

Set-Membership Extrinsic Calibration of a 3D LiDAR and a Camera

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DFG Research Training Group (RTG 2159)
i.c.sens - Integrity and Collaboration in Dynamic Sensor Networks

Motivation: Complementary Sensors

- Camera and laser scanner
 - Complementary information

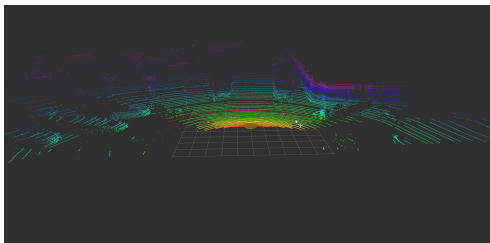
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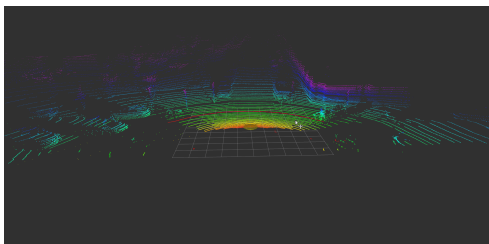
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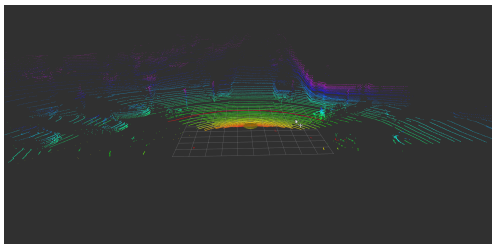
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 - Complementary information
- Extrinsic calibration parameters required to fuse information
 - Rigid body transformation



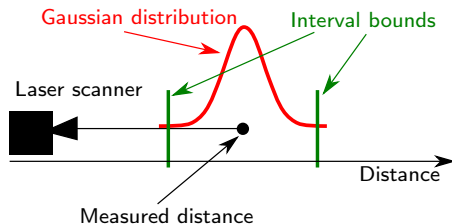
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- Extrinsic calibration parameters required to fuse information
 - Rigid body transformation
 - Uncertainties must be taken into account



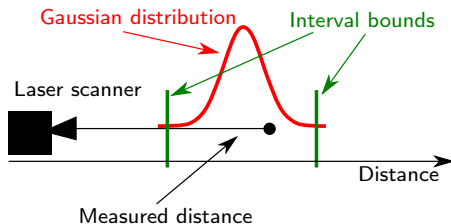
Motivation: Why Unknown But Bounded Errors?

- Error distribution is often unknown



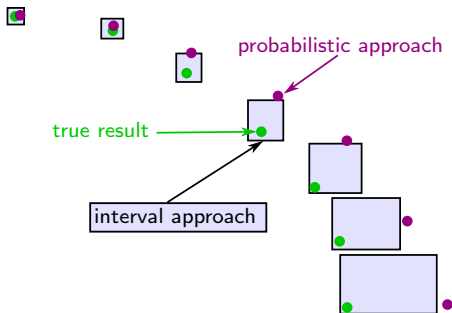
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- Error distribution is often unknown
 - Unknown systematic errors



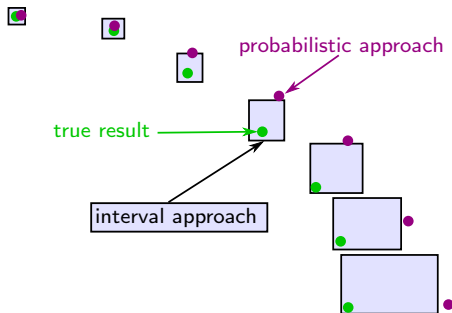
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- Error distribution is often unknown
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- Results can be guaranteed



