



HAL
open science

Dynamic Scene Understanding and Upcoming Collision Prediction to improve Autonomous Driving Safety: A Bayesian Approach

Christian Laugier

► **To cite this version:**

Christian Laugier. Dynamic Scene Understanding and Upcoming Collision Prediction to improve Autonomous Driving Safety: A Bayesian Approach. RWIA 2018 - International Conference on Robotic Welding, Intelligence and Automation, Dec 2018, Guangzhou, China. pp.1-26. hal-01970468

HAL Id: hal-01970468

<https://inria.hal.science/hal-01970468v1>

Submitted on 7 Jan 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Dynamic Scene Understanding & Upcoming Collision Prediction to improve Autonomous Driving Safety: A Bayesian Approach

Christian LAUGIER, Research Director at Inria

*Inria Chroma team & IRT nanoelec & Scientific Advisor for Probayes and for Baidu China
christian.laugier@inria.fr*

Contributions from

L. Rummelhard, A. Negre, N. Turro, J.A. David, J. Lussereau, C. Tay Meng Keat, S. Lefevre



Invited Plenary Speech

*2018 International Conference on Robotic Welding, Intelligence and Automation (RWIA'2018) Guangzhou (China),
December 7-10 2018*

Autonomous Cars & Driverless Vehicles

- Strong involvement of Car Industry & GAFA & Large media coverage
- An expected market of 500 B€ in 2035... *but Legal & Regulation issues unclear*
- Technologies Validation & Certification => *Numerous recent & on-going real-life experiments (insufficient) + Simulation & Formal methods (e.g. EU Enable13)*



Tesla Autopilot based on Radar & Mobileye
Commercial ADAS product => tested by customers



Waymo: Lidars & Dense 3D mapping
Numerous Vehicles & 25,000 km/day



Numerous EU projects in last 2 decades
Cybus experiment, La Rochelle 2012 (EU CityMobil project & Inria)



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



“Robot Taxi” testing in US (Uber, Waymo) & Singapore (nuTonomy)
 => *Autonomous Mobility Service, Numerous Sensors + “Safety driver” during testing*
 => *Uber: Disengagement every 0.7 miles in 2017, improved now*
 => *Waymo 2018 (10 years R&D, 25,000 km/day, 1st US Self Driving Taxi Service in Phoenix)*



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: *Example of the Tesla accident (May 2016)*

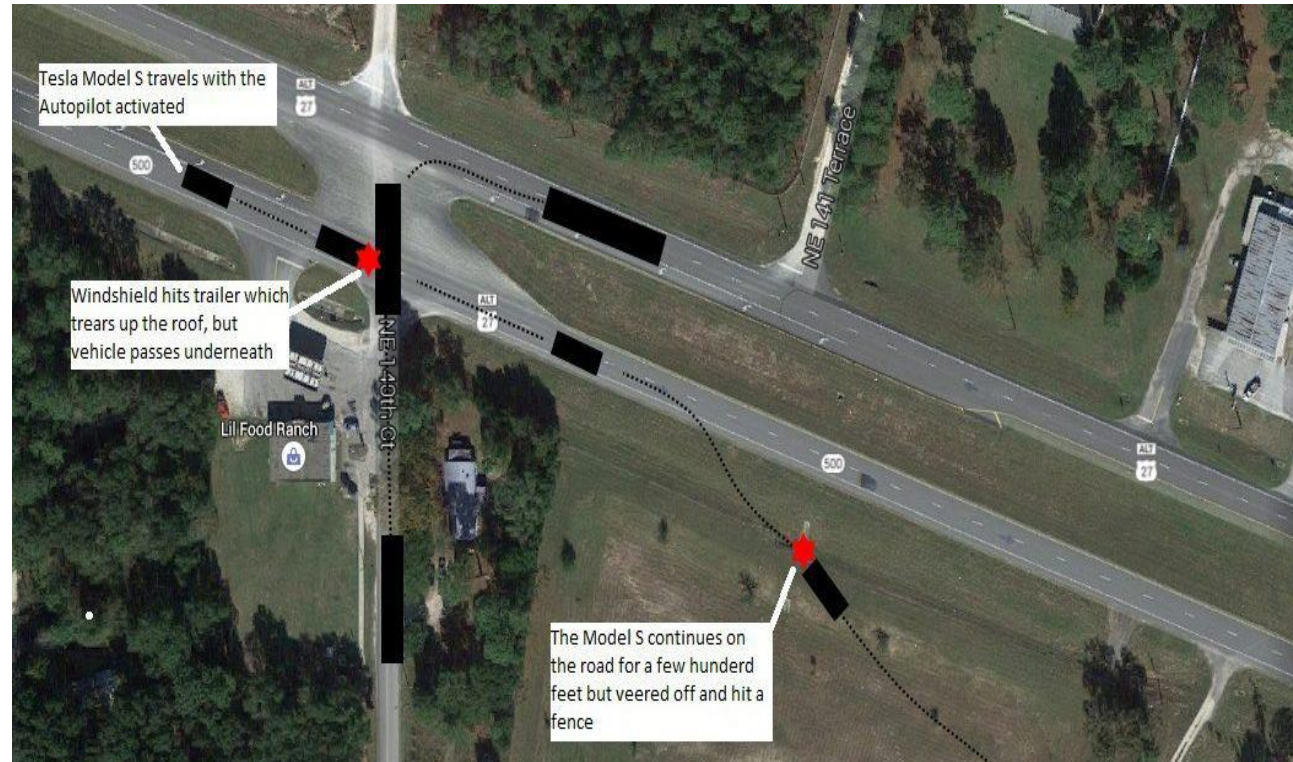
- ❑ On May 7th 2017, Tesla driver killed in a crash with Autopilot active
- ❑ The Human driver was not vigilant => *A false sense of Safety for the user ?*
- ❑ The Autopilot didn't detected the trailer as an obstacle (*truck turned left & obstructed the road*)
 - *Camera => White color against a brightly lit sky ?*
 - *Radar => High ride height of the trailer probably confused the radar into thinking it is an overhead road sign ?*



