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Elastic LiDAR Fusion: Dense Map-Centric CT-SLAM

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Alberto Elfes, Clinton Fookes, Sridha Sridharan

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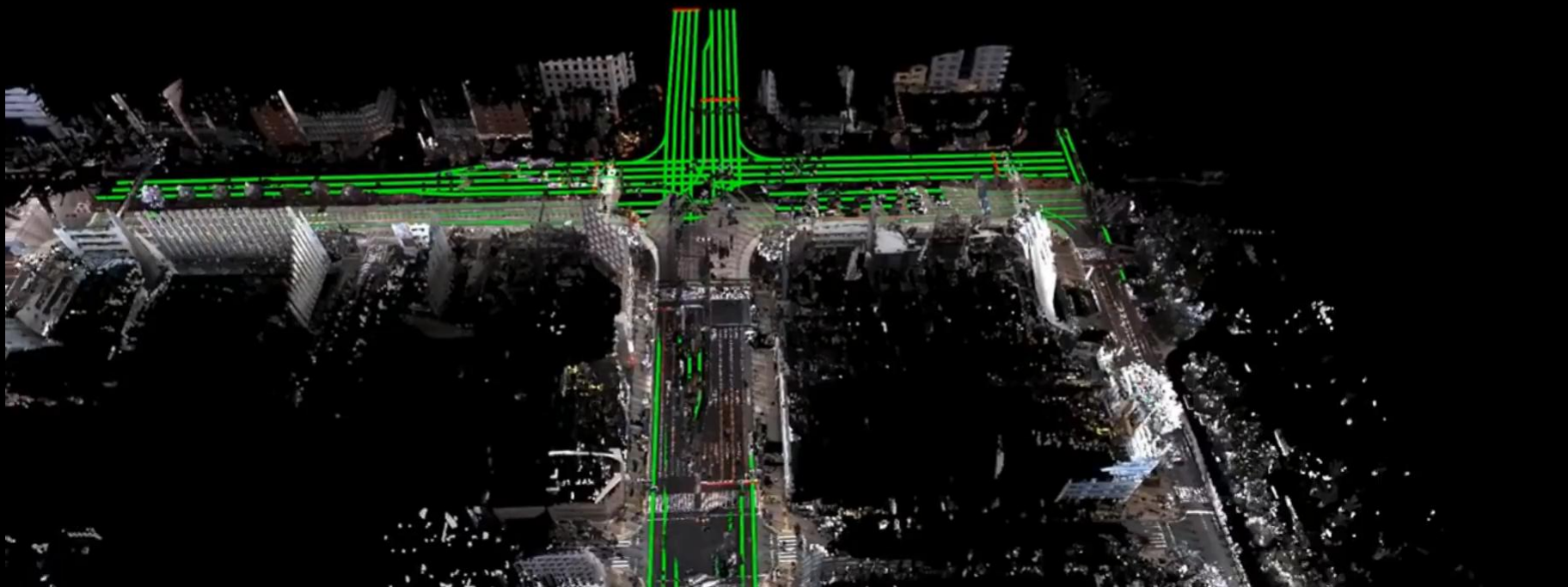
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QUT Supervisors: Sridha Sridharan, Clinton Fookes, Jonathon Roberts



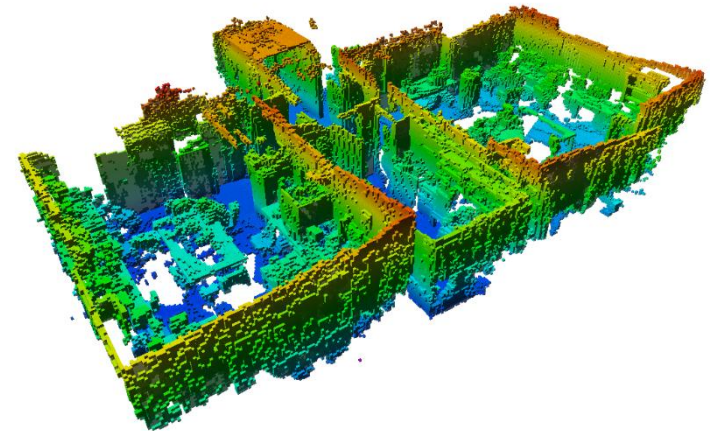
Introduction



State of the art in LiDAR SLAM



- Plenty have limitations
 - Trajectory-centric
 - No online loop closure
 - Offline operation
 - No fusion of redundant observations
 - Non-scalable
 - Difficulties in multi-modal sensor fusion
 - Map is discretised or full of redundant elements



State of the art

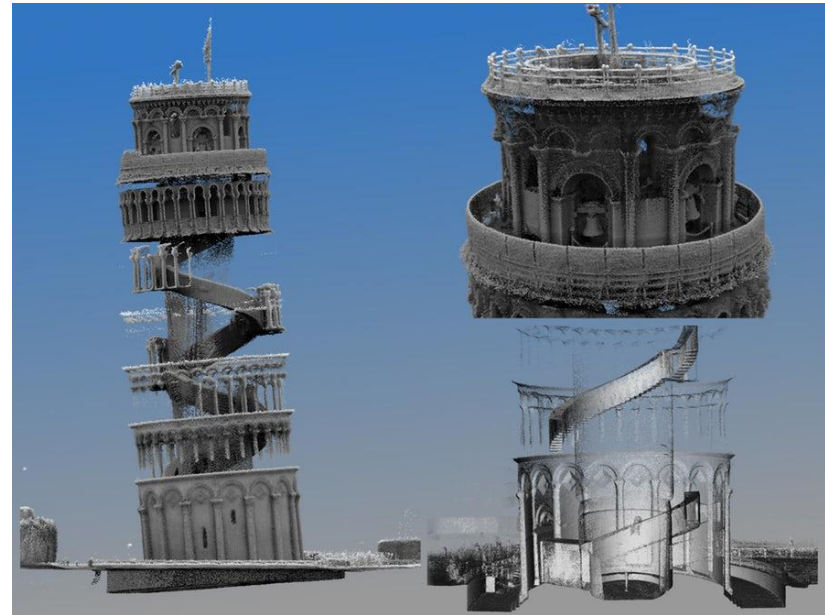
- Zebedee(2012), V-LOAM(2015)
 - Nicely handle LiDAR motion distortion



