中国科学技术大学
University of Science and Technology of China

GAMES102

GAMES 102在线课程

几何建模与处理基础

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GAMES 102在线课程：几何建模与处理基础

曲面重建

建模(modeling)：设计与重建

- 曲面设计(Design)
  - 不存在的物体：通过人工交互凭空设计出新的物体
    - CAGD (NURBS)、mesh modeling
  - 存在的物体：通过人工交互编辑修改构建出新的物体
    - Editing, deformation
- 曲面重建(Reconstruction)
  - 存在的物体：对其采集并进行数字化构建
  - 也称为：逆向工程、扫描重建
    - Reverse engineering, scanning

建模(modeling)：设计与重建

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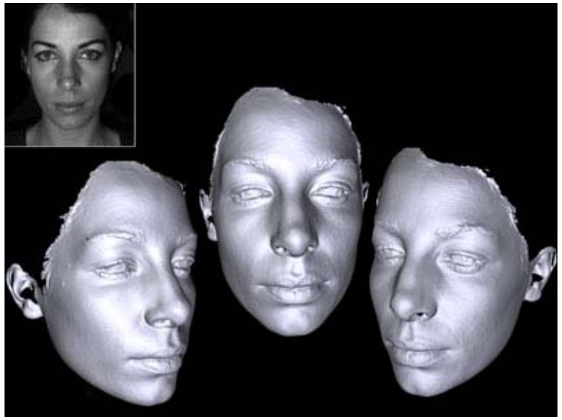
Digitalization of Real Objects



Reverse Engineering

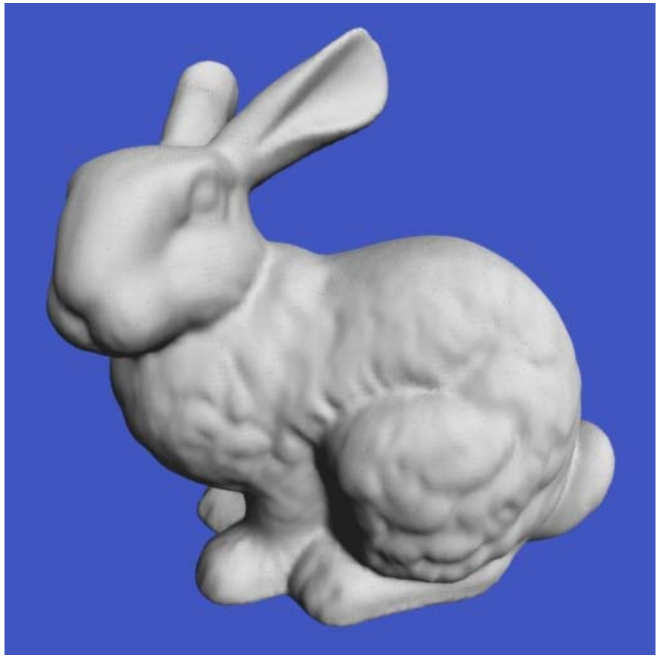
Real Object

CAD/Graphics model

Build new real objects

Getting Meshes from Real Objects

- Many models used in Computer Graphics are obtained from real objects
  - Ex.: Well known Stanford bunny model

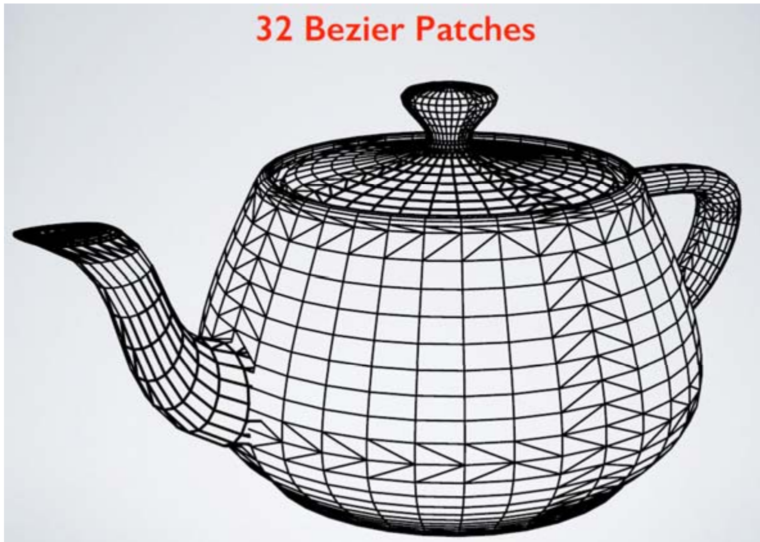


3D mesh surface

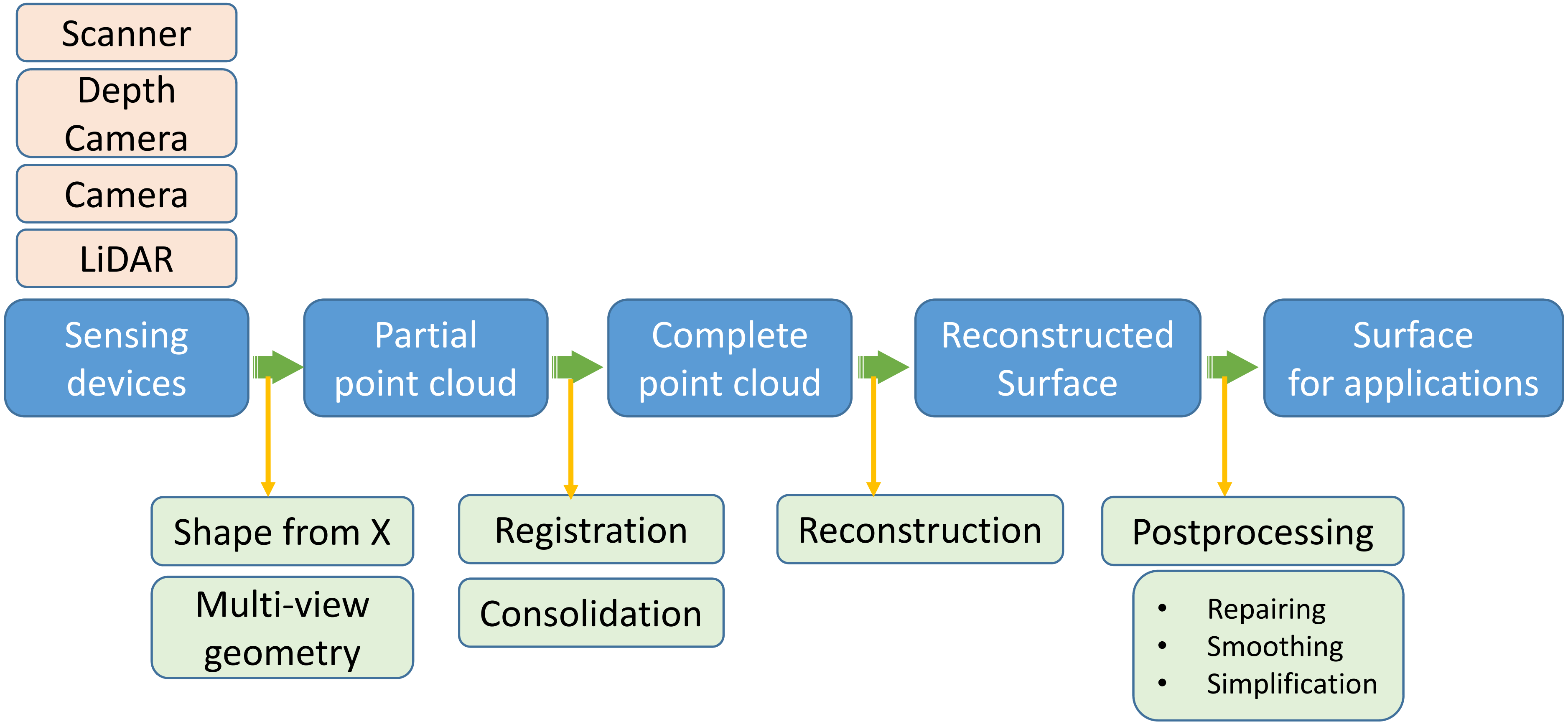
Photo of real Stanford Bunny

Designed Utah Teapot (NURBS)

Photo of real Utah teapot



Outline



Scanner
Depth Camera
Camera
LiDAR
Sensing devices
Partial point cloud
Complete point cloud
Reconstructed Surface
Surface for applications
Shape from X
Multi-view geometry
Registration
Consolidation
Reconstruction
Postprocessing
Repairing
Smoothing
Simplification

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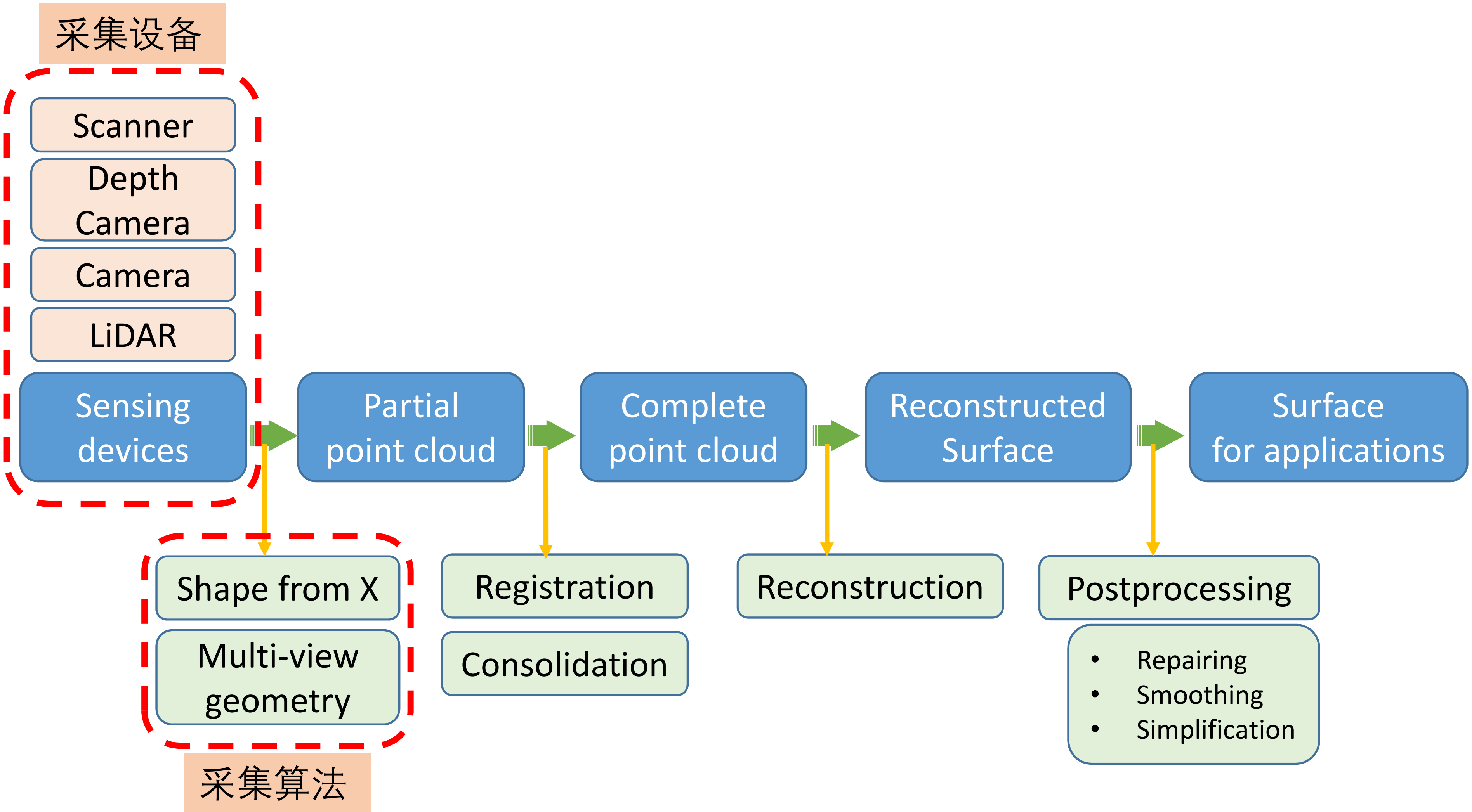
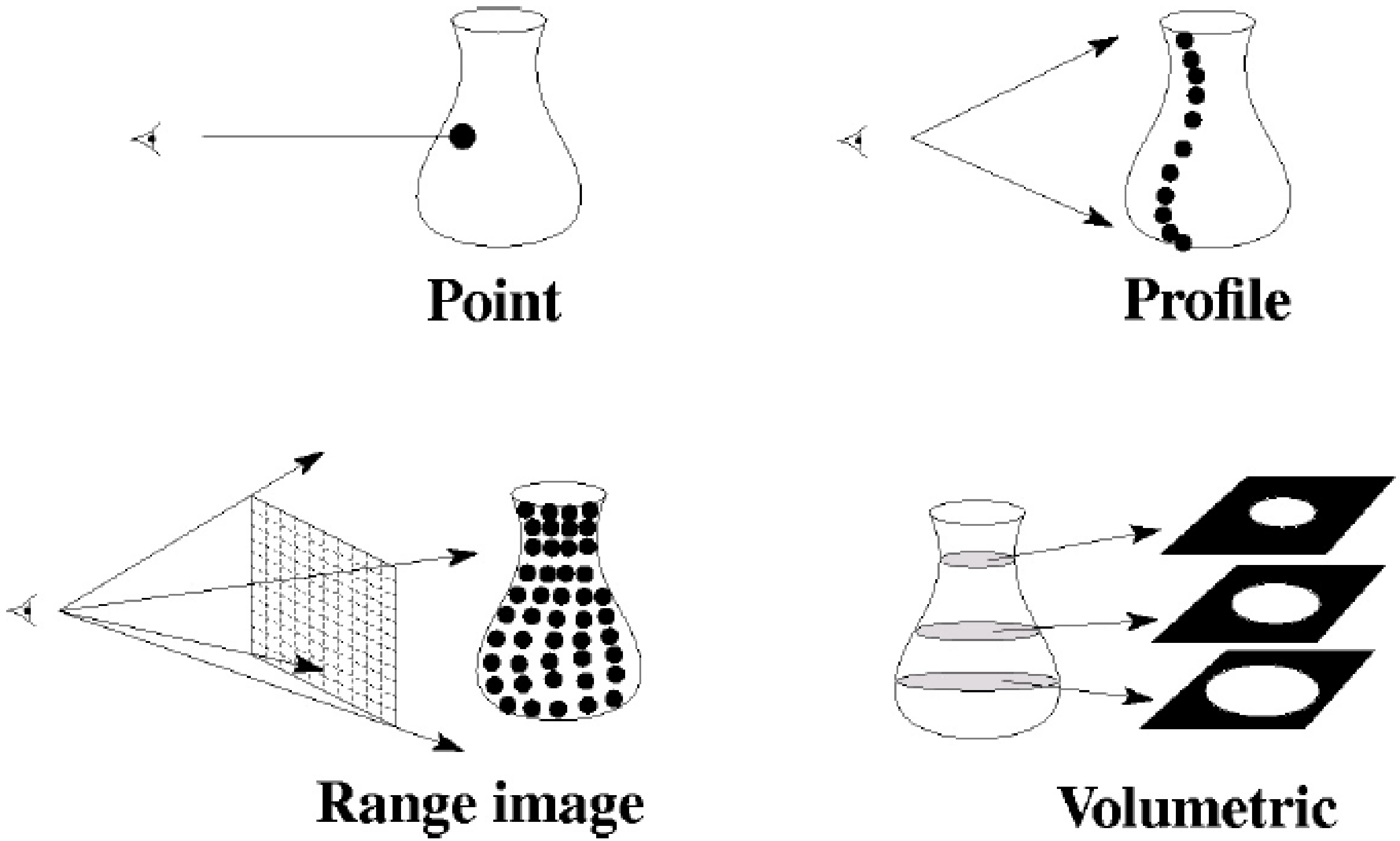
1. Acquisition

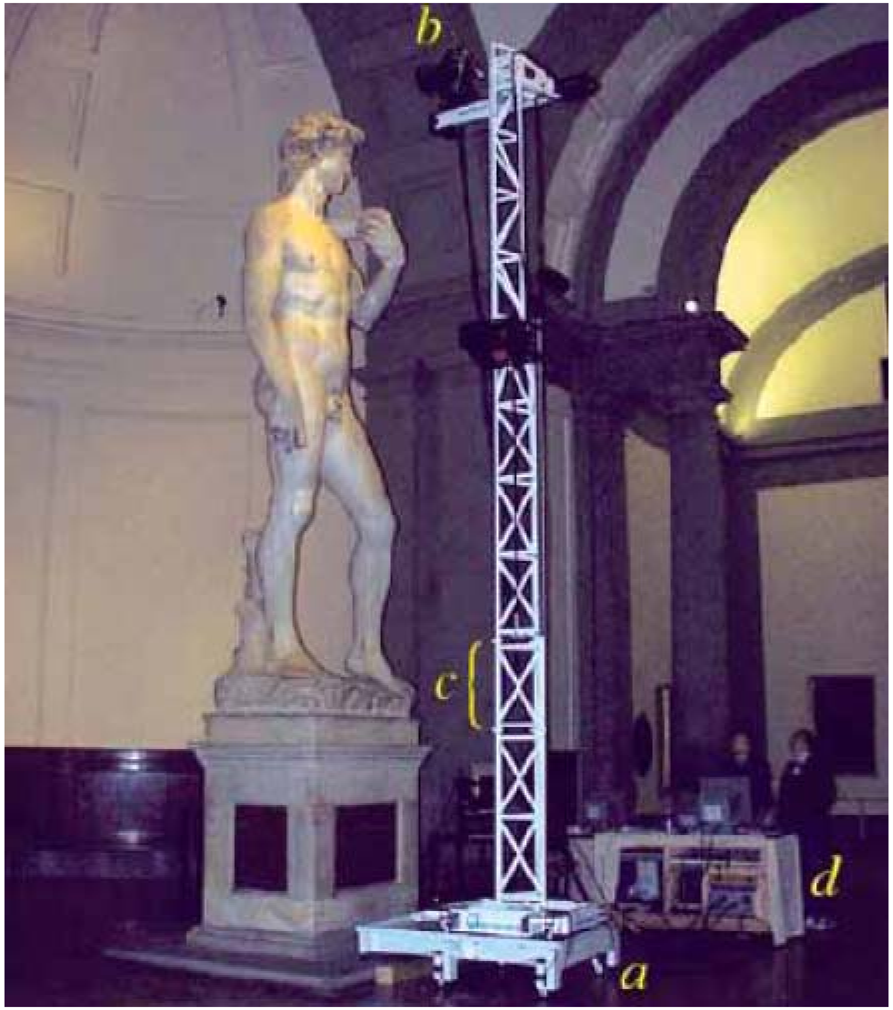
1. Acquisition （数据采集）



Structure of Data



Sensing devices (scanner)

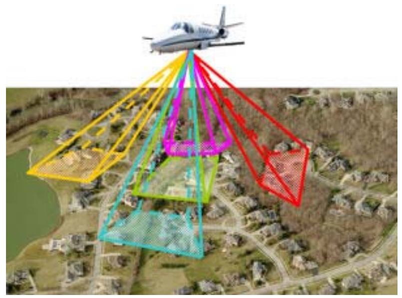


More sensing devices…

单个相机

深度相机

车载激光扫描仪

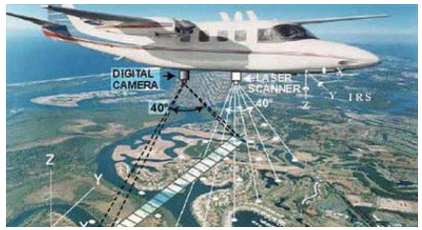


倾斜摄影

多个相机

激光扫描仪(**LiDAR**)

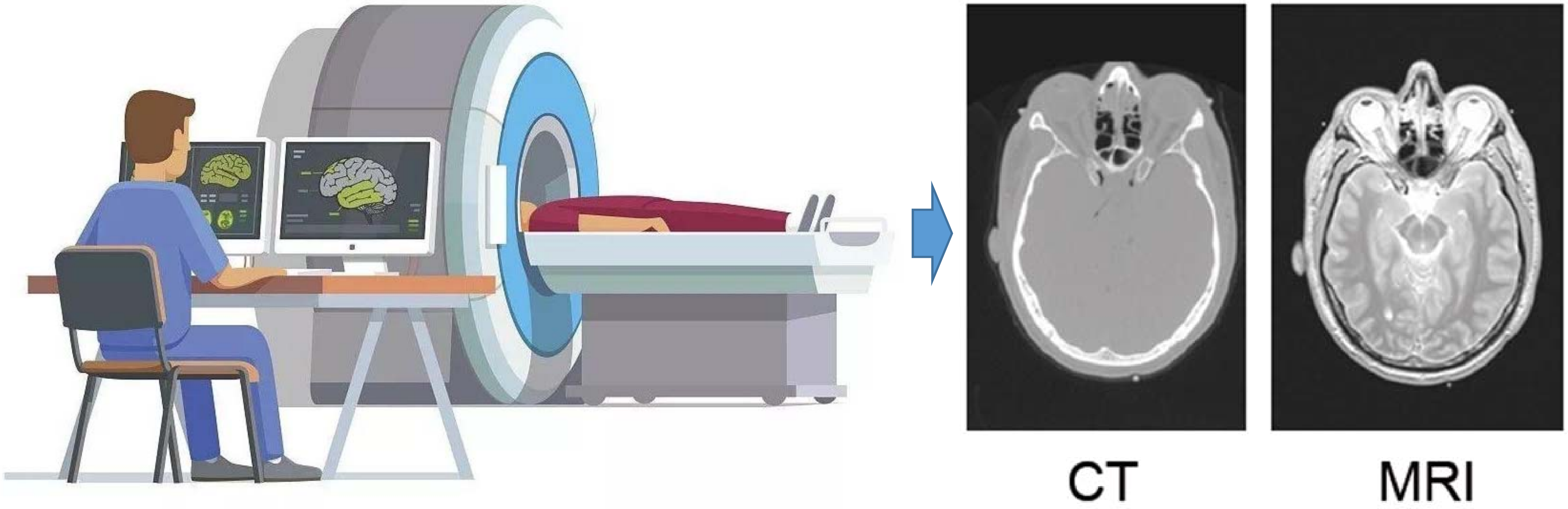
全站仪



遥感

1.1 Volume Scanning

- Input: a sequence of slice images
- Output: 3D models of human organs



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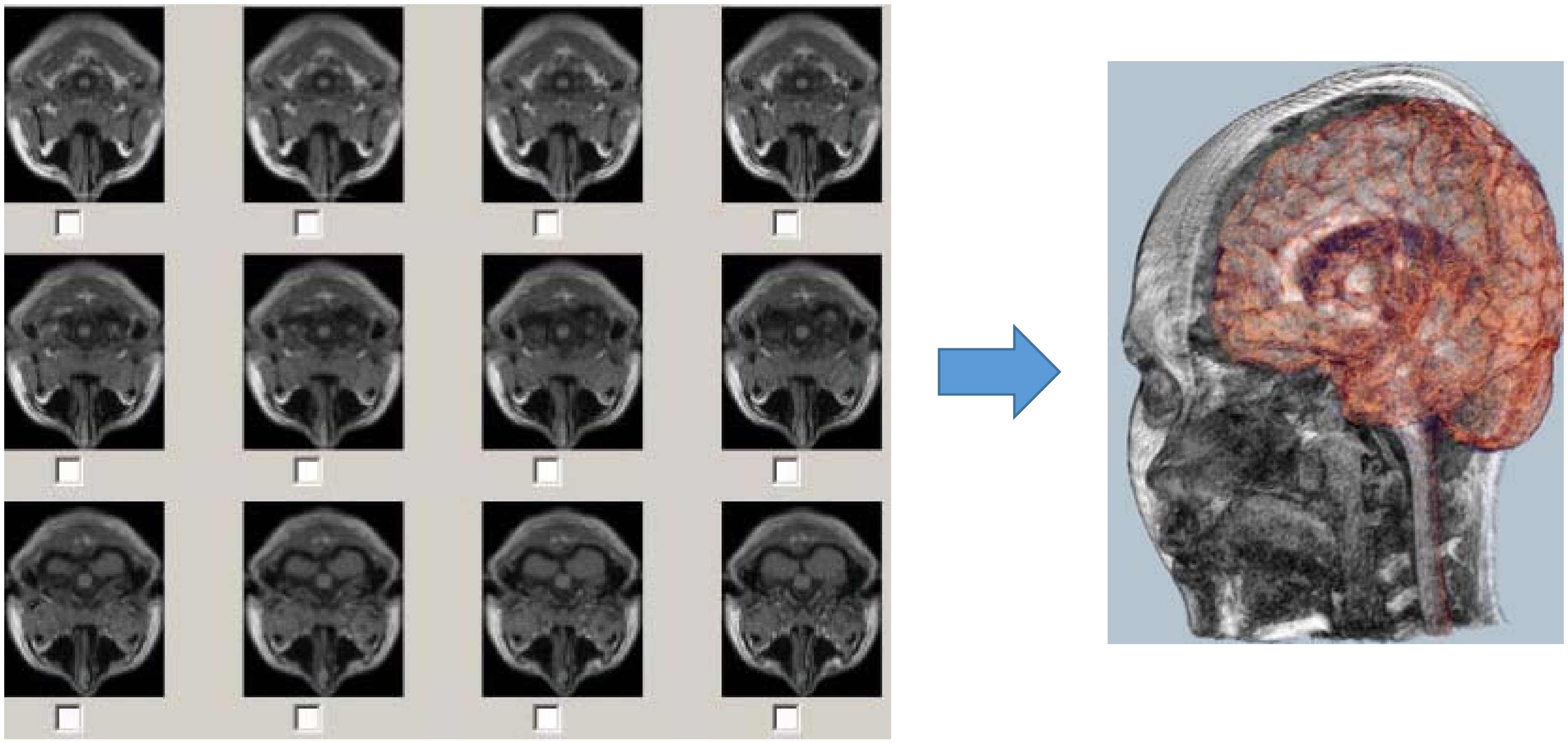


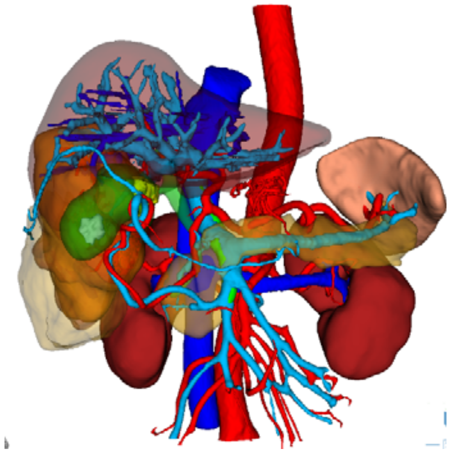
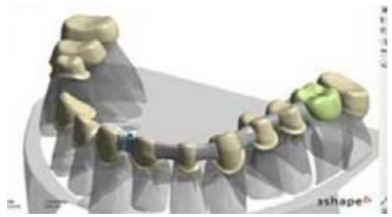
3D Imaging

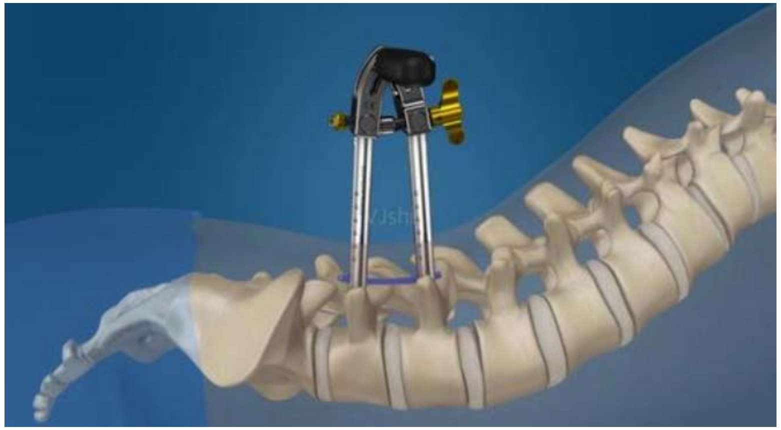
- Wave based sensors
  - Ultrasound
  - Magnetic Resonance Imaging (MRI)
  - X-Ray
  - Computed Tomography (CT)
- Alternative - slice object, take photographs of slices
- Outputs
  - volumetric data (voxels)
  - contour lines (use imaging techniques)

医学图像的三维重建


1.获取二维医学断层图像
2.预处理断层图像
医学图像
三维重建
3. 分割图像
4.切片重组、插值
5.三维重建
6.显示重建的结果

医学图像三维重建的软件

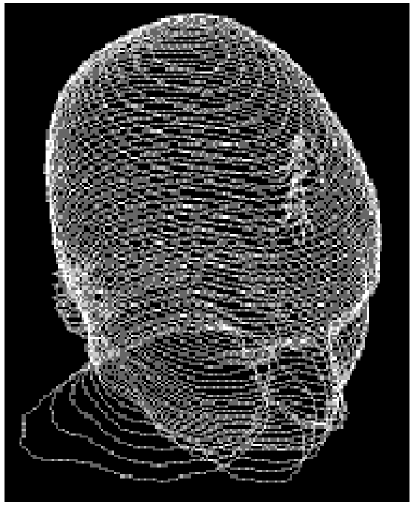




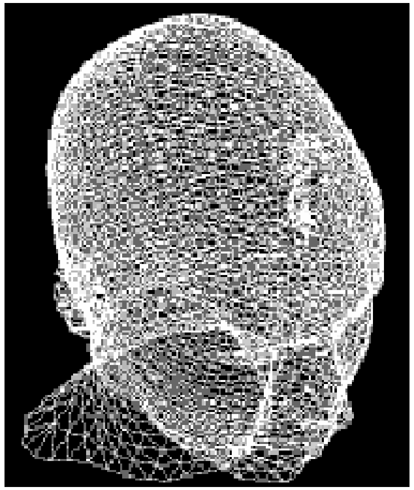


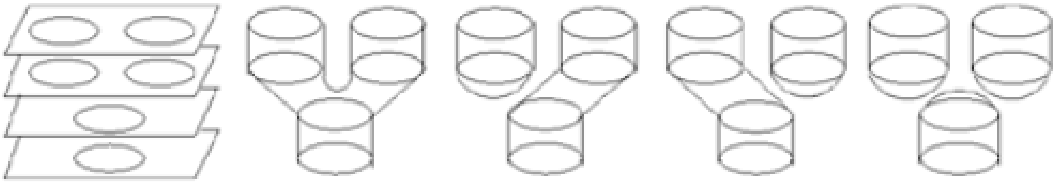
Materialise Mimics, Simpleware, Able 3D-DOCTOR, Visage Imaging Amira, Medical Imaging ToolKit (MITK), …

Reconstruction from 2D contours

- Stack contours
- Triangulate "strips" between contours





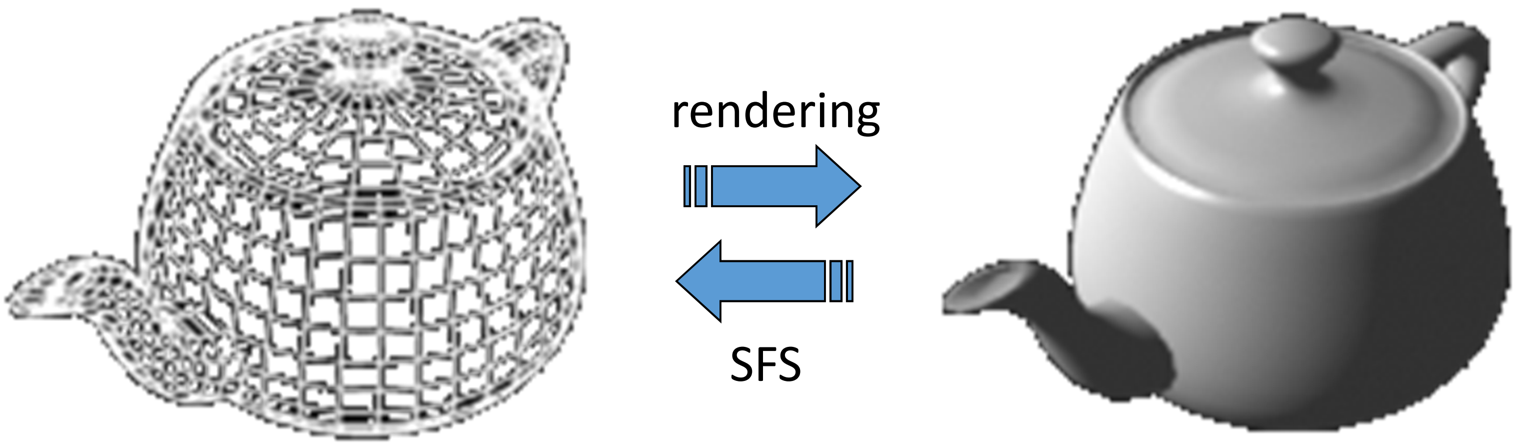


(a) (b) (c) (d) (e)

- Note: contour topology can change

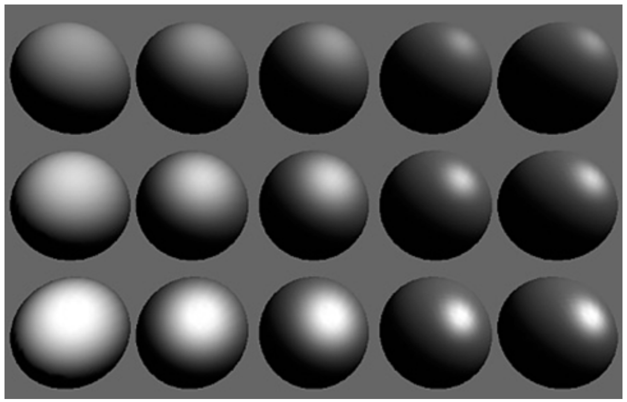
1.2 Shape from shading (SFS)

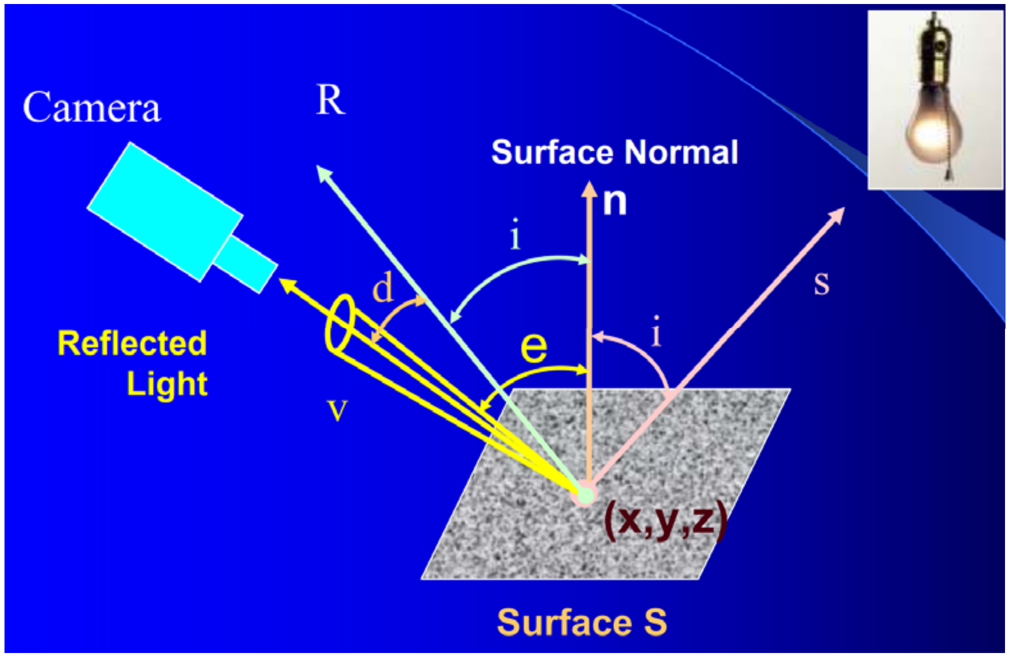
- Input: a single image
- Output: a 3D model (with albedo, normal, etc.)
- Method: Inverse of rendering
  - Solving from rendering equation [Horn 1980]



Shape from shading (SFS)

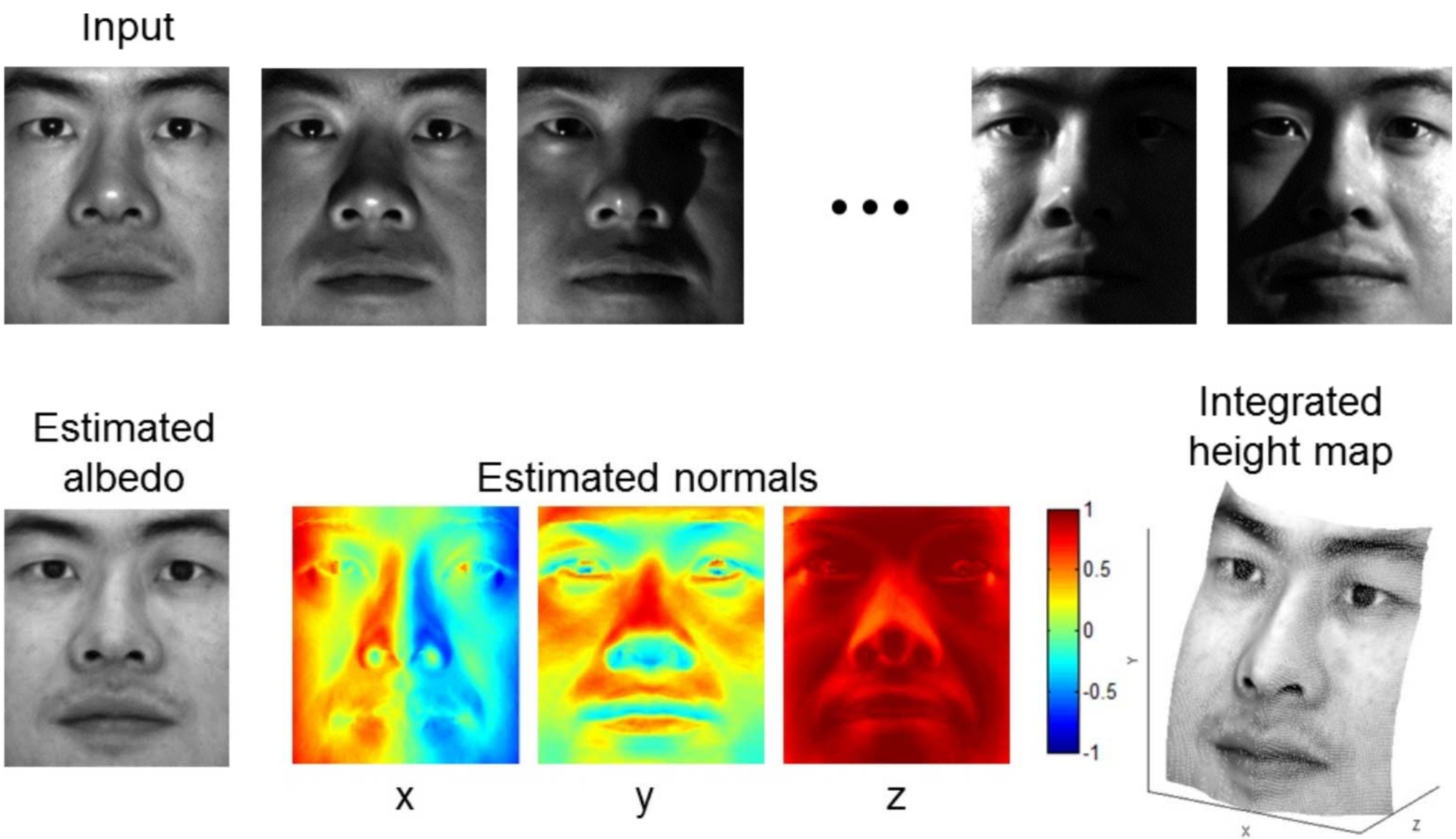
- Solving from the Phong shading equation
- Reflectance models: Lambertian models



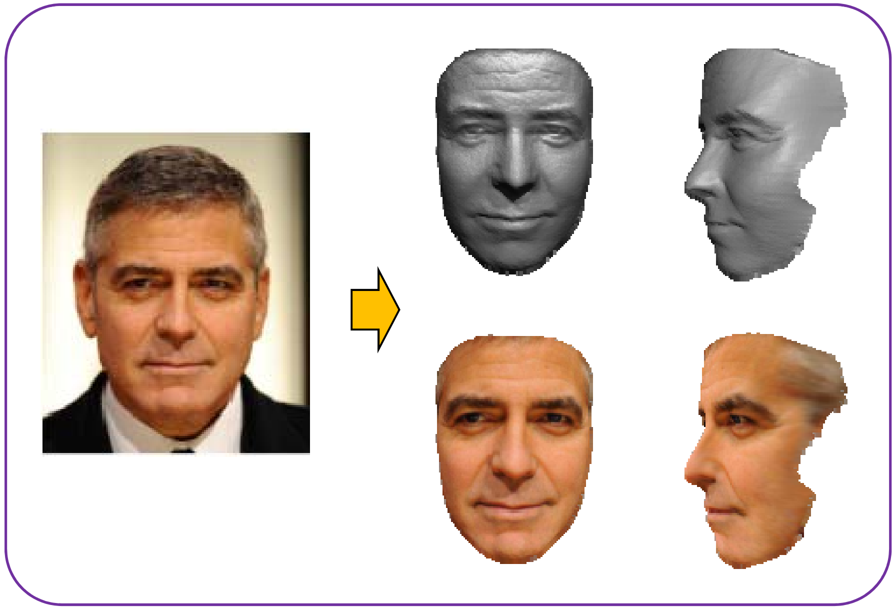


Shape from shading

- From multiple images

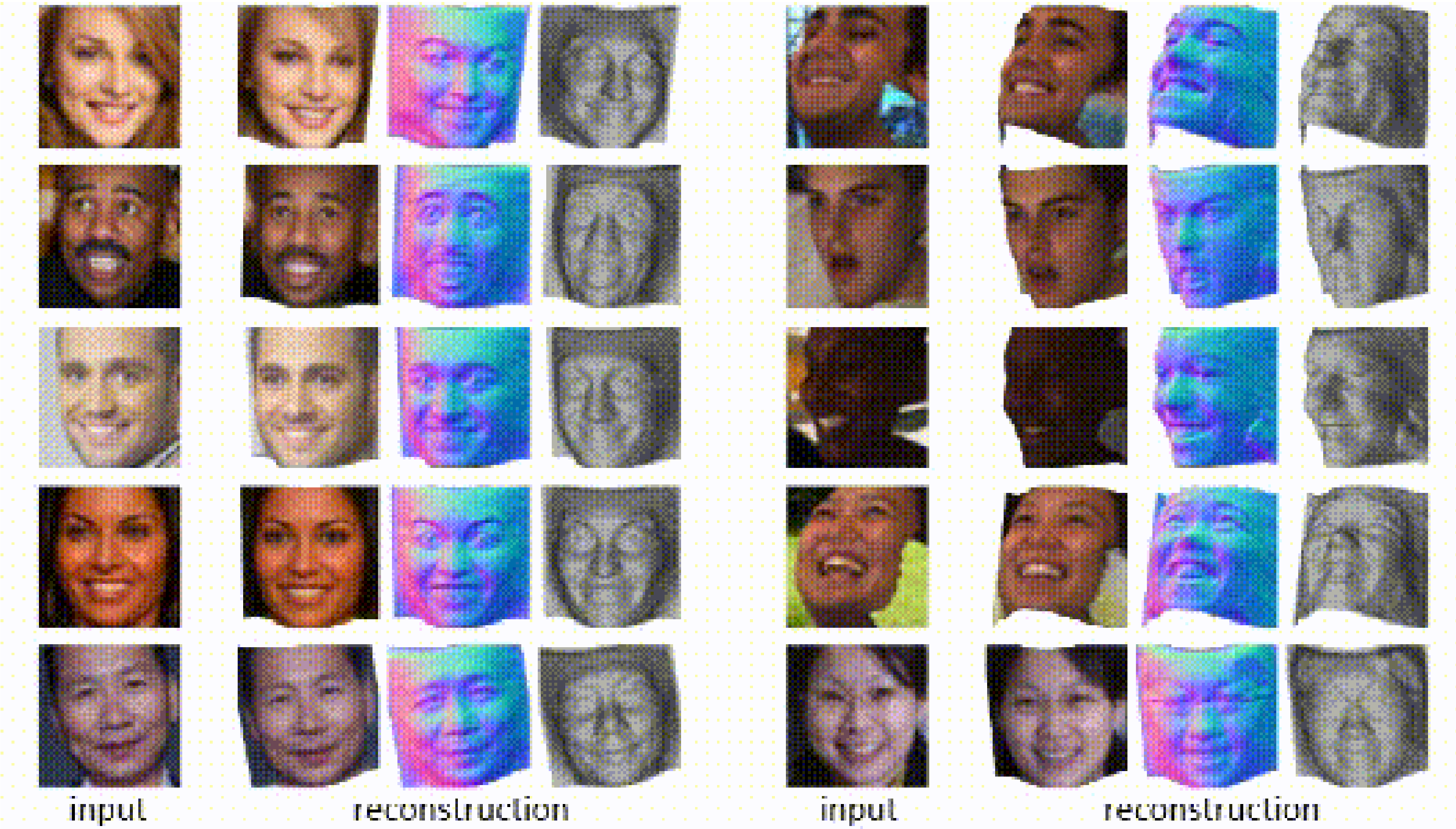


Shape from a single image



Jiang et al. 3D Face Reconstruction with Geometry Details from a Single Image. IEEE Transactions on Image Processing, 2018.
Xu et al. Shading-based Surface Detail Recovery under General Unknown Illumination. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2018.

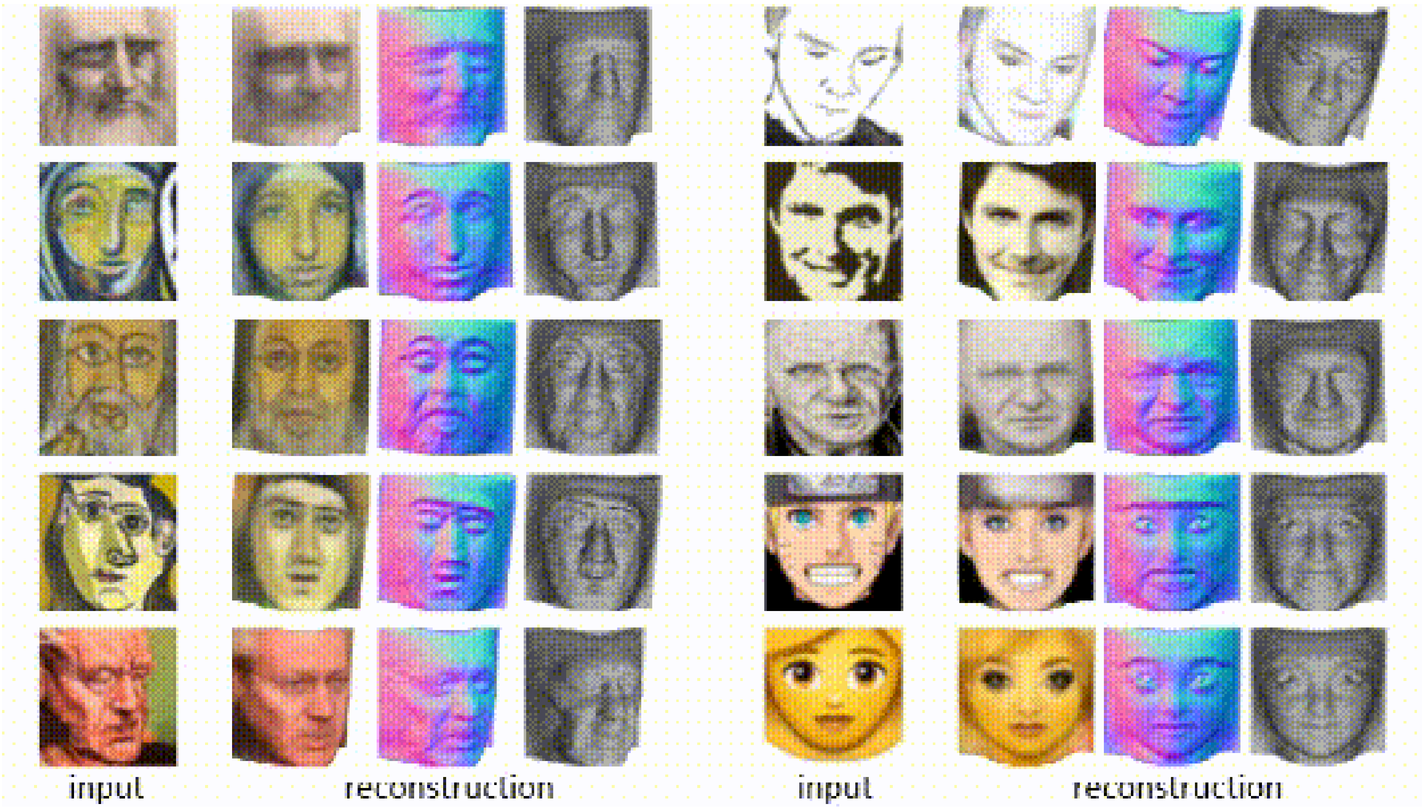
Shape from a single image – Learning based method



Wu et al. Unsupervised learning of probably symmetric deformable 3D objects fro images in the wild. CVPR 2020. (Best paper award)

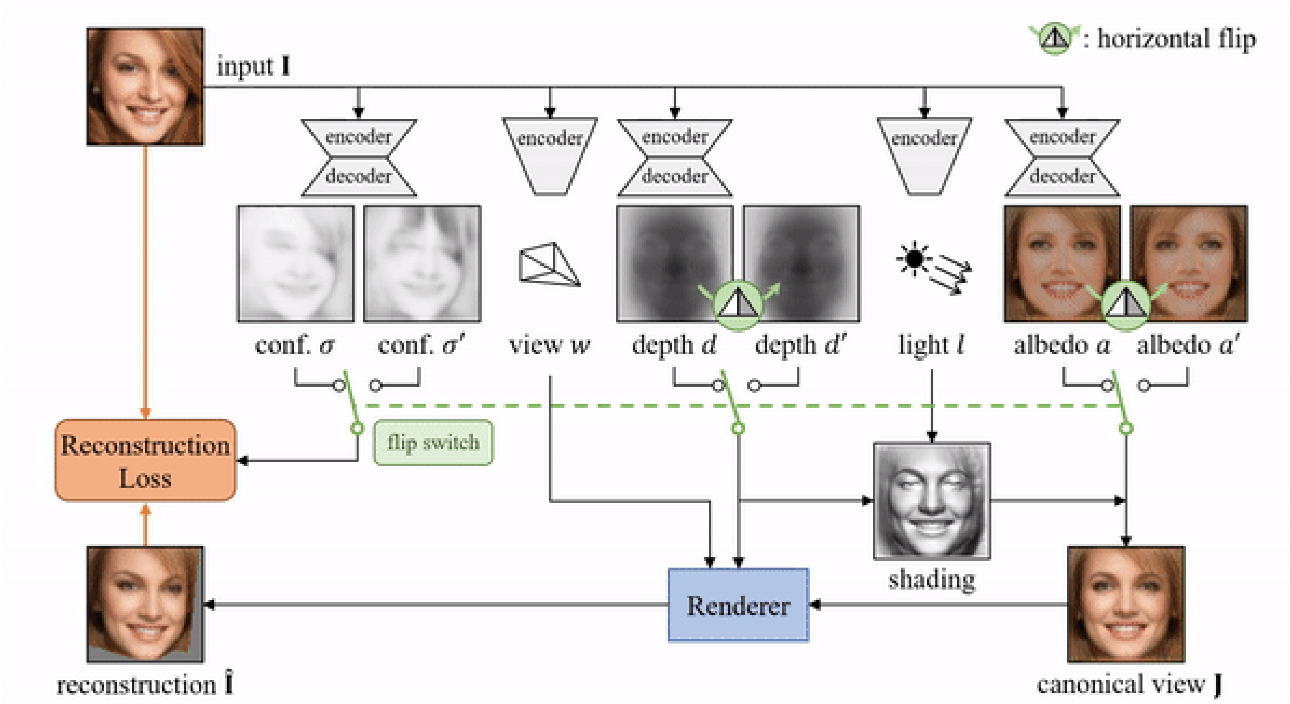
Shape from a single image – Learning based method

抽象图片与动漫图片



Wu et al. Unsupervised learning of probably symmetric deformable 3D objects fro images in the wild. CVPR 2020. (Best paper award)

Shape from a single image – Learning based method

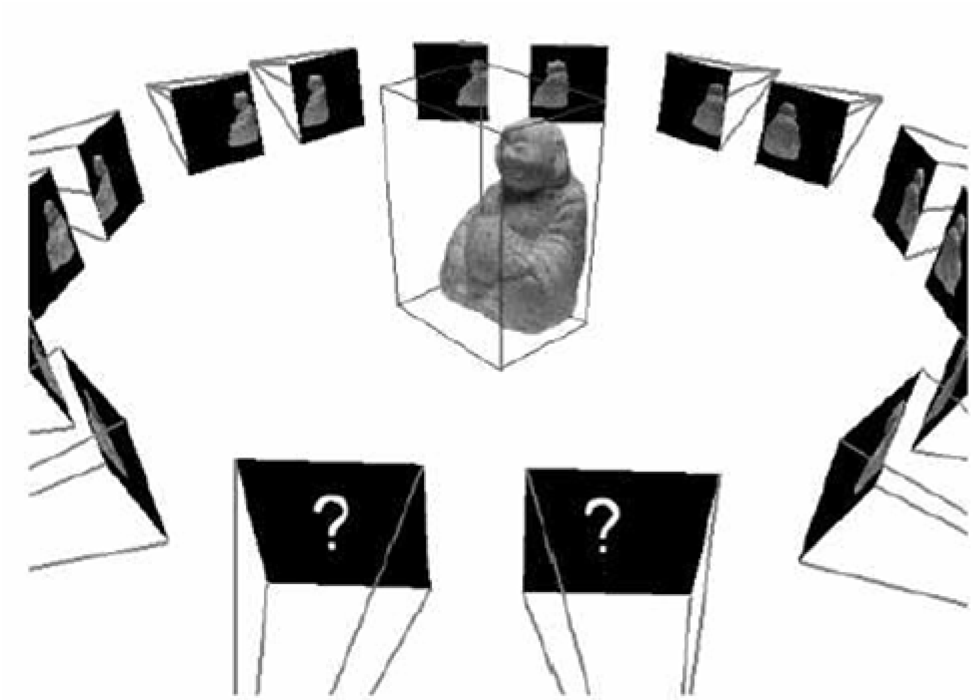


Two confidence-adjusted reconstruction losses are minimized at the same time with asymmetric weights.

