# A Study of Different Observation Models for Cooperative Localization in Platoons

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ITSC 2023 2nd iLoc Workshop:
High-integrity Localization for Automated Vehicles

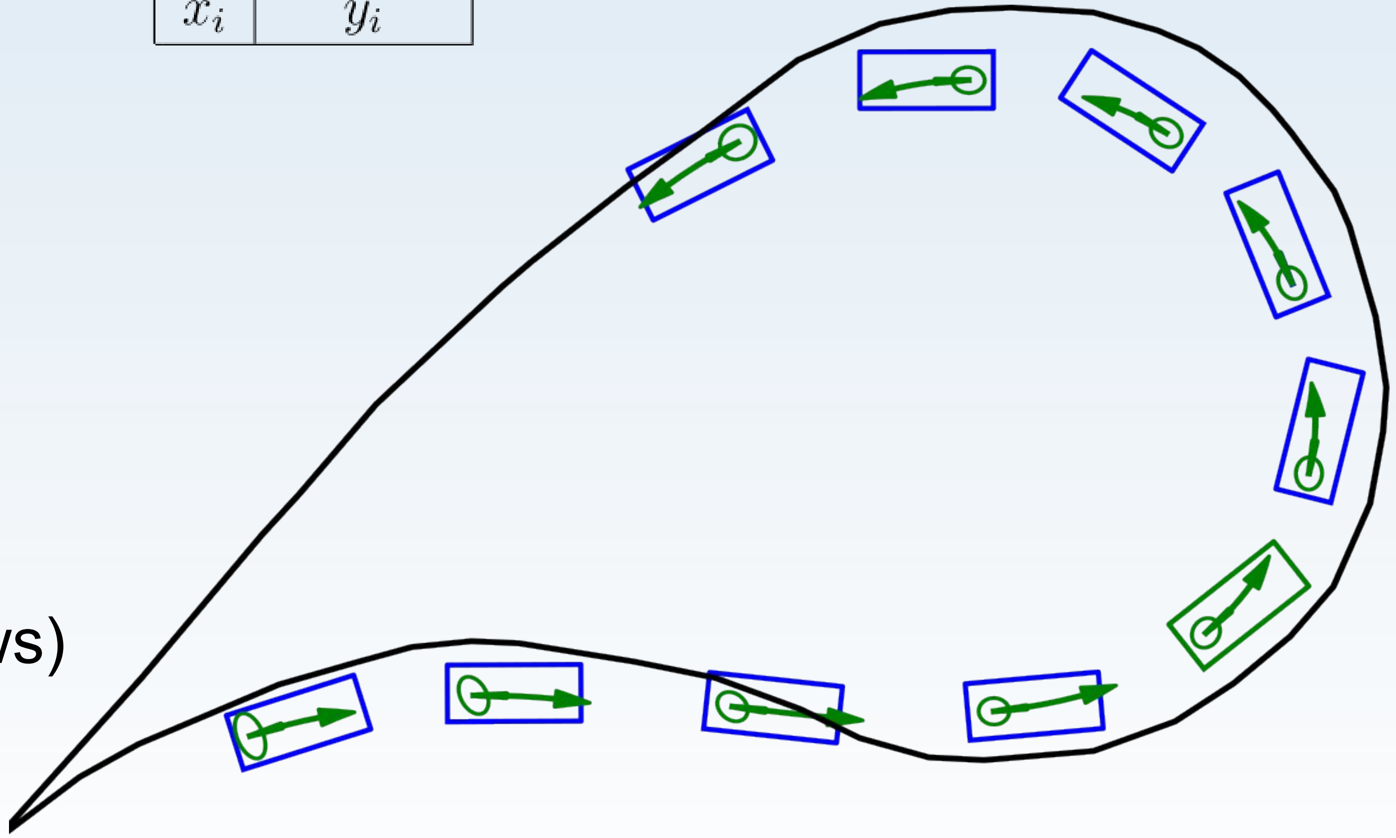
# Introduction

- Dynamic map to represent the states (position, orientation, speed and yaw rate) of the ego vehicle and every surrounding vehicles

- Cooperative Localisation based on communication and perception

- Different observation models (Cartesian and polar relative poses, distances, bearings and relative yaws)

| Dynamic map: $X$ | | | | | | |
|---|---|---|---|---|---|---|
| … | Vehicle i state: $X_i$ | | | | | … |
| | pose: $q_i$ | | | velocity: $u_i$ | | |
| | position: $p_i$ | | yaw: $\theta_i$ | speed: $v_i$ | yaw rate: $w_i$ | |
| | $x_i$ | $y_i$ | | | | |



# Overview

- Introduction
- Data fusion
- Hybrid simulation from a real dataset
- Results
- Conclusion and perspectives

