dyson
Robotics Lab

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London

The Future of Real-Time SLAM

Where we are now

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18th December 2015 (ICCV Workshop)

Probabilistic SLAM Formulation

Given

Measurements $\mathbf{z}$ are samples from a **distribution** $p(\mathbf{z}|\mathbf{x})$ given the variables $\mathbf{x}$ (robot states plus usually the map).

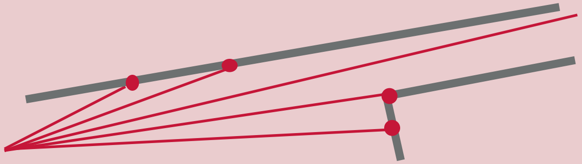
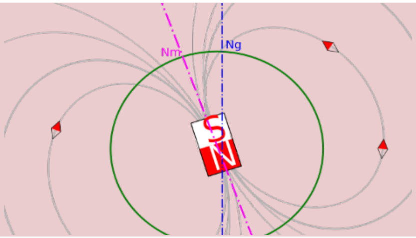
Find

- Values for variables $\mathbf{x}$ that best explain all the measurements (**maximum likelihood, ML**).
- Values for $\mathbf{x}$ that best explain all the measurements and a prior $p(\mathbf{x})$ (**maximum a posteriori, MAP**).

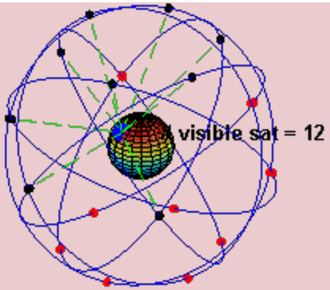
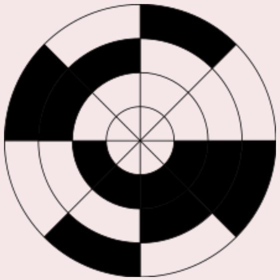
What our research consists of:

- **Decide** for a state and map representation $\mathbf{x}$.
- **Model** the likelihood function $p(\mathbf{z}|\mathbf{x})$ and prior $p(\mathbf{x})$ (e.g. regulariser).
- **Choose** approximations to solve the ML/MAP problem, e.g. marginalisation (filtering), or iterative minimisation.
- **Find** some way to bootstrap, associate data, and initialise.

Typical Sensors – Exteroceptive

Sensor	Measurement	
Laser Scanner	3D points	
Camera	(Colour) image (RGB-D: with depth!)	
Magnetometer	3D magnetic field	
Pressure sensor	Air pressure (altitude / airspeed)	

Typical Sensors – Proprioceptive

Sensor	Measurement	
GPS	pseudo-ranges (position)	
Encoders	Joint / wheel angles	
Inertial Measurement Unit (IMU)	Rotation rates and accelerations (with caution: orientation)	

Why Visual-Inertial

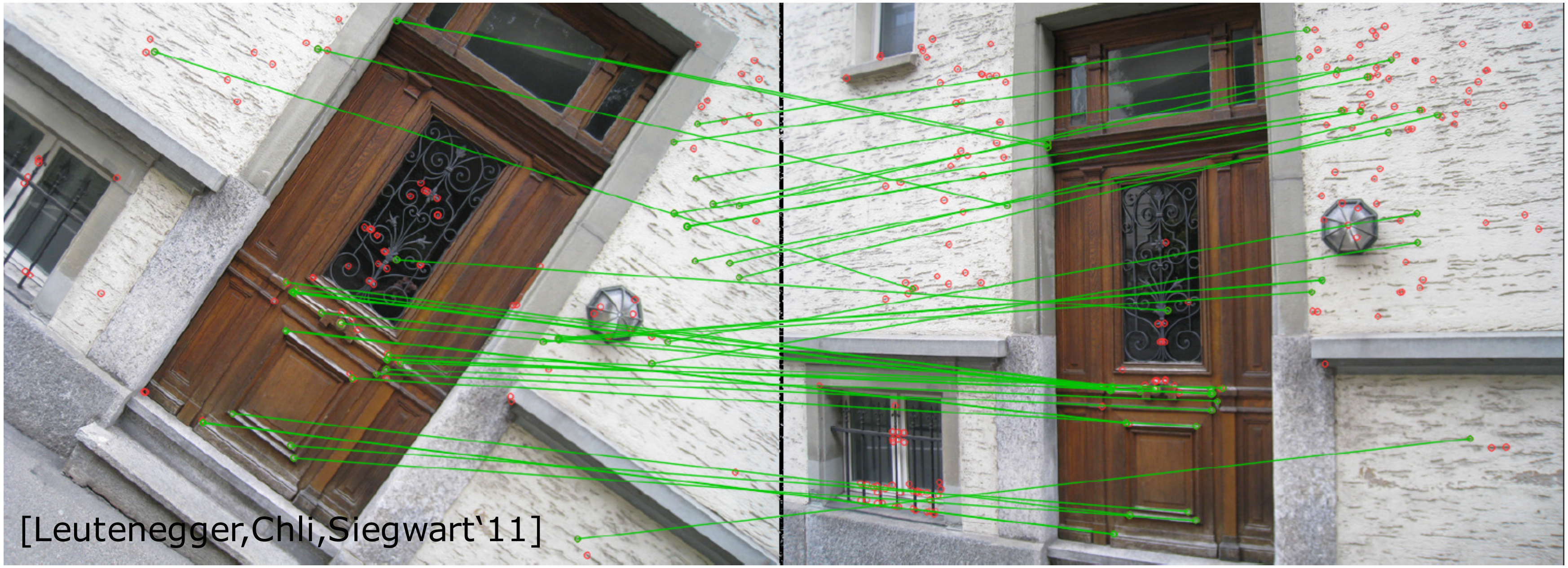
- Spatial relative pose constraints
- Information on structure

