Urban scene modeling from airborne data

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Inria

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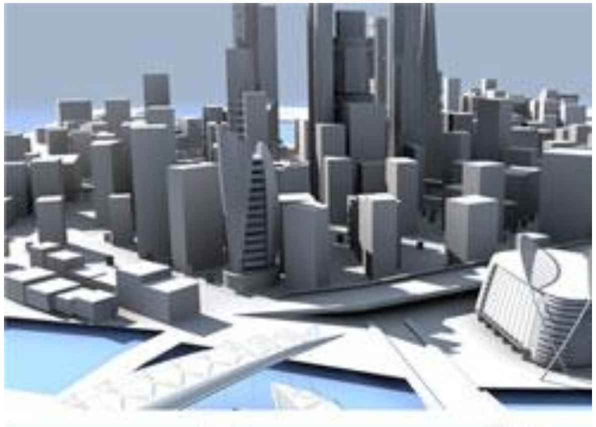
3D urban reconstruction

3D urban reconstruction

- Geometry

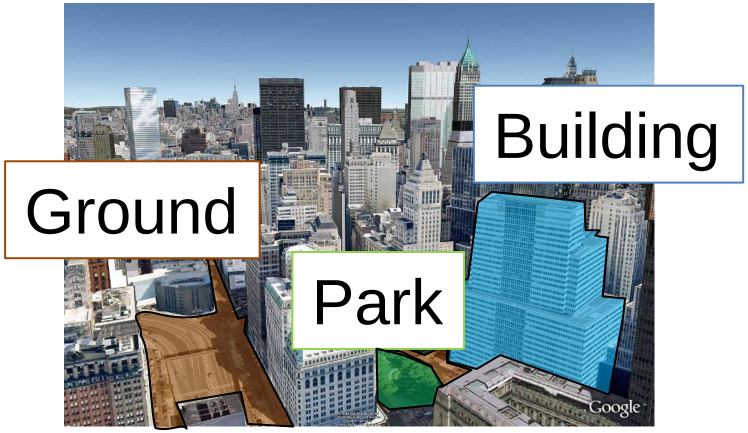


3D urban reconstruction

- Geometry
- Radiometry

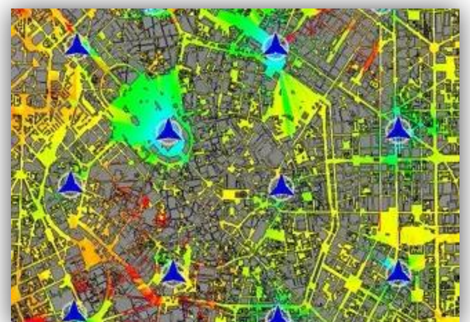
3D urban reconstruction

- Geometry
- Radiometry
- Semantics



Applications

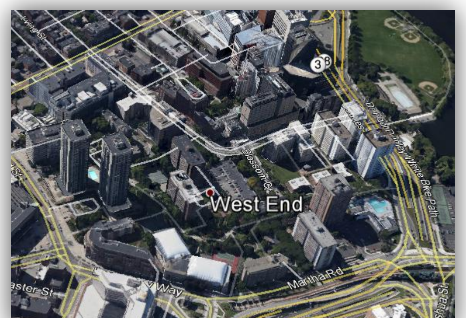
- Applications for 3D urban reconstruction



Radio planning

Movie

Computer game



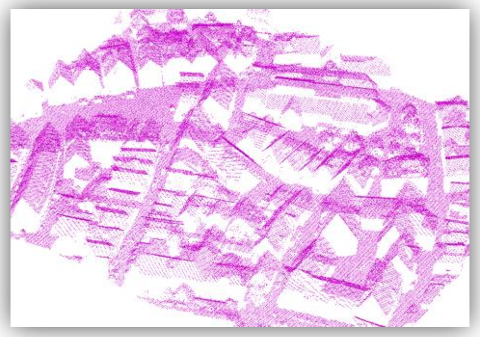
Online services

Urban planning

Drone planning

Problem statement

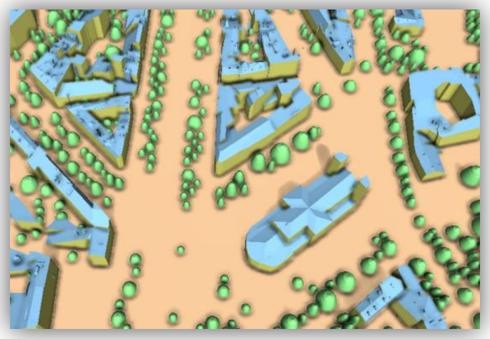
Airborne Acquisition



Lidar data

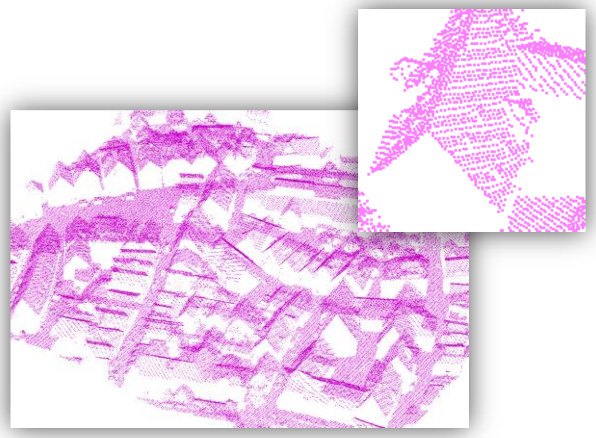
Meshes from Multi-View Stereo

?

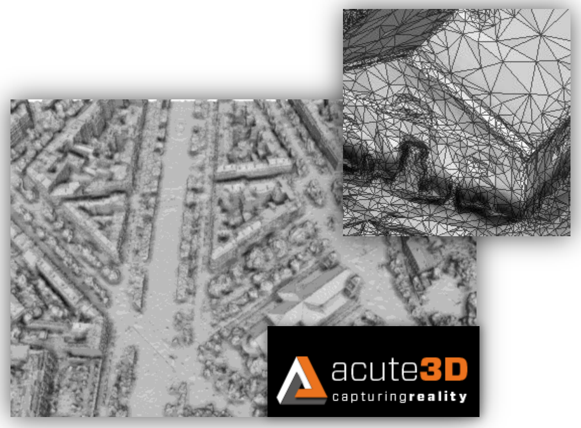


Urban scene modeling

Airborne data

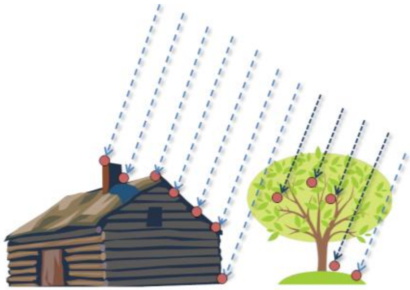


Lidar data

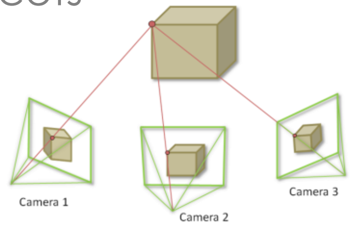


Meshes from Multi-View Stereo

- Point cloud
- Accurate
- Not dense
- Incomplete



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



Requirements

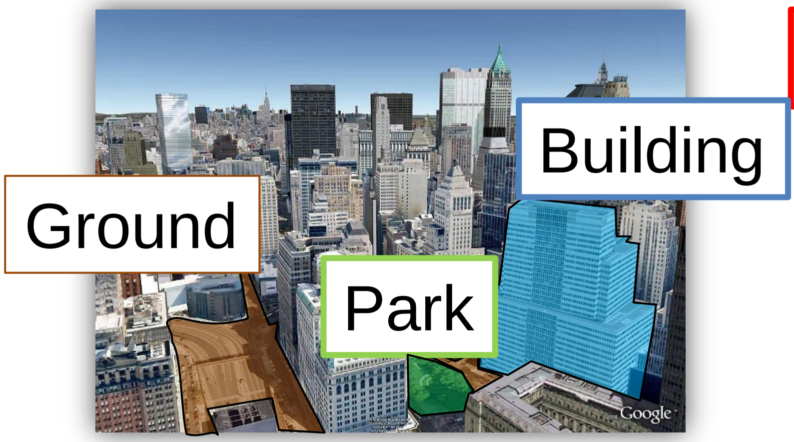
5 criteria:

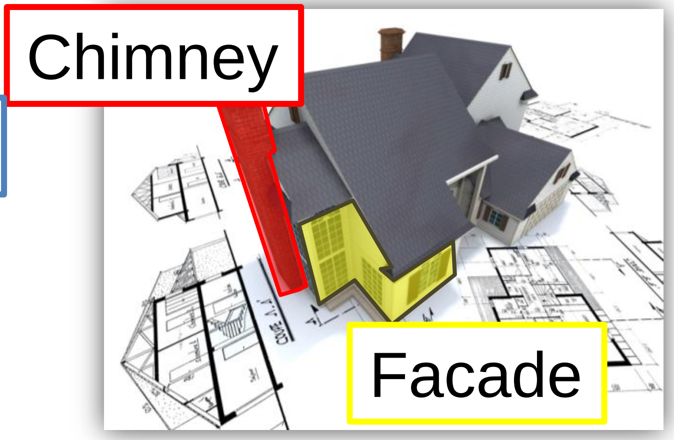
- Geometric accuracy

Requirements

5 criteria:

- Geometric accuracy
- Semantic-aware

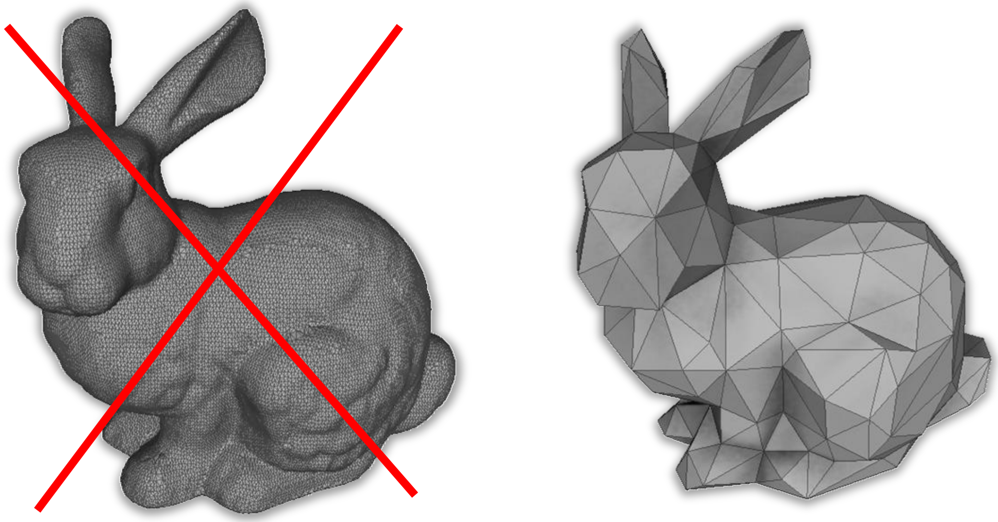




Requirements

5 criteria:

- Geometric accuracy
- Semantic-aware
- Low complexity



Requirements

5 criteria:

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

Size of the scene

small → large

Requirements

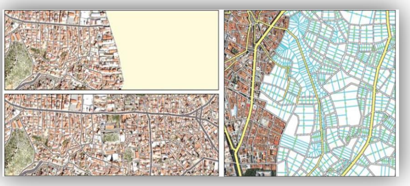
5 criteria:

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

Surveys

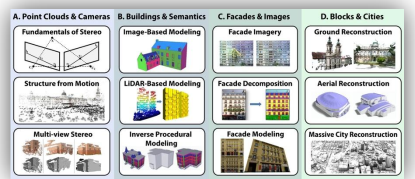
3 major surveys:

Modeling the Appearance and Behavior of Urban Spaces



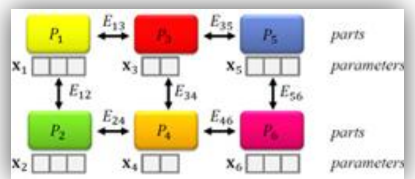
[Vanegas et al. Eurographics 09]

A survey of Urban Reconstruction



[Musialski et al. Eurographics 12]

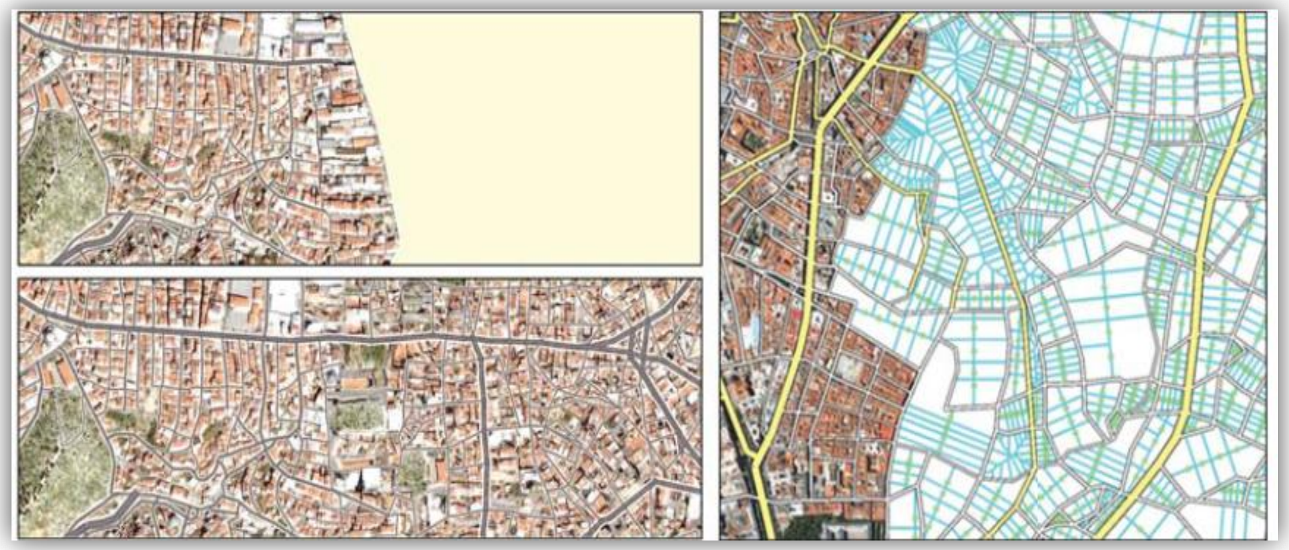
Structure-Aware Shape Processing



[Mitra et al. Eurographics 13]

Surveys

"Modeling the Appearance and Behavior of Urban Spaces"

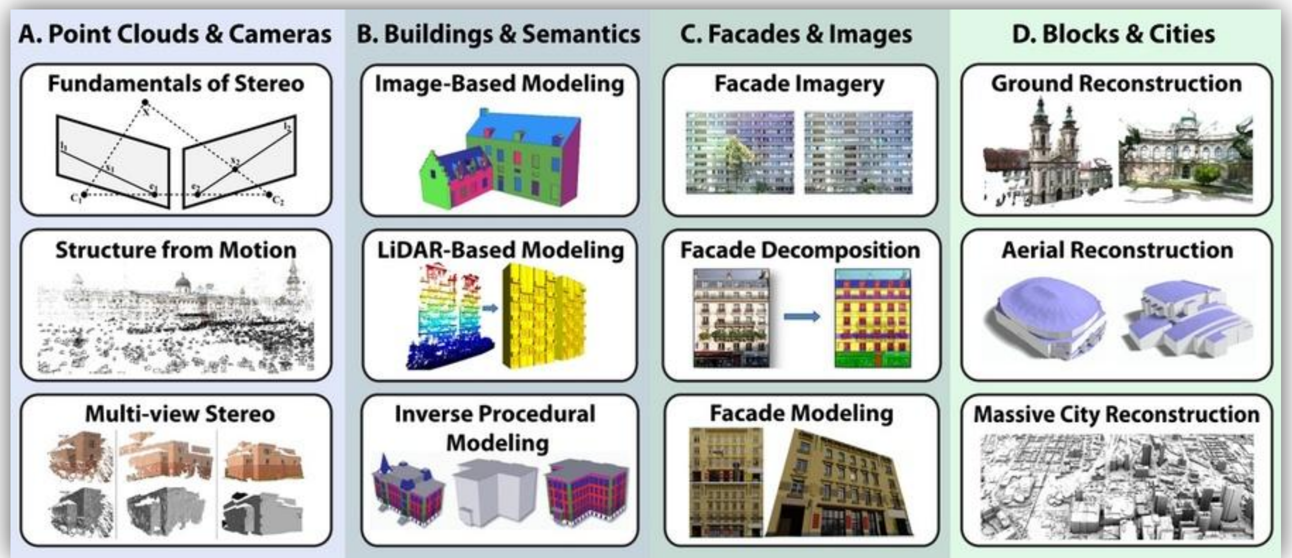


[Vanegas et al., Eurographics 09]

→ procedural modeling

Surveys

"A survey of Urban Reconstruction"