# Data fusion

Dynamic Map of vehicle 1 → prediction →

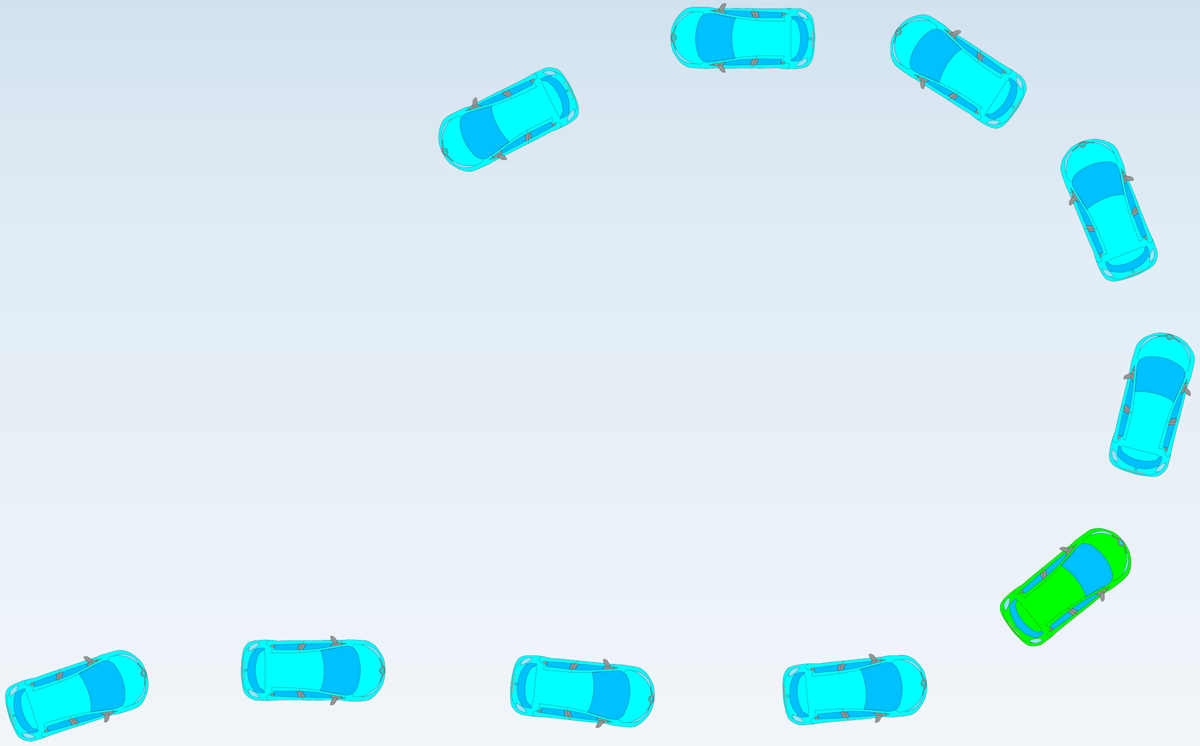
Dynamic Map of vehicle 2 → prediction →

⋮

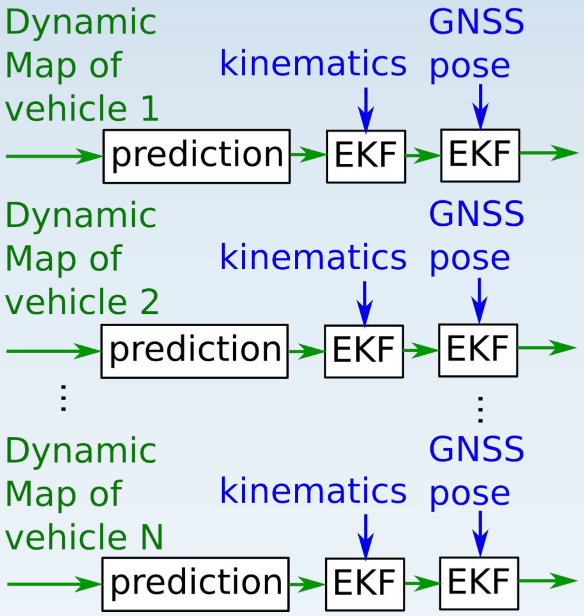
Dynamic Map of vehicle N → prediction →

$$X_{t_k} = \mathrm{evo}(X_{t_{k-1}}) = X_{t_{k-1}} + V_{t_{k-1}} \Delta t$$

$$\begin{pmatrix} \vdots \\ x_i \\ y_i \\ \theta_i \\ v_i \\ \omega_i \\ \vdots \end{pmatrix}_{t_k} = \begin{pmatrix} \vdots \\ x_i \\ y_i \\ \theta_i \\ v_i \\ \omega_i \\ \vdots \end{pmatrix}_{t_{k-1}} + \begin{pmatrix} \vdots \\ v_i \Delta t \cos(\theta_i + \frac{\Delta t}{2}\omega_i) \\ v_i \Delta t \sin(\theta_i + \frac{\Delta t}{2}\omega_i) \\ \omega_i \Delta t \\ 0 \\ 0 \\ \vdots \end{pmatrix}_{t_{k-1}}$$

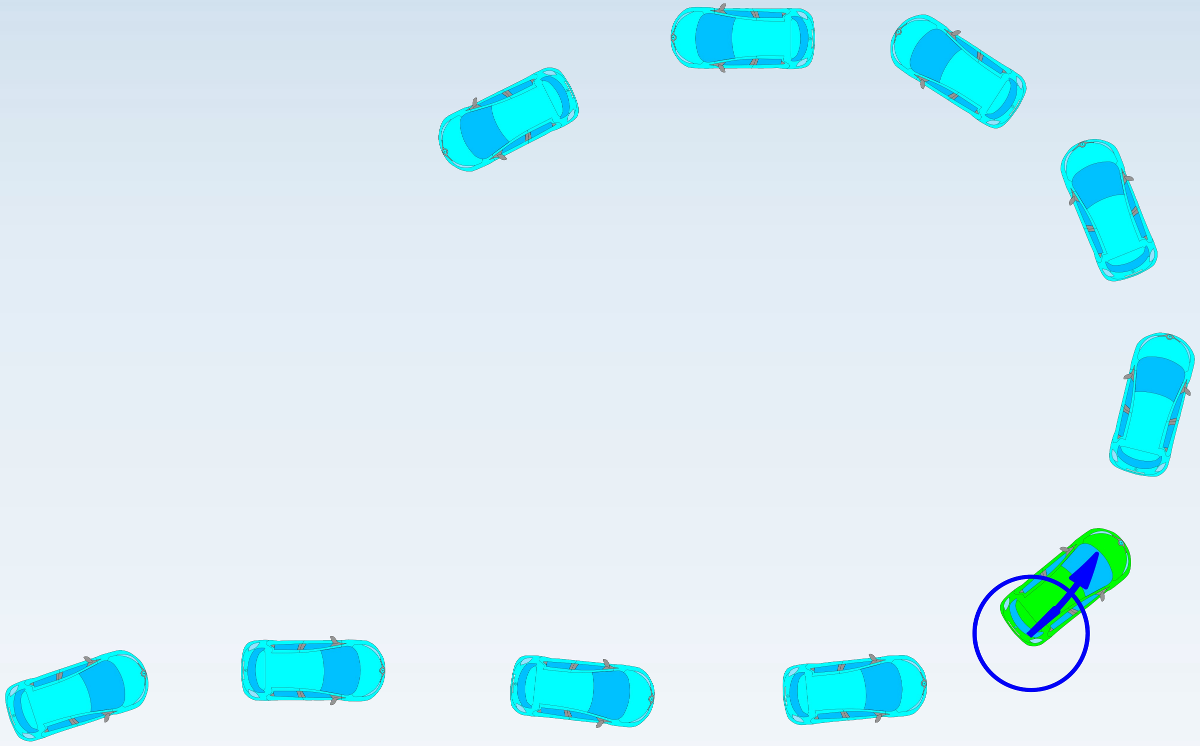


# Data fusion




$$\mathrm{obs}_{\mathrm{vel}}(X) = \begin{pmatrix} v_{\mathrm{ego}} \\ \omega_{\mathrm{ego}} \end{pmatrix}$$

$$\mathrm{obs}_{\mathrm{pose}}(X) = \begin{pmatrix} x_{\mathrm{ego}} \\ y_{\mathrm{ego}} \\ \theta_{\mathrm{ego}} \end{pmatrix}$$



