Long-Term Visual Route Following for Mobile Robots

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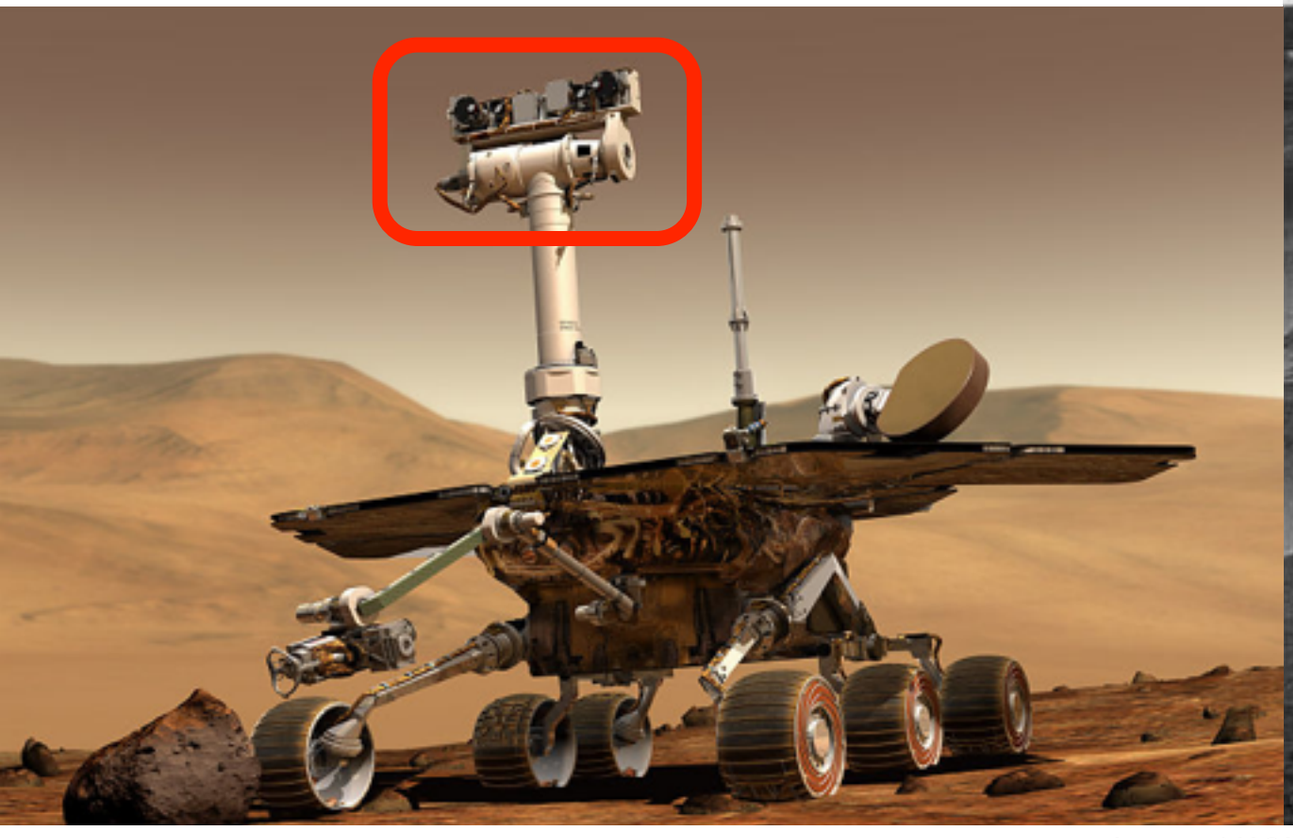
Guest Lecture
CSC420: Introduction to Image Understanding
October 29, 2015

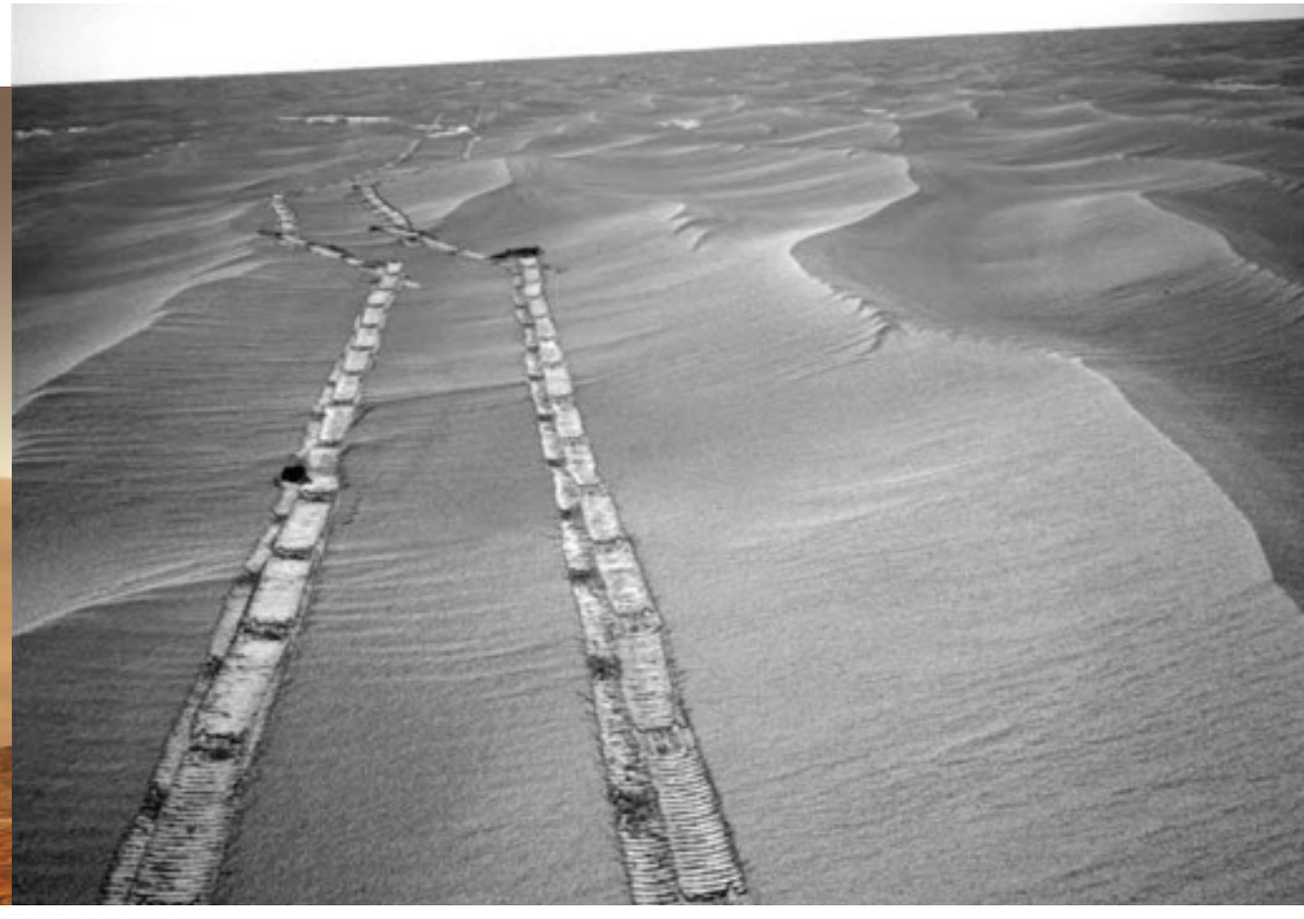
Outline

- **visual route following**
  - motivation
  - background on visual teach and repeat
- **can this work in the long term?**
  - dealing with lighting change
  - maintaining maps over the lifetime of a robot

Stereo Visual Odometry

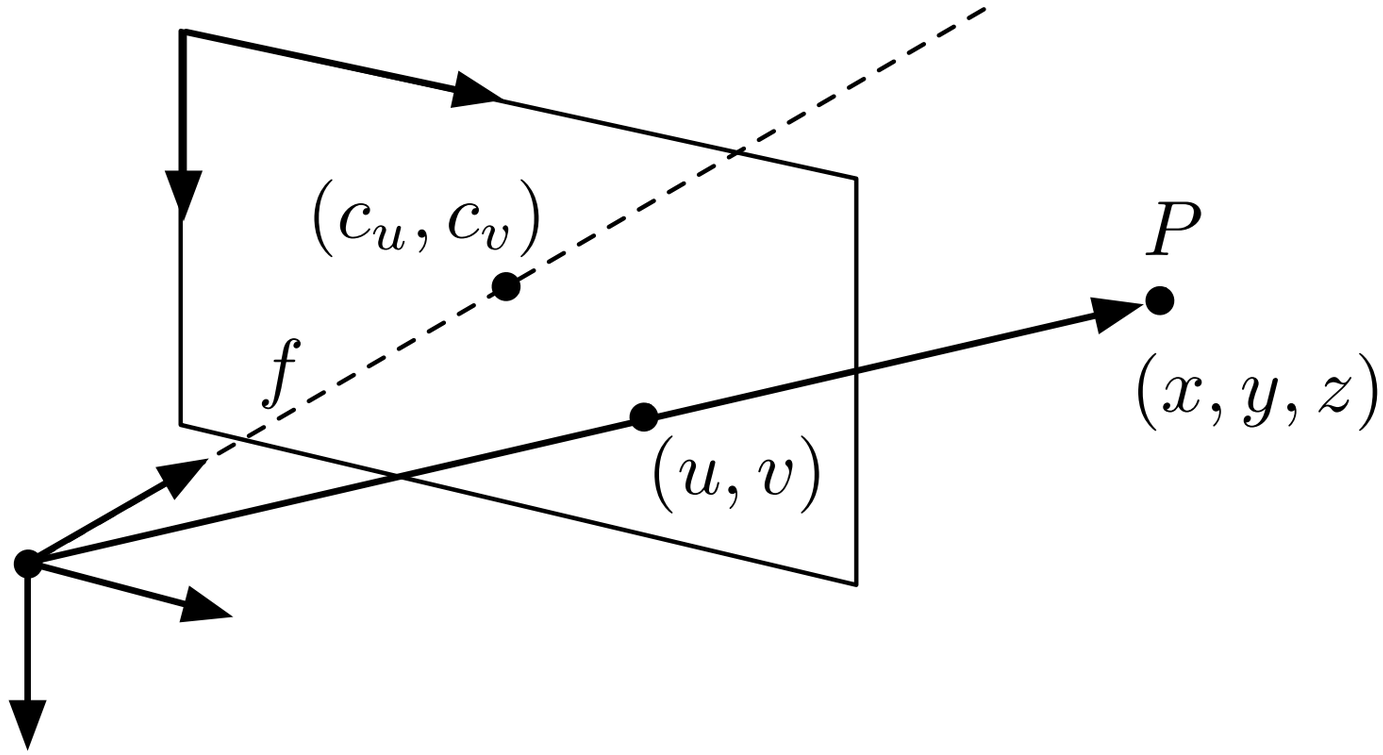
- on nominal terrain, the Mars rovers (Spirit, Opportunity, and Curiosity) use wheel odometry to track position changes
- visual odometry (VO) provides accurate localization in high-wheel-slip environments
- pioneered by Moravec (1980), Matthies (1987) and extended by many others





Images: NASA/JPL/Caltech

Camera Model



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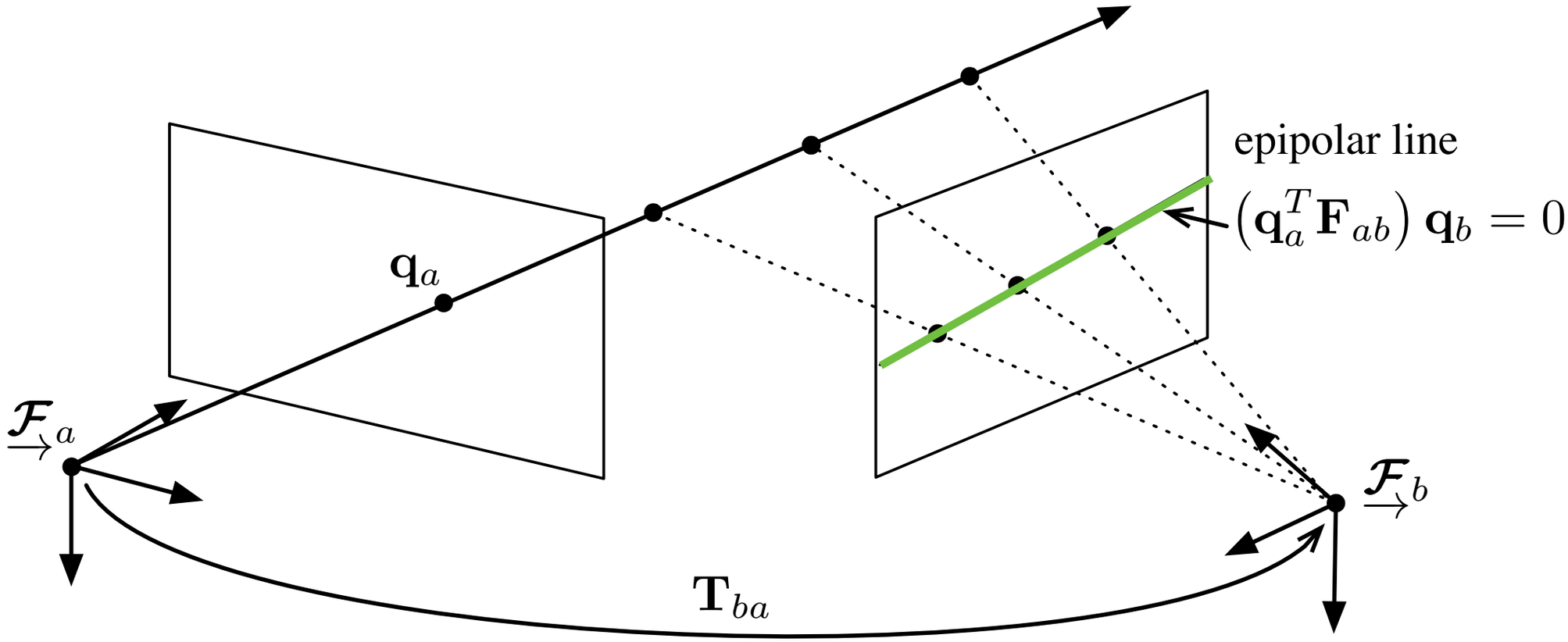
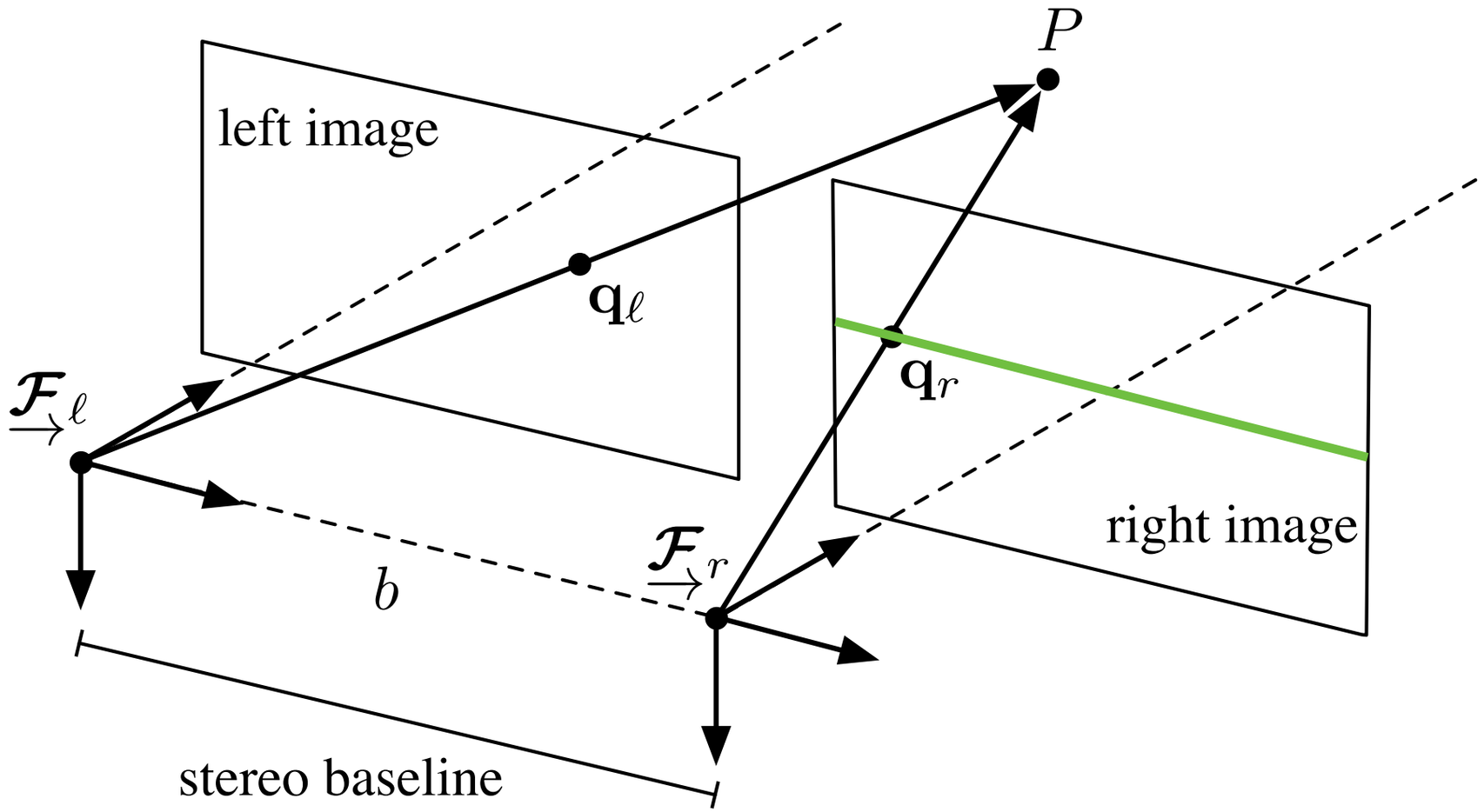
Multiview Geometry



