Spatio-temporal data fusion for autonomous vehicle localization

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European Union

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utc Recherche

heudiasyc

This work is carried out within SIVALab, a shared laboratory between Heudiasyc and Renault.

Plan

- Problem Statement
- Localization System
- Matching Problem
- Map Reliability

Problem Statement

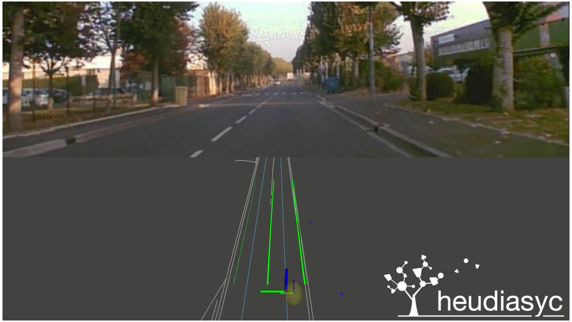
$$\boldsymbol{x}_k = \begin{bmatrix} x_k \\ y_k \\ \theta_k \\ v_k \\ \omega_k \end{bmatrix}$$

Localization needs to be **accurate** and **reliable.**

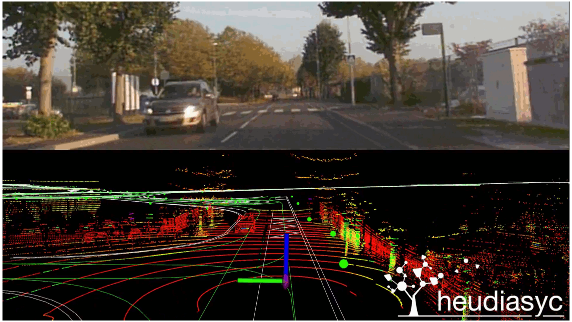
Sensor overview

Perception Sensors

Mobileye

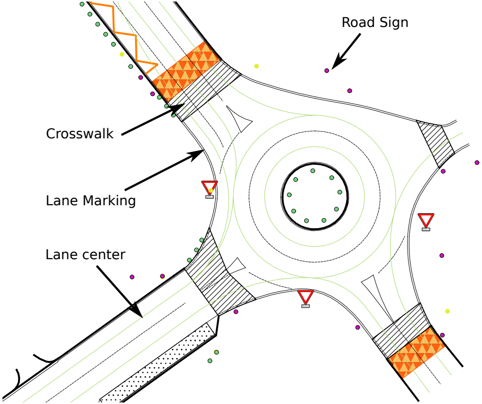


Velodyne



Sensor overview
HD Maps

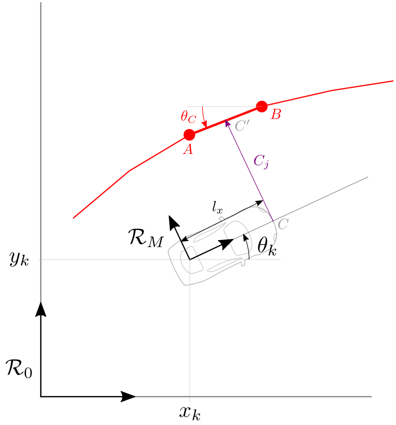
HD Map



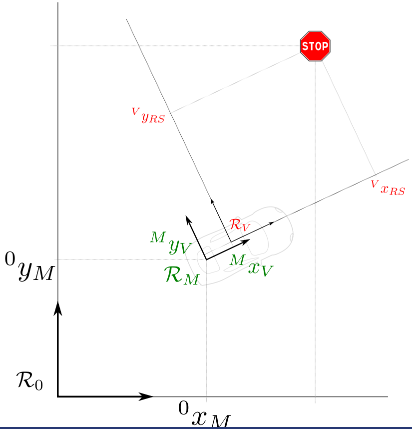
Streetview

Sensor overview
Observation Model

Mobileye



Velodyne



Sensor overview
Observation Model

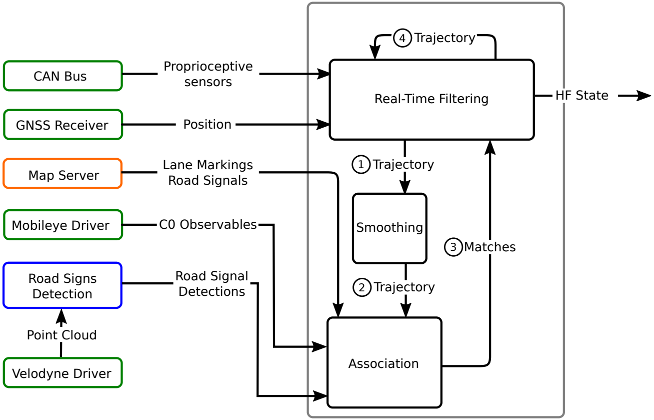
Mobileye

$$C_i = h^m(\mathbf{x}_k) = \frac{(l_x \sin\theta_k + y_k - y^A)\, x^{AB} - (l \cos\theta_k + x_k - x^A)\, y^{AB}}{x^{AB}\cos\theta_k + y^{AB}\sin\theta_k}$$

Velodyne

$$\begin{bmatrix} {}^{M}x_i \\ {}^{M}y_i \end{bmatrix} = h_i^s(\mathbf{x}_k) = \begin{bmatrix} \cos\theta_k & \sin\theta_k \\ -\sin\theta_k & \cos\theta_k \end{bmatrix} \begin{bmatrix} x_i^S - x_k \\ y_i^S - y_k \end{bmatrix}$$