Tesla Model S – Autopilot

Front perception:

Camera (Mobileye) + Radar + US sensors



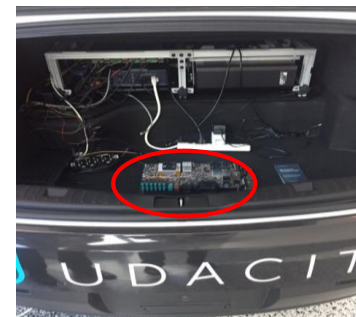
Safety issue: *Example of the Uber Accident (March 2018)*


- ❑ **Self-driving Uber kills a woman in first fatal crash involving pedestrian**
Tempe, Arizona, March 2018
- ❑ **The vehicle was moving at 40 mph and didn't reduced its speed before the crash**
=> In spite of the presence of multiple onboard sensors (several lidars, cameras ...), the perception system didn't predicted the collision !
- ❑ **The Safety Driver didn't appropriately reacted (he was not attentive enough)**
=> Two dysfunctions: Failure of the Perception System & Disengagement process (the safety driver reacted less than 1s before the crash and started to brake after the crash)




Perception: Main Today's Limitations

- ❑ **Embedded Perception & Dynamic Scene Understanding** is still one of the major bottleneck for Motion Autonomy => *Perception errors may obviously generate uncontrolled behaviors & accidents*
e.g. False or missed obstacle detection, classification or tracking errors, wrong motion prediction, unreliable collision risk assessment, wrong scene interpretation ...
- ❑ **Current lack of Robustness & Efficiency & Embedded integration** is still a major obstacle to a full deployment of Autonomous Driving technologies



Lack of Robustness & Efficiency 

Lack of Integration into Embedded Sw/Hw 

- *Until recently, car trunks was most of the time full of electronics & computers & processor units*
- *Towards integrated high computational capabilities & dedicated software (e.g. Nvidia Drive-PX, Ambarella embedded vision SoC presented at IROS 2018...)*

Embedded Perception & Scene Understanding

Overview

Complex Dynamic Scenes understanding



Situation Awareness & Decision-making

ADAS & Autonomous Driving



Dealing with unexpected events
e.g. Road Safety Campaign, France 2014



Anticipation & Prediction
for avoiding upcoming accidents
=> FoA + Short-term collision risk

Main features

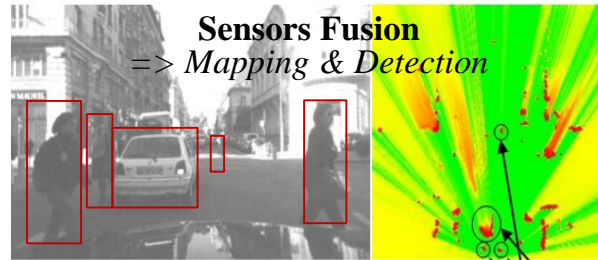
- ✓ Dynamic & Open Environments => *Real-time processing & Reactivity*
- ✓ Incompleteness & Uncertainty => *Appropriate Model & Algorithms (probabilistic approaches)*
- ✓ Sensors limitations (no sensor is perfect) => *Multi-Sensors Fusion*
- ✓ Human in the loop => *Interaction & Behaviors & Social Constraints (including traffic rules)*
- ✓ Hardware / Software integration => *Satisfying Embedded constraints*