Stereo Camera Model



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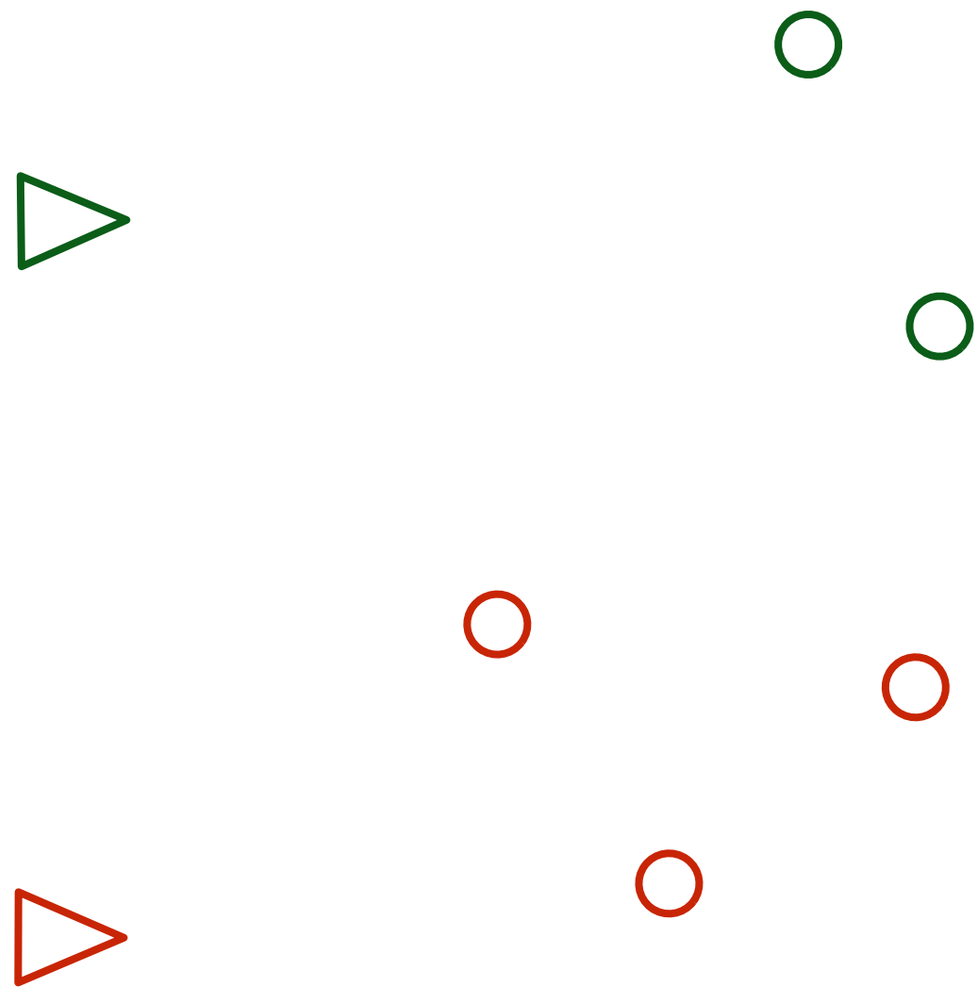
Stereo Visual Odometry

Stereo Visual Odometry



Stereo Visual Odometry

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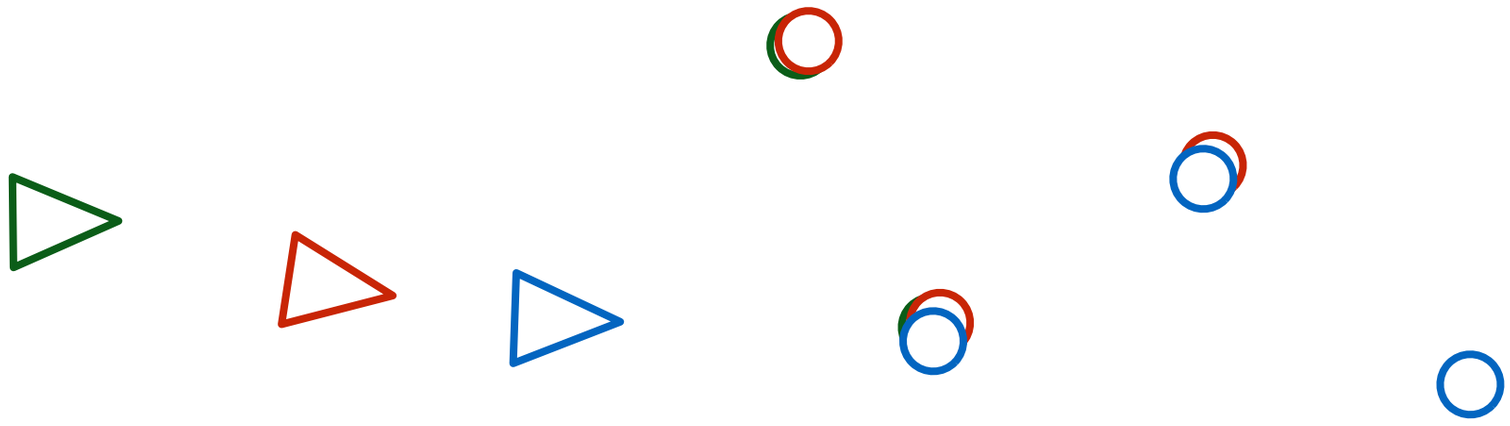

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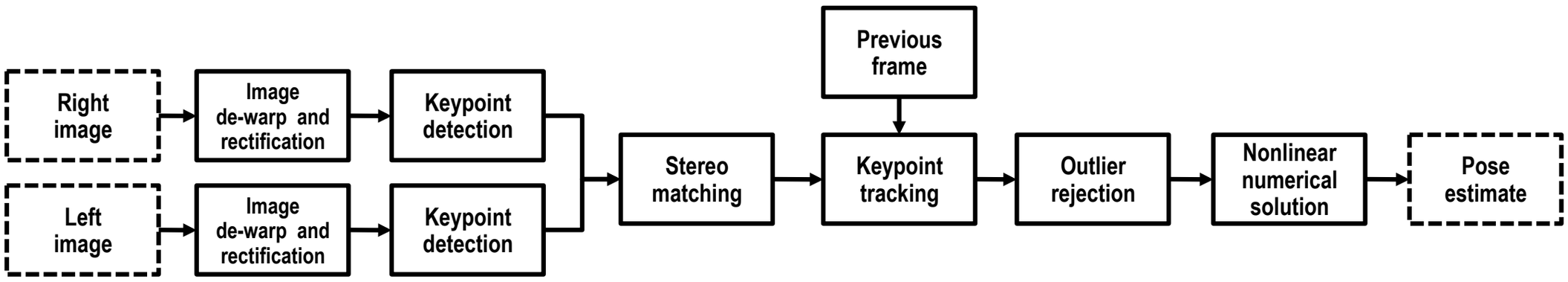
Stereo Visual Odometry Pipeline



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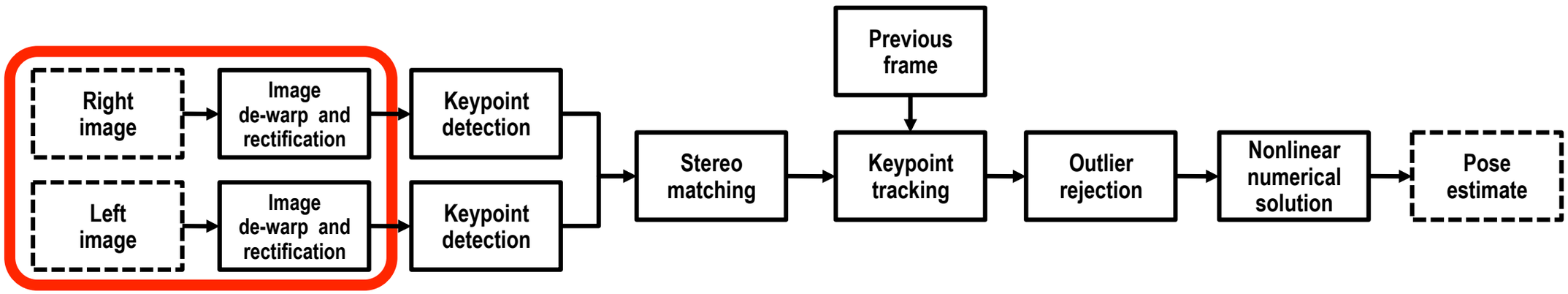
Stereo Visual Odometry Pipeline

Devon Island 2008



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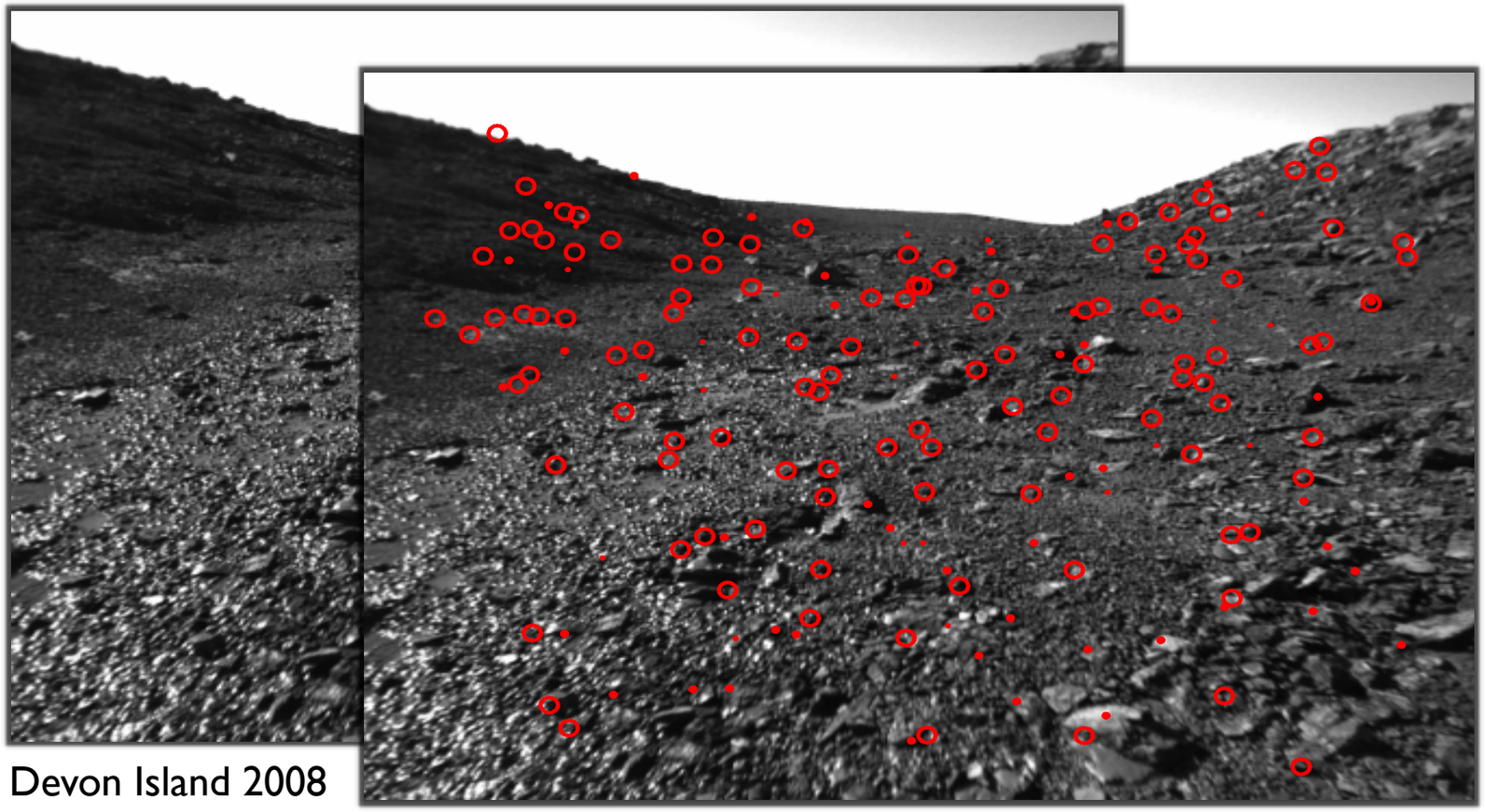

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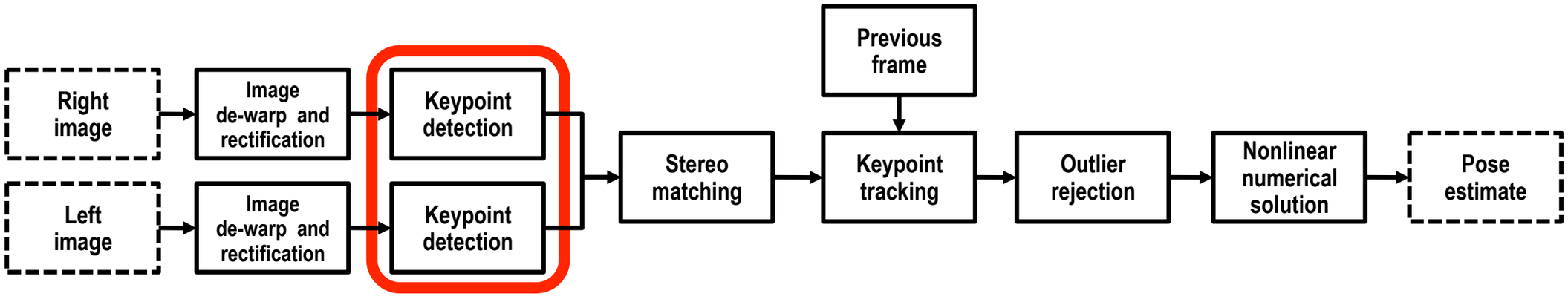

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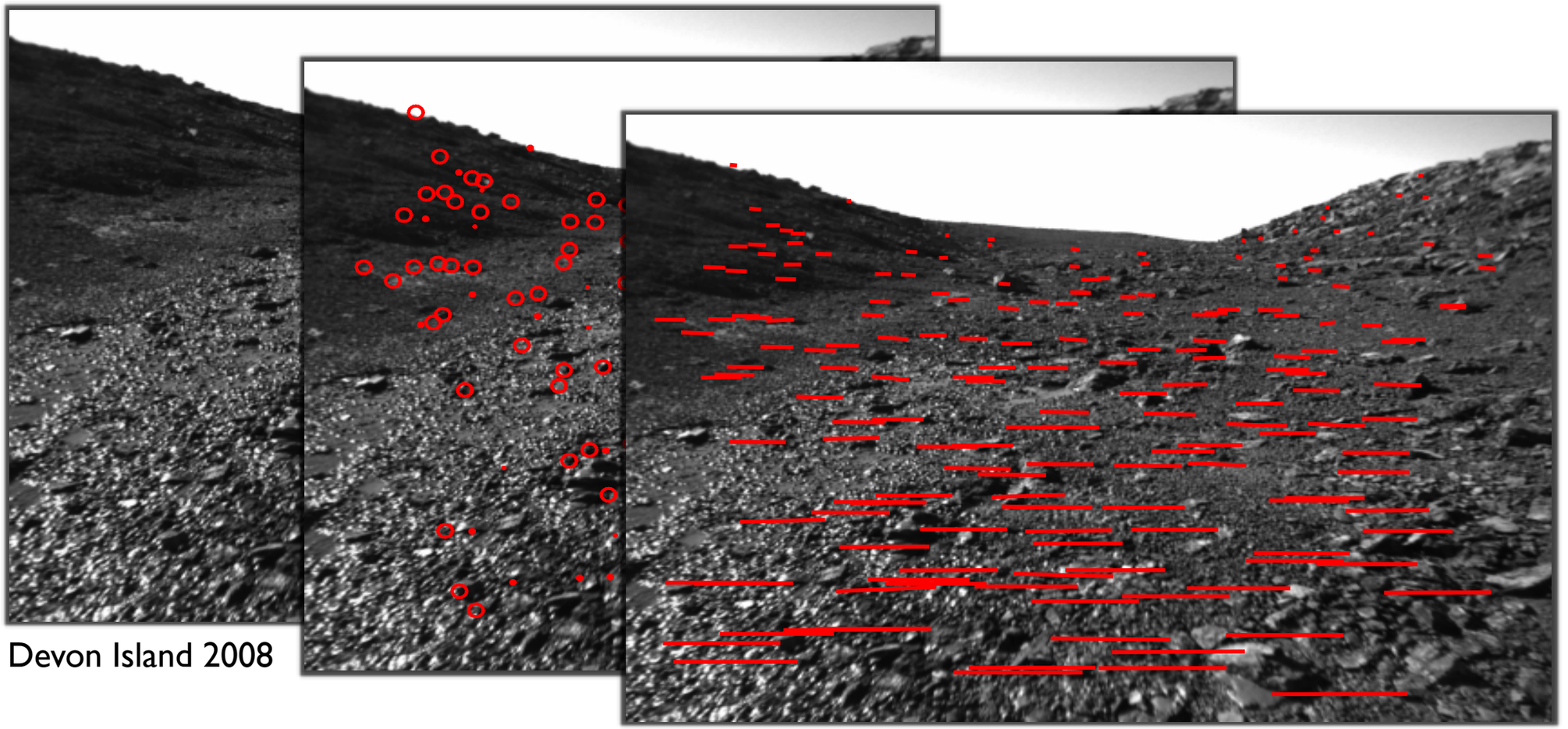