Wu et al. Unsupervised learning of probably symmetric deformable 3D objects fro images in the wild. CVPR 2020. (Best paper award)

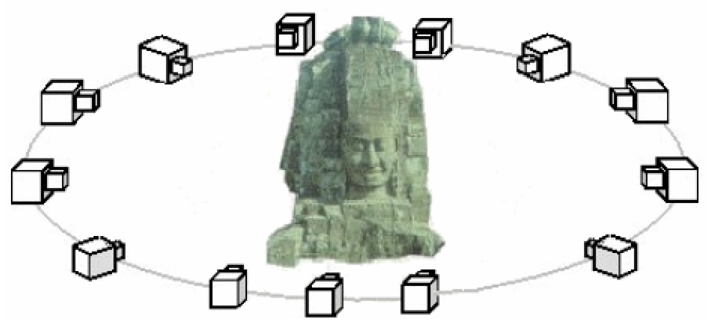
1.3 Image based modeling (IBM)

- Input: multiple photos from different views
- Output: 3D models

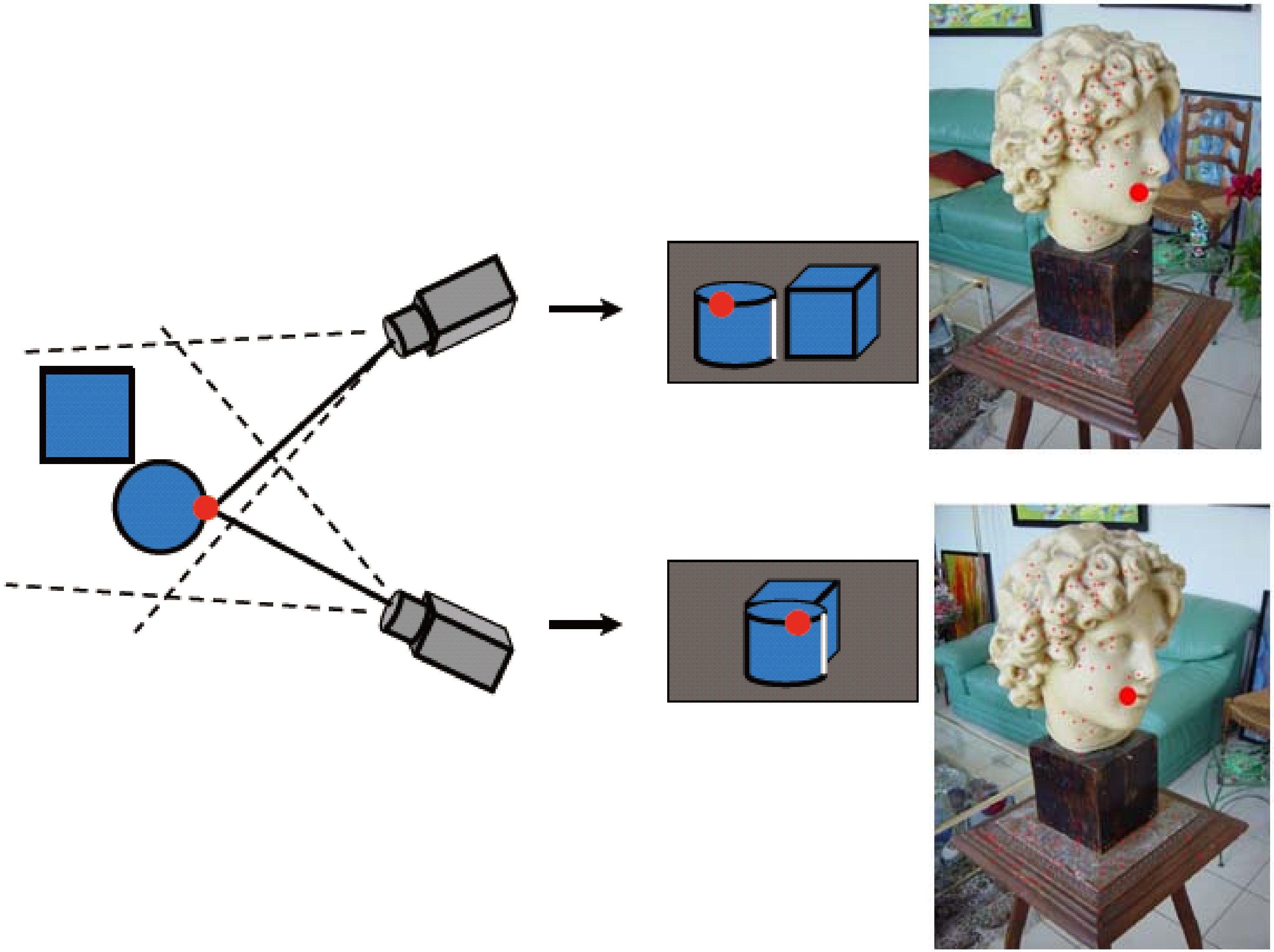


Mathematics: projective imaging

- A 3D point corresponds different pixels in different images
- Key: Finding pixel correspondence between images

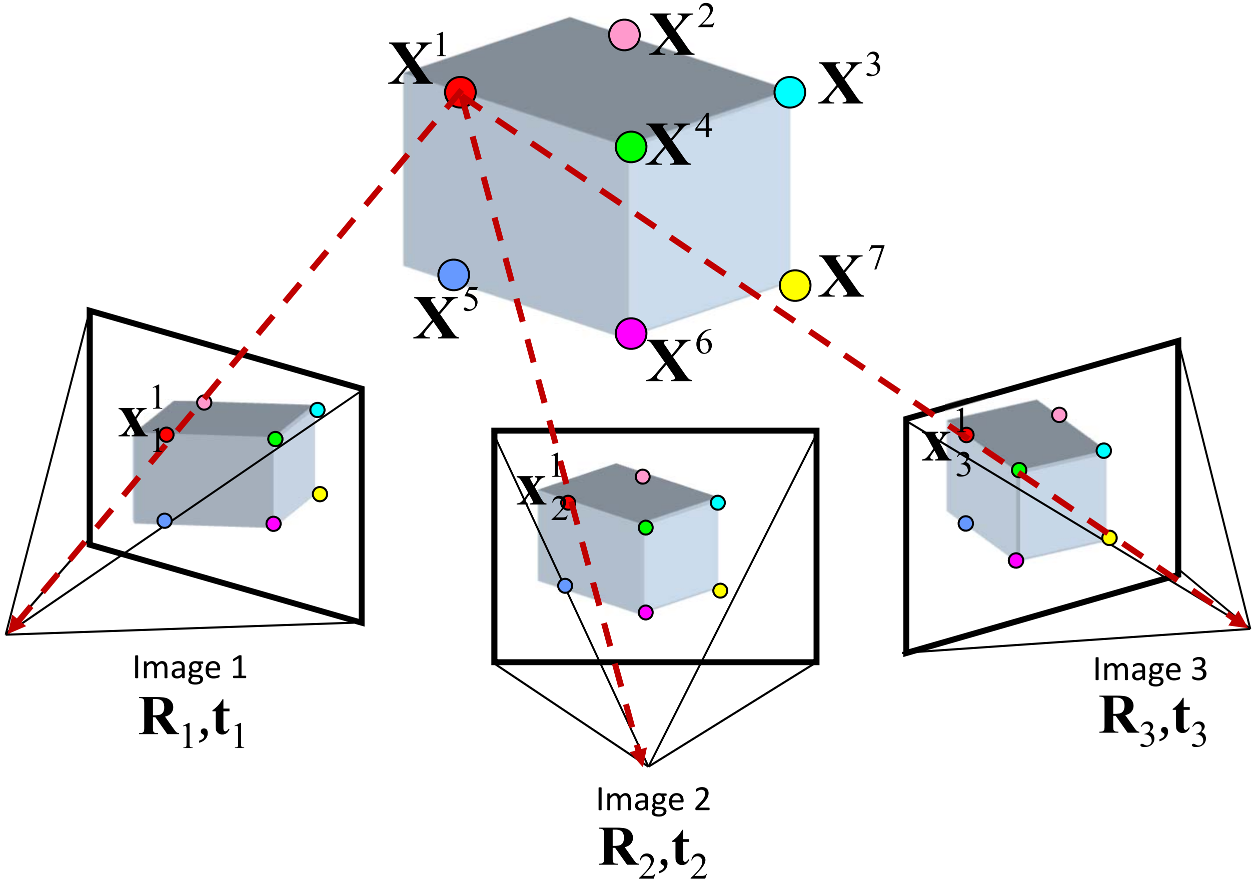


Theory: Multi-view geometry

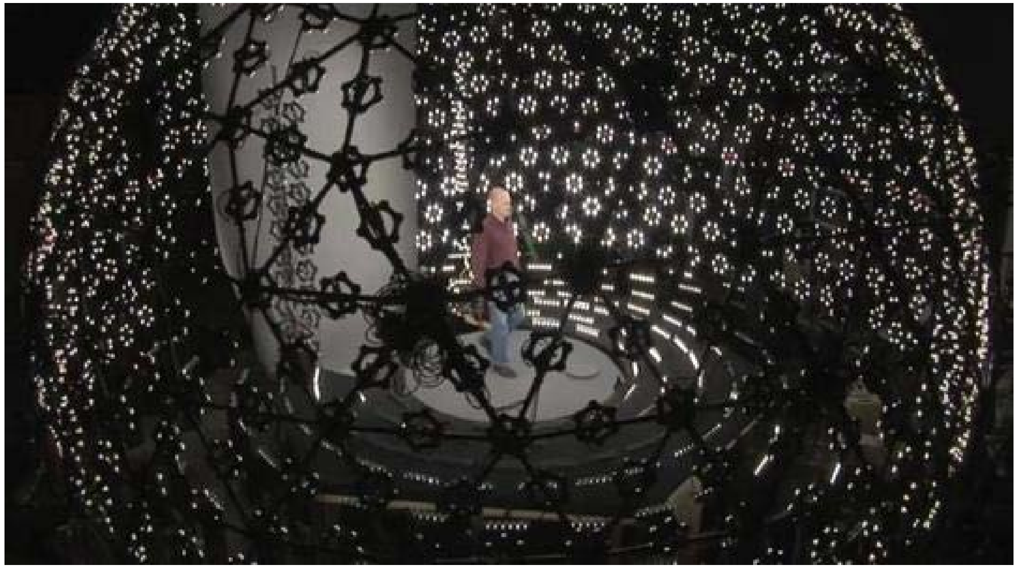


Theory: Multi-view geometry

	Point 1	Point 2	Point 3
Image 1	$\mathbf{x}_1^1 = \mathbf{K}\left[\mathbf{R}_1 \vert \mathbf{t}_1\right]\mathbf{X}^1$	$\mathbf{x}_1^2 = \mathbf{K}\left[\mathbf{R}_1 \vert \mathbf{t}_1\right]\mathbf{X}^2$	
Image 2	$\mathbf{x}_2^1 = \mathbf{K}\left[\mathbf{R}_2 \vert \mathbf{t}_2\right]\mathbf{X}^1$	$\mathbf{x}_2^2 = \mathbf{K}\left[\mathbf{R}_2 \vert \mathbf{t}_2\right]\mathbf{X}^2$	$\mathbf{x}_2^3 = \mathbf{K}\left[\mathbf{R}_2 \vert \mathbf{t}_2\right]\mathbf{X}^3$
Image 3	$\mathbf{x}_3^1 = \mathbf{K}\left[\mathbf{R}_3 \vert \mathbf{t}_3\right]\mathbf{X}^1$		$\mathbf{x}_3^3 = \mathbf{K}\left[\mathbf{R}_3 \vert \mathbf{t}_3\right]\mathbf{X}^3$

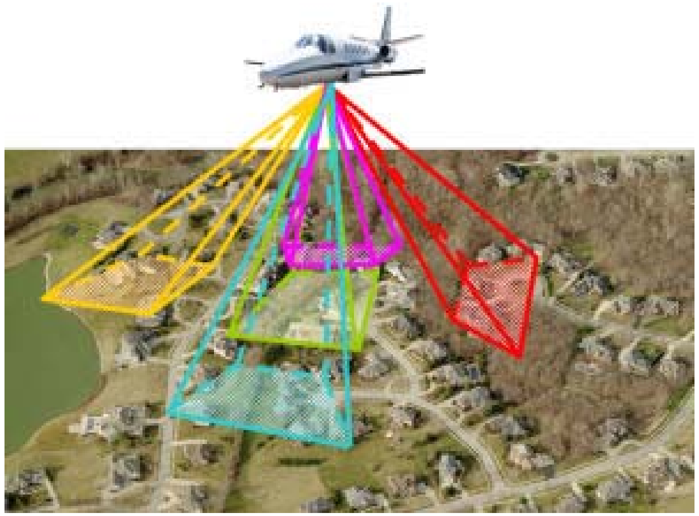


Multi-view Capturing Systems



IBM Commercial Software

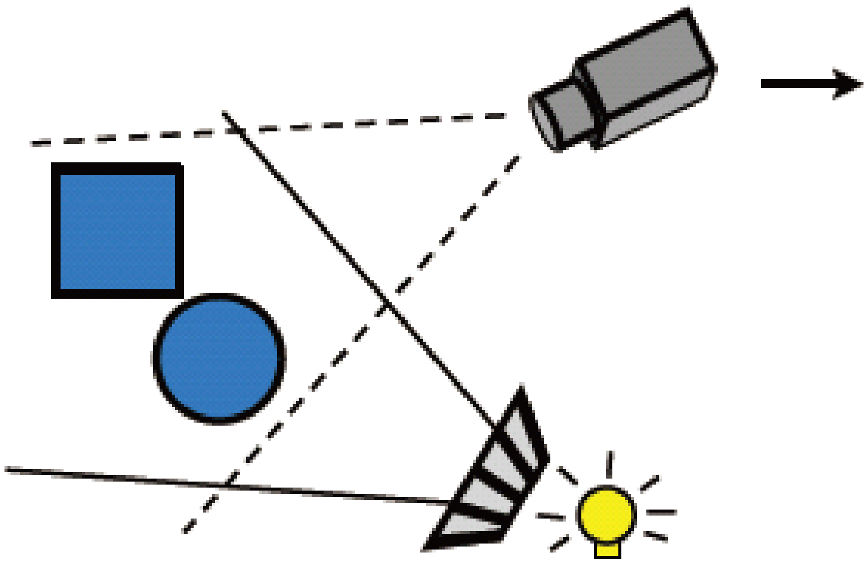
Autodesk 123D Catch

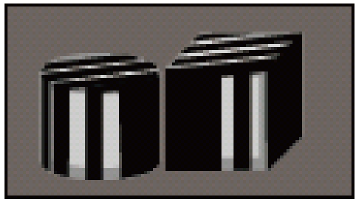


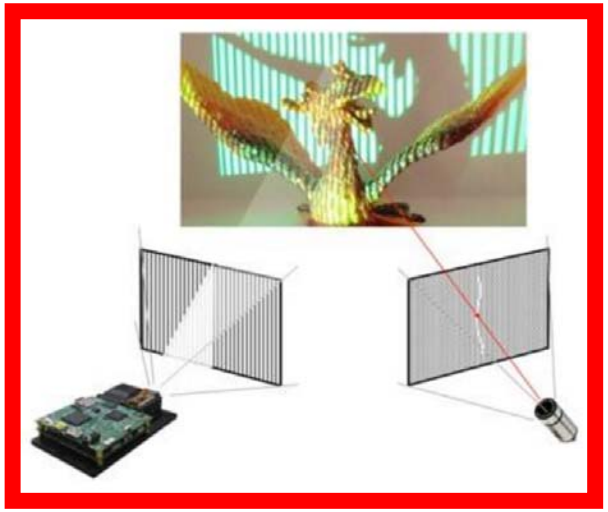
Smart3D, Altizure
（倾斜摄影）

倾斜摄影案例（Altizure）

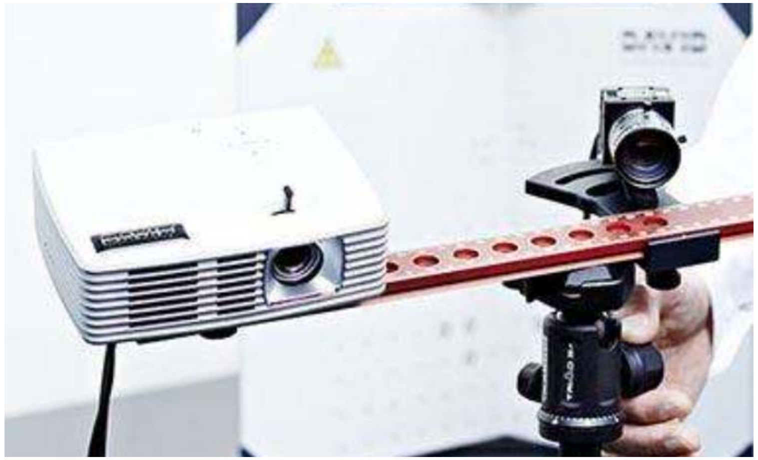
1.4 Structured light （结构光/白光）







结构光3D扫描仪：多用于CAD建模



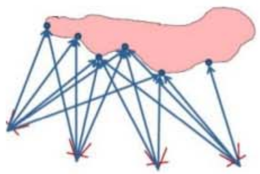
1.5 SfM & SLAM

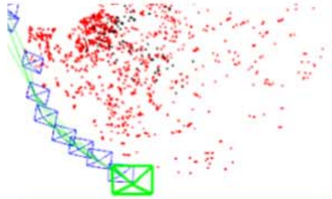
- SfM: Structure from Motion
- SLAM: Simultaneous Localization and Mapping

SfM	SLAM
Vision	Robotics
Structure	Mapping
Camera poses	Location
3D reconstruction	Localization
Feature tracking	Prediction

SLAM的主要流程

RGB图 深度图 IMU测量值

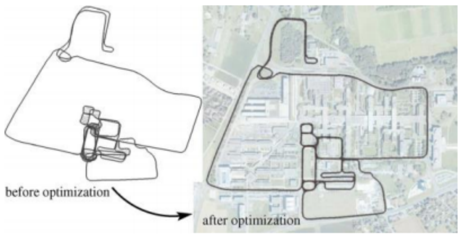




输入
- 传感器数据

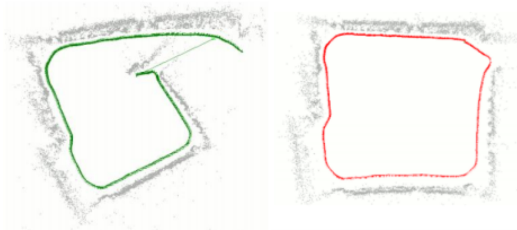
前台线程
- 根据传感器数据进行跟踪求解，实时恢复每个时刻的位姿

输出
- 设备实时位姿
- 三维点云



优化以减少误差累积

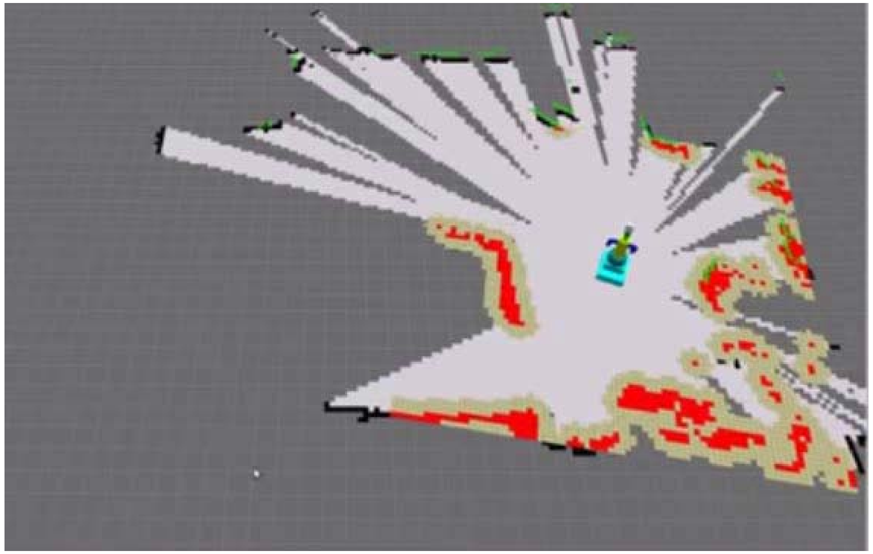
后台线程
- 进行局部或全局优化，减少误差累积
- 场景回路检测



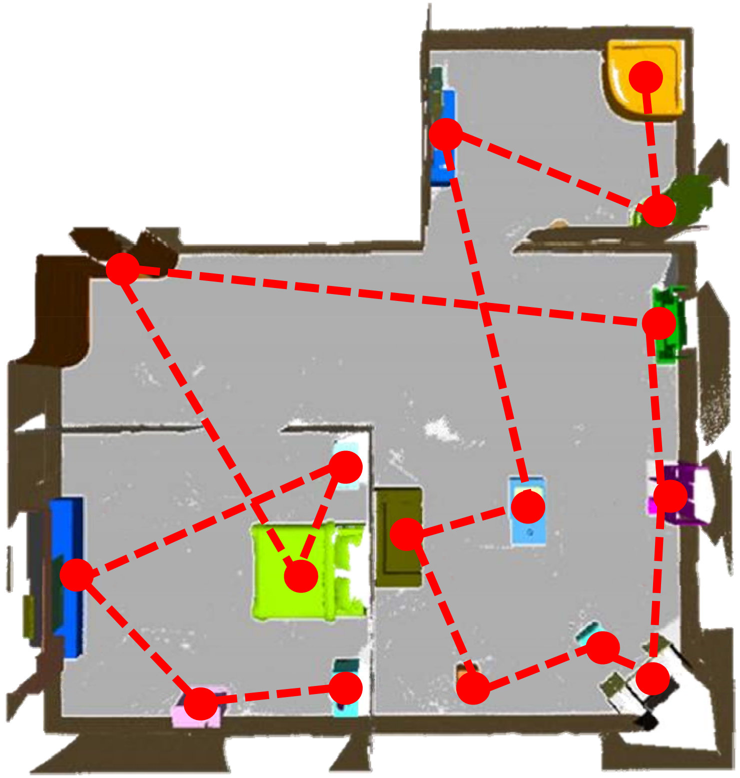
回路检测

机器人扫描与重建三维场景

SLAM + Guidance



Frontier-based exploration
[Yamauchi et al. 1997]

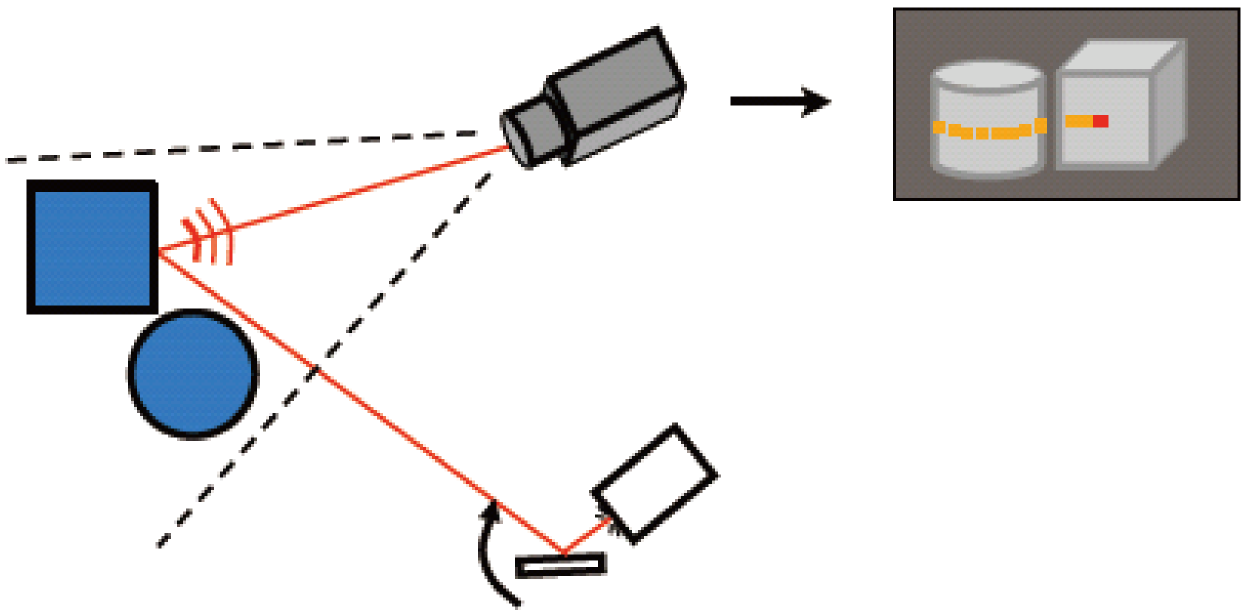


Object-guided exploration
[Liu et al. Siggraph 2018]

Liu et al. Object-aware Guidance for Autonomous Scene Reconstruction. Siggraph 2018.

1.6 Laser Radar （激光雷达测距）

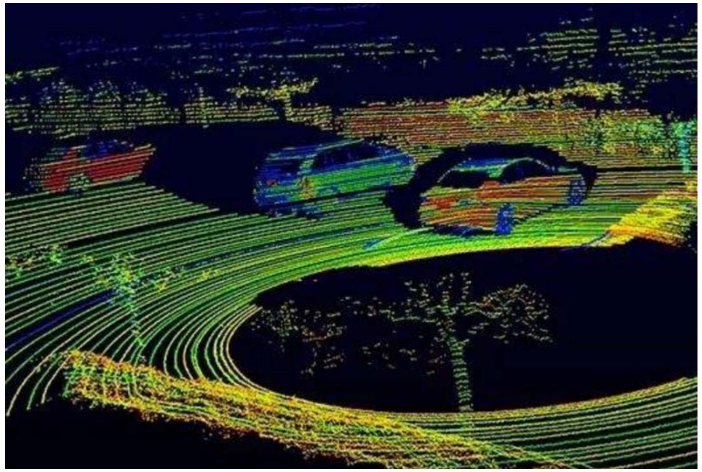
- Light Detection And Ranging, LiDAR
- 原理：主动向目标发射探测信号（激光束）,然后将接收到的从目标反射回来的信号（目标回波）与发射信号进行比较（三角测距）



激光测点

车载移动激光测距与扫描设备

Riegl

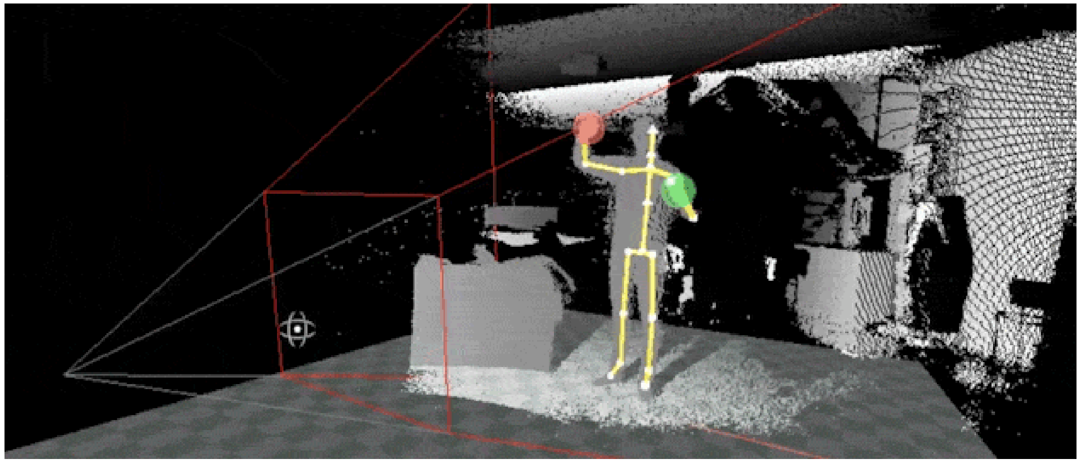


1.7 Depth Images

- Microsoft Kinect
- Apple Primesense
- Intel RealSense
- Google Project Tango
- Asus Xtion
- iPhone XI/XII

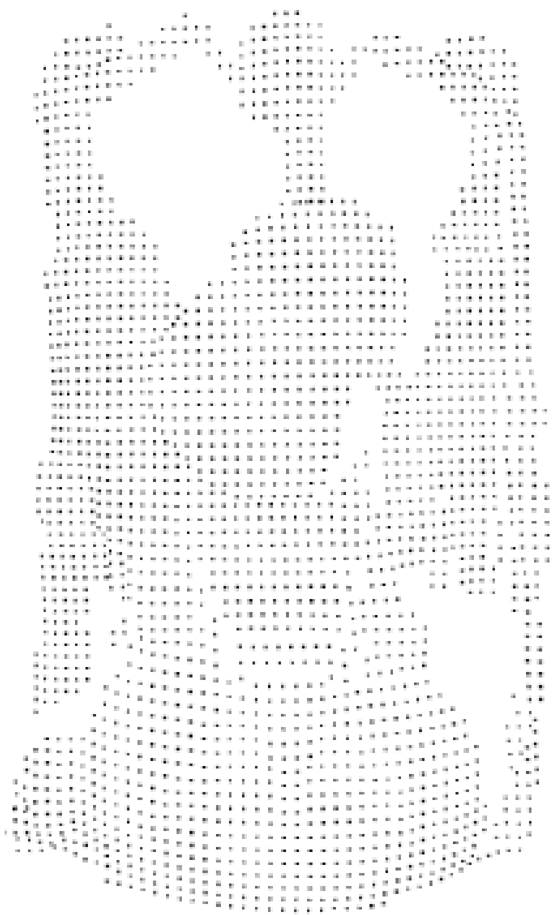
RGBD数据

(R,G,B) D

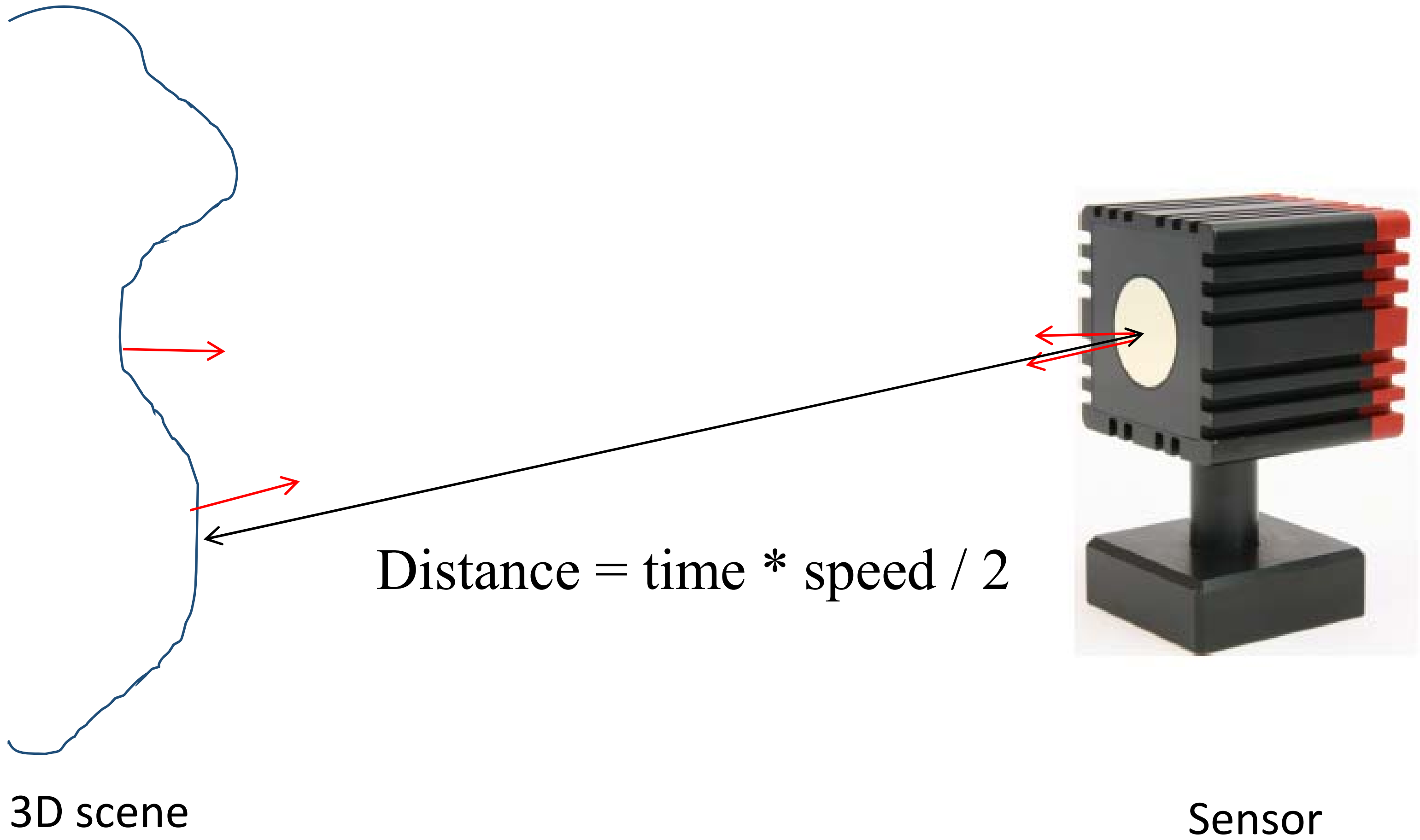


Depth Data: Grid Points

- 2.5D image

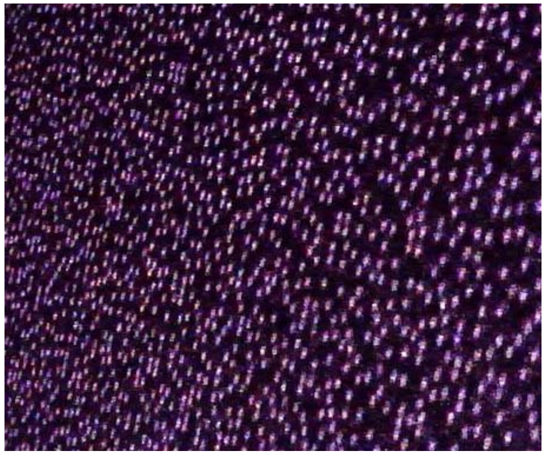


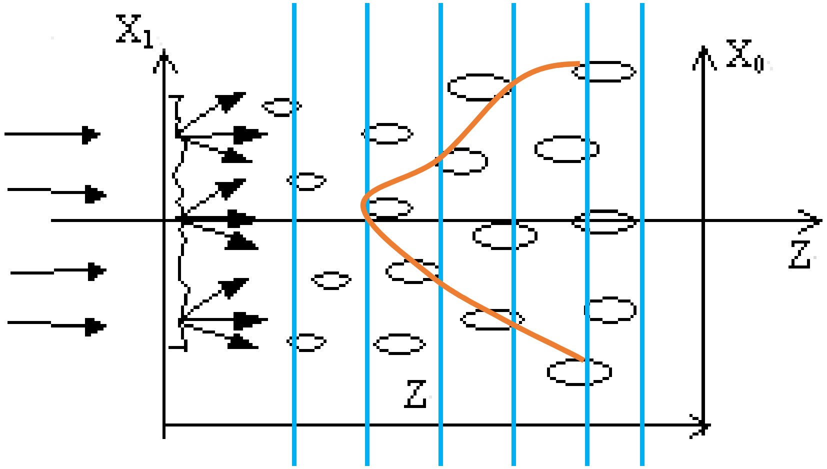
深度相机原理 (Time of flight, TOF)



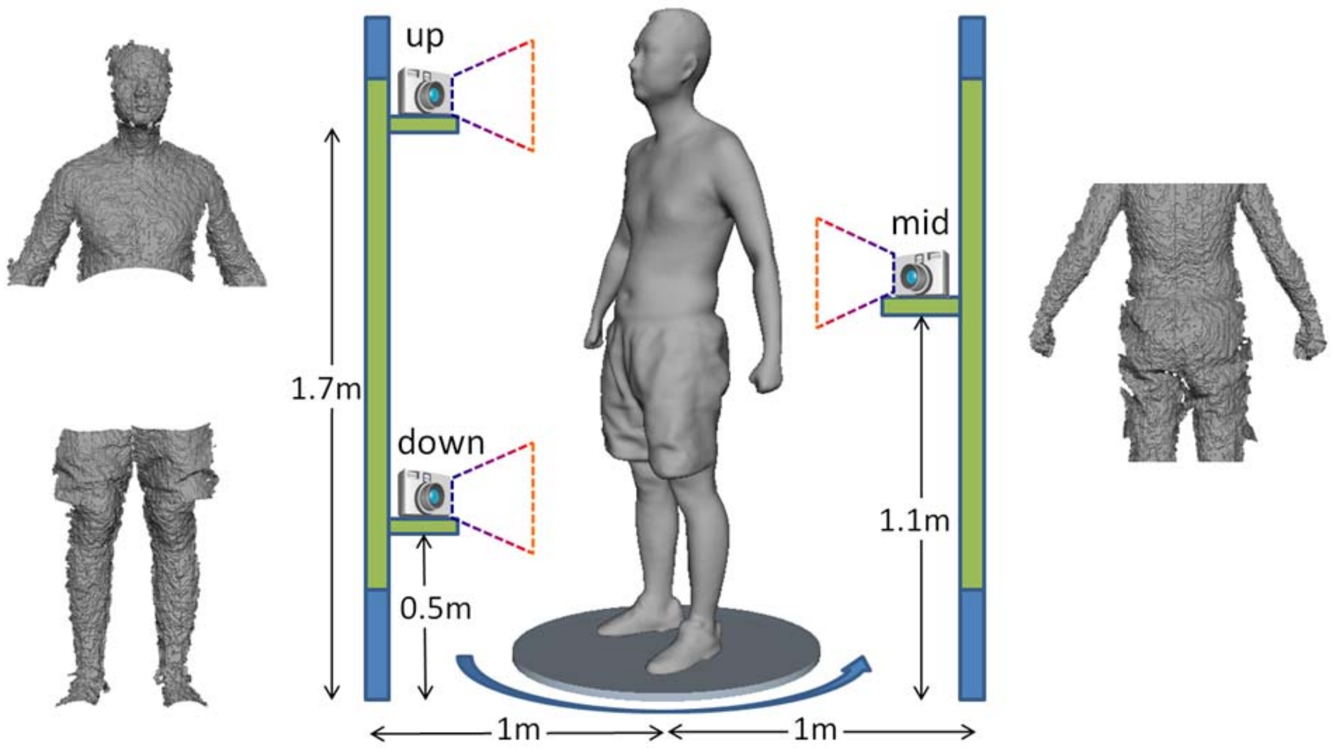
深度相机原理 (Kinect)

- 当激光穿透毛玻璃后形成随机衍射斑点，这些散斑（laser speckle）具有高度的随机性，而且会随着距离的不同变换图案。空间中任意两处散斑图案都不同
- Light coding打出了一个具有三维纵深的“体编码”，只要看物体表面的散斑图案，就可以知道这个物体在什么位置





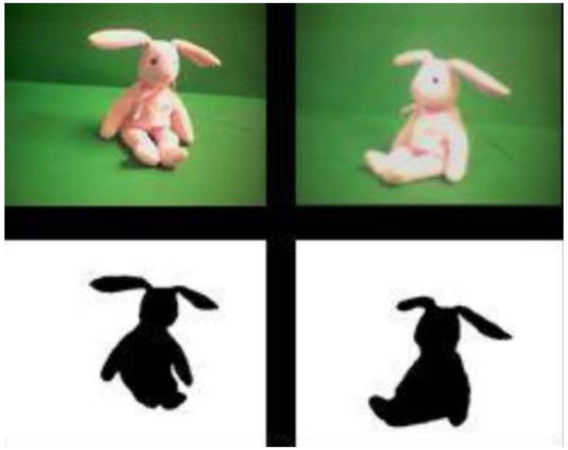
基于Kinects的人体扫描

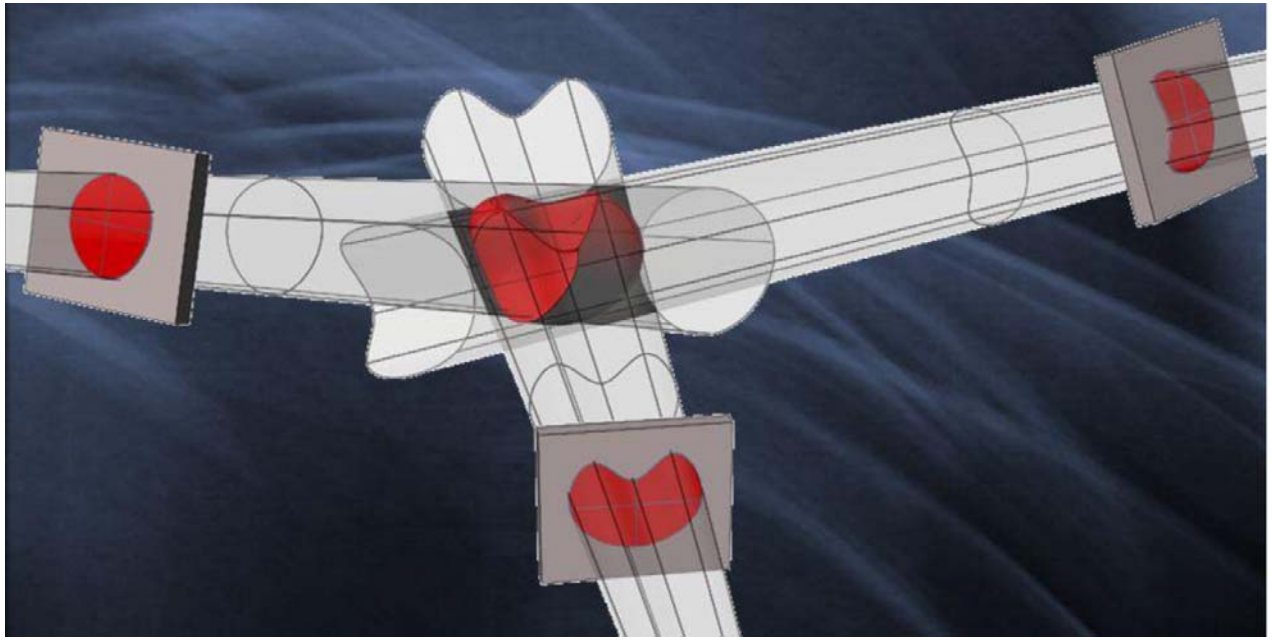


Tong et al. Scanning 3D Full Human Bodies using Kinects. IEEE Transactions on Visualization and Computer Graphics, 2012

KinectFusion [2013]

1.8 Shape from Silhouette/Contours





Intersection of visual hulls

1.9 Probing

- Probing
  - position probe on object
  - record the location
- Output
  - point cloud data
- Problematic
  - Labour intensive
  - Error prone

1.10 全景相机 (Panorama)

- 多张图片拼接而成（拟三维：非真三维）

千亿像素图片

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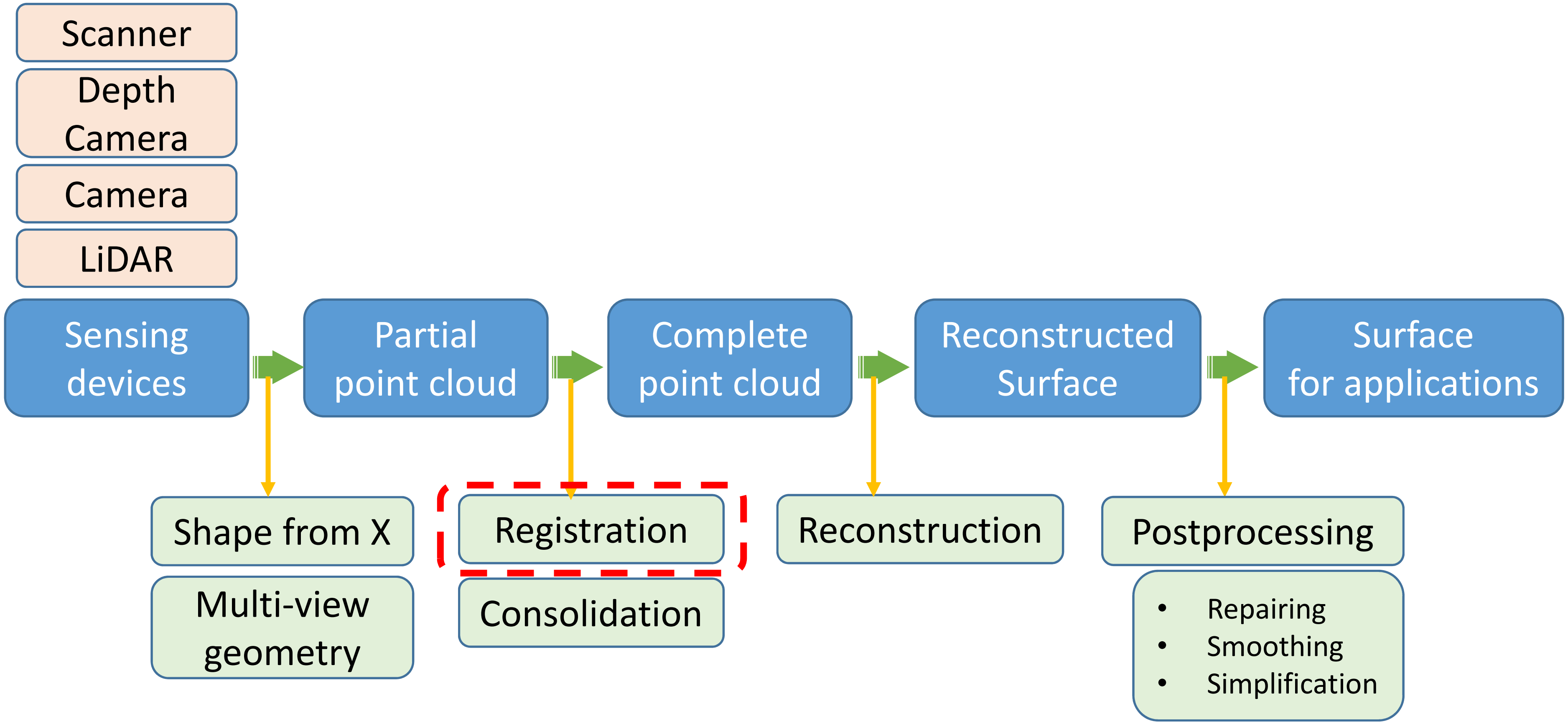
University of Science and Technology of China

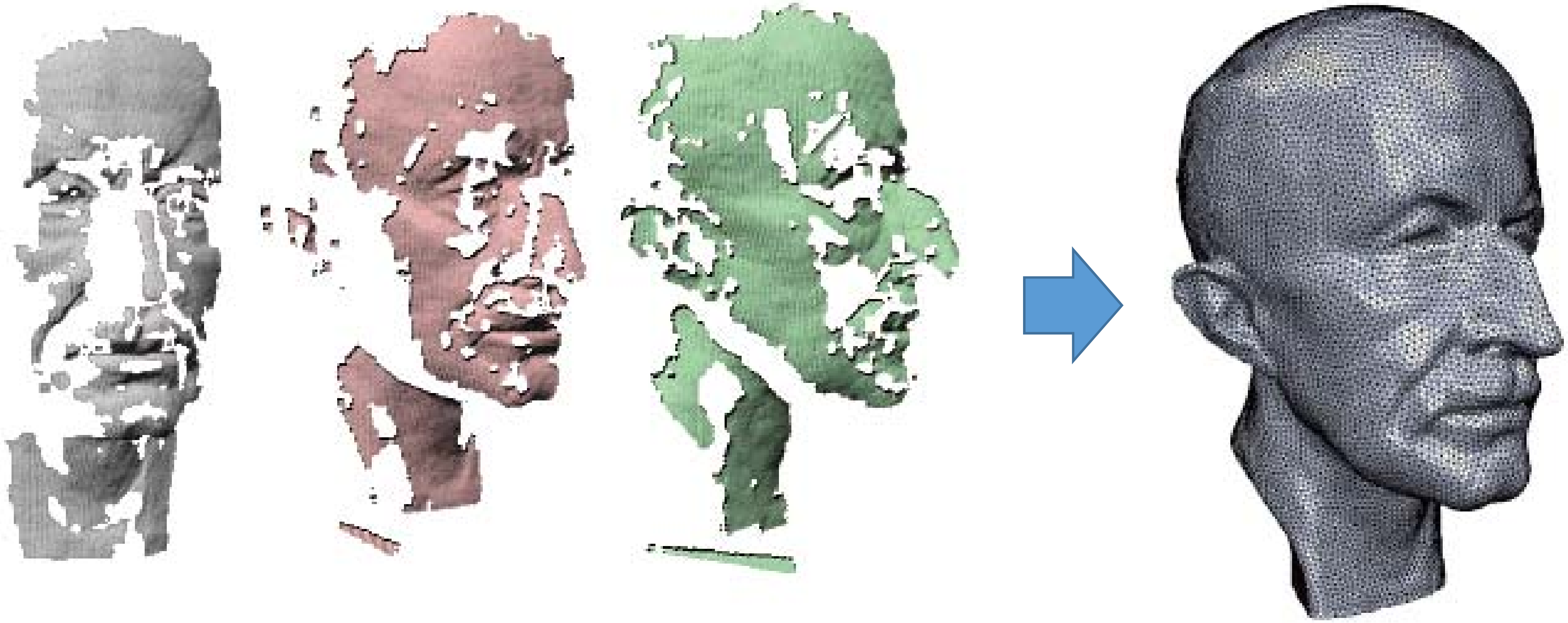
GAMES102

2. Registration

2. Registration



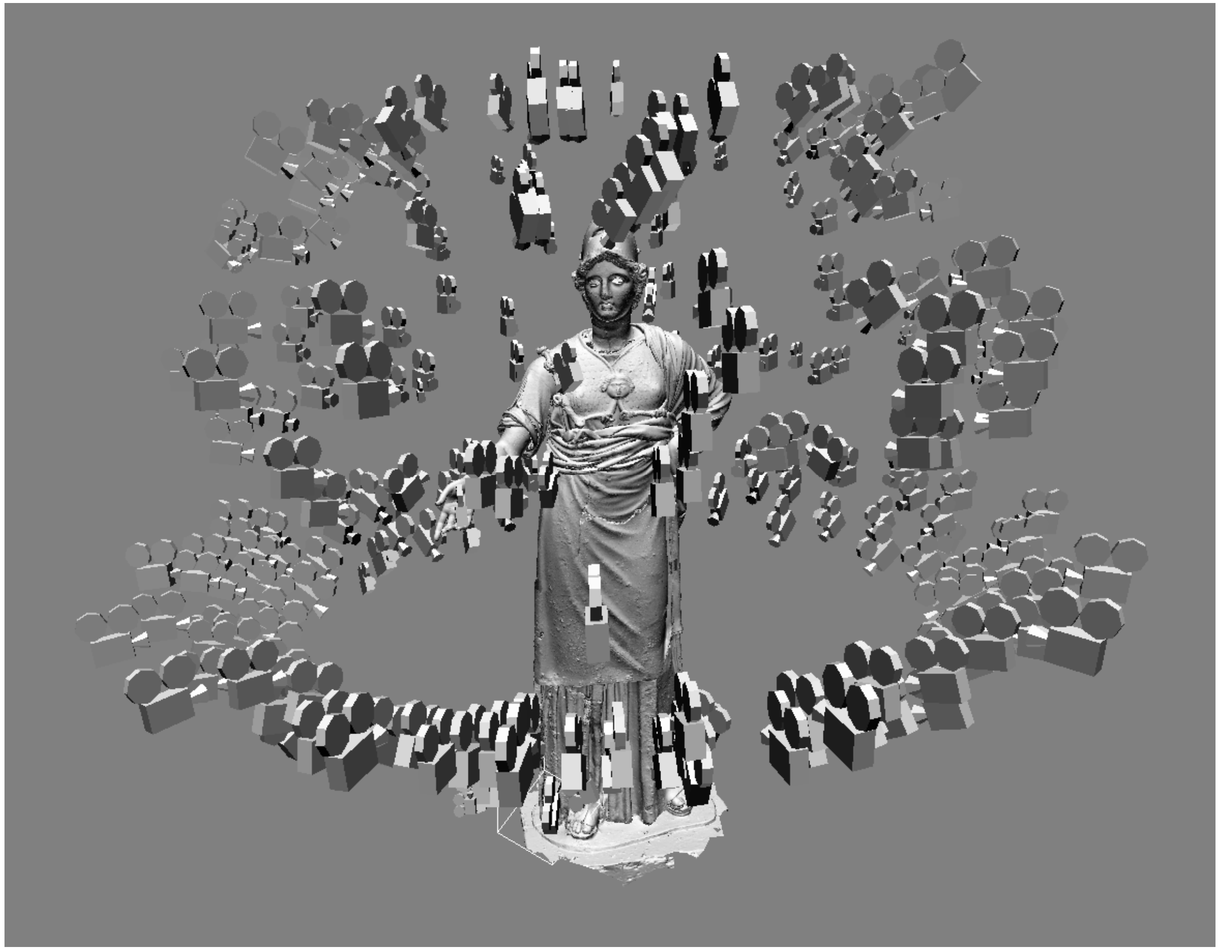
Goal: Reconstruction from scans



Set of raw scan data

Reconstruction

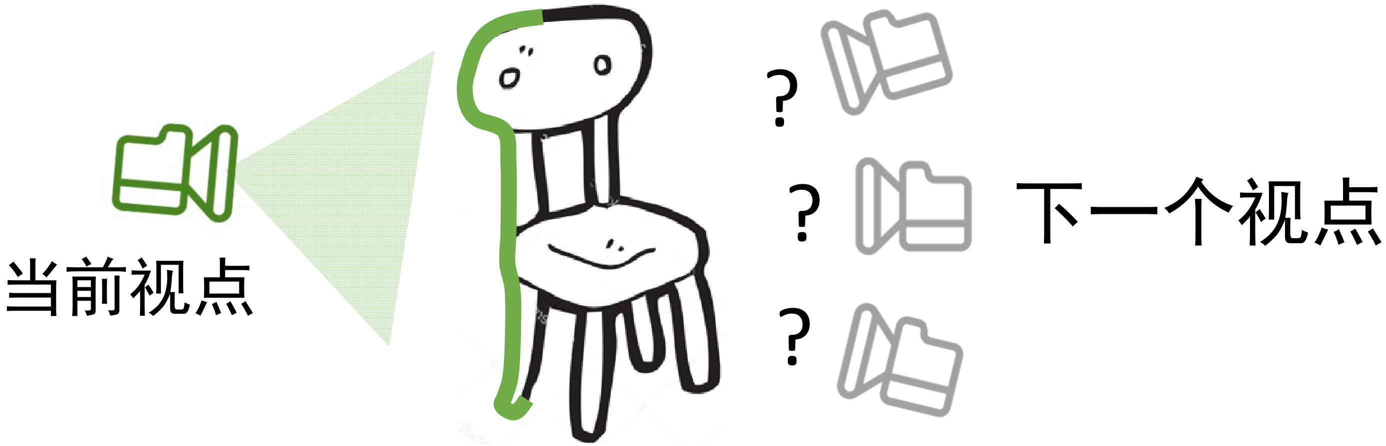
Acquisition Planning



Selecting the set of views is not easy

多个视点的扫描

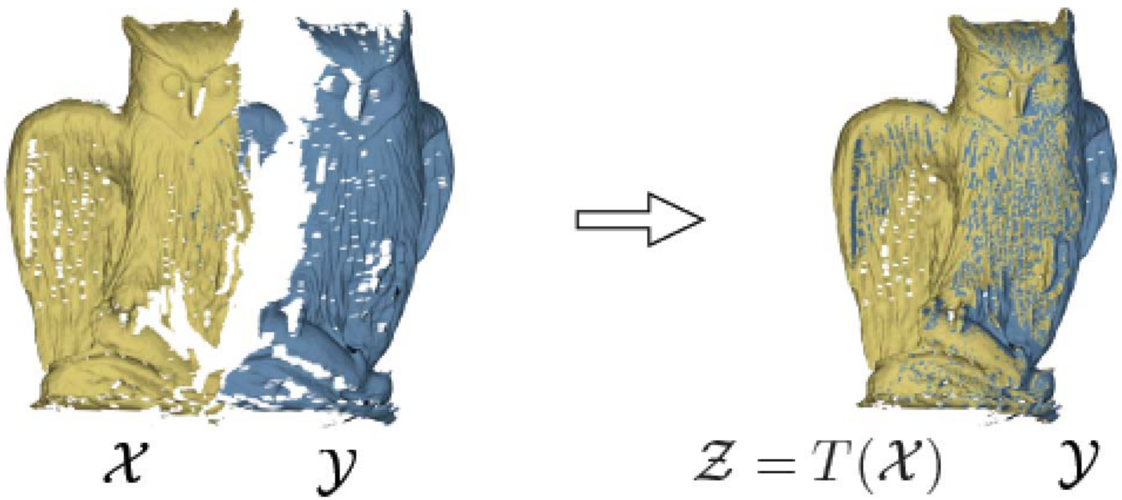
- 每个视点得到分片3D数据
- **问题**：如何将这些分片数据合并成一个整体数据？



Registration

Pairwise Registration

- Align a *source model* $\mathcal{X}$ onto a *target model* $\mathcal{Y}$
  - find a *transformation* $T(\mathcal{X})$ that brings $\mathcal{X}$ into alignment with $\mathcal{Y}$
- Two main questions:
  - How do we measure the quality of the alignment?
  - What transformations are acceptable?



Registration as energy minimization

source

$$\arg\min_{T} E_{\mathrm{reg}}(T, \mathcal{X}, \mathcal{Y})$$

transformation

target

$$E_{\mathrm{reg}}(T, \mathcal{X}, \mathcal{Y}) = E_{\mathrm{match}}(T, \mathcal{X}, \mathcal{Y}) + E_{\mathrm{prior}}(T)$$

Alignment Error

How do we measure the quality of the alignment?

Transformation Error

What transformations are allowed / good?

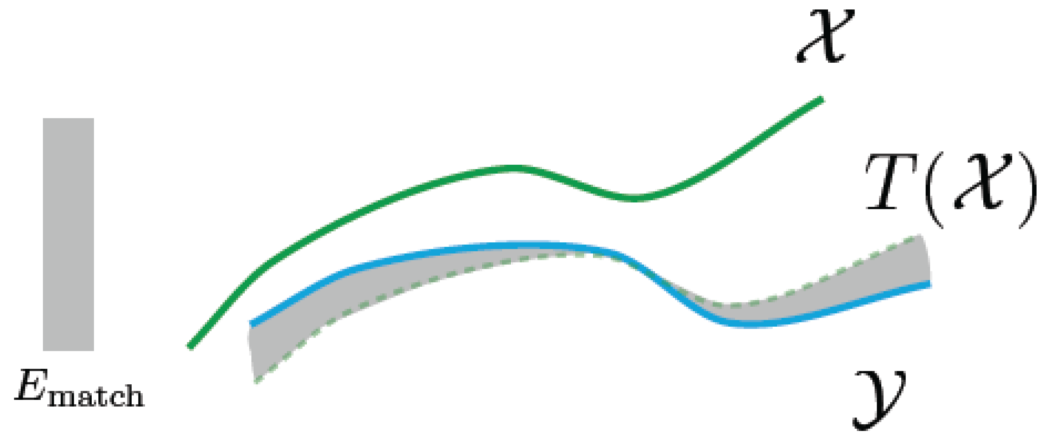
Alignment Error

- Alignment Error

$$E_{\text{reg}} = \boxed{E_{\text{match}}} + E_{\text{prior}}$$

$$E_{\text{match}}(T, \mathcal{X}, \mathcal{Y}) = \int_{\mathcal{X}} \varphi(T(\mathbf{x}), \mathcal{Y})d\mathbf{x}$$

distance function

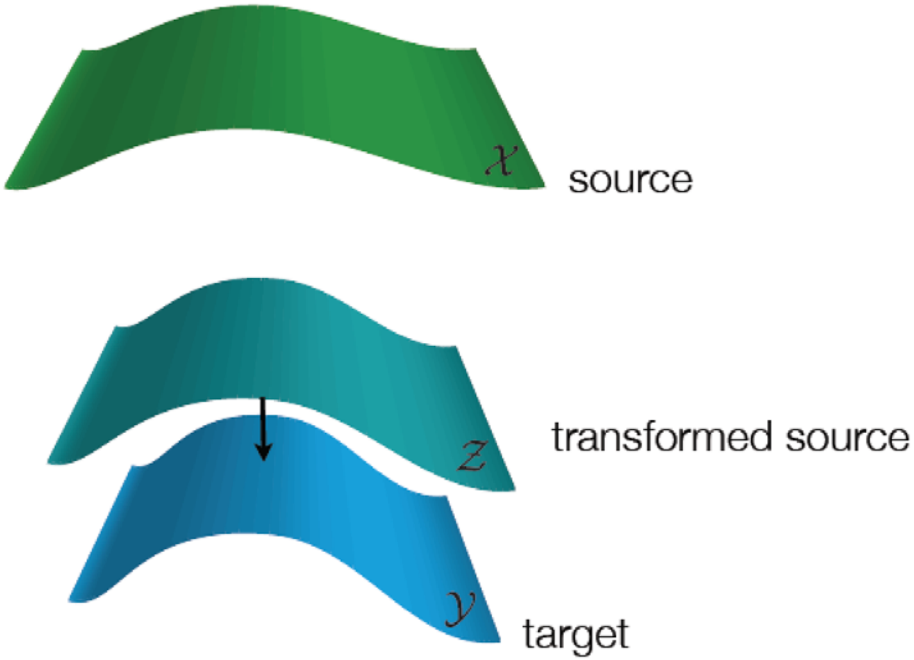


Alignment Error

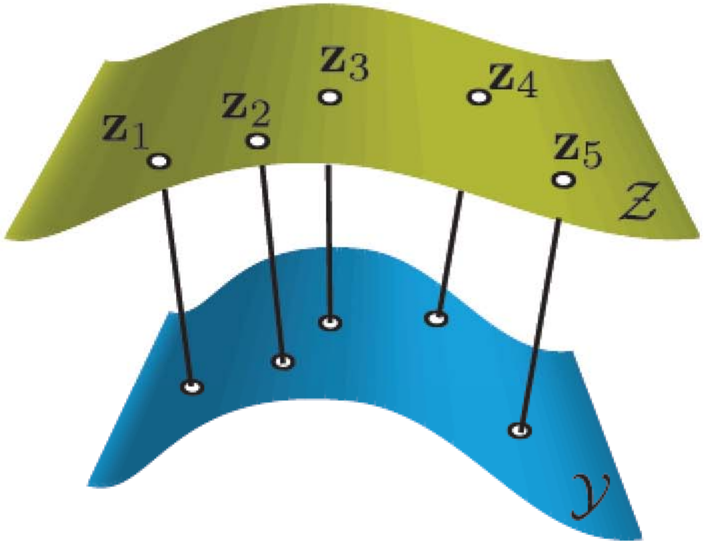
$$E_{\text{reg}} = \boxed{E_{\text{match}}} + E_{\text{prior}}$$

$$E_{\text{match}}(\mathcal{Z}) = \int_{\mathcal{Z}} \varphi(\mathbf{z}, \mathcal{Y}) d\mathbf{z}$$

distance function



Alignment Error



discretized matching cost based on point correspondences

$$E_{\text{reg}} = E_{\text{match}} + E_{\text{prior}}$$

$$E_{\text{match}}(\mathcal{Z}) = \int_{\mathcal{Z}} \varphi(\mathbf{z}, \mathcal{Y}) d\mathbf{z}$$

$$\Downarrow$$

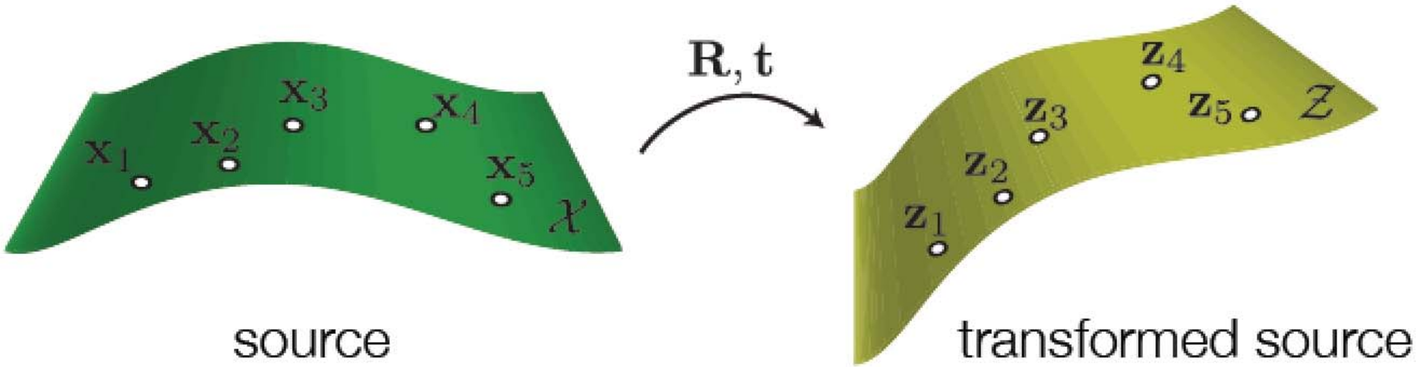
$$E_{\text{match}}(Z) = \sum_{i=1}^{n} w_i \|\mathbf{z}_i - P_{\mathcal{Y}}(\mathbf{z}_i)\|_2^2$$

weights

corresponding point on target

Prior Error – 1 (Rigid objects)

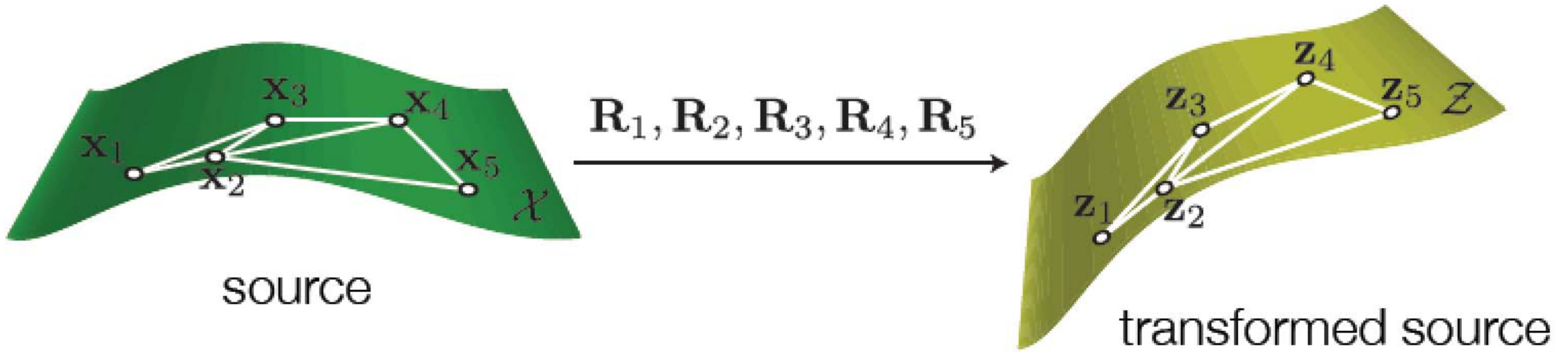
- Global Rigidity $$E_{\text{reg}} = E_{\text{match}} + \boxed{E_{\text{prior}}}$$



$$E_{\text{prior}}(Z, \mathbf{R}, \mathbf{t}) = \sum_{i=1}^{n} \|\mathbf{z}_i - (\mathbf{R}\mathbf{x}_i + \mathbf{t})\|_2^2$$

Prior Error – 2 (Elastic objects)

- Local Rigidity $$E_{\text{reg}} = E_{\text{match}} + \boxed{E_{\text{prior}}}$$

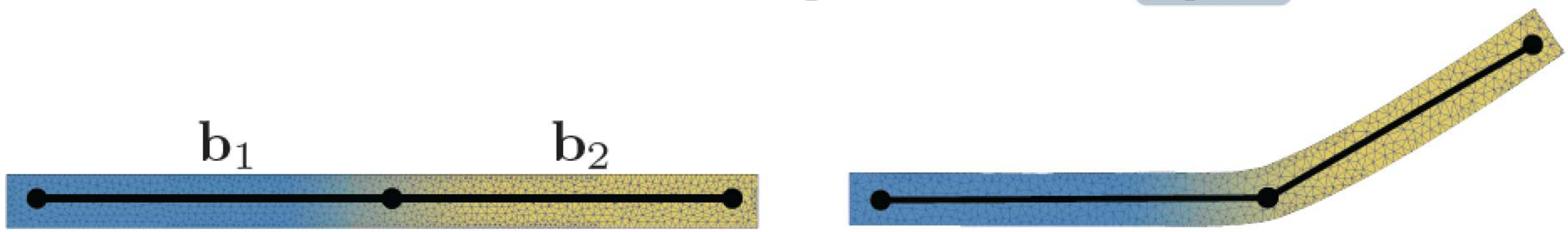


$$E_{\text{prior}}(Z, \{\mathbf{R}_i\}) = \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_i} \|(\mathbf{z}_j - \mathbf{z}_i) - \mathbf{R}_i(\mathbf{x}_j - \mathbf{x}_i)\|_2^2$$

Prior Error – 3 (Articulated objects)

- Linear Blend Skinning

$$E_{\text{reg}} = E_{\text{match}} + \boxed{E_{\text{prior}}}$$



$$E_{\text{prior}}(Z, \mathbf{R}_j, \mathbf{t}_j) = \sum_{i=1}^{n} \overbrace{\sum_{j \in \mathcal{B}} w_{i,j}}^{\text{blended}} \|\mathbf{z}_i - \underbrace{(\mathbf{R}_j \mathbf{x}_i + \mathbf{t}_j)}_{\text{rigid transformations}})\|_2^2$$