Filtering Scheme



Prediction

$$\hat{\boldsymbol{x}}_{k|k-1} = \boldsymbol{f}_k\left(\hat{\boldsymbol{x}}_{k-1|k-1}\right),$$

$$\boldsymbol{P}_{k|k-1} = \boldsymbol{F}_k \boldsymbol{P}_{k-1|k-1} \boldsymbol{F}_k^T + \boldsymbol{Q}_k,$$

Update

$$\tilde{\boldsymbol{y}}_k = \boldsymbol{z}_k - \boldsymbol{h}_k\left(\hat{\boldsymbol{x}}_{k|k-1}\right),$$

$$\boldsymbol{S}_k = \boldsymbol{H}_k \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^T + \boldsymbol{R}_k,$$

$$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^T \boldsymbol{S}_k^{-1},$$

$$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k \tilde{\boldsymbol{y}}_k,$$

$$\boldsymbol{P}_{k|k} = \left(\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}_k\right) \boldsymbol{P}_{k|k-1},$$

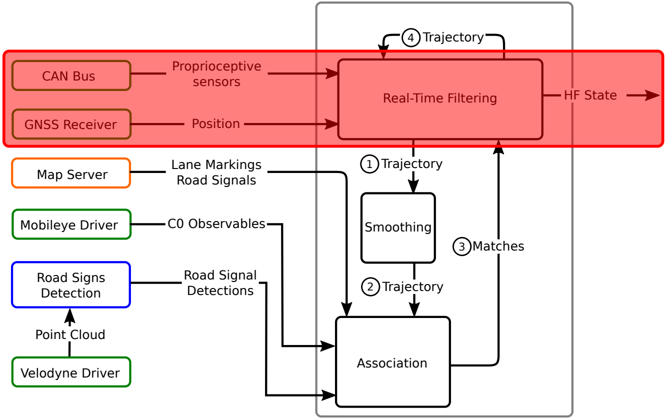
Smoothing

$$\boldsymbol{J}_k = \boldsymbol{P}_{k|k} \boldsymbol{F}_{k+1}^T \boldsymbol{P}_{k+1|k}^{-1}$$

$$\hat{\boldsymbol{x}}_{k|N} = \hat{\boldsymbol{x}}_{k|k} + \boldsymbol{J}_k\left(\hat{\boldsymbol{x}}_{k+1|N} - \hat{\boldsymbol{x}}_{k+1|k}\right),$$

$$\boldsymbol{P}_{k|N} = \boldsymbol{P}_{k|k} + \boldsymbol{J}_k\left(\boldsymbol{P}_{k+1|N} - \boldsymbol{P}_{k+1|k}\right)\boldsymbol{J}_k^T.$$

