A multiple model PHD approach to tracking of cars under an assumed rectangular shape

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Karl Granström*, Stephan Reuter†, Daniel Meissner†, Alexander Scheel†

*Department of Electrical Engineering
Linköping University, Linköping, Sweden

†Institute of Measurement, Control and Microtechnology
Ulm University, Ulm, Germany

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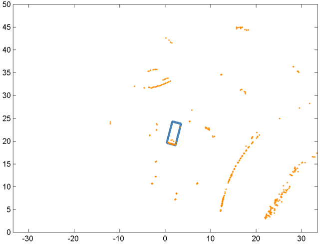
Introduction

Laser range sensors:

- Used for robotic mapping and localization
- Increasing attention from automotive industry



Problem formulation:

- Track cars using laser data

Outside scope:

- Data segmentation

Paper contents

Problem formulation:

- Track cars using laser data

Approach:

- Multiple motion & measurement models
- Multiple Model Extended Target PHD filter
- Occlusion model

Experimental evaluation:

- Multiple data sets; single & multiple targets
- Stationary & moving sensor
- Comparison to GPS+IMU ground truth

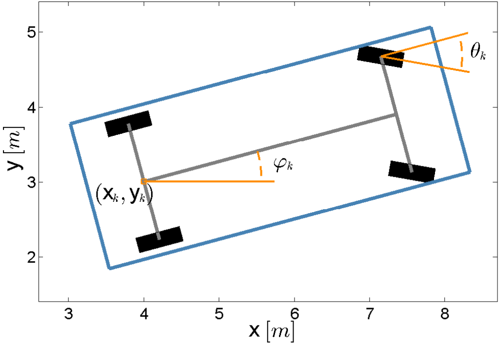
Target state

Extended target state: $\xi_k = (\mathbf{x}_k, o_k)$

Kinematic state $\mathbf{x}_k$:

$$\mathbf{x}_k = \begin{bmatrix} x_k \\ y_k \\ v_k \\ \varphi_k \\ \theta_k \\ \ell_k \\ w_k \end{bmatrix}$$

Assumed rectangular shape



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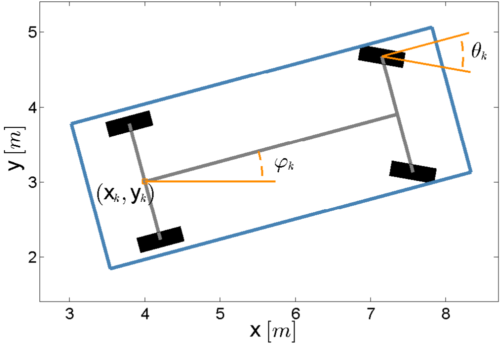


Mode o_k:

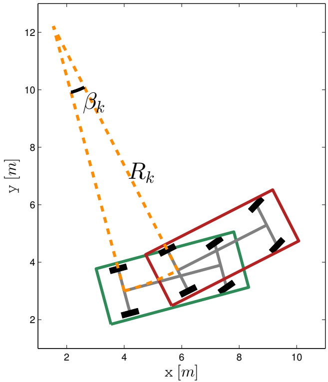
- Motion modes: straight ($\theta_k \approx 0$), or turning (constant $\theta_k \neq 0$)
- Measurement modes: from either one or two sides of the car.

Single track ("bicycle") motion model

Turning, $\theta_k \neq 0$:

Turning angle $\beta_k = \frac{Tv_k}{\ell_k^w} \tan(\theta_k)$
Turning radius $R_k = Tv_k / \beta_k$

$$f(\mathbf{x}_k) = \begin{bmatrix} x_k - R_k \sin(\varphi_k) + R_k \sin(\varphi_k + \beta_k) \\ y_k + R_k \cos(\varphi_k) + R_k \cos(\varphi_k + \beta_k) \\ v_k \\ \varphi_k + \beta_k \\ \theta_k \\ \ell_k \\ w_k \end{bmatrix}.$$



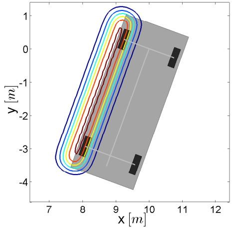
Straight, $\theta_k \approx 0$:
$f(\mathbf{x}_k)$ reduces to CV model.

