



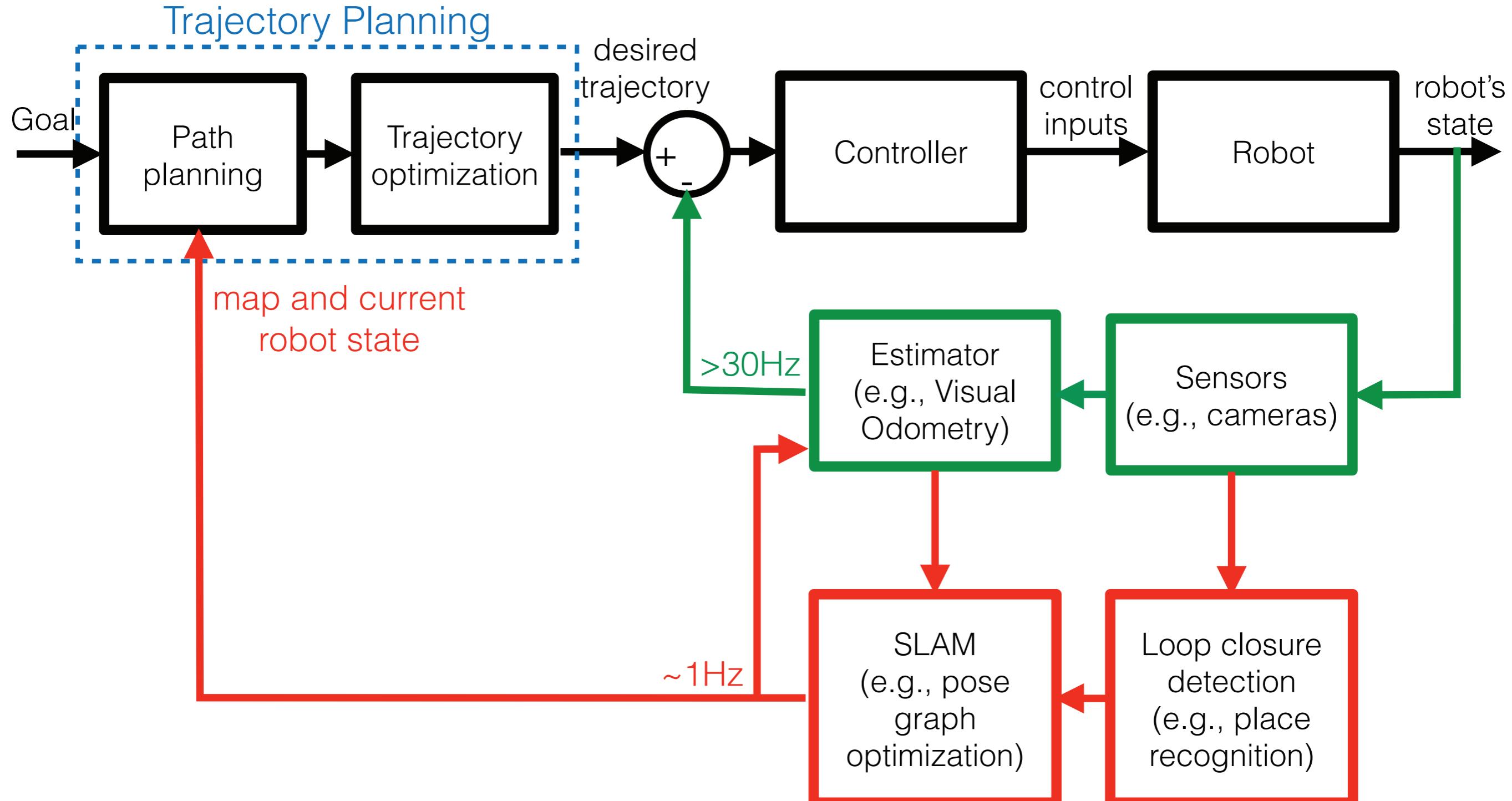
16.485: VNAV - Visual Navigation for Autonomous Vehicles

Luca Carlone

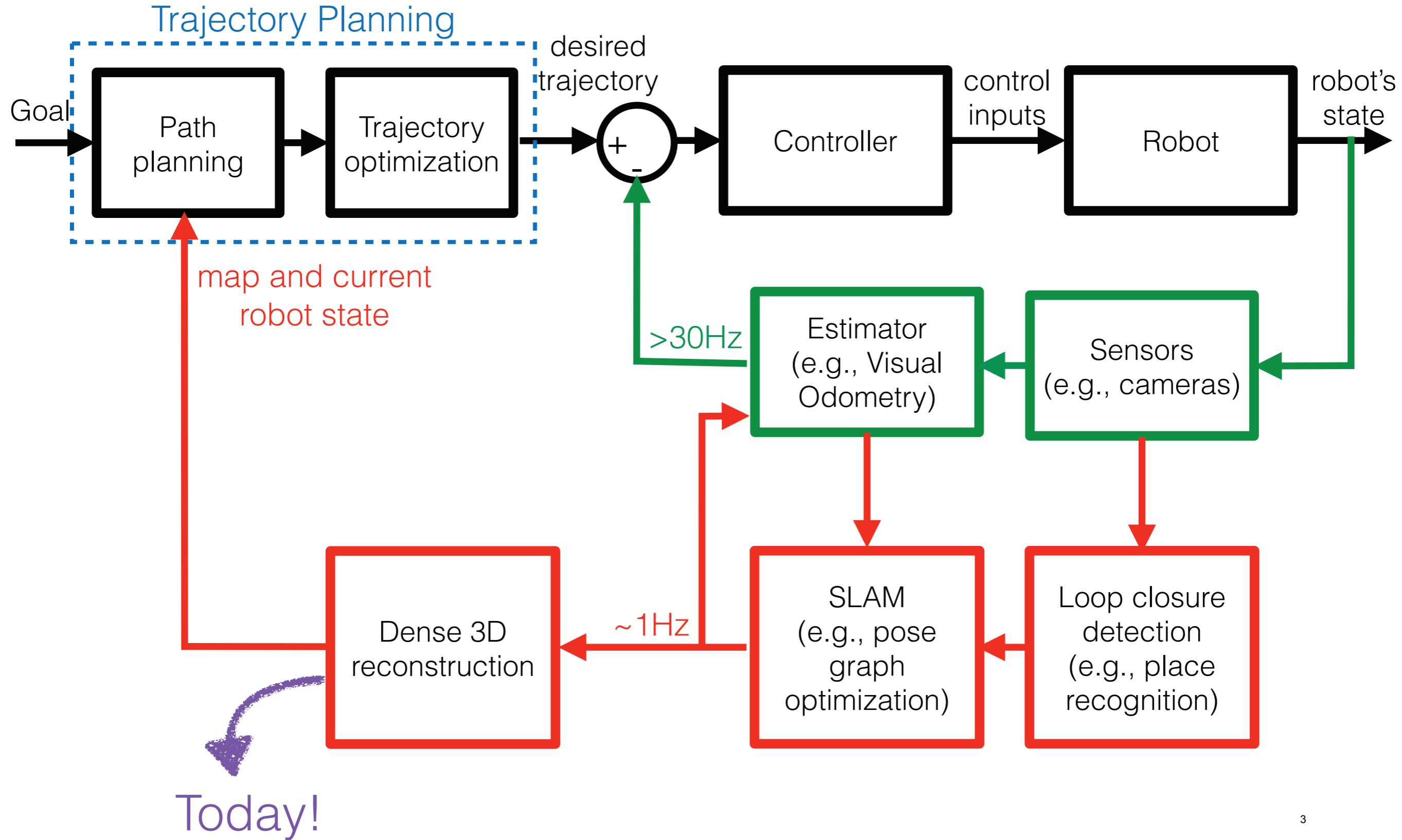
Lecture 25: Advanced topics:
Dense 3D Reconstruction



Big Picture



Big Picture



Today

- Dense Reconstruction
 - 3D representations
 - (Some) Multi-view Stereo
 - Depth fusion
- Final thoughts

Figure 1 in R. A. Newcombe et al., "KinectFusion: Real-time dense surface mapping and tracking," 2011 10th IEEE International Symposium on Mixed and Augmented Reality, Basel, Switzerland, 2011, pp. 127-136, doi: 10.1109/ISMAR.2011.6092378. © IEEE. All rights reserved. This content is excluded from our Creative Commons license. For more information, see <https://ocw.mit.edu/help/faq-fair-use/>

KinectFusion: Real-Time Dense Surface Mapping and Tracking*

Richard A. Newcombe
Imperial College London

Andrew J. Davison
Imperial College London

Shahram Izadi
Microsoft Research

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Microsoft Research

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Jamie Shotton
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2011

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Multi-View Stereo: A Tutorial 2015

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ElasticFusion: Dense SLAM Without A Pose Graph

Thomas Whelan*, Stefan Leutenegger*, Renato F. Salas-Moreno†, Ben Glocker† and Andrew J. Davison*

*Dyson Robotics Laboratory at Imperial College, Department of Computing, Imperial College London, UK

†Department of Computing, Imperial College London, UK

{t.whelan, s.leutenegger, r.salas-moreno10, b.glocker, a.davison}@imperial.ac.uk

2016

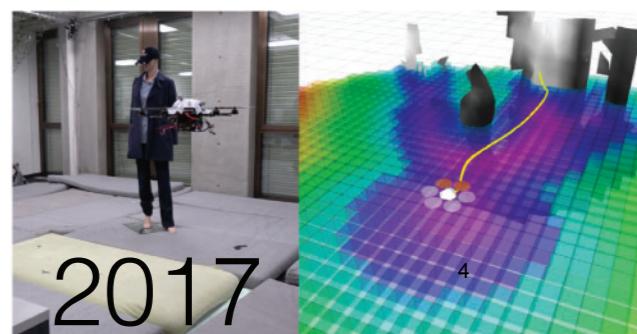
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Voxblox: Incremental 3D Euclidean Signed Distance Fields for On-Board MAV Planning

Helen Oleynikova, Zachary Taylor, Marius Fehr, Roland Siegwart, and Juan Nieto
Autonomous Systems Lab, ETH Zürich

