

Urban scene modeling from airborne data

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INRIA Sophia Antipolis, Titane/Ayin Teams



October 15, 2013

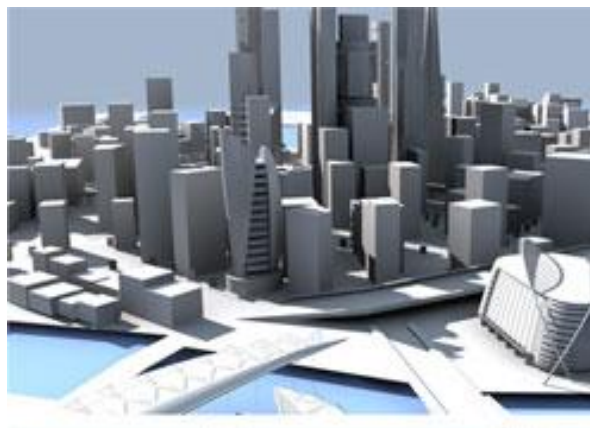
3D urban reconstruction



3D urban reconstruction



- Geometry



3D urban reconstruction



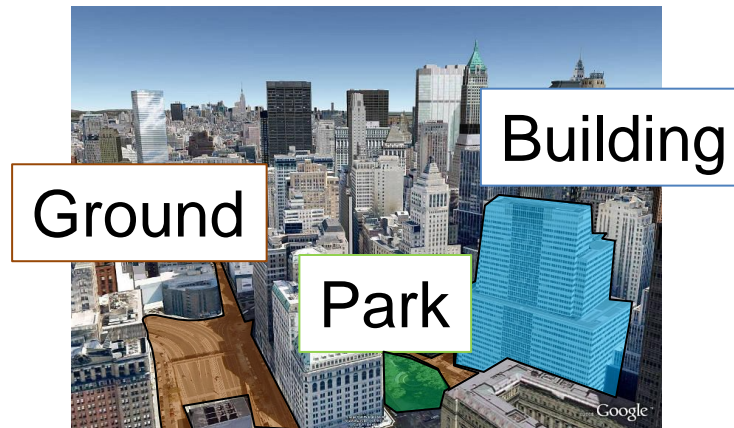
- Geometry
- Radiometry



3D urban reconstruction

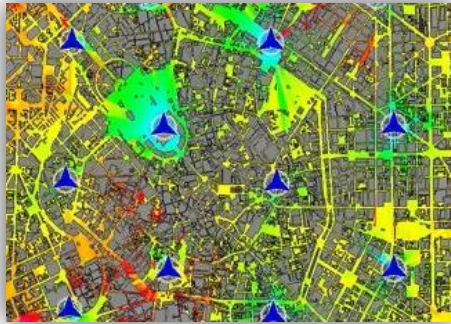


- Geometry
- Radiometry
- Semantics



Applications

- Applications for 3D urban reconstruction



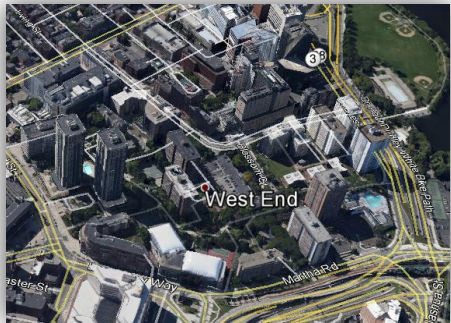
Radio planning



Movie



Computer game



Online services



Urban planning

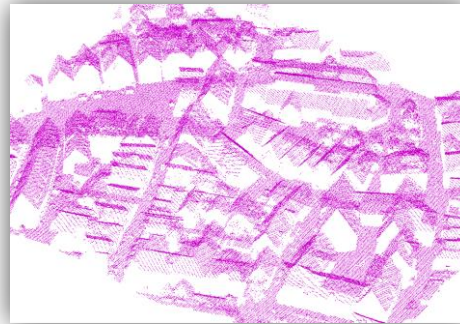


Drone planning

Problem statement



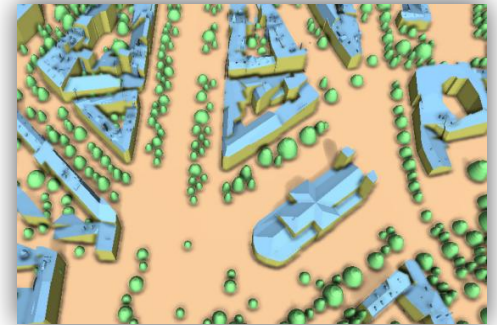
Airborne Acquisition



Lidar data

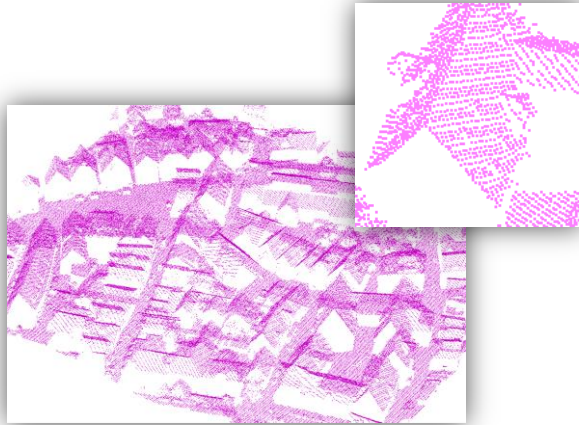


Meshes from Multi-View Stereo

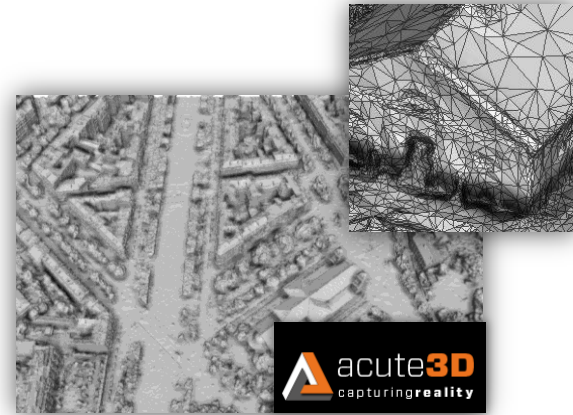


Urban scene modeling

Airborne data

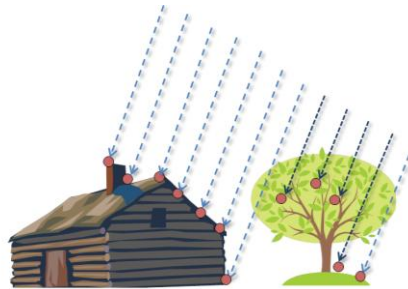


Lidar data

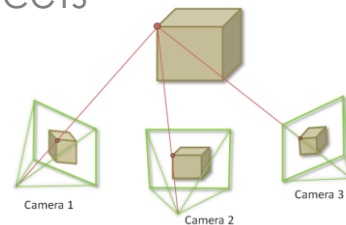


Meshes from Multi-View Stereo

- Point cloud
- Accurate
- Not dense
- Incomplete



- Mesh with triangular facets
- Complete surface
- Dense
- Potential defects



Requirements

5 criteria:

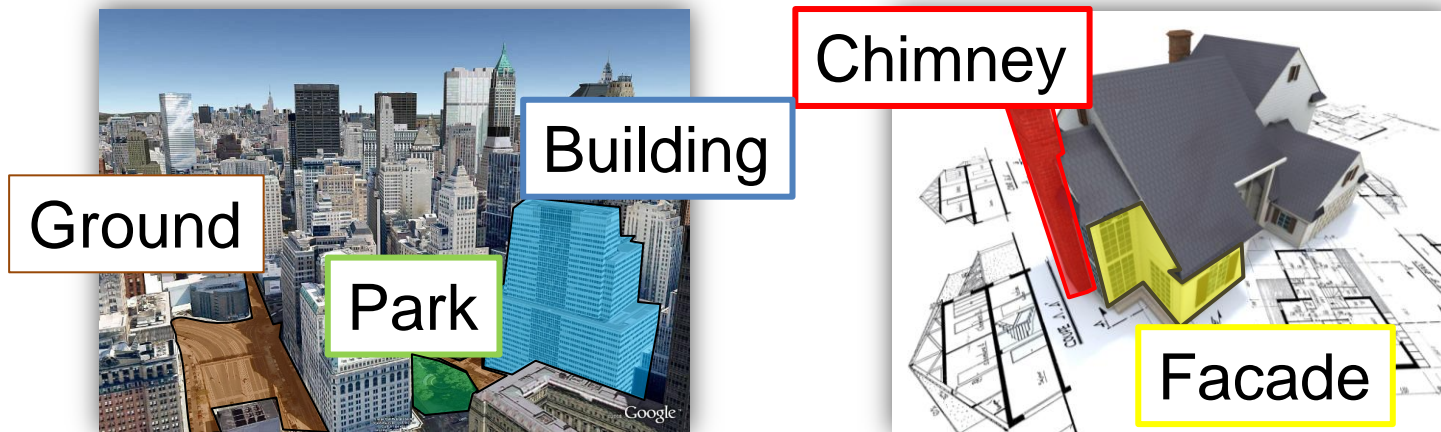
- Geometric accuracy



Requirements

5 criteria:

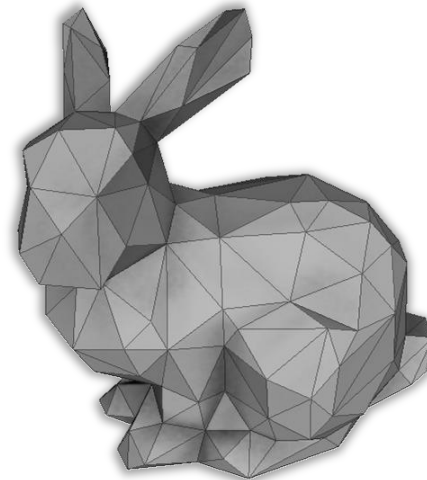
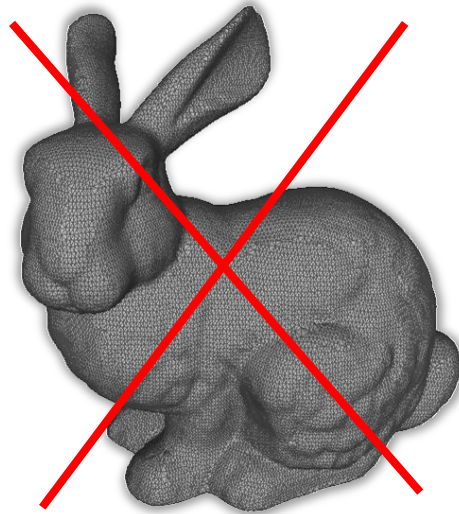
- Geometric accuracy
- Semantic-aware



Requirements

5 criteria:

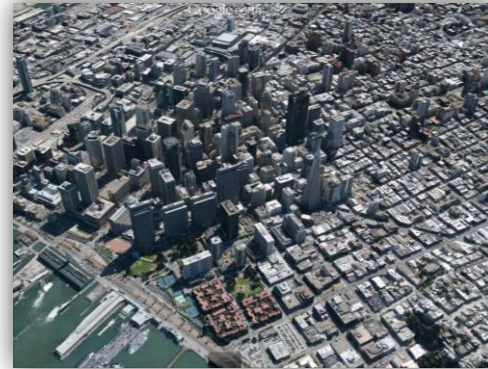
- Geometric accuracy
- Semantic-aware
- Low complexity



Requirements

5 criteria:

- Geometric accuracy
- Semantic-aware
- Low complexity
- Scalability



Size of the scene



Requirements

5 criteria:

- Geometric accuracy
- Semantic-aware
- Low complexity
- Scalability
- Automatic



Surveys

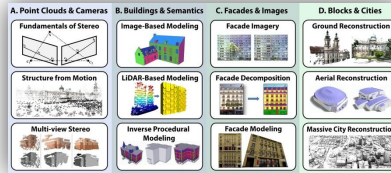
3 major surveys:

Modeling the Appearance and Behavior of Urban Spaces



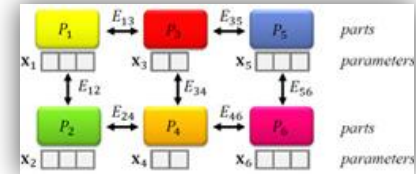
[Vanegas et al. Eurographics 09]

A survey of Urban Reconstruction



[Musialski et al. Eurographics 12]

Structure-Aware Shape Processing



[Mitra et al. Eurographics 13]

Surveys

“Modeling the Appearance and Behavior of Urban Spaces”

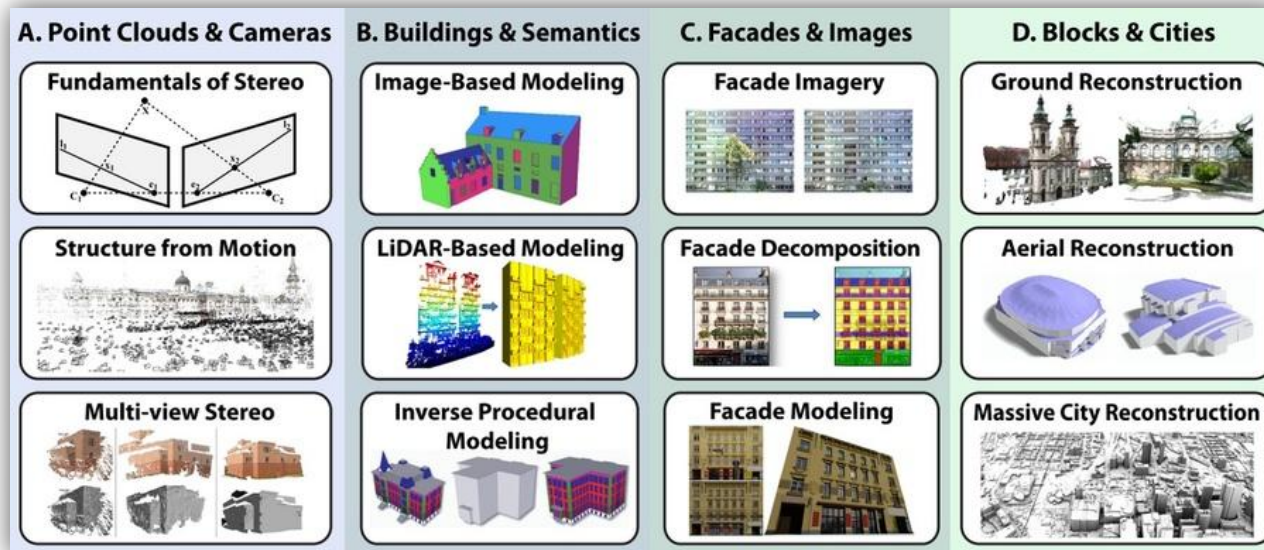


[Vanegas et al., Eurographics 09]

→ procedural modeling

Surveys

“A survey of Urban Reconstruction”

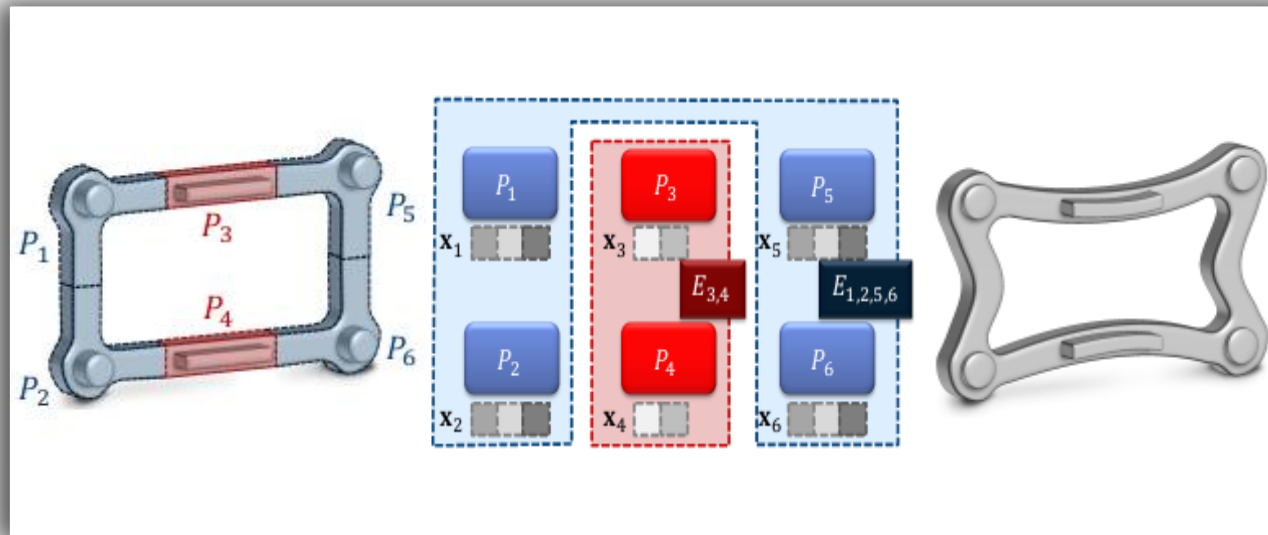


[Musialski et al., Eurographics 12]

➔ broad overview of the literature on urban reconstruction

Surveys

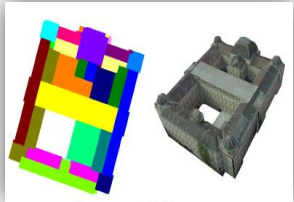
“Structure-Aware Shape Processing”



[Mitra et al., Eurographics 13]

→ structures to enhance, regularize and manipulate existing meshes

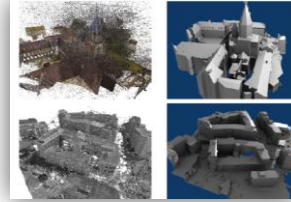
Overview of existing methods



[Zebedin et al.,
ECCV 08]



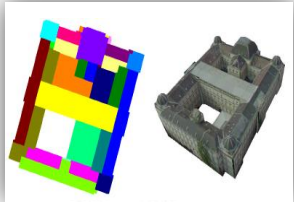
[Toshev et al.,
CVPR 09]



[Chauve et al.,
CVPR 10]

