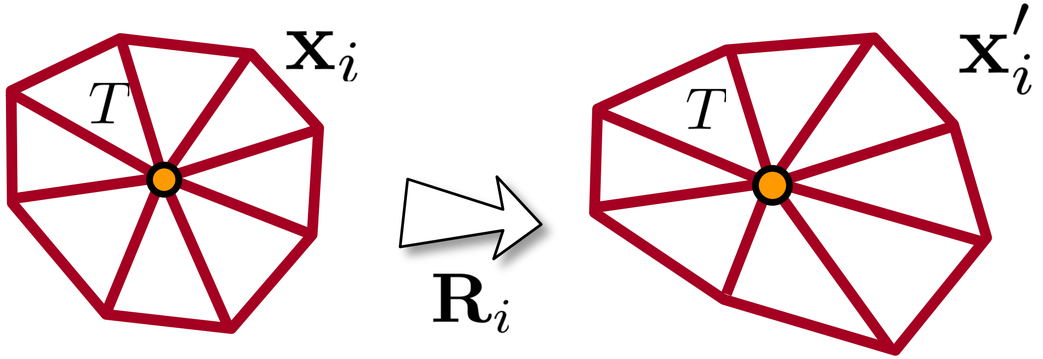
08 - As Rigid As Possible (ARAP) Deformation

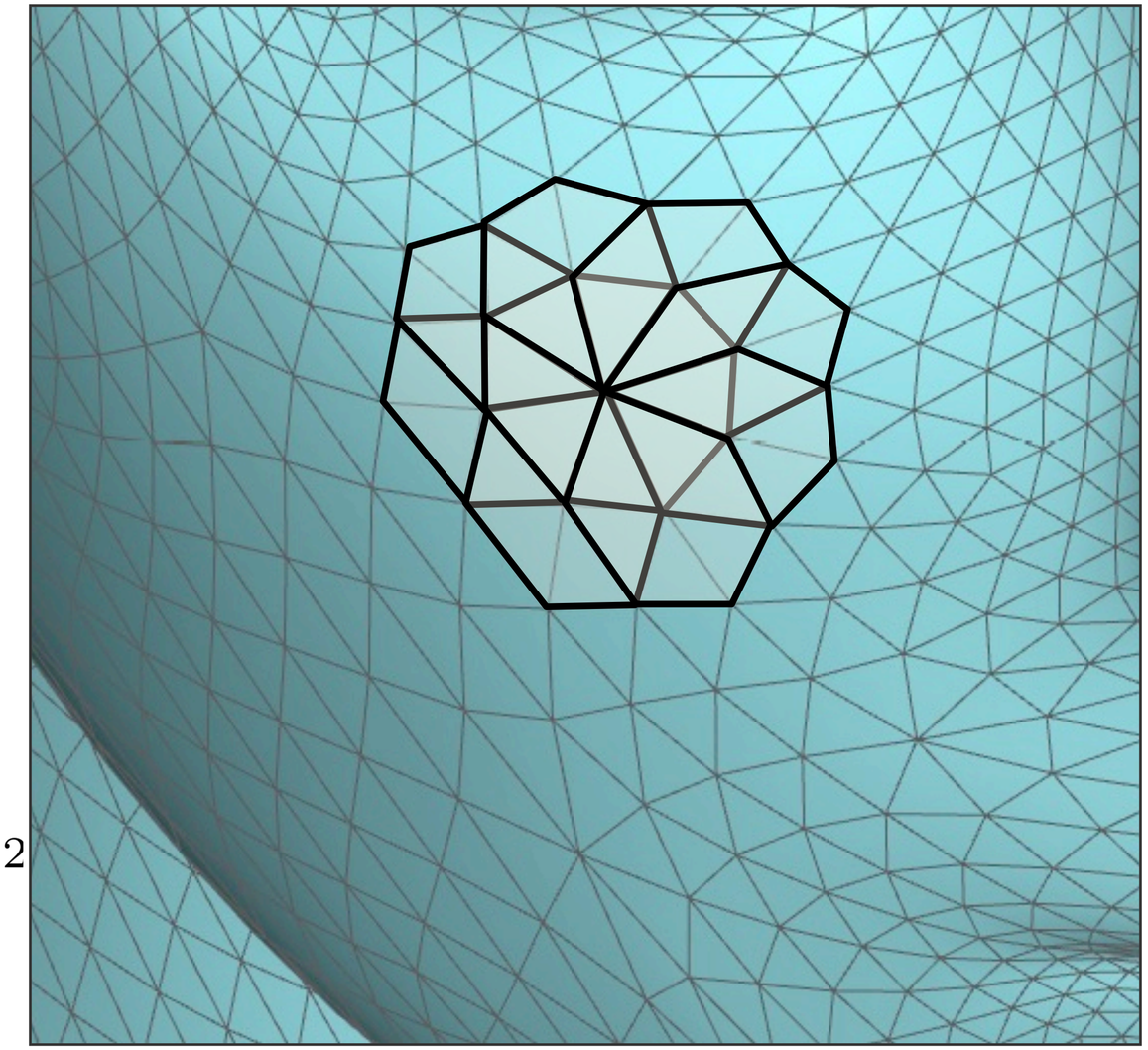
Acknowledgements: Daniele Panozzo

As-Rigid-As-Possible Deformation

- Preserve shape of cells covering the surface
- Ask each cell i to transform **rigidly** by best-fitting rotation $\mathbf{R}_i$

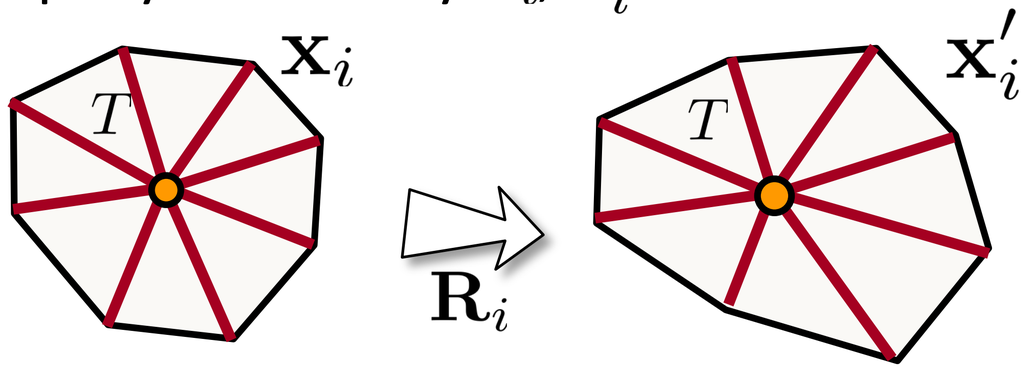


$$\min \sum_{T \in \mathrm{Cell}_i} \sum_{(j,k) \in T} \|(\mathbf{x}'_j - \mathbf{x}'_k) - \mathbf{R}_i(\mathbf{x}_j - \mathbf{x}_k)\|^2$$



As-Rigid-As-Possible Deformation

- Optimal $\mathbf{R}_i$ is uniquely defined by $\mathbf{x}_i, \mathbf{x}'_i$

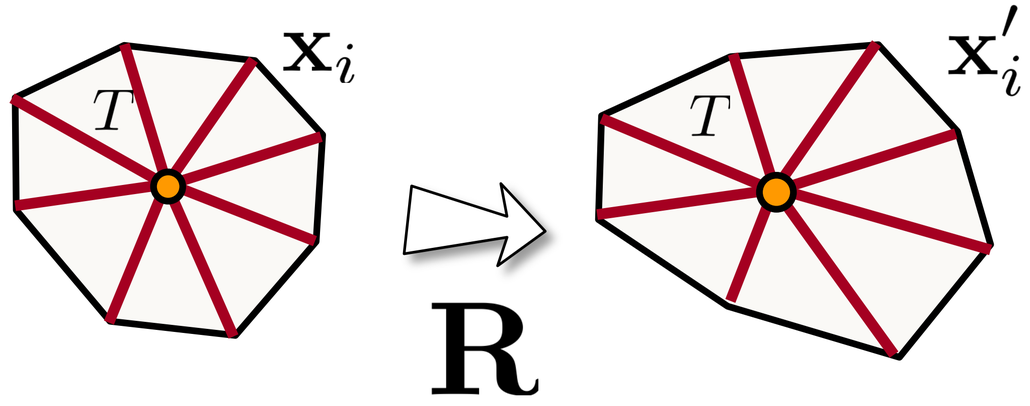


$$\min \sum_{T \in \mathrm{Cell}_i} \sum_{(j,k) \in T} \|(\mathbf{x}'_j - \mathbf{x}'_k) - \mathbf{R}_i(\mathbf{x}_j - \mathbf{x}_k)\|^2$$

- so-called shape-matching problem, solved by a 3x3 SVD

$\mathbf{R}_i$ is a nonlinear function of $\mathbf{x}$

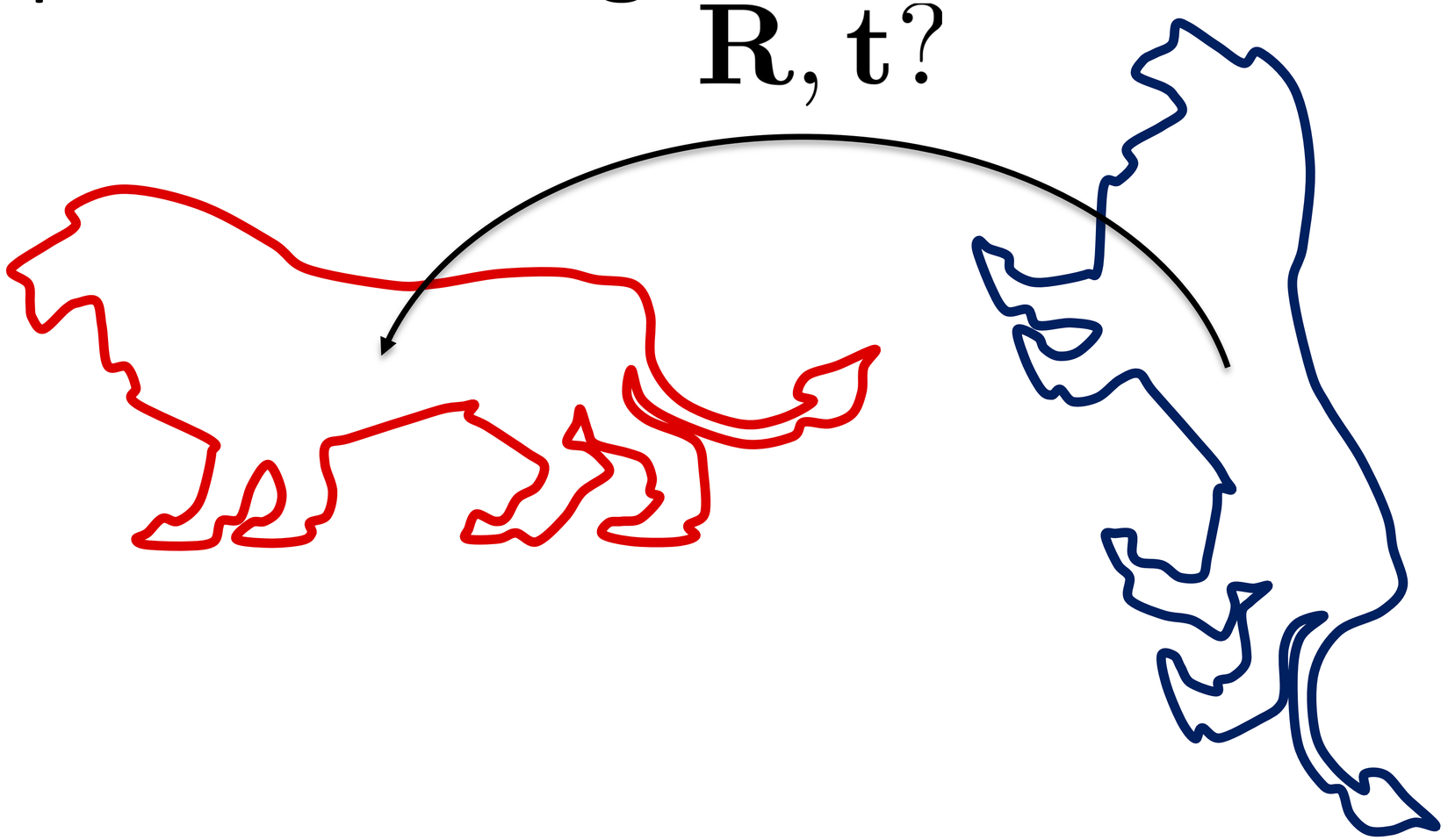
Optimal Rotation



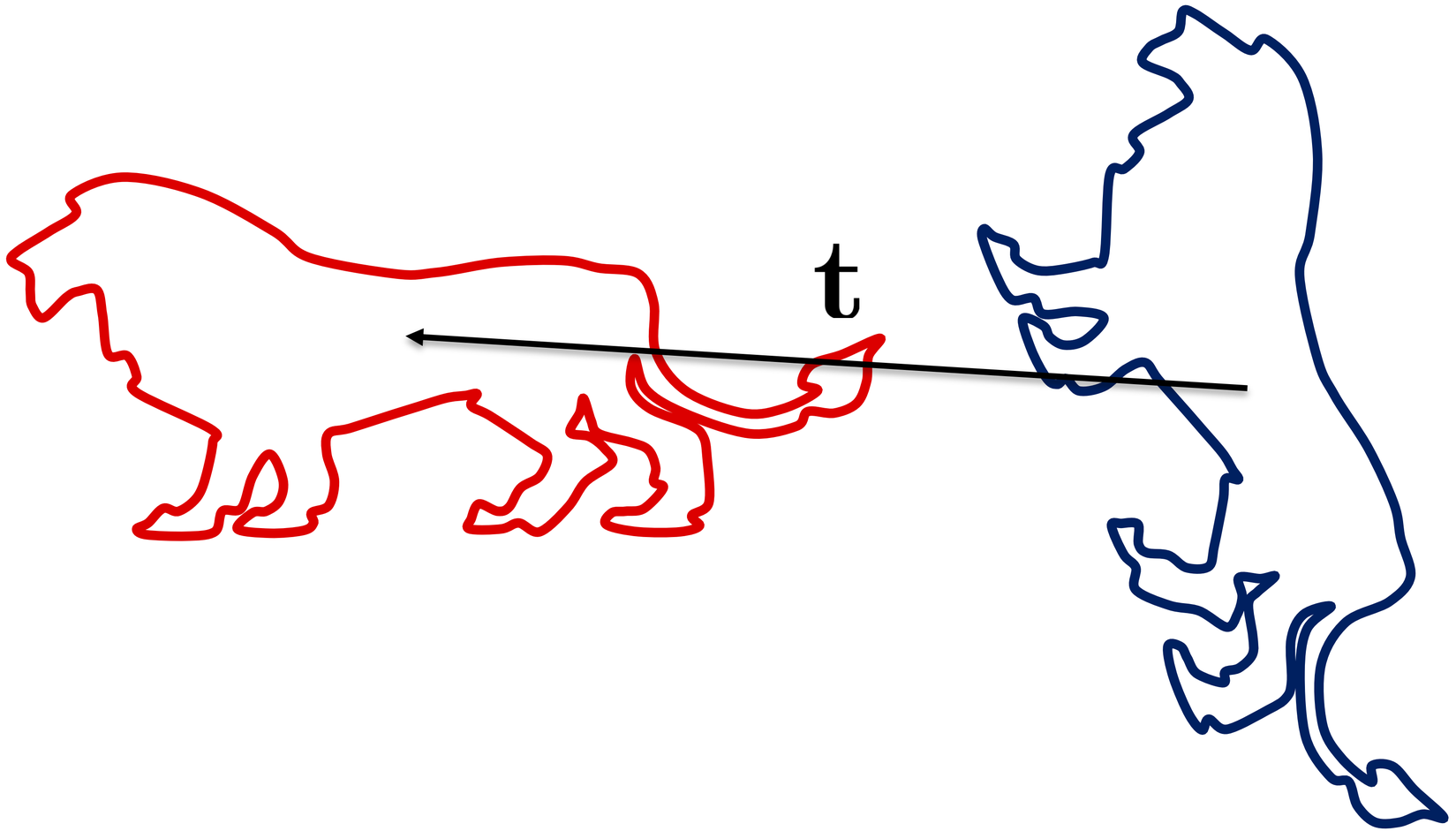
$$\min_{\mathbf{R}\in SO(3)} \sum_{T\in \mathrm{Cell}_i} \sum_{(j,k)\in T} \|(\mathbf{x}'_j - \mathbf{x}'_k) - \mathbf{R}(\mathbf{x}_j - \mathbf{x}_k)\|^2$$

