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Embedded Sensor Fusion and Perception for Autonomous Vehicle

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Embedded Sensor Fusion & Perception for Autonomous Vehicles

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IS Auto Europe 2019
Berlin, Germany, 9-10 April 2019

Technology status & Ongoing challenges for AV

- Strong involvement of Car Industry & GAFA + Large media coverage
- An expected market of 500 B€ in 2035... *but Legal & Regulation issues still unclear*
- Technologies Validation & Certification => *Numerous experiments in real traffic conditions since 2010 (Disengagement reports ↔ Insights on system maturity)*
=> *But insufficient ... Realistic Simulation & Formal methods are also needed (e.g. EU Enable-S3)*



Tesla Autopilot L2 with Radar & Mobileye/Intel
Commercial ADAS product => Tested by customers



Drive Me trials (Volvo, 2017)
• 100 Test Vehicles in Göteborg, 80 km, 70km/h
• No pedestrians & Plenty of separations between lanes

Future Mobility Services

EU CityMobil project & Inria

Google WAYMO

Google

UBER

nuTonomy

Numerous EU projects in last 2 decades
Cybus, 3 months experimental low speed
La Rochelle 2012

Dense 3D mapping & Numerous vehicles
10 years R&D, 8 millions km covered since 2010 & 25 000 km/day

“Self-Driving Taxi Service” testing in US (Uber, Waymo) & Singapore (nuTonomy)

- ⇒ *Autonomous Mobility Service, Numerous Sensors + “Safety driver” during testing*
- ⇒ *Uber: System testing since 2017, Disengagement every 0.7 miles in 2017 (improved now)*
- ⇒ *Waymo: 1st US Self Driving Taxi Service launched in Phoenix in Dec 2018*
- ⇒ *Disengagement reports provide insights on the technology maturity*

Millions of miles driven since 2010 (Google, Tesla, Waymo, Uber...)
Several benign & serious accidents in past few years
Safety is still not guaranteed!

Safety issue: *Tesla Autopilot “level 2” fatal accident (May 2016)*

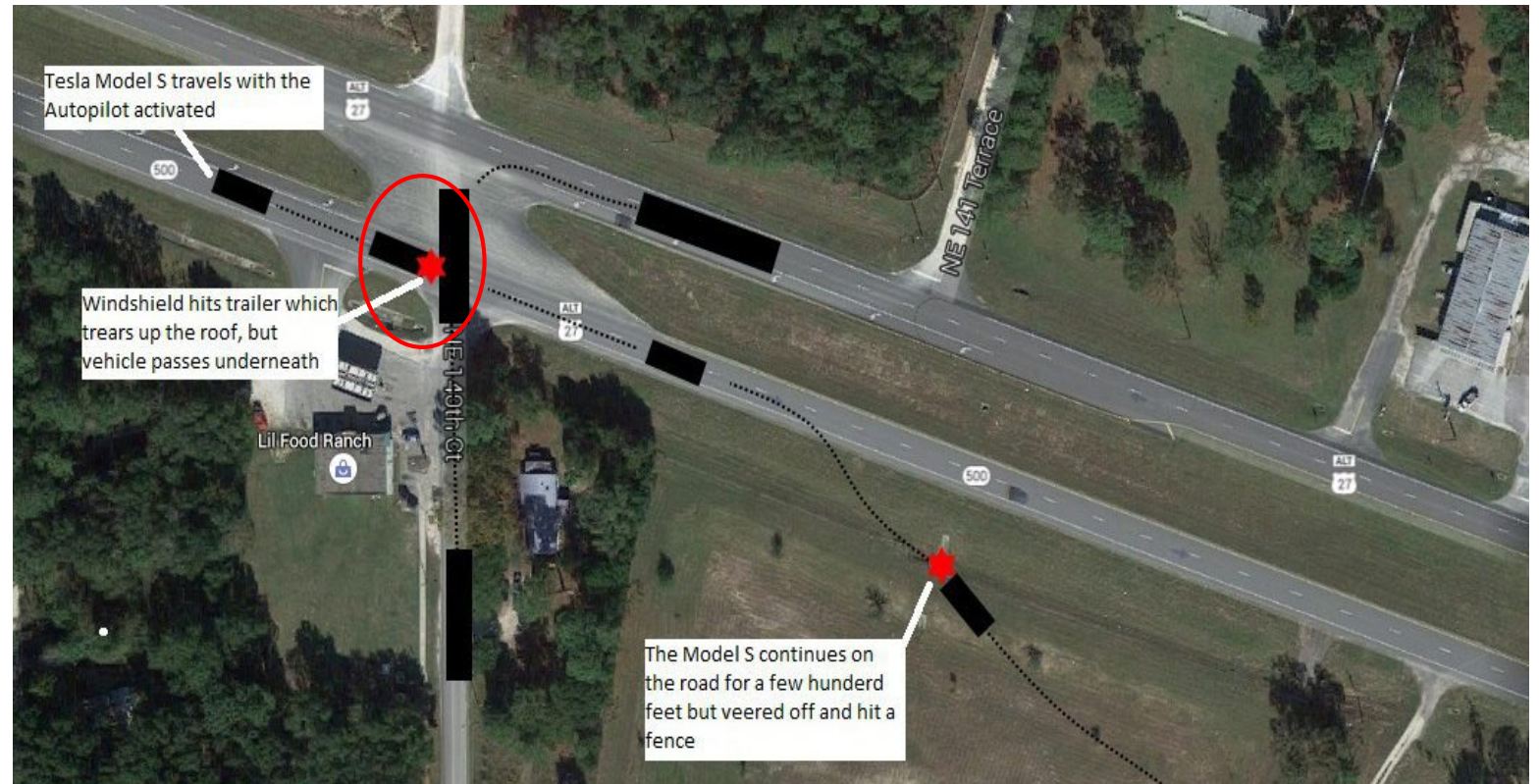
- ❑ Tesla driver killed in a crash with Autopilot “level 2” active (ADAS mode)
- ❑ The Autopilot failed to detect a white moving truck, with a brightly lit sky
 - *Camera => White color against a brightly lit sky ?*
 - *Radar => High height of the trailer probably confused the radar into thinking it is an overhead road sign ?*
- ❑ The human driver was not vigilant



Tesla Model S – Autopilot

Front perception:

Camera (Mobileye) + Radar + US sensors



Safety issue: *Uber “level 3” AV fatal accident (March 2018)*

- ❑ **Self-driving Uber AV kills a woman in the first fatal crash involving a pedestrian**
Tempe, Arizona, March 2018
- ❑ **The vehicle was moving at 40 mph and didn't reduced its speed before the crash**
 - *Despite the presence of multiple sensors, the perception system failed to detect the pedestrian in a poor lighting condition*
 - *The AV didn't disengaged*
- ❑ **The Safety Driver reacted too late** => *He was not attentive enough, and he reacted less than 1s before the crash & started to brake 1s after the crash*



Embedded Perception & Scene Understanding – Overview

Complex Dynamic Scenes understanding



Situation Awareness & Decision-making

- ⇒ Sensing + Prior knowledge + Interpretation
- ⇒ Navigation strategy



Perception & Decision-making for Safe Intentional Navigation

Dealing with unexpected events

e.g. Road Safety Campaign, France 2014



Anticipation & Prediction

for avoiding upcoming accidents

- ⇒ Focus of Attention + Sensing + Collision Risk
- ⇒ Collision avoidance strategy

Main features

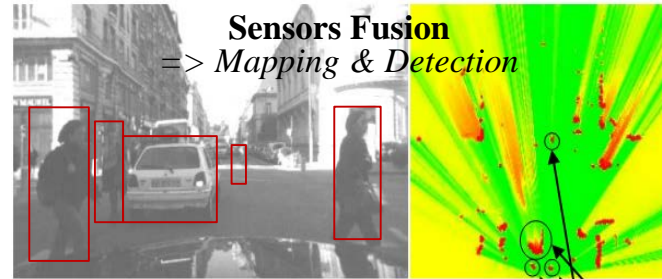
- ✓ Dynamic & Open Environments ⇒ *Real-time processing & Reactivity*
- ✓ Incompleteness & Uncertainty ⇒ *Appropriate Model & Algorithms (probabilistic approaches)*
- ✓ Sensors limitations (no sensor is perfect) ⇒ *Multi-Sensors Fusion*
- ✓ Hardware / Software integration ⇒ *Satisfying Embedded constraints*
- ✓ Human in the loop (mixed traffic) ⇒ *Human Aware Decision-making*
Taking into account Interactions + Behaviors + Social rules (including traffic rules)

Paradigm 1: Embedded Bayesian Perception



Embedded Multi-Sensors Perception

⇒ *Continuous monitoring of the dynamic environment*



❑ Main challenges

- ✓ *Noisy data, Incompleteness, Dynamicity, Discrete measurements*
- ✓ *Strong Embedded & Real time constraints*

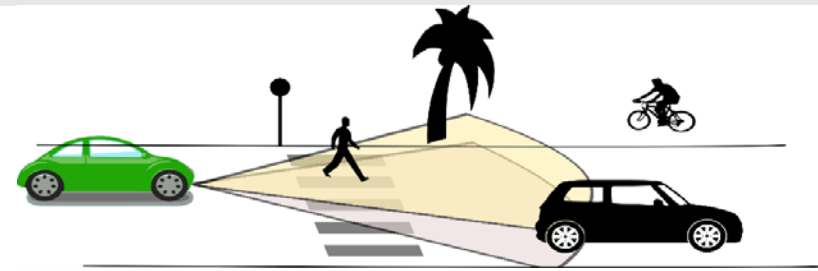
❑ Our Approach: Embedded Bayesian Perception

- ✓ *Reasoning about Uncertainty & Time window (Past & Future events)*
- ✓ *Improving robustness using Bayesian Sensors Fusion*
- ✓ *Interpreting the dynamic scene using Contextual & Semantic information*
- ✓ *Software & Hardware integration using GPU, Multicore, Microcontrollers...*

Bayesian Perception : Basic idea

□ Multi-Sensors Observations

Lidar, Radar, Stereo camera, IMU ...