Primitive-based
building reconstruction

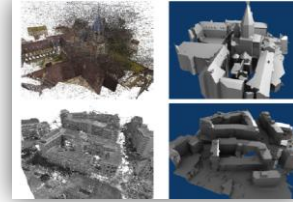
Overview of existing methods



[Zebedin et al.,
ECCV 08]



[Toshev et al.,
CVPR 09]

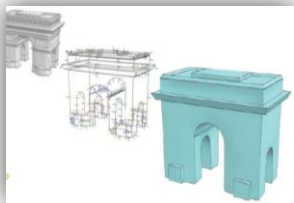


[Chauve et al.,
CVPR 10]

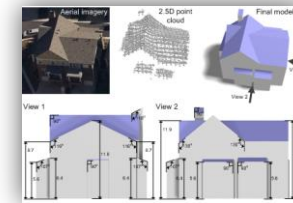
Primitive-based
building reconstruction



[Pauly et al.,
Siggraph 08]



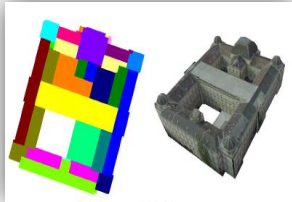
[Mehra et al.,
Siggraph Asia 09]



Zhou and Neumann,
CVPR12]

Structure-aware
building modeling

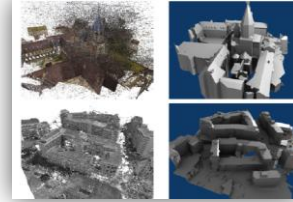
Overview of existing methods



[Zebedin et al.,
ECCV 08]



[Toshev et al.,
CVPR 09]

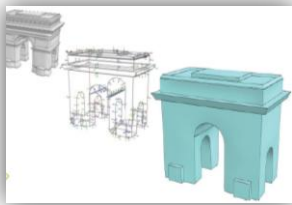


[Chauve et al.,
CVPR 10]

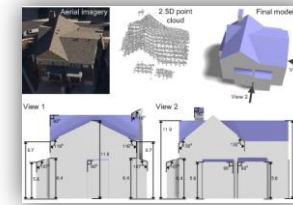
Primitive-based
building reconstruction



[Pauly et al.,
Siggraph 08]



[Mehra et al.,
Siggraph Asia 09]

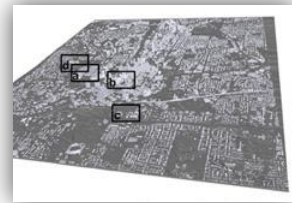


[Zhou and Neumann,
CVPR12]

Structure-aware
building modeling



[Poullis and You,
CVPR09]



[Zhou and Neumann,
CVPR09]



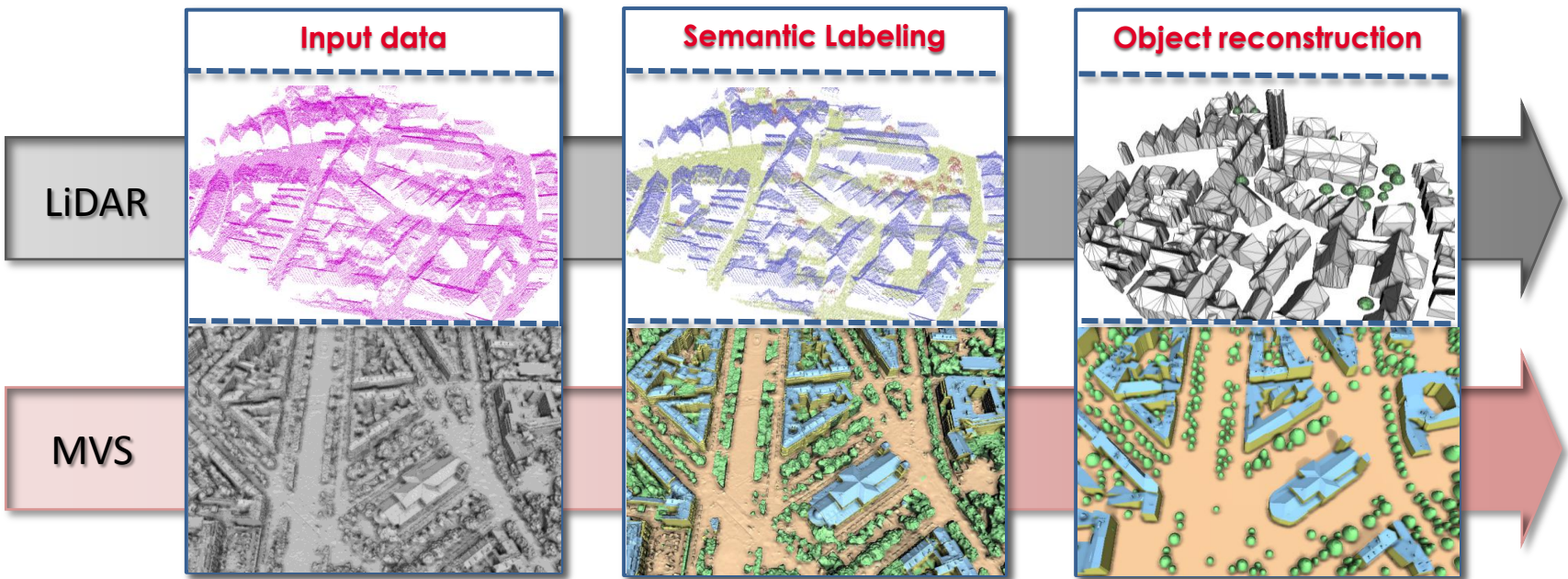
[Lafarge and Mallet,
IJCV11]

Automatic large scale
urban reconstruction

→ still many unsolved problems

Contribution

General pipelines for MVS and LiDAR data



Outline

- ① Introduction
- ② Semantic labeling
- ③ Object Reconstruction: parametric-based object detection
- ④ Object Reconstruction: mesh-based object reconstruction
- ⑤ Conclusion and future work

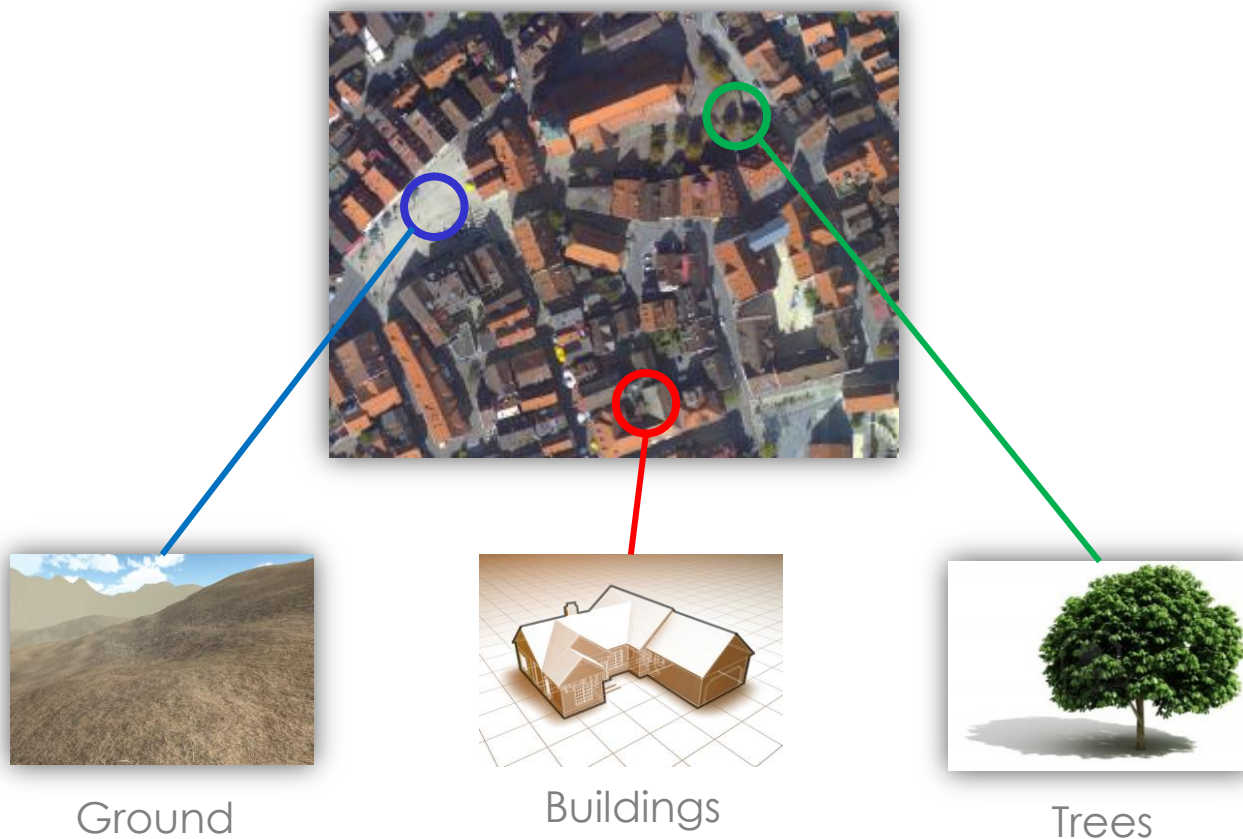
Outline

- ① Introduction
- ② **Semantic labeling**
- ③ Object Reconstruction: parametric-based object detection
- ④ Object Reconstruction: mesh-based object reconstruction
- ⑤ Conclusion and future work

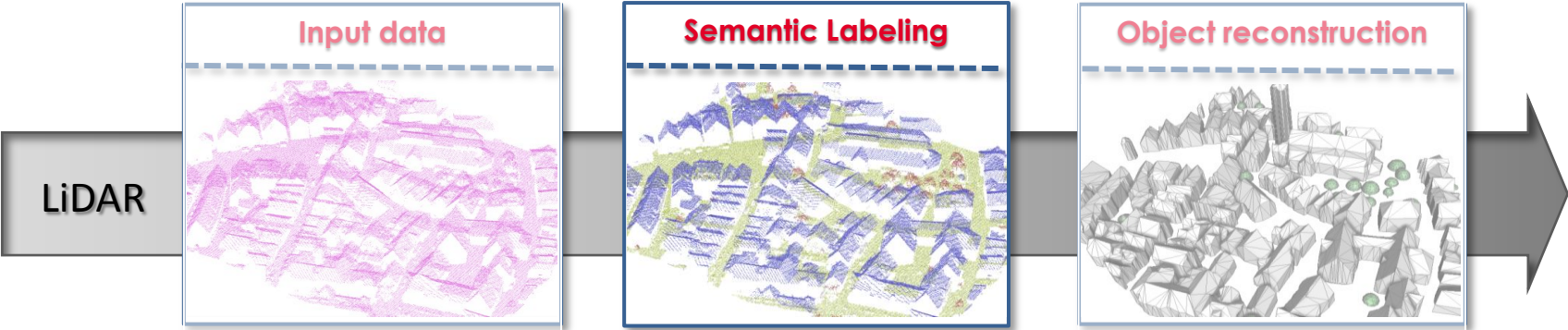
Semantic labeling

What is important ?

→ In many cases, majority of urban scenes can be explained by 3 classes of objects

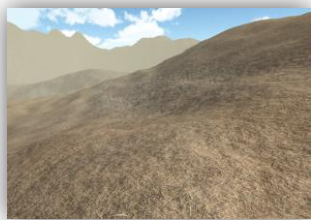


Semantic labeling for Lidar



Semantic labeling for Lidar

Classes for Lidar data



Ground



Trees



Buildings



Clutters

→ need for geometric features that discriminate the classes

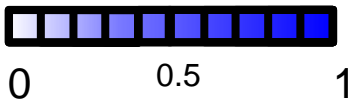
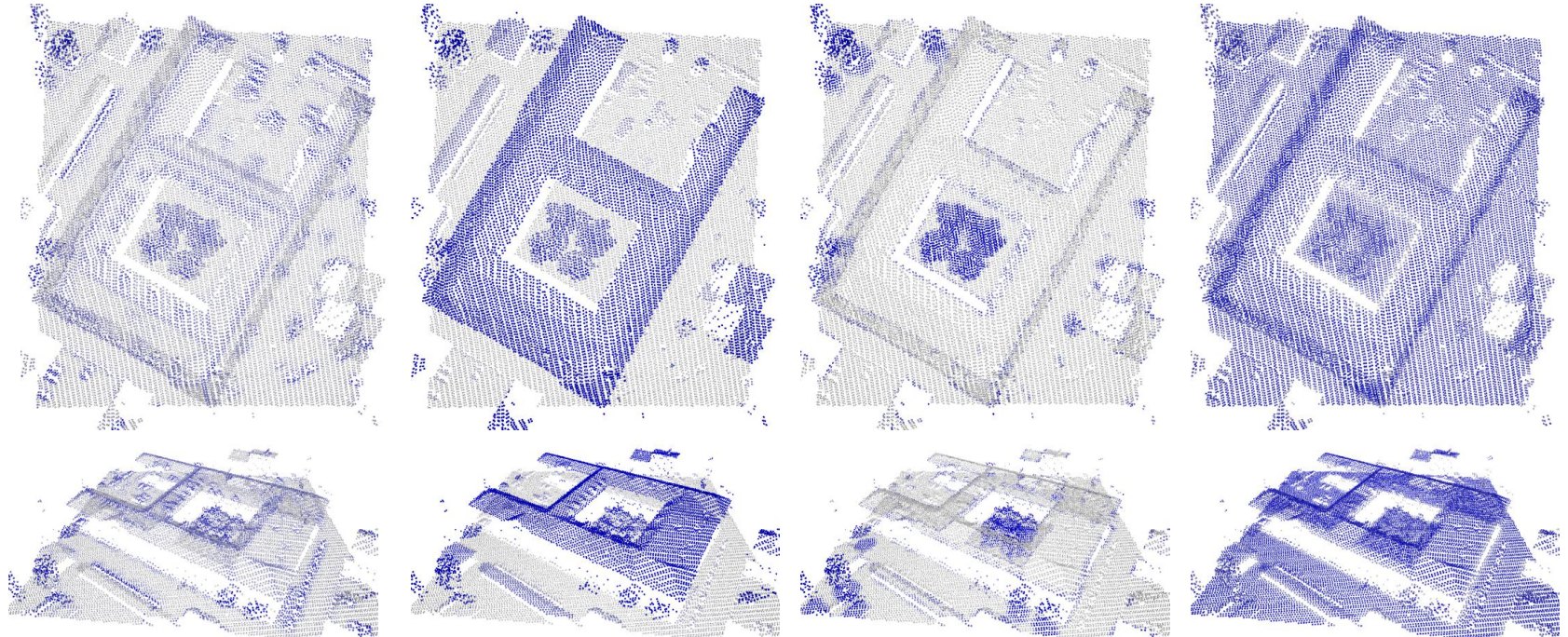
Discriminative geometric features for Lidar

Local non-planarity β_p

Elevation β_e


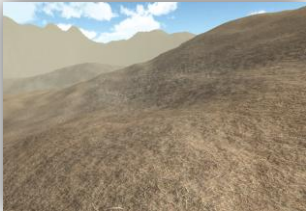


Local dispersion β_s

Local linearity β_l



→ Combine the features to discriminate the classes

Confidence functions for Lidar

Trees		High non-planarity β_p	High elevation β_e
		High local dispersion β_s	Local linearity β_l
Ground		Low non-planarity β_p	Low elevation β_e
		Low local dispersion β_s	Local linearity β_l
Buildings		Low non-planarity β_p	High elevation β_e
		Low local dispersion β_s	Local linearity β_l
Clutters		High non-planarity β_p	Elevation β_e
		High local dispersion β_s	Low local linearity β_l

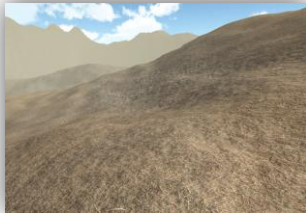
Confidence functions for Lidar

Trees



$$\arg \min_x \sum D(x_i)$$

Ground



$$D(x_i) = \begin{cases} D_{tree}(x_i) & \text{if } x_i = \text{tree} \\ D_{ground}(x_i) & \text{if } x_i = \text{ground} \\ D_{building}(x_i) & \text{if } x_i = \text{building} \\ D_{clutter}(x_i) & \text{if } x_i = \text{clutter} \end{cases}$$

Buildings



Clutters



→ Need for spatial consistency

Energy minimization over a Markov Random Field

$$U(x) = \sum D(x_i) + \lambda \sum_{\{i,j\} \in E} V_{ij}(x_i, x_j)$$

$$D(x_i) = \begin{cases} D_{tree}(x_i) & \text{if } x_i = tree \\ D_{ground}(x_i) & \text{if } x_i = ground \\ D_{building}(x_i) & \text{if } x_i = building \\ D_{clutter}(x_i) & \text{if } x_i = clutter \end{cases}$$

Potts model:

$$V_{ij}(x_i, x_j) = \delta(x_i \neq x_j)$$

Spherical neighborhood such as

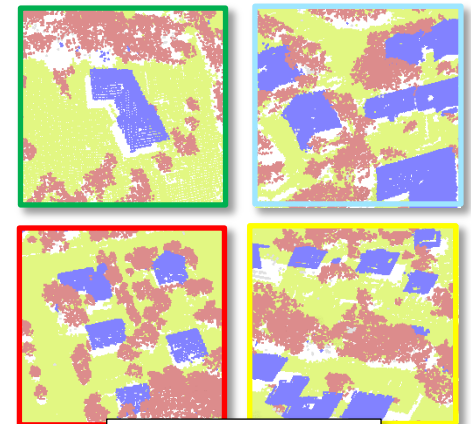
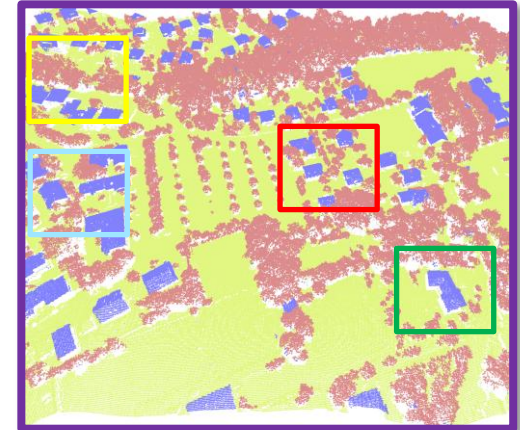
$$\{i, j\} \in E \Leftrightarrow \|i - j\|_2 < r$$

