Multi-sensor Data Fusion For Lane Boundaries Detection Applied To Autonomous Vehicle

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PhD candidate - 14th January 2022

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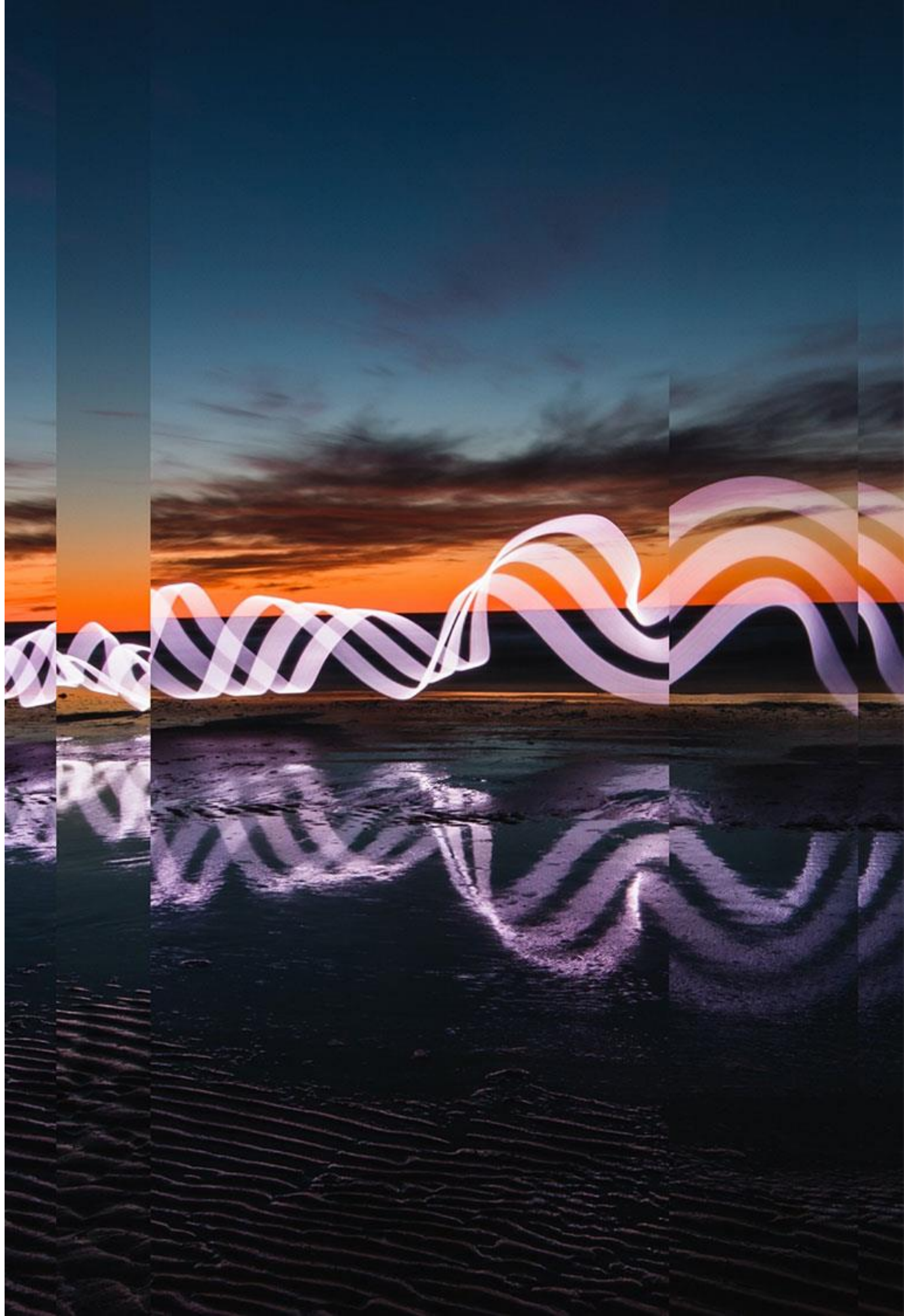
Franck Davoine, Heydiasyc
Bruno Durand, Renault Group

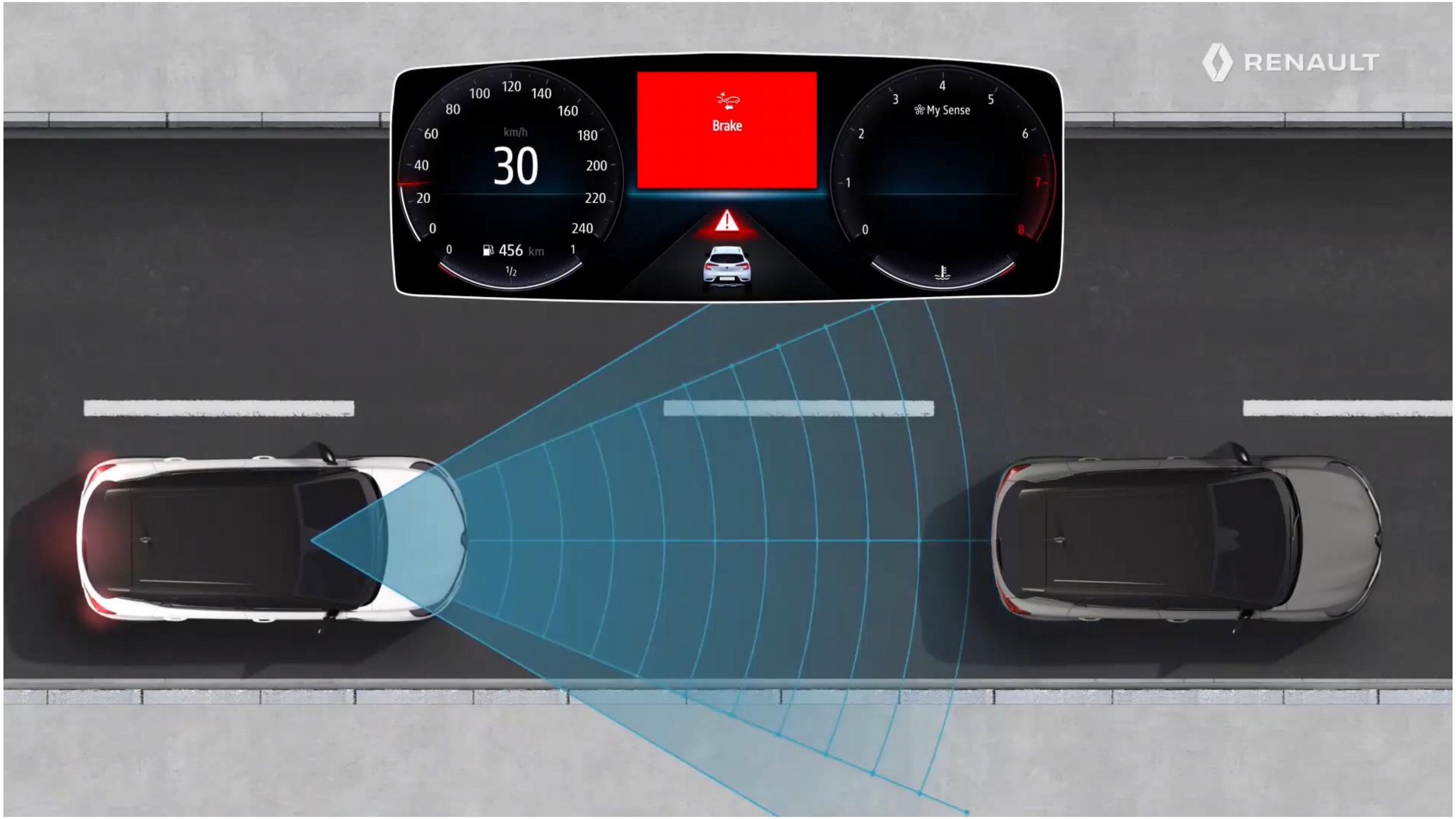
Summary

01

Thesis introduction



AD & ADAS



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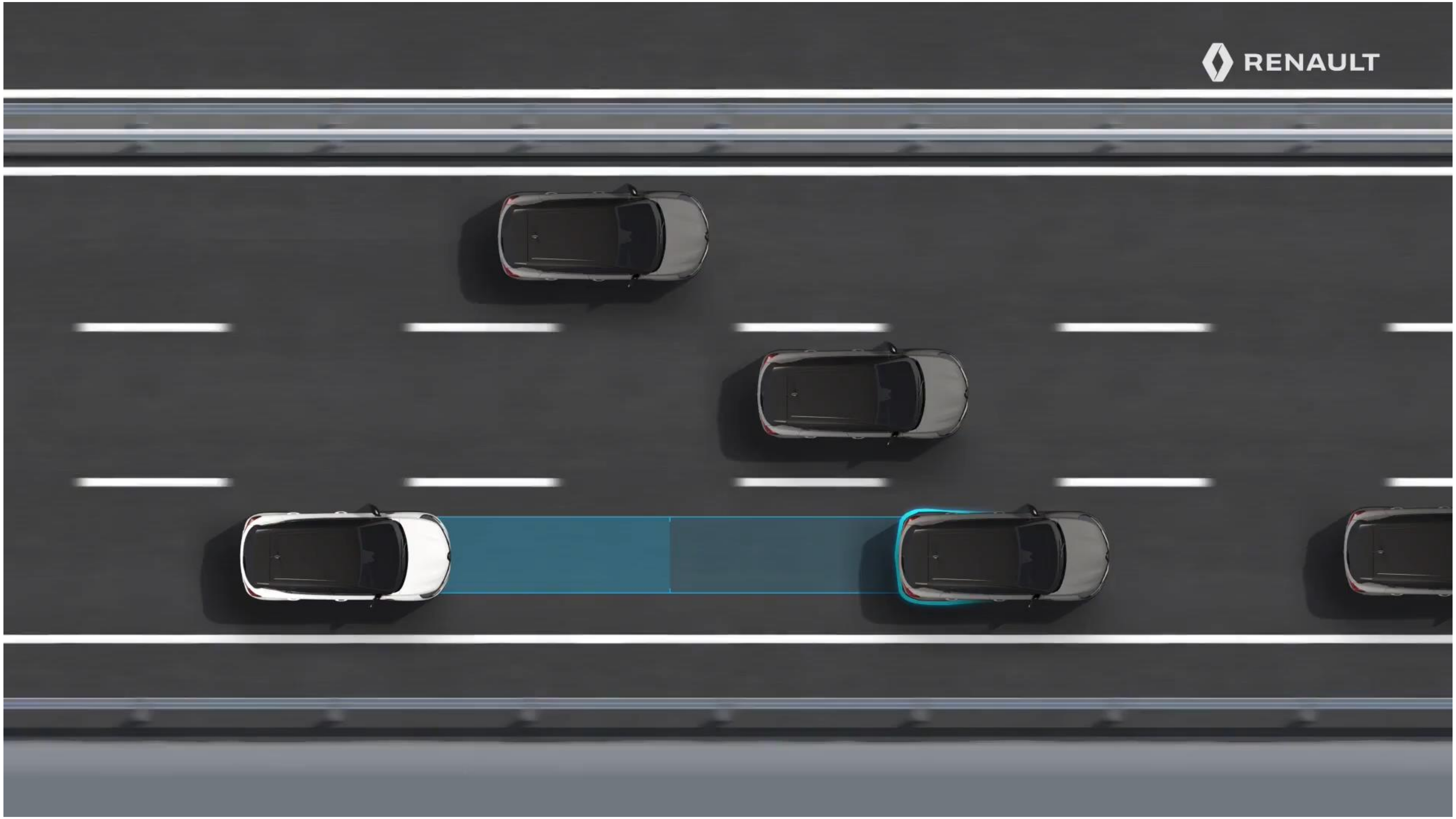


AD & ADAS

AD & ADAS

Informative ADAS

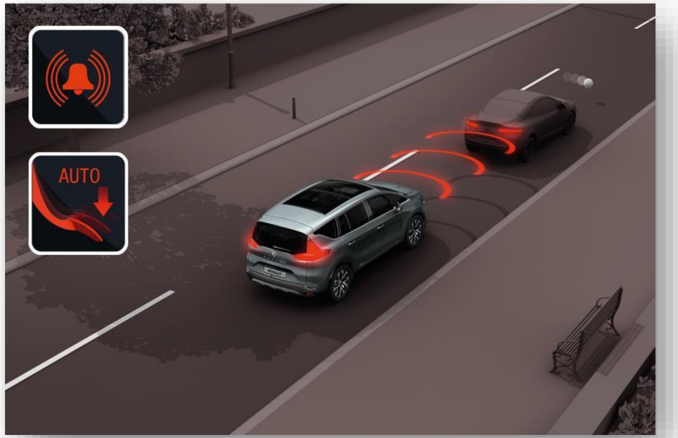
- Lane Departure Warning (LDW)
- Blind Spot Warning (BSW)
- Parking Sensor
- Driver Monitoring System (DMS)

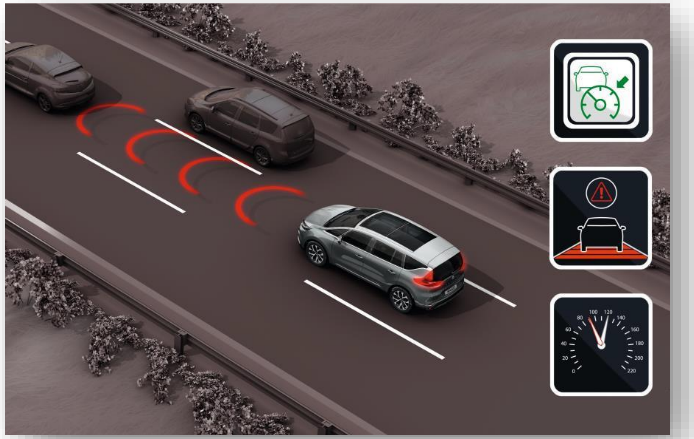
Actuating ADAS

- Adaptive Cruise Control (ACC)
- Lane Keeping Assistance (LKA)
- Lane Centering Assistance (LCA)
- Automatic Emergency Braking (AEB)
- Traffic Jam Pilot (TJP)
- Automatic Parking

Automated driving

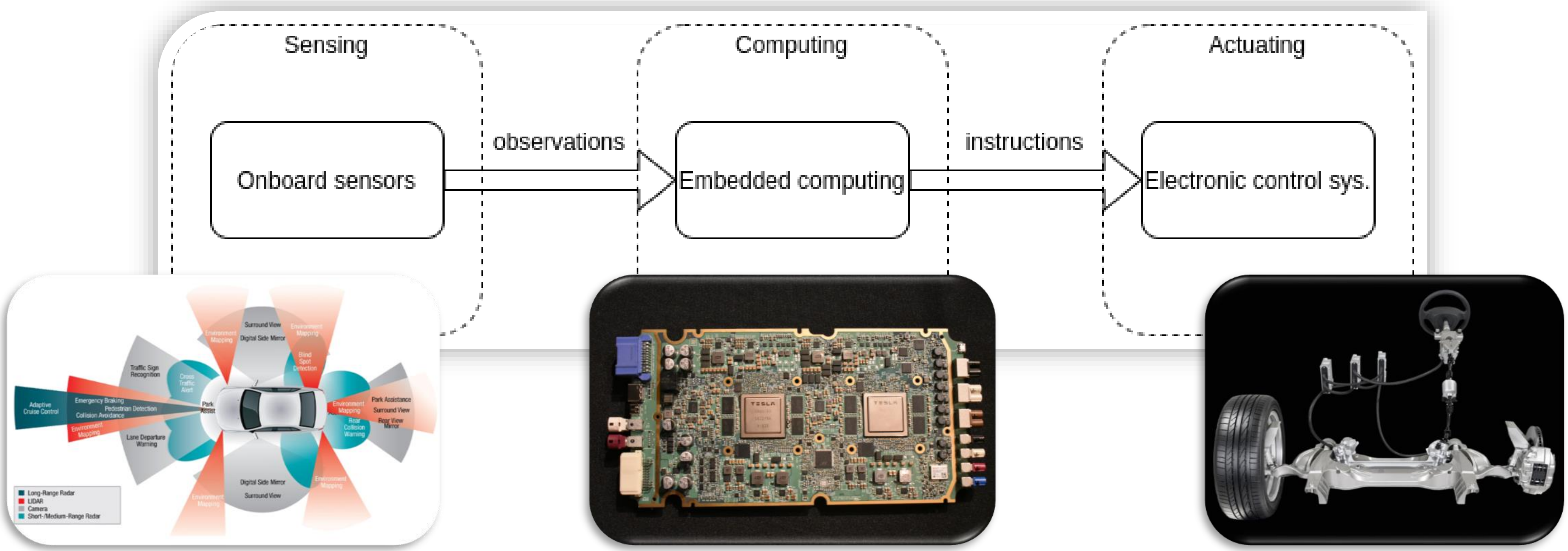
- Level 0 – No Automation
- Level 1 – Driver Assistance
- Level 2 – Partially Automated Driving
- Level 3 – Conditionally Automated Driving
- Level 4 – Highly Automated Driving
- Level 5 – Fully Automated Driving





INTELLIGENT VEHICLES TECHNOLOGY

1. **Sensing** – On board sensors
2. **Computing** – Embedded computing
3. **Actuating** – Electronic control systems



THESIS SCOPE : MULTI-SENSOR FUSION

- Perception diversity compensates sensor weaknesses

SENSOR TECHNOLOGIES : PROS & CONS

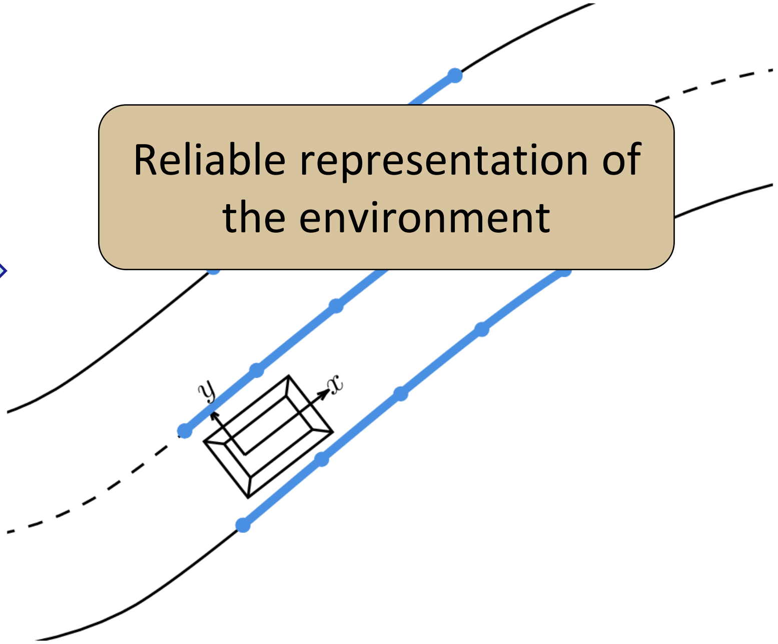
	Dazzling light	Harsh weather	Guardrails	Lines	Black objects	Low contrast	Occlusion
RADAR	+	+	+	−	+	+	+
LIDAR	+	−	+	+	−	+	−
CAMERA	−	−	+	+	+	−	−

THESIS SCOPE : INDUSTRIAL CONTEXT (1)

- Car manufacturers integrate sensing solutions from Tier-1 suppliers : **smart sensors**

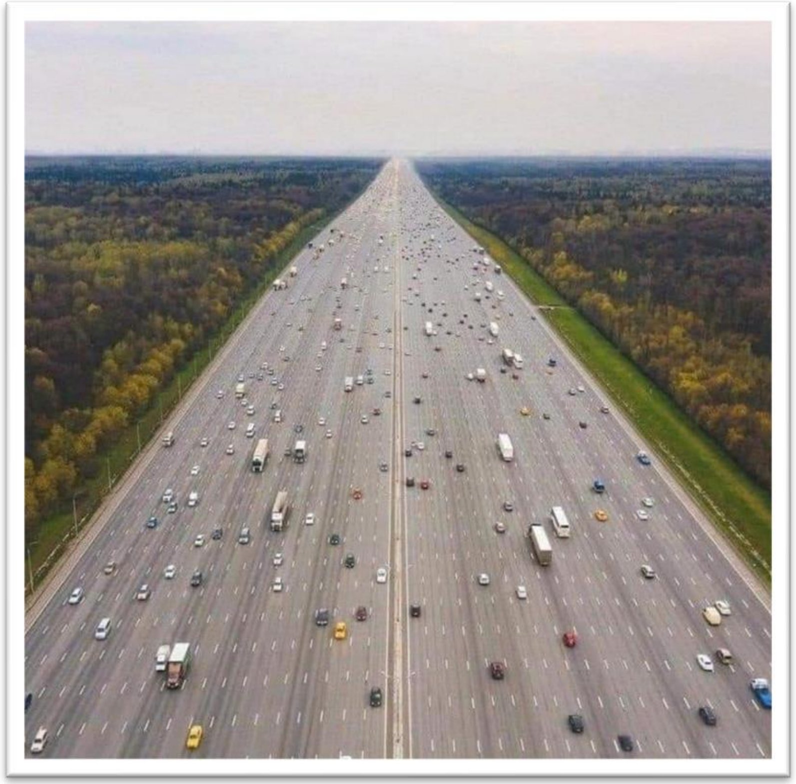
THESIS SCOPE : INDUSTRIAL CONTEXT (2)

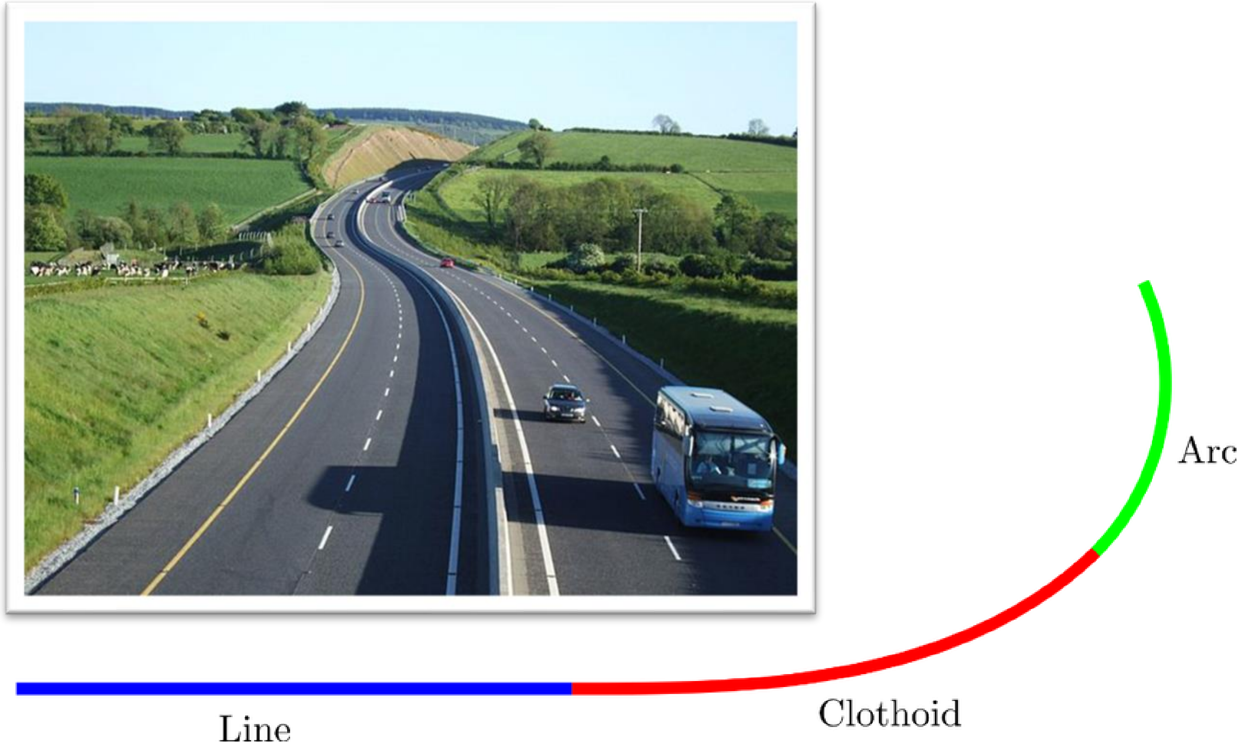
- This work is developed within:
  - Sivalab (Hediasyc X Renault joint laboratory)
  - Renault's Fusion Team (DEA-LEA1: Algorithmes Fusion et Véhicule Autonome)
- ADAS software development platform available
- Ad-hoc equipped Renault Espace for Conditionally Automated Driving L3 (Level 3)