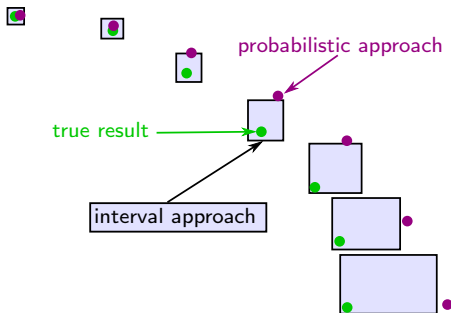
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- Error distribution is often unknown
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- Results can be guaranteed
 - Important for safety-critical systems



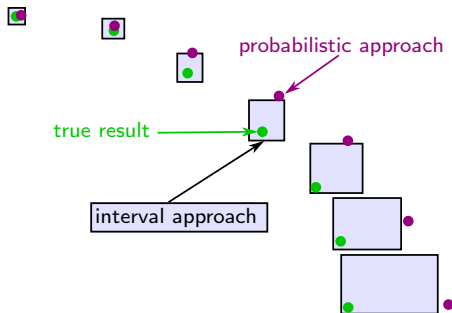
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- Reverse view:
 - Dismiss infeasible solutions



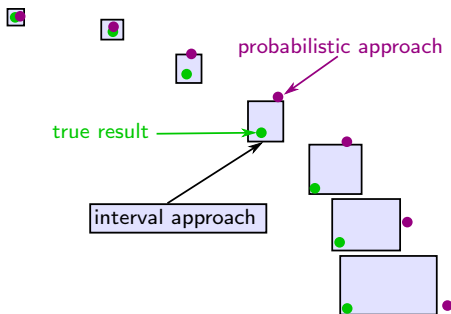
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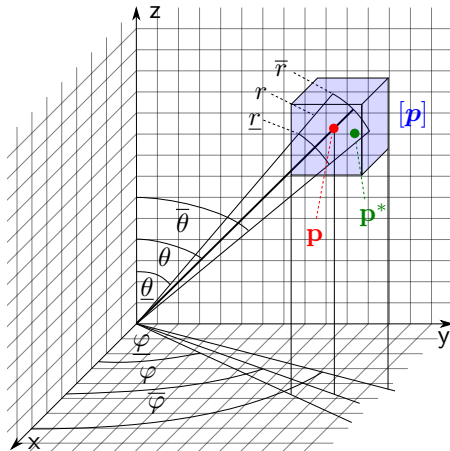
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- Reverse view:
 - Dismiss infeasible solutions
- Computations are deterministic
 - Proofs become possible



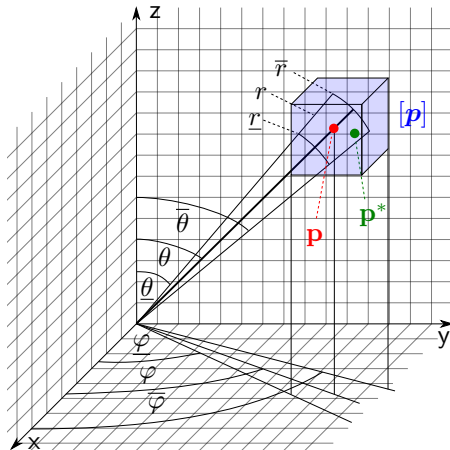
Bounded Sensor Error Models: Laser Scanner

- Unknown but bounded errors for:



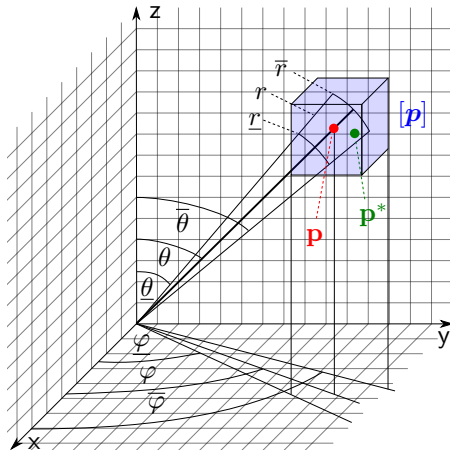
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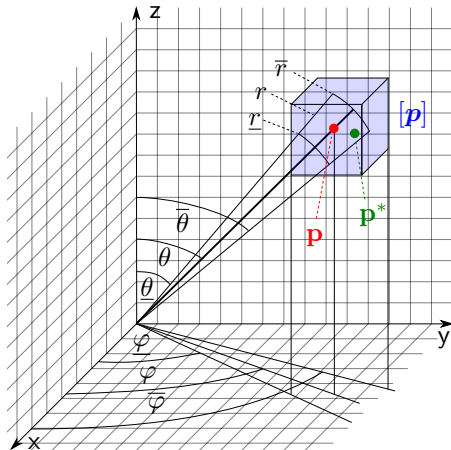
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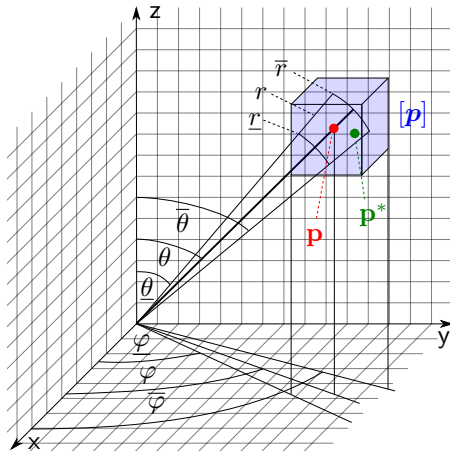
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- Conversion into Cartesian coordinates



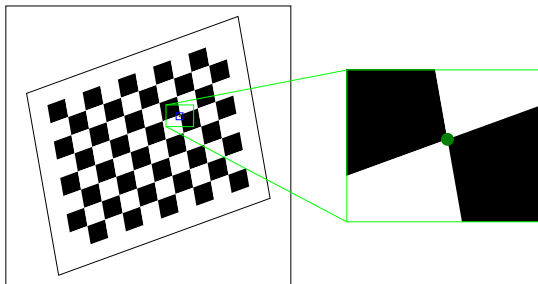
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 - Angular components $[\theta] = [\underline{\theta}, \bar{\theta}]$ and $[\varphi] = [\underline{\varphi}, \bar{\varphi}]$
- Conversion into Cartesian coordinates
 - 3D box that is guaranteed to contain the true 3D point: $\mathbf{p}^* \in [p]$



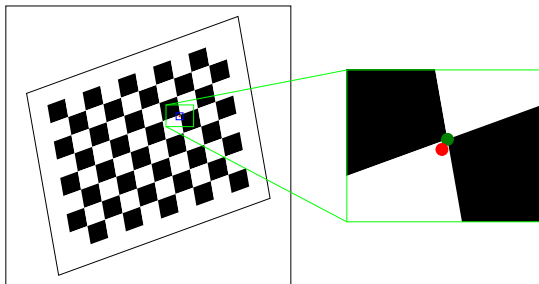
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- Unknown but bounded errors:
 - Detection of checkerboard corners



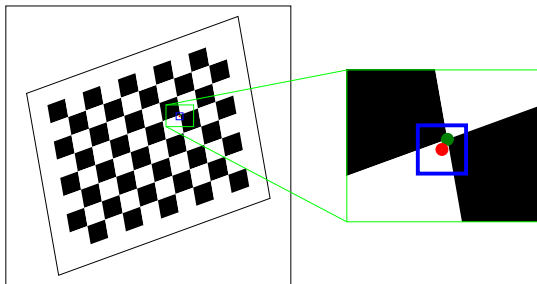
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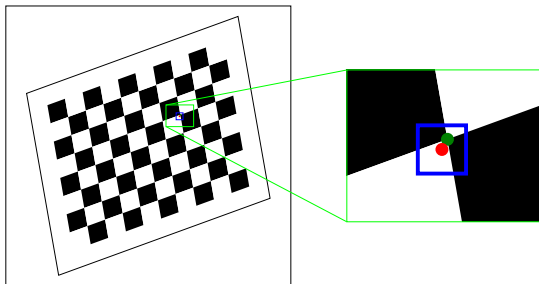
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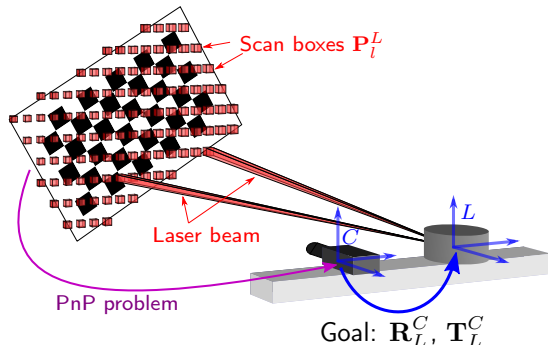
Bounded Sensor Error Models: Camera

