

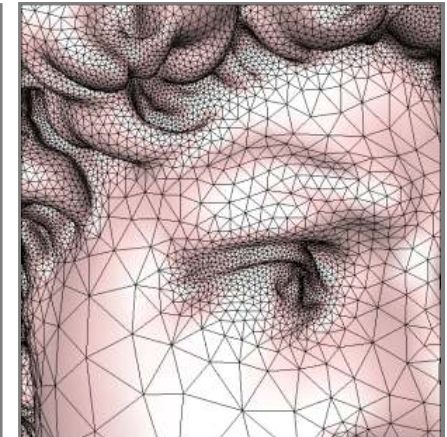
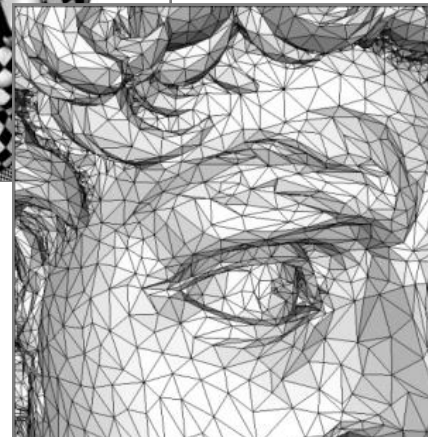
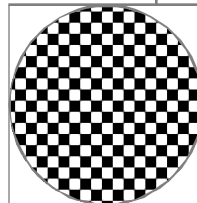
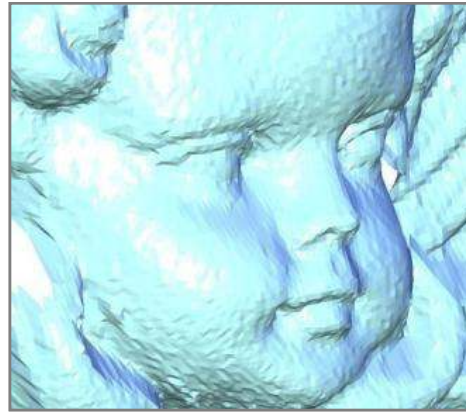
CS 523: Computer Graphics, Spring 2011

# Shape Modeling

Digital Geometry Processing

# Topics

- Smoothing
- Simplification
- Parameterization
- Remeshing



# Mesh Smoothing

Curve smoothing

Taubin smoothing

Implicit fairing

Laplacian mesh optimization

# Laplacian smoothing

2D Curve

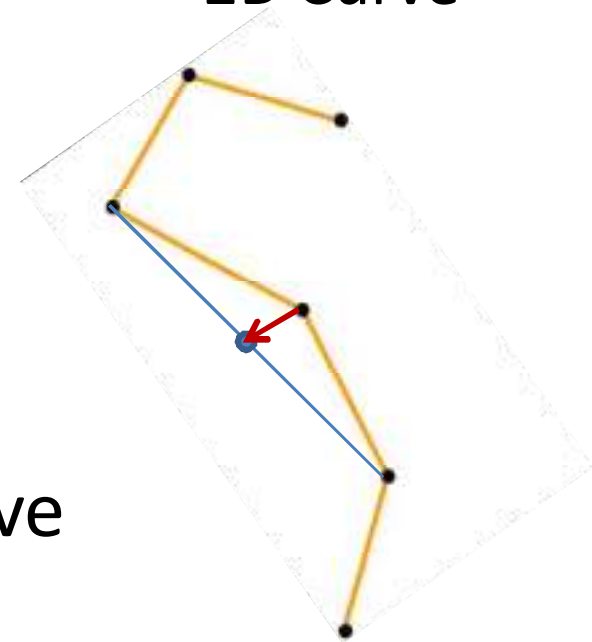
- Discrete Laplacian for a single vertex

$$\Delta \mathbf{x}_i = \frac{1}{2}(\mathbf{x}_{i-1} - \mathbf{x}_i) + \frac{1}{2}(\mathbf{x}_{i+1} - \mathbf{x}_i)$$

- In matrix-vector form for the whole curve

$$\Delta \mathbf{x} = -\mathbf{K} \mathbf{x}$$

$$\mathbf{K} = \frac{1}{2} \begin{pmatrix} 2 & -1 & & & -1 \\ -1 & 2 & -1 & & \\ & \ddots & \ddots & \ddots & \\ & & -1 & 2 & -1 \\ -1 & & & -1 & 2 \end{pmatrix}$$



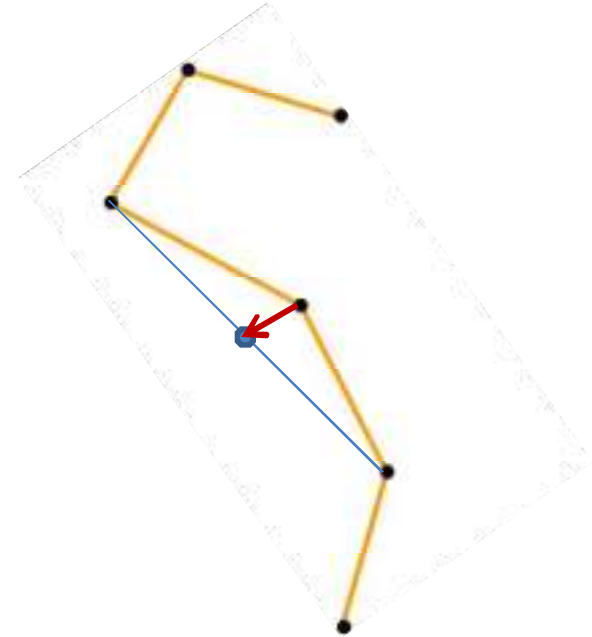


# Smoothing

- Gaussian filtering

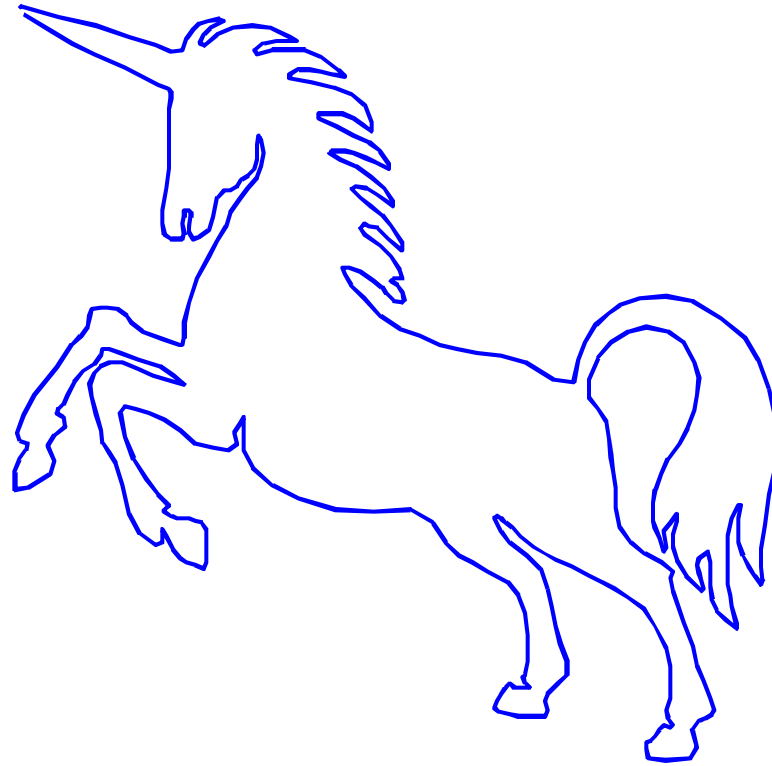
$$\mathbf{x}'_i = \mathbf{x}_i + \lambda \Delta \mathbf{x}_i$$

- Scale factor  $0 < \lambda < 1$
- Matrix-vector form  $\mathbf{x}' = \mathbf{x} - \lambda \mathbf{K}\mathbf{x}$
- Works identical for surface smoothing
  - Choose (normalized) Laplacian weights
- Drawbacks
  - Causes the curve/mesh to shrink



# Laplacian smoothing

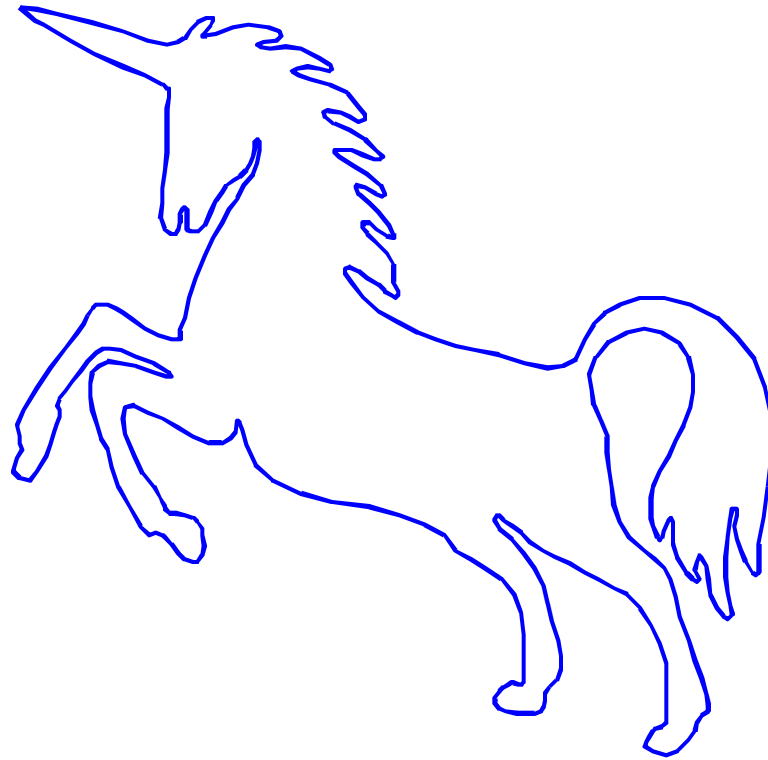
2D Curve – Example



Original curve

# Laplacian smoothing

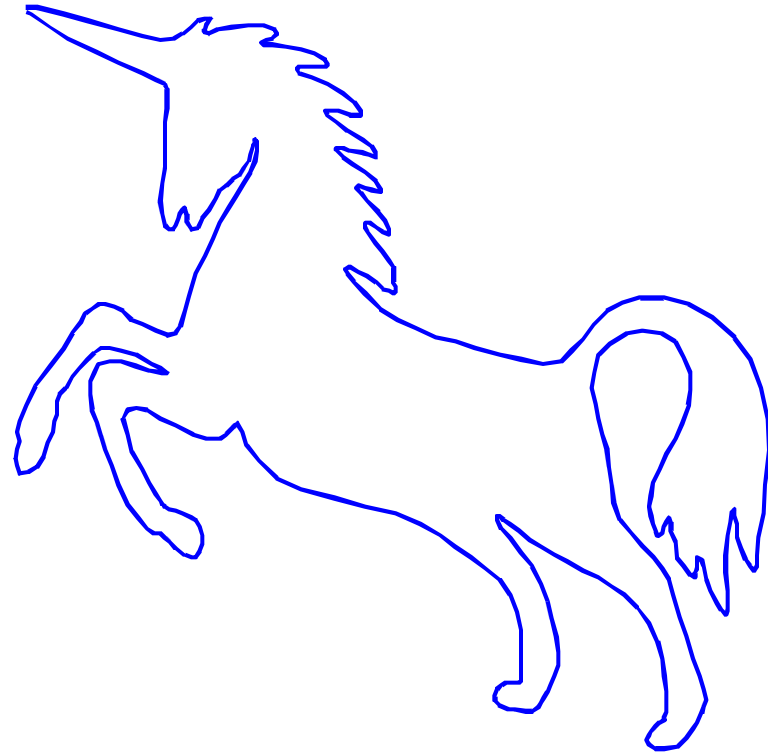
2D Curve – Example



1st iteration;  $\lambda=0.5$

# Laplacian smoothing

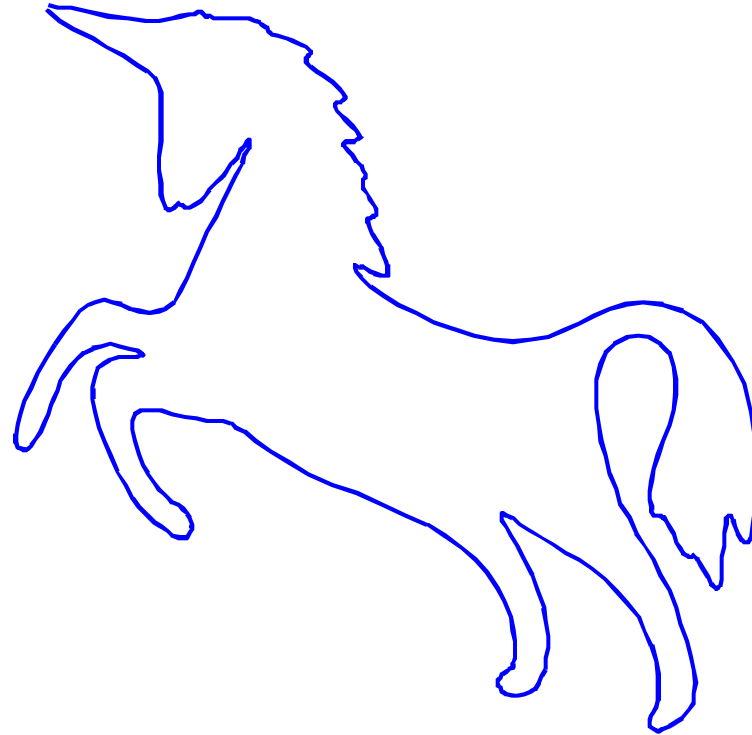
2D Curve – Example



2nd iteration;  $\lambda=0.5$

# Laplacian smoothing

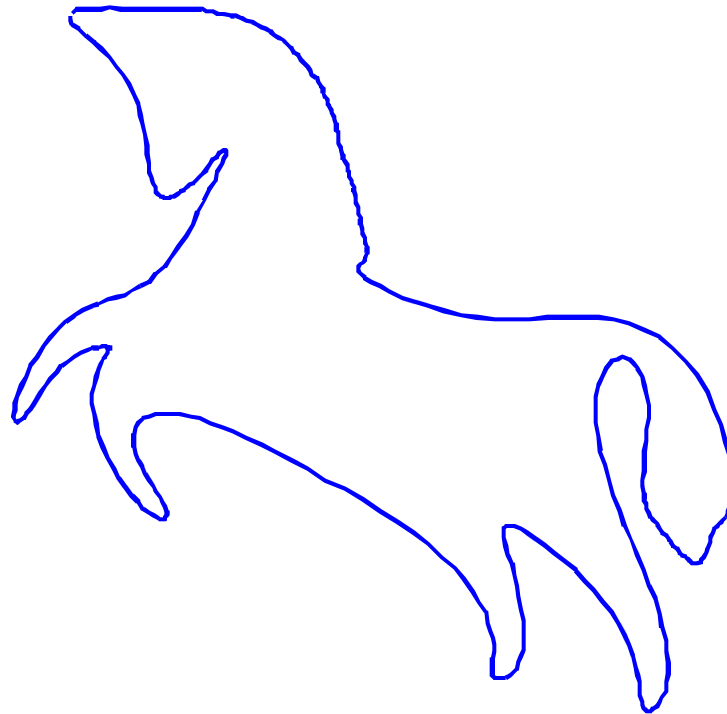
2D Curve – Example



8th iteration;  $\lambda=0.5$

# Laplacian smoothing

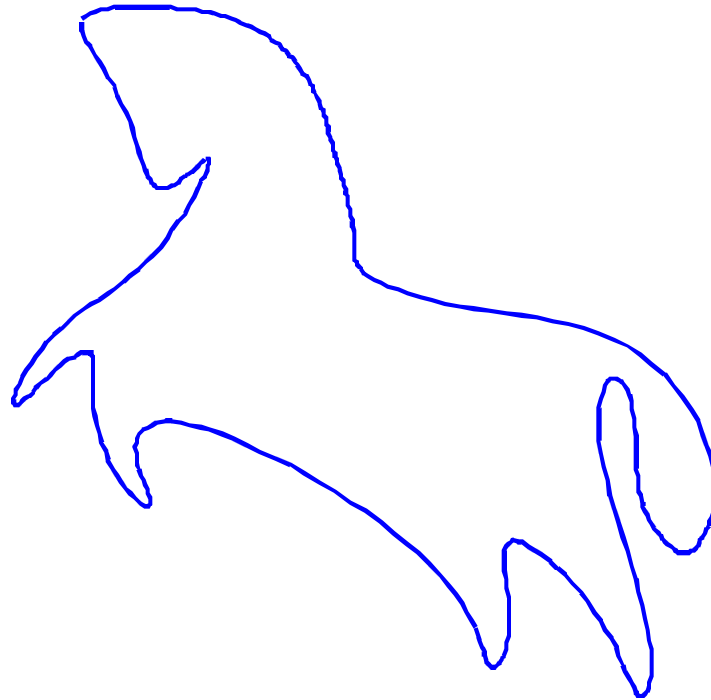
2D Curve – Example



27th iteration;  $\lambda=0.5$

# Laplacian smoothing

2D Curve – Example

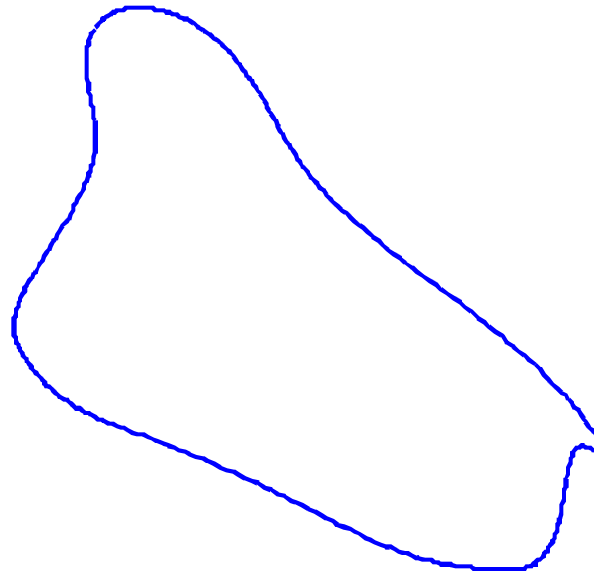


50th iteration;  $\lambda=0.5$



# Laplacian smoothing

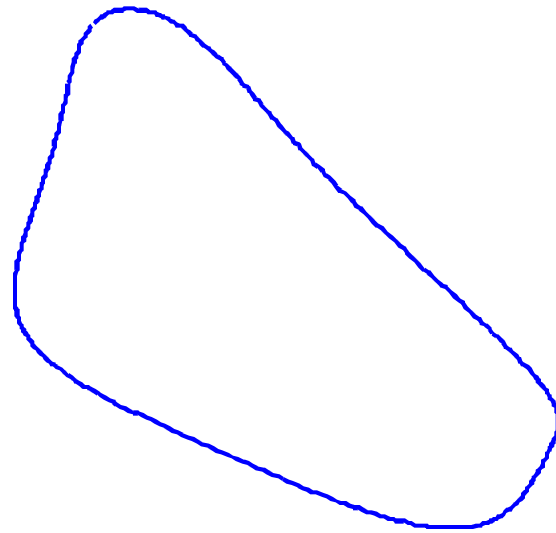
2D Curve – Example



500th iteration;  $\lambda=0.5$

# Laplacian smoothing

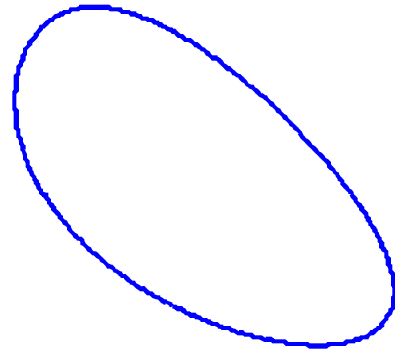
2D Curve – Example



1000th iteration;  $\lambda=0.5$

# Laplacian smoothing

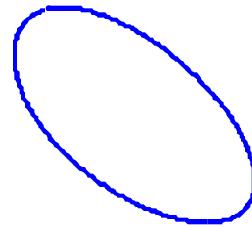
2D Curve – Example



5000th iteration;  $\lambda=0.5$

# Laplacian smoothing

2D Curve – Example



10000th iteration;  $\lambda=0.5$

# Laplacian smoothing

2D Curve – Example



50000th iteration;  $\lambda=0.5$

# Surface smoothing

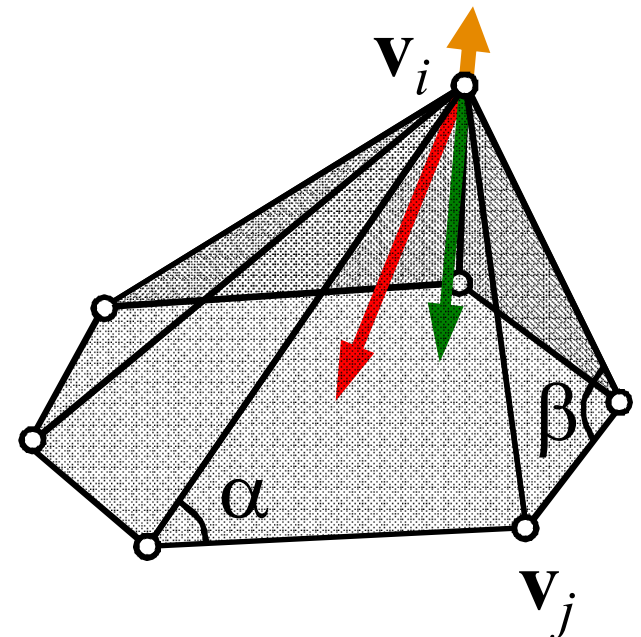
- Normalized Laplacian weights  $\sum_{\{i,j\} \in E} w_{ij} = 1$

