



Cooperative Estimation for Autonomous Navigation

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Flottes intelligentes de robots

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Intelligent robot fleets

- An intelligent robot fleet is a set of robots designed to work together in a coordinated way, with no (or minimal) human intervention
 - Autonomy
Each robot can act in a standalone way with its own sensors
 - Communication between robots
To exchange mission status, tasks, positions...
 - Coordination and tasks distribution
Robots do not do the same thing or interfere with each other
 - Adaptation
To react to a change in context, such as a failure, obstacle...s
- Possible architectures
 - Centralized: a robot (supervisor) decides for the entire fleet
 - Decentralized: each robot makes local decisions while exchanging with the others
 - Hybrid: a central node for supervision, data harvesting, etc. but the robots retain some autonomy

There are many closely related problems depending on the context

- Cooperative multi-robot system
 - There is no single global mission; each robot follows distinct individual objectives
- Robot fleet operating within an intelligent connected environment
 - In this setup, a local infrastructure is used to exchange information with the robots, to help with localization, traffic management, task allocation, safety, and mission coordination.
- Fleet of autonomous robots with GNSS assistance
 - GNSS creates a dependency on an external positioning infrastructure
- ...

Technical challenges

- Challenges:
 - Unstable/limited communication
 - Localization and mapping
 - Obstacle/collision avoidance
 - Multi-agent planning
 - Reliability when one member of the fleet fails
 - Cybersecurity
 - Energy consumption
 - ...

Outline

Intelligent autonomous vehicles

Examples of cooperative autonomous navigation

- Virtual Platooning
- Cooperative Perception
- Cooperative Localization
- Cooperative SLAM

Uncertainty management in cooperative estimation methods

Conclusion and perspectives

Intelligent autonomous vehicles

Part 1

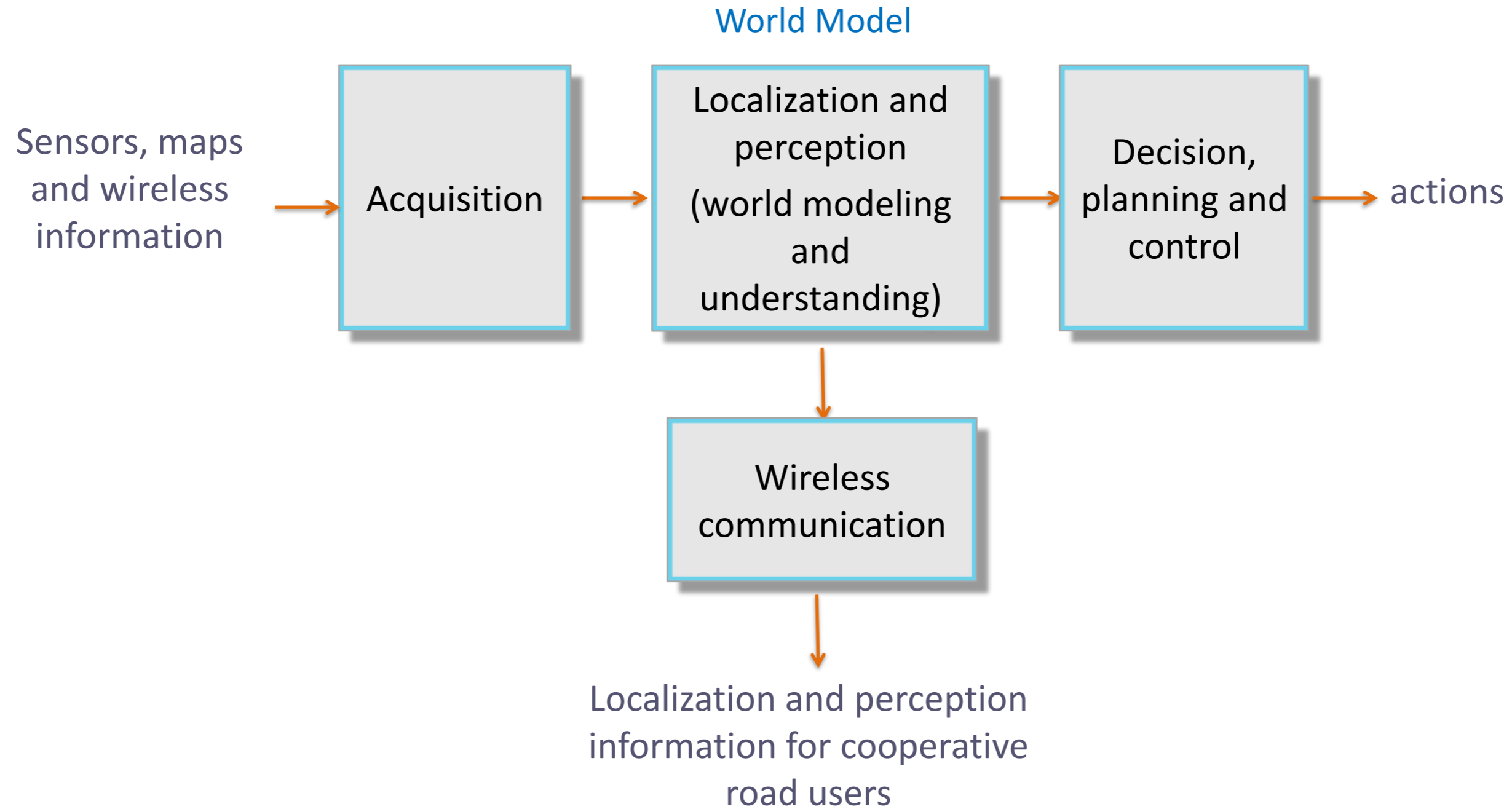
Intelligent autonomous vehicles

- **Intelligent vehicle**
 - Any kind of homologated motorized vehicle with sensors operating on roads opened to public traffic making part of an Intelligent transportation System (ITS)
- **An intelligent autonomous vehicle is designed to:**
 - Perceive its environment using sensors and machine learning
 - Understand the situation
 - Decide on actions (braking, changing lanes, overtakings) in an open environment
 - Act autonomously, controlling its movements in real time.
- **Key Technologies**
 - Sensors and Perception
 - Localization and Mapping (HD maps, SLAM - Simultaneous Localization and Mapping)
 - V2X Communication (Vehicle-to-Everything)

Sources of information for autonomous navigation



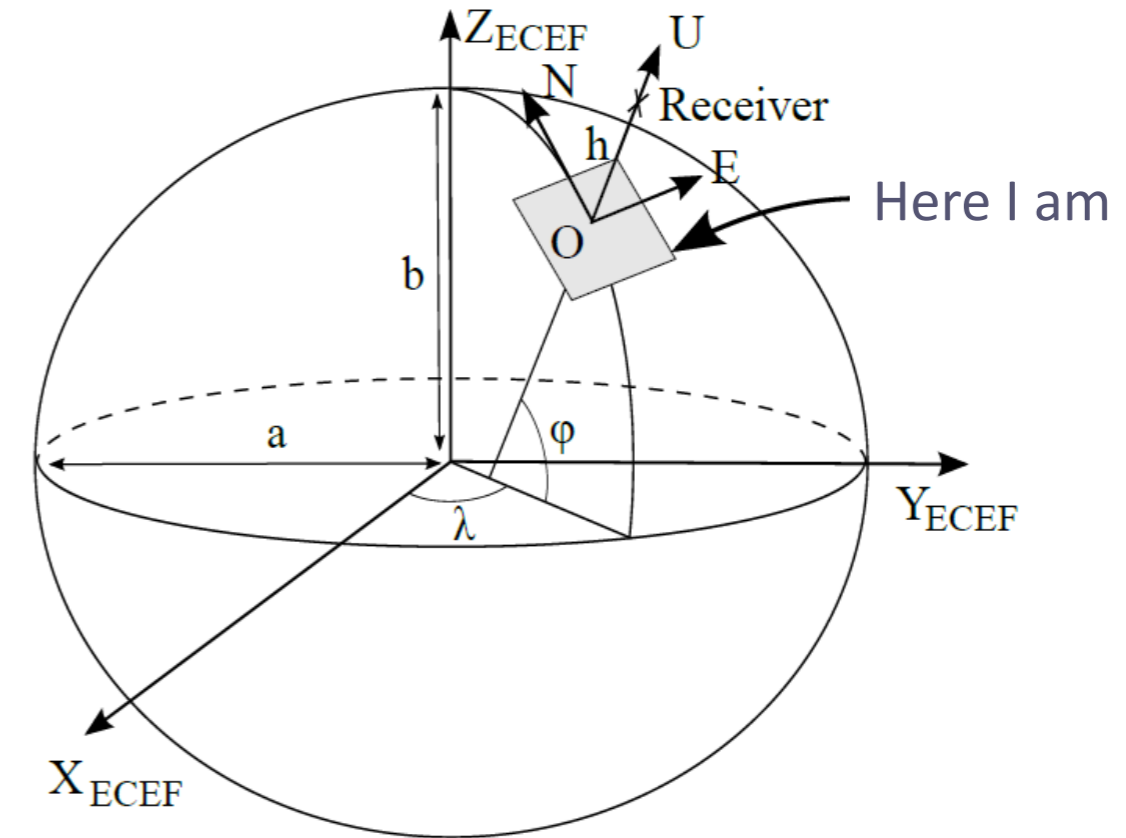
Autonomous navigation stack



Localization and perception

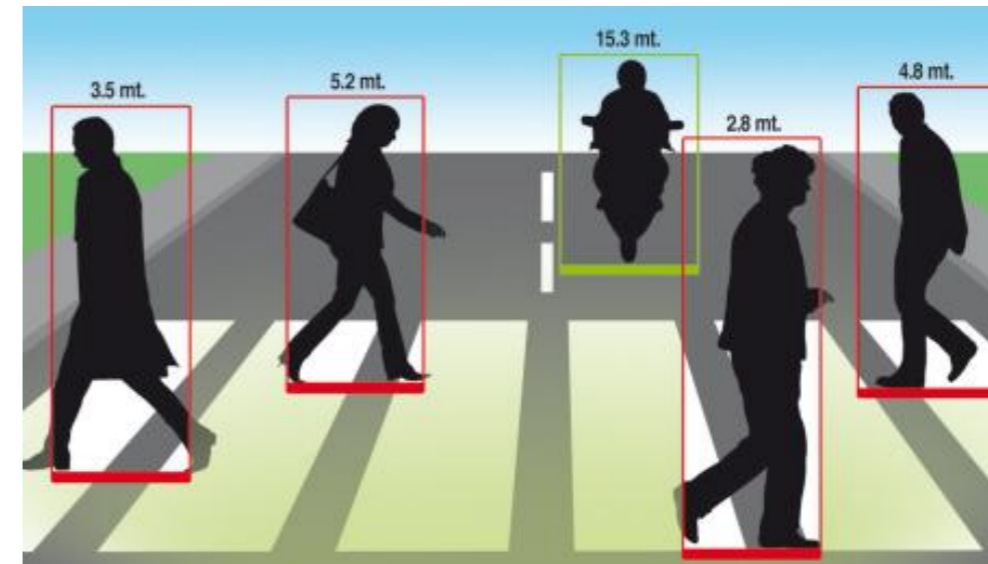
Localization system

—allows the vehicle to estimate its pose, absolutely or relatively, in its evolution environment



Perception system

—equips the vehicle with understanding and prediction capabilities of its immediate environment.



Communication ITS standards

Wireless medium

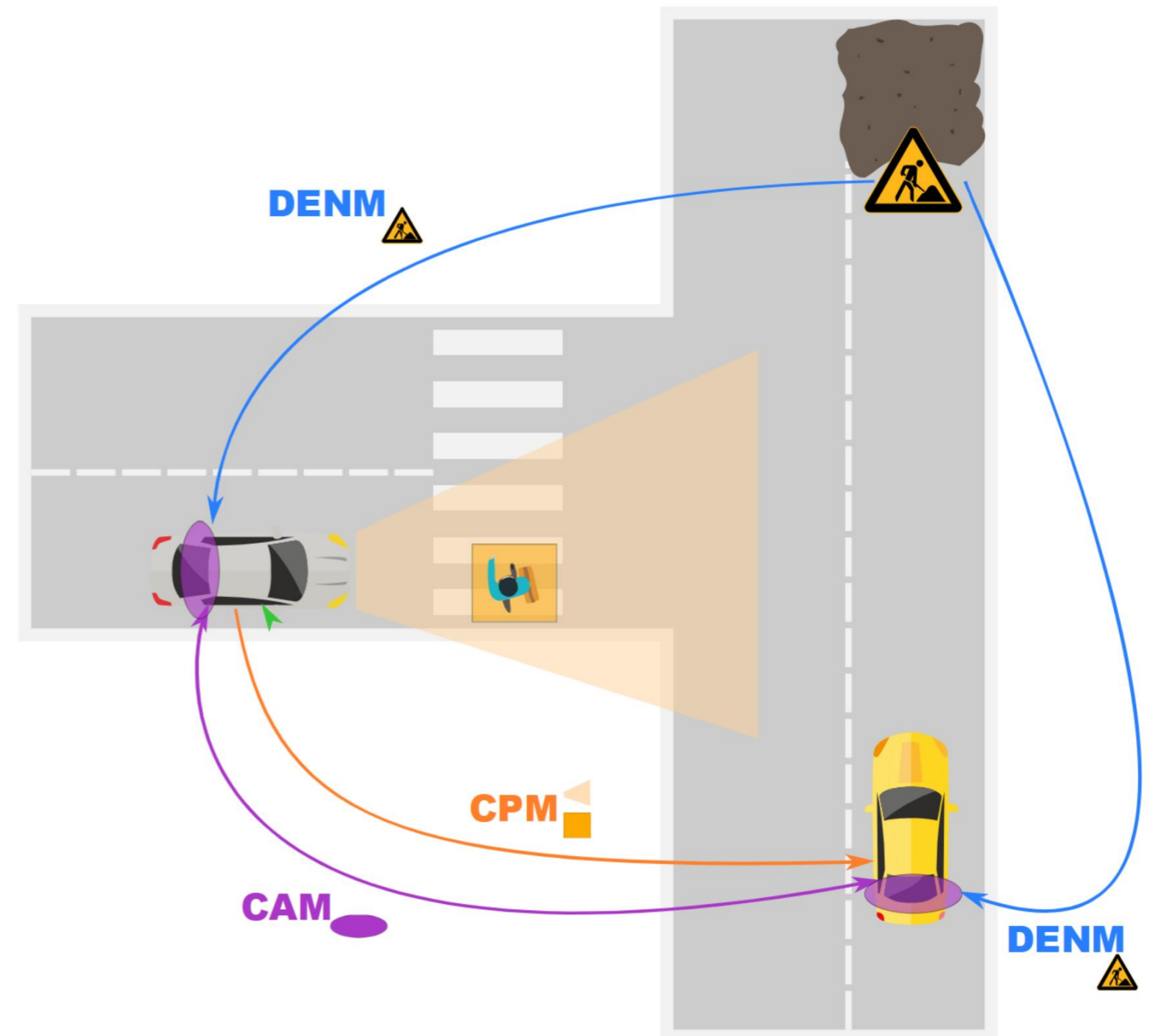
- DSRC, cV2X

Standards

- ETSI, IEEE 802.11p WAVE, etc...

Standard messages

- CAM (position) (Cooperative Awareness)
- DENM (events)
- CPM (BBox, FOV, FS) (Cooperative Perception)
- ...



