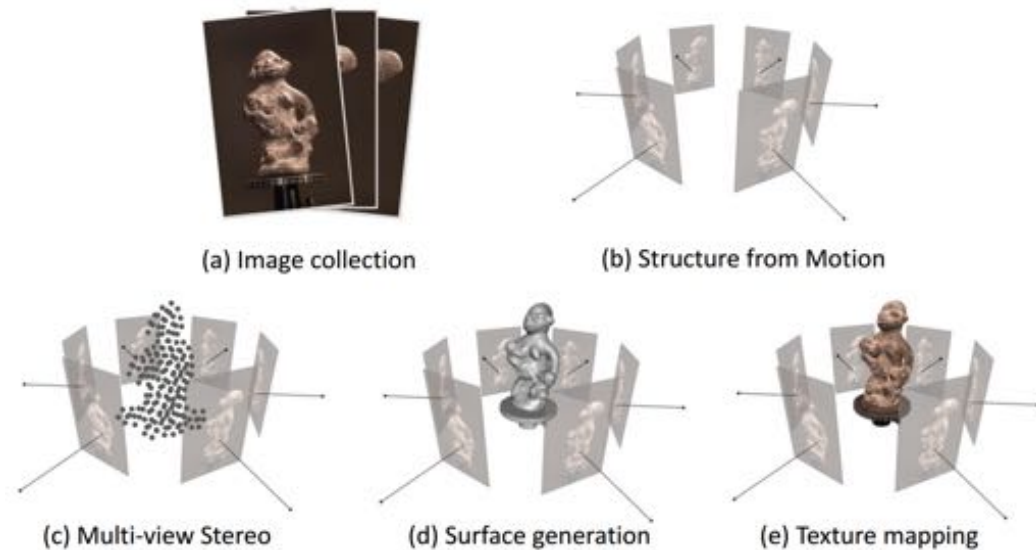


Part II

Long Quan

High-quality Textured Surface Reconstruction from Registered Images: State-of-the-art methods



The pipeline of image-based 3D reconstruction



(a) Image collection



(b) Structure-from-Motion



(c) Multi-view Stereo



(d) Surface generation



(e) Texture mapping



The pipeline of image-based 3D reconstruction



(a) Image collection



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The pipeline of image-based 3D reconstruction



(a) Image collection



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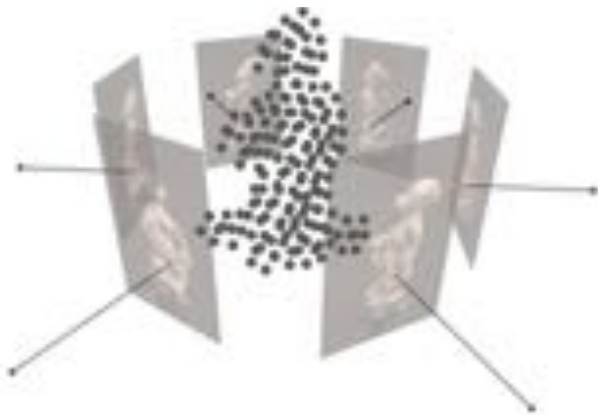
The pipeline of image-based 3D reconstruction



(a) Image collection



(b) Structure-from-Motion



(c) Multi-view Stereo



(d) Surface generation



(e) Texture mapping



The pipeline of image-based 3D reconstruction



(a) Image collection



(b) Structure-from-Motion



(c) Multi-view Stereo



(d) Surface generation



(e) Texture mapping



The pipeline of image-based 3D reconstruction



(a) Image collection



(b) Structure-from-Motion



(c) Multi-view Stereo



(d) Surface generation
+ Surface refinement



(e) Texture mapping



The pipeline of image-based 3D reconstruction



(a) Image collection



(b) Structure-from-Motion



(c) Multi-view Stereo



(d) Surface generation



(e) Texture mapping



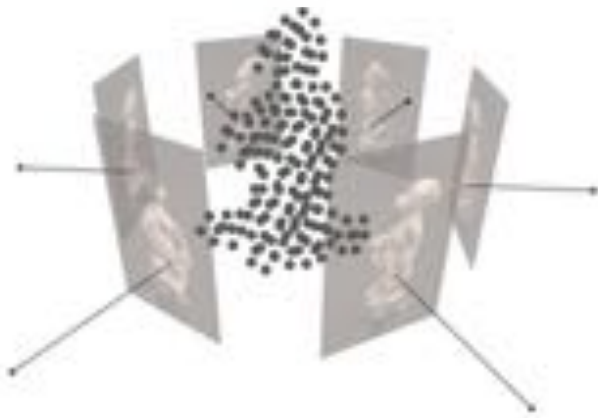
The pipeline of image-based 3D reconstruction



(a) Image collection



(b) Structure-from-Motion



(c) Multi-view Stereo



(d) Surface generation

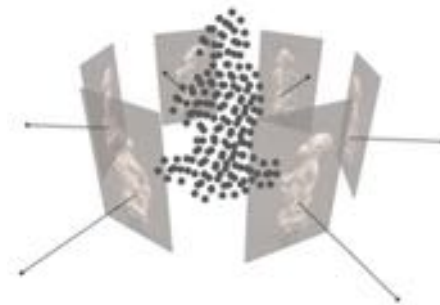


(e) Texture mapping



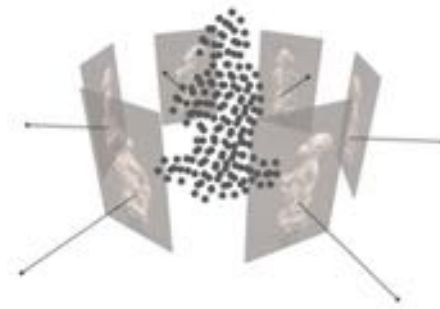
Content

- Multi-view Stereo
 - Pairwise Stereo
 - Propagation Stereo
- Surface generation
 - Surface extraction
 - Surface refinement
- Texture mapping
 - View selection
 - Color adjustment and blending



Content

- Multi-view Stereo
 - Pairwise Stereo
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Multi-view Stereo

- Problem definition: given several **registered images** of the same object or scene, compute a **dense representation** of its 3D shape
- “Registered images of same object or scene”
 - Known camera parameter
 - Arbitrary number of images (from two to thousands)
- “Dense representation of 3D shape”
 - Depth maps
 - Point clouds
 - Patch clouds
 - Meshes
 - Voxels



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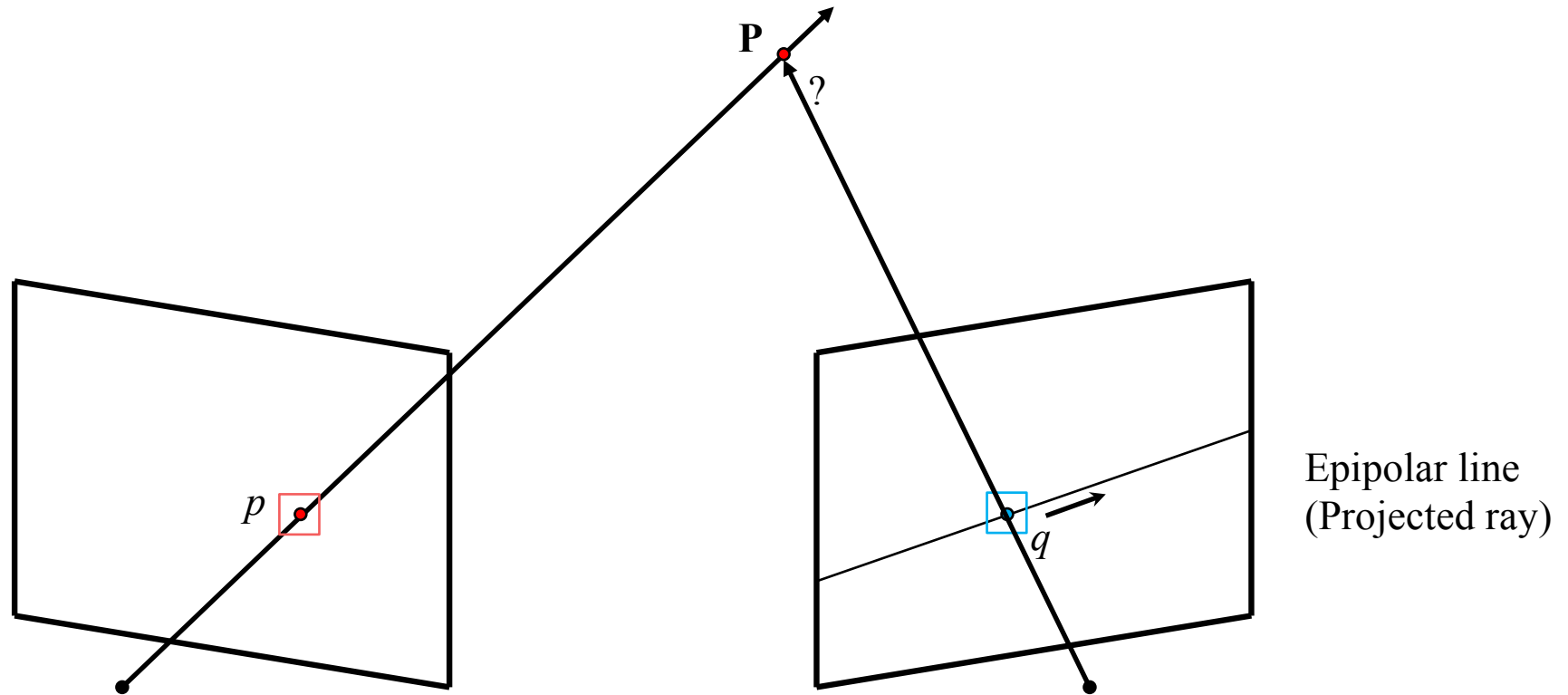


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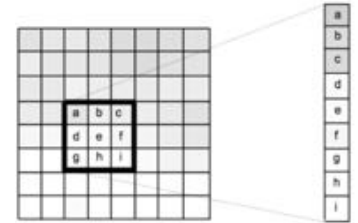
Multi-view Stereo: 1D matching problem



Compare the similarity between p and q , find the best q

Multi-view Stereo: Similarity measure

- Convert the patches p  and q  in to vectors f and g



SSD (Sum of Squared Differences)

$$\rho_{SSD}(f, g) = \|f - g\|^2$$

- Pros: efficient, derivable
- Cons: sensitive to bias/gain

SAD (Sum of Absolute Differences)

$$\rho_{SAD}(f, g) = \|f - g\|_1$$

- Pros: efficient, robust to salt/pepper noise
- Cons: non-derivable, sensitive to bias/gain

NCC (Normalized Cross Correlation)

$$\begin{aligned}\rho_{NCC}(f, g) &= \left\langle \frac{f}{\|f\|}, \frac{g}{\|g\|} \right\rangle \\ &= \frac{f \cdot g}{\|f\| \cdot \|g\|}\end{aligned}$$

- Pros: robust to gain, derivable
- Cons: sensitive to bias

ZNCC (Zero-mean Normalized Cross Correlation)

