Part C
Applications to Computer Vision problems

Florent Lafarge

Outlines

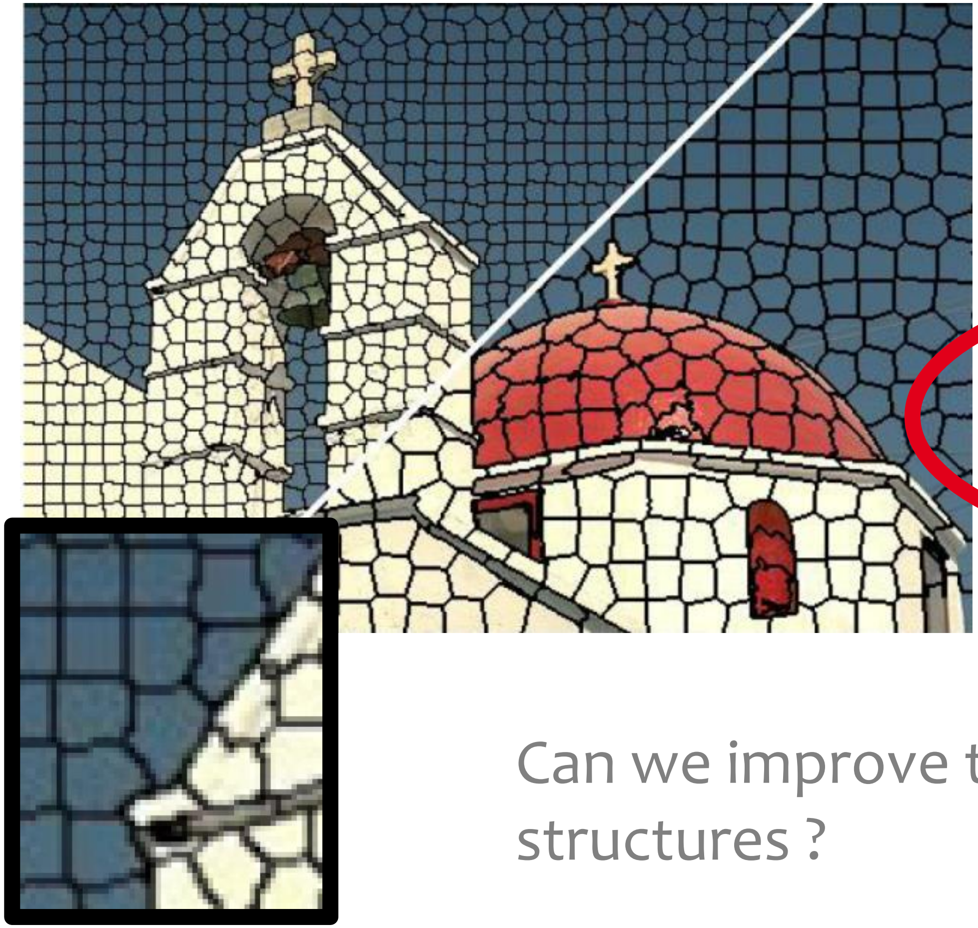
Image segmentation (Voronoi diagrams)

MultiView Stereo (Delaunay triangulations)

Urban reconstruction (3D arrangments)

1
Image segmentation

Superpixels

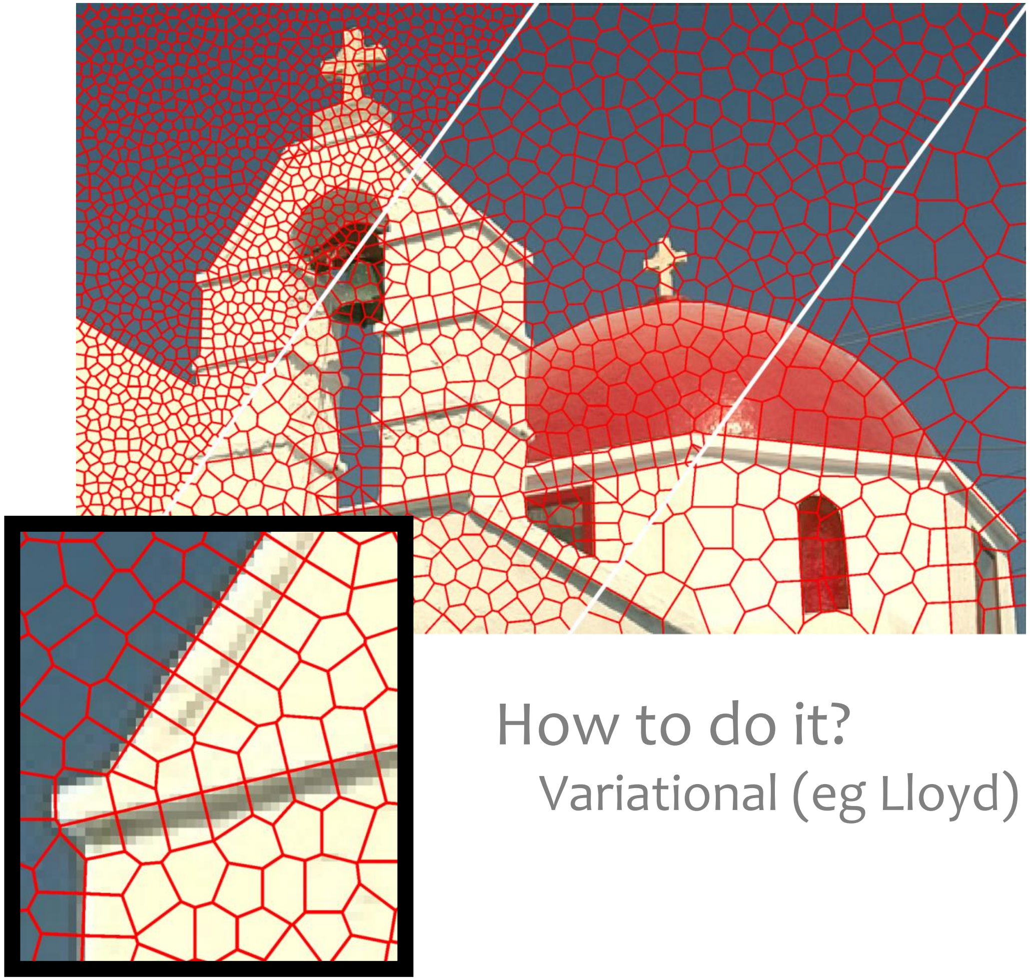


Over-segmentation of images

- ✓ contour preservation
- ✓ algorithmic complexity
- ✗ storage
- ✗ control on region shapes
- ✗ region adjacency

Can we improve this with geometric data-structures ?

Superpixels as Voronoi cells



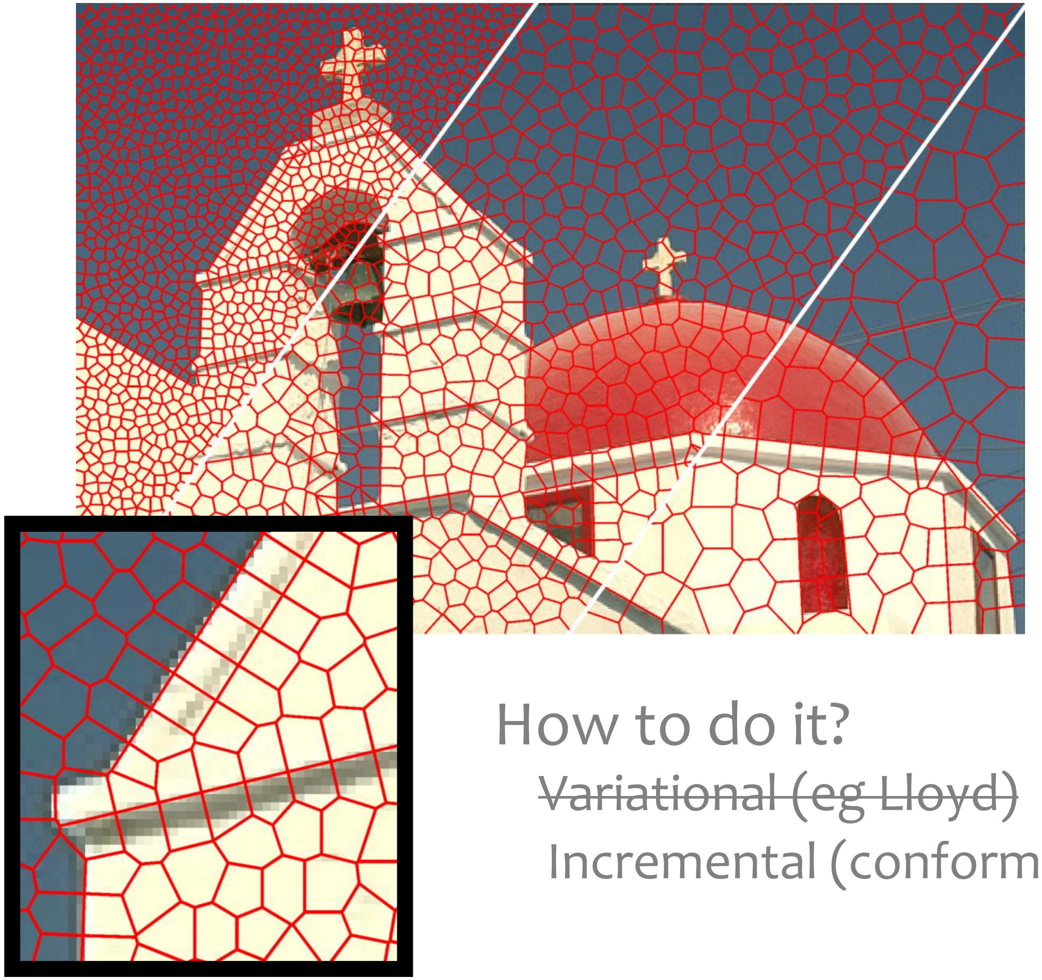
✓ storage
(2D Delaunay triangulation)

✓ control on region shapes
(convex polygons)

✓ region adjacency
(uniqueness)

How to do it?
Variational (eg Lloyd)

Superpixels as Voronoi cells



✓ storage
(2D Delaunay triangulation)

✓ control on region shapes
(convex polygons)

✓ region adjacency
(uniqueness)

How to do it?

~~Variational (eg Lloyd)~~

Incremental (conforming diagrams to geometric shapes)

Voronoi-based Image partitioning

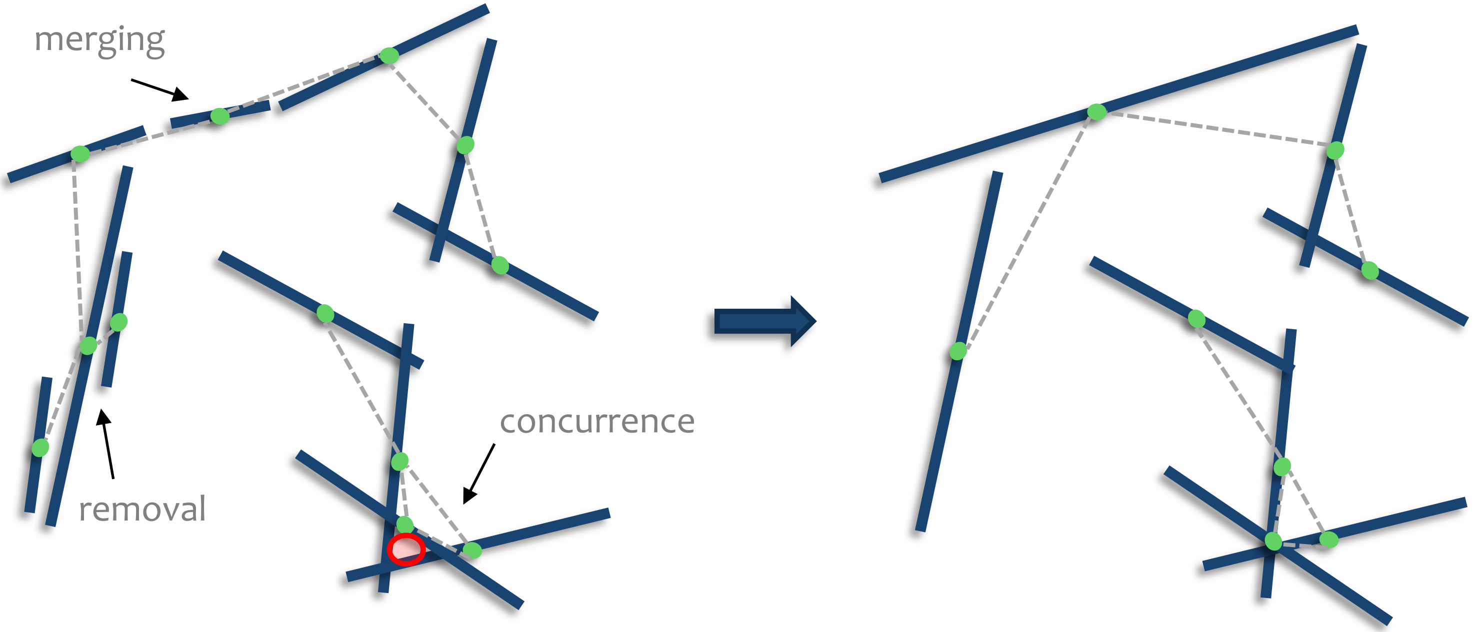
[Duan and Lafarge, Partitioning images into convex polygons, CVPR 2015]

Step 1: extraction of geometric shapes

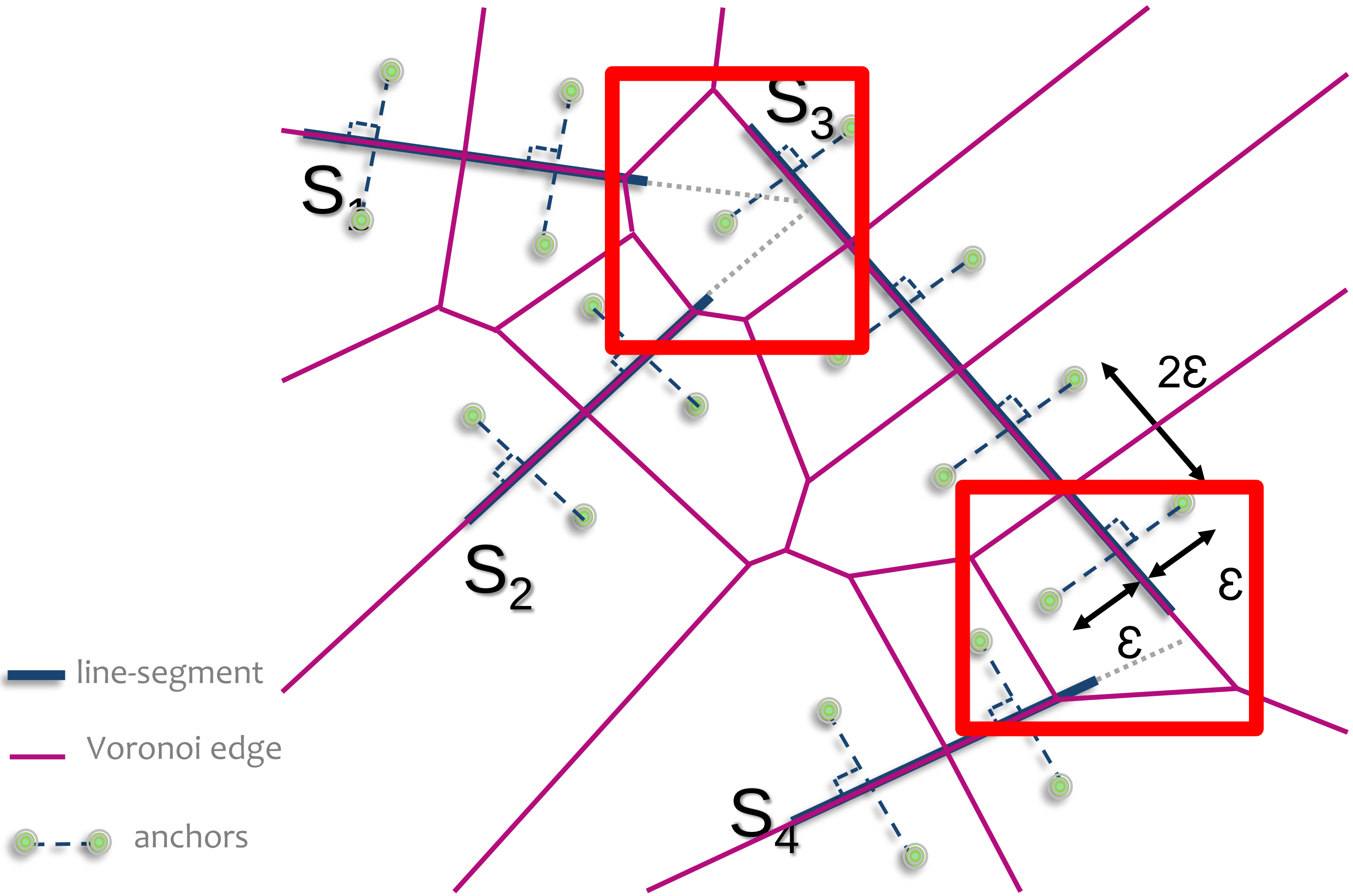
Detection of line-segments

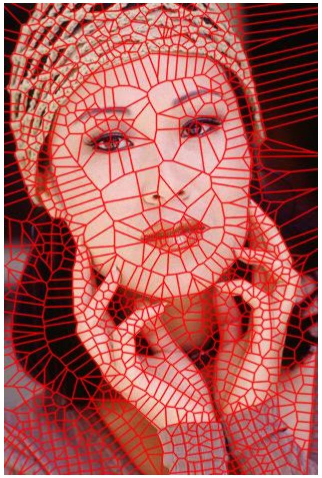
[Von Gioi et al., Lsd: A fast line segment detector with a false detection control, PAMI 2010]

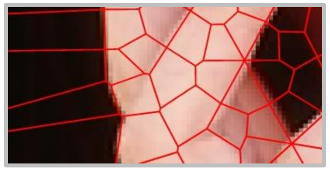
Consolidation of line-segments



Step 2: anchoring







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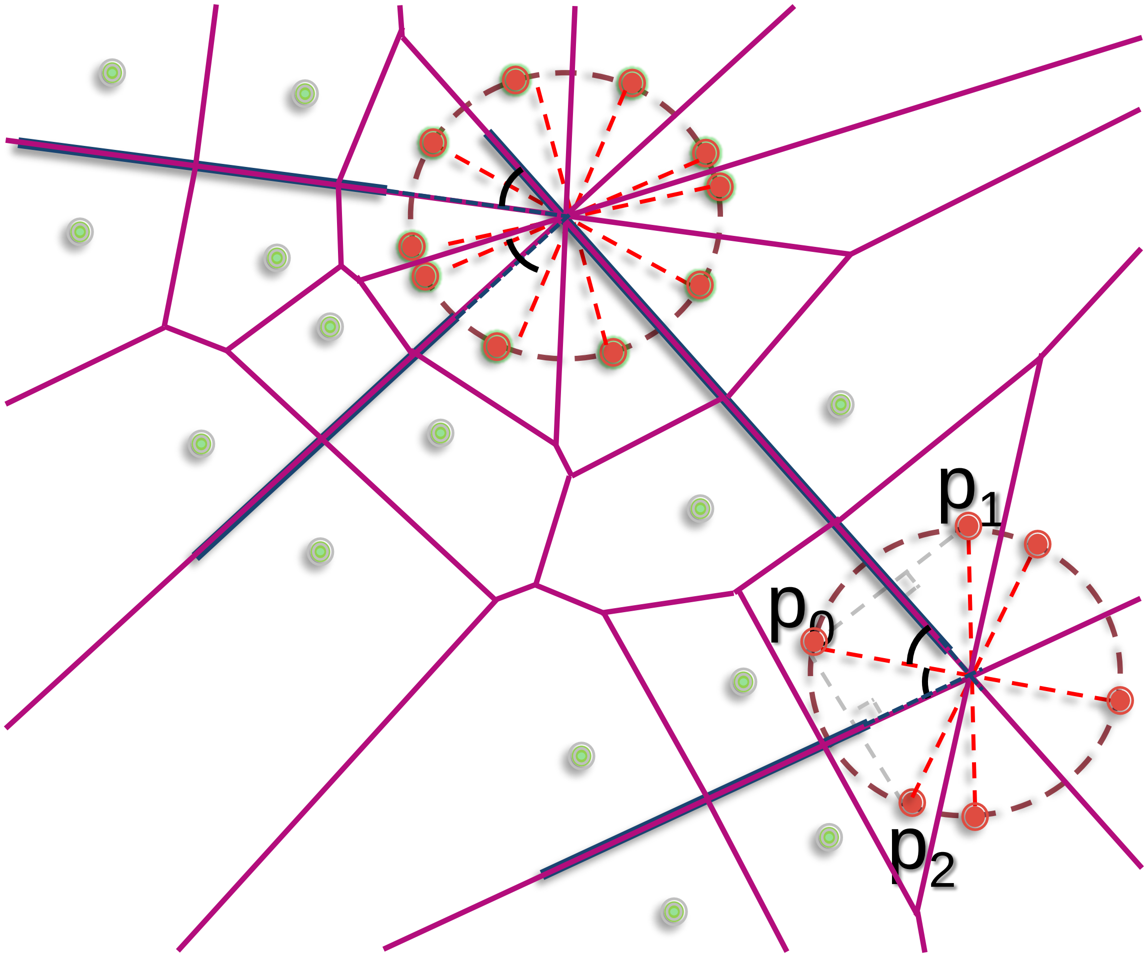
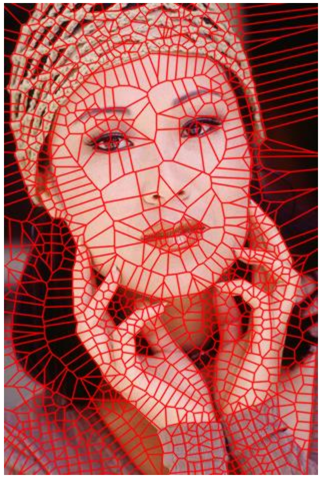
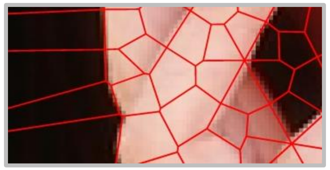






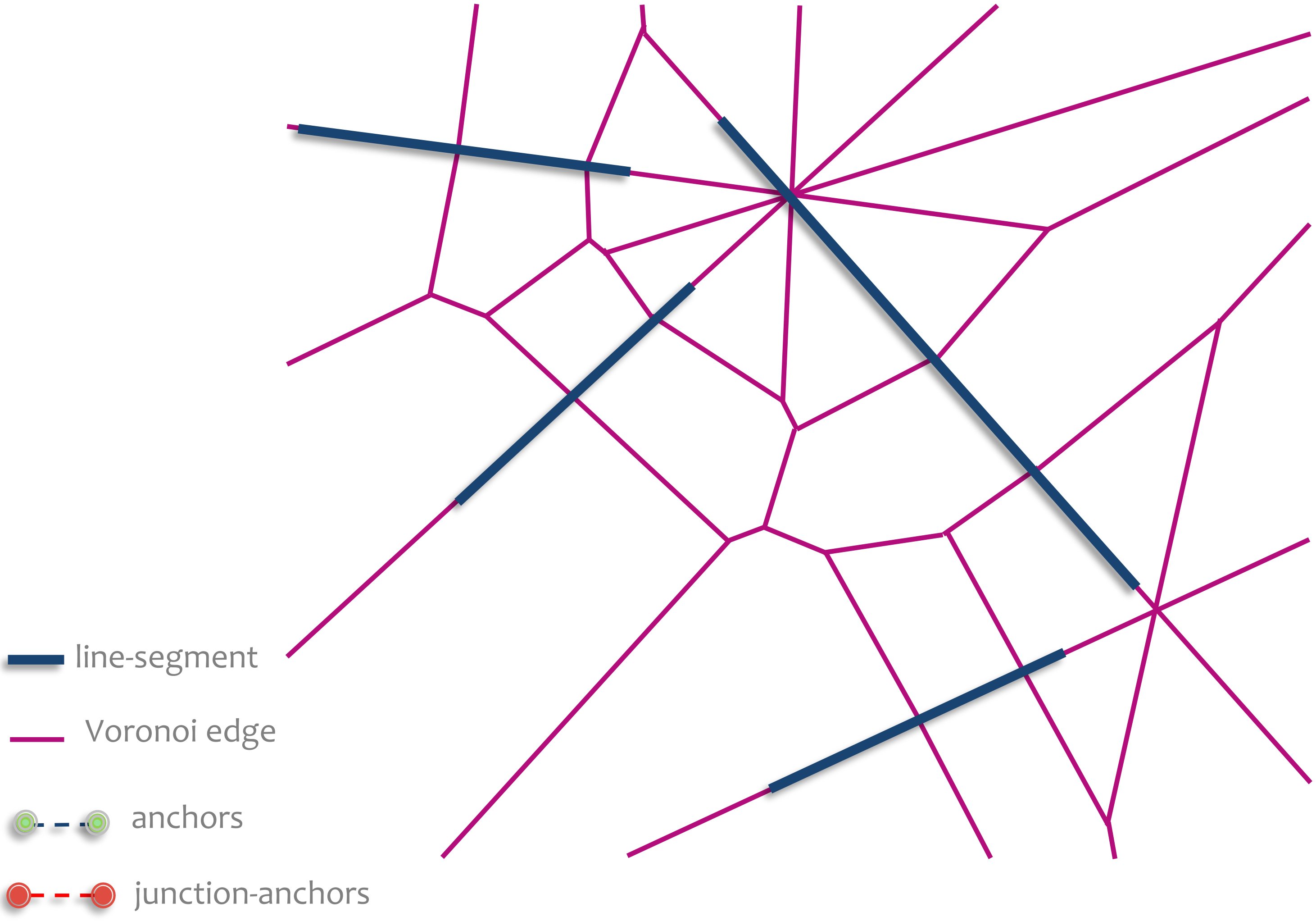
line-segment

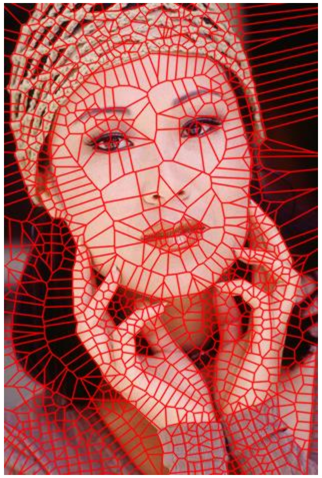
Voronoi edge

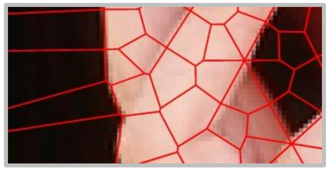
anchors

junction-anchors

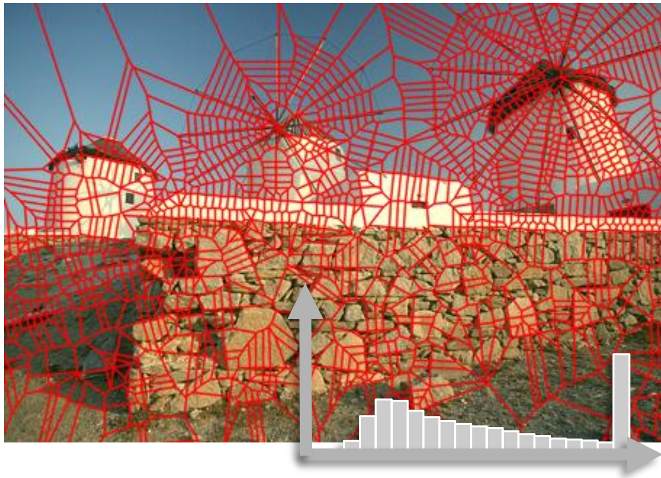
Step 2: anchoring



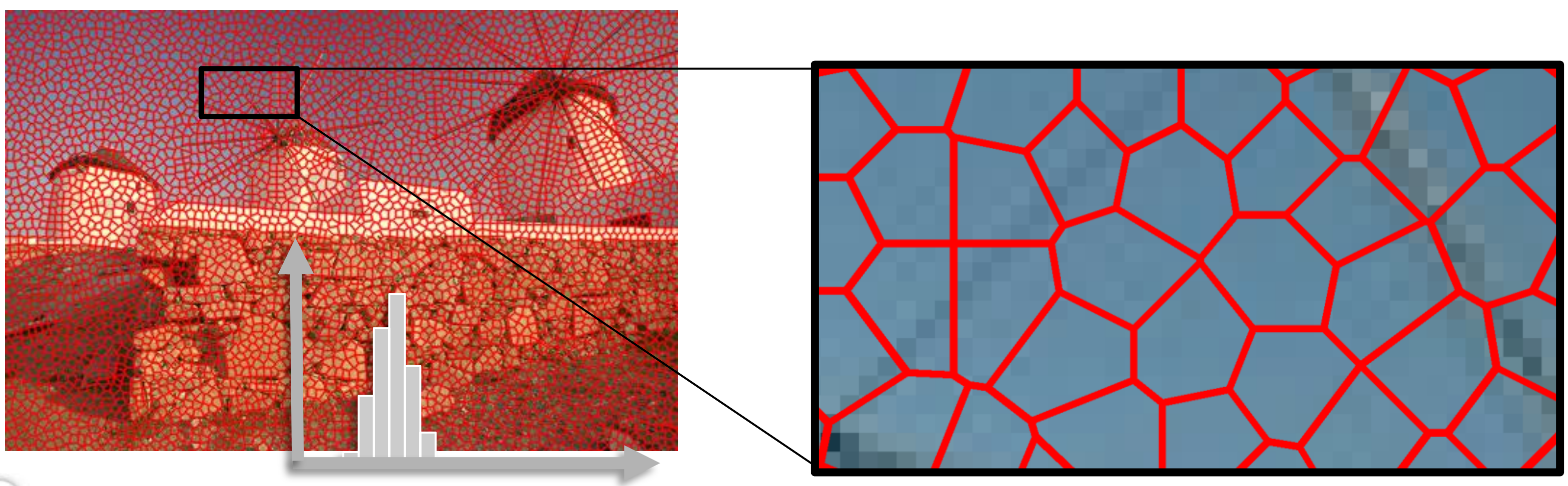




Step 3: homogeneization



Poisson disk sampling



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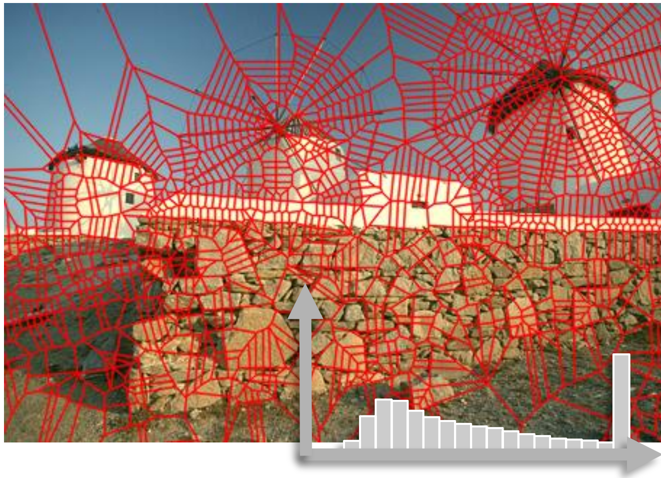
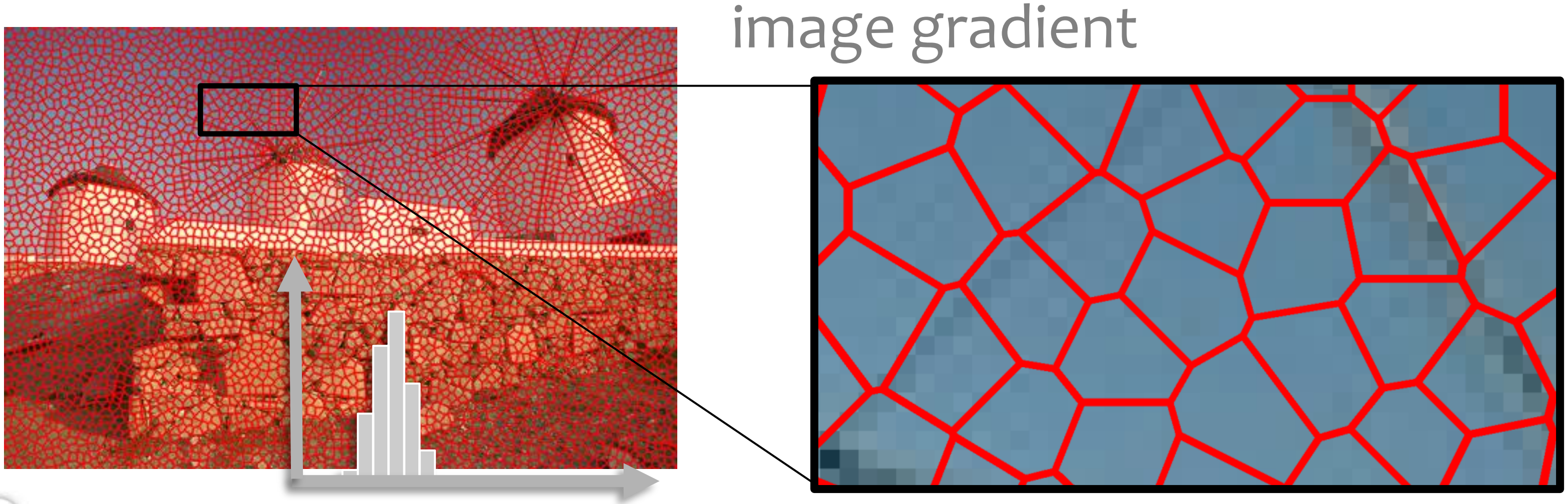
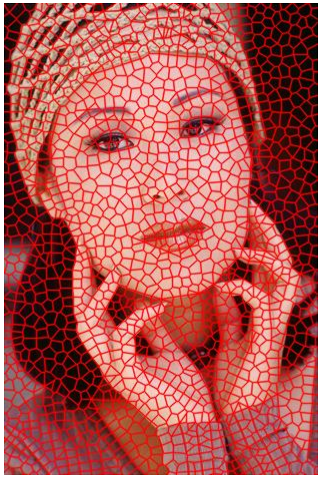
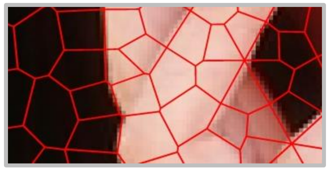


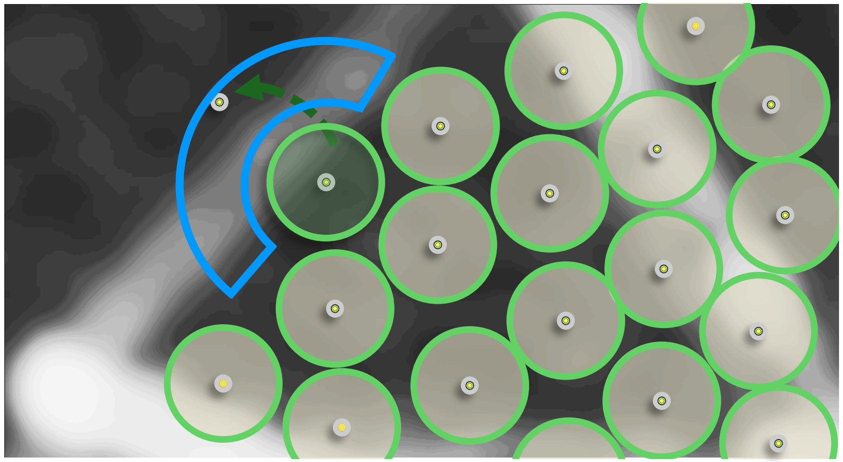


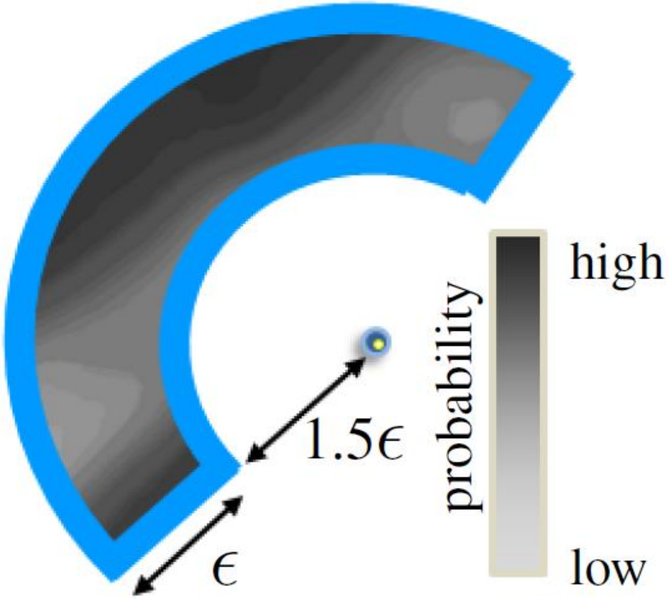
Poisson disk sampling guided by image gradient