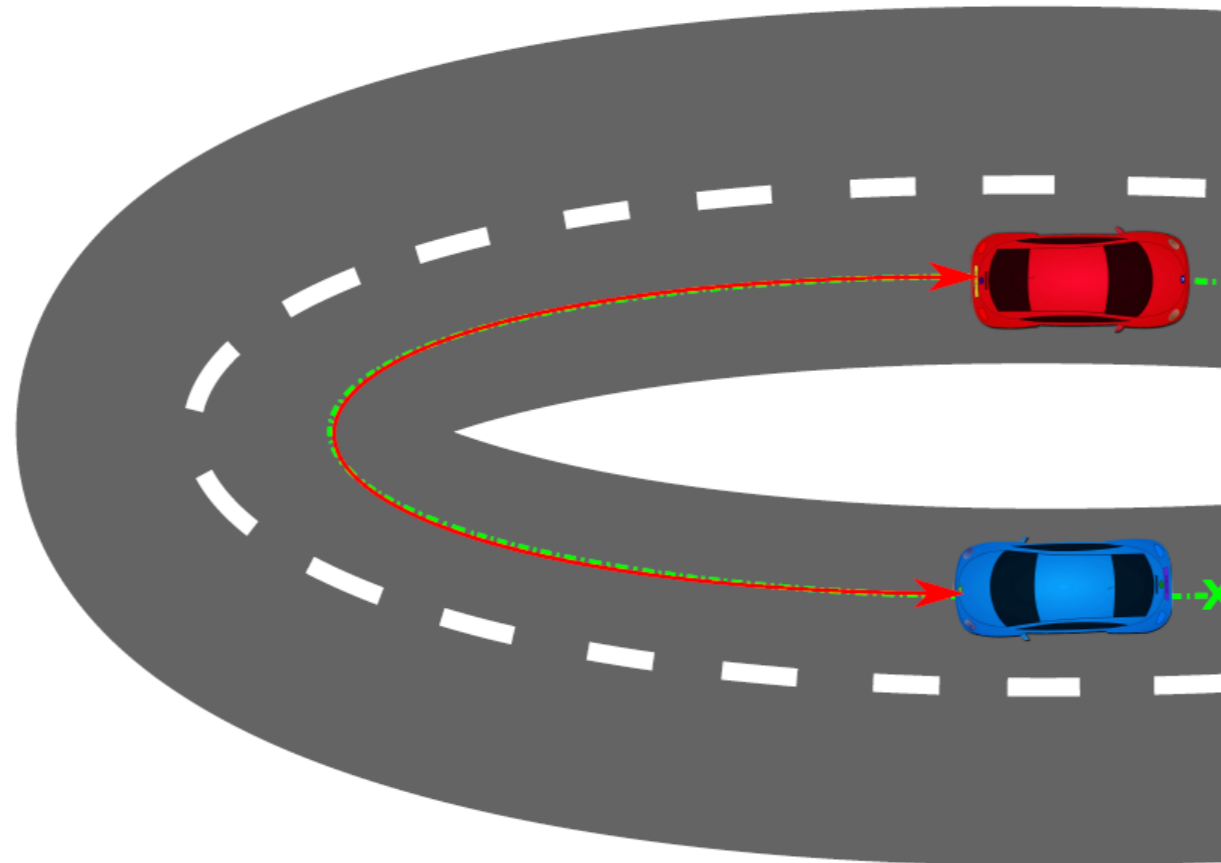
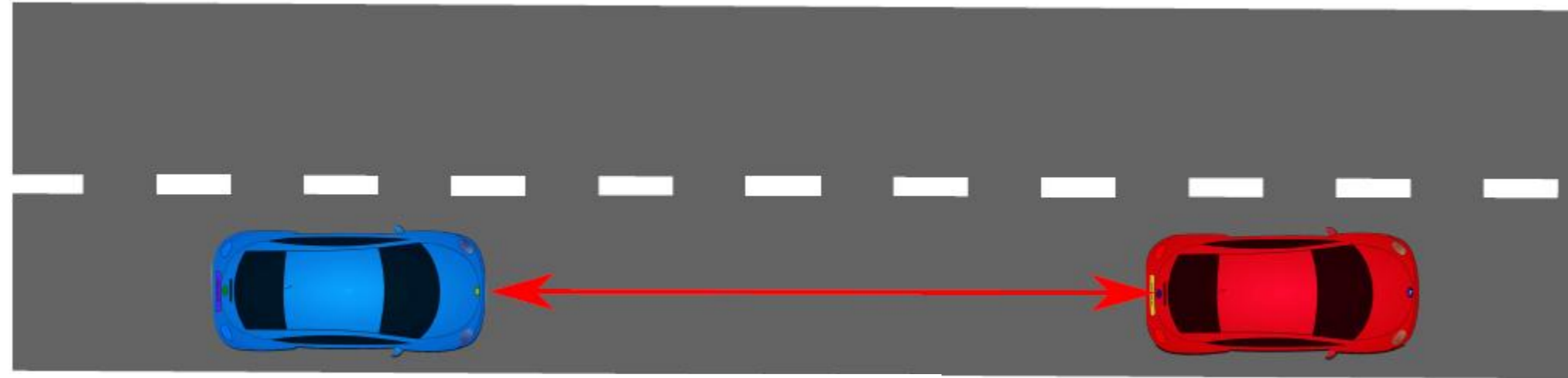
Examples of cooperative autonomous navigation

Part 2

Virtual Platooning

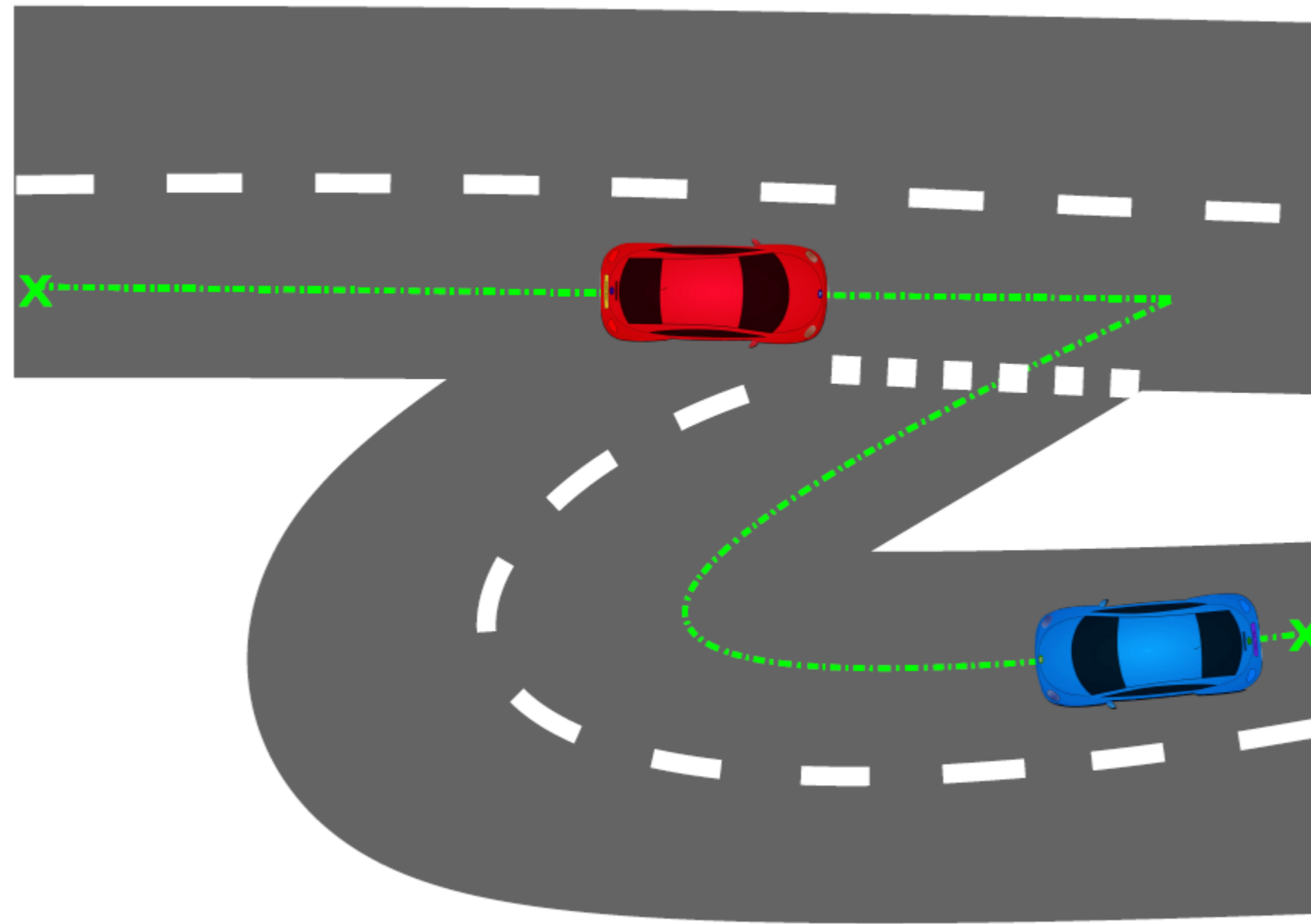
Inter-distance for platooning

In a straight road, inter-distance is easy to measure (e.g. lidar or radar)



In a curved road, compute the inter-distance along the map by using positions exchanged by wireless communication

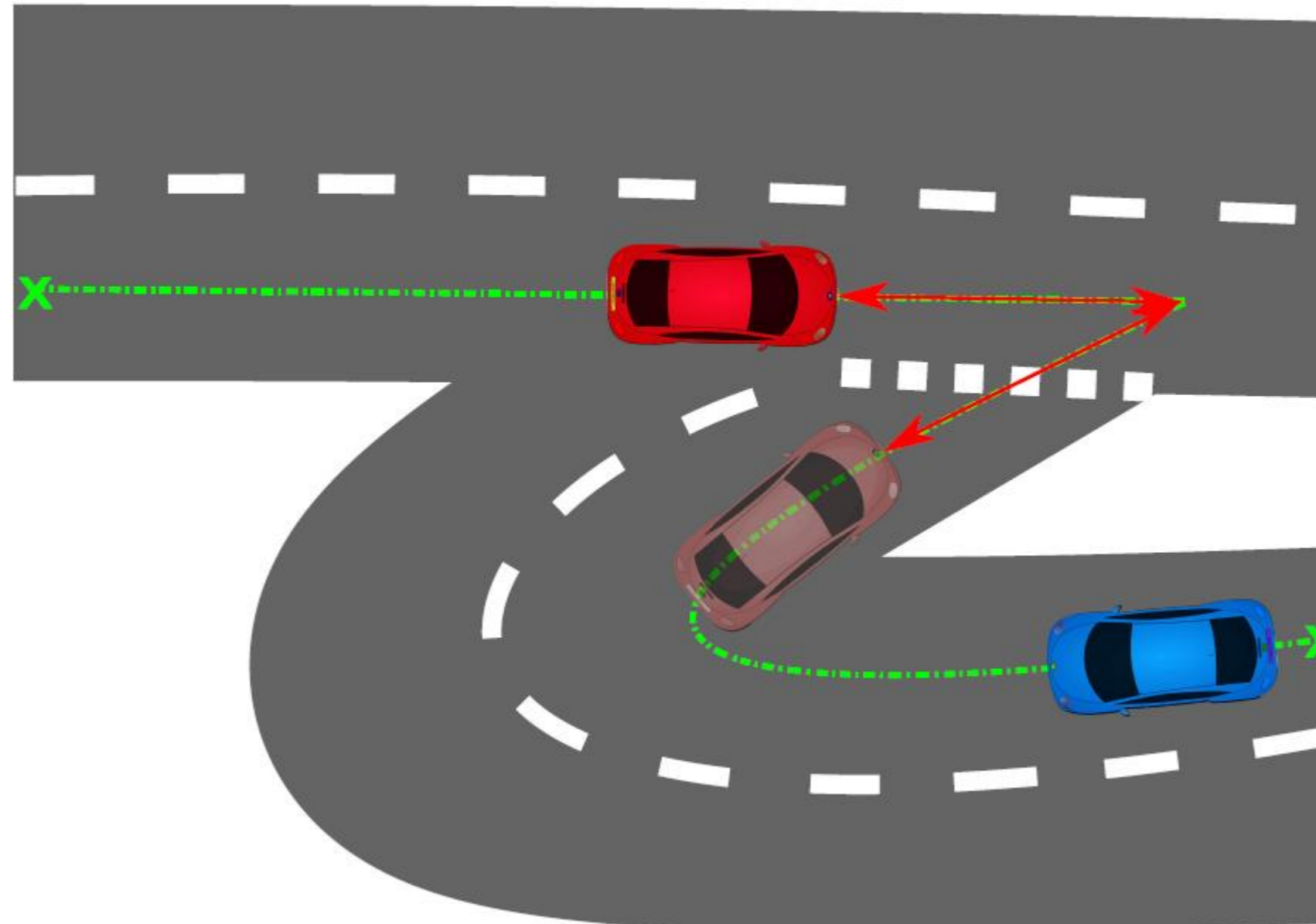
Cooperative merging using virtual platooning



The virtual platooning concept

Every vehicle

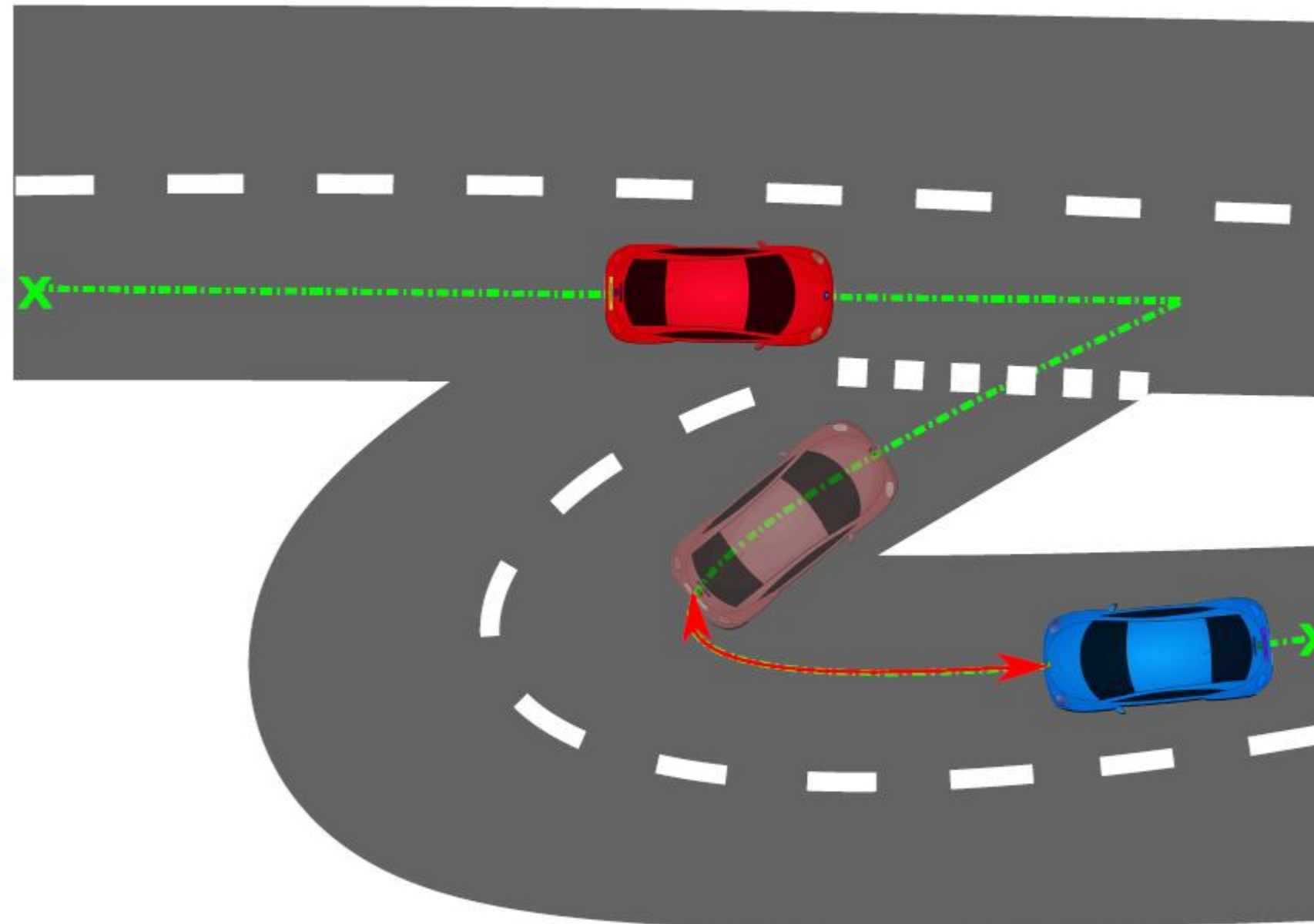
- Computes its distance to the crossing point
- Such that the others can localize it on their own path



The virtual platooning concept

Here, the red vehicle is the closest to the intersection point and becomes the (virtual) leader

Then the blue one does platooning



Intersection crossing during the GCDC

An application of the virtual platooning concept



Grand Cooperative Driving Challenges 2016

Cooperative perception

Cooperative perception using direct communication (V2V)

If there are enough connected vehicles, perception of the traffic scene can be extended thanks to cooperation.