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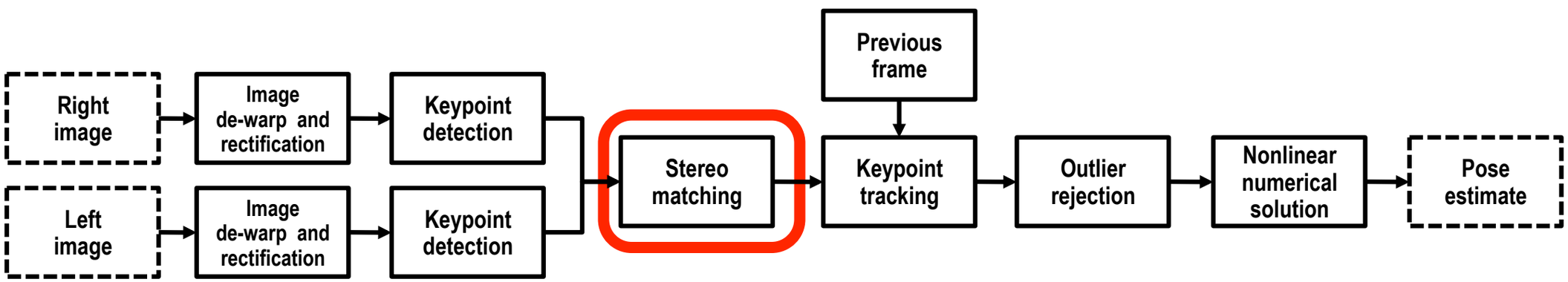

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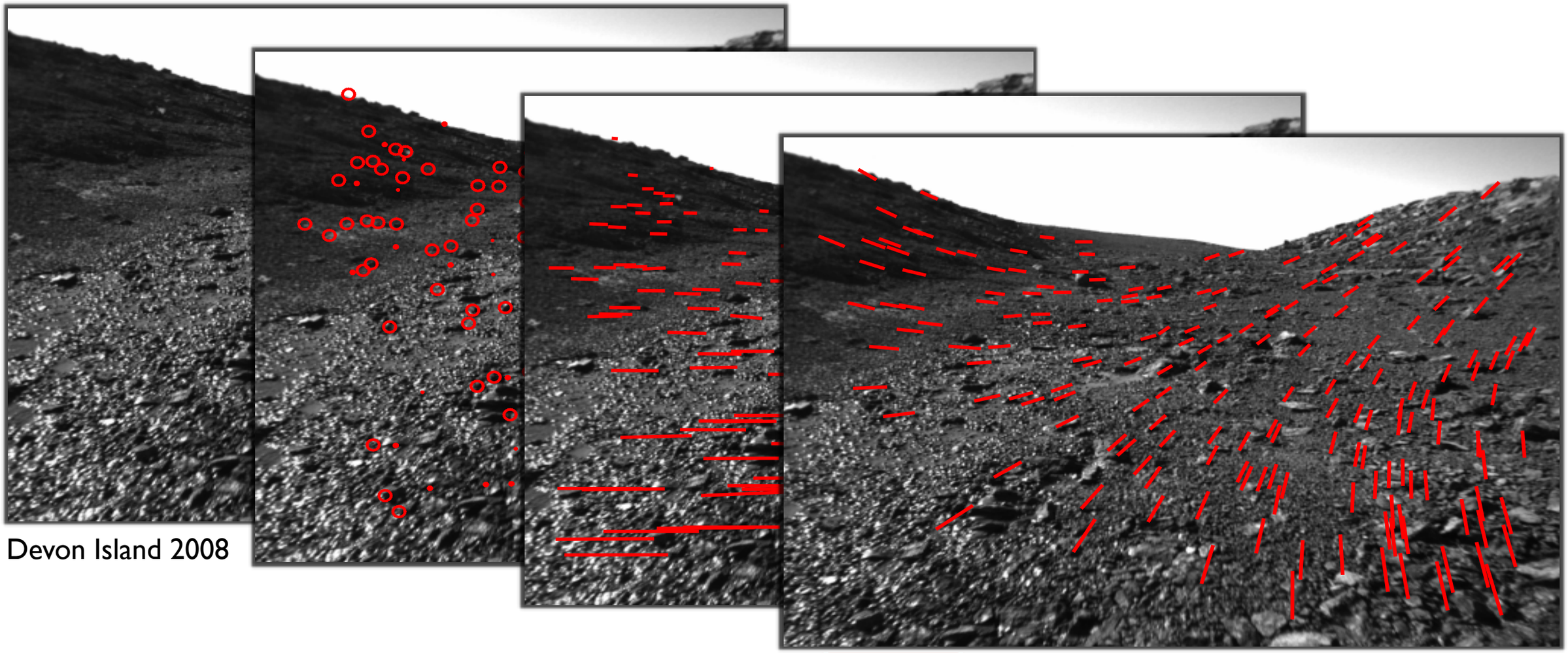

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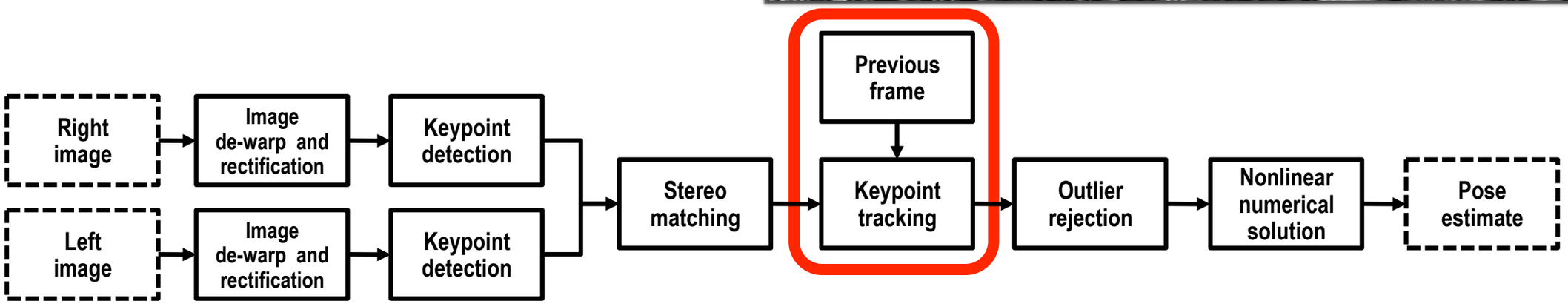

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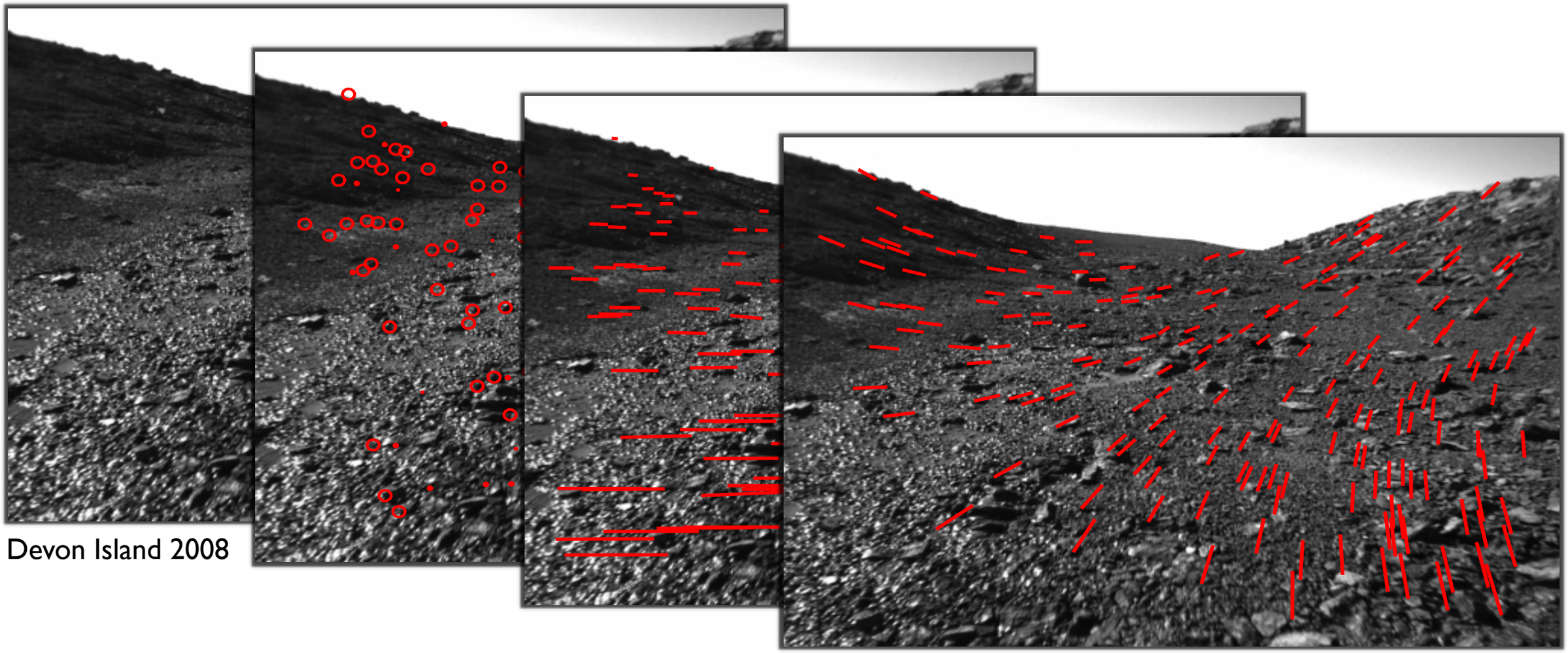

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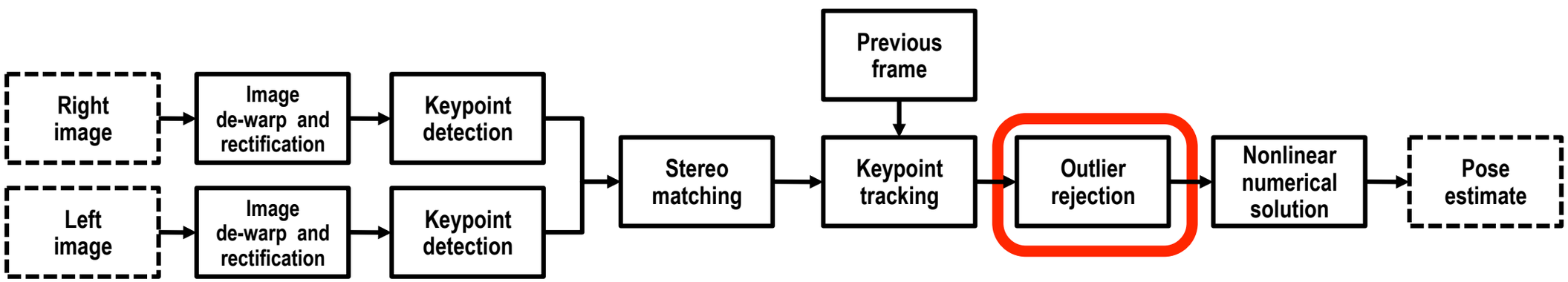

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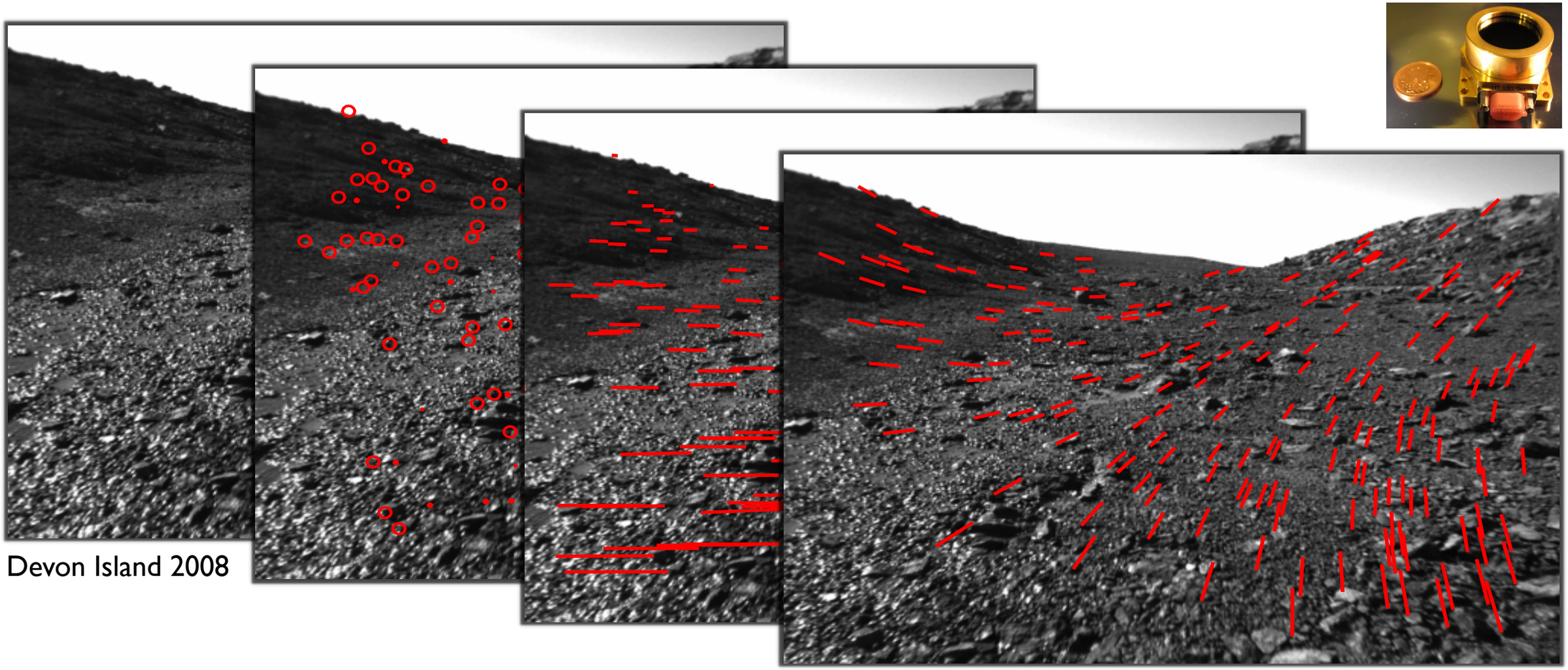

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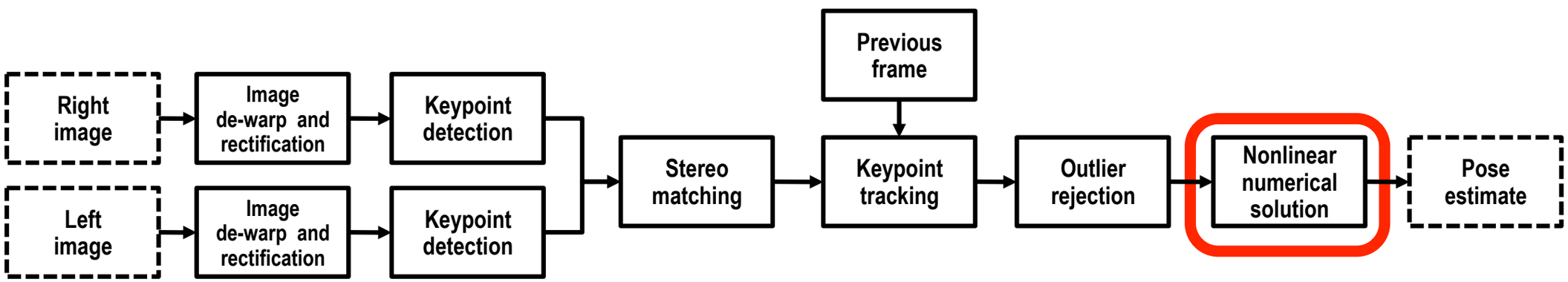