Step 3: homogeneization

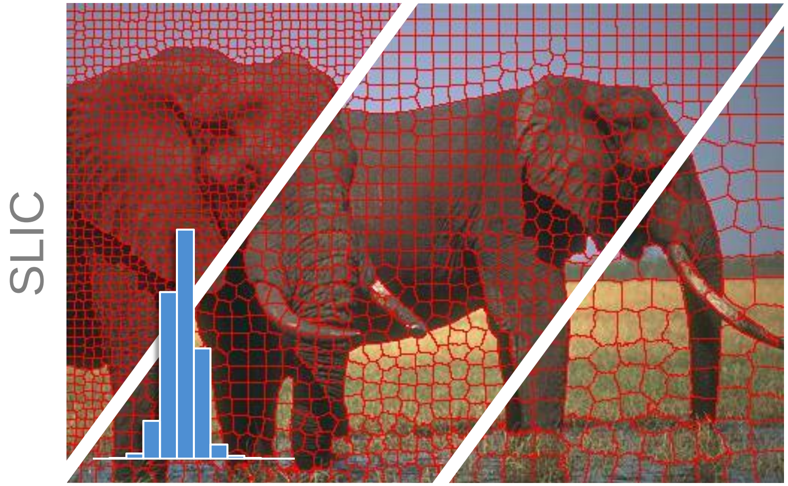


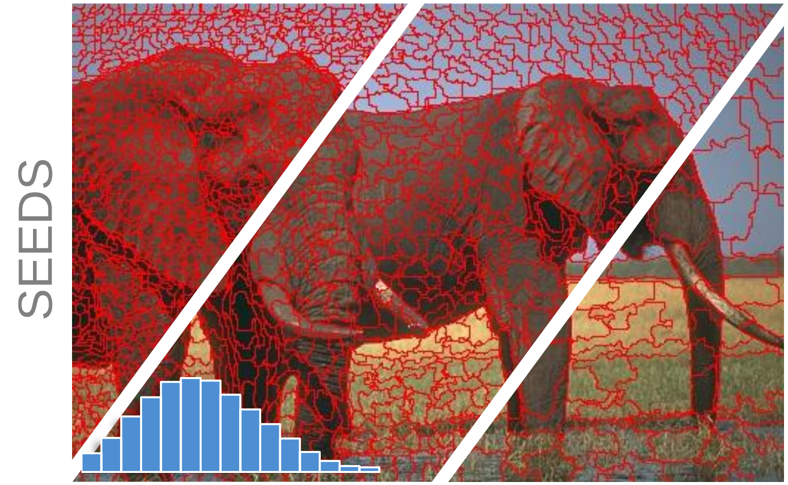


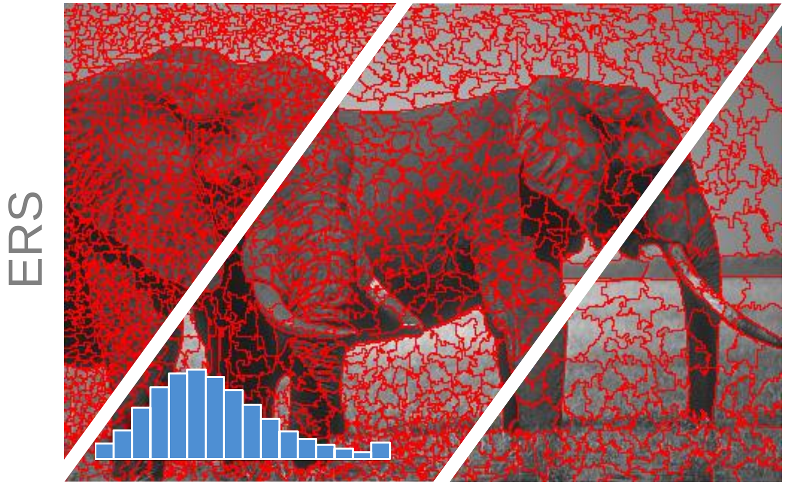


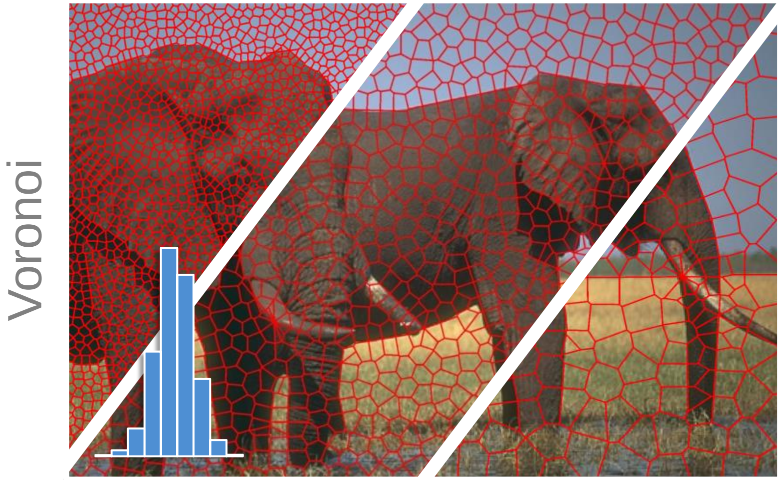


Comparisons with superpixel methods









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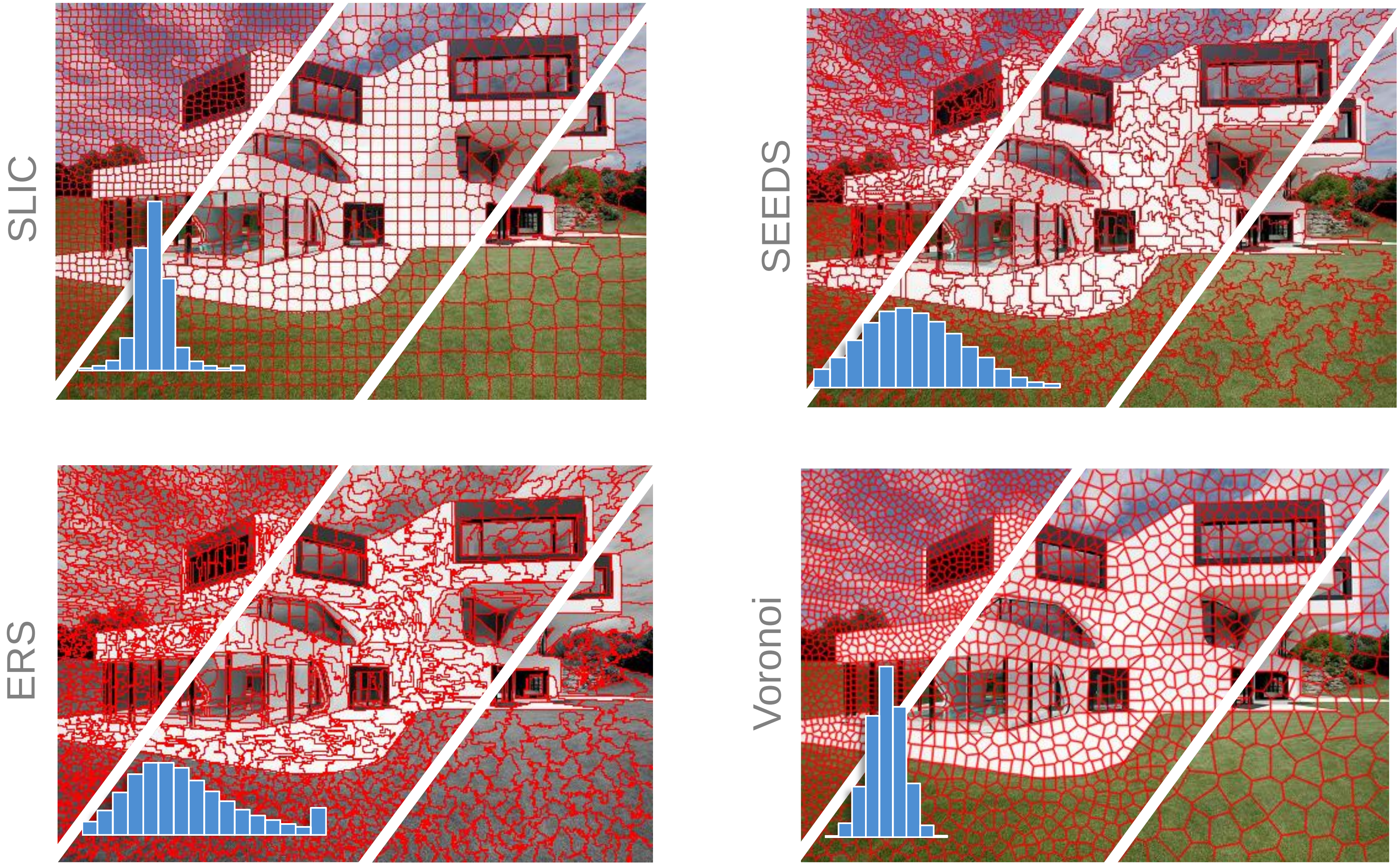

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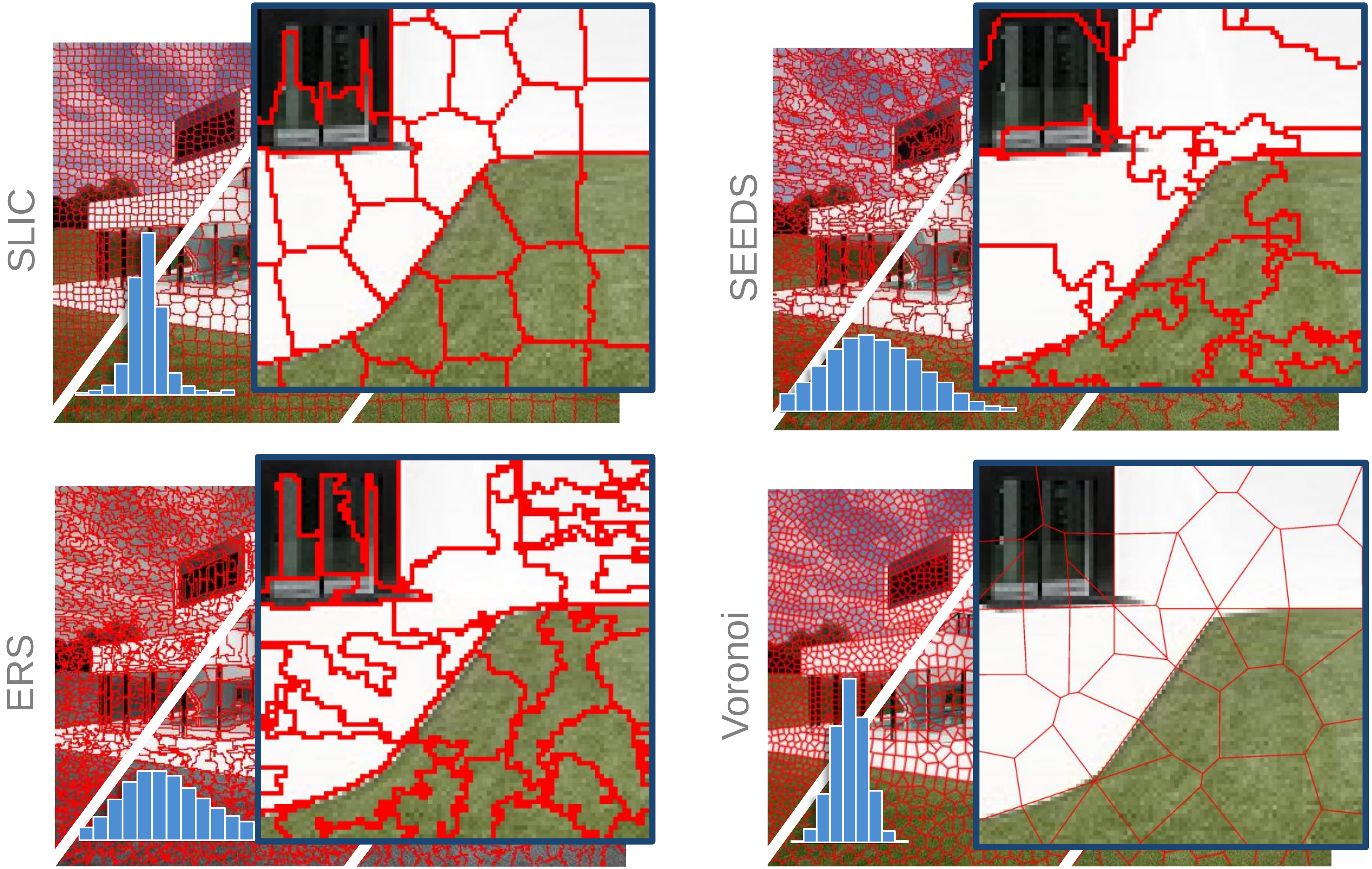

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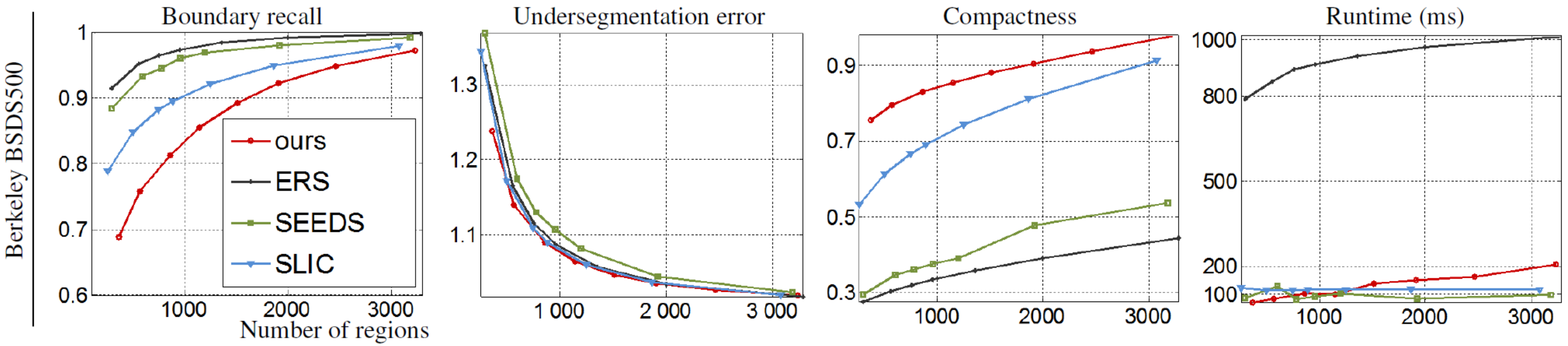

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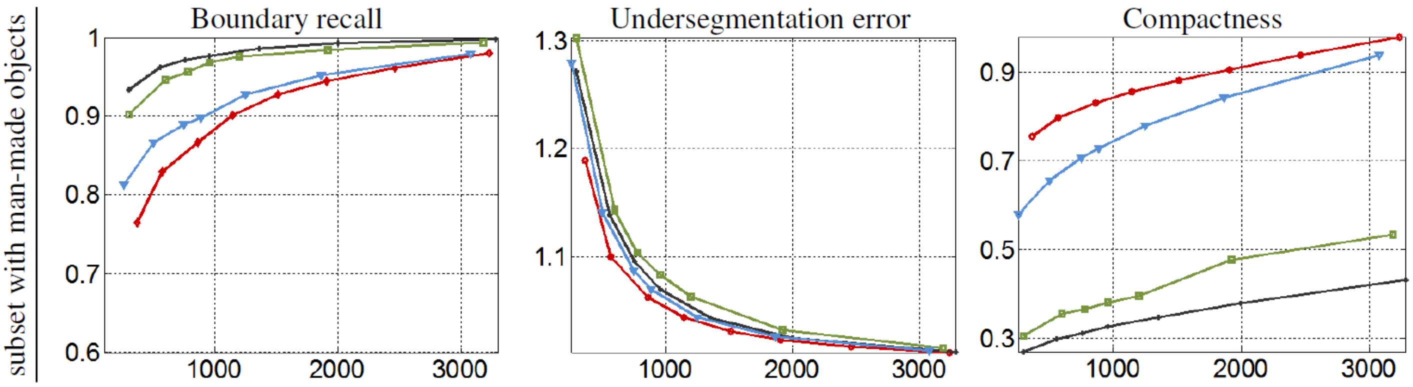
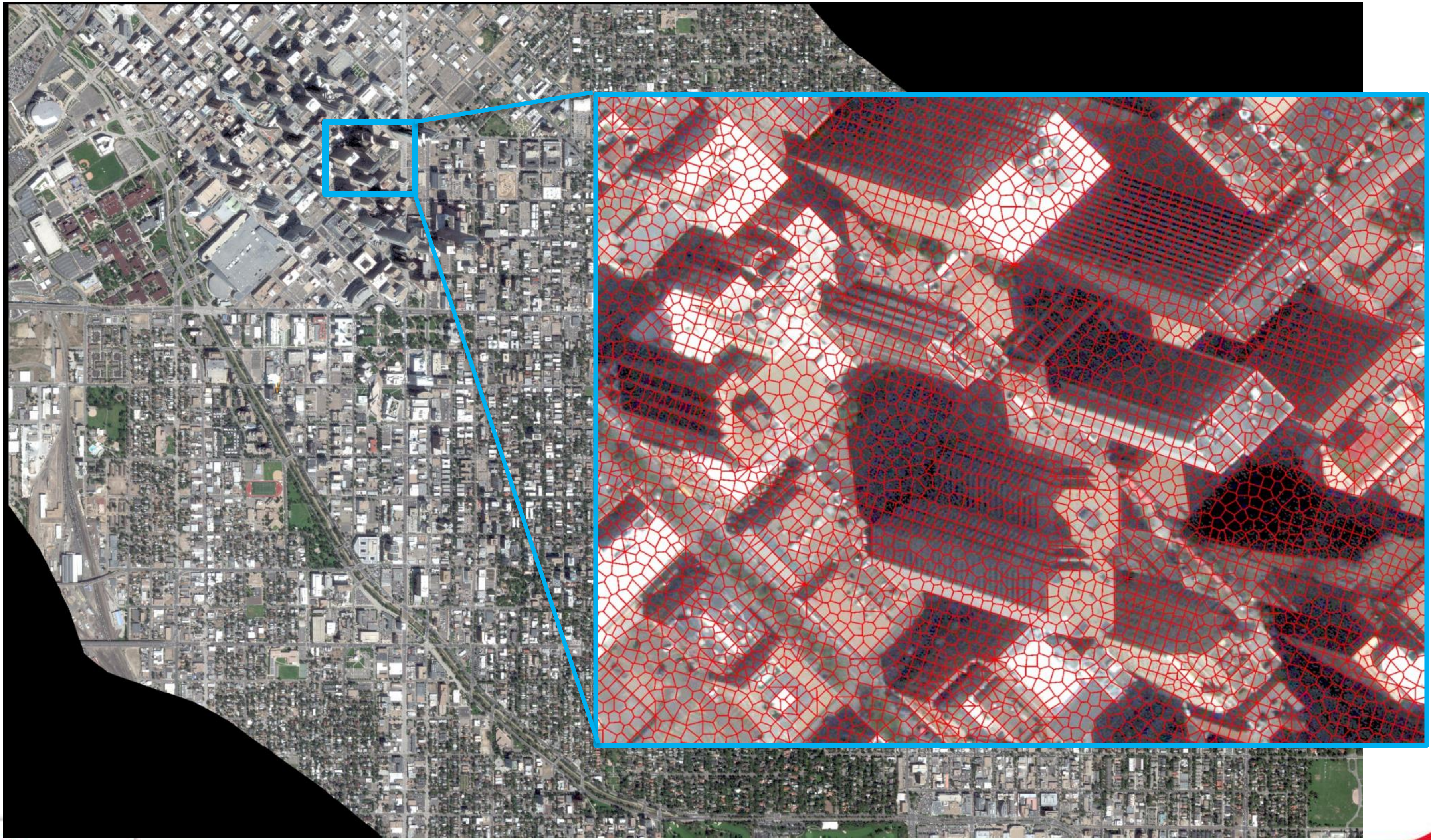
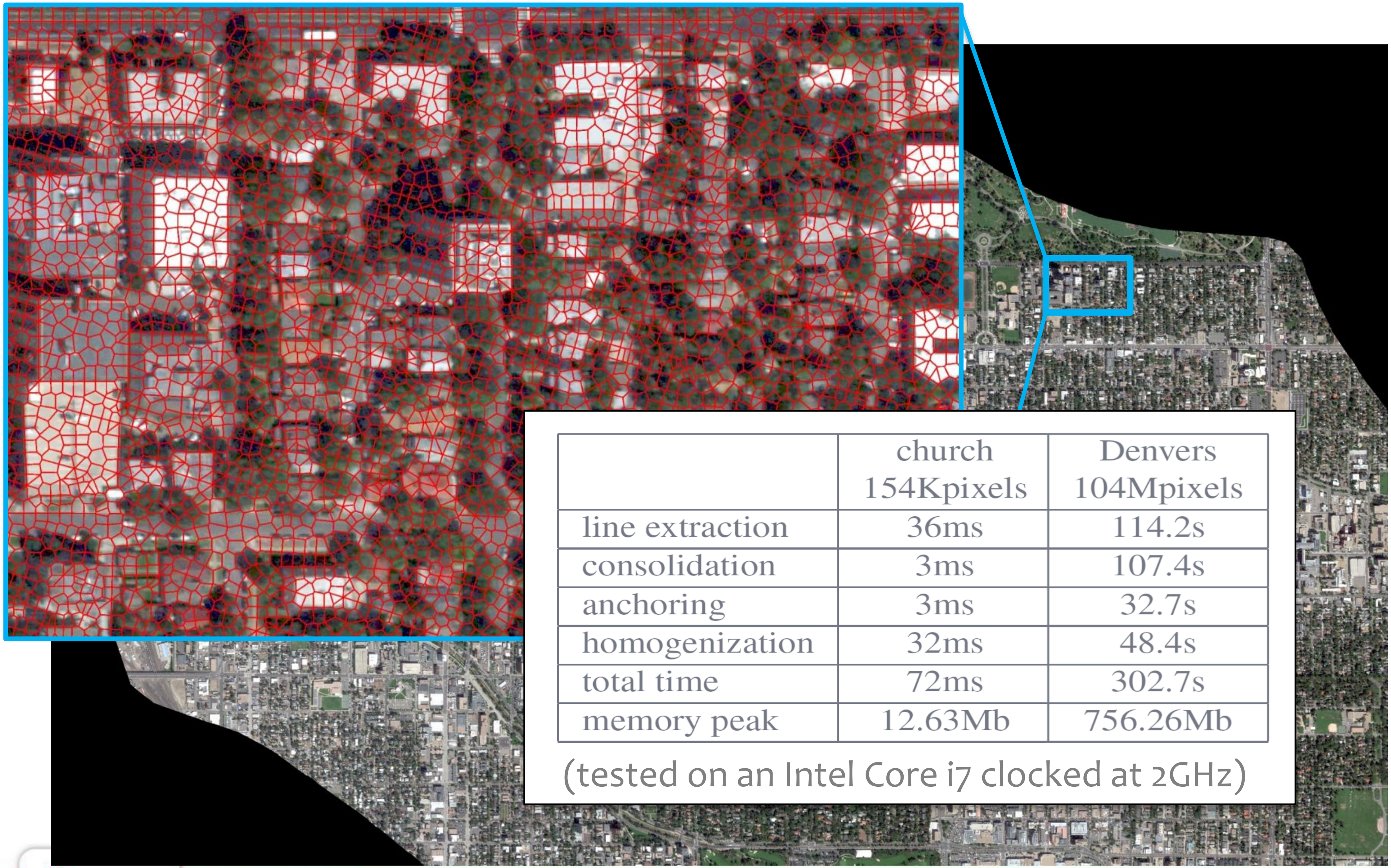


Results on very big images



Results on very big images



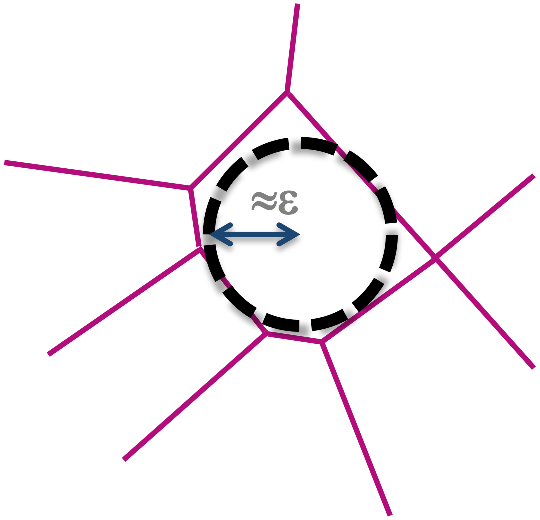
	church 154Kpixels	Denvers 104Mpixels
line extraction	36ms	114.2s
consolidation	3ms	107.4s
anchoring	3ms	32.7s
homogenization	32ms	48.4s
total time	72ms	302.7s
memory peak	12.63Mb	756.26Mb

(tested on an Intel Core i7 clocked at 2GHz)

Demo

One parameter

ε : expected width of the Voronoi cells



Voronoi-based Image partitioning: some applications

Application to object polygonalization

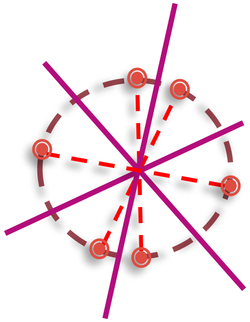
Application to object polygonalization

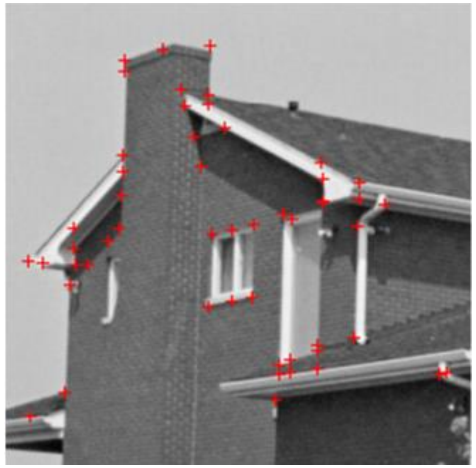
[Sun et al., Free-shape polygonal object localization, ECCV 2014]

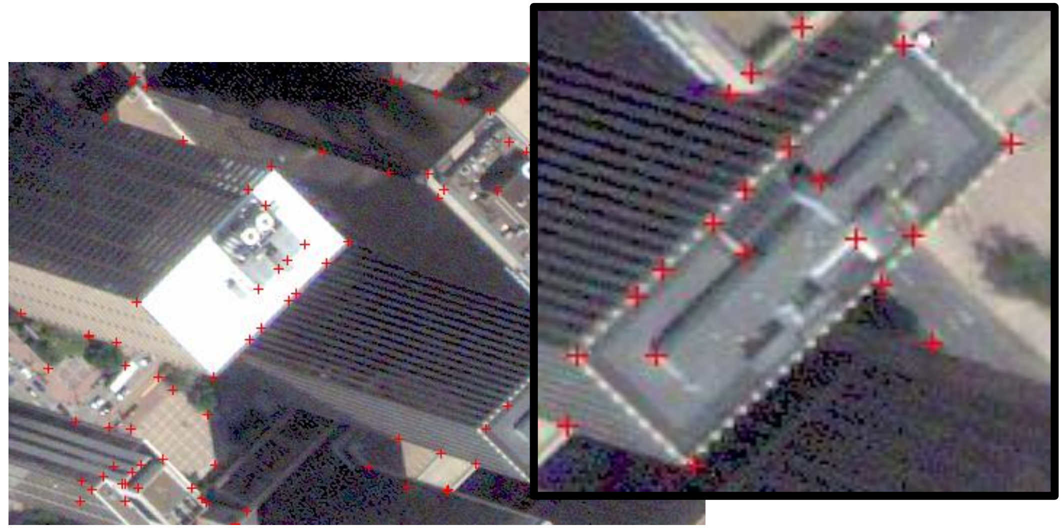
CR

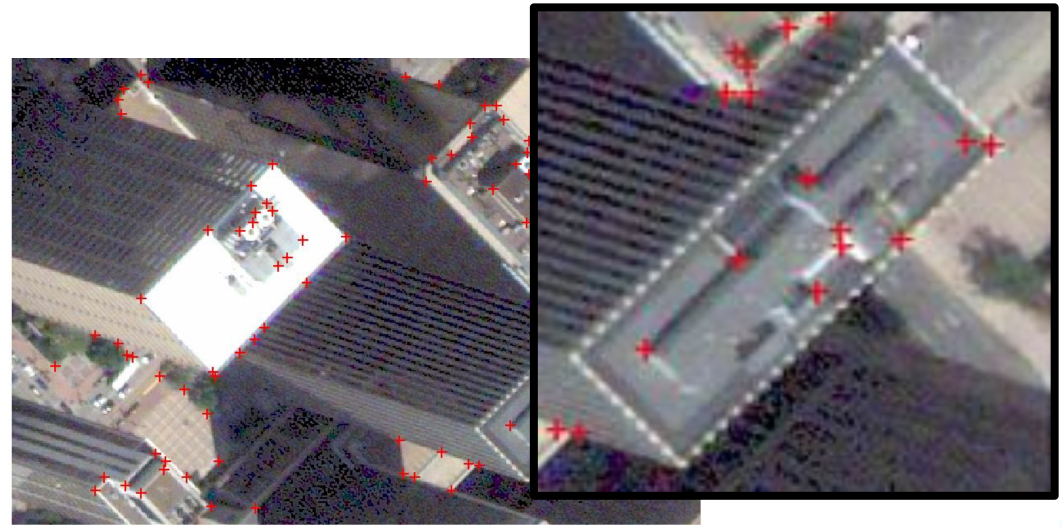
Application to corner detection

Junction- anchors as corner detectors



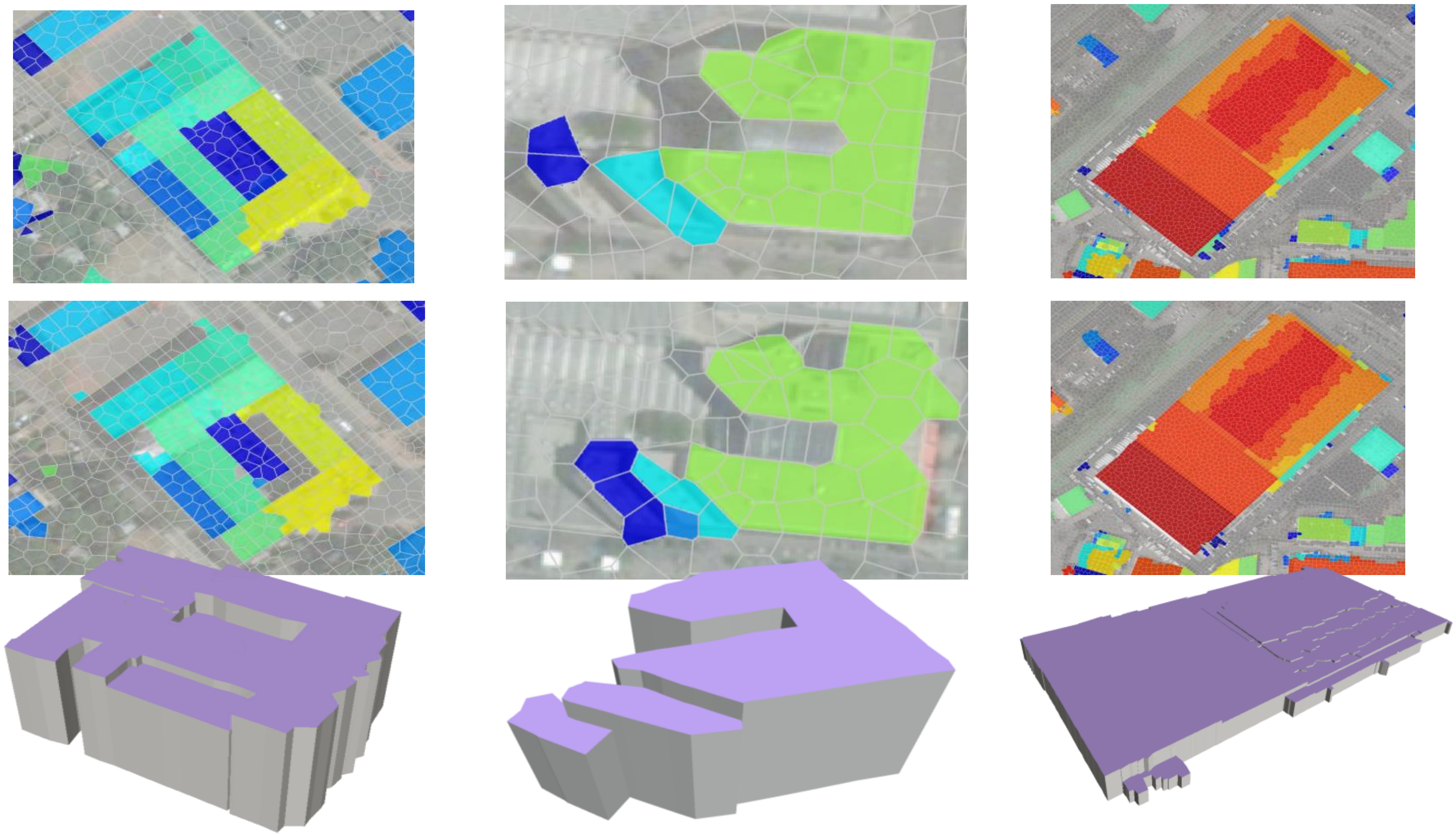






[Xia et al., Accurate junction detection and characterization in natural images, IJCV 2014]

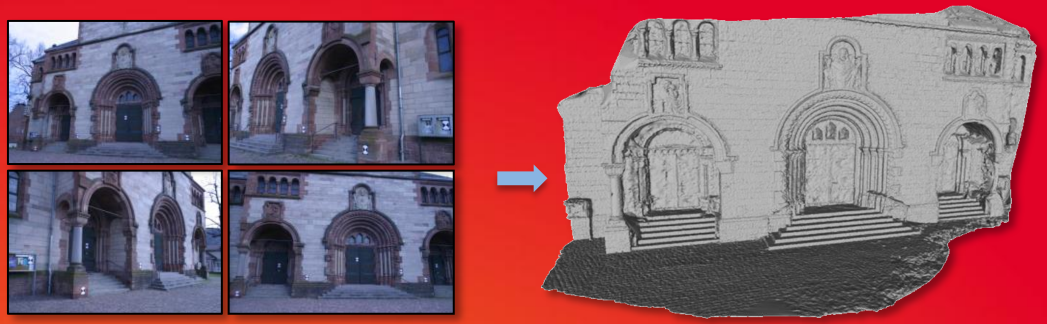
Application to 3D reconstruction of buildings



[Duan and Lafarge, Towards large-scale city reconstruction from satellites, ECCV 2016]

Thursday 13
from 11 to 12:30

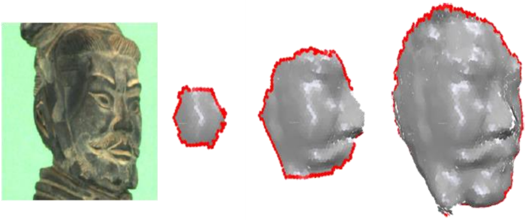
2
Multi View Stereo



Literature

Surface growing

[Goesele07][Furakawa07][Habecke07]…



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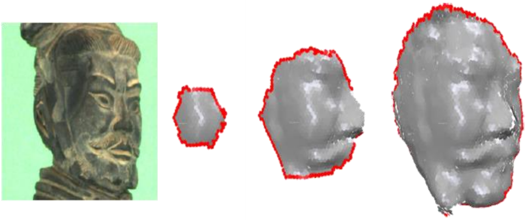
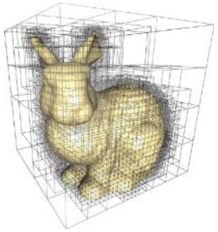


Volumetric labeling
[Hornung06][Vogiatzis2007][Vu09][Hane13]…



Literature

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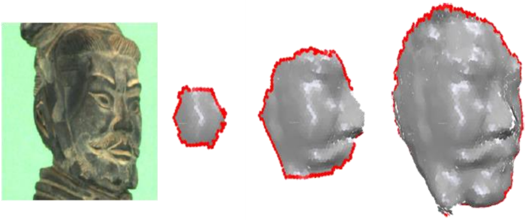

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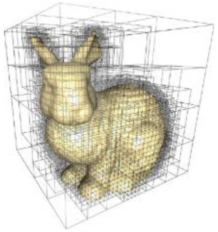

- ➢ Partitioning the 3D space into elementary volumes

Literature

Surface growing
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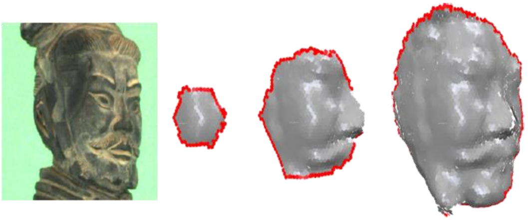

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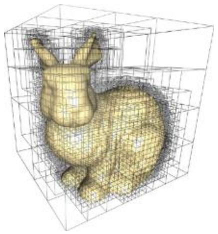
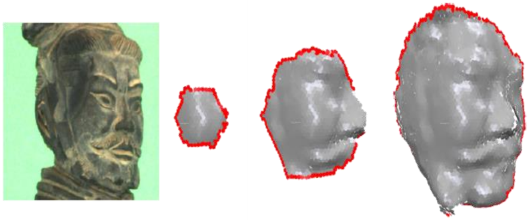


- Partitioning the 3D space into elementary volumes
- Labeling each elementary volume as *outside* or *inside*

Literature

Surface growing

[Goesele07][Furakawa07][Habecke07]…



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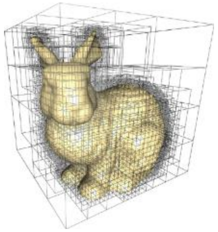
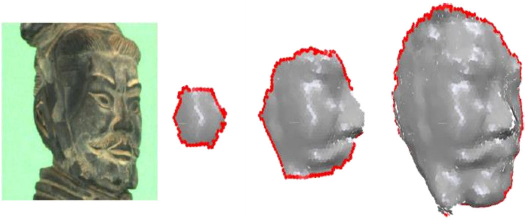


- Partitioning the 3D space into elementary volumes
- Labeling each elementary volume as *outside* or *class1 or class2 or…*

Literature

Surface growing

[Goesele07][Furakawa07][Habecke07]...



Volumetric labeling

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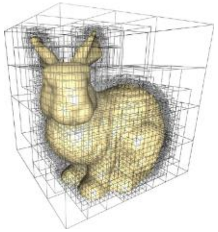
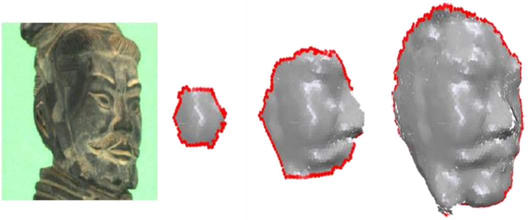


- Partitioning the 3D space into elementary volumes
- Labeling each elementary volume as *outside* or *inside*
- eventually refining the surface

Literature

Surface growing

[Goesele07][Furakawa07][Habecke07]…



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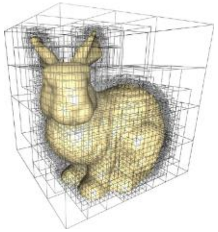

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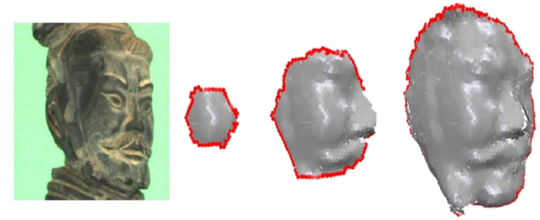

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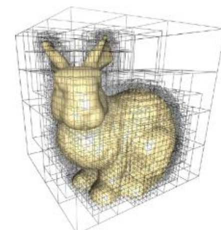


- Partitioning the 3D space into elementary volumes
- Labeling each elementary volume as *outside* or *inside*
- eventually refining the surface

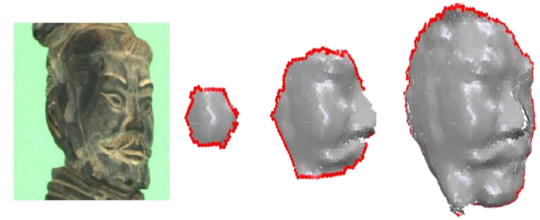
What is a good 3D data structure?

memory-efficiency
time-efficiency to (i) construct, (ii) answer queries, and (iii) modify
Data-driven

Literature

Surface growing

[Goesele07][Furakawa07][Habecke07]…



Volumetric labeling

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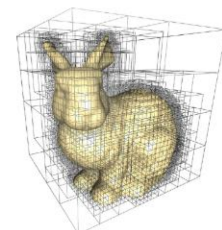


- Partitioning the 3D space into elementary volumes
- Labeling each elementary volume as *outside* or *inside*
- eventually refining the surface

What is a good 3D data structure? voxel grid

✗✗ memory-efficiency

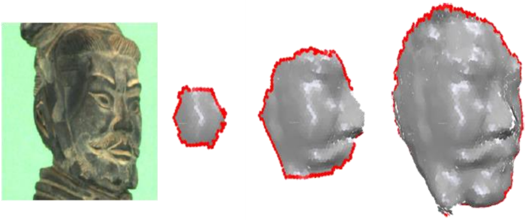
time-efficiency to (i) construct ✓, (ii) answer queries ✓, and (iii) modify ✗

✗ Data-driven

Literature

Surface growing

[Goesele07][Furakawa07][Habecke07]…



Volumetric labeling

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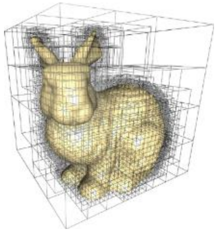


- Partitioning the 3D space into elementary volumes
- Labeling each elementary volume as *outside* or *inside*
- eventually refining the surface

What is a good 3D data structure? octree

✗ memory-efficiency

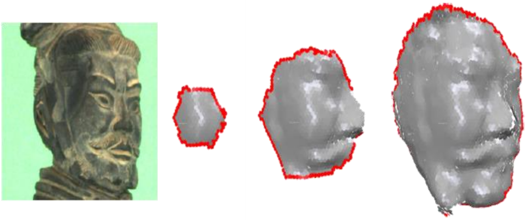
time-efficiency to (i) construct ✓, (ii) answer queries ✓, and (iii) modify ✗

✓ Data-driven

Literature

Surface growing

[Goesele07][Furakawa07][Habecke07]…



Volumetric labeling

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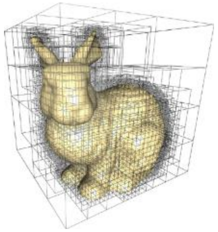

- Partitioning the 3D space into elementary volumes
- Labeling each elementary volume as *outside* or *inside*
- eventually refining the surface

What is a good 3D data structure?