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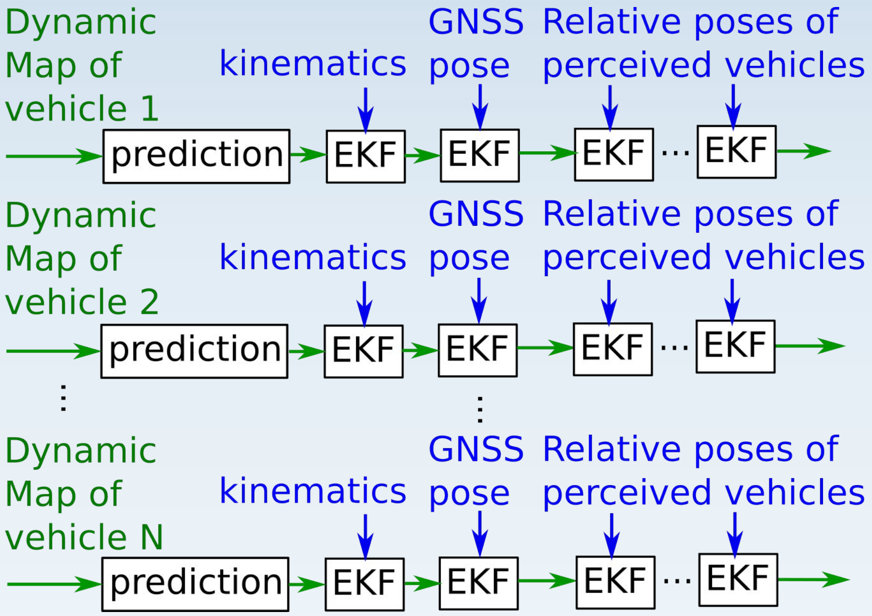
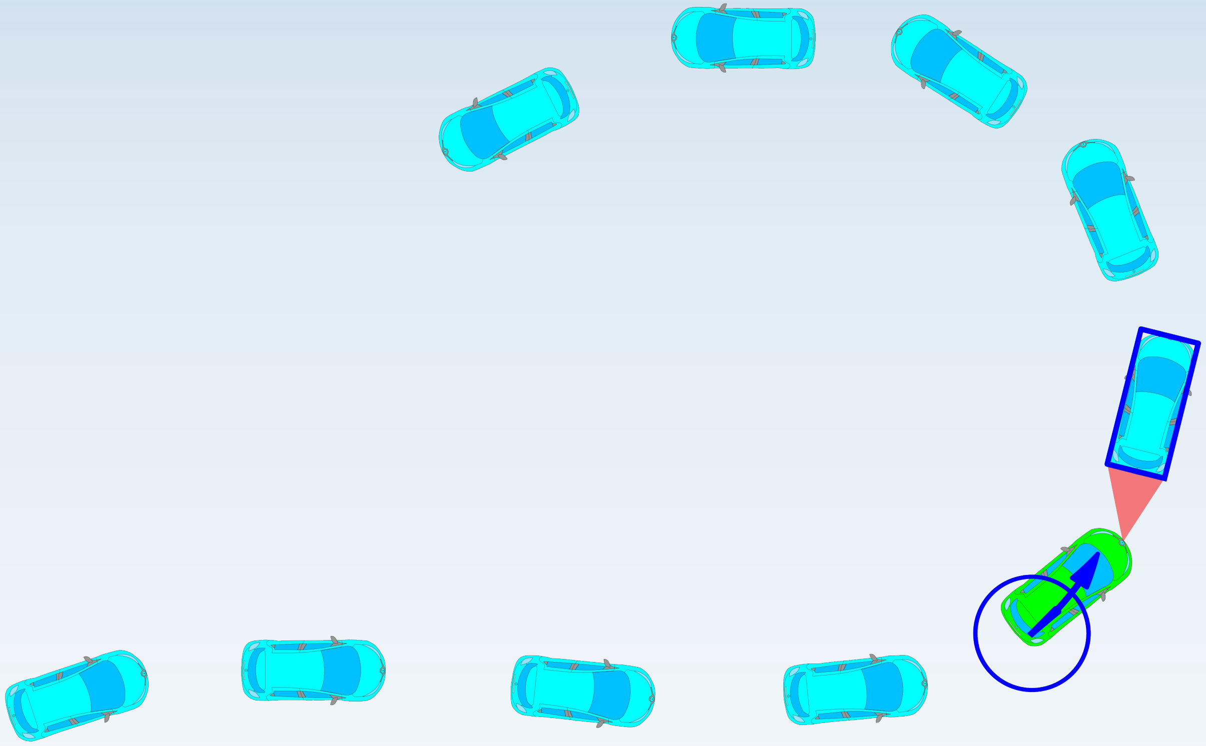
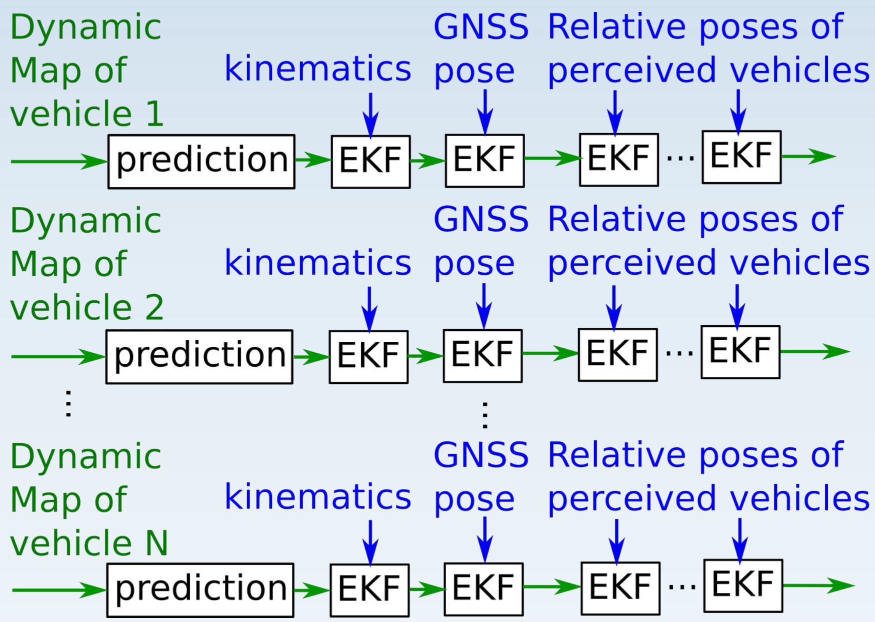