Filtering Scheme



Prediction

$$\hat{\boldsymbol{x}}_{k|k-1} = \boldsymbol{f}_k\left(\hat{\boldsymbol{x}}_{k-1|k-1}\right),$$
$$\boldsymbol{P}_{k|k-1} = \boldsymbol{F}_k\boldsymbol{P}_{k-1|k-1}\boldsymbol{F}_k^T + \boldsymbol{Q}_k,$$

Update

$$\tilde{\boldsymbol{y}}_k = \boldsymbol{z}_k - \boldsymbol{h}_k\left(\hat{\boldsymbol{x}}_{k|k-1}\right),$$
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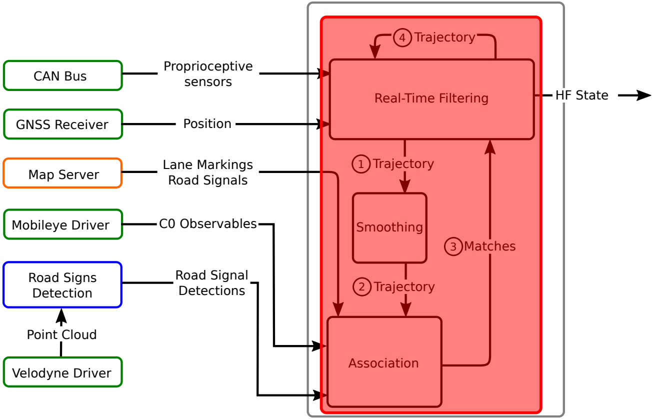
$$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1}\boldsymbol{H}_k^T\boldsymbol{S}_k^{-1},$$
$$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k\tilde{\boldsymbol{y}}_k,$$
$$\boldsymbol{P}_{k|k} = \left(\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{H}_k\right)\boldsymbol{P}_{k|k-1},$$

Smoothing

$$\boldsymbol{J}_k = \boldsymbol{P}_{k|k}\boldsymbol{F}_{k+1}^T\boldsymbol{P}_{k+1|k}^{-1}$$
$$\hat{\boldsymbol{x}}_{k|N} = \hat{\boldsymbol{x}}_{k|k} + \boldsymbol{J}_k\left(\hat{\boldsymbol{x}}_{k+1|N} - \hat{\boldsymbol{x}}_{k+1|k}\right),$$
$$\boldsymbol{P}_{k|N} = \boldsymbol{P}_{k|k} + \boldsymbol{J}_k\left(\boldsymbol{P}_{k+1|N} - \boldsymbol{P}_{k+1|k}\right)\boldsymbol{J}_k^T.$$

Filtering Scheme



Prediction

$$\hat{\boldsymbol{x}}_{k|k-1} = \boldsymbol{f}_k\left(\hat{\boldsymbol{x}}_{k-1|k-1}\right),$$
$$\boldsymbol{P}_{k|k-1} = \boldsymbol{F}_k \boldsymbol{P}_{k-1|k-1} \boldsymbol{F}_k^T + \boldsymbol{Q}_k,$$