3D Delaunay triangulation

✓ memory-efficiency

time-efficiency to (i) construct ✓, (ii) answer queries ✓, and (iii) modify ✓

✓ Data-driven

Literature

Surface growing

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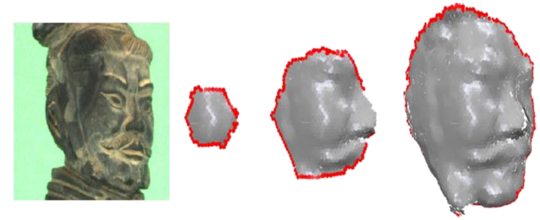
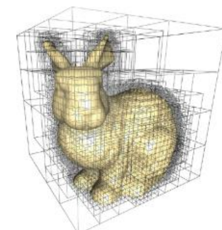


Volumetric labeling

[Hornung06][Vogiatzis2007][Vu09][Hane13]…



- Partitioning the 3D space into elementary volumes
- Labeling each elementary volume as *outside* or *inside*
- eventually refining the surface

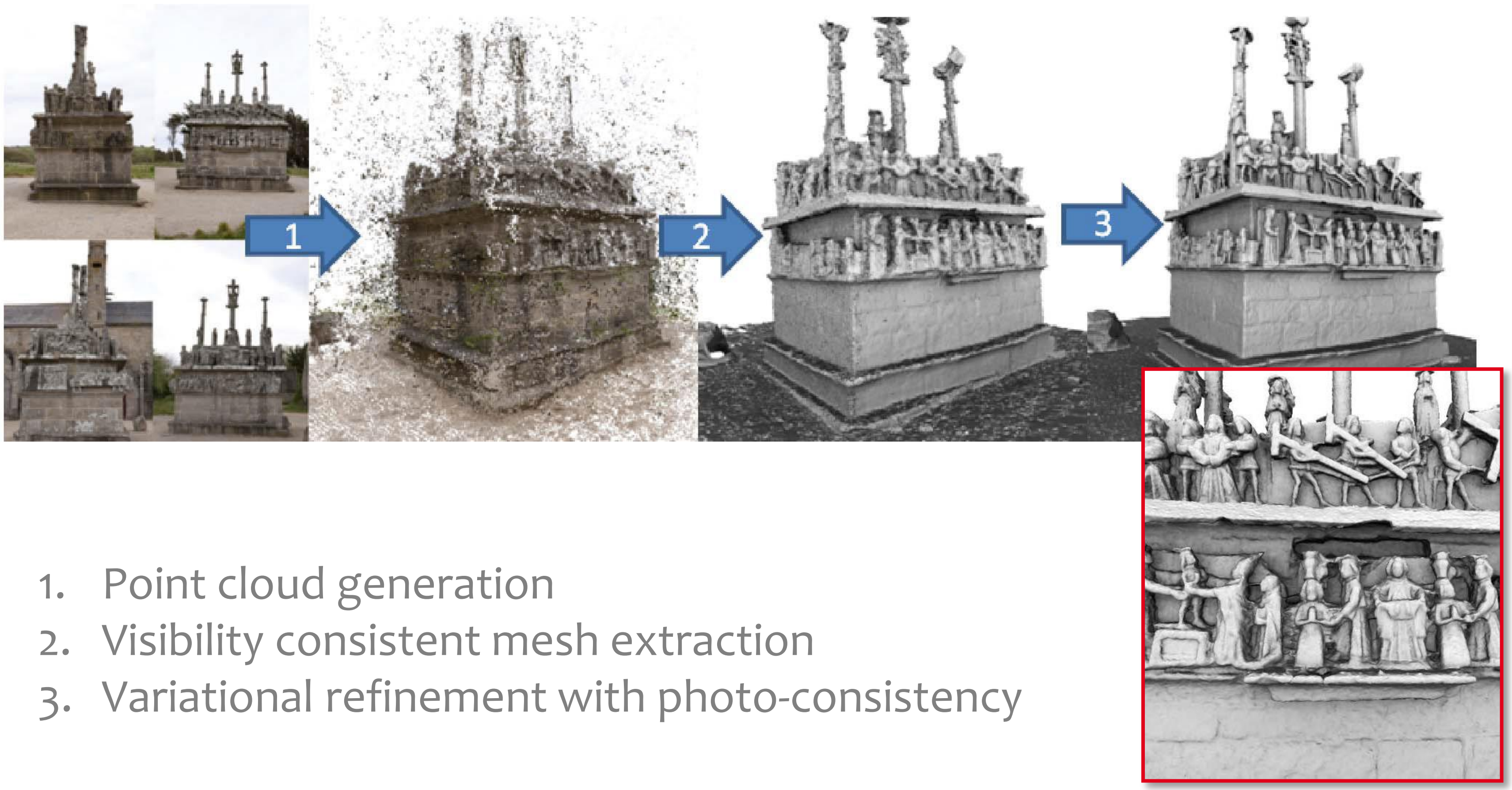
acute3D capturing reality

Bentley® Sustaining Infrastructure

Delaunay-based MVS

[Vu, Keriven, Labatut and Pons, Towards high-resolution large-scale multi-view stereo, CVPR 2009]

[Vu09]

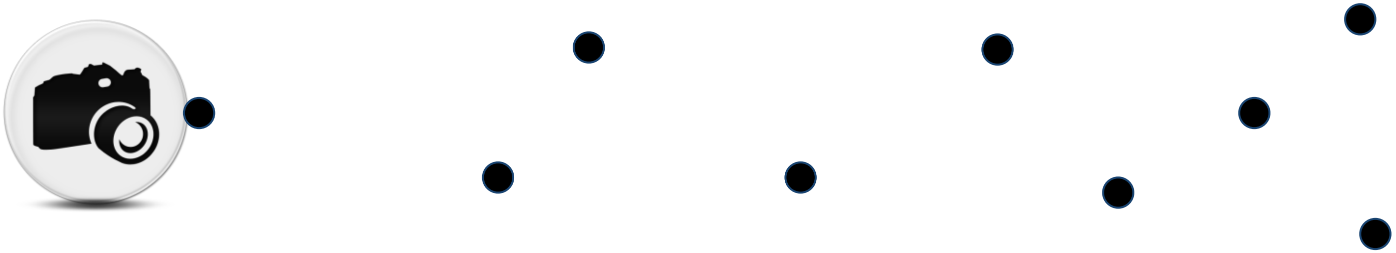


1. Point cloud generation
2. Visibility consistent mesh extraction
3. Variational refinement with photo-consistency

[Vu09]

2. Visibility consistent mesh extraction

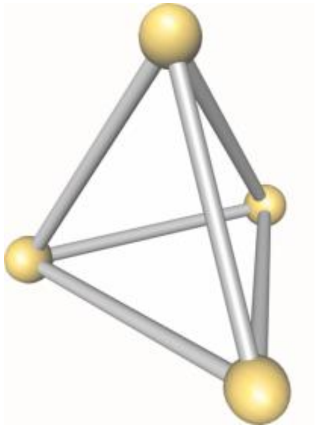
➢ Partition the space with a 3D Delaunay triangulation

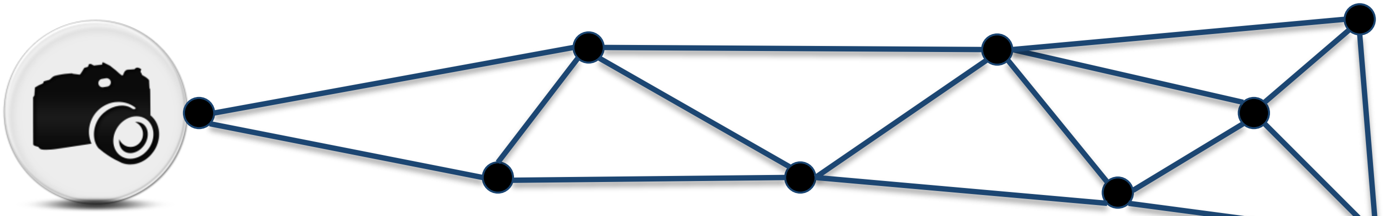


[Vu09]

2. Visibility consistent mesh extraction

- Partition the space with a 3D Delaunay triangulation

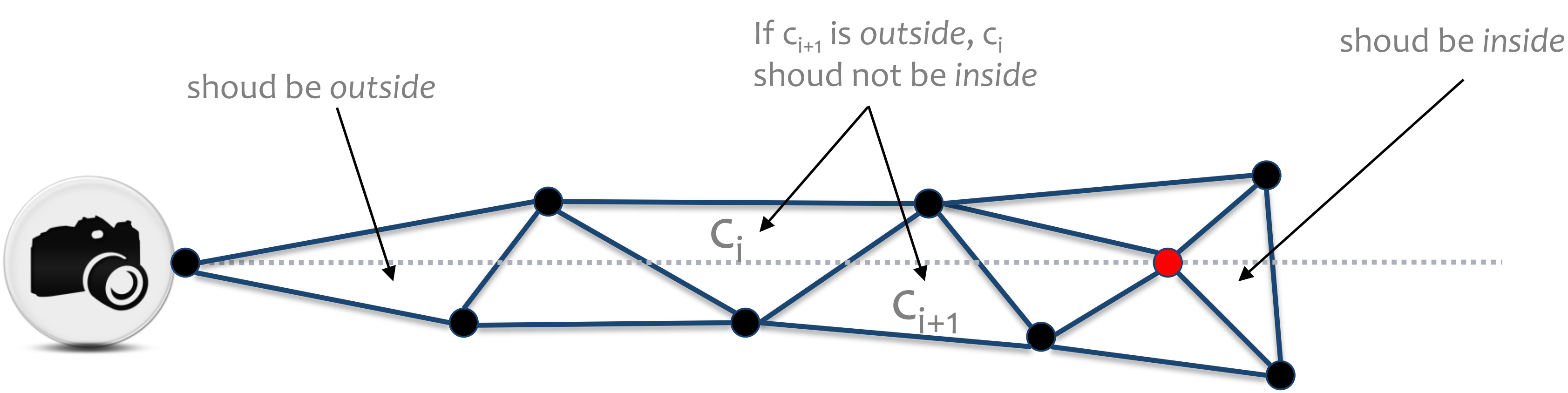




[Vu09]

2. Visibility consistent mesh extraction

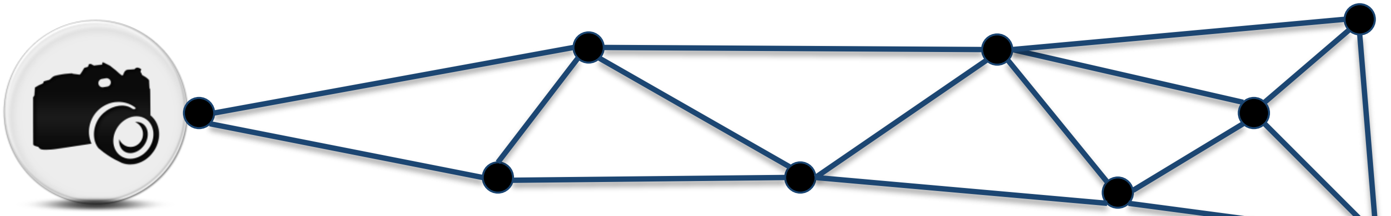
- Partition the space with a 3D Delaunay triangulation
- Label each Delaunay cell as inside or outside the observed objects using **visibility**

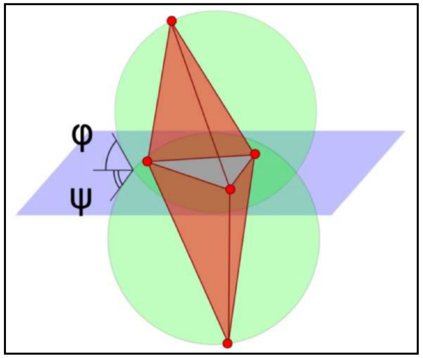


[Vu09]

2. Visibility consistent mesh extraction

- Partition the space with a 3D Delaunay triangulation
- Label each Delaunay cell as inside or outside the observed objects using visibility and **geometric quality**



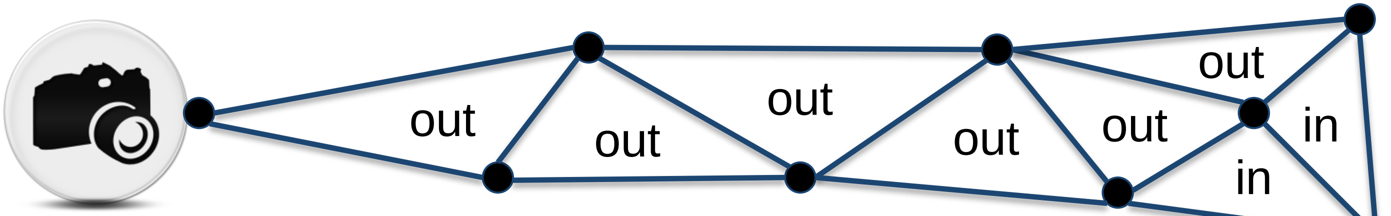


Favor facets with large empty circumspheres

[Vu09]

2. Visibility consistent mesh extraction

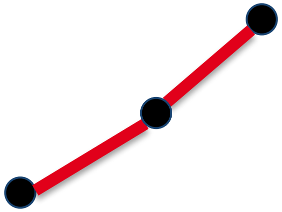
- Partition the space with a 3D Delaunay triangulation
- Label each Delaunay cell as inside or outside the observed objects using visibility and geometric quality



[Vu09]

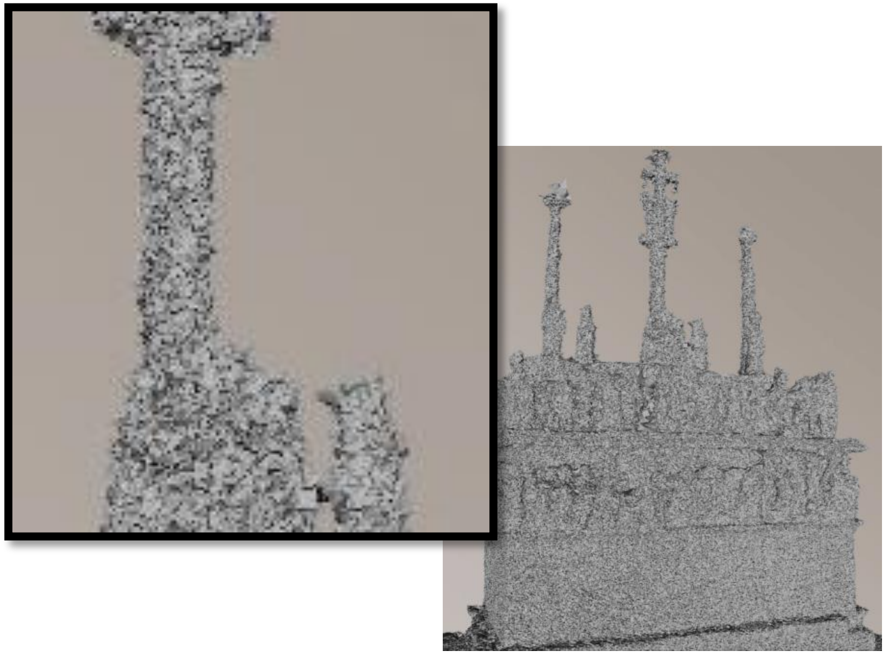
2. Visibility consistent mesh extraction

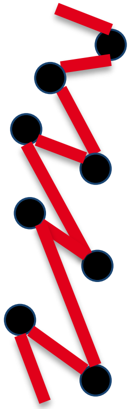
- Partition the space with a 3D Delaunay triangulation
- Label each Delaunay cell as inside or outside the observed objects using visibility and geometric quality



[Vu09]

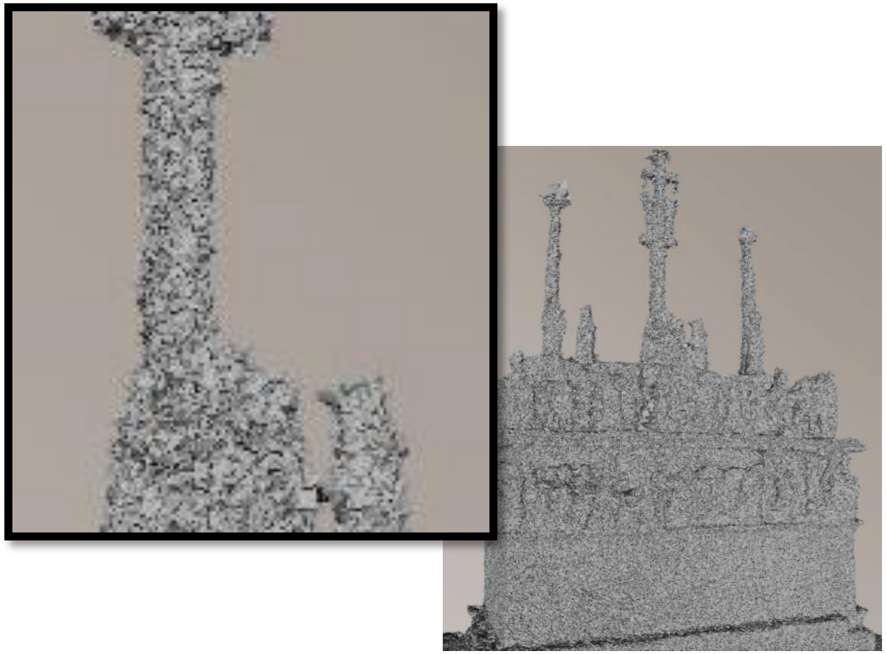
3. Variational refinement with photo-consistency

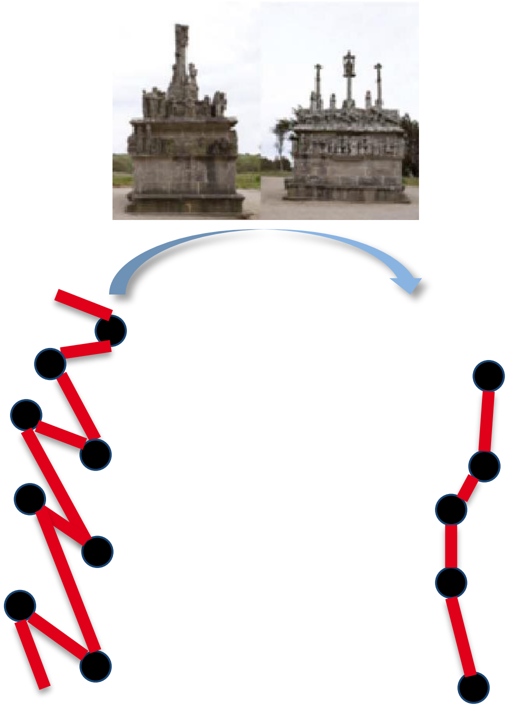




[Vu09]

3. Variational refinement with photo-consistency

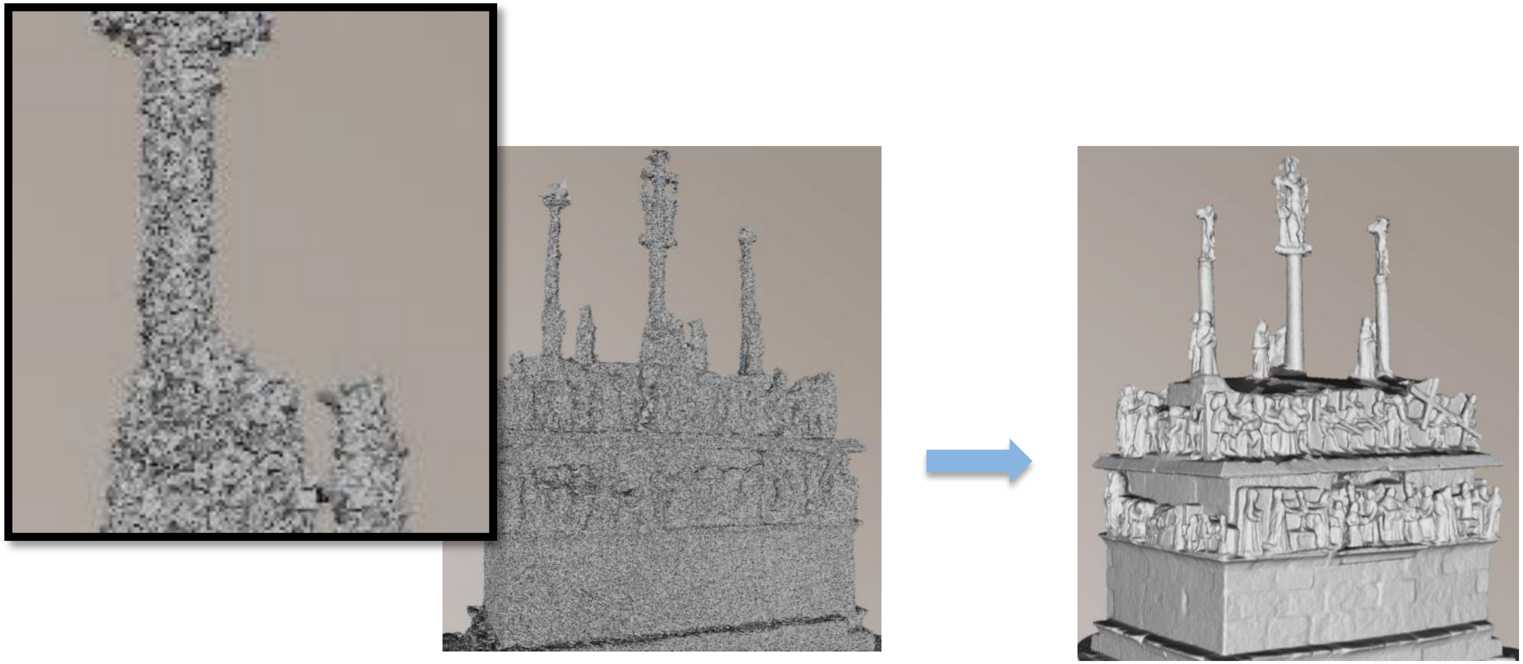




[Vu09]

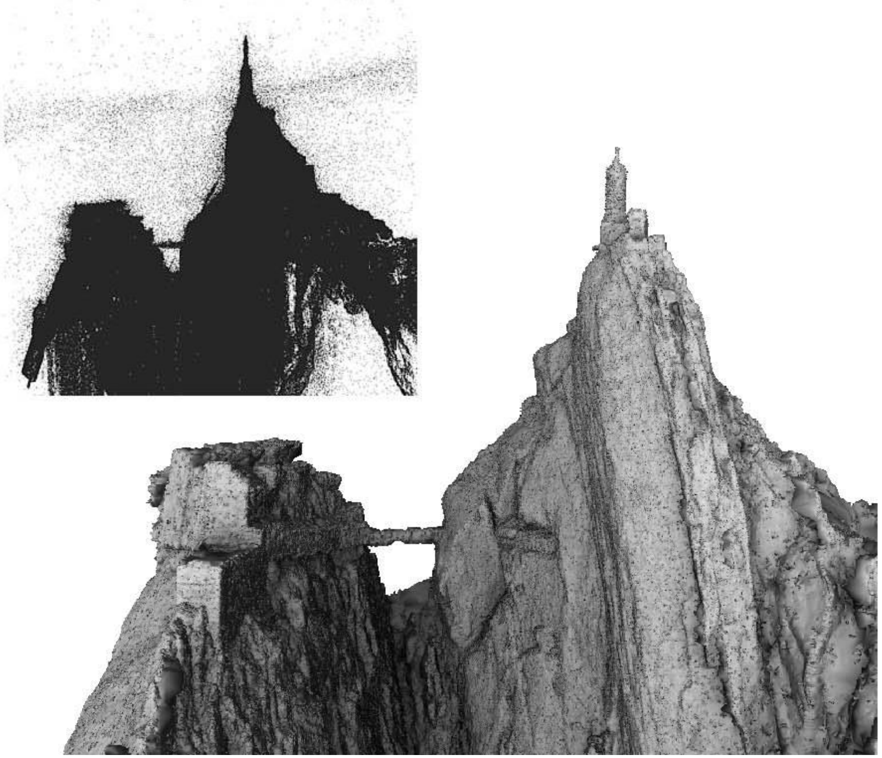
3. Variational refinement with photo-consistency

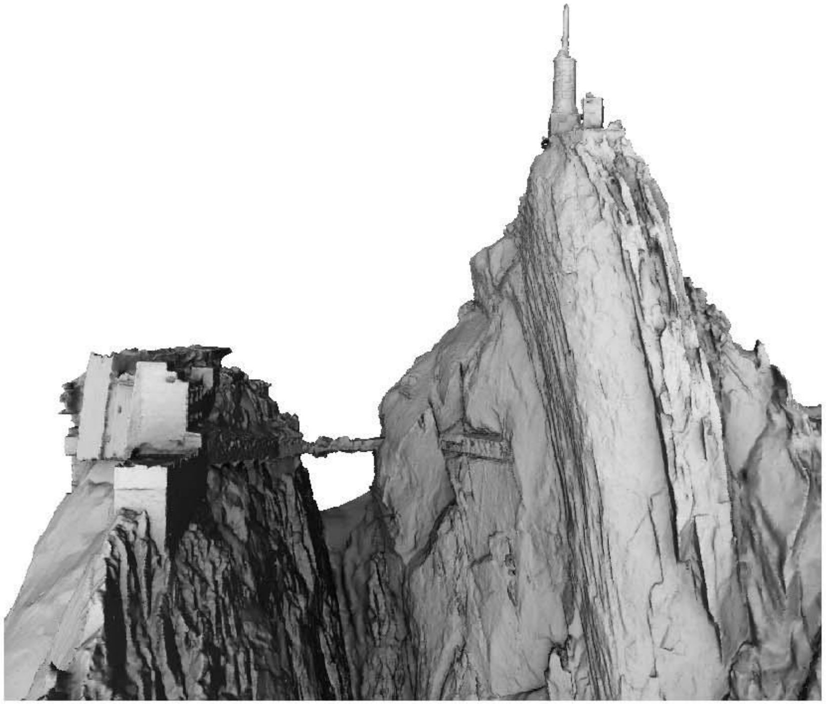
➢ Minimize the reprojection error induced by the surface



[Vu09]

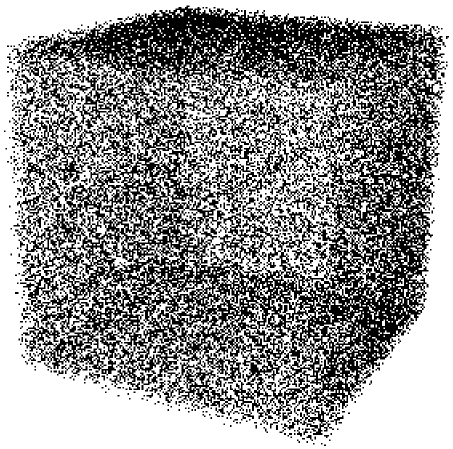
51 input images of 5Mpixels
Output mesh of 600K triangles



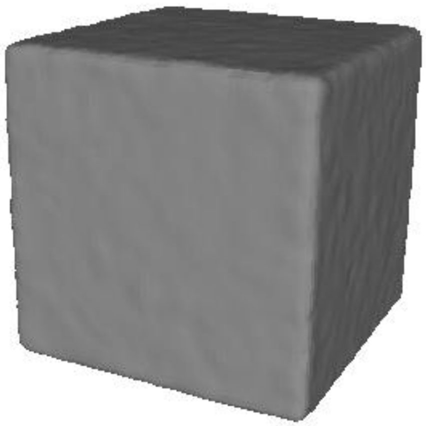


Surface reconstruction without structure priors

100K input points

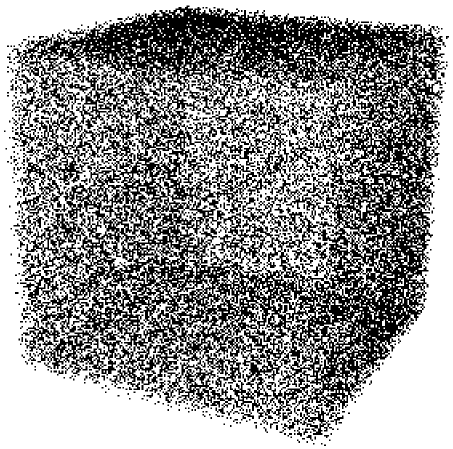


70K output triangles

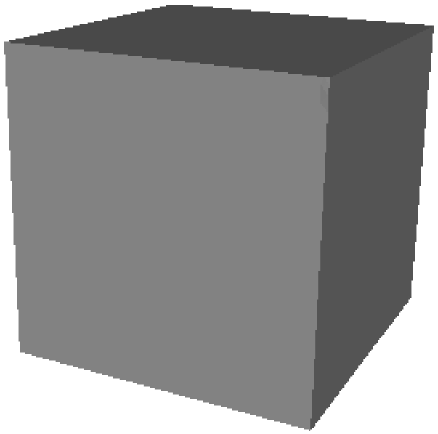


Surface reconstruction with structure priors

100K input points

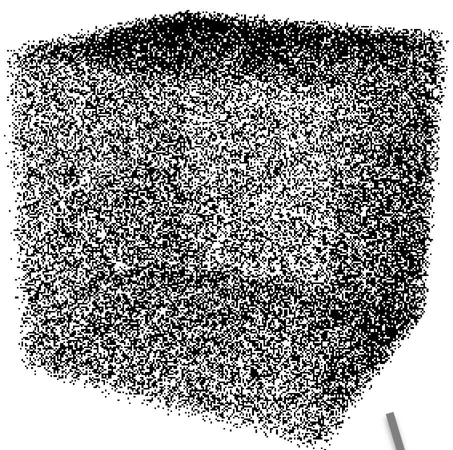


8 vertices, 6 facets

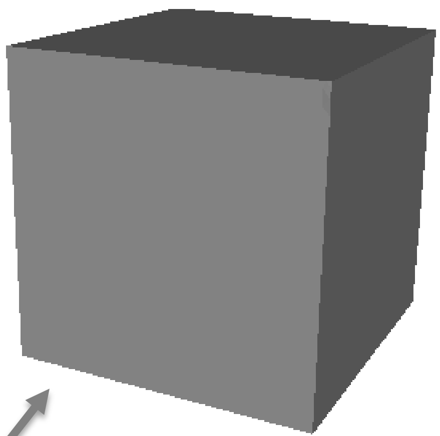


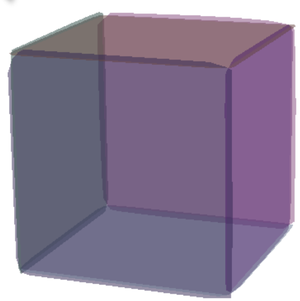
Surface reconstruction with structure priors

100K input points



8 vertices, 6 facets



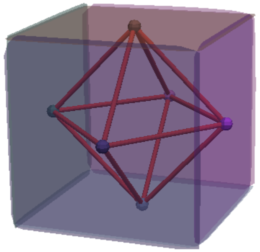


Geometric primitive extraction
[Schnabel07][Li11][Monszpart15][Oesau16]…

Surface reconstruction with structure priors

but…

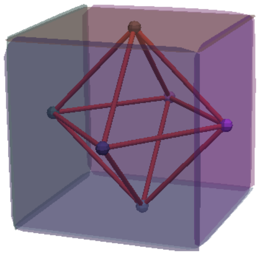
- no guarantee of finding the right primitive configuration and right adjacency graph



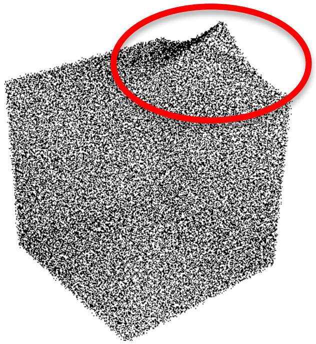
Surface reconstruction with structure priors

but…

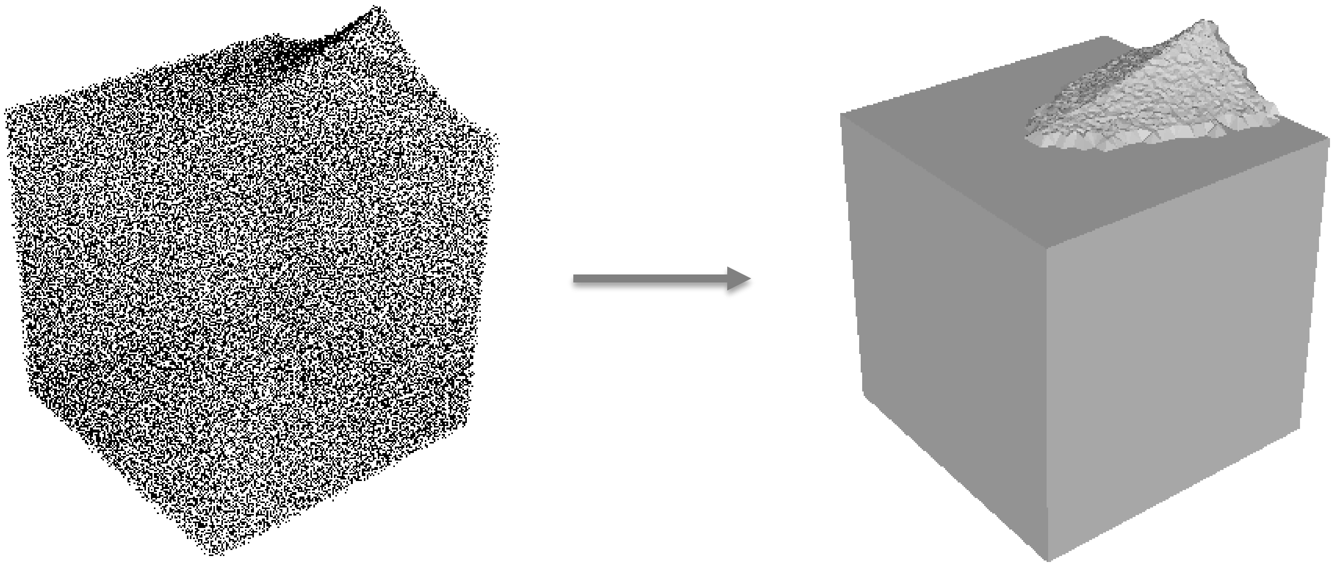
- no guarantee of finding the right primitive configuration and right adjacency graph



- no guarantee that the object can be entirely explained by geometric primitives



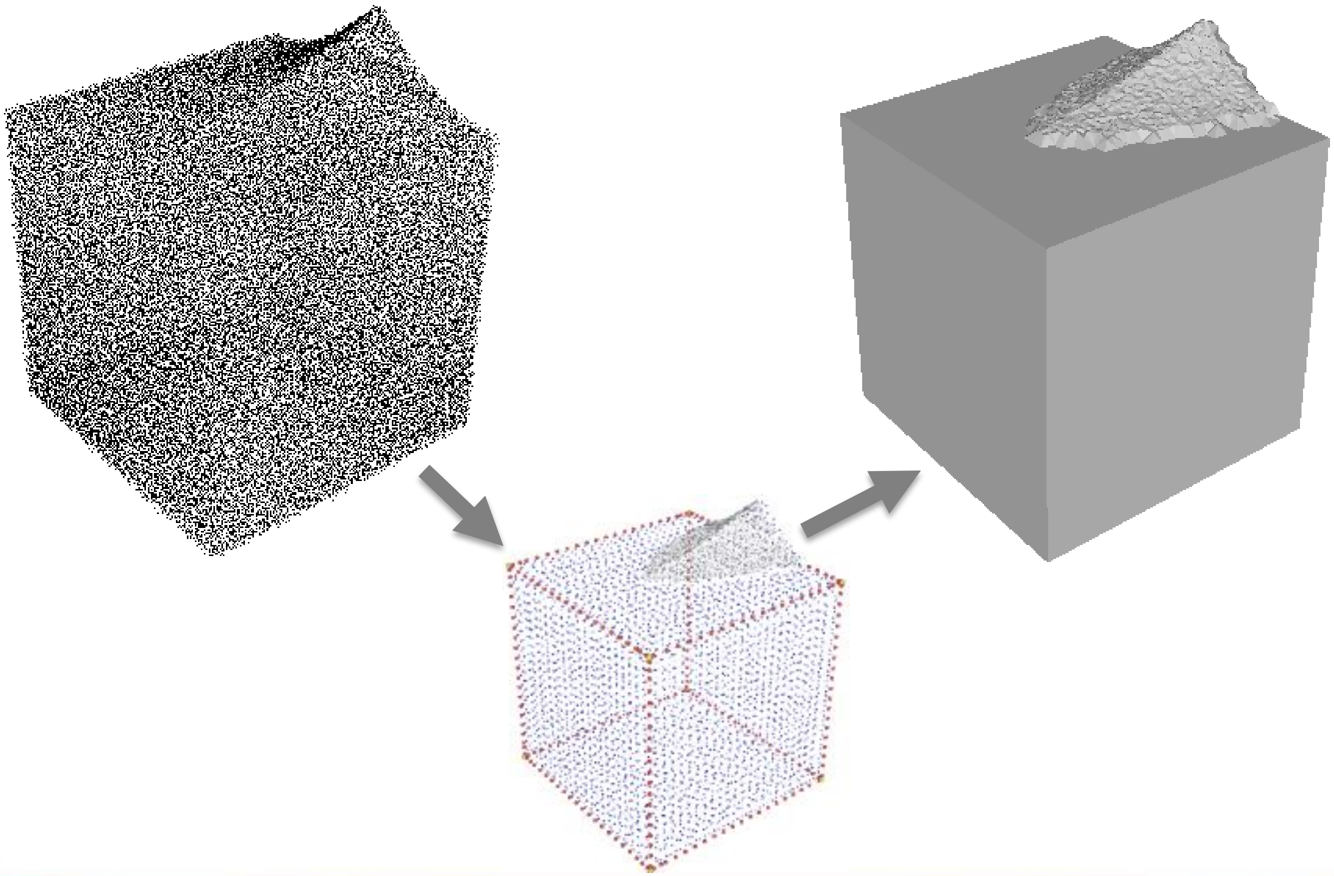
Surface reconstruction with structure priors



hybrid surface

Point set structuring

Idea: transforming 3D points to insert structural information

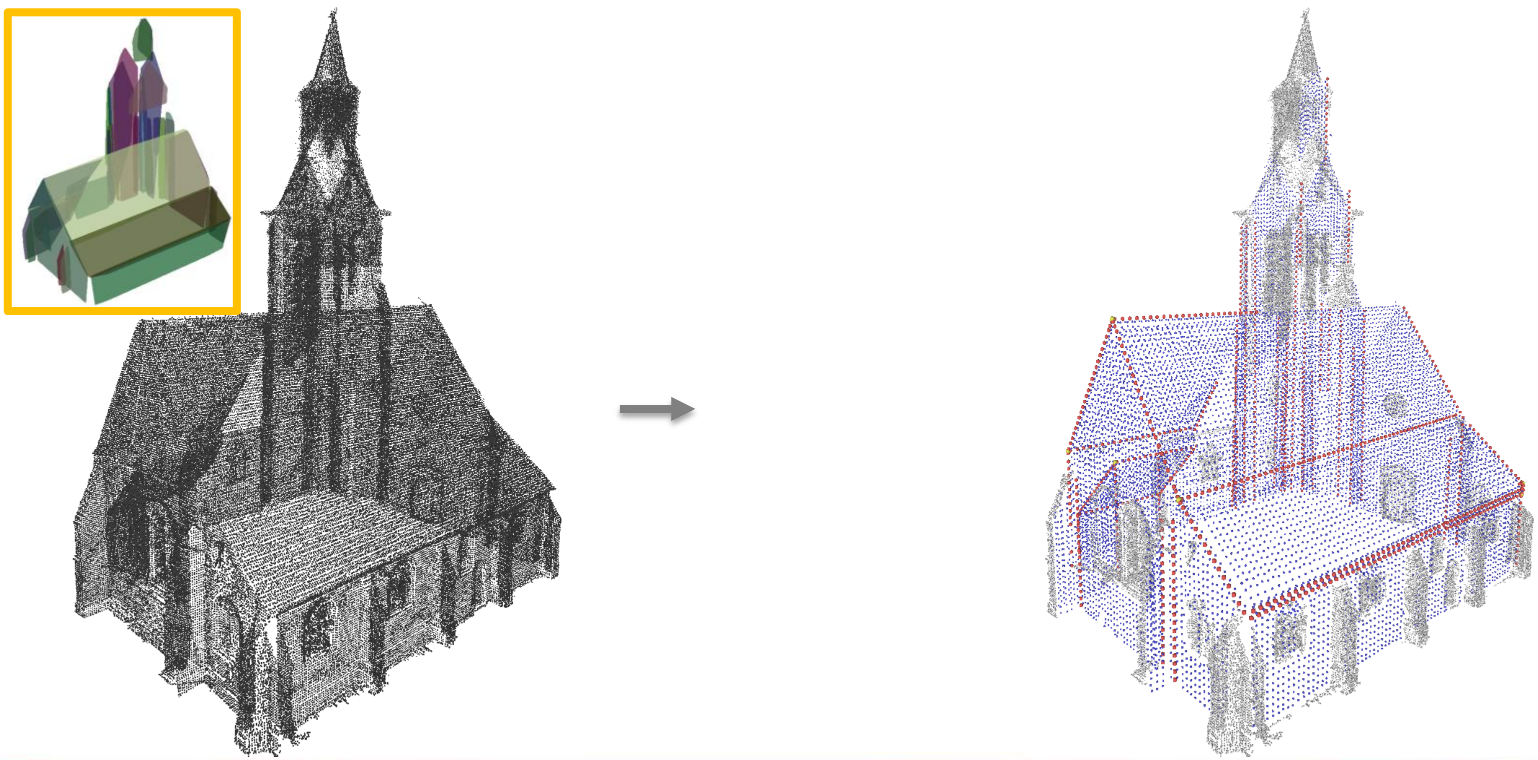


Point set structuring

[Lafarge, Alliez, surface reconstruction through point set structuring, Eurographics13]

