Monocular Visual Teach and Repeat Aided by Local Ground Planarity

Lee Clement, Jonathan Kelly, and Timothy D. Barfoot

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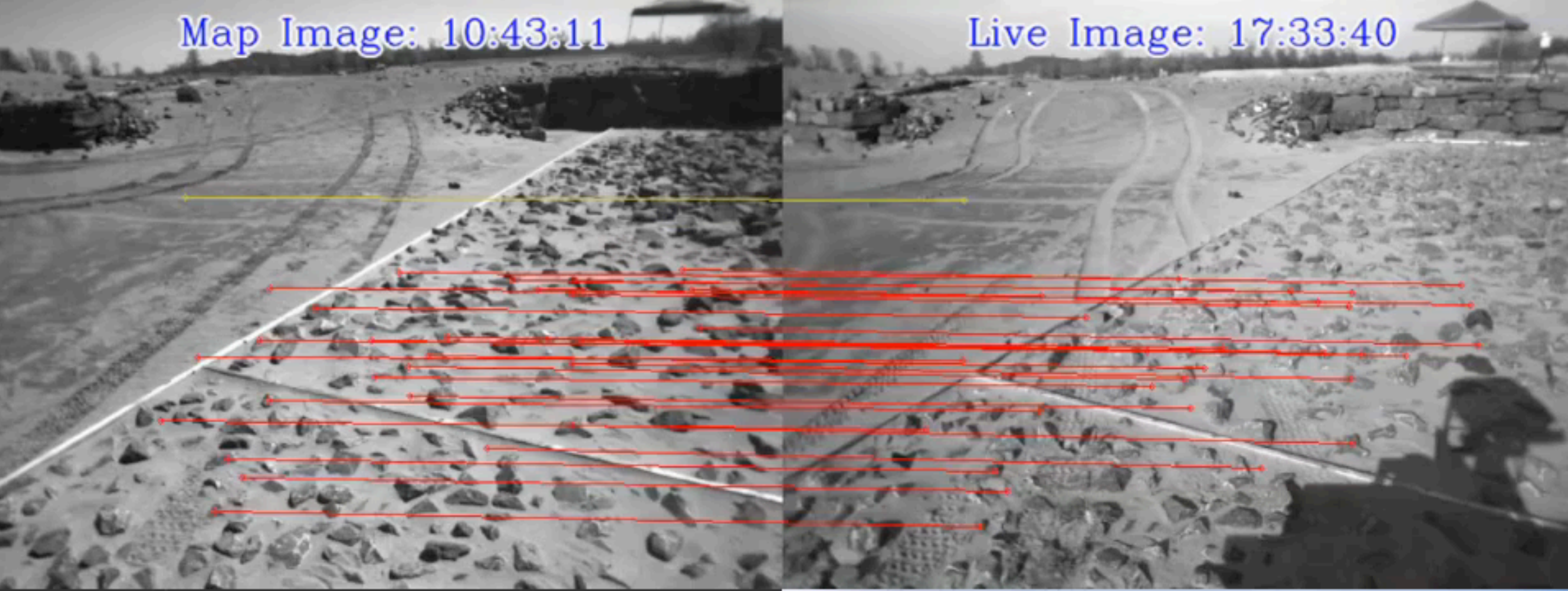
Institute for Aerospace Studies
UNIVERSITY OF TORONTO

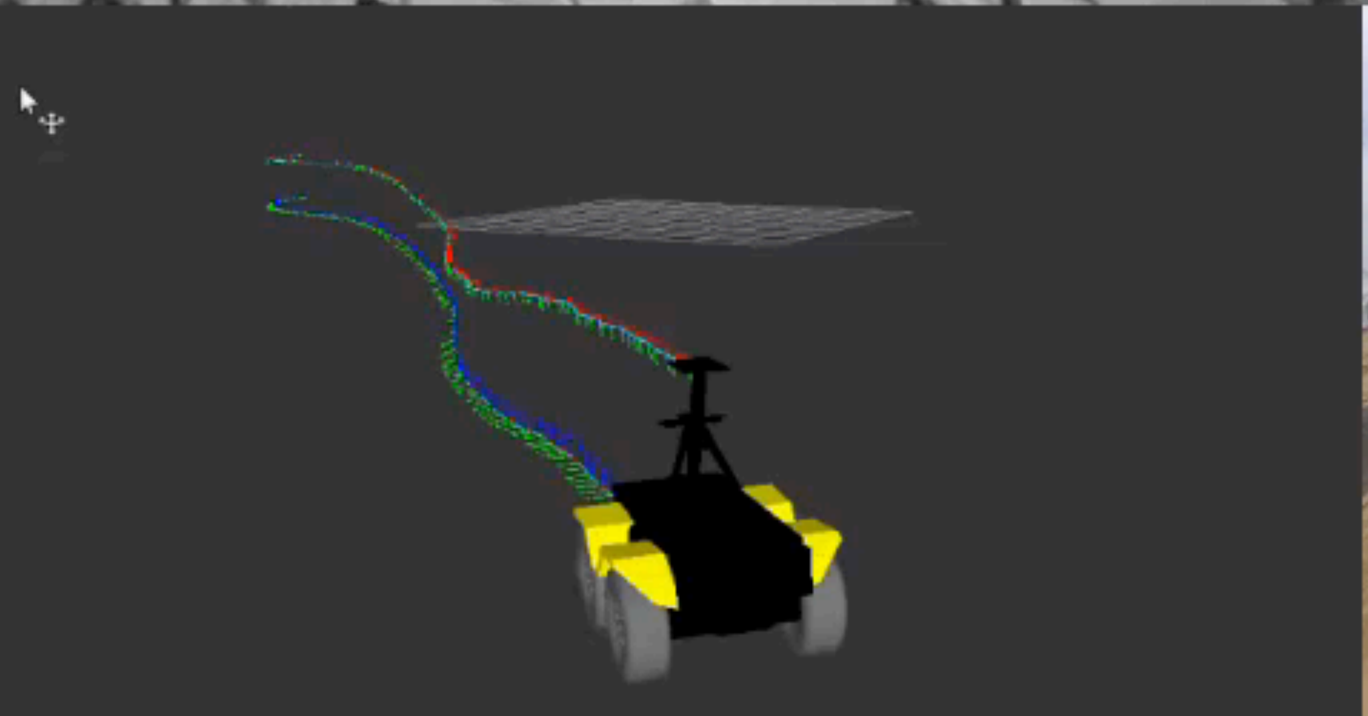
STARS LABORATORY

ASRL

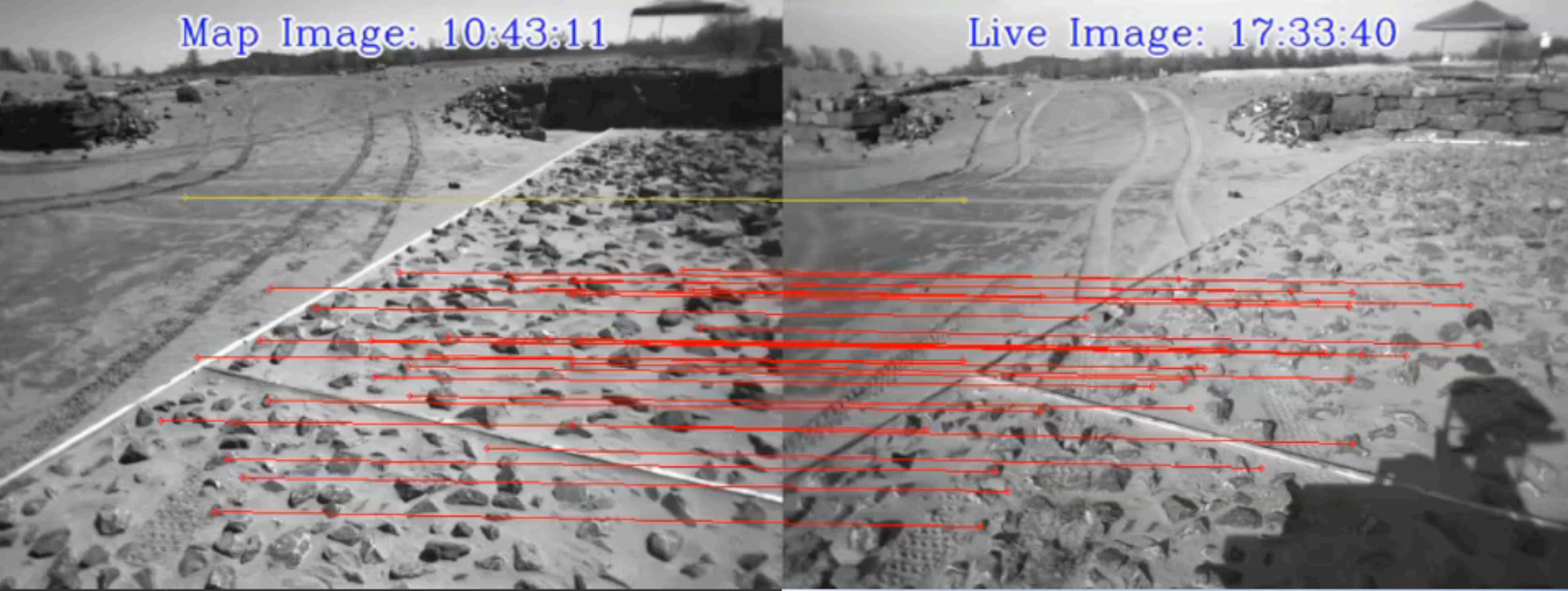
Motivation: Autonomous Navigation for Monocular Robots

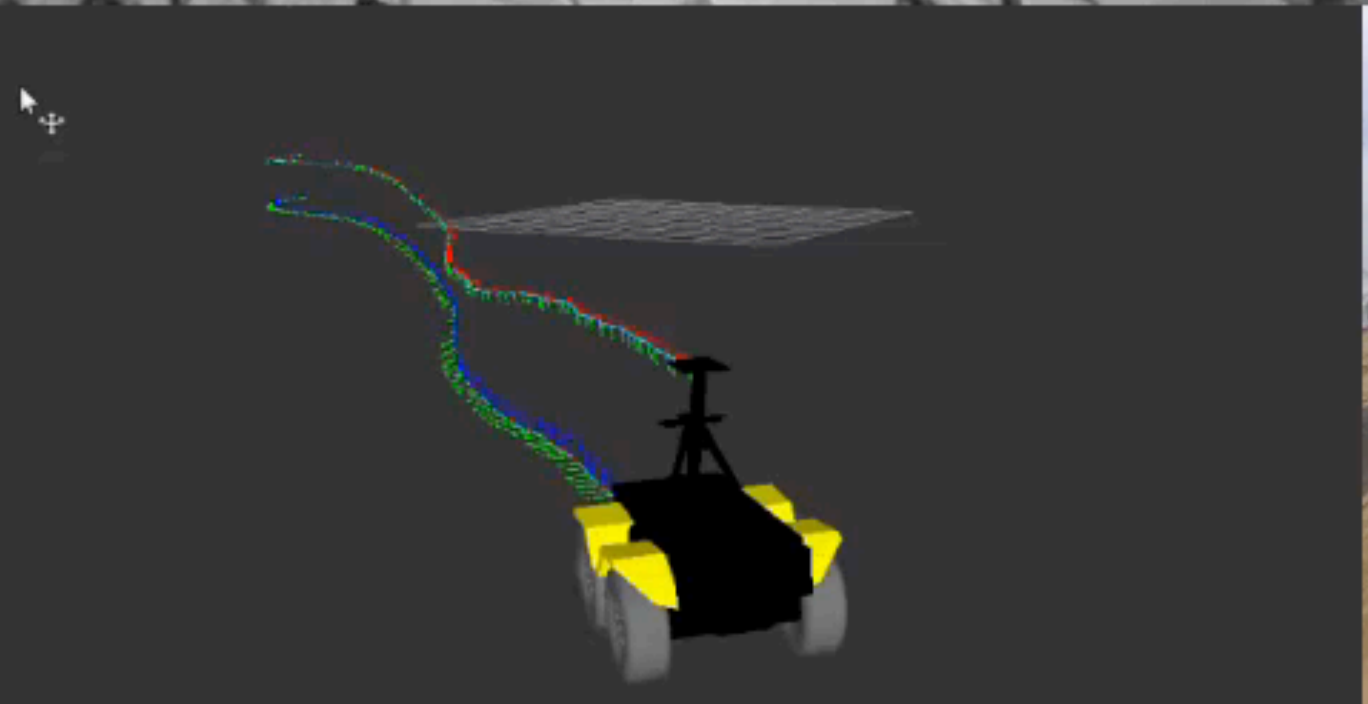
Many robots with **monocular cameras** need to perform **repetitive navigation** tasks — use **Visual Teach & Repeat**!





VT&R: Autonomous Vision-Based Route Following





VT&R: Autonomous Vision-Based Route Following

VT&R: The Basics

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Teach Pass

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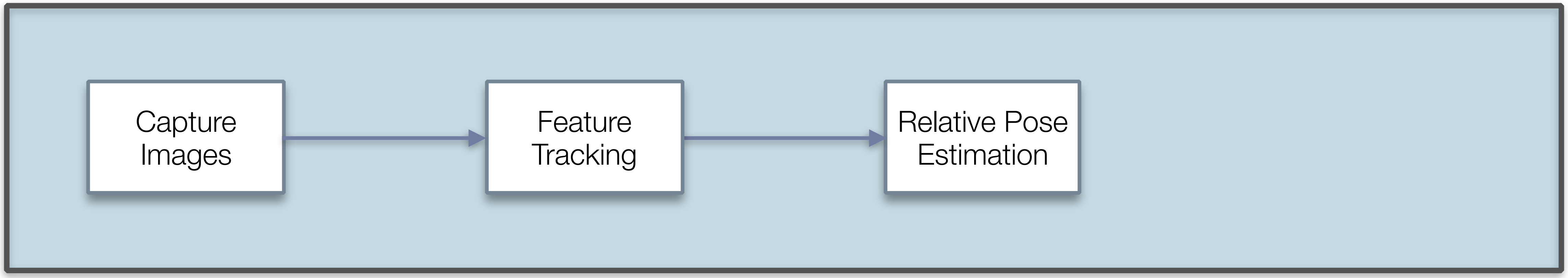

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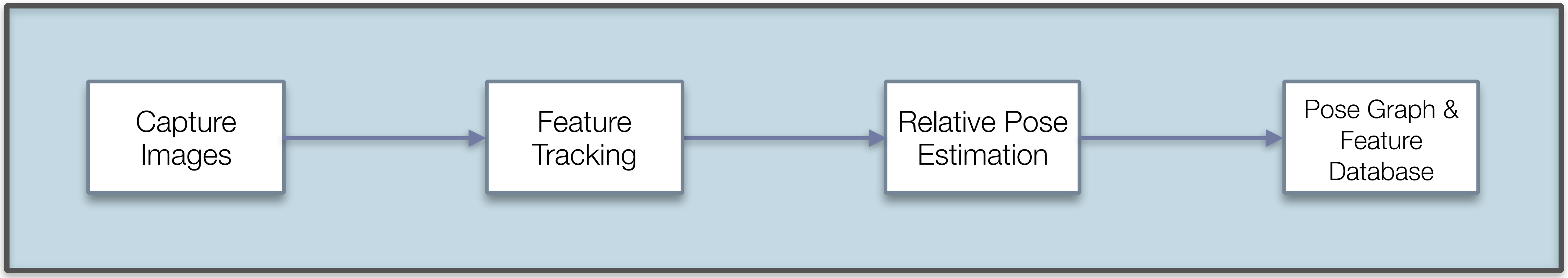

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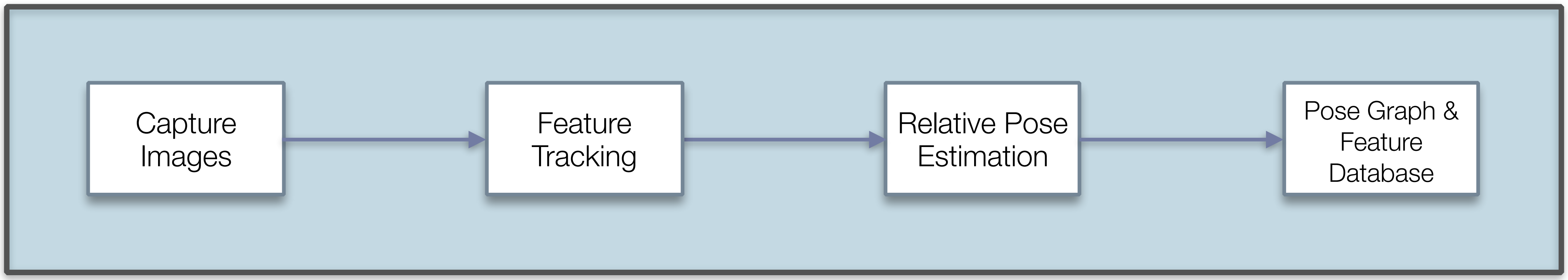