THESIS SCOPE : REPRESENTATION OF ROAD ENVIRONMENT

- Oriented lane corridors enable safe and predictable navigation for road users





- Because of geographical constraints, roads are designed connecting straight and circular segments with ***clothoid segments***

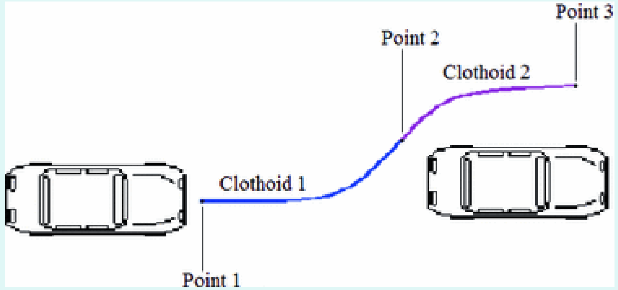
THESIS SCOPE : CLOTHOIDS

- A *Clothoid* is a curve whose curvature changes linearly with its curve length
- Its Cartesian coordinates are given by the Fresnel integrals :

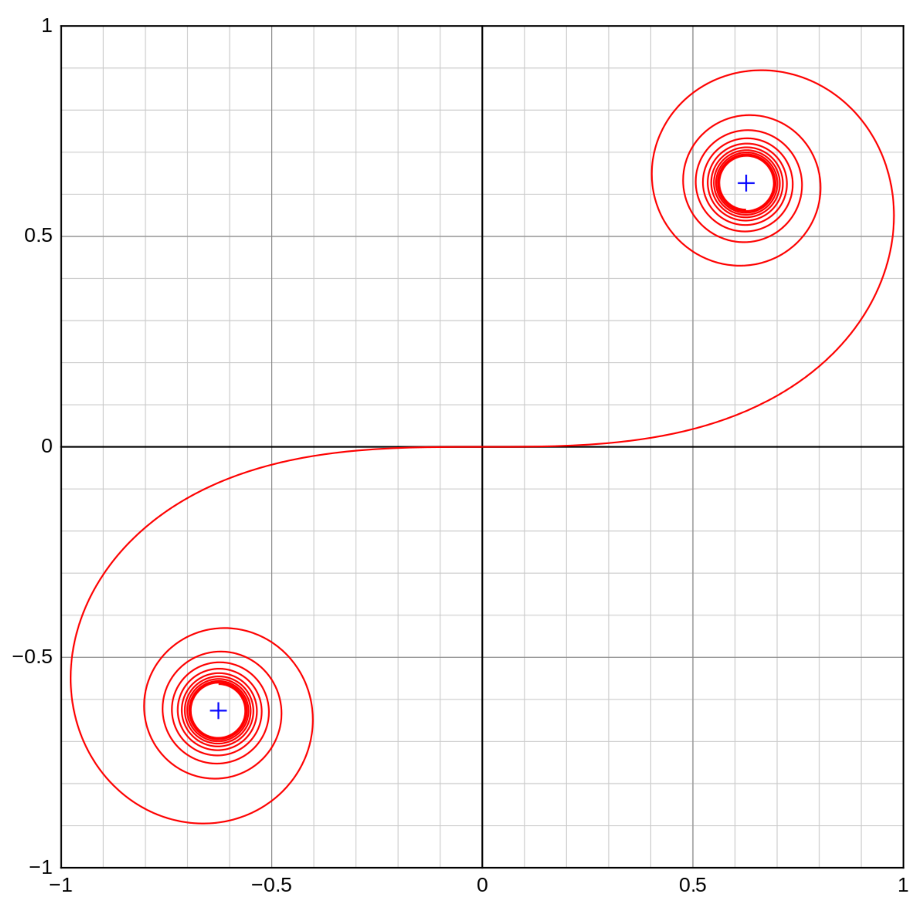
$$x(s) = x_0 + \int_0^s cos\left(\frac{1}{2}\kappa_1\tau^2 + \kappa_0\tau + \psi_0\right) d\tau,\ s \in [0, l]$$

$$y(s) = y_0 + \int_0^s sin\left(\frac{1}{2}\kappa_1\tau^2 + \kappa_0\tau + \psi_0\right) d\tau,\ s \in [0, l]$$

- Application of clothoids to road designed allow comfortable transitions road segments:



THESIS SCOPE : CLOTHOIDS

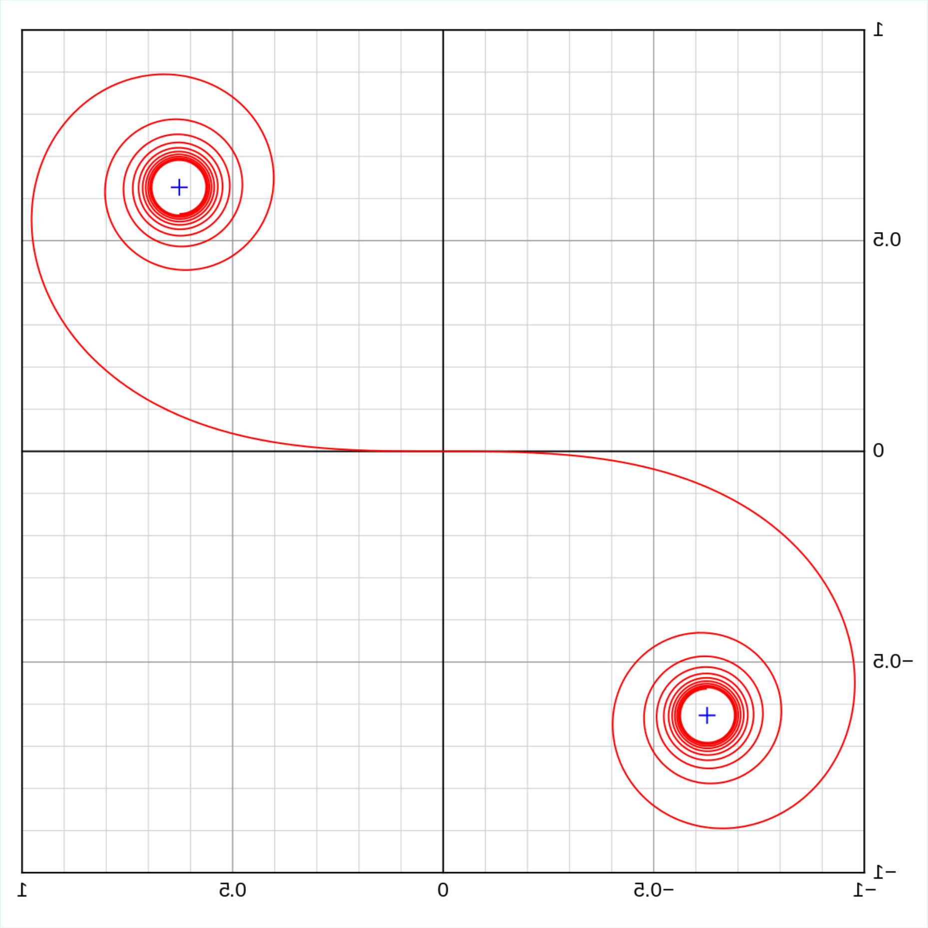


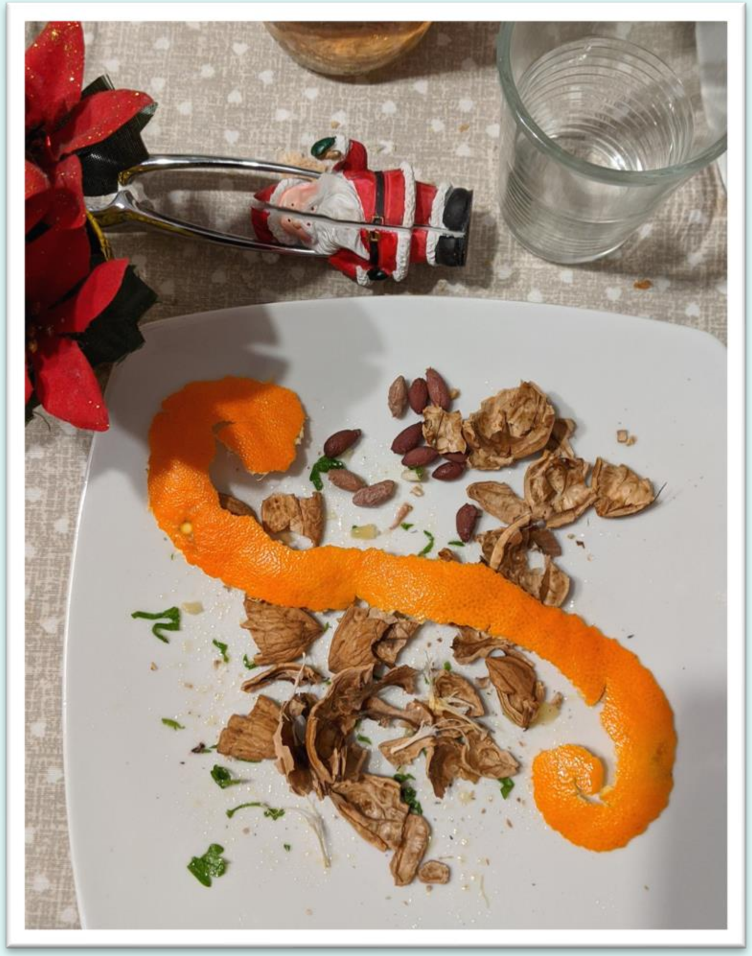
$$x(s) = x_0 + \int_0^s cos\left(\frac{1}{2}\kappa_1\tau^2 + \kappa_0\tau + \psi_0\right) d\tau,\ s \in [0, l]$$

$$y(s) = y_0 + \int_0^s sin\left(\frac{1}{2}\kappa_1\tau^2 + \kappa_0\tau + \psi_0\right) d\tau,\ s \in [0, l]$$

x_0	starting point abscissa
y_0	starting point ordinate
ψ_0	starting orientation angle
κ_0	starting curvature
κ_1	curvature rate

THESIS SCOPE : CLOTHOIDS

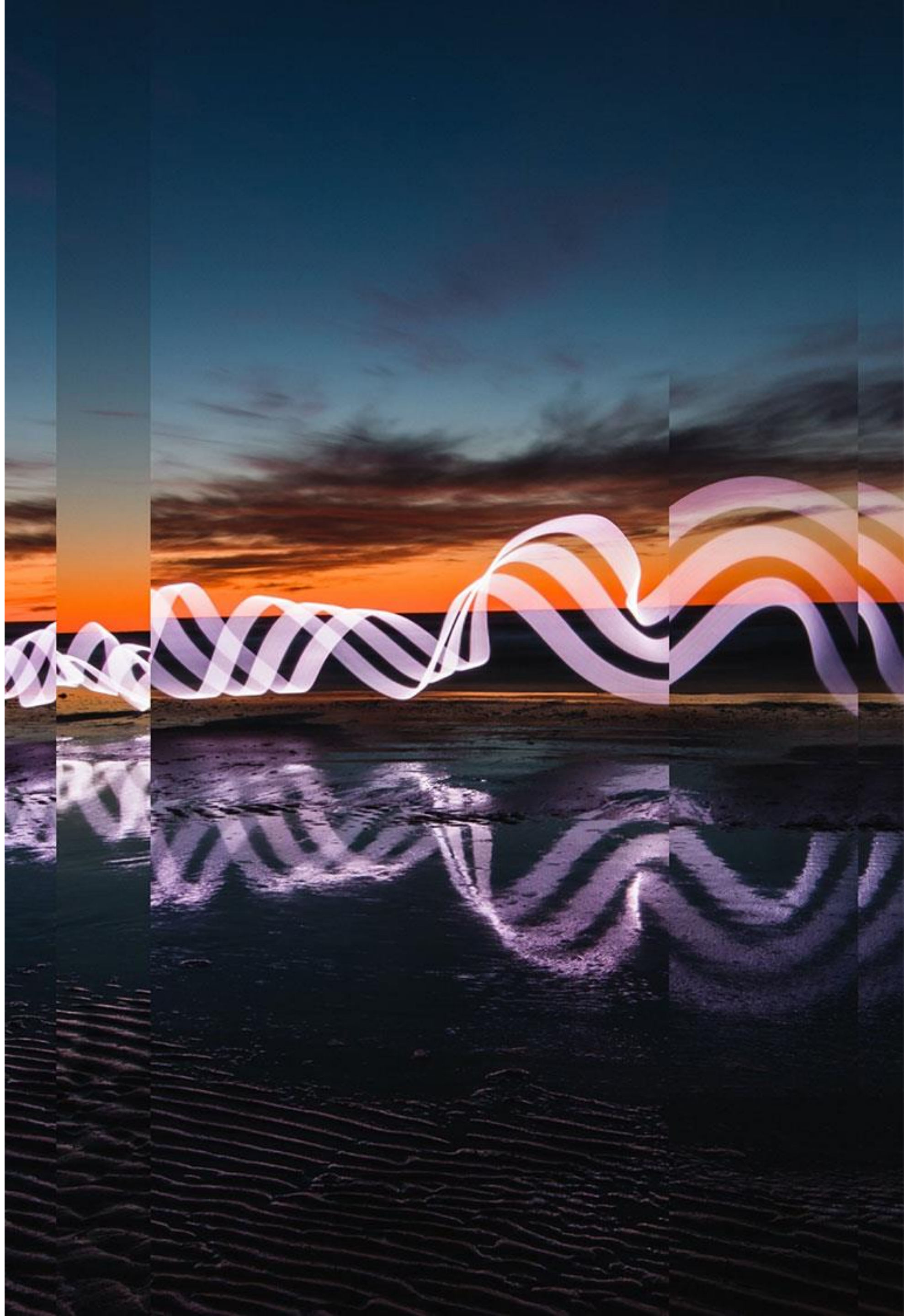




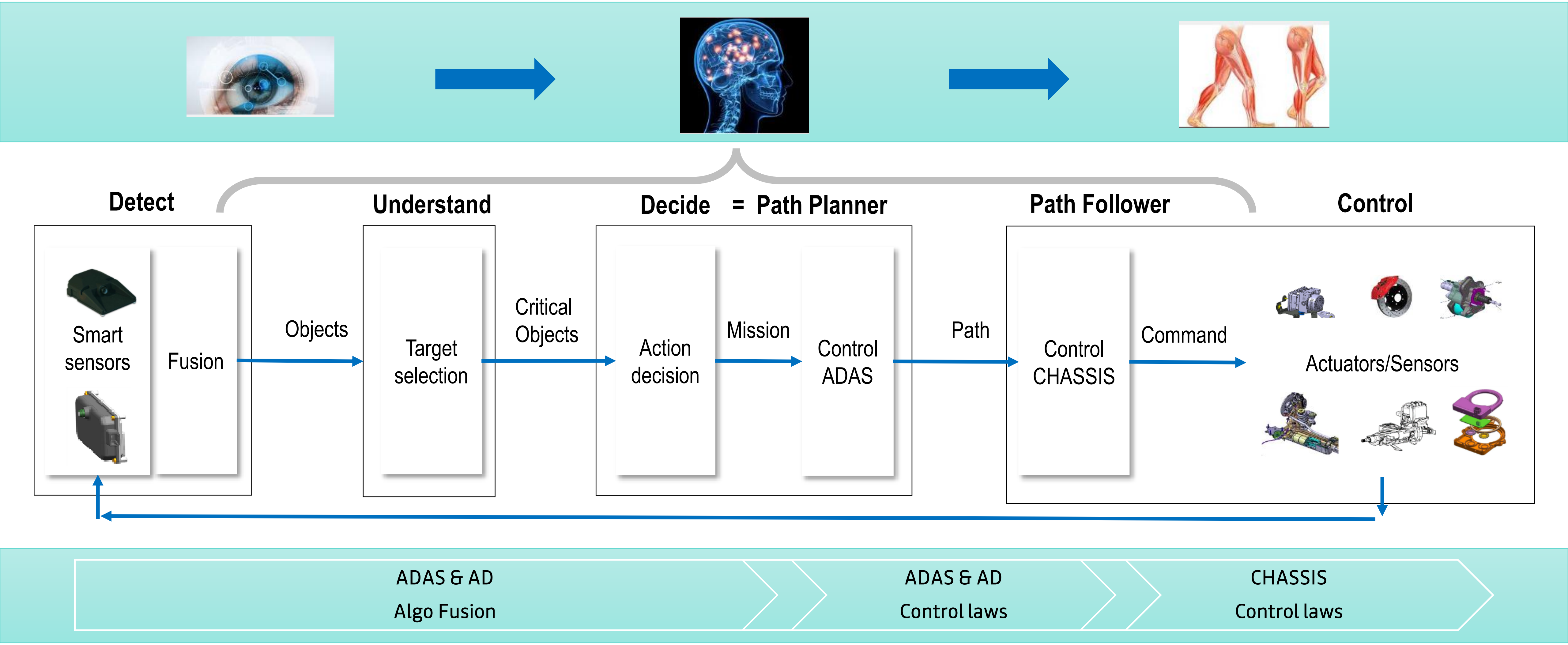
Bartholdi, Laurent & Henriques, André. (2012). Orange Peels and Fresnel Integrals. The Mathematical Intelligencer. 34. 10.1007/s00283-012-9304-1.