Point set structuring

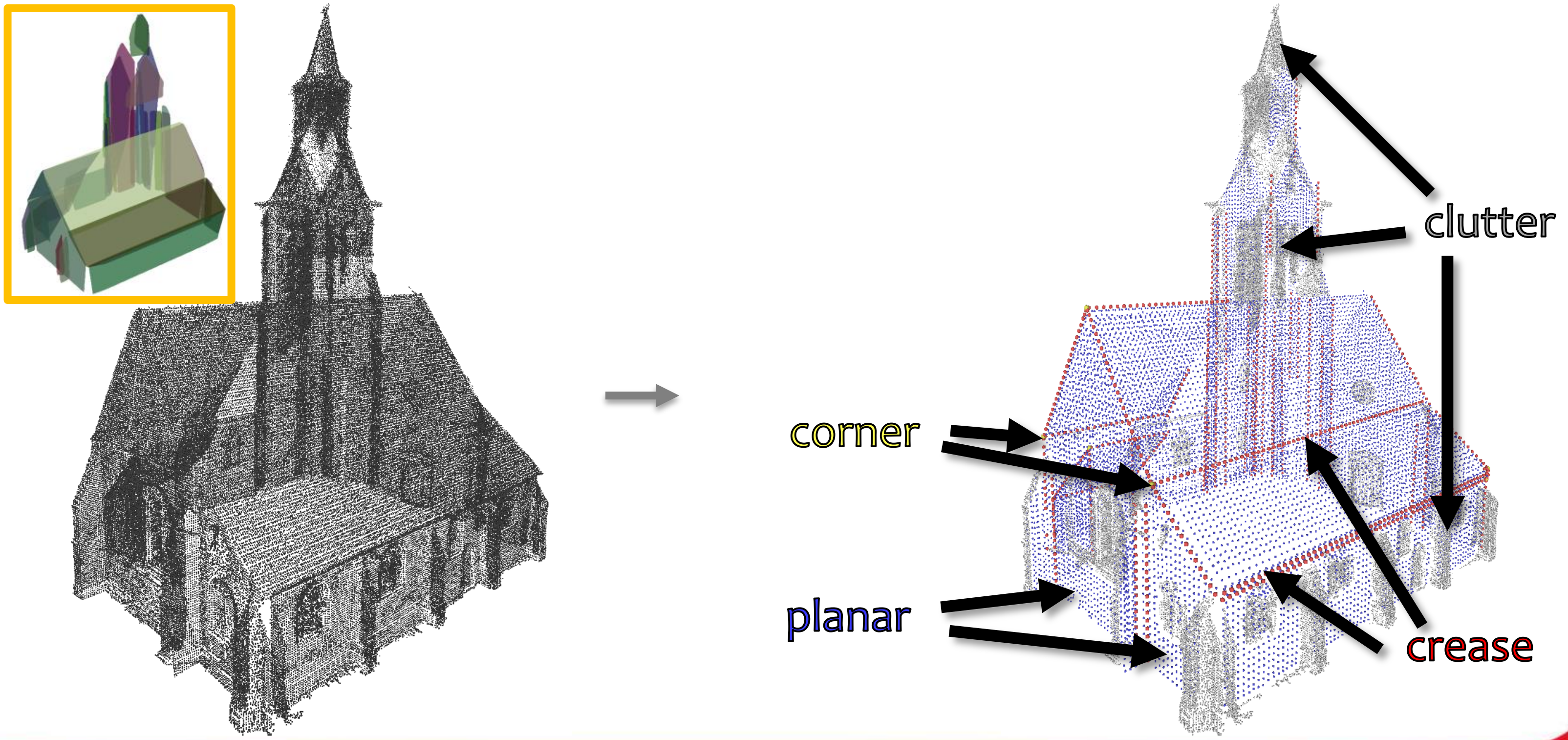
3 ideas



Point set structuring

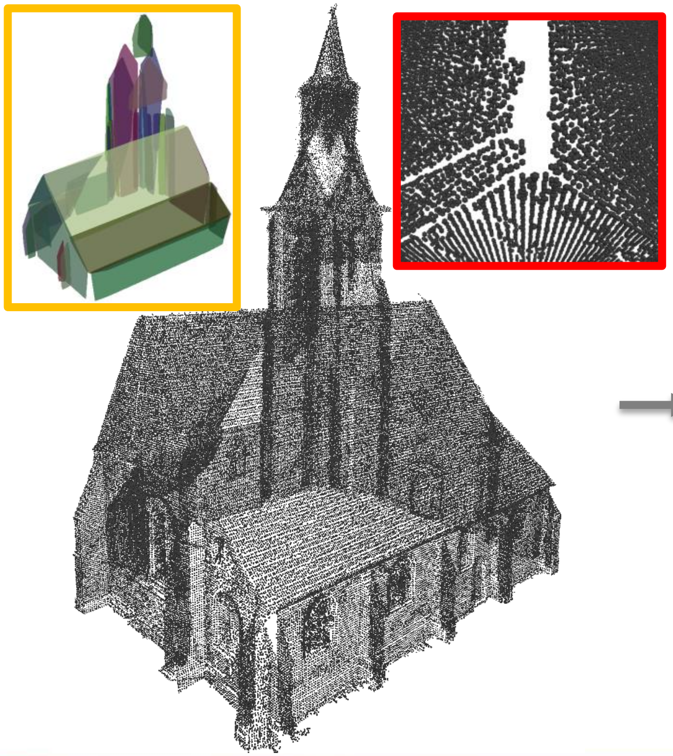
3 ideas

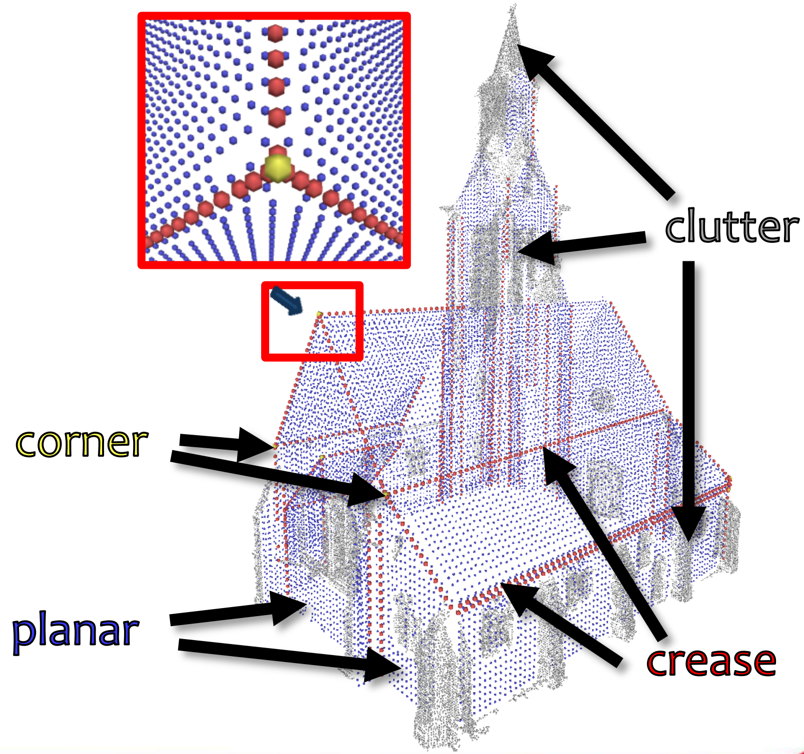
- **insertion of structural meaning**



Point set structuring

3 ideas
- insertion of structural meaning
- **repositioning of points**

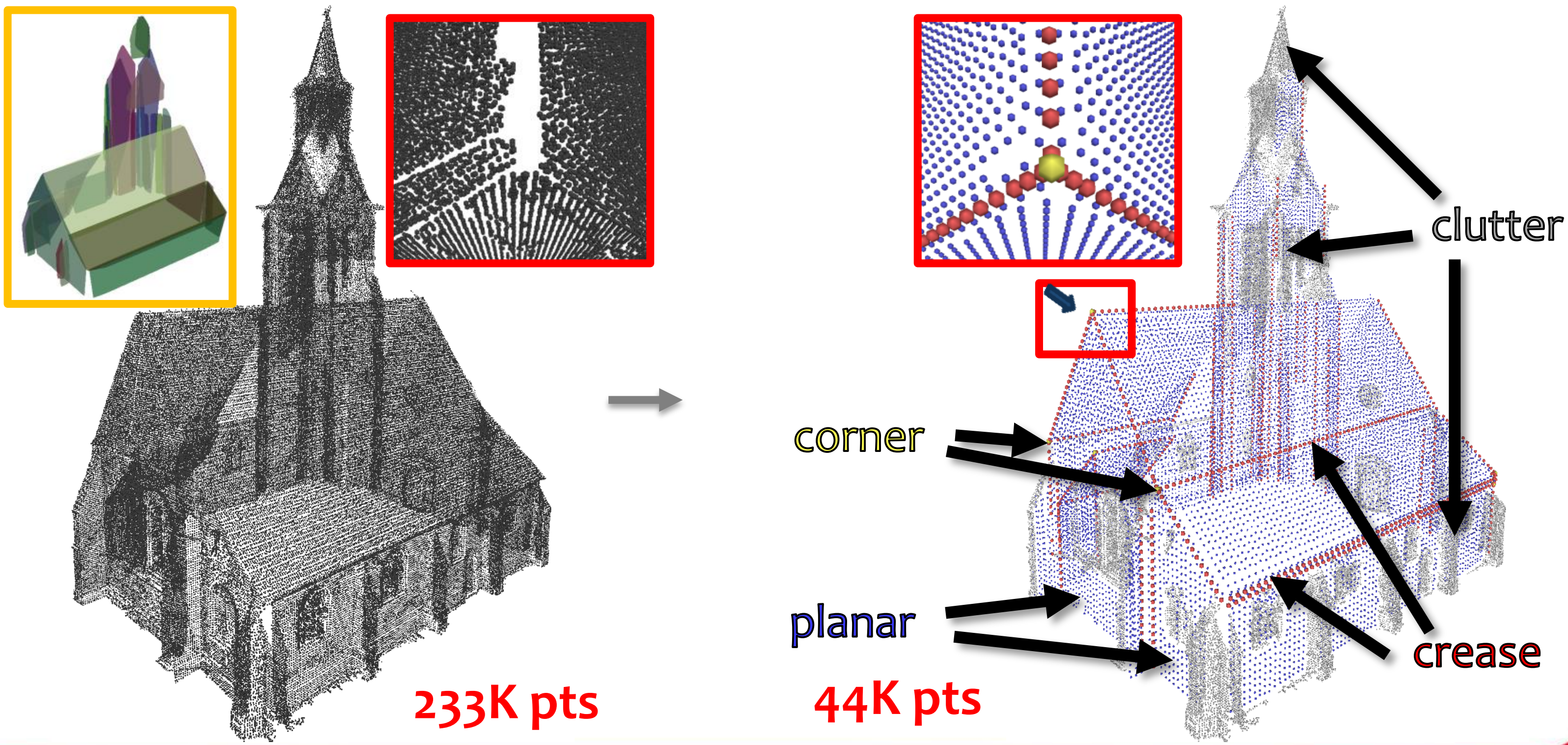




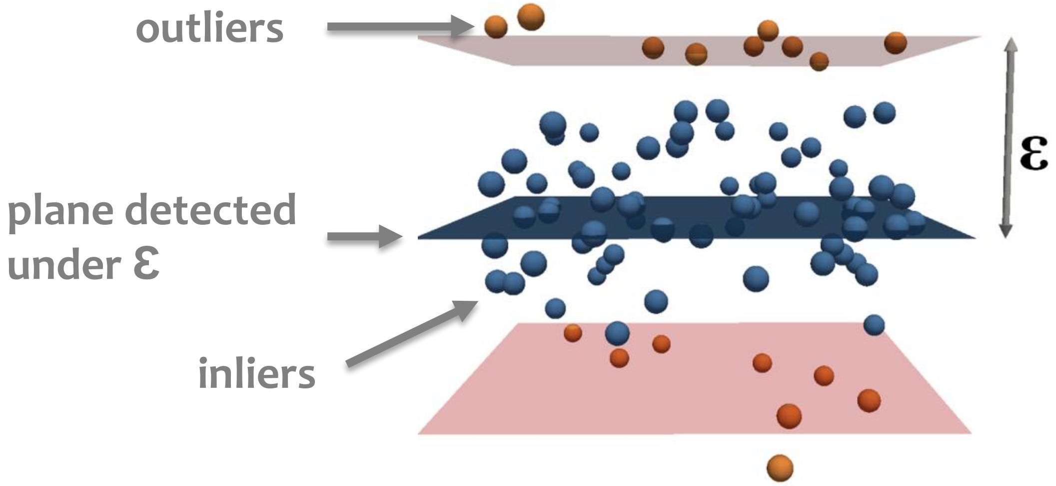
Point set structuring

3 ideas

- insertion of structural meaning
- repositioning of points
- **reduction of complexity**

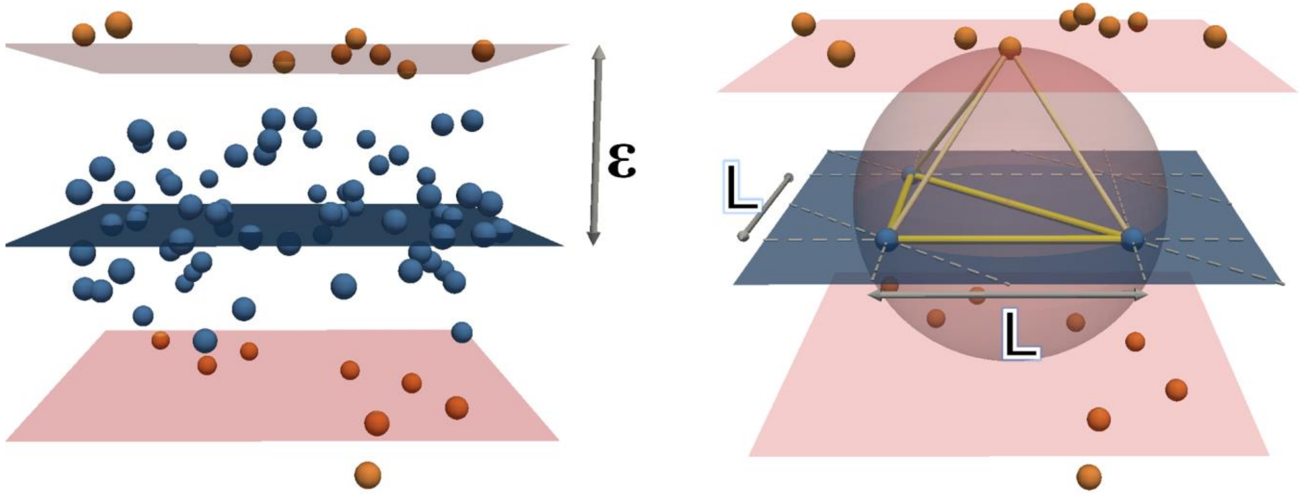


Creation of *planar* points



Creation of *planar* points

inliers replaced by planar points over an occupancy 2D-grid

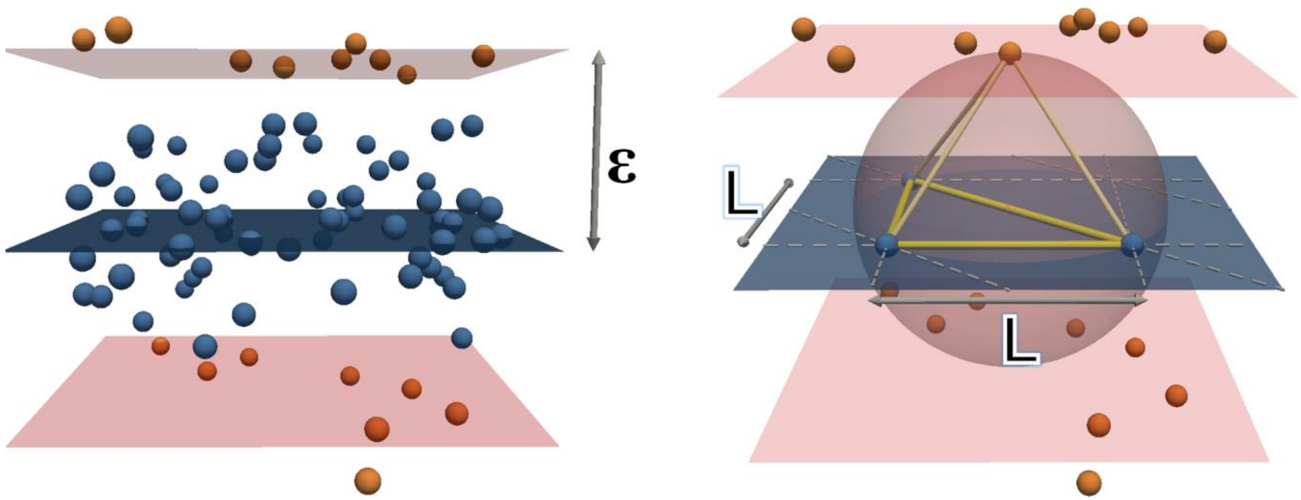


Creation of *planar* points

inliers replaced by planar points over an occupancy 2D-grid

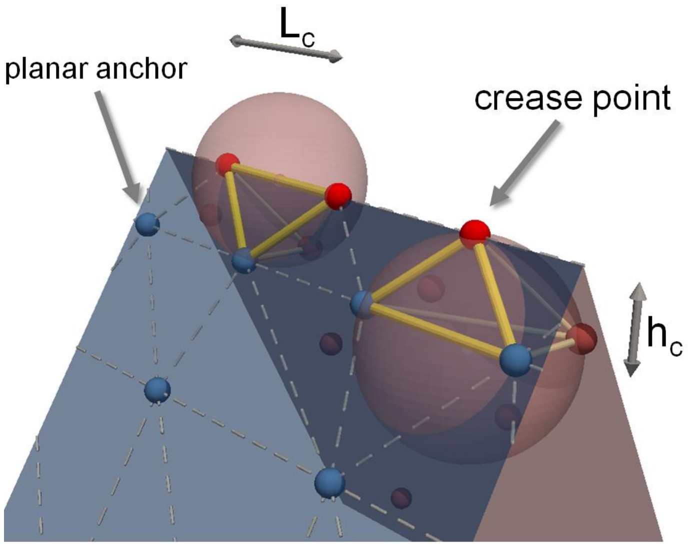
width L of the grid elements fixed by the facet existence condition in Delaunay

$$L < \sqrt{2}\,\varepsilon$$



Creation of *crease* points

Occupancy 1D-grid projected on the intersection line

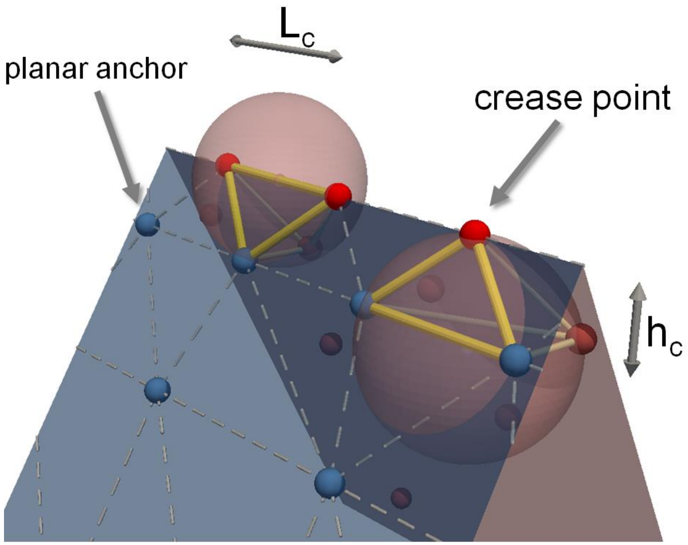


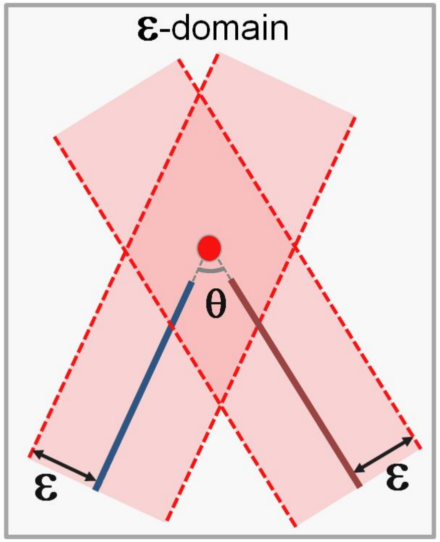
Creation of *crease* points

Occupancy 1D-grid projected on the intersection line

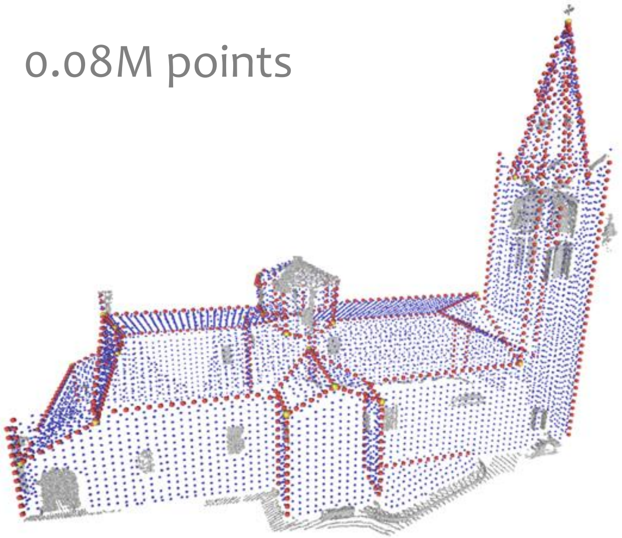
Facet existence condition in Delaunay

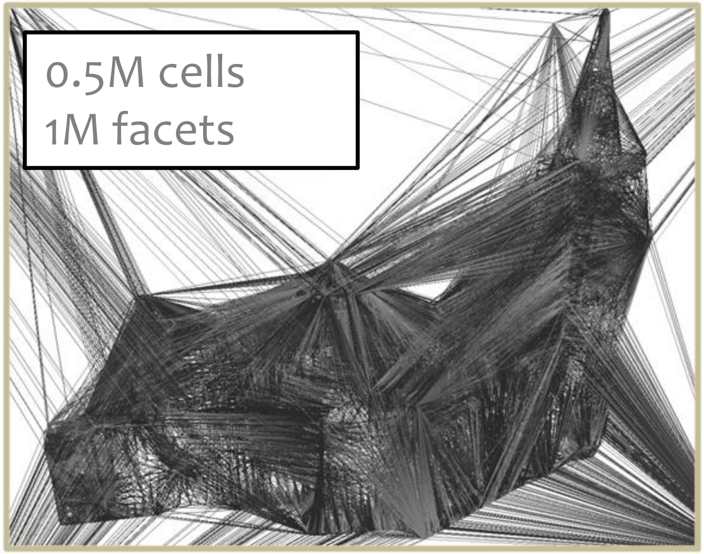
$$\begin{cases} L_c = 2\varepsilon \\ h_c = \varepsilon \times \cos\frac{\theta}{2} \end{cases}$$





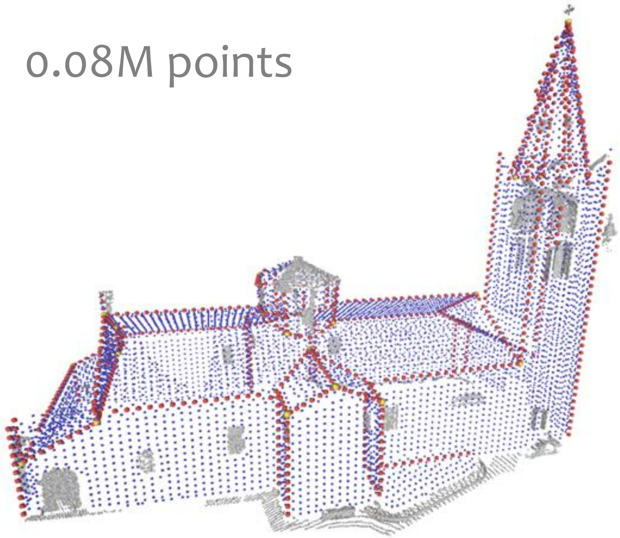
Delaunay on a structured point set



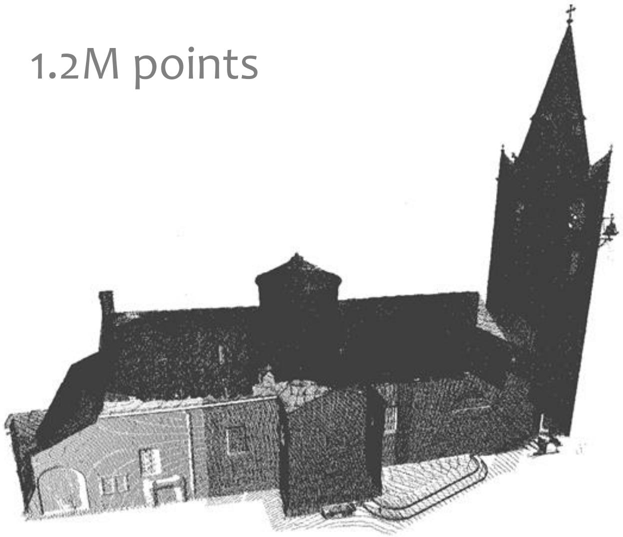


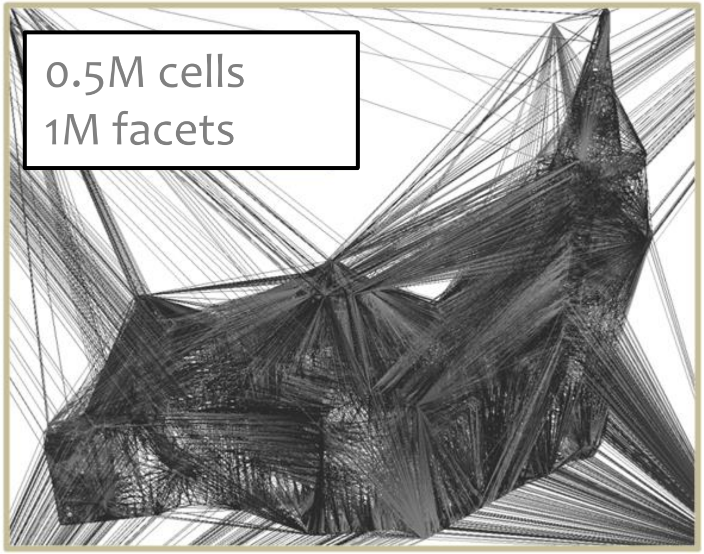
Delaunay on a structured point set

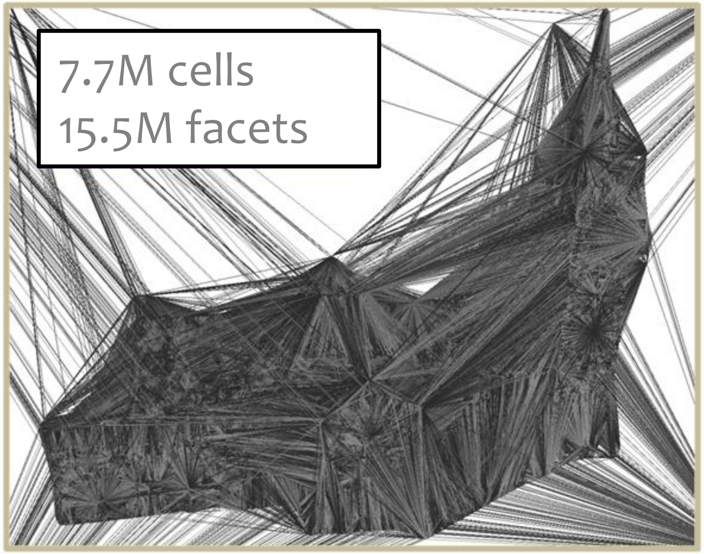
0.08M points



1.2M points

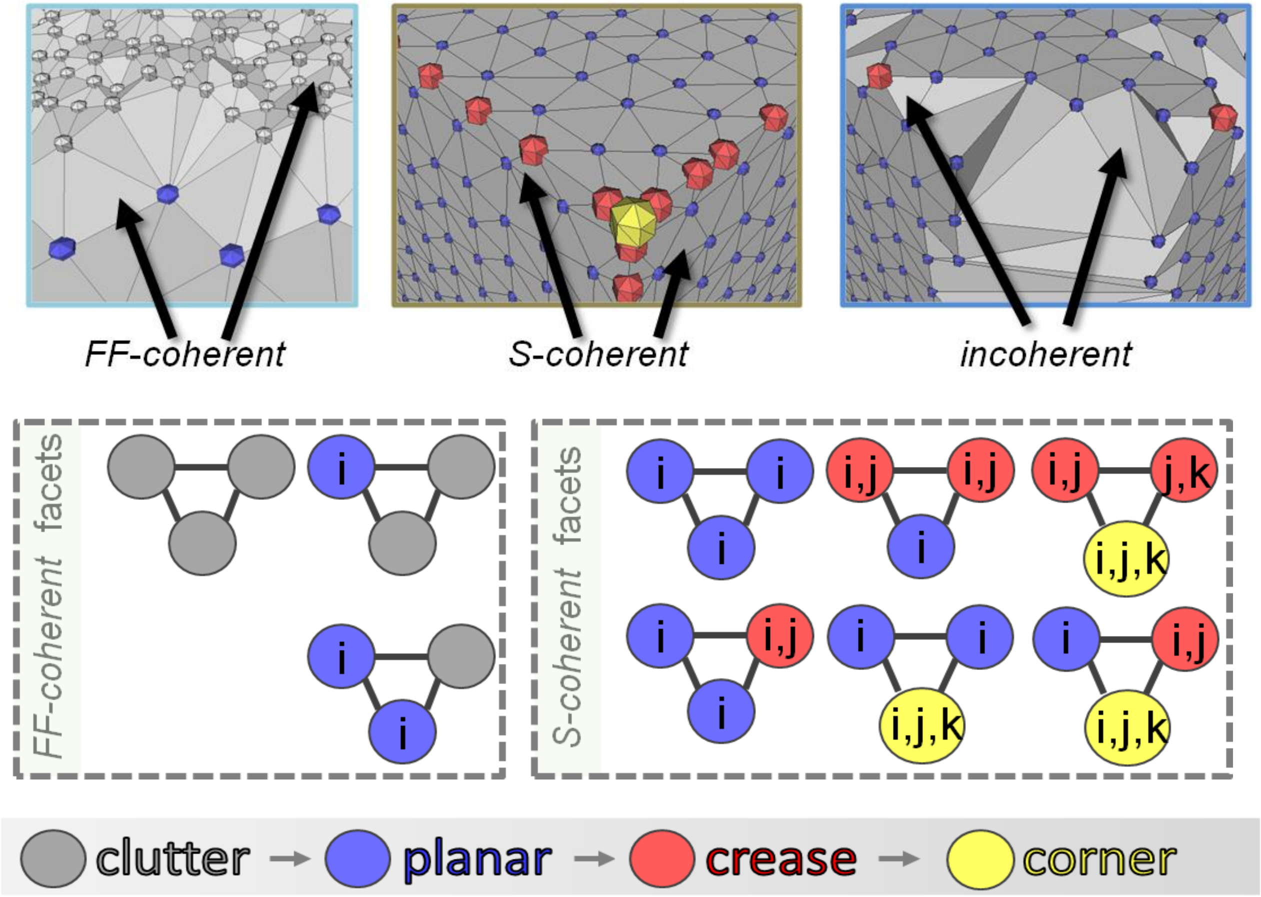






Labeling the Delaunay cells

Geometric quality of facets based on structural coherence

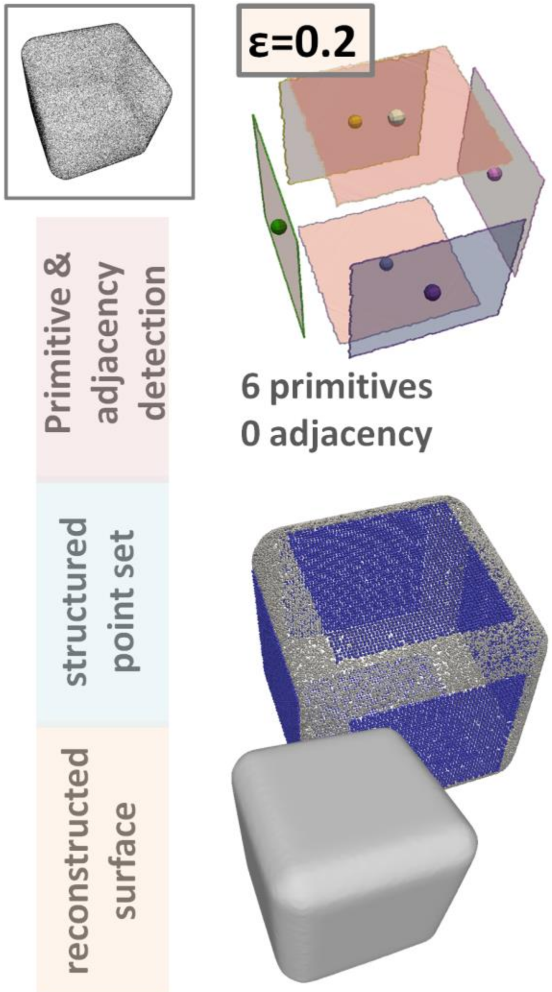


FF-coherent facets:
weak penalty [Vu09]

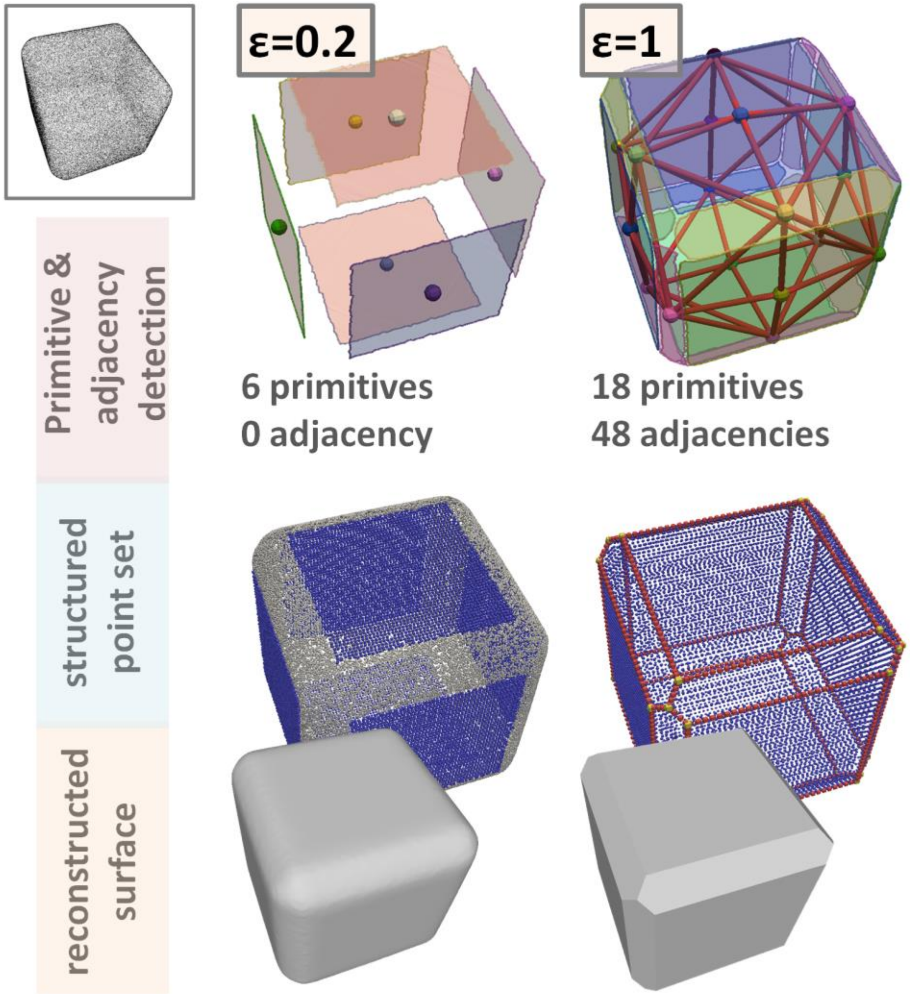
S-coherent facets:
no penalty

incoherent facets:
strong penalty

Smooth cube

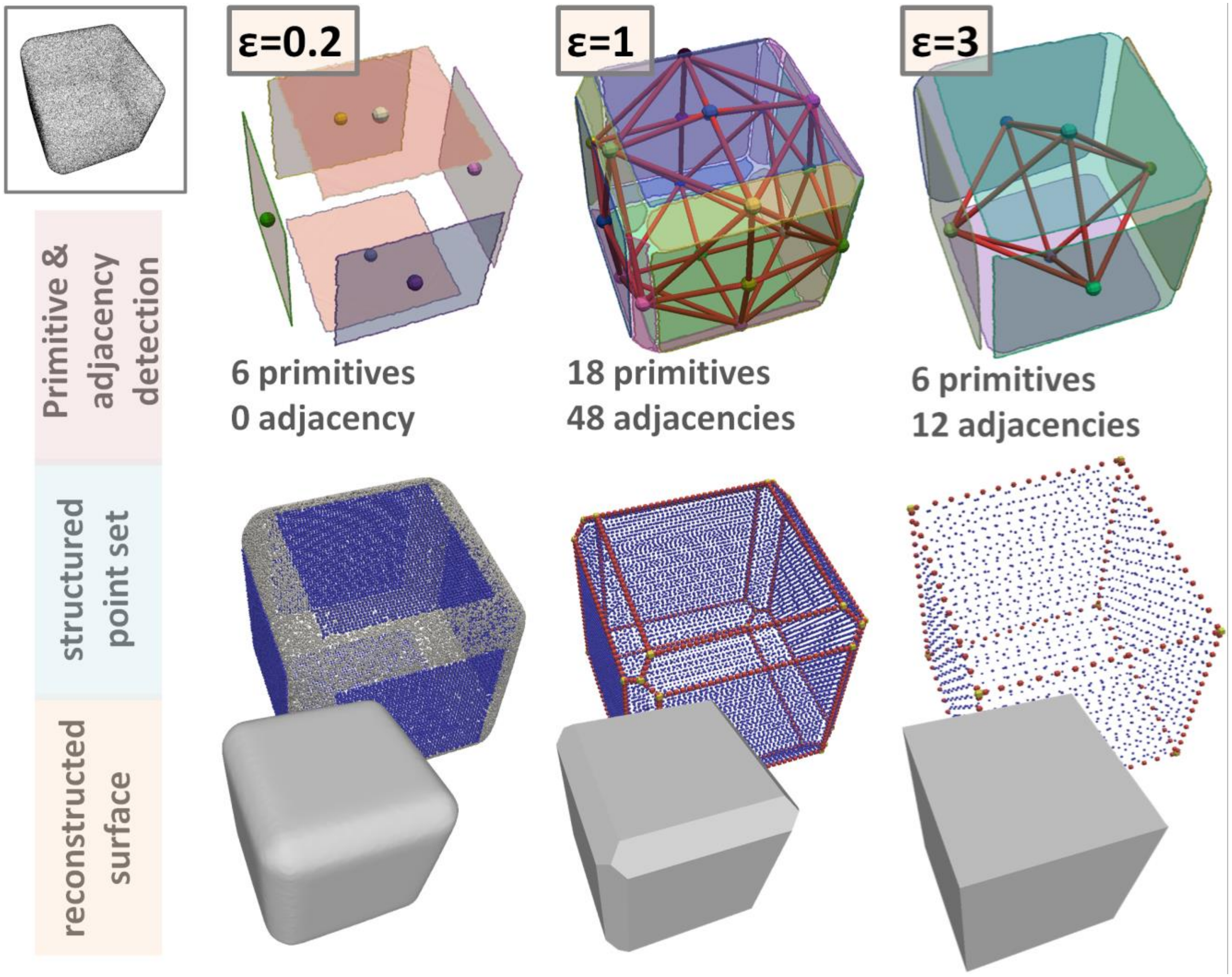

ε=0.2
Primitive & adjacency detection
6 primitives
0 adjacency
structured point set
reconstructed surface

