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Semantic Decomposition and Reconstruction of Residential Scenes from LiDAR Data

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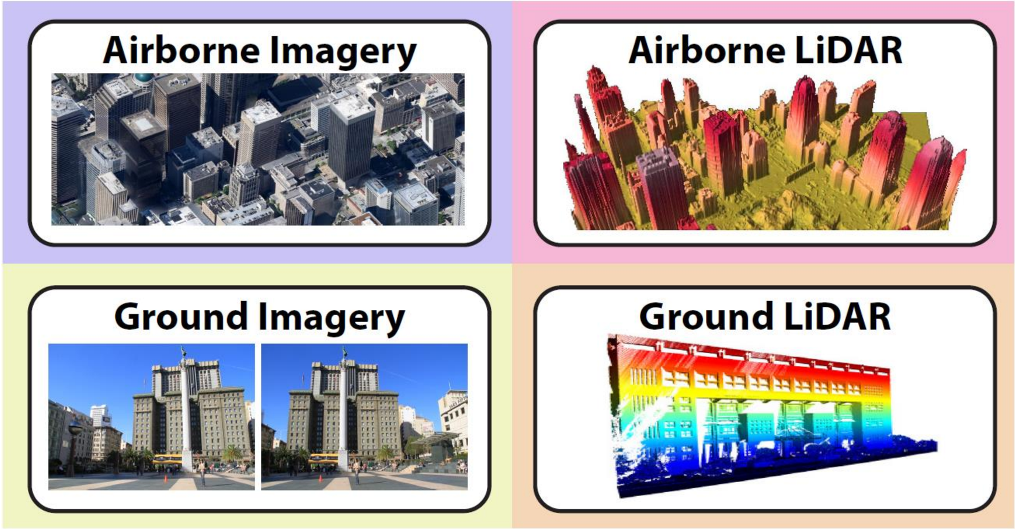
Semantic Decomposition and Reconstruction of Residential Scenes from LiDAR Data

- Introduction
- Related Work
- Algorithm Insight and Overview
  - Semantic Segmentation
  - House Modeling
  - Model Enhancement
- Experimental Results
- Limitation
- Conclusion

Urban Environment Modeling



[Musialski et al. 2012]

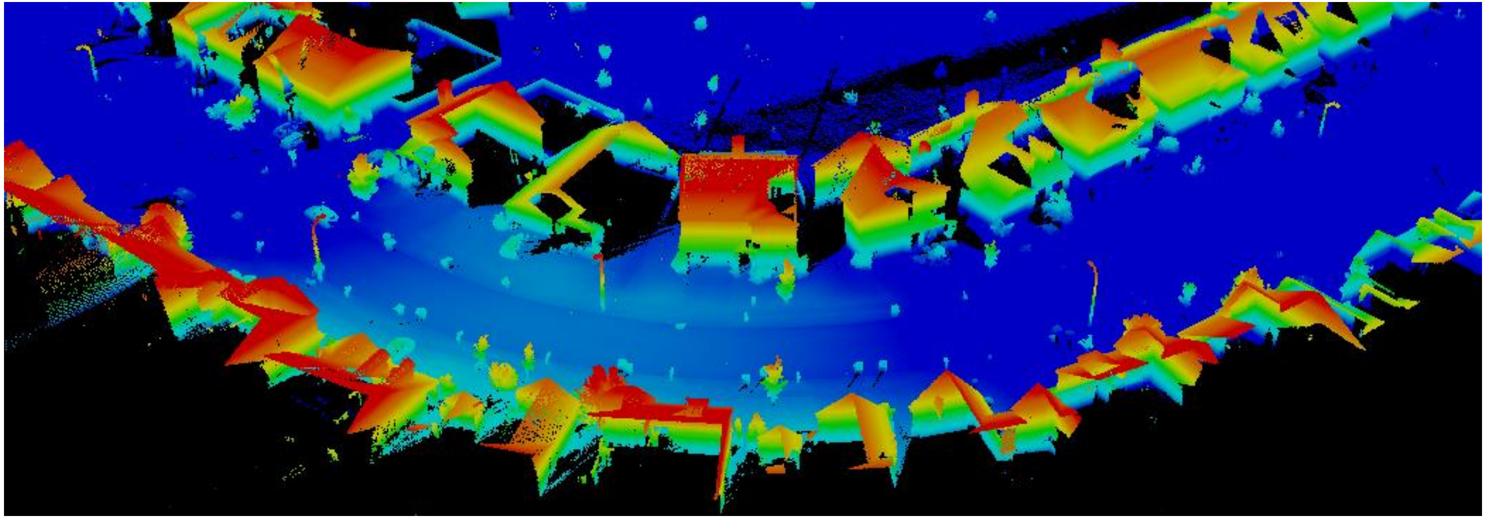
- Automatic large-scale reconstruction remains an open problem
- Typically focus on multiple-story or high-rise buildings
  - Repetitive and regular structural details

Residential Scene Modeling

- Receives little attention but equally important!
- They are everywhere!

Residential Scene Modeling

- Input: ground-based LiDAR point clouds with geo-registered images



Residential Scene Modeling

- Output: ***complete*** 3D models with textures of common objects in a residential scene

A Short Video of
Reconstruction Results

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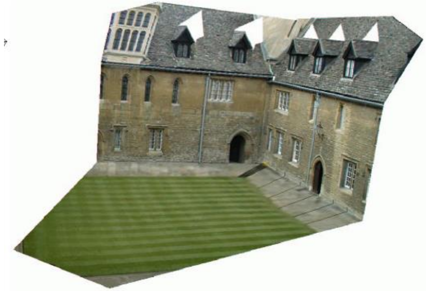
Related Work

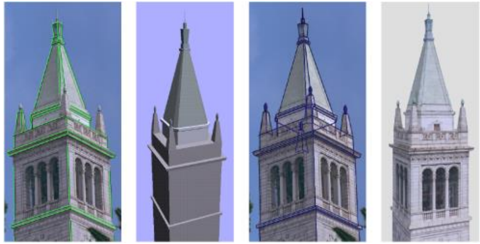
- Image-based



[Werner and Zisserman 2002]

[Akbarzadeh et al. 2006]

[Xiao et al. 2008]



[Debevec et al. 1996]

[Sinha et al. 2008]

[Frahm et al. 2010]

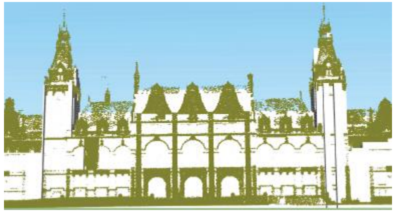
Related Work

- Repetitive and regular structures; shape grammars

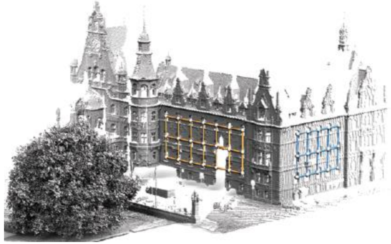
[Müller et al. 2006]

[Müller et al. 2007]

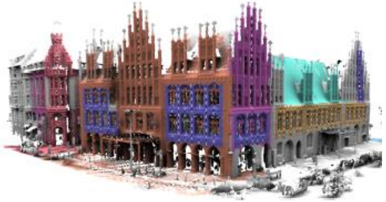
[Nan et al. 2010]



