, \dots, \mathbf{d}_n) \end{pmatrix}$$

find the displacement $\mathbf{d}(\mathbf{x})$ that minimizes the nonlinear least squares error

$$E(\mathbf{d}_1, \dots, \mathbf{d}_n) = \frac{1}{2} \|\mathbf{e}(\mathbf{d}_1, \dots, \mathbf{d}_n)\|^2$$

Gauss-Newton Method

- Start with initial guess \mathbf{d}_0
- Iterate until convergence
 - Find descent direction as $(\mathbf{J}(\mathbf{d})^T \mathbf{J}(\mathbf{d})) \mathbf{h} = -\mathbf{J}(\mathbf{d})^T \mathbf{e}$
 - Find step size λ
 - Update $\mathbf{d} = \mathbf{d} + \lambda \mathbf{h}$
- Properties
 - + Fast convergence if close to minimum
 - + Needs full-rank $\mathbf{J}(\mathbf{d})$, needs 1st derivatives for $\mathbf{J}(\mathbf{d})$

Nonlinear Optimization

- Has to solve a linear system each frame
 - Matrix changes in each iteration!
 - Factorize matrix each time
 - Numerically more complex
 - No guaranteed convergence
 - Might need several iterations
 - Converges to closest local minimum
- ➔ Spend more time on fancy solvers...

Nonlinear Surface Deformation

- Nonlinear Optimization
- **Shell-Based Deformation**
- (Differential Coordinates)

Shell-Based Deformation

- **Discrete Shells**
[Grinspun et al, SCA 2003]
- **Rigid Cells**
[Botsch et al, SGP 2006]
- **As-Rigid-As-Possible Modeling**
[Sorkine & Alexa, SGP 2007]

Discrete Shells

- Main idea
 - Don't discretize continuous energy
 - Define **discrete** energy instead
 - Leads to simpler (still nonlinear) formulation
- Discrete energy
 - How to measure stretching on meshes?
 - How to measure bending on meshes?

Discrete Shell Energy

- **Stretching:** Change of edge lengths

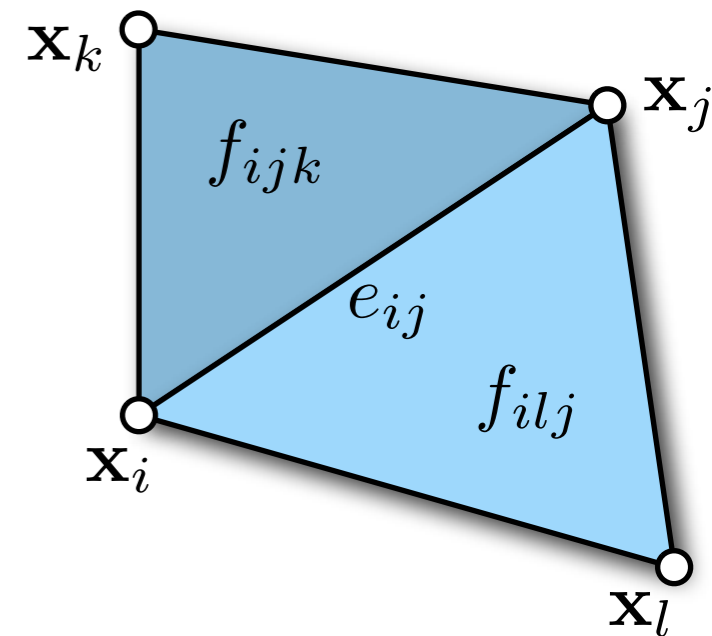
$$\sum_{e_{ij} \in E} \lambda_{ij} (|e_{ij}| - |\bar{e}_{ij}|)^2$$

- **Stretching:** Change of triangle areas

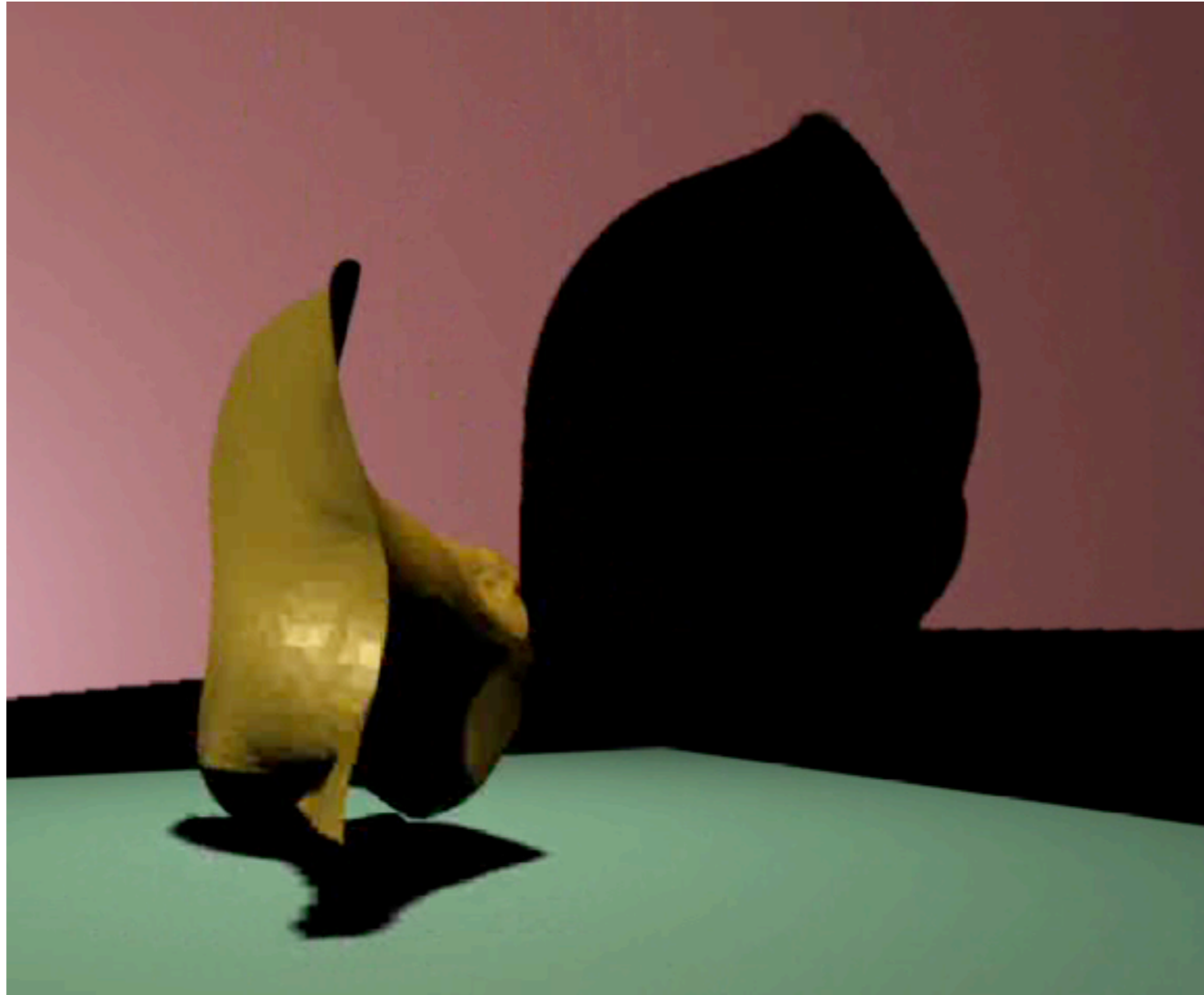
$$\sum_{f_{ijk} \in F} \lambda_{ijk} (|f_{ijk}| - |\bar{f}_{ijk}|)^2$$

- **Bending:** Change of dihedral angles

$$\sum_{e_{ij} \in E} \mu_{ij} (\theta_{ij} - \bar{\theta}_{ij})^2$$

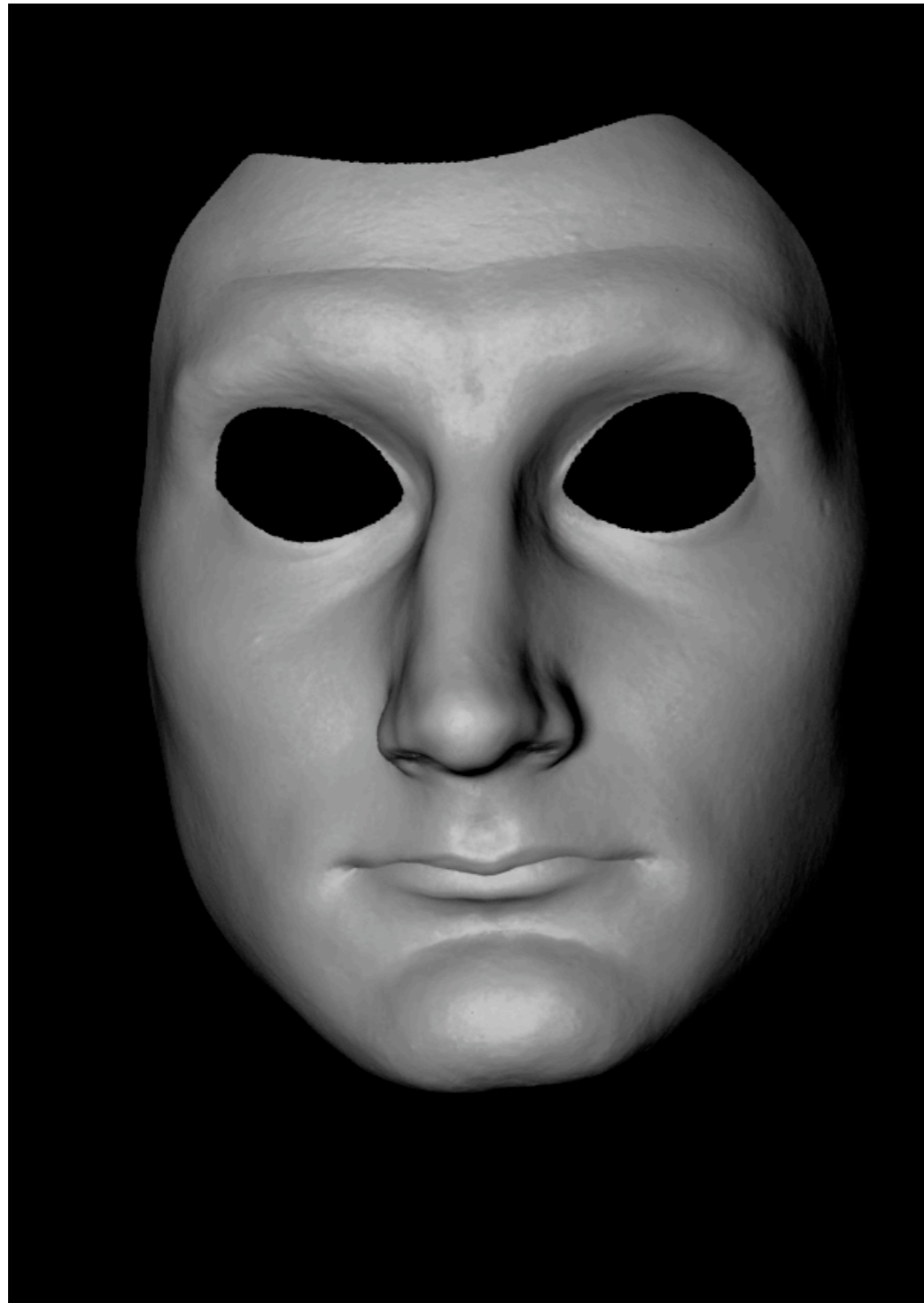


Discrete Shells



[Grinspun 2003]

Realistic Face Animations



Linear model



Nonlinear model

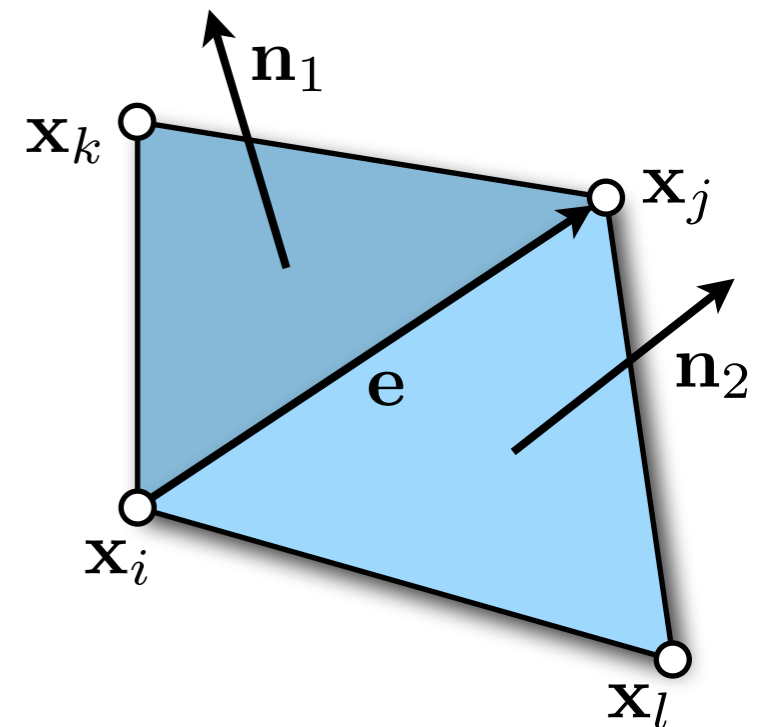
Discrete Energy Gradients

- Gradients of edge length

$$|e_{ij}| = \|\mathbf{x}_j - \mathbf{x}_i\|$$

$$\frac{\partial |e_{ij}|}{\partial \mathbf{x}_i} = \frac{-\mathbf{e}}{\|\mathbf{e}\|}$$

$$\frac{\partial |e_{ij}|}{\partial \mathbf{x}_j} = \frac{\mathbf{e}}{\|\mathbf{e}\|}$$



Discrete Energy Gradients

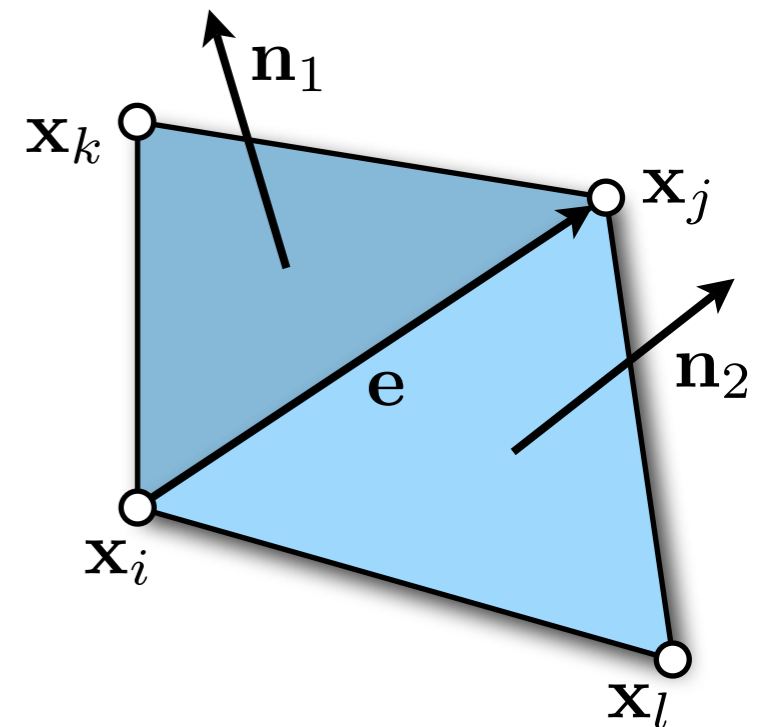
- Gradients of triangle area

$$|f_{ijk}| = \frac{1}{2} \|\mathbf{n}_1\|$$

$$\frac{\partial |f_{ijk}|}{\partial \mathbf{x}_i} = \frac{\mathbf{n}_1 \times (\mathbf{x}_k - \mathbf{x}_j)}{2 \|\mathbf{n}_1\|}$$

$$\frac{\partial |f_{ijk}|}{\partial \mathbf{x}_j} = \frac{\mathbf{n}_1 \times (\mathbf{x}_i - \mathbf{x}_k)}{2 \|\mathbf{n}_1\|}$$

$$\frac{\partial |f_{ijk}|}{\partial \mathbf{x}_k} = \frac{\mathbf{n}_1 \times (\mathbf{x}_j - \mathbf{x}_i)}{2 \|\mathbf{n}_1\|}$$



Discrete Energy Gradients

- Gradients of dihedral angle

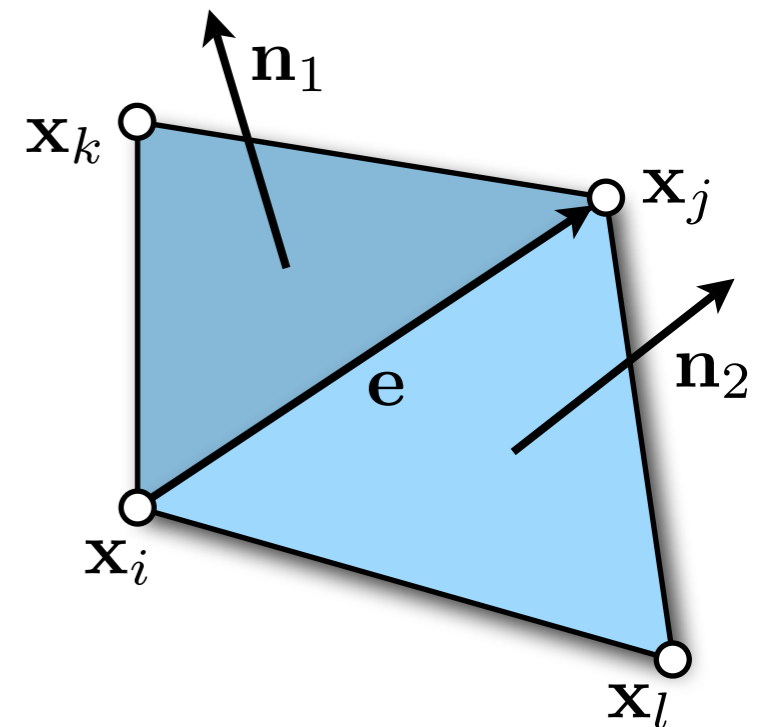
$$\theta = \text{atan}\left(\frac{\sin \theta}{\cos \theta}\right) = \text{atan}\left(\frac{(\mathbf{n}_1 \times \mathbf{n}_2)^T \mathbf{e}}{\mathbf{n}_1^T \mathbf{n}_2 \cdot \|\mathbf{e}\|}\right)$$

$$\frac{\partial \theta}{\partial \mathbf{x}_i} = \frac{(\mathbf{x}_k - \mathbf{x}_j)^T \mathbf{e}}{\|\mathbf{e}\|} \cdot \frac{-\mathbf{n}_1}{\|\mathbf{n}_1\|^2} + \frac{(\mathbf{x}_l - \mathbf{x}_j)^T \mathbf{e}}{\|\mathbf{e}\|} \cdot \frac{-\mathbf{n}_2}{\|\mathbf{n}_2\|^2}$$

$$\frac{\partial \theta}{\partial \mathbf{x}_j} = \frac{(\mathbf{x}_i - \mathbf{x}_k)^T \mathbf{e}}{\|\mathbf{e}\|} \cdot \frac{-\mathbf{n}_1}{\|\mathbf{n}_1\|^2} + \frac{(\mathbf{x}_i - \mathbf{x}_l)^T \mathbf{e}}{\|\mathbf{e}\|} \cdot \frac{-\mathbf{n}_2}{\|\mathbf{n}_2\|^2}$$