02

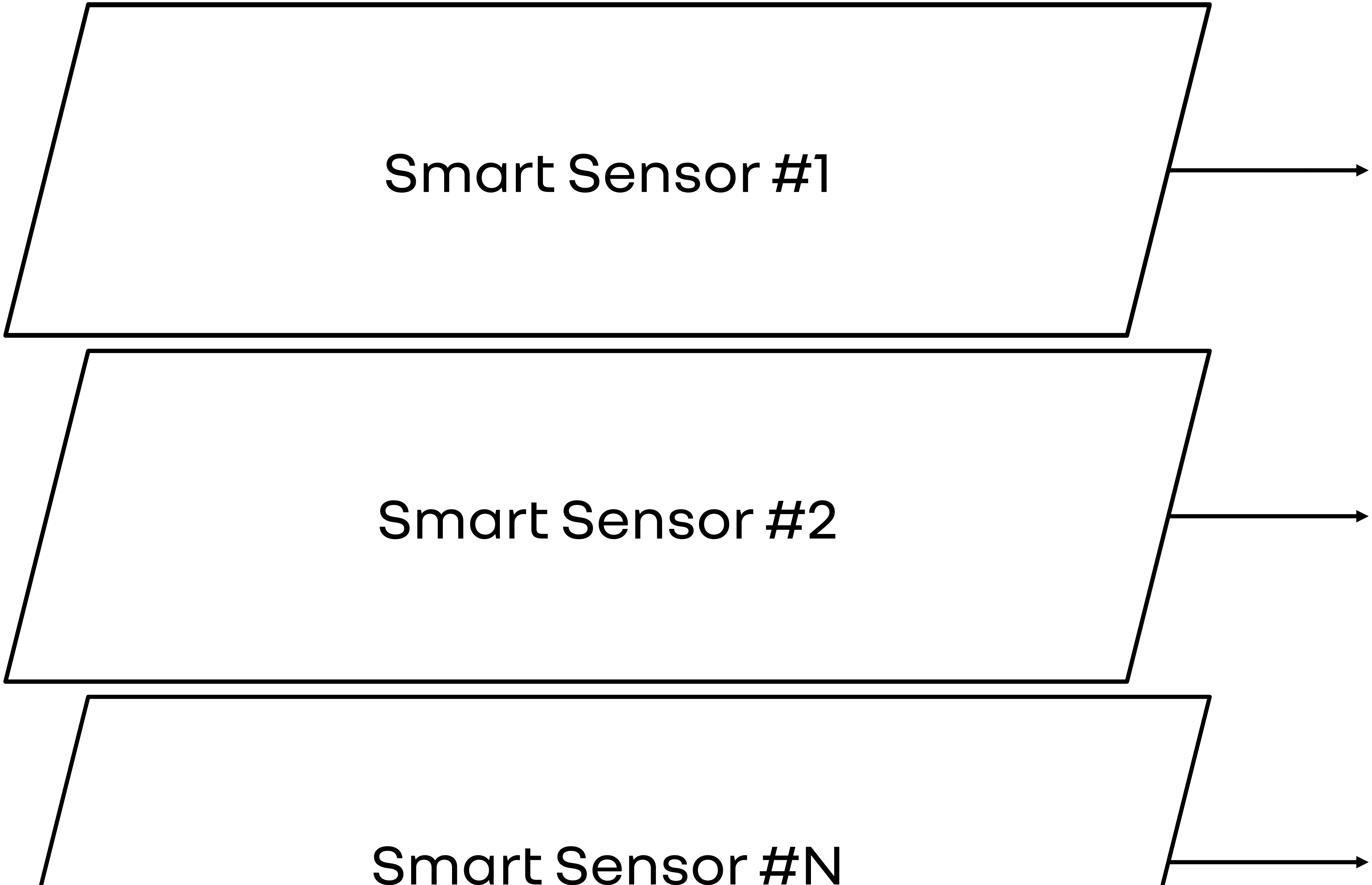
Problem formulation



AUTOMATED DRIVING PIPELINE : ADOPTED PIPELINE



SMART SENSORS : STATE OF THE ART



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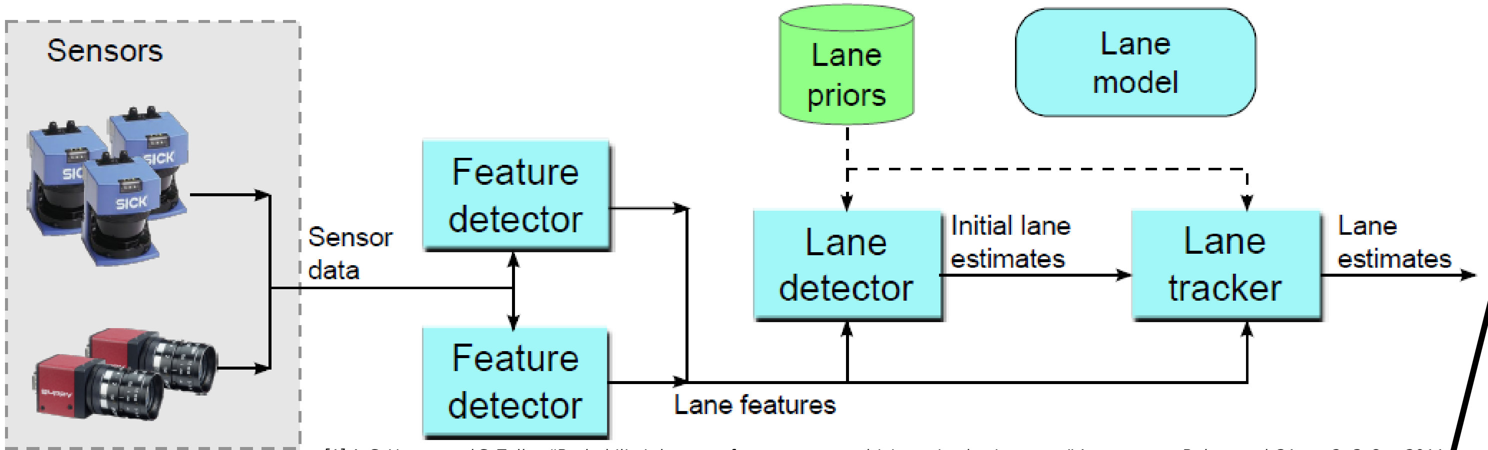
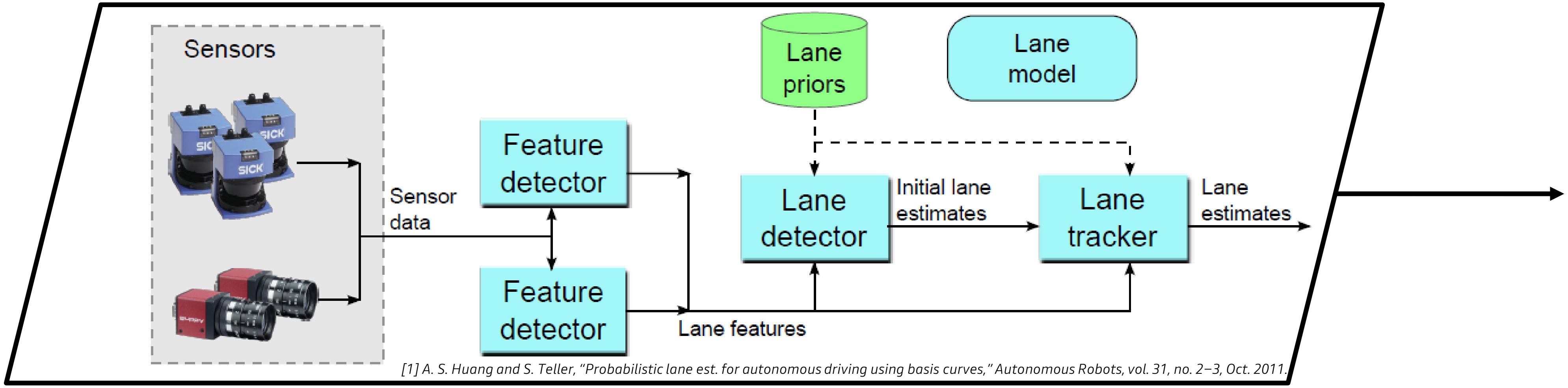


[1] *A. S. Huang and S. Teller, "Probabilistic lane est. for autonomous driving using basis curves," Autonomous Robots, vol. 31, no. 2–3, Oct. 2011.*

Smart Sensor #2

Smart Sensor #N

SMART SENSORS : STATE OF THE ART



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1. Feature extraction
2. Detection and tracking
3. Lane (boundary) model

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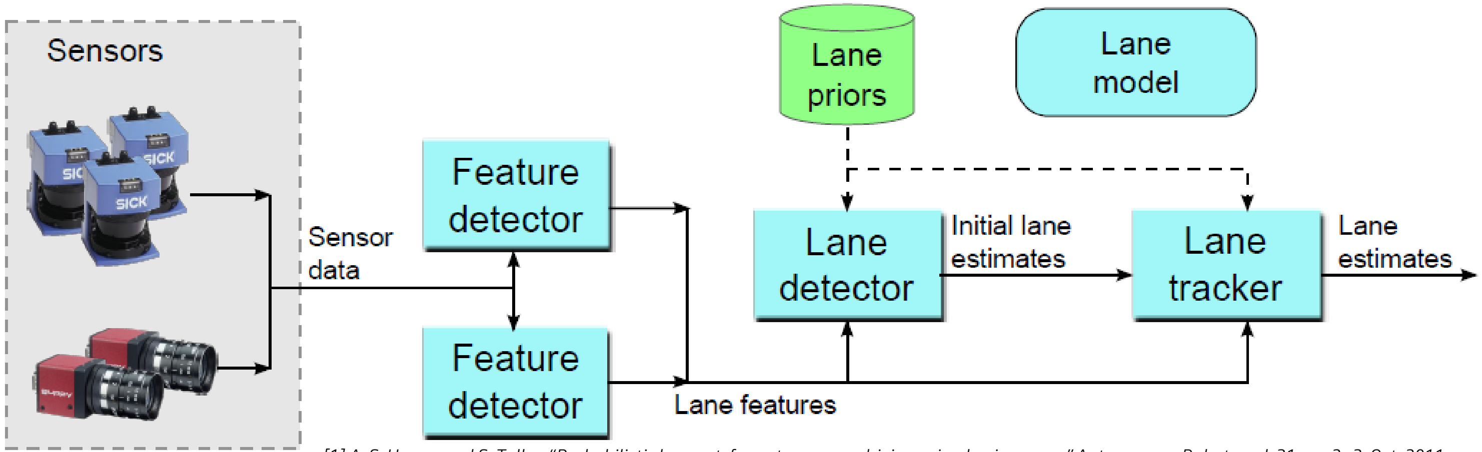
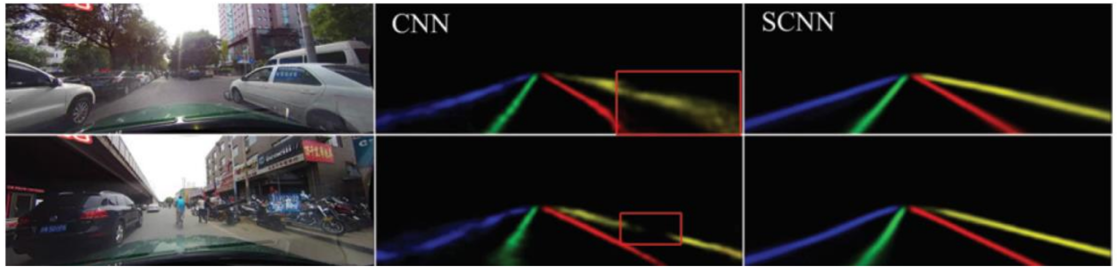
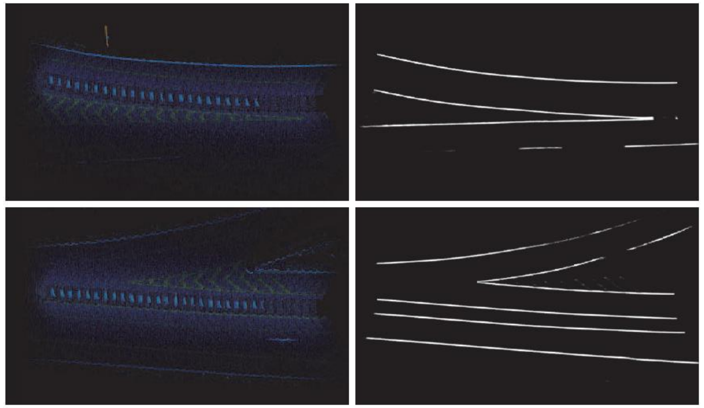


[1] A. S. Huang and S. Teller, "Probabilistic lane est. for autonomous driving using basis curves," Autonomous Robots, vol. 31, no. 2–3, Oct. 2011.

1. **Feature extraction**
2. Detection and tracking
3. Lane (boundary) model



[2] X. Pan, J. Shi, P. Luo, X. Wang, and X. Tang, "Spatial as Deep: Spatial CNN for Traffic Scene Understanding"



[3] B. He, R. Ai, Y. Yan, and X. Lang, "Lane marking detection based on Convolution Neural Network from point clouds," in 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), 2016, pp. 2475–2480

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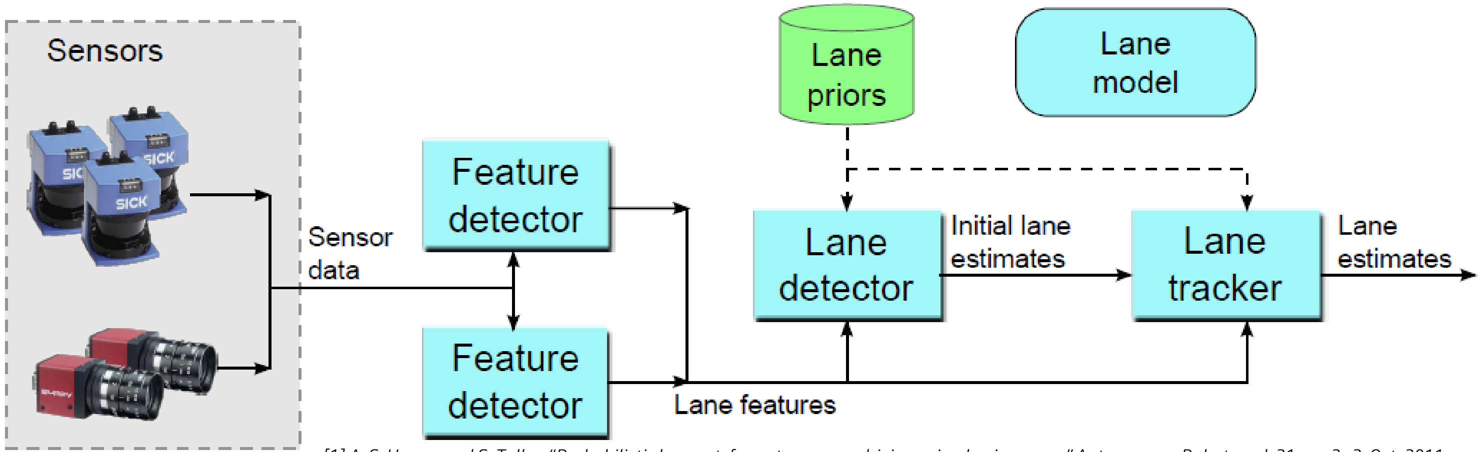

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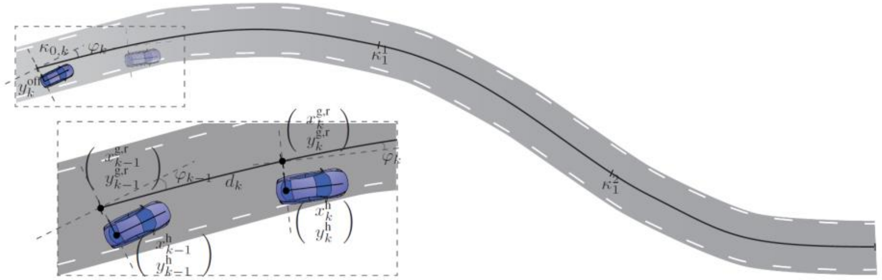
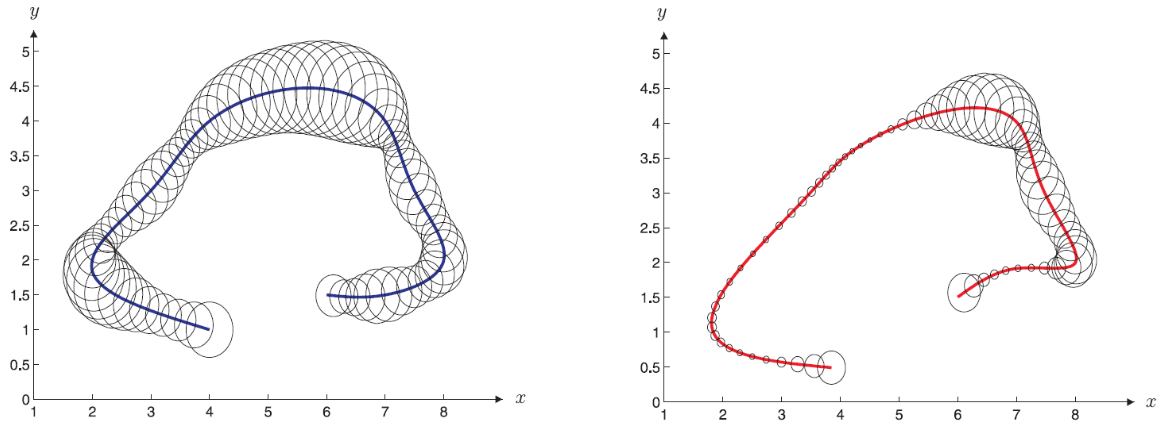
1. Feature extraction
2. **Detection and tracking**
3. Lane (boundary) model



[4] M. Fatemi, L. Hammarstrand, L. Svensson, and A. F. Garcia-Fernandez, "Road geometry estimation using a precise clothoid road model and observations of moving vehicles," 2014, pp. 238–24



[5] C. Hasberg and S. Hensel, "Online-Estimation of Road Map Elements using Spline Curves,"

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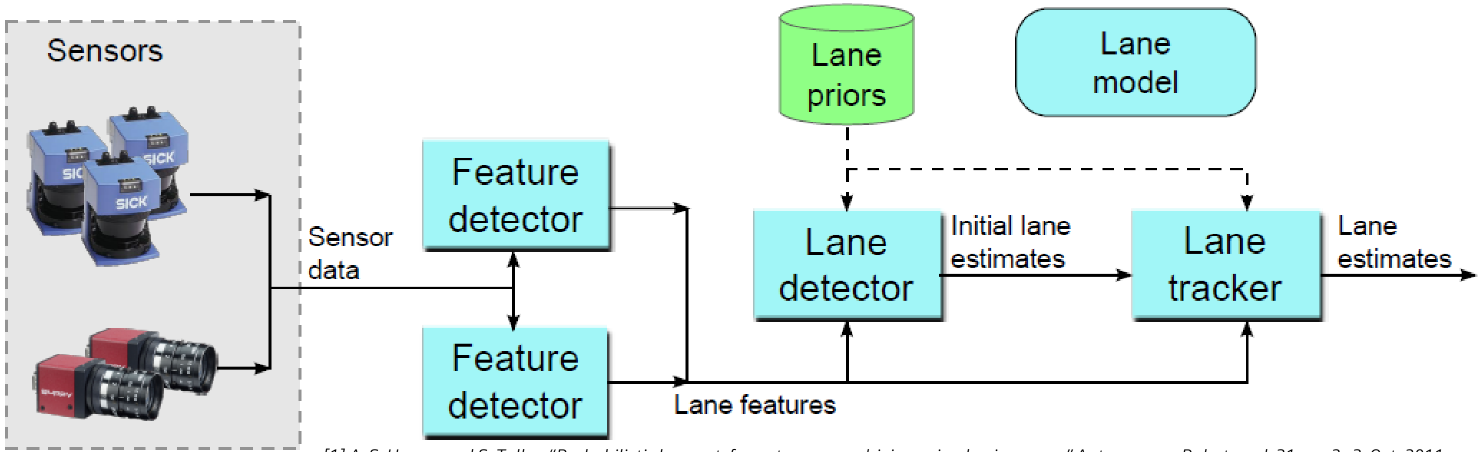

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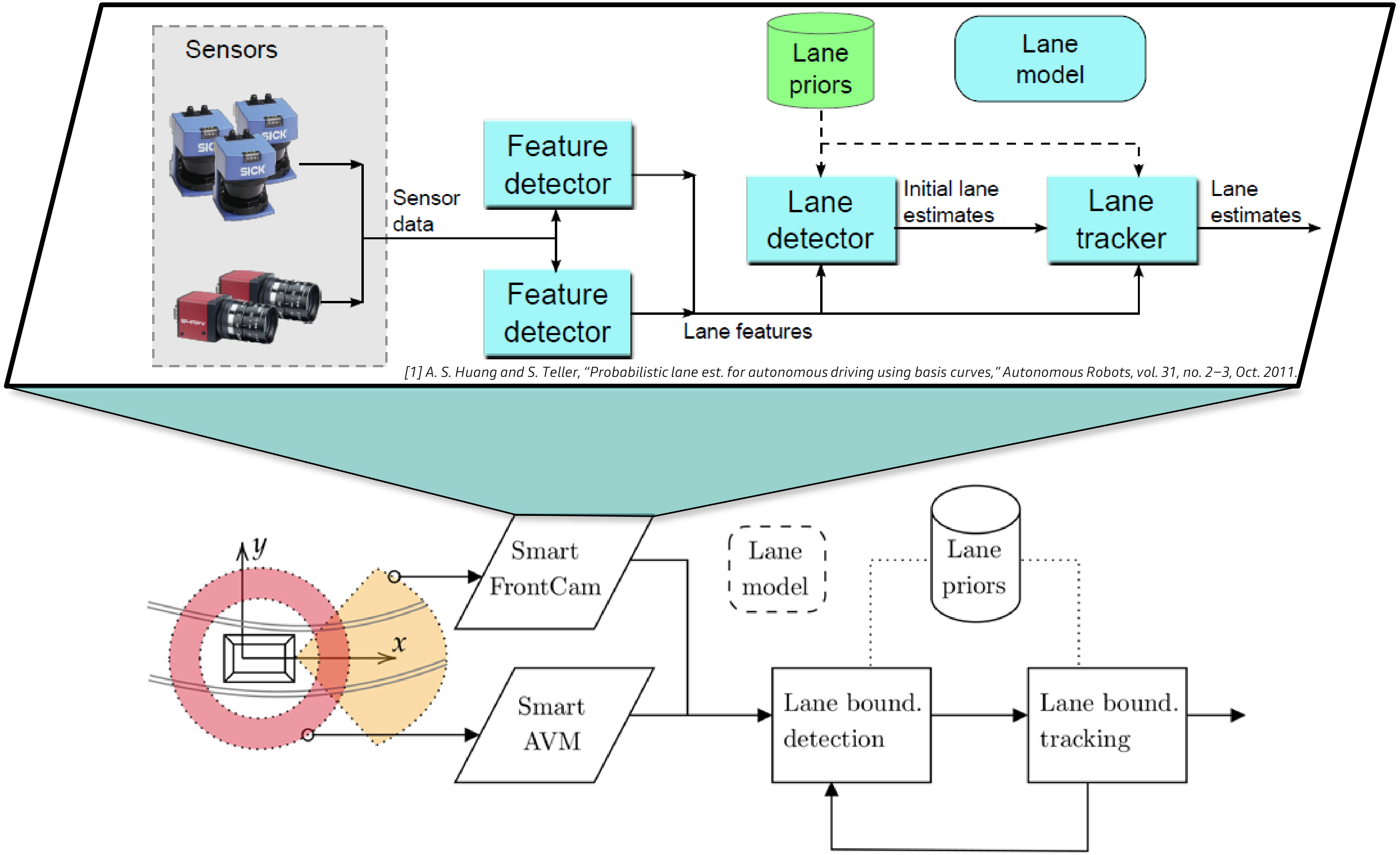
1. Feature extraction
2. Detection and tracking
3. **Lane (boundary) model**
   - Parametric: straight line, polynomials
   - Non-parametric: pixels
   - Semi-parametric: spline

THESIS USE CASE



- Two smart sensors: **Smart FrontCam** and **Smart AVM**

SMART SENSOR MODEL

- Smart sensor delivery contains lane boundaries detection
- Single measurements describe the form of the lane boundary
- In the L3 sensor set, both Smart Camera and Smart AVM deliver:

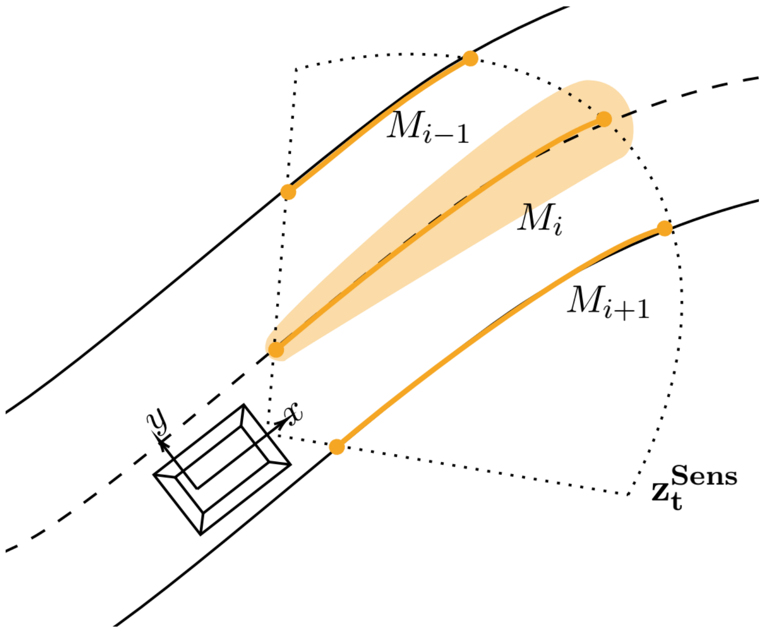
$$M_i = [c_0, c_1, c_2, c_3, x_{min}, x_{max}, \mathbf{\Sigma}_P, M_{type}] \in \mathbf{z}_\mathbf{t}^{\mathbf{Sens}}$$

- Where $P(x)$ polynomial describes the curve:

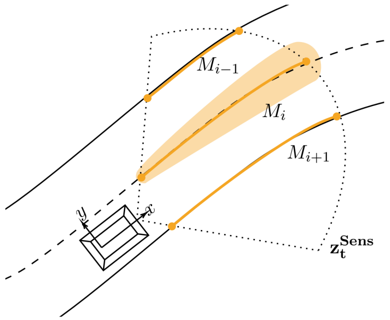
$$P(x) = c_0 + c_1 x + c_2 x^2 + c_3 x^3,\ x \in [x_{min}, x_{max}]$$

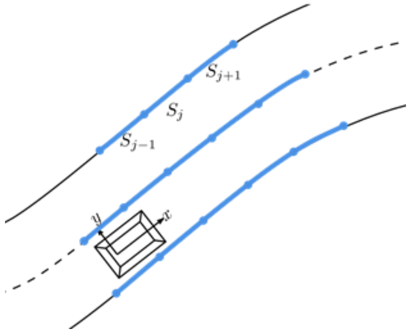
- And $\boldsymbol{\Sigma}_P$ is the measurement error:

$$\mathbf{\Sigma}_P = \begin{bmatrix} \sigma_{xx}^2 & & & 0 & 0 \\ & \sigma_{c_0c_0}^2 & & & 0 \\ & & \sigma_{c_1c_1}^2 & & \\ 0 & & & \sigma_{c_2c_2}^2 & \\ 0 & 0 & & & \sigma_{c_3c_3}^2 \end{bmatrix}$$