IDS uEye

+

ADIS166448

- Strong short-term temporal pose constraints



[Leutenegger,Chli,Siegwart‘11]

IMU Kinematics with Sensor Error Models

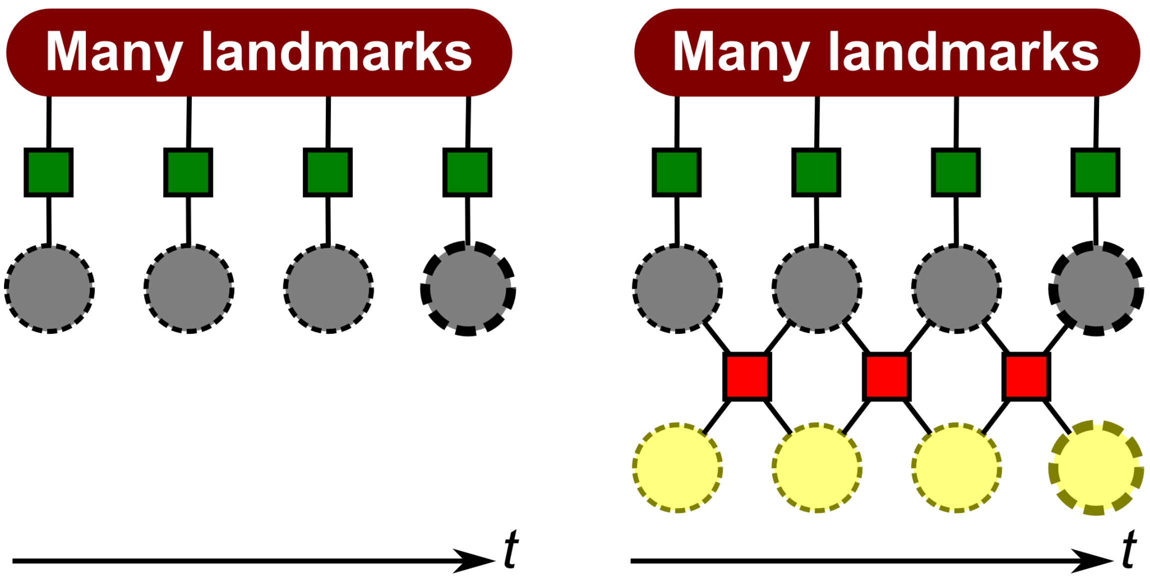
$$
{}_W\dot{\mathbf{r}}_S = {}_W\mathbf{v}\,,
$$

$$
\dot{\mathbf{q}}_{WS} = \frac{1}{2}\begin{bmatrix} {}_S\tilde{\boldsymbol{\omega}} + \mathbf{w}_{\mathrm{g}} - \mathbf{b}_{\mathrm{g}} \\ 0 \end{bmatrix}^{\oplus} \mathbf{q}_{WS}\,,
$$

$$
{}_W\dot{\mathbf{v}} = \mathbf{C}_{WS}\left({}_S\tilde{\mathbf{a}} + \mathbf{w}_{\mathrm{a}} - \mathbf{b}_{\mathrm{a}}\right) + {}_W\mathbf{g},
$$

$$
\left.\begin{aligned}
\dot{\mathbf{b}}_{\mathrm{g}} &= \mathbf{w}_{b_{\mathrm{g}}}\,, \\
\dot{\mathbf{b}}_{\mathrm{a}} &= -\frac{1}{\tau}\mathbf{b}_{\mathrm{a}} + \mathbf{w}_{b_{\mathrm{a}}}\,.
\end{aligned}\right\} \text{IMU biases}
$$

Vision-Only vs. Visual-Inertial in Nonlinear Optimisation



● Pose

○ Speed / IMU bias'