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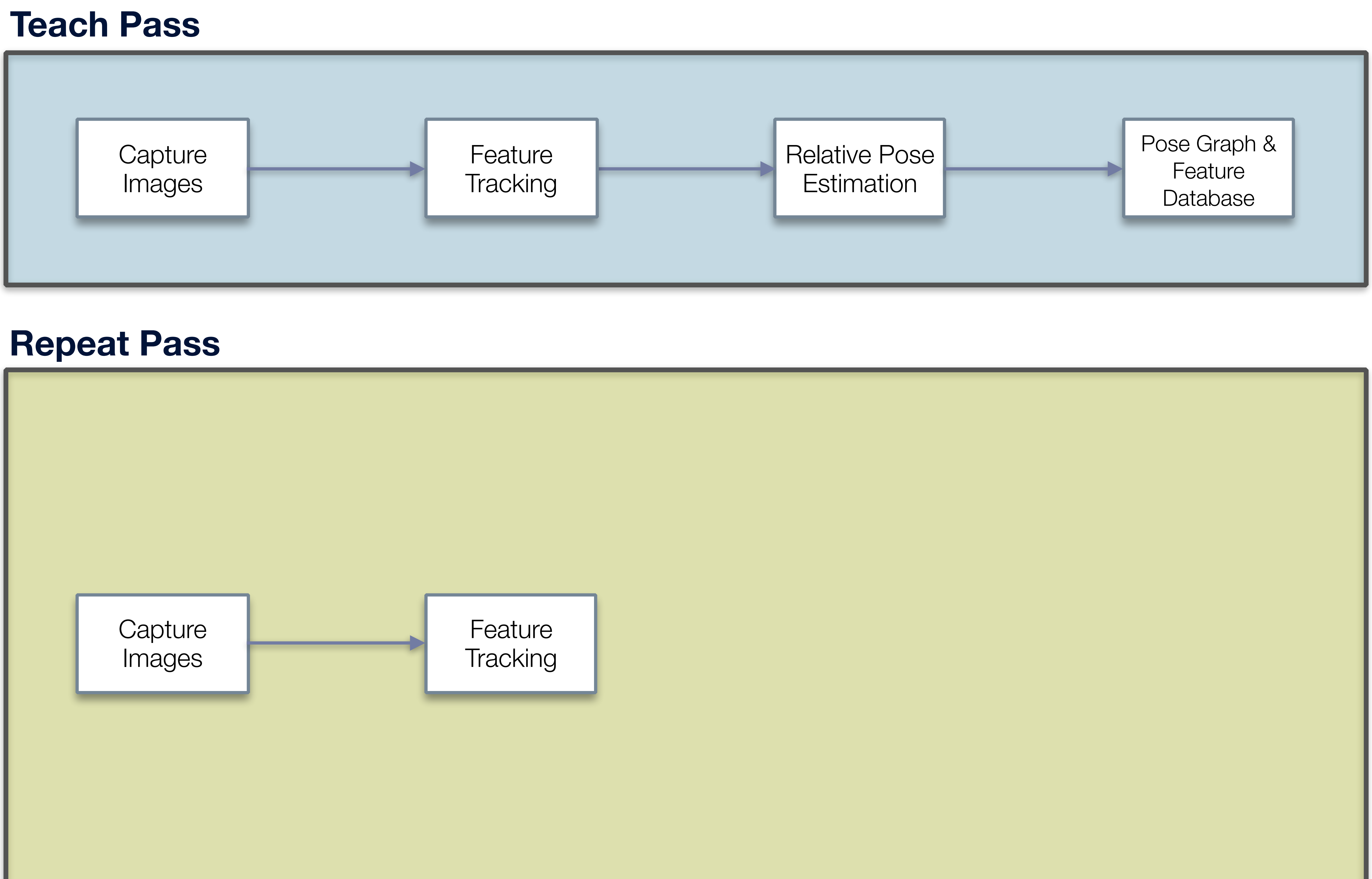

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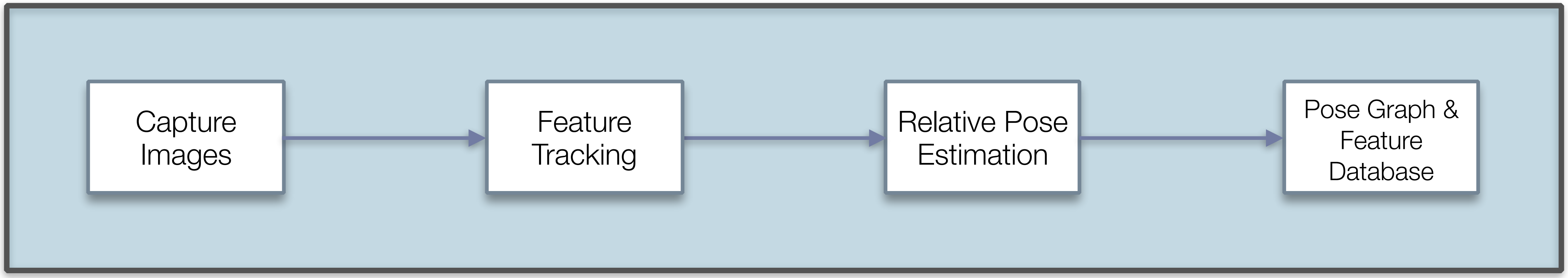

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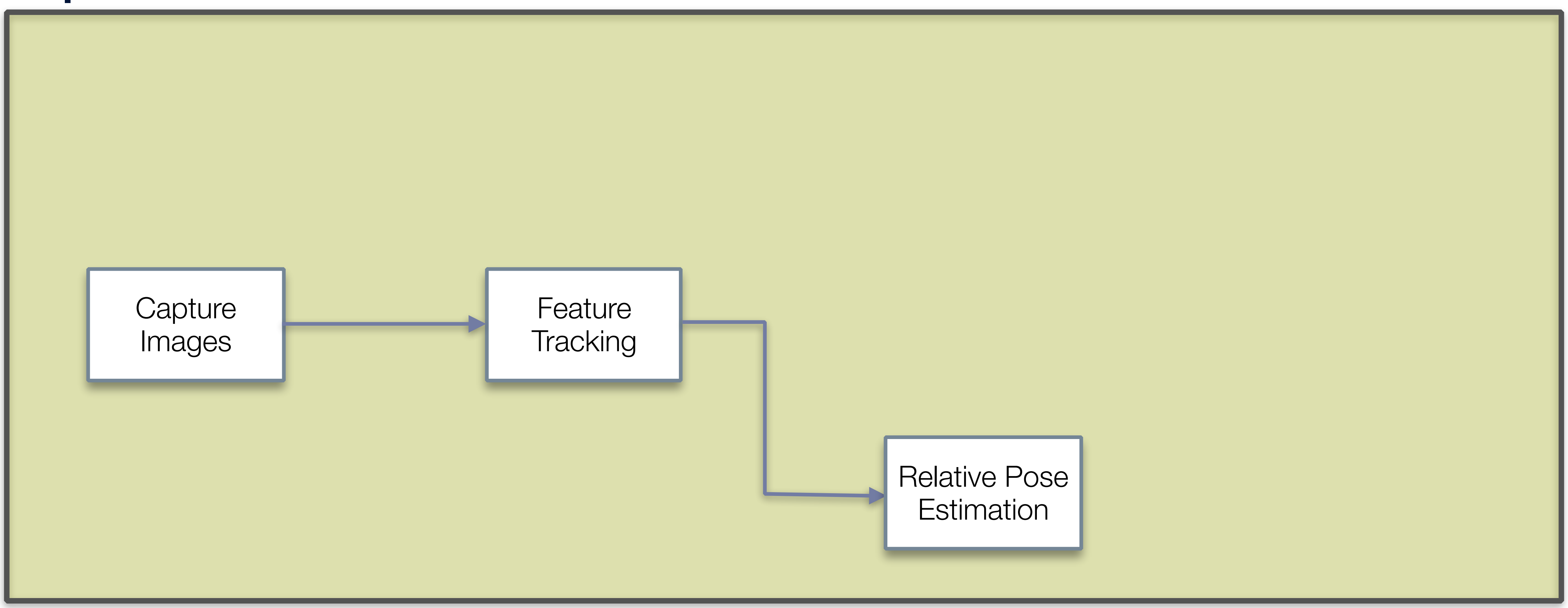

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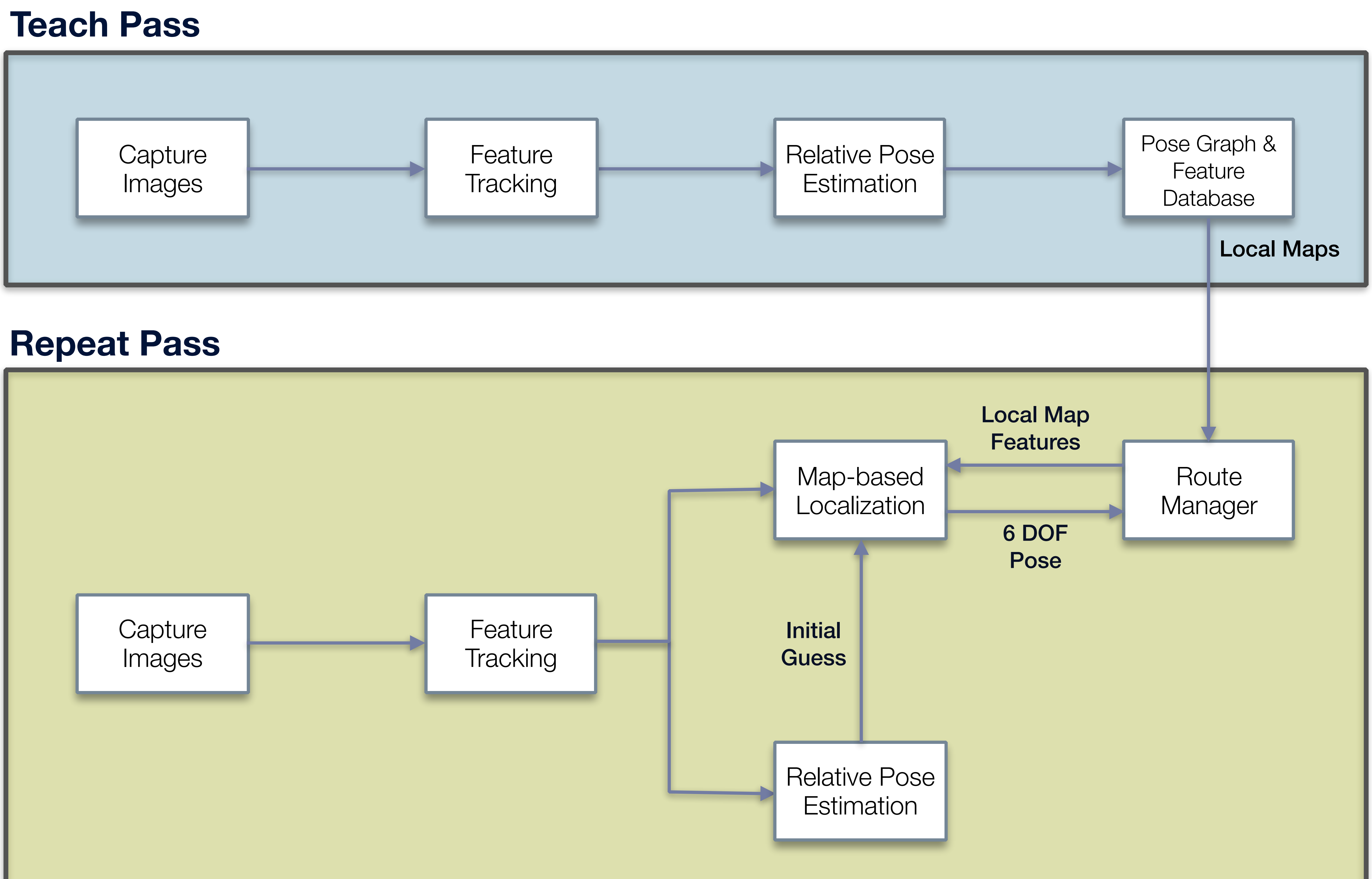

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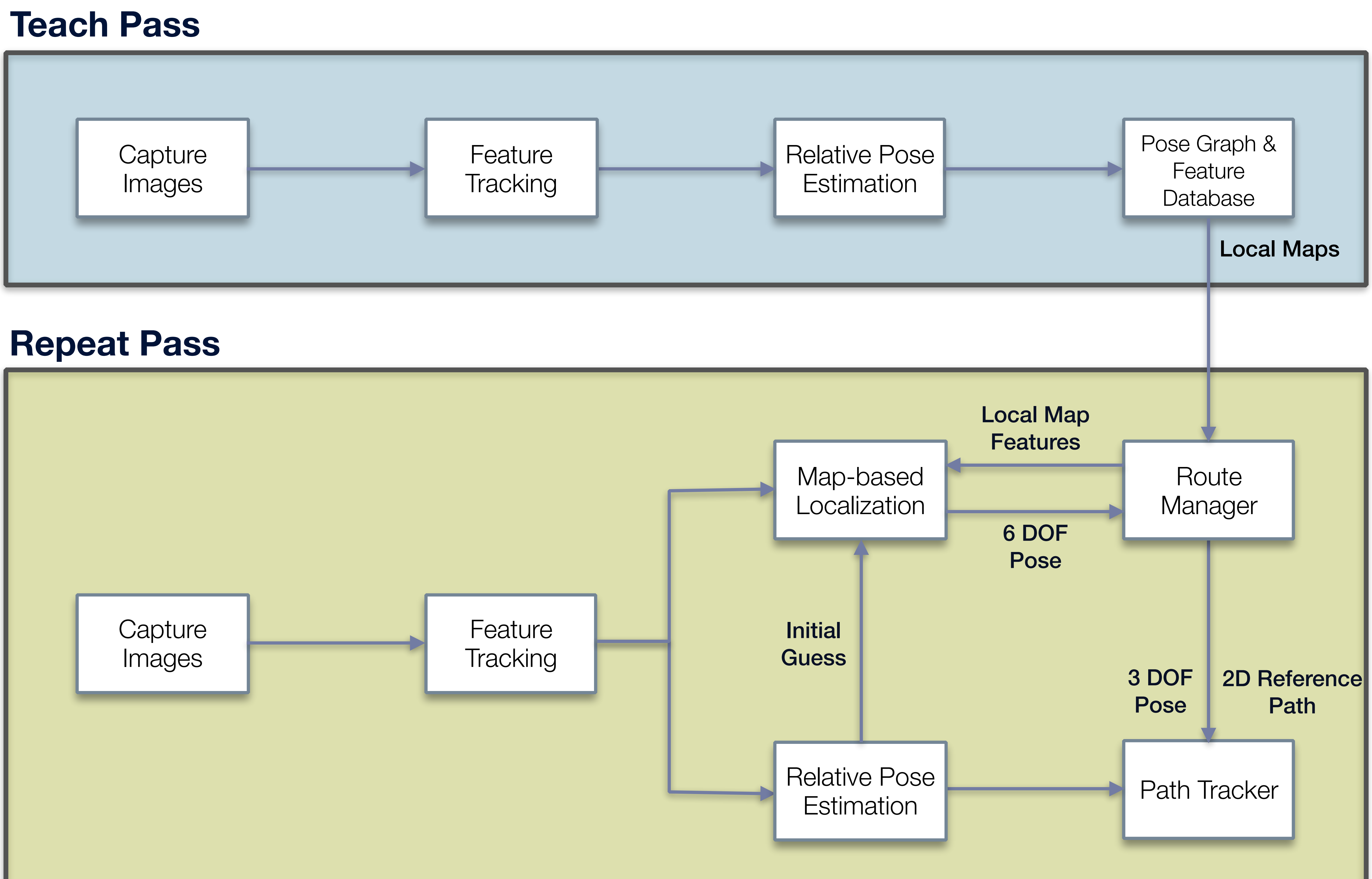