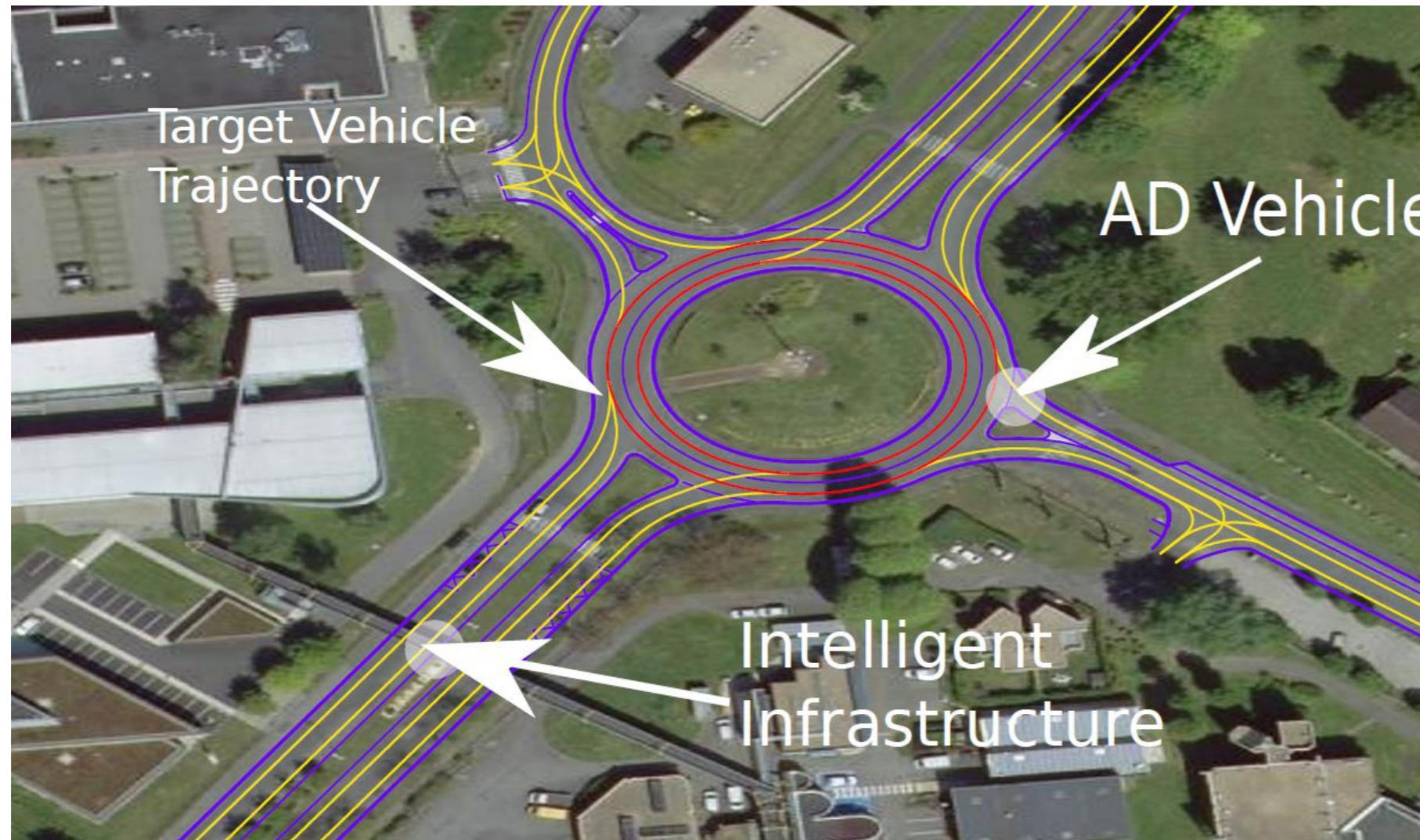
Antoine Lima's PhD thesis

Cooperative Intelligent Infrastructure

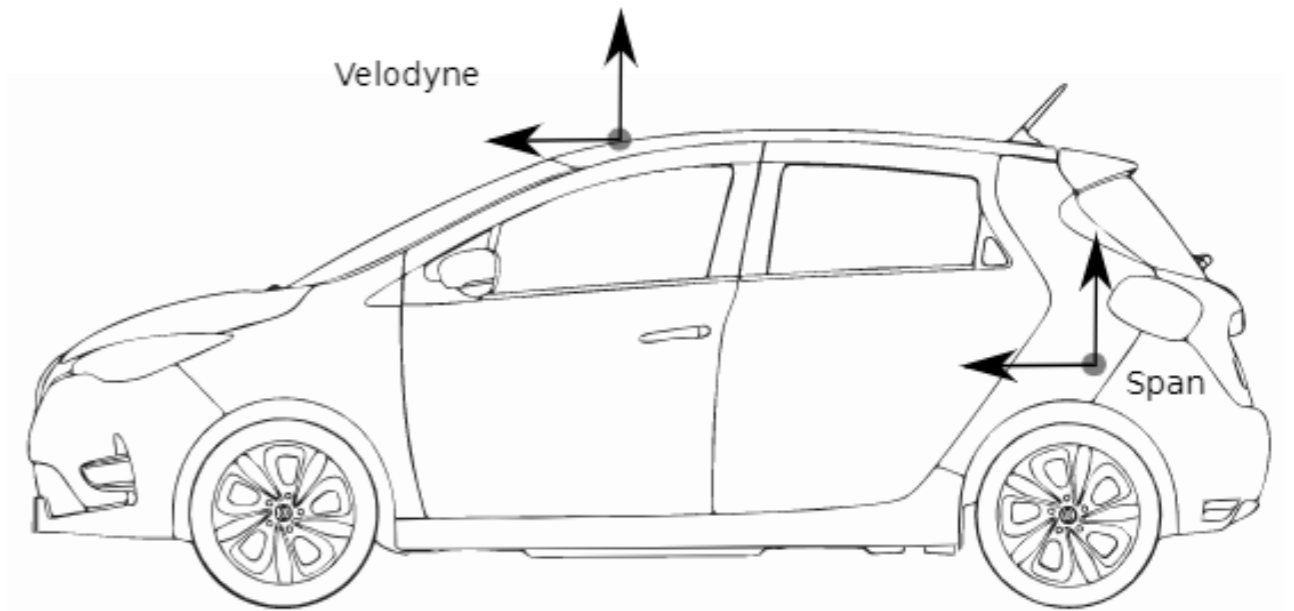
Some complex areas can be equipped with a trustworthy communication infrastructure



Experimental Setup



UTC research center (Compiègne)



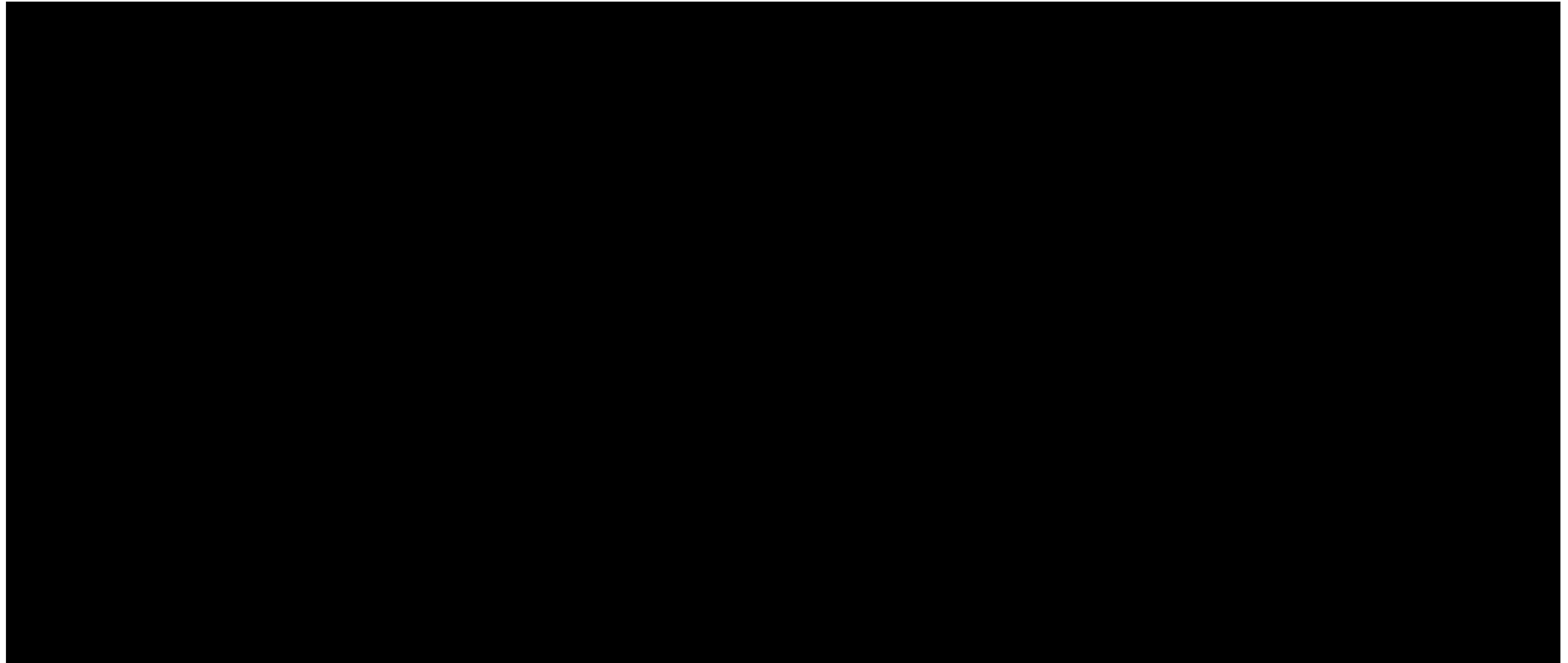
Infrastructure Perception



Objects projection
in HD map frame

Camera Vehicles detection
(YOLO)

Extended cooperative perception to enhance the field of view



Roundabouts crossing with cooperative infrastructure



Tornado Project Rambouillet 2021

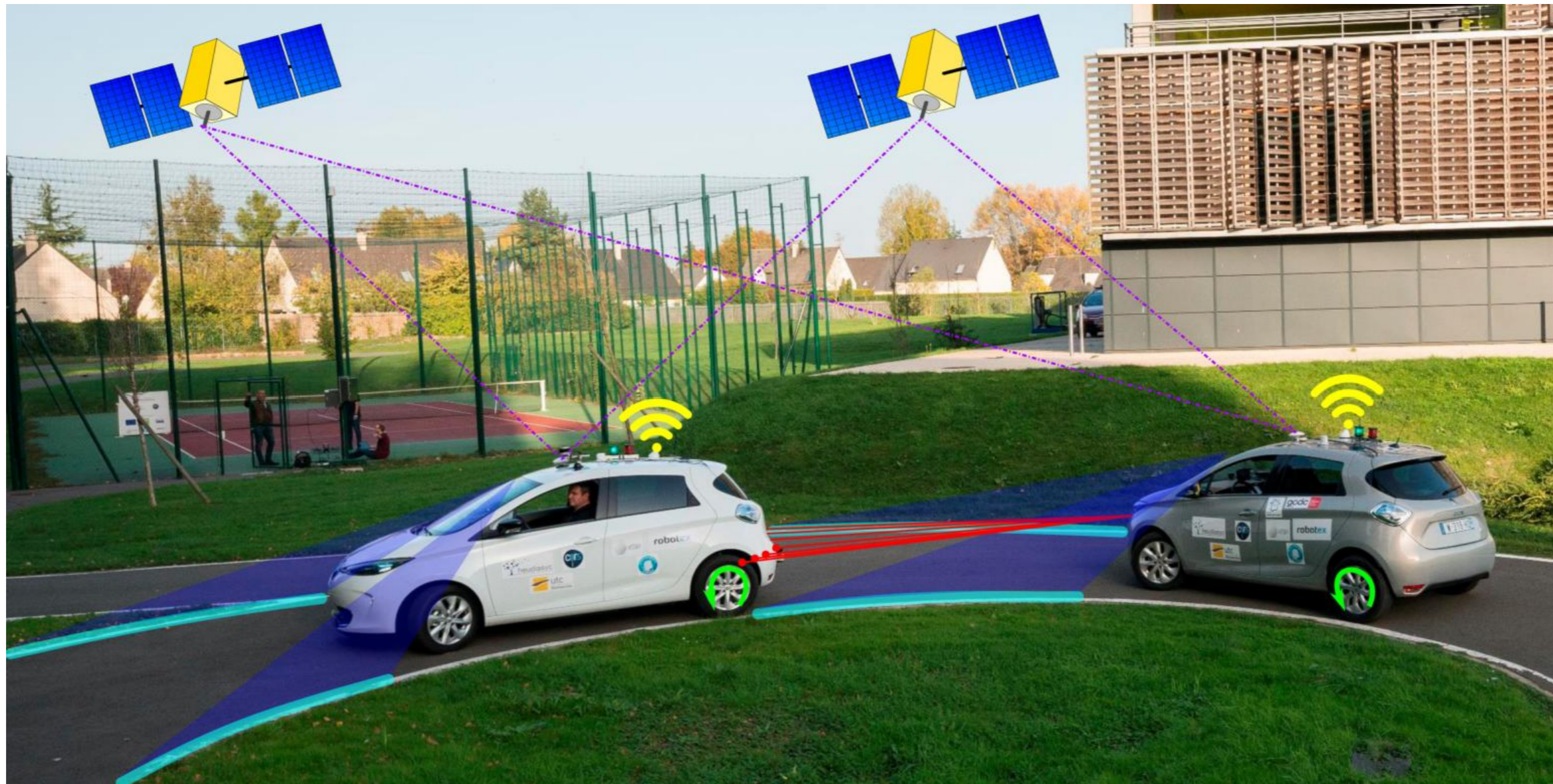
Autonomous Driving with cooperative infrastructure



Tornado Project Rambouillet 2021

Cooperative Localization

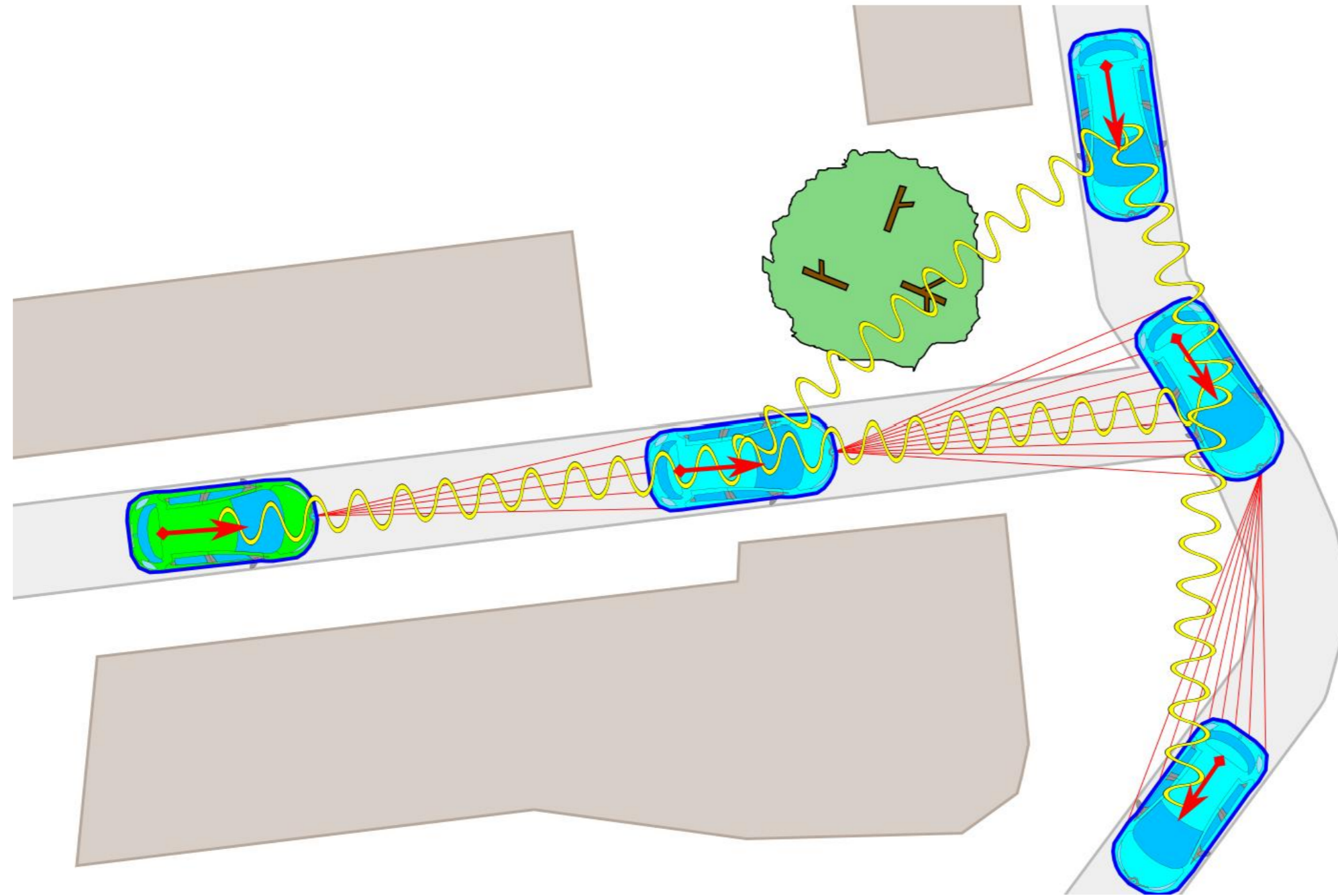
Cooperative Localization using direct/relative observations