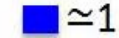


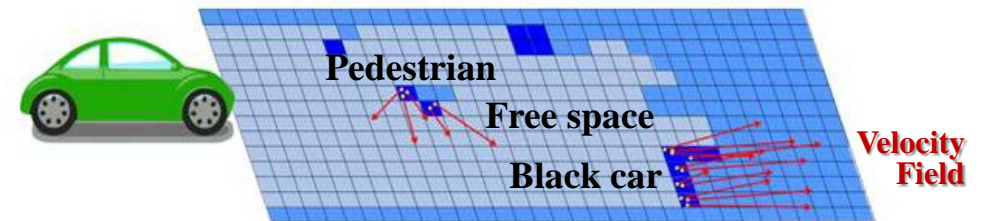
Bayesian
Multi-Sensors Fusion

Real-time

□ Probabilistic Environment Model

- ✓ *Sensor Fusion*
- ✓ *Occupancy grid integrating uncertainty*
- ✓ *Probabilistic representation of Velocities*
- ✓ *Prediction models*

$P[o|Z,C]$:  $\simeq 0$  $\simeq 0.5$  $\simeq 1$



Concept of “Dynamic Probabilistic Grid”

⇒ *Occupancy & Velocity probabilities*

⇒ *Embedded models for Motion Prediction*

□ Main philosophy

Reasoning at the grid level as far as possible for both :

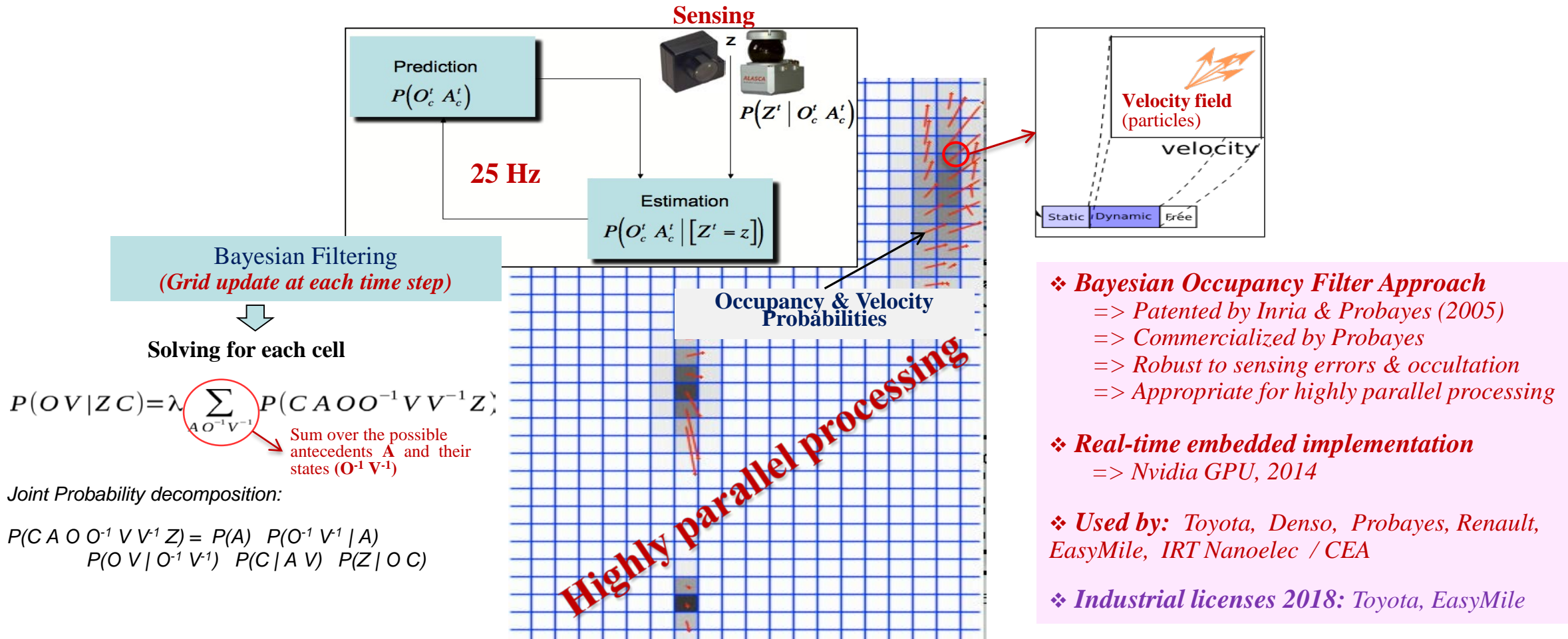
- *Improving efficiency => highly parallel processing*
- *Avoiding traditional object level processing problems (e.g. detection errors, wrong data association...)*

The “Dynamic Probabilistic Grids” paradigm

- ⇒ A more and more popular approach for Autonomous Vehicles
- ⇒ A clear distinction between Static & Dynamic & Free components

Pioneer concept of “Bayesian Occupancy Filter” (Inria)

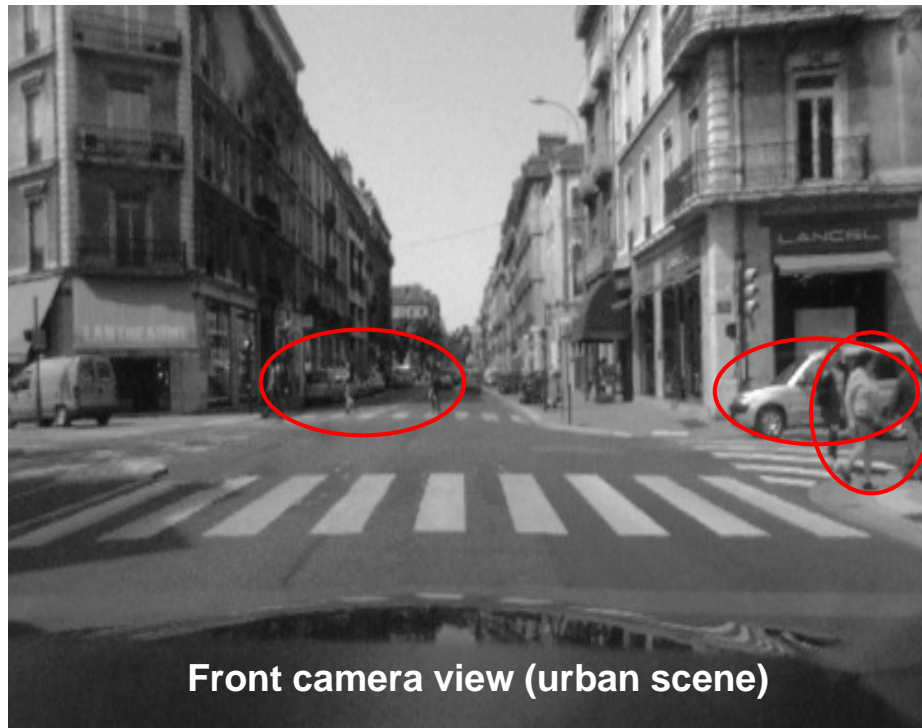
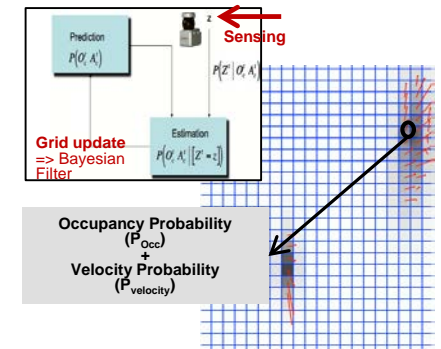
[PhD Thesis Coué 2005] [Coué & Laugier IJRR 05] [Laugier et al ITSM 2011] [Laugier, Vasquez, Martinelli Mooc uTOP 2015]