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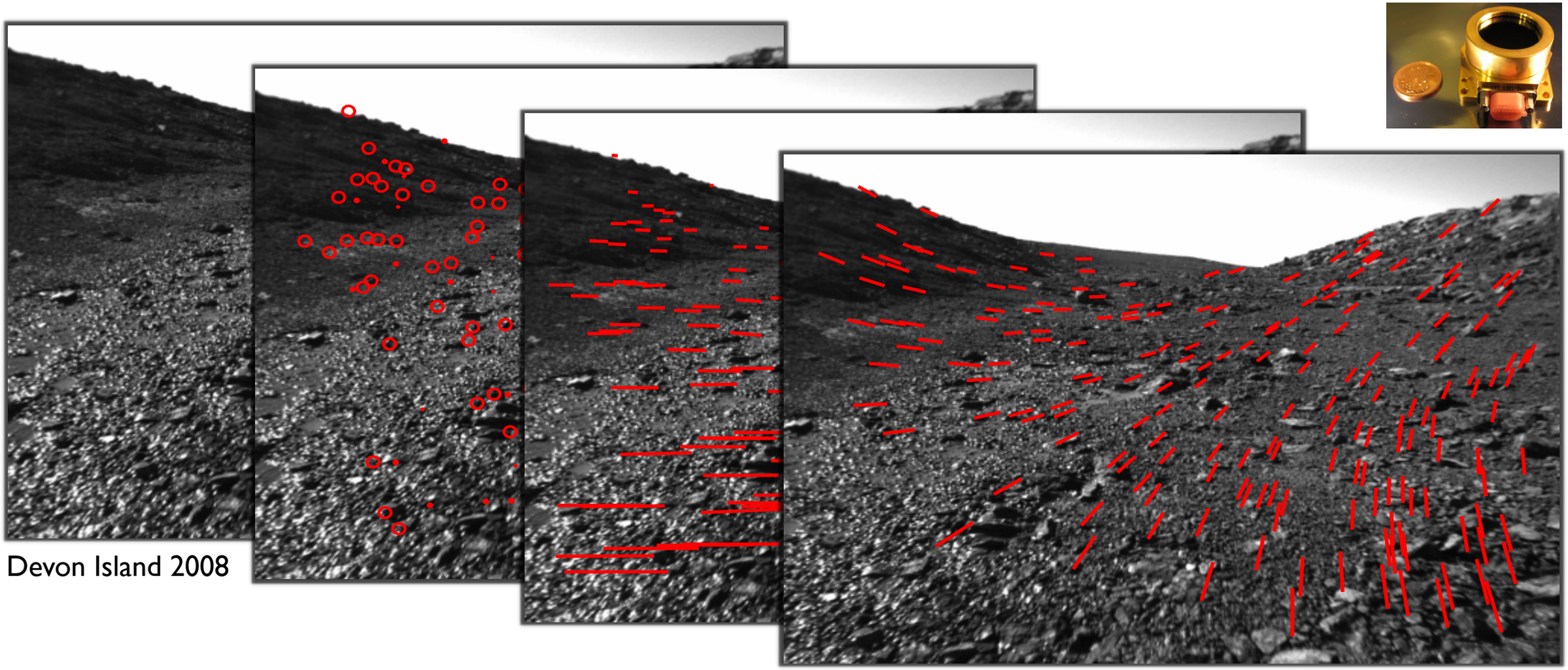

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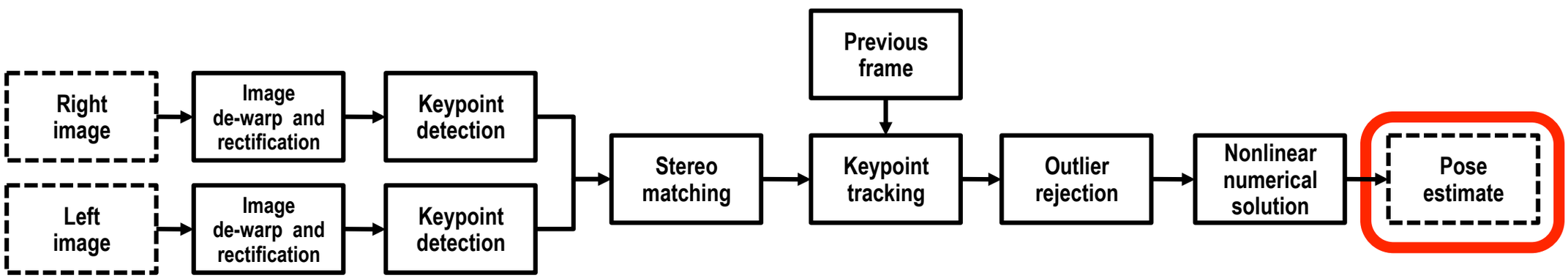

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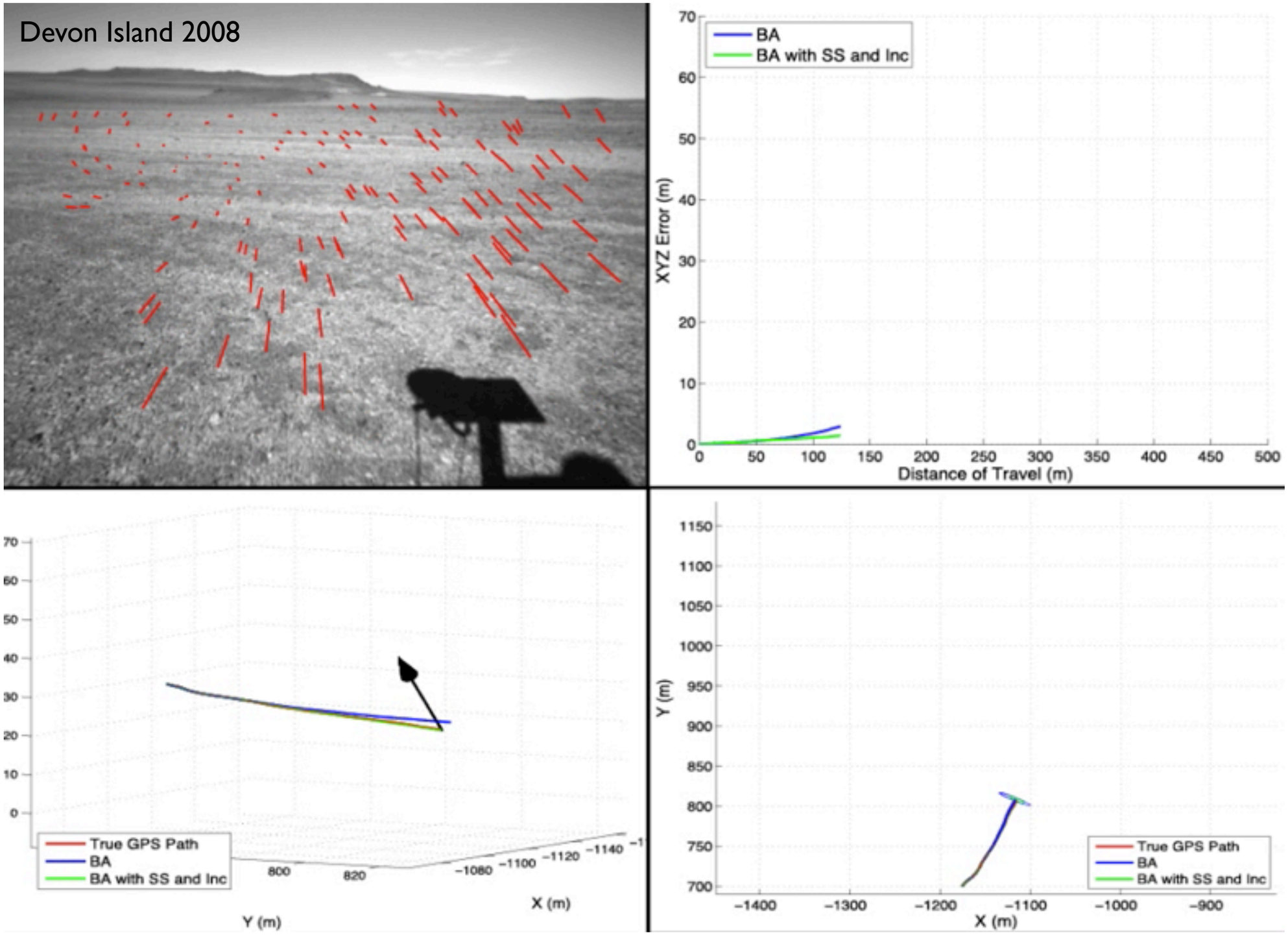
Stereo Visual Odometry Example



Lambert A, Furgale P T, Barfoot T D, and Enright J. “Field Testing of Visual Odometry Aided by a Sun Sensor and Inclinometer”. Journal of Field Robotics, 29(3):426–444, 2012.

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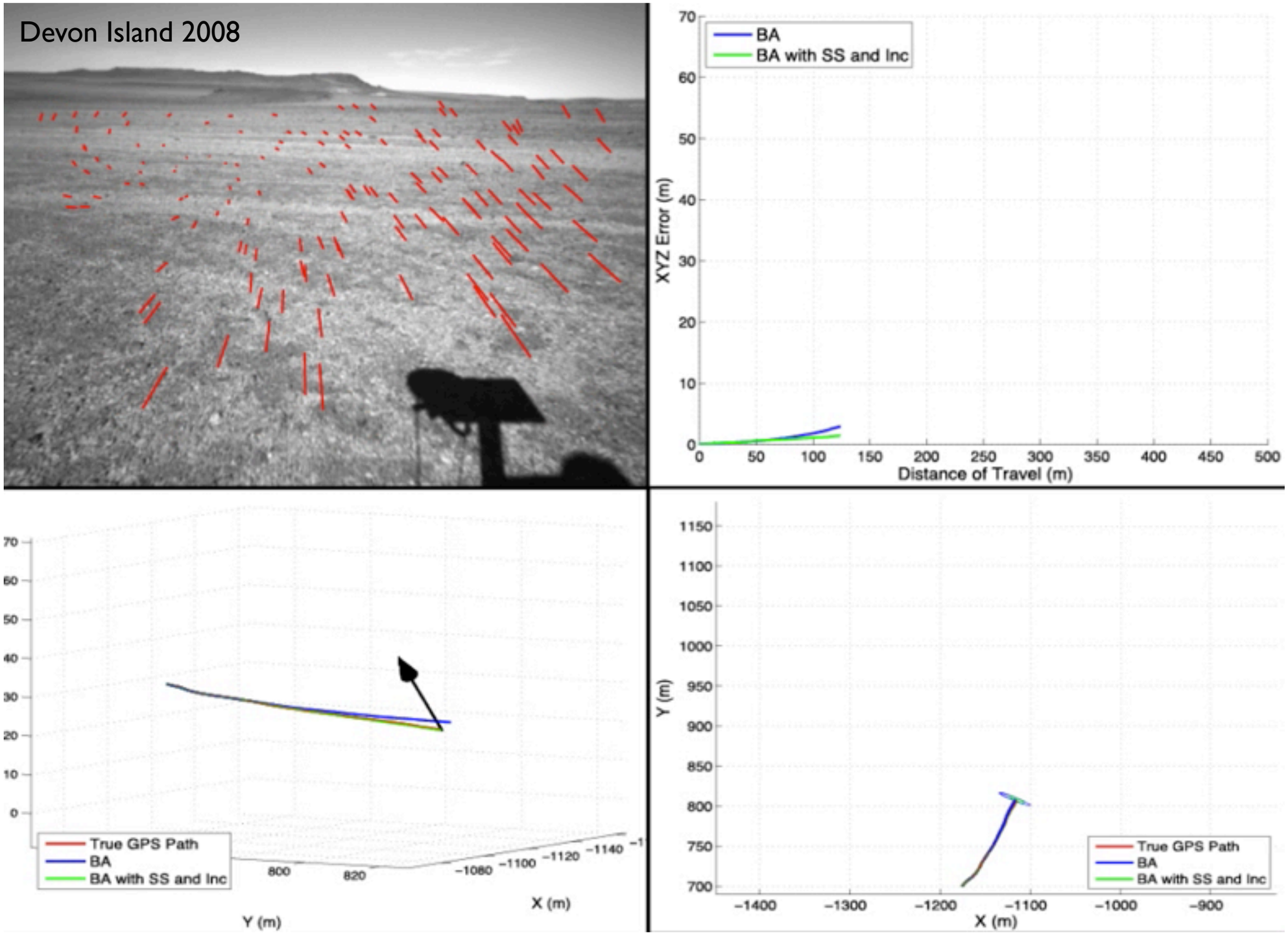

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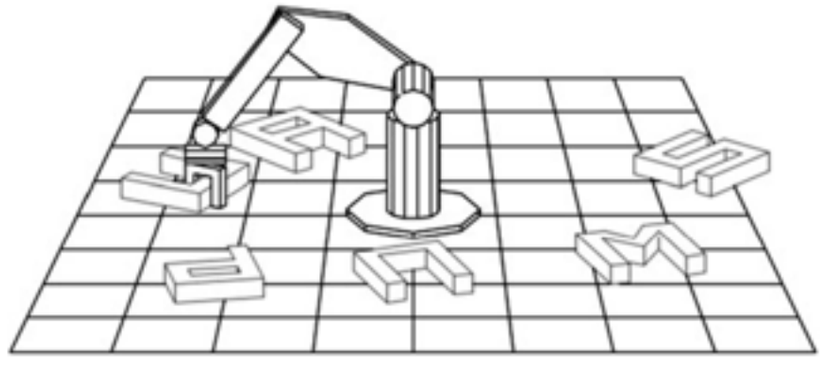
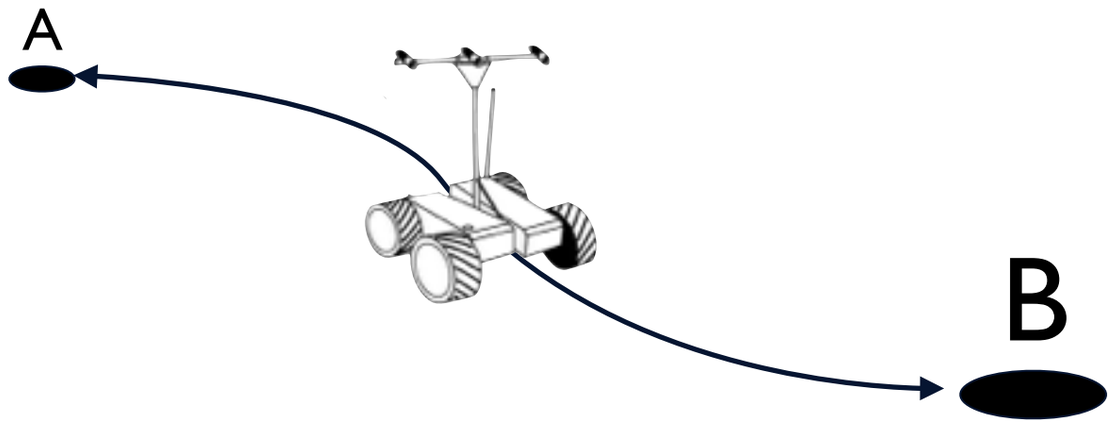
Building Blocks, Teach and Repeat

‘pick and place’



‘visual route following’



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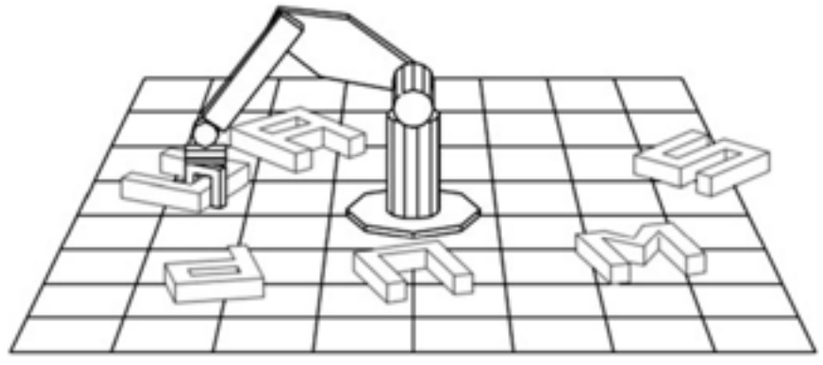
Building Blocks, Teach and Repeat

‘pick and place’



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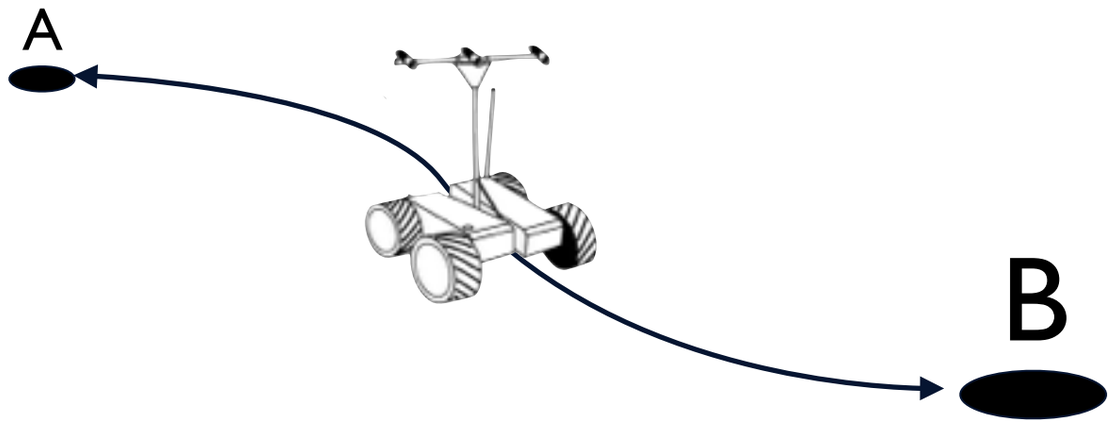