Rotation group

Shape Matching Problem



Shape Matching Problem



Shape Matching Problem

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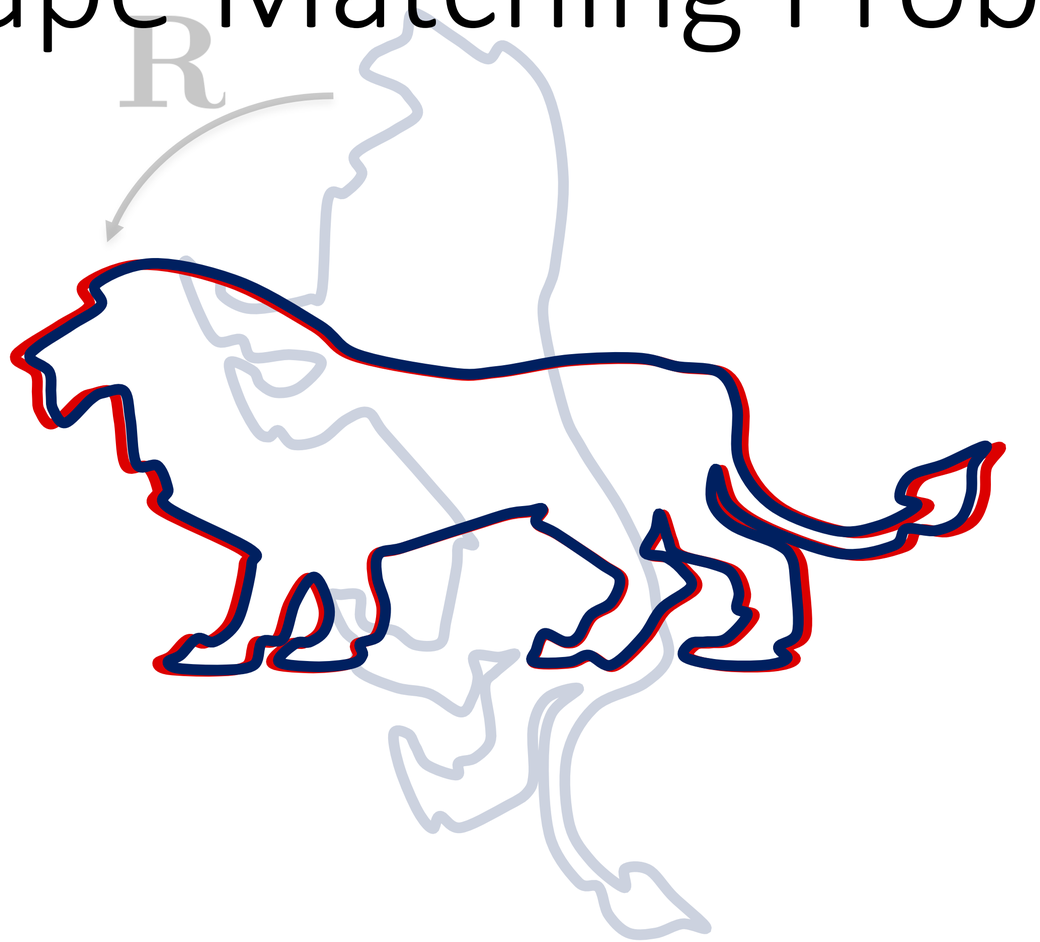


Shape Matching Problem

- Align two point sets

$$\mathcal{P} = \{\mathbf{p}_1, \ldots, \mathbf{p}_n\} \text{ and } \mathcal{Q} = \{\mathbf{q}_1, \ldots, \mathbf{q}_n\}$$

- Find a translation vector $\mathbf{t}$ and rotation matrix $\mathbf{R}$ so that

$$\sum_{i=1}^{n} \|(\mathbf{R}\mathbf{p}_i + \mathbf{t}) - \mathbf{q}_i\|^2 \text{ is minimized}$$

Shape Matching – Solution

- Solve for translation first (w.r.t. **R**, **p**, and **q**)

$$\frac{\partial}{\partial \mathbf{t}} \sum_{i=1}^{n} \|(\mathbf{R}\mathbf{p}_i + \mathbf{t}) - \mathbf{q}_i\|^2 = \sum_{i=1}^{n} 2\left((\mathbf{R}\mathbf{p}_i + \mathbf{t}) - \mathbf{q}_i\right) \stackrel{!}{=} 0$$

$$\mathbf{R}\sum_{i=1}^{n} \mathbf{p}_i + \sum_{i=1}^{n} \mathbf{t} - \sum_{i=1}^{n} \mathbf{q}_i = 0$$

$$\mathbf{t} = \underbrace{\left(\frac{1}{n}\sum_{i=1}^{n} \mathbf{q}_i\right)}_{\bar{\mathbf{q}}} - \mathbf{R}\underbrace{\left(\frac{1}{n}\sum_{i=1}^{n} \mathbf{p}_i\right)}_{\bar{\mathbf{p}}}$$

Finding the Rotation $\mathbf{R}$

- To find the optimal $\mathbf{R}$, we bring the centroids of both point sets to the origin

$$\mathbf{v}_i = \mathbf{p}_i - \bar{\mathbf{p}}, \qquad \mathbf{v}'_i = \mathbf{q}_i - \bar{\mathbf{q}}$$

- We want to find $\mathbf{R}$ that minimizes

$$\sum_{i=1}^{n} \|\mathbf{R}\mathbf{v}_i - \mathbf{v}'_i\|^2$$

Finding the Rotation $\mathbf{R}$

$$\sum_{i=1}^{n} \|\mathbf{R}\mathbf{v}_i - \mathbf{v}'_i\|^2 = \sum_{i=1}^{n} (\mathbf{R}\mathbf{v}_i - \mathbf{v}'_i)^T (\mathbf{R}\mathbf{v}_i - \mathbf{v}'_i) =$$

$$= \sum_{i=1}^{n} \left(\mathbf{v}_i^T \underbrace{\mathbf{R}^T \mathbf{R}}_{\mathbf{I}} \mathbf{v}_i - \mathbf{v}'^T_i \mathbf{R}\mathbf{v}_i - \mathbf{v}_i^T \mathbf{R}^T \mathbf{v}'_i + \mathbf{v}'^T_i \mathbf{v}'_i \right)$$

These terms do not depend on **R**,
so we can ignore them in the minimization

Finding the Rotation $\mathbf{R}$

$$\underset{\mathbf{R}\in SO(3)}{\operatorname{argmin}} \sum_{i=1}^{n} \left(-\mathbf{v}_i'^T \mathbf{R} \mathbf{v}_i - \mathbf{v}_i^T \mathbf{R}^T \mathbf{v}_i' \right) = \underset{\mathbf{R}\in SO(3)}{\operatorname{argmax}} \sum_{i=1}^{n} \left(\mathbf{v}_i'^T \mathbf{R} \mathbf{v}_i + \mathbf{v}_i^T \mathbf{R}^T \mathbf{v}_i' \right) =$$

$$= \boxed{\underset{\mathbf{R}\in SO(3)}{\operatorname{argmax}} \sum_{i=1}^{n} \mathbf{v}_i'^T \mathbf{R} \mathbf{v}_i}$$

$$\mathbf{v}_i^T \mathbf{R}^T \mathbf{v}_i' = \left(\mathbf{v}_i^T \mathbf{R}^T \mathbf{v}_i' \right)^T = \mathbf{v}_i'^T \mathbf{R} \mathbf{v}_i$$

Finding the Rotation $\mathbf{R}$

$$\sum_{i=1}^{n} \mathbf{v}_i'^T \mathbf{R} \mathbf{v}_i = tr\left(\mathbf{V}'^T \mathbf{R} \mathbf{V}\right)$$

$$\underbrace{\begin{bmatrix} \mathbf{v}_1'^T \\ \mathbf{v}_2'^T \\ \vdots \\ \mathbf{v}_n'^T \end{bmatrix}}_{\mathbf{V}'^T} \mathbf{R} \underbrace{\begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_2 & \cdots & \mathbf{v}_n \end{bmatrix}}_{\mathbf{V}} = \begin{bmatrix} \mathbf{v}_1'^T \\ \mathbf{v}_2'^T \\ \vdots \\ \mathbf{v}_n'^T \end{bmatrix} \begin{bmatrix} \mathbf{R}\mathbf{v}_1 & \mathbf{R}\mathbf{v}_2 & \cdots & \mathbf{R}\mathbf{v}_n \end{bmatrix}$$

Finding the Rotation $\mathbf{R}$

$$\sum_{i=1}^{n} \mathbf{v}_i'^T \mathbf{R} \mathbf{v}_i = tr\left(\mathbf{V}'^T \mathbf{R} \mathbf{V}\right)$$

$$\begin{bmatrix} \mathbf{v}_1'^T \\ \mathbf{v}_2'^T \\ \vdots \\ \mathbf{v}_n'^T \end{bmatrix} \begin{bmatrix} \mathbf{R}\mathbf{v}_1 & \mathbf{R}\mathbf{v}_2 & \cdots & \mathbf{R}\mathbf{v}_n \end{bmatrix} = \begin{bmatrix} \mathbf{v}_1'^T \mathbf{R}\mathbf{v}_1 & & & \\ & \mathbf{v}_2'^T \mathbf{R}\mathbf{v}_2 & & \\ & & \ddots & \\ & & & \mathbf{v}_n'^T \mathbf{R}\mathbf{v}_n \end{bmatrix}$$

Finding the Rotation $\mathbf{R}$

Take a look at the Matrix Cookbook!

- Find $\mathbf{R}$ that maximizes

$$tr\left(\mathbf{V'}^T\mathbf{R}\mathbf{V}\right) = tr\left(\mathbf{R}\mathbf{V}\mathbf{V'}^T\right)$$

- SVD:

$$\mathbf{V}\mathbf{V'}^T = \mathbf{U}\mathbf{\Sigma}\tilde{\mathbf{U}}^T$$

$$tr\left(\mathbf{R}\mathbf{V}\mathbf{V'}^T\right) = tr\left(\underline{\mathbf{R}\,\mathbf{U}}\underline{\mathbf{\Sigma}\tilde{\mathbf{U}}^T}\right) = tr\left(\Sigma\,\underline{\tilde{\mathbf{U}}^T\mathbf{R}\mathbf{U}}\right)$$

orthonormal matrix

Finding the Rotation $\mathbf{R}$

- We want to maximize $tr\left(\Sigma\,\mathbf{M}\right)$

$\mathbf{M}$: orthonormal matrix
all entries ≤ 1

$$\begin{bmatrix} \sigma_1 & & \\ & \sigma_2 & \\ & & \sigma_3 \end{bmatrix} \begin{bmatrix} m_{11} & \cdots & \\ \vdots & m_{22} & \vdots \\ & \cdots & m_{33} \end{bmatrix}$$

$$tr\left(\Sigma\,\mathbf{M}\right) = \sum_{i=1}^{3} \sigma_i\, m_{ii} \leq \sum_{i=1}^{3} \sigma_i$$

Finding the Rotation $\mathbf{R}$

$$tr\left(\Sigma\,\mathbf{M}\right) = \sum_{i=1}^{3} \sigma_i\, m_{ii} \leq \sum_{i=1}^{3} \sigma_i$$

- Our best shot is $m_{ii} = 1$, i.e. to make **M = I**

$$\begin{aligned} \mathbf{M} = \tilde{\mathbf{U}}^T \mathbf{R} \mathbf{U} &\stackrel{!}{=} \mathbf{I} \\ \mathbf{R}\mathbf{U} &= \tilde{\mathbf{U}} \\ \boxed{\mathbf{R} &= \tilde{\mathbf{U}}\mathbf{U}^T} \end{aligned}$$

Summary of Rigid Alignment

- Translate the input points to the centroids

$$\mathbf{v}_i = \mathbf{p}_i - \bar{\mathbf{p}}, \qquad \mathbf{v}'_i = \mathbf{q}_i - \bar{\mathbf{q}}$$

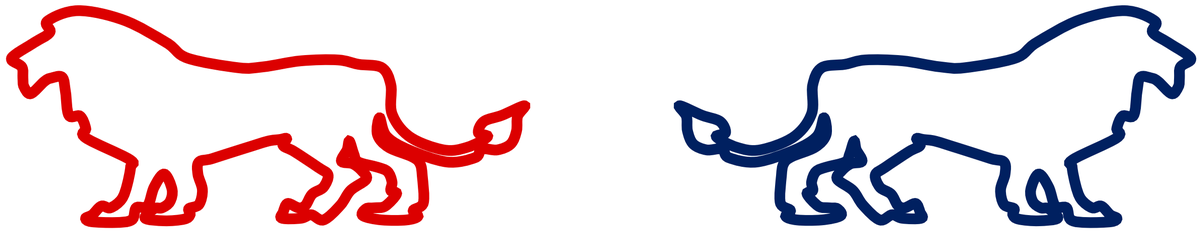
- Compute the "covariance matrix" $\mathbf{V}\mathbf{V}'^T$

- Compute its SVD: $\mathbf{V}\mathbf{V}'^T = \mathbf{U}\mathbf{\Sigma}\tilde{\mathbf{U}}^T$

- The optimal orthonormal **R** is $\mathbf{R} = \tilde{\mathbf{U}}\mathbf{U}^T$

Sign Correction

- It is possible that $\det(\tilde{\mathbf{U}}\mathbf{U}^T) = -1$: sometimes reflection is the best orthonormal transform



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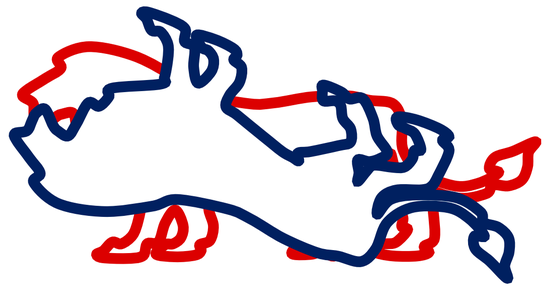
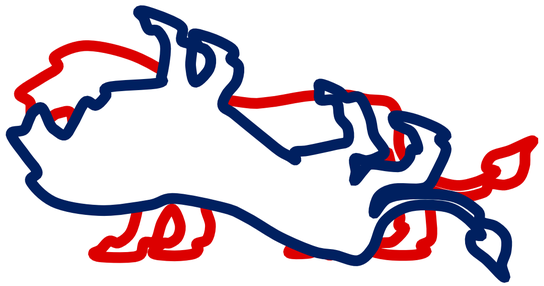


Sign Correction

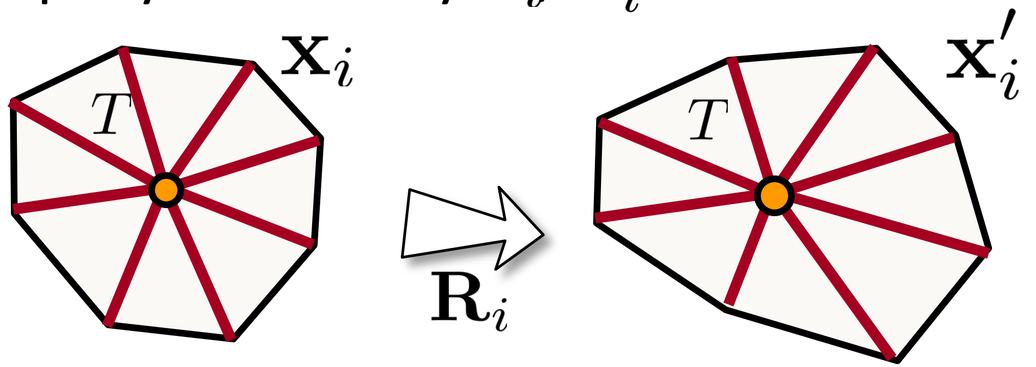
- To restrict ourselves to rotations only:
  take the last column of $\mathbf{U}$ (corresponding to the smallest singular value) and invert its sign.