Bayesian Occupancy Filter Approach – *Main Features*

=> *Exploiting the Dynamic Information for a better understanding of the scene*

- ❑ Estimate **Spatial occupancy** for each cell of the grid $P(O|Z)$
- ❑ **Grid update** is performed in each cell in parallel (using *BOF equations*)
- ❑ **Extract Motion Field** (using *Bayesian filtering & Fused Sensor data*)
- ❑ **Reason at the Grid level** (i.e. *no object segmentation at this reasoning level*)



Front camera view (urban scene)

Sensors data fusion
+
Bayesian Filtering
+
Extracted Motion Fields



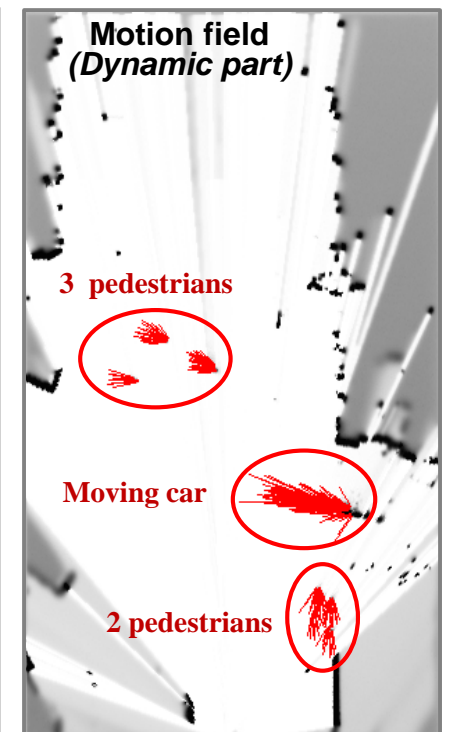
HSBOF

*1st Embedded & Optimized
version (patent 2014)*



Occupancy Grid
(static part)

Free space
+
Static obstacles



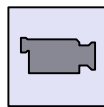
Motion field
(Dynamic part)

3 pedestrians

Moving car

2 pedestrians

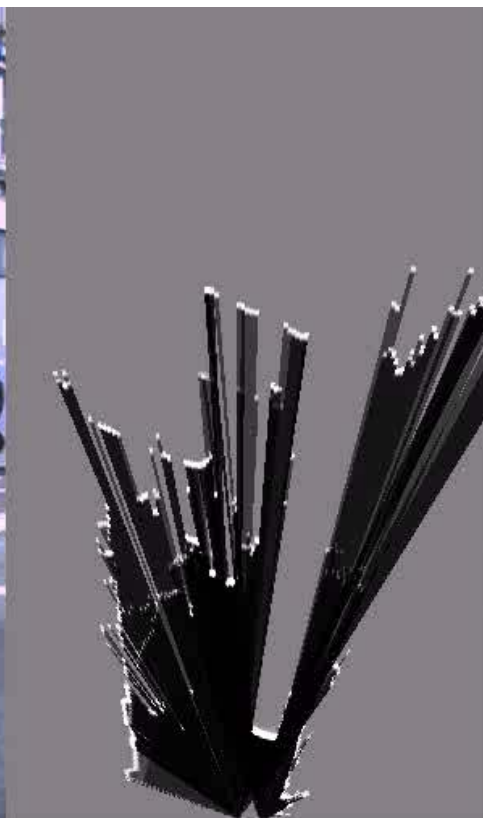
Experimental Results in dense Urban Environments



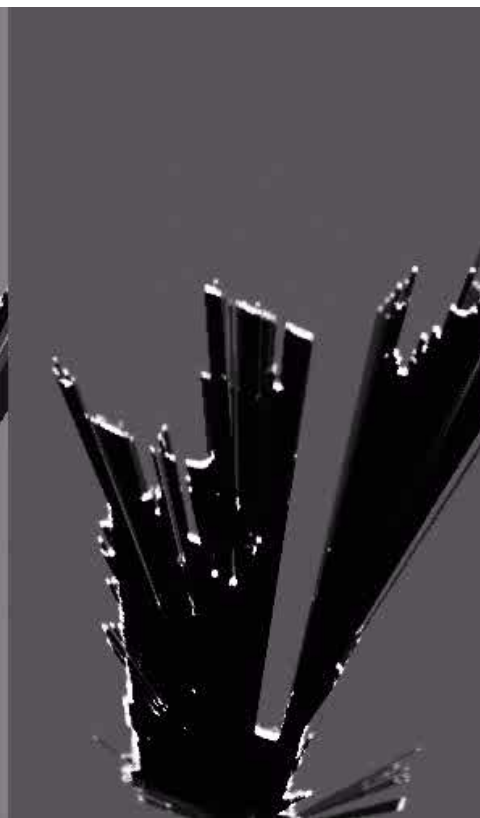
Observed Urban Traffic scene



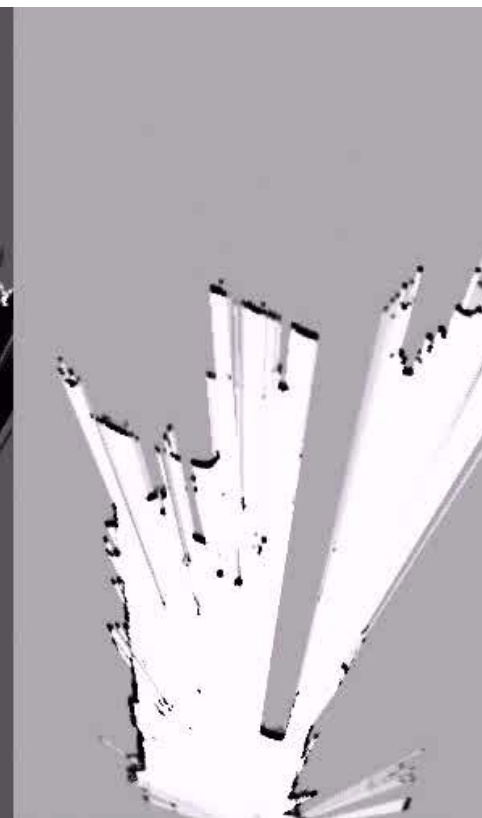
Ego Vehicle (*not visible in the video*)



OG Left Lidar



OG Right Lidar



OG Fusion
+
Velocity Fields

Patented Improvements & Implementations



=> Several models & implementations more and more adapted to *Embedded constraints & Scene complexity*

❖ Hybrid Sampling Bayesian Occupancy Filter (HSBOF, patent 2014)

[Negre et al 14]
[Rummelhard et al 14]

=> *Drastic memory size reduction (factor 100) + Increased efficiency (complex scenes)*
+ *More accurate Velocity estimation (using Particles & Motion data from ego-vehicle)*

❖ Conditional Monte-Carlo Dense Occupancy Tracker (CMCDOT, 2015)

[Rummelhard et al 15]

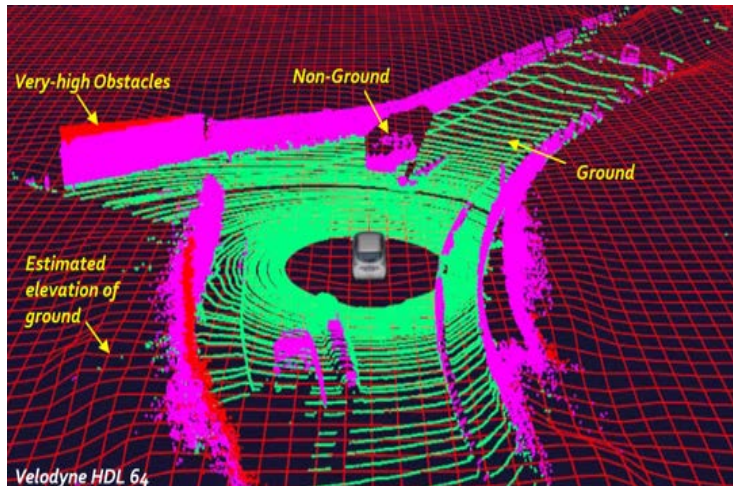
=> *Increased efficiency using “state data” (Static, Dynamic, Empty, Unknown) + Integration of a “Dense Occupancy Tracker” (Object level, Using particles propagation & ID)*



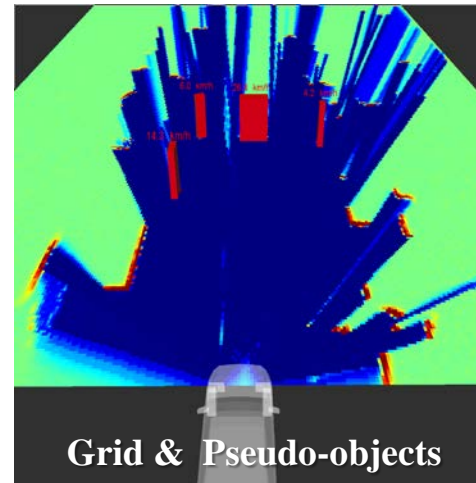
❖ CMCDOT + Ground Estimator (Patent 2017)