$$\delta_i = \sum_{\{i,j\} \in E} w_{ij} (\mathbf{v}_j - \mathbf{v}_i) = \left[ \sum_{\{i,j\} \in E} w_{ij} \mathbf{v}_j \right] - \mathbf{v}_i$$

$$w_{ij} = \frac{\omega_{ij}}{\sum_{\{i,k\} \in E} \omega_{ik}}$$

$$\underline{\omega_{ij}} = 1,$$

$$\underline{\omega_{ij}} = \cot \alpha + \cot \beta$$



# Surface smoothing

- Matrix-vector notation for  $L(\mathbf{x}) = \mathbf{L}\mathbf{x}$

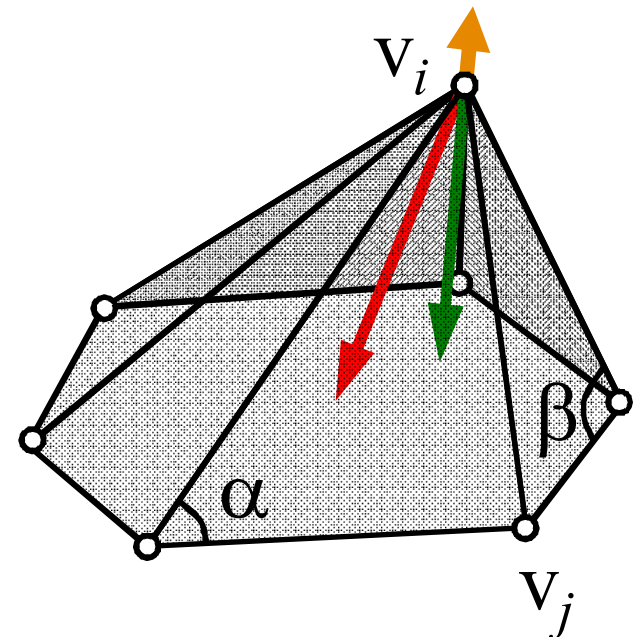
$$\mathbf{L}_{ij} = \begin{cases} -1 & i = j \\ w_{ij} & (i, j) \in \mathbf{E} \\ 0 & \text{otherwise} \end{cases}$$

$$w_{ij} = \frac{\omega_{ij}}{\sum_{\{i,k\} \in \mathbf{E}} \omega_{ik}}$$

$$\omega_{ij} = 1,$$

$$\omega_{ij} = \cot \alpha + \cot \beta$$

$\mathbf{L}$  is the  $n \times n$   
Laplacian Matrix





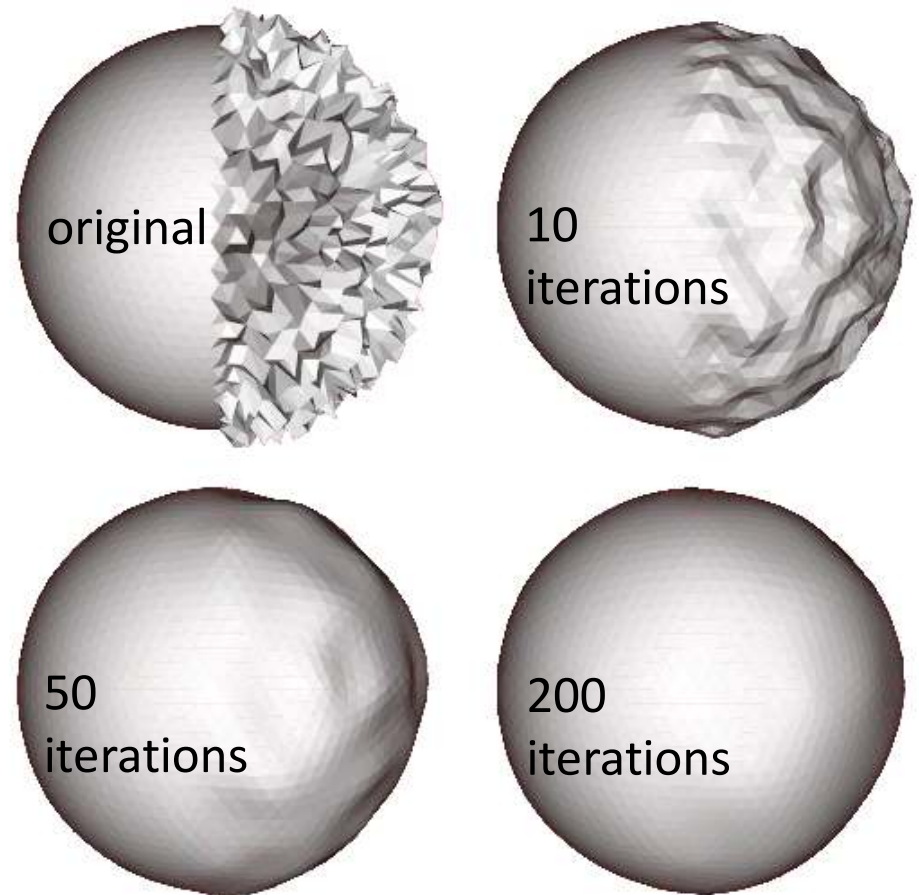
# Taubin smoothing

- Idea: perform *inflation* after shrinking step
- Pick a  $\mu < -\lambda$
- Iterate the following two steps

$$\mathbf{x}'_i = \mathbf{x}_i + \lambda \Delta \mathbf{x}_i$$

$$\mathbf{x}'_i = \mathbf{x}_i + \mu \Delta \mathbf{x}_i$$

- Simple to implement
- Requires many iterations
- Need to tweak  $\mu$  and  $\lambda$



# Implicit fairing

- Model smoothing as a diffusion process

$$\frac{\partial X}{\partial t} = \lambda L(X)$$

- Scale  $\lambda$  by simulation parameter time  $t$

$$X^{n+1} = (I + \lambda dt L) X^n$$

- Backward Euler for unconditional stability

$$X^{n+1} = X^n + \lambda dt L(X^{n+1})$$
$$(I - \lambda dt L) X^{n+1} = X^n$$

# Implicit fairing

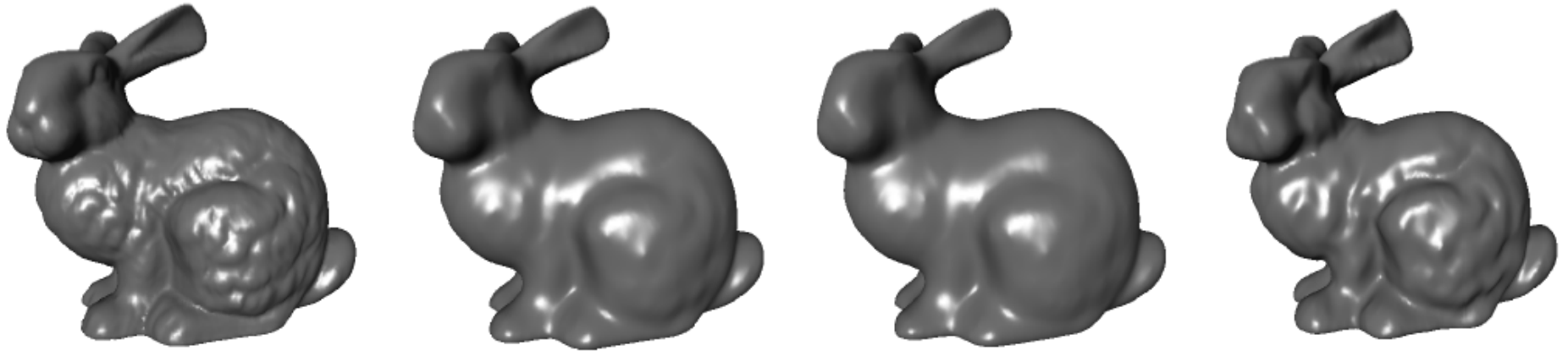
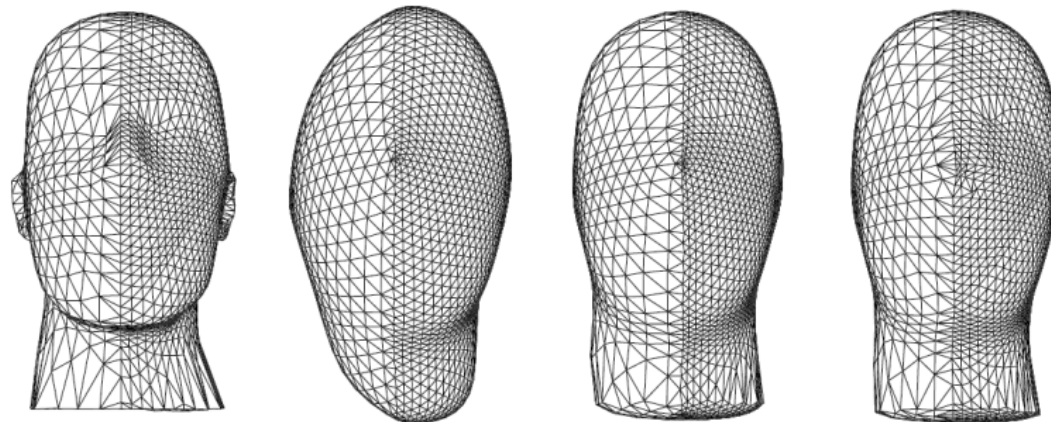
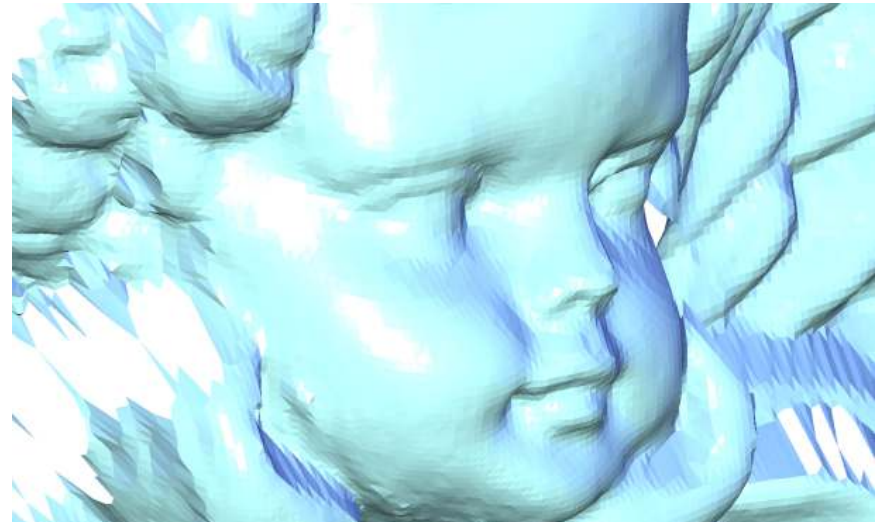
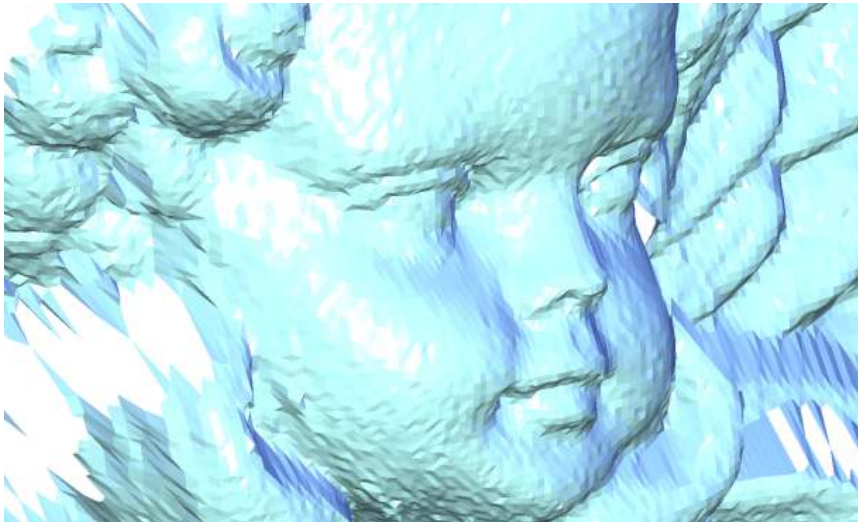


Figure 4: Stanford bunnies: (a) The original mesh, (b) 10 explicit integrations with  $\lambda dt = 1$ , (c) 1 implicit integration with  $\lambda dt = 10$  that takes only 7 PBCG iterations (30% faster), and (d) 20 passes of the  $\lambda|\mu$  algorithm, with  $\lambda = 0.6307$  and  $\mu = -0.6732$ . The implicit integration results in better smoothing than the explicit one for the same, or often less, computing time. If volume preservation is called for, our technique then requires many fewer iterations to smooth the mesh than the  $\lambda|\mu$  algorithm.

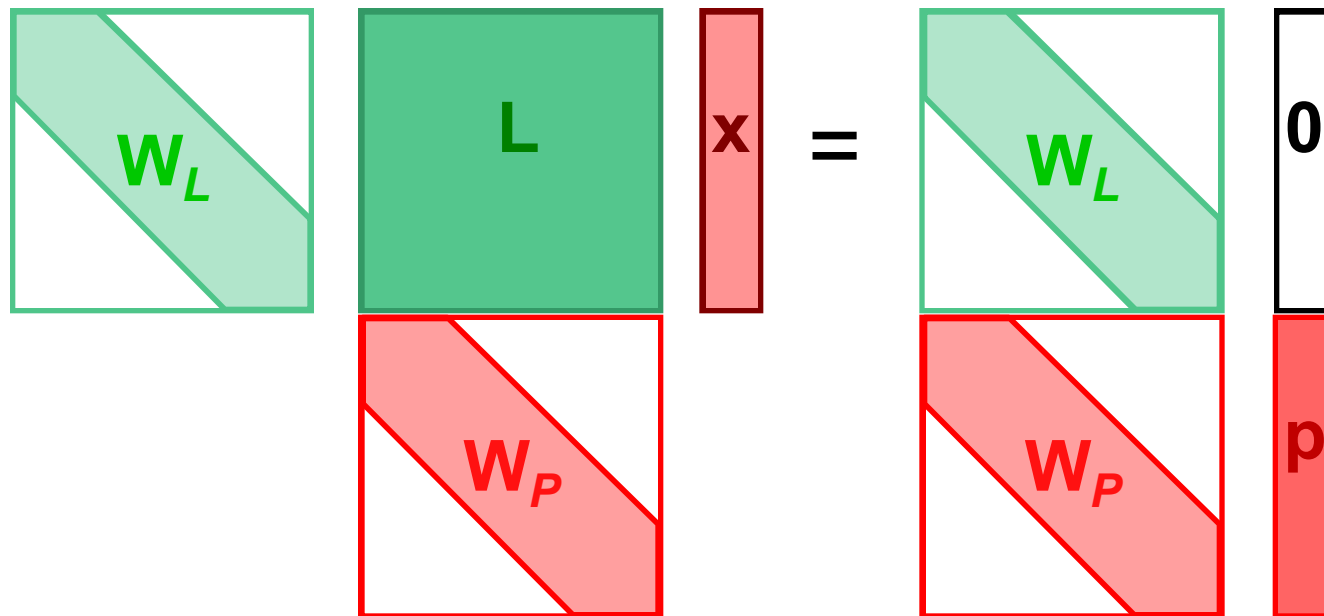
- Use cotangent instead of uniform Laplacian



# Laplacian mesh optimization



# Laplacian mesh optimization



- **Mesh smoothing**  $L = L_{cot}$  (outer fairness) or  $L = L_{uni}$  (outer and inner fairness)
- Controlled by  $W_p$  and  $W_L$  (Intensity, Features)
- Least squares solve using normal equations
 
$$A^T A \mathbf{x} = A^T \mathbf{b}$$

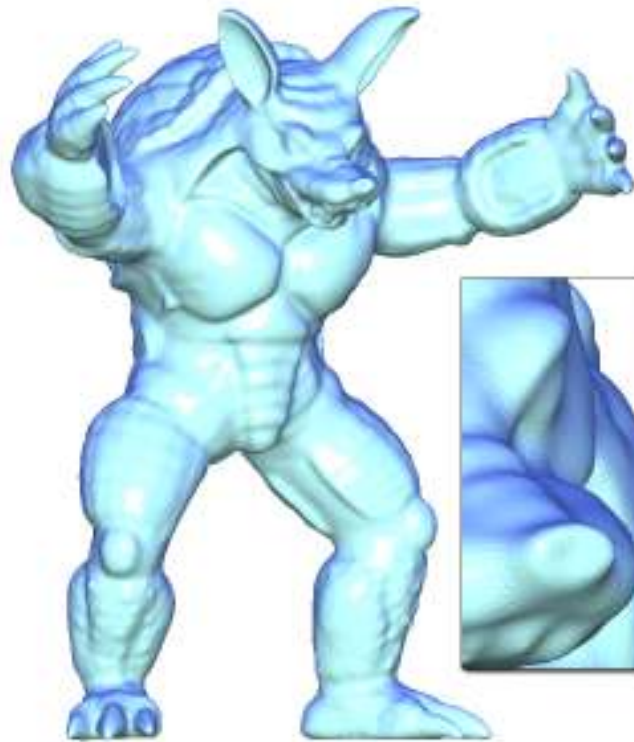
$$\mathbf{x} = (A^T A)^{-1} A^T \mathbf{b}$$

$$\begin{bmatrix} W_L & \\ & L \end{bmatrix} x = \begin{bmatrix} W_L & \\ & W_P \end{bmatrix} \begin{bmatrix} 0 \\ p \end{bmatrix}$$

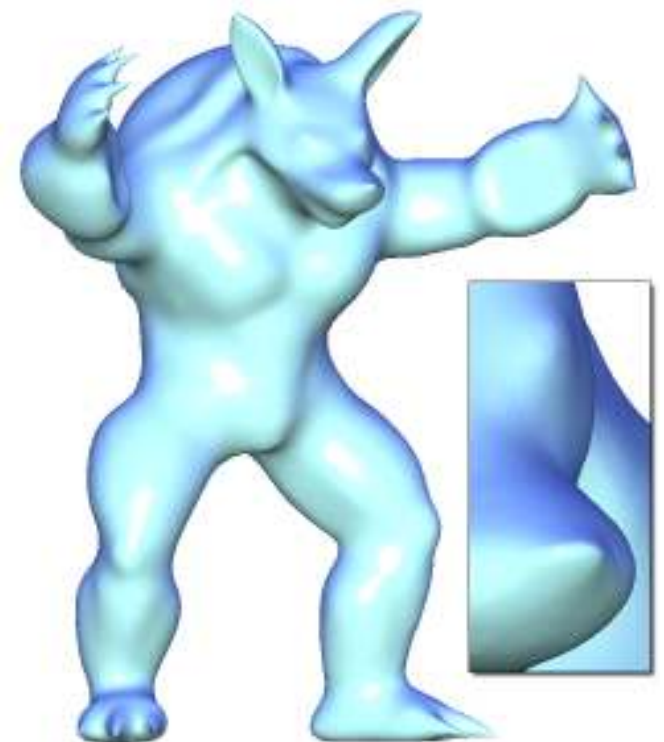
Using  $W_P$



(a) original (173k)



(c) cdf weights (s = 0.2)