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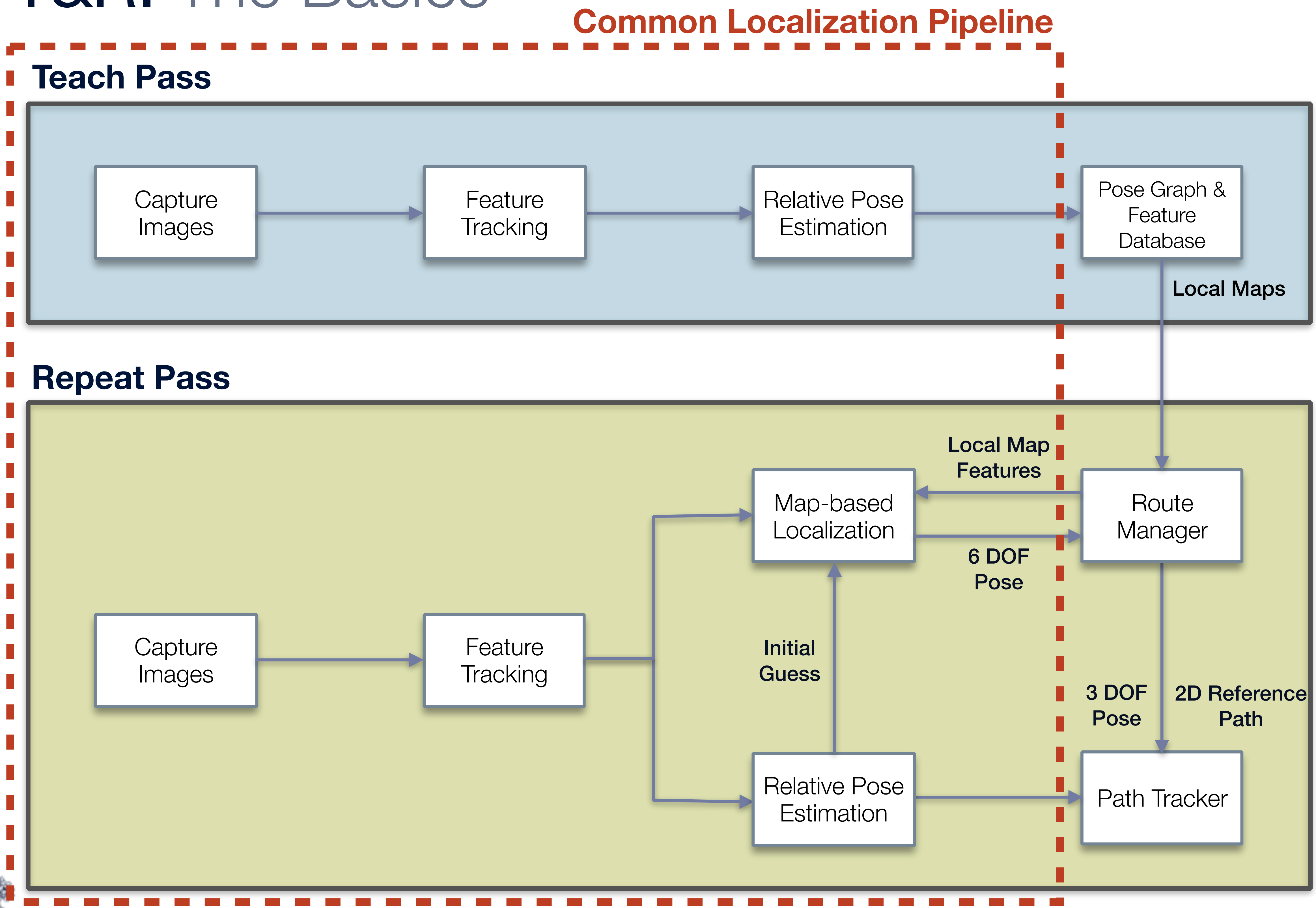

VT&R: Localization Pipeline

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Stereo Pipeline
(Furgale & Barfoot, 2010)

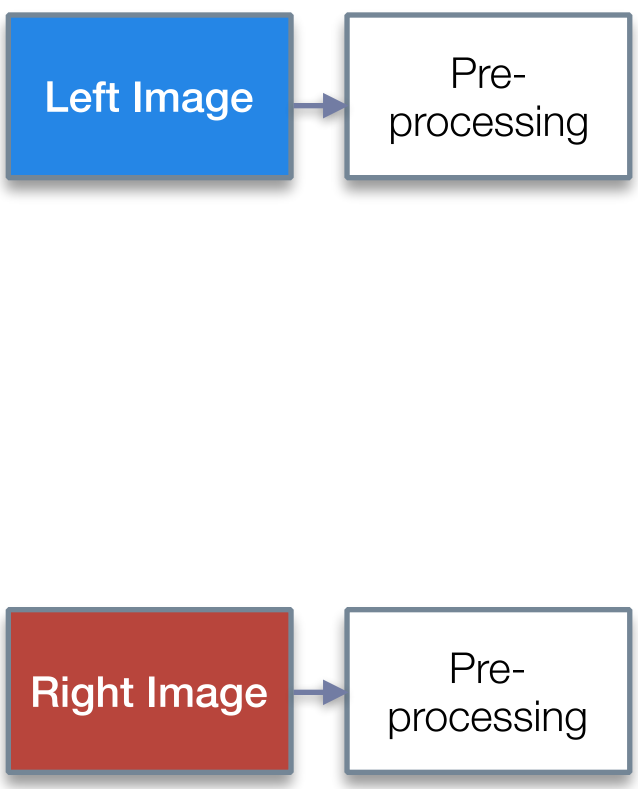
Left Image

Right Image

VT&R: Localization Pipeline

Stereo Pipeline

(Furgale & Barfoot, 2010)



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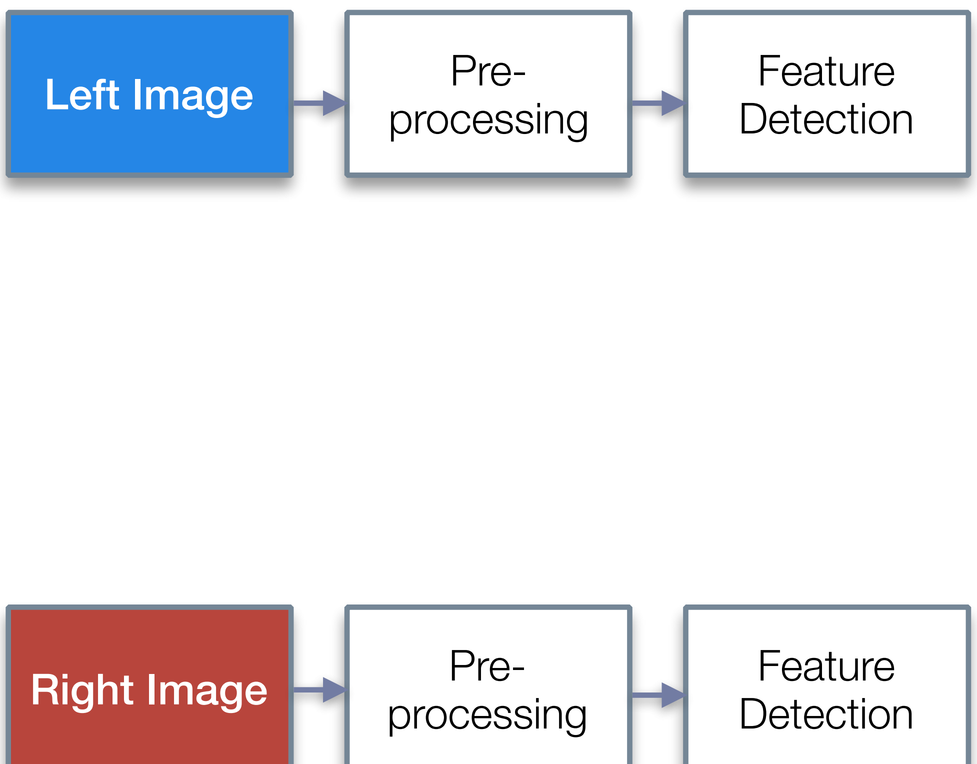

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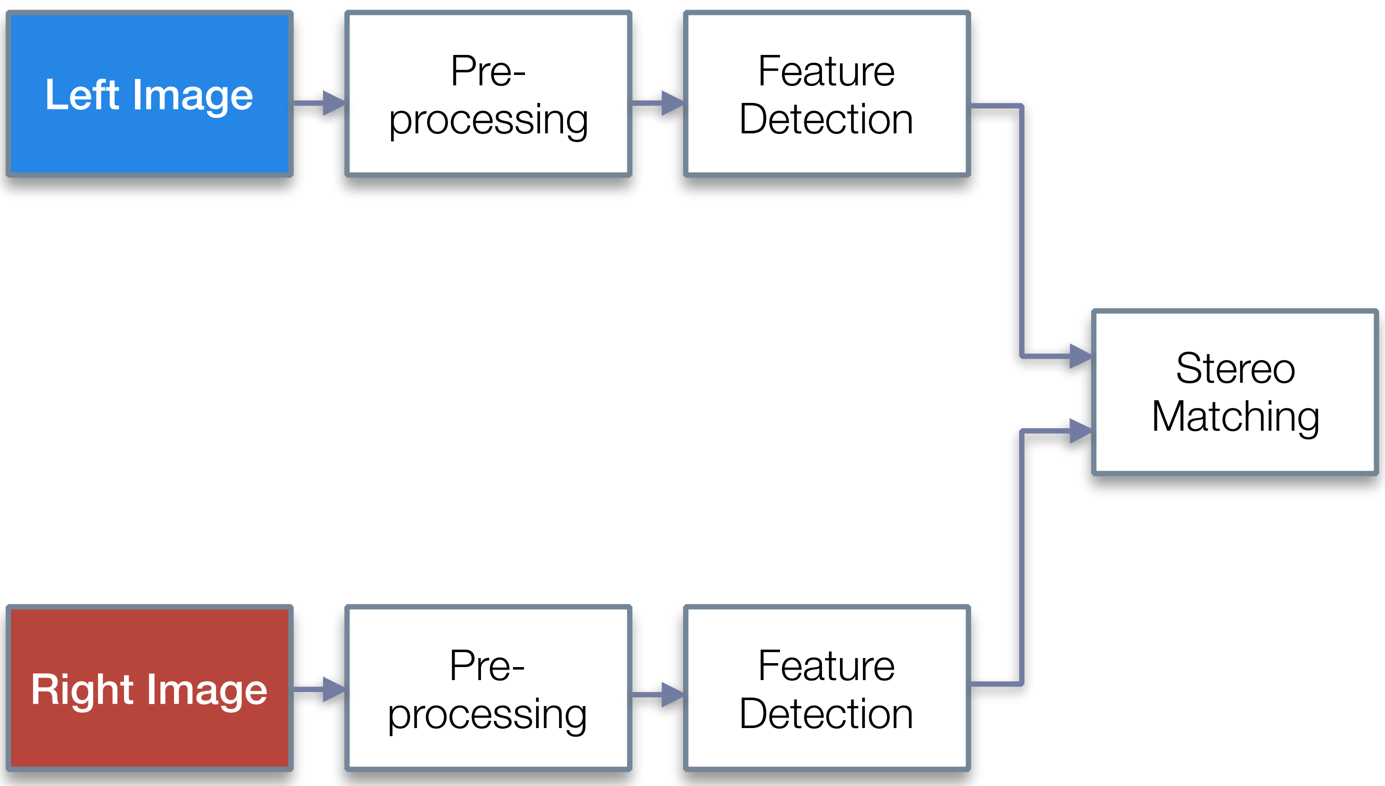

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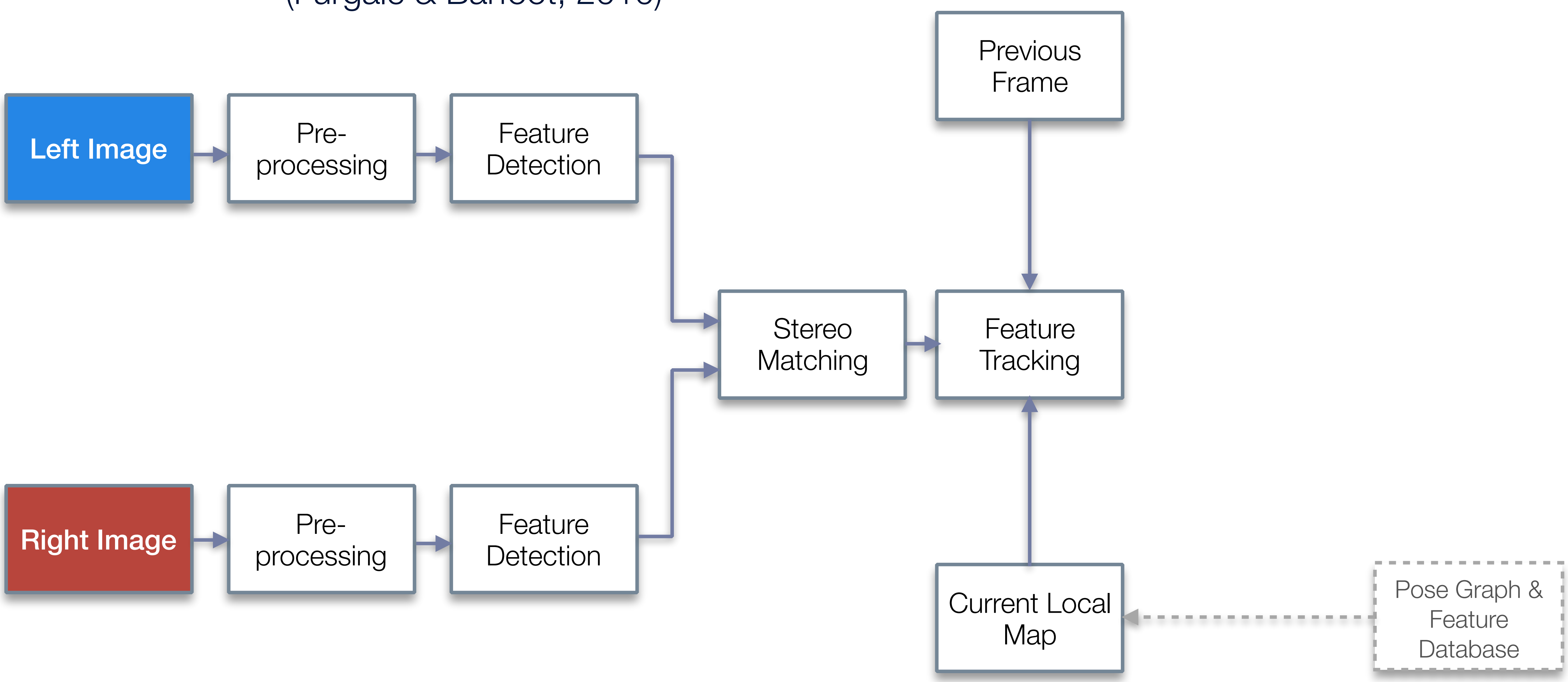

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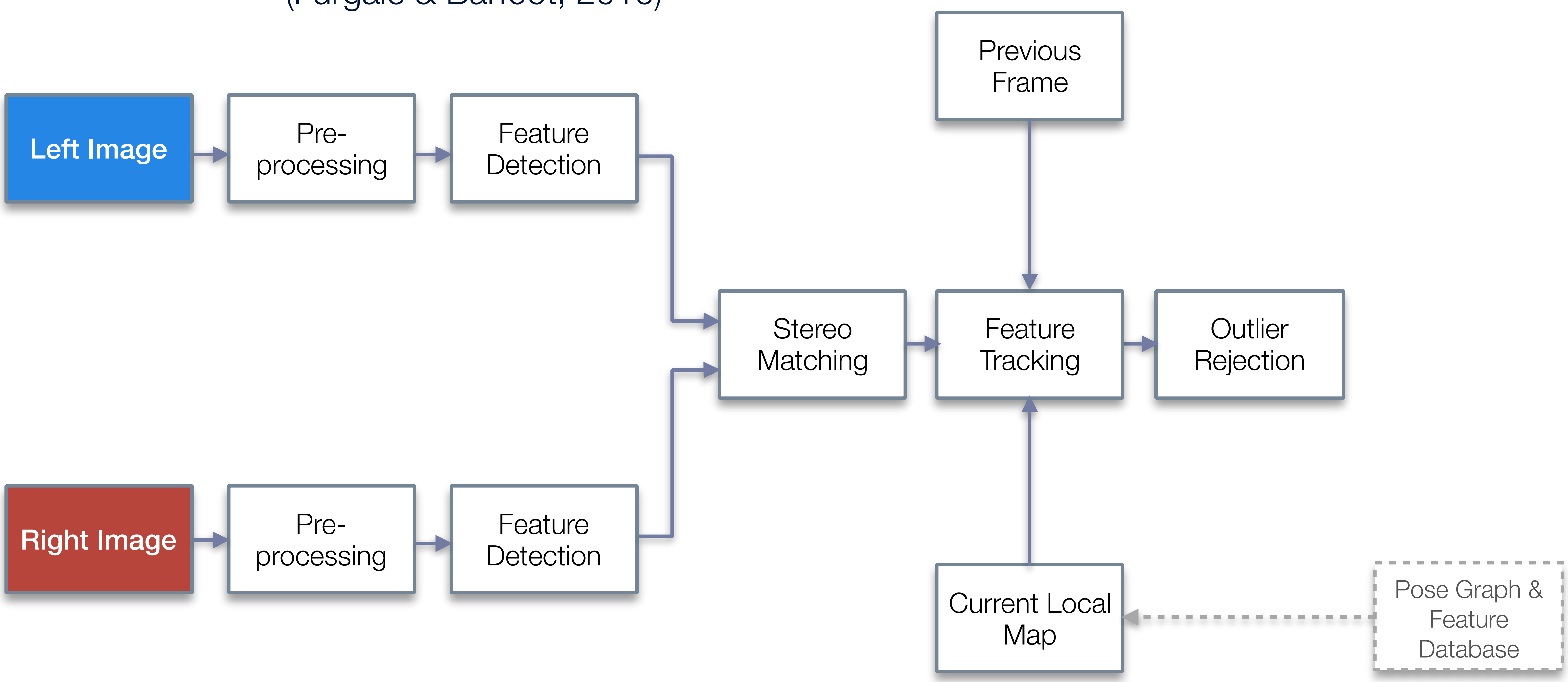

