Institute of Systems Engineering
Real Time Systems Group

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Bounded-Error Visual-LiDAR Odometry on Mobile Robots Under Consideration of Spatiotemporal Uncertainties

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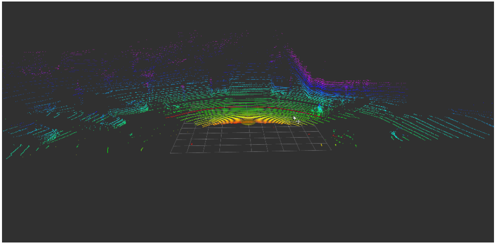
DFG Research Training Group (GRK2159)
i.c.sens - Integrity and Collaboration in dynamic sensor networks

Motivation: Need for Visual-LiDAR Odometry

- Localization (dead reckoning) of mobile robots
- Urban canyon
- GNSS not available/reliable
- Many visual features for localization
- Motion estimation difficult using monocular images
  - Distance difficult to estimate from 2D images

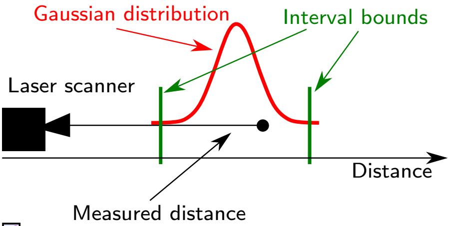
Motivation: Complementary Sensors

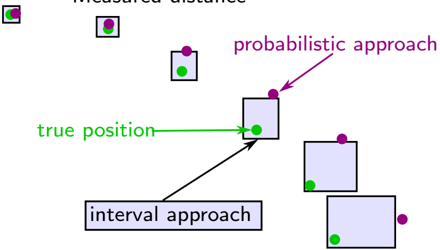
- Camera, laser scanner and IMU
  - Complementary information
- Spatiotemporal calibration parameters required to fuse information
  - Extrinsic transformation
  - Time offset between sensor clocks
  - Uncertainties must be taken into account



Motivation: Why Unknown But Bounded Errors?

- Error distribution is often unknown
  - Unknown systematic errors
- Results can be guaranteed
  - Important for safety-critical systems
- Reverse view:
  - Dismiss infeasible solutions
- Computations are deterministic
  - Proofs become possible



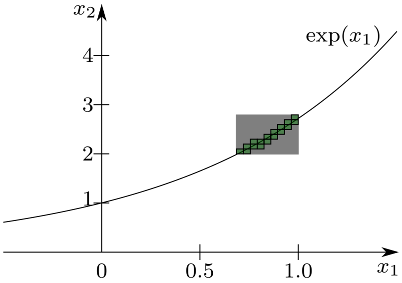


Set Inversion Via Interval Analysis (SIVIA)

- Goal: Invert (non-linear) function $\mathbf{f}$ (e.g. measurement function) to find a solution set $\mathbb{X}$ consistent with an observation $\mathbb{Y}$

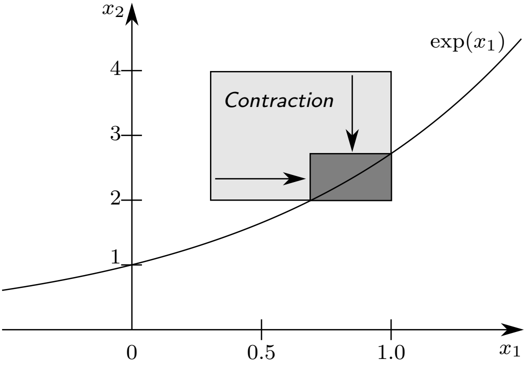
$$\mathbb{X} = \{\, \mathbf{x} \in \mathbb{R}^n \mid \mathbf{f}(\mathbf{x}) \in \mathbb{Y} \,\} = \mathbf{f}^{-1}(\mathbb{Y})$$

- Idea: Branch and bound
- Problem: High computational complexity (exponential on number of variables)