Iterative Closest Point (ICP) Algorithm
[Besl+92]

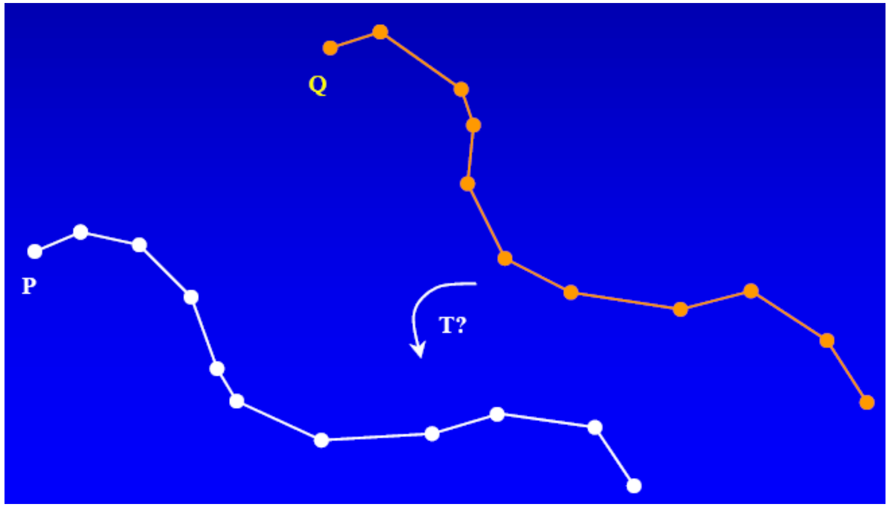
- **Step 1:** find correspondences using closest points for fixed transformation

  → efficient data structures

Iterate until convergence

- **Step 2:** find best rigid transformation for fixed correspondences

  → closed form solution



$$E = \sum_{i}^{N_P} \left\| Tq_i - p_i \right\|^2$$

Implementations

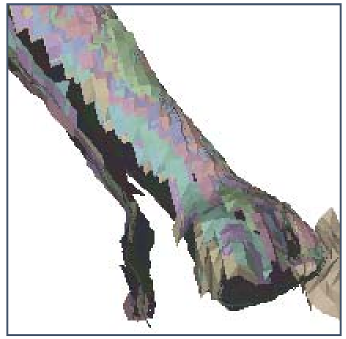
- Iterative Closest Point (ICP) Algorithm

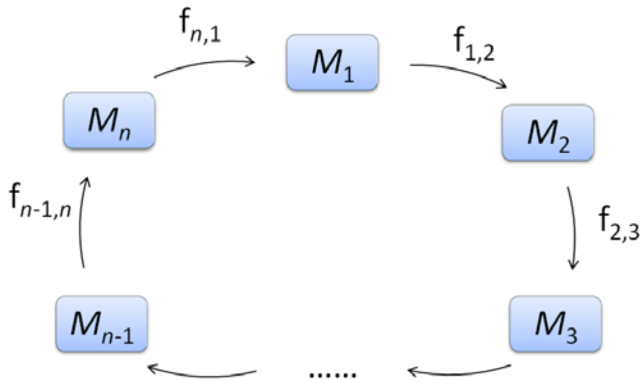
$$E_{\text{match}}(Z) = \sum_{i=1}^{n} w_i \|\mathbf{z}_i - P_{\mathcal{Y}}(\mathbf{z}_i)\|_2^2$$

- Implementations
  - (approximate) closest points→ (more) efficient data structures
  - weight accounts for importance and confidence
  - heuristics to prune or down-weight bad correspondences
- Error norm
  - squared Euclidean distance is sensitive to outliers
  - robust norms reduce this sensitivity

More…

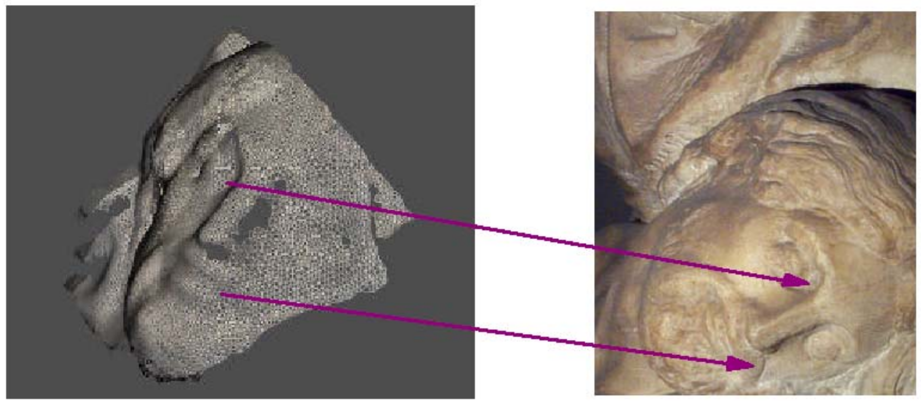
- Pairwise Sequential vs. Global [Pulli99]
  - Global: loop closure problem
- Using Color in registration [Bernardini00]






before

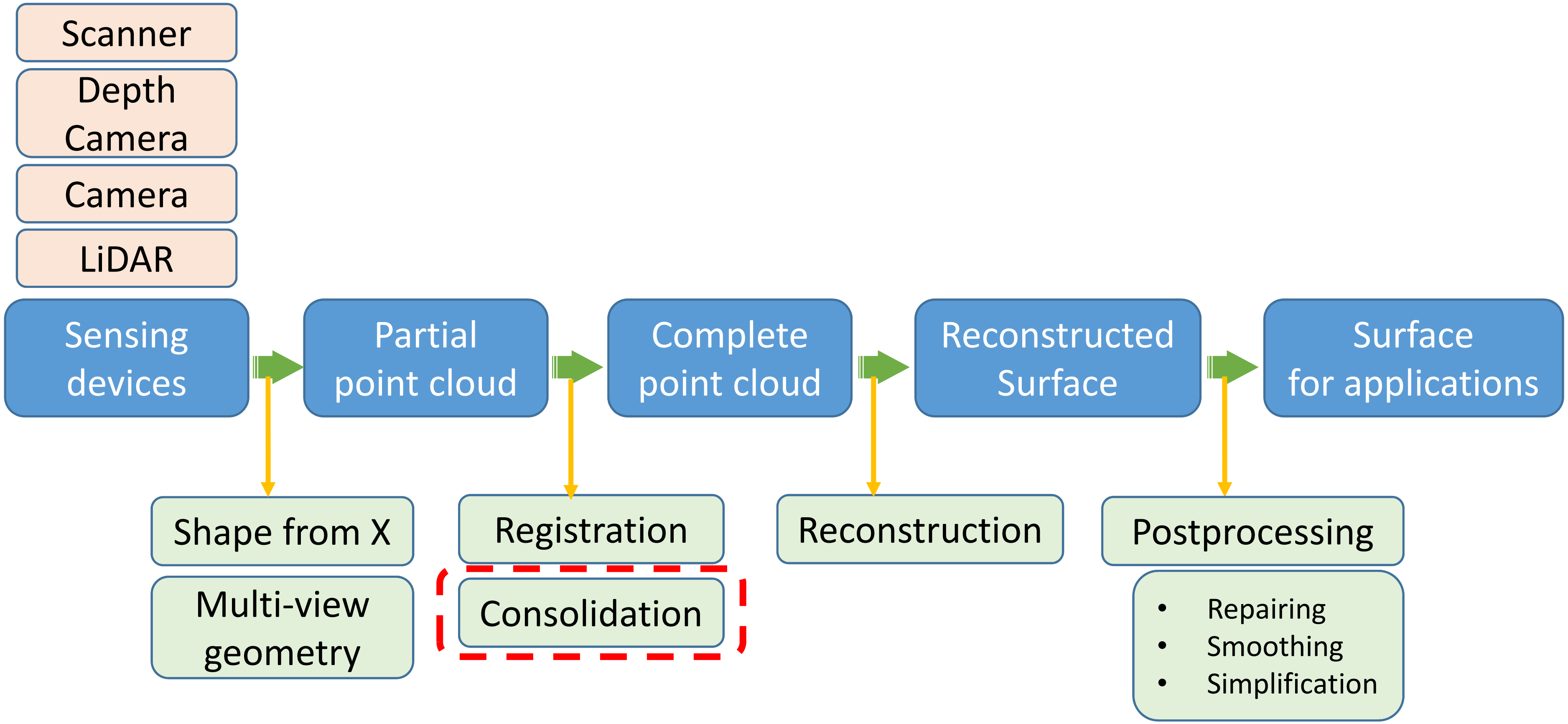

after


mesh

texture map image

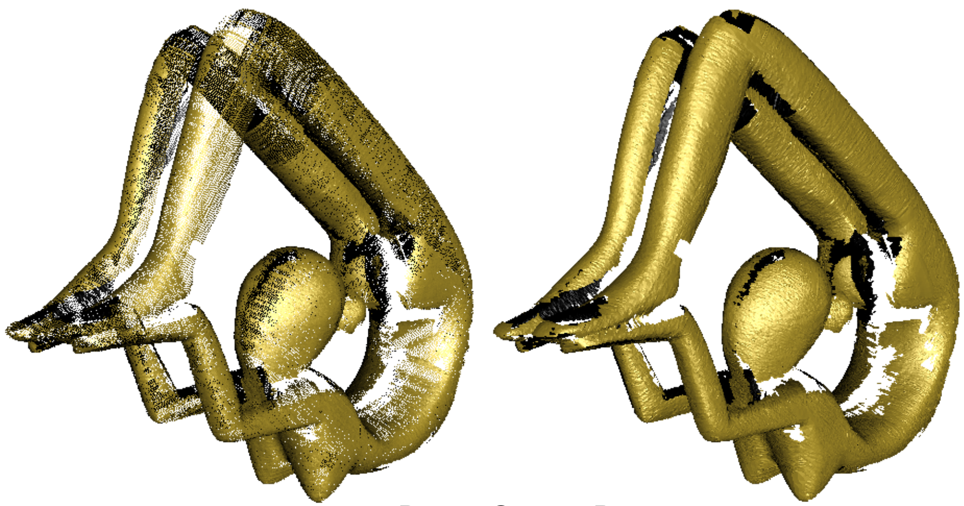
3. Consolidation

3. Consolidation



Imperfect Acquisition

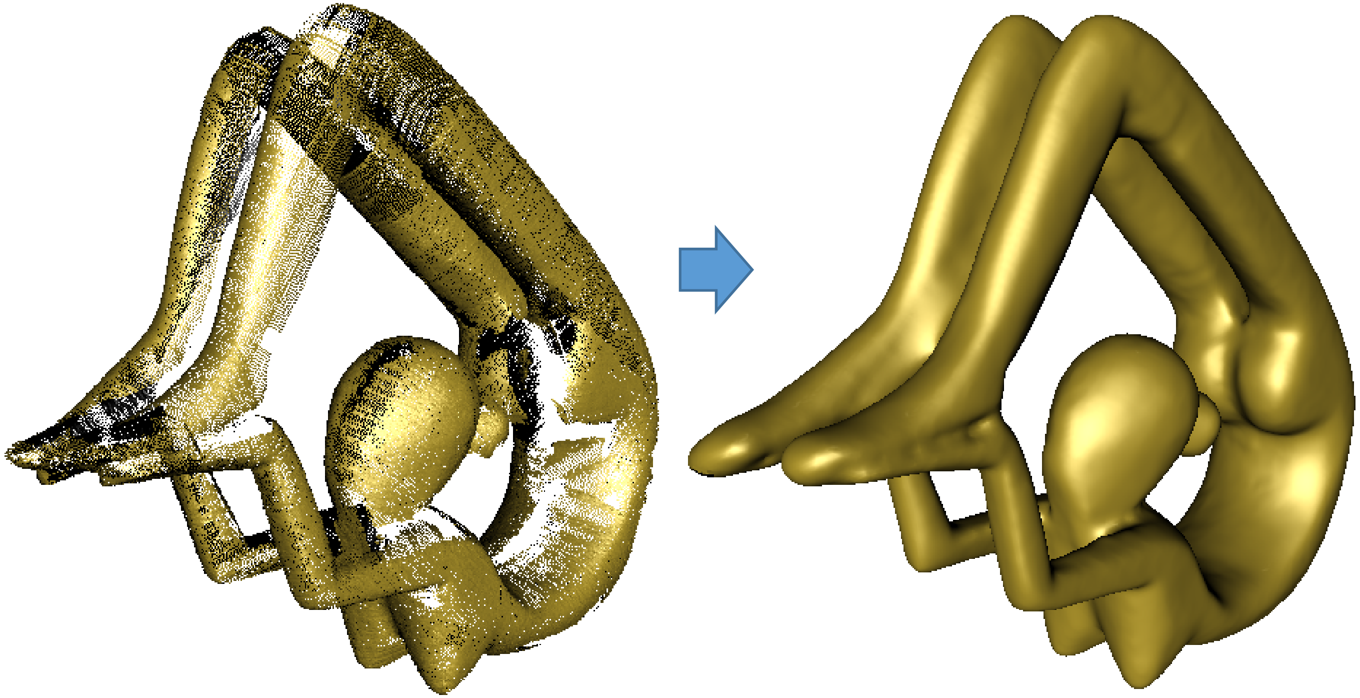
- Outliers
- Noisy data
- Orientation
- Large missing parts
- Non-uniform sampling
- Blurred features
- …



Raw Scan Data

Consolidation

- Goal: obtain a surface/point-cloud with good quality (noise-free, orient-consistent, complete, continuous…)



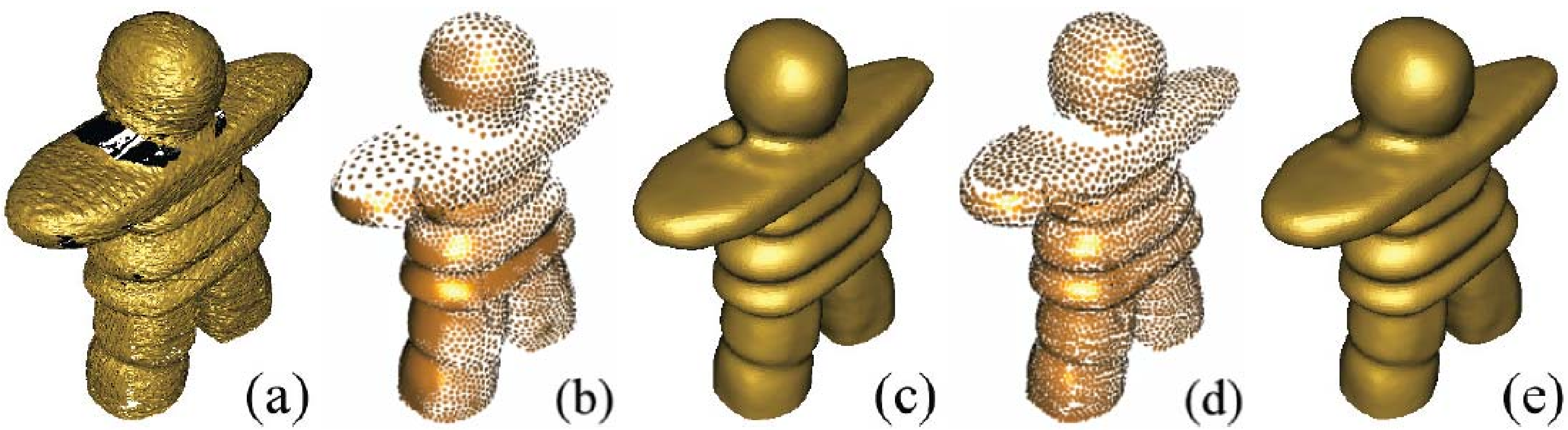
Point Cloud Consolidation

Input

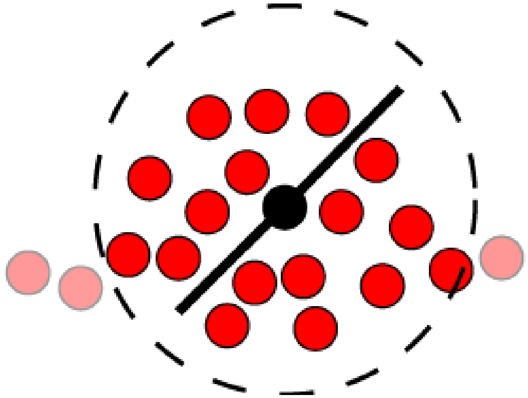
Unorganized
Noisy
Thick
Outliers
Non-uniform
Un-oriented

Output

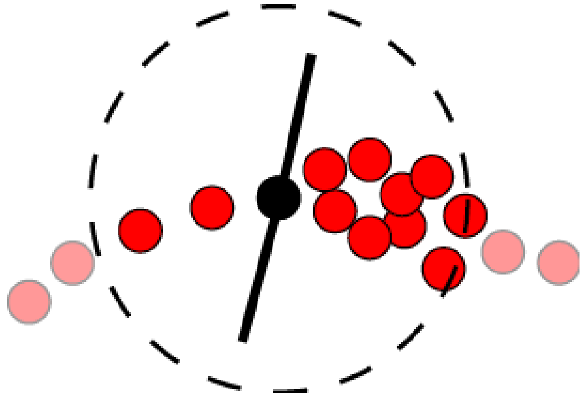
Consolidated
Clean
Thin
Outlier-free
Uniform
Oriented



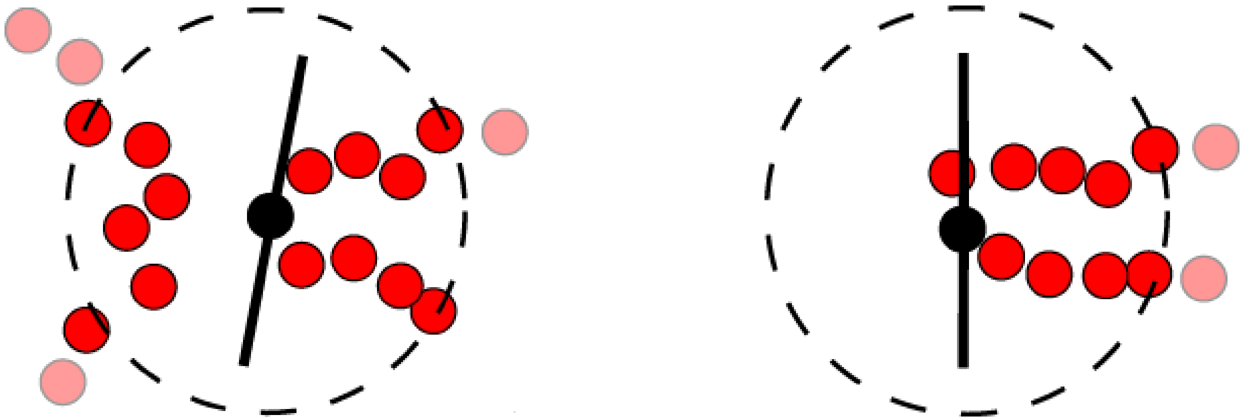
Challenges



Thick cloud



Non-uniform distribution



Close-by surface sheets

Outlier Removal and Denoising

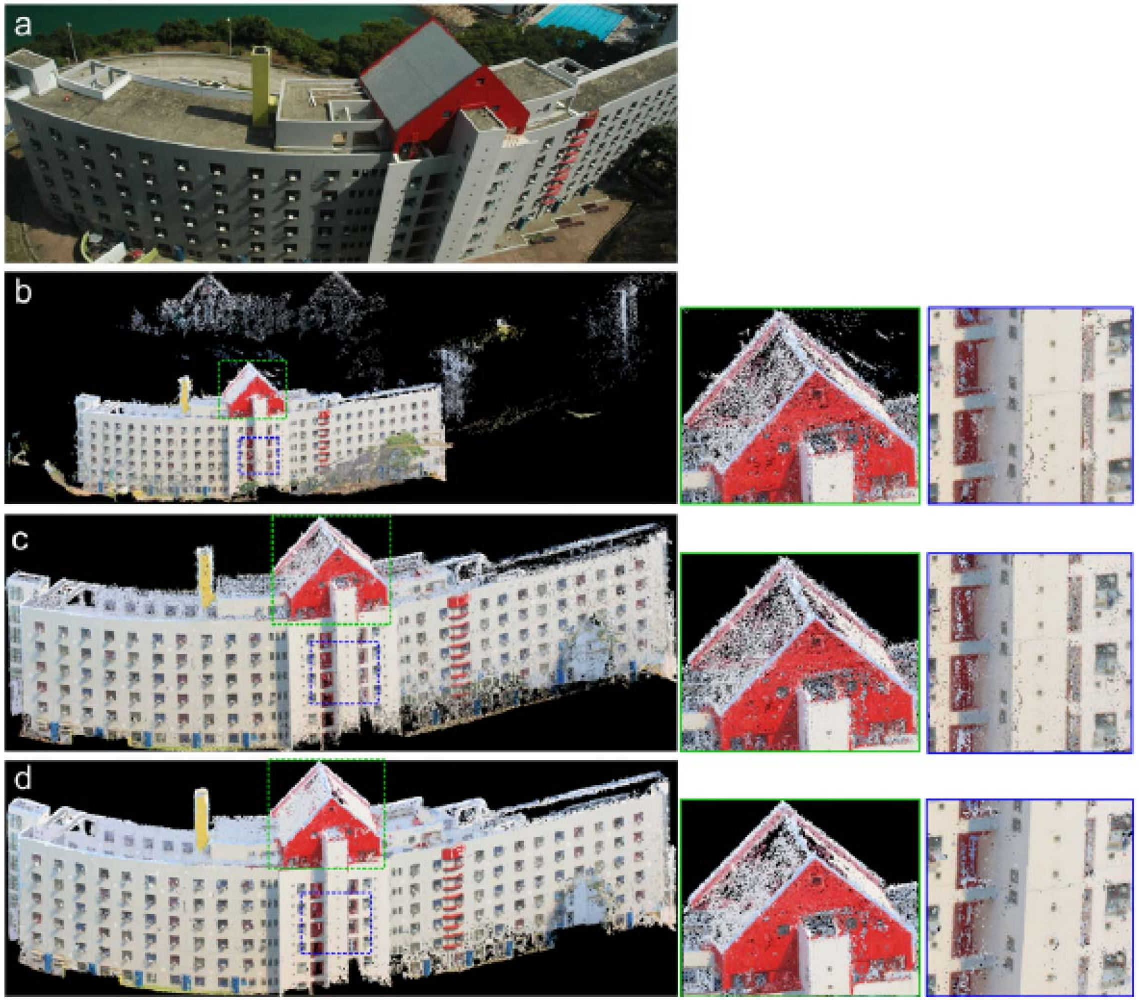


Photo of the building

Input 3D points

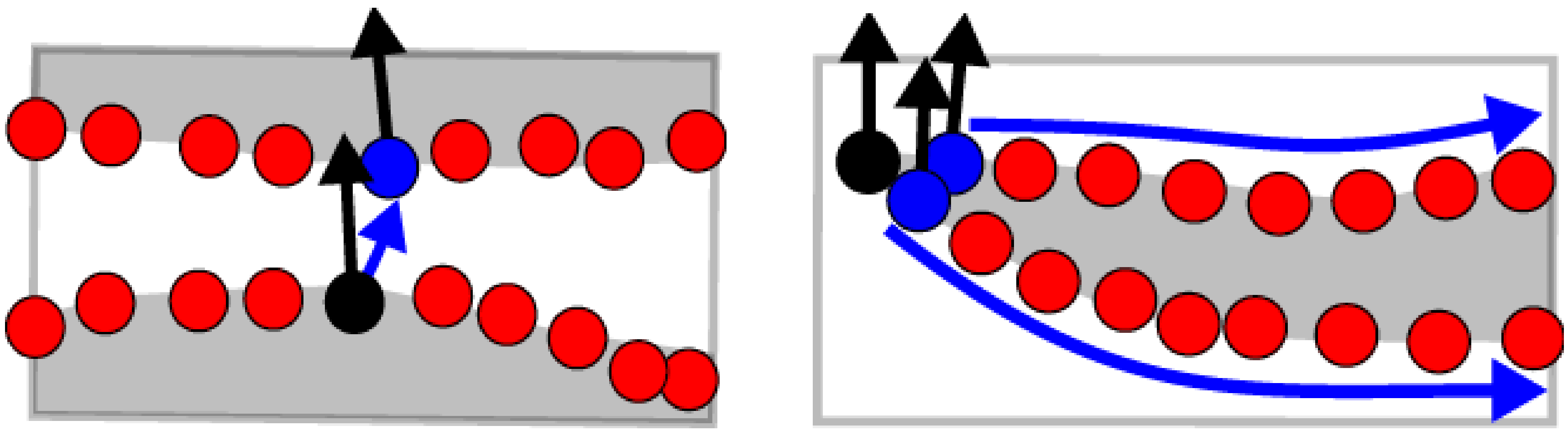
Outlier removal

Denoising

Wu et al. Deep points consolidation. Siggraph Asia 2015.
Wang et al. Consolidation of Low-quality Point Clouds from Outdoor Scenes. SGP 2013.
Huang et al. Consolidation of Unorganized Point Clouds for Surface Reconstruction. Siggraph Asia 2009.

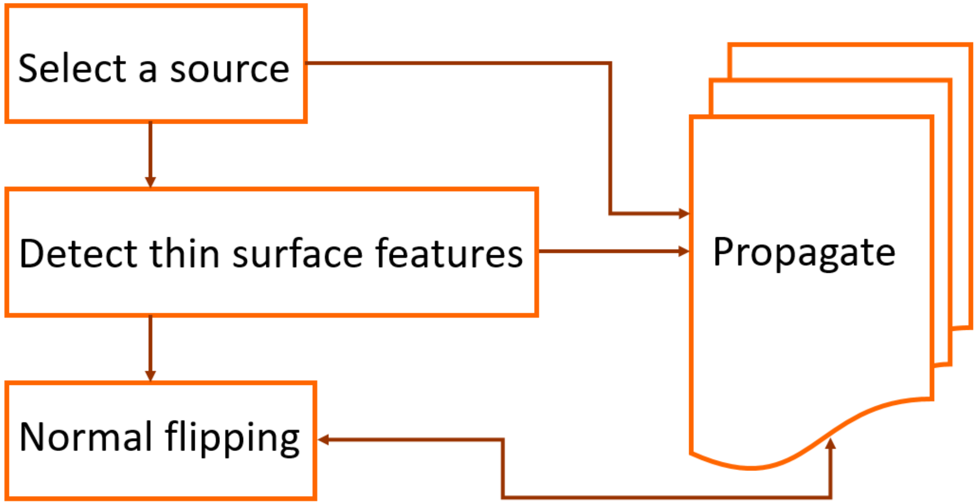
Normal (Oriented) Consistency

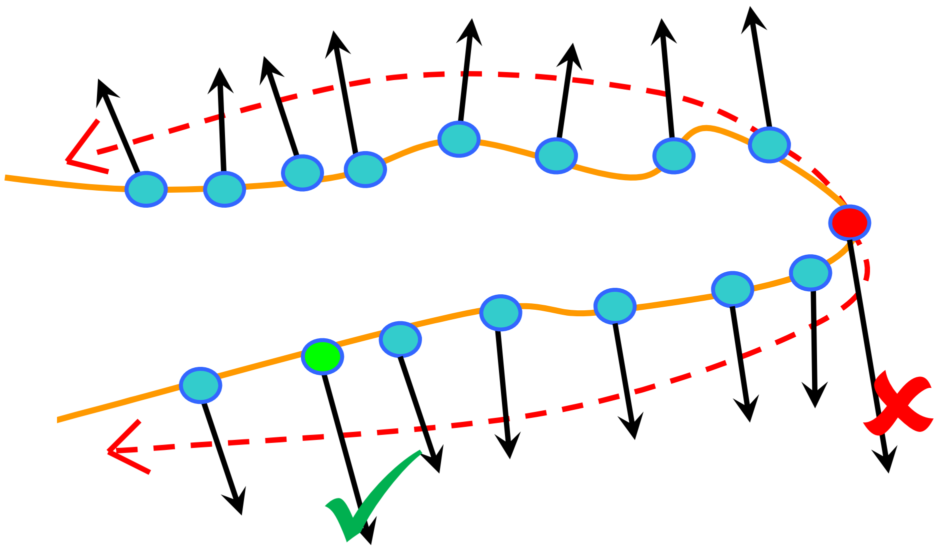
- Based on angles between unsigned normals
- May produce errors on close-by surface sheets



Zhang et al. Multi-Normal Estimation via Pair Consistency Voting. IEEE TVCG, 2019.
Liu et al. Quality Point Cloud Normal Estimation by Guided Least Squares Representation. SMI 2015.
Huang et al. Consolidation of Unorganized Point Clouds for Surface Reconstruction. Siggraph Asia 2009.

Normal Propagation

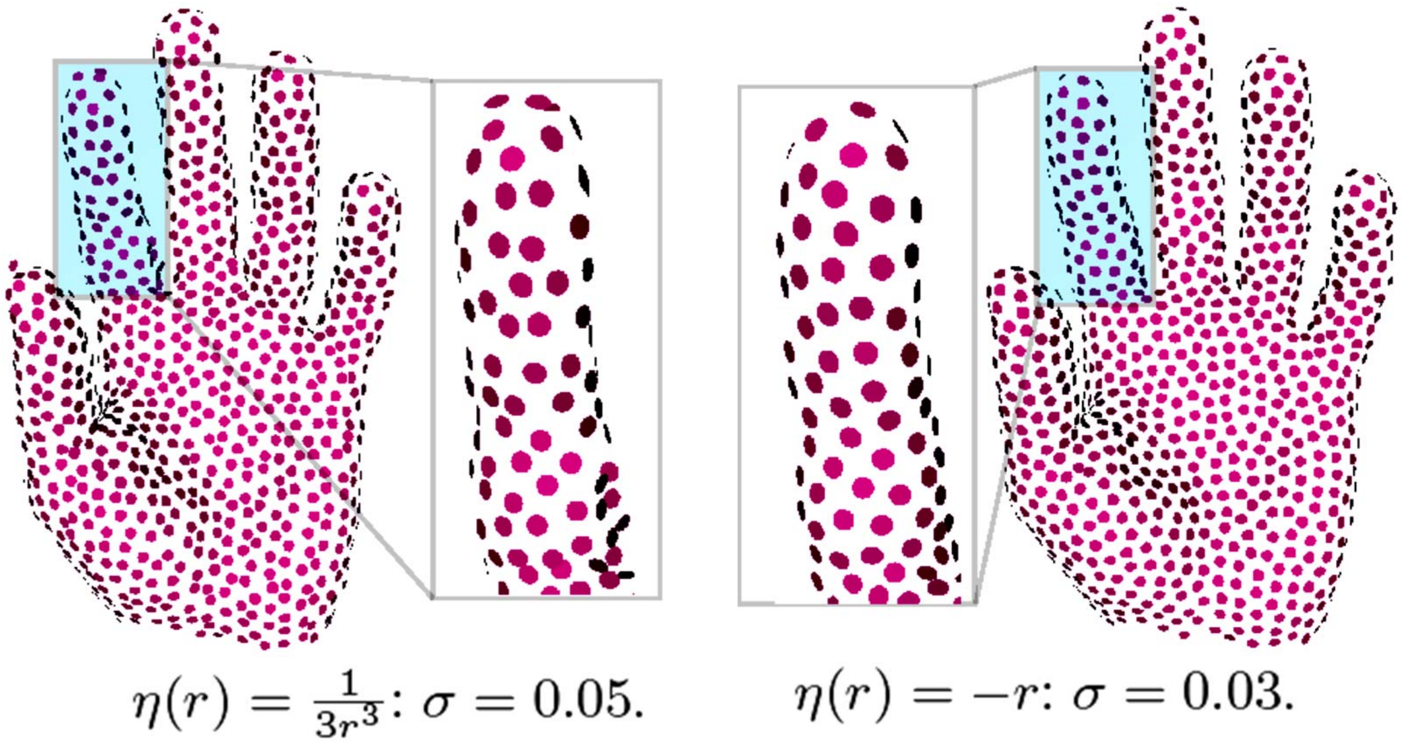




Huang et al. Consolidation of Unorganized Point Clouds for Surface Reconstruction. Siggraph Asia 2009.

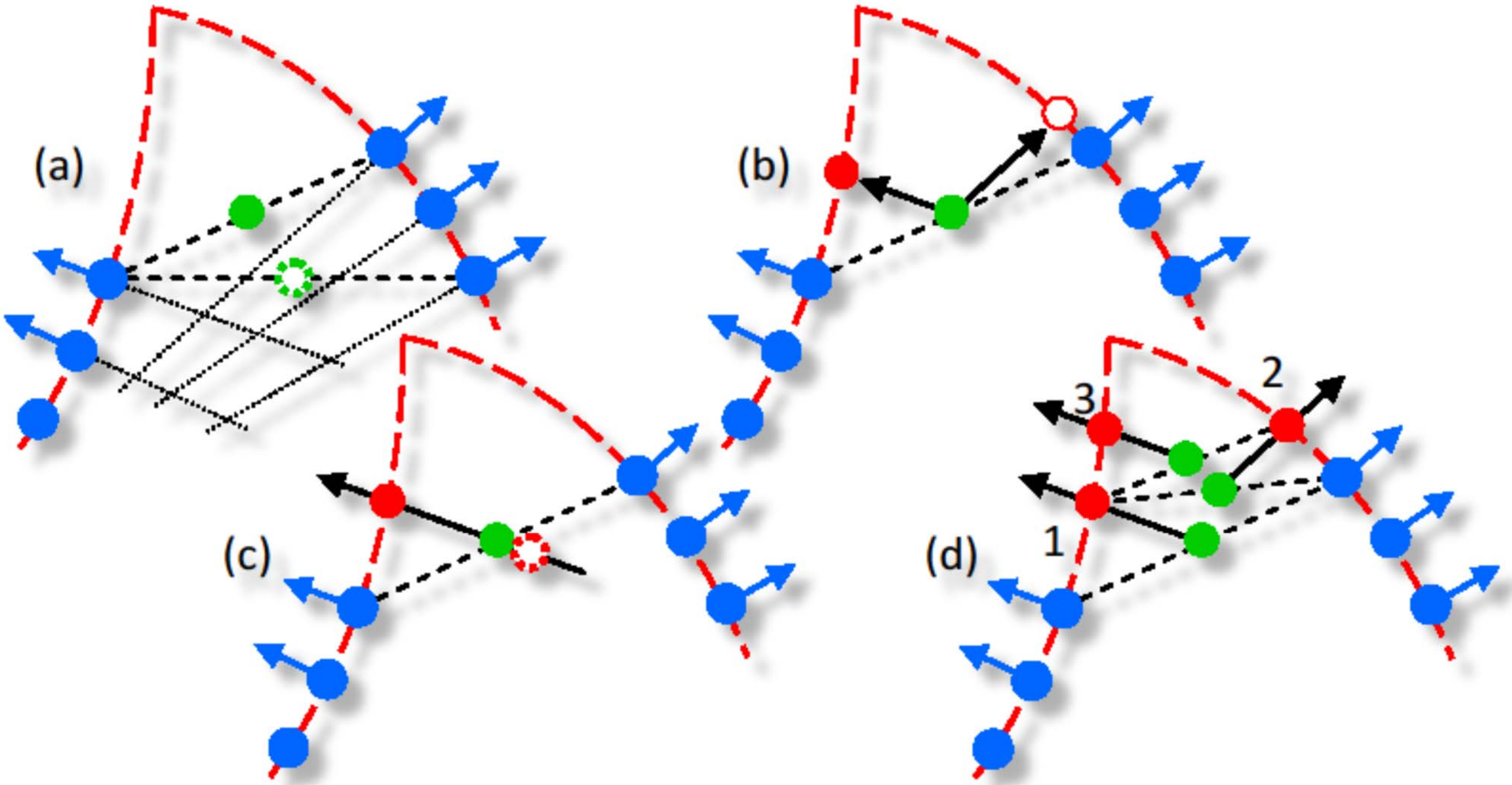
Resampling

- More locally regular point distribution
  - Locally Optimal Projection (LOP) and WLOP



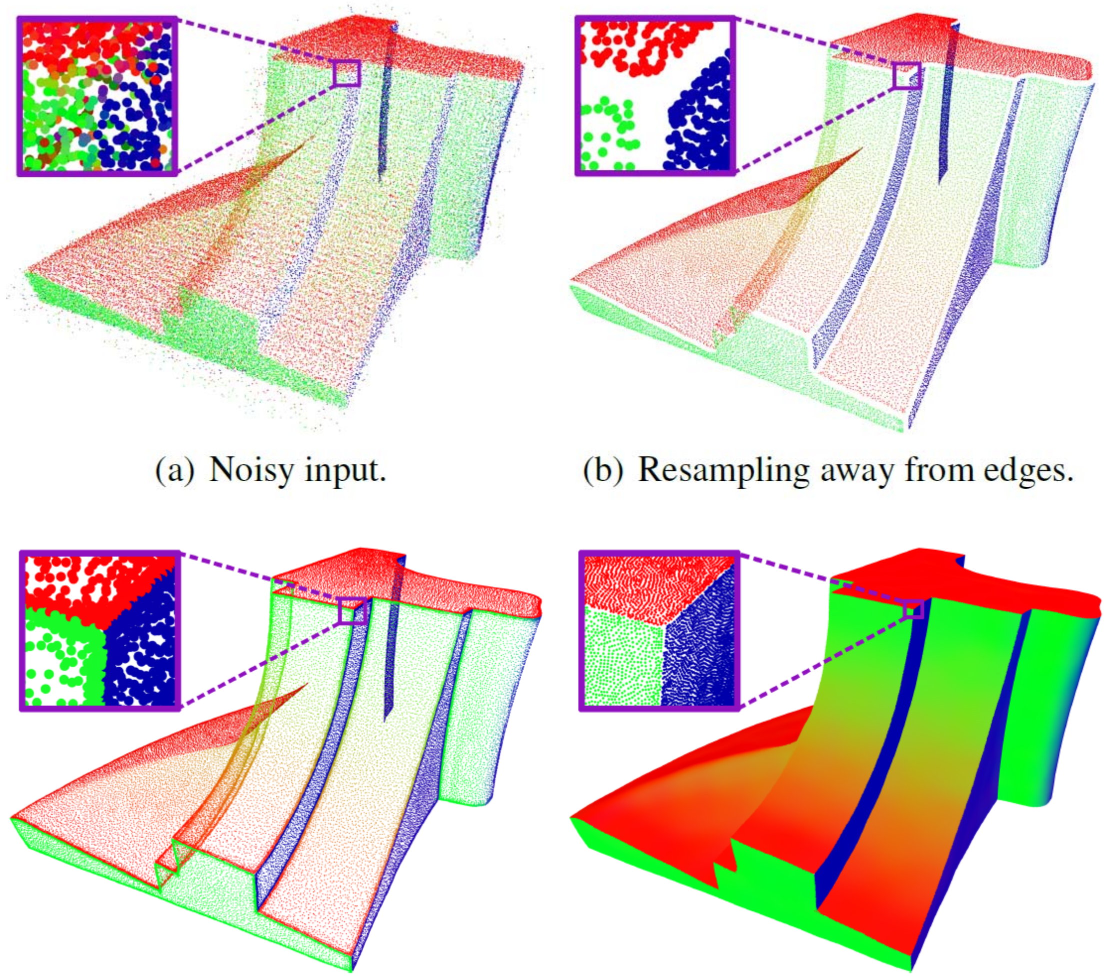
Huang et al. Consolidation of Unorganized Point Clouds for Surface Reconstruction. Siggraph Asia 2009.

Edge-Aware Resampling (2D)



Huang et al. Edge-Aware Point Set Resampling. ACM TOG 2013.

Edge-Aware Resampling (3D)

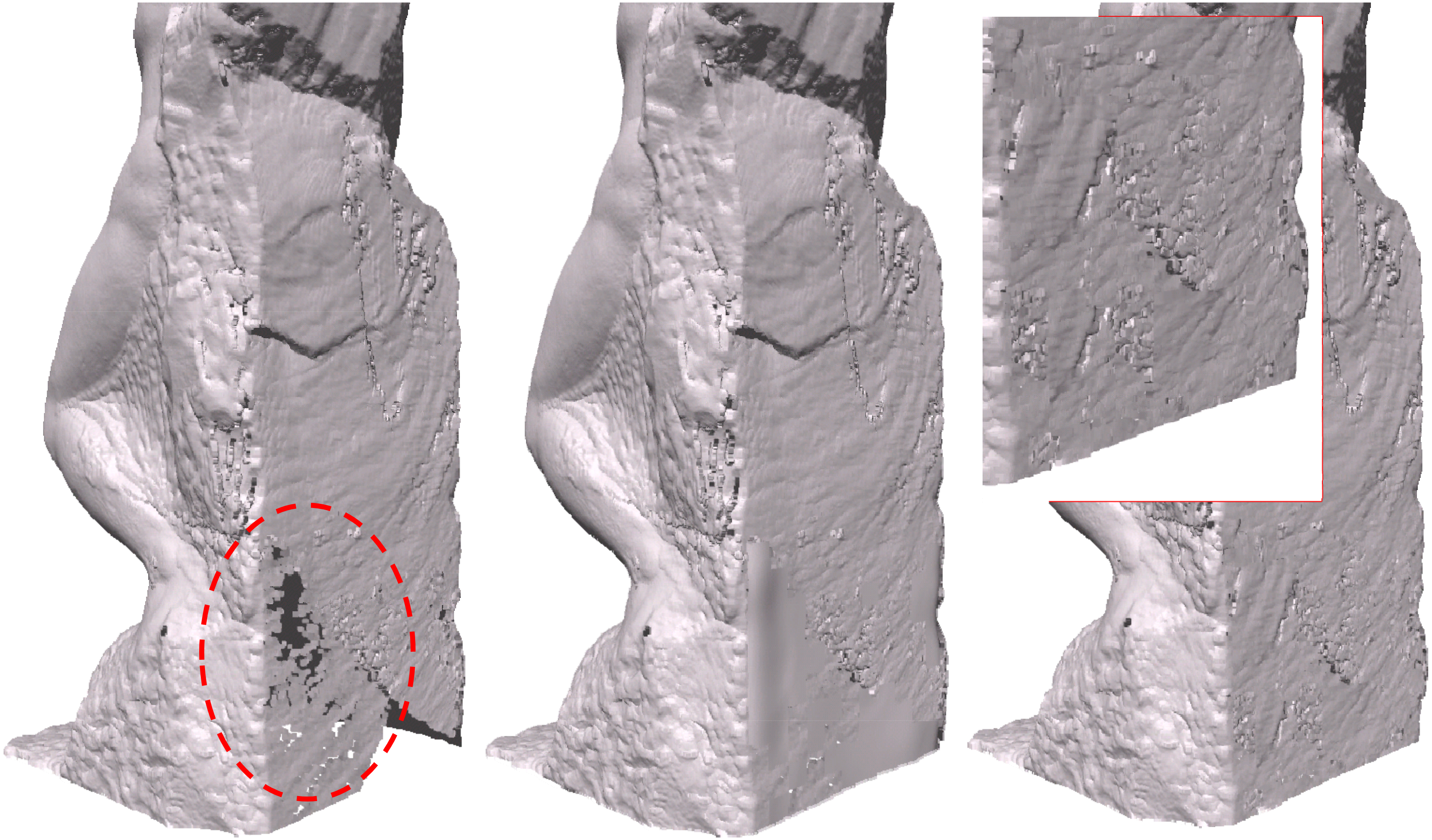


(a) Noisy input. (b) Resampling away from edges.

(c) Edge-aware upsampling. (d) Upsampling for rendering.

Huang et al. Edge-Aware Point Set Resampling. ACM TOG 2013.

Filling Holes (Completion)



Sharf et al. Context-based Surface Completion. Siggraph 2004.

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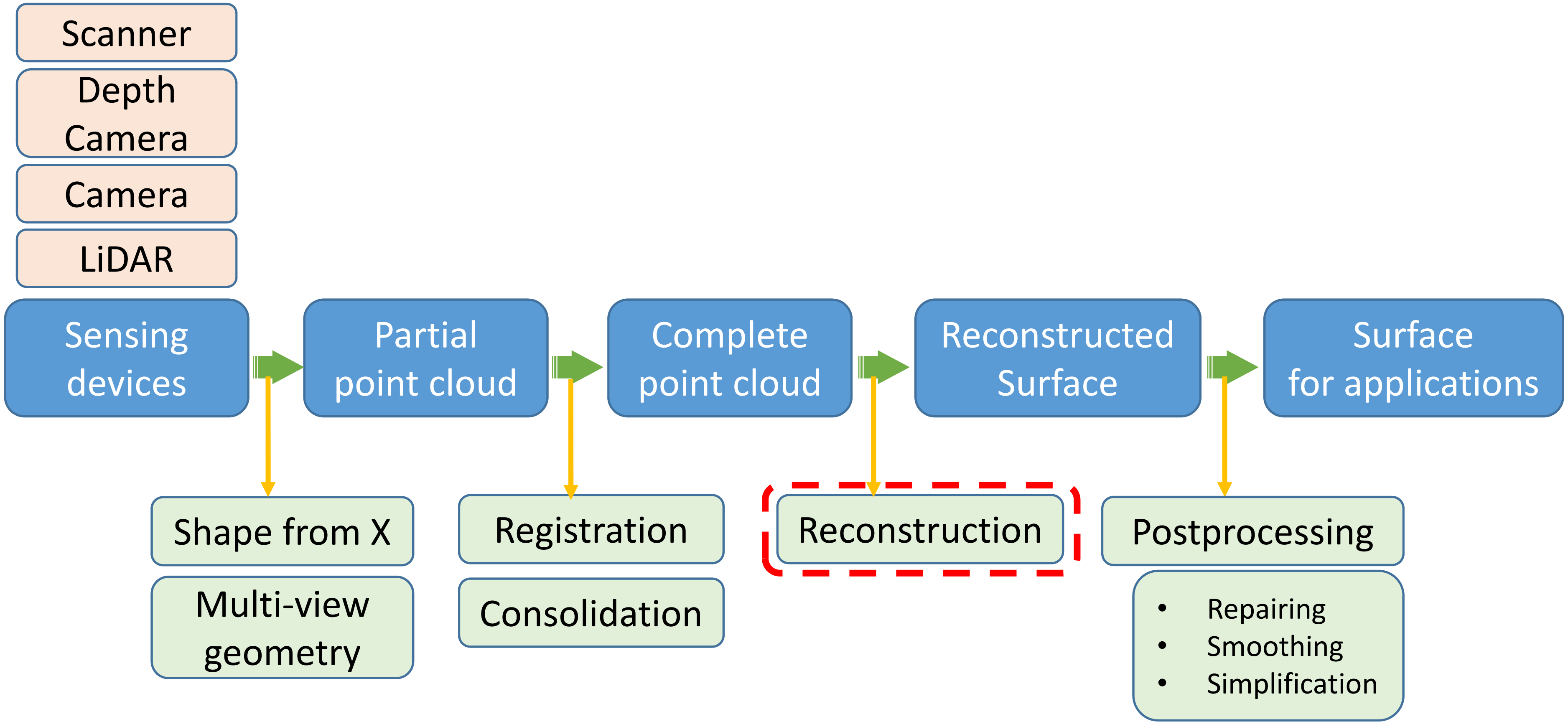
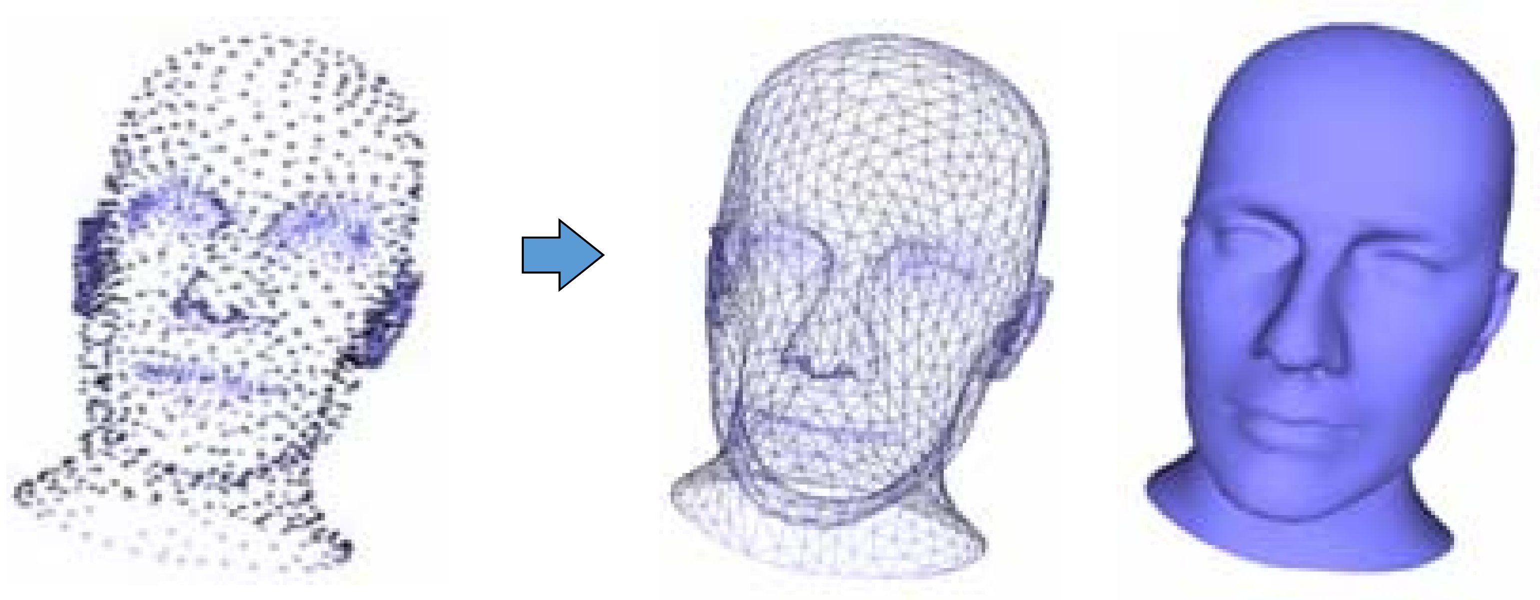
4. Reconstruction

4. Reconstruction



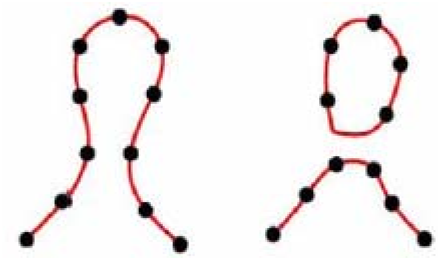
Surface Reconstruction

- Input
  - A set of points in 3D that sampled from a model surface
- Output
  - A 2D manifold mesh surface that closely approximates the surface of the original model



Desirable Properties

- No restriction on topological type



- Representation of range uncertainty
- Utilization of all range data
- Incremental and order independent updating
- Time and space efficiency
- Robustness
- Ability to fill holes in the reconstruction

Solutions

- Approximation methods: Constructing continuous functions (Scattered data interpolation schemes)
  - NURBS surfaces
  - Signed distances [Hoppe et al. 1992]
  - Radial basis function reconstruction [Carr et al. 2001]
  - Poisson reconstruction [Kazhdan et al. 2006]
- Discrete methods: Constructing triangle meshes directly
  - [Amenta & Bern 1998]
  - Power-crust [Amenda et al. 2001]
  - Cocone [Dey & Giesen 2001]
  - [Cazals & Giesen 2006]
  - …

Solutions

- Approximation methods: Constructing continuous functions (Scattered data interpolation schemes)
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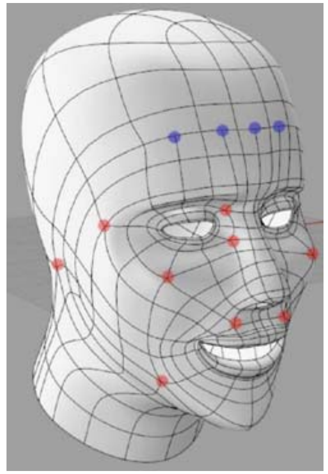
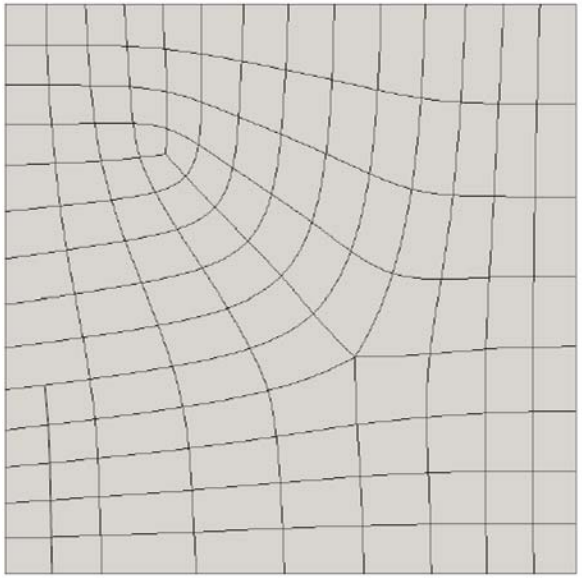
  - Power-crust [Amenda et al. 2001]
  - Cocone [Dey & Giesen 2001]
  - [Cazals & Giesen 2006]
  - …

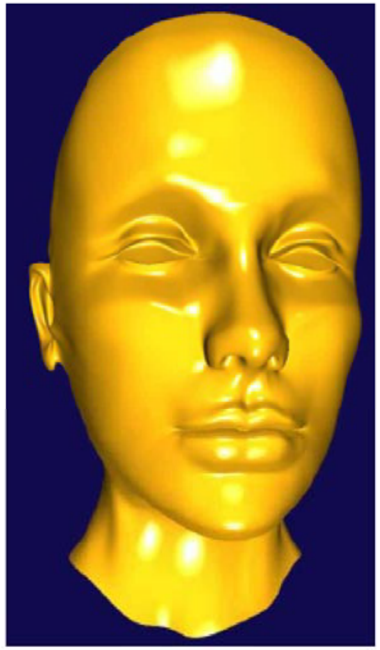
NURBS Approximation

- 须分解为四边形区域
- 拼接光滑性约束（角点光滑性约束）



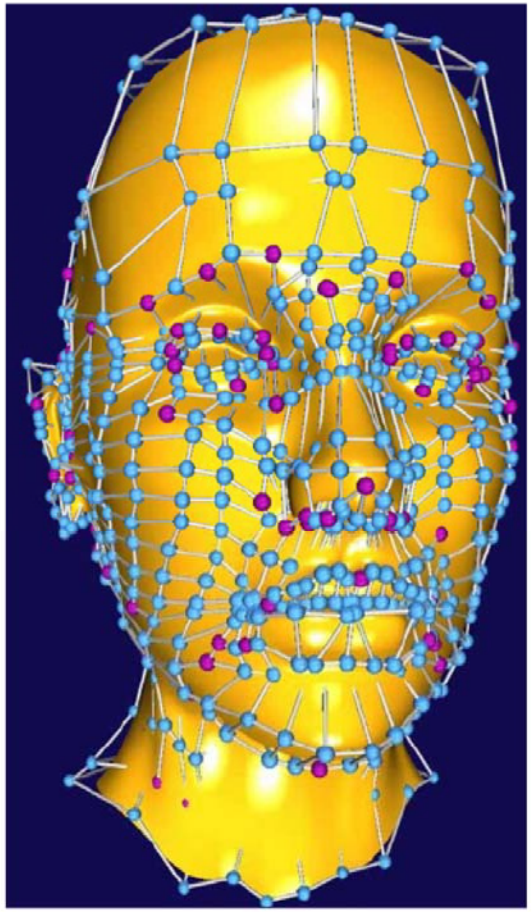


NURBS control grid



T-Spline Approximation

NURBS
4712 control points



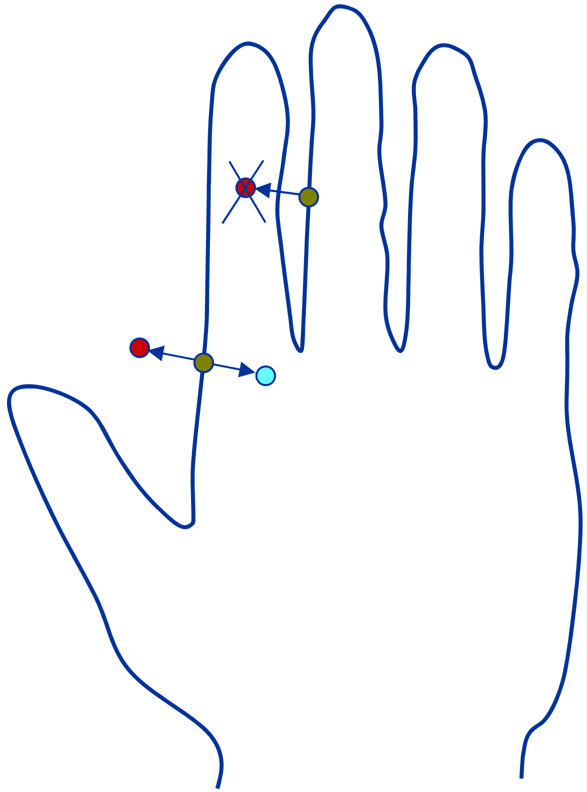
T-Splines:
1109 control points

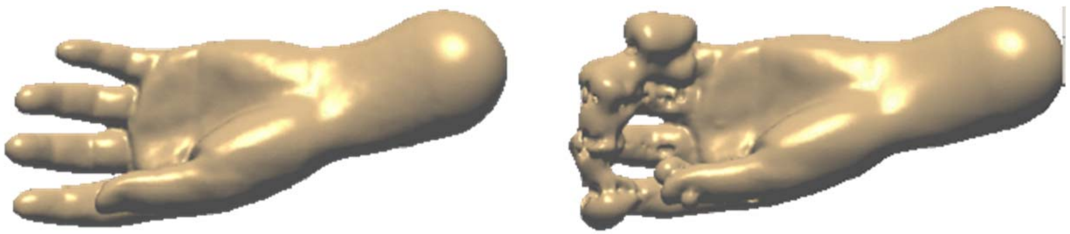
Implicit Approximation Methods
(similar to GAMES 102-9)

- Convert point cloud into a signed distance field
- Construct an implicit function whose iso-surface with iso-value 0 to approximate the field
- Extract the mesh surfaces from the implicit function
  - Marching cube methods

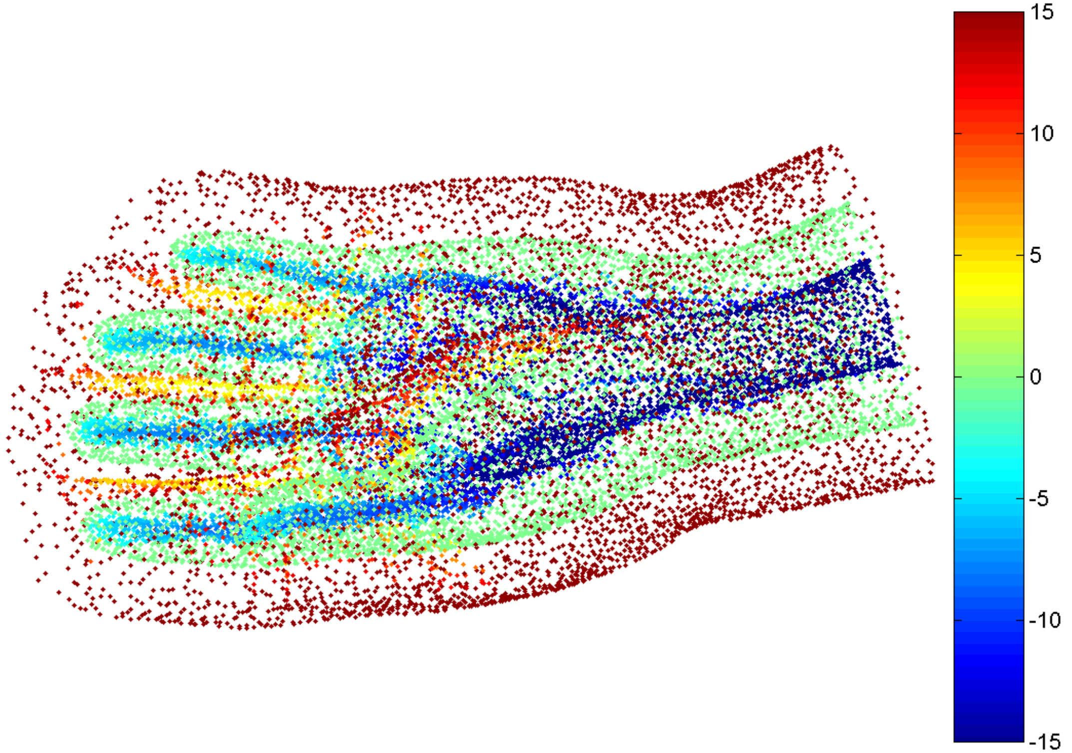
Signed Distance Fields

- For every point, add two *off-surface* points, one inside and one outside the surface in the direction of the normal
- Add a point only if it is closest to its source
- N≈3n points