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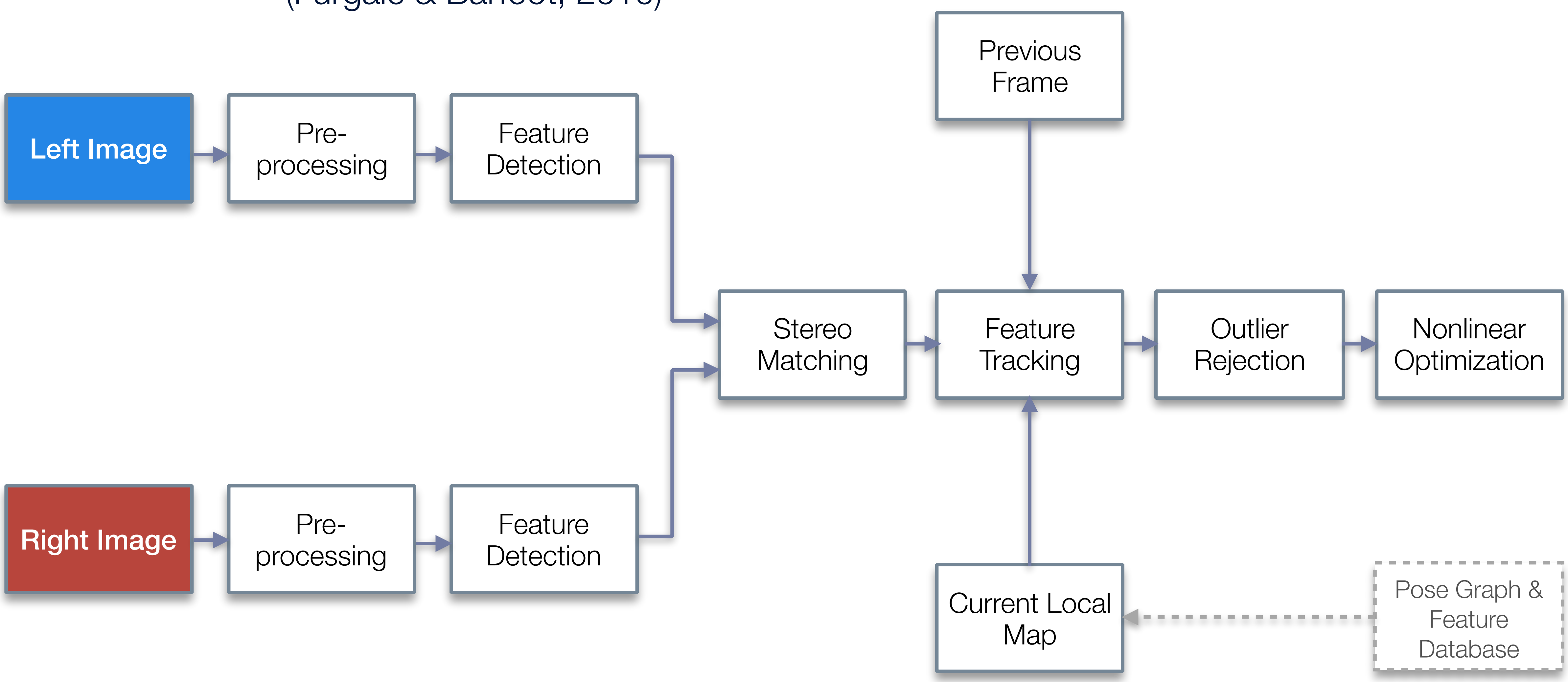

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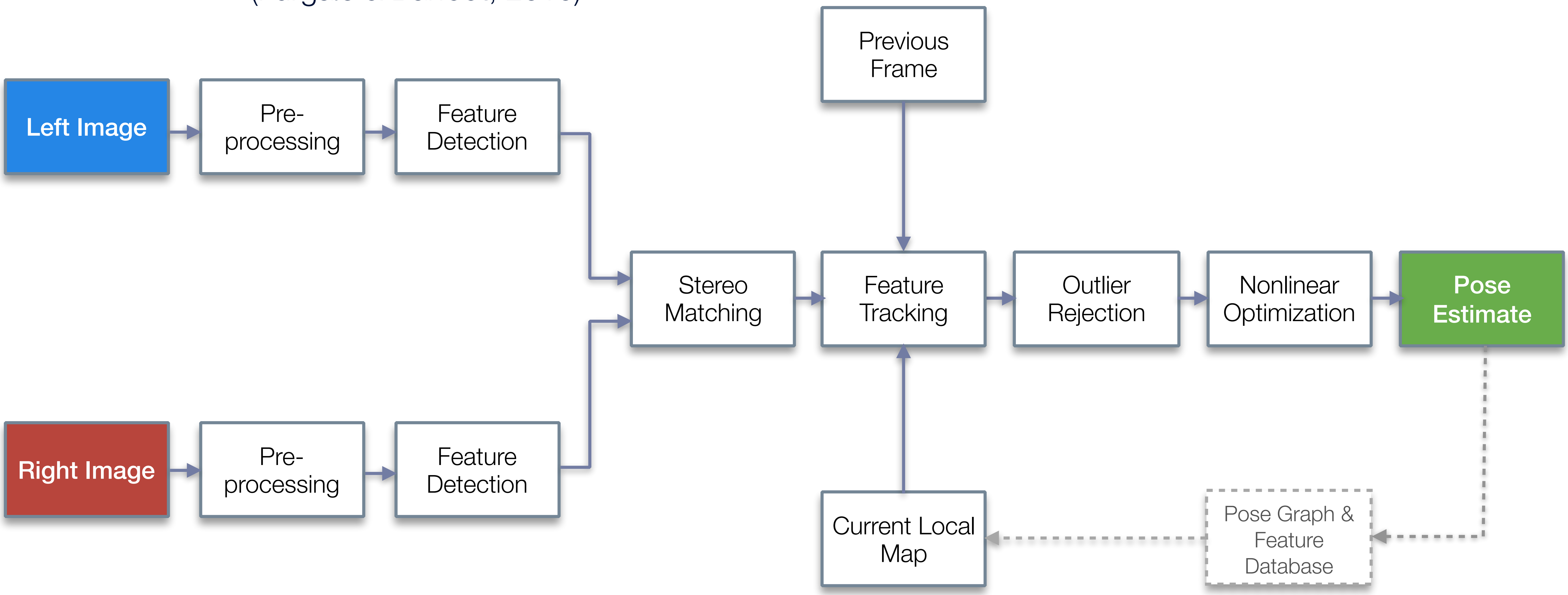

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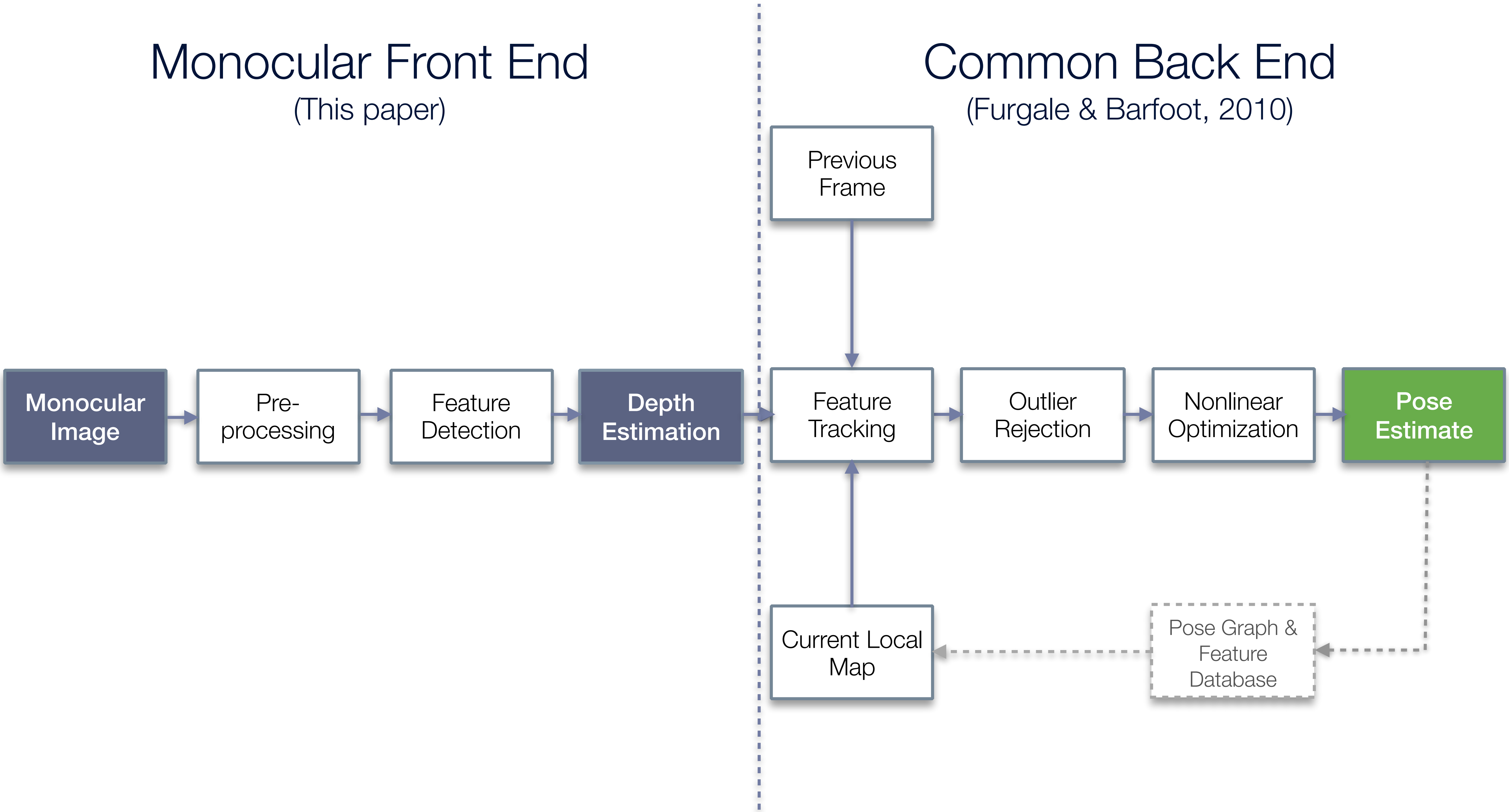
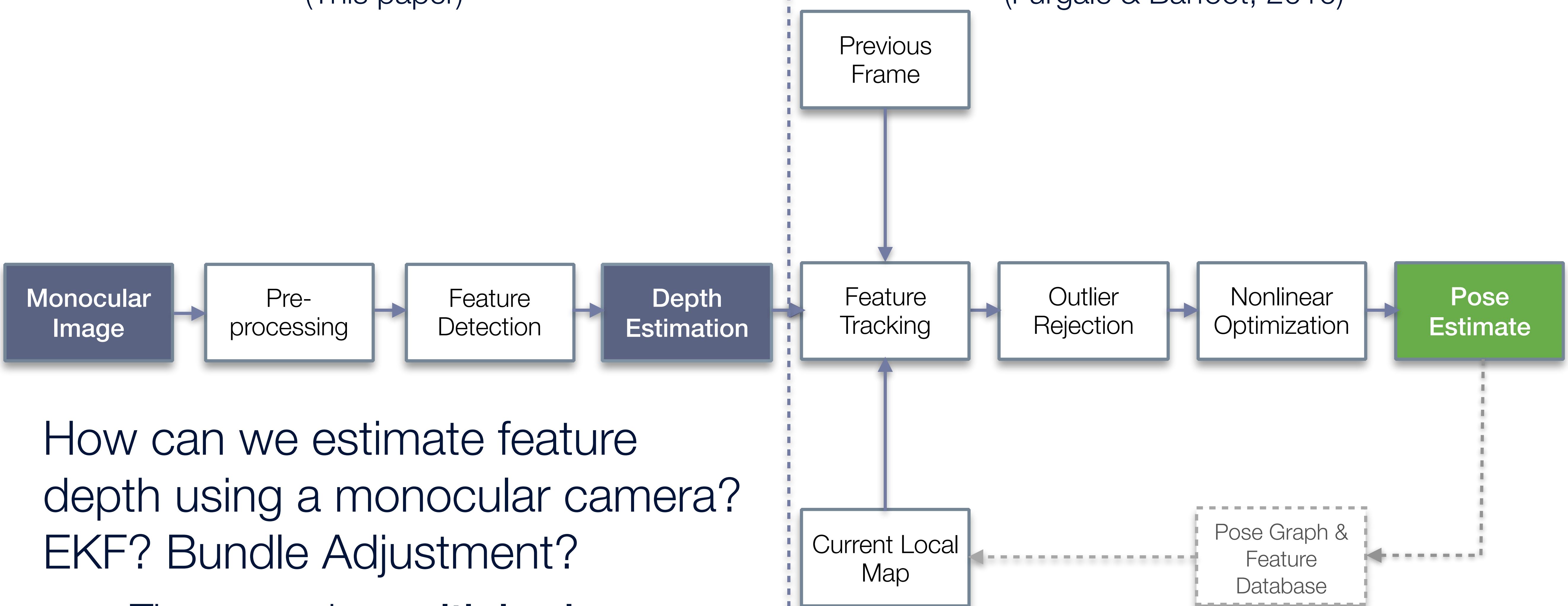


VT&R: Localization Pipeline

Monocular Front End
(This paper)

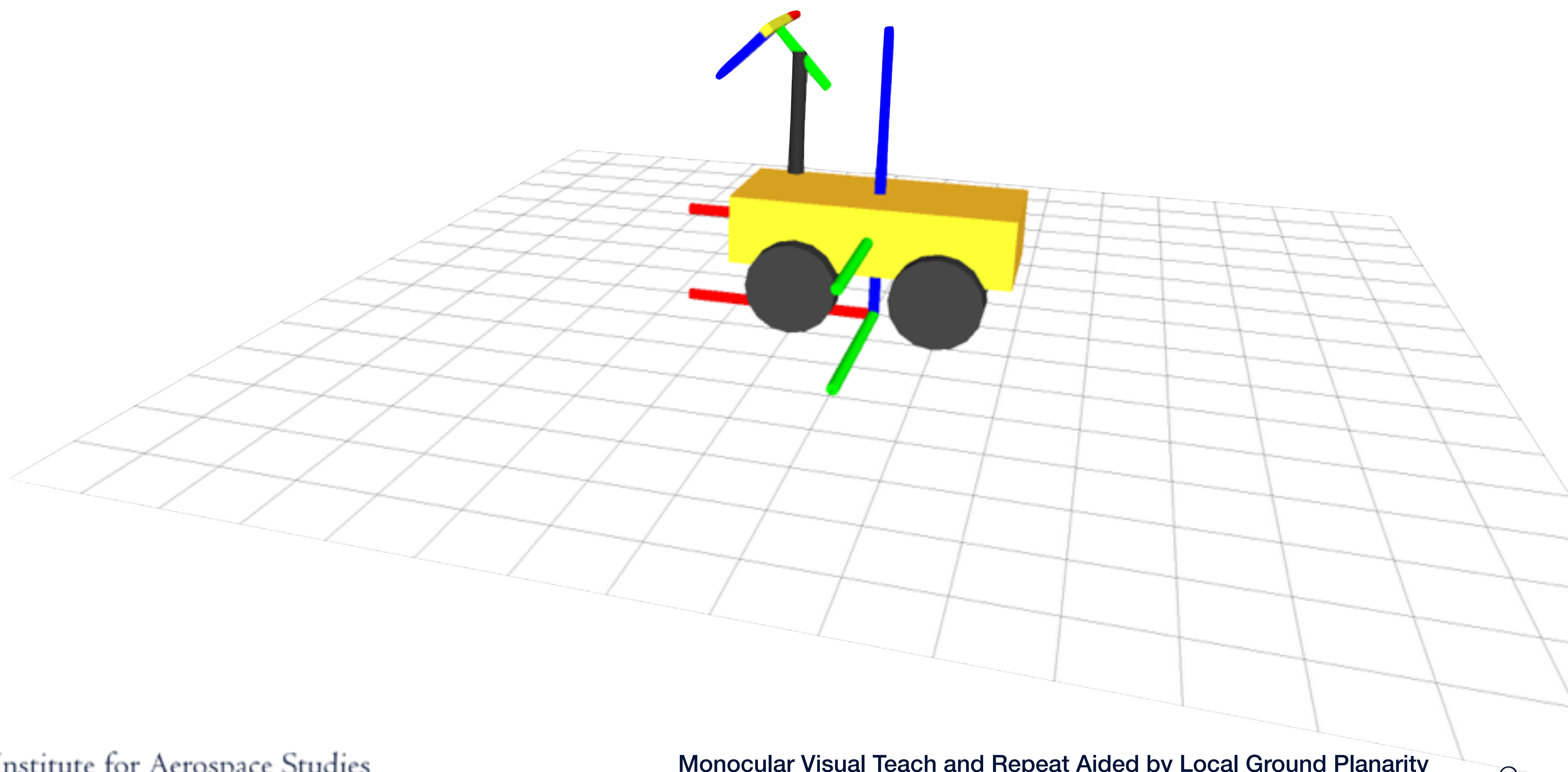
Common Back End
(Furgale & Barfoot, 2010)



How can we estimate feature depth using a monocular camera? EKF? Bundle Adjustment?

