Dense image matching and surface reconstruction

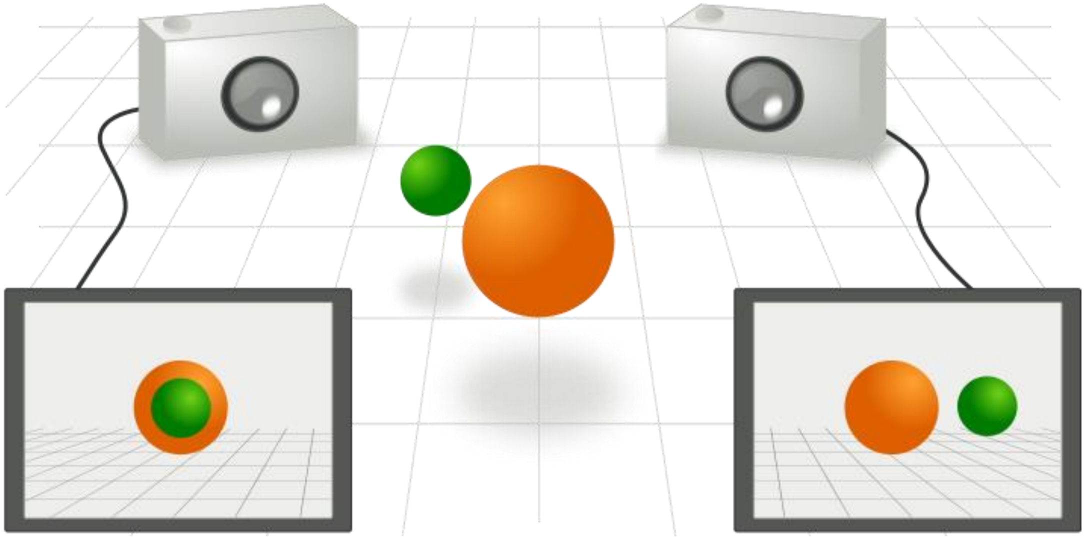
when photogrammetry meets computational geometry

Florent Lafarge

Sophia Antipolis - France

Problem statement

Given (at least) two (calibrated) images observing the same scene, what type of 3D information can we extract ?



Problem statement

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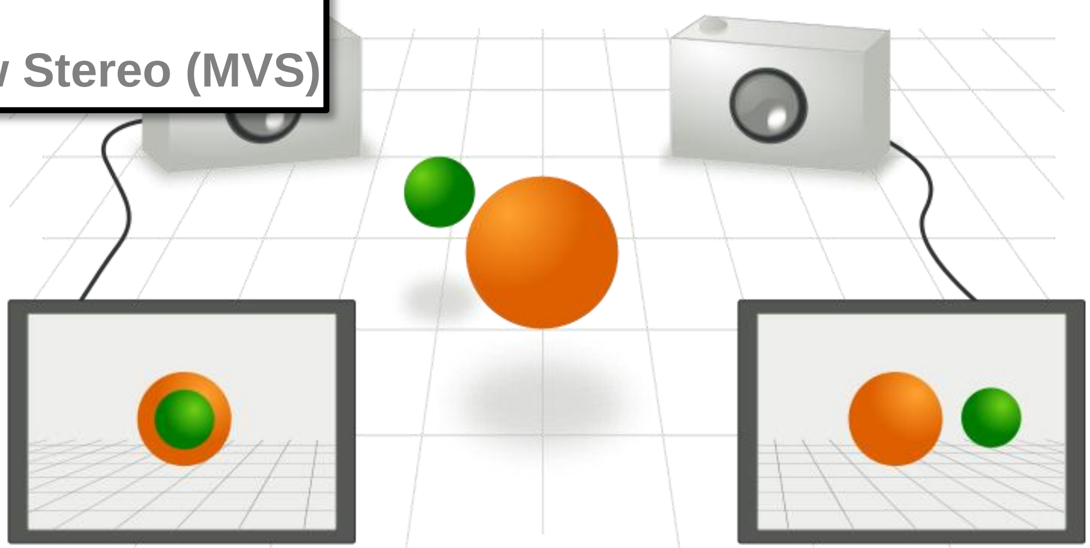
=2 : Stereo Matching

>2 : Multi-View Stereo (MVS)

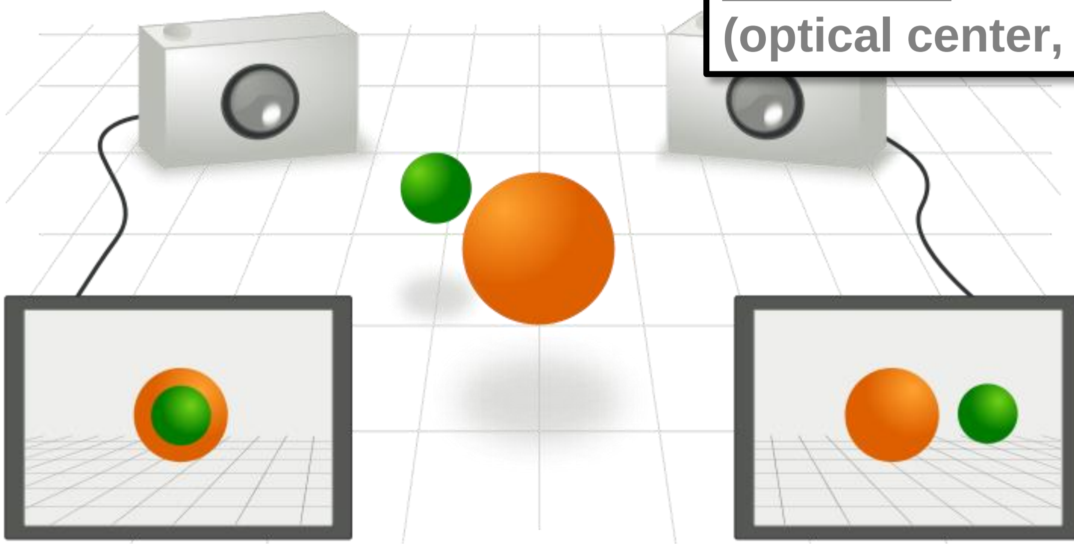


Problem statement

Given (at least) two **(calibrated)** images observing the same scene, what type of 3D information can we extract ?

Intrinsics
(focal length, radial distortion..)

Extrinsics
(optical center, camera orentation)



Overview

Stereo matching

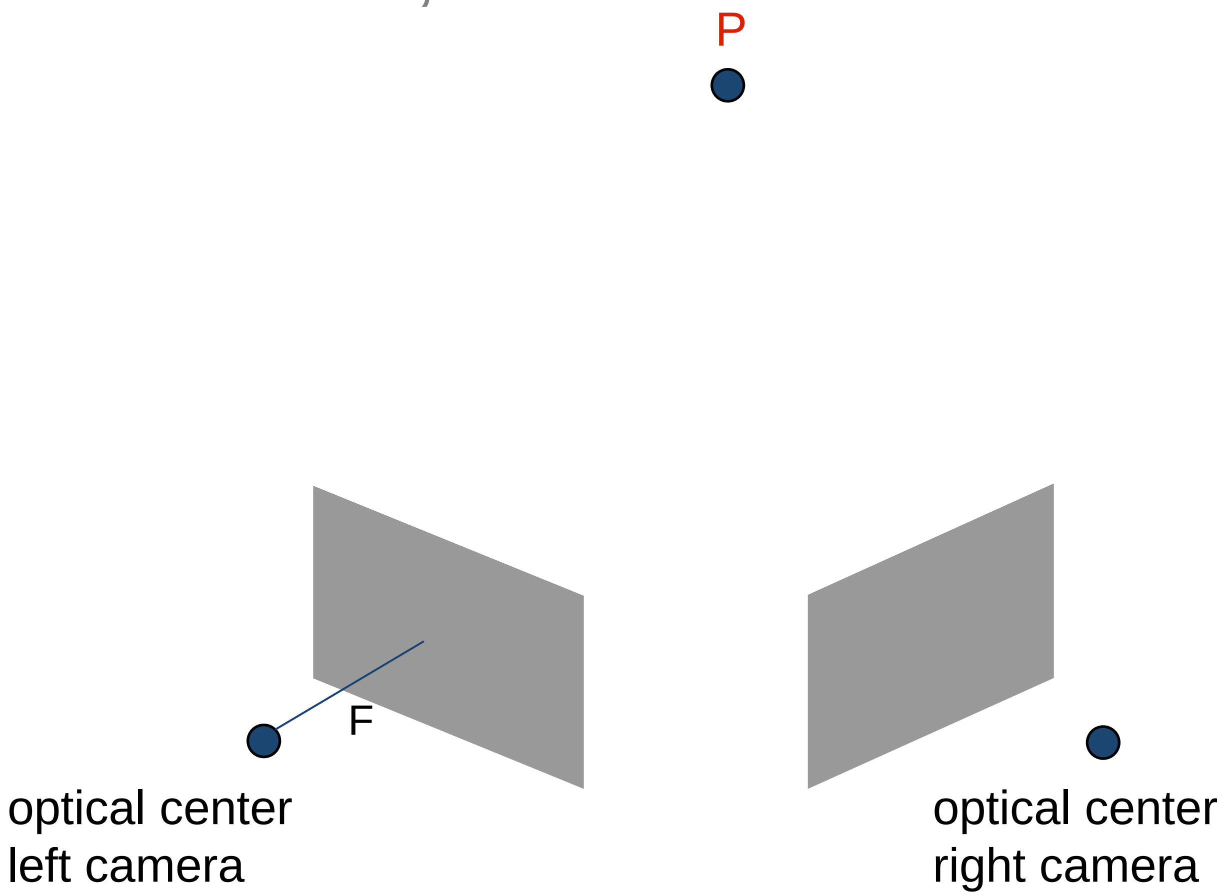
Multi-View Stereo

Beyond free-form surface reconstruction

1. Stereo matching

Principle

In the 3D world,



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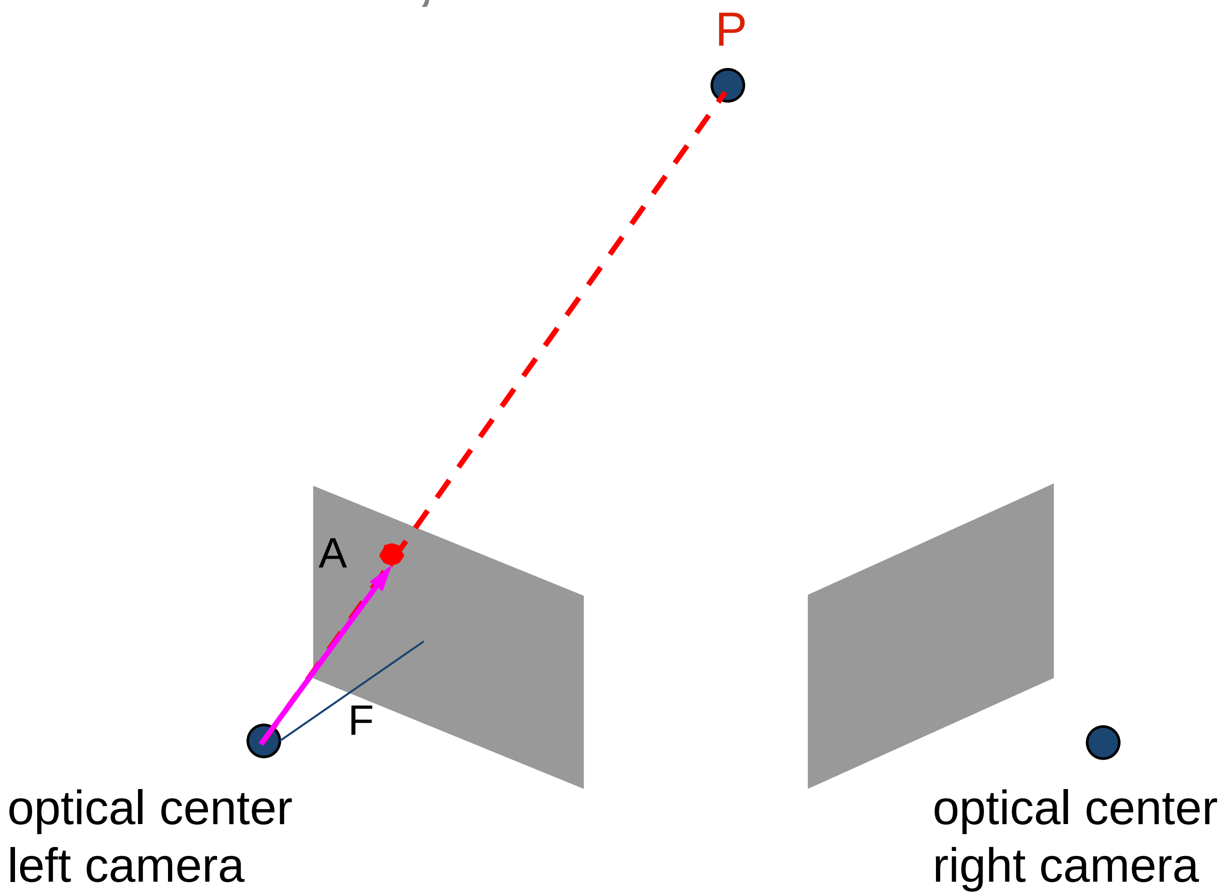

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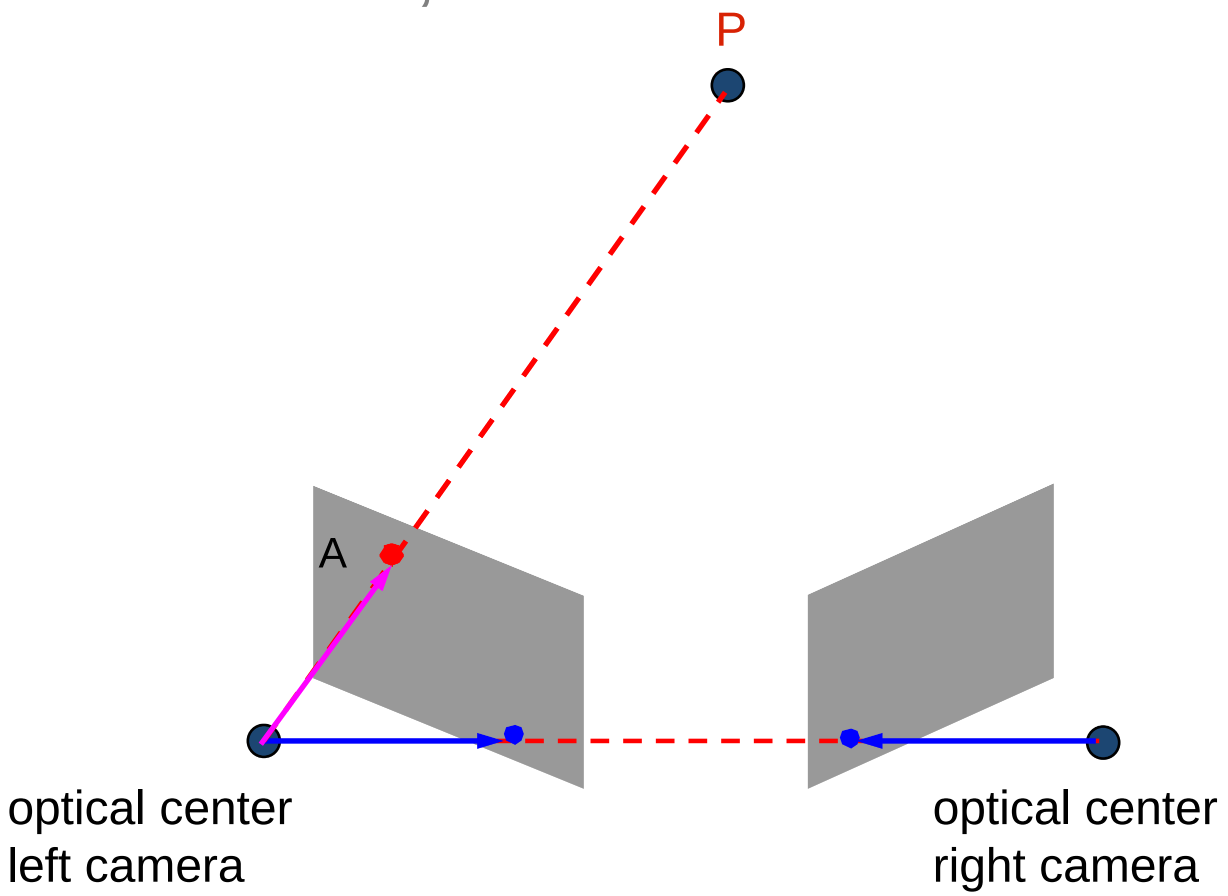

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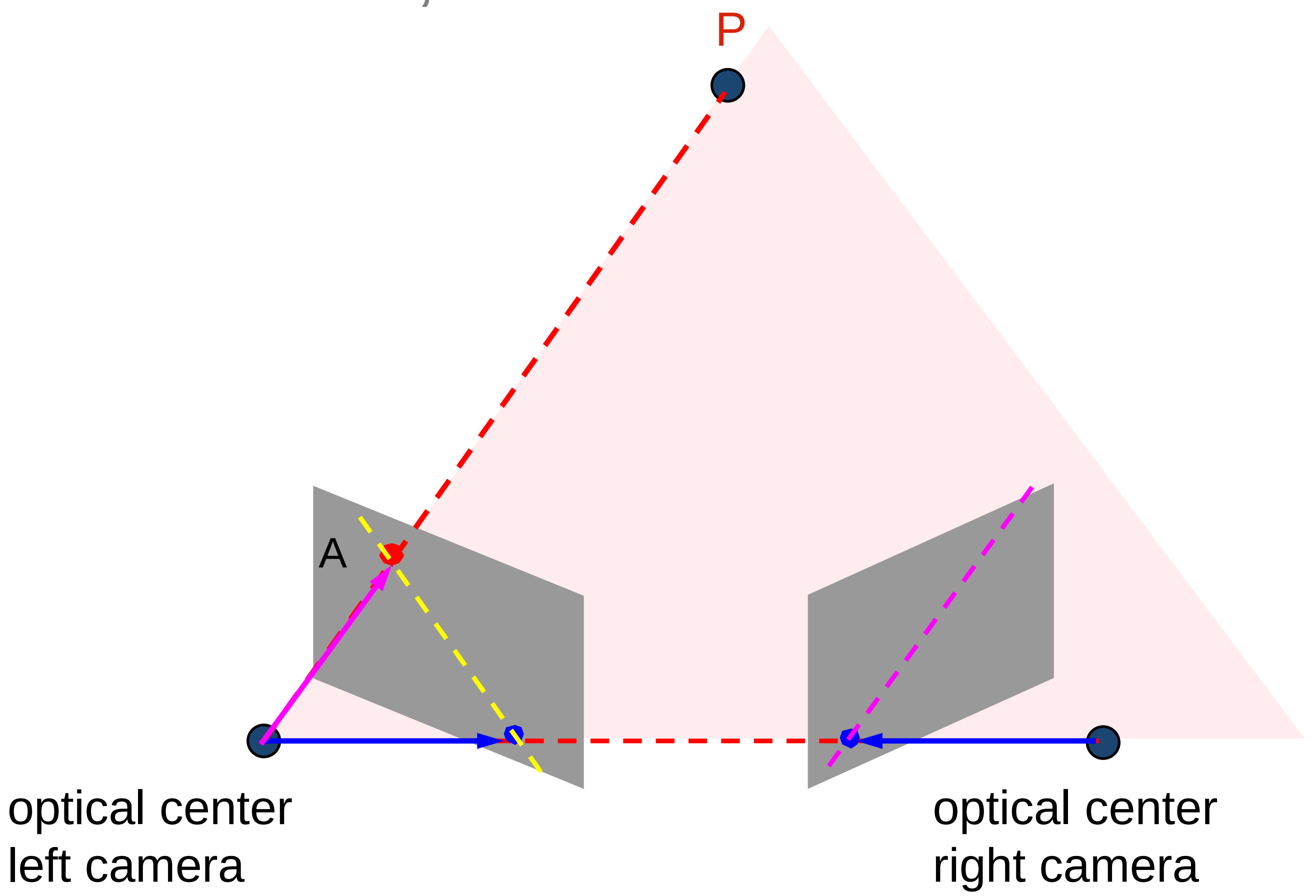

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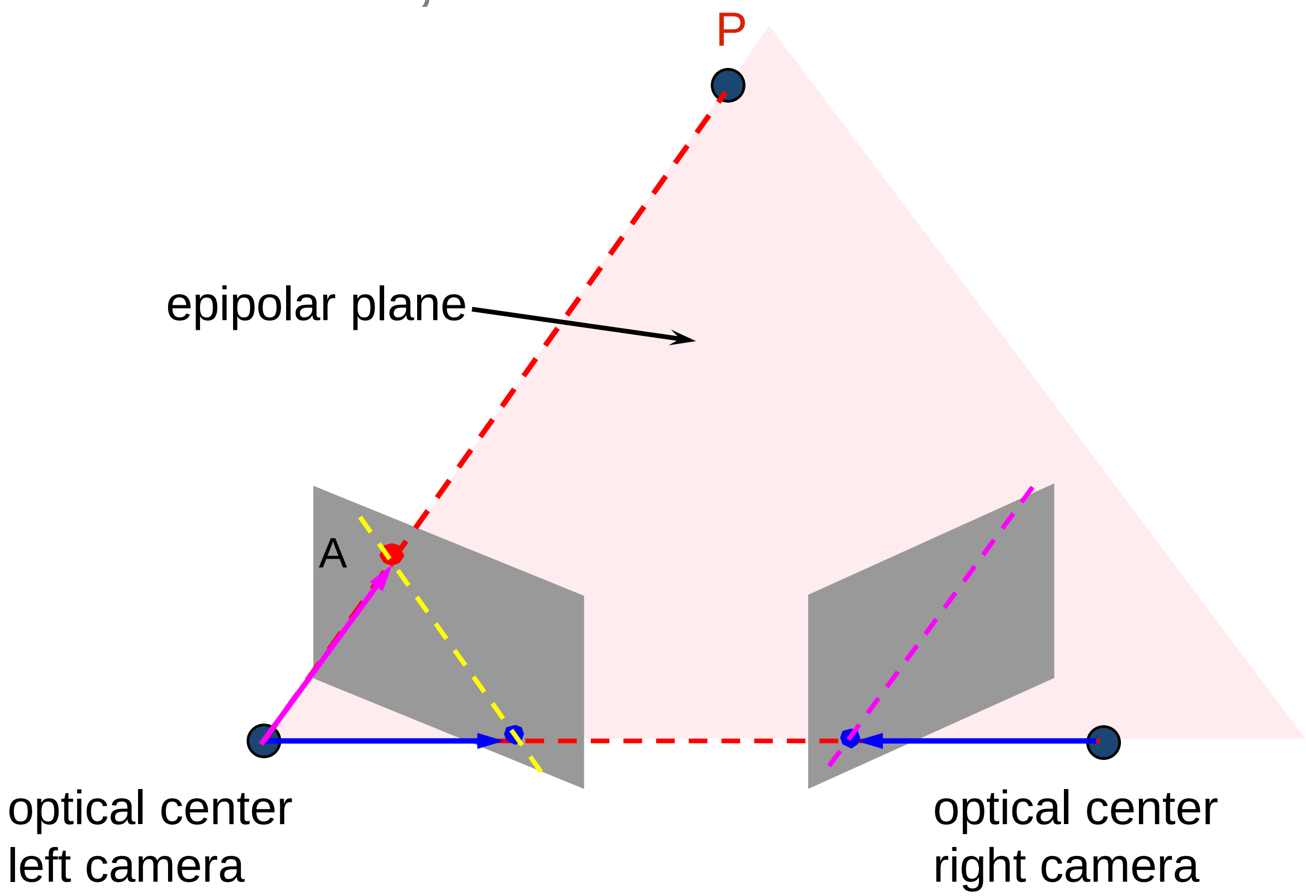

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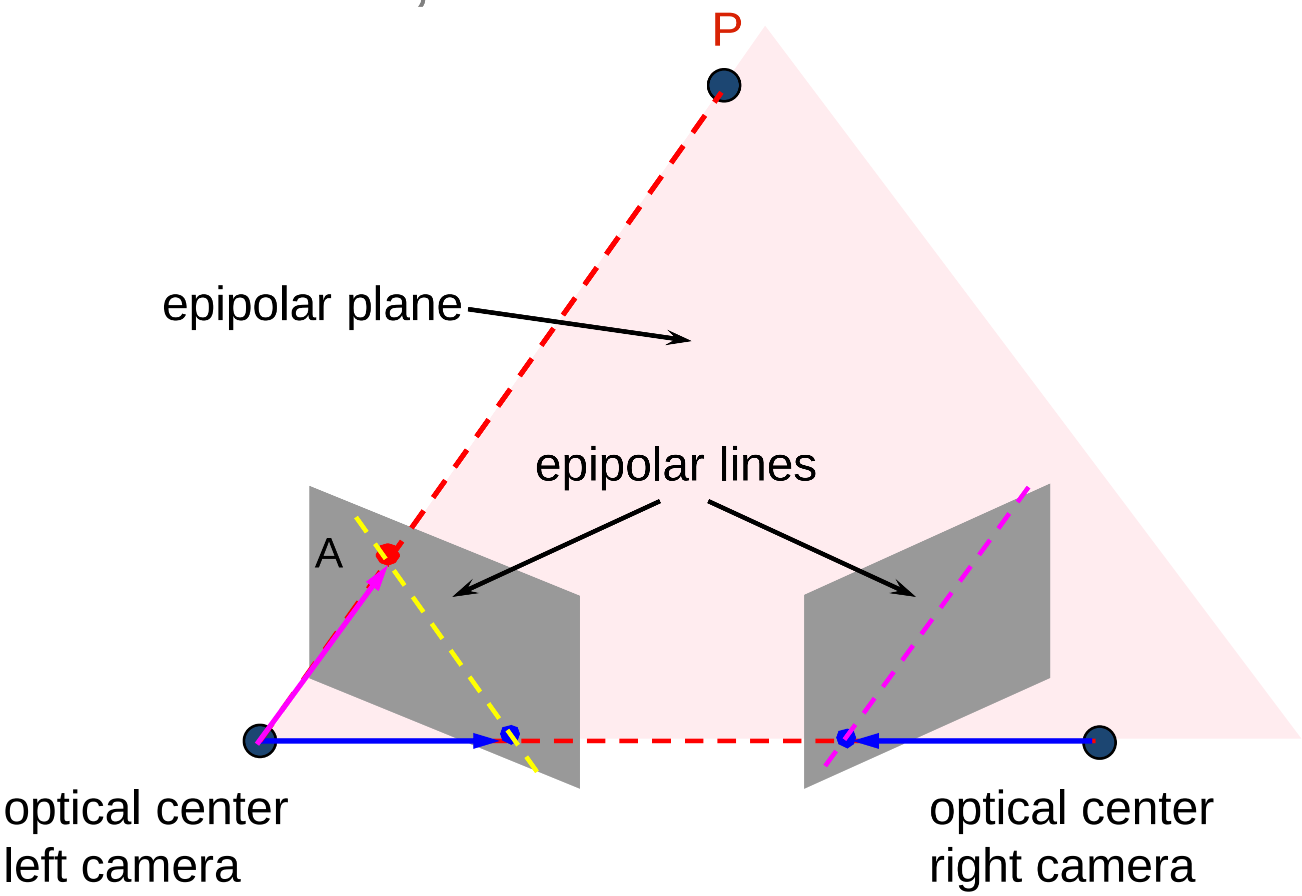

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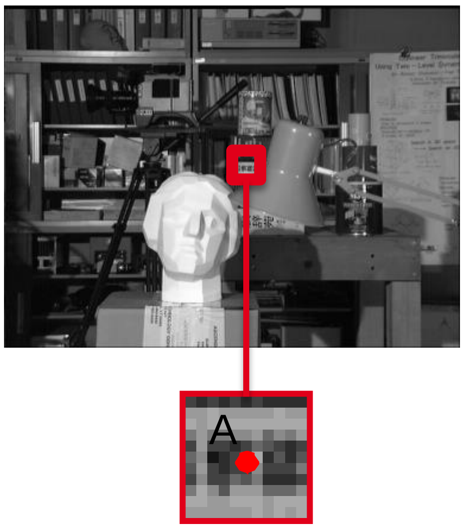
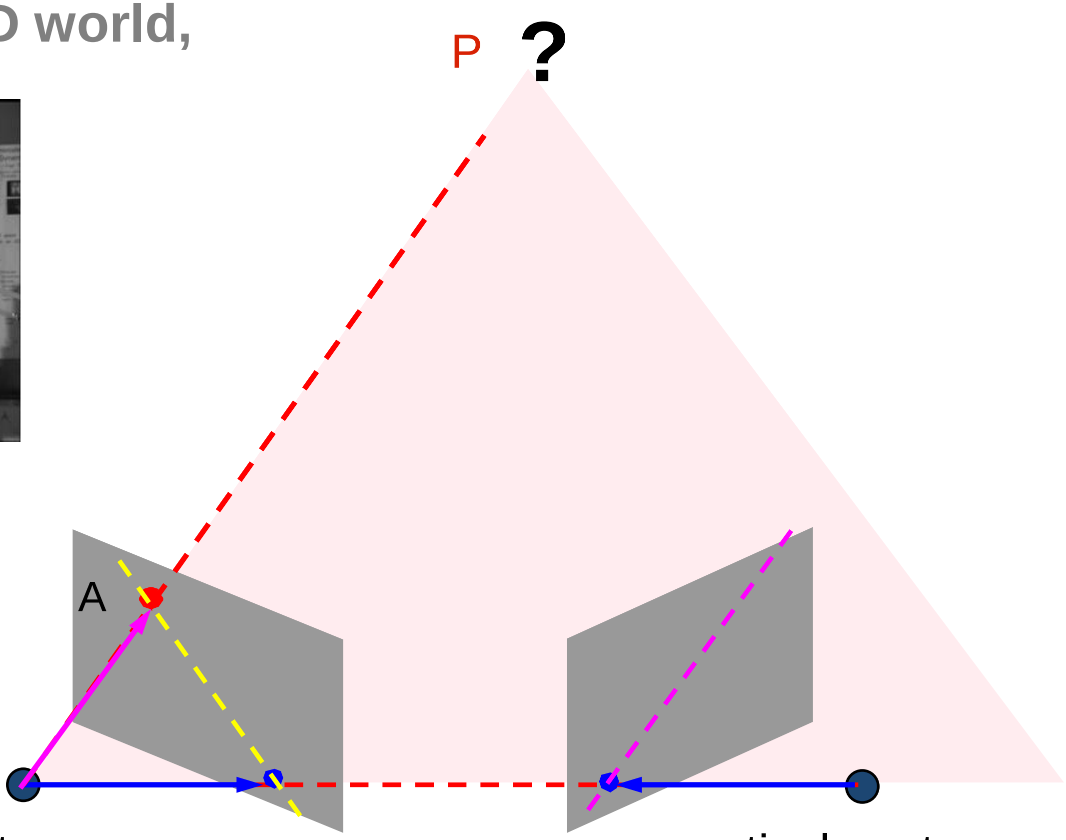


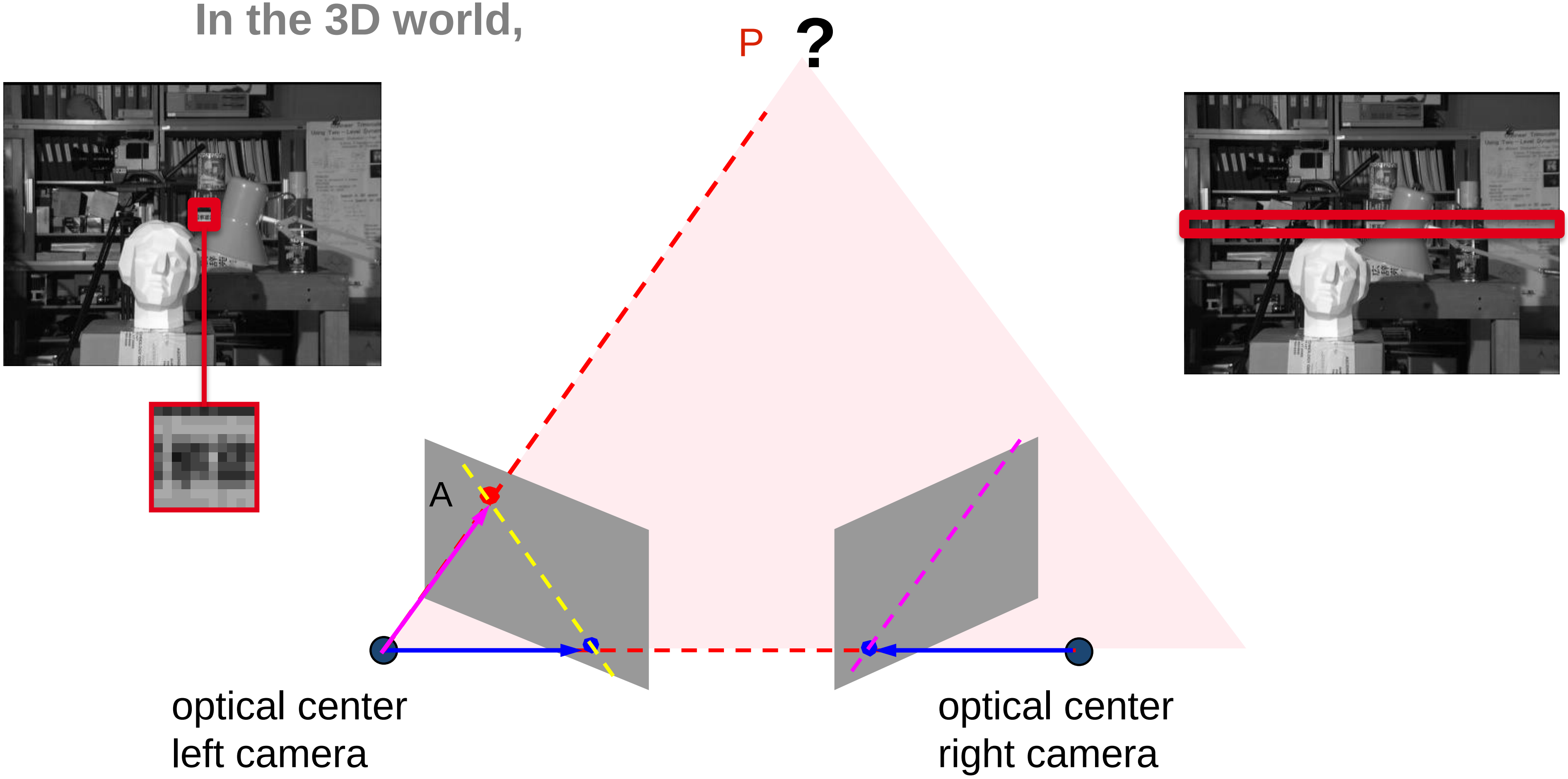


optical center
left camera

optical center
right camera

Principle

In the 3D world,



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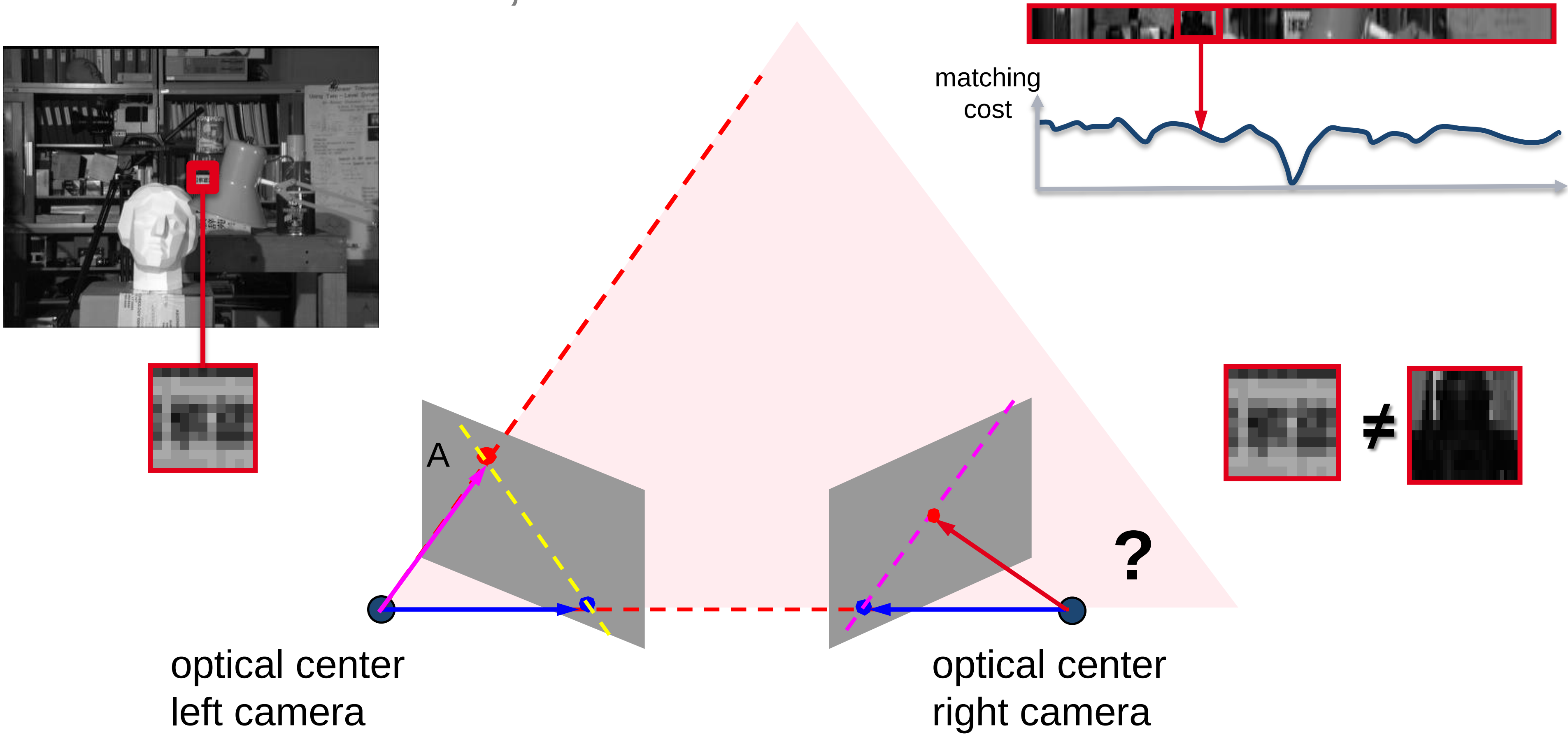