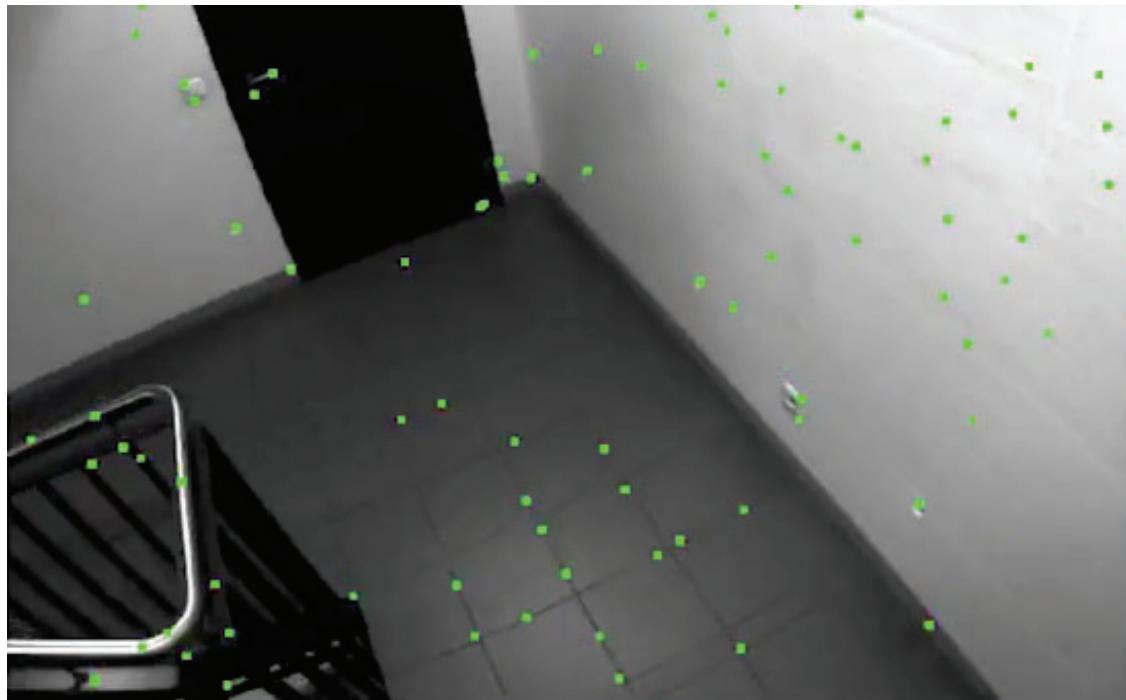
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2017

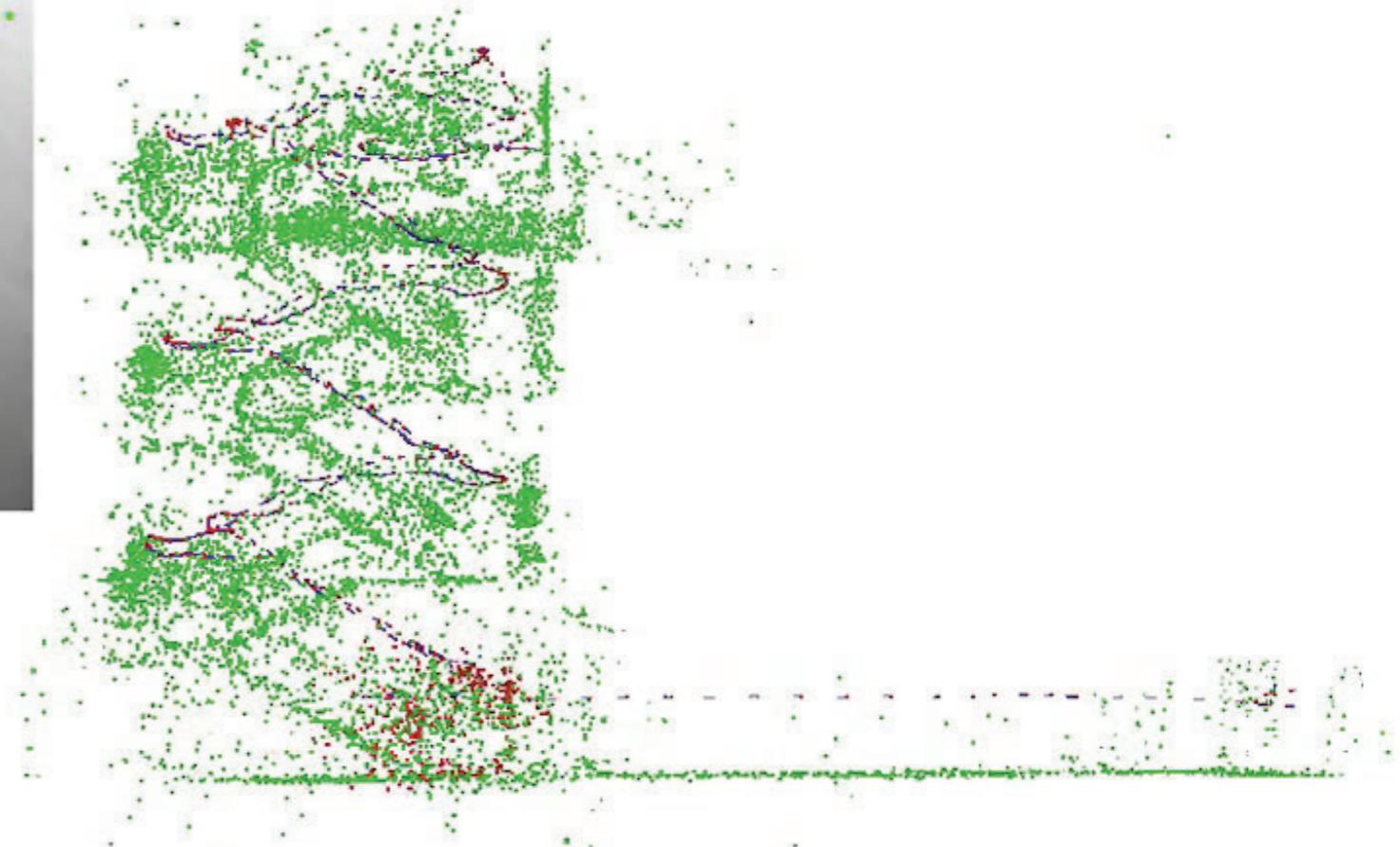
Point Clouds



Point Clouds

✗

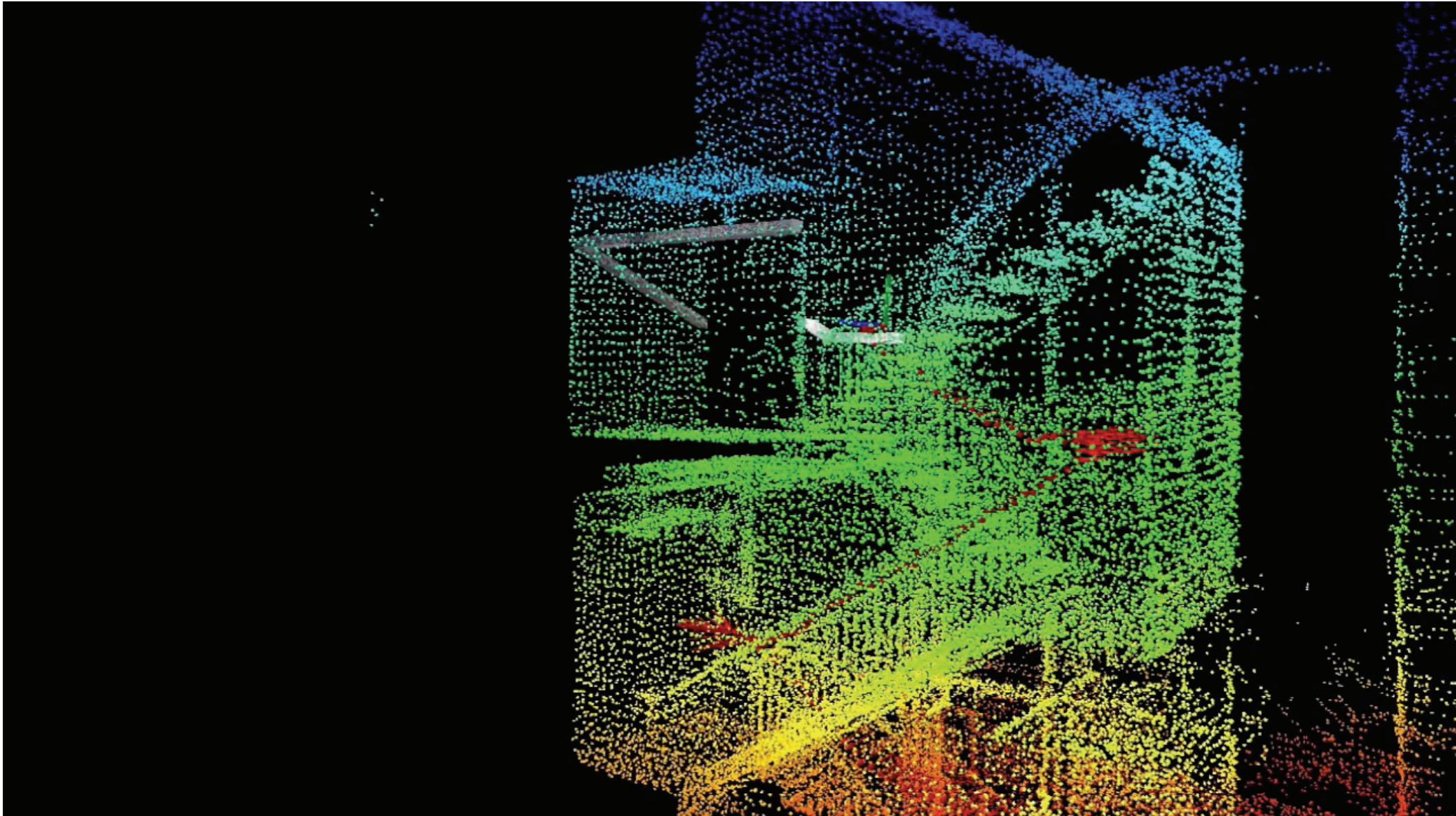
✓/✗
No, if Dense



✗

✓/✗
No, if Sparse

Point Clouds



Map representation	3D Topology?	Lightweight?	Filters Noise/ Outliers?	Semantics?	Generality
--------------------	--------------	--------------	-----------------------------	------------	------------

