Incremental Surface Reconstruction from Sparse Structure-from-Motion Point Clouds

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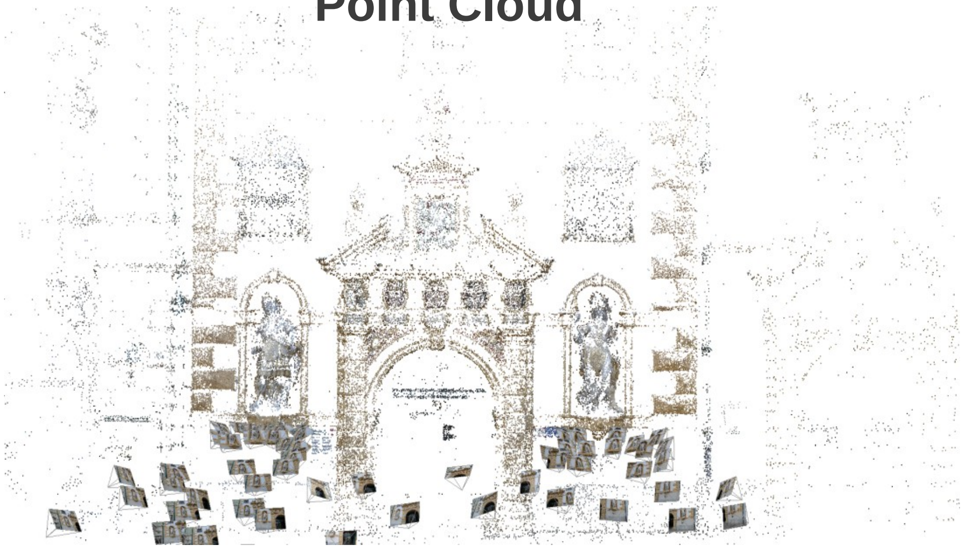
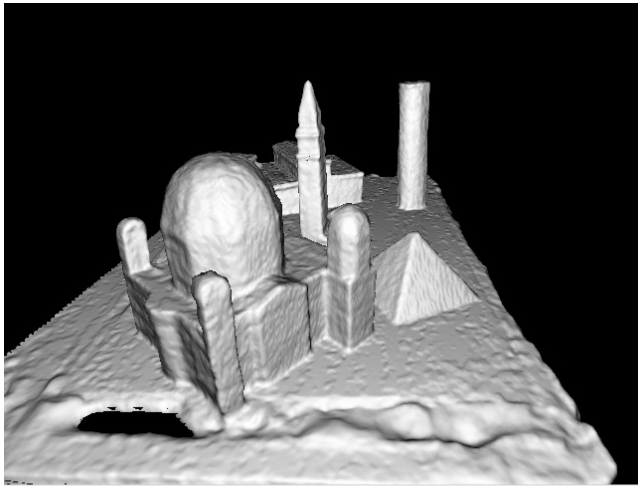
Motivation

Structure-from-Motion Point Cloud



- Up to City Scale
- Obtained in real-time (SLAM)
- Sparse representation
- AR and robotics require surface
- Not suitable for occlusion handling, navigation etc.

Volumetric Surface Reconstruction*

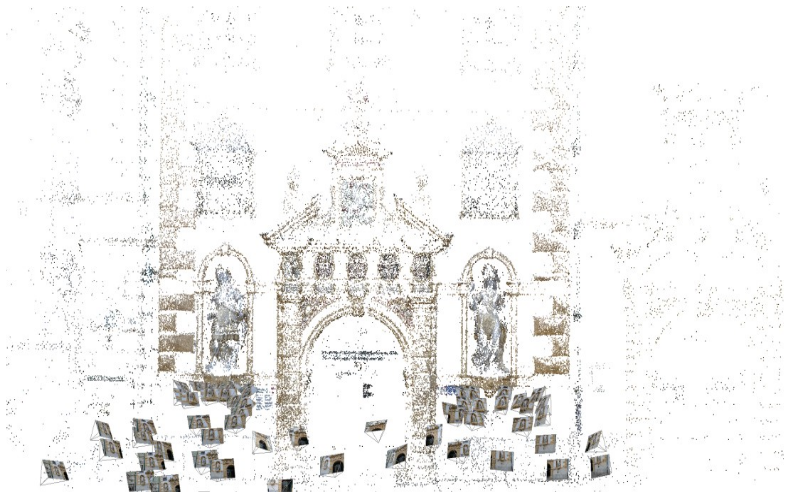


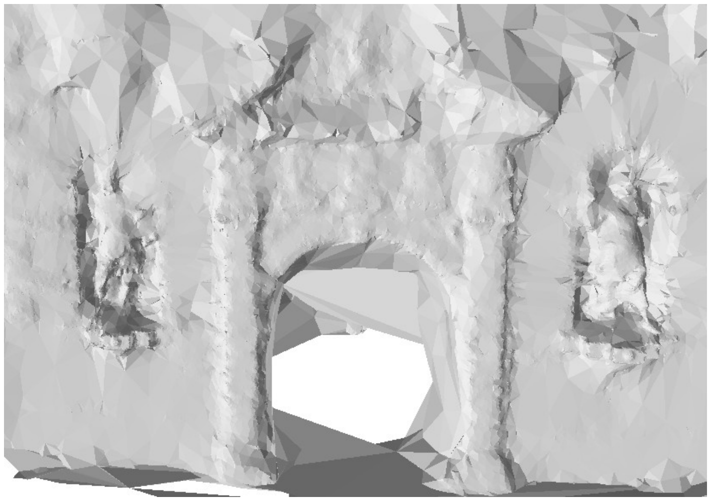
- High quality surface reconstruction
- Volumetric approach
- Limited scene size
- GPGPU required to handle computational effort

* Image taken from [Graber 2012]

Motivation

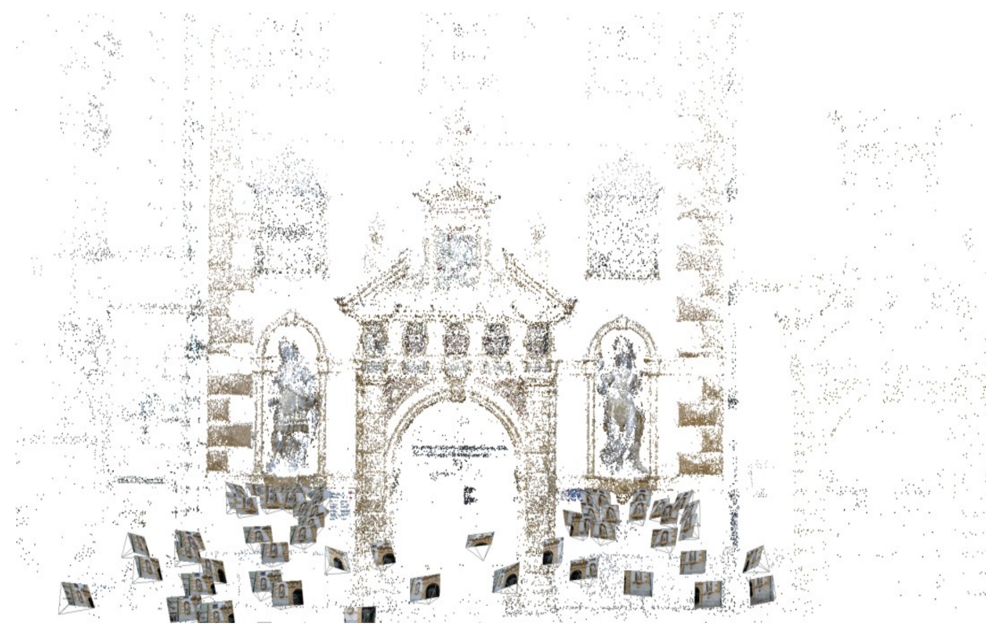
- Can we reconstruct a surface from sparse SfM points?
  - **Consistent** surface
    - Robust against outliers
  - Fully **incremental** to be integrated into SLAM
  - In **real-time**
  - **Arbitrary** camera motion





Challenges

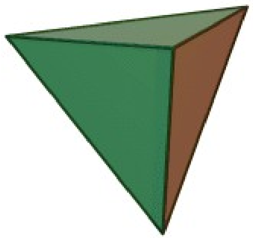
- **Inhomogeneous** density of the scene information
- Severe **outliers**
- When using in combination with SLAM
  - Continuously **growing**
  - **Arbitrary camera motion** - “revisiting” of already reconstructed parts



Outline

- Related Work
- Formulation as Labeling Problem
- Incremental Surface Reconstruction
- Experiments

Related Work



- Irregular discretization of space into tetrahedra
- Perform 3D Delaunay triangulation of sparse 3D points
  - Fast, can be incrementally updated
- Classification into free / occupied space using visibility information
  - Interface is between free and occupied is surface
- Methods
  - Free-space carving [Lovi et al. 2010]

