Visual Route Following for Mobile Robots

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UTIAS: Highlights

- aircraft flight systems, flight dynamics, and simulation
- aerodynamics, fluid dynamics, and propulsion
- materials, structures, and multidisciplinary optimization
- dynamics & control for robotics and spacecraft

- first human-powered ornithoptor (2010)
- first ornithoptor
- first human-powered helicopter (2013)
- MOST microsatellite (2003)
- computational fluid dynamics
- Arctic test of planetary rover
- helped rescue of Apollo 13
ASRL: Recent Research Projects

- visual odometry for motion estimation in the absence of GPS
  - visual sensors (stereo, lidar) plus celestial sensors (sun sensor, star tracker)
- motion compensation for sweeping sensors such as lidar
- visual teach and repeat for autonomous route following
  - stereo camera, lidar (intensity imagery), Kinect camera
- learning for improved path tracking over time
- path planning/exploration using a network of reusable paths
  - a new paradigm for localization and mapping
- localization using a priori maps
  - lidar-to-orbital, celestial-to-catalogue
- terrain mapping using a mobile robot
  - simultaneous localization and mapping
Today’s Outline

- A low-cost, mapping/localization approach for visual route following
  - *stereo visual teach & repeat*
- Long-term autonomy: how do we make a robot repeat a path forever?
  - *scene change: lighting change ➔ appearance-based lidar*
  - *vehicle-terrain change: learning to track paths better with repetition*
  - *route obstructions: path repair ➔ planning for loop closure*
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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
Stereo Visual Odometry Pipeline

- **Left image**
  - Image de-warp and rectification
  - Keypoint detection

- **Right image**
  - Image de-warp and rectification
  - Keypoint detection

- Stereo matching
- Keypoint tracking
- Outlier rejection
- Nonlinear numerical solution
- Pose estimate

Previous frame
Stereo Visual Odometry Pipeline

1. **Left image**
   - Image de-warp and rectification
   - Keypoint detection

2. **Right image**
   - Image de-warp and rectification
   - Keypoint detection

3. **Stereo matching**

4. **Keypoint tracking**

5. **Outlier rejection**

6. **Nonlinear numerical solution**

7. **Pose estimate**

8. **Previous frame**

Devon Island 2008
Stereo Visual Odometry Results
What about Mars Sample Return?

- Mars Sample Return is the flagship mission of the next decade according to the US Planetary Decadal Survey.
- May require the ability to do over-the-horizon retrotraverse.
- Visual odometry will not work in both directions.
- Any dead reckoning method will diverge over a long enough distance unless periodic position corrections are applied.

Artist's Concept, Image: NASA
Low-Cost Relative Mapping

A relative map is...

- a sequence of relative pose changes
- with local metric/appearance data at each pose

A local map can be resolved in some reference frame as needed (on-demand)
Stereo VT&R: Repeat Pipeline

- 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
Relative Localization
Relative Localization
Relative Localization
Stereo VT&R Example
Stereo VT&R Example

VT&R keeps LELR almost directly in its outbound tracks
(allowing for safe route repeating since the taught path was obstacle free)

Montreal 2012
Stereo VT&R Example
Networks of Reusable Paths: Goal Seeking
Networks of Reusable Paths: Steep Terrain Exploration

5 x Actual Speed
Autonomous Repeat

UTIAS 2013
Networks of Reusable Paths: Steep Terrain Exploration

Haughton Crater on Devon Island (Artist’s Impression)
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Stereo VT&R Issues

- **issue #1, scene change:** information around a path changes making it impossible for the robot to recognize where it is
  - *lighting changes*
  - *objects in scene move / change*
    - fast scene changes hard to handle
    - gradual scene changes require incremental map update

- **issue #2, vehicle/terrain model errors:** vehicle model is poor resulting in bad path tracking
  - *vehicle could change over time*
  - *vehicle may not be modeled well to begin with*

- **issue #3, path obstructions:** something physically blocks a path making it not reusable
  - *e.g., someone parks a car on the path*
  - need to ‘repair’ the path
  - find a detour or a new path
Issue #1: Scene Change

Long-range
Long-duration
Lighting change

Initial Image | Failed Match (4 hours later) | Successful Match Next Day

Devon 2009
Lidar Intensity Images

Appearance-Based Lidar VT&R: Repeat Pipeline

UTIAS 2010

Lidar intensity image

Image processing

Keypoint detection

Range, azimuth, elevation images

Form augmented keypoints

Previous frame

Keypoint tracking

Outlier rejection

Current local map

Nonlinear numerical solution

Star tracker, IMU

Pose estimate

SURF keypoint

Intensity

Elevation

Azimuth

Range
ABL VT&R Example
ABL VT&R Example

1154 m route

Sudbury 2011

11:10 pm start
Motion Distortion

- non-affine image distortion occurs due to scanning while moving
- we need to deal with this to improve the metric accuracy of the lidar VO pipeline
- we’d prefer to not introduce another sensor such as an IMU as this has its own problems
ABL VO: Scanning While Moving

UTIAS 2010
currently carrying out a study of motion distortion on different feature detectors/descriptors

as expected, preliminary results show strong matching degradation at high speeds

fold whole-image motion compensation into RANSAC for very high speeds?

constant-velocity RANSAC to produce better feature tracks in motion-distorted imagery

continuous-time robot trajectories to account for unique timestamps of all the landmarks
Motion-Compensated RANSAC

Fig. 3. This figure shows the inlying feature tracks after applying the classic RANSAC algorithm to our lidar intensity/range data. Due to fast motion and a slow vertical scan, only a small temporal band of features are matched.