- Unknown but bounded errors:
 - Detection of checkerboard corners
- Error bounds:
 - From calibration process (maximum reprojection error)



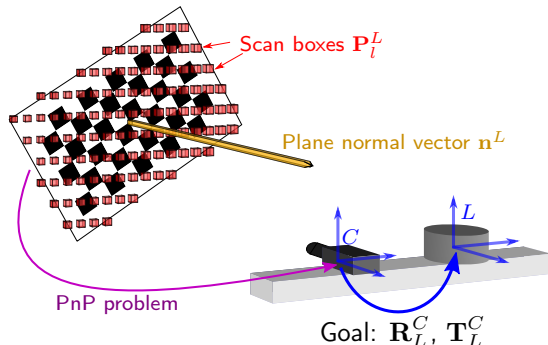
Extrinsic Calibration Between Camera and Laser Scanner

- Solve PnP problem under interval uncertainty [1]
- Extract corresponding features on checkerboard:



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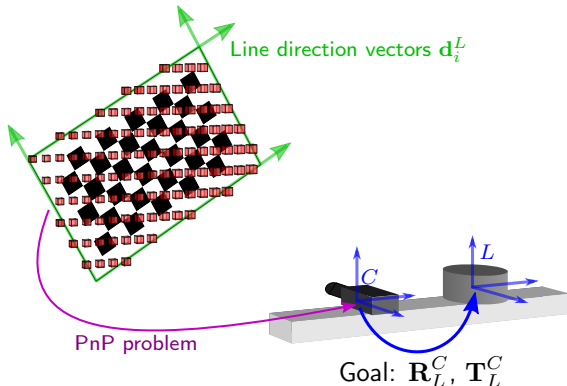
- Solve PnP problem under interval uncertainty [1]
- Extract corresponding features on checkerboard:
 - Plane parameters



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

Extrinsic Calibration Between Camera and Laser Scanner

- Solve PnP problem under interval uncertainty [1]
- Extract corresponding features on checkerboard:
 - Plane parameters
 - Boundary line parameters

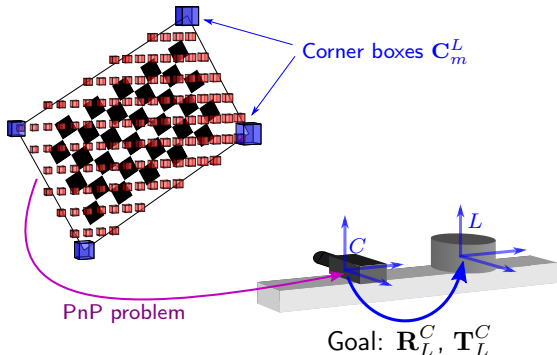


$$3. \quad \mathbf{R}_L^C \mathbf{d}_i^L = \mathbf{d}_i^C$$

$$4. \quad \left(\mathbf{I} - \mathbf{d}_i^C \left(\mathbf{d}_i^C \right)^\top \right) \left(\mathbf{R}_L^C \mathbf{Q}_{ij}^L + \mathbf{T}_L^C - \mathbf{Q}_{ik}^C \right) = \mathbf{0}$$