Update

$$\tilde{\boldsymbol{y}}_k = \boldsymbol{z}_k - \boldsymbol{h}_k\left(\hat{\boldsymbol{x}}_{k|k-1}\right),$$
$$\boldsymbol{S}_k = \boldsymbol{H}_k \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^T + \boldsymbol{R}_k,$$
$$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^T \boldsymbol{S}_k^{-1},$$
$$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k \tilde{\boldsymbol{y}}_k,$$
$$\boldsymbol{P}_{k|k} = \left(\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}_k\right) \boldsymbol{P}_{k|k-1},$$

Smoothing

$$\boldsymbol{J}_k = \boldsymbol{P}_{k|k} \boldsymbol{F}_{k+1}^T \boldsymbol{P}_{k+1|k}^{-1}$$
$$\hat{\boldsymbol{x}}_{k|N} = \hat{\boldsymbol{x}}_{k|k} + \boldsymbol{J}_k\left(\hat{\boldsymbol{x}}_{k+1|N} - \hat{\boldsymbol{x}}_{k+1|k}\right),$$
$$\boldsymbol{P}_{k|N} = \boldsymbol{P}_{k|k} + \boldsymbol{J}_k\left(\boldsymbol{P}_{k+1|N} - \boldsymbol{P}_{k+1|k}\right) \boldsymbol{J}_k^T.$$

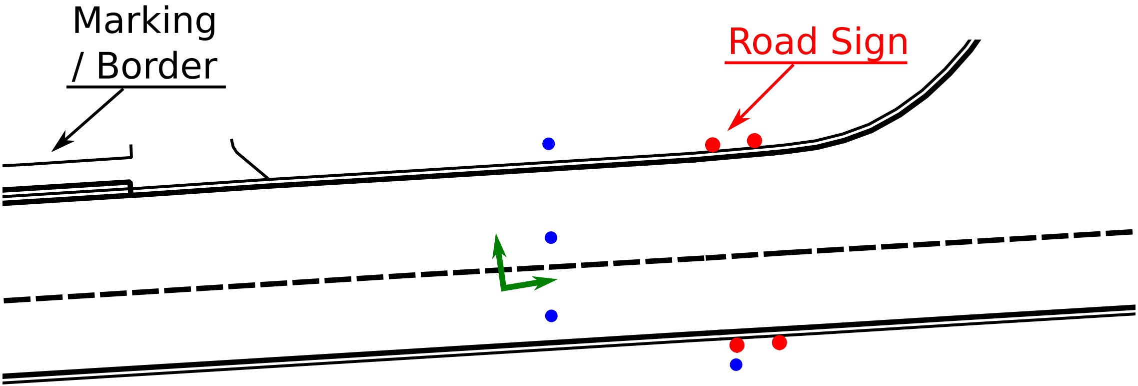
Matching Problem
Problem Statement

The observations need to be matched to map features to be used for localization. Matching is hard because:

- The state estimate has uncertainty
- There are few measurements leading to ambiguities
- The map can be incomplete

Matching Problem
Snapshot view

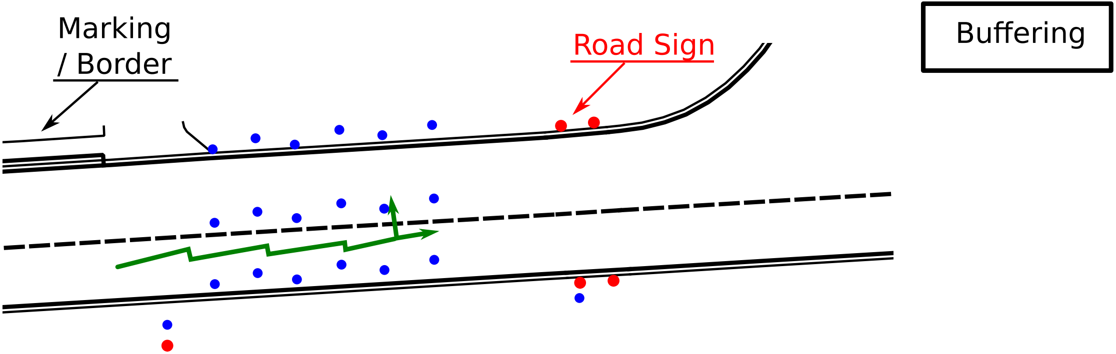
In real-time, few observations are available.