Point Clouds

✗

✓/✗
No, if Dense

✗

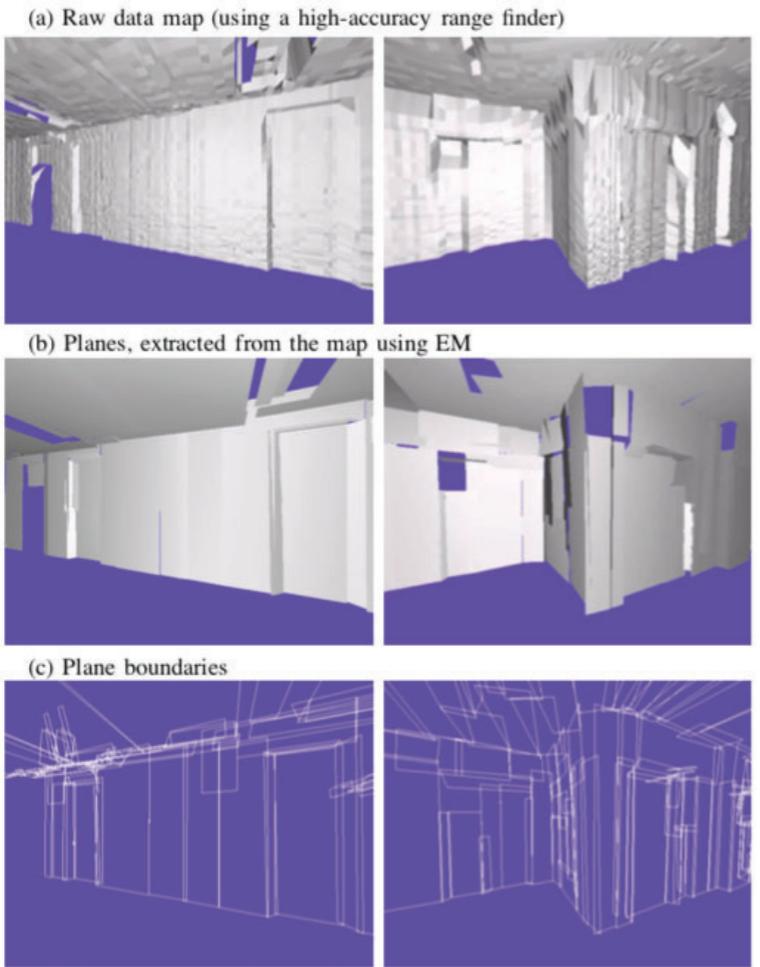
✓/✗
No, if Sparse

✓

Geometric Primitives

Point, lines, planes

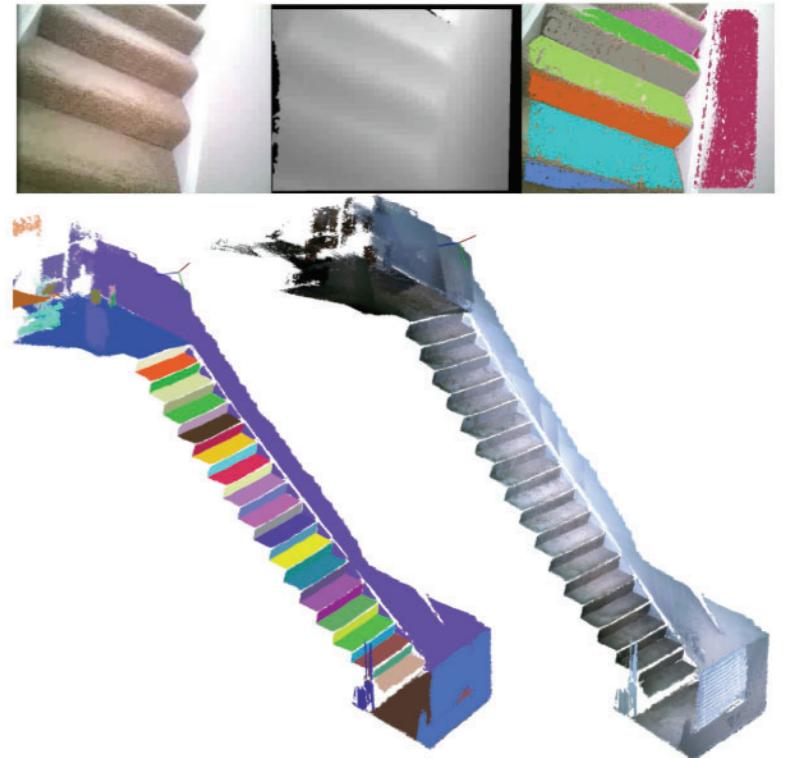
[Thrun et al.
2004]



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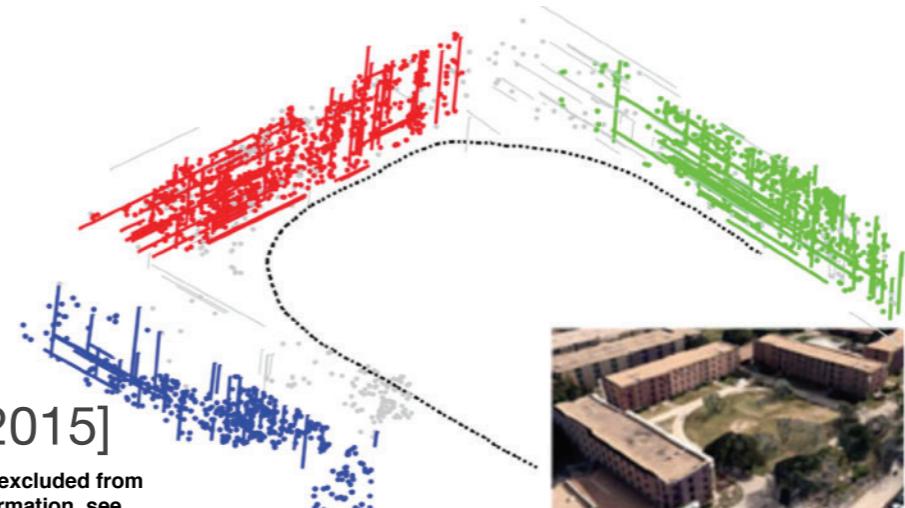
[Kaess 2015]

Figure 1 in Michael Kaess, "Simultaneous Localization and Mapping with Infinite Planes." June 2015 Proceedings - IEEE International Conference on Robotics and Automation 2015:4605-4611. © IEEE. All rights reserved. This content is excluded from our Creative Commons license. For more information, see <https://ocw.mit.edu/help/faq-fair-use/>



[Lu et al. 2015]

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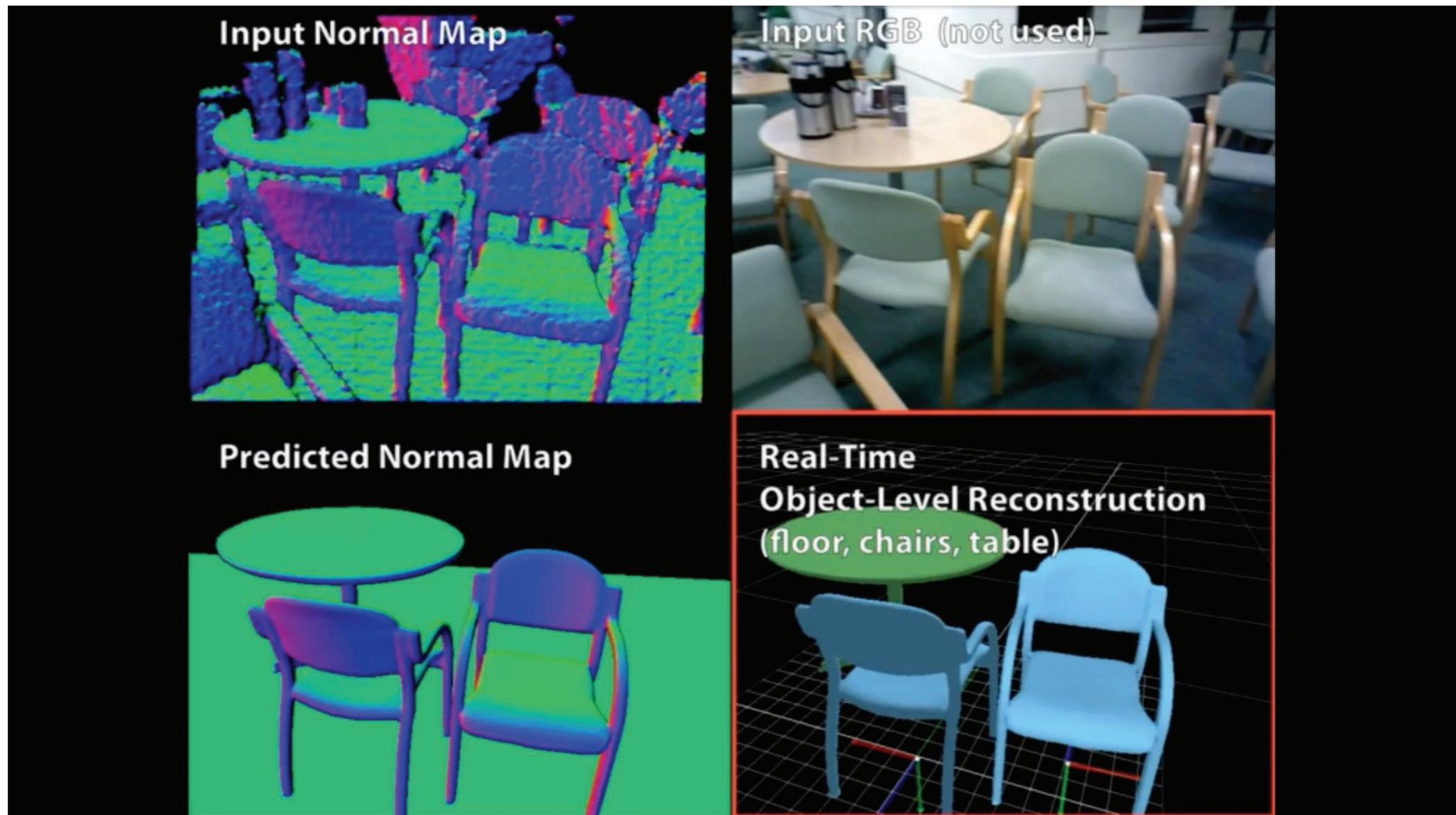


Map representation	3D Topology?	Lightweight?	Filters Noise/ Outliers?	Semantics?	Generality
Point Clouds	✗	✓/✗ No, if Dense	✗	✓/✗ No, if Sparse	✓
Geometric primitives	✗	✓	✓	✓/✗ No, if Sparse	✗

