Hybrid Interval–Probabilistic Localization in Building Maps

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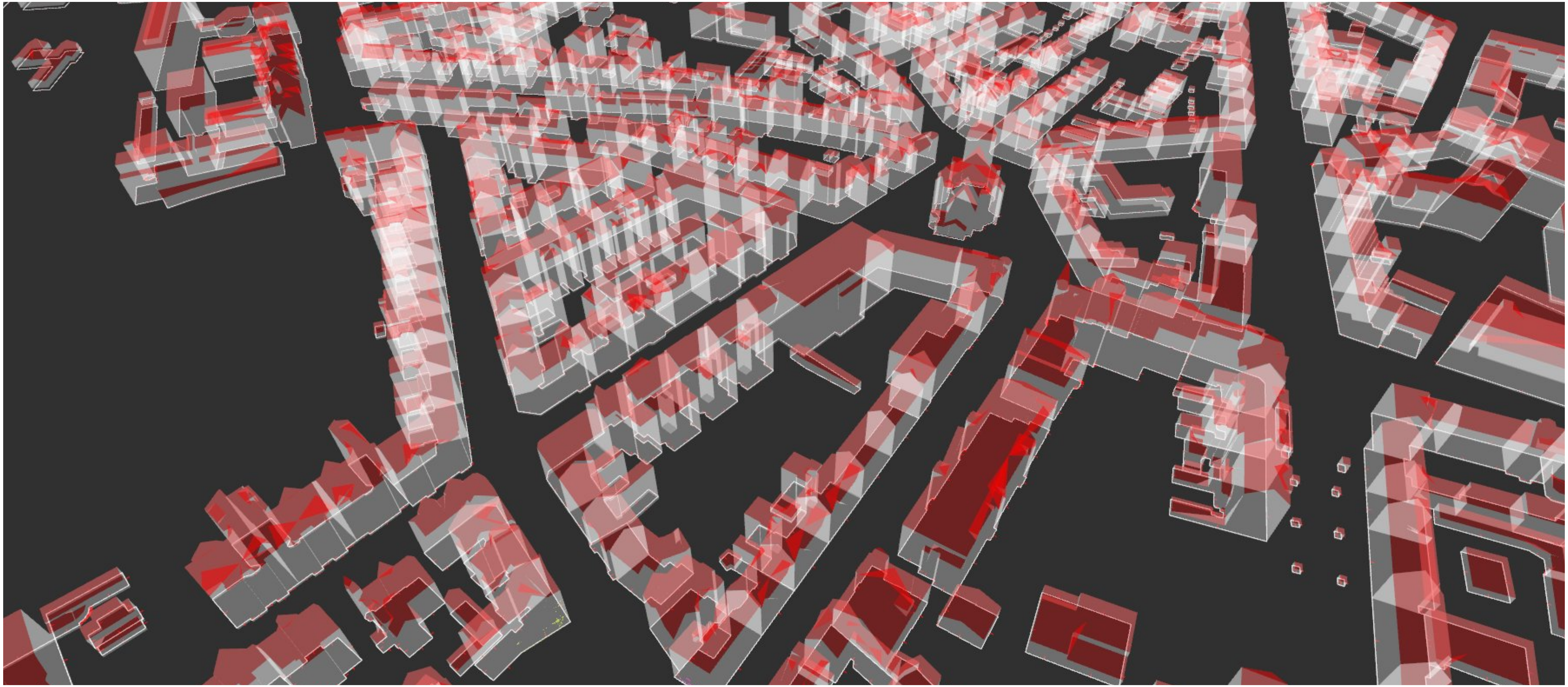
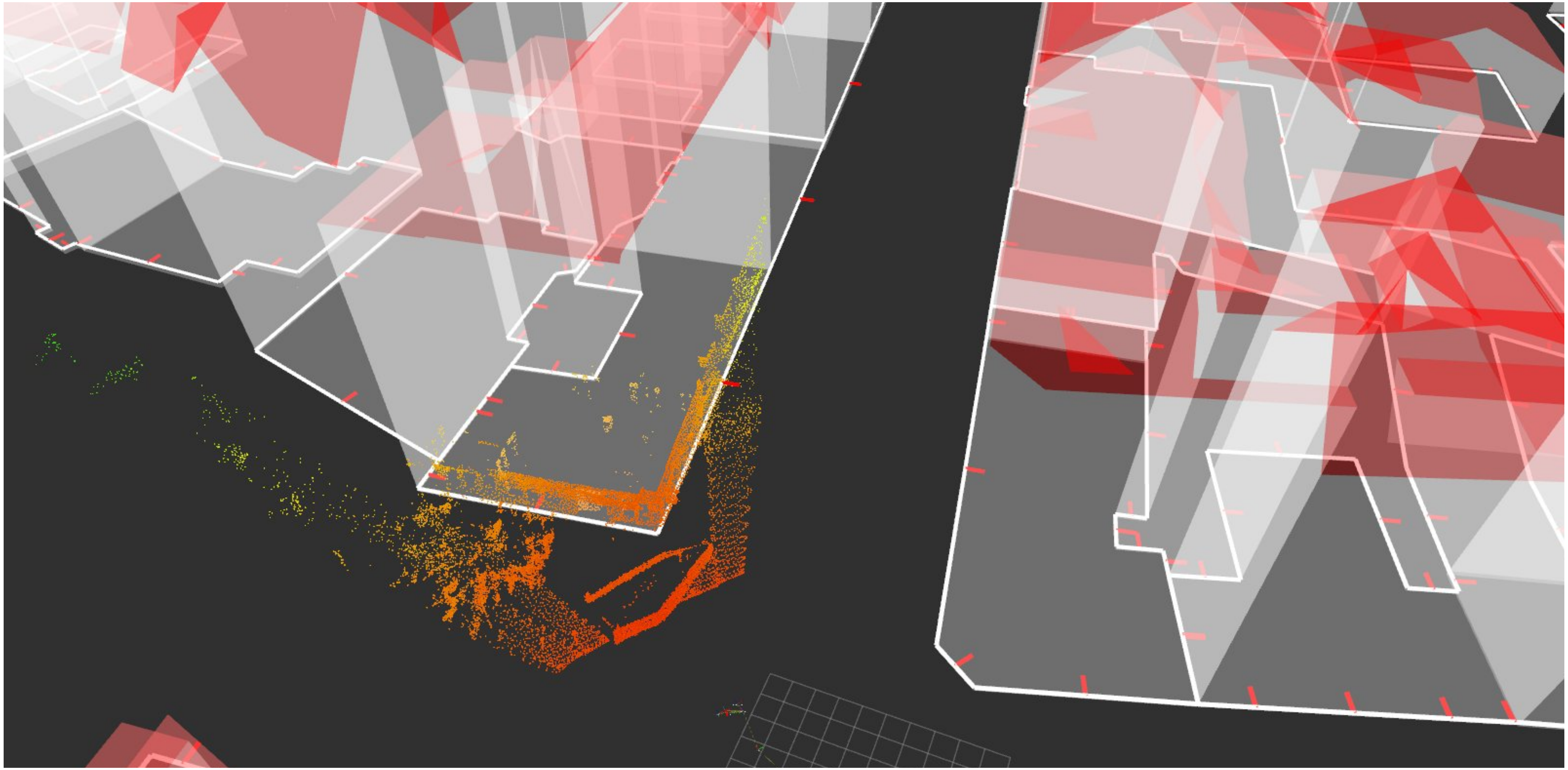
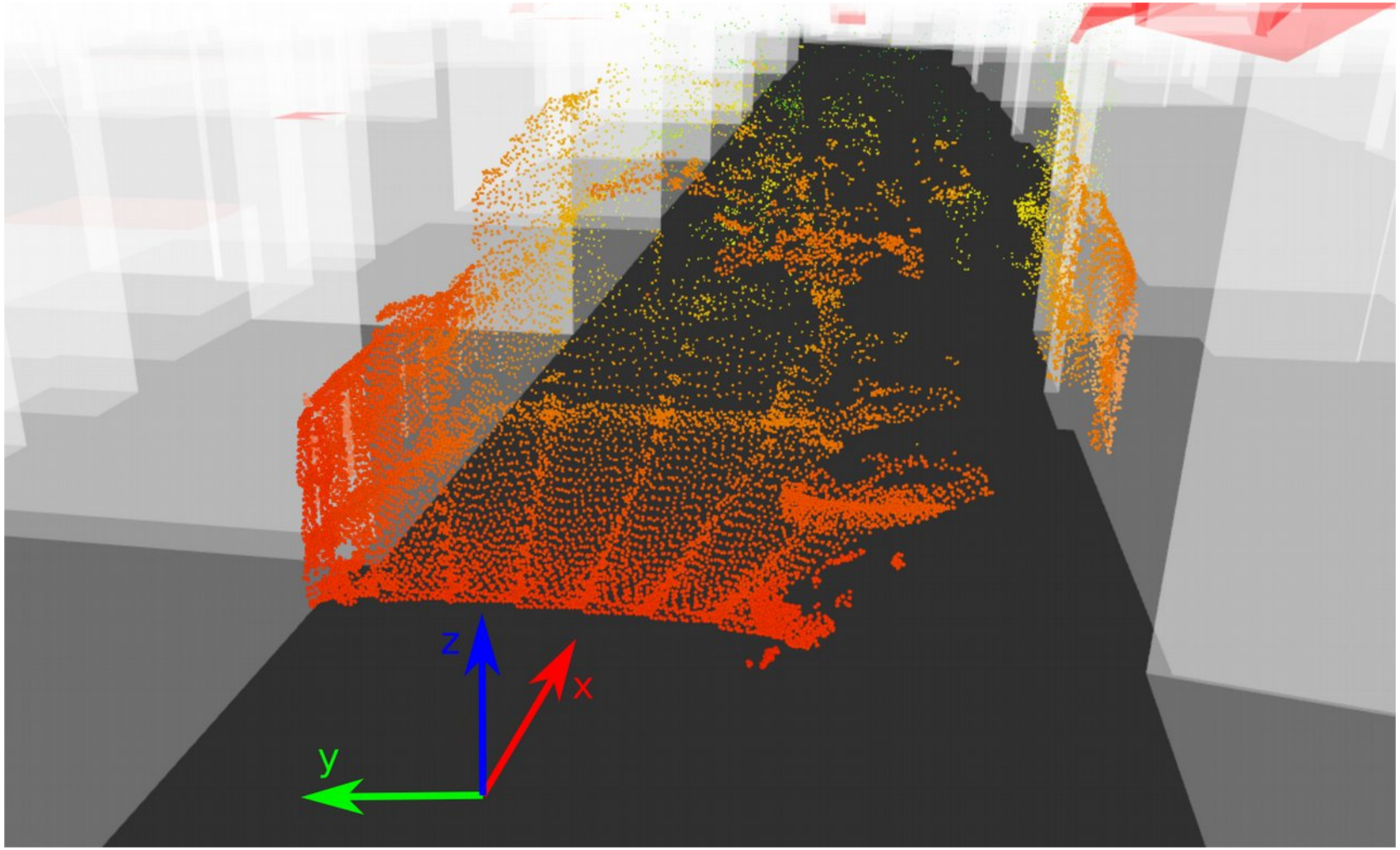
Motivation