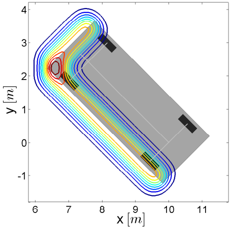
Measurement model

- At most two sides can be seen by sensor
- Measurement $\mathbf{z}$: random point $\mathbf{y}$ measured in Gaussian noise, where $\mathbf{y}$ are uniformly distributed along sides
- Measurement likelihood

$$p(\mathbf{z}|\xi) = \int p(\mathbf{z}|\mathbf{y})p(\mathbf{y}|\xi)\mathrm{d}\mathbf{y} = \int \mathcal{N}\left(\mathbf{z}\,;\,\mathbf{y},\Sigma\right)p(\mathbf{y}|\xi)\mathrm{d}\mathbf{y}$$

- Examples where sensor is located in origin



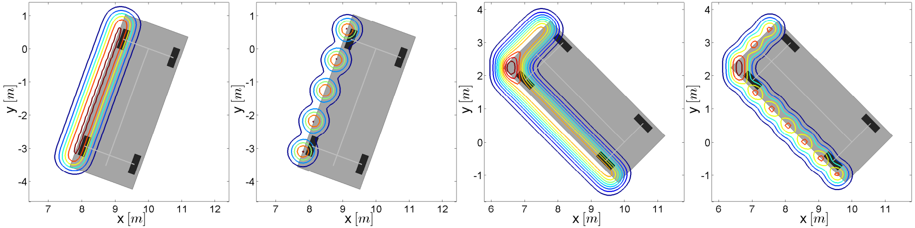


Measurement likelihood approximation

- Likelihood approximated by Gaussian mixture

$$p(\mathbf{z}|\xi) \approx \sum_{i=1}^{N} w^{(i)} \mathcal{N}\left(\mathbf{z}\,;\, \mathbf{y}^{(i)}(\xi), R^{(i)}\right), \qquad \sum_{i=1}^{N} w^{(i)} = 1.$$

- Allows use of EKF/UKF measurement update
- Examples: $N = 5$ and $N = 10$



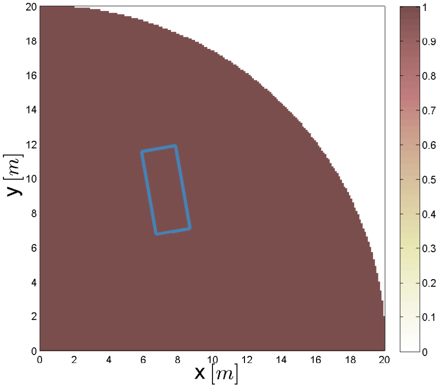
Occlusion model

- Along defined bearings, sensor measures distance to closest object
- An object blocks sensor's view of what is behind the object
- If occlusions are not modeled, PHD filter may loose track of targets during occlusions
- Occlusion model: non-homogeneous detection probability

$$P_D(\xi_k)$$

Occlusion model: approximation of occluded area

- Start with constant p_D (white is low p_D)
- Blue: predicted estimate



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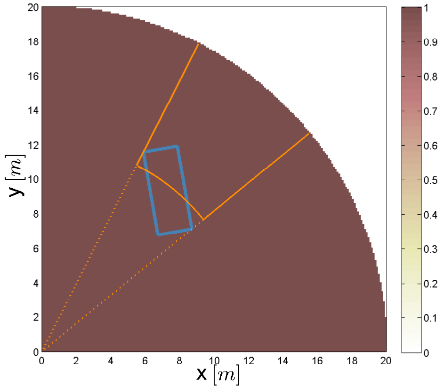
- Mean range, min and max bearings, to corners



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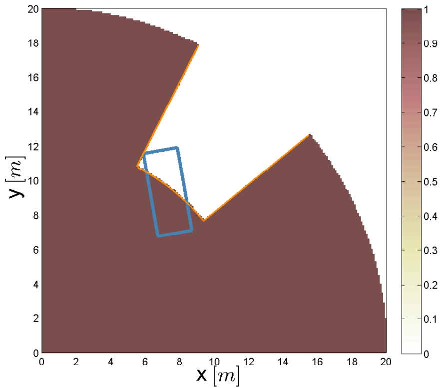

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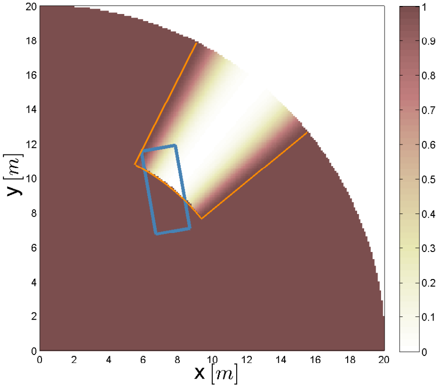
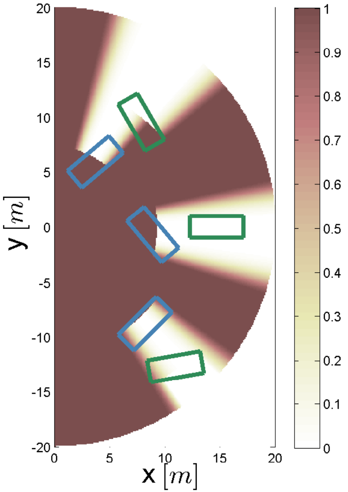
- Gaussian smoothing gives conservative occlusion model