Object-based Maps

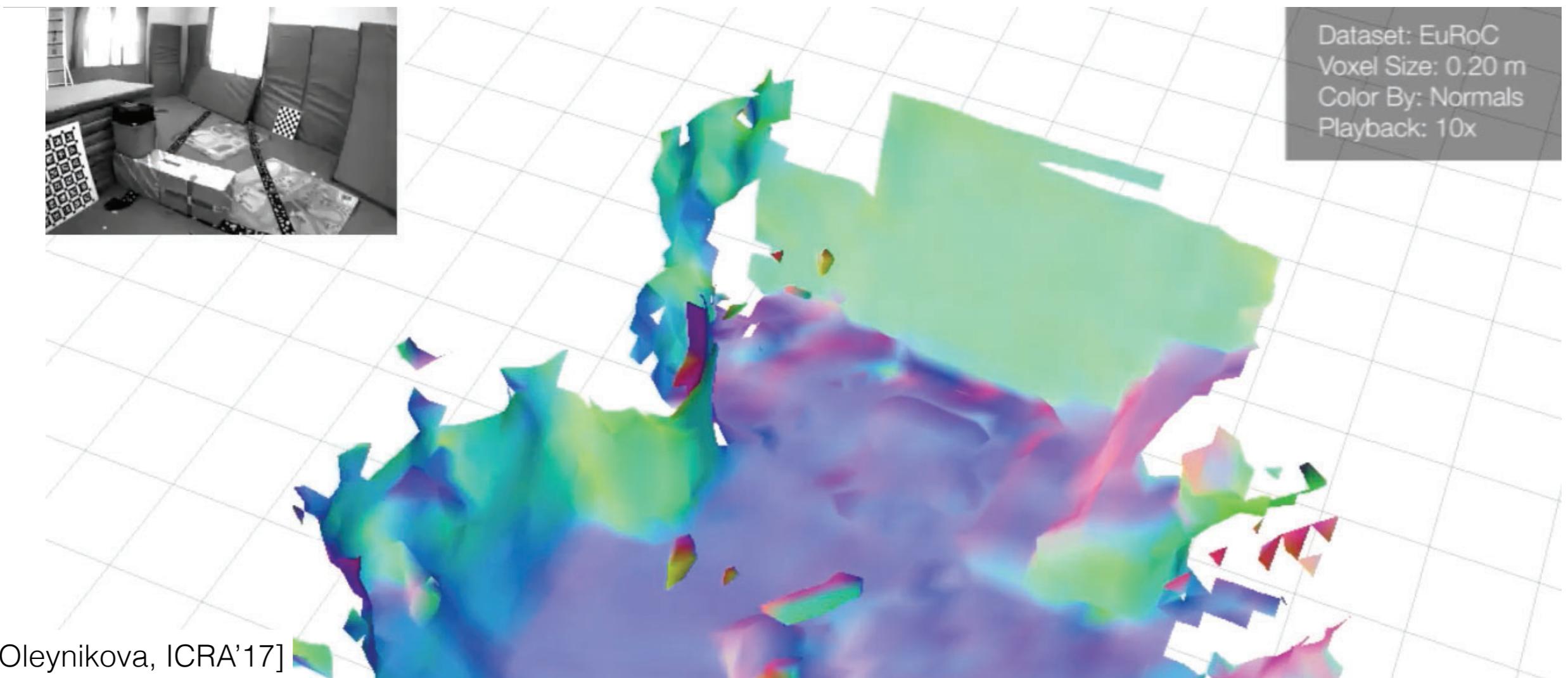
[Salas-Moreno et al, 2014]

Figure 3 in R. F. Salas-Moreno, R. A. Newcombe, H. Strasdat, P. H. J. Kelly and A. J. Davison, "SLAM++: Simultaneous Localisation and Mapping at the Level of Objects," 2013 IEEE Conference on Computer Vision and Pattern Recognition, Portland, OR, USA, 2013, pp. 1352-1359, doi: 10.1109/CVPR.2013.178 © IEEE. All rights reserved. This content is excluded from our Creative Commons license. For more information, see <https://ocw.mit.edu/help/faq-fair-use/>



Map representation	3D Topology?	Lightweight?	Filters Noise/Outliers?	Semantics?	Generality
Point Clouds	✗	✓/✗ No, if Dense	✗	✓/✗ No, if Sparse	✓
primitives & objects	✗	✓	✓	✓/✗ No, if Sparse	✗

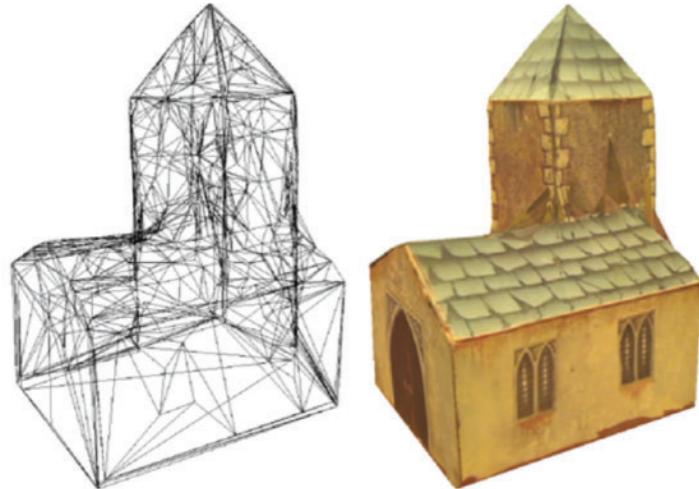
Volumetric Methods: Voxels/Octrees



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Map representation	3D Topology?	Lightweight?	Filters Noise/Outliers?	Semantics?	Generality
Point Clouds	✗	✓/✗ No, if Dense	✗	✓/✗ No, if Sparse	✓
primitives & objects	✗	✓	✓	✓/✗ No, if Sparse	✗
Voxels	✓	✓/✗ No, if small voxel	✓	✓/✗ No, if large	✓ 9

Meshes



Map representation	3D Topology ?	Lightweight?	Filters Noise/ Outliers?	Semantics?	Generalit y
Point Clouds	✗	✓/✗ No, if Dense	✗	✓/✗ No, if Sparse	✓
primitives & objects	✗	✓	✓	✓/✗ No, if Sparse	✗
Voxels	✓	✓/✗ No, if small voxel	✓	✓/✗ No, if large voxel	✓
3D Mesh	✓	✓	✗	✓	✓

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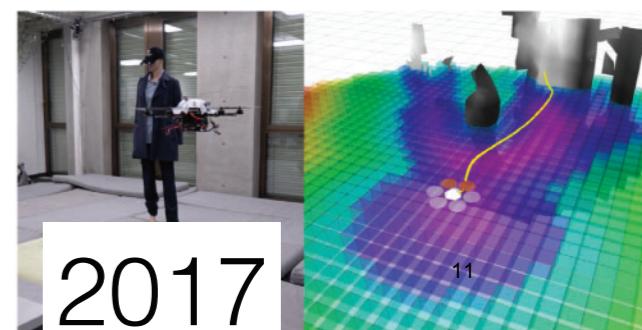
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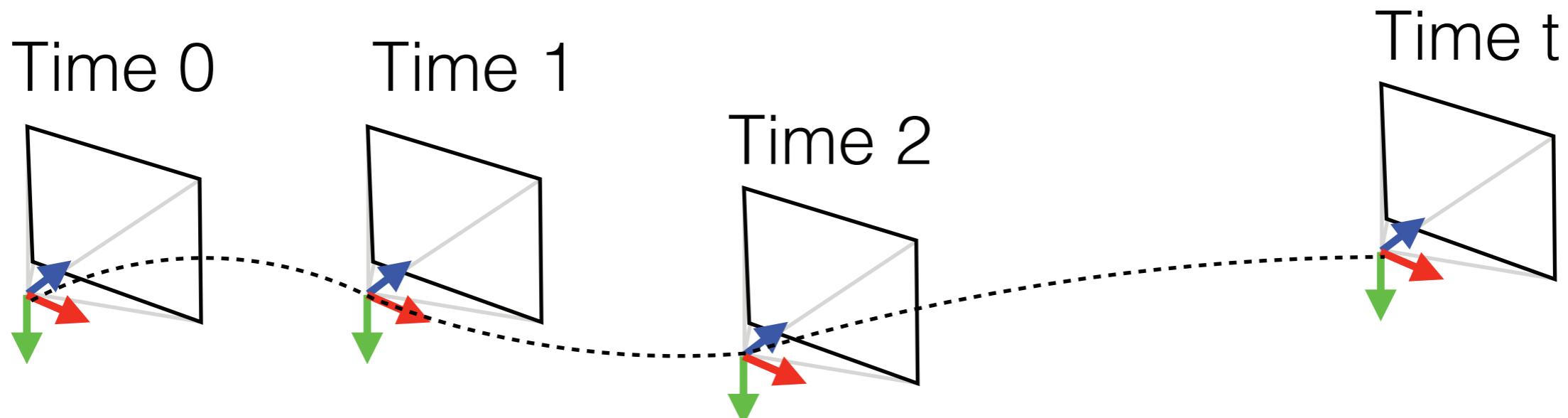
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2017

Multi-view Stereo

From previous lectures: we know how to use SLAM to get a good estimate of the poses of the cameras



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Stereo

[courtesy of N. Snavely]



Multi-view stereo

Multi-view Stereo

Towards Internet-scale
Multi-view Stereo

CVPR 2010

Yasutaka Furukawa¹ Brian Curless²

Steven M. Seitz^{1,2} Richard Szeliski³

Google Inc.¹
University of Washington²
Microsoft Research³

Multi-view Stereo

The Visual Turing Test for Scene Reconstruction Supplementary Video

Qi Shan⁺ Riley Adams⁺ Brian Curless⁺

Yasutaka Furukawa^{*} Steve Seitz^{+*}

⁺University of Washington

^{*}Google

3DV 2013

Multi-view Stereo

Patch-based methods:

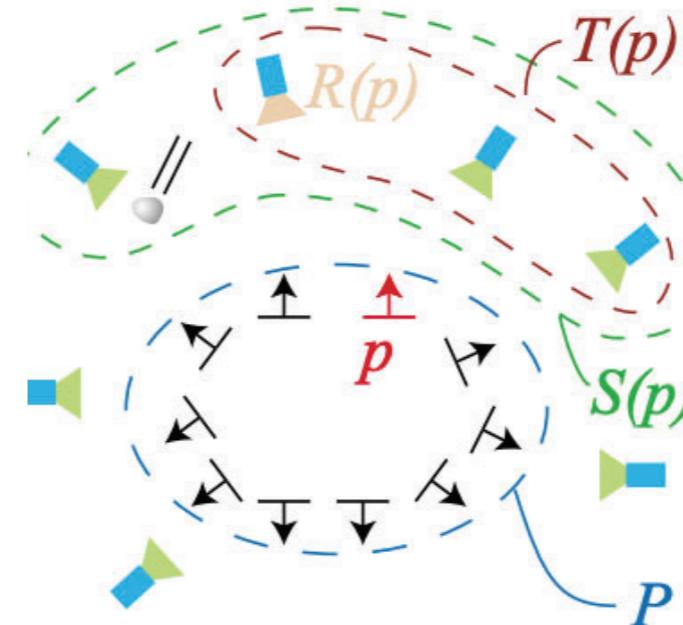
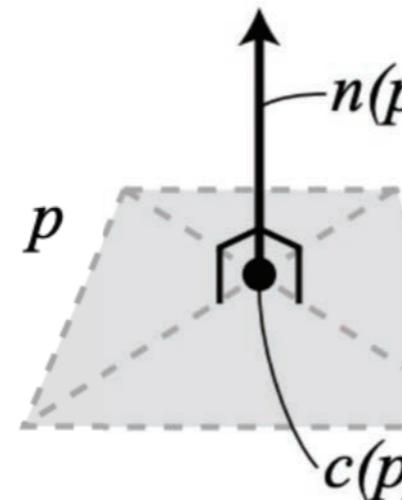


Figure 2. Definition of a patch (left) and of the images associated with it (right). See text for the details.