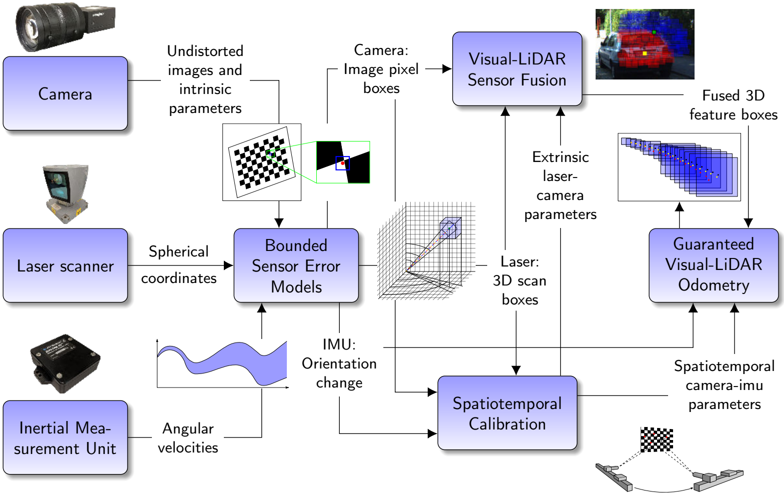


Contractors

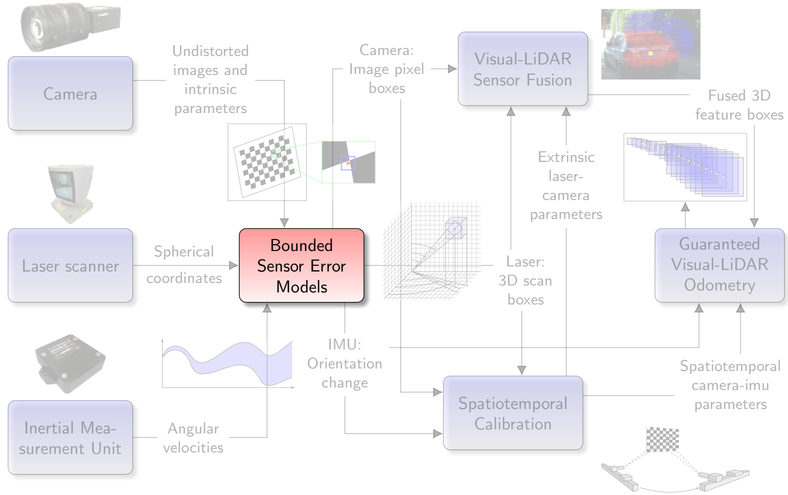
- Interval computations to *contract* the initial box to a smaller box
  - Without losing part of the solution
- Possibly non-linear functions (constraints) link the variables
- Forward-backward contractor



Guaranteed Visual-LiDAR Odometry

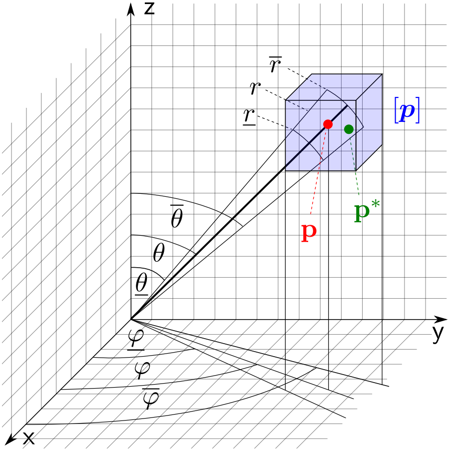


Guaranteed Visual-LiDAR Odometry



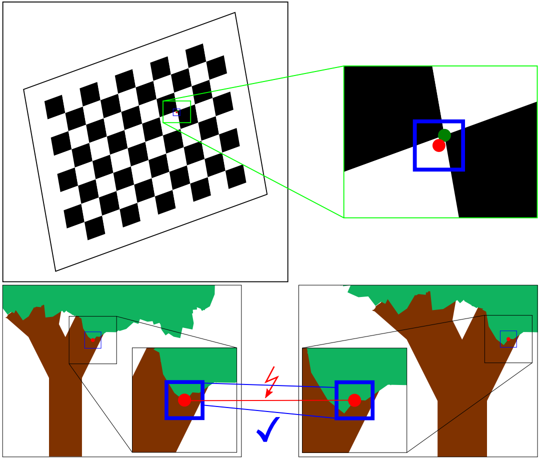
Bounded Sensor Error Models: Laser Scanner

- Unknown but bounded errors for:
  - Distance measurement $[r] = [\underline{r}, \overline{r}]$
  - Angular components $[\theta] = [\underline{\theta}, \overline{\theta}]$ and $[\varphi] = [\underline{\varphi}, \overline{\varphi}]$
- Conversion into Cartesian coordinates
  - 3D box that is guaranteed to contain the true 3D point: $\mathbf{p}^* \in [\boldsymbol{p}]$



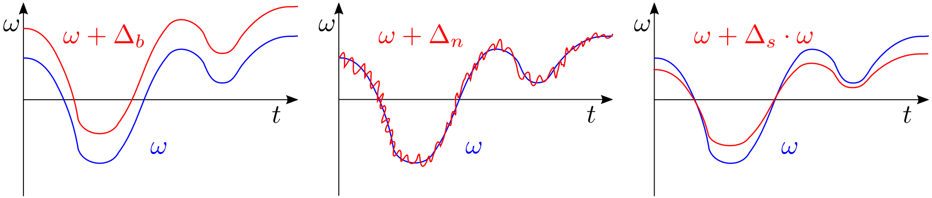
Bounded Sensor Error Models: Camera

- Unknown but bounded errors:
  - Detection of checkerboard corners
  - Detection and matching of image features
- Error bounds:
  - From calibration process (maximum reprojection error)
  - Empirically under consideration of outliers



Bounded Sensor Error Models: IMU

- Three different error sources for gyroscope measurements



Bias/systematic error

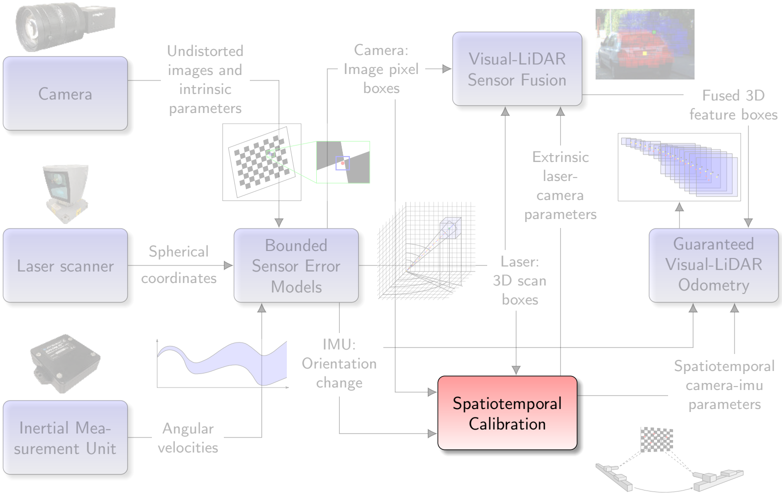
Noise (simplified; technically discontinuous)