- Why? See http://igl.ethz.ch/projects/ARAP/svd_rot.pdf

As-Rigid-As-Possible Deformation

- Optimal $\mathbf{R}_i$ is uniquely defined by $\mathbf{x}_i$, $\mathbf{x}'_i$



$$\min \sum_{T \in \mathrm{Cell}_i} \sum_{(j,k) \in T} \|(\mathbf{x}'_j - \mathbf{x}'_k) - \mathbf{R}_i(\mathbf{x}_j - \mathbf{x}_k)\|^2$$

- so-called shape-matching problem, solved by a 3x3 SVD

$\mathbf{R}_i$ is a nonlinear function of $\mathbf{x}$

As-Rigid-As-Possible Deformation

- Total ARAP energy: sum up for all the cells i

$$\sum_{i} \sum_{T \in \mathrm{Cell}_i} \sum_{(j,k) \in T} \left\| (\mathbf{x}'_j - \mathbf{x}'_k) - \mathbf{R}_i (\mathbf{x}_j - \mathbf{x}_k) \right\|^2$$

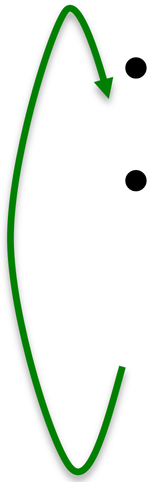
- Treat $\mathbf{x}$ and $\mathbf{R}$ as separate sets of variables
- Simple **local-global** iterative optimization process
  - Decreases the energy at each step

As-Rigid-As-Possible Deformation

- Total ARAP energy: sum up for all the cells i

$$\sum_{i} \sum_{T \in \mathrm{Cell}_i} \sum_{(j,k) \in T} \left\| (\mathbf{x}'_j - \mathbf{x}'_k) - \mathbf{R}_i (\mathbf{x}_j - \mathbf{x}_k) \right\|^2$$

- Local step: keep $\mathbf{x}$' fixed, find optimal $\mathbf{R}_i$ per cell i
- Global step: keep $\mathbf{R}_i$ fixed, solve for $\mathbf{x}$' – quadratic minimization problem



$$\mathbf{L}\mathbf{x}' = \mathbf{b}$$

As-Rigid-As-Possible Deformation

- Total ARAP energy: sum up for all the cells i

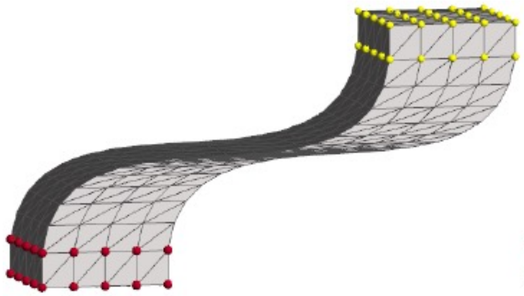
$$\sum_i \sum_{T \in \mathrm{Cell}_i} \sum_{(j,k) \in T} \|(\mathbf{x}'_j - \mathbf{x}'_k) - \mathbf{R}_i(\mathbf{x}_j - \mathbf{x}_k)\|^2$$

- Local step: keep $\mathbf{x}$' fixed, find optimal $\mathbf{R}_i$ per cell i
- Global step: keep $\mathbf{R}_i$ fixed, solve for $\mathbf{x}$' – quadratic minimization problem
  - The matrix $\mathbf{L}$ stays fixed, can pre-factorize

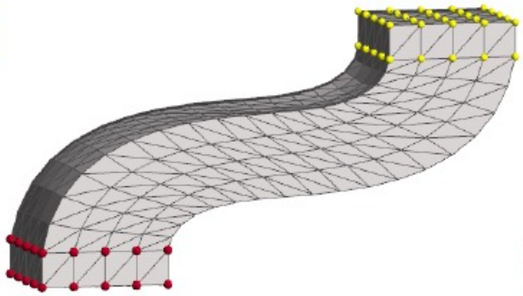
$$\Rightarrow \mathbf{L}\mathbf{x}' = \mathbf{b}$$

Initial Guess

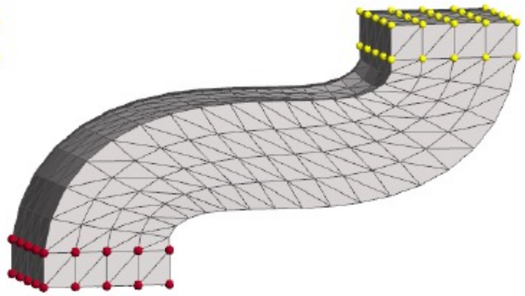
- Can use naïve Laplacian editing



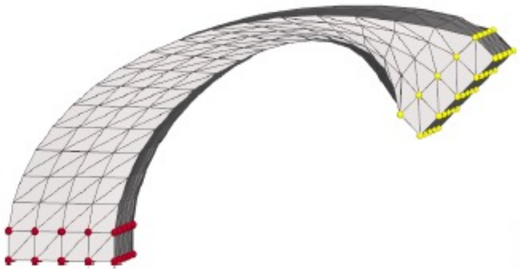
initial guess



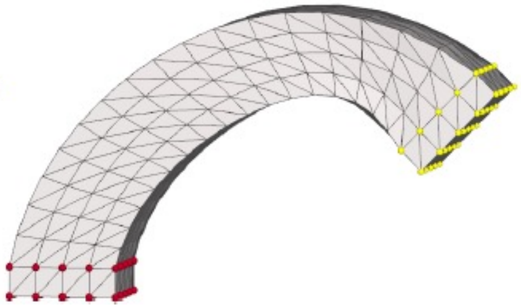
1 iteration



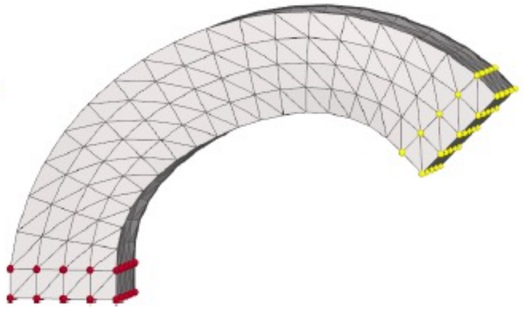
2 iterations



initial guess



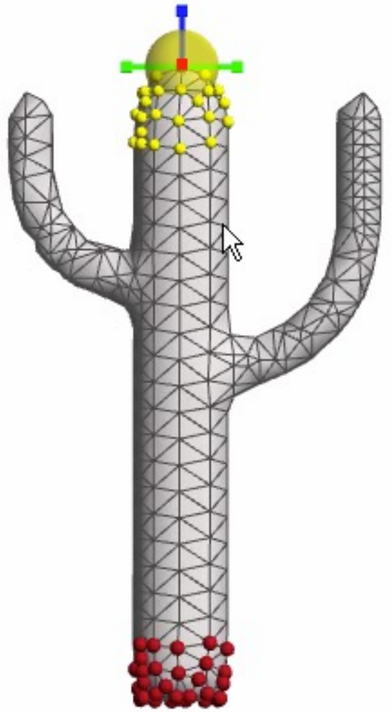
1 iterations



4 iterations

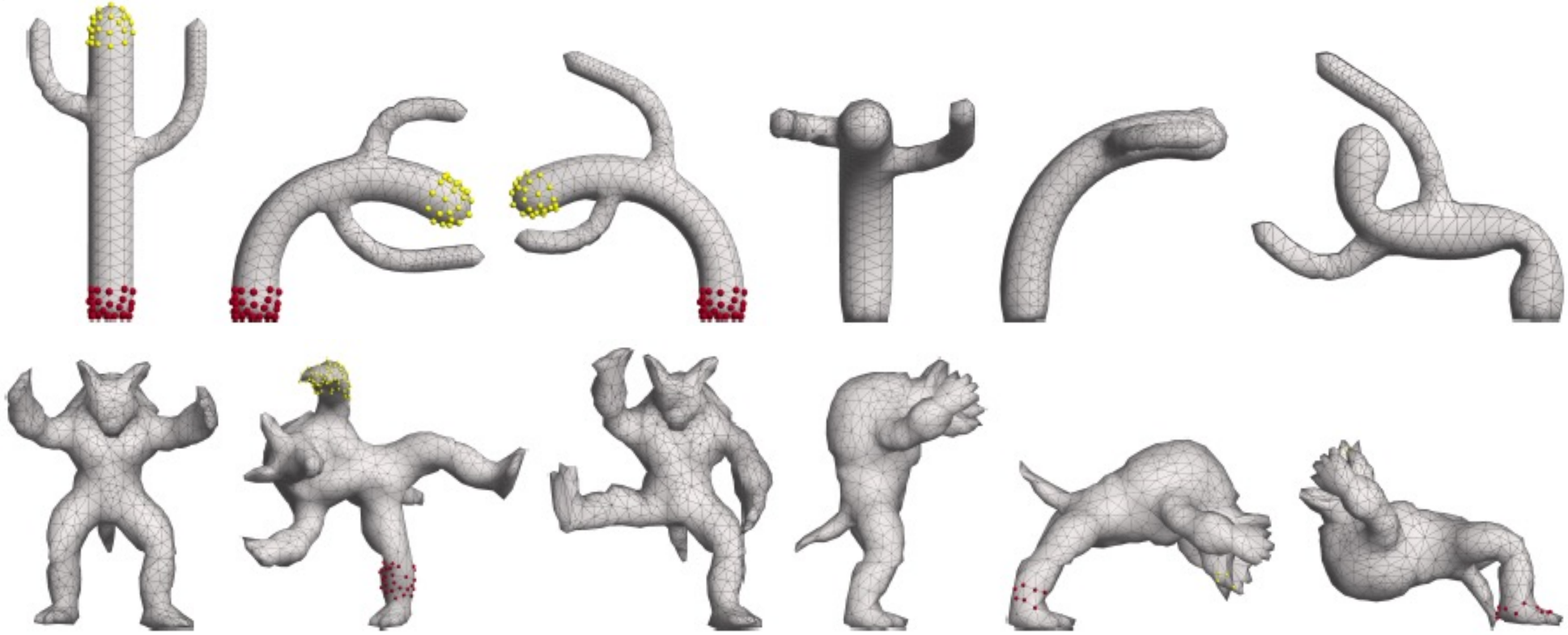
Initial Guess

- Can also use the previous frame
- Replace all handle vertex position by the currently prescribed ones
- Fast convergence

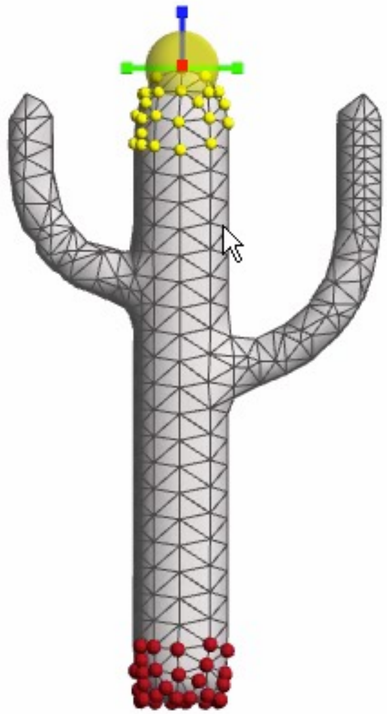


Large Rotations

- Use previous frame as the initial guess



Examples



Discussion

- Nonlinear deformation that models a kind of elastic behavior
- Very simple to implement, no parameters to tune except number of iterations
- Each step is guaranteed to not increase the energy
  - Compare with Gauss-Newton…
- Each iteration is relatively cheap, no matrix re-factorization necessary

Discussion

- Works fine on small meshes
- On larger meshes: slow convergence
  - Each iteration is more expensive
  - Need more iterations because the conditioning of the system becomes worse as the matrix grows
- Material stiffness depends on the cell size
  - lots of wrinkles for fine meshes when using 1-rings as cells

Acceleration using Subspace Techniques

- Subspace created by int
- Drastically reduces the optimization

Alec Jacobson, Ilya Baran, Ladislav Kavan, Jovan Popović, and Olga Sorkine. “Fast Automatic Skinning Transformations,” 2012.

Acceleration using Subspace Techniques

- Subspace created by influence weight functions for each handle
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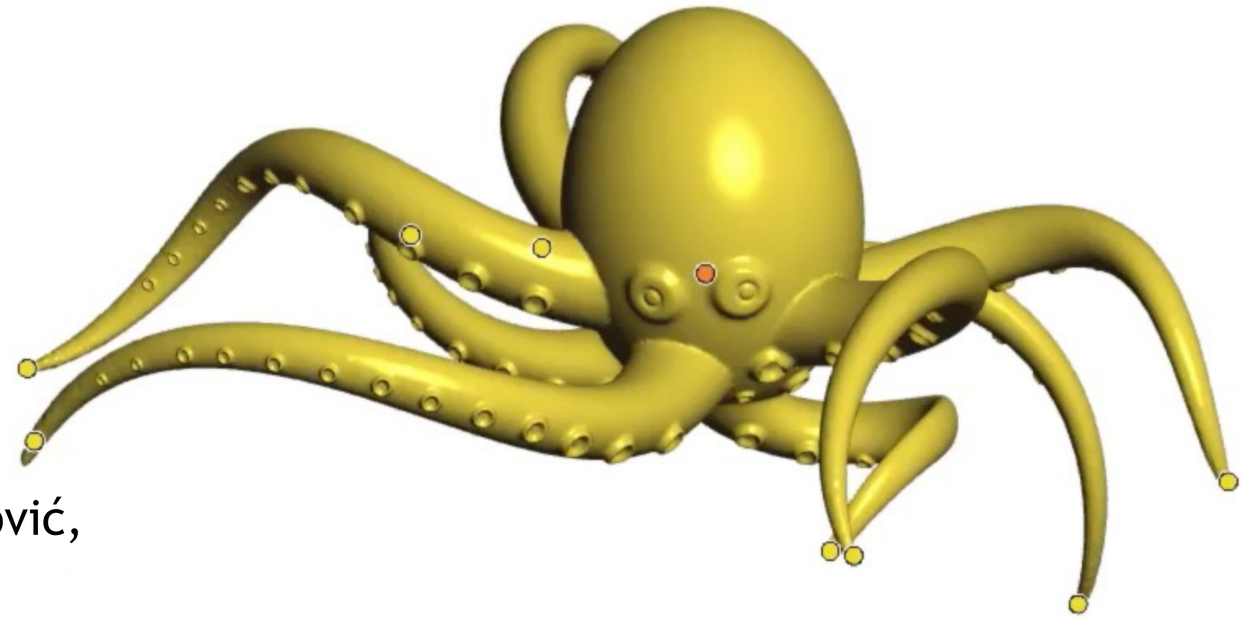

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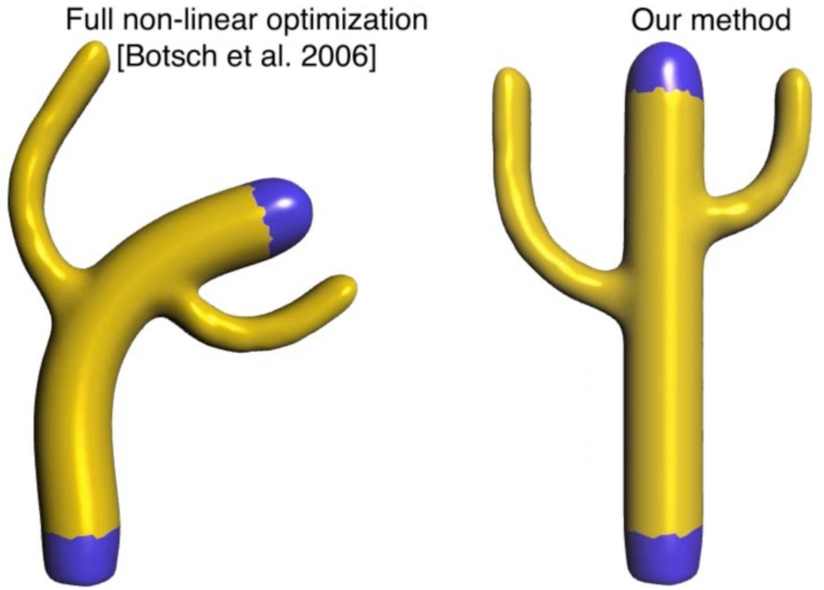

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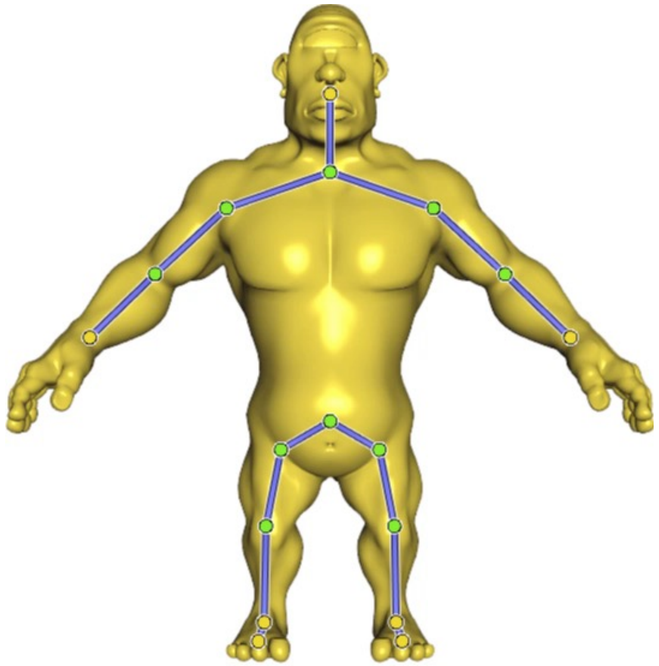
08 - Linear Blend Skinning

