Institute of Systems Engineering
Real Time Systems Group

Leibniz Universität Hannover

RGB-Laser Odometry Under Interval Uncertainty for Guaranteed Localization

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SWIM 2018

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

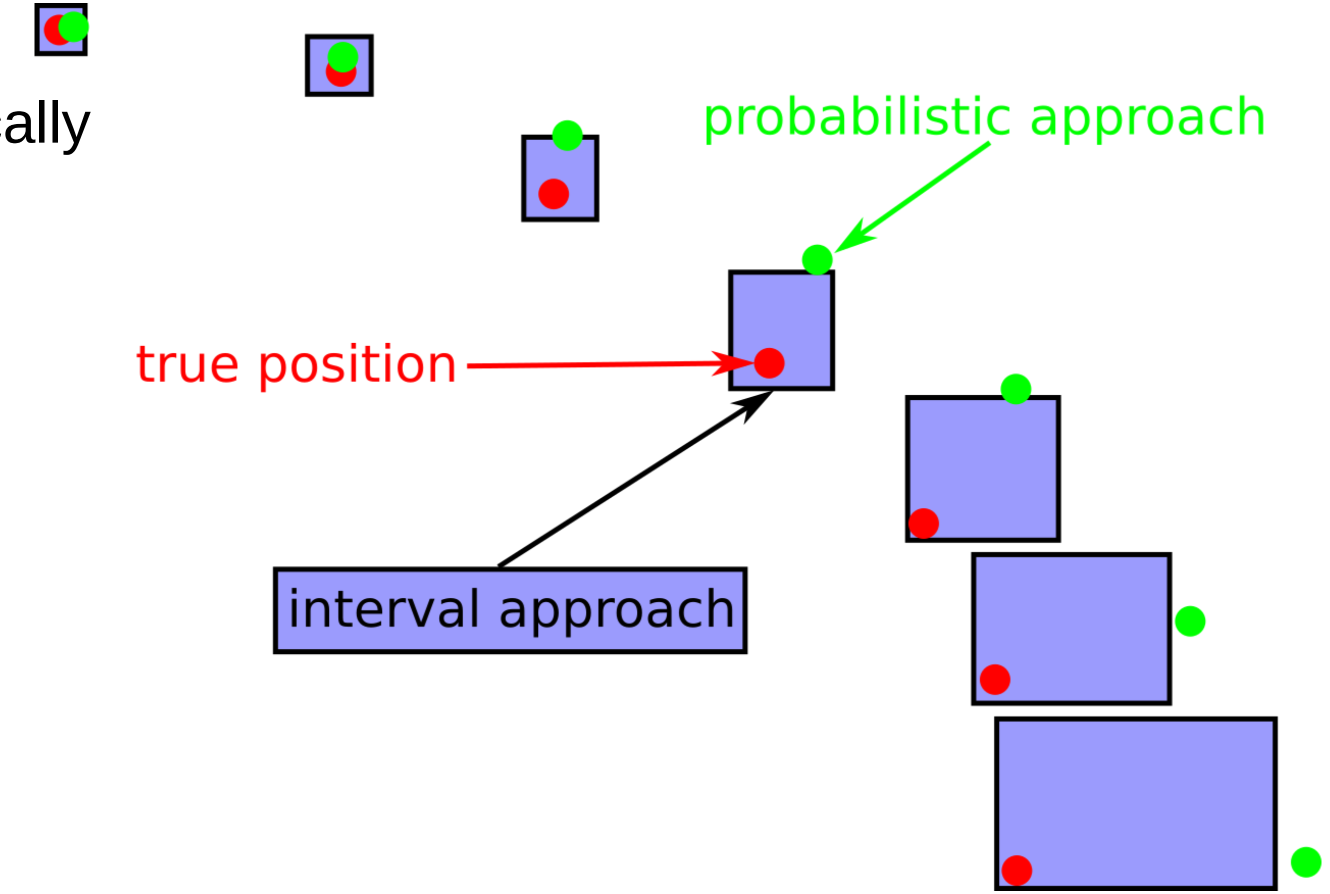
DFG Research Training Group (GRK2159)
i.c.sens - Integrity and Collaboration in dynamic sensor networks

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]

