

# Processing Point Set Surfaces

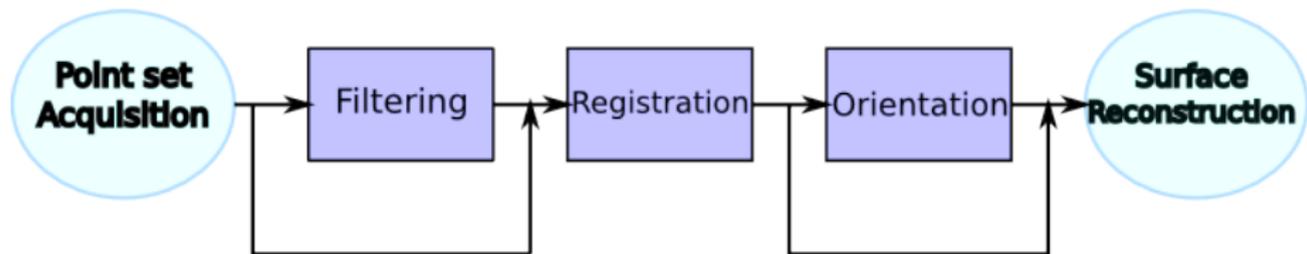
Julie Digne



LIRIS - Équipe GeoMod - CNRS

12/09/2018

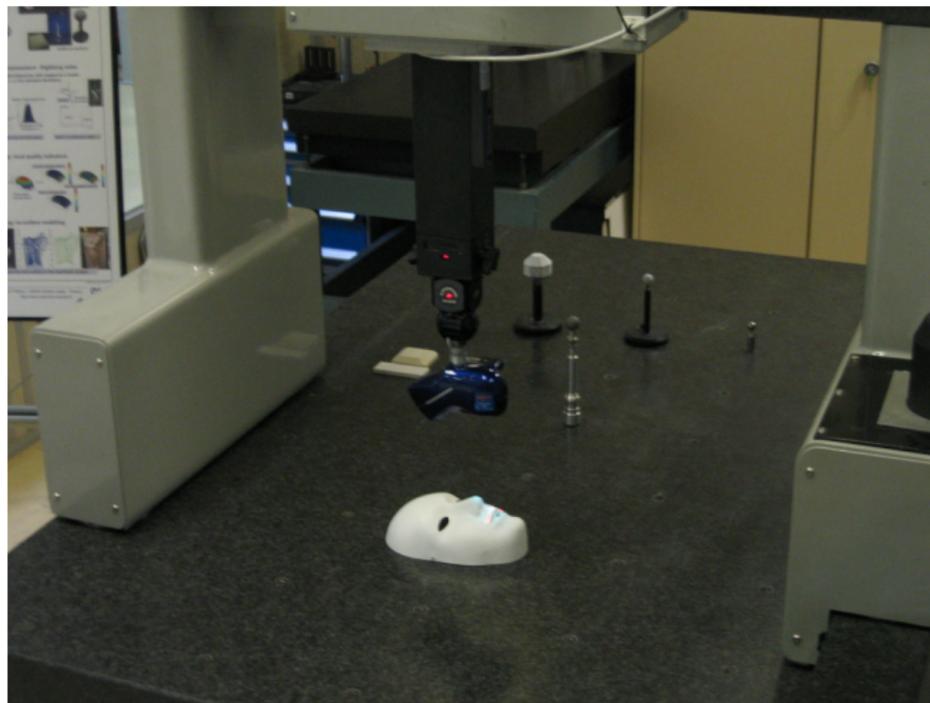
# Introduction



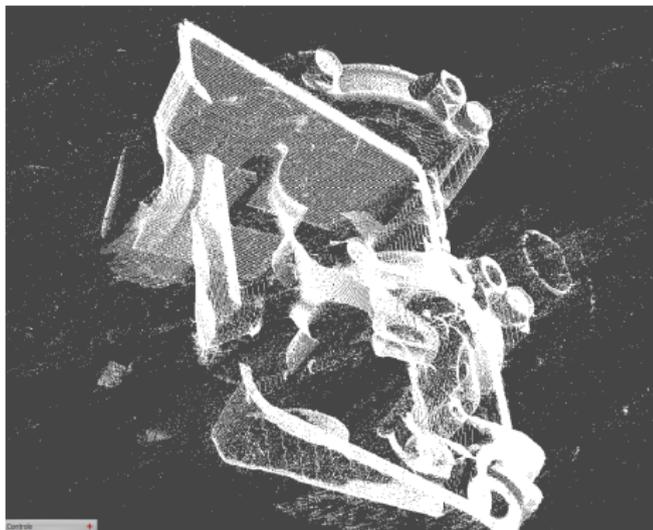
- Each of these blocks is a challenge!
- Sampling of the existing methods

Thanks to Pierre Alliez and Misha Kazhdan for providing some of the slides.

# Introduction: Acquisition of point clouds



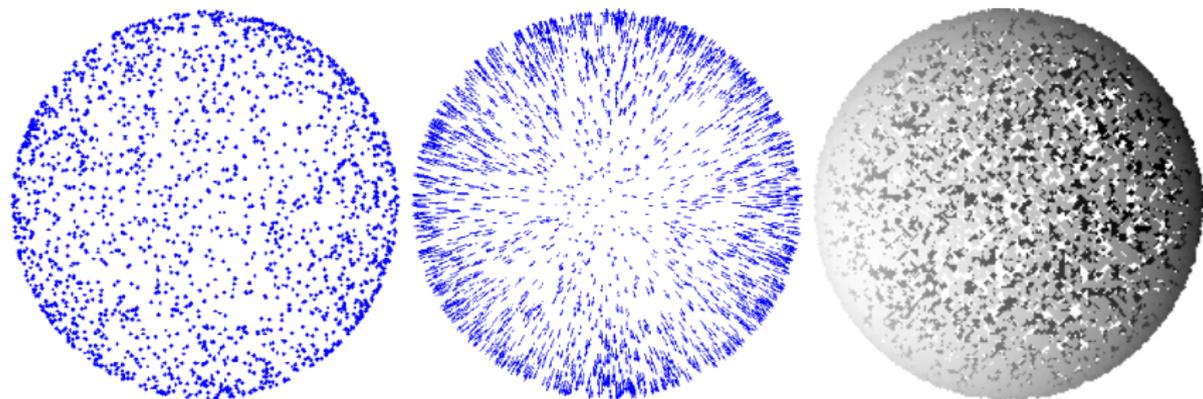
## 3d surfaces typical challenges: Cleaning the physical measure



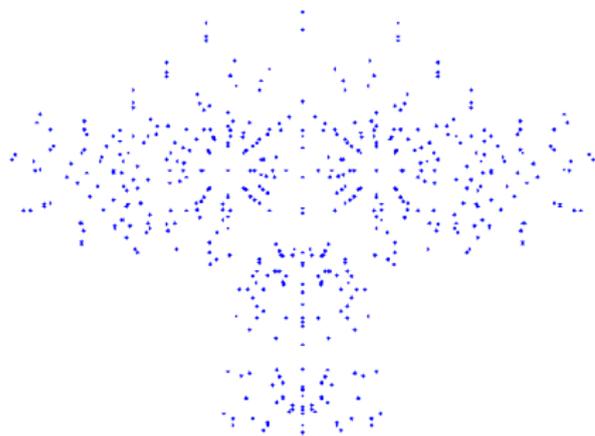
## 3d surfaces typical challenges: Registering and merging scans



## 3d surfaces typical challenges: Orienting the point set

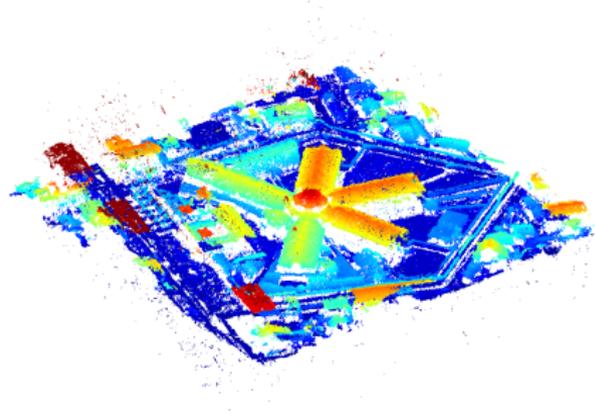
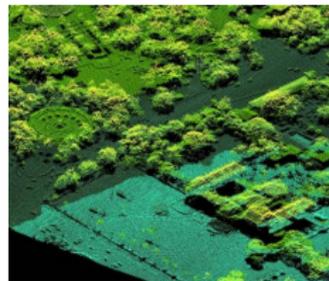
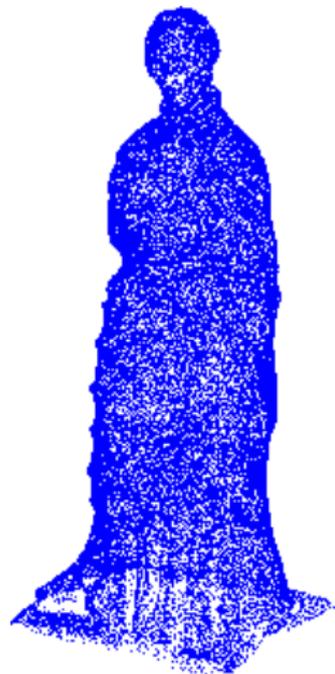


# 3d surfaces typical challenges: Building a mesh from a set of points



Shape courtesy of *blender*

# Results of the acquisition process



# Outline

1 Geometry Processing basics

2 Surface reconstruction: Methods from Computational Geometry

3 Surface Reconstruction: Potential Field Methods

# Riemannian surface definition

## Riemann Surface

A Riemann surface  $S$  is a separated (Hausdorff) topological space endowed with an atlas: For every point  $x \in S$  there is a neighborhood  $V(x)$  containing  $x$  homeomorphic to the unit disk of the complex plane. These homeomorphisms are called charts. The transition maps between two overlapping charts are required to be holomorphic.

# Riemannian surface definition

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- At each point of the surface one can find an intrinsic parameterization  $T(u, v)$ .

# Riemannian surface definition

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- At each point of the surface one can find an intrinsic parameterization  $T(u, v)$ .
- We restrict this small introduction to surfaces of dimension 2 embedded in  $\mathbb{R}^3$ .

Let  $\mathcal{S}$  be a smooth surface embedded in  $\mathbb{R}^3$ , parameterized over a bounded domain  $\Omega \subset \mathbb{R}^2$  with parameterization:

$$\mathbf{x}(u, v) = \begin{pmatrix} x(u, v) \\ y(u, v) \\ z(u, v) \end{pmatrix}$$

- Define  $\mathbf{x}_u(u_0, v_0) = \frac{\partial \mathbf{x}}{\partial u}(u_0, v_0)$
- $\mathbf{x}_v(u_0, v_0) = \frac{\partial \mathbf{x}}{\partial v}(u_0, v_0)$  is tangent to the curve on the surface defined by  $s \rightarrow \mathbf{x}(u_0, v_0 + s)$ .
- $\mathbf{x}_u(u_0, v_0)$  and  $\mathbf{x}_v(u_0, v_0)$  are two vectors tangent to the surface  $\mathcal{S}$ .
- If the parameterization is *regular*, ( $\|\mathbf{x}_u \times \mathbf{x}_v\| \neq 0$ ), these vectors span the tangent plane to the surface at  $\mathbf{x}(u_0, v_0)$ .

## Normal computation

- If the parameterization is *regular*, the normal to the surface is computed as:

$$\mathbf{n} = \frac{x_u \times x_v}{\|x_u \times x_v\|}$$

- *Directional derivatives* Given a direction  $w$  in the tangent plane, the directional derivative of  $\mathcal{S}$  in direction  $w$  is the tangent to the curve  $C_w(t) = x(u_0, v_0 + tw)$

# First Fundamental Form

## Definition (First Fundamental Form)

The **First Fundamental Form** is defined as  $I = J \cdot J^T$  ( $2 \times 2$  matrix), or equivalently:

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

where  $J$  is the Jacobian matrix of  $\mathcal{S}$ :  $J = (\mathbf{x}_u \quad \mathbf{x}_v)$  ( $3 \times 2$  matrix).

## Why is the first fundamental useful?

- If  $\mathbf{a}$  is a vector of  $\Omega$ ,  $\tilde{\mathbf{a}}$  its corresponding tangent vector, then:  
 $\|\mathbf{a}\|^2 = \tilde{\mathbf{a}}^T J^T J \tilde{\mathbf{a}} = \tilde{\mathbf{a}}^T I \tilde{\mathbf{a}}$
- Compute the length of a curve  $C(t) = \mathbf{x}(u(t), v(t))$ :

$$l_{[a,b]} = \int_{[a,b]} (u_t v_t) I (u_t v_t)^T$$

- The Surface Area  $\mathcal{A} = \int \int_{\mathcal{A}} \sqrt{\det I} du dv$

## Second Fundamental Form

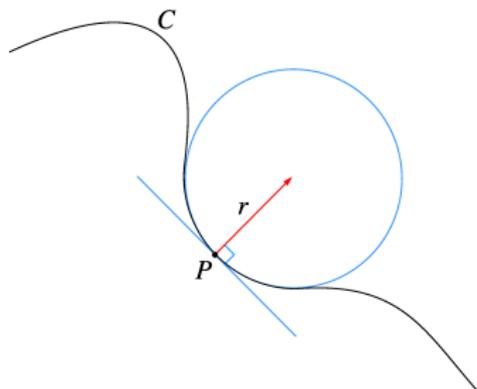
### Definition (Second Fundamental Form)

The **Second fundamental form** characterizes the way a surface bends:

$$II = \begin{pmatrix} x_{uu}^T \cdot n & x_{uv}^T \cdot n \\ x_{uv}^T \cdot n & x_{vv}^T \cdot n \end{pmatrix}$$

It is a quadratic form on the tangent plane to the surface.

## As a starter: curvature of a curve



# Normal Curvature

## Definition (Normal Curvature)

For each tangent vector  $\mathbf{t}$  at a point  $p$  of the surface, the normal curvature is defined as:

$$\kappa_n(\mathbf{t}) = \frac{\mathbf{t}^T \cdot \mathbf{II} \cdot \mathbf{t}}{\mathbf{t}^T \cdot \mathbf{I} \cdot \mathbf{t}}$$

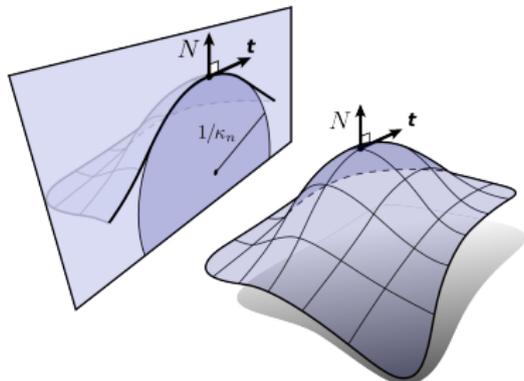


Image from Crane et al. 2013

- The normal curvature varies with  $\mathbf{t}$ .