→ Optimisation with graph-cut and alpha-beta swap
[Boykov et al, PAMI 2001]

Semantic labeling for Lidar data

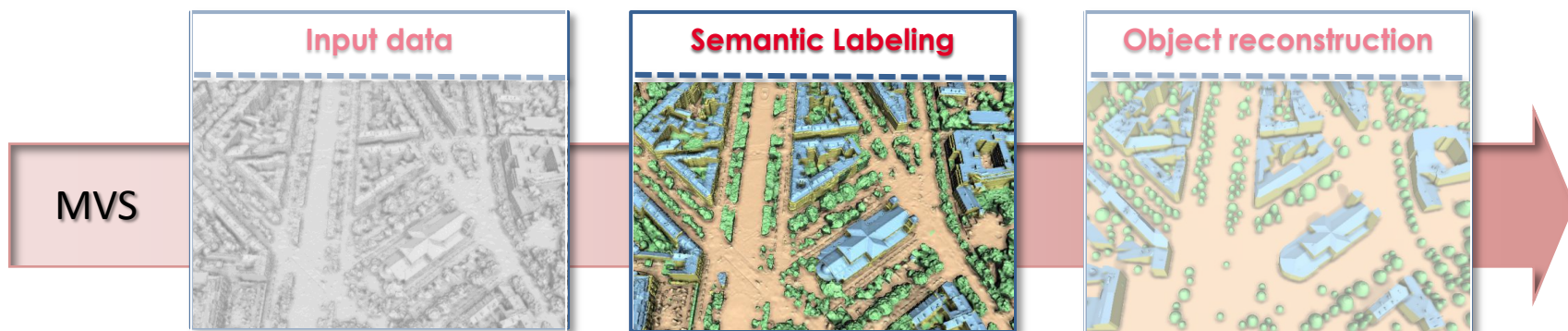


Visual reference from Google map



Close-up

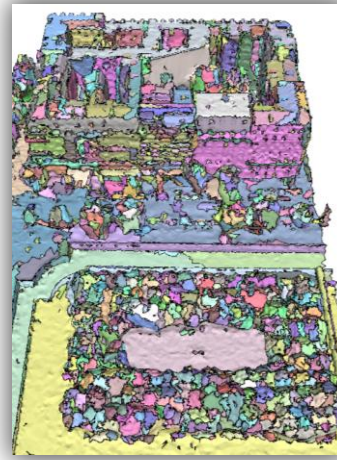
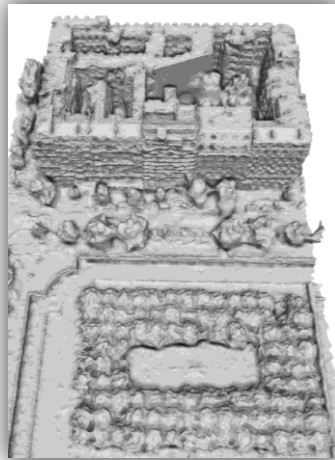
Semantic labeling for MVS



Semantic labeling for MVS

Difference with semantic labeling for Lidar data

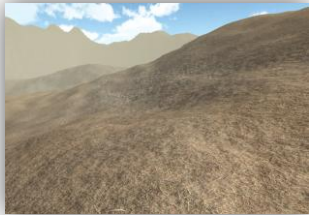
- **Regroup facets into "f-clusters"**
 - Tractable
 - Enforce local coherency



Semantic labeling for MVS

Difference with semantic labeling for Lidar data

- Compute f-clusters
- **Building class splits in two sub-classes**



Ground



Trees



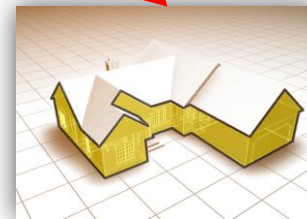
Buildings



Clutters



Roofs



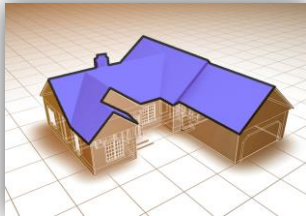
Facades

Semantic labeling for MVS

Difference with semantic labeling for Lidar data

- Compute f-clusters
- **Building class splits in two sub-classes**

Roofs

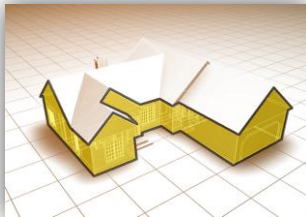


Low non-planarity β_p

High elevation β_e

Low verticality β_v

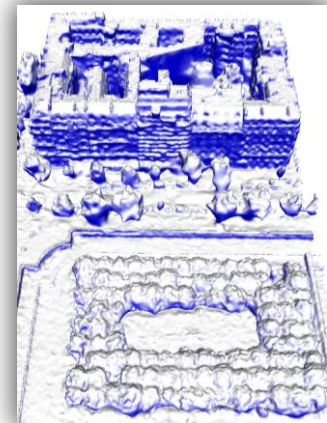
Facades



Low non-planarity β_p

High verticality β_v

Verticality β_v



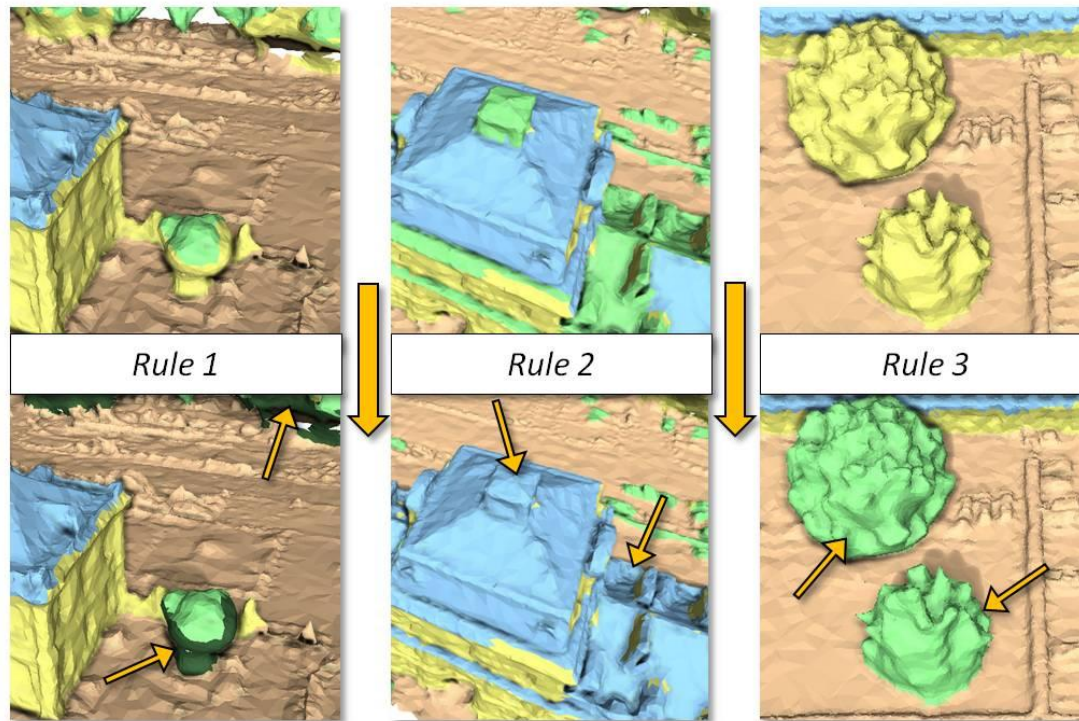
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Semantic labeling for MVS

Difference with semantic labeling for Lidar data

- Compute f-clusters
- *Building* class splits in two sub-classes
- **Correction rules**



Semantic labeling

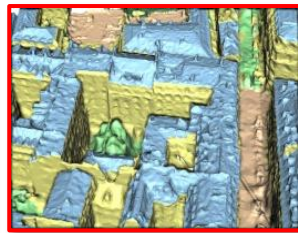
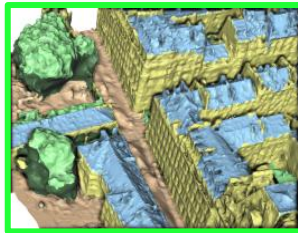
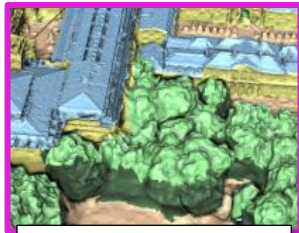
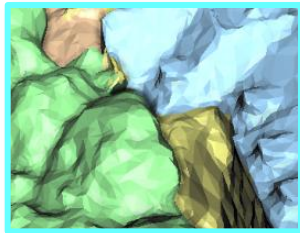


- Roof
- Facade
- Vegetation
- Ground

MVS data



Classification

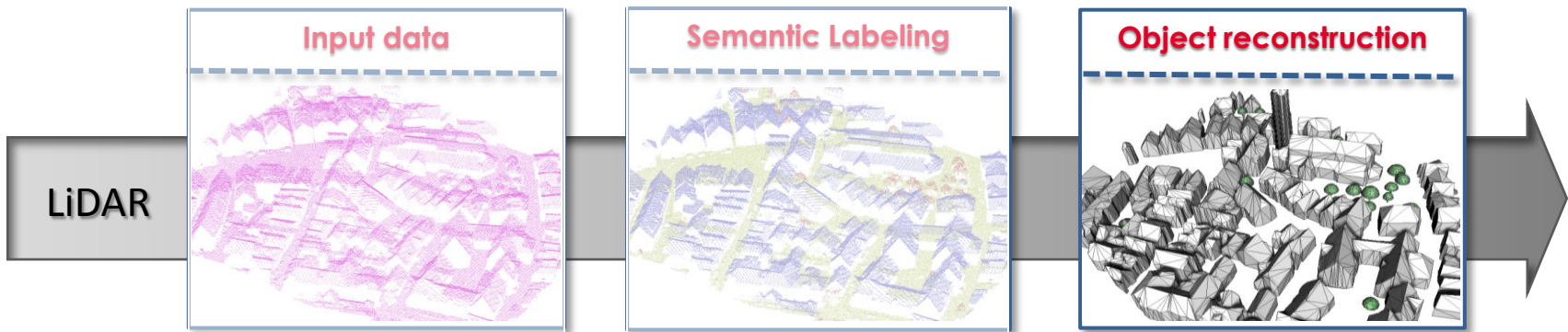


Close-up

Outline

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- ② Semantic labeling
- ③ **Object Reconstruction: parametric-based object detection**
- ④ Object Reconstruction: mesh-based object reconstruction
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Object Reconstruction for Lidar



➔ Focus on tree detection and reconstruction from Lidar

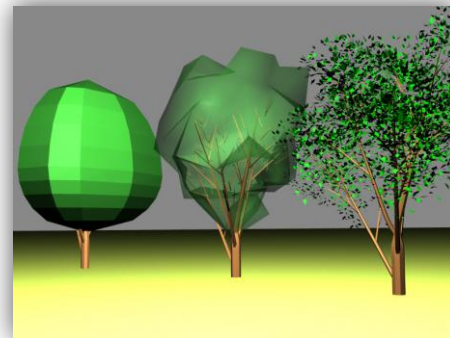
Parametric-based object detection

Objective:

- Localize and reconstruct simple objects



Buildings are too complex structures



Trees can be approximated by simple shapes

Parametric-based object detection

Objective:

- Localize and reconstruct simple objects
- Detection in large scenes



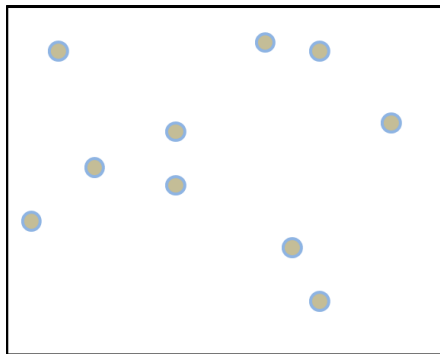
Thousands of simple objects (e.g. trees) are in the scene

→ Use Marked Point Processes (MPP)

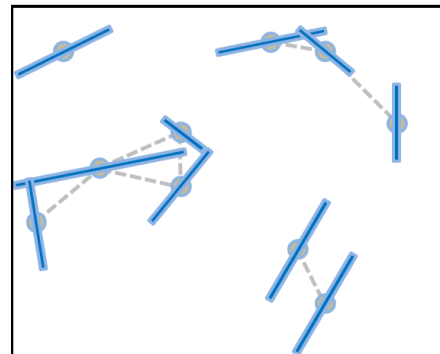
Marked Point Processes

Preliminary:

- A point process describes random configurations of points (of unknown size) in a continuous bounded set K .
- A marked point process is a point process where each point is associated with a parametric objects.



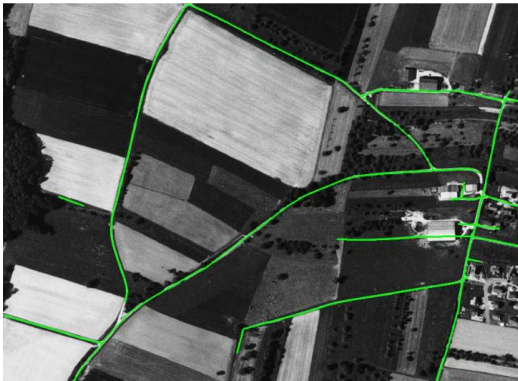
Point process



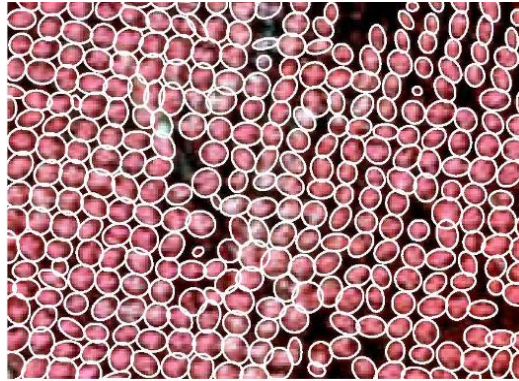
Marked Point Process
of 2D segments

Marked Point Processes

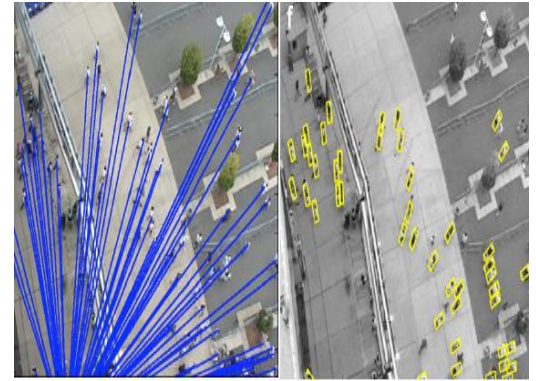
Previous work:



[Lacoste et al., PAMI05]

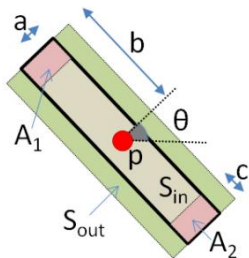


[Perrin et al., EMMCVPR05]

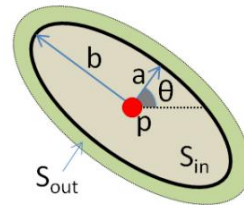


[Ge et al., CVPR09]

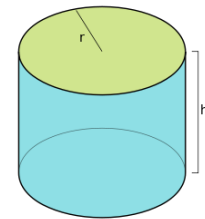
Line-segment



Ellipse



Cylinder



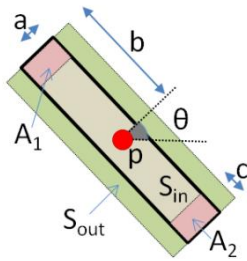
Marked Point Processes

Requirements:

1) Simple parametric objects

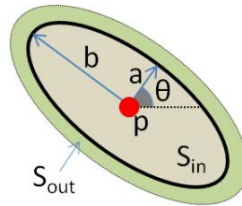
➔ Object characterized by a limited number of parameters

Line-segment



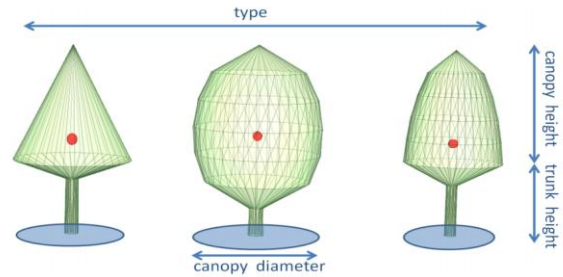
5 parameters

Ellipse



5 parameters

Cone, Ellipsoid, Semi-ellipsoid



7 parameters

Marked Point Processes

Requirements:

1) Simple parametric objects

2) Energy measuring the quality of a configuration of objects

Standard form of energy:

$$\forall \mathbf{x} \in \mathcal{S}, U(\mathbf{x}) = \sum_{p_i \in \mathbf{x}} D(p_i) + \sum_{p_i \sim p_j} V(p_i, p_j)$$

with \sim the symmetric neighborhood relationship such as:

$$p_i \sim p_j = \{(p_i, p_j) \in \mathbf{x}^2 : i > j, \|p_i - p_j\|_2 < \epsilon\}$$

Marked Point Processes

Requirements:

1) Simple parametric objects

2) Energy

3) Minimization method

- Unknown number of objects
- Minimize non-convex energy

→ Use Reversible-Jump Monte Carlo Markov Chain (RJ-MCMC)
[Green 1995]

Optimization method

RJ-MCMC:

- Sequential algorithm with a two-step update mechanism
 - a) Proposition step
 - New configuration is proposed from a proposal density (kernel)
 - New configuration must be close to the current one
 - b) Acceptance step depending on
 - Random variable
 - Energy variation
 - Stochastic relaxation

Optimization method

RJ-MCMC:

- Sequential algorithm with a two-step update mechanism
 - a) Proposition step
 - New configuration is proposed from a proposal density (kernel)
 - New configuration must be close to the current one (**local perturbation**)
 - b) Acceptance step depending on
 - Random variable
 - Energy variation
 - Stochastic relaxation