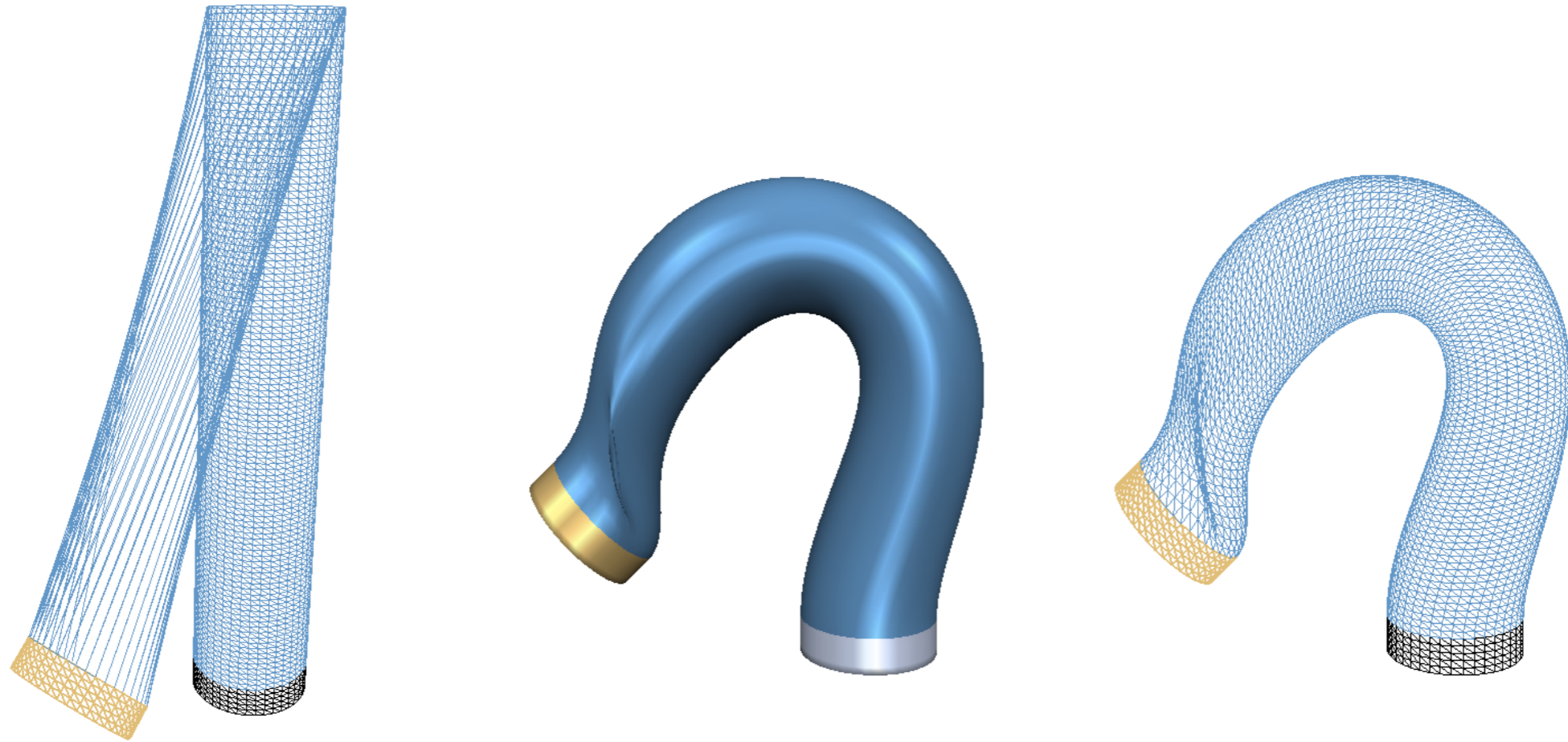
$$\frac{\partial \theta}{\partial \mathbf{x}_k} = \|\mathbf{e}\| \cdot \frac{-\mathbf{n}_1}{\|\mathbf{n}_1\|^2}$$

$$\frac{\partial \theta}{\partial \mathbf{x}_l} = \|\mathbf{e}\| \cdot \frac{-\mathbf{n}_2}{\|\mathbf{n}_2\|^2}$$



Discrete Shell Editing

- Problems with large deformation
 - Bad initial state causes numerical problems



Shell-Based Deformation

- Discrete Shells
[Grinspun et al, SCA 2003]
- **Rigid Cells**
[Botsch et al, SGP 2006]
- As-Rigid-As-Possible Modeling
[Sorkine & Alexa, SGP 2007]

Nonlinear Shape Deformation

- *Nonlinear* editing too instable?
 - *Physically plausible* vs. physically correct
- ➔ Trade physical correctness for
- Computational efficiency
 - Numerical robustness

Elastically Connected Rigid Cells

- Qualitatively emulate thin-shell behavior
- Thin volumetric layer around center surface
- Extrude polygonal cell C_i per mesh face



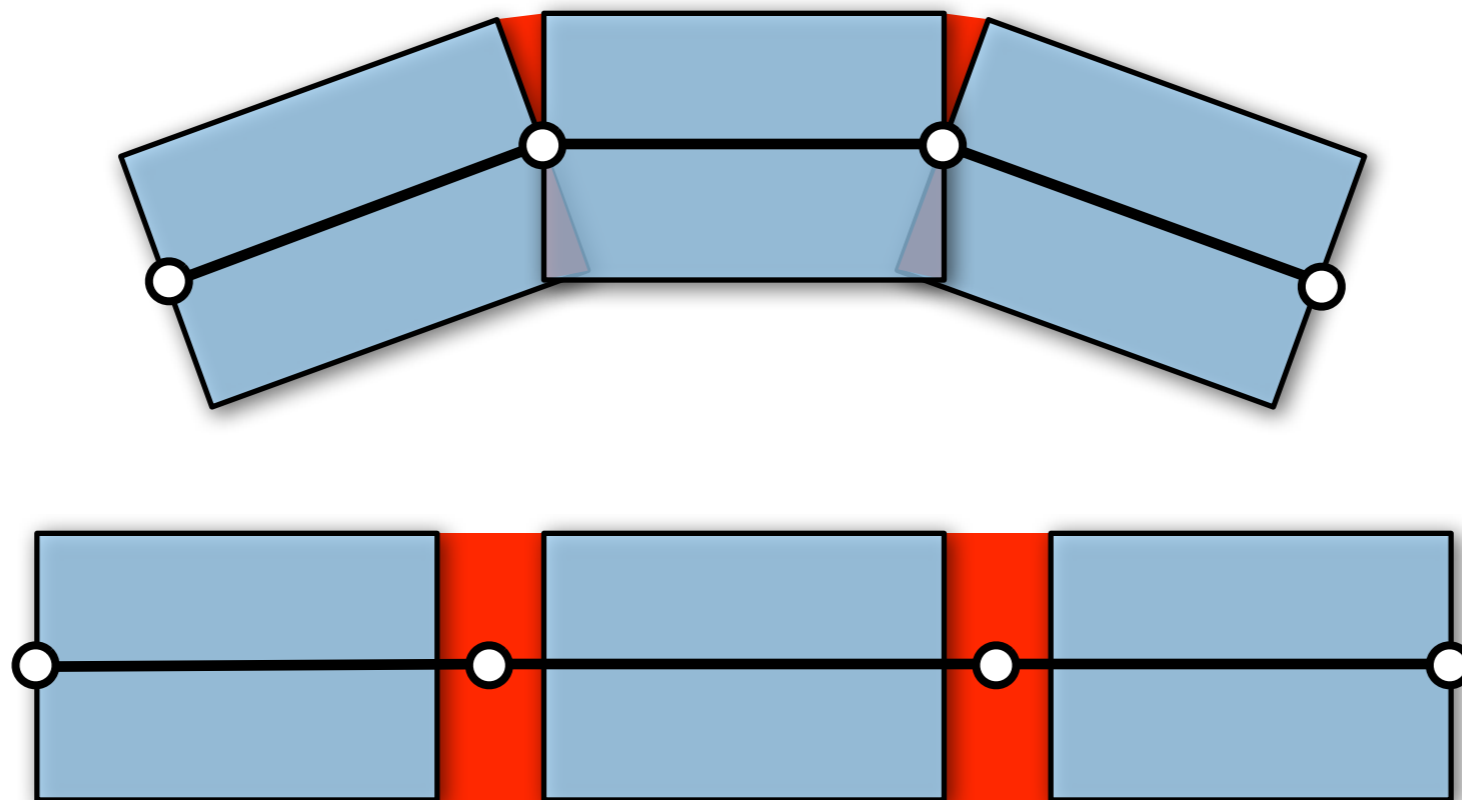
Elastically Connected Rigid Cells

- Aim for robustness
 - Prevent cells from degenerating
 - ➔ Keep cells *rigid*



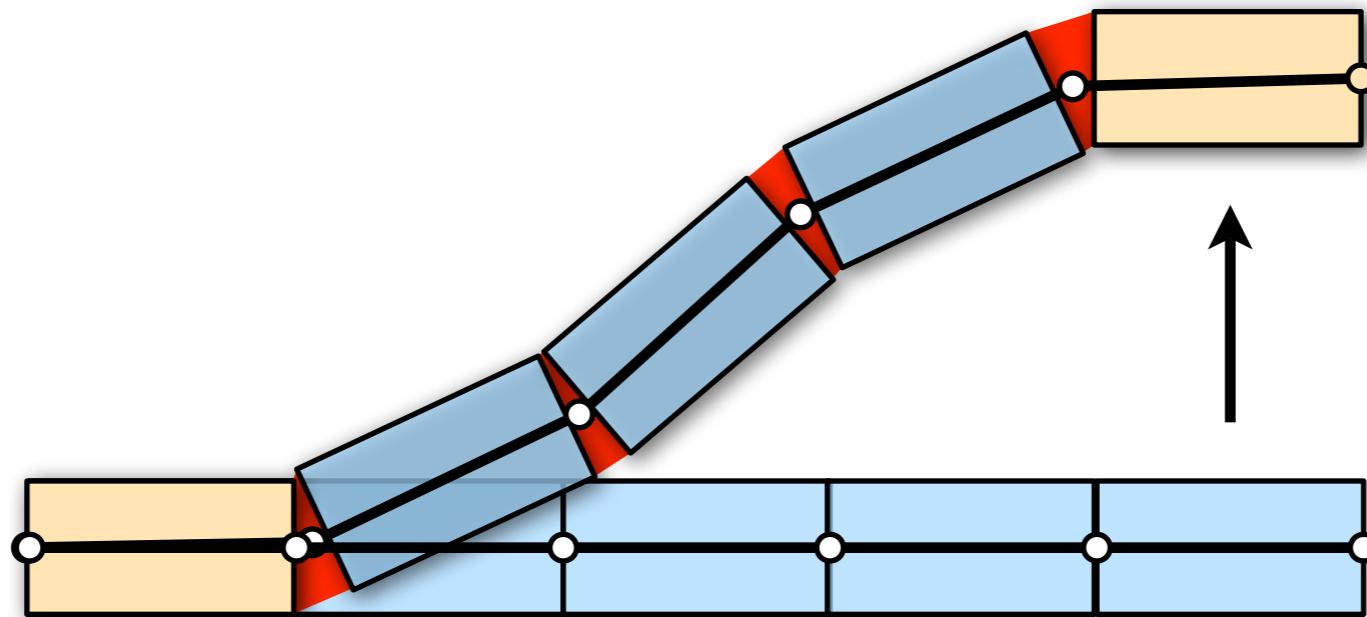
Elastically Connected Rigid Cells

- Connect cells along their faces
 - Nonlinear elastic energy
 - Measures bending, stretching, twisting, ...



Cell-Based Surface Deformation

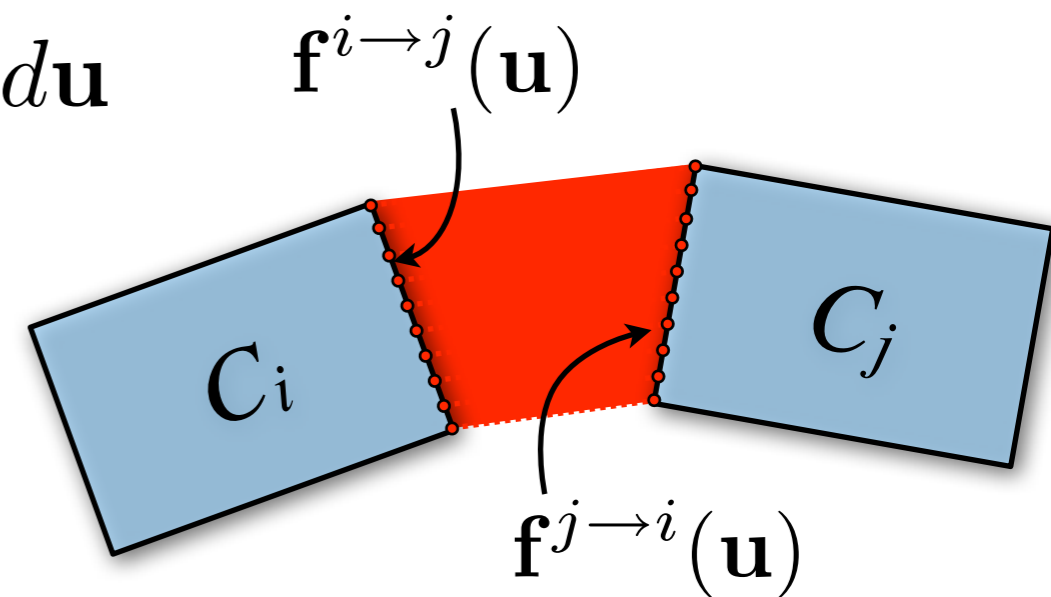
1. Prescribes position/orientation for cells
2. Find optimal rigid motions per cell
3. Update vertices by average cell transformations



Elastically Connected Rigid Cells

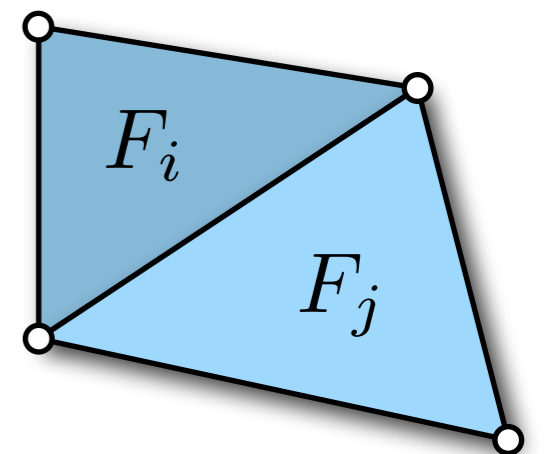
- Pairwise energy

$$E_{ij} = \int_{[0,1]^2} \|\mathbf{f}^{i \rightarrow j}(\mathbf{u}) - \mathbf{f}^{j \rightarrow i}(\mathbf{u})\|^2 d\mathbf{u}$$



- Global energy

$$E = \sum_{\{i,j\}} w_{ij} \cdot E_{ij} \quad , \quad w_{ij} = \frac{\|\mathbf{e}_{ij}\|^2}{|F_i| + |F_j|}$$



Nonlinear Minimization

- Find *rigid* motion \mathbf{T}_i per cell C_i

$$\min_{\{\mathbf{T}_i\}} \sum_{\{i,j\}} w_{ij} \int_{[0,1]^2} \|\mathbf{T}_i(\mathbf{f}^{i \rightarrow j}(\mathbf{u})) - \mathbf{T}_j(\mathbf{f}^{j \rightarrow i}(\mathbf{u}))\|^2 d\mathbf{u}$$

- Generalized global *shape matching* problem
 - Robust geometric optimization
 - Nonlinear Newton-type minimization
 - Hierarchical multi-grid solver

Newton-Type Iteration

1. Linearization of rigid motions

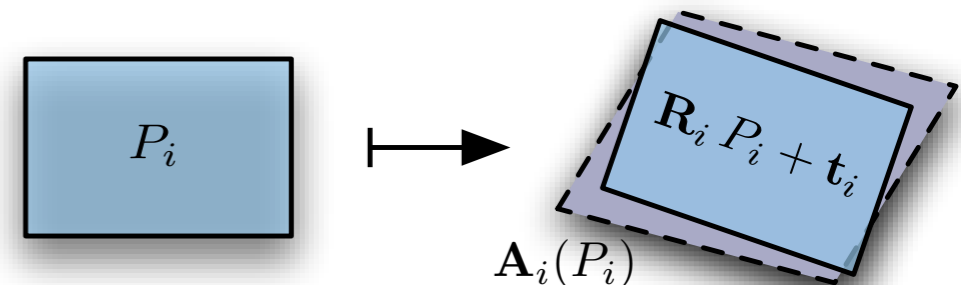
$$\mathbf{R}_i \mathbf{x} + \mathbf{t}_i \approx \mathbf{x} + (\boldsymbol{\omega}_i \times \mathbf{x}) + \mathbf{v}_i =: \mathbf{A}_i \mathbf{x}$$

2. Quadratic optimization of velocities

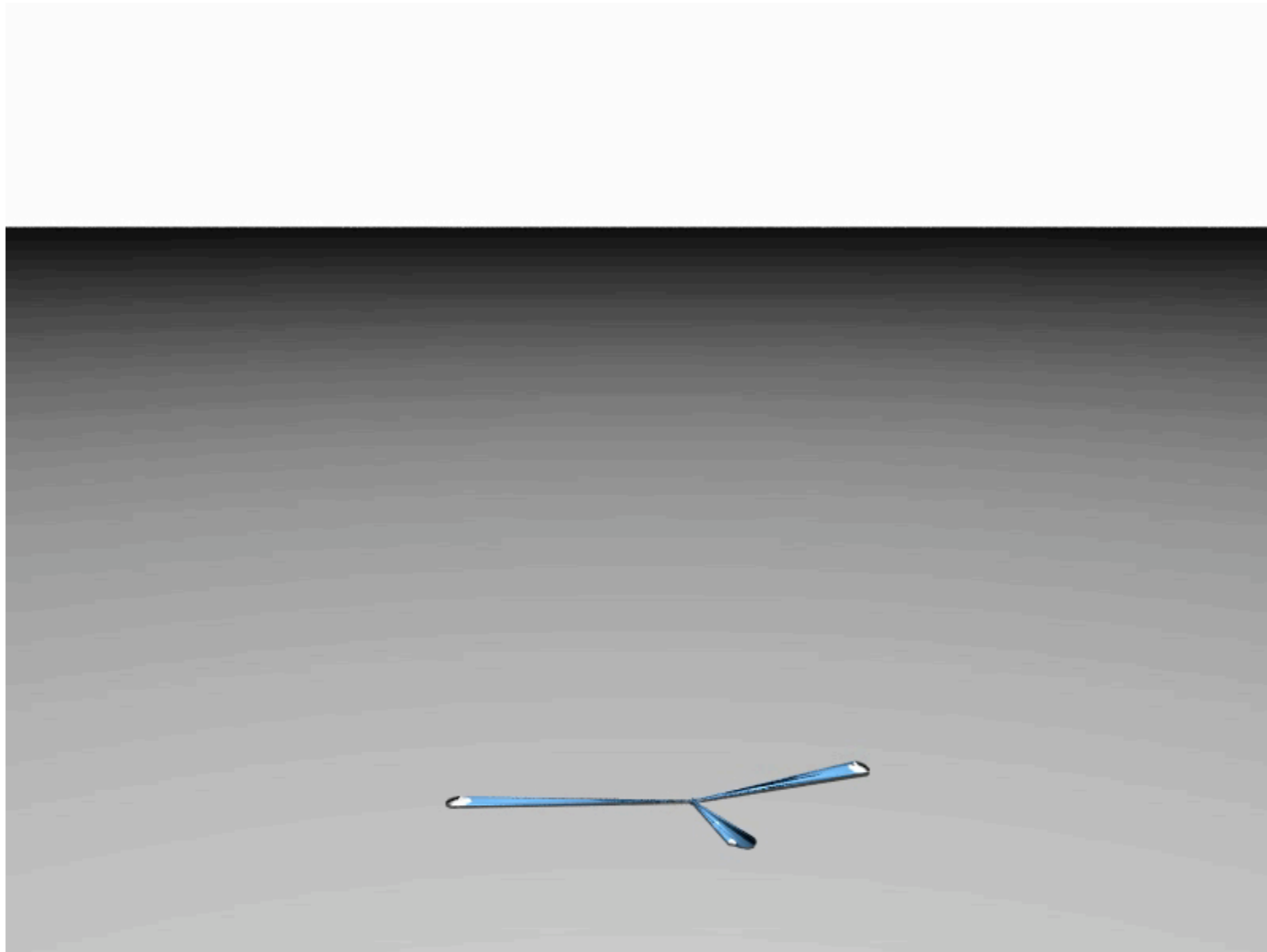
$$\min_{\{\mathbf{v}_i, \boldsymbol{\omega}_i\}} \sum_{\{i,j\}} w_{ij} \int_{[0,1]^2} \|\mathbf{A}_i(\mathbf{f}^{i \rightarrow j}(\mathbf{u})) - \mathbf{A}_j(\mathbf{f}^{j \rightarrow i}(\mathbf{u}))\|^2 d\mathbf{u}$$