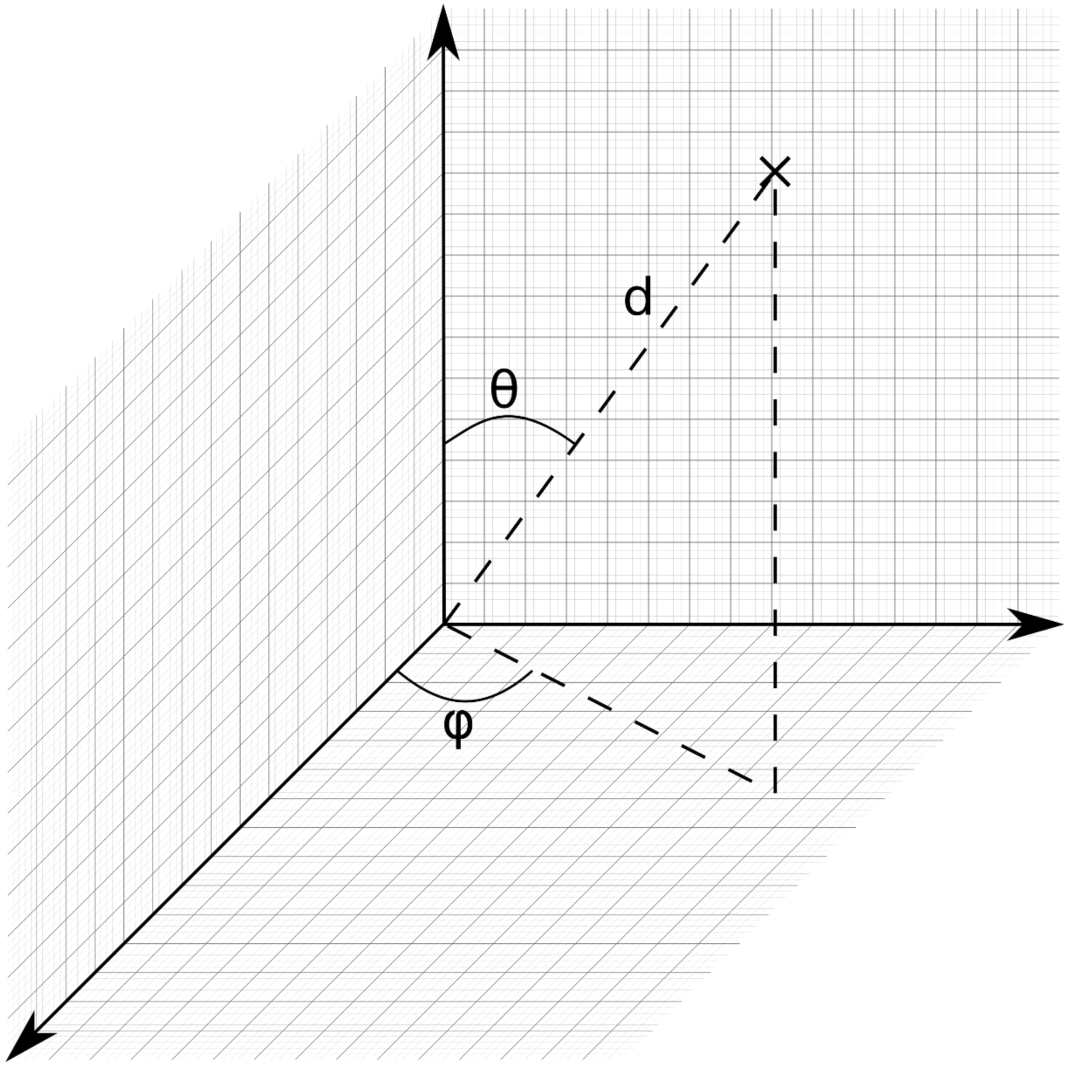
Motivation

- 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



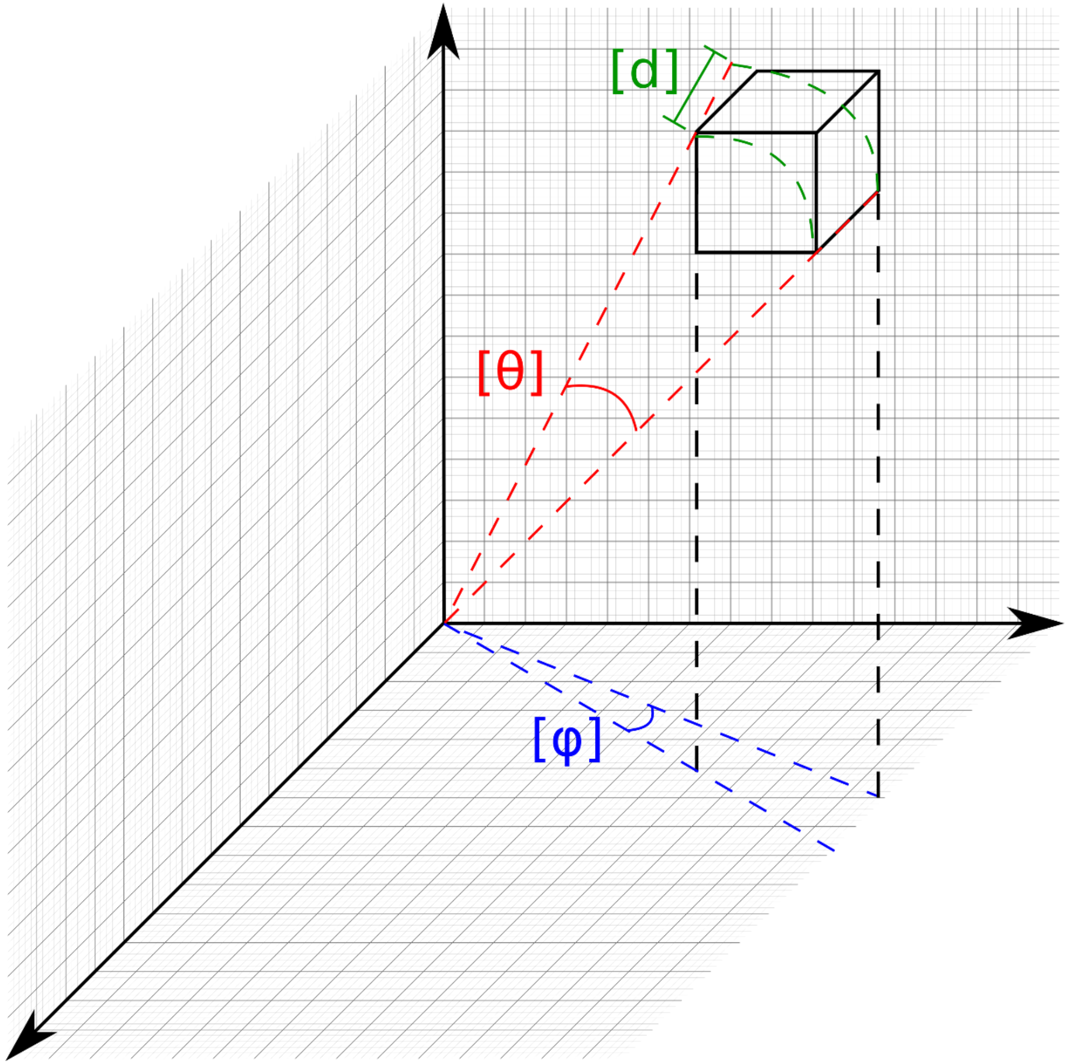
Modelling Laser Scanner Error Under Interval Uncertainty

- Classical model
- Distance measurement: d
- Angular components: φ and θ
- Computation of Cartesian coordinates
  - 3D point



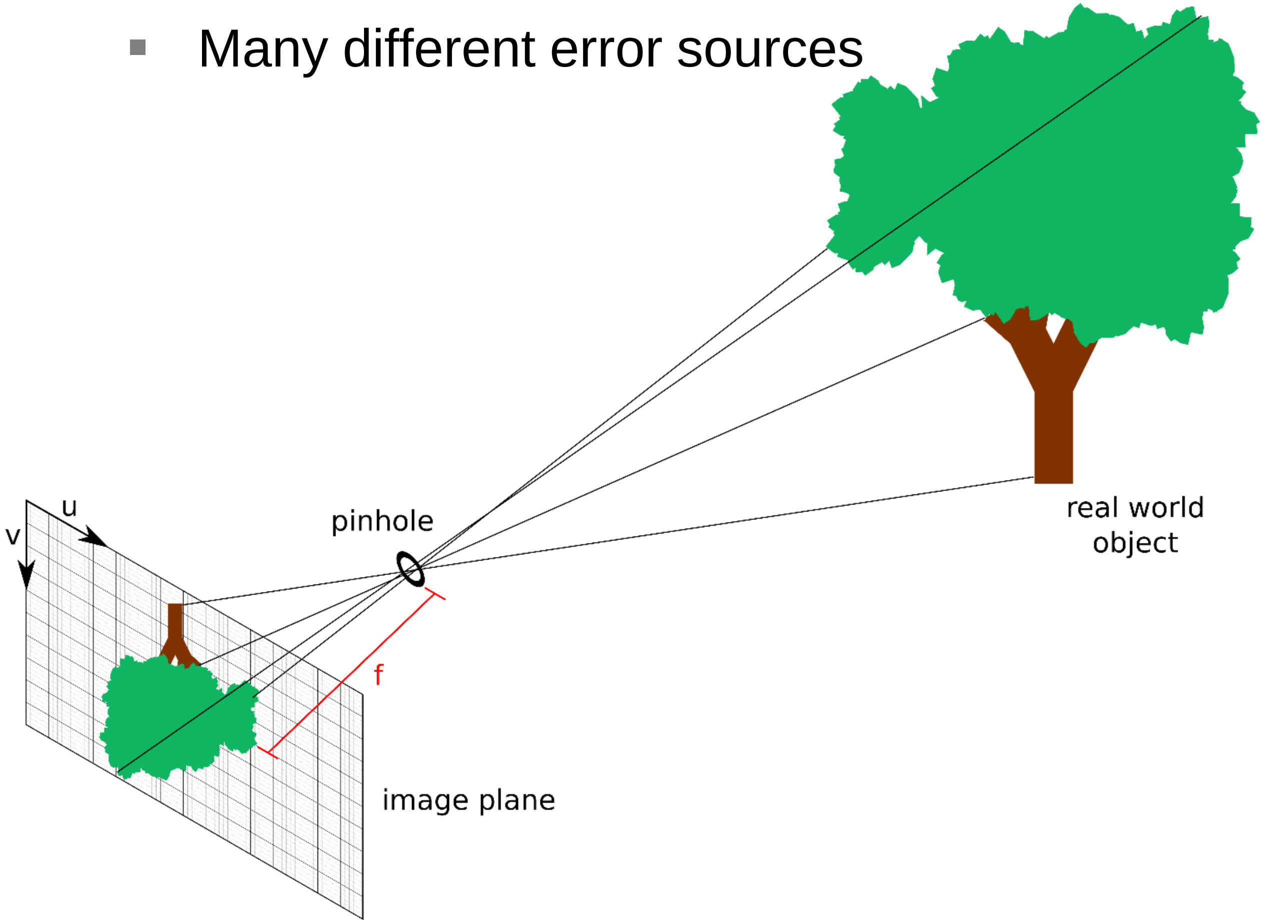
Modelling Laser Scanner Error Under Interval Uncertainty