Slow in practice

➔ Focus on improving performance of RJ-MCMC

Marked Point Processes

Requirements:

1) Simple parametric objects

2) Energy

3) Minimization method

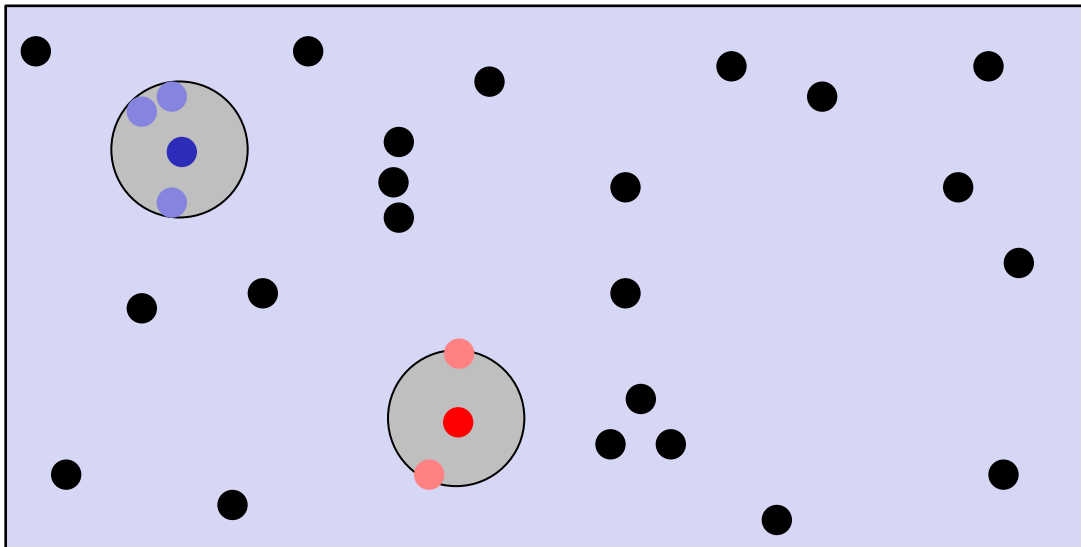
- unknown number of objects
- minimize non-convex energy

Novel optimization method based on RJ-MCMC

- Exploit two properties for a faster optimization
- Exploit GPU capability

(1) Parallelization

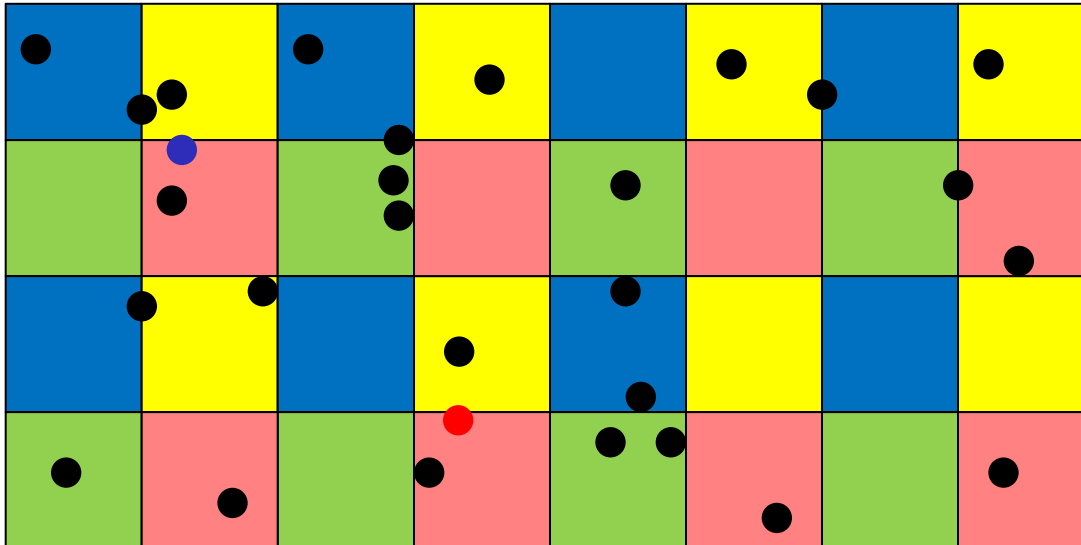
The Markovian property in the energy: $\Pr(x_i | x) = \Pr(x_i | x_{N(i)})$



→ the blue object and the red object can be updated by MCMC **at the same time.**

(1) Parallelization

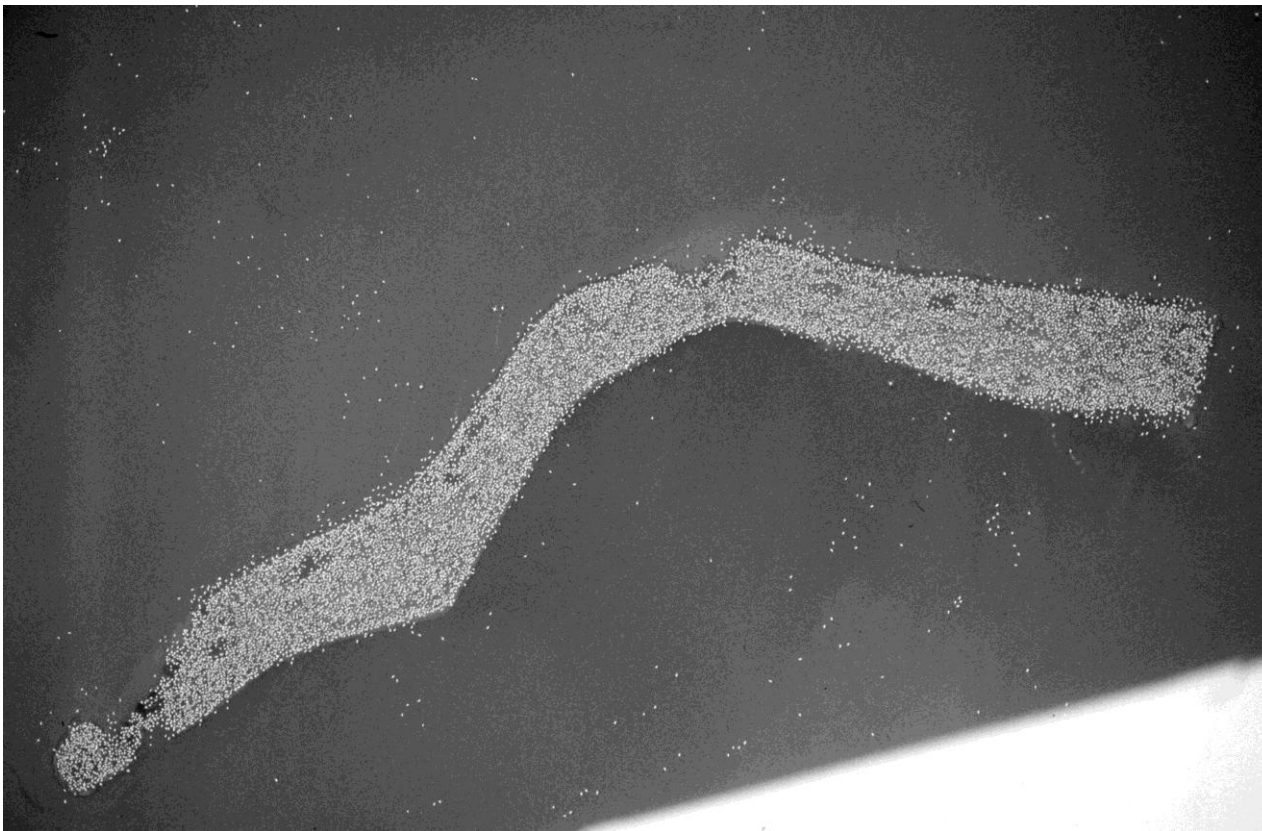
- 4-cell subdivision scheme generates 4 mic-sets {    }.
(cell width=diameter of the neighborhood relation+maximal length of a move)



- Mic-Set: a set of Mutually Independant Cells

(2) Non-uniform point densities

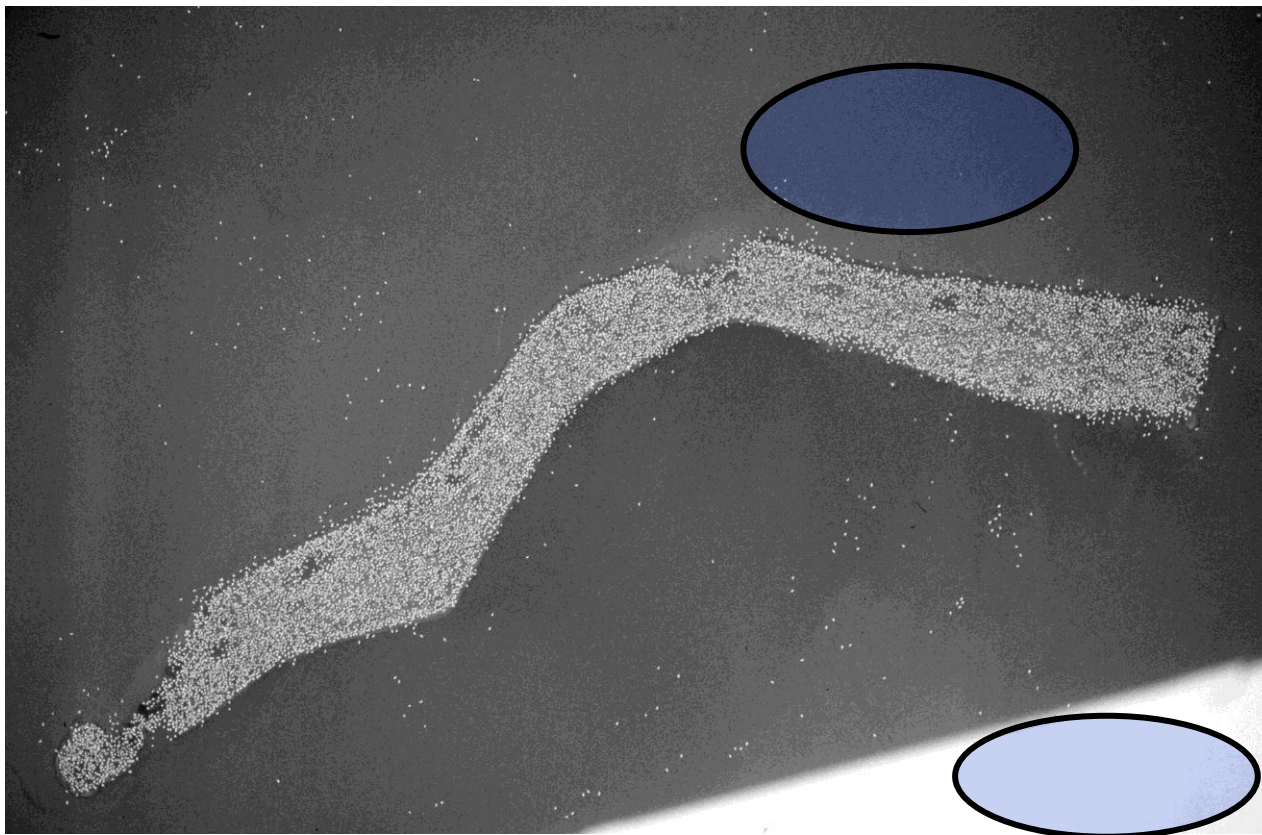
How many Birds ?



(2) Non-uniform point densities

How many Birds ?

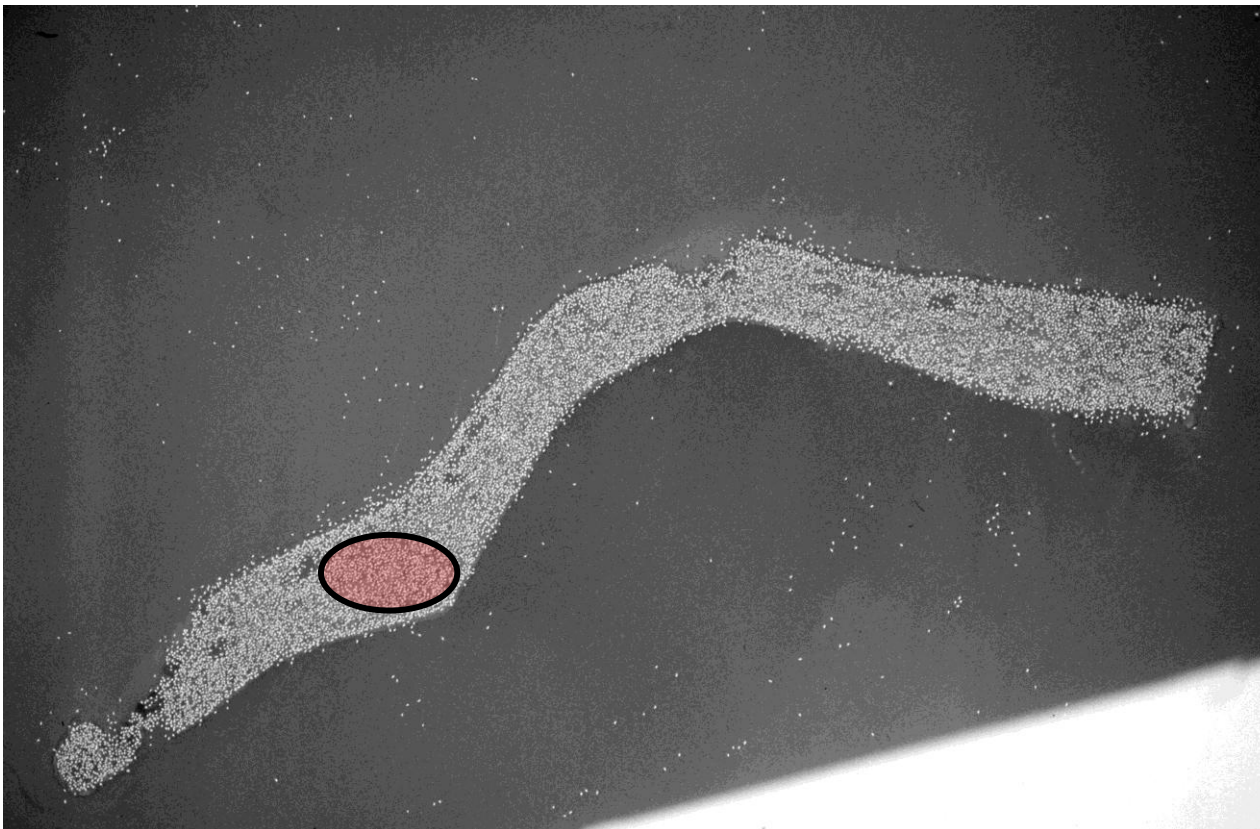
Low probability



(2) Non-uniform point densities

How many Birds ?

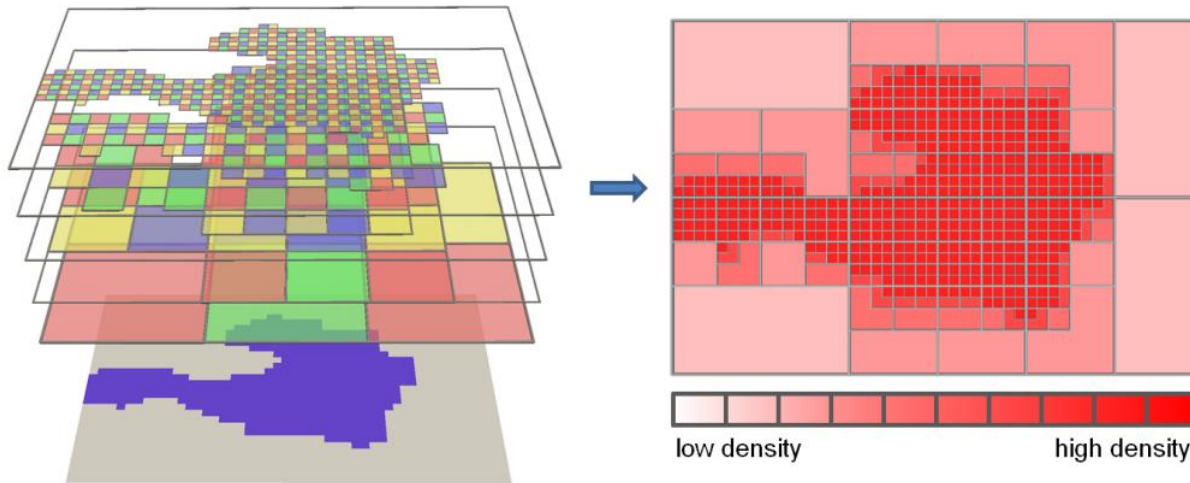
High probability



(2) Non-uniform point densities

We proposed

- quadtree data partitioning for 2D space.
- octree data partitioning for 3D space.