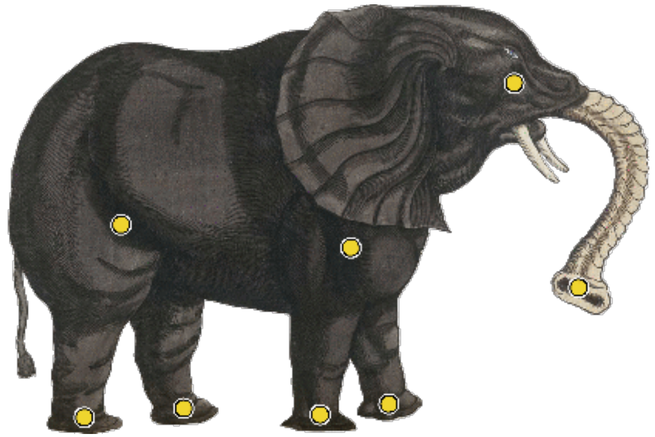
Acknowledgements: Daniele Panozzo

LBS generalizes to different handle types

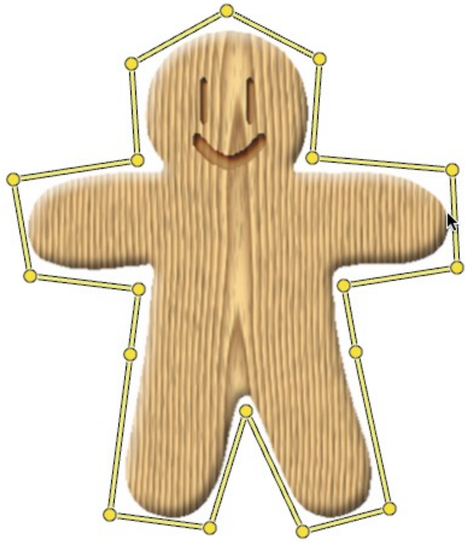


skeletons

regions

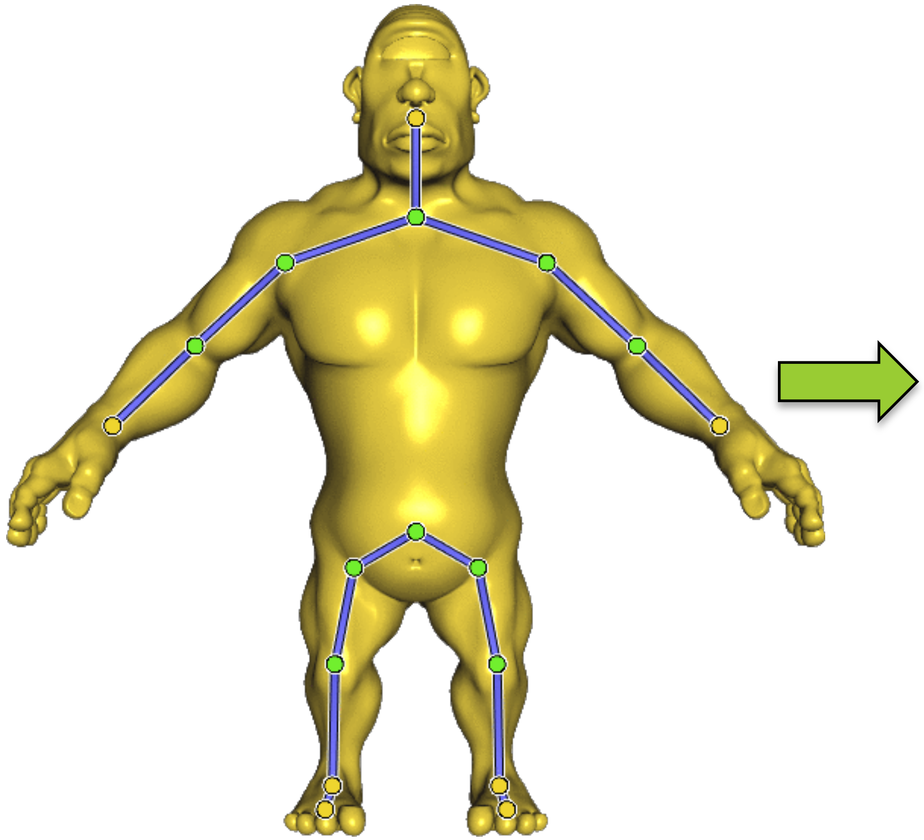


points



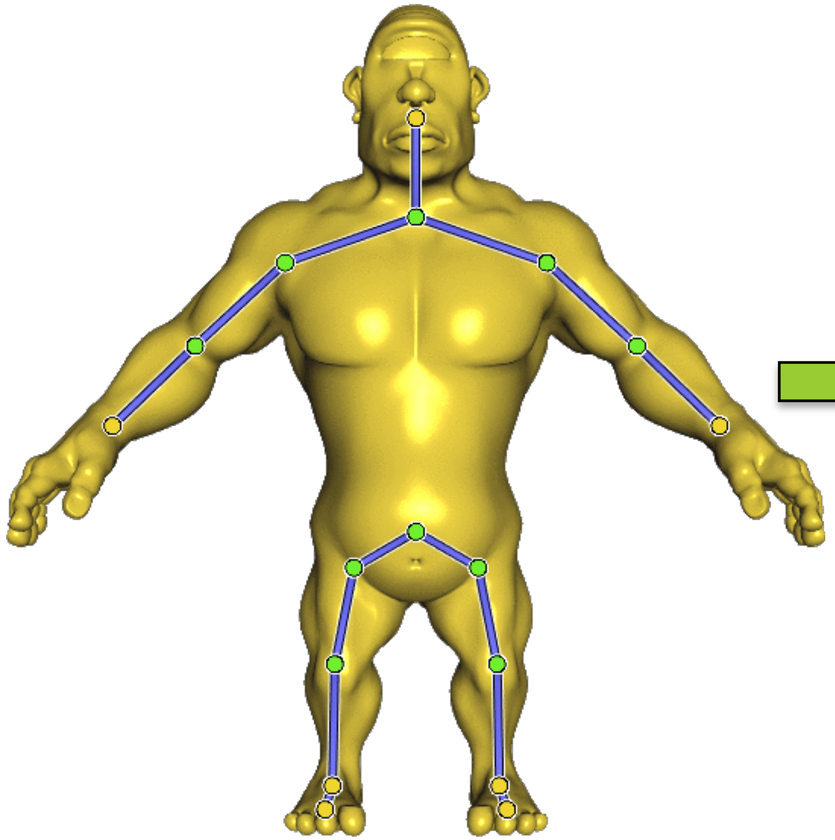
cages

Linear Blend Skinning rigging preferred for its real-time performance

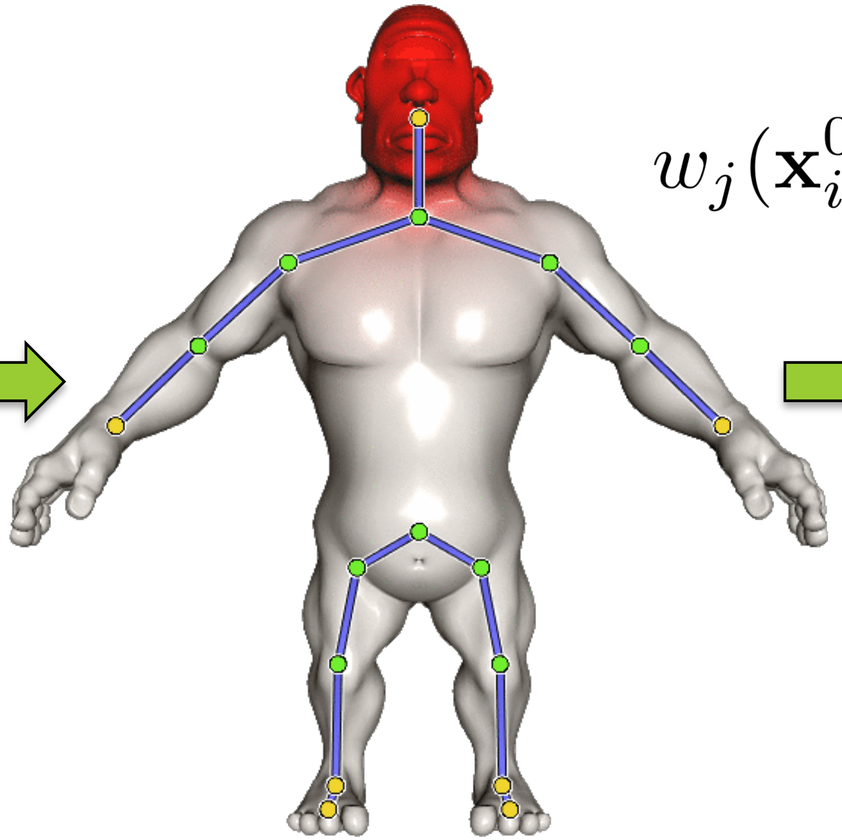


place handles in shape

Linear Blend Skinning rigging preferred for its real-time performance

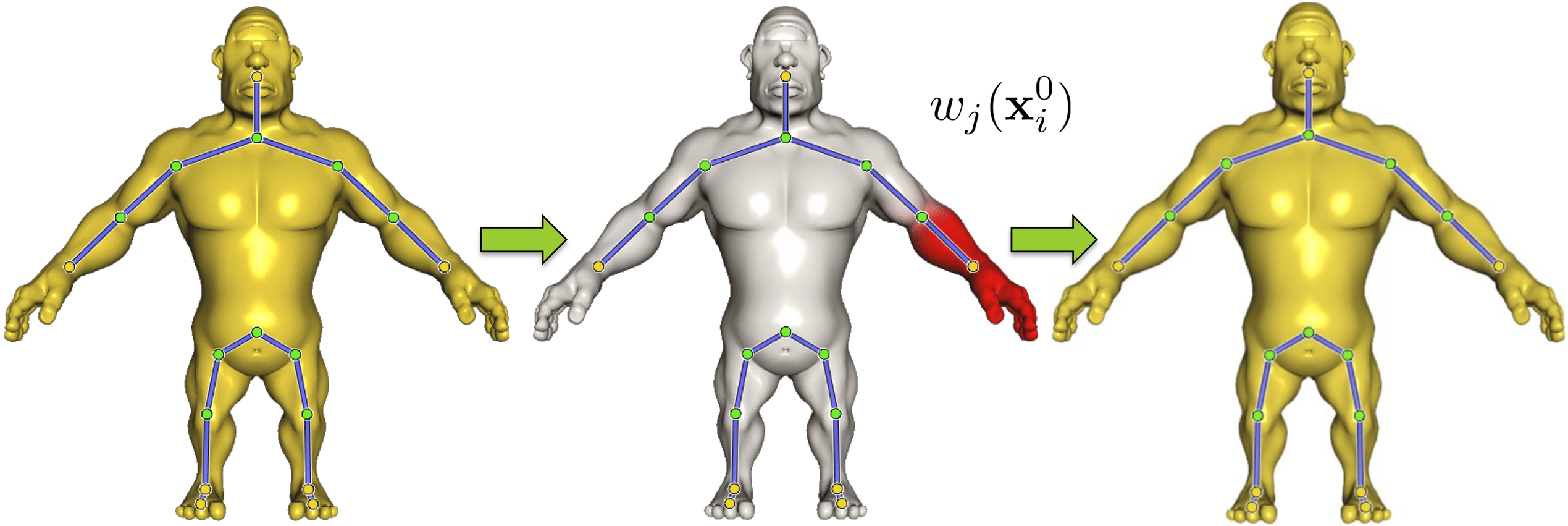


place handles in shape



paint weights

Linear Blend Skinning rigging preferred for its real-time performance

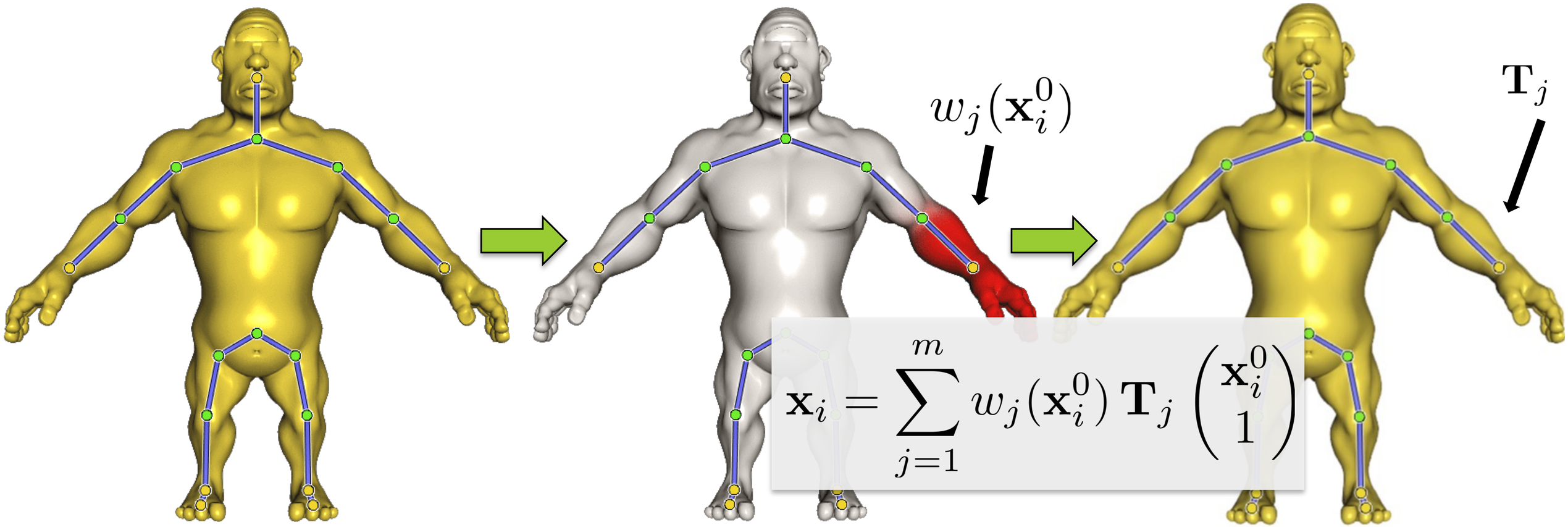


place handles in shape

paint weights

deform handles

Linear Blend Skinning rigging preferred for its real-time performance

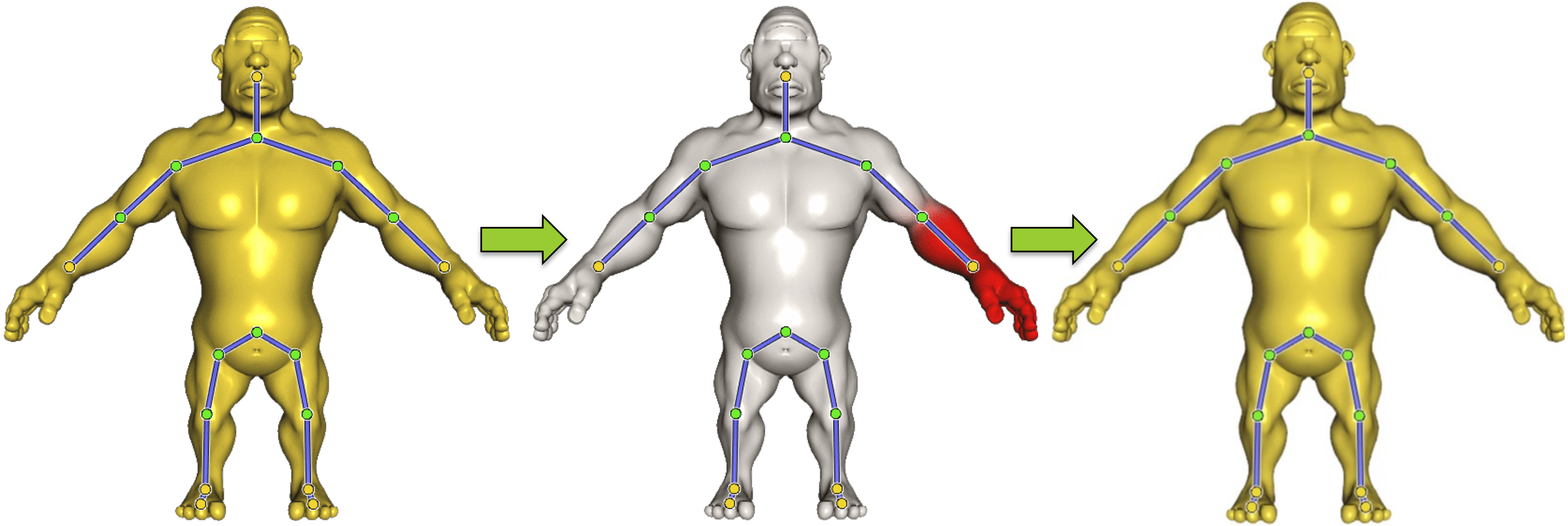


place handles in shape

paint weights

deform handles

Linear Blend Skinning rigging preferred for its real-time performance



place handles in shape

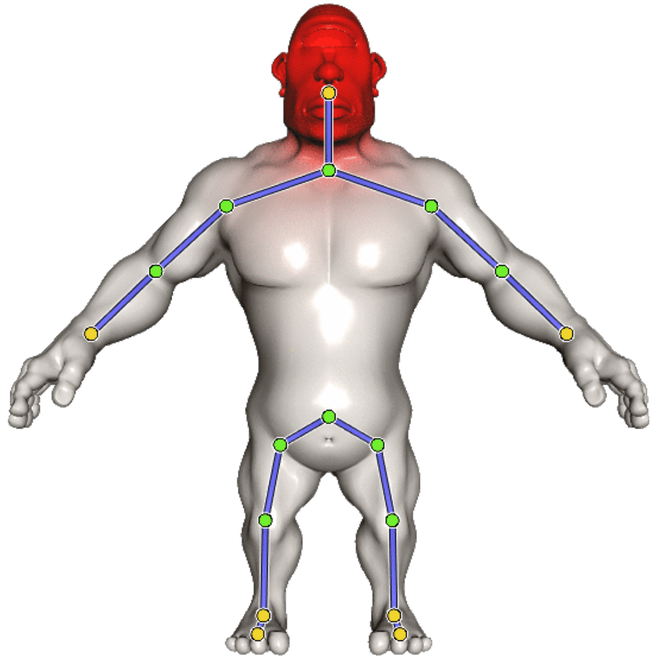
paint weights

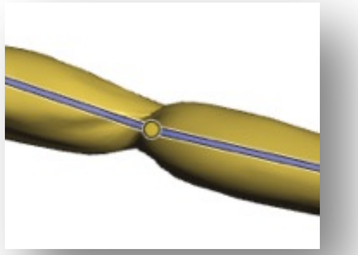
deform handles

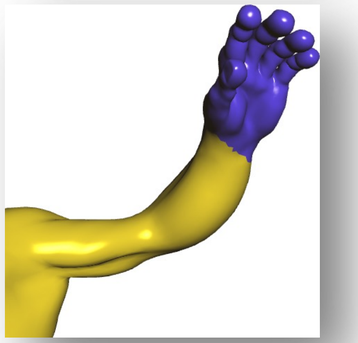
Challenges with LBS

- Weight functions w_j
  - Need intuitive, general and automatic weights
- Degrees of freedom $\mathbf{T}_j$
  - Let the energy decide!
- Richness of achievable deformations
  - Want to avoid common LBS pitfalls – candy wrapper, collapses

$$\mathbf{x}_i = \sum_{j=1}^{m} w_j(\mathbf{x}_i^0)\, \mathbf{T}_j \begin{pmatrix} \mathbf{x}_i^0 \\ 1 \end{pmatrix}$$