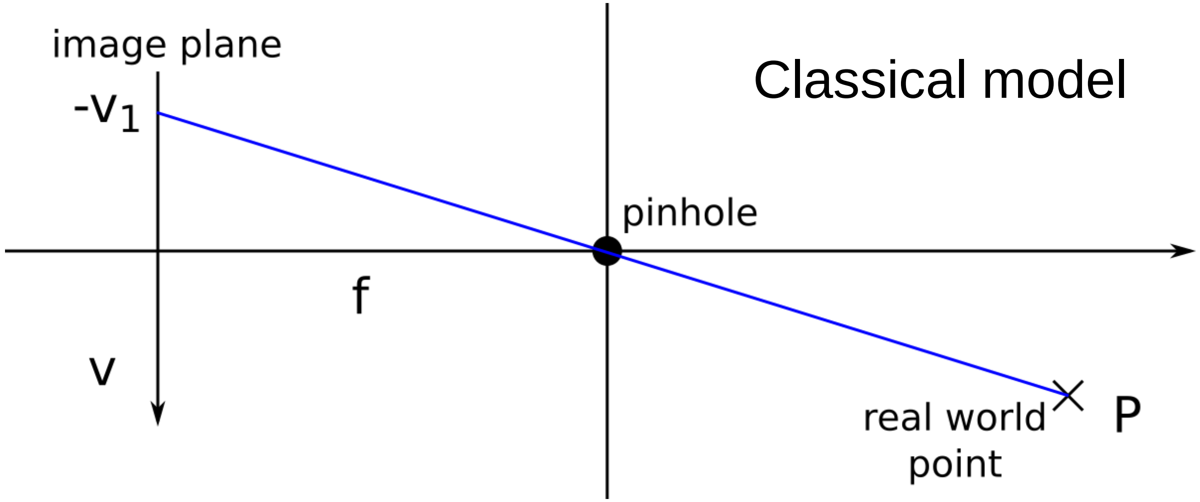
- Bounded error model
- Interval for distance measurement: [d]
- Interval for angular components: $[\varphi]$ and $[\theta]$
- Computation of Cartesian coordinates
  - 3D interval box