    → not robust to outlier
  - Formulation as labeling problem solved with graph cuts [Labatut et al. 2007]

    → Energy function motivated by free-space carving

    → robust against outliers, not suitable for incremental reconstruction
  - Aggregation of “free” tetrahedra for incremental reconstruction

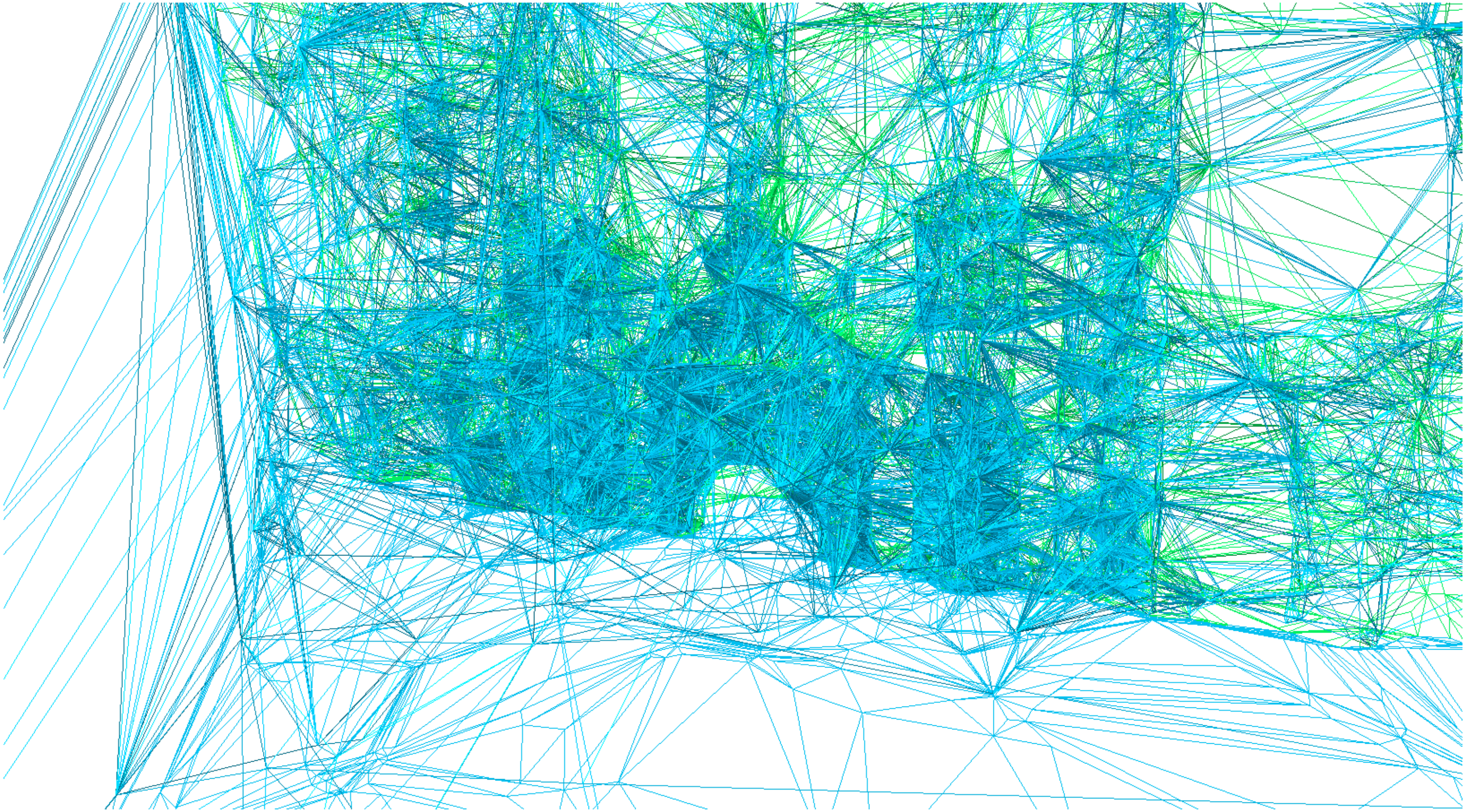
    → [Poster yesterday, Litvinov et al. 2013, Lhuillier et al. 2013]

Contributions

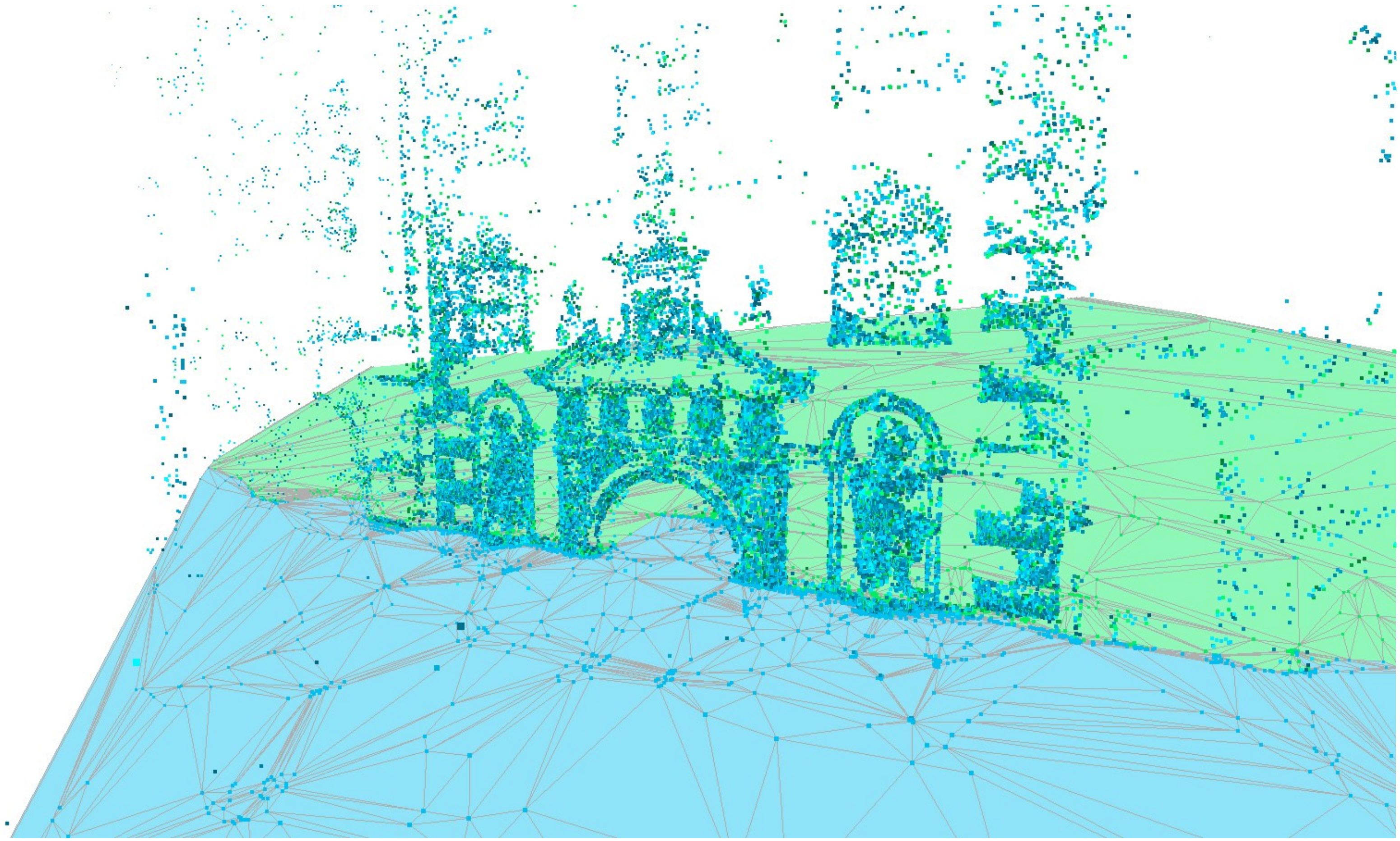
- Robust free / occupied labeling of Delaunay triangulated sparse point cloud
- Formulation as Conditional Random Field
- Energy function can be easily adapted to modified Delaunay triangulation (DT)
  - New 3D points can be easily integrated into the DT
- Integration of new scene information leads to series of energy functions
  - Optimization using dynamic graph cuts