3. Project \mathbf{A}_i onto rigid motion manifold

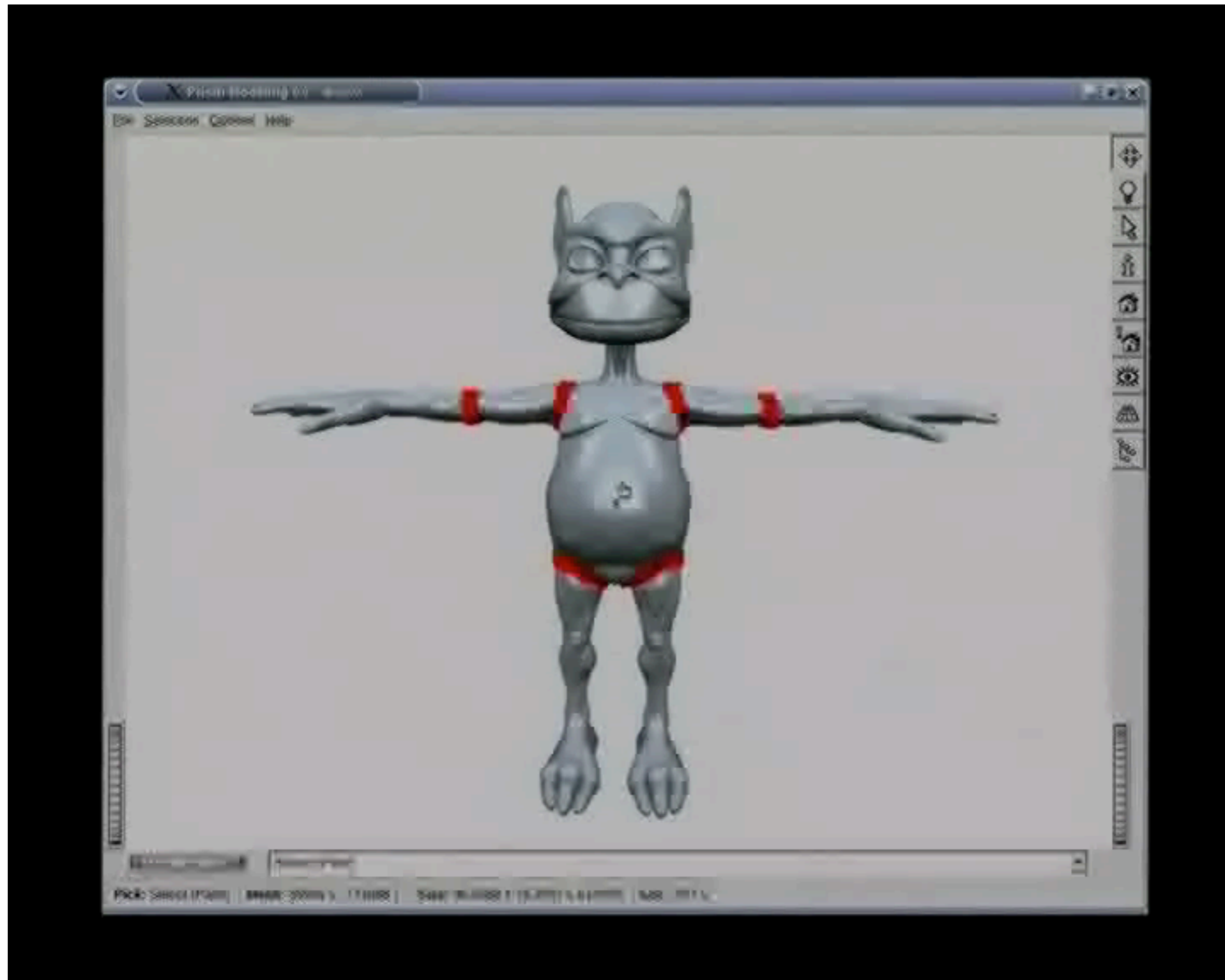
➡ Local shape matching



Robustness

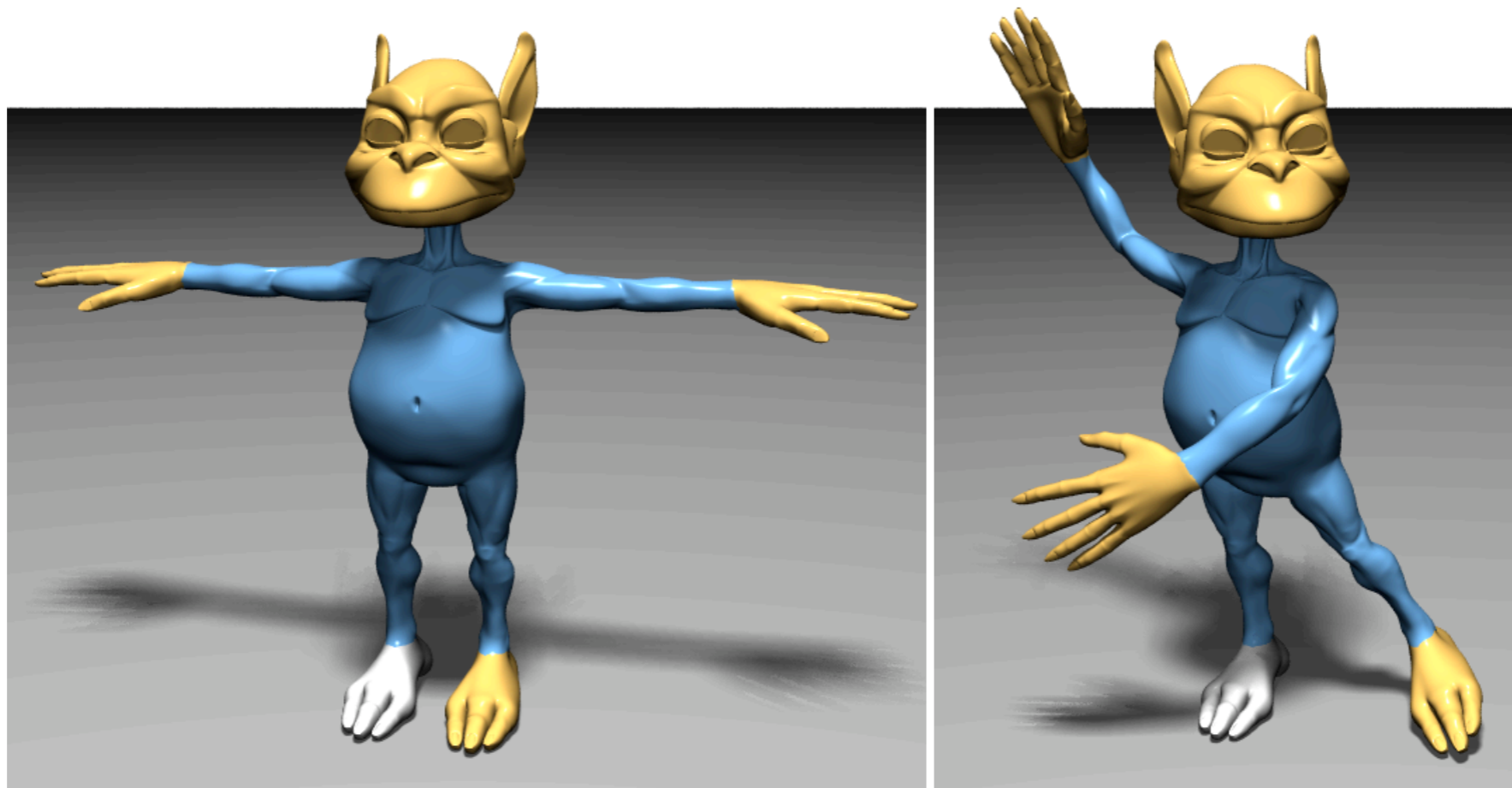


Character Posing



Goblin Posing

- Intuitive large scale deformations
- Whole session < 5 min

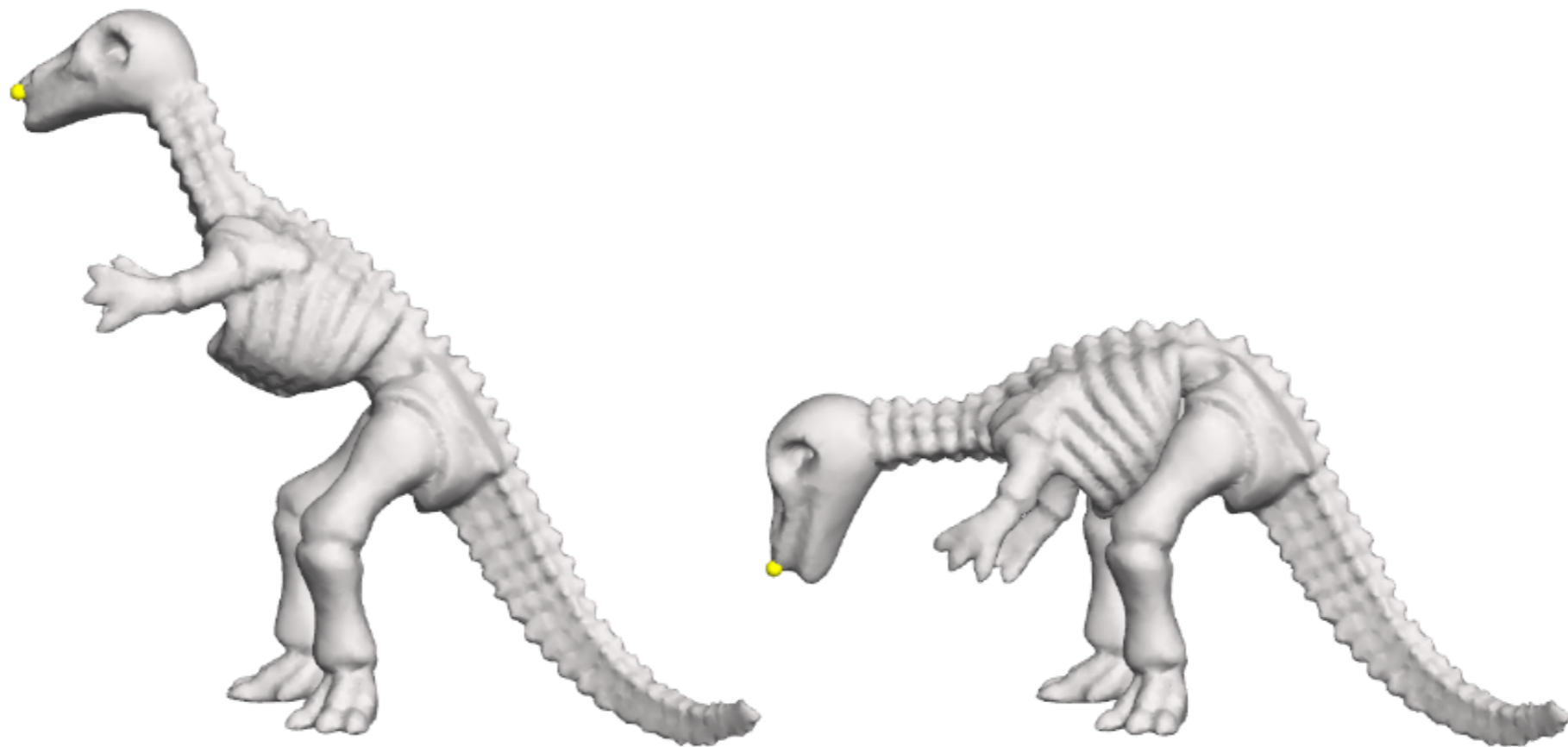


Shell-Based Deformation

- Discrete Shells
[Grinspun et al, SCA 2003]
- Rigid Cells
[Botsch et al, SGP 2006]
- **As-Rigid-As-Possible Modeling**
[Sorkine & Alexa, SGP 2007]

Surface Deformation

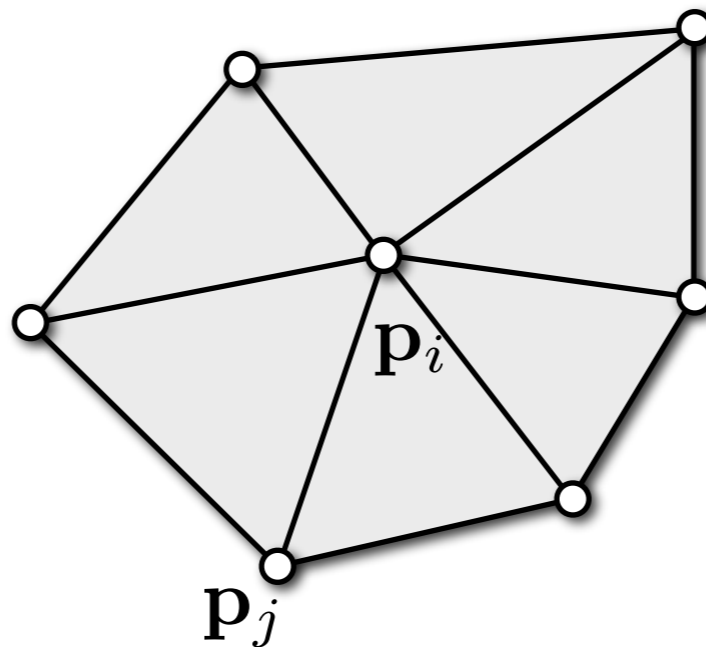
- Smooth large scale deformation
- Local as-rigid-as-possible behavior
 - Preserves small-scale details



Cell Deformation Energy

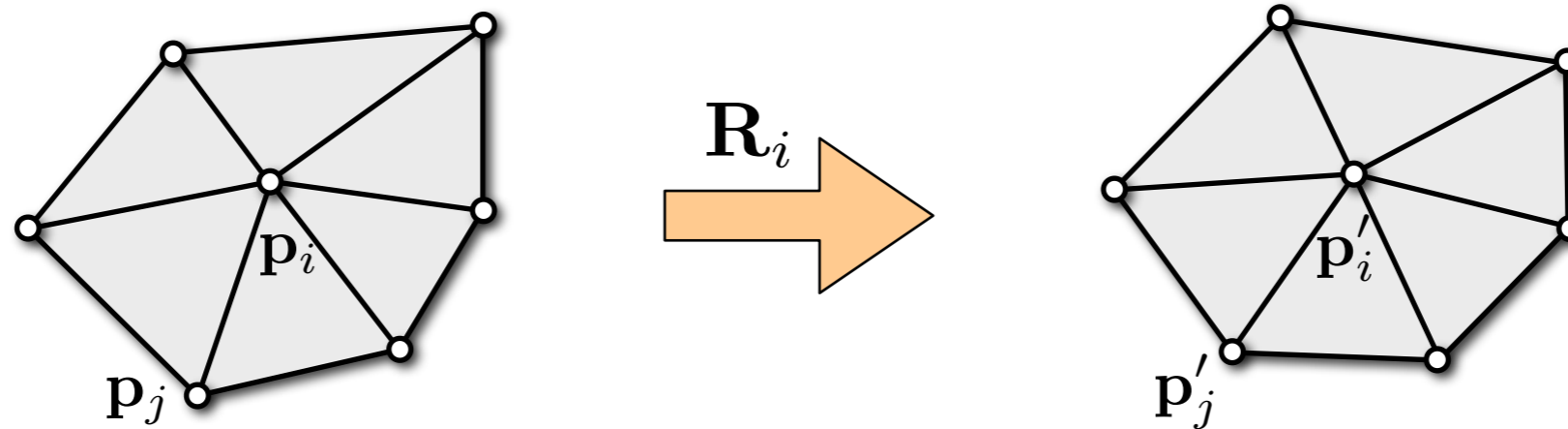
- Vertex neighborhoods should deform rigidly

$$\sum_{j \in N(i)} \left\| (\mathbf{p}'_j - \mathbf{p}'_i) - \mathbf{R}_i (\mathbf{p}_j - \mathbf{p}_i) \right\|^2 \rightarrow \min$$



Cell Deformation Energy

- If \mathbf{p} , \mathbf{p}' are known then \mathbf{R}_i is uniquely defined



- *Shape matching* problem
 - Build covariance matrix $\mathbf{S} = \mathbf{P}\mathbf{P}'^T$
 - SVD: $\mathbf{S} = \mathbf{U}\mathbf{\Sigma}\mathbf{W}^T$
 - Extract rotation $\mathbf{R}_i = \mathbf{U}\mathbf{W}^T$

Total Deformation Energy

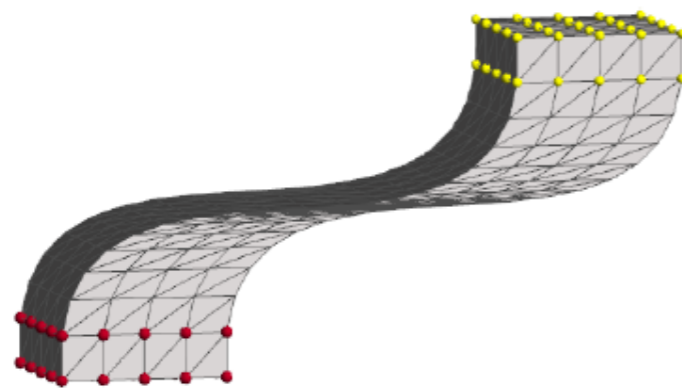
- Sum over all vertex

$$\min_{\mathbf{p}'} \sum_{i=1}^n \sum_{j \in N(i)} \left\| (\mathbf{p}'_j - \mathbf{p}'_i) - \mathbf{R}_i (\mathbf{p}_j - \mathbf{p}_i) \right\|^2$$

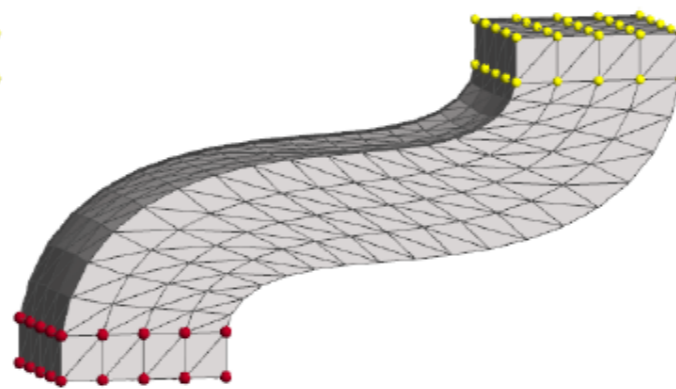
- Treat \mathbf{p}' and \mathbf{R}_i as separate variables
- Allows for alternating optimization
 - Fix \mathbf{p}' , find \mathbf{R}_i : Local shape matching per cell
 - Fix \mathbf{R}_i , find \mathbf{p}' : Solve Laplacian system

As-Rigid-As-Possible Modeling

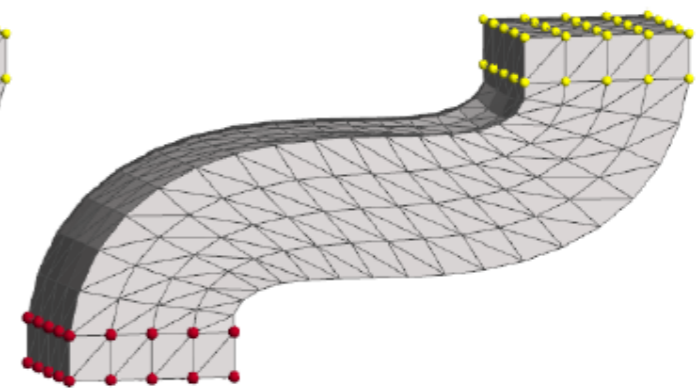
- Start from naïve Laplacian editing as initial guess