Fig. 4. This figure shows the how loosening the threshold on the tolerable measurement error, for the rigid RANSAC filter, allows for a larger number of inliers (green), but also introduces the possibility of outliers (red).

Fig. 5. This figure shows the inlying matches after applying the Motion-Compensated RANSAC algorithm; by using a constant velocity to model the motion of the sensor, the filter is able to more properly account for the distortion of the image.

- each iteration of RANSAC usually solves for the best pose change given two sets of points
  - either finds too few features or allows outliers
- each iteration of MC-RANSAC solves for the best constant velocity given two sets of motion-distorted points
  - to appear to IROS 2013
Issue #2: Vehicle/Terrain Model Errors

path tracker systematically drives out of the tracks in some places – in this case due to a sideslope
Iterative Learning Control

- vision system can measure the path-tracking errors
  - we know when the robot is out of the tracks!
- over a few trials, we learn a mapping from the systematic errors to the control input
- we then apply this as a feedforward correction to the steering rate
  - e.g., we start turning early to preempt the systematic error
- this one approach works for ANY type of disturbance!
ILC: Compensating for Sideslope

In practice, ILC iteratively learns a feedforward control navigation system [8]. A real-time Visual Teach and Repeat (VT&R) mapping and practical, nonholonomic, mobile robot within the context of Control (ILC) as an added-benefit, feedforward control for a also provides an opportunity for learning behavior. Learning the use and reuse of paths reduces the need for repeated challenge for robotics. In many mobile robot applications, denied, extreme environments. The paper presents results — This paper presents a path-repeating, mobile robot where

Fig. 7. Experiment 1: Husky A200 path side-slope angle. The path selected maximum and RMS lateral errors are reduced significantly within the first trial of ten trials. As can be seen in Figure 12, ILC was and noise.

In the second experiment, the ILC algorithm successfully and adjusting localization of the VT&R algorithm.

In practice, we used the update law included a steep side-slope around sandy and gravel floor valleys defined by a set of impassable gravel hills.

The experiment consisted of two parts: (i) a test with a 50-m-long path with speeds up to three times the speed for and adjusting the facility in Toronto, Ontario, Canada. The facility provides a network of path through tight valleys and over a combination of gravel and sandy surfaces as shown in Figure 8.

Fig. 6. Experiment 1: Husky A200 path at the Canadian Space Agency’s Macbook Pro with an Intel 2.4 Ghz Core2Duo processor and 4 GB of RAM. The resulting real-time localization and path-

Fig. 8. Experiment 2: ROC6 at the start of the path in the MarsDome 4 GB of RAM. The resulting real-time localization and path-

Trial Lateral Error vs Distance Along Path

Trial 1 Lateral Error
Trial 3 Lateral Error
Trial 6 Lateral Error

Lateral Error (m)

Distance Along Path (m)

Side–Slope Angle vs Distance Along Path

Path Side–Slope Angle (deg)

Distance Along Path (m)
IC: Incrementally Driving Faster

In equation 2, the gains

\[ e_i = \begin{cases} k_{Hi} \cos(\theta_i) - k_{Li} \sin(\theta_i) \\ k_{Hi} \sin(\theta_i) + k_{Li} \cos(\theta_i) \end{cases} \]

where \( \theta_i \) represents the desired state and is identically zero.

Orange Arrows: ILC Disabled

\[ u_j = \begin{cases} k_{Hi} \cos(\theta_i) - k_{Li} \sin(\theta_i) \\ k_{Hi} \sin(\theta_i) + k_{Li} \cos(\theta_i) \end{cases} \]

Fig. 6. Experiment 1: Husky A200 path at the Canadian Space Agency’s MarsDome. The speed test was conducted in the University of Toronto school of computer science’s mars dome. A 50-m-long path with speeds up to three times the speed for MarsDome, 2012.


REFERENCES


ILC: Incrementally Driving Faster

Issue #3: Path Obstructions
The Need for Loop Closure

- we can branch to get around obstacles but not yet close the loop
  - physical embodiment of an RRT
- to detour around small obstructions we need to strategically plan for loop closure
  - need to get back in our tracks
Future Directions

- issue #1, scene change:
  - continuous-time framework for lidar-based motion estimation
  - map update to cover different lighting/weather situations
    - see what Paul Newman’s group is doing on this at Oxford - really cool!
- issue #2, vehicle/terrain model errors:
  - improving path tracking over repeat runs using iterative learning
  - applying knowledge to novel paths never previously driven
- issue #3, path obstructions:
  - path repair: planning for loop closure strategically
  - terrain assessment in novel environments
- related stuff
  - open-source VT&R package for ROS for stereo/kinect/lidar (maybe)
  - lightweight version of VT&R for UAVs
  - autonomous navigation on a steep terrain using a tethered robot
Thanks!

Questions?
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