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*

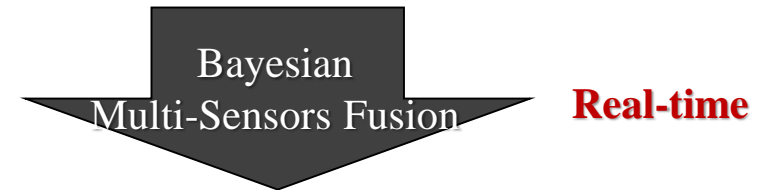
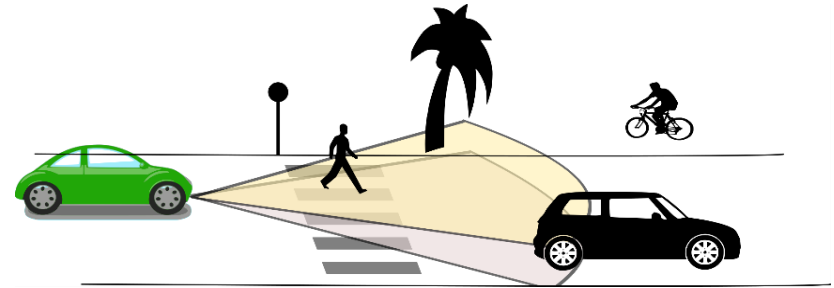
❑ Our Approach: Embedded Bayesian Perception

- ✓ *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

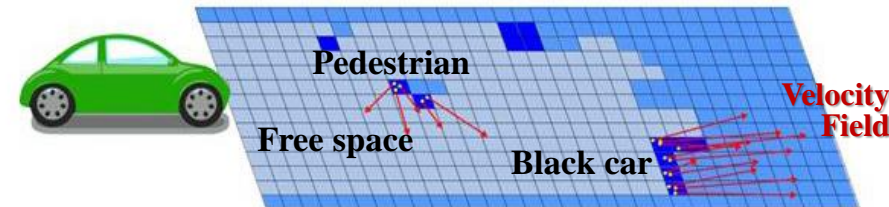
Lidar, Radar, Stereo camera, IMU ...



□ Probabilistic Environment Model

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

$P[o|Z,C]$:  ≈ 0  ≈ 0.5  ≈ 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 :

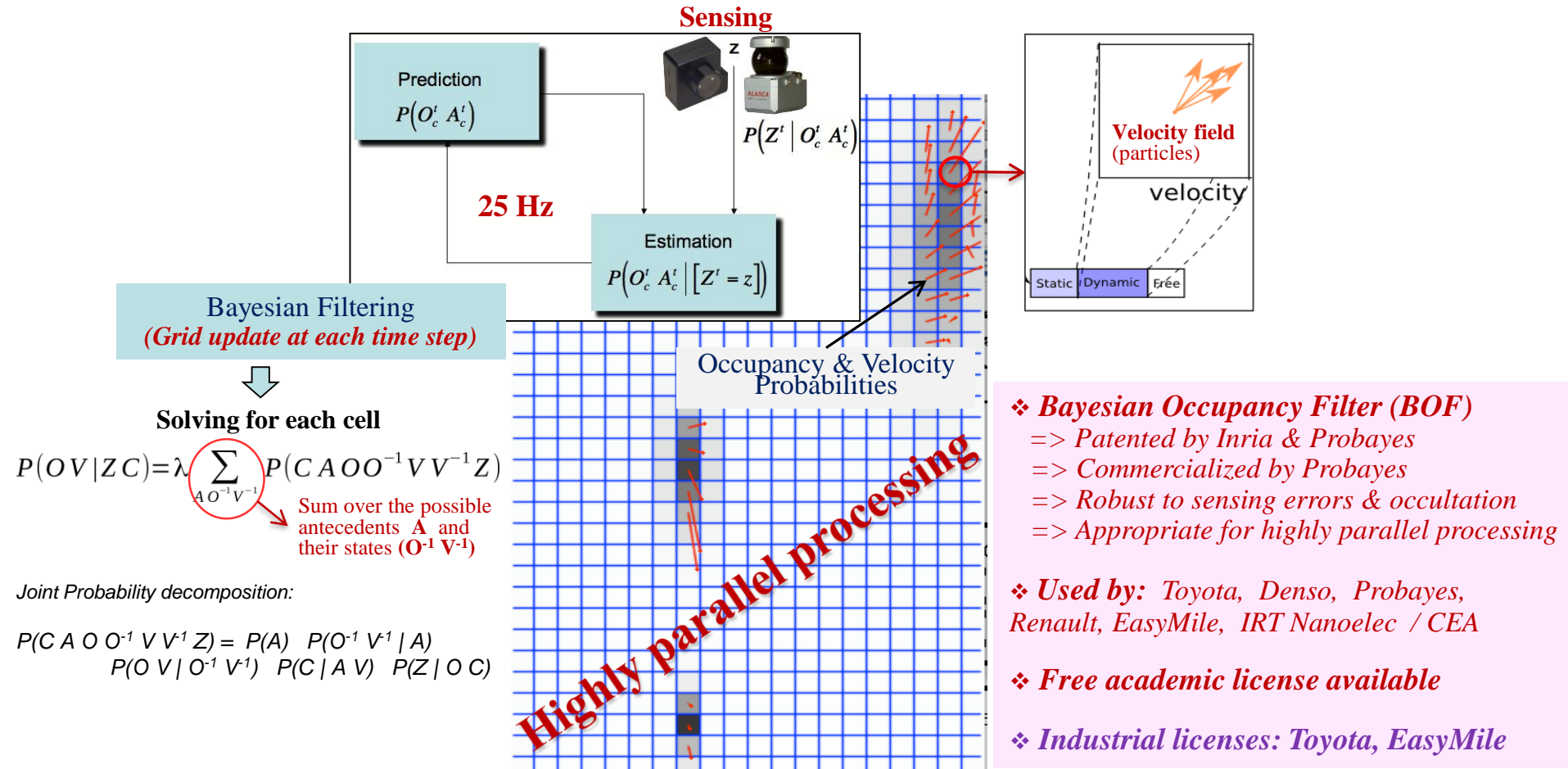
- **Improving efficiency** => *highly parallel processing*
- **Avoiding traditional object level processing problems** (e.g. *detection errors, wrong data association...*)