➔ Compatible with the parallelization scheme (1)

Novel optimization method

1-Initialize $X_0 = \mathbf{x}_0$ and T_0 at $t = 0$;

2-Compute a space-partitioning tree \mathcal{K} ;

3-At iteration t , with $X_t = \mathbf{x}$,

- ▶ Choose a mic-set $S_{mic} \in \mathcal{K}$ and a kernel type $t \in \mathcal{T}$ according to probability $\sum_{c \in S_{mic}} p_{c,t}$

- ▶ For each cell $c \in S_{mic}$,

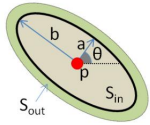
- ▶ Perturb \mathbf{x} in the cell c to a configuration \mathbf{y} according to $Q_{c,t}(\mathbf{x} \rightarrow \cdot)$
- ▶ Calculate the Green ratio

$$R = \frac{Q_{c,t}(\mathbf{y} \rightarrow \mathbf{x})}{Q_{c,t}(\mathbf{x} \rightarrow \mathbf{y})} \exp\left(\frac{U(\mathbf{x}) - U(\mathbf{y})}{T_t}\right)$$

- ▶ Choose $X_{t+1} = \mathbf{y}$ with probability $\min(1, R)$, and $X_{t+1} = \mathbf{x}$ otherwise

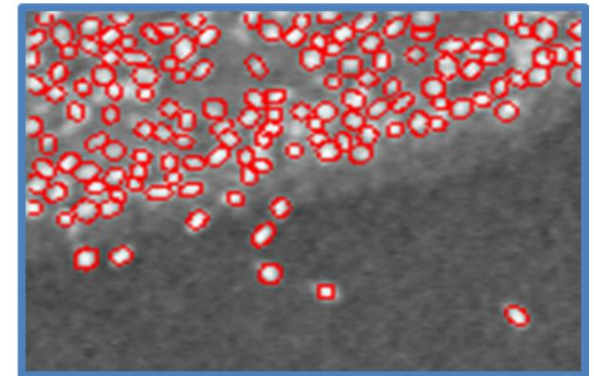
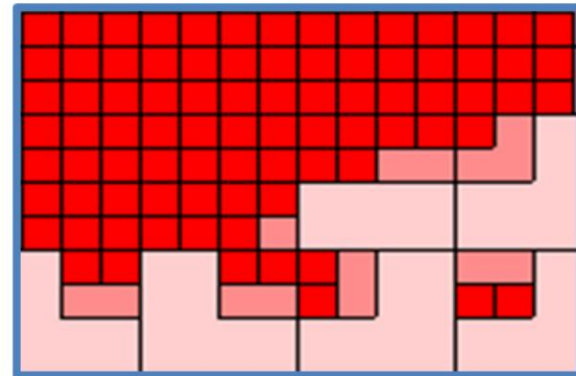
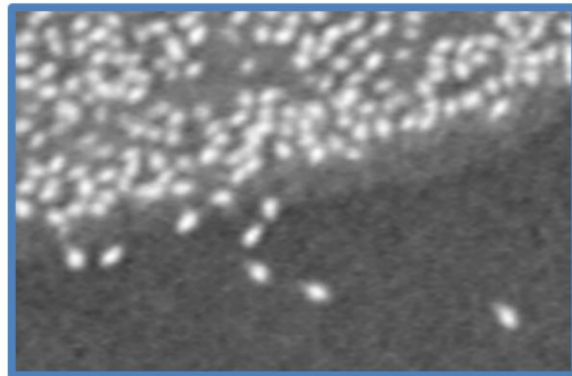
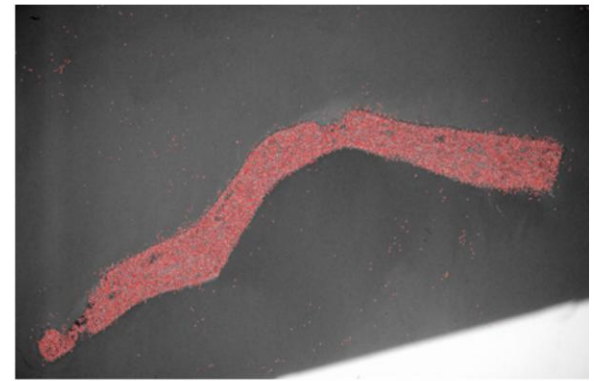
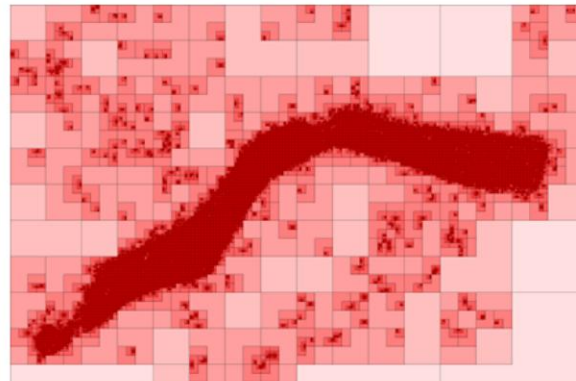
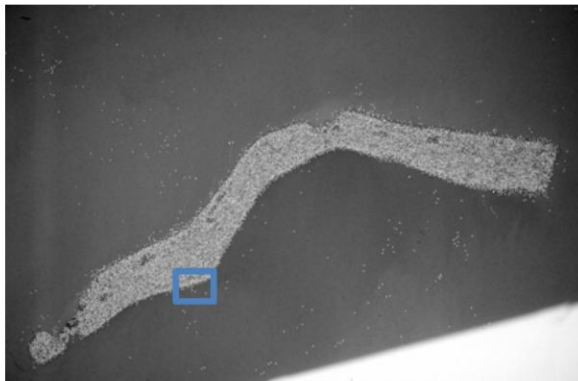
Proposition step

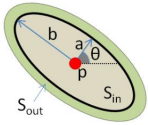
Acceptance step



2D Ellipsoidal objects

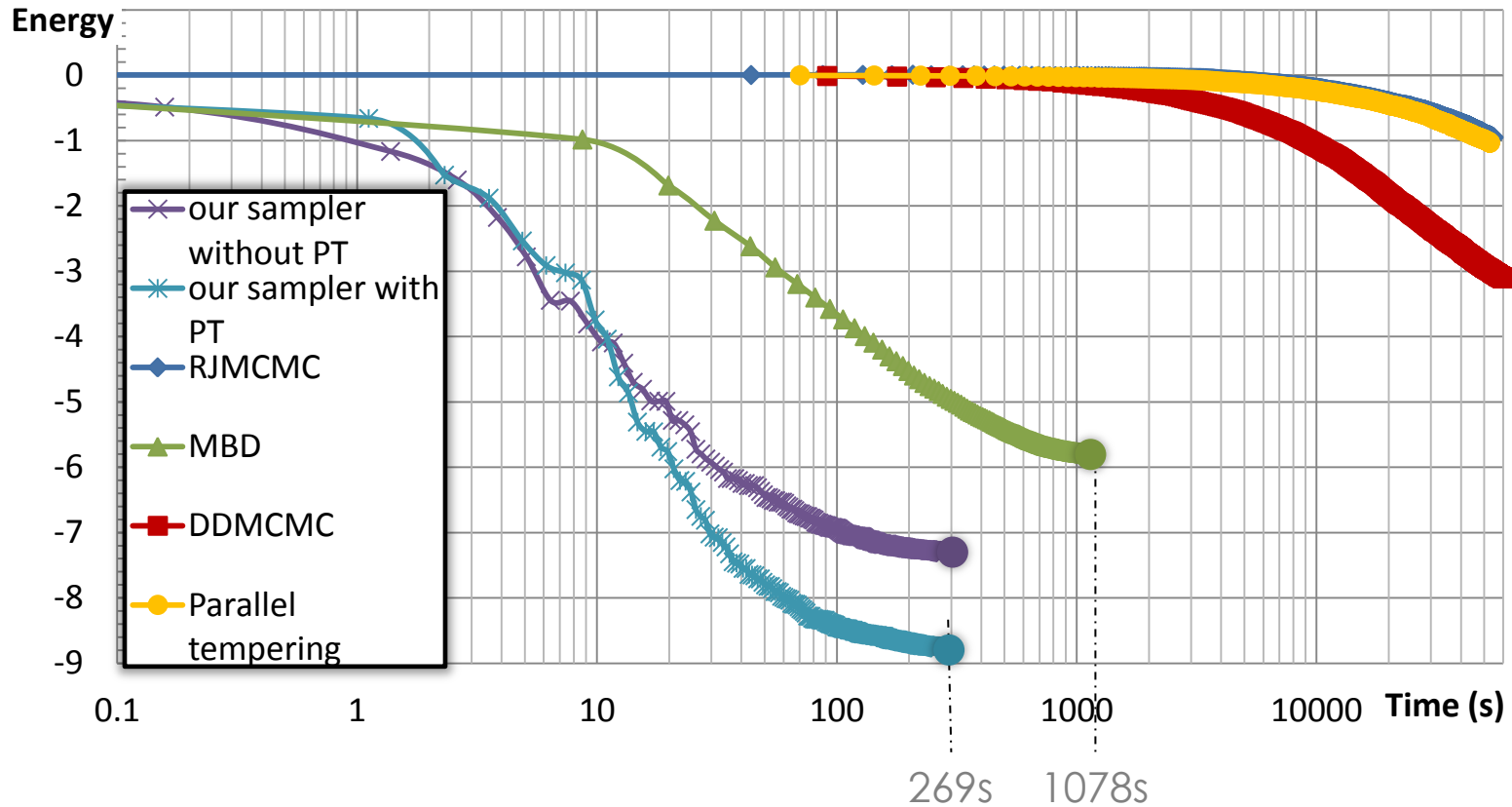
10800 objects detected, 269 sec (image size: 8Mpixels)

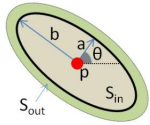




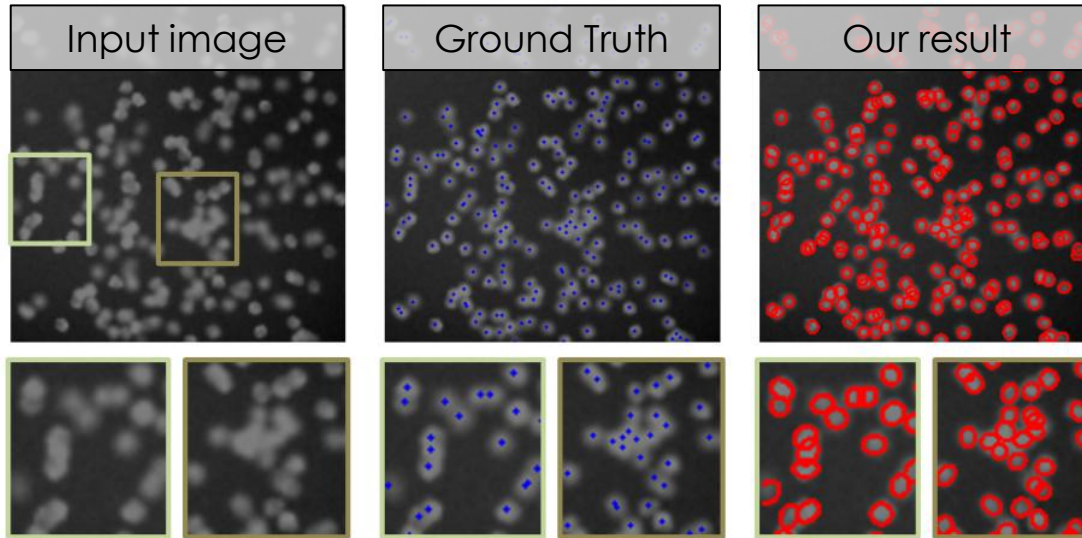
2D Ellipsoidal objects

Time to converge



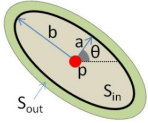


[Lempitsky and Zisserman, NIPS2010]

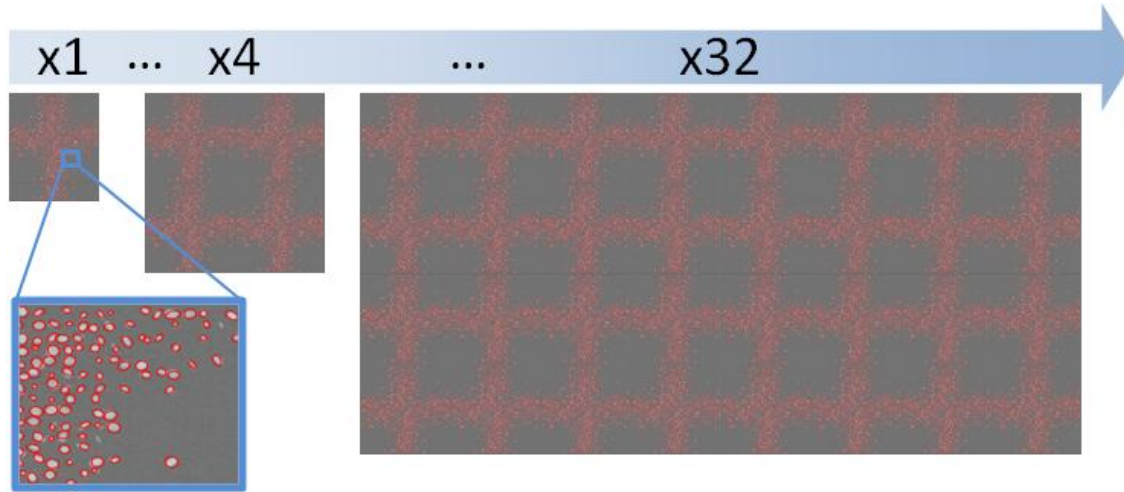


	our method	Lempitsky ($L1$ -reg.)	Lempitsky (Tikhonov-reg.)	Ground Truth
<i>cell17</i>	209	202.9	194.1	213
<i>cell18</i>	184	184.6	175.9	185
<i>cell19</i>	187	192.2	180.1	188
<i>cell20</i>	169	174.1	170.4	169
<i>cell21</i>	147	148.6	144.4	149
<i>cell22</i>	184	182.6	176.5	184
<i>cell23</i>	159	158.3	157.6	161
RMSE	1.93	4.71	9.21	-

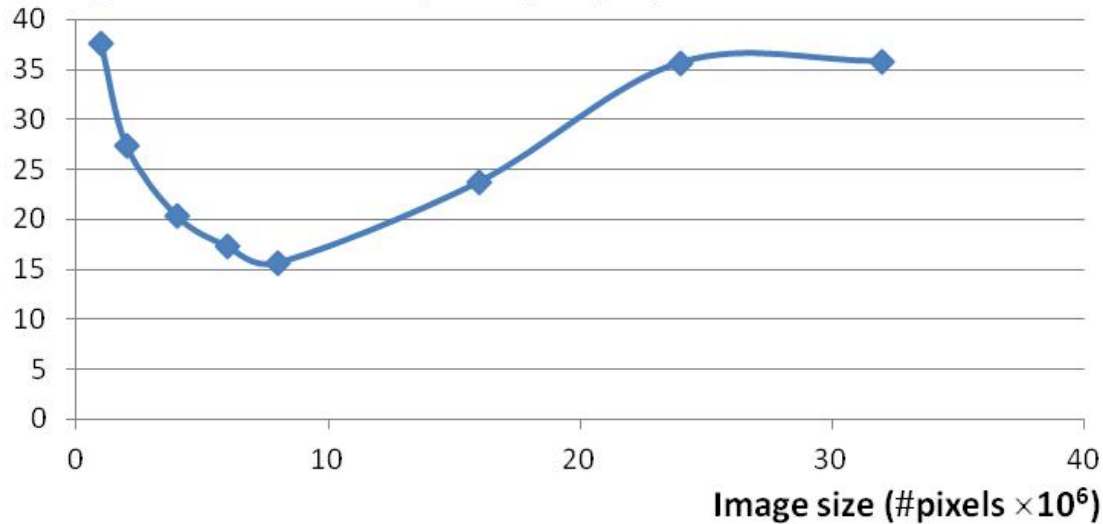
Ellipse



GPU occupancy



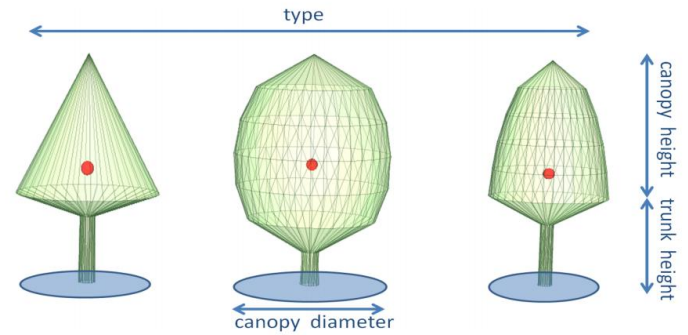
Average time of detection per object (ms)





3D Objects

- Three parametric objects
 - 7 parameters



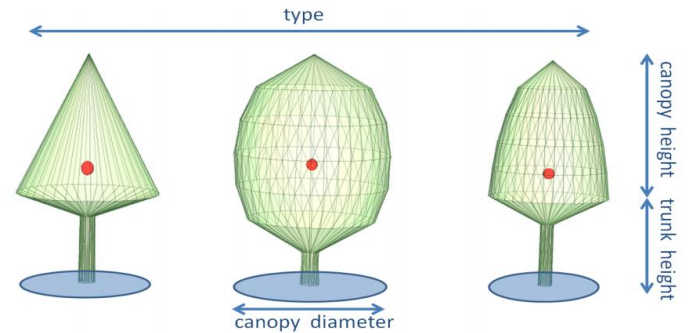


3D Objects

- Three parametric objects
- New energy formulation

$$D(x_i) = \frac{1}{|\mathcal{C}x_i|} \prod_{p_c \in \mathcal{C}x_i} \gamma(d(p_c, \partial x_i))$$

$$V(x_i, x_j) = \beta_1 V_{\text{overlap}}(x_i, x_j) + \beta_2 V_{\text{competition}}(x_i, x_j)$$



$d(p_c, \partial x_i)$ is a distance measuring the coherence of the point p_c with respect to the object surface ∂x_i