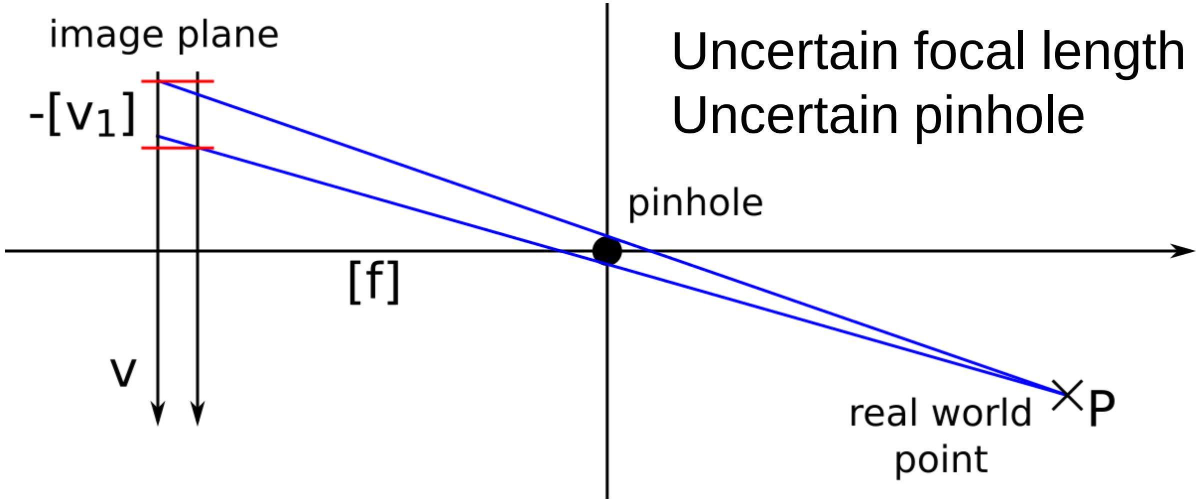


Modelling Camera Error Under Interval Uncertainty

- Pinhole camera model
- Many different error sources

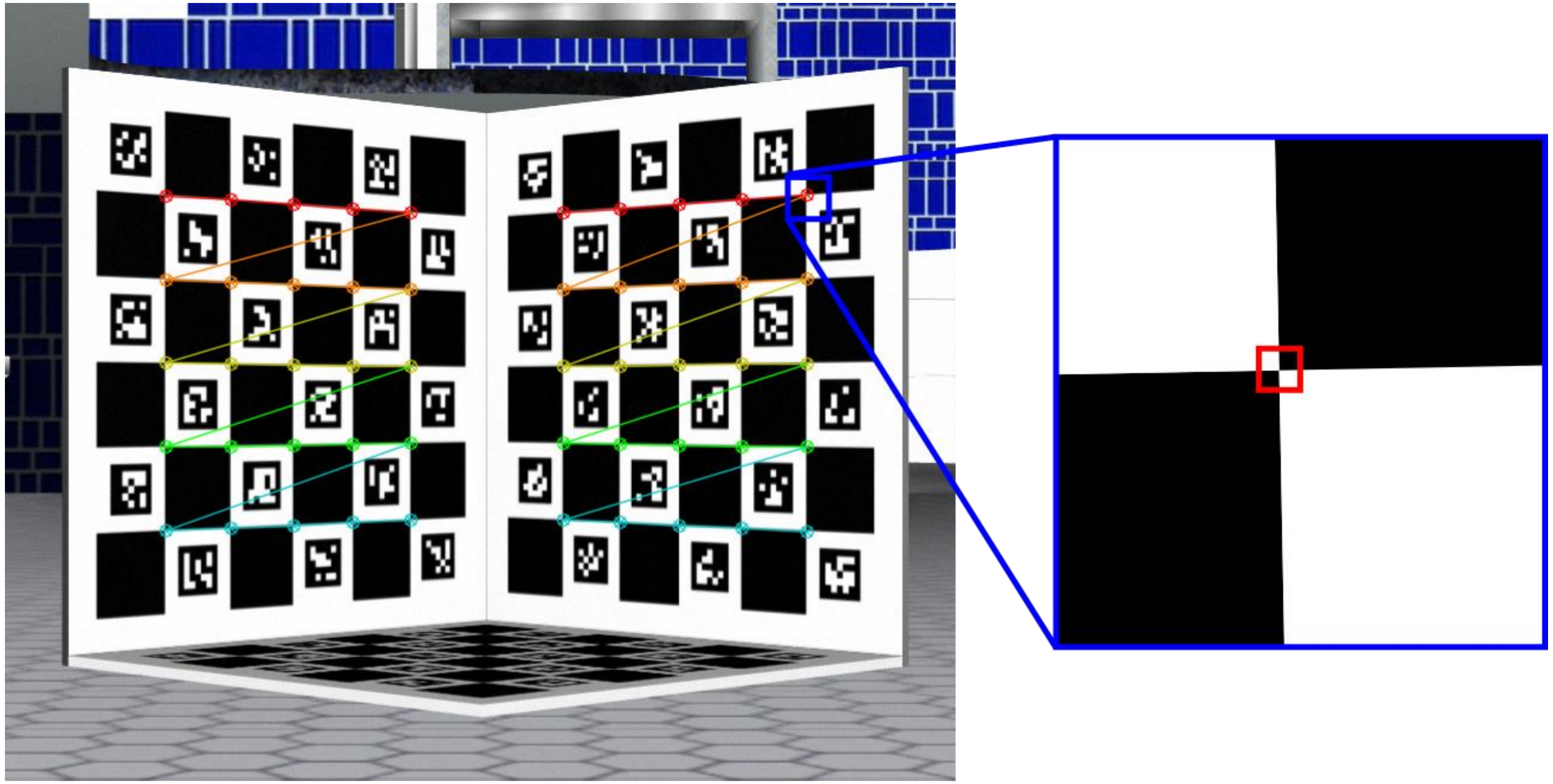






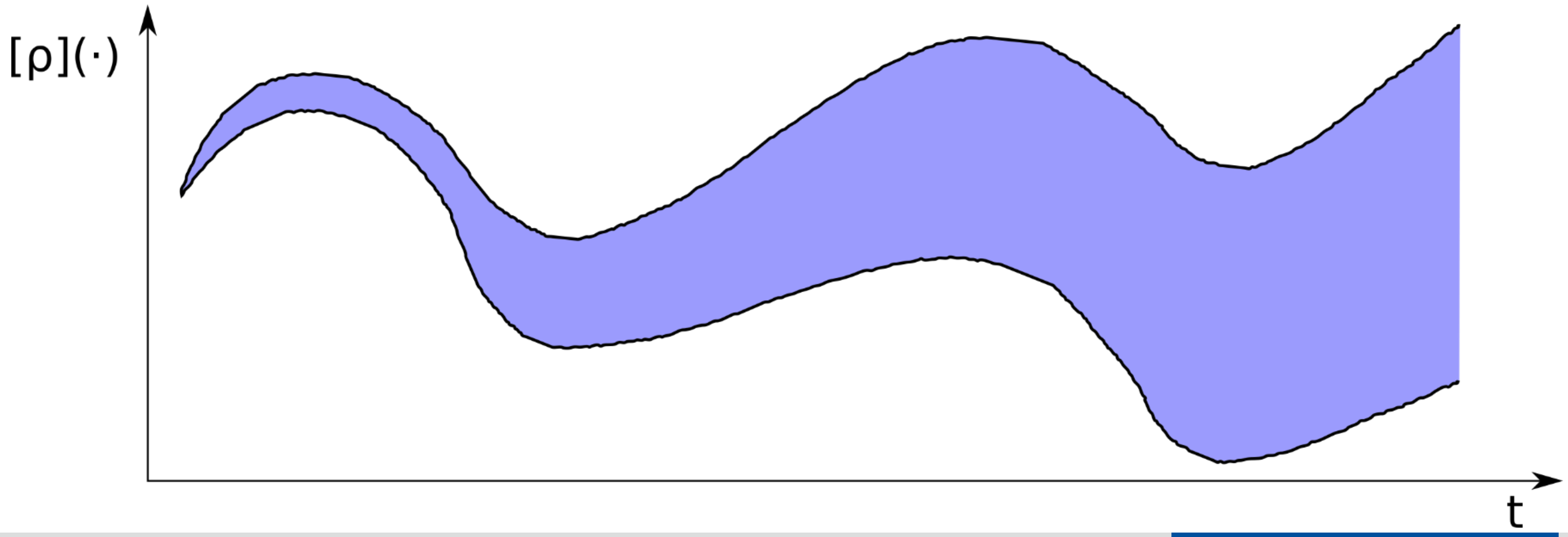
Modelling Camera Error Under Interval Uncertainty

- 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



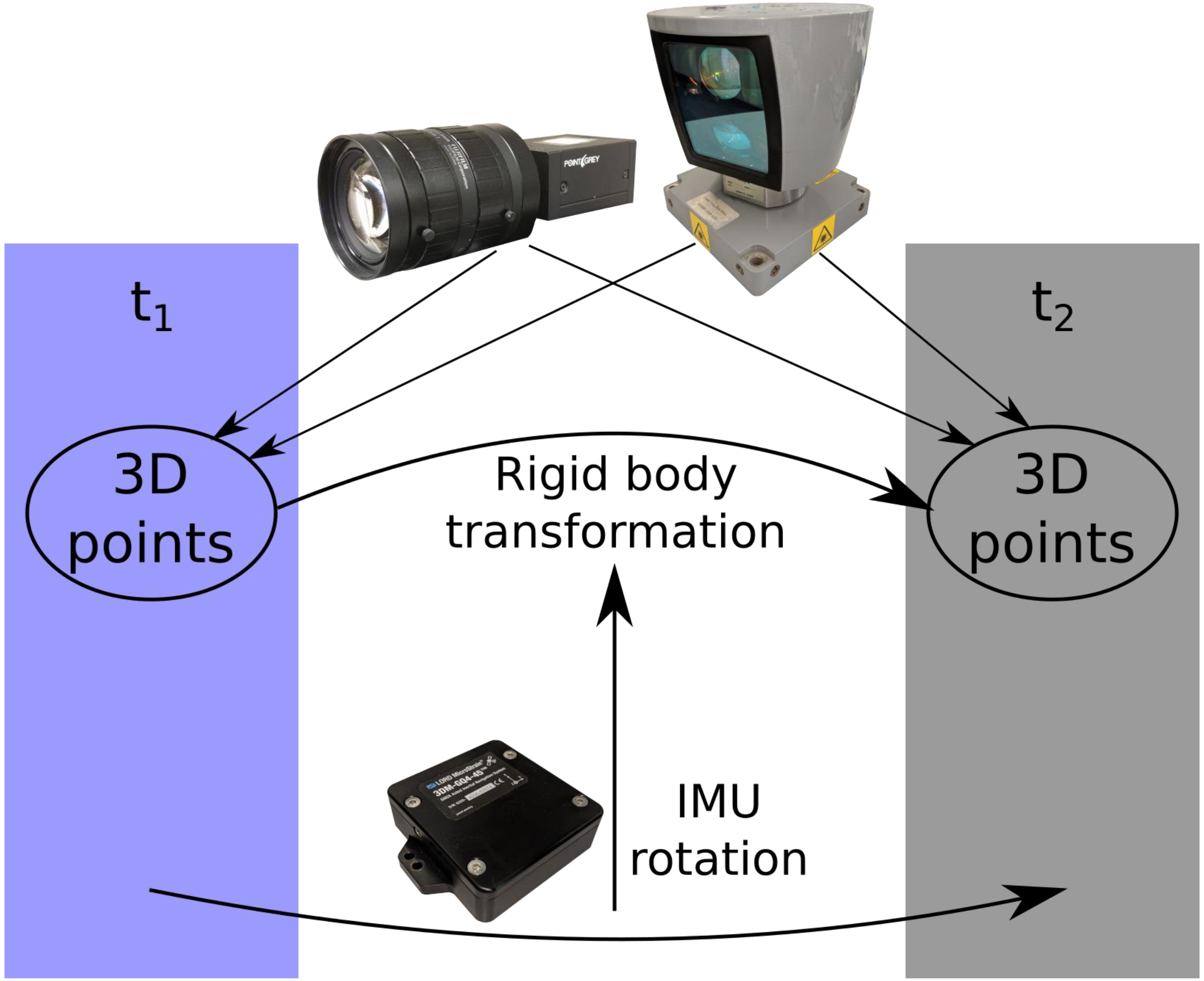
Modelling IMU Error Under Interval Uncertainty