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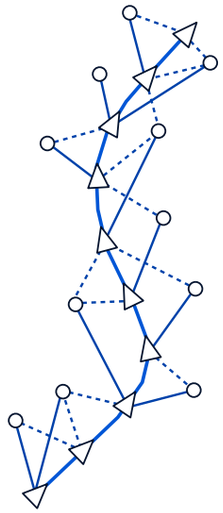
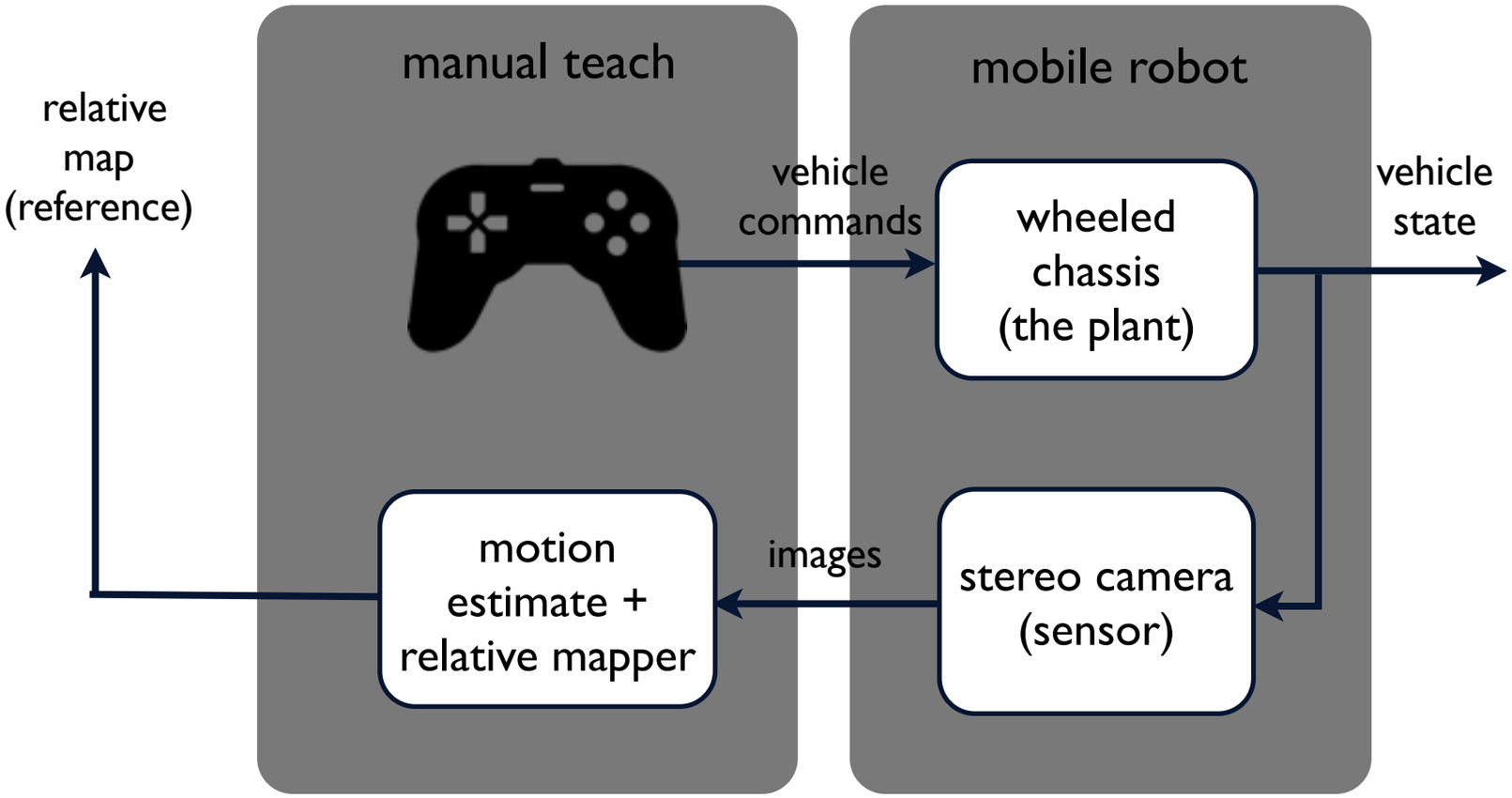
Teach Phase





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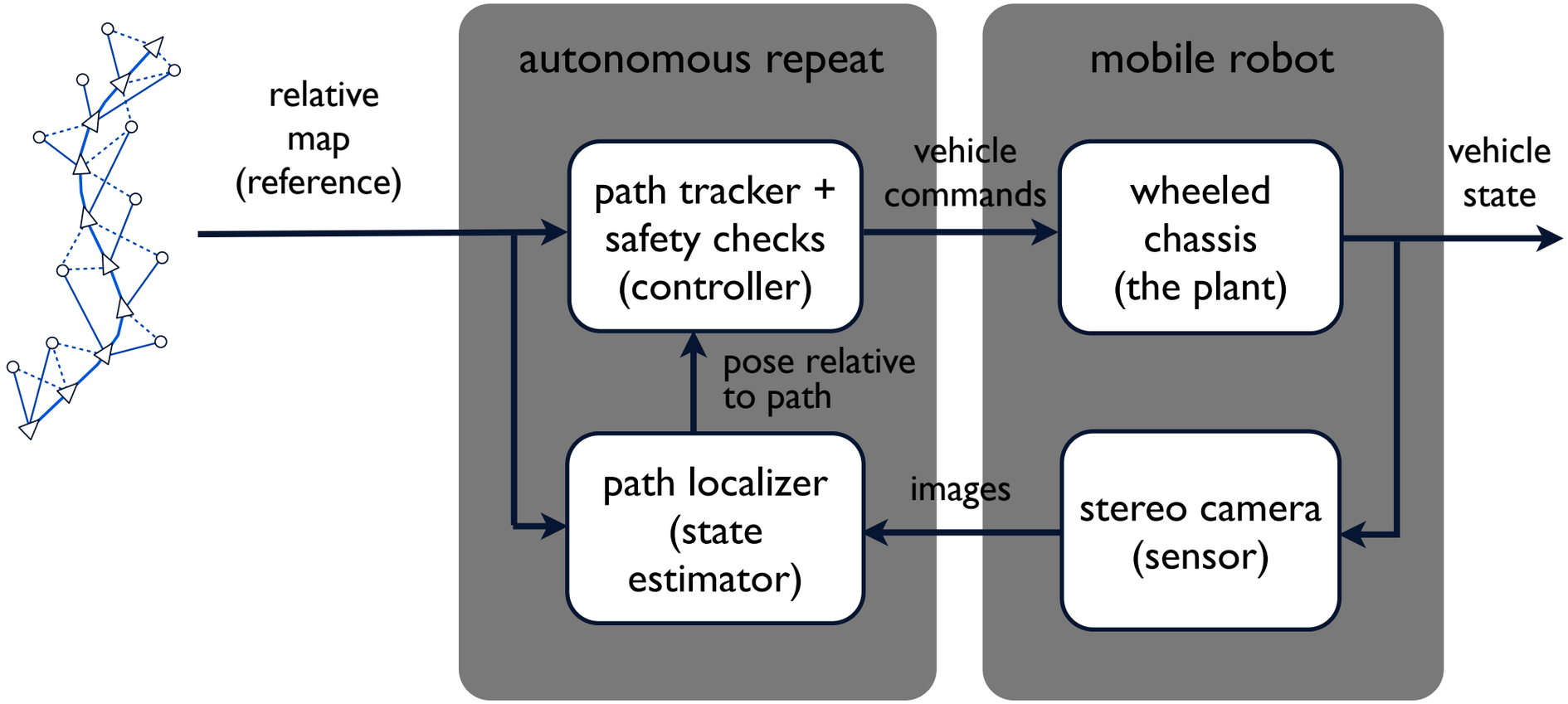
Repeat Phase



Furgale P T and Barfoot T D. “Visual Path Following on a Manifold in Unstructured Three-Dimensional Terrain”, ICRA 2010 Kuka Service Robotics Best Paper Award

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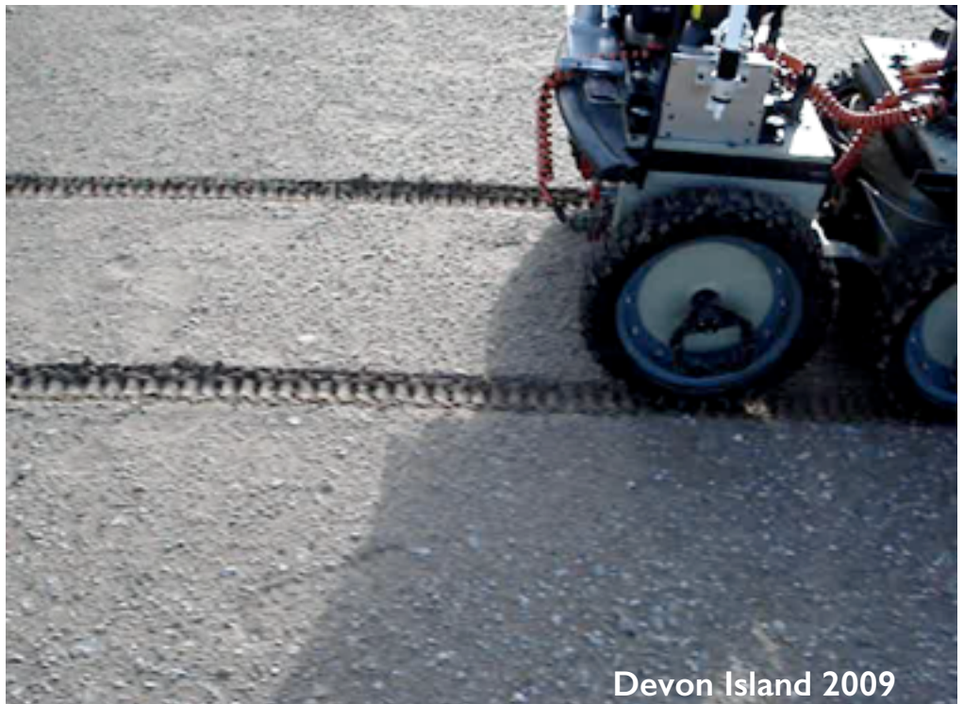
Devon Island 2009

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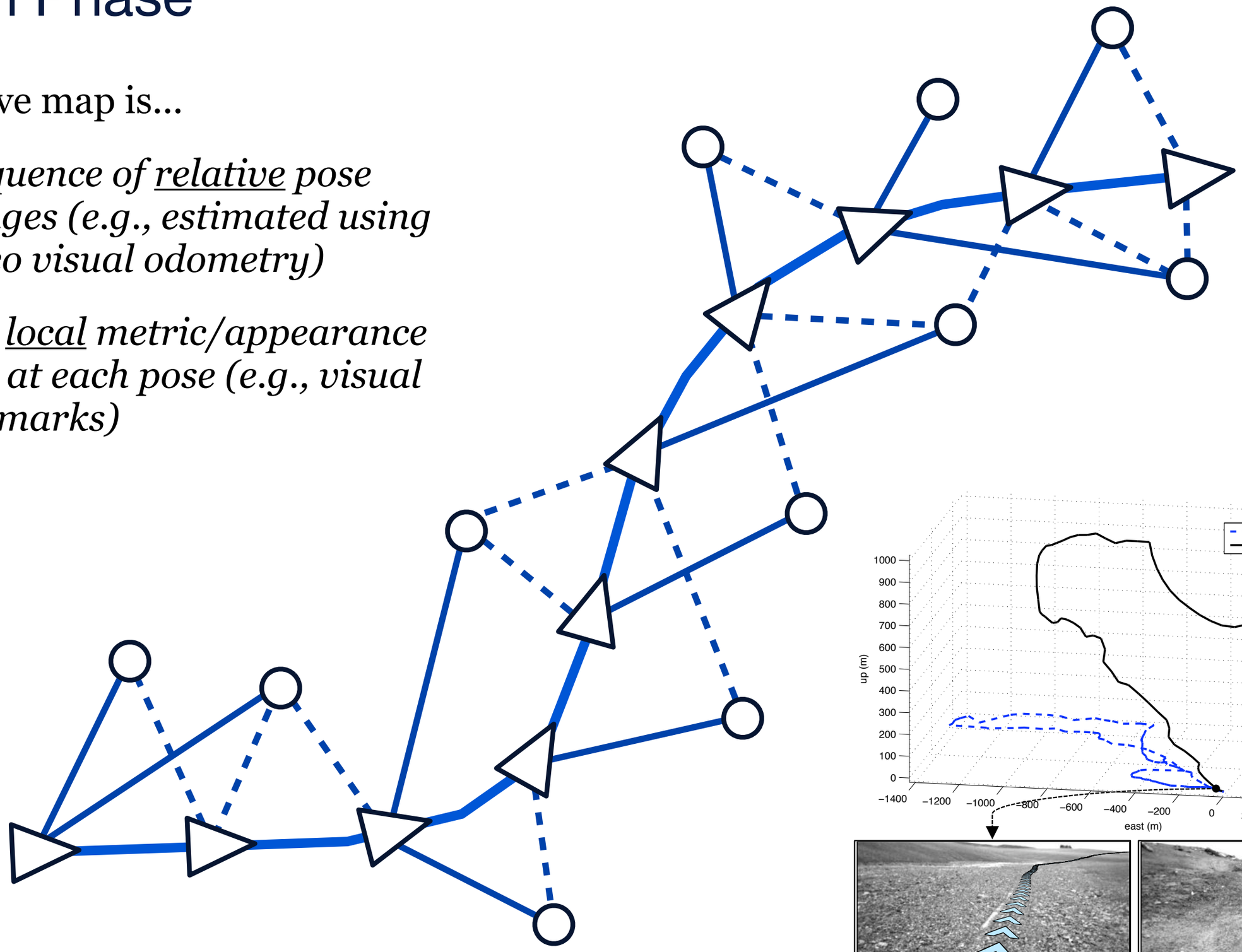
Teach Phase

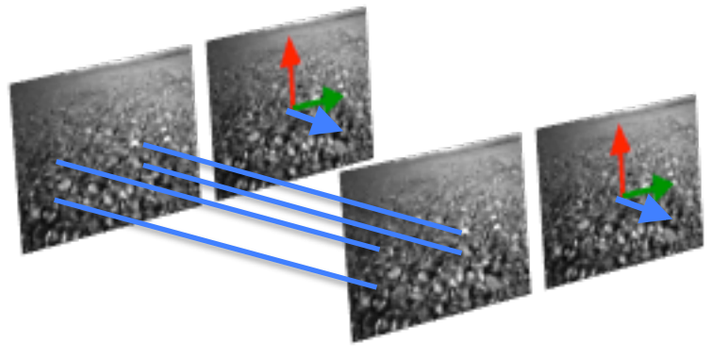
A relative map is…

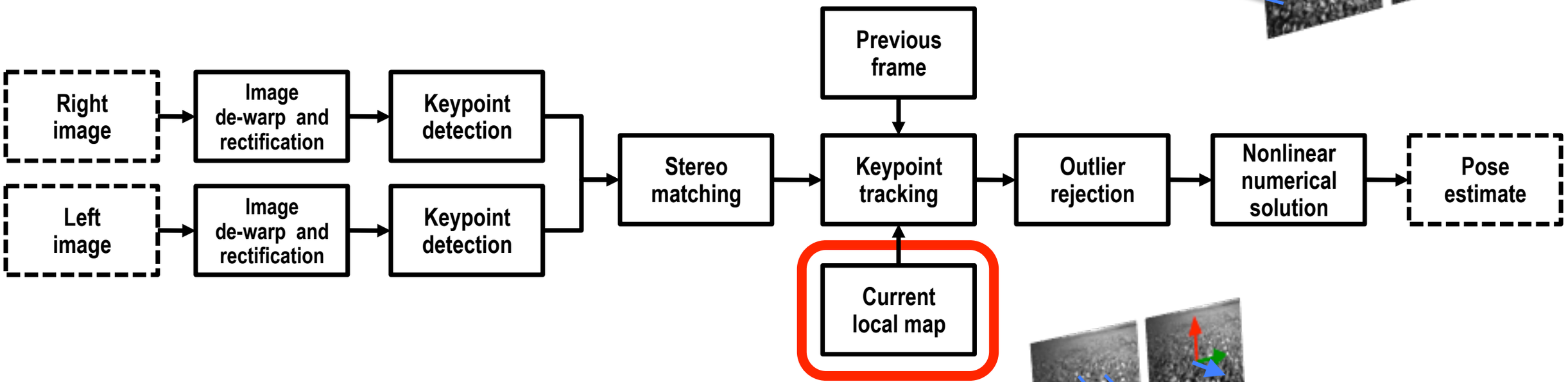
- *a sequence of relative pose changes (e.g., estimated using stereo visual odometry)*
- *with local metric/appearance data at each pose (e.g., visual landmarks)*