Estimate normal and center of patch to maximize **photometric consistency**:

$$C_{ij}(p) = \rho(I_i(\Omega(\pi_i(p))), I_j(\Omega(\pi_j(p))))$$

Projection To camera

Matching Score

Image Intensity

Rectangular Patch

3D point

Example of matching score:

$$1 - \sum_{x,y} |W_1(x,y) - W_2(x,y)|^2$$

Y. Furukawa and J. Ponce, "Accurate, Dense, and Robust Multi-View Stereopsis," 2007 IEEE Conference on Computer Vision and Pattern Recognition, Minneapolis, MN, USA, 2007, pp. 1-8, doi: 10.1109/CVPR.2007.383246. © IEEE. All rights reserved. This content is excluded from our Creative Commons license. For more information, see <https://ocw.mit.edu/help/faq-fair-use/>

Multi-view Stereo

Enforcing regularity: Markov Random Fields

Find depth k_p of point “p” such that point is photo-consistent and depth changes smoothly..

$$E(\{k_p\}) = \sum_p \Phi(k_p) + \sum_{(p,q) \in \mathcal{N}} \Psi(k_p, k_q)$$

Unary potentials

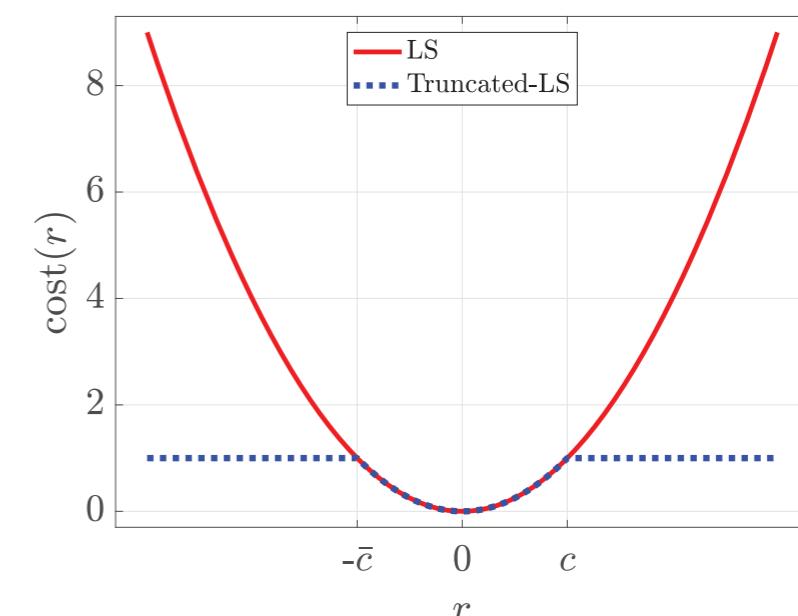
(similar to previous slides)

$$\Phi(k_p = d) = \min(\tau_u, 1 - \mathcal{C}(p, d))$$

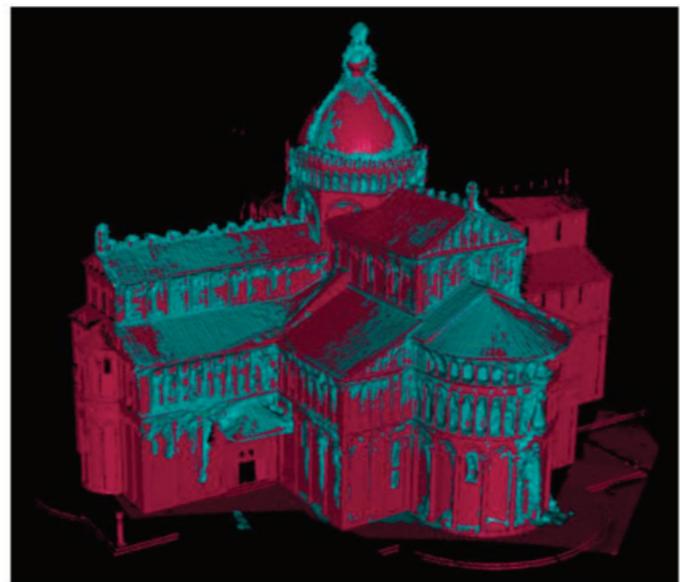
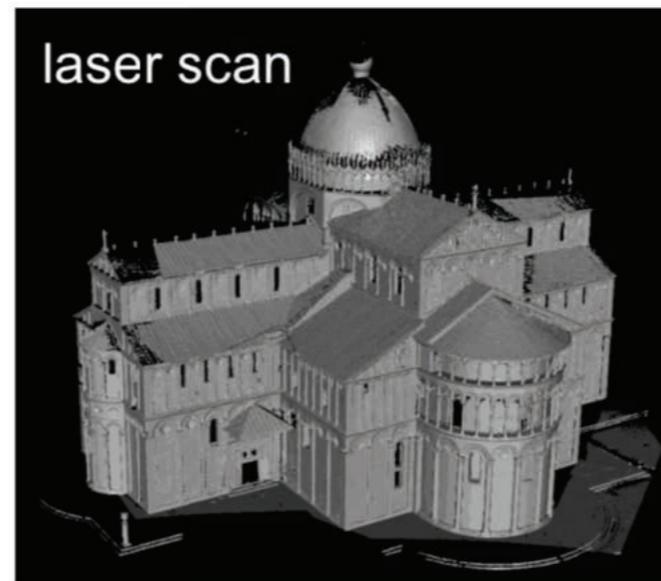
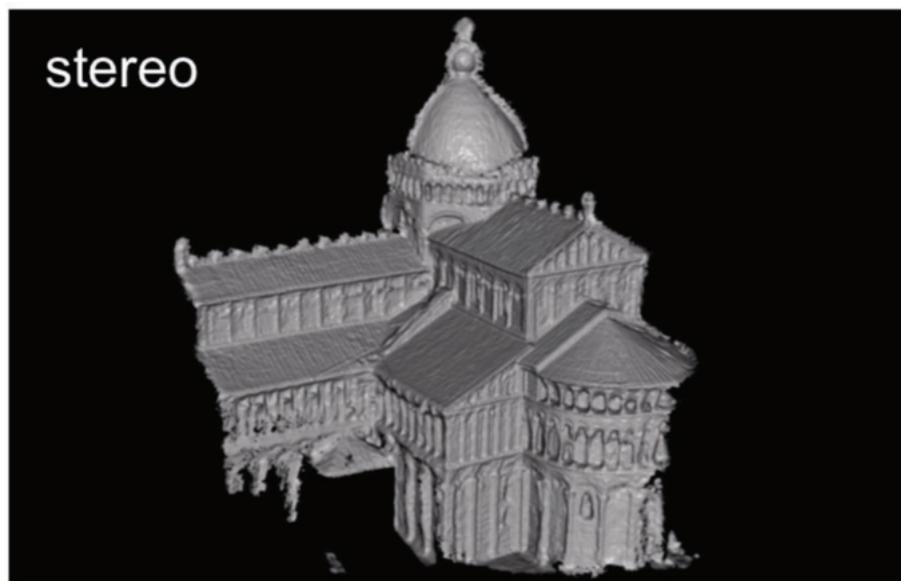
Depth is typically discretized before solving..

Pairwise potentials

$$\Psi(k_p = d_1, k_q = d_2) = \min(\tau_p, |d_1 - d_2|)$$



How Accurate is Multi-view Stereo?



Comparison: 90% of points
within 0.128 m of laser scan
(building height 51m)

Space Carving Results: African Violet



Source: S. Seitz

Space Carving Results: Hand



M. Goesele, N. Snavely, B. Curless, H. Hoppe, S. Seitz, [Multi-View Stereo for Community Photo Collections](#), ICCV 2007

Figure 7 in M. Goesele, N. Snavely, B. Curless, H. Hoppe and S. M. Seitz, "Multi-View Stereo for Community Photo Collections," 2007 IEEE 11th International Conference on Computer Vision, Rio de Janeiro, Brazil, 2007, pp. 1-8, doi: 10.1109/ICCV.2007.4408933. © IEEE. All rights reserved. This content is excluded from our Creative Commons license. For more information, see <https://ocw.mit.edu/help/faq-fair-use/>

Many methods: volumetric stereo, space carving,
Shape from silhouettes, carved visual hull