- 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



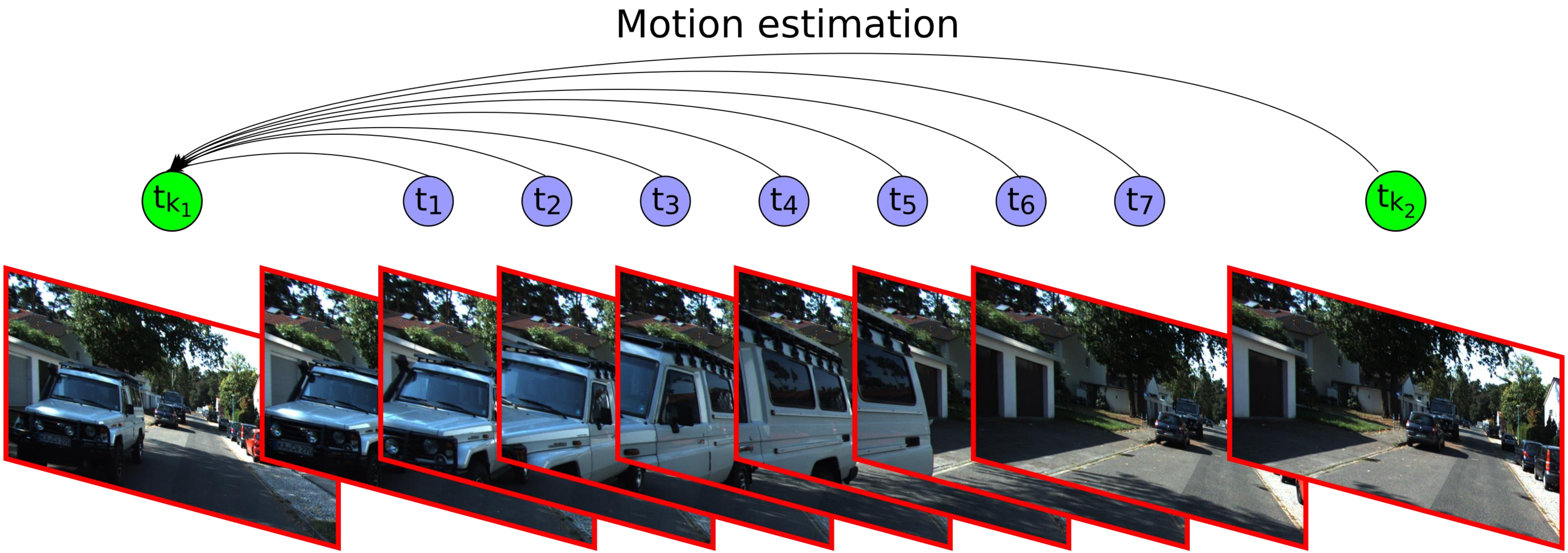
General Idea

- 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

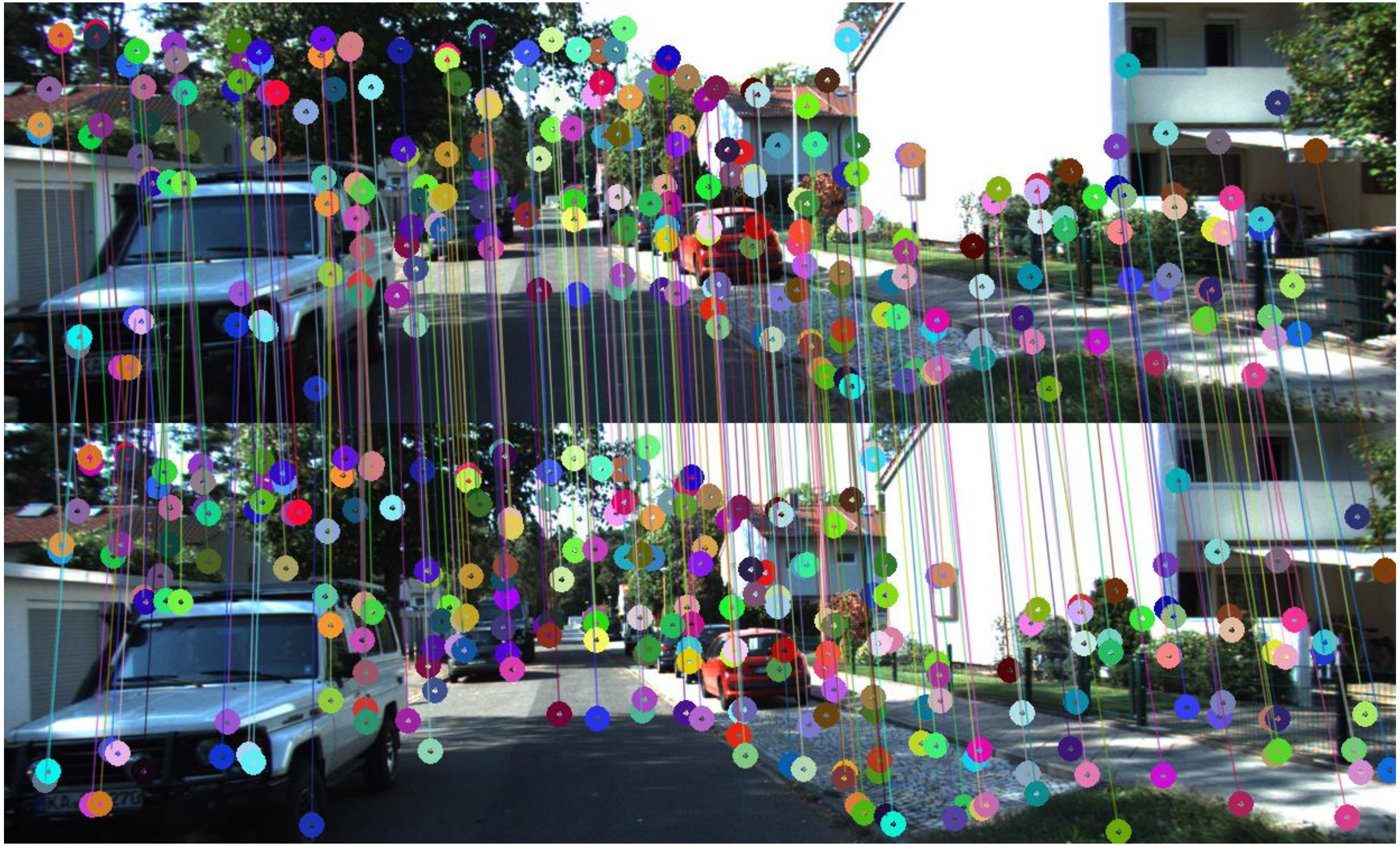
- Not image to image, but keyframe-based
- Prevents some drift (no unnecessary error propagation)