Demo(2016)

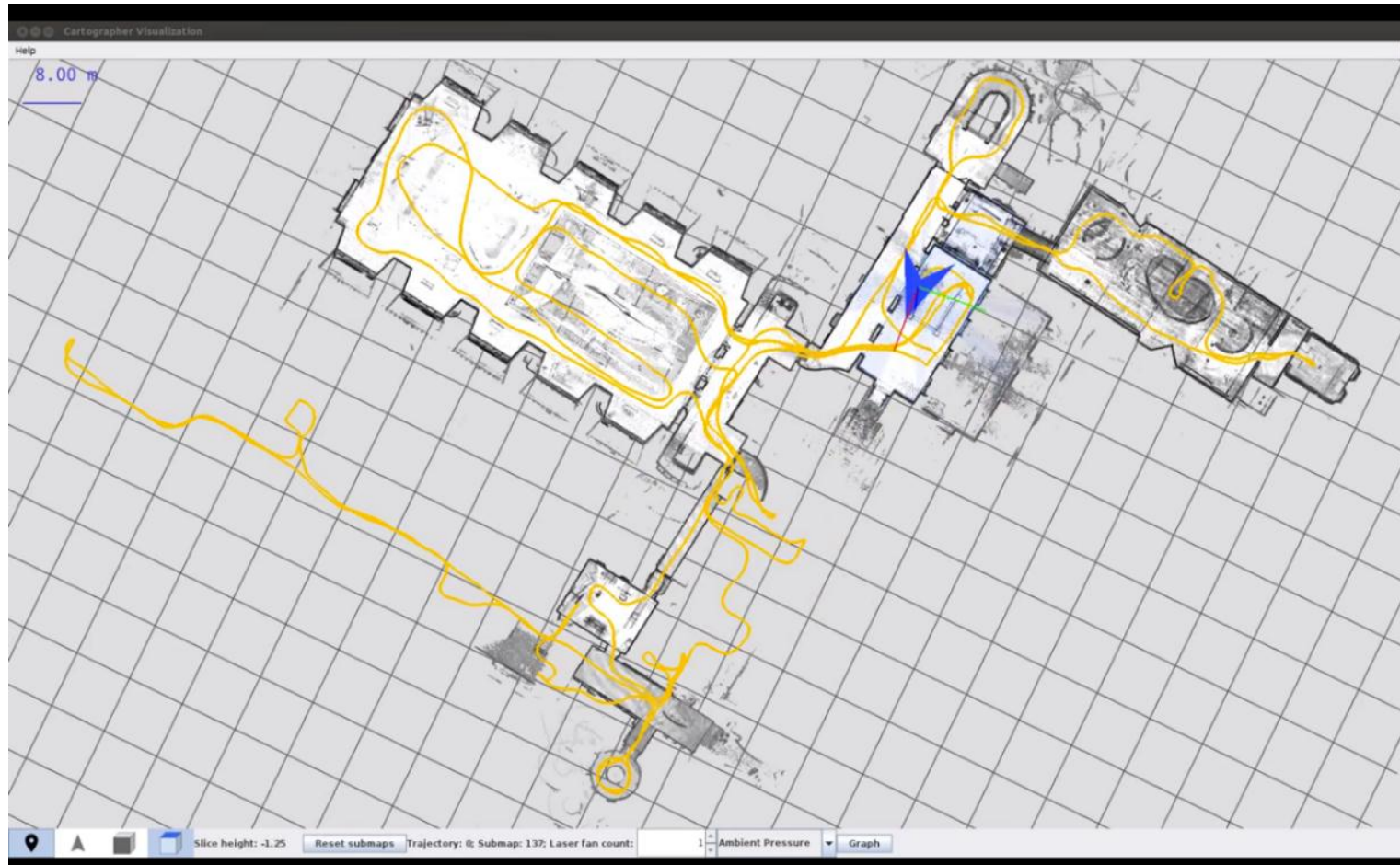


Zebedee(2012)



State of the art

- Google Cartographer(2014)