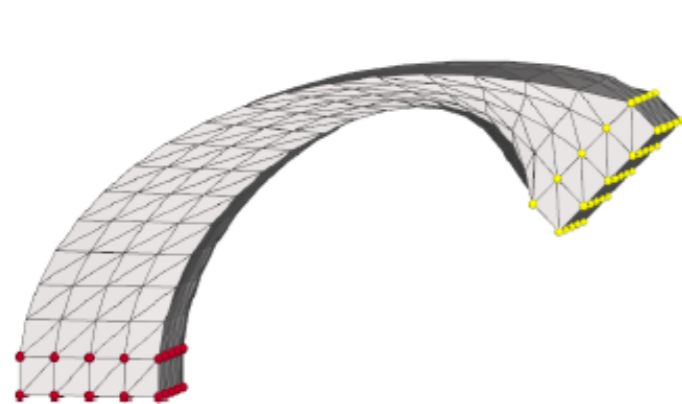
initial guess



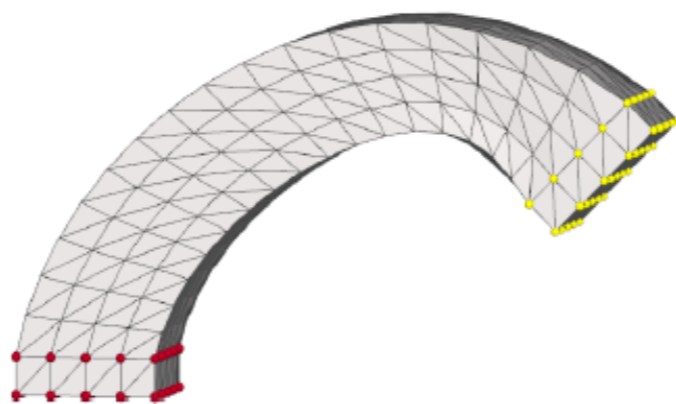
1 iteration



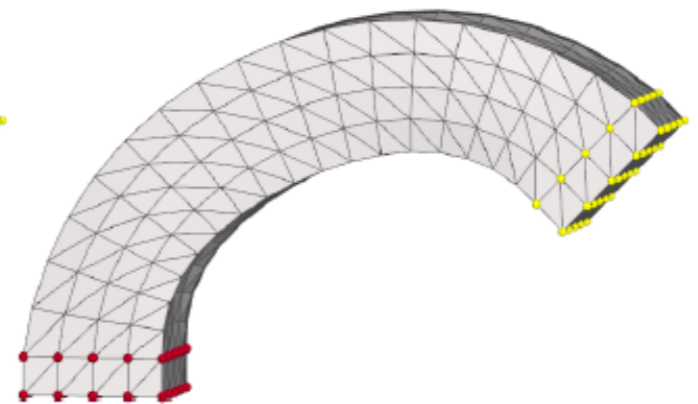
2 iterations



initial guess

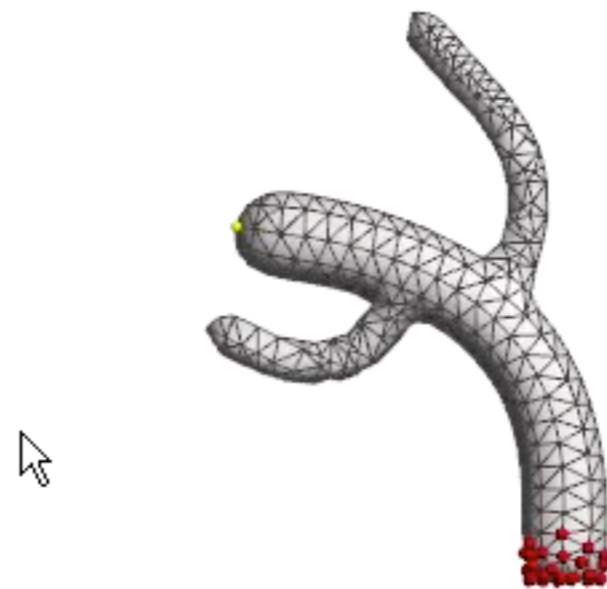


1 iterations



4 iterations

As-Rigid-As-Possible Modeling



Shell-Based Deformation

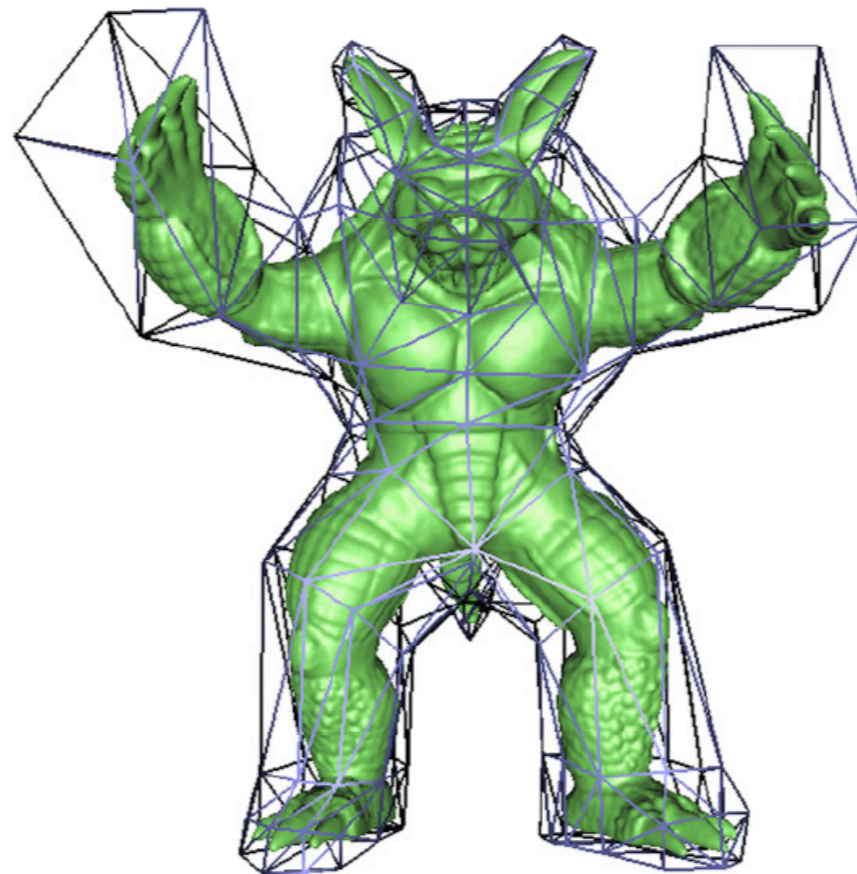
- **Discrete Shells**
[Grinspun et al, SCA 2003]
- **Rigid Cells**
[Botsch et al, SGP 2006]
- **As-Rigid-As-Possible Modeling**
[Sorkine & Alexa, SGP 2007]

Nonlinear Surface Deformation

- Limitations of Linear Methods
- Shell-Based Deformation
- **(Differential Coordinates)**

Subspace Gradient Deformation

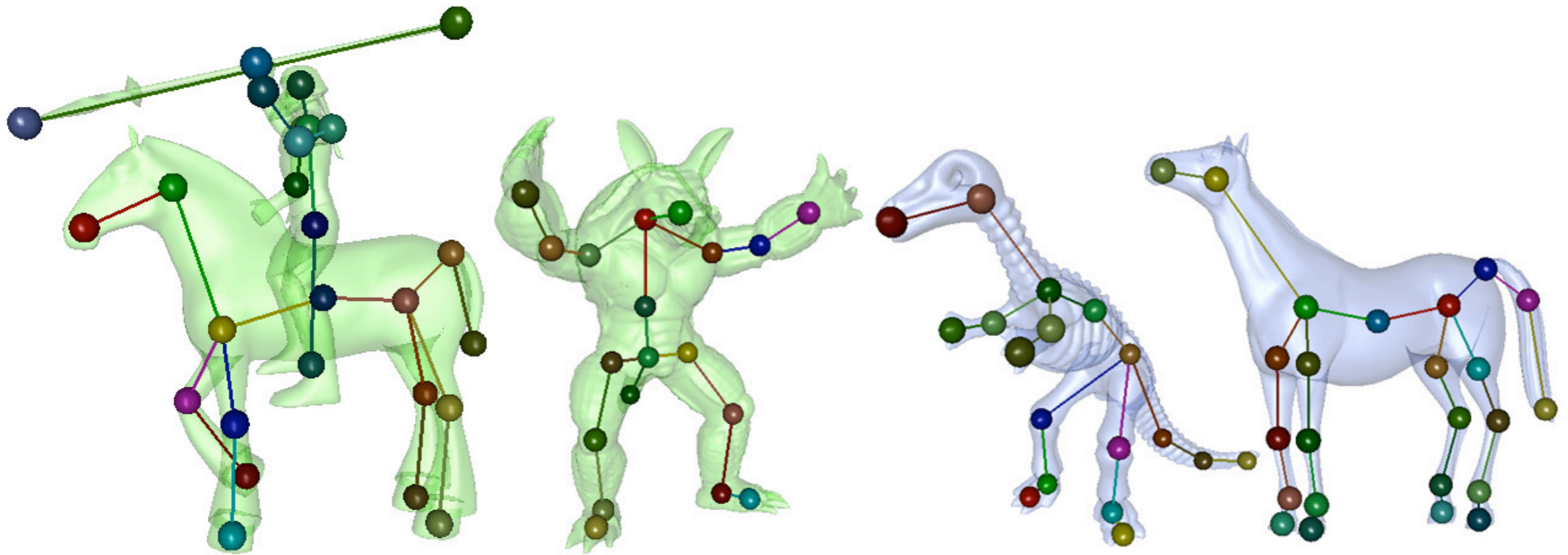
- Nonlinear Laplacian coordinates
- Least squares solution on coarse cage subspace



[Huang et al, SIGGRAPH 06]

Mesh Puppetry

- Skeletons and Laplacian coordinates
- Cascading optimization



[Shi et al, SIGGRAPH 07]

Nonlinear Surface Deformation

- Limitations of Linear Methods
- Shell-Based Deformation
- (Differential Coordinates)



Eurographics 2009

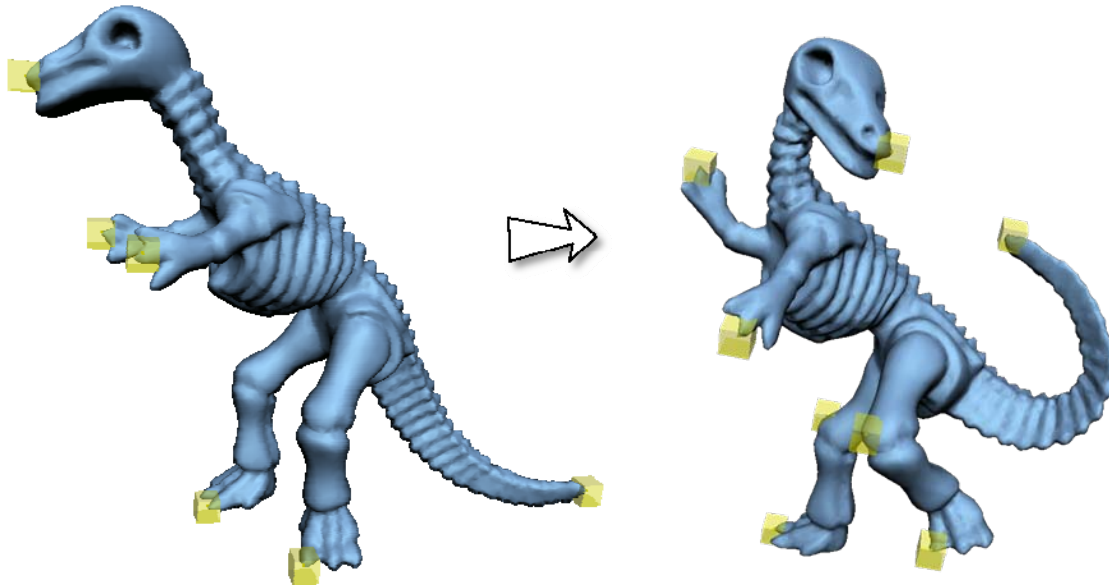
Interactive Shape Modeling and Deformation

T3: Half-Day Tutorial

Nonlinear Space Deformations

Nonlinear Space Deformations

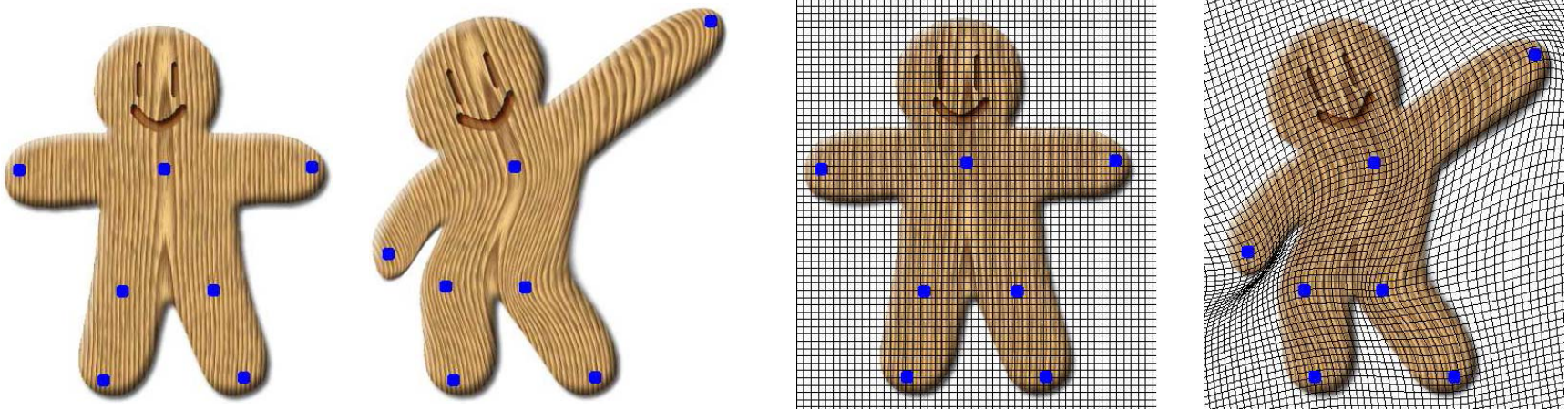
- Involve nonlinear optimization
- Enjoy the advantages of space warps
- Additionally, have shape-preserving properties



As-Rigid-As-Possible Deformation

Moving-Least-Squares (MLS) approach [Schaefer et al. 2006]

- Points or segments as control objects
- First developed in 2D and later extended to 3D by Zhu and Gortler (2007)



As-Rigid-As-Possible Deformation

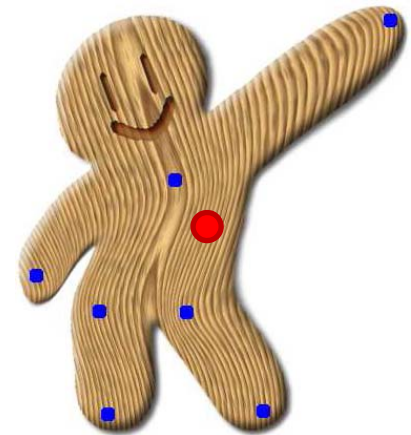
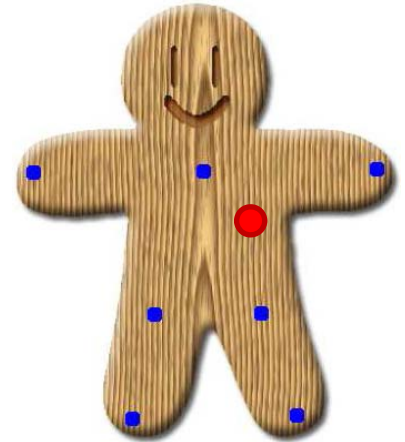
Moving-Least-Squares (MLS) approach [Schaefer et al. 2006]

- Attach an affine transformation to each point $\mathbf{x} \in \mathbb{R}^3$:

$$A_{\mathbf{x}}(\mathbf{p}) = M_{\mathbf{x}}\mathbf{p} + \mathbf{t}_{\mathbf{x}}$$

- The space warp:

$$\mathbf{x} \rightarrow A_{\mathbf{x}}(\mathbf{x})$$



As-Rigid-As-Possible Deformation

Moving-Least-Squares (MLS) approach [Schaefer et al. 2006]

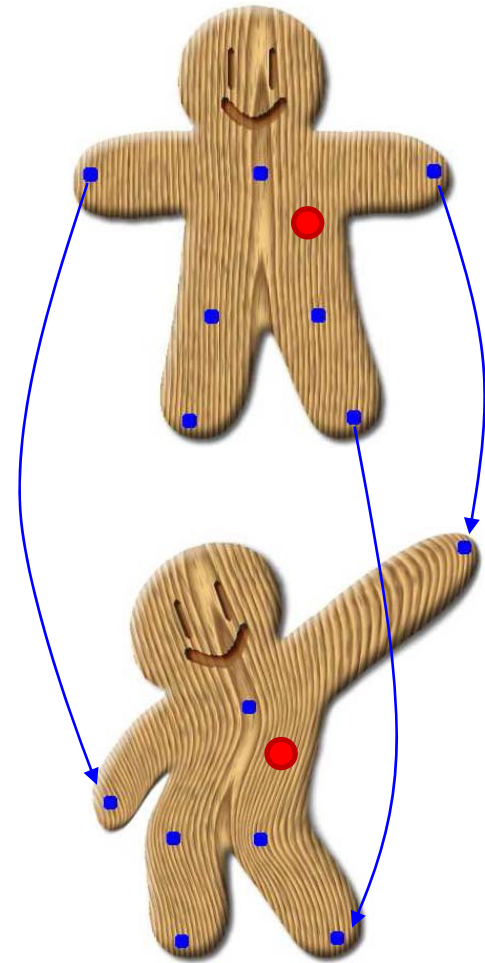
- Handles \mathbf{p}_i are displaced to \mathbf{q}_i
- The local transformation at \mathbf{x} :

$$\mathbf{A}_{\mathbf{x}}(\mathbf{p}) = \mathbf{M}_{\mathbf{x}}\mathbf{p} + \mathbf{t}_{\mathbf{x}} \quad \text{s.t.}$$

$$\sum_{i=1}^k w_i(\mathbf{x}) \|\mathbf{A}_{\mathbf{x}}(\mathbf{p}_i) - \mathbf{q}_i\|^2 \rightarrow \min$$

- The weights depend on \mathbf{x} :

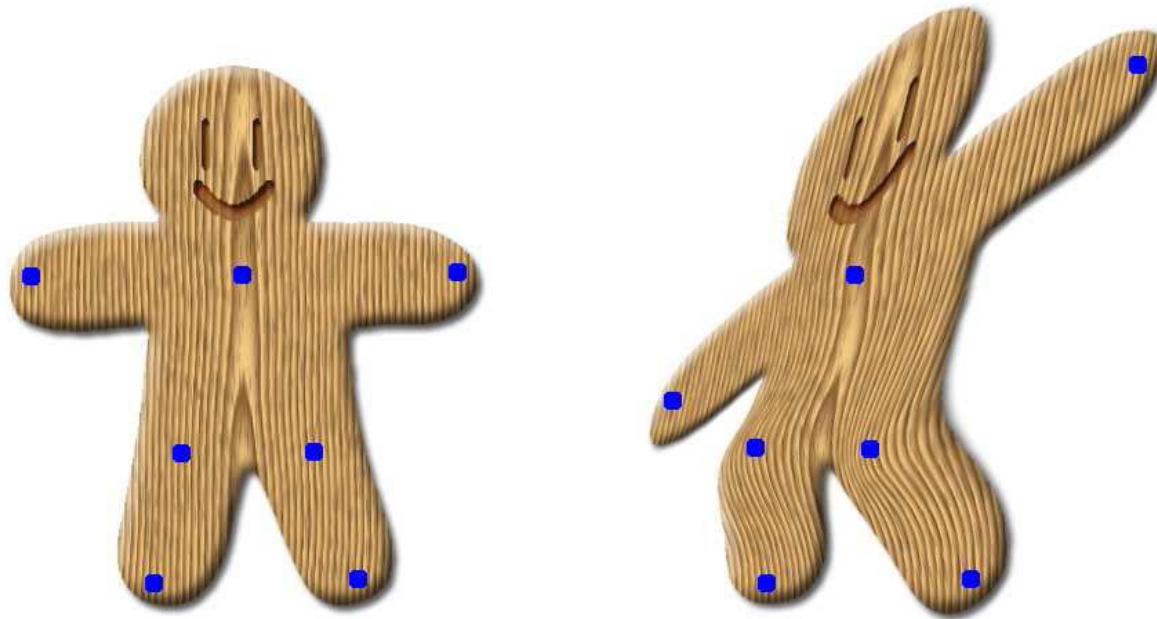
$$w_i(\mathbf{x}) = \|\mathbf{p}_i - \mathbf{x}\|^{-2\alpha}$$