- These require **multiple views**
- Need **scale** for control

Depth Estimation: Local Ground Planarity



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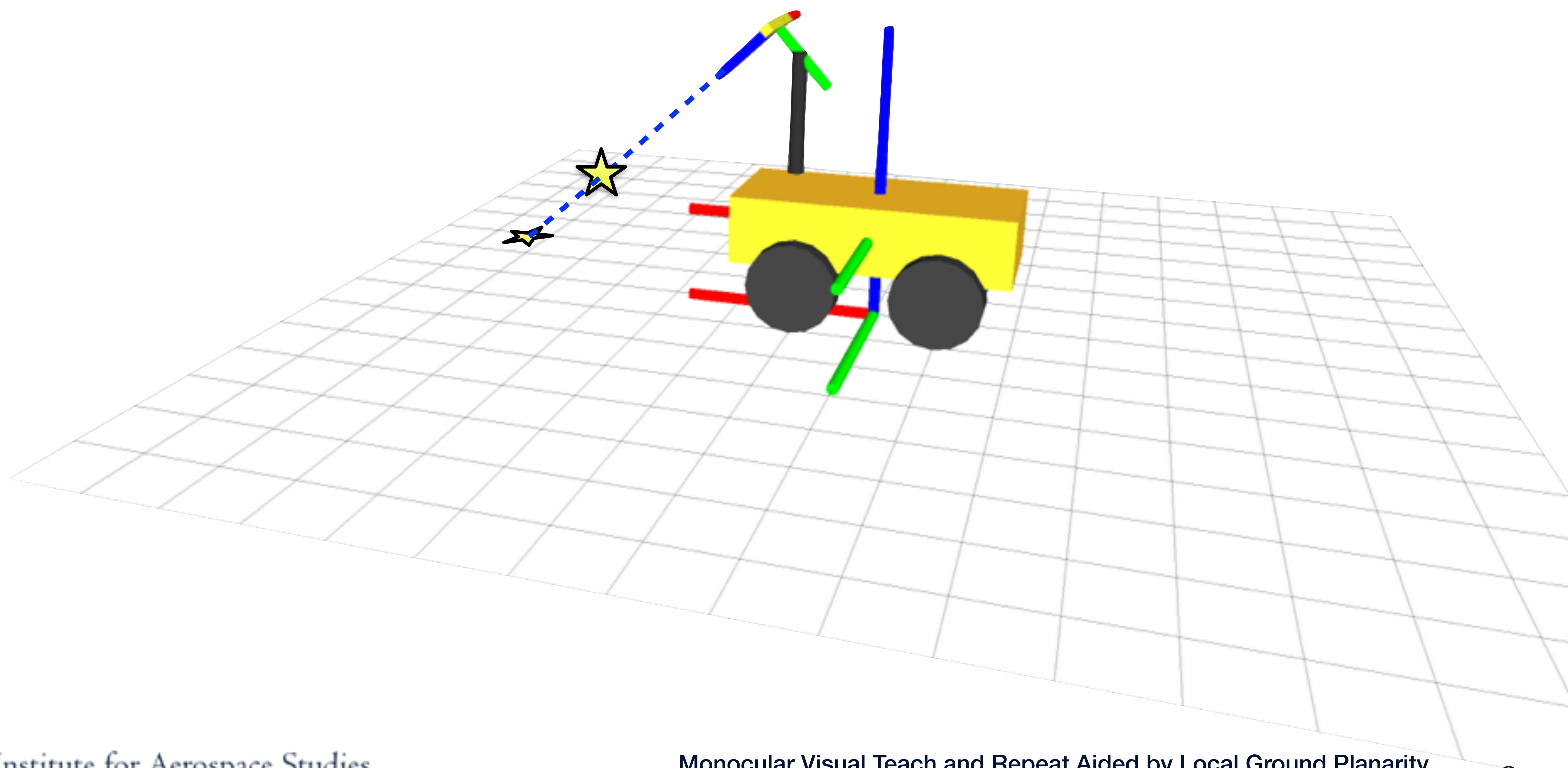

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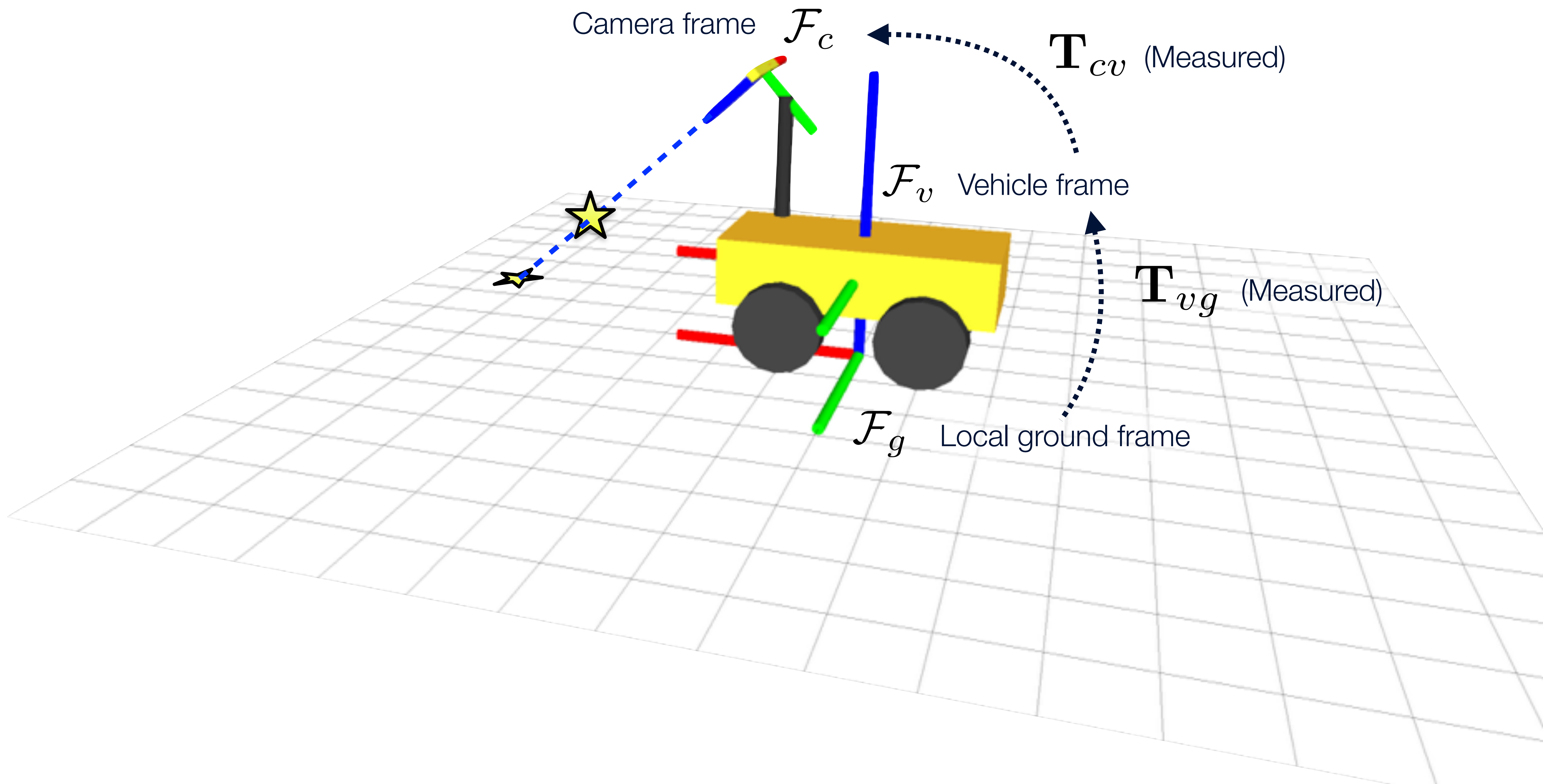
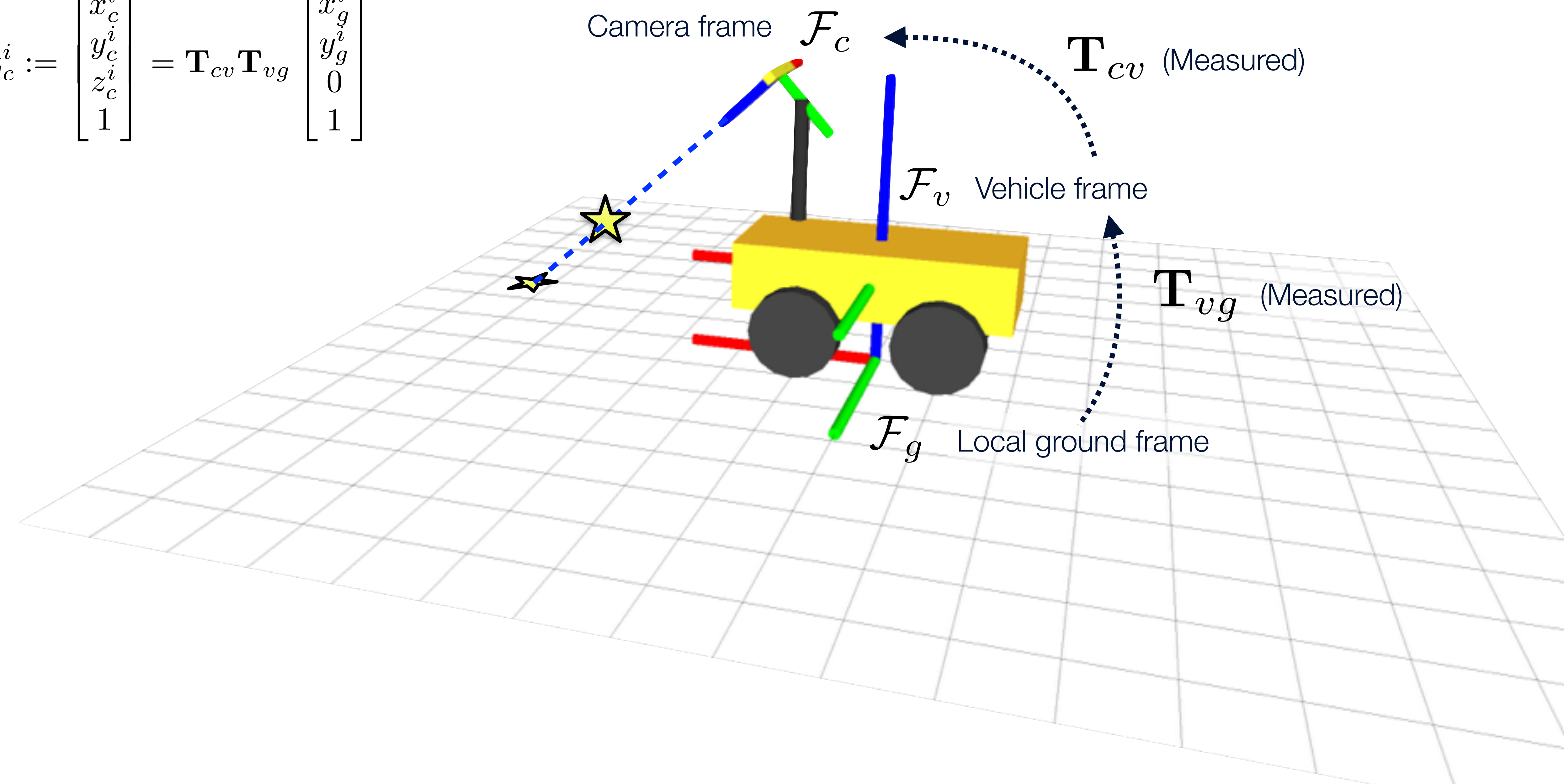


Depth Estimation: Local Ground Planarity

Ground feature coordinates in camera frame:

$$\mathbf{z}_c^i := \begin{bmatrix} x_c^i \\ y_c^i \\ z_c^i \\ 1 \end{bmatrix} = \mathbf{T}_{cv}\mathbf{T}_{vg}\begin{bmatrix} x_g^i \\ y_g^i \\ 0 \\ 1 \end{bmatrix}$$



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Projective coordinates of feature point:

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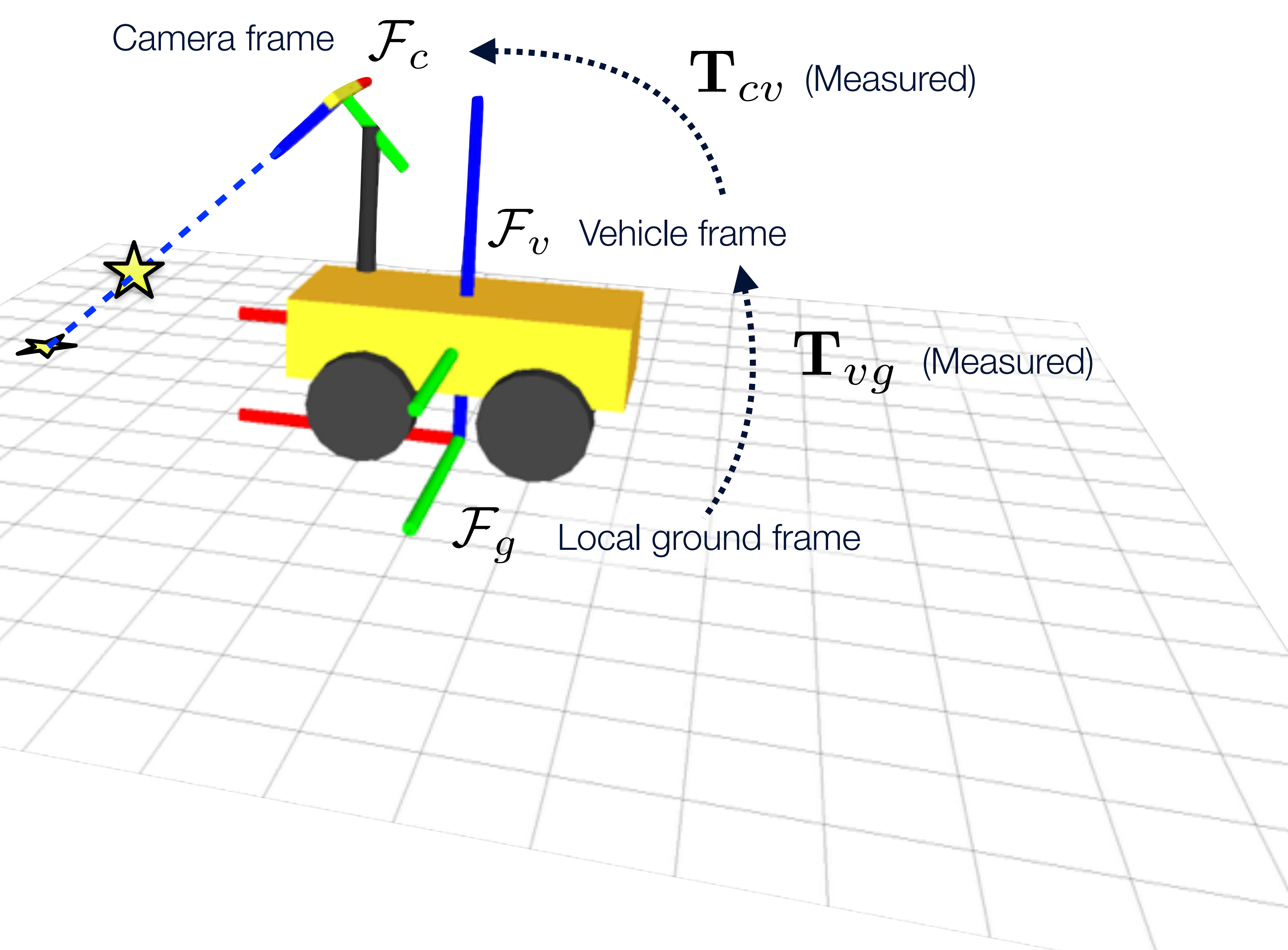