# Principal curvatures and directions

## Definition (Principal curvature)

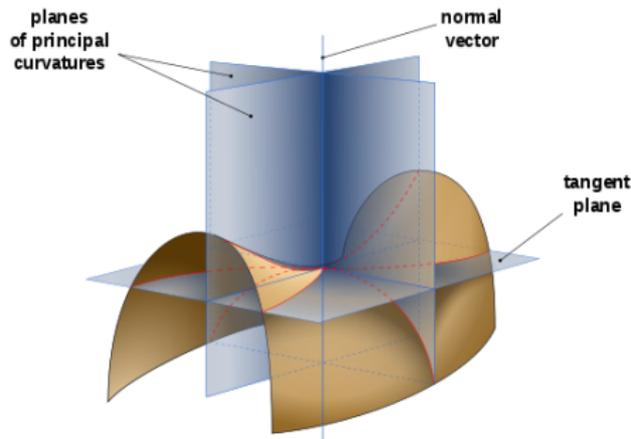
Let  $\kappa_1$  be the minimum of  $\kappa_n(\mathbf{t})$  (normal curvature at  $p$ ) and  $\kappa_2$  be the maximum of  $\kappa_n(\mathbf{t})$ .  $\kappa_1$  and  $\kappa_2$  are called the *principal curvatures* of the surface at  $p$ .

- If  $\kappa_1 \neq \kappa_2$ , the two associated tangent vectors  $\mathbf{t}_1$  and  $\mathbf{t}_2$  are called principal directions and they are orthogonal
- $\kappa_1, \kappa_2, \mathbf{t}_1, \mathbf{t}_2$  are the eigenvalues and eigenvectors of the *Shape Operator*:

$$S = I^{-1} \cdot II$$

# Principal curvatures and directions

- If  $\kappa_1 = \kappa_2$ , the point is called an umbilic or umbilical point and the surface is locally spherical.
- $\kappa_n(\mathbf{t}) = \kappa_1 \cos^2 \phi + \kappa_2 \sin^2 \phi$  (Euler)  
( $\phi$  is the angle between  $\mathbf{t}_1$  and  $\mathbf{t}$ )
- $(\mathbf{t}_1, \mathbf{t}_2, \mathbf{n})$  is called the local intrinsic coordinate system.



# Curvature Tensor

## Definition (Curvature Tensor)

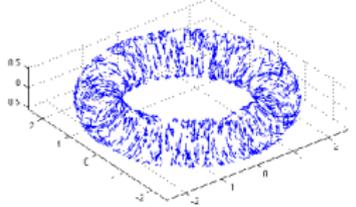
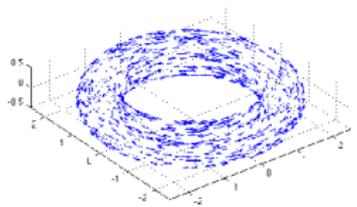
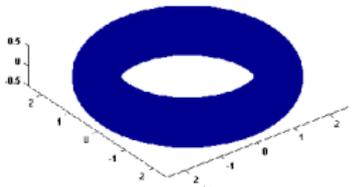
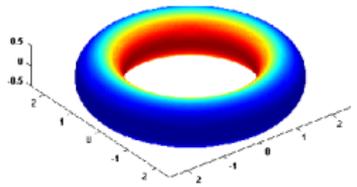
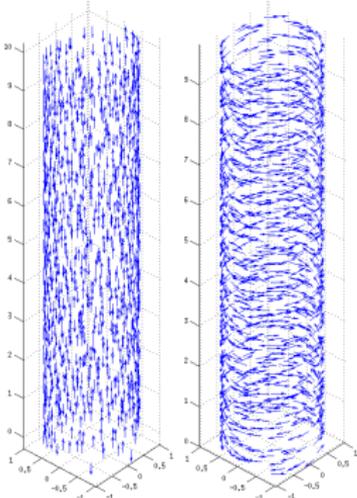
The **Curvature Tensor** is a symmetric  $3 \times 3$  matrix  $C$  whose eigenvalues are  $(\kappa_1, \kappa_2, 0)$  and corresponding eigenvectors  $(\mathbf{t}_1, \mathbf{t}_2, \mathbf{n})$ . More precisely:

$$C = PDP^{-1}$$

where  $P$  is the matrix whose columns are  $\mathbf{t}_1, \mathbf{t}_2, \mathbf{n}$  and  $D$  is a diagonal matrix with diagonal values  $\kappa_1, \kappa_2, 0$ .

- **Mean curvature** average of the normal curvature:  $H = \frac{\kappa_1 + \kappa_2}{2}$
- **Gaussian curvature** product of the principal curvature  $K = \kappa_1 \cdot \kappa_2$

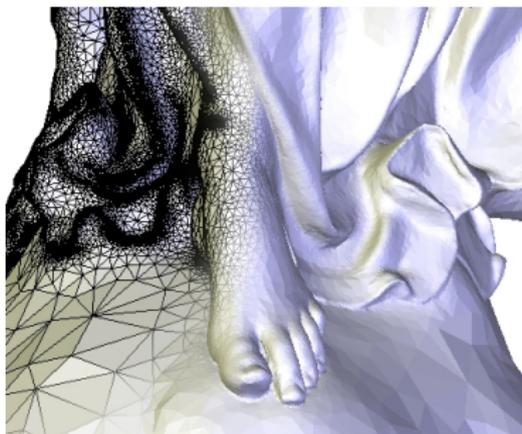
# Examples



# Representing manifold surfaces

## Mesh Surface

Polygonal meshes are a piecewise linear approximation of the shape. It is a set of polygons linked together by edges.

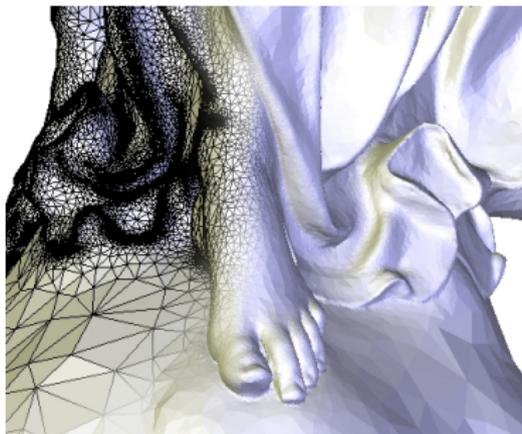


# Representing manifold surfaces

## Mesh Surface

Polygonal meshes are a piecewise linear approximation of the shape. It is a set of polygons linked together by edges.

- Triangular or quadrilateral meshes are used.



# Triangular Meshes

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## Euler Formula

Link between the number of triangles  $F$ , edges  $E$  and vertices  $V$  of a closed non-intersecting triangular mesh [Coxeter89] with genus  $g$  (number of handles in the surface).

$$V - E + F = 2(1 - g)$$

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- “Manifoldness”: at each point, the surface is locally homeomorphic to a disk (or half disk if the point lies on the boundary).

# Differential quantities estimation

## Normal estimation

Compute the normal per triangle. For each vertex compute a (possibly weighted) average of the normals of incident triangles.

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## Curvature tensor estimation

**Normal Cycles:** For each edge of the meshed surface,  $\kappa_2 = 0$  and  $\kappa_1 = \beta(e)$  is the dihedral angle between the normals of the two facets adjacent to edge  $e$ . Let:  $\bar{e} = e/\|e\|$

$$C(v) = \frac{1}{A(v)} \sum_{e \in \mathcal{N}(v)} \beta(e) \|e \cap A(v)\| \bar{e} \cdot \bar{e}^T.$$

Morvan, Cohen-Steiner 2003

# Our data: point clouds

## Point Clouds

A set of 3D coordinates  $(x_i, y_i, z_i)_{i=0 \dots N-1}$  **without any graph structure**

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## Point Clouds

A set of 3D coordinates  $(x_i, y_i, z_i)_{i=0 \dots N-1}$  **without any graph structure**

- We can still estimate differential quantities
- We need some notion of neighborhoods: **K-nearest neighbors or fixed radius neighborhood**

# Differential Quantities Estimation

## Moving Least Squares

Around each point  $p$  fit a regression surface, and estimate the  $\{Curvature, Gradient, Normal, \dots\}$  on this surface.

$$\sum_{q \in \mathcal{N}(p)} w(p, q) \|f(x_q, y_q) - z_q\|^2$$

- Deriving the first and second fundamental form from  $f$  is easy.

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## Special Cases

- Normal direction: eigenvector corresponding to the least eigenvalue of the local covariance matrix [Hoppe92, Mitra2003]
- Mean curvature: proportional to the displacement induced by projecting a point to its local regression plane [Digne2011]

$$\mathcal{P}(p) - p = -\frac{1}{4}H(p)r^2 + O(r^2)$$

# Adding a graph structure to a point cloud

## Goal

Build a surface mesh (a set of triangles glued by edges) that represents the surface.

- Interpolating/Approximating?
- Closed surface reconstruction? Boundary preserving surface reconstruction?
- Smooth/piecewise smooth surface?
- Detail preservation/representation sparsity?

Different reconstruction methods depending on the application

# Outline

1 Geometry Processing basics

2 Surface reconstruction: Methods from Computational Geometry

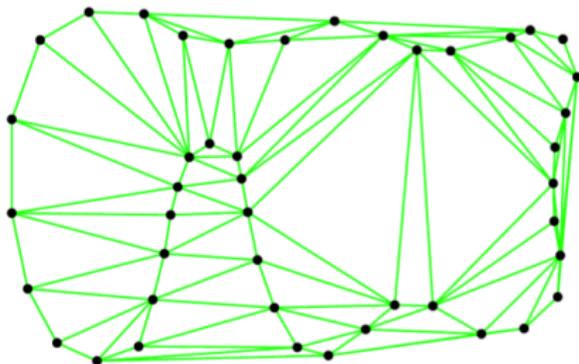
3 Surface Reconstruction: Potential Field Methods

# Methods coming from computational geometry

- Convex Hulls...
- Crust, Eigencrust, powercrust
- Delaunay filtering
- $\alpha$ -shapes
- Ball Pivoting Algorithm

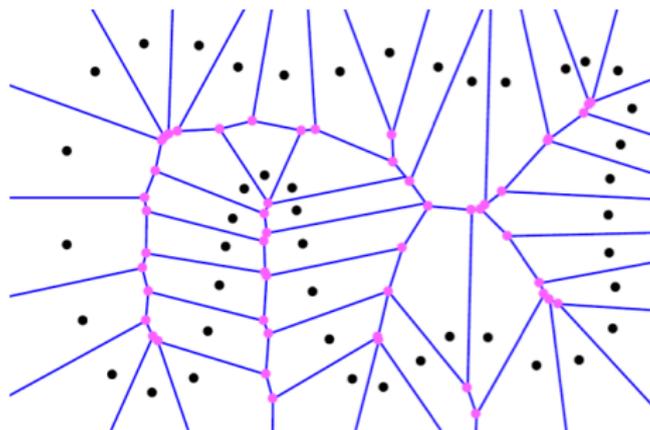
# Delaunay triangulation

- A Delaunay Triangulation of  $S$  is the set of all triangles with vertices in  $S$  whose circumscribing circle contains no other points in  $S^*$ .
- *Compactness Property*: this is a triangulation that maximizes the minimum angle



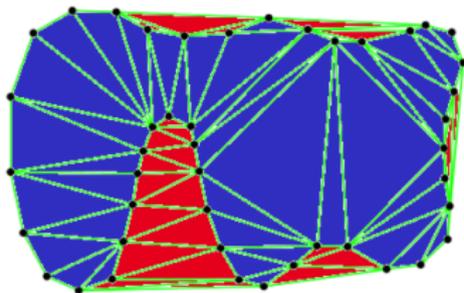
# Computational Geometry

- The Voronoi Diagram of  $S$  is a partition of space into regions  $V(p)$  ( $p \in S$ ) such that all points in  $V(p)$  are closer to  $p$  than any other point in  $S$ .
- For a vertex, we can draw an empty circle that just touches the three points in  $S$  around the vertex.
- Each Voronoi vertex is in one-to-one correspondence with a Delaunay triangle



## From Delaunay to a surface mesh

- Given a set of points, we can construct the Delaunay triangulation
- Label each triangle/tetrahedron as inside/outside
- Reconstruction = set of edges/facets that lie between inside and outside triangles/tetrahedra
- Different ways of assigning the labels [Boissonat 84], tight cocoone [Dey Goswami 2003], Powercrust [Amenta et al. 2001] Eigencrust [Kolluri et al. 2004]



# The Crust Algorithm [Amenta et al. 1998]

- If we consider the Delaunay Triangulation of a point set, the shape boundary can be described as a subset of the Delaunay edges.
- How do we determine which edges to keep?
- Two types of edges:
  - ▶ Those connecting adjacent points on the boundary
  - ▶ Those traversing the shape
- Discard those that traverse the shape

# The Crust Algorithm [Amenta et al. 1998]

In 2D:

- Given a point set  $S$  compute its Voronoi diagram and Voronoi vertices  $V$
- Compute the Delaunay triangulation of  $S \cup V$
- Keep only edges that connects points in  $S$  (eq. to keeping all edges for which there is a circle that contains the edge but no Voronoi vertices)

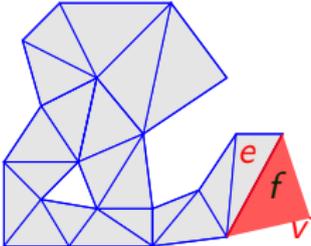
In 3D: Not all Voronoi Vertices are added to the set. Only the poles (furthest points of the Voronoi cell) are considered.