Goal: Localize the Vehicle by Matching the Point Cloud to the Facades



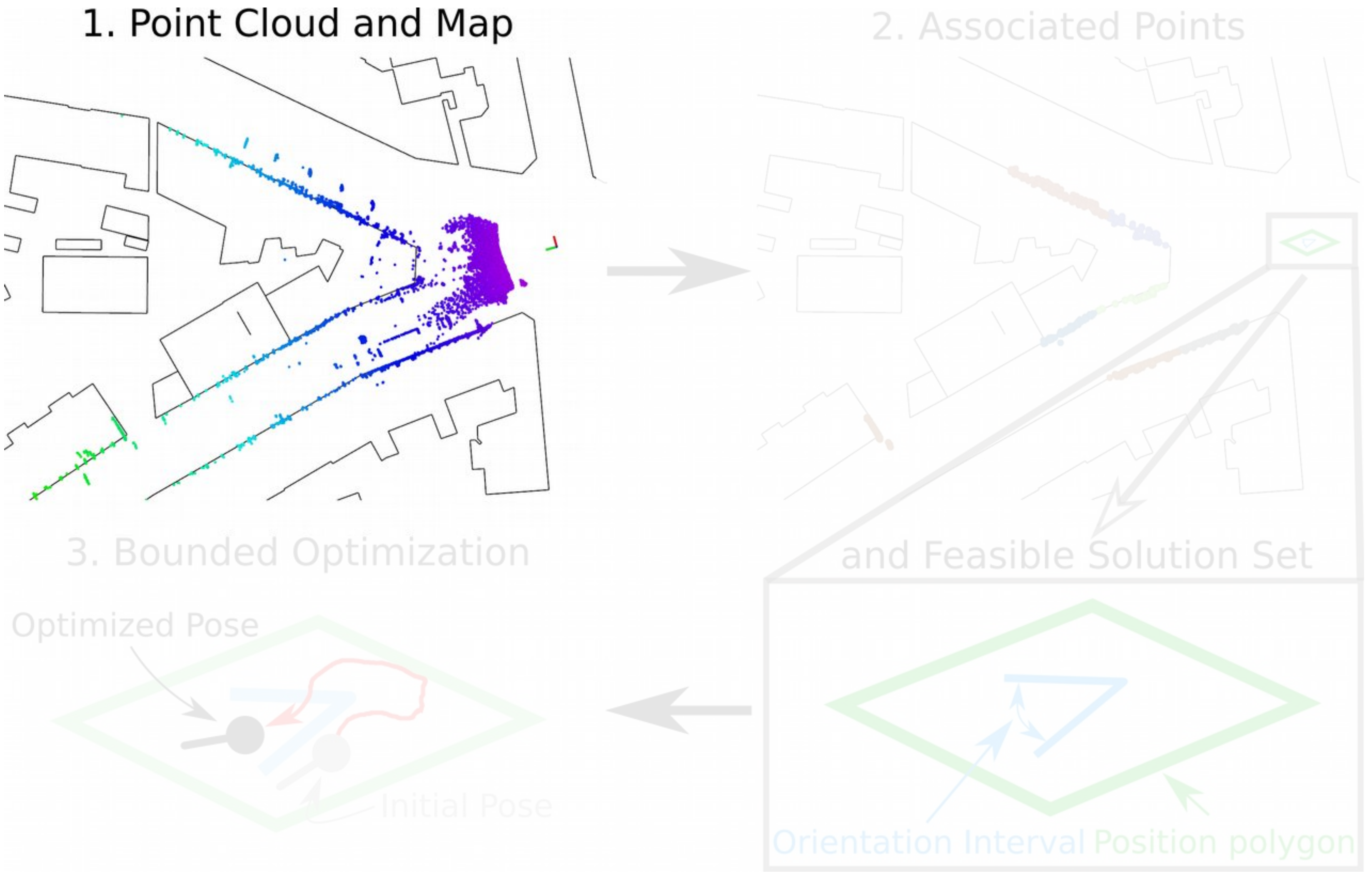
Which Pose-Parameters can be constrained?



- **Translation:**
  - x-direction: ○
  - y-direction: ✓
  - z-direction: ✗
- **Rotation:**
  - x-Axis: ✓
  - y-Axis: ○
  - z-Axis: ✓
- **Reduce the pose to 2D!**
  - Less parameters leads to less dependencies in the equations
  - Better contraction coming with the cost of negecting 3 parameters