[Rummelhard et al 17]

=> *Ground shape estimation & Improve obstacle detection => Avoid false detections on the ground surface*



Ground Estimation & Point Cloud Classification (2017)



Grid & Pseudo-objects



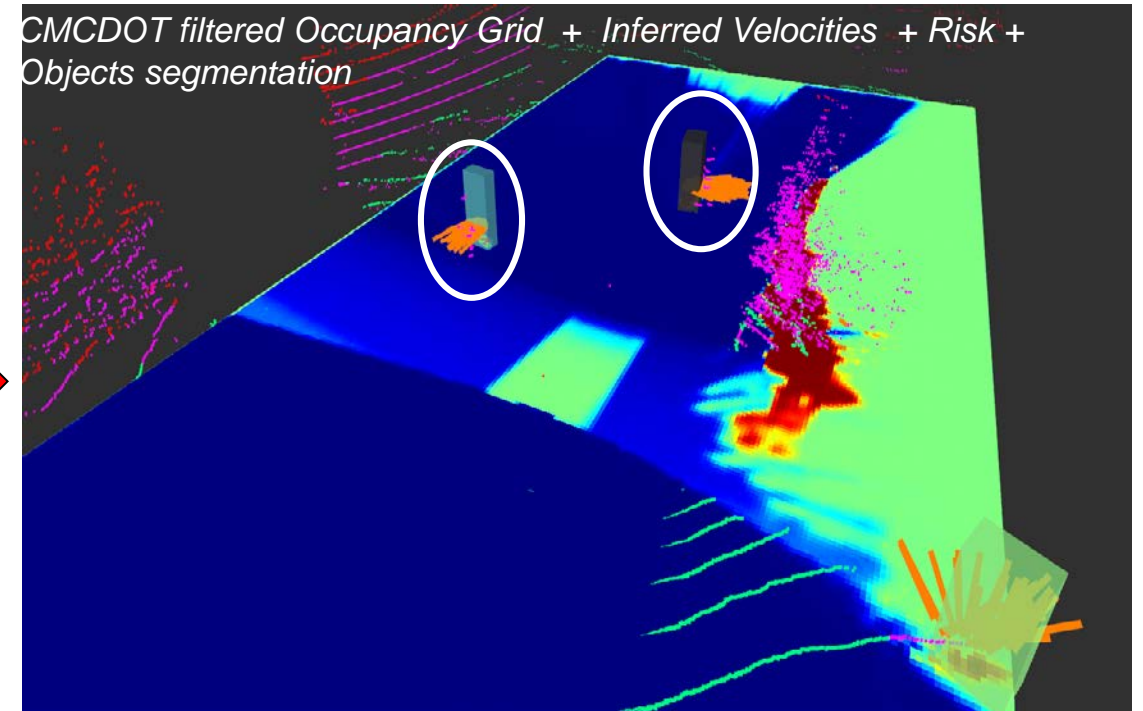
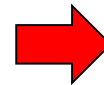
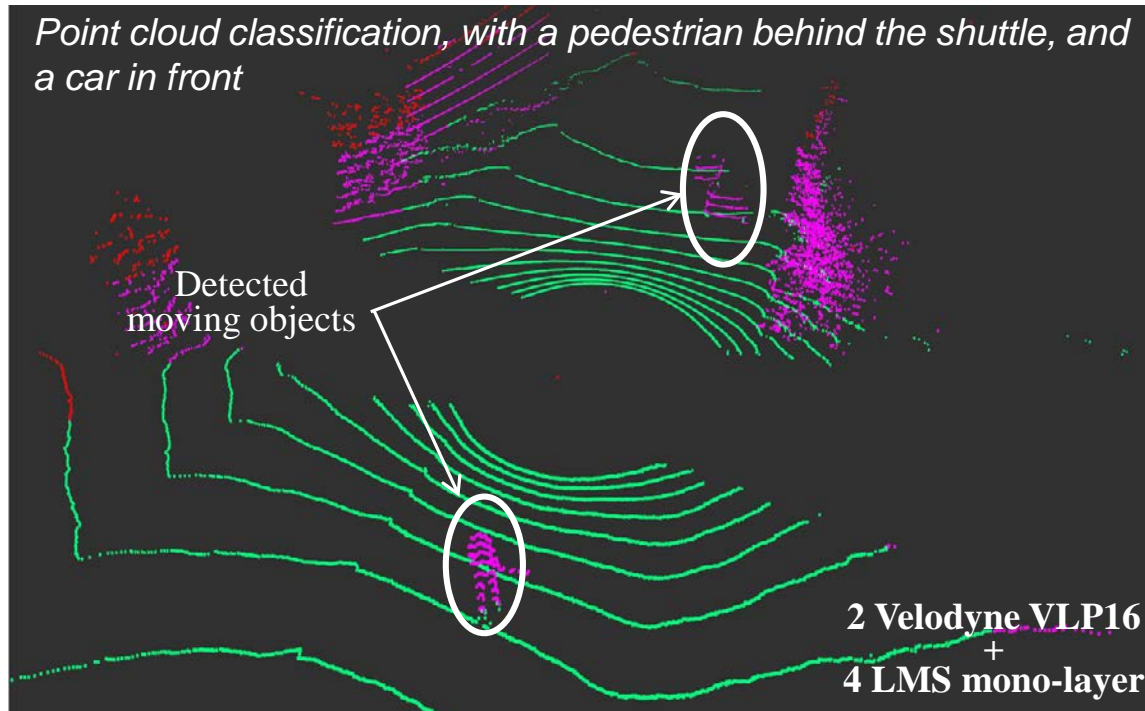
Classification (using Deep Learning)

Moving Objects Detection & Tracking & Classification (2015)

System Integration on a commercial vehicle (2018)

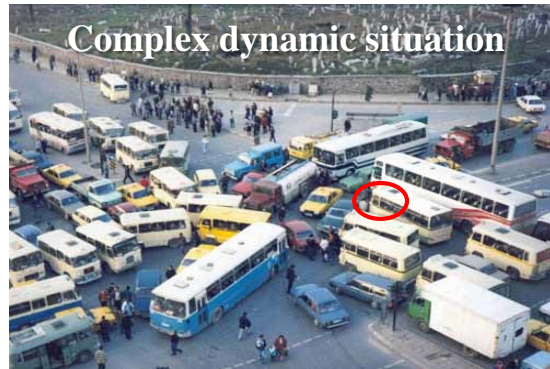


- **POC 2018: Complete system implemented on Nvidia TX1**, and easily connected to the shuttle system network *in a few days* (using ROS)
- **Shuttle sensors data** has been fused and processed in **real-time**, with a successful Detection & Characterization of the **Moving & Static Obstacles**
- **Full integration on a commercial product** under development with an industrial company (confidential)



Paradigm 2: Risk Assessment & Decision-making

=> *Decision-making for avoiding Pending & Future Collisions*



□ Main challenges

*Uncertainty, Partial Knowledge, World changes, Real time
Human in the loop + Unexpected events*

□ Approach: Prediction + Risk Assessment + Bayesian Decision-making

- ✓ *Reason about Uncertainty & Contextual Knowledge (using History & Prediction)*
- ✓ *Estimate Probabilistic Collision Risk at a given **time horizon** $t+\delta$ ($\delta =$ a few seconds)*
- ✓ *Make Driving Decisions by taking into account the **Predicted behavior** of all the observed surrounding traffic participants (cars, cycles, pedestrians ...) & **Social / Traffic rules***

□ Two levels of collision risk have to be considered

- ✓ *Short-term collision risk => Imminent collisions, time horizon $<3s$, conservative hypotheses*
- ✓ *Long-term collision risk => Future potential collisions, context & semantics, behavior models*

Concept 1: Short-term collision risk – *Basic idea*

How to deal with unexpected events ? => Exploit previous observations for anticipating a potential future collision

Autonomous
Vehicle (Cycab)



Parked Vehicle
(occultation)

**Pioneer Results
(2005)**

*[PhD Thesis C. Coué 2004]
[Coué & Laugier IJRR 05]*

Thanks to the prediction capability of the BOF technology, the Autonomous Vehicle “anticipates” the pedestrian motion and brakes
(even if the pedestrian is temporarily hidden by the parked vehicle)

Short-term collision risk – *Main features*

=> *Grid level & Conservative motion hypotheses (proximity perception)*

□ Main Features

- Detect “**Risky Situations**” a few seconds ahead (3-5s)
- Risky situations are **both localized in Space & Time**
 - ⇒ *Conservative Motion Prediction in the grid (Particles & Occupancy)*
 - ⇒ *Collision checking with Car model (shape & velocity) for every future time steps (horizon h)*
- Resulting information can be used for choosing **Avoidance Maneuvers**