# Ball Pivoting Algorithm [Bernardini et al. 99]

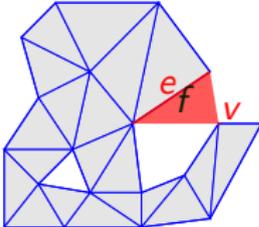
- BPA computes a triangle mesh *interpolating* a given point cloud
- Three points form a triangle if a ball of a user-specified radius  $\rho$  touches them without containing any other point
- Start with a seed triangle
- The ball pivots around an edge until it touches another point, forming another triangle
- Expand the triangulation over all edges then start with a new seed

# Different types of expansion

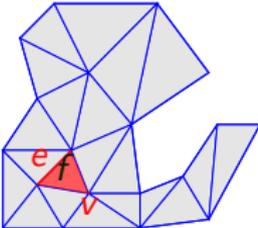
- Advancing front triangulation
- Front is a set of edges



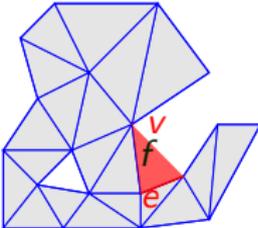
(f) Expansion case



(g) Gluing case

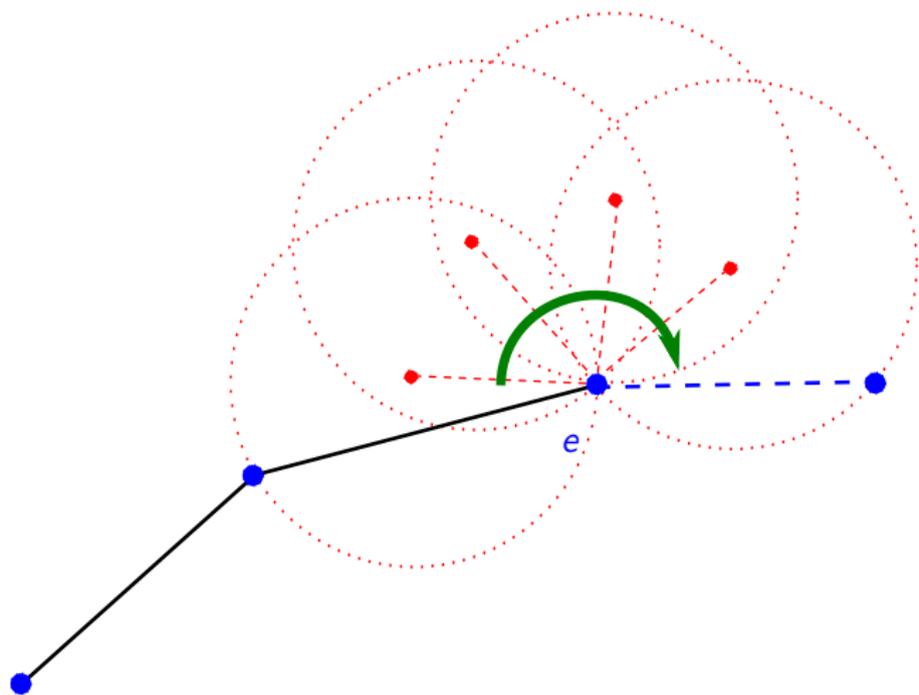


(h) Hole filling case

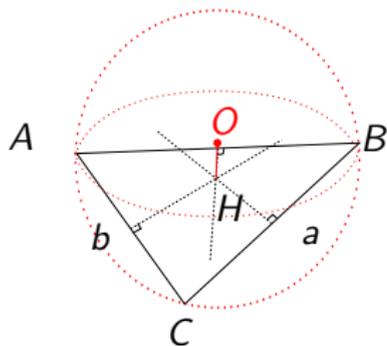
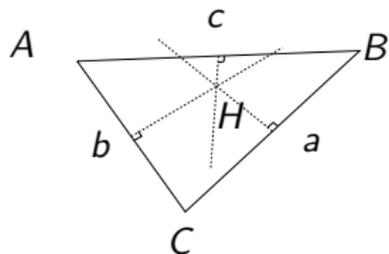


(i) Ear filling case

## Rotating the sphere



## Finding the $R$ -circumsphere



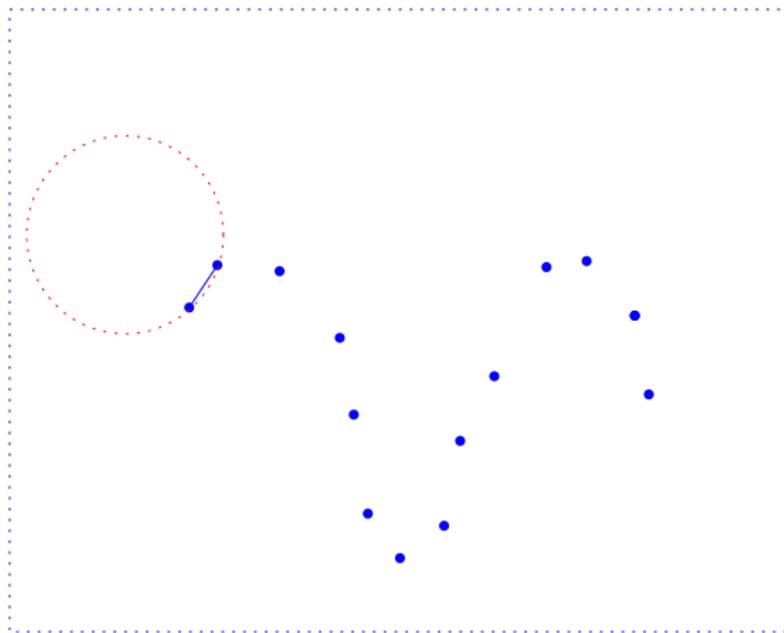
- Such a sphere exists only if  $R_b^2 - R^2 \geq 0$ .
- Let us denote by  $\mathbf{n}$  the normal to the triangle plane, oriented such that it has a nonnegative scalar product with the vertices normals. Provided  $R_b^2 - R^2 \geq 0$  (hence the sphere existence), the center  $O$  of the sphere can be found as:

$$O = H + \sqrt{R_b^2 - R^2} \cdot \mathbf{n}.$$

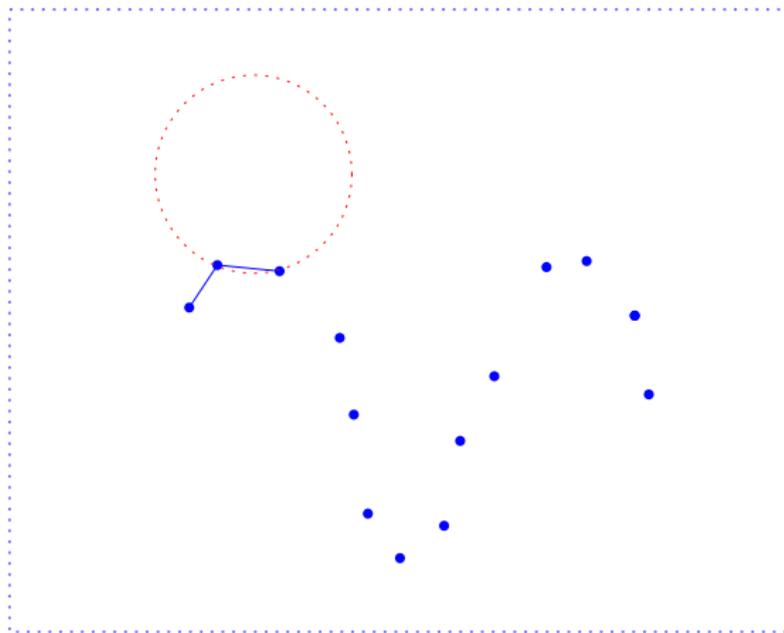
# Properties and Guarantees of the resulting mesh

- The surface is guaranteed to be self-intersection free (no triangle will intersect each other except at an edge or vertex, and at most two triangles can be adjacent to an edge).
- Normal coherence on a facet.
- For each triangle there exists an empty ball incident to the three vertices with empty interior