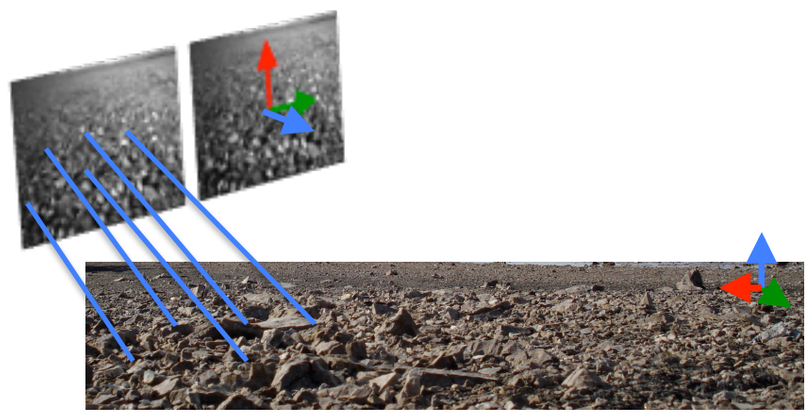
Repeat Phase: Path Localizer

- matching against the previous frame is still performed to carry the system past areas where map matching fails
  - *helps with lighting variations*

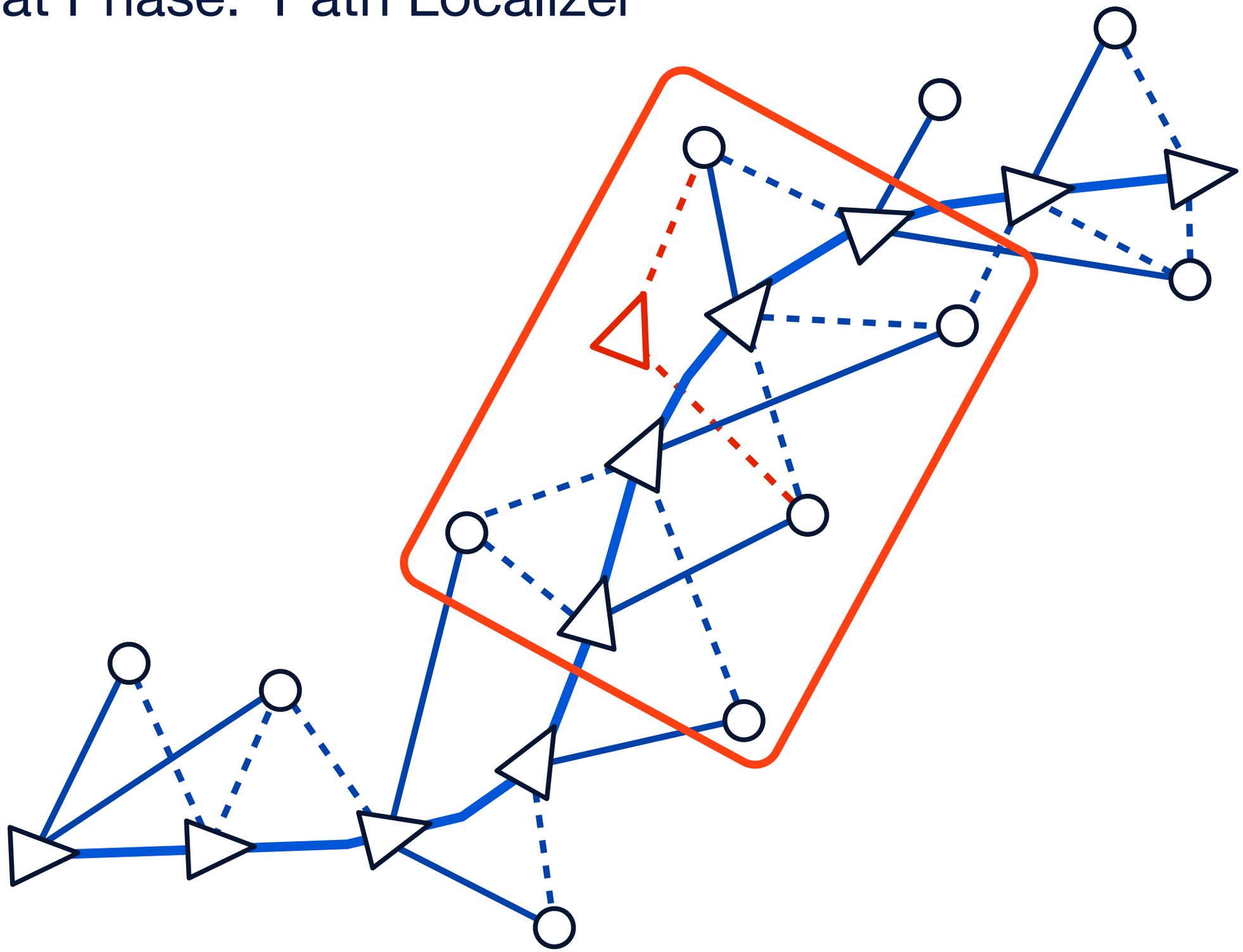




- we also match against the current local map gathered during teaching phase
  - *maps are loaded from disk as needed*



Repeat Phase: Path Localizer



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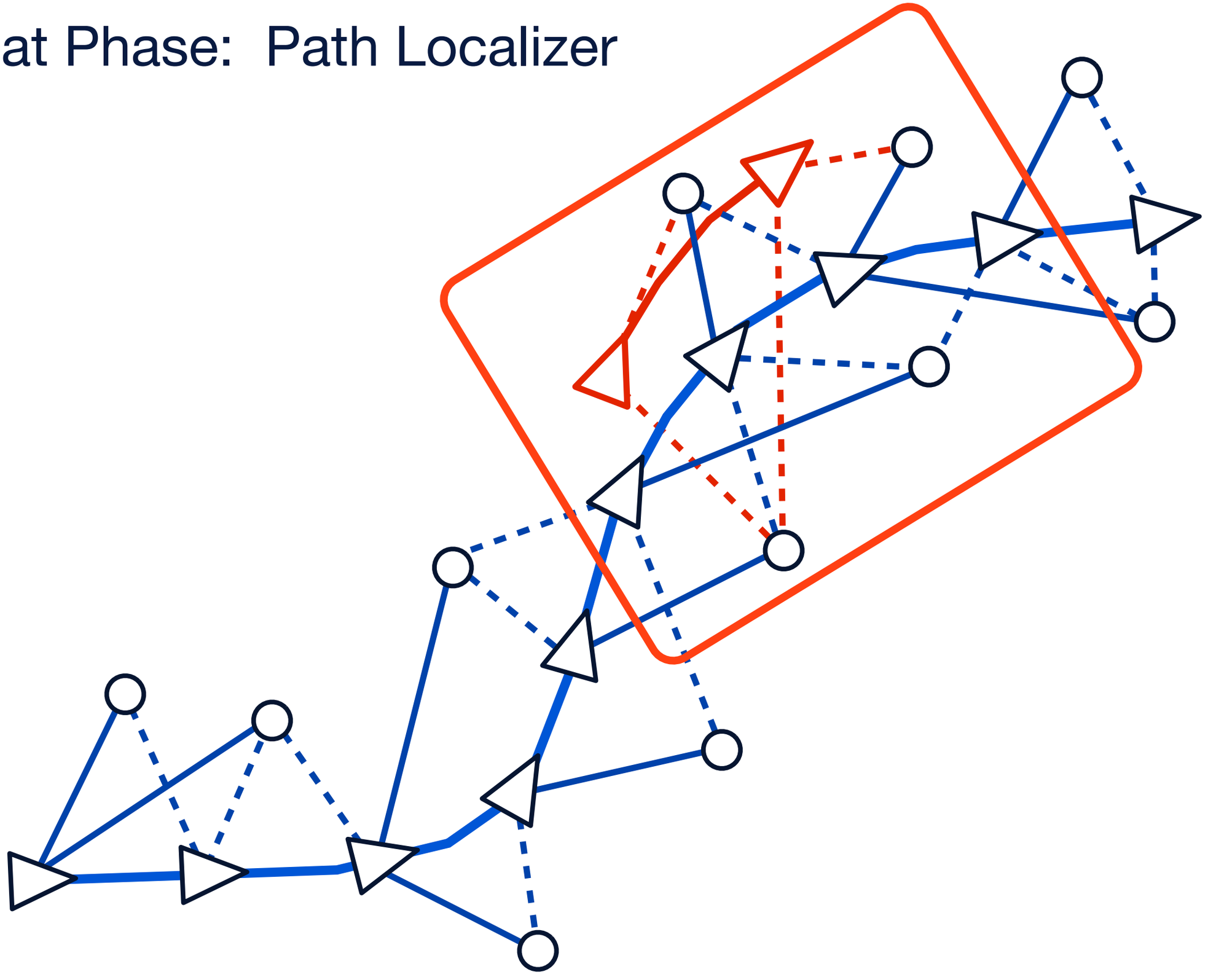
Repeat Phase: Path Localizer



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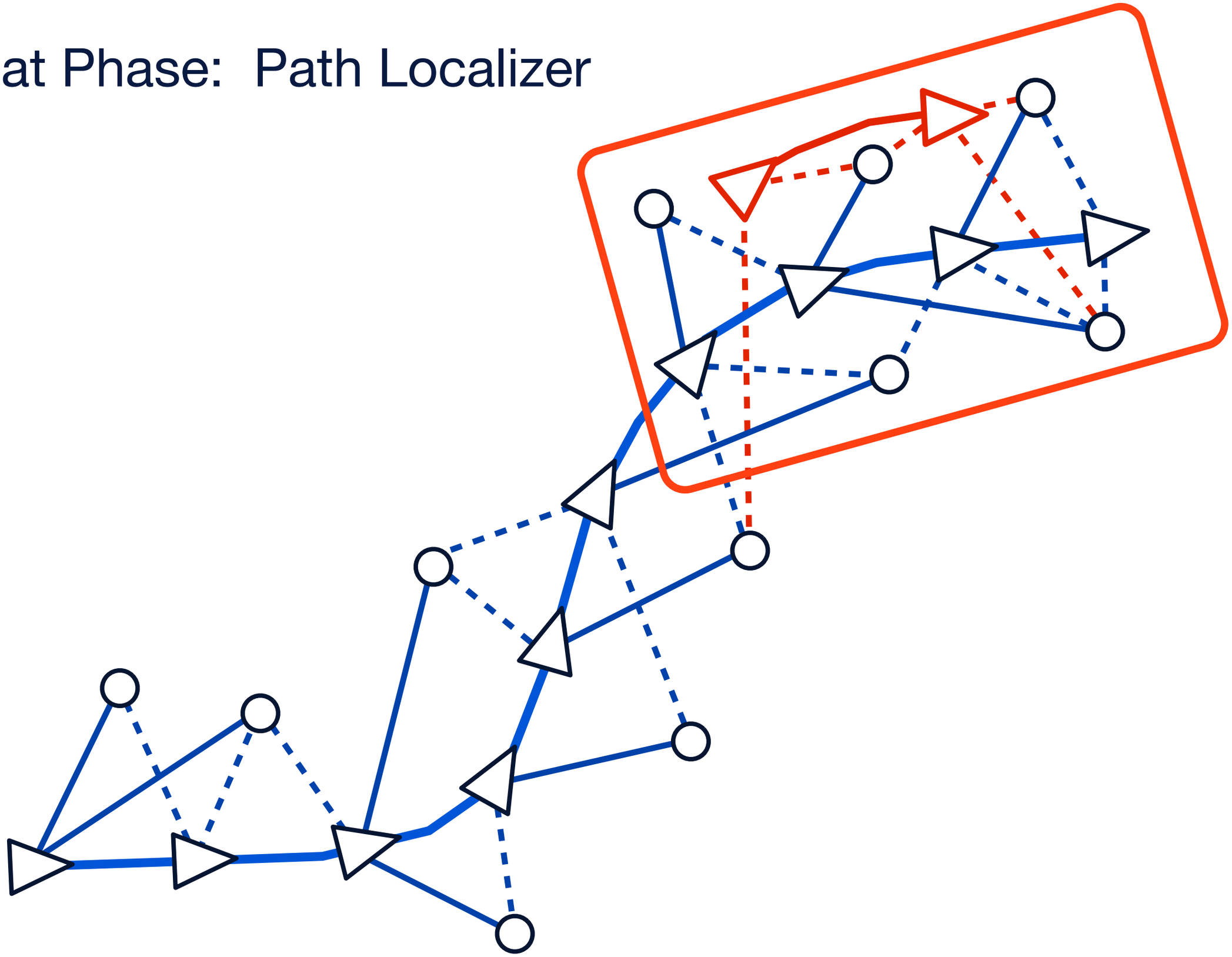
Repeat Phase: Path Localizer



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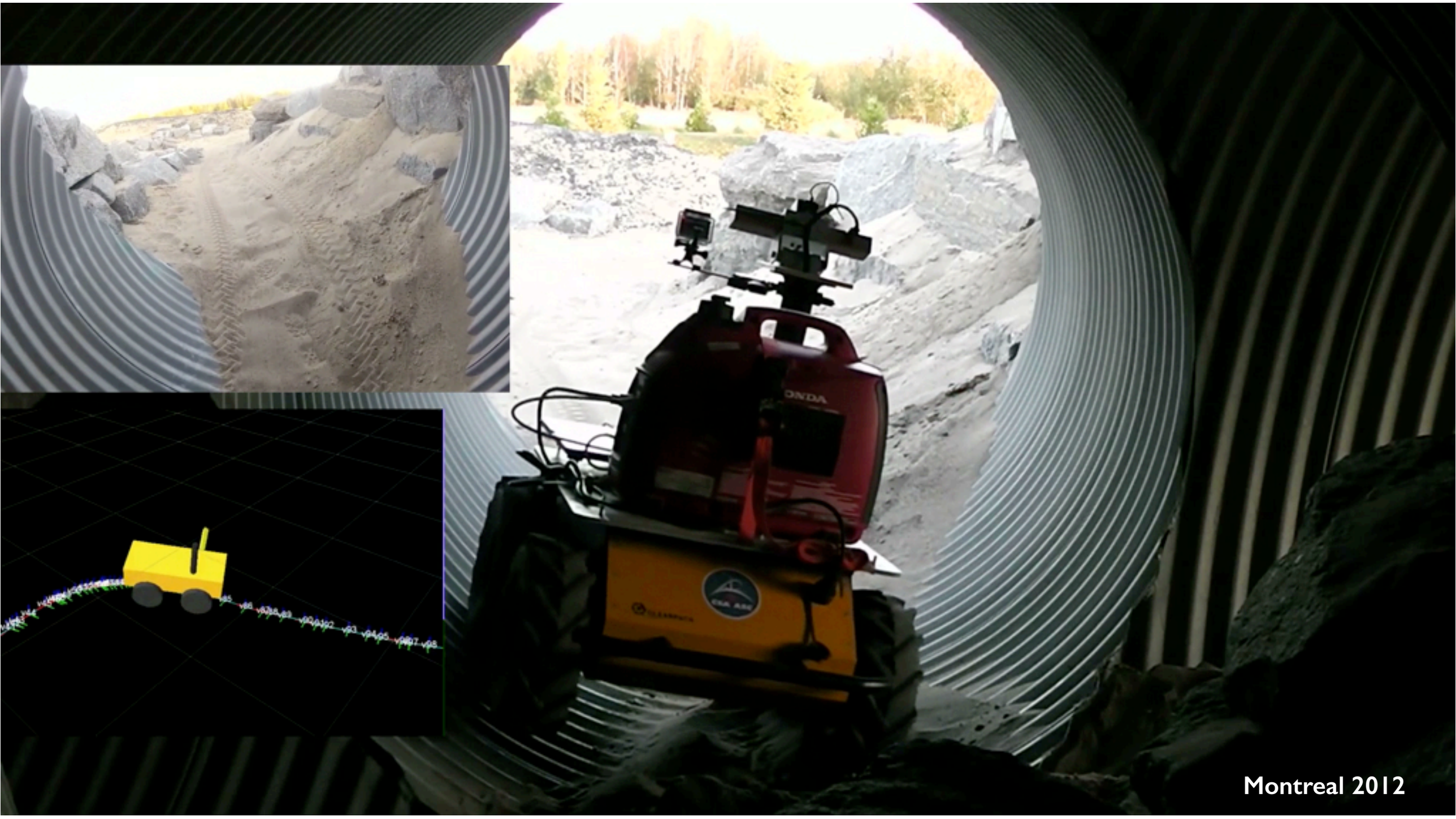
Stereo VT&R Example



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Furgale P T and Barfoot T D. “Visual Teach and Repeat for Long-Range Rover Autonomy”, JFR 2010

Stereo VT&R Example

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VT&R ➜ Network of Reusable Paths