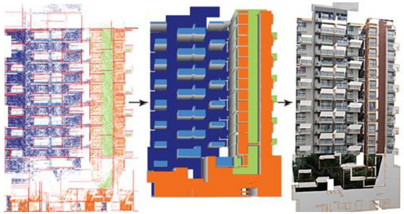
[Vanegas et al. 2012]



[Pauly et al. 2008]



[Bokeloh et al. 2009]



[Li et al. 2011]

[Wu et al. 2010]

Related Work

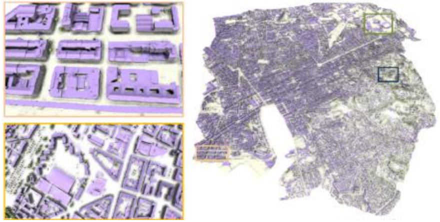
- Large-scale

[Frueh et al. 2005]

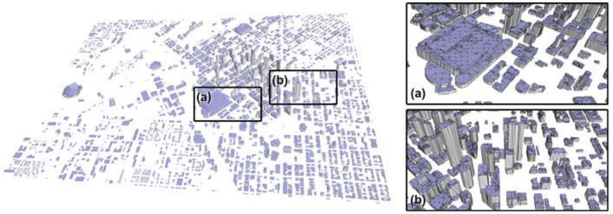
[Irschara et al. 2012]

[Xiao et al. 2008]

[Poullis and You 2009]



[Lafarge and Mallet 2011]



[Zhou and Neumann 2011]

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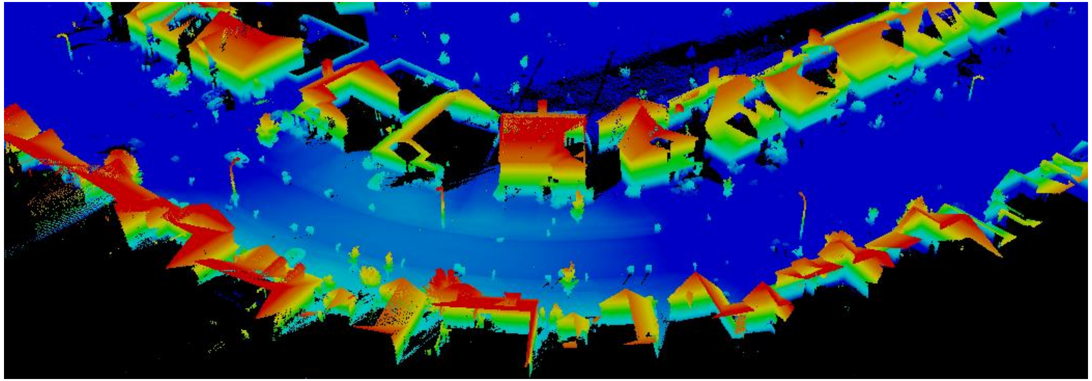
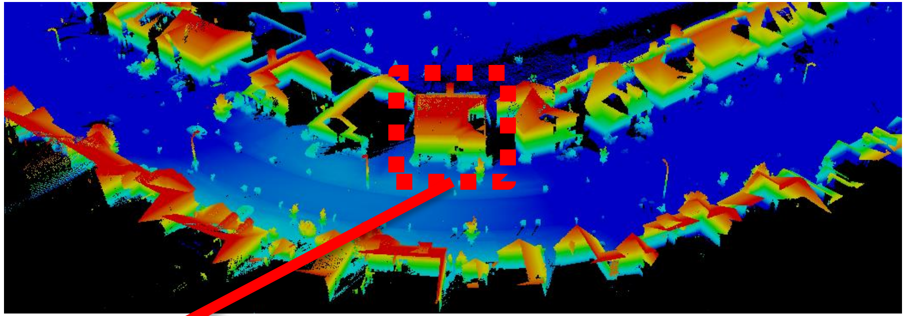
Residential Scene Modeling

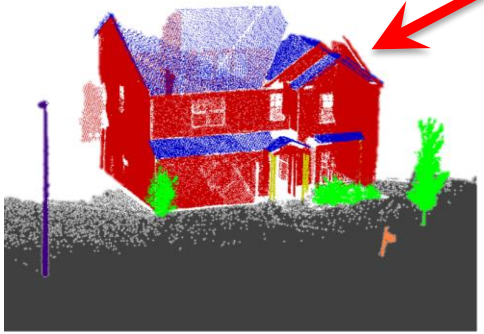
- Ground-based LiDAR point clouds
  + Ground-level details
  – Incomplete
  – Clutter
  + Large-scale



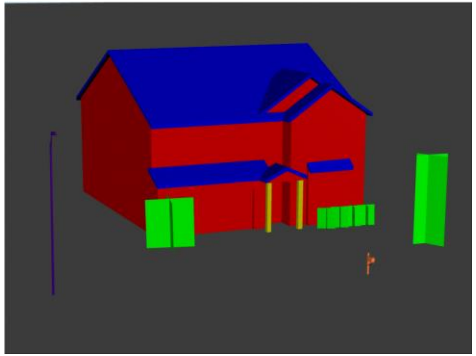
- Low-rise buildings
  – Less repetition and regularities

Our Solutions:
Semantic Decomposition and Reconstruction





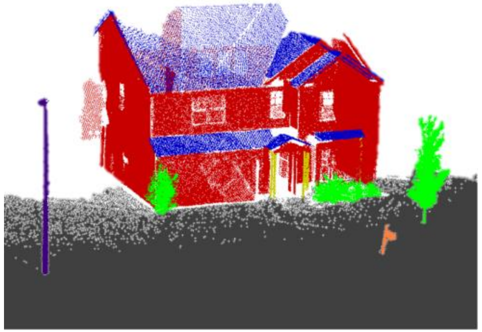
Semantic Segmentation



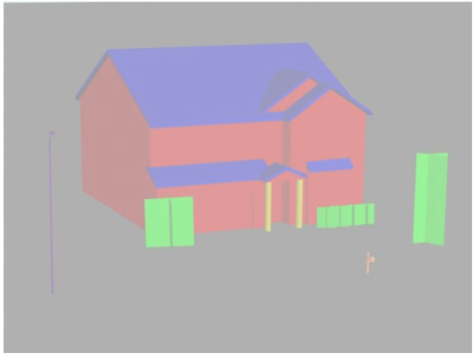
House Modeling

Texture Mapping
Landscape Modeling

Algorithm Overview



Semantic Segmentation

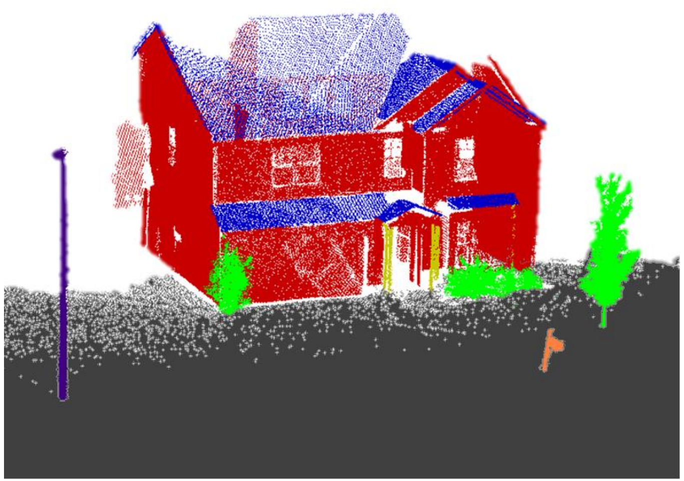


House Modeling

Texture Mapping
Landscape Modeling

Semantic Segmentation

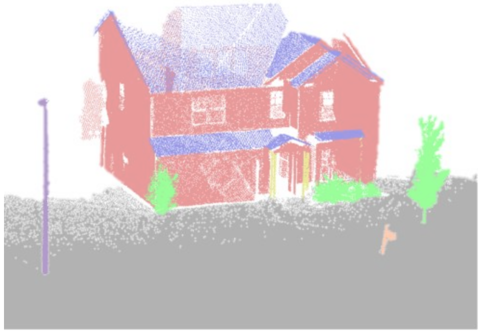
- Categories
  - Ground, plants, mailboxes, street lights, waste bins, cars
  - Houses
    - Columns, roofs, walls
- Supervised Learning
  - Super-points & Super-regions
  - Features: height, volume, normal, distance to road, etc
  - Scene Parsing [Zhang ECCV 2010]