Scale factor

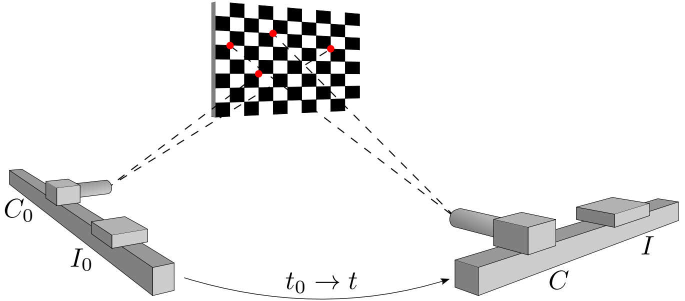
measured

- $[\boldsymbol{\omega}](t) = \boldsymbol{\omega}(t) + [\boldsymbol{\Delta}_b] + [\boldsymbol{\Delta}_n] + [\Delta_s]\,\boldsymbol{\omega}(t)$
- Integration of velocity measurements to compute rotation
- Rotation uncertainty increases due to drift

Guaranteed Visual-LiDAR Odometry



Spatiotemporal Calibration Between Camera and IMU



measured

unknown

$$\forall t: \quad \mathbf{R}_C^{C_0}(t) = \left(\mathbf{R}_C^I \right)^\intercal \cdot \mathbf{R}_I^{I_0}(t + \tau) \cdot \mathbf{R}_C^I \,,$$

$$\mathbf{R}_C^{C_0}(\cdot) \in [\mathbf{R}_C^{C_0}](\cdot), \mathbf{R}_I^{I_0}(\cdot) \in [\mathbf{R}_I^{I_0}](\cdot), \mathbf{R}_C^I \in [\mathbf{R}_C^I], \tau \in [\tau].$$

Spatiotemporal Calibration Between Camera and IMU

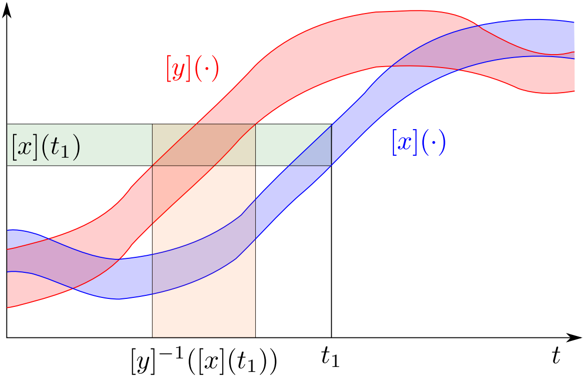
$$\forall t: \; \mathbf{R}_C^{C_0}(t) = \left(\mathbf{R}_C^I\right)^\intercal \cdot \mathbf{R}_I^{I_0}(t+\tau) \cdot \mathbf{R}_C^I,$$
$$\mathbf{R}_C^{C_0}(\cdot) \in [\mathbf{R}_C^{C_0}](\cdot), \mathbf{R}_I^{I_0}(\cdot) \in [\mathbf{R}_I^{I_0}](\cdot), \mathbf{R}_C^I \in [\mathbf{R}_C^I], \tau \in [\tau].$$

- Decompose the constraint into:
  - $\forall t: \; \hat{\mathbf{R}}_I^{I_0}(t) = \left(\mathbf{R}_C^I\right)^\intercal \cdot \mathbf{R}_I^{I_0}(t) \cdot \mathbf{R}_C^I$ (only multiplication),
  - $\forall t: \; \mathbf{R}_C^{C_0}(t) = \hat{\mathbf{R}}_I^{I_0}(t+\tau)$ (new contractor required).

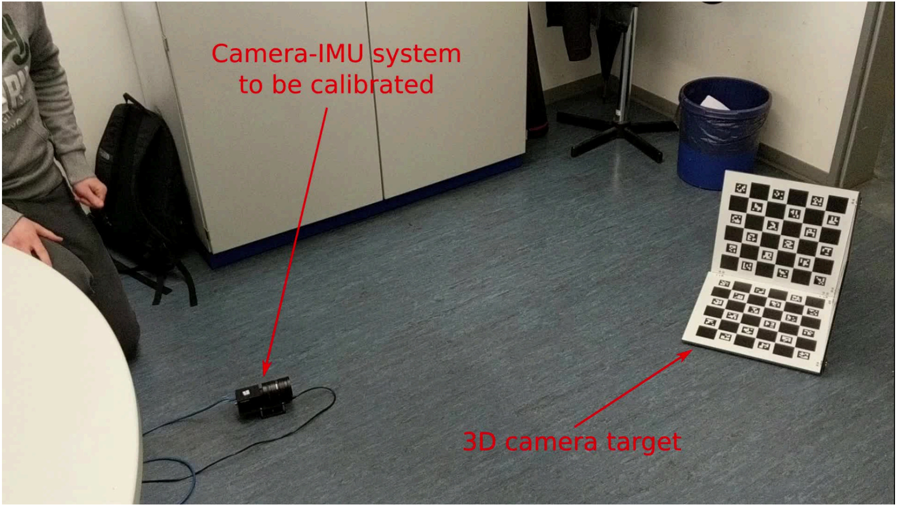
Time Delay Contractor $\mathcal{C}_{delay}$