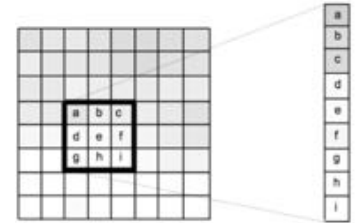
$$\begin{aligned}\rho_{ZNCC}(f, g) &= \left\langle \frac{f - \hat{f}}{\|f - \hat{f}\|}, \frac{g - \hat{g}}{\|g - \hat{g}\|} \right\rangle \\ &= \frac{(f - \hat{f}) \cdot (g - \hat{g})}{\sigma_f \sigma_g}\end{aligned}$$

- Pros: robust to bias/gain, derivable
- Cons: less efficient



Multi-view Stereo: Similarity measure

- Convert the patches p  and q  in to vectors f and g



SSD (Sum of Squared Differences)

$$\rho_{SSD}(f, g) = ||f - g||^2$$

- Pros: efficient, derivable
- Cons: sensitive to bias/gain

NCC (Normalized Cross Correlation)

$$\begin{aligned}\rho_{NCC}(f, g) &= \left\langle \frac{f}{||f||}, \frac{g}{||g||} \right\rangle \\ &= \frac{f \cdot g}{||f|| \cdot ||g||}\end{aligned}$$

- Pros: robust to gain, derivable
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$$\rho_{SAD}(f, g) = ||f - g||_1$$

- Pros: efficient, robust to salt/pepper noise
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$$\begin{aligned}\rho_{ZNCC}(f, g) &= \left\langle \frac{f - \hat{f}}{||f - \hat{f}||}, \frac{g - \hat{g}}{||g - \hat{g}||} \right\rangle \\ &= \frac{(f - \hat{f}) \cdot (g - \hat{g})}{\sigma_f \sigma_g}\end{aligned}$$

- Pros: robust to bias/gain, derivable
- Cons: less efficient



Multi-view Stereo: two branches of methods

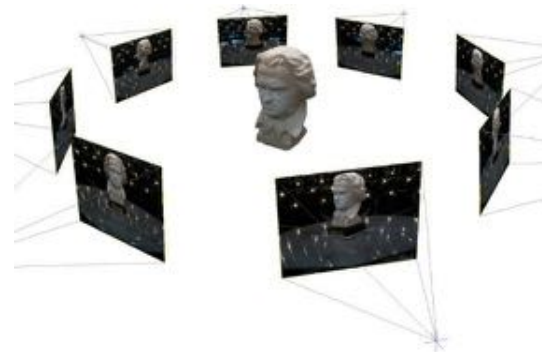
- Pairwise depth map reconstruction

- Input two images
- Output per-image depth map
- Need fusion afterwards



- Global point cloud propagation

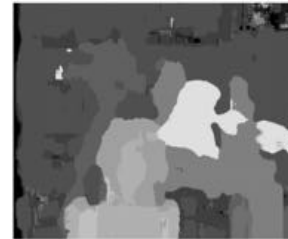
- Input N images
- Output global 3D points
- Difficult parallelism



Multi-view Stereo: matching strategy



Local matching



Naive winner-take-all



Image segmentation
Gerrits et.al., CRV2006

Global regularization



Graph cuts
Kolmogorov et.al. ICCV2001



Semi-global matching
Hirschmüller, CVPR2006



Belief Propagation
Klaus et.at. ICPR2006

Deep learning

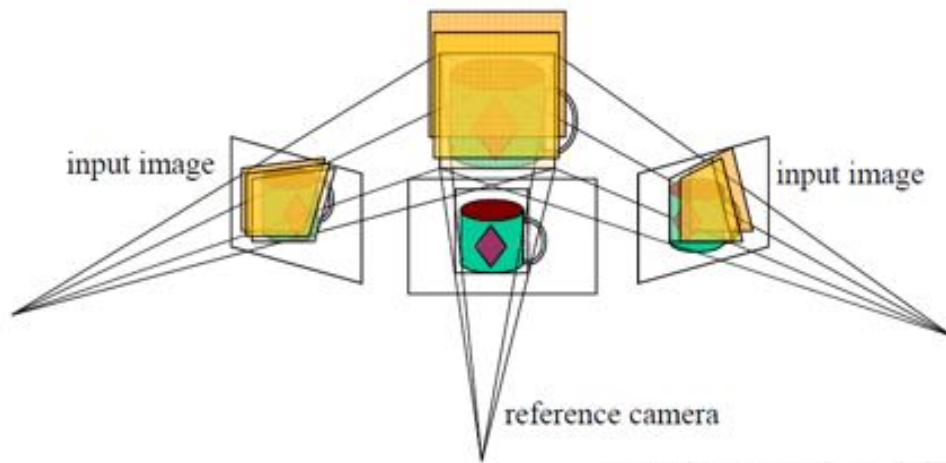


CNN
Žbontar and LeCun. CVPR2015

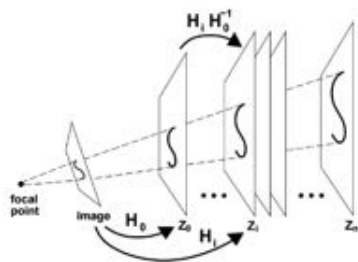
next.....?



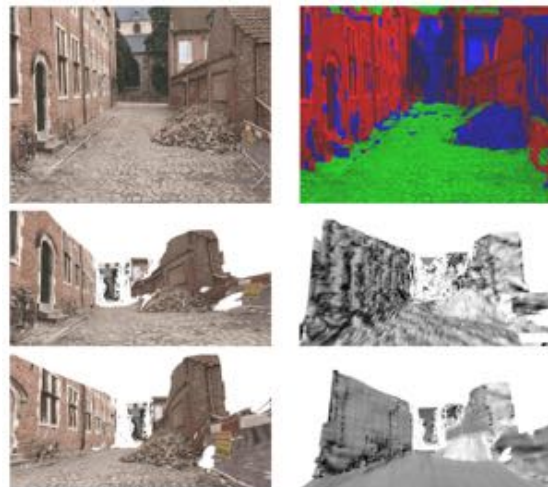
Multi-view Stereo: plane sweep stereo



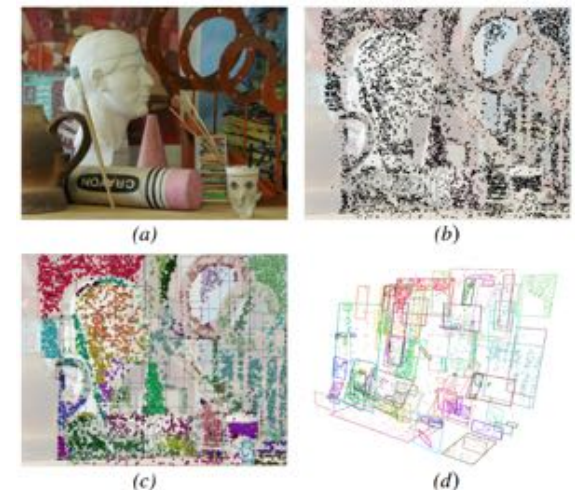
- Winner-take-all
- GPU projective texture mapping
- Highly efficient and parallelable
- Noisy output, need filter afterwards



Space-sweep
(Pioneer)
Collins, 1996



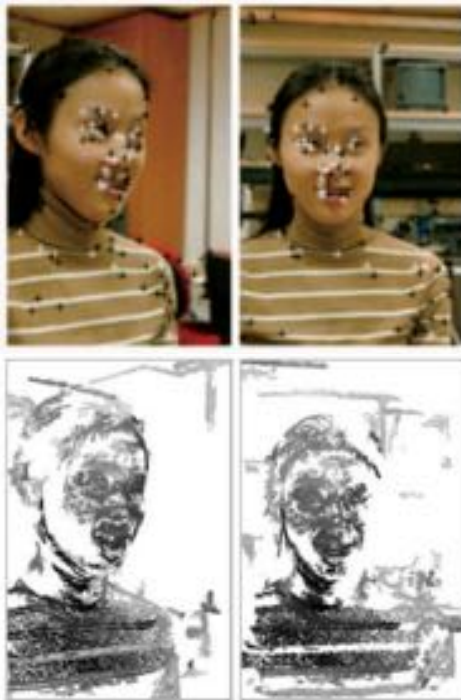
Multi-direction Planesweep
Gallup et.al. CVPR2007



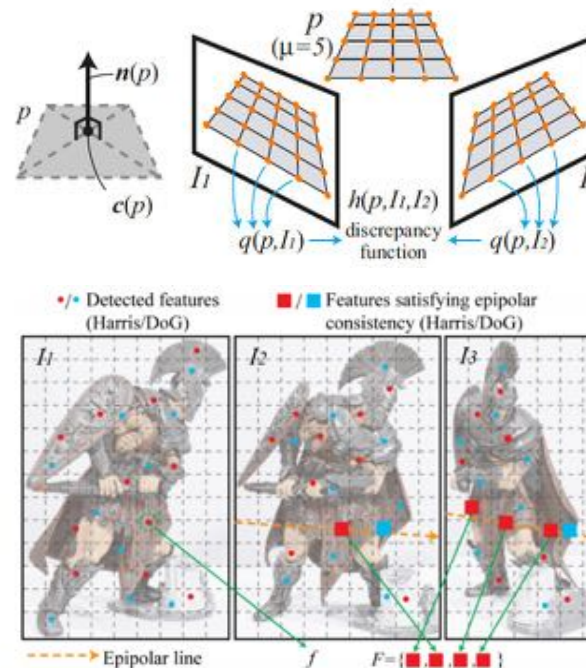
Local Planesweep
Sinha et.al. CVPR2014



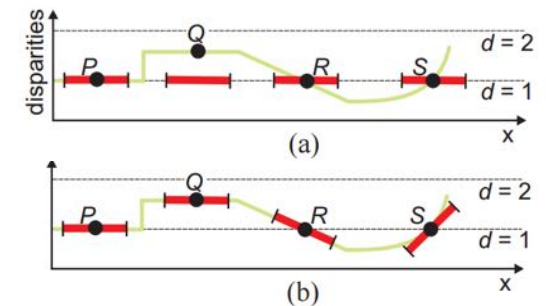
Multi-view Stereo: point cloud propagation



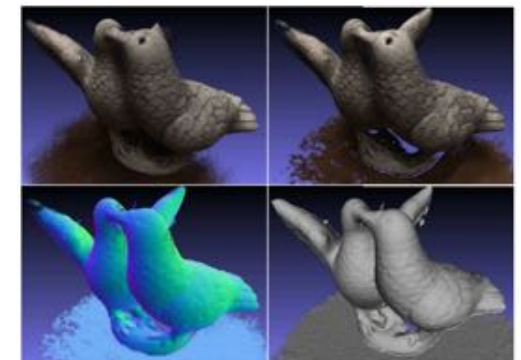
Pioneer: Quasi-dense approach
Lhuillier and Quan. PAMI2005