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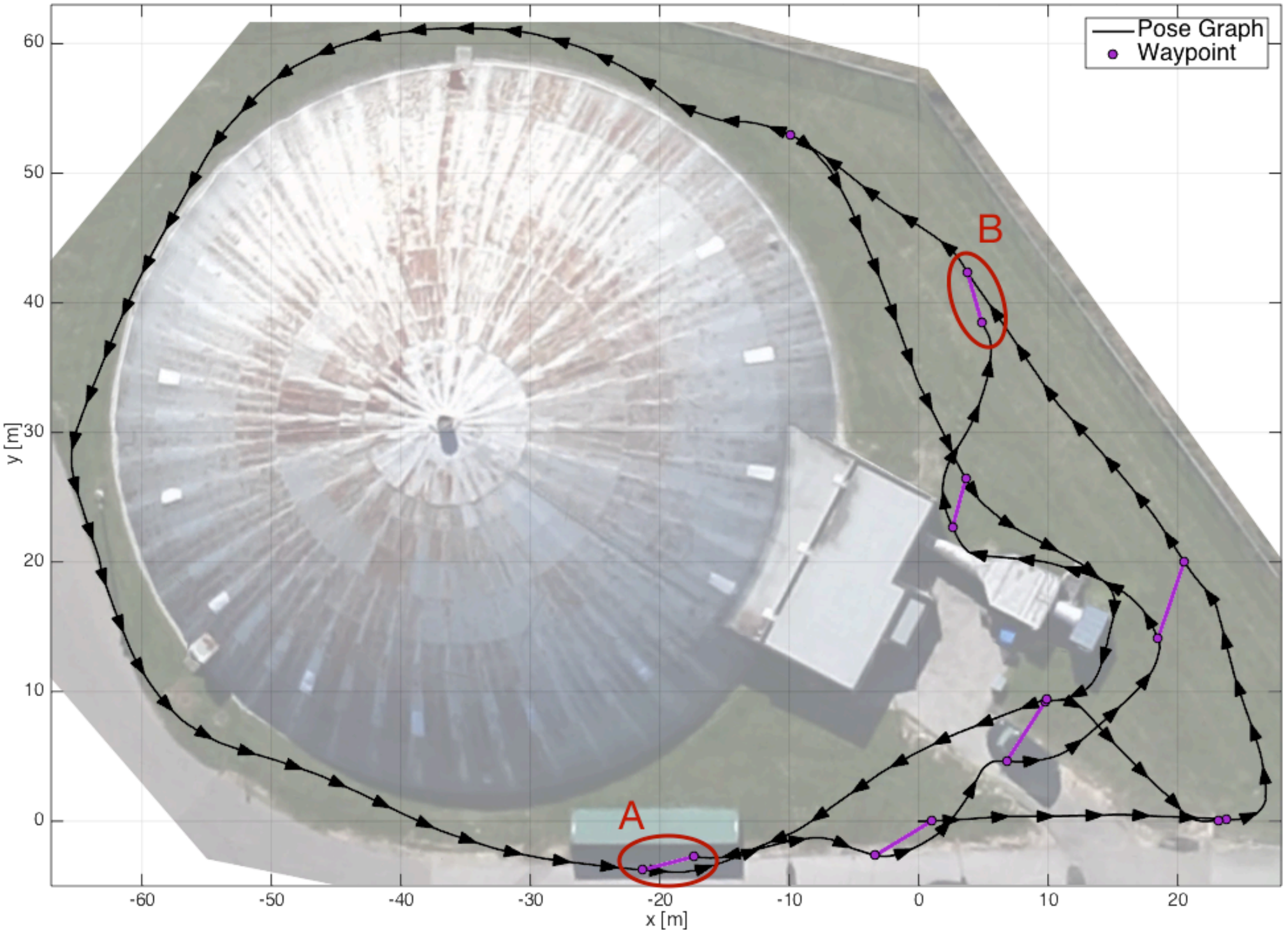
Stenning B E, McManus C, and Barfoot T D. “Planning using a Network of Reusable Paths: A Physical Embodiment of a Rapidly Exploring Random Tree”, JFR 2013

VT&R ➜ Network of Reusable Paths



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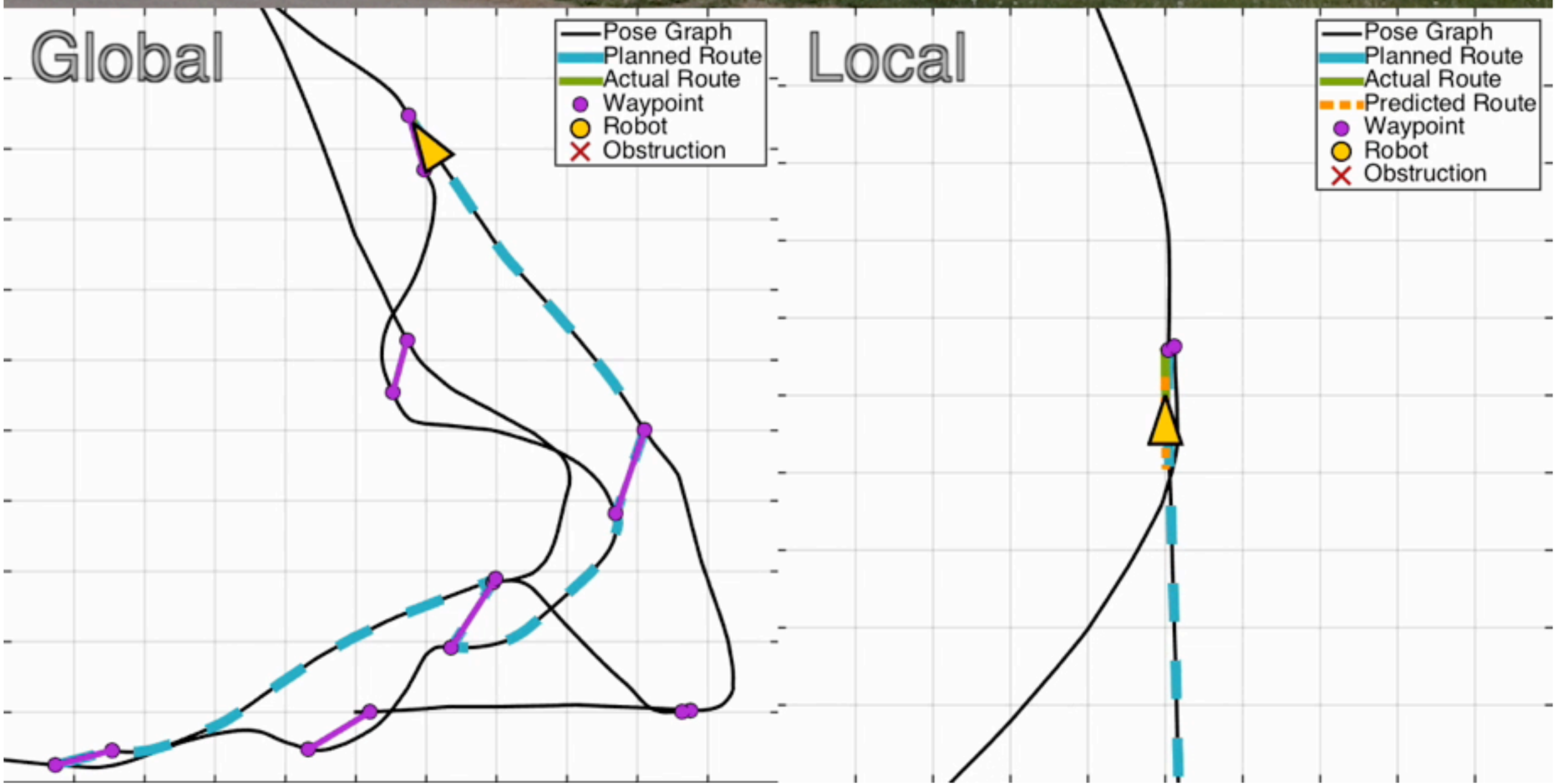
van Es S K and Barfoot T D. “Being in Two Places at Once: Smooth Visual Path Following on Globally Inconsistent Pose Graphs”, CRV 2015

VT&R ➜ Network of Reusable Paths



VT&R Gallery











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Visual Route Following Pros and Cons

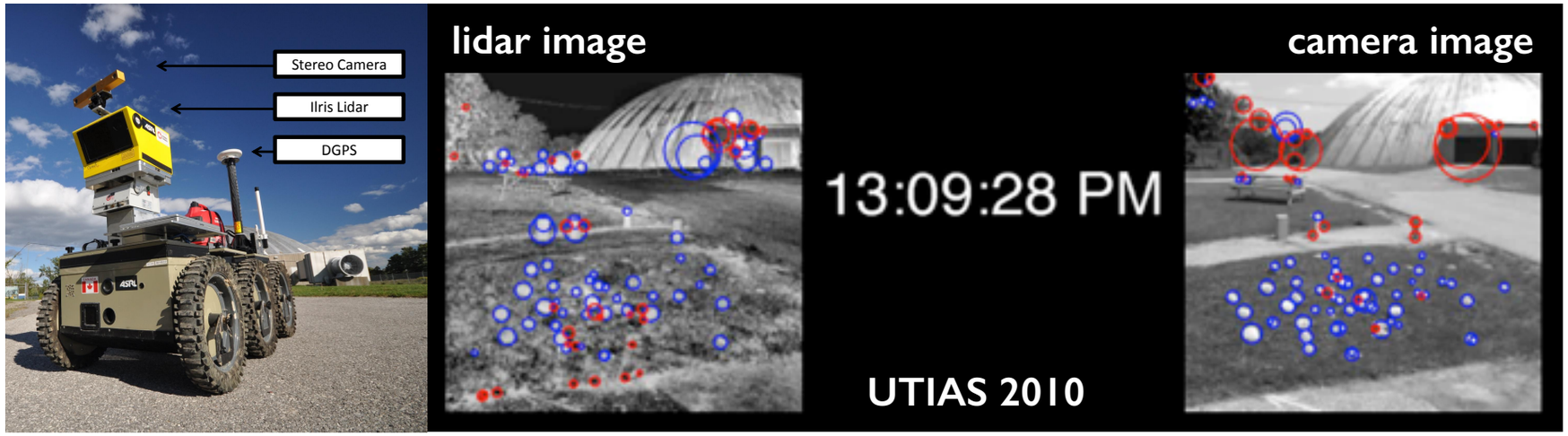
PROS

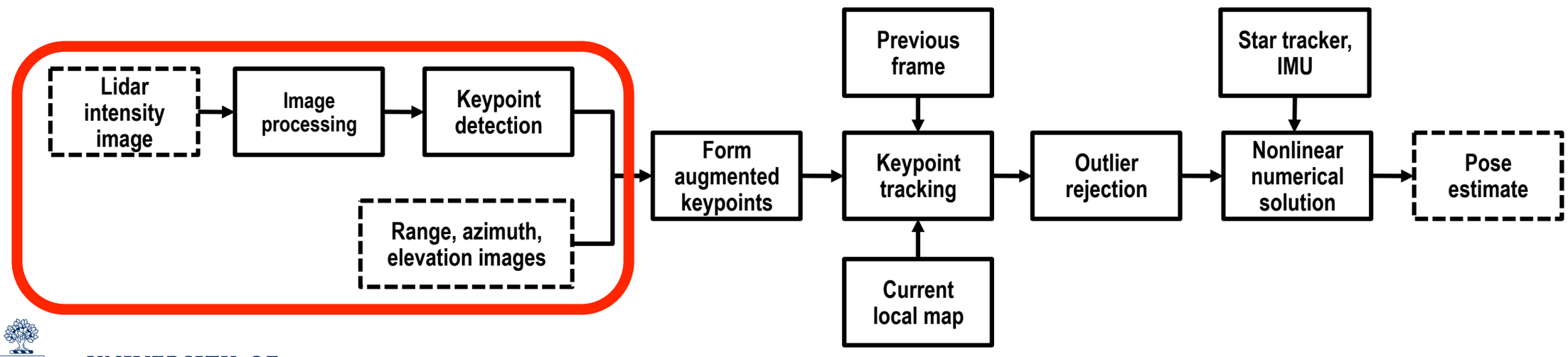
- low-computational-cost point-to-point autonomous driving in GPS-denied environments
- exploits human experience for in-situ path planning
- exploits strengths of computer vision by keeping viewpoints the same between mapping and localization

CONS

- scene appearance can change (e.g., lighting, weather)
- scene geometry can change (e.g., vegetation growth, construction)

Lighting-Invariant VT&R using Lidar Intensity Images





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McManus, Furgale, Stenning, and Barfoot, "Lighting-Invariant Visual Teach and Repeat Using Appearance-Based Lidar", ICRA 2012 ⇒ JFR 2013

ABL VT&R Example

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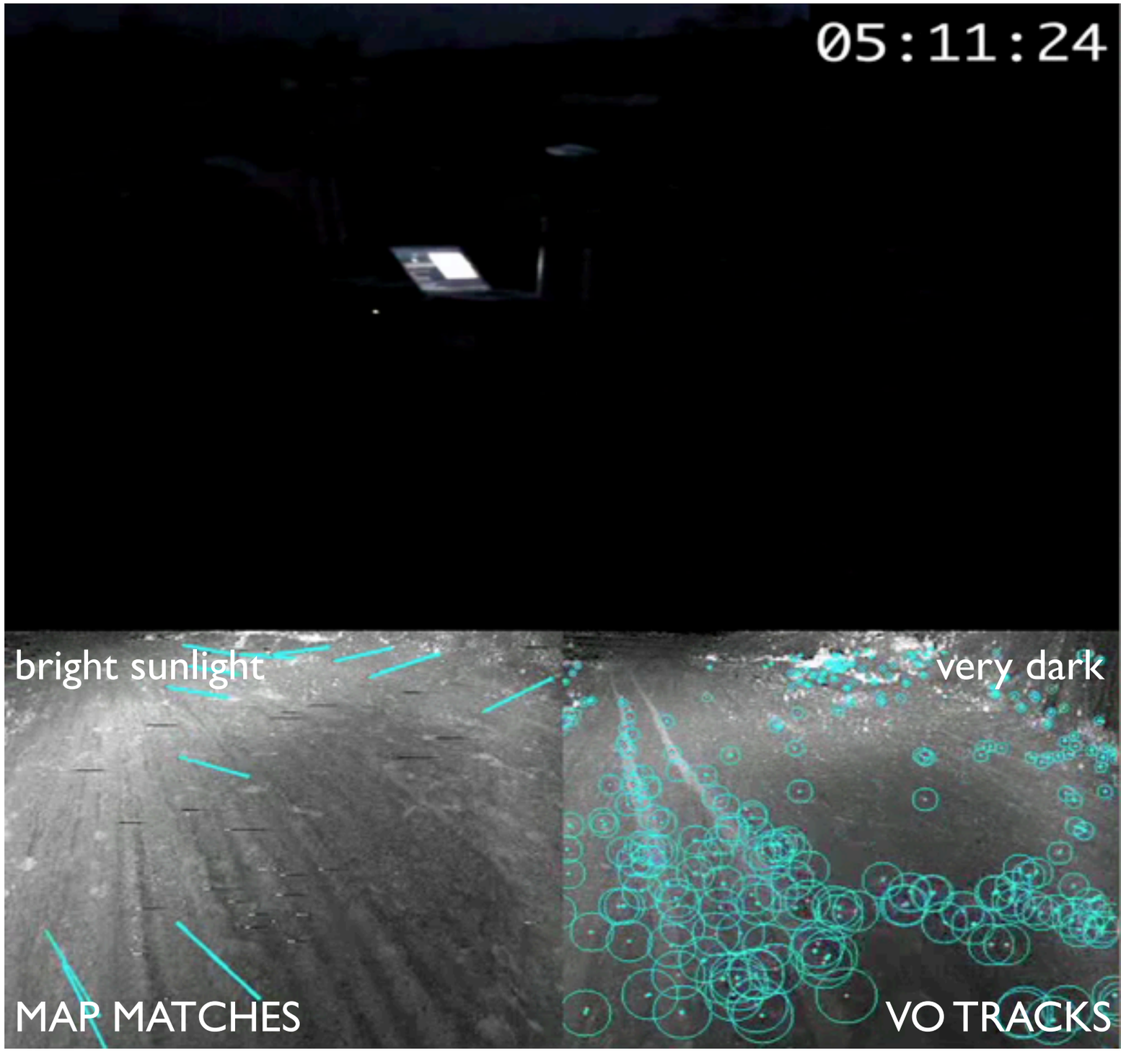
Lighting-Invariant VT&R using Lidar Intensity Images