Smooth cube

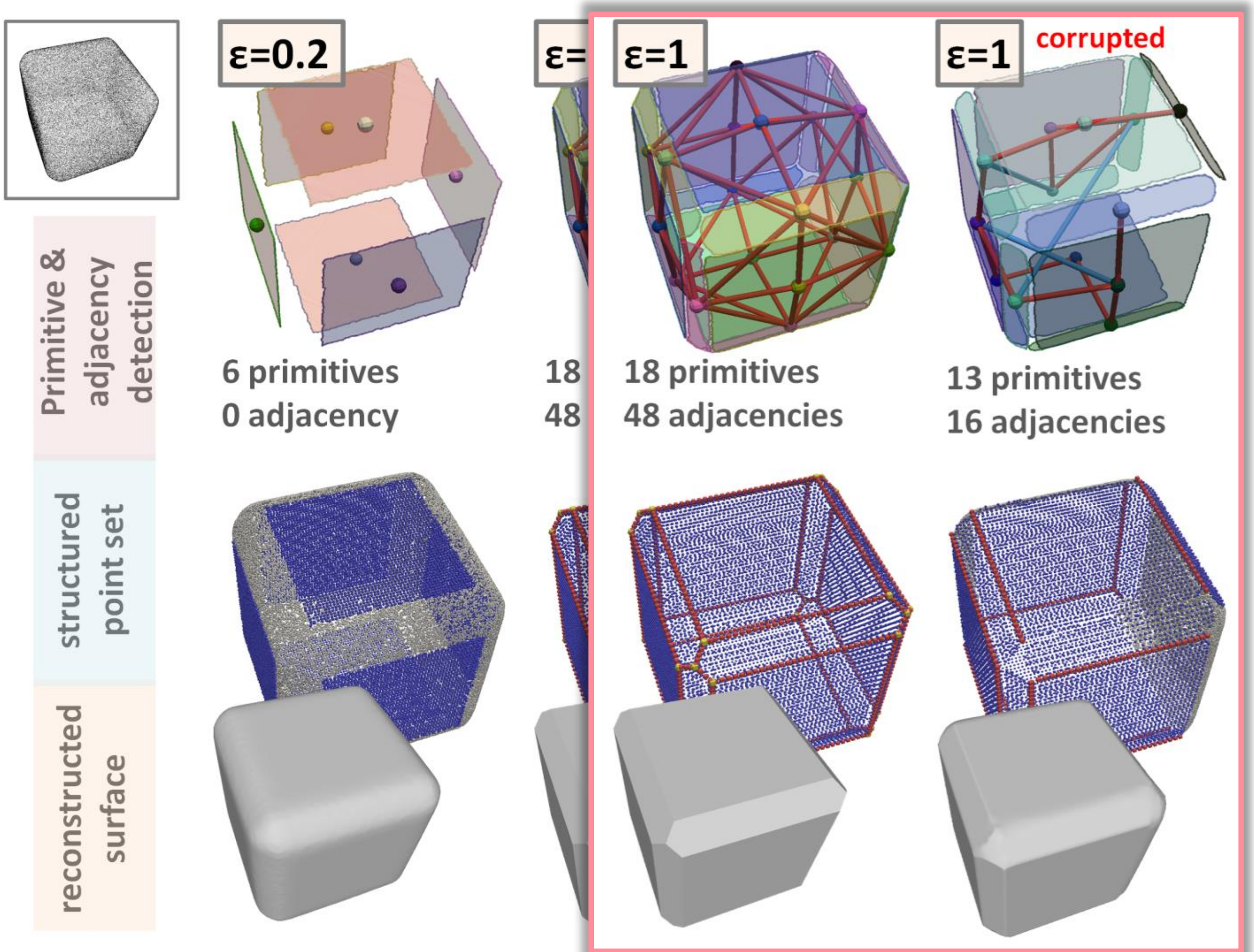


ε=0.2
ε=1
Primitive & adjacency detection
6 primitives
0 adjacency
18 primitives
48 adjacencies
structured point set
reconstructed surface

Smooth cube

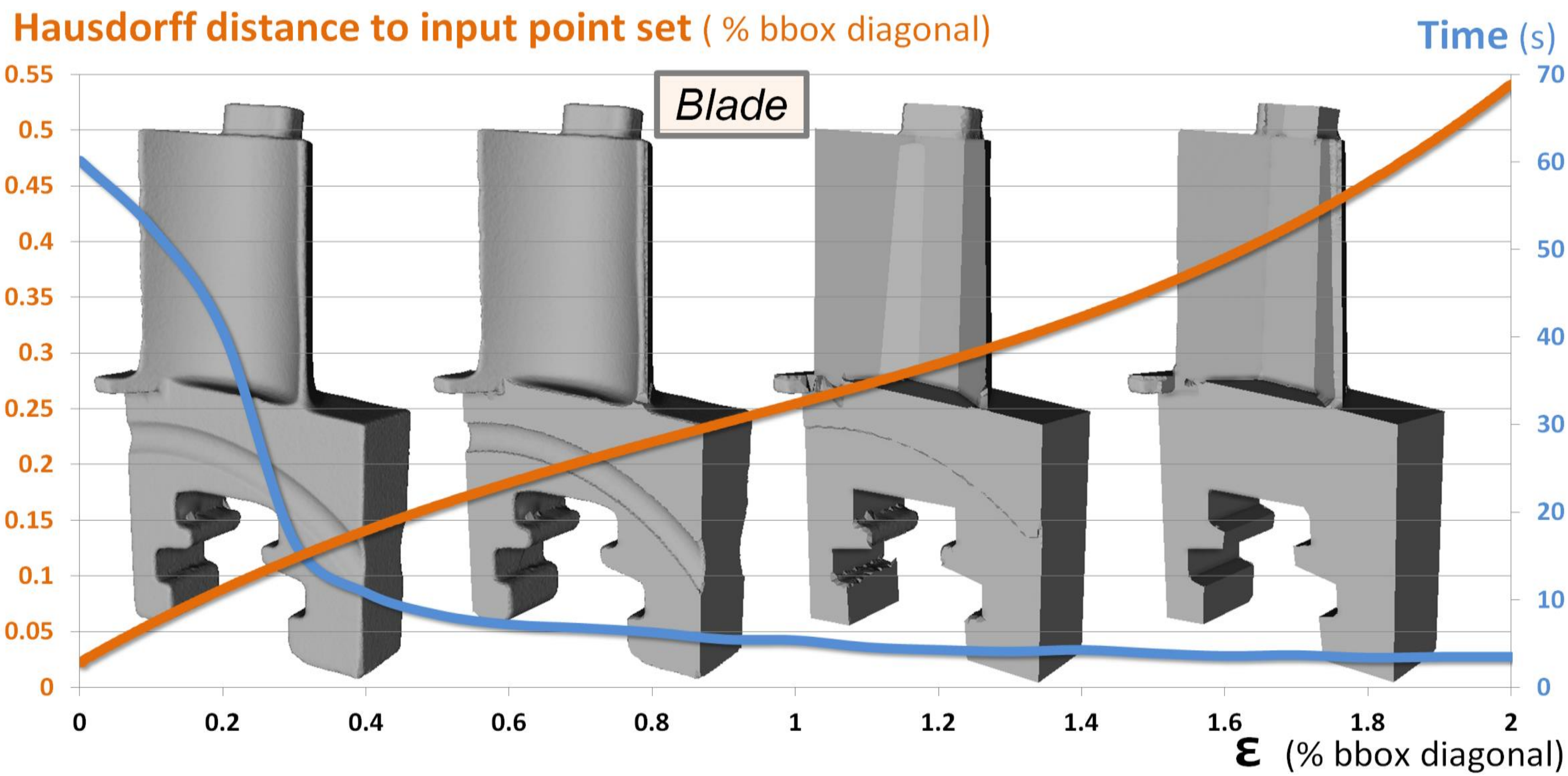

ε=0.2
ε=1
ε=3
Primitive & adjacency detection
6 primitives
0 adjacency
18 primitives
48 adjacencies
6 primitives
12 adjacencies
structured point set
reconstructed surface

Smooth cube



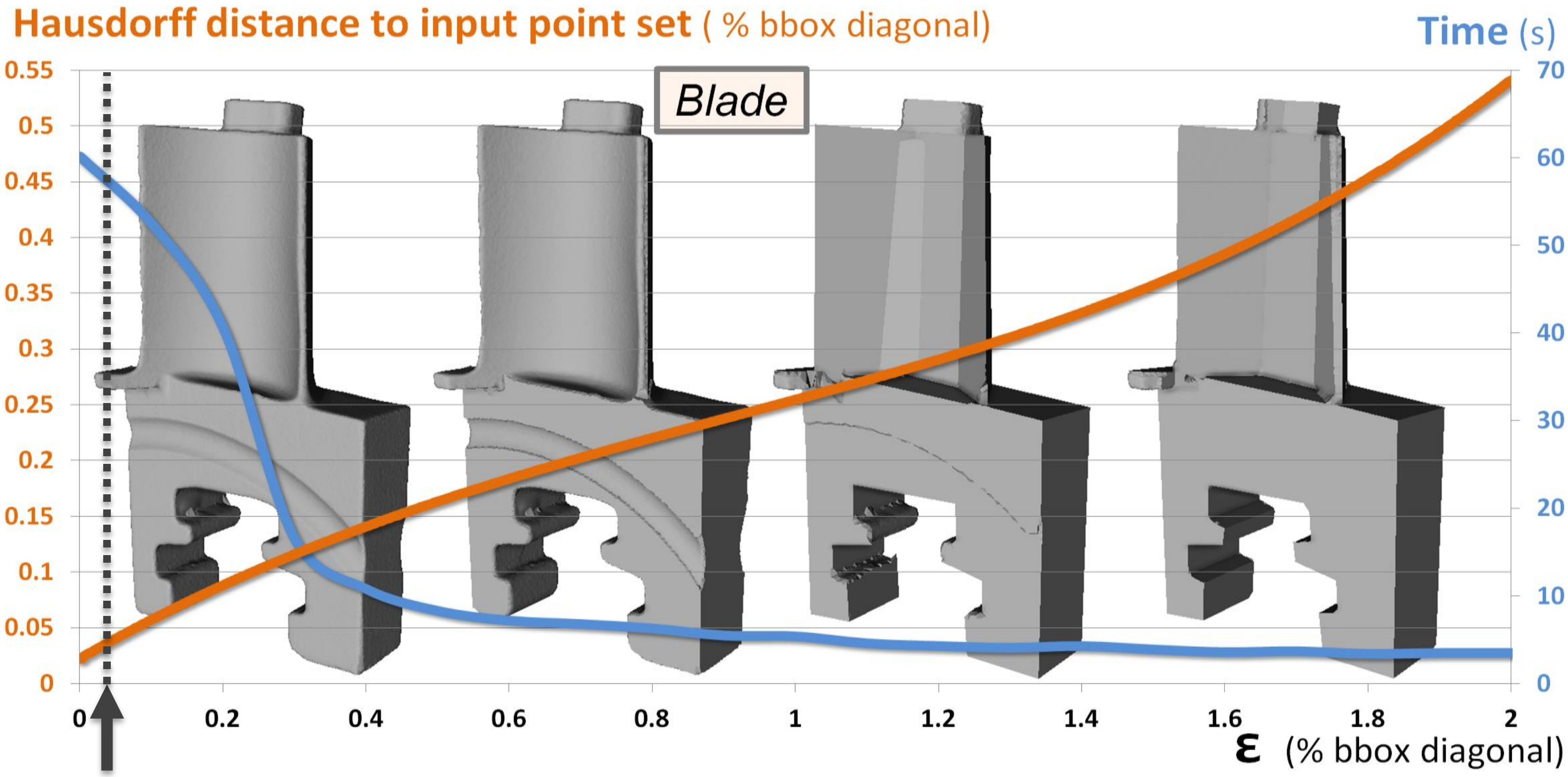
ε=0.2
ε=
ε=1
ε=1
corrupted
Primitive & adjacency detection
structured point set
reconstructed surface
6 primitives
0 adjacency
18
48
18 primitives
48 adjacencies
13 primitives
16 adjacencies

Blade



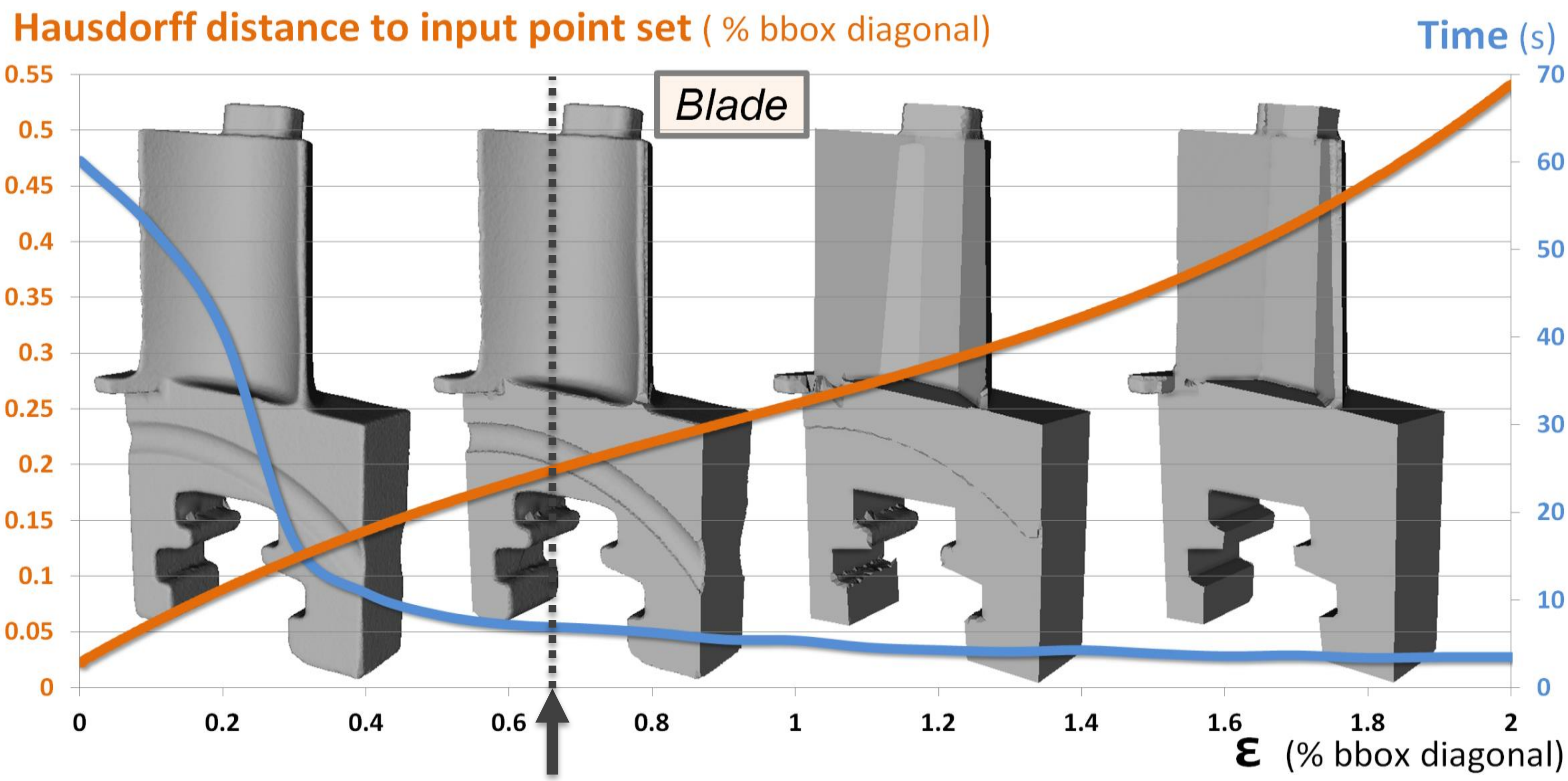
Hausdorff distance to input point set (% bbox diagonal)
Time (s)
Blade
0.55
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
70
60
50
40
30
20
10
0
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
ε (% bbox diagonal)

Blade



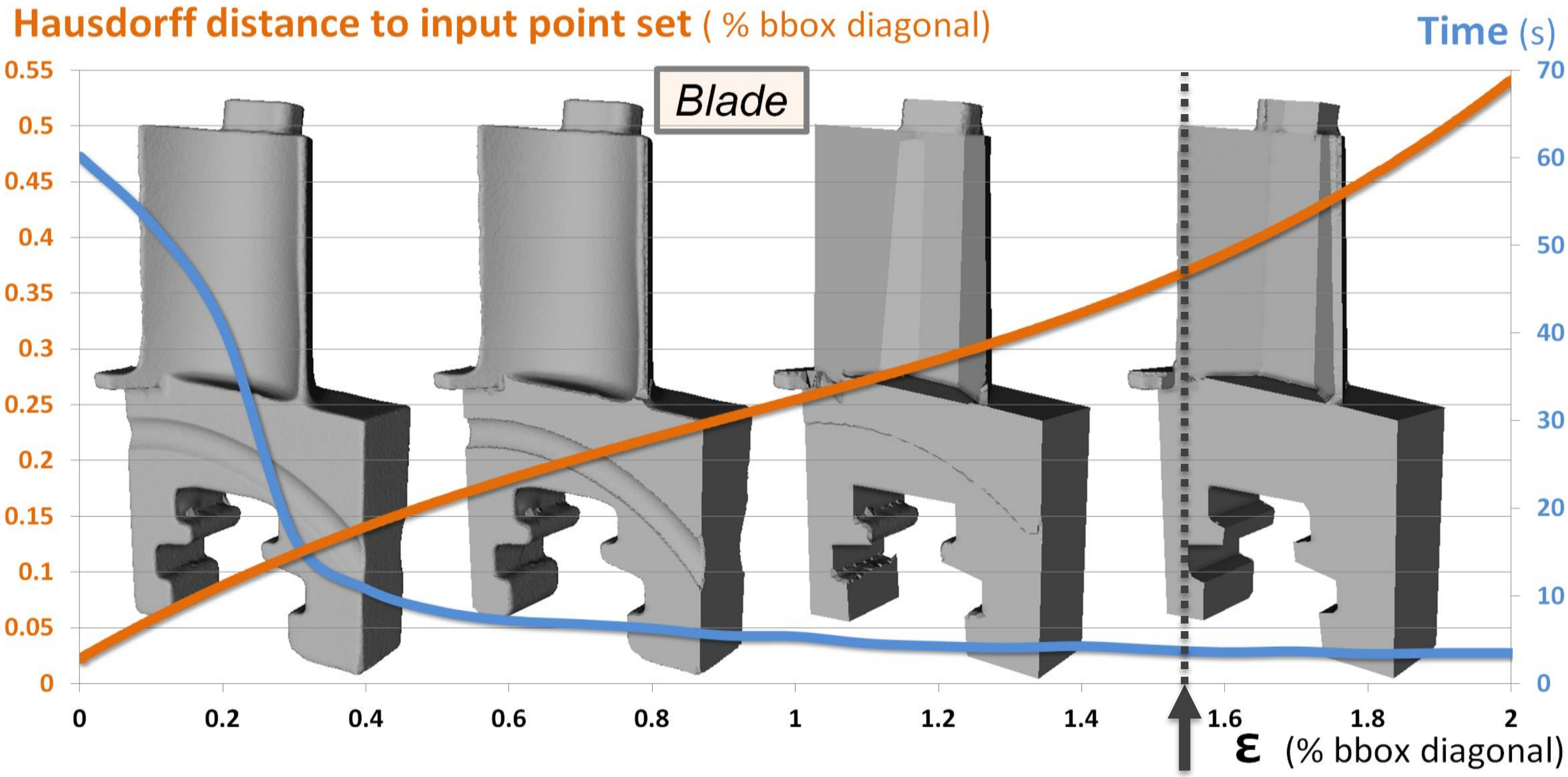
highly freeform (no structure)
high accuracy
high running time

Blade



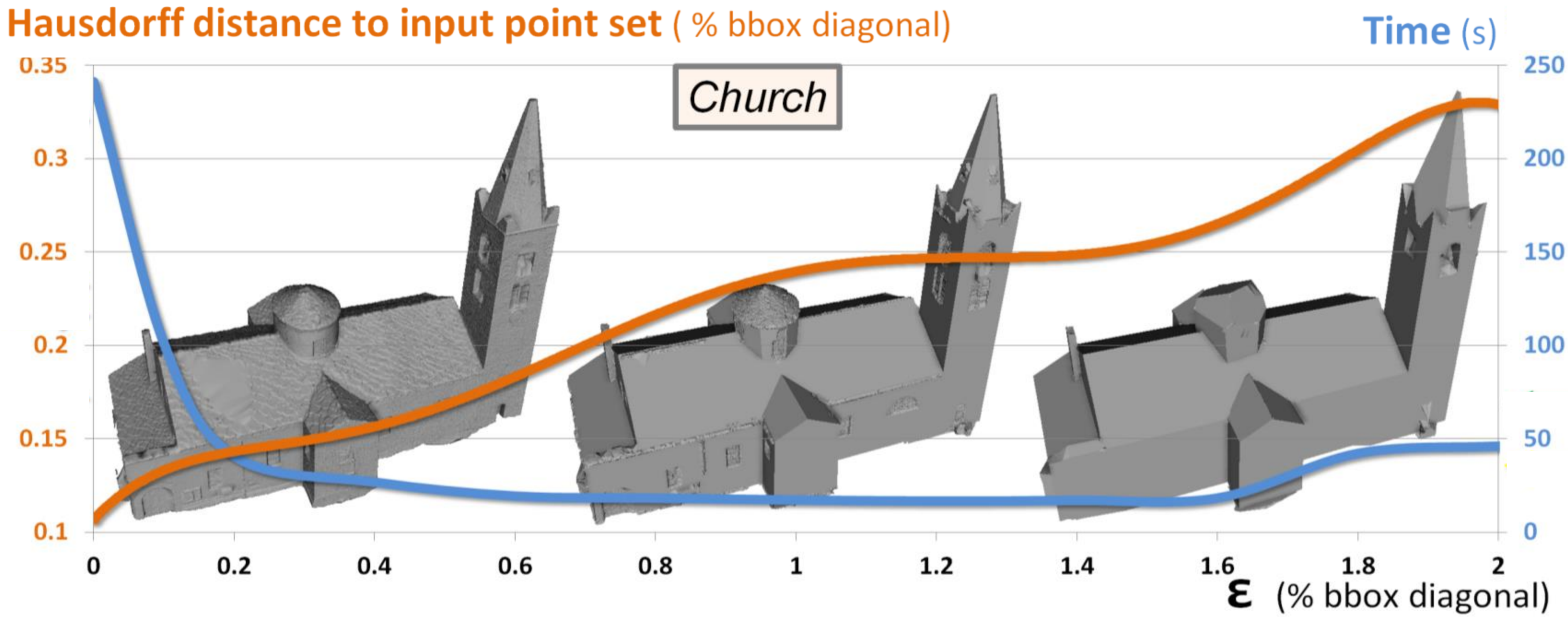
structure ↑ (freeform ↓)
accuracy ↓
running time ↓

Blade



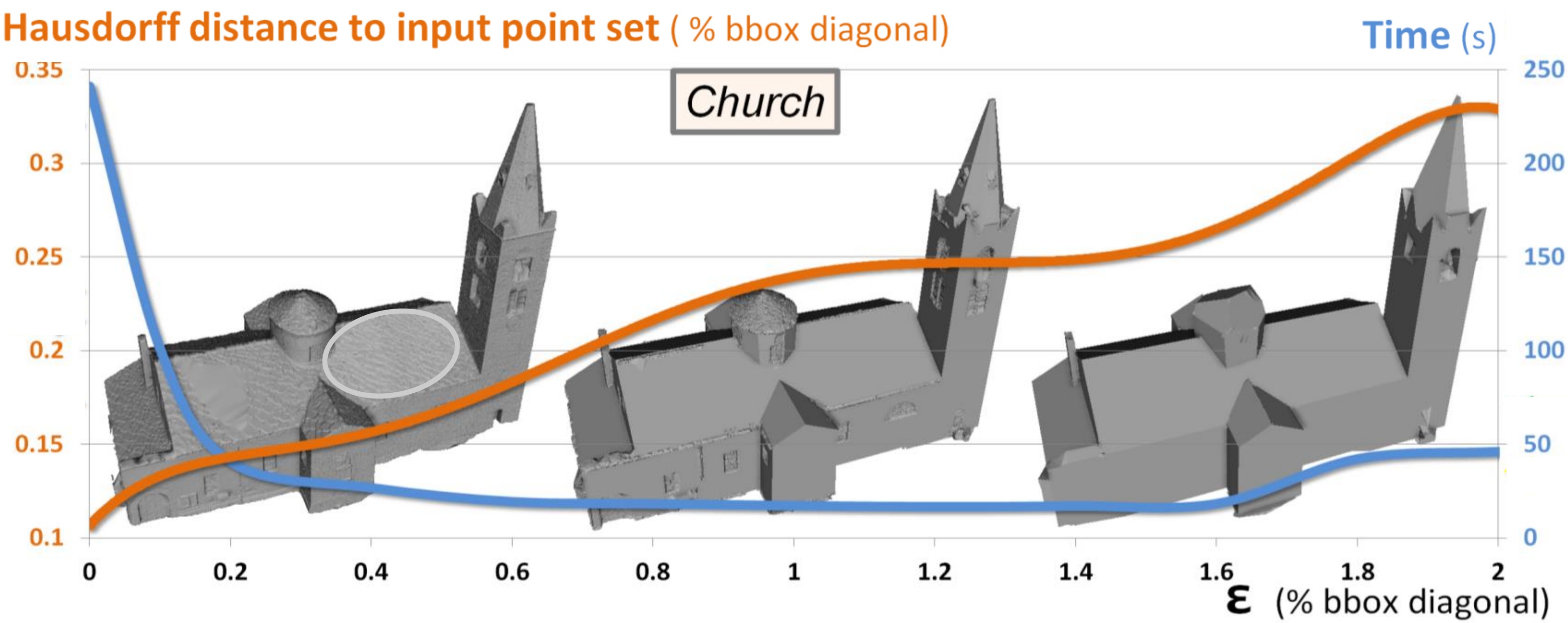
fully structured
low accuracy
low running time

Church



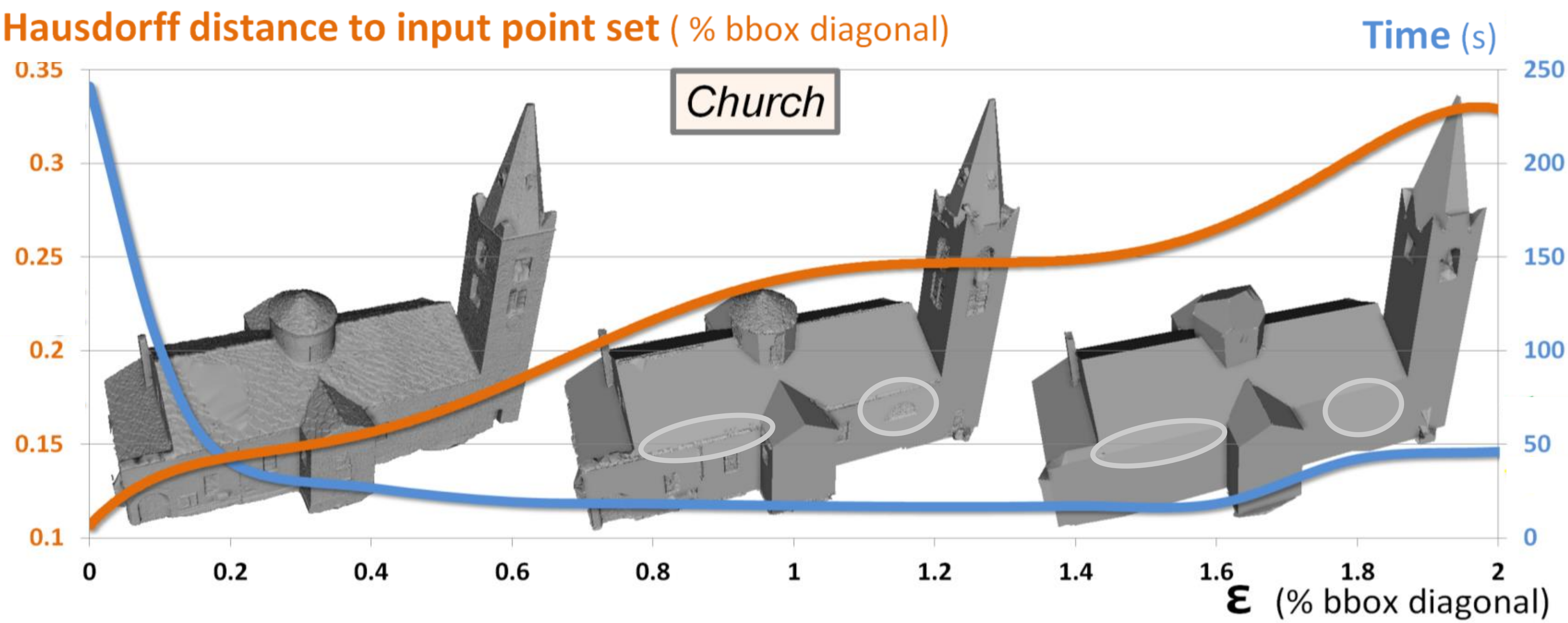
Hausdorff distance to input point set (% bbox diagonal)
Time (s)
Church
0.35
0.3
0.25
0.2
0.15
0.1
250
200
150
100
50
0
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
ε (% bbox diagonal)

Church

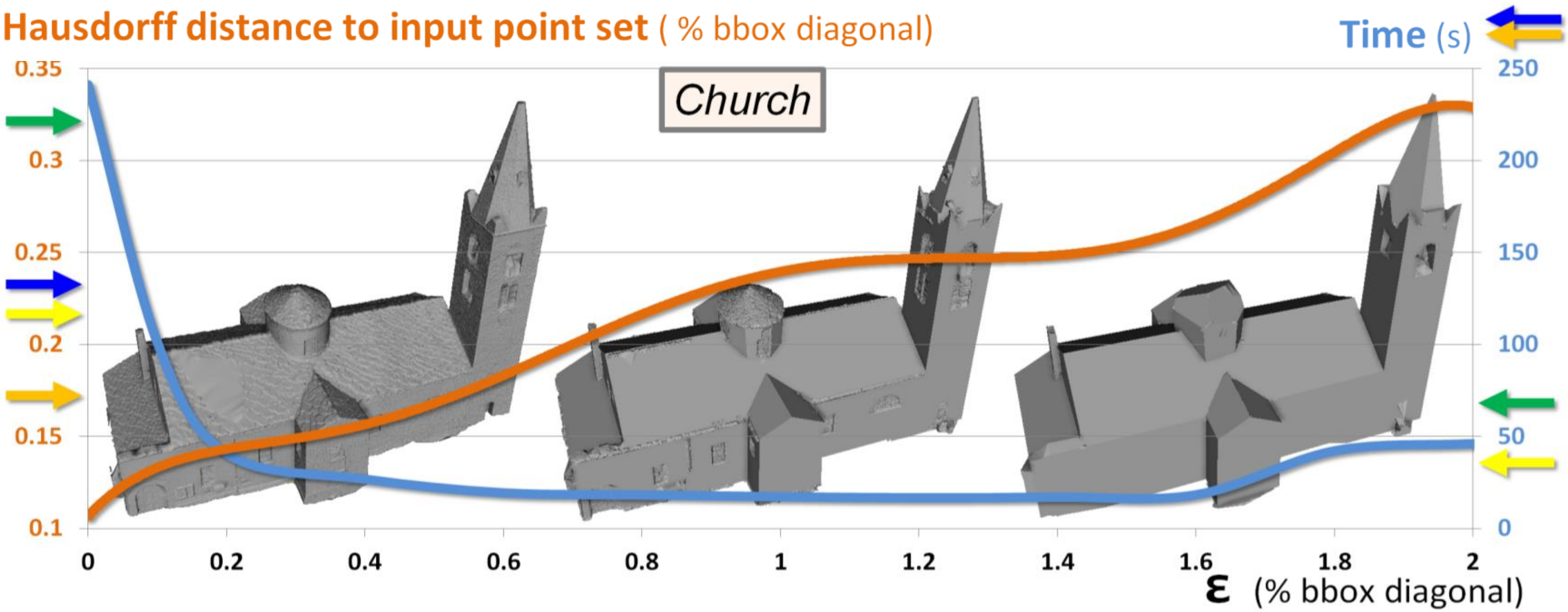


Hausdorff distance to input point set (% bbox diagonal)
Time (s)
Church
0.35
0.3
0.25
0.2
0.15
0.1
250
200
150
100
50
0
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
ε (% bbox diagonal)

Church

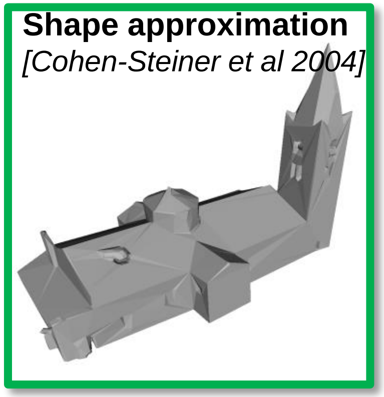

Hausdorff distance to input point set (% bbox diagonal)
Time (s)
Church
0.35
0.3
0.25
0.2
0.15
0.1
250
200
150
100
50
0
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
ε (% bbox diagonal)

Church



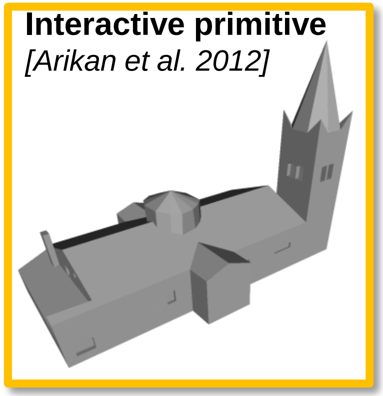
Hausdorff distance to input point set (% bbox diagonal)
Time (s)
Church
0.35
0.3
0.25
0.2
0.15
0.1
250
200
150
100
50
0
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
ε (% bbox diagonal)

smooth
[Kazhdan et al. 2006]



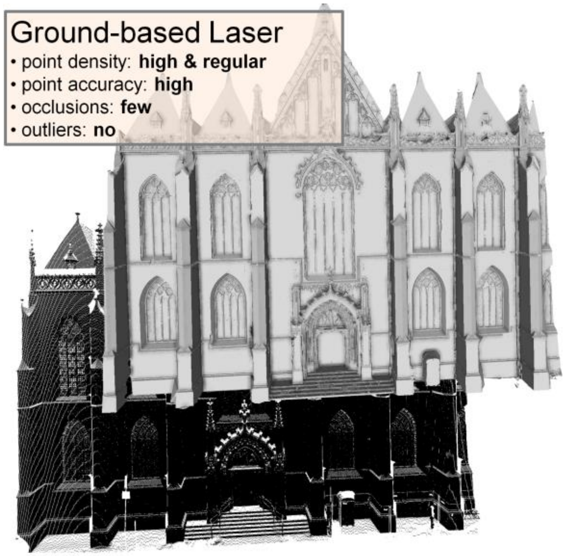
Shape approximation
[Cohen-Steiner et al 2004]

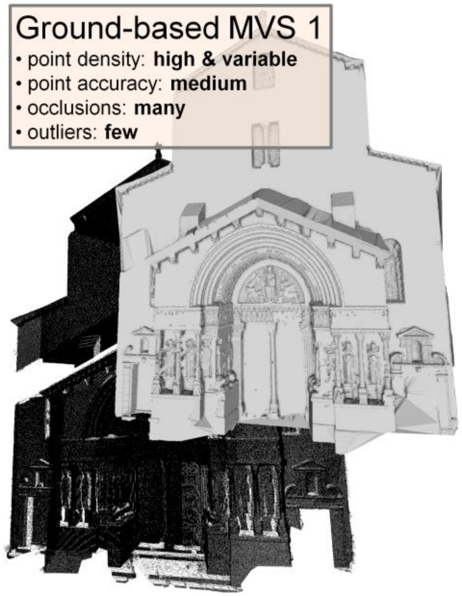
Piecewise-smooth
[Salman et al. 2010]

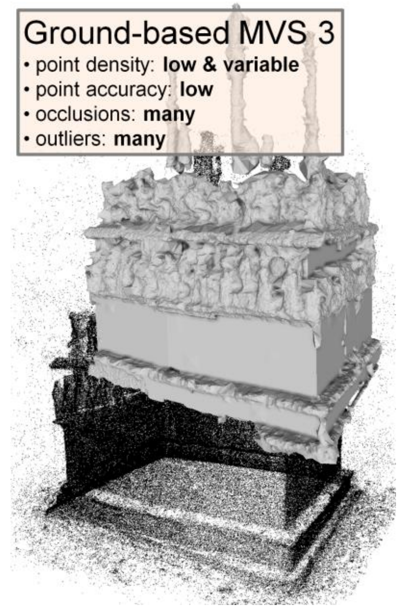


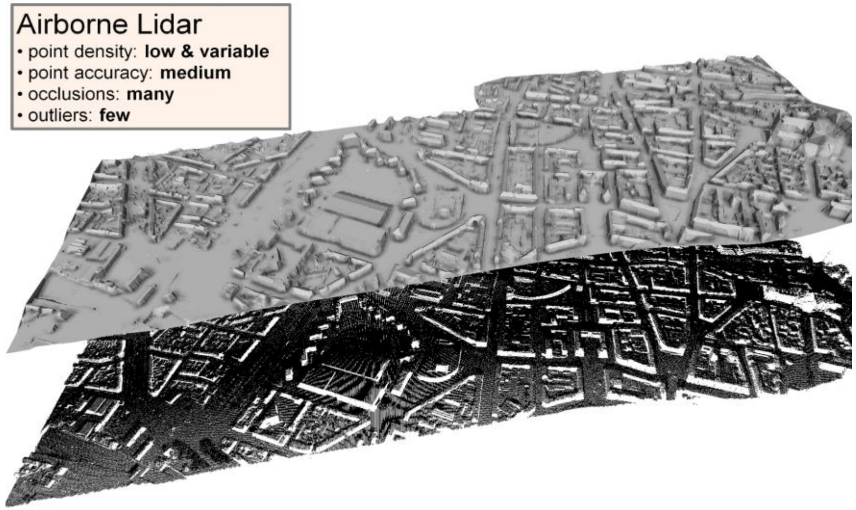
Interactive primitive
[Arikan et al. 2012]