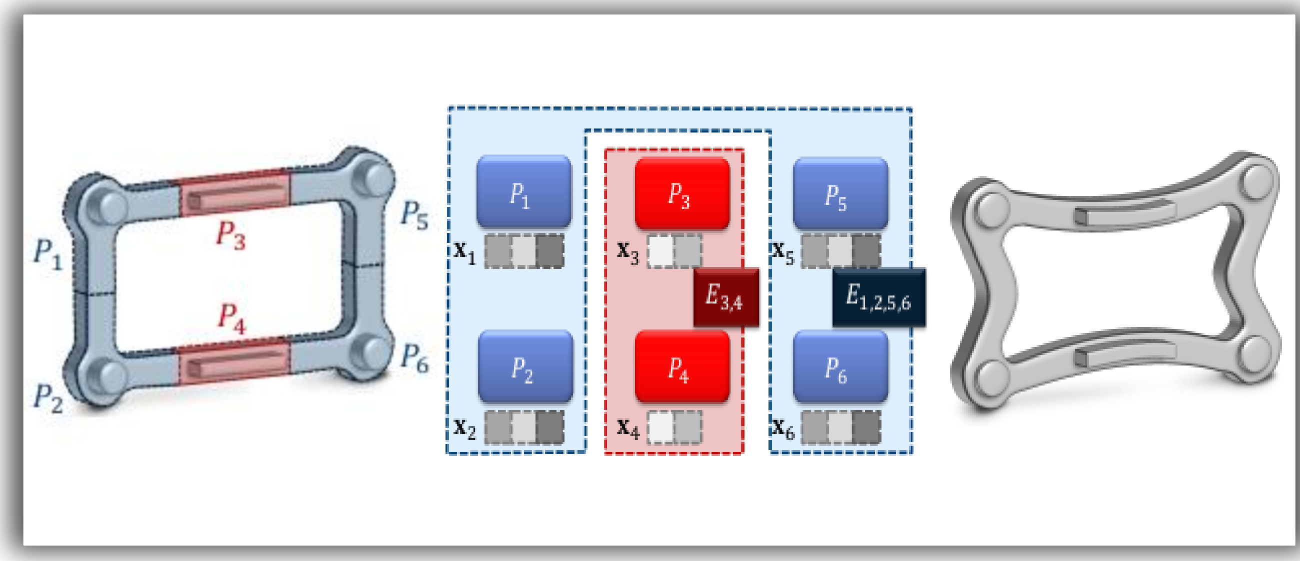


[Musialski et al., Eurographics 12]

→ broad overview of the literature on urban reconstruction

Surveys

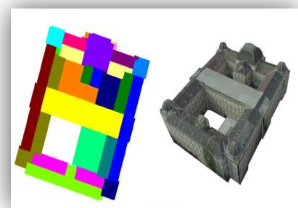
"Structure-Aware Shape Processing"



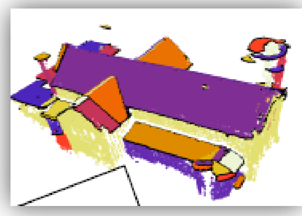
[Mitra et al., Eurographics 13]

→ structures to enhance, regularize and manipulate existing meshes

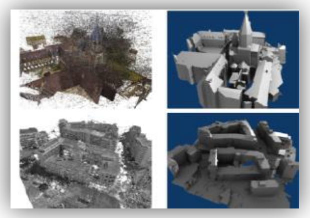
Overview of existing methods



[Zebedin et al., ECCV 08]



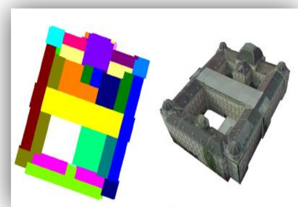
[Toshev et al., CVPR 09]



[Chauve et al., CVPR 10]

Primitive-based building reconstruction

Overview of existing methods



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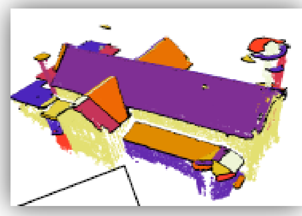

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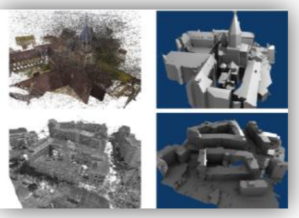
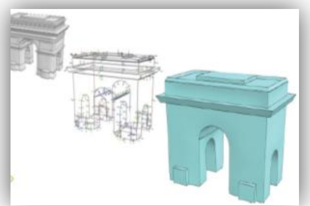


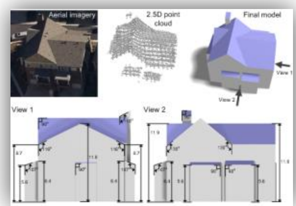
[Chauve et al., CVPR 10]

Primitive-based building reconstruction

[Pauly et al., Siggraph 08]



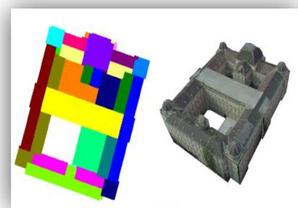
[Mehra et al., Siggraph Asia 09]



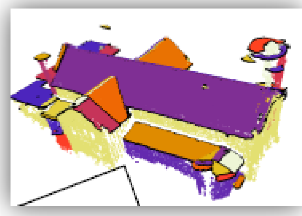
Zhou and Neumann, CVPR12]

Structure-aware building modeling

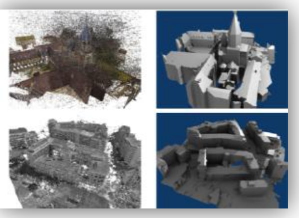
Overview of existing methods



[Zebedin et al., ECCV 08]



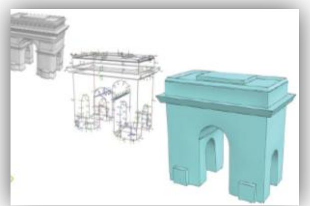
[Toshev et al., CVPR 09]



[Chauve et al., CVPR 10]

Primitive-based building reconstruction

[Pauly et al., Siggraph 08]



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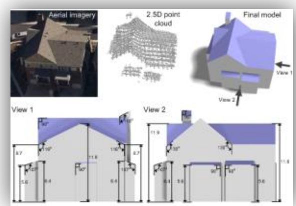
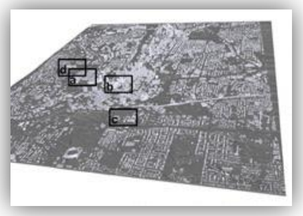


[Zhou and Neumann, CVPR12]

Structure-aware building modeling

[Poullis and You, CVPR09]



[Zhou and Neumann, CVPR09]

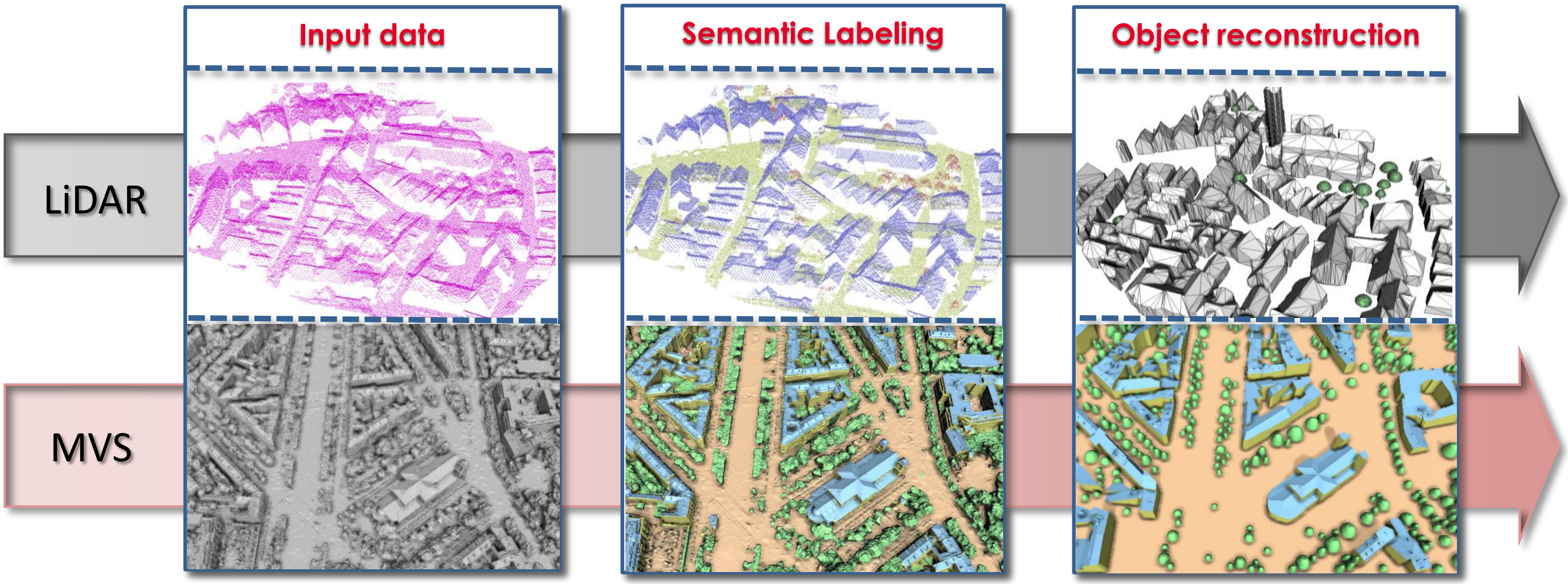
[Lafarge and Mallet, IJCV11]

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

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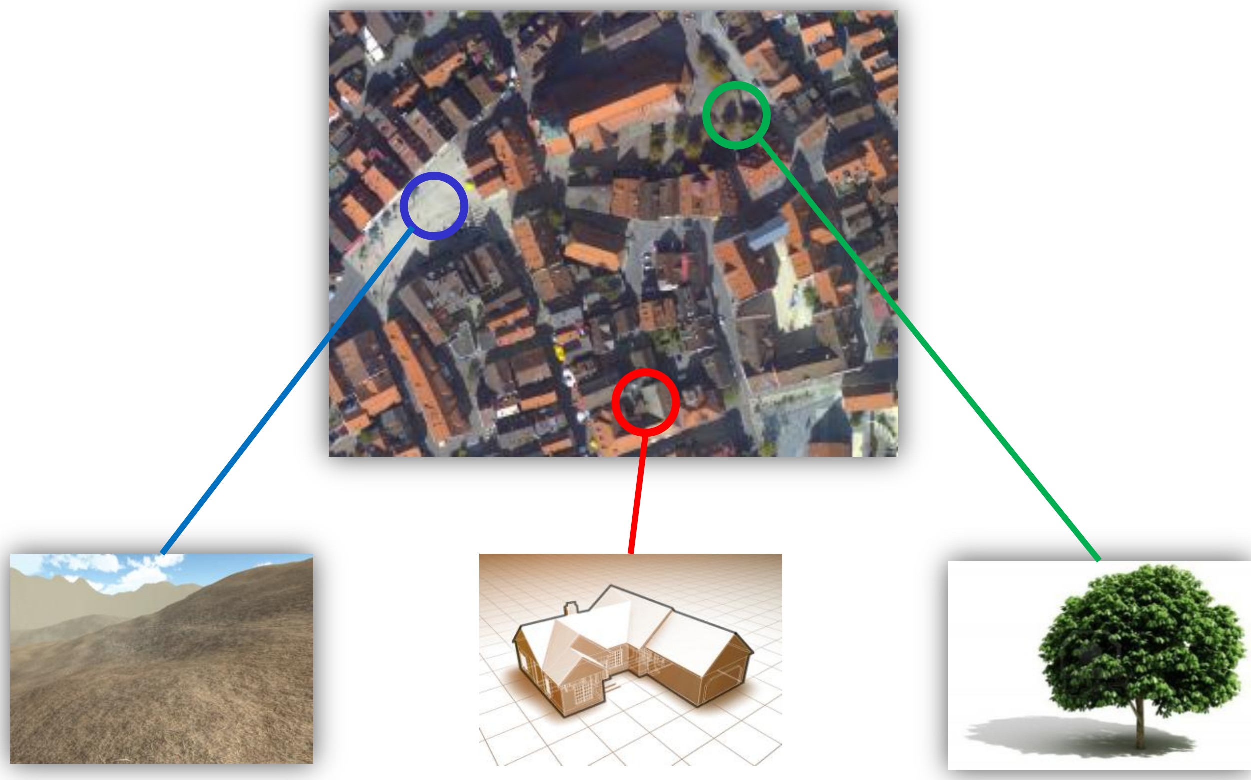
⑤ Conclusion and future work

Semantic labeling

What is important ?

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

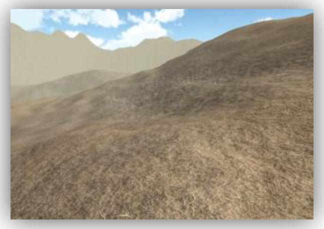


Ground Buildings Trees

Semantic labeling for Lidar

Semantic labeling for Lidar

Classes for Lidar data



Ground

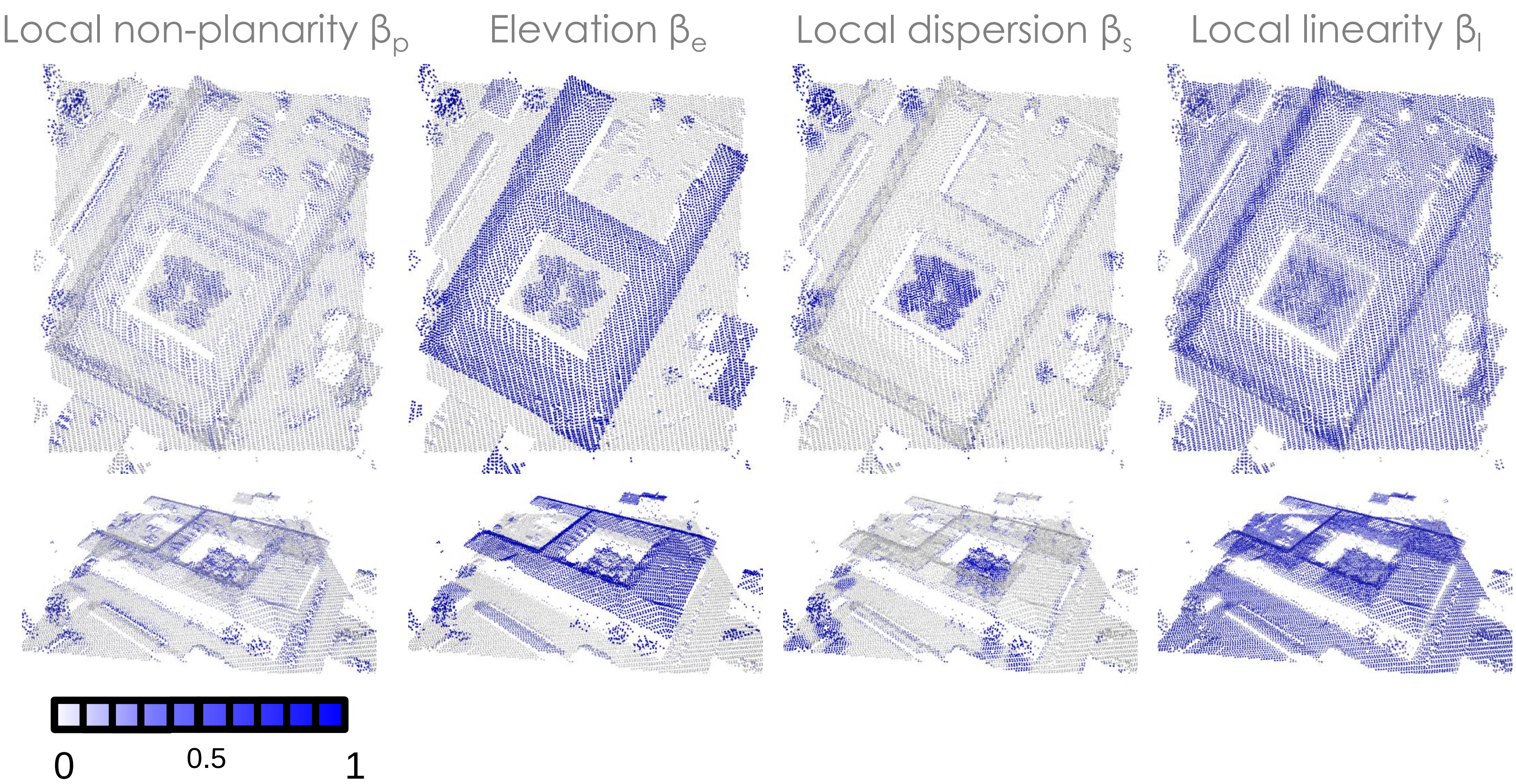
Trees

Buildings

Clutters

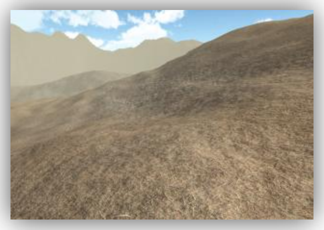
→ need for geometric features that discriminate the classes

Discriminative geometric features for Lidar



→ Combine the features to discriminate the classes

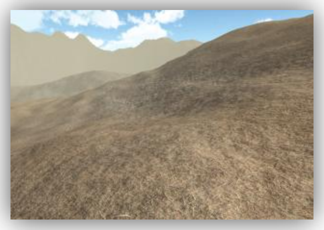
Confidence functions for Lidar

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 βl~~
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

Ground



Buildings

Clutters

$$\arg\min_{x} \sum D(x_i)$$

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

→ Need for spatial consistency

Energy minimization over a Markov Random Field

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

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

Potts model:

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

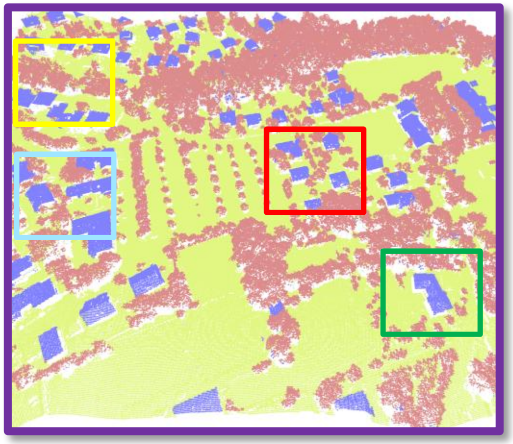
Spherical neighborhood such as

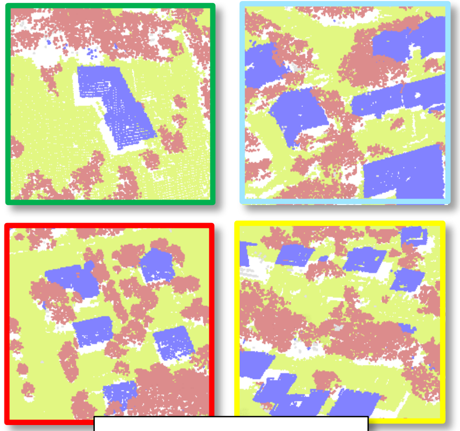
$$\{i, j\} \in E \Leftrightarrow \|i - j\|_2 < r$$

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

Semantic labeling for Lidar data

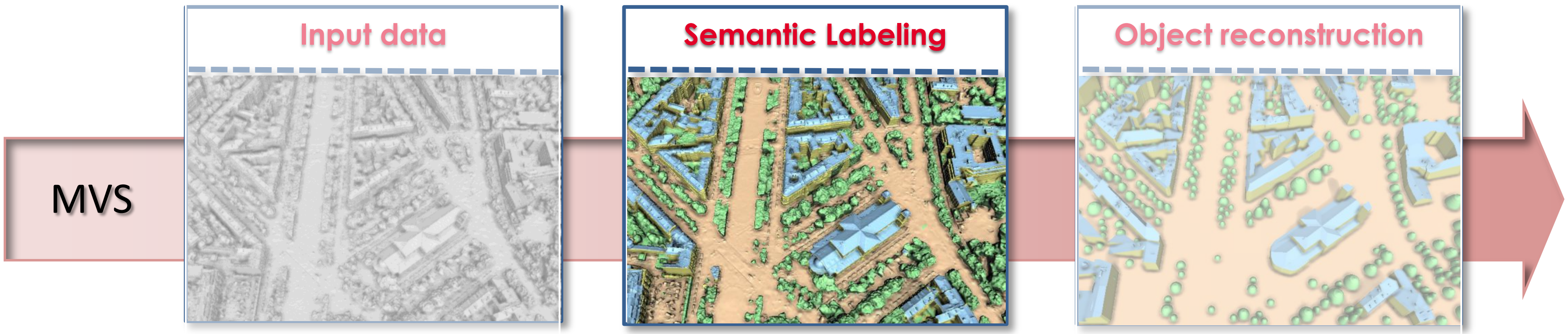
Visual reference from Google map





Close-up

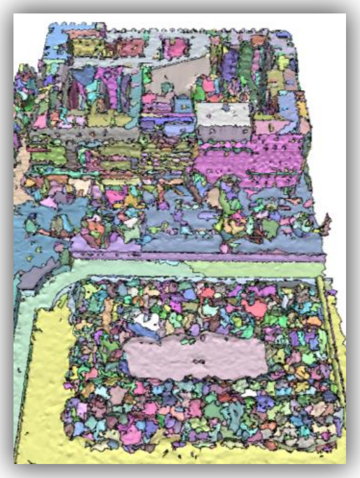
Semantic labeling for MVS



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

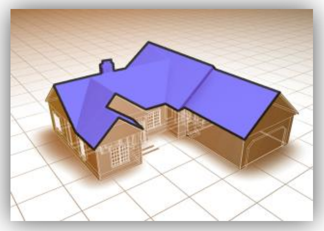
- Compute f-clusters
- ***Building* class splits in two sub-classes**

Semantic labeling for MVS

Difference with semantic labeling for Lidar data

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

Roofs

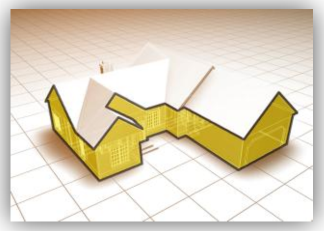


Low non-planarity β_p

High elevation β_e

Low verticality β_v

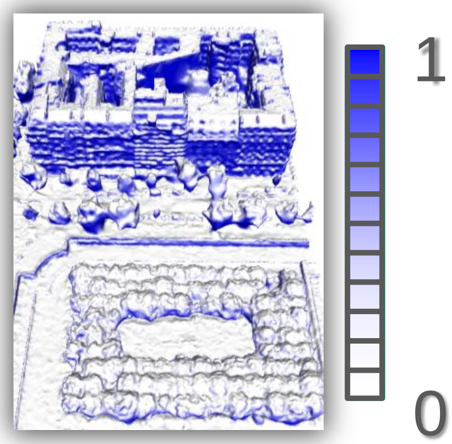
Facades



Low non-planarity β_p

High verticality β_v

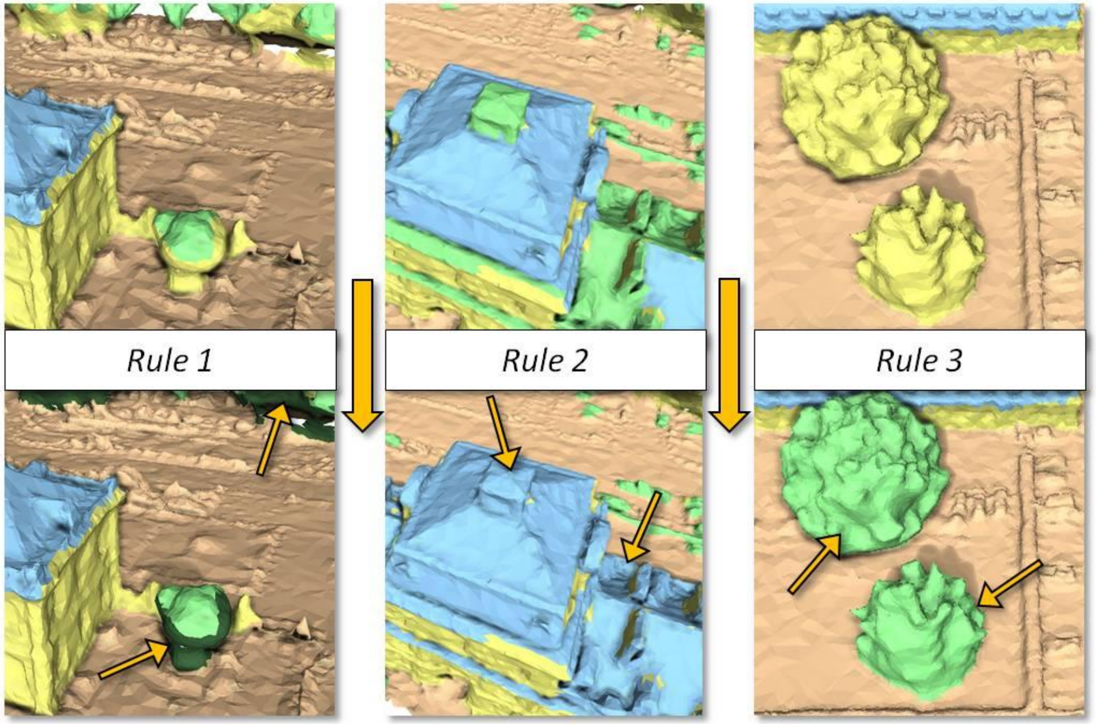
Verticality β_v



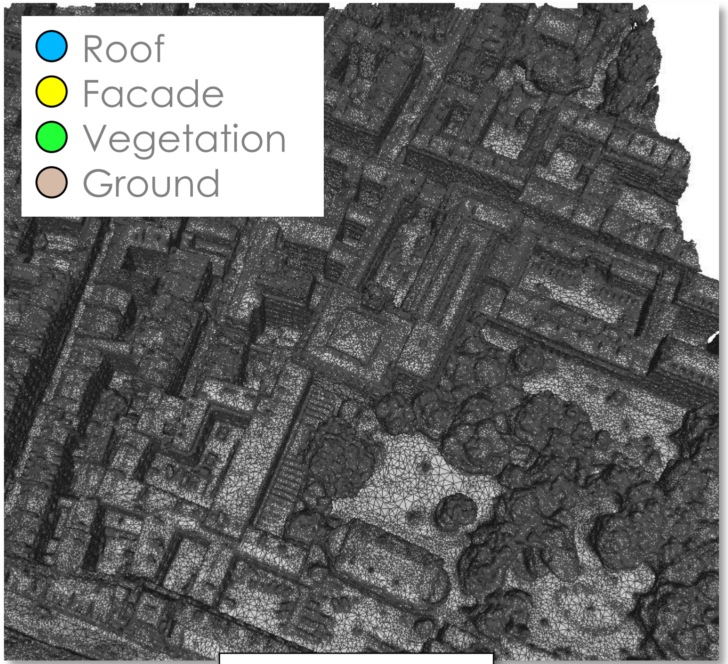
Semantic labeling for MVS

Difference with semantic labeling for Lidar data

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

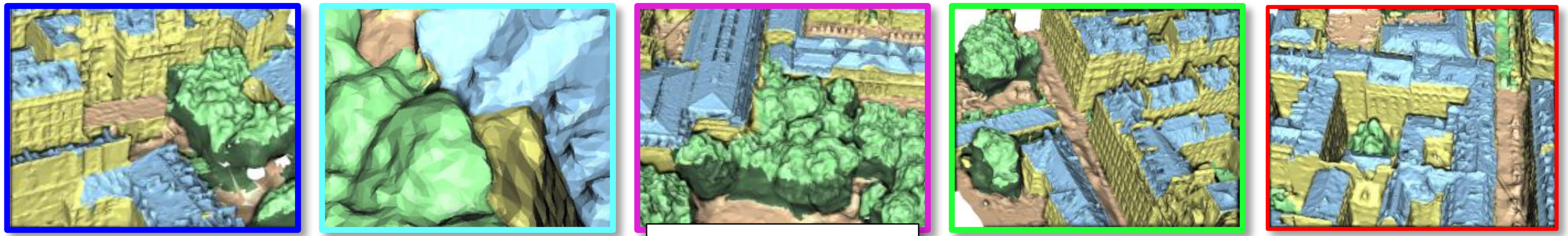


Semantic labeling



MVS data

Classification

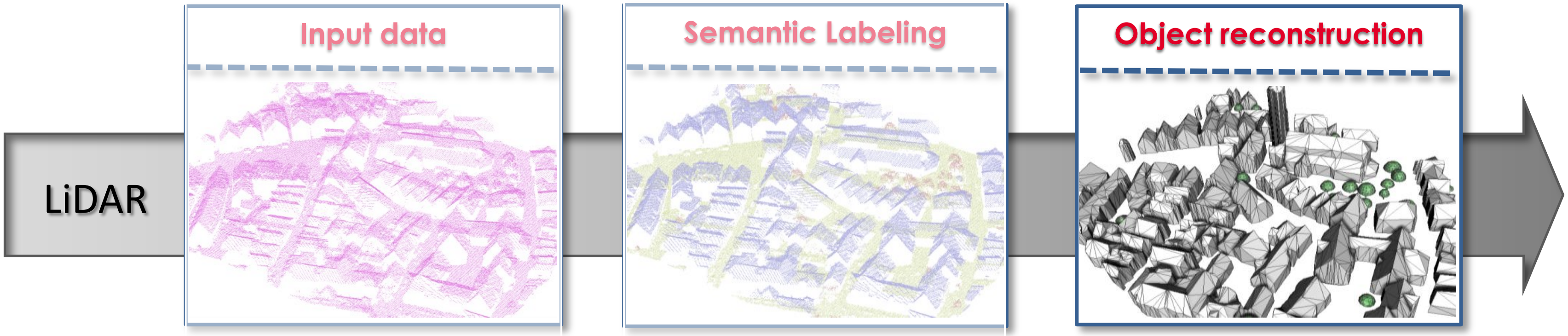


Close-up

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

Object Reconstruction for Lidar



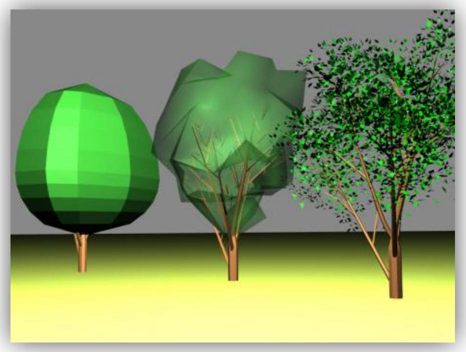
→ Focus on tree detection and reconstruction from Lidar

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

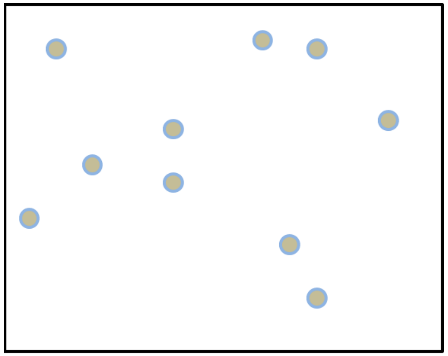
→ Use Marked Point Processes (MPP)

Marked Point Processes

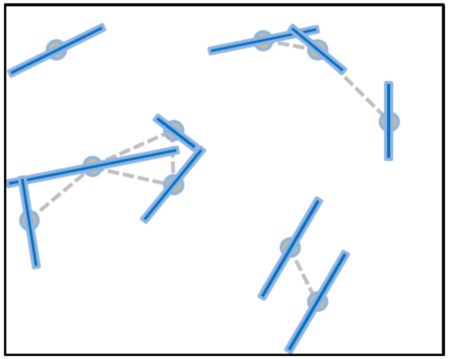
Preliminary:

- 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.**



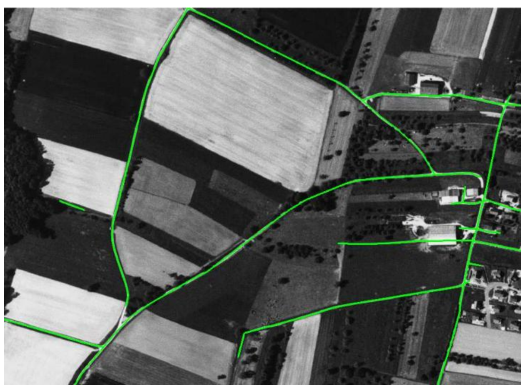
Point process



Marked Point Process
of 2D segments

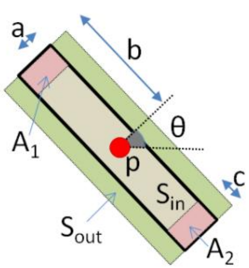
Marked Point Processes

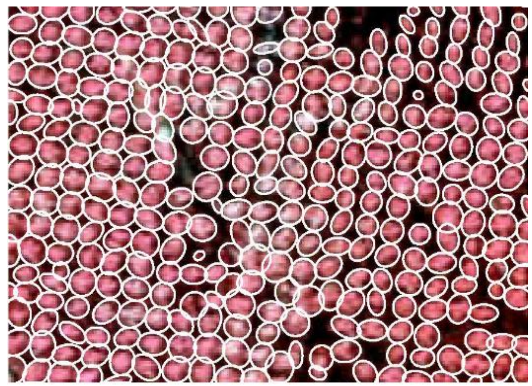
Previous work:



[Lacoste et al.,PAMI05]

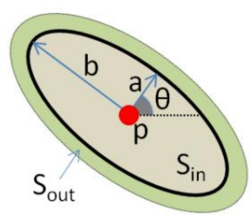
Line-segment

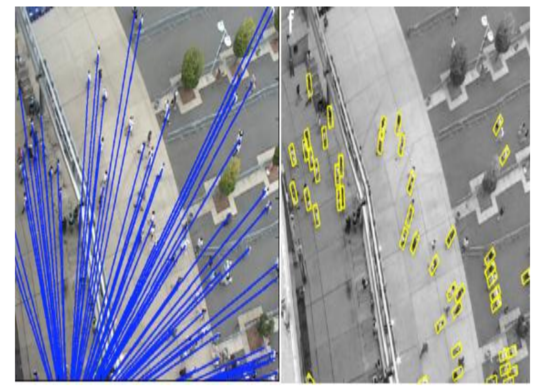




[Perrin et al., EMMCVPR05]

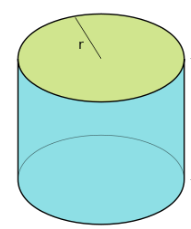
Ellipse





[Ge et al., CVPR09]

Cylinder



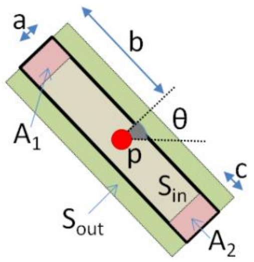
Marked Point Processes

Requirements:

1) Simple parametric objects

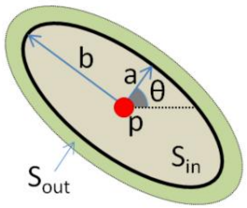
→ Object characterized by a limited number of parameters

Line-segment



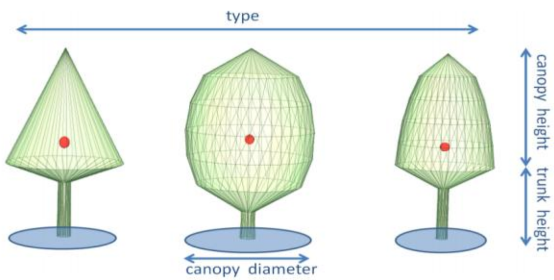
5 parameters

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:

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

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)

Slow in practice

  b) Acceptance step depending on
     - Random variable
     - Energy variation
     - Stochastic relaxation

→ Focus on improving performance of RJ-MCMC

Marked Point Processes

Requirements:

1) Simple parametric objects

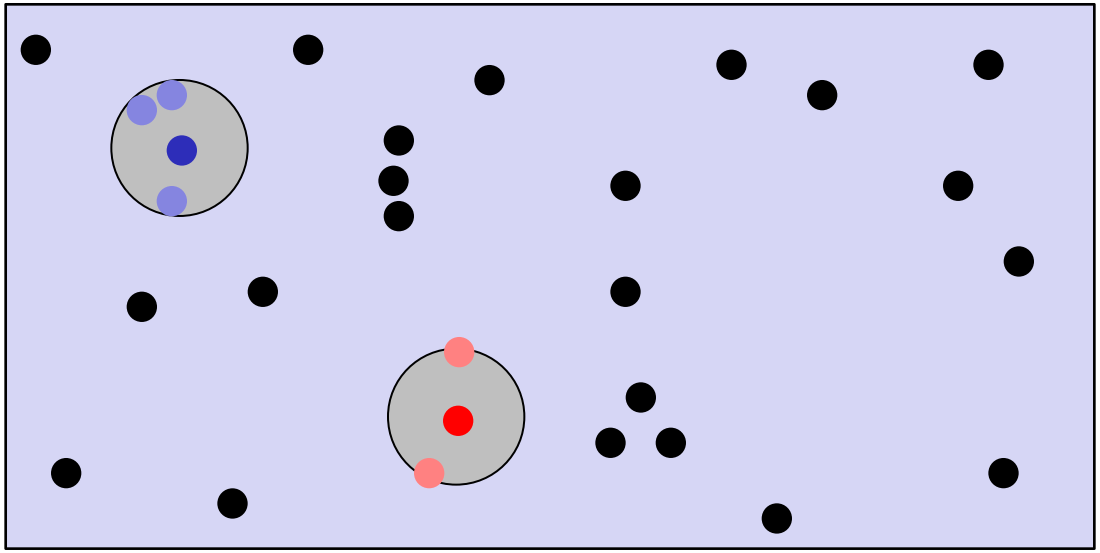
2) Energy

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

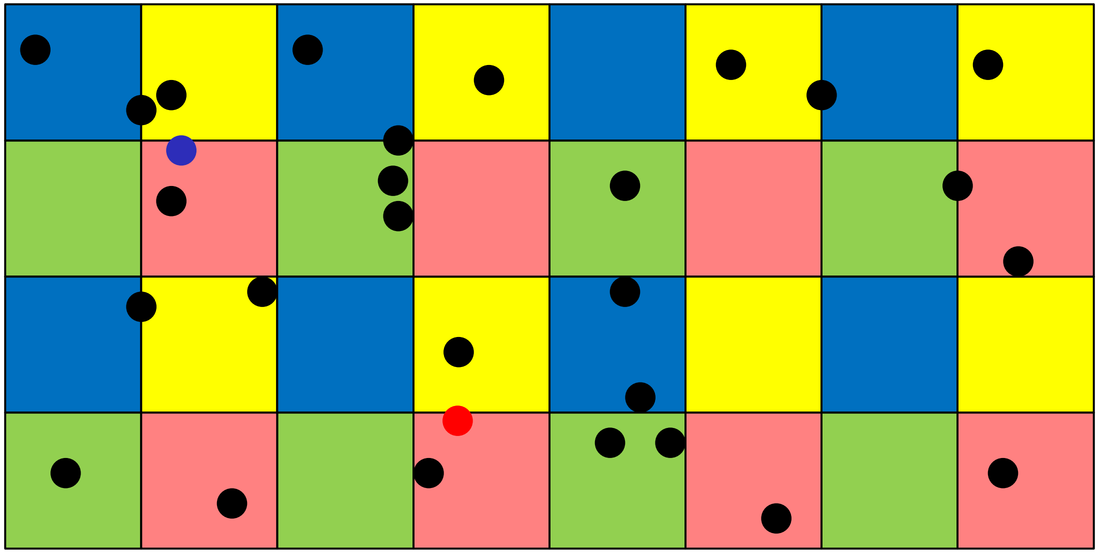
The Markovian property in the energy: $\Pr(x_i \mid x) = \Pr(x_i \mid x_{N(i)})$



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

(1) Parallelization

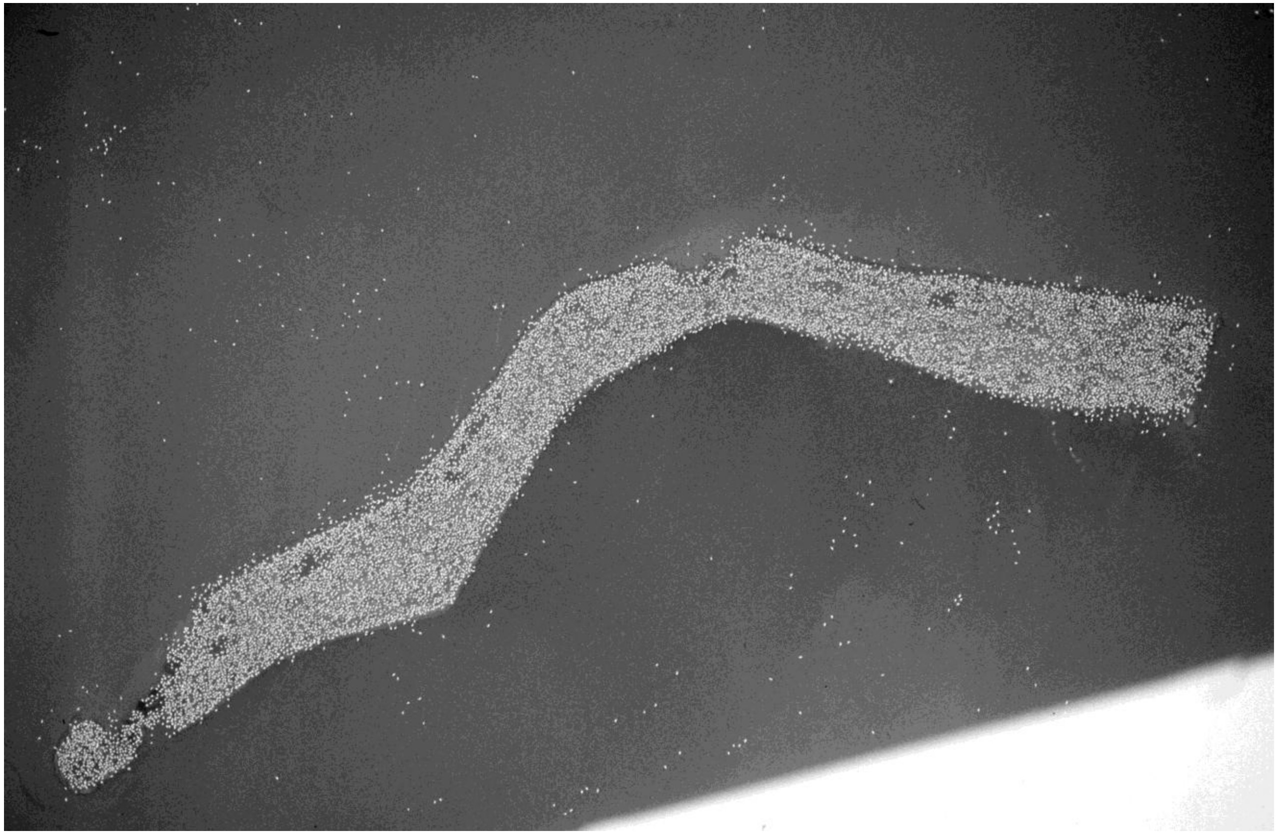
- 4-cell subdivision scheme generates 4 mic-sets { , , , }.
(cell width=diameter of the neighborhood relation+maximal length of a move)



- Mic-Set: a set of Mutually Independant Cells

(2) Non-uniform point densities

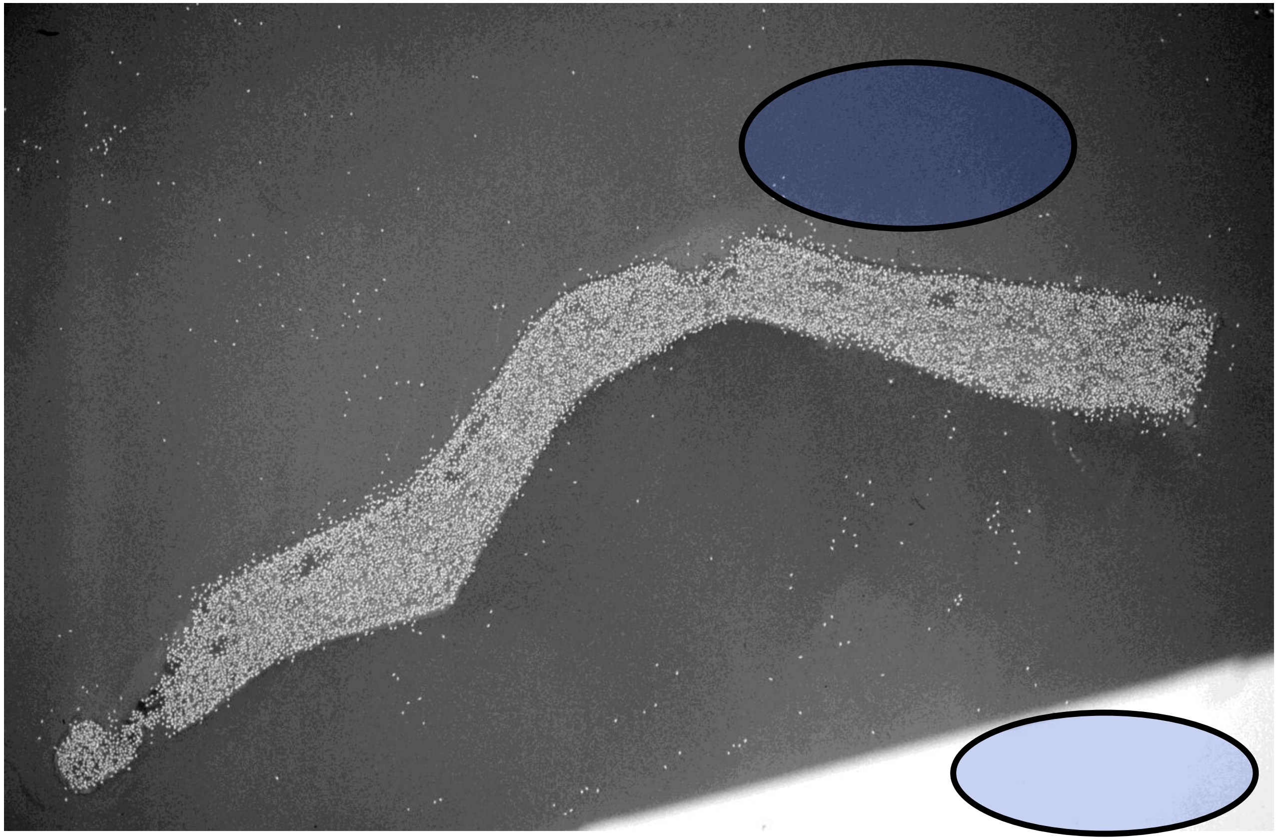
How many Birds ?



(2) Non-uniform point densities

How many Birds ?

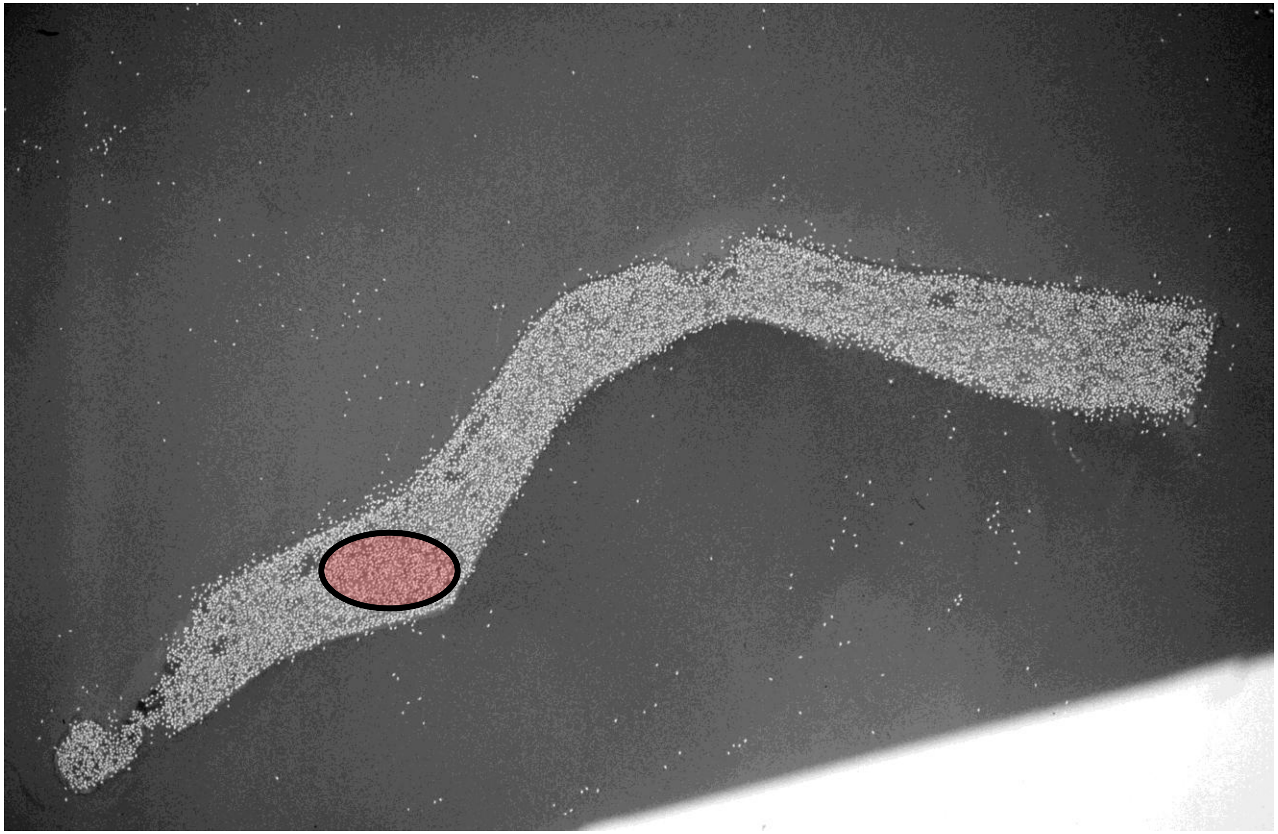
Low probability



(2) Non-uniform point densities

How many Birds ?

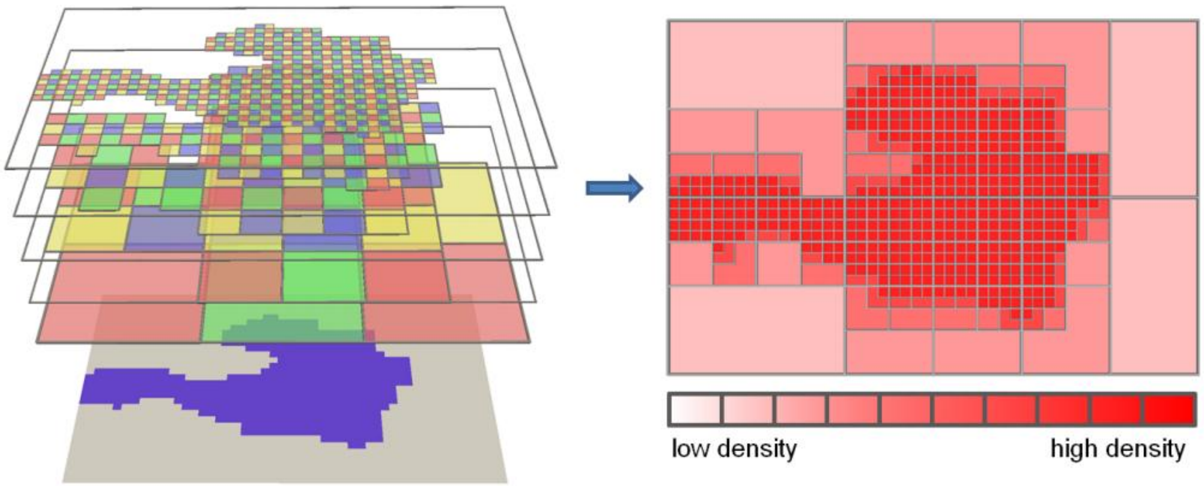
High probability



(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 $X_0 = \boldsymbol{x}_0$ and T_0 at $t = 0$;

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

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

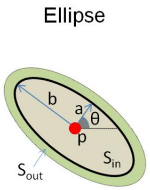
- Choose a mic-set $S_{mic} \in \mathcal{K}$ and a kernel type $t \in \mathcal{T}$ according to probability $\sum_{c \in S_{mic}} p_{c,t}$
- For each cell $c \in S_{mic}$,
  - Perturb $\boldsymbol{x}$ in the cell c to a configuration $\boldsymbol{y}$ according to $Q_{c,t}(\boldsymbol{x} \to .)$
  - Calculate the Green ratio

$$R = \frac{\mathcal{Q}_{c,t}(\boldsymbol{y} \to \boldsymbol{x})}{\mathcal{Q}_{c,t}(\boldsymbol{x} \to \boldsymbol{y})} \exp\left(\frac{U(\boldsymbol{x}) - U(\boldsymbol{y})}{T_t}\right)$$