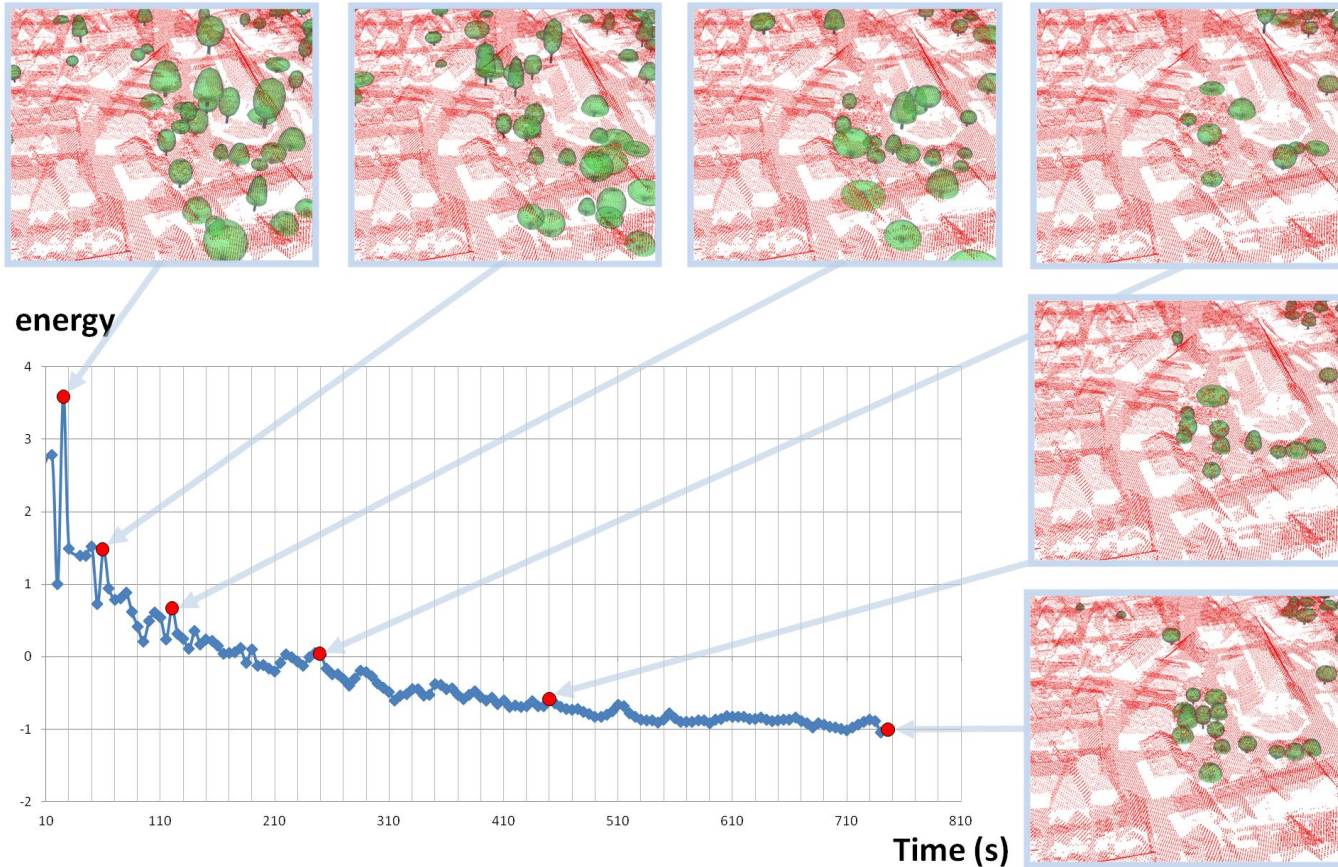
penalizes the overlapping between objects

favors area with similar type of objects



3D Objects

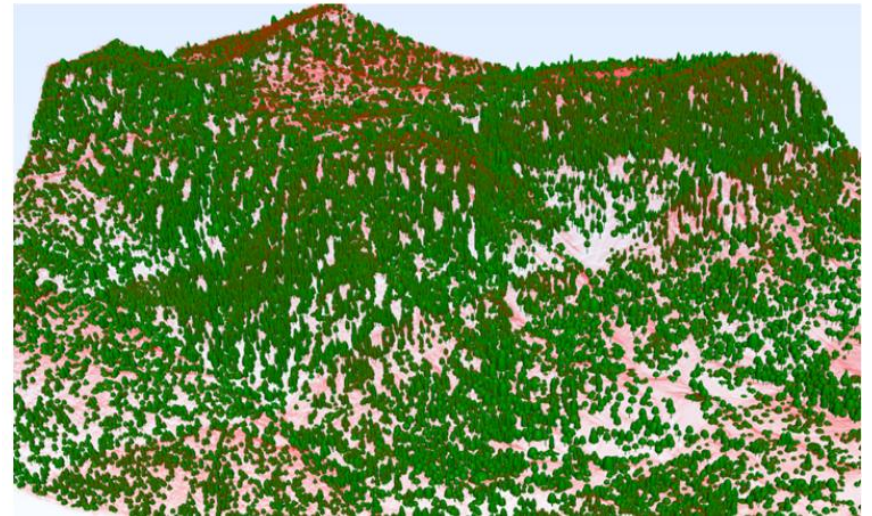
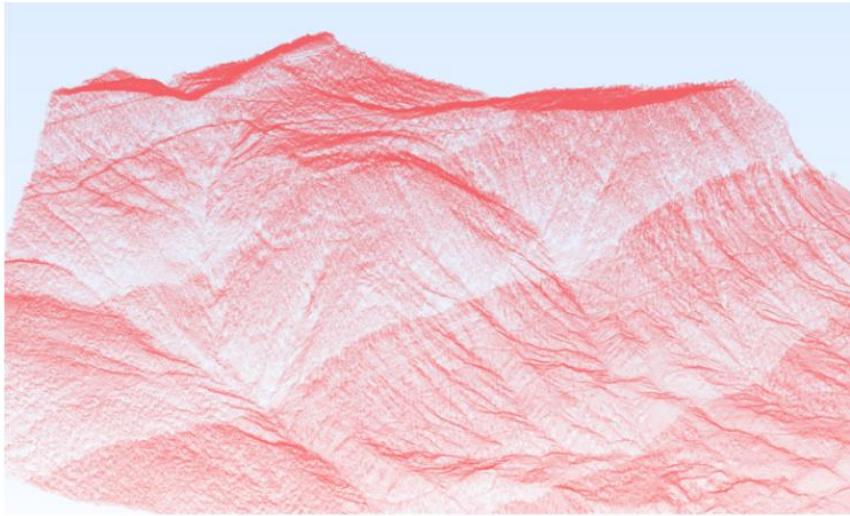
Evolution of the configuration





3D Objects

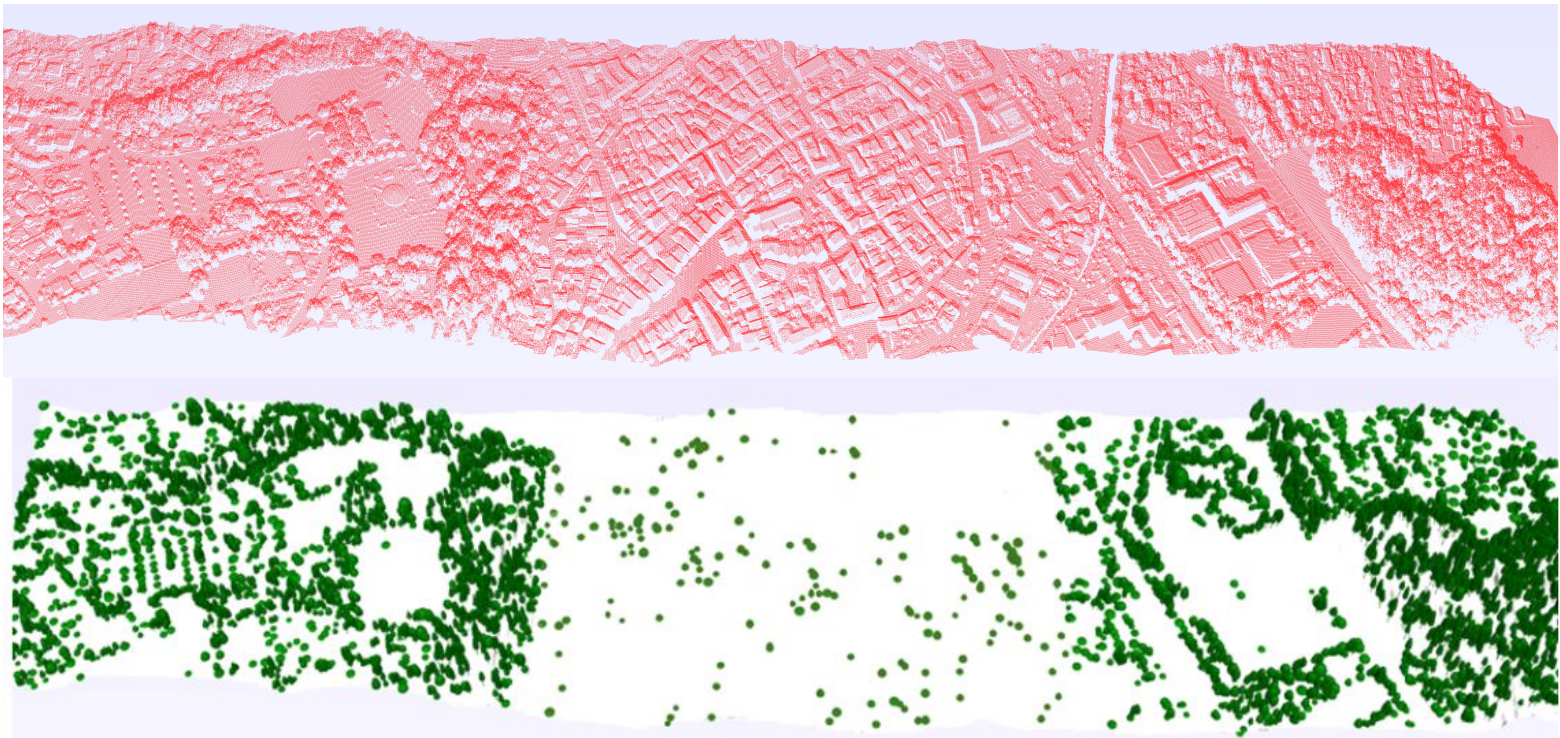
30k trees in 96min (3.7km² / 12.8M points)





3D Objects

5 .4k trees in 53min (1km² / 2.3M points)





3D Objects

Details on cropped area

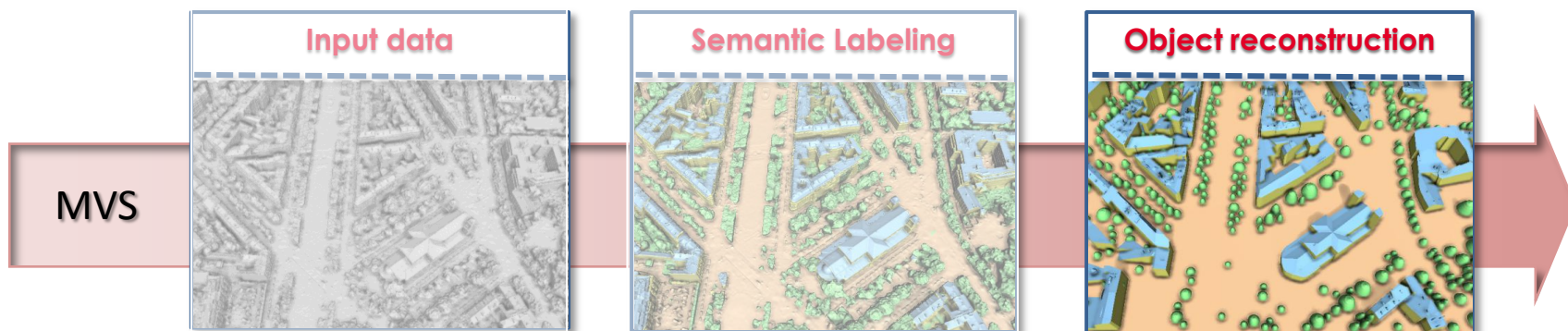


Visual reference from Google map

Outline

- ① Introduction
- ② Semantic labeling
- ③ Object Reconstruction: parametric-based object detection
- ④ **Object Reconstruction: mesh-based object reconstruction**
- ⑤ Conclusion and future work

Mesh-based object reconstruction

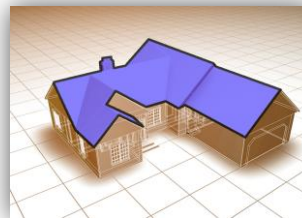


➔ Focus on the building reconstruction from MVS

Facades



Roofs



Contributions on building reconstruction from MVS

We propose

- **Multiple Level of Details (LOD)**
 - Definition of the City Geography Markup Language

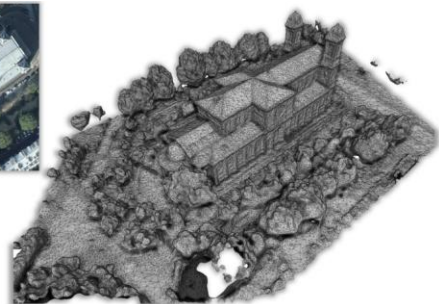
LOD1 – Building as “blocks model, without any roof structures or textures”

LOD2 – Building with “differentiated roof structures”

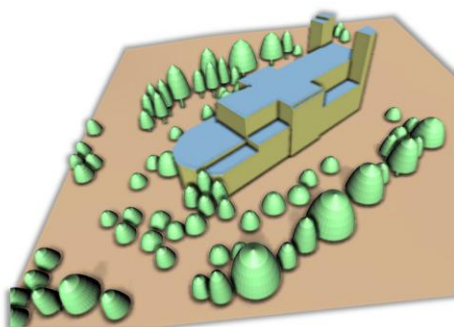
LOD3 – Building as “architectural model with detailed wall and roof structures”

[Kolbe et al., 2005]

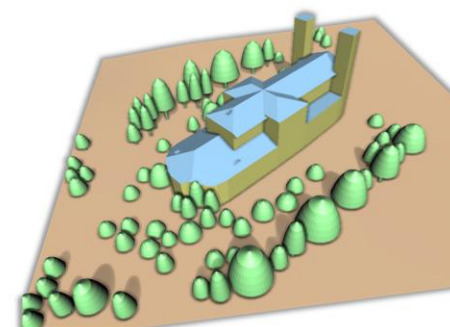
- Visually more appealing
- More adapted to certain urban applications



original



LOD1



LOD3

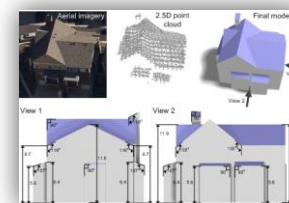
Contributions on building reconstruction from MVS

We propose

- Multiple Level of Details (LOD)
- **Efficient plane regularization**
 - Predominant in urban environment
 - Support the LOD scheme
 - Efficient on large scale

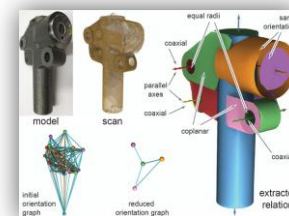
➔ Existing solutions un-adapted:
accurate but too slow for our application

Global regularities



[Zhou and Neumann, CVPR12]

GLOBFIT

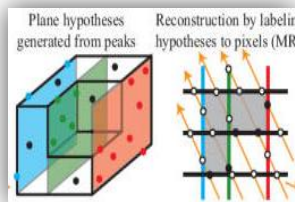


[Li et al., Siggraph11]

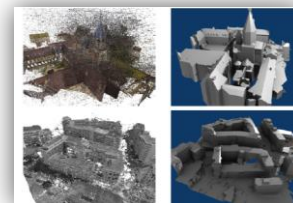
Contributions on building reconstruction from MVS

We propose

- Multiple Level of Details (LOD)
- Efficient plane regularization
- **Efficient Binary Space Partitioning (BSP)**
 - Exact geometry for BSP is costly (slow)



[Furukawa et al.,
CVPR 09]



[Chauve et al.,
CVPR 10]

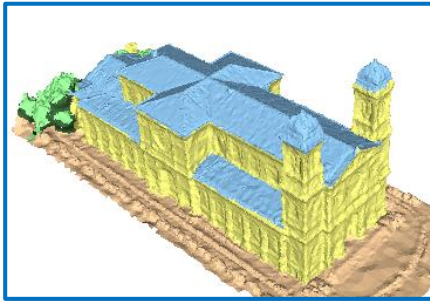
→ use a new discrete formulation

Contributions on building reconstruction from MVS

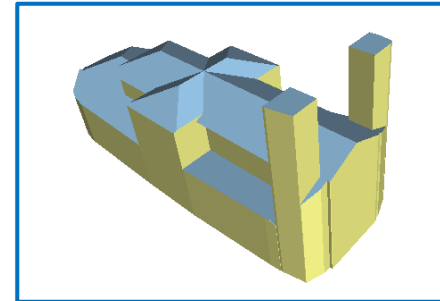
We propose

- Multiple Level of Details (LOD)
- Efficient plane regularization
- **Efficient Binary Space Partitioning (BSP)**
 - Advantages:
 - ➔ reconstruct with exact geometry only a subset of cells
 - ➔ the plane regularization limits the number of different planes (lower BSP complexity)

Building reconstruction from MVS data

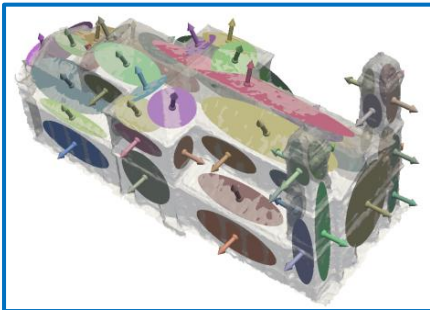


Labeling

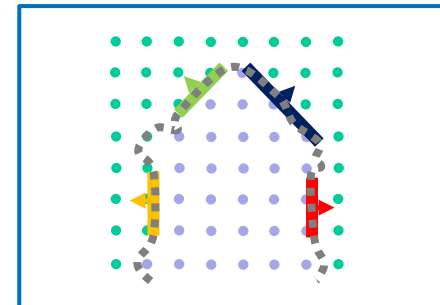


Surface extraction

Plane hypothesis from roof and facade f-clusters



Plane regularization



Discrete space partitioning

Building reconstruction from MVS data

Plane regularization:

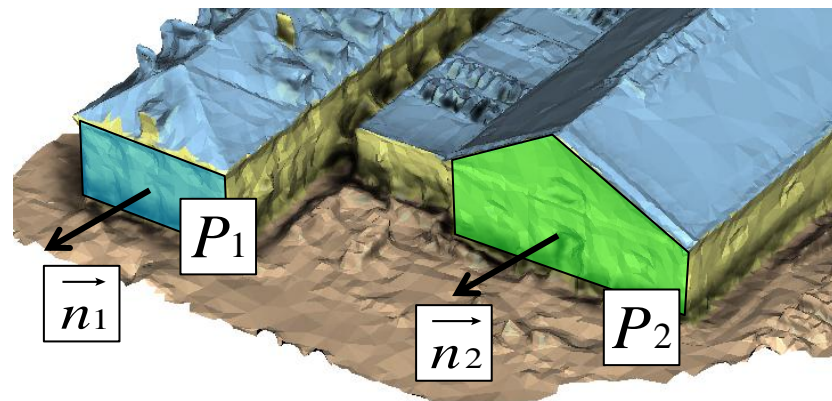
- 4 pairwise relationships controlled with two parameters ε and d

Building reconstruction from MVS data

Plane regularization:

- 4 pairwise relationships controlled with two parameters ε and d
 - **Parallelism**