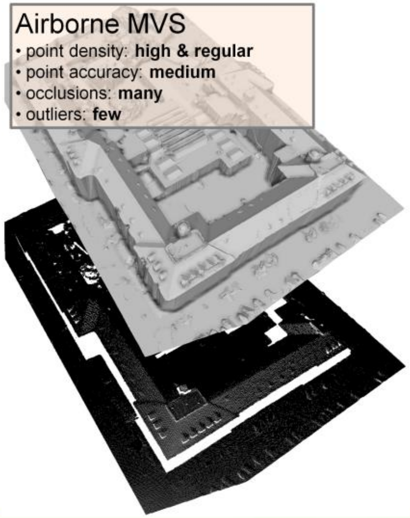
Various types of input

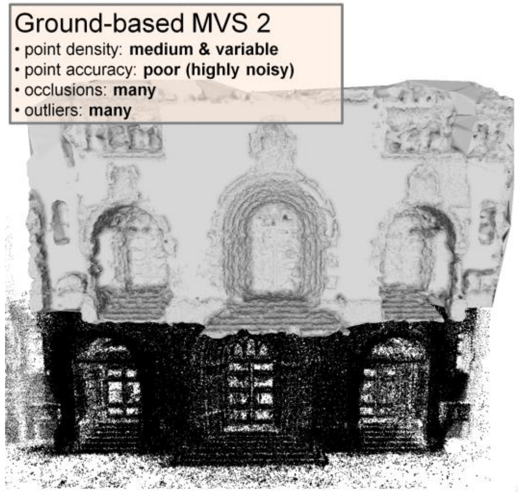




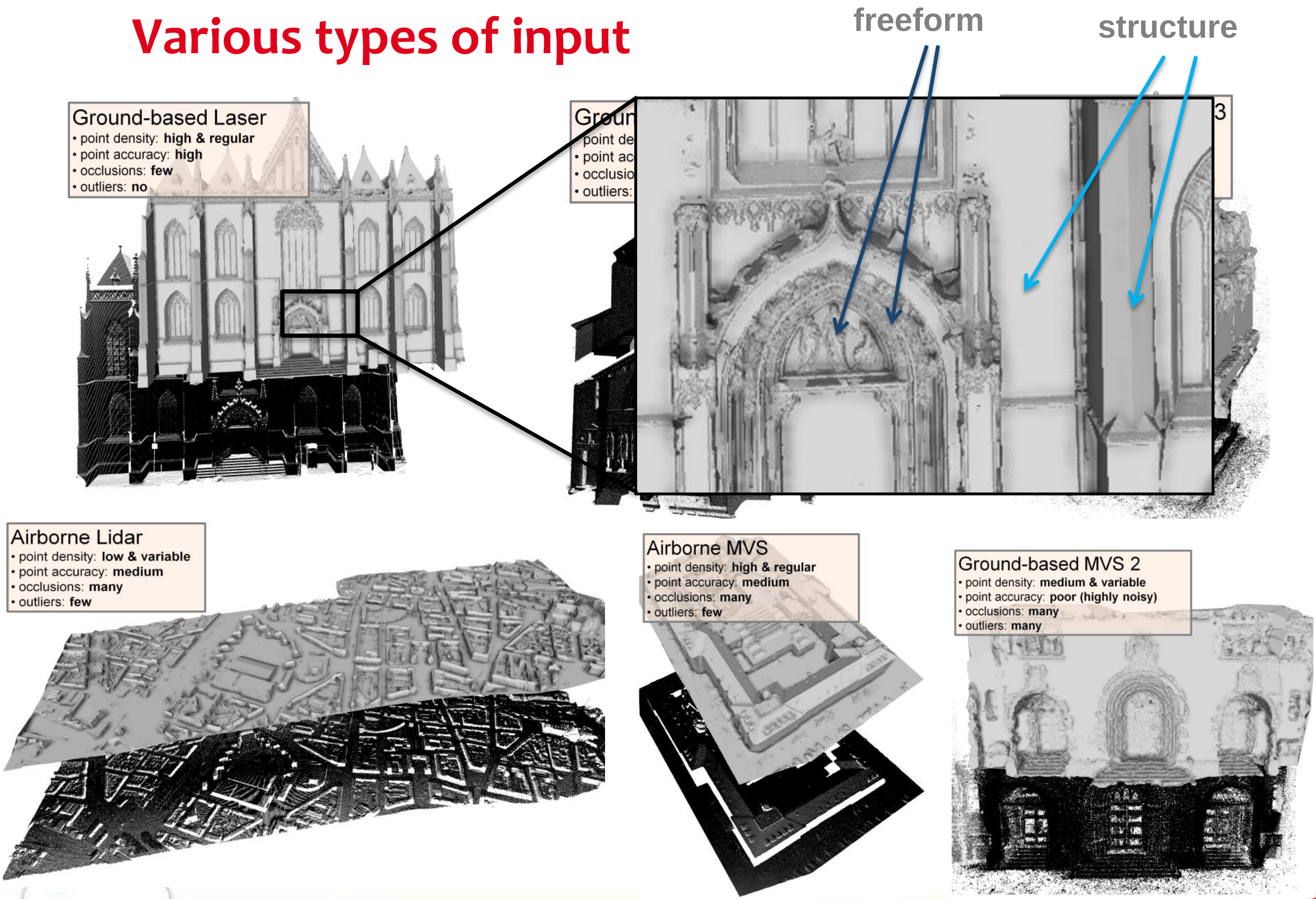




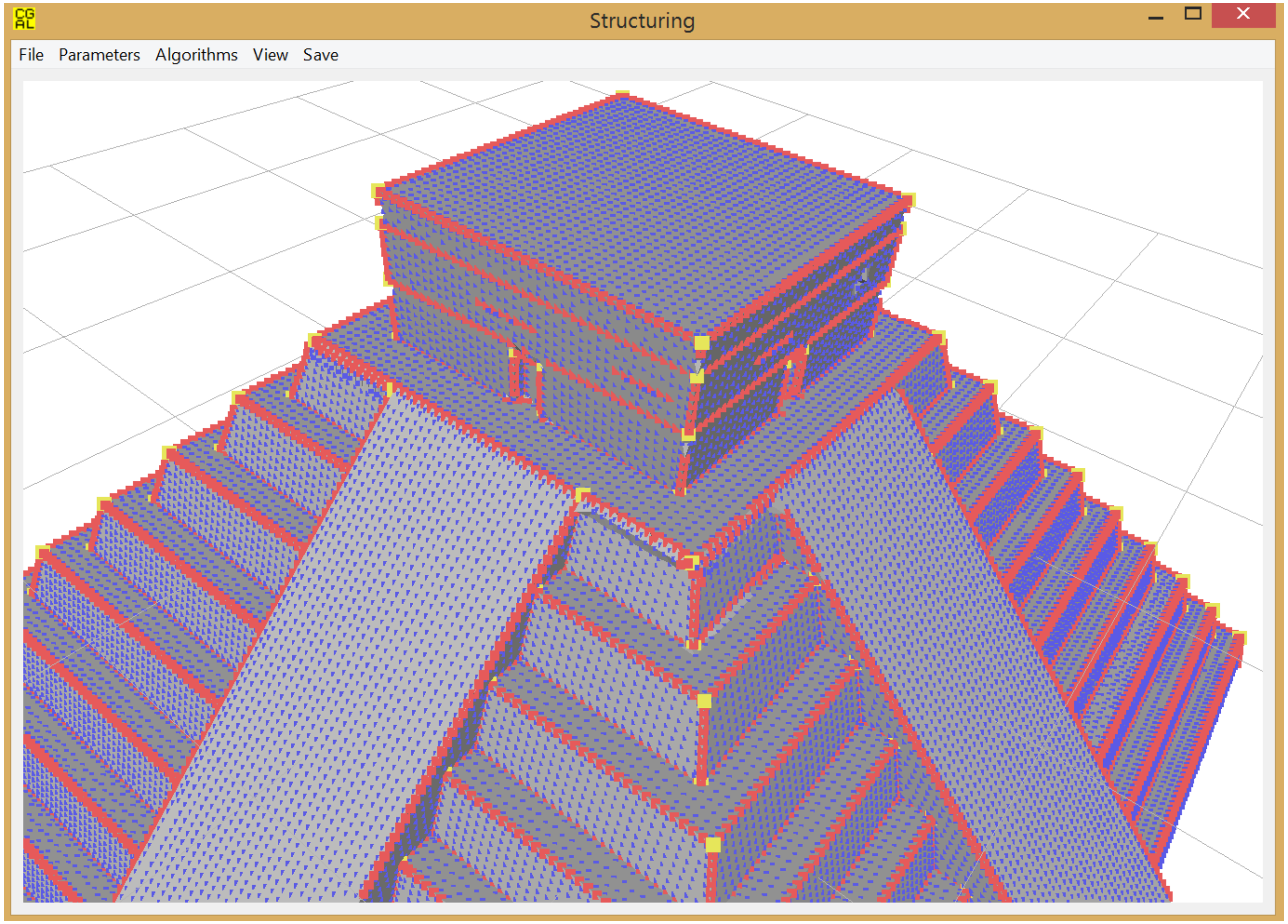




Various types of input



Demo



Multiple shape sampling

[Lafarge, Keriven, Bredif, Vu, a hybrid MVS algorithm for modeling urban scenes, PAMI13]

Multiple shape sampling

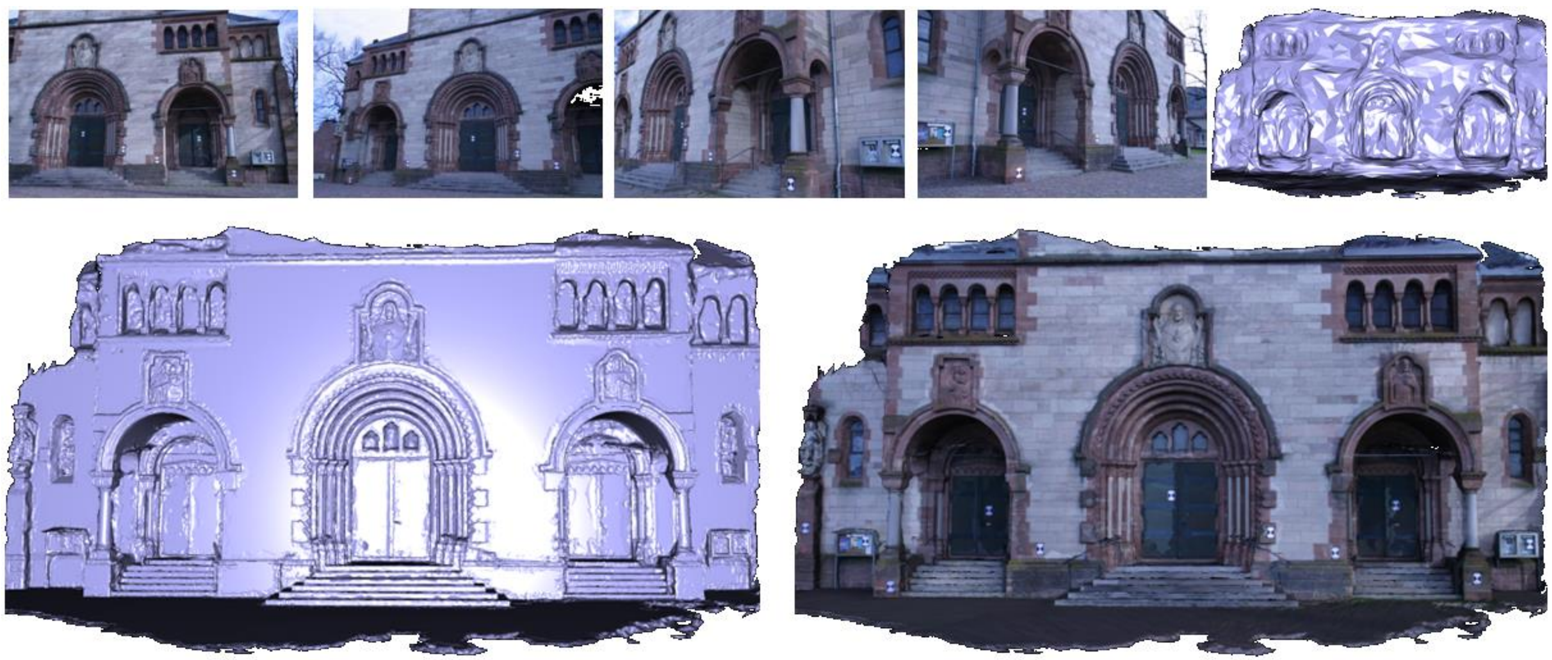
Joint sampling of primitives and free-form patches

- **input:** MVS images and a rough initial surface

Multiple shape sampling

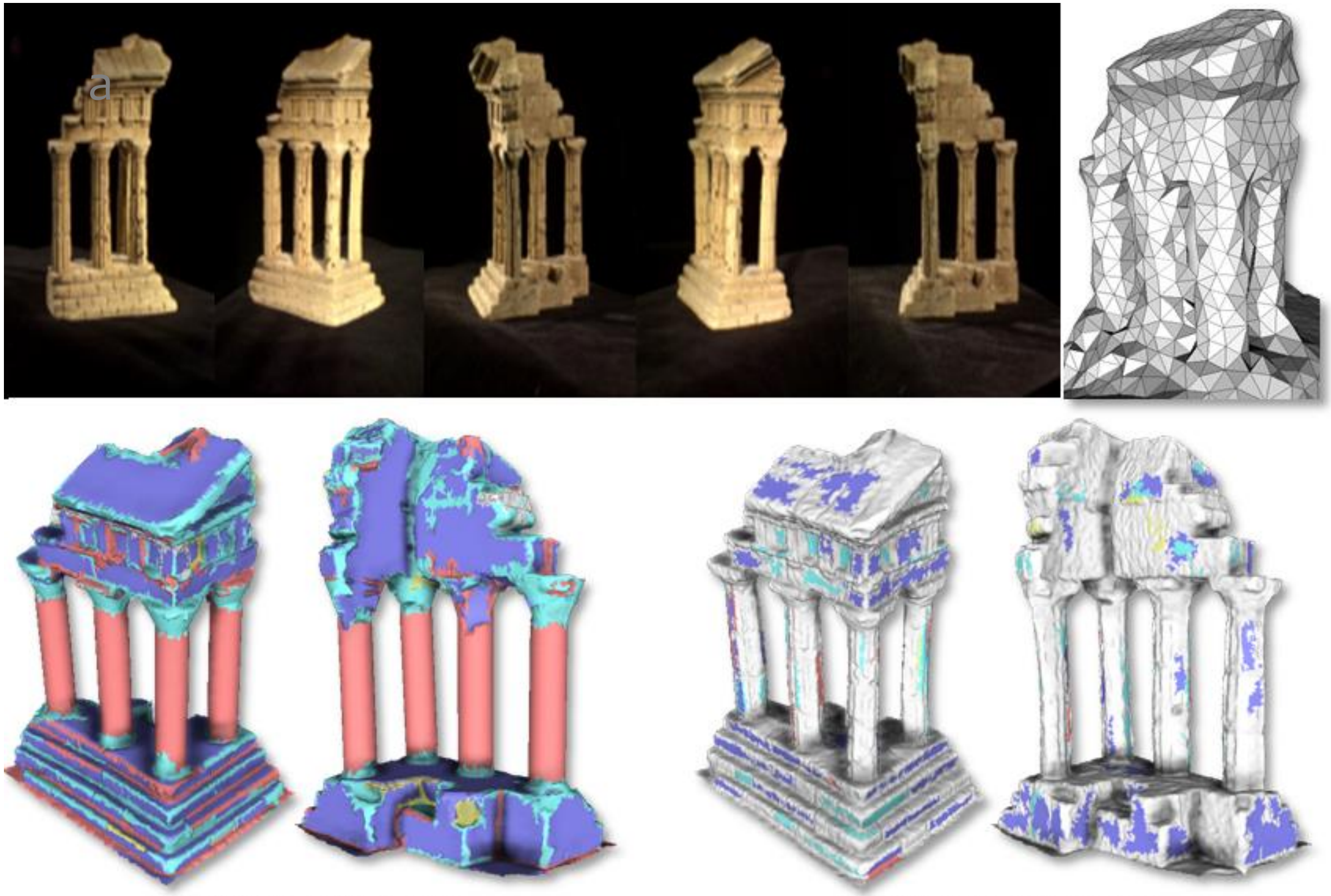
Joint sampling of primitives and free-form patches

- input: MVS images and a rough initial surface
- **output:** hybrid surface



Multiple shape sampling

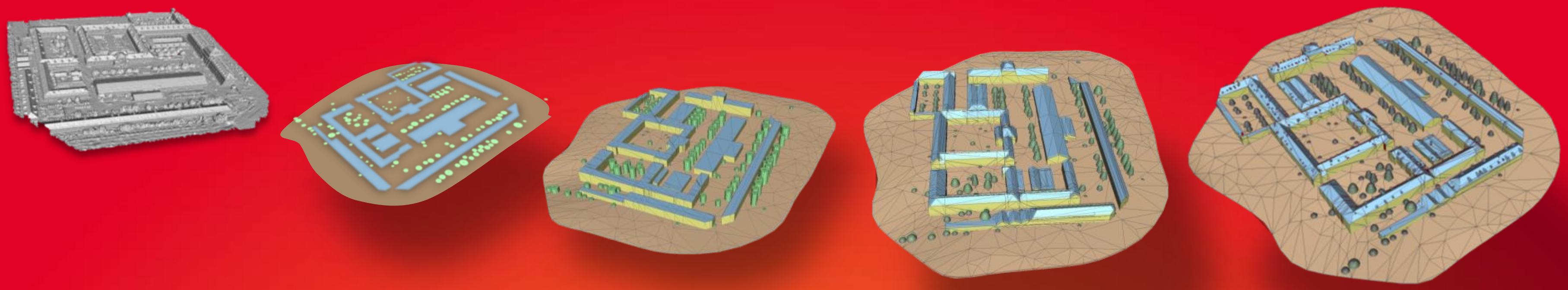
Control of the primitive/free-form dominance



Primitive-dominant *Free-form-dominant*

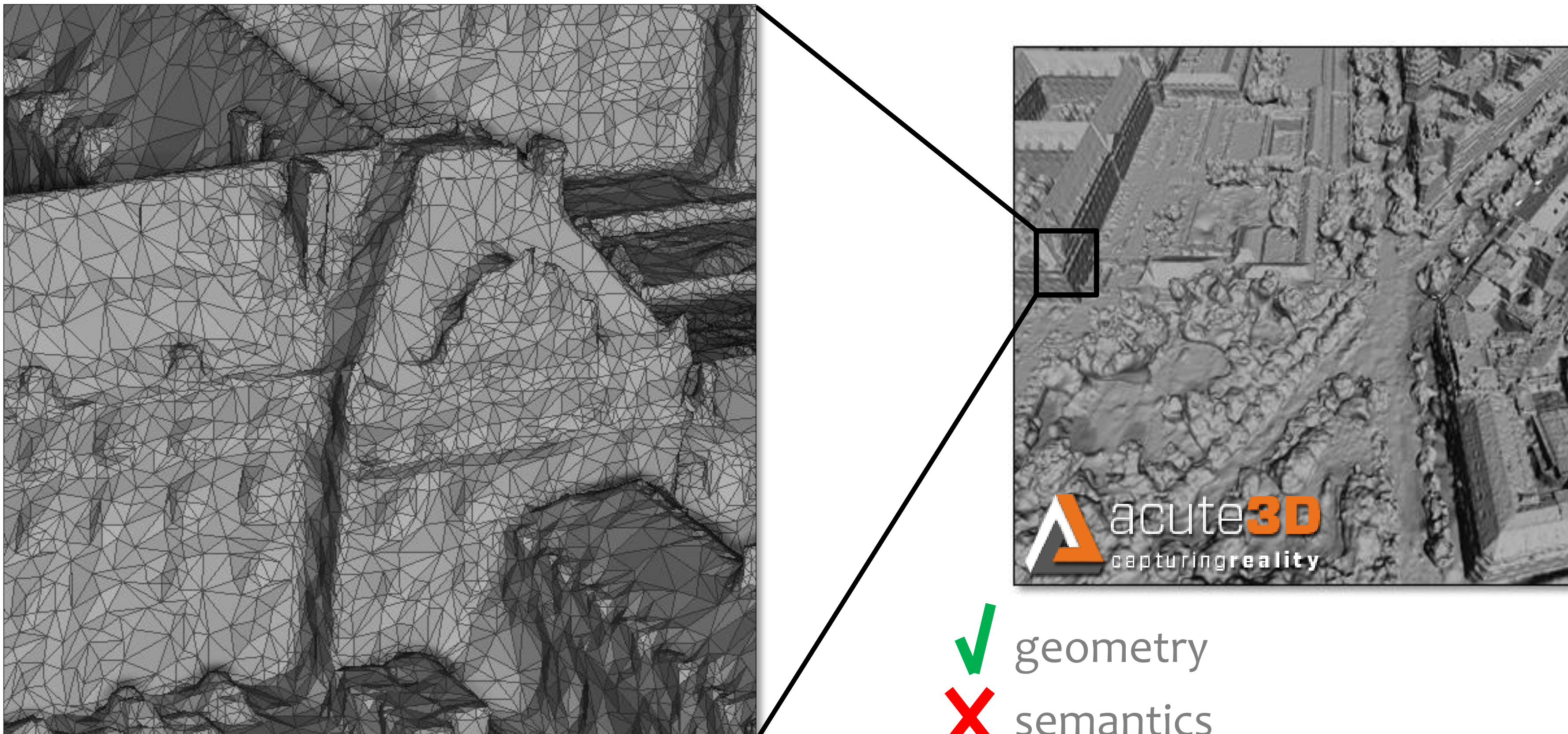
3

Urban reconstruction



Geometry, semantics and structure

For some applications, pure geometry is not enough



✓ geometry

✗ semantics

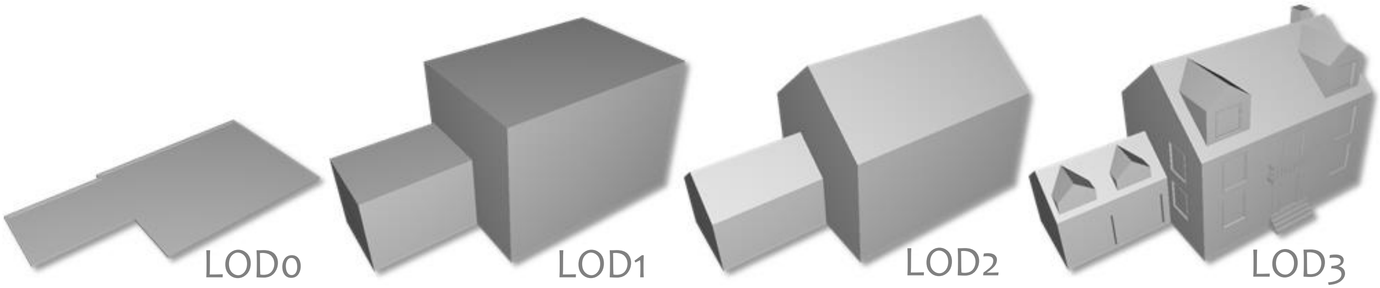
✗ structure

Geometry, semantics and structure

Need of semantic- and structure- aware 3D models

Geometry, semantics and structure

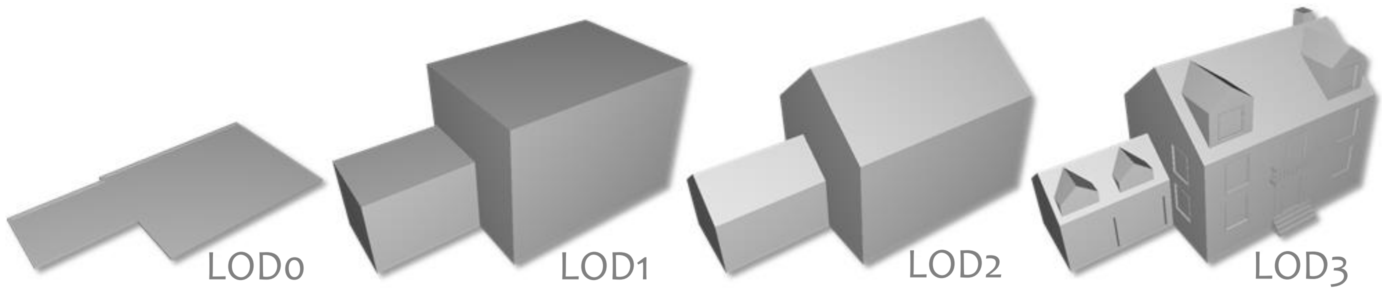
Need of semantic- and structure- aware 3D models



CityGML
formalism

Geometry, semantics and structure

Need of semantic- and structure- aware 3D models



CityGML formalism

application scenarios

- transportation
  drainage
- radio planning
  disaster control
- urban planning
  navigation
- entertainment
  defense

Geometry, semantics and structure

How to combine geometry, semantics and structure?

Geometry, semantics and structure

How to combine geometry, semantics and structure?

Semantic reconstruction [Hane13] [Cabezas15][Blaha16]...

- natural and elegant
- scalability challenges and complex inference
- no structure

Geometry, semantics and structure

How to combine geometry, semantics and structure?

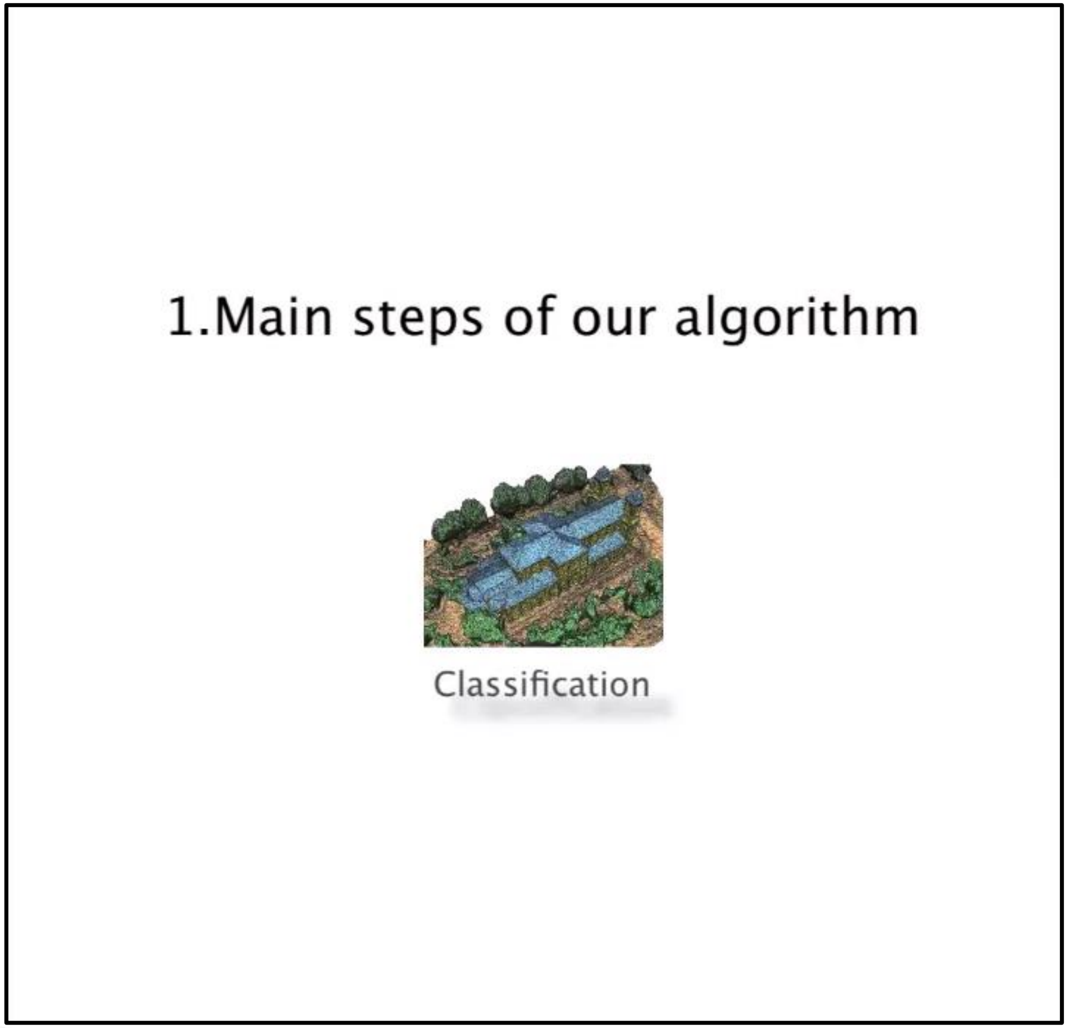
Semantic reconstruction [Hane13] [Cabezas15][Blaha16]…
- natural and elegant
- scalability challenges and complex inference
- no structure

Semantics first [Musialski13]…
- traditional but efficient
- easy parallelization
- error accumulation

LOD generation for urban scenes

[Verdie, Lafarge and Alliez, LOD generation for urban scenes, ToG15]

LOD generation for urban scenes



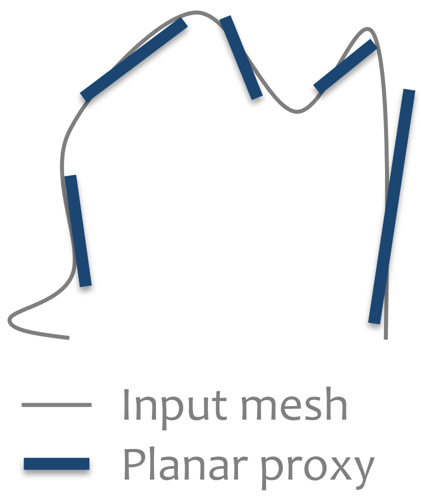
heavy machinery!

Crops on two key ingredients:

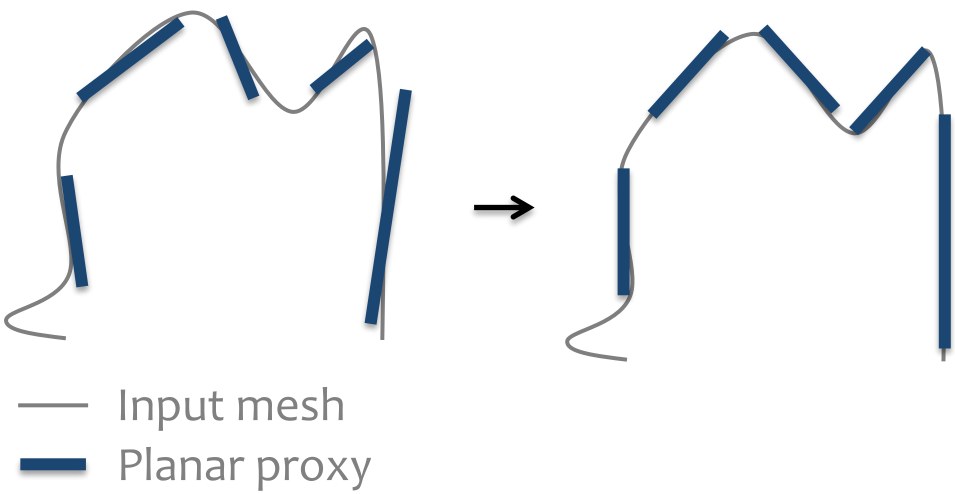
Proxy regularization

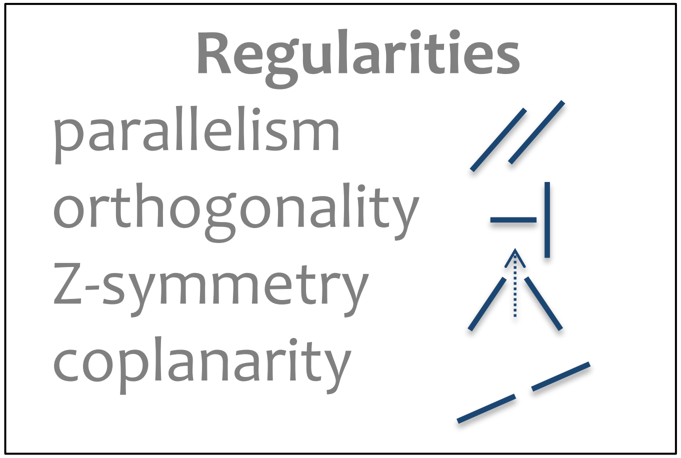
3D discrete arrangement

Ingredient 1: regularization of planar proxies

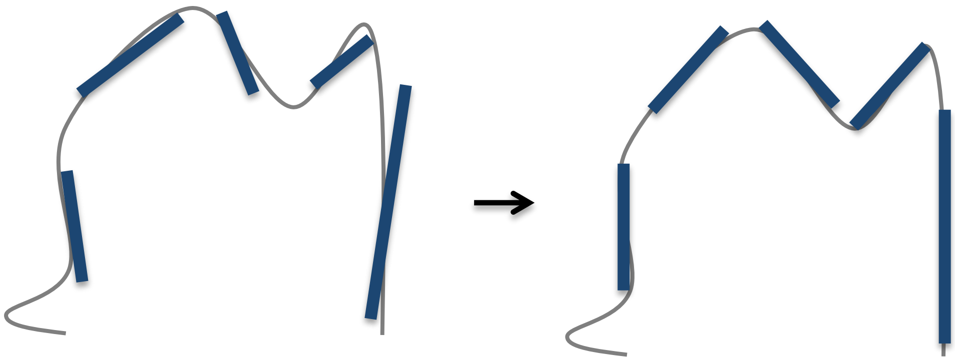


Ingredient 1: regularization of planar proxies



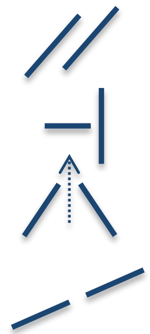


Ingredient 1: regularization of planar proxies



— Input mesh
▬ Planar proxy

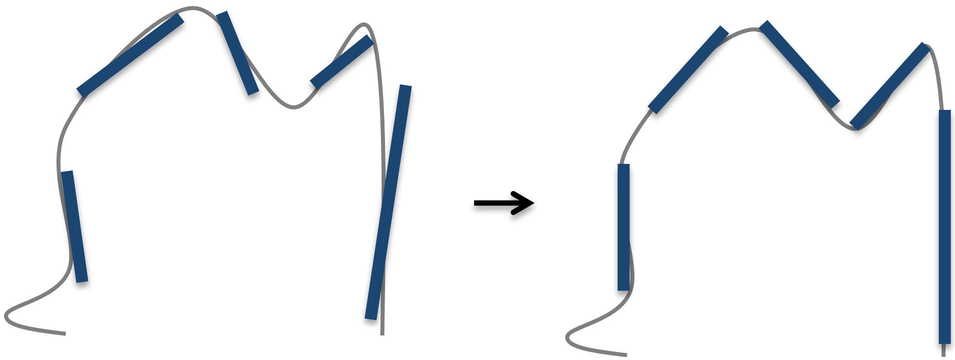
Regularities



parallelism
orthogonality
Z-symmetry
coplanarity

→ reduce the complexity of subsequent reconstruction
→ increase the visual quality of output surfaces

Ingredient 1: regularization of planar proxies



— Input mesh
▬ Planar proxy

Regularities

parallelism
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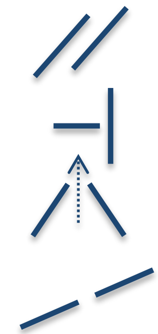
Z-symmetry
coplanarity

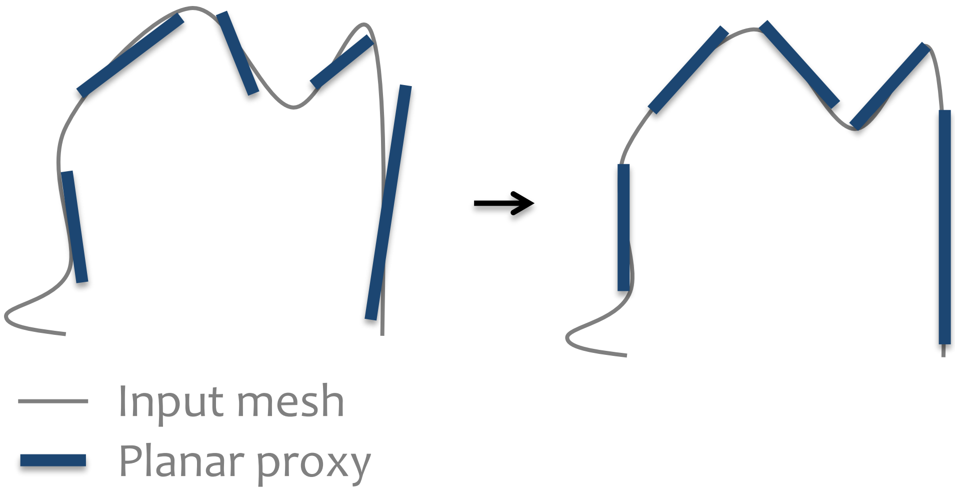


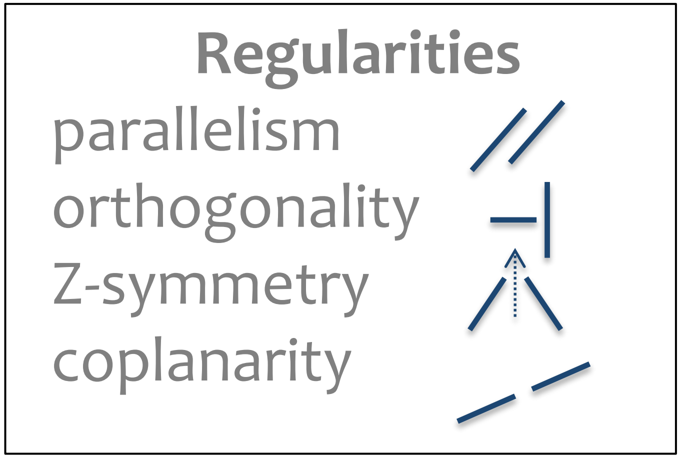
→ reduce the complexity of subsequent reconstruction

→ increase the visual quality of output surfaces

must be fast, scalable and urban-specific

Ingredient 1: regularization of planar proxies

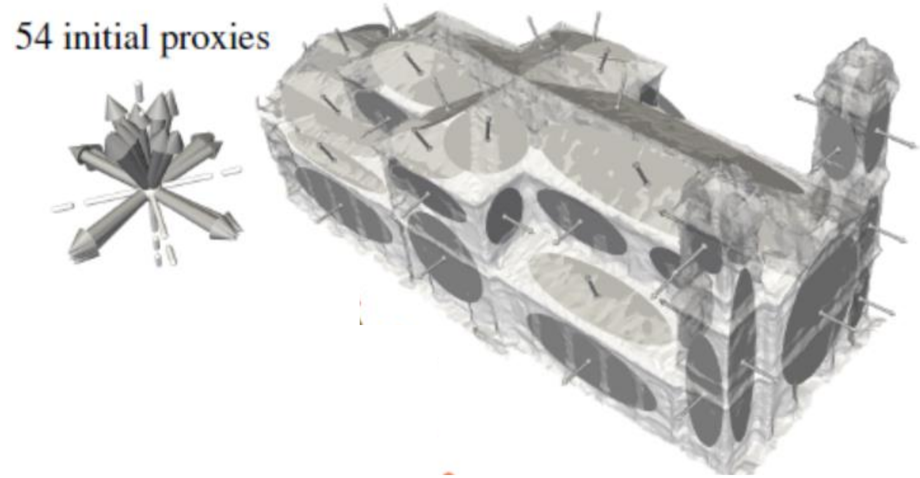




Idea: create a hierarchy between regularities within a *detection-then-regularization* approach

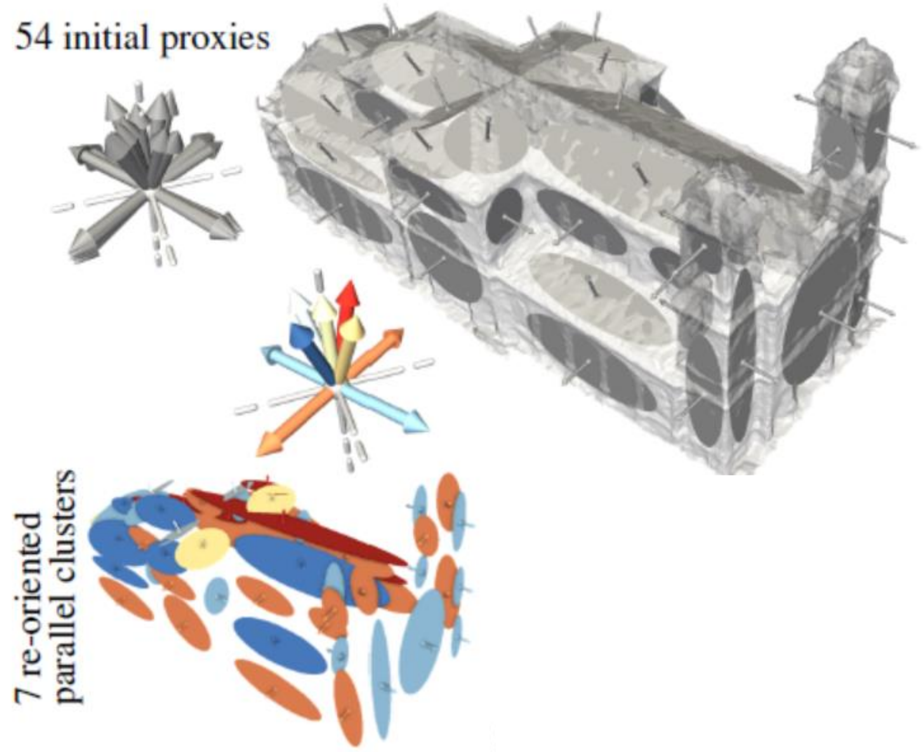
Ingredient 1: regularization of planar proxies