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

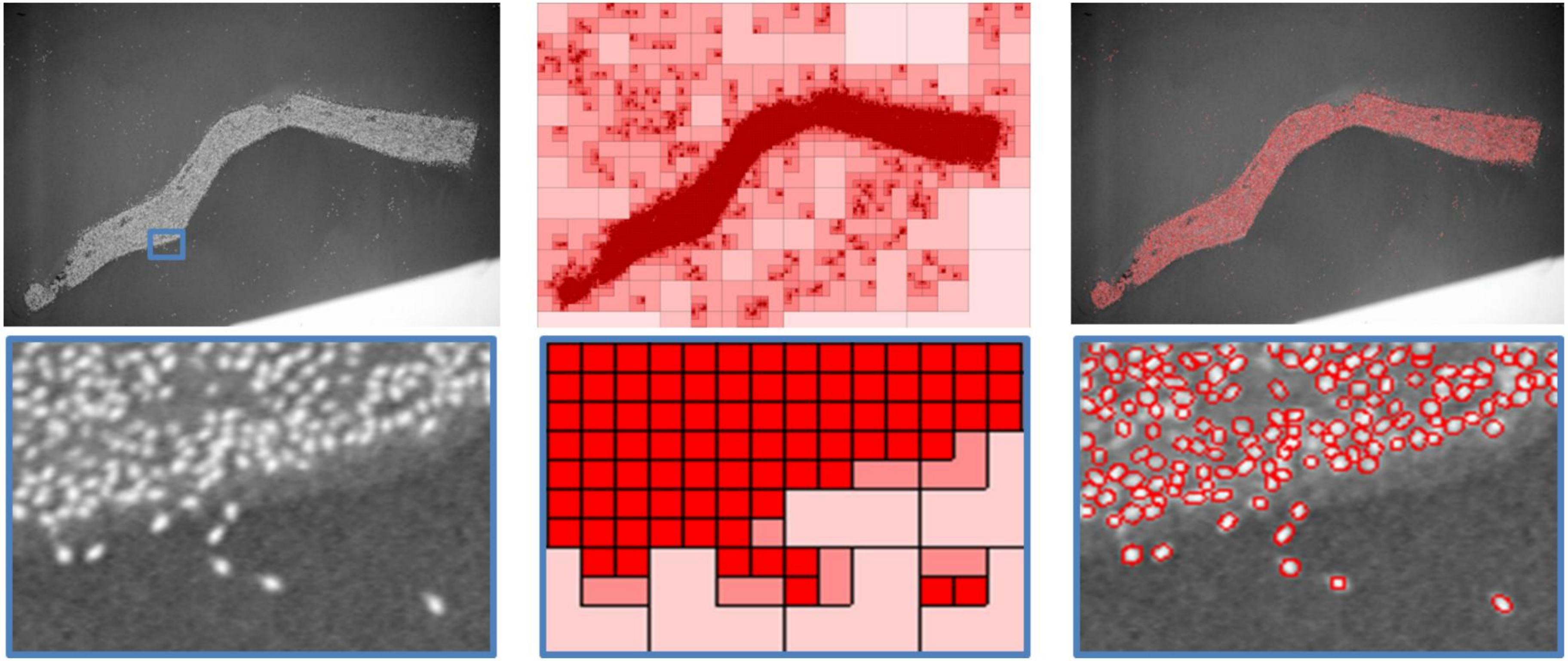
Proposition step

Acceptance step

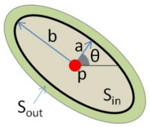


2D Ellipsoidal objects

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

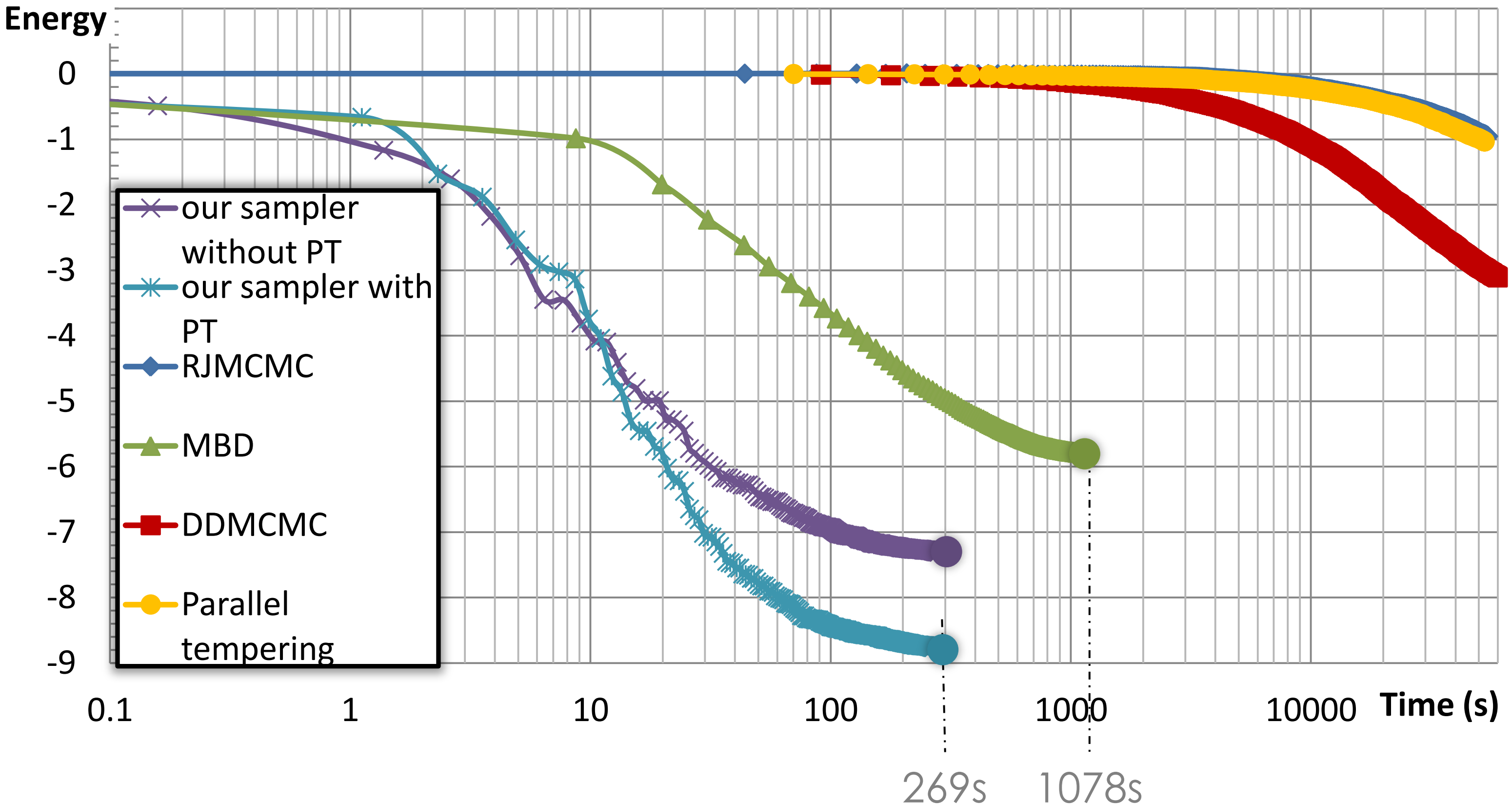


Ellipse

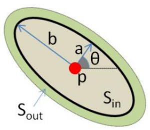


2D Ellipsoidal objects

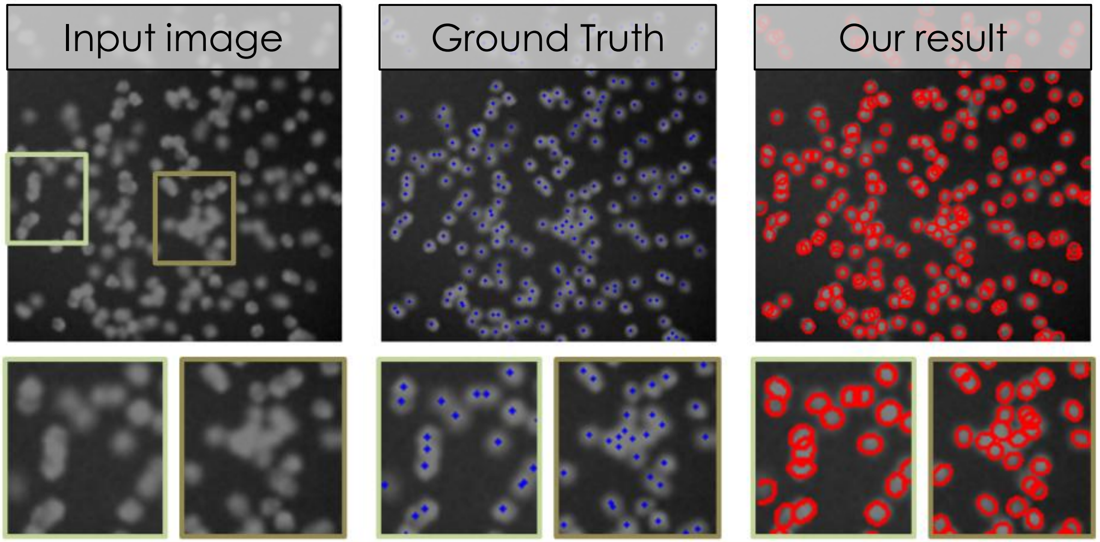
Time to converge



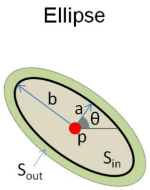
Ellipse



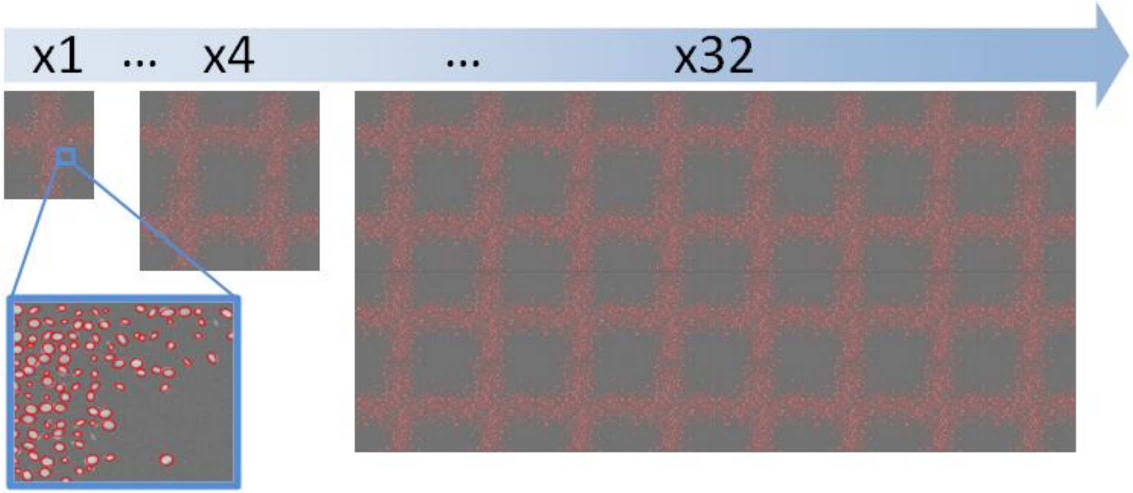
[Lempitsky and Zisserman, NIPS2010]

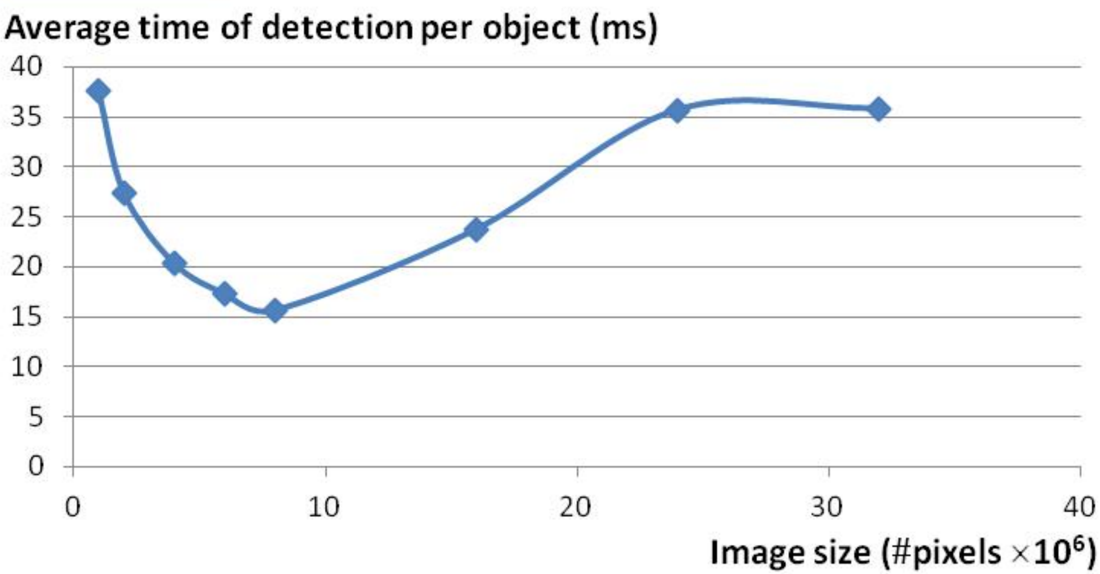


	our method	Lempitsky ($L1$-reg.)	Lempitsky (Tikhonov-reg.)	Ground Truth
cell17	**209**	202.9	194.1	213
cell18	184	**184.6**	175.9	185
cell19	**187**	192.2	180.1	188
cell20	**169**	174.1	170.4	169
cell21	147	**148.6**	144.4	149
cell22	**184**	182.6	176.5	184
cell23	**159**	158.3	157.6	161
RMSE	**1.93**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



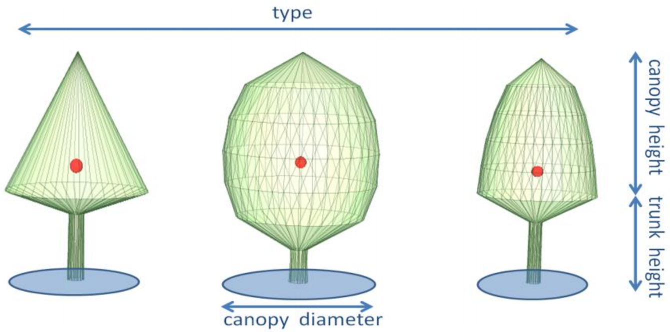
GPU occupancy





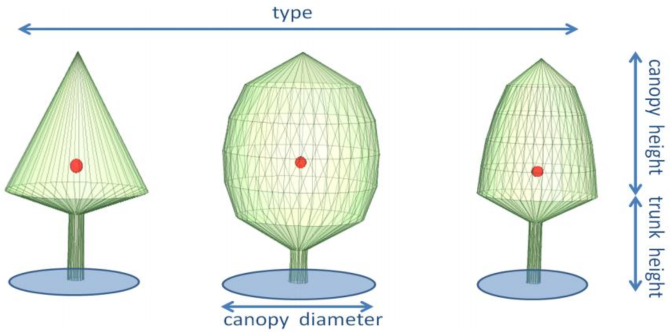
3D Objects

- Three parametric objects
  - 7 parameters



3D Objects

- Three parametric objects
- New energy formulation



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

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

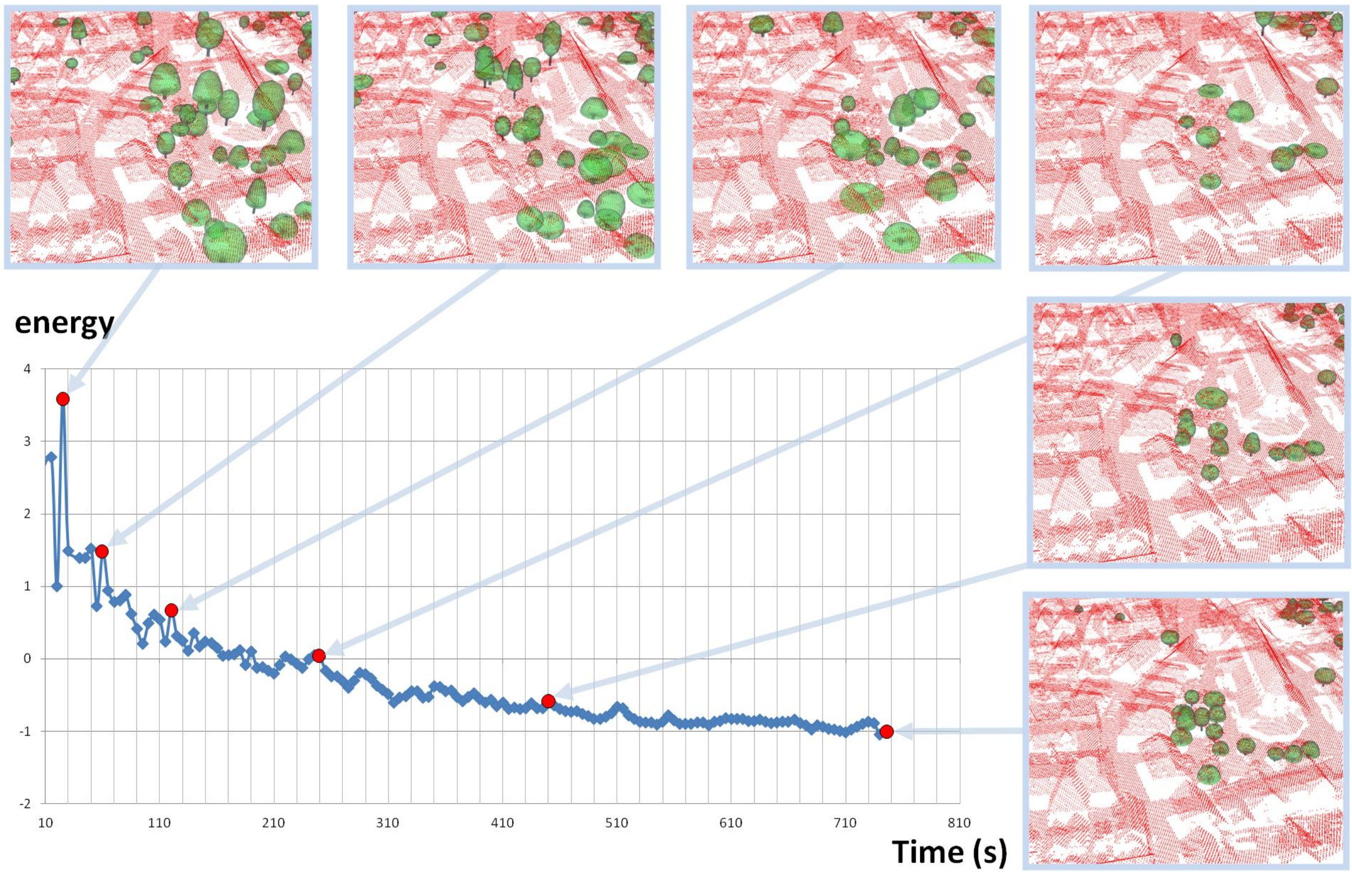
$d(p_c, \partial x_i)$ is a distance measuring the coherence of the point p_c with respect to the object surface ∂x_i