As-Rigid-As-Possible Deformation

Moving-Least-Squares (MLS) approach [Schaefer et al. 2006]

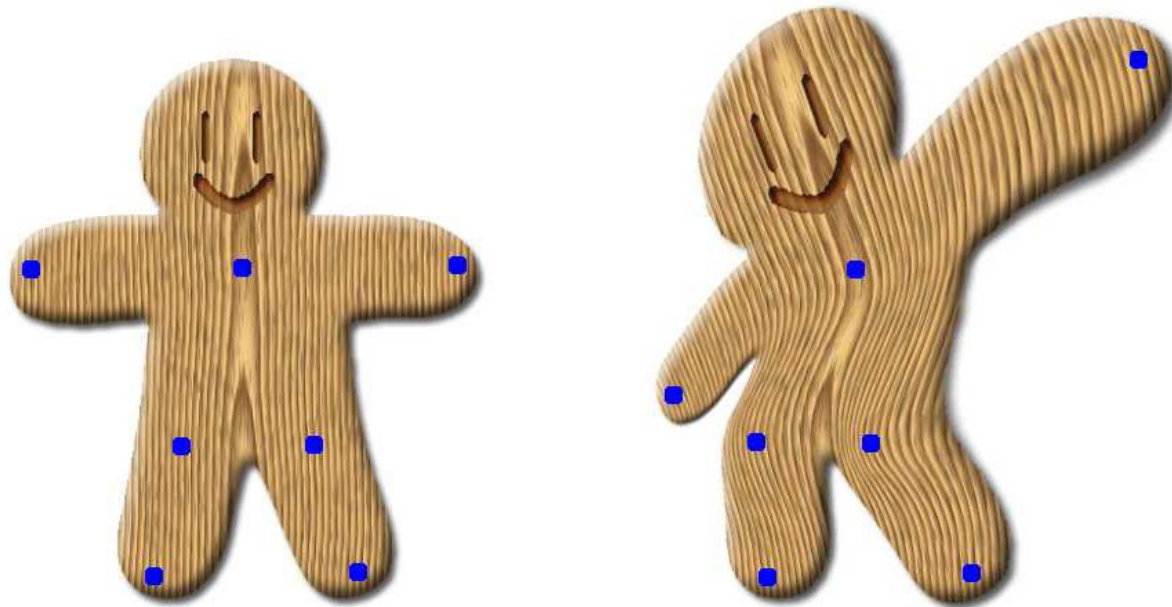
- No additional restriction on $A_{\mathbf{x}}(\cdot)$ – affine local transformations



As-Rigid-As-Possible Deformation

Moving-Least-Squares (MLS) approach [Schaefer et al. 2006]

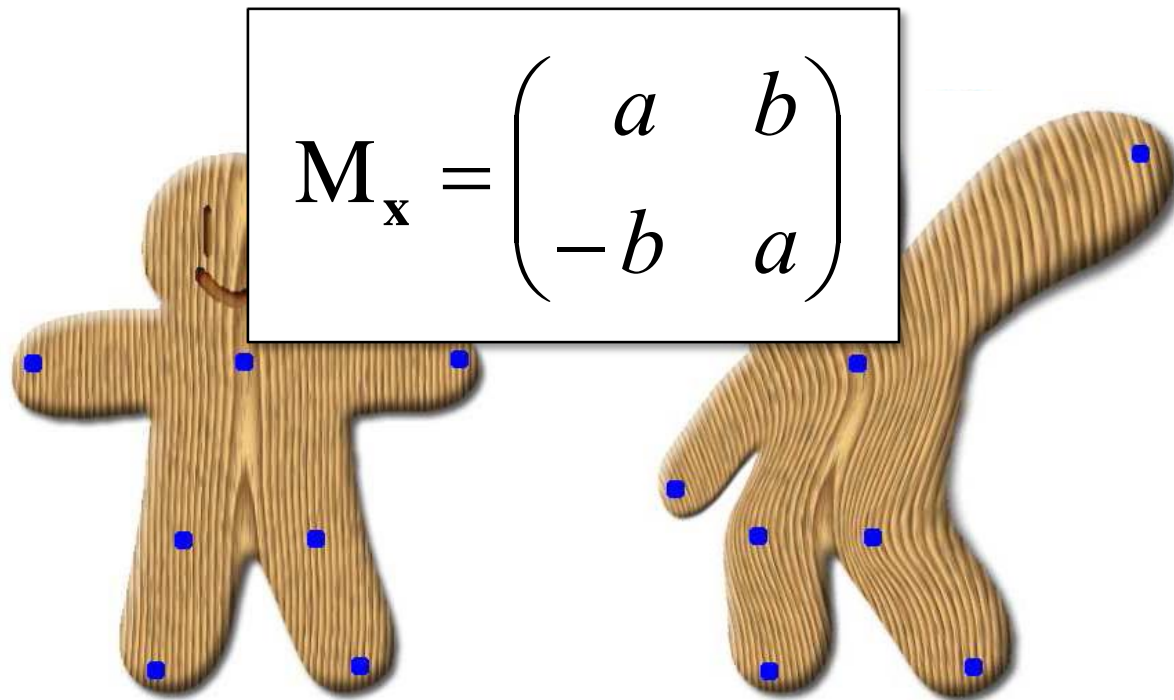
- Restrict $A_x(\cdot)$ to similarity



As-Rigid-As-Possible Deformation

Moving-Least-Squares (MLS) approach [Schaefer et al. 2006]

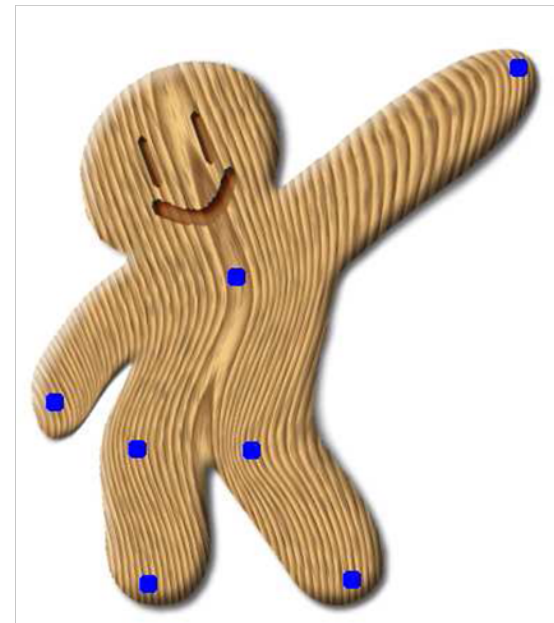
- Restrict $A_{\mathbf{x}}(\cdot)$ to similarity



As-Rigid-As-Possible Deformation

Moving-Least-Squares (MLS) approach [Schaefer et al. 2006]

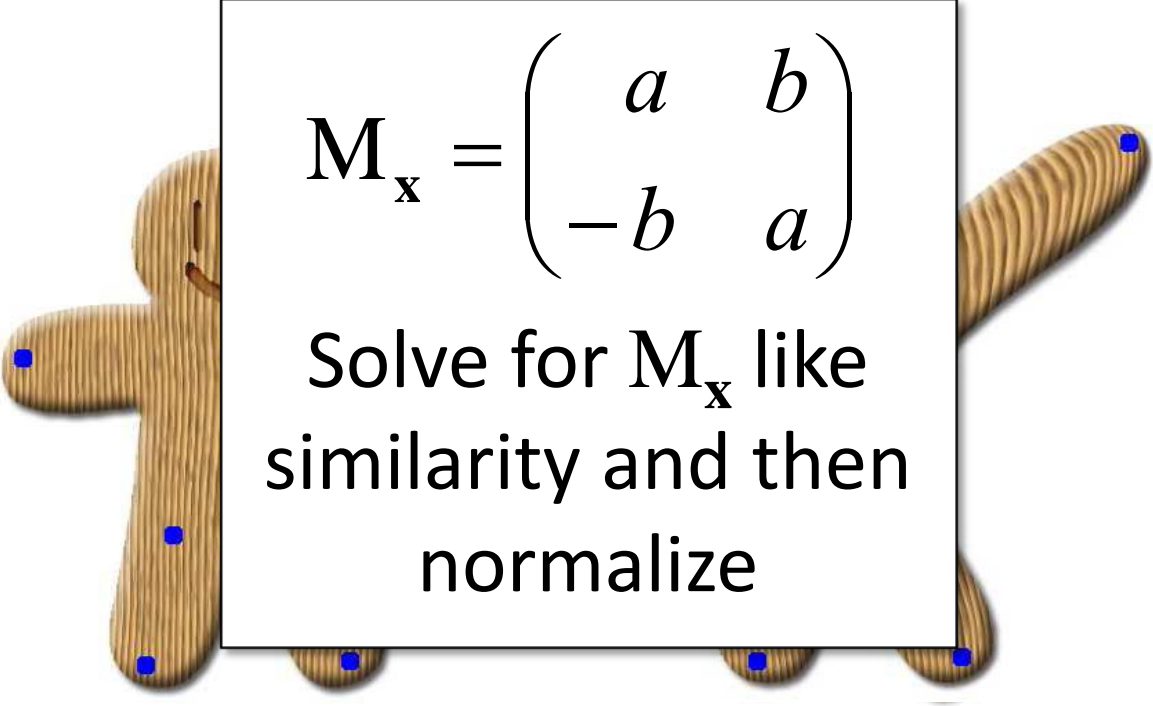
- Restrict $A_x(\cdot)$ to rigid



As-Rigid-As-Possible Deformation

Moving-Least-Squares (MLS) approach [Schaefer et al. 2006]

- Restrict $A_x(\cdot)$ to rigid


$$M_x = \begin{pmatrix} a & b \\ -b & a \end{pmatrix}$$

Solve for M_x like
similarity and then
normalize

As-Rigid-As-Possible Deformation

Moving-Least-Squares (MLS) approach [Schaefer et al. 2006]

- Examples



As-Rigid-As-Possible Deformation

MLS approach – extension to 3D [Zhu & Gortler 2007]

- No linear expression for similarity in 3D
- Instead, can solve for the minimizing rotation

$$\arg \min_{\mathbf{R} \in \text{SO}(3)} \sum_{i=1}^k w_i(\mathbf{x}) \|\mathbf{R}\mathbf{p}_i - \mathbf{q}_i\|^2$$

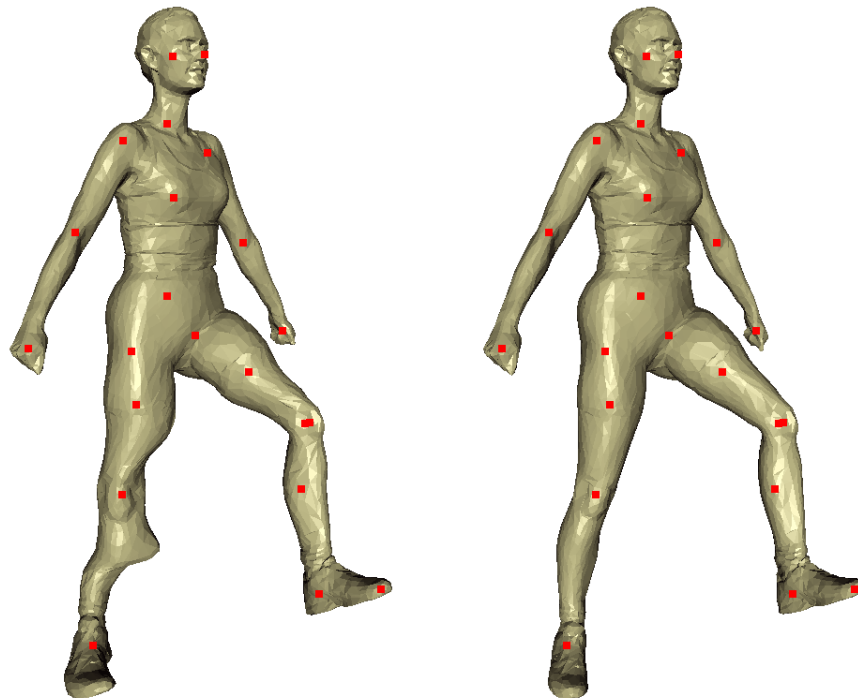
by polar decomposition of the 3×3 covariance matrix

As-Rigid-As-Possible Deformation

MLS approach – extension to 3D [Zhu & Gortler 2007]

- Zhu and Gortler also replace the Euclidean distance in the weights by “distance within the shape”

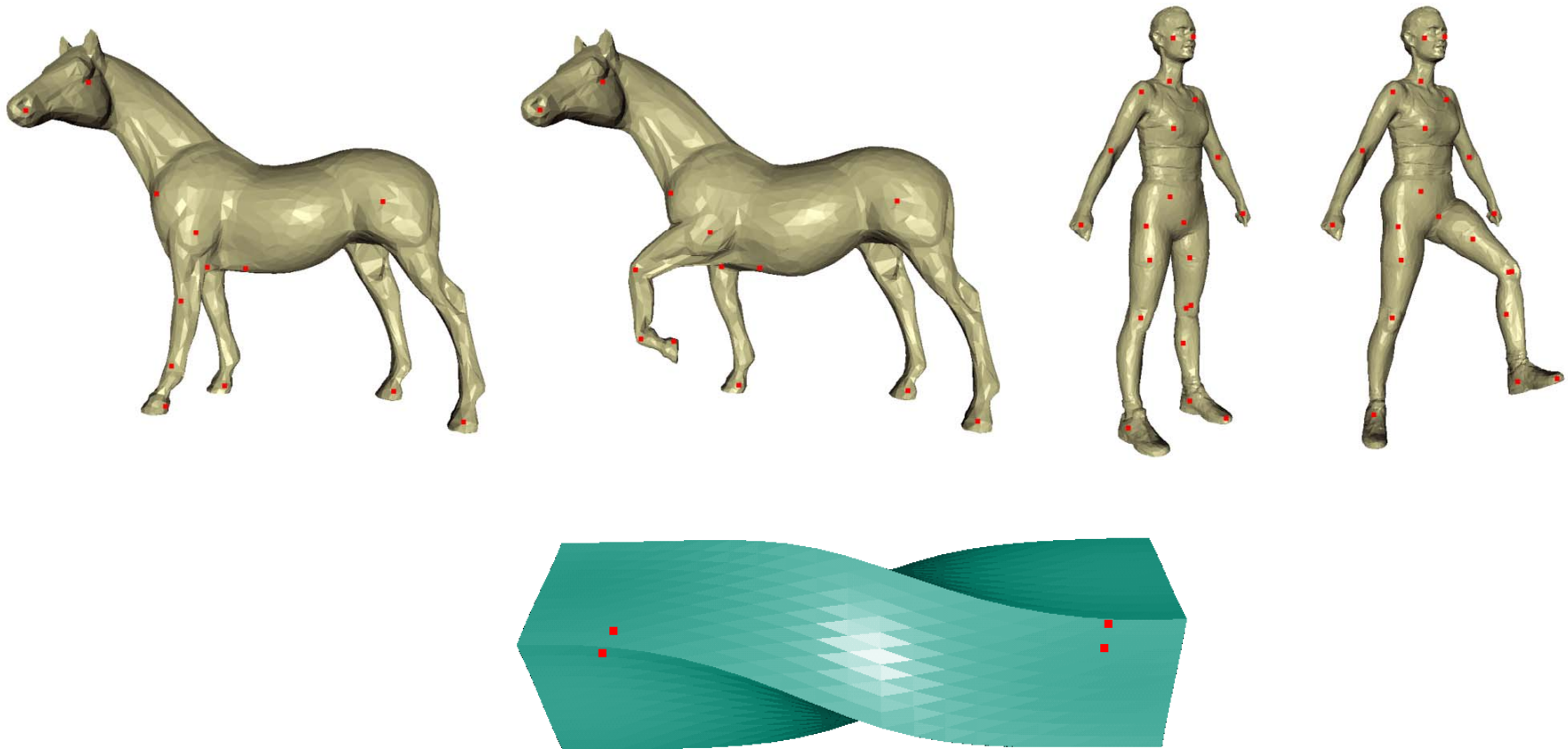
$$w_i(\mathbf{x}) = d(\mathbf{p}_i, \mathbf{x})^{-2\alpha}$$



As-Rigid-As-Possible Deformation

MLS approach – extension to 3D [Zhu & Gortler 2007]

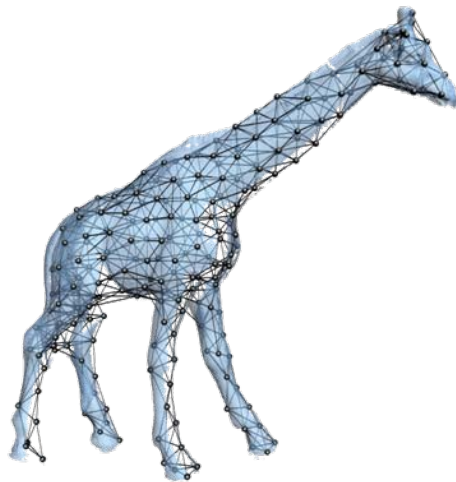
- More results



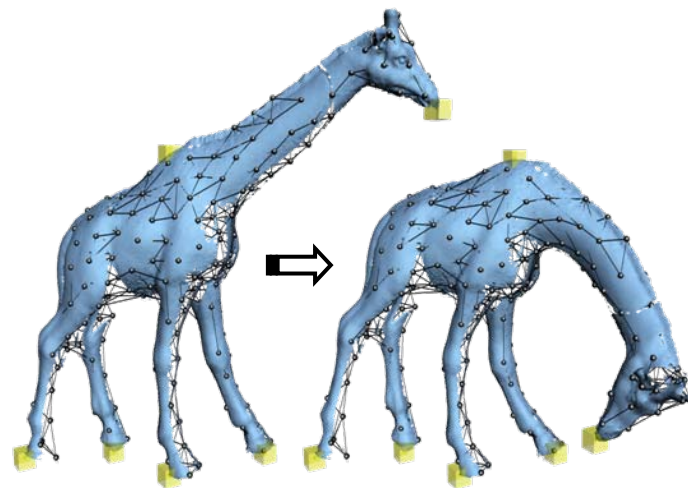
As-Rigid-As-Possible Deformation

Deformation Graph approach [Sumner et al. 2007]

- Surface handles as interface
- Underlying graph to represent the deformation; nodes store rigid transformations
- Decoupling of handles from def. representation