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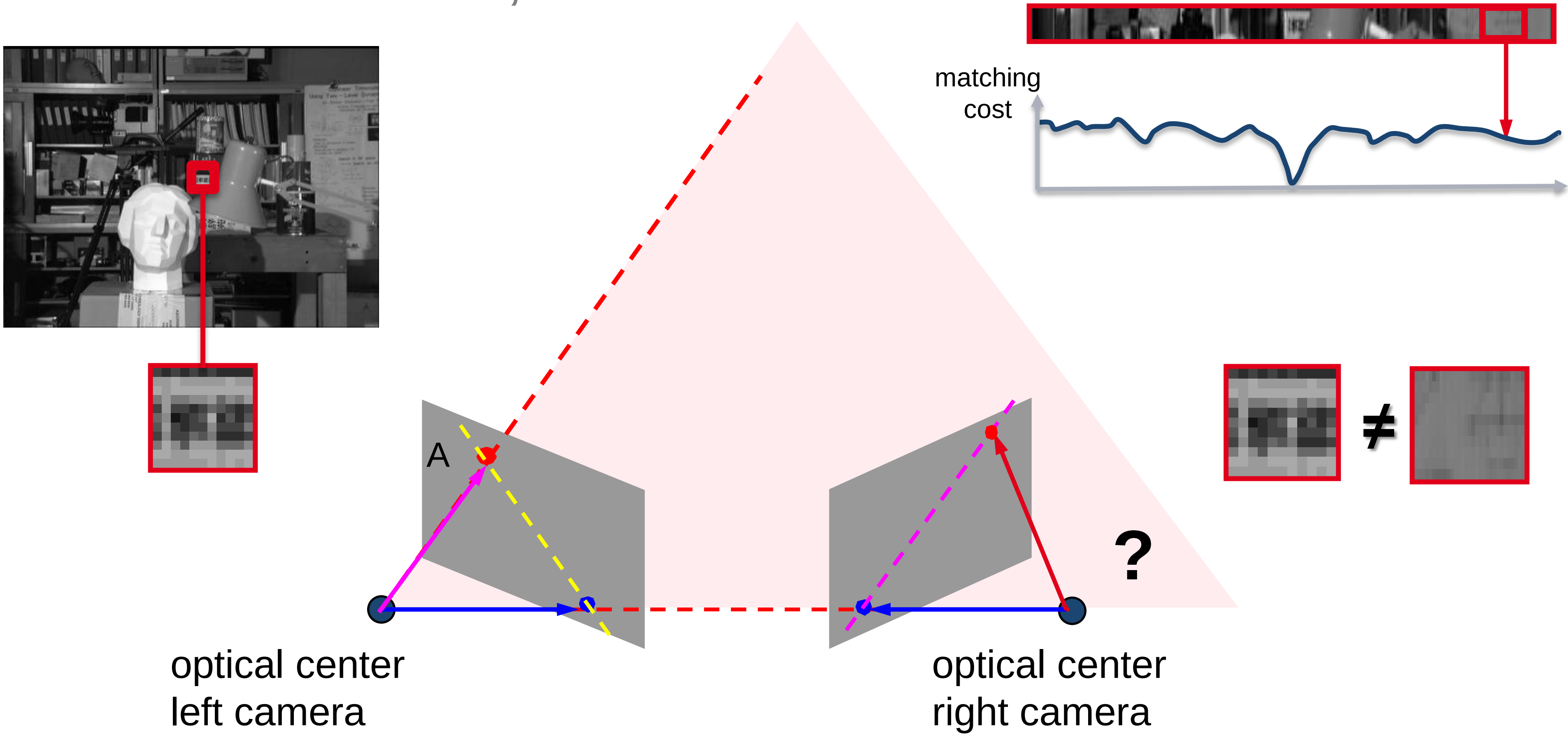

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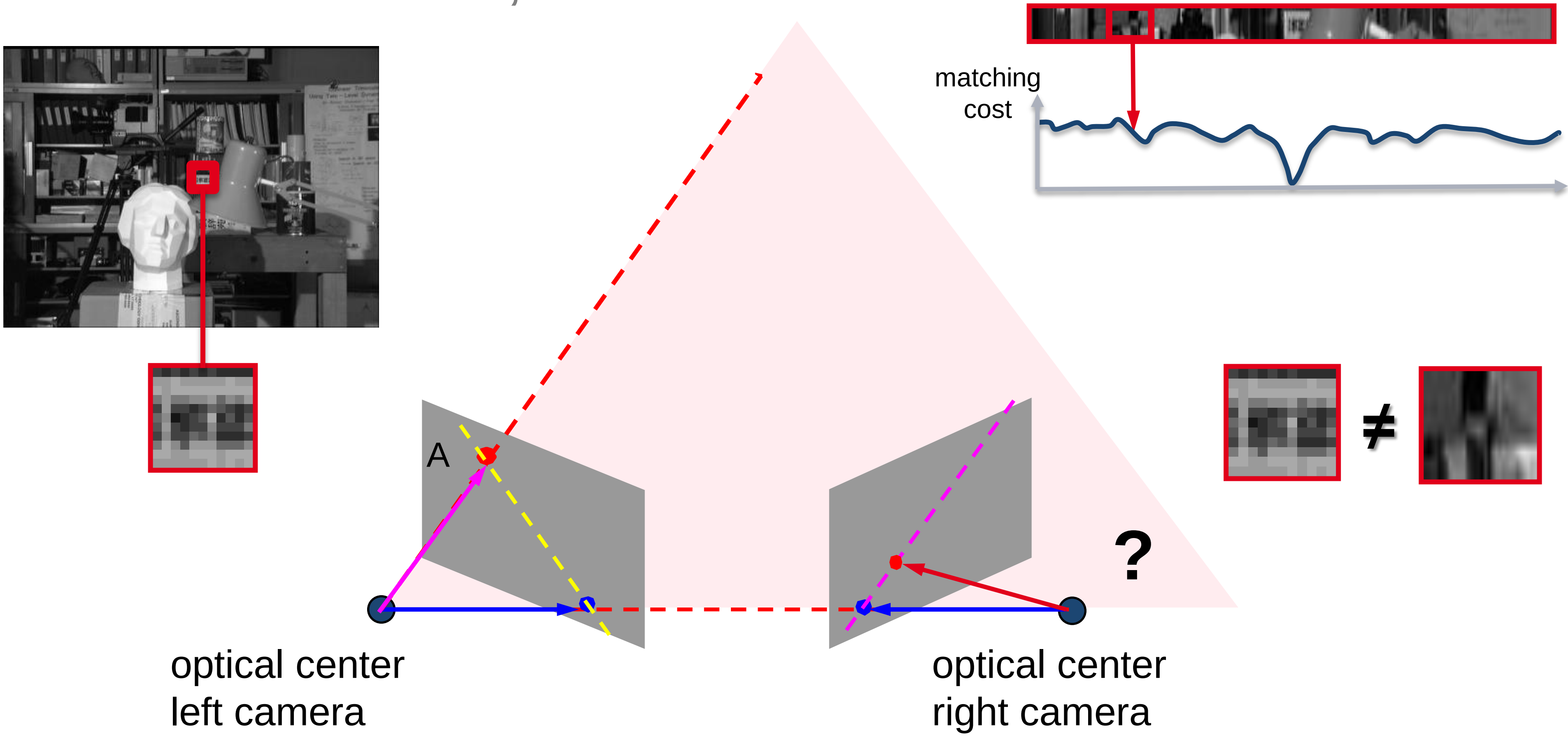

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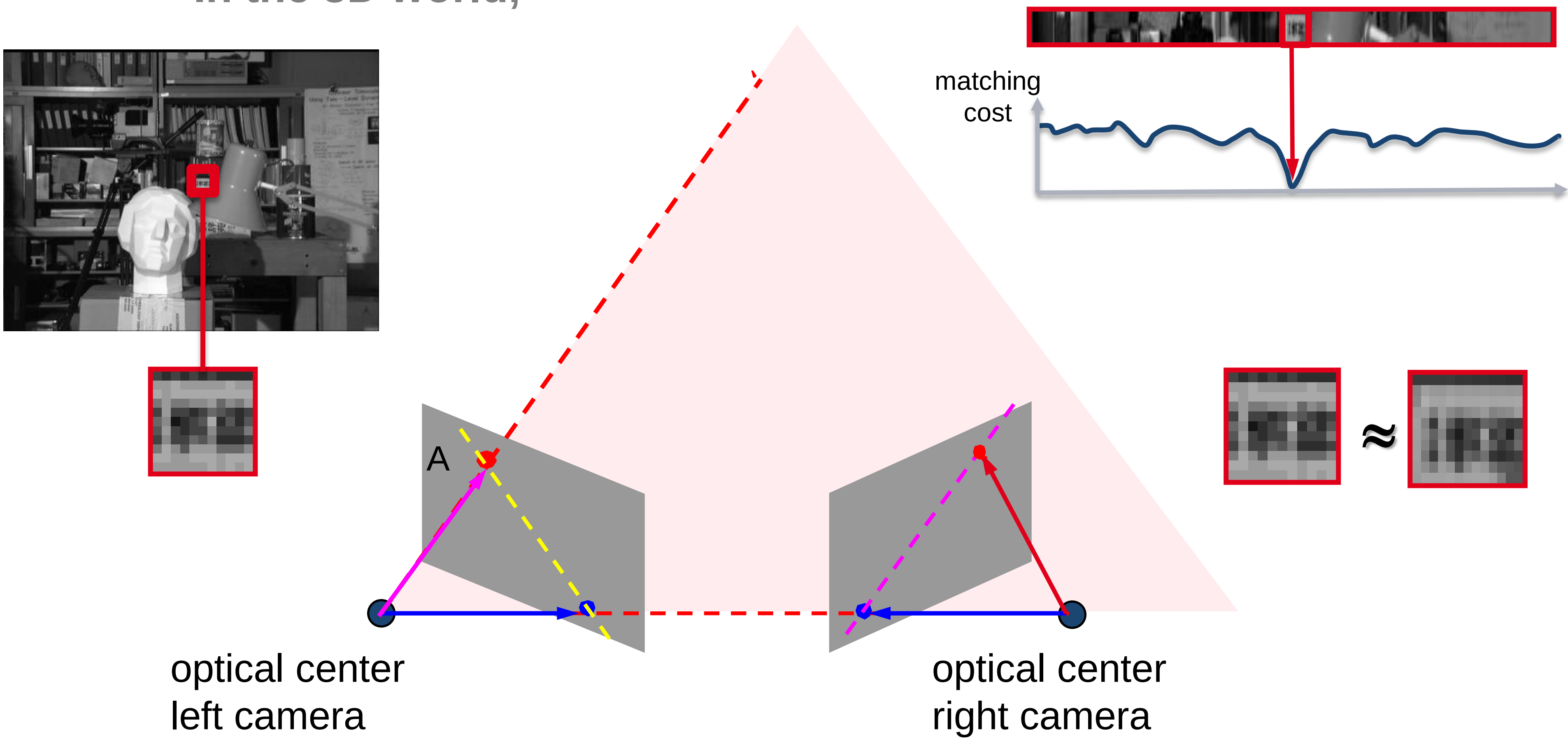

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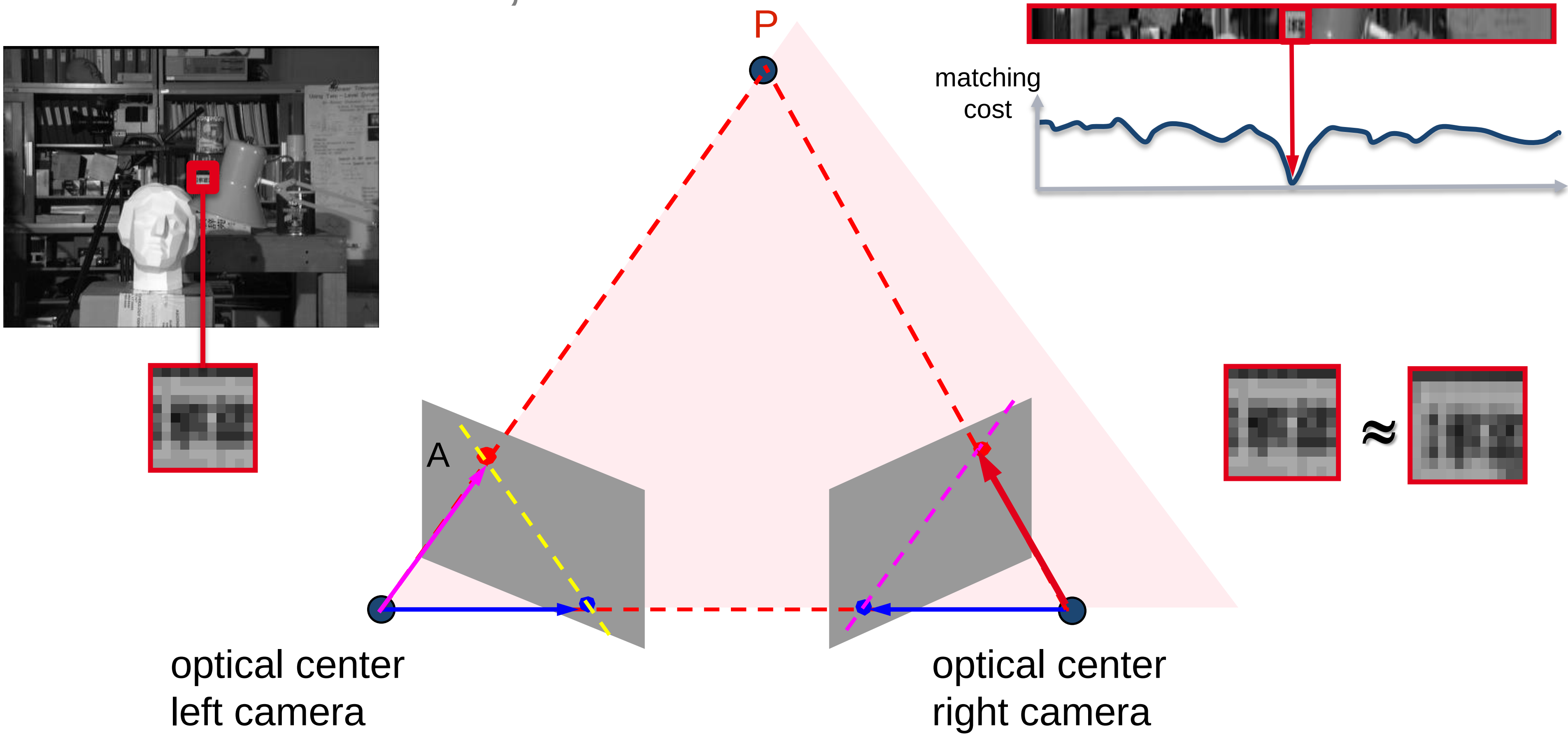
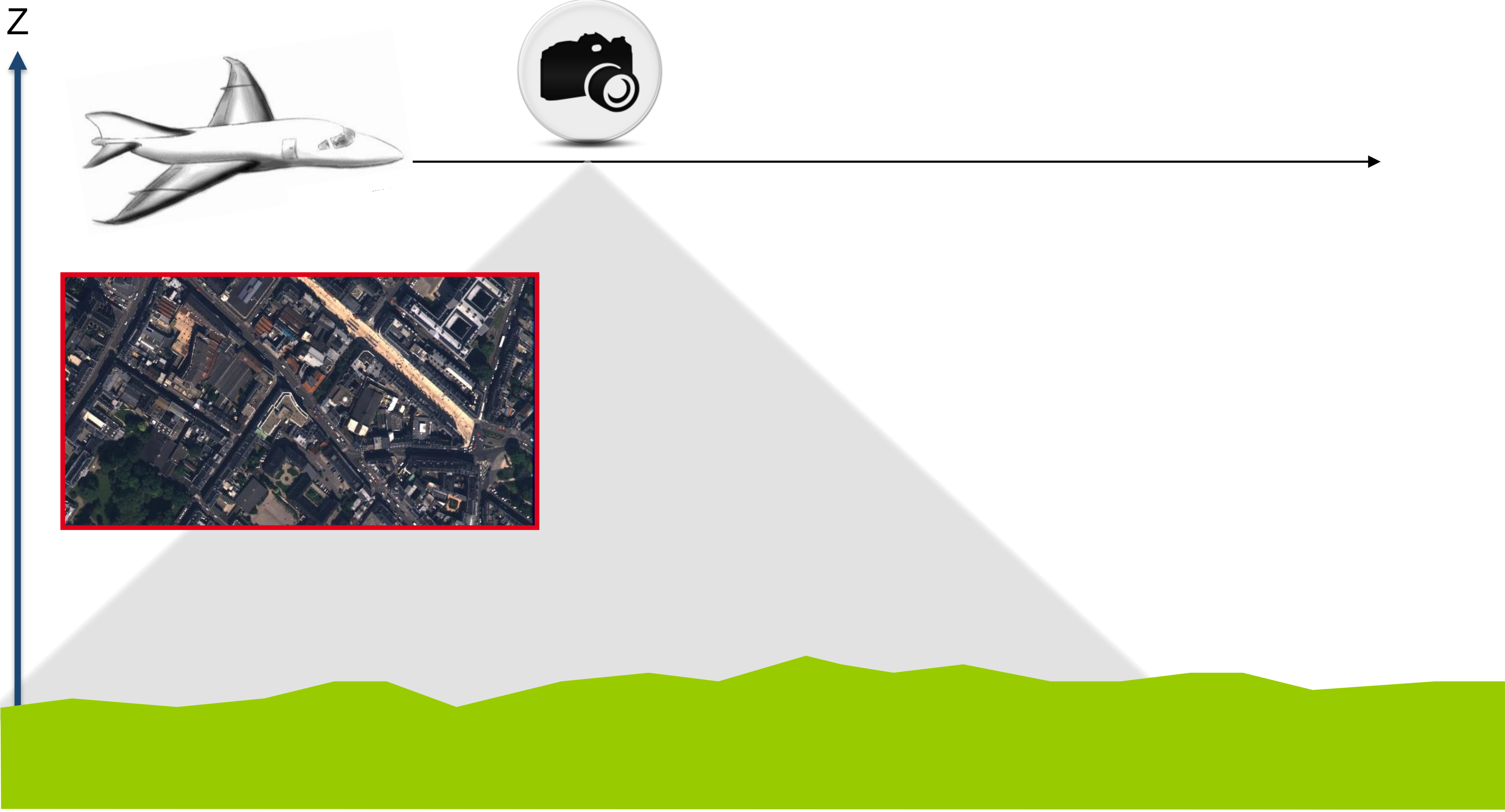
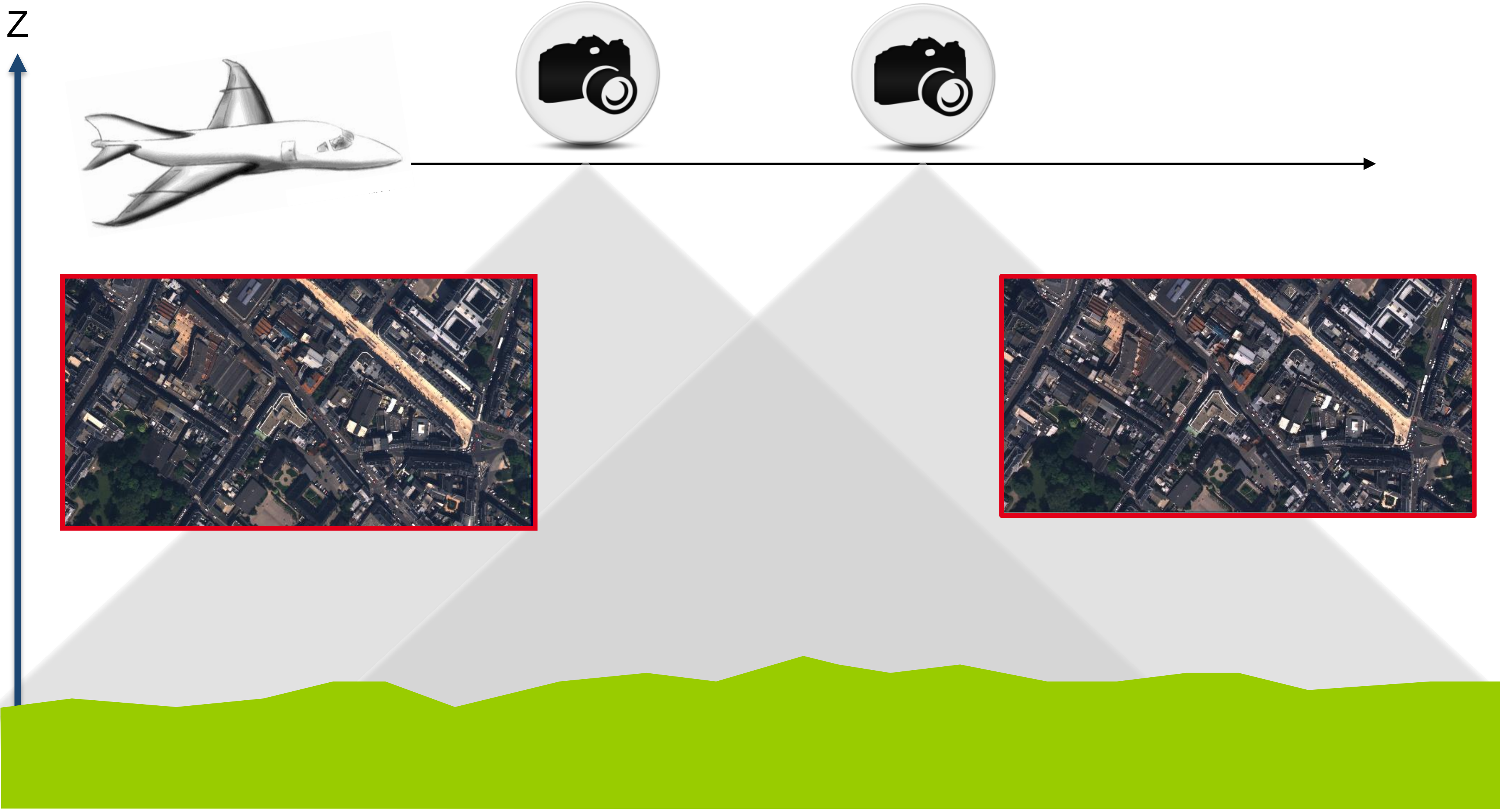


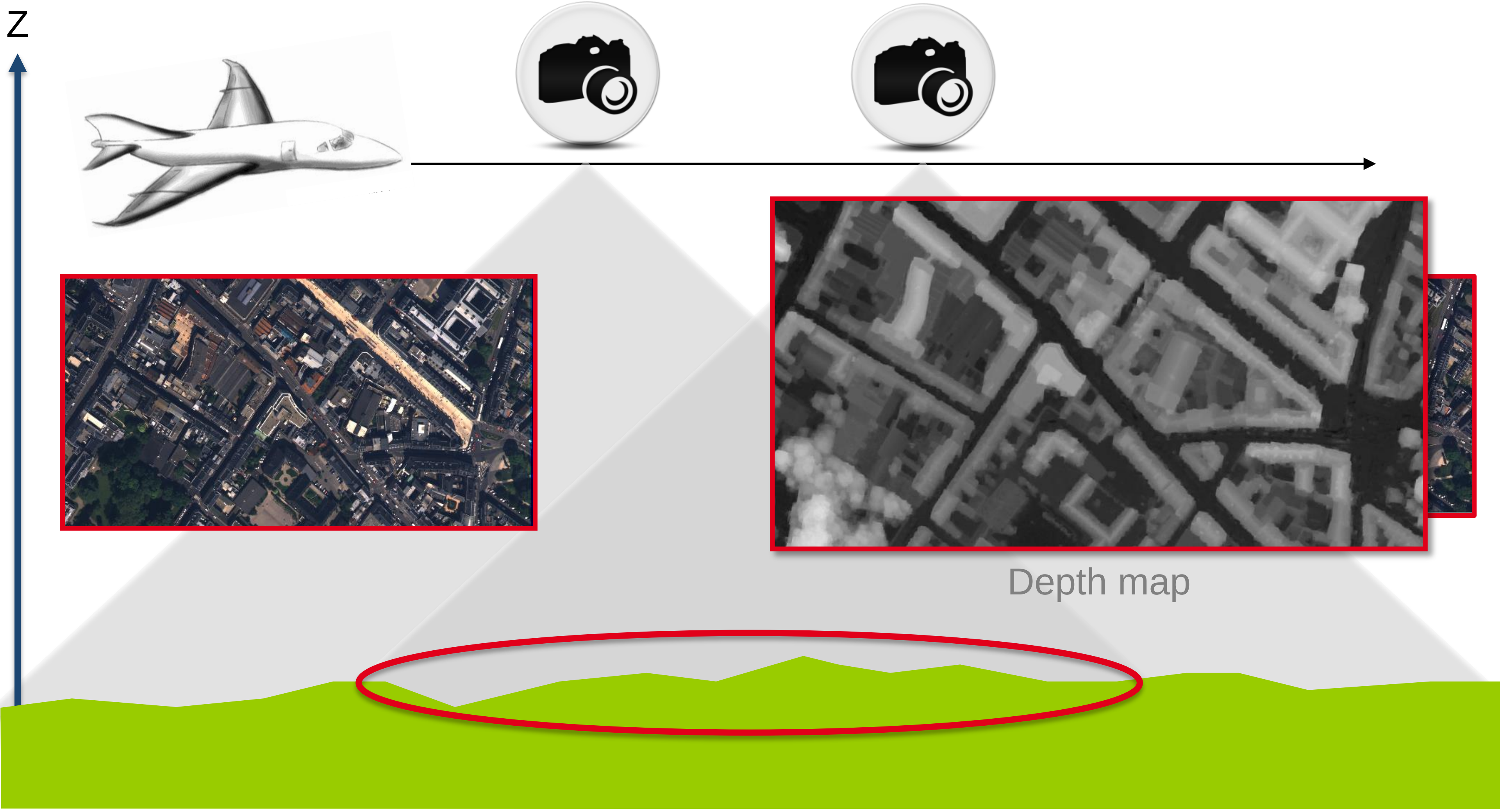
Principle



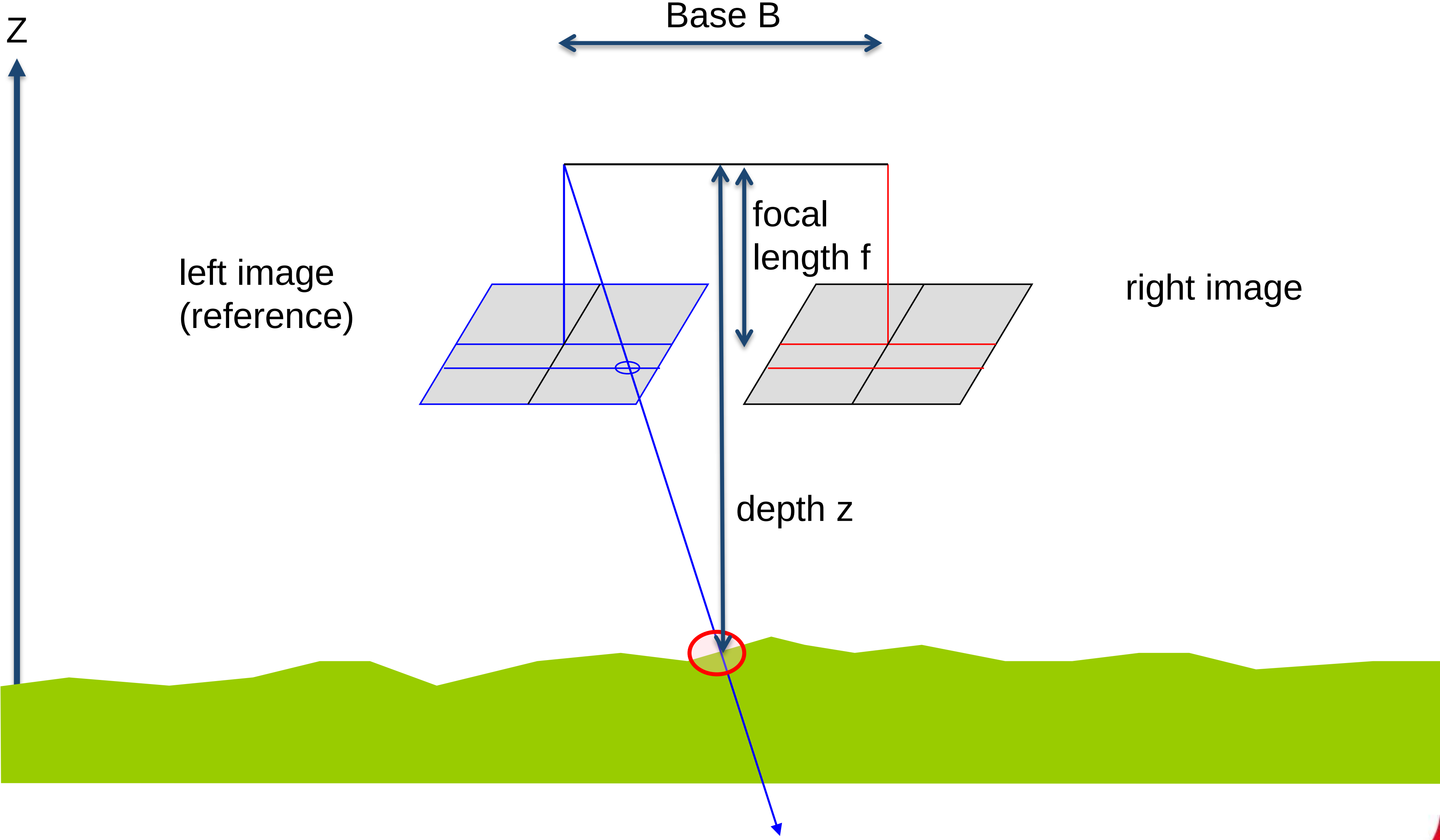
Principle



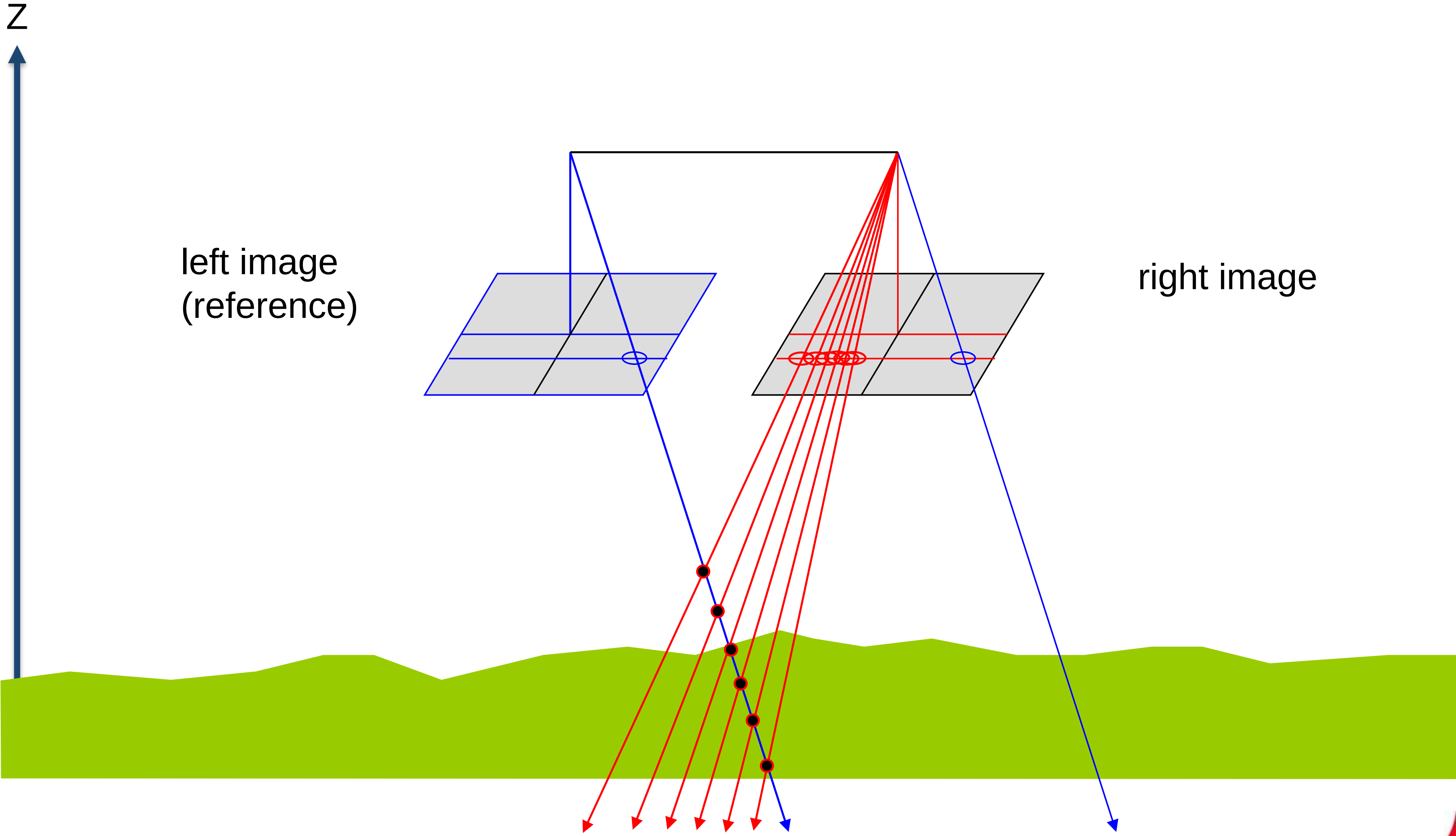
Principle



Principle


Z
Base B
focal
length f
left image
(reference)
right image
depth z

Principle



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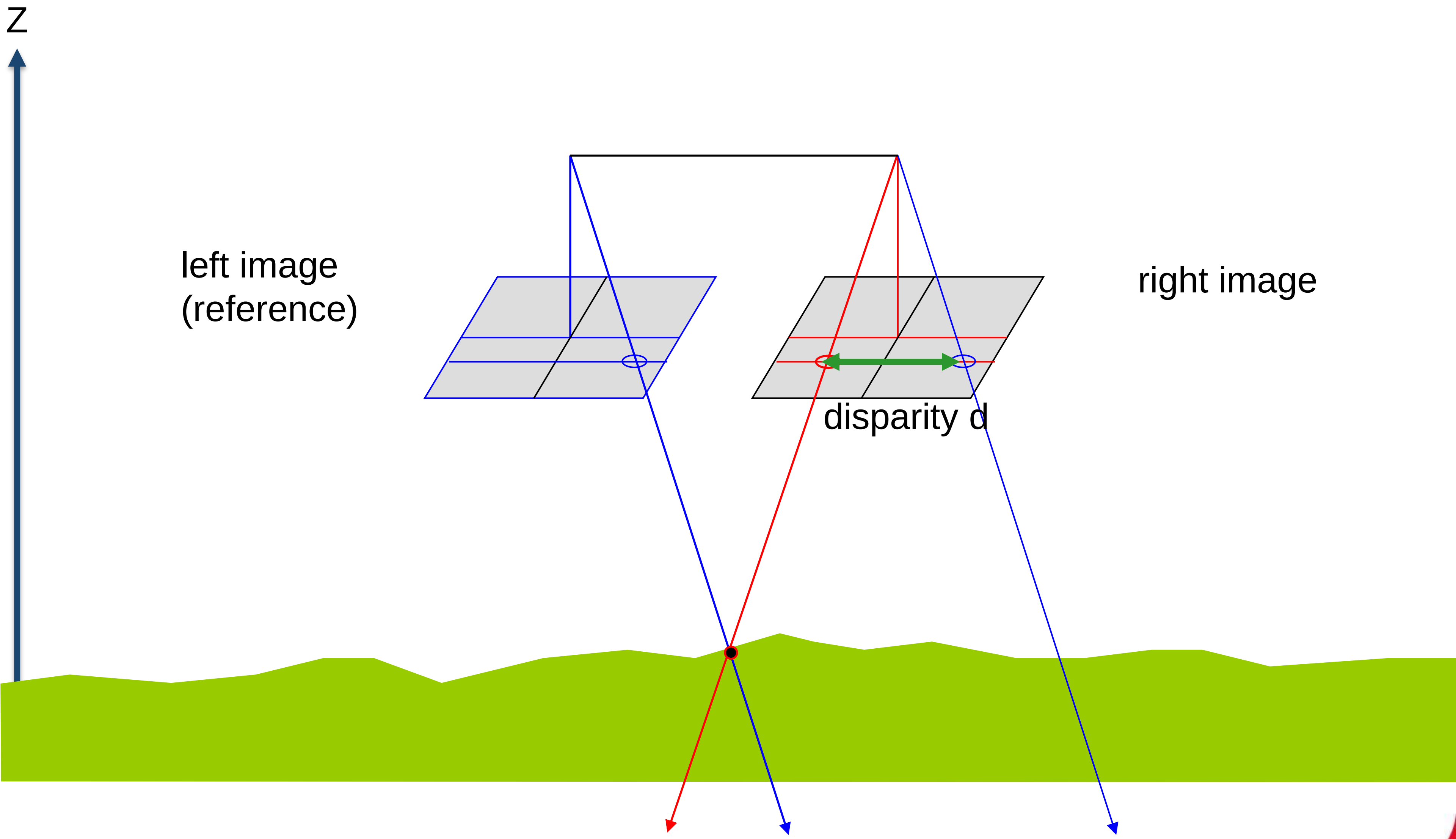