🟩 Many keypoint measurements

🟥 IMU measurements

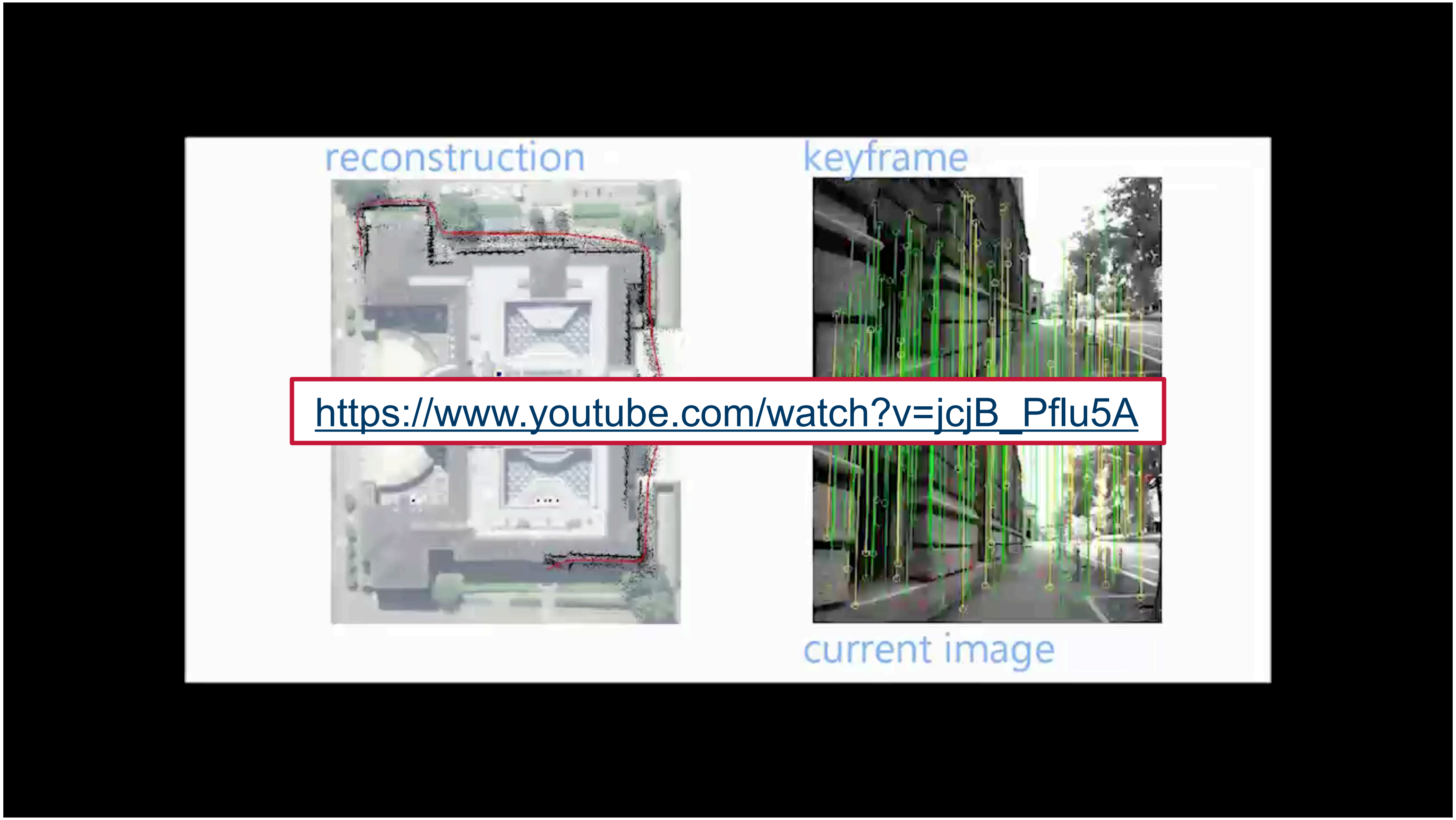
$$J(\mathbf{x}) := \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{j\in\mathcal{J}(i,k)} {\mathbf{e}_{\mathrm{r}}^{i,j,k}}^T \mathbf{W}_{\mathrm{r}}^{i,j,k}\mathbf{e}_{\mathrm{r}}^{i,j,k} + \sum_{k=1}^{K-1} {\mathbf{e}_{\mathrm{s}}^{k}}^T \mathbf{W}_{\mathrm{s}}^{k}\mathbf{e}_{\mathrm{s}}^{k}.$$

Cost

Reprojection errors:
Diff. between detected 2D keypoints and projected 3D landmarks