ROAD MODEL : PRO & CONS

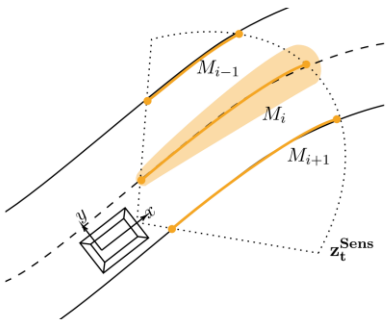


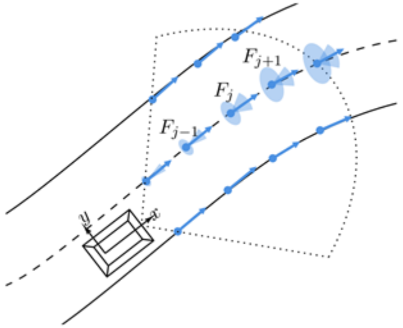


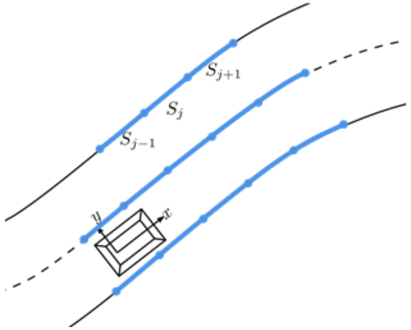
	Polynomial	Clothoid-spline
Computation	Immediate (everywhere) ✔ ✔	Open integrals ✘ (eff. approx. method exist ✔)
Tracking evolution	Hard ✘	Hard ✘
Descriptiveness	Limited ✘	Complete (for road) ✔
Curvature-based navigation support	No ✘	Yes ✔
Uncertainty representation	Coefficients ✘	Clothoid params ✘

VS

ROAD MODEL : PRO & CONS

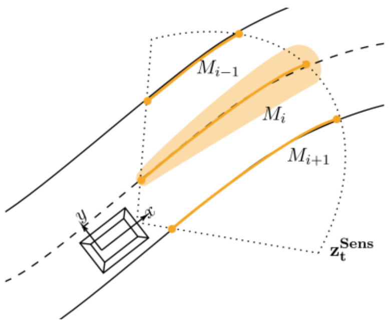


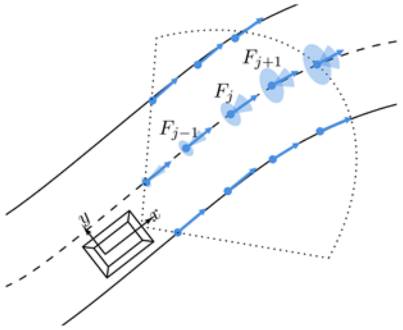


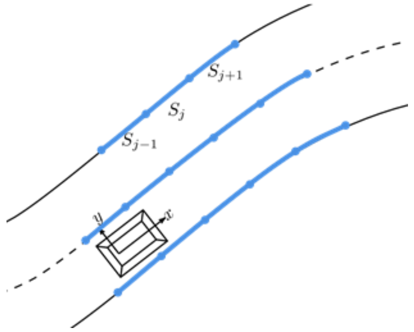


	Polynomial	Road features	Clothoid-spline
Computation	Immediate (everywhere) ✔ ✔	Immediate (punctually) ✔ —	Open integrals ✗ (eff. approx. method exist ✔)
Tracking evolution	Hard ✗	Easy ✔	Hard ✗
Descriptiveness	Limited ✗	Complete (for any curve) ✔	Complete (for road) ✔
Curvature-based navigation support	No ✗	Discrete representation — (can turn into any curve ✔)	Yes ✔
Uncertainty representation	Coefficients ✗	Spatial ✔	Clothoid params ✗

ROAD MODEL : PRO & CONS







	Polynomial	Road features	Clothoid-spline
Computation	Immediate (everywhere) ✓ ✓	Immediate (puncutally) ✓ —	Open integrals ✗ (eff. approx. method exist ✓)
Tracking evolution	Hard ✗	Easy ✓	Hard ✗
Descriptiveness	Limited ✗	Complete (for any curve) ✓	Complete (for road) ✓
Curvature-based navigation support	No ✗	Discrete representation — (can turn into any curve ✓)	Yes ✓
Uncertainty representation	Coefficients ✗	Spatial ✓	Clothoid params ✗

IN

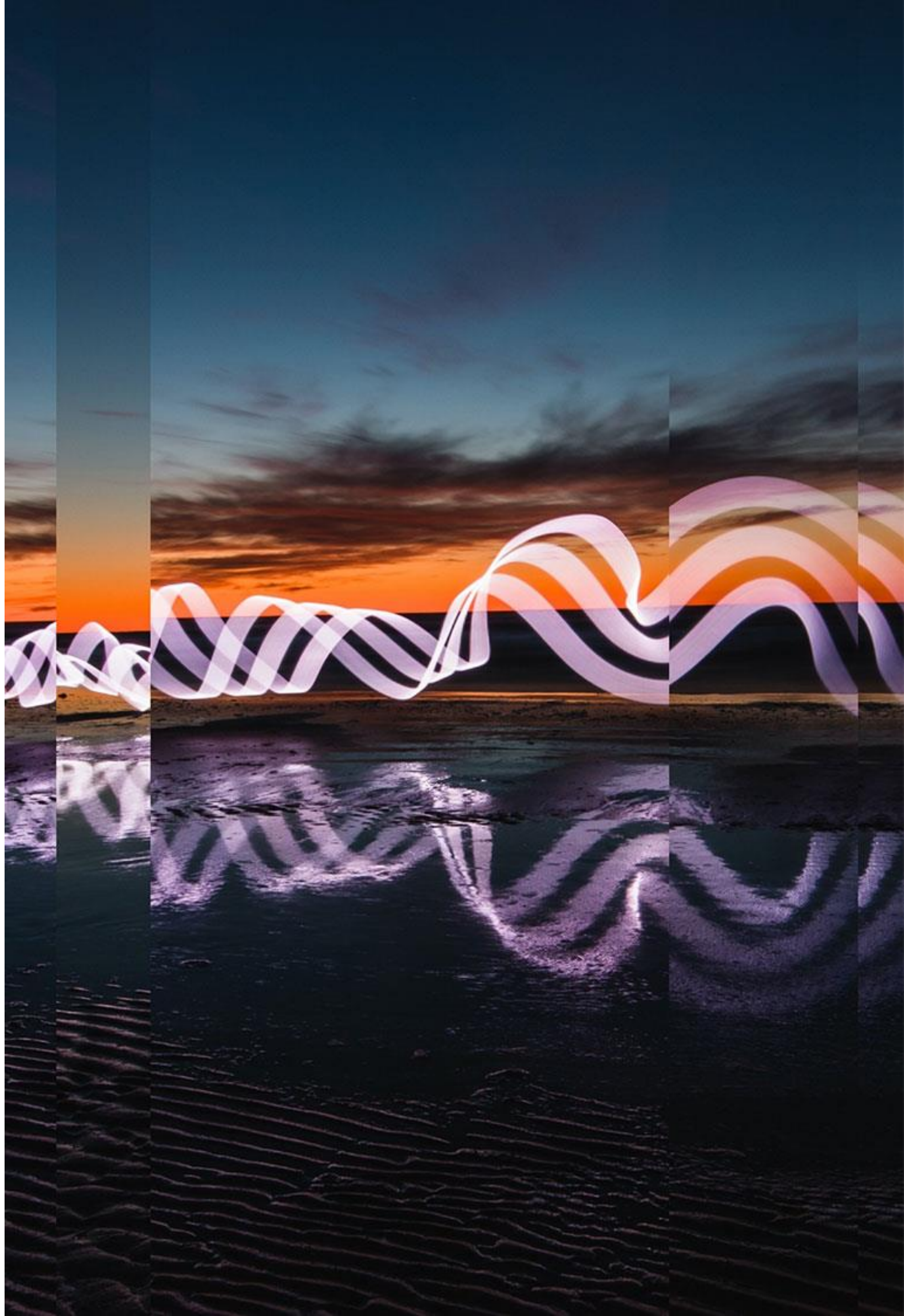
DURING estimation

OUT

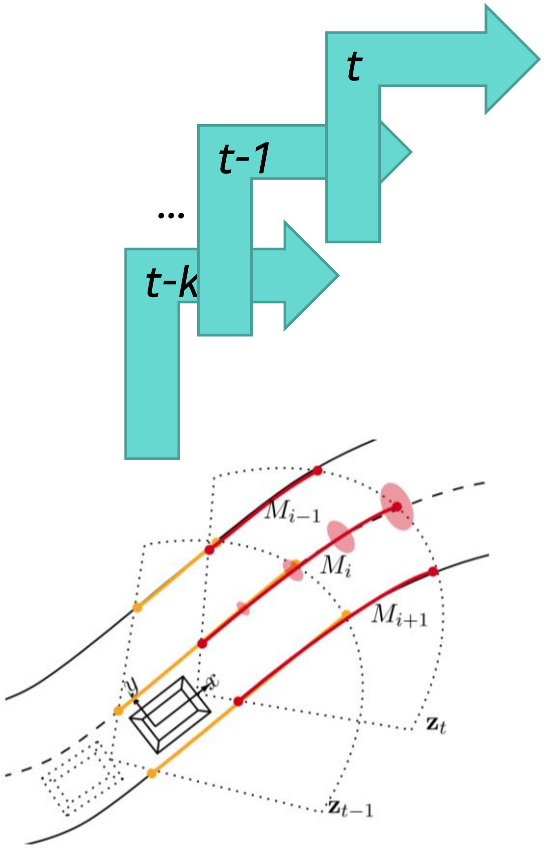
Summary

03

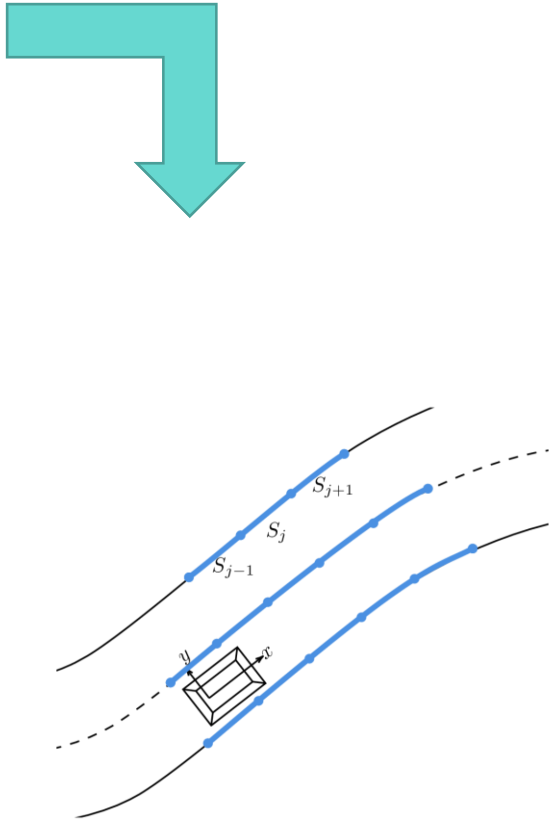
Multi-sensor fusion for lane boundaries estimation



PROPOSED SOLUTION : FEATURE-TRACKING



1. Initialization
2. Prediction
3. Association
4. Update
5. Output



PROPOSED SOLUTION : FEATURE-TRACKING

1. **Initialization**
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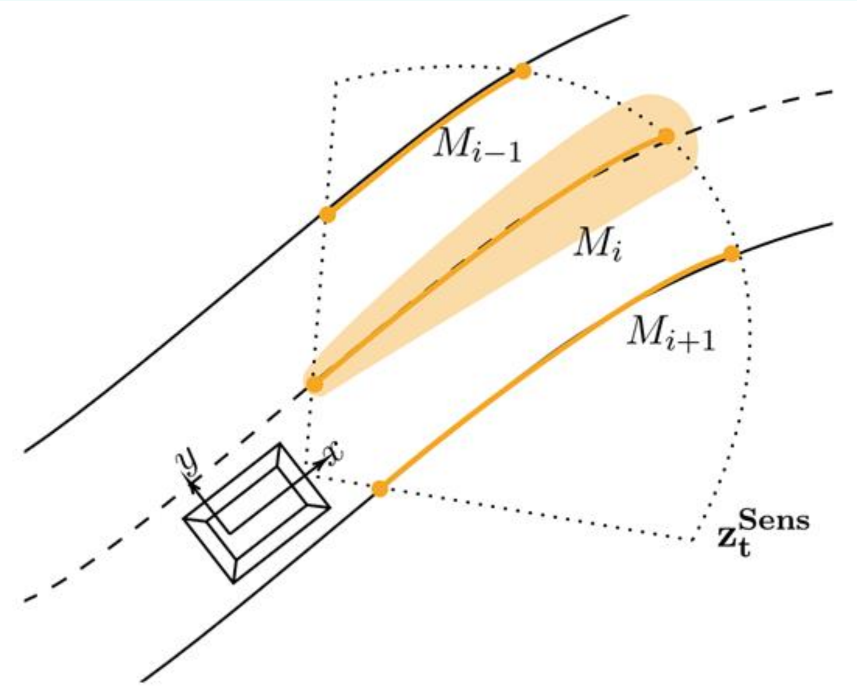

- First or non-associated measurements initialize distinct tracks for lane boundaries.
- Each measurement is delivered from the smart sensor in the form:

$$M_i = [c_0, c_1, c_2, c_3, x_{min}, x_{max}, \mathbf{\Sigma}_P, M_{type}] \in \mathbf{z}_\mathbf{t}^\mathbf{Sens}$$

$$P(x) = c_0 + c_1 x + c_2 x^2 + c_3 x^3,\ x \in [x_{min}, x_{max}]$$

PROPOSED SOLUTION : FEATURE-TRACKING

1. **Initialization**
2. Prediction
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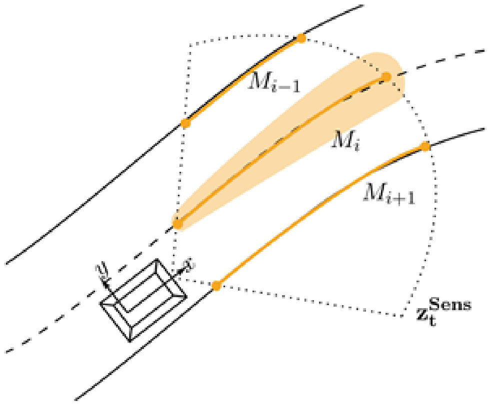
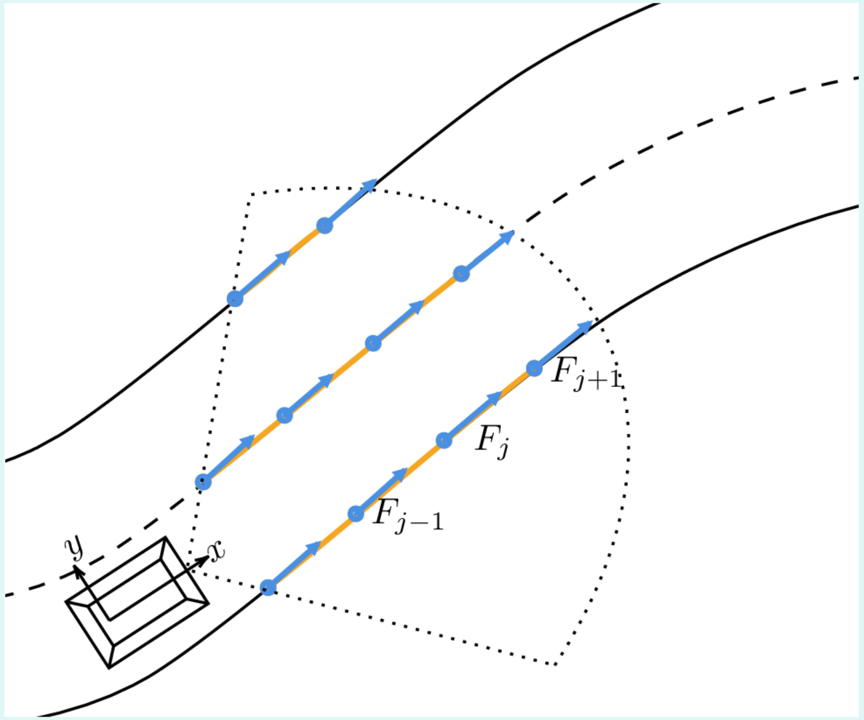
4. Update
5. Output



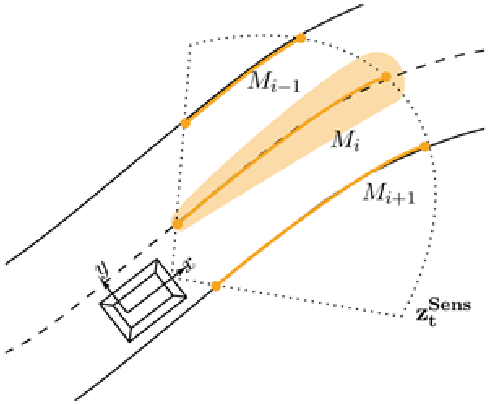


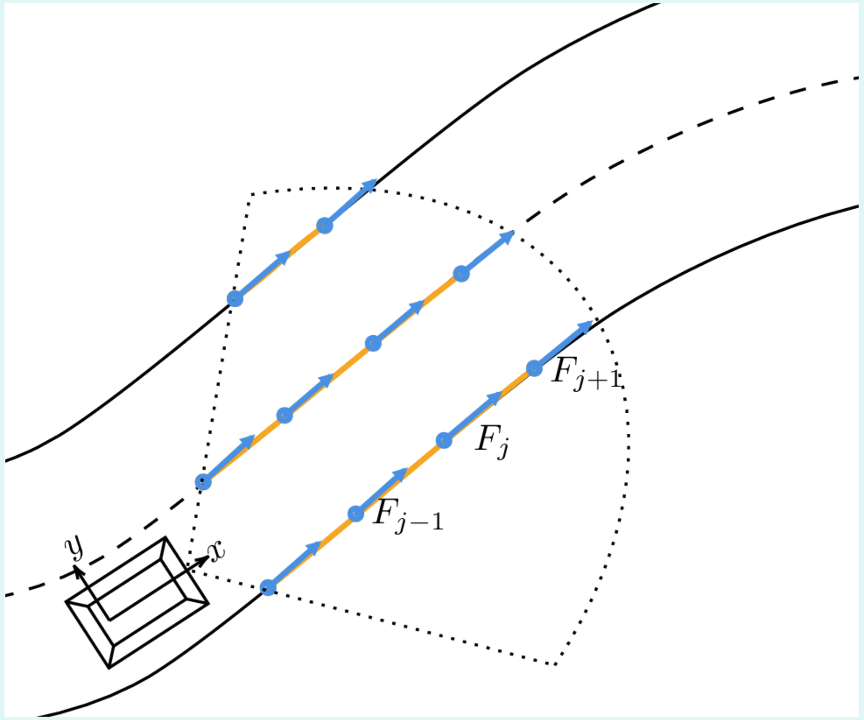
- Lane boundary **tracks are collections of road features**
- At constant interdistance, new features are sampled (according to the **sensor model**) as:

$$F_j = \begin{bmatrix} x_j \\ y_j \\ \theta_j \end{bmatrix} = \begin{bmatrix} x_j \\ P(x_j) \\ \arctan(P'(x_j)) \end{bmatrix} = \begin{bmatrix} x_j \\ c_0 + c_1 x_j + c_2 {x_j}^2 + c_3 {x_j}^3 \\ \arctan(c_1 + 2c_2 x_j + 3c_3 {x_j}^2) \end{bmatrix}$$

PROPOSED SOLUTION : FEATURE-TRACKING

1. Initialization
2. **Prediction**
3. Association
4. Update
5. Output





- Ego-vehicle motion is estimated and delivered as :

$$\Delta Ego_t = [dx, dy, d\theta, \mathbf{\Sigma}_E]$$

- After transformation into current reference frame, Kalman prediction step follows according to the trivial evolution model:

$$\mathbf{x_t} = \mathbf{x_{t-1}} + \mathbf{w_t}$$
$$\mathbf{w_t} \sim \mathcal{N}(0, \mathbf{\Sigma}_E)$$

PROPOSED SOLUTION : FEATURE-TRACKING

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2. Prediction
3. **Association**
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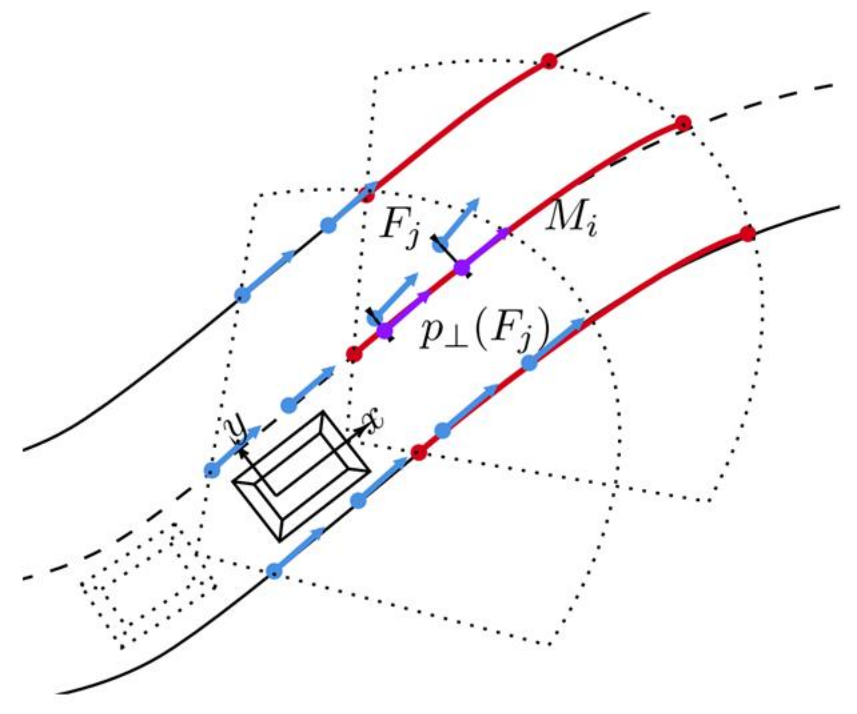
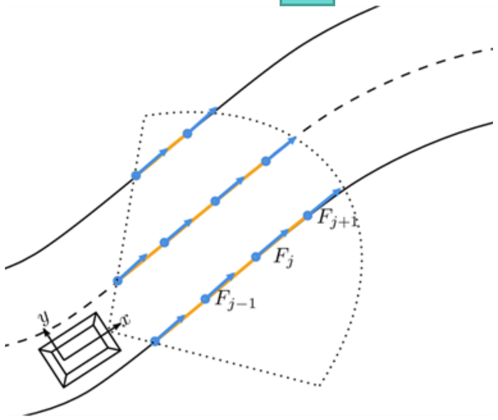