Matching Problem

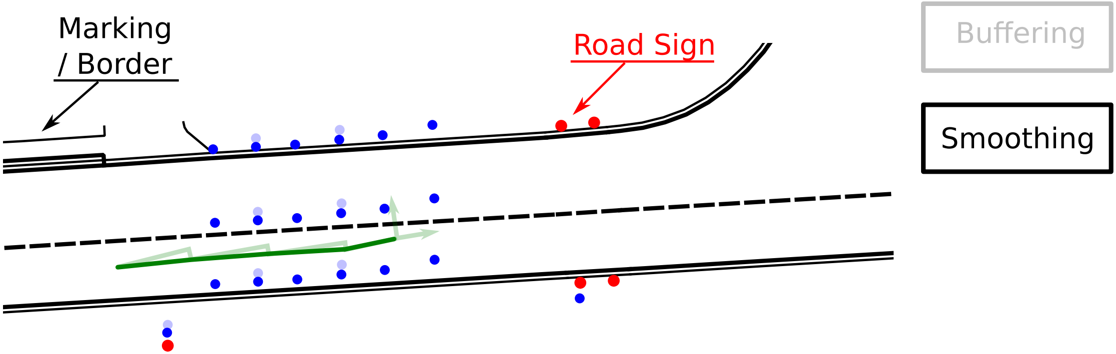
Observation Buffer

To limit ambiguities, an observation and a state estimate buffer can be used.



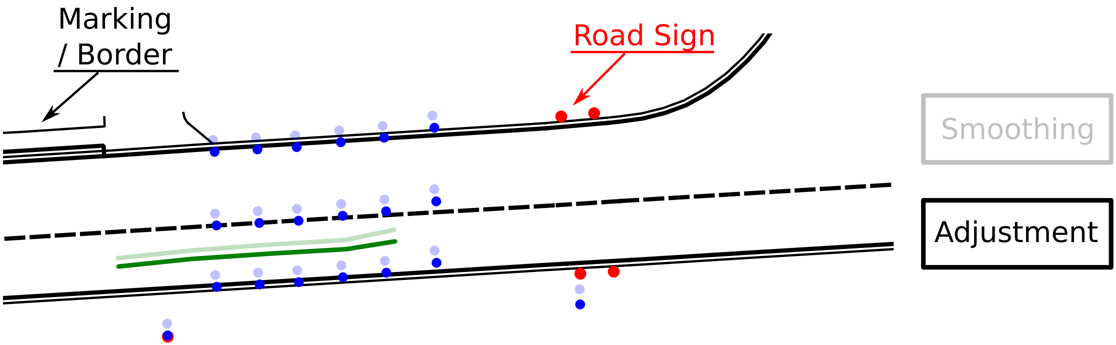
Matching Problem
Kalman Smoothing

Kalman smoothing propagates the state estimates backward improving the trajectory.



Matching Problem
trajectory Adjustment

The trajectory is adjusted such that the observations and the map best coincide.



Matching Problem
Likelihood definition

The adjusted trajectory:

$$\tilde{\mathbf{x}}_k = \begin{bmatrix} \tilde{x}_k \\ \tilde{y}_k \\ \tilde{\theta}_k \end{bmatrix} = \begin{bmatrix} \cos\delta_\theta & -\sin\delta_\theta & 0 \\ \sin\delta_\theta & \cos\delta_\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \hat{x}_{k|K} \\ \hat{y}_{k|K} \\ \hat{\theta}_{k|K} \end{bmatrix} + \begin{bmatrix} \delta_x \\ \delta_y \\ \delta_\theta \end{bmatrix}$$