Our Approach

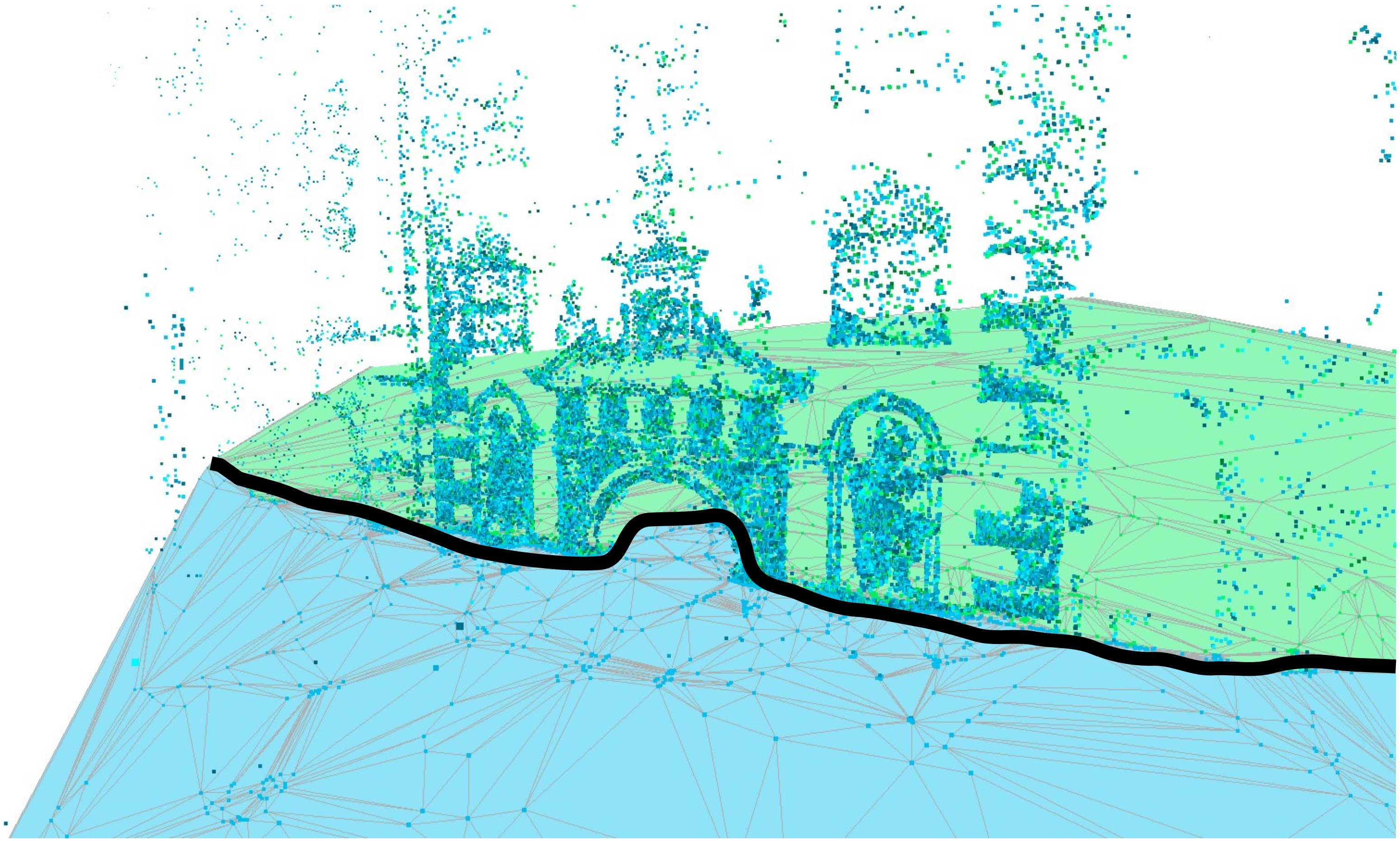
Our Approach



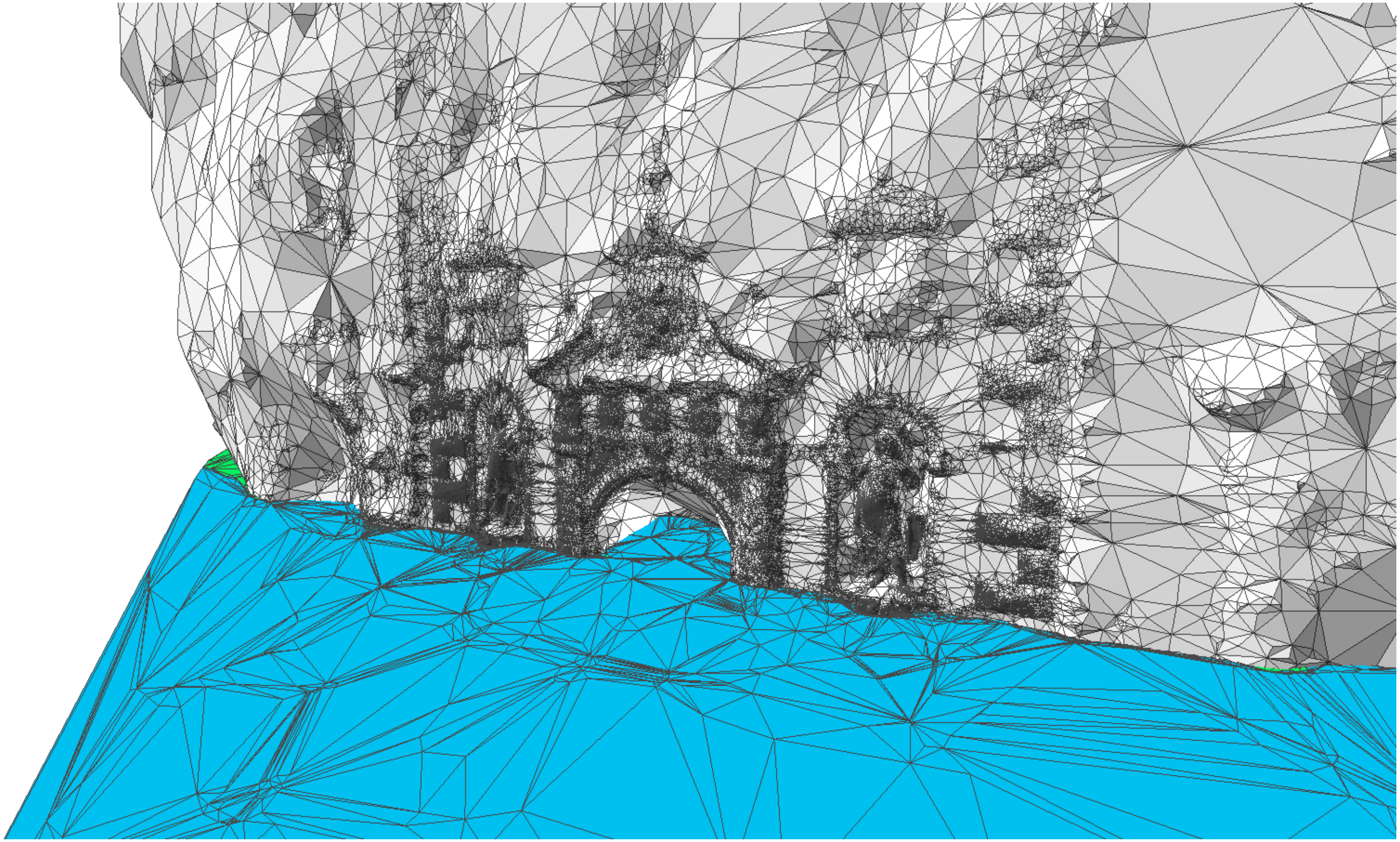
Our Approach



Our Approach



Our Approach



Random Field Formulation

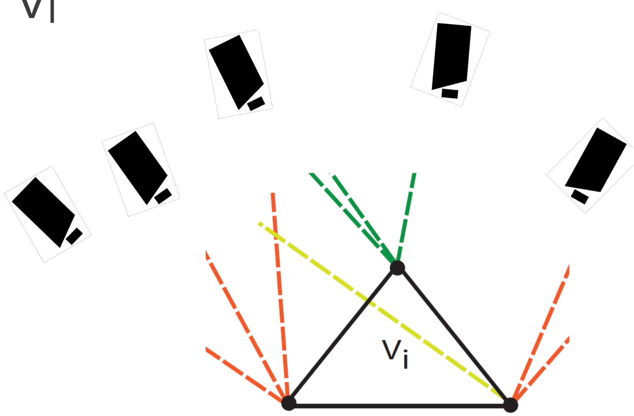
- **Goal:** Classify each tetrahedron V_i into free or occupied given the visibility information / rays R
- R set of all line segments that connects a sparse 3D point to a camera center
- Energy function to minimize

$$E(\mathcal{L}) = \sum_i \left(E_u(V_i,\mathcal{R}_i) + \sum_{j\in\mathcal{N}_i} E_b(V_i,V_j,\mathcal{R}_i)\right)$$

probability tetrahedron free or occupied

Smoothness across neighbouring tetrahedra

- R_i line segments connected to the vertices of the tetrahedron V_i
- **Unary and binary potentials only depend on local ray information R_i**
- Submodular function → Can be optimized by graph cuts