Generic contractor for the constraint $x(t) = y(t+\tau)$

$$\begin{pmatrix}[\tau]\\ [x](t)\\ [y](t)\end{pmatrix} \xrightarrow[\forall t\in\mathbb{R}]{\mathcal{C}_{delay}} \begin{pmatrix}[\tau]\cap \bigcap\limits_{\forall t_1\in\mathbb{R}} \left([y]^{-1}\left([x]\left(t_1\right)\right)-t_1\right)\\ [x](t)\cap[y]\left(t+[\tau]\right)\\ [y](t)\cap[x]\left(t-[\tau]\right)\end{pmatrix}.$$

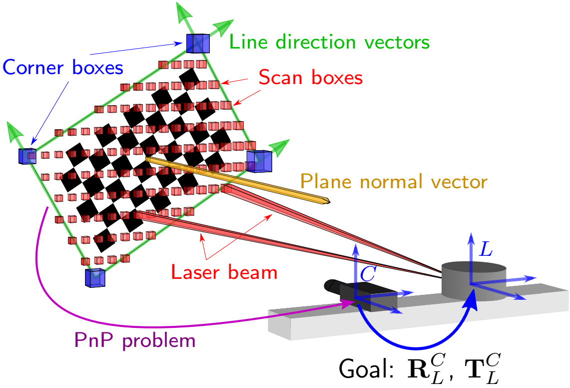


Spatiotemporal Calibration Between Camera and IMU



Extrinsic Calibration Between Camera and Laser Scanner

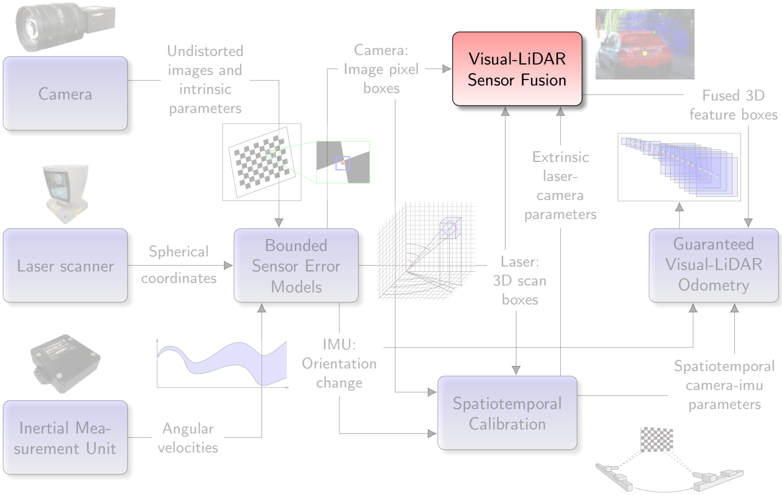
- Extract corresponding features on checkerboard:
  - Plane parameters
  - Boundary line parameters
  - 3D corner points
- Multiple checkerboard poses
- SIVIA with forward-backward contractors to compute $[\mathbf{R}_L^C]$ and $[\mathbf{T}_L^C]$



$$1.\quad \mathbf{R}_L^C \mathbf{n}^L = \mathbf{n}^C$$

$$2.\quad \mathbf{n}^C \cdot \left(\mathbf{R}_L^C \mathbf{P}_l^L + \mathbf{T}_L^C \right) + d^C = 0$$

Guaranteed Visual-LiDAR Odometry



Visual-LiDAR Sensor Fusion

- Goal: Assign distance information to 2D image features
- Project 3D laser scan boxes onto the 2D image plane
- Extrinsic transformation between camera and laser scanner required
- Sensor clocks are assumed to be synchronized

Traditional projection without considering uncertainties.

Interval boxes enclosing the projected laser scan points. The color of each box corresponds to the midpoint of the depth interval.

Visual-LiDAR Sensor Fusion

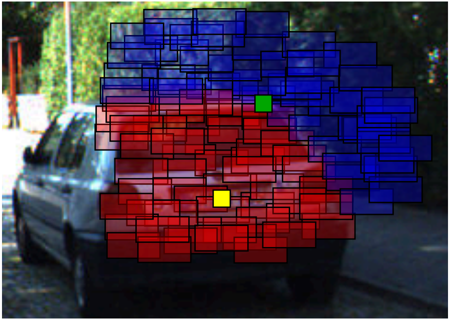
- Set of all projected scan boxes that have a non-empty intersection with the image feature:

$$\mathcal{S}_j = \{\, i \in \{1, \ldots, N_l\} \mid [\tilde{\mathbf{X}}_i^C] \cap [\tilde{\mathbf{X}}_j^C] \neq \varnothing \,\}$$