penalizes the overlapping between objects

favors area with similar type of objects

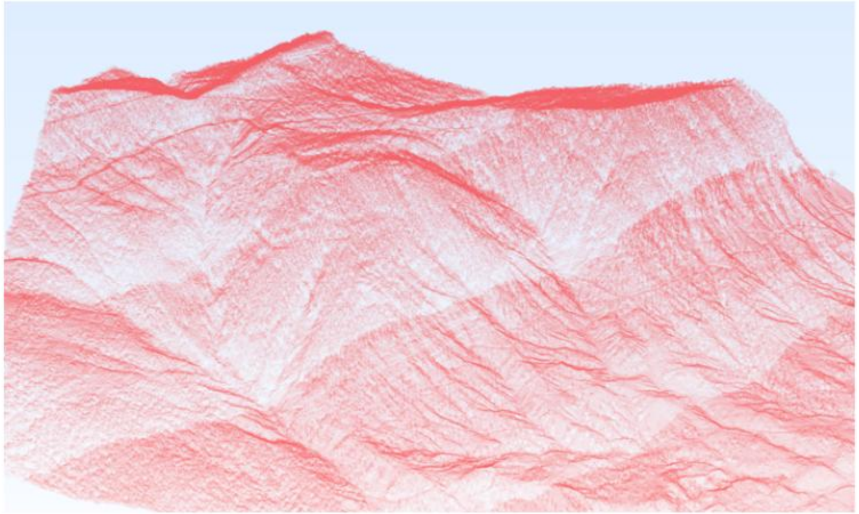
3D Objects

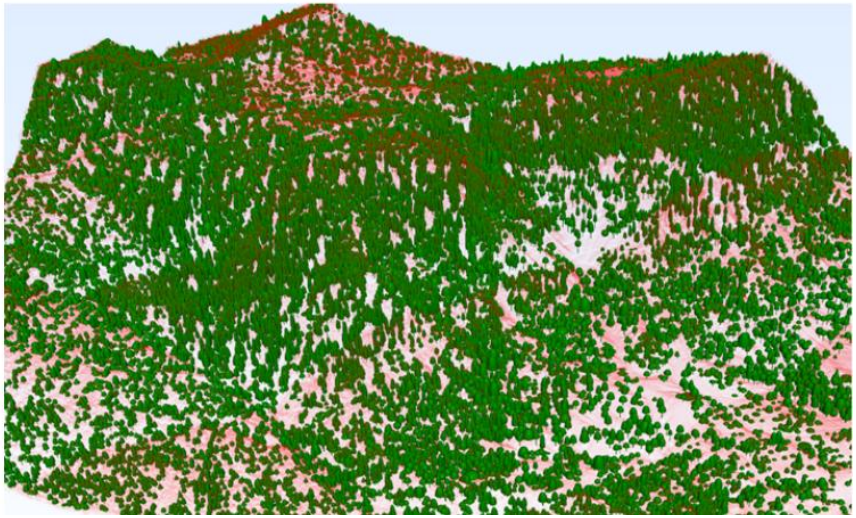
Evolution of the configuration

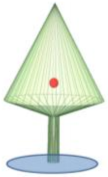


3D Objects

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

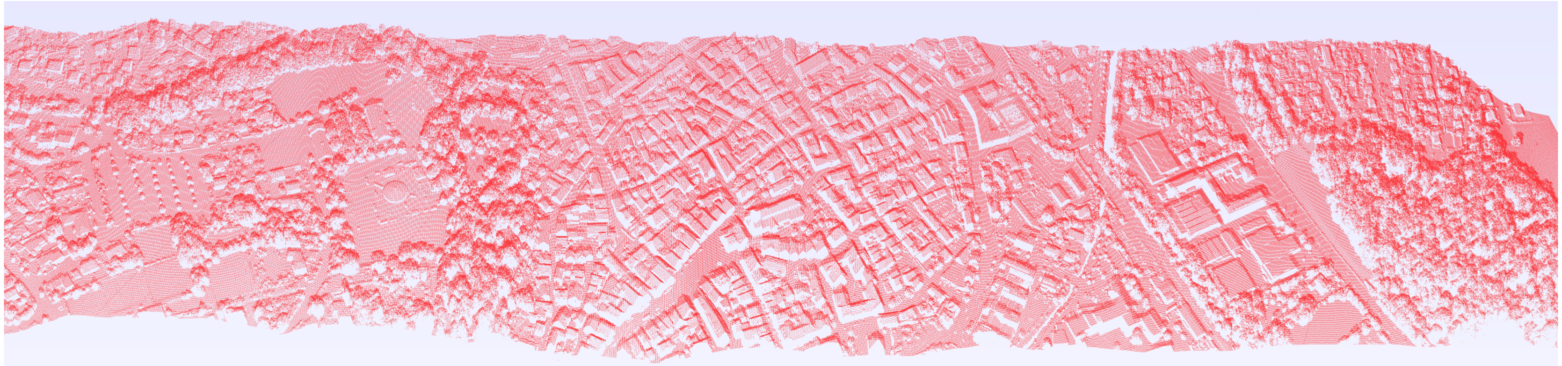






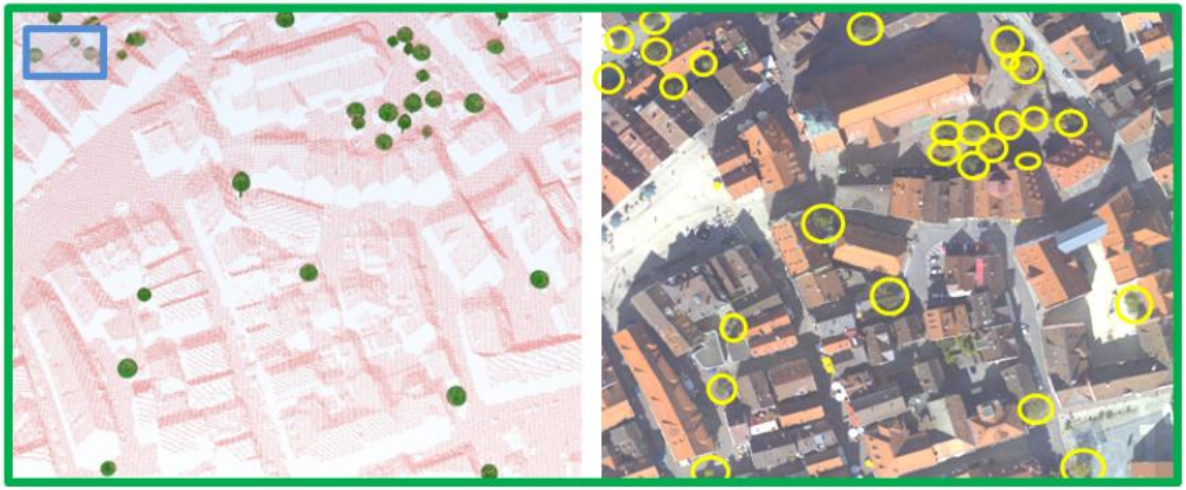
3D Objects

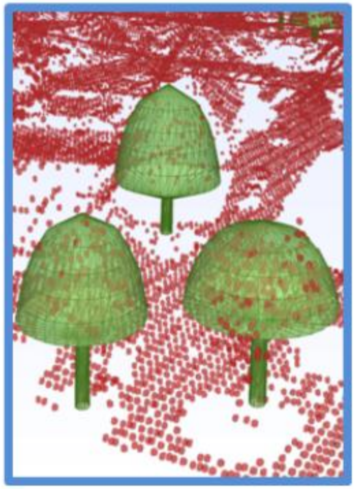
5 .4k trees in 53min (1km2 / 2.3M points)



3D Objects

Details on cropped area





Visual reference from Google map

Outline

① Introduction

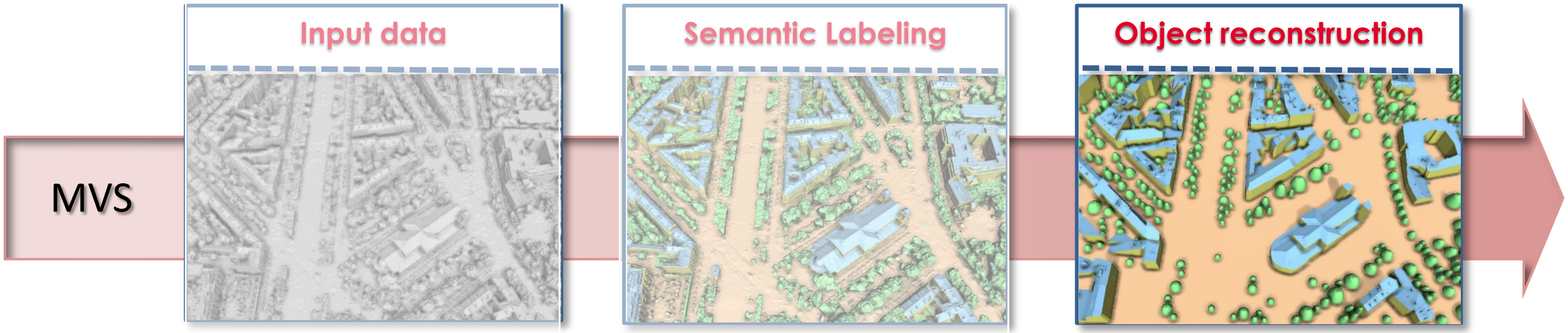
② Semantic labeling

③ Object Reconstruction: parametric-based object detection

④ Object Reconstruction: mesh-based object reconstruction

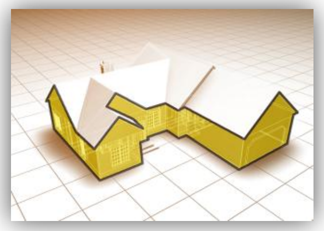
⑤ Conclusion and future work

Mesh-based object reconstruction

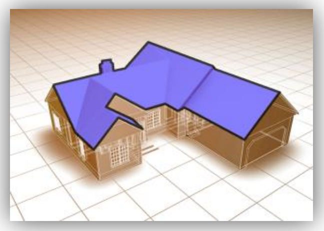


→ Focus on the building reconstruction from MVS

Facades



Roofs



Contributions on building reconstruction from MVS

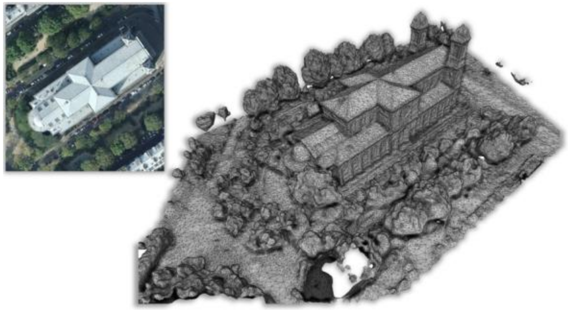
We propose

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

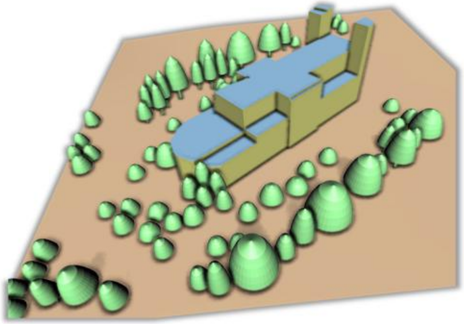
LOD1 – Building as "blocks model, without any roof structures or textures"
LOD2 – Building with "differentiated roof structures"
LOD3 – Building as "architectural model with detailed wall and roof structures"

[Kolbe et al., 2005]

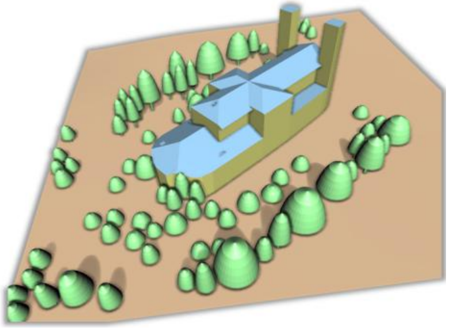
  - Visually more appealing
  - More adapted to certain urban applications



original



LOD1



LOD3

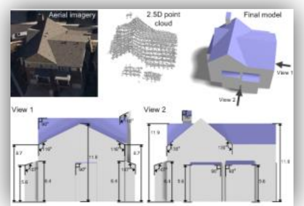
Contributions on building reconstruction from MVS

We propose

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

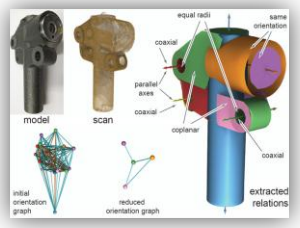
→ Existing solutions un-adapted: accurate but too slow for our application

Global regularities



[Zhou and Neumann, CVPR12]

GLOBFIT

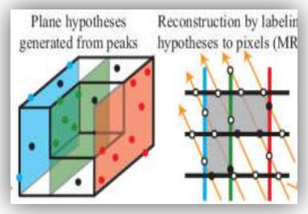


[Li et al., Siggraph11]

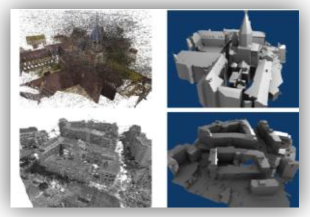
Contributions on building reconstruction from MVS

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

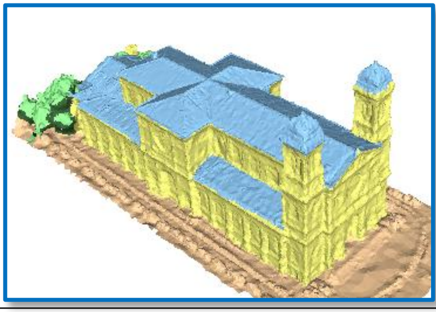
- Multiple Level of Details (LOD)
- Efficient plane regularization
- **Efficient Binary Space Partitioning (BSP)**

  - Advantages:

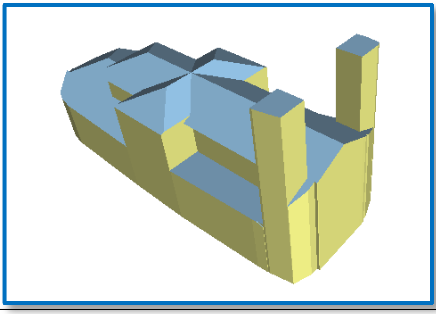
→ reconstruct with exact geometry only a subset of cells

→ the plane regularization limits the number of different planes (lower BSP complexity)

Building reconstruction from MVS data

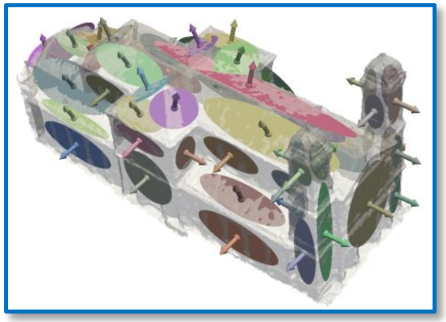


Labeling

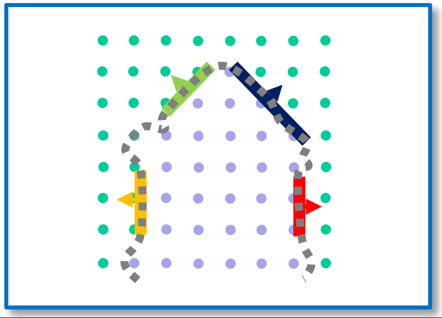


Surface extraction

Plane hypothesis from roof and facade f-clusters



Plane regularization



Discrete space partitioning

Building reconstruction from MVS data

Plane regularization:

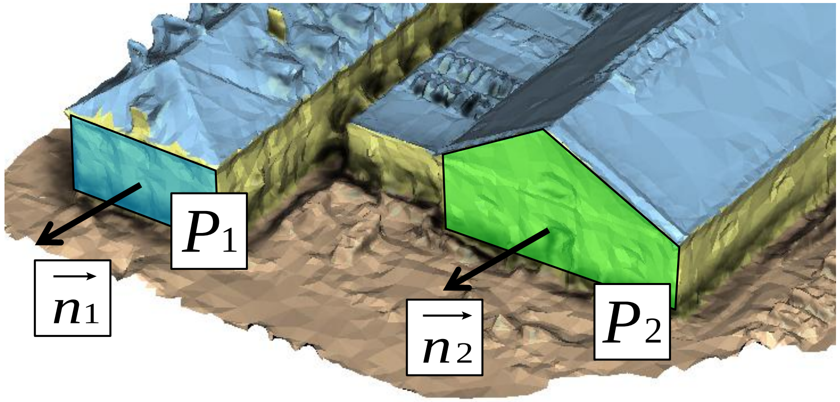
- 4 pairwise relationships controlled with two parameters $\boldsymbol{\varepsilon}$ and $\boldsymbol{d}$