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2011

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2016

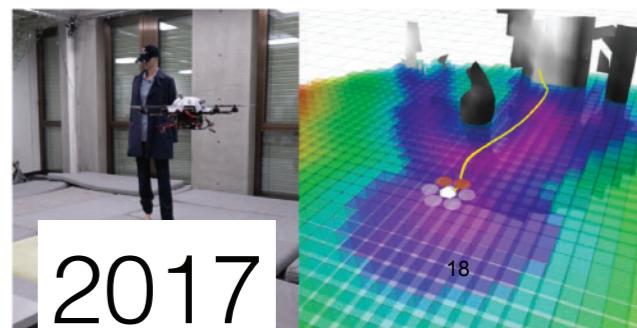
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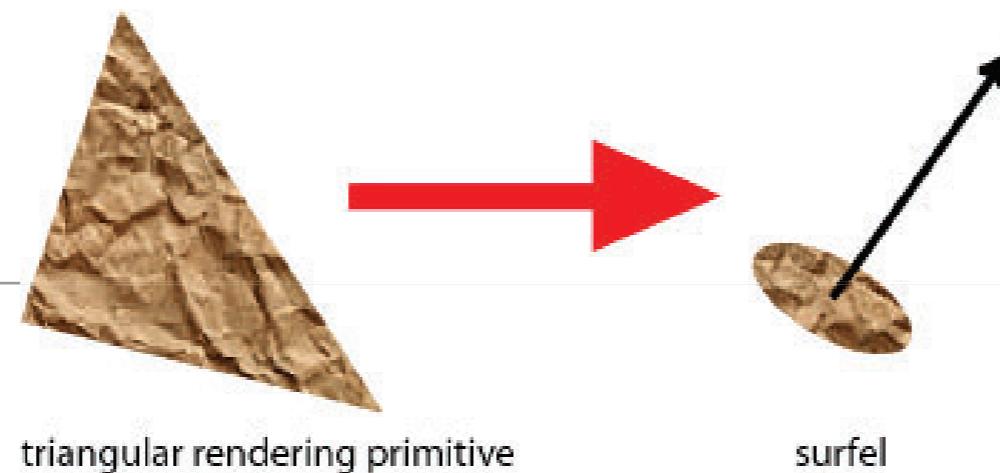
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2017

Surfels



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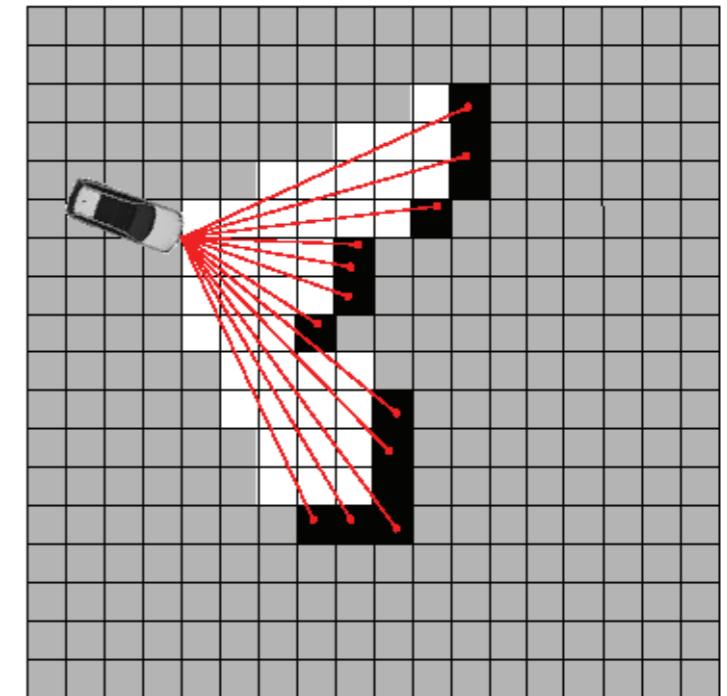
Imperial College London

note: still based on RGB-D (contrarily to multi-view stereo)

A Gentle Start: 2D Occupancy Grid Maps



- discretize the environment into cells
- Each cell holds real number [0,1], representing the probability of the cell being occupied



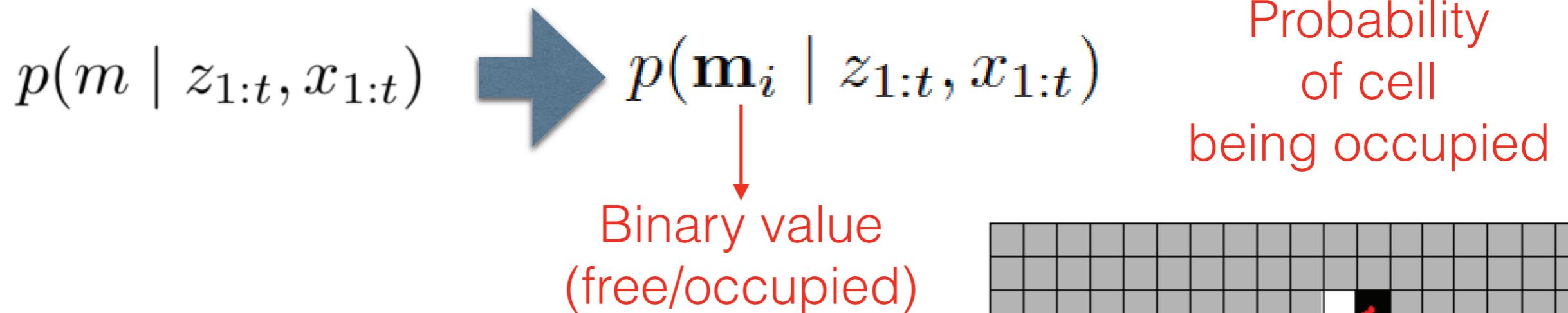
Map posterior

$$p(m \mid z_{1:t}, x_{1:t})$$

Unknown
Map

Known sensor
Depth and robot poses

A Gentle Start: 2D Occupancy Grid Maps



Bayes rule (omitting “x” for simplicity):

$$p(m_i \mid z_{1:t+1}) = \frac{p(z_{t+1} \mid m_i)p(m_i \mid z_{1:t})}{p(m_i)}$$

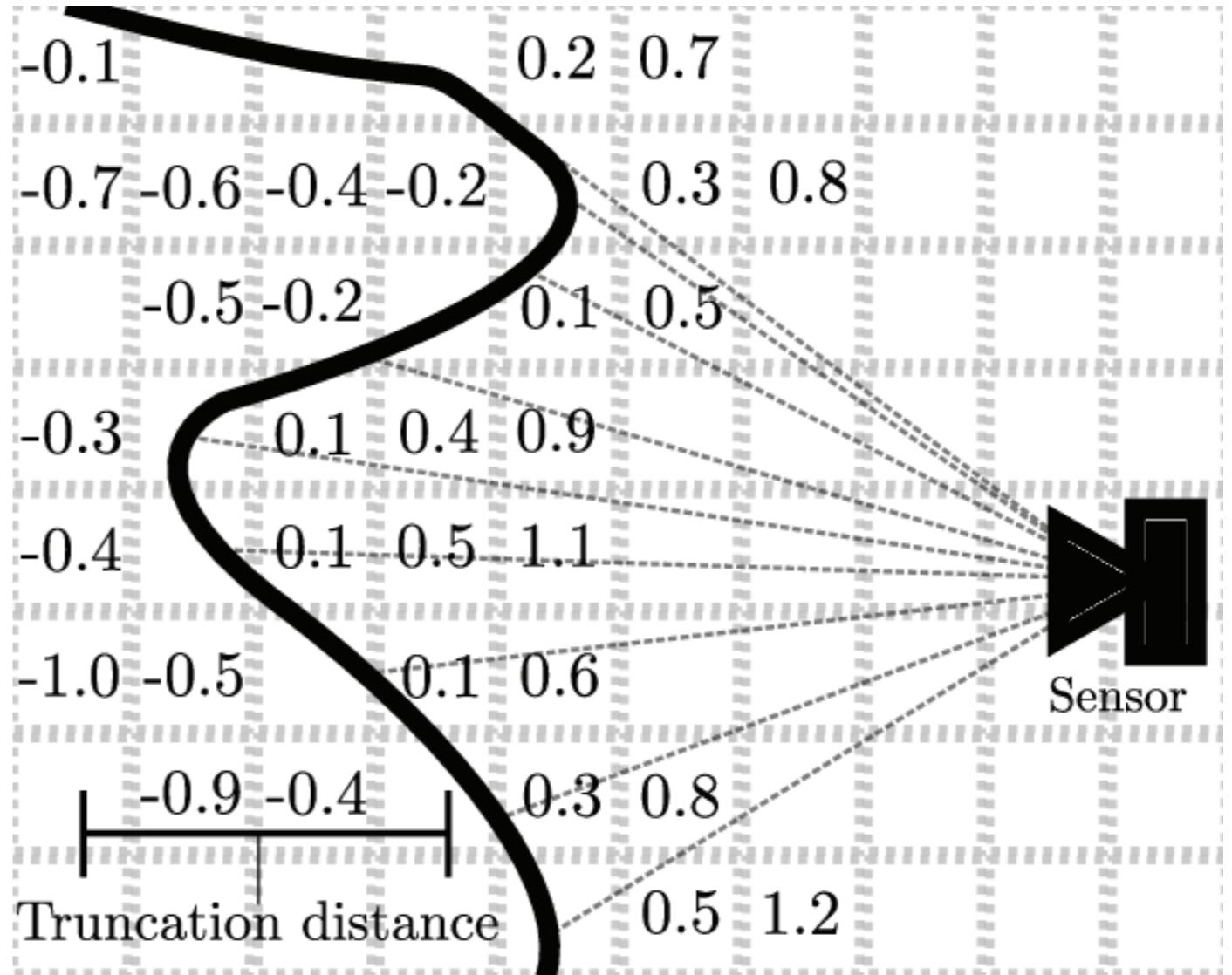
Uninformative Prior

Log-odd representation is typically used to avoid numerical instabilities

$$\frac{p(\mathbf{m}_i \mid z_{1:t}, x_{1:t})}{1 - p(\mathbf{m}_i \mid z_{1:t}, x_{1:t})} \rightarrow l_{t,i} = \log \frac{p(\mathbf{m}_i \mid z_{1:t}, x_{1:t})}{1 - p(\mathbf{m}_i \mid z_{1:t}, x_{1:t})}$$

Truncated Signed Distance Function (SDF)

- Store distance to nearest obstacle (with sign)
- Only update around obstacle itself
(implicit surface model)



Update rule:

$$d(\mathbf{x}, \mathbf{p}, \mathbf{s}) = \|\mathbf{p} - \mathbf{x}\| \operatorname{sign}((\mathbf{p} - \mathbf{x}) \bullet (\mathbf{p} - \mathbf{s})) \quad (1)$$

$$w_{\text{const}}(\mathbf{x}, \mathbf{p}) = 1 \quad (2)$$

$$D_{i+1}(\mathbf{x}, \mathbf{p}) = \frac{W_i(\mathbf{x})D_i(\mathbf{x}) + w(\mathbf{x}, \mathbf{p})d(\mathbf{x}, \mathbf{p})}{W_i(\mathbf{x}) + w(\mathbf{x}, \mathbf{p})} \quad (3)$$

$$W_{i+1}(\mathbf{x}, \mathbf{p}) = \min(W_i(\mathbf{x}) + w(\mathbf{x}, \mathbf{p}), W_{\max}) \quad (4)$$