Patch-based MVS (PMVS)
Furukawa and Ponce. PAMI2010



PatchMatch Stereo
Bleyer et.al. BMVC2011

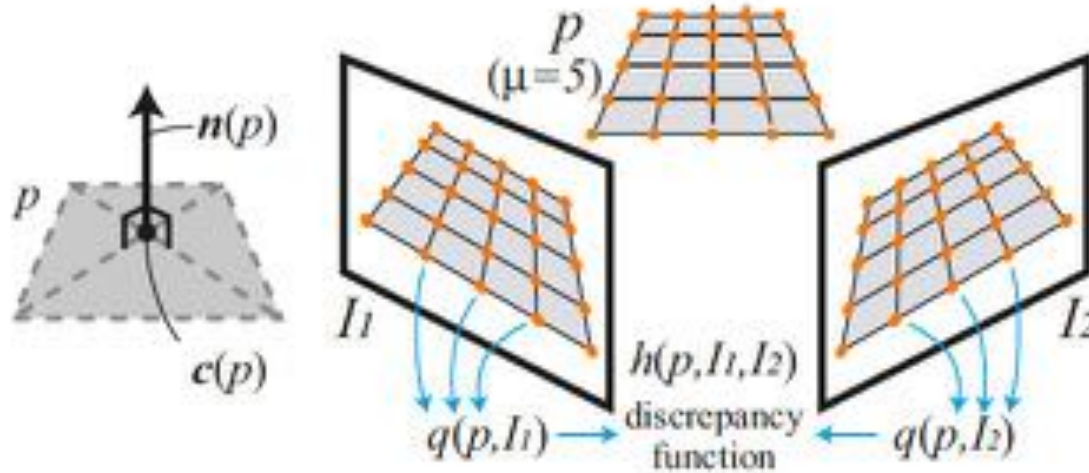


GPU PatchMatch
Galliani et.al. ICCV2015



Multi-view Stereo: PMVS

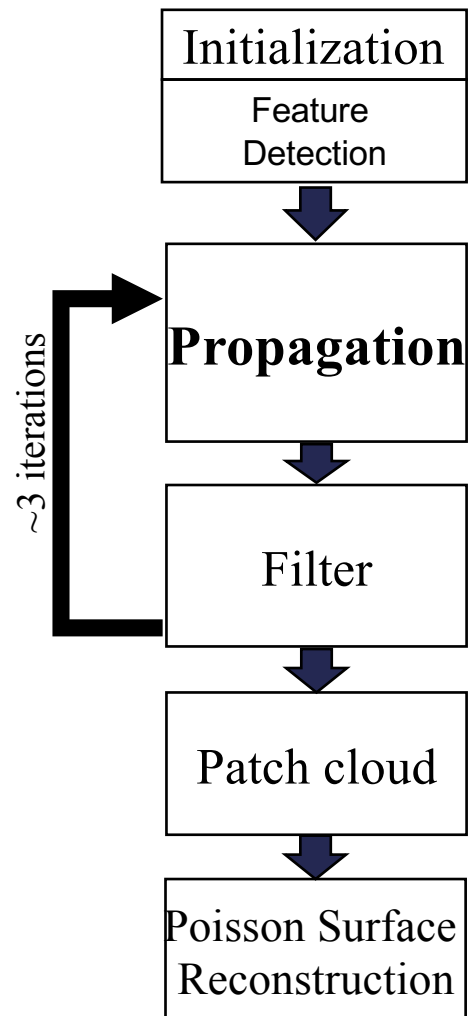
- Patch model



- A 3D patch has
 - Position
 - Normal
 - Scale
 - Visibility



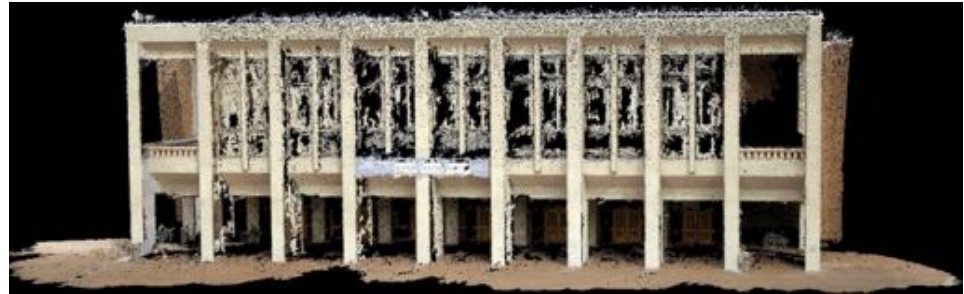
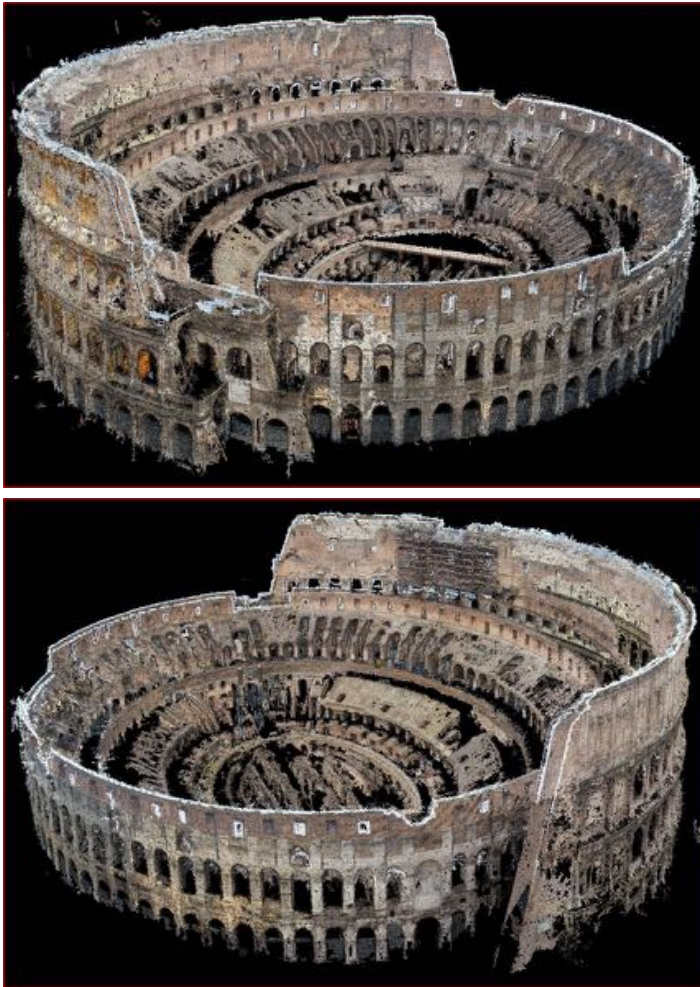
Multi-view Stereo: PMVS



- Harris and DoG
- Sparse seed patches
- Propagation, then optimize
- Optimize via Levenberg–Marquardt
 - Position
 - Normal
- Confidence filter
- Visibility filter
- Small group filter
- Point cloud with **orientations**



Multi-view Stereo: PMVS



Content

- Multi-view Stereo
 - Pairwise Stereo
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Surface representation

	Meshes	Volumetric
Space Discretization	Adaptive	Yes
Topology Handling	Difficult (Self intersections,...)	Naturally handled
Memory	Compact, Limited	Large
Parallelization	Sometimes	Very good
Scalability	Very good	Difficult
Adaptive Resolution	Very good	Difficult (Octree, Narrow band)
Surface extraction	Natural	Precision Loss (Marching cubes)

Mesh rocks! triangular mesh is more suitable for mesh processing

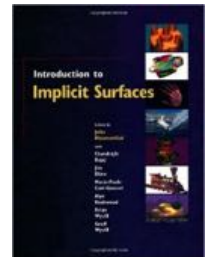


Surface extraction from point cloud

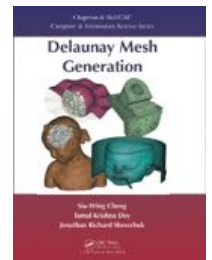


Definition: Given a set of points $\mathbf{P} = \{P_i\}_{i \in [1, N]} \in \mathbf{R}^3$ sampled from a surface S , find a best approximate surface S' to the original S .

- Implicit surface (Computer Graphics)
 - Model the surface implicitly with a function $f(x, y, z) = 0$
- Delaunay approach (Computational geometry)
 - Based on Delaunay triangulation/tetrahedra, find the best mesh surface



Bloomenthal, 1997



Cheng et.al. 2012

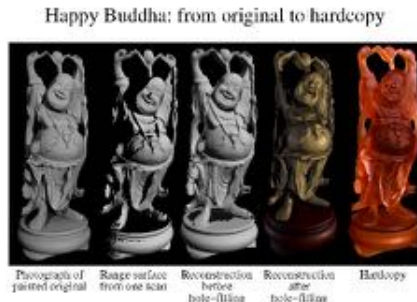


Implicit Surface

Distance functions



Local tangent plane + MST
Hoppe et.al. SIGGRAPH1992



Happy Buddha: from original to hardcopy

Line of sight distance weighted
Curless & Levoy. SIGGRAPH1996

Radial basis functions (RBF)

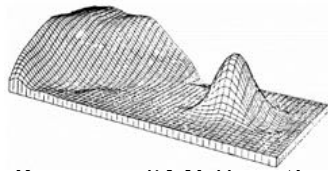


RBF approximation
Carr et.al. SIGGRAPH2001

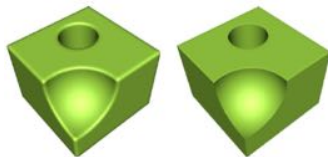


Multi-level partition of unity
Ohtake et.al. SIGGRAPH2003

Moving Least-squares (MLS)



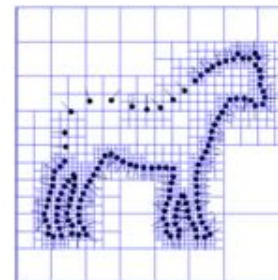
Pioneer of MLS method
Lancaster and Salkauskas. 1981



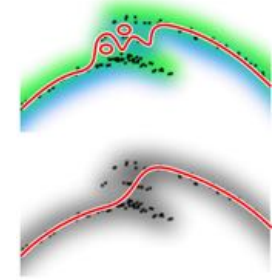
Least-MEDIAN-of-squares
Fleishman et.al. SIGGRAPH2005



Interactive, constrained
Shen et.al. SIGGRAPH2004



Poisson Surface
Kazhdan et.al. SGP2006



Signed distance function
Hornung & Kobbelt. SGP2006



Implicit Surface: Poisson method

- Reconstruct the surface of the model by solving for the indicator function of the shape.