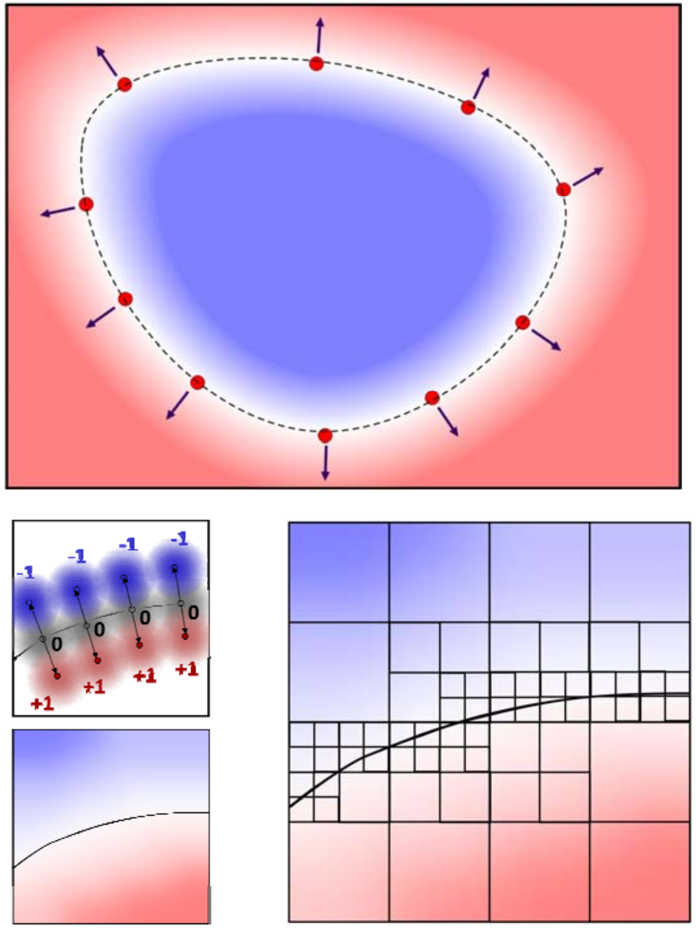


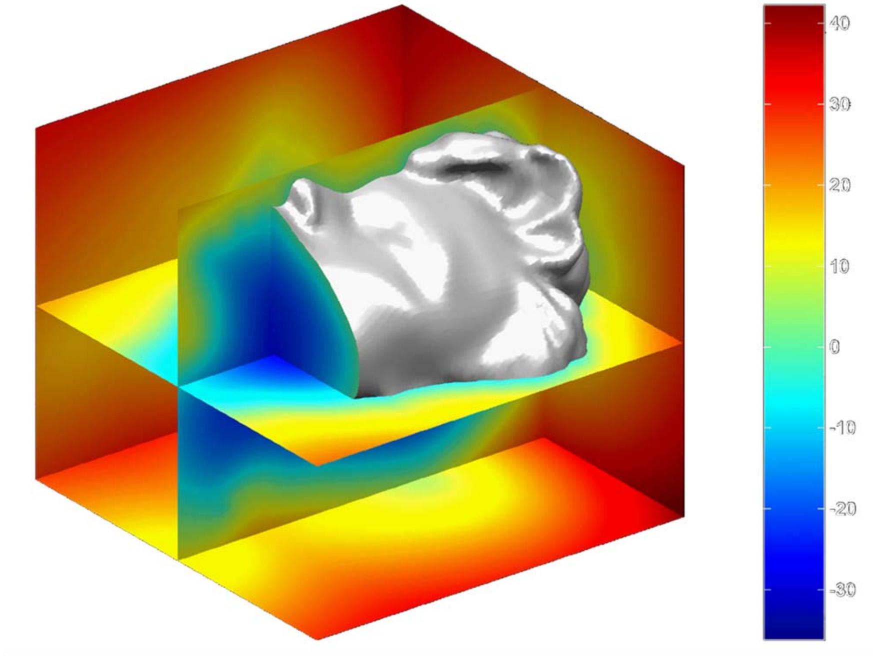


Signed Distance Fields



Signed Distance Fields



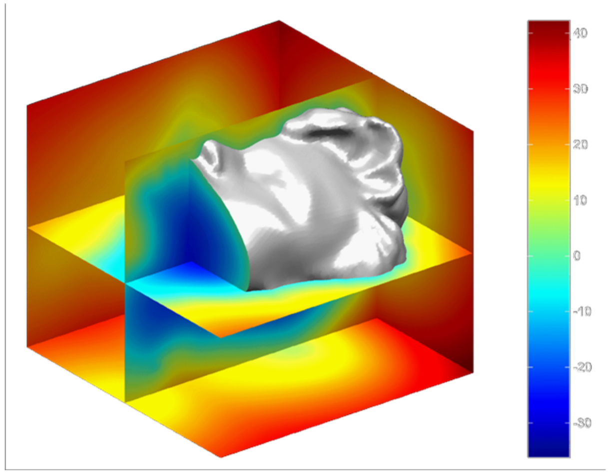


(1) Radial Bases Function (RBF)

- RBF function:

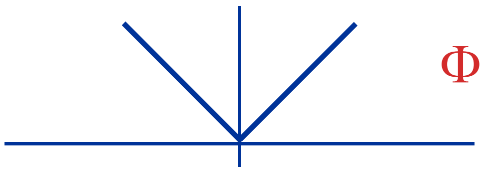
$$f(x) = \sum_{i=1}^{n} w_i \Phi\left(\left\|x - x_i\right\|\right)$$

  - Φ is a radially symmetric function
  - The trivial solution is wi=0



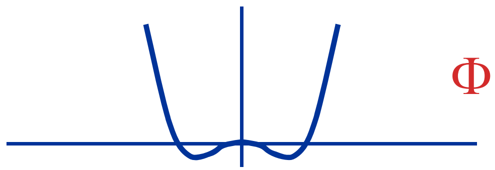
Radial basis functions

$$f(x) = \sum_{i=1}^{n} w_i \Phi(\|x - x_i\|)$$



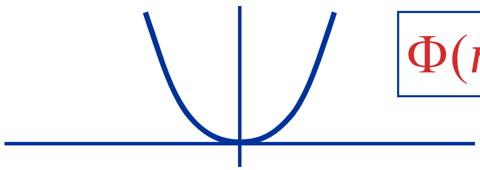
$$\Phi(r) = |r|$$

Minimizes 2nd derivative in 3D



$$\Phi(r) = r^2 \log r$$

Minimizes 2nd derivative in 2D



$$\boxed{\Phi(r) = r^3}$$

Minimizes 3rd derivative in 3D

Computing the weights

- Input : $\{x_i\}$, $\{f_i\}$
- Compute $\{w_i\}$

$$f(x) = \sum_{i=1}^{n} w_i \Phi\left(\left\| x - x_i \right\|\right)$$

Unknowns to compute

$$\left(A_{NxN}\right)\left(W\right) = \left(f\right)$$

Function values

Matrix dependent on the locations of
the data points

Solving the linear system

$$\begin{pmatrix} \Phi(\|x_1 - x_1\|) & \Phi(\|x_2 - x_1\|) & \cdots & \Phi(\|x_N - x_1\|) \\ \Phi(\|x_1 - x_2\|) & \Phi(\|x_2 - x_2\|) & & \Phi(\|x_N - x_2\|) \\ \vdots & & & \vdots \\ \Phi(\|x_1 - x_N\|) & \Phi(\|x_2 - x_N\|) & \cdots & \Phi(\|x_N - x_N\|) \end{pmatrix} \begin{pmatrix} W_1 \\ W_2 \\ \vdots \\ W_N \end{pmatrix} = \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{pmatrix}$$

- Symmetric positive matrix

Alternative

Alternative:

- Use locally supported basis functions (e.g. B-Splines)
- Employ an additional regularization term to make the solution smoother
- Optimize the energy function

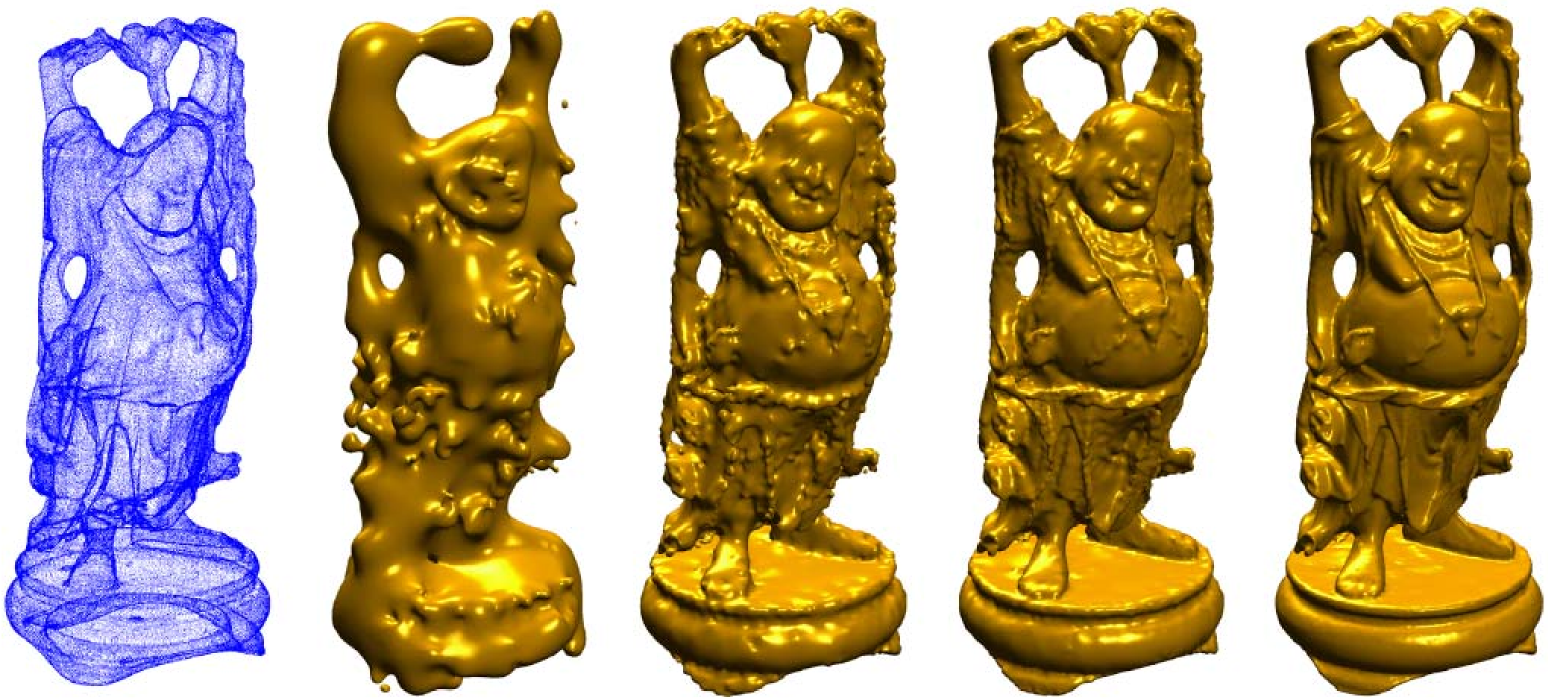
$$E(\lambda) = \sum_{i=1}^{n} f(\boldsymbol{x}_i)^2 + \mu \int_{\Omega} \left(\left[\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} + \frac{\partial^2}{\partial z^2} + \frac{2\partial^2}{\partial x \partial y} + \frac{2\partial^2}{\partial y \partial z} + \frac{2\partial^2}{\partial x \partial z} \right] f(\boldsymbol{x}) \right)^2 d\boldsymbol{x}$$

with $f(\boldsymbol{x}) = \sum_{i=1}^{m} \lambda_i b(\boldsymbol{x} - \boldsymbol{x}_j)$

- The critical point is the solution to a linear system

Simplification (center reduction)

- Reduce the number of centers (points)
- Greedy algorithm, reduce points as long as the surface is close enough



Carr et al. Reconstruction and representation of 3D objects with Radial Basis Functions, SIGGRAPH 2001.

Complexity

Straight-forward method:

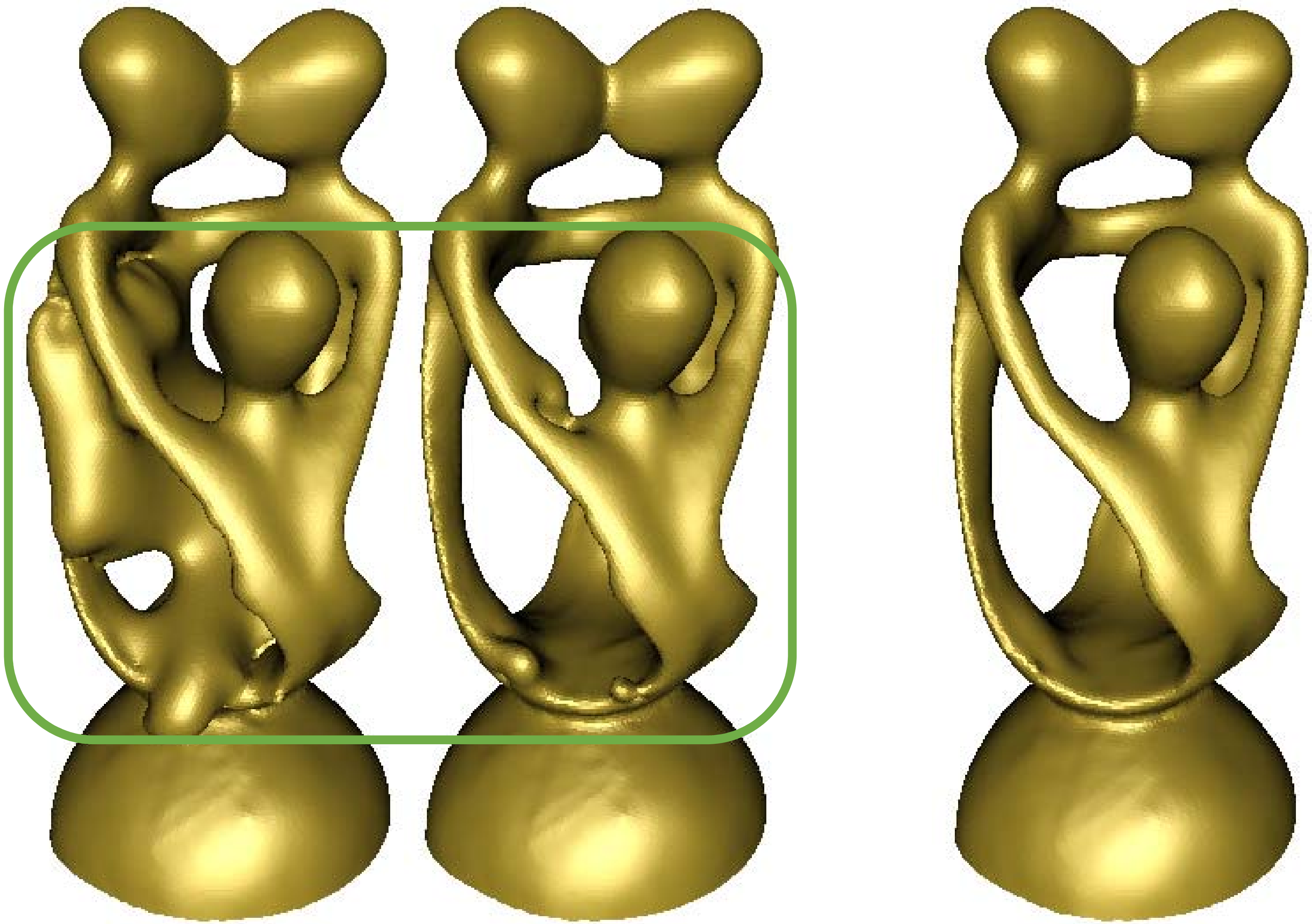
- Storage $O(N^2)$
- Solving the W_i $O(N^3)$
- Evaluating f(x) O(N)

Fast method [Carr01]

- Storage O(N)
- Solving the W_i O(NlogN)
- Evaluating f(x)
  O(1) + O(NlogN) setup

Carr et al. Reconstruction and representation of 3D objects with Radial Basis Functions, SIGGRAPH 2001.

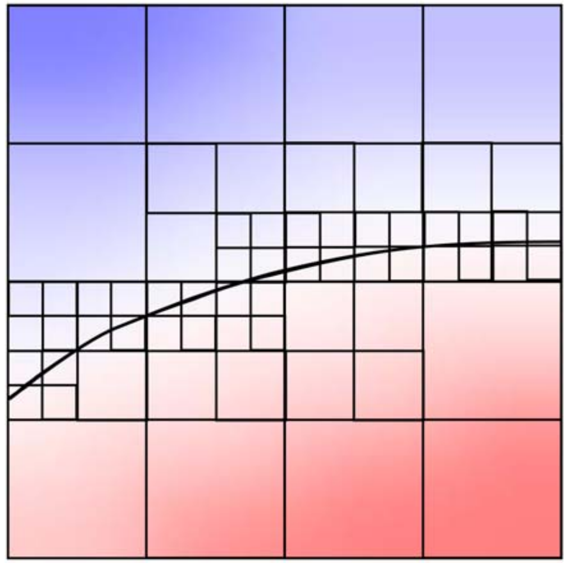
Sensitive to Normals



(2) MPU Implicits

Multi-level partition of unity implicits:

- Hierarchical implicit function approximation
  - Given: data points with normal
  - Computes: hierarchical approximation of the signed distance function



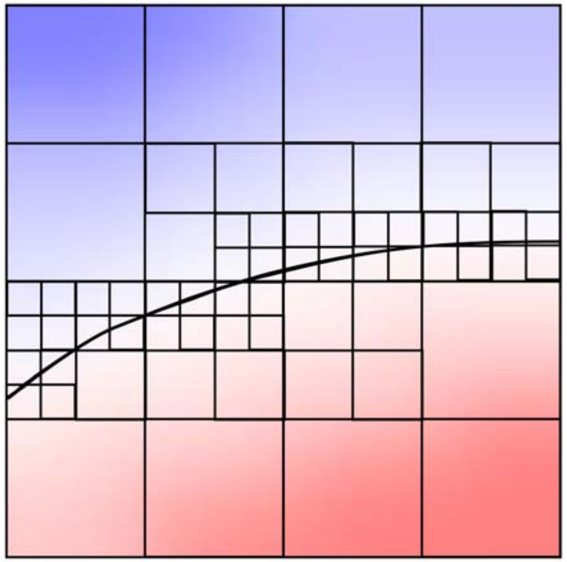
Ohtake et al. Multi-level Partition of Unity Implicits, SIGGRAPH 2003

MPU Implicits

Multi-level partition of unity implicits:

- Octree decomposition of space
- In each octree cell, fit an implicit quadratic function to points
    - $f(\boldsymbol{x}_i) = 0$ at data points
    - Additional normal constraints
- Stopping criterion:
    - Sufficient approximation accuracy

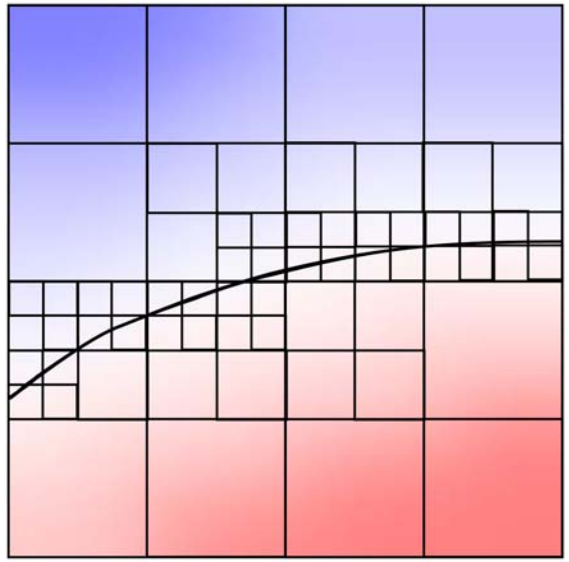
  (evaluate f at data points to calculate distance)
    - At least 15 points per cell.



MPU Implicits

Multi-level partition of unity implicits:

- This gives an adaptive grid of local implicit function approximations
- Problem: How to define a global implicit function?
- Idea: Just blend between local approximants using a windowing function

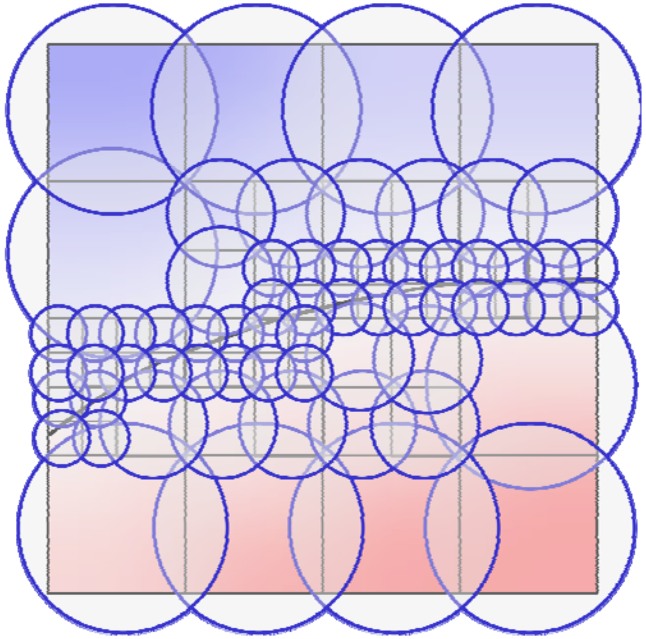


MPU Implicits

Multi-level partition of unity implicits:

- Windowing function:
  - Use smooth windowing function w
    - B-splines / normal distribution
    - Original formulation: quadratic tensor product B-spline function, support = $1.5 \times$ cell diagonal
  - Renormalize to form partition of unity:

$$f(\boldsymbol{x}) = \frac{\sum_{i=1}^{n} w(\boldsymbol{x} - \boldsymbol{x}_i) f_i(\boldsymbol{x})}{\sum_{i=1}^{n} w(\boldsymbol{x} - \boldsymbol{x}_i)}$$

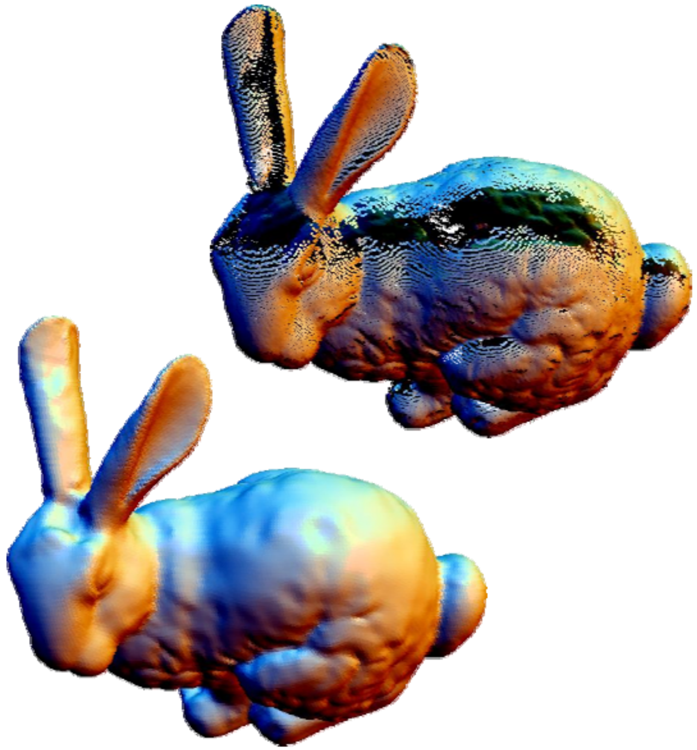


MPU Implicits

Multi-level partition of unity implicits:

- Sharp features:
  - If a leaf cell with a few points has strongly varying normal, this might be a sharp feature.
  - Multiple functions can be fitted to parts of the data
  - Boolean operations to obtain composite distance field

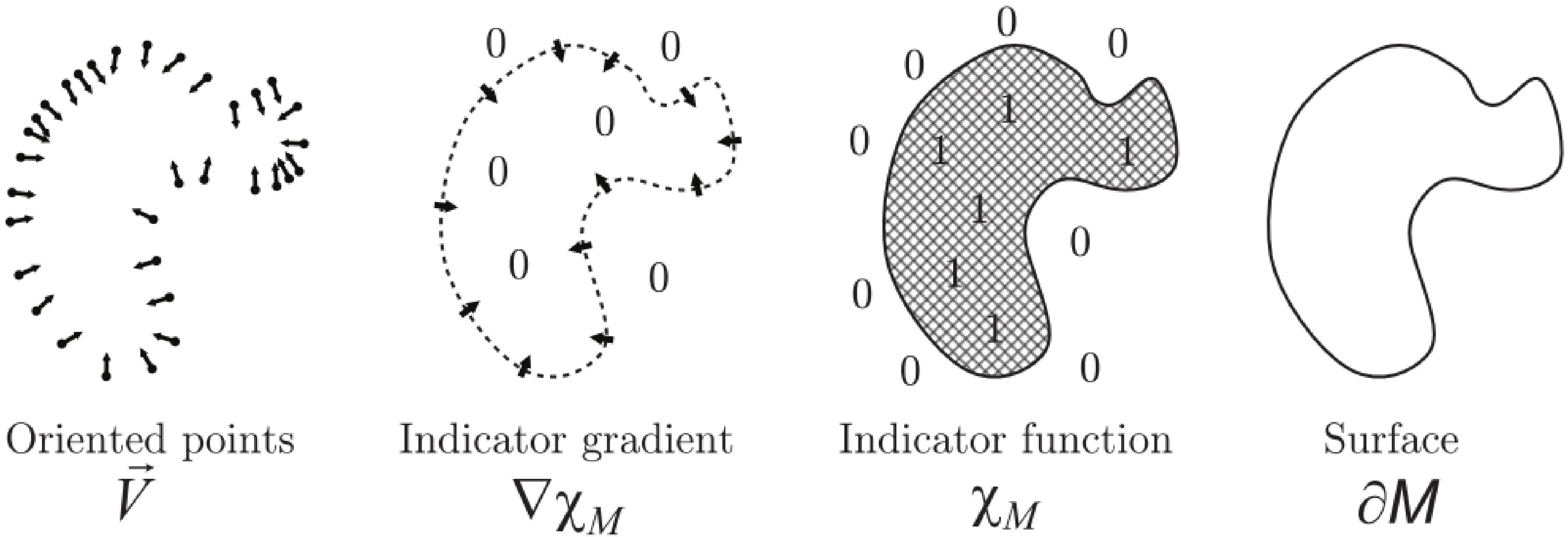
Examples



(3) Possion reconstruction

- Idea: fitting an indicator function

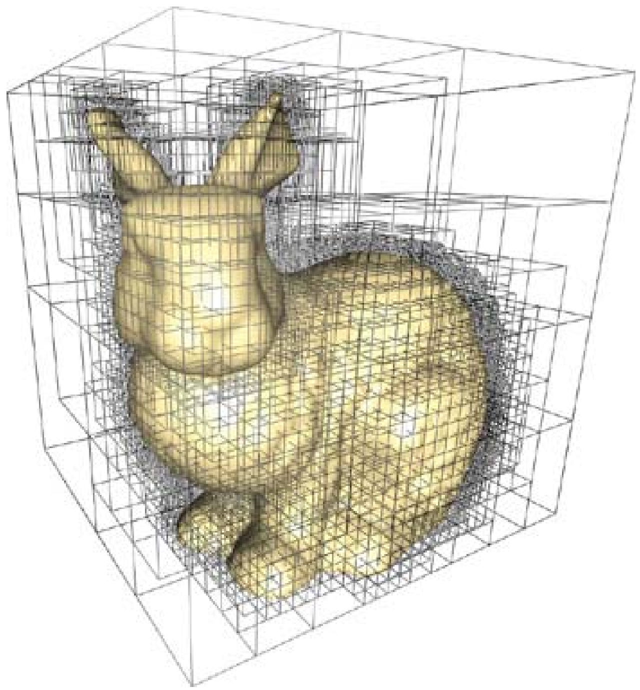
$$\chi_M(x) = \begin{cases} 1 & x \in M \\ 0 & x \notin M \end{cases}$$



Kazhdan et al. Poisson surface reconstruction. SGP 2006.

Solving Possion Equation

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



(4) Marching Cube

- Marching cubes: method for approximating surface defined by isovalue α, given by grid data

- <u>Input:</u>
  - Grid data (set of 2D images)
  - Threshold value (isovalue) α

- <u>Output:</u>
  - Triangulated surface that matches isovalue surface of α

Marching Cubes

- First pass
  - Identify voxels which intersect isovalue

- Second pass
  - Examine those voxels
  - For each voxel produce set of triangles
    - approximate surface inside voxel

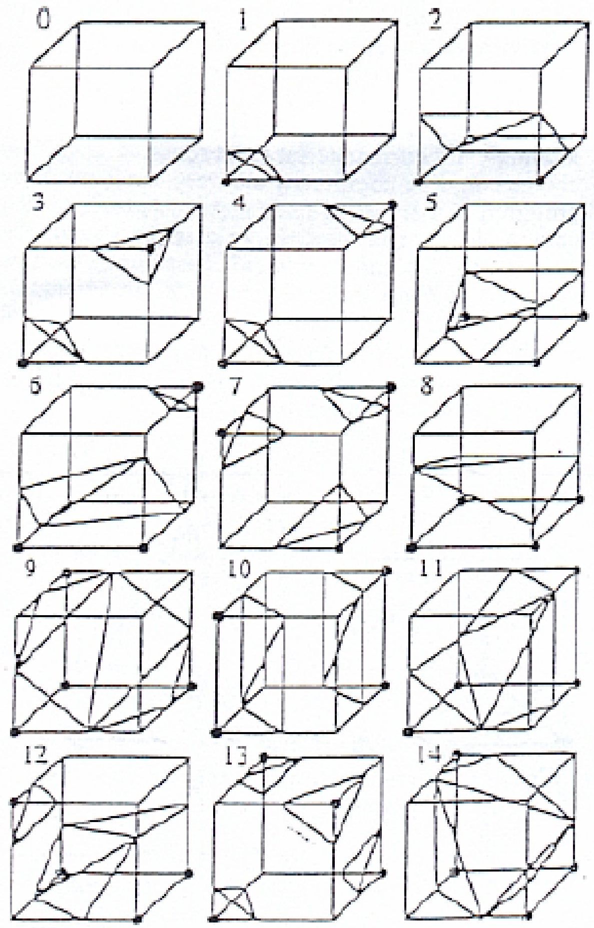


Figure 2. Configurations.

Problems & Many Improvements

- Marching Cubes method can produce erroneous results
  - E.g. isovalue surfaces with "holes"
- Example:
  - voxel with configuration 6 that shares face with complement of configuration 3:

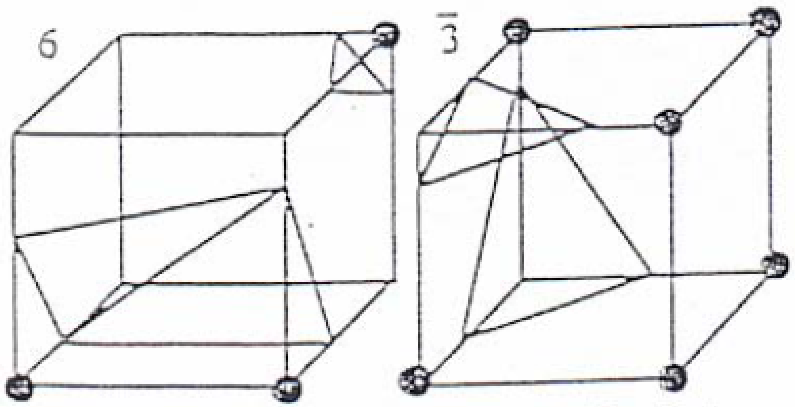


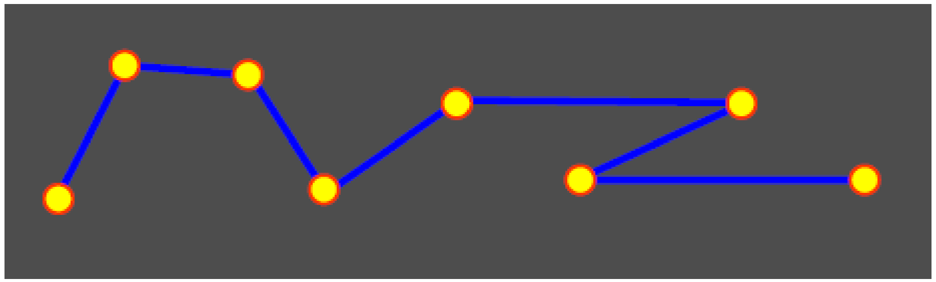
Figure 3. An example illustrating the flaw in the marching cubes method.

Solutions

- Approximation methods: Constructing continuous functions (Scattered data interpolation schemes)
  - NURBS surfaces
  - Signed distances [Hoppe et al. 1992]
  - Radial basis function reconstruction [Carr et al. 2001]
  - Poisson reconstruction [Kazhdan et al. 2006]
- Discrete methods: Constructing triangle meshes directly
  - [Amenta & Bern 1998]
  - Power-crust [Amenda et al. 2001]
  - Cocone [Dey & Giesen 2001]
  - [Cazals & Giesen 2006]
  - …

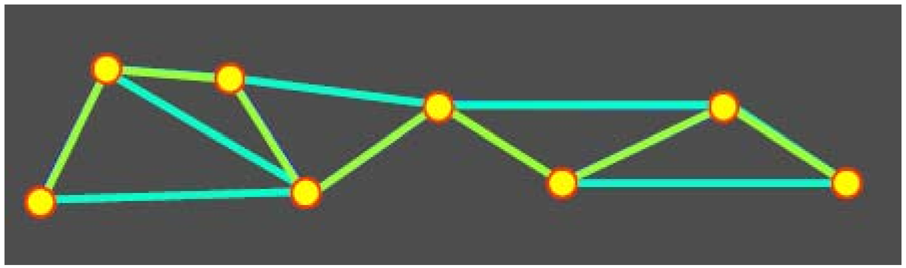
Curve from Points
- Connect the Dots (1)

- Given unordered set of points P
  - connect them by linear segments



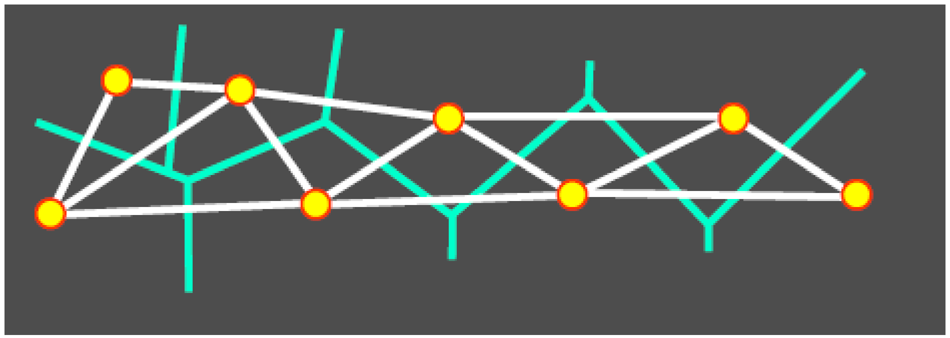
Curve from Points
- Connect the Dots (2)

- Can be ambiguous
- Harder when topology not known



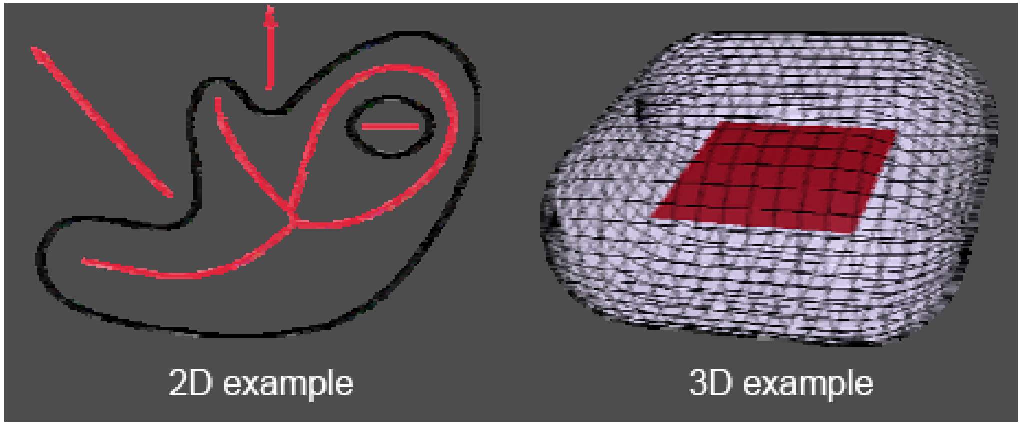
Curve from Points
- Connect the Dots (3)

- Use Voronoi Diagram
- Construct Delaunay triangulation
- Which edges to choose?



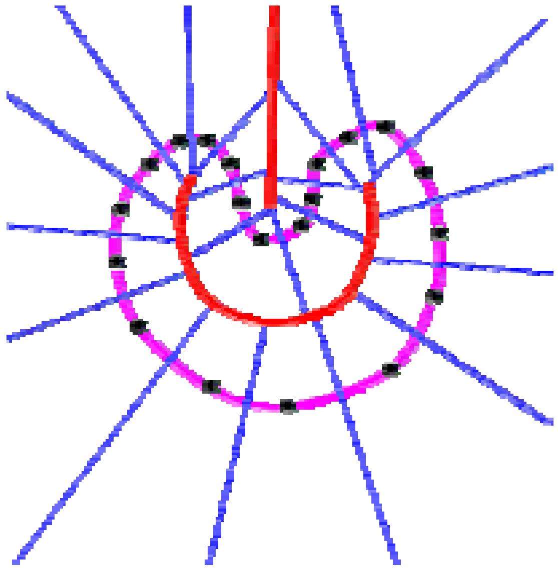
Medial Axis

- Medial axis of (d-1)-dimensional surface in R^d - set of points with more than one closest point on the surface
- Alternative definition: locus of centers of maximal inscribed spheres



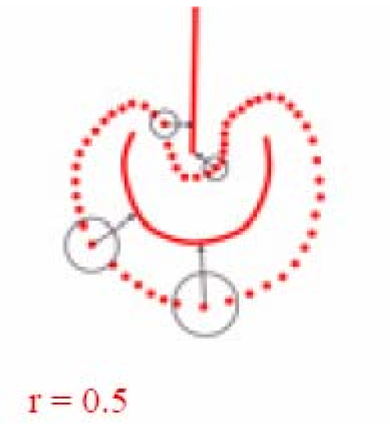
Medial Axis and Voronoi Diagram

- Voronoi diagram of set of points on curve approximates Medial Axis
  - if points sampled densely enough



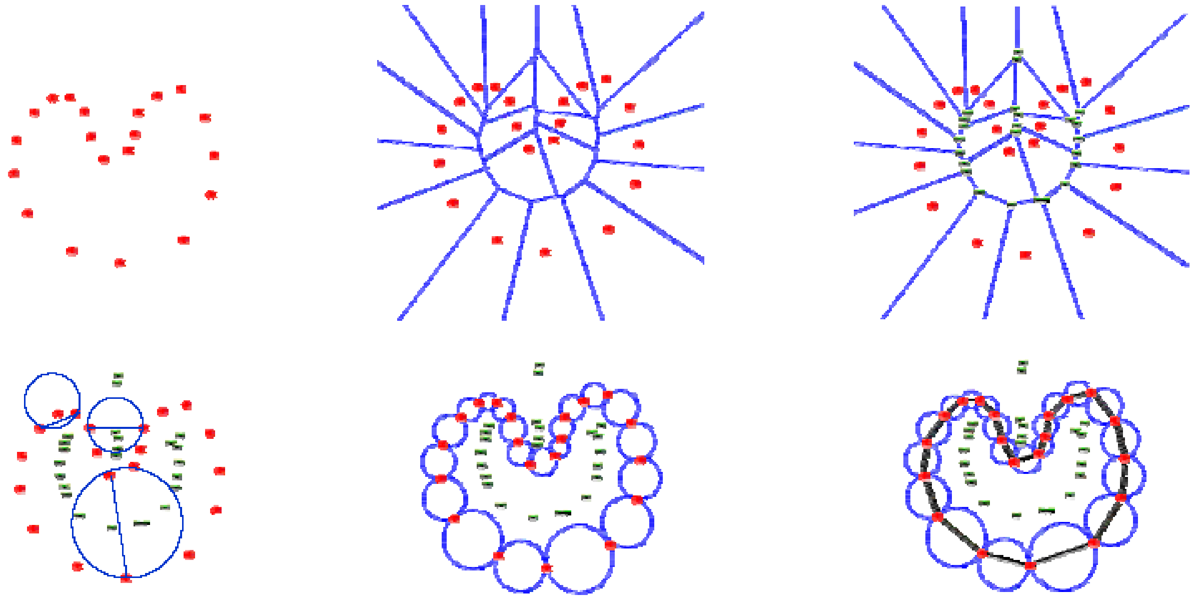
Sampling Criterion

- Good sample - sampling density (at least) inversely proportional to distance from medial axis
- r-sample : distance from any point on surface to nearest sample point ≤ r * distance from point to medial axis
  - In general, r ∈ (0,1]
  - r=0.5 good enough
- Inherently takes into account
  - curvature of the surface
  - proximity of other parts of the surface



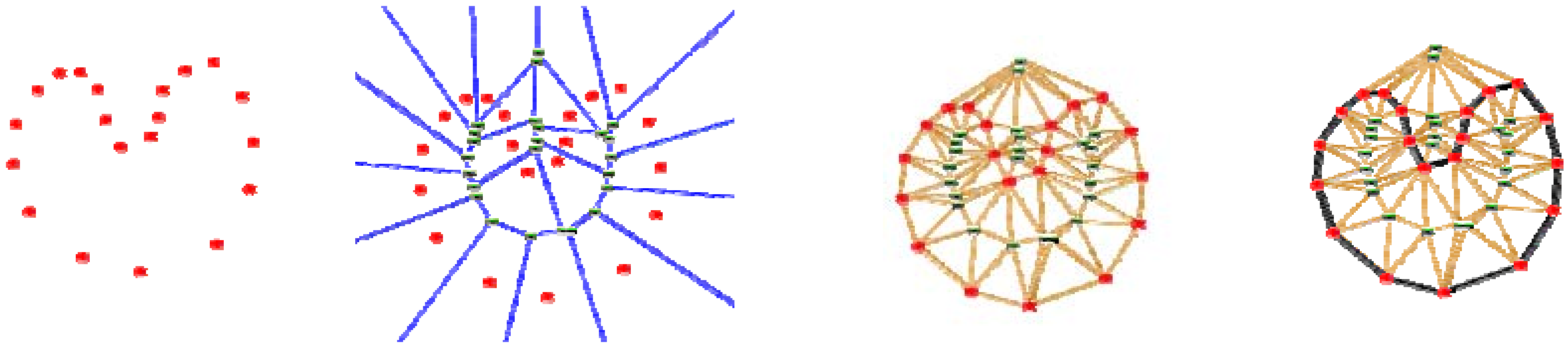
2D Crust Algorithm

- Idea
  - Adopt Delaunay edges which are “far” from MA
  - To represent MA use Voronoi vertices
  - Edge e in crust <=> circumcircle of e contains no other sample points or Voronoi vertices of S



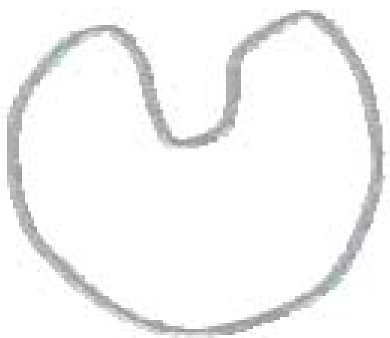
Crust Algorithm

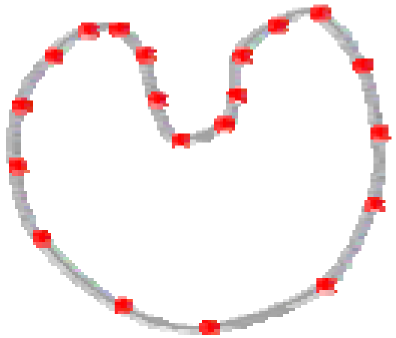
- Compute Voronoi diagram of S
  - let V be set of Voronoi vertices
- Compute Delaunay triangulation of SUV
- Return all Delaunay edges between points of S

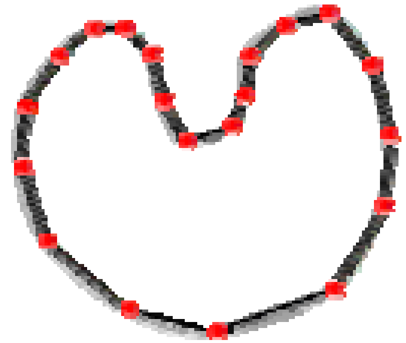


Theory

- **Theorem**: The crust of an *r*-sample from a smooth curve *F*, for $r \leq 0.25$ connects only adjacent samples of *F*



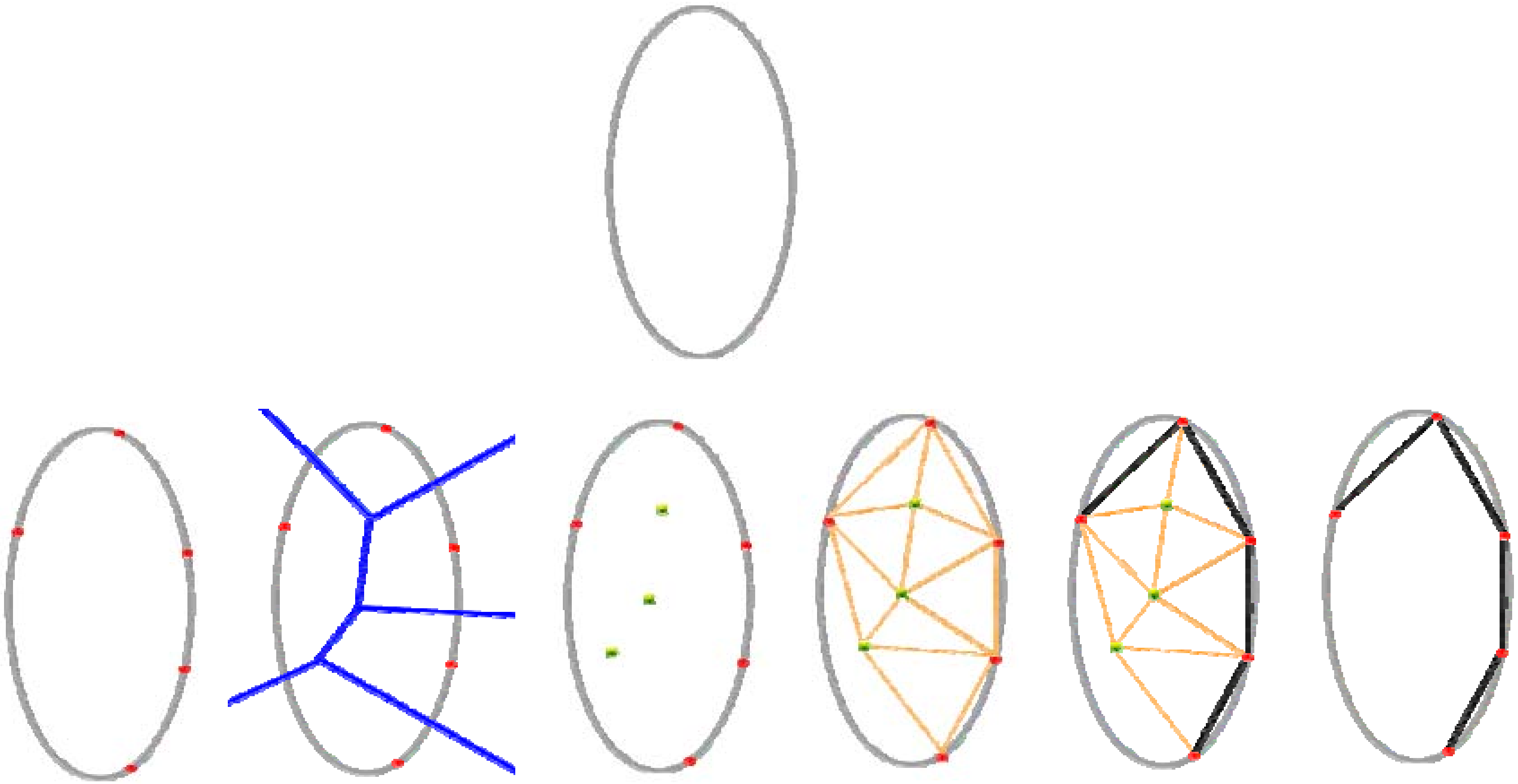




Smooth Curve *F* | *r*-sample ($r \leq 0.25$) | The crust

Theory

- The algorithm may fail when r is too large



(1) 3D Crust Algorithm

- Extend 2D approach
- Voronoi cells are polyhedra
- Voronoi vertex is equidistant from 4 sample points
- BUT in 3D not all Voronoi vertices are near medial axis (regardless of sampling density)

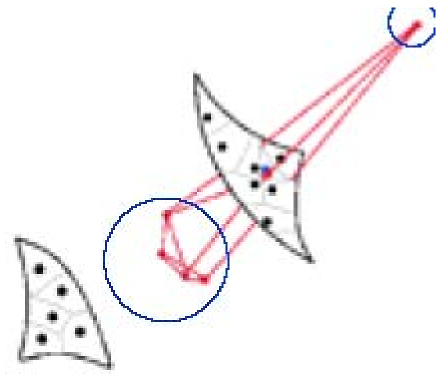
Amenta et al. A New Voronoi-Based Surface Reconstruction Algorithm. Siggraph 1998

Concepts

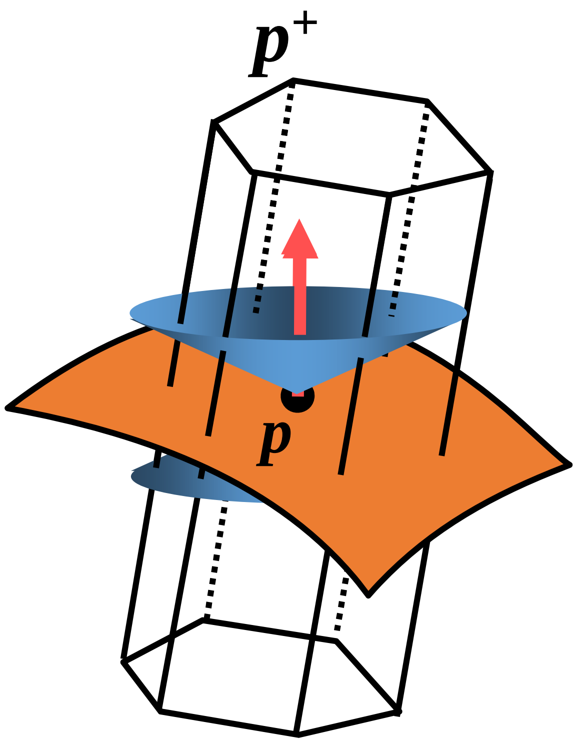
- Poles
  - Farthest Voronoi vertices for a sample point that are on opposite sides
- Crust
  - Shell created to represent the surface

Problem

- But some vertices of the Voronoi cell are near medial axis
- Intuitively – cell is closed not just from the sides but also from both sides of the surface



Observation

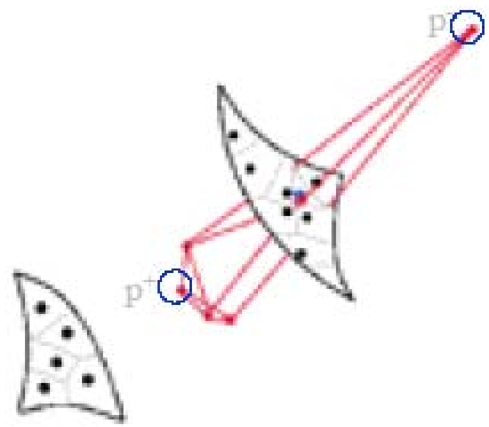


Voronoi cell of ***p***

- ***p+ ≡*** pole of ***p*** = point in the Voronoi cell farthest from ***p***
- $\varepsilon < 0.1 \rightarrow$
  - the vector from ***p*** to ***p+*** is within $\pi/8$ of the true surface normal
  - The surface is nearly flat within the cell

Solution

- Solution
  - use only two farthest vertices of Vs - one on each side of the surface
- Call vertices poles of s: $p^+(s)$, $p^-(s)$

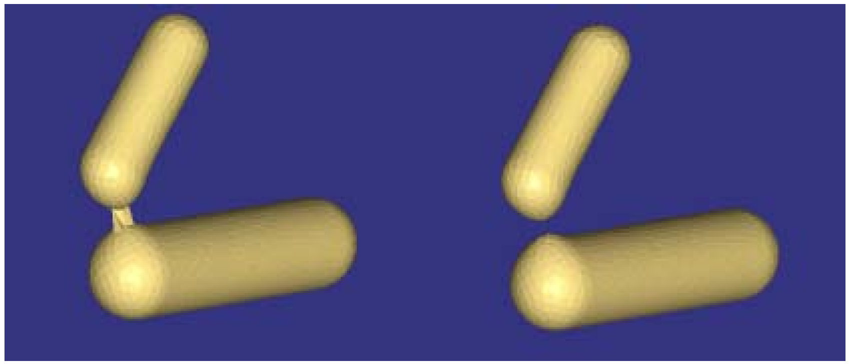


3D Algorithm

- Compute Voronoi diagram of S
- For each $s \in S$, identify the poles $p^+(s)$ and $p^-(s)$
  - $p^+(s)$ is the vertex of Vs most distant from s
  - $p^-(s)$ is the vertex of Vs most distant from s in the opposite direction
- Let P be the set of all poles
- Compute Delaunay triangulation T of S U P
- Add to crust all triangles in T with vertices only in S

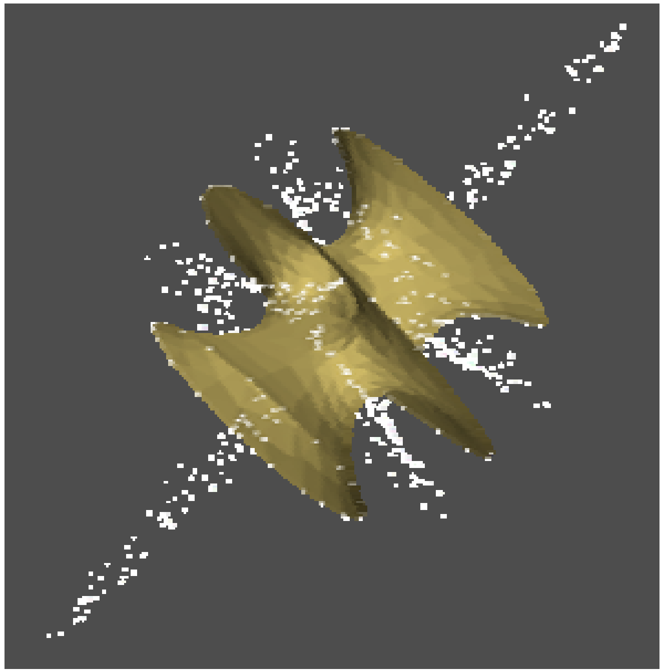
Post-processing

- Delete triangles whose normals differ too much from the direction vectors from the triangle vertices to their poles
- Orient triangles consistently with its neighbors and remove sharp dihedral edges to create a manifold

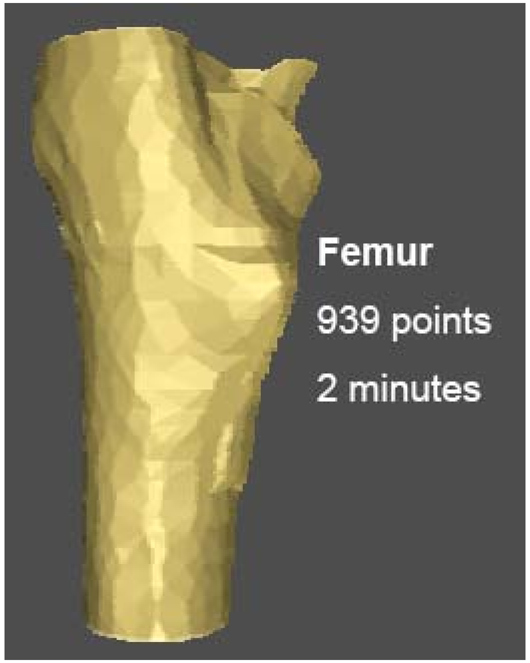


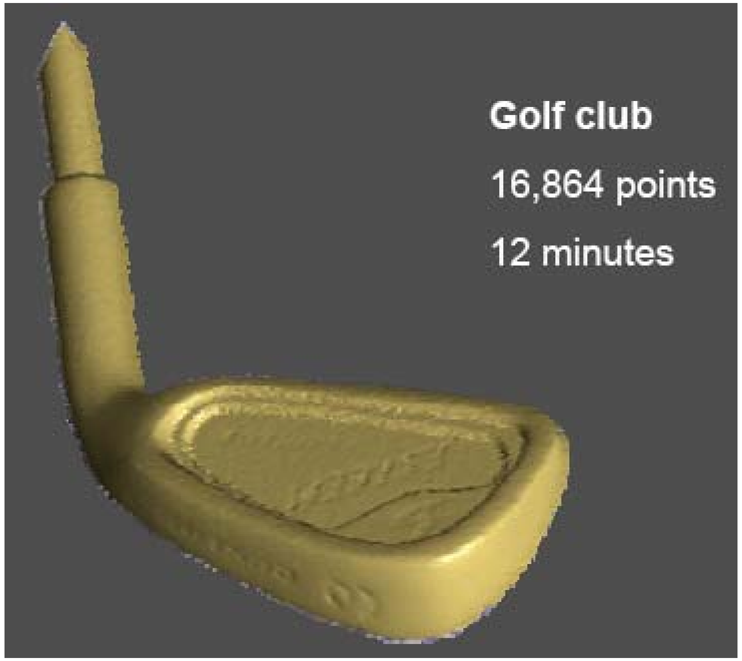
Example

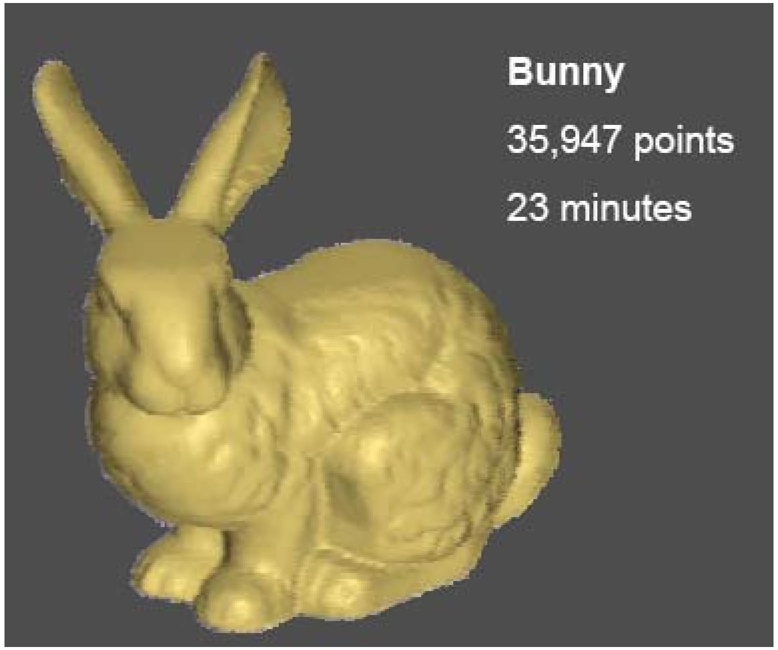
- Crust of set of points and poles used in its reconstruction



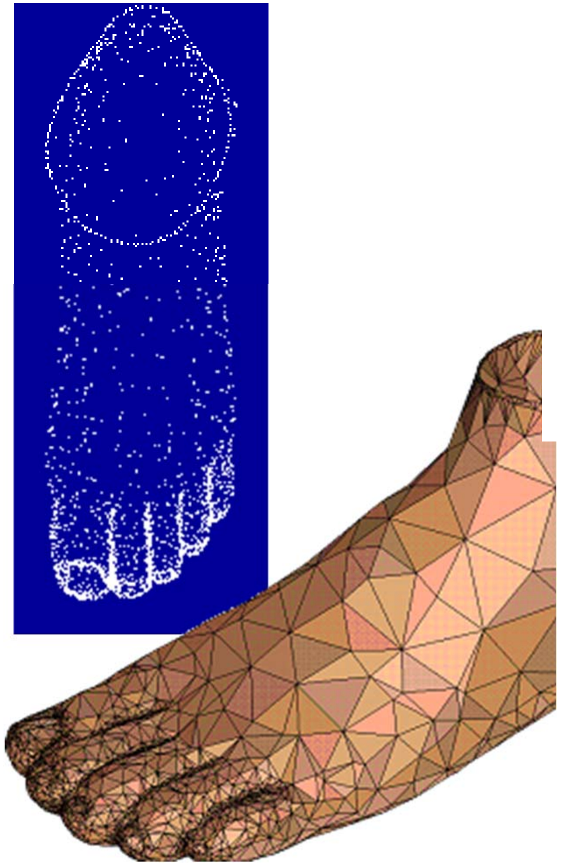
Examples


Femur
939 points
2 minutes

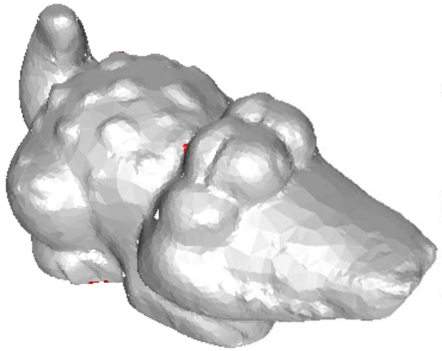

Golf club
16,864 points
12 minutes

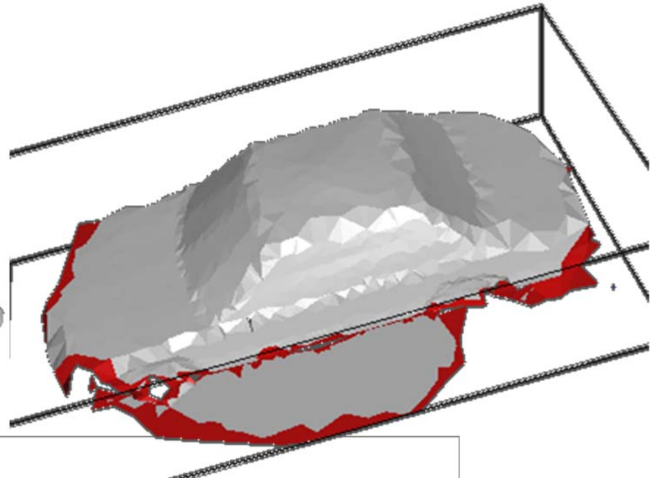

Bunny
35,947 points
23 minutes

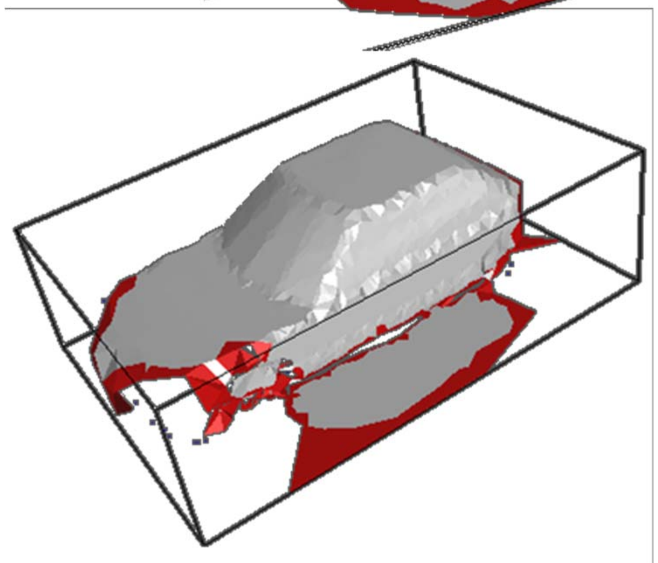
Examples



Foot images from Prof. Dey







Advantages

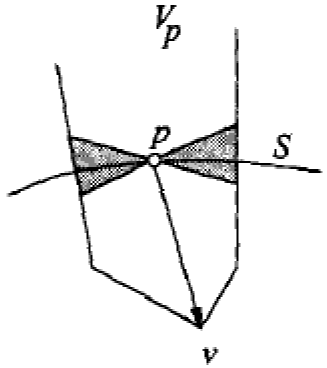
- No need for experimental parameters in basic algorithm
- Not sensitive to distribution of points