Matching Problem

Likelihood definition

The adjusted trajectory:

$$\tilde{\mathbf{x}}_k = \begin{bmatrix} \tilde{x}_k \\ \tilde{y}_k \\ \tilde{\theta}_k \end{bmatrix} = \begin{bmatrix} \cos\delta_\theta & -\sin\delta_\theta & 0 \\ \sin\delta_\theta & \cos\delta_\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \hat{x}_{k|K} \\ \hat{y}_{k|K} \\ \hat{\theta}_{k|K} \end{bmatrix} + \begin{bmatrix} \delta_x \\ \delta_y \\ \delta_\theta \end{bmatrix}$$

We search for the adjustment δ that maximizes the likelihood knowing the observations and the map.

$$L(\boldsymbol{\delta} \,|\mathbf{Z}_K) = \prod_{k \in [\![K-S,K]\!]} \prod_{\mathbf{z}_j^{(k)} \in \mathbf{Z}^{(k)}} L\left(\tilde{\mathbf{x}}_k \middle| \mathbf{z}_j^{(k)}\right)$$

Matching Problem

Likelihood definition

The adjusted trajectory:

$$\widetilde{\mathbf{x}}_k = \begin{bmatrix} \widetilde{x}_k \\ \widetilde{y}_k \\ \widetilde{\theta}_k \end{bmatrix} = \begin{bmatrix} \cos\delta_\theta & -\sin\delta_\theta & 0 \\ \sin\delta_\theta & \cos\delta_\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \widehat{x}_{k|K} \\ \widehat{y}_{k|K} \\ \widehat{\theta}_{k|K} \end{bmatrix} + \begin{bmatrix} \delta_x \\ \delta_y \\ \delta_\theta \end{bmatrix}$$

We search for the adjustment δ that maximizes the likelihood knowing the observations and the map.

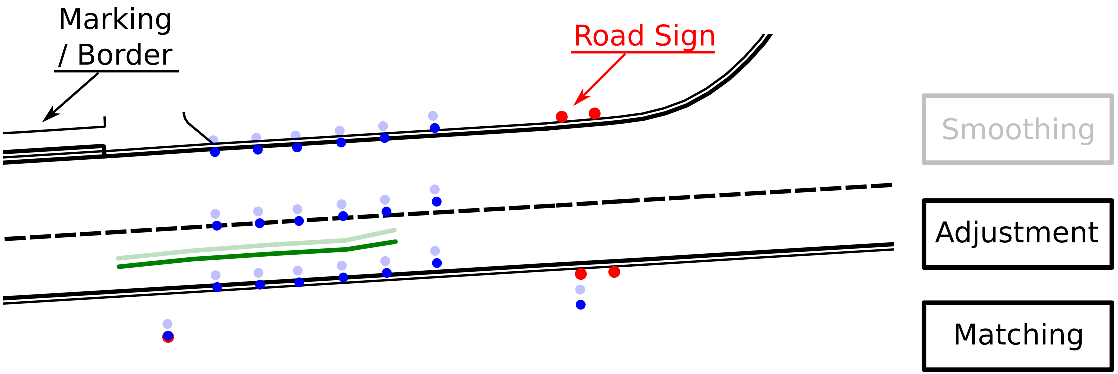
$$L(\boldsymbol{\delta} \,|\mathbf{Z}_K) = \prod_{k \in [\![K-S, K]\!]} \prod_{\mathbf{z}_j^{(k)} \in \mathbf{Z}^{(k)}} L\left(\widetilde{\mathbf{x}}_k \middle| \mathbf{z}_j^{(k)}\right)$$

with the likelihood given a single observation being

$$L\left(\widetilde{\mathbf{x}}_k \middle| \mathbf{z}_j^{(k)}\right) = \sum_{\mathbf{m}_i \in \mathbf{M}} L_{i,j}\left(\widetilde{\mathbf{x}}_k \middle| \mathbf{z}_j^{(k)}\right) \mathbb{P}_{i,j} + L_{\emptyset,j} \mathbb{P}_{\emptyset,j}$$

Matching Problem
trajectory Adjustment

Using the adjusted trajectory, matches can be selected.