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



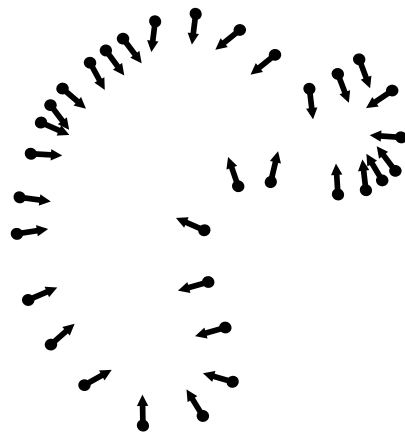
Indicator function

χ_M

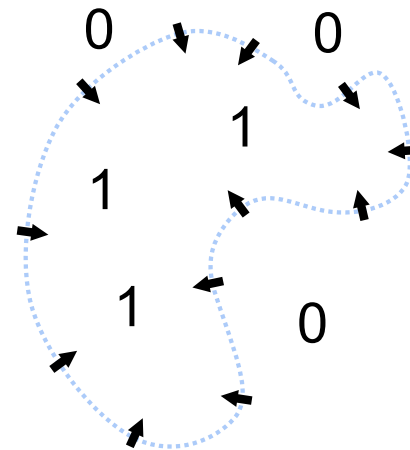
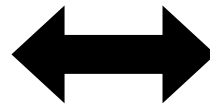


Implicit Surface: Poisson method

- There is a relationship between the normal field and gradient of indicator function



points + oriented normals



Indicator gradient
 $\nabla \chi_M$



Implicit Surface: Poisson method

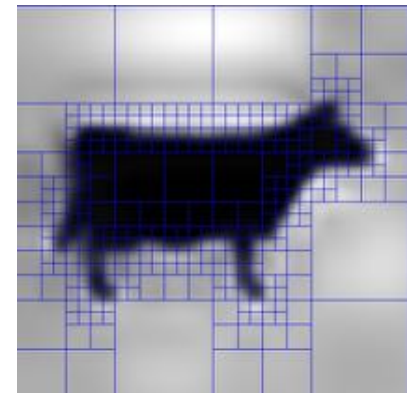
- Represent the points by a vector field \vec{V}
- Find the function χ whose gradient best approximates \vec{V} :

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

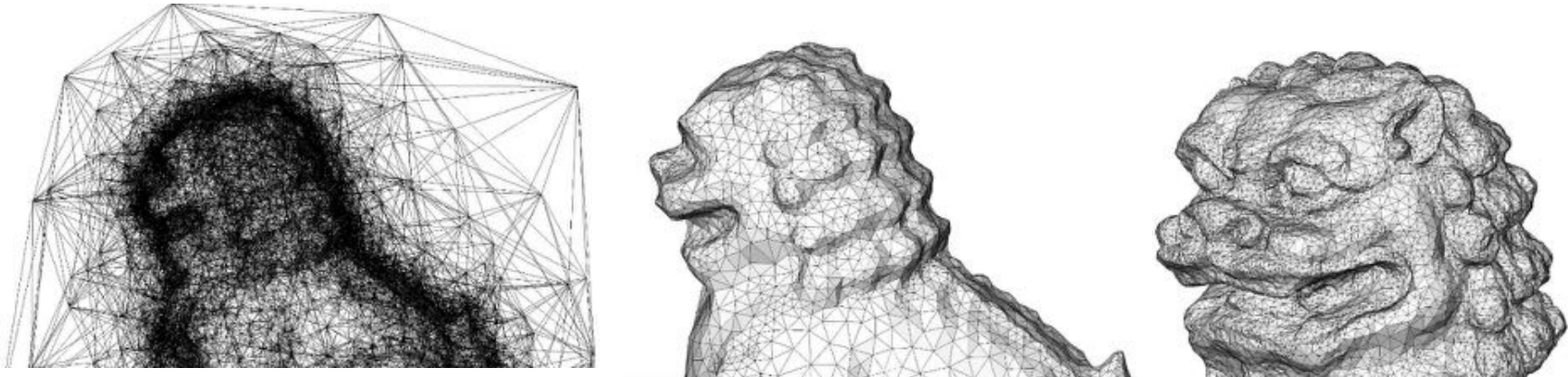
- Applying the divergence operator, we can transform this into a **Poisson** problem:

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

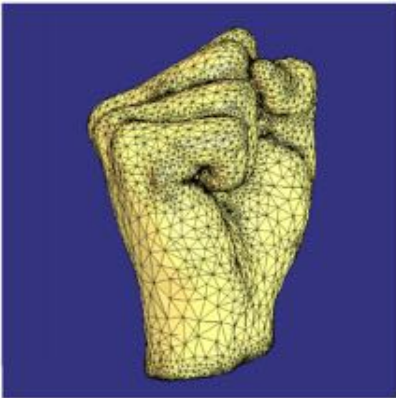
- Discretize from coarse-to-fine over an octree.