Sensors : Dead-Reckoning, Lidar and non-differential GNSS

Elwan Héry's PhD Thesis

Cooperative Localization using direct observations



Local Dynamic Map

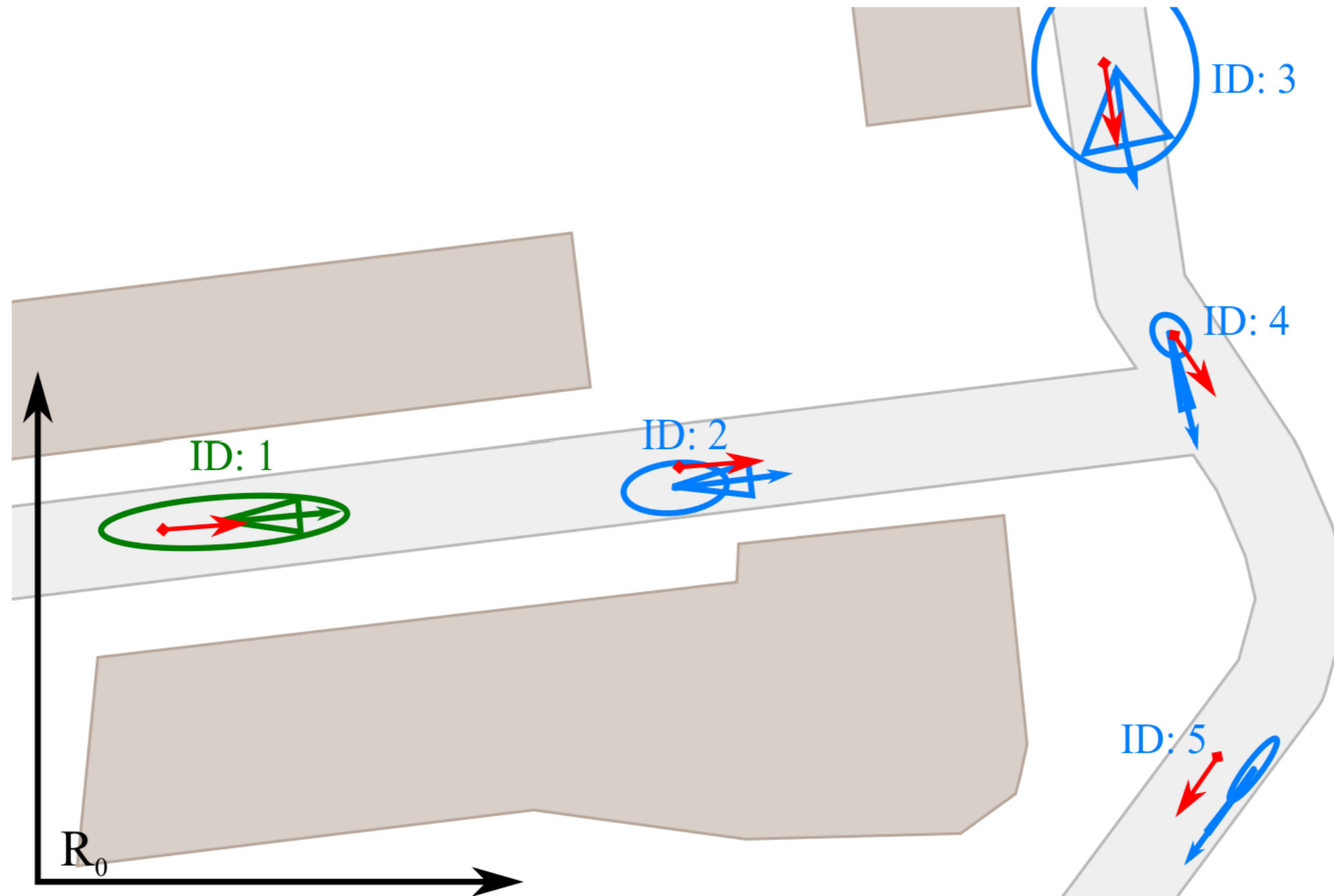
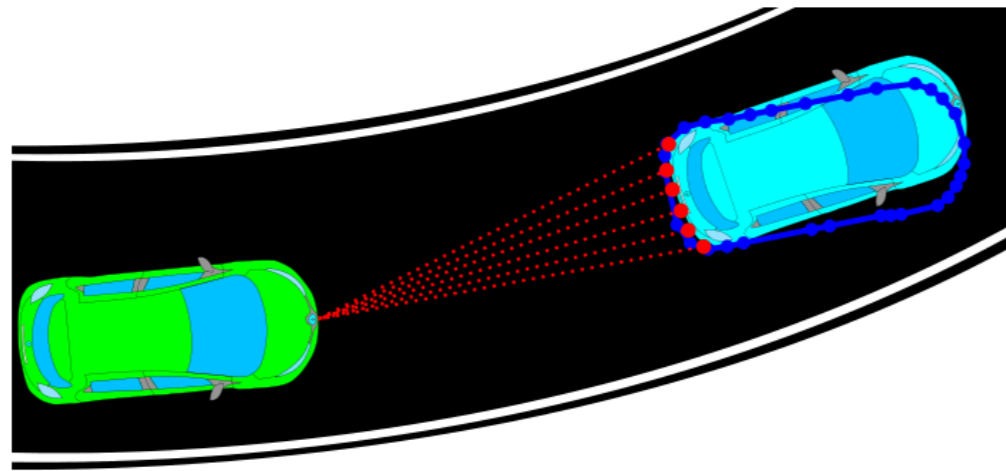


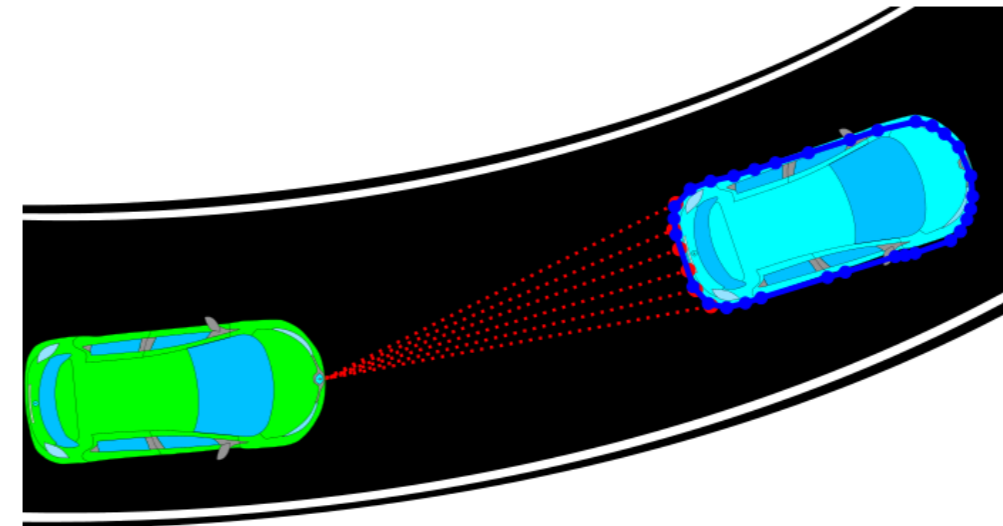
Illustration of the output of the cooperative estimation process

Relative Localization

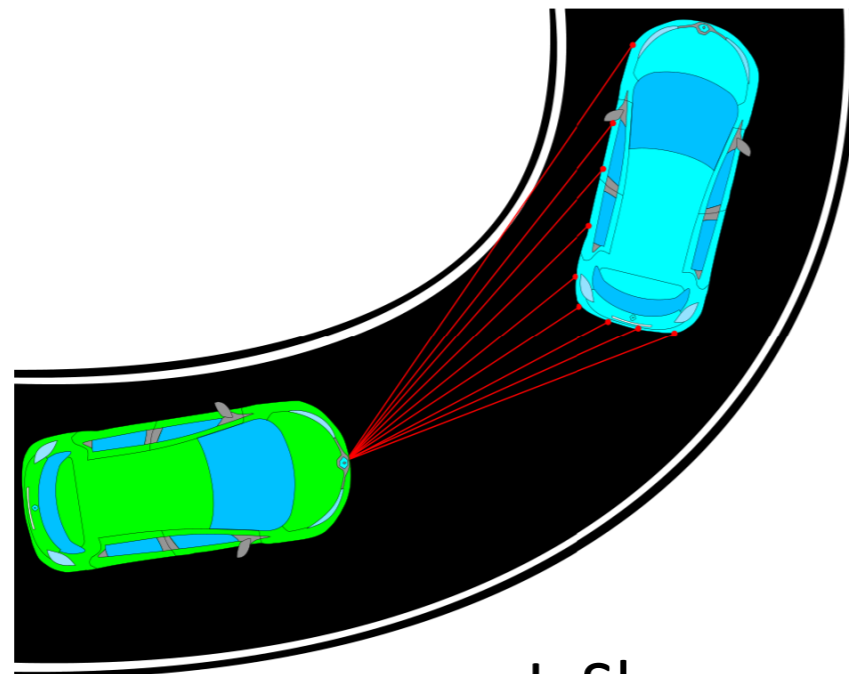
To get an accurate relative localization, a model of the visible shape of each vehicle is needed



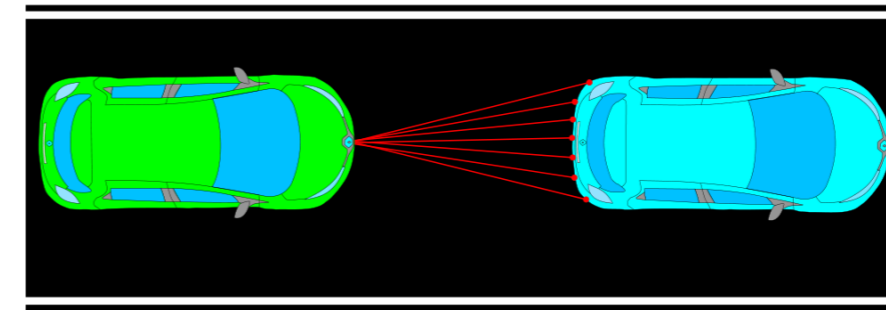
Init



Model fitting after convergence

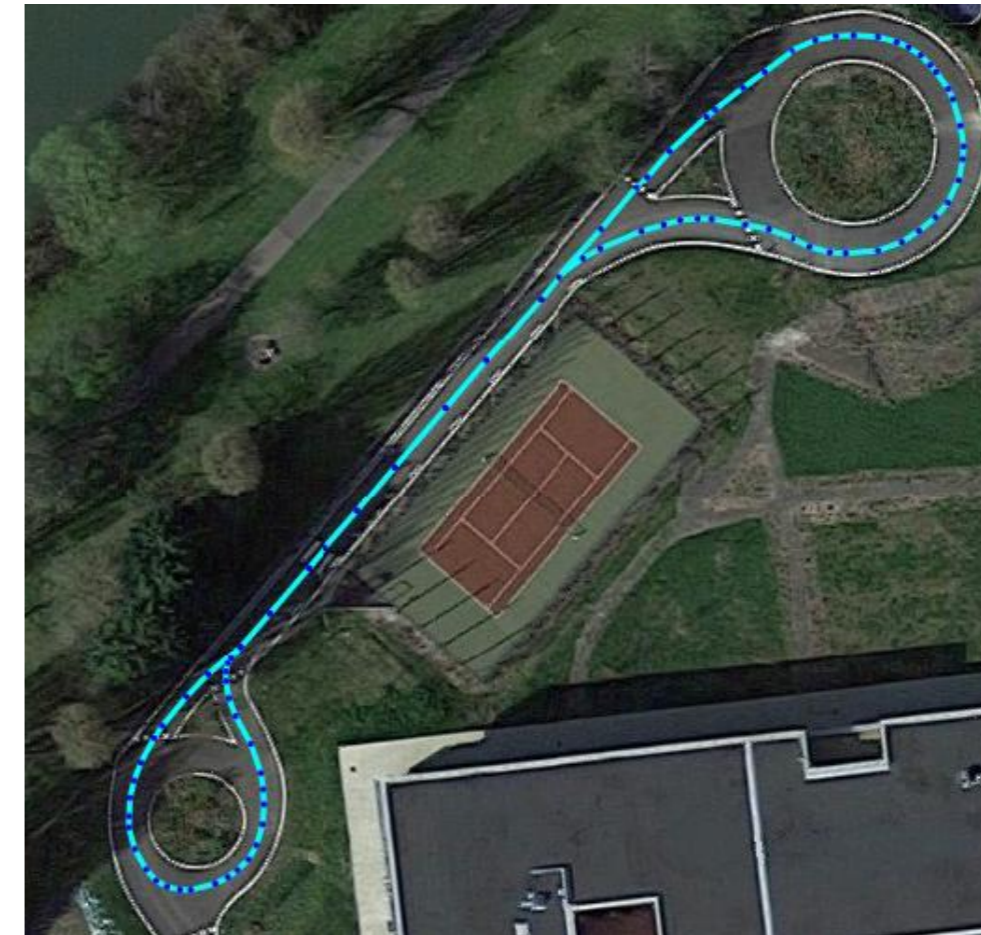
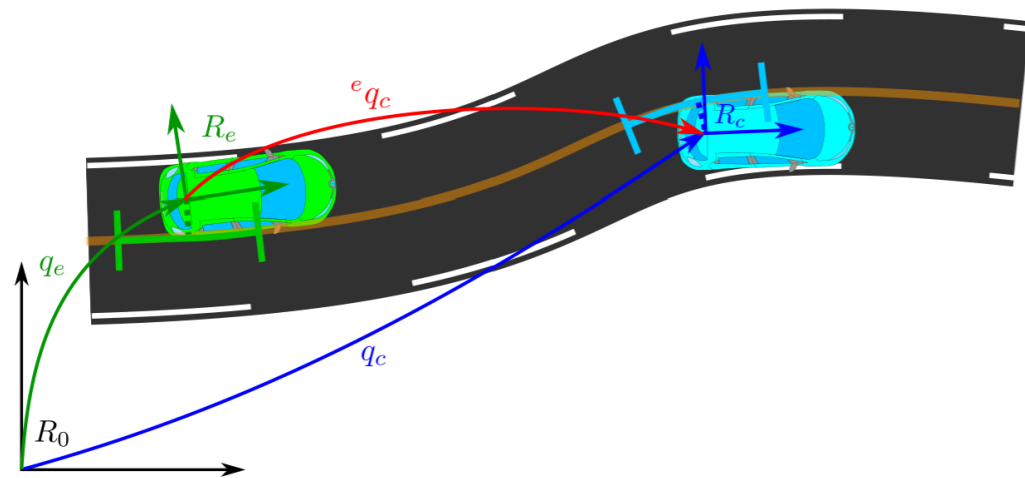


L-Shape

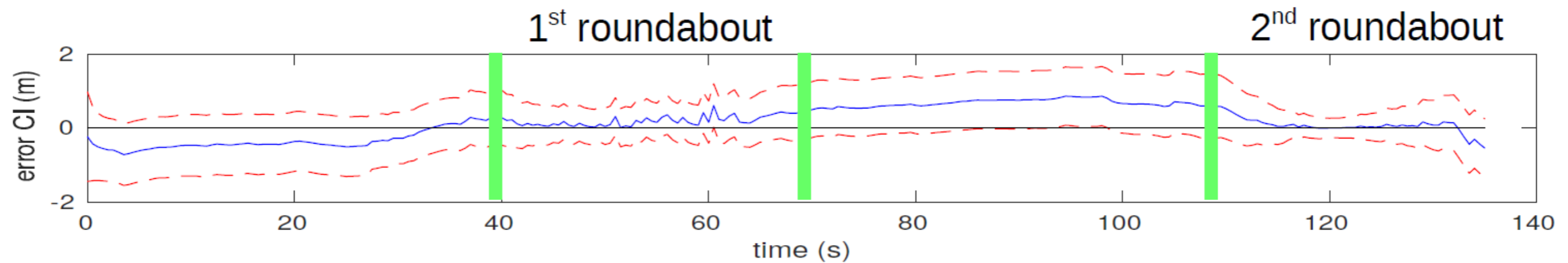


C-Shape less accurate

Experimental results



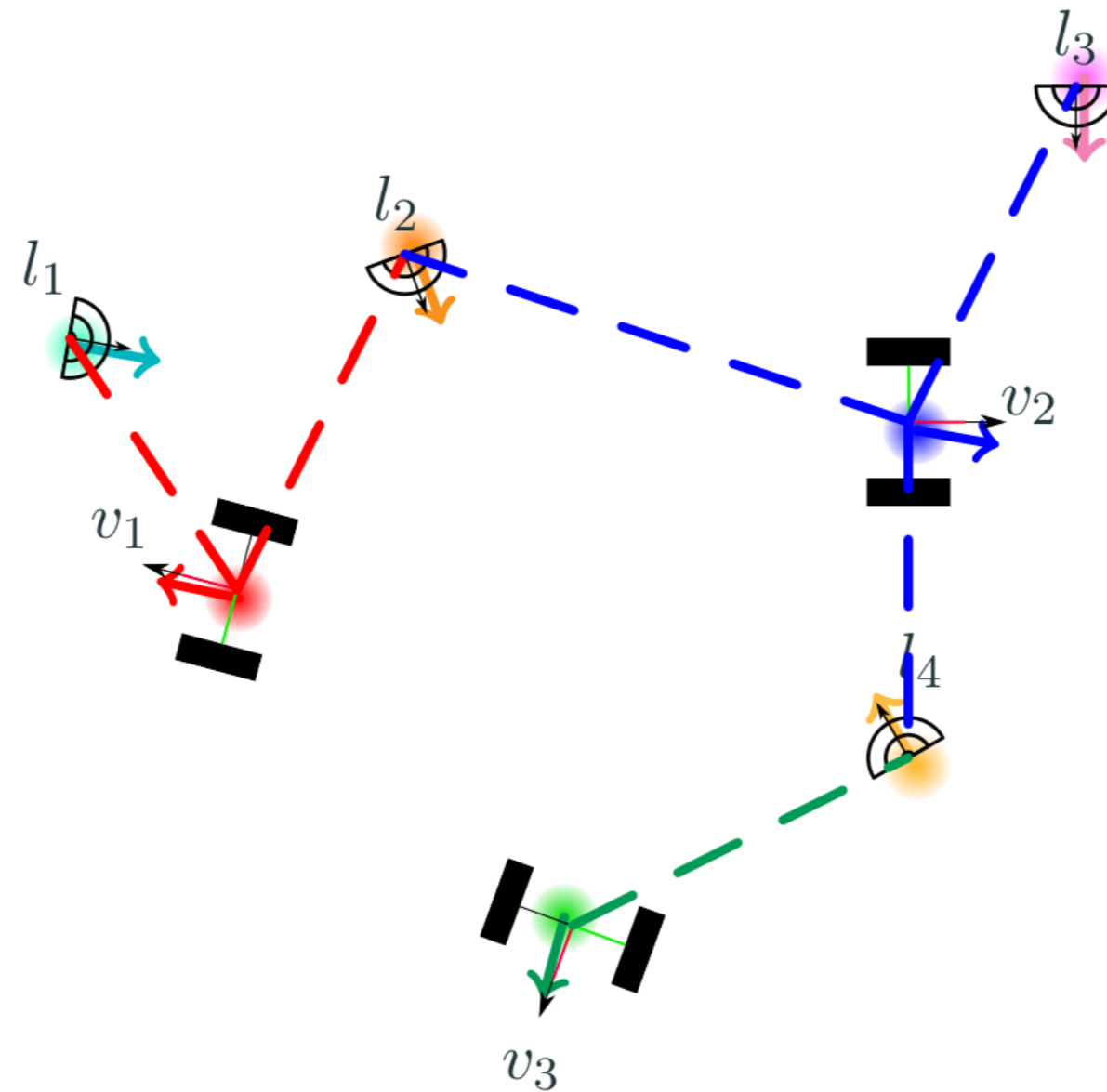
Mutual cooperation particularly efficient
in curved lane