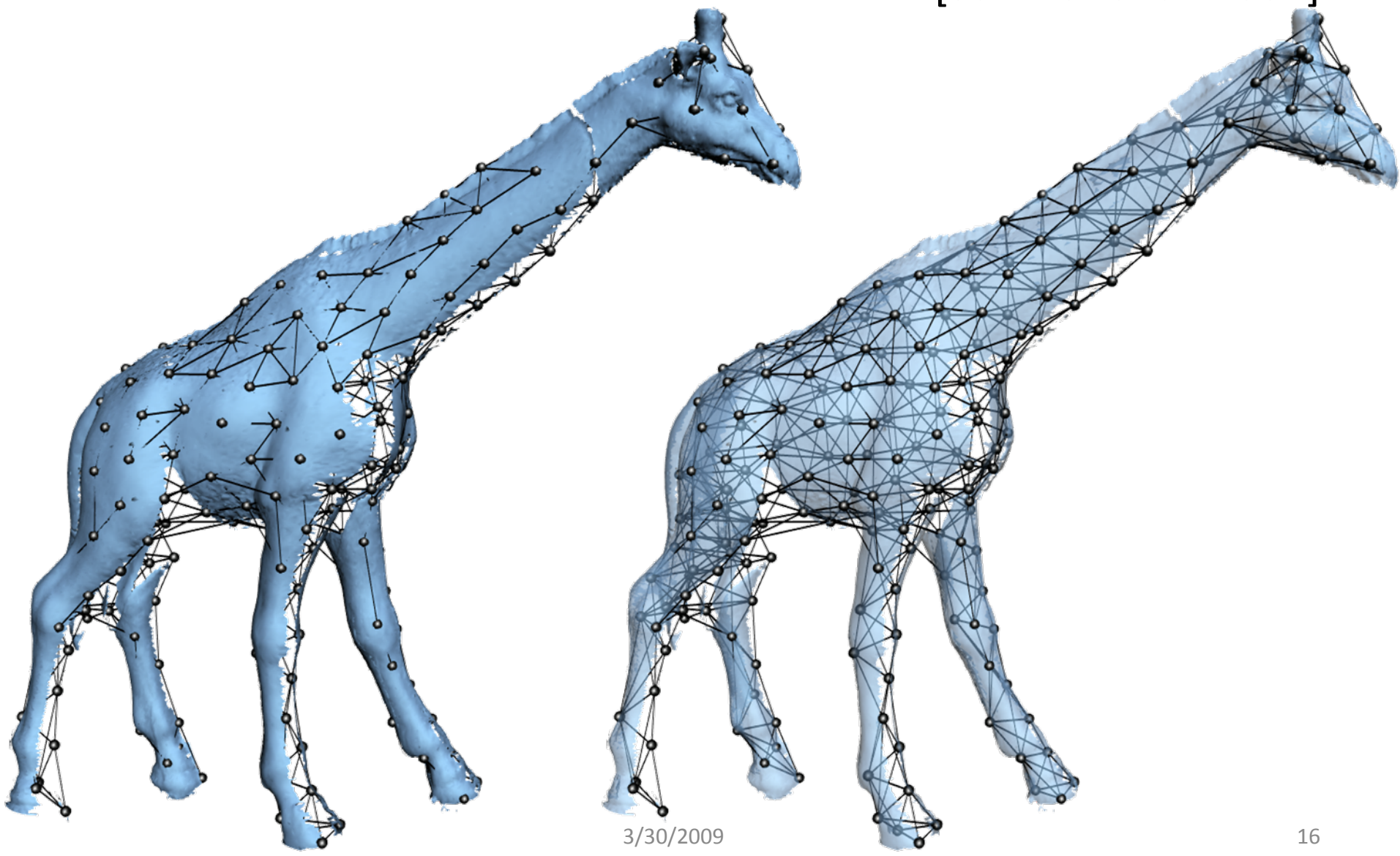
Deformation Graph



Optimization Procedure

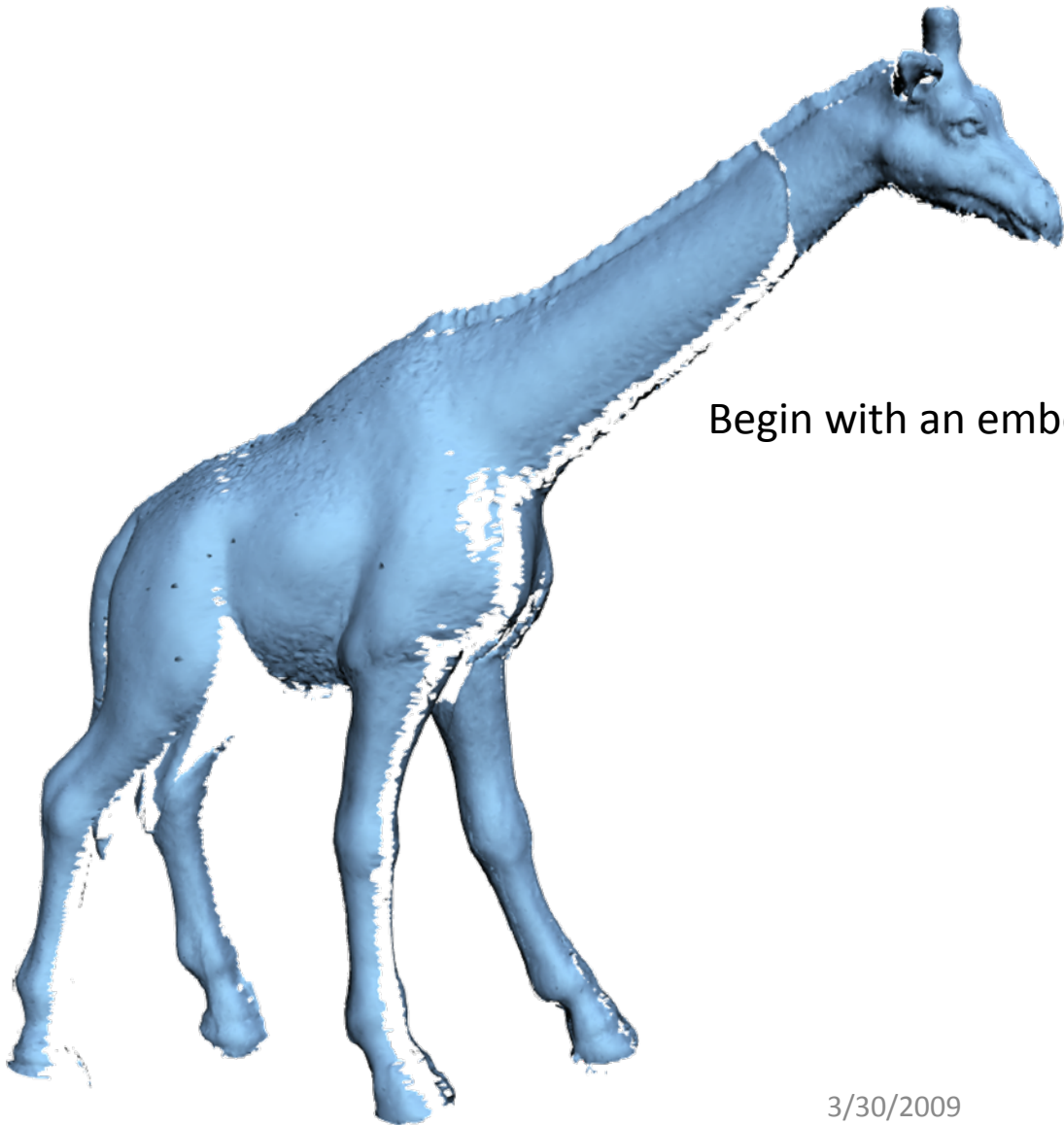
Deformation Graph

[Sumner et al. 2007]



Deformation Graph

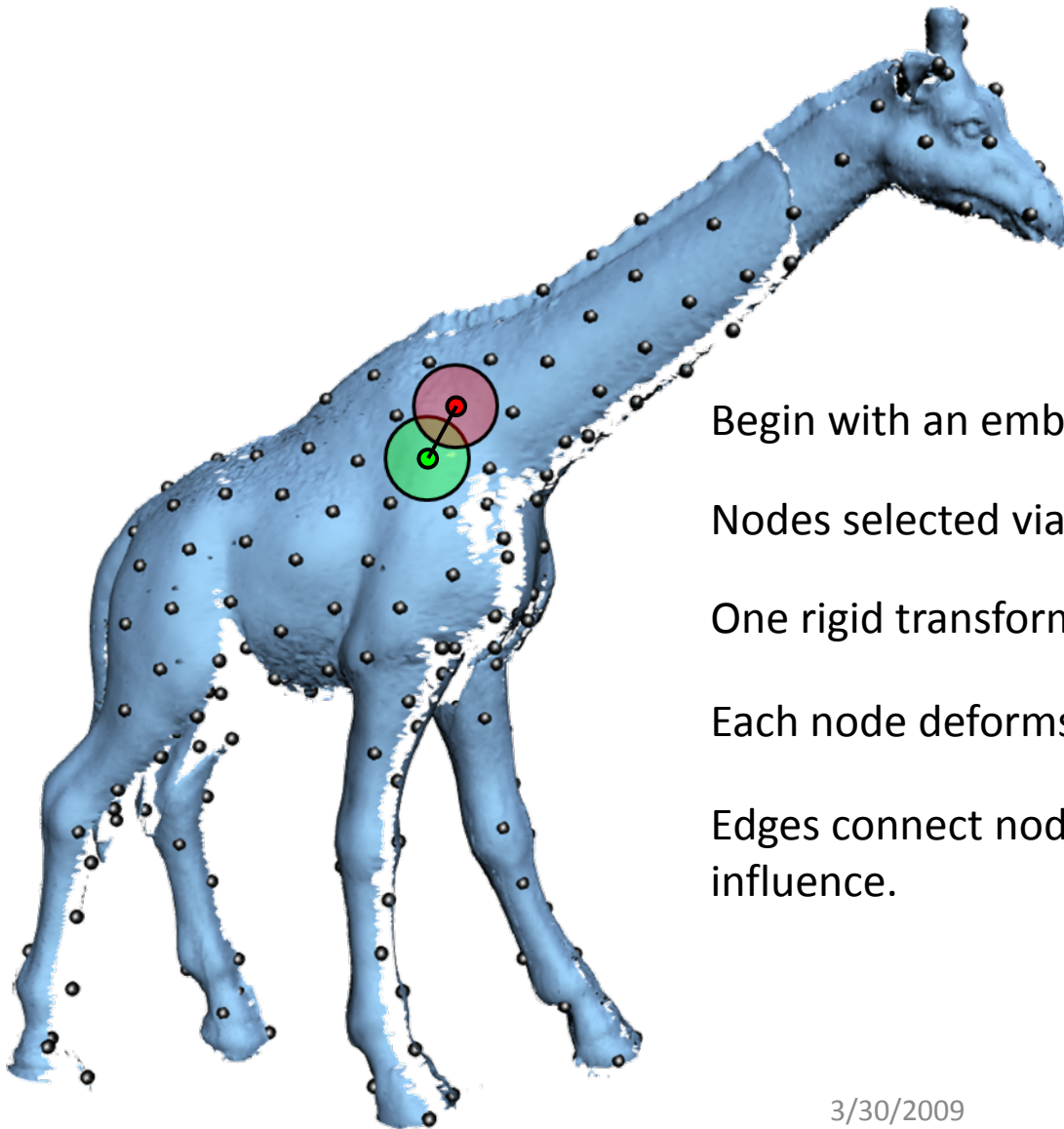
[Sumner et al. 2007]



Begin with an embedded object.

Deformation Graph

[Sumner et al. 2007]



Begin with an embedded object.

Nodes selected via uniform sampling; located at \mathbf{g}_j

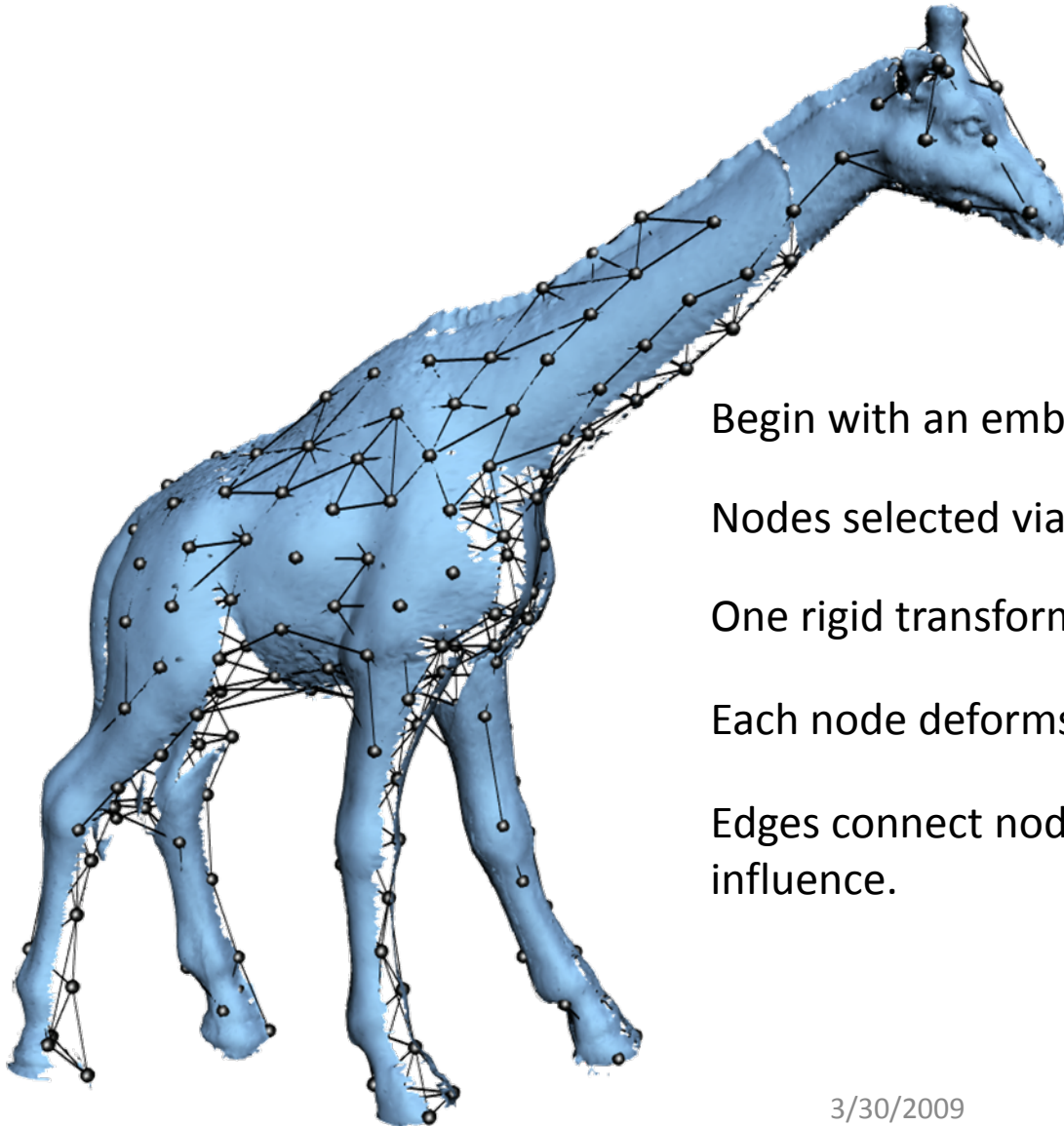
One rigid transformation for each node: $\mathbf{R}_j, \mathbf{t}_j$

Each node deforms nearby space.

Edges connect nodes of overlapping influence.

Deformation Graph

[Sumner et al. 2007]



Begin with an embedded object.

Nodes selected via uniform sampling; located at \mathbf{g}_j

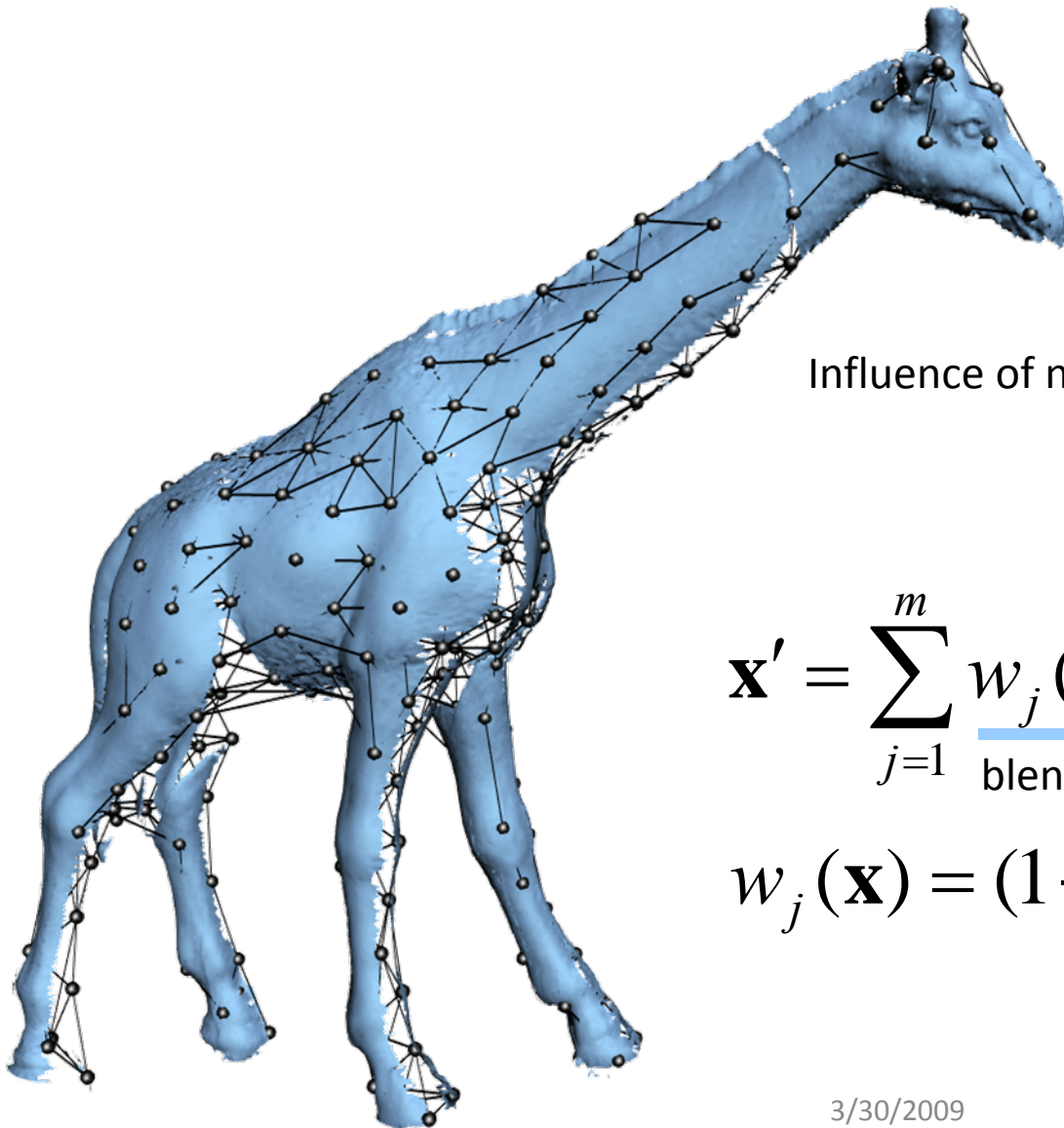
One rigid transformation for each node: $\mathbf{R}_j, \mathbf{t}_j$

Each node deforms nearby space.

Edges connect nodes of overlapping influence.