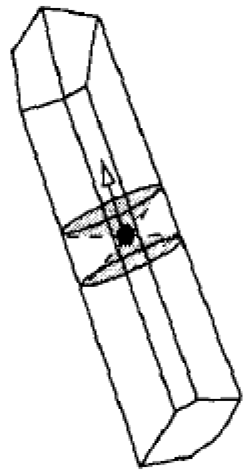
Problems

- Sampling of points needs to be dense
  - Undersampling causes holes
- Problems at sharp corners
- Another way to choose poles gives better reconstruction
  - choosing the farthest and the second farthest Voronoi vertices, regardless of direction
- Correct, BUT slow

Revised (1)

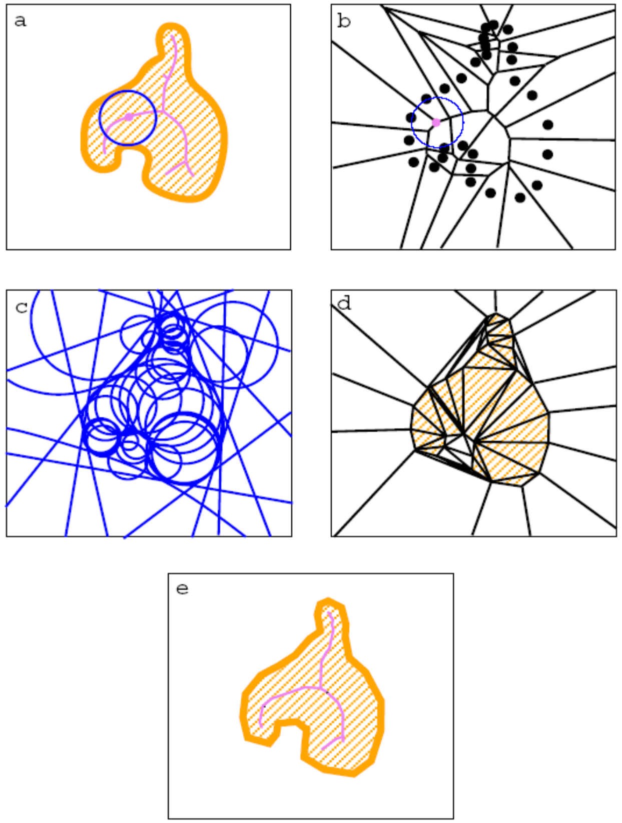
- Co-cones
  - Cone with apex at sample point and aligned with poles
  - Algorithm only requires one Voronoi diagram computation
  - Eliminates normal trimming step
  - Still does not support sharp edges





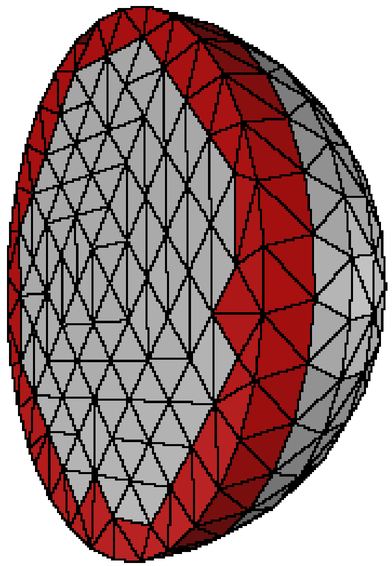
Revised (2)

- The power crust
  - Use polar balls and power diagrams to separate the inside and outside of the surface
  - Approximates medial axis



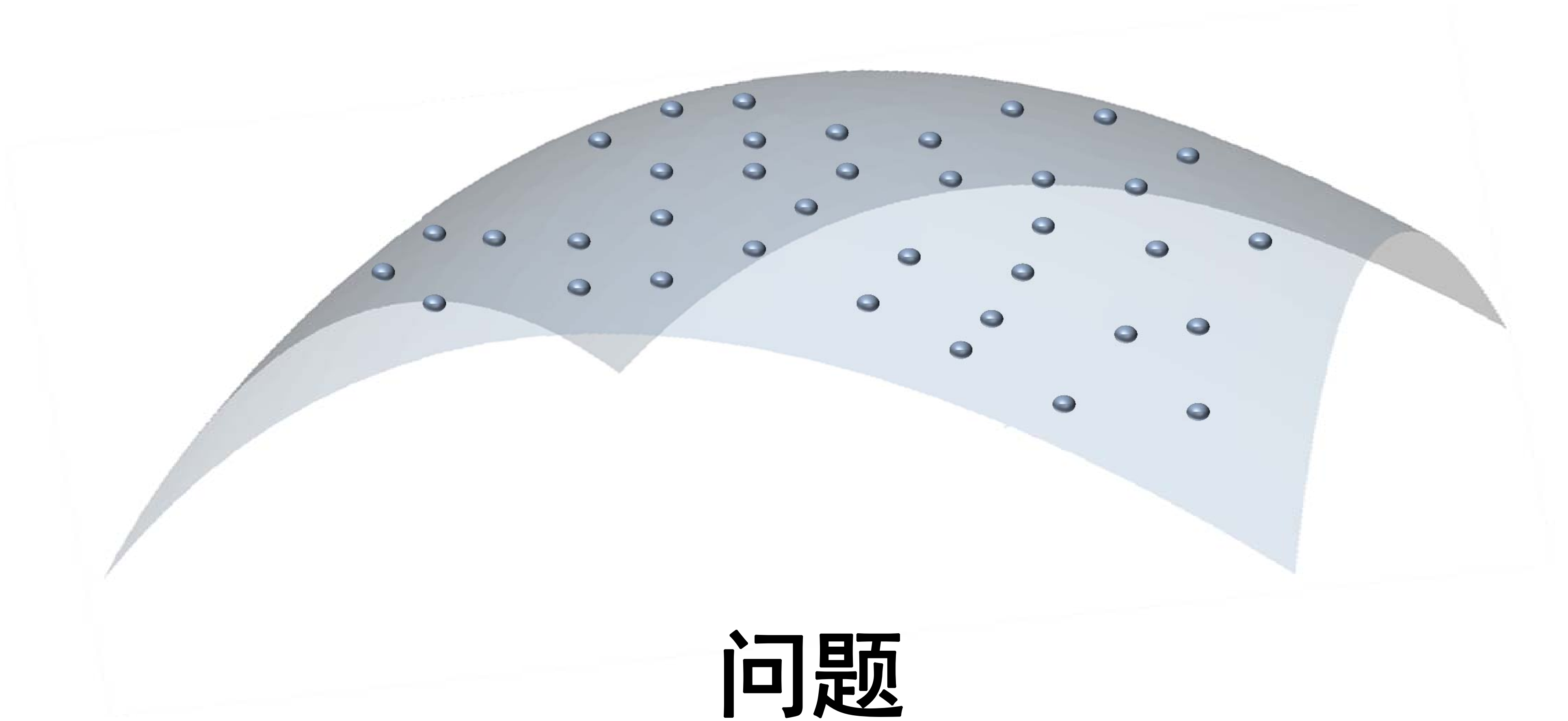
Revised (3)

- Detecting Undersampling
  - Fat Voronoi cells or dissimilarly oriented neighboring Voronoi cells imply undersampling. Add sample points to accommodate
  - This accounts for sharp edges and boundaries
- Tight Co-cone
  - After detecting undersampling, stitch up holes



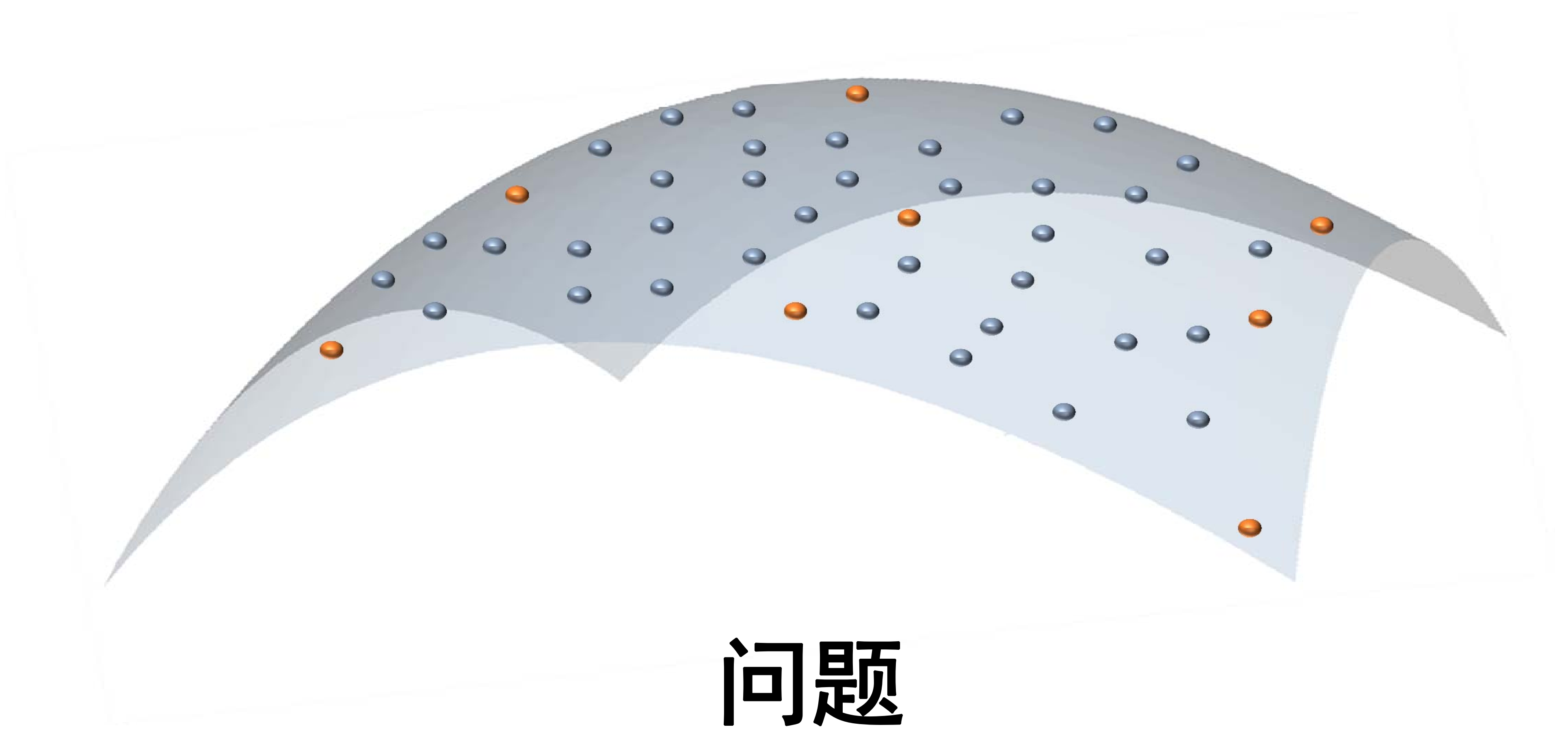
(2) 基于字典学习的曲面重建

Xiong et al. Robust Surface Reconstruction via Dictionary Learning. Siggraph Asia 2014.



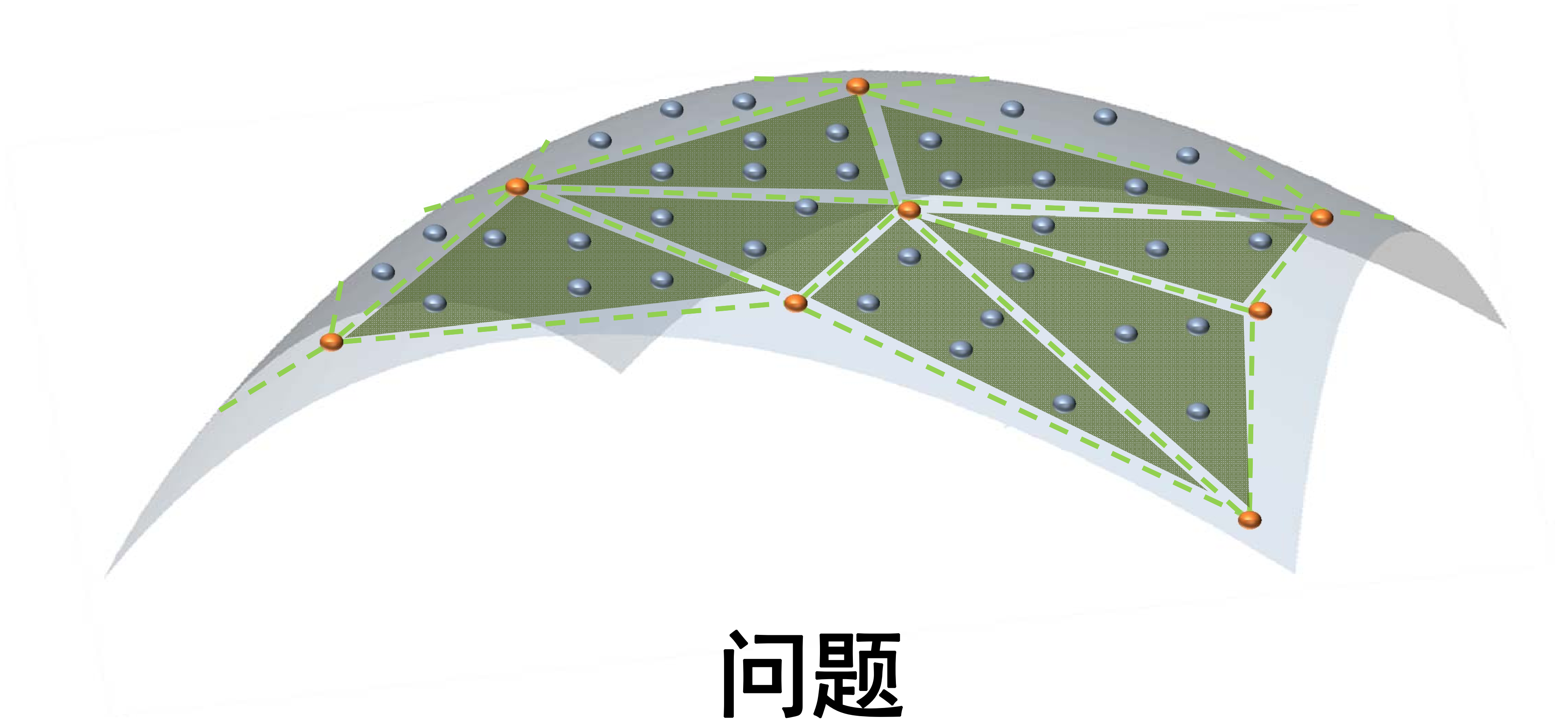
问题

- 输入：三维点集（蓝色点）



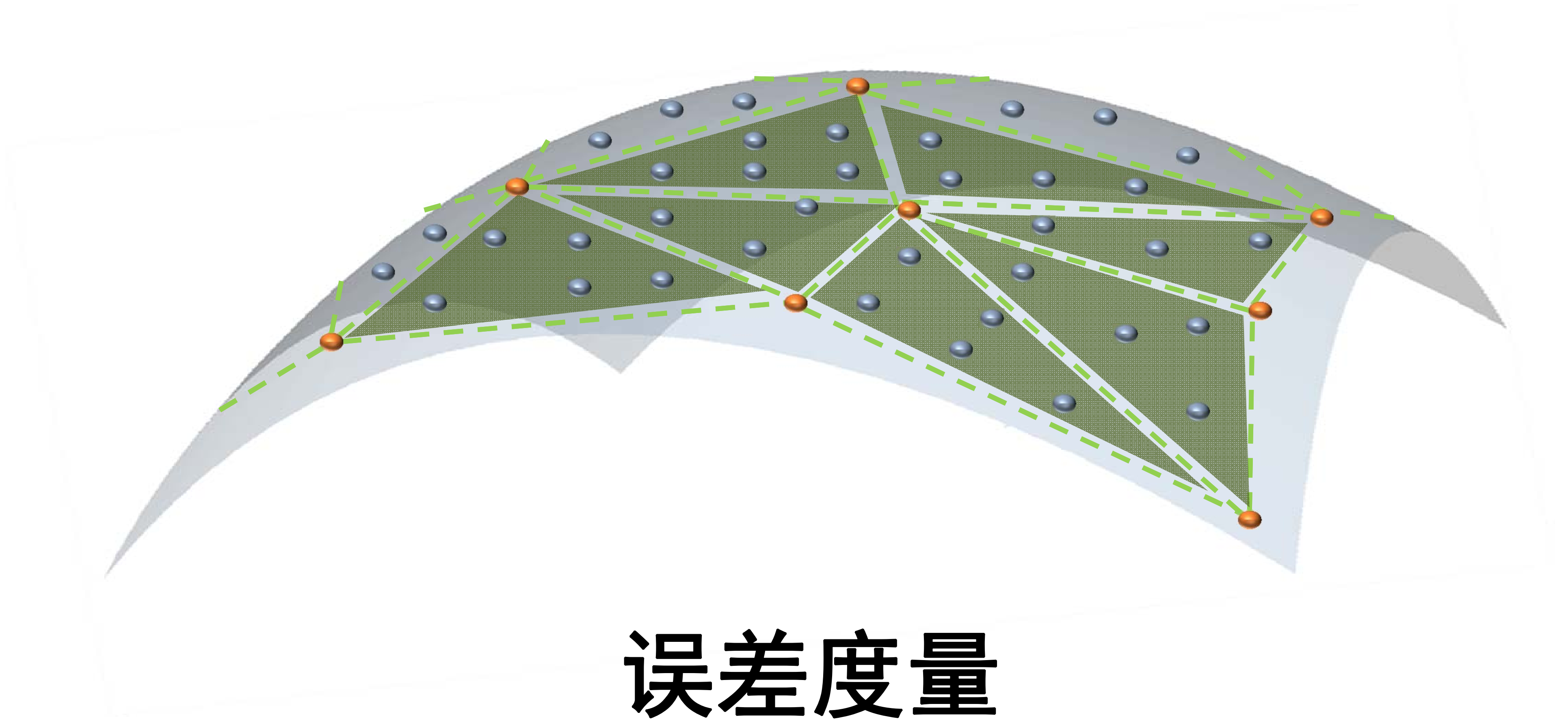
问题

- 输入：三维点集（蓝色点）
- 输出
  - 采样点集（红色点）



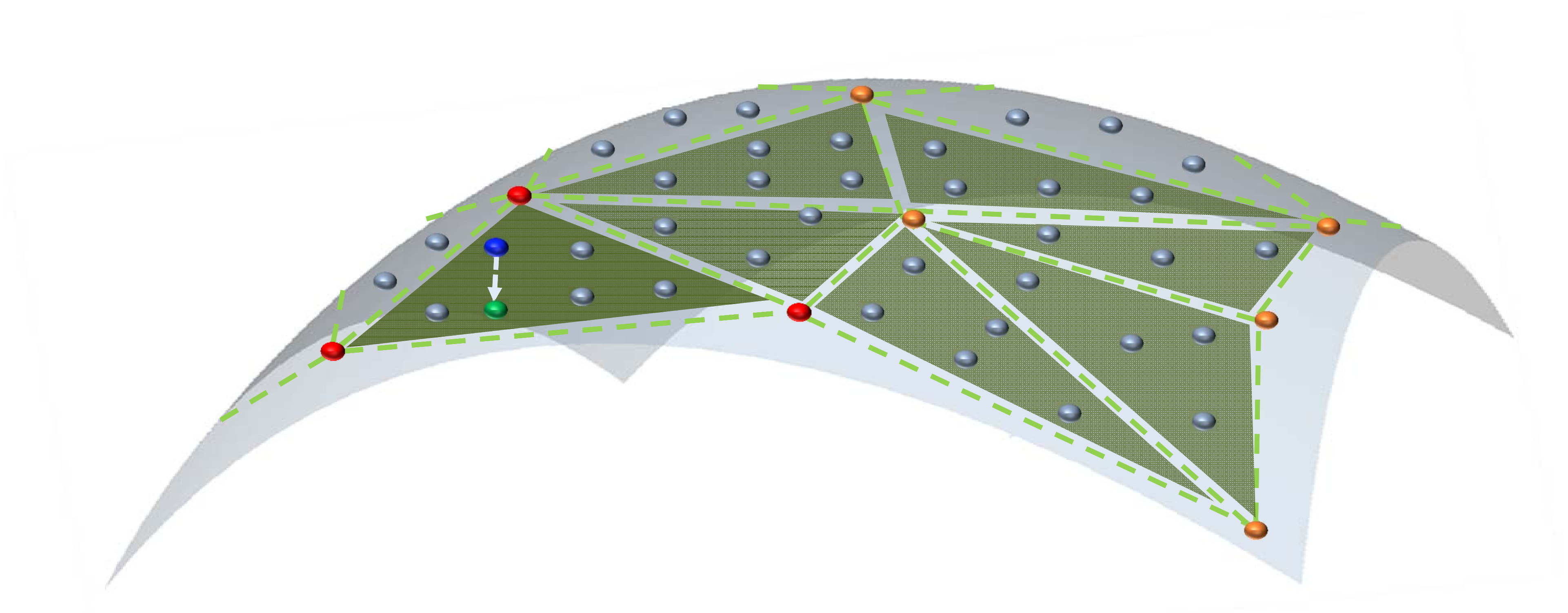
问题

- 输入：三维点集（蓝色点）P
- 输出
  - 采样点集（红色点）V
  - V构成的三角网格M，使得M逼近P



误差度量

- 如何度量点集P与网格M之间的误差?

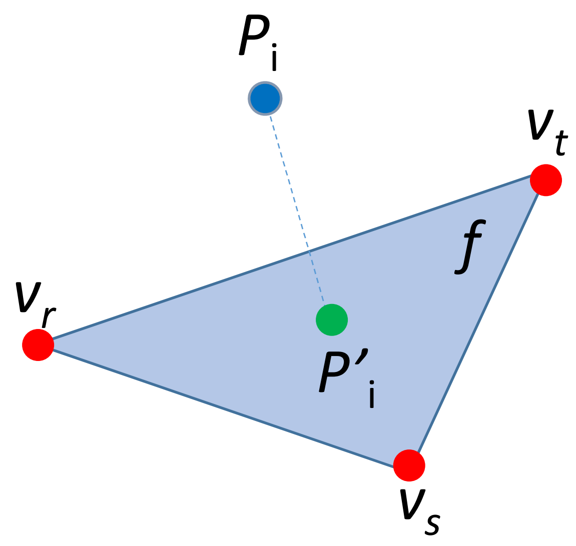


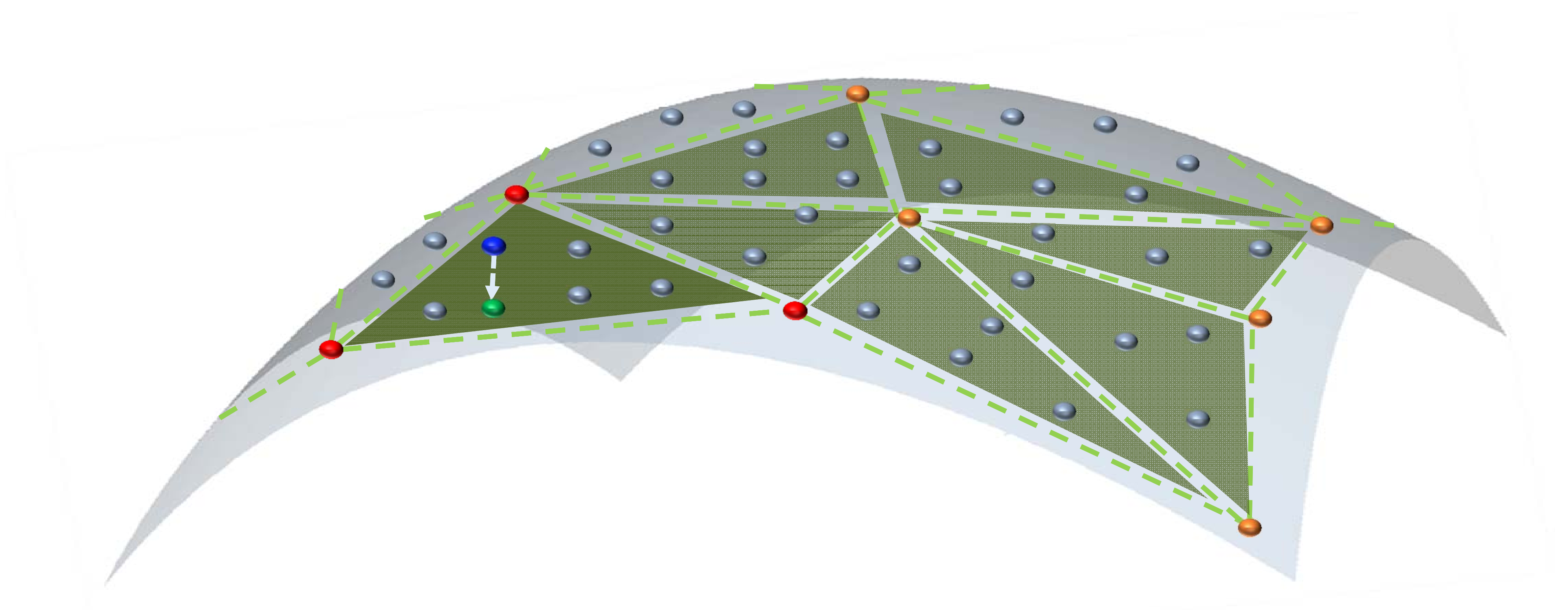
某个点到三角形的距离

$$d(\mathbf{p}_i, f) = \|\mathbf{p}_i - \mathbf{p}_i'\|$$
$$= \min_{\substack{\alpha+\beta+\gamma=1 \\ \alpha,\beta,\gamma\geq 0}} \|\mathbf{p}_i - (\alpha\mathbf{v}_r + \beta\mathbf{v}_s + \gamma\mathbf{v}_t)\|$$

$$\mathbf{p}_i' = \alpha^*\mathbf{v}_r + \beta^*\mathbf{v}_s + \gamma^*\mathbf{v}_t$$

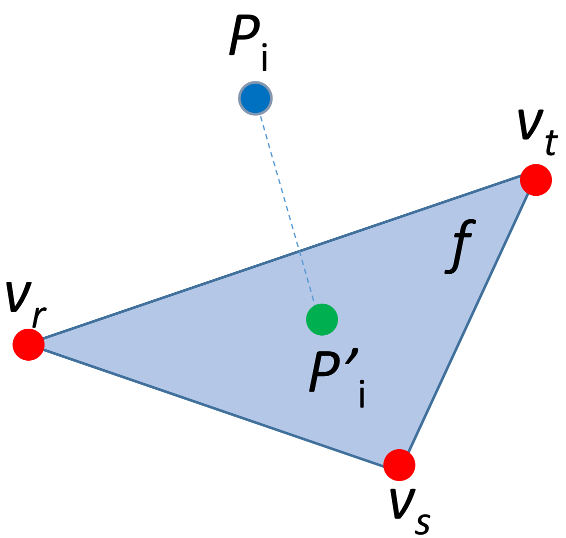
$(\alpha^*, \beta^*, \gamma^*)$ ：P'_i 相对与 f的重心坐标





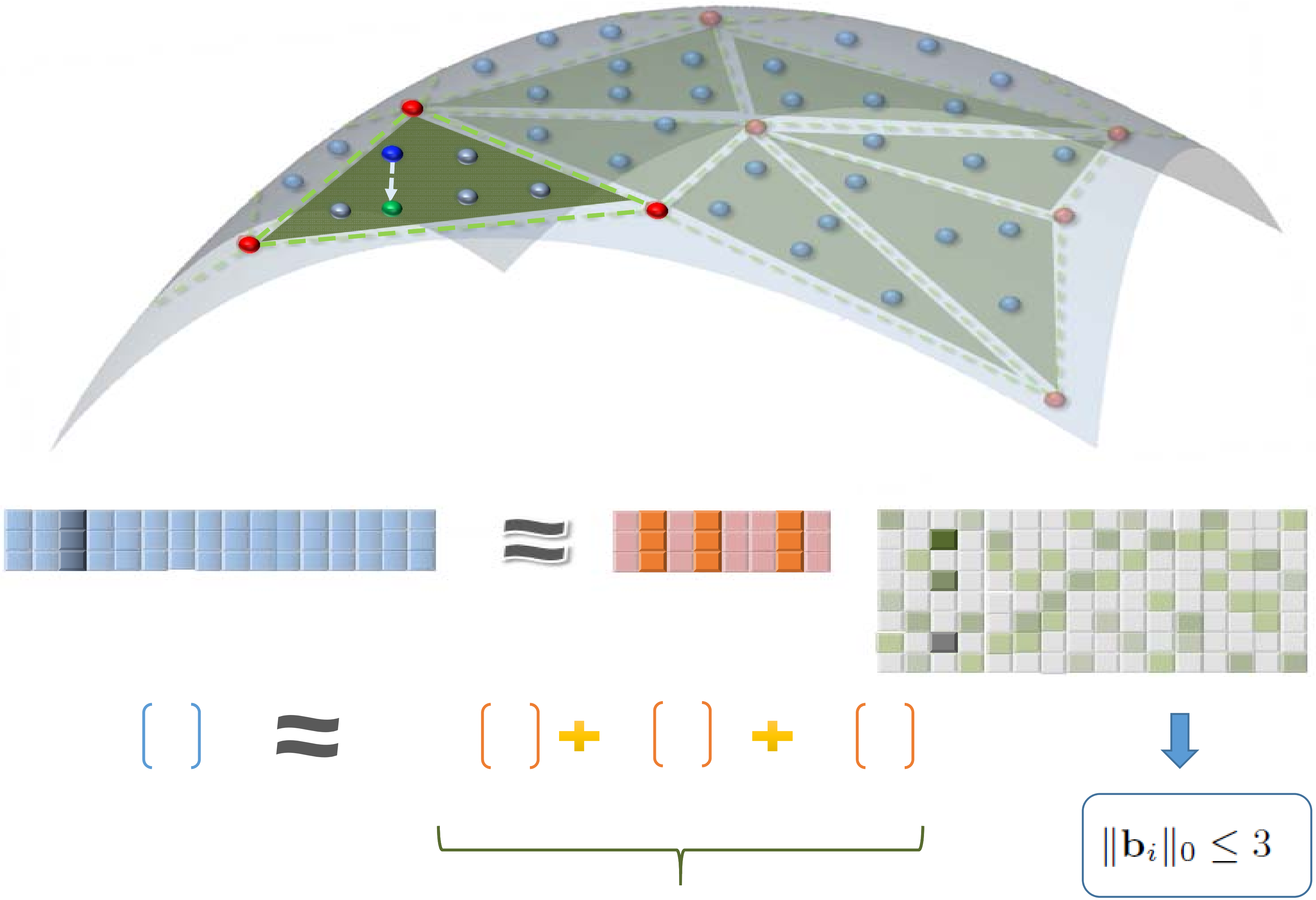
某个点到三角形的距离

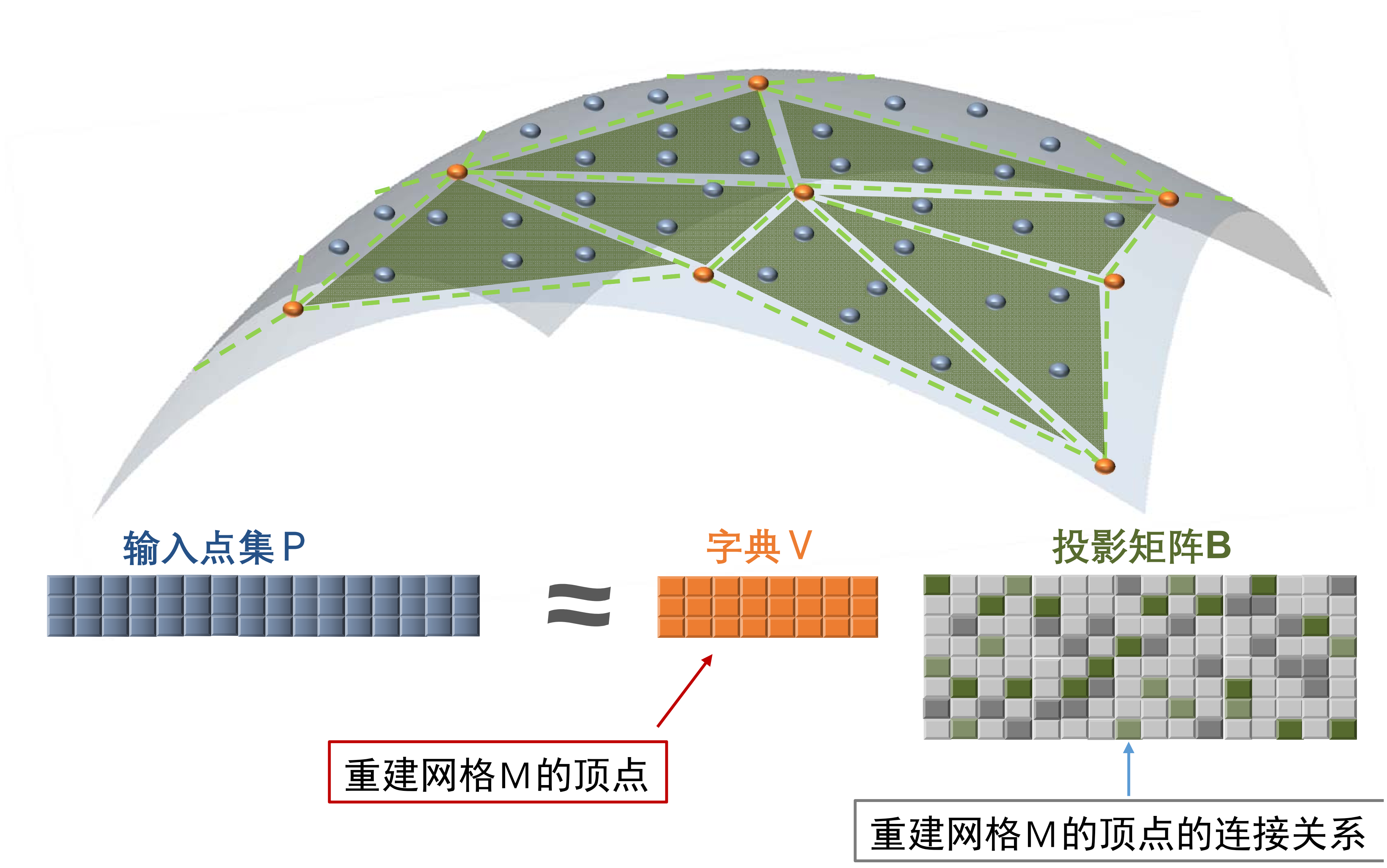
$$d(\mathbf{p}_i, f) = \|\mathbf{p}_i - \mathbf{p}'_i\|$$
$$= \min_{\substack{\alpha+\beta+\gamma=1 \\ \alpha,\beta,\gamma\geq 0}} \|\mathbf{p}_i - (\alpha\mathbf{v}_r + \beta\mathbf{v}_s + \gamma\mathbf{v}_t)\|$$



$$\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_m] \in \mathbb{R}^{3\times m}$$

Vertex matrix of M


$\|\mathbf{b}_i\|_0 \leq 3$



输入点集 P
≈
字典 V
投影矩阵B
重建网格M的顶点
重建网格M的顶点的连接关系

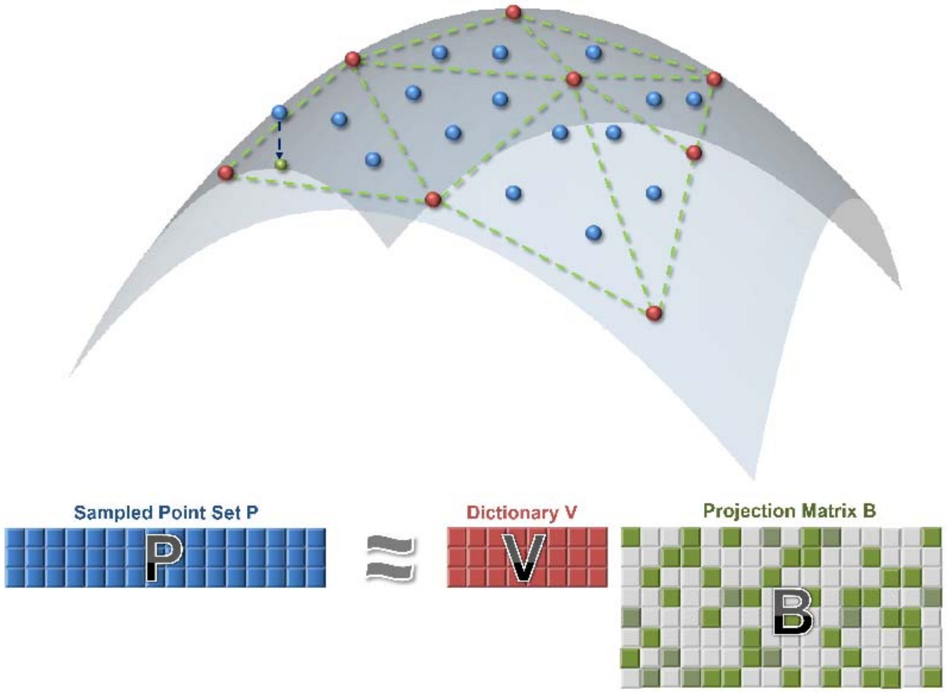
Approximation Error

Denote

$$\mathbf{P} = [\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_n]$$
$$\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_m]$$
$$\mathbf{B} = [\mathbf{b}_1, \mathbf{b}_2, \cdots, \mathbf{b}_n]$$
$$\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \cdots, \mathbf{z}_n]$$

then

$$\mathbf{P} = \mathbf{VB} + \mathbf{Z}$$



From the **dictionary learning** perspective:

P: the given signal

V: the dictionary

B: the sparse coding matrix

Z: the approximation residual

全局误差

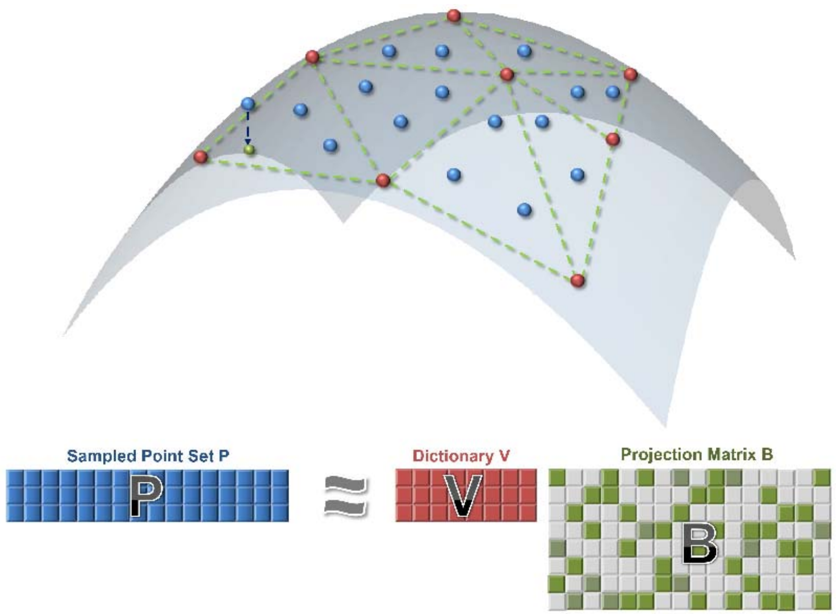
$$\mathbf{P} = \mathbf{V}\mathbf{B} + \mathbf{Z}$$

$$E_{\text{appr}} = \frac{1}{n}\|\mathbf{Z}\|_{2,q} = \frac{1}{n}\|\mathbf{P} - \mathbf{V}\mathbf{B}\|_{2,q}$$

$$= \frac{1}{n}\sum_{i=1}^{n}\|\mathbf{p}_i - \mathbf{V}\mathbf{b}_i\|_2^q$$

s.t.

$$\|\mathbf{b}_i\|_0 \leq 3, \quad \|\mathbf{b}_i\|_1 = 1, \quad \mathbf{b}_i \geq 0, \ \forall i$$



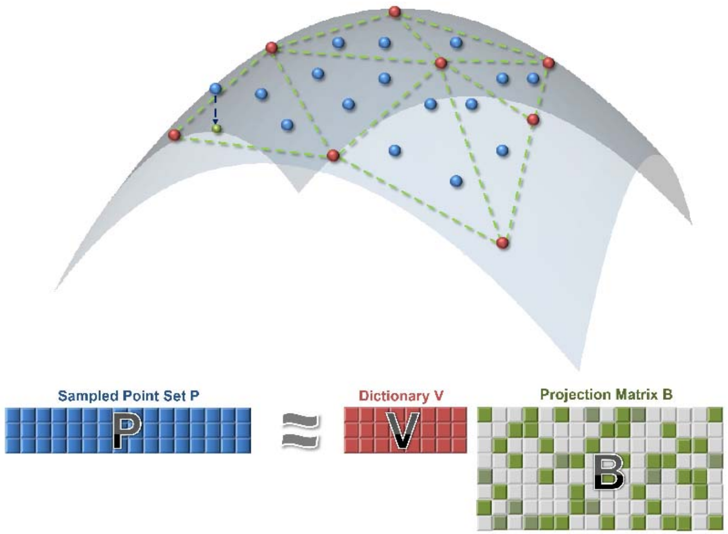
数学优化模型

$$\min_{\mathbf{V},\mathbf{B}} \quad E = E_{\text{appr}} + E_{\text{reg}}$$

$$\text{s.t.} \quad \|\mathbf{b}_i\|_0 \le 3, \quad \|\mathbf{b}_i\|_1 = 1, \quad \mathbf{b}_i \ge 0, \qquad \forall i$$

$$\mathbf{B} \in \mathbb{MT}$$

V: the vertices (geometry)
B: encodes the connectivity of V (topology)



优化方法

$$\min_{\mathbf{V},\mathbf{B}} \quad E = E_{\text{appr}} + E_{\text{reg}}$$

$$\text{s.t.} \quad \|\mathbf{b}_i\|_0 \leq 3, \quad \|\mathbf{b}_i\|_1 = 1, \quad \mathbf{b}_i \geq 0, \qquad \forall i$$

$$\mathbf{B} \in \mathbb{MT}$$

Input:

Point cloud: $\mathbf{P} = [\mathbf{p}_1, \cdots, \mathbf{p}_n] \in \mathbb{R}^{3\times n}$;

1: Initialize dictionary $\mathbf{V}$ and sparse coding matrix $\mathbf{B}$ from $\mathbf{P}$;

2: **repeat**

3: Update matrix $\mathbf{B}$ (Sparse Coding);

4: Update $\mathbf{V}$ (Dictionary Update);

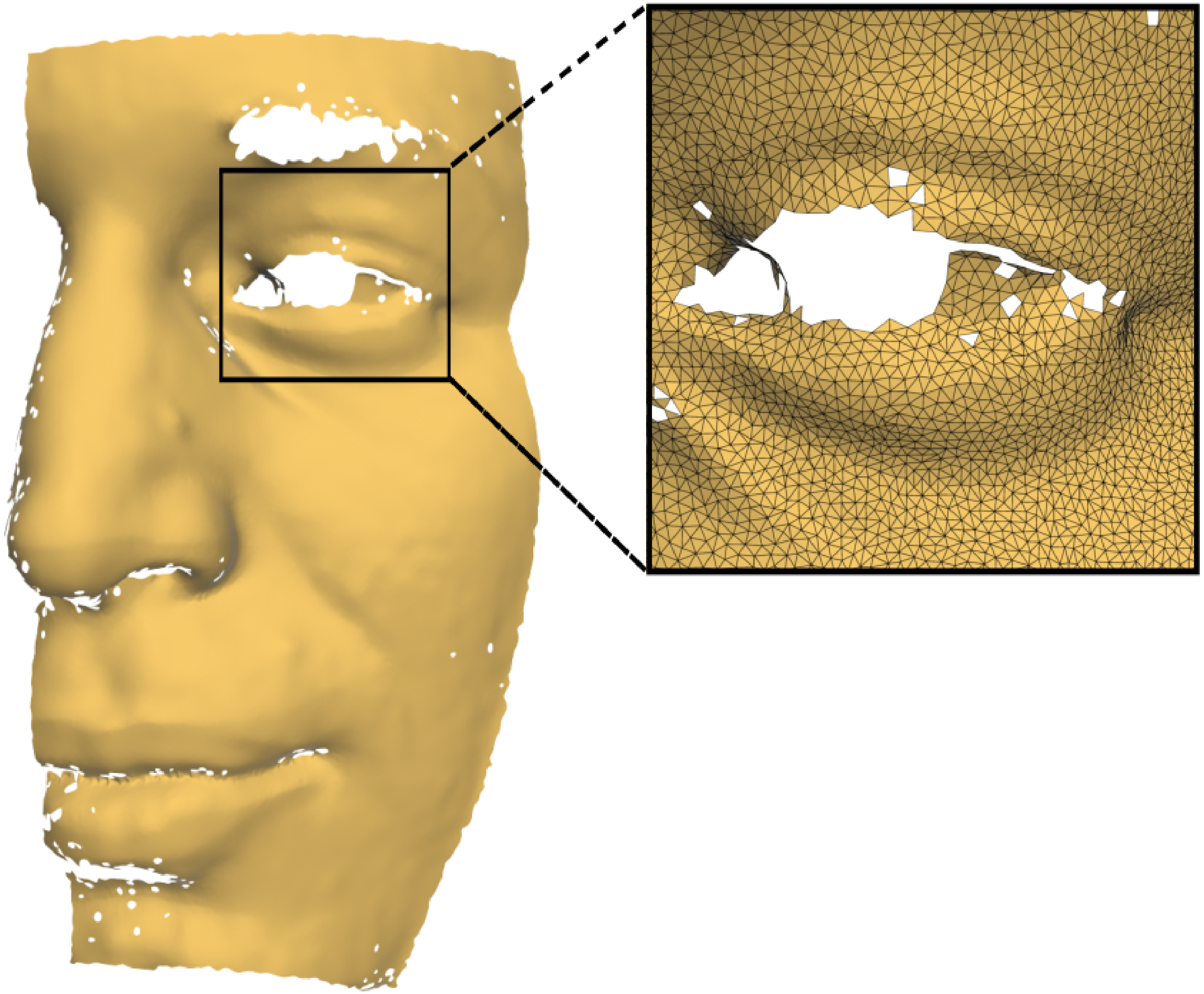
5: **until** convergence

6: **return** Mesh $M(\mathbb{V}, \mathbb{F})$;