P_1 and P_2 are ε -parallel if $|\mathbf{n}_1 \cdot \mathbf{n}_2| \geq 1 - \varepsilon$

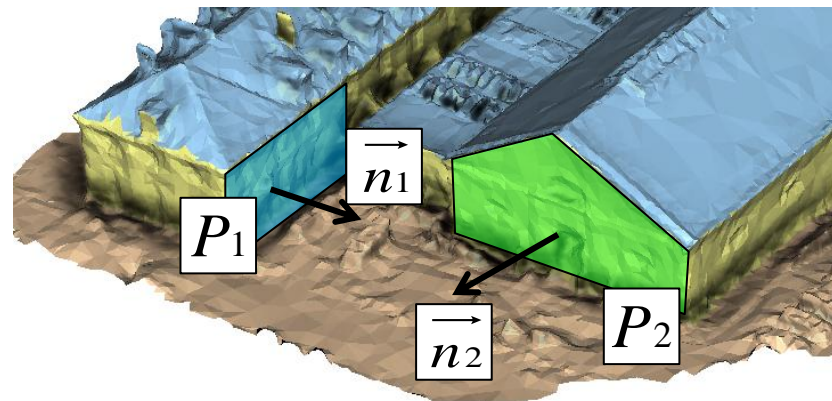


Building reconstruction from MVS data

Plane regularization:

- 4 pairwise relationships controlled with two parameters ε and d
 - Parallelism
 - **Orthogonality**

P_1 and P_2 are ε -parallel if $|\mathbf{n}_1 \cdot \mathbf{n}_2| \geq 1 - \varepsilon$

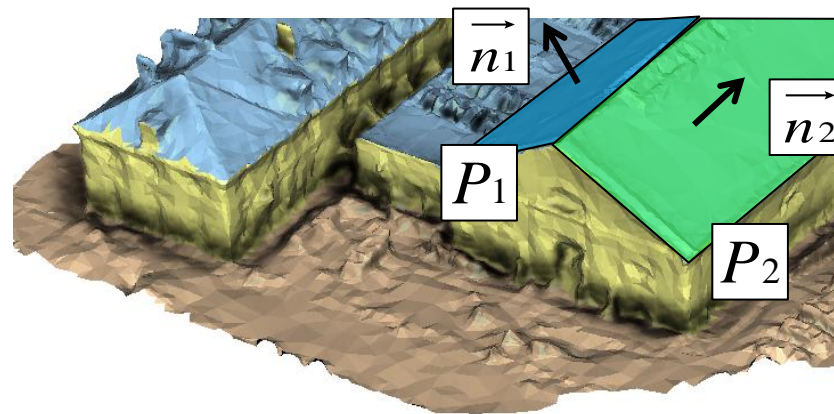


Building reconstruction from MVS data

Plane regularization:

- 4 pairwise relationships controlled with two parameters ε and d
 - Parallelism
 - Orthogonality
 - **Z-symmetry**

P_1 and P_2 are ε -Z-symmetric if $\left| |\mathbf{n}_1 \cdot \mathbf{n}_z| - |\mathbf{n}_2 \cdot \mathbf{n}_z| \right| \leq \varepsilon$,

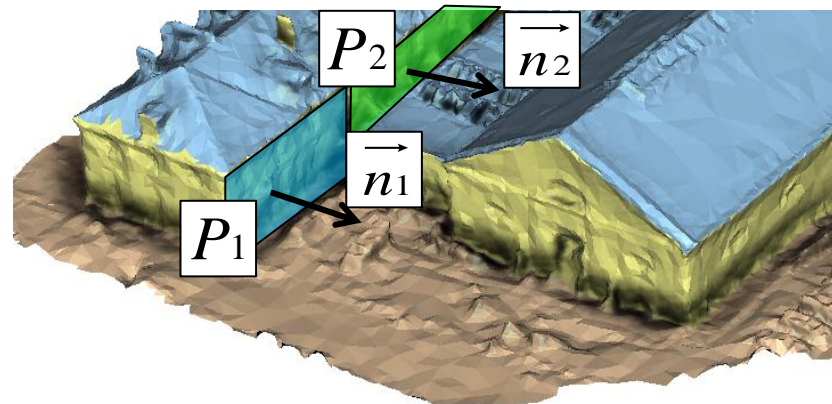


Building reconstruction from MVS data

Plane regularization:

- 4 pairwise relationships controlled with two parameters ε and d
 - Parallelism
 - Orthogonality
 - Z-symmetry
 - **Coplanarity**

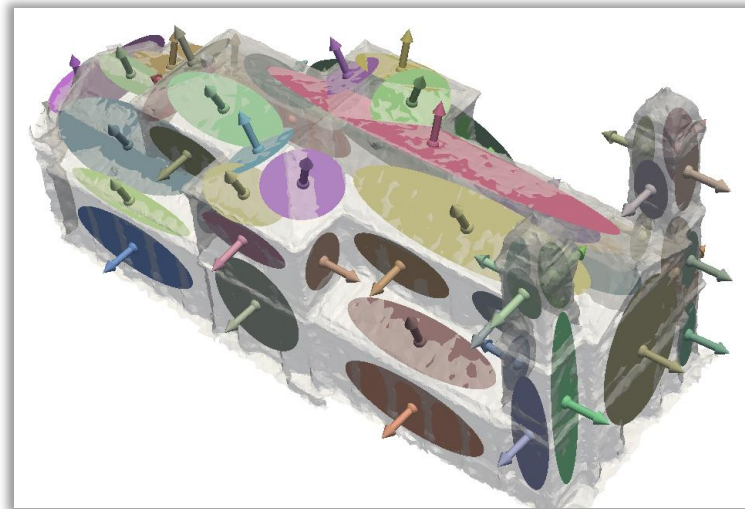
P_1 and P_2 are d - ε -coplanar if they are ε -parallel and
 $|d_{\perp}(c_1, P_2) + d_{\perp}(c_2, P_1)| < 2d$,



Building reconstruction from MVS data

Plane regularization:

- 4 pairwise relationships
- **Groups of *parallel* planes**

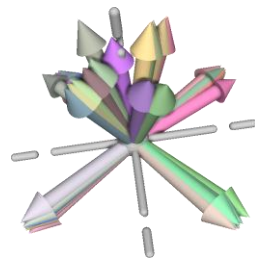


Building reconstruction from MVS data

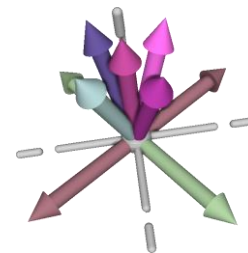
Plane regularization:

- 4 pairwise relationships
- Groups of *parallel* planes
- 2-step strategy:
 - 1) **Orientation correction:** propagate *orthogonality* and *z-symmetry* relationships from large groups to smaller

→ the barycenter of each group is fixed



Before orientation correction

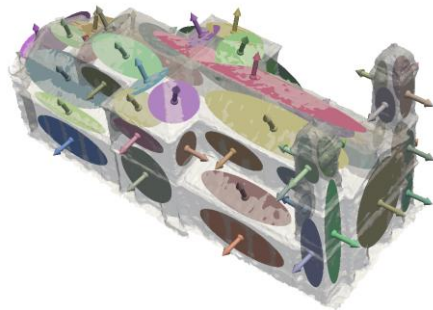


After orientation correction

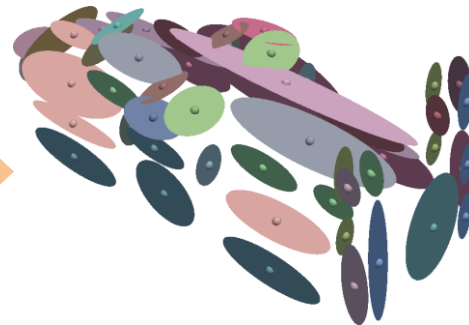
Building reconstruction from MVS data

Plane regularization:

- 4 pairwise relationships
- Groups of *parallel* planes
- 2-step strategy:
 - 1) Orientation correction: propagate *orthogonality* and *z-symmetry* relationships from large groups to smaller
 - 2) **Position correction:** merge *co-planar* groups



Before position correction



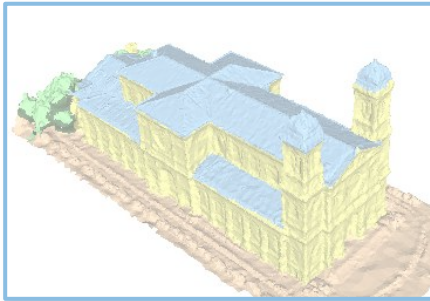
After position correction

Building reconstruction from MVS data

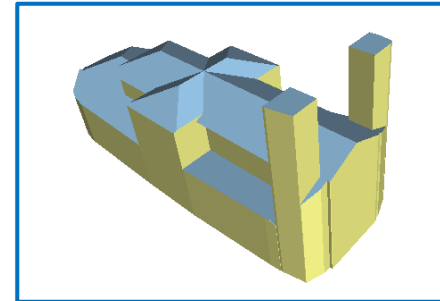
Plane regularization:

- 4 pairwise relationships
 - Groups of *parallel* planes
 - 2-step strategy:
 - 1) Orientation correction: propagate *orthogonality* and *z-symmetry* relationships from large groups to smaller
 - 2) Position correction: merge *co-planar* groups
- ➔ Converge very fast (no data refitting)
Thousand of planes in few seconds

Building reconstruction from MVS data

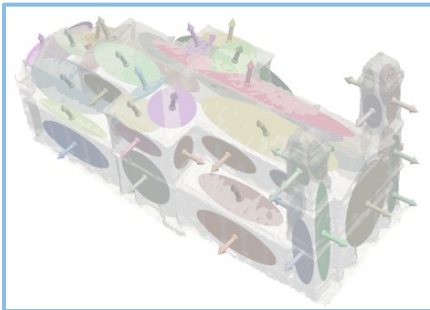


Labeling

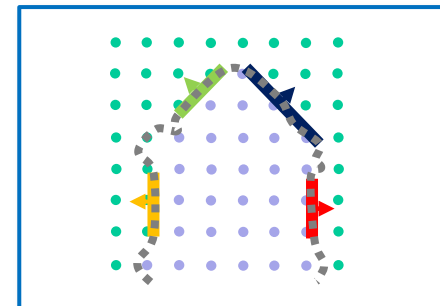


Surface extraction

Plane hypothesis from roof and facade f-clusters



Plane regularization

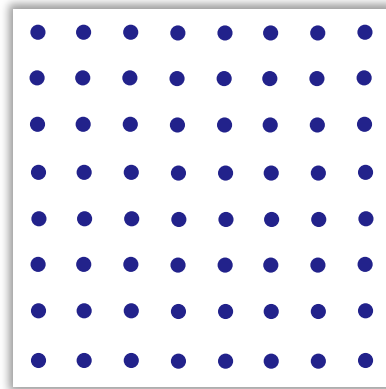


Discrete space
partitioning

Building reconstruction from MVS data

Discrete space partitioning:

- Volumetric occupancy grid

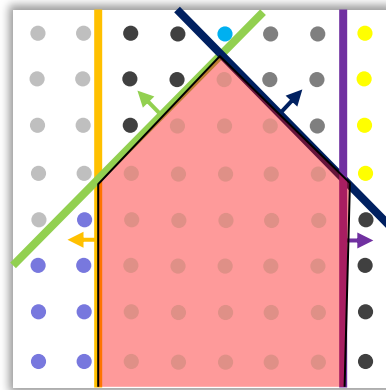


Building reconstruction from MVS data

Discrete space partitioning:

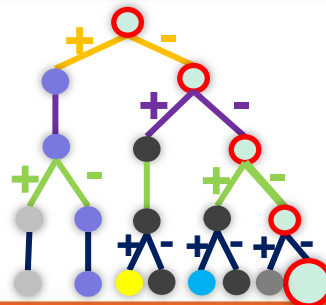
- Volumetric occupancy grid
- Binary Space Partitioning (BSP)

→ Red volume = a path in the BSP



?

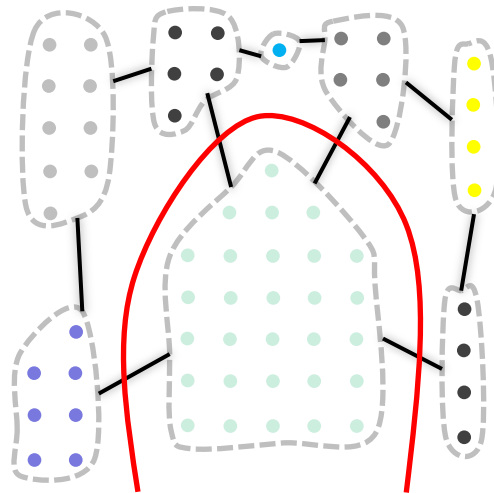
selection of the right path



Building reconstruction from MVS data

Surface extraction:

- The targeted surface is at the **boundary** between **inside and outside volumes**



$$\text{Surface} = \{ \text{---} + \text{ \ } + \text{ / } + \text{ \ } \}$$

- A min-cut formulation is used to label the volumes.
Optimized with min-max flow [Boykov and Kolmogorov, PAMI04]

Building reconstruction from MVS data

Surface extraction:

- The targeted surface is at the **boundary** between **inside and outside volumes**
- **Min-cut formulation:**

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

V_{c_k} is the discrete volume of cell c_k

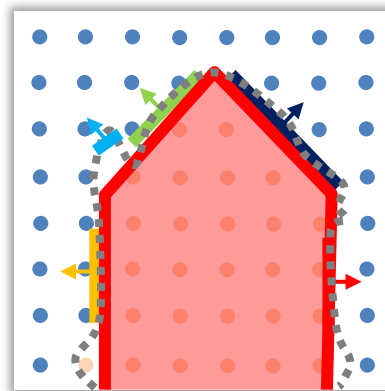
$g(c_k)$ is function of the ratio of inside anchors of cell c_k

$\sum_{e_i \in \mathcal{S}} A_{e_i}$ is the discrete area of the resulting surface

Building reconstruction from MVS data

Surface extraction:

- The targeted surface is at the **boundary** between **inside and outside volumes**
- **Min-cut formulation:**



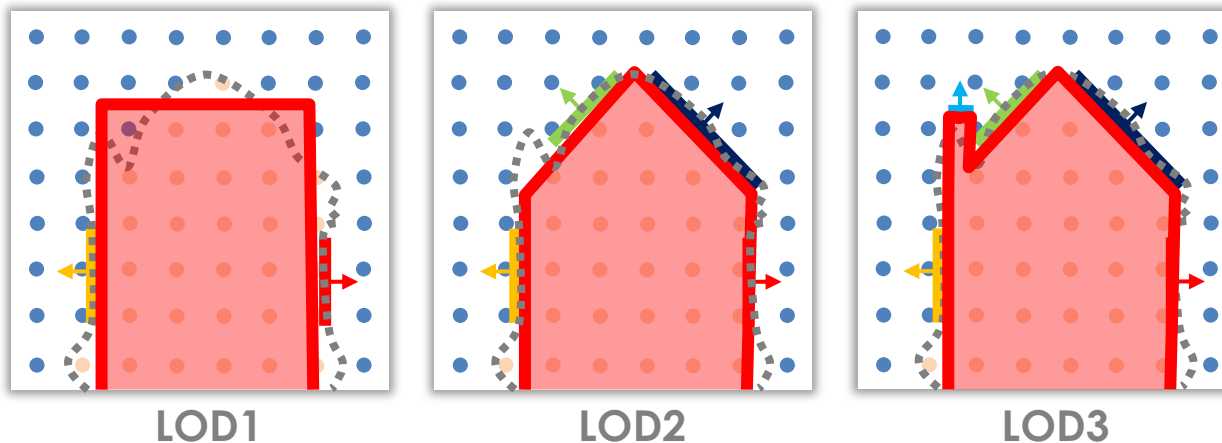
- input surface
- ↑ detected plane
- interior anchor
- exterior anchor

→ The boundary of the inside volume represents the targeted surface

Building reconstruction from MVS data

Surface extraction:

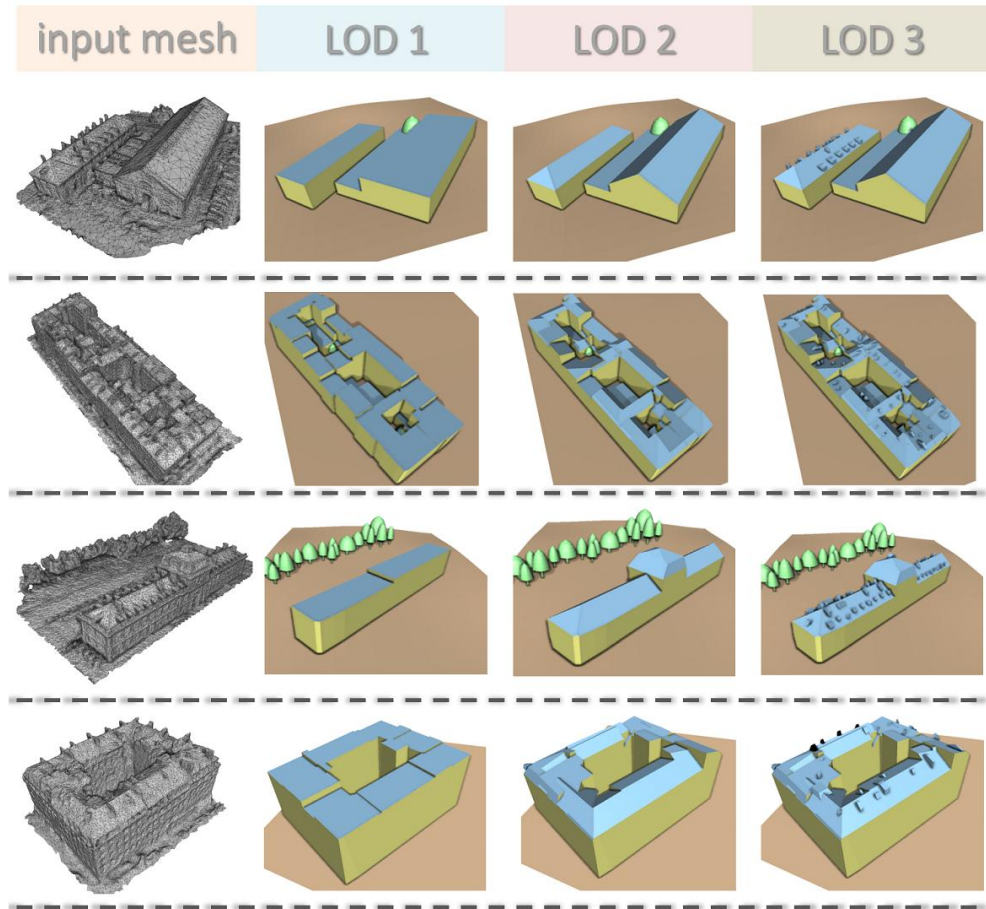
- The targeted surface is at the **boundary** between **inside and outside volumes**
- **Min-cut formulation:**