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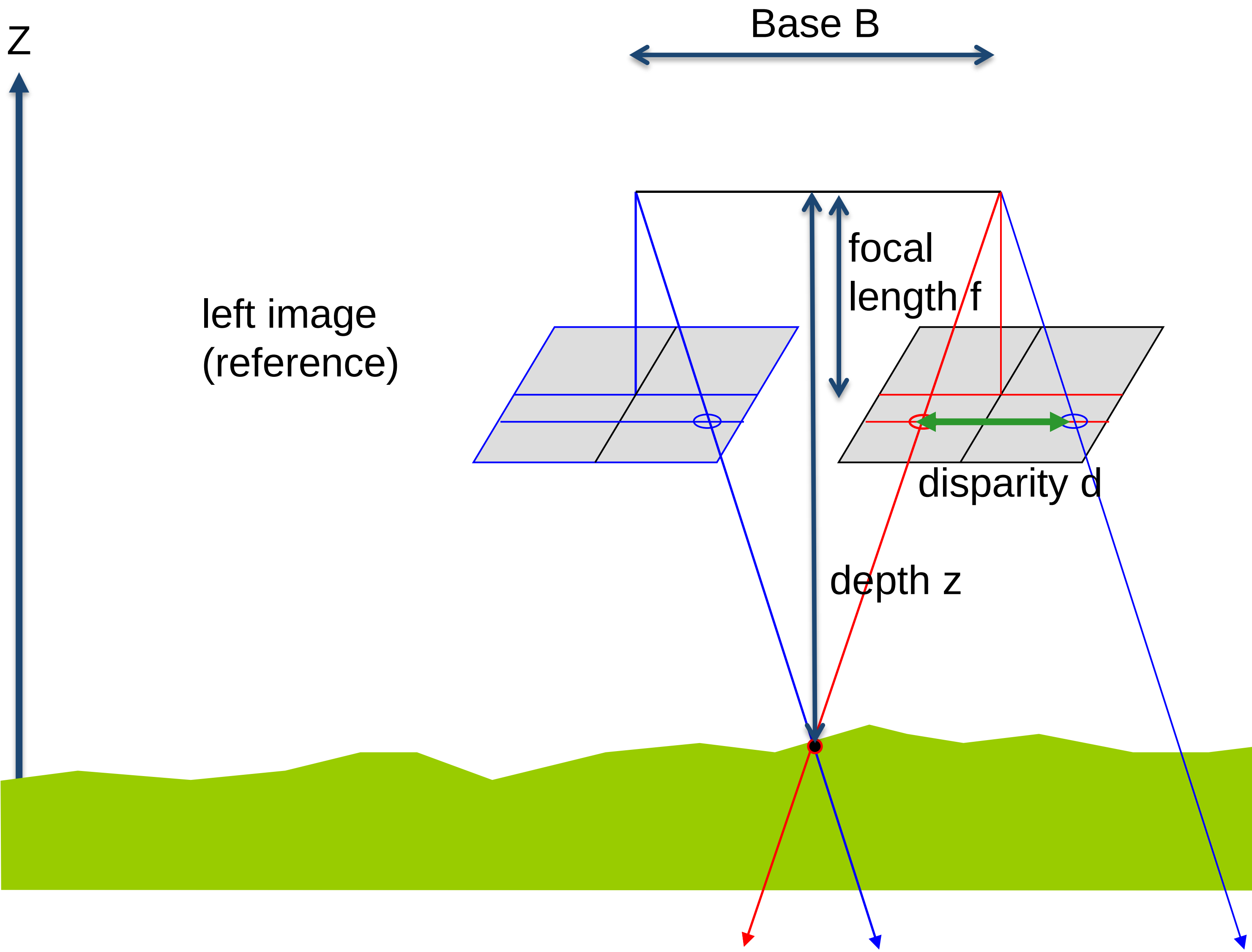
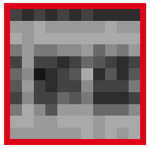
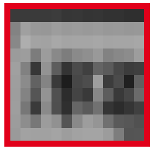
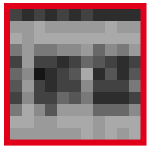
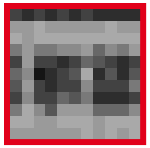
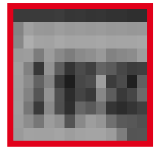
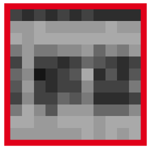


$$z = \frac{B \cdot f}{d}$$

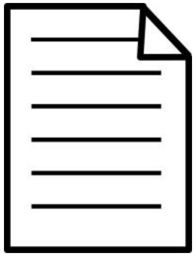
What matching cost ?

C( , ) ≈ 0 and C( , ) > 0

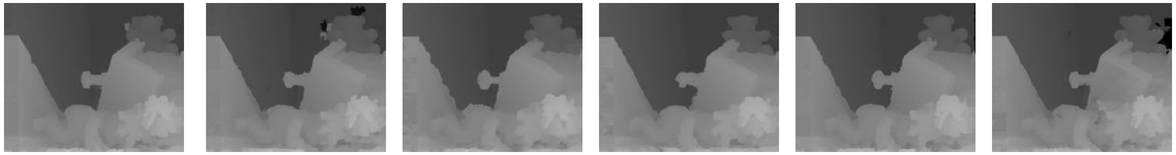
What matching cost ?

C( , ) ≈ 0 and C( , ) > 0

- Sum of Absolute Distances (SAD)
- Sum of Square Differences (SSD)
- Normalized Cross Correlation (NCC)
- Mutual Information (MI)
- … potentially object-based, eg line segments



[Hirschmuller and Scharstein, Evaluation of cost functions for stereo matching, CVPR 2007]



What matching constraints ?

- Uniqueness
- Ordering
- Spatial coherence (or smoothness)
- Sharp feature preservation
- …

What mechanism ?

- **Local**
  greedy local matching, *eg* **pixel-per-pixel matching**
- **Semi-global**
  spatial coherence along multiple 1D paths, *eg* **SGM**
- **Global**
  spatial coherence in 2D domain, eg **MRF-based**

Middlebury benchmark

~150 algorithms evaluated

Stereo | Evaluation • Datasets • Code • Submit

Middlebury Stereo Evaluation - Version 2

New features and main differences to version 1.
Submit and evaluate your own results.

Open a new window for each link

Error Threshold = 1 | Error Threshold... | Sort by nonocc | Sort by all | Sort by disc

Algorithm	Avg. Rank	Tsukuba ground truth nonocc	Tsukuba all	Tsukuba disc	Venus ground truth nonocc	Venus all	Venus disc	Teddy ground truth nonocc	Teddy all	Teddy disc	Cones ground truth nonocc	Cones all	Cones disc	Average percent of bad pixels (explanation)
TSGO [143]	9.8	0.87 3	**1.13** 1	4.66 5	0.11 6	0.24 8	1.47 9	5.61 36	8.09 17	13.8 30	**1.67** 1	**6.16** 1	**4.95** 1	4.06
ADCensus [82]	13.0	1.07 18	1.48 15	5.73 21	0.09 2	0.25 11	1.15 2	4.10 15	6.22 7	10.9 13	2.42 18	7.25 15	6.95 19	3.97
AdaptingBP [16]	16.5	1.11 21	1.37 9	5.79 23	0.10 4	0.21 7	1.44 8	4.22 17	7.06 15	11.8 17	2.48 22	7.92 28	7.32 27	4.23
CoopRegion [39]	17.2	0.87 5	1.16 2	4.61 4	0.11 5	0.21 5	1.54 13	5.16 29	8.31 20	13.0 24	2.79 39	7.18 14	8.01 46	4.41
RDP [87]	22.2	0.97 10	1.39 11	5.00 10	0.21 38	0.38 28	1.89 23	4.84 21	9.94 32	12.6 21	2.53 25	7.69 20	7.38 28	4.57
MultiRBF [129]	22.6	1.33 46	1.56 20	6.02 31	0.13 10	0.17 2	1.84 20	5.09 27	6.36 8	13.4 28	2.90 47	6.76 8	7.10 24	4.39
DoubleBP [34]	23.3	0.88 7	1.29 6	4.76 8	0.13 11	0.45 46	1.87 22	3.53 12	8.30 19	9.63 8	2.90 46	8.78 57	7.79 38	4.19
MDPM [140]	23.4	1.15 23	1.59 23	6.14 34	0.14 16	0.36 25	1.52 12	3.79 13	5.78 5	11.1 15	2.74 33	8.38 41	7.91 41	4.22
CVW-RM [148]	23.4	1.12 22	1.42 13	5.99 30	0.16 24	0.36 26	1.40 7	4.70 20	6.94 13	12.1 18	2.96 52	7.71 21	7.72 35	4.38
OutlierConf [40]	23.7	0.88 6	1.43 14	4.74 7	0.18 27	0.26 13	2.40 38	5.01 23	9.12 28	12.8 23	2.78 38	8.57 47	6.99 20	4.60
SegAggr [146]	25.1	1.99 87	2.39 78	8.59 86	0.12 7	0.21 6	1.68 15	2.19 2	**3.73** 1	7.02 2	2.16 7	6.52 3	6.37 7	3.58
AdaptiveGF [127]	27.8	1.04 14	1.53 16	5.62 16	0.17 26	0.41 36	1.98 26	5.71 39	11.3 46	14.3 37	2.44 20	8.22 35	7.05 23	4.98
SOS [135]	28.5	1.45 57	1.63 27	7.83 75	0.21 36	0.32 18	2.29 37	3.13 8	8.45 22	9.74 9	2.43 19	7.10 13	7.02 21	4.30
SubPixSearch [109]	29.2	2.04 91	2.48 82	6.40 41	0.14 15	0.40 35	1.74 17	4.00 14	6.39 9	11.0 14	2.24 11	6.87 10	6.50 11	4.18
SubPixDoubleBP [29]	30.1	1.24 31	1.76 41	5.98 29	0.12 9	0.46 48	1.74 17	3.45 11	8.38 21	10.0 11	2.93 49	8.73 54	7.91 40	4.39
SurfaceStereo [71]	30.1	1.28 40	1.65 30	6.78 50	0.19 29	0.28 14	2.61 51	3.12 7	5.10 3	8.65 4	2.89 45	7.95 31	8.26 57	4.06
LLR [117]	32.1	1.05 15	1.65 29	5.64 17	0.29 64	0.81 79	3.07 64	4.56 18	9.81 31	12.2 19	2.17 8	8.02 32	6.42 9	4.64
WarpMat [50]	34.0	1.16 24	1.35 8	6.04 32	0.18 28	0.24 10	2.44 42	5.02 24	9.30 29	13.0 26	3.49 68	8.47 45	9.01 72	4.98
MultiAgg [139]	34.1	1.52 63	1.82 45	8.20 83	0.16 20	0.39 34	2.03 28	5.09 26	10.5 36	13.8 31	2.27 12	7.49 17	6.71 14	5.00
ObjectStereo [84]	35.1	1.22 30	1.62 24	6.36 38	0.59 92	0.69 71	4.61 92	4.13 16	7.59 16	11.2 16	2.20 9	6.99 11	6.36 6	4.46
TreeFilter [149]	35.8	1.02 13	1.54 18	5.52 14	0.24 47	0.41 38	2.86 57	5.86 41	11.2 44	13.6 29	3.00 54	7.00 12	8.49 62	5.06
LM3C [134]	36.8	2.10 94	2.44 79	8.01 80	0.12 8	0.39 33	1.23 3	5.46 33	10.9 40	14.9 46	2.12 4	7.59 18	6.14 3	5.12
TF_ASW [130]	37.1	1.65 69	1.96 57	5.90 26	0.14 14	0.31 17	1.51 11	6.25 56	11.8 63	15.1 48	2.49 24	8.32 38	7.02 22	5.21
LAMC-DSM [123]	37.9	1.61 67	2.18 70	5.86 25	0.24 49	0.60 61	3.12 65	4.63 19	10.4 35	12.7 22	2.09 3	8.31 37	6.10 2	4.83
PMF [119]	38.1	1.74 74	2.04 64	8.07 81	0.33 70	0.49 52	4.16 85	2.52 3	5.87 6	8.30 3	2.13 5	6.80 9	6.32 5	4.06
HybridTree [150]	38.2	1.29 42	1.71 34	6.95 59	0.15 18	0.30 16	1.23 3	6.12 50	11.4 50	15.8 57	2.82 41	8.68 53	7.76 36	5.35
FastNLGC [138]	38.3	1.28 39	1.57 21	6.79 51	0.09 3	0.17 3	1.24 5	5.28 30	6.64 12	13.9 33	4.23 98	9.06 67	11.4 98	5.13
SegmentTree [126]	38.7	1.25 32	1.68 33	6.69 46	0.20 30	0.30 15	1.77 19	6.00 45	11.9 64	15.0 47	2.77 34	8.82 60	7.81 39	5.35
RelativeGrad [128]	39.7	1.18 26	1.27 4	5.91 27	0.23 44	0.24 9	1.28 6	6.89 77	12.3 76	16.0 59	3.31 64	7.94 30	8.24 54	5.40
PatchMatch [96]	39.9	2.09 93	2.33 75	9.31 94	0.21 35	0.39 31	2.62 52	2.99 5	8.16 18	9.62 7	2.47 21	7.80 23	7.11 25	4.59
HEBF [105]	40.4	1.10 20	1.38 10	5.74 22	0.22 41	0.33 21	2.41 40	6.54 66	11.8 59	15.2 49	2.78 37	9.28 71	8.10 49	5.41
HistoAggr2 [122]	40.5	1.93 83	2.30 74	6.39 39	0.16 21	0.46 49	2.22 33	5.88 42	11.3 47	14.7 41	2.41 17	7.78 22	6.89 18	5.20
imprNLCA [121]	41.5	1.38 49	1.83 48	7.38 66	0.21 37	0.41 37	2.26 35	5.99 43	11.5 52	14.3 38	2.85 43	6.68 5	7.98 45	5.23
PM-Huber [125]	41.5	3.49 125	4.09 113	9.12 91	0.22 39	0.43 41	2.50 44	3.38 9	5.56 4	10.7 12	2.15 6	6.69 6	6.40 8	4.56

http://vision.middlebury.edu/stereo/

2. Multi-View Stereo

Principle

Stereo Matching

- 2 input images
- 2.5D output representation
  (depth maps)

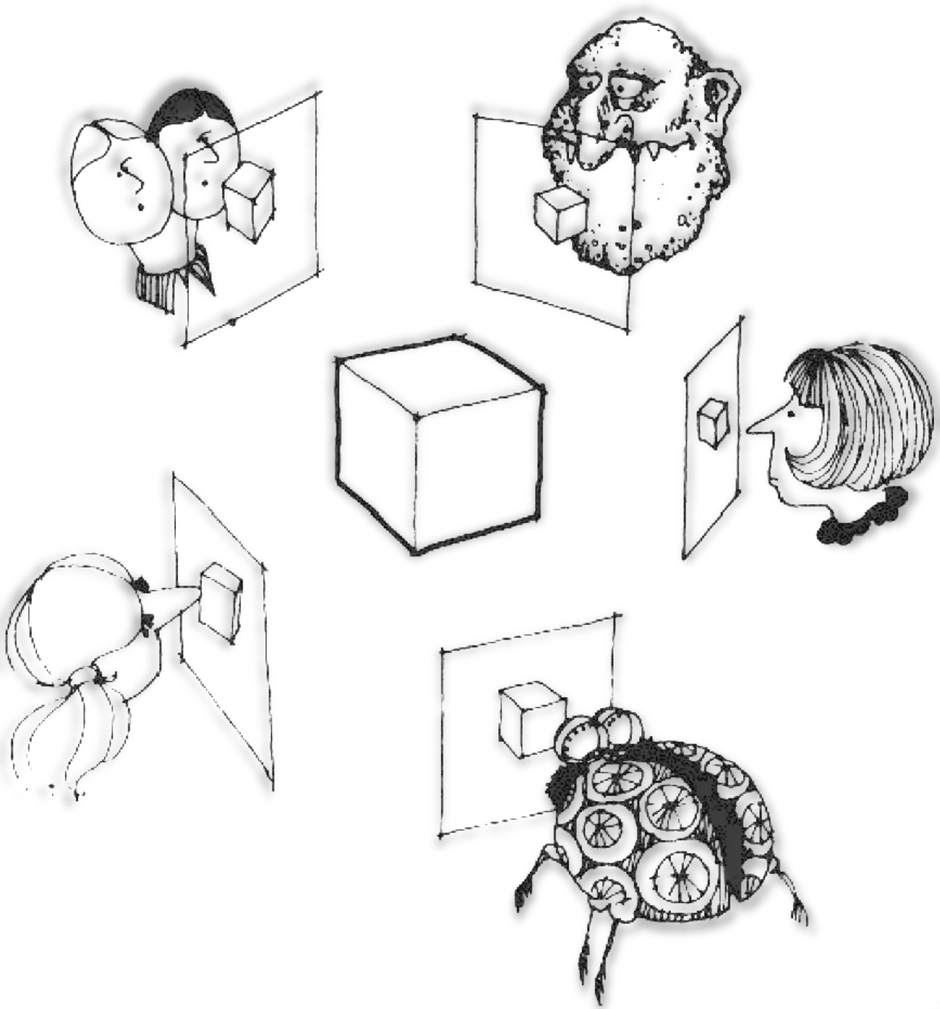
Principle

Stereo Matching

- 2 input images
- 2.5D output representation (depth maps)

Multi-View Stereo (MVS)

- N input images
- 3D output representation (*eg* meshes)



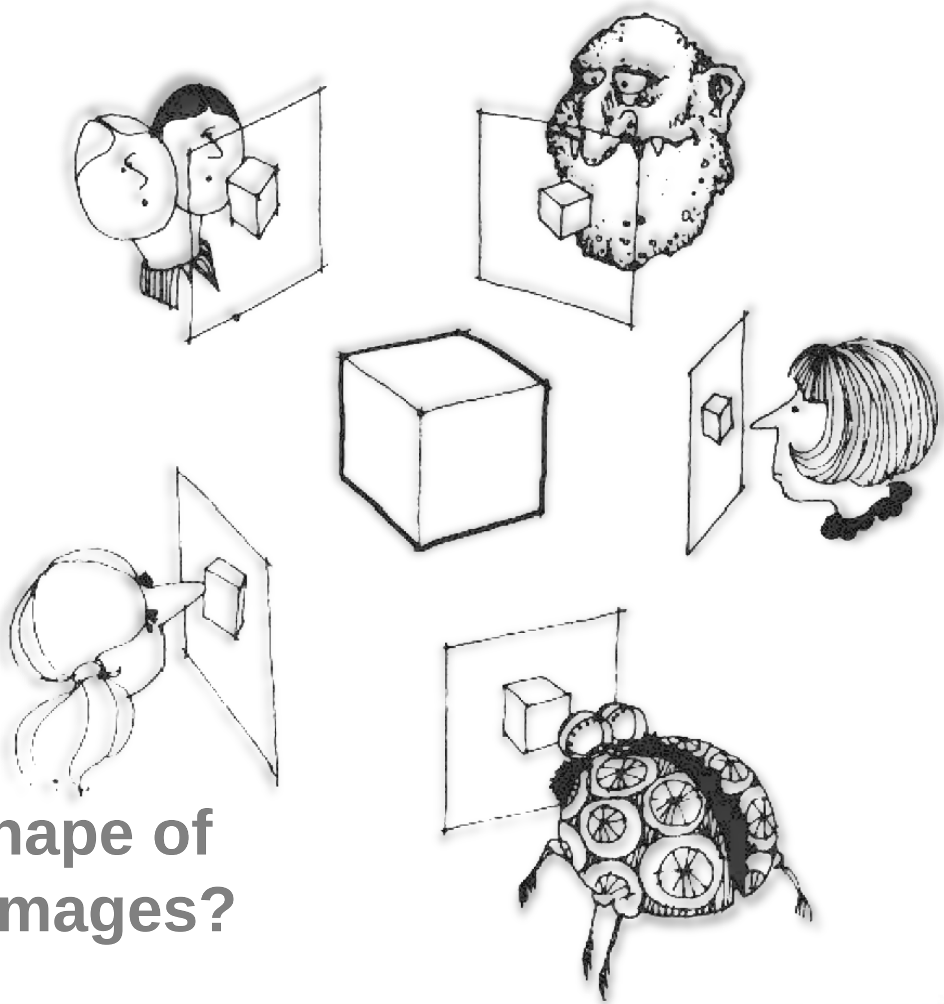
Principle

Stereo Matching

- 2 input images
- 2.5D output representation (depth maps)

Multi-View Stereo (MVS)

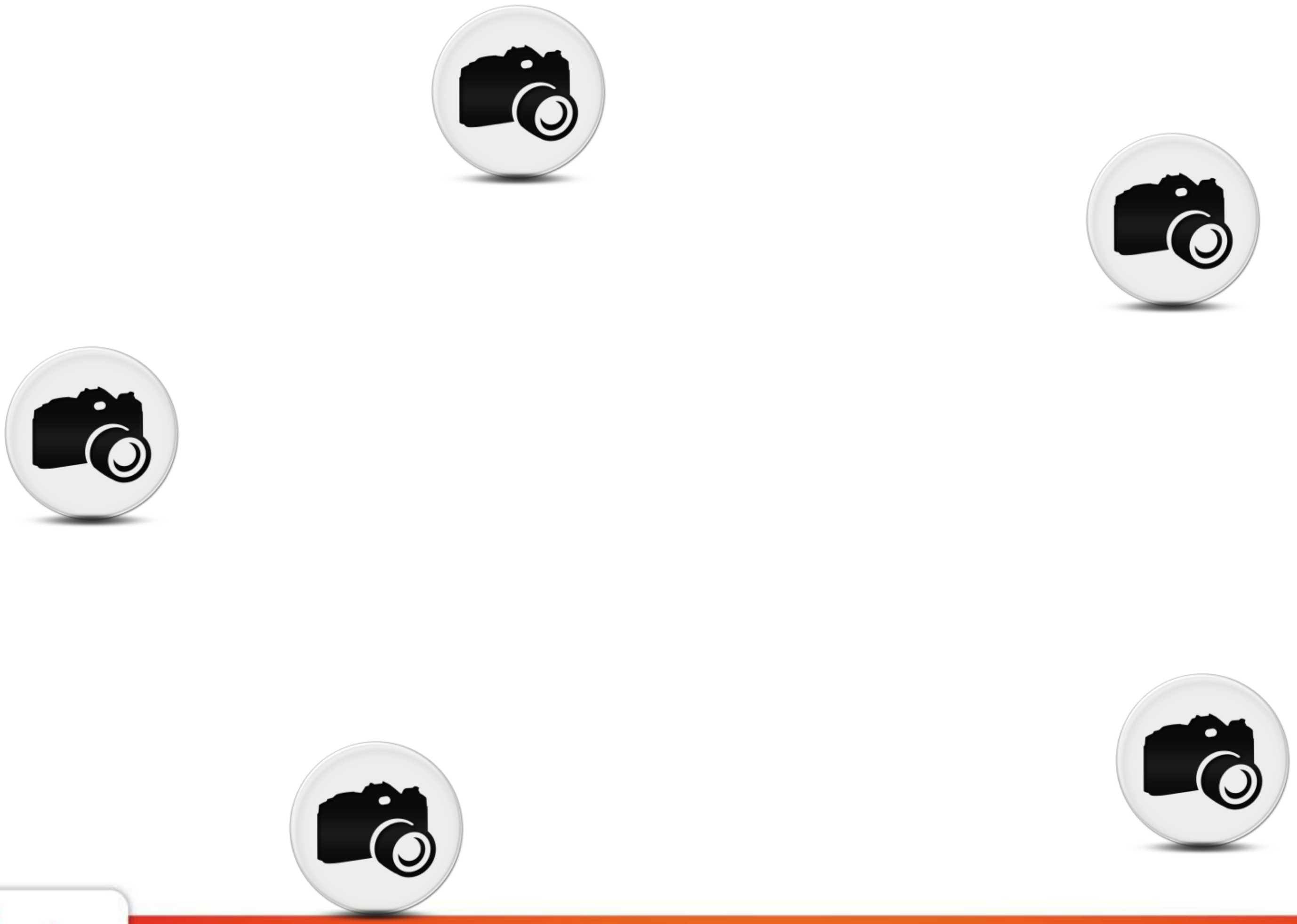
- N input images
- 3D output representation (*eg* meshes)



How to reconstruct the 3D shape of an object from N calibrated images?

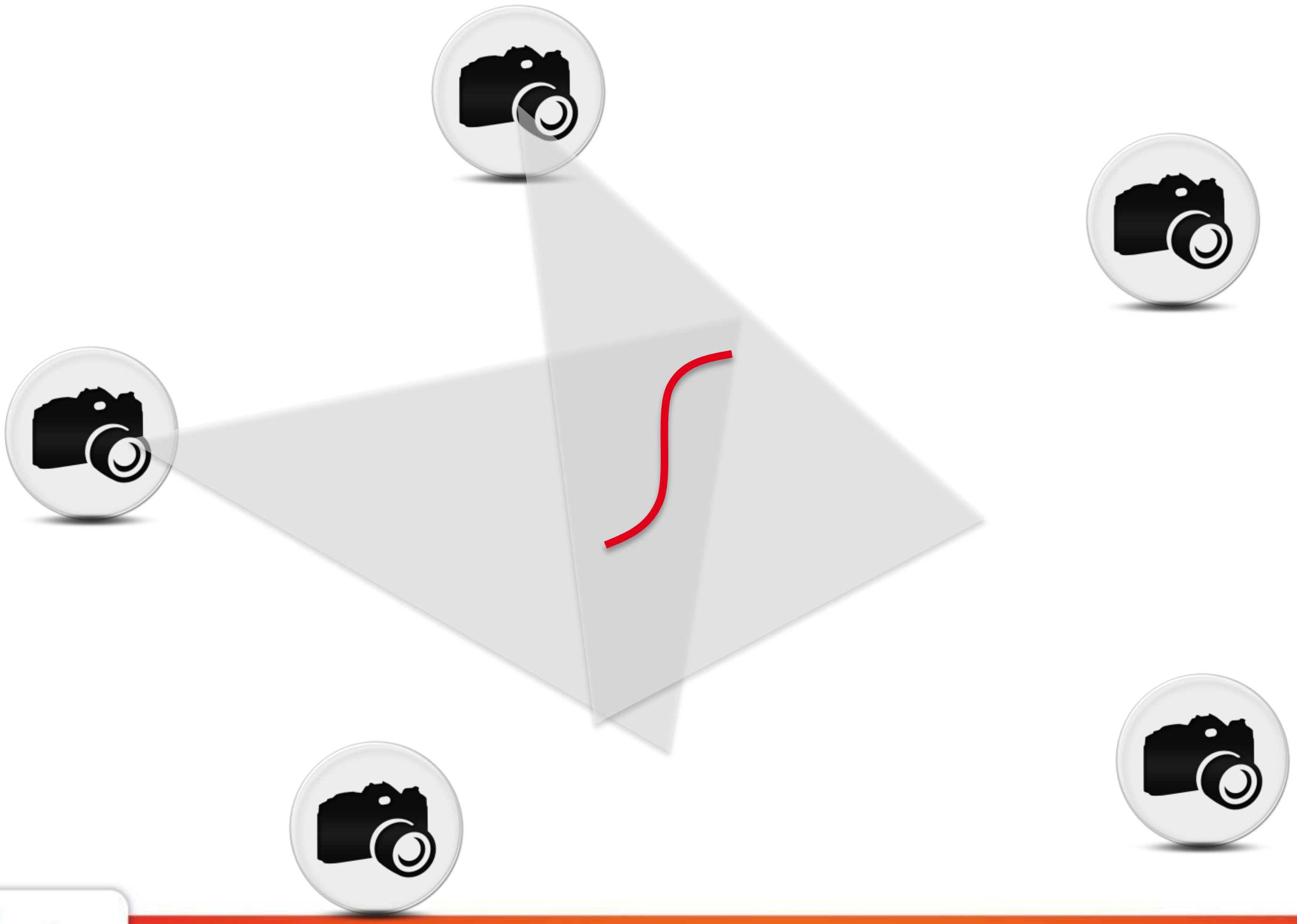
Depth map fusion

A natural extension of Stereo Matching



Depth map fusion

A natural extension of Stereo Matching



Depth map fusion

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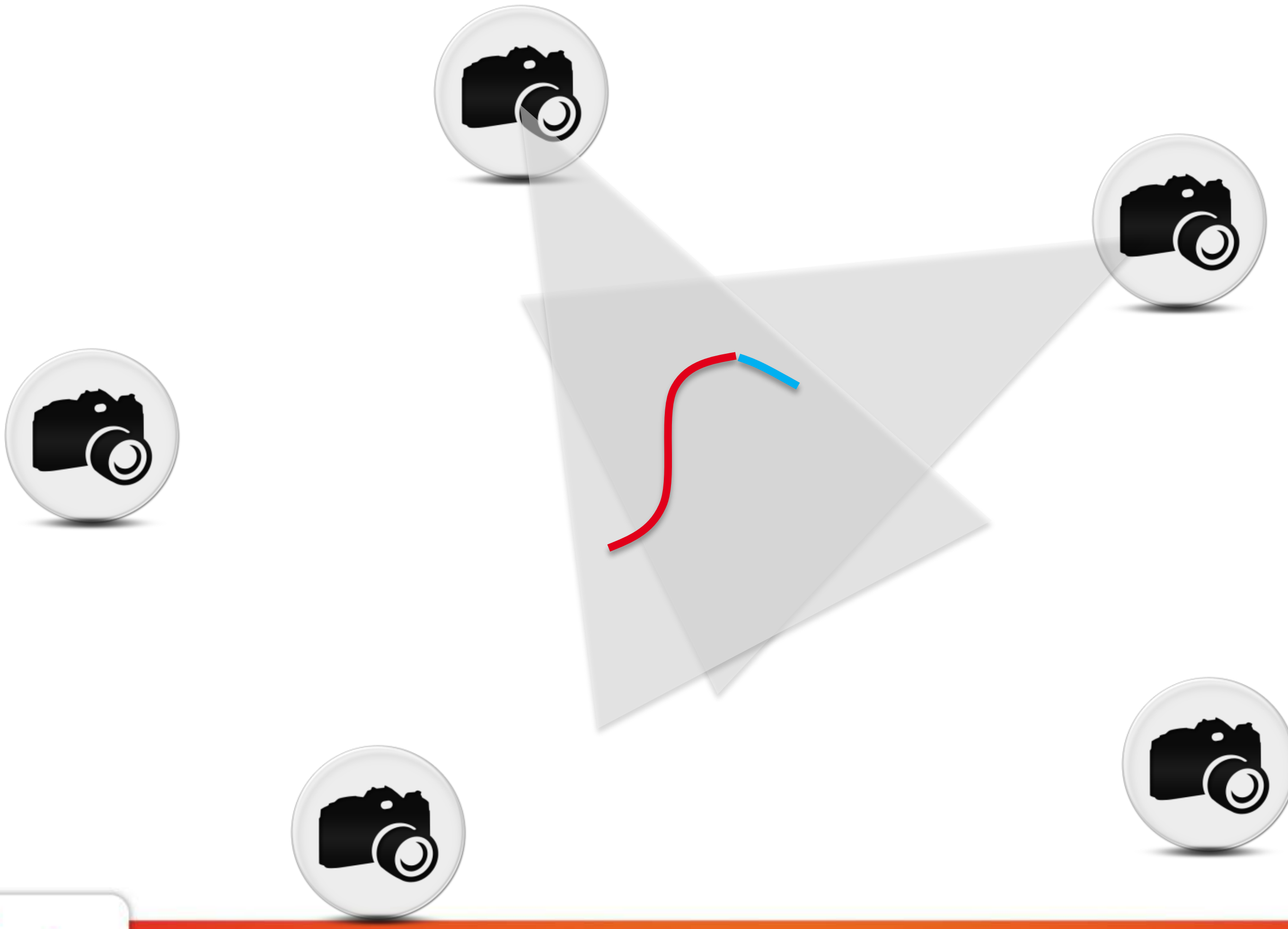