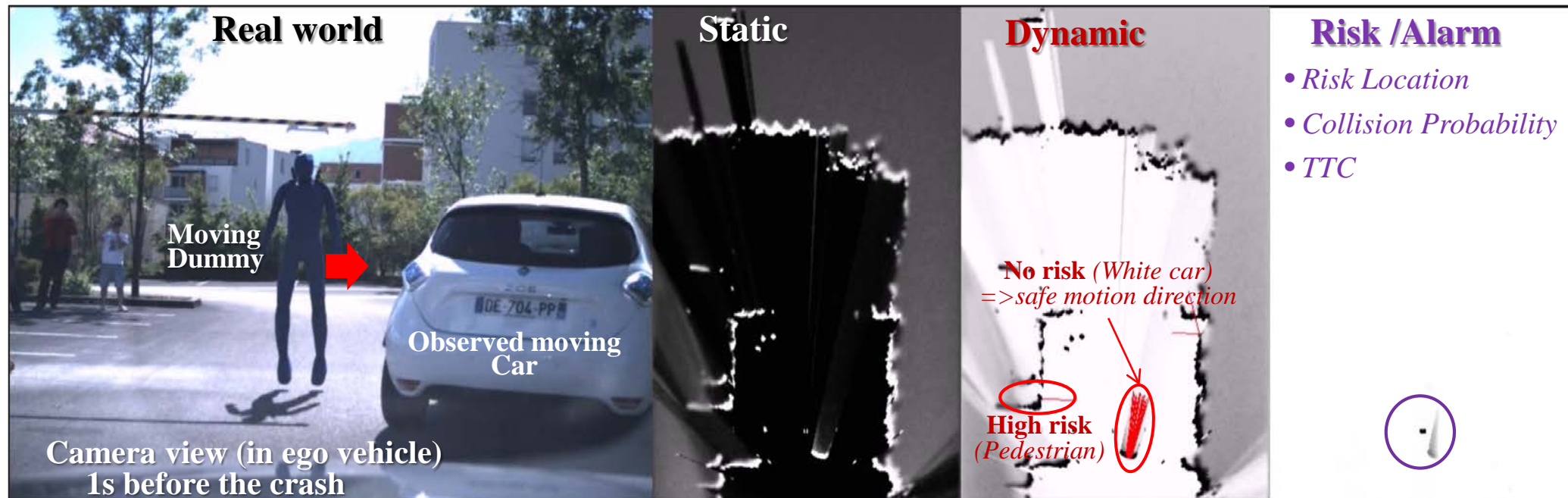
Proximity perception: $d < 100m$ and $t < 5s$

$\delta = 0.5s$ => Precrash

$\delta = 1s$ => Collision mitigation

$\delta > 1.5s$ => Warning / Emergency Braking

□ System output (real time)



Short-term collision risk – *Experimental results*

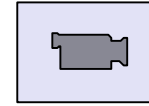
- ⇒ *Detect potential upcoming collisions*
- ⇒ *Reduce drastically false alarms*



Short-term collision risk – *Experimental results (video)*

CMCDOT – Collision Risk Assessment (video – 0:45)

- **Yellow** => *time to collision: 3s*
- **Orange** => *time to collision: 2s*
- **Red** => *time to collision: 1s*

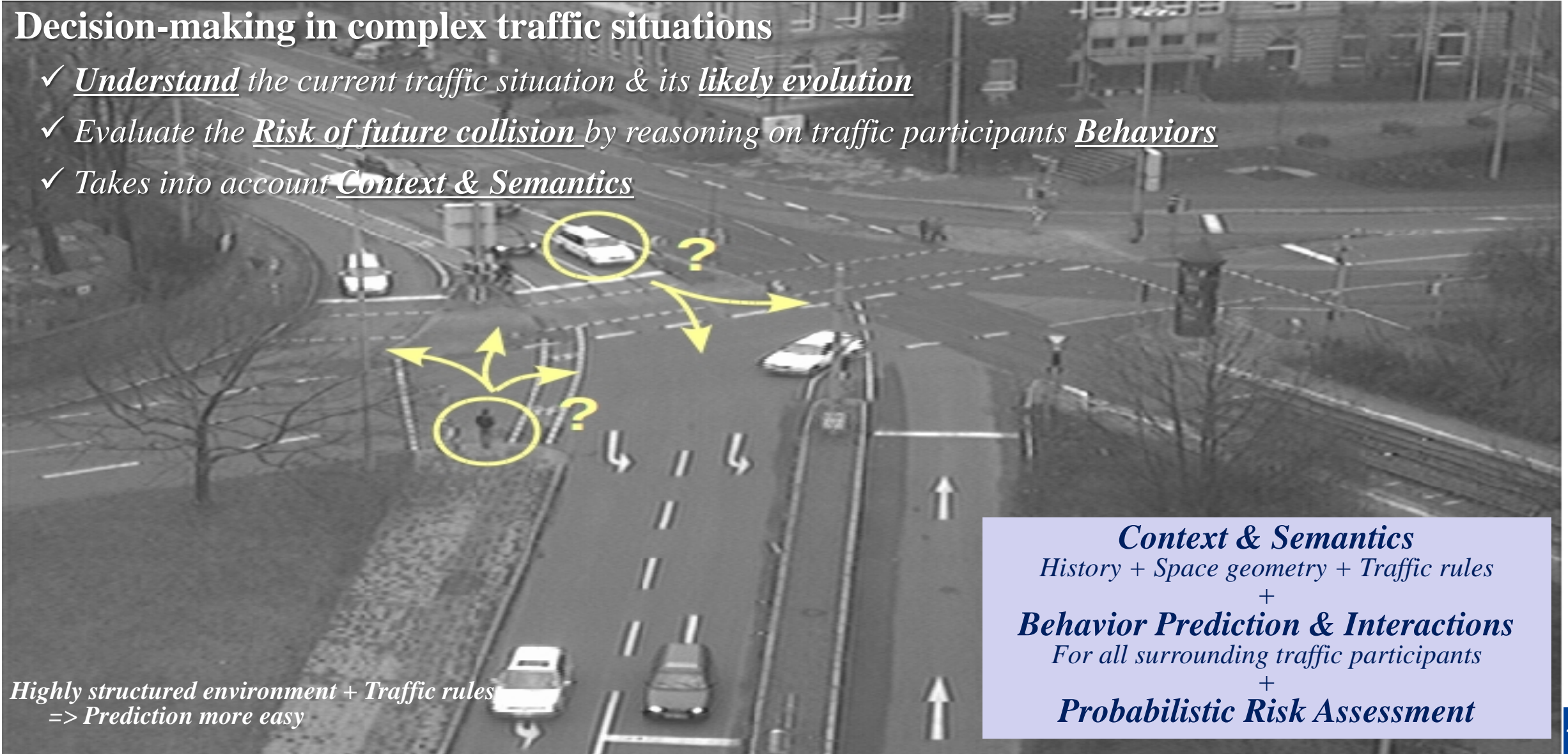


Concept 2: Long-term Risk Assessment (*Object level*)

- => Increasing time horizon & complexity using *context & semantics*
- => Key concepts: *Behaviors Modeling & Prediction + Interactions*

Decision-making in complex traffic situations

- ✓ Understand the current traffic situation & its likely evolution
- ✓ Evaluate the Risk of future collision by reasoning on traffic participants Behaviors
- ✓ Takes into account Context & Semantics



Highly structured environment + Traffic rules
=> Prediction more easy

Context & Semantics
History + Space geometry + Traffic rules
+
Behavior Prediction & Interactions
For all surrounding traffic participants
+
Probabilistic Risk Assessment