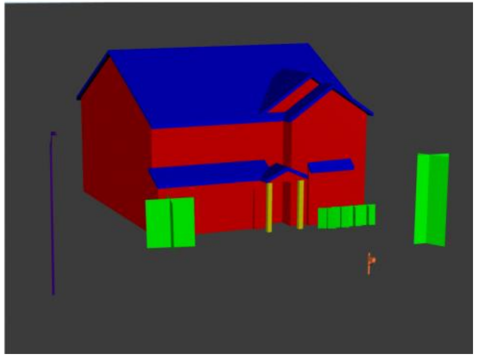
Semantic Segmentation

- Categories
  - Manually label a section as training data
  - Group nearby points into superpoints, analogues to superpixel in image segmentation
  - Adaboost classifier
  - Superreigon, which means superpoints that have similar features but at different scales, then additional features need to be involved: height, volume, area, length
- Segmentation of House
  - Roof, wall, column

Algorithm Overview



Semantic Segmentation



House Modeling

Texture Mapping
Landscape Modeling

House Modeling: Inspiration

- Various building styles:

American Colonial

Neoclassical

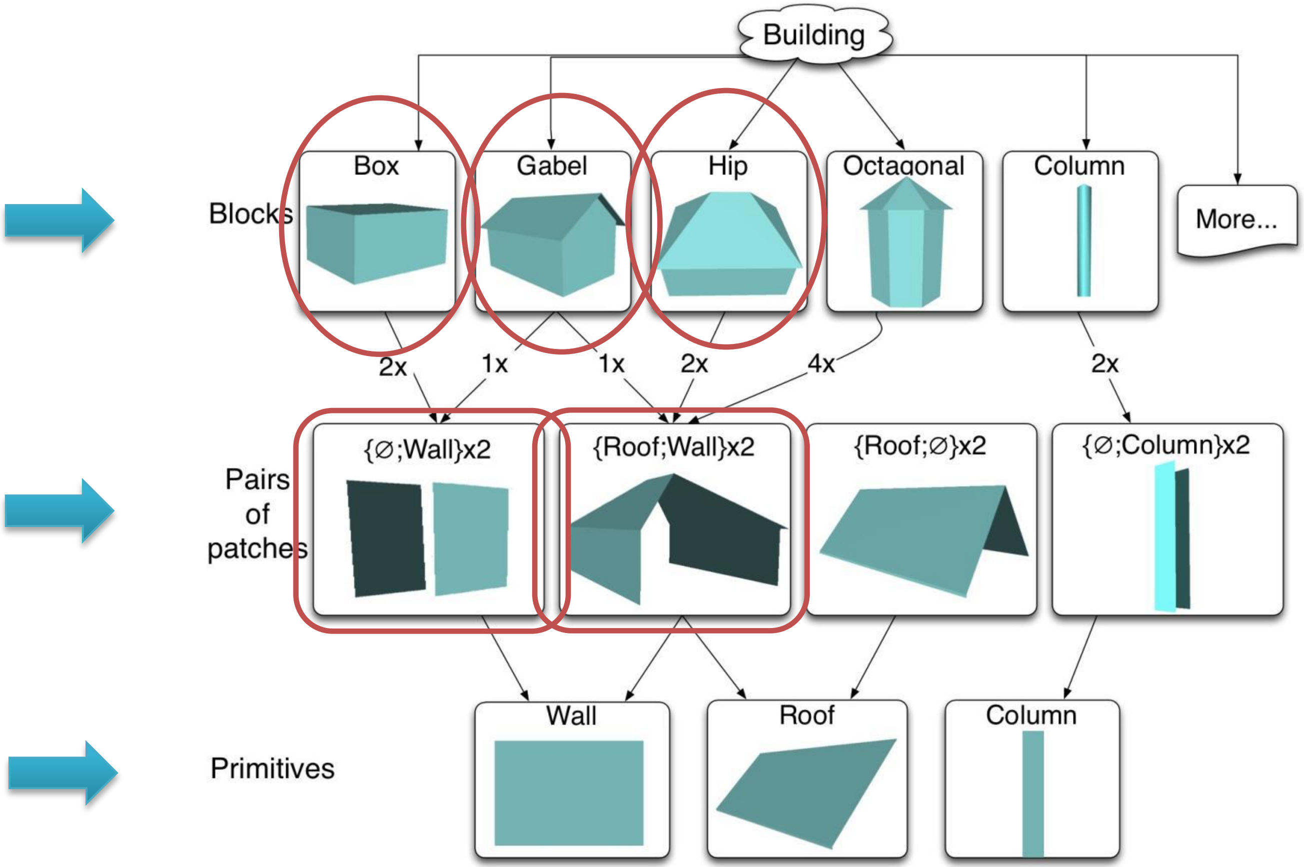
Victorian

Bungalow

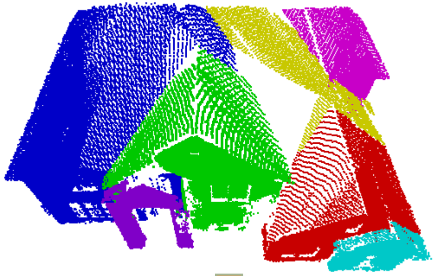
Neo

- While the fundamental structures are the same!
- A combination of convex & symmetric blocks with tilted roofs!

Hierarchical Tree Representation



Hierarchical Tree Representation



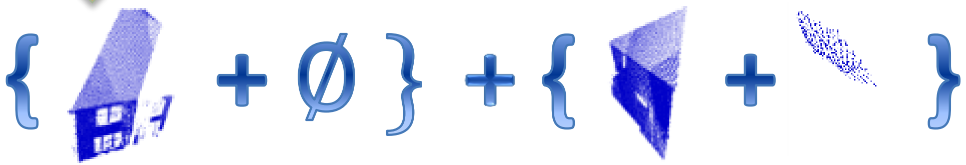
$$Building = \bigcup_i Block_i$$

$$Block = \bigcup_j Pair_j \; of \; patches$$

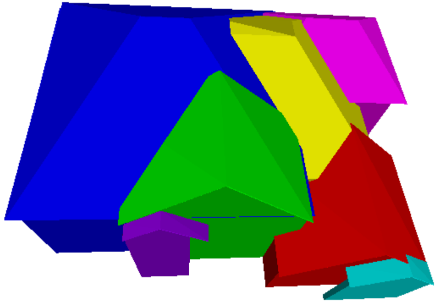
$$Patch = \{Roof; Wall\} \text{ or } \{\emptyset; Column\}$$