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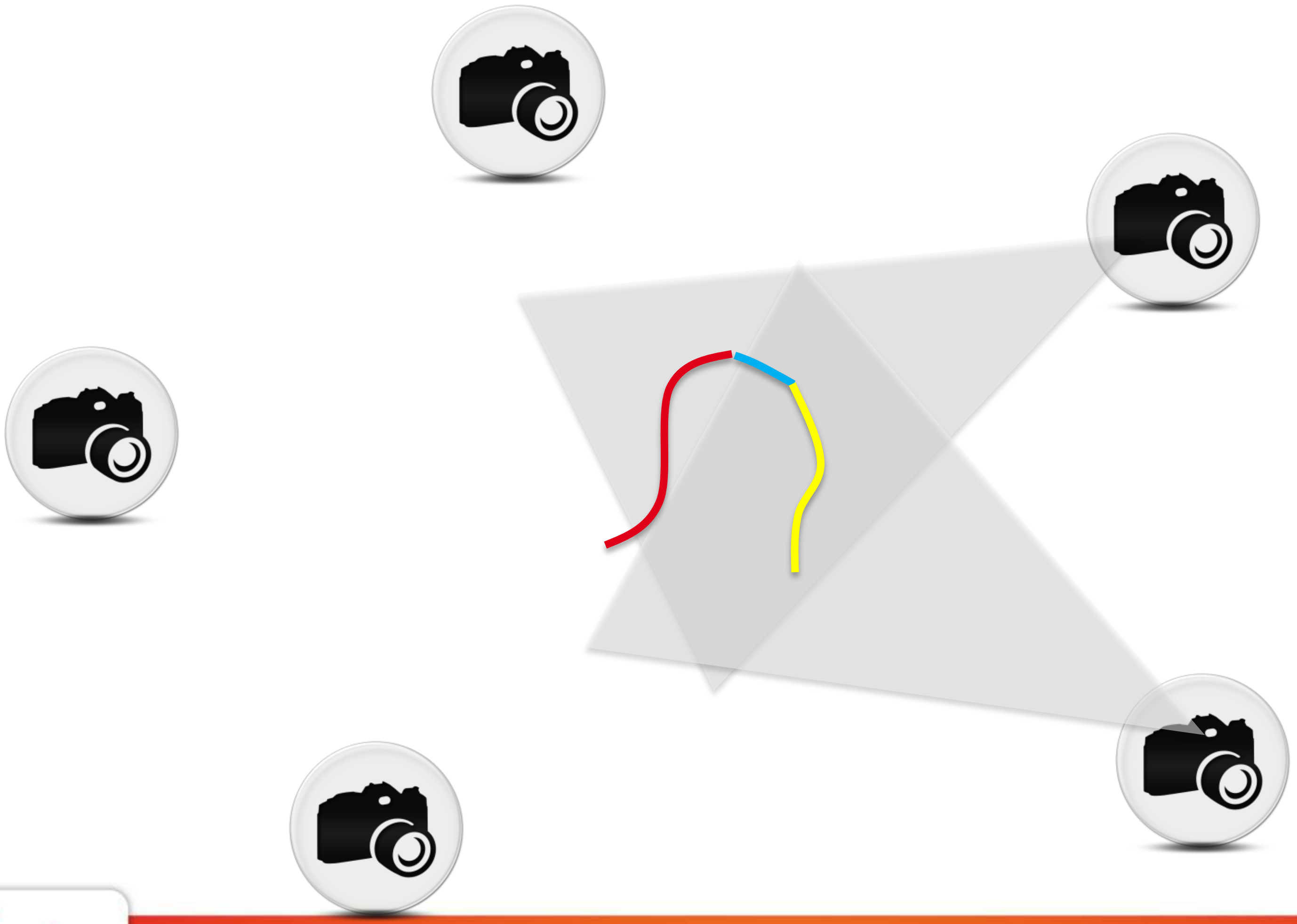

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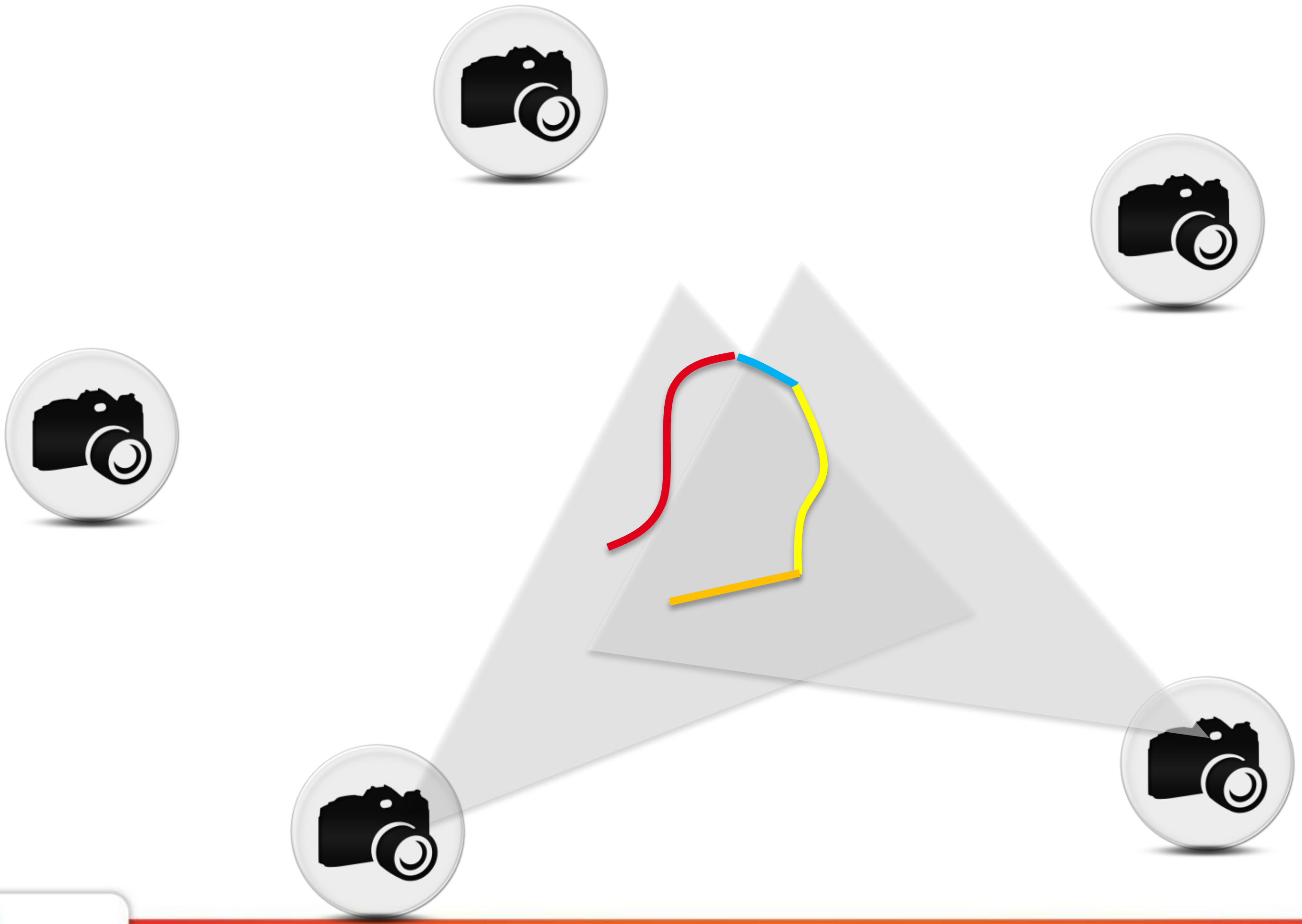

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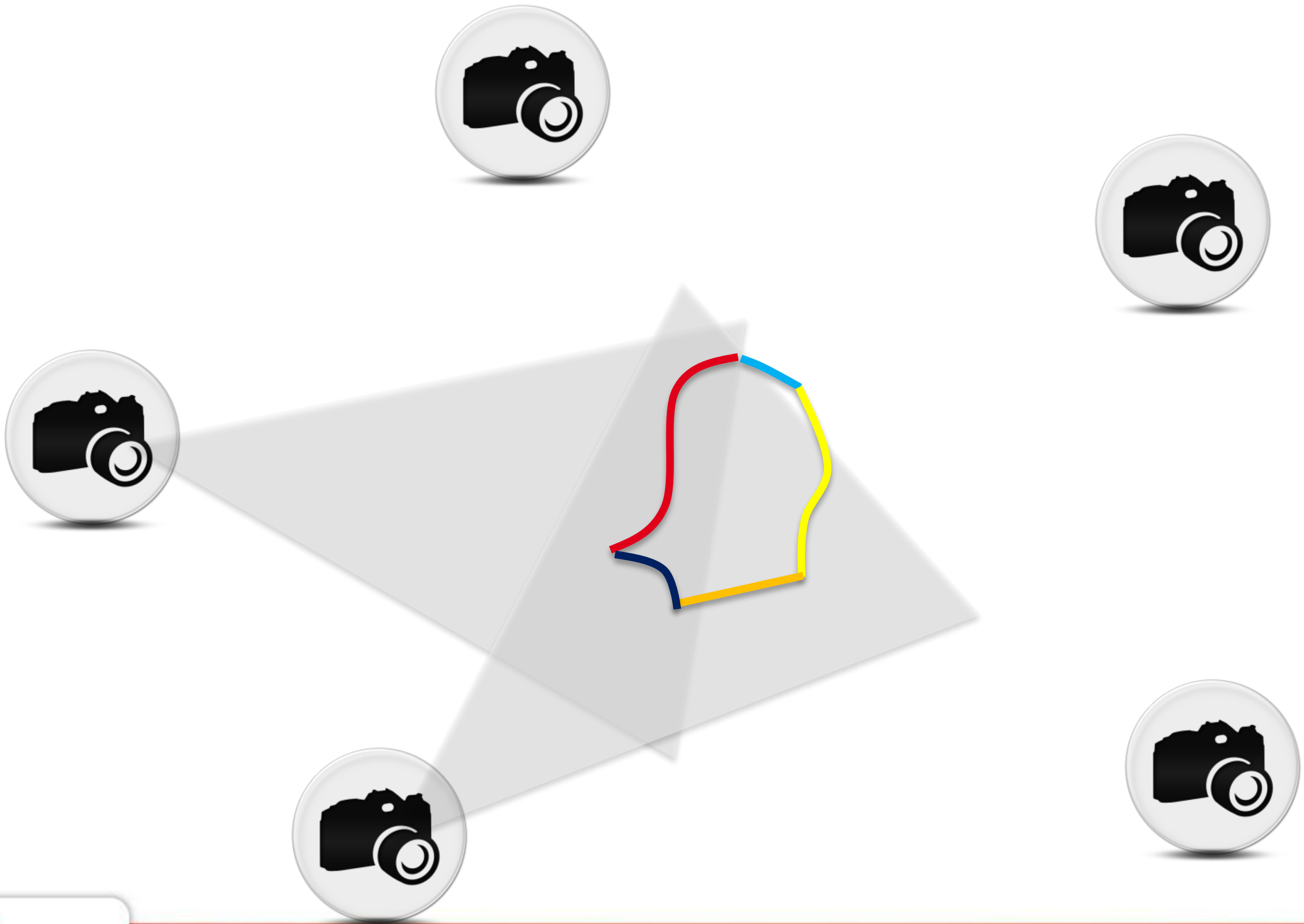

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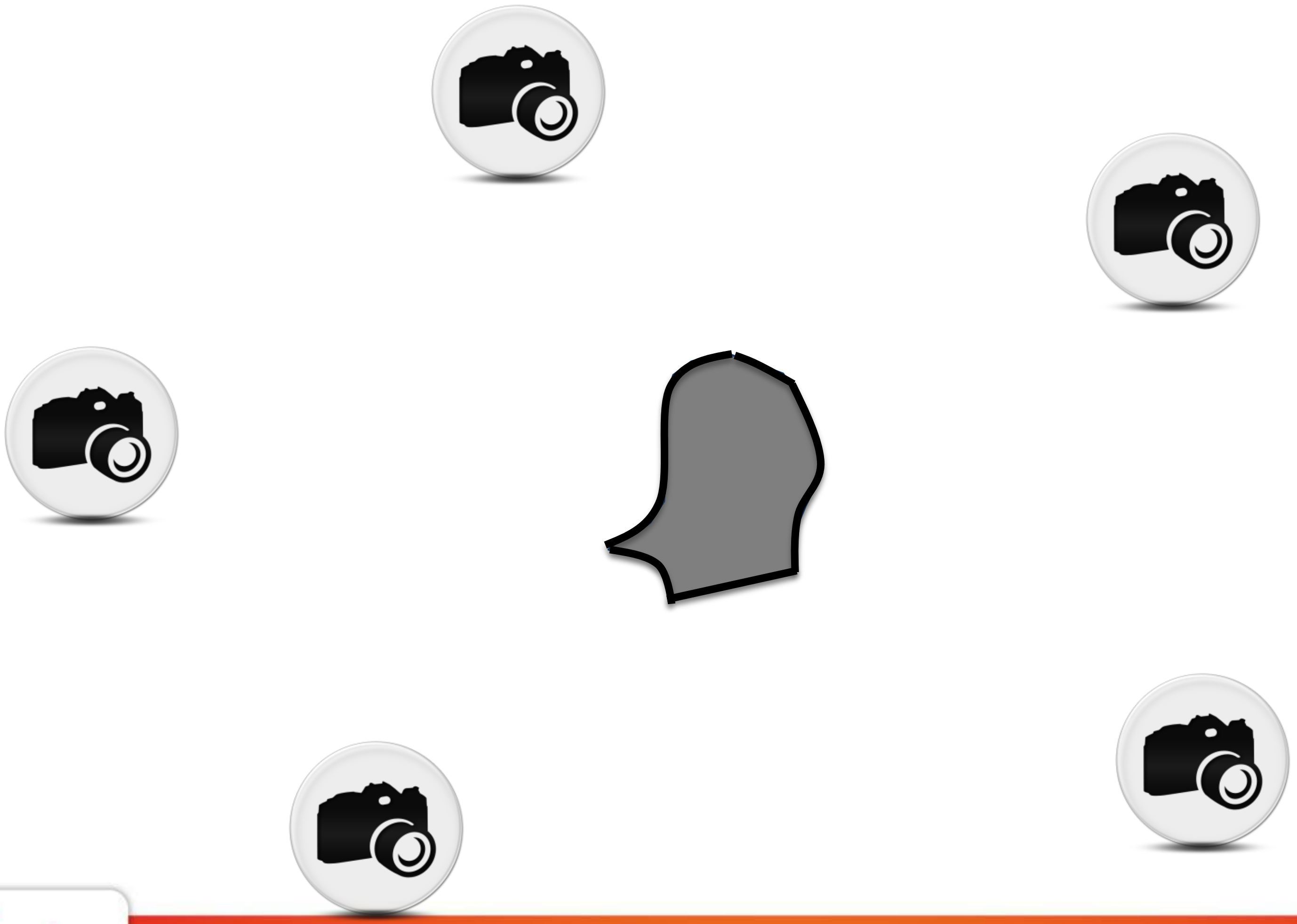
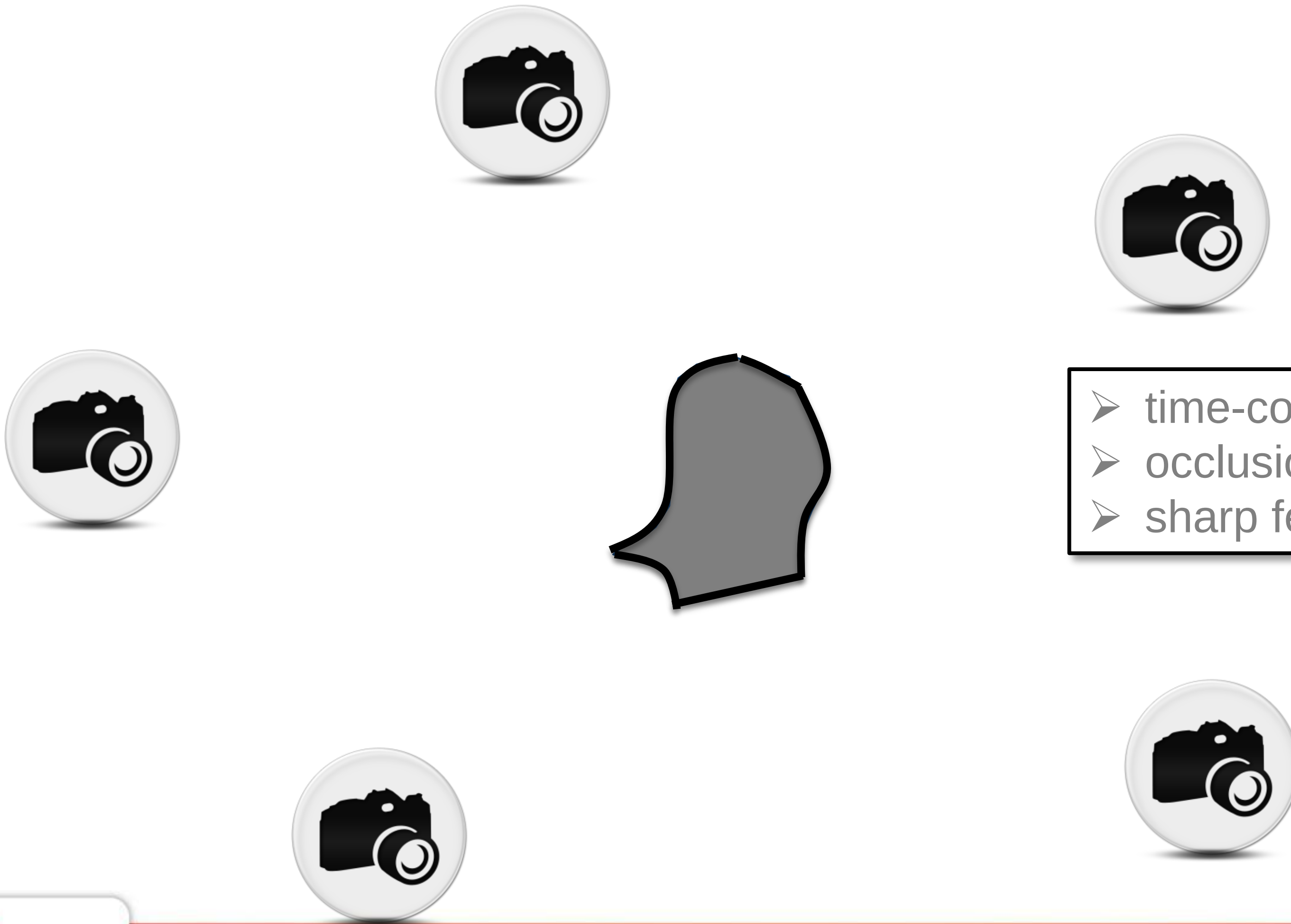


Depth map fusion

A natural extension of Stereo Matching



- time-consuming
- occlusions & conflicts
- sharp features

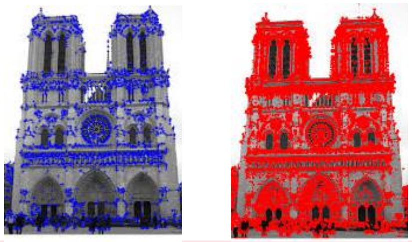
Point cloud generation

Why not using 3D points instead of depth maps ?

Point cloud generation

Why not using 3D points instead of depth maps ?

For each pair of images,

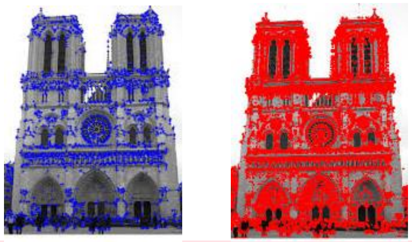


Keypoint extraction
(SIFT, Harris corners..)

Point cloud generation

Why not using 3D points instead of depth maps ?

For each pair of images,



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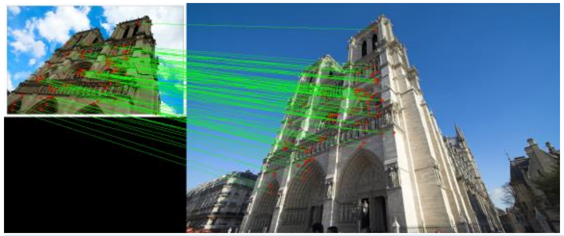

Keypoint descriptor
matching

Point cloud generation

Why not using 3D points instead of depth maps ?

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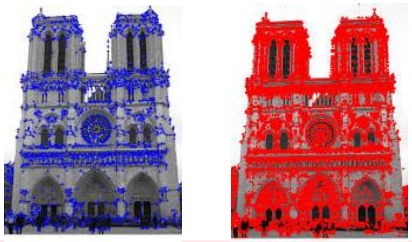

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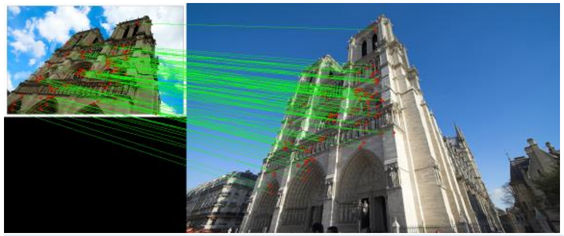

Keypoint descriptor
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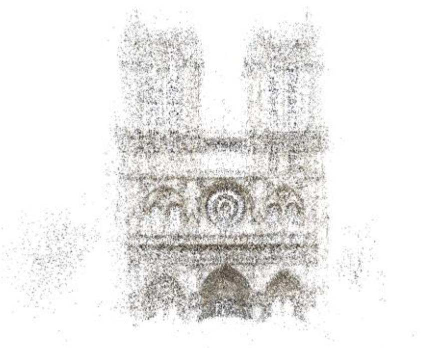

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Why not using 3D points instead of depth maps ?

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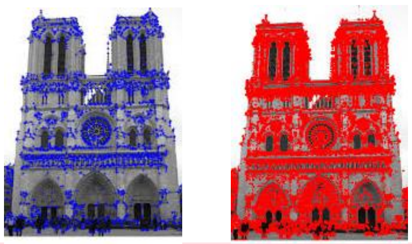

Keypoint extraction
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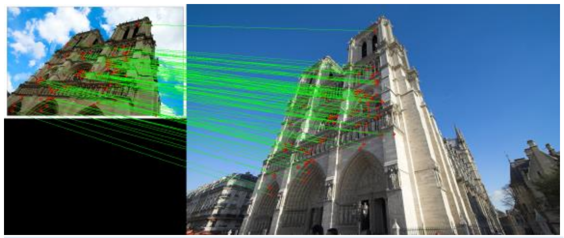
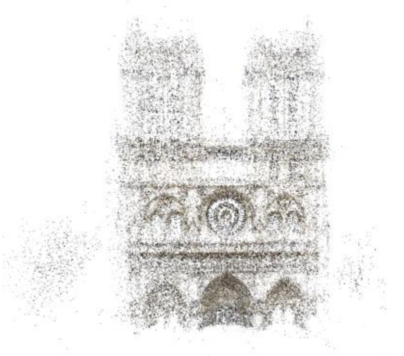


Keypoint descriptor
matching

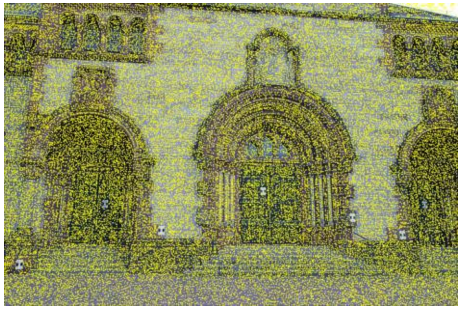


- natural unit element in 3D
- fast
- capture well sharp features

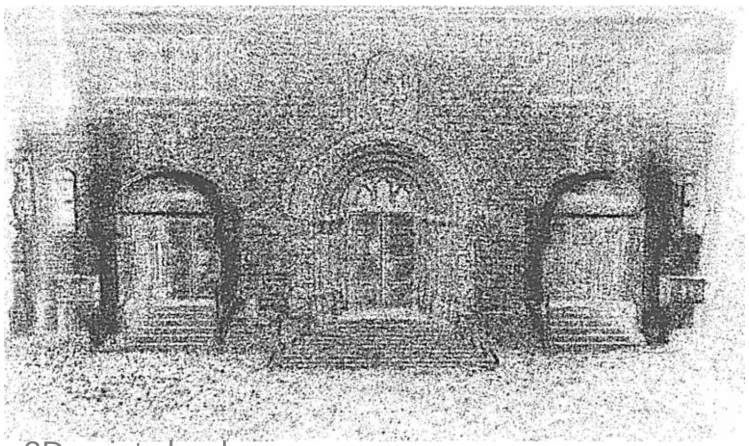
Point cloud generation

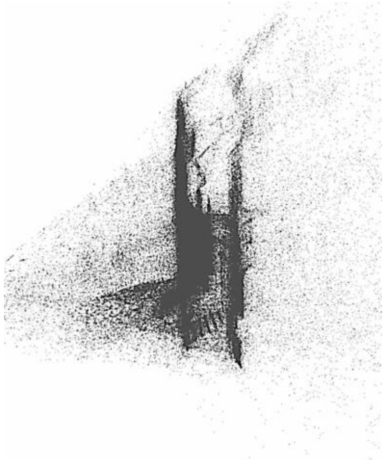
At the scale of a facade

Input images



Keypoints detected in one image



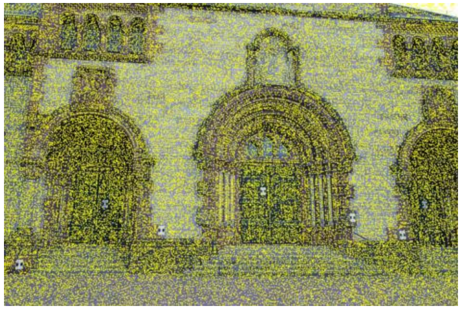


3D point cloud

Point cloud generation

At the scale of a facade

Input images



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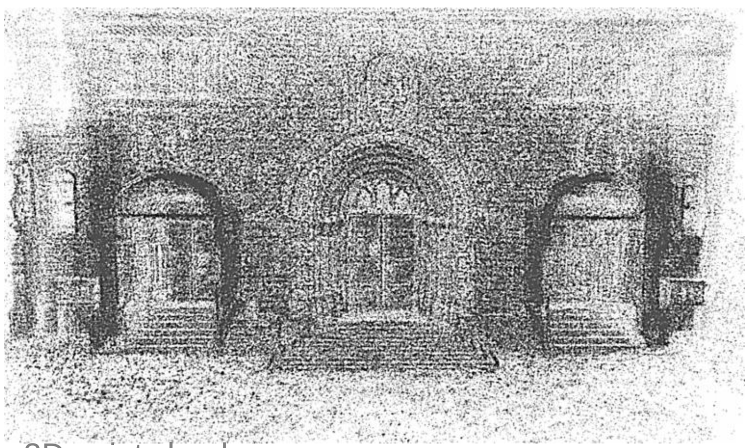
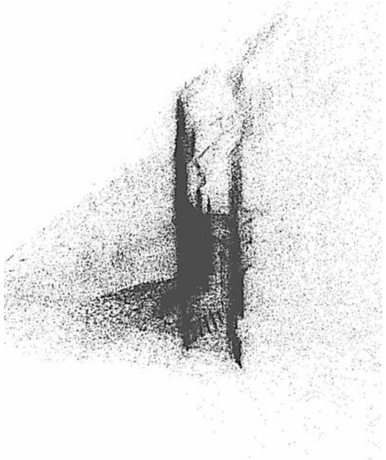


3D point cloud



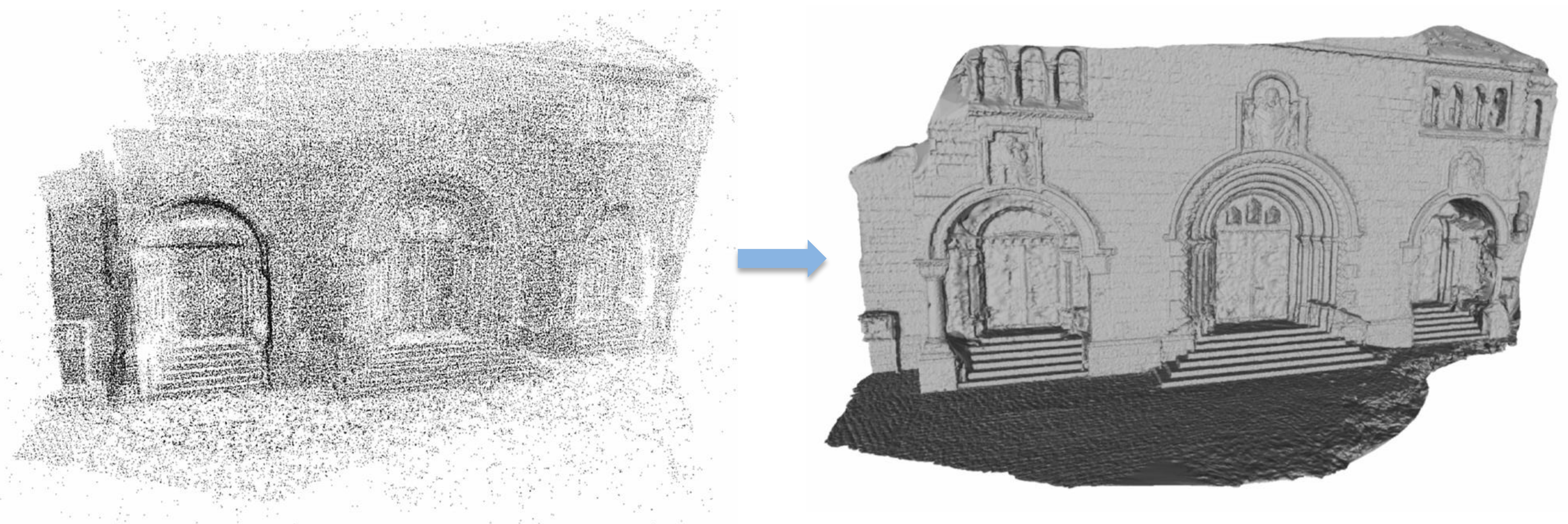
Noise & outliers !

Point cloud generation

At the scale of a city

Surface reconstruction

From (defect-laden) point cloud to surface/volume representations

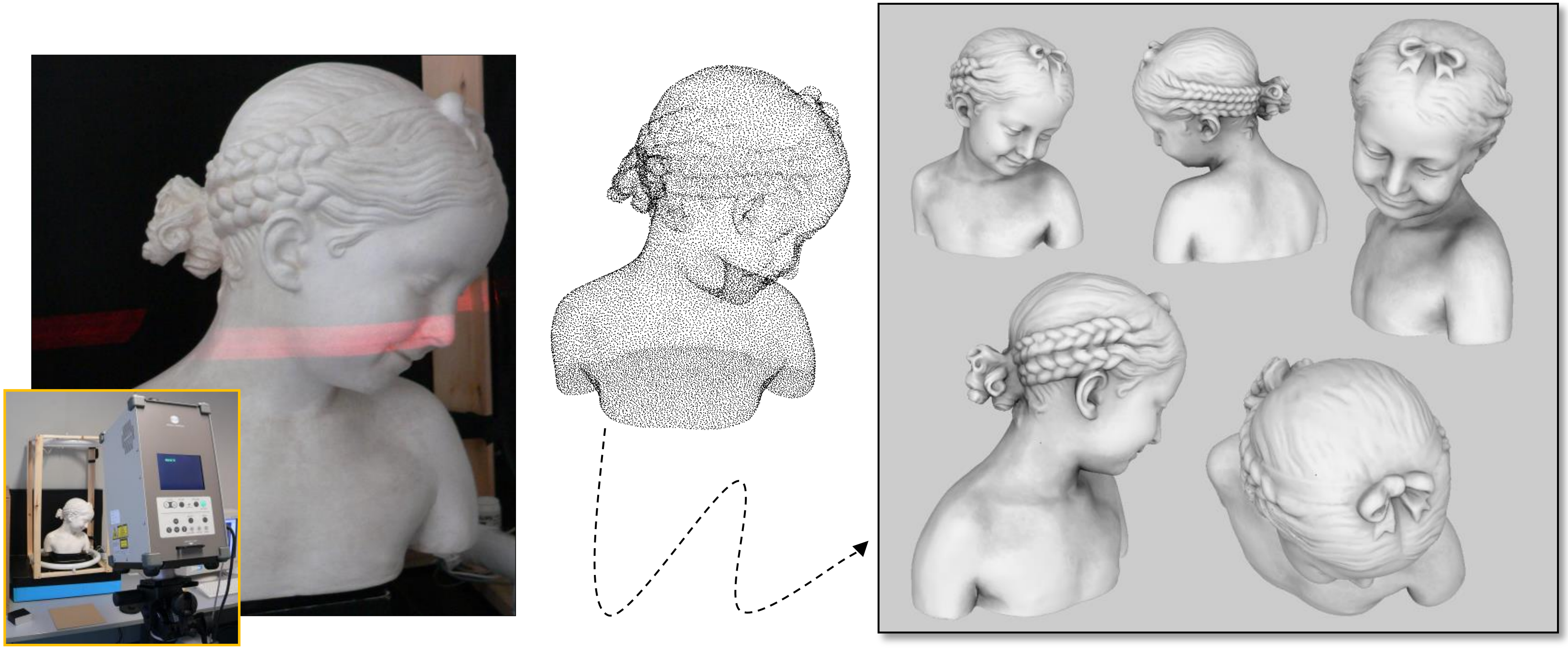


Data-structure : mesh with triangular facets

- with borders
- watertight

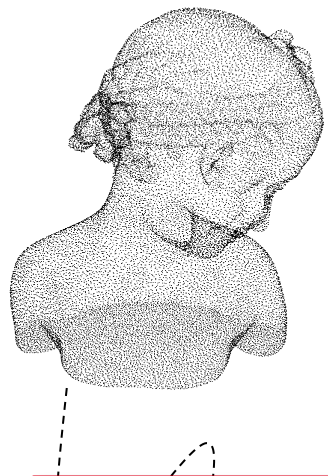
Surface reconstruction

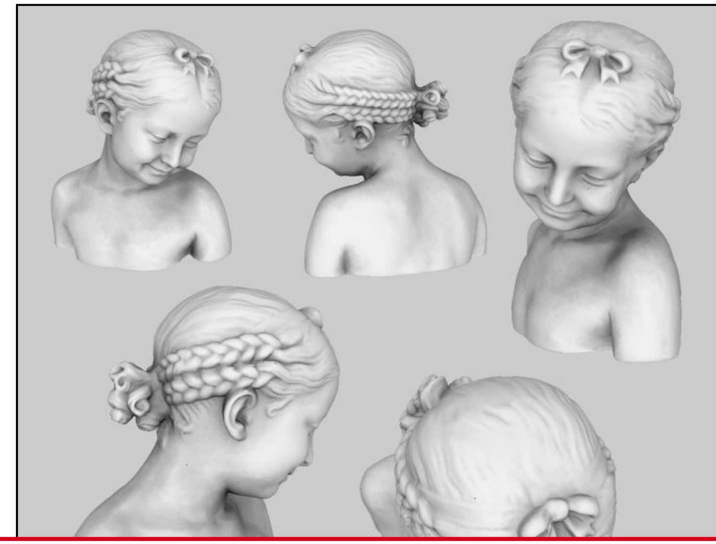
An old topic in computer graphics



Surface reconstruction

An old topic in computer graphics





[Berger et al, State of the art in surface reconstruction from point clouds, Eurographics 2014]