Delaunay method



Points \rightarrow Delaunay tetrahedron \rightarrow Mesh surface



Power Crust

Amata et.al. SIGGRAPH1998



Robust Cocone

Dey & Goswami. SoSMA2003



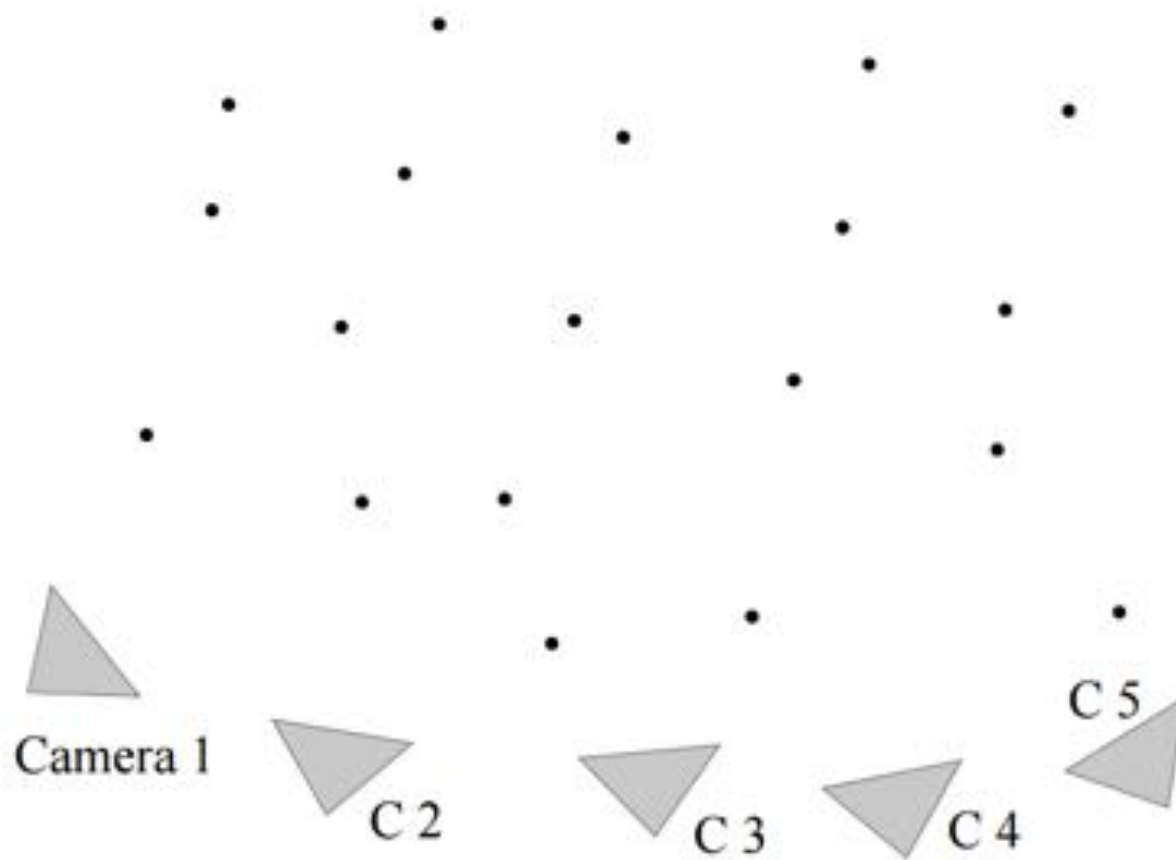
Visibility-consistent

Vu et.al. PAMI2012



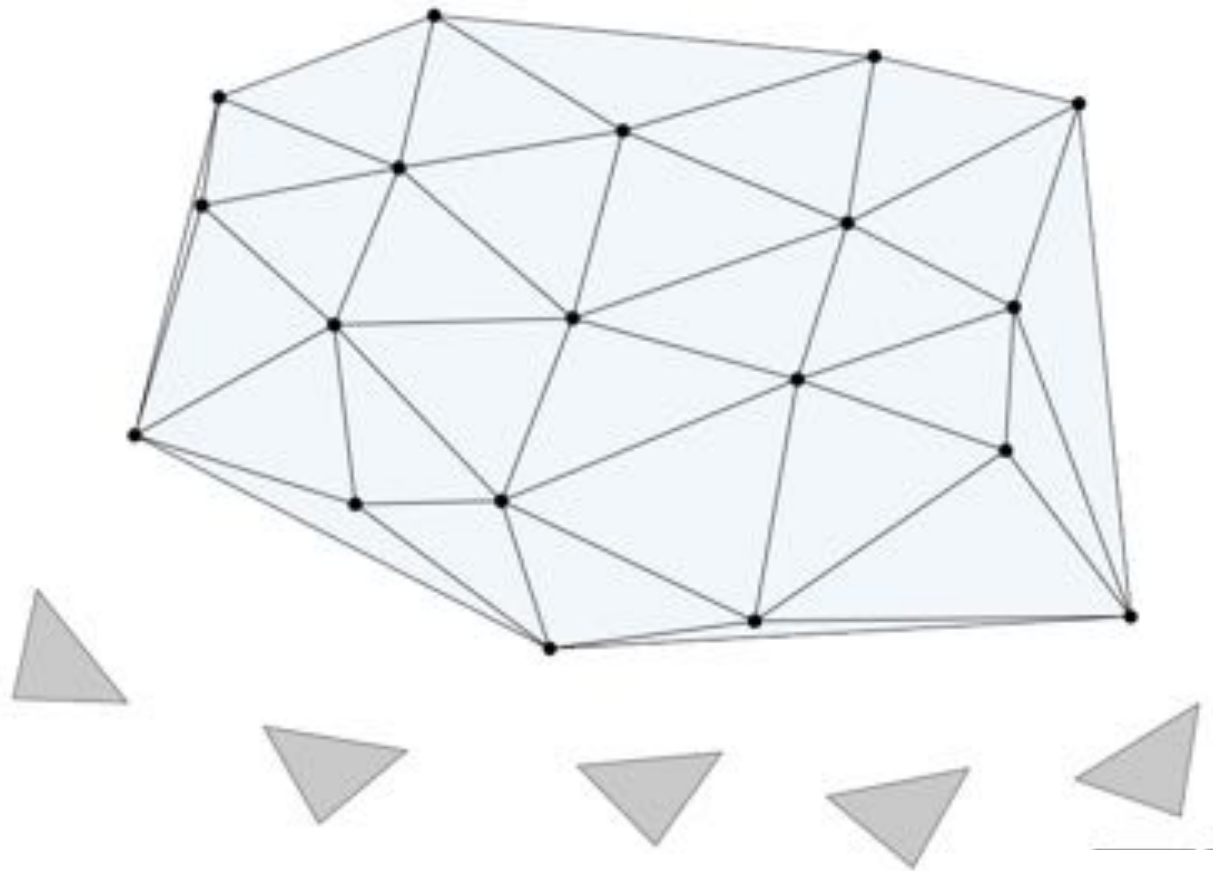
Delaunay method: visibility-consistent

Point cloud reconstructed by multi-view images



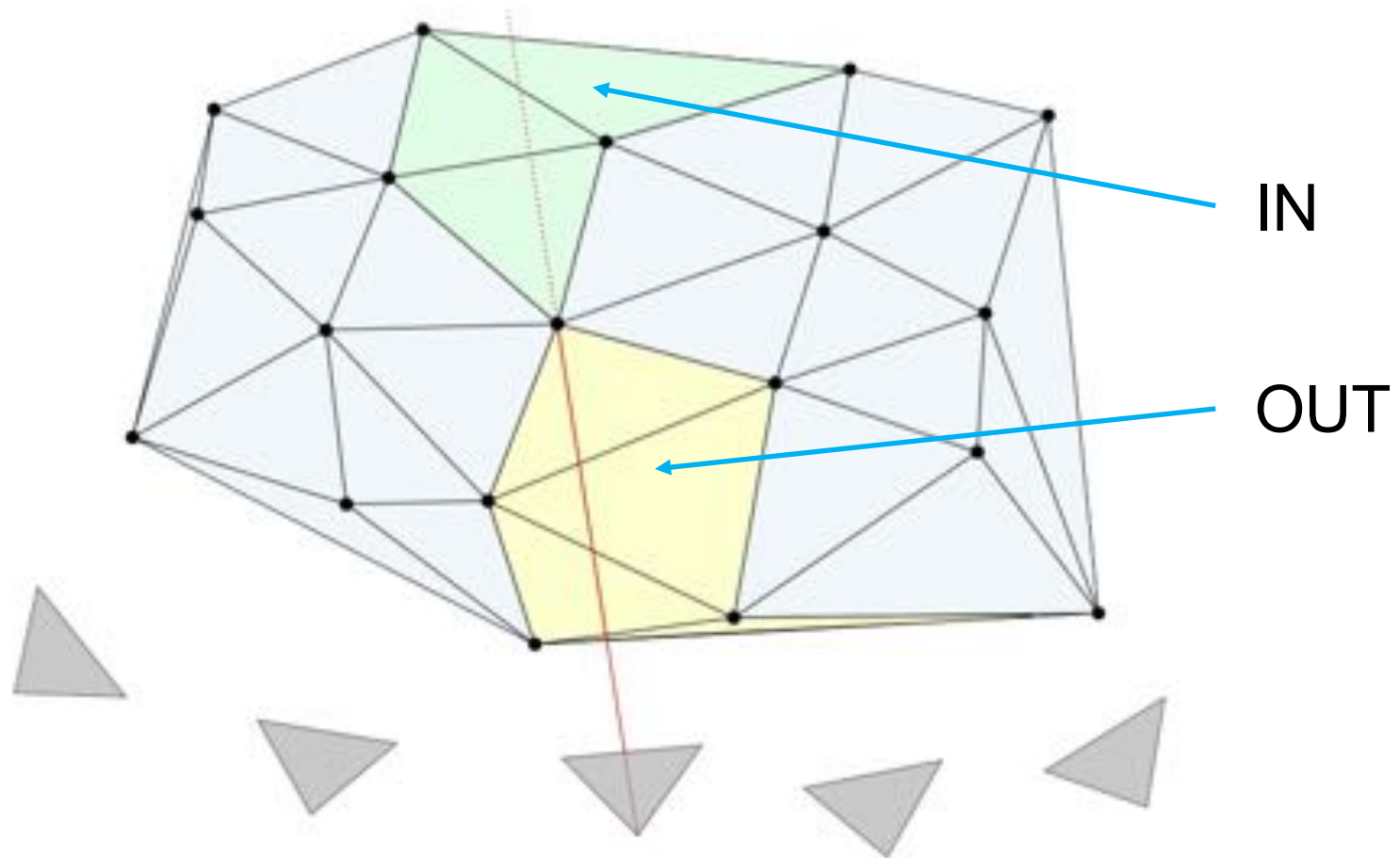
Delaunay method: visibility-consistent

Delaunay Triangulation of Point cloud



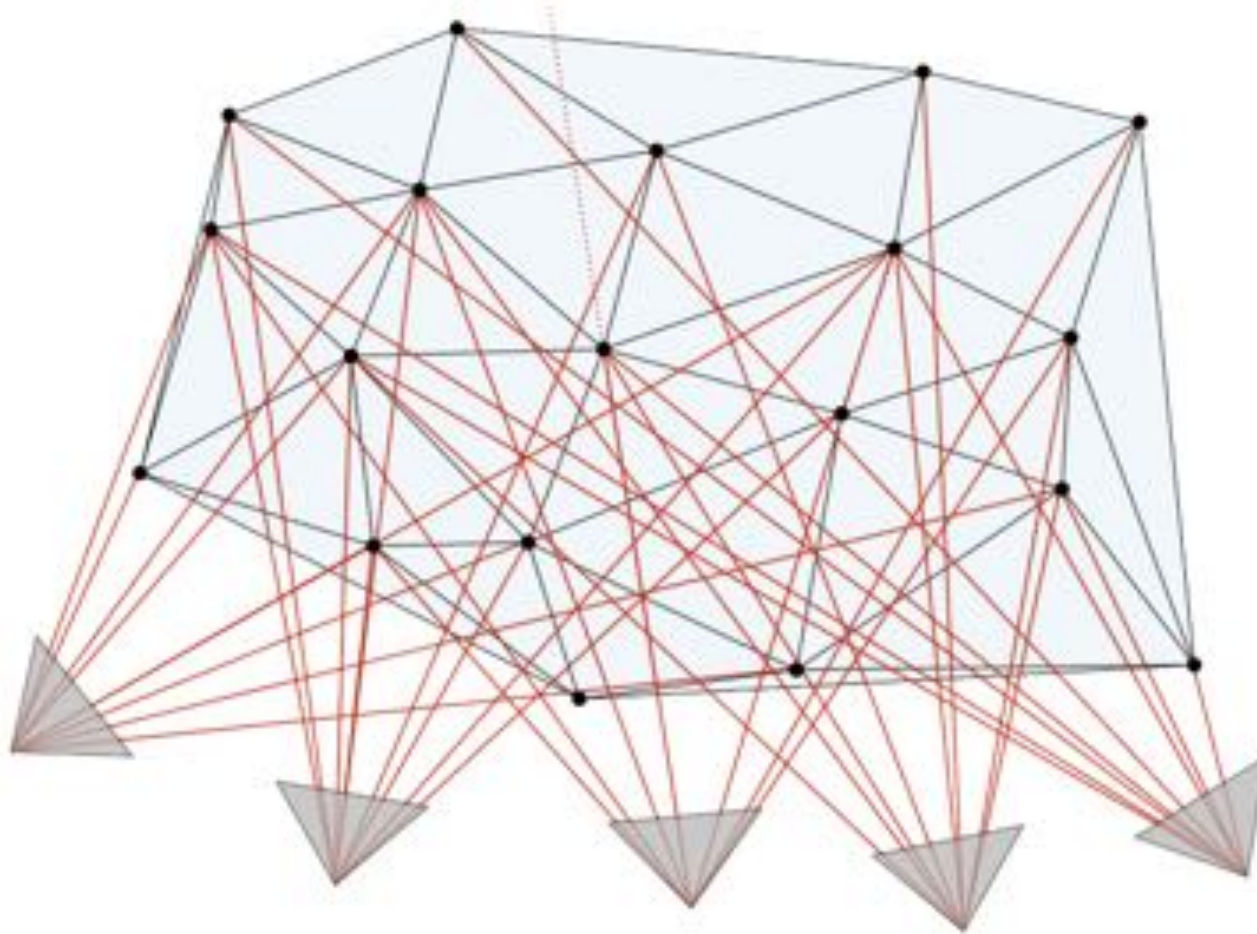
Delaunay method: visibility-consistent

Visibility of a vertex, labeling the tetrahedra



Delaunay method: visibility-consistent

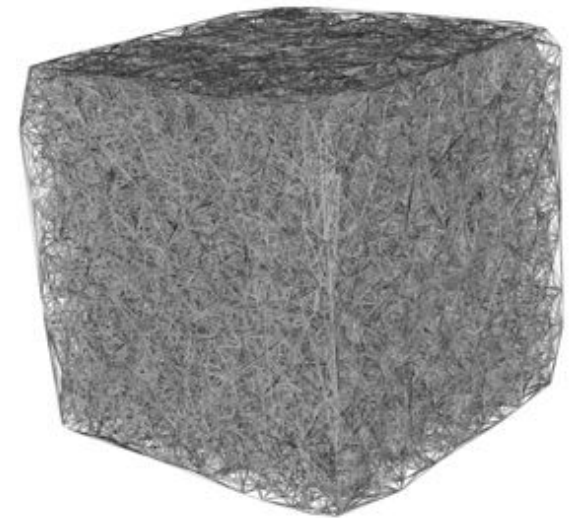
Visibility conflicts



Delaunay method: visibility-consistent

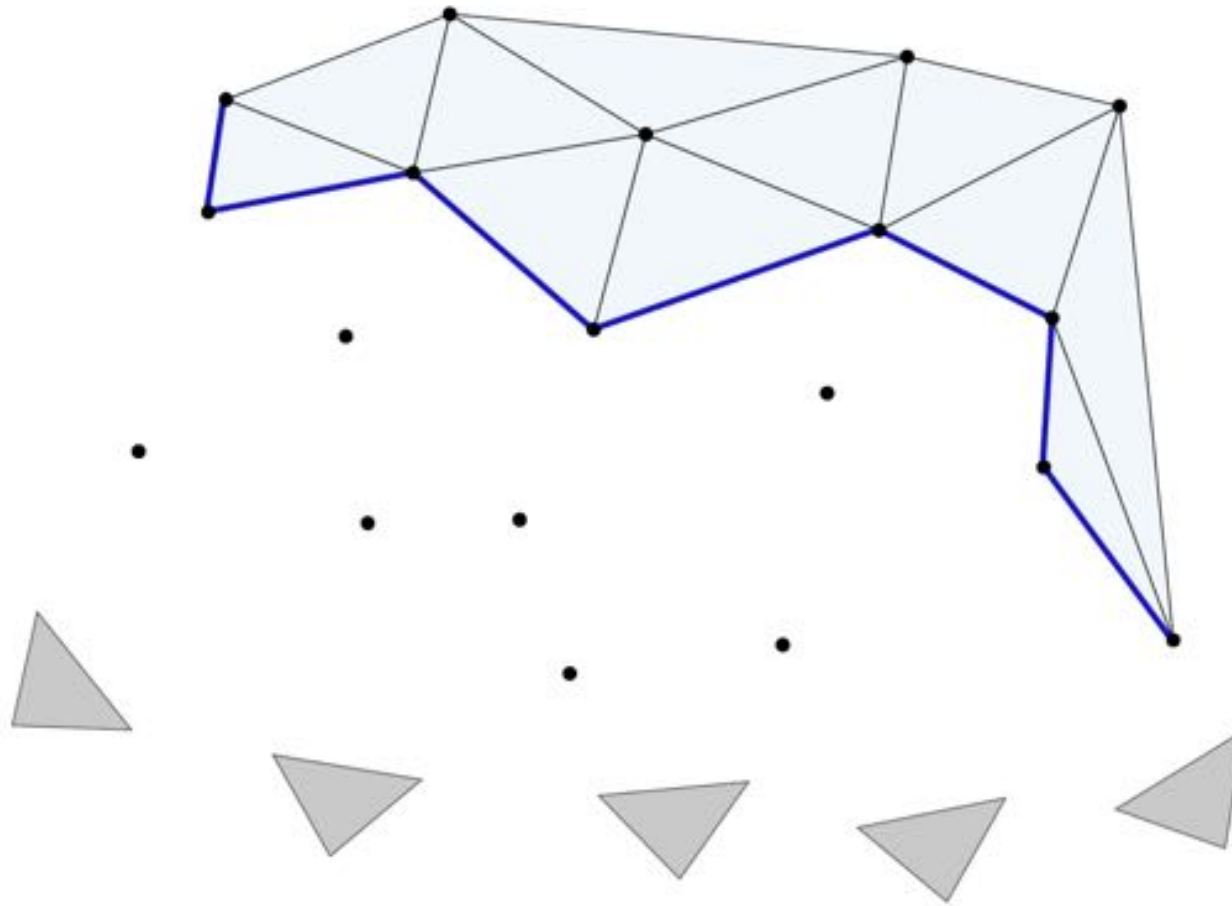
Extract a mesh surface from tetrahedron

- A tetrahedron is a graph
 - Every tetrahedral (cell) is a node
 - Linking the source and sink by visibility
 - Smoothness by neighboring relations
 - Additional terms
 - Surface area
 - Photo-consistency
- Energy minimization via Graph Cuts