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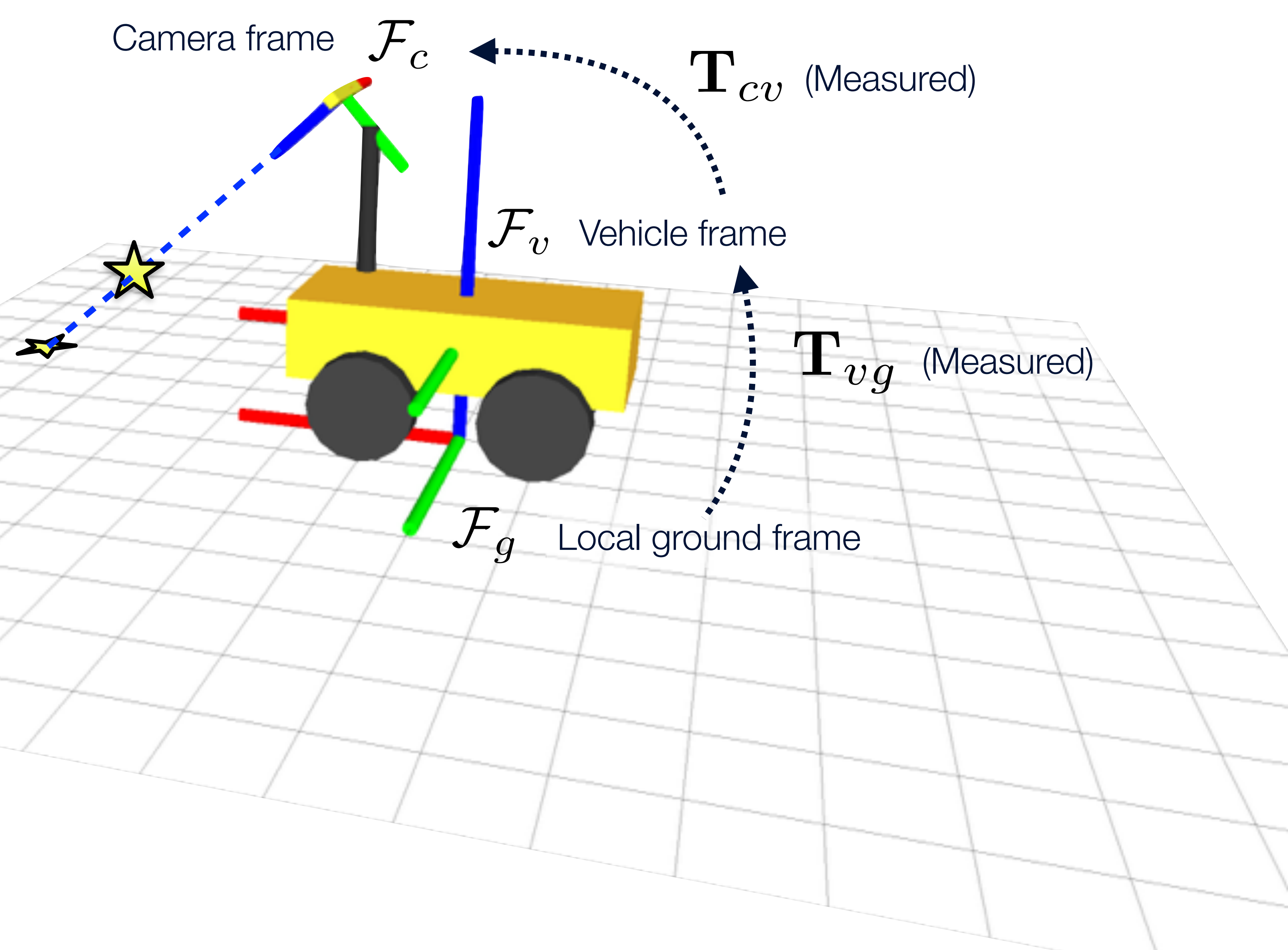

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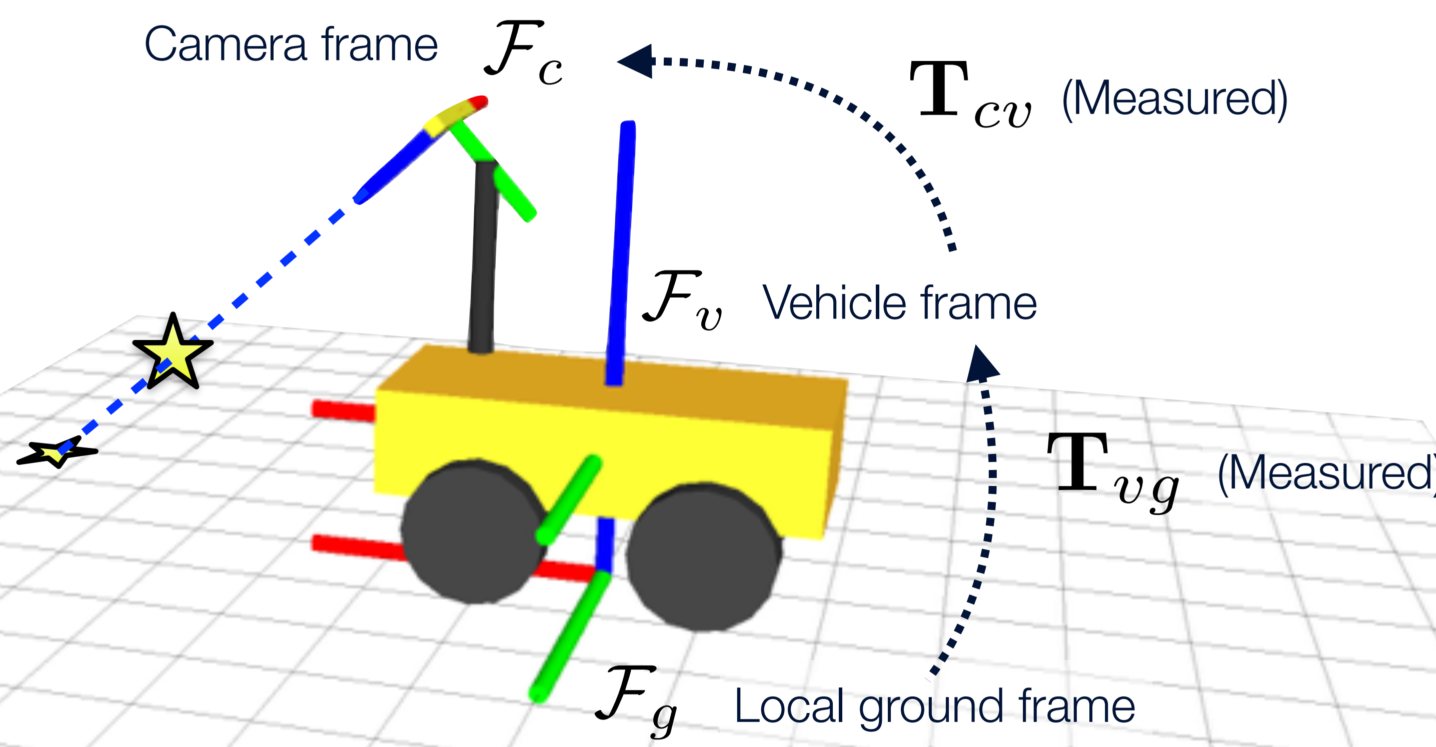

This works well for 3DOF **visual odometry**, but not so well for **mapping**!

Depth Estimation: Uncertainty?

The ground isn't perfectly flat, but locally it's close!

Idea: Model the ground plane as a Gaussian distribution on SE(3)

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Covariance of 2D feature pixel coordinates

Covariance of ground plane distribution on SE(3)

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Observation model Jacobian

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$$\mathbf{z}_c^i \sim \mathcal{N}(\bar{\mathbf{z}}_c^i, \mathbf{G}_i \mathbf{R}_i \mathbf{G}_i^T)$$

Gaussian approximation of 3D feature coordinates

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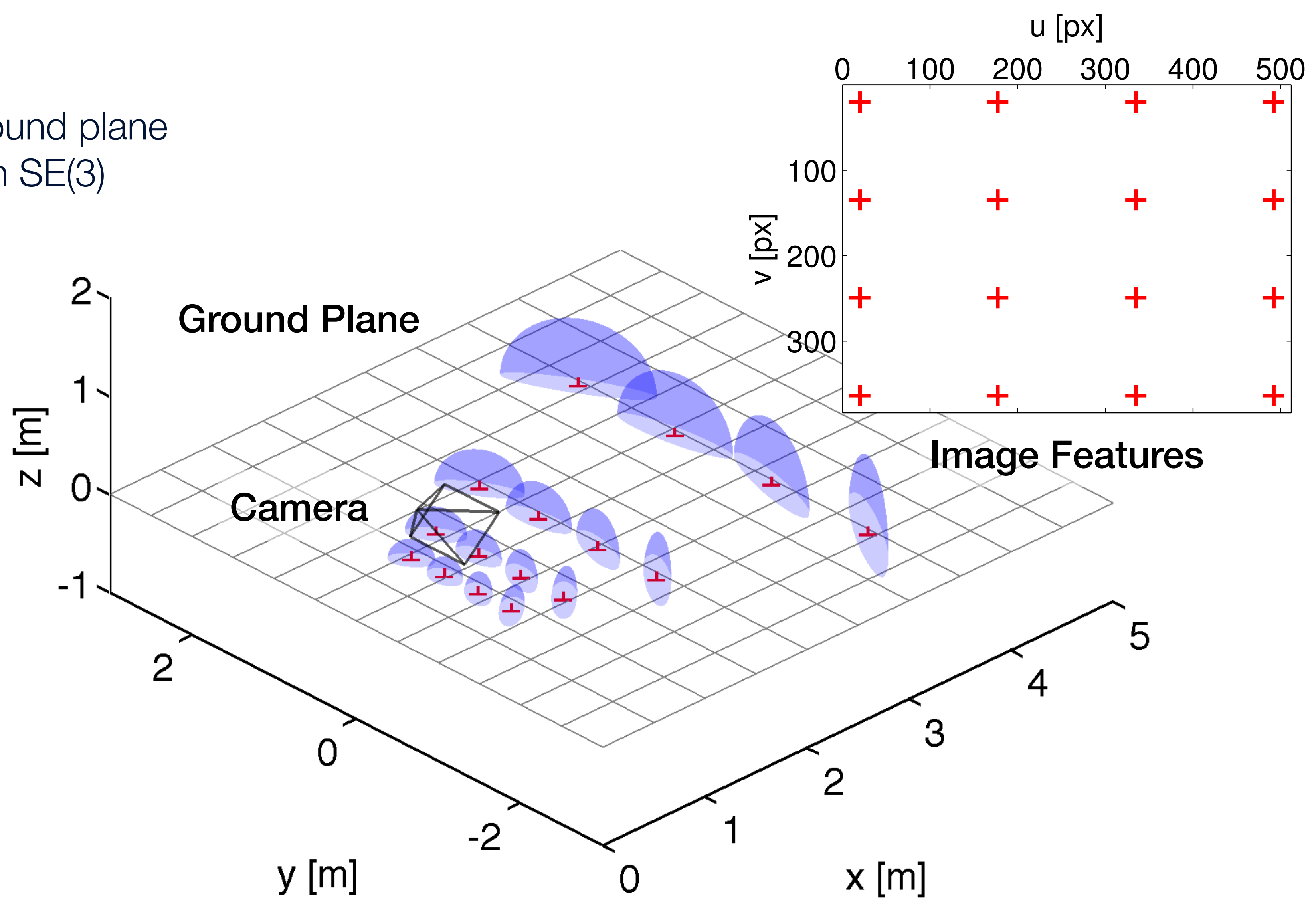

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Field Testing: Goals

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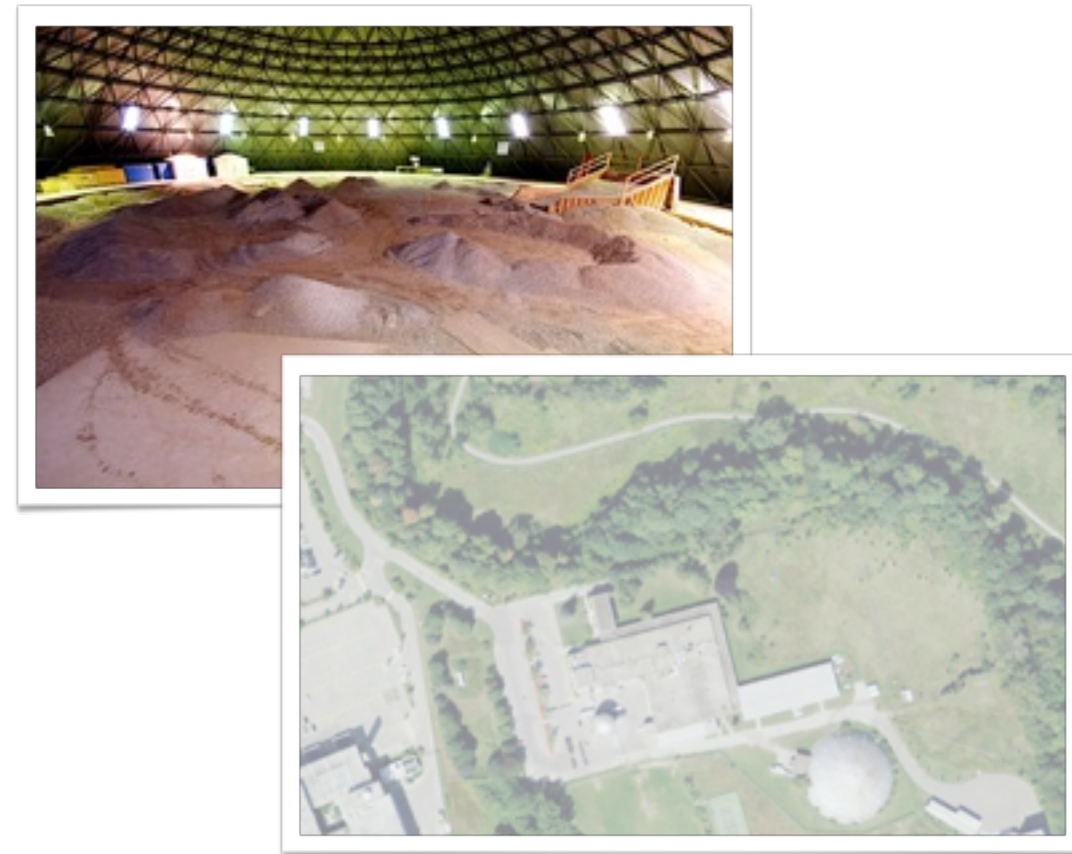
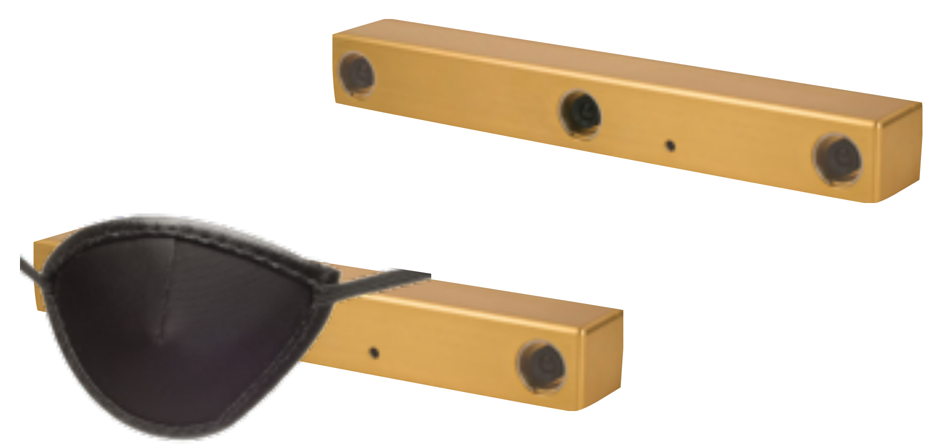
1

Characterize the performance of Monocular VT&R over long routes in different conditions.