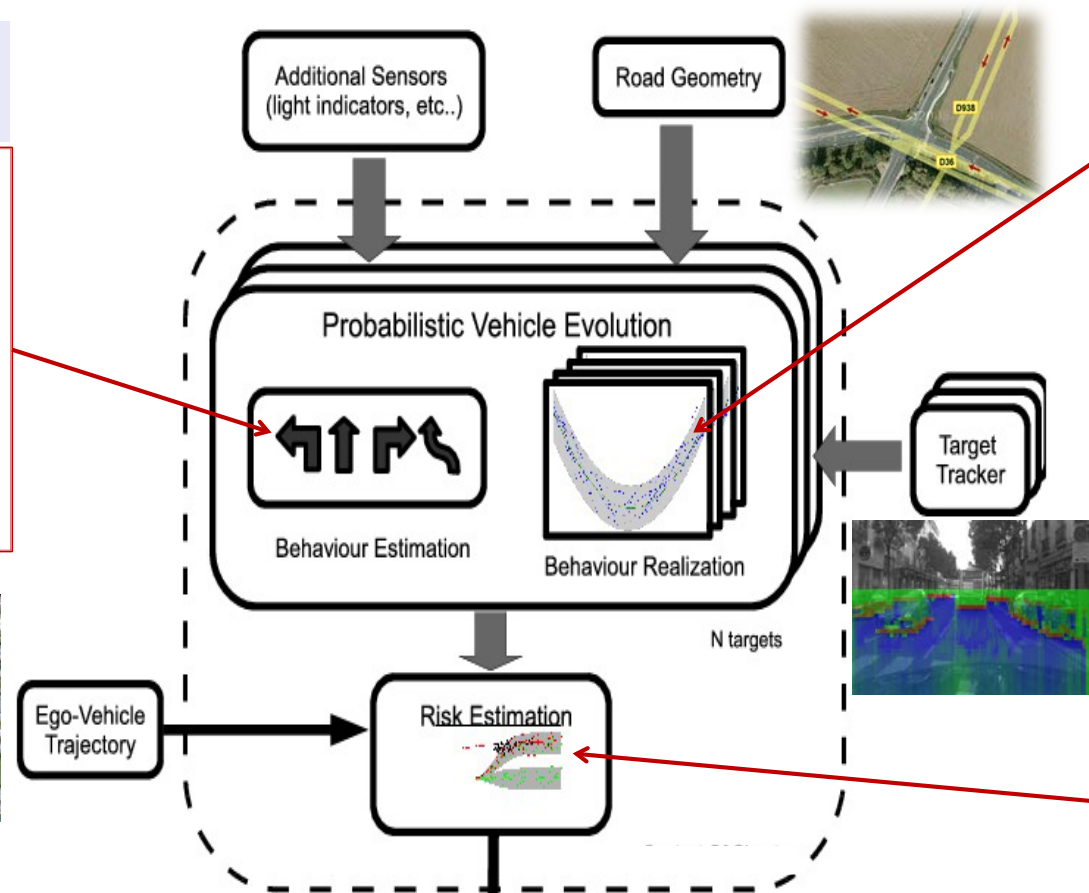
Behavior-based Collision risk (*Object level*)

Approach 1: Trajectories Prediction & Collision Risk Estimation

Patent Inria & Toyota & Probayes 2010 + [Tay thesis 2009] [Laugier et al 2011]

Behavior modeling & learning
+
Behavior Prediction

Layered HMM

$$P(B_t | O_{1:t}) = L_{B_t}(O_{1:t}) \sum_{B_{t-1}} P(B_{t-1}) P(B_t | B_{t-1})$$


From behaviors to trajectories

Gaussian Process + LSCM

Collision risk assessment (Probabilistic)

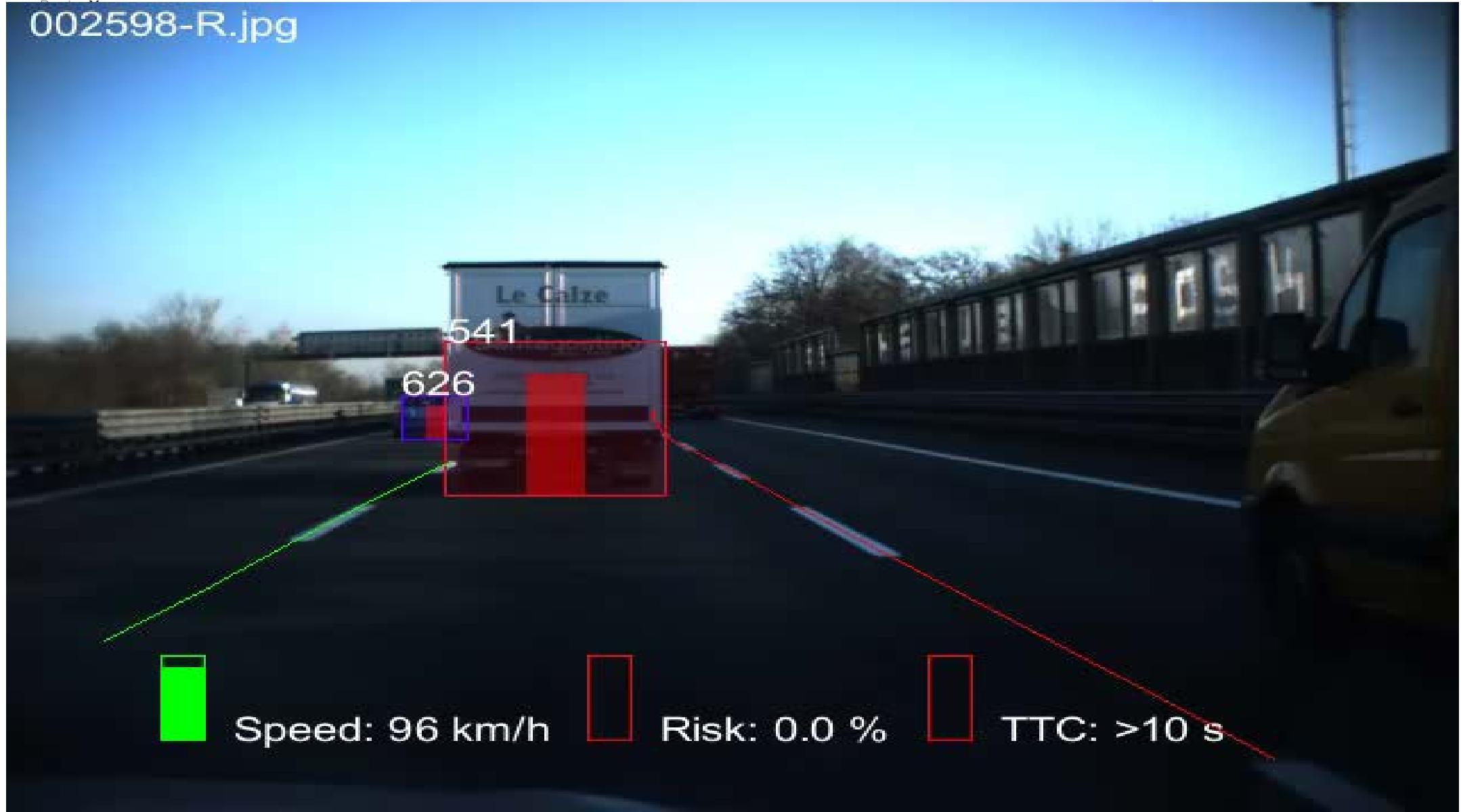
MC simulation

Experimental results: *Prediction Approach 1 – Highways*



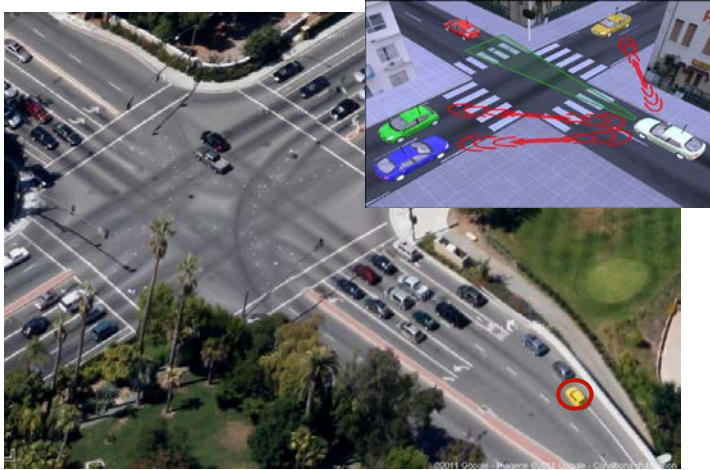
Behavior Prediction & Risk Assessment on highway
Video (Courtesy Probayes)

002598-R.jpg



Behavior-based Collision risk (*Object level*)

Approach 2: Intention & Expectation Comparison => Interdependent behaviors & Mixed Traffic



[Lefevre thesis 13] [Lefevre & Laugier IV'12, Best student paper]

Patent Inria & Renault 2012 (*risk assessment at road intersection*)

Patent Inria & Berkeley 2013 (*postponing decisions for safer results*)

Inria
informatics mathematics



A Human-like reasoning paradigm => *Detect Drivers Errors & Colliding behaviors*

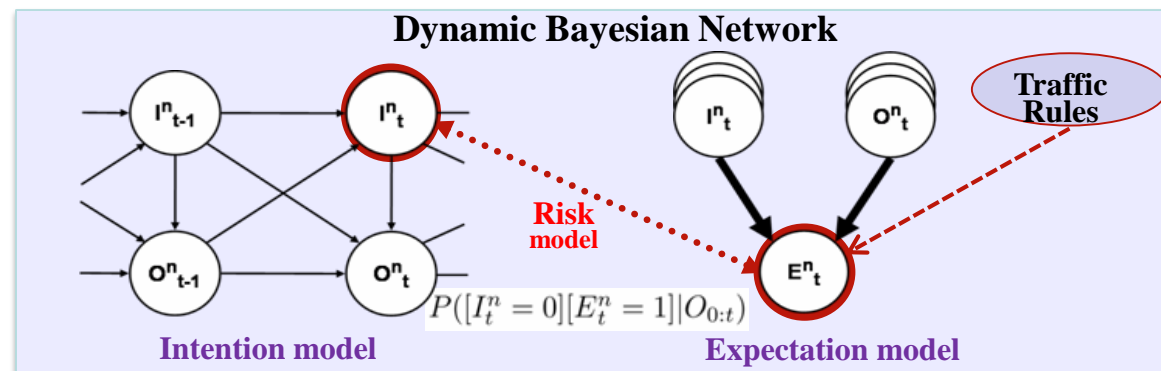
✓ Estimating “Drivers Intentions” from Vehicles States Observations ($X Y \theta S TS$) => *Embedded Perception and/or V2X*