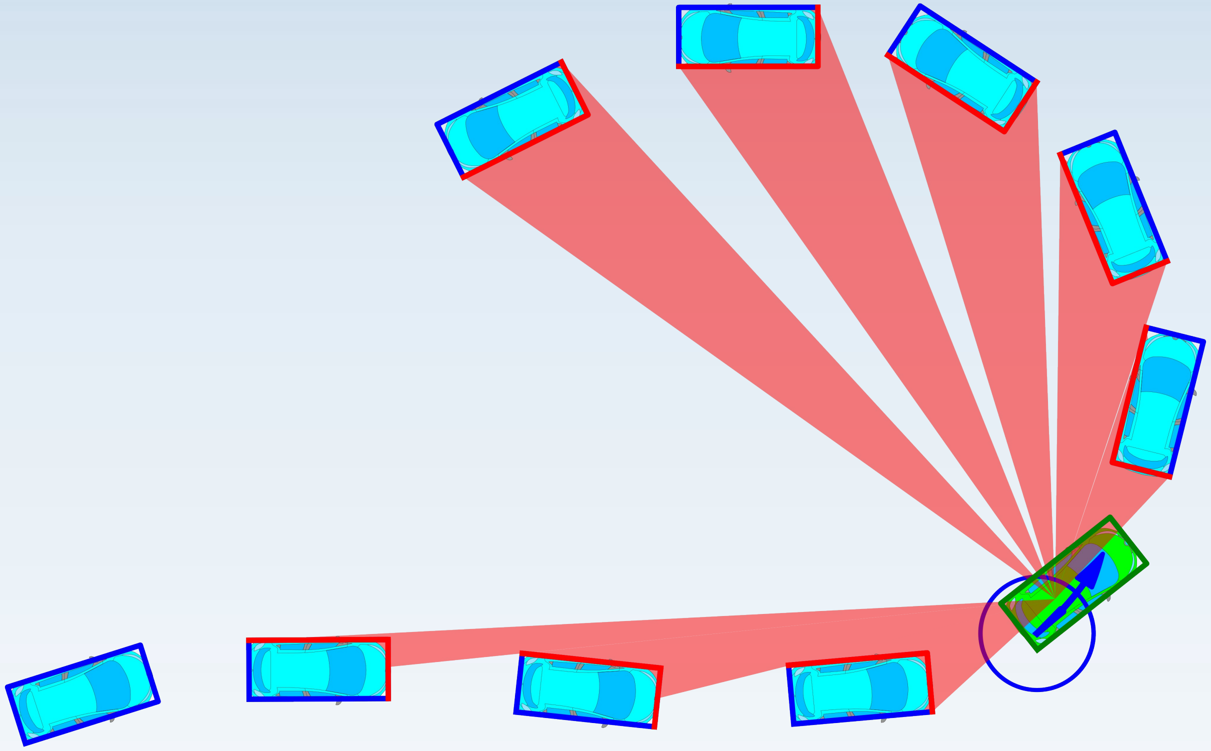



$$\mathrm{obs}_{\mathrm{pose\_cartesian}}(X) = {}^{\mathrm{ego}}q_i = \begin{pmatrix} {}^{\mathrm{ego}}x_i \\ {}^{\mathrm{ego}}y_i \\ {}^{\mathrm{ego}}\theta_i \end{pmatrix} = R_{\mathrm{ego}}(q_i - q_{\mathrm{ego}})$$

$$R_{\mathrm{ego}} = \begin{pmatrix} \cos\theta_{\mathrm{ego}} & \sin\theta_{\mathrm{ego}} & 0 \\ -\sin\theta_{\mathrm{ego}} & \cos\theta_{\mathrm{ego}} & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

# Data fusion



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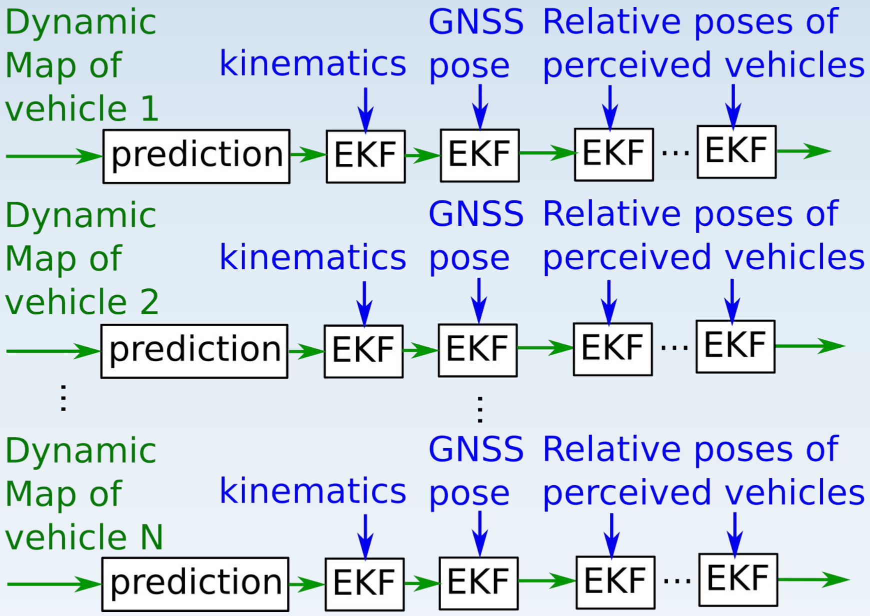
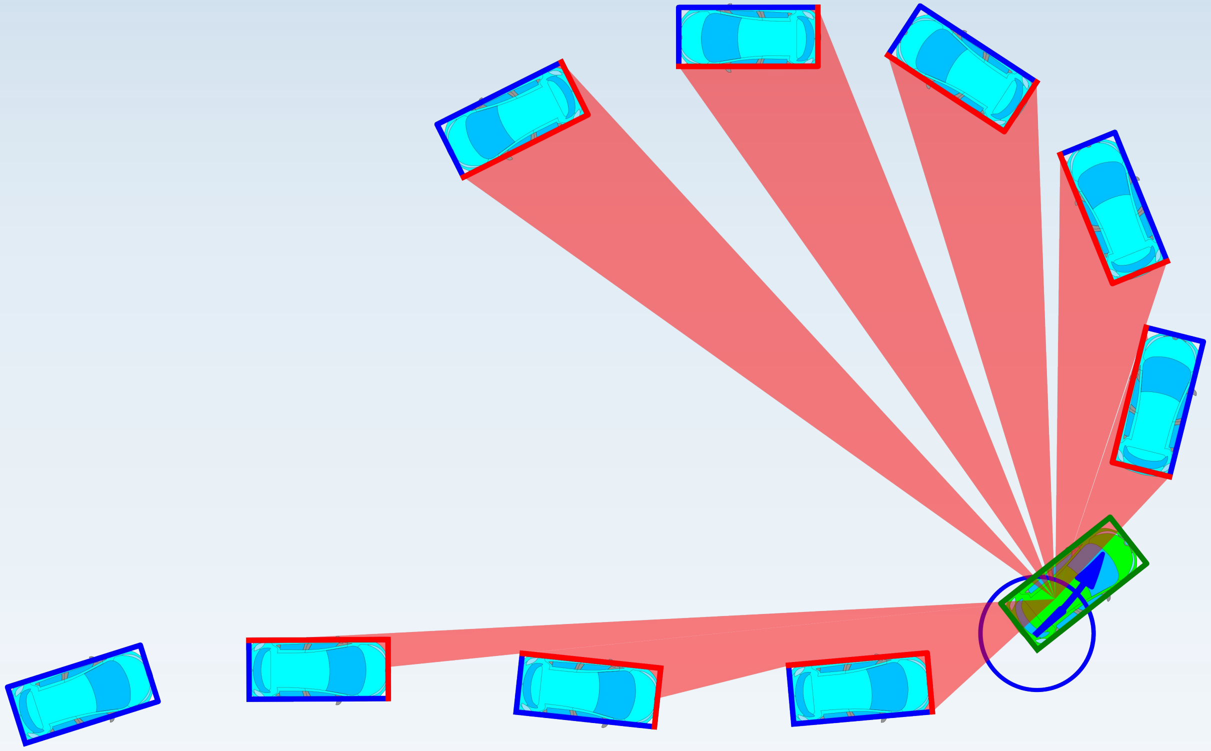
# Data fusion



$$\mathrm{obs}_{\mathrm{pose\_polar}}(X) = \begin{pmatrix} {}^{\mathrm{ego}}r_i \\ {}^{\mathrm{ego}}\alpha_i \\ {}^{\mathrm{ego}}\theta_i \end{pmatrix}$$

$$= \begin{pmatrix} \sqrt{(x_i - x_{\mathrm{ego}})^2 + (y_i - y_{\mathrm{ego}})^2} \\ \arctan 2(y_i - y_{\mathrm{ego}}, x_i - x_{\mathrm{ego}}) - \theta_{\mathrm{ego}} \\ \theta_i - \theta_{\mathrm{ego}} \end{pmatrix}$$