- **initial planar proxy from large superfacets**



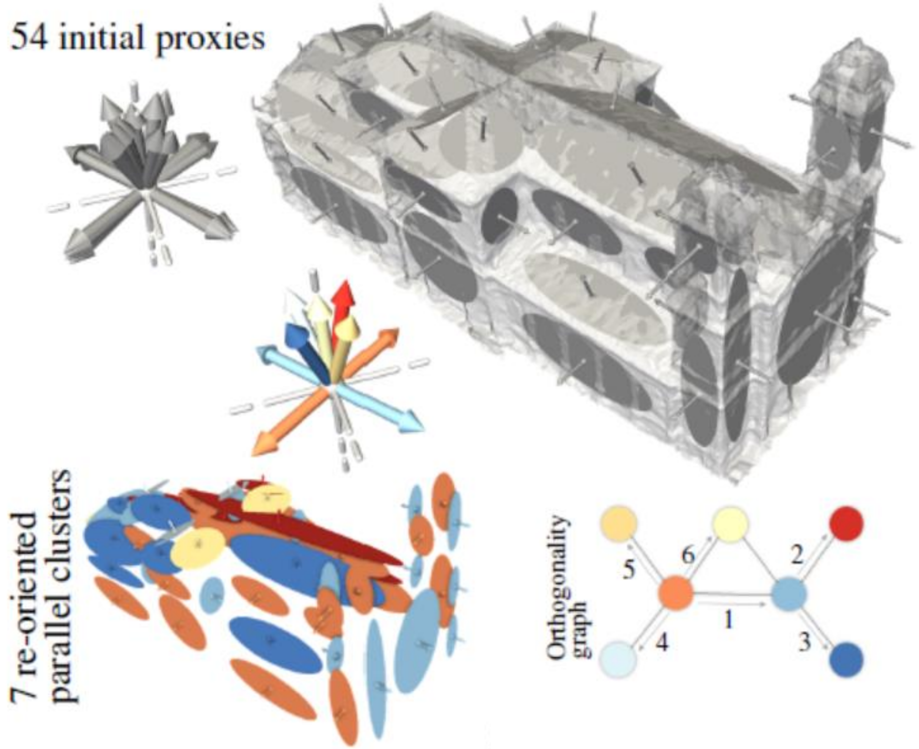
Ingredient 1: regularization of planar proxies

- initial planar proxy from large superfacets
- **grouping of proxies wrt parallelism**



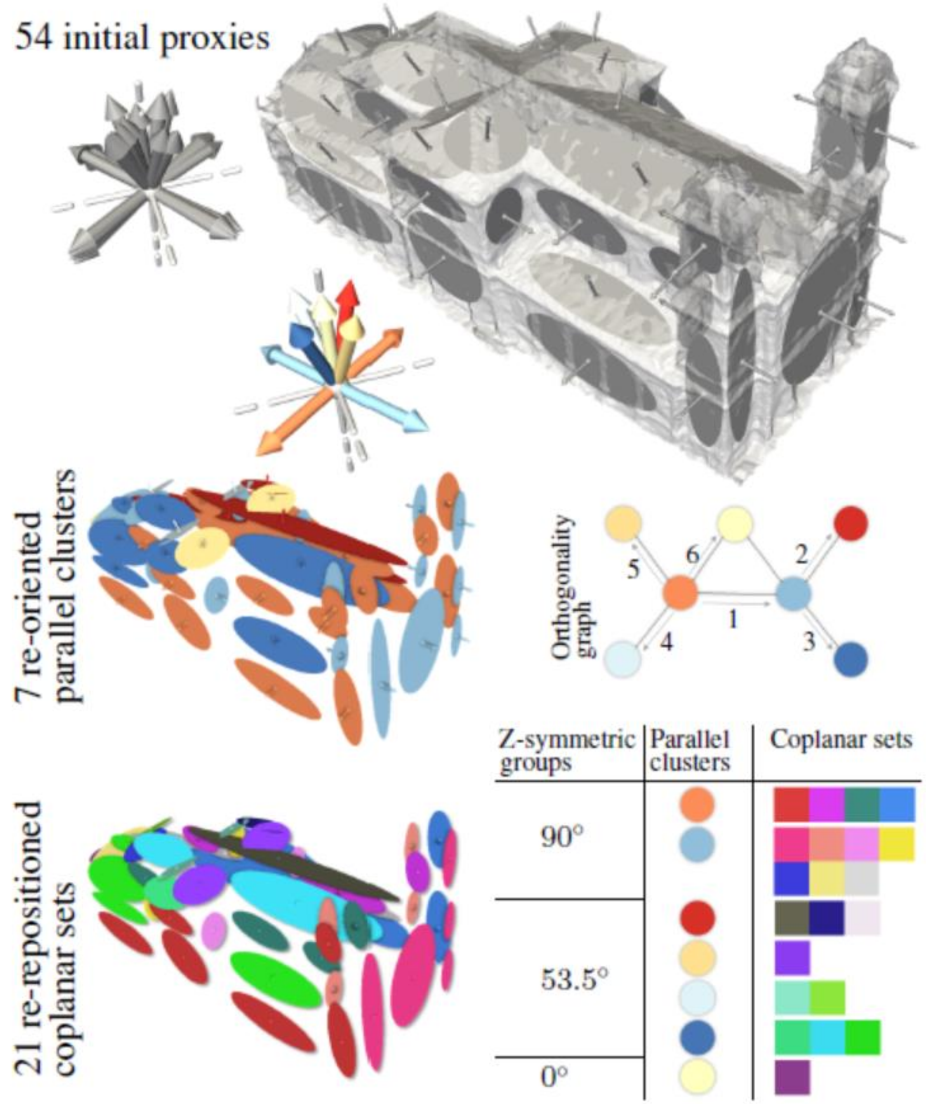
Ingredient 1: regularization of planar proxies

- initial planar proxy from large superfacets
- grouping of proxies wrt parallelism
- **re-orientation parallel clusters wrt orthogonality and Z-symmetry**

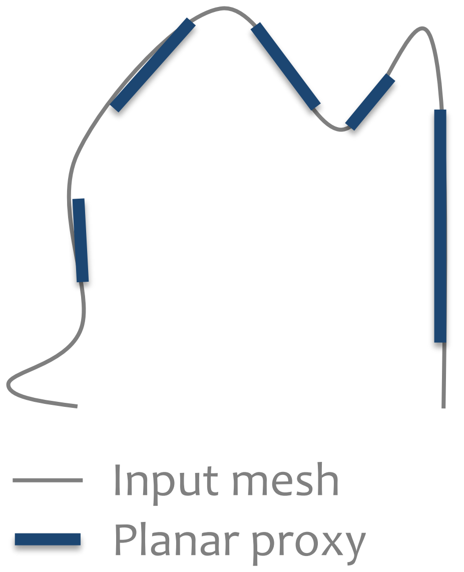


Ingredient 1: regularization of planar proxies

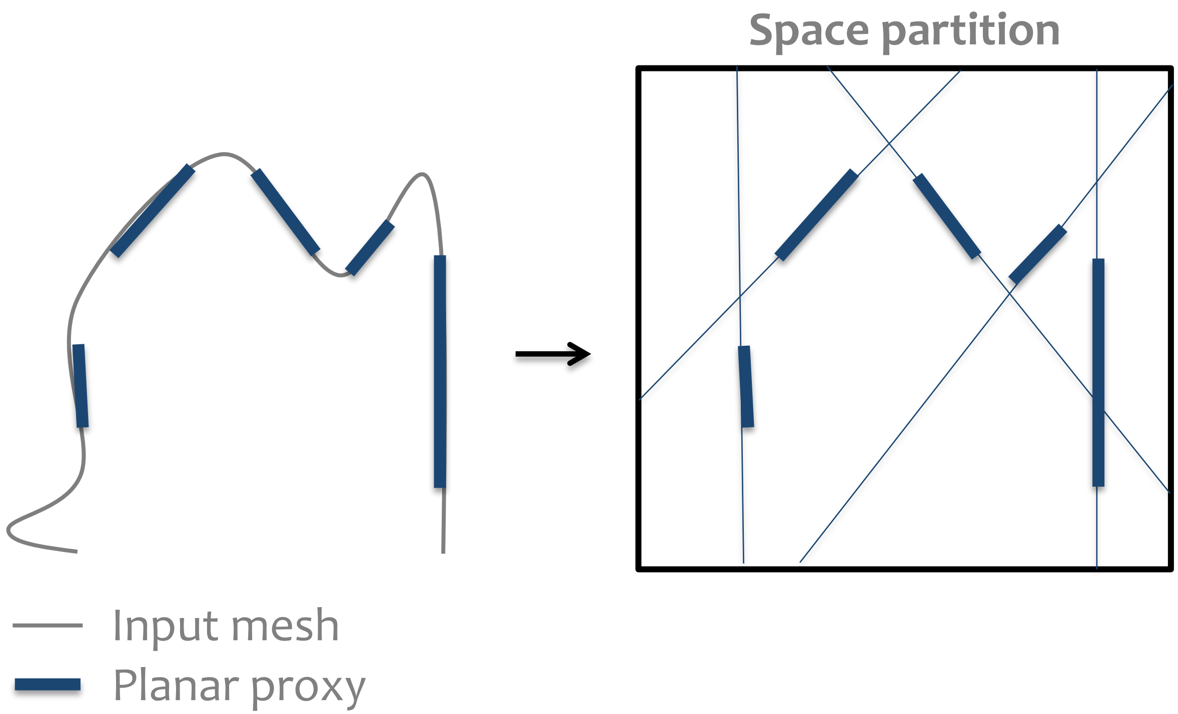
- initial planar proxy from large superfacets
- grouping of proxies wrt parallelism
- re-orientation parallel clusters wrt orthogonality and Z-symmetry
- **Re-positioning of proxies wrt coplanarity**



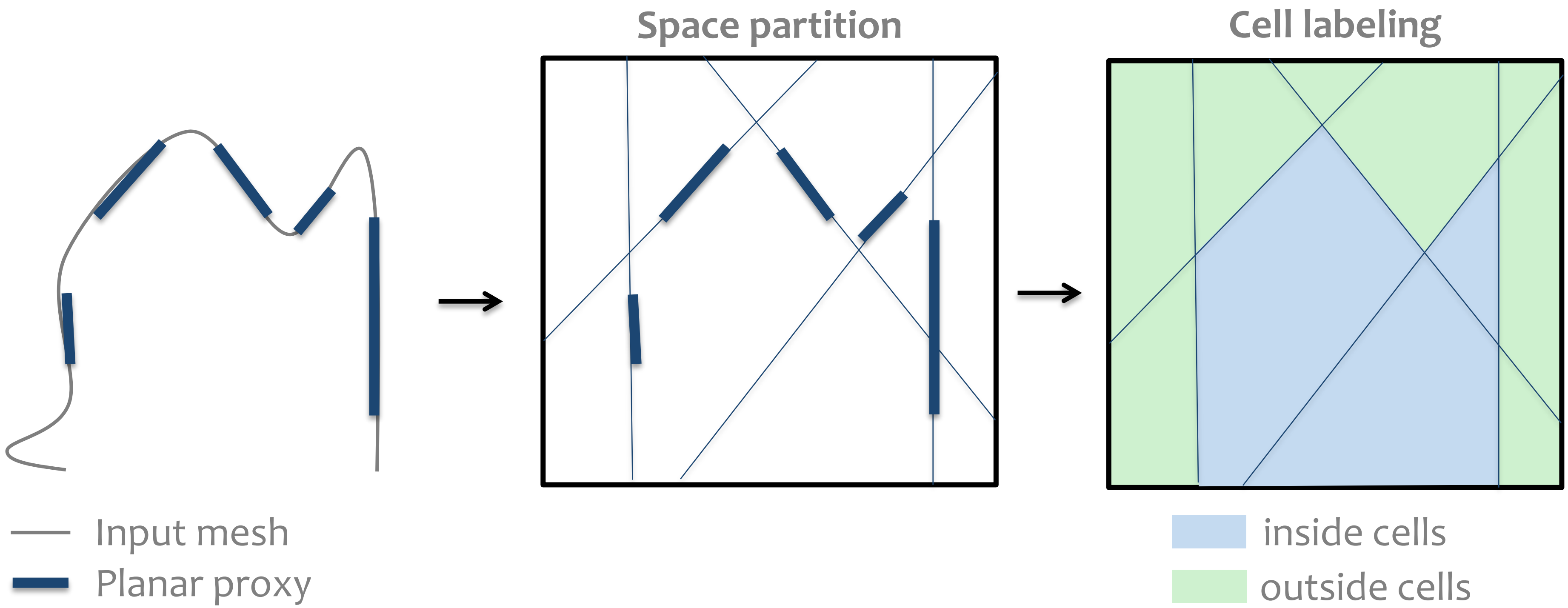
Ingredient 2: discrete 3D arrangement



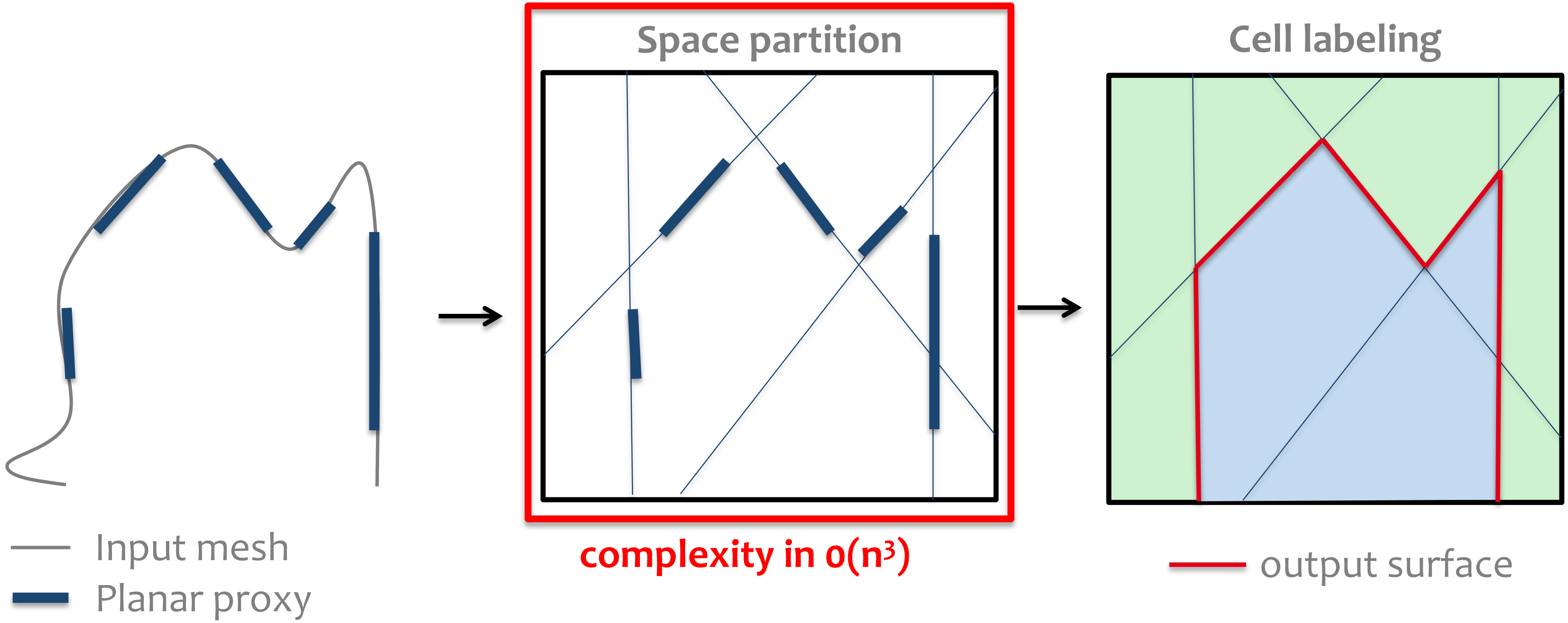
Ingredient 2: discrete 3D arrangement



Ingredient 2: discrete 3D arrangement



Ingredient 2: discrete 3D arrangement

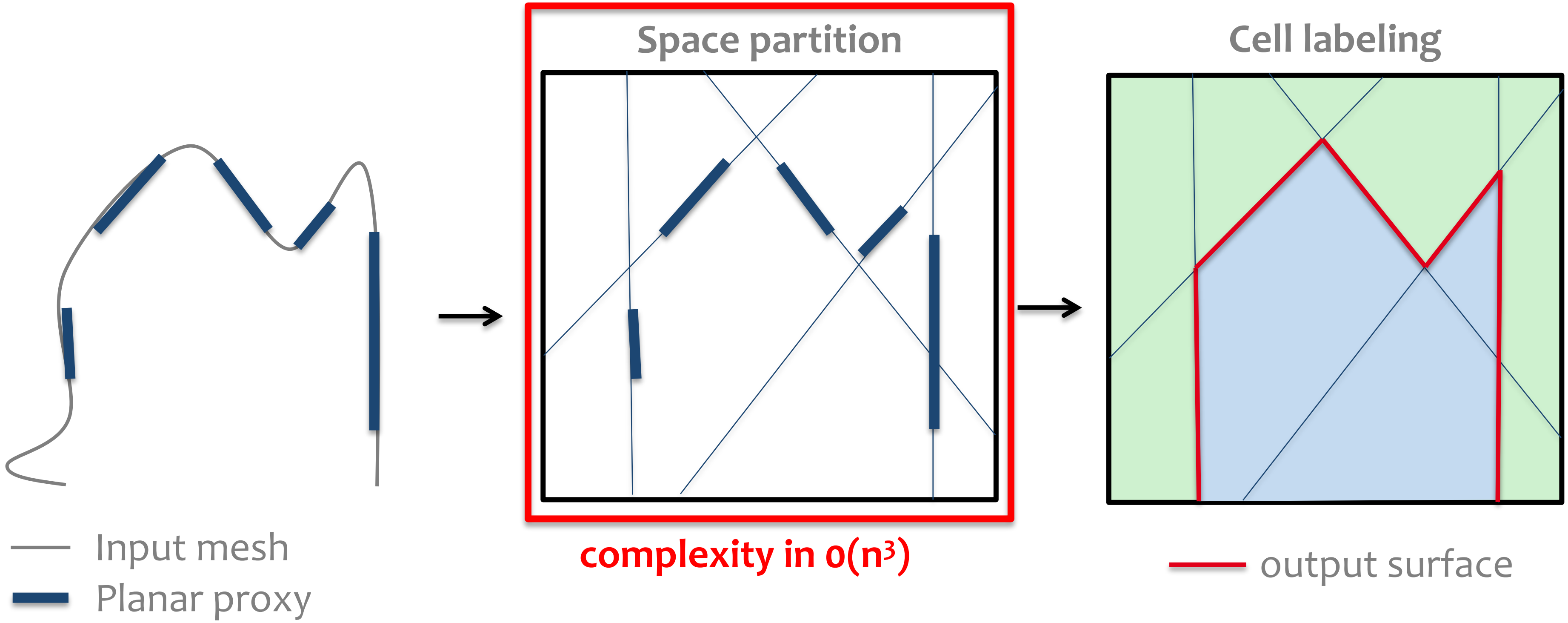


Use of strong geometric assumptions

- restriction to axis-aligned proxies (eg Manhattan-World)
- multi-layer of 2D arrangements

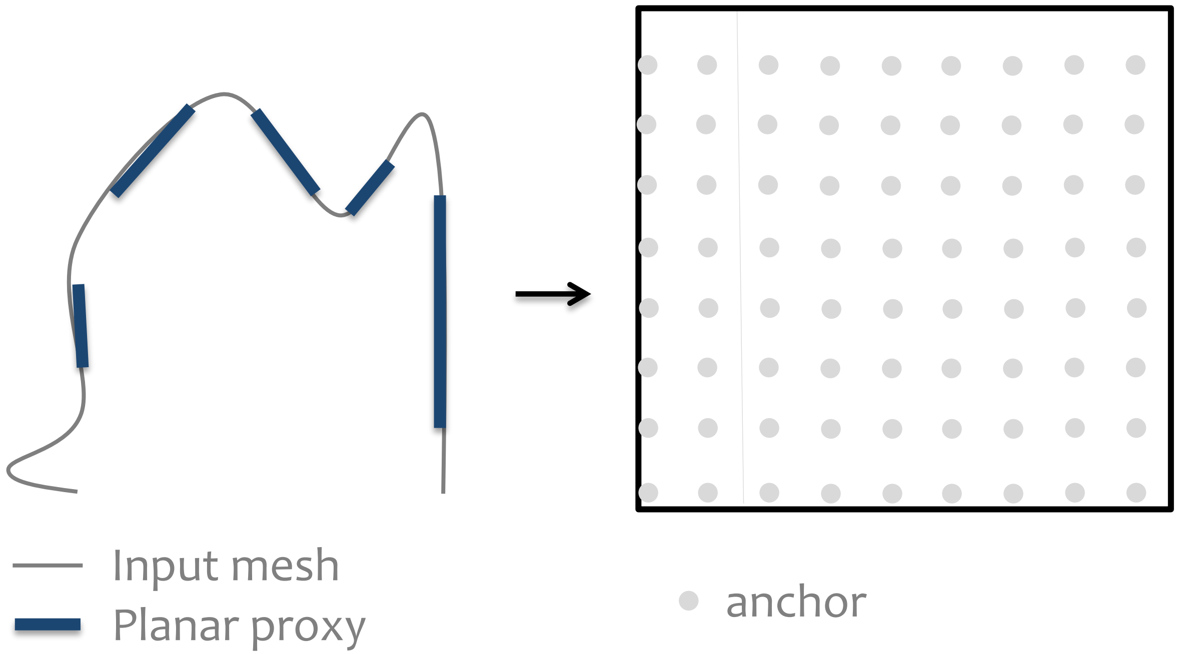
valid only in specifc cases

Ingredient 2: discrete 3D arrangement



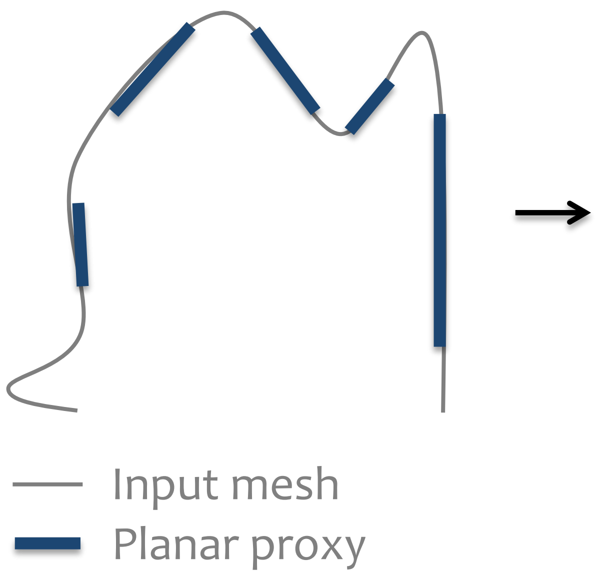
Idea: use a discrete partition to avoid computing the exact geometry

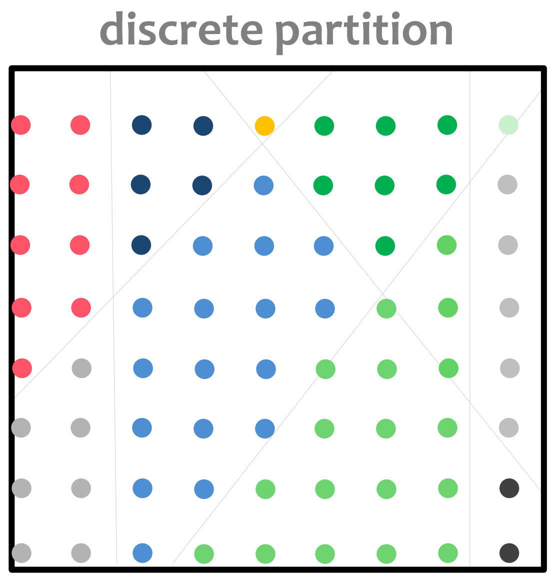
Ingredient 2: discrete 3D arrangement



Idea: use a discrete partition to avoid computing the exact geometry

Ingredient 2: discrete 3D arrangement

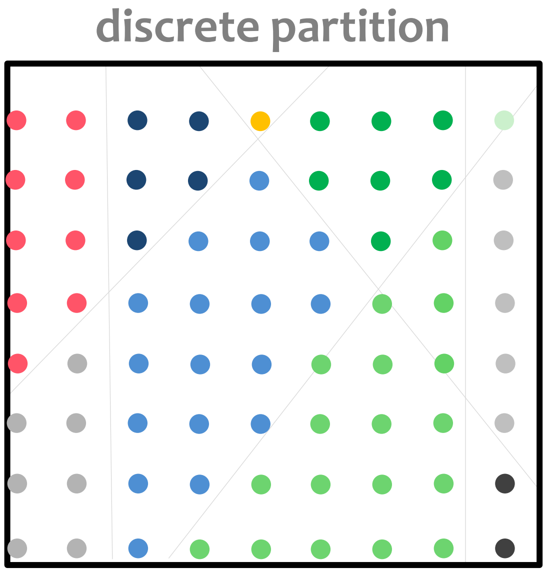




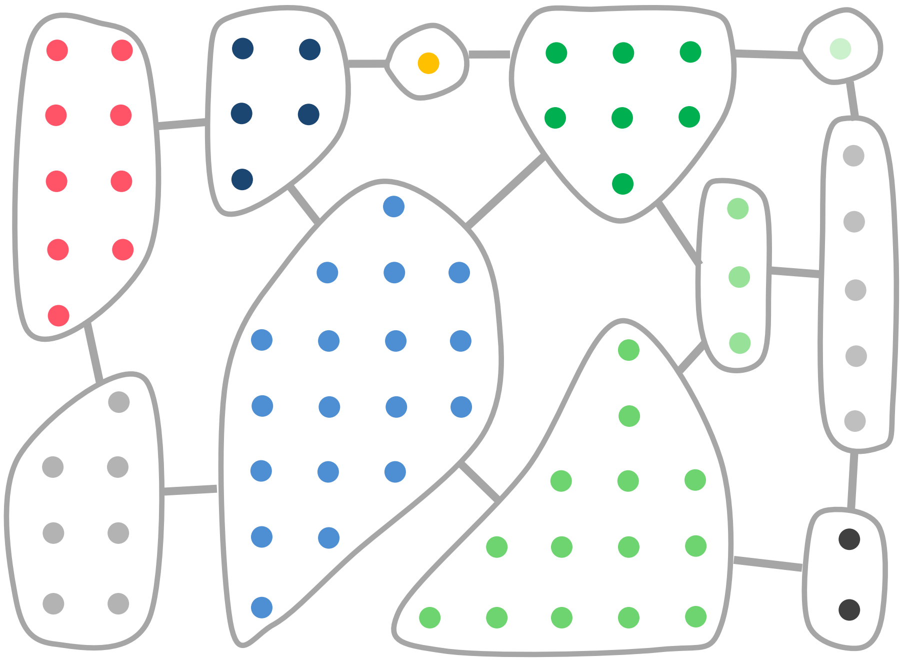
complexity in o(n log(k))

Idea: use a discrete partition to avoid computing the exact geometry

Ingredient 2: discrete 3D arrangement

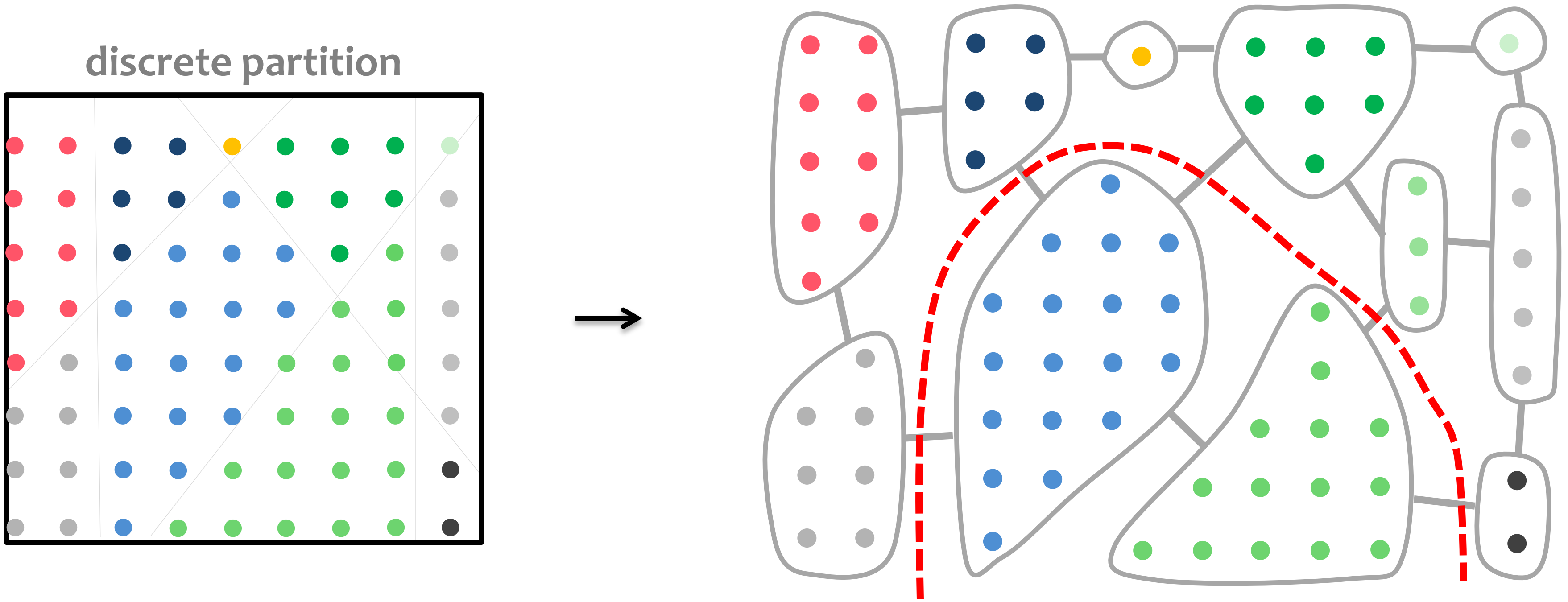


→



Ingredient 2: discrete 3D arrangement

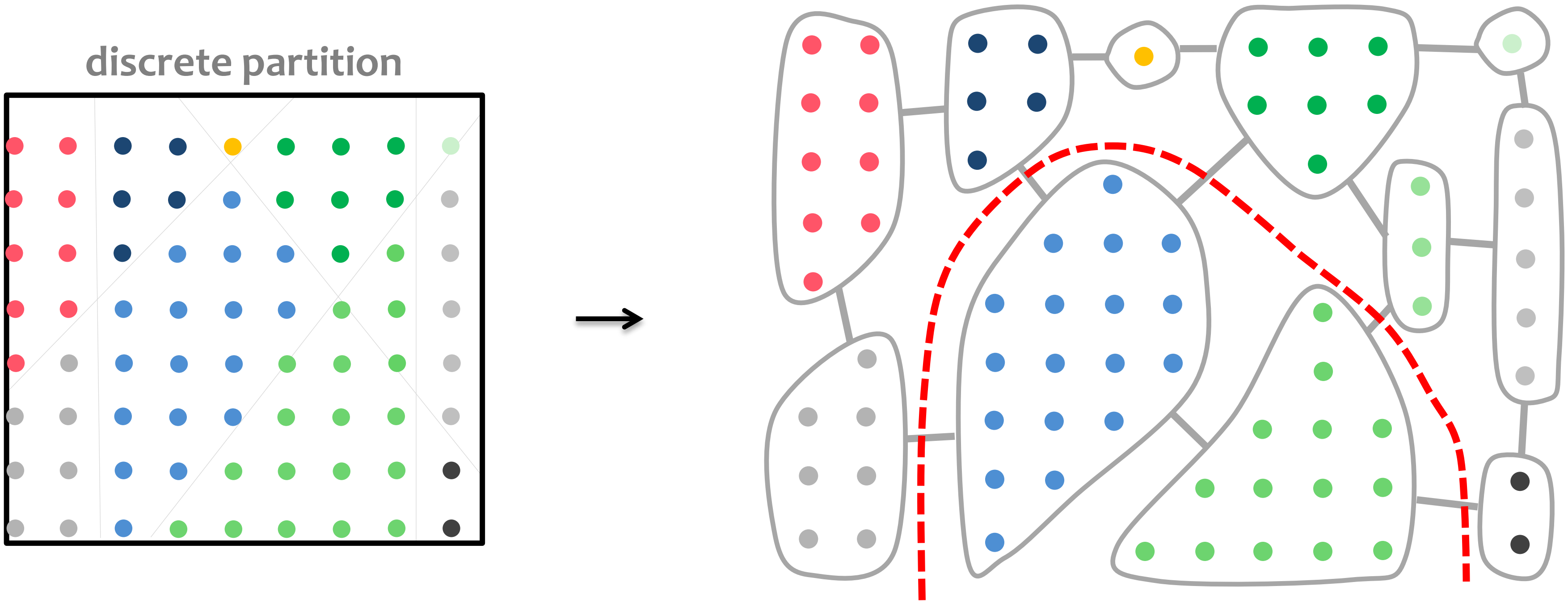
discrete partition



Quality of a cut $S=\{C_{in},C_{out}\}$

$$C(\mathcal{S}) = \sum_{c_k \in \mathcal{C}_{out}} V_{c_k}\, g(c_k) + \sum_{c_k \in \mathcal{C}_{in}} V_{c_k}\, (1 - g(c_k)) + \beta \sum_{f_i \in \mathcal{S}} A_{f_i}$$

Ingredient 2: discrete 3D arrangement



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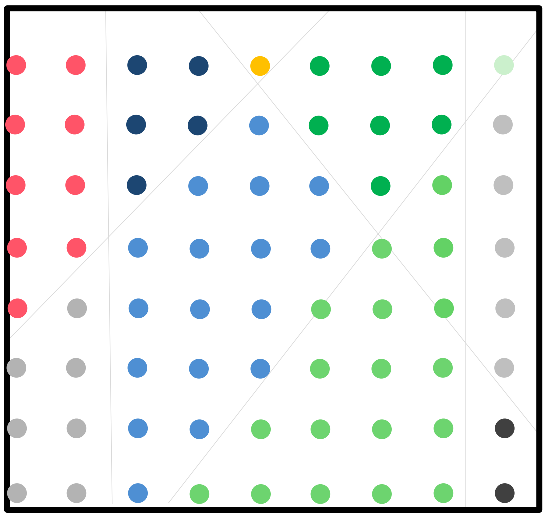
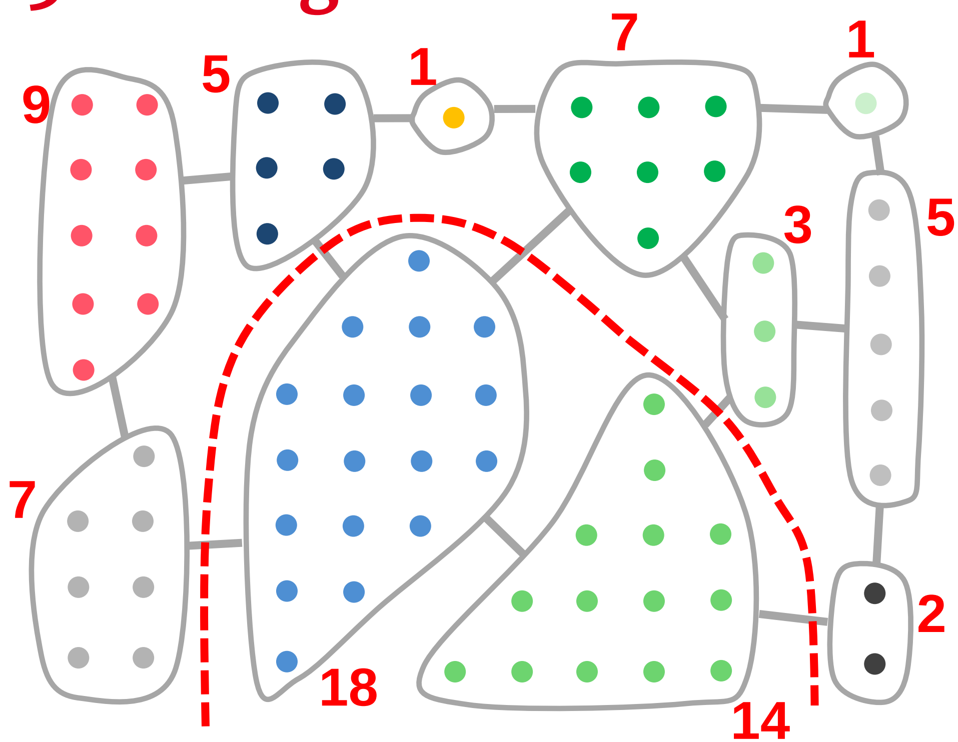
Data term

Ingredient 2: discrete 3D arrangement

discrete partition



→



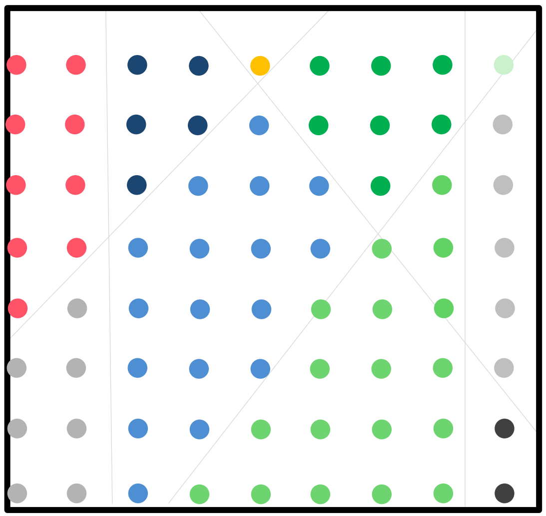
Quality of a cut $S=\{C_{in},C_{out}\}$

$$C(S) = \sum_{c_k \in \mathcal{C}_{out}} \boxed{V_{c_k}}\, g(c_k) + \sum_{c_k \in \mathcal{C}_{in}} \boxed{V_{c_k}}\,(1 - g(c_k)) + \beta \sum_{f_i \in S} A_{f_i}$$

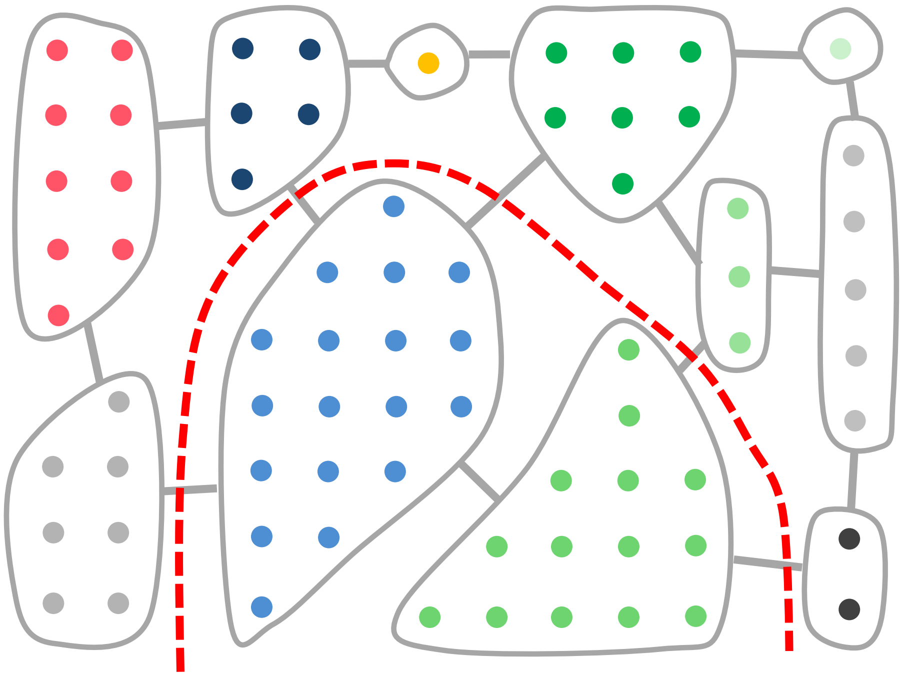
Data term

Ingredient 2: discrete 3D arrangement

discrete partition



→

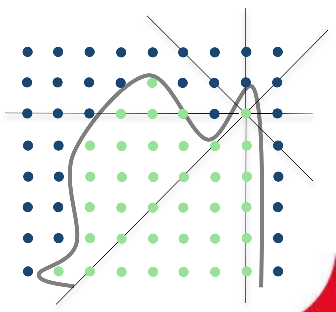


Quality of a cut $S=\{C_{in},C_{out}\}$

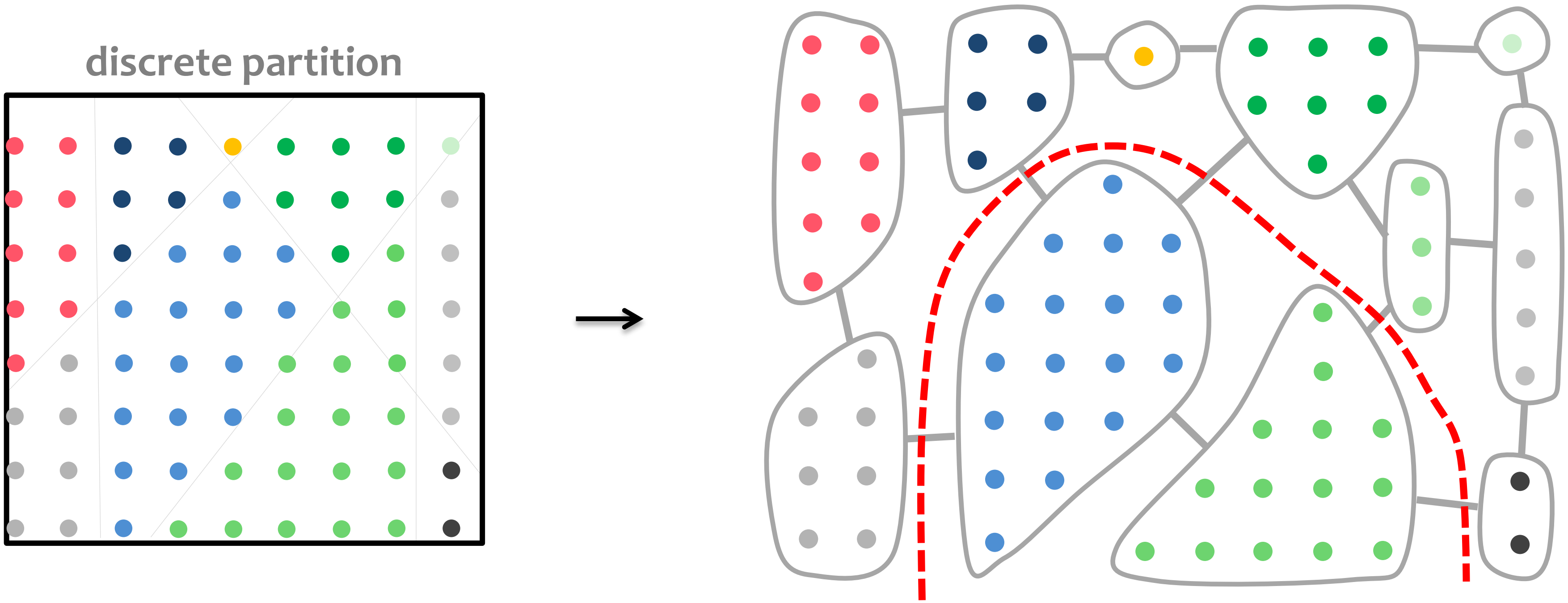
$$C(\mathcal{S}) = \sum_{c_k \in \mathcal{C}_{out}} V_{c_k}\, g(c_k) + \sum_{c_k \in \mathcal{C}_{in}} V_{c_k}\,(1 - g(c_k)) + \beta \sum_{f_i \in \mathcal{S}} A_{f_i}$$