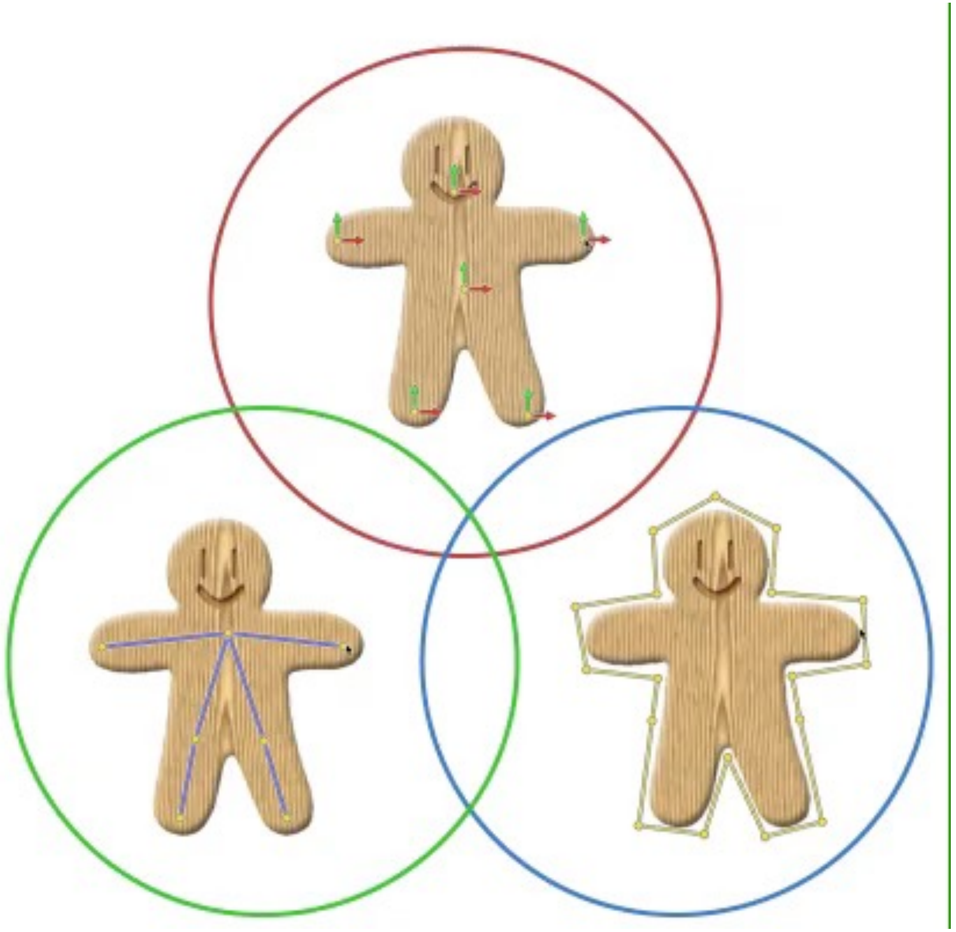




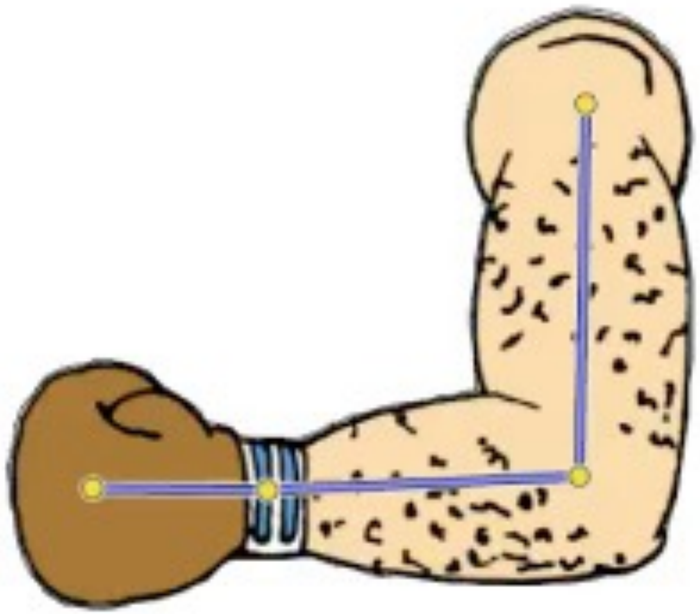
Bounded Biharmonic Weights

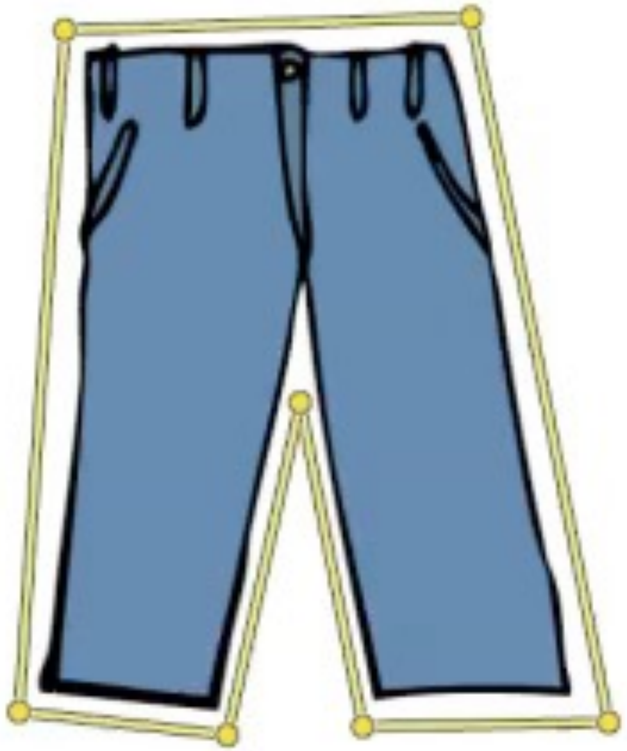
Alec Jacobson, Ilya Baran, Jovan Popović, Olga Sorkine-Hornung

Automatic weights that unify points, skeletons and cages



Weights should be smooth,
shape-aware, positive and ***intuitive***



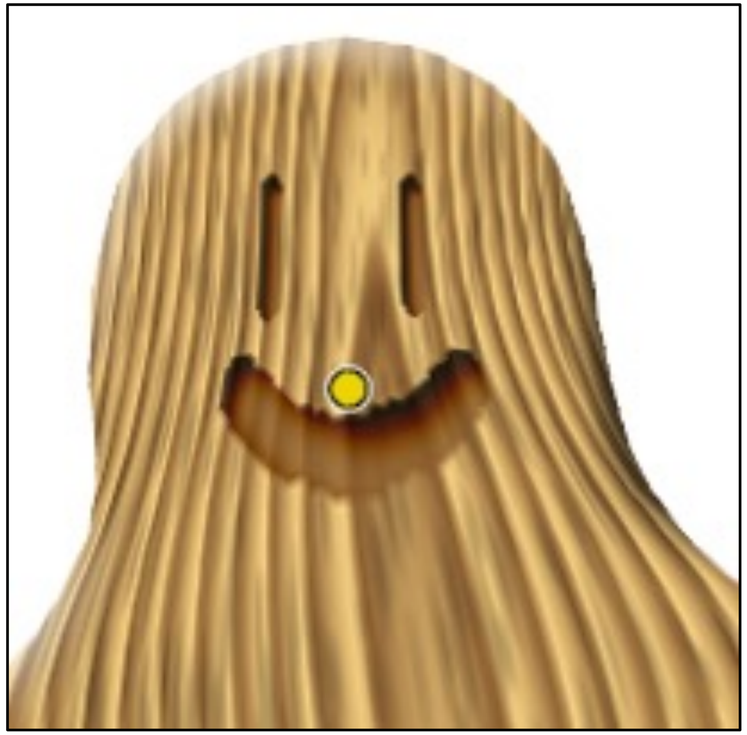


Weights must be smooth everywhere, ***especially*** at handles

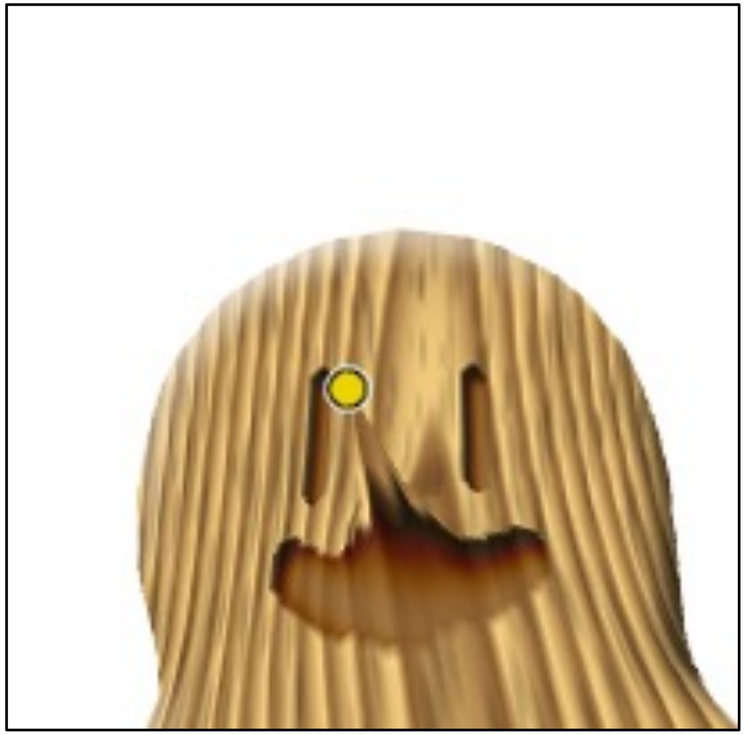
Bounded Biharmonic Weights

Extension of Harmonic Coordinates
[Joshi et al. 2005]

Weights must be smooth everywhere, ***especially*** at handles

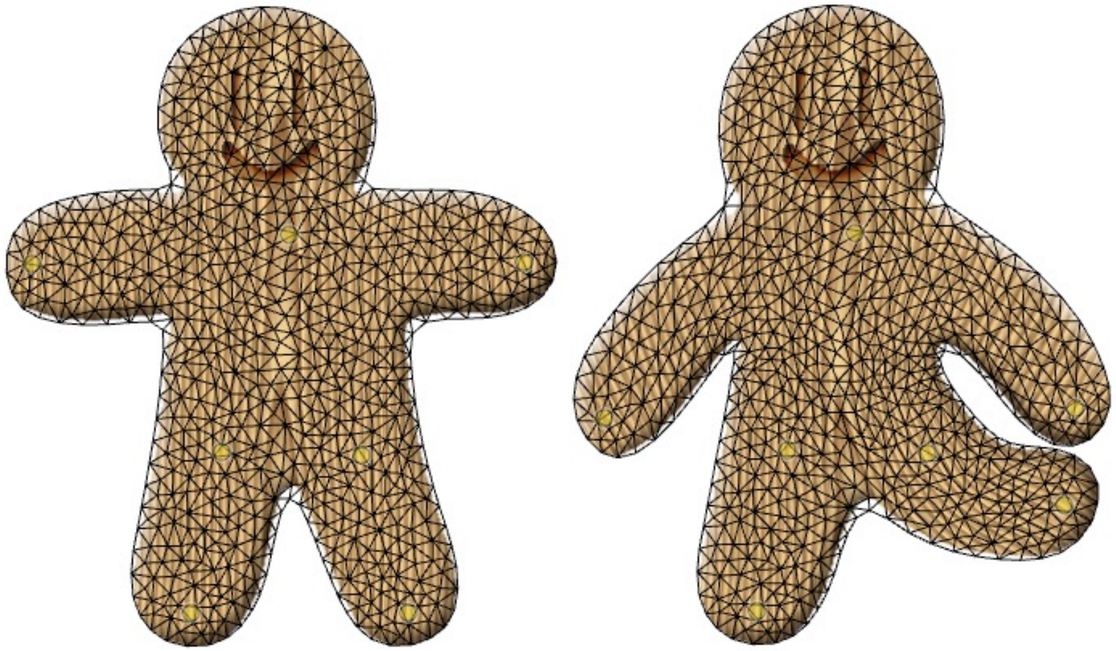


Bounded Biharmonic Weights

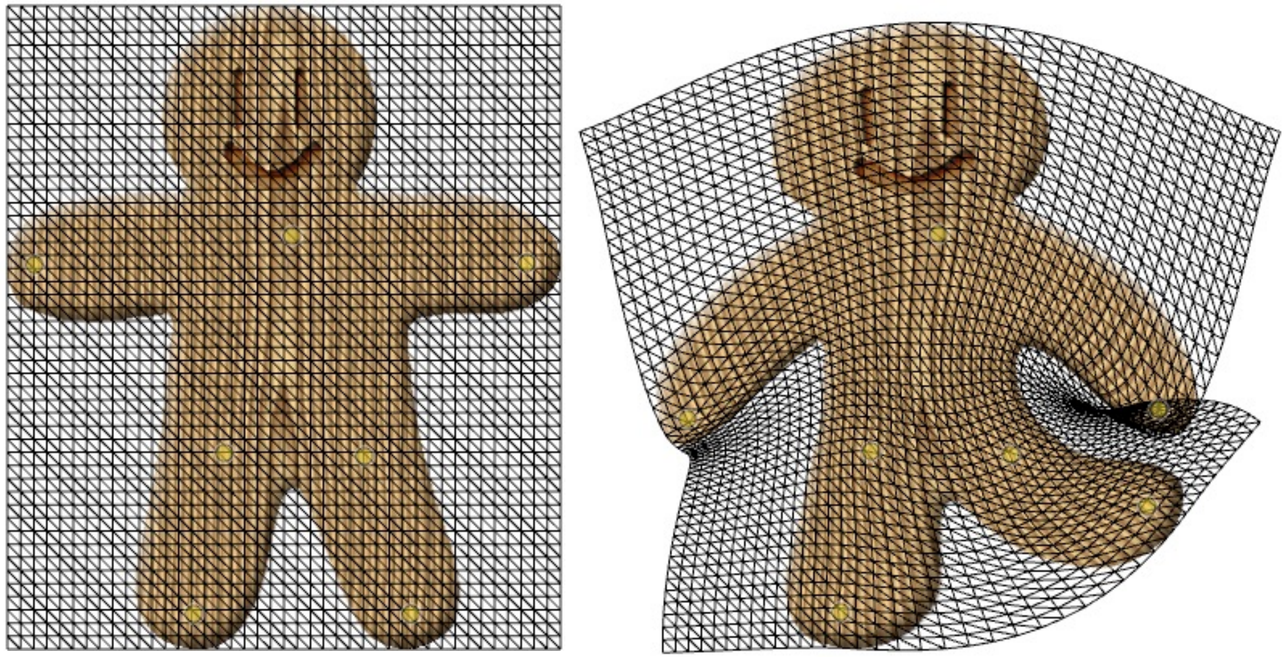


Extension of Harmonic Coordinates
[Joshi et al. 2005]