Extrinsic Calibration Between Camera and Laser Scanner

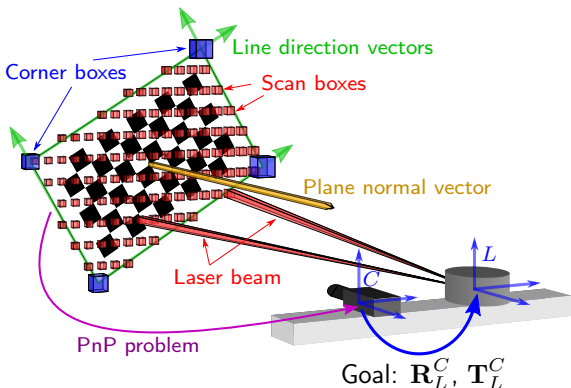
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$$5. \quad R_L^C C_m^L + T_L^C = C_m^C$$

Extrinsic Calibration Between Camera and Laser Scanner

- Solve PnP problem under interval uncertainty [1]
- 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 $[\mathbf{T}_L^C]$



Experimental Results

- Real data



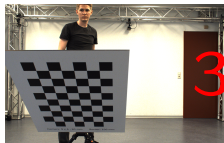
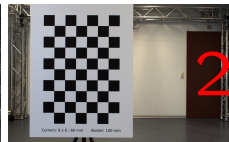
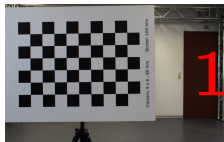
Experimental Results

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



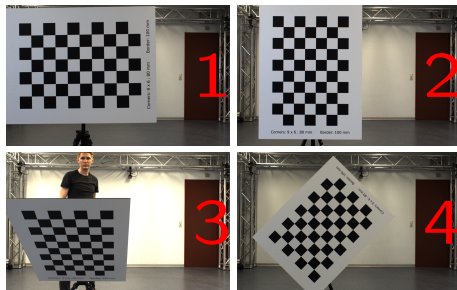
Experimental Results

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



Experimental Results

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



Pose	$w([\phi_L^C])$ (°)	$w([\theta_L^C])$ (°)	$w([\psi_L^C])$ (°)	$w([x_L^T])$ (cm)	$w([y_L^T])$ (cm)	$w([z_L^T])$ (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

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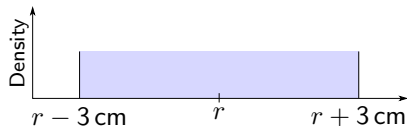
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- Simulated data
- Two different error distributions for the laser scanner distance measurement

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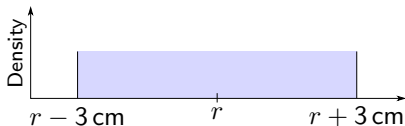


Uniform error distribution with zero-mean error.

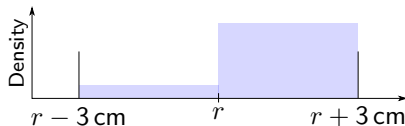
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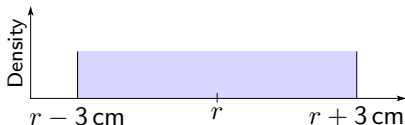


Error distribution exhibiting a systematic error (bias) of 1 cm.

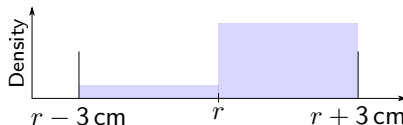
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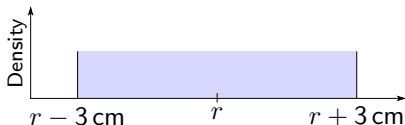
Error distribution exhibiting a systematic error (bias) of 1 cm.