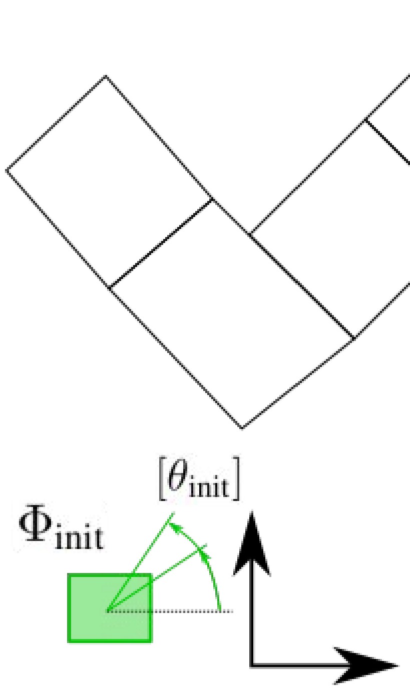
Overview

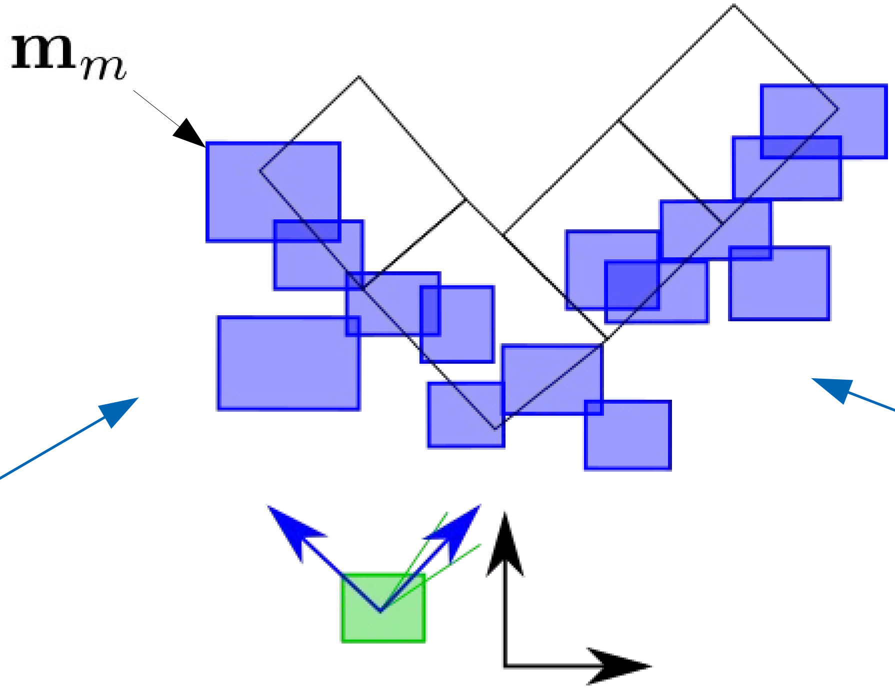
- **Input Data:**
  - LiDAR point cloud
  - Building footprints
  - Initial pose is roughly known
- **Interval-Based Localization:**
  - Interval-based point-to-facade association
  - Interval-based Hough Transformation (iHT)
  - Contract orientation and determine minimal position polygon
- **Bounded Optimization:**
  - Least squares optimization with rigid bounds



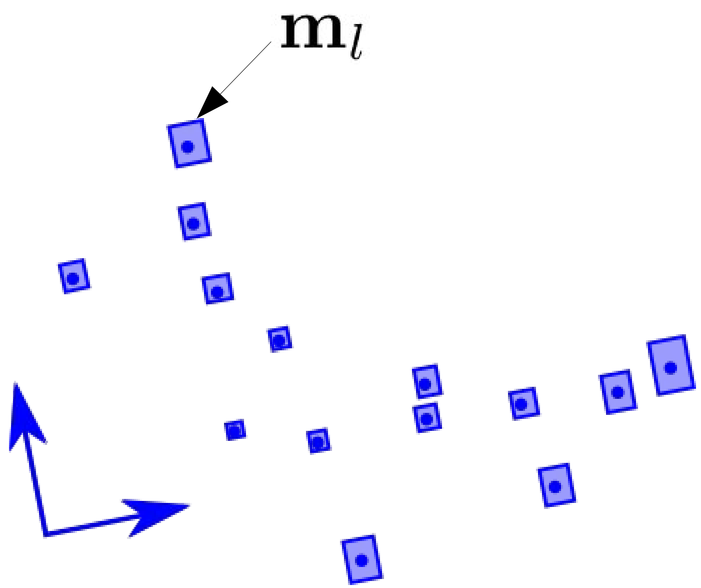
Interval-based Point-to-Facade Association

Map





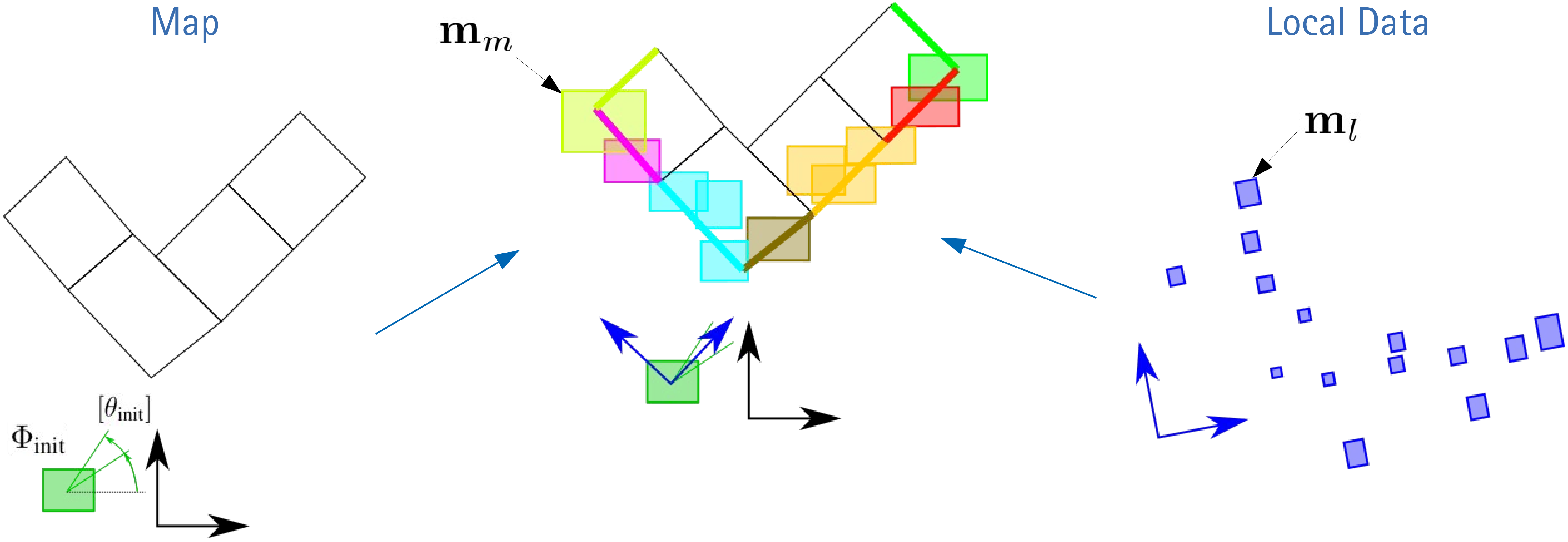
Local Data



$$\mathbf{m}_m = \begin{pmatrix} \cos(\theta_{\text{init}}) & -\sin(\theta_{\text{init}}) \\ \sin(\theta_{\text{init}}) & \cos(\theta_{\text{init}}) \end{pmatrix} \cdot \mathbf{m}_l + \begin{pmatrix} t_{x,\text{init}} \\ t_{y,\text{init}} \end{pmatrix}$$

$$\mathbf{m}_m \in [\mathbf{m}_m], \quad \theta_{\text{init}} \in [\theta_{\text{init}}], \quad \mathbf{m}_l \in [\mathbf{m}_l] \text{ and } \begin{pmatrix} t_{x,\text{init}} & t_{y,\text{init}} \end{pmatrix} \in \Phi_{\text{init}}$$

Interval-based Point-to-Facade Association



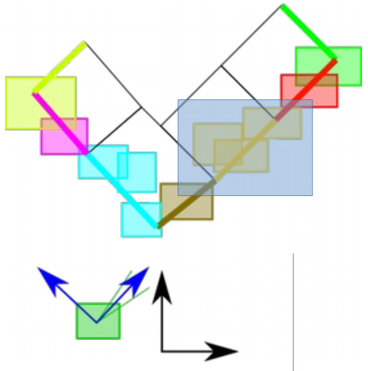
Interval-based Point-to-Facade Association