A set of blocks

A set of paired primitive patches



Configuration Constraints



- Possible more than one configuration
- To find unique and most plausible configuration
- Configuration constraints
  - Planarity
  - Block-level symmetry
  - Block-level convexity

Configuration Constraints

Planarity Constraint

——RANSAC [Schnabel et al. 2007]

Configuration Constraints

- Block-Level Symmetry Constraint
  - parallel-symmetry
  - intersecting-symmetry

To ensure the symmetry of basic blocks, we further require that for each pair of patches {Roof1;Wall1}; {Roof2;Wall2}, Roof1 and Roof2 be intersecting-symmetric, and Wall1 and Wall2 be parallel-symmetric

- Block-Level Convexity Constraint

the projection of a basic sub-convex block onto a carefully chosen plane can have the shape of letter “U”, but not “Z”

Connection graph

A global connection graph C (undirected, weighted) is constructed from all planar primitives. The vertices are connected by an edge in the following conditions

- for two parallel primitives
  - co-planar
  - the shortest distance between the two planar point sets is less than a predefined threshold (0.5m)
- for two non-parallel primitives
  - the shortest distances of the two planar point sets to the intersection line are both less than a threshold (0.75m)

Connection graph

For each edge e_{uv} connecting vertices u,v, its connection score, or weight, W_{uv}, is calculated as

$$W_{uv} = \Psi(D_{uv}) + (-\infty)\chi_B(u, v)$$

Ψ: predefined monotone decreasing step function

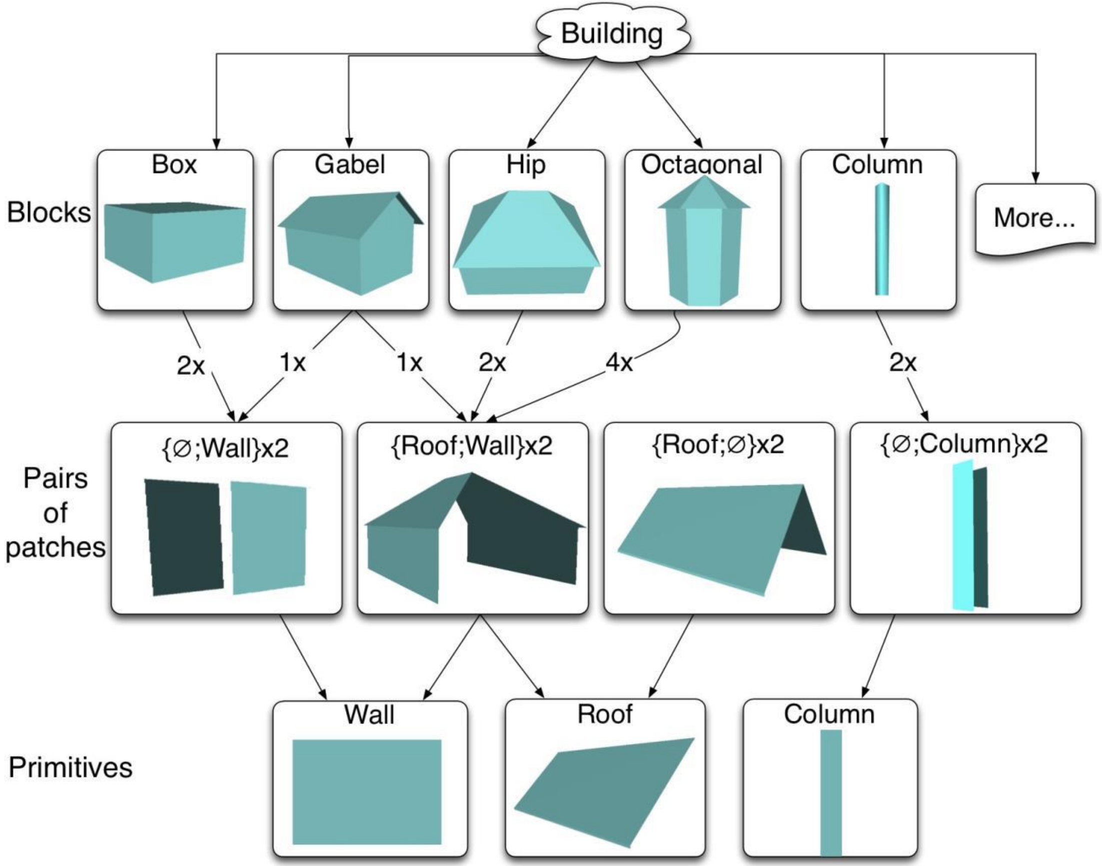
D_{uv}: the spatial distance between the primitives represented by u; v

χ_B: indicator function whose value is 1 if u, v satisfy backward relation

where two roof primitives form a "V" shape

Iterative Decomposition and Reconstruction

The aim is finding the plausible cut of the connection graph so that the sum of the connection scores on vertices inside each block is locally maximized

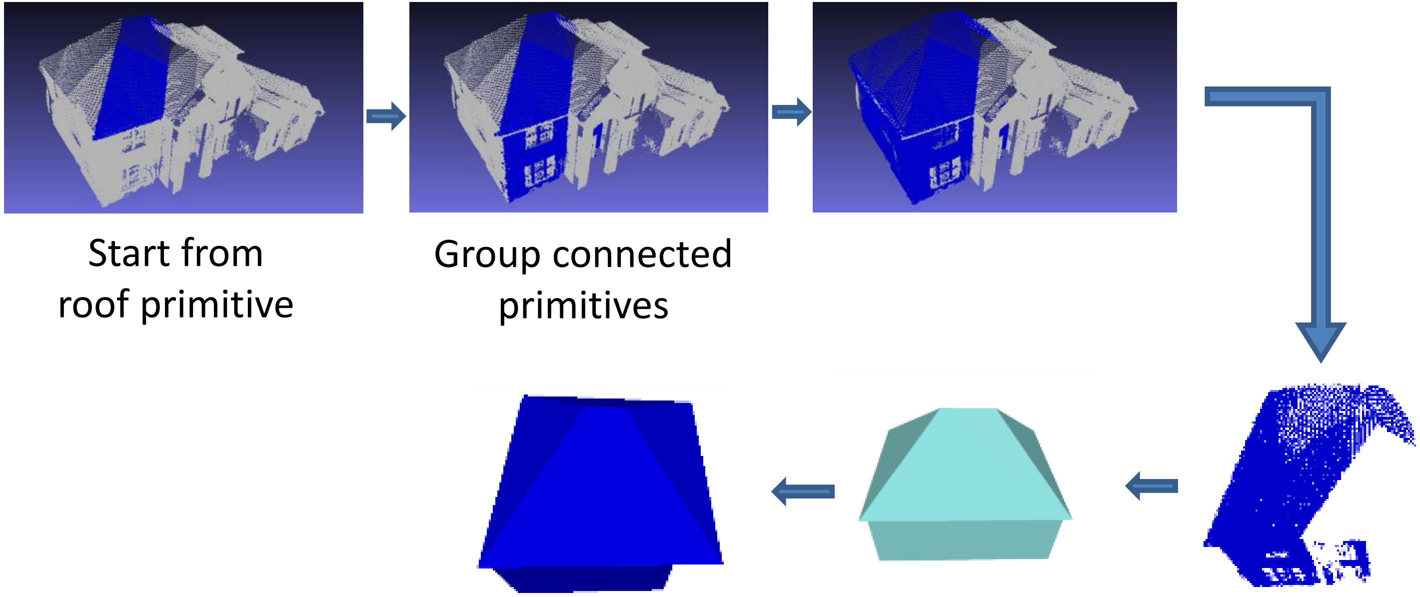


Algorithm: Hierarchical Tree Generation

Input: a set of primitives $PS := \bigcup_i \{P_i\}$
Output: a hierarchical tree T

```
while PS ≠ ∅ do
    P_0 ← largest primitive in PS
    G ← {P_0}
    Decomposition: Update G using a greedy grouping algorithm
    Reconstruction: Update hierarchical tree T from G
    for P_j ∈ G do
        Remove P_j from PS
    end for
end while
```