Delaunay method: visibility-consistent

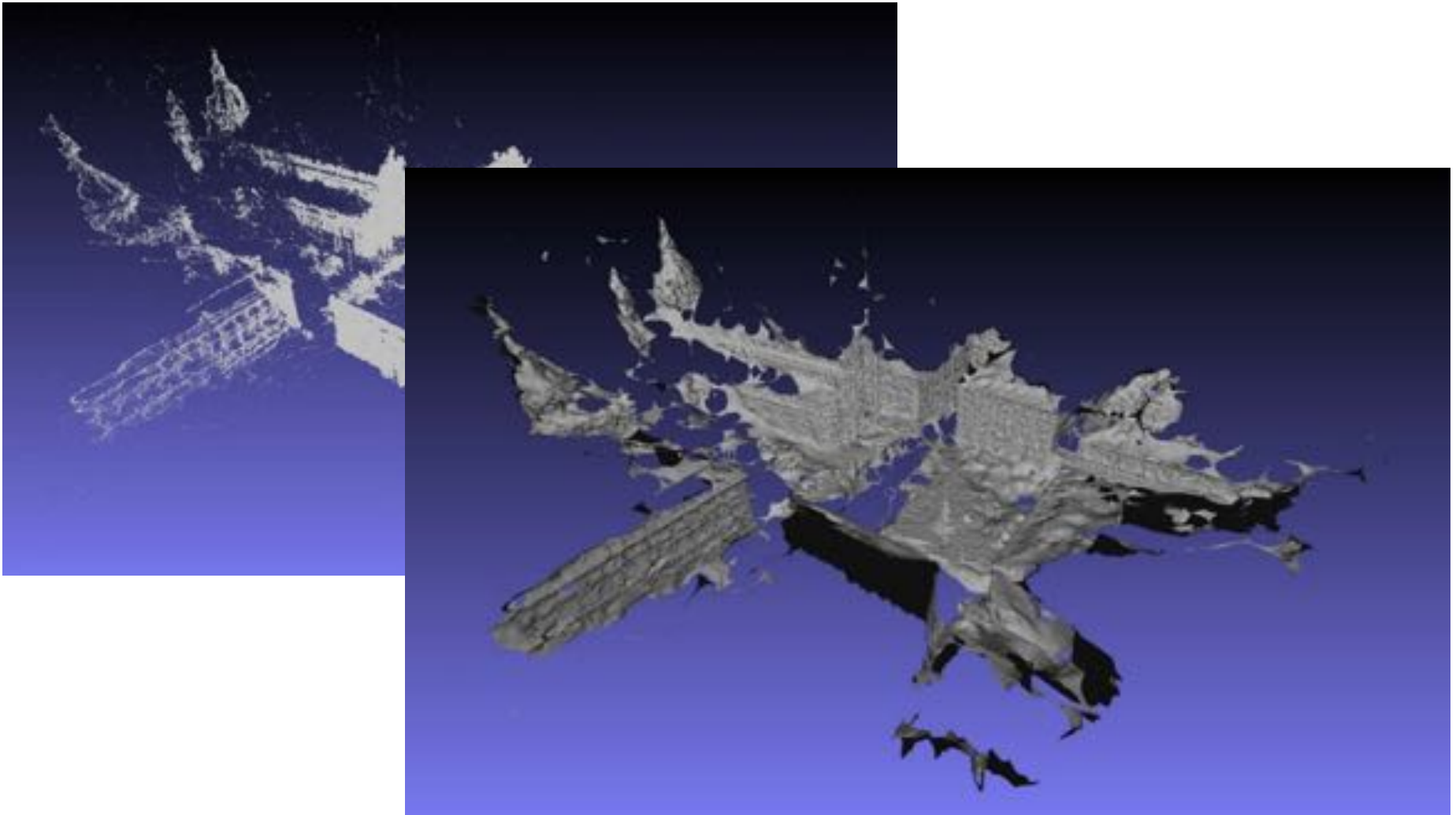
Mesh surface as the boundary between IN and OUT



Delaunay method: visibility-consistent

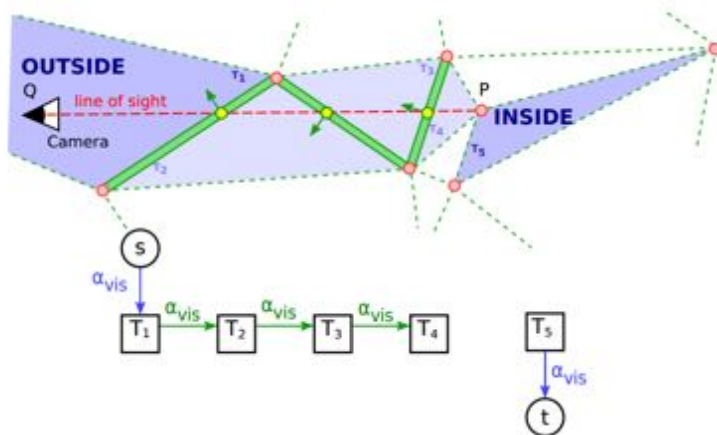


Delaunay method: visibility-consistent

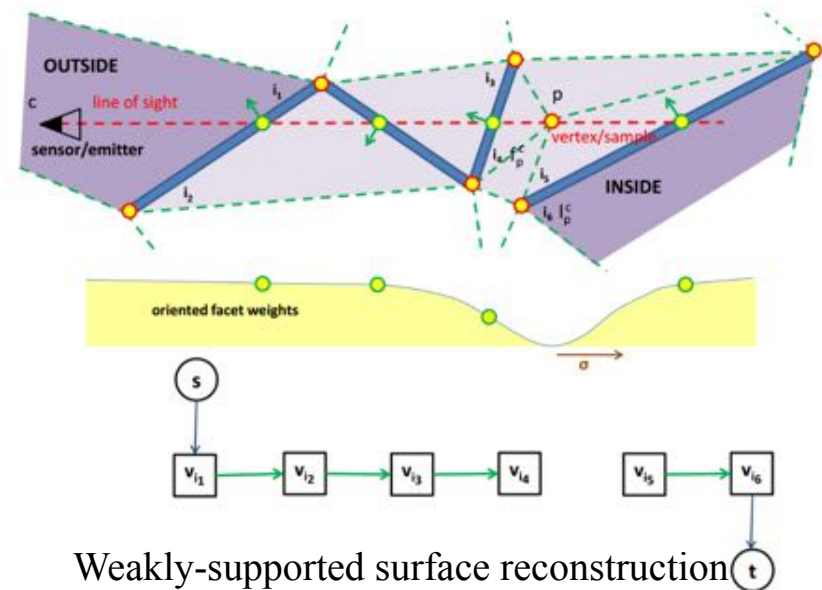


Delaunay method: visibility-consistent EXT

Preserving weakly supported surface



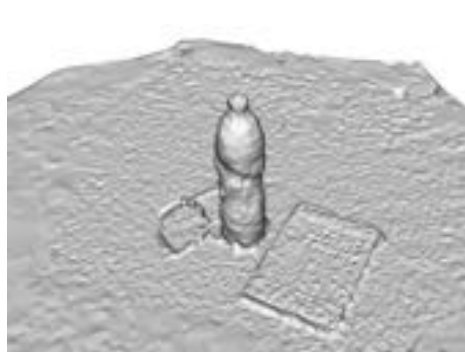
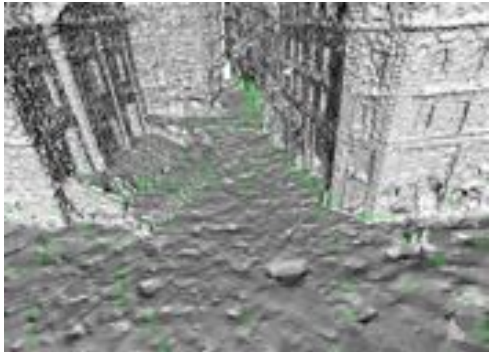
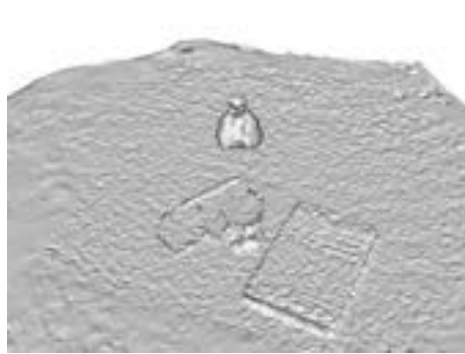
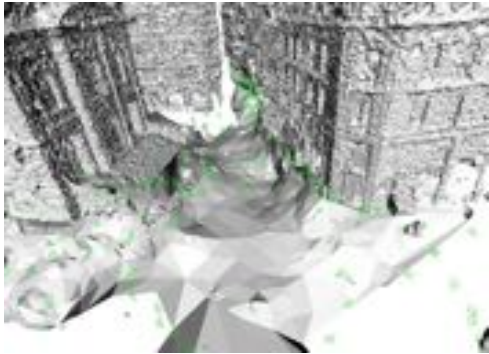
Visibility-consistent surface reconstruction
Vu et.al. PAMI2012



Weakly-supported surface reconstruction
Jancosek & Pajdla. CVPR2013



Surface extraction from point cloud



Weakly-supported surface reconstruction
Jancosek & Pajdla. CVPR2013
Visibility-consistent surface reconstruction
Vu et.al. PAMI2012

Surface refinement: crucial to high accuracy!