Error and confidence bound computed for the follower

Cooperative SLAM

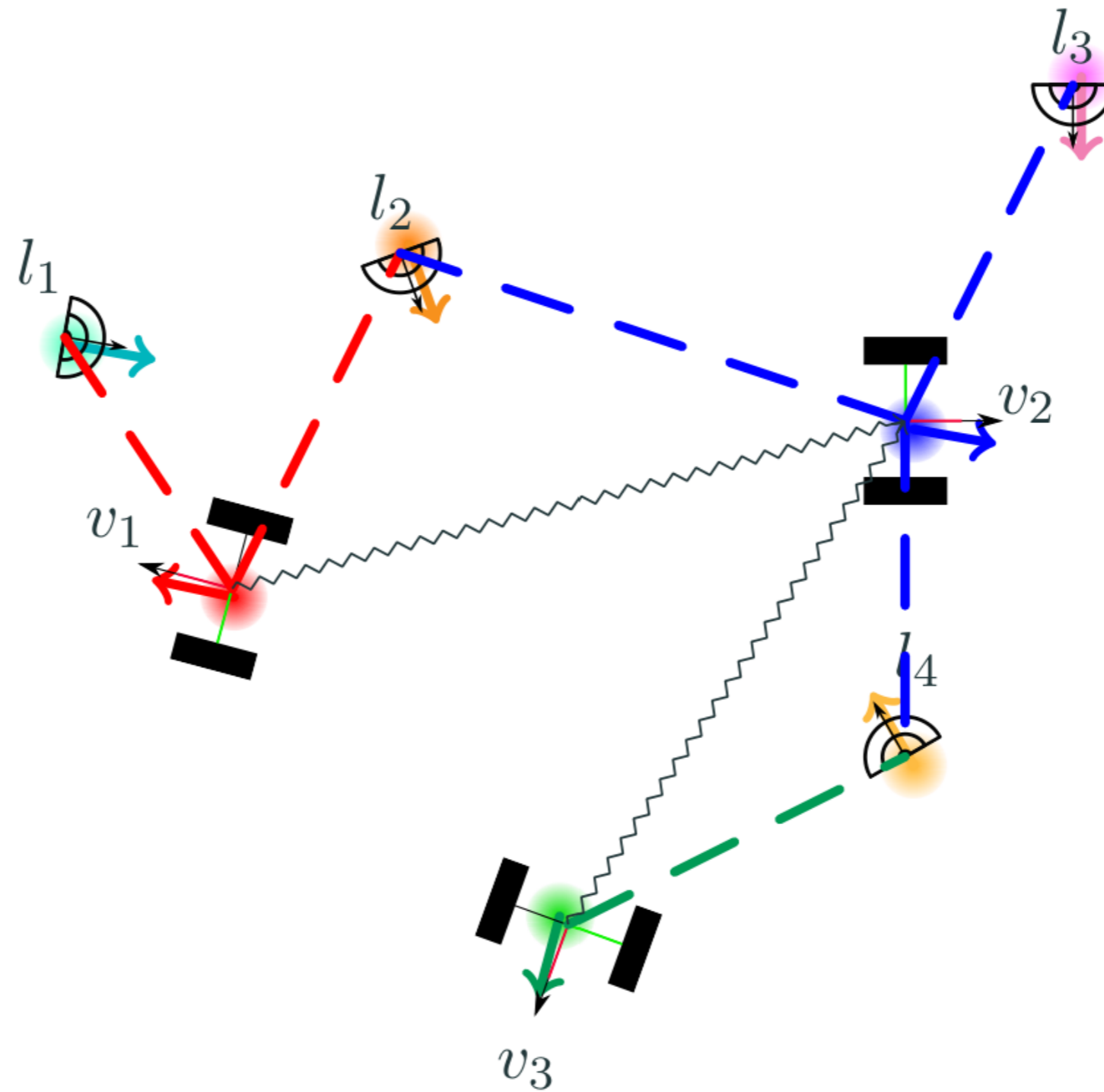
Cooperative SLAM with Prior Map



Indirect observations

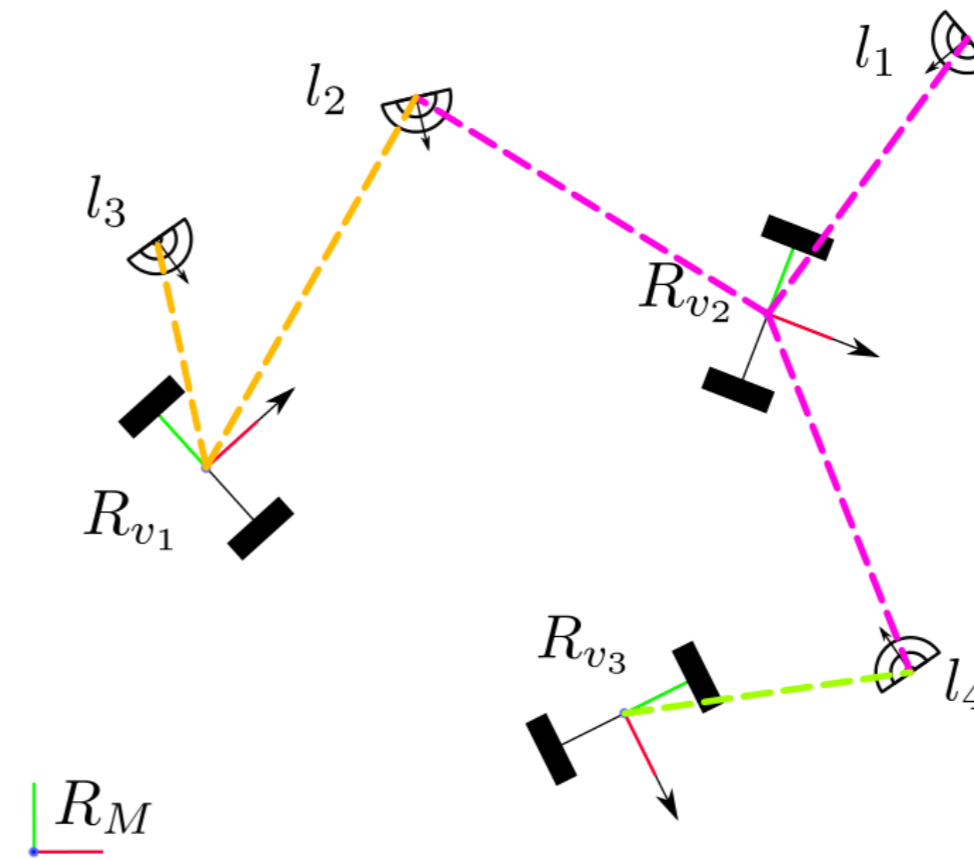
Maxime Escourrou PhD thesis

Collaboration through indirect observations: joint observation of a common landmark



Robots observing landmarks

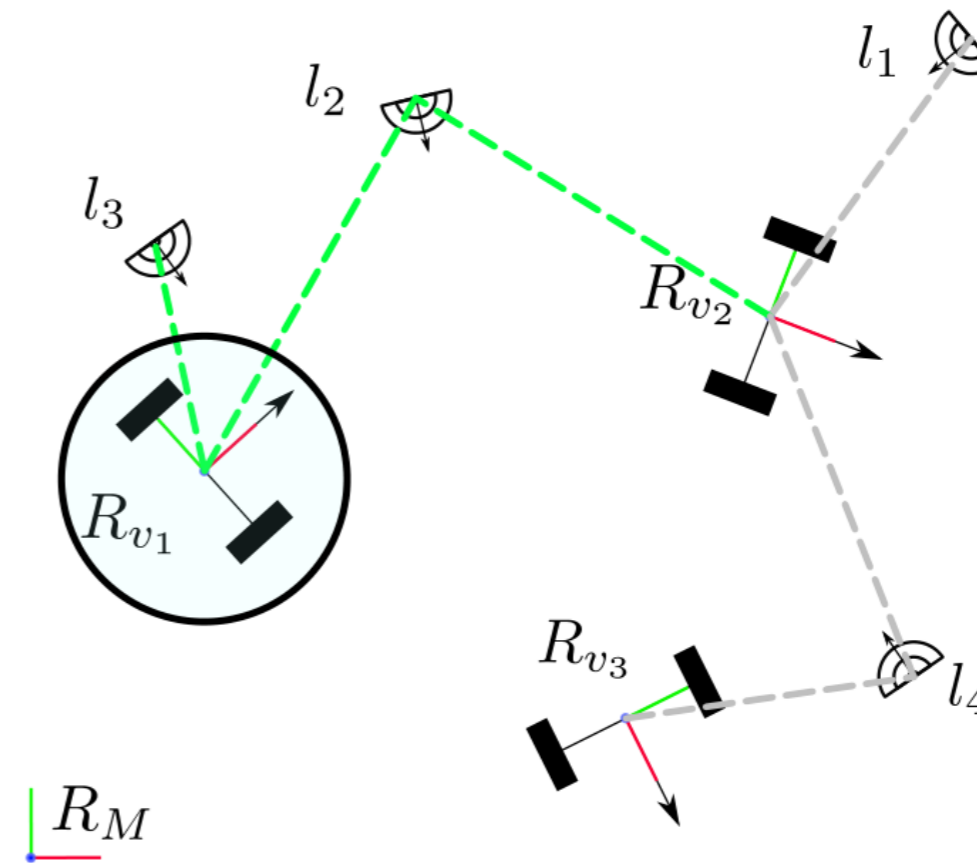
	v_1	v_2	v_3	l_1	l_2	l_3	l_4	
								$Z_{l_3}^{v_1}$
								$Z_{l_2}^{v_1}$
								$Z_{l_1}^{v_2}$
								$Z_{l_2}^{v_2}$
								$Z_{l_4}^{v_2}$
								$Z_{l_4}^{v_3}$



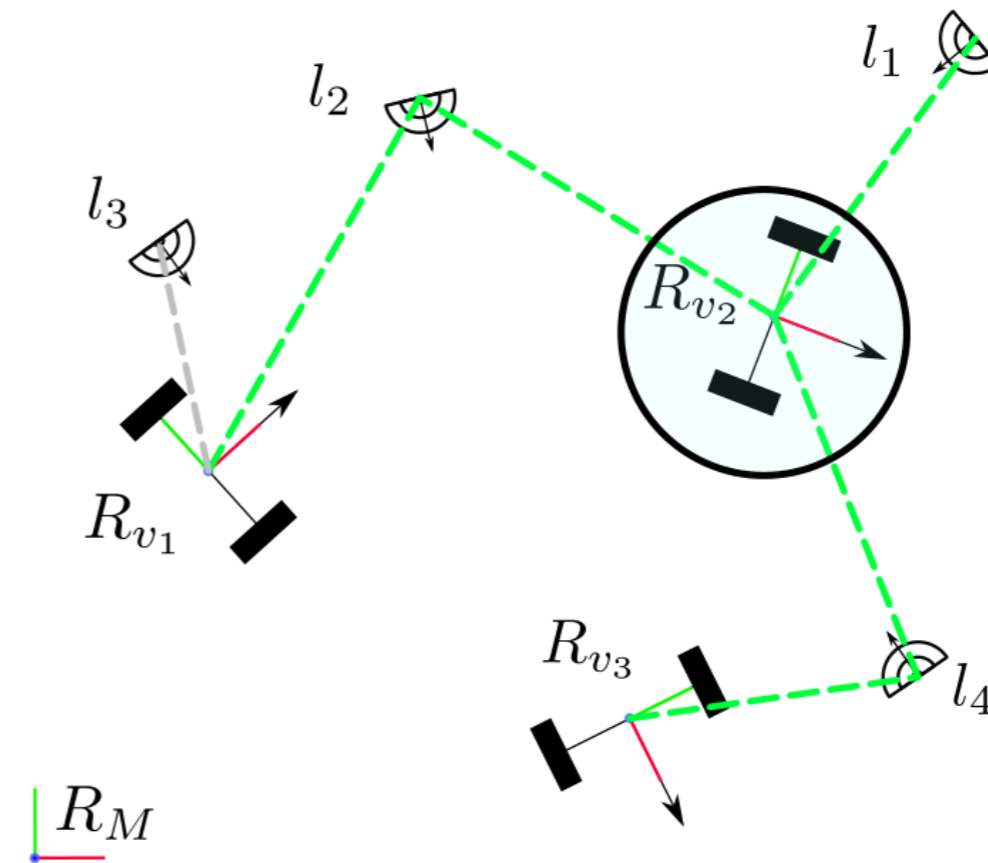
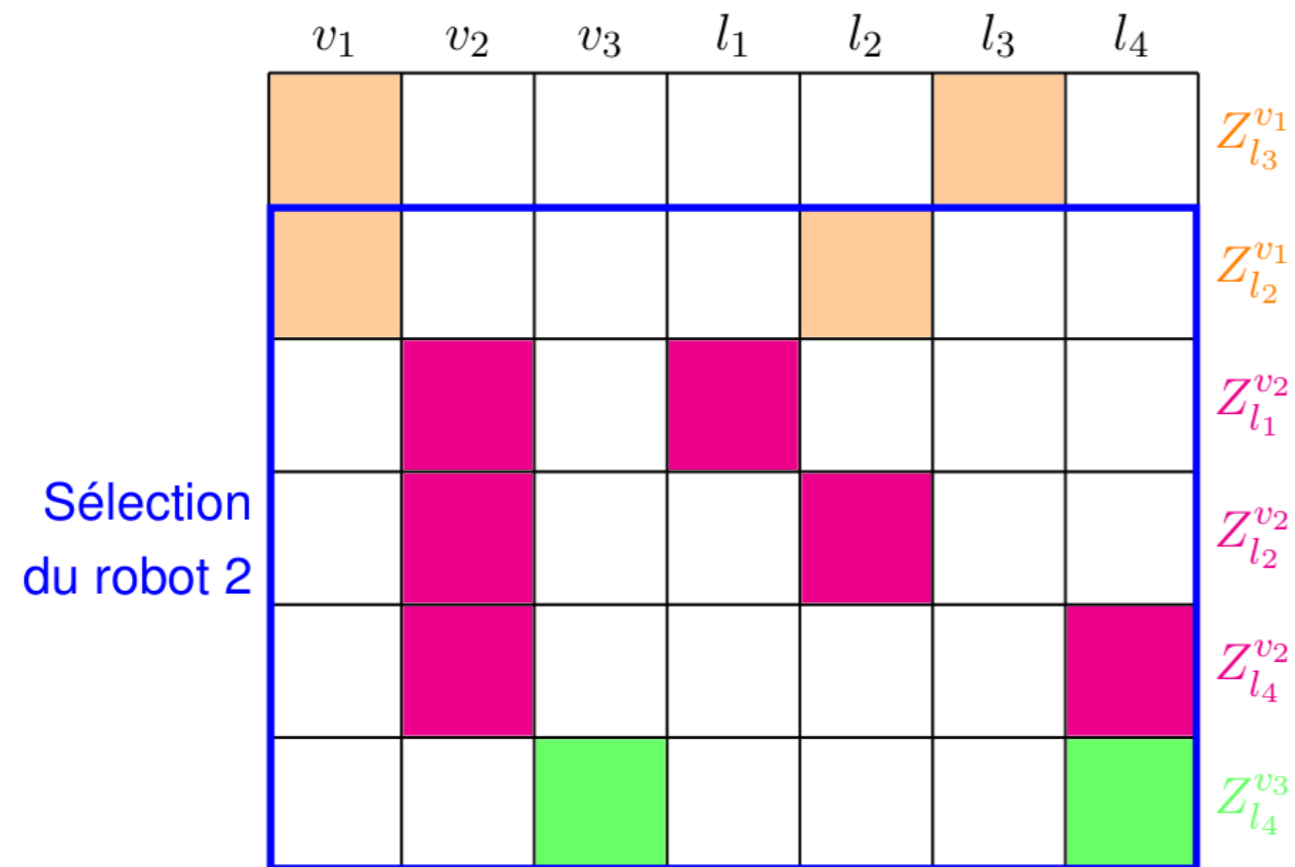
Information in Robot 1 after information sharing