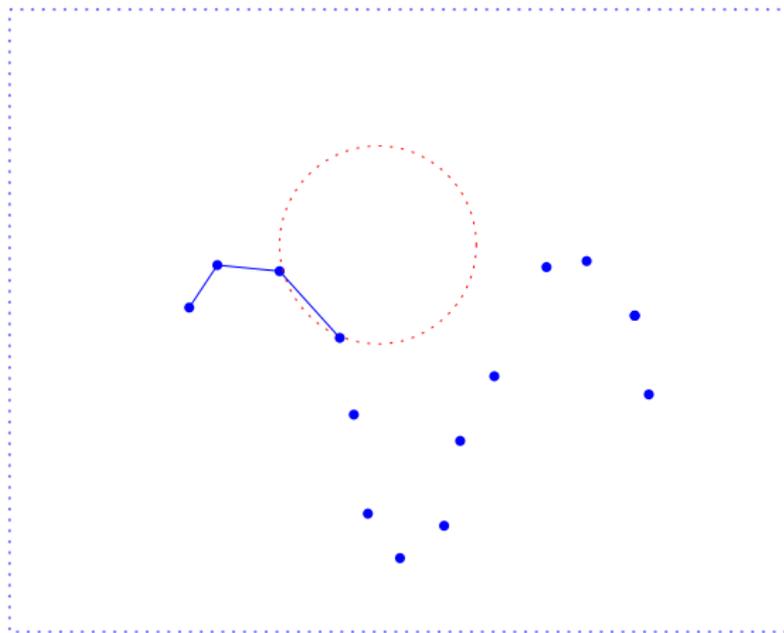
## Detailed area



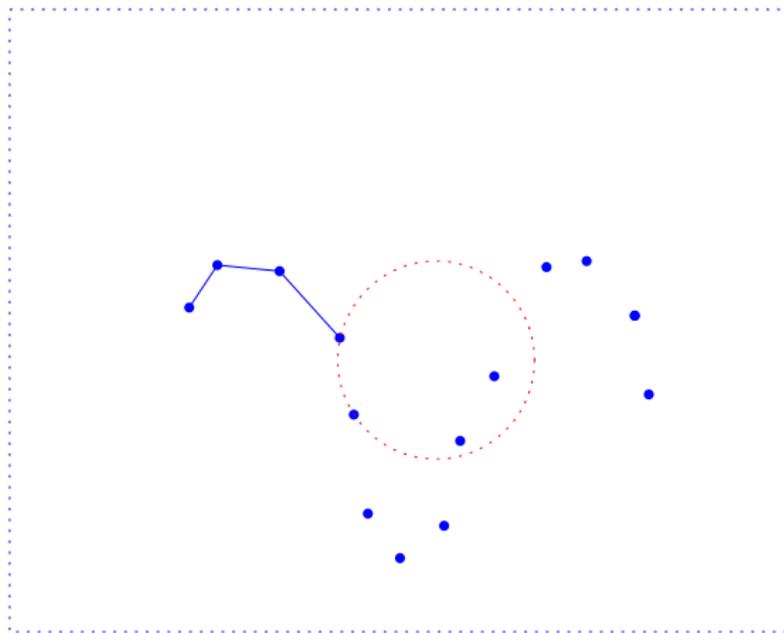
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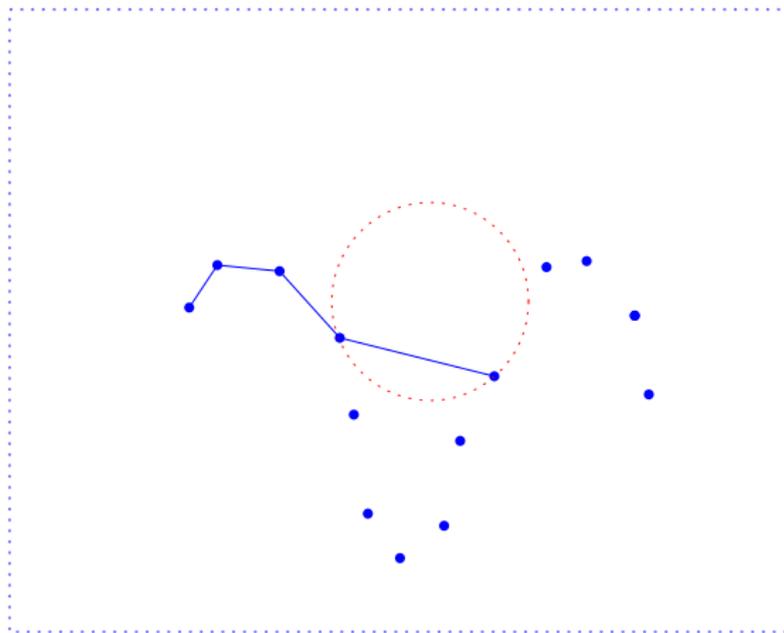
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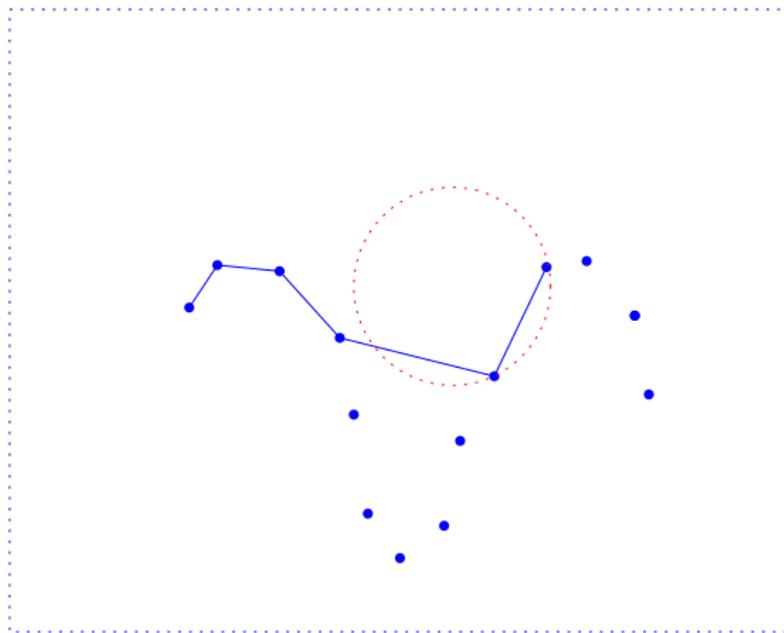
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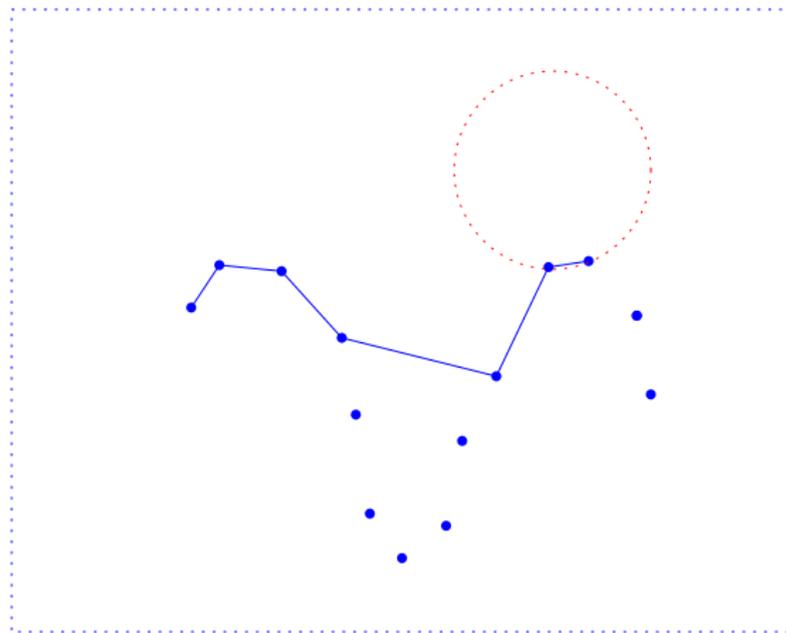
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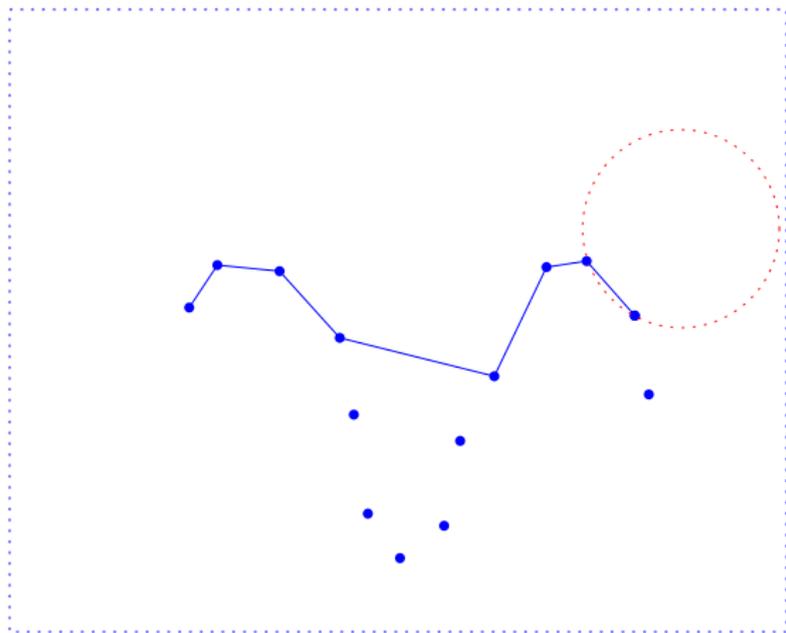
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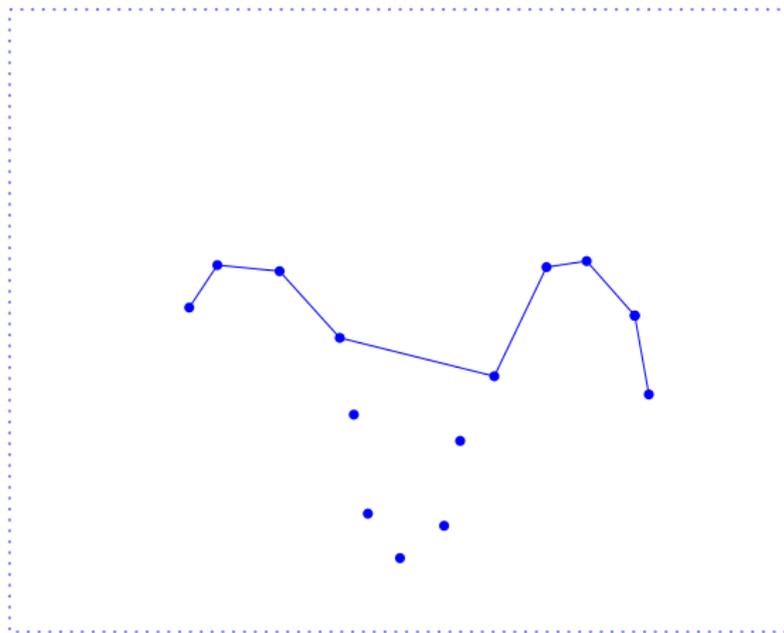
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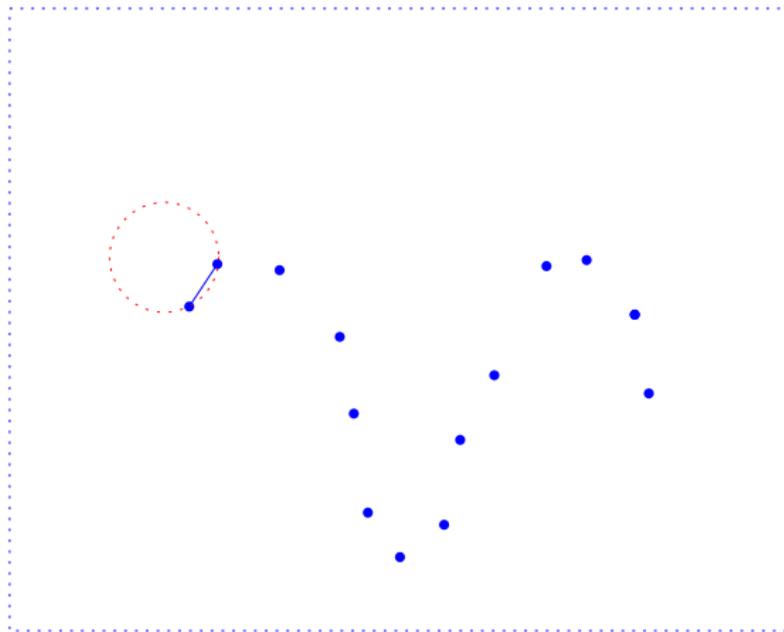
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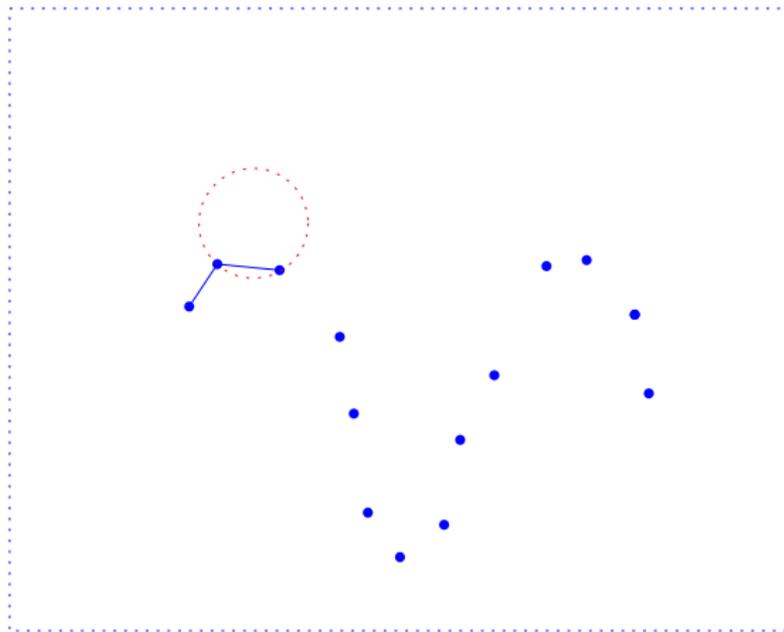
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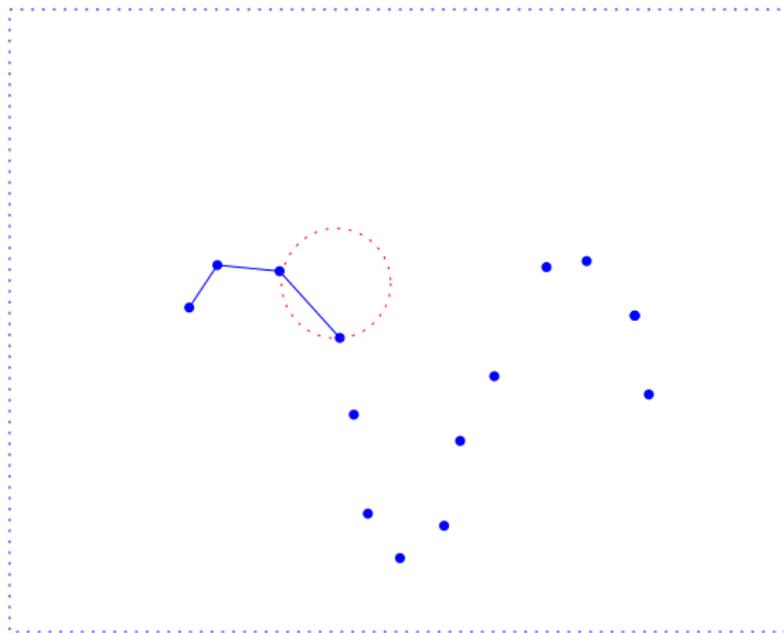
## Smaller ball radius



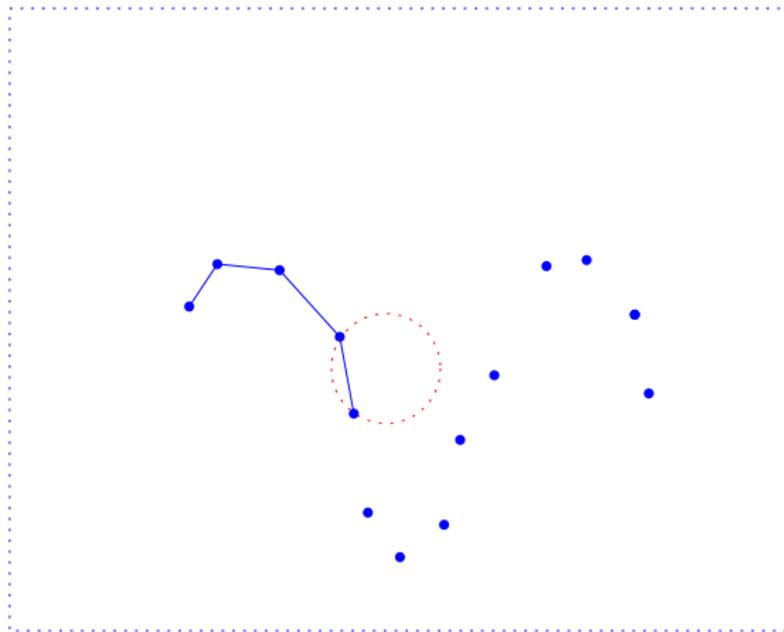
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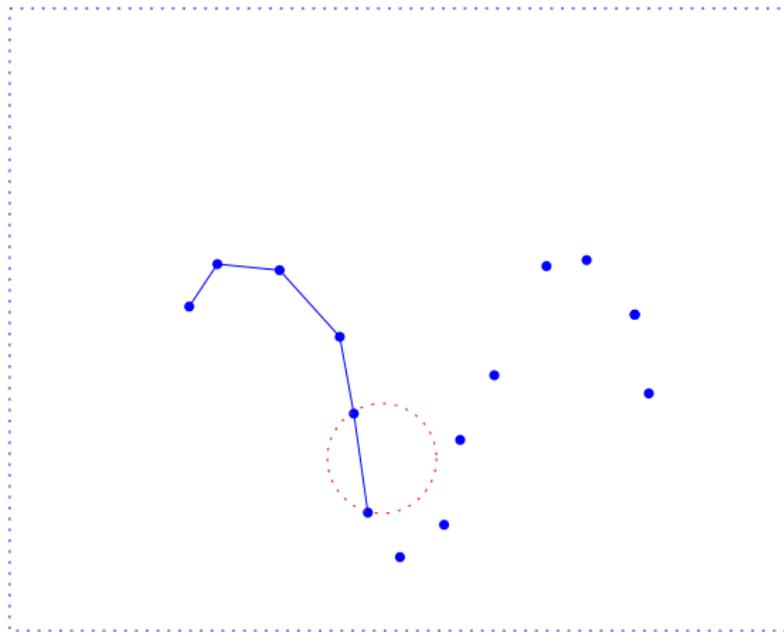
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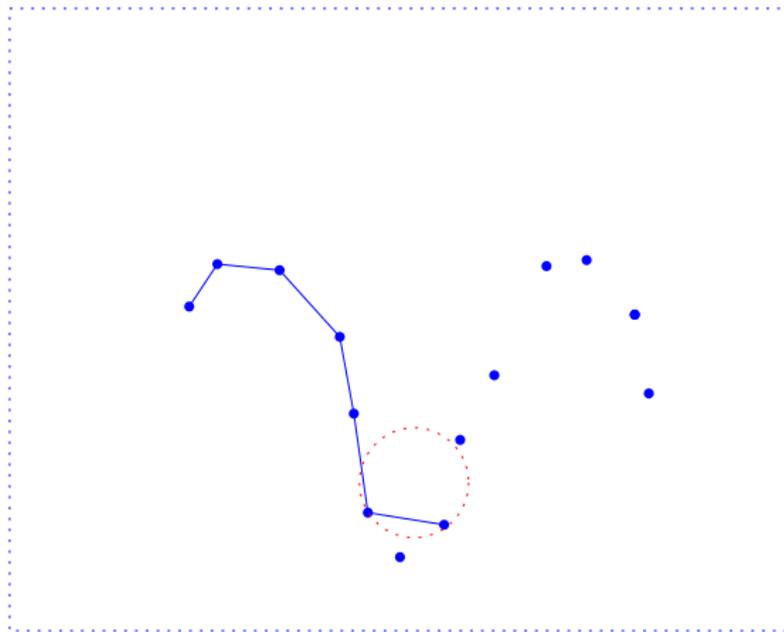
## Smaller ball radius