✓ Inferring “Behaviors Expectations” from Drivers Intentions & Traffic rules

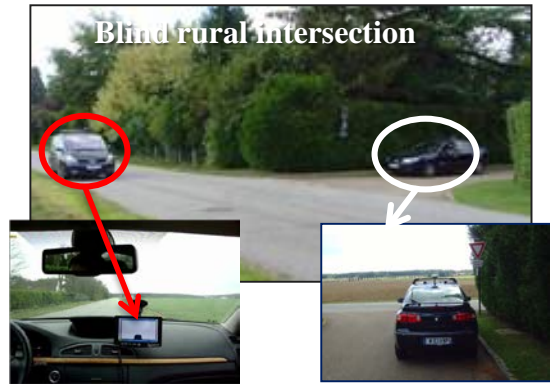
✓ Risk = Comparing Maneuvers Intention & Expectation

=> Taking **traffic context** into account (*Topology, Geometry, Priority rules, Vehicles states*)

=> **Digital map** obtained using “Open Street Map”



Experimental results: *Approach 2 – Road intersection & Mixed traffic*



informatics mathematics
Inria



Experimental Vehicles & Connected Perception Units

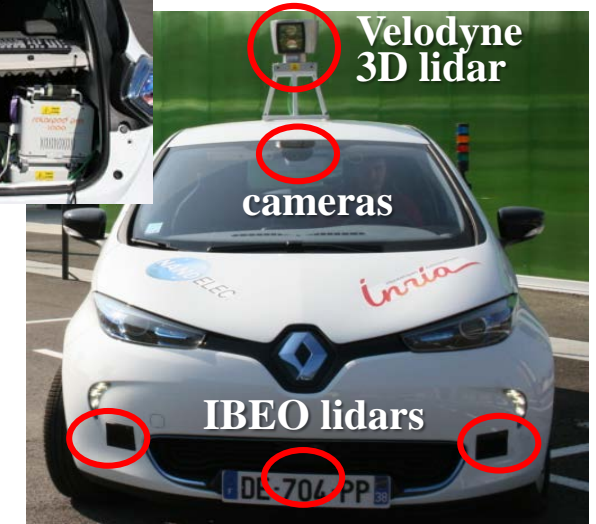
Toyota Lexus



ROS
RT-Maps
under development



Renault Zoé



Connected Perception Unit (infrastructure)

Same embedded perception systems than in vehicles => Exchanging only Collision Risk information



Experimental Areas

- ❑ Protected experimental area => *Testing Autonomous Driving L3 & L4*



Crash test track



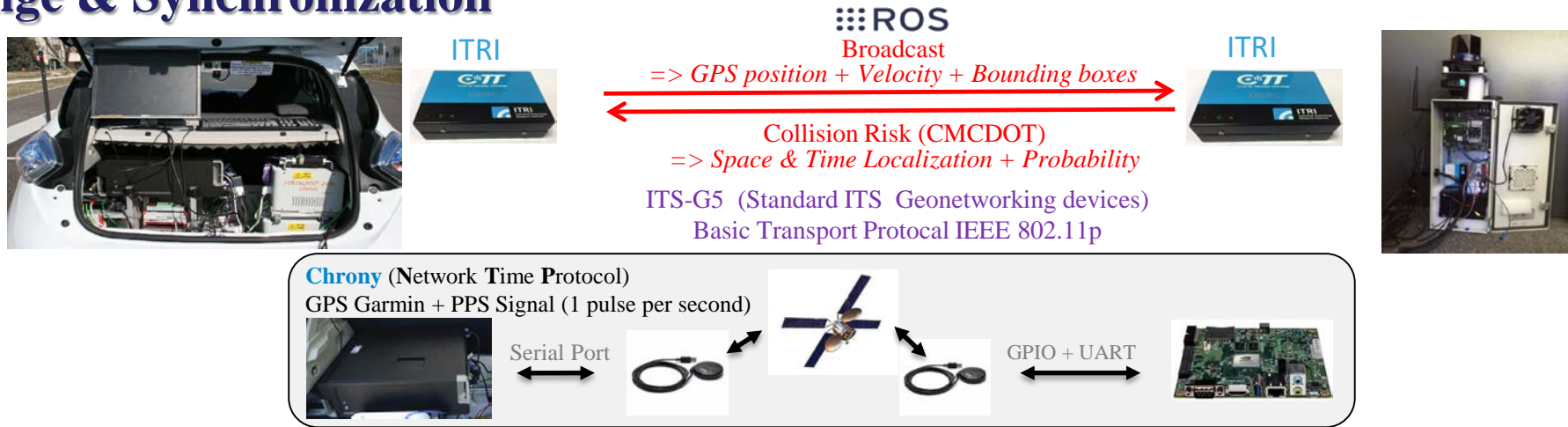
Connected Perception Unit



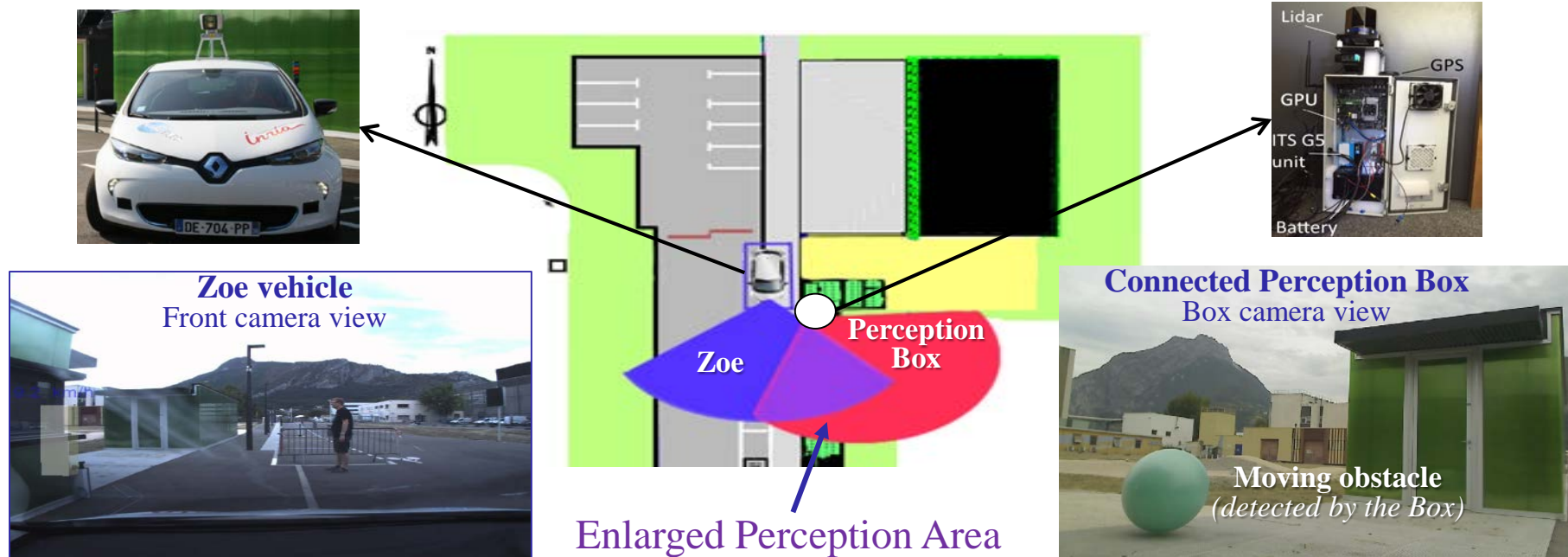
- ❑ Open real traffic (Urban & Highway) => *Testing Autonomous Driving L2 (ADAS)*



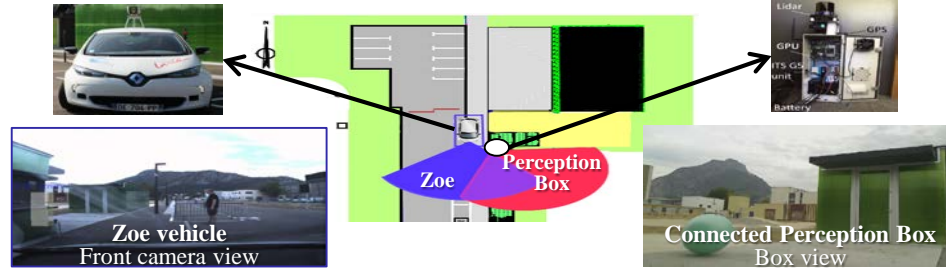
□ Data exchange & Synchronization



□ Experimental platform



Distributed Bayesian Perception – *Experimental results*



The screenshot shows a software interface with a menu bar at the top containing options: "Interact", "Move Camera", "Select", "Focus Camera", "Measure", "2D Pose Estimate", "2D Nav Goal", and "Publish Point". Below the menu are two main camera view windows. The left window, titled "Image", shows a "Perception Box View" of a green structure with a blue sphere in the foreground. The right window, titled "Camera", shows a "Car Front View" from the driver's perspective. Below these is a 3D scene model titled "Scene modeled by the Perception Box", showing a top-down view of a car on a road with a speed indicator of "0.5 km/h". A "Reset" button is visible in the bottom left corner of the 3D view. The bottom right corner of the interface displays "22 fps".