Sélection du robot 1

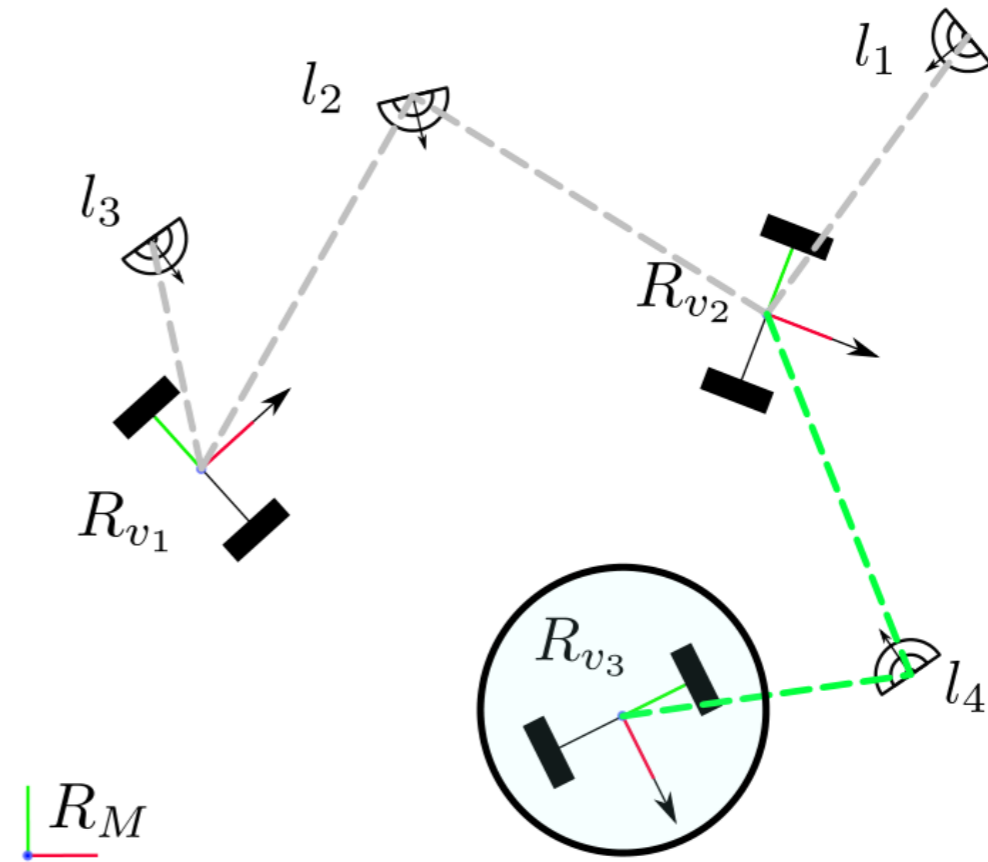
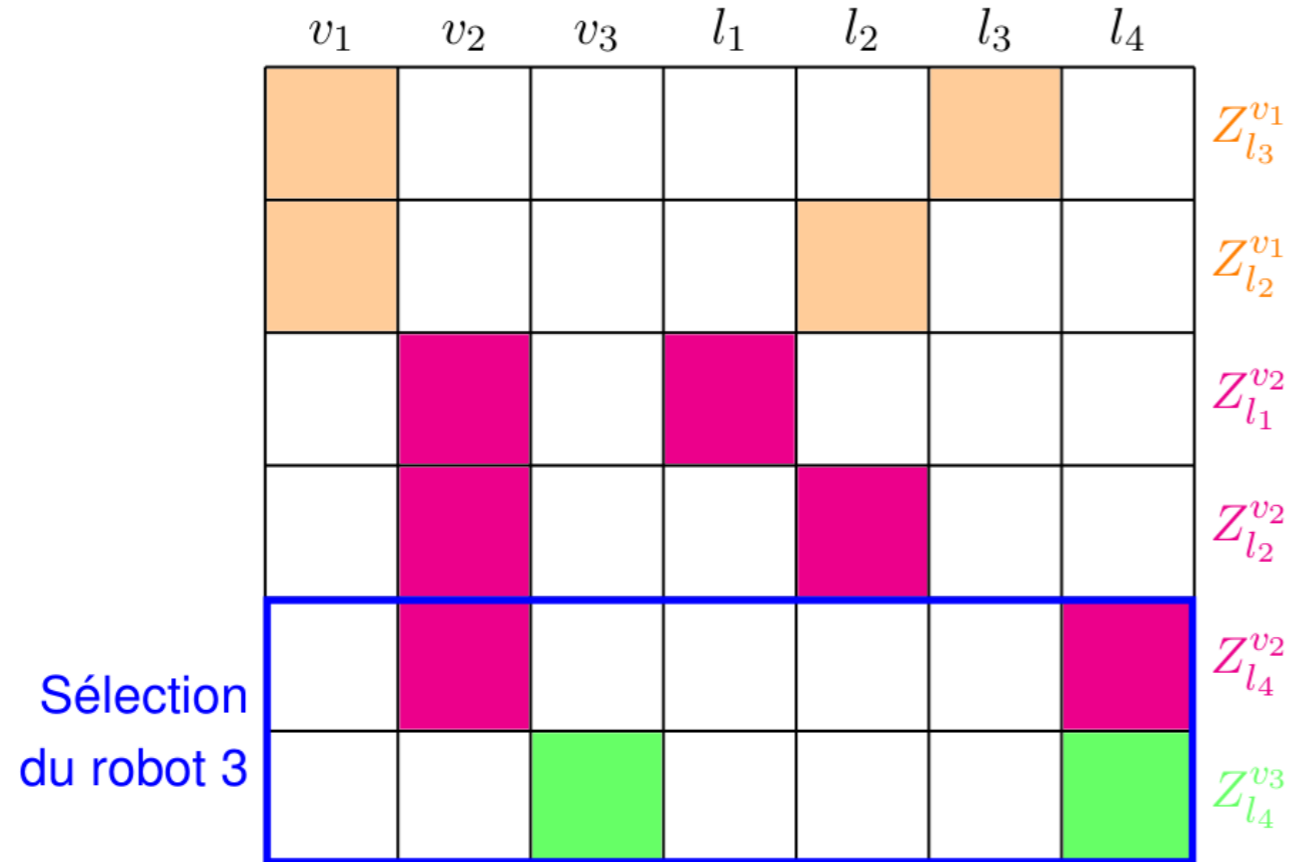
	v_1	v_2	v_3	l_1	l_2	l_3	l_4	
								$Z_{l_3}^{v_1}$
								$Z_{l_2}^{v_1}$
								$Z_{l_1}^{v_2}$
								$Z_{l_2}^{v_2}$
								$Z_{l_4}^{v_2}$
								$Z_{l_4}^{v_3}$



Information in Robot 2 after information sharing

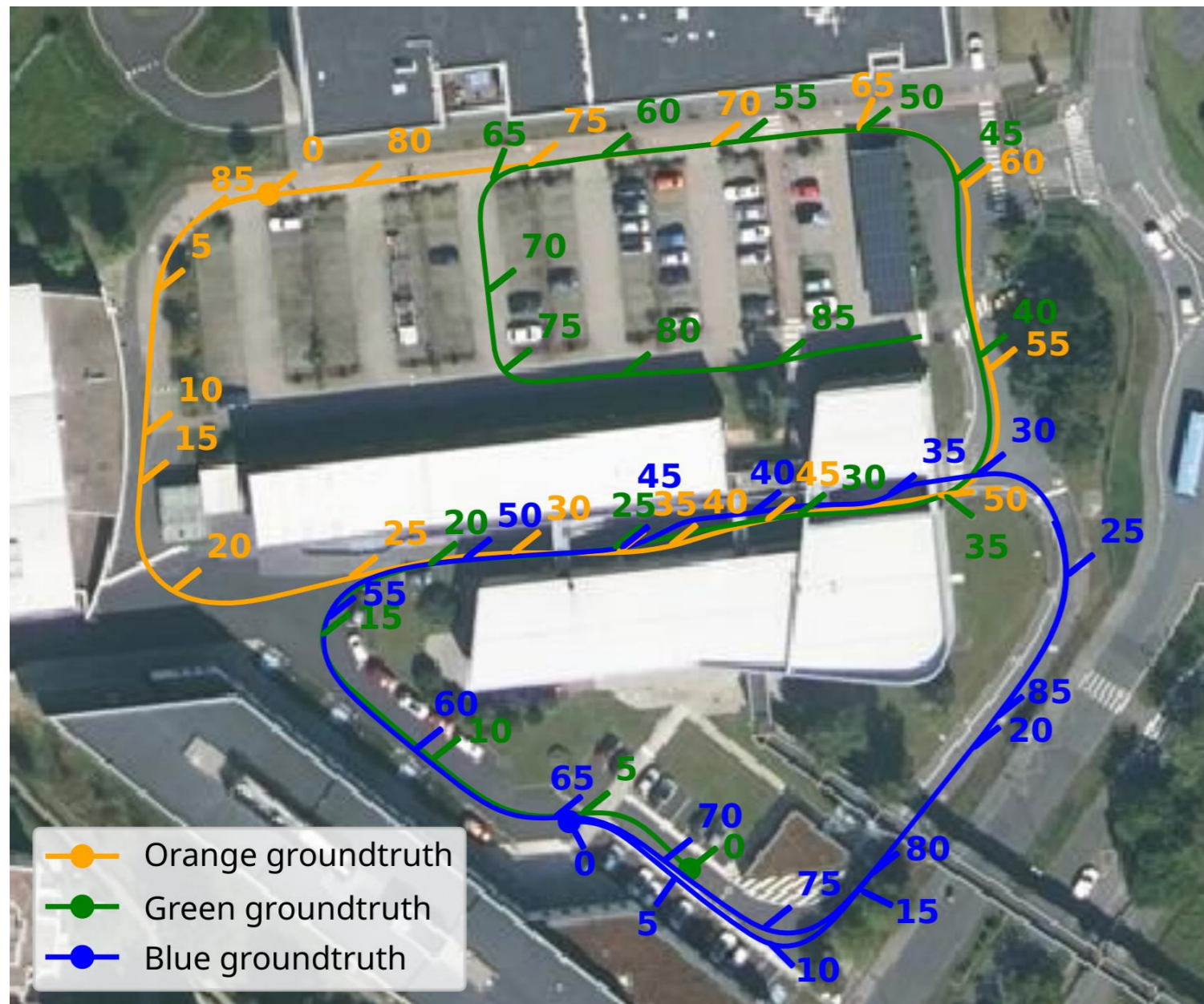


Information in Robot 3 after information sharing



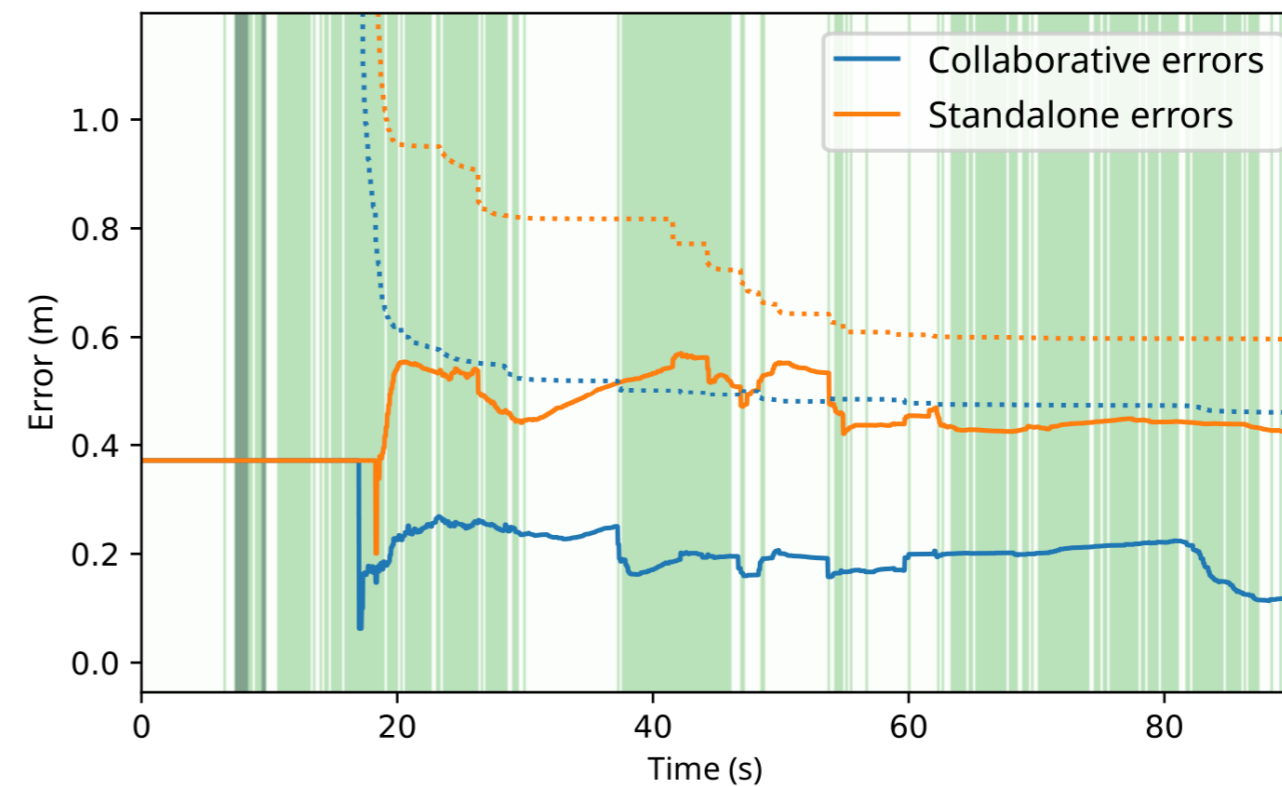
Experimental Results

Schmidt Kalman Filter (SKF) estimating only a part of the state vector, while considering the impact of the non-estimated part



Vehicle	Mean absolute error (cm)	
	Collaborative	Standalone
Blue	39.4	46.5
Green	50.9	62.6
Orange	57.9	64.6
All	49.4	57.9