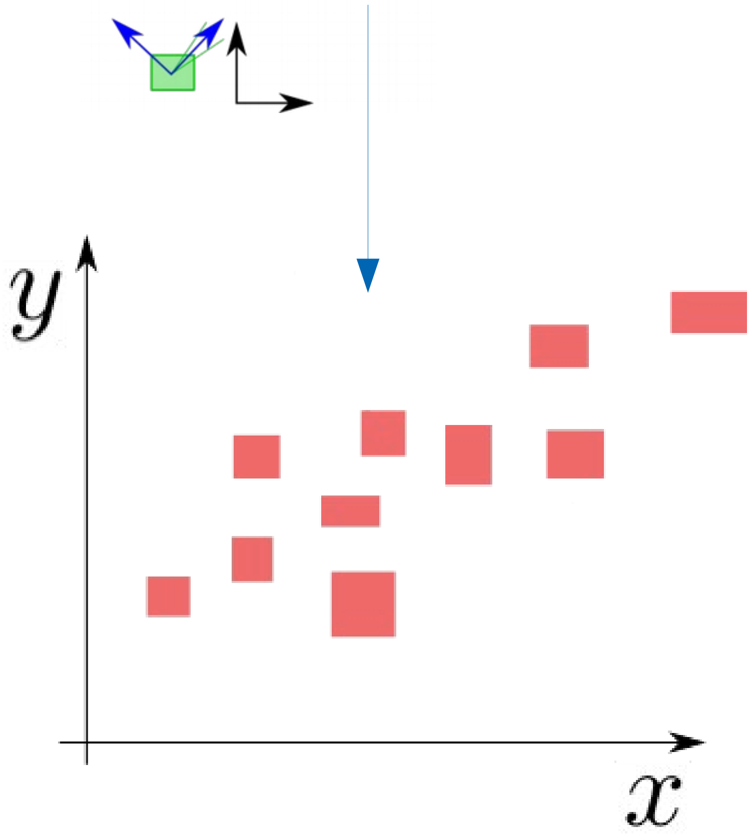
Output: Cloud of boxes that are associated to the map facades

Problems:

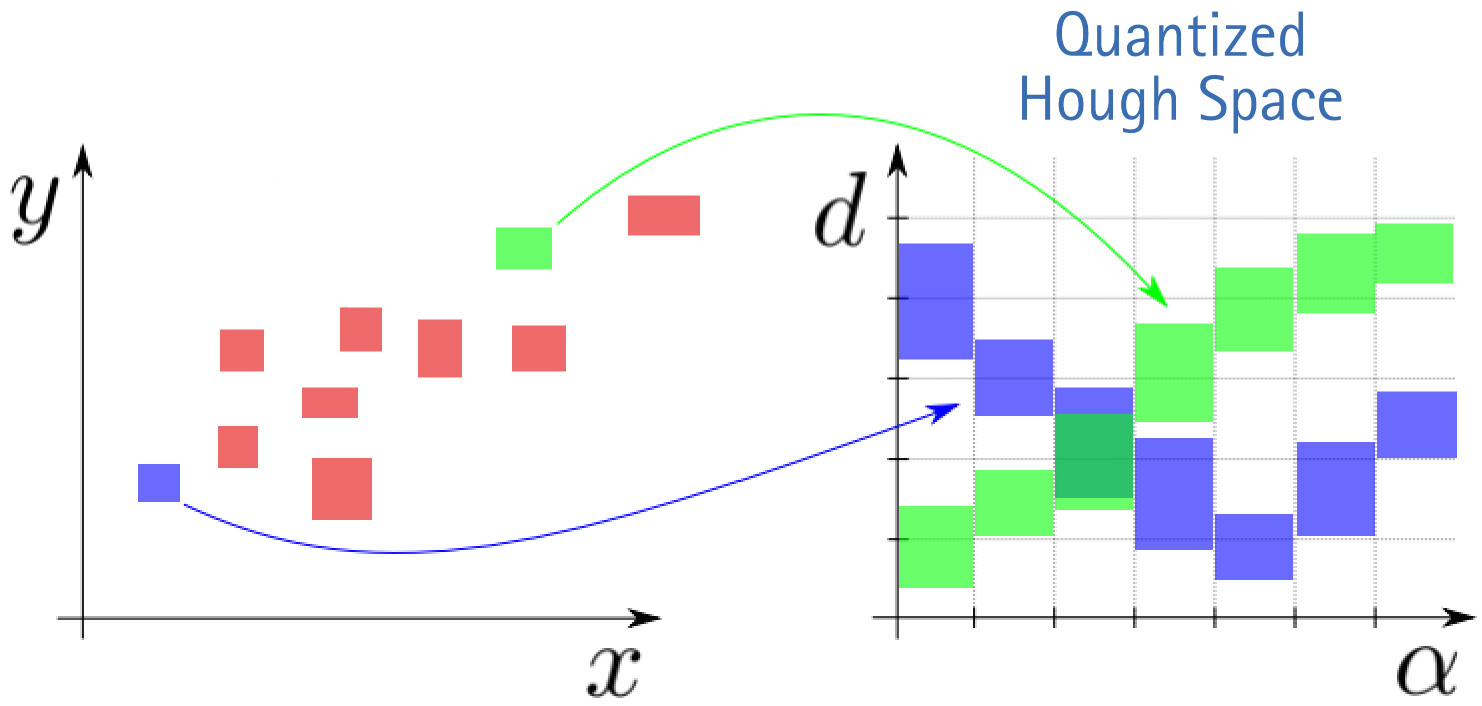
- Balconies, ornaments, close objects, ... may be associated
- Extract line-parameters from a cloud of boxes representing the uncertainty

Our Solution: Interval-based Hough Transformation (iHT)





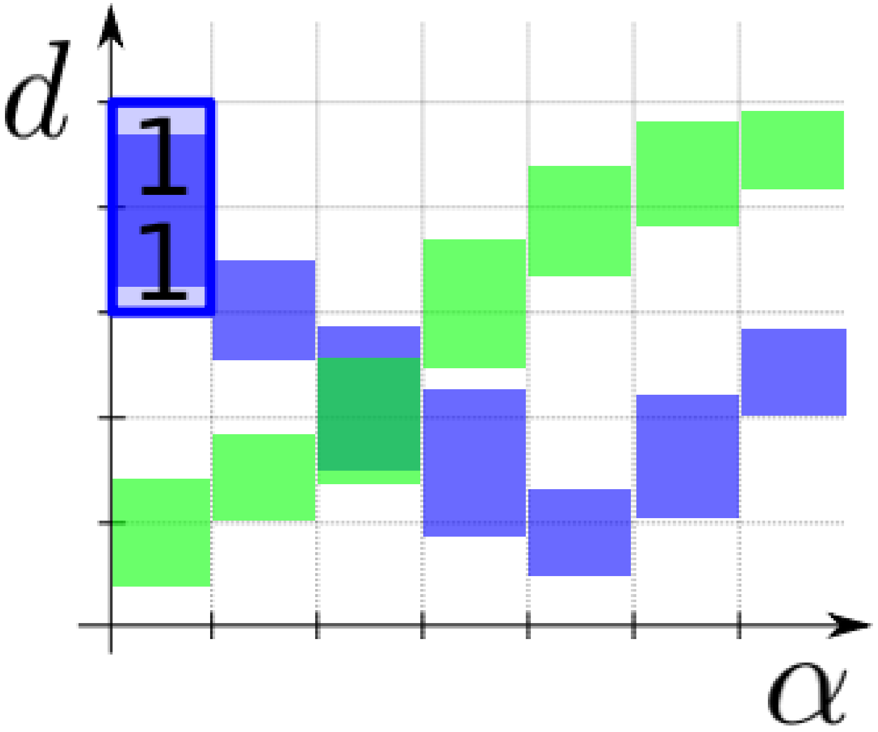
Interval-based Hough Transformation – Accumulator



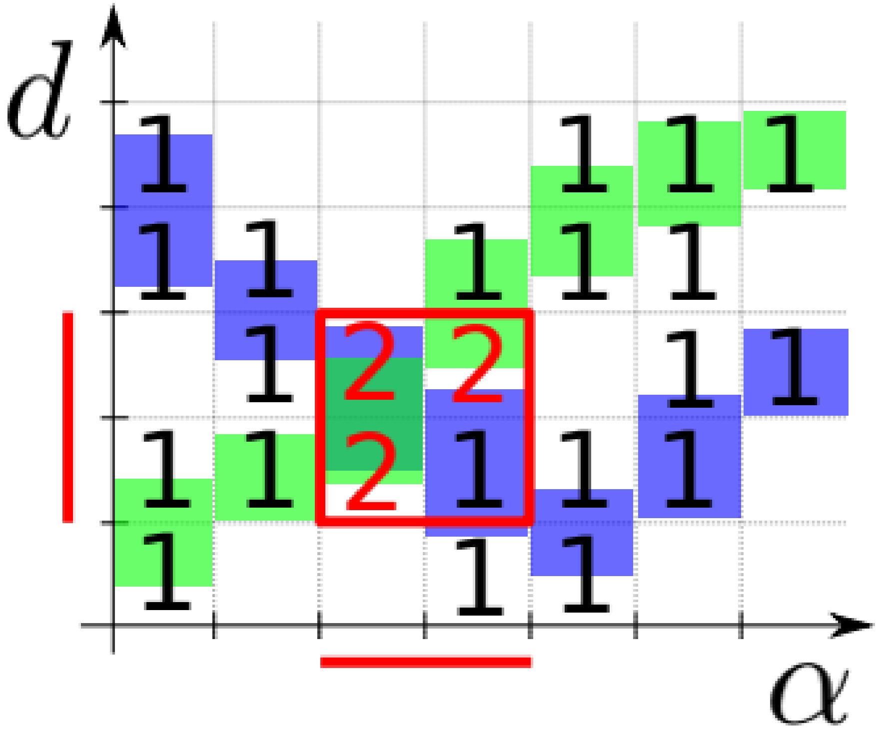
$$\mathbf{n}^T \cdot \mathbf{a} - d = \begin{pmatrix}\cos(\alpha) & \sin(\alpha)\end{pmatrix} \cdot \begin{pmatrix} x \\ y \end{pmatrix} - d = 0$$