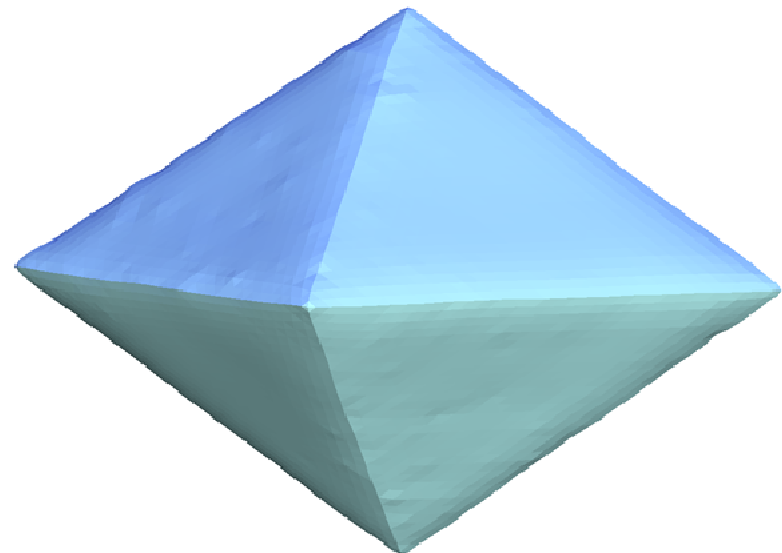
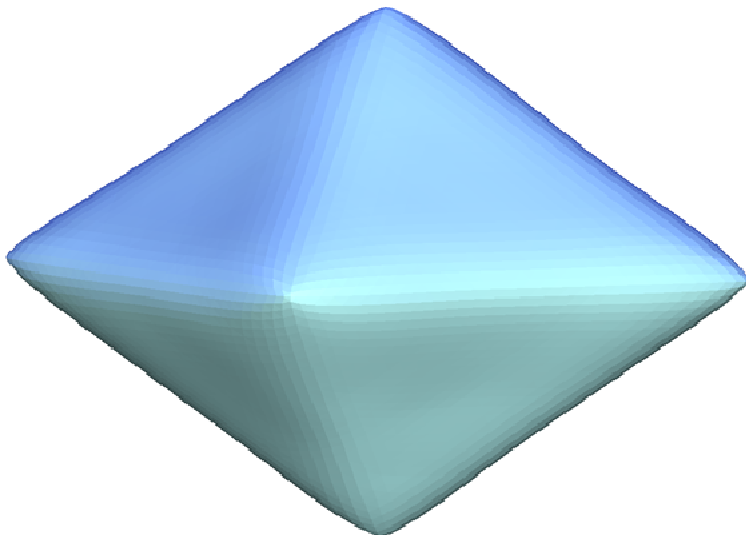
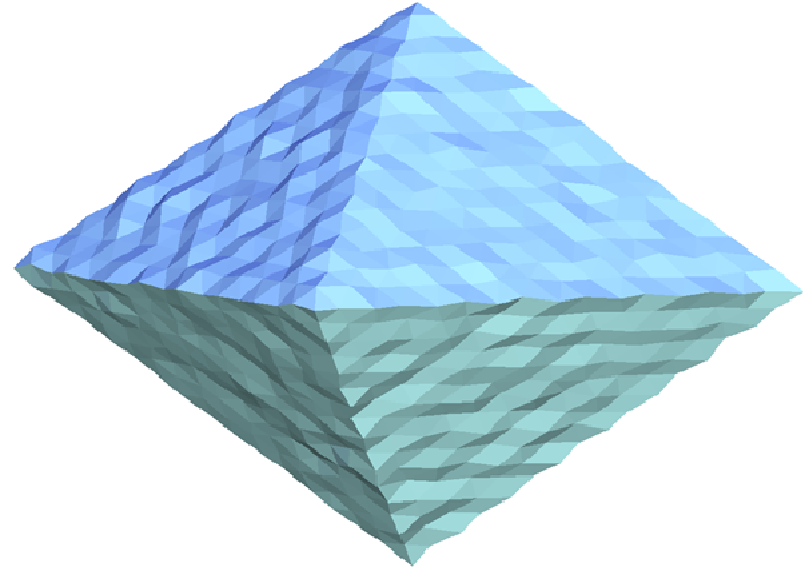
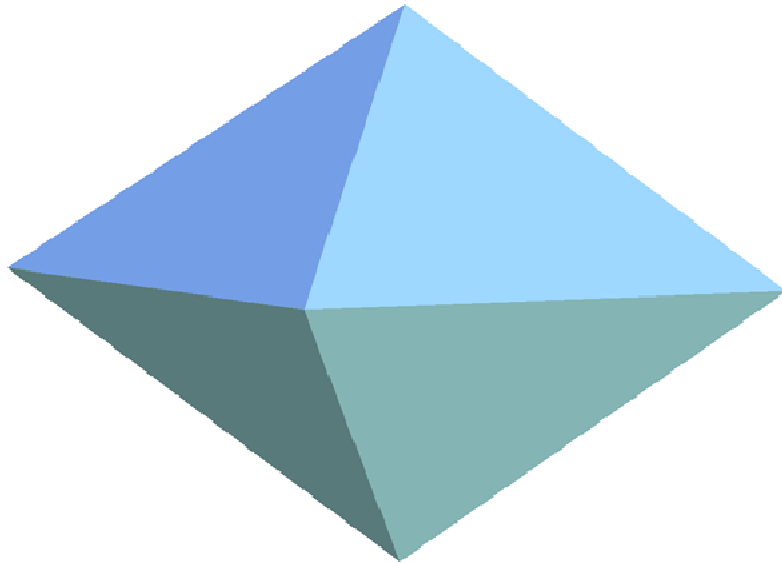


(f) cdf weights (s = 0.02)



$$\begin{bmatrix} W_L & 0 \\ 0 & W_P \end{bmatrix} \begin{bmatrix} L \\ x \end{bmatrix} = \begin{bmatrix} W_L & 0 \\ 0 & W_P \end{bmatrix} \begin{bmatrix} 0 \\ p \end{bmatrix}$$

Using  $W_P$  and  $W_L$





# Mesh Simplification

Level of detail (LOD)

Hausdorff distance

Mesh optimization

Error quadrics

# Progressive representations

- Polygon simplification and level of detail (LOD) reduce geometric complexity of (small) objects



## Preprocess

Compute Levels of Detail (LOD)



## Runtime

Select LOD based on screen size

# Simplification

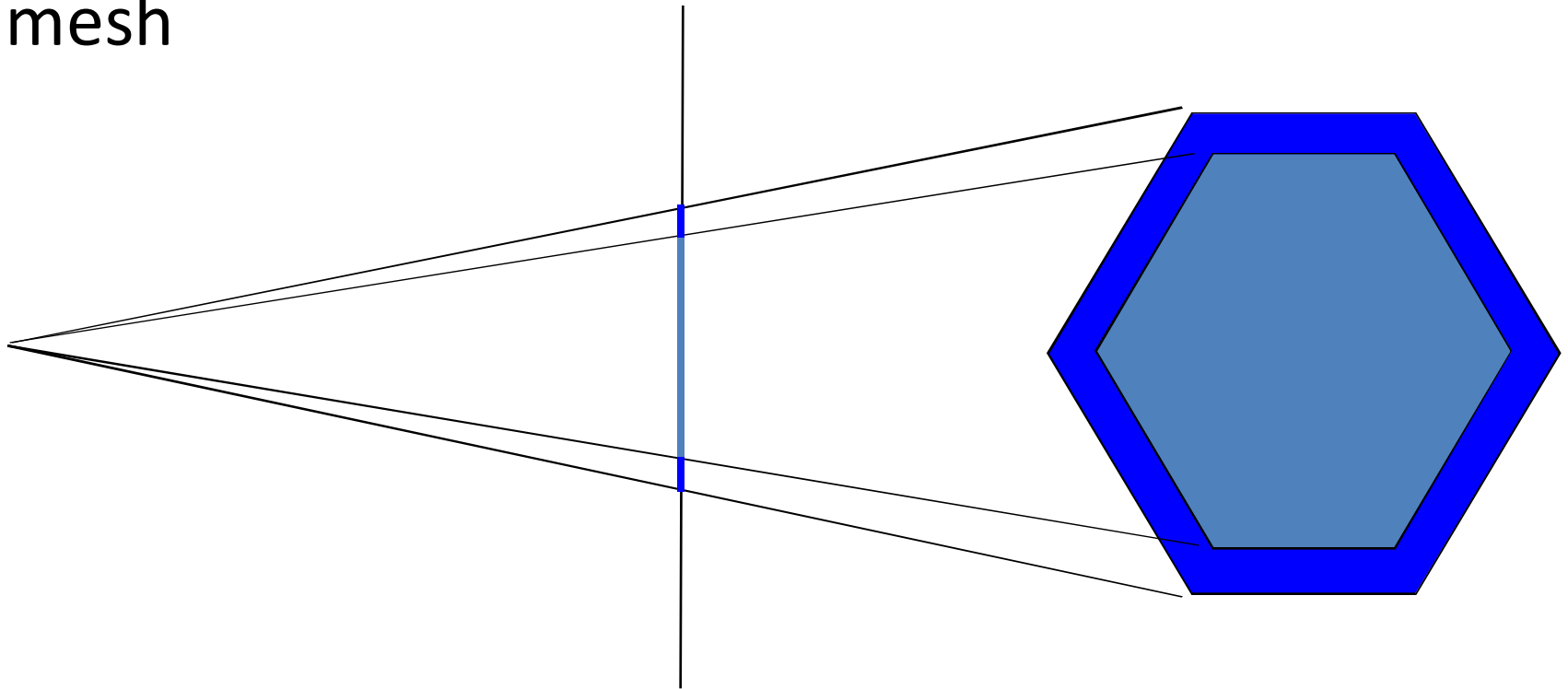
## Criteria

- Usually based on visual error
  - Difficult to quantify
  - Often used
    - **Geometric distance** between original und simplified object
    - **Volume** between original and simplified object
    - Difference between **surface normals** between original and simplified object
    - Combination of multiple criteria

# Simplification

Criteria

- Why geometric distance?
  - Fails for occluded/foreshortened parts of the mesh



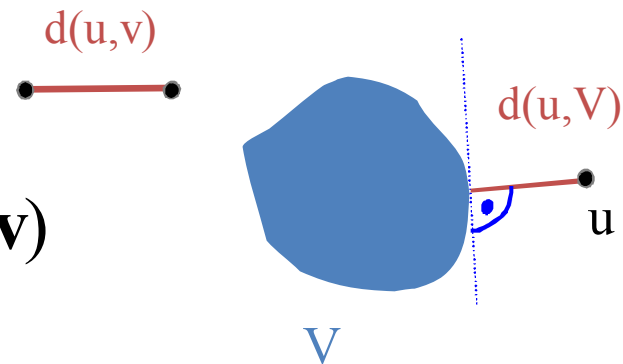
# Approximation criteria

## Geometric distance

- Hausdorff distance (distance between point sets):

$$\mathbf{u}, \mathbf{v} \in \mathbb{R}^d : d(\mathbf{u}, \mathbf{v}) = \|\mathbf{u} - \mathbf{v}\|$$

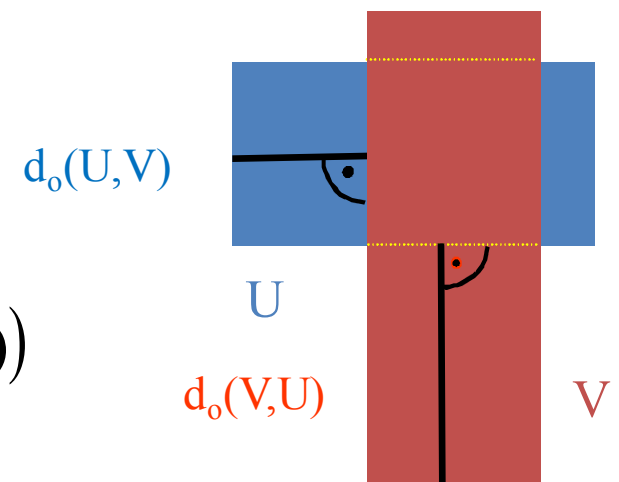
$$\mathbf{u} \in \mathbb{R}^d, \mathbf{V} \subset \mathbb{R}^d : d(\mathbf{u}, \mathbf{V}) = \inf_{\mathbf{v} \in \mathbf{V}} d(\mathbf{u}, \mathbf{v})$$



$$\mathbf{U} \subset \mathbb{R}^d, \mathbf{V} \subset \mathbb{R}^d : d_o(\mathbf{U}, \mathbf{V}) = \sup_{\mathbf{u} \in \mathbf{U}} \inf_{\mathbf{v} \in \mathbf{V}} d(\mathbf{u}, \mathbf{v})$$

$$d_o(\mathbf{U}, \mathbf{V}) \neq d_o(\mathbf{V}, \mathbf{U})$$

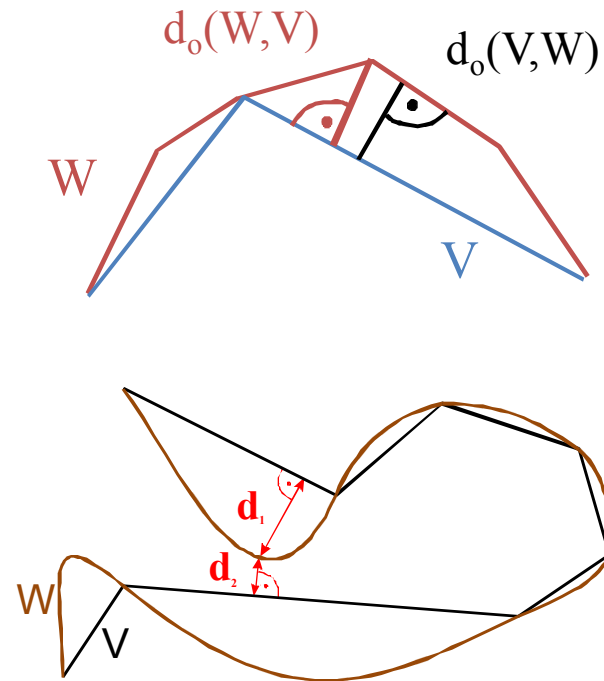
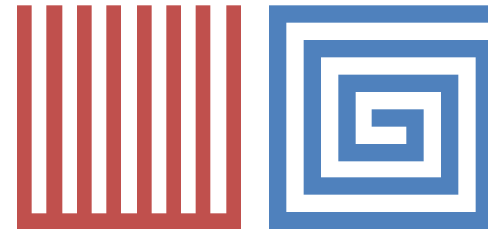
$$\mathbf{U} \subset \mathbb{R}^d, \mathbf{V} \subset \mathbb{R}^d : d_H(\mathbf{U}, \mathbf{V}) = \max(d_o(\mathbf{U}, \mathbf{V}), d_o(\mathbf{V}, \mathbf{U}))$$



# Approximation criteria

Geometric distance

- Hausdorff distance
  - Generally bad for orientation or shape comparison
  - Very good metric for comparing original to simplified model
  - Topological correspondence improves results



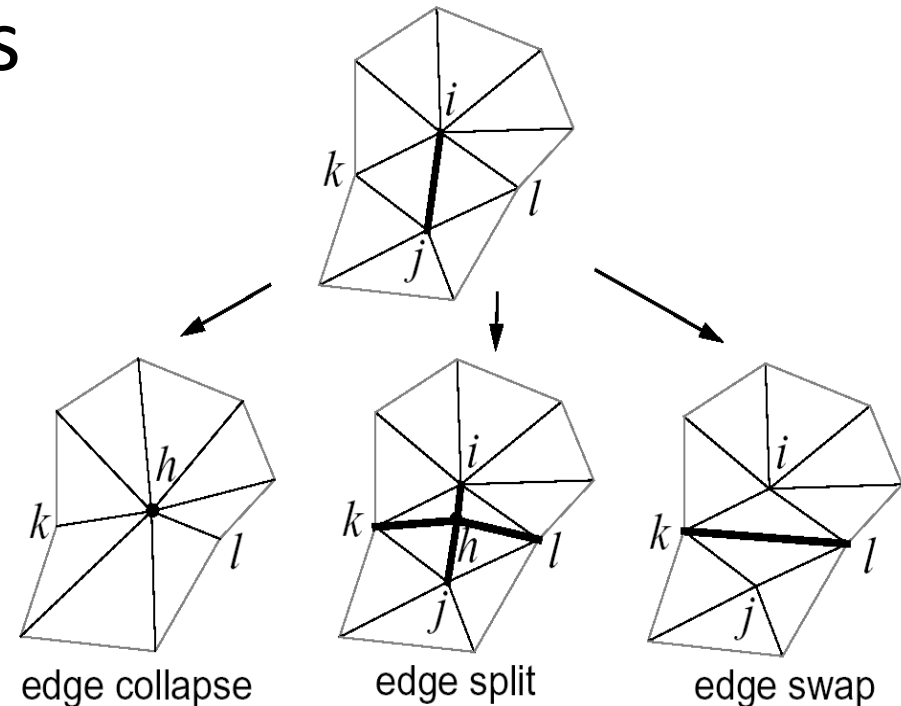
# Mesh optimization

Local operations

- Three local operations

**[Hoppe 1993]**

- Edge Collapse
- Edge Split
- Edge Swap/Flip



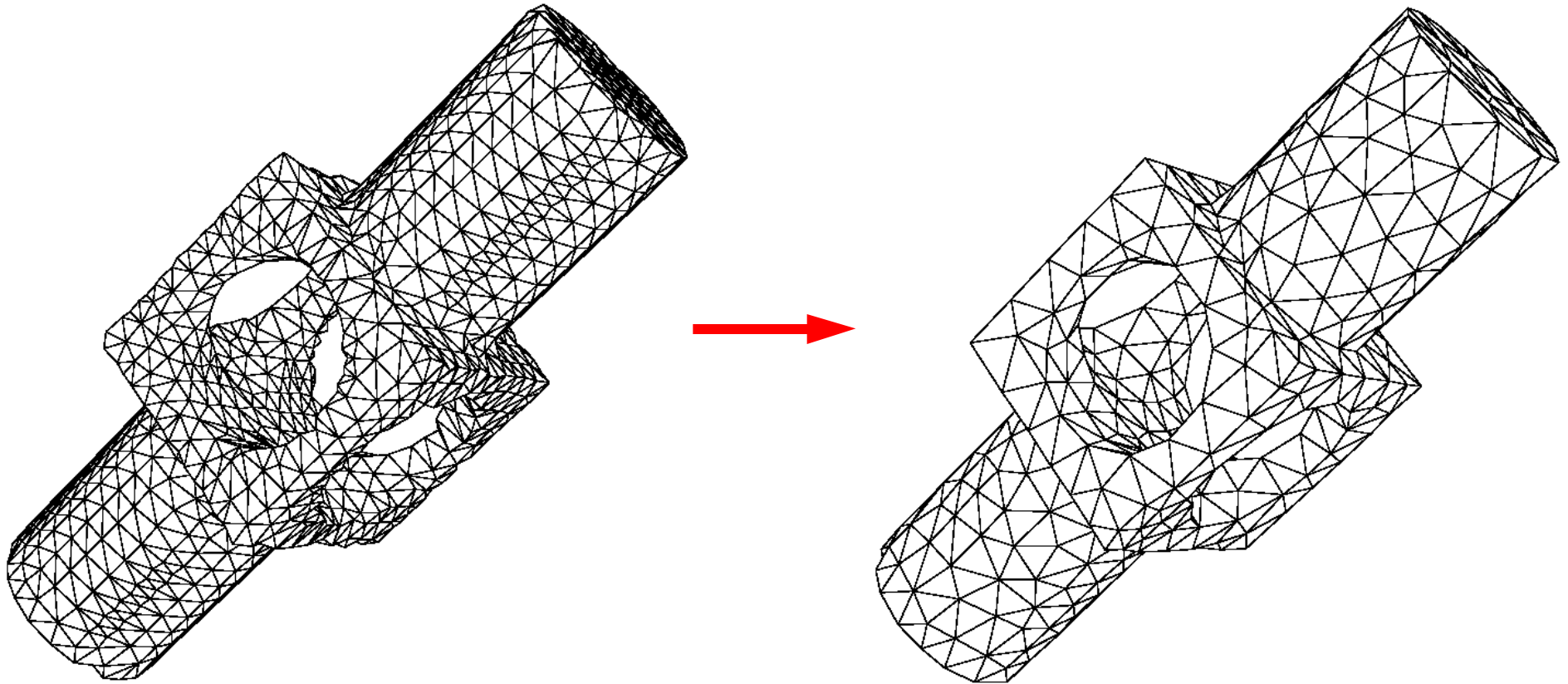
- Minimize some global energy

$$E(K, V) = E_{dist}(K, V) + E_{rep}(K) + E_{spring}(K, V)$$



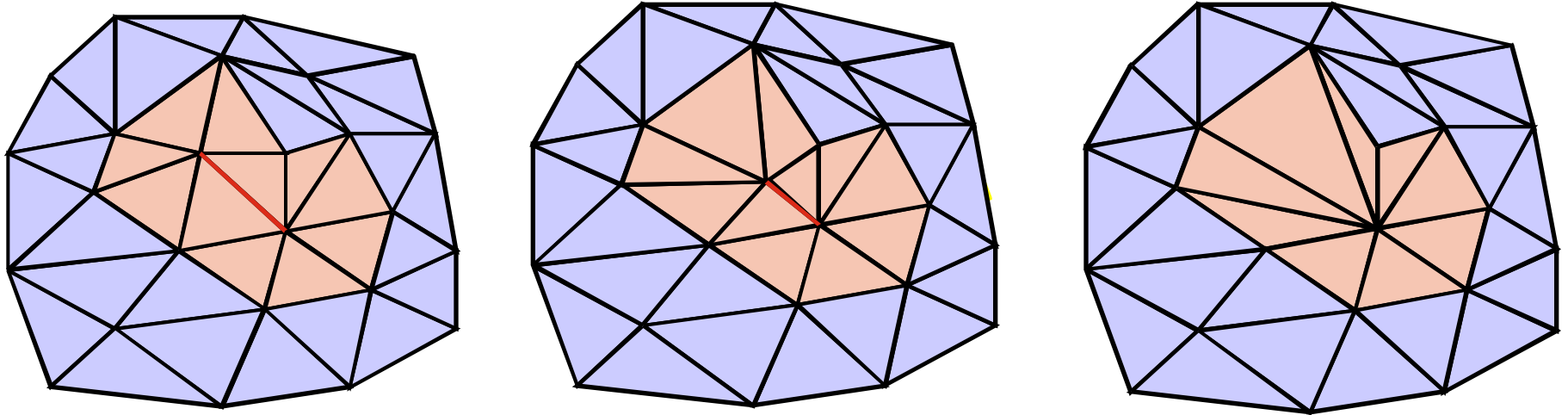
# Mesh optimization

Results



# Simplification

Edge collapse



# Simplification

Evaluating the operations

- For edge collapse selection, the approximation error must be evaluated
- Possibilities:
  - Hausdorff distance (expensive)
  - One-sided Hausdorff distance
  - Accumulate squared distances to planes (Error quadrics)
    - Basic operation: edge collapse