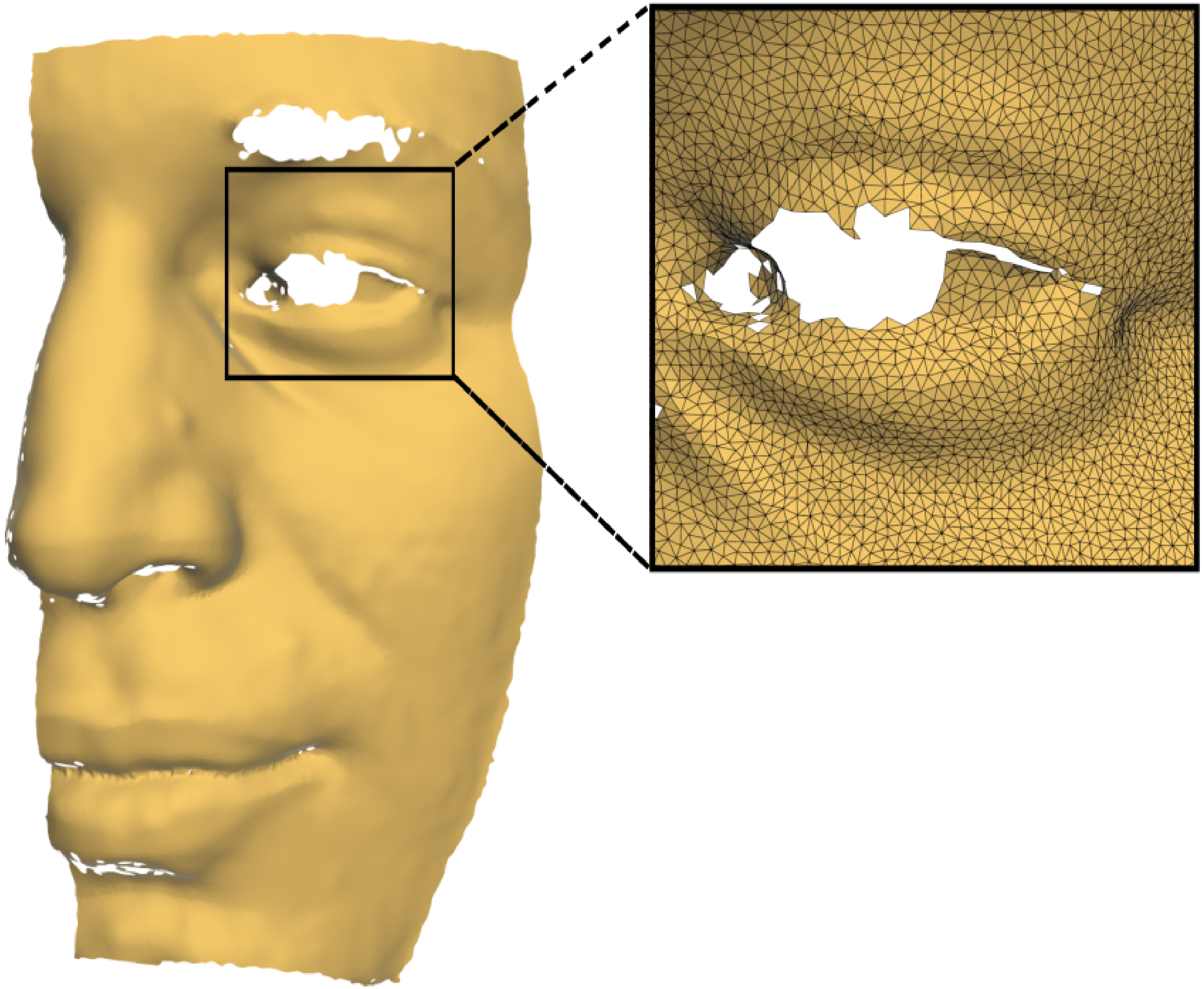
Experimental Results

Input Point Cloud

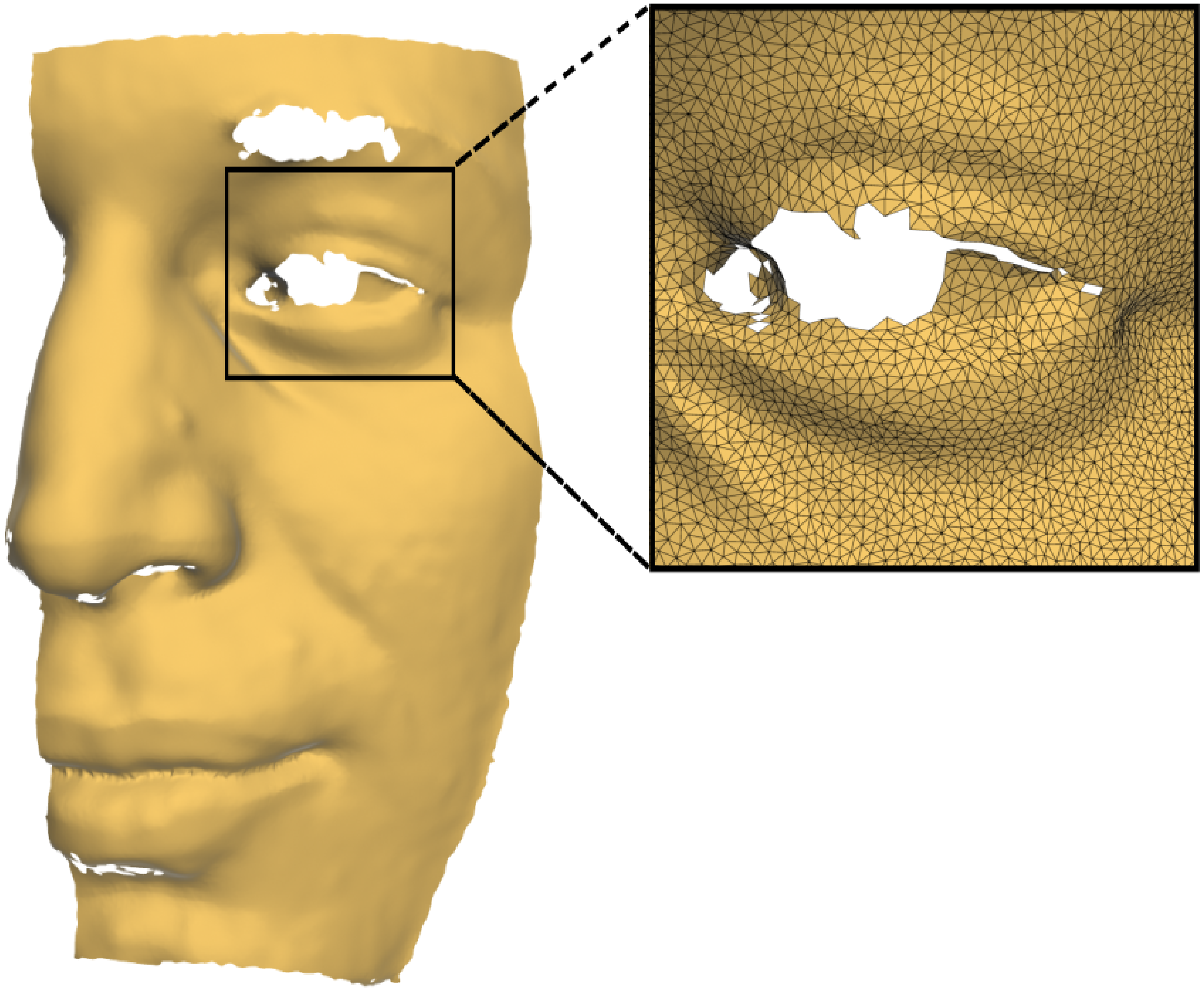
Iter 1



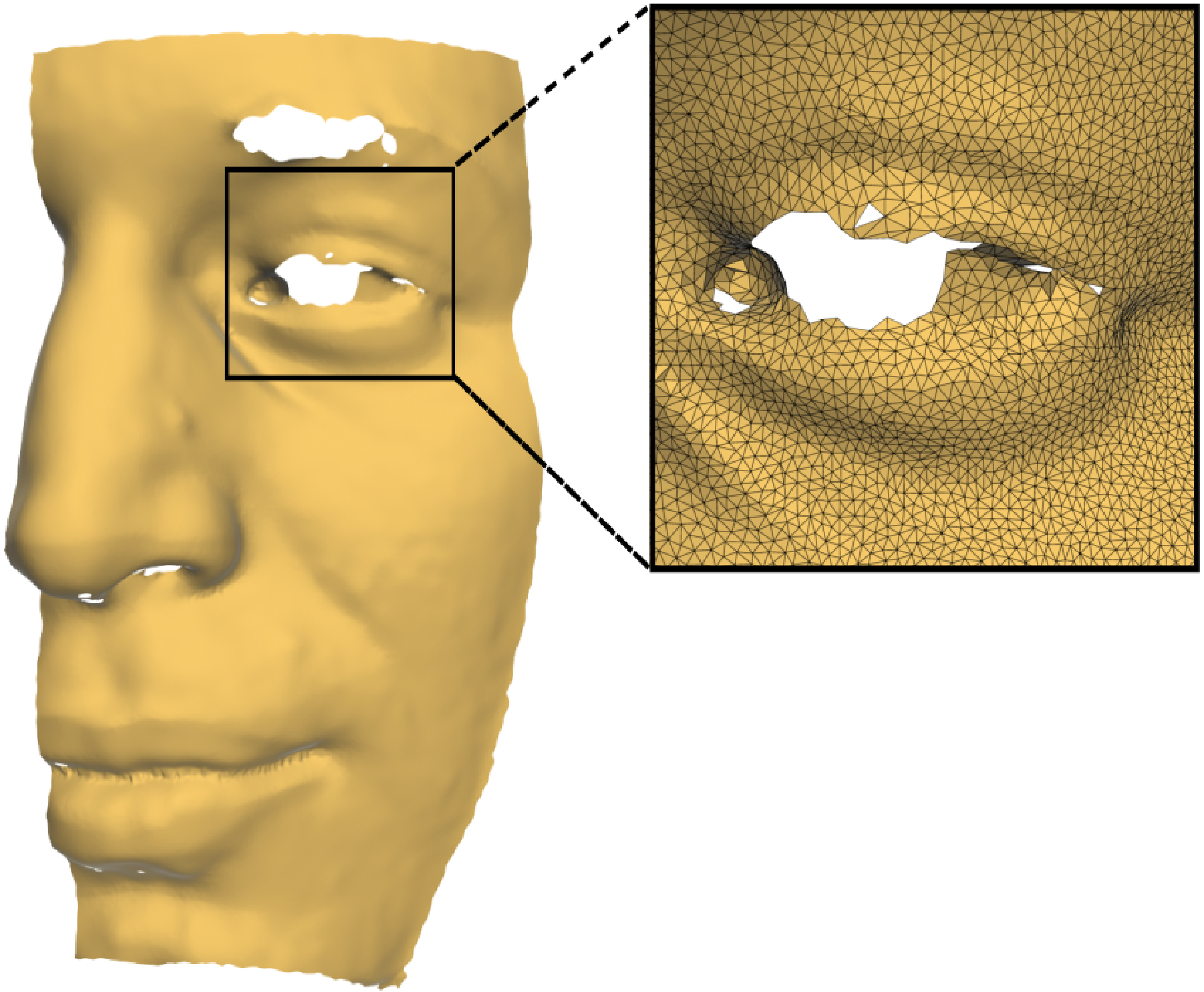
Iter 2



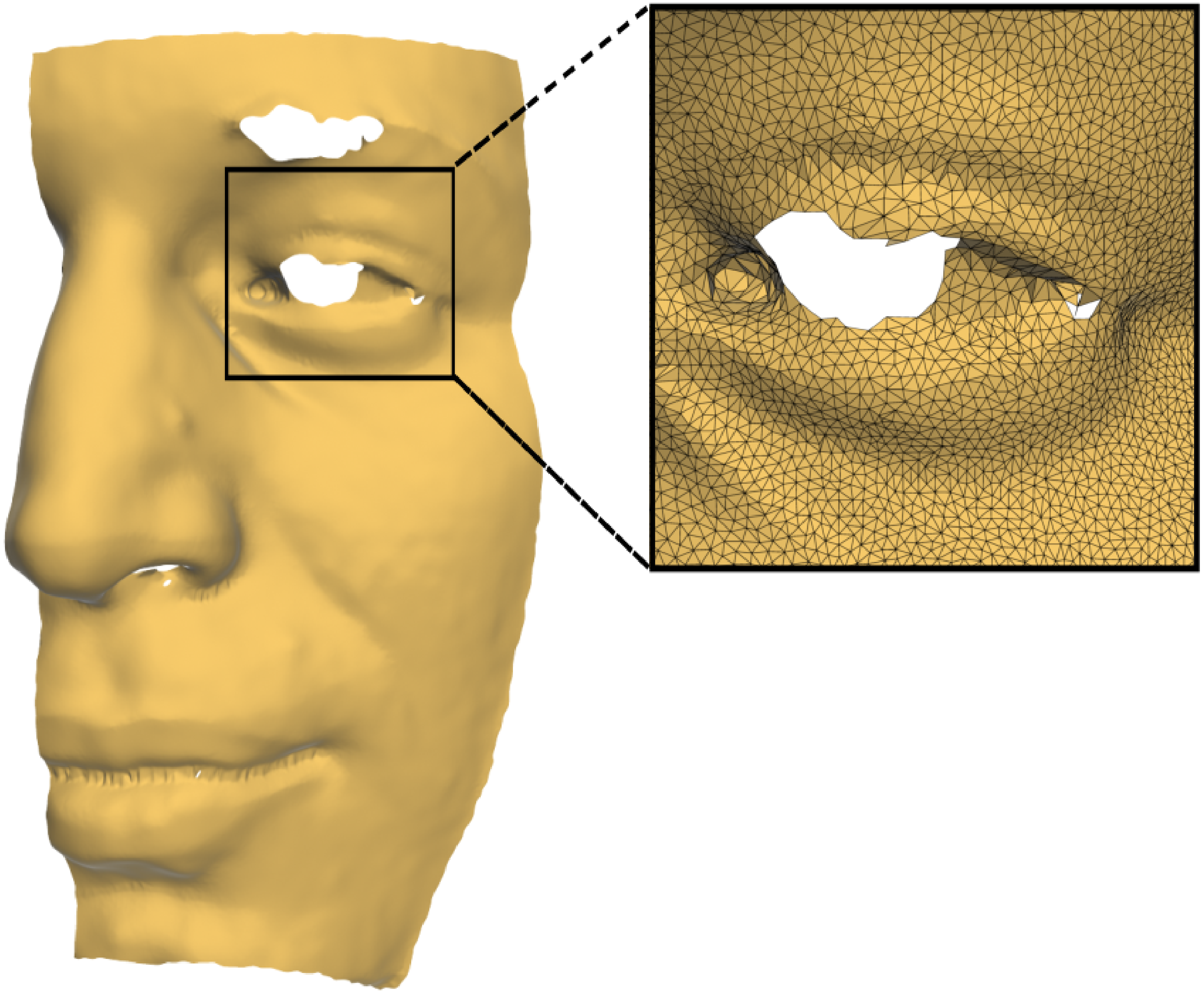
Iter 3



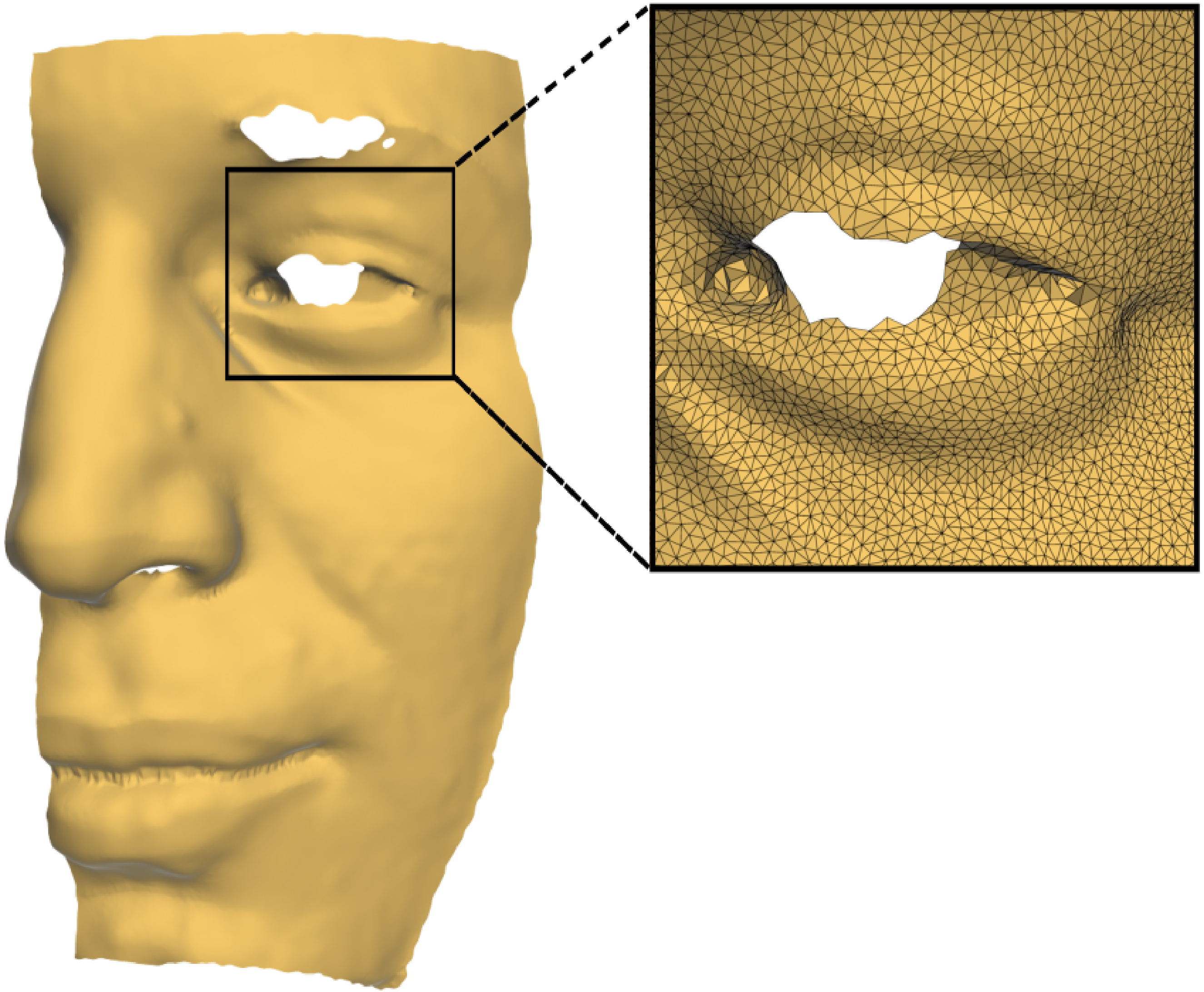
Iter 4



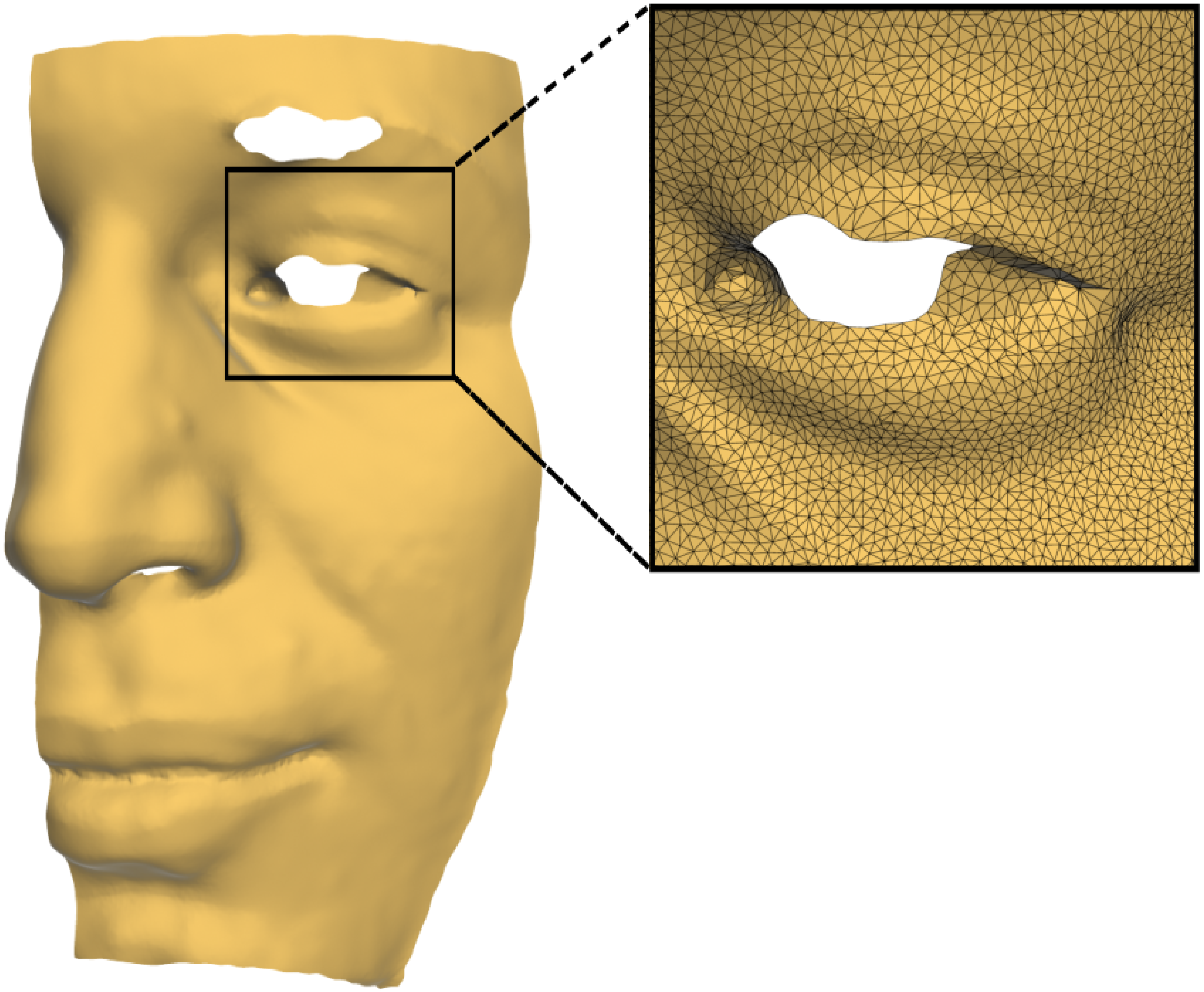
Iter 5



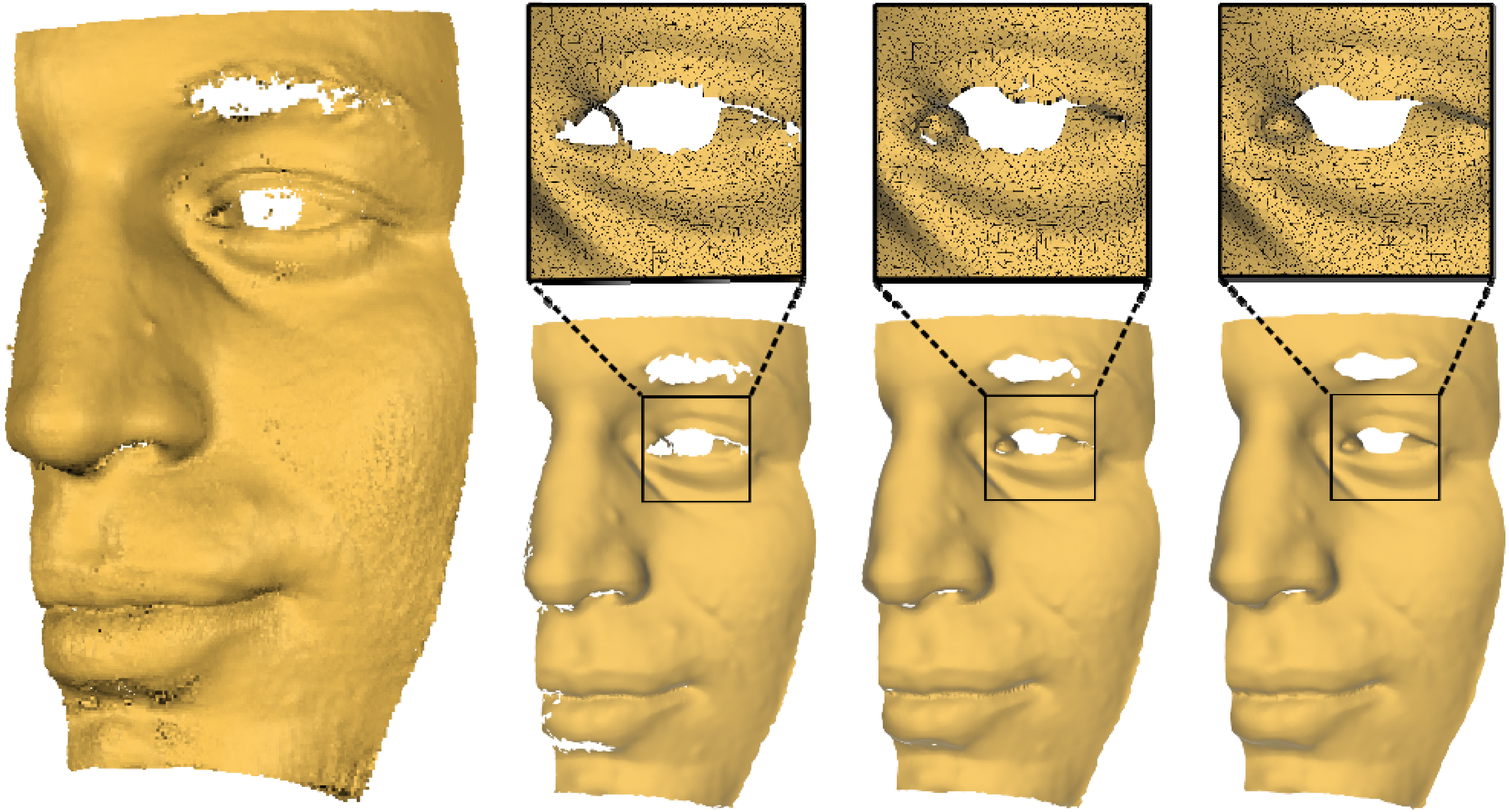
Iter 6



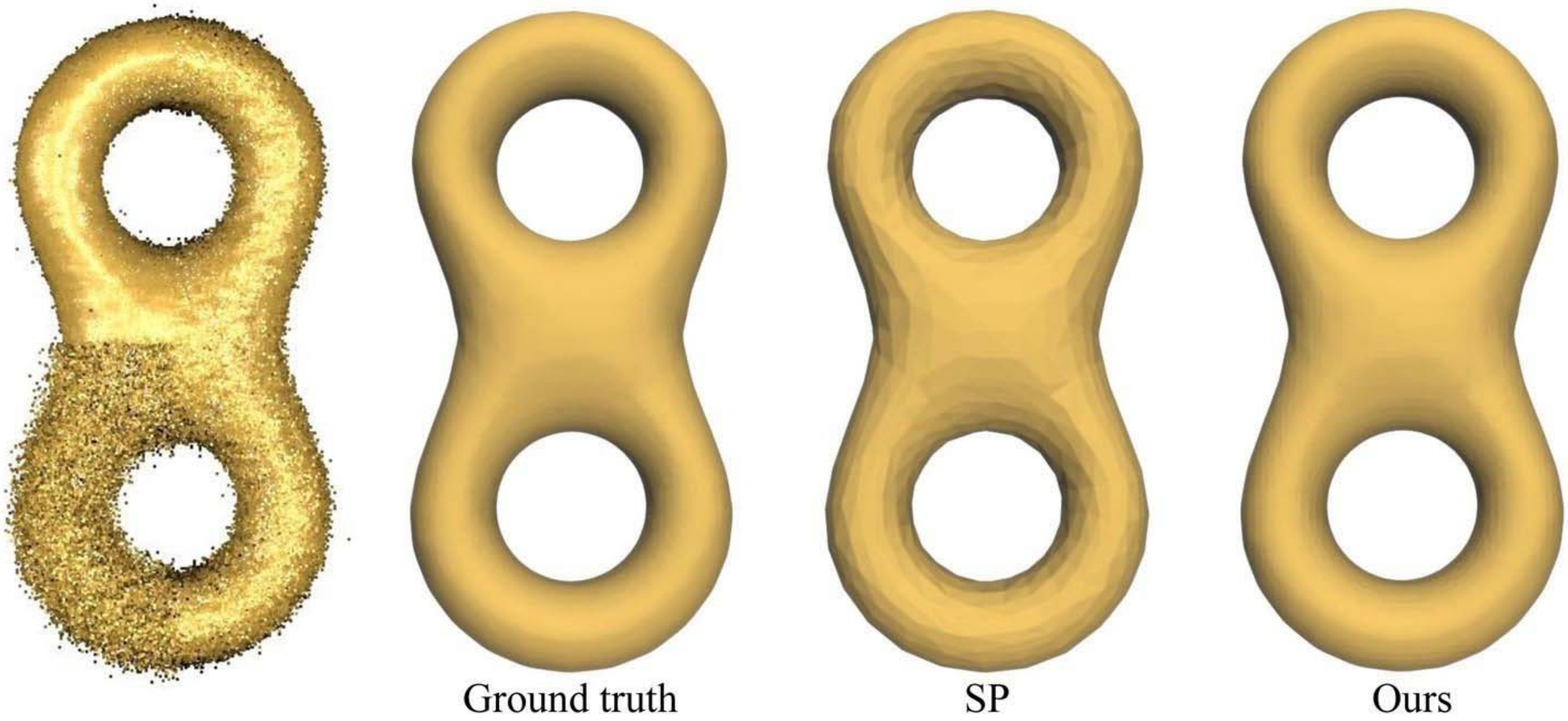
Iter 7



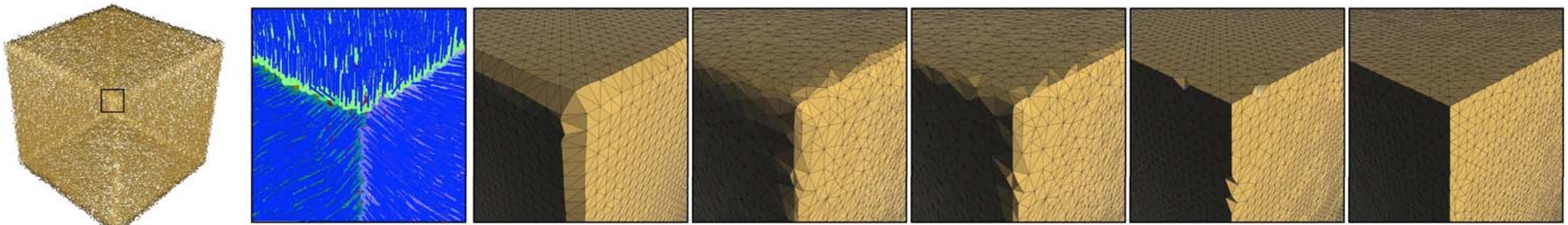
Iterative Refinement



Resistant to Noise



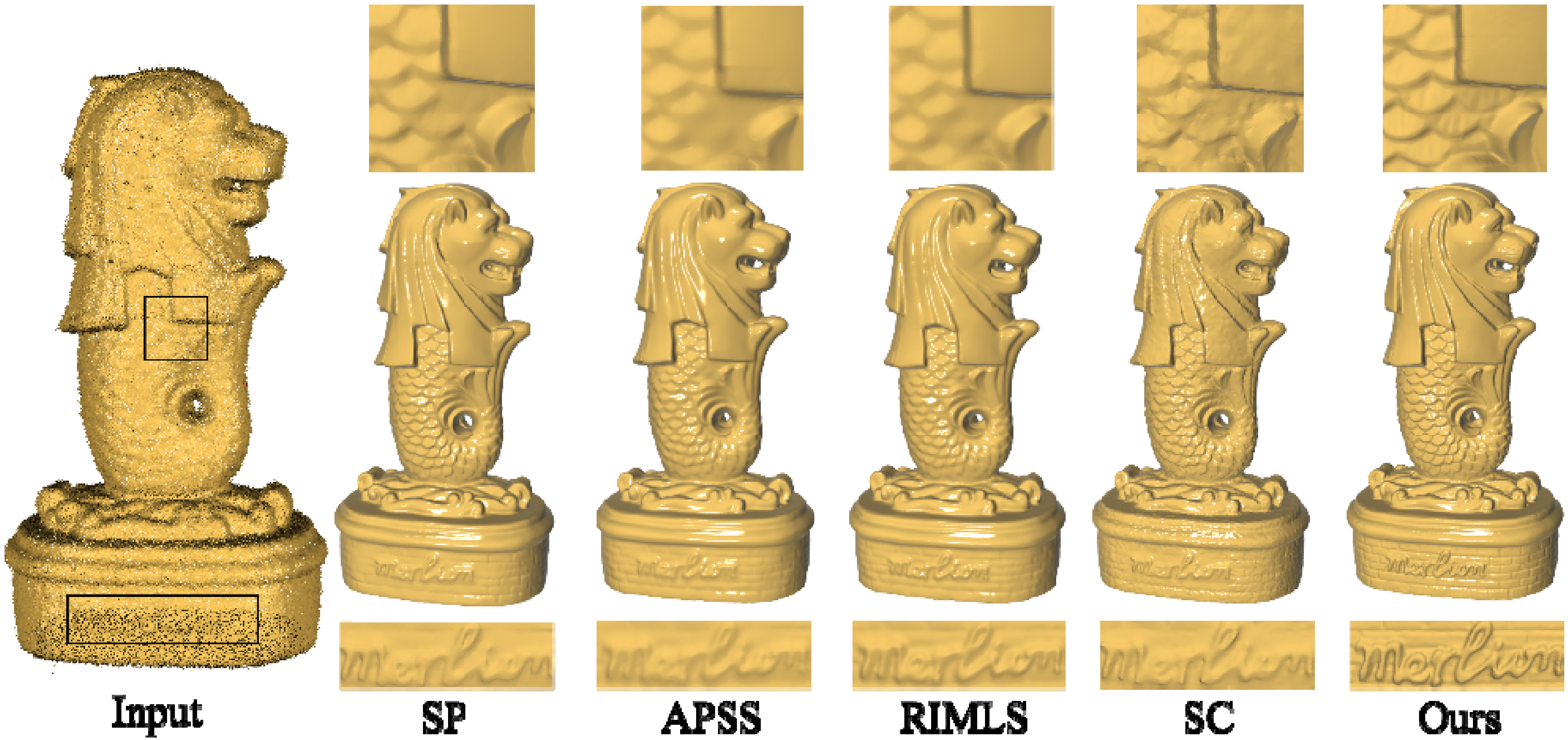
Feature Preserving



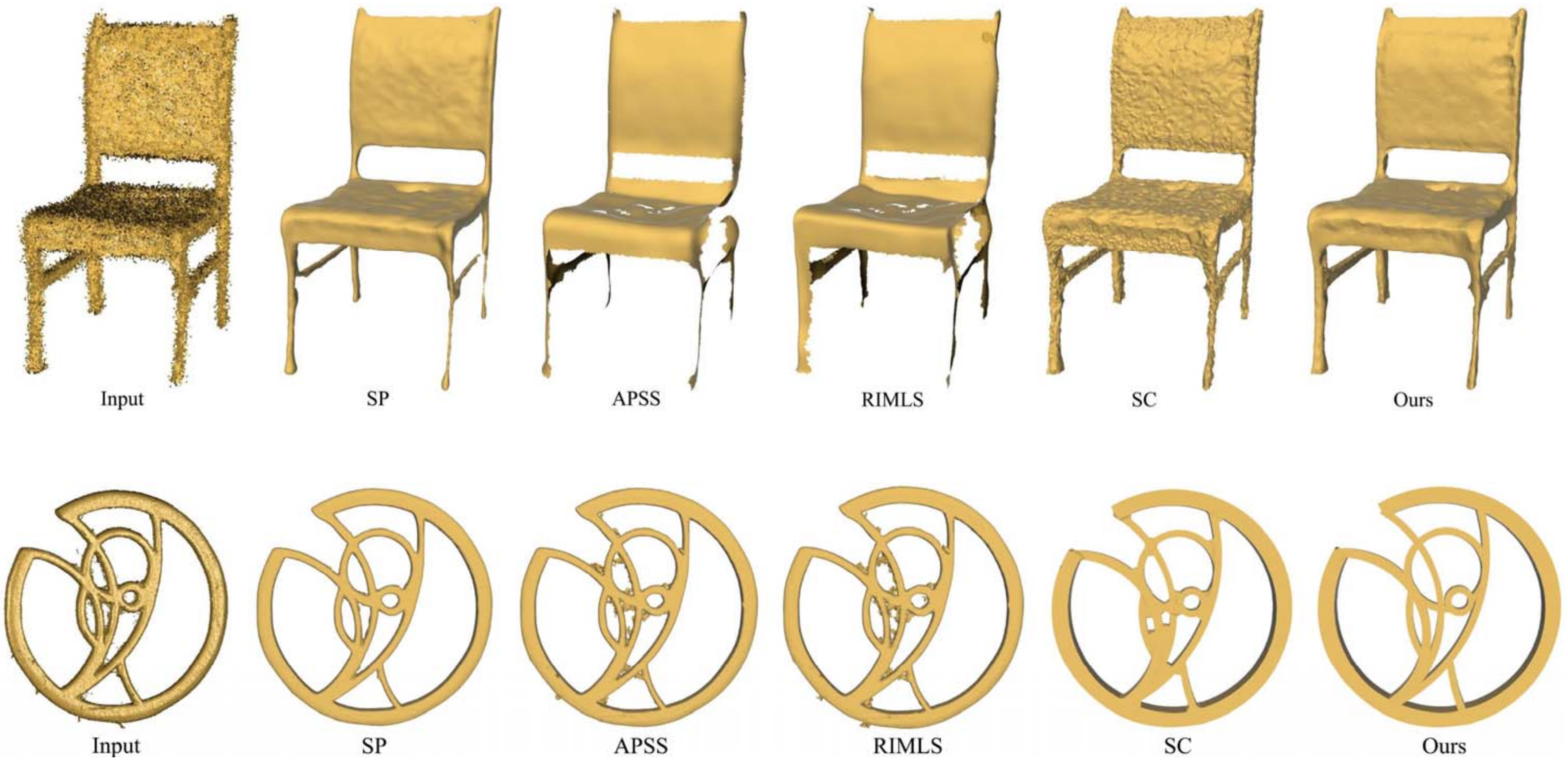
Input Normal(EAR) SP APSS RIMLS SC Ours

Implicit methods need normal information, while normal estimation is another challenging problem.

Comparisons



Real Scanned Data

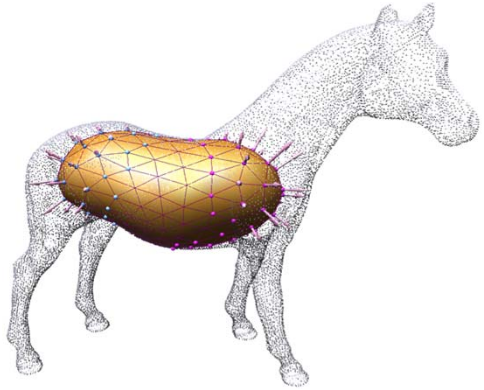


Conclusion

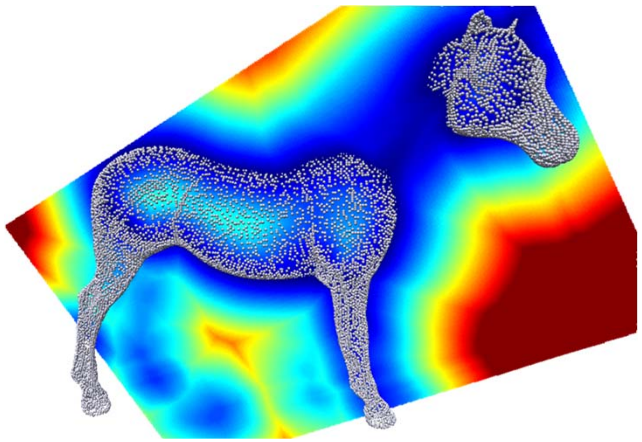
- Model the surface reconstruction problem via dictionary learning
- VS Implicit method
  - Straightforward
  - Approximation error is considered
- VS Existing Explicit method
  - Denoising the input point cloud
  - Global approximation error

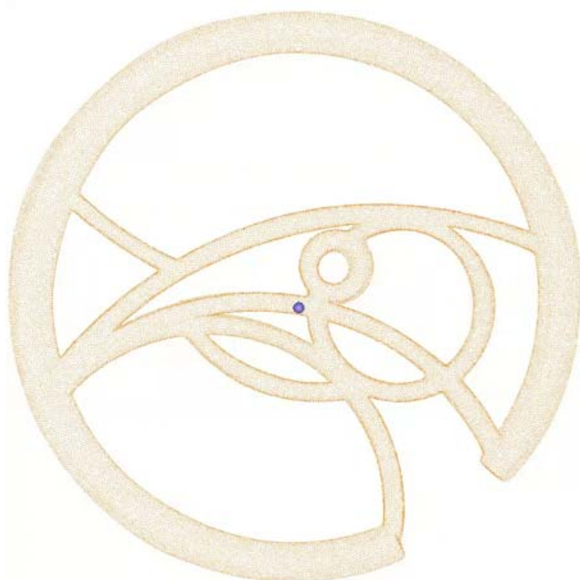
Hybrid Methods

(1) Competing Fronts



- Deformable model reconstruction
  - Implicit coarse guidance field or attraction field
  - Explicit deformable model (a mesh)
- Property
  - Watertight guarantee
  - Topology control

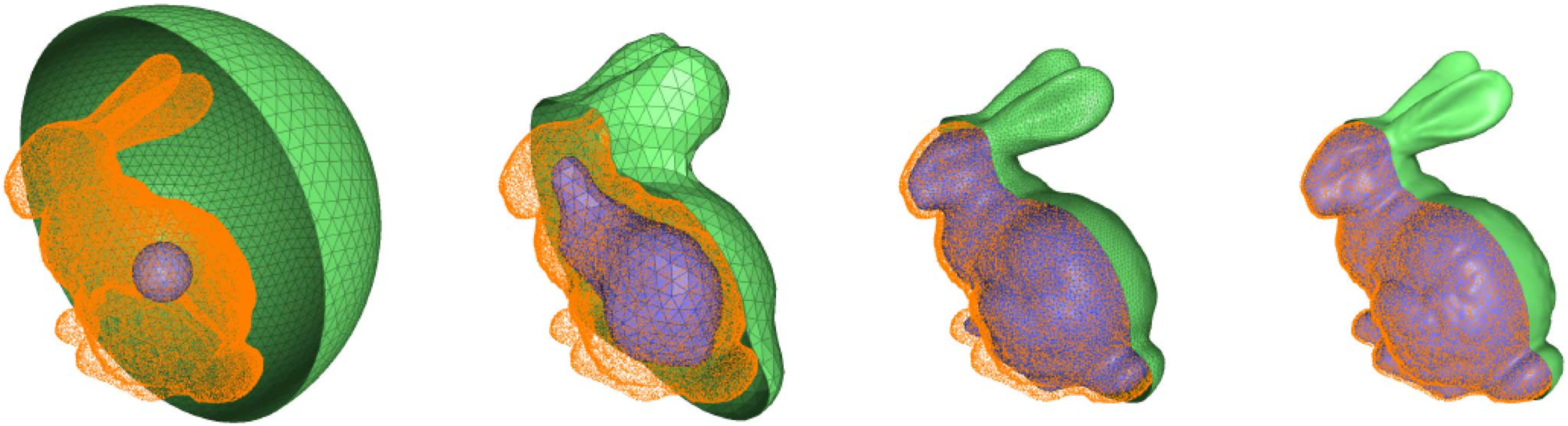




Sharf et al. Competing Fronts for Coarse–to–Fine Surface Reconstruction. Eurographics 2006.

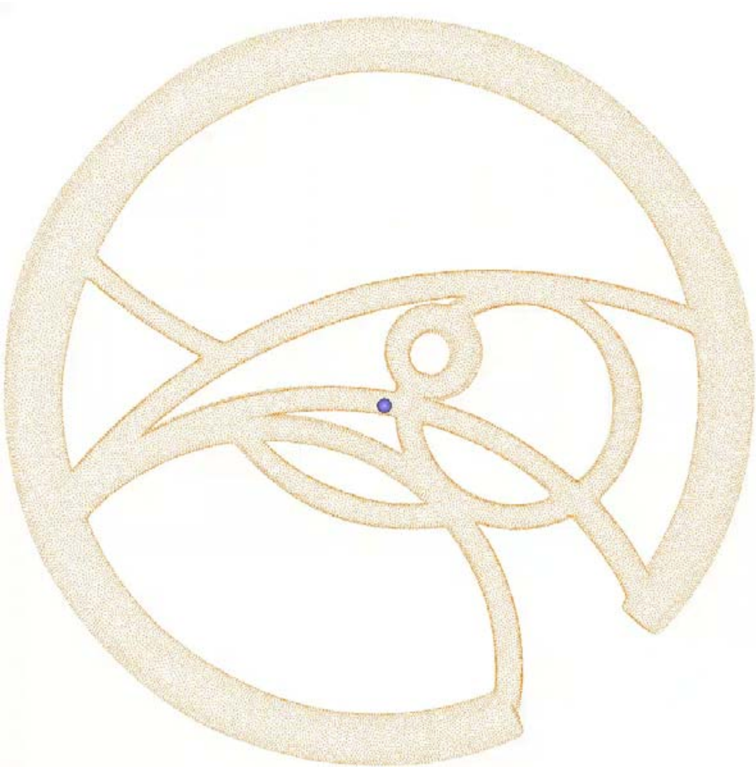
(2) Cooperative Evolutions

- Two deformable models
  - One from interior
  - The other from exterior
- Alternative evolutions

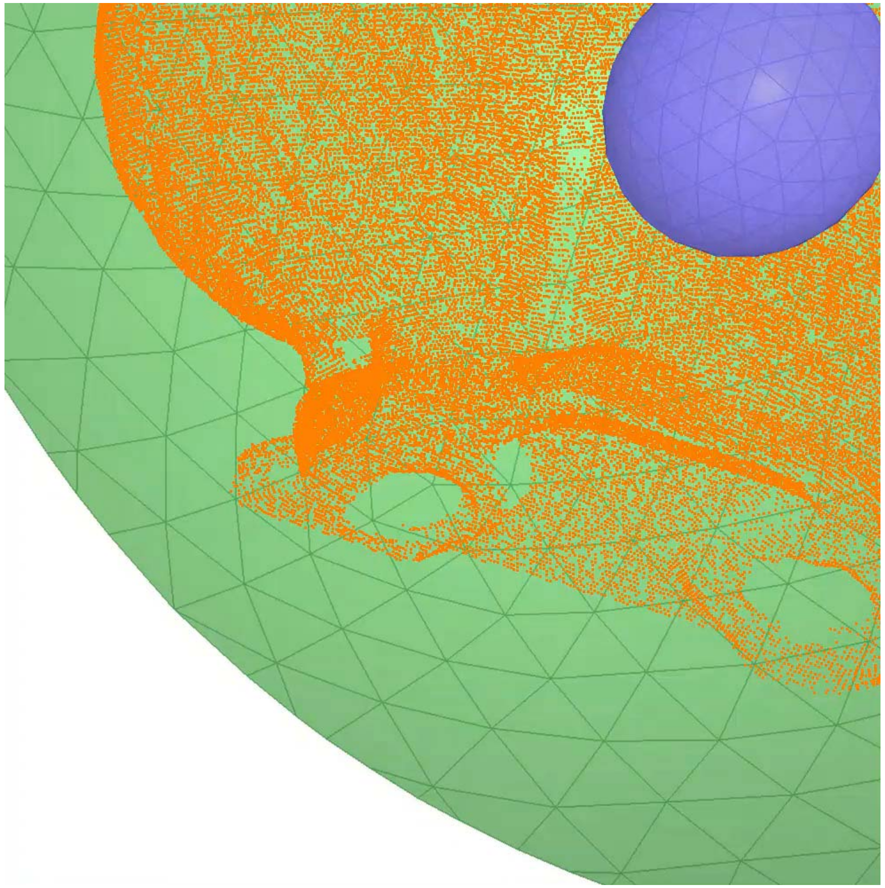


Lu and Liu. Surface Reconstruction via Cooperative Evolutions. CAGD 2020.

(2) Cooperative Evolutions



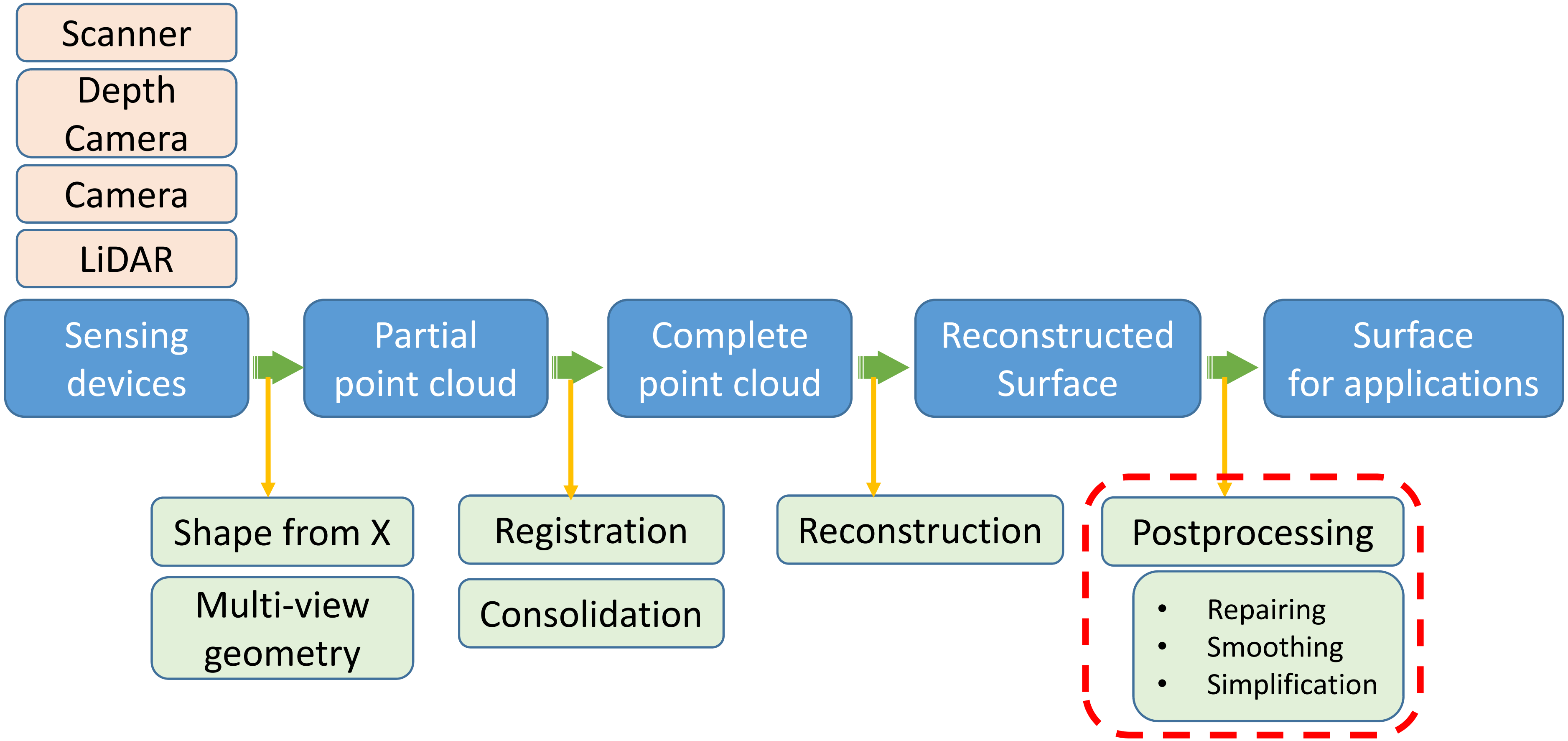
Evolution of interior mesh



Alternative evolutions of both meshes

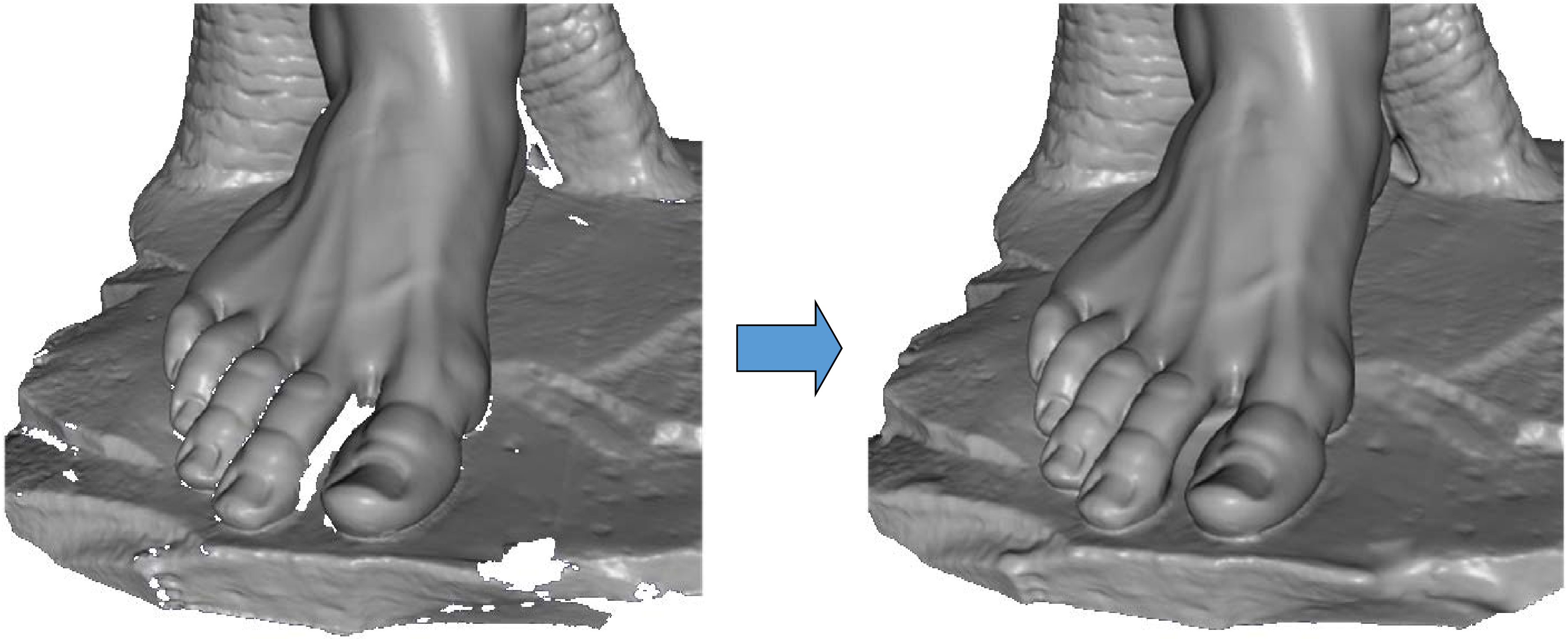
5. Post-processing

5. Post-processing



Post-processing

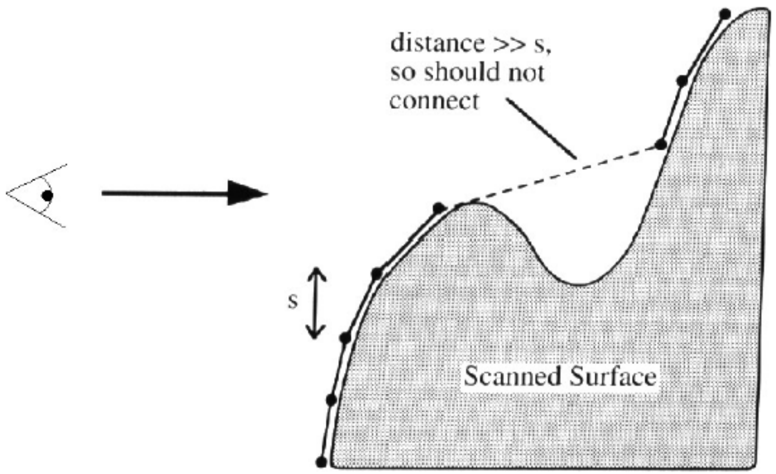
- Repairing, denoising, smoothing, simplification…



Repairing (completion, hole-filling, restoration)

Hole Generation

- Occlusion



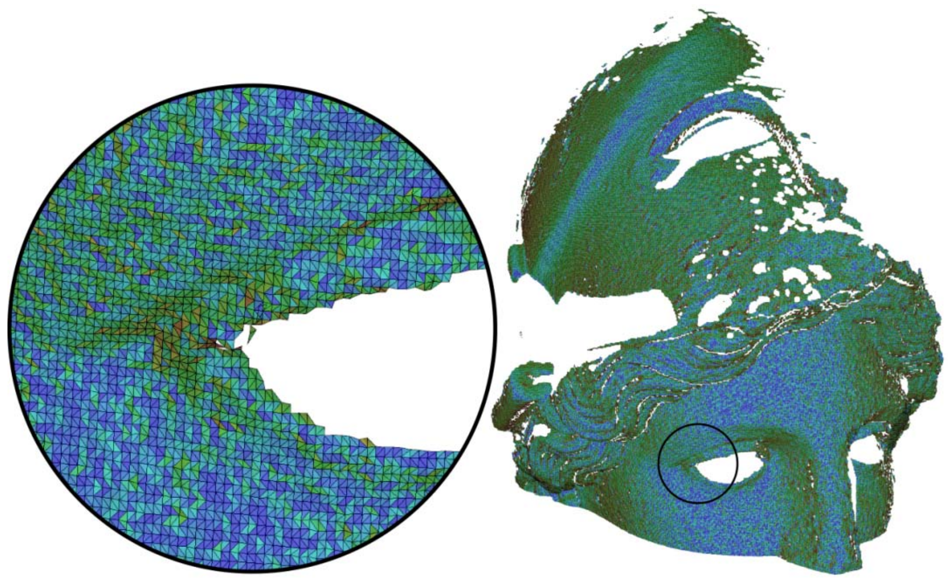
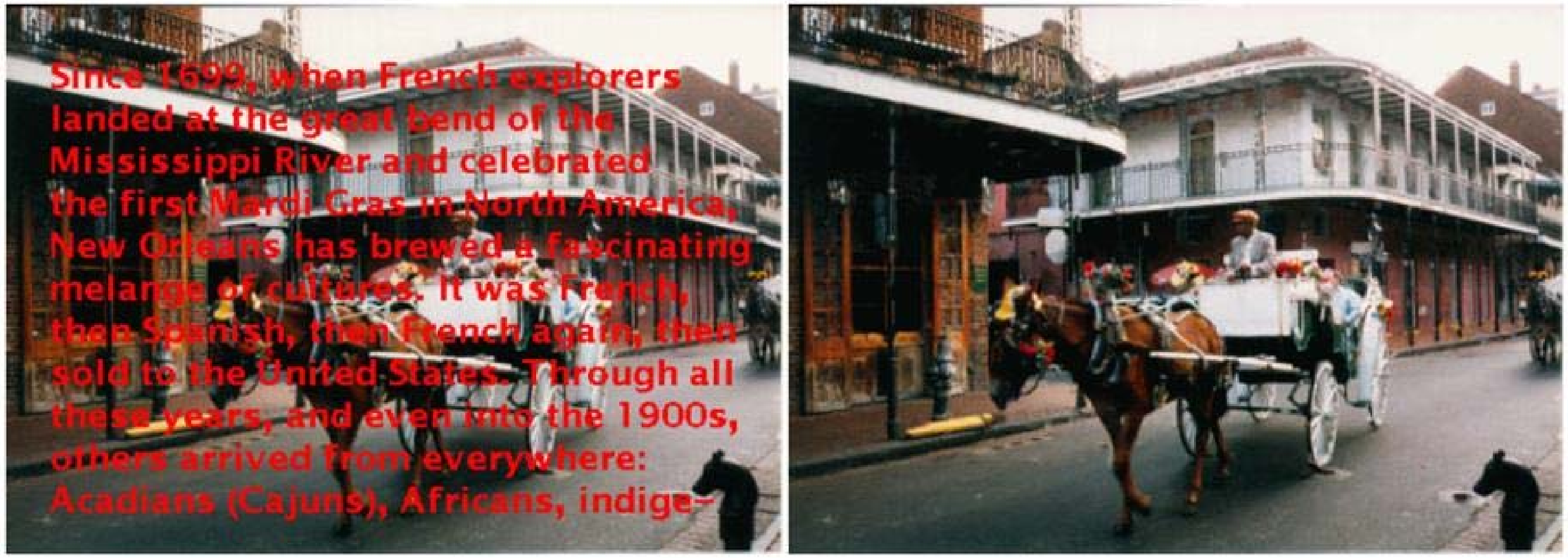


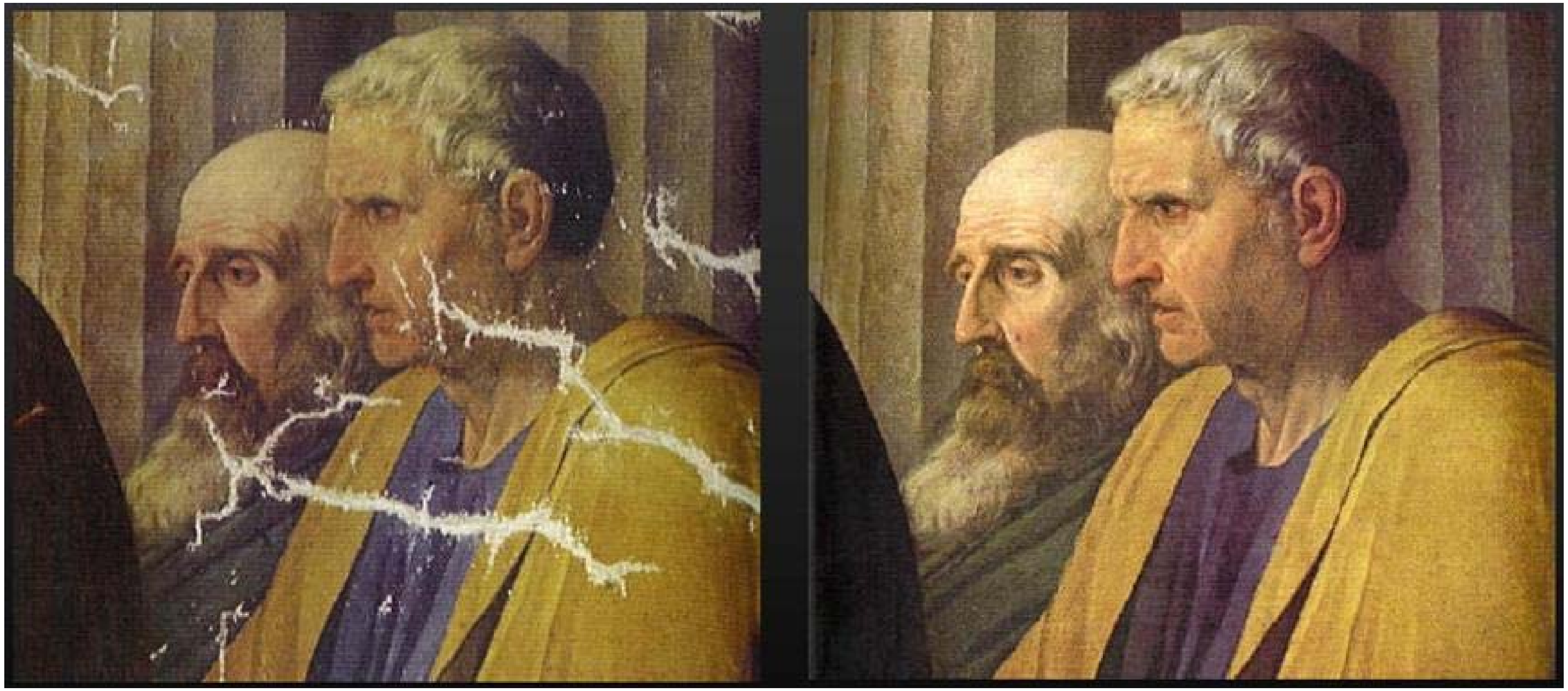
Image Inpainting

"Digital Image Inpainting is an iterative method for repairing damaged pictures or removing unnecessary elements from pictures"



"Fast Digital Image Inpainting",
Manuel M. Oliveira, Brian Bowen, Richard McKenna and Yu-Sung Chang

Photo Restoration



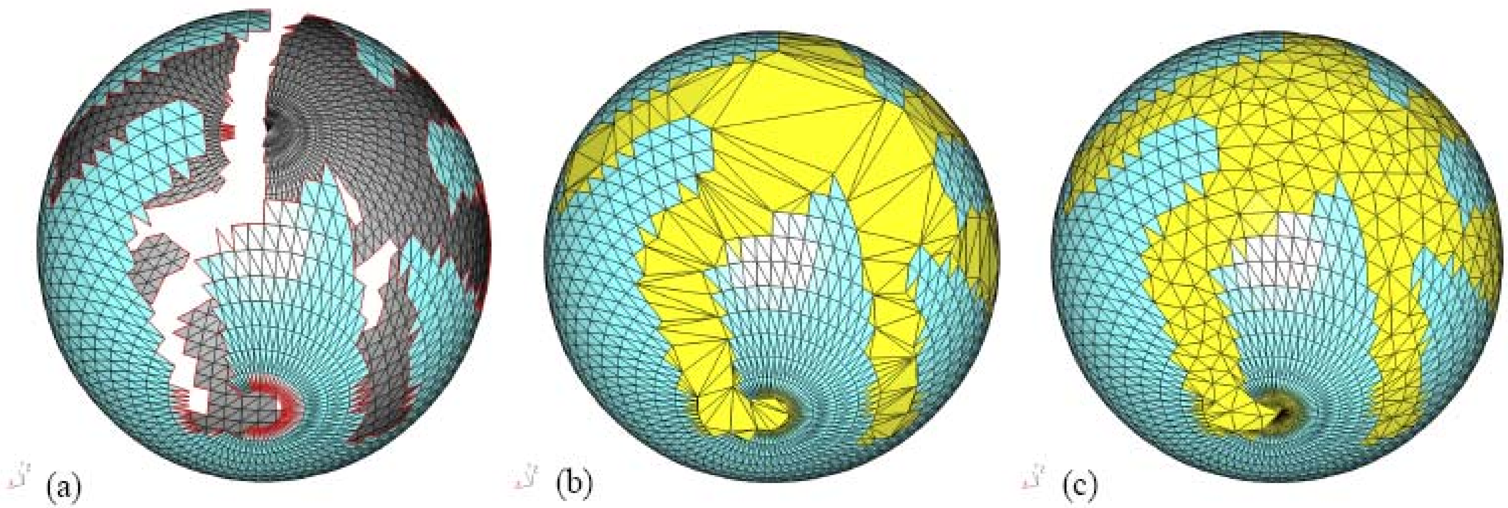
"Image Inpainting : An Overview",
Guillermo Sapiro

(1) Filling Holes in Meshes

[Liepa, SGP 2003]

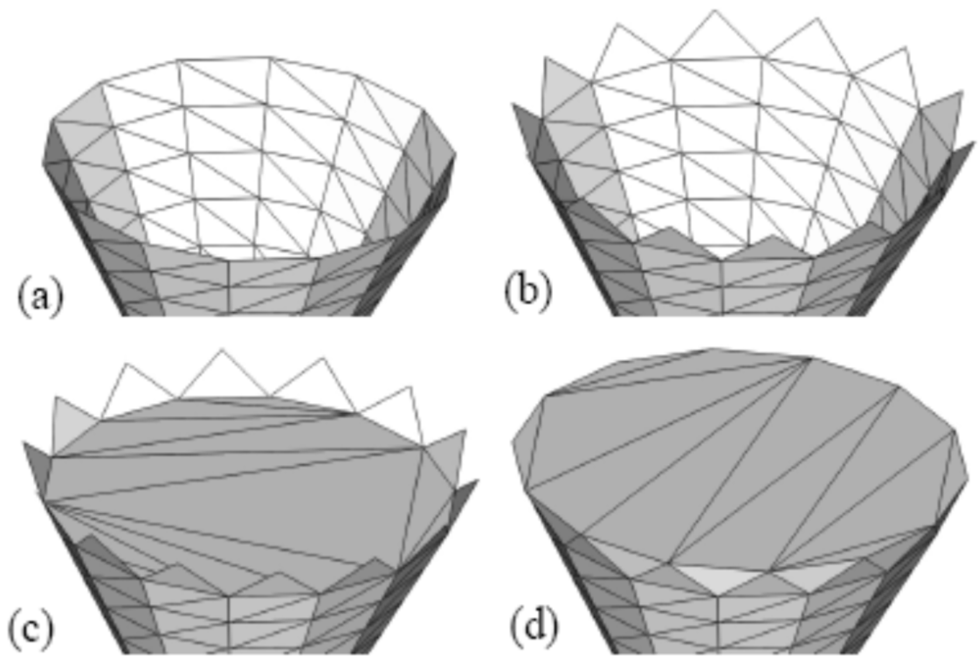
Pipeline

1. Hole identification
2. Hole triangulation
3. Mesh refinement
4. Mesh fairing

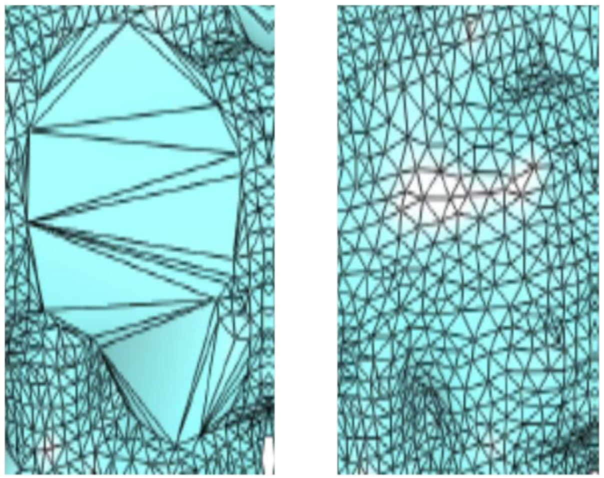


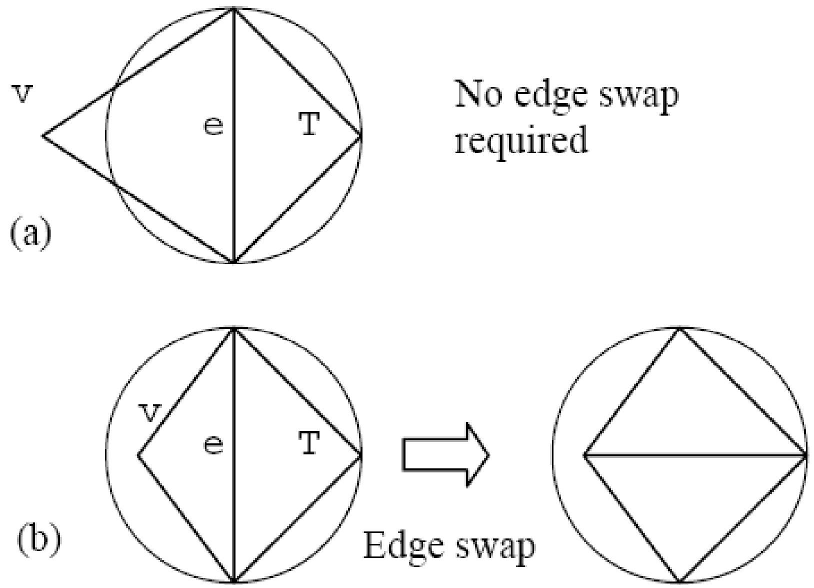
Triangulation of 3D Polygons

- Minimum area triangulation
- Min-max dihedral angel triangulation



Mesh Refinement





1. Subdivision

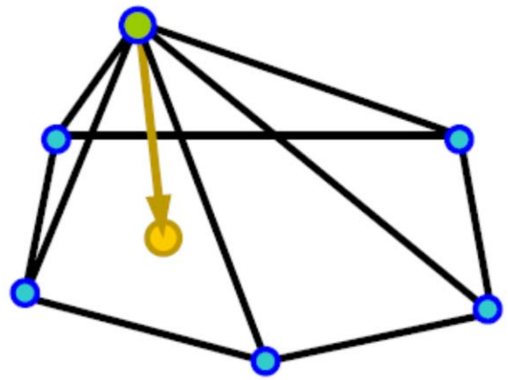
2. Edge Relaxation

Fairing

- Weighted umbrella-operator

$$\mathbf{U}_{\omega}(v) = -v + \frac{1}{\omega(v)} \sum_i \omega(v, v_i) v_i \ ,$$

$$v = v + \mathrm{U}_{\omega}(v)$$



- Uniform : $\omega(v_i, v_j) = 1$
- Scale-dependent :

$$\omega(v_i, v_j) = 1 / \|v_i - v_j\|$$

Summary

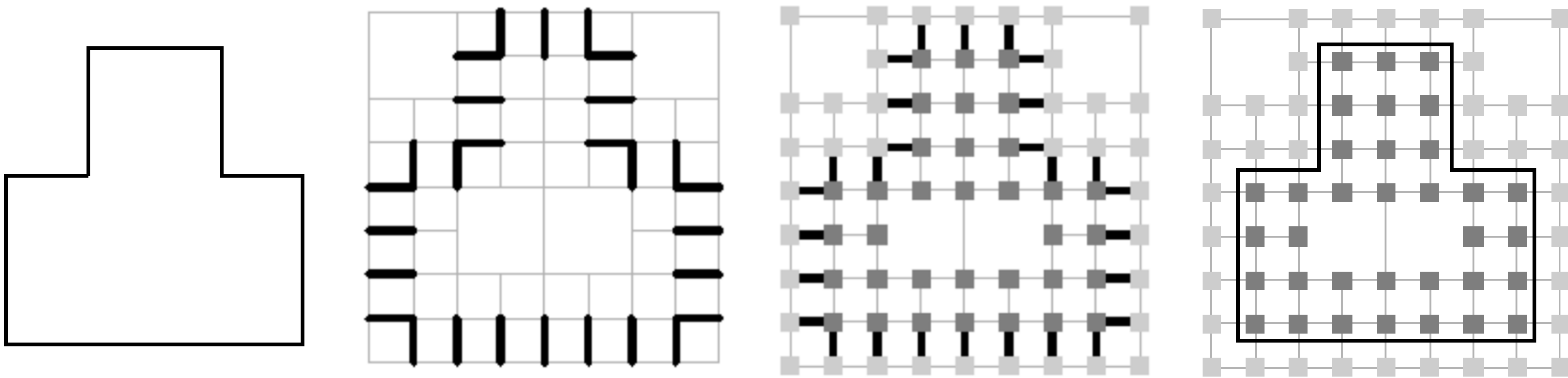
- Easy to implement
- Focus algorithm on holes
- Triangulation may self-intersect
- Can’t fill holes with islands
- Fairing weaken original surface feature

(2) Robust Repair of Polygonal Models

[Ju, Siggraph 2004]