- Compute the z-coordinate (depth) of the image feature as the union over the z-coordinates of all overlapping scan boxes:

$$[z_j^C] = \bigcup_{i \in \mathcal{S}_j} [z_i^C]$$

- Results in re-identifiable 3D features with information about accuracy



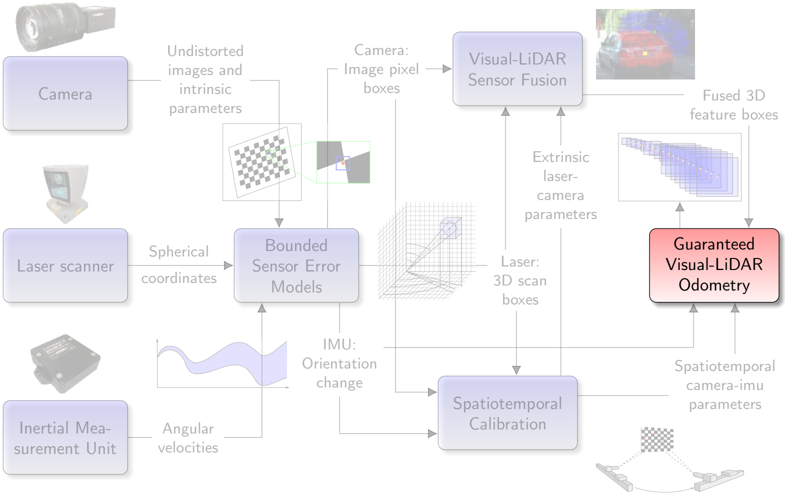
Visual-LiDAR Sensor Fusion

- Exemplary results of the approach for Visual-LiDAR data fusion

Colored by depth (red: close, blue: distant). Features without depth information are colored pink.

Colored by depth accuracy (red: accurate, blue: inaccurate).

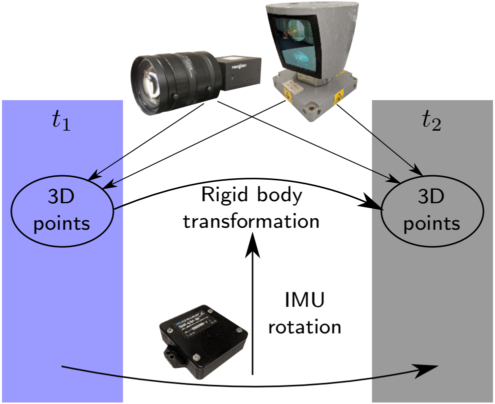
Guaranteed Visual-LiDAR Odometry



Guaranteed Visual-LiDAR Odometry

General idea

- Dead reckoning
- Visual-LiDAR sensor fusion
  - Corresponding 3D points
  - Extrinsic transformation required
- Integrate angular velocities to constrain rotation
  - Spatiotemporal calibration parameters required
- Compute 6 DOF rigid body transformation under interval uncertainty



Guaranteed Visual-LiDAR Odometry

Rigid body transformation

- Distance information found for the feature i at both t_1 and t_2:

$$\mathbf{X}_i^{t_1} = \mathbf{R}_{t_2}^{t_1} \cdot \mathbf{X}_i^{t_2} + \mathbf{T}_{t_2}^{t_1}$$

- Distance information **only** at t_2:

$$z_i^{t_1} \; \tilde{\mathbf{X}}_i^{t_1} = \mathbf{R}_{t_2}^{t_1} \cdot \mathbf{X}_i^{t_2} + \mathbf{T}_{t_2}^{t_1}$$

unknown z-coordinate

normalized image coordinates

- No distance information at all:

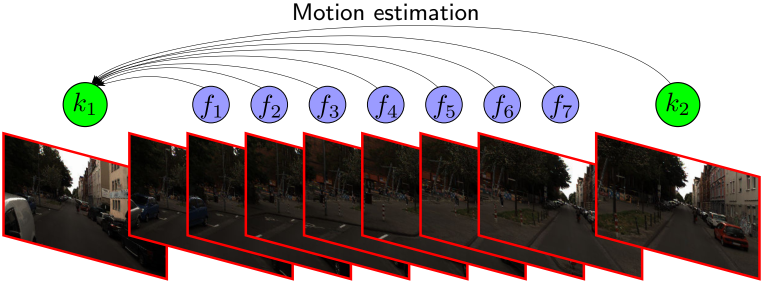
$$z_i^{t_1} \; \tilde{\mathbf{X}}_i^{t_1} = \mathbf{R}_{t_2}^{t_1} \cdot \; z_i^{t_2} \; \tilde{\mathbf{X}}_i^{t_2} + \mathbf{T}_{t_2}^{t_1}$$

- Forward-backward contractors for every feature i
- Intersection of those contractor allows to contract $[\mathbf{R}_{t_2}^{t_1}]$ and $[\mathbf{T}_{t_2}^{t_1}]$
  - Initialization: $[\mathbf{R}_{t_2}^{t_1}]$ set using integrated angular velocity measurements
  - Initialization: $[\mathbf{T}_{t_2}^{t_1}] = ([-\infty, \infty], [-\infty, \infty], [0, \infty])$
- Consideration of outliers by using a relaxed intersection