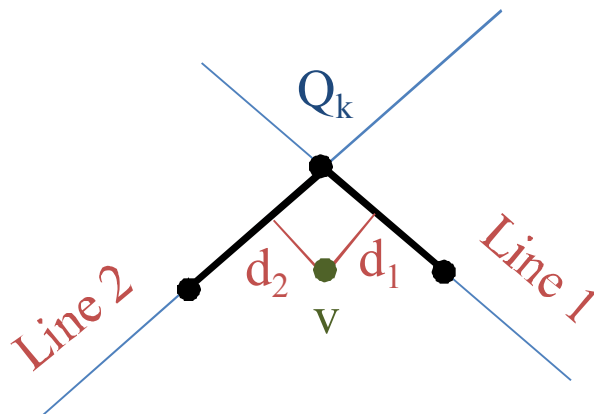
# Simplification

## Error quadrics

- Compute squared distance to planes
- Example: planar polygons

$$g_1 : a_1x + b_1y + c_1, \quad a_1^2 + b_1^2 = 1$$

$$g_2 : a_2x + b_2y + c_2, \quad a_2^2 + b_2^2 = 1$$



$$d_1^2 + d_2^2 = \mathbf{v}^T \mathbf{Q}_k \mathbf{v}$$

$$\begin{aligned} d_i^2 &= (a_i v_x + b_i v_y + c_i)^2 \\ &= \left( (v_x, v_y, 1) (a_i, b_i, c_i)^T \right)^2 \\ &= (v_x, v_y, 1) \mathbf{Q}_{ik} (v_x, v_y, 1)^T, \end{aligned}$$

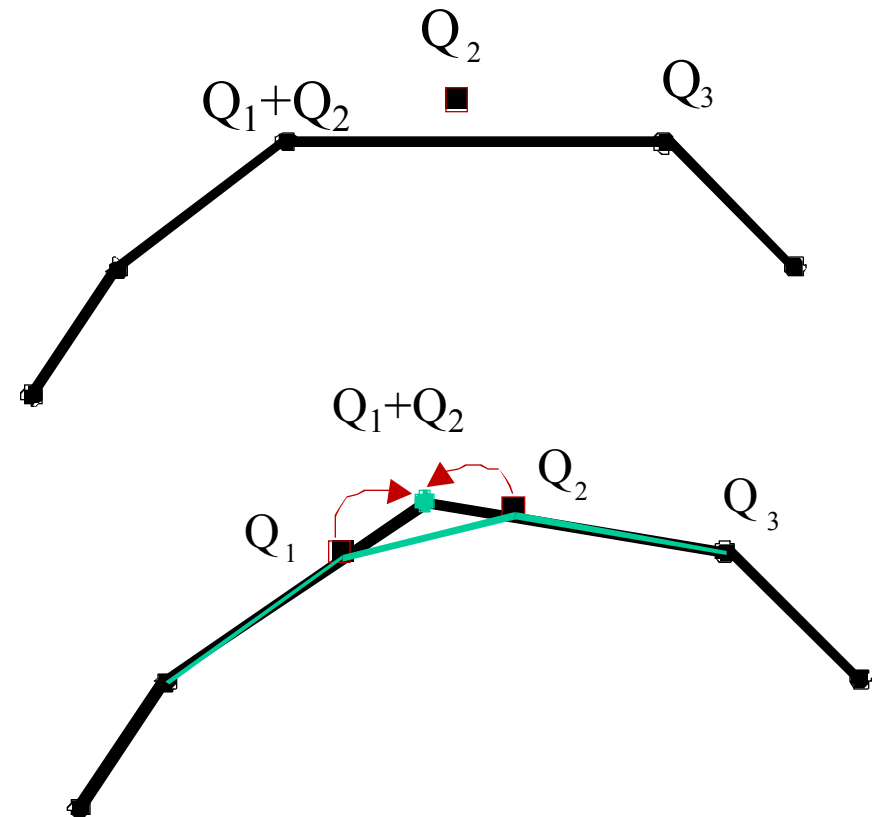
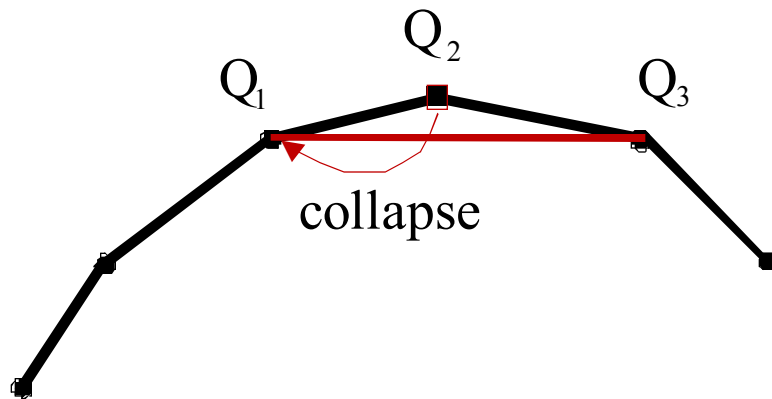
$$\begin{aligned} \mathbf{Q}_{ik} &= (a_i, b_i, c_i) (a_i, b_i, c_i)^T \\ &= \begin{pmatrix} a_i^2 & a_i b_i & a_i c_i \\ a_i b_i & b_i^2 & b_i c_i \\ a_i c_i & b_i c_i & c_i^2 \end{pmatrix} \end{aligned}$$

$$\mathbf{Q}_k = \mathbf{Q}_{1k} + \mathbf{Q}_{2k}$$

# Simplification

Error quadrics

- **[Garland/Heckbert 97]:**  
propagate error quadric by addition

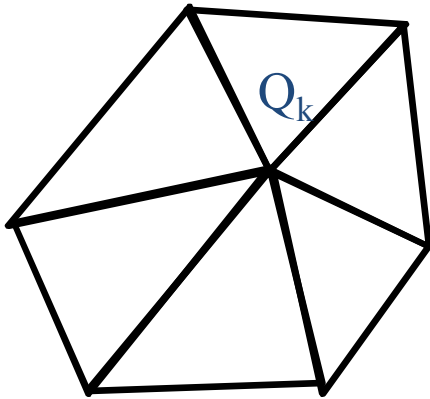


# Simplification

## Error quadrics

- Triangle meshes

$$p_{ik} : a_i x + b_i y + c_i z + d_i, \quad a_i^2 + b_i^2 + c_i^2 = 1$$



$$\begin{aligned} e_i^2 &= (a_i v_x + b_i v_y + c_i v_z + d_i)^2 \\ &= \left( (v_x, v_y, v_z, 1) (a_i, b_i, c_i, d_i) \right)^2 \\ &= (v_x, v_y, v_z, 1) \mathbf{Q}_{ik} (v_x, v_y, v_z, 1)^T, \end{aligned}$$

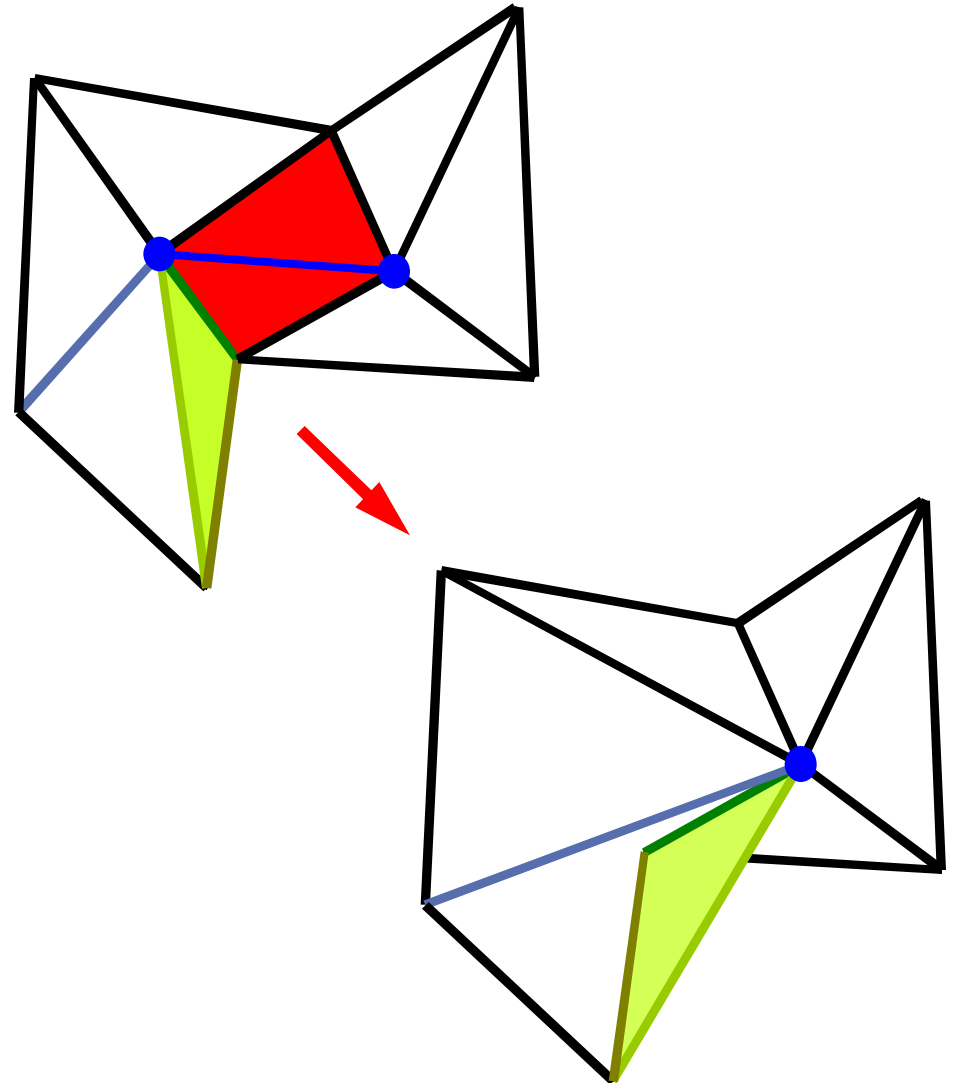
$$\begin{aligned} \mathbf{Q}_{ik} &= (a_i, b_i, c_i, d_i) (a_i, b_i, c_i, d_i)^T \\ &= \begin{pmatrix} a_i^2 & a_i b_i & a_i c_i & a_i d_i \\ a_i b_i & b_i^2 & b_i c_i & b_i d_i \\ a_i c_i & b_i c_i & c_i^2 & c_i d_i \\ a_i d_i & b_i d_i & c_i d_i & d_i^2 \end{pmatrix} \end{aligned}$$

$$\mathbf{Q}_k = \sum_i \mathbf{Q}_{ik}$$

# Simplification

Error quadrics

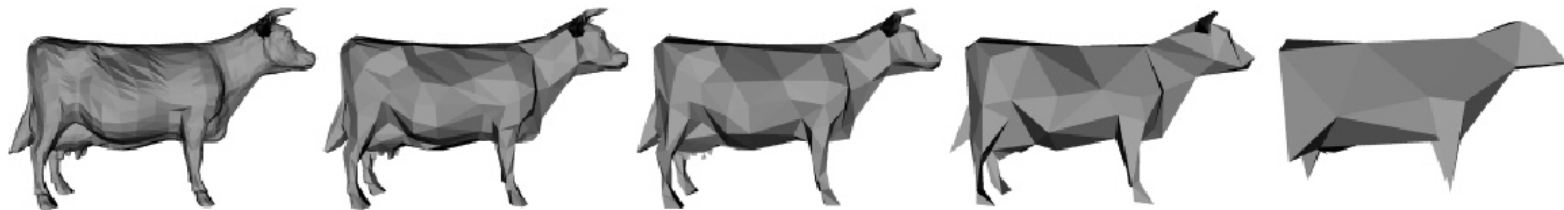
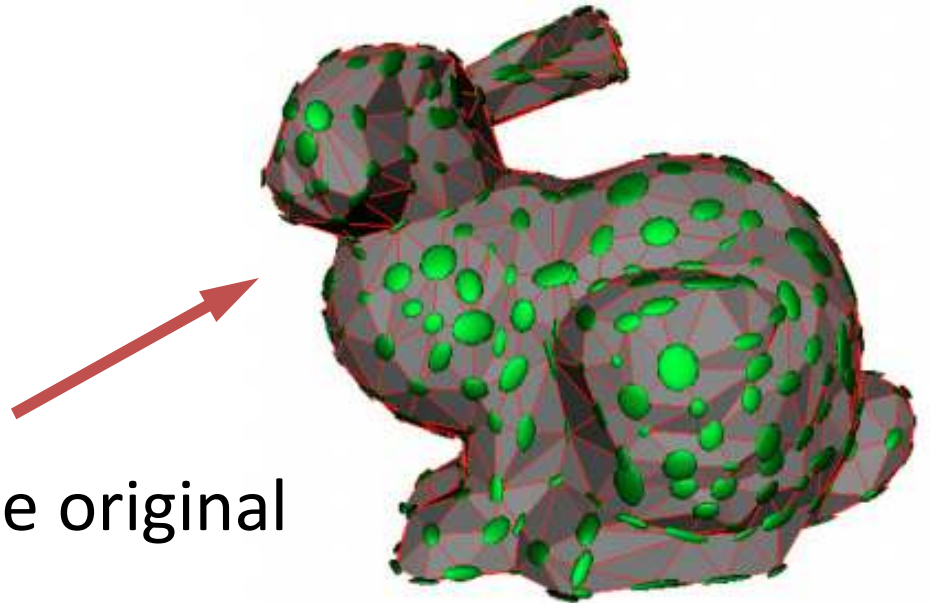
- Special cases
  - Face Flips: in collapsing the blue edge, the normal of the green face has flipped
  - These cases must be detected and avoided
  - OpenMesh takes care of this for you
  - OpenMesh has error quadrics implemented



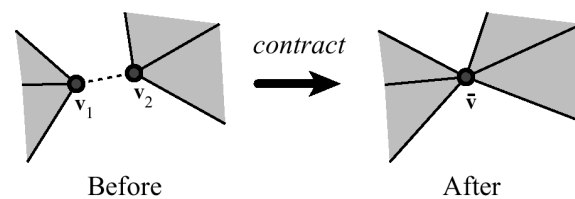
# Simplification

Error quadrics

- Advantages
  - Simple error computation
  - Very fast
  - Geometric interpretation
  - Good approximation of the original



- Can collapse vertices that are not connected via edges

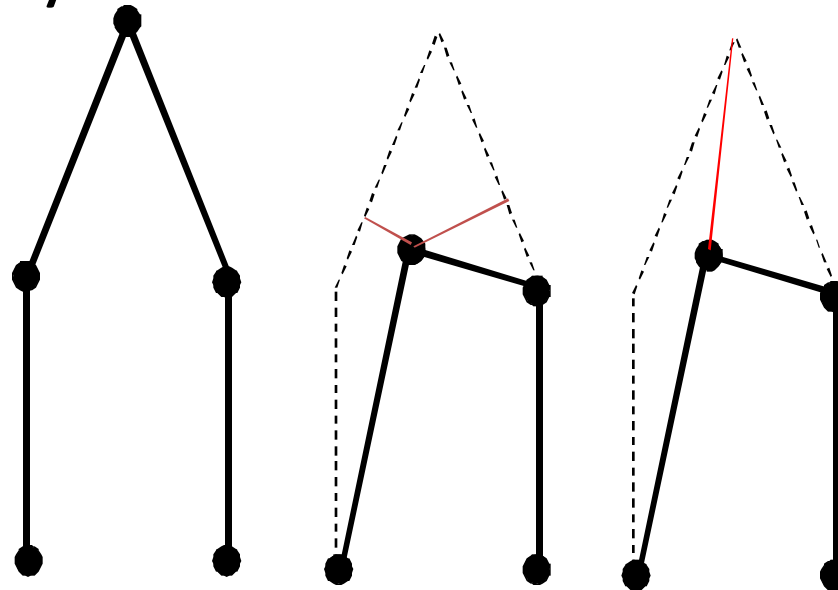




# Simplification

Error quadrics

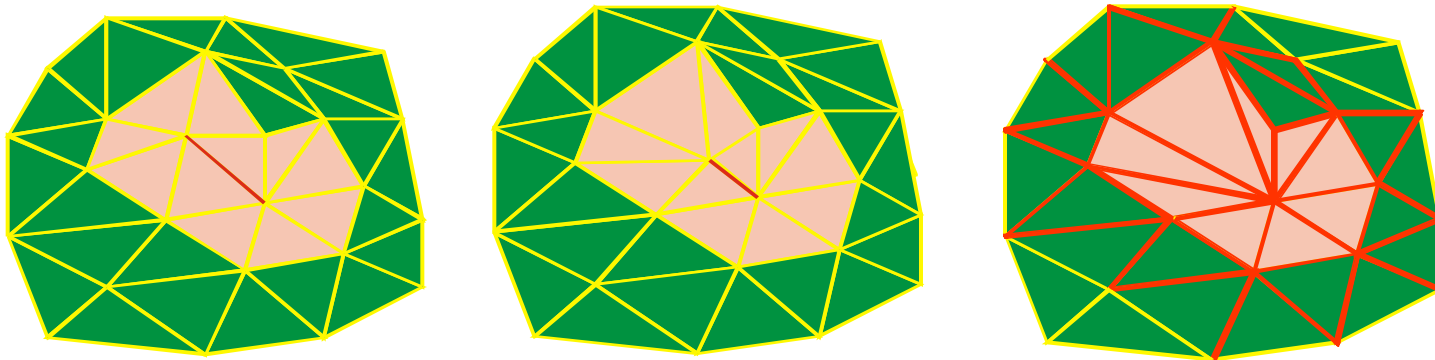
- Disadvantages
  - One sided distance only (from new to original)
  - Loss of symmetry



# Simplification

## Algorithm

- Operation and error metric define algorithm
  - Compute error for every atomic simplification operation
  - Create a priority queue based on the error
  - While the queue is non-empty
    - Perform first simplification operation and remove from queue
    - Recompute the error for neighboring operations and update the priority queue accordingly



# Simplification

*Mesh Saliency* [Lee et al. 2005]

- Take salient features into account when simplifying the mesh



Original  
(346K triangles)



99% simplification  
(3.5K triangles)



98% simplification  
(6.9K triangles)



98.5% simplification  
(5.2K triangles)



99% simplification  
(3.5K triangles)

(a) Simplification by Qslim



Saliency



99% simplification  
(3.5K triangles)



98% simplification  
(6.9K triangles)



98.5% simplification  
(5.2K triangles)



99% simplification  
(3.5K triangles)

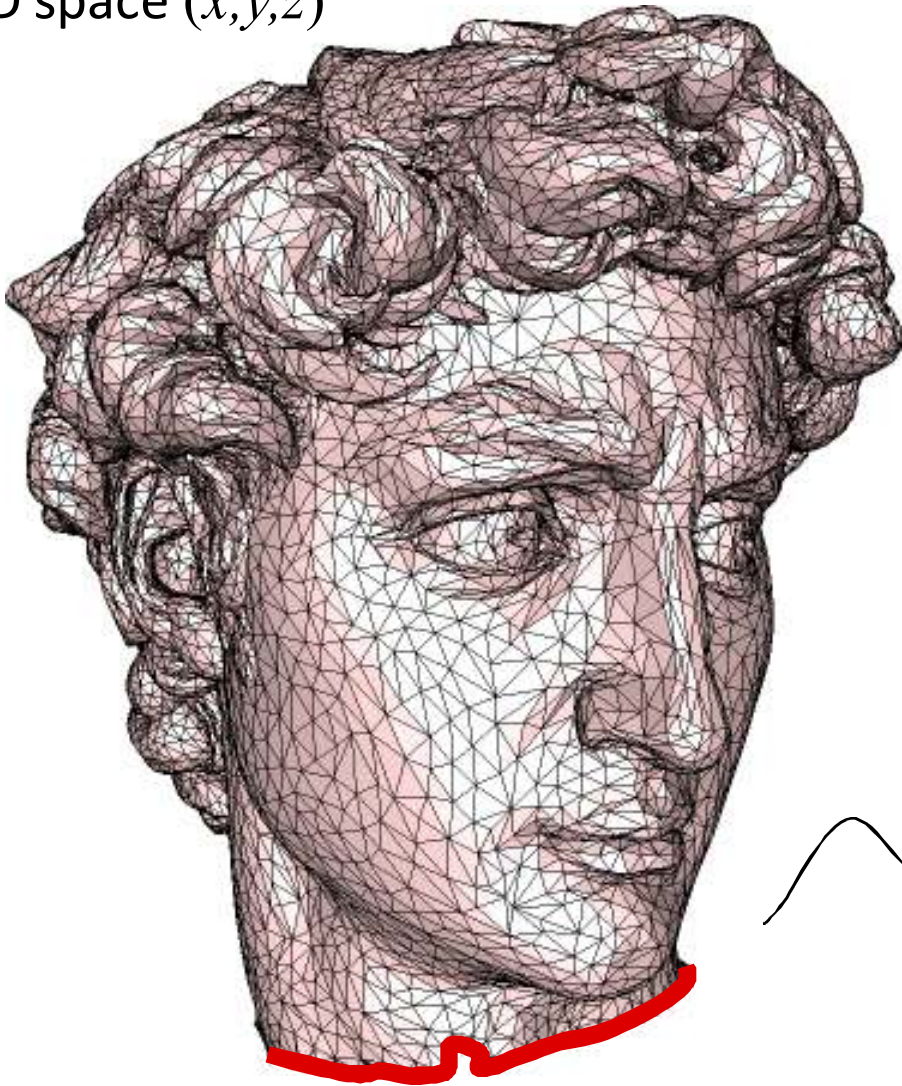
(b) Simplification guided by saliency  
2/22/2011