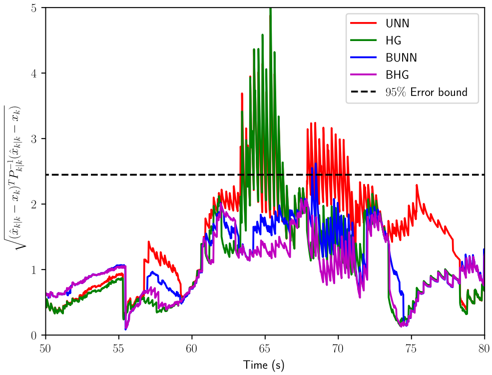


Matching Problem
Results

More matches

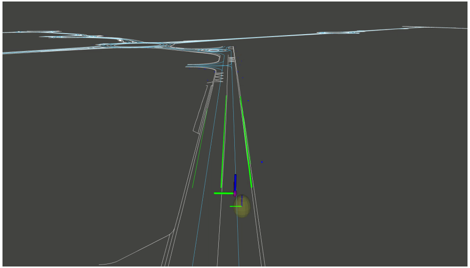
- observation can be matched later
- the adjustment makes mathing easier

Improved consistency



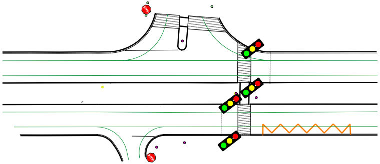
Map Reliability
Problem Statement

Incorrectly referenced marking



Change affecting one feature

Change affecting an area

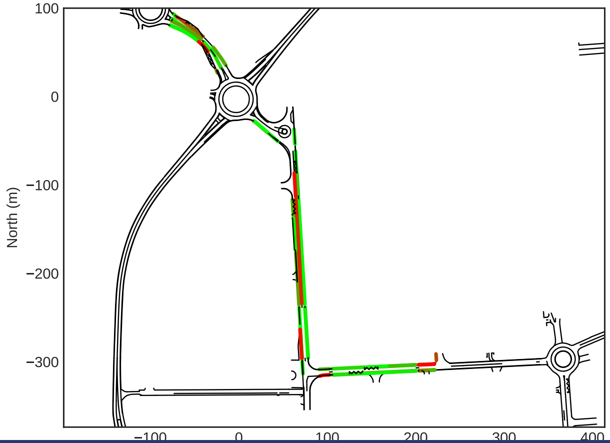


Map Reliability
First work

$$p_m = \exp\left(-\frac{\overline{y_m^2}}{\alpha^2}\right)$$

with

$$y_m = \sum_i \left| C^i - h^m(\mathbf{x}_k) \right|$$



Map Reliability

Perspectives

- Using the residuals $\boldsymbol{y}$ with their covariance matrices $\boldsymbol{S}$ to decide to reject or not a map feature
- All residuals attributed to a feature m_i can be merged by covariance intersection
- A test is performed to check if the residuals are within the chosen risk tolerance

$$\boldsymbol{y}\boldsymbol{S}^{-1}\boldsymbol{y}^T < \frac{\gamma\left(\frac{dim(\boldsymbol{y})}{2}, \frac{1-\alpha}{2}\right)}{\Gamma\left(\frac{dim(\boldsymbol{y})}{2}\right)}$$

- The residuals can be updated as new trajectories are recorded

$$\boldsymbol{y} = \left(\boldsymbol{S}_1^{-1} + \boldsymbol{S}_2^{-1}\right)^{-1}\left(\boldsymbol{S}_1^{-1}\boldsymbol{y}_1 + \boldsymbol{S}_2^{-1}\boldsymbol{y}_2\right)$$