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[Curless and Levoy, “A Volumetric Method for Building Complex Models from Range Images”, 2007]

Kinect Fusion (2011)

SIGGRAPH Talks 2011

KinectFusion:

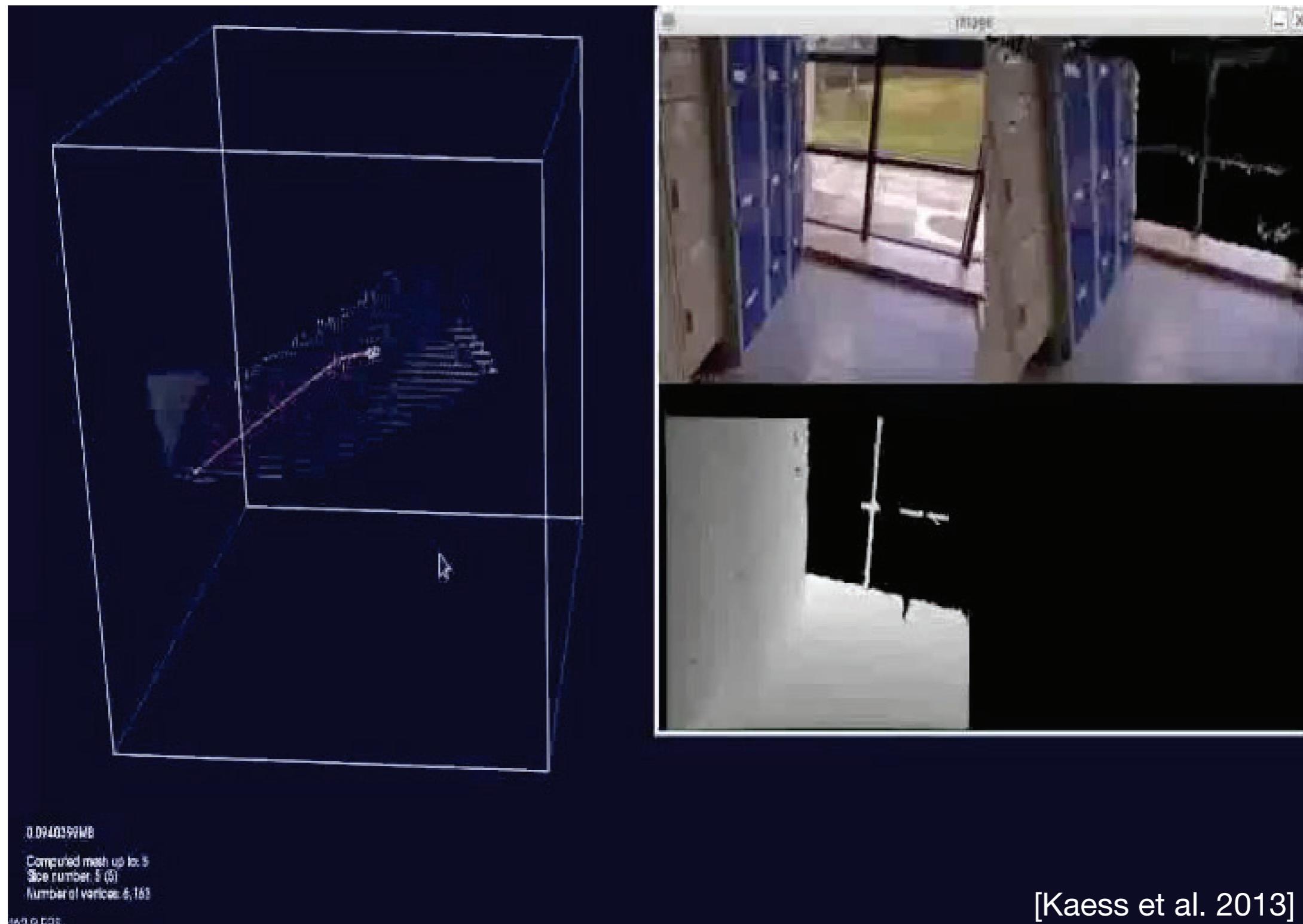
Real-Time Dynamic 3D Surface Reconstruction and Interaction

**Shahram Izadi 1, Richard Newcombe 2, David Kim 1,3, Otmar Hilliges 1,
David Molyneaux 1,4, Pushmeet Kohli 1, Jamie Shotton 1,
Steve Hodges 1, Dustin Freeman 5, Andrew Davison 2, Andrew Fitzgibbon 1**

1 Microsoft Research Cambridge 2 Imperial College London
3 Newcastle University 4 Lancaster University
5 University of Toronto

GPU, memory ...

Kintinuous (2013)

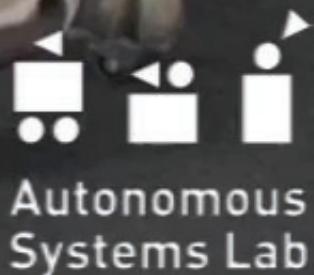


GPU, bounded memory ...

VoxBlox (2017)

Voxblox: Building 3D Signed Distance Fields for Planning

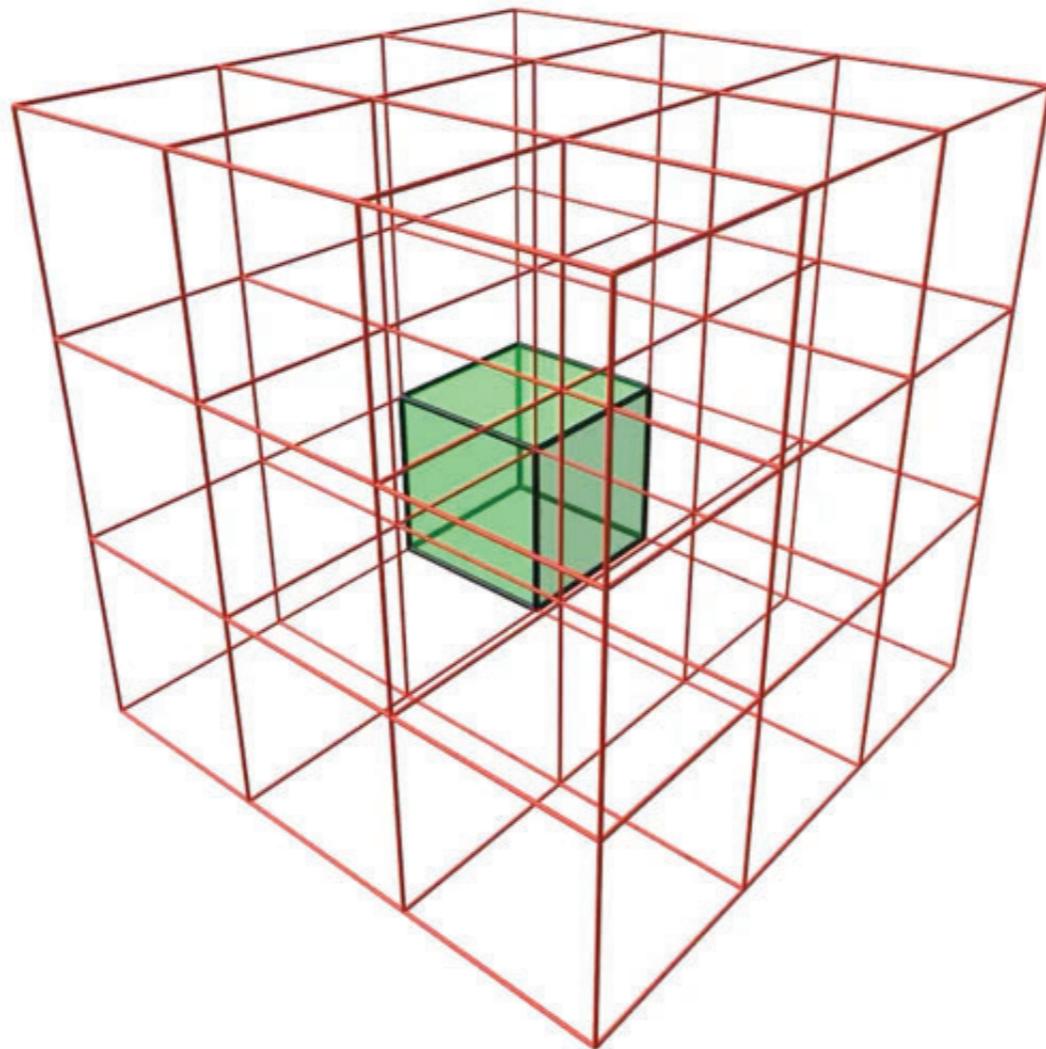
Helen Oleynikova, Zachary Taylor, Marius Fehr, Juan Nieto, and Roland Siegwart