Occlusion model: approximation of probability of detection

For each target estimate

- Discretize visible part of shape into points separated by 10cm



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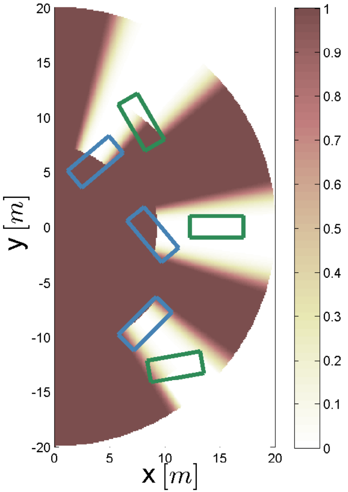

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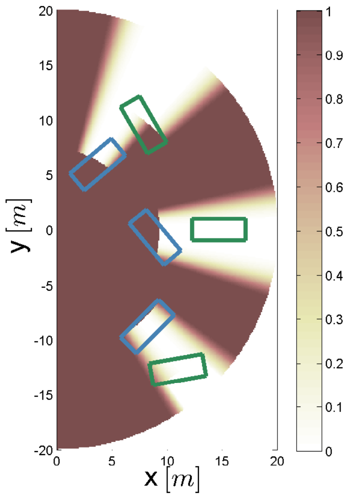

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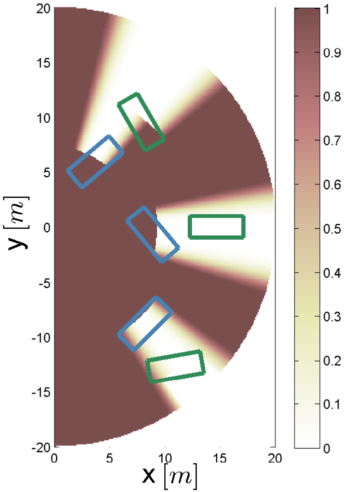

Occluded estimates (green), P_D: 99% (top), 1% (middle), 50% (bottom).

Experimental data

Results from three different data sets:

- **D1** Moving ego vehicle, single target driving in front of ego vehicle. Ego vehicle and target equipped with GPS+IMU.
- **D2** Ego vehicle stationary next to roundabout. Multiple targets with occlusions, one target equipped with GPS+IMU.
- **D3** Ego vehicle stationary next to T-intersection. Multiple targets, no occlusions.

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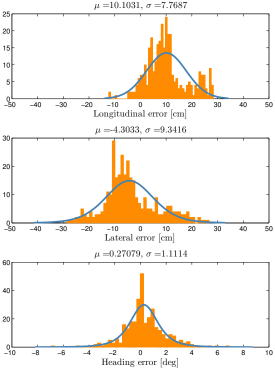
Where there is ground truth, we compute estimation errors for

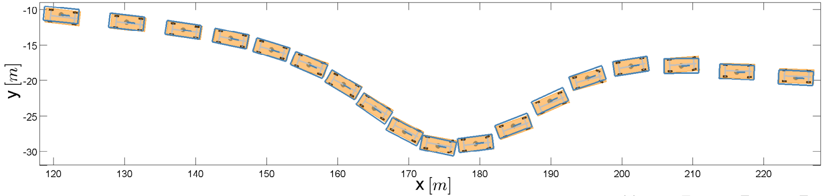
- Longitudinal position
- Lateral position
- Heading
- Length
- Width

Experiment 1 – Moving sensor

- Moving sensor (GPS+IMU)
- Single target
- GPS+IMU ground truth
- Size initialized with ground truth