Field Testing: Goals



1. **Characterize** the performance of Monocular VT&R over long routes in different conditions.



2. **Compare** the performance of Monocular VT&R to Stereo VT&R on the same routes, using the same hardware.

Field Testing: Hardware

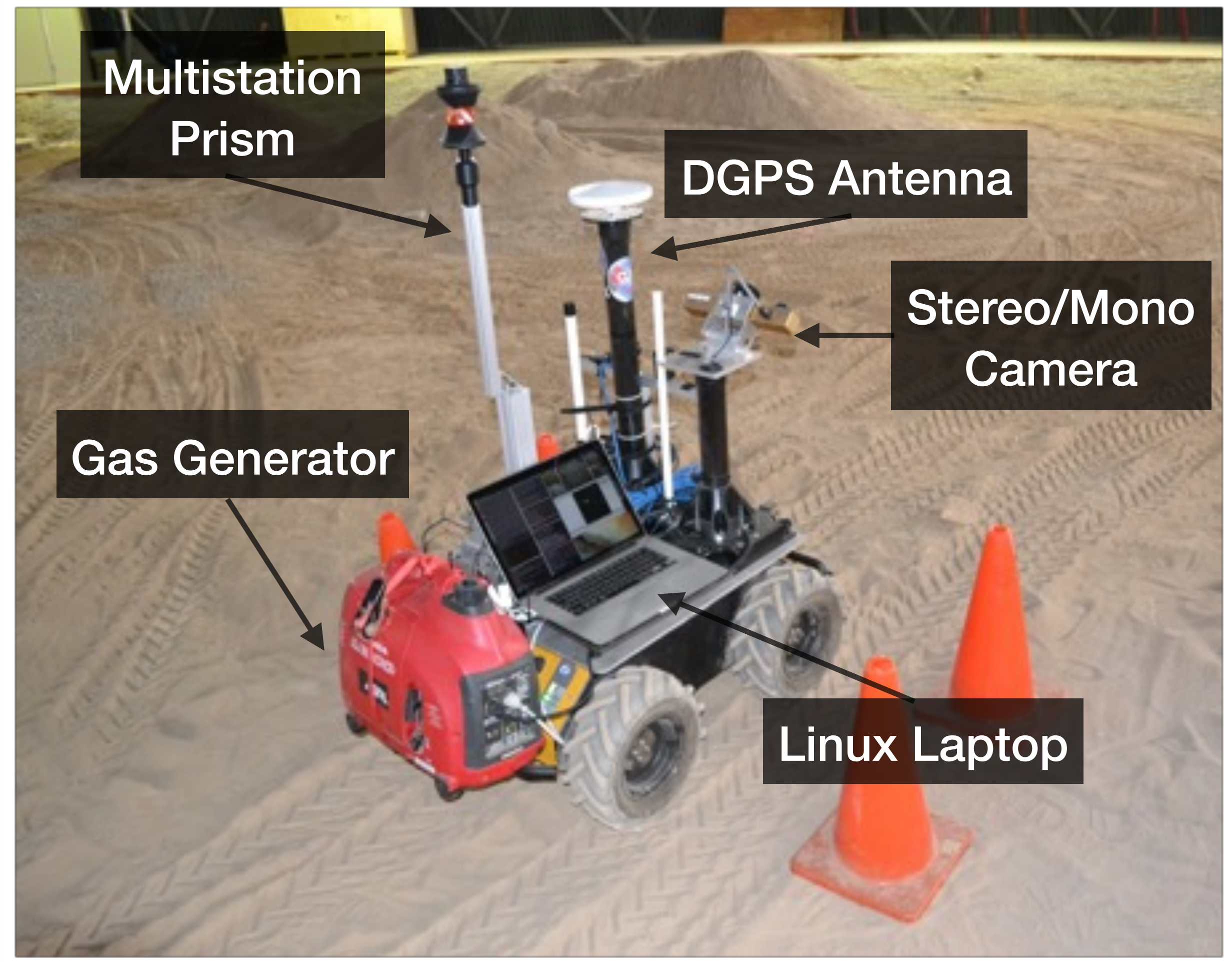
Vehicle:
- Clearpath Husky A200 Rover

Sensor:
- PointGrey Bumblebee XB3 Stereo Camera (1 m from ground, 47° to horizontal)

Computation:
- MacBook Pro (Ubuntu 12.04, ROS Hydro)

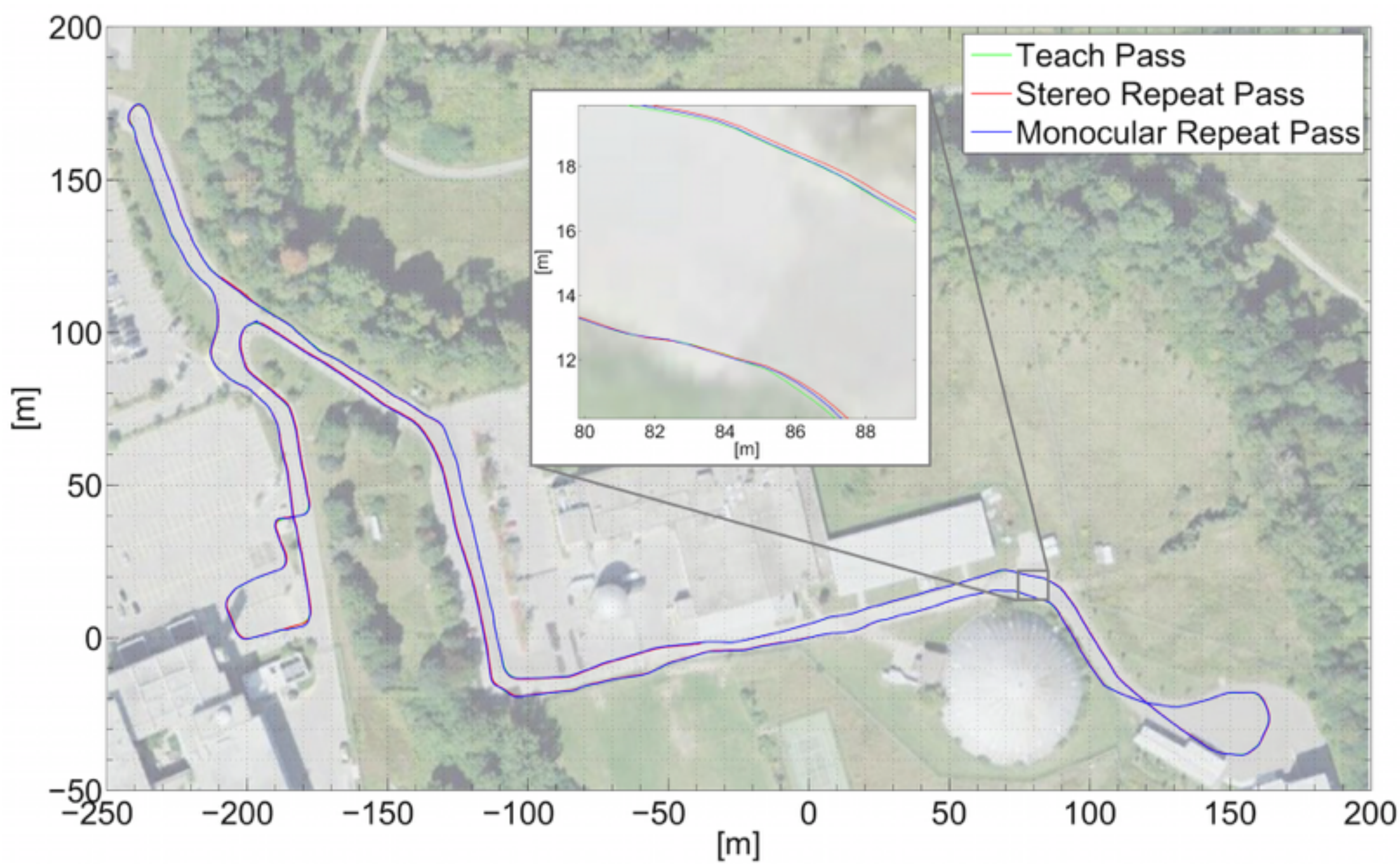
Ground Truthing:
- Ashtech DG14 DGPS (Outdoor)
- Leica Nova MS50 Multistation (Indoor)

Other:
- 1 kW Gas Generator



Field Testing: 1.4 km UTIAS Outdoor Route

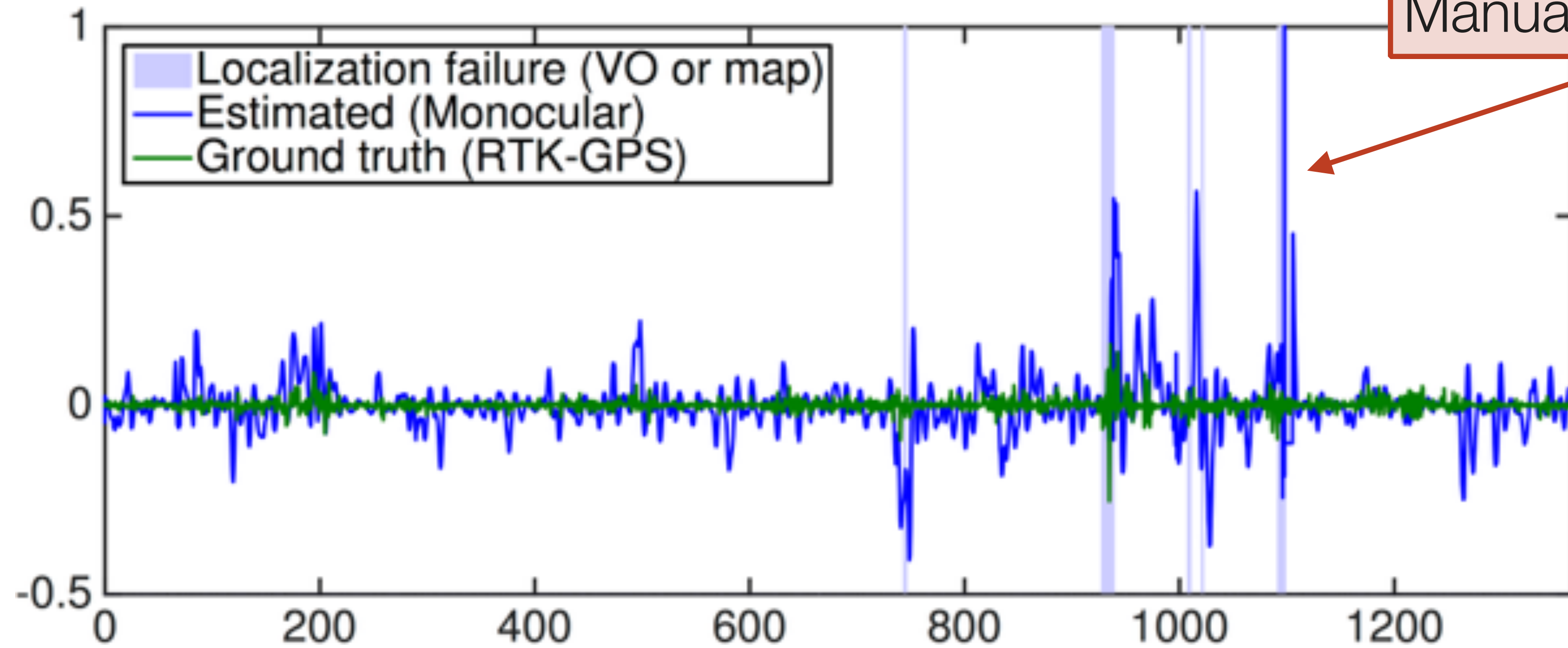
Ground Truth: RTK-GPS



Field Testing: 1.4 km UTIAS Outdoor Route

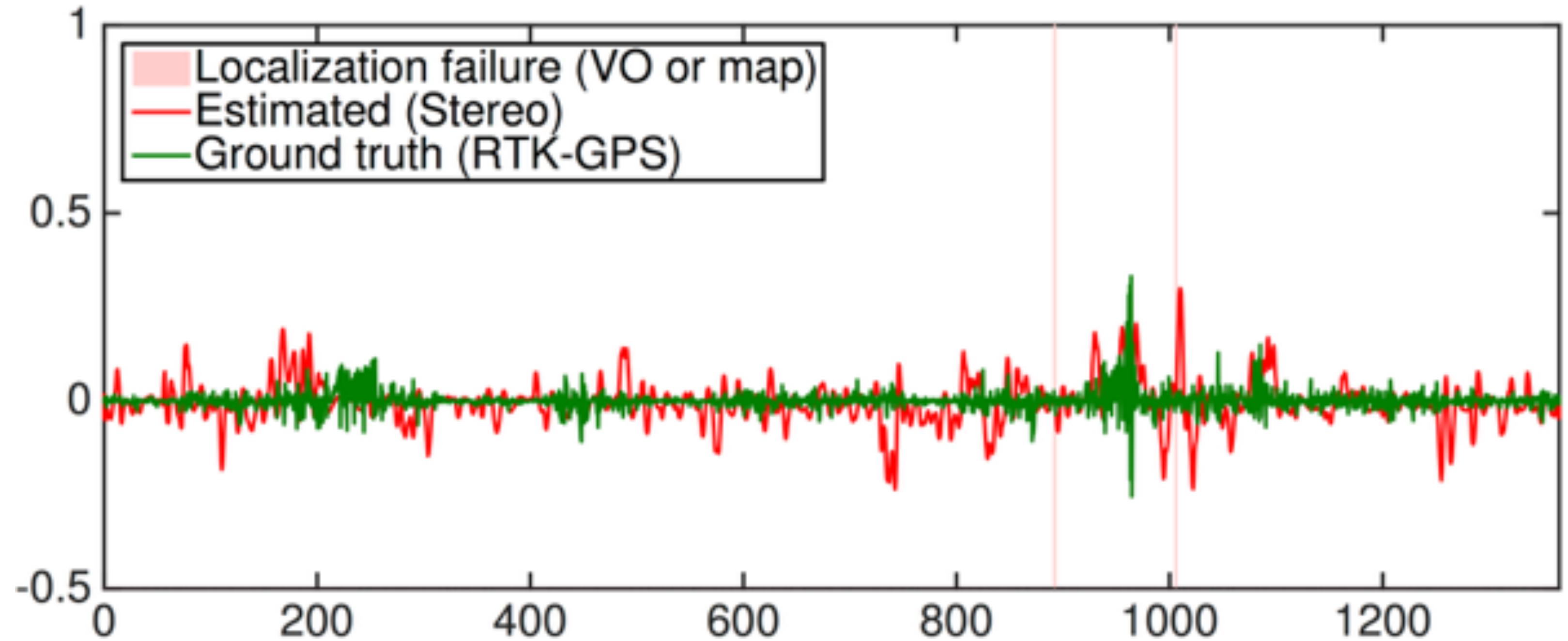
Manual intervention

Lateral Path-Tracking Error [m]



Monocular
99.9% autonomy

Lateral Path-Tracking Error [m]



Stereo
100% autonomy

Distance Traveled [m]