Building reconstruction from MVS data

Plane regularization:

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

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

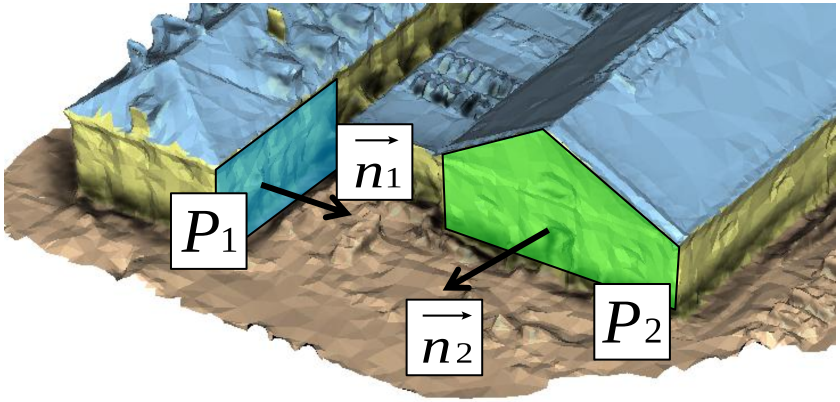


Building reconstruction from MVS data

Plane regularization:

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

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

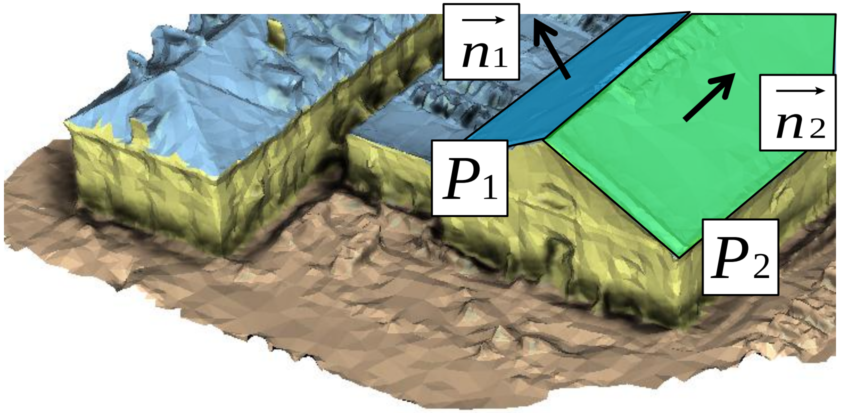


Building reconstruction from MVS data

Plane regularization:

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

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



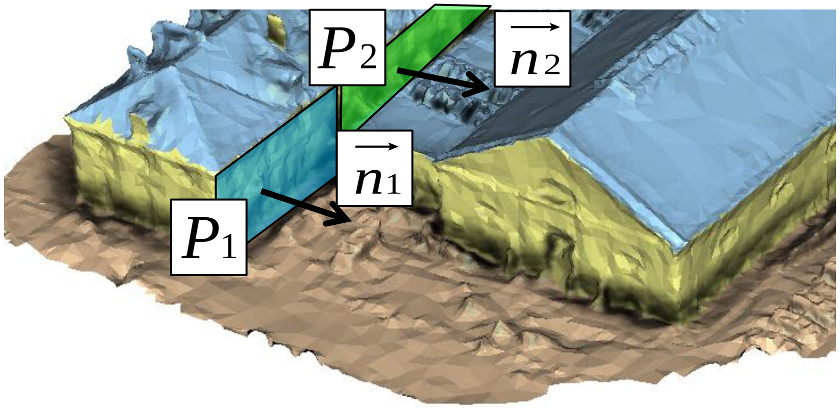
Building reconstruction from MVS data

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

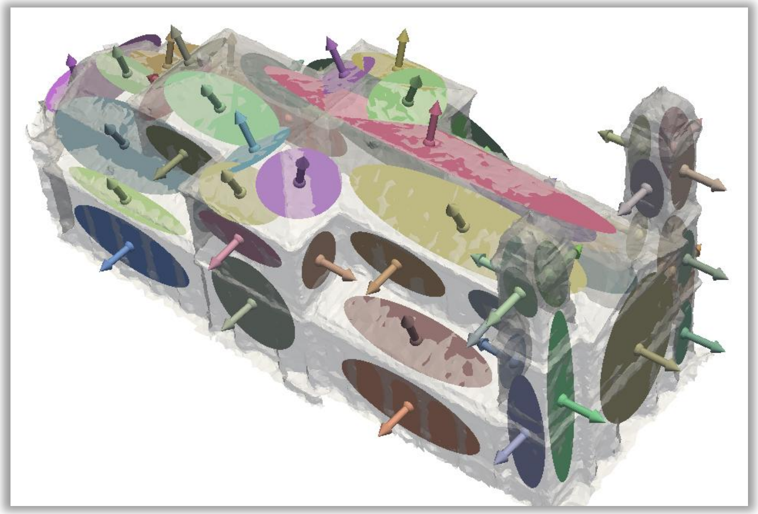
$$|d_\perp(c_1, P_2) + d_\perp(c_2, P_1)| < 2d,$$



Building reconstruction from MVS data

Plane regularization:

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

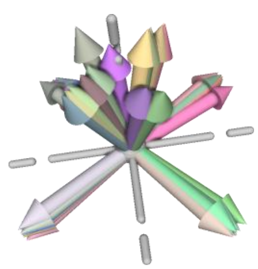


Building reconstruction from MVS data

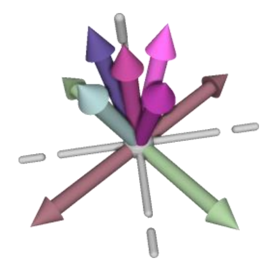
Plane regularization:

- 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



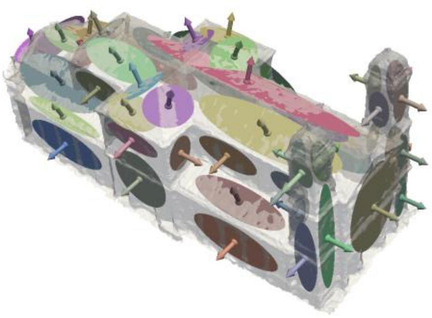
After orientation correction

Building reconstruction from MVS data

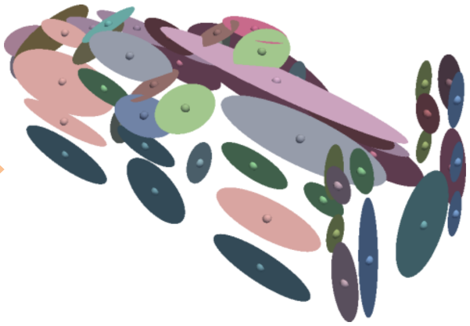
Plane regularization:

- 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

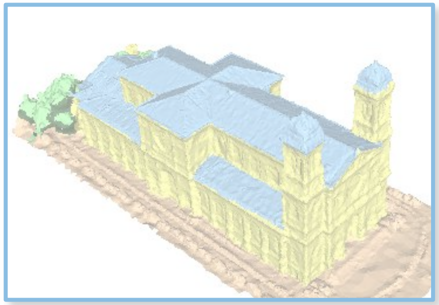
Plane regularization:

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

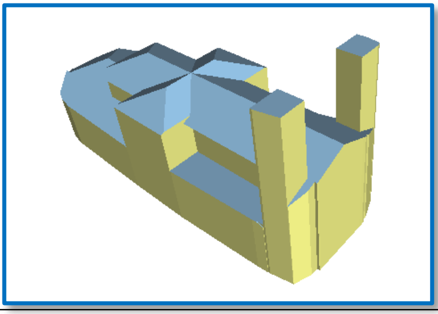
  2) Position correction: merge *co-planar* groups

→ Converge very fast (no data refitting)
Thousand of planes in few seconds

Building reconstruction from MVS data

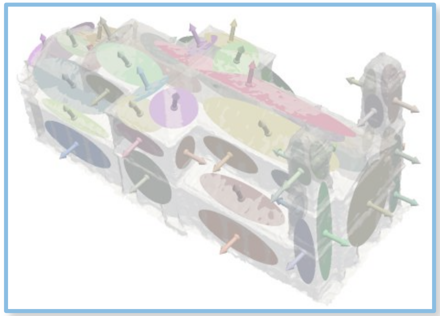


Labeling

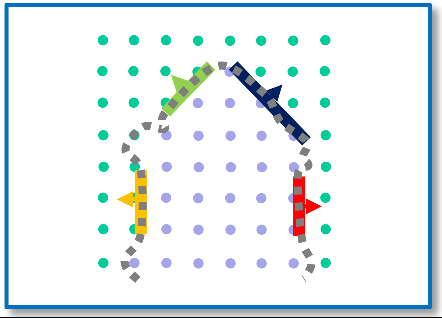


Surface extraction

Plane hypothesis from roof and facade f-clusters



Plane regularization

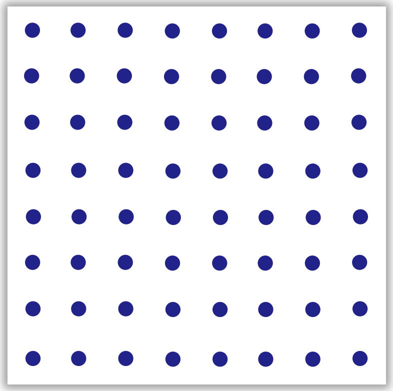


Discrete space partitioning

Building reconstruction from MVS data

Discrete space partitioning:

- Volumetric occupancy grid

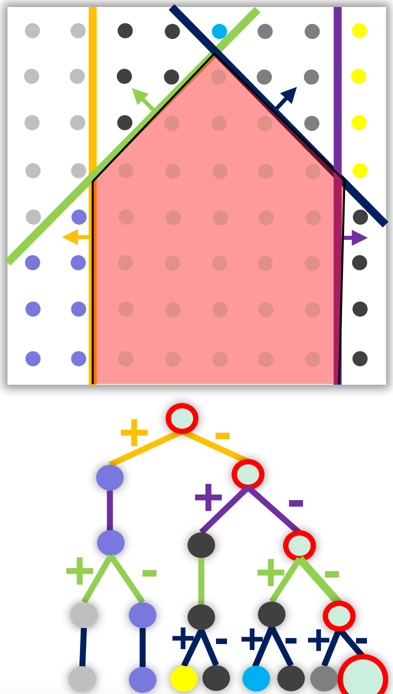


Building reconstruction from MVS data

Discrete space partitioning:

- Volumetric occupancy grid
- Binary Space Partitioning (BSP)

→ Red volume = a path in the BSP



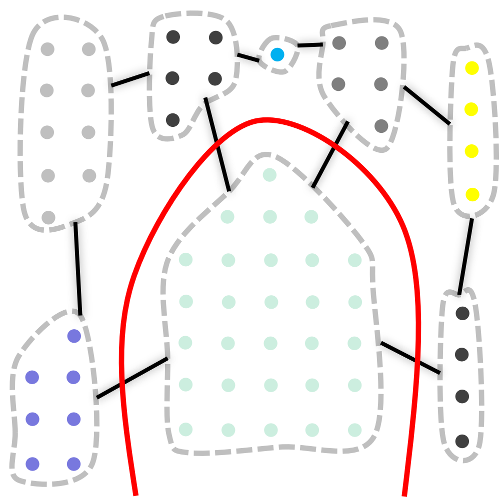
?

selection of the right path

Building reconstruction from MVS data

Surface extraction:

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



Surface = { / + \ + / + \ }

→ 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:**

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

V_{c_k} is the discrete volume of cell ck

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

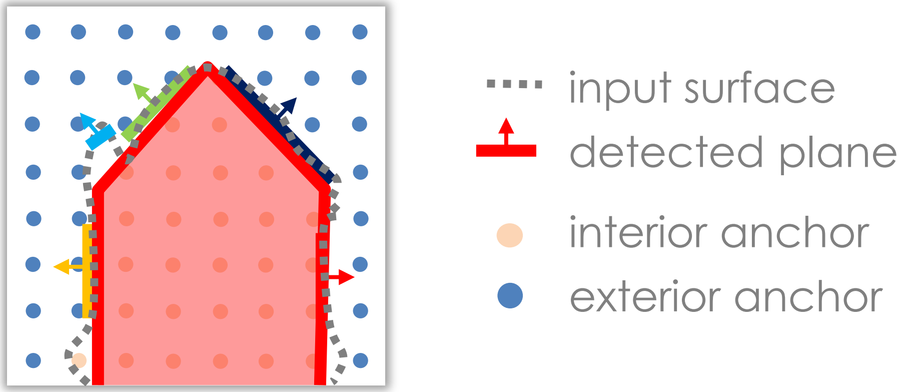
$\sum_{e_i \in \mathcal{S}} A_{e_i}$ is the discrete area of the resulting surface

Building reconstruction from MVS data

Surface extraction:

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

- **Min-cut formulation:**



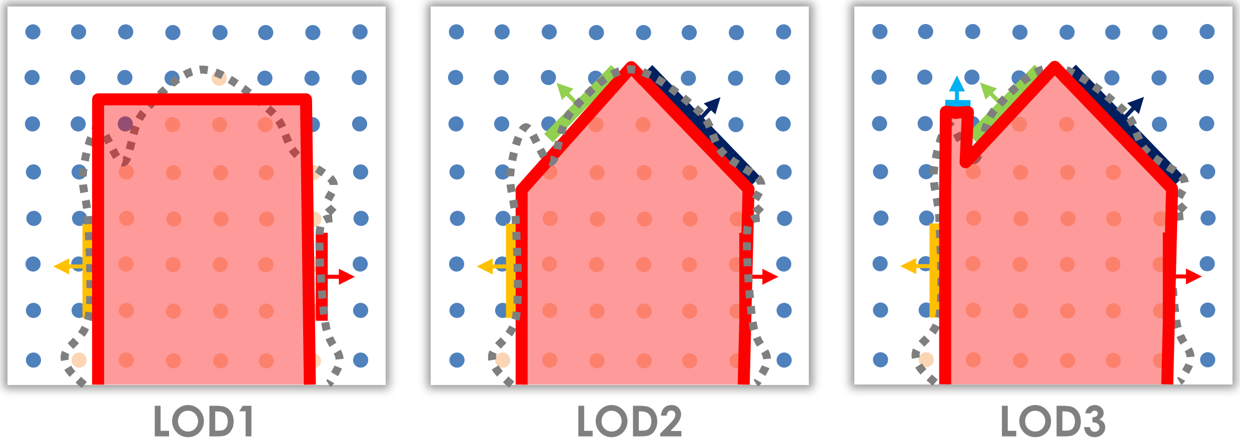
→ The boundary of the inside volume represents the targeted surface

Building reconstruction from MVS data

Surface extraction:

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

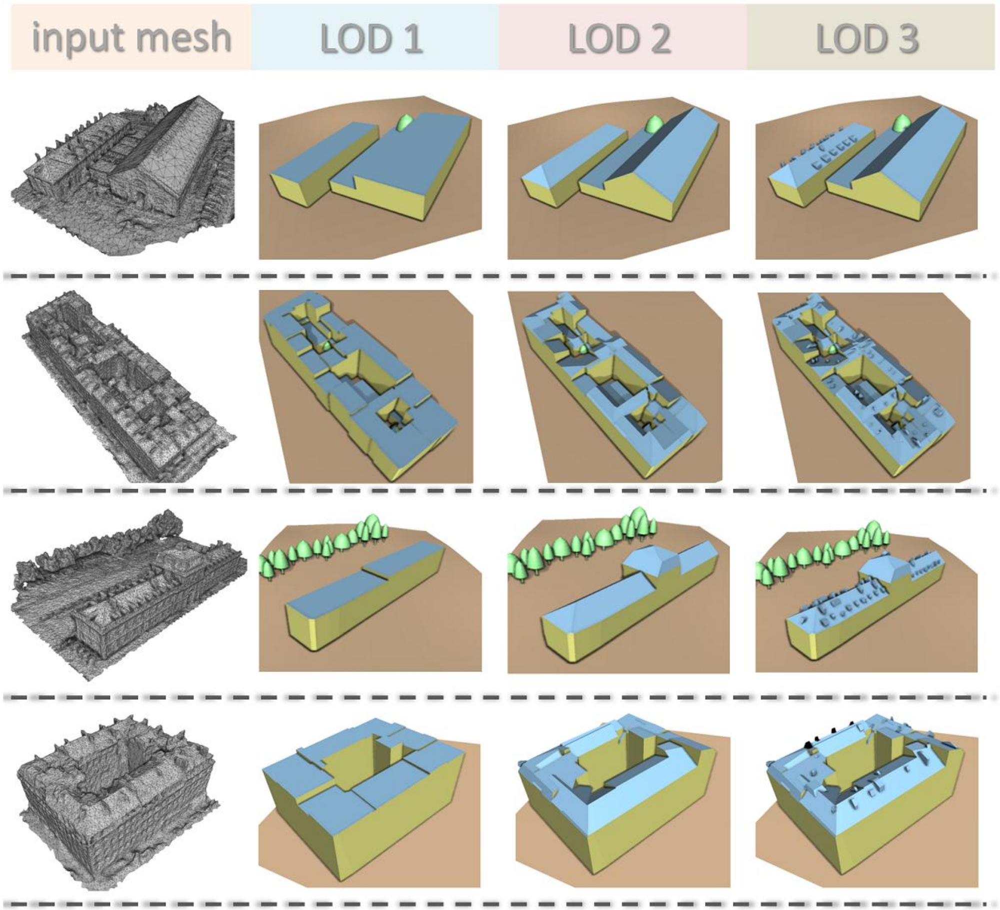
- **Min-cut formulation:**



The boundary of the inside volume represents the targeted surface

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

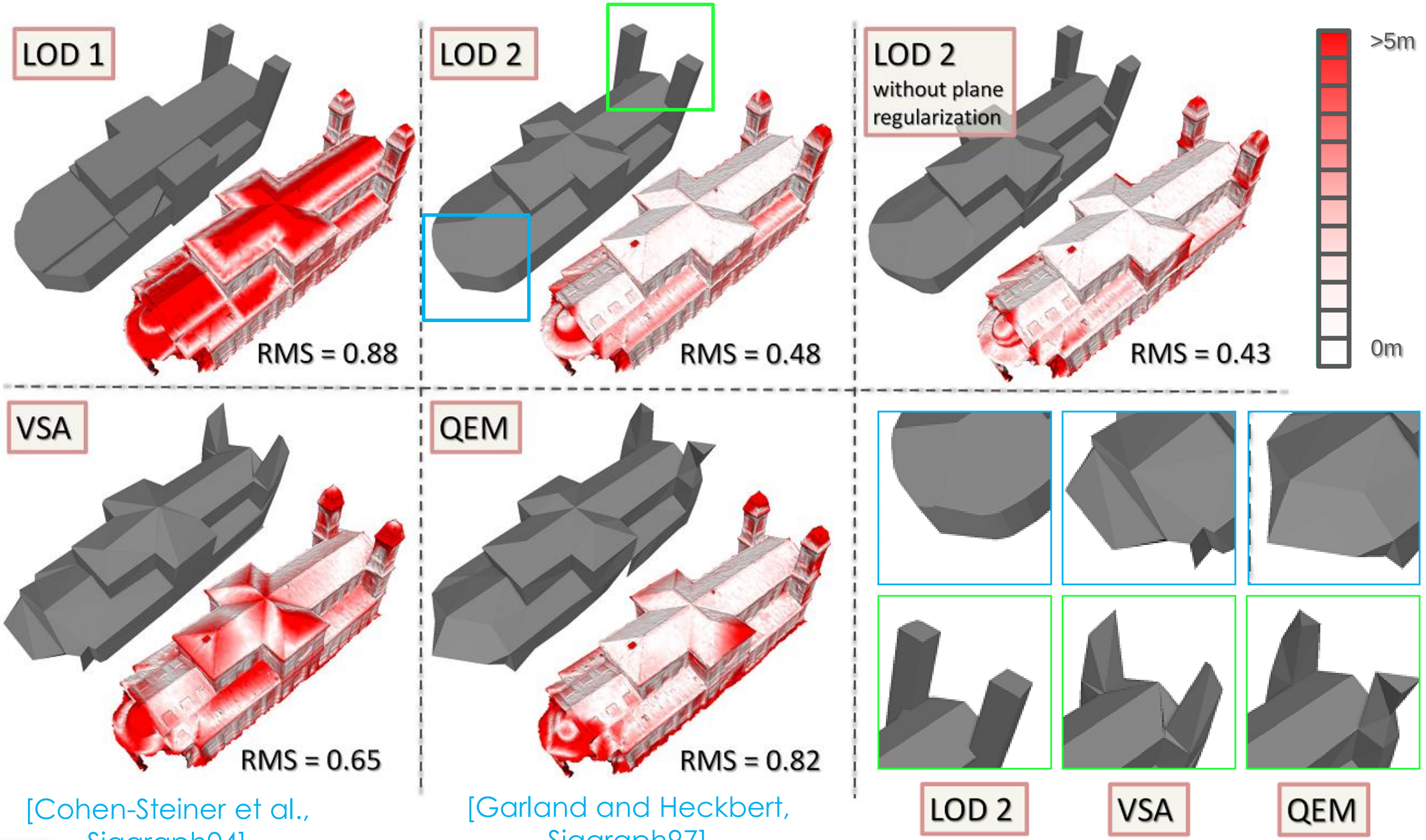
Various buildings: (LOD)



Various buildings: 170k facets, ~3min

Experiments

Geometric accuracy (Hausdorff distance) and structure awareness

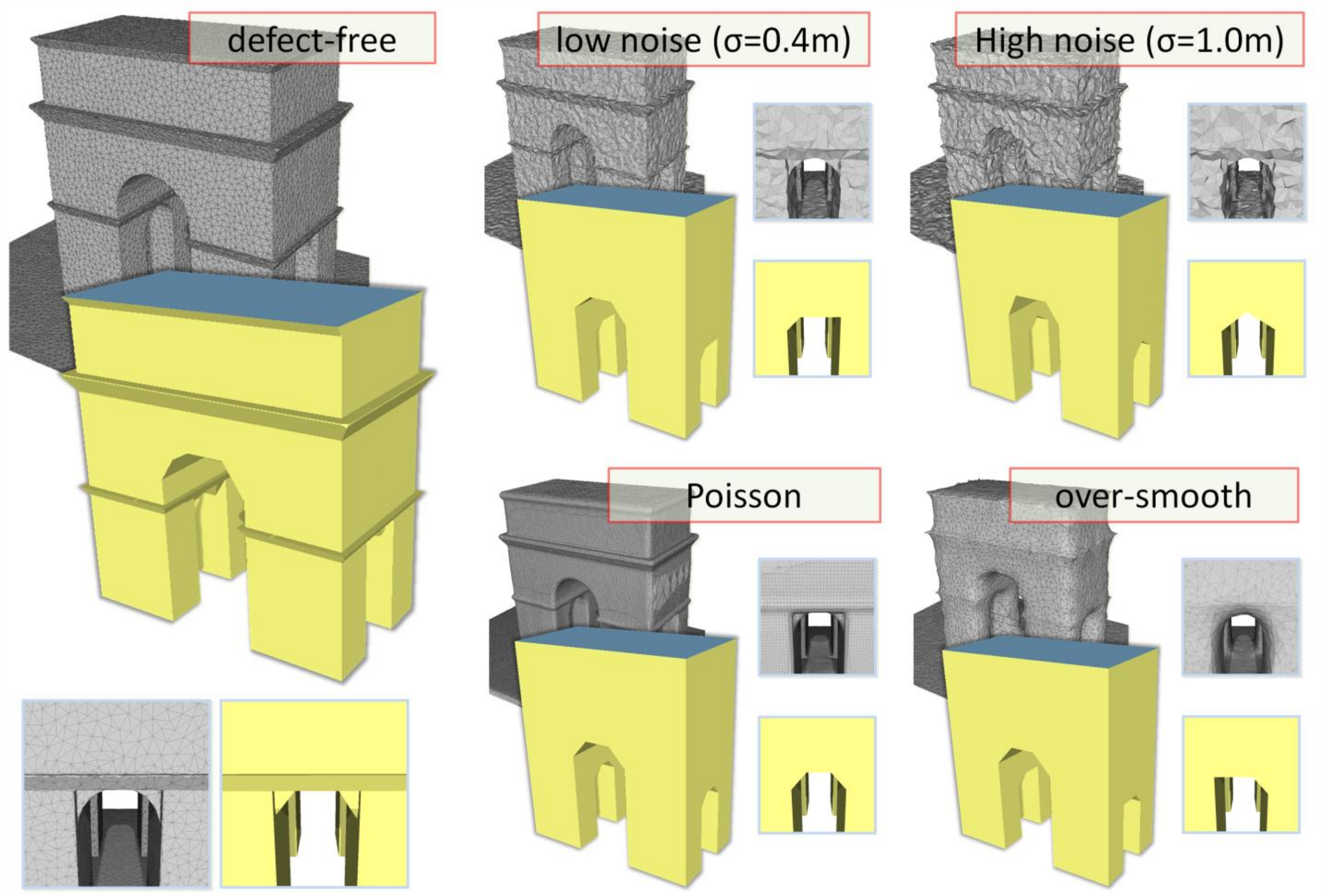


[Cohen-Steiner et al., Siggraph04]

[Garland and Heckbert, Siggraph97]

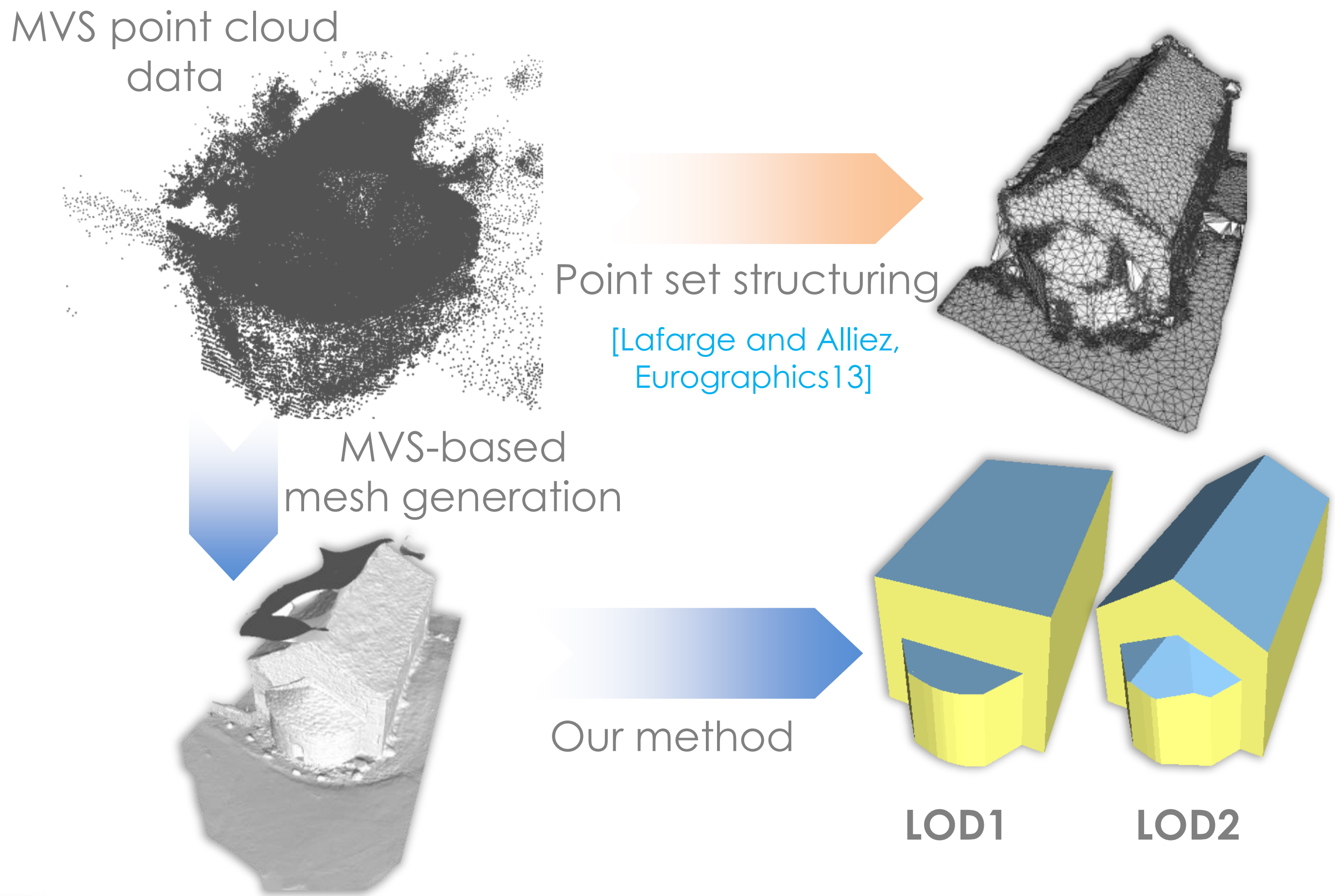
Experiments

Robustness assessment

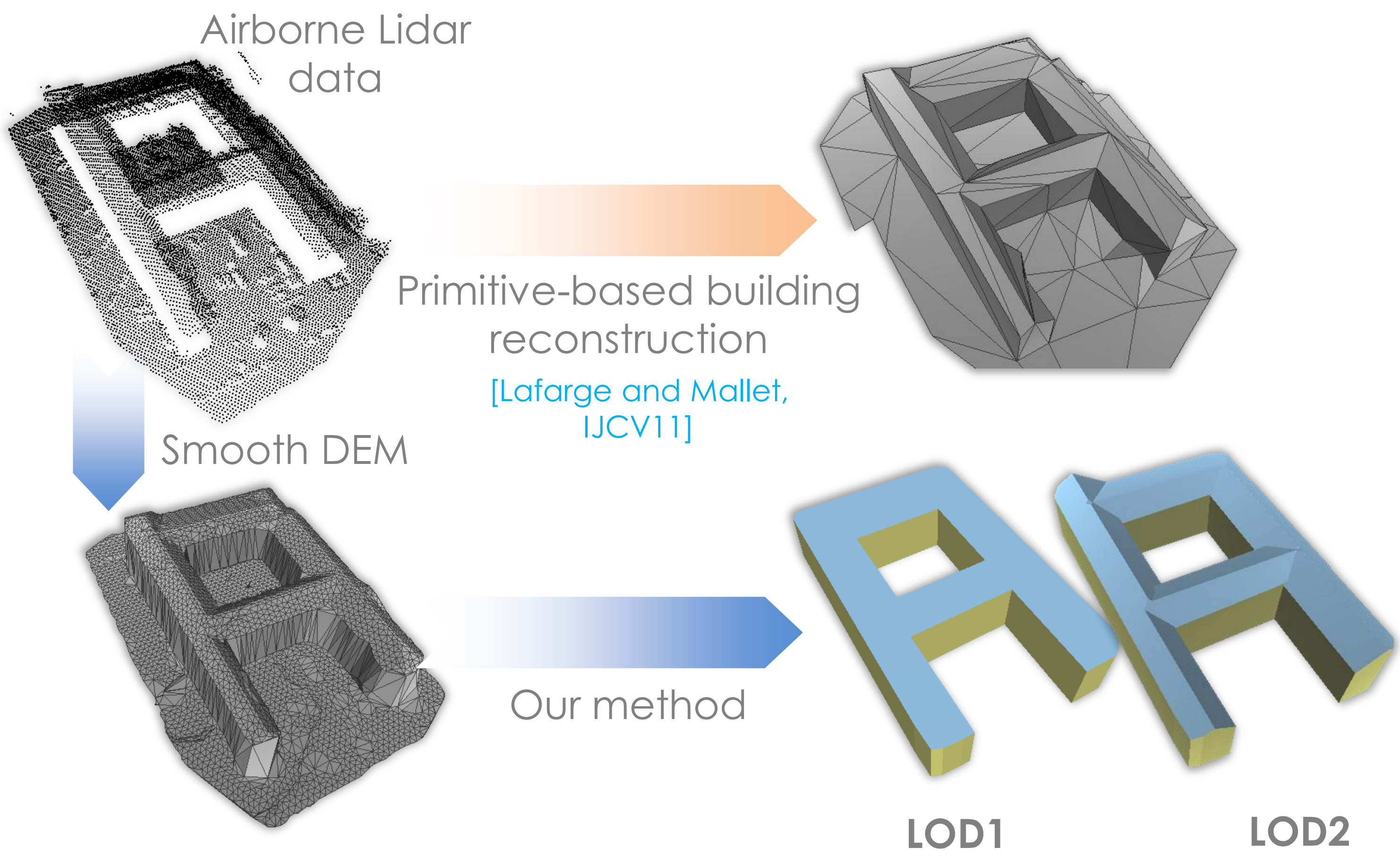


Experiments

Robustness assessment



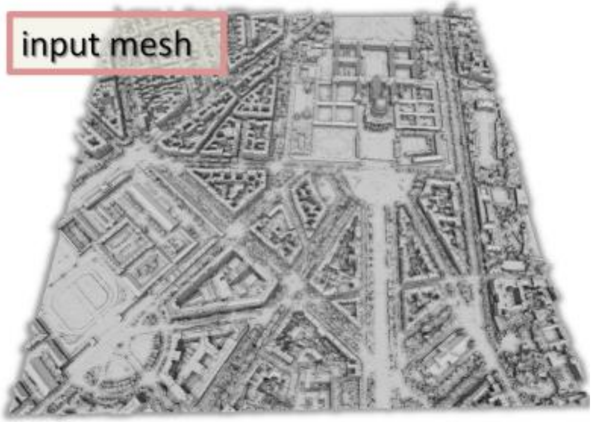
Choice of the input: mesh or point cloud



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**

Inria

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

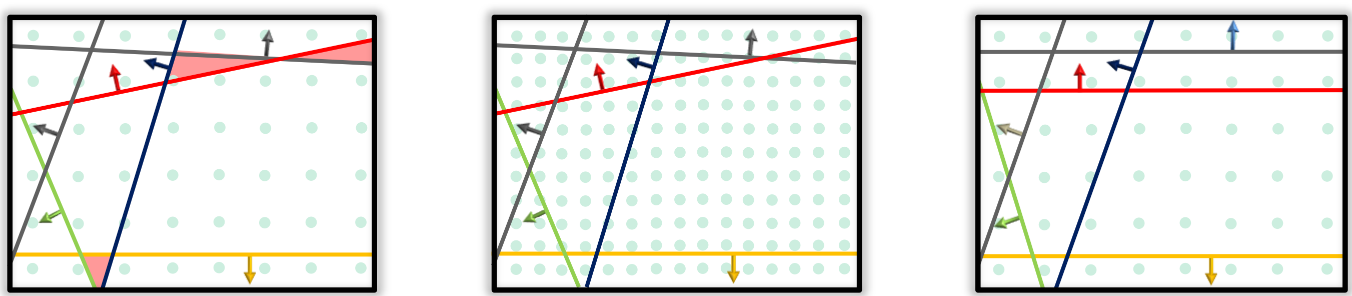
- Classes of objects limited

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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