Localization is more accurate



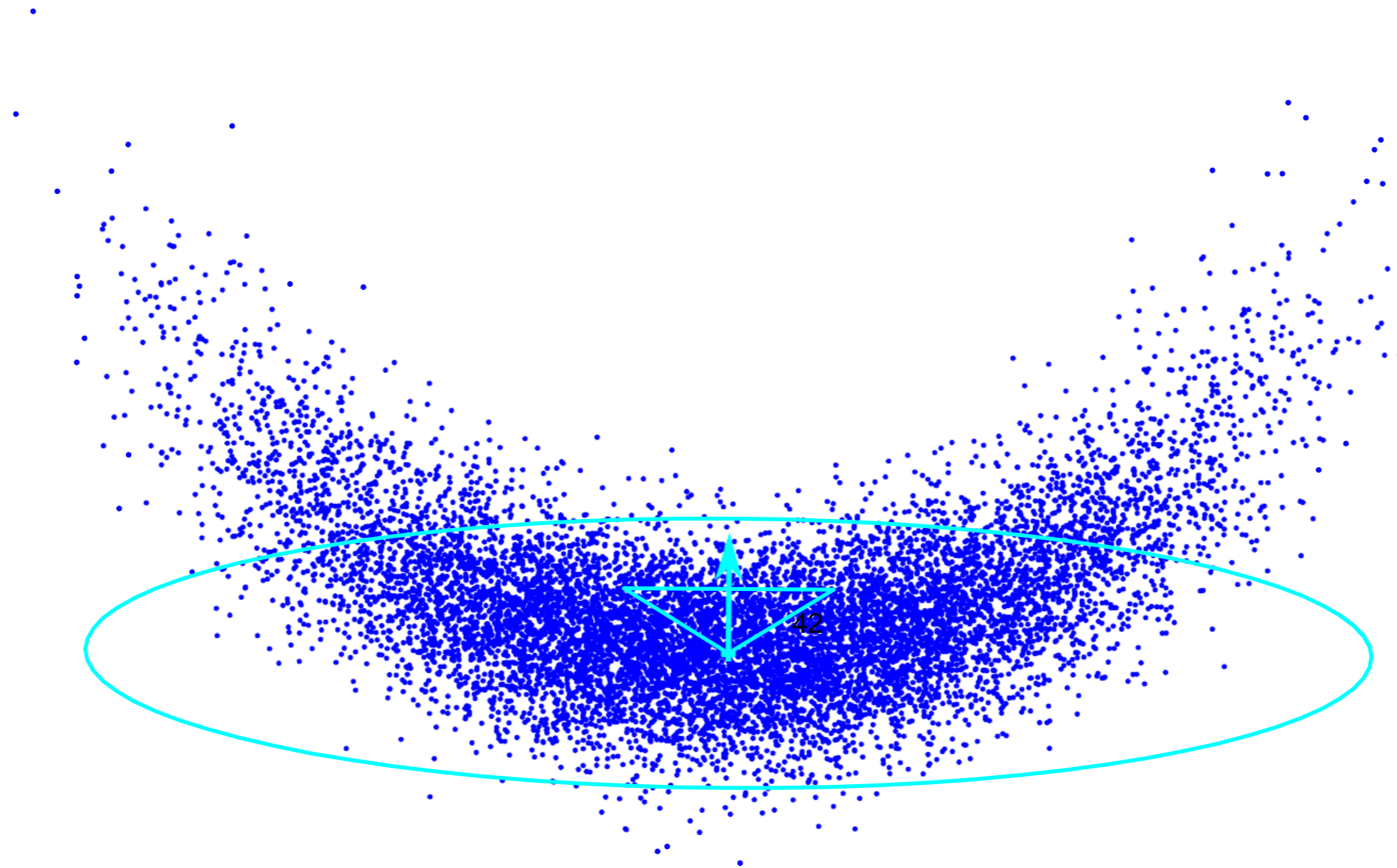
Mapping is more accurate

Spatial uncertainty management in cooperative estimation methods

Part 3

Uncertainty propagation

Observation models are non-linear

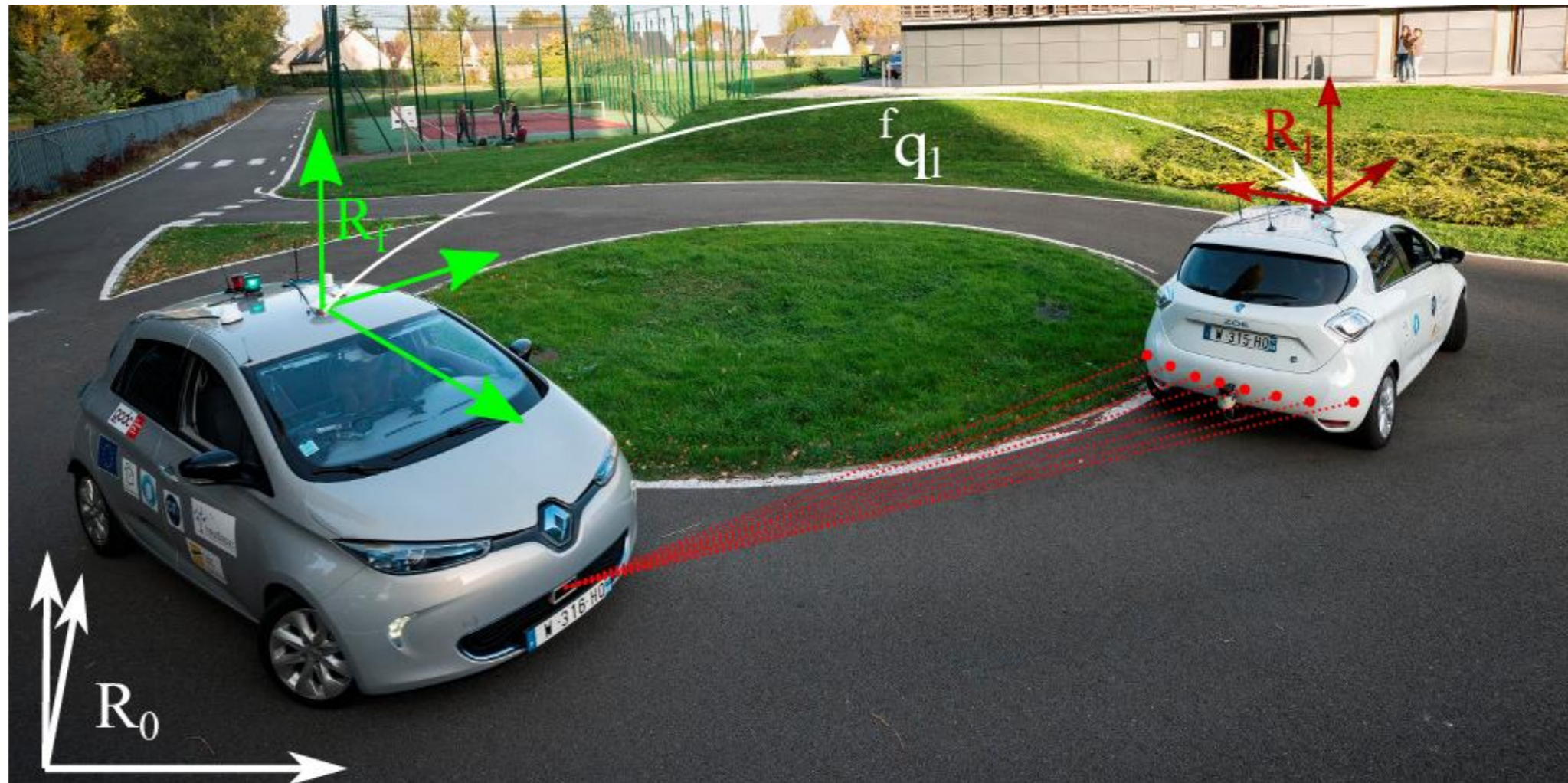


Monte Carlo propagation compared to Gaussian propagation

Case study

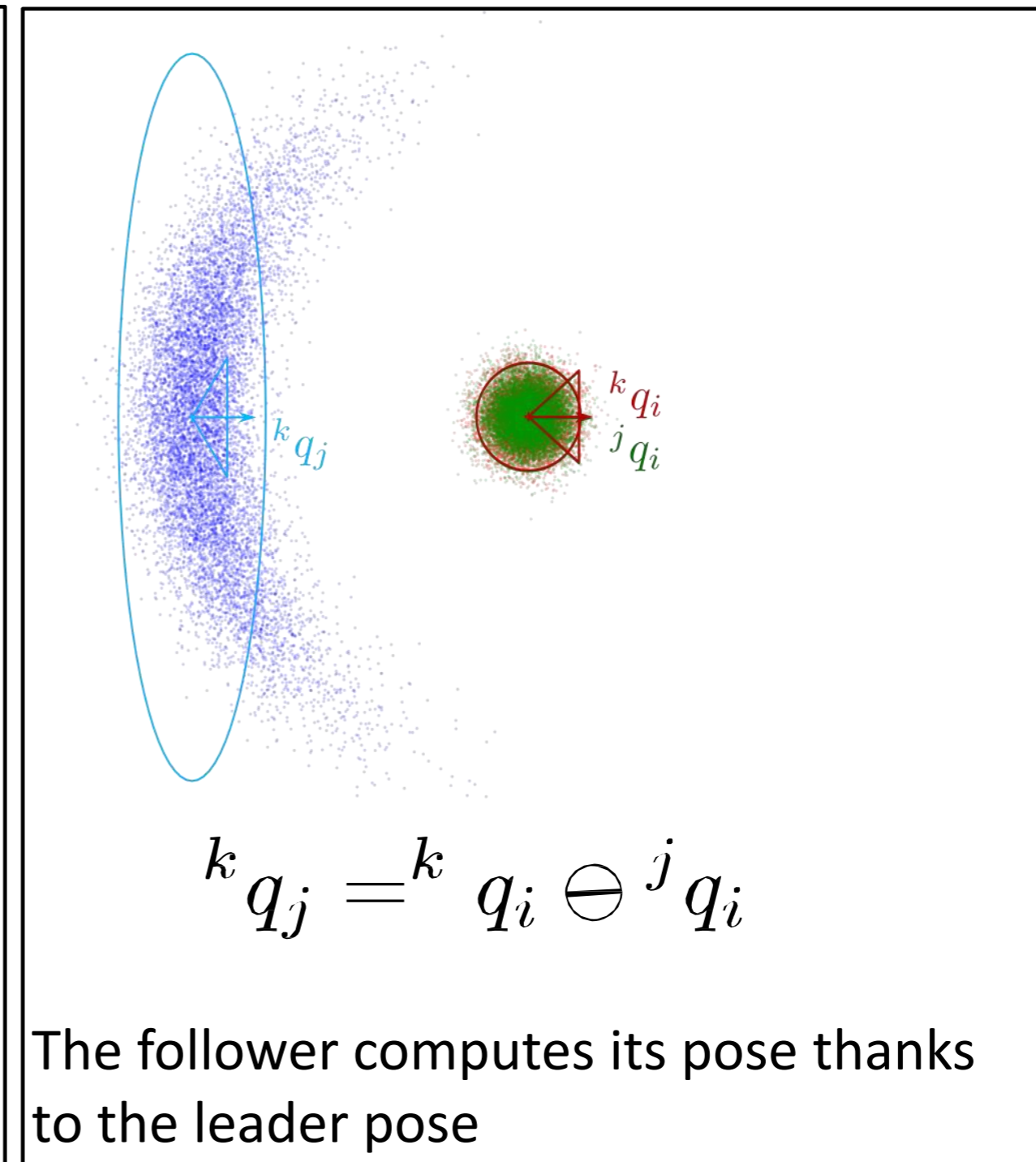
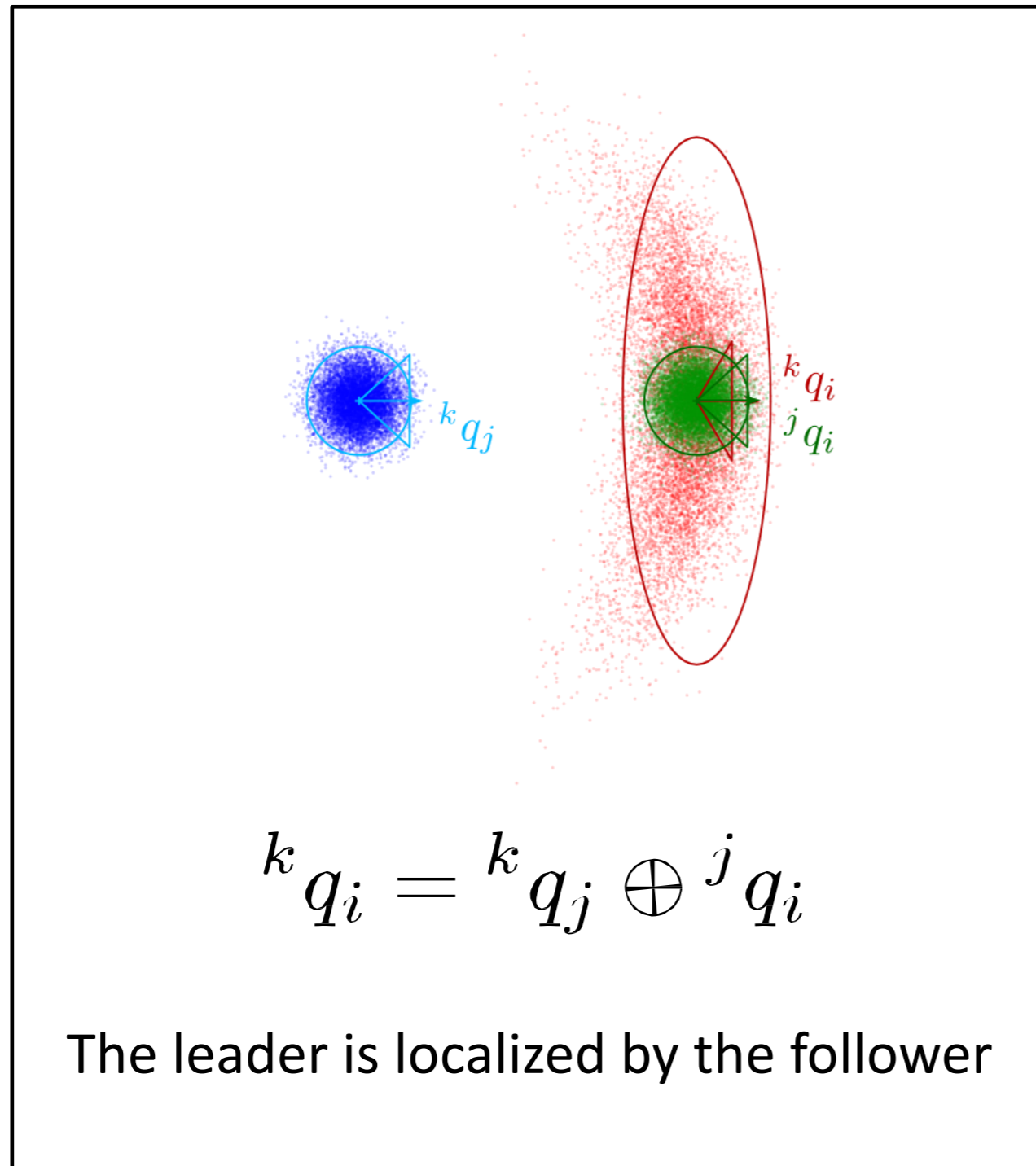
Two vehicles:

- The follower localizes the leader in its body frame (lidar)
- The follower knows its GNSS pose in the working frame R_0
- ➔ The follower can estimate the pose of the leader in R_0 and share this information



Non linearity issues during uncertainty propagation

Errors have been exaggerated to amplify the phenomenon

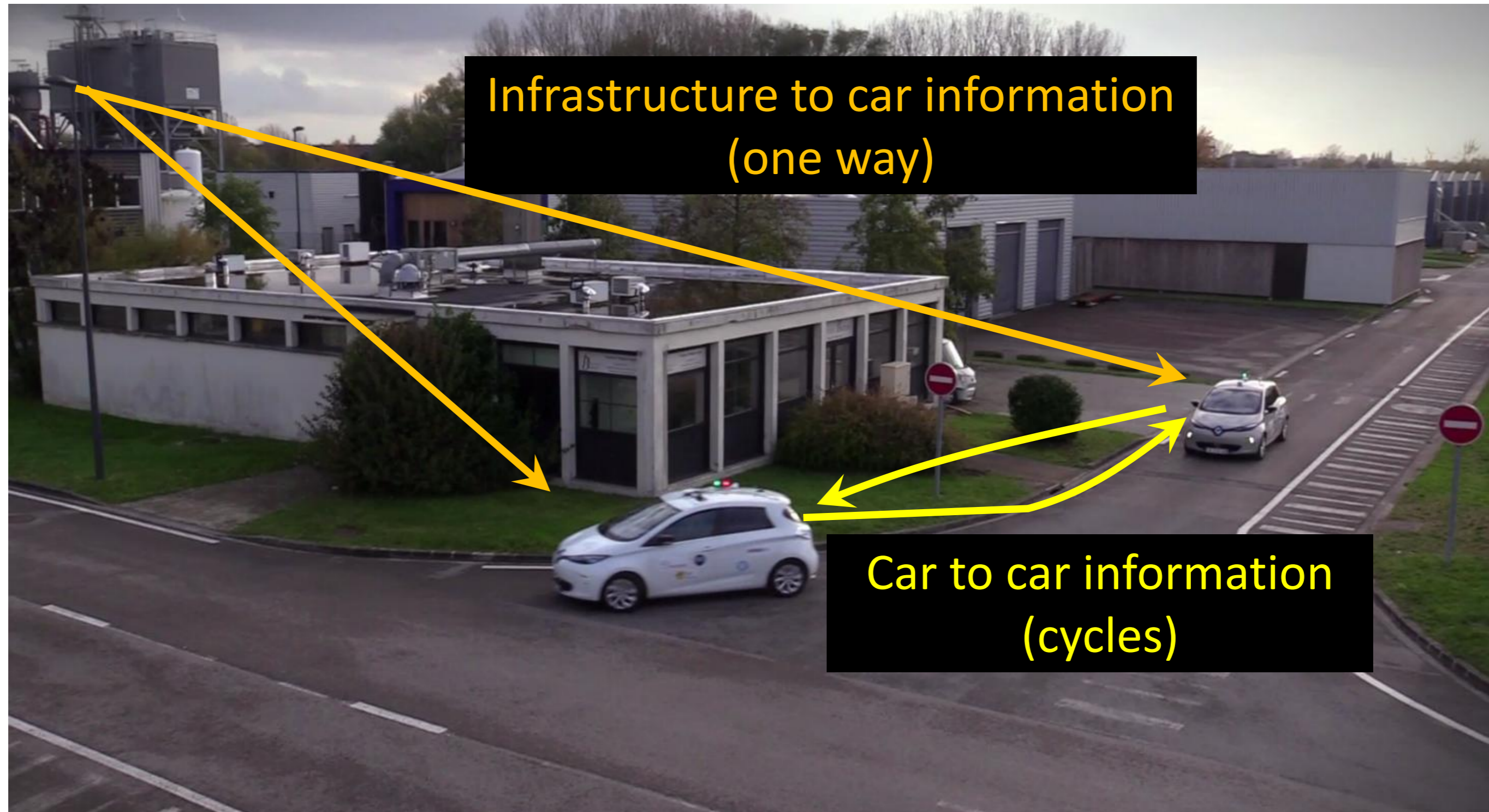


Error propagation is not symmetrical!