Deformation Graph

[Sumner et al. 2007]



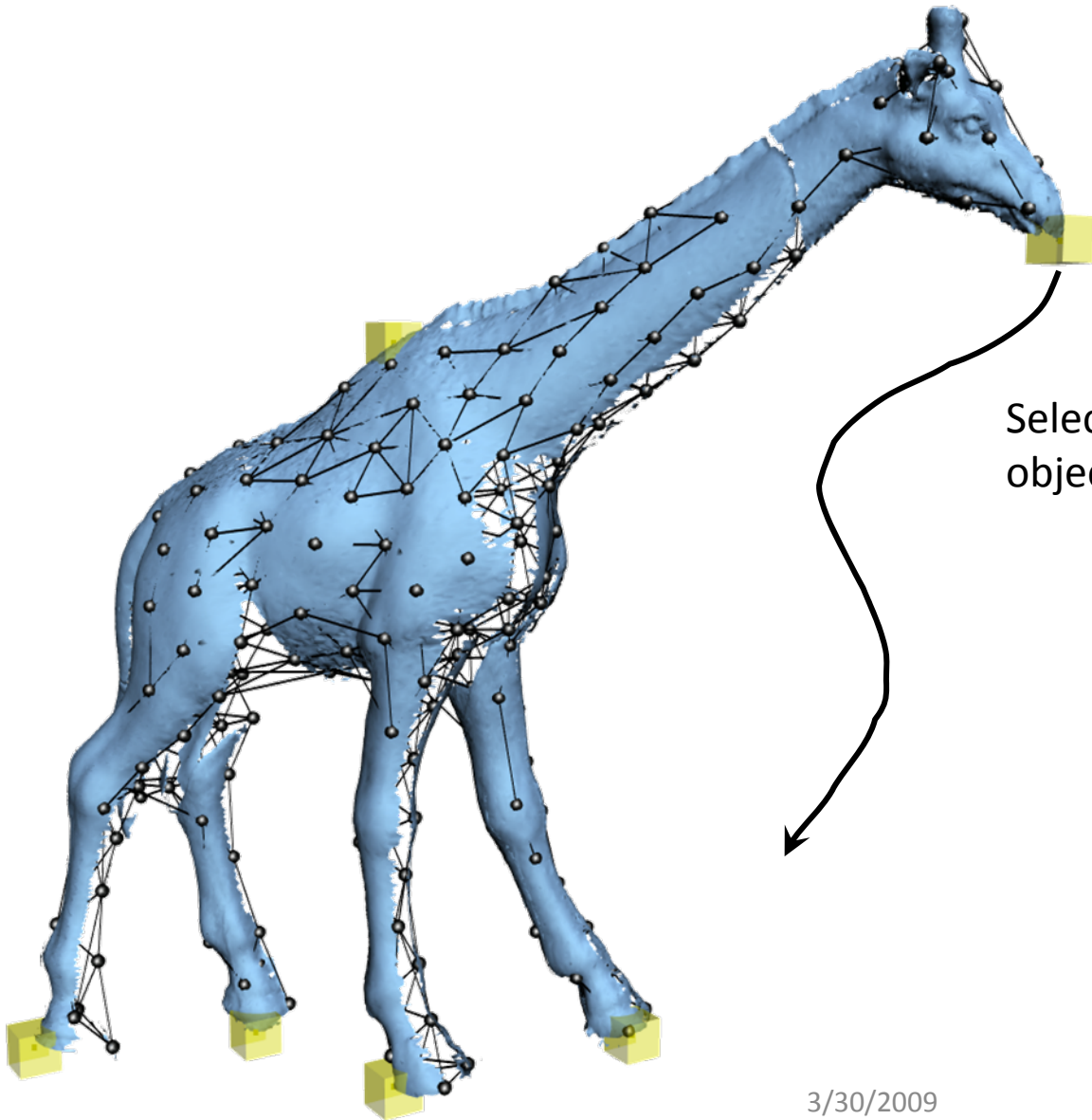
Influence of nearby transformations is blended.

$$\mathbf{x}' = \sum_{j=1}^m \underbrace{w_j(\mathbf{x})}_{\text{blending weights}} \left[\underbrace{\mathbf{R}_j(\mathbf{x} - \mathbf{g}_j) + \mathbf{g}_j + \mathbf{t}_j}_{\text{point } \mathbf{x} \text{ transformed by node } j} \right]$$

$$w_j(\mathbf{x}) = \left(1 - \frac{\|\mathbf{x} - \mathbf{g}_j\|}{d_{\max}} \right)^2$$

Optimization

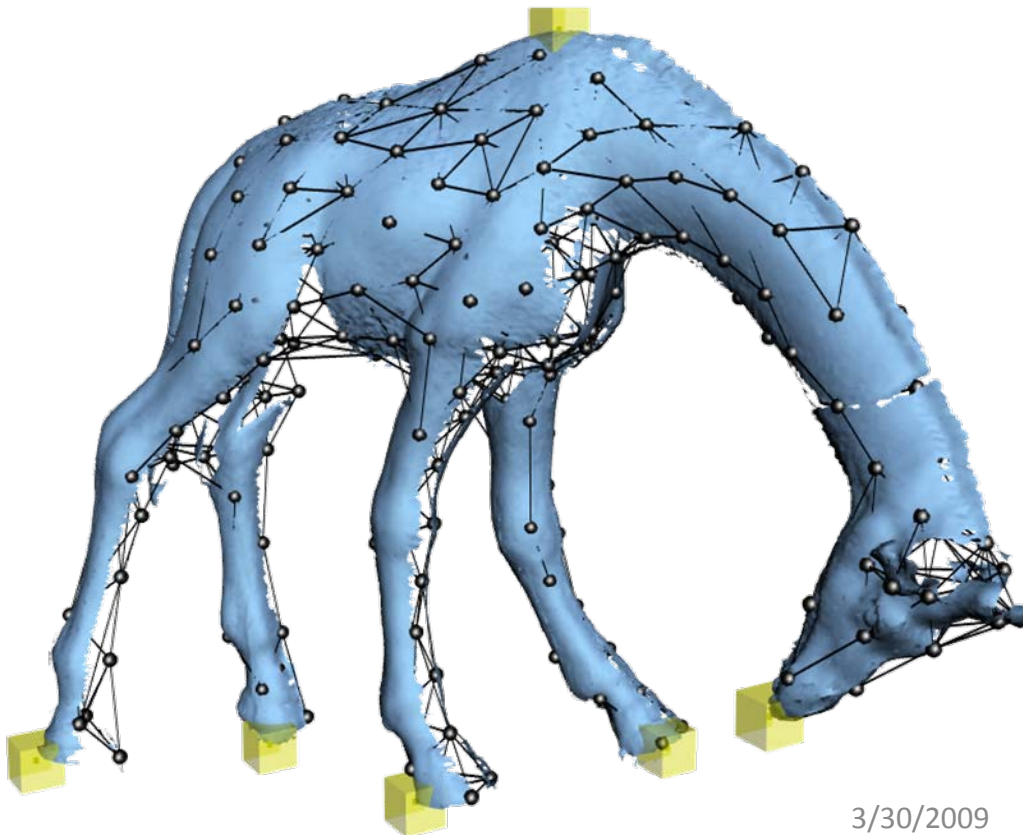
[Sumner et al. 2007]



Select & drag vertices of embedded object.

Optimization

[Sumner et al. 2007]



Select & drag vertices of embedded object.

Optimization finds

deformation parameters \mathbf{R}_j , \mathbf{t}_j .

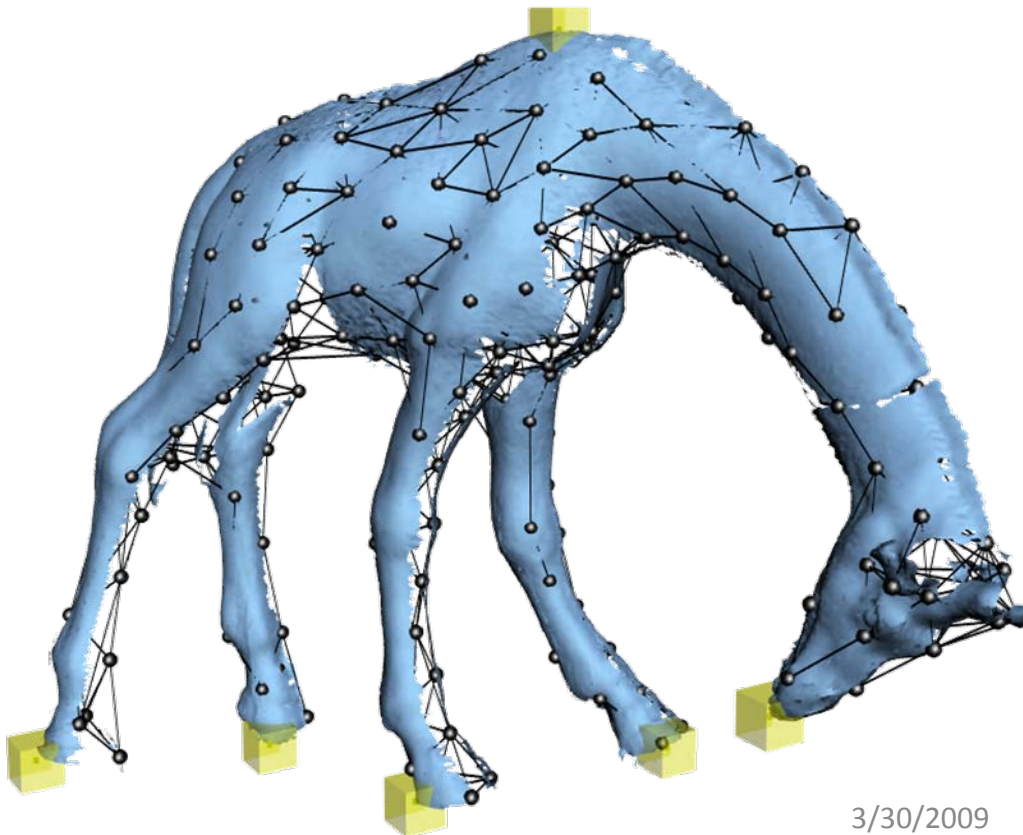
$$\min_{\mathbf{R}_1, \mathbf{t}_1, \dots, \mathbf{R}_m, \mathbf{t}_m} \underbrace{w_{\text{rot}} \mathbf{E}_{\text{rot}}}_{\text{Rotation term}} + \underbrace{w_{\text{reg}} \mathbf{E}_{\text{reg}}}_{\text{Regularization term}} + \underbrace{w_{\text{con}} \mathbf{E}_{\text{con}}}_{\text{Constraint term}}$$

Graph
parameters

Rotation
term

Regularization
term

Constraint
term

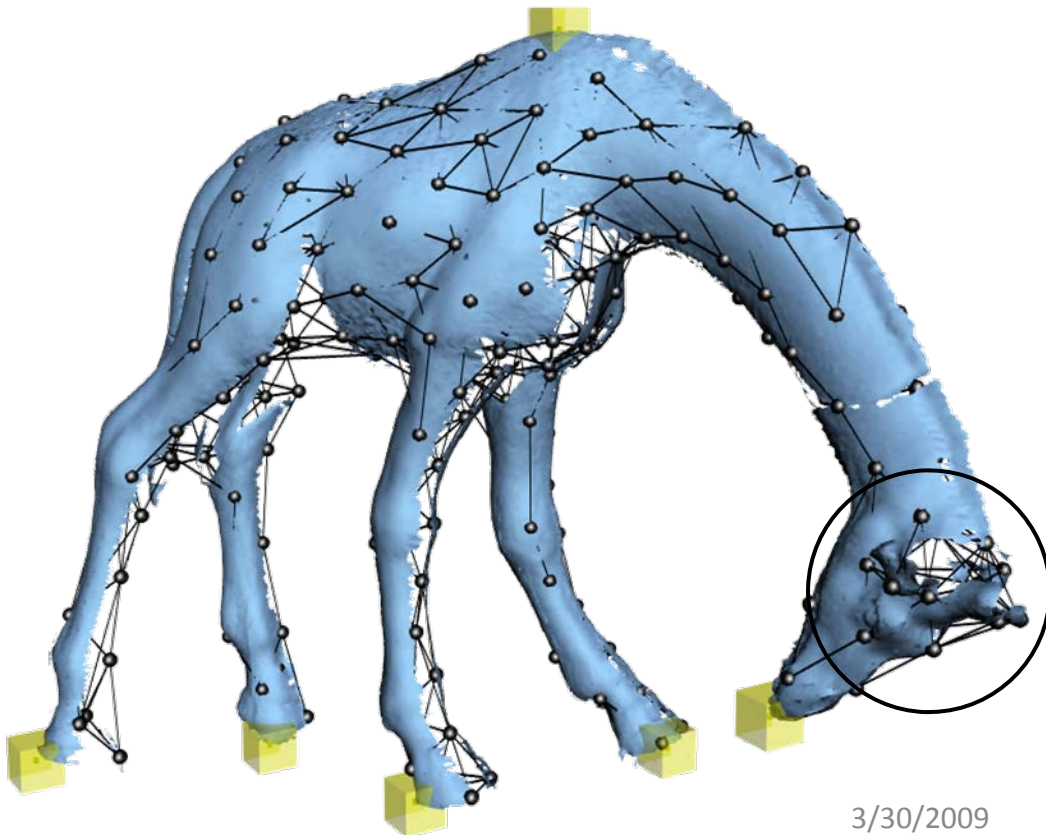


Select & drag vertices of embedded object.

Optimization finds deformation parameters $\mathbf{R}_j, \mathbf{t}_j$.

$$\min_{\mathbf{R}_1, \mathbf{t}_1, \dots, \mathbf{R}_m, \mathbf{t}_m} \quad \underline{w_{\text{rot}} \mathbf{E}_{\text{rot}}} + w_{\text{reg}} \mathbf{E}_{\text{reg}} + w_{\text{con}} \mathbf{E}_{\text{con}}$$

$$\text{Rot}(\mathbf{R}) = (\mathbf{c}_1 \cdot \mathbf{c}_2)^2 + (\mathbf{c}_1 \cdot \mathbf{c}_3)^2 + (\mathbf{c}_2 \cdot \mathbf{c}_3)^2 + \\ (\mathbf{c}_1 \cdot \mathbf{c}_1 - 1)^2 + (\mathbf{c}_2 \cdot \mathbf{c}_2 - 1)^2 + (\mathbf{c}_3 \cdot \mathbf{c}_3 - 1)^2$$



$$\mathbf{E}_{\text{rot}} = \sum_{j=1}^m \text{Rot}(\mathbf{R}_j)$$

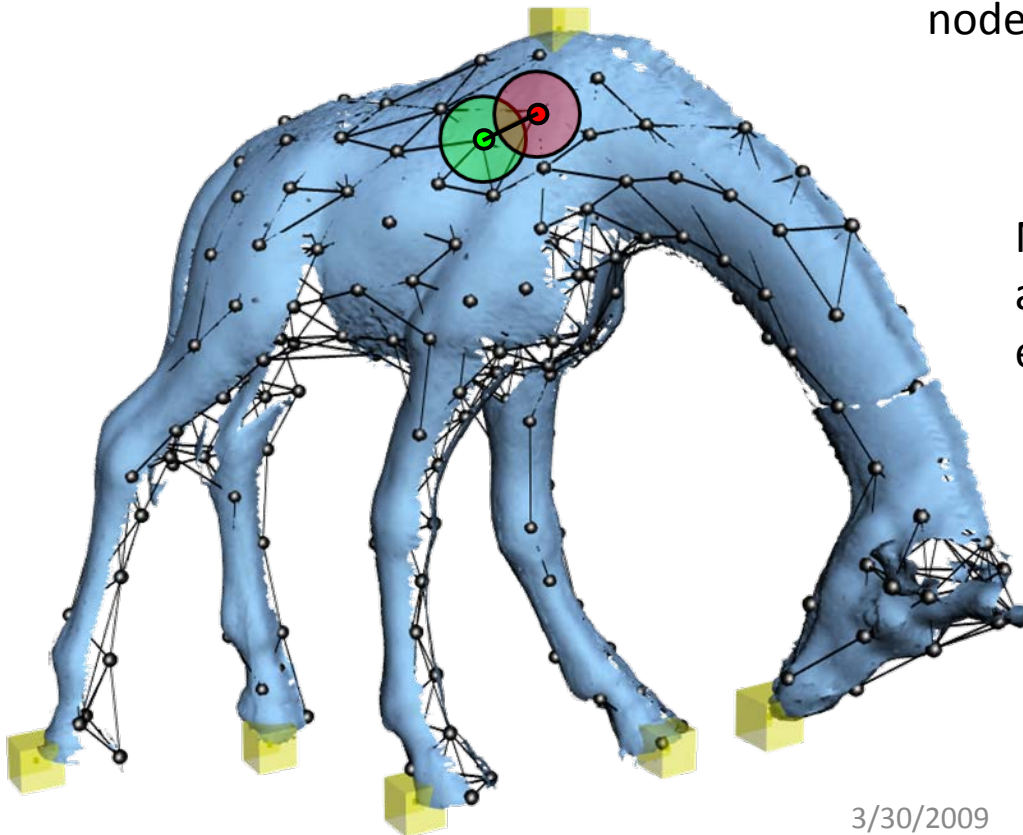
For detail preservation,
features should rotate and
not scale or skew.

$$\min_{\mathbf{R}_1, \mathbf{t}_1, \dots, \mathbf{R}_m, \mathbf{t}_m} w_{\text{rot}} \mathbf{E}_{\text{rot}} + w_{\text{reg}} \mathbf{E}_{\text{reg}} + w_{\text{con}} \mathbf{E}_{\text{con}}$$

$$\mathbf{E}_{\text{reg}} = \sum_{j=1}^m \sum_{k \in \mathcal{N}(j)} \alpha_{jk} \left\| \mathbf{R}_j (\mathbf{g}_k - \mathbf{g}_j) + \mathbf{g}_j + \mathbf{t}_j - (\mathbf{g}_k + \mathbf{t}_k) \right\|_2^2$$

where node j thinks
node k should go

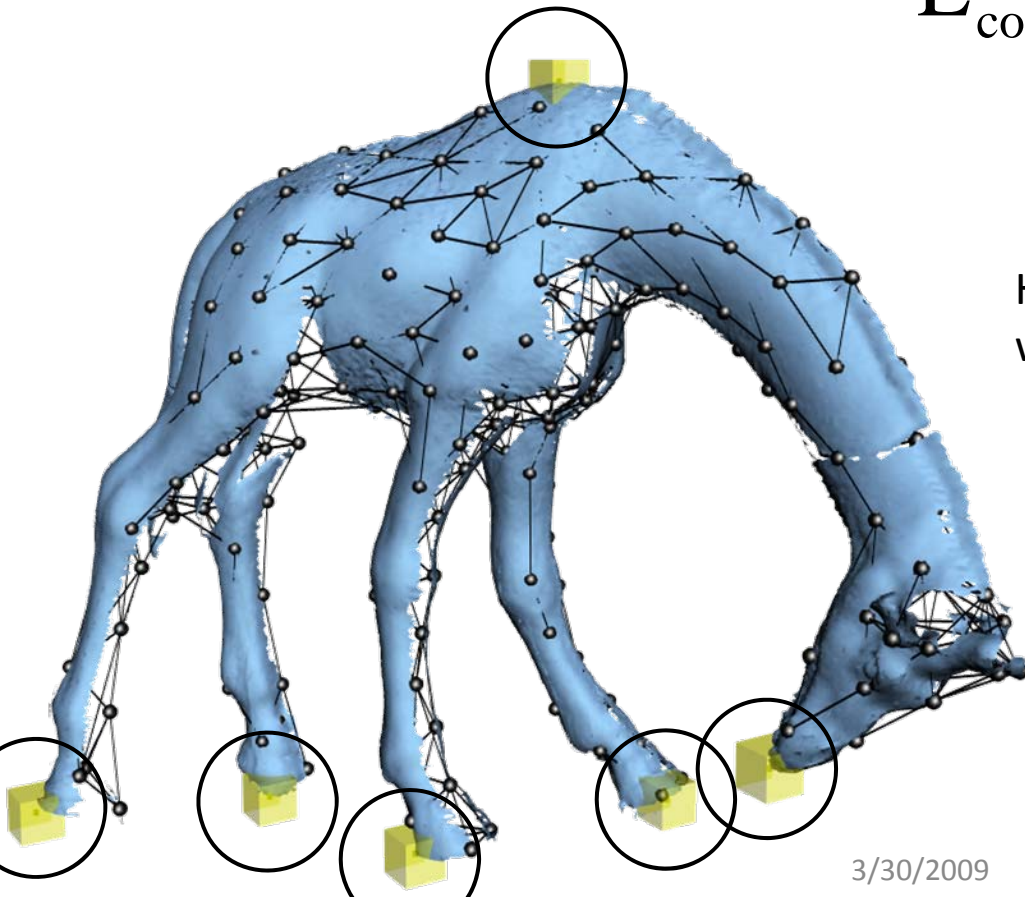
where node k
actually goes



Neighboring nodes should
agree on where they transform
each other.