The boundary of the inside volume represents the targeted surface

→ A control on the sets of planes composing the BSP gives different LODs

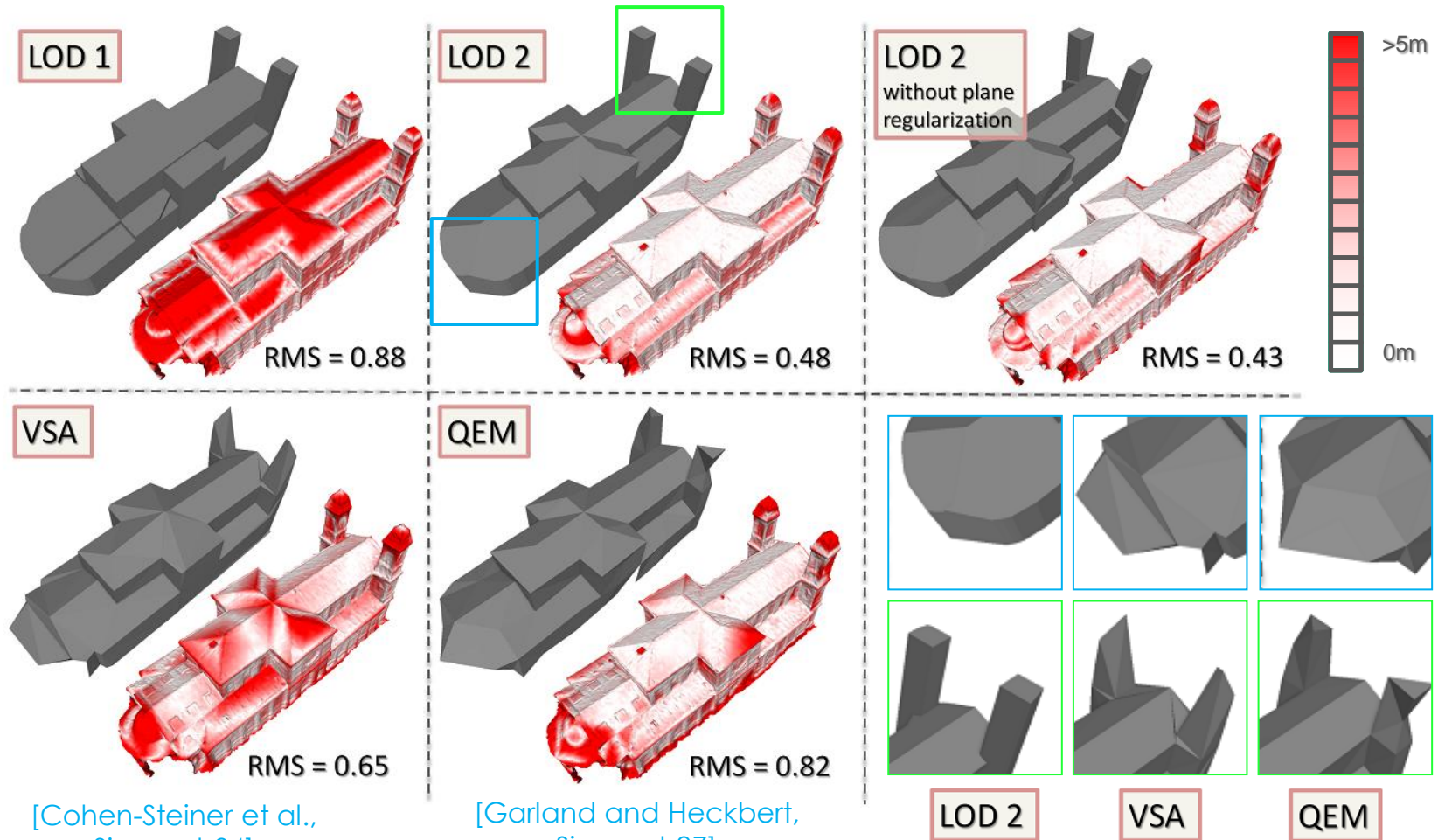
Various buildings: (LOD)



Various buildings: 170k facets, ~3min

Experiments

Geometric accuracy (Hausdorff distance) and structure awareness

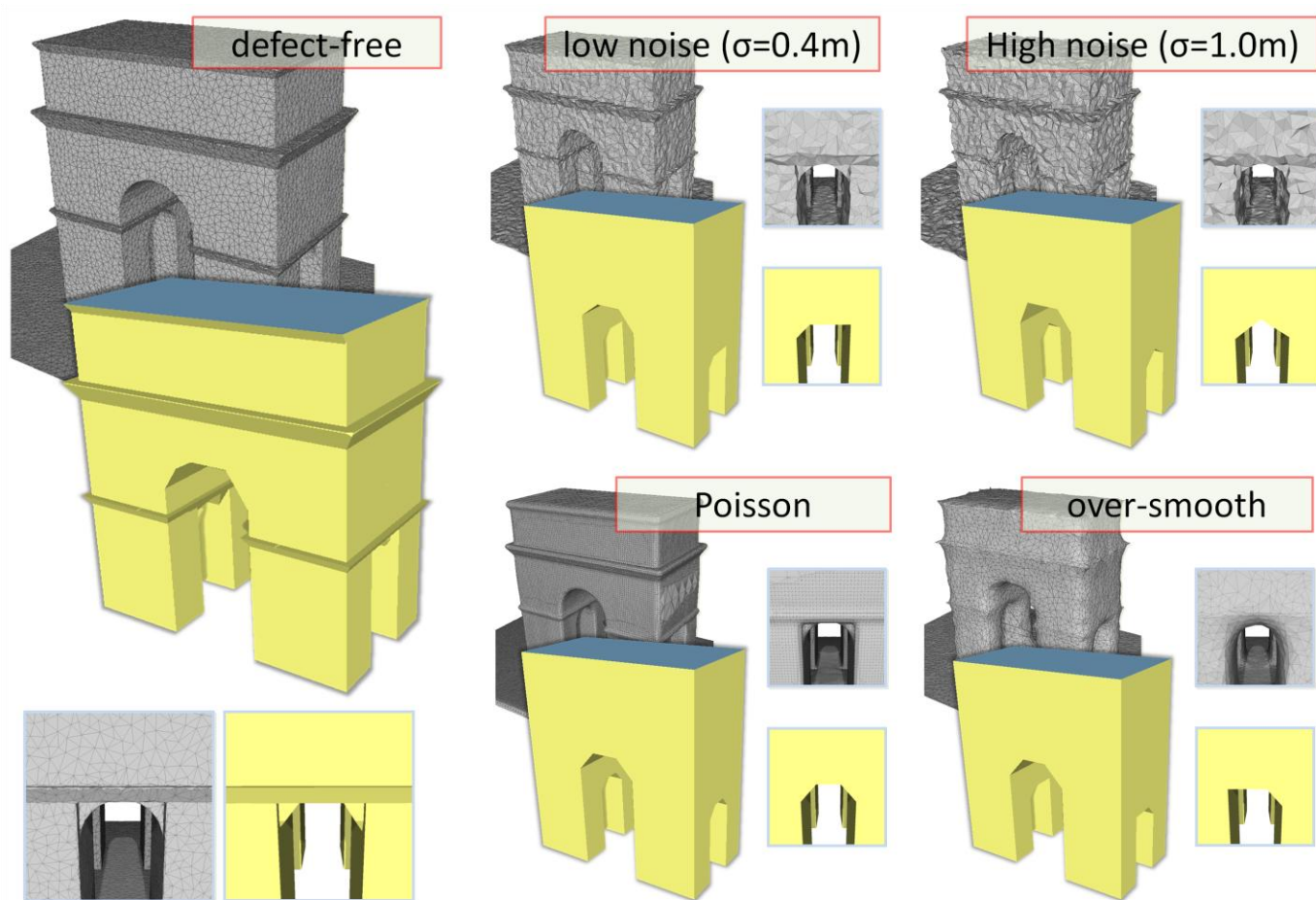


[Cohen-Steiner et al.,
Siggraph04]

[Garland and Heckbert,
Siggraph97]

Experiments

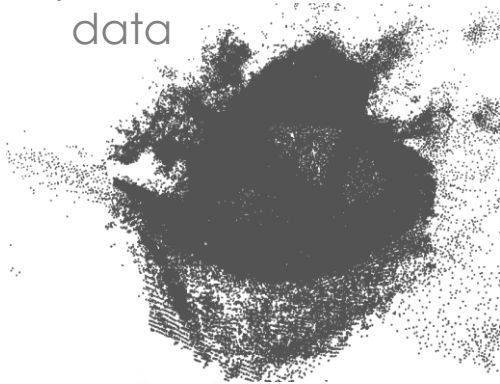
Robustness assessment



Experiments

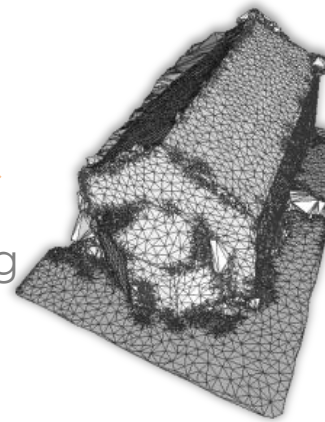
Robustness assessment

MVS point cloud data

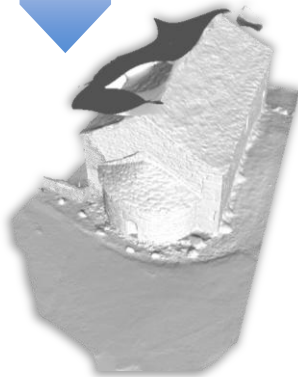


Point set structuring

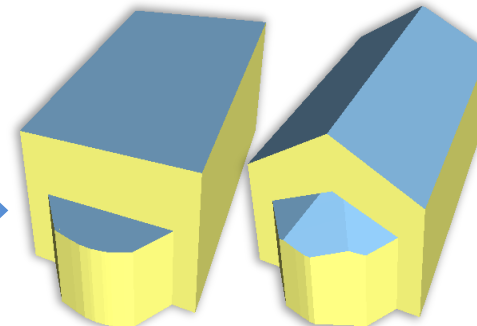
[Lafarge and Alliez, Eurographics13]



MVS-based mesh generation



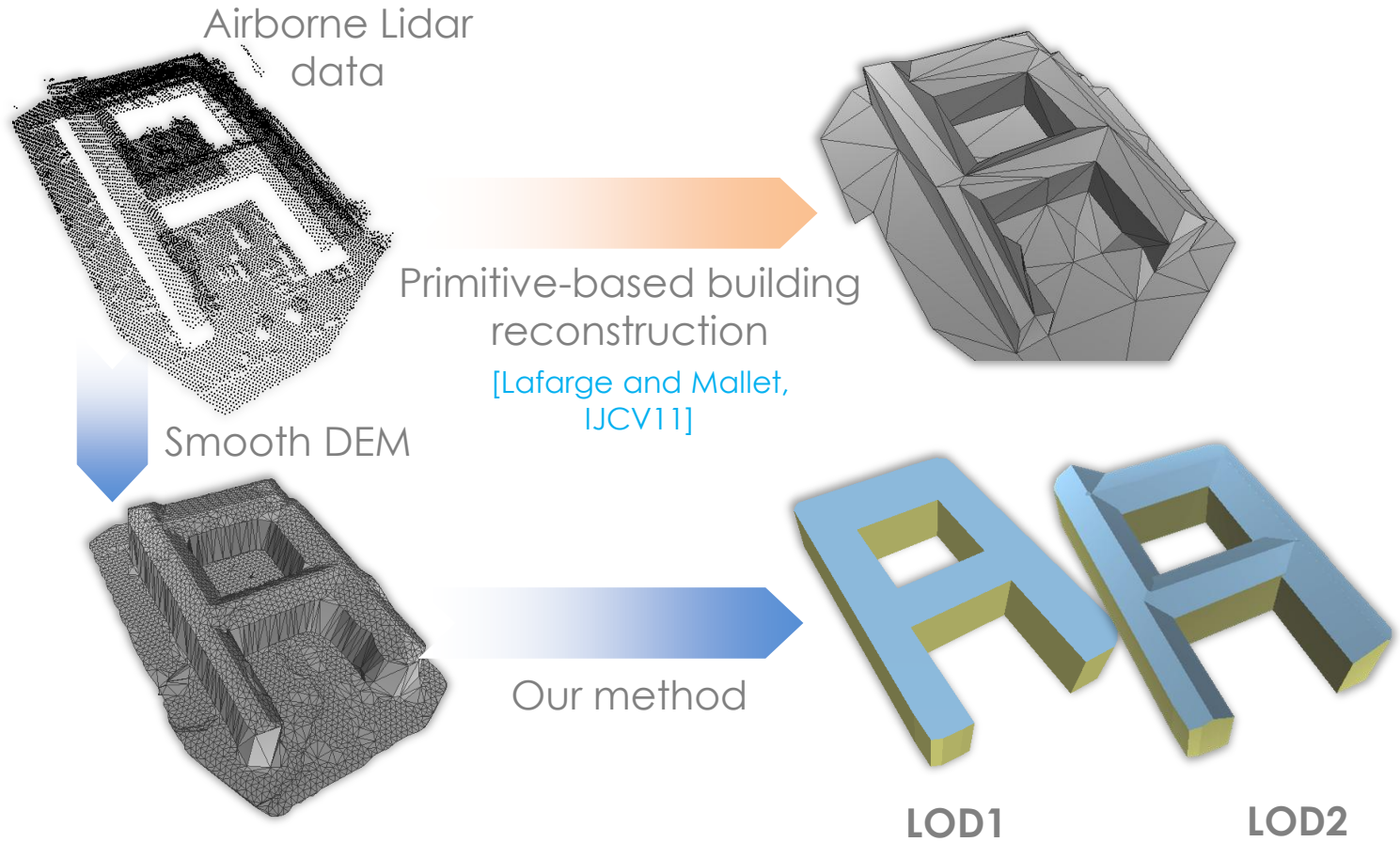
Our method



LOD1

LOD2

Choice of the input: mesh or point cloud

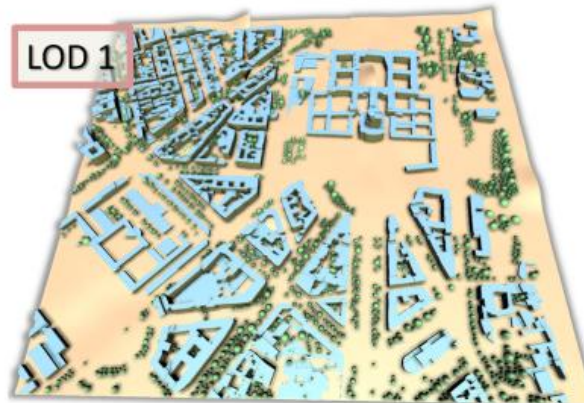


Experiments

Large scale experiments (scalability)



from Google map



Paris, 7th district: 11M facets, ~2hours

Outline

- ① Introduction
- ② Semantic labeling
- ③ Object Reconstruction: parametric-based object detection
- ④ Object Reconstruction: mesh-based object reconstruction
- ⑤ **Conclusion and future work**

Contribution summary

Applicative contributions

- Two pipelines for Lidar and MVS data
 - Semantical and structural enhancement of purely-geometric meshes
 - Geometrically accurate reconstruction and visually convincing
 - Scalable and adapted to wide range of applications

Contribution summary

Methodological contributions

- Sampler for Marked Point Processes (MPP) using a parallel scheme
 - Exploit GPU architecture
 - Outperforms current samplers for MPP
- Efficient Binary Space Partitioning (BSP)
 - Rely on a discrete energy formulation for fast approximation

Limitations

Urban labeling

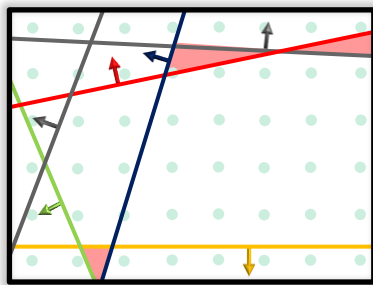
- Classes of objects limited

Sampler for Marked Point Processes

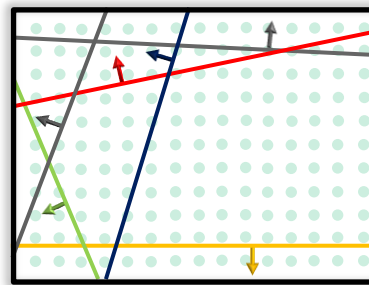
- Efficient only when performed on large scenes for small objects

Building reconstruction

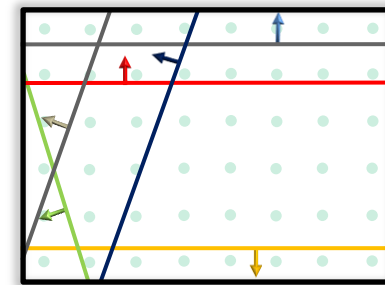
- Piecewise-planar buildings
- Primitive dependant
- Discrete formulation misses details (empty cells)



large grid width
no plane regularization



short grid width
no plane regularization



large grid width
with plane regularization

Future Work

Extensions:

Urban labeling

- Add more classes of interest for a better labeling (bridge, water,...)

Building reconstruction

- Generalize the BSP for other primitives (spheres, cylinder,...)
- Complete LOD3 representation with facade modeling
 - Use data regularization
 - Grammar rules for façade

Future Work

Future directions:

Multiple source of data

- Use multiple source of data together (terrestrial and aerial Lidar, MVS, images,...)

Functional analysis

- Combine structure-aware techniques with semantic understanding of urban scenes

THANK YOU

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