# Parameterization and Remeshing

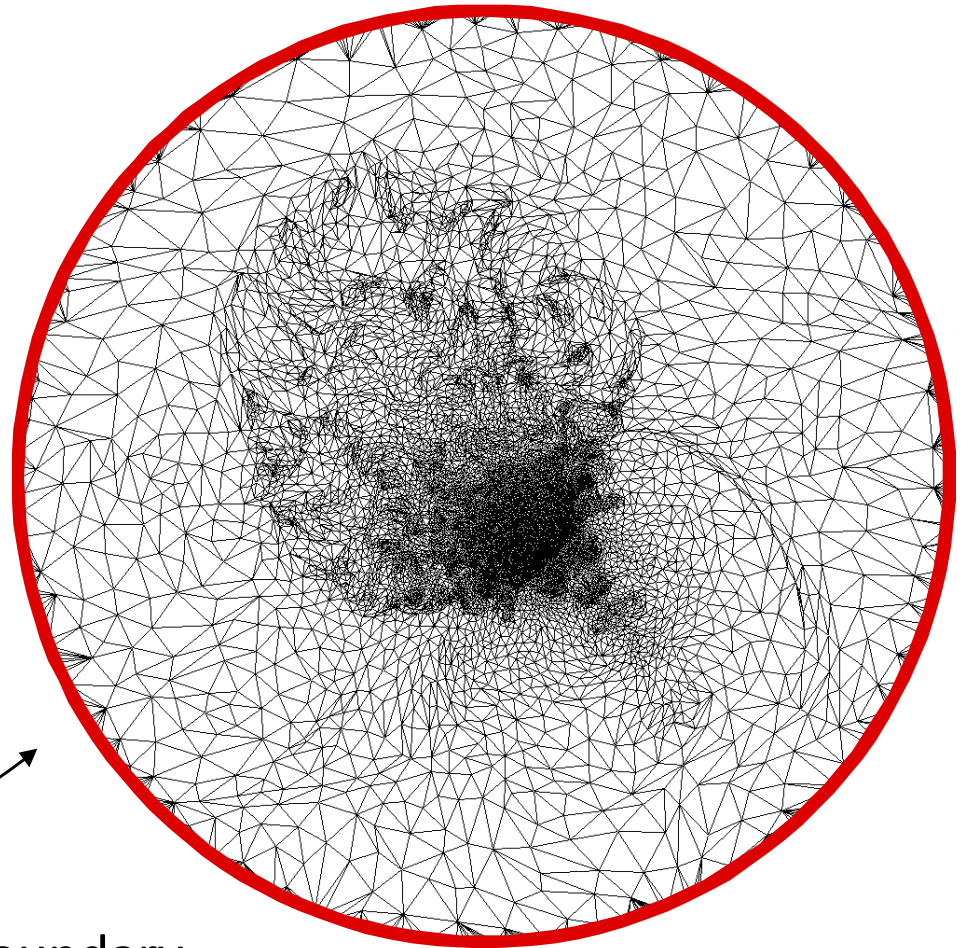


# Surface parameterization

3D space  $(x,y,z)$



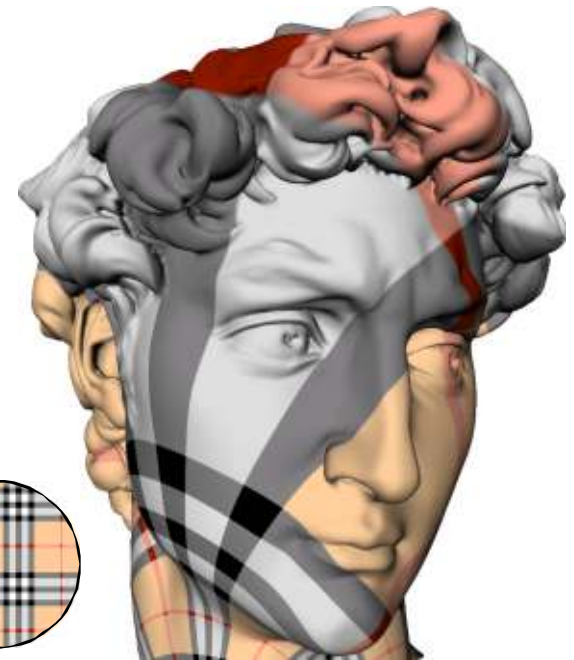
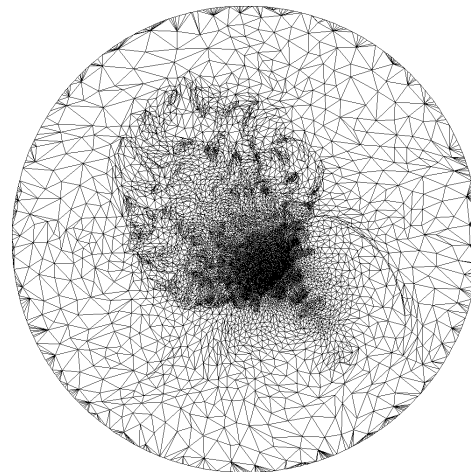
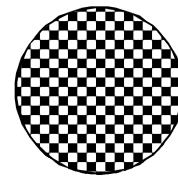
2D parameter domain  $(u,v)$



boundary

boundary

# Texture mapping





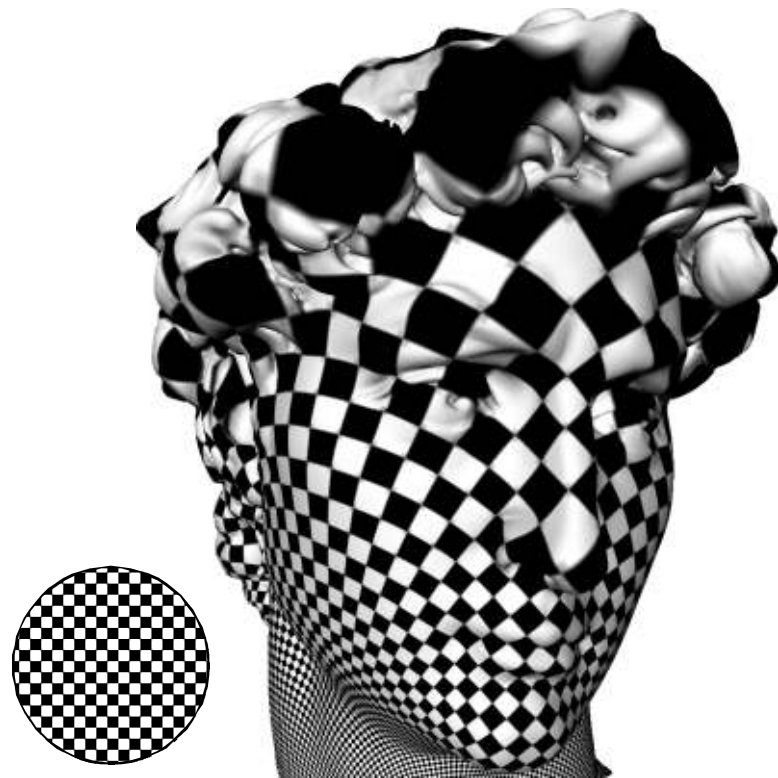
# Texture mapping



# Mesh parameterization

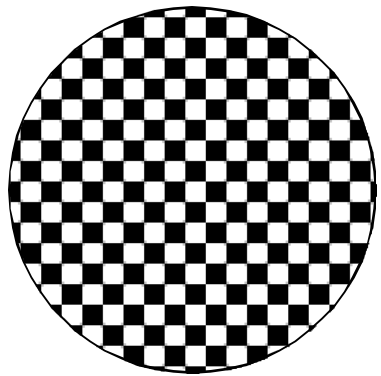
## Requirements

- Bijective (1-1 and onto): No triangles fold over.
- Minimal “distortion”
  - Preserve 3D angles
  - Preserve 3D distances
  - Preserve 3D areas
  - No “stretch”

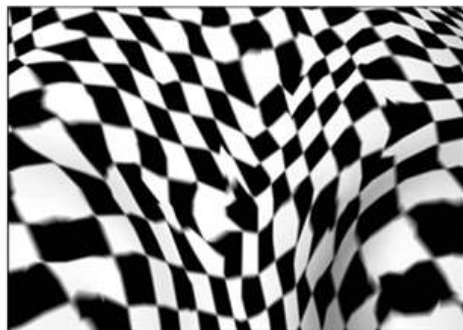
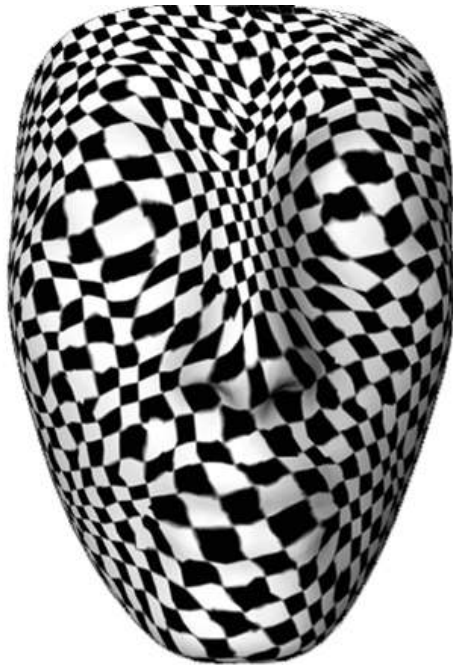




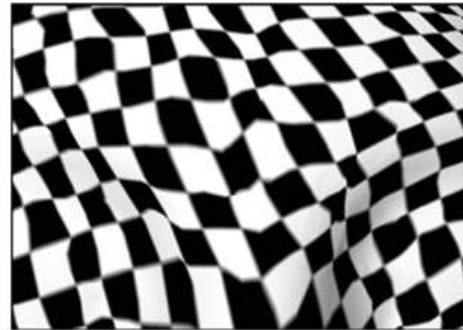
# Distortion minimization



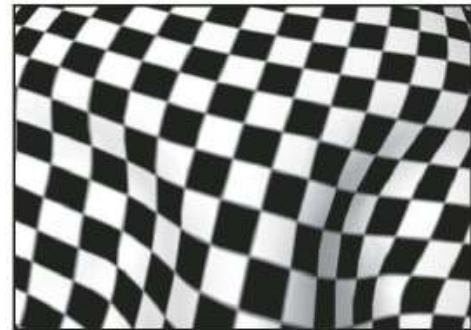
Texture map



Kent et al '92

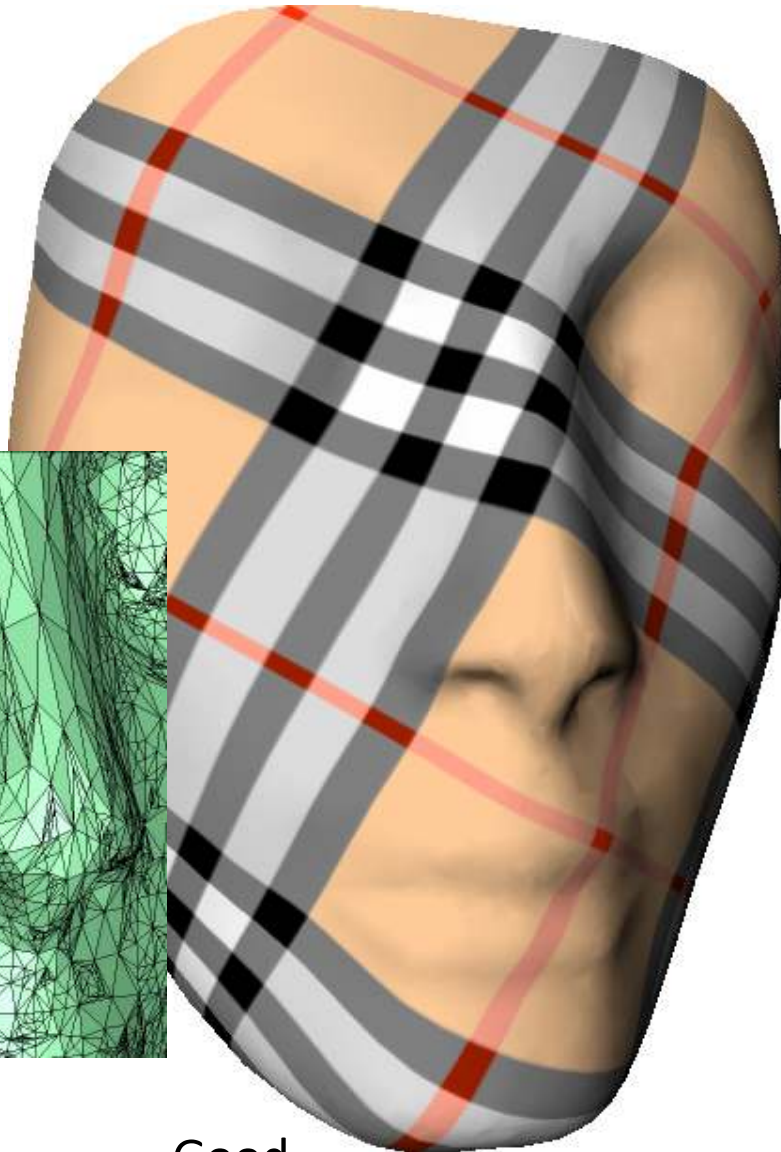
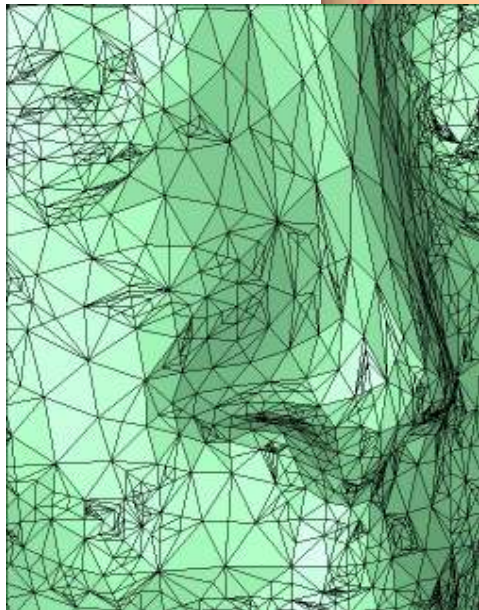
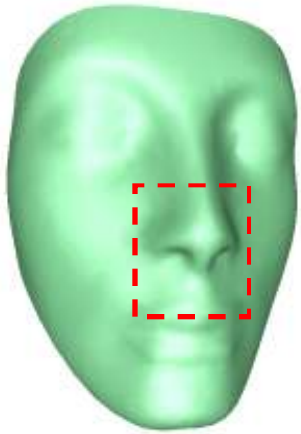


Floater 97



Sander et al '01

# Sensitivity to mesh quality



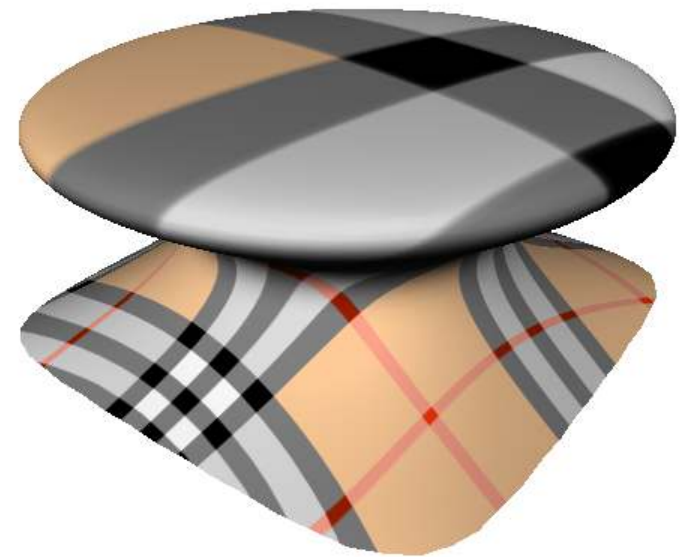
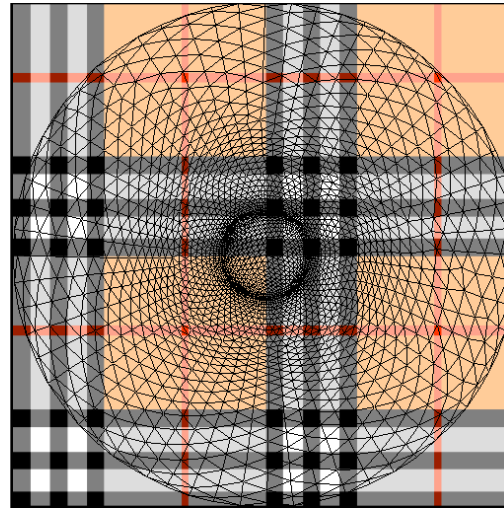
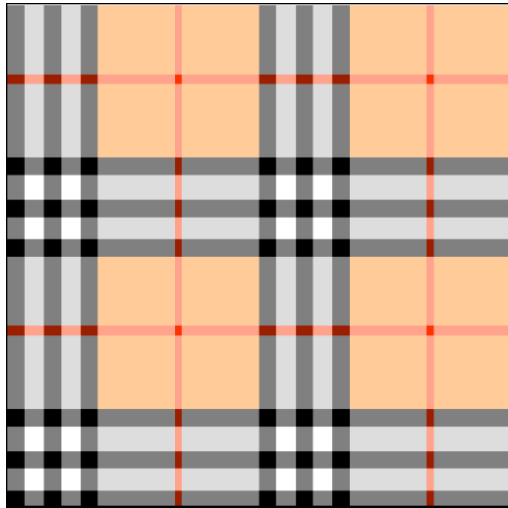
Good  
parameterization algorithm



Not so good  
parameterization algorithm



# Area distortion vs. angle distortion

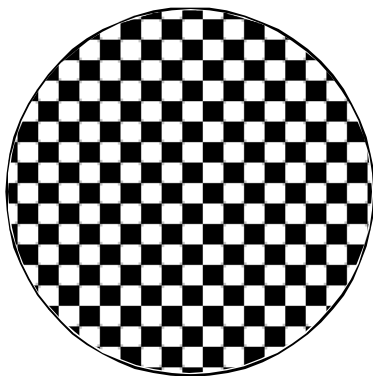
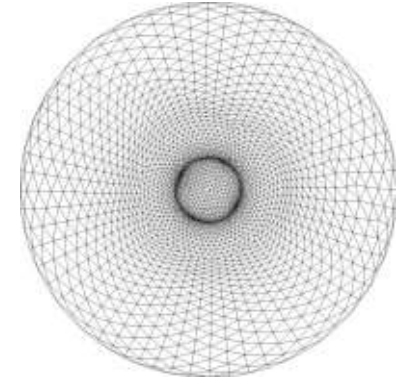
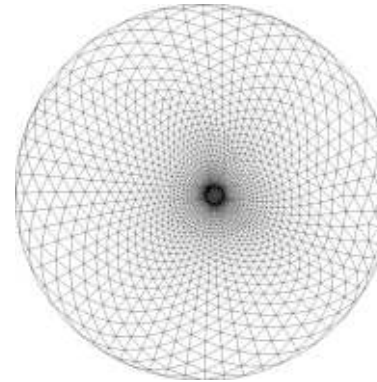
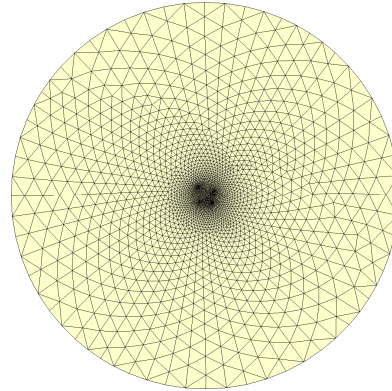
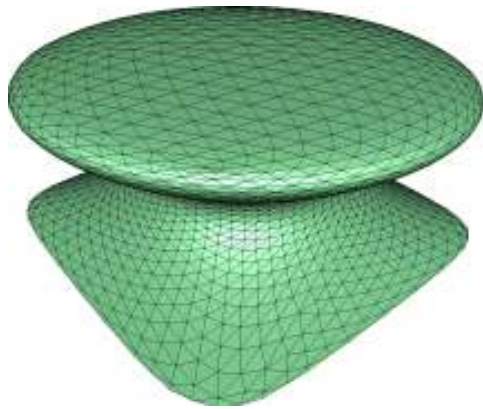