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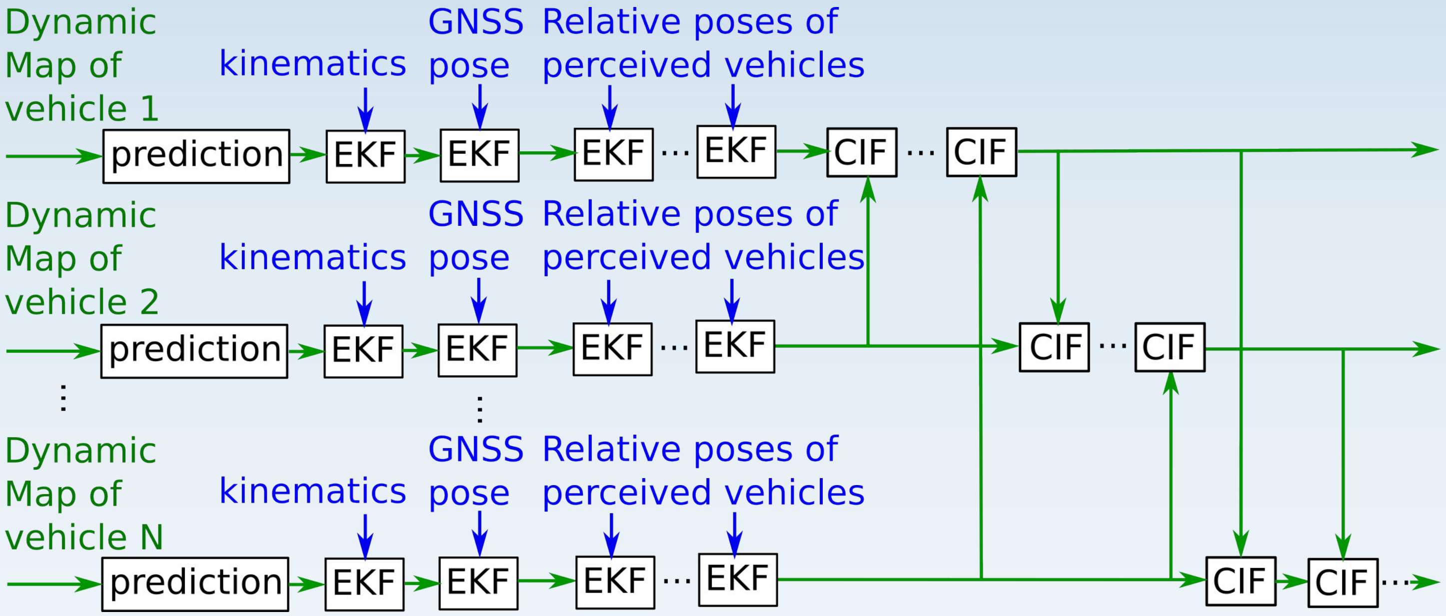
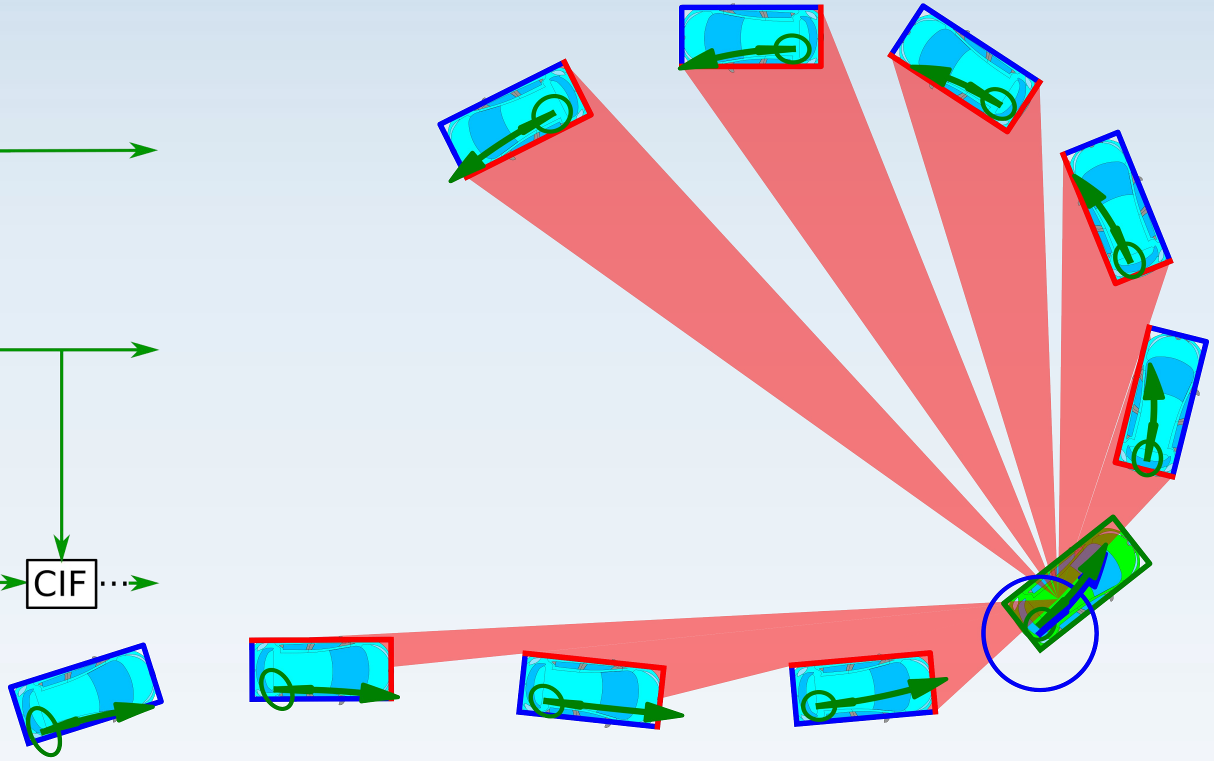
# Data fusion



Covariance Intersection Filter (CIF) for the communication of the dynamic map to avoid data incest.