input images



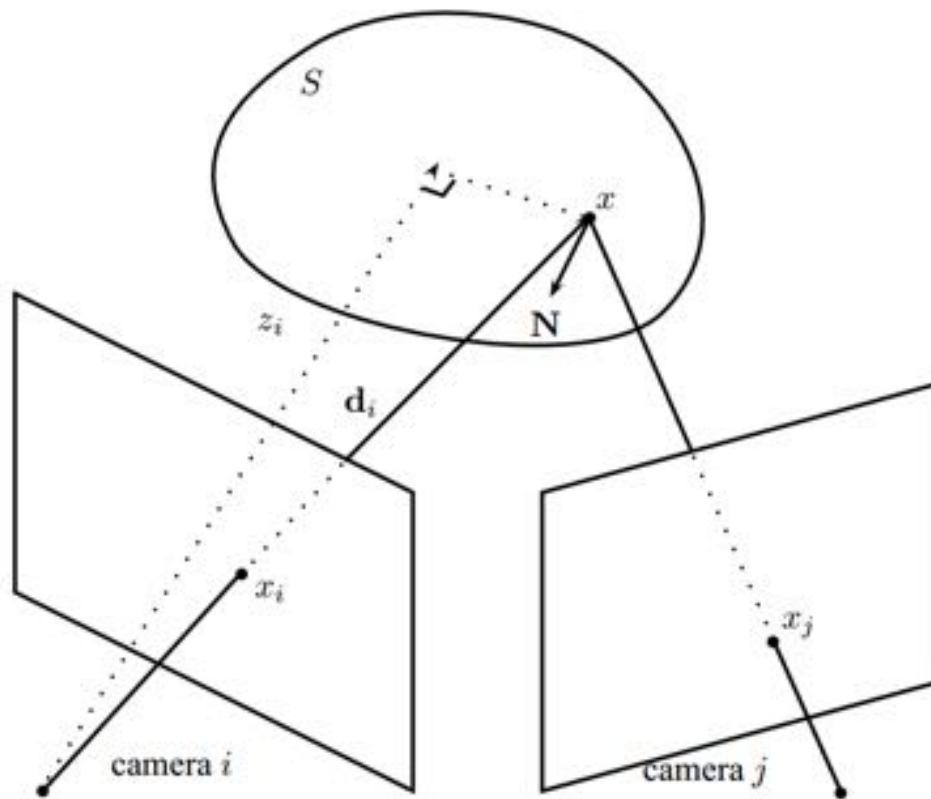
initial surface



Refined surface

dataset: Cluny-161-Small

Surface refinement: formulation



Minimizing the error between the observed **image i** and **reprojection of image j** :

$$E_{\text{error}}(S) = \sum_{i,j} \int_{\Omega_{ij}^S} h(I_i, I_{ij}^S)(x_i) dx_i$$

- Ill-posed, difficult to solve directly
 - Local minima
 - Bad initialization
- Can be modeled via *variational methods*

Variational surface refinement
Vu et.al. PAMI2012

Surface refinement: formulation

Continuous (level-set)

Discretized (triangular mesh)

Energy
formulation

$$\mathcal{M}(S) = \sum_i \sum_{j \neq i} \mathcal{M}_{ij}(S),$$

$$\mathcal{M}_{ij}(S) = \frac{M}{|\Omega_i \cap \Pi_i(S_j)|} \left(\underbrace{I_i}_{\text{similarity measure}}, \underbrace{I_j \circ \Pi_j \circ \Pi_{i,S}^{-1}}_{\text{reprojection image } j} \right).$$

observed image i

$$E_{\text{error}}(S) = \sum_{i,j} \int_{\Omega_{ij}^S} \overset{\text{similarity measure}}{h(I_i, I_{ij}^S)}(x_i) dx_i$$

observed image i reprojection image j

Variations/
derivative

$$\left. \frac{\partial \mathcal{M}_{ij}(S + \epsilon \delta S)}{\partial \epsilon} \right|_{\epsilon=0} = - \int_{S_i \cap S_j} \left[\partial_2 M(\mathbf{x}_i) D I_j(\mathbf{x}_j) D \Pi_j(\mathbf{x}) \frac{\mathbf{d}_i}{z_i^3} \right] [\mathbf{N}^T \delta S(\mathbf{x})] d\mathbf{x}.$$

$$\frac{dE_{\text{error}}(S)}{dX} = \int_S \phi(x) \sum_{i,j} \nabla \mathcal{M}_{ij}(x) dx$$

$$= \sum_{i,j} \int_{\Omega_{ij}} \phi(x) f_{ij}(x_i) / (\mathbf{N}^T \mathbf{d}_i) \mathbf{N} dx_i$$

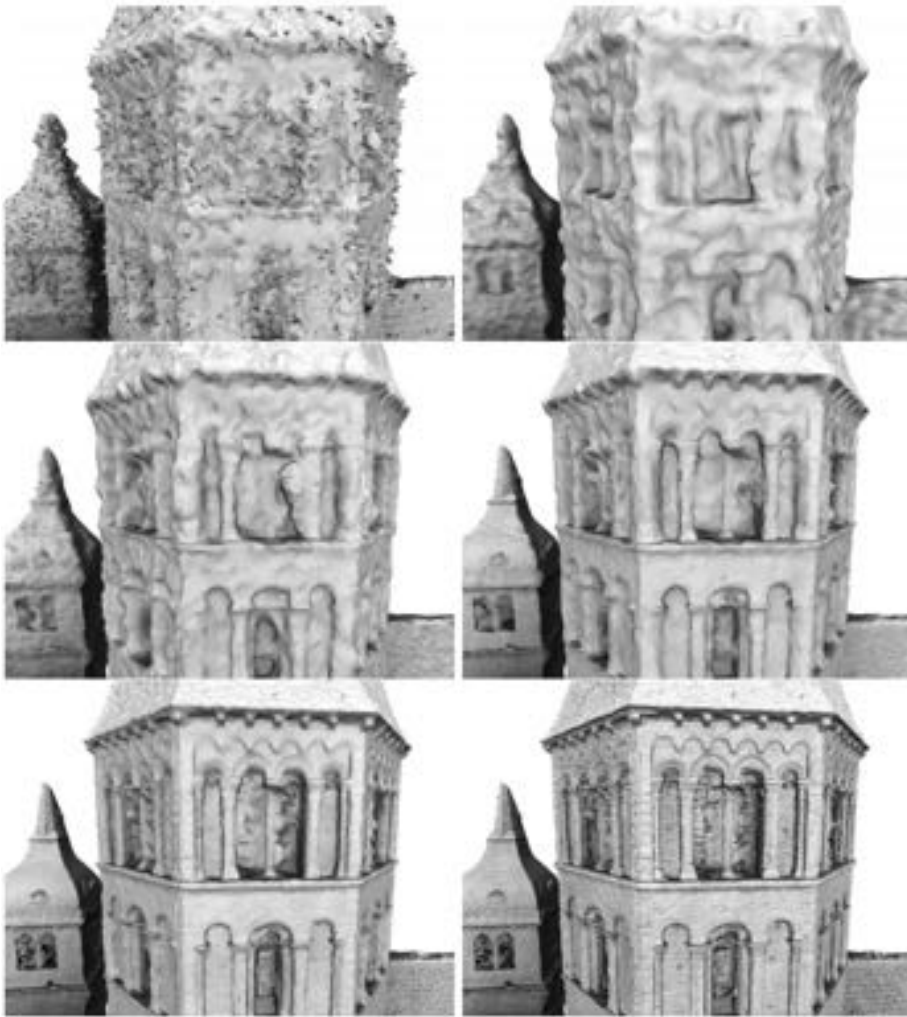
Regularization

$$E_{\text{fair}}(S) = \int_S (\kappa_1^2 + \kappa_2^2) dS$$

Umbrella operator on mesh



Surface refinement: results



Top to bottom: evolution of iterative refinement



Refinement recovers the fine details of the scene

Variational surface refinement
Vu et.al. PAMI2012



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Surface refinement: problems?

- Iterative, repeated computations of
 - visibility
 - image reprojection
 - image similarity



Surface refinement: problems?

- Iterative, repeated computations of
 - visibility
 - image reprojection
 - image similarity
- Not all regions contribute equally
 - Potential regions may gain details



- A flat plane is still a flat plane



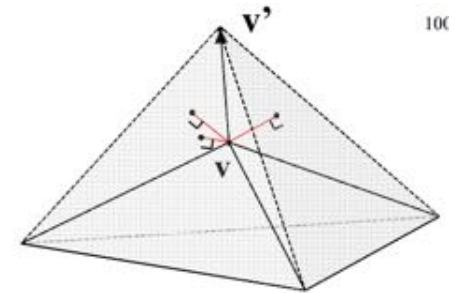
Surface refinement: adaptive refinement

1. Evaluate the importance of a vertex movement

$$gc_v = \max_{\mathbf{p} \in \text{planes}(\mathbf{v}')} \{(\mathbf{p}^t \mathbf{v})^2\}$$

$$gc_t = \frac{1}{3} \sum g_{c_{v_i}},$$

where $\mathbf{p} = [a \ b \ c \ d]^t$ represents a plane and $\mathbf{v}' = [v'_x \ v'_y \ v'_z \ 1]$.



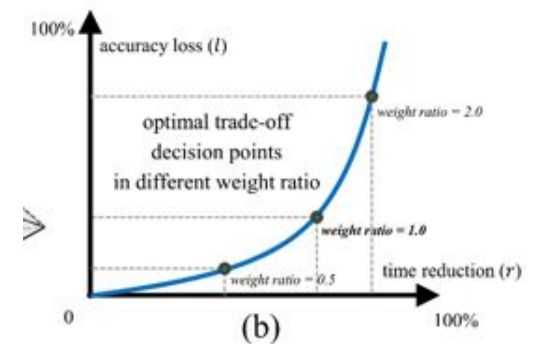
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2. Optimal trade-off between accuracy & efficiency