Data term

inside/outside prediction function
estimated by ray casting



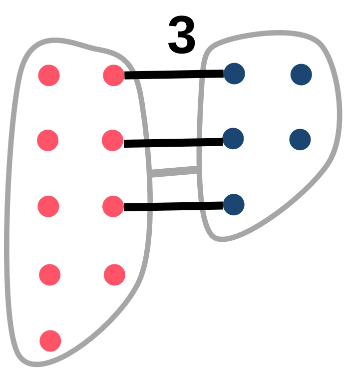
Ingredient 2: discrete 3D arrangement



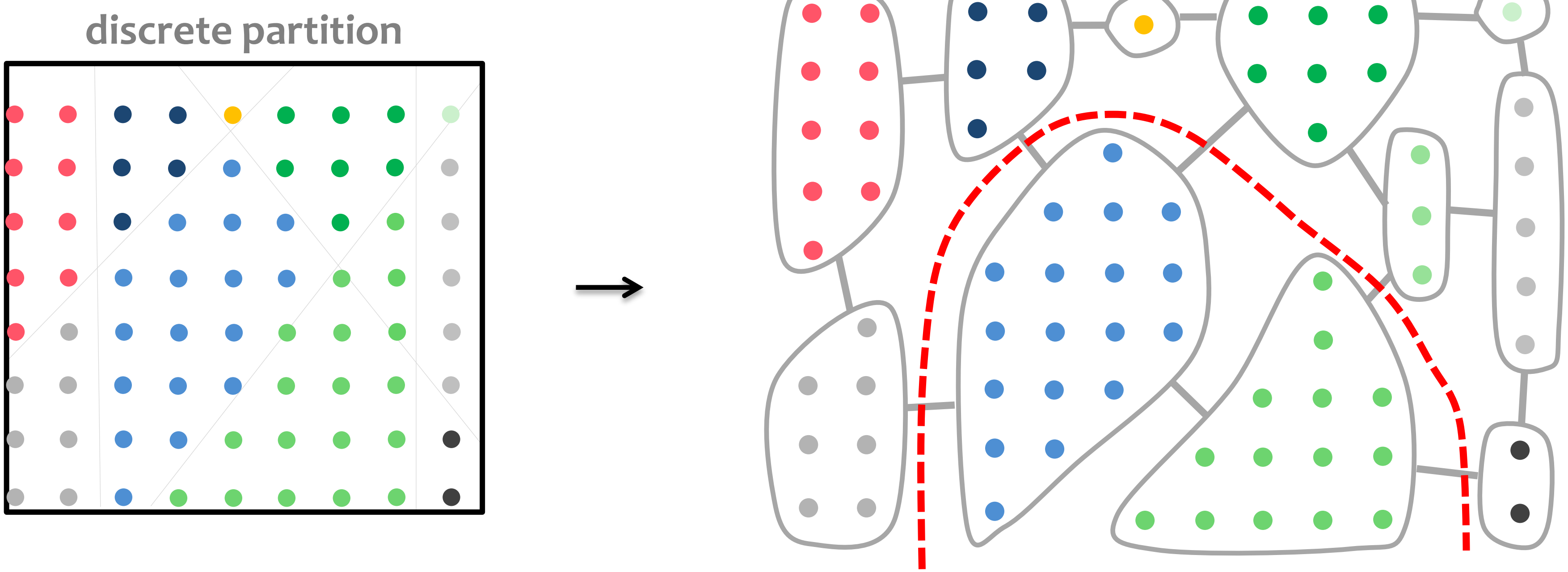
Quality of a cut $S=\{C_{in},C_{out}\}$

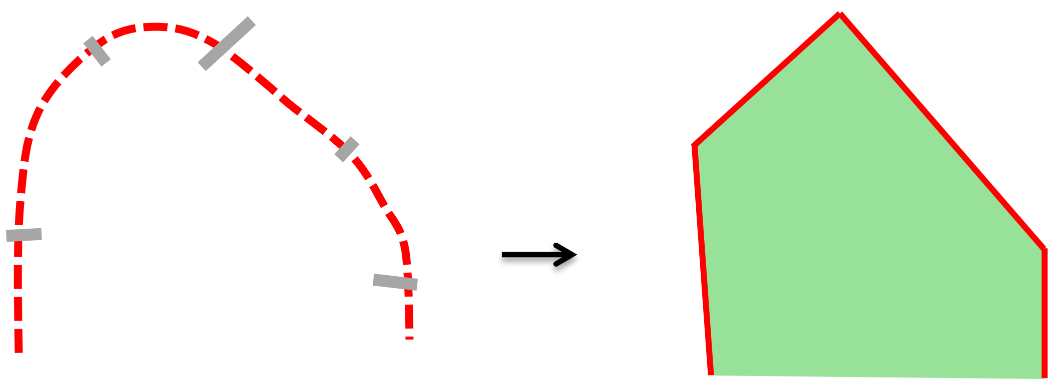
$$C(\mathcal{S}) = \sum_{c_k \in \mathcal{C}_{out}} V_{c_k}\, g(c_k) + \sum_{c_k \in \mathcal{C}_{in}} V_{c_k}\, (1 - g(c_k)) + \beta \sum_{f_i \in \mathcal{S}} A_{f_i}$$

complexity

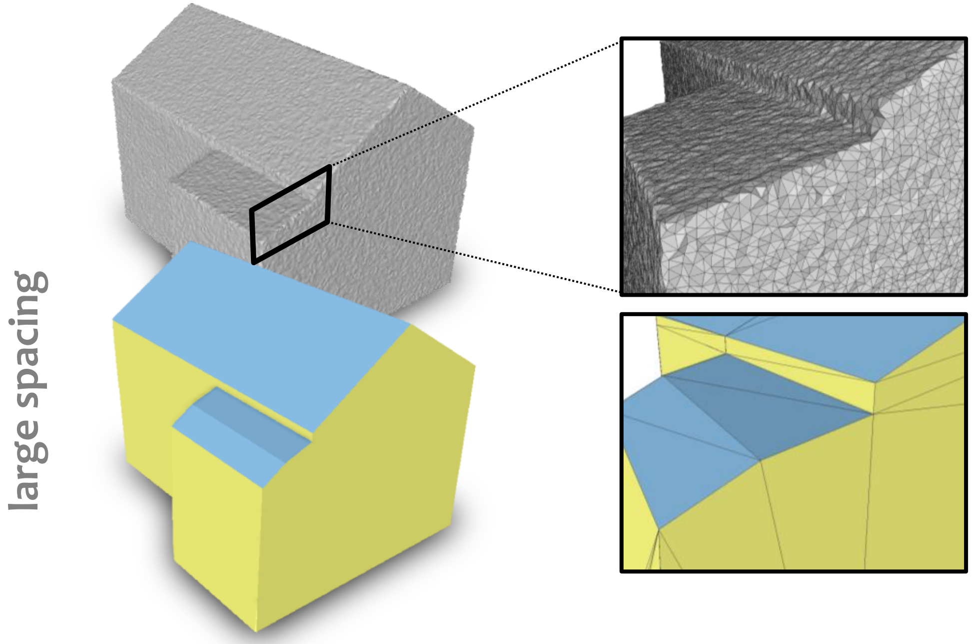


Ingredient 2: discrete 3D arrangement

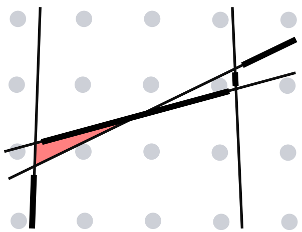




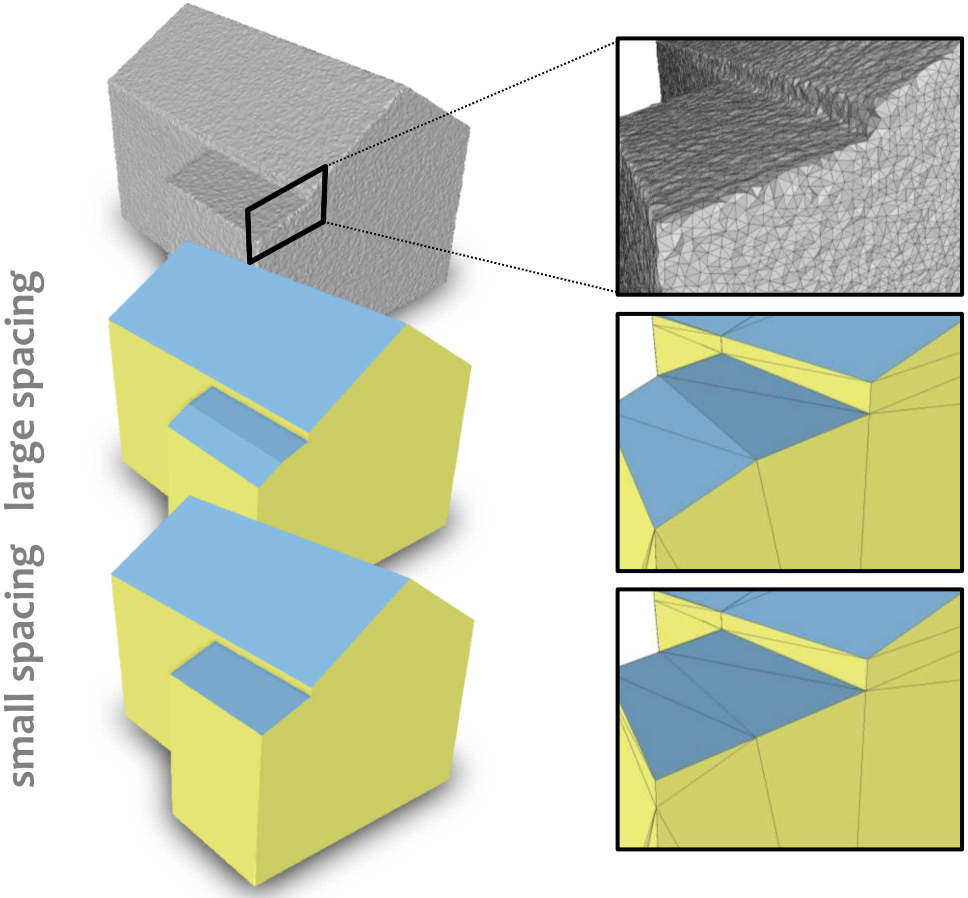
Anchor spacing setting



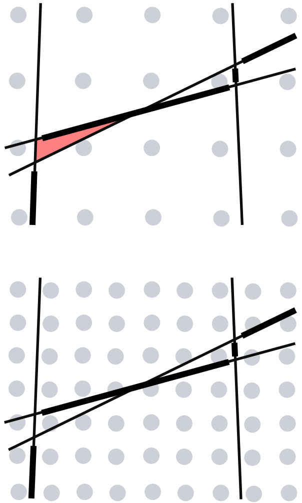
Trade-off between accuracy and time



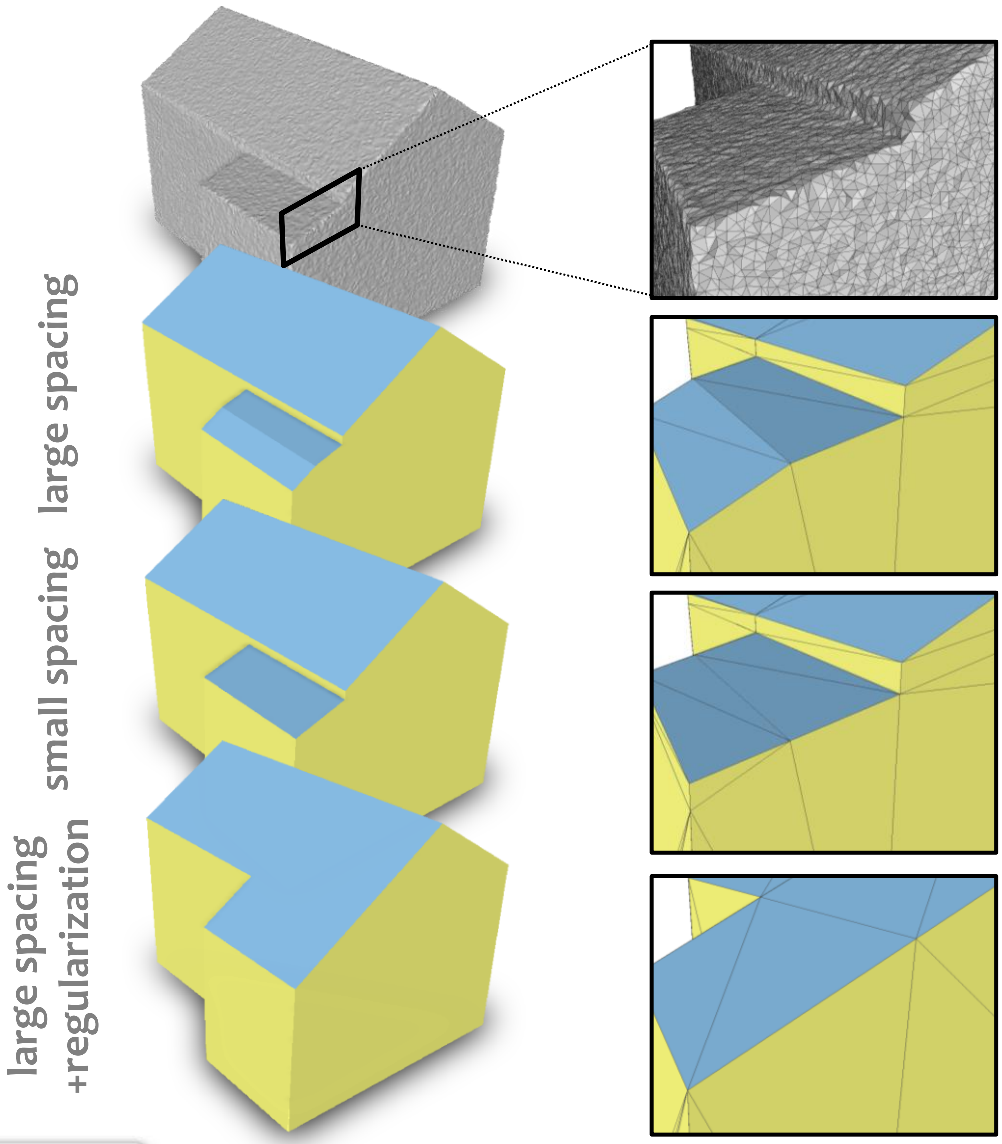
Anchor spacing setting



Trade-off between accuracy and time



Anchor spacing setting



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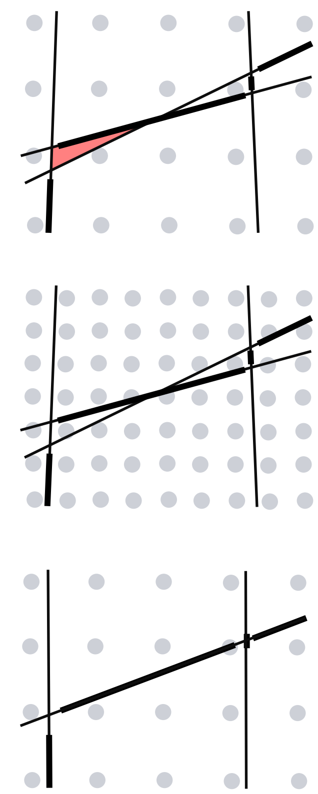


Reconstruction at various LOD

Planar proxy filtering

LOD0
→ only *facade* planar proxies

LOD1
→ LOD0 + constant roof height estimation

LOD2
→ all planar proxies

LOD3
→ LOD2 + roof and facade icons

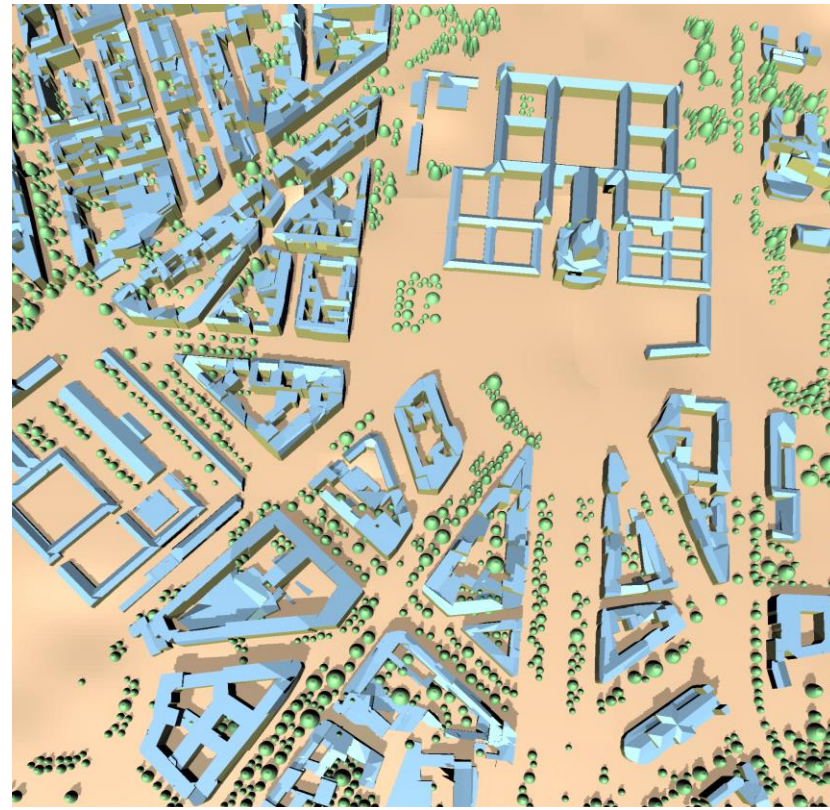
Large-scale reconstruction

input mesh
(11M facets)

LOD1
(10K facets for buildings)

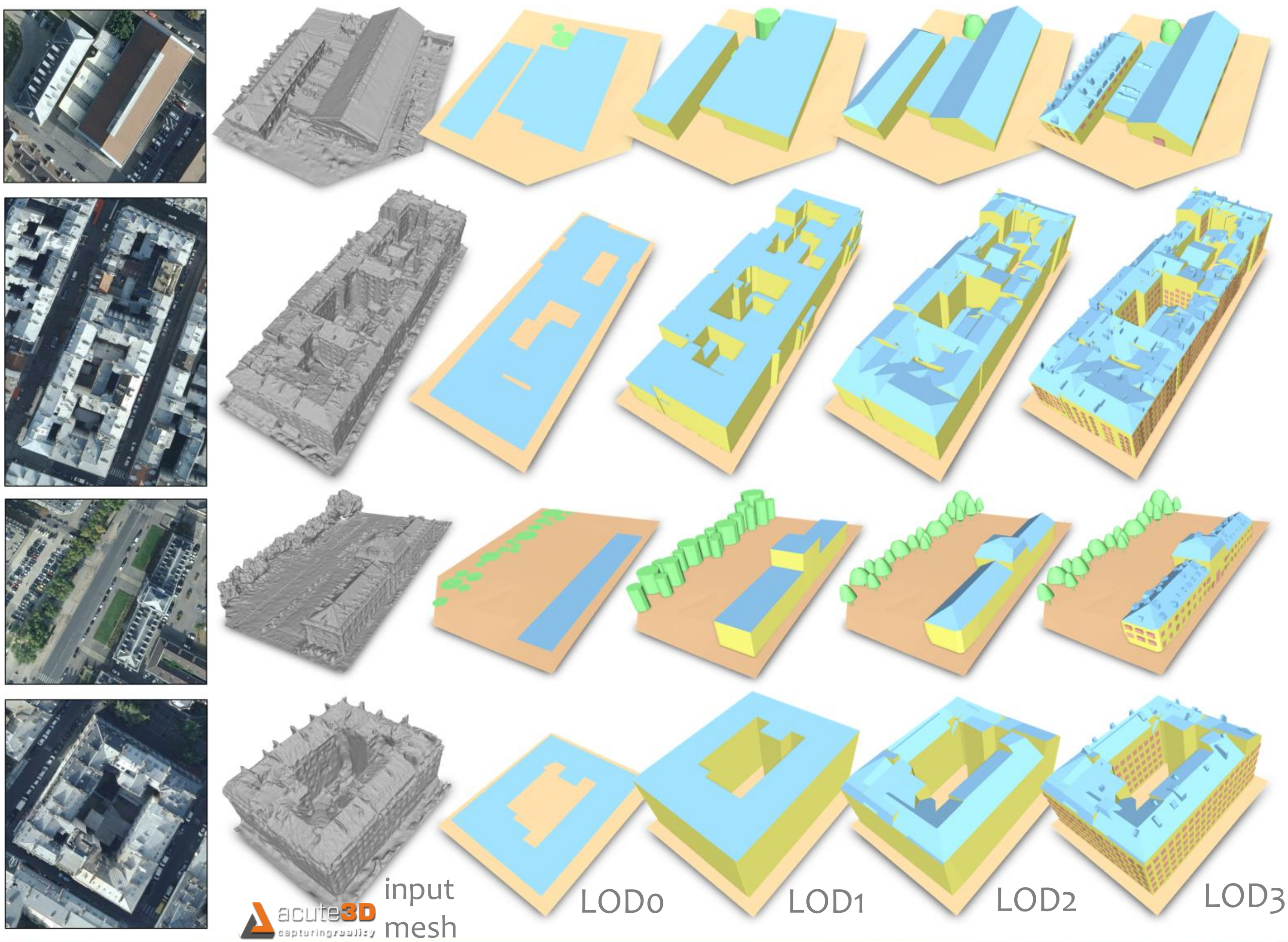
Large-scale reconstruction

input mesh
(11M facets)

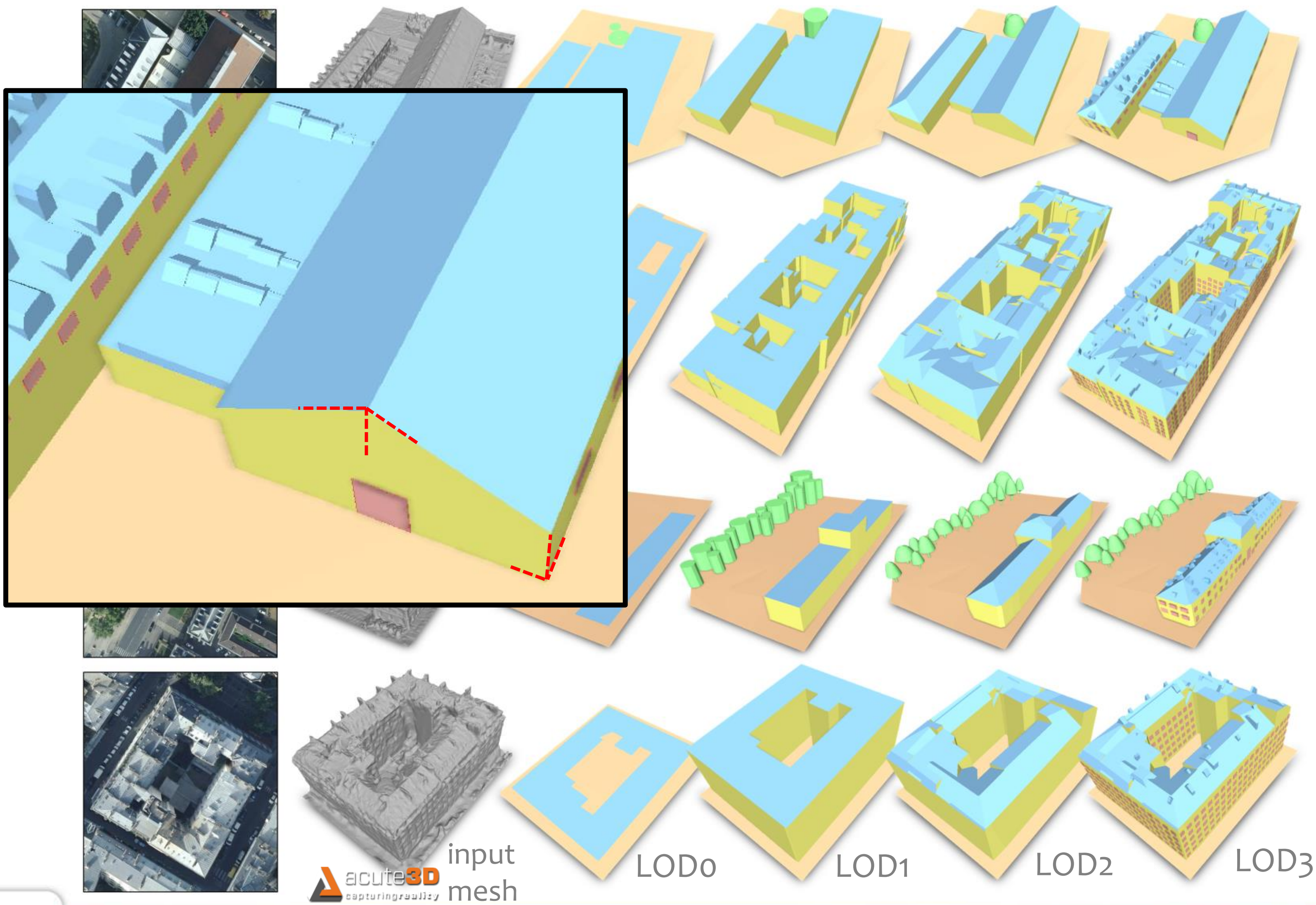


LOD2
(170K facets for buildings)

Building reconstruction



Building reconstruction

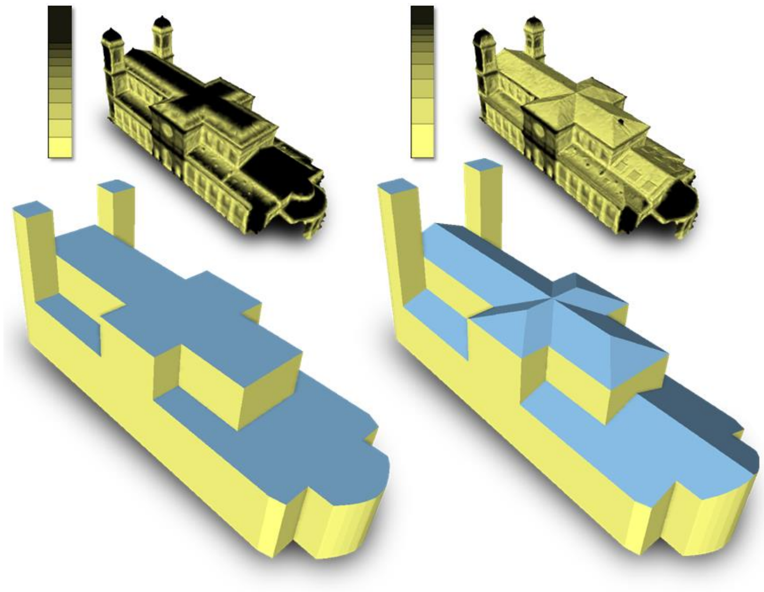


Accuracy and structure-awareness

error (meter)

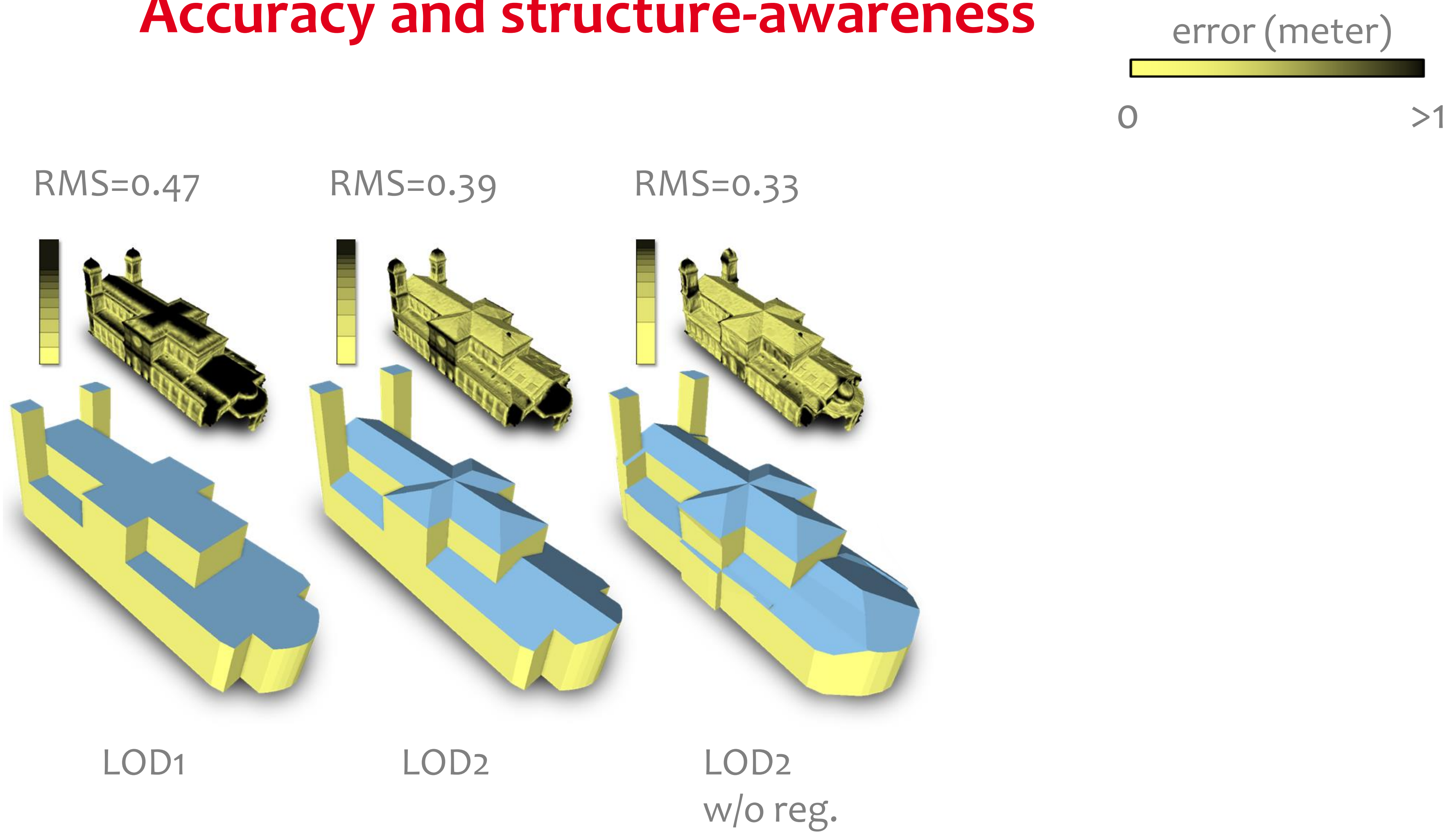
0 >1

RMS=0.47 RMS=0.39



LOD1 LOD2

Accuracy and structure-awareness

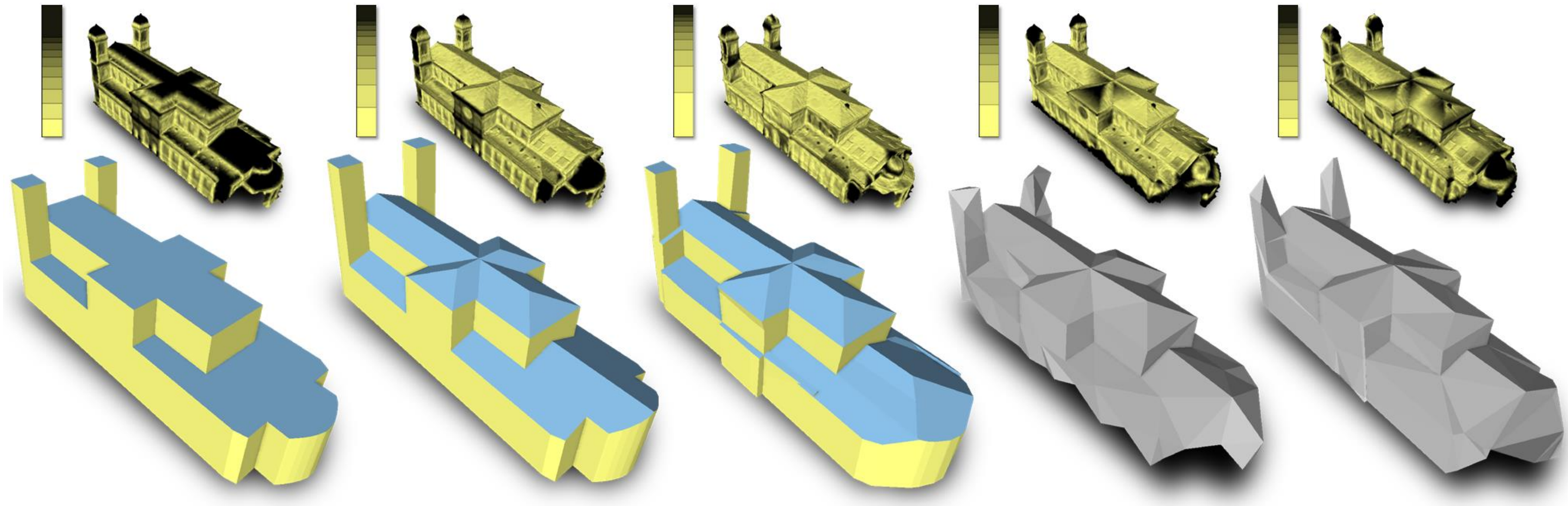


Accuracy and structure-awareness

error (meter)

0 >1

RMS=0.47 | RMS=0.39 | RMS=0.33 | RMS=0.4 | RMS=0.43



LOD1

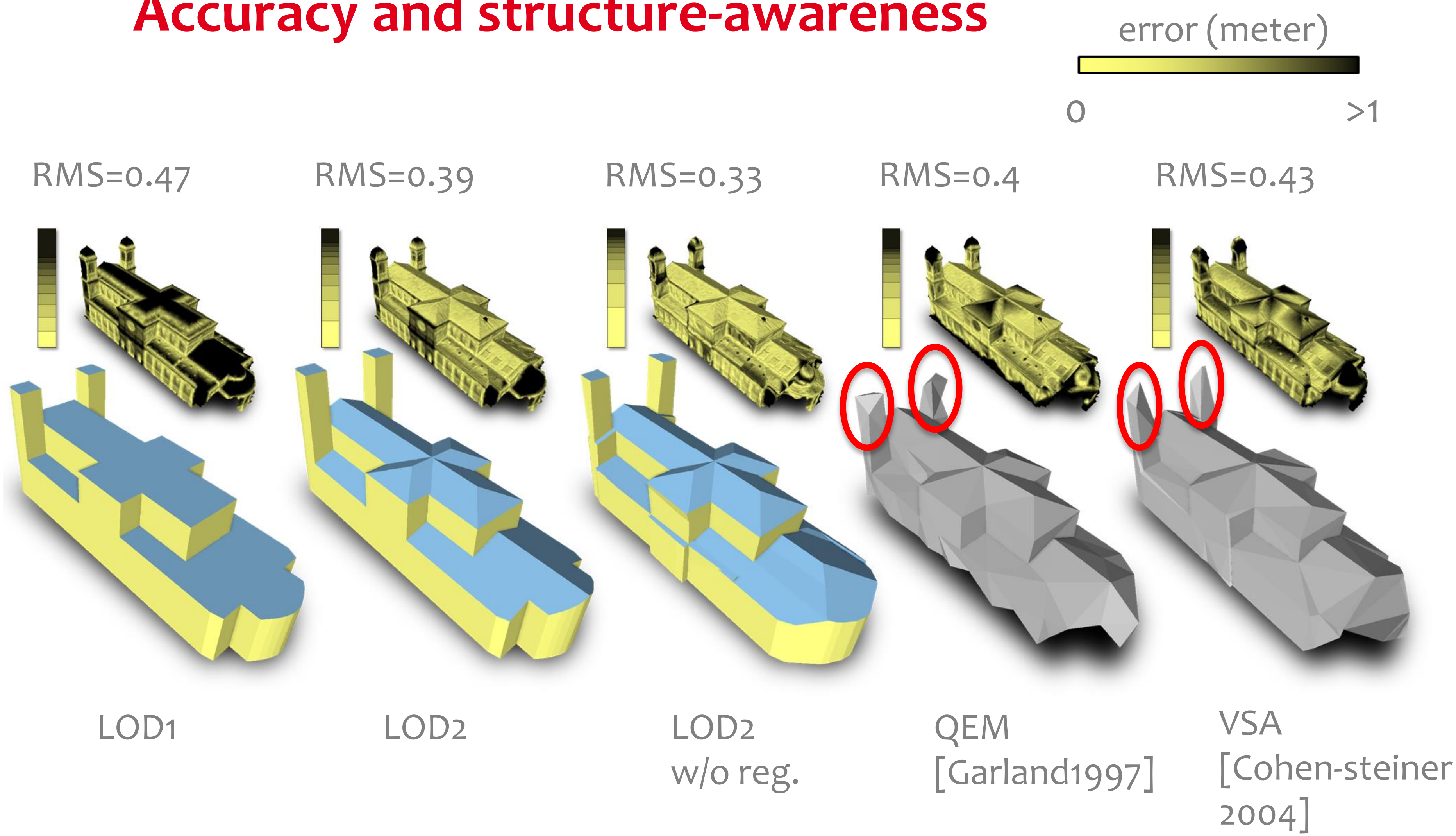
LOD2

LOD2
w/o reg.

QEM
[Garland1997]

VSA
[Cohen-steiner
2004]

Accuracy and structure-awareness



Conclusion

Computational Geometry and Computer Vision

High potential in image segmentation and 3D reconstruction

But not only

Large-scale methods, calibration, face and gesture, motion and tracking, geometric deep learning, compression, shape representation, stochastic methods, …

Don't be afraid of data-structures and geometric algorithms from Computational Geometry !

Thank you!

Code

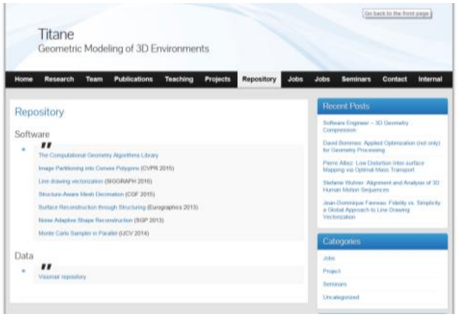
Voronoi partition

Point set structuring

Primitive extraction

Primitive regularization

Urban classification



https://team.inria.fr/titane/software/

CGAL

http://www.cgal.org