Iterative Decomposition and Reconstruction



Decomposition

Start from roof primitive

Group connected primitives

Reconstruction

Extract roof-wall patches

Detected Block type

Complete model

Details of Reconstruction

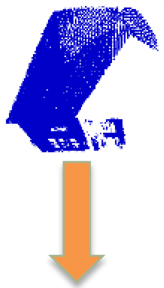
- the roof-wall patches are extracted and parameterized to form the block representation
- a surface mesh is generated as the block model
- such parameters are then adjusted by maximizing the number of points that “fit” into the block model
- For missing patches, the algorithm first fulfills the missing roof or wall with a virtual primitive, and then “extend” the block model to handle the incomplete data
- new planar primitives are formed from the unfit points

How to handling missing data

- for aerial data
  - automatically fulfilling the Roof-Wall patches with aligned virtual walls
- for terrestrial data
  - generating a virtual primitive with respect to the symmetry constraint
  - Pushing it out along its normal direction until an actual planar primitive overlaps it
  - updating the block model if such a planar primitive is found, or keeping it as a node in the hierarchical tree otherwise

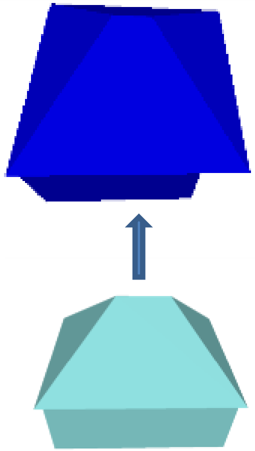
What I think

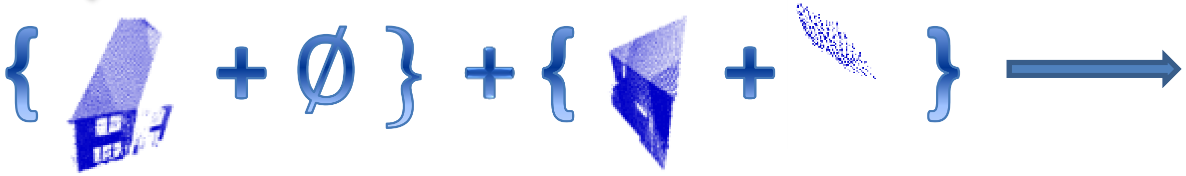
The real method is block-model-based water-tight building reconstruction



Strong Assumption

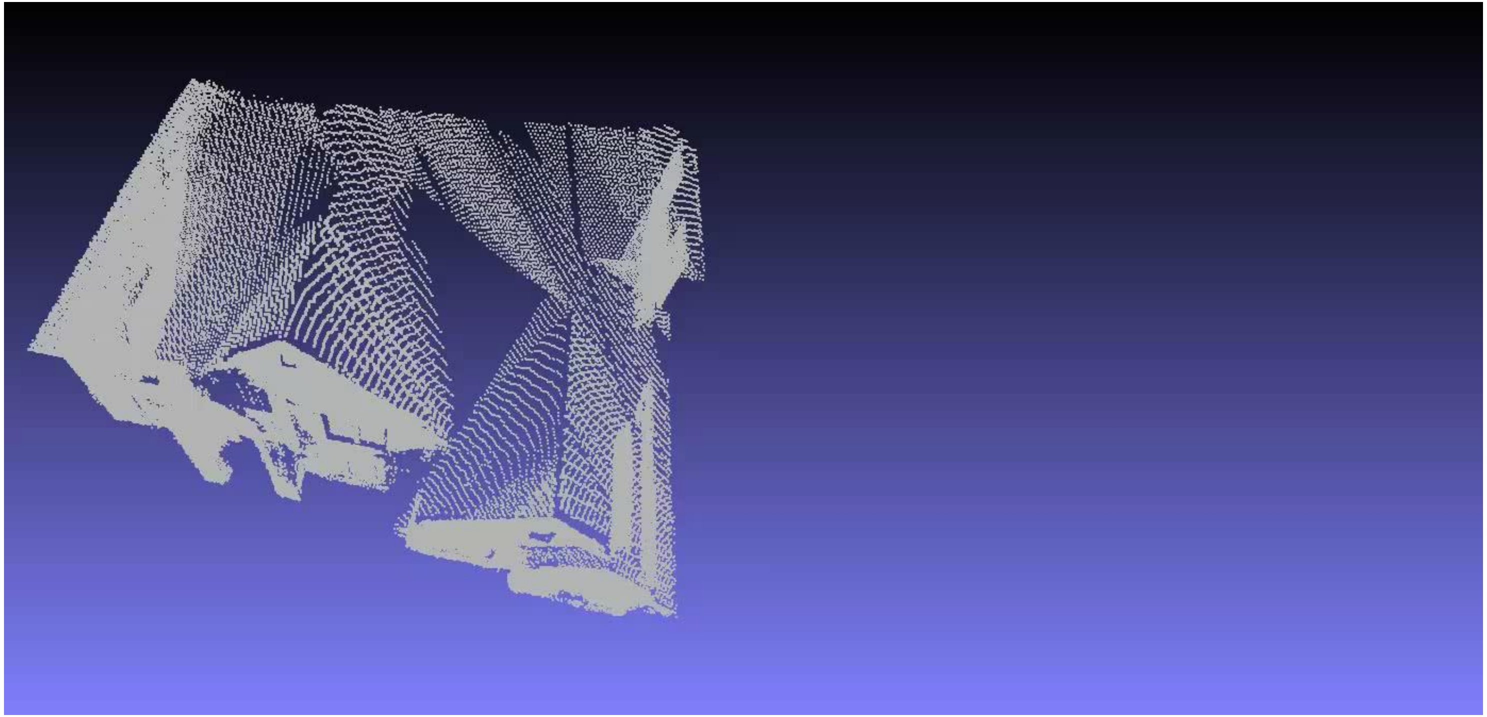
Based on finite block types





Iterative Decomposition and Reconstruction

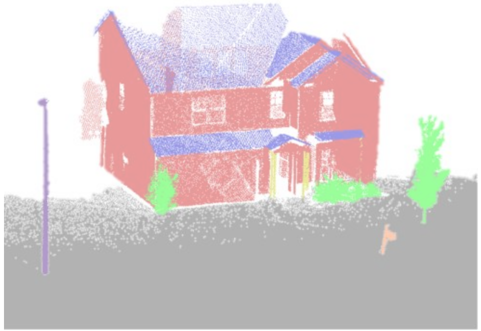
similar to CSG (Constructive Solid Geometry) in CG