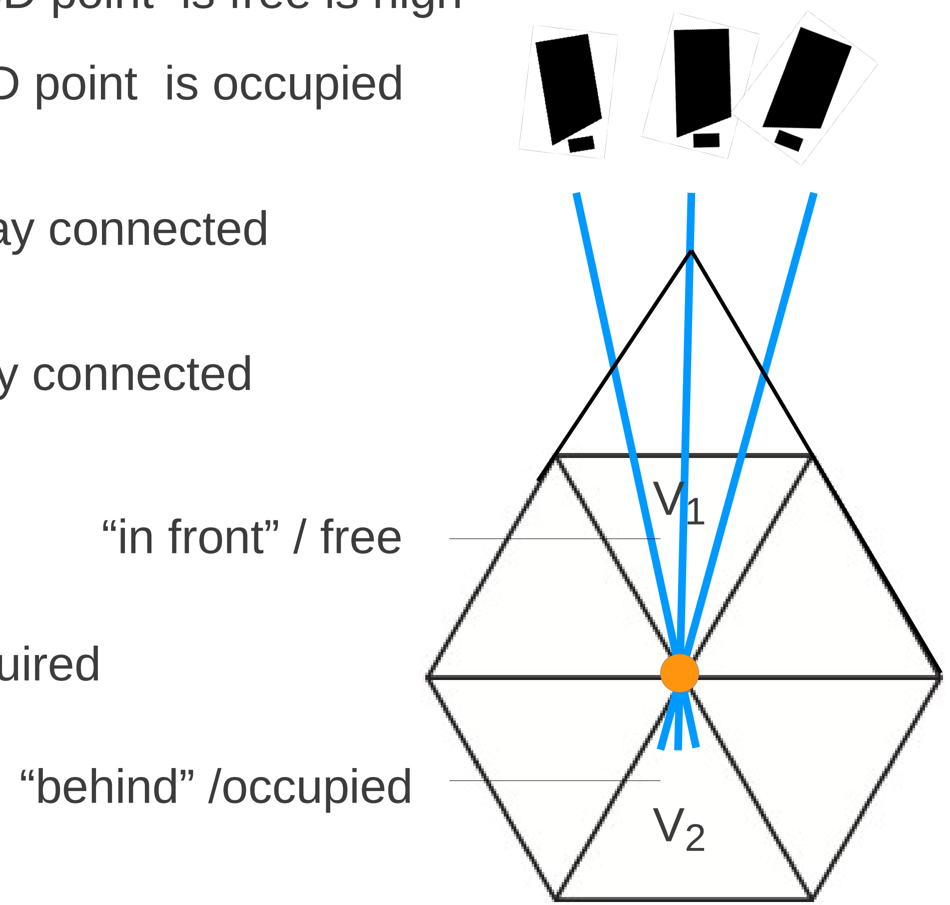


Unary Potentials

- Unary terms motivated by truncated signed distance function
- Probability that a tetrahedron “in front“ of 3D point is free is high
- Probability that a tetrahedron “behind“ a 3D point is occupied is high
- “In front” → tetrahedron intersected by a ray connected to its vertices
- “Behind” → tetrahedron is in extent of a ray connected to its vertices
- Counting how often a tetrahedron is “in front” or “behind”

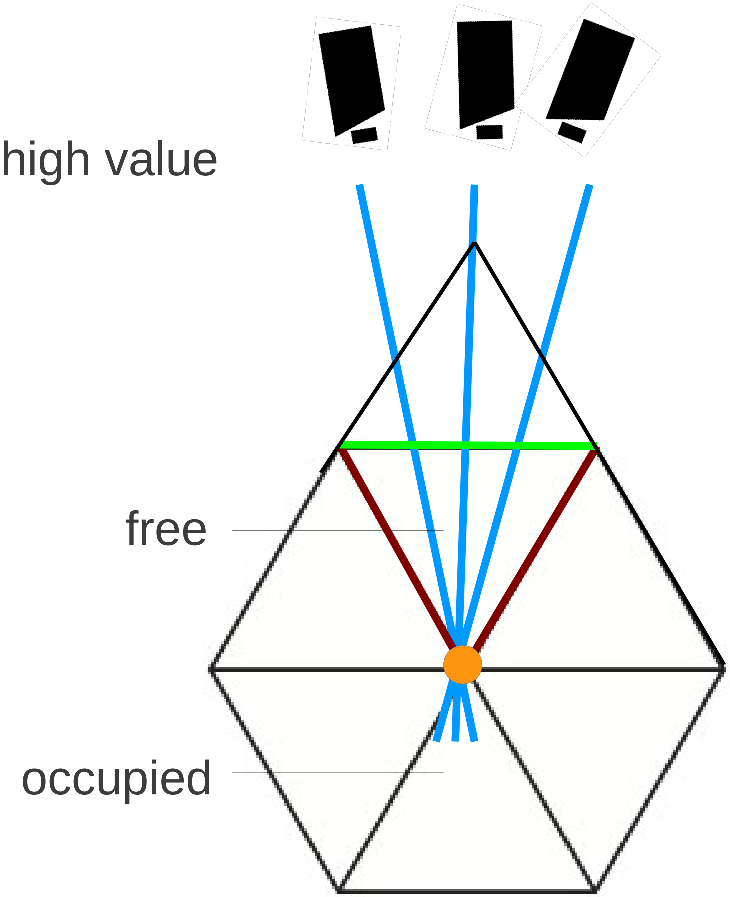
  → No ray/tetrahedron intersection required

  → Delaunay data structure speeds up the counting



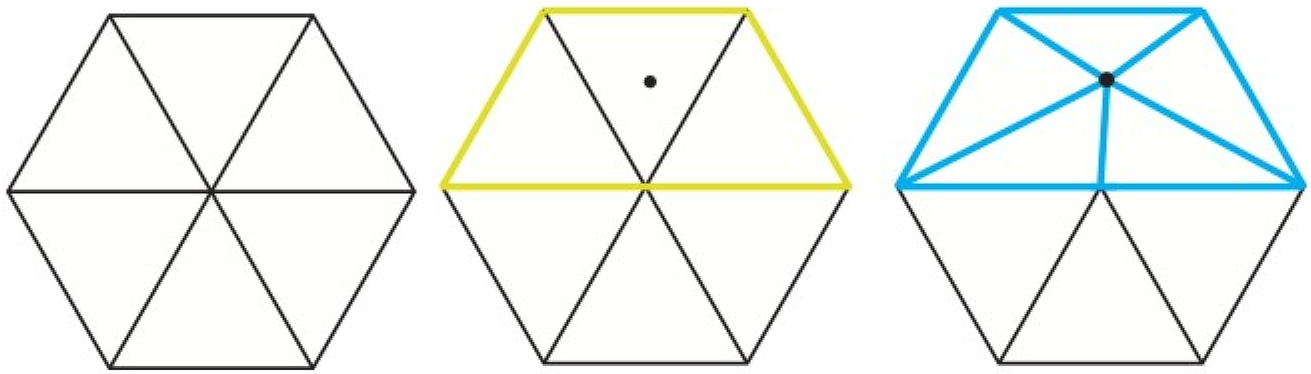
Binary Potentials

- Typically only 50% of all tetrahedra obtain unary potentials
  - → Strong regularization required
- It is very unlikely that (Vi,Vj) obtain different labels
  - → Costs for assigning different labels is set to a high value
- Except neighboring tetrahedra that are not crossed by common rays



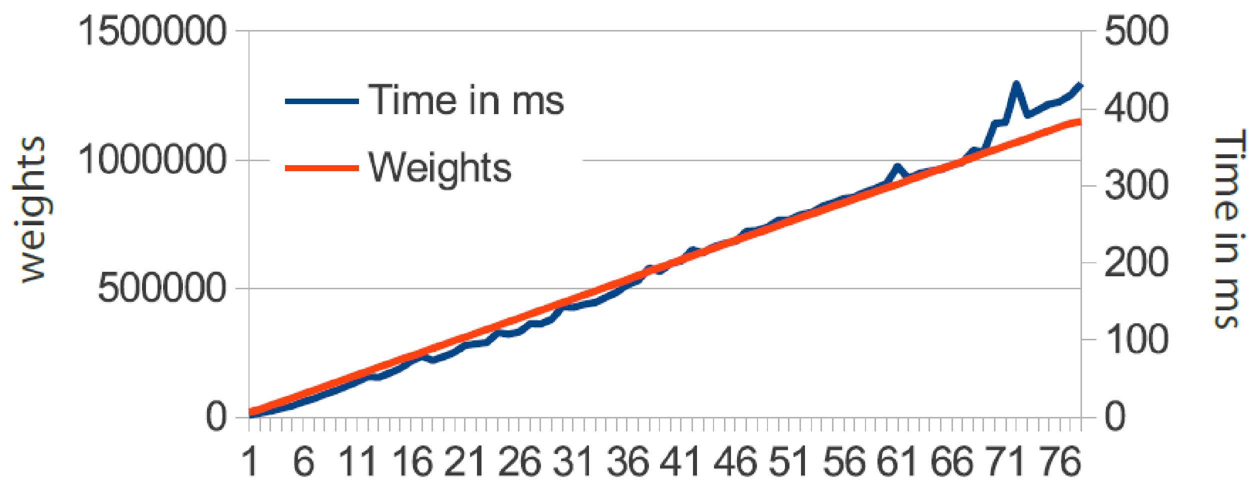
Incremental Energy Update

- New 3D point changes the Delaunay triangulation
  - But only locally
- Existing tetrahedra are deleted, new ones are created
- Energy has to be updated $E_n \rightarrow E_{n+1}$
  - → Deletion of tetrahedra removes terms from the energy
  - → New tetrahedra add new terms
- Unaries and binaries depend only on local visibility information
- Energy update is quite fast → 1000 points require 0.5 seconds