Interval-based Hough Transformation – Accumulator Quantization

Quantization



Line Extraction
Set of lines with highest support



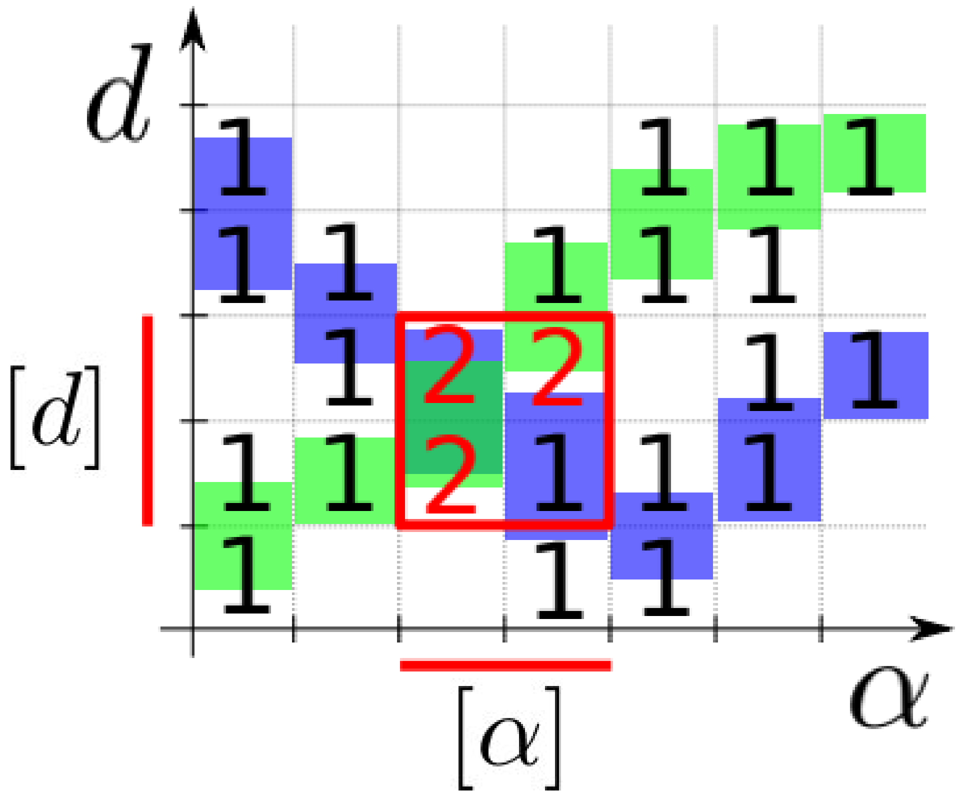
Interval-based Hough Transformation – Line Extraction

Line extraction based on the quantized accumulator:

- The highest accumulator value is v
- Consider all accumulator cells with >0.95v
- For good line structures, those cell are close together, while for bad line structures there is no significant peak

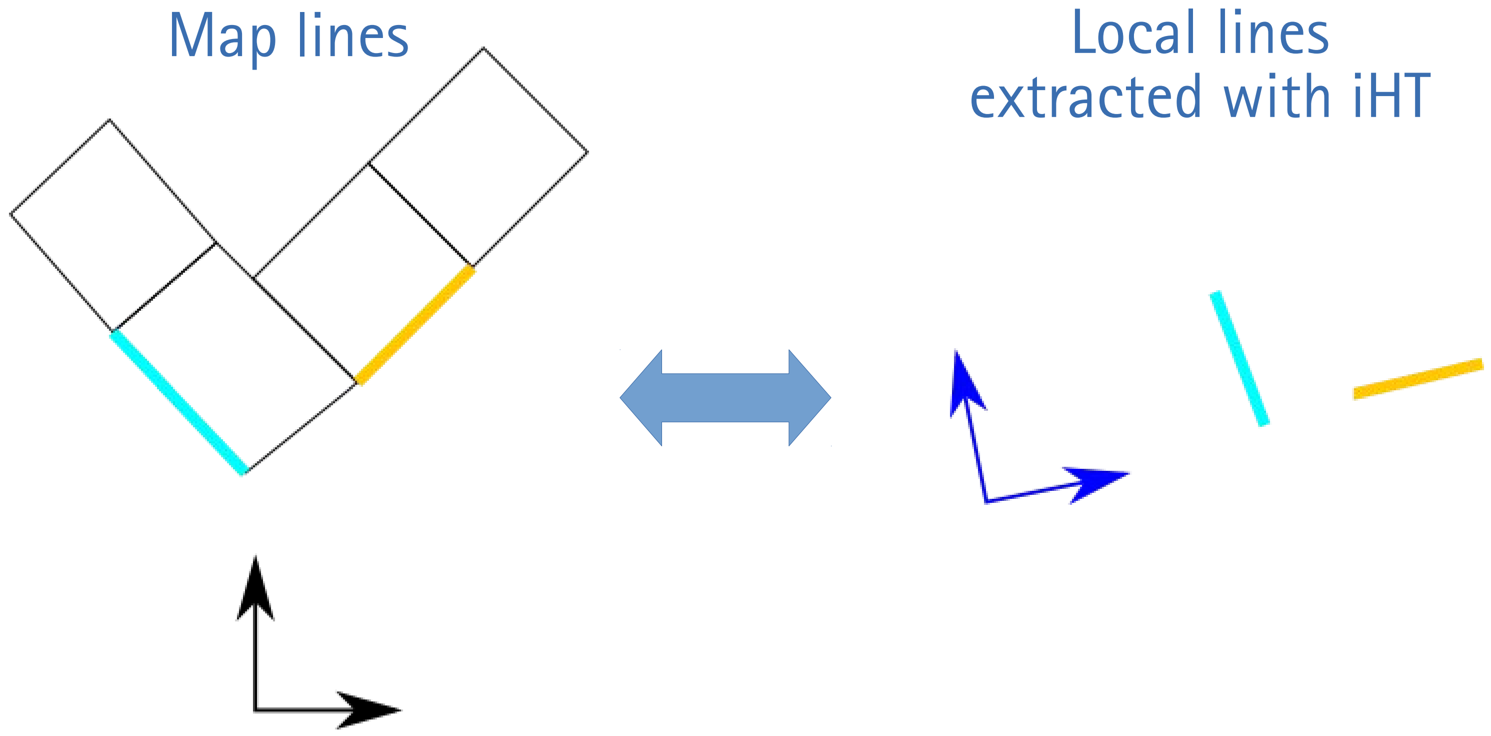
  → Only select clusters with significant peak
- Take the hull of the cluster