Pipeline

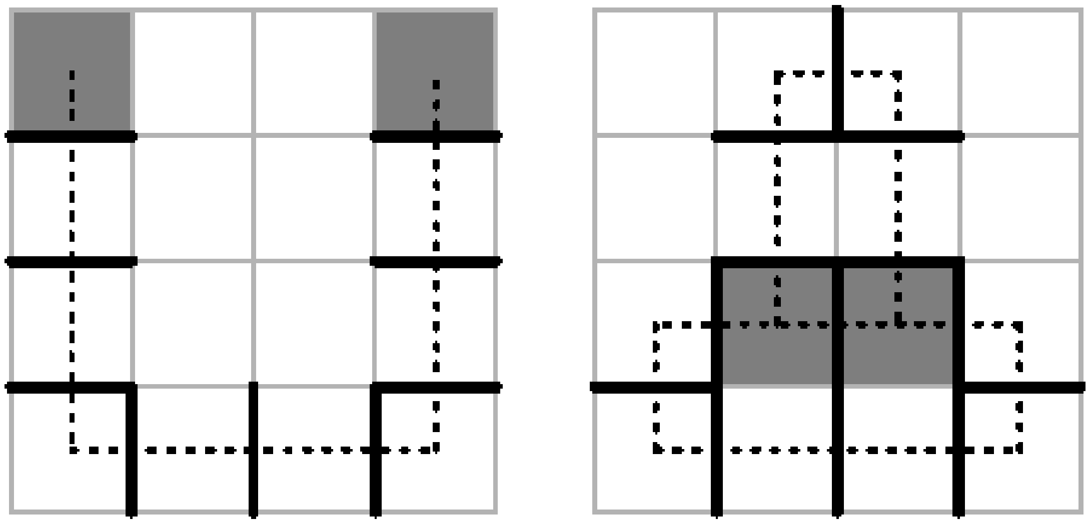
I. Scan-conversion
II. Sign generation
III. Surface reconstruction



a b c d

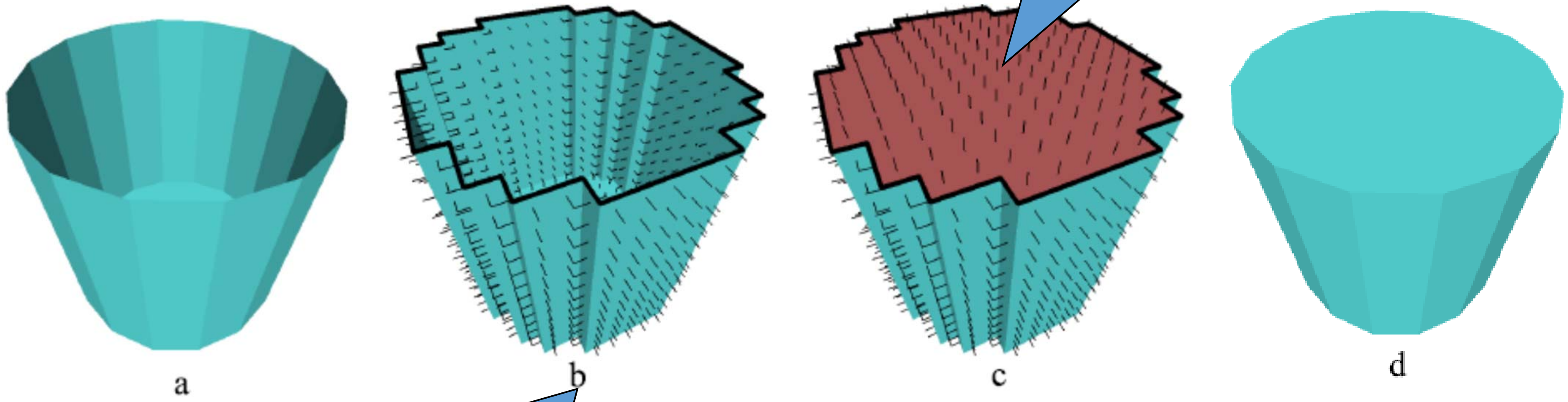
Sign Generation

- Cell faces containing an odd number of intersection edges



Patch Boundary Circles

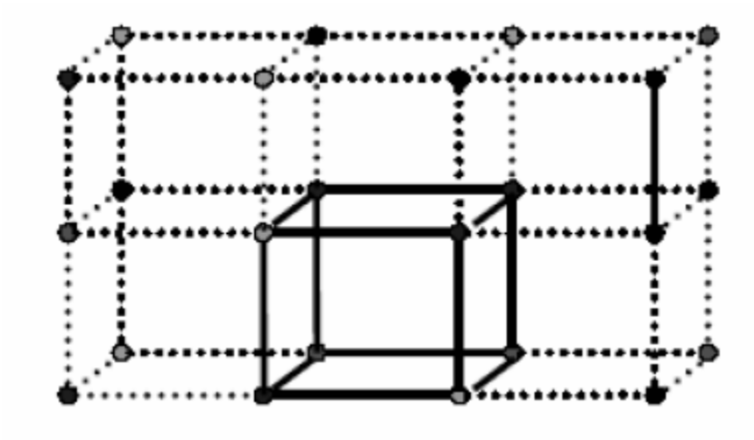
Patching dual surface



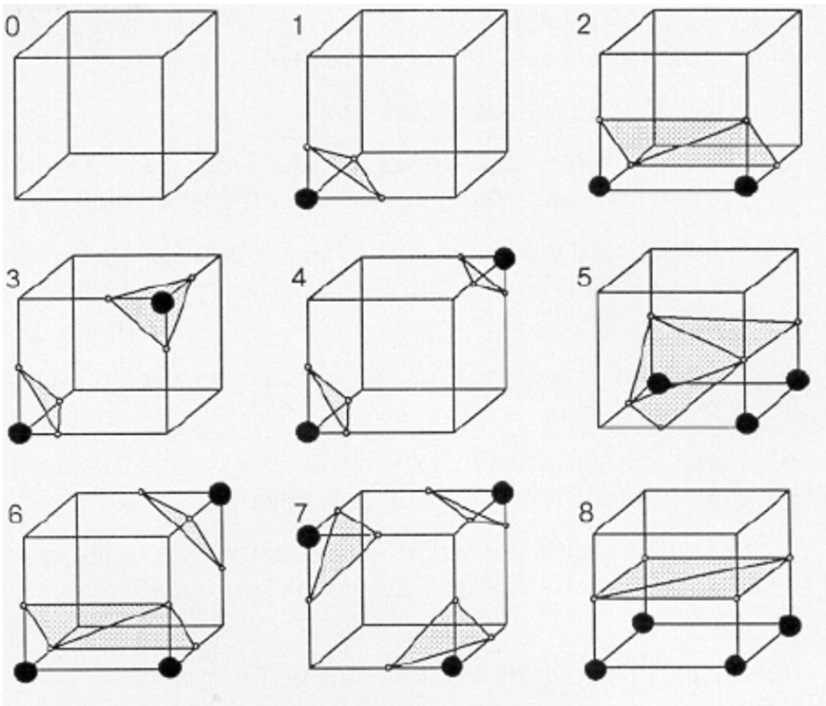
Edges intersected with the model and the corresponding ***dual surface***

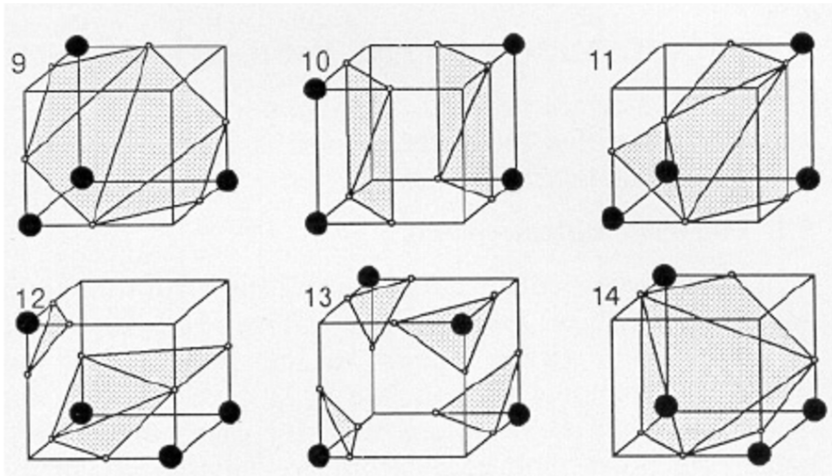
Marching Cubes

- Cube with signs at eight corners

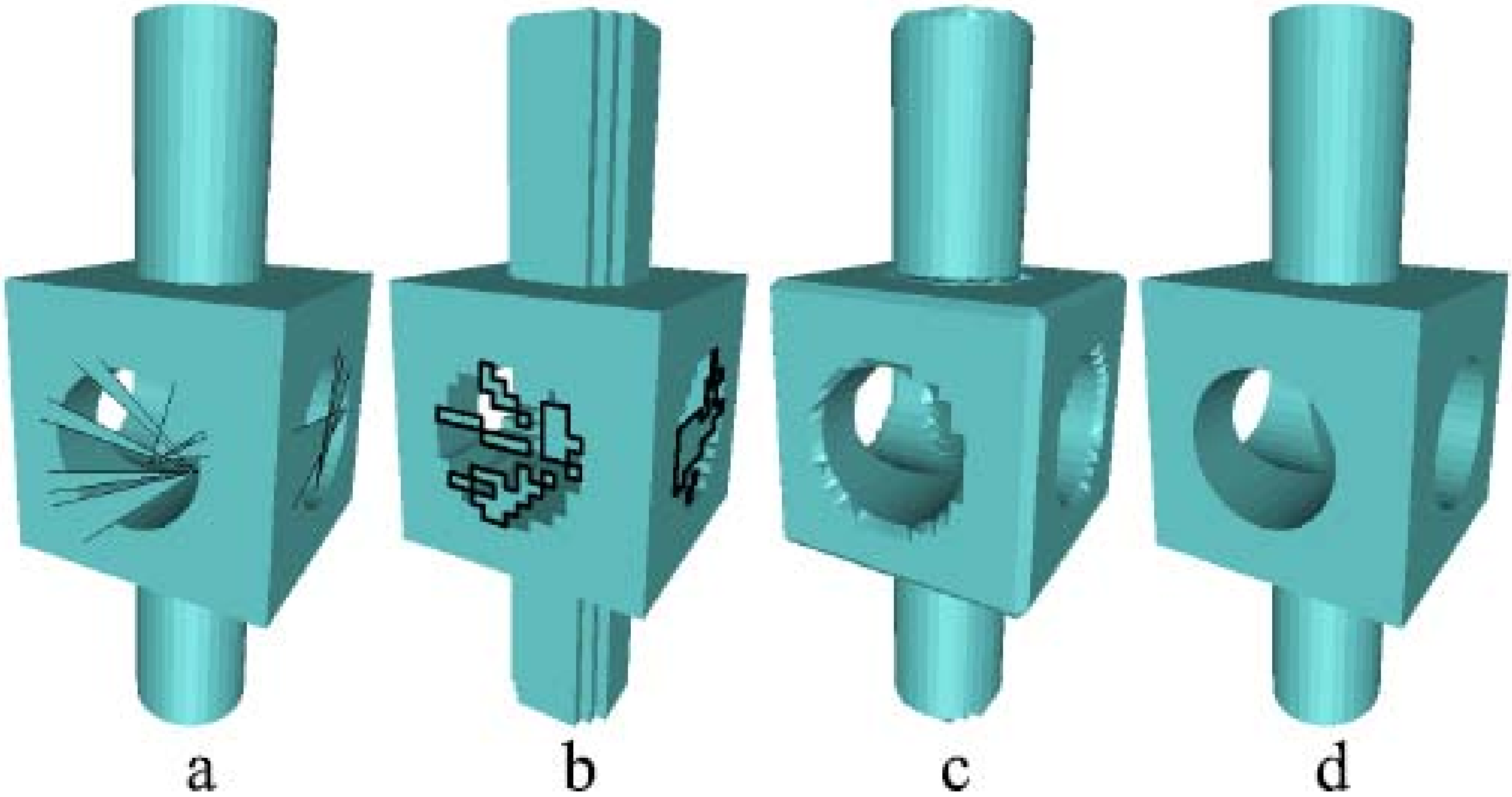


Marching Cubes

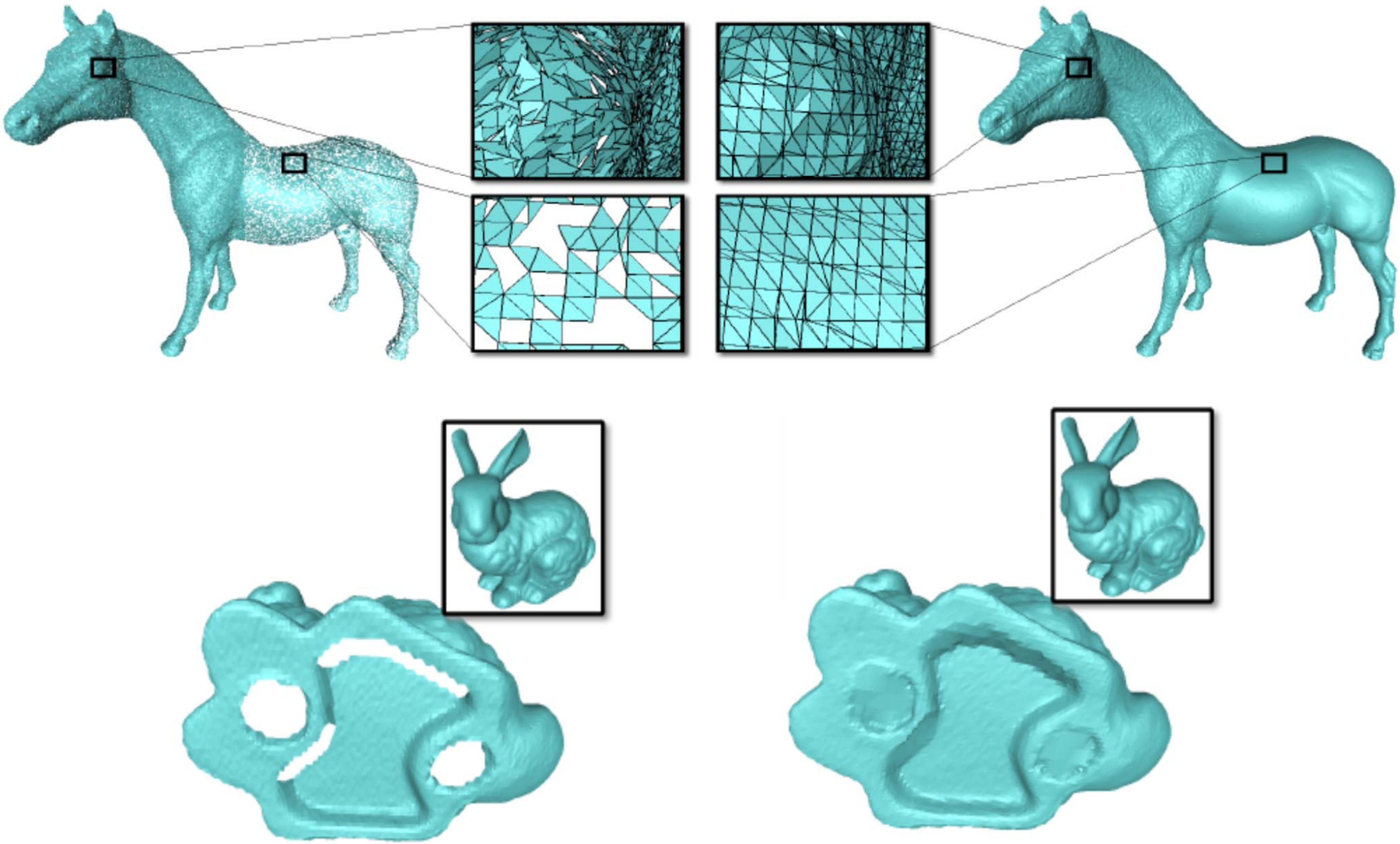




Results



Results



Summary

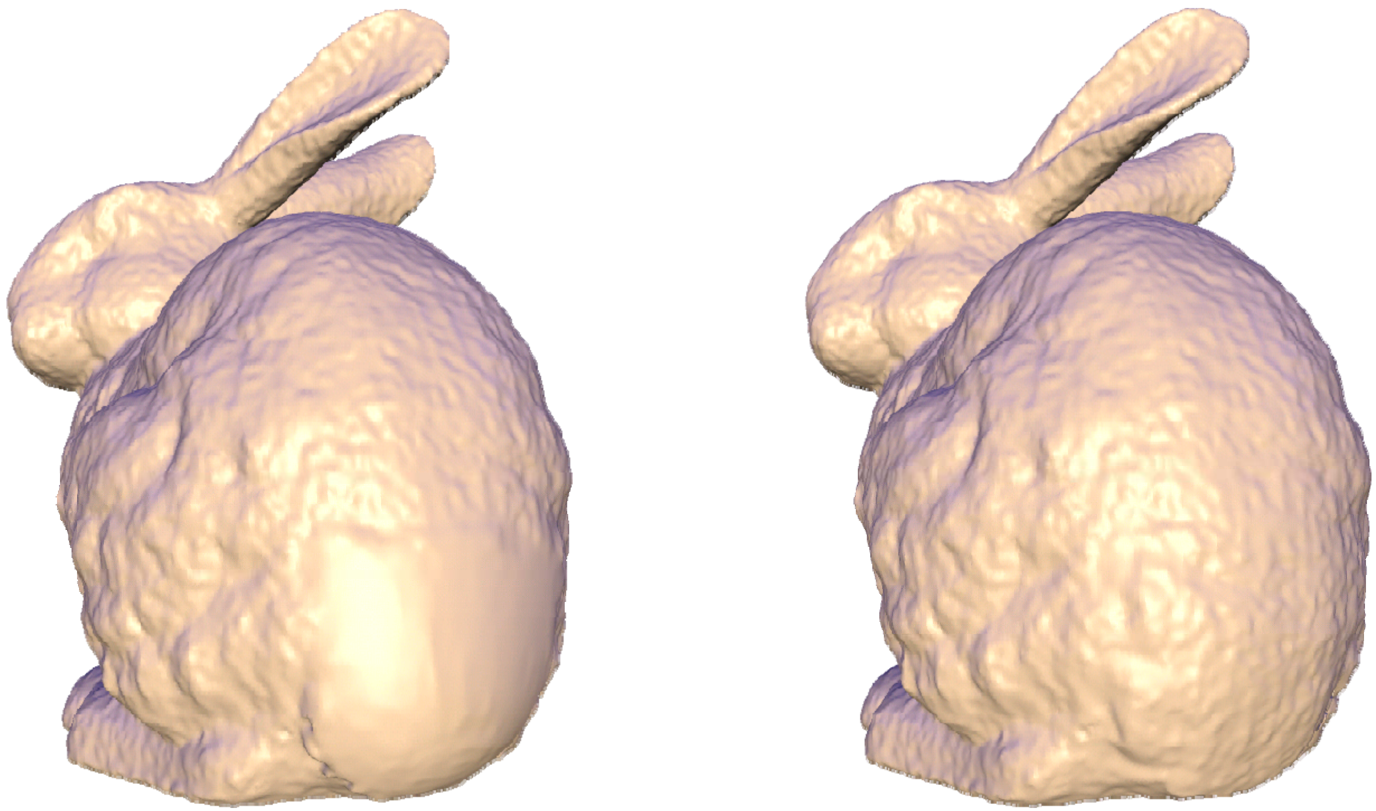
- Employ a space-efficient octree grid
- Produce closed, manifold surface for any input model

(3) Context-based Surface Completion

[Sharf et al., Siggraph 2004]

Motivation

Complete the missing region with patches that conform with its context

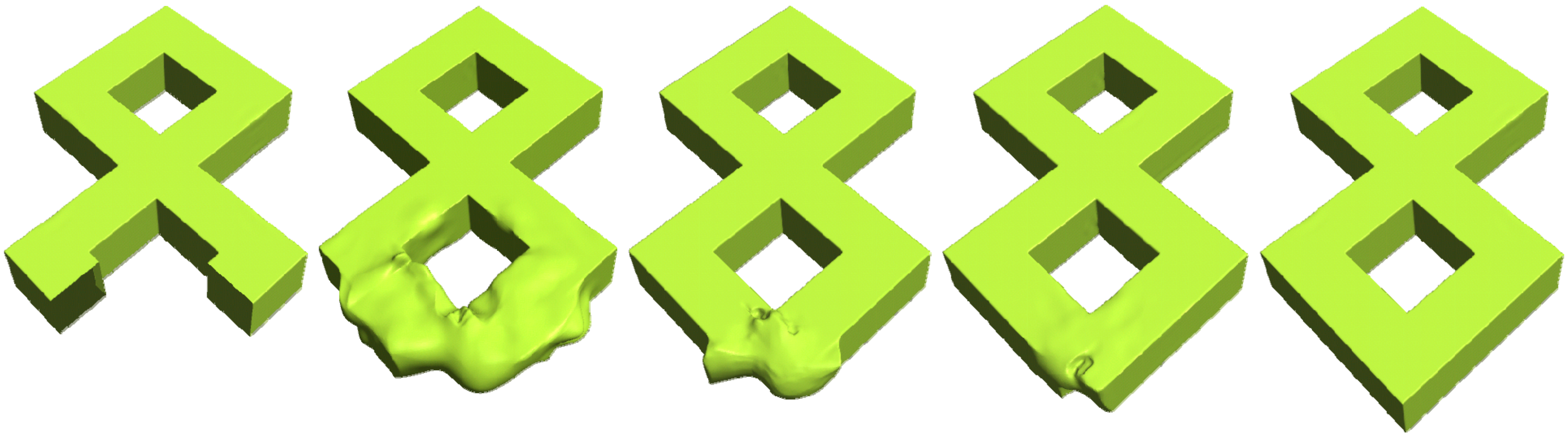


Smooth Context-based

Method

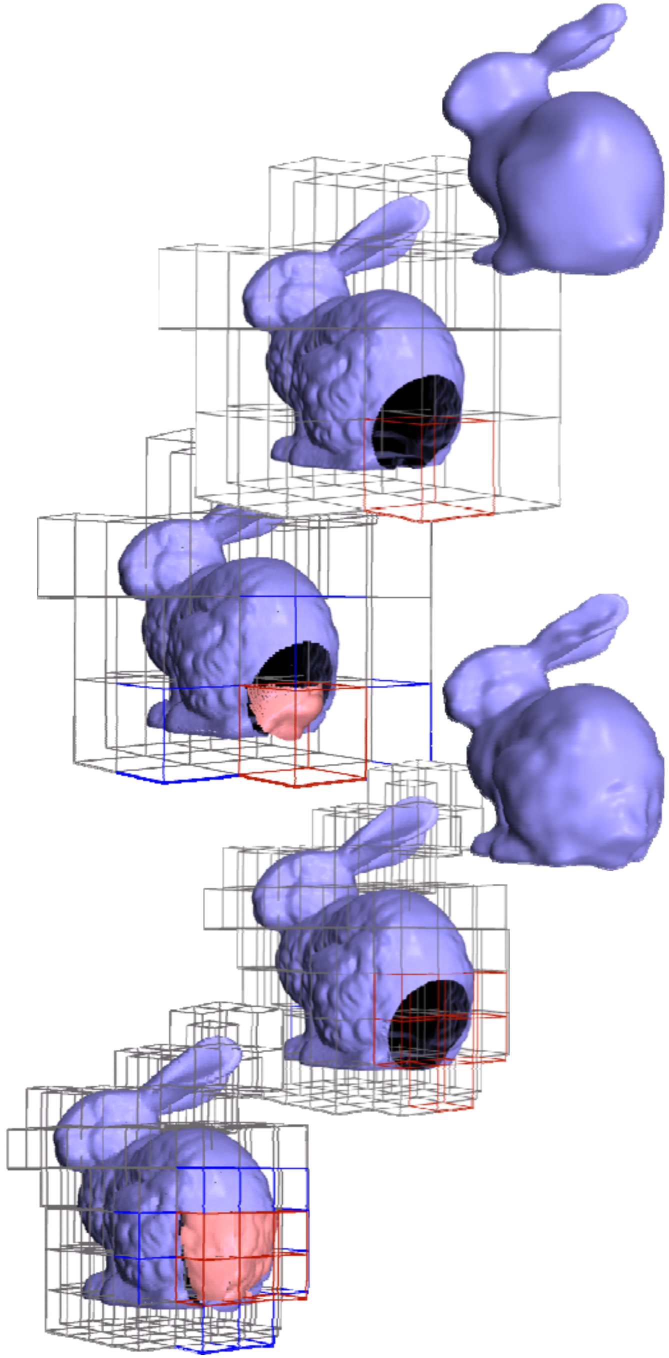
Import patches with matching context from the surface itself :

- Analyze surface characteristics.
- Find best matching patch.
- Fit imported patch to boundary.

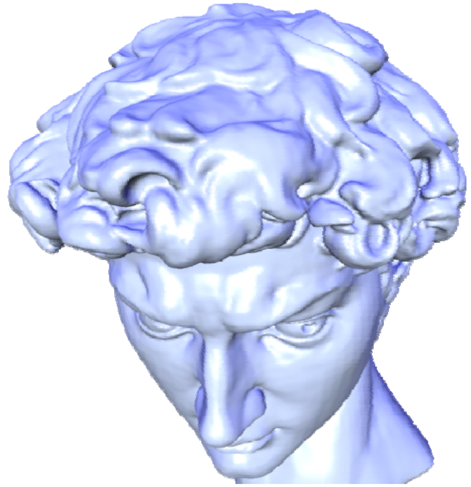


Algorithm

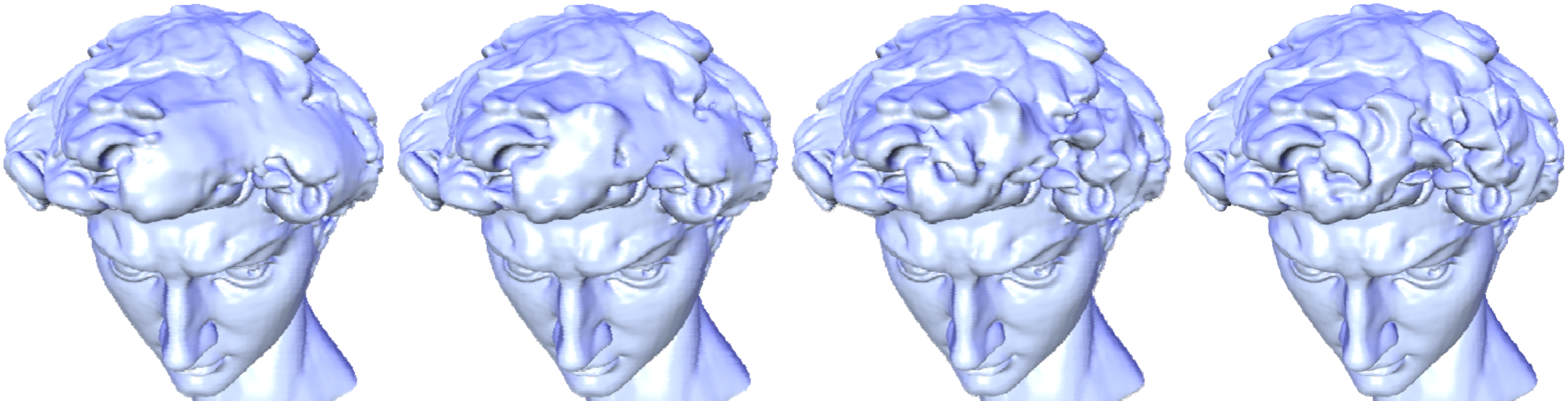
- Create initial spatial subdivision
- For each cell
  - Compute a local shape representation.
  - Compute a shape signature.
- For each empty cell:
  - Find matching nonempty cell ω'.
  - Copy patch of ω' into ω.
- Subdivide cells and repeat
- Until completed region matches its neighborhood



Completion Process



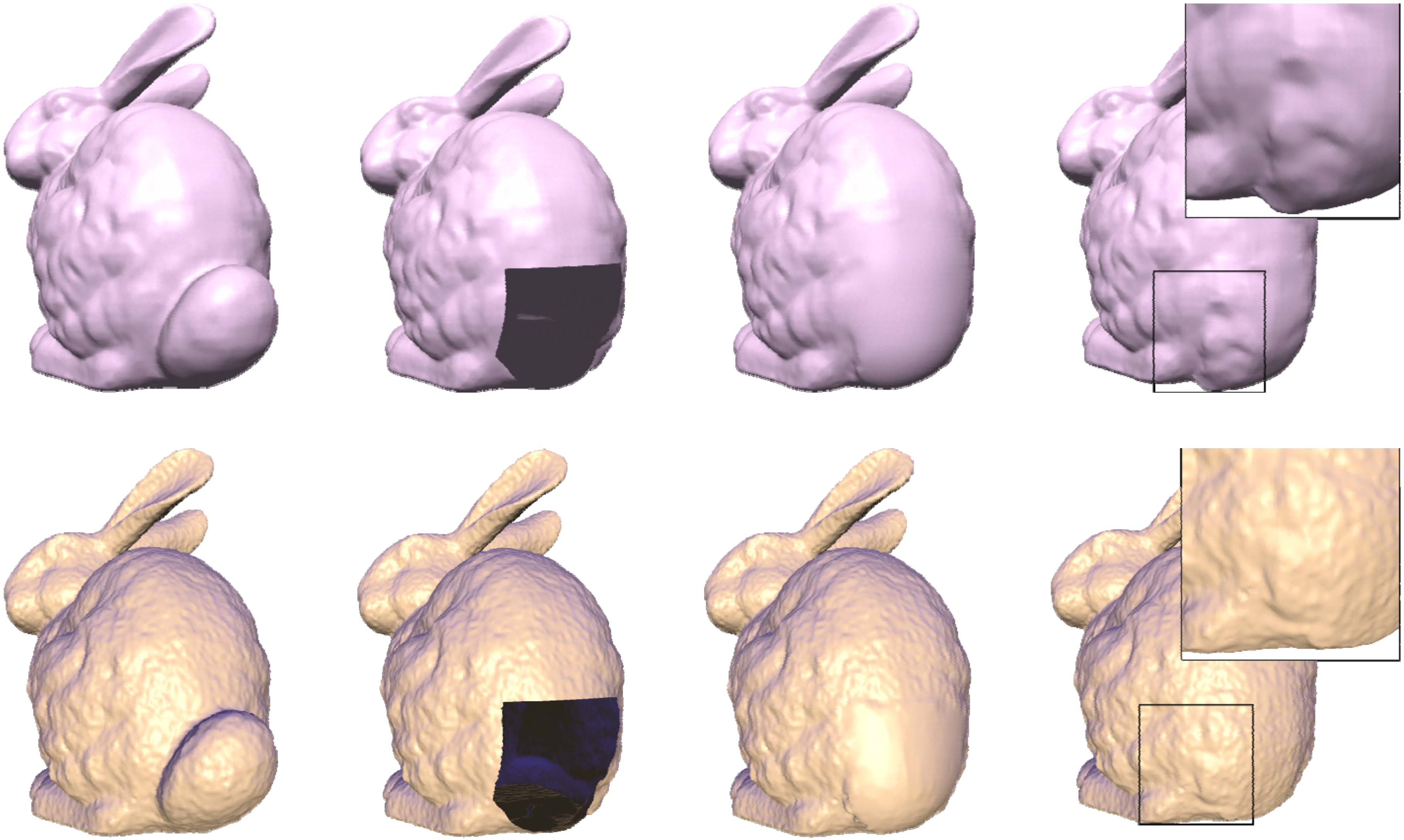
Original



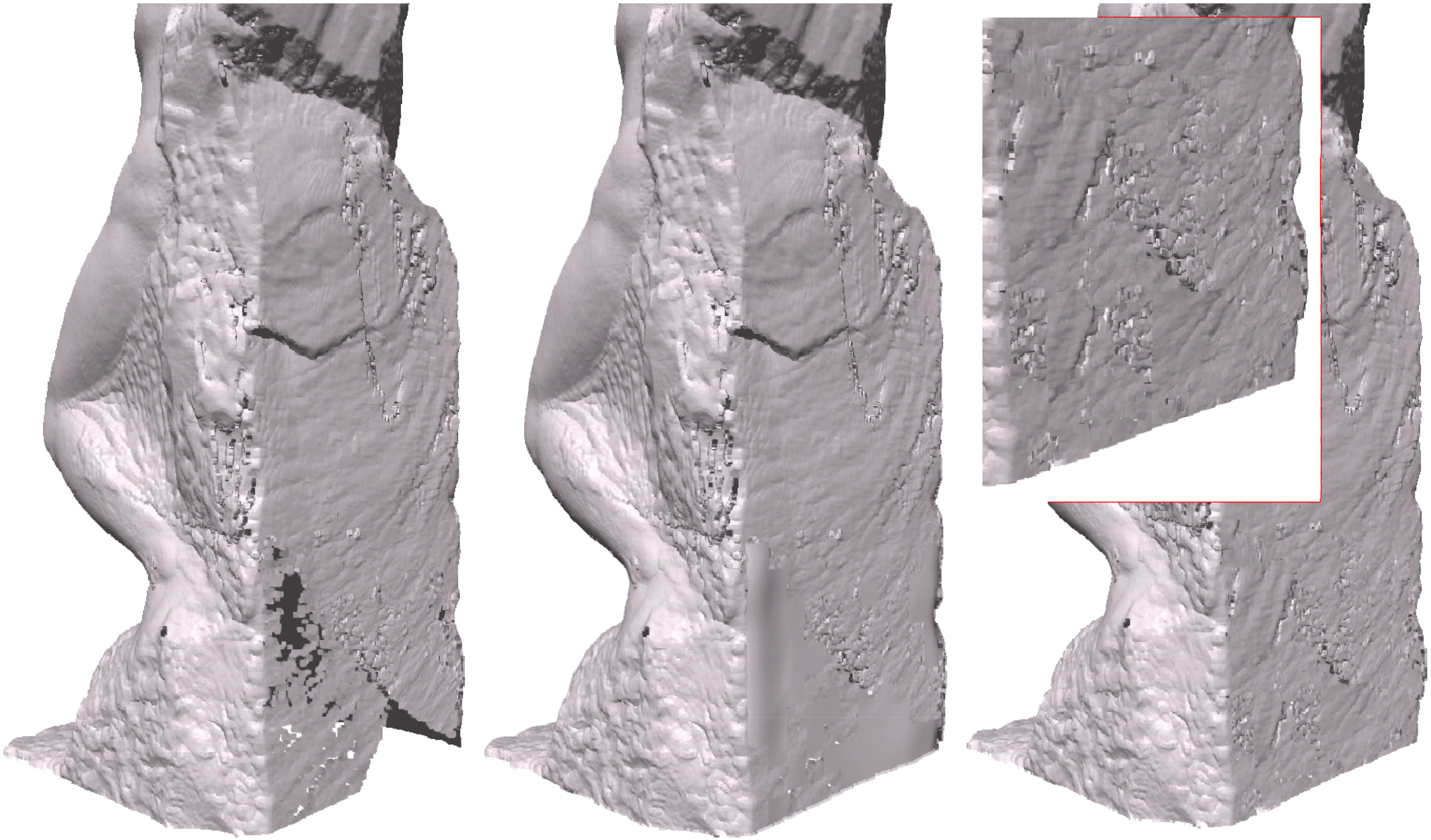
Initial approximation

Final result

Manual Editing of Bunny Model



Scan of “Youth” Statue

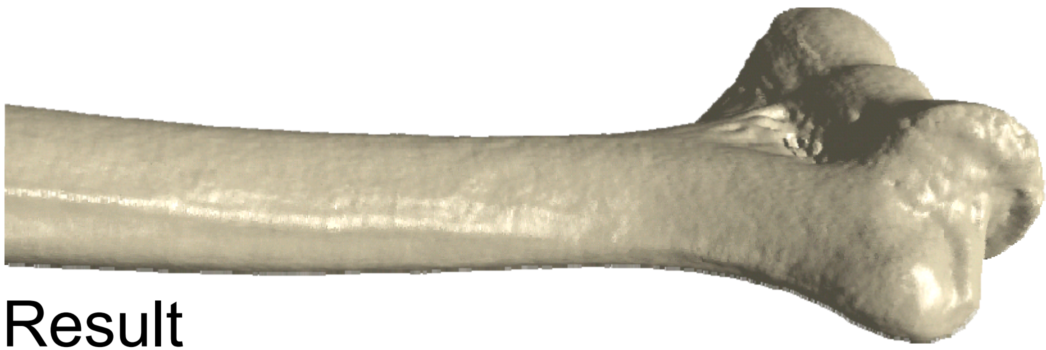


Original Smooth Result

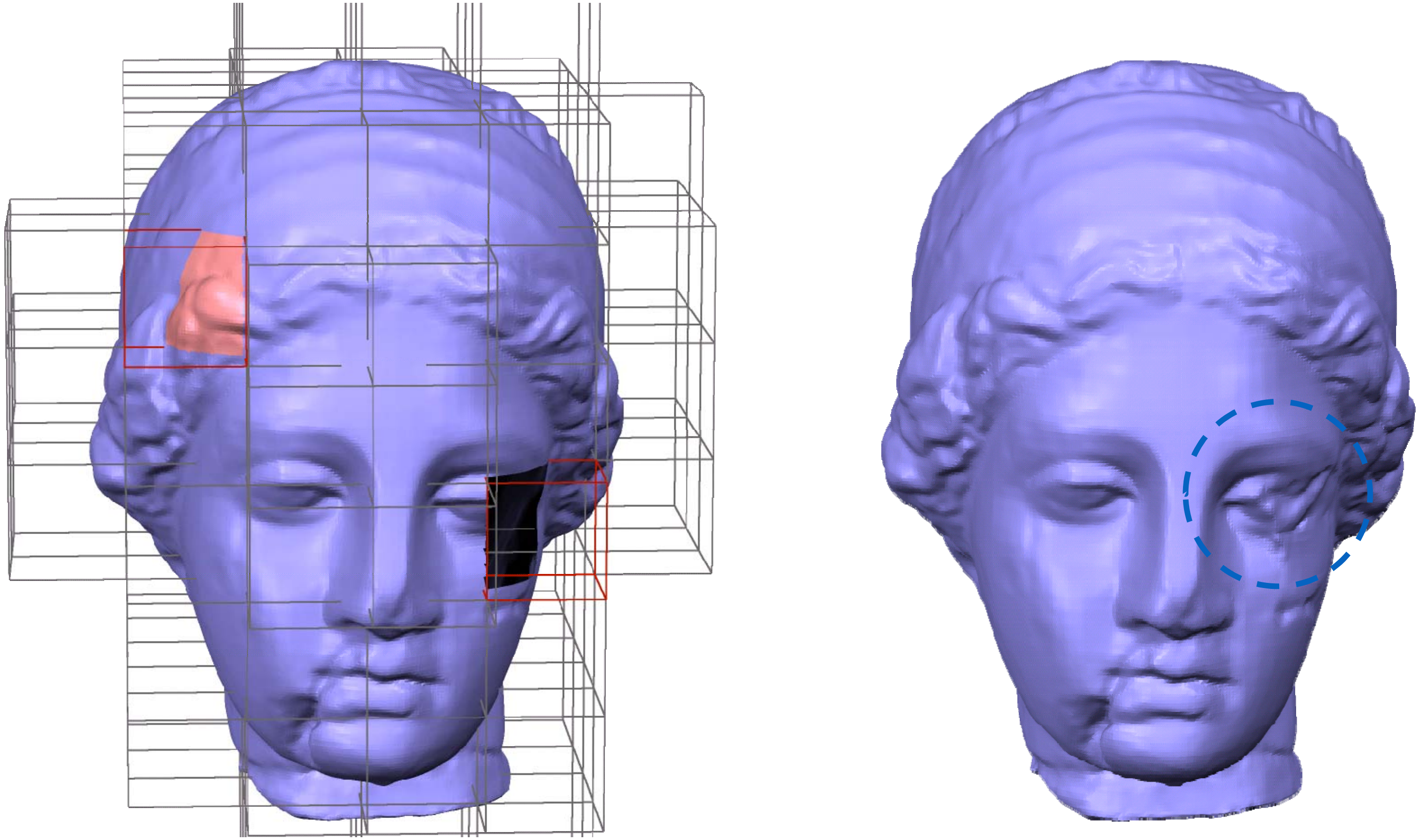
Scan of Human Bone


Original


Smooth


Result

Limitations: Semantics



Summary

- A fully automatic method to complete a missing region in a surface from its context.
  - Completed patches geometrically conform with neighborhood.
  - Incremental scale-space framework for finer approximation of the unknown region.

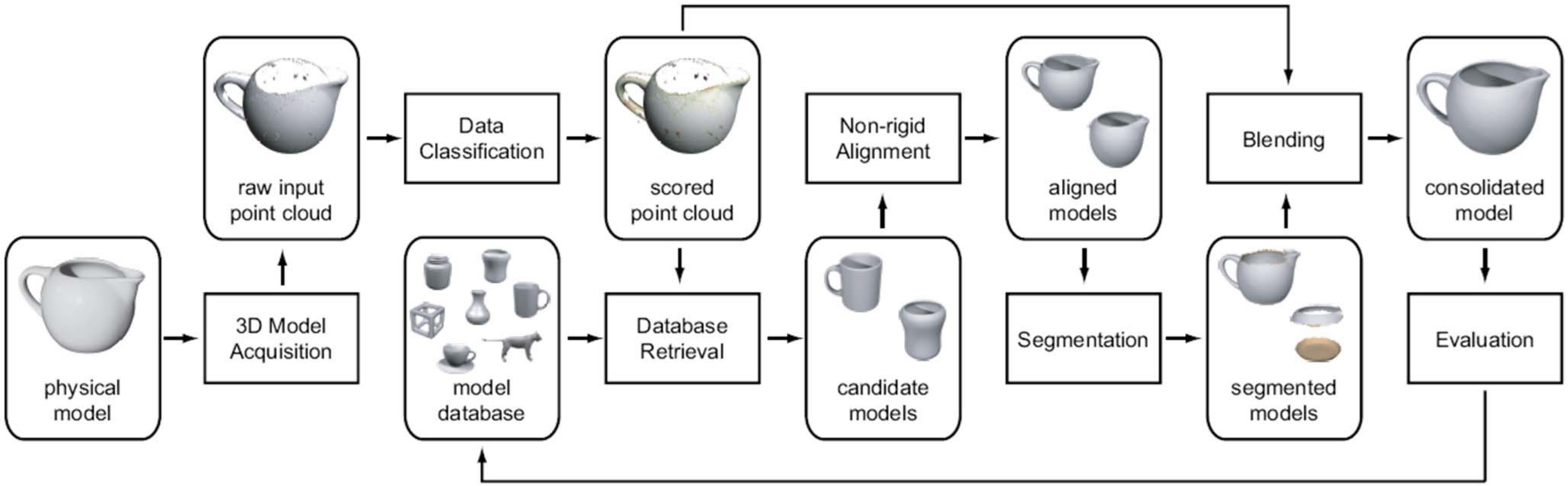
(4) Example-based Surface Completion

[Pauly et al., SGP 2005]

Solution

- Use ***3D model database*** to provide geometric priors for shape completion
- Apply ***non-rigid transforms*** on the models
  - More deformation $\Rightarrow$ less likely completion
- ***Consistently*** combine geometric information from multiple context models
- Final result comes with ***confidence values***

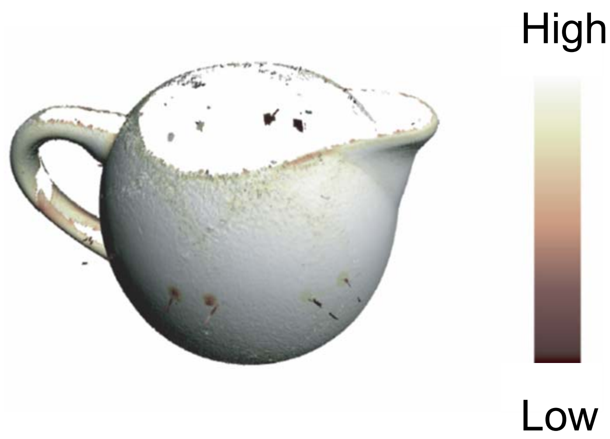
Shape Completion Pipeline



Data Classification

Local analysis

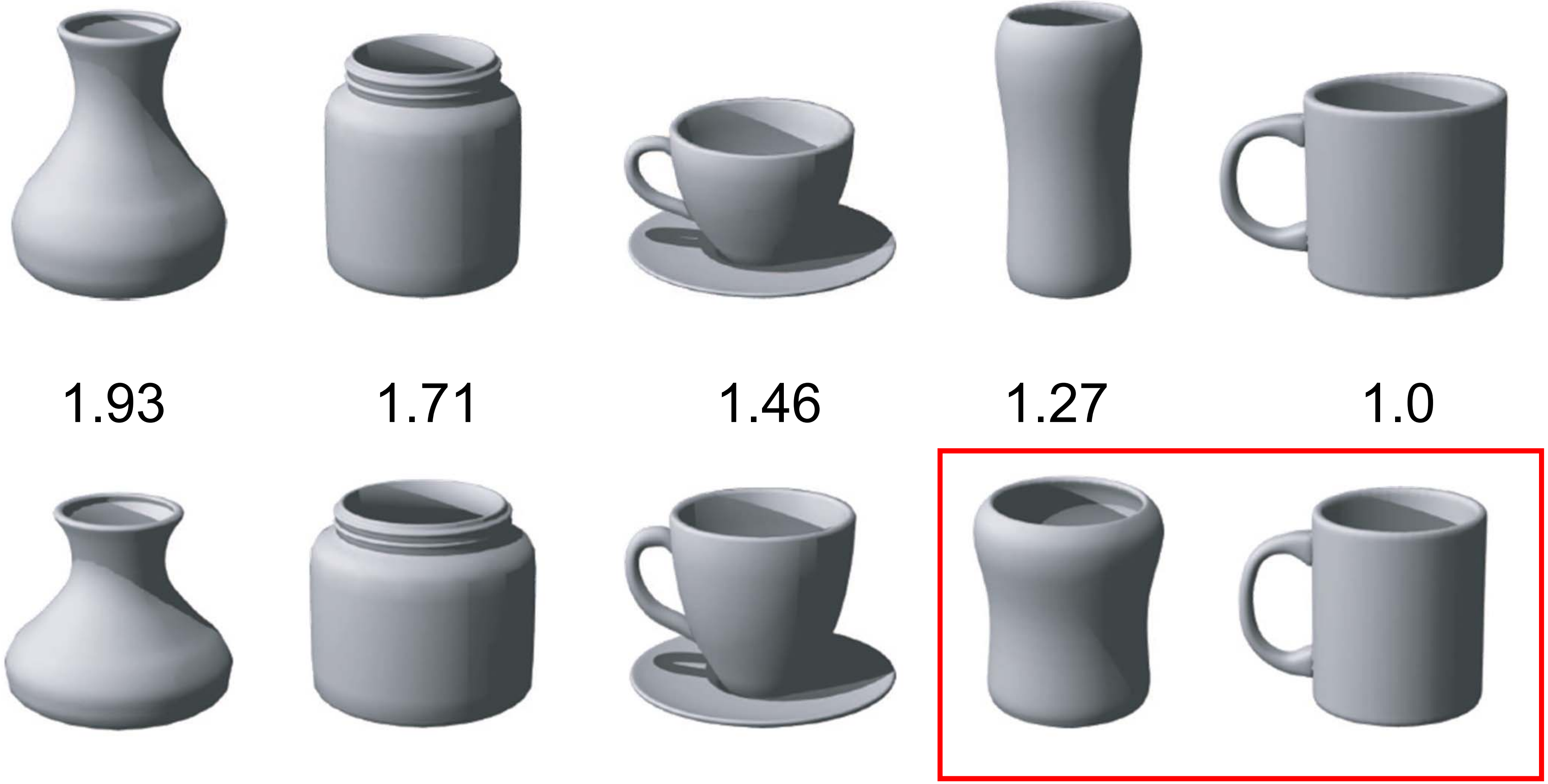
- quality of fit
- uniformity of sample distribution



Scored Point Cloud

- confidence value assigned to each point

Database Retrieval



Non-rigid Alignment

Similar to the approaches proposed by:

- Allen, Curless and Popovic, 2003.
- Sumner and Popovic, 2004.

Non-rigid Alignment

Deformation Model

- Piecewise linear.
  Each vertex of the mesh assigned an independent displacement vector.

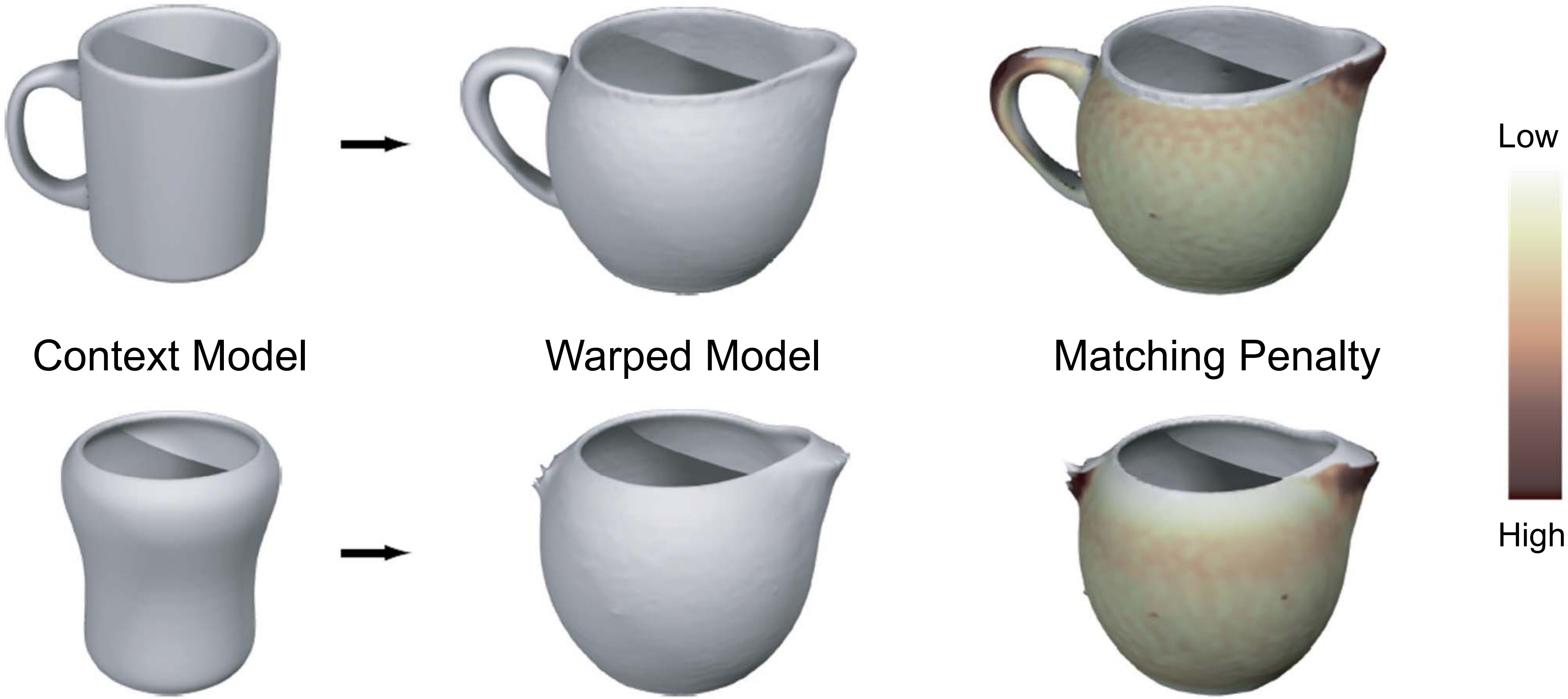
Optimize for smallest ***Shape Matching Penalty***

- Distortion Measure
- Geometric Error

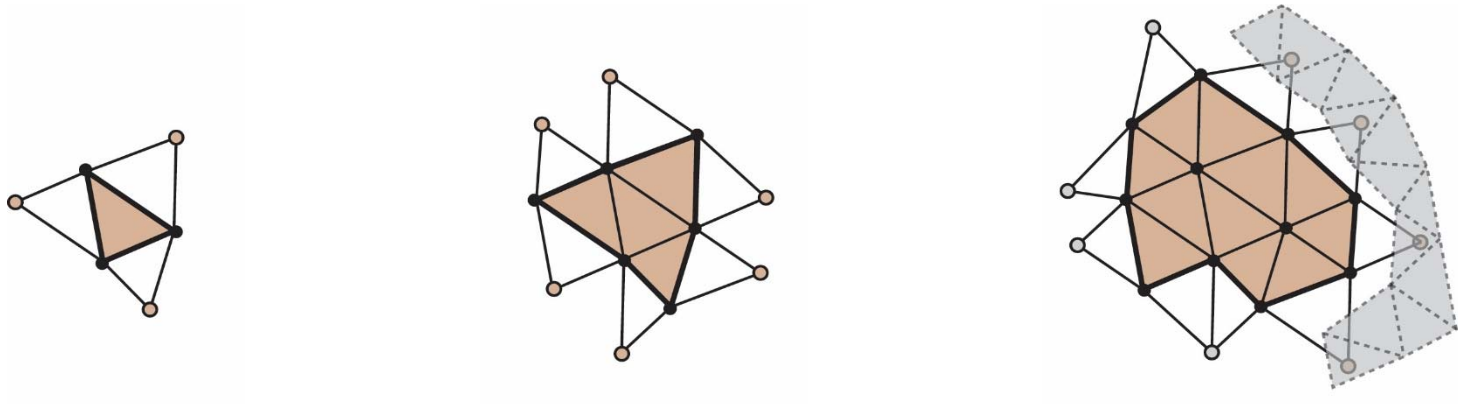
Derived in the continuous setting to allow *consistent comparison* between *different context models.*

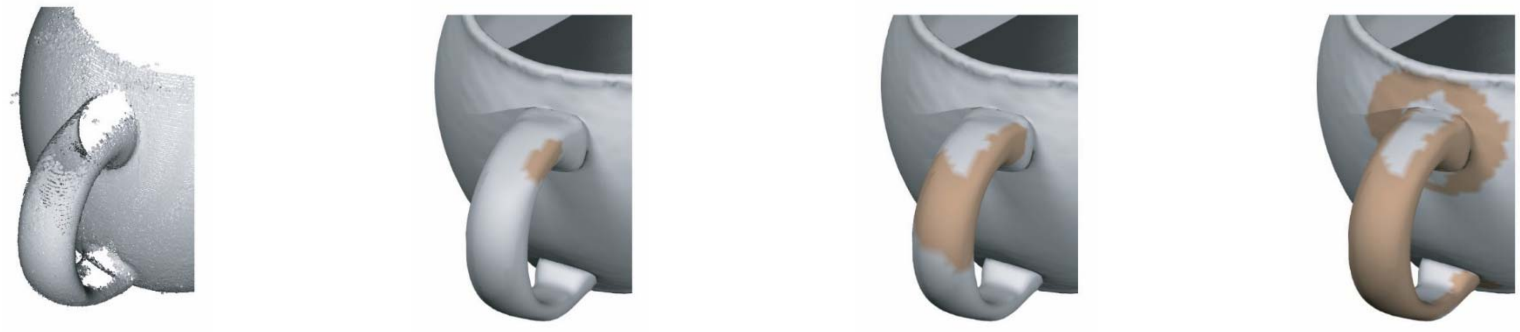
Feature Correspondence

Warped Models



Initial Segmentation





Input Data

Warped Context Model

Patch Growing

Initial Segmentation

Final Segmentation

Result

Giraffe Example

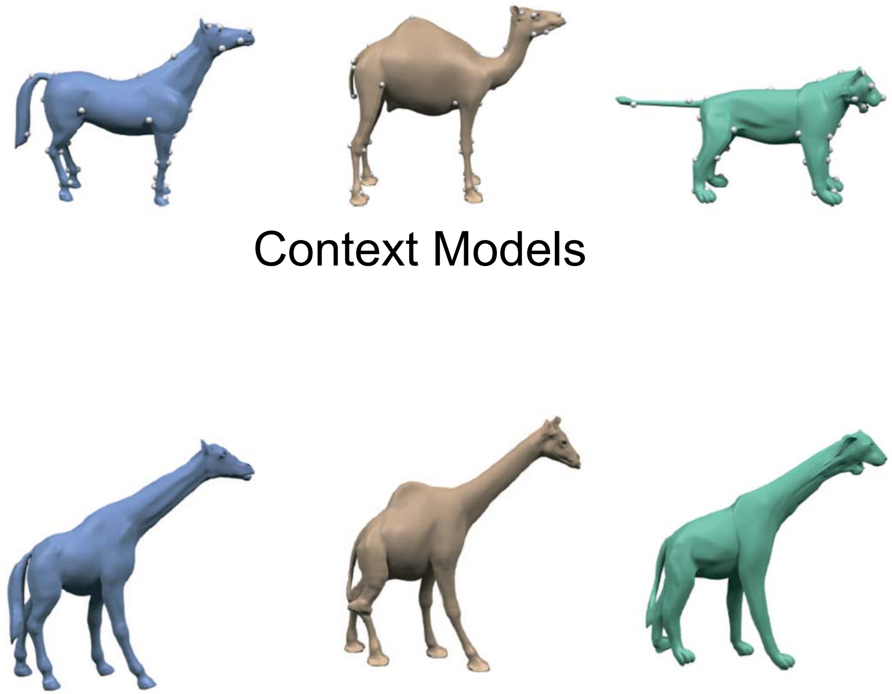
Context Models

Deformed Models

Segmentation

Giraffe Example

Final Model



Evaluation

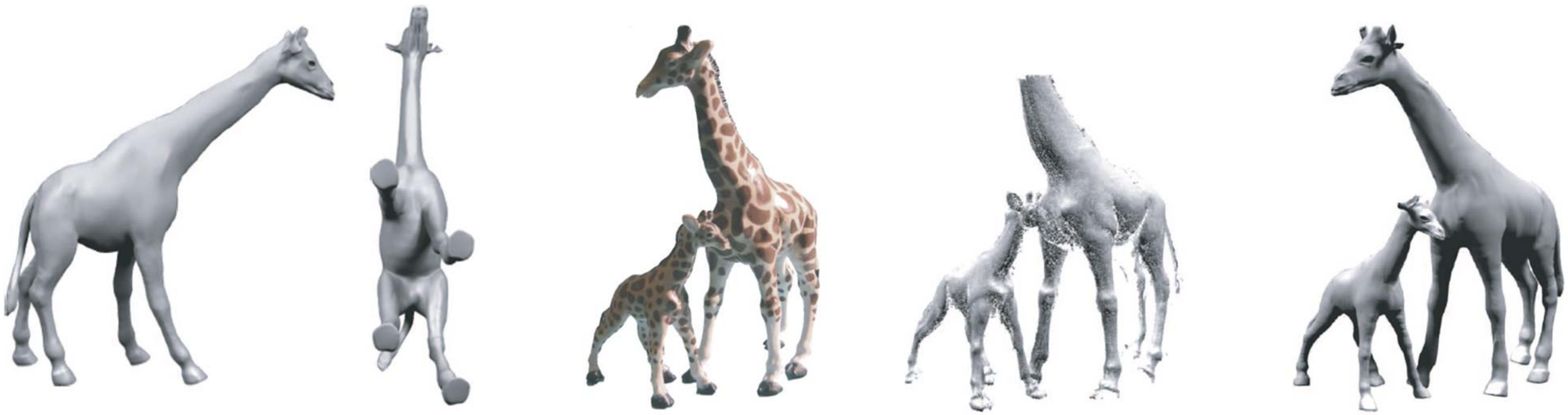
Input Data

Context Model

Final Model

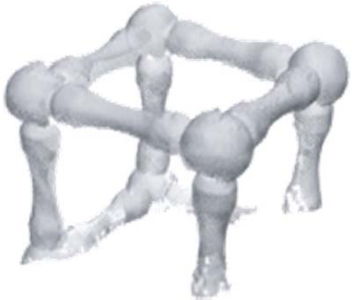
Evaluation

Enriching the Database

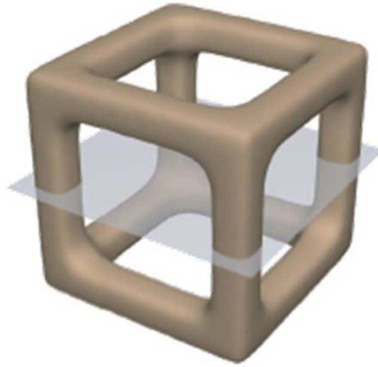


Additional Constraints

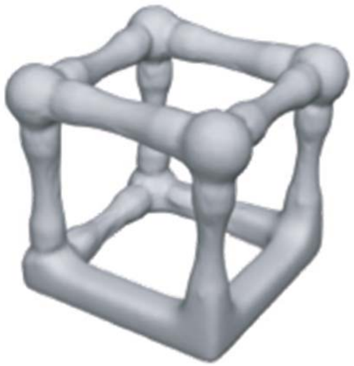
Physical Model



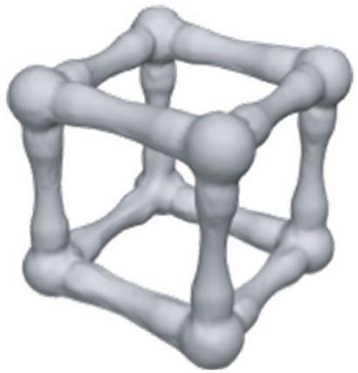
Acquired Data



Context Model



No Constraints



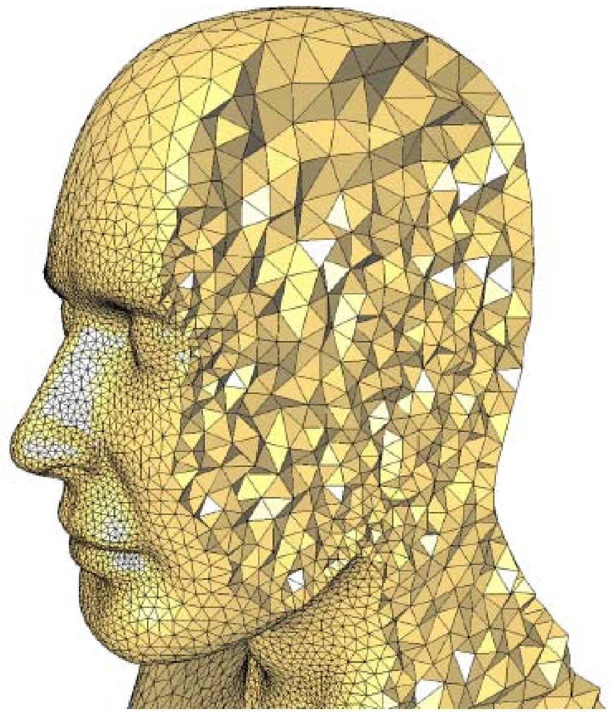
Symmetry Constraints

(5) Atomic Volumes for Mesh Completion

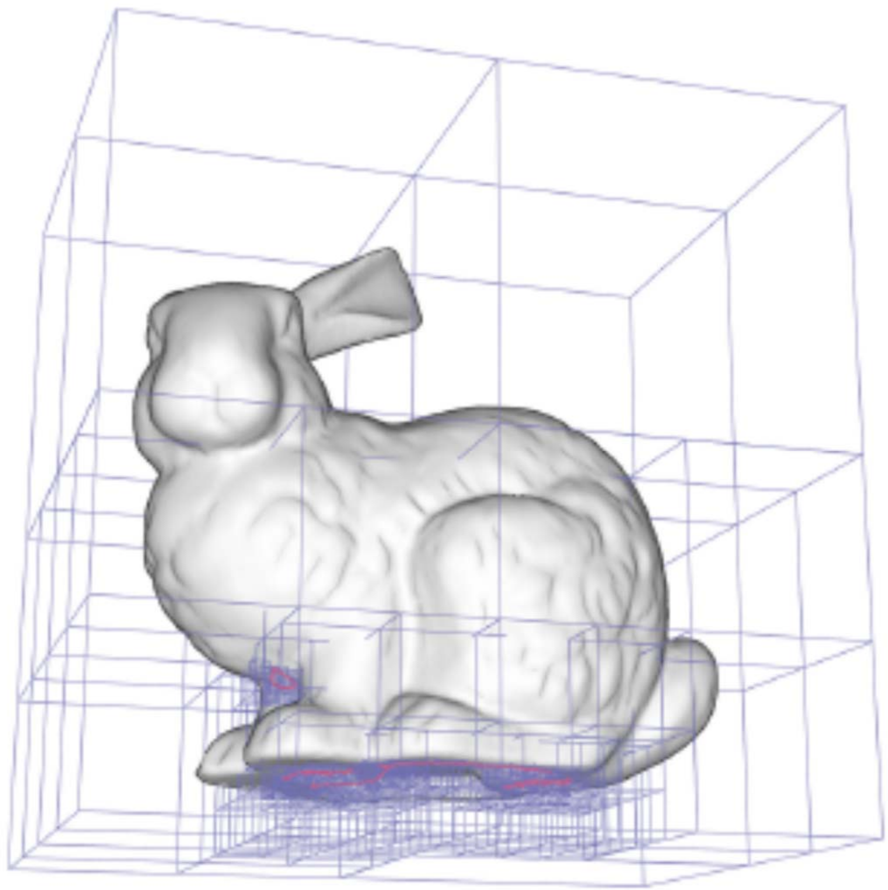
[Podolak and Rusinkiewicz, SGP 2005]

Atomic Volumes

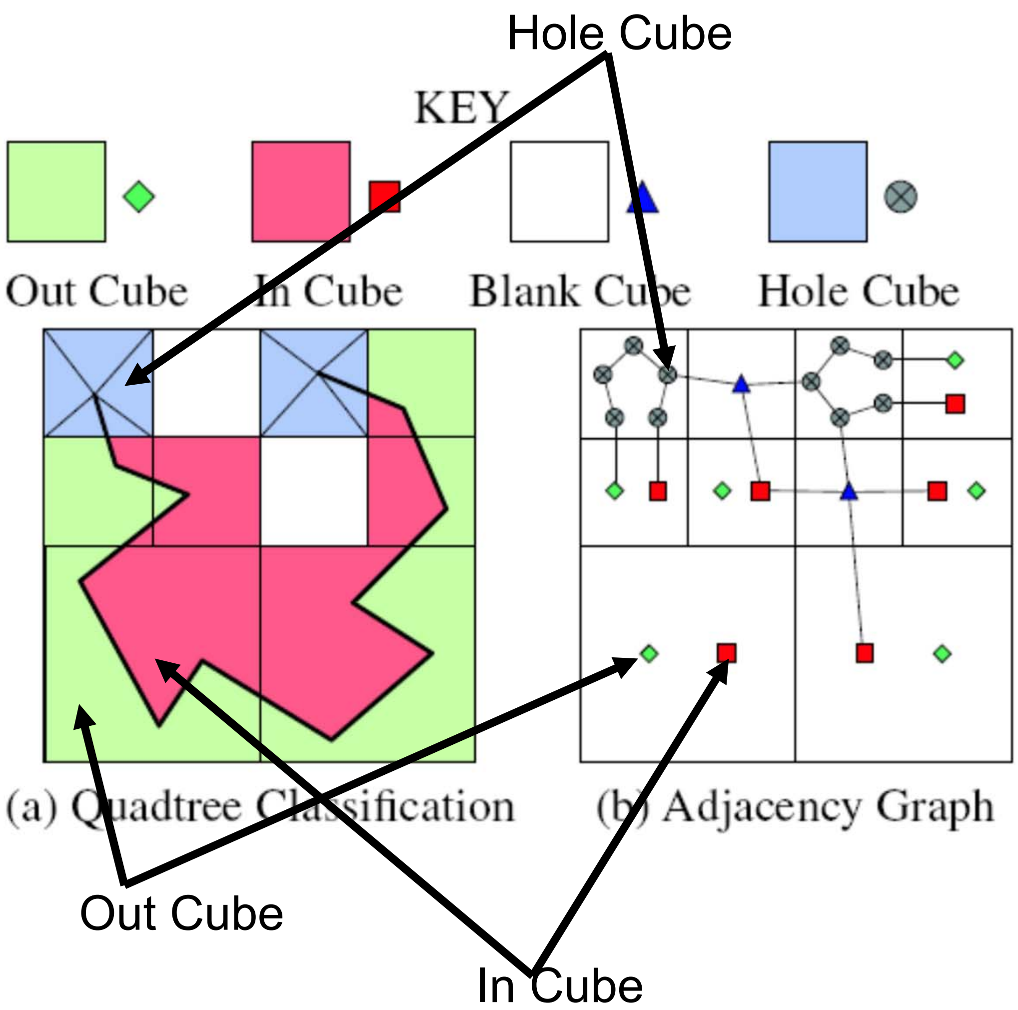
- A volume is *atomic* if it doesn't intersect the polygons of the mesh.