# Conformal parameterization

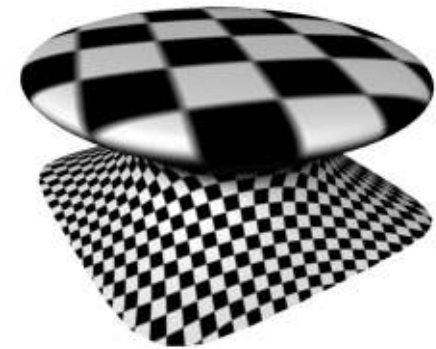
Tutte

Shape-preserving

Conformal

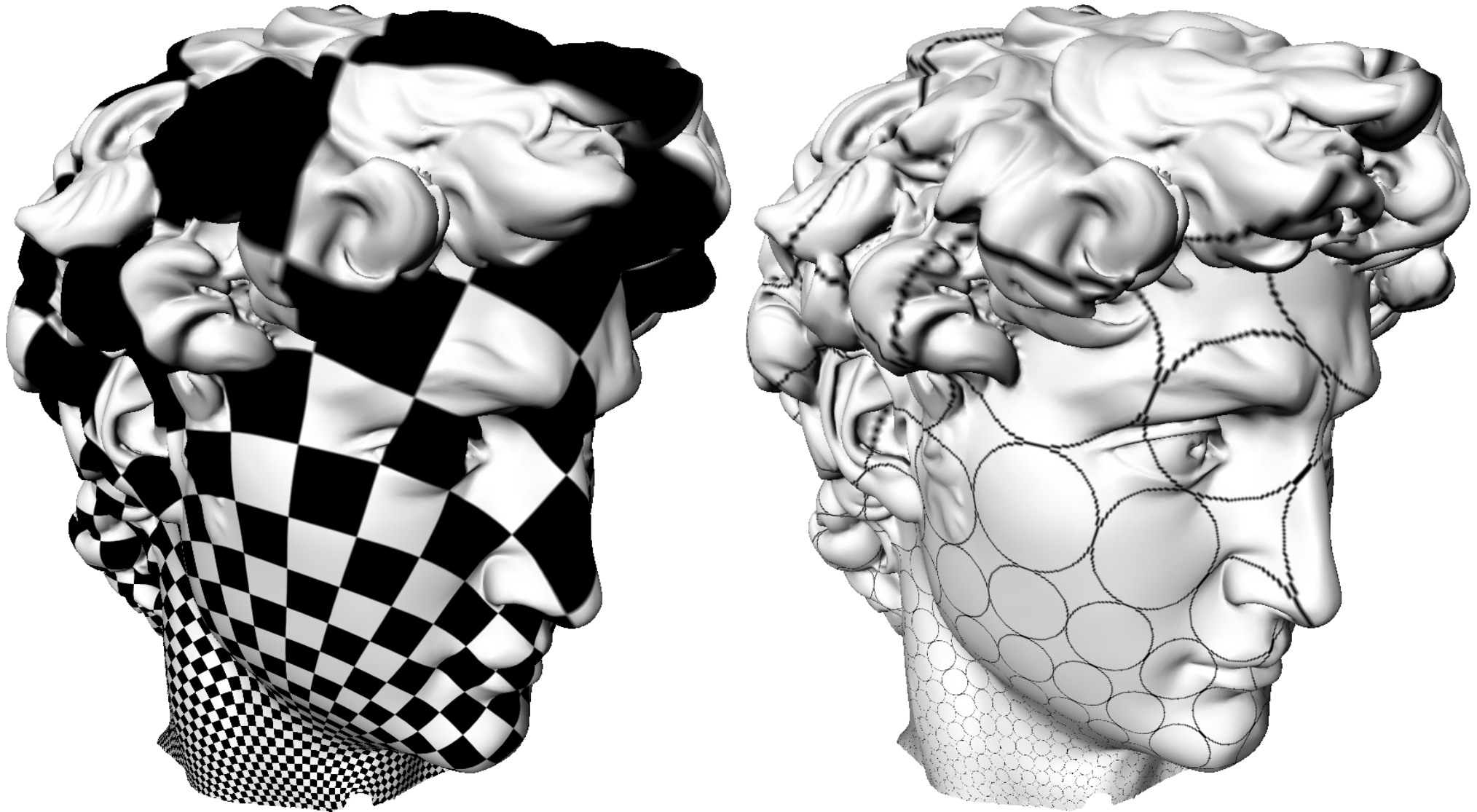


Texture map

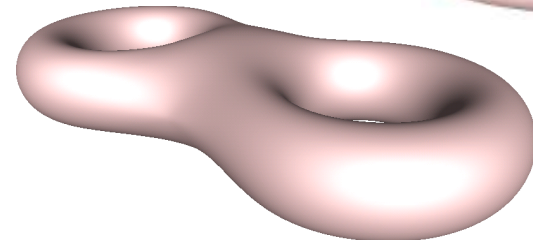
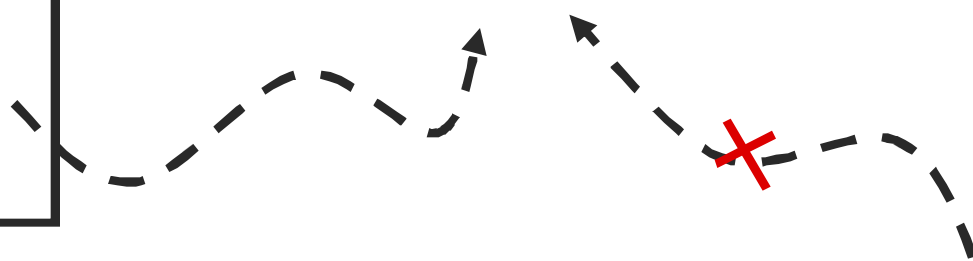
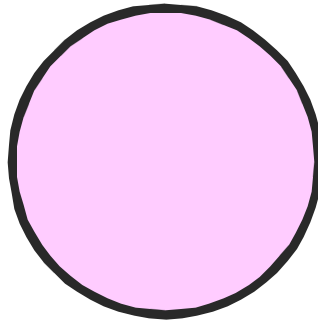
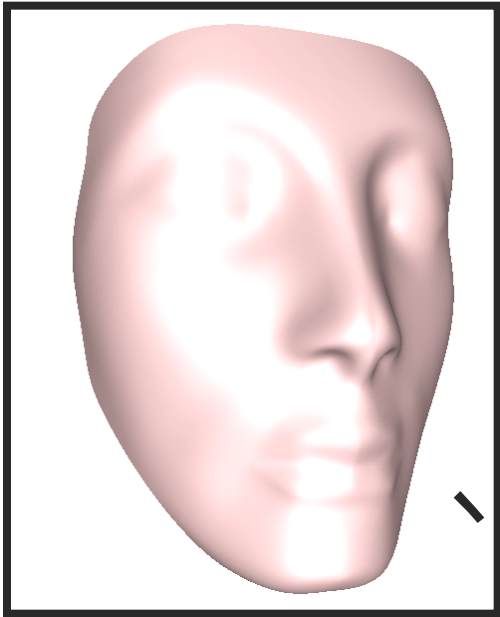


# Conformal parameterization

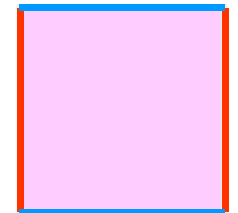
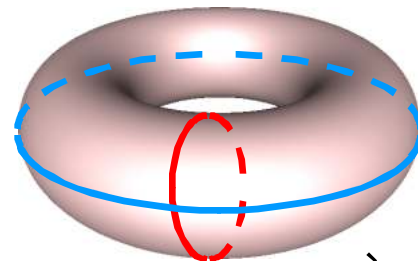
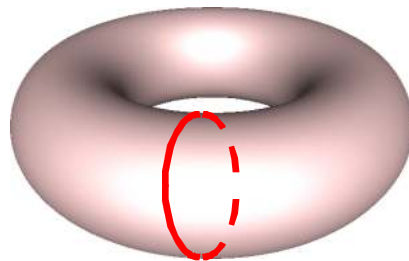
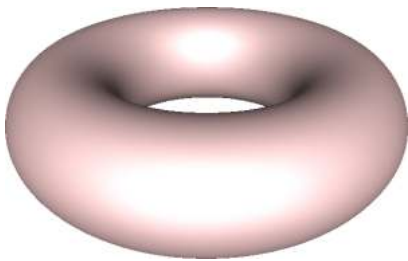
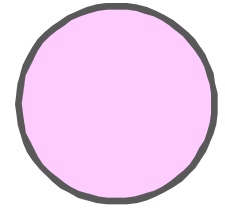
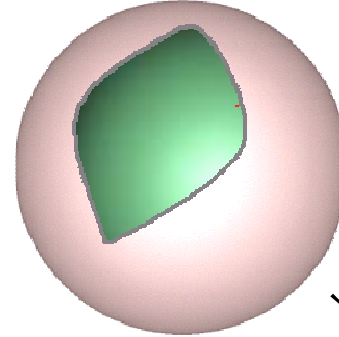
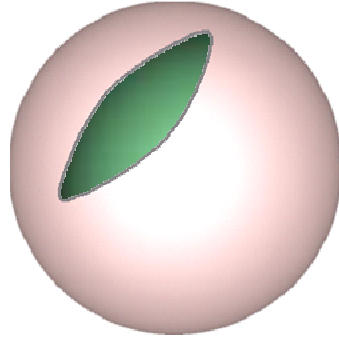
angle preservation; circles are mapped to circles



# Non-disk domains

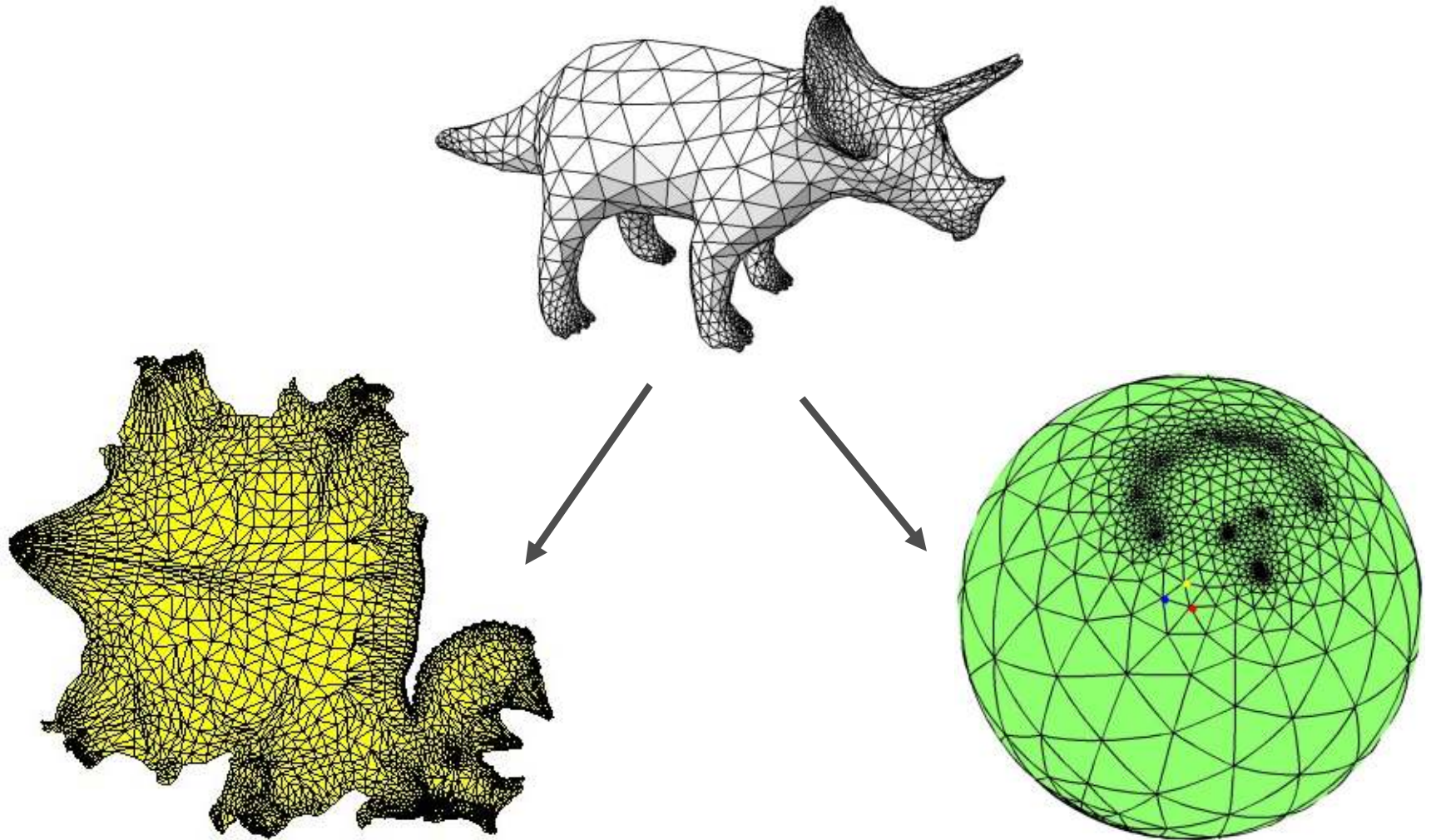


# Cutting





# Parameterization of closed genus-0 triangle meshes



Non-Constrained Planar

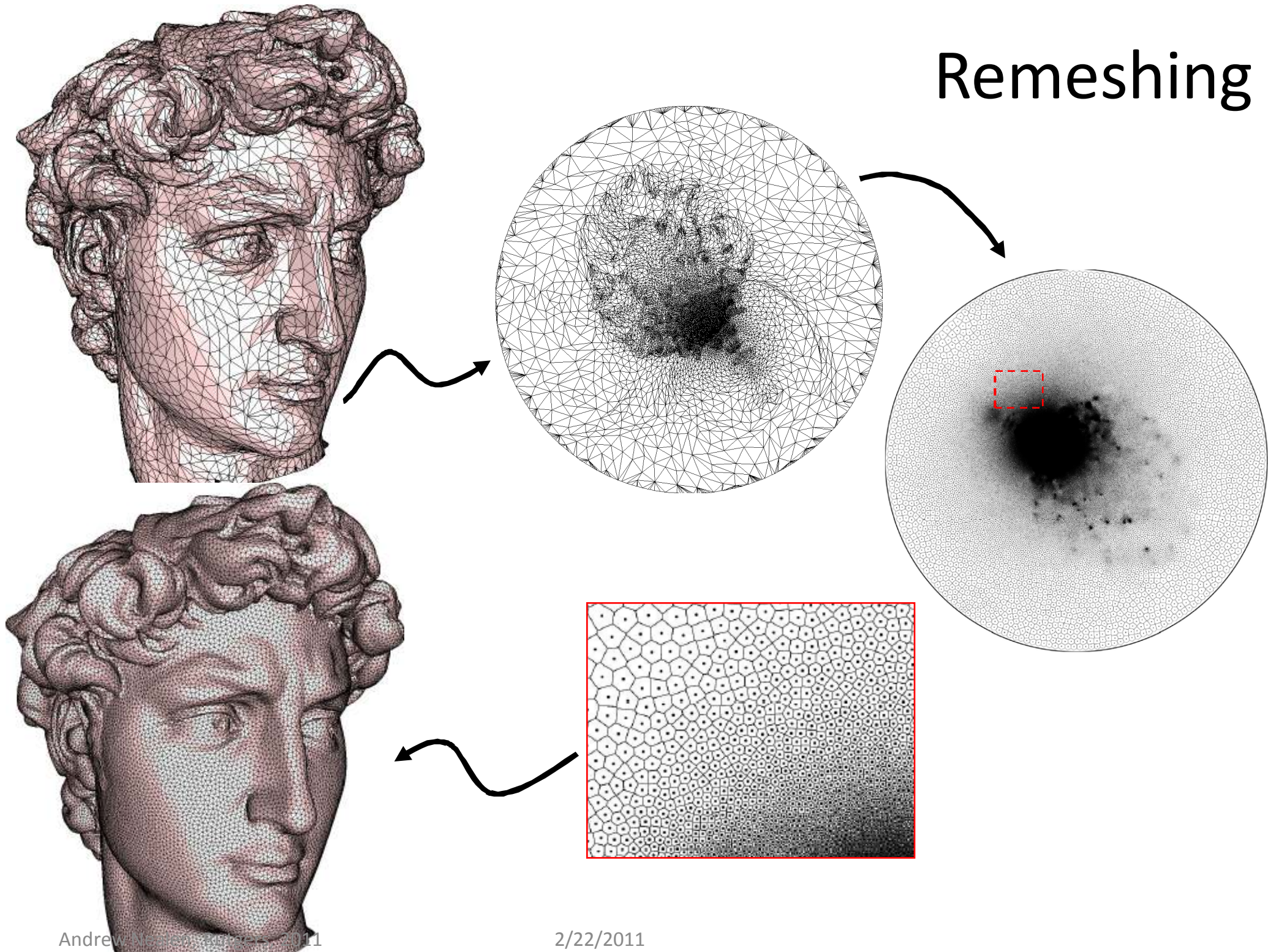
Spherical



# Why parameterization?

- Allows us to do many things in 2D and then map those actions onto the 3D surface
- It is often easier to operate in the 2D domain
- Mesh parameterization allows to use some notions from continuous surface theory

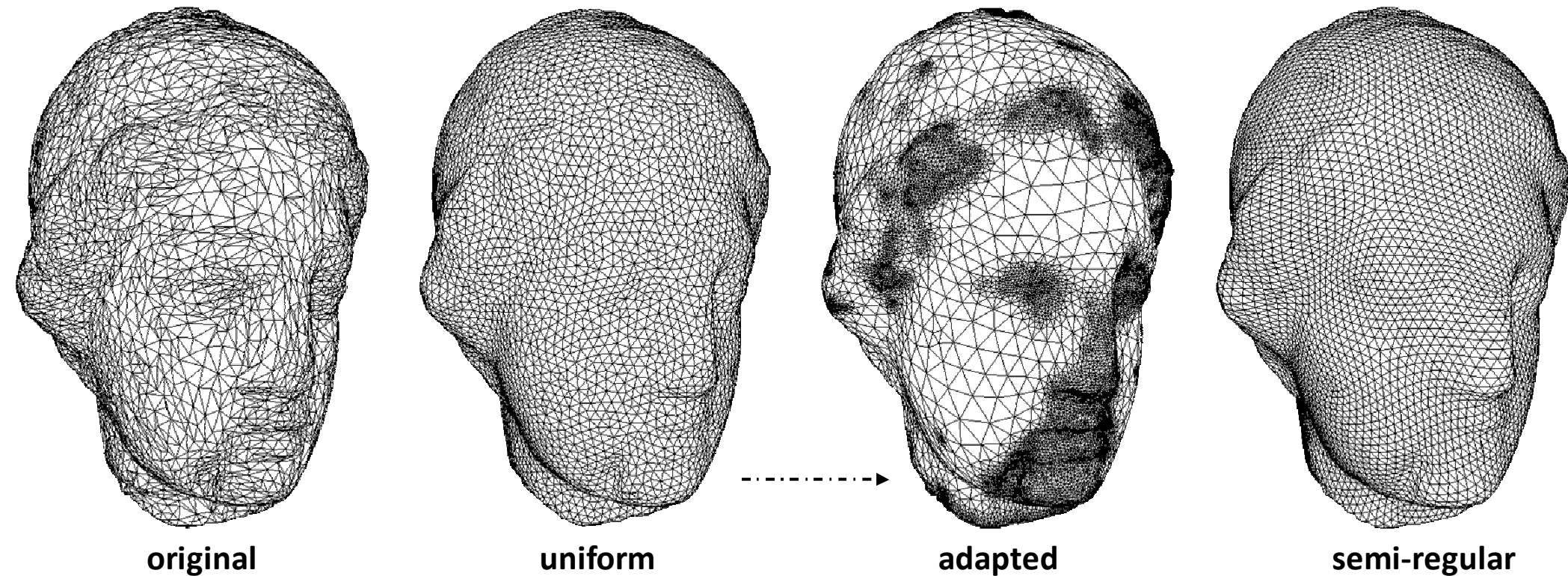
# Remeshing





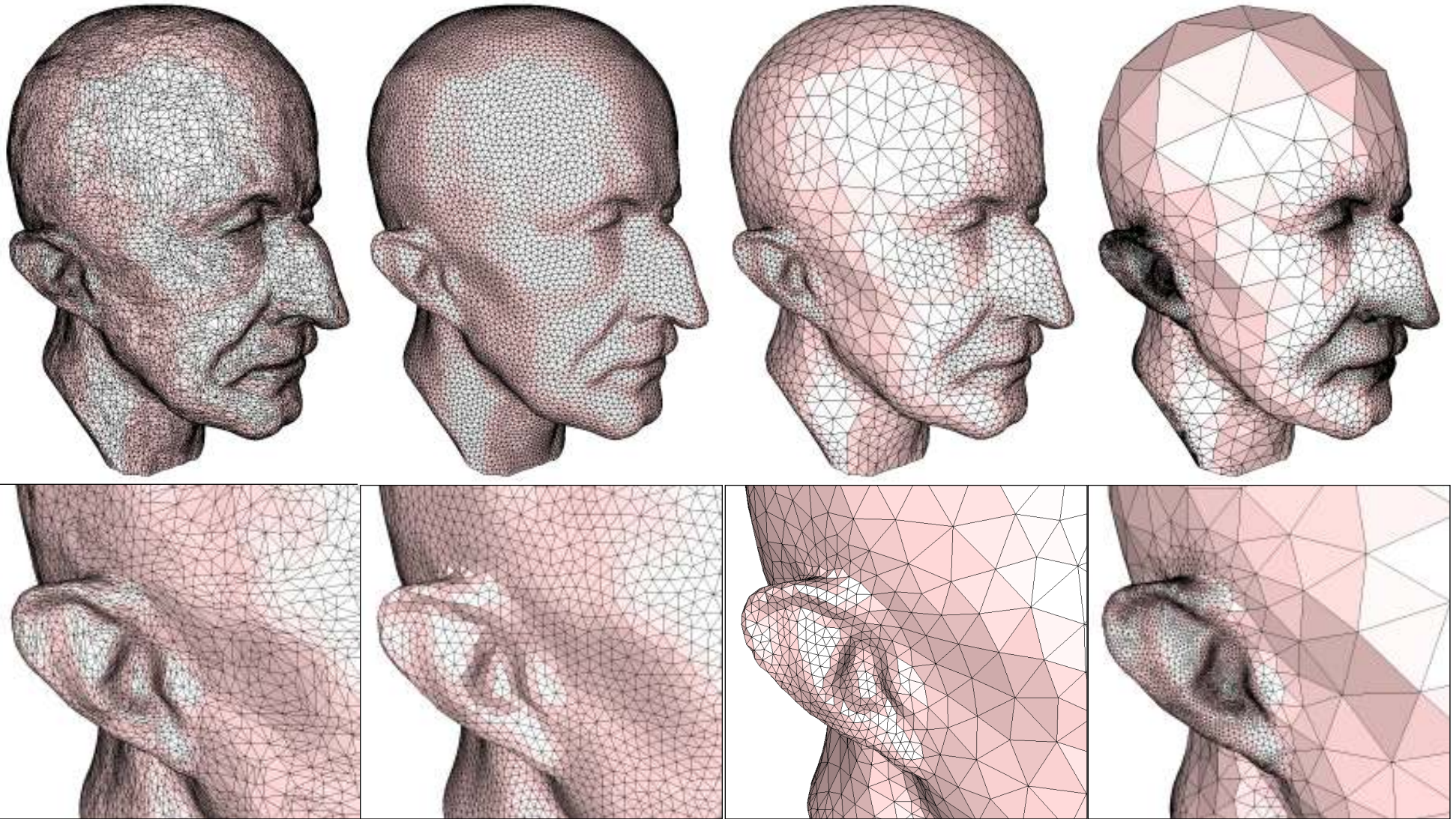
# Remeshing

- Particular remeshing type according to application





# Remeshing examples



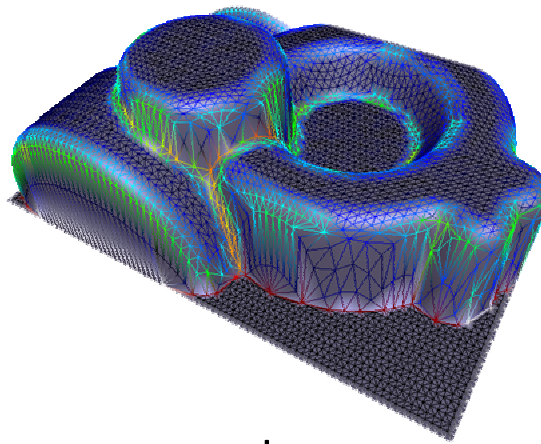


# Interactive geometry remeshing

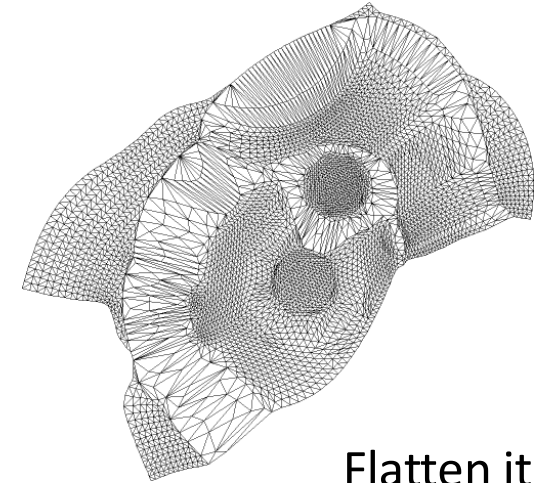
[Alliez et al., SIGGRAPH 2002]