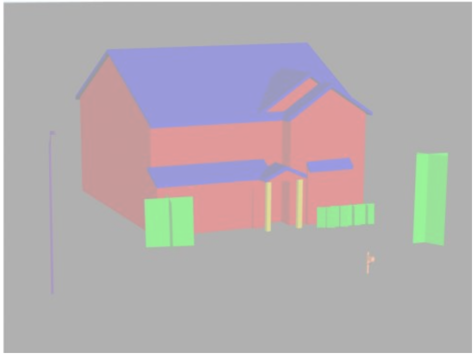
Refinement of Primitive Labels and Model

- Eave Primitive
  - Vertically thin (<0.3m)
  - Adjacently beneath a roof
- Garage Door
  - Be parallel-symmetric and connected in the connection graph C
  - The point cloud forms a “Π” shape
- Chimney Extraction
  - The block type is box structure (meaning no slanted roof)
  - its highest position on z-direction is higher than that of the entire building structure minus 1m

Algorithm Overview



Semantic Segmentation

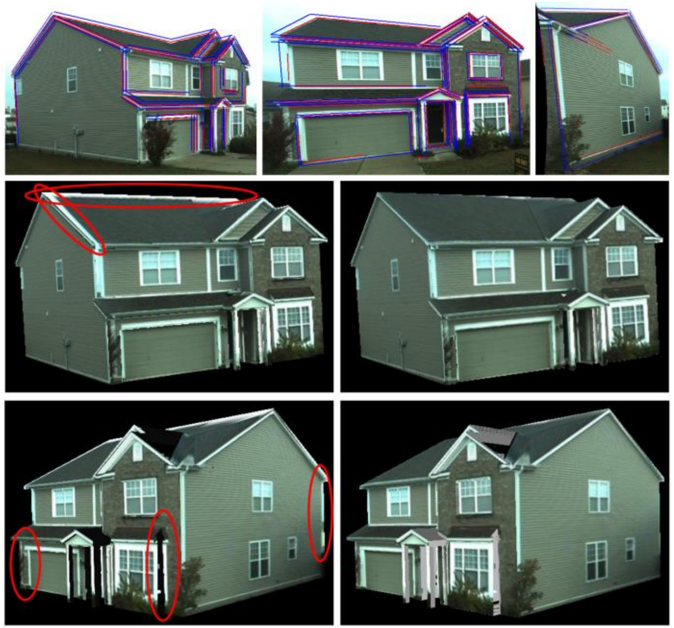


House Modeling

Texture Mapping
Landscape Modeling

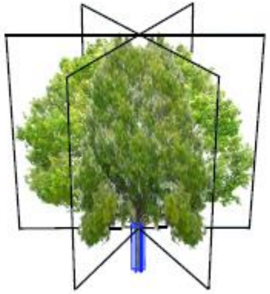
Texture Mapping

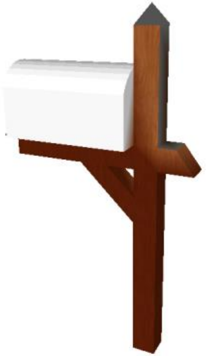
- Geo-registered Images
  - Not very accurate
  - Cloud have noticeable misalignment
- Interactive 3D architectural modeling
  - [Sinha et al. 2008]



Landscape Modeling

- Billboard models for plants
  - Two orthogonal planes
  - One billboard image
- Model Replacement for mailboxes, waste bins, street lights, etc.
  - Google 3D warehouse
  - PCA estimating scale and pose
  - ICP alignment





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Results on Semantic Segmentation

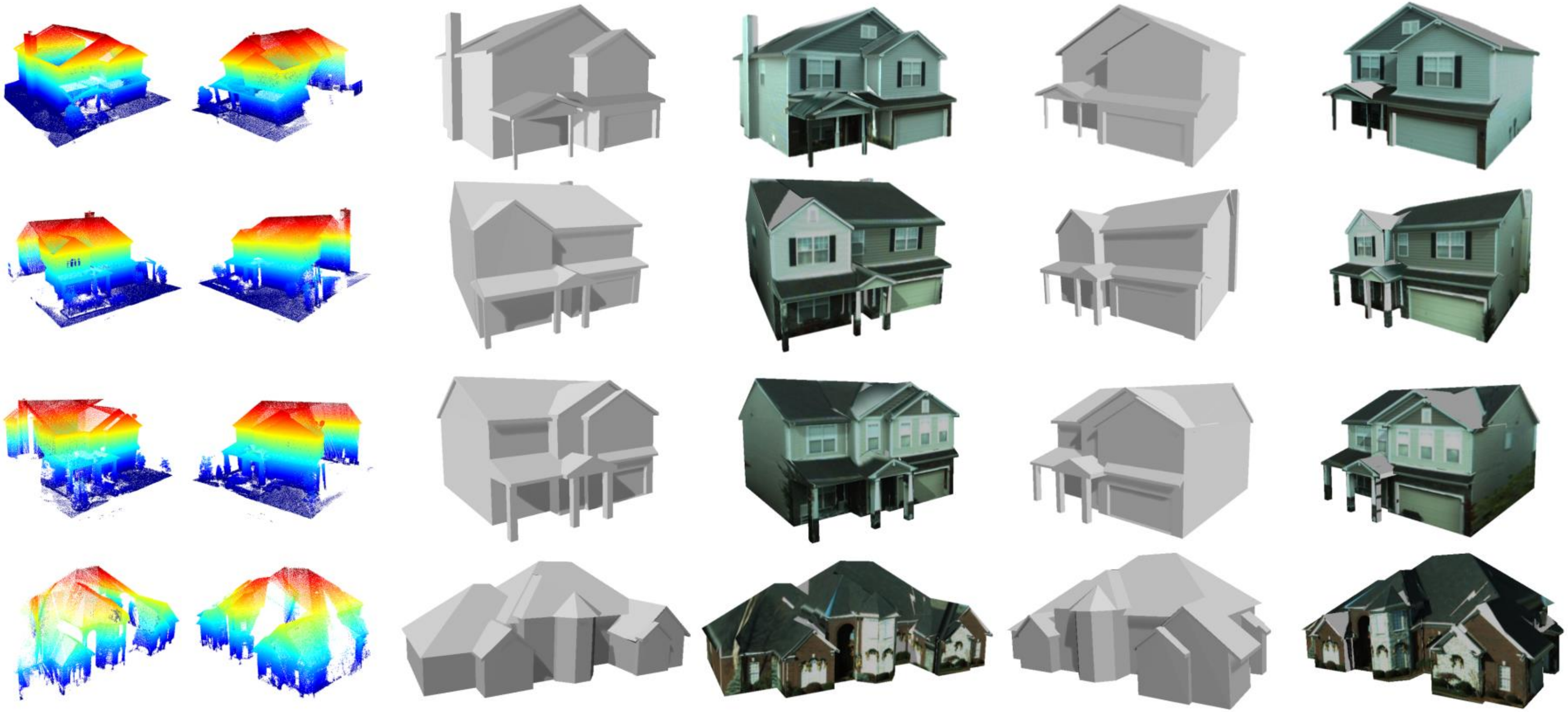
- Category result

	Car	Ground	House	Mailbox	Plant	Road sign	Street light	Waste bin
Precision	0.68	0.89	0.88	0.91	0.91	0.91	0.92	0.71
Recall	0.70	0.85	0.83	0.85	0.94	0.57	0.42	0.80