Finding and Matching Image Features Between Frames

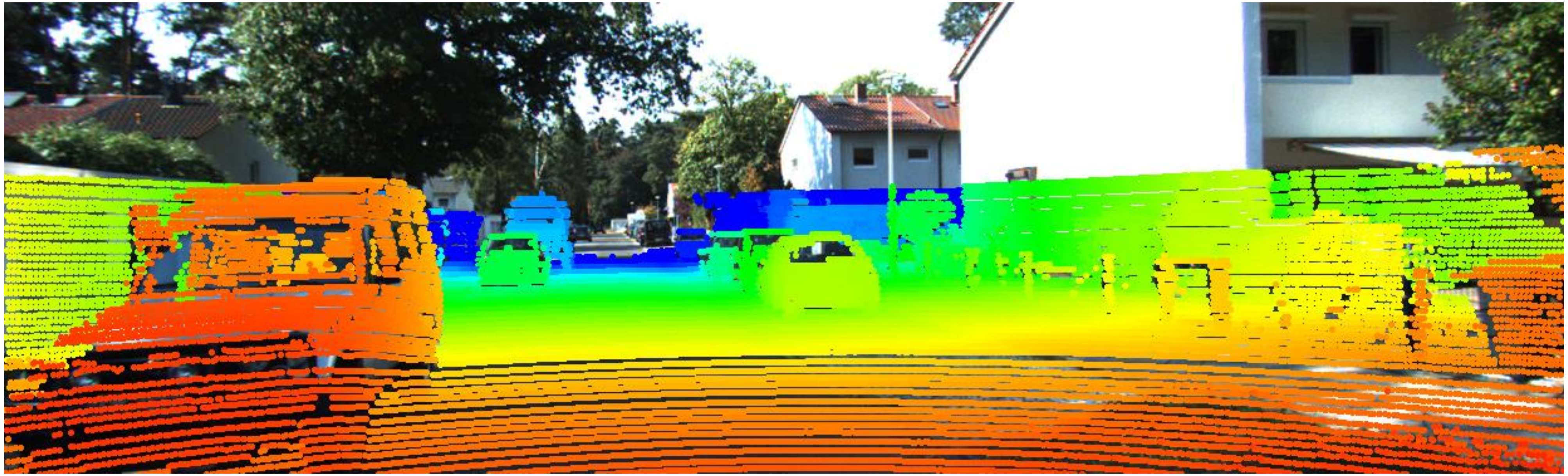
- Scale-Invariant Feature Transform (SIFT) [3] to find and match image features

- Discard wrong matches by using the SIFT ratio test



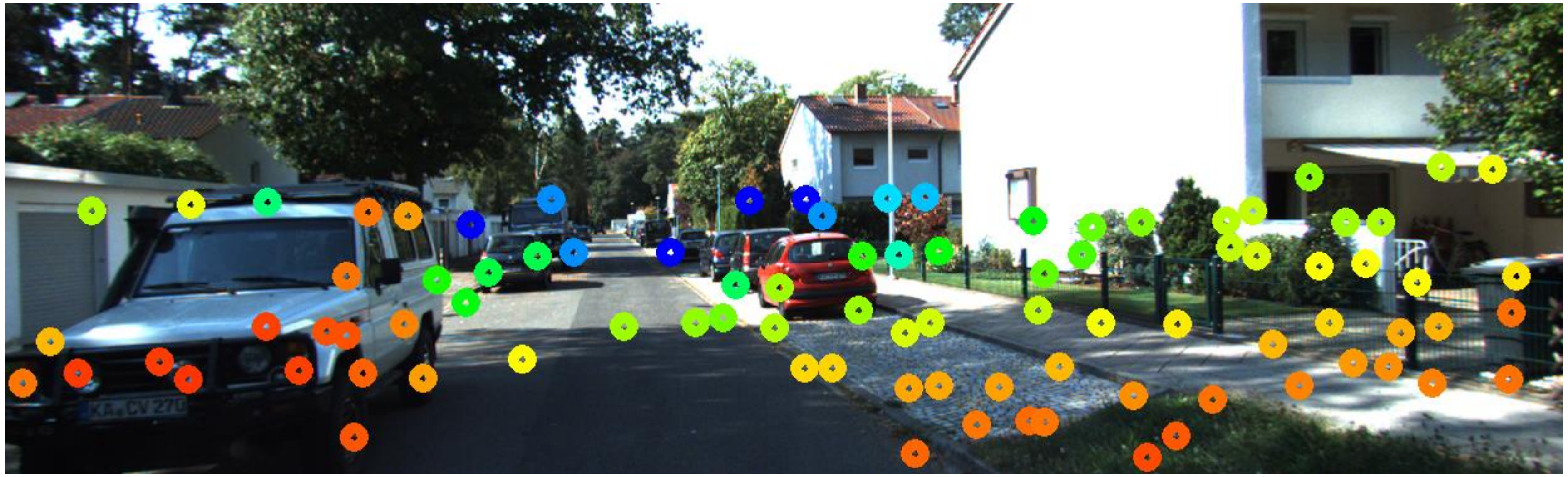
Assigning Depth to Image Features

1. Interval uncertainty for image feature i → 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

$$\underbrace{X_i^k}_{\text{3D feature } i \text{ in keyframe}} = \underbrace{R}_{\text{3x3 rotation matrix}} \underbrace{X_i^c}_{\text{3D feature } i \text{ in current frame}} + \underbrace{T}_{\text{3x1 translation vector}}$$

- $T_3 \geq 0$: moving forward only
- Use IMU rotation measurements to find an initial enclosure for R
- Express R using three Euler Angles (→ 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