Incremental Labeling

- Delaunay triangulation update-able
- Energy function easily update-able
  - Series of energies E_n to be optimized
- Problem: Number of terms in energy grow over time
- Solving from scratch prevents scalability



Incremental Labeling

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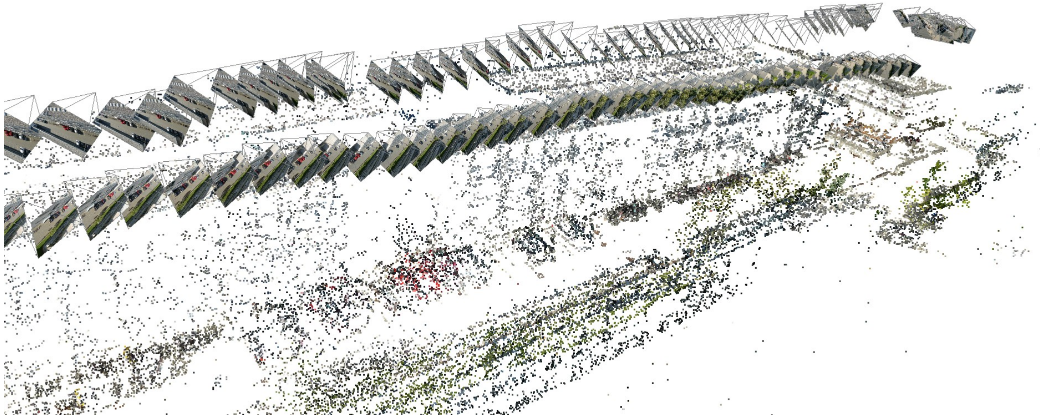
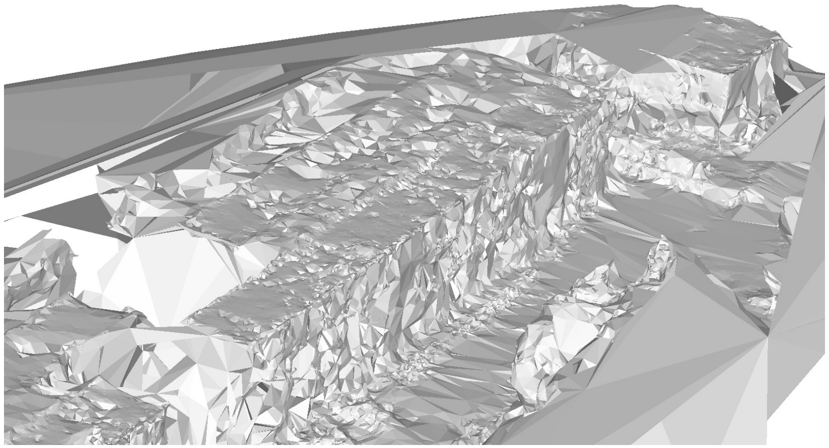
- **Solution:** Dynamic graph cut [Kohli et al. 2007]
  - Optimization of series of energies that can be solved by graph cuts
  - Re-use result from minimization of E_{n-1}
  - Complexity depends on the number of **changed** terms, not on the overall number of terms

Experiments – Static

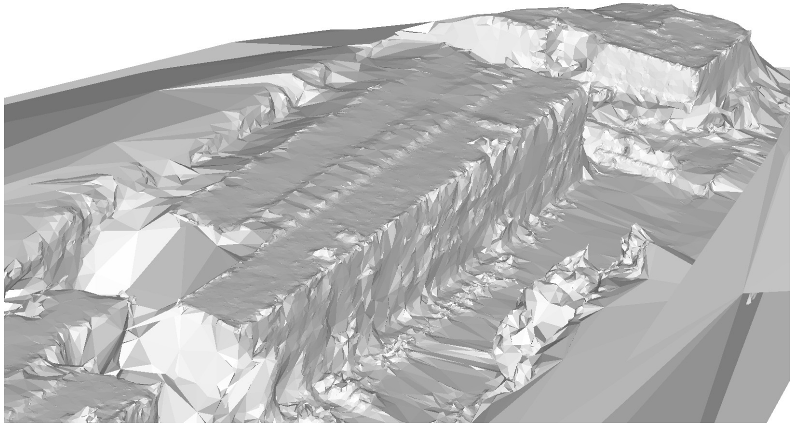
- Static case
  - All 3D points and visibility information is available
- Input: SfM point cloud obtained by standard SfM pipeline like Bundler

  → 77,300 3D points, connected to 4.4 rays on average
- Size of reconstructed area: 200m x 50m