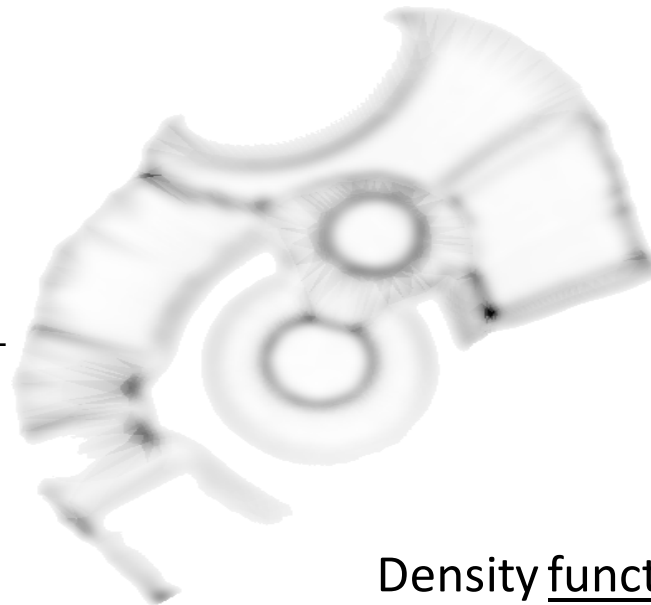
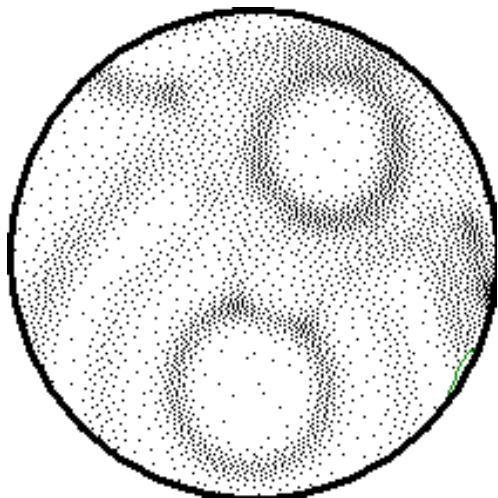
Model



Measure curvature



Flatten it  
**conformally**

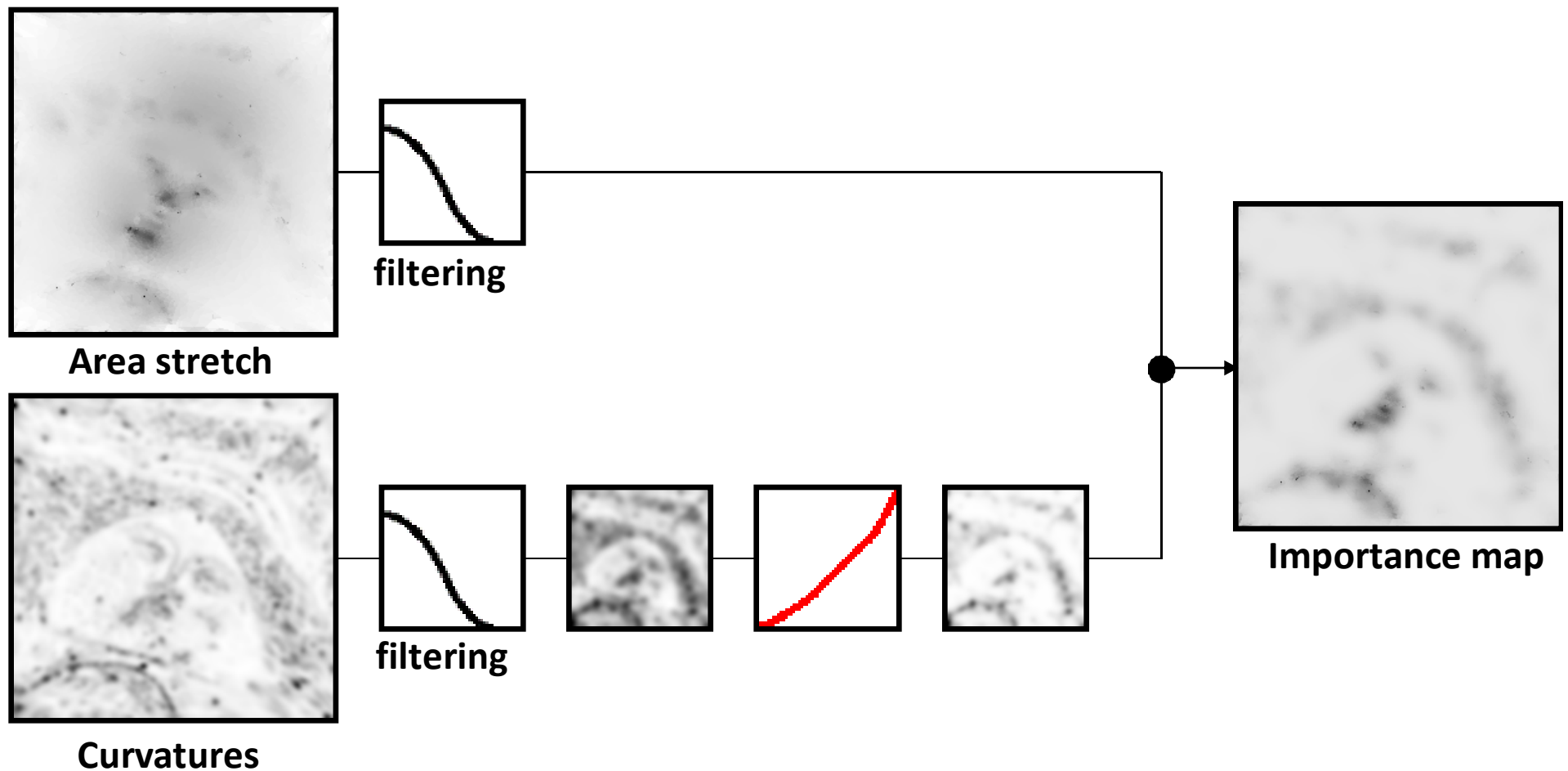


Density function in parameter space

# Interactive geometry remeshing

[Alliez et al., SIGGRAPH 2002]

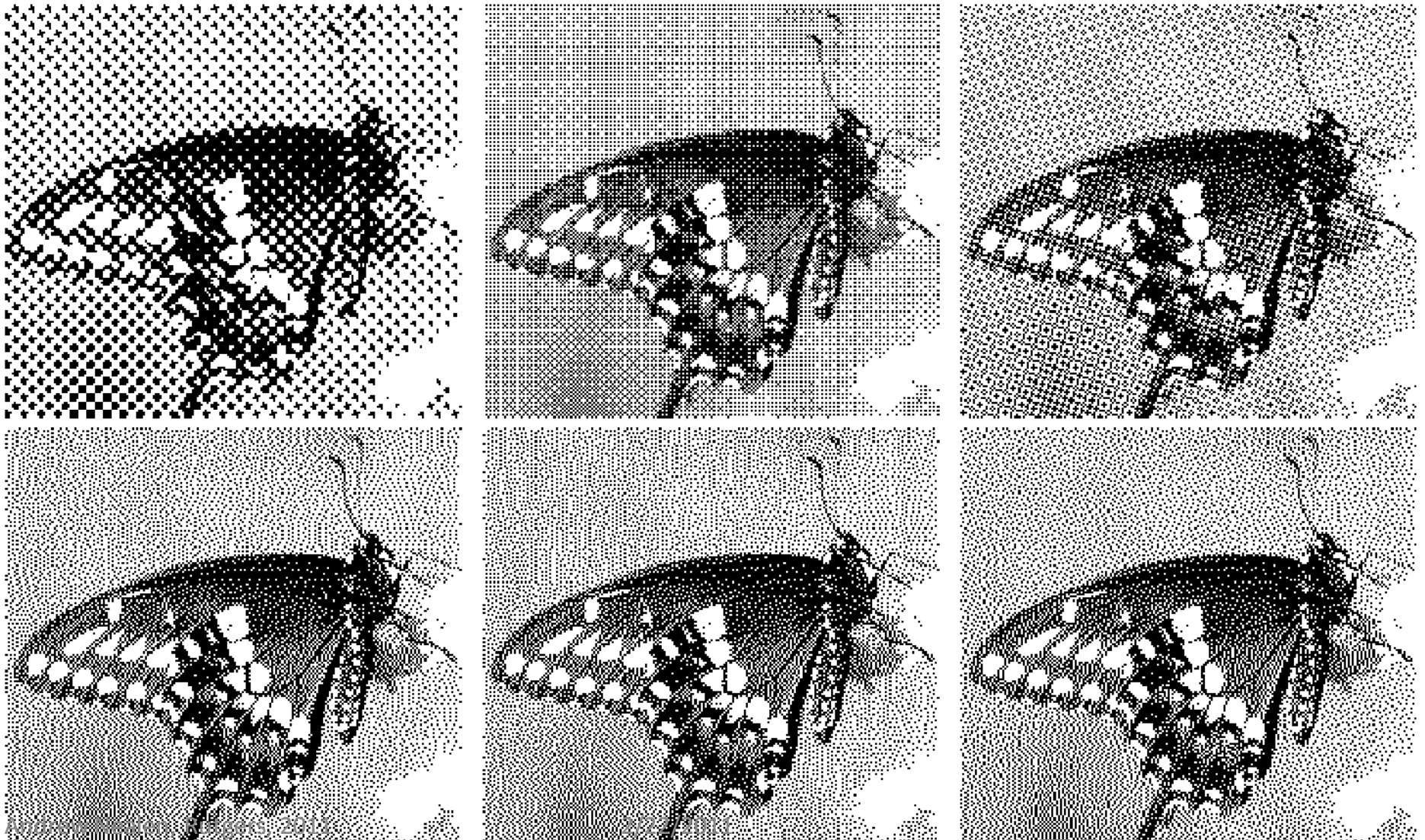
- Importance map created according to application needs



# Interactive geometry remeshing

[Alliez et al., SIGGRAPH 2002]

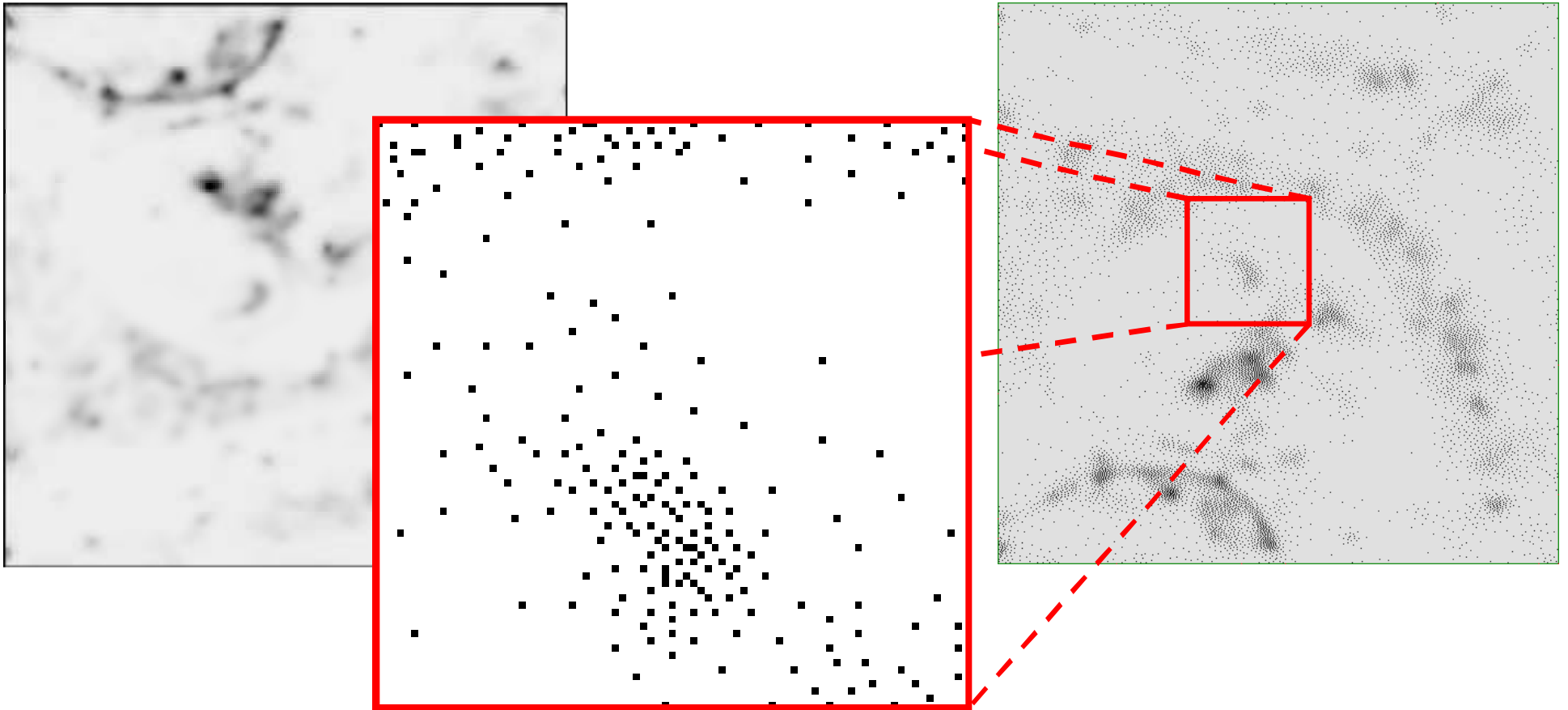
- Importance map is sampled by points – as in halftoning



# Interactive geometry remeshing

[Alliez et al., SIGGRAPH 2002]

- Importance map is sampled by points – as in halftoning (error diffusion process)

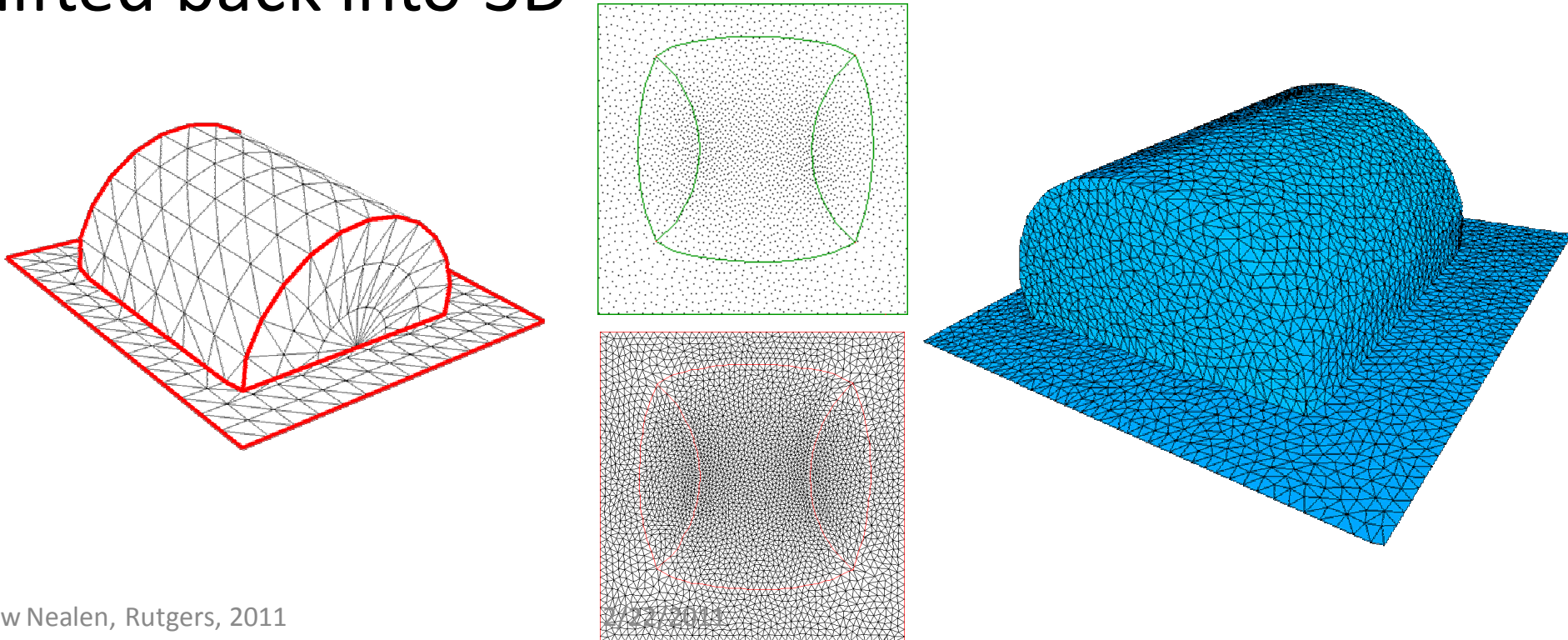




# Interactive geometry remeshing

[Alliez et al., SIGGRAPH 2002]