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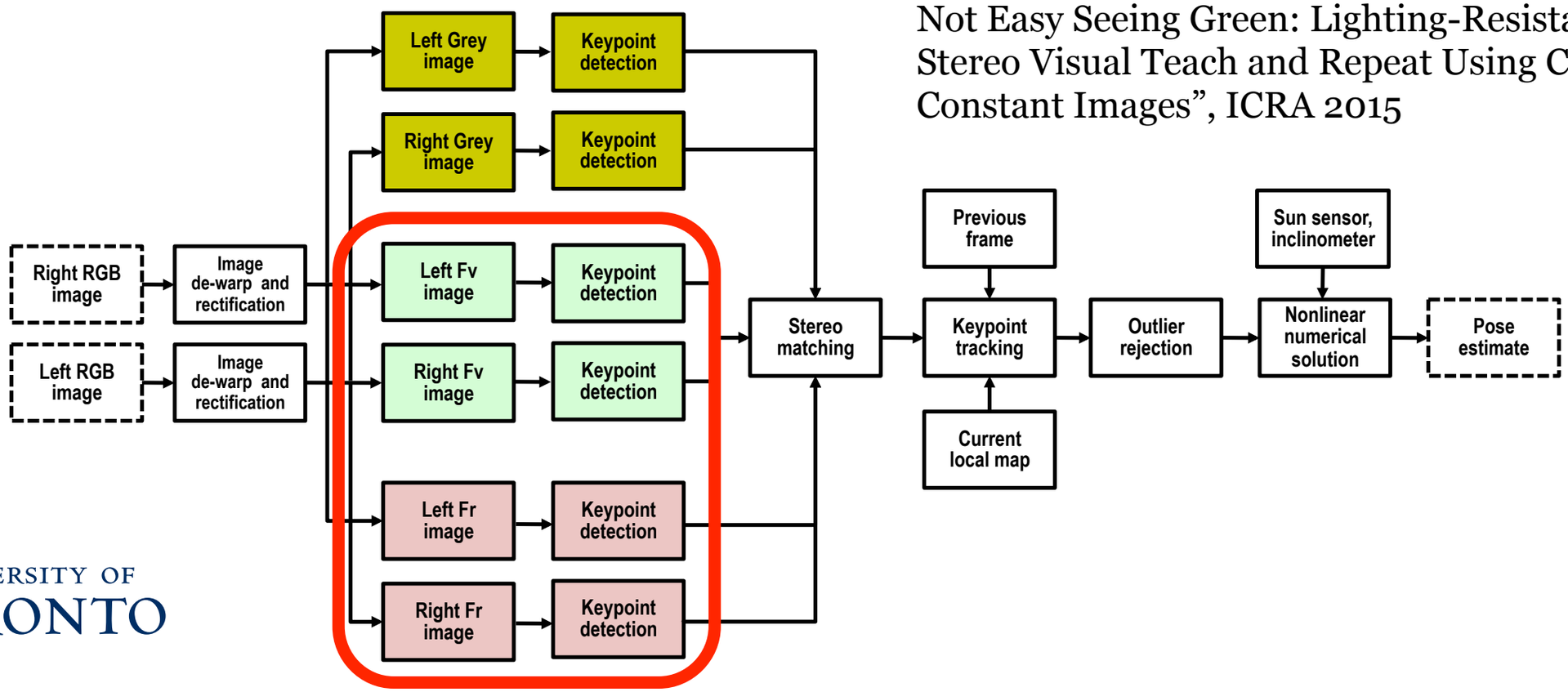
Lighting-Resistant Stereo VT&R using Colour-Constant Images

Colin McManus, Winston Churchill, Will Maddern, Alex Stewart and Paul Newman, “Shady Dealings: Robust, Long-Term Visual Localisation using Illumination Invariance”, ICRA 2014

Peter Corke, Rohan Paul, Winston Churchill and Paul Newman, “Dealing with Shadows: Capturing Intrinsic Scene Appearance for Image-based Outdoor Localisation”, IROS 2013

$$\mathcal{I} = \log G - \alpha \log B - \beta \log R$$

Paton, MacTavish, Ostafew, and Barfoot, “It’s Not Easy Seeing Green: Lighting-Resistant Stereo Visual Teach and Repeat Using Color-Constant Images”, ICRA 2015



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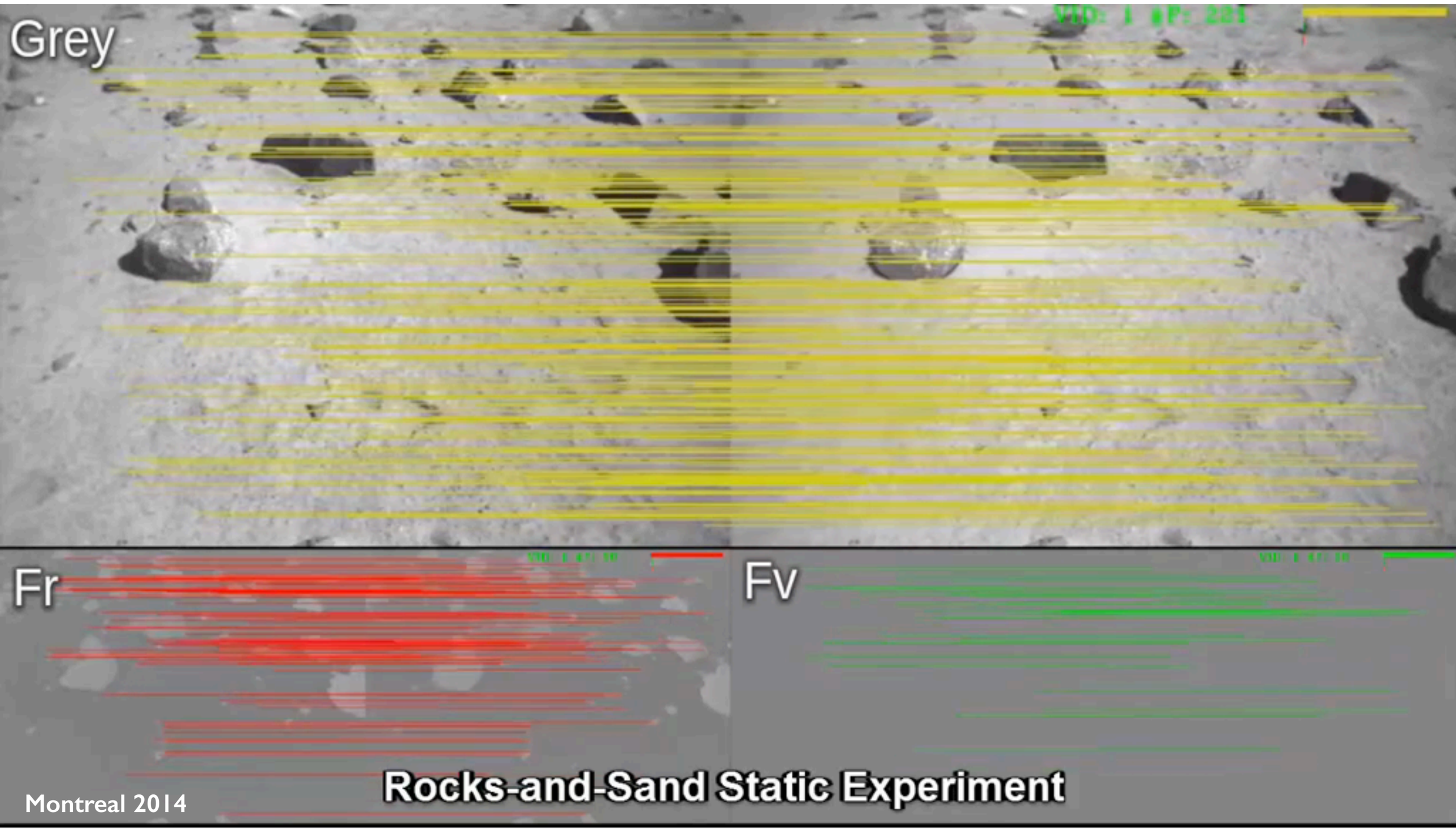
Lighting-Resistant Stereo VT&R using Colour-Constant Images



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Visual Route Following, State of Affairs

- **where have we been?**
  - stereo VO
  - place revisiting (a short time later)

hours

- **where are we now?**
  - dealing with lighting change
    - lidar images
    - illumination-invariant images

days to week

- **where are we going?**
  - next steps in long-term visual navigation
  - many real applications need to work for years

10 years

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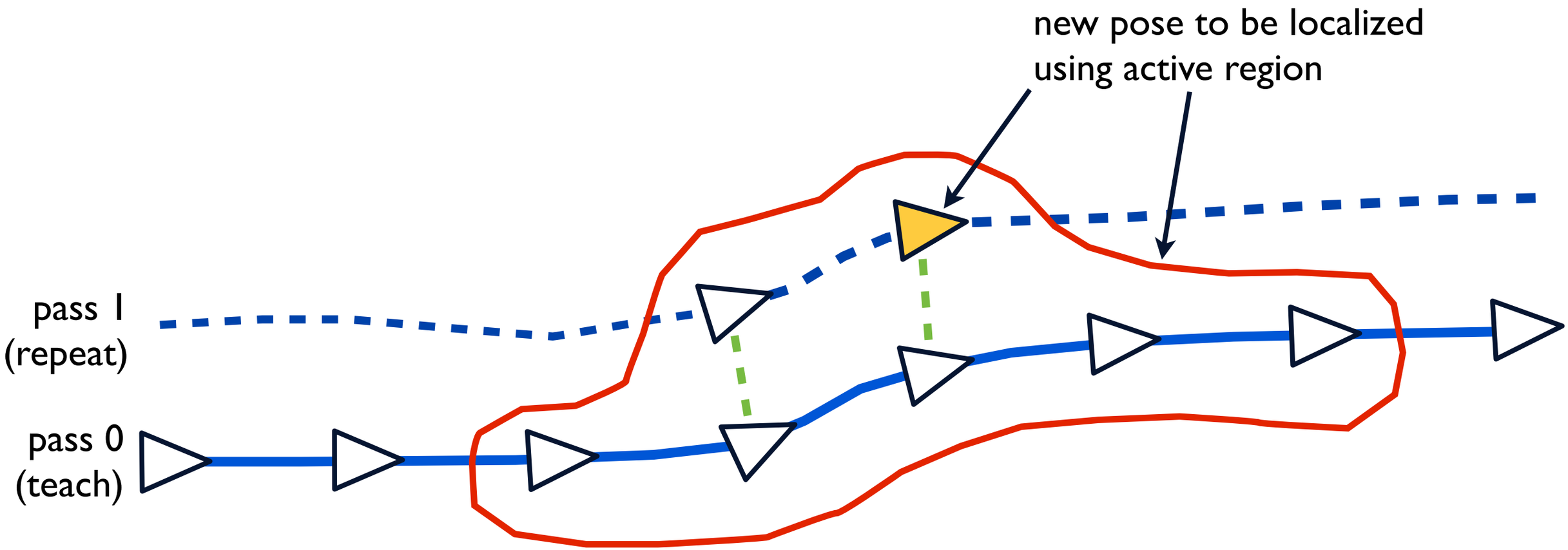
Applying Bandaids to Static Maps Isn't Good Enough



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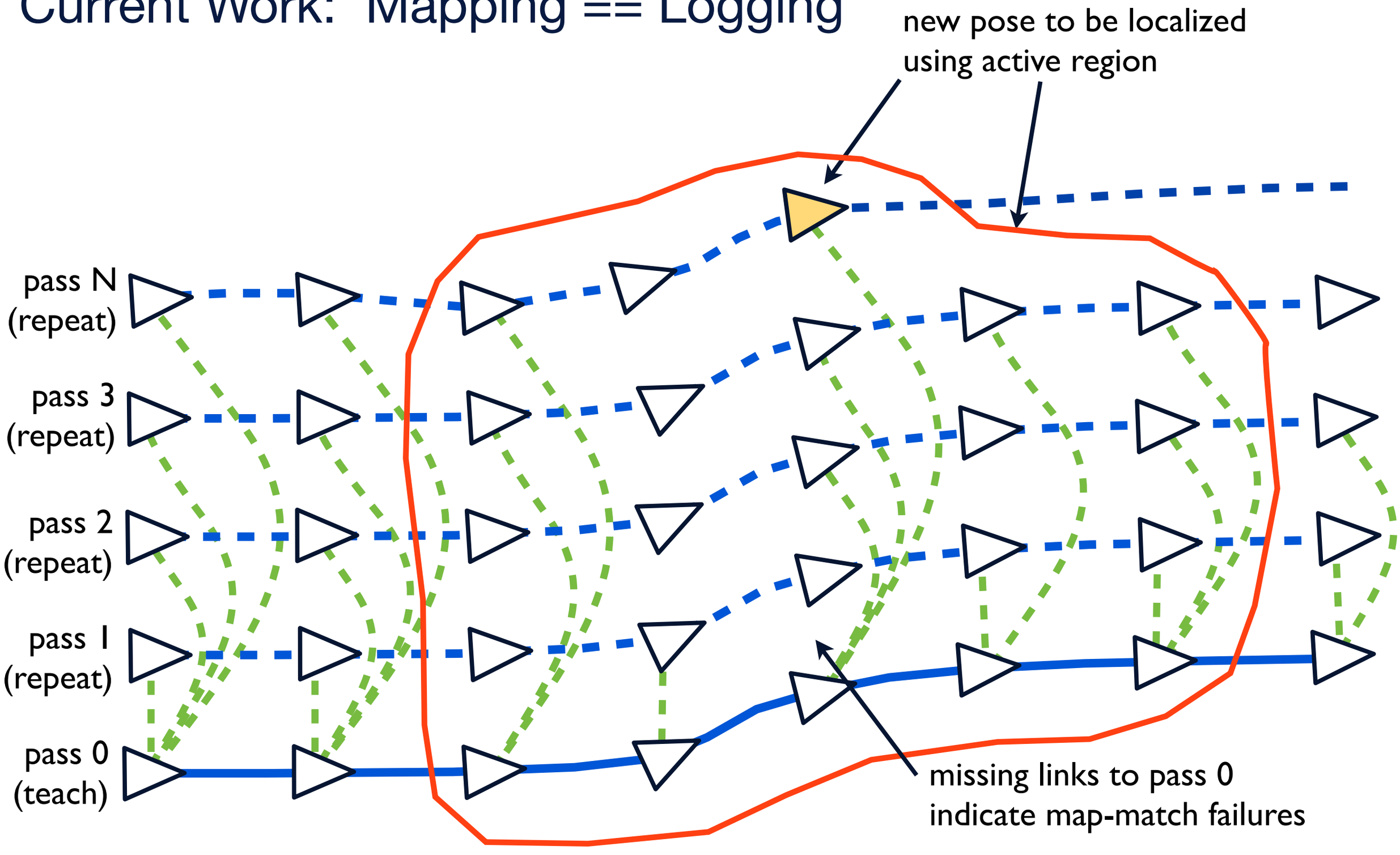
Current Work: Mapping == Logging



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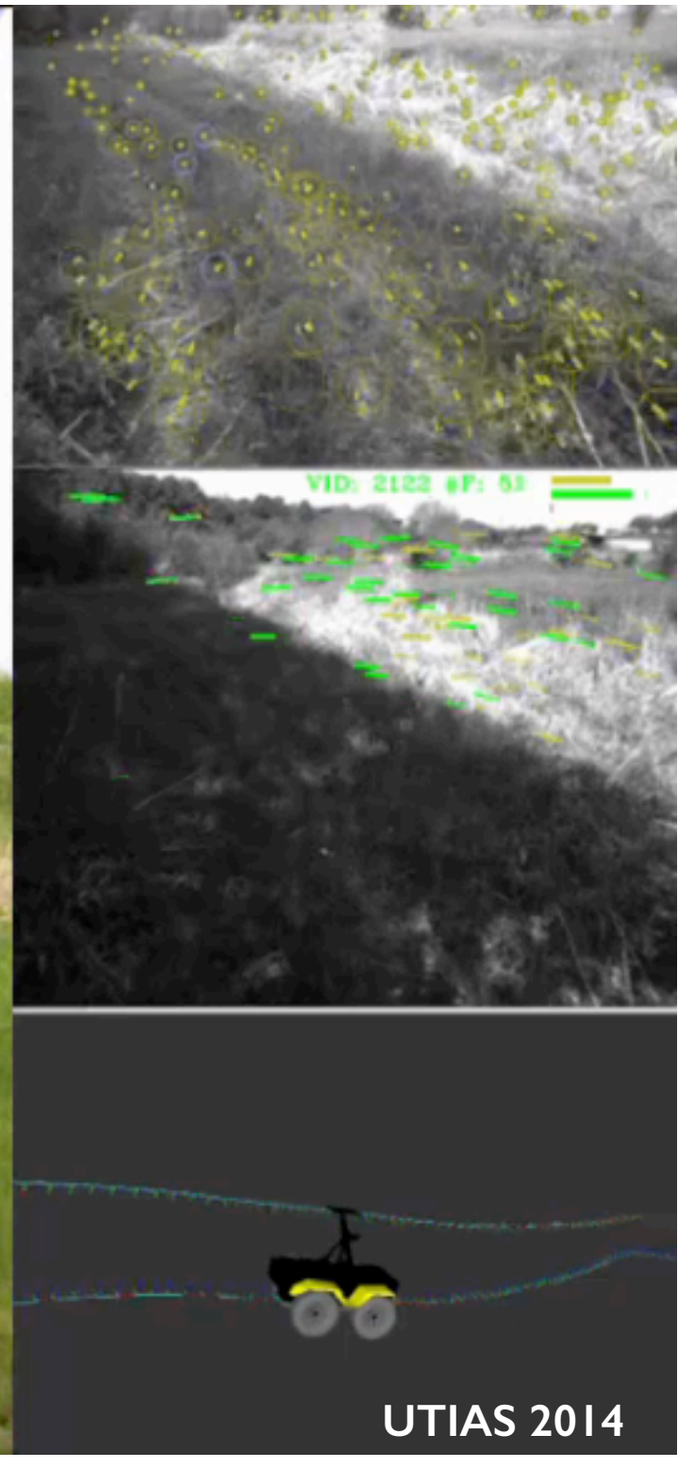
Winston Churchill and Paul Newman, “Experience-based Navigation for Long-term Localisation”, IJRR, 2013

Thanks for listening!

Looking for CS grad students!
APPLY NOW



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