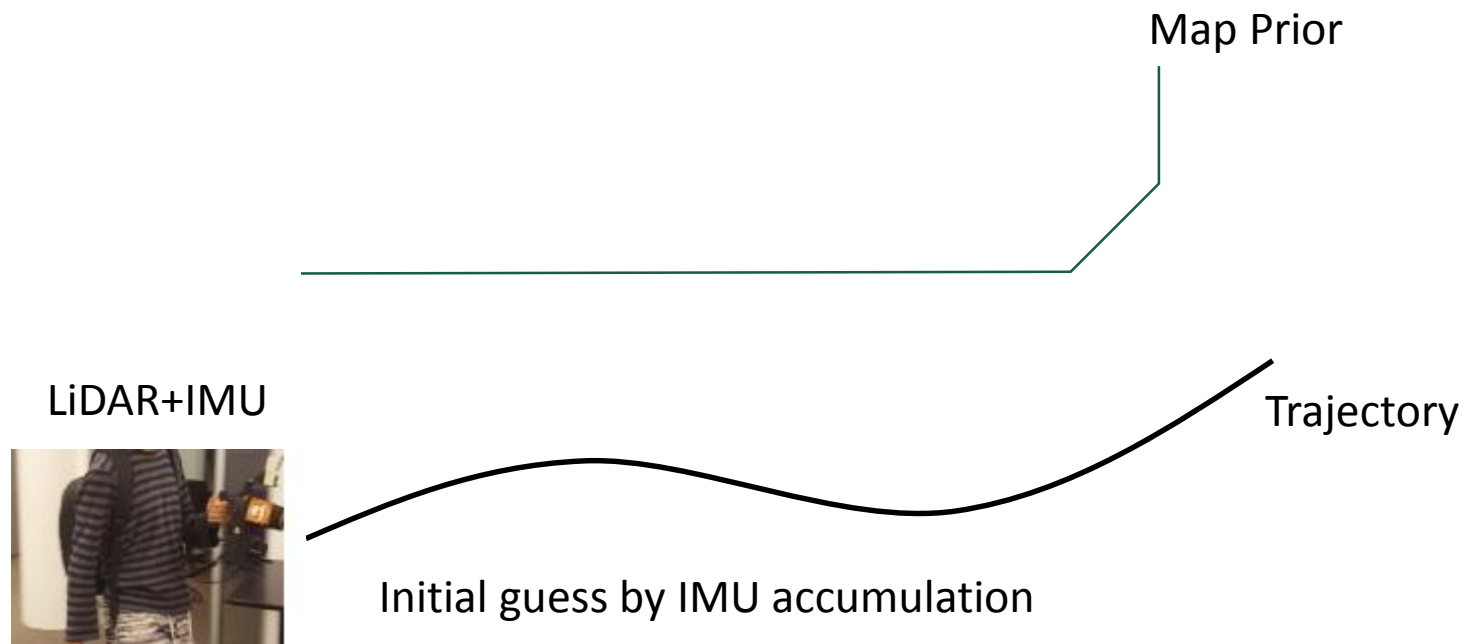
Introducing Elastic LiDAR Fusion



- First LiDAR based map-centric approach
 - Loop closure by map
 - Fuse all the measurements
- Easy multi-modal sensor fusion
 - We combine CT-SLAM with a map-centric approach
 - LiDAR-Inertial fusion is proposed

How it works:

Continuous-time local trajectory estimation



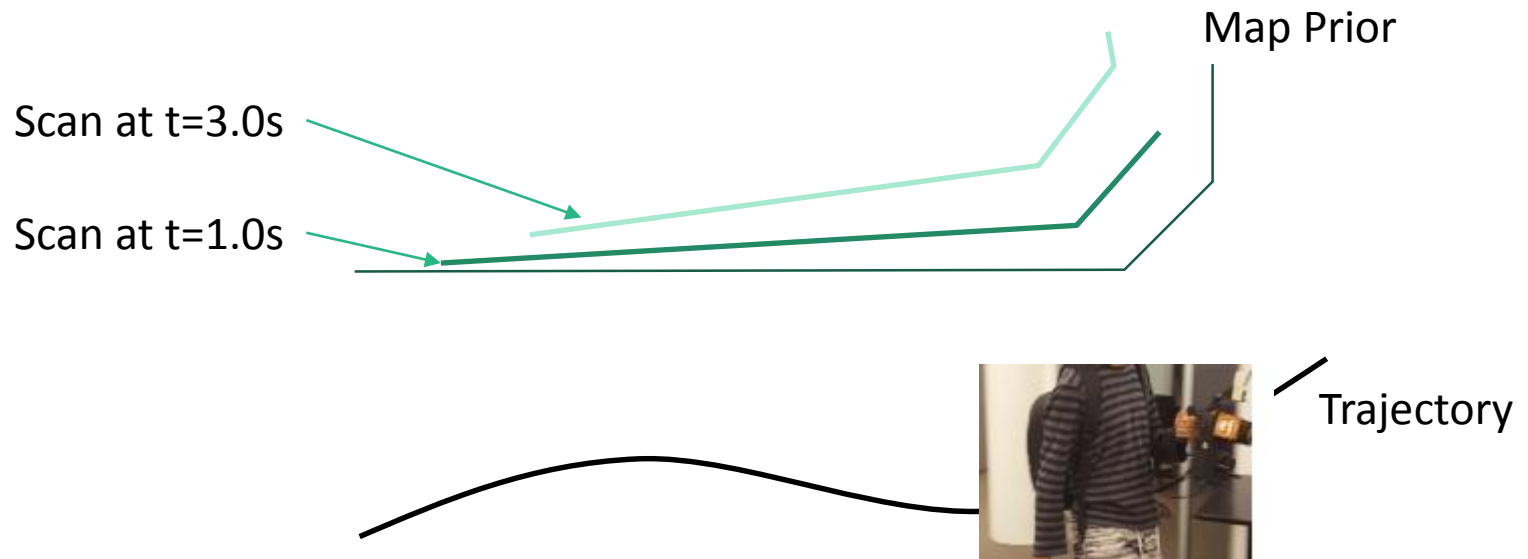
How it works:

Continuous-time local trajectory estimation



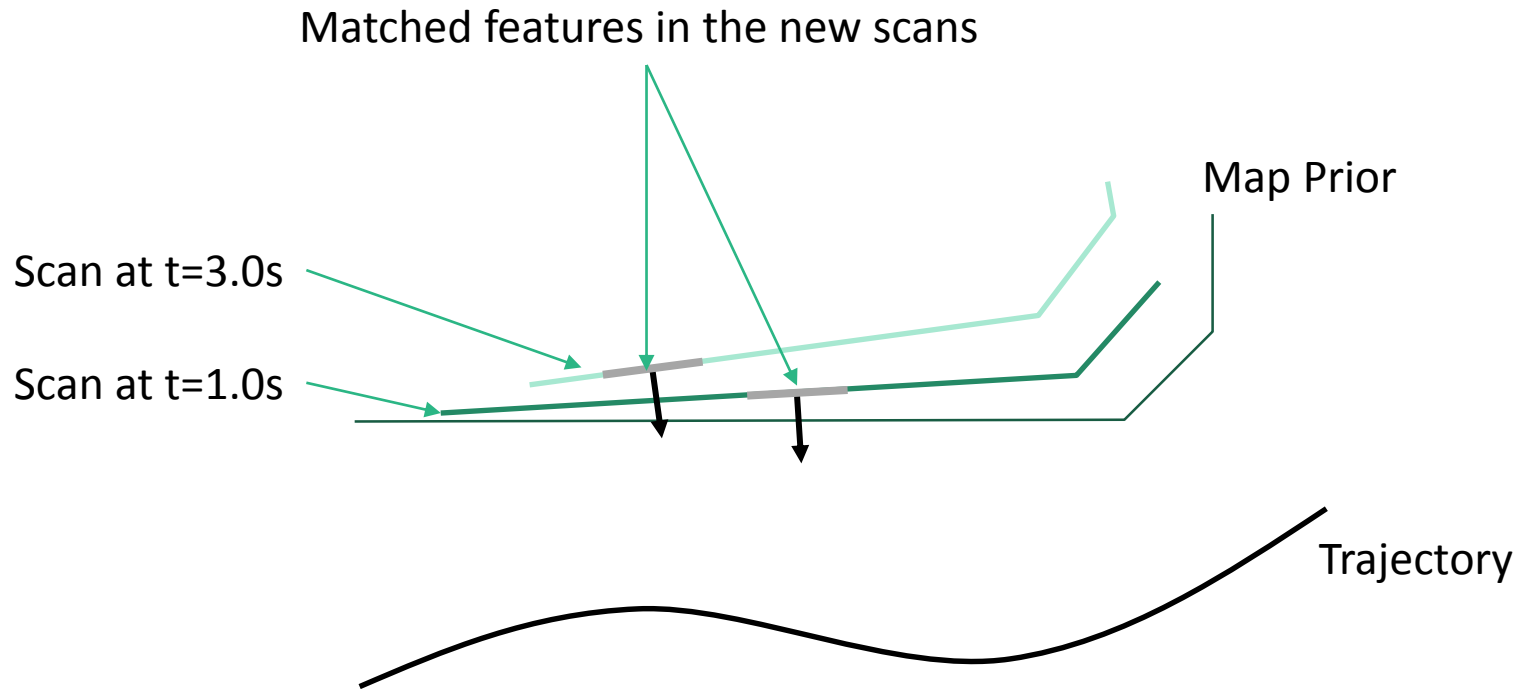
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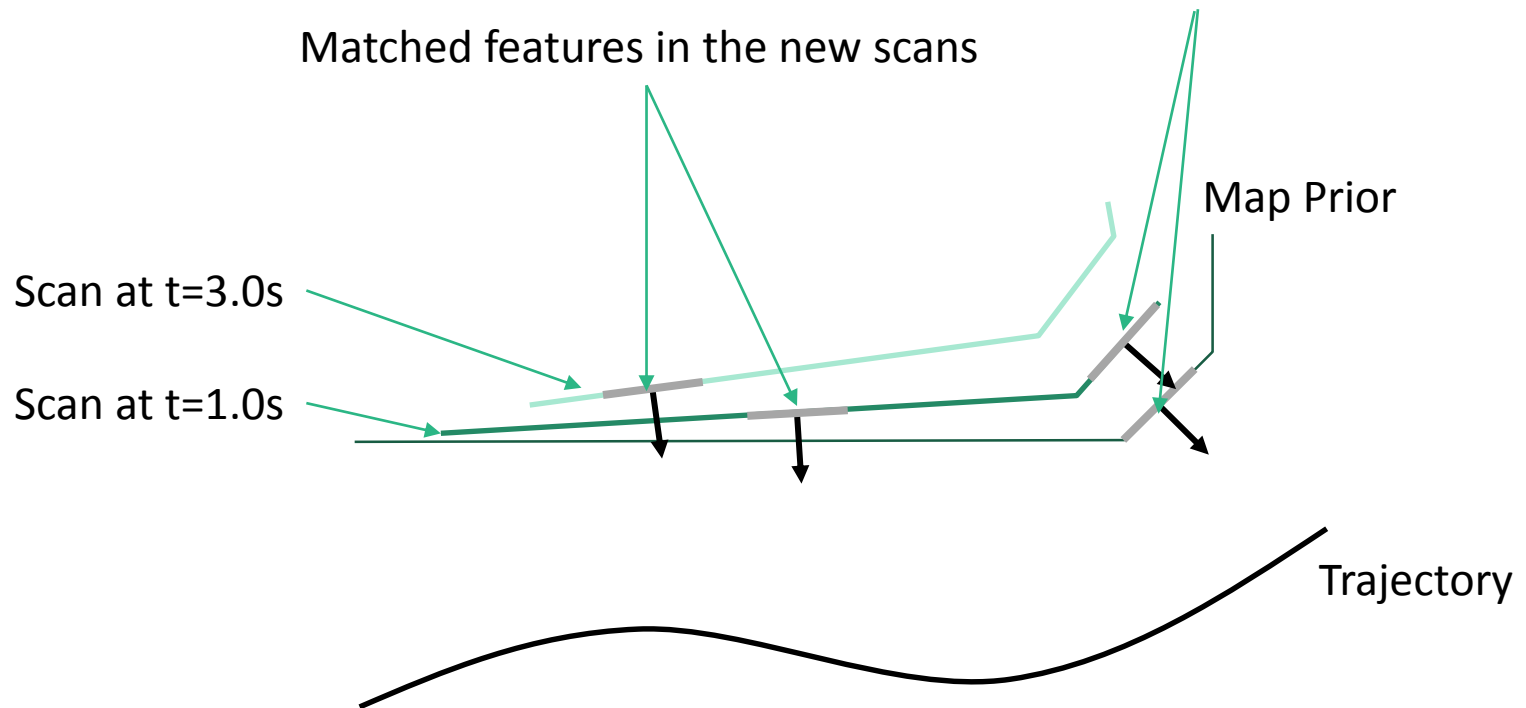


How it works:

Continuous-time local trajectory estimation



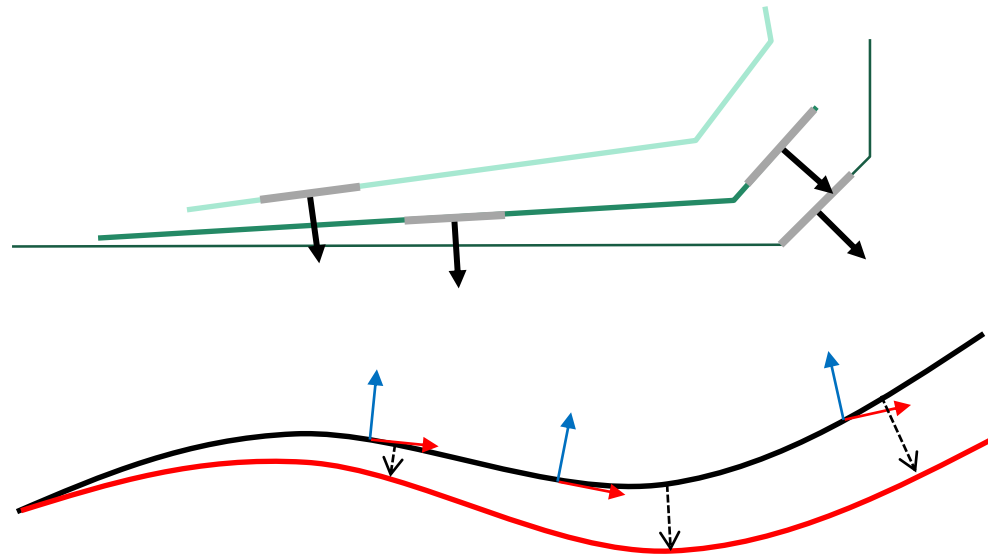
Matched features btw map prior and new scan



How it works:

Continuous-time local trajectory estimation

1. Find a new trajectory

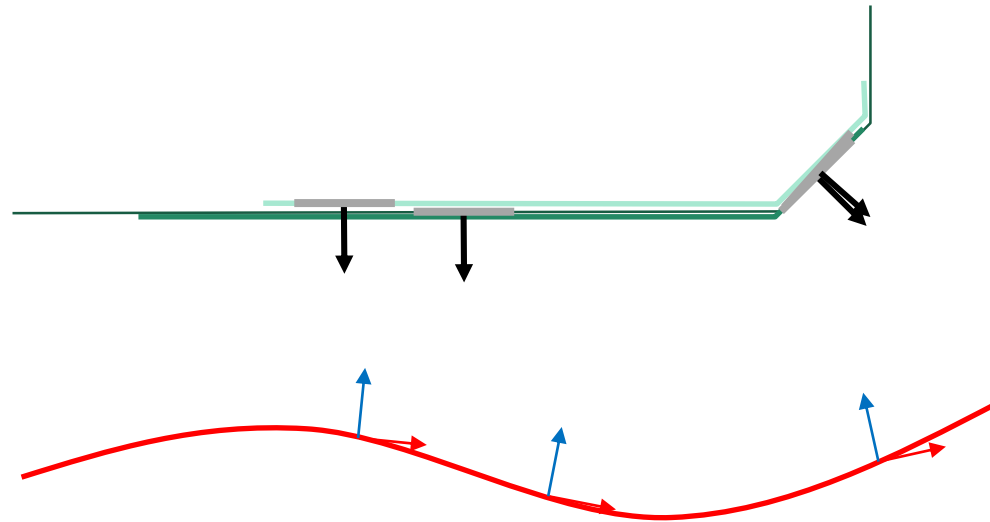


Corrected Trajectory

How it works:

Continuous-time local trajectory estimation

1. Find a new trajectory
2. Reproject points cloud



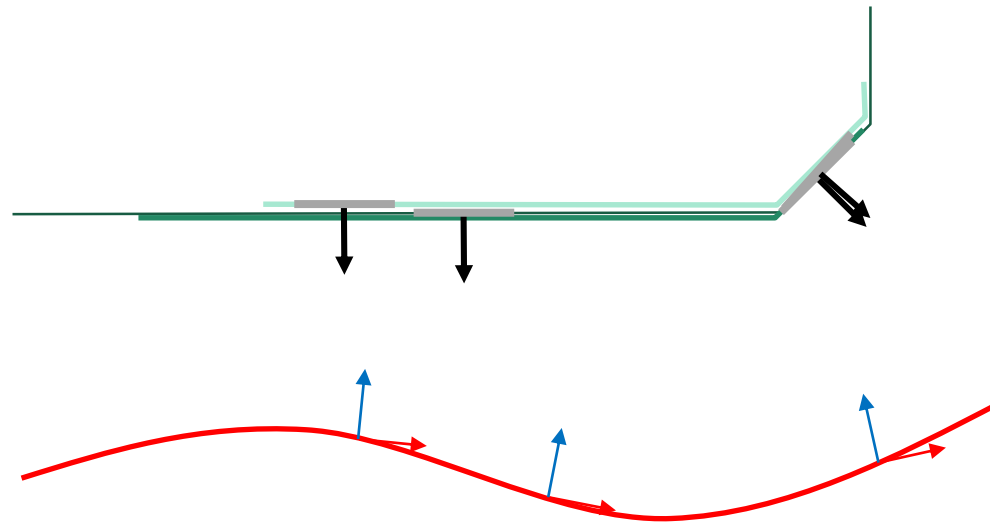
Corrected Trajectory

How it works:

Continuous-time local trajectory estimation



1. Find a new trajectory
2. Reproject points cloud
3. New scans become another map prior

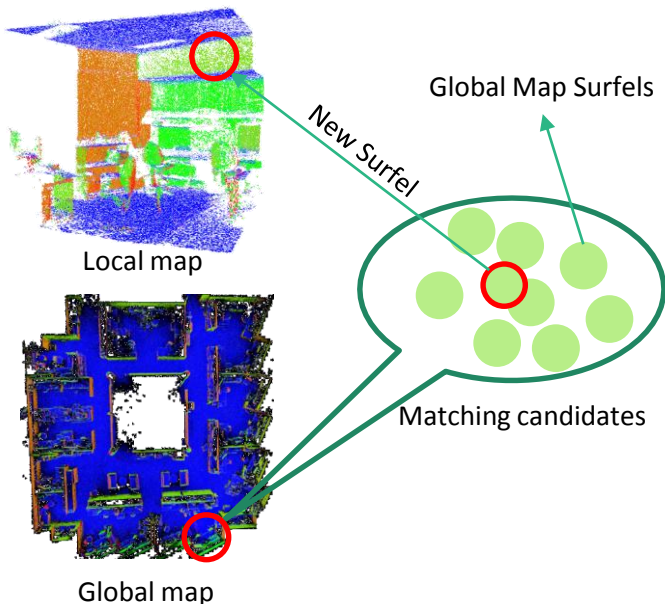


Corrected Trajectory

How it works:

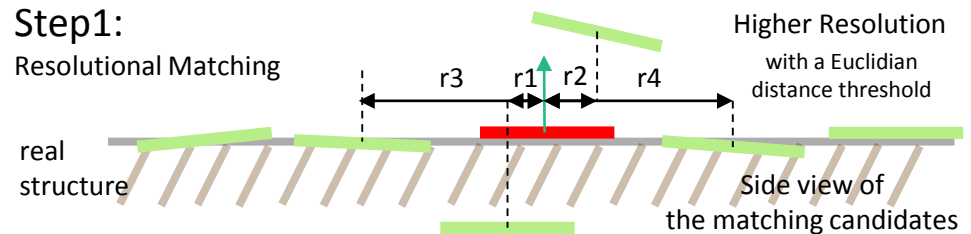
Surfel Fusion

- Fuses surfels from the local window into the global map
 - Data association



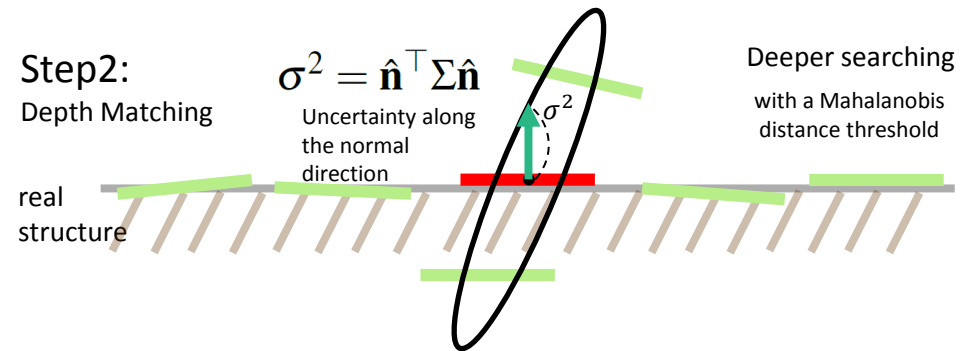
Step1:

Resolutonal Matching



Step2:

Depth Matching



- Surfel fusion
 - Normal, Centre, Colour with Bayesian Fusion

How it works:

Loop closure by deformation

- Previous two stages just keep building map
 - What about the loop closure?



How it works:

Loop closure by deformation

- Previous two stages just keep building map
 - What about the loop closure? -> Map deformation

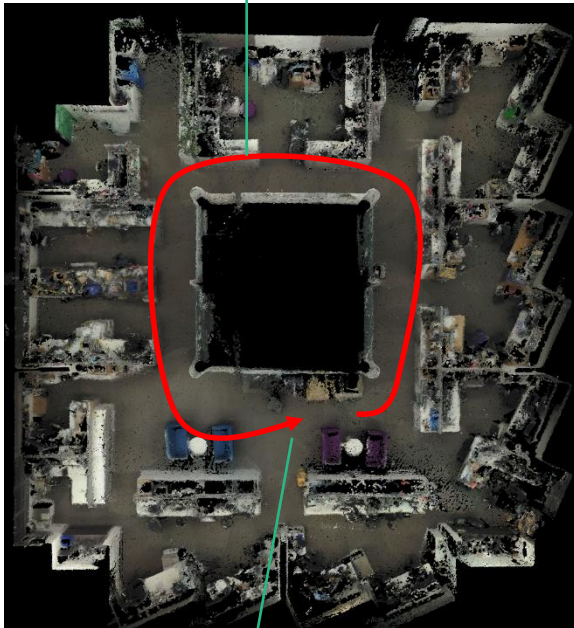


How it works:

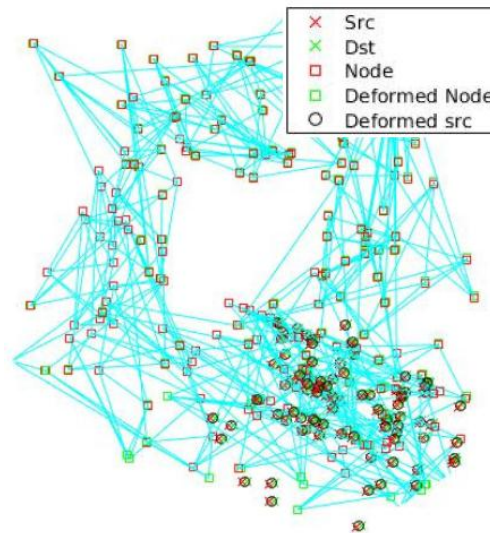
Loop closure by deformation

- Previous two stages just keep building map
 - What about the loop closure? -> Map deformation

Trajectory



Loop closure detection



Graph for a deformation

$$\mathbf{e}_{loop} = \sum \|\mathbf{p}'_{src} - \mathbf{p}_{dest}\|^2$$
$$\mathbf{e}_{pin} = \sum \|\mathbf{p}'_{dest} - \mathbf{p}_{dest}\|^2$$
$$\mathbf{e}_{reg} = \sum_j^m \sum_{k \in \mathcal{V}(\mathbf{g}_j)} \|\mathbf{R}_j(\mathbf{g}_k - \mathbf{g}_j) + \mathbf{g}_j + \mathbf{t}_j - \mathbf{g}_k - \mathbf{t}_k\|^2$$
$$[\hat{\mathbf{R}}_j, \hat{\mathbf{t}}_j] = \underset{\mathbf{R}_j, \mathbf{t}_j \in SE(4)}{\operatorname{argmin}} \omega_{reg} \mathbf{e}_{reg} + \omega_{pin} \mathbf{e}_{pin} + \omega_{loop} \mathbf{e}_{loop}$$

Deformation constraints

A white hexagonal grid pattern is overlaid on a teal background, covering the top half of the slide.