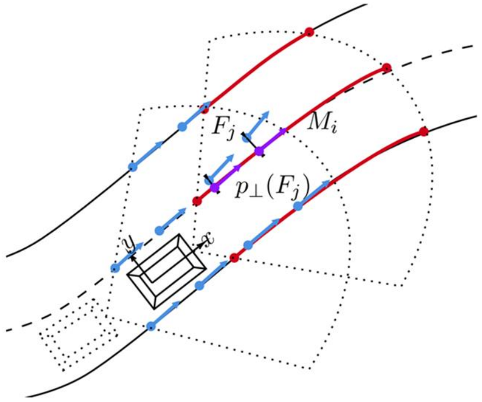
- Existing features are projected onto measurements identifying Feature-to-Feature Mahalanobis distance:

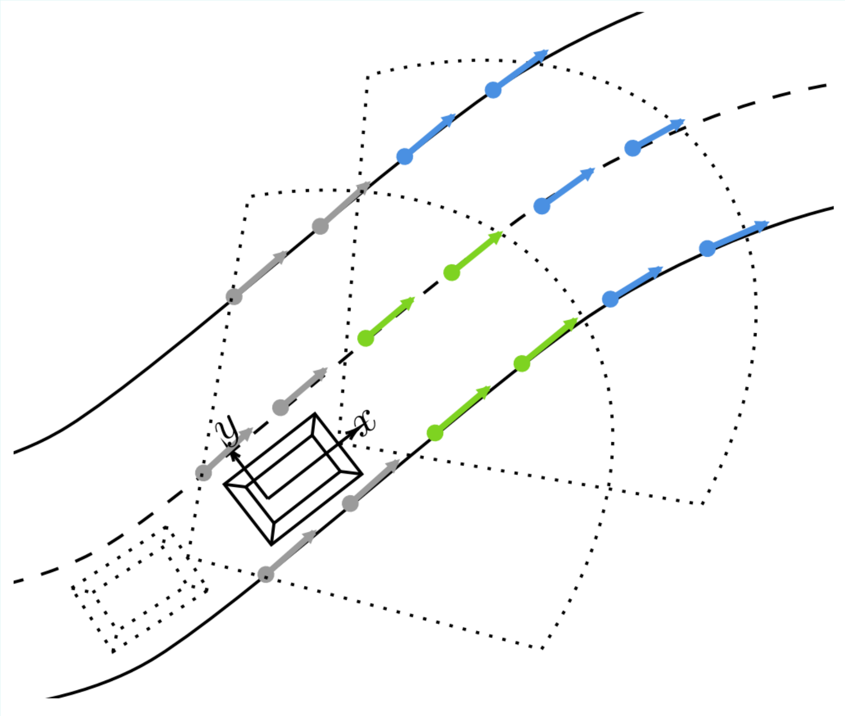
$$d(p_\perp(F_j), F_j) = \sqrt{(p_\perp(F_j) - F_j)^T(\mathbf{\Sigma}_M(x_\perp, y_\perp) + \mathbf{\Sigma}_F)^{-1}(p_\perp(F_j) - F_j)}$$

- Measure-to-track metric for GNN association: $d(M, C_i) = \max_{F_j \in C_i} d(p_\perp(F_j), F_j)$

PROPOSED SOLUTION : FEATURE-TRACKING

1. Initialization
2. Prediction
3. Association
4. **Update**
5. Output



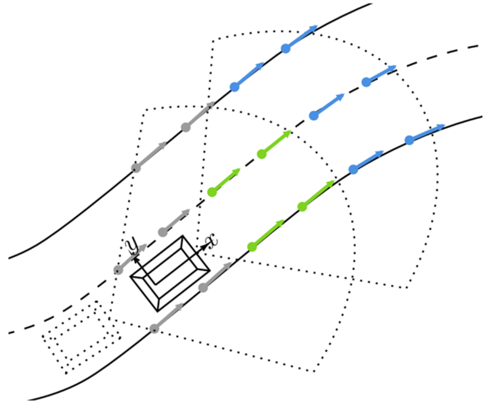


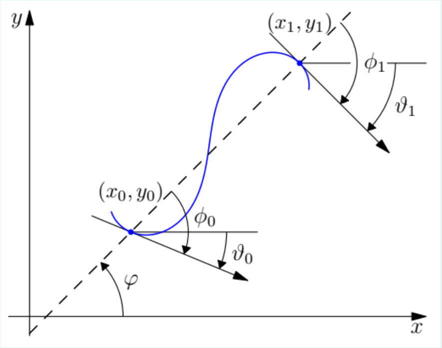
Three cases present depending on observability of road features :

1. Observed features are updated following Kalman update step
2. Unobserved features can be suppressed if distant or obsolete
3. Newly discovered features (sampled at constant interdistance) extend existing tracks

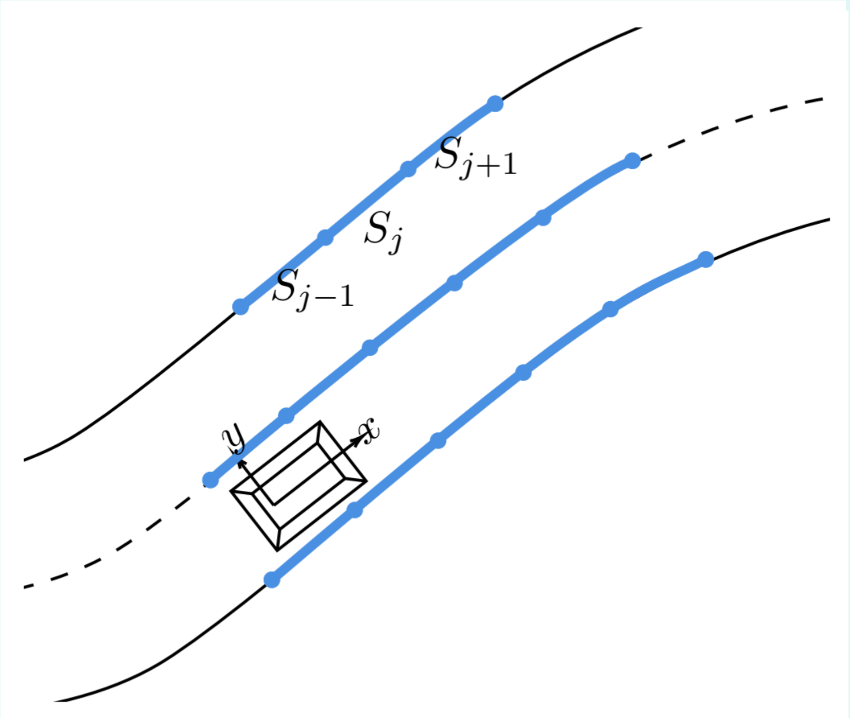
PROPOSED SOLUTION : FEATURE-TRACKING

1. Initialization
2. Prediction
3. Association
4. Update
5. **Output**





$$S_j = [x_0, y_0, \psi_0, \kappa_0, \kappa_1, l, \mathbf{\Sigma}_S]$$



- A road **feature collection can be turned into clothoid-spline** via interpolation
- Using the efficient interpolation method proposed in [6] between successive road features, the **resulting clothoid-spline attains G1-continuity** (heading angle of the curve is continuous all along its length) which makes it ideal for vehicle control

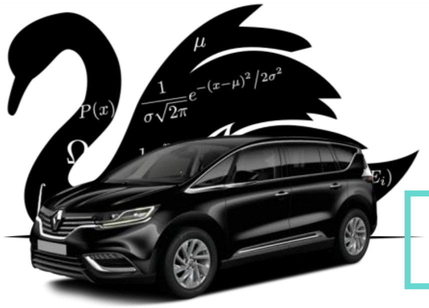
[6] E. Bertolazzi and M. Frego, "G1 fitting with clothoids," Mathematical Methods in the Applied Sciences, vol. 38, no. 5, pp. 881–897, Mar. 2015

EXPERIMENTAL RESULTS

1. Development setup
2. Evaluation setup
3. On-board setup

EXPERIMENTAL RESULTS (1)

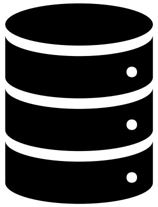
- Development setup



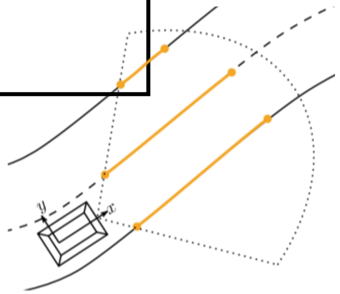
- Proprioceptives
- Smart FrontCam
  30Hz, FoV: 53°x 120 m
- Smart AVM (4 cameras)
  20Hz, FoV: 360°x 20 m

Sensors

Recording data



Re-playing data



Fusionrunner environment

- Object tracking

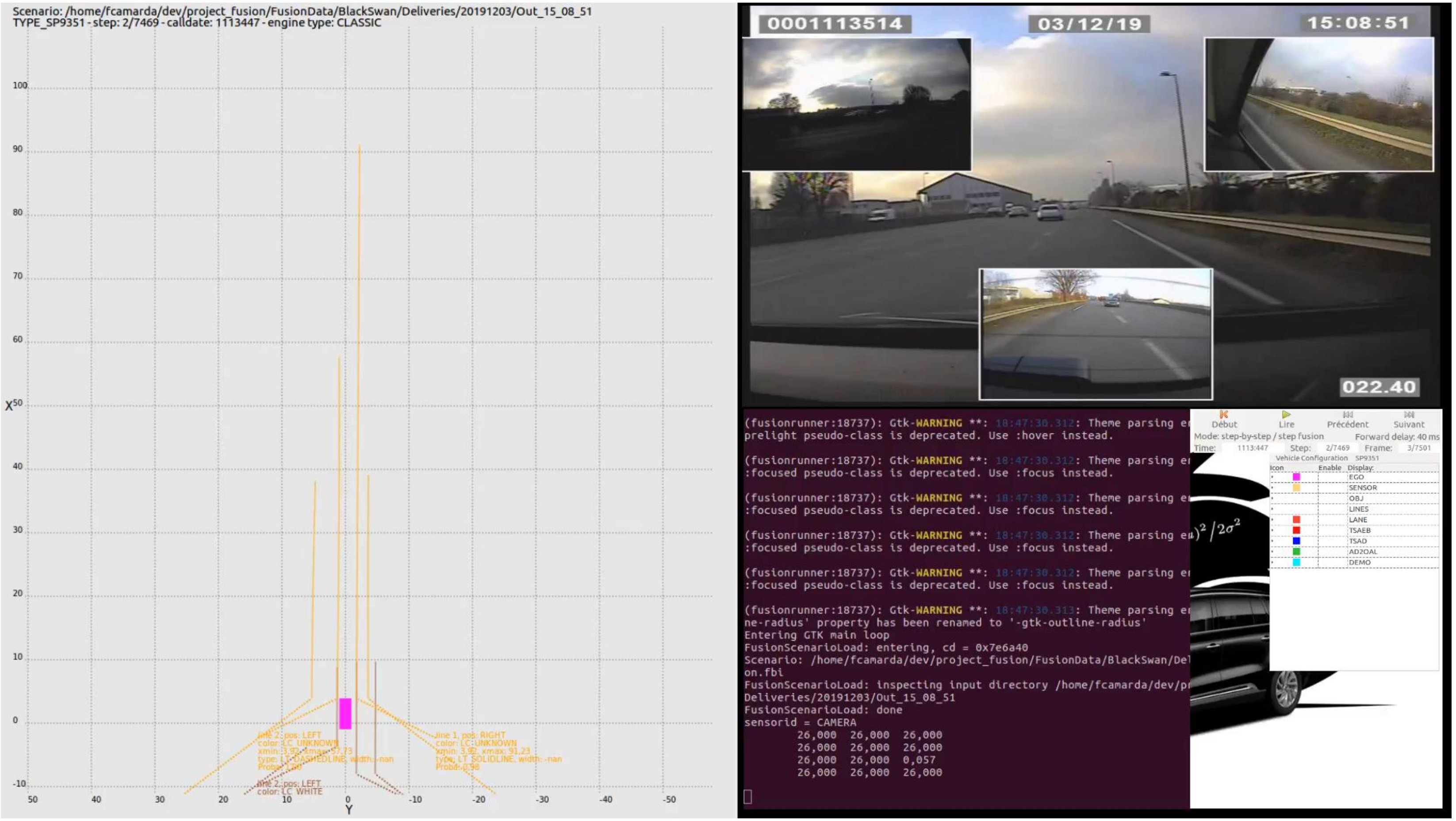
  ...

- Ego-motion tracking
- Lane boundary tracking

Fusion results and context camera

EXPERIMENTAL RESULTS (1)

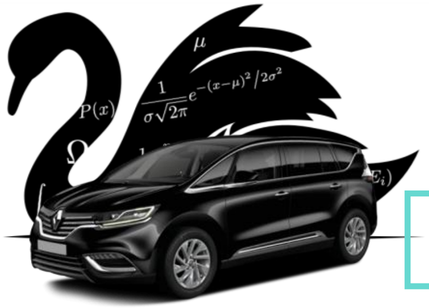
- Execution in *Fusionrunner* environment



- Ego-vehicle
- Smart FrontCam measurements
- Smart AVM measurements
- Fusion result (road features)
- Road features uncertainty
- Fusion result (clothoid-spine)

EXPERIMENTAL RESULTS (2)

- Evaluation setup

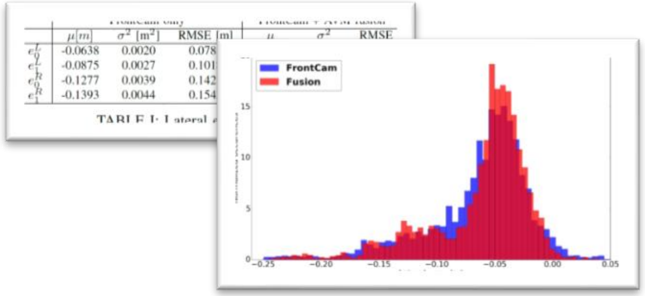


- Proprioceptives
- **Smart FrontCam**
  30Hz, FoV: 53°x 120 m
- **Smart AVM** (4 cameras)
  20Hz, FoV: 360°x 20 m

Sensors

Recording data

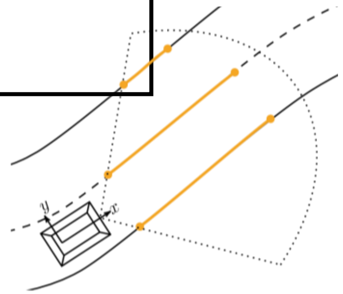
- **Performance indicators**
  Mean error at a given range, variance



Re-playing data

Fusionrunner environment

- Object tracking
  ...
- Ego-motion tracking
- Lane boundary tracking

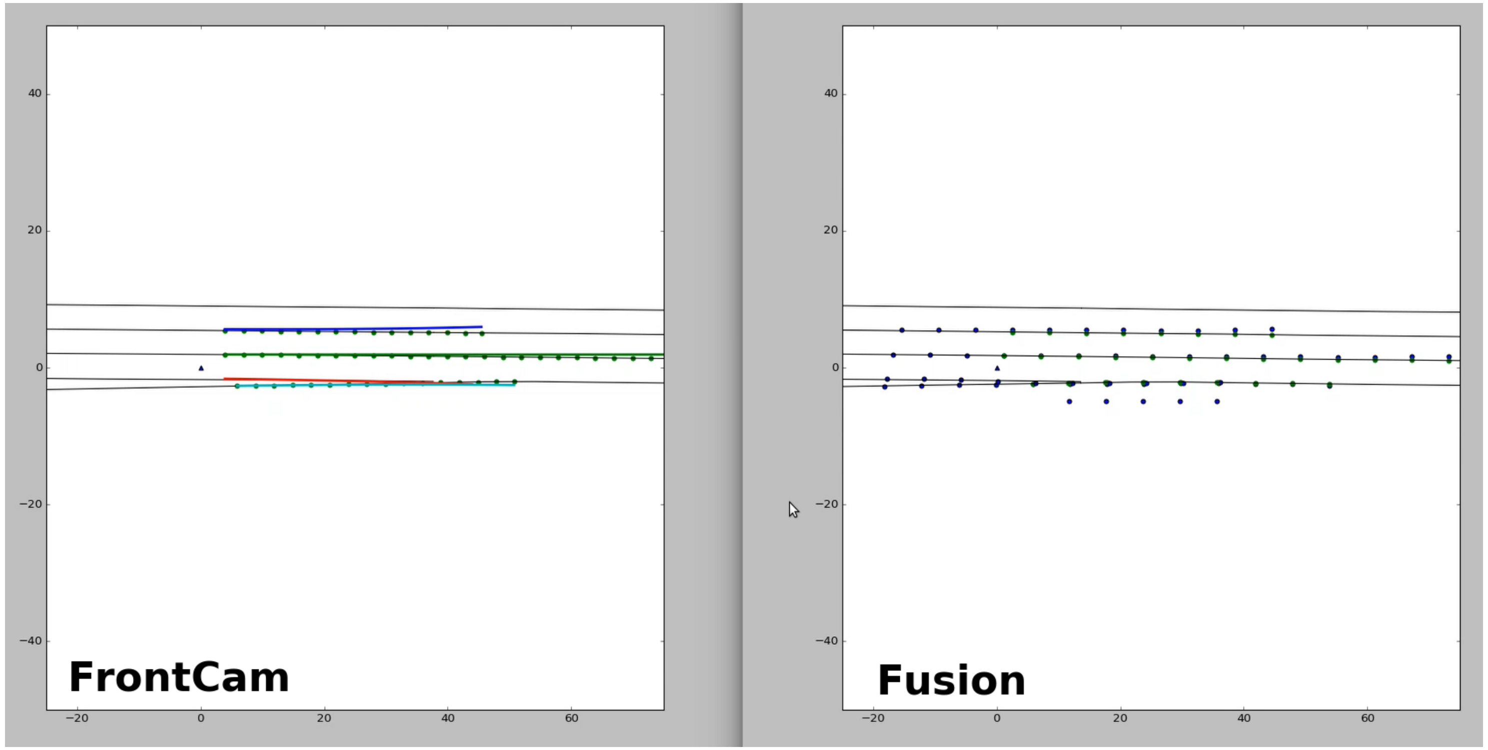


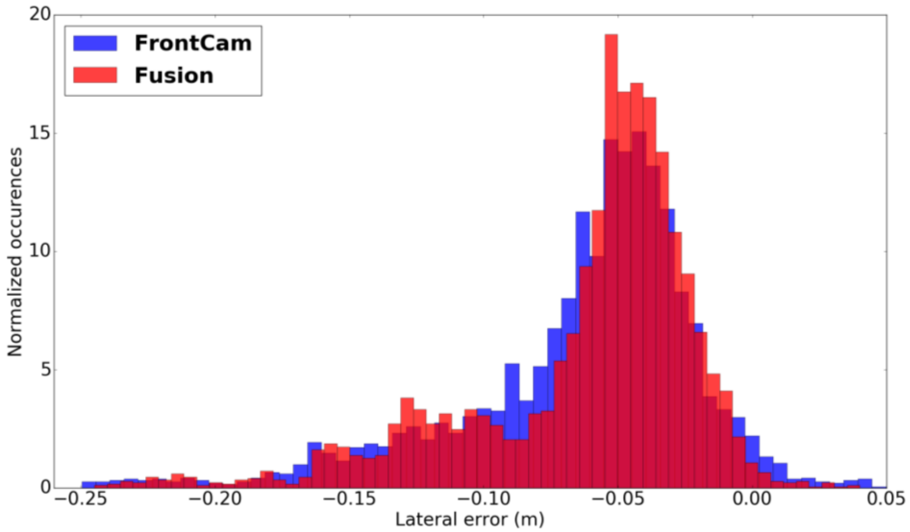
VS

- **Lane-level ground truth**
  RTK localization + HD Map

EXPERIMENTAL RESULTS (2)

- FrontCam only vs FrontCam+AVM Fusion
  - Lateral error at given range is computed w.r.t. lane-level GT
  - Fusion smoothing effect reflects in lateral error at 0m distribution



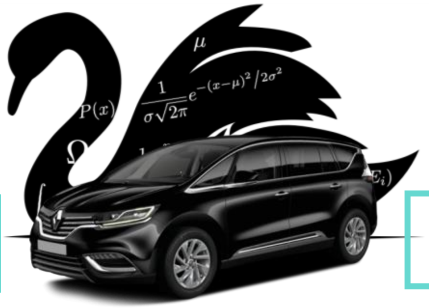


	FrontCam only			FrontCam + AVM fusion		
	$\mu[m]$	σ^2 $[m^2]$	RMSE [m]	μ	σ^2	RMSE
e_0^L	-0.0638	0.0020	0.0781	-0.0620	0.0019	0.0755
e_1^L	-0.0875	0.0027	0.1018	-0.0773	0.0022	0.0906
e_0^R	-0.1277	0.0039	0.1421	-0.1018	0.0024	0.1131
e_1^R	-0.1393	0.0044	0.1543	-0.1254	0.0037	0.1394

TABLE I: Lateral error benchmark

EXPERIMENTAL RESULTS (3)

- On-board setup



- Proprioceptives
- **Smart FrontCam**
  30Hz, FoV: 53°x 120 m
- **Smart AVM** (4 cameras)
  20Hz, FoV: 360°x 20 m

Actuators

Sensors

- User via HMI

On-board PC / Control ECU

- ACC, Speed regulation
- Keep/Change Lane
- AEB

On-board PC / Fusion ECU

- Object tracking
  …
- Ego-motion tracking
- Lane boundary tracking

EXPERIMENTAL RESULTS (3)

1. ACC is activated, **Keep lane**
2. Lane boundaries are detected by FrontCam + AVM and fused
3. Left turn signal is activated, **Change lane** (to left)
4. Back to **Keep lane**
5. Right turn signal is activated, **Change lane** (to right)

- **Change Lane** based FrontCam + AVM : successful on-board execution ✔

SECTION CONCLUSIONS

Multi-sensor architecture for tracking of lane boundaries has been introduced and validated

Can support potentially any multi-modal smart sensor set, providing **redundancy** and **perception diversity**