Guaranteed Visual-LiDAR Odometry

Concept of keyframes

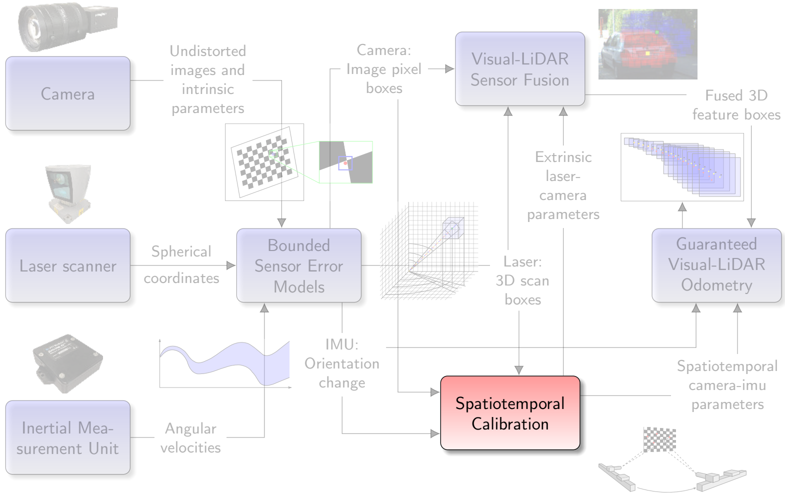
- Estimate motion relative to the last keyframe k_1 until we have to insert a new keyframe k_2
- As few keyframes as possible, but as much as necessary



- Dynamic insertion of keyframes depending on the 6D pose uncertainty
- High pose uncertainty $\Leftrightarrow$ insufficient constraints $\Leftrightarrow$ inaccurate 3D features

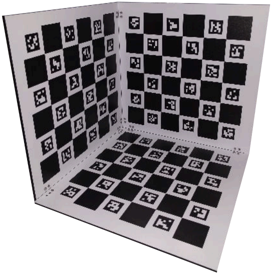
Experimental Results

Guaranteed Visual-LiDAR Odometry



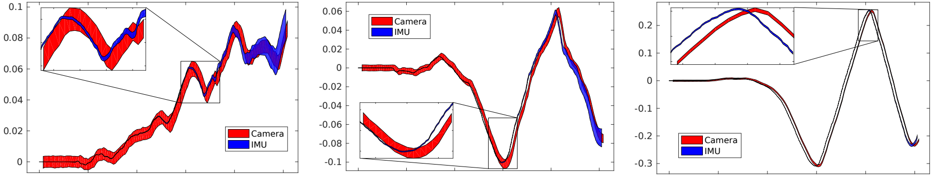
Spatiotemporal Calibration Between Camera and IMU

- Real data
  - Setup rotated by hand for a few seconds
- Sensor error bounds
  - IMU: data sheet
  - Camera: intrinsic calibration
- Different trials:
  1. Rotation around one axis only
  2. Low rotation speed
  3. Medium rotation speed
  4. High rotation speed



Spatiotemporal Calibration Between Camera and IMU

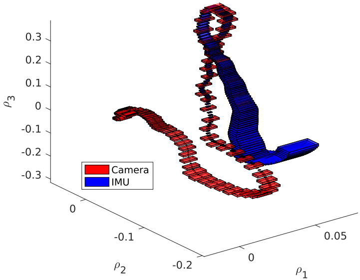
- Different trials:
  1. Rotation around one axis only
  2. Low rotation speed
  3. Medium rotation speed
  4. High rotation speed
- Assuming the extrinsic 3D rotation to be known



$[\rho_x](\cdot)$ $[\rho_y](\cdot)$ $[\rho_z](\cdot)$

Spatiotemporal Calibration Between Camera and IMU

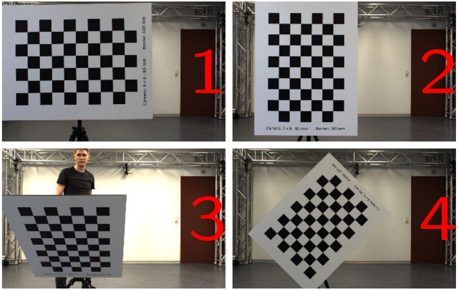
- Different trials:
  1. Rotation around one axis only
  2. Low rotation speed
  3. Medium rotation speed
  4. High rotation speed

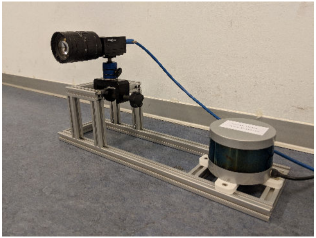


Trial	$[\tau]$ (ms)	$w([\tau])$ (ms)	$w([\theta])$ (°)
1	$[43.0, 65.4]$	22.4	100.72
2	$[27.3, 68.4]$	41.1	12.77
3	$[35.2, 57.6]$	22.4	12.24
4	$[37.1, 51.8]$	14.7	12.93

Extrinsic Calibration Between Camera and Laser Scanner

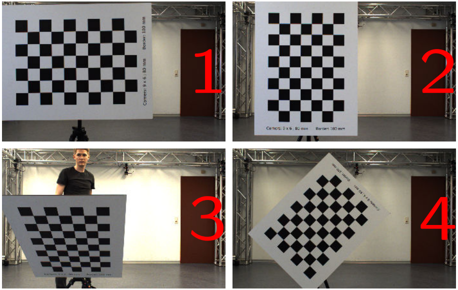
- Real data
- Sensor error bounds
  - Laser scanner: data sheet
  - Camera: intrinsic calibration
- Different checkerboard poses