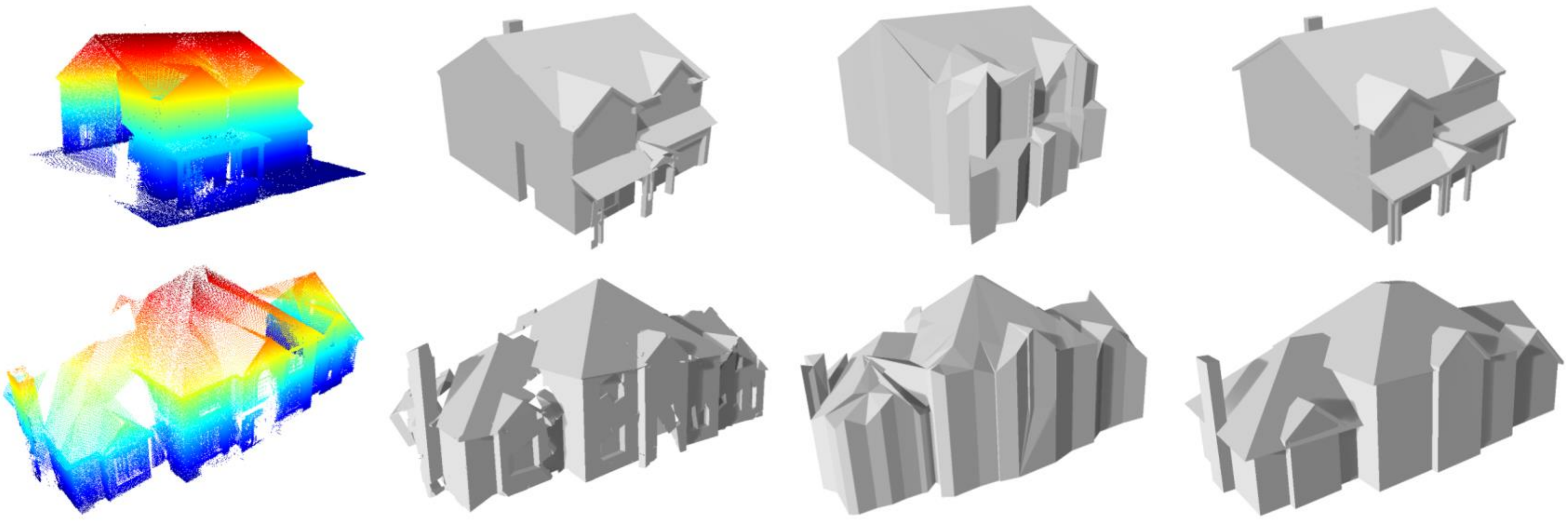
- House Classes

	Wall	Roof	Column
Precision	0.94	0.94	0.72
Recall	0.98	0.81	0.87

Results of Houses



Comparison



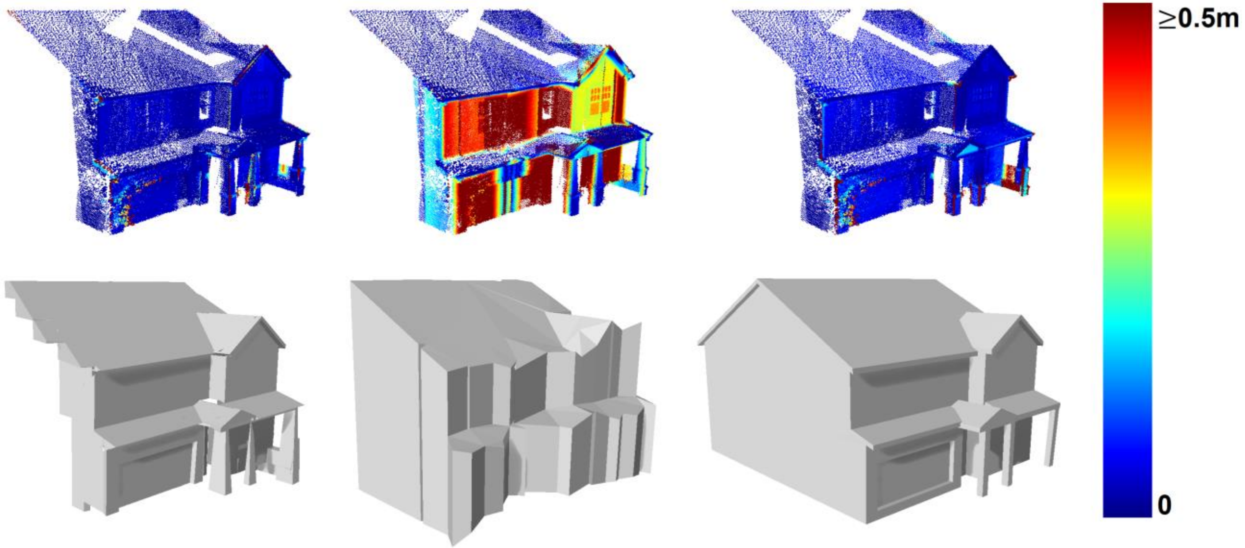
Point cloud

Piecewise Planar Surface Reconstruction (PPSR) [Chauve et al. 2010]

2.5D Dual Contouring (2.5D DC) [Zhou and Neumann 2010]