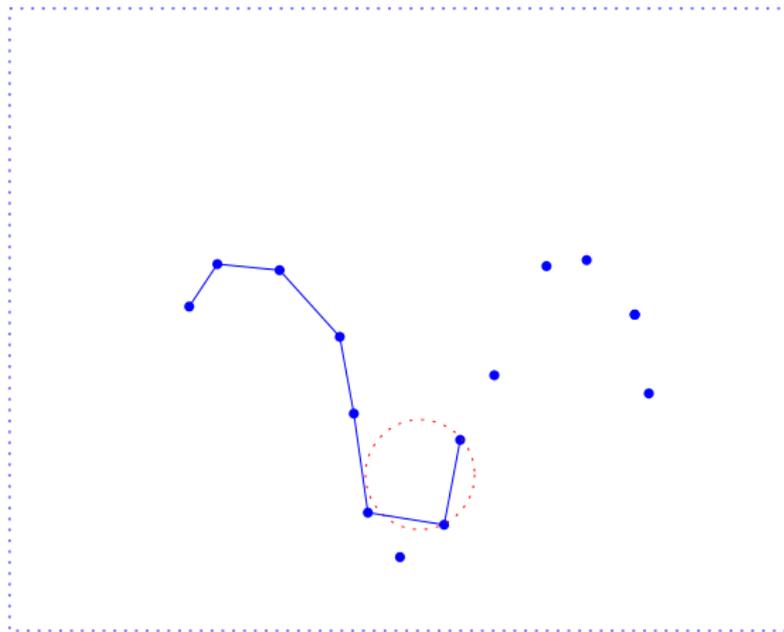
## Smaller ball radius



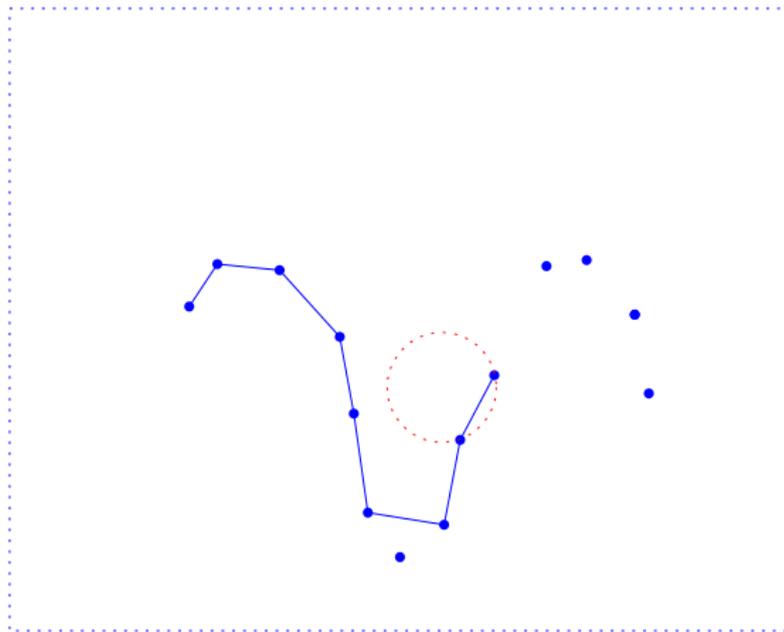
## Smaller ball radius



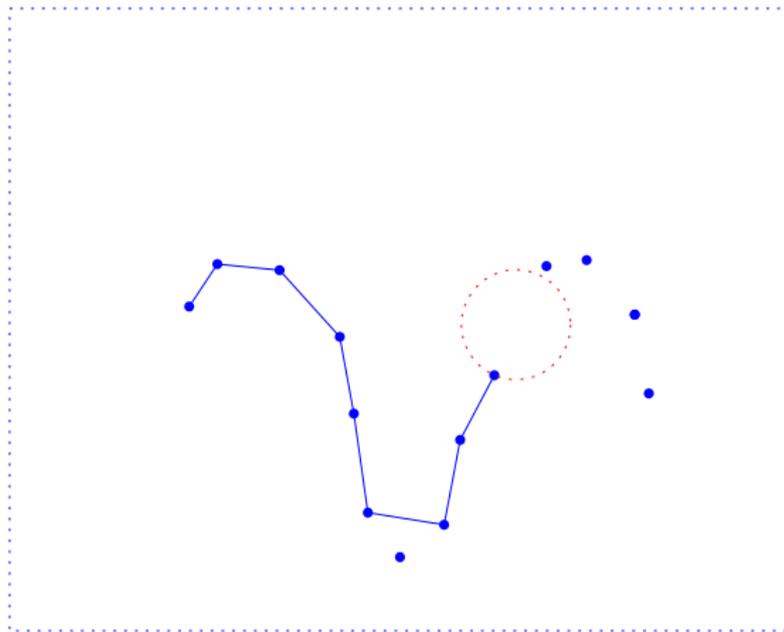
## Smaller ball radius



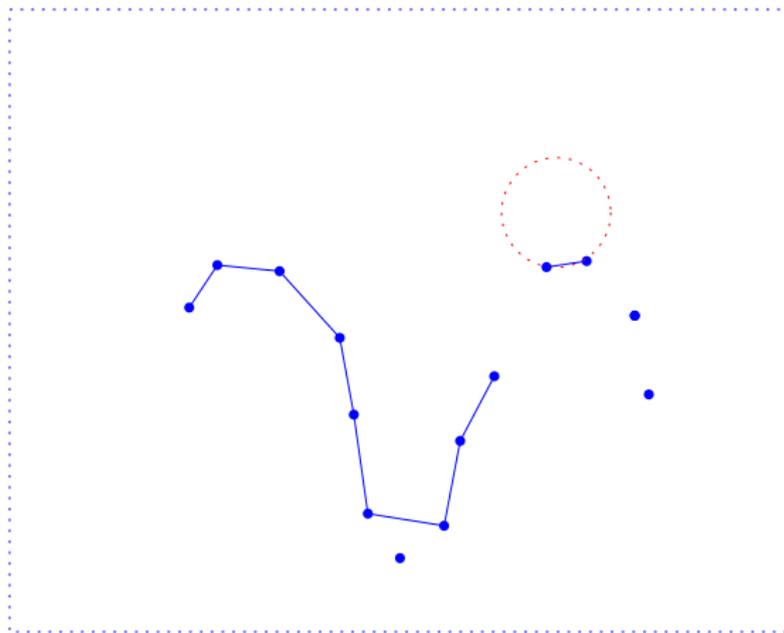
## Smaller ball radius



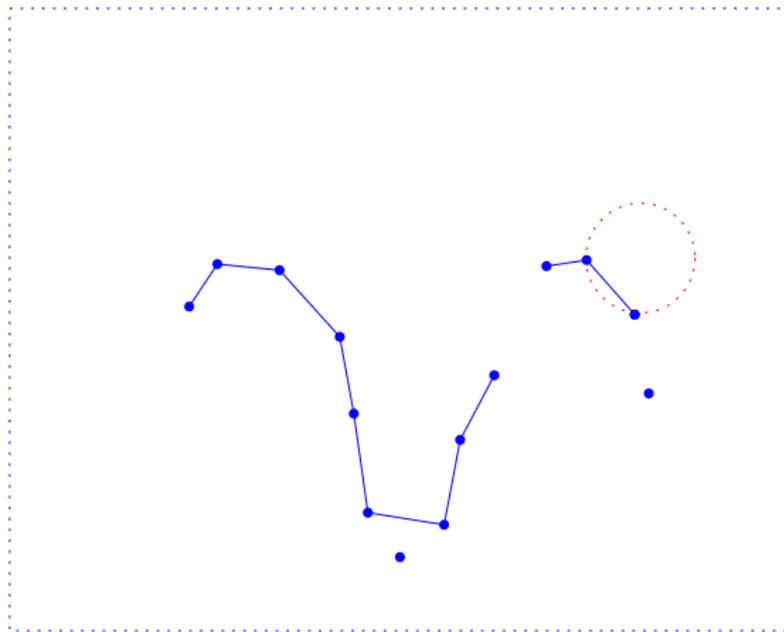
## Smaller ball radius



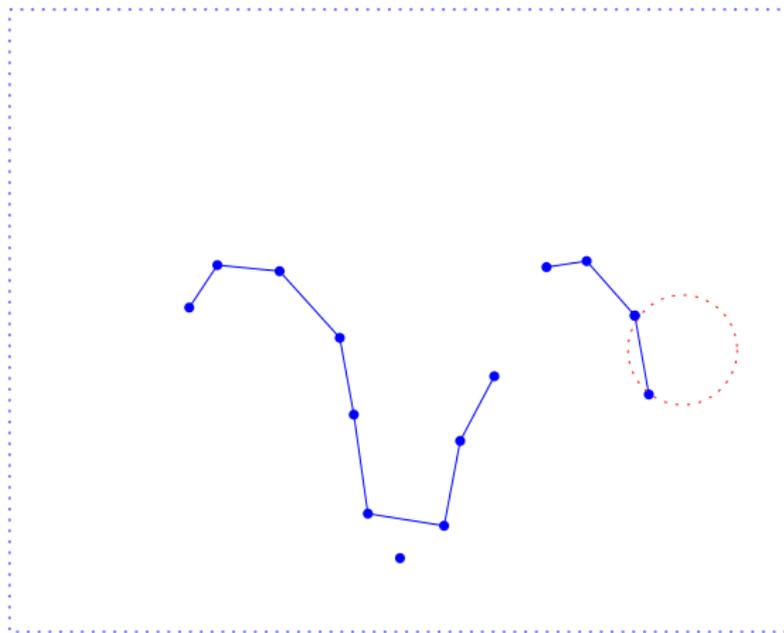
## Smaller ball radius



## Smaller ball radius

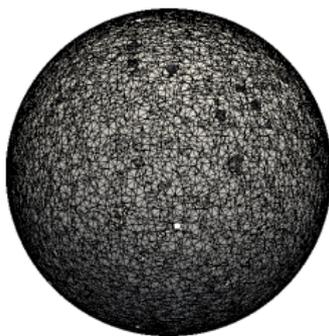


## Smaller ball radius

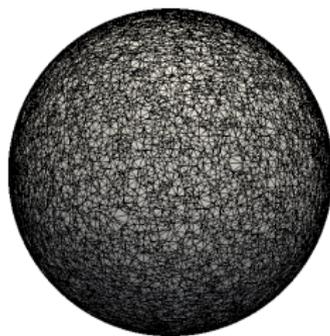




(j)  $r = 0.02$



(k)  $r = 0.03$



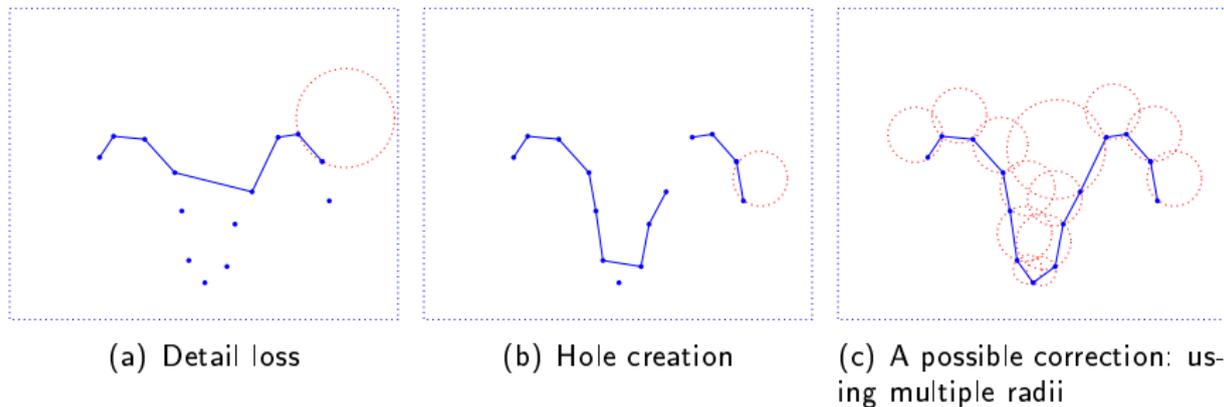
(l)  $r = 0.05$

**Figure:** Radius too small: areas with lower density are not triangulated. Large radius : higher computation times + detail loss.

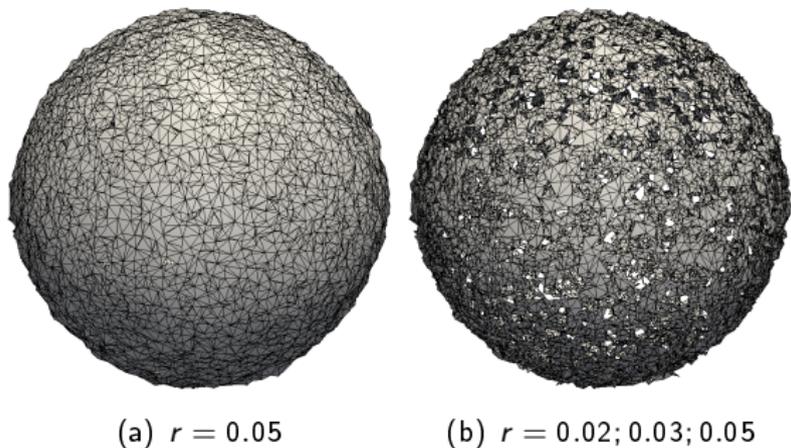


**Figure:** Reconstructing the Stanford Bunny point cloud, with a single radius (0.0003), two radii (0.0003; 0.0005) and three radii (0.0003; 0.0005; 0.002).

Radius	Time(s)	vertices	facets	boundary edges
0.0003	10s	318032	391898	272832
0.0003; 0.0005	21s	356252	698963	22727
0.0003; 0.0005; 0.002	29s	361443	713892	7897



**Figure:** Detail loss and hole creation due to a too large radius (left) and a too small one (middle). A possible solution is to use multiple radii (right).



**Figure:** Applying the ball pivoting to a noisy sphere:  $r = 0.05$  (left) and  $r = 0.02; 0.03; 0.05$  (right). A single radius does not allow to interpolate the input data and applying multiple radii is not a solution in addition to being difficult to tune.

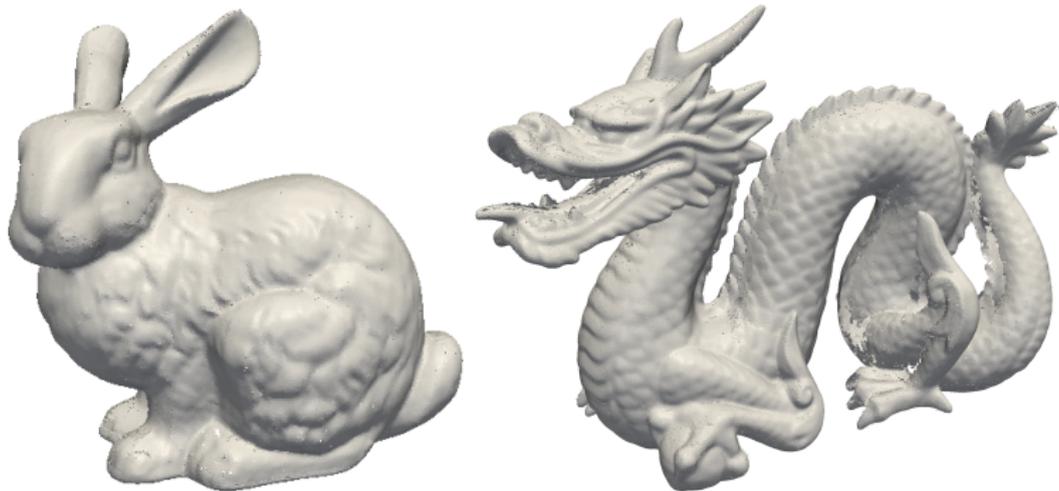


Figure: Bunny and Dragon reconstruction

# Problems and solutions

- The larger the ball radius the slower the computation
- The larger the ball radius the more details will be lost
- The smaller the ball radius the more dependent on the sampling
- Varying ball radius  $\leftarrow$  slow down the process
- Use of a *scale space*: a multiscale representation of the point cloud.