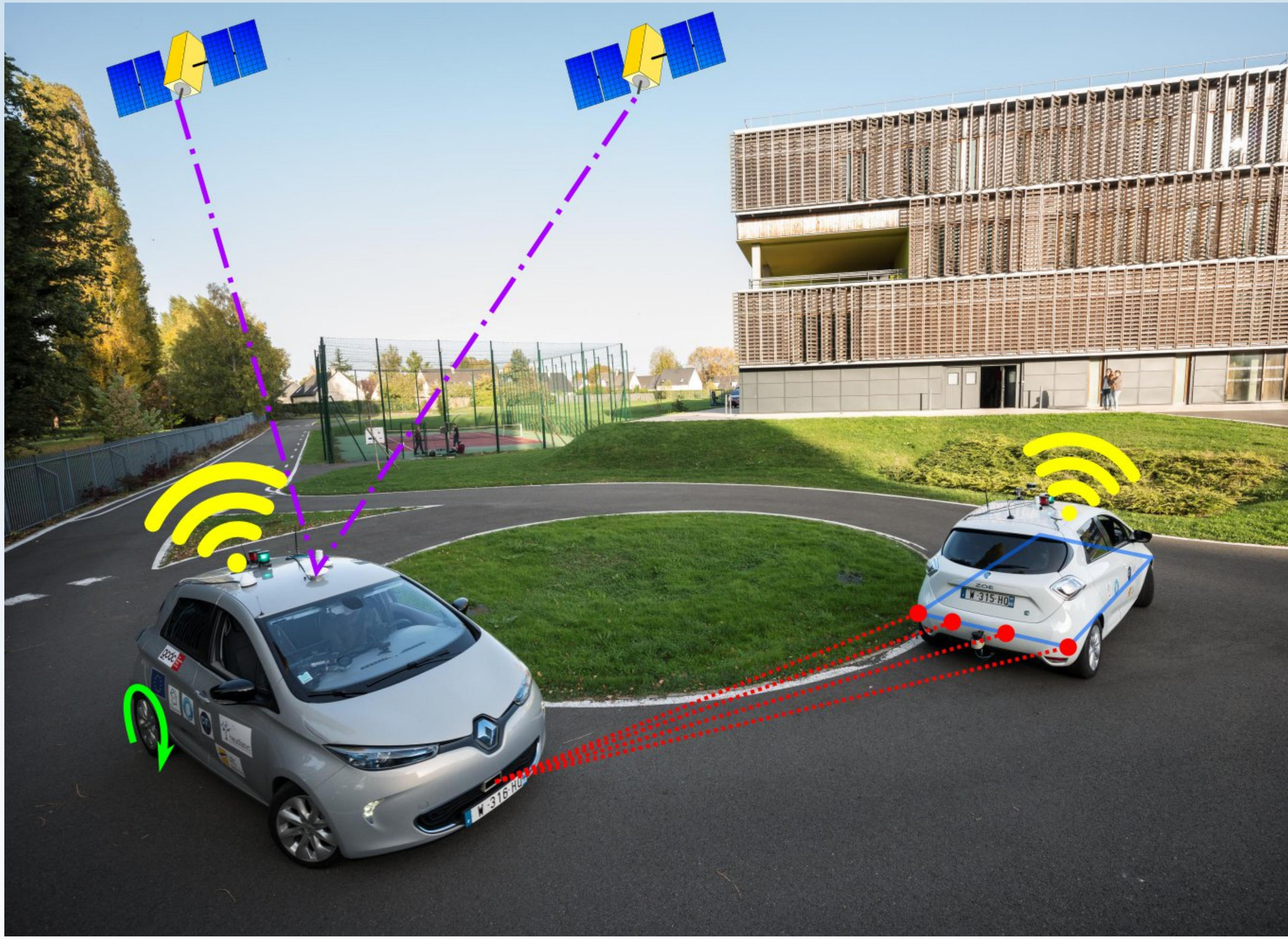
# Hybrid simulation from a real dataset[1]

**Generated from the same vehicle data with time delays**

- Dead reackoning from CAN bus
- Low cost GNSS (GPS, GLONASS) receiver Ublox 8 (unbiased)

**Fully simulated**

- LiDAR perception simulated from ray casting
- V2V communication



[1]https://datasets.hds.utc.fr/project/2

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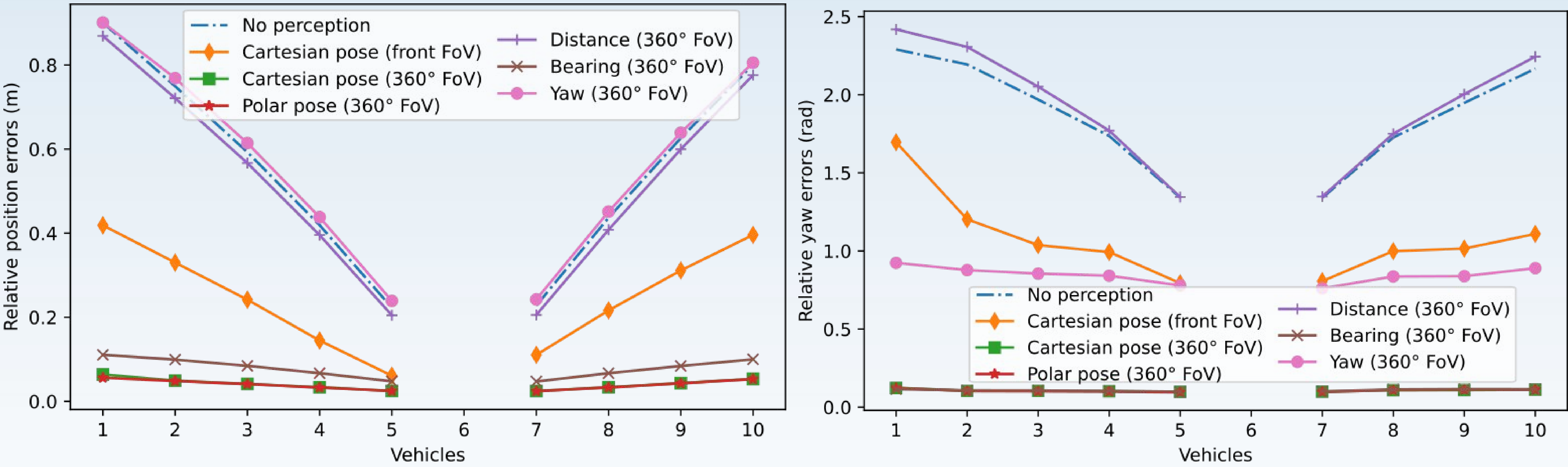
# Results