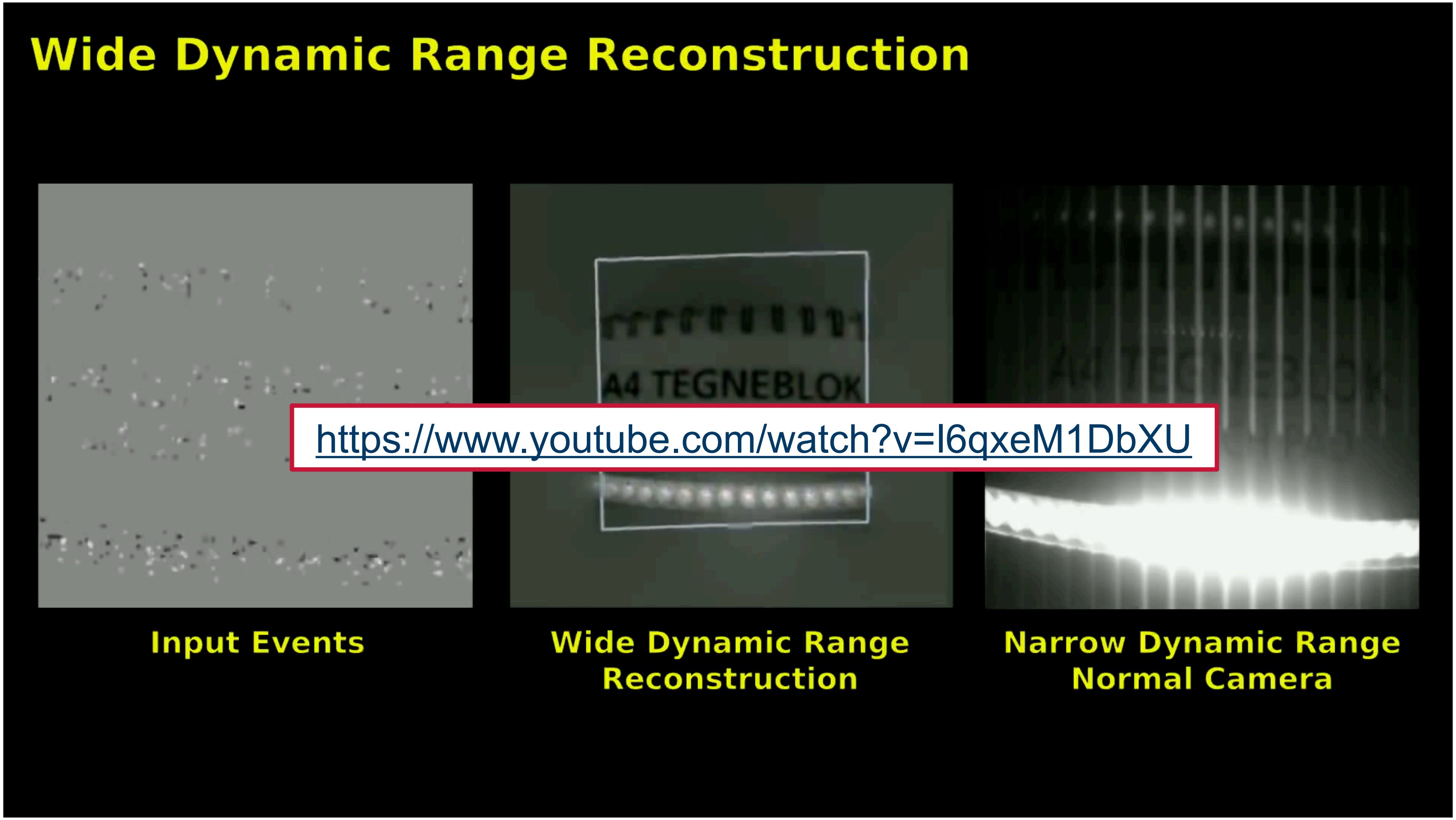
IMU terms:
Using the IMU kinematics model