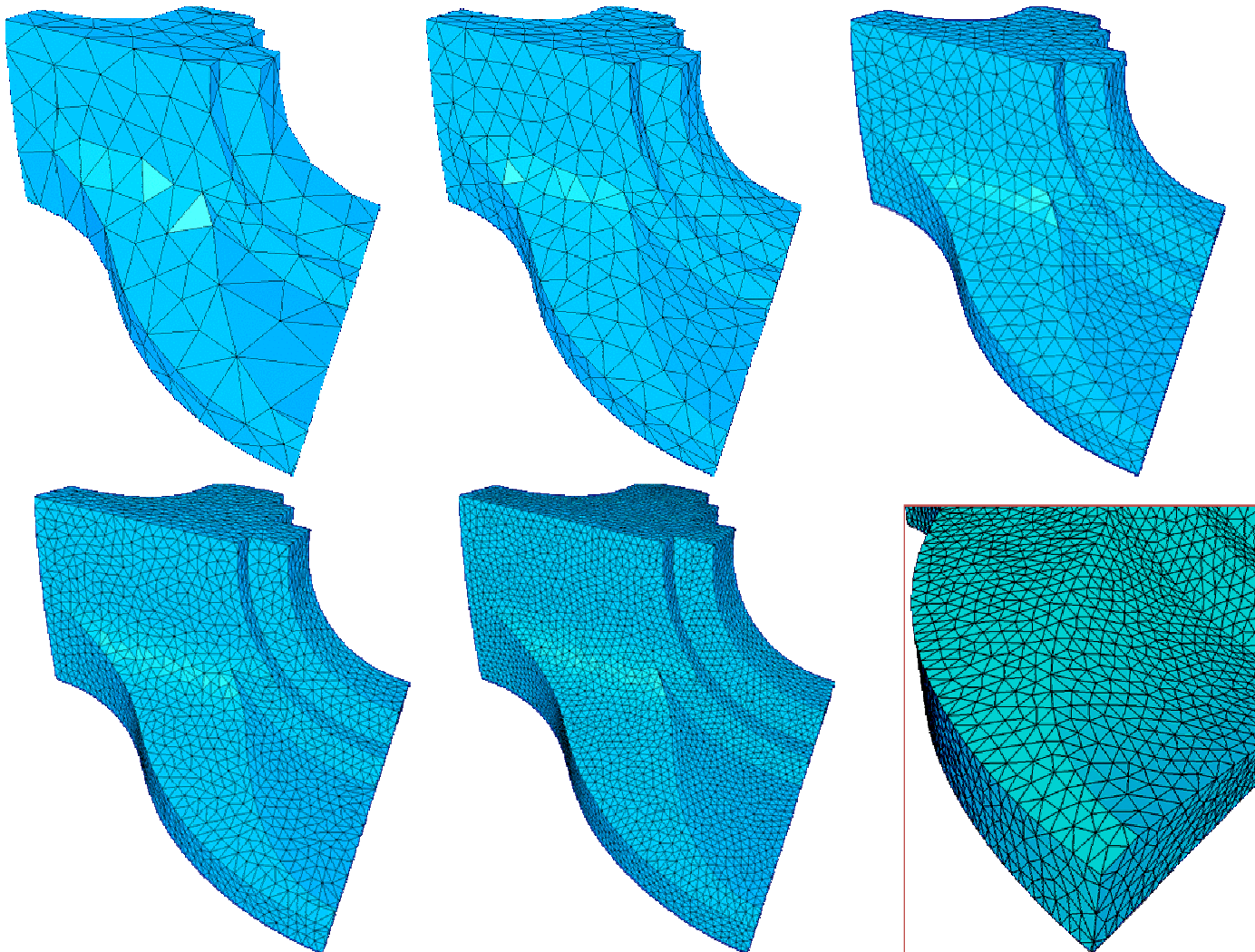
- Sampled points are triangulated using Delaunay
- Using the parameterization, the 2D points are lifted back into 3D



# Interactive geometry remeshing

[Alliez et al., SIGGRAPH 2002]

- More results

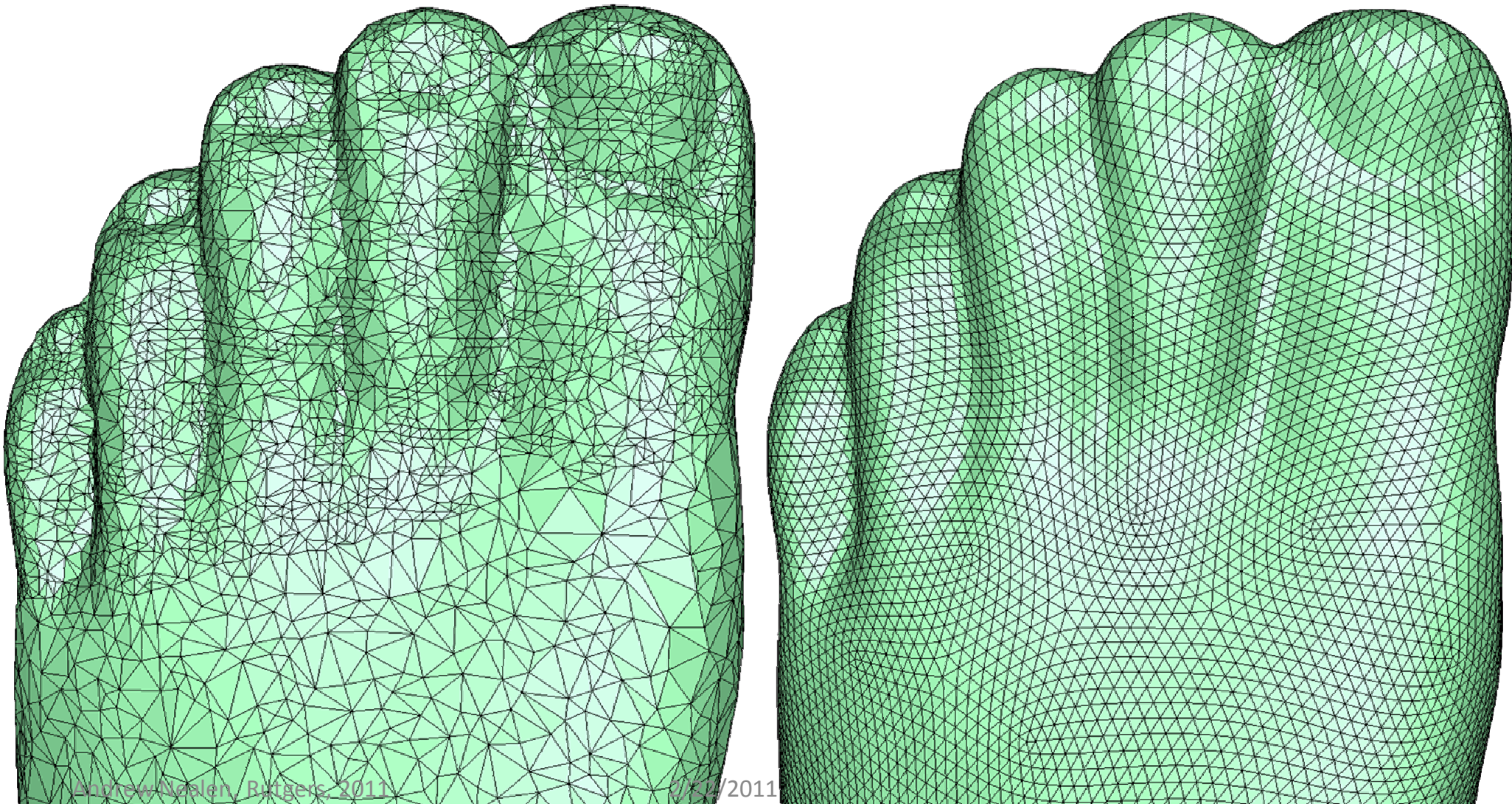




# Interactive geometry remeshing

[Alliez et al., SIGGRAPH 2002]

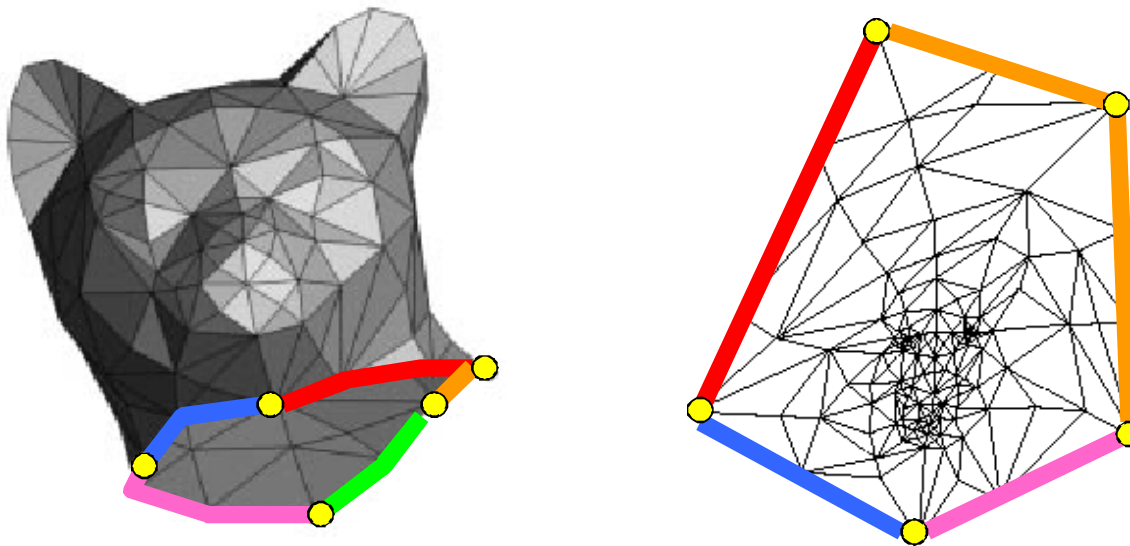
- More results



# Computing parameterizations

# Convex mapping (Tutte, Floater)

- Works for meshes equivalent to a disk
- First, we map the boundary to a convex polygon
- Then we find the inner vertices positions



$\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$  – inner vertices;  $\mathbf{v}_n, \mathbf{v}_{n+1}, \dots, \mathbf{v}_N$  – boundary vertices

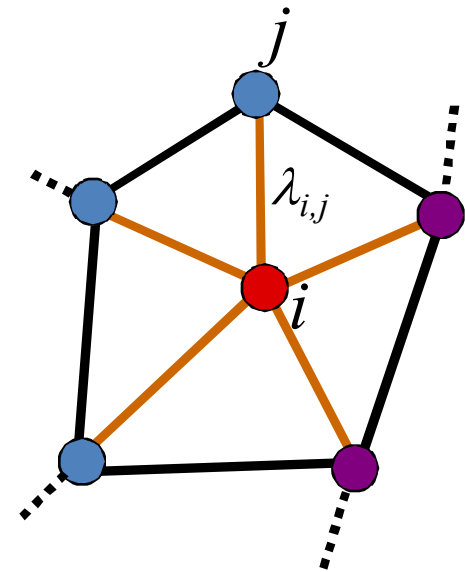
# Inner vertices

- We constrain each inner vertex to be a weighted average of its neighbors:

$$\mathbf{v}_i = \sum_{j \in N(i)} \lambda_{i,j} \mathbf{v}_j, \quad i = 1, 2, \dots, n$$

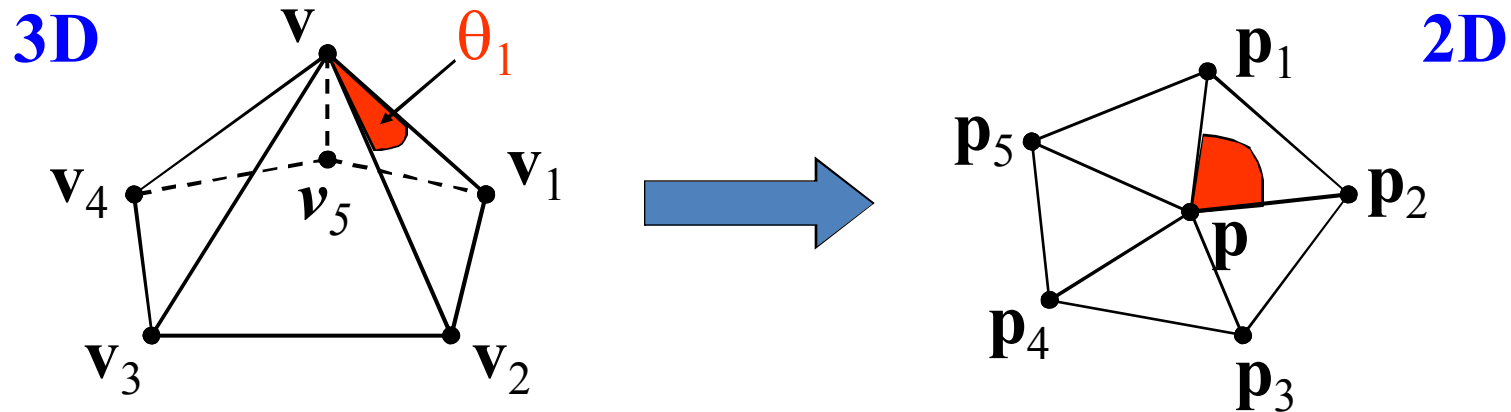
$$\lambda_{i,j} = \begin{cases} 0 & i, j \text{ are not neighbors} \\ > 0 & (i, j) \in E \text{ (neighbours)} \end{cases}$$

$$\sum_{j \in N(i)} \lambda_{i,j} = 1$$





# Shape preserving weights



To compute  $\lambda_1, \dots, \lambda_5$ , a local embedding of the patch is found:

$$1) \quad \|\mathbf{p}_j - \mathbf{p}\| = \|\mathbf{v}_j - \mathbf{v}\|$$

$$2) \quad \text{angle}(\mathbf{p}_j, \mathbf{p}, \mathbf{p}_{j+1}) = (2\pi / \sum \theta_j) \text{angle}(\mathbf{v}_j, \mathbf{v}, \mathbf{v}_{j+1})$$

$$\exists \lambda_i, \begin{cases} \mathbf{p} = \sum \lambda_i \mathbf{p}_i \\ \lambda_i > 0 \\ \sum \lambda_i = 1 \end{cases} \Rightarrow \text{use these } \lambda \text{ as edge weights.}$$



# Linear system of equations

- A **unique** solution always exists
- Important: the solution is legal (**bijjective**). The proof is not trivial.
- The system is **sparse**, thus fast numerical solution is possible
- Numerical problems (because the vertices in the middle might get very dense...)

# Conformal mapping

Also called harmonic

- Another way to find inner vertices
- Strives to preserve angles (conformal)
- We treat the mesh as a system of **springs**.
- Define spring energy:

$$E_{\text{harm}} = \frac{1}{2} \sum_{(i,j) \in E} k_{i,j} \|\mathbf{v}_i - \mathbf{v}_j\|^2$$

where  $\mathbf{v}_i$  are the flat position (remember that the boundary vertices  $\mathbf{v}_n, \mathbf{v}_{n+1}, \dots, \mathbf{v}_N$  are constrained).

# Energy minimization – least squares

- We want to find flat positions that minimize the energy.
- Solve the linear least squares problem!

$$\mathbf{v}_i = (x_i, y_i)$$

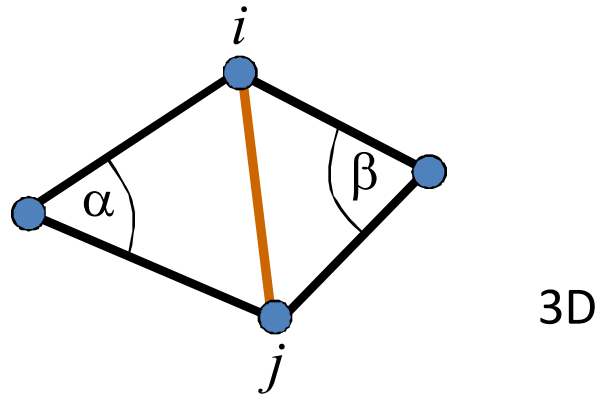
$$\begin{aligned} E_{\text{harm}}(x_1, \dots, x_n, y_1, \dots, y_n) &= \frac{1}{2} \sum_{(i,j) \in E} k_{i,j} \|\mathbf{v}_i - \mathbf{v}_j\|^2 = \\ &= \frac{1}{2} \sum_{(i,j) \in E} k_{i,j} \left( (x_i - x_j)^2 + (y_i - y_j)^2 \right). \end{aligned}$$

$E_{\text{harm}}$  is function of  $2n$  variables

# The spring constants $k_{i,j}$

- The weights  $k_{i,j}$  are chosen to minimize angle distortion:

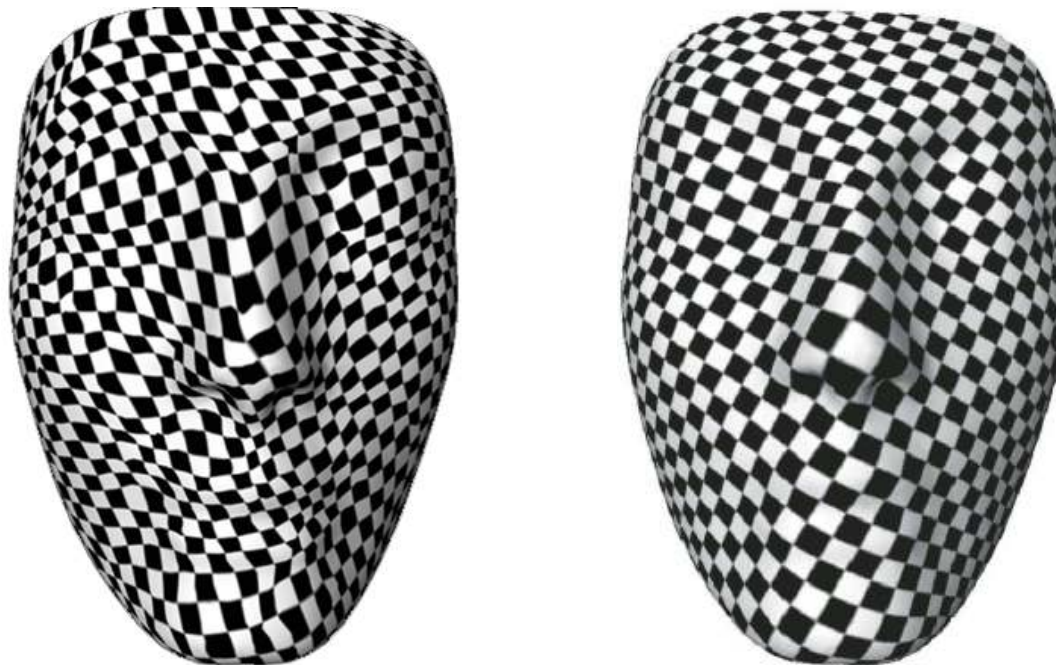
$$k_{i,j} = \cot \alpha + \cot \beta$$



- The matrix of the normal equations is the **cotan Laplacian** (without area weighting)

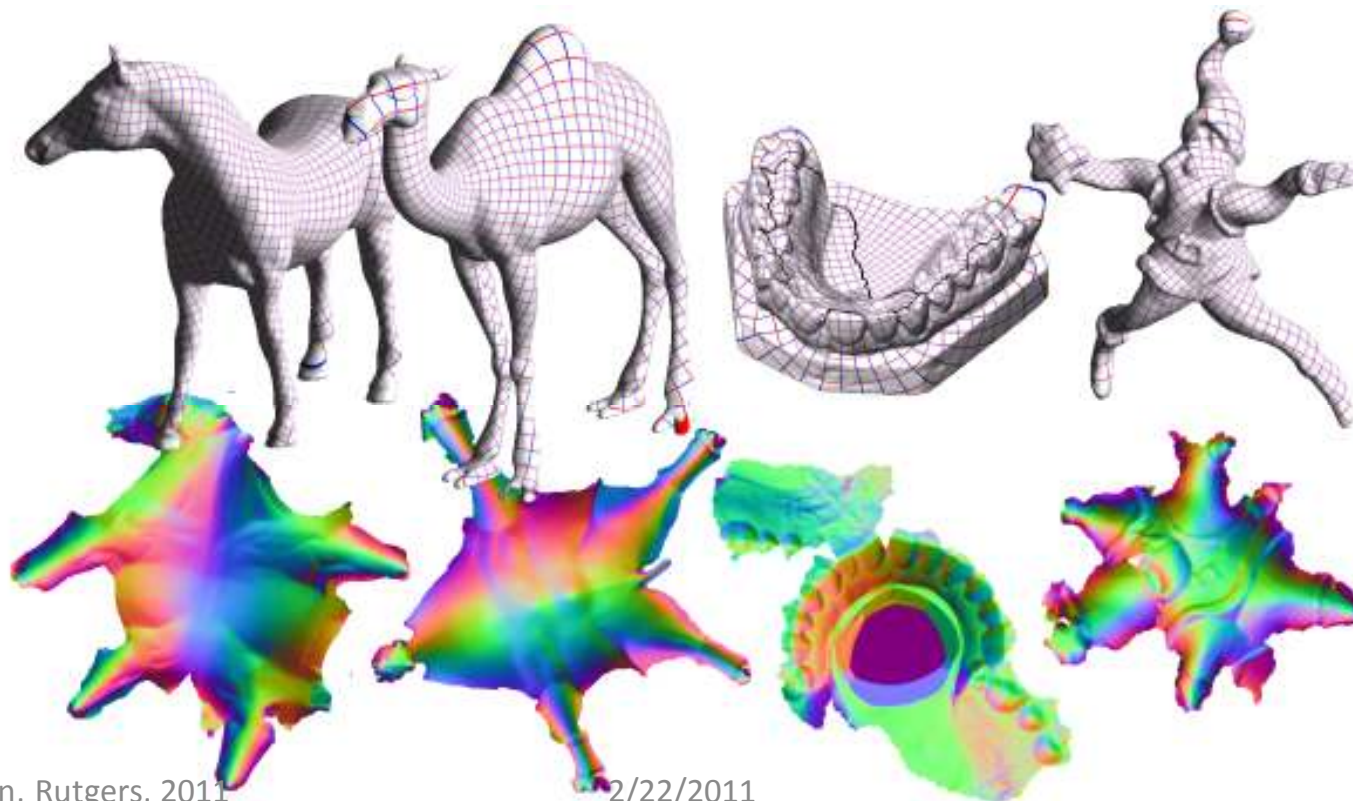
# Discussion

- The results of **harmonic** mapping are **better** than those of **convex** mapping (local area and angles preservation).
- But: the mapping is **not always legal** (the weights can be negative for badly-shaped triangles...)



# Discussion

- Both mappings have the problem of **fixed boundary** – it constrains the minimization and causes **distortion**.
- More advanced methods do not require boundary conditions (see references on the website).



ABF++ method,  
Sheffer et al.