## Relative position and yaw errors between each vehicle and the vehicle 6

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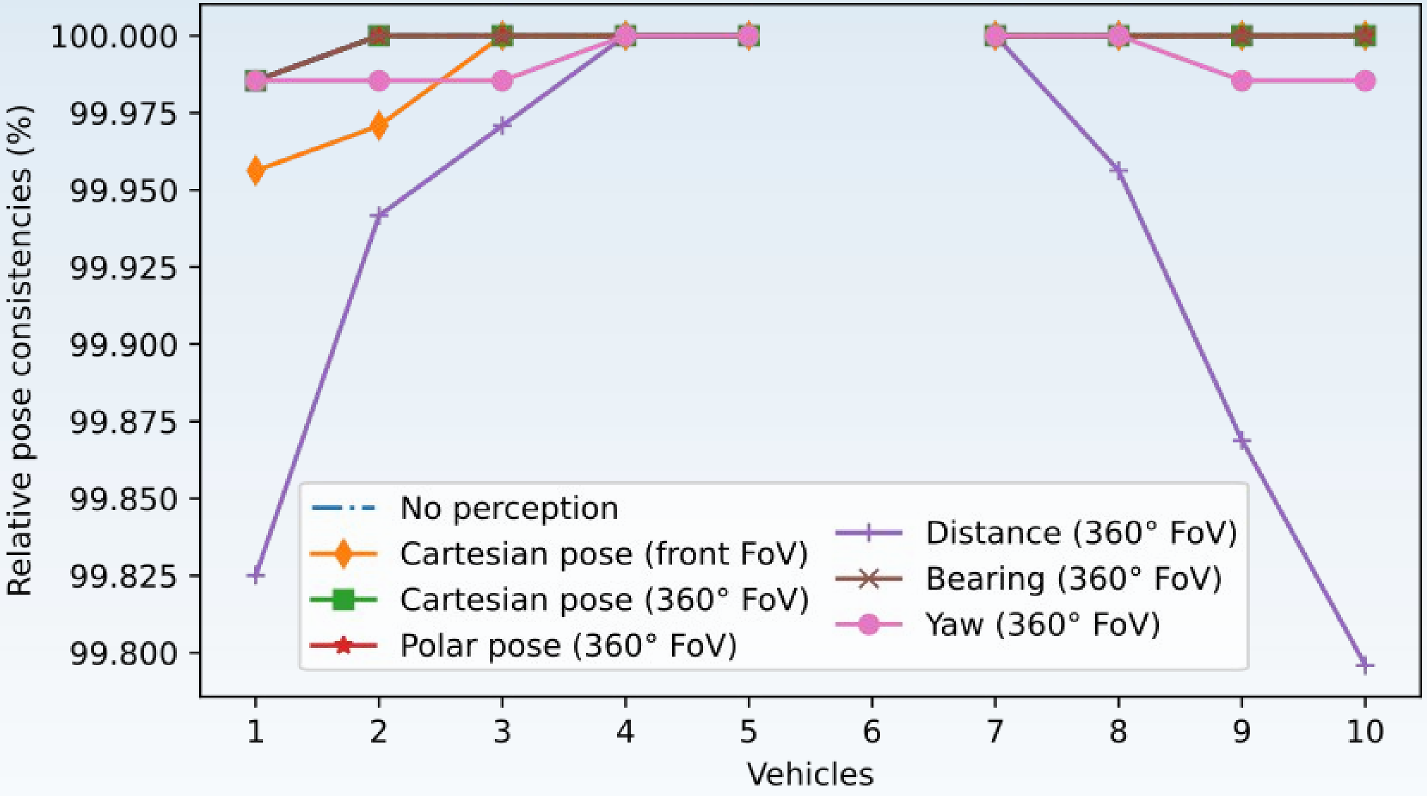
# Results

**Relative pose between each vehicle and the vehicle 6 consistencies with a chi2 test for a probability of 95 %**

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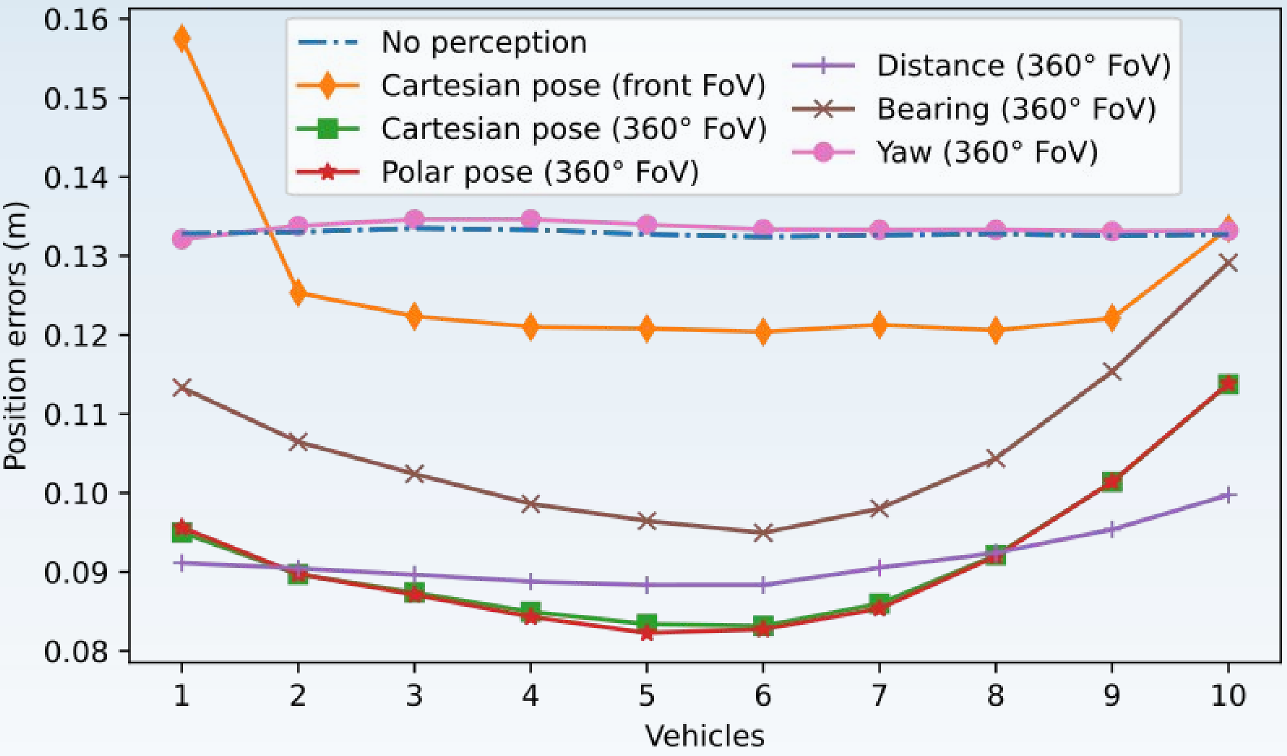
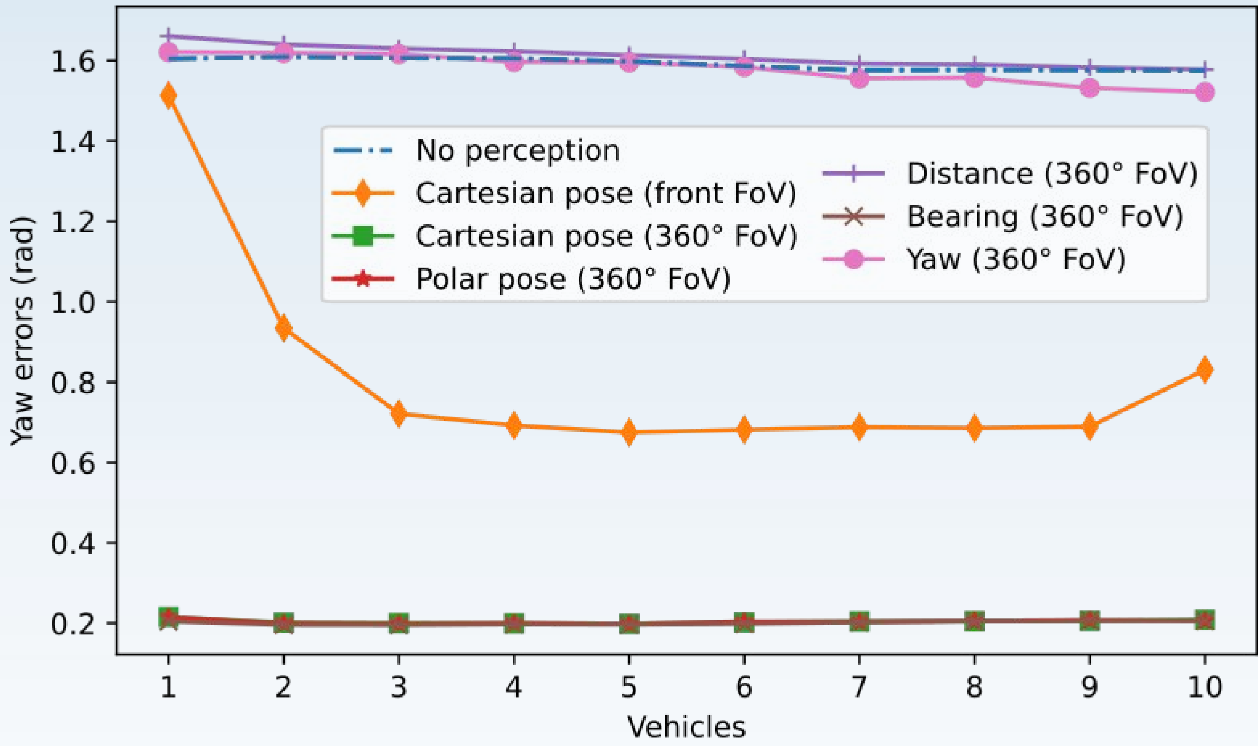
# Results