$$u(r_o, l_o) = \max_{(r,l) \in \text{curve}} u(r, l)$$

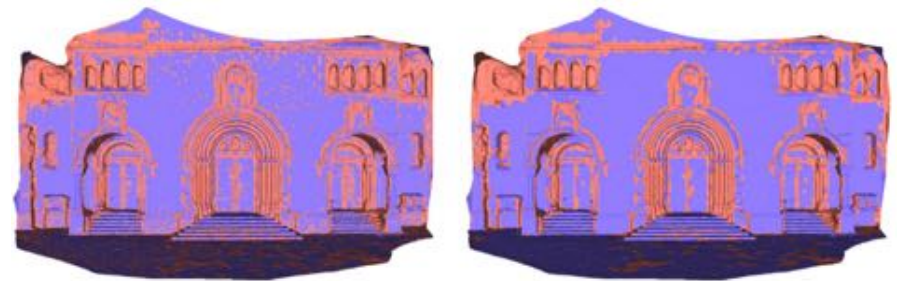
$$u(r, l) = u(r) + u(l)$$

$$= w_r \cdot r + w_l \cdot (1 - l)$$

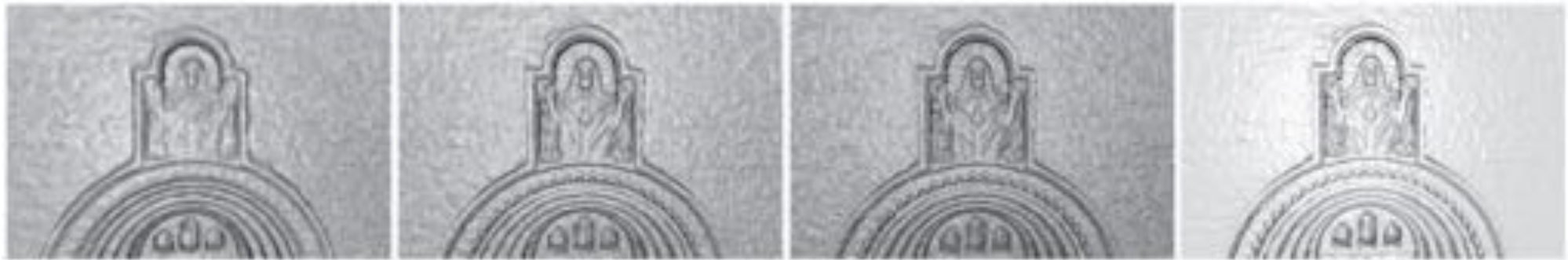


3. Graph cuts optimization

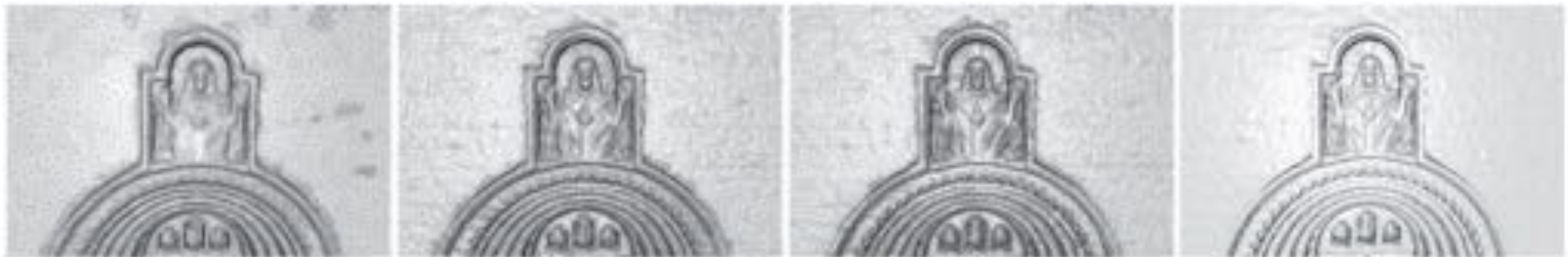
$$\mathbf{E}(f) = \mathbf{E}_{\text{optimality}}(f) + \mathbf{E}_{\text{smoothness}}(f) + \mathbf{E}_{\text{prior}}(f).$$



Surface refinement: adaptive refinement



Uniform refinement, Vu et.al. PAMI2012



5th iteration

10th iteration

15th iteration

Final mesh

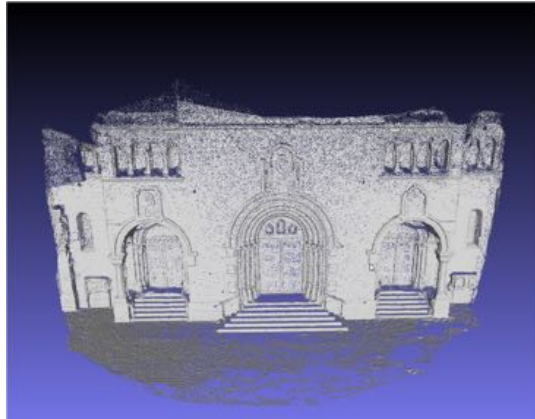
Adaptive refinement, our method

- Adaptive refinement
 - ~**5x more efficient** than uniform refinement
 - much more compact mesh
 - Similar reconstruction details.



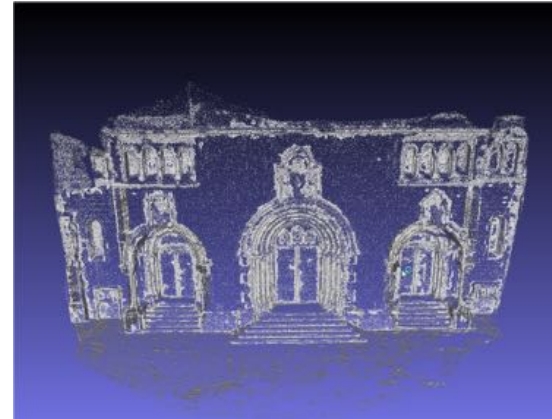
Surface refinement: adaptive refinement

Uniform refinement



2,414,767 #vertex, 4,829,450 #triangle

Adaptive refinement



817,254 #vertex, 1,592,022 #triangle



Herz-Jesu-P25



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Content

- Multi-view Stereo
 - Pairwise Stereo
 - Propagation Stereo
- Surface generation
 - Surface extraction
 - Surface refinement
- Texture mapping
 - View selection
 - Color adjustment and blending



Texture mapping (for 3D reconstruction)

- Texturing a point cloud
 - Trivial, directly fetch color from image for every 3D point
- Texturing a triangular mesh surface
 - Non-trivial
 - Triangle view selection
 - For each triangle, select its best image for texture (data term)
 - Minimize number of texture seam (smoothness term)
 - Color adjustment and blending
 - Alleviate the artifacts at seams between two texture patches (atlas), due to inaccurate camera or imbalance illumination

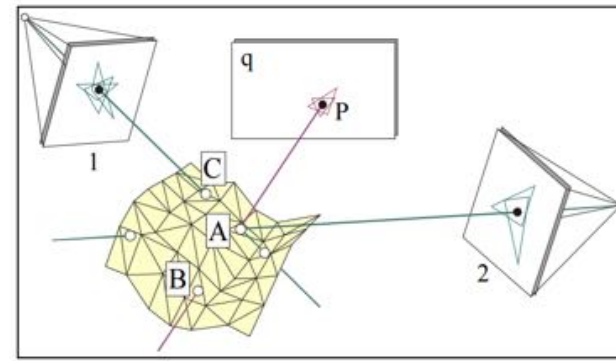


Texture mapping: Triangle view selection

- For each triangle, select multiple view

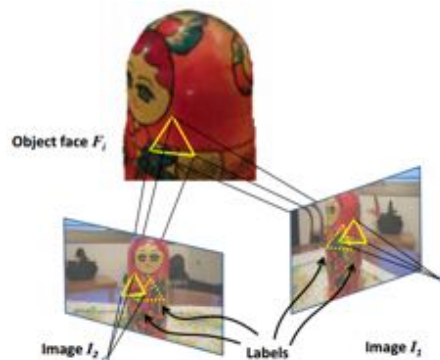


blending multiple image
Callieri et.al. CG2008

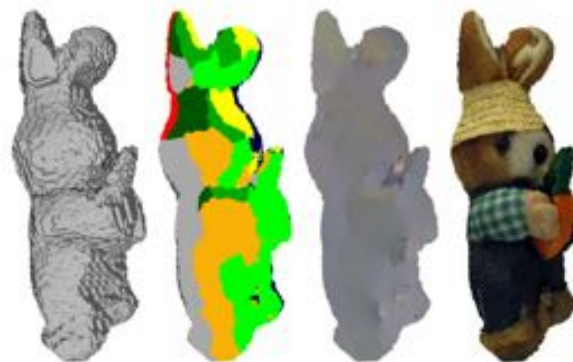


Color interpolation
Grammatikopoulos et.al. ISPRS2007

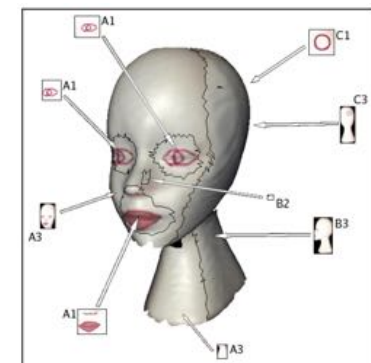
- For each triangle, select one best view



Seam optimization
Gal et.al. CG2010



MRF+Poisson blending
Lempitsky & Ivanov. CVPR2007



Continuous color optimization
Velho & Sossai. CVPR2007



Texture mapping: Triangle view selection

- Triangle view selection as a MRF problem

$$E(l) = \sum_{F_i \in Faces} E_{data}(F_i, l_i) + \sum_{(F_i, F_j) \in Edges} E_{smooth}(F_i, F_j, l_i, l_j),$$

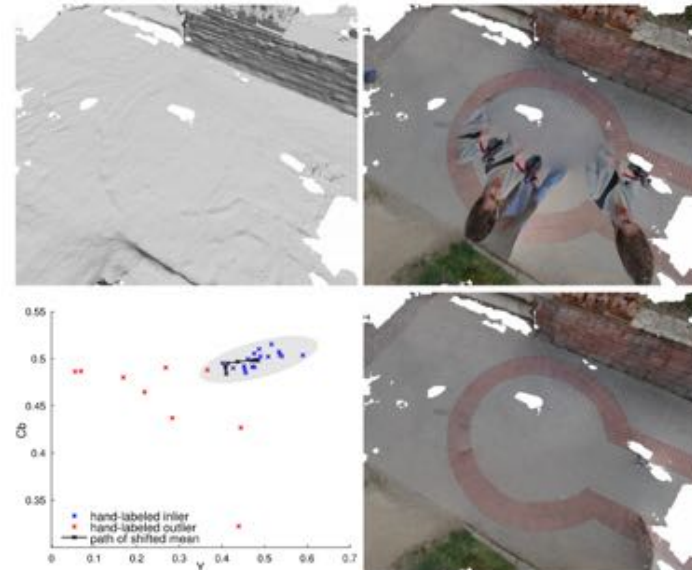
- Each triangle selects a best view
 - Neighboring triangles select same view
- Solved by alpha expansion



Texture mapping: Triangle view selection

- Difficulties:
 - dynamic objects

Handle by photo-consistency check and outlier removal



- out-of-focus image

Handle by weighting the gradient magnitude



Large-scale texturing. Waechter et.al. ECCV2014



Texture mapping: Color adjustment and blending

- Let f be the original intensity, g be the adjustment (gain)

$$\arg \min_g \sum_{v_{left/right}} (f_{v_{left}} + g_{v_{left}} - (f_{v_{right}} + g_{v_{right}}))^2 + \frac{1}{\lambda} \sum_{i,j} (g_i - g_j),$$

- Minimize the difference of neighboring intensity
- Minimize the imposed adjustment (be as much original as possible)

- Blending

- Alpha blending causes ghosting effect
- Poisson blending:



Poisson Image Editing
Perez et.al. SIGGRAPH2003



Unsolved problems and future work

- **local camera optimization** for MVS
 - SfM computes globally optimized camera, which is not locally optimized
 - Inaccurate camera is detrimental
 - Related work: (Zhu et.al. CVPR2014)
- Simultaneously surface **refinement** + **texturing**
 - Repeated computations of depth, visibility, etc.
 - Not an end-to-end optimization
 - Optimize the surface **geometry** and **textures**, for the rendering photo-realism
- **Fine-scale object** reconstruction (such sticks, wire)
 - Due to sparse point cloud at that objects
 - Can be improved by more structural point cloud, such as adding connectivity information