Shape-awareness ensures respect of domain's features



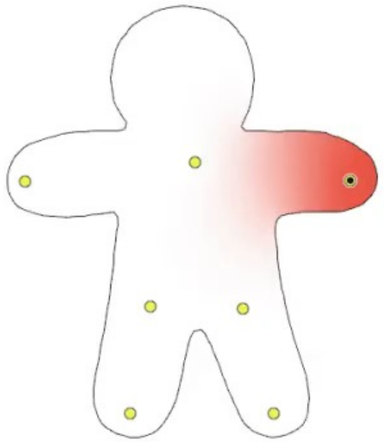
Bounded Biharmonic Weights



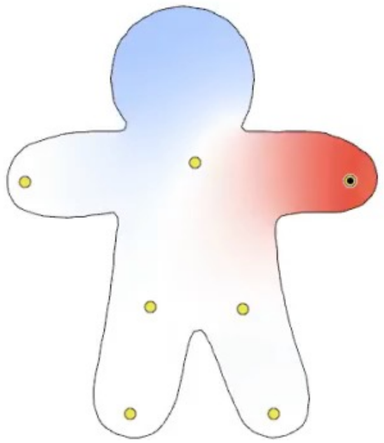
Non-shape-aware methods
e.g. [Schaefer et al. 2006]

Non-negative weights are necessary for intuitive response

Bounded Biharmonic Weights



Unconstrained biharmonic
[Botsch and Kobbelt 2004]



Weights must maintain other simple, but important properties

$$\sum_{j \in H} w_j(\mathbf{x}^0) = 1$$

Partition of unity

Handle vertices

$$w_j \Big|_{H_k} = \delta_{jk}$$

w_j is linear along cage faces

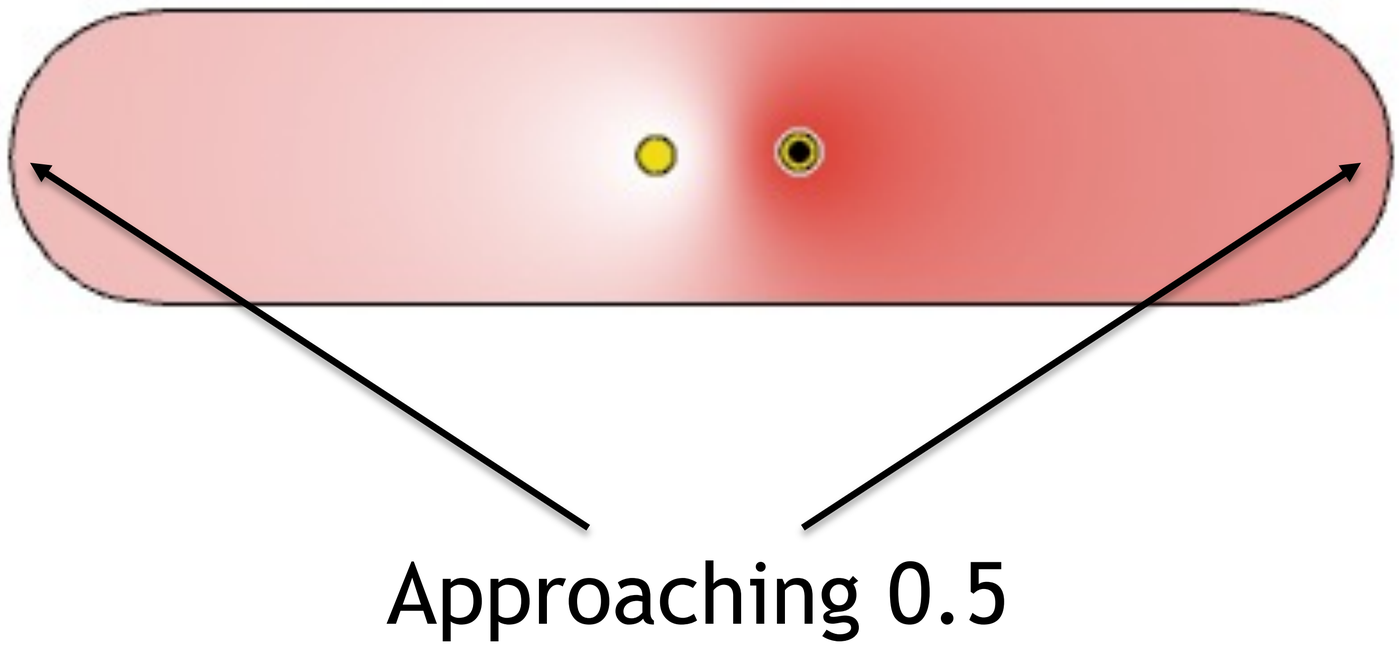
Interpolation of handles

How about $w_j(\mathbf{x}^0) = d(\mathbf{x}^0, H_j)^{-1}$?

Inverse distance methods inherently suffer from *fall-off effect*

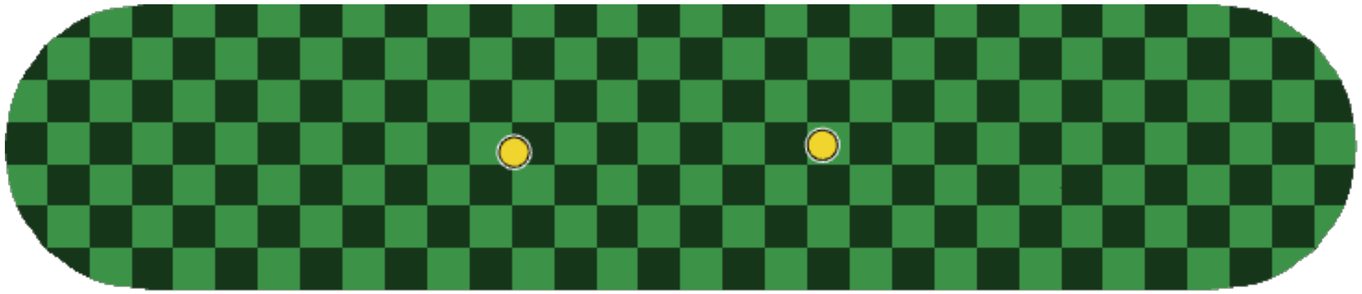
Inverse distance methods inherently suffer from ***fall-off effect***

Inverse distance methods inherently suffer from ***fall-off effect***

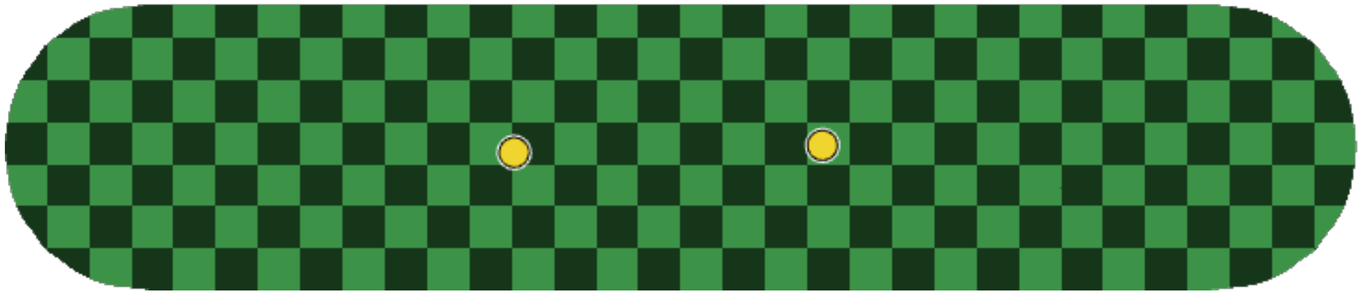


Inverse distance methods inherently suffer from *fall-off effect*

Inverse-distance weights



BBW



Bounded biharmonic weights enforce properties as constraints to minimization

$$\arg\min_{w_j} \frac{1}{2}\int_{\Omega} |\Delta w_j|^2 dV$$

$$w_j\Big|_{H_k} = \delta_{jk}$$

w_j is linear along cage faces

Bounded biharmonic weights enforce properties as constraints to minimization

$$\arg\min_{w_j} \frac{1}{2}\int_\Omega |\Delta w_j|^2 dV$$

$$w_j\Big|_{H_k} = \delta_{jk}$$

w_j is linear along cage faces

Constant inequality constraints

$$0 \leq w_j(\mathbf{x}^0) \leq 1$$

Partition of unity

$$\sum_{j \in H} w_j(\mathbf{x}^0) = 1$$

Bounded biharmonic weights enforce properties as constraints to minimization

$$\arg\min_{w_j} \frac{1}{2}\int_\Omega |\Delta w_j|^2 dV$$

$$w_j\Big|_{H_k} = \delta_{jk}$$

w_j is linear along cage faces

Constant inequality constraints

$$0 \leq w_j(\mathbf{x}^0) \leq 1$$

Solve independently and normalize

$$w_j(\mathbf{x}^0) = \frac{w_j(\mathbf{x}^0)}{\sum_{i\in H} w_i(\mathbf{x}^0)}$$