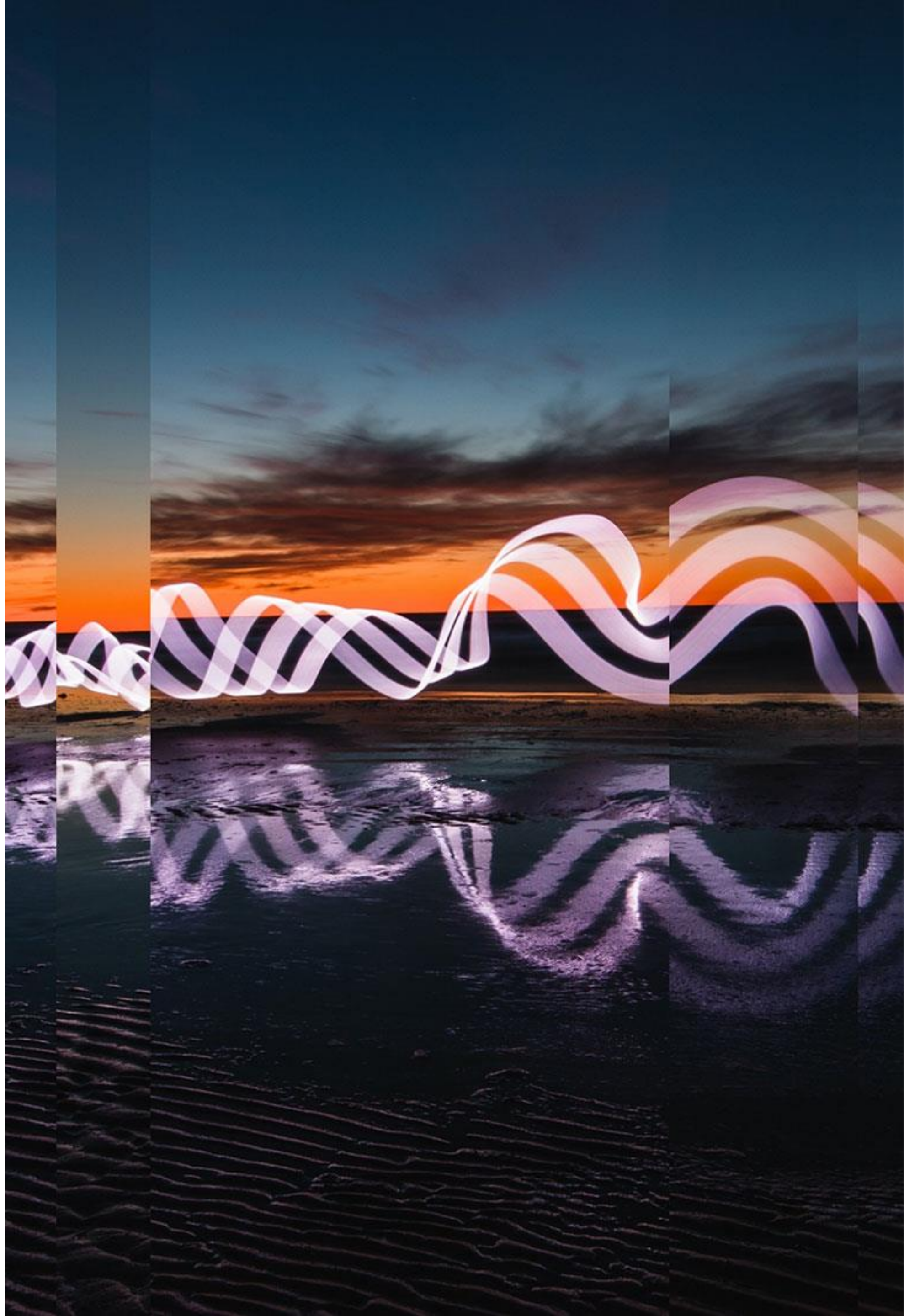
Real-time implementation and on-board experiments confirm **exploitability in quasi-industrial use cases**

✓ Work accepted as contributed paper at : 2020 IEEE Intelligent Vehicles Symposium (IV 2020)

Summary

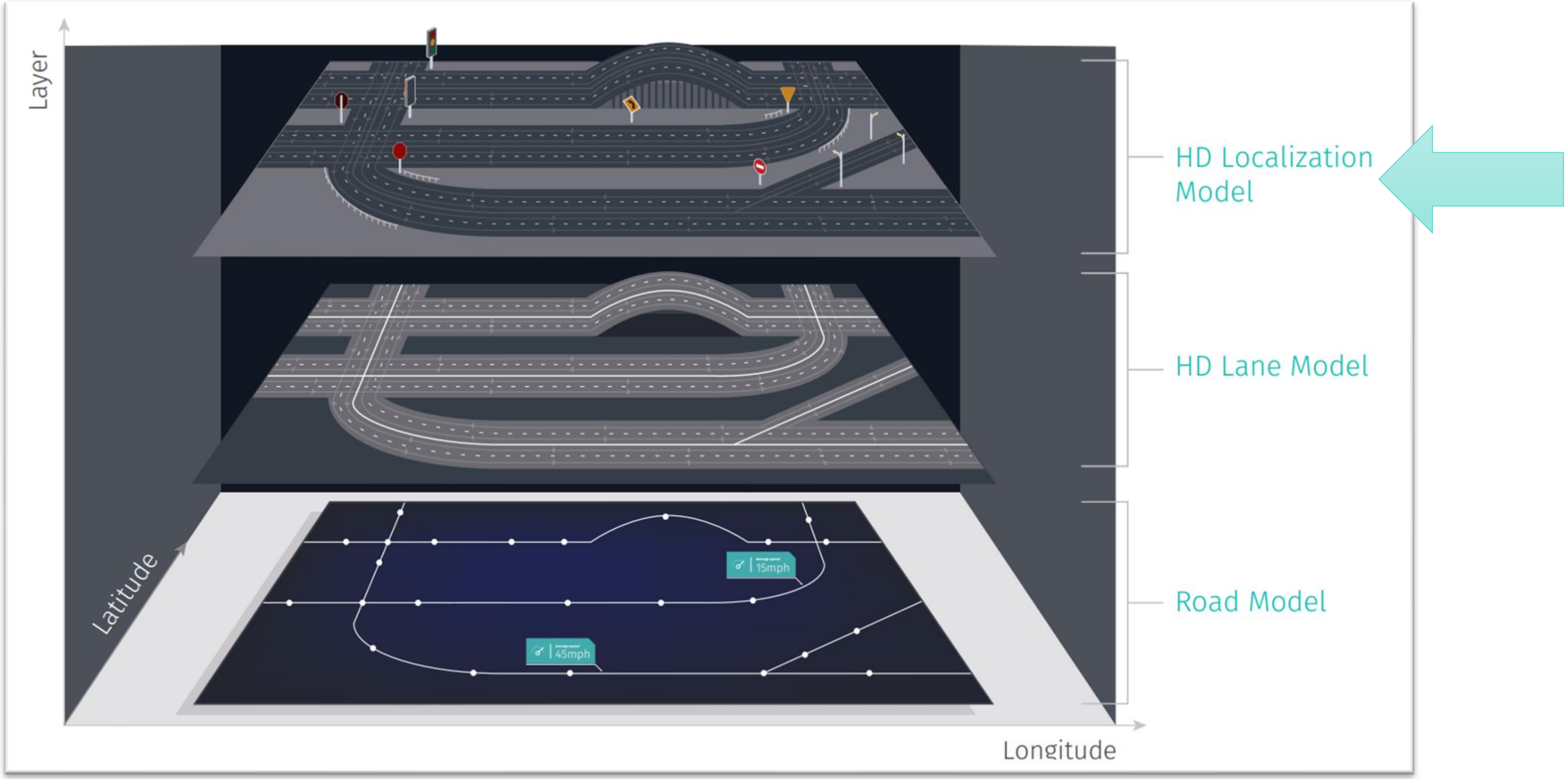
04

Map-aided multi-sensor fusion for lane boundaries estimation



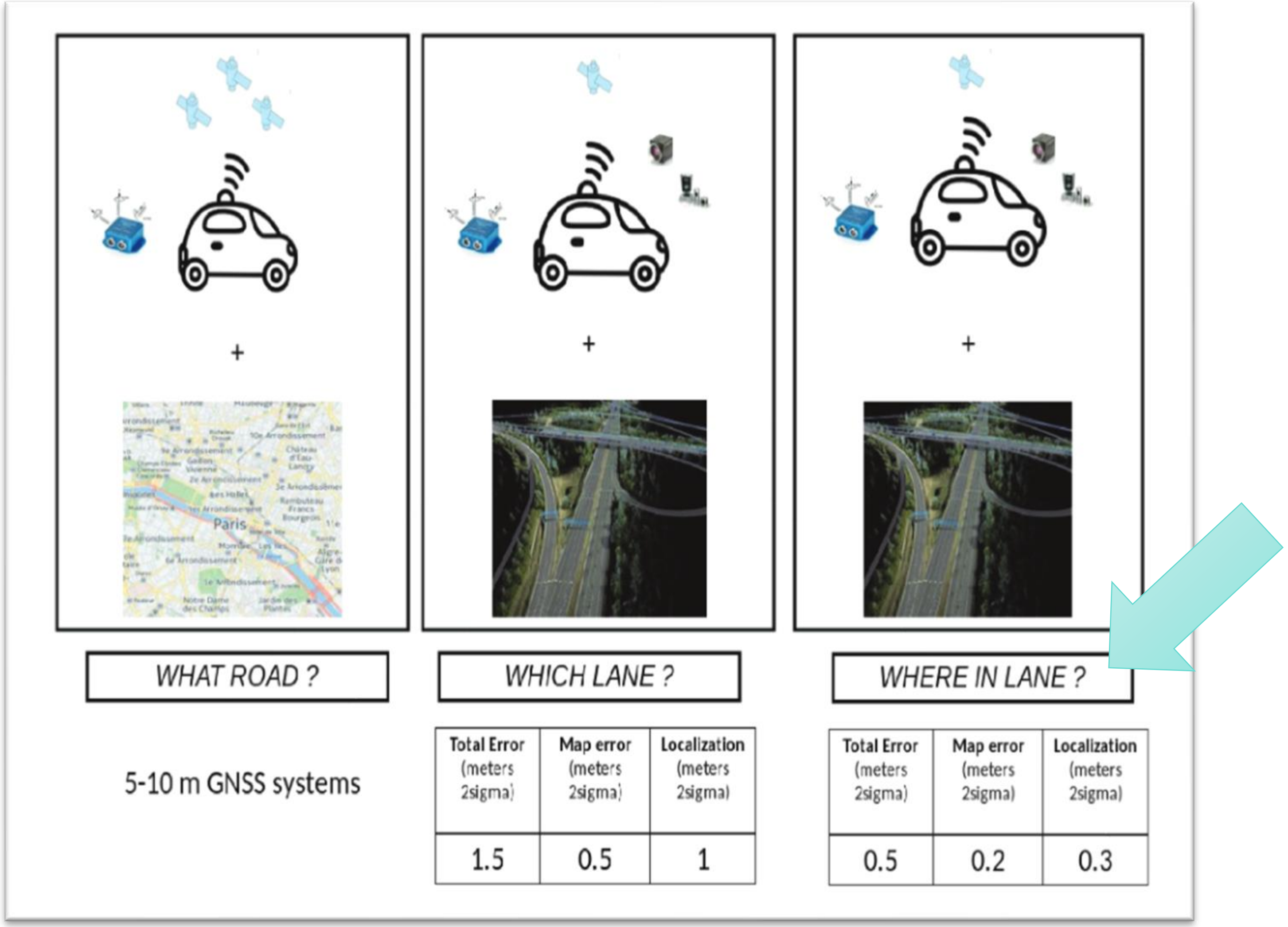
MAP-PROVIDERS : STATE OF THE ART

- Mapping and Localization

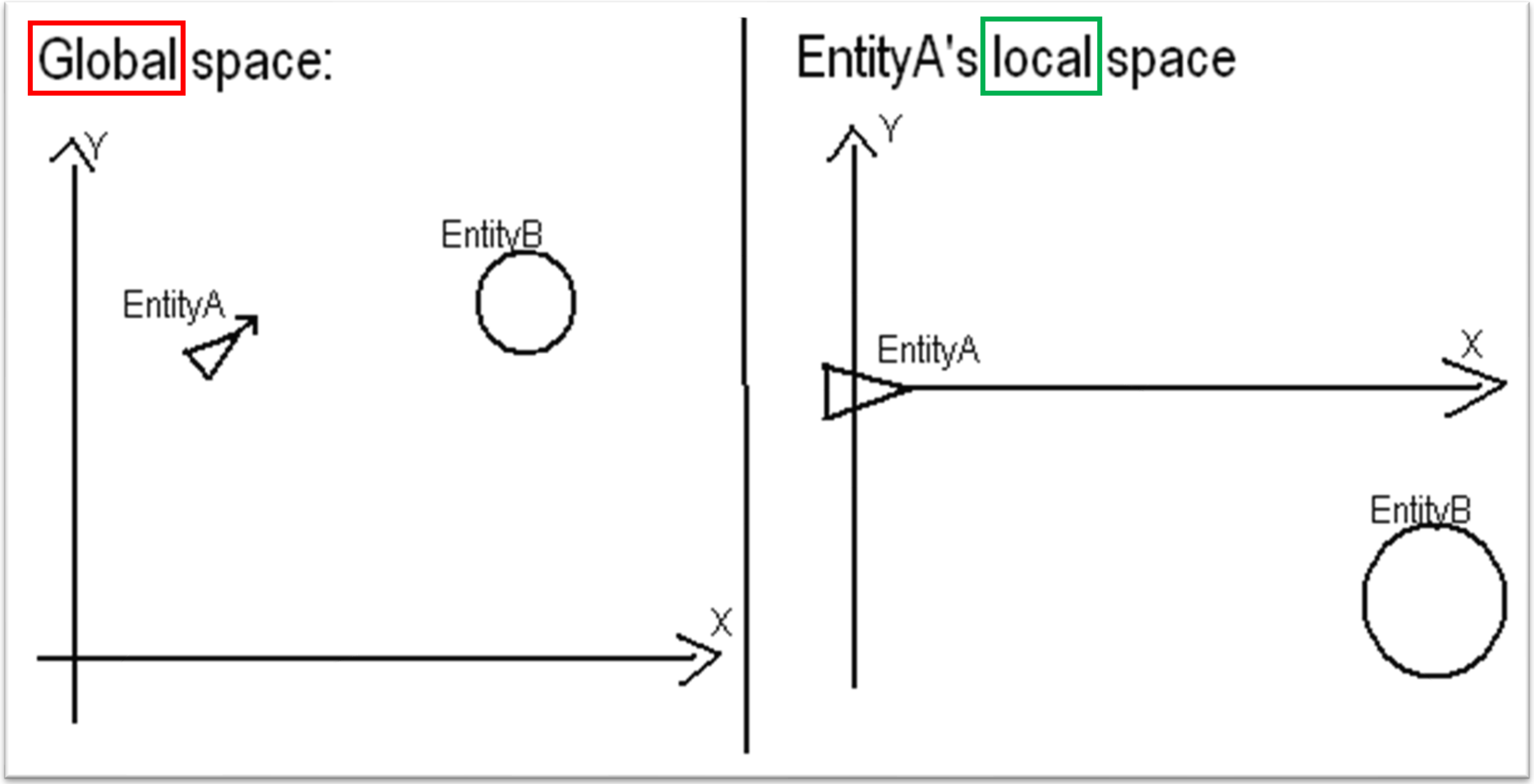


MAP-PROVIDERS : STATE OF THE ART

- Mapping and **Localization**

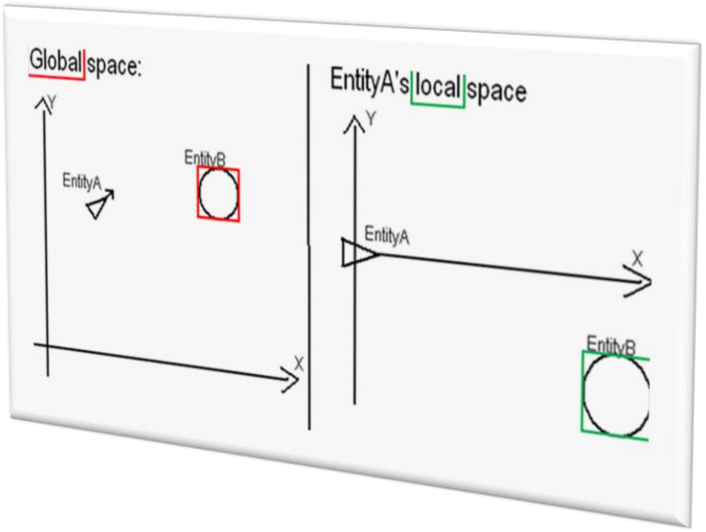


MAP-PROVIDER MODEL : GLOBAL AND LOCAL FRAME



- *EntityA* is **ego-vehicle** – *EntityB* is a **map-node**

MAP-PROVIDER MODEL : UNCERTAINTY REPRESENTATION



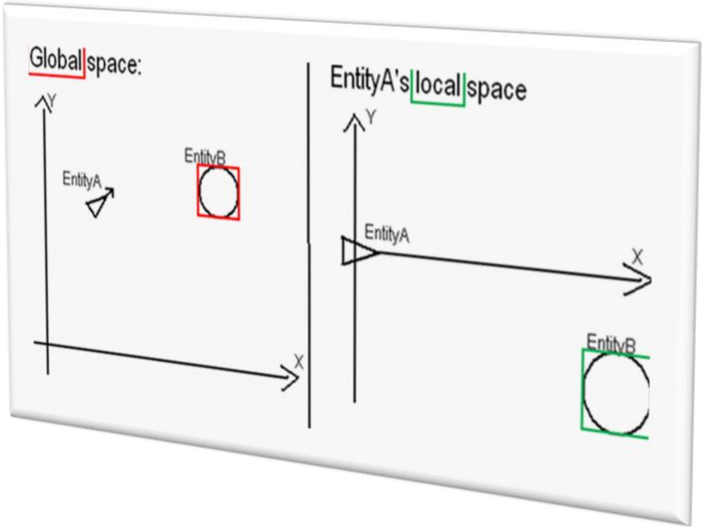
- Map-node in the global frame

$$^{\boxed{O}}\mathbf{X}_i = \begin{bmatrix} ^{O}x_i \\ ^{O}y_i \end{bmatrix}$$

- Map-node in the local frame

$$^{\boxed{M}}\mathbf{X}_i = \begin{bmatrix} ^{M}x_i \\ ^{M}y_i \end{bmatrix} = {}^{M}\mathbf{R}_O \left(\begin{bmatrix} ^{O}x_i \\ ^{O}y_i \end{bmatrix} - \begin{bmatrix} ^{O}x_M \\ ^{O}y_M \end{bmatrix} \right) = f(^{O}\mathbf{X}_M, \theta, {}^{O}\mathbf{X}_i)$$

MAP-PROVIDER MODEL : UNCERTAINTY REPRESENTATION



- Uncertainty of map-node in the global frame

$$Var({}^{\boxed{O}}\mathbf{X}_i) = Var({}^{O}\mathbf{X}_{Map}) \forall i = 1..N_i$$

- Uncertainty of map-node in the local frame

$$Var({}^{\boxed{M}}\mathbf{X}_i) = \left[\frac{\partial f}{\partial\, {}^{O}\mathbf{X}_5}\right] \begin{bmatrix} {}^{O}\mathbf{\Sigma}_M & \mathbf{0} \\ \mathbf{0} & Var({}^{O}\mathbf{X}_i) \end{bmatrix} \left[\frac{\partial f}{\partial\, {}^{O}\mathbf{X}_5}\right]^T$$

Takes into account both **mapping** and **localization error** ! ✔

- where:

$$\left[\frac{\partial f}{\partial\, {}^{O}\mathbf{X}_5}\right] = \begin{bmatrix} -\cos(\theta) & -\sin(\theta) & {}^{\boxed{M}}y_i & \cos(\theta) & \sin(\theta) \\ \sin(\theta) & -\cos(\theta) & -{}^{\boxed{M}}x_i & -\sin(\theta) & \cos(\theta) \end{bmatrix}$$

Do not depend on global coordinates ! Can be computed after map-provider delivered ✔

MAP-PROVIDERS : UNCERTAINTY REPRESENTATION

- Definitions:

$$ {}^{O}\mathbf{X}_i = \begin{bmatrix} {}^{O}x_i \\ {}^{O}y_i \end{bmatrix} $$

$$ {}^{M}\mathbf{R}_O = {}^{O}\mathbf{R}_M{}^T = \begin{bmatrix} \cos(\theta) & \sin(\theta) \\ -\sin(\theta) & \cos(\theta) \end{bmatrix} $$

$$ {}^{M}\mathbf{X}_i = \begin{bmatrix} {}^{M}x_i \\ {}^{M}y_i \end{bmatrix} = {}^{M}\mathbf{R}_O \left(\begin{bmatrix} {}^{O}x_i \\ {}^{O}y_i \end{bmatrix} - \begin{bmatrix} {}^{O}x_M \\ {}^{O}y_M \end{bmatrix} \right) = f({}^{O}\mathbf{X}_M, \theta, {}^{O}\mathbf{X}_i) $$

$$ Var({}^{O}\mathbf{X}_i) = Var({}^{O}\mathbf{X}_{Map}) \forall i = 1..N_i $$

$$ {}^{O}\mathbf{\Sigma}_M = Var\left(\begin{bmatrix} {}^{O}x_M \\ {}^{O}y_M \\ \theta \end{bmatrix} \right) $$

$$ {}^{O}\mathbf{X}_5 = ({}^{O}\mathbf{X}_M, \theta, {}^{O}\mathbf{X}_i) $$

- Then:

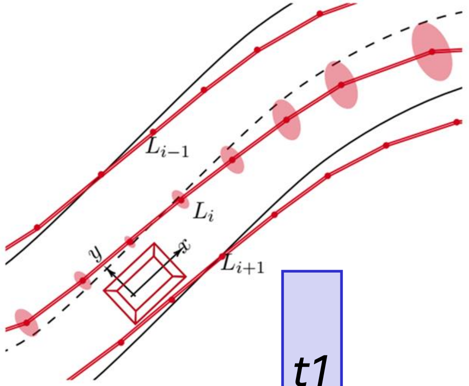
$$ f({}^{O}\mathbf{X}_M, \theta, {}^{O}\mathbf{X}_i) = \begin{bmatrix} ({}^{O}x_i - {}^{O}x_M)\cos(\theta) + ({}^{O}y_i - {}^{O}y_M)\sin(\theta) \\ -({}^{O}x_i - {}^{O}x_M)\sin(\theta) + ({}^{O}y_i - {}^{O}y_M)\cos(\theta) \end{bmatrix} $$

$$ \left[\frac{\partial f}{\partial\, {}^{O}\mathbf{X}_5} \right] = \begin{bmatrix} -\cos(\theta) & -\sin(\theta) & -({}^{O}x_i - {}^{O}x_M)\sin(\theta) + ({}^{O}y_i - {}^{O}y_M)\cos(\theta) & \cos(\theta) & \sin(\theta) \\ \sin(\theta) & -\cos(\theta) & -({}^{O}x_i - {}^{O}x_M)\cos(\theta) - ({}^{O}y_i - {}^{O}y_M)\sin(\theta) & -\sin(\theta) & \cos(\theta) \end{bmatrix} $$

$$ = \begin{bmatrix} -\cos(\theta) & -\sin(\theta) & {}^{M}y_i & \cos(\theta) & \sin(\theta) \\ \sin(\theta) & -\cos(\theta) & -{}^{M}x_i & -\sin(\theta) & \cos(\theta) \end{bmatrix} $$