3D feature i in keyframe; 3x3 rotation matrix; 3D feature i in current frame; 3x1 translation vector

$$X_i^k = R X_i^c + T$$

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

$$\lambda_i^k \tilde{X}_i^k = R X_i^c + T$$

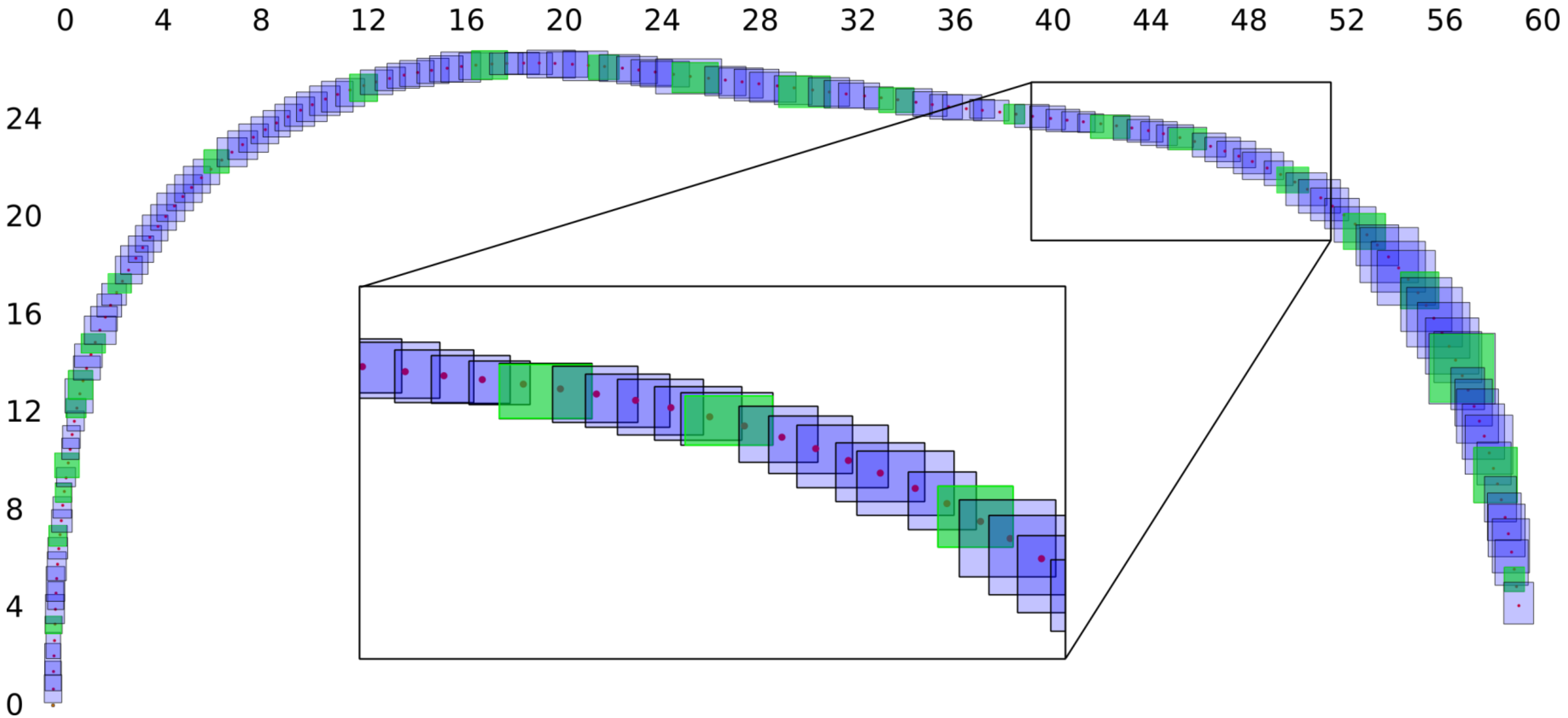
Unknown scale/depth

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

$$\lambda_i^k \tilde{X}_i^k = R \lambda_i^C \tilde{X}_i^c + T$$

First Results

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



First Results

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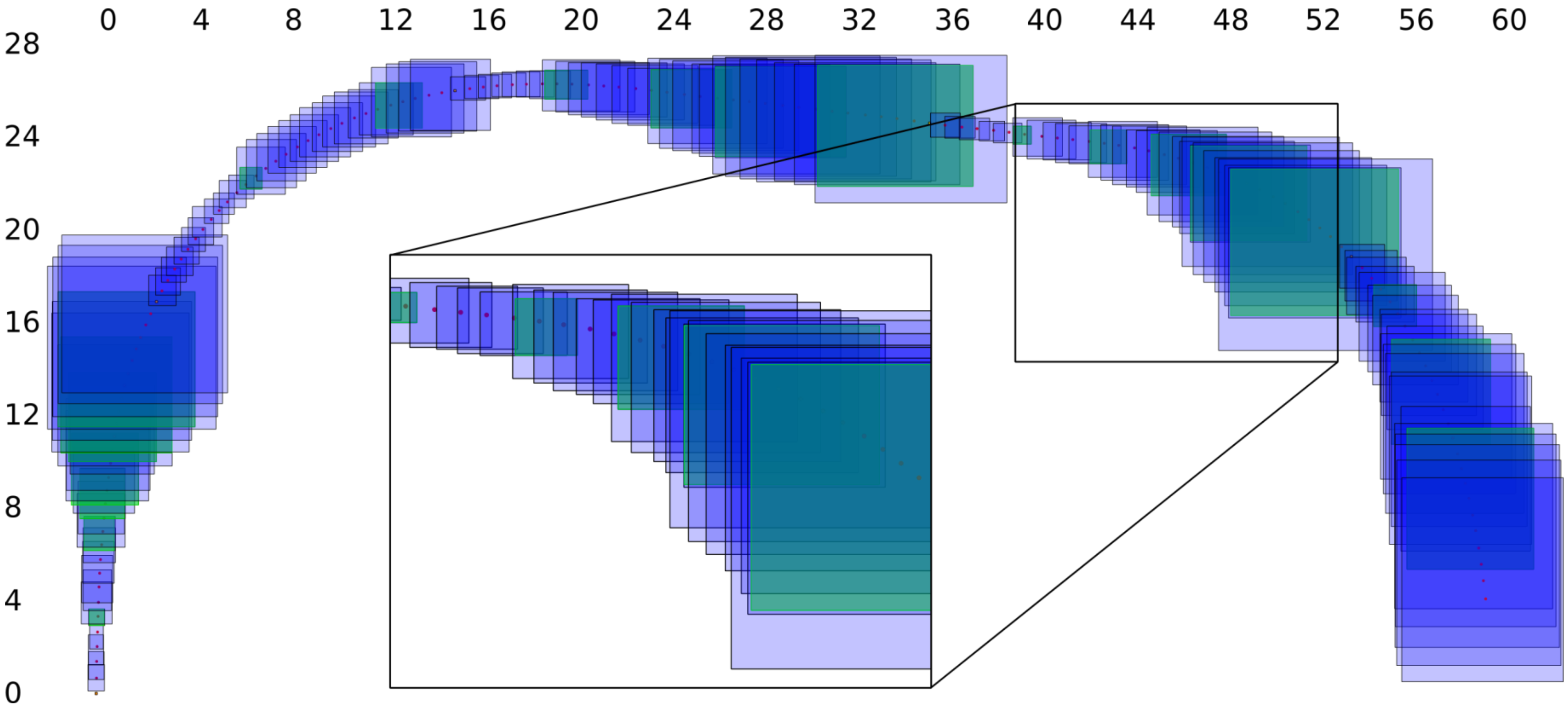
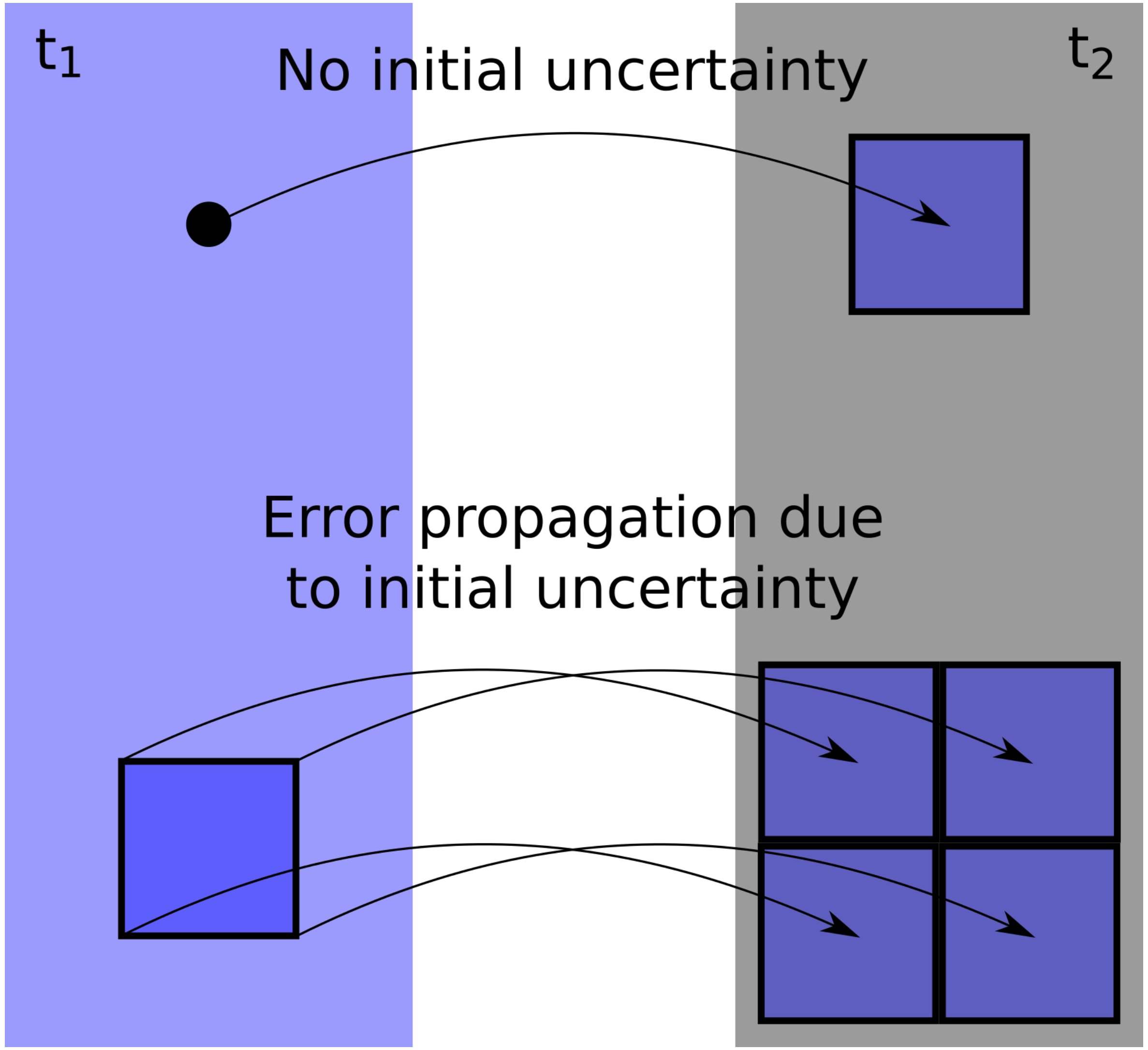