# Summary: Advantages/Drawbacks of the ball pivoting

## Drawbacks

- Size of the ball?
- No suppression of redundant points
- No hole closure

## Advantages

- Control on the size of the triangles created
- Radius of the ball determines what is a hole
- Surface boundary preservation

Modification through the use of a *scale space* for better detail preservation [Digne et al. 2011].

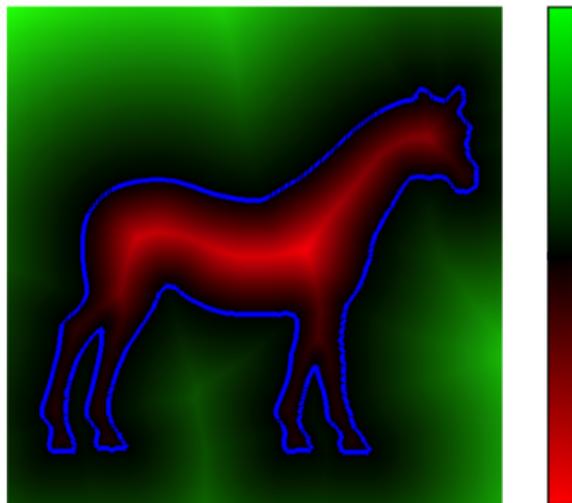
# Outline

1 Geometry Processing basics

2 Surface reconstruction: Methods from Computational Geometry

3 Surface Reconstruction: Potential Field Methods

## Implicit surface reconstruction - Level set methods



- See the surface as an isolevel of a given function
- Extract the surface by some contouring algorithm: Marching cubes [Lorensen Cline 87], Particle Systems [Levet et al. 06]

# Surface reconstruction from unorganized points

[Hoppe et al. 92]

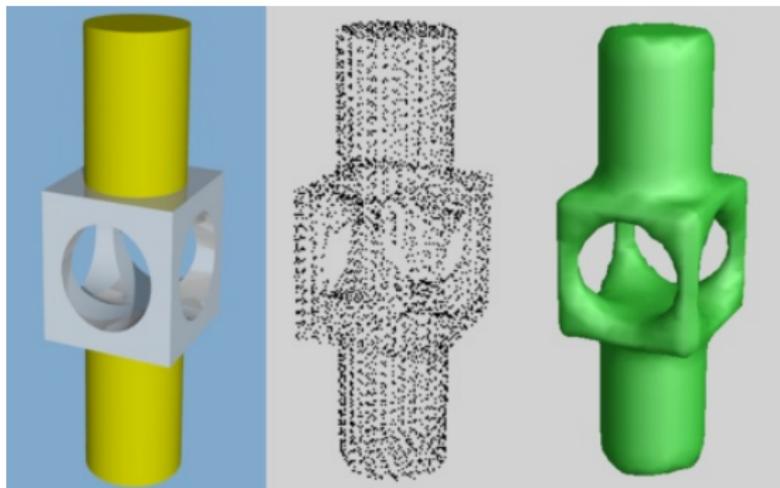
- Input: a set of 3D points
- *Idea*: for points on the surface the signed distance transform has a gradient equal to the normal

$$F(p) = \pm \min_{q \in \mathcal{S}} \|p - q\|$$

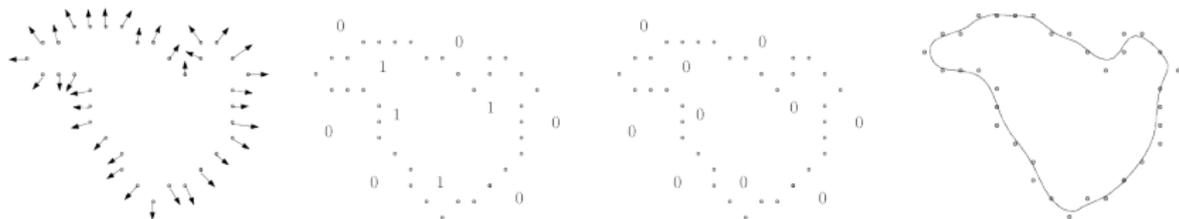
- 0 is a regular value for  $F$  and thus the isolevel extraction will give a manifold
- Compute an associated tangent plane  $(o_i, n_i)$  for each point  $p_i$  of the point set
- Orientation of the tangent planes as explained before.

# Surface reconstruction from unorganized points [Hoppe et al. 92]

- Once the points are oriented
- For each point  $p$ , find the closest centroid  $o_i$
- Estimated signed distance function:  $\hat{f}(p) = n_i \cdot (p - o_i)$



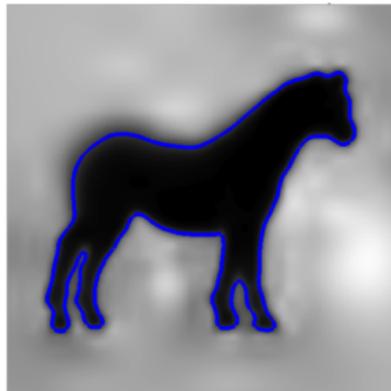
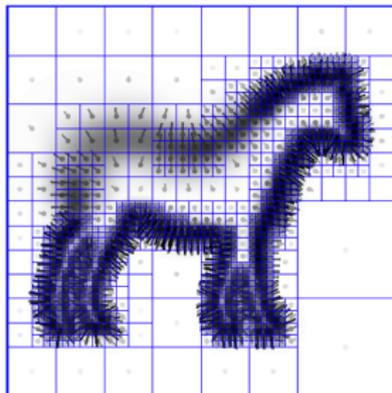
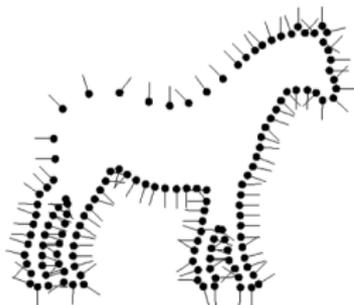
# Poisson Surface Reconstruction [Kazhdan et al. 2006]



- Input: a set of oriented samples
- Reconstructs the indicator function of the surface and then extracts the boundary.
- Trick: Normals sample the function's gradients

# Poisson Surface Reconstruction [Kazhdan et al. 2006]

- 1 Transform samples into a vector field
- 2 Fit a scalar-field to the gradients
- 3 Extract the isosurface

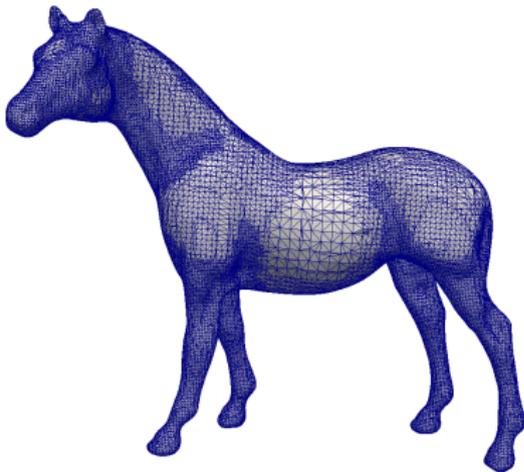
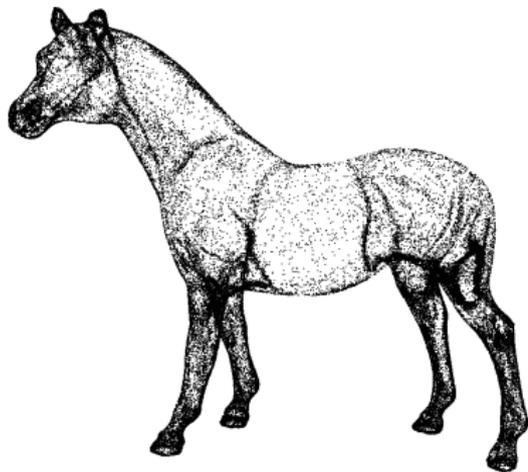


# Poisson Surface Reconstruction [Kazhdan et al. 2006]

- To fit a scalar field  $\chi$  to gradients  $\vec{V}$ , solve:

$$\min_{\chi} \|\nabla\chi - \vec{V}\|$$

$$\nabla \cdot (\nabla\chi) - \nabla \cdot \vec{V} = 0 \Leftrightarrow \Delta\chi = \nabla \cdot \vec{V}$$



- Gradient Function of an indicator function = unbounded values on the surface boundaries
- We use a smoothed indicator function

## Lemma

*The gradient of the smoothed indicator function is equal to the smoothed normal surface field.*

$$\nabla \cdot (\chi \star \tilde{F})(q_0) = \int_{\partial M} \tilde{F}(q_0 - p) \cdot \vec{N}_{\partial M}(p) dp$$

Chicken and Egg problem: to compute the gradient one must be able to compute an integral over the surface!!

- Approximate the integral by a discrete summation
- Surface partition in patches  $\mathcal{P}(s)$ :

$$\nabla \cdot (\chi \star \tilde{F})(q_0) = \sum_s \int_{\mathcal{P}(s)} \tilde{F}(q_0 - p) \cdot \vec{N}_{\partial M}(p) dp$$

- Approximation on each patch:

$$\nabla \cdot (\chi \star \tilde{F})(q_0) = \sum_s |\mathcal{P}(s)| \tilde{F}(q_0 - s) \cdot \vec{N}(s)$$

- Let us define  $V(q_0) = \sum_s |\mathcal{P}(s)| \tilde{F}(q_0 - s) \cdot \vec{N}(s)$

# Problem Discretization

- Build an adaptive octree  $\mathcal{O}$
- Associate a function  $F_o$  to each node  $o$  of  $\mathcal{O}$  so that:  $F_o(q) = F\left(\frac{q-o.c}{o.w}\right)\frac{1}{o.w^3}$   
( $o.c$  and  $o.w$  are the center and width of node  $o$ ).  $\Rightarrow$  multiresolution structure
- The base function  $F$  is the  $n$ th convolution of a box filter with itself

- 

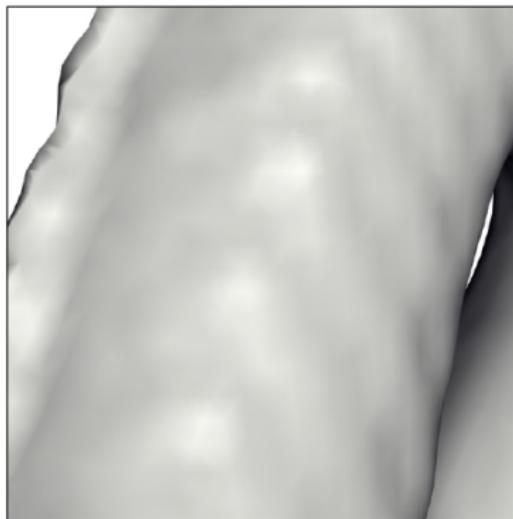
$$\vec{V}(q) = \sum_{s \in S} \sum_{o \in \mathcal{N}(s)} \alpha_{o,s} F_o(q) s \cdot \vec{N}$$

- Look for  $\chi$  such that its projection on  $\text{span}(F_o)$  is closest to  $\nabla V$  :
- Minimize  $\sum_{o \in \mathcal{O}} \langle \Delta\chi - \nabla \cdot V, F_o \rangle^2$
- Extracted isovalue: mean value of  $\chi$  at the sample positions

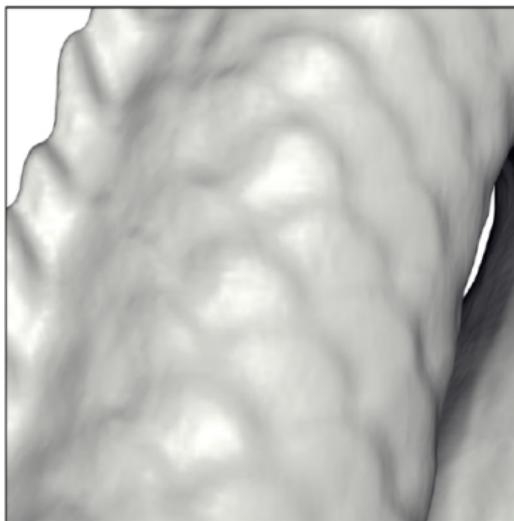
## Varying octree depth



## Varying octree depth



## Varying octree depth



# Resilience to bad normals

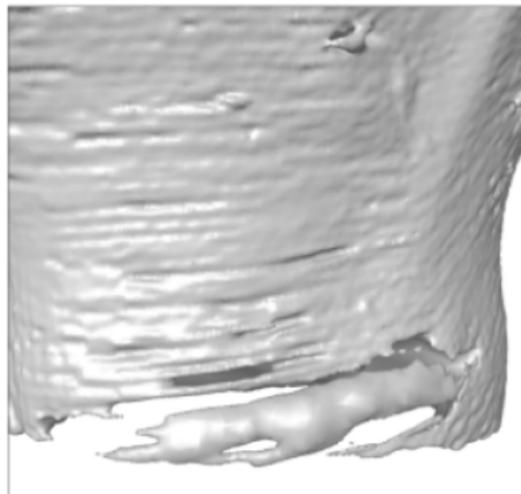


Image from Mullen et al. *Signing the unsigned*, 2010

## detail preservation



Poisson



BPA



Scale Space + BPA

# Advantages and drawbacks of the Implicit surface reconstruction methods

## Drawbacks

- Only semi-sharp, loss of details
- Final mesh not interpolating the initial pointset
- Marching cubes introduces artefacts
- Watertight surface, very bad with open boundaries

## Advantages

- Noise robustness
- Watertight surface, hole closure
- Most standard way of reconstructing a surface