Weights optimized as precomputation at bind-time

$$\arg\min_{w_j} \frac{1}{2}\int_\Omega |\Delta w_j|^2 dV$$

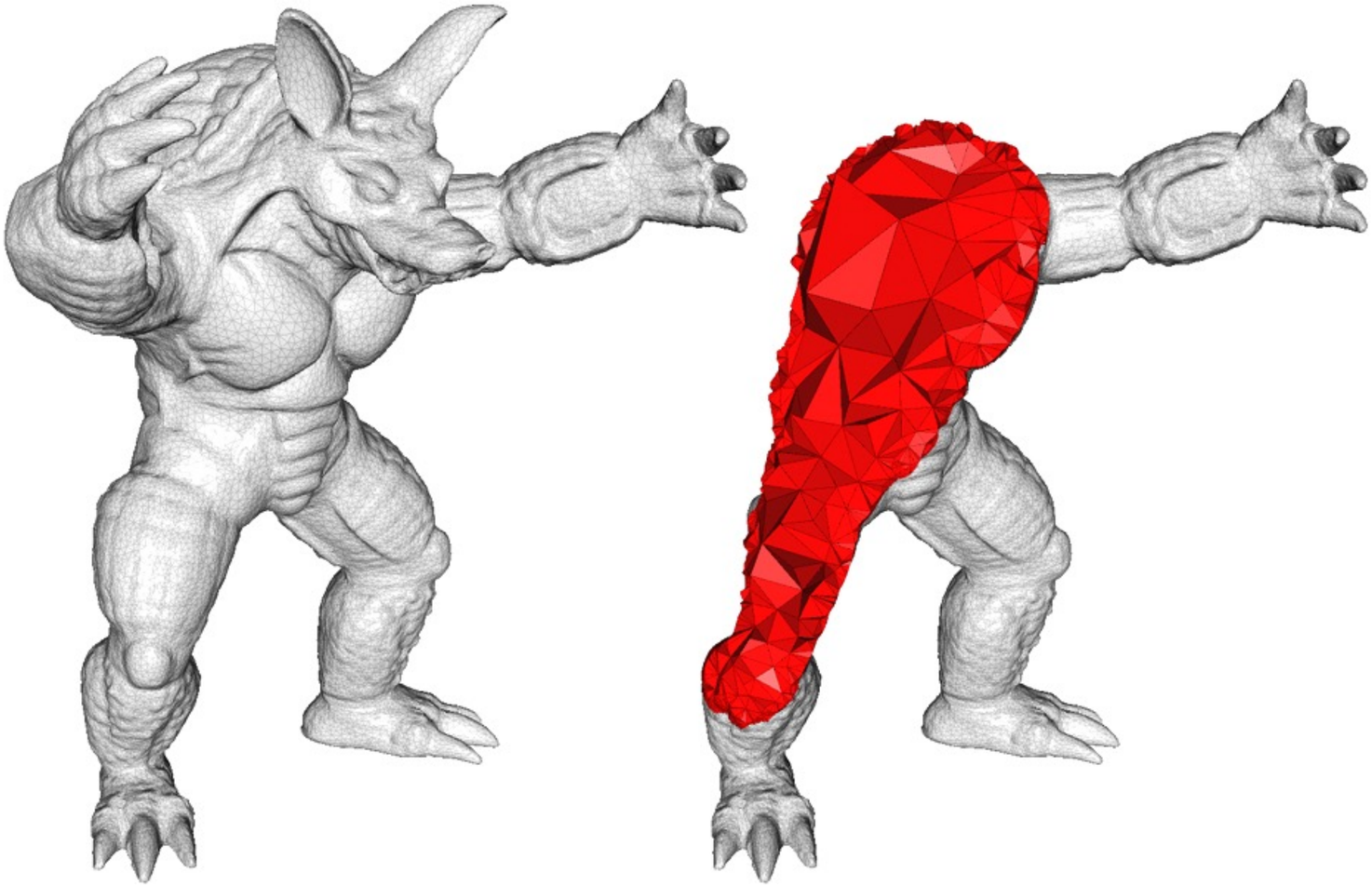
$$w_j\big|_{H_k} = \delta_{jk}$$

w_j is linear along cage faces

$$0 \le w_j(\mathbf{x}^0) \le 1$$

FEM discretization

2D → Triangle mesh
3D → Tet mesh



Weights optimized as precomputation at bind-time

$$\arg\min_{w_j} \frac{1}{2}\int_\Omega |\Delta w_j|^2 dV$$

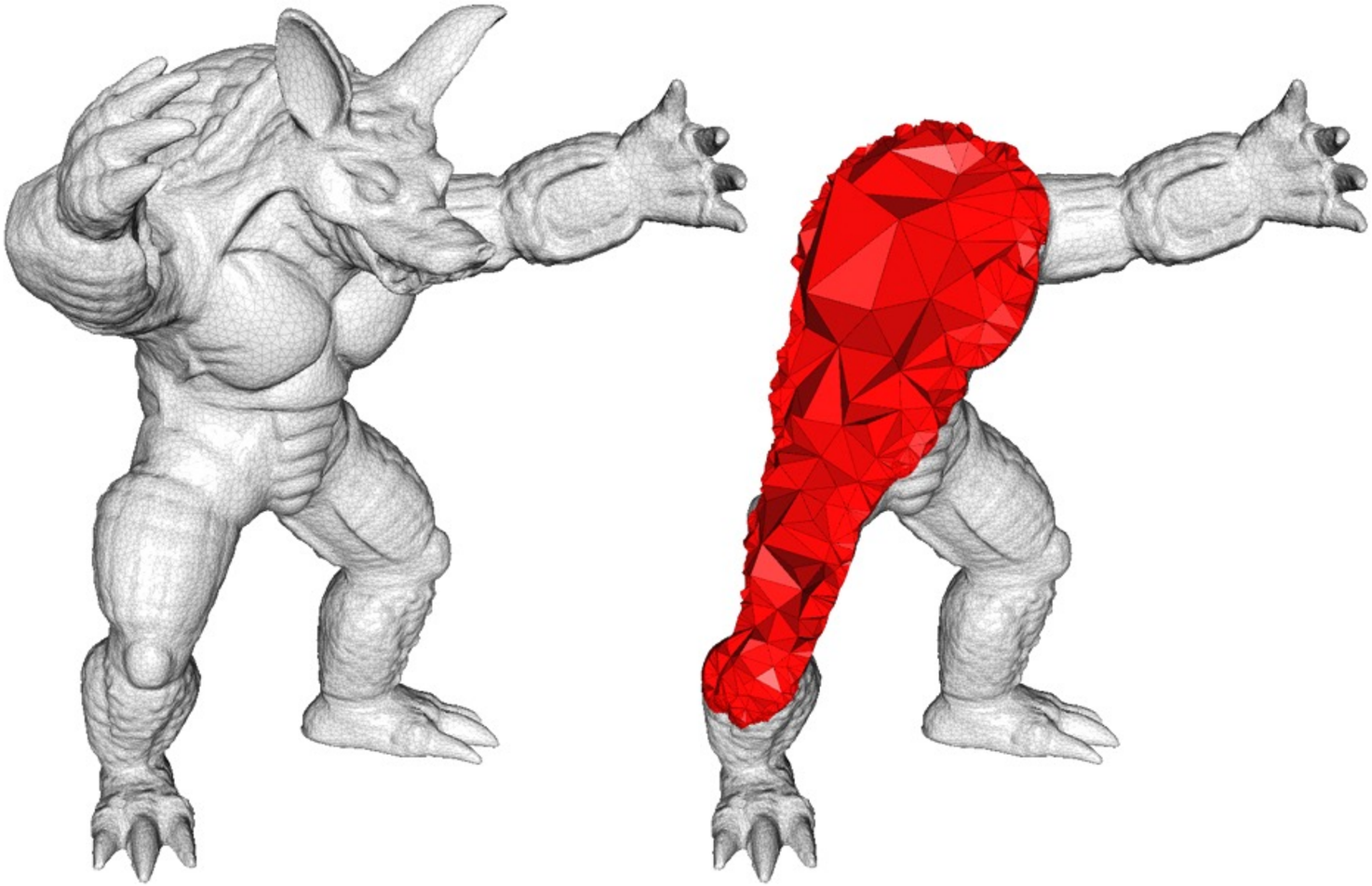
$$w_j\big|_{H_k} = \delta_{jk}$$

w_j is linear along cage faces

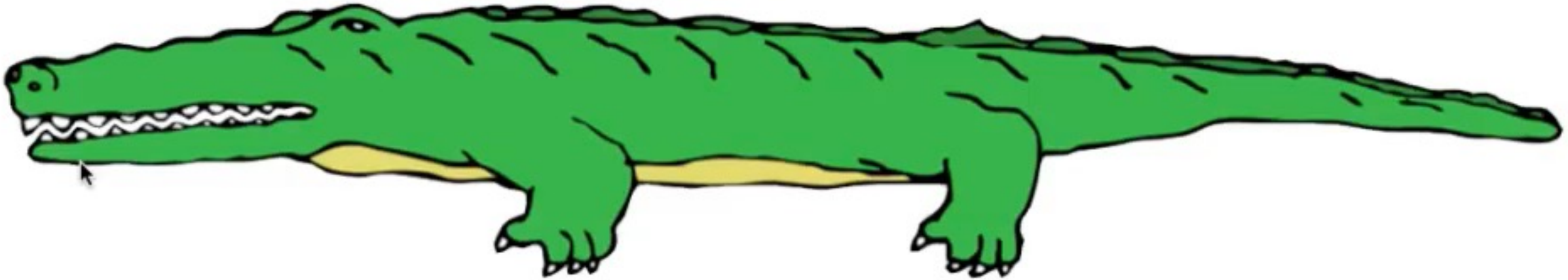
$$0 \le w_j(\mathbf{x}^0) \le 1$$

Sparse quadratic programming with constant inequality constraints

- 2D → less than second per handle
- 3D → tens of seconds per handle



Some examples of BBW in action



Some examples of BBW in action

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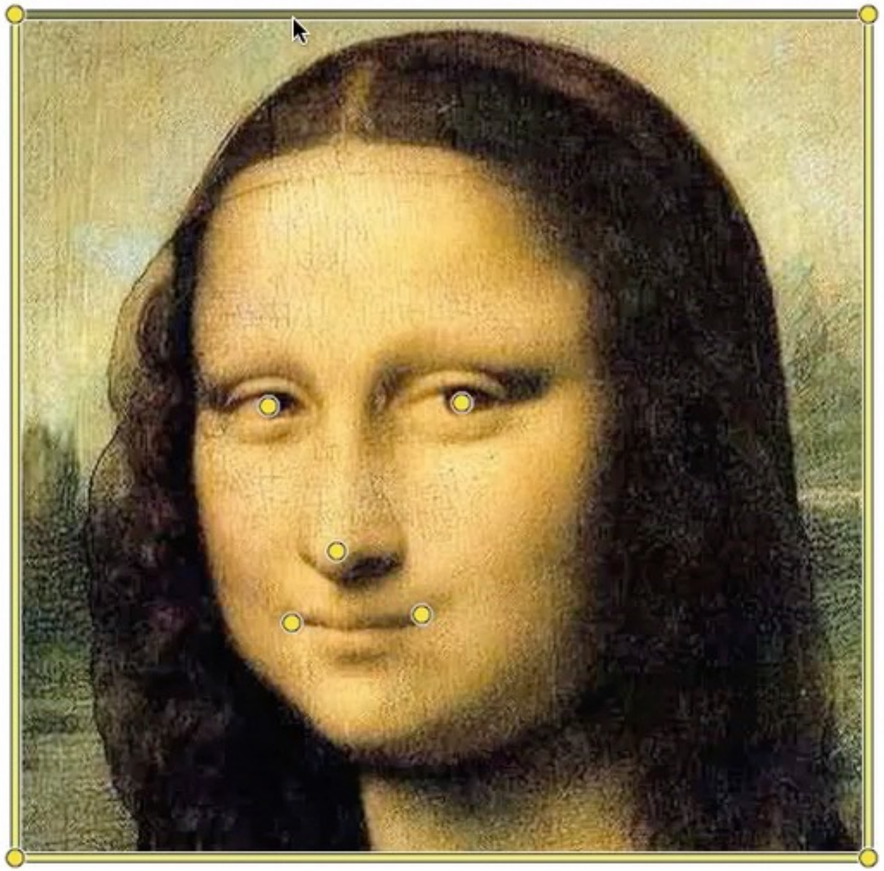
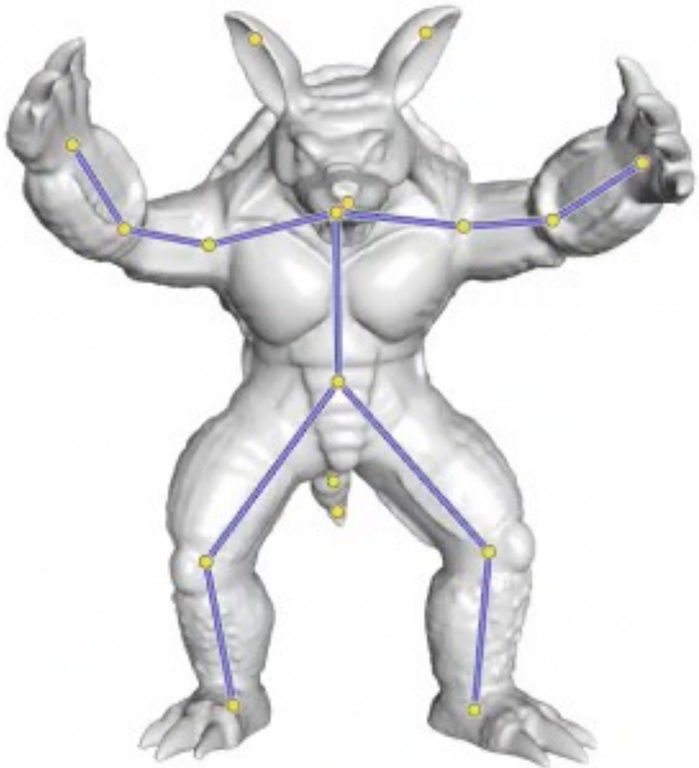


3D Characters



Demo

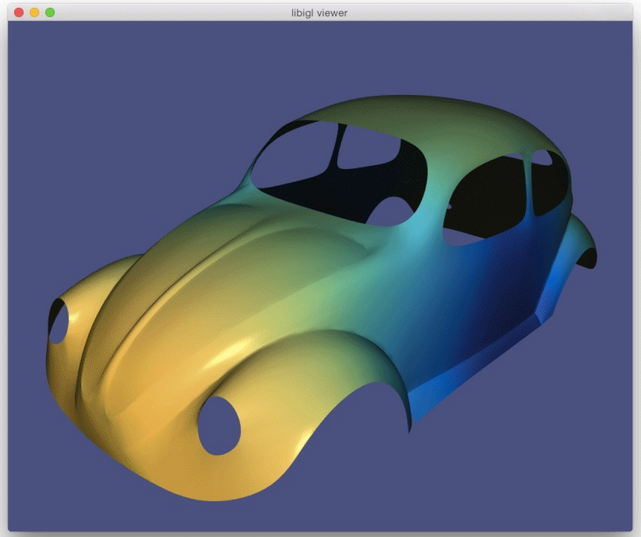
- Libigl demo 403

08 - Summary

Acknowledgements: Daniele Panozzo

Geometric Modeling and Processing

- The shape of an object is an important characteristic (not the only one…)

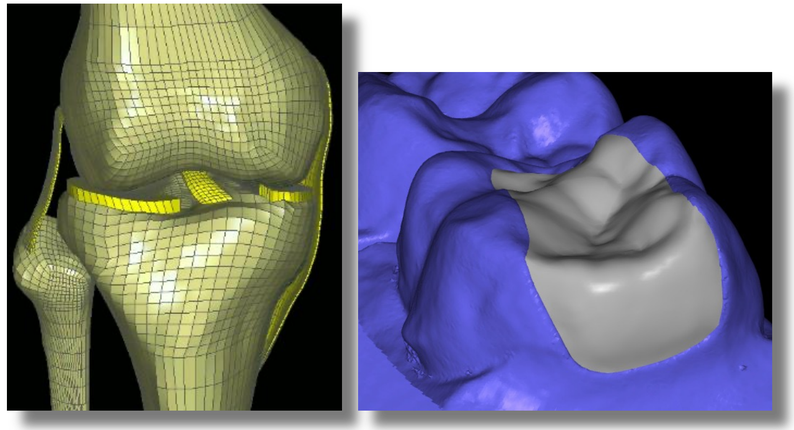


- Geometry processing: computerized modeling of 2D/3D geometry

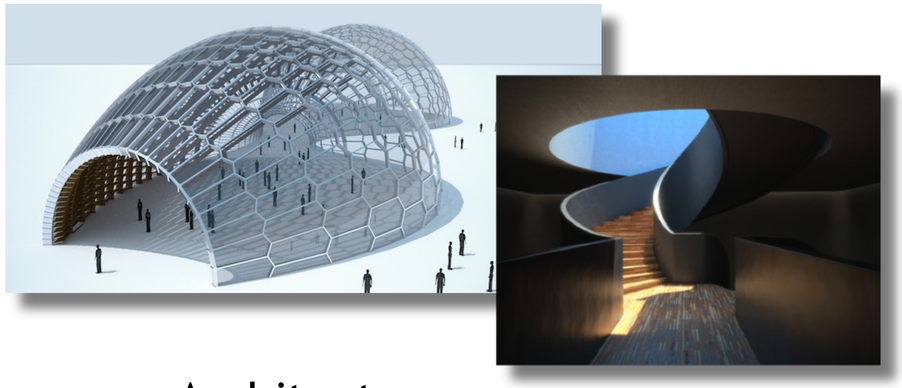
Copyright: Blender

Applications

Product design and prototyping



Medicine, prosthetics



Architecture

Cultural heritage

C++

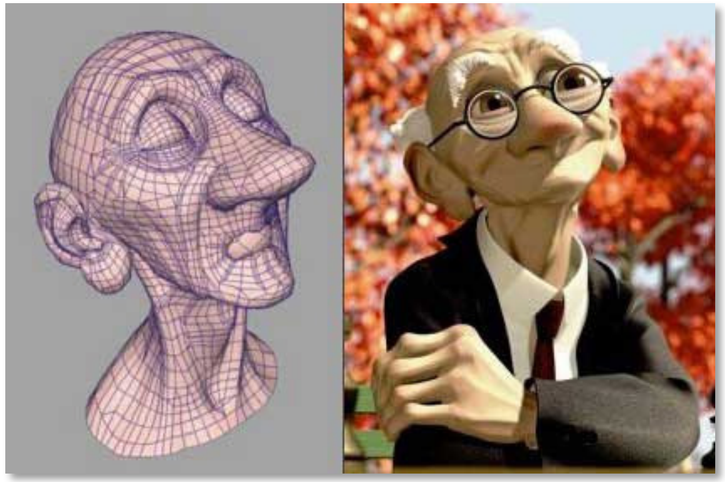
- It is flexible, and many of the features are optional:
  - it can be used as an extension of C, with no objects
  - it can be used as a fully object oriented language
  - it has many advanced features such as “templates” that are useful to write efficient code that *is also readable*

CMAKE

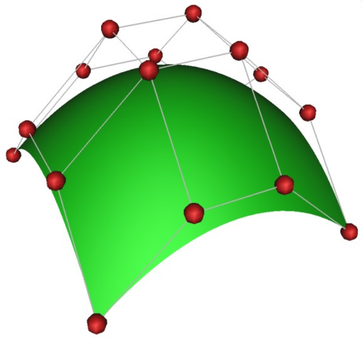
- If your project is in a folder Assignment_1, you need to:
  - mkdir build; cd build
  - cmake ../
- This will create the project. To compile it:
  - make (macosx/linux)
  - Open the project with visual studio on windows
- As an alternative, you can use Clion/Xcode/VS code that does all of this for you!

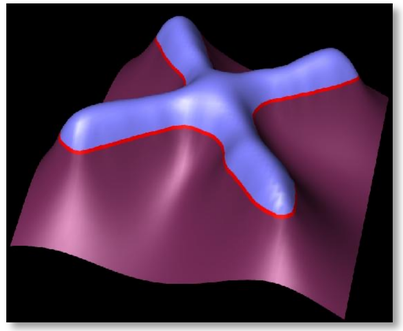
Course Topics

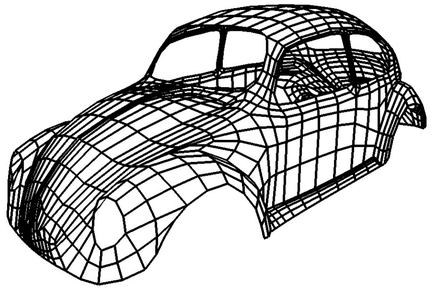
- Overview of shape representations
  - Parametric curves/surfaces
  - Implicits
  - Polygonal meshes



Pixar

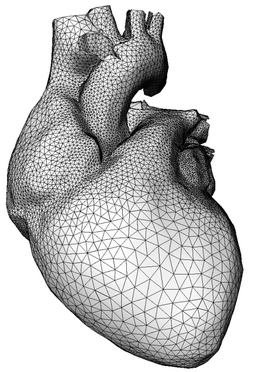


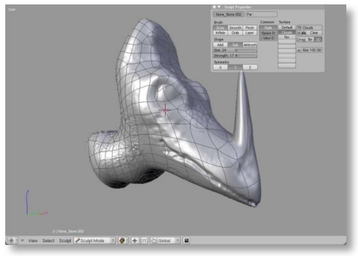


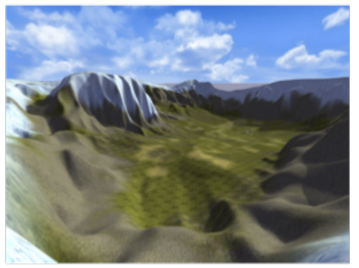


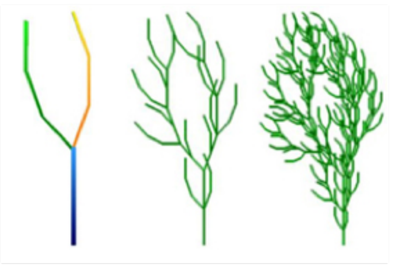
Shape Representation: Origin- and Application-Dependent

- Acquired real-world objects:
  - Discrete sampling
  - Points, meshes
- Modeling “by hand”:
  - Higher-level representations, amendable to modification, control
  - Parametric surfaces, subdivision surfaces, implicits
- Procedural modeling
  - Algorithms, grammars