Line Extraction
Set of lines with highest support



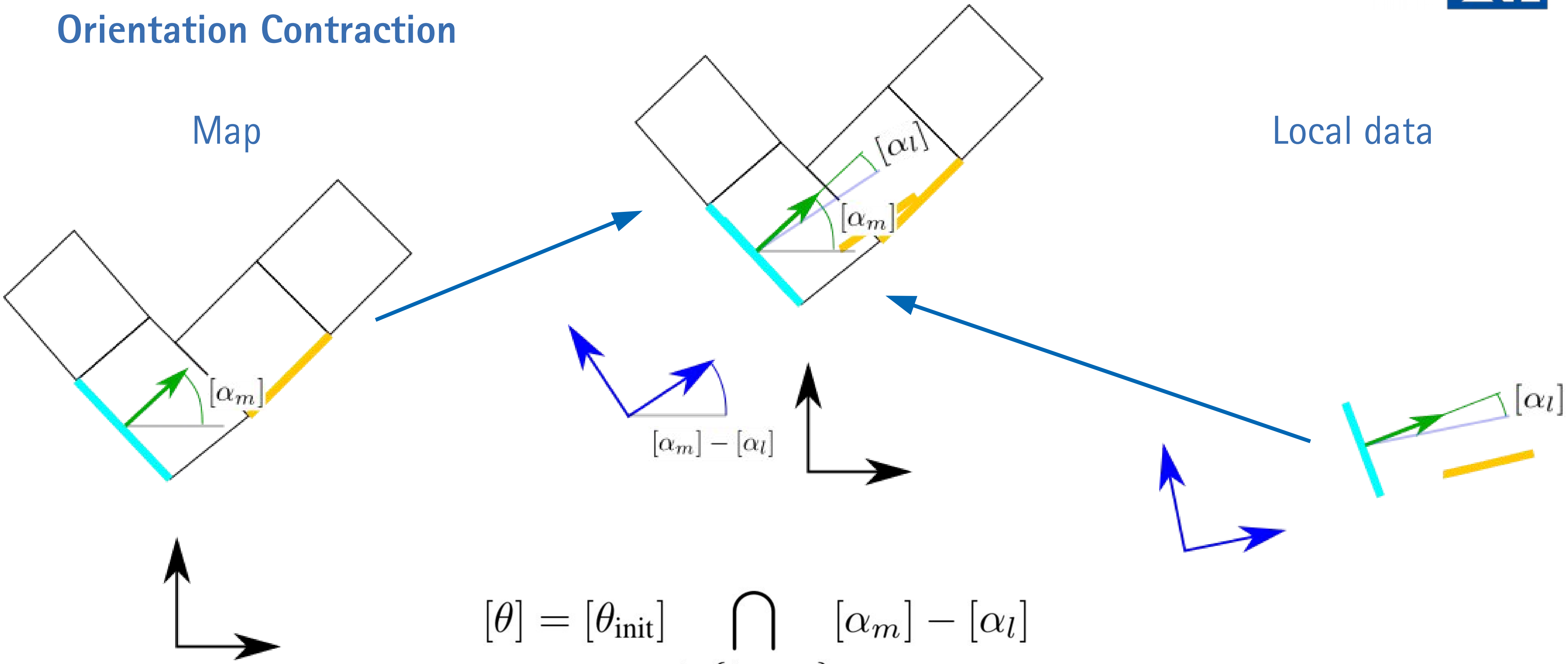
Interval-based Hough Transformation

Output: Local lines are extracted and we know to which map facades they correspond



Goal: Determine orientation and position of the robot in the map

Orientation Contraction



$$[\theta] = [\theta_{\text{init}}] \bigcap_{i \in \{1,\dots,n\}} [\alpha_m] - [\alpha_l]$$

Position Polygon

Approximation: For long facades the orientation uncertainty is small and does not have a strong impact on the position → Simplify the orientation interval of a facade to a scalar by taking the mid

Only the distance parameter is „flexible" (interval)

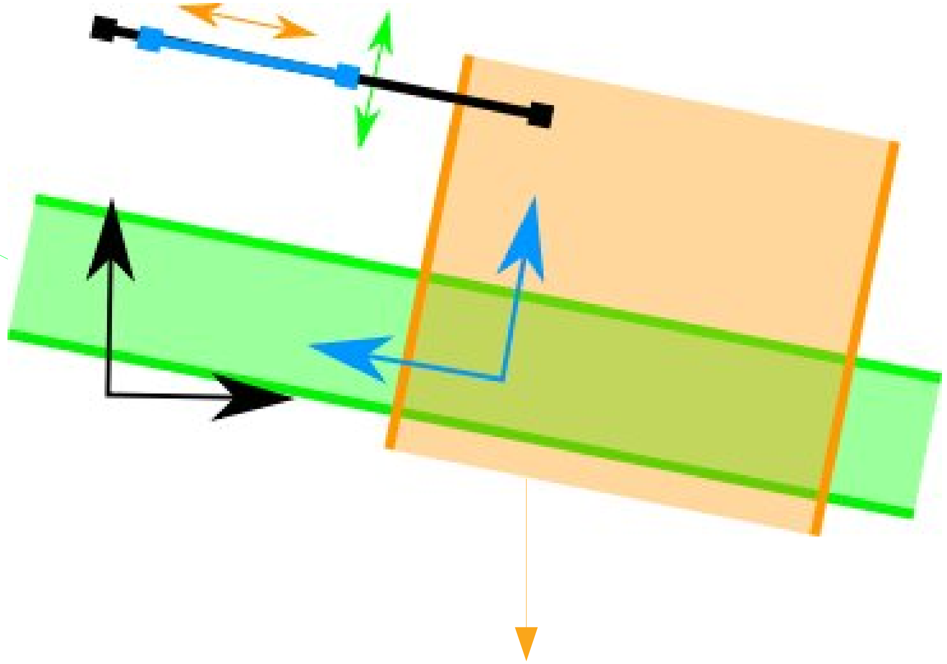
$$\begin{pmatrix}\cos \alpha_{m,\text{mid}} & \sin \alpha_{m,\text{mid}}\end{pmatrix} \cdot \begin{pmatrix} t_x \\ t_y \end{pmatrix} = d_m - d_l$$

Unknown:

$$t_x \in [t_x]$$
$$t_y \in [t_y]$$

Known:

$$d_m \in [d_m]$$
$$d_l \in [d_l]$$



Each Line-Facade correspondence provides two stripes that constrain the position.

Similar Equations (Orthogonal)

Position Polygon

A stripe is defined by the form

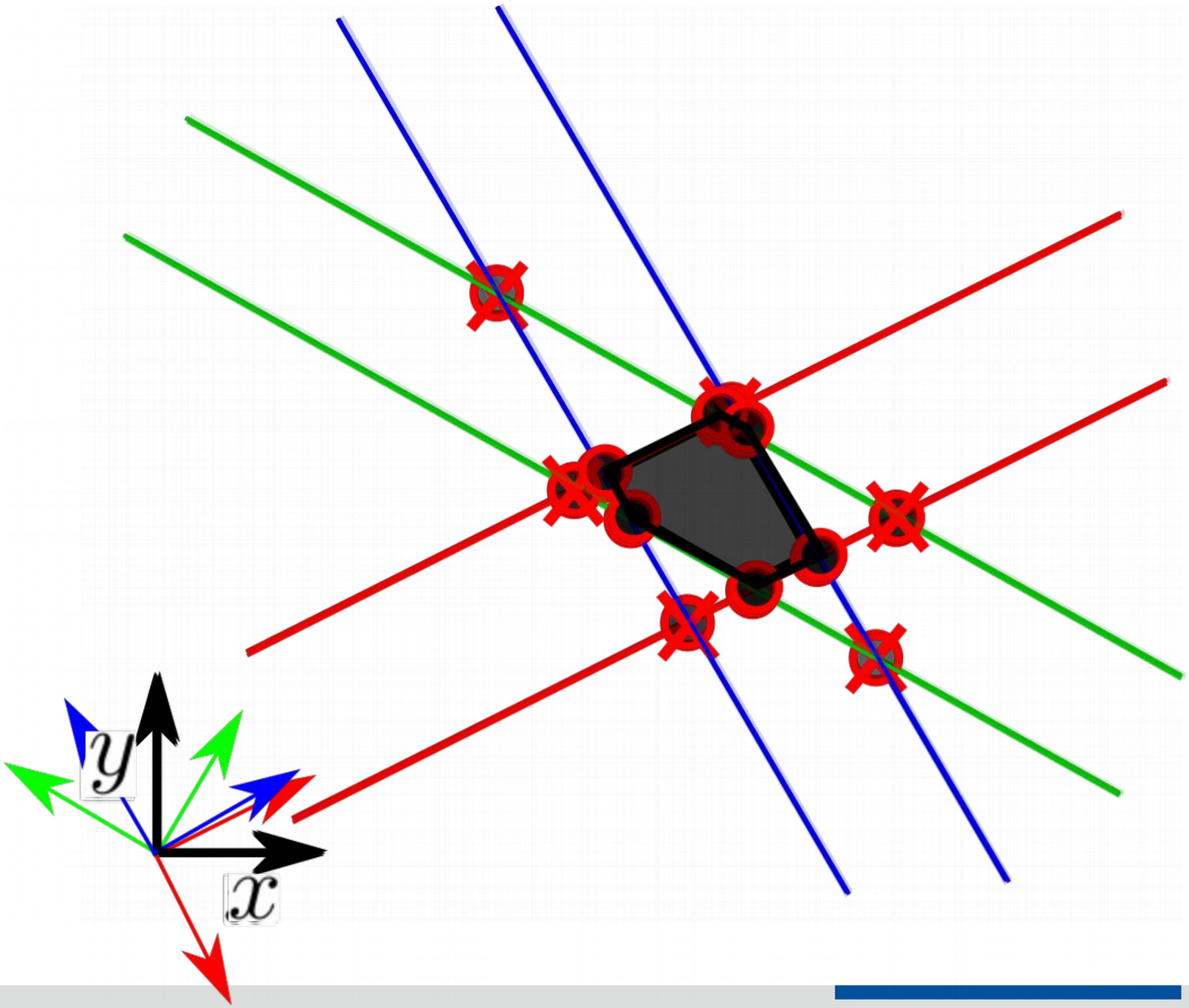
$$\begin{pmatrix}\cos(\alpha) & \sin(\alpha)\end{pmatrix} \cdot \begin{pmatrix} x \\ y \end{pmatrix} = d$$