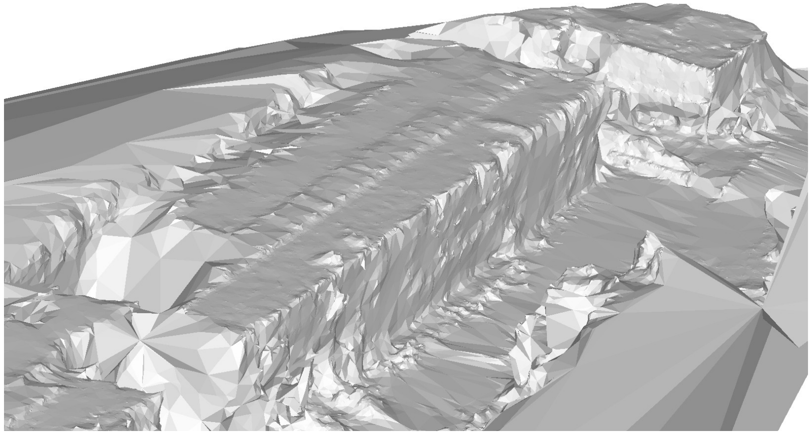




Free-space carving
78 seconds



Labatut et al.
79 seconds

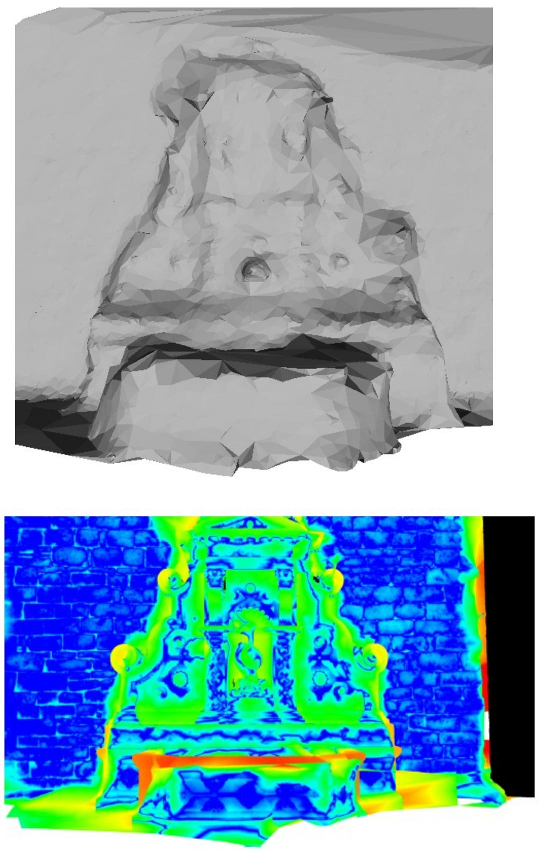


Ours
32 seconds

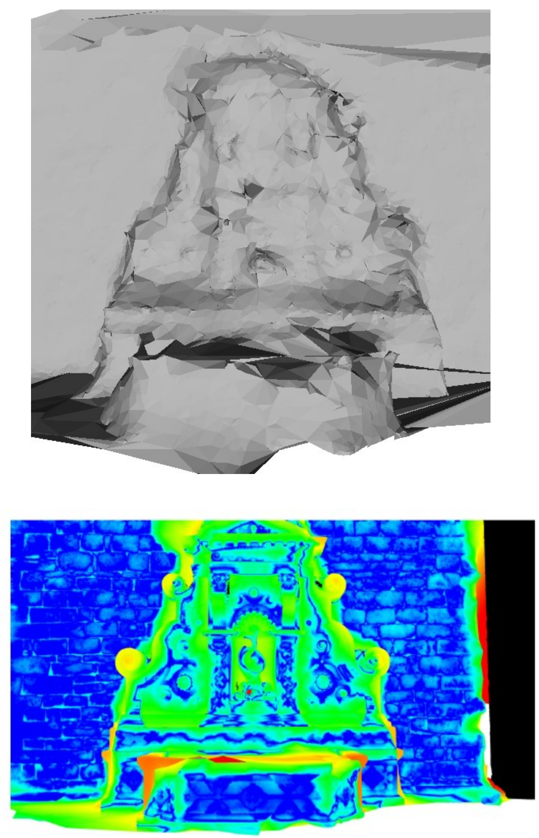
Intel i7, Single Core

Experiments – Static

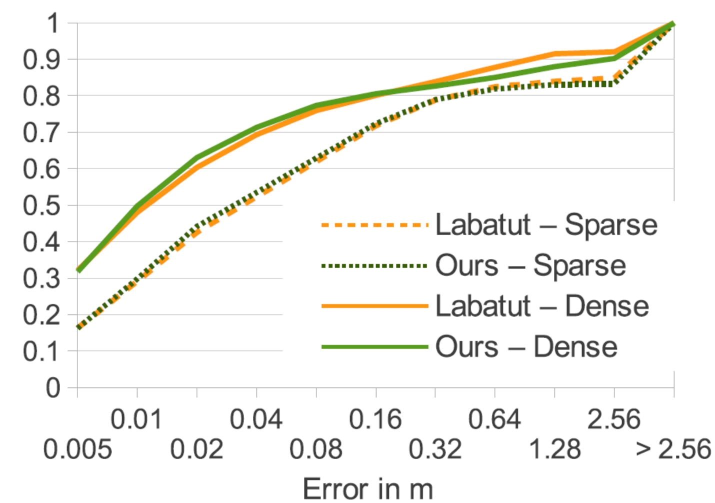
- Strecha Fountain 11 dataset
- 7123 3D points



Labatut et al.