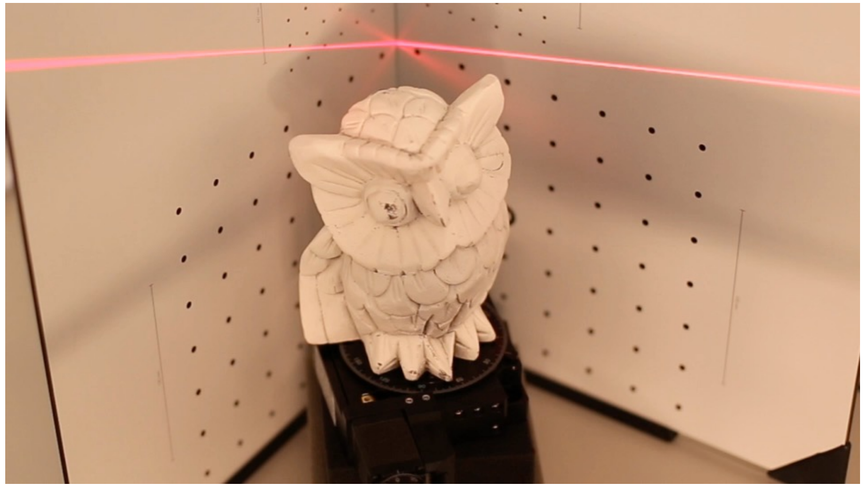


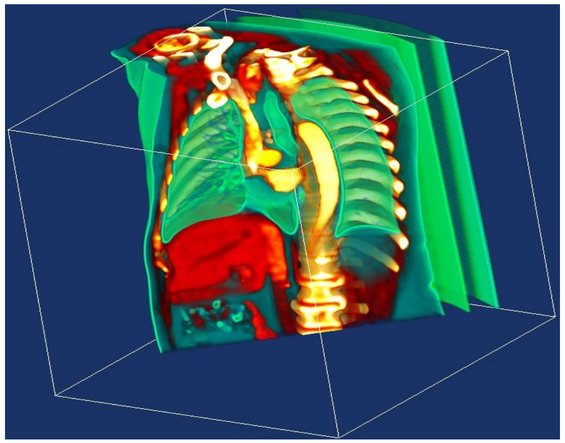


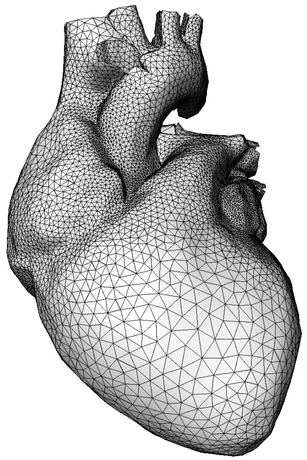


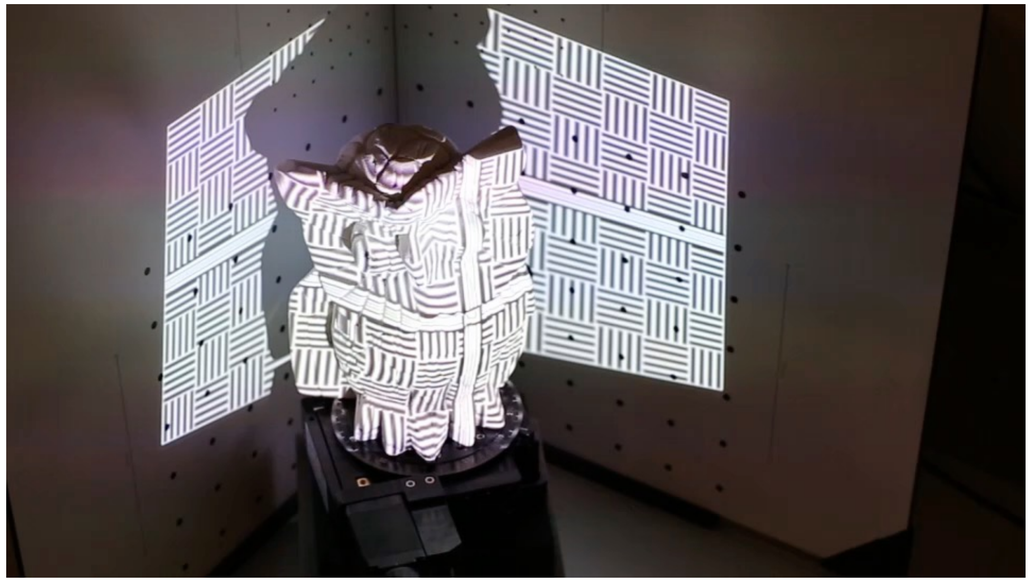
Course Topics

- Shape acquisition
  - Scanning/imaging
  - Reconstruction









Geometry Acquisition Pipeline

Scanning:
results in range images

Registration:
bring all range images to one coordinate system

Stitching/reconstruction:
Integration of scans into a single mesh

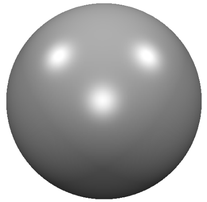
Postprocess:
- Topological and geometric filtering
- Remeshing
- Compression

Euler-Poincaré Formula

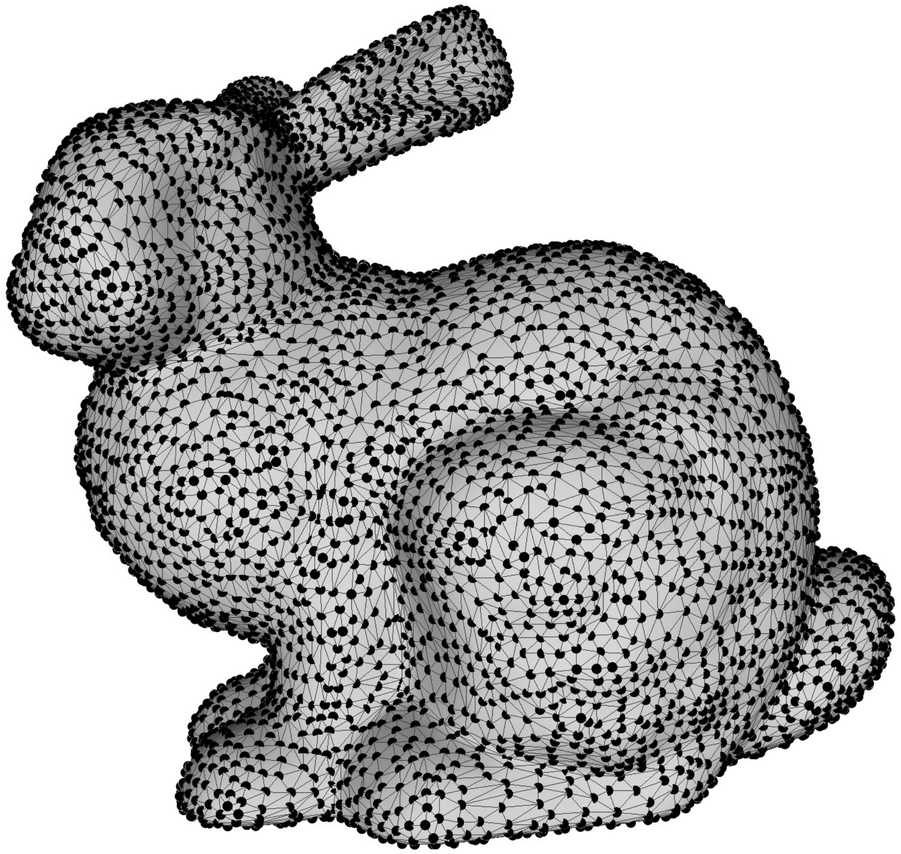
- For orientable meshes:

$$v - e + f = 2(c - g) - b = \chi(M)$$

  - c = number of connected components
  - g = genus
  - b = number of boundary loops

$\chi($  $) = 2$ $\chi($  $) = 0$

Problem Assumptions

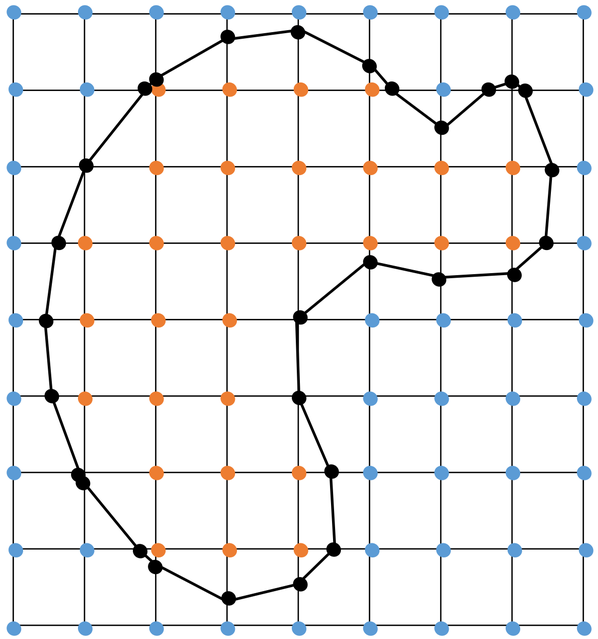


Interpolation

Approximation

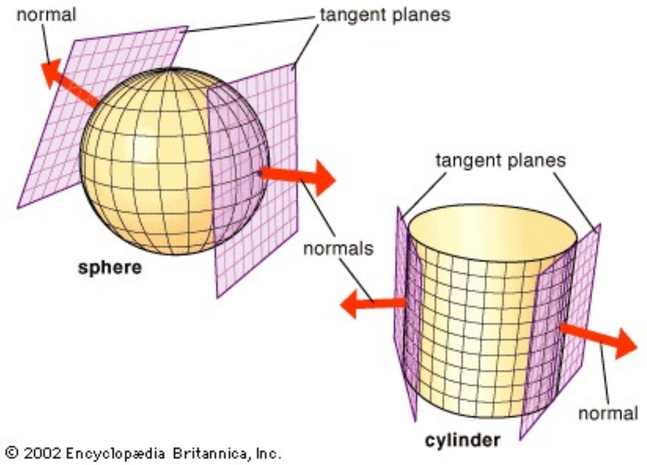
Implicit Reconstruction

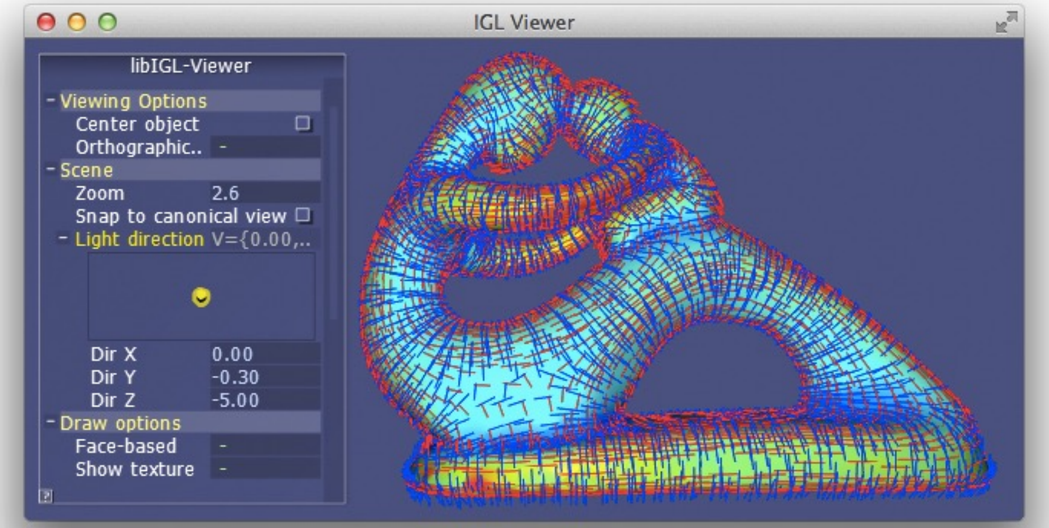
1. Estimate normal (Optional)
2. Compute function $F(x)$
3. Discretize function $F(x)$
4. Extract zero Iso-surface



Course Topics

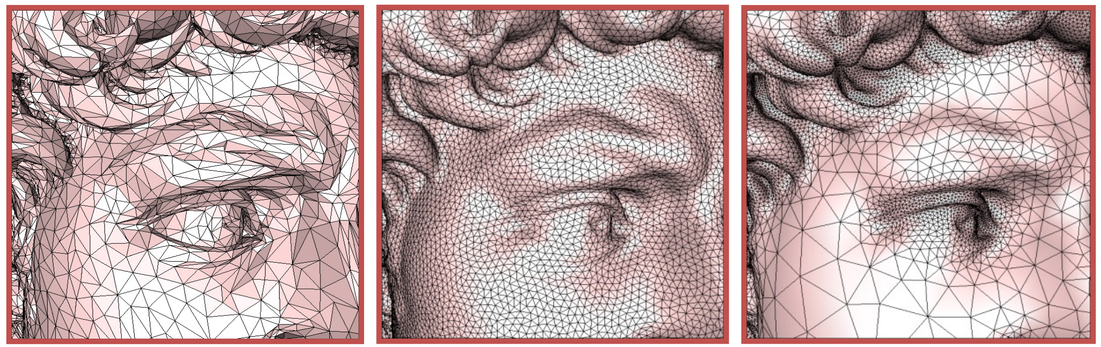
- Differential geometry
  - Continuous and (mostly) discrete
  - Powerful tool to analyze and model shapes

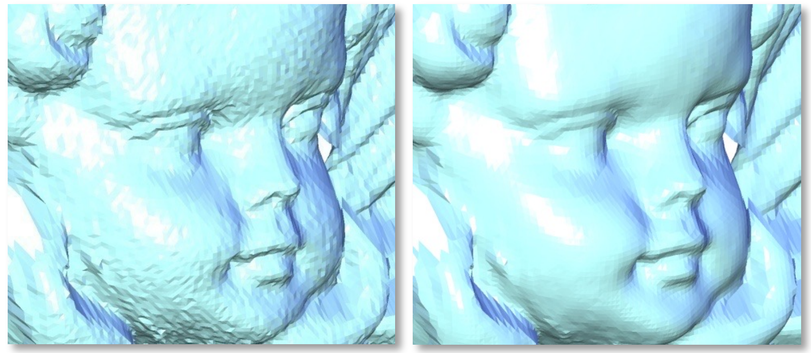




Course Topics

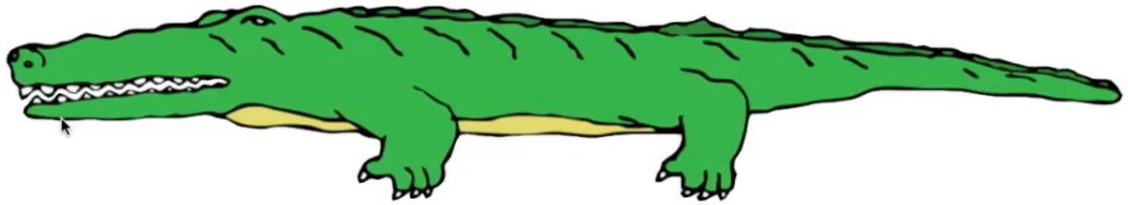
- Digital geometry processing
  - Denoising, smoothing, simplification, remeshing, parameterization, compression



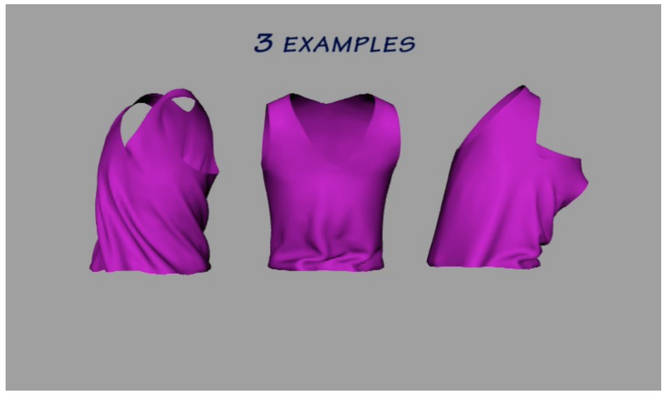


Course Topics

- Skinning, animation



http://youtu.be/P9fqm8vgdB8



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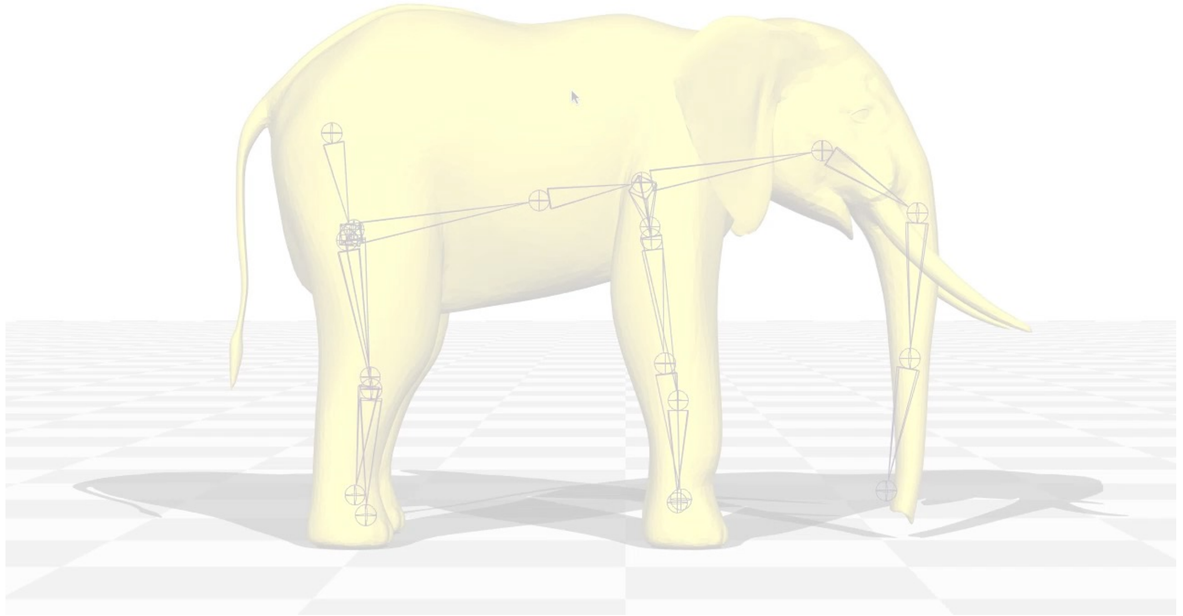

Thank you