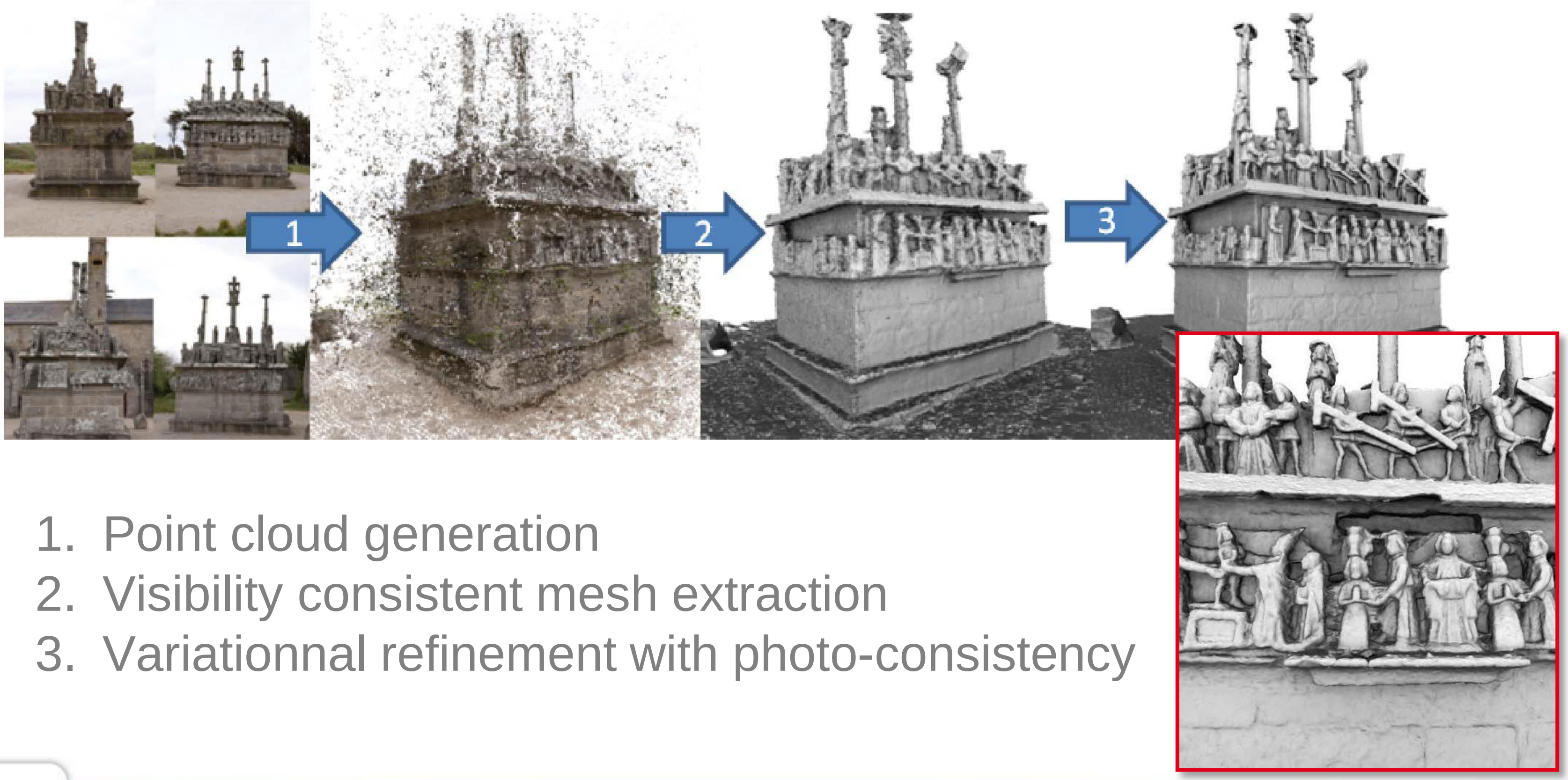
but without considering photo-consistency

Surface reconstruction

Focus on [Vu et al, High accuracy and visibility-consistent dense multiview Stereo, PAMI 2012]

Surface reconstruction

Focus on [Vu et al, High accuracy and visibility-consistent dense multiview Stereo, PAMI 2012]



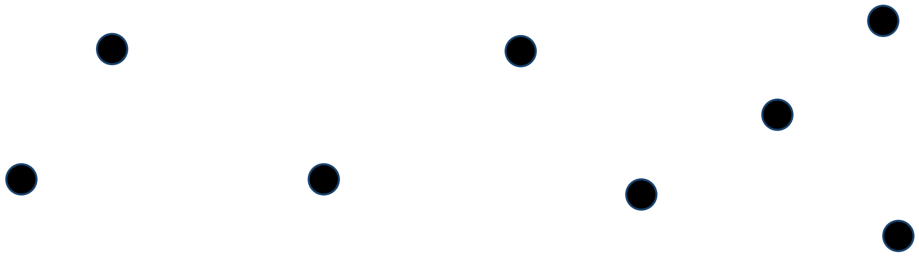
1. Point cloud generation
2. Visibility consistent mesh extraction
3. Variationnal refinement with photo-consistency

Surface reconstruction

Focus on [Vu et al, High accuracy and visibility-consistent dense multiview Stereo, PAMI 2012]

2. Visibility consistent mesh extraction

- ➢ Partition the space with a 3D Delaunay triangulation



Surface reconstruction

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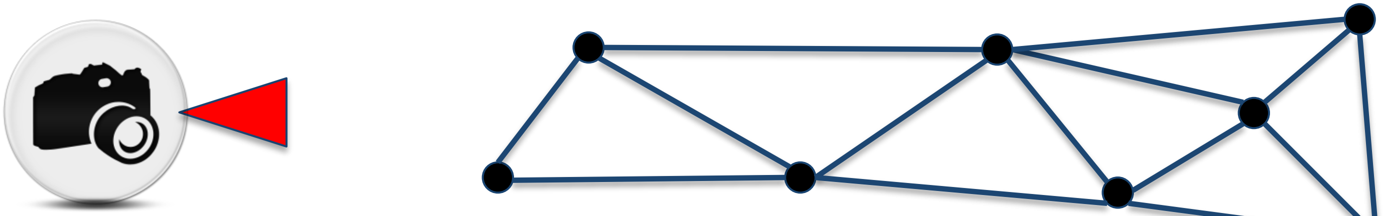
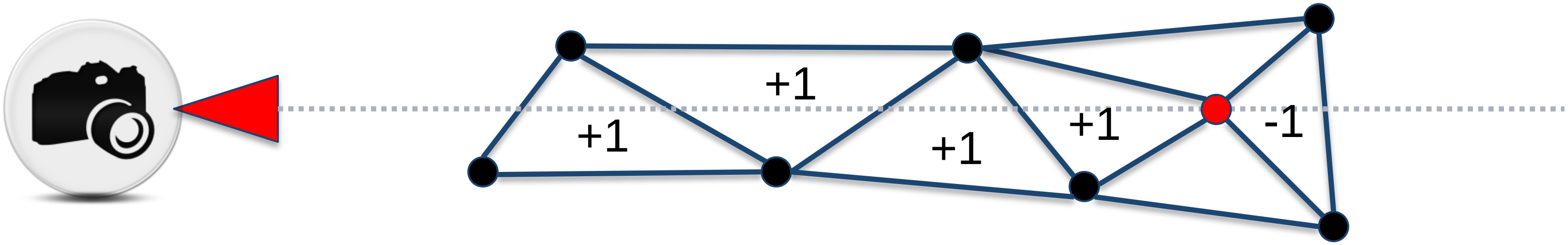


Surface reconstruction

Focus on [Vu et al, High accuracy and visibility-consistent dense multiview Stereo, PAMI 2012]

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



Before the vertex: +1 (outside)
After the vertex: -1 (inside)

Surface reconstruction

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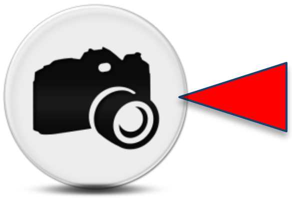

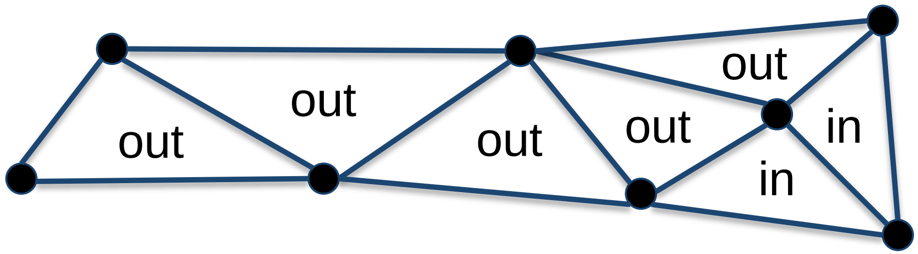

Surface reconstruction

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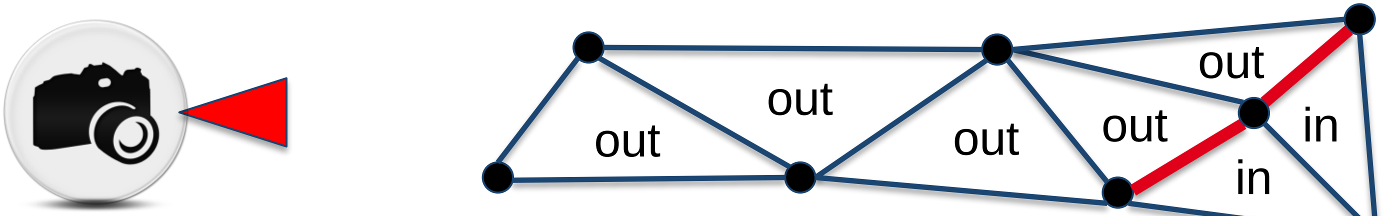

Surface reconstruction

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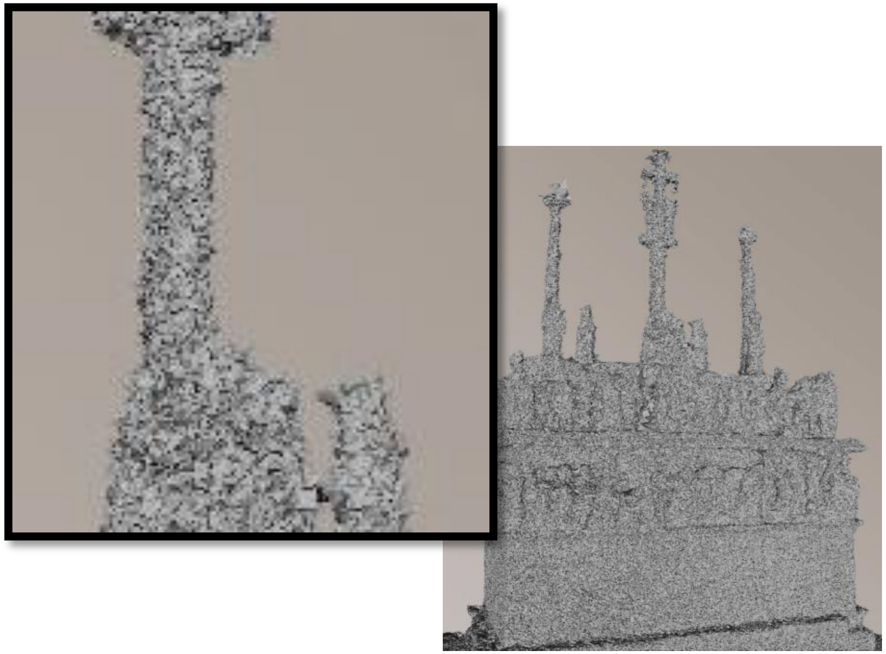
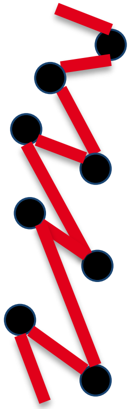
Surface reconstruction

Focus on [Vu et al, High accuracy and visibility-consistent dense multiview Stereo, PAMI 2012]

3. Variationnal refinement with photo-consistency





Surface reconstruction

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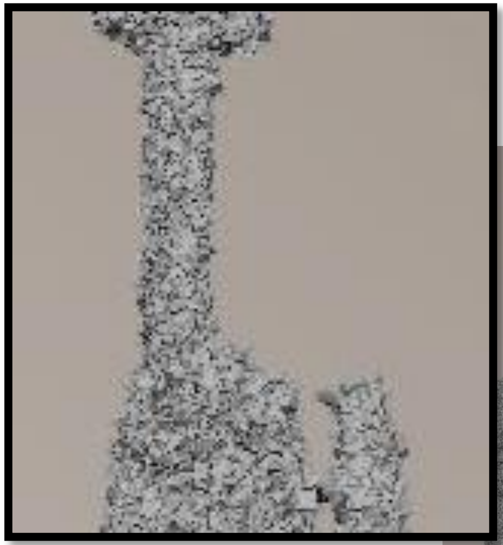
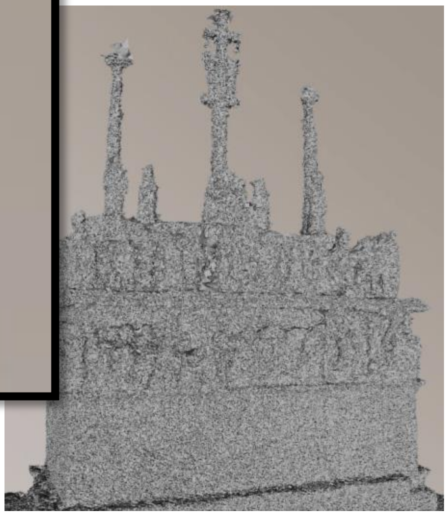
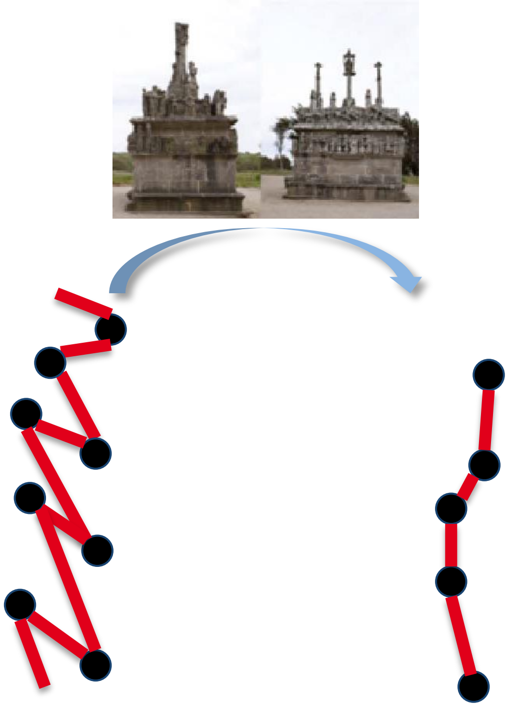




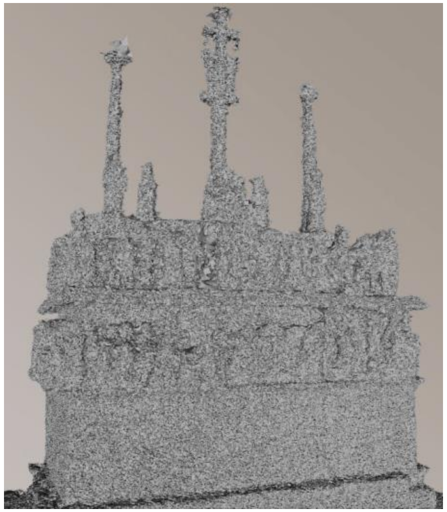


Surface reconstruction

Focus on [Vu et al, High accuracy and visibility-consistent dense multiview Stereo, PAMI 2012]

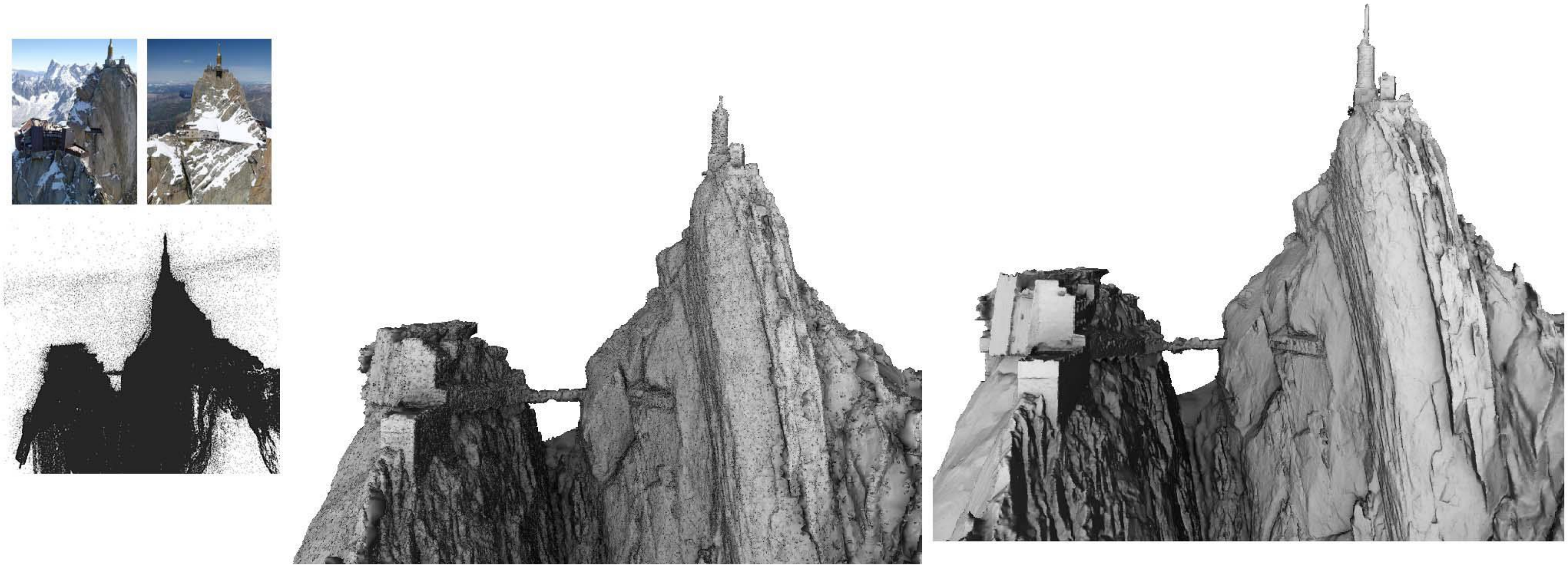
3. Variationnal refinement with photo-consistency

- Minimize the reprojection error of image 1 into image 2 according to the surface S



Surface reconstruction

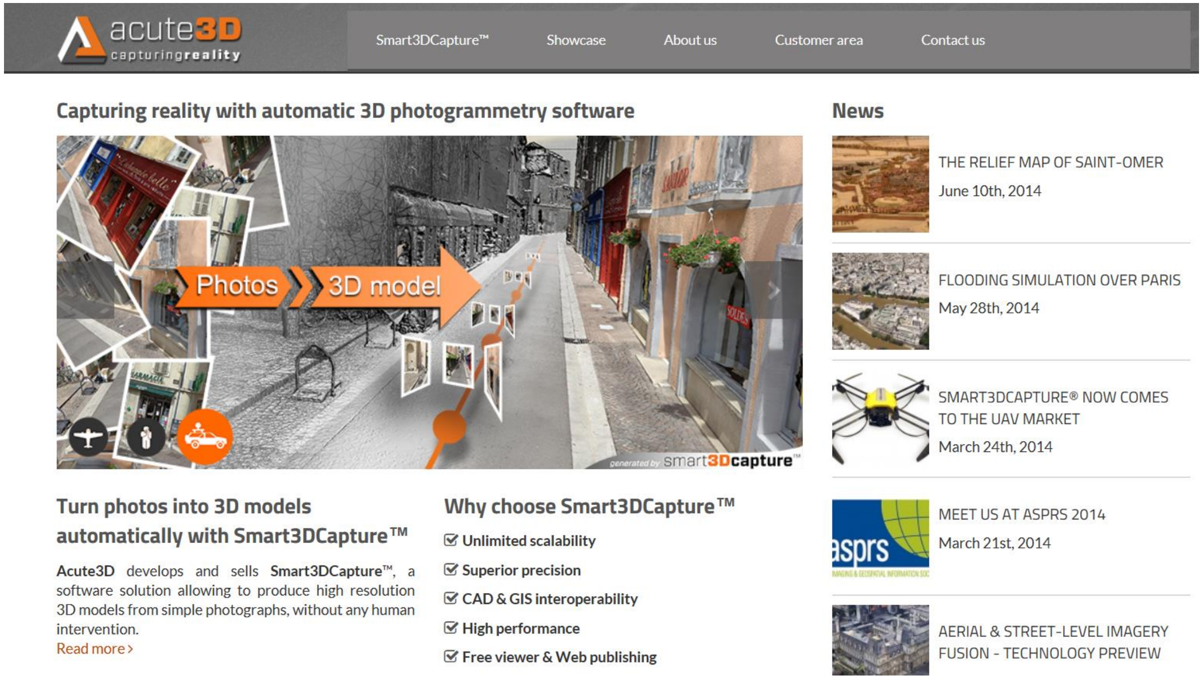
Focus on [Vu et al, High accuracy and visibility-consistent dense multiview Stereo, PAMI 2012]



Surface reconstruction

Focus on [Vu et al, High accuracy and visibility-consistent dense multiview Stereo, PAMI 2012]

now a company

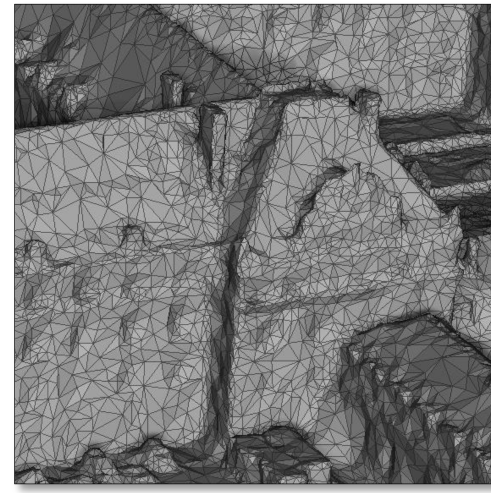


3. Beyond free-form surface reconstruction

What can we do next ?

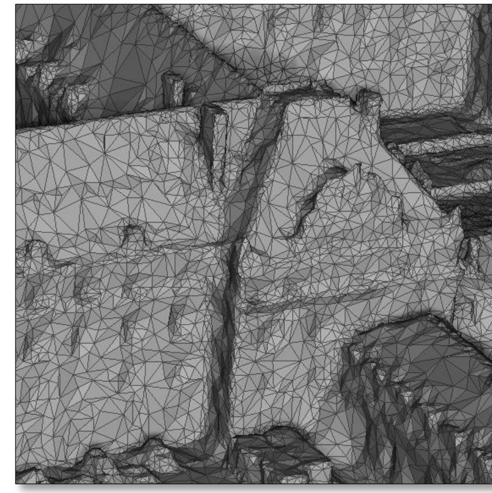
acute3D
capturingreality

What can we do next ?



More compact and meaningful mesh

What can we do next ?

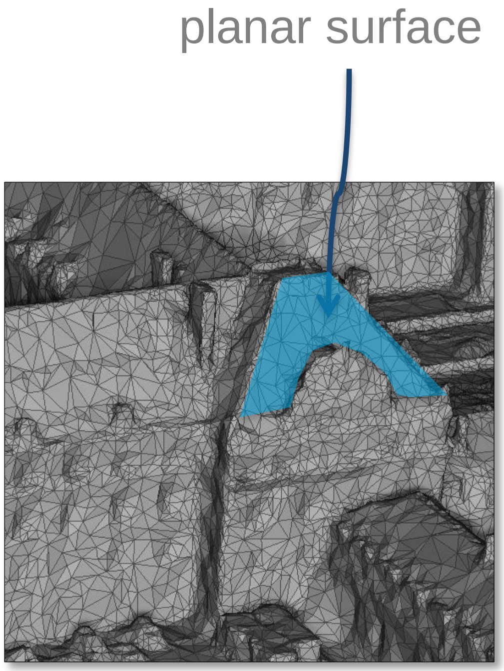


More **compact** and meaningful mesh

- High model complexity

11M facets

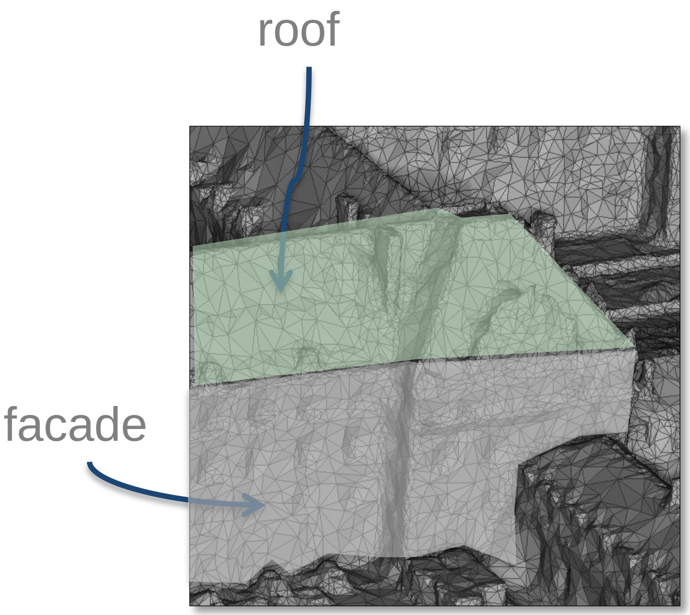
What can we do next ?



More compact and **meaningful** mesh

- ➢ Free of geometric structure

What can we do next ?



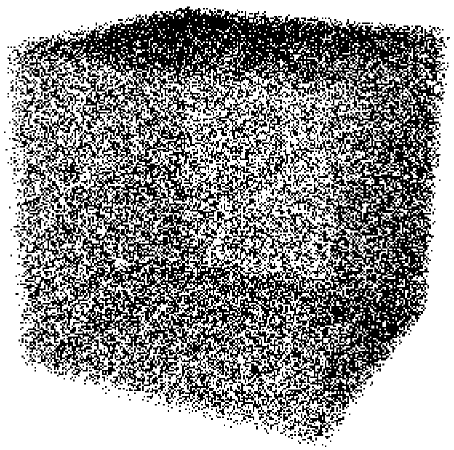
More compact and **meaningful** mesh

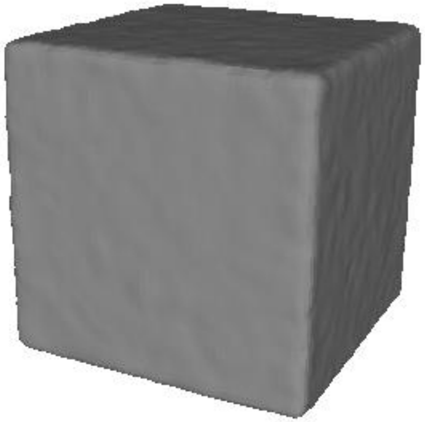
- ➢ Free of geometric structure
- ➢ Free of semantics

1^{st} idea: Hybrid surfaces

High model complexity

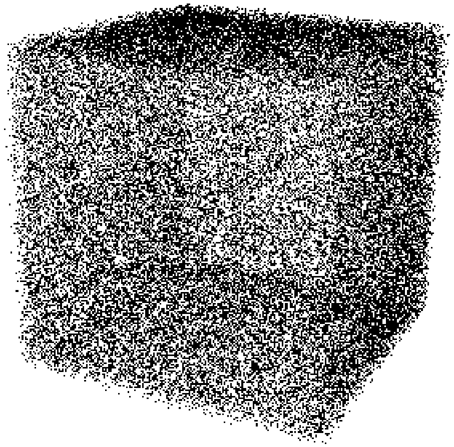
No structure

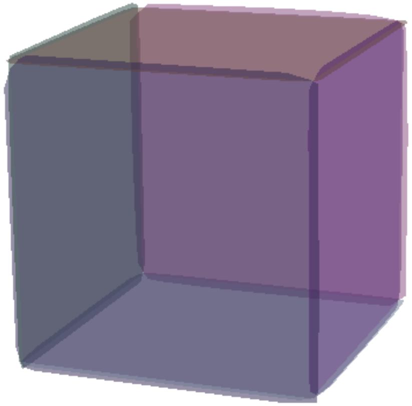




Free-form reconstruction (Poisson algorithm)

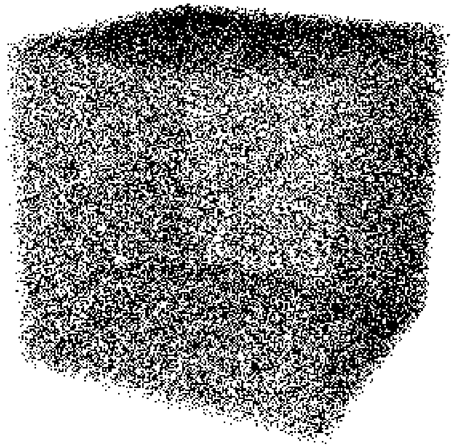
1^{st} idea: Hybrid surfaces

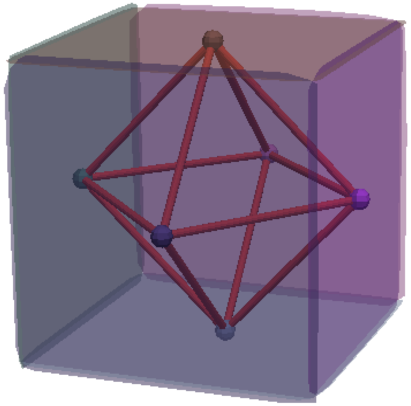




If you can detect the right
set of geometric primitives

1st idea: Hybrid surfaces



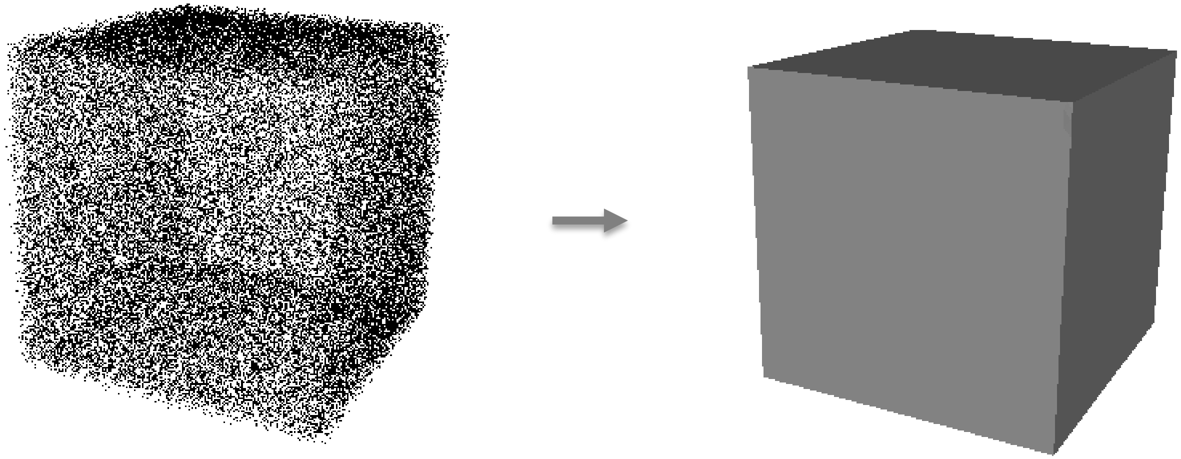


and the right primitive adjacencies

1st idea: Hybrid surfaces

low model complexity

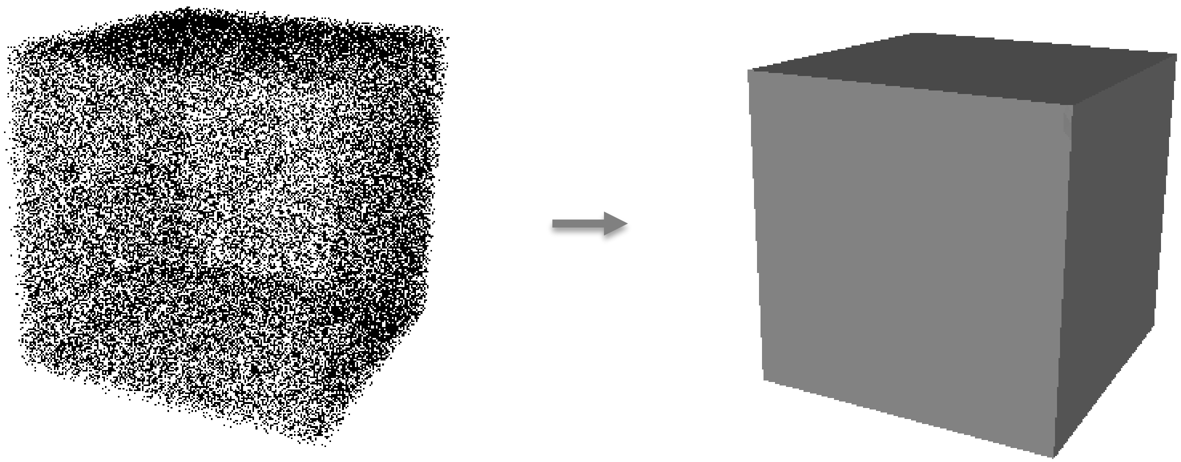
structure-aware



1st idea: Hybrid surfaces

low model complexity

structure-aware



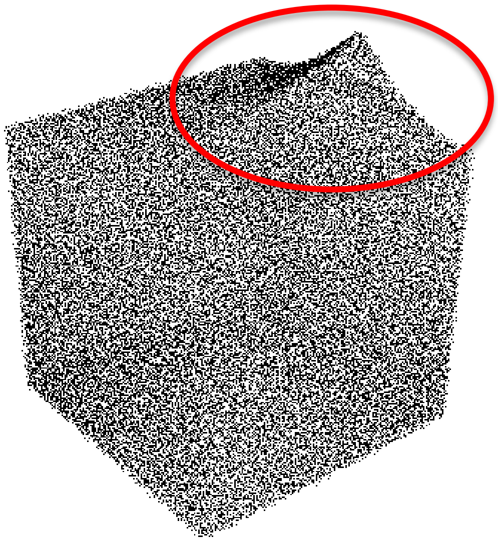
But

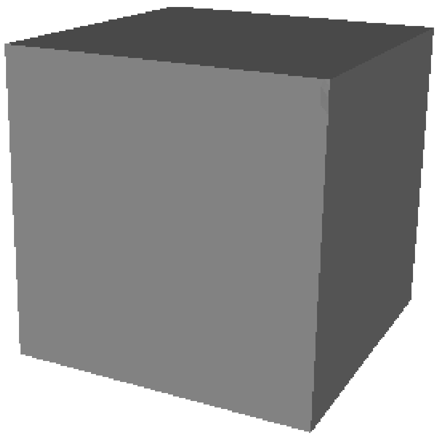
- ➢ No guarantee of finding the right primitives and right adjacency graph

1st idea: Hybrid surfaces

low model complexity

structure-aware

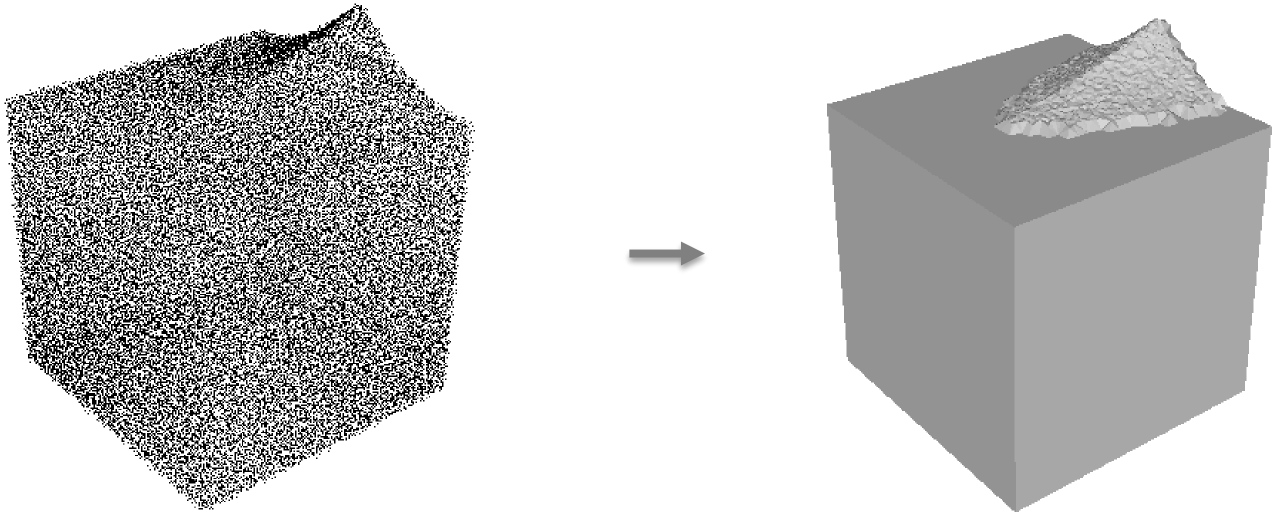




But

- ➢ No guarantee of finding the right primitives and right adjacency graph
- ➢ No guarantee that the object can be entirely explained by primitives

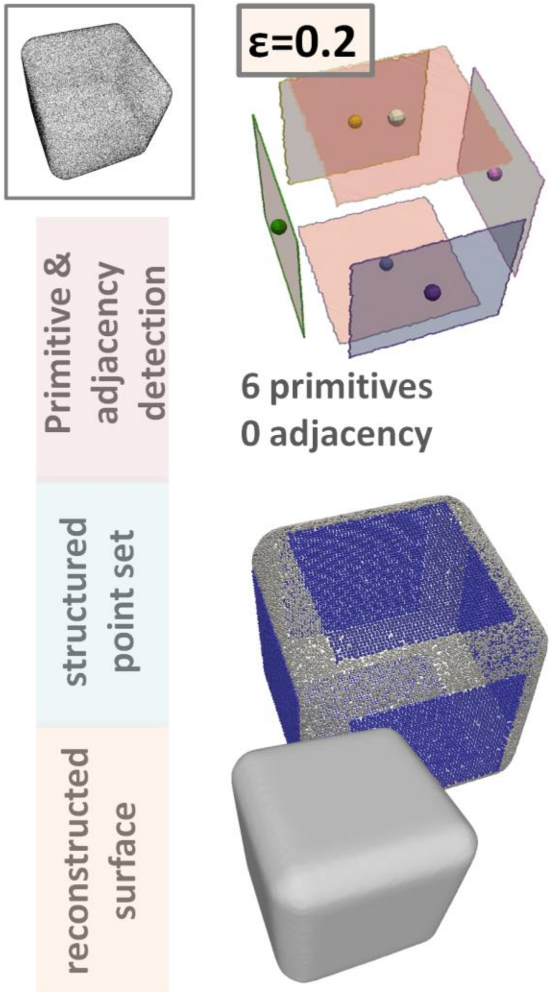
1^{st} idea: Hybrid surfaces



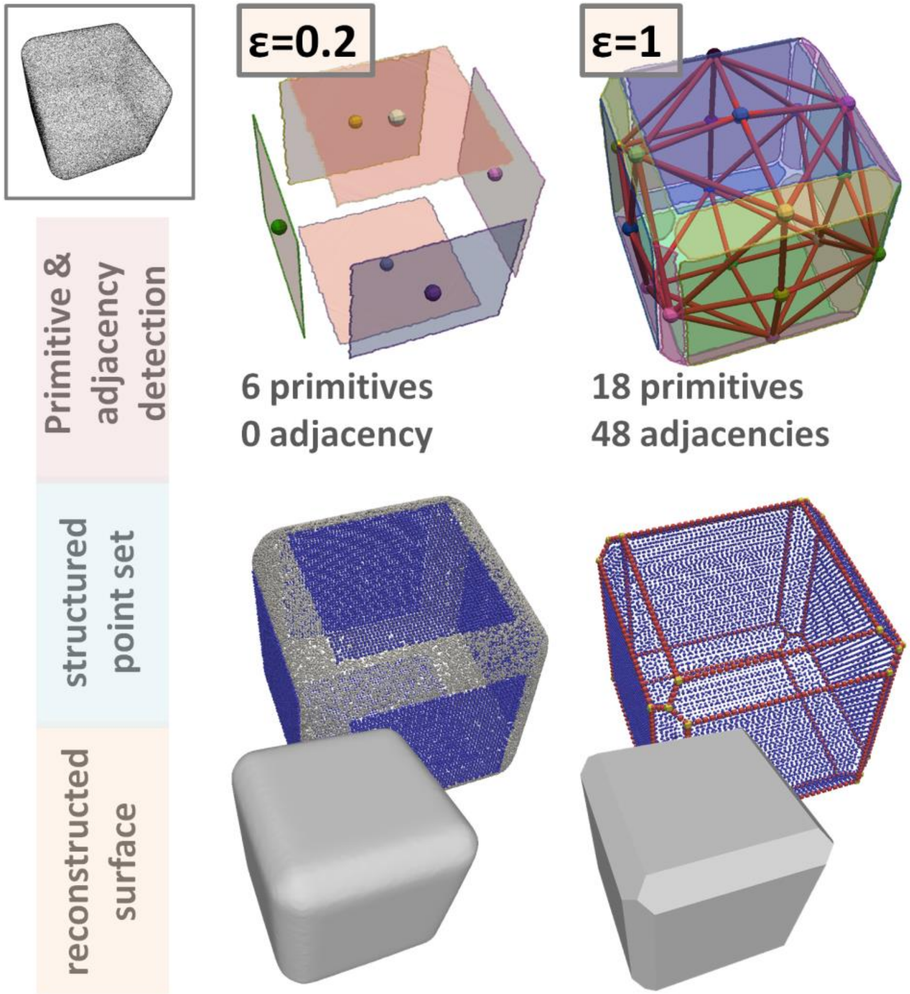
We need both structure and free-form!