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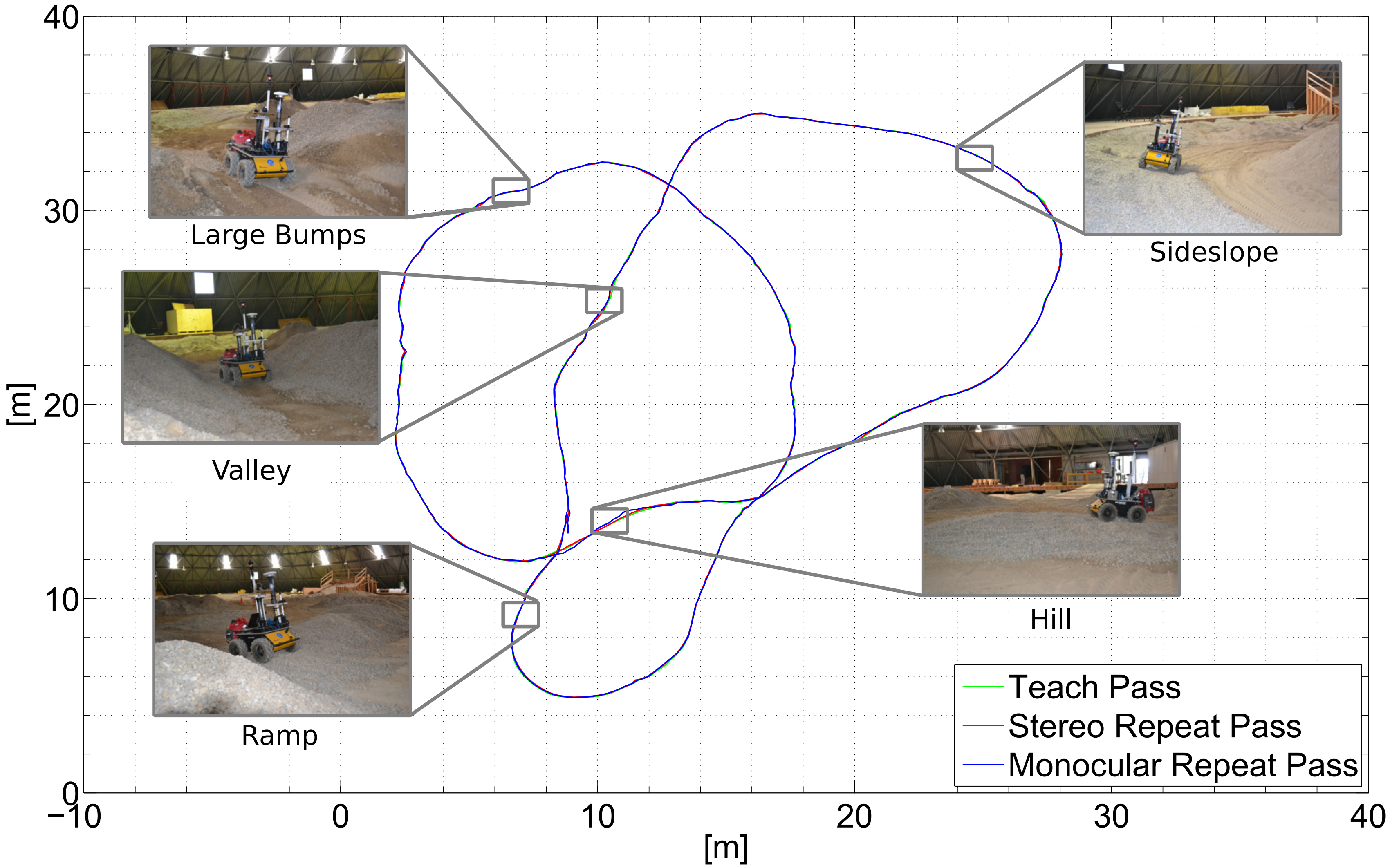
UNIVERSITY OF TORONTO

Field Testing: 140 m MarsDome Indoor Route



Ground Truth:
Leica Nova MS50 Multistation

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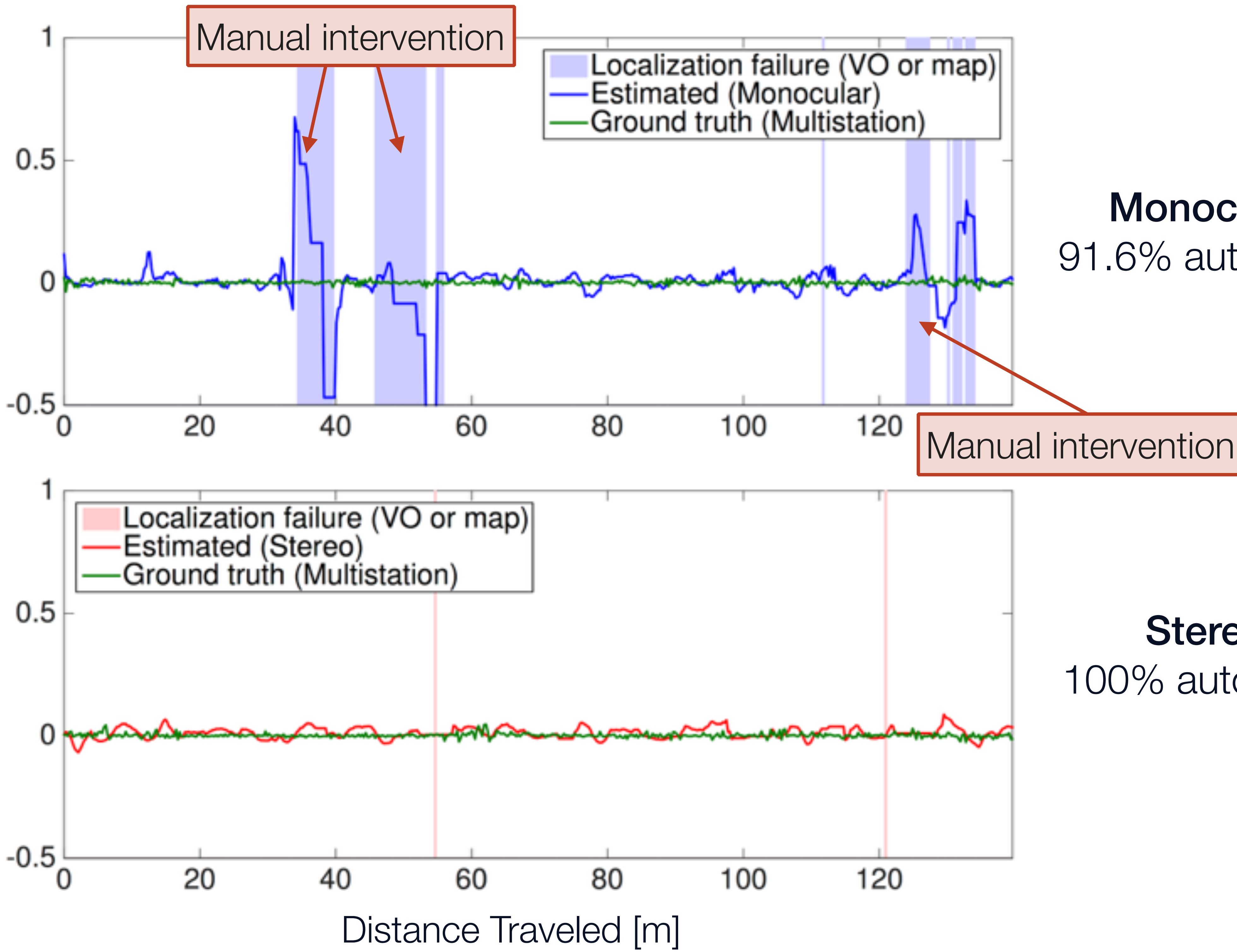

Monocular
91.6% autonomy

Lateral Path-Tracking Error [m]

Stereo
100% autonomy

Field Testing: Summary

Trial	Route	Path length	Repeat speed	Local start time (UTC-4)			Autonomy rate	
				Teach	Mono	Stereo	Mono	Stereo
1	Outdoor	1370 m	0.6 m/s	09:56:46	10:35:10	12:08:30	99.71%†	100.00%
2	Outdoor	1360 m	0.6 m/s	11:45:40	12:22:26	13:43:49	99.88%	100.00%
3	Outdoor	1361 m	0.6 m/s	13:26:41	14:00:12	15:20:12	99.74%	100.00%
4	Indoor	126 m	0.3 m/s	13:32:23	13:40:53	14:02:46	96.28%	100.00%
5	Indoor	140 m	0.3 m/s	12:18:57	12:32:20	12:59:11	91.60%	100.00%

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Total distance driven	4298 m†	4357 m
Total distance autonomously traversed	99.41%	100.00%

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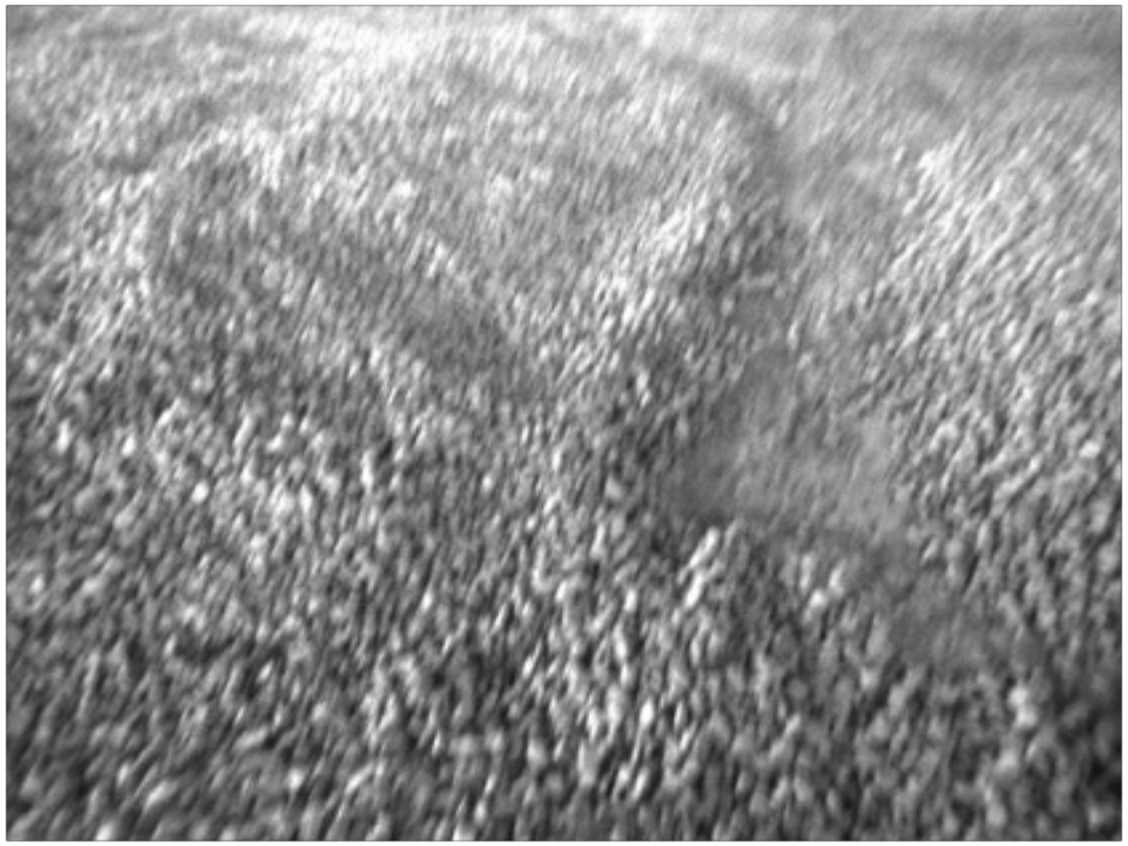
Why were monocular autonomy rates lower?

Not because of rough terrain!

Field Testing: Failure Cases



Motion Blur (Low Light)

Self-similar Terrain

Field Testing: Failure Cases

Motion Blur (Low Light)

Self-similar Terrain

+

High spatial uncertainty

=

Bad feature matching!

Summary: Monocular Visual Teach & Repeat

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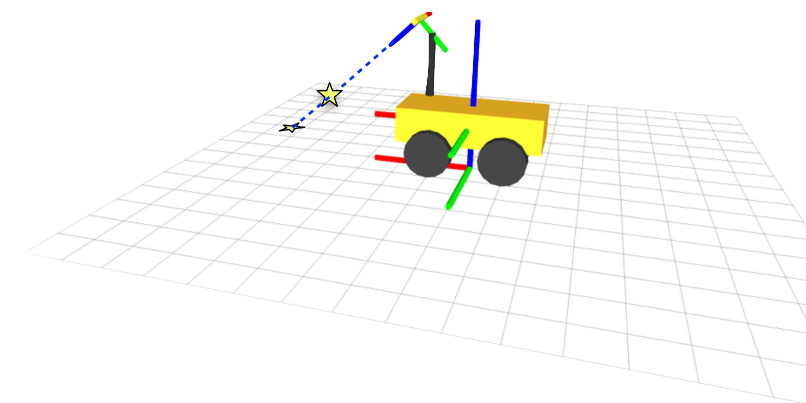
1 The flat-ground approximation works for high-accuracy monocular route following, given an appropriate uncertainty model.



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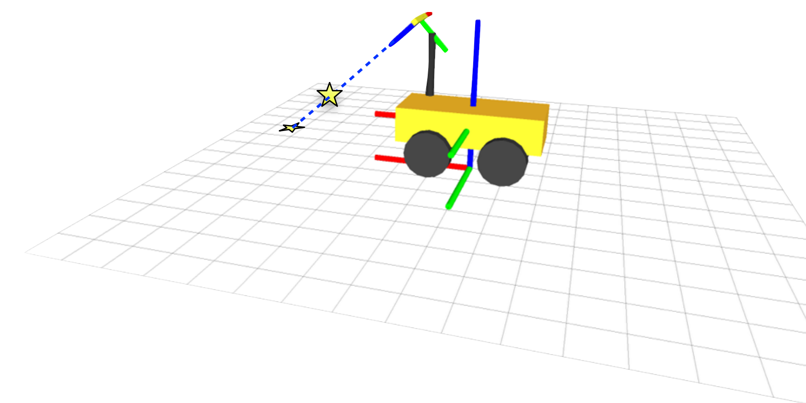
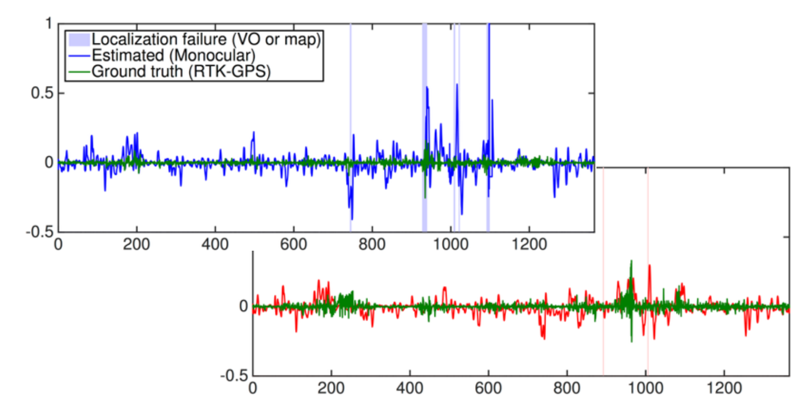


2 Monocular VT&R is just as accurate as Stereo VT&R, but less robust in places where feature matching is hard.



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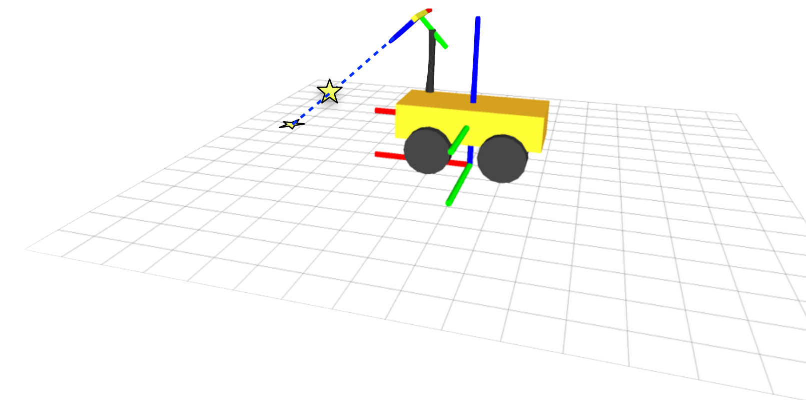

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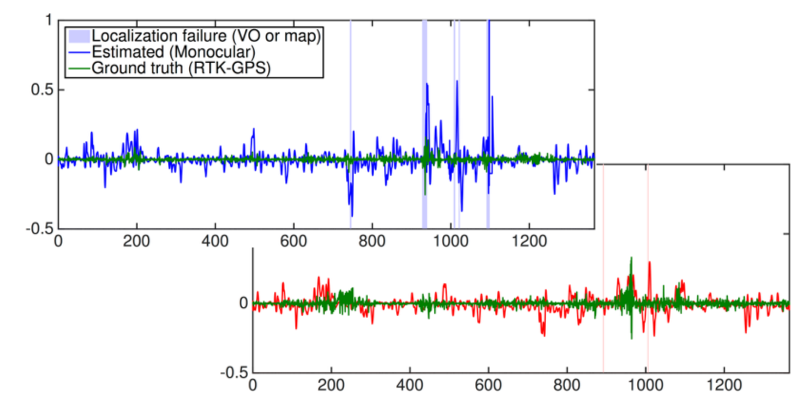

3 Existing monocular robots can now do repetitive navigation tasks autonomously, without additional sensors.

Thanks!
Questions?

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