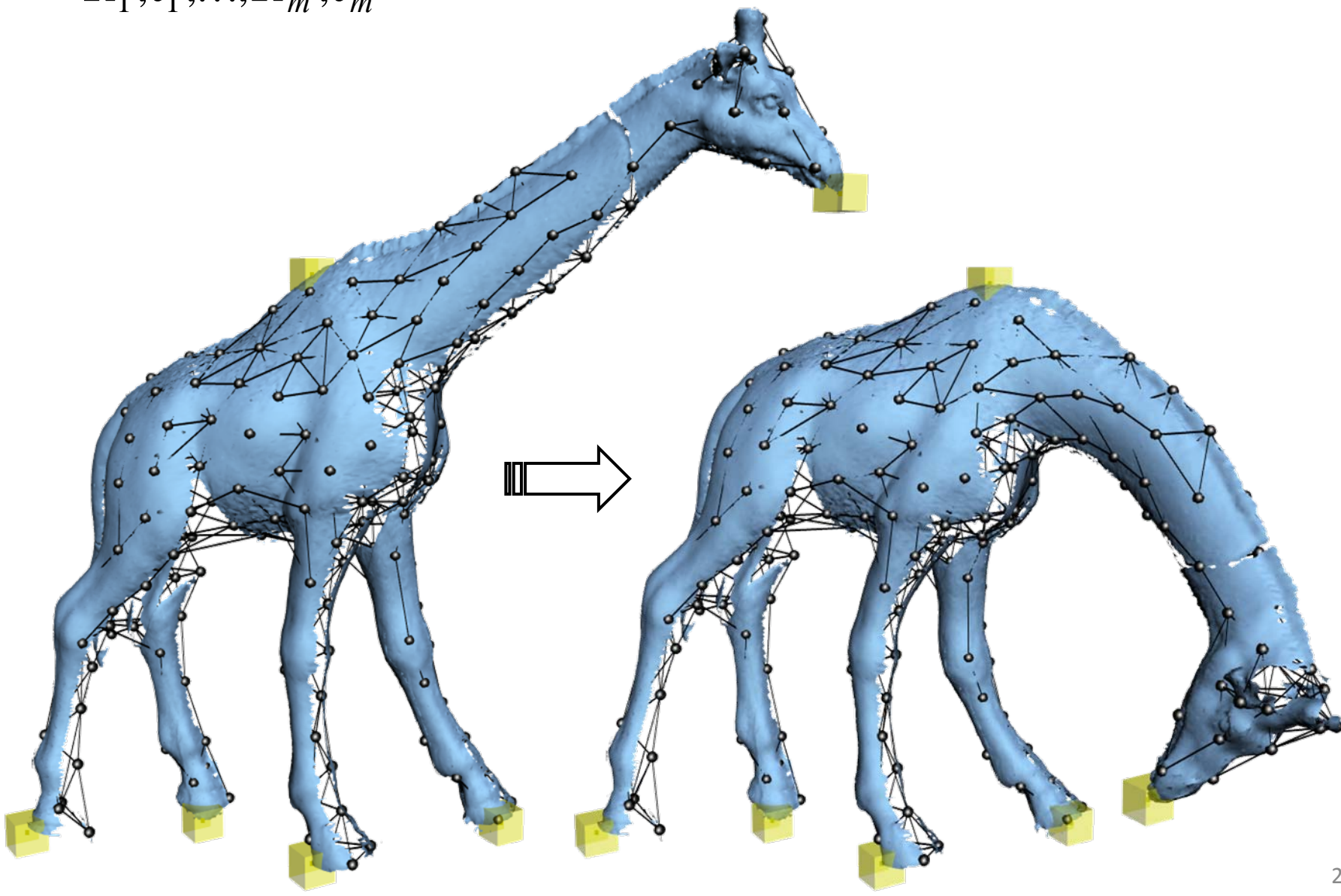
$$\min_{\mathbf{R}_1, \mathbf{t}_1, \dots, \mathbf{R}_m, \mathbf{t}_m} w_{\text{rot}} \mathbf{E}_{\text{rot}} + w_{\text{reg}} \mathbf{E}_{\text{reg}} + \underline{w_{\text{con}} \mathbf{E}_{\text{con}}}$$

$$\mathbf{E}_{\text{con}} = \sum_{l=1}^p \left\| \tilde{\mathbf{v}}_{\text{index}(l)} - \mathbf{q}_l \right\|_2^2$$



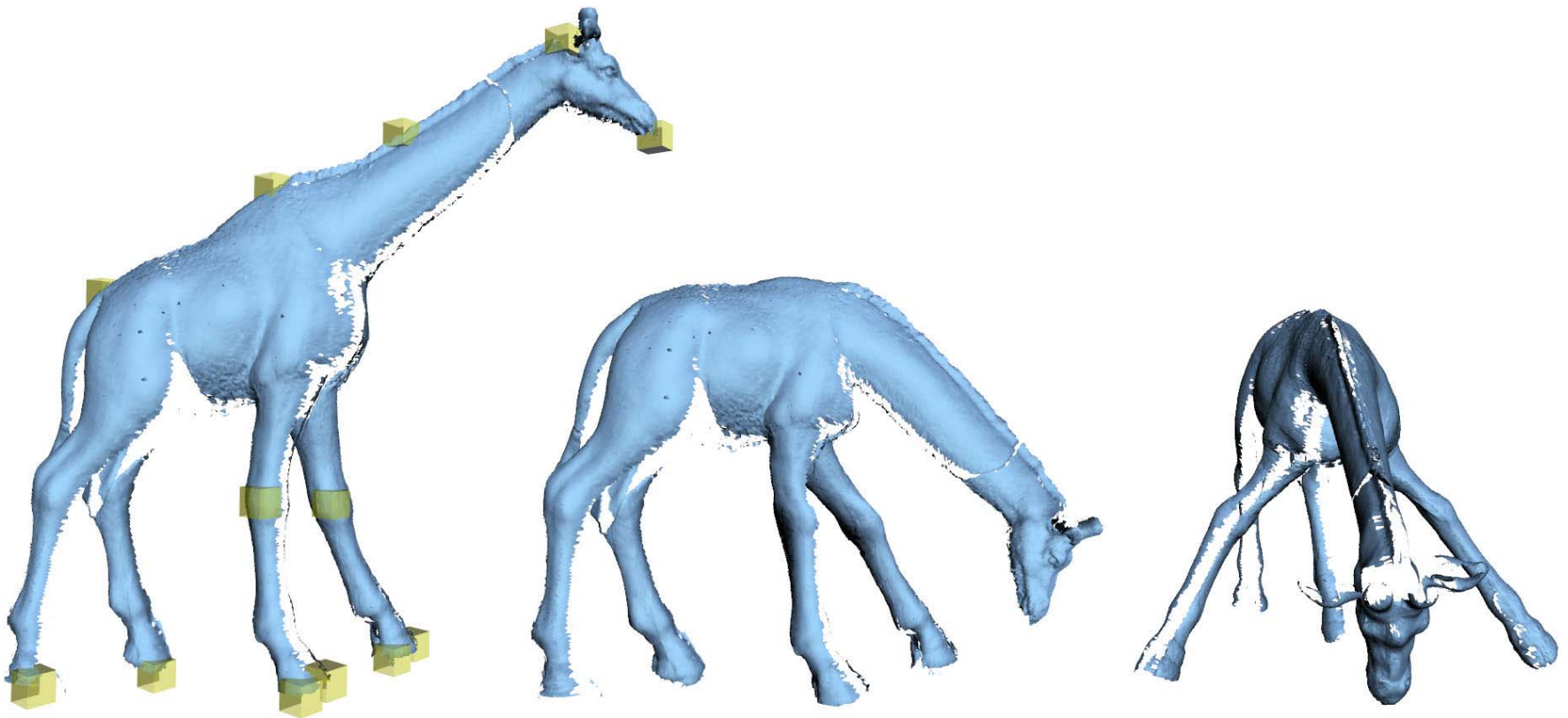
Handle vertices should go where the user puts them.

$$\min_{\mathbf{R}_1, \mathbf{t}_1, \dots, \mathbf{R}_m, \mathbf{t}_m} w_{\text{rot}} \mathbf{E}_{\text{rot}} + w_{\text{reg}} \mathbf{E}_{\text{reg}} + w_{\text{con}} \mathbf{E}_{\text{con}}$$



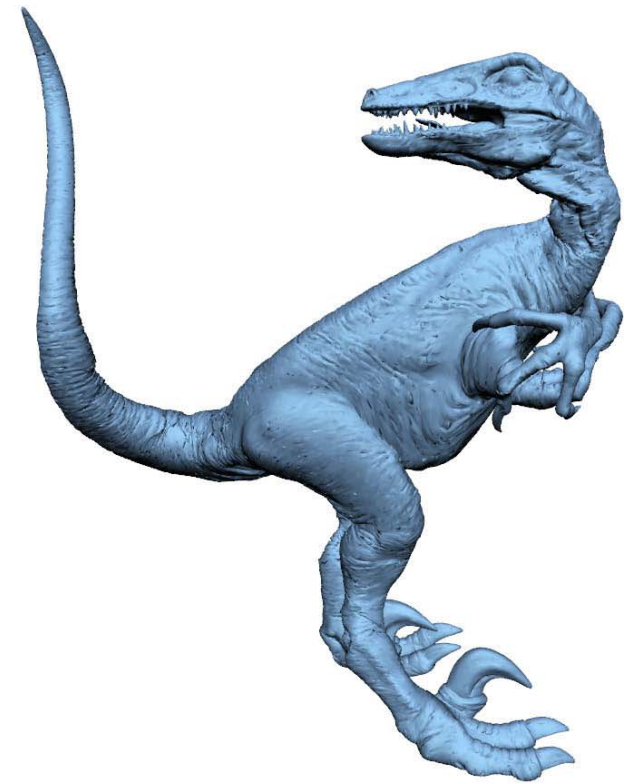
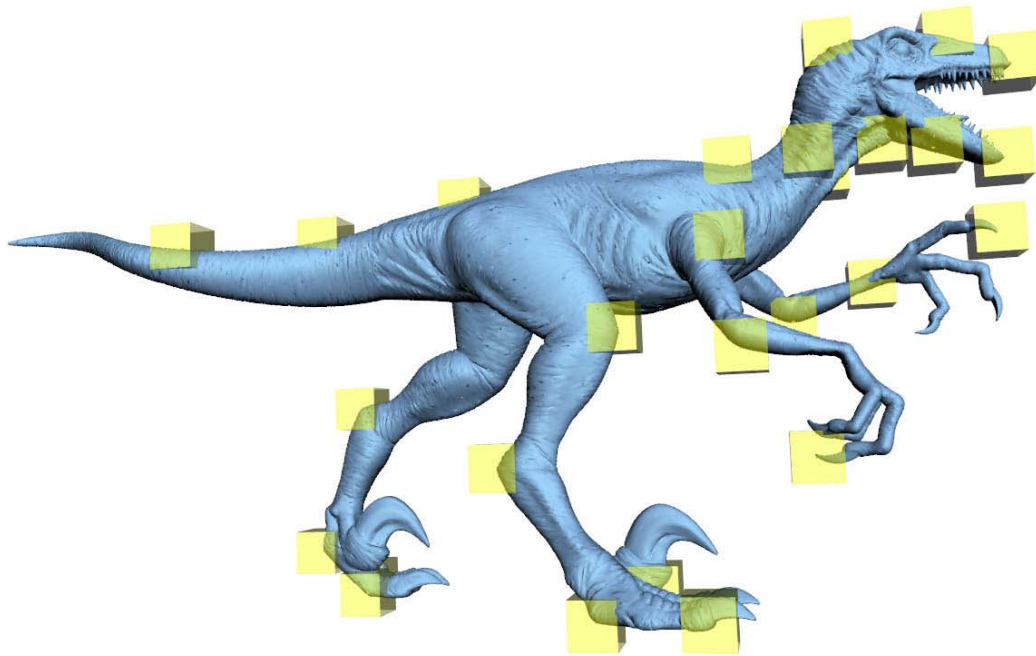
Results: Polygon Soup

[Sumner et al. 2007]



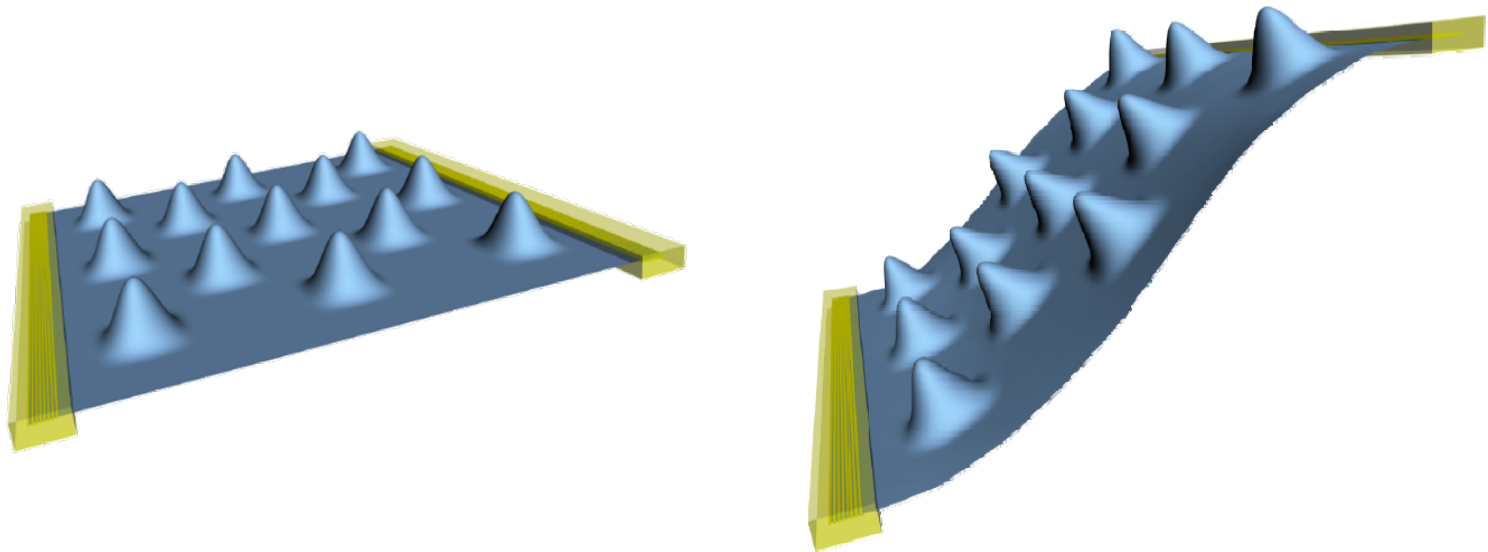
Results: Giant Mesh

[Sumner et al. 2007]



Results: Detail Preservation

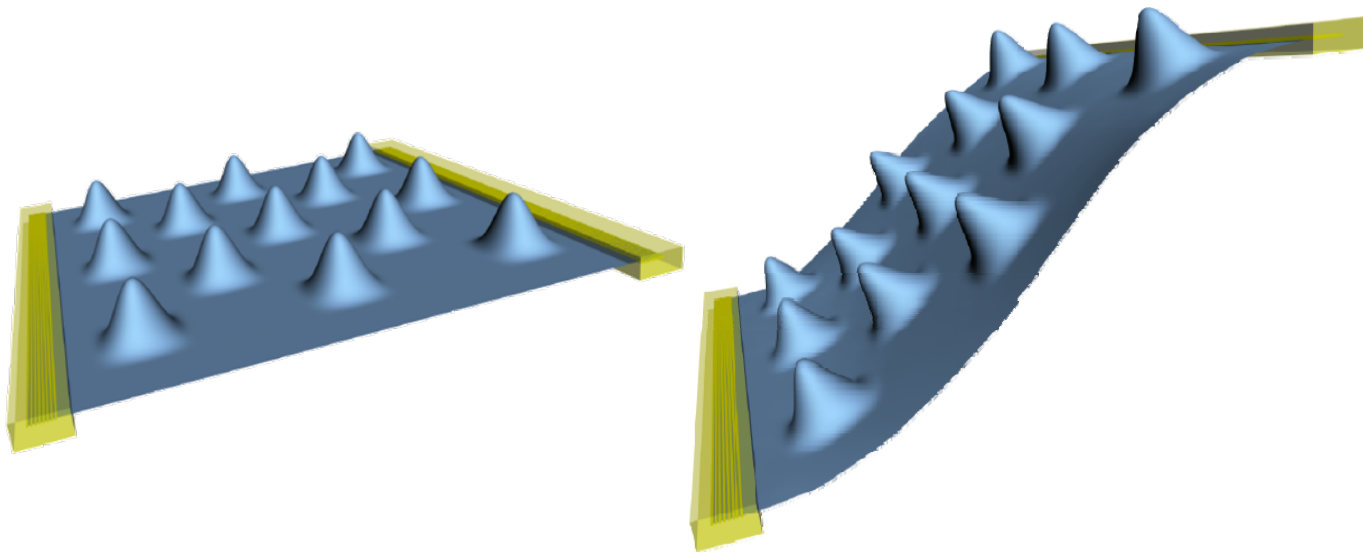
[Sumner et al. 2007]



Demo

Discussion

- Decoupling of deformation complexity and model complexity
- Nonlinear energy optimization – results comparable to surface-based approaches





Eurographics 2009

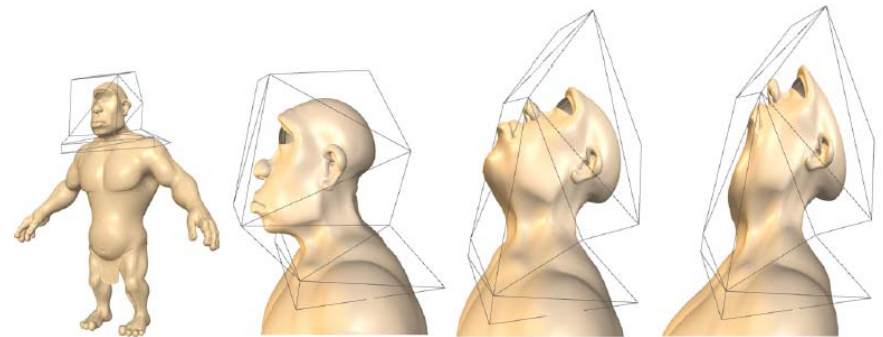
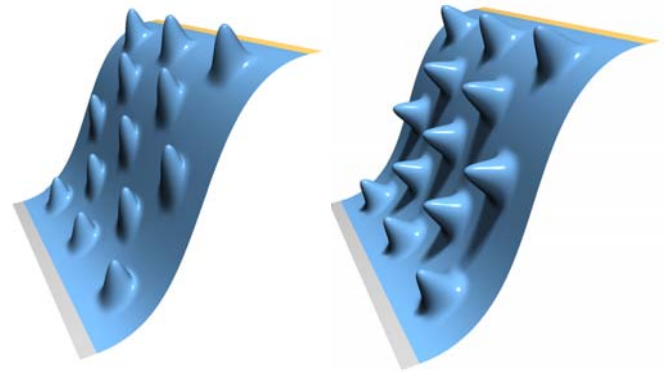
Interactive Shape Modeling and Deformation

T3: Half-Day Tutorial

Wrap-up

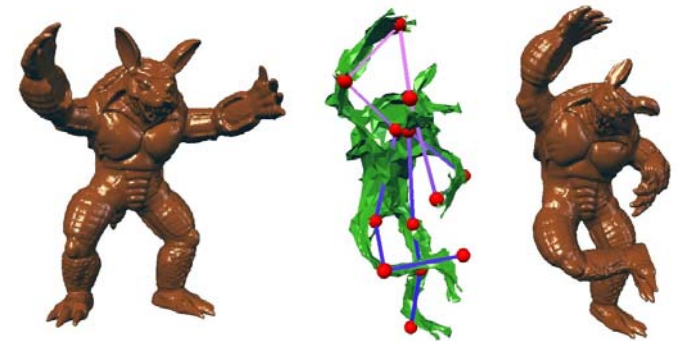
Research trends

- From linear to nonlinear techniques
- Surface-based methods and space warps developed simultaneously



Future work?

- Higher-level editing
 - ... with semantic understanding of the shape
 - ... with “pseudo-physics” automatically set up from that understanding
- Hybrids between surface- and space-based methods



Acknowledgments

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