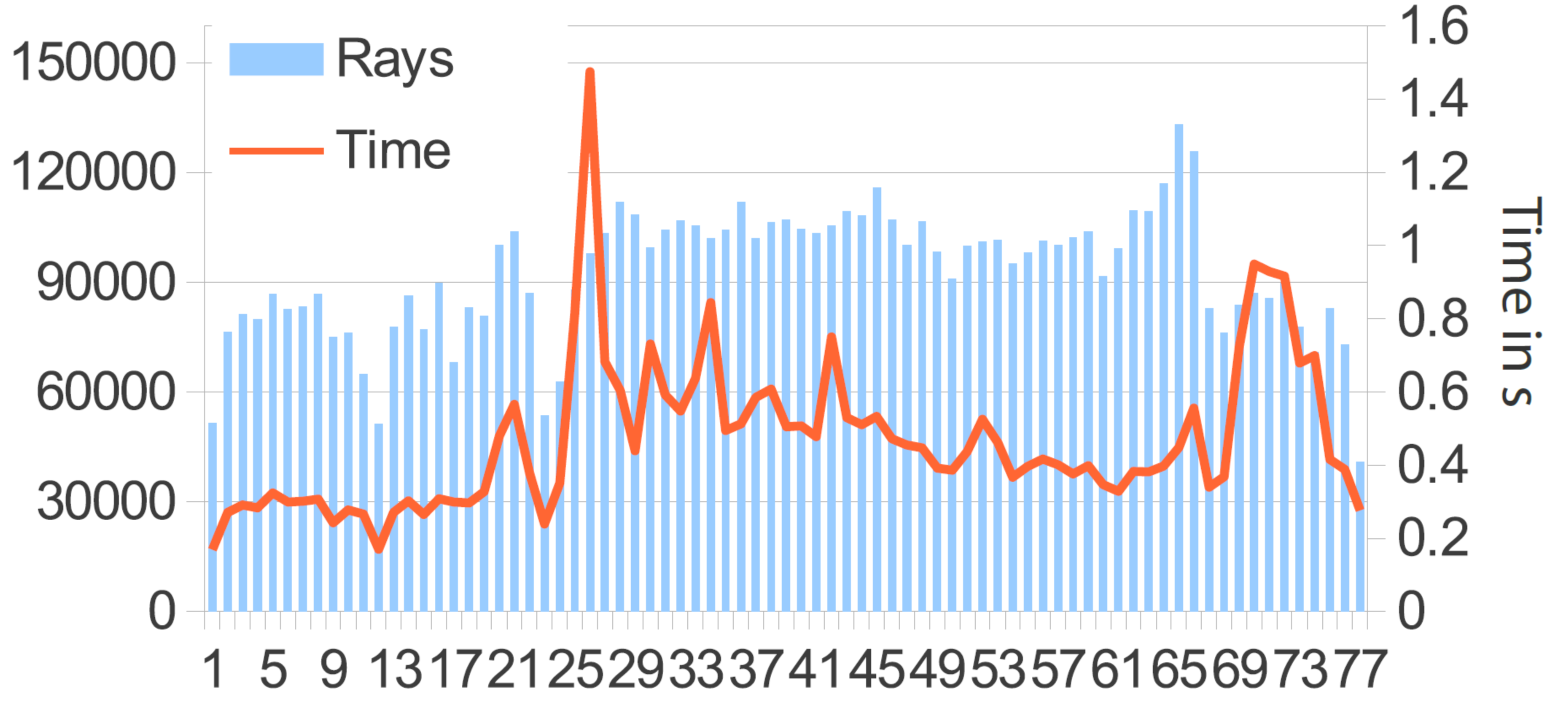
Ours



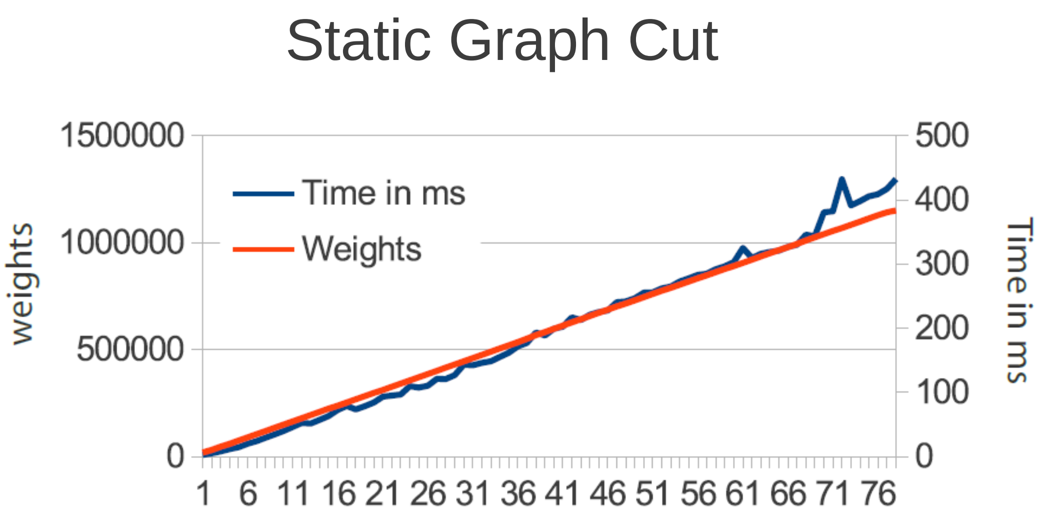
Experiments – Incremental

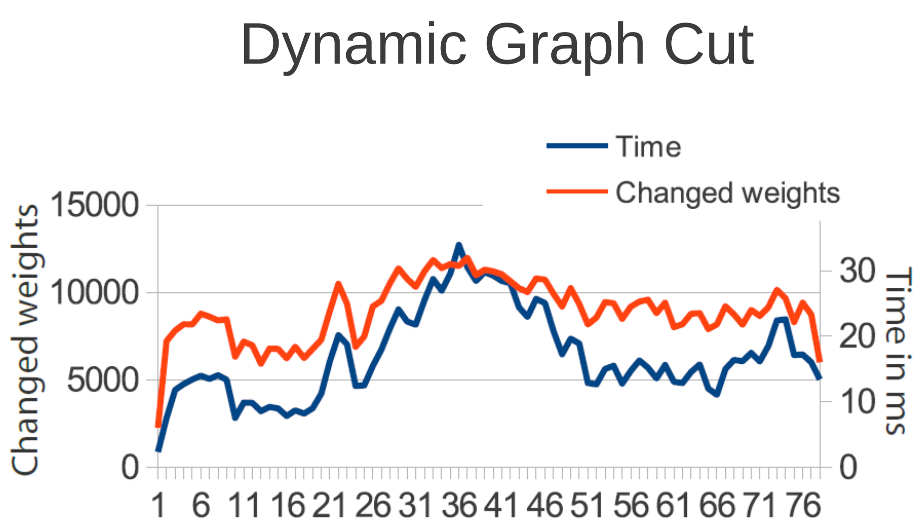
Experiments – Incremental

Time for integrating 1000 new points



Dynamic Graph Cut





Conclusion

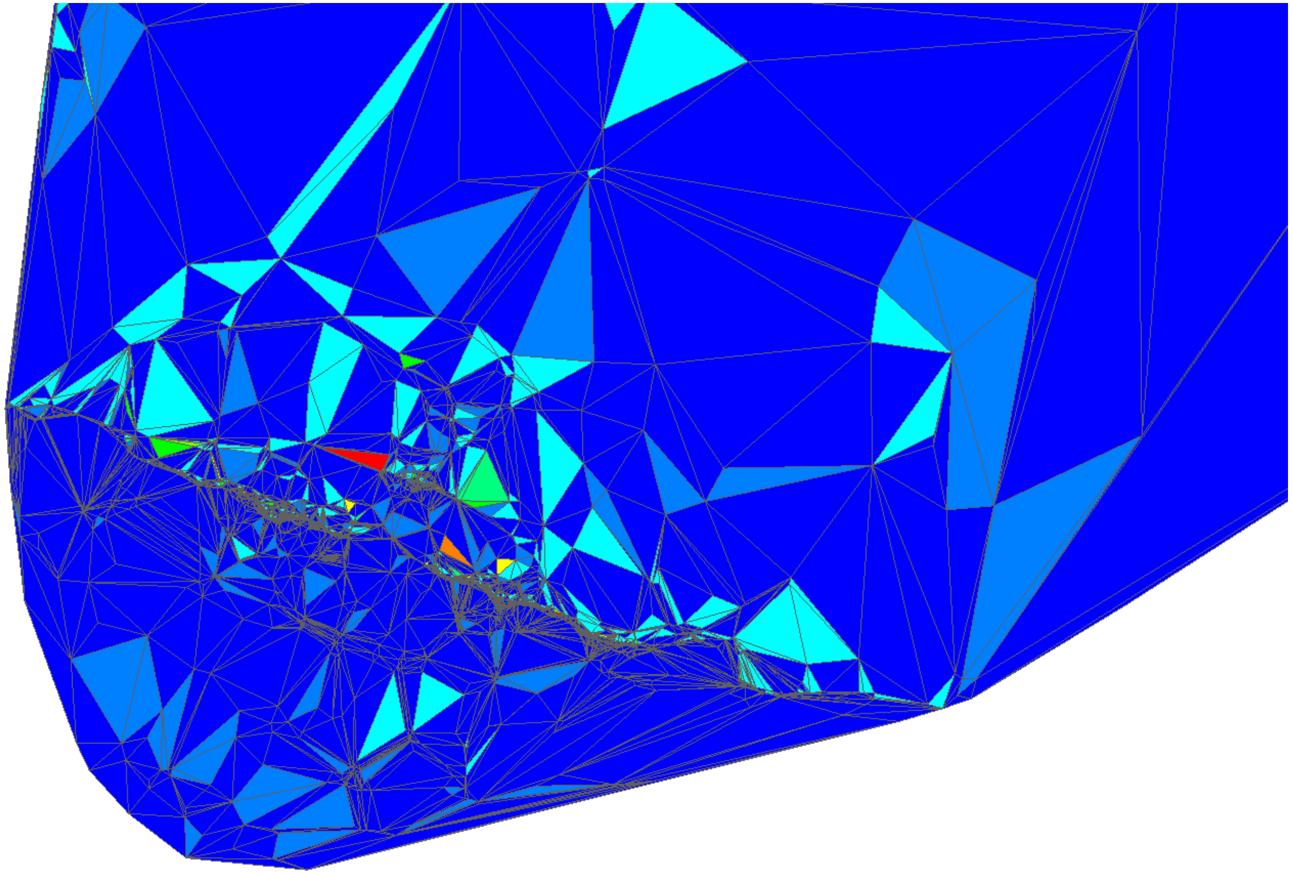
- Can we reconstruct a **consistent** mesh from a sparse 3D point cloud?
  - Robustness by random field formulation labeling
- Can we reconstruct it **incrementally** and in **real time?**
  - 2000 sparse 3D points per second
  - Independent from overall scene size thanks to dynamic graph cut
  - Without GPGPU
- Are we limited to **specific camera** motion?
  - No, 3D points can be inserted on arbitrary parts in the scene
- Is it difficult to **implement**?
  - No, thanks to libraries like CGAL (DT) and the publicly available dynamic graph cut

Thanks for your attention!

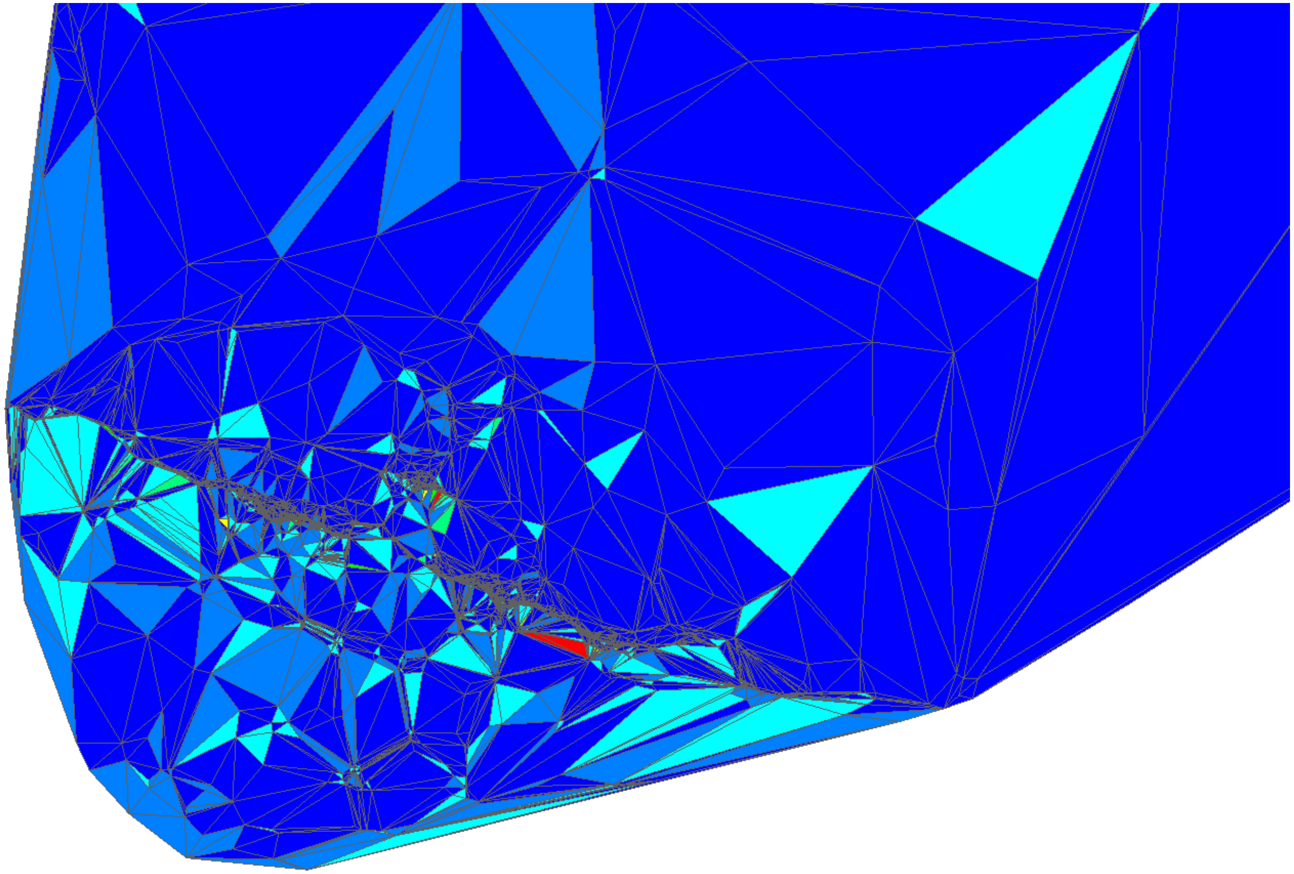
[Kohli et al. 2007] P. Kohli and P.H.S. Torr. Dynamic graph cuts for efficient inference in markov random fields. TPAMI, 2007
[Labatut et al. 2007] P. Labatut, J.P. Pons, and R. Keriven. Efficient multi-view reconstruction of large-scale scenes using interest points, delaunay triangulation and graph cuts. ICCV, 2007.
[Graber 2012] G. Graber, Realtime 3D reconstruction, Masterthesis, TU Graz
[Lhuillier et al. 2013] Manifold surface reconstruction of an environment from sparse Structure-from-Motion data, CVIU, 2013
[Lovi et al 2010] D. Lovi, N. Birkbeck, D. Cobzas, and M. Jaegersand. Incremental free-space carving for real-time 3D reconstruction. 3DPVT, 2010.