Autonomous
Systems Lab

From Voxels to Meshes

Marching cubes



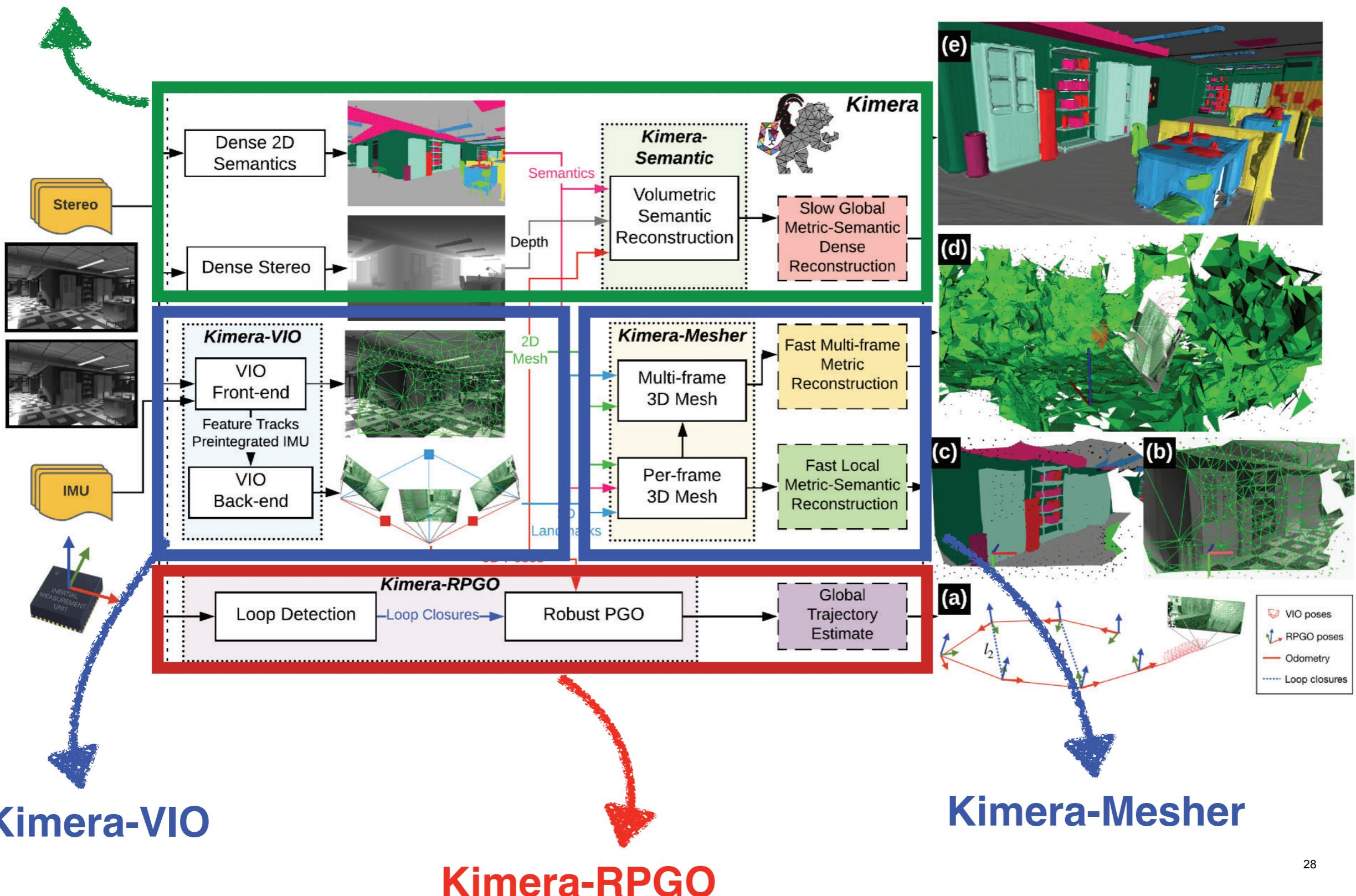
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Kimera (2020)

Kimera-VIO tracks sparse 3D landmarks for fast and accurate state estimation

Metric-semantic 3D Reconstruction

Kimera-Semantics



Kimera-VIO

Kimera-RPGO

Kimera-Mesher

Today

- Dense Reconstruction
 - 3D representations
 - (Some) Multi-view Stereo
 - Depth fusion
- Final thoughts

Multi-View Stereo: A Tutorial 2015

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ElasticFusion: Dense SLAM Without A Pose Graph 2016

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2016

Figure 1 in H. Oleynikova, Z. Taylor, M. Fehr, R. Siegwart and J. Nieto, "Voxblox: Incremental 3D Euclidean Signed Distance Fields for on-board MAV planning," 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Vancouver, BC, 2017, pp. 1366-1373, doi: 10.1109/IROS.2017.8202315. © IEEE. All rights reserved. This content is excluded from our Creative Commons license. For more information, see <https://ocw.mit.edu/help/faq-fair-use/>

KinectFusion: Real-Time Dense Surface Mapping and Tracking*

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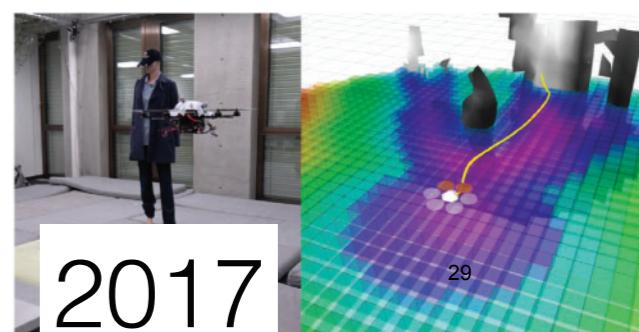


2011

Figure 1: Example output from our system, generated in real-time with a handheld Kinect depth camera and no other sensing infrastructure. Normal maps (colour) and Phong-shaded renderings (greyscale) from our dense reconstruction system are shown. On the left for comparison is an example of the live, incomplete, and noisy data from the Kinect sensor (used as input to our system).

Abstract— Micro Aerial Vehicles (MAVs) that operate in unstructured, unexplored environments require fast and flexible local planning, which can replan when new parts of the map are explored. Trajectory optimization methods fulfill these needs, but require obstacle distance information, which can be given by Euclidean Signed Distance Fields (ESDFs).

We propose a method to incrementally build ESDFs from Truncated Signed Distance Fields (TSDFs), a common implicit surface representation used in computer graphics and vision. TSDFs are fast to build and smooth out sensor noise over many observations, and are designed to produce surface meshes. Meshes allow human operators to get a better assessment of the robot's environment, and set high-level mission goals.

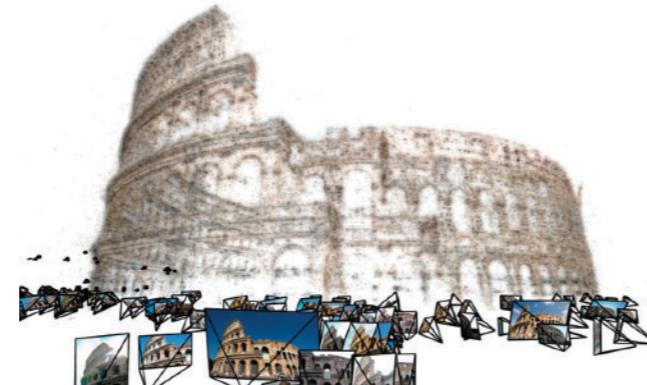


2017

Robot Perception or Computer Vision?

Computer vision

.. “a day on a cluster with 500 compute cores”



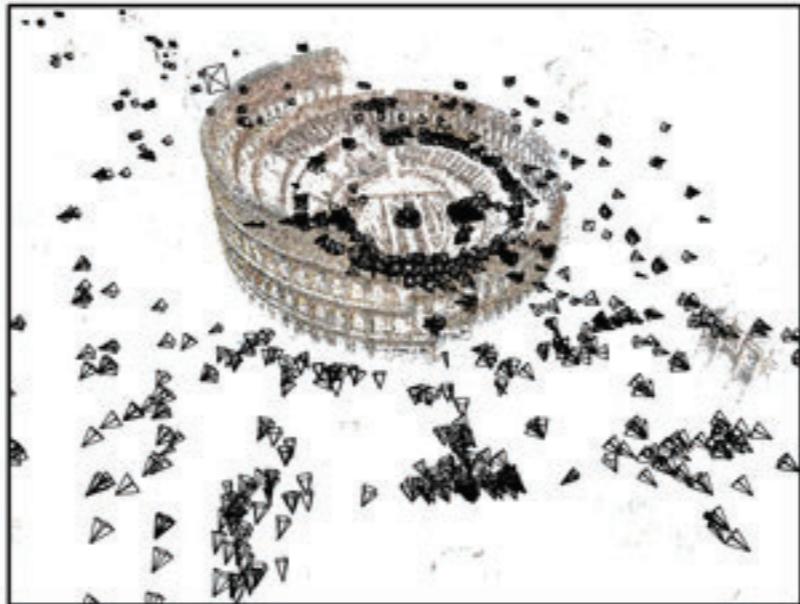
Robotics



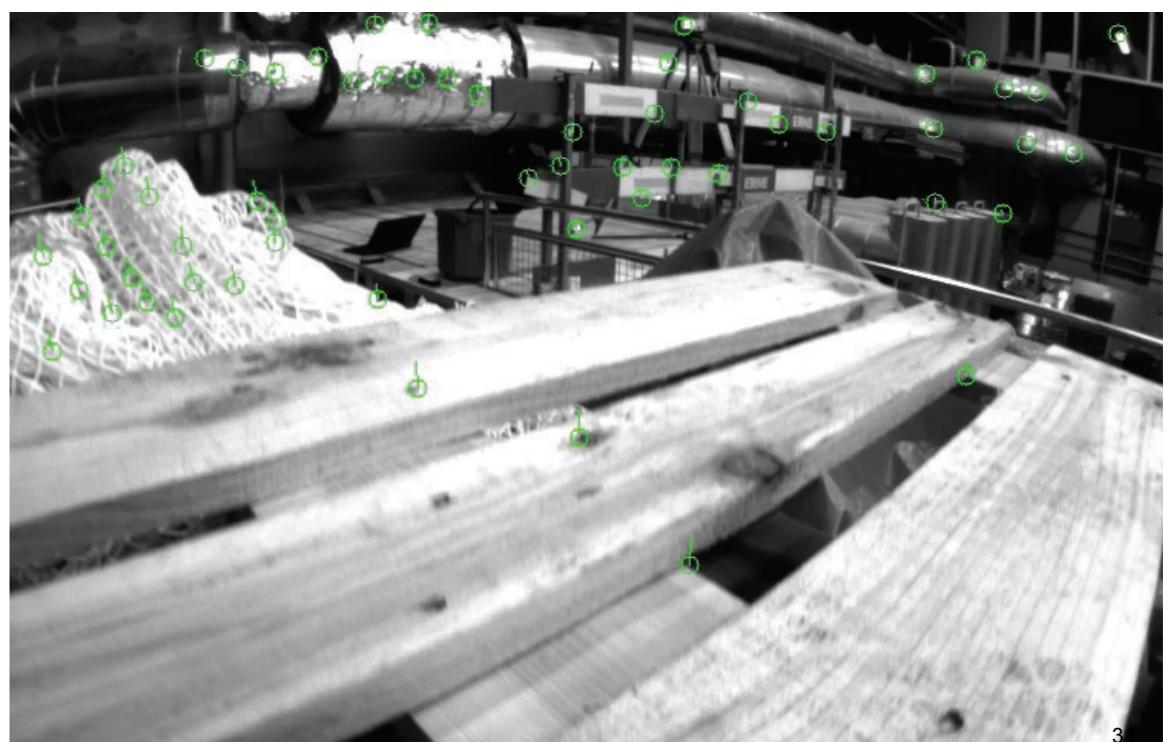
50-100ms latency,
embedded,
incremental

No longer a dichotomy for many vision applications!

Robot Perception or Computer Vision?



Unordered
Vs
Sequential



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16.485 Visual Navigation for Autonomous Vehicles (VNAV)

Fall 2020

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