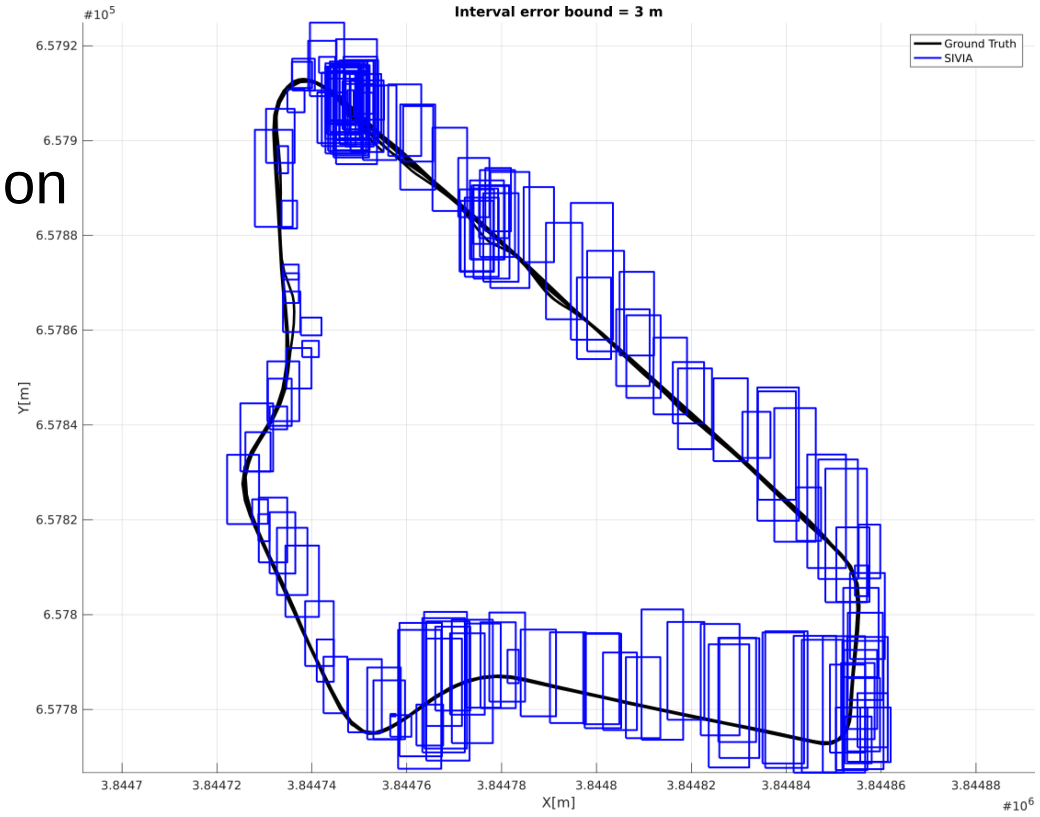
Conclusions

- 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

[1] A. Geiger, P. Lenz, C. Stiller and R. Urtasun, Vision meets robotics: The KITTI dataset, The International Journal of Robotics Research, vol. 10, no. 11, pp. 1231–1237, 2013.

[2] J. Zhang, M. Kaess and S. Singh, Real-time Depth Enhanced Monocular Odometry, IEEE International Conference on Intelligent Robots and Systems (IROS), Chicago, IL, USA, 2014.

[3] David G. Lowe, Distinctive Image Features from Scale-Invariant Keypoints, International Journal of Computer Vision, vol. 60, pp. 91–110, 2004.

[4] H. Dbouk and S. Schön, Comparison of Different Bounding Methods for Providing GPS Integrity Information, Proceedings of IEEE/ION PLANS, Monterey, CA, USA, 2018.

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