This work has been supported by the Austrian Research Promotion Agency (FFG) FIT-IT project Construct (830035) and the FP7-ICT EU project Nr. 601139 CultAR

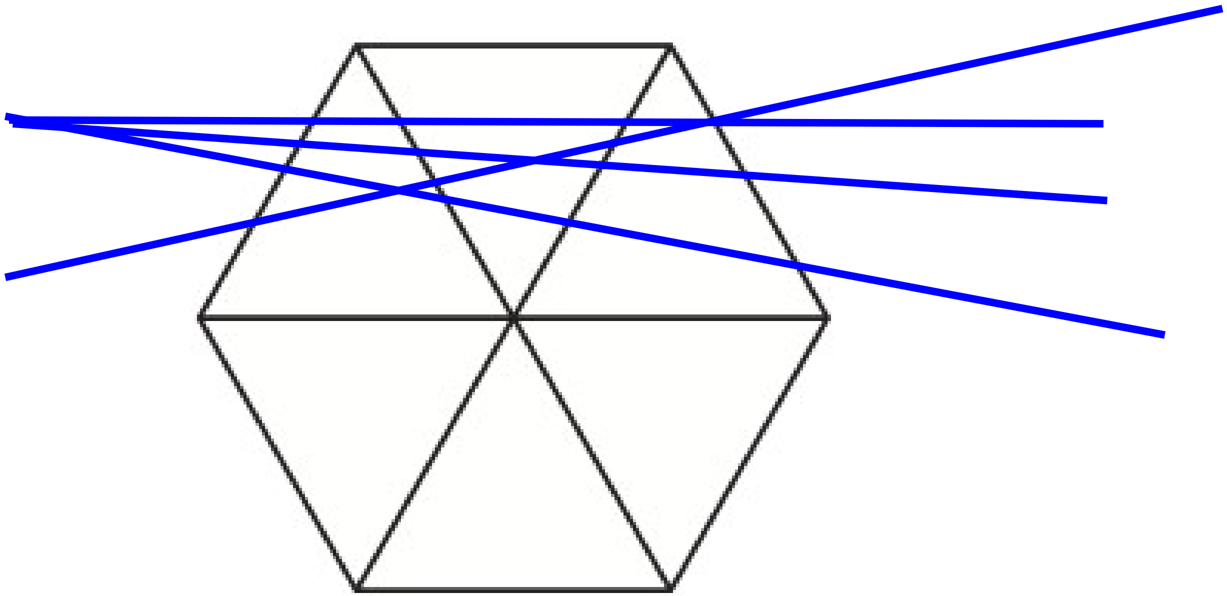
Unary - Occupied



Unary - Free

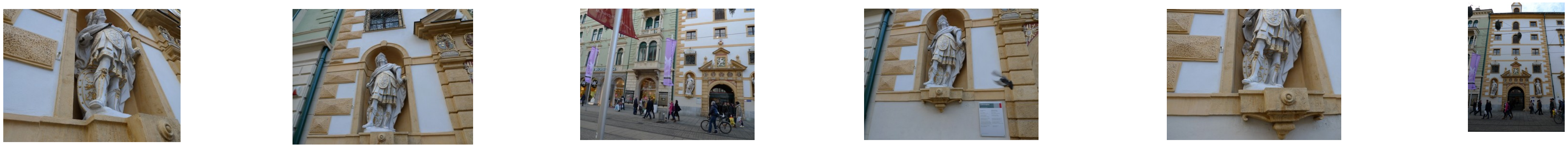


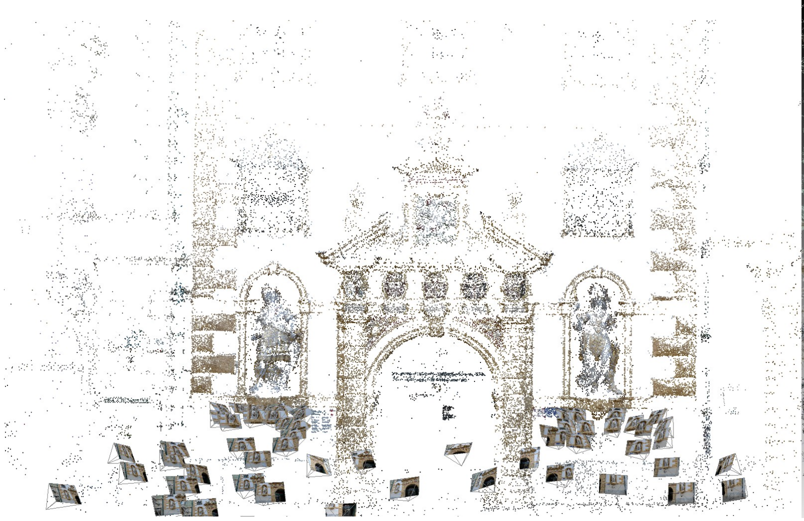
Free Space Carving



Structure-from-Motion

- High-resolution, overlapping images
- Estimation of camera poses
- Estimation of sparse / dense 3D scene points

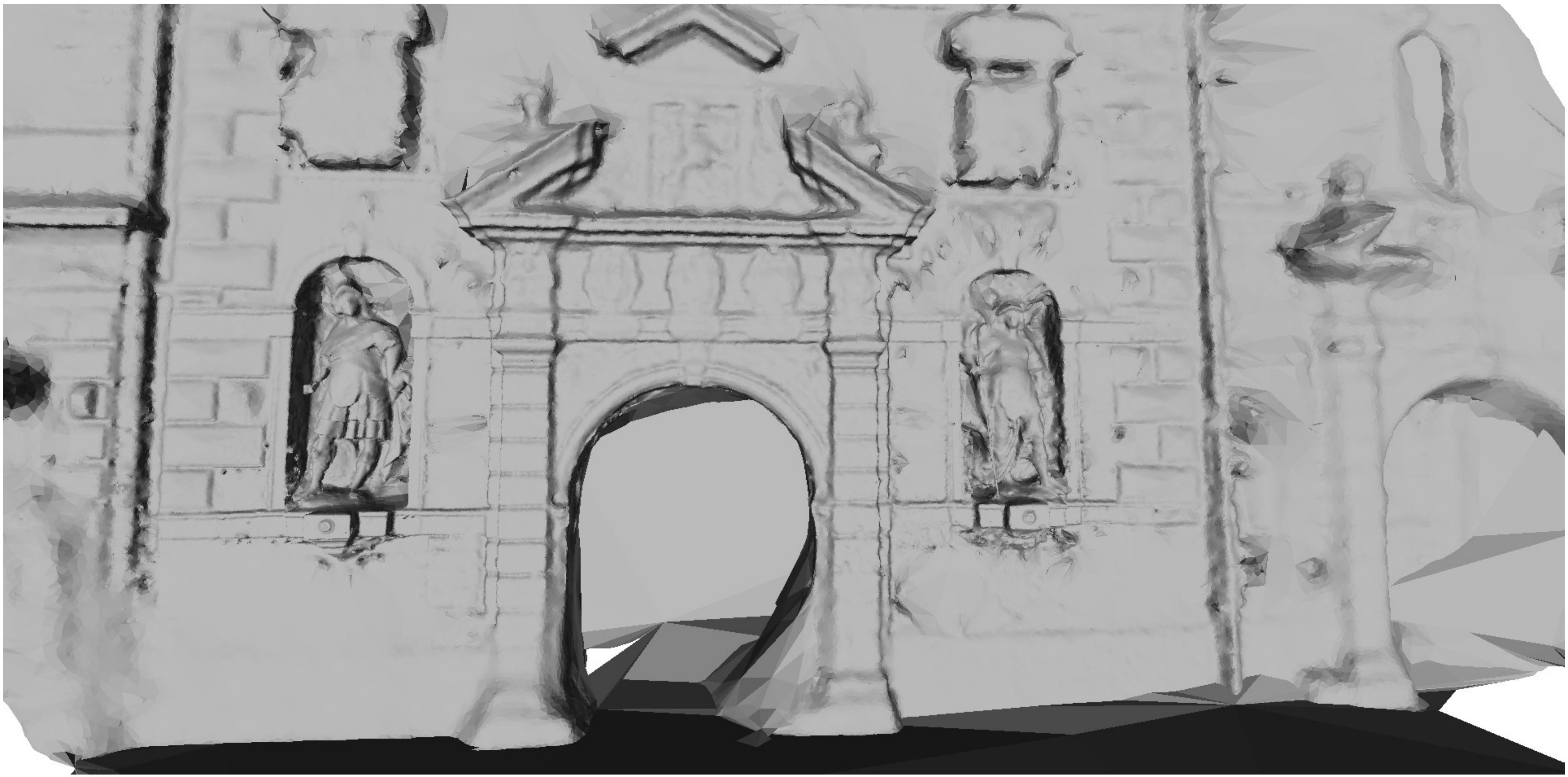




Sparse

Densified

Mesh

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