On going work

□ Perception + Decision-making + Control integration



Autonomous Shuttles
(~15 km/h)



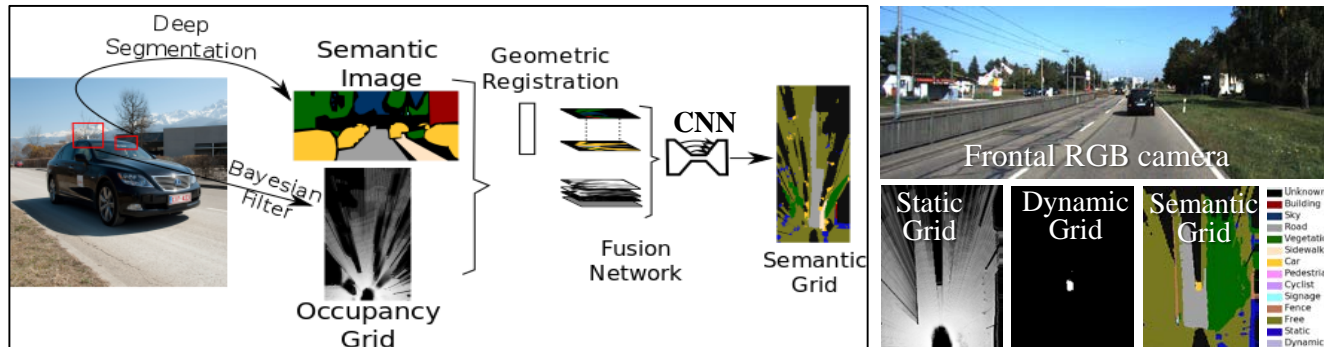
Autonomous Bus (Iveco)
(up to 70 km/h, Urban traffic)



Autonomous Renault Zoe
(up to 70 km/h, Urban traffic)

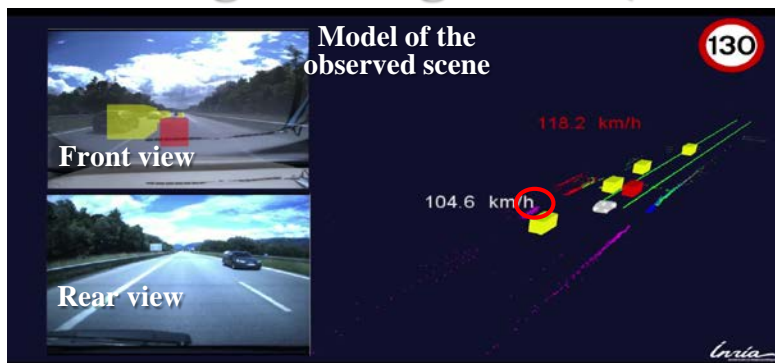
- Various Dynamics & Motion constraints & Contexts
- Adapted “Collision Risk” & “Collision avoidance maneuvers” (Risk & Maneuver characterization)
- Cooperation IRT Nanoelec, Renault, Iveco ...

□ Models enrichment using Semantic Segmentation & Deep Learning



- “Semantic Grids” concept
- Improved scene understanding & decision-making
- Cooperation Toyota
- 1 Patent & 2 publications (IROS’18, ICARCV’18)

□ Learning Driving Skills (Prediction & Planning) for Autonomous Driving



- **Driver Behavior modeling** using Driving dataset & Inverse Reinforcement Learning => *Human-like Driver Model* (for mixed traffic)
- **Motion Prediction & Driving Decision-making for AD** performed by combining “learned Driver models” & “Dynamic evidences”
- Cooperation Toyota
- 2 Patents & 3 publications (ITSC 2016, ICRA 2017, ICRA 2018) & PhD Thesis 2019

Start-up incubation – *Innovative concept for micro mobility*

Micro mobility

STARlink

WE PROVIDE URBAN MICRO MOBILITY SERVICES AT THE CITIZENS' FRONT DOOR WITH
ON DEMAND AUTONOMOUS ELECTRIC LIGHT VEHICLES.



A FREE FLOATING SOLUTION THAT MAKES SENSE

- / ON DEMAND DOOR TO DOOR MOBILITY SERVICE
- / NO RANDOM & UNCONTROLLED PARKING
- / AUTONOMOUS DISPATCH & CHARGING
- / LOW OPERATING COSTS
- / REAL TIME SPEED LIMITATIONS
- / ZERO EMISSION SOLUTION

READY TO OPEN A NEW ERA FOR THE FIRST & LAST MILE



PARTNERSHIP PROGRAM



AUTONOMOUS
FUNCTIONALITY



ENVIRONMENT
DETECTION



MOTOR CONTROL
& ENERGY
MANAGEMENT

Start-up incubation – *Key Features*

// VALUE PROPOSITION

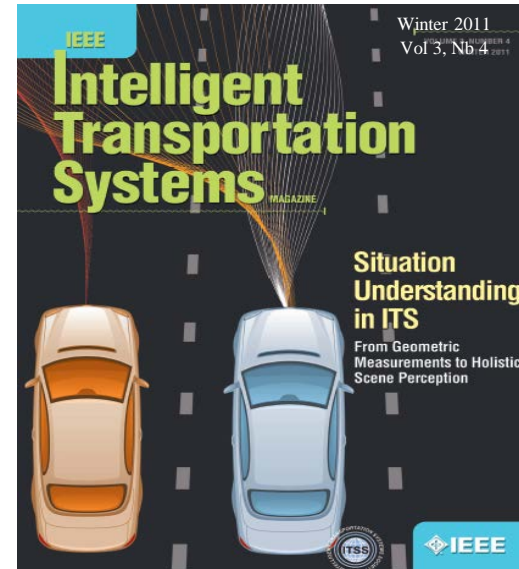
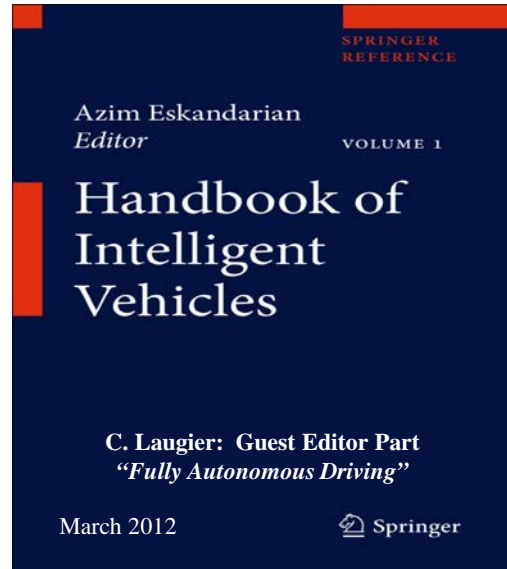
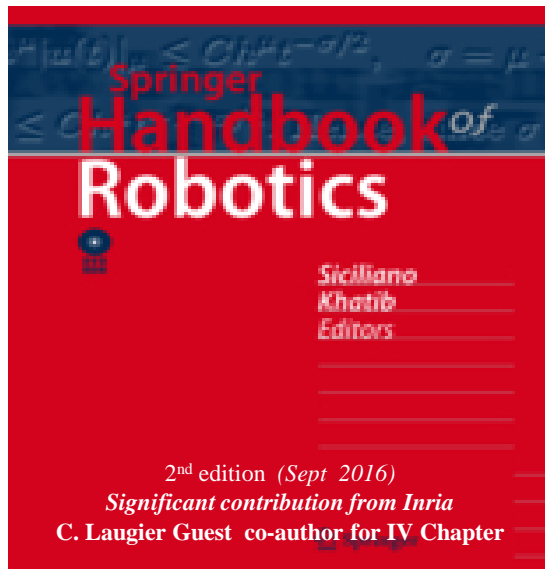
STARlink

STARLINK provides urban micro mobility services at the citizens' front door with on demand autonomous electric light vehicles.

STARLINK's technology makes mobility operators' life easier and optimize their revenues.

STARLINK's concept provides a clear contribution to environmental issues for better places to live.





Thank You - Any questions ?