Keyframe VIO Results Overview



https://www.youtube.com/watch?v=jcjB_Pflu5A

New Sensors: Event Cameras

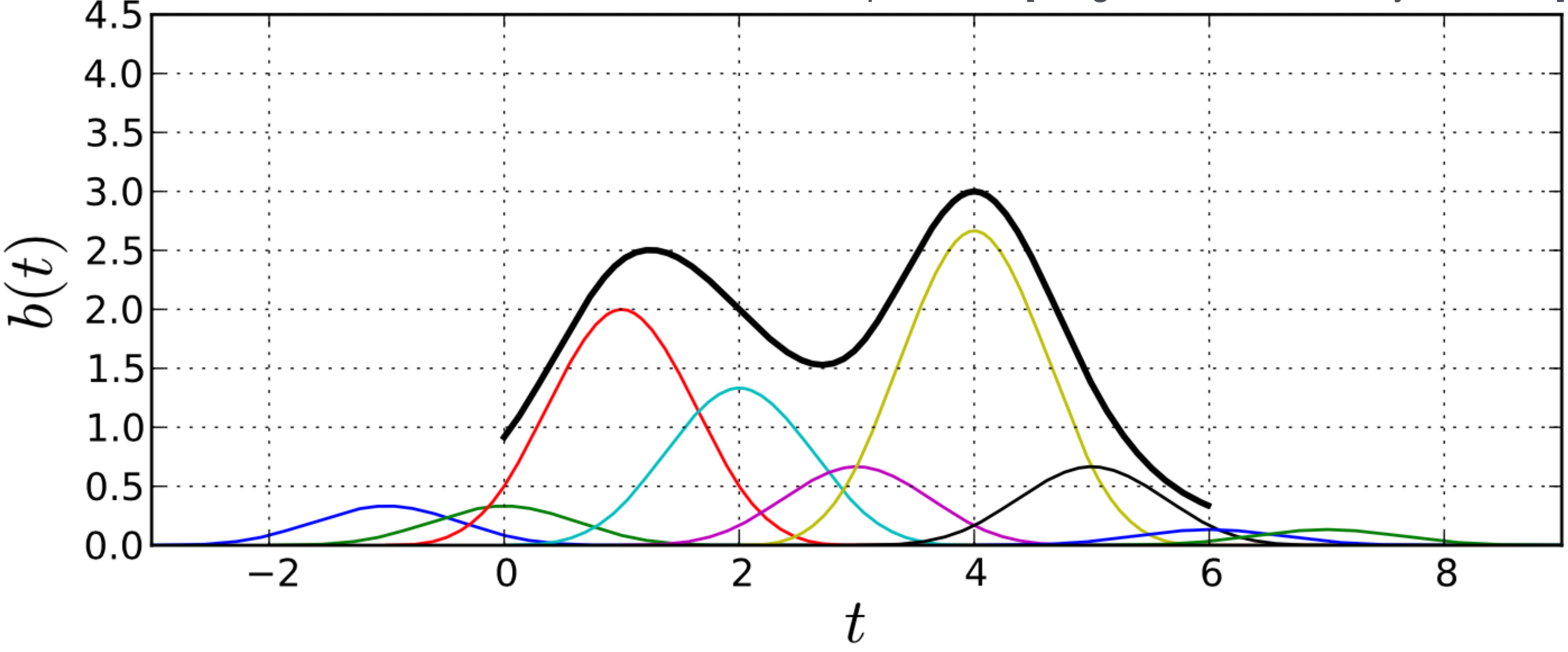


https://www.youtube.com/watch?v=I6qxeM1DbXU

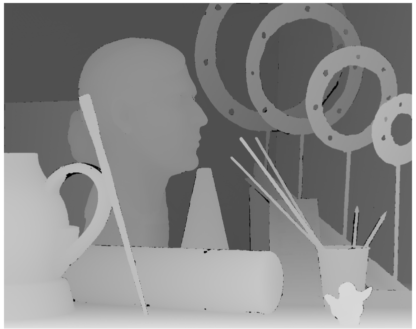
State Representations: Discrete vs. Continuous-Time

Suggestion to replace traditional discrete time trajectory with continuous-time [Furgale, Barfoot, Sibley, ICRA'13] using a basis functions

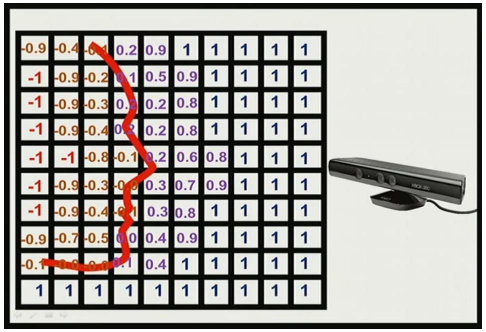
Copied from [Furgale, Barfoot, Sibley, ICRA'13]



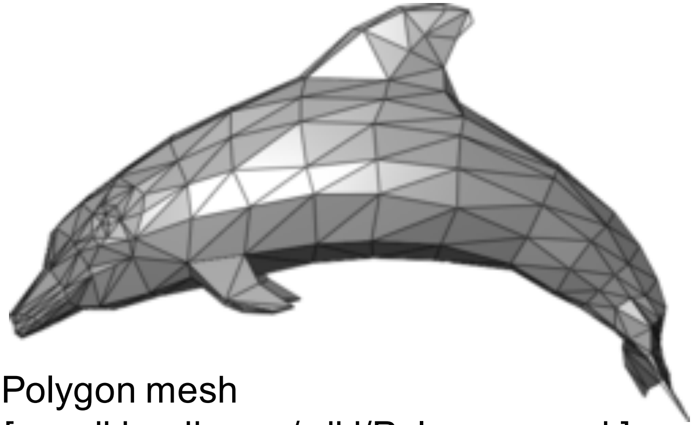
Map Representations



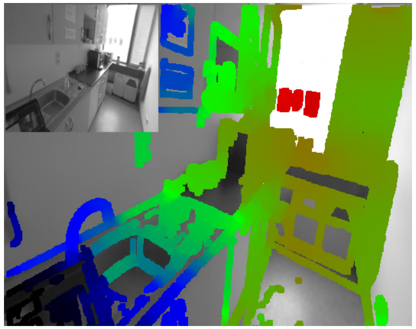
Depth maps
[vision.middlebury.edu]