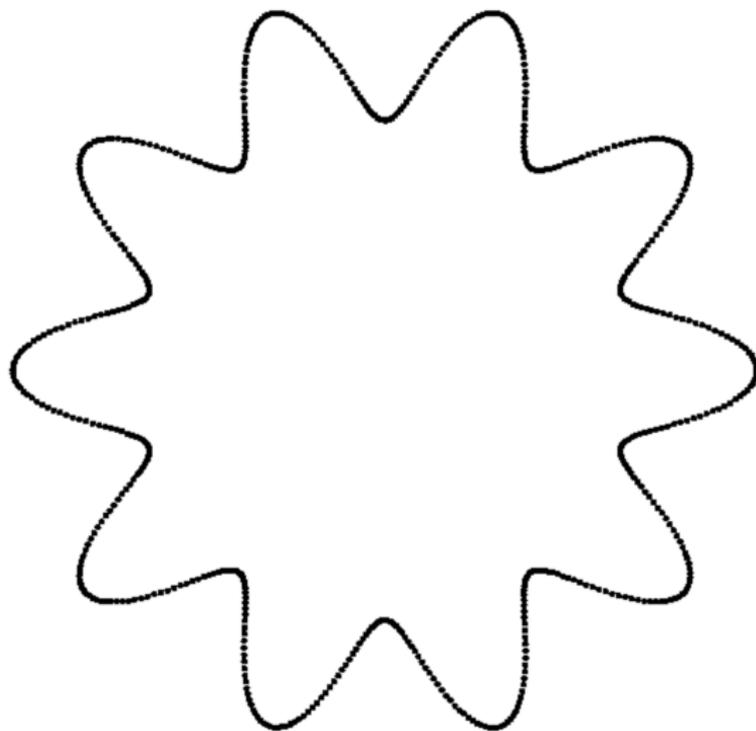
# From the signed distance function to the mesh

- At each point in  $\mathbb{R}^3$ , the signed distance function to the surface can be estimated
- Extract the 0 levelset of this function: points where this function is 0

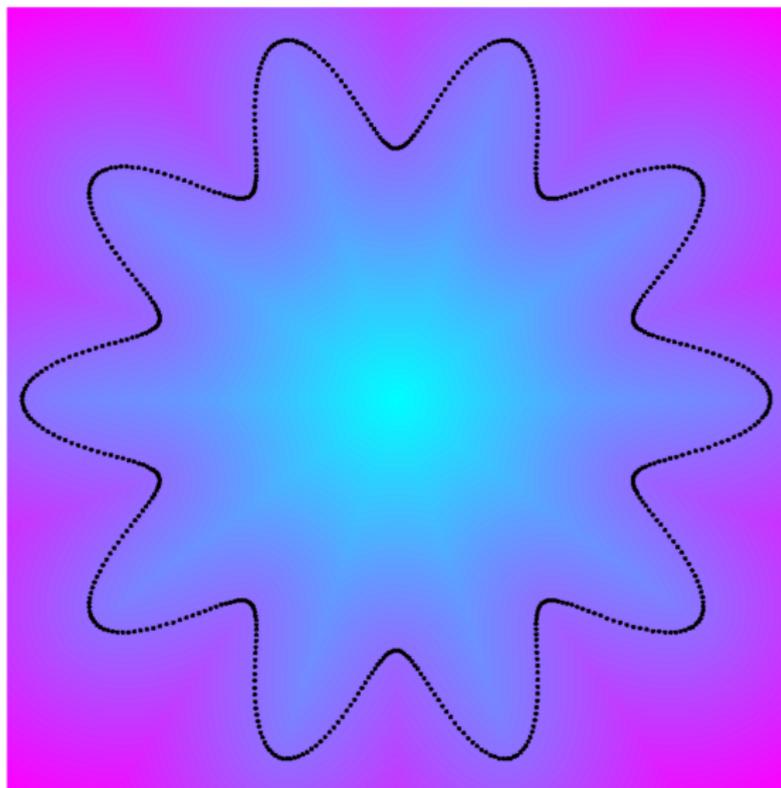
## Approximation

Evaluate the function at the vertices of a grid and deduce the local geometry of the surface in each grid cube.

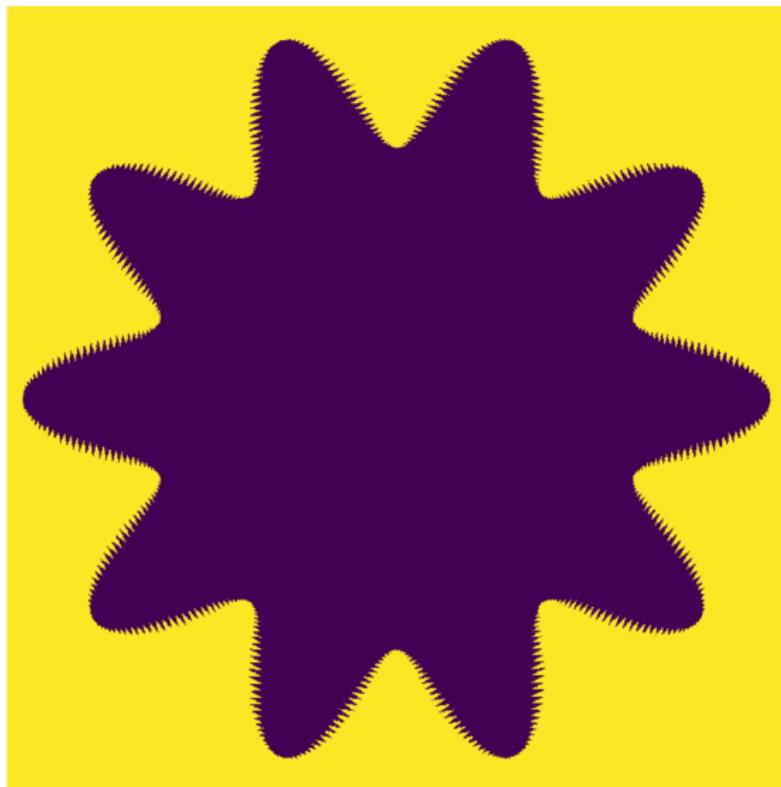
## Example in 2D



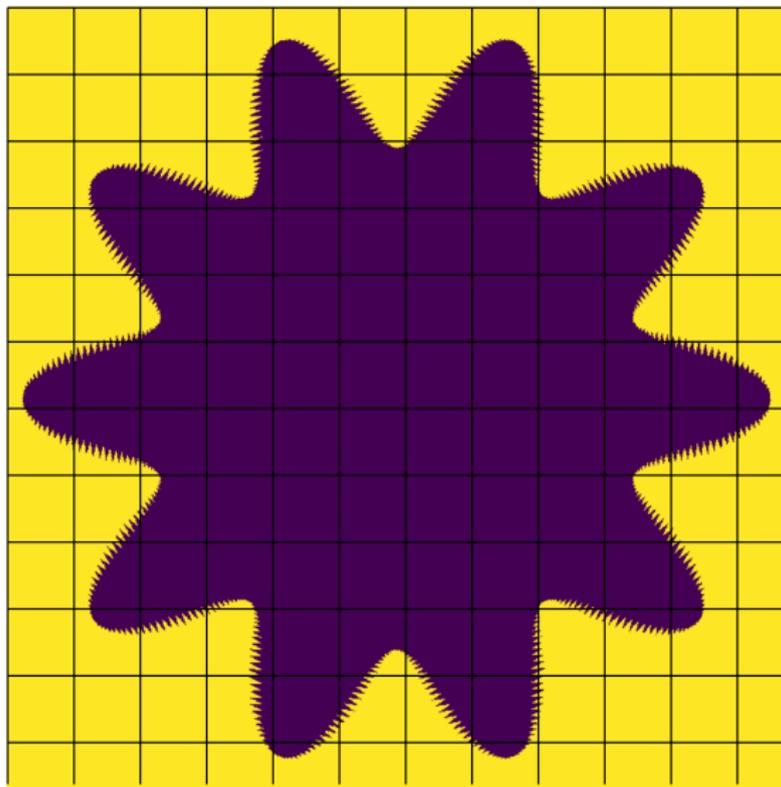
## Example in 2D



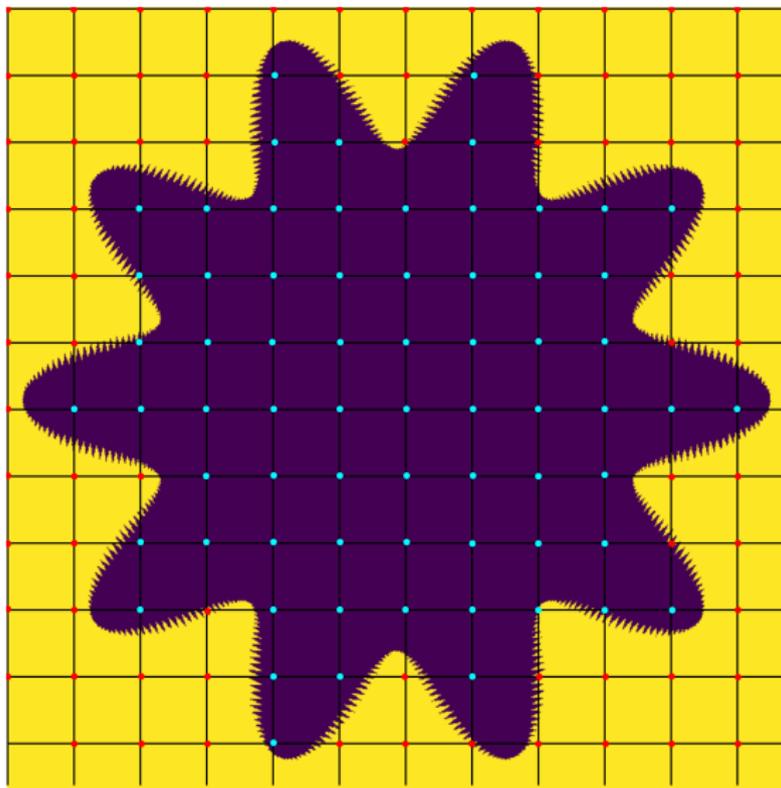
## Example in 2D



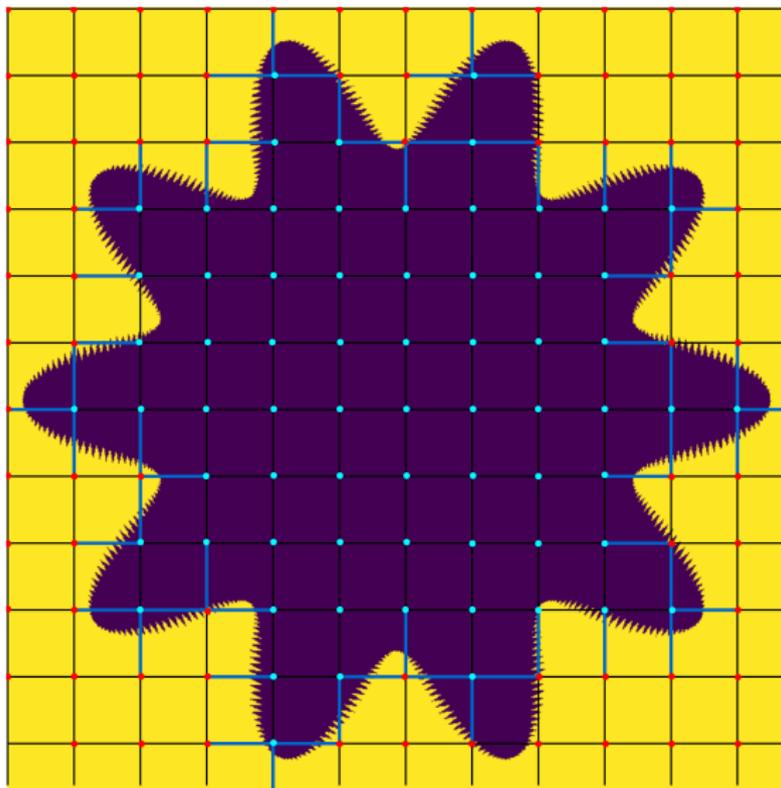
## Example in 2D



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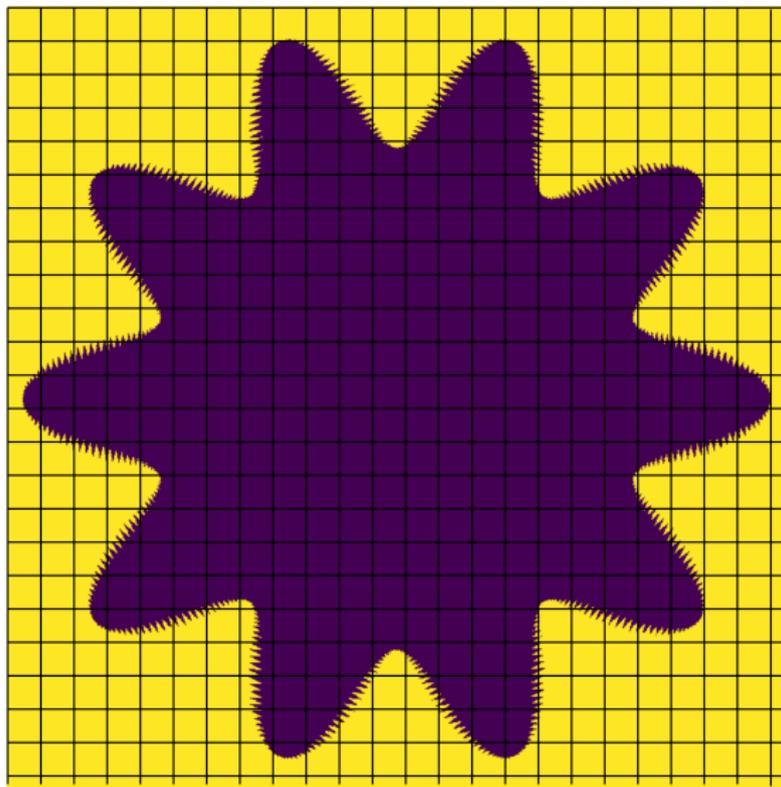