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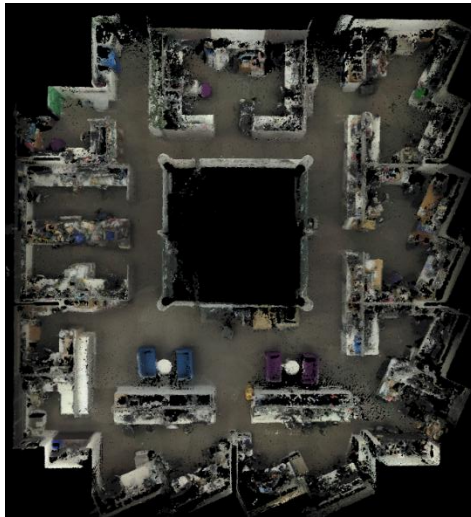


Experiment results

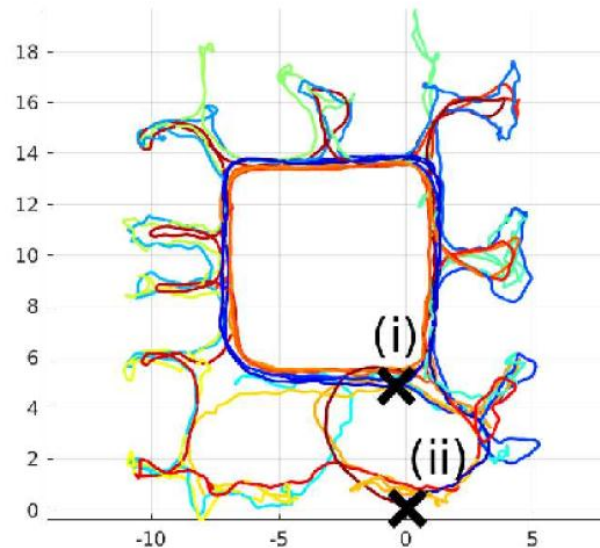
Loop Closure Cost Comparison

How fast is our method?

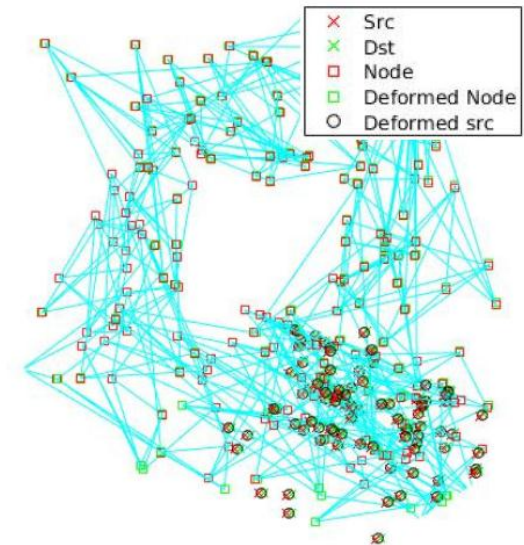
Types	Optimization*	No.State	Elapsed Time (sec)
Proposed	Fig. 5 (i)	192	0.12
CT-SLAM [6]	Fig. 5 (ii)	3396	195.4