- Structure: primitive assembling for describing regular components
- Free-form: smooth mesh for preserving the details

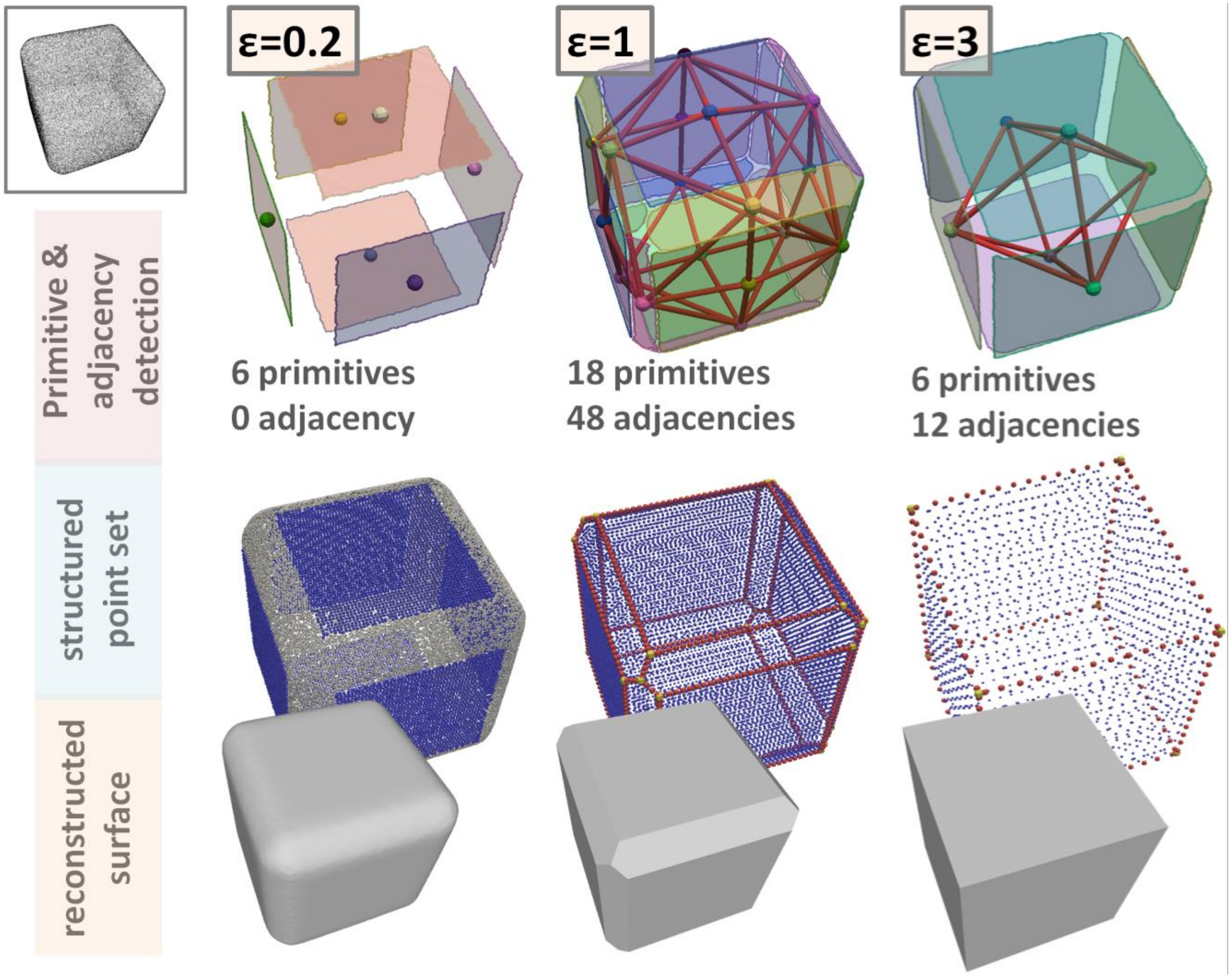
Hybrid surfaces (by point set structuring)



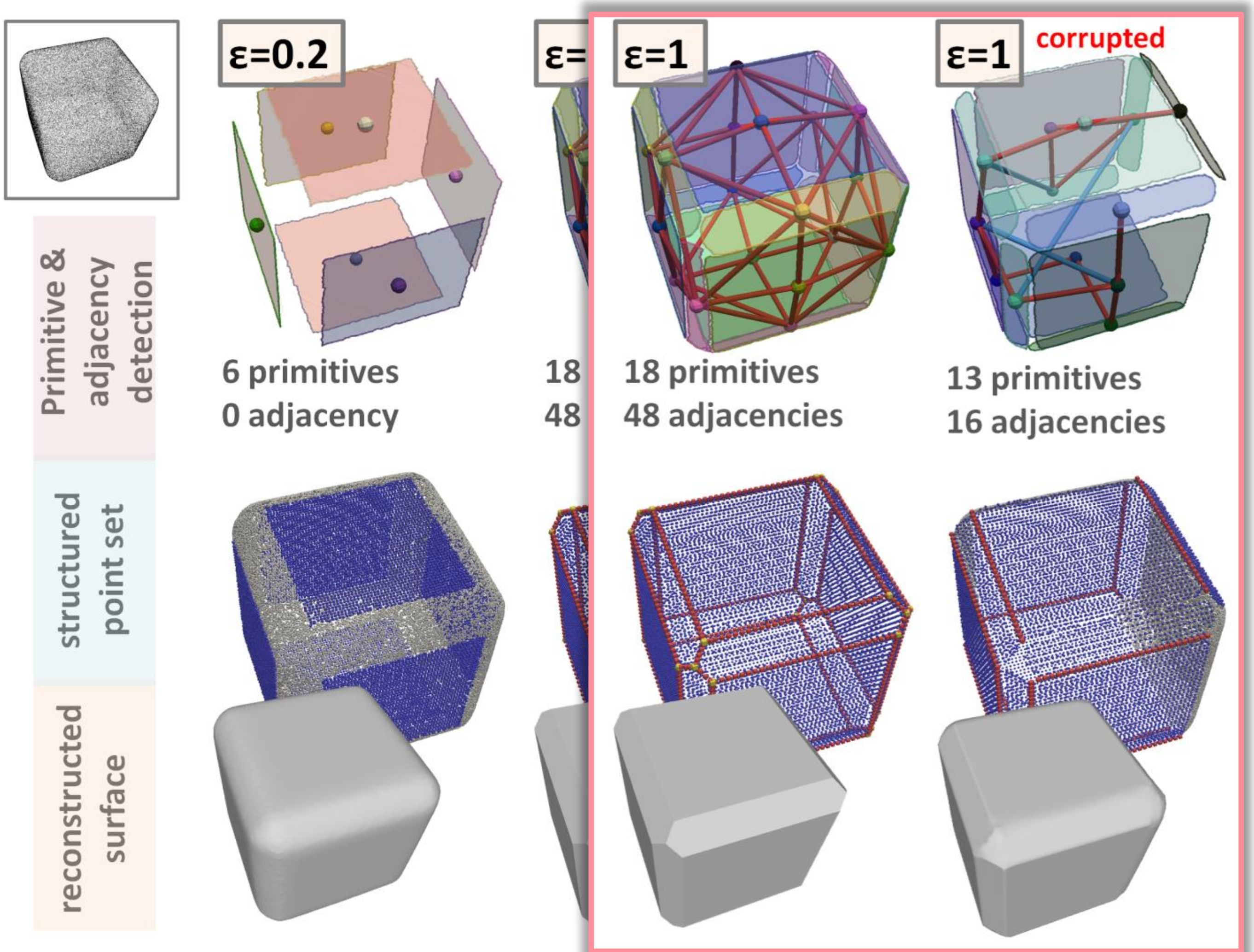
Hybrid surfaces (by point set structuring)



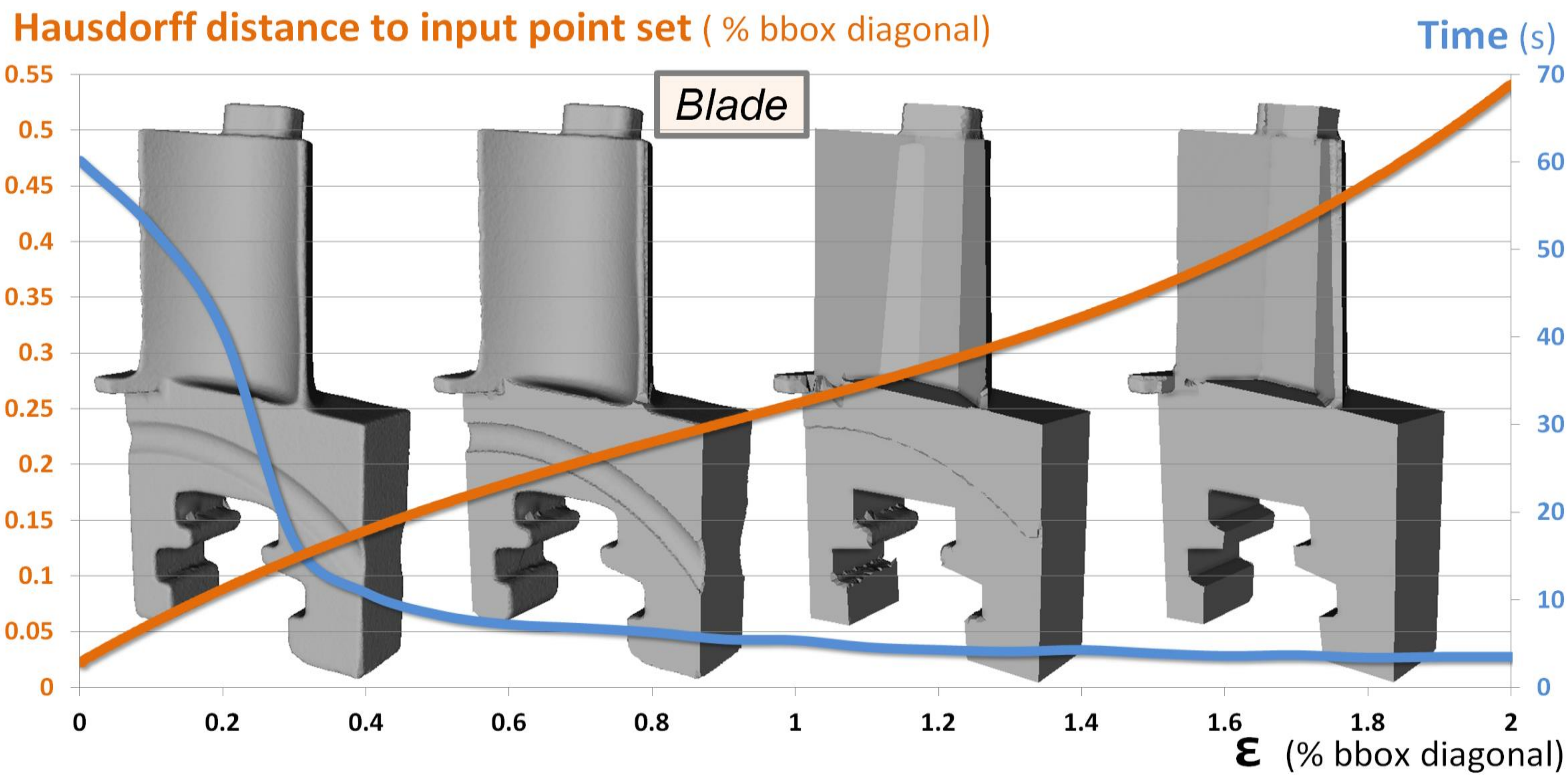
Hybrid surfaces (by point set structuring)



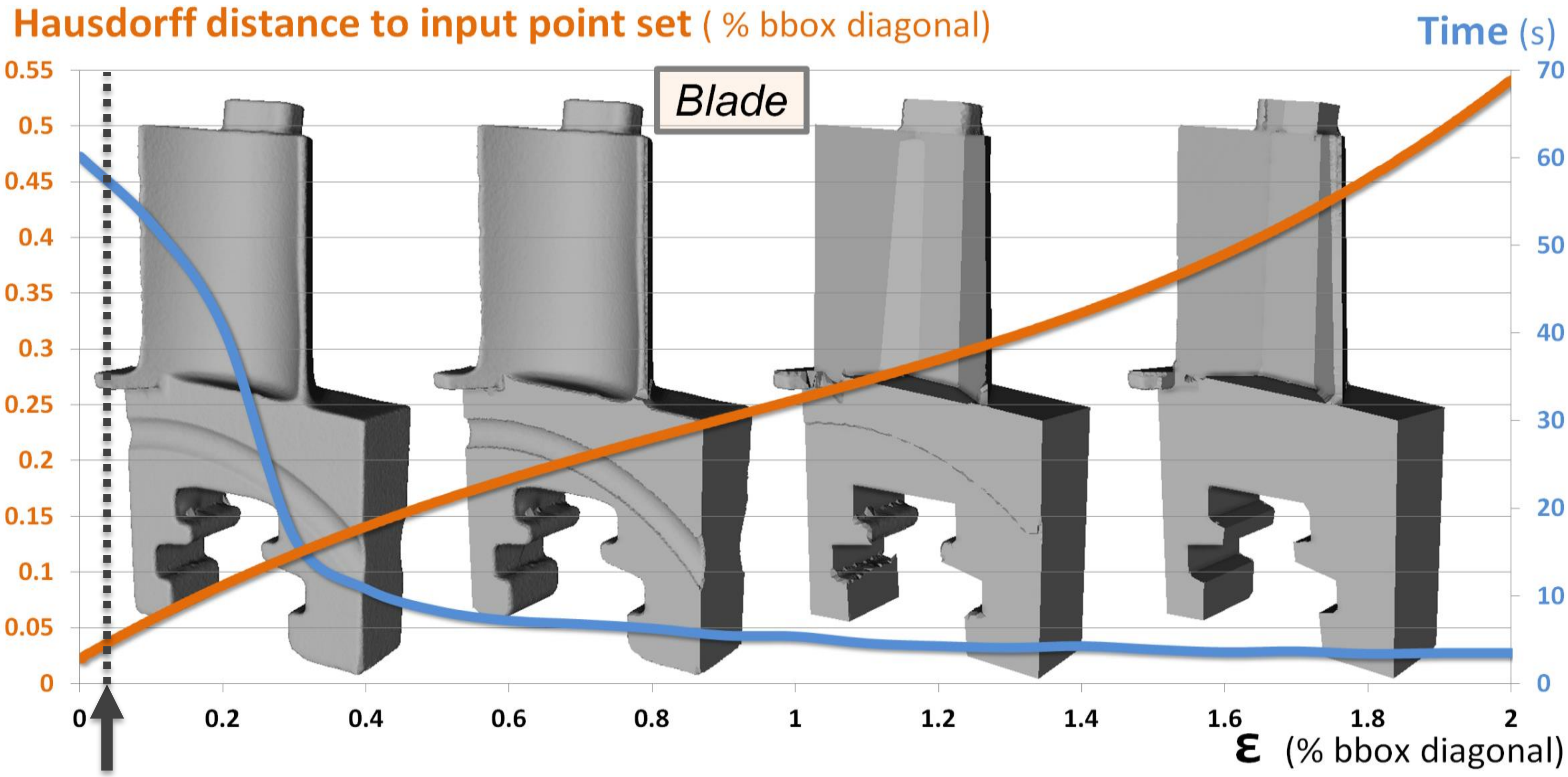
Hybrid surfaces (by point set structuring)



Hybrid surfaces (by point set structuring)

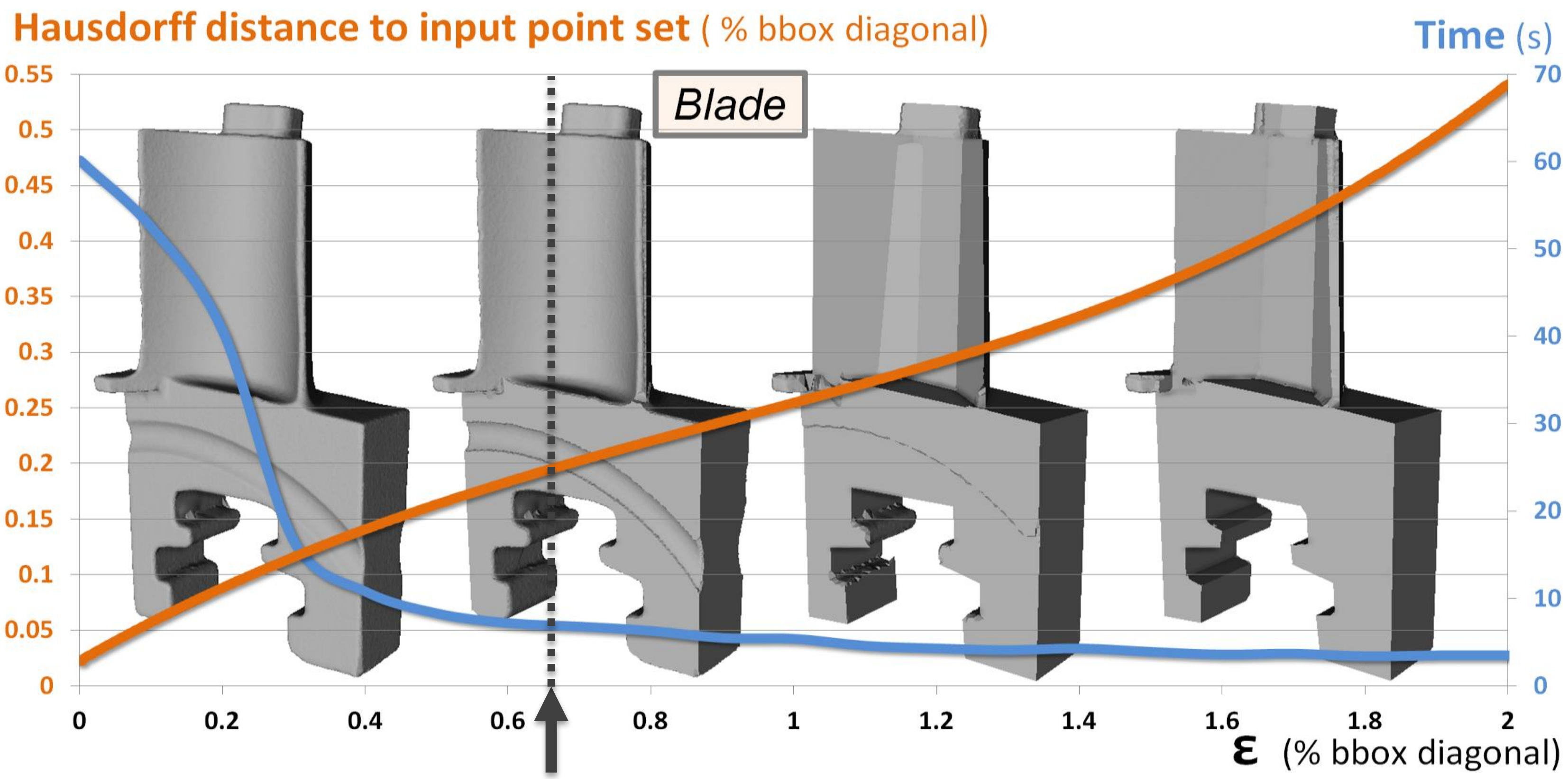


Hybrid surfaces (by point set structuring)



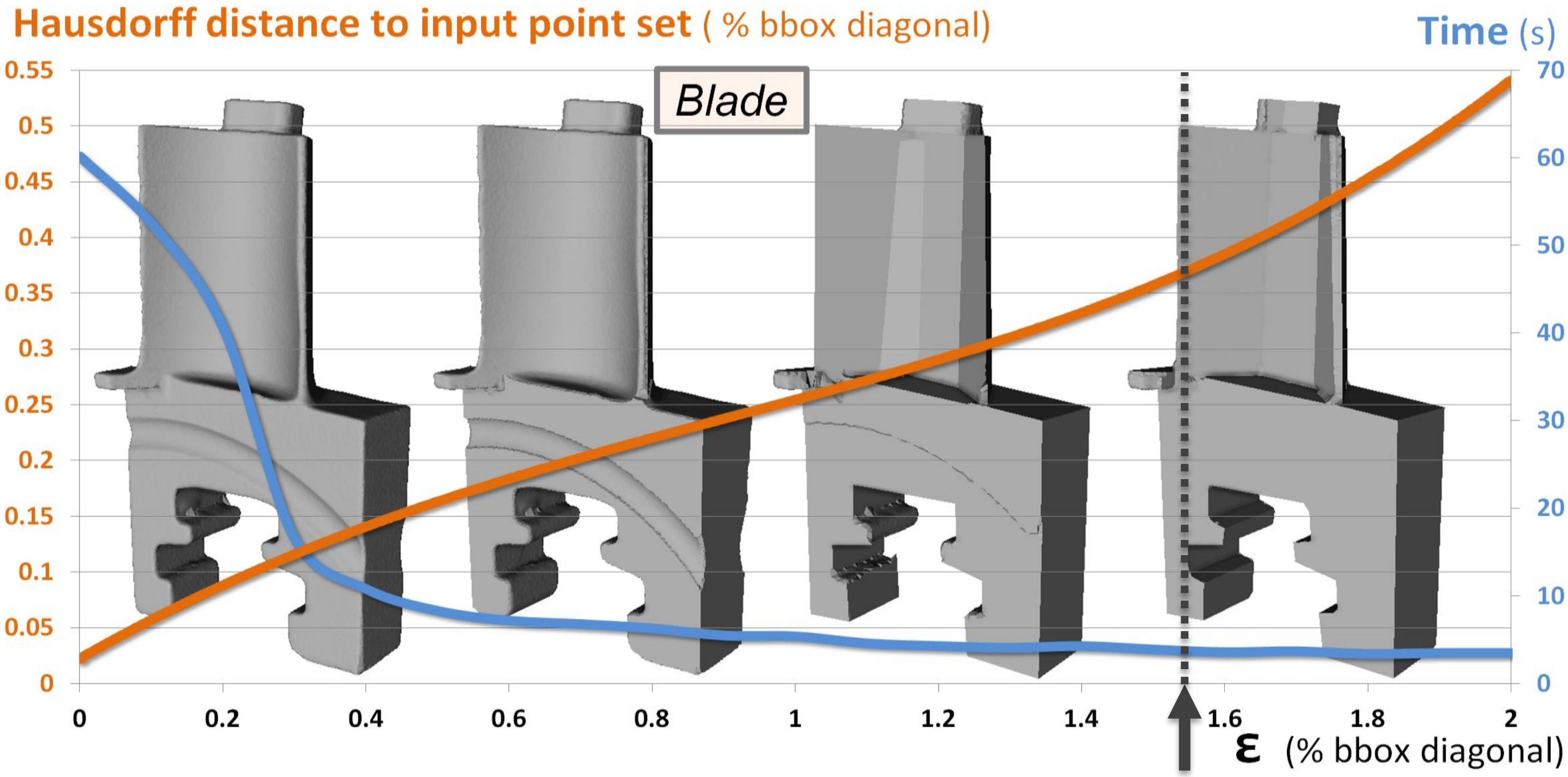
highly freeform (no structure)
high accuracy
high running time

Hybrid surfaces (by point set structuring)



structure ↑ (freeform ↓)
accuracy ↓
running time ↓

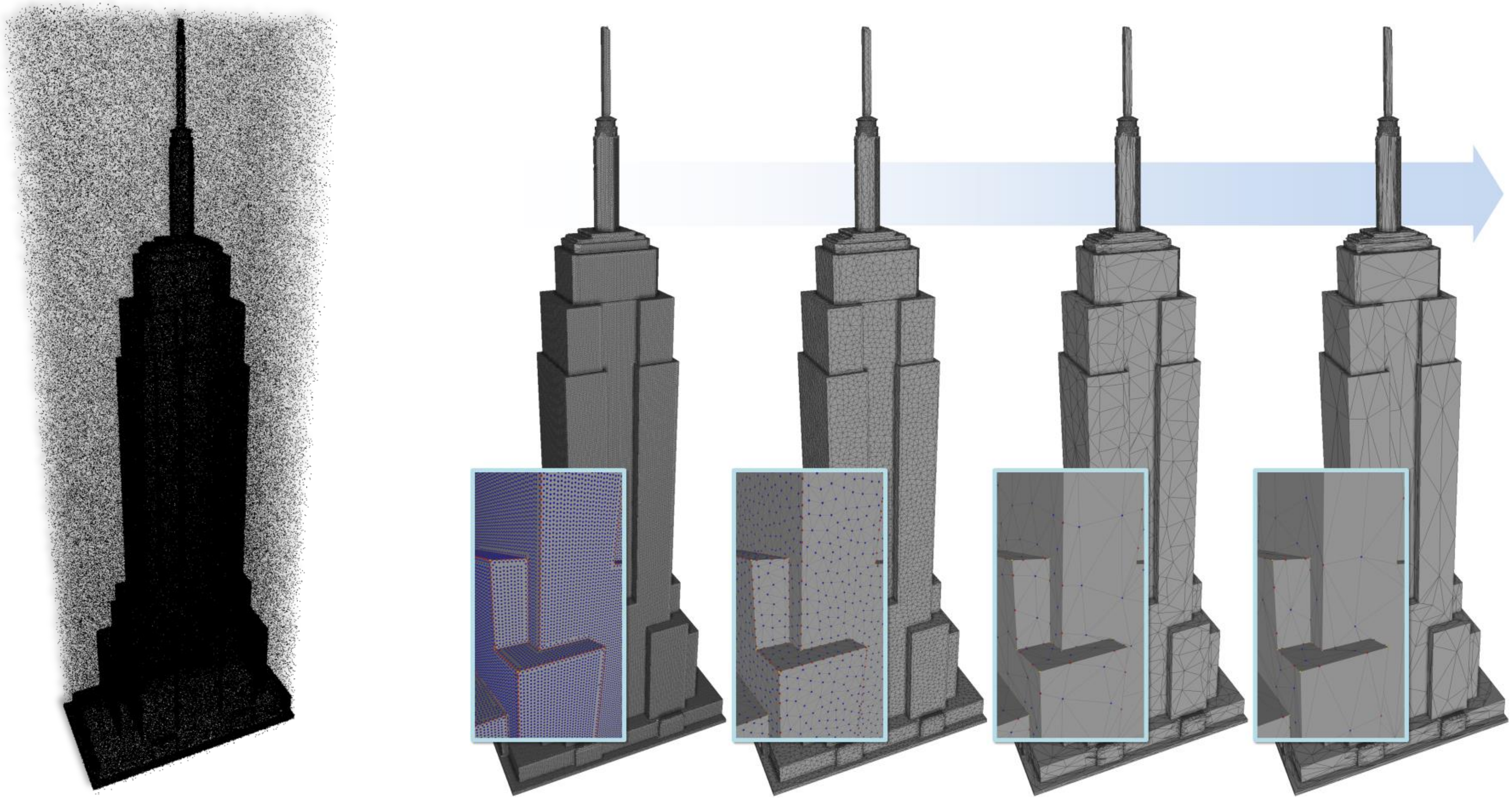
Hybrid surfaces (by point set structuring)



fully structured
low accuracy
low running time

Hybrid surfaces (by point set structuring)

Reduction of the structure complexity while preserving details



Hybrid surfaces (by shape sampling)

MVS images and a rough initial surface

Hybrid surfaces (by shape sampling)

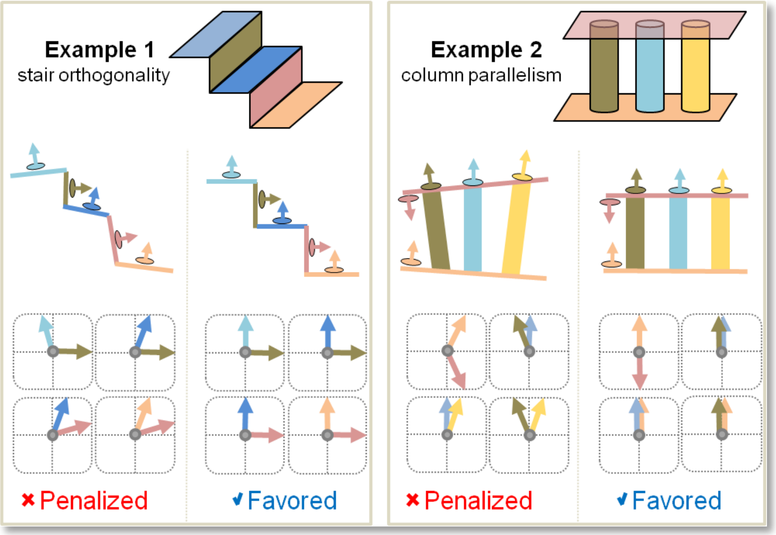
MVS images and a rough initial surface

Goal: refine the surface while sampling geometric primitives (planes, cylinders…) by Jump-Diffusion

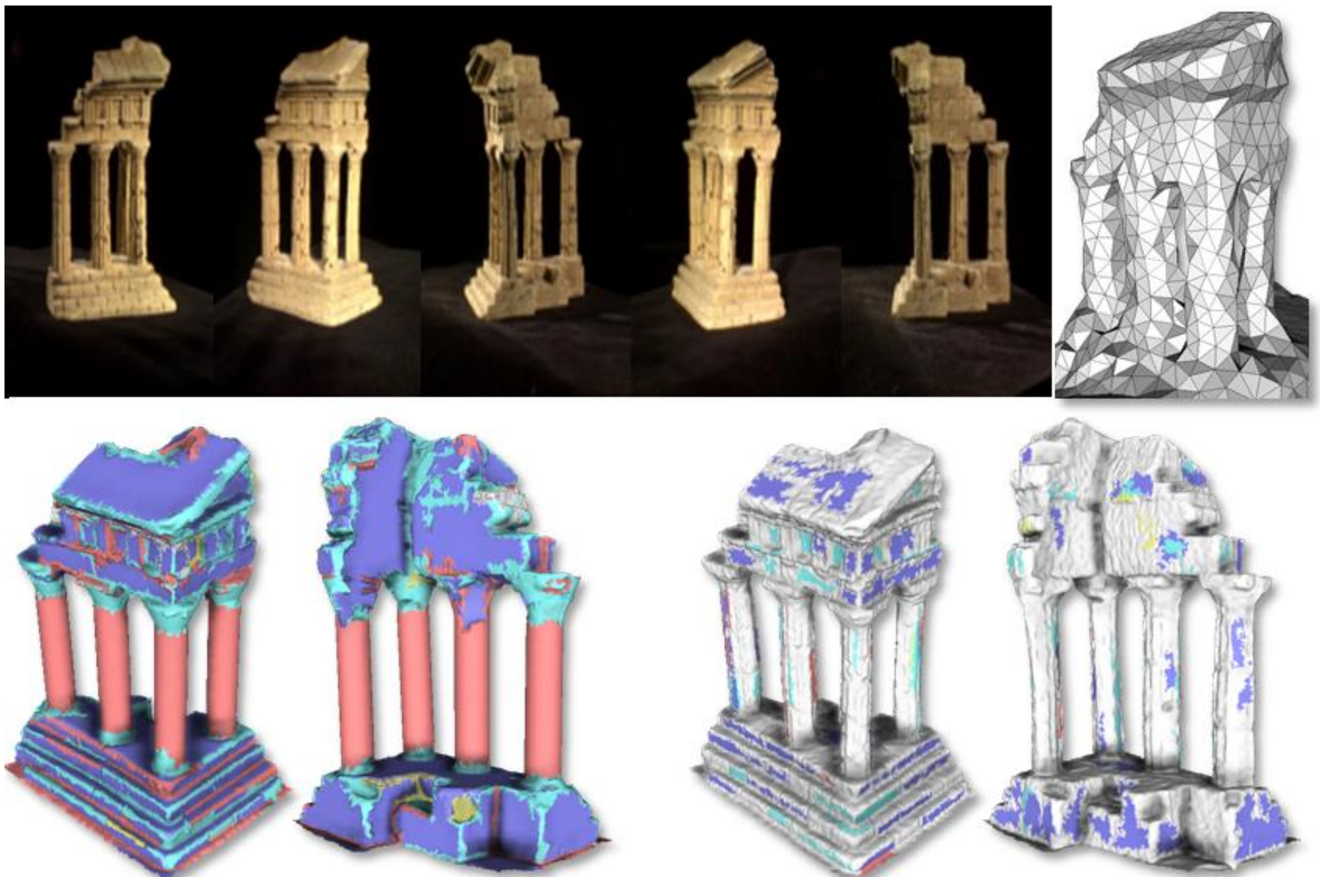
Hybrid surfaces (by shape sampling)