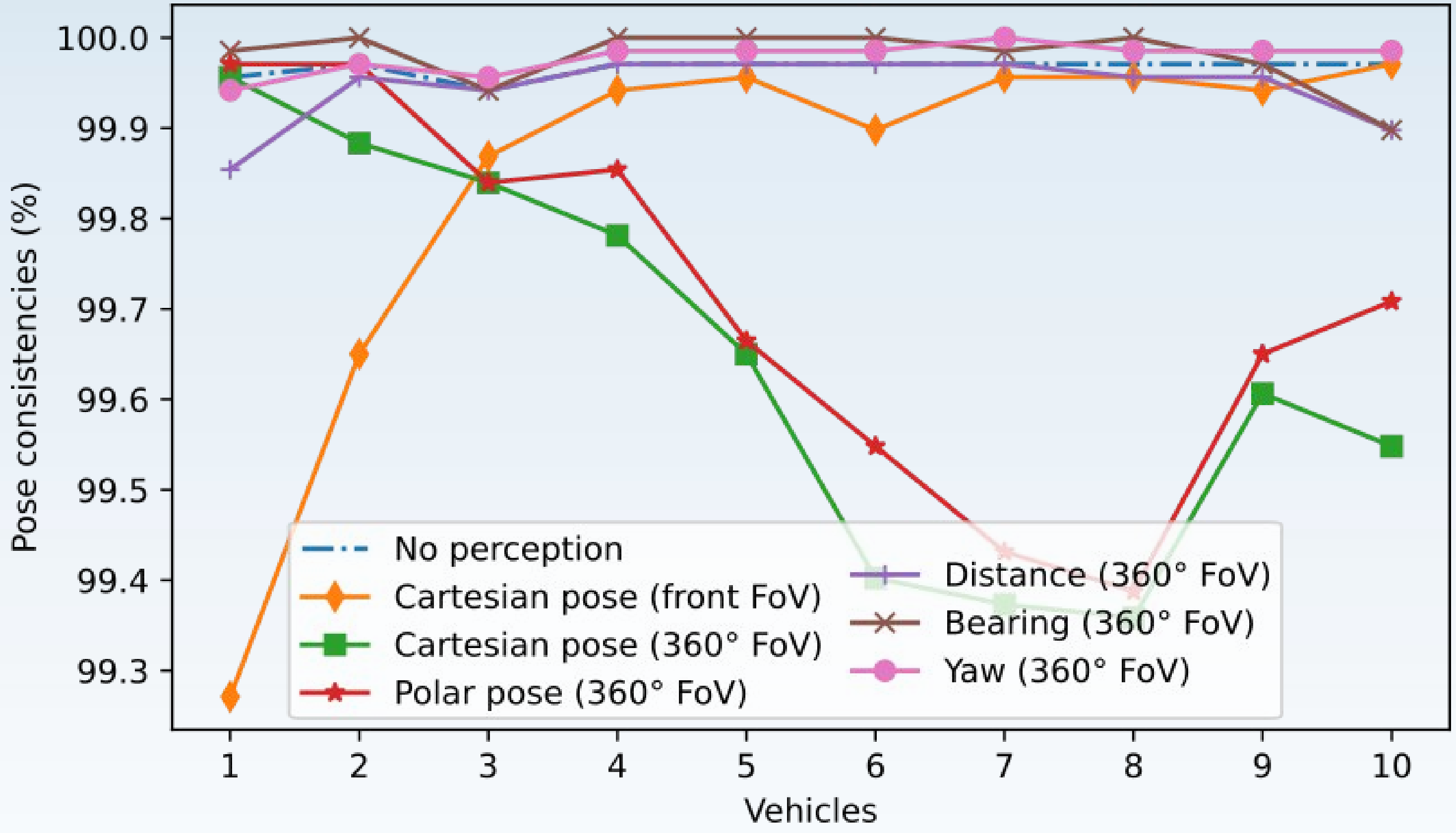
## Position and yaw errors



# Results

## Pose consistencies with a chi2 test for a probability of 95 %



# Conclusion

- Comparison of different observation models (Cartesian and polar relative poses, distances, bearings and relative yaws).
- Evaluation on a hybrid simulation generated from a real dataset and completed with simulations to obtain a platoon of 10 vehicles.
- The cartesian or polar relative pose observation models give the best results as all the informations are available.
- The distances improve the global position only.
- The bearings improve both the global and relative positions.

# Perspectives

- Extend dynamic map with different type of dynamic agents (e.g. cars, bicycles, pedestrians...)

- Data fusion based on graph optimization

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