Importance of consistency in cooperative estimation

- It is important to have well-estimated covariance matrices in data fusion
 - because they determine how each information source is weighted
- Directly affects the accuracy and consistency of the final estimates
 - Suboptimal weighting reduces the quality of the estimates (biases)
 - In state filtering, an incorrect estimate of the covariance can lead to filter divergence
 - Numerical stability issues
- Fault detection and exclusion methods often make use of covariance
 - Inaccurate estimates of covariances reduce the robustness of filters
- In practice, covariance matrices are often underestimated (over-convergence)

The data incest issue



The same information may be counted multiple times

Data incest management

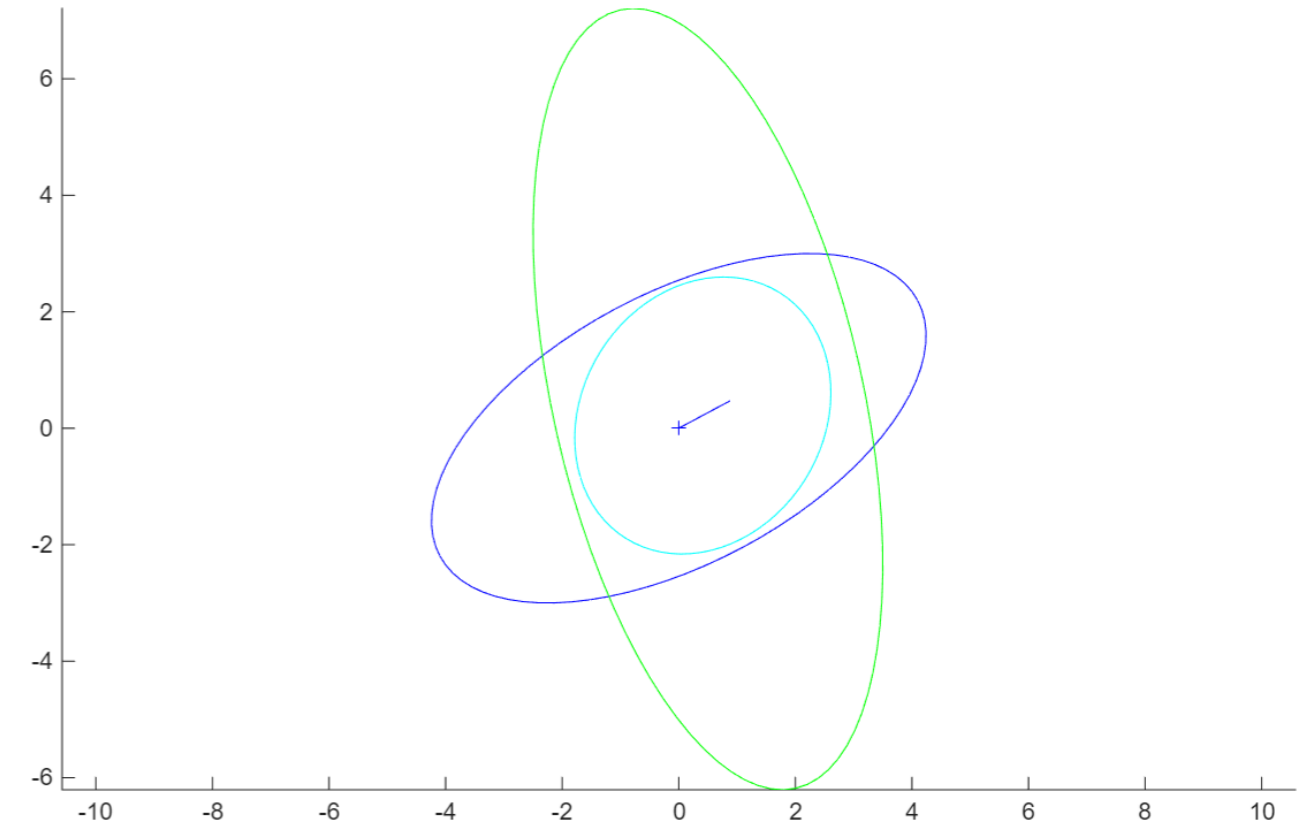
Problem

- Fusion operators often rely on the assumption that errors are uncorrelated

$$P^{-1} = P_1^{-1} + P_2^{-1}$$
$$\hat{x} = P. \left(P_1^{-1} x_1 + P_2^{-1} x_2 \right)$$

Solutions

- Manage metadata in information exchange protocols to ensure data is processed only once
- Turn the problem into a directed acyclic graph (if possible)
- Consensus Filters (Olfati-Saber 2007)
 - Get the agents to converge on a common estimate
- Robust Data fusion methods
 - Merging without knowing the correlation



Fusion of 2 random vectors with uncorrelated errors

Covariance Intersection

$$P^{-1} = \omega P_1^{-1} + (1 - \omega) P_2^{-1} \quad \text{with } 0 < \omega < 1$$
$$\hat{x} = P. \left(\omega P_1^{-1} x_1 + (1 - \omega) P_2^{-1} x_2 \right)$$

The resulting information matrix is obtained by a convex combination

—i.e. a linear combination of points where all coefficients are non-negative and sum to 1

Julier-Uhlmann 1997

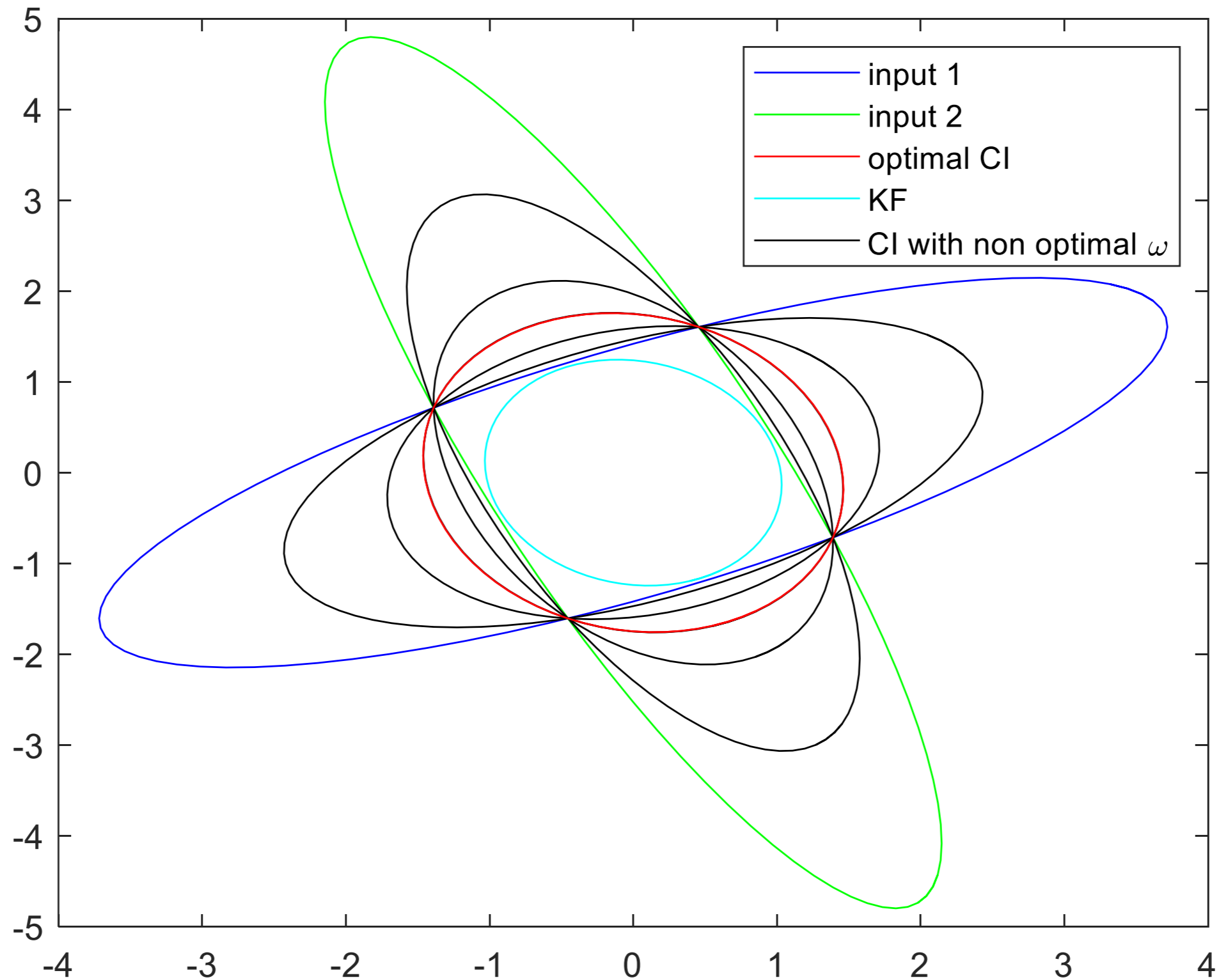
Computation of w

$$\omega_{opt} = \underset{\omega}{\operatorname{argmin}} (\det(P(\omega))) \quad \text{with } 0 < \omega < 1$$

$$\omega_{opt} = \underset{\omega}{\operatorname{argmin}} \left(\det \left(\left[\omega P_1^{-1} + (1 - \omega) P_2^{-1} \right]^{-1} \right) \right) \quad \text{with } 0 < \omega < 1$$

It is therefore necessary to solve an optimization problem during the update

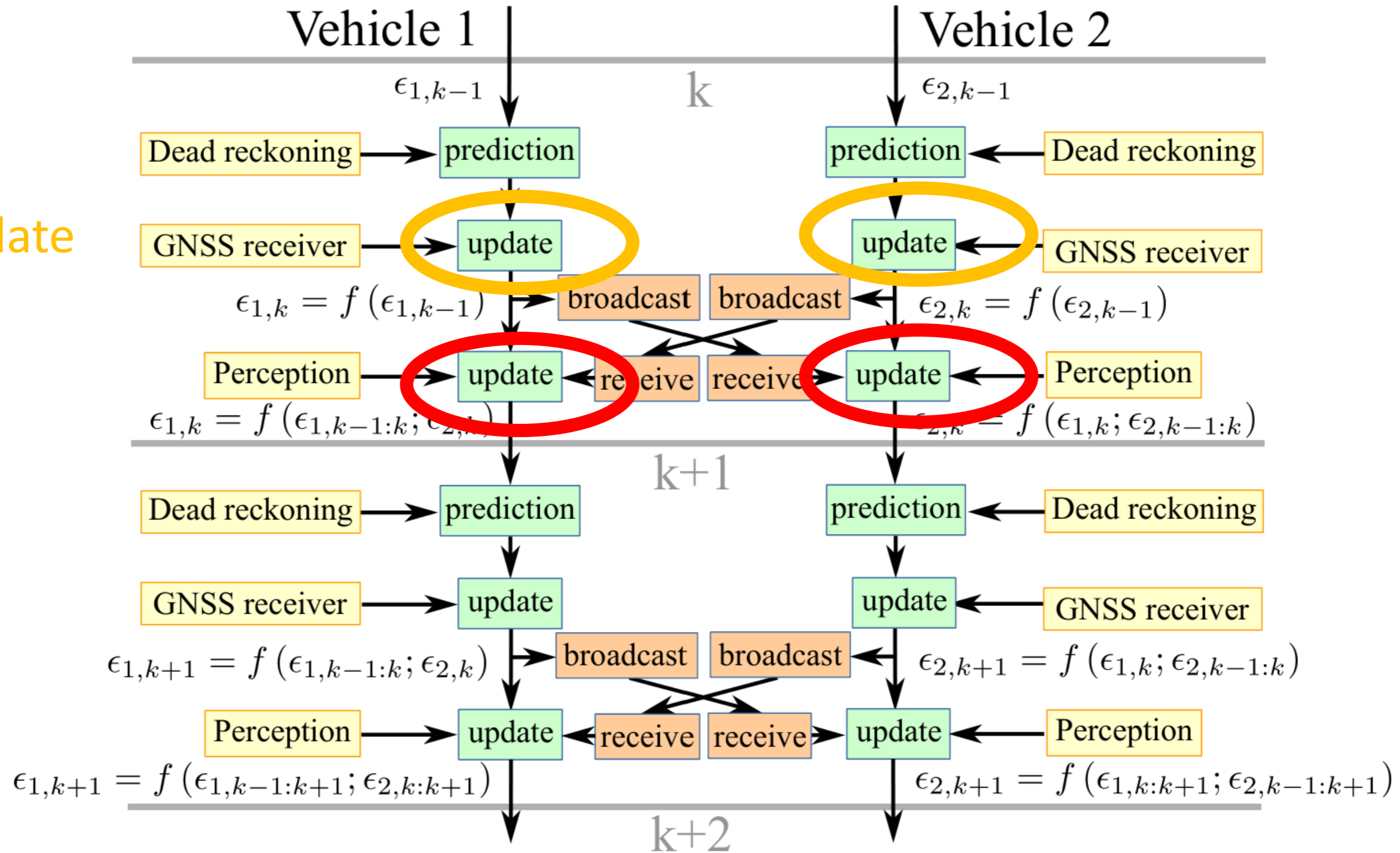
Covariance Intersection Illustration



Cooperative localization with CI

Kalman Update

CI Update

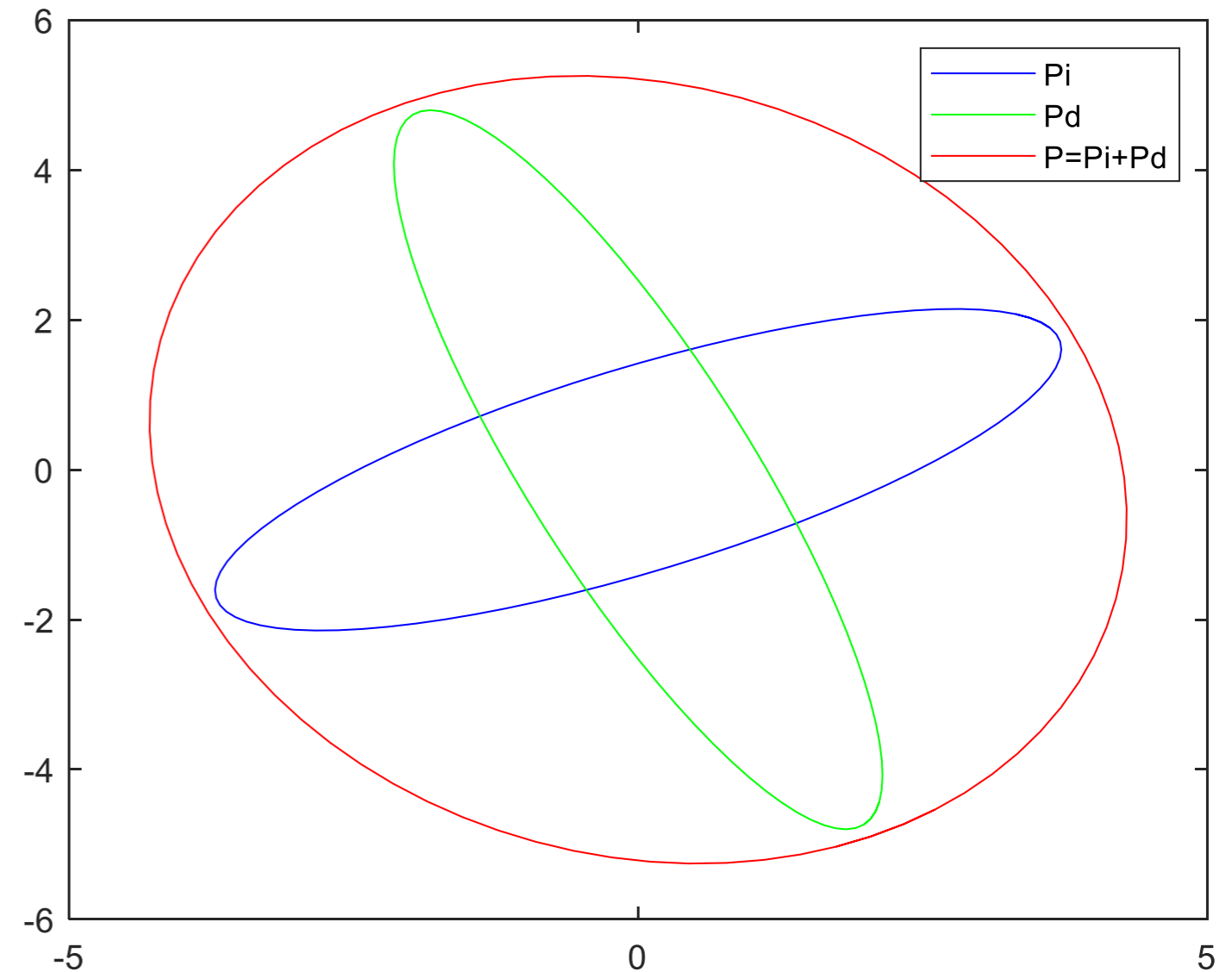


Split Covariance Intersection Filter

State estimation method which combines Kalman filtering with covariance intersection

The covariance matrix P is split into two components:

- One containing the estimation error that is conditionally uncorrelated to the model and observation errors
- One describing the covariance of the estimation error that might contain correlation with the model and observation errors.



Update stage

$$\left\{ \begin{array}{l} P_1 = \frac{1}{\omega} P_{1,d} + P_{1,i} \\ P_2 = \frac{1}{1-\omega} P_{2,d} + P_{2,i} \\ K = P_1 C^T (C P_1 C^T + P_2)^{-1} \\ x = x_1 + K(x_2 - C x_1) \\ P = [I - KC] P_1 \\ P_i = (I - KC) P_{1,i} (I - KC)^T + K P_{2,i} K^T \\ P_d = P - P_i \end{array} \right. \quad \begin{array}{l} \text{with } \omega \neq 1 \text{ and } \omega \neq 0 \\ \% \text{ cov of the prediction} \\ \% \text{ cov of the observation} \\ \% \text{ gain} \\ \% \text{ new estimate} \\ \% \text{ new cov of the estimate} \\ \% \text{ cov of the independ error} \\ \% \text{ cov of the depend error} \end{array}$$

Fusion with Kullback-Leibler Average (KLA)

In C-SLAM, each robot estimates its own map and collaboratively refines it using observations from other vehicles during update steps

—This leads to differences in the map estimates

When they exchange data, the estimates have to be fused

—Full state (including all vehicles and landmarks)

$$X^{v_i} = \begin{bmatrix} X_V^{v_i} \\ X_L^{v_i} \end{bmatrix}$$

Fusion of the full states after data exchange

$$\bar{P}_{k|k-1}^{-1} = \frac{1}{m} \sum_{j=1}^m (P_{k|k-1}^{v_j})^{-1},$$

$$\bar{X}_{k|k-1} = \bar{P}_{k|k-1} \frac{1}{m} \sum_{j=1}^m (P_{k|k-1}^{v_j})^{-1} X_{k|k-1}^{v_j}$$

KLA is equivalent to the use of a covariance intersection filter with a fixed $\omega=1/m$ resulting in a conservative fusion

Conclusion

- Decentralized architecture case studies
 - Cooperative estimation is particularly useful in a fleet of robots
 - It allows each robot to use observations from its neighbors to improve its own localization and perception of the environment
 - It enables the creation of an intelligent and resilient system whose performance exceeds the sum of its individual performances
- Improves accuracy in perception, localization and mapping
Extends coverage

Perspectives and open issues

- Study how Cooperative estimation which provides redundancy is useful for
 - improving fault detection/isolation/correction
 - enabling fault tolerance
- Nonlinearity of observation models with large errors
- Data incest
 - While we now have effective methods for addressing it in certain cases, there are still unresolved problems
- Collective observability and convergence conditions
- Robustness and integrity of estimates
- Decentralization and scalability for large fleets

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Thank you for your attention!

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