Ours

Comparison



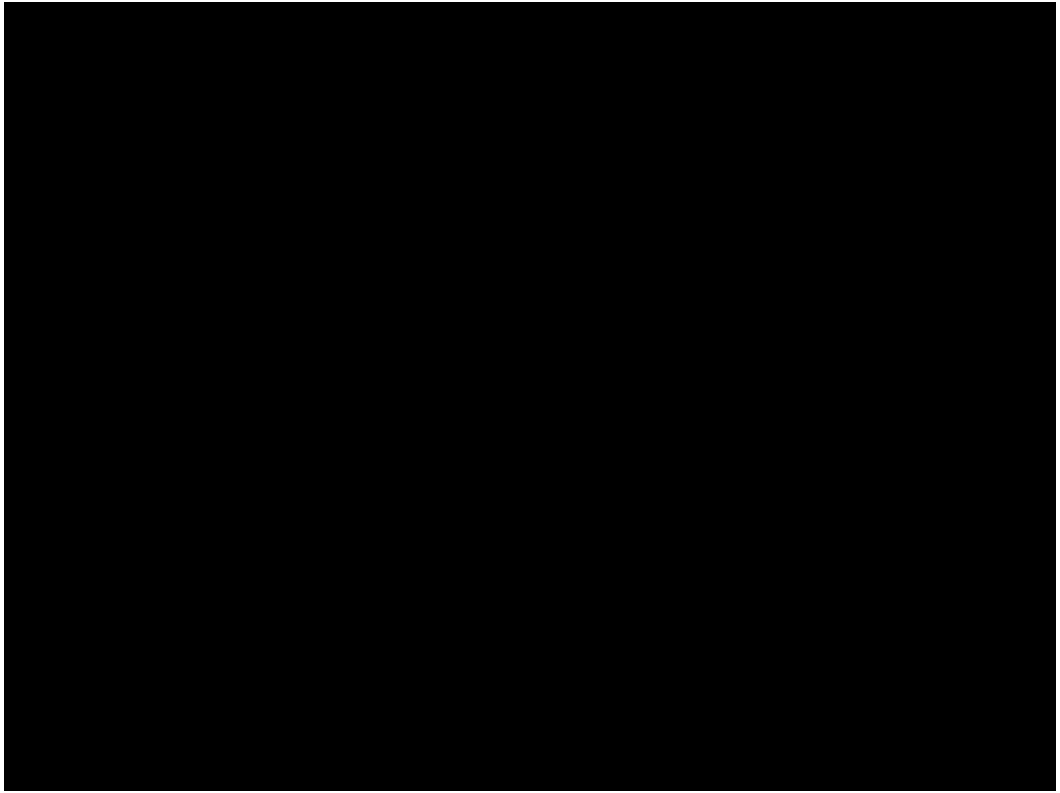
PPSR
Overall Error:
0.0290±0.0865m

2.5D DC
Overall Error:
0.3591±0.2972m

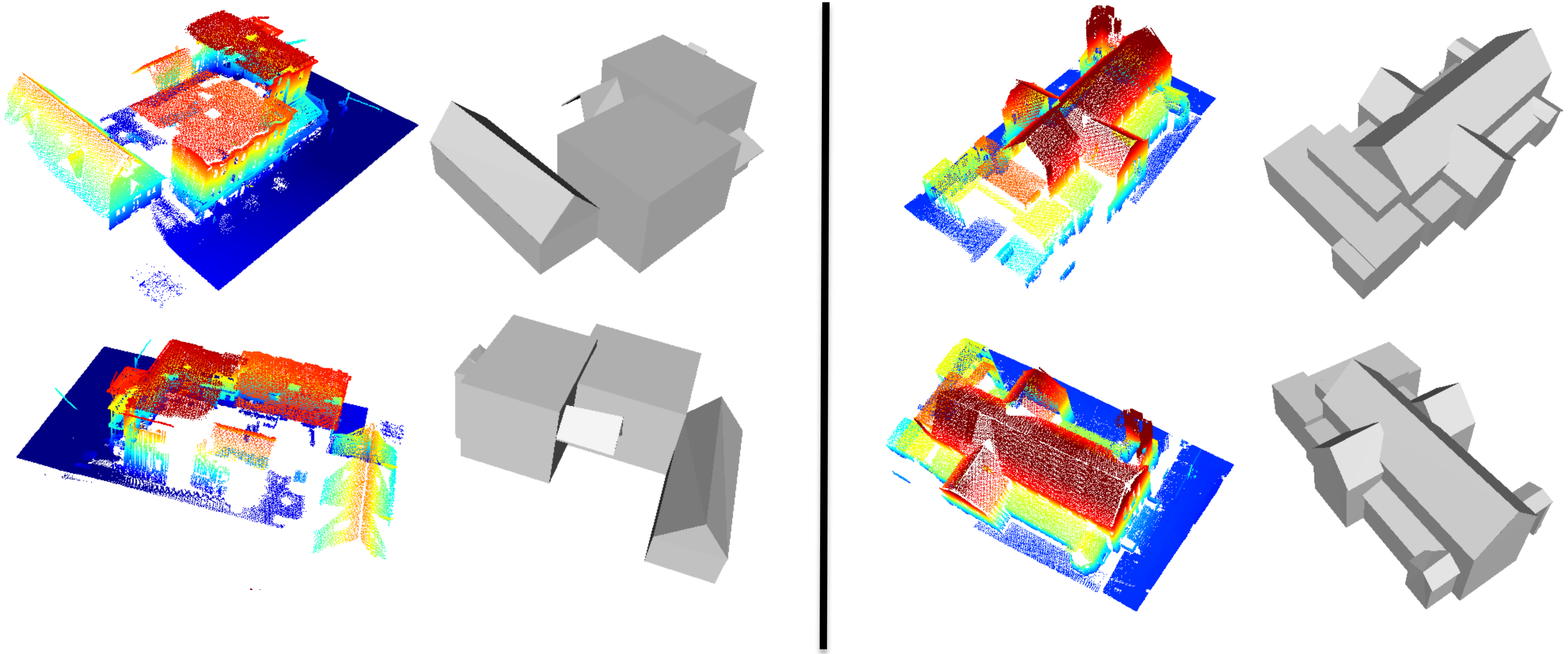
Ours
Overall Error:
0.0598±0.1174m

Results of the whole view

Video of the 3D Reconstruction Results



Wright-State-100 Airborne Dataset



Timing Performance

- Semantic Segmentation
  - subdivision of 53 houses
  - 40 minutes
- House Modeling
  - 350K to 600K points per house
  - **15 to 22 seconds** per house
  - PPSR takes 15-20 minutes per house

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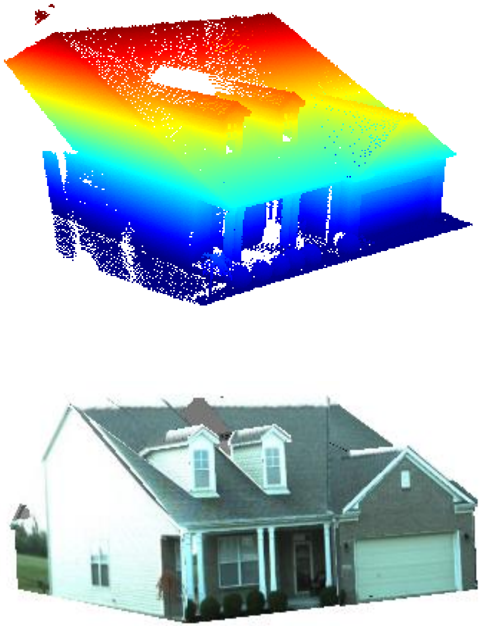
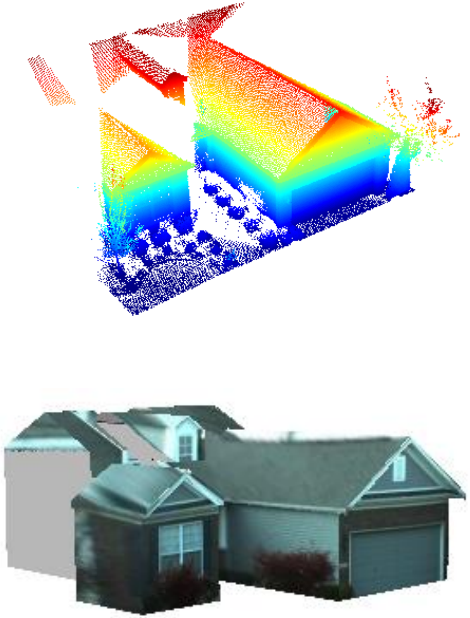
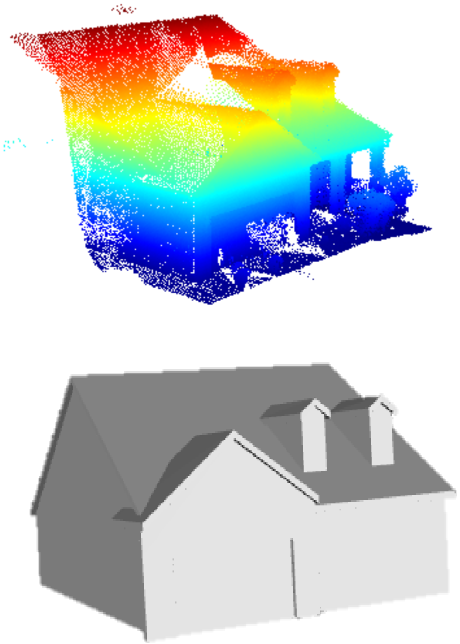
Limitation



Asymmetry



Severe occlusion



Missing column extraction

Conclusion

- An automatic system for residential scene modeling
- A novel representation for houses
- A divide and conquer decomposition and reconstruction approach
  - Efficient and effective
  - Various input data
  - Significant incomplete data handling

Thank You!