- Position errors: 5 to 10 cm (2" to 4")
- Heading error close to zero

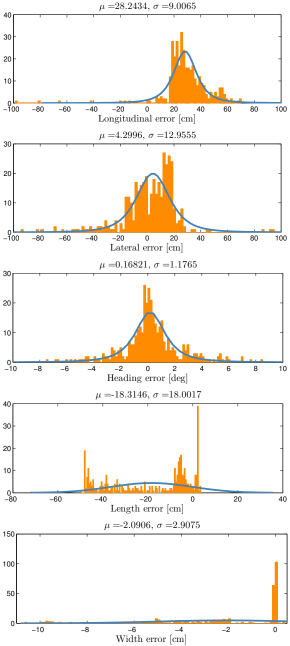




Experiment 2 – Roundabout

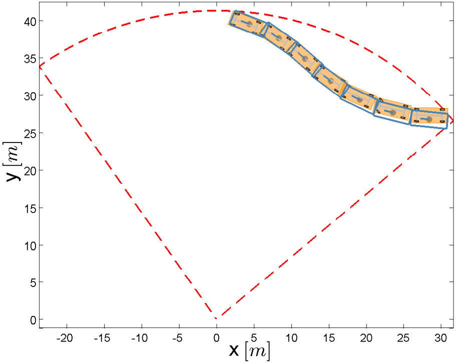
- Stationary sensor
- Multiple targets, occlusions
- GPS+IMU ground truth (1 target)
- Size initialized with
  $\ell = 5m,\ w = 2m.$

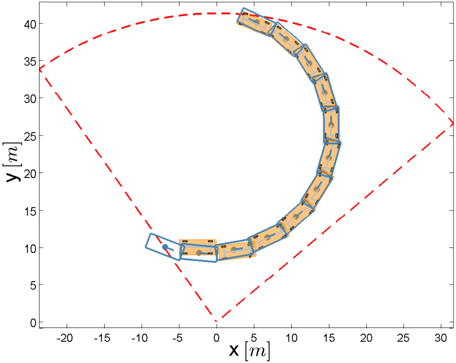
- Small lateral error: 4 cm (1.6")
- Larger longitudinal position error
- Heading error close to zero
- Length error > width error
- Occlusions do not increase errors



Experiment 2 – Roundabout

Example results:

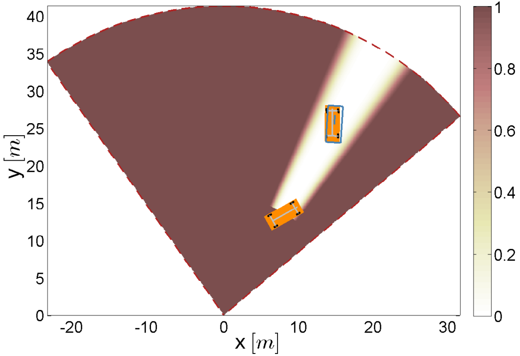


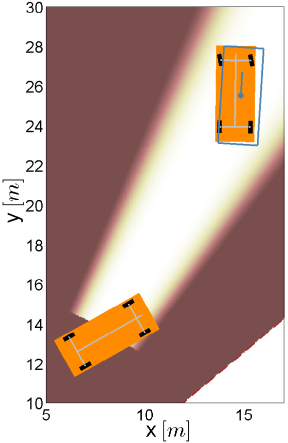


Convergence typically takes 5 – 10 time steps (0.4 – 0.8 seconds)

Experiment 2 – Roundabout

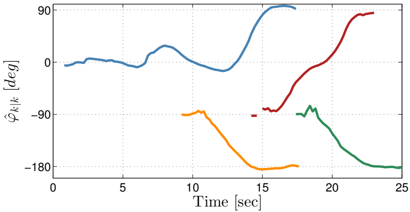
Non-homogeneous detection probability + accurate motion model, enables tracking with low error during occlusions

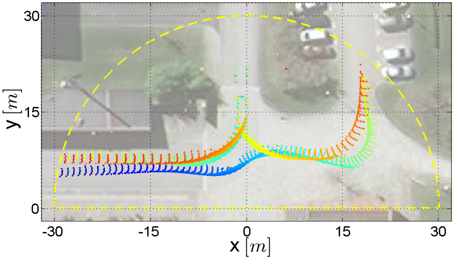


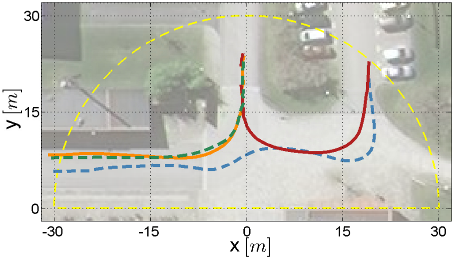


Experiment 3 – T-intersection

- Stationary sensor
- Multiple targets, no occlusions
- No ground truth
- Size initialized with $\ell = 5m,\ w = 2m.$







Experiment 3 – T-intersection

Conclusions & Future work

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- Multiple model PHD filter with occlusion model
- Small estimation errors, especially for lateral position and heading.

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Future work:

- Sensors with multiple layers
- Multiple target types: e.g. include pedestrians and bicycles.

Thank you for listening!

Questions?