Extrinsic Calibration Between Camera and Laser Scanner

- Individual checkerboard poses
- Geometry influences accuracy
- Width (accuracy) of computed parameters

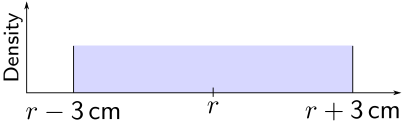


Pose	$w([\phi_L^C])$ (°)	$w([\theta_L^C])$ (°)	$w([\psi_L^C])$ (°)	$w([{}_xT_L^C])$ (cm)	$w([{}_yT_L^C])$ (cm)	$w([{}_zT_L^C])$ (cm)
1	2.9	2.2	1.9	9.8	100.0	**3.5**
2	2.4	2.6	1.6	11.1	100.0	4.2
3	1.0	2.4	2.9	11.1	88.5	**100.0**
4	4.9	5.1	1.0	23.4	21.4	5.9

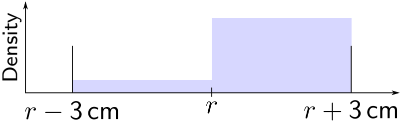
Extrinsic Calibration Between Camera and Laser Scanner

Influence of systematic errors

- Simulated data
- Two different error distributions for the laser scanner distance measurement



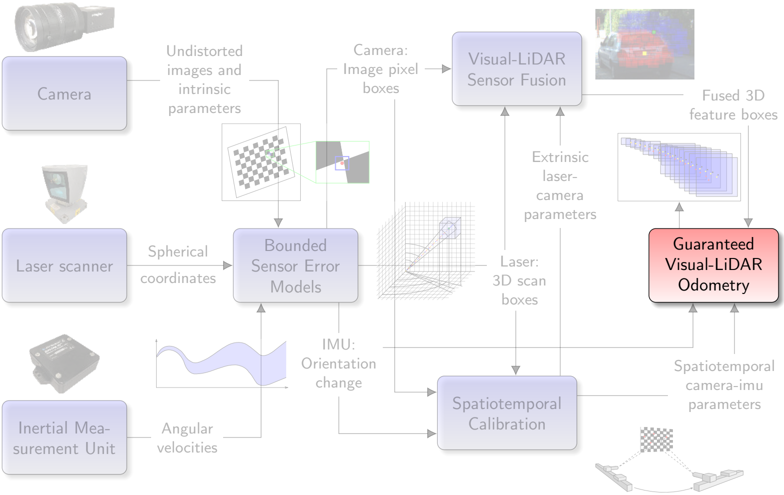
Uniform error distribution with zero-mean error.



Error distribution exhibiting a systematic error (bias) of 1 cm.

	ϕ_L^C (°)	θ_L^C (°)	ψ_L^C (°)	${}_xT_L^C$ (cm)	${}_yT_L^C$ (cm)	${}_zT_L^C$ (cm)
True	90.0	0.0	0.0	-27.0	15.0	-12.0
Zhou [1], no bias	90.01	-0.01	-0.04	-27.00	14.96	-11.91
Our, no bias	$[89.6, 90.3]$	$[-0.4, 0.3]$	$[-0.1, 0.3]$	$[-28.8, -25.0]$	$[13.1, 16.7]$	$[-13.1, -11.0]$
Zhou [1], bias	89.98	0.01	0.04	-27.09	14.88	-12.97
Our, bias	$[89.7, 90.3]$	$[-0.4, 0.5]$	$[-0.4, 0.3]$	$[-29.5, -25.0]$	$[13.0, 16.8]$	$[-13.1, -10.9]$

Guaranteed Visual-LiDAR Odometry



Guaranteed Visual-LiDAR Odometry

- i.c.sens dataset [2] with error bounds derived from:
  - IMU + LiDAR: data sheet
  - Camera: empirical values (maximum 5 % outliers)
  - Extrinsic calibration between camera and LiDAR: proposed approach
  - Time offset between camera and IMU: proposed approach
  - Extrinsic calibration between camera and IMU: i.c.sens calibration
- Keyframe insertion once uncertainty exceeds 5 m^2

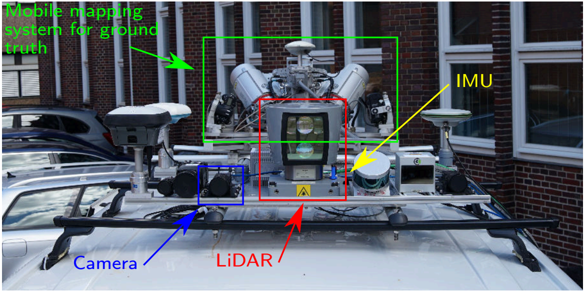
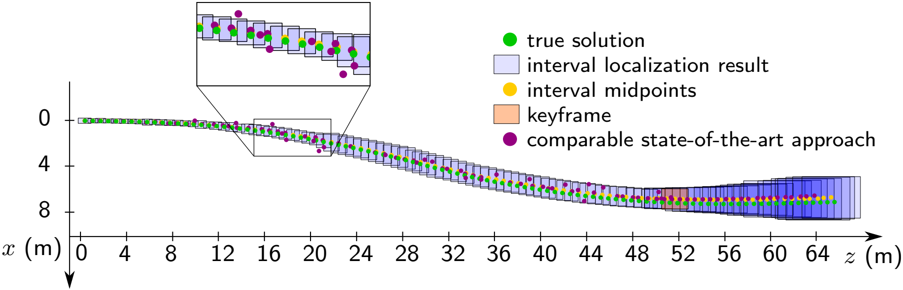