- $\cos(\alpha)$, $\sin(\alpha)$: Scalar, known
- x, y: Intervals, unknowns
- d: Interval, known

As multiple facades provide multiple stripes, we seek to solve the interval equation system:

$$\begin{pmatrix}\cos(\alpha_1) & \sin(\alpha_1) \\ \vdots & \vdots \\ \cos(\alpha_n) & \sin(\alpha_n)\end{pmatrix} \begin{pmatrix} t_x \\ t_y \end{pmatrix} = \begin{pmatrix} d_1 \\ \vdots \\ d_n \end{pmatrix}$$

t_x, t_y: Robot position



Bounded Optimization

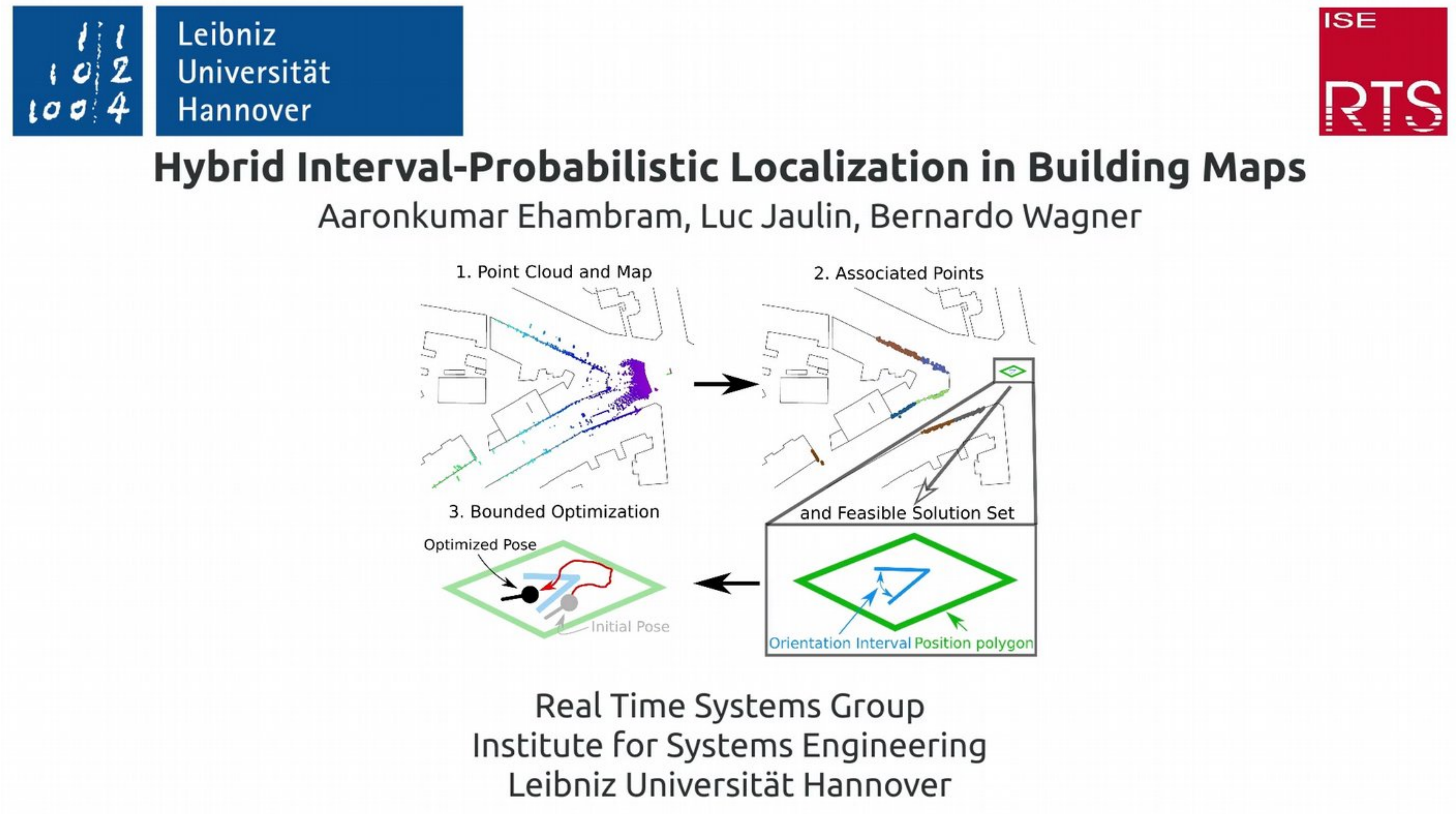
Interval-based localization provides a polygon bound for the position and an interval for the orientation

Goal: Find the most likely solution in the feasible set!

→ From now on we assume a Gaussian distribution of the error. The MLE becomes a Least-Squares Problem

- Minimization for all measurements and all facades
- Levenberg-Marquardt Optimization
- To account for the rigid bounds:
  If an update leads to a pose outside the feasible set, recompute the update with higher damping factor

Experimental Results



Conclusion

We propose a novel hybrid interval-probabilistic localization approach that…

- … provides an orientation interval and a position polygon for a given LiDAR scan and a building map.
- … works in real-time.
- … outperforms classical methods regarding robustness and calculation speed (comparison with MCL).
- … combines interval error models and probabilistic error models. The Interval localization provides the rigid bounds for the MLE method to prevent significant divergence.
- … can not deal with ambiguous localization.
- … does not solve the global localization problem, instead it can robustly tracks the robot if the initial pose is given up to known uncertainty.

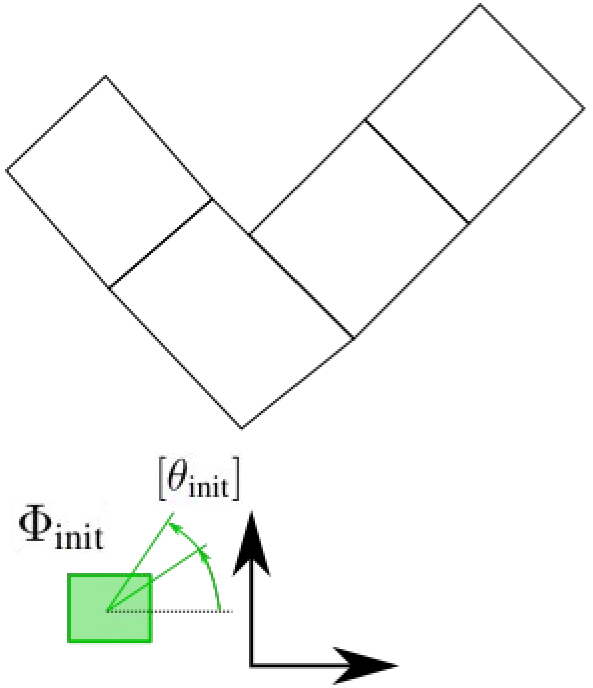
Future Work:

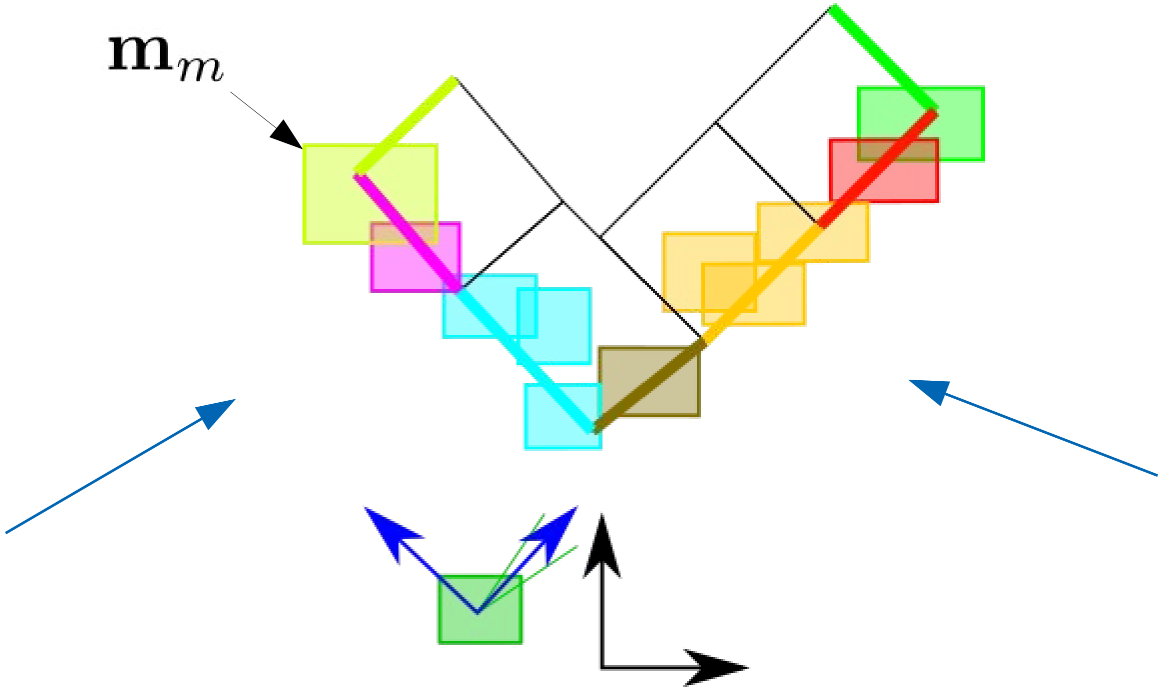
- Extend the localization for ambiguous localization
- Global localization


Thank you for watching!

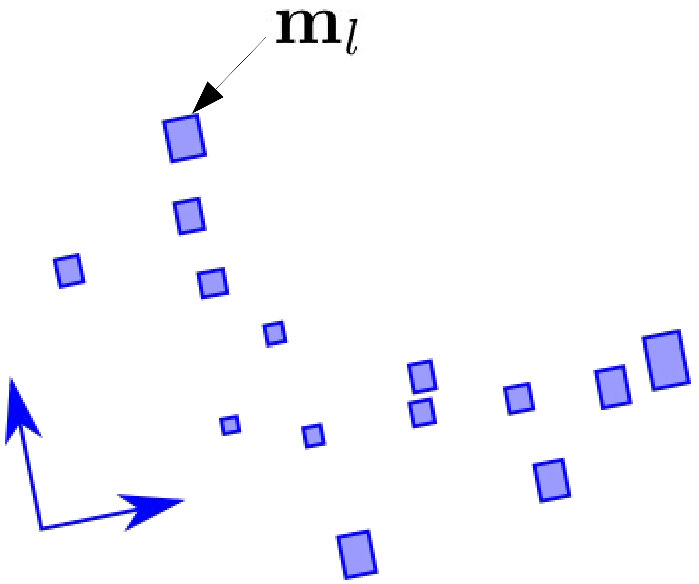
Interval-based Point-to-Facade Association

Map





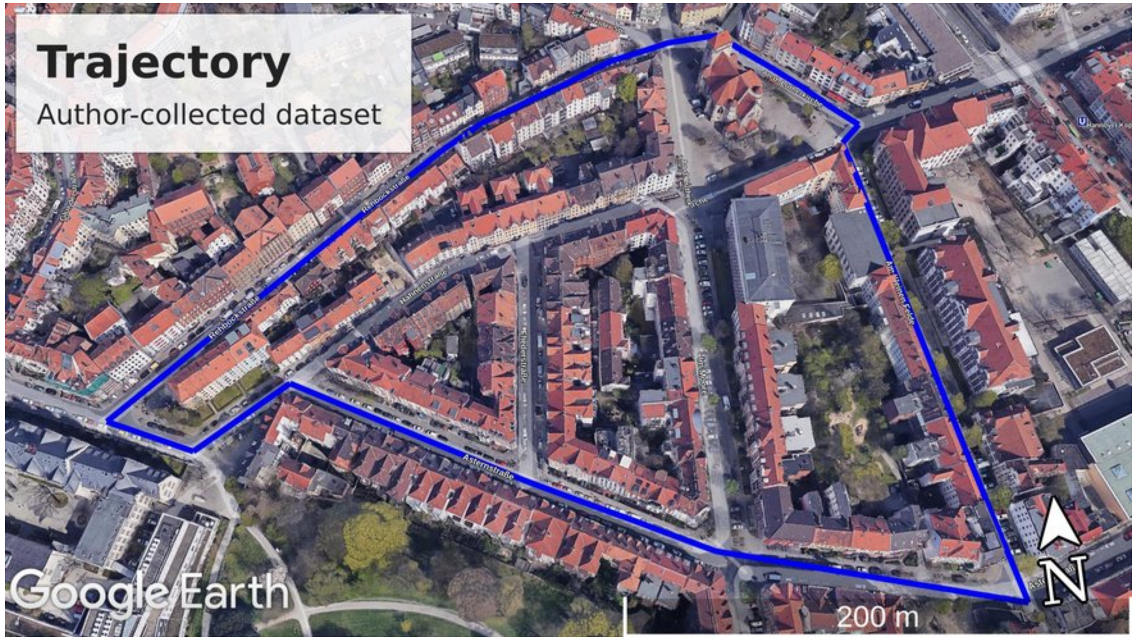
Local Data



$$\begin{cases} \text{i)} \ \left(\cos([\alpha_m]) \quad \sin([\alpha_m])\right) \cdot [\mathbf{m}_m] \cap [d_m] \neq \emptyset \\ \text{ii)} \ \left([\mathbf{a}_{m,1}] \sqcup [\mathbf{a}_{m,2}]\right) \cap [\mathbf{m}_m] \neq \emptyset \end{cases}$$

$$F_i = \{[\mathbf{a}_{m,1}], [\mathbf{a}_{m,2}], [\alpha_m], [d_m]\}$$

Experimental Results



Method	Hybrid Localization		MCL
Encloses ground truth pose	99.8 %		–
Average radius of smaller side	0.91 m		–
Average radius of larger side	4.2 m		–
Average orientation interval radius	1.8°		–
Optimization	Bounded	Unbounded	–
Translation RMSE	**0.237** m	0.241 m	0.81 m
Average orientation error	**0.339**°	0.343°	0.75°
Largest translation error	**2.83** m	2.994 m	4.67 m
Largest orientation error	**2.921**°	5.935°	6.1°
Result outside feasible pose sets	0.0 %	0.725 %	–

TABLE I: Evaluation of T_1 with LOD2 Map.

Method	Hybrid Localization		MCL
Encloses ground truth pose	99.8 %		–
Average radius of smaller side	1.79 m		–
Average radius of larger side	5.23 m		–
Average orientation interval radius	2.39°		–
Optimization	Bounded	Unbounded	–
Translation RMSE	**0.615** m	0.645 m	0.85 m
Average orientation error	**0.818**°	0.843°	0.83°
Largest translation error	5.03 m	8.137 m	**3.5** m
Largest orientation error	6.54°	6.543°	**3.92**°
Result outside feasible pose sets	0.0 %	4.178 %	–

TABLE II: Evaluation of T_1 with OSM data.

Experimental Results

Method	Hybrid Localization		MCL
Encloses ground truth pose	100 %		–
Average radius of smaller side	1.94 m		–
Average radius of larger side	3.48 m		–
Average orientation interval radius	2.7°		–
Optimization	Bounded	Unbounded	–
Translation RMSE	**1.12** m	1.3 m	1.18 m
Average orientation error	**1.149°**	1.78°	1.2°
Largest translation error	4.4 m	6.5 m	**3.5** m
Largest orientation error	9.99°	81.7°	**2.4°**
Result outside feasible pose sets	0.0 %	11.7 %	–

TABLE III: Evaluation of KITTI 0027 with OSM data.

Experimental Results