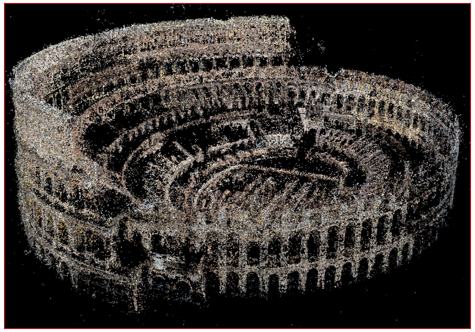
Truncated Signed Distance Function [pointclouds.org]



Polygon mesh
[en.wikipedia.org/wiki/Polygon_mesh]



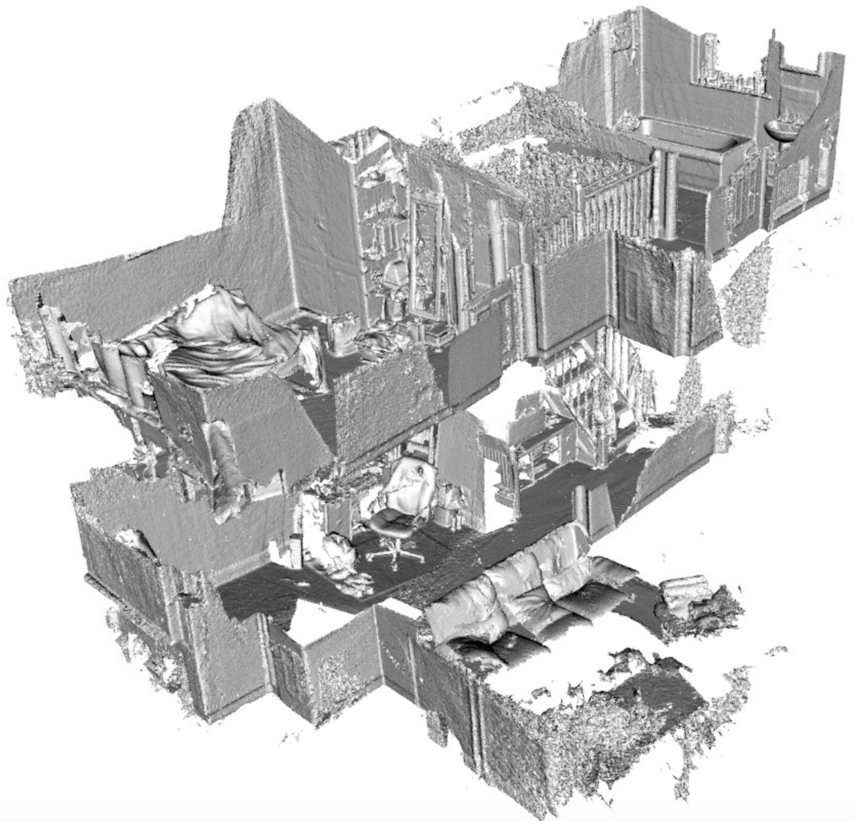
Semi-dense depth maps
[vision.in.tum.de]



Point clouds (here: sparse)
[grail.cs.washington.edu]