Office map



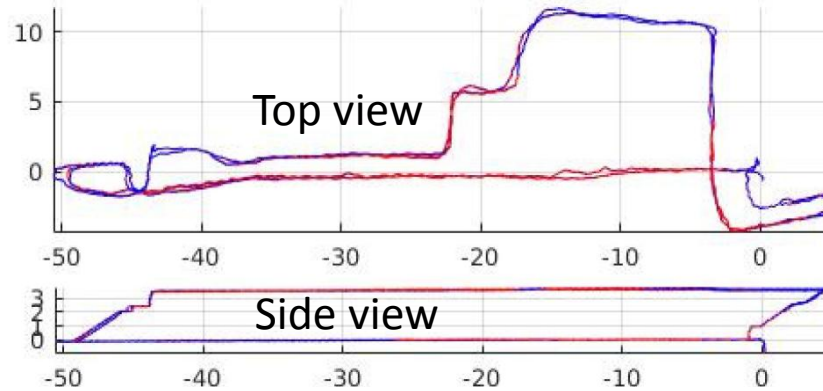
Trajectory map



Deformation graph

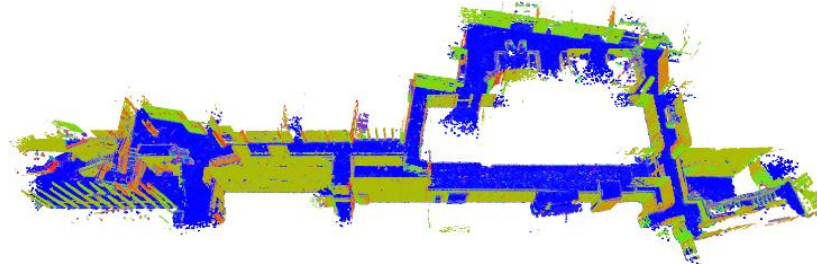
Trajectory Estimation Error

Trajectory



Blue: trajectory by an offline batch optimization
Red: Proposed method

Map

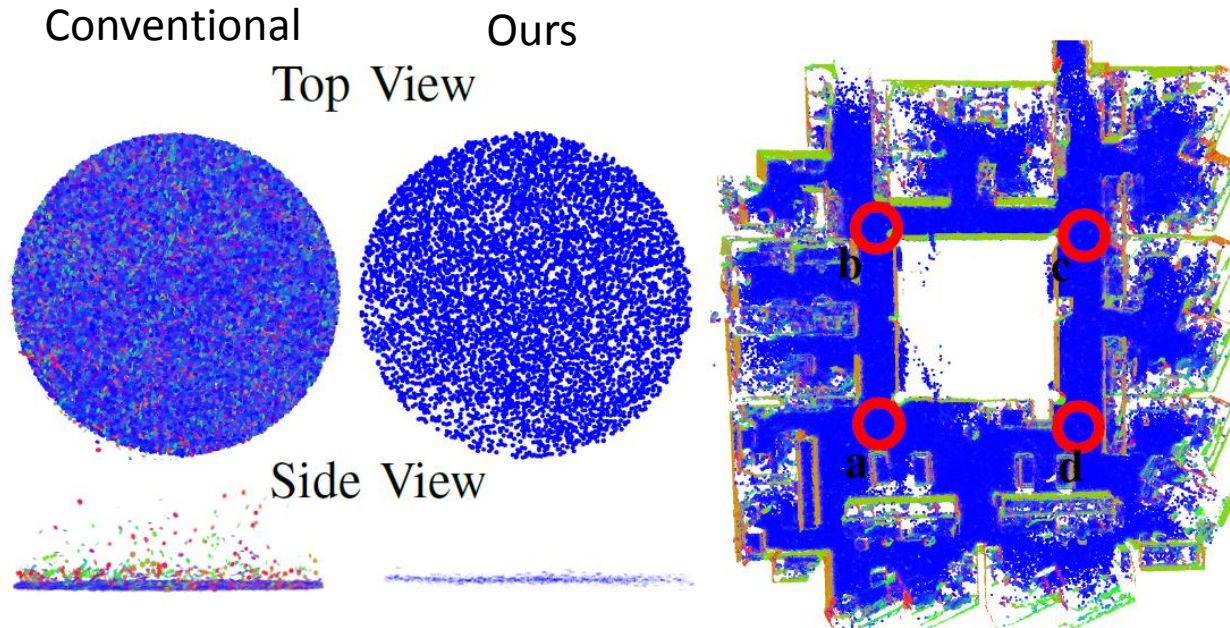


Difference

Dataset	Traj Error(m)	Length(m)	Time(min)	Size(m)
Fig. 1	0.047	330	14.6	20×20
Fig. 7 (i)	0.041	130	6.1	10×6
Fig. 7 (ii)	0.056	300	11.4	55×20
Fig. 7 (iii)	0.076	360	9.1	60×25

Only small difference!

Surface Estimation Error



Location	No.Points	No.Surfel	CT-Err	Prop (mm)
a	47.8×10^4	3.7×10^3	16.08	7.72
b	37.8×10^4	4.1×10^3	15.78	5.79
c	40.6×10^4	3.8×10^3	16.43	10.39
d	56.3×10^4	3.8×10^3	19.40	13.07

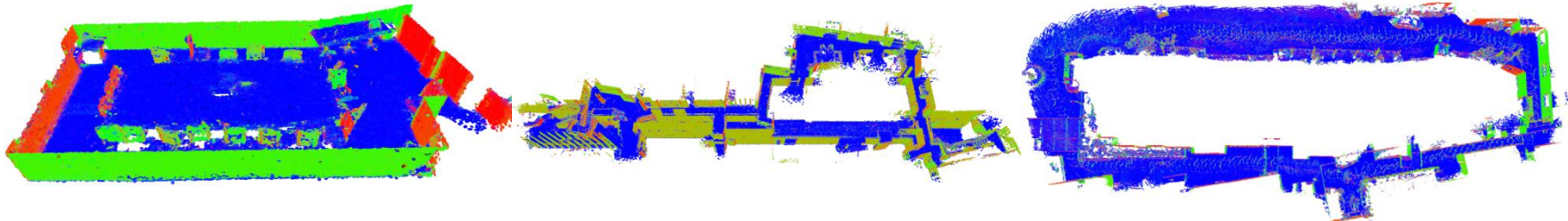
10 times less map elements

Less noise

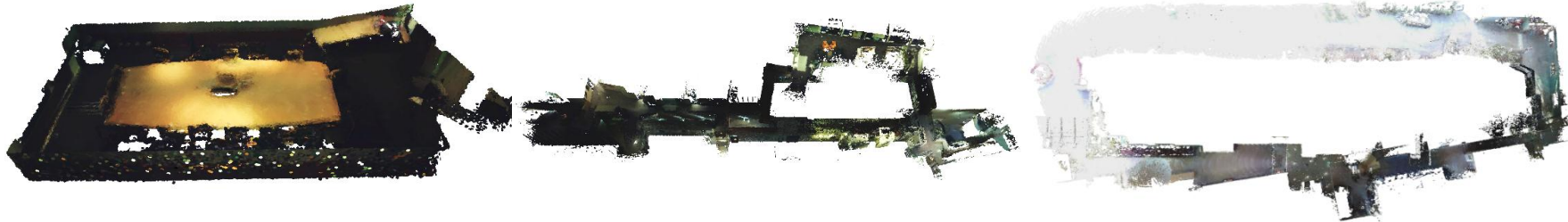
Datasets



Normal
map



Colour
map



Details



Small map

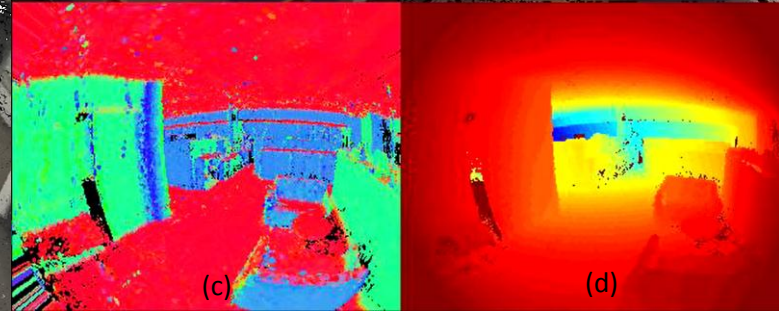
Multi-Floors

Indoor outdoor mixed

Surfel Scene Representation

Colour Img

Synthesized Img



Normal map

Disparity map

Demo video



Summary



- Long-term mapping
 - Loop closure by map deformation
 - No global batch optimization at the end
 - Fusion of LiDAR estimations
 - Map size is dependent on space. Not time!
 - Accurate map estimation
- Easy handling of asynchronous, high-rate sensor fusion and motion distortion



Question?

Surfel Scene Representation