MVS images and a rough initial surface

Goal: refine the surface while sampling geometric primitives (planes, cylinders…) by Jump-Diffusion

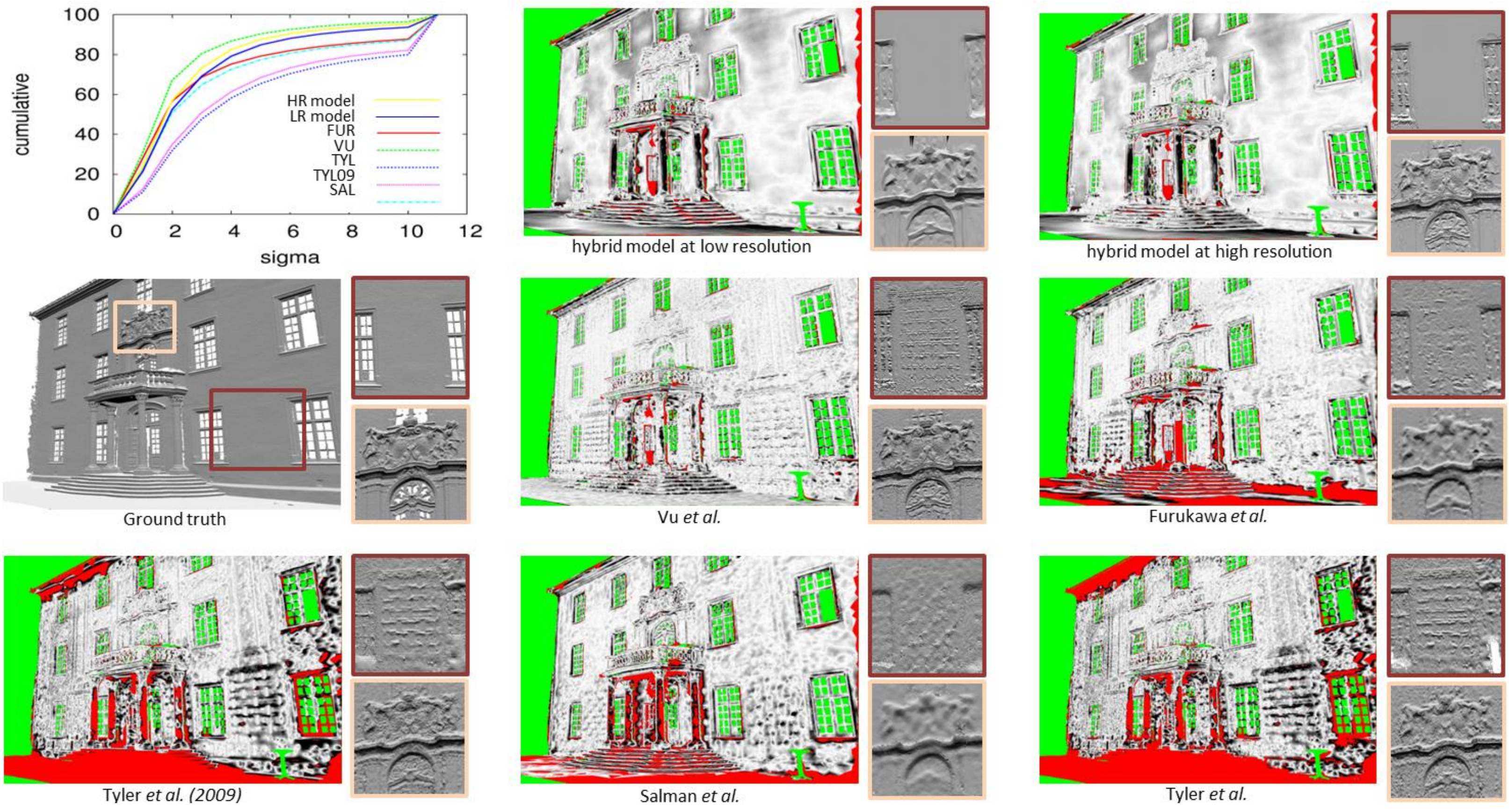


Hybrid surfaces (by shape sampling)

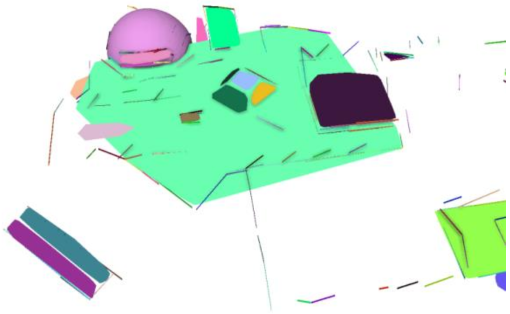


Primitive-dominant *Free-form-dominant*

Hybrid surfaces (by shape sampling)

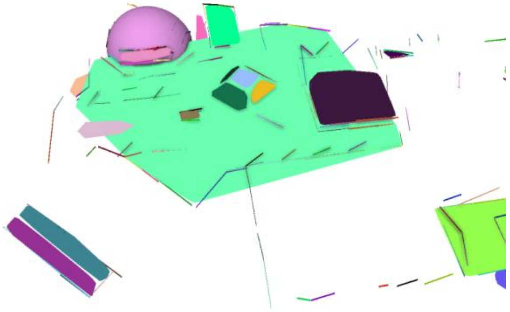


Hybrid surfaces (by planimetric map)

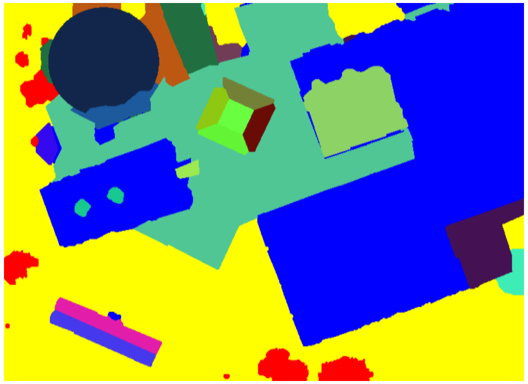


3D Primitive detection

Hybrid surfaces (by planimetric map)

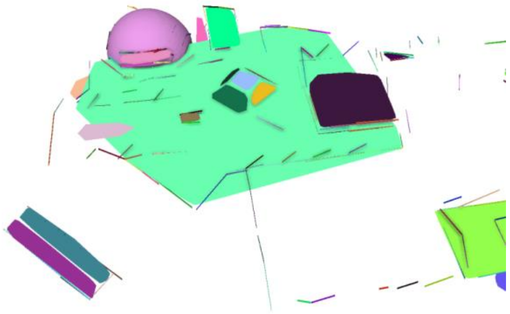


3D Primitive detection

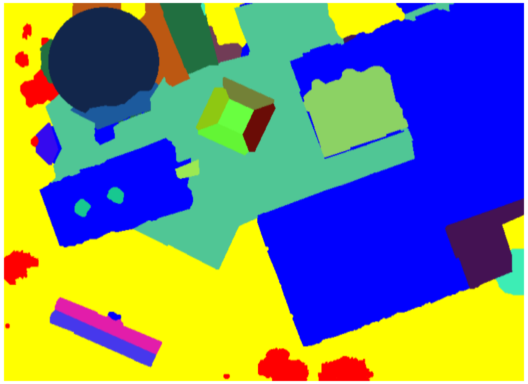


2.5D planimetric map

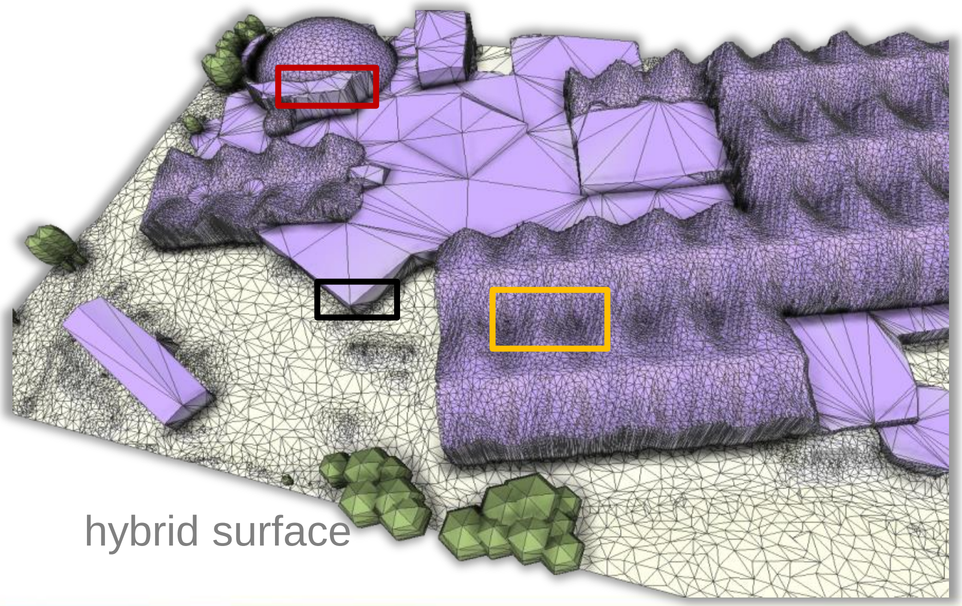
Hybrid surfaces (by planimetric map)



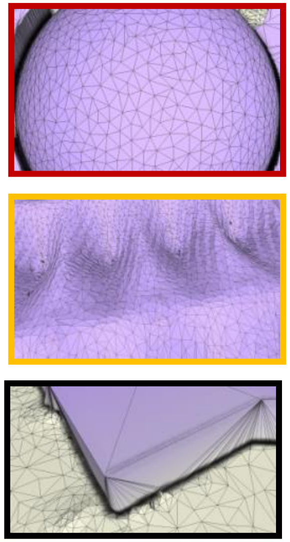
3D Primitive detection



2.5D planimetric map



hybrid surface

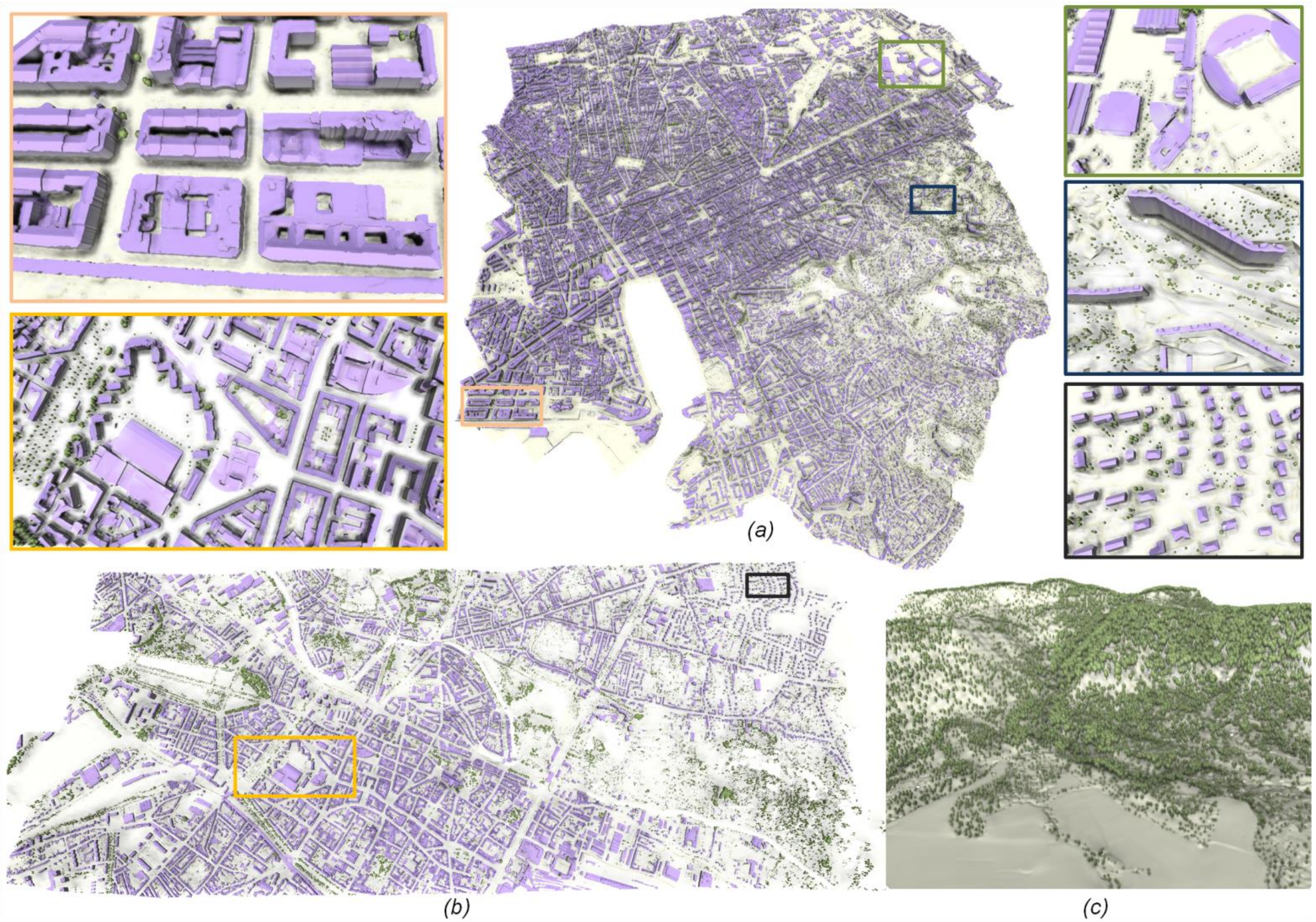


Hybrid surfaces (by planimetric map)

Aerial image (from Google Maps)

3D-model

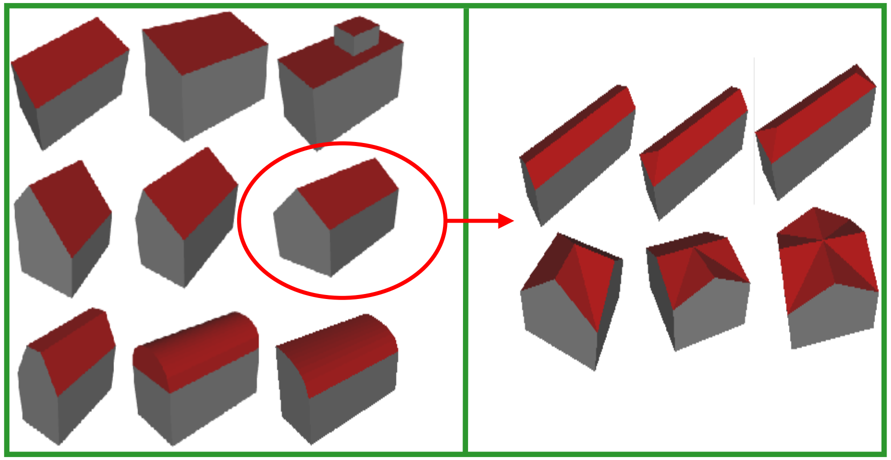
Hybrid surfaces (by planimetric map)

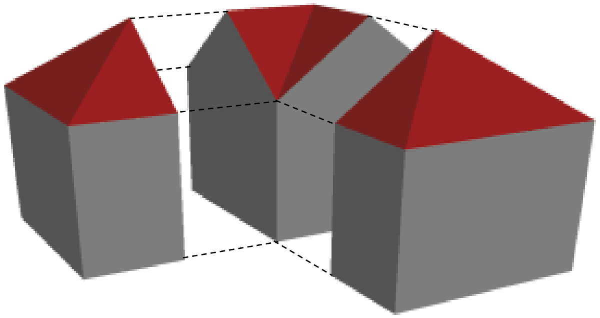


	#input points ($\times 10^6$)	area (km^2)	altimetric variation (m)	#primitives ($\times 10^3$)	#trees ($\times 10^3$)	computing time (hour)	compaction (Mo)
Marseille, France *(a)*	38.67	19.8	192	108.6	35.7	2.52	131
Amiens, France *(b)*	24.52	11.57	76	56.7	22.8	1.34	93
Mountain area *(c)*	22.67	3.41	525	0.01	21.1	0.31	34

2nd idea: 3D-Block assembling

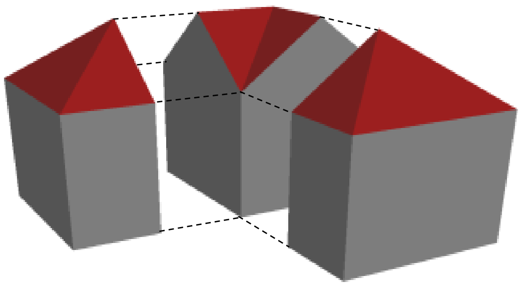
A building = an assemblage of elementary urban 3D-models

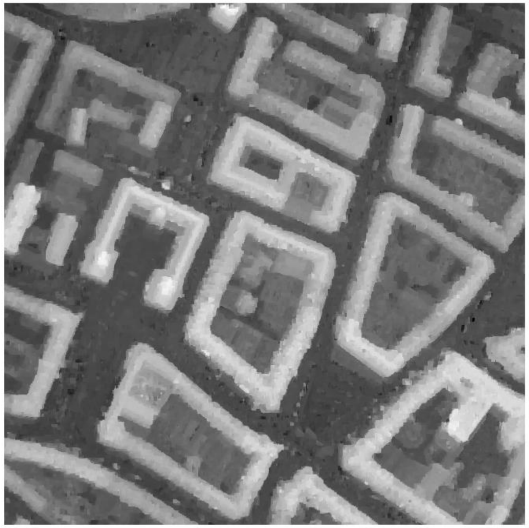




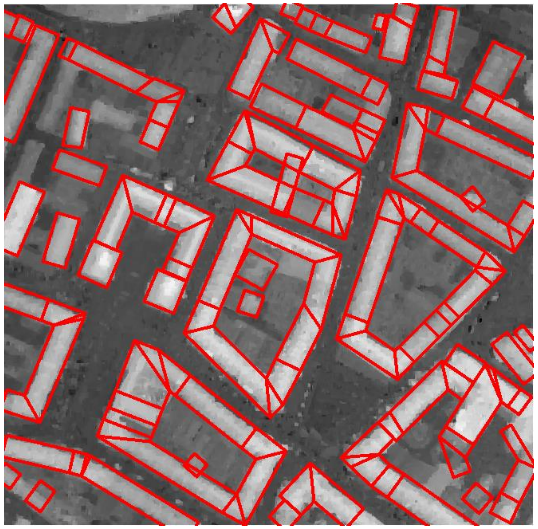
2^{nd} idea: 3D-Block assembling

A building = an assemblage of elementary urban 3D-models





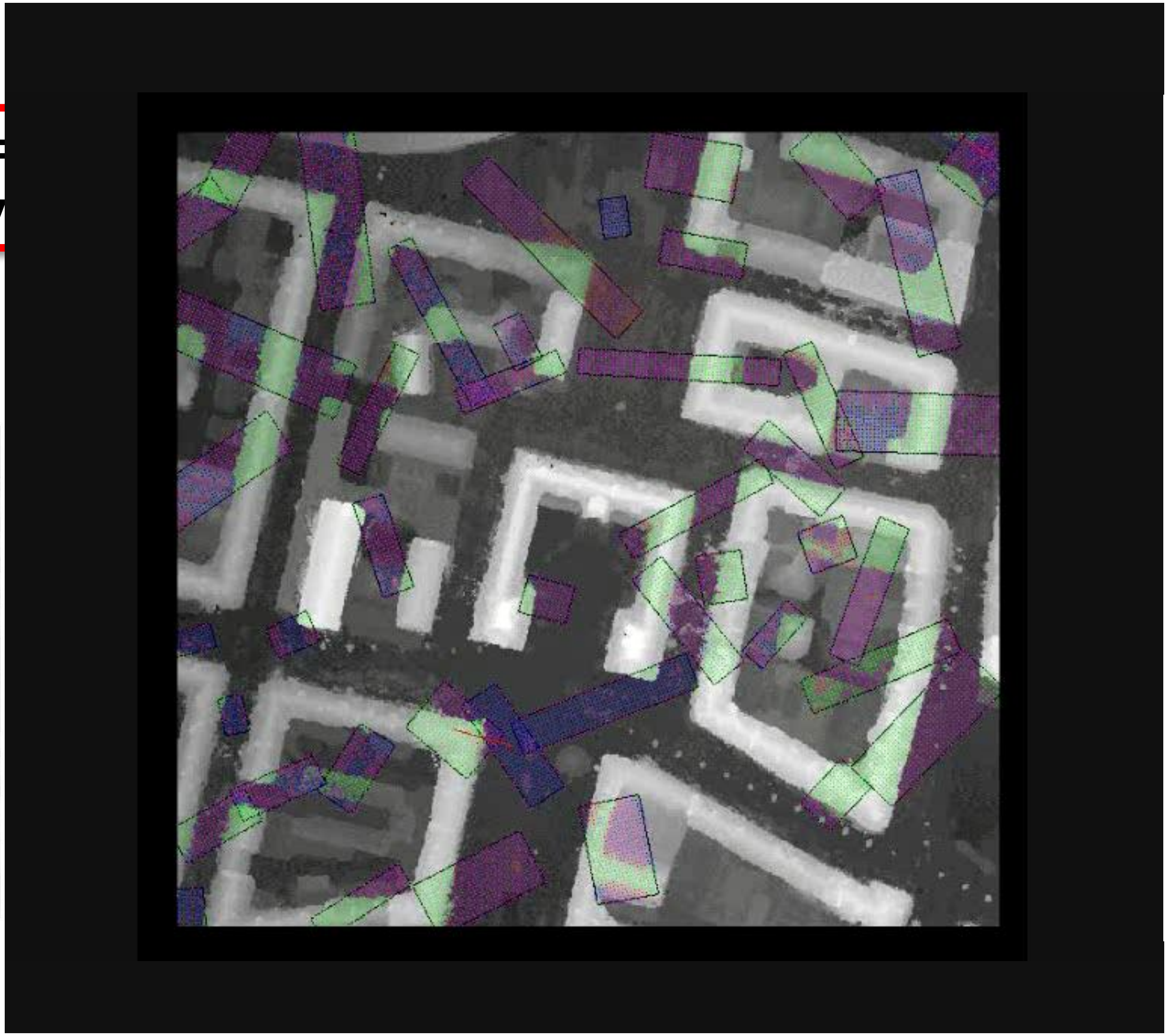
Elevation map (DEM)

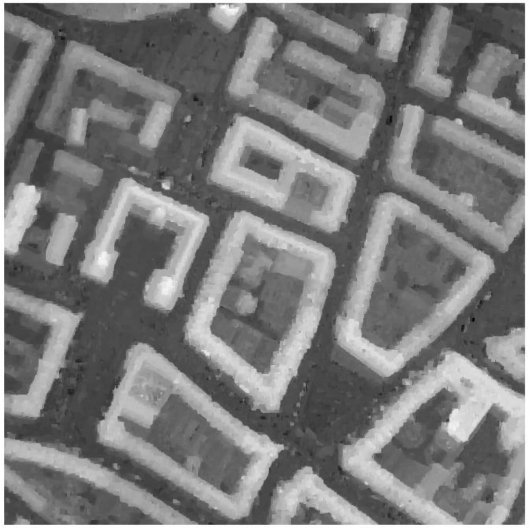


Polygonalization of building footprints by point process

2nd idea: 3D-Block assembling

A building =
elementary

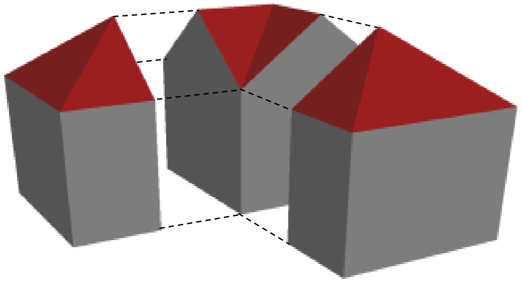


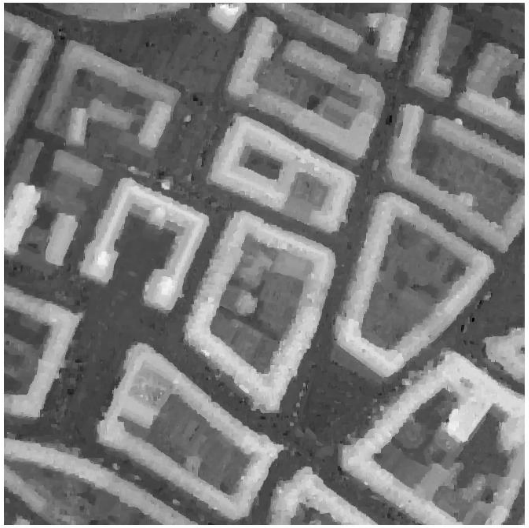


Elevation map (DEM)

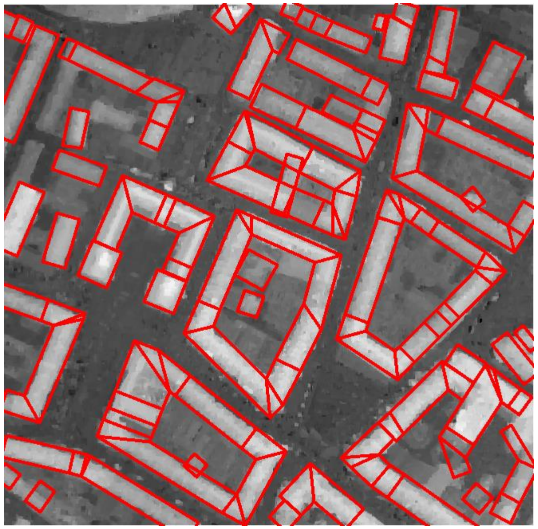
2nd idea: 3D-Block assembling

A building = an assemblage of elementary urban 3D-models





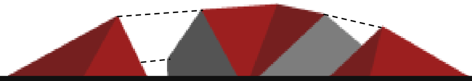
Elevation map (DEM)



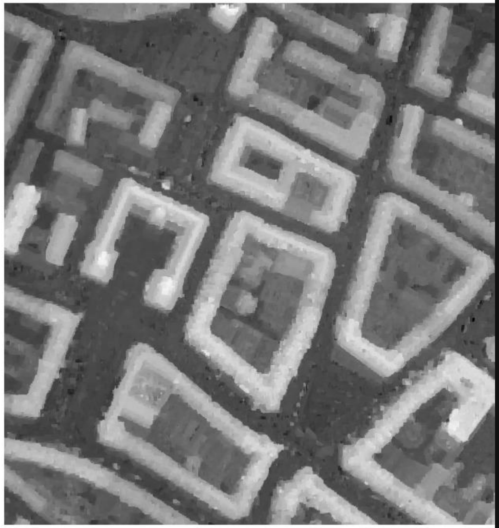
Polygonalization of building footprints by point process

Building reconstruction by 3D-block sampling

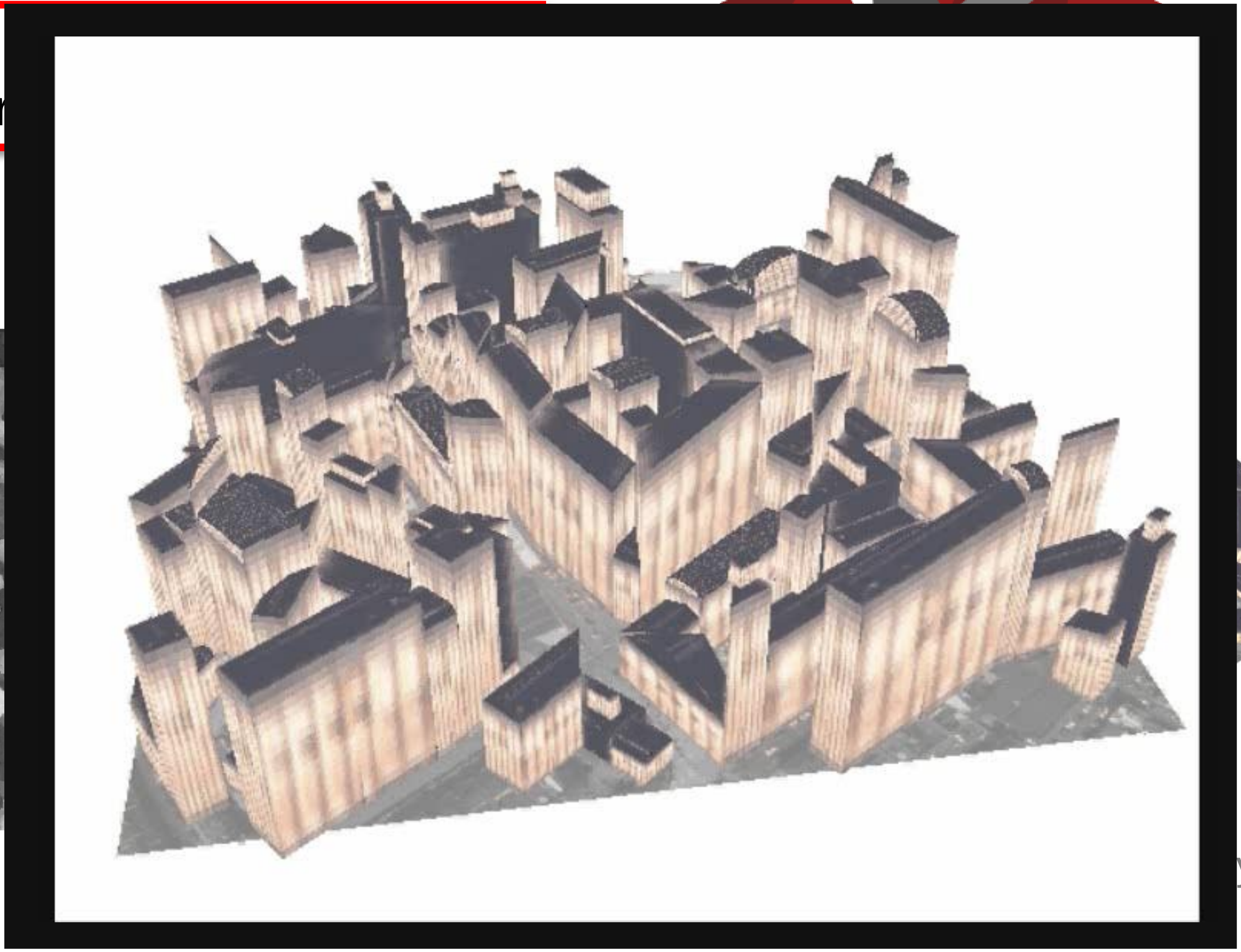
2nd idea: 3D-Block assembling



A building
elementar

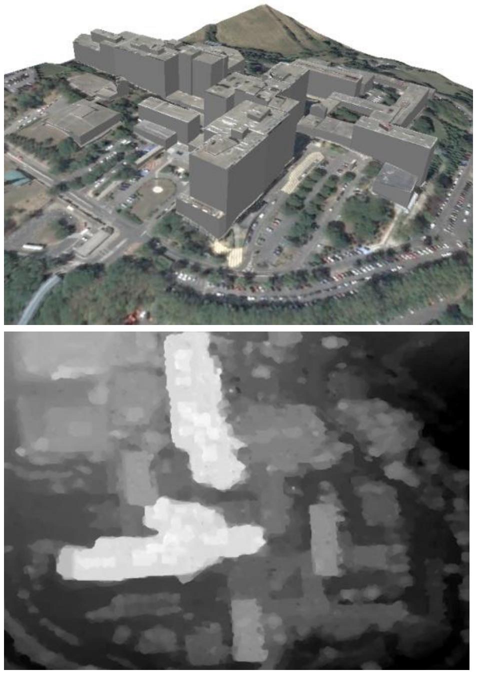


Elevation map (DEM)