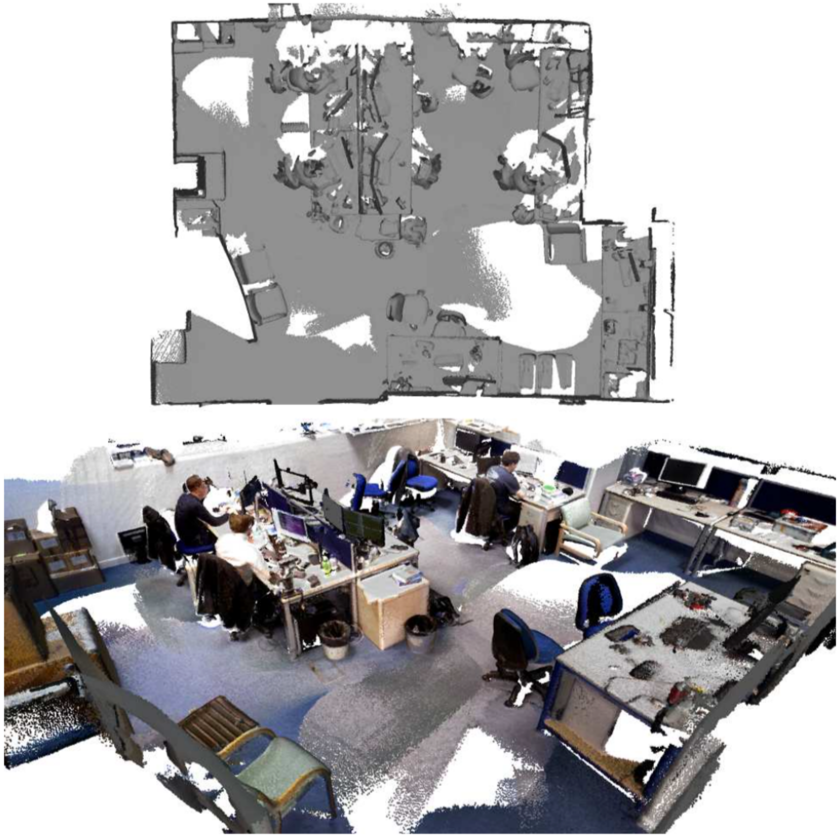
Surfel maps
[wp.doc.ic.ac.uk/thefutureofslam]

Scalability: Keeping Map AND Trajectory Consistent



Kintinuous

[T. Whelan, M. Kaess, M.F. Fallon, H. Johannsson, J. J. Leonard and J.B. McDonald. RSS Workshop on RGB-D 2012]