Image credit: Sören Vogel

Guaranteed Visual-LiDAR Odometry

Dead reckoning **with** error propagation at keyframes



- Desired guarantees are provided
- Inconsistencies of the state-of-the-art approach [3, 4] can be detected
- after 10 s: area of 18 m^2 and a volume of 52 m^3
  - No "global" constraints ⇒ uncertainty accumulates quickly (drift)

Guaranteed Visual-LiDAR Odometry

Dead reckoning **without** error propagation at keyframes

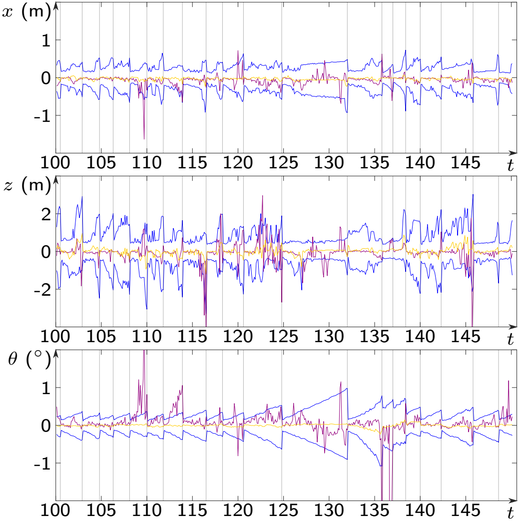
- Uncertainty is "reset" at every keyframe
- Quantitative results

Correct (%)	Volume (m^3)	Area (m^2)	Rotation accuracy ($^\circ$)	Features w. depth	Distance per keyframe (m)	Inconsistencies (%)
100	0.77	1.30	0.77	105	11.35	29.9

- Desired guarantees are provided
- Inconsistencies of state-of-the-art approach [3, 4] are reliably detected

Guaranteed Visual-LiDAR Odometry

- Relative error for a smaller section (50 s) of the experiment
  - Zero is ground truth
- Color coding:
  - lower and upper interval bounds
  - their respective midpoints
  - comparable state-of-the-art approach
  - Insertion of a keyframe: vertical gray line



Guaranteed Visual-LiDAR Odometry

Exemplary image features for a detected inconsistency


Stochastic features colored by depth (red: close, blue: distant, violet: no depth).

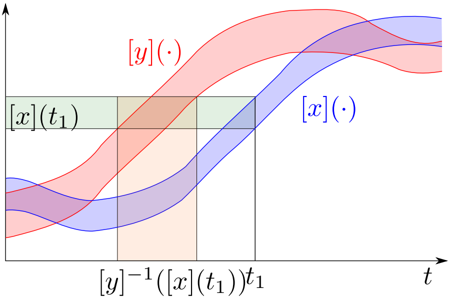

Interval features colored by depth midpoint (red: close, blue: distant, violet: no depth).


Interval features colored by uncertainty (red: certain, blue: uncertain).

Conclusions

Spatiotemporal calibration between camera and IMU

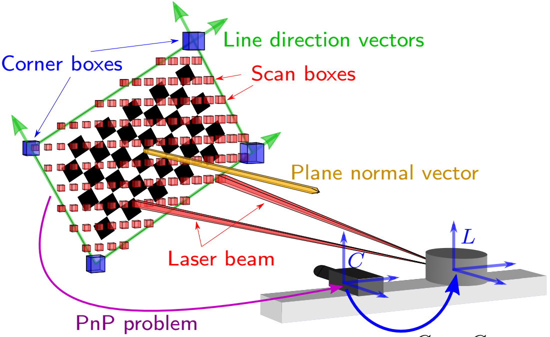
- Introduction of the time delay contractor $\mathcal{C}_{delay}$
- Time offset can be determined reasonably accurate
- Extrinsic rotation too uncertain for sensor fusion
  - Motion range is limited
  - Uncertainty of IMU rotation estimates grows too quickly
  - Usage of angular velocities to avoid integration



Conclusions

Extrinsic calibration between camera and laser scanner

- Interval-based algorithm for the Perspective-n-Point (PnP) problem
- Extraction of checkerboard features under interval uncertainty
- Calibration parameters sufficiently accurate for sensor fusion



Goal: $\mathbf{R}_L^C$, $\mathbf{T}_L^C$

Conclusions

Guaranteed Visual-LiDAR Odometry

- New approach for dead reckoning using camera, laser scanner and IMU
- Consideration of all error sources
  - Bounded sensor error models
  - Bounded spatiotemporal calibration parameters
- Uncertainty grows quickly ("drift")
  - Global constraints required in the future
- Desired guarantees are obtained
- Uncertainty of pose estimates can be assessed
  - Allows warnings if uncertainty grows too large (integrity)
- Faults of state-of-the-art approach can be detected
  - Combination with probabilistic methods in the future

References

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