Spatial Partitioning

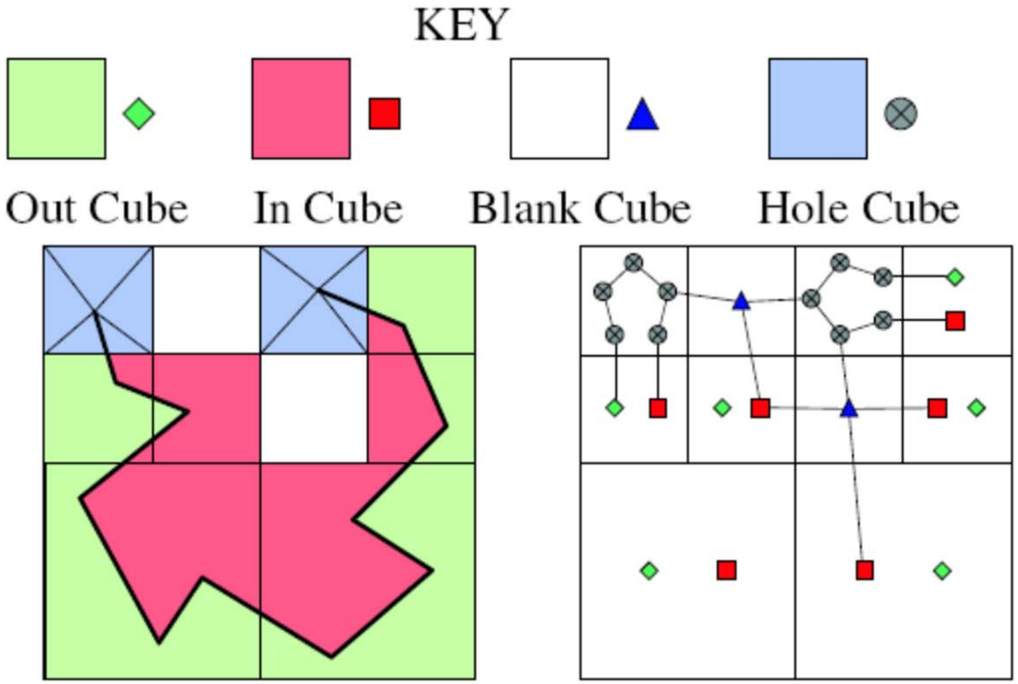


Pipeline



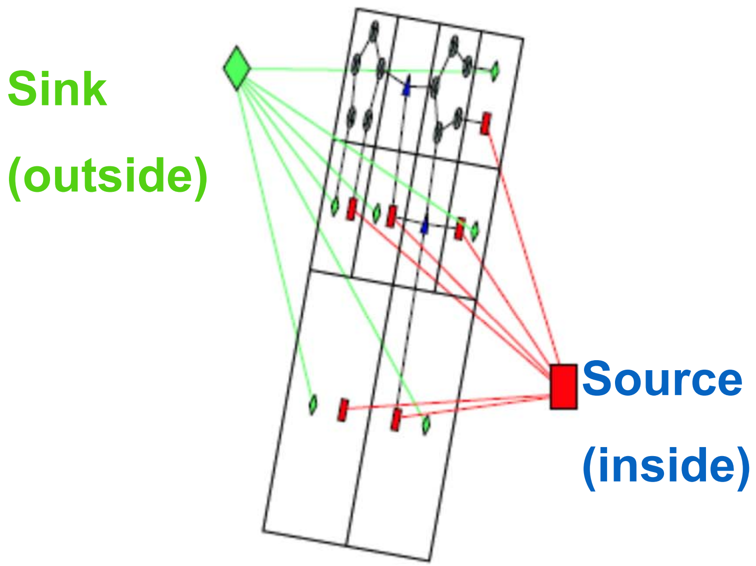
Hole Cube
KEY
Out Cube
In Cube
Blank Cube
Hole Cube
(a) Quadtree Classification
(b) Adjacency Graph
Out Cube
In Cube

Pipeline

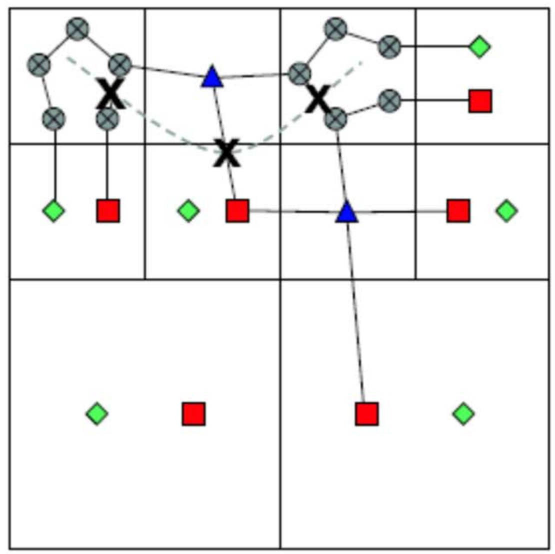


(a) Quadtree Classification (b) Adjacency Graph

Pipeline

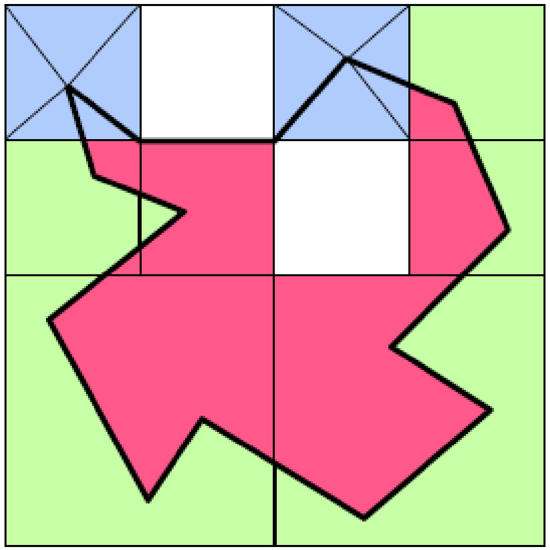


(c) Constraint Edges

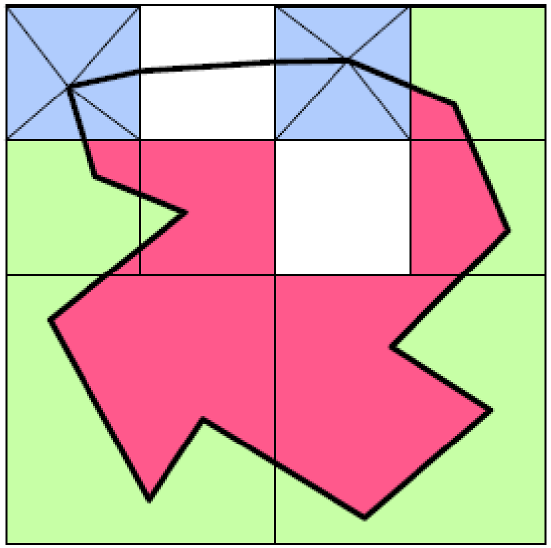


(d) Min Cut

Pipeline

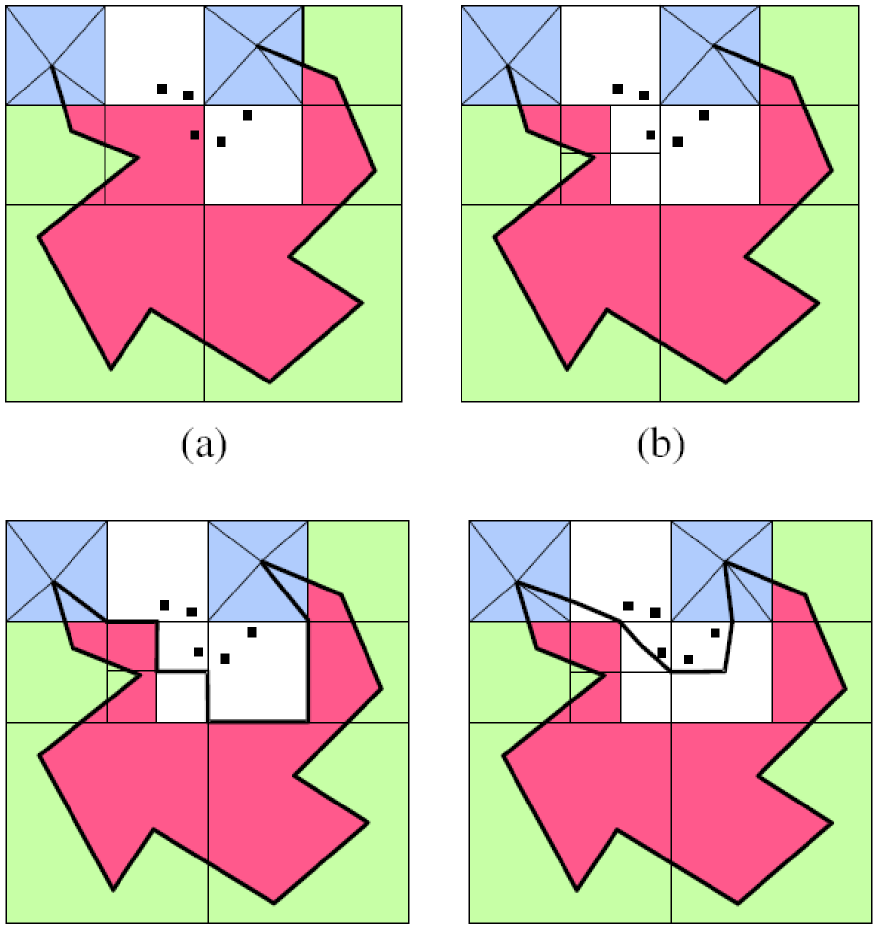


(e) Adding Faces

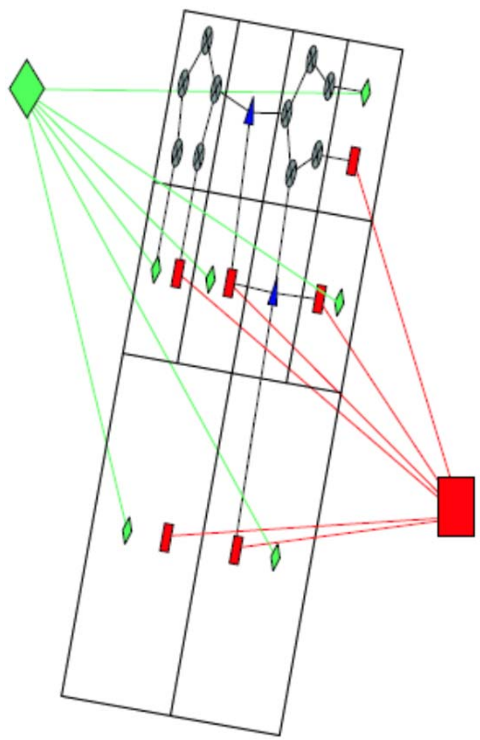


(f) Smoothing

User Constraints

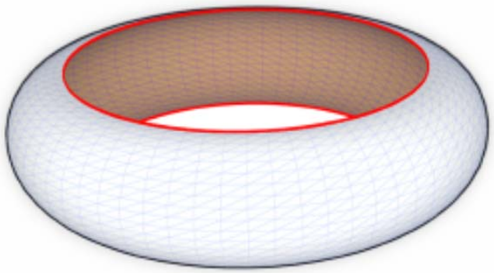


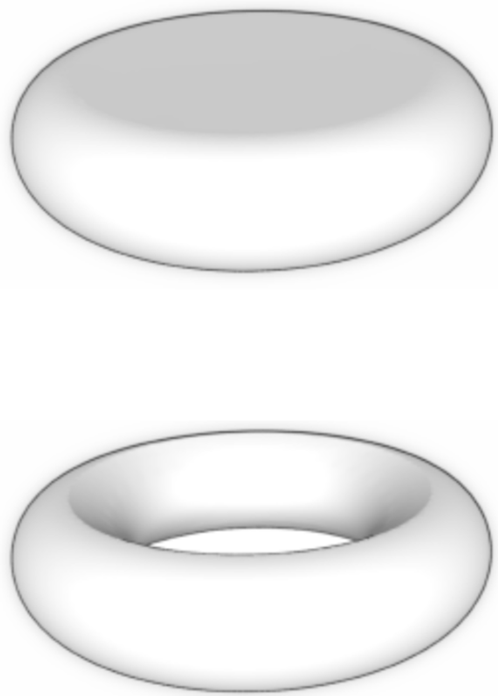
(a) (b) (c) (d)



Constraint Edges

Results





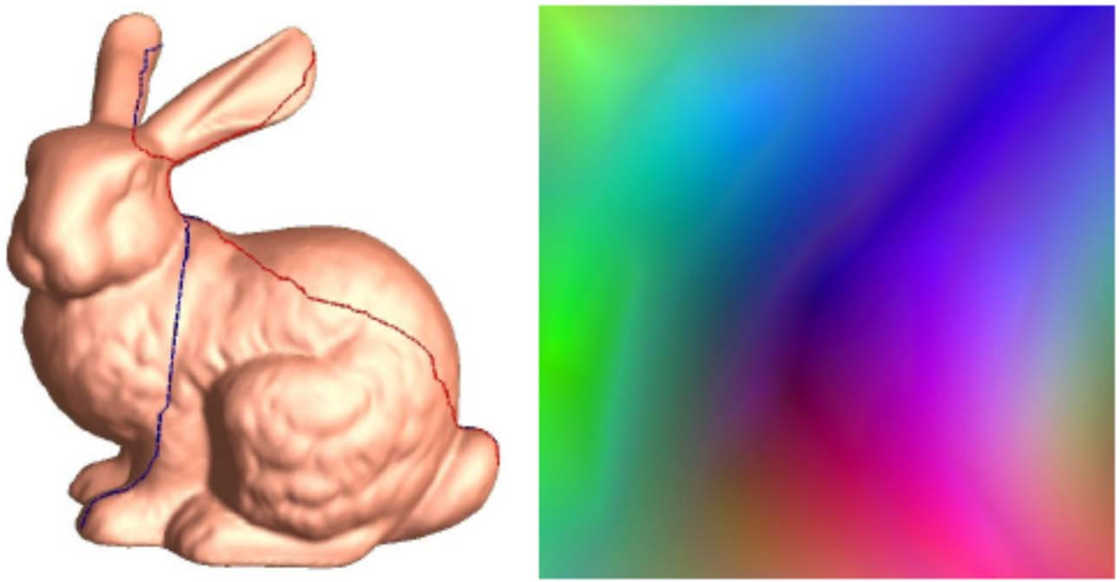
Summary

- Avoid changing, approximating or re-sampling the original mesh data
- Incorporate user constraints
- Can't process holes with islands

(6) Geometry Completion by Texture Synthesis

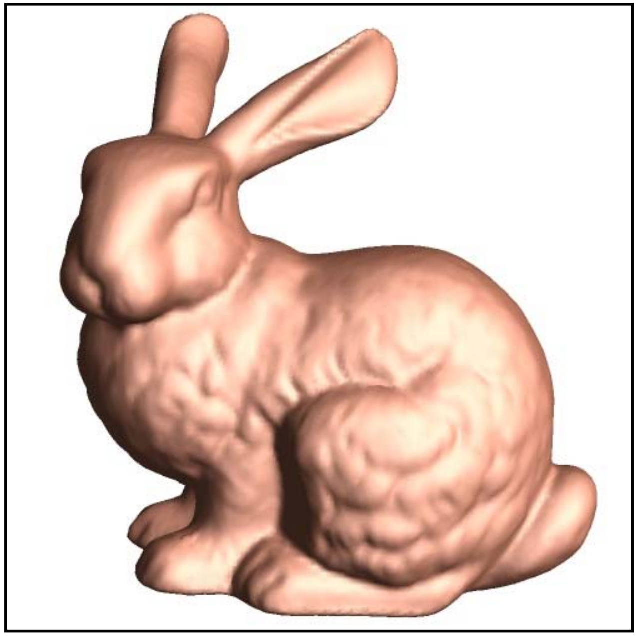
[Nguyen et al., PG 2005]

Geometry Image

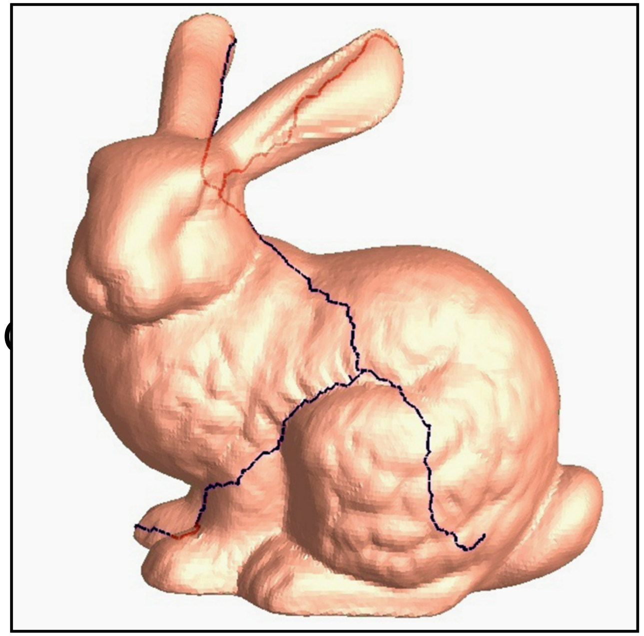


(a) Original mesh with cut (b) Geometry image 257×257

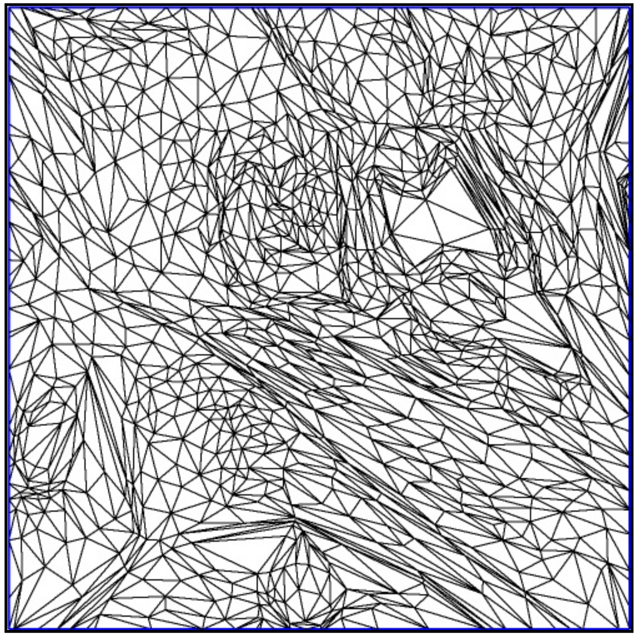
Basic idea



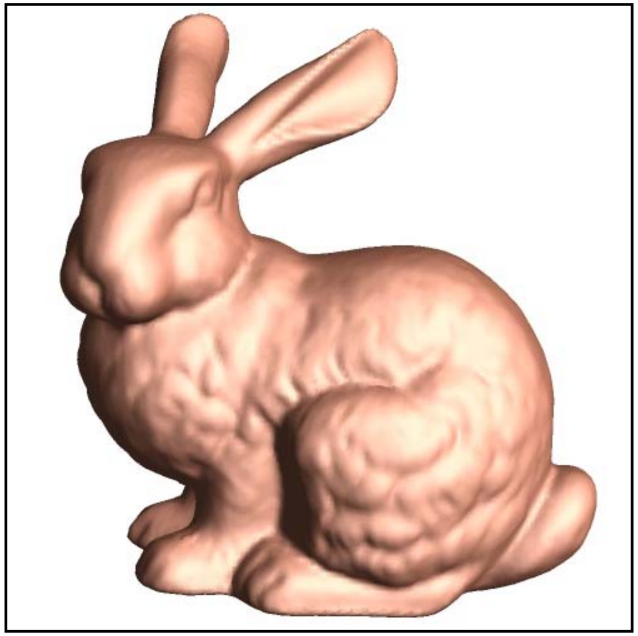
cut



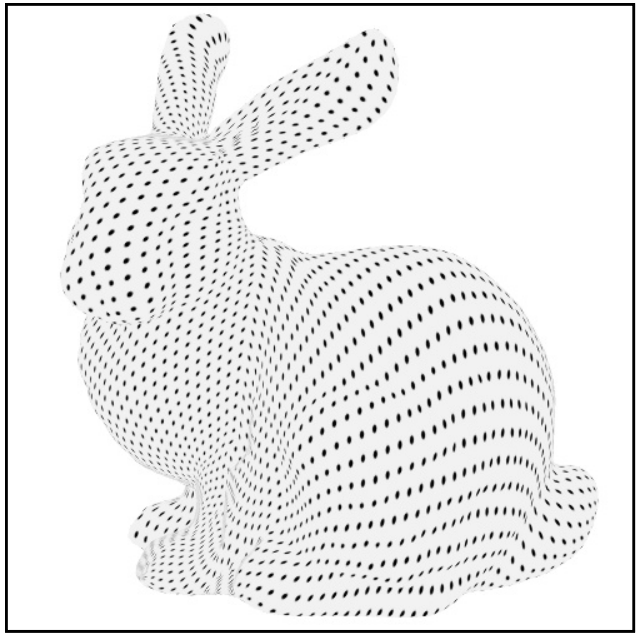
parametrize



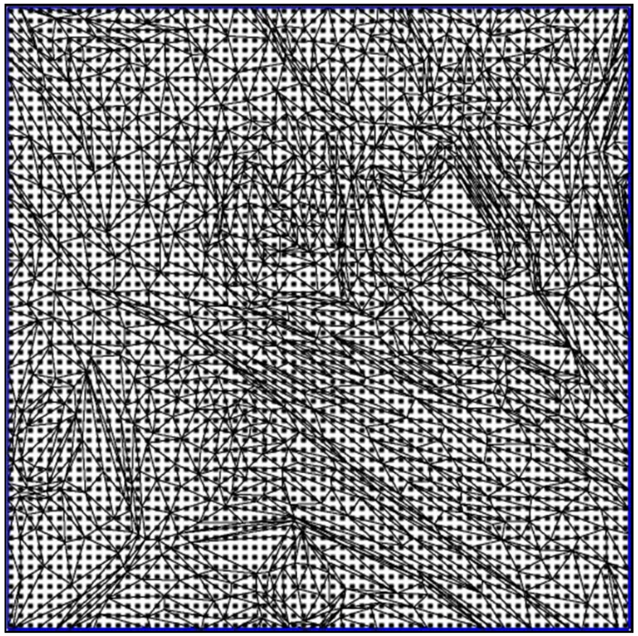
Basic idea



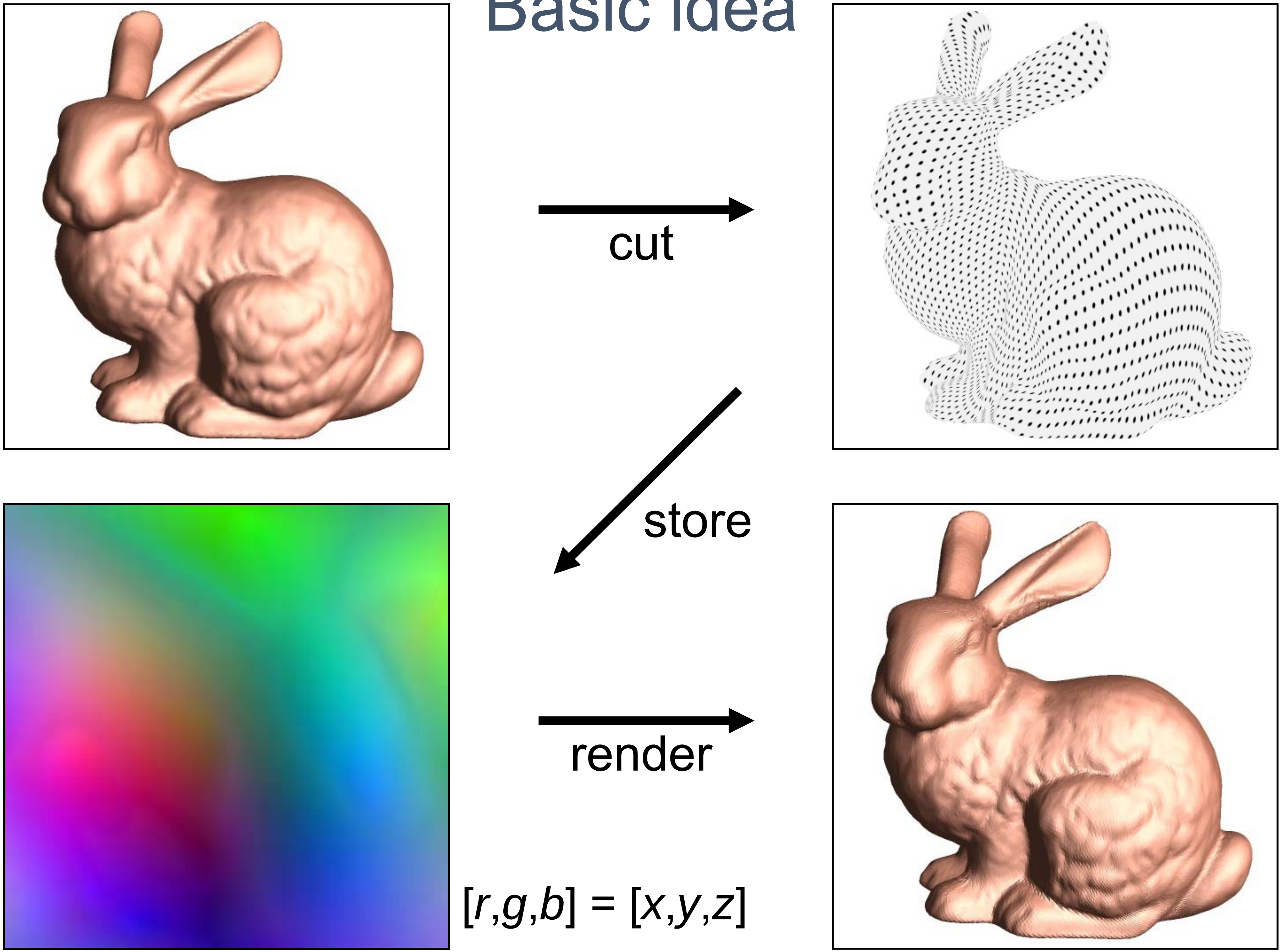
cut

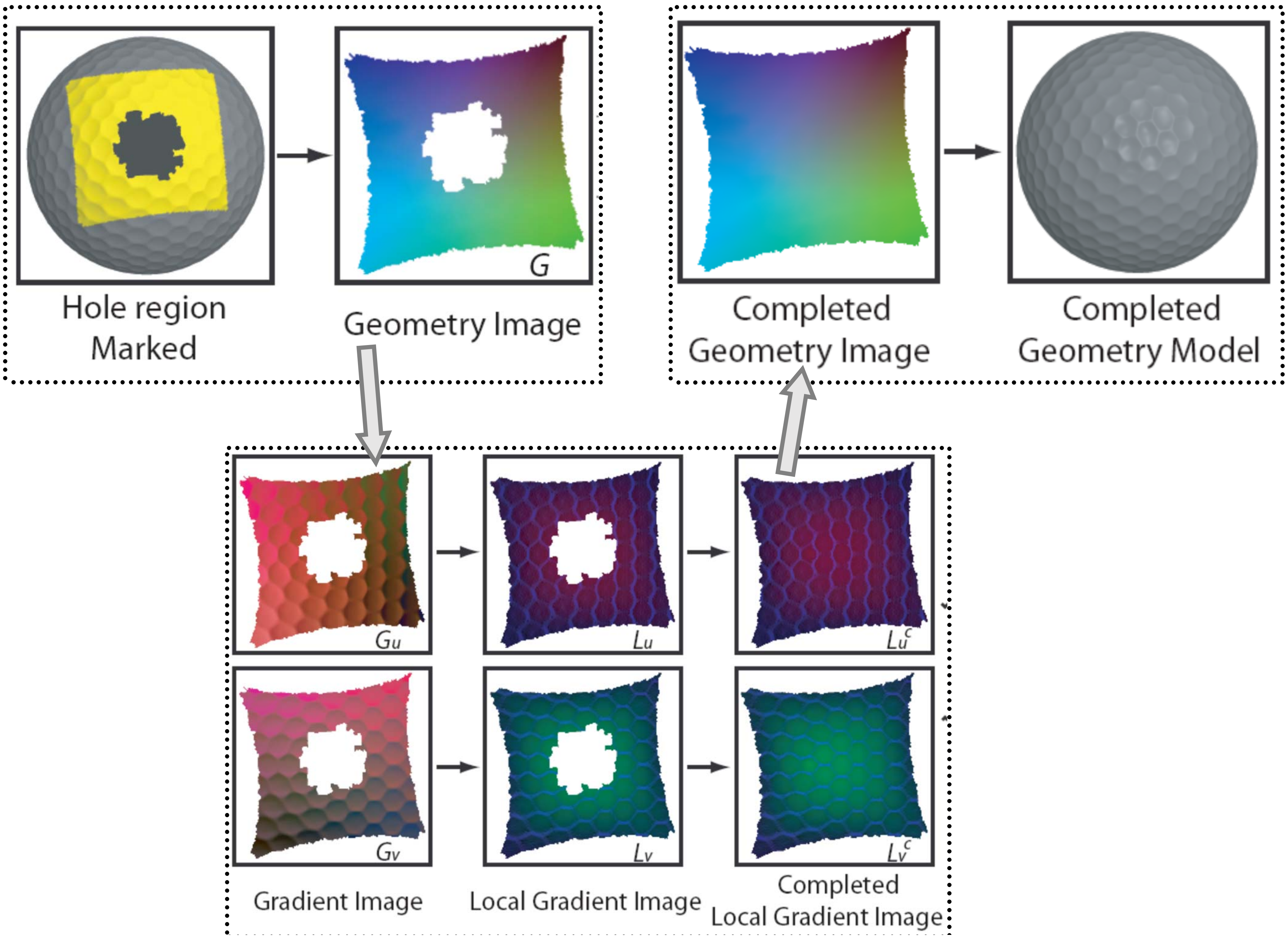


sample



Basic idea



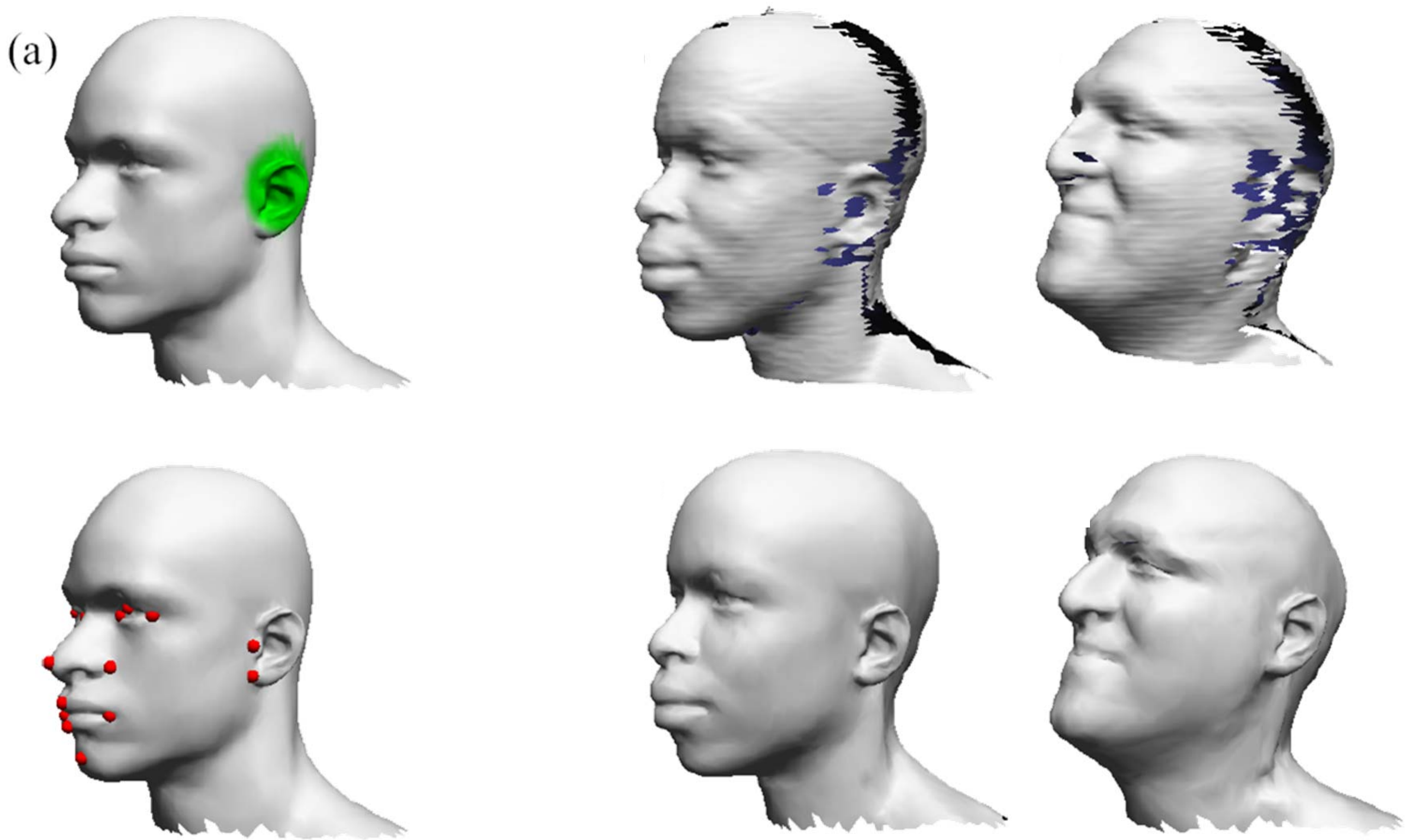


G
Hole region
Marked
Geometry Image
Completed
Geometry Image
Completed
Geometry Model
Gu
Lu
Lu^c
Gv
Lv
Lv^c
Gradient Image
Local Gradient Image
Completed
Local Gradient Image

(7) Others

Template based Solution

(Allen, Curless, Popovic, 2003; Kraevoy and Sheffer, 2005)



More…

- Marco Attene, Marcel Campen, Leif Kobbelt. Polygon Mesh Repairing: An Application Perspective. ACM Computing Surveys, 2012.

- Learning based 3D data completion in recent years
  - Han et al. High Resolution Shape Completion Using Deep Neural Networks for Global Structure and Local Geometry Inference. ICCV 2017.
  - Han et al. Deep Reinforcement Learning of Volume-guided Progressive View Inpainting for 3D Point Scene Completion from a Single Depth Image. CVPR 2019.
  - Nie et al. Skeleton-bridged Point Completion: From Global Inference to Local Adjustment. NeuIPS 2020.

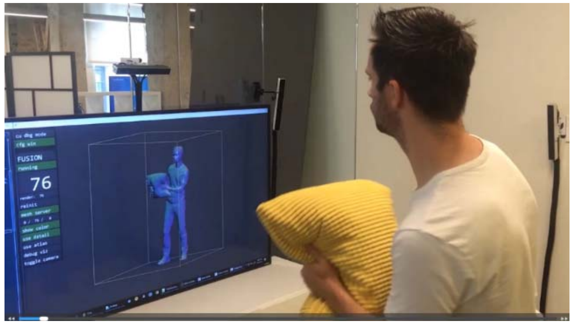
中国科学技术大学
University of Science and Technology of China

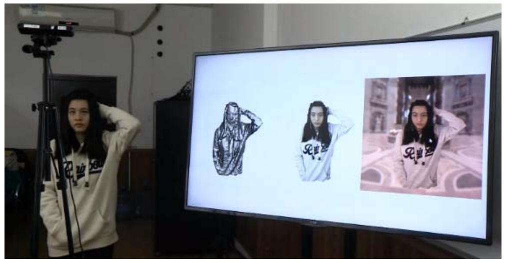
GAMES102

动态物体的3D重建

3D 动态重建的困难性

- 数据量大
- 数据采集困难
    - Single-Camera
    - Multi-Camera
- 数据结构复杂
    - Geometry
    - Color
    - Topology
- 硬件需求高





[Guo.2016]

Single-view

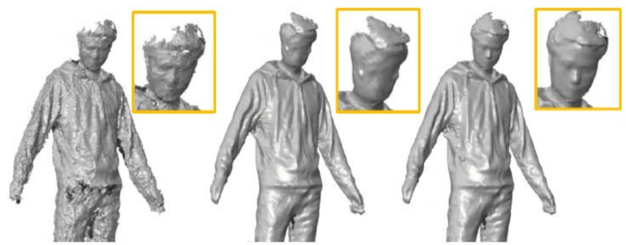
[Colletet al. 2015]

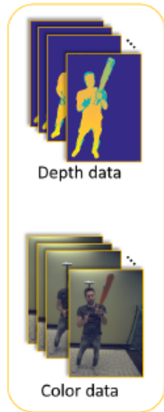
Multi-view

General Pipeline

- 数据采集

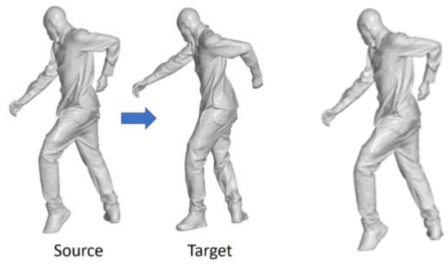
数据采集	系统建立	数据预处理	输出
• Kinect • 自定义的相机组	• 各视角相机坐标系对齐校准 • 各相机颜色一致性调整 • 各相机拍照频率一致	• 生成Depth map/image • Depth 去噪/补洞 • 背景或无用信息剔除	Depth image/color image



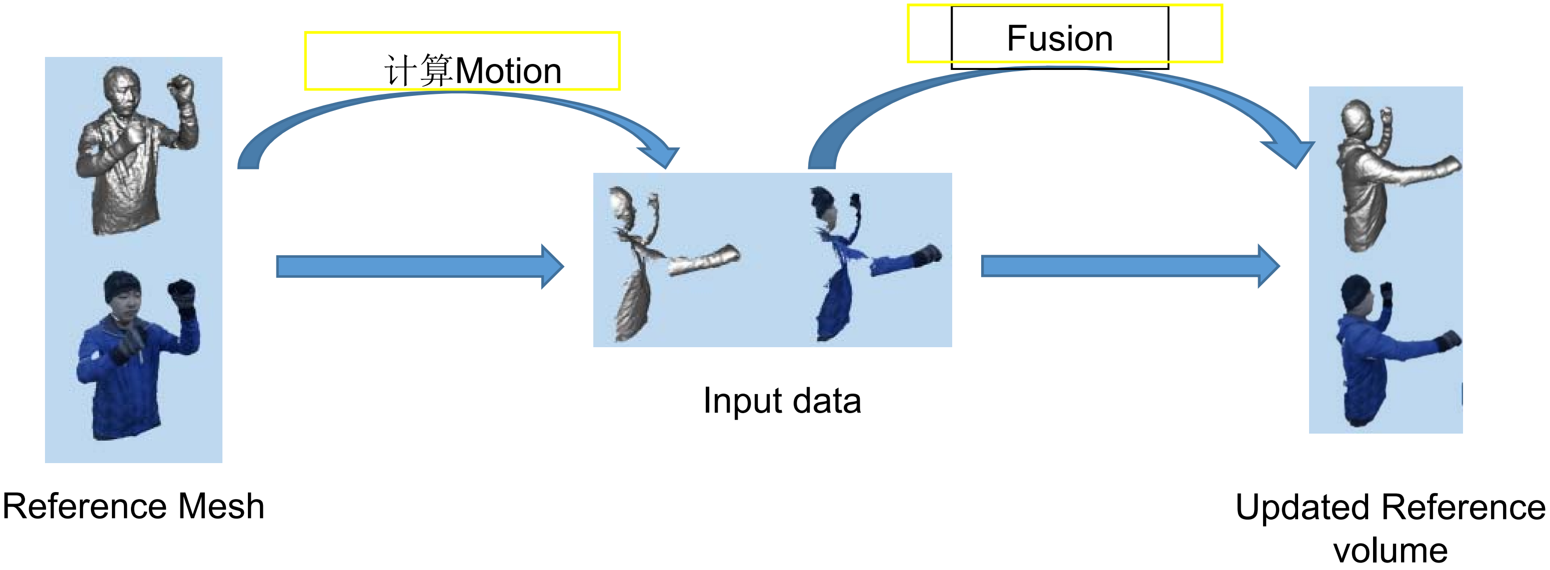


General Pipeline

- 生成3D mesh/surface



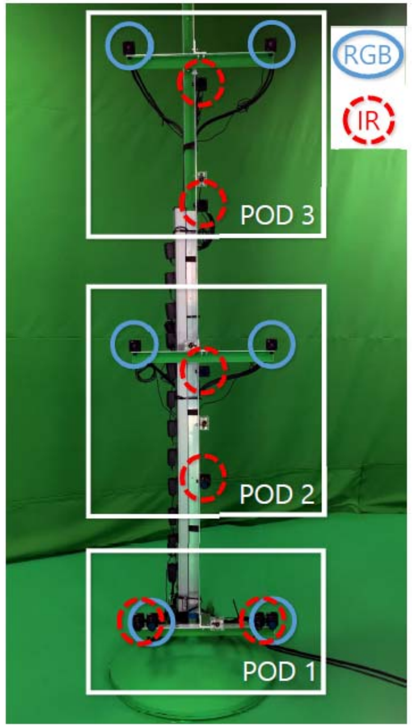
Motion



人体动态重建
（Human Performance Capturing）

- 离线高质量的动态重建方法
- 实时动态的人体重建方法
- 基于深度学习的人体重建方法

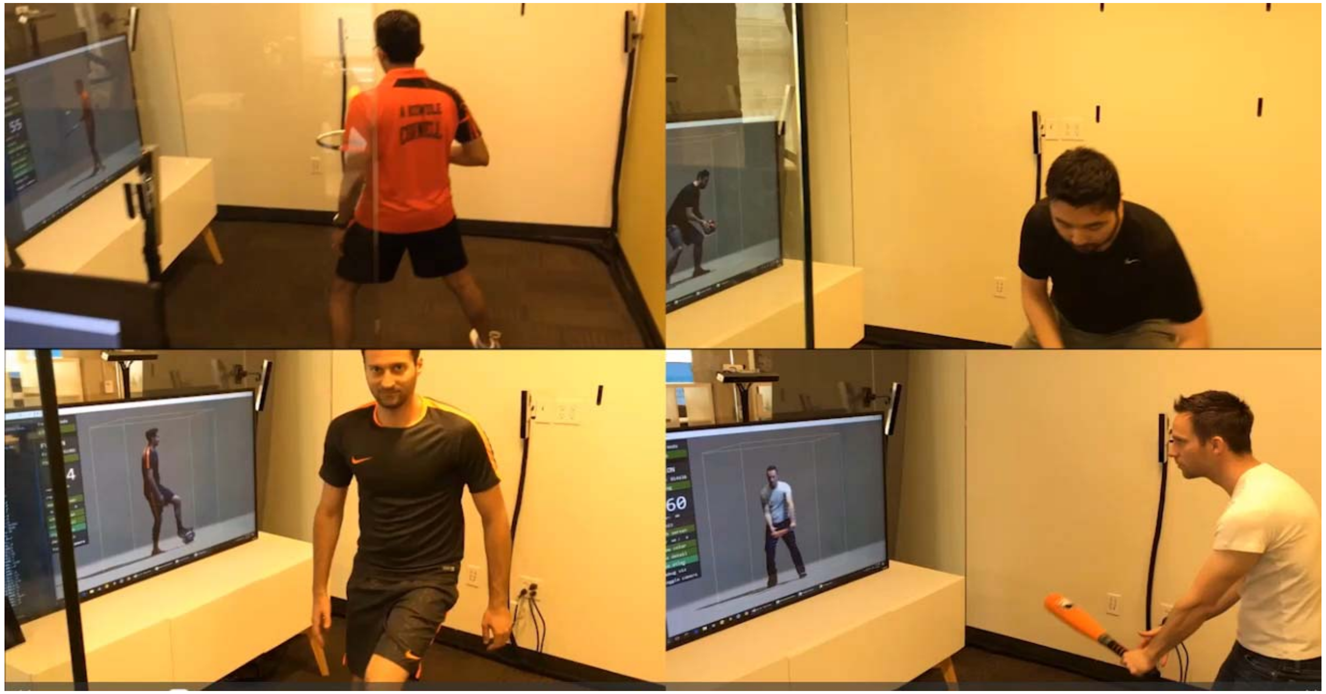
2.1 离线高质量动态重建



离线高质量动态重建

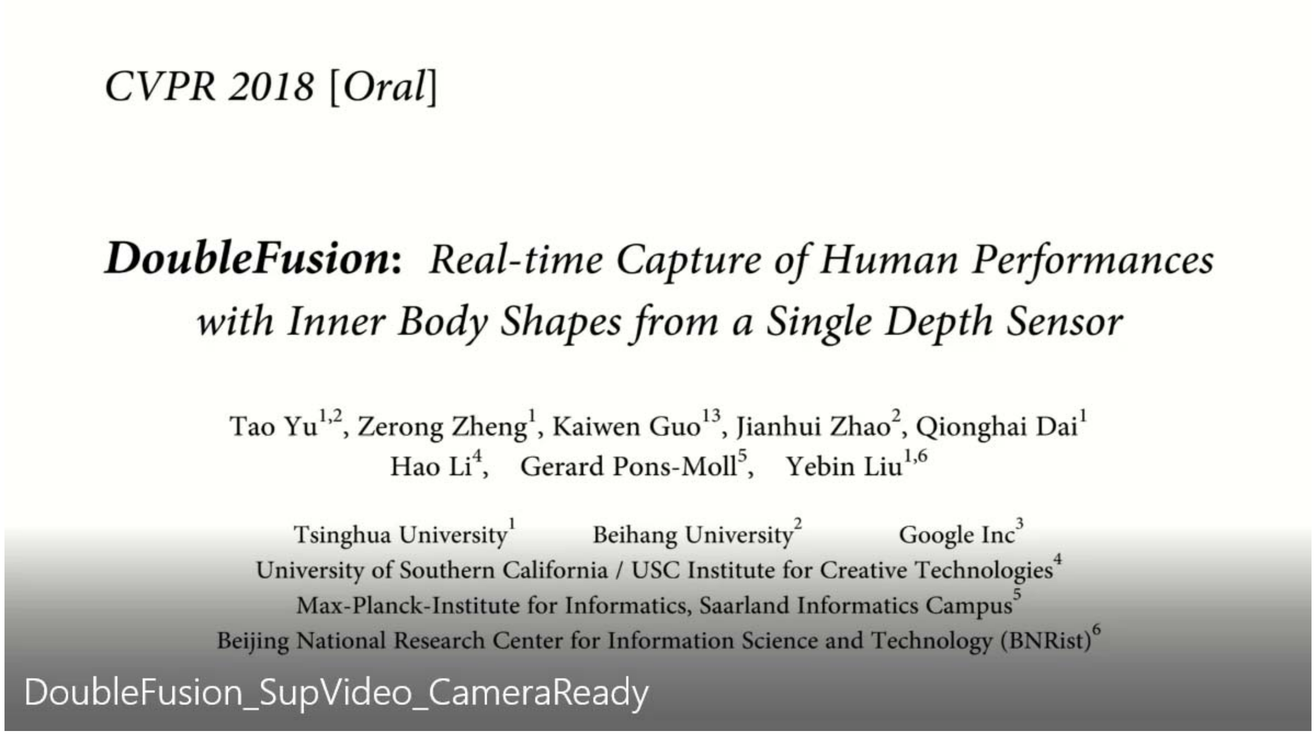
High-quality streamable free-viewpoint video (SIGGRAPH 2015)

2.2 实时动态人体重建



[Motion2Fusion 2017]

实时动态人体重建



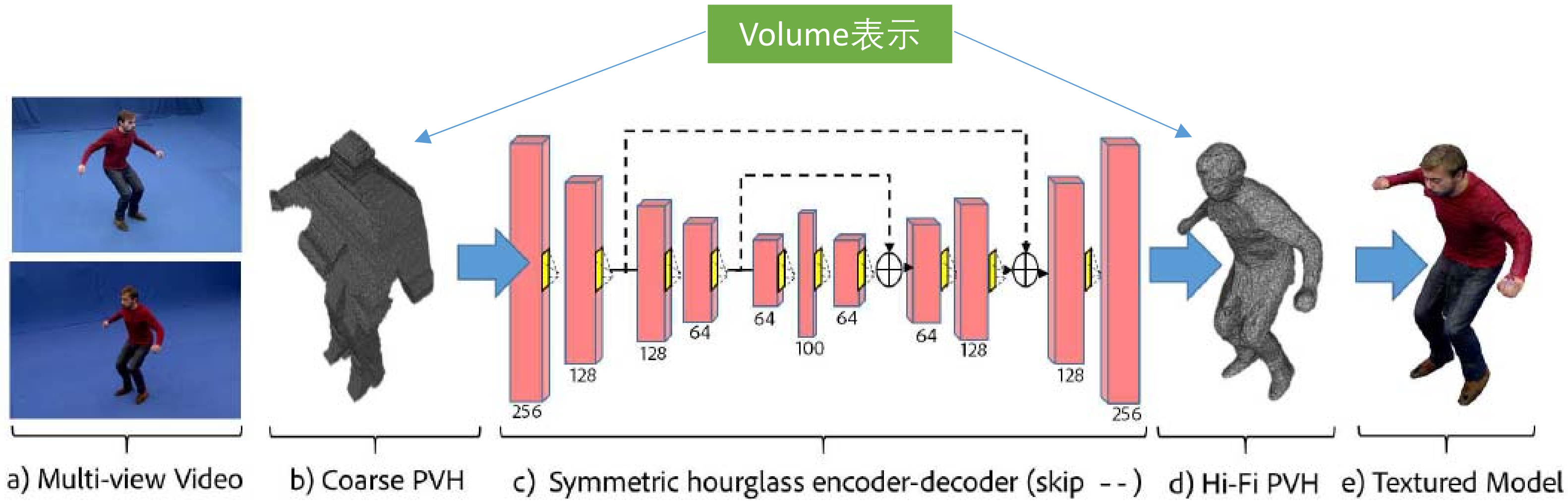
CVPR 2018 [Oral]

DoubleFusion: *Real-time Capture of Human Performances with Inner Body Shapes from a Single Depth Sensor*

Tao Yu[1,2], Zerong Zheng[1], Kaiwen Guo[13], Jianhui Zhao[2], Qionghai Dai[1]
Hao Li[4], Gerard Pons-Moll[5], Yebin Liu[1,6]

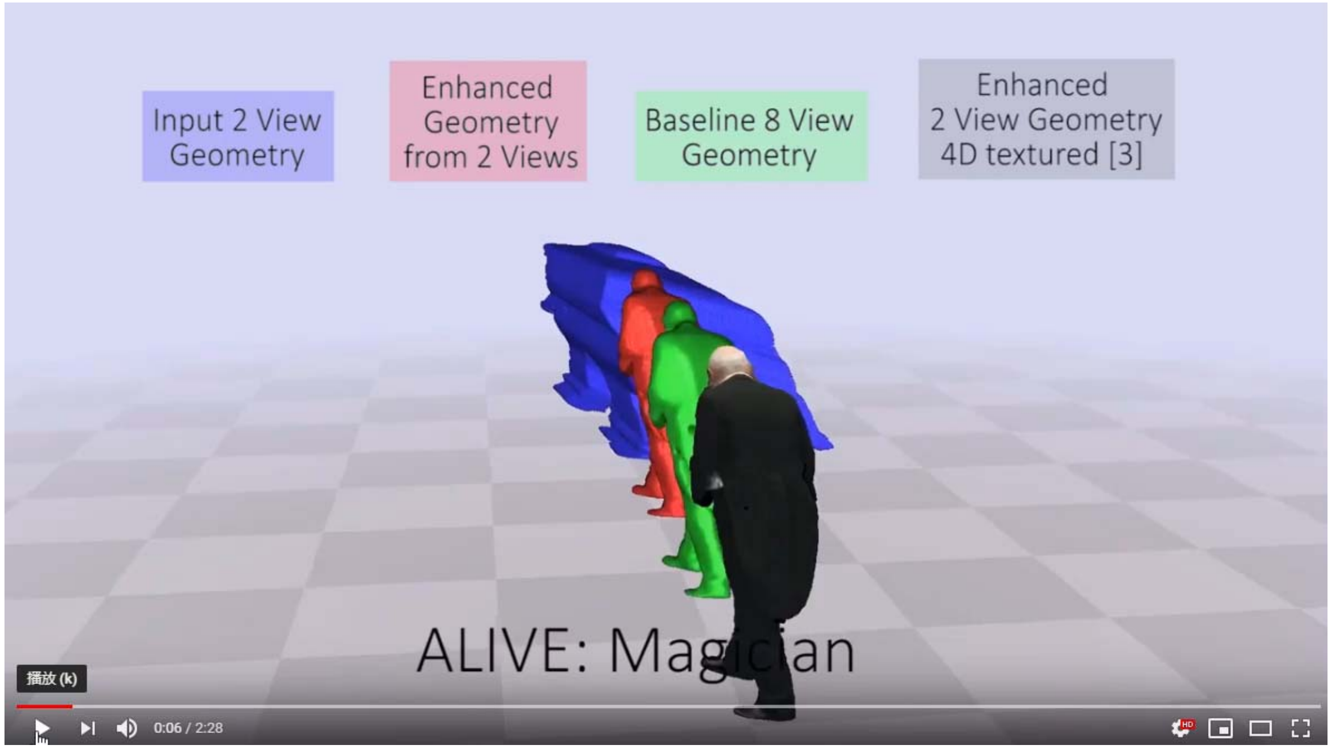
Tsinghua University[1] Beihang University[2] Google Inc[3]
University of Southern California / USC Institute for Creative Technologies[4]
Max-Planck-Institute for Informatics, Saarland Informatics Campus[5]
Beijing National Research Center for Information Science and Technology (BNRist)[6]

2.3 基于深度学习的动态人体重建方法



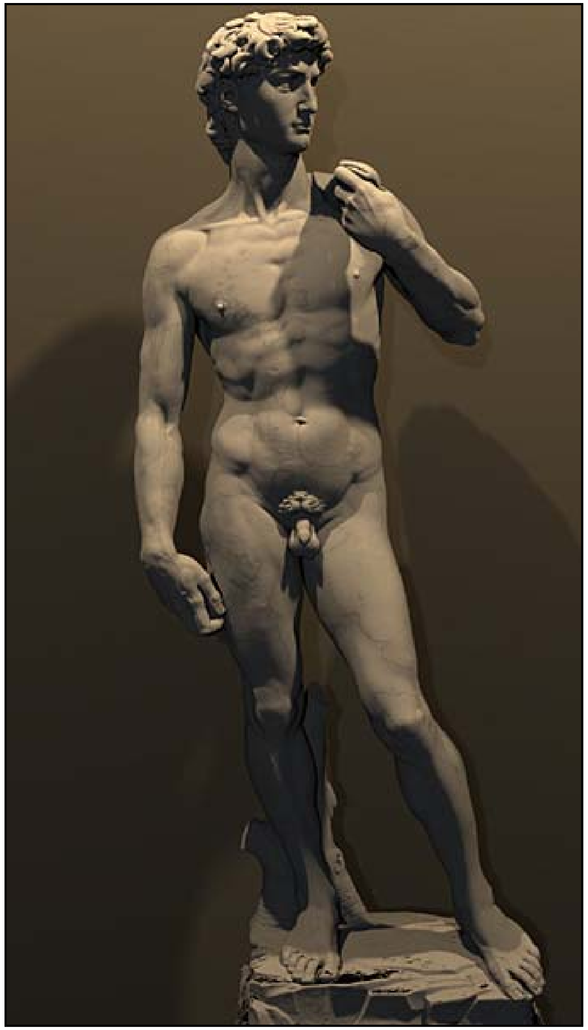
Volumetric performance capture from minimal camera viewpoints (ECCV 2018)

基于深度学习的动态人体重建方法



Summary

Statistics About the Scan of David



- 480 individually aimed scans
- 0.3 mm sample spacing
- 2 billion polygons
- 7,000 color images
- 32 gigabytes
- 30 nights of scanning
- 22 people

Reconstruction is still hard…

- Still no fully automatic tools
- Many many corner cases in practice!!!

作业10

- 任务（3选1）
  - 实现曲面重建的Crust算法
  - 实现RBF重建算法
  - 实现Poisson重建算法 (*)
- 目的
  - 学习曲面重建的基本算法
  - 注：如需要，可参考使用现成的Marching Cubes代码
- Deadline：2021年1 月16日晚

谢 谢 ！