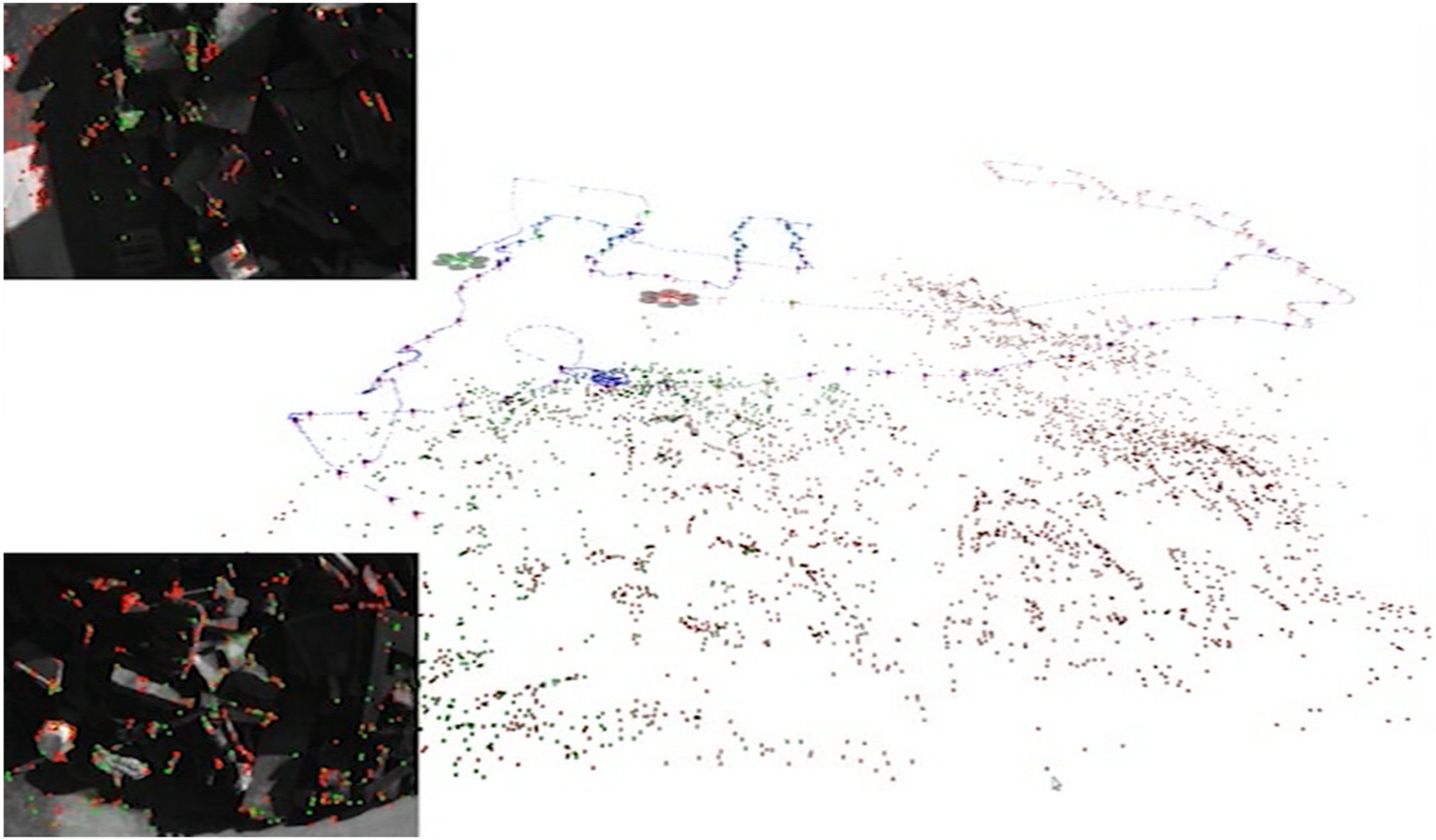
ElasticFusion

[T. Whelan, S. Leutenegger, R. F. Salas-Moreno, B. Glocker and A. J. Davison, RSS’15]

Scalability: Life-Long Mapping

[Winston Churchill and Paul Newman, IJRR’13]

Scalability: Multi-Agent SLAM

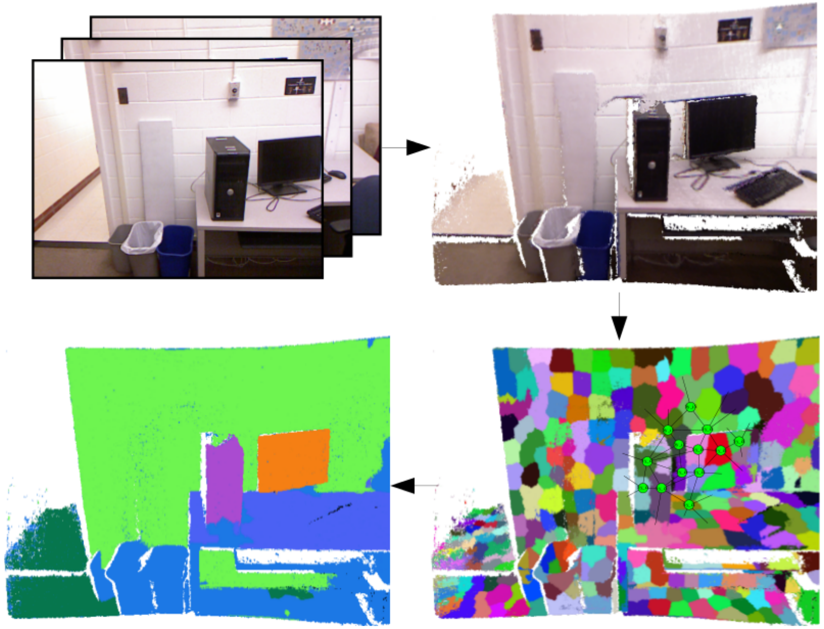


[Christian Forster, Simon Lynen, Laurent Kneip, Davide Scaramuzza, IROS’13]

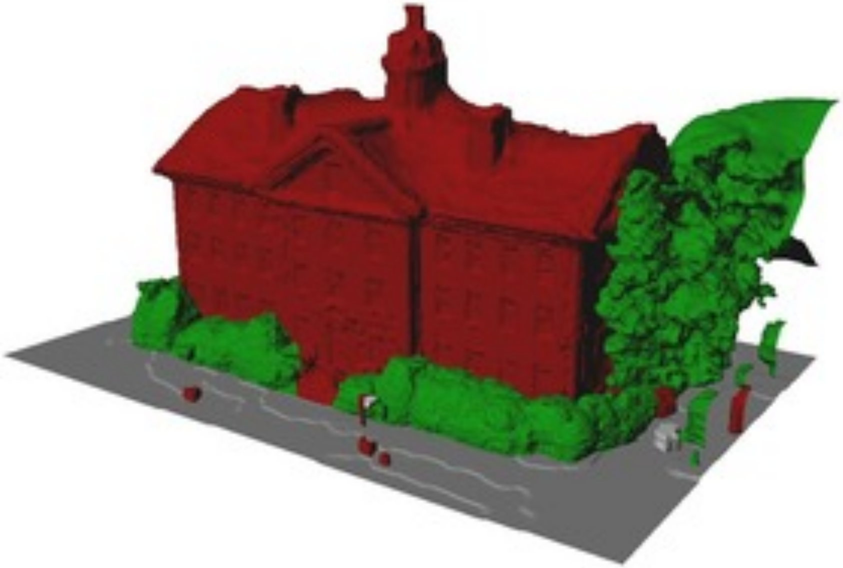
Dealing with Dynamic Scene Content

[Richard A. Newcombe, Dieter Fox, Steven M. Seitz, CVPR 2015]

Better Semantics With Maps and Better Maps With Semantics



[O Kaehler and I D Reid, ICCV'13]



[R. Karimi, C. Häne, M. Pollefeys, CVPR'15]