RGB-Laser Odometry Under Interval Uncertainty for Guaranteed Localization

Raphael Voges and Bernardo Wagner

SWIM 2018

https://rts.uni-hannover.de/
https://www.icsens.uni-hannover.de/

DFG Research Training Group (GRK2159)
i.c.sens - Integrity and Collaboration in dynamic sensor networks
Introduction

- Urban canyon
- GPS not available
- But many visual features for localization
- Motion estimation not possible with visual features alone
- Estimate ego-motion gradually using camera + laser scanner
- Evaluation using the KITTI dataset [1]
Motivation

- Most approaches [2] focus on computing a point-valued position
  - Uncertainty of pose estimation is neglected or modeled stochastically
  - Unknown, systematic errors cannot be modeled
- Probabilistic optimization approaches rely on linearization
- Interval analysis overcomes these problems
  - Another advantage: outliers can be identified easily
Modelling Laser Scanner Error Under Interval Uncertainty

- Classical model
- Distance measurement: d
- Angular components: \( \varphi \) and \( \theta \)
- Computation of Cartesian coordinates
  - 3D point
Modelling Laser Scanner Error Under Interval Uncertainty

- Bounded error model
- Interval for distance measurement: \([d]\)
- Interval for angular components: \([\varphi]\) and \([\theta]\)
- Computation of Cartesian coordinates
  - 3D interval box
Modelling Camera Error Under Interval Uncertainty

- Pinhole camera model
- Many different error sources

Classical model

Uncertain focal length
Uncertain pinhole

Real world point

P

Real world point

P

Pinhole

f

\(-v_1\)

\([v_1]\)

\([f]\)
Modelling Camera Error Under Interval Uncertainty

- Hard to model all different error sources (chessboard detector, distortion, …)

- Interval boxes instead of point-valued feature detections

- Error bounds can be found from calibration process
  - Maximum reprojection error
Modelling IMU Error Under Interval Uncertainty

- Gyroscope data for orientation measurement: angular velocities
- Two sources of error:
  - Bias/noise \( [b] \): offset from 0
  - Scale factor \([s]\): proportional scaling from measured velocity to true velocity
- Intervals for the velocity measurements: \( [\omega](\cdot) = \omega_m(\cdot) + [b] + [s] \cdot \omega_m(\cdot) \)
- Integration of velocity to find orientation \( [\rho](\cdot) \)
- Interval width increases over time due to drift
General Idea

- Estimate ego-motion gradually
- Fuse information from camera and laser scanner to find corresponding 3D points
- Find rigid body transformation under interval uncertainty
- Use IMU measurements to constrain motion
General Idea: Keyframe

- Not image to image, but keyframe-based
- Prevents some drift (no unnecessary error propagation)
Finding and Matching Image Features Between Frames

- Scale-Invariant Feature Transform (SIFT) [3] to find and match image features
- Discard wrong matches by using the SIFT ratio test
Assigning Depth to Image Features

1. Interval uncertainty for image feature $i \rightarrow$ box on image plane
2. Project laser scan boxes (interval uncertainty) onto image plane
3. Find all scan boxes ($s \in S$) that intersect the image feature box $i$
4. Depth of $i$ is the union over all scan boxes’ depths: $[d(i)] = \bigcup_{s \in S} [d(s)]$
Assigning Depth to Image Features

Feature image color coded by depth/distance (red: close, blue: distant)

Feature image color coded by depth uncertainty (red: certain, blue: uncertain)
Rigid Body Transformation

\[ X_i^k = RX_i^c + T \]

- \( T_3 \geq 0 \): moving forward only
- Use IMU rotation measurements to find an initial enclosure for \( R \)
- Express \( R \) using three Euler Angles (\( \rightarrow \) six unknowns in total)
  - Three nonlinear equations
  - Forward-backward contractor to contract further
- Linear equations if we try to find twelve unknowns (nine for \( R \) + three for \( T \))
  - Linear contractor
  - Additional constraint for rotation matrix: \( RR^T = I \)
  - Extract Euler Angles from \( R \)
Rigid Body Transformation

If depth is unknown for feature in keyframe:
- Only 2 equations per feature
- Perspective-n-Point problem
- Additional constraints in forward-backward contractor

If depth is completely unknown
- Only 1 equation per feature
- Additional constraint in forward-backward contractor

\[ X_i^k = RX_i^c + T \]

\[ \lambda_i^k \tilde{X}_i^k = RX_i^c + T \]

\[ \lambda_i^k \tilde{X}_i^k = R \lambda_i^c \tilde{X}_i^c + T \]
First Results

- Red dots: true solution
- Blue boxes: Localization boxes
- Green boxes: New keyframe
- GPS at every keyframe to prevent drift
First Results

- Red dots: true solution
- Blue boxes: Localization boxes
- Green boxes: New keyframe
- GPS every three seconds to prevent drift
Conclusions

- 100% of position estimates contain true solution
- Insertion of new keyframe leads to increasing uncertainty
  - No “global” constraints
  - Error that accumulated until keyframe cannot be contracted
- Computation time feasible for future real time applications
Future Work

- Improve RGB-Laser odometry by using different contractors
  - Less pessimism
  - Less computation time

- Extend odometry by interval-based GNSS solution
  - Collaboration with Hani Dbouk [4]
  - “Global” contractor

- Extend odometry to SLAM
  - Build map consisting of interval boxes
  - Use map as “global” contractor
References


This work was supported by the German Research Foundation (DFG) as part of the Research Training Group i.c.sens [RTG 2159].