## Example in 2D

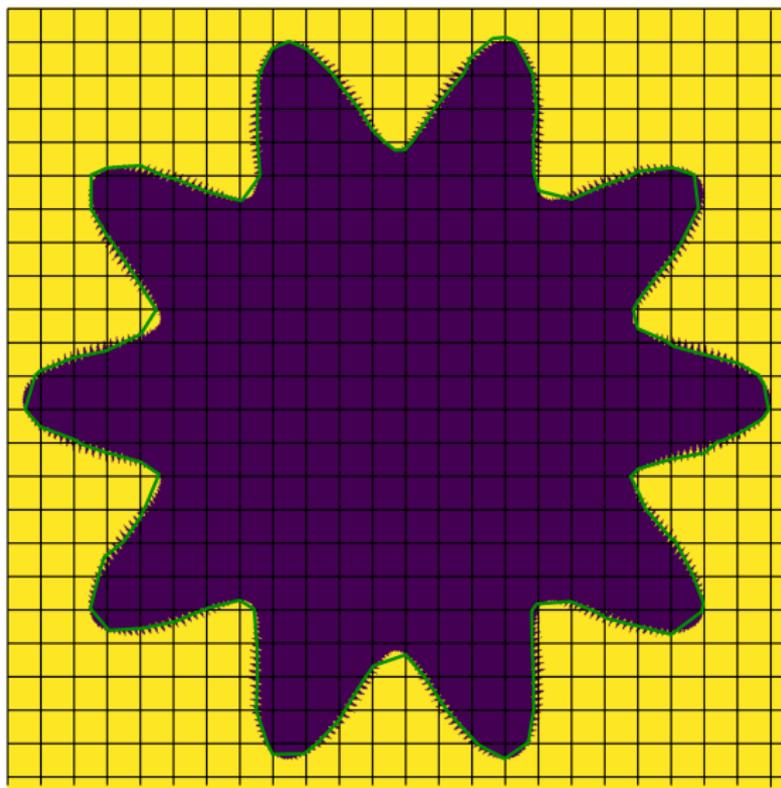




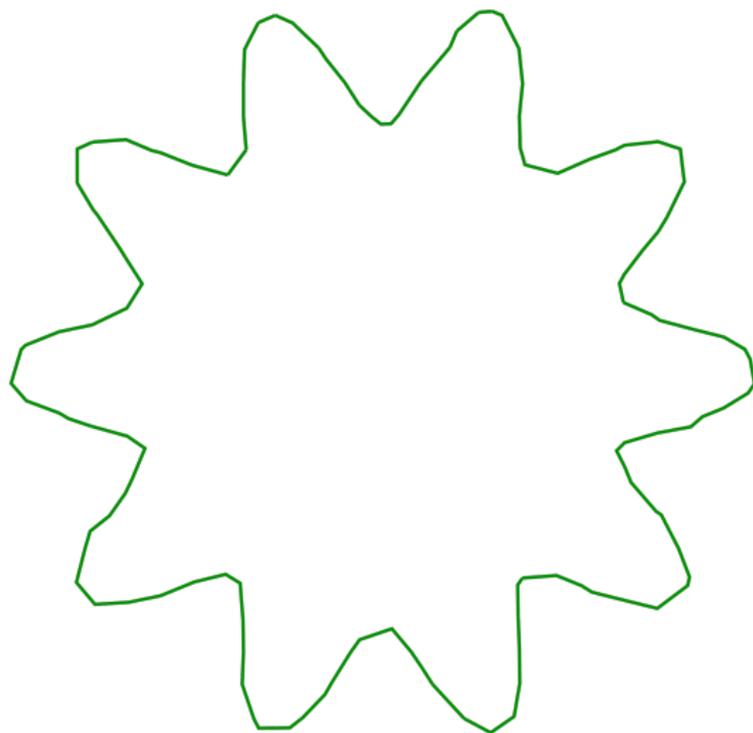
## Example in 2D



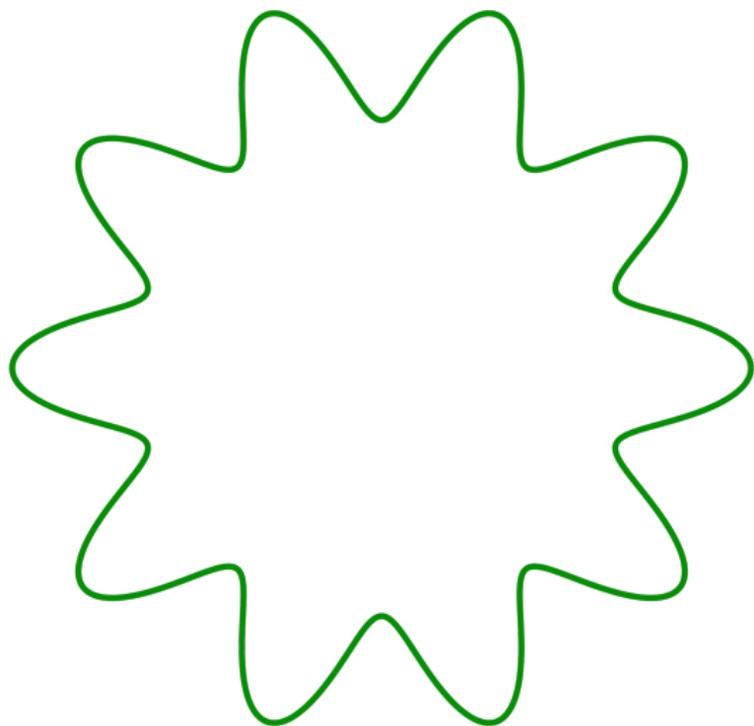
## Example in 2D



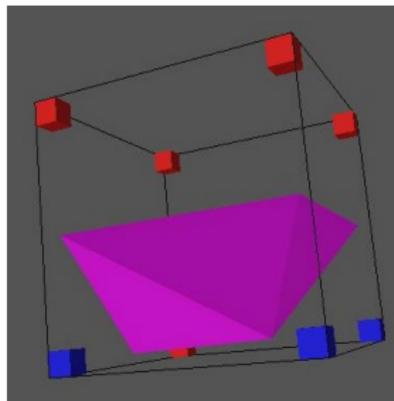
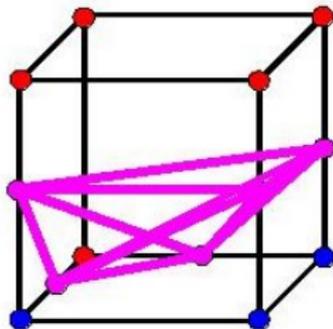
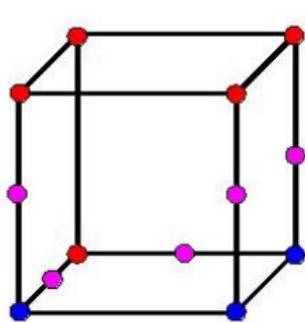
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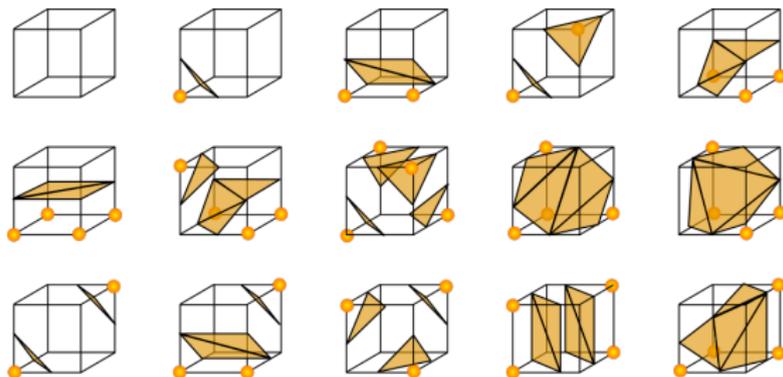
# From Marching Squares to Marching Cubes



Drawing lines between intersection points is ambiguous and does not give a surface patch.

Images by Ben Anderson

# Look-up tables



- There are  $2^8 = 256$  possible cases for cube corner values.
- By symmetry + rotation arguments it reduces to 15 cases.
- It is thus possible to build a look-up table giving the grid cell triangulation based on the corner values case.

# And then? Laplace-Beltrami discretization on a mesh

- Mesh triangles are not regular in general
  - ▶ Triangle edges DO NOT have constant length
  - ▶ Triangle angles ARE NOT constant
- Yet we need to account for the function variations on the surface

## Mesh Laplacian

There exist many different Laplacians. We follow the terminology of [Zhang et al. 2007] and [Vallet and Levy 2008]

# Combinatorial Laplacian

## Definition

Given a triangular manifold mesh with  $N$  vertices  $(v_i)_{i=1\dots N}$ , let  $E$  be the set of edges. The uniform Laplacian, *umbrella operator* is defined as a matrix  $L$  such that:

$$L_{i,j} = \begin{cases} 1, & \text{if } (v_i, v_j) \in E \\ 0 & \text{otherwise} \end{cases}$$

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- Directly derived from the graph Laplacian.

# Combinatorial Laplacians

- **Tutte Laplacian**

$$L_{ij} = \begin{cases} \frac{1}{d_i} & \text{if } (i,j) \in E \\ 0 & \text{otherwise} \end{cases}$$

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- **Normalized Graph Laplacian**

$$L_{ij} = \begin{cases} \frac{1}{\sqrt{d_i d_j}} & \text{if } (i,j) \in E \\ 0 & \text{otherwise} \end{cases}$$

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- Other Discretizations: Mean Value Coordinates, Wachspress coordinates....

# Combinatorial Laplacian

## Combinatorial Laplacian

A combinatorial Laplacian depends solely on the connectivity of the mesh.

# Combinatorial Laplacian

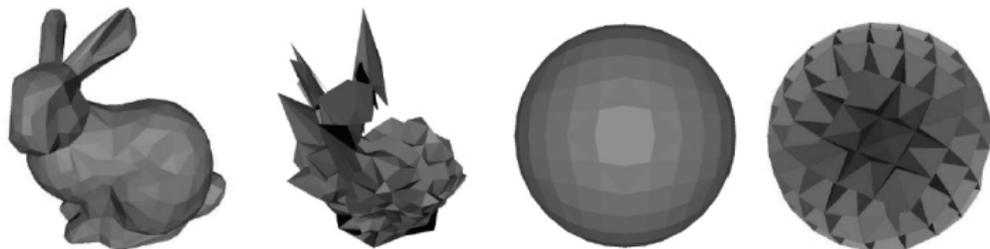
## Combinatorial Laplacian

A combinatorial Laplacian depends solely on the connectivity of the mesh.

- The Laplacian is computed independently of its geometrical embedding



# Processing with Combinatorial Laplacians



Original bunny. GL compression. Original sphere. GL compression.

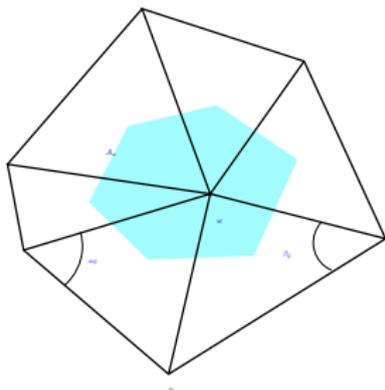
Compression using Normalized Graph Laplacian

Image from Zhang et al. 2004

# Geometric Laplacian

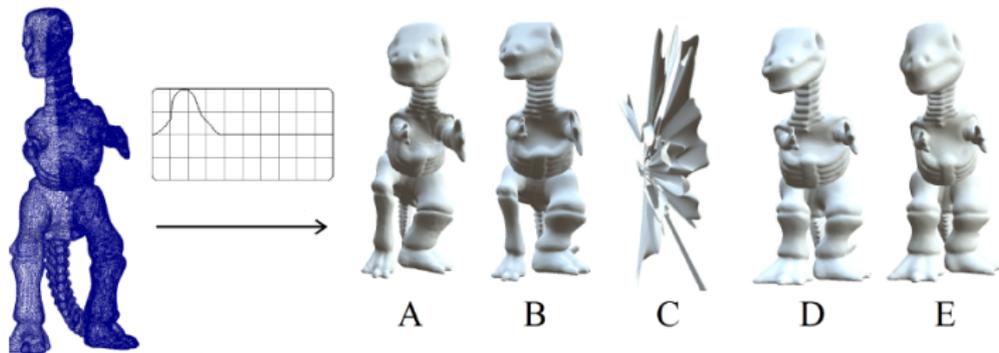
Pinkall Polthier 93

$$(Lf)_i = \sum_{j \in N_i} \frac{1}{2} (\cot \alpha_{ij} + \cot \beta_{ij}) (f_i - f_j)$$



- There is no perfect Laplacian discretization on triangle meshes [Wardetsky et al. 2007]

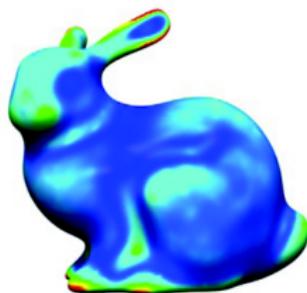
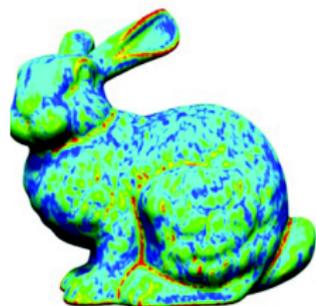
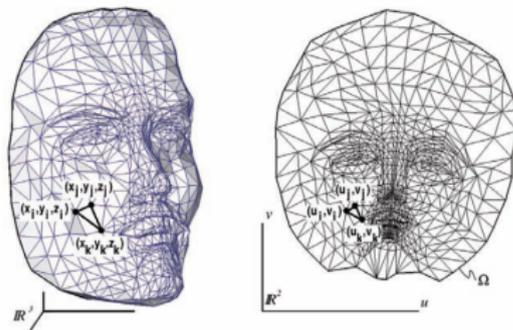
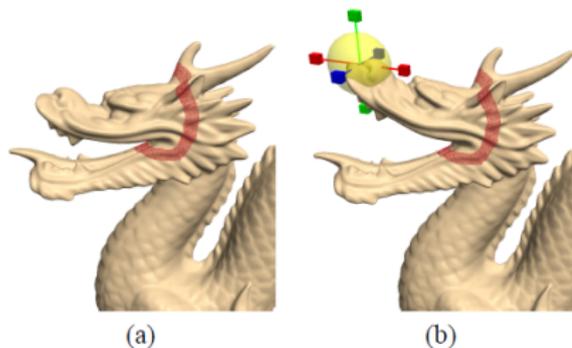
# Laplacian Comparisons



Combinatorial Laplacian, unweighted cotan, weighted cotan, two versions of the symmetrized weighted cotan

Image from [Vallet and Lévy 2008]

# Applications of the Laplace-Betrami Operator



# Conclusion

- Point Set = raw output of many measurement devices
- Graph structure not always necessary for early processing
- Topics not addressed: denoising, entire shape matching, normal orientation, rendering...