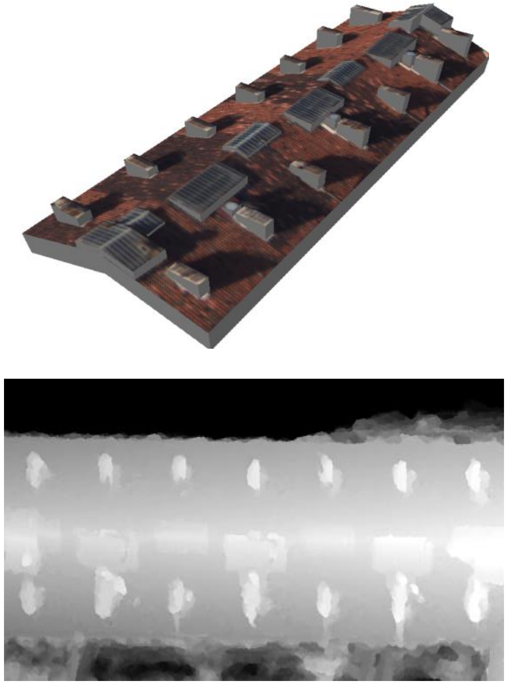


y

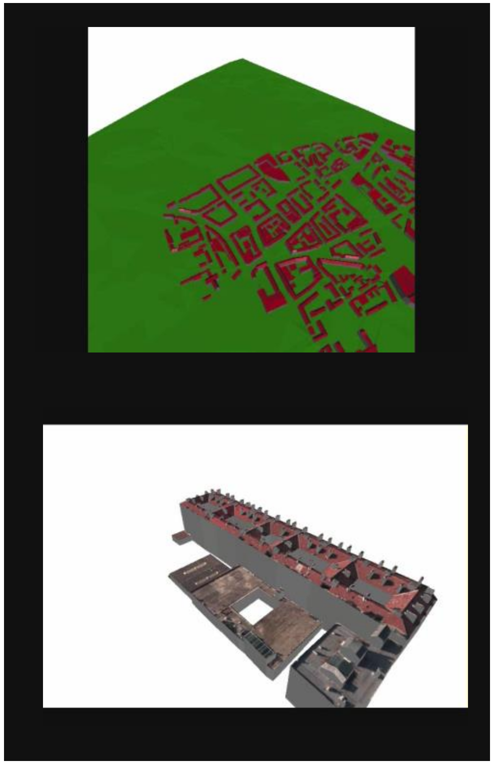
3D-Block assembling



Pixel resolution: 0.70 m

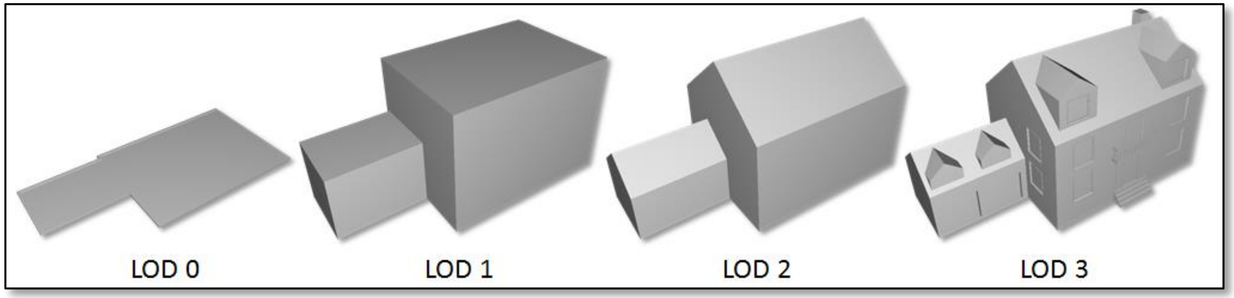


Pixel resolution: 0.10 m



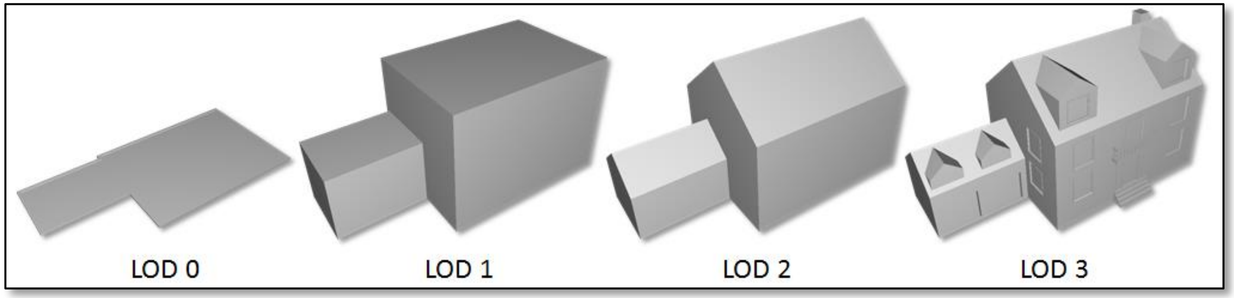
3rd idea: LOD generation

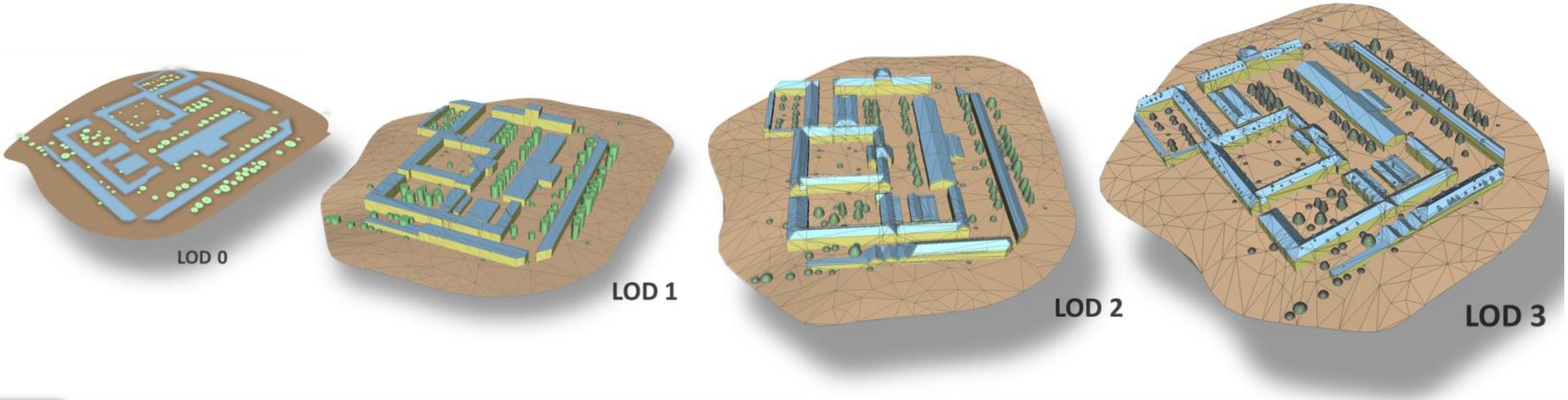
Urban 3D models with different Levels Of Details



3rd idea: LOD generation

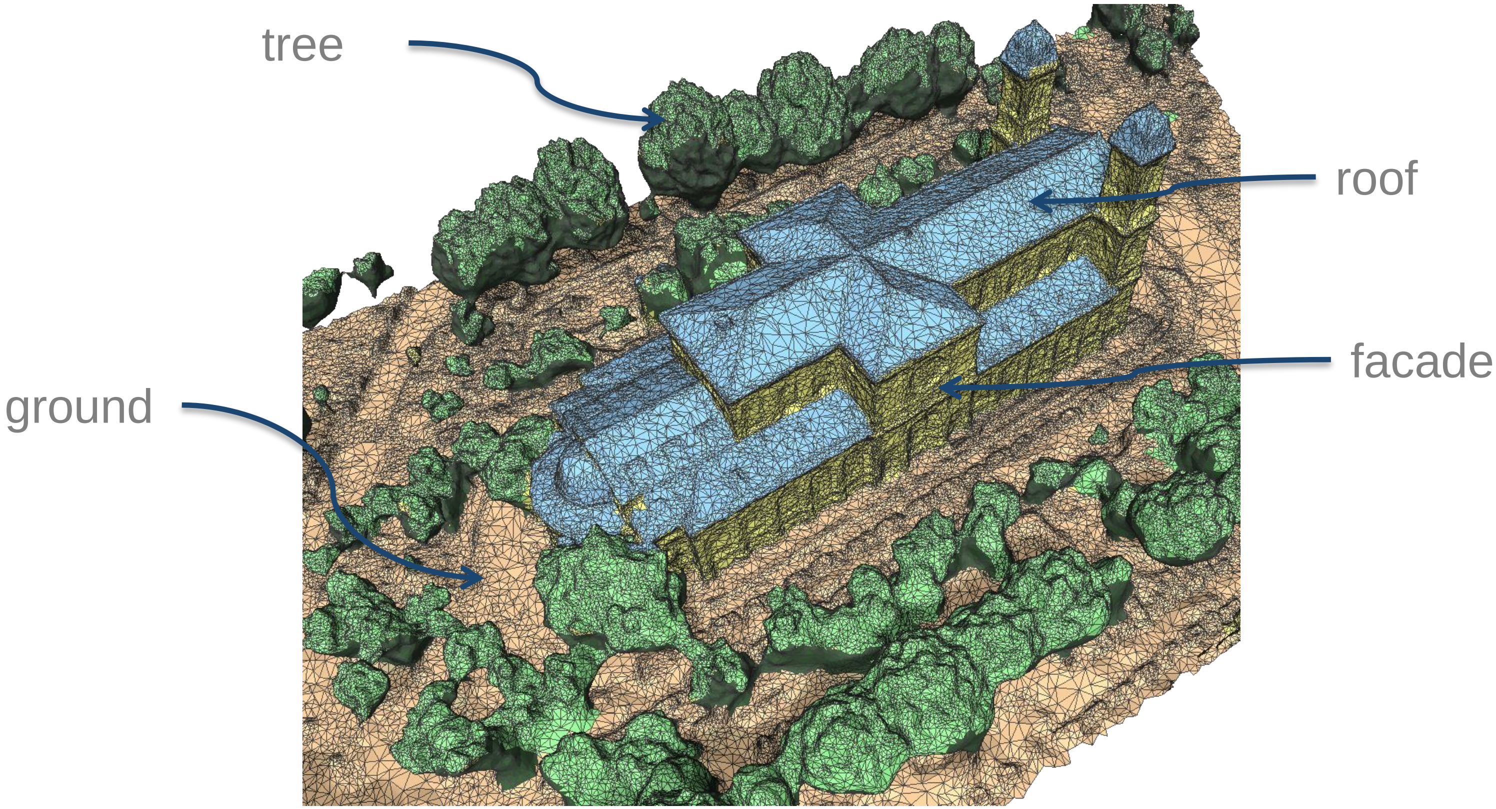
Urban 3D models with different Levels Of Details





LOD generation

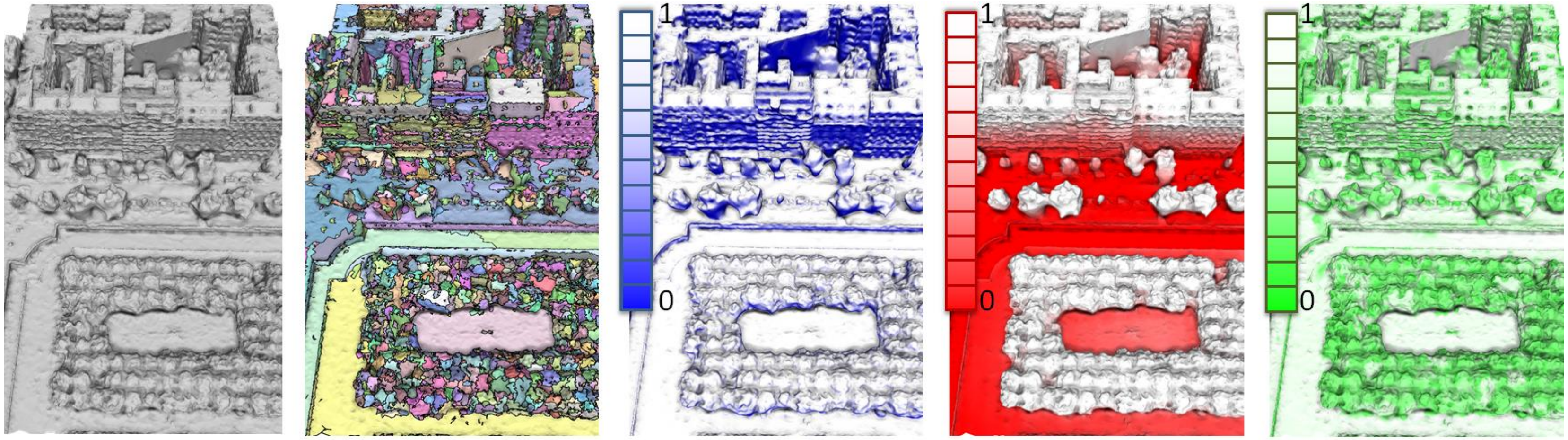
1. **Semantical segmentation of dense mesh into 4 classes of interest**



LOD generation

1. **Semantical segmentation of dense mesh into 4 classes of interest**

- Geometric descriptors

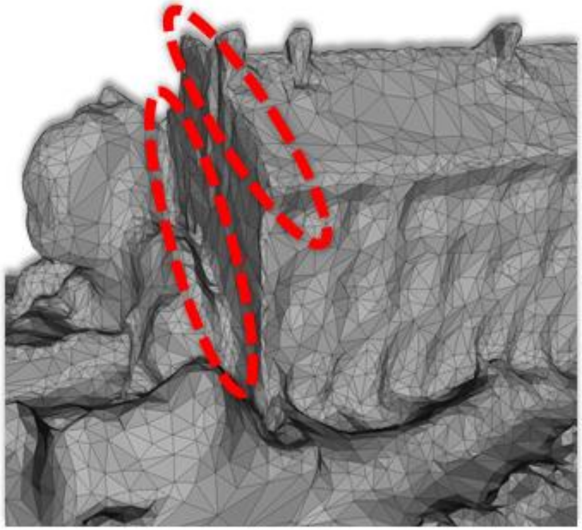


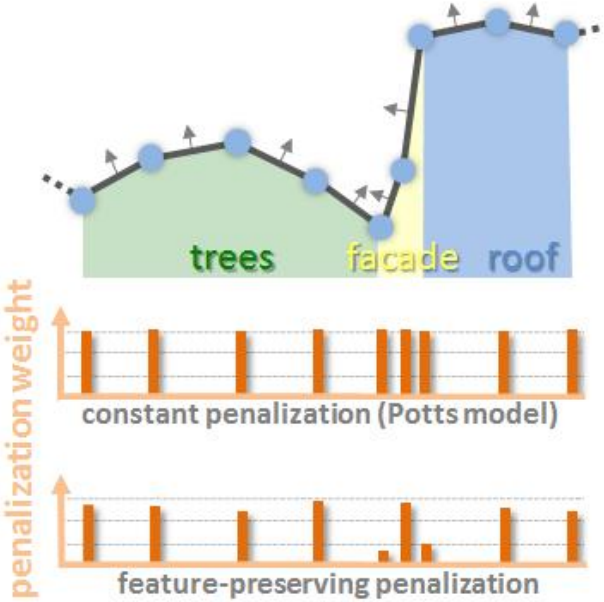
Input mesh Superfacets Horizontality Elevation Planarity

LOD generation

1. **Semantical segmentation of dense mesh into 4 classes of interest**

- ➢ Geometric descriptors
- ➢ Markov Random Fields with feature-preserving potential





LOD generation

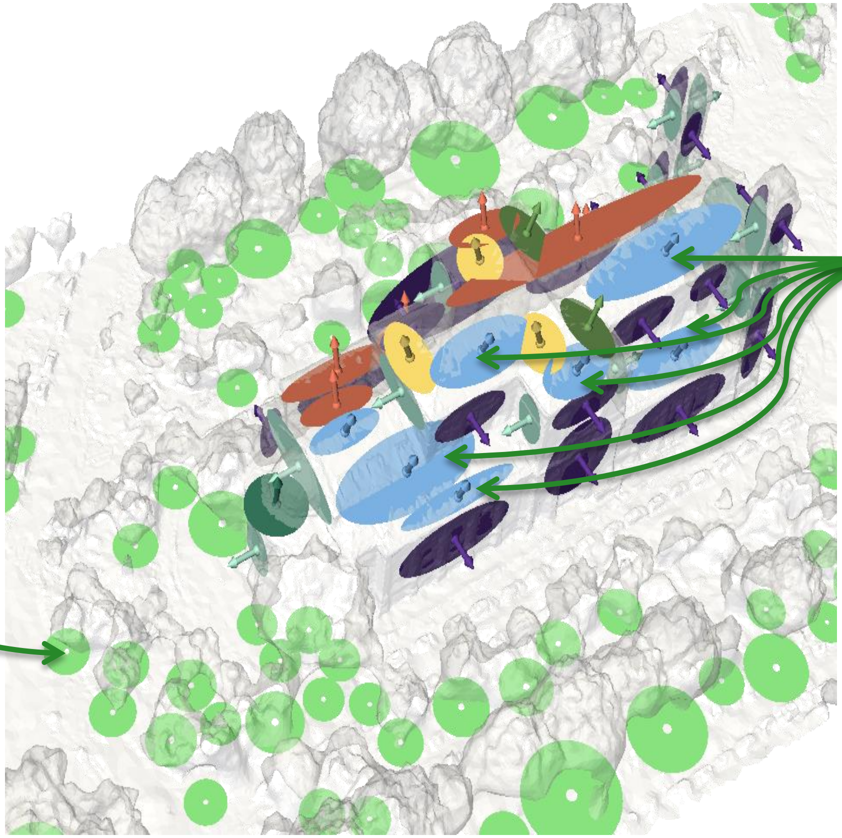
1. **Semantical segmentation of dense mesh into 4 classes of interest**

- Geometric descriptors
- Markov Random Fields with feature-preserving potential

LOD generation

2. Abstraction of urban objects

Tree localization

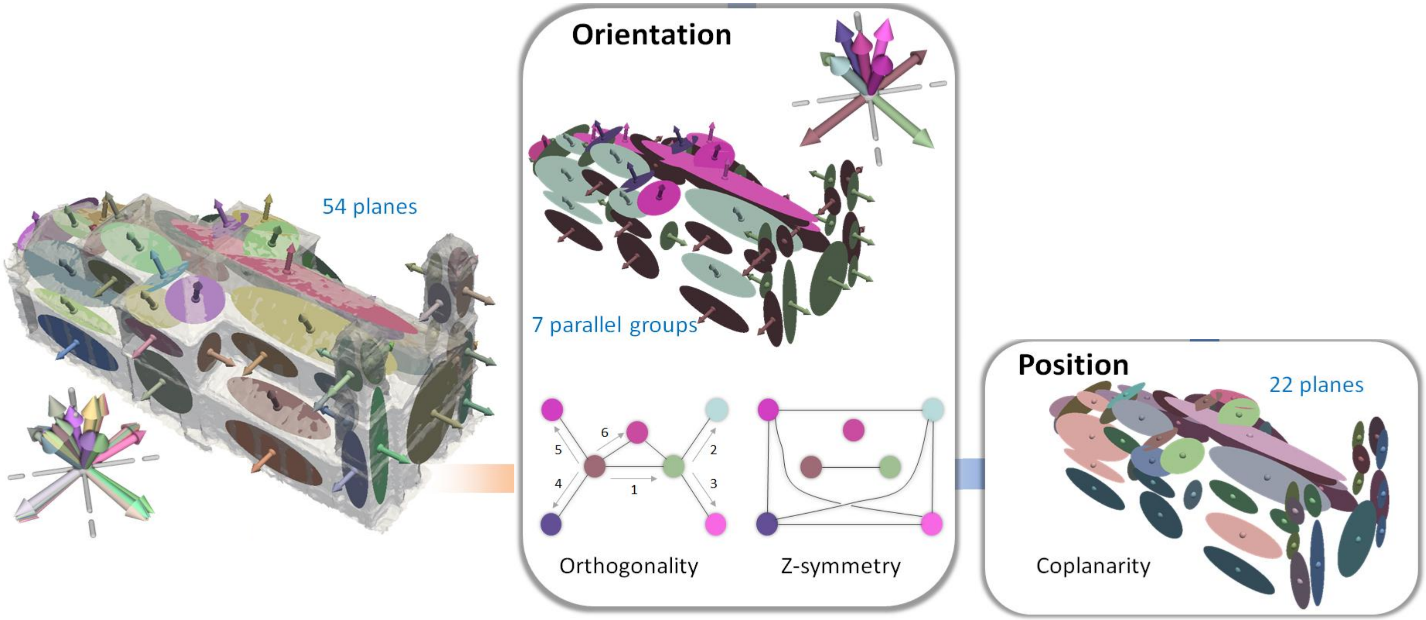


Planar hypotheses
globally consistent

LOD generation

2. Abstraction of urban objects

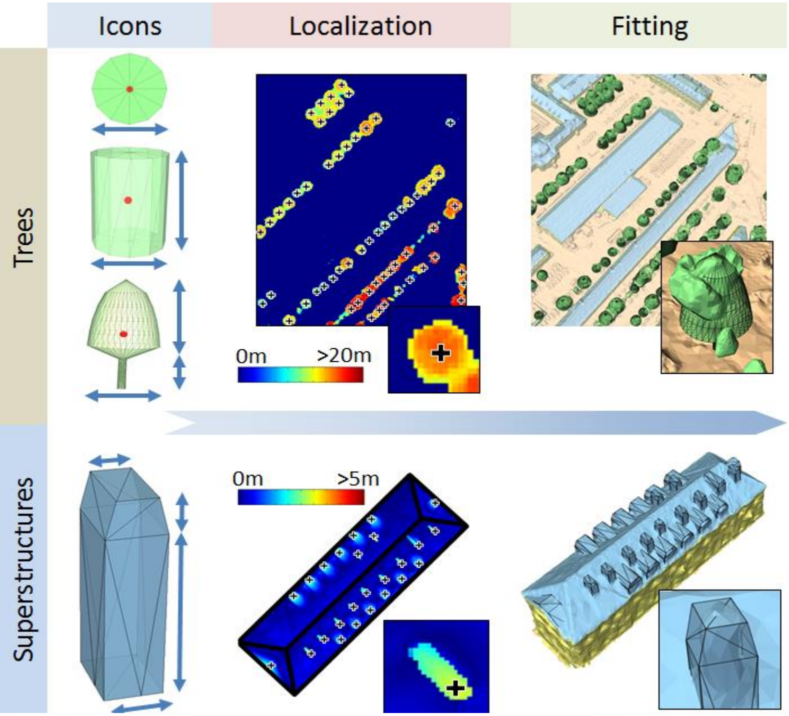
- Detection of planar primitives with global regularities (parallelism, orthogonality, Z-symmetry, coplanarity)



LOD generation

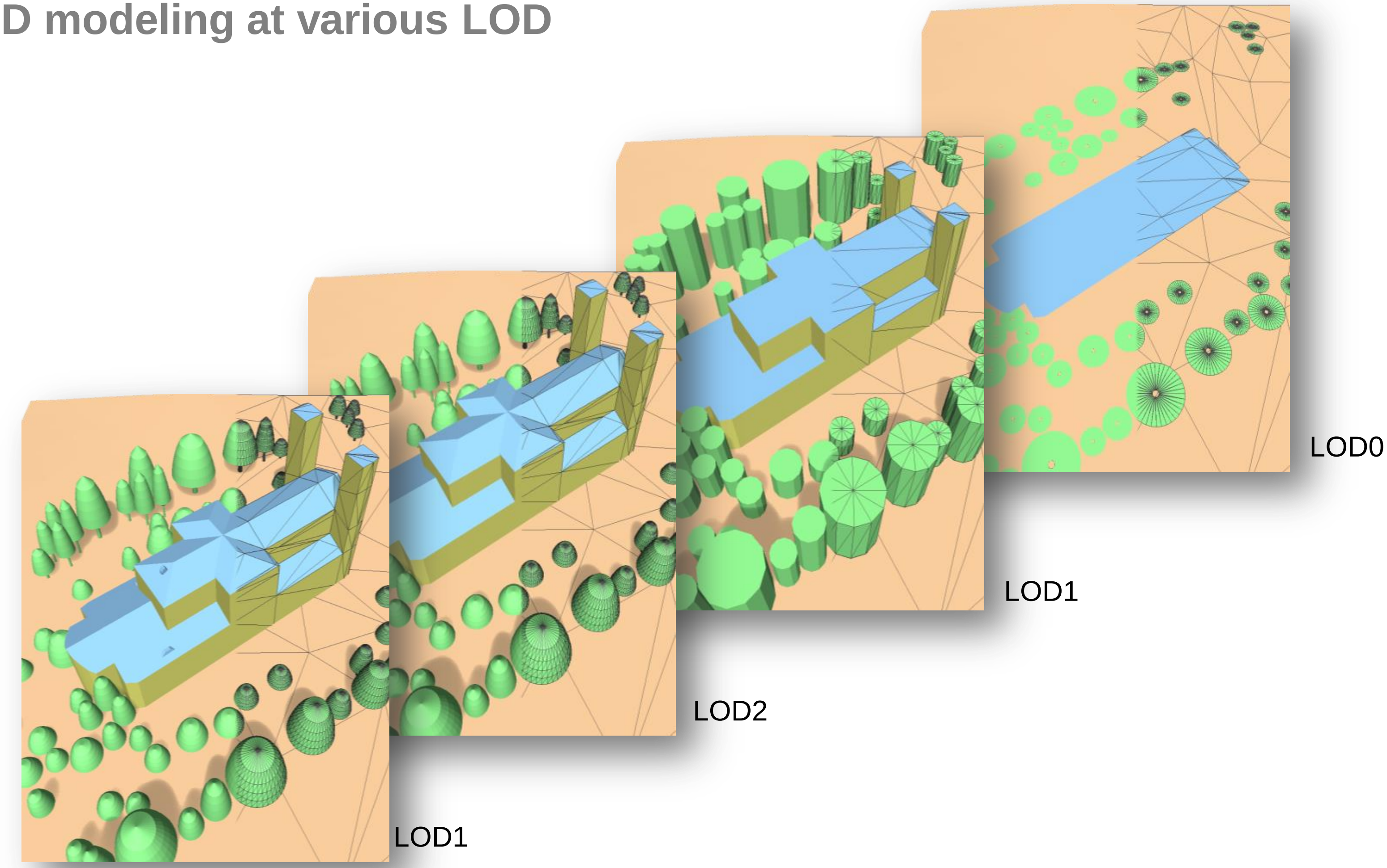
2. Abstraction of urban objects

- Detection of planar primitives with global regularities
- Iconization of trees and superstructures



LOD generation

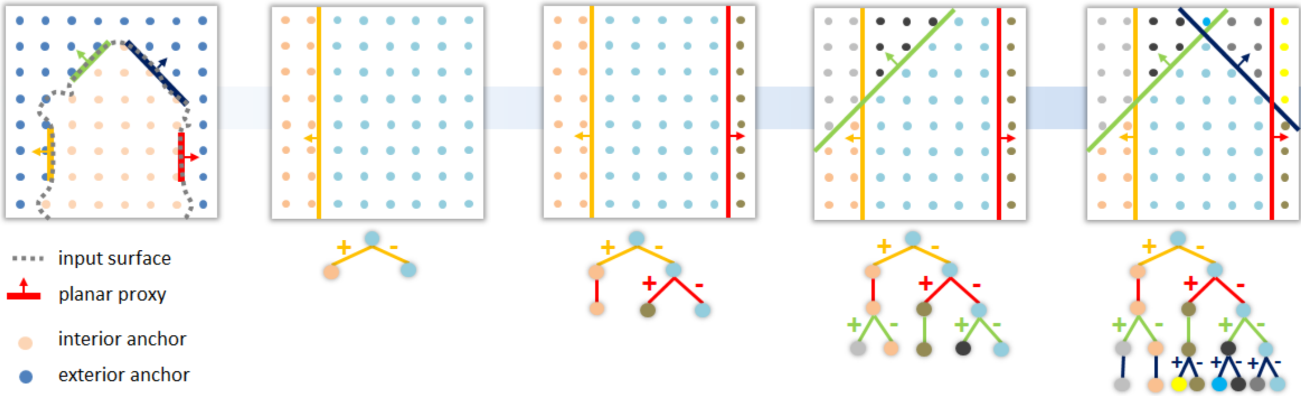
3. 3D modeling at various LOD



LOD generation

3. 3D modeling at various LOD

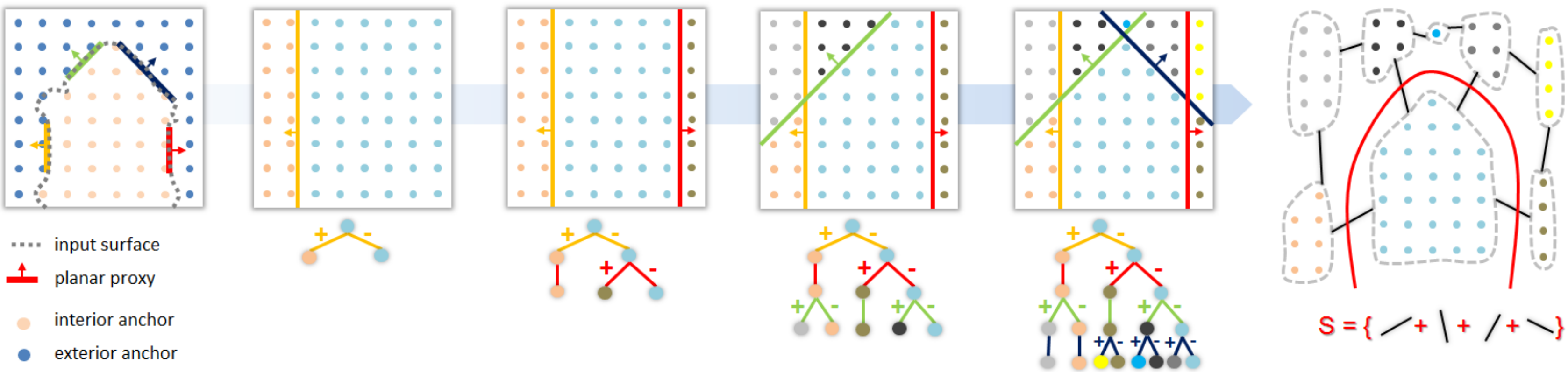
- 3D arrangement of planar primitives filtered at a given LOD



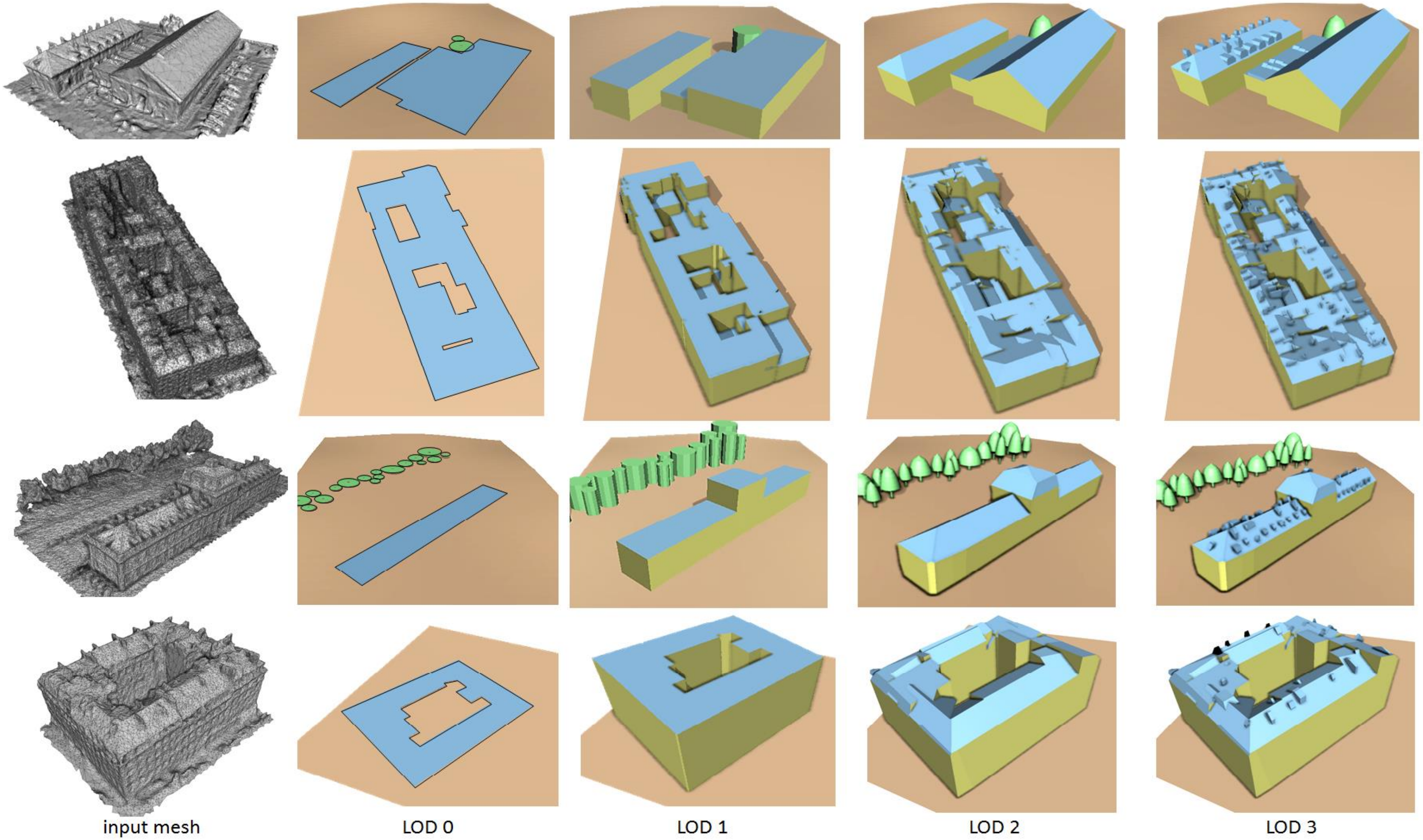
LOD generation

3. 3D modeling at various LOD

- 3D arrangement of planar primitives filtered at a given LOD
- Min-cut formulation with a discrete cost estimation



LOD generation

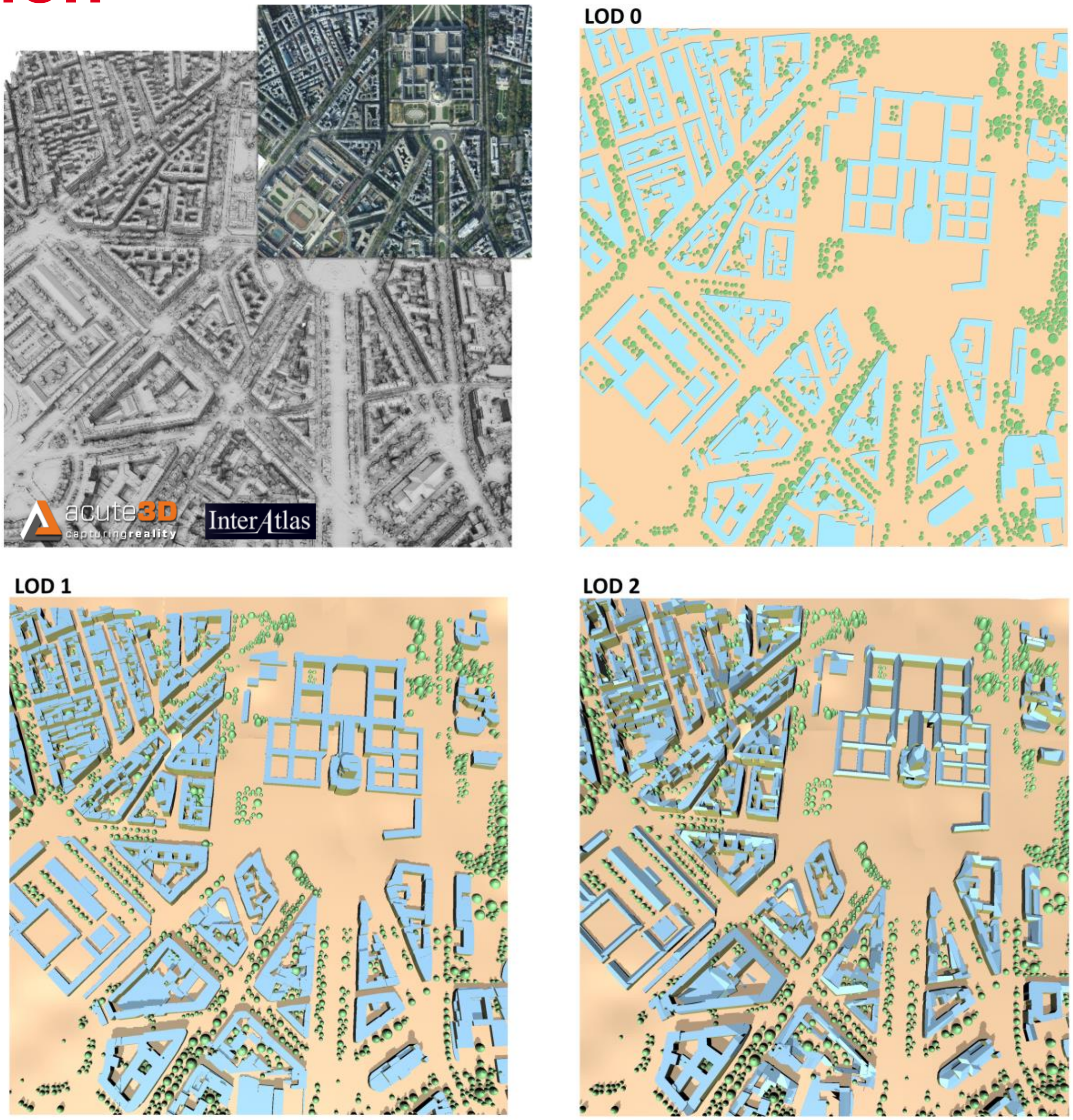


LOD generation

~1 km² of Paris

input mesh: ~11M facets

output: 175K facets (LOD2)



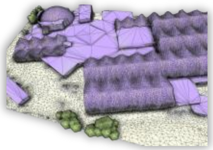
References

- Hybrid surfaces by point set structuring

Surface reconstruction through point set structuring, Eurographics'13

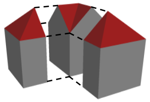
- Hybrid surfaces by shape sampling

A hybrid multi-view stereo algorithm for modeling urban scenes, IEEE PAMI 2013



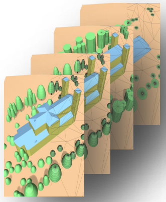
- Hybrid surfaces by planimetric map

Creating large-scale city models from 3D-point clouds: A robust approach with hybrid representation, IJCV 2012



- 3D-block assembling

Structural approach for building reconstruction from a single DSM, IEEE PAMI 2010



- LOD generation

Recently submitted..

Thank you!