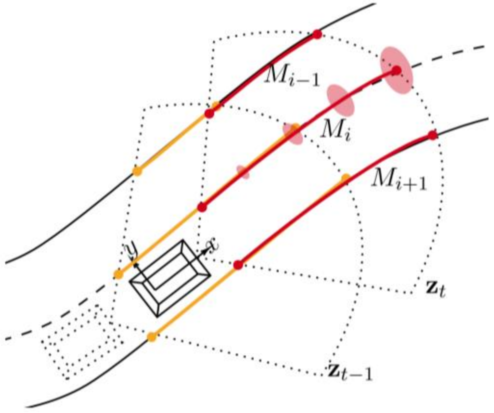
$$ Var({}^{M}\mathbf{X}_i) = \left[\frac{\partial f}{\partial\, {}^{O}\mathbf{X}_5} \right] \begin{bmatrix} {}^{O}\mathbf{\Sigma}_M & \mathbf{0} \\ \mathbf{0} & Var({}^{O}\mathbf{X}_i) \end{bmatrix} \left[\frac{\partial f}{\partial\, {}^{O}\mathbf{X}_5} \right]^T $$

PROPOSED SOLUTION : LANE BOUNDARIES ASSOCIATION

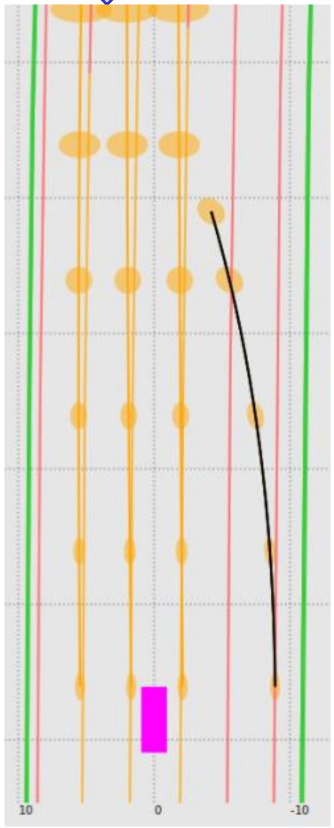


t1

t2

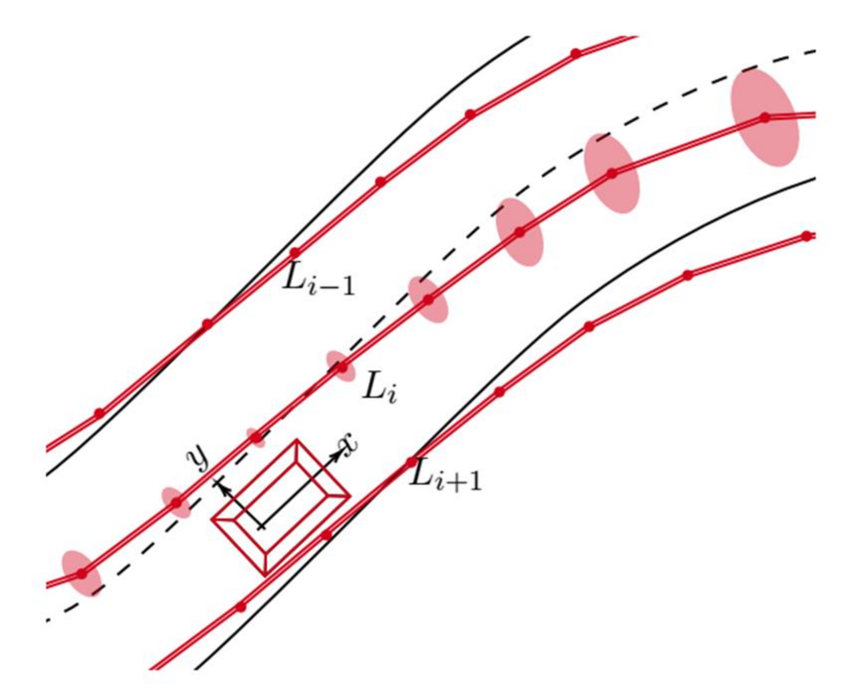


1. Initialization
2. Prediction
3. Association
4. Label



PROPOSED SOLUTION : LANE BOUNDARIES ASSOCIATION

1. **Initialization**
2. Prediction
3. Association
4. Label

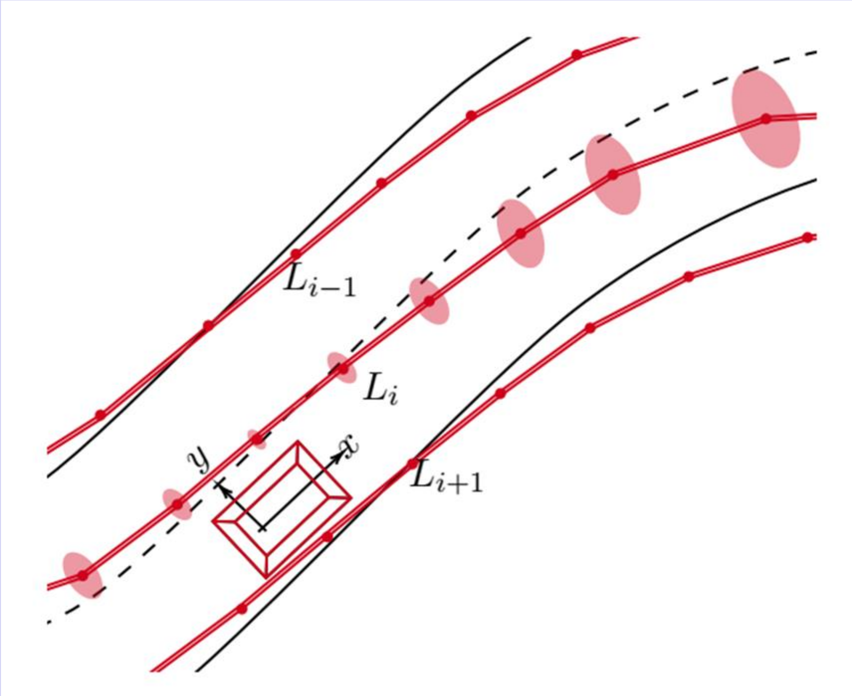


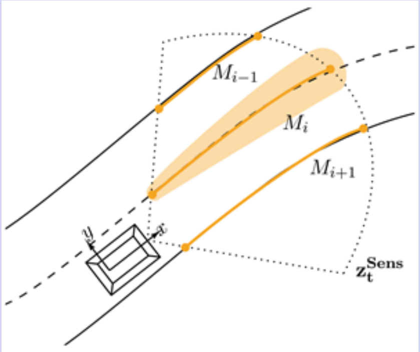
- Road feature are initialized from map-provider delivery and according to mapping and localization error model:

$$F_j = [x_j, y_j, \theta_j, \mathbf{\Sigma}_F] \qquad \mathbf{\Sigma}_F = Var(^M\mathbf{X}_i)$$

PROPOSED SOLUTION : LANE BOUNDARIES ASSOCIATION

1. Initialization
2. **Prediction**
3. Association
4. Label





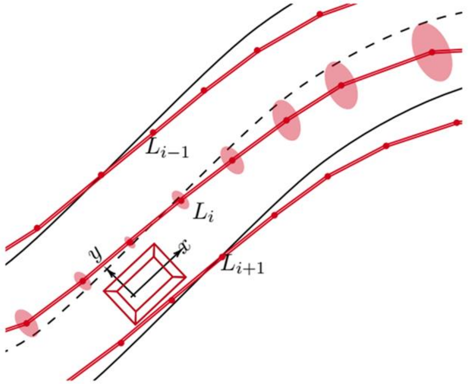
- Predict the status of the (map-provided) road features according to ego-movement estimation:

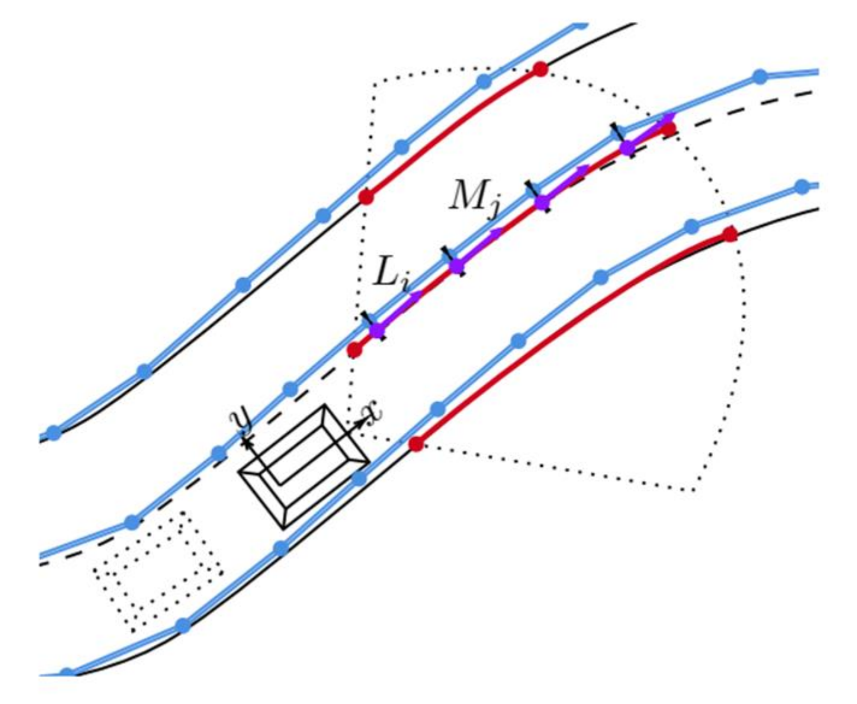
$$\Delta Ego_t = [dx, dy, d\theta, \mathbf{\Sigma}_E]$$
$$\mathbf{w_t} \sim \mathcal{N}(0, \mathbf{\Sigma}_E)$$

- Up to the latest smart sensor delivery measure date

PROPOSED SOLUTION : LANE BOUNDARIES ASSOCIATION

1. Initialization
2. Prediction
3. **Association**
4. Label





- Map-nodes (as road features) are projected onto measurements identifying Feature-to-Feature Mahalanobis distance:

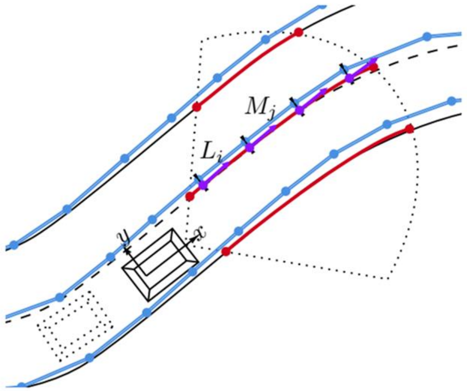
$$d^2(p_\perp(F_j), F_j) = (p_\perp(F_j) - F_j)^T({}^M\mathbf{\Sigma}_F + Var({}^M\mathbf{X}_i))^{-1}(p_\perp(F_j) - F_j)$$

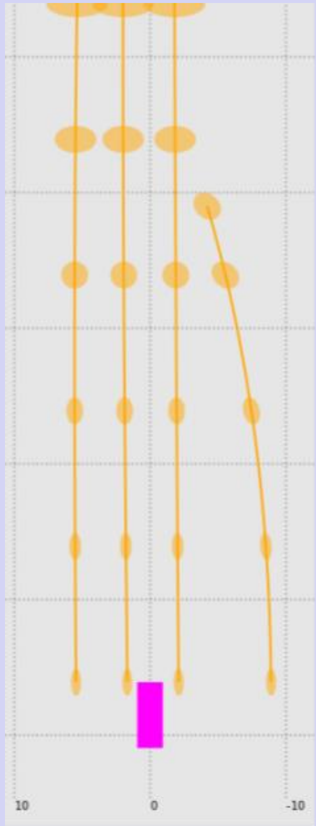
- *M* to *L* distance metric for GNN association:

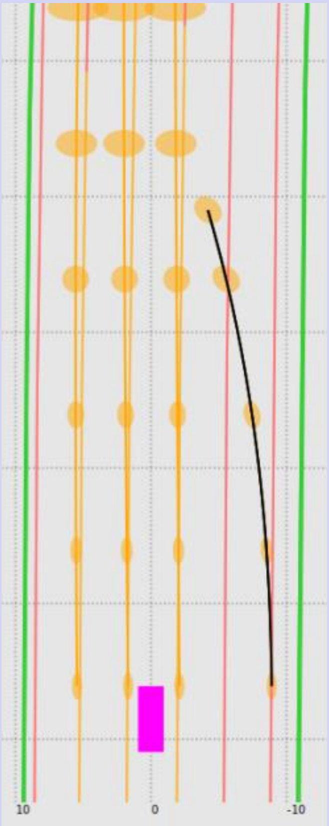
$$d(M, L) = \max_{F_j \in L} d(p_\perp(F_j), F_j)$$

PROPOSED SOLUTION : LANE BOUNDARIES ASSOCIATION

1. Initialization
2. Prediction
3. Association
4. **Label**







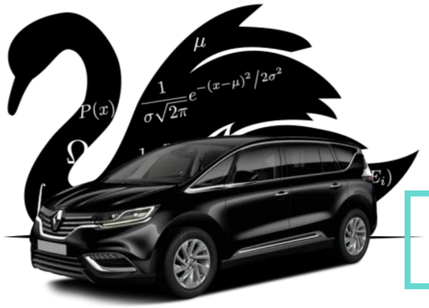
- The HD-map is supposed to be complete of all detectable lane boundaries
- Then Non-Associated smart sensor measurements are **labeled** as False Positives

EXPERIMENTAL RESULTS

1. Development setup
2. Application for false positives detection
3. Scoring for multiple hypotheses of ego-vehicle localization

EXPERIMENTAL RESULTS

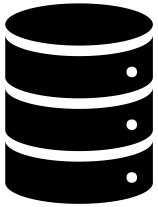
- Development setup



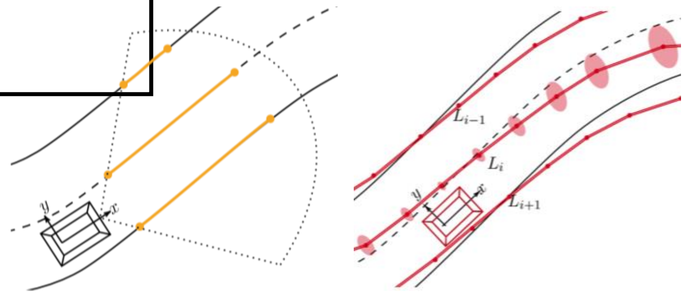
- Proprioceptives
- **eHorizon**
  1Hz, FoV: 360°x 200 m
- **Smart FrontCam**
  30Hz, FoV: 53°x 120 m
- **Smart AVM** (4 cameras)
  20Hz, FoV: 360°x 20 m

Sensors

Recording data



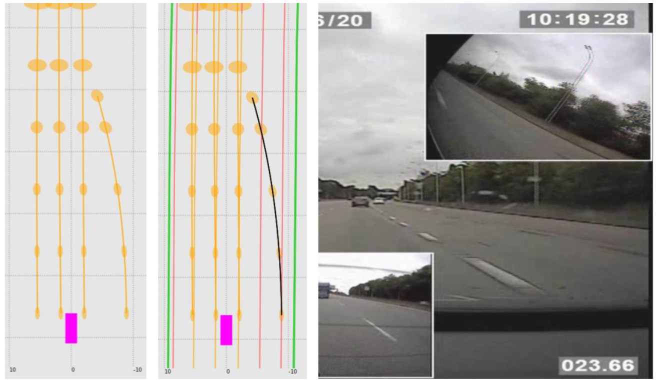
Re-playing data



Fusionrunner environment

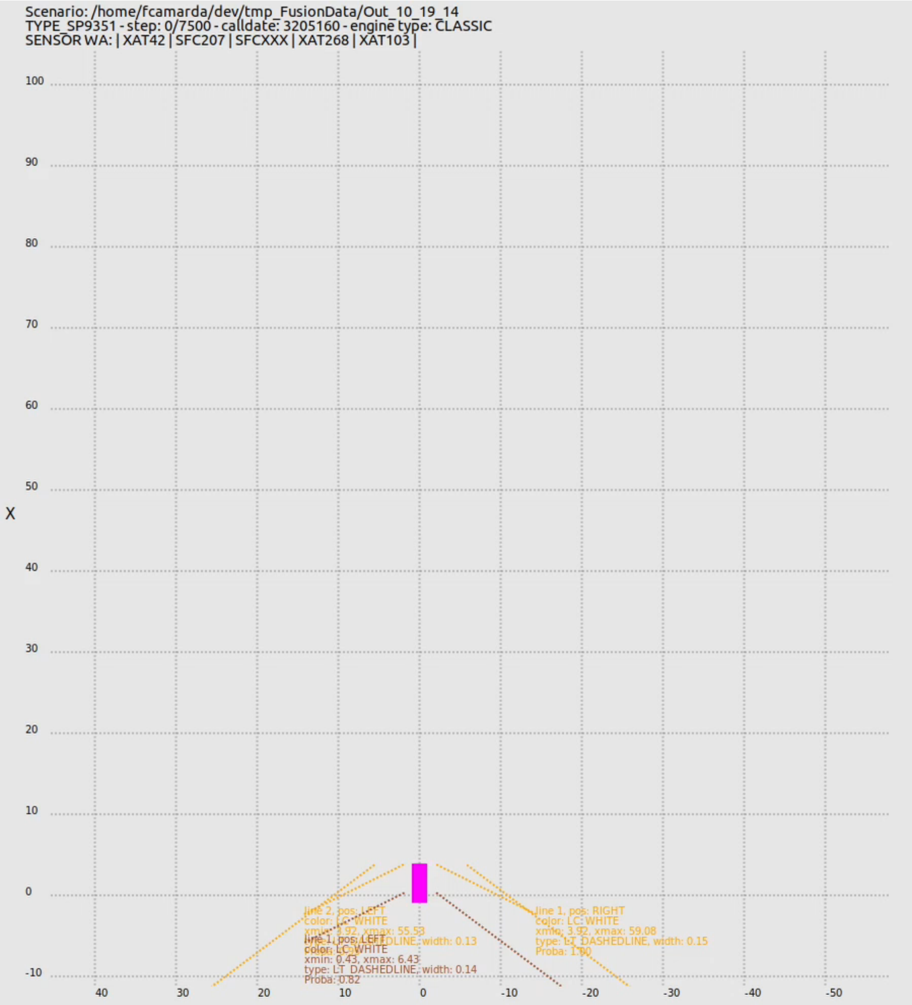
- Object tracking
- ...
- Ego-motion tracking
- Lane boundary tracking

Fusion results and context camera



EXPERIMENTAL RESULTS

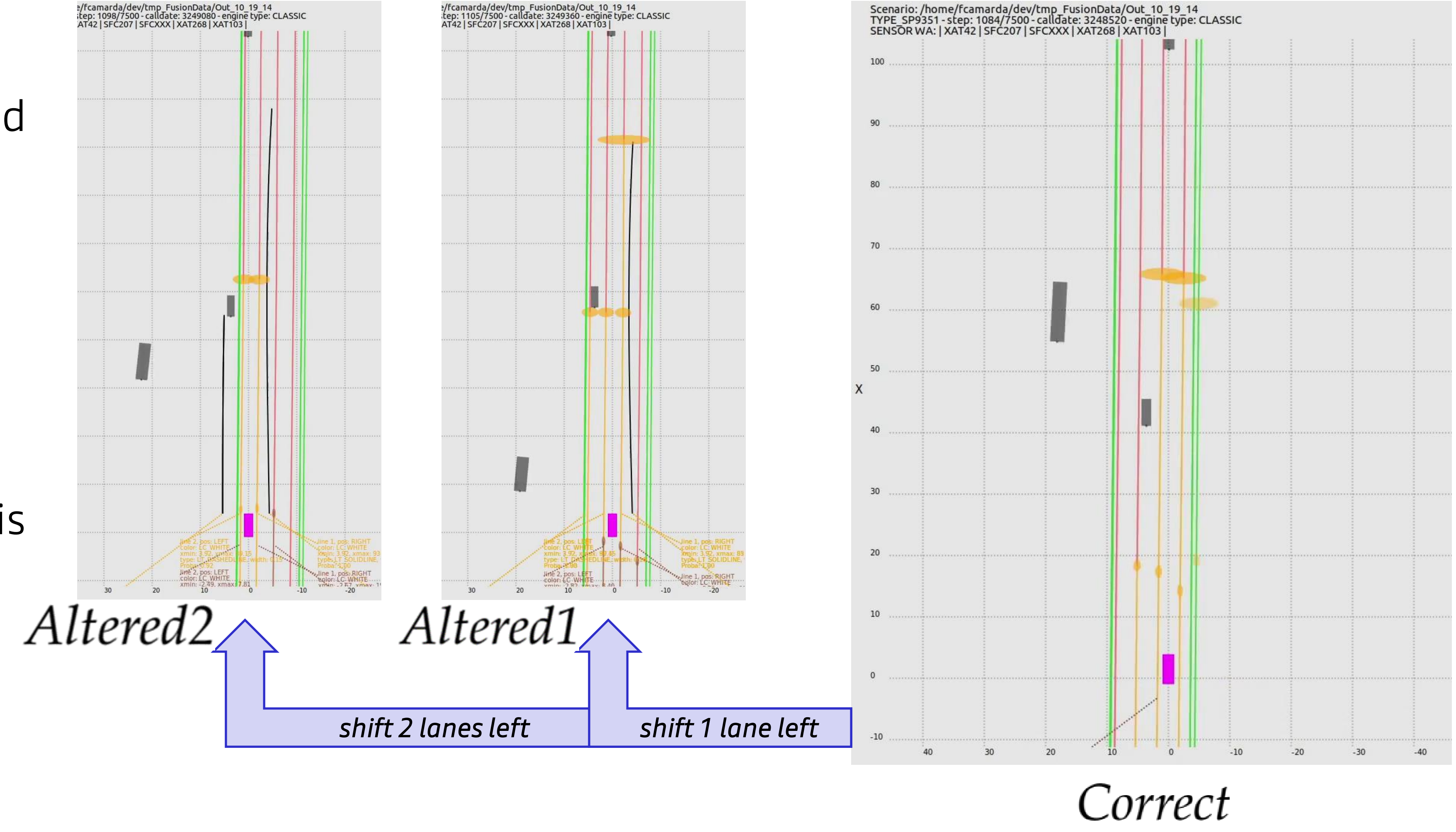
- Execution in *Fusionrunner* environment : qualitative evaluation



- Ego-vehicle
- Other vehicles
- **Map lane b.** (road markings)
- **Map lane b.** (barriers)
- Map lane b. **associated to Smart FrontCam** measurements
- Map lane b. **associated to Smart AVM** measurements
- Road features uncertainty
- **Non-associated** Smart Sensor measurements