	ϕ_L^C (°)	θ_L^C (°)	ψ_L^C (°)	x_L^{TC} (cm)	y_L^{TC} (cm)	z_L^{TC} (cm)
True	90.0	0.0	0.0	-27.0	15.0	-12.0

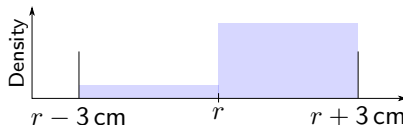
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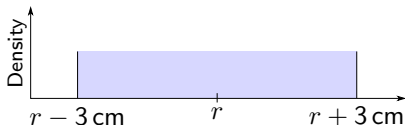
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Zhou [2], no bias	90.01	-0.01	-0.04	-27.00	14.96	-11.91
Our, no bias	[89.6, 90.3]	[-0.4, 0.3]	[-0.1, 0.3]	[-28.8, -25.0]	[13.1, 16.7]	[-13.1, -11.0]

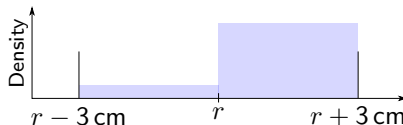
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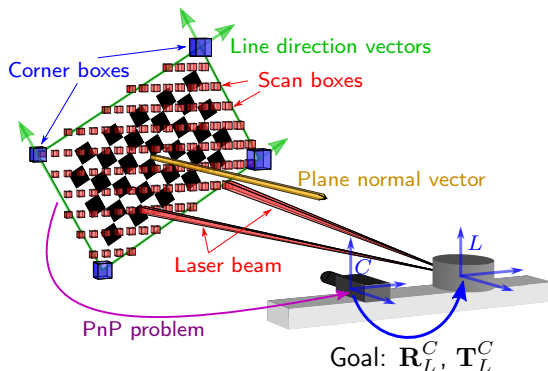
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Conclusions

- Set-membership extrinsic calibration of a 3D LiDAR and a camera

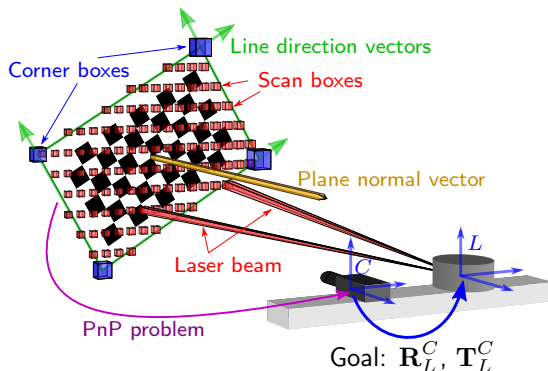
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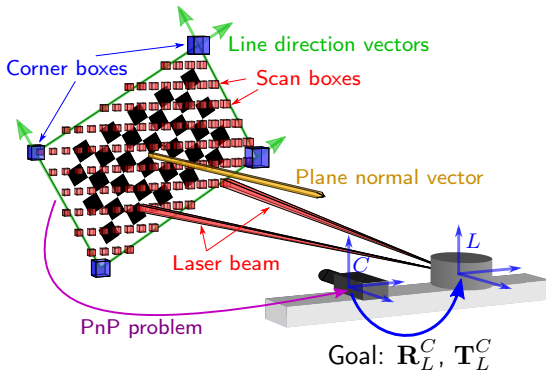
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- Set-membership extrinsic calibration of a 3D LiDAR and a camera
 - Extraction of checkerboard features under interval uncertainty
- Calibration parameters sufficiently accurate for sensor fusion
- Approach is compatible with unknown systematic errors



References

- [1] R. Voges and B. Wagner, "Timestamp Offset Calibration for an IMU-Camera System Under Interval Uncertainty," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Madrid, Spain, Oct. 2018.
- [2] L. Zhou, Z. Li, and M. Kaess, "Automatic Extrinsic Calibration of a Camera and a 3D LiDAR Using Line and Plane Correspondences," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Madrid, Spain, Oct. 2018.

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