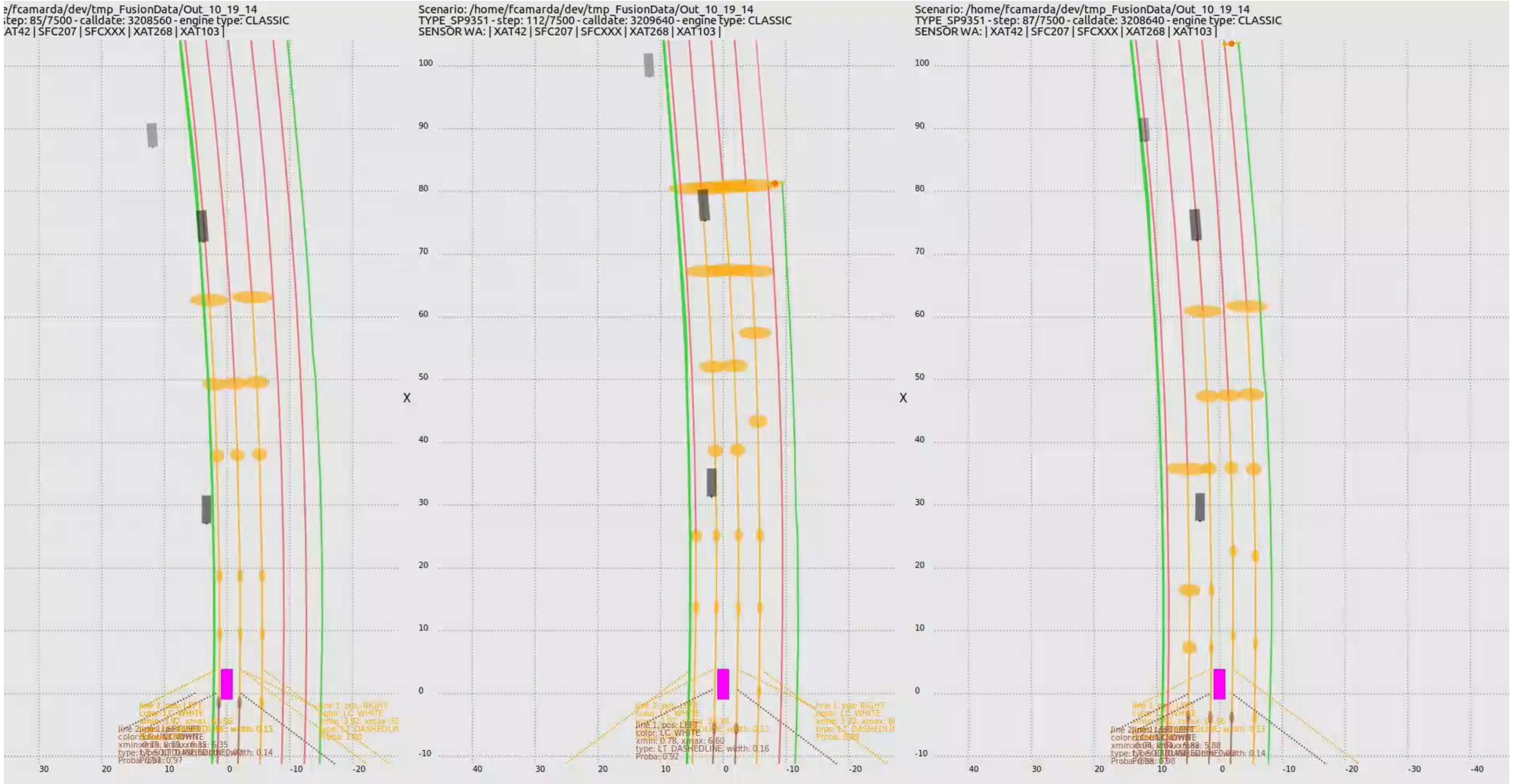
EXPERIMENTAL RESULTS : METHOD VALIDATION

- Execution in ***Fusionrunner*** environment : simulated localization fault generation
- In absence of better ground truth, two alterations of the recorded data are generated:
  - ***Correct*** *(authentic)*
  - ***Altered1*** *(shifted 1 lane left)*
  - ***Altered2*** *(shifted 2 lanes left)*
- Context camera can confirm which alteration is correct



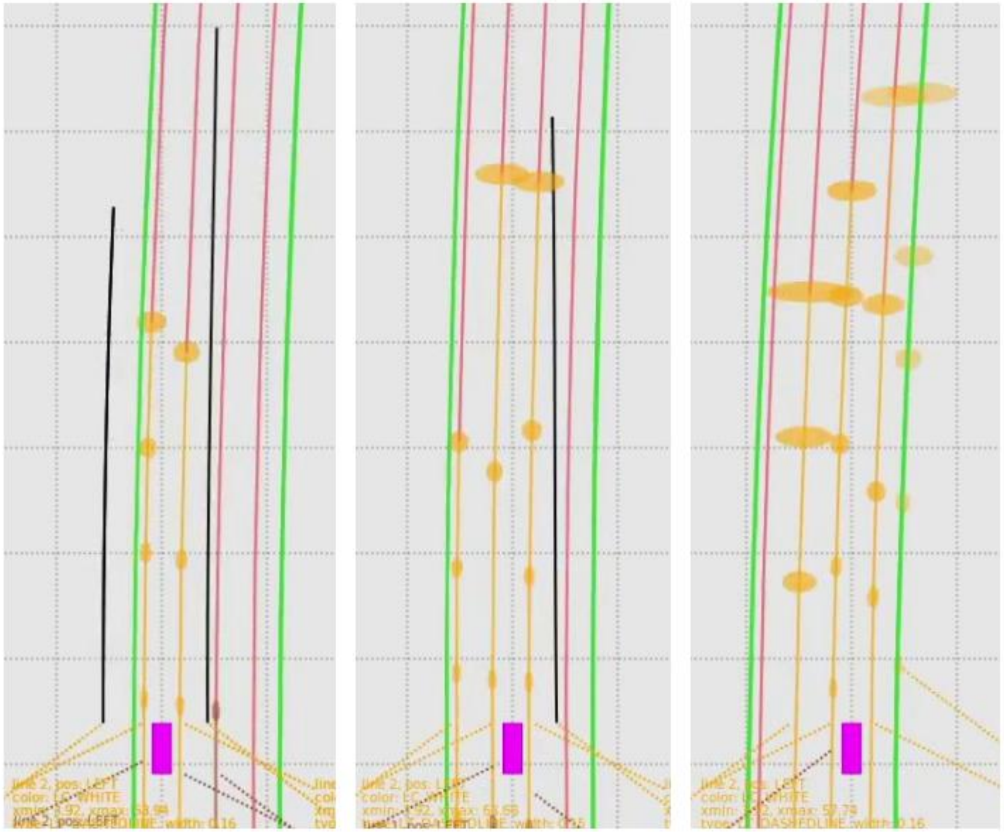
EXPERIMENTAL RESULTS : METHOD VALIDATION

- Execution in ***Fusionrunner*** environment : three variations of same data record



Confidential C

EXPERIMENTAL RESULT : METHOD VALIDATION

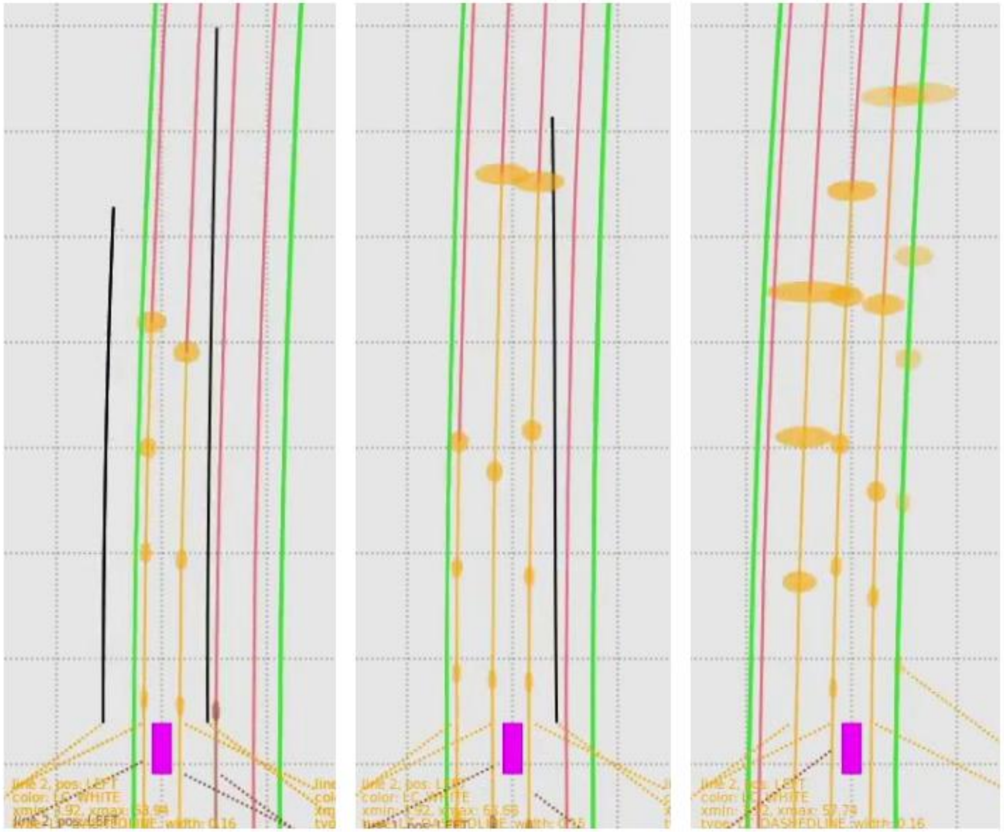


Altered2	*Altered1*	*Correct*
#FP = 2	#FP = 1	#FP = 0
#TP = 2	#TP = 3	#TP = 4
Precision = 0,5	Precision = 0,75	Precision = 1

- Enumerating FP and TP within a sliding window of 5 seconds, the ***Precision*** indicator is defined:

$$Precision(t-5,t) = \frac{TP}{TP+FP}$$

EXPERIMENTAL RESULT : METHOD VALIDATION



Altered2	*Altered1*	*Correct*
#FP = 2	#FP = 1	#FP = 0
#TP = 2	#TP = 3	#TP = 4
Precision = 0,5	Precision = 0,75	Precision = 1

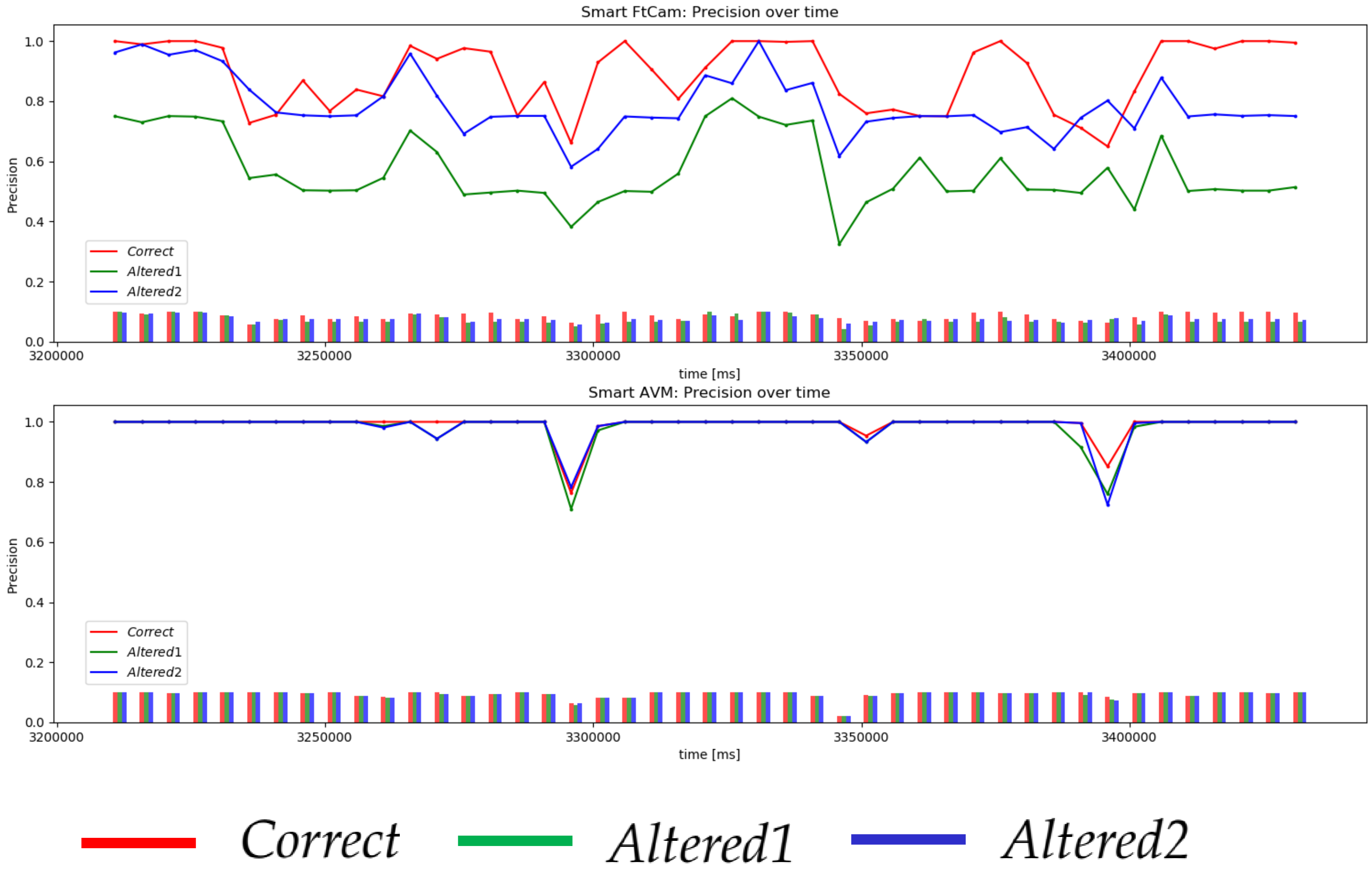
- Enumerating FP and TP within a sliding window of 5 seconds, the ***Precision*** indicator is defined:

$$Precision(t-5,t) = \frac{TP}{TP+FP}$$

Question : can the the **Precision** indicator **discriminate faulty localization** of ego-vehicle?

Localization in HD-map is incorrect → Method detects more FPs from sensors → Proposed association method is validated ✔

EXPERIMENTAL RESULTS



- The proposed method can **successfully detect** altered localization
  - If information in sensor delivery is enough (FrontCam > AVM)
- This detection is confirmed using Smart FrontCam and indicator ***Precision(0,end)***:

	Smart FrontCam	Smart AVM
Correct	89.43%	99.07%
Altered1	57.31%	98.31%
Altered2	79.00%	98.60%

SECTION CONCLUSIONS

Lane boundaries probabilistic association method has been introduced and implemented

Detection of false positives measurements from smart sensors validated the proposed method

Application of the method for **scoring multiple hypothesis of ego-vehicle localization** reveals Smart FrontCam can better detect a localization fault rather than Smart AVM

✓ Work resulted in pending application for **Renault/UTC/CNRS patent**

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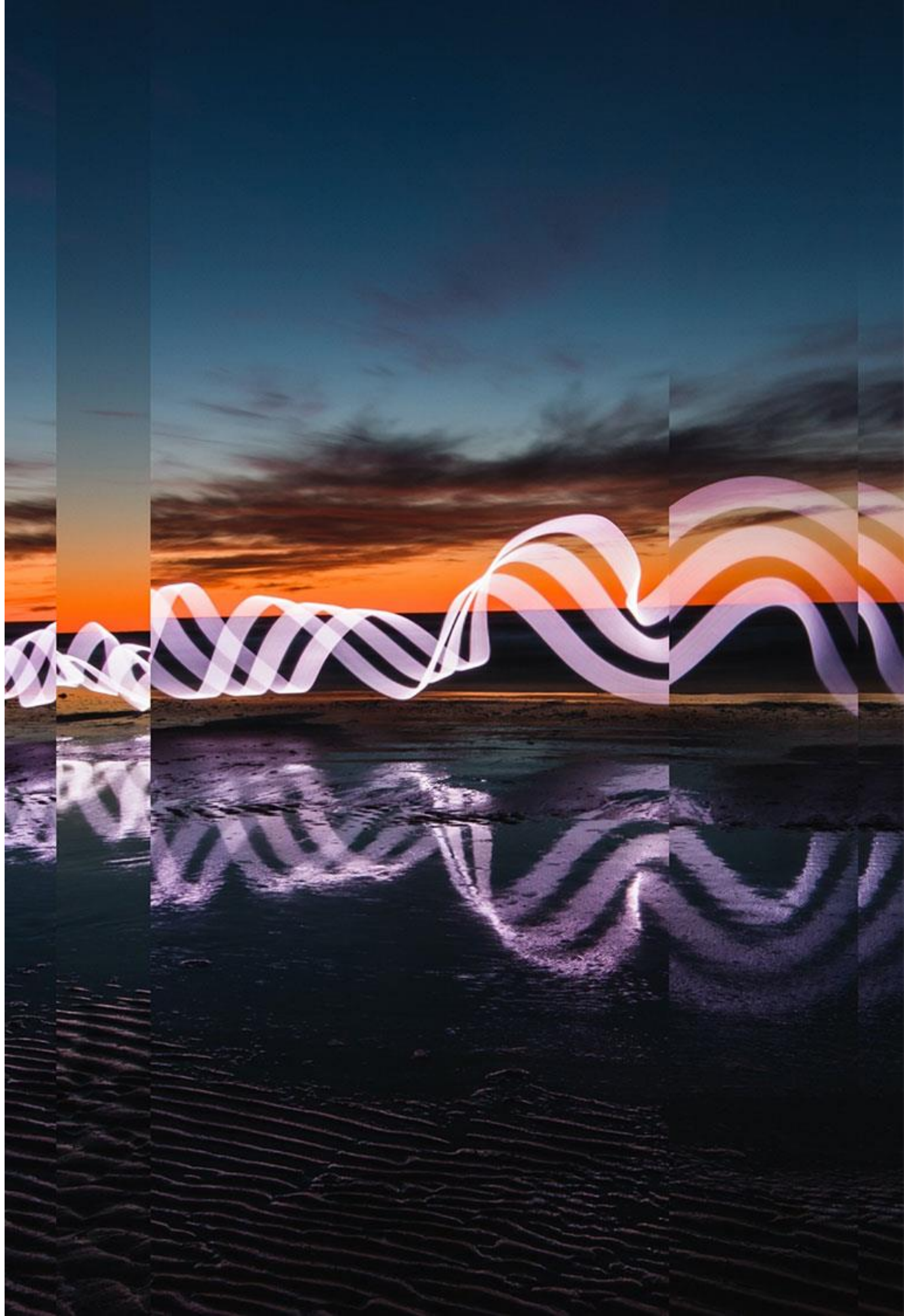
Conclusion



THESIS CONTRIBUTIONS

- **Feature-tracking**, method for multi-sensor fusion of lane boundaries issued of smart sensors
  - Deployed on-vehicle in Renault L3 experimentations
- **Quantitative evaluation** w.r.t. HD-map of lane boundaries tracking methods in terms of lateral RMSE
  - Resulted in a publication at international conference IV2020
- **Lane boundaries probabilistic association** method enabling measure-to-track pairing in our tracking proposals
  - Resulted in application for Renault/CNRS patent
- **Map-tracking**, method for multi-sensor fusion of lane boundaries issued of smart sensors and map-providers (not presented)
- Usage of **Precision** metric enabling false-positives detection and multi-hypotheses localization scoring

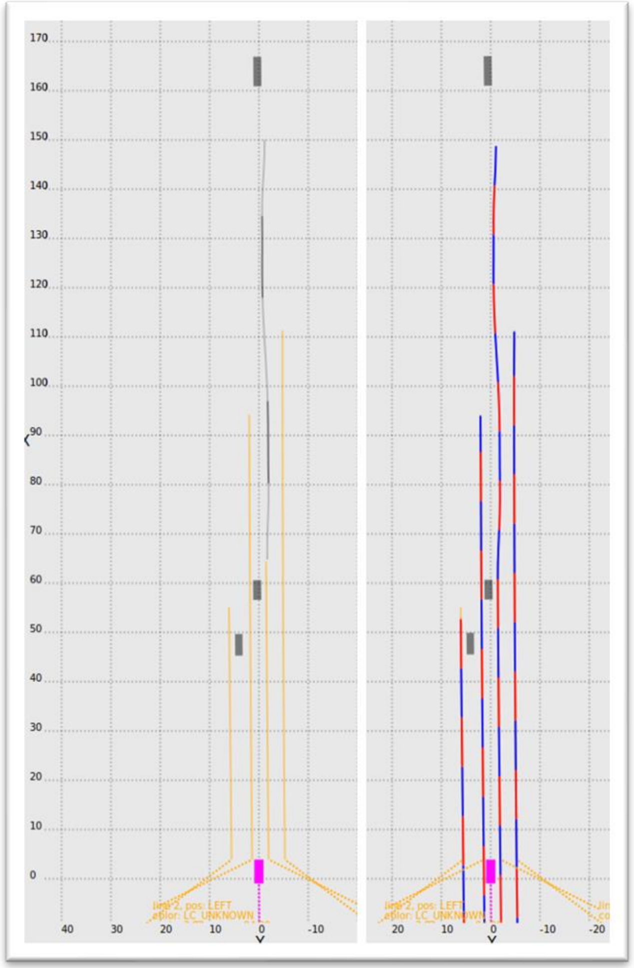
References :

F. Camarda, F. Davoine, V. Cherfaoui, B. Durand. *Multisensor Tracking of Lane Boundaries based on Smart Sensor Fusion*. IEEE Intelligent Vehicles Symposium (IV 2020), Oct 2020, Las Vegas, United States.

F. Camarda, B. Durand, F. Davoine, V. Cherfaoui. *Procédé de détection d’une limite d’une voie de circulation*. Renault/UTC/CNRS patent. Applied for French patenting at Institut National de la Propriété Industrielle (INPI) under the identifier n°2110938, Oct 2021.

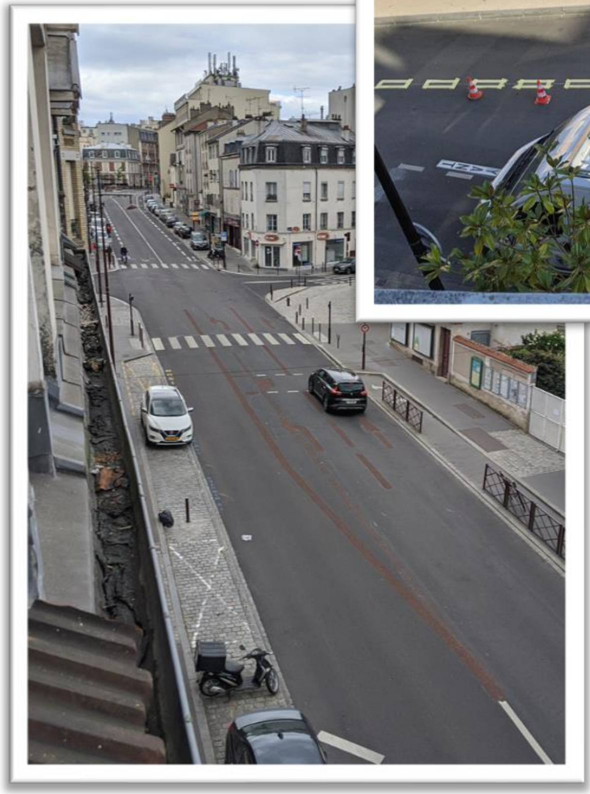
RESEARCH PERSPECTIVES

- Integrate other vehicles trails in data fusion
  - Range extension



- Release *"unvarying HD-map"* assumption
  - Lane boundaries can evolve!

Compiègne, April 2021



Versailles, April 2020

Thank you

Questions, domande, questions