A new framework: Dynamic Probabilistic Grids

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

Concept of “Bayesian Occupancy Filter” (Inria)

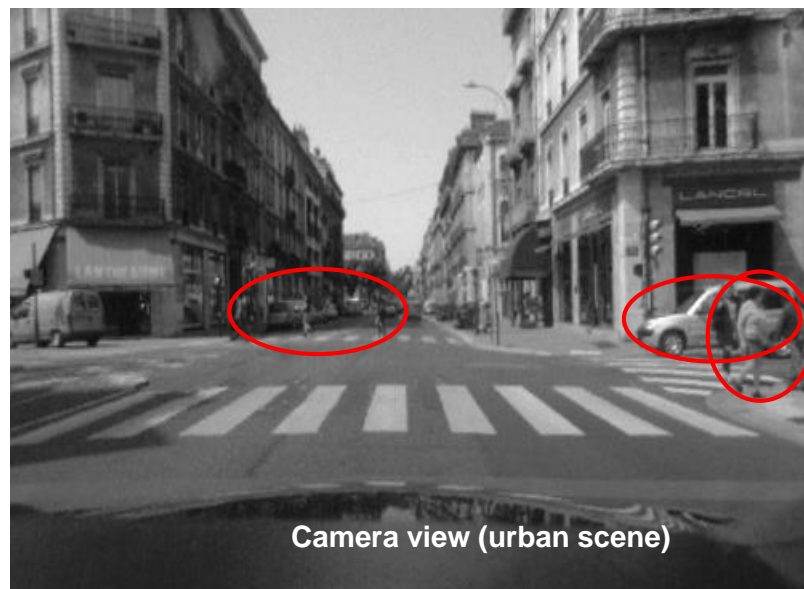
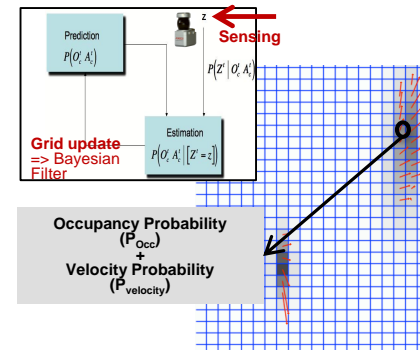
[Coué & Laugier IJRR 05] [Laugier et al ITSM 2011] [Laugier, Vasquez, Martinelli Mooc uTOP 2015]



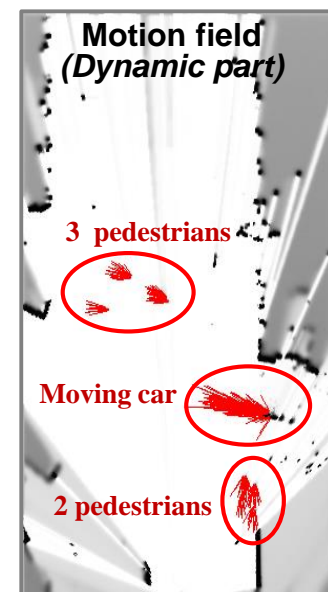
Bayesian Occupancy Filter Approach – *Main Features*

=> *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*)



Sensors data fusion
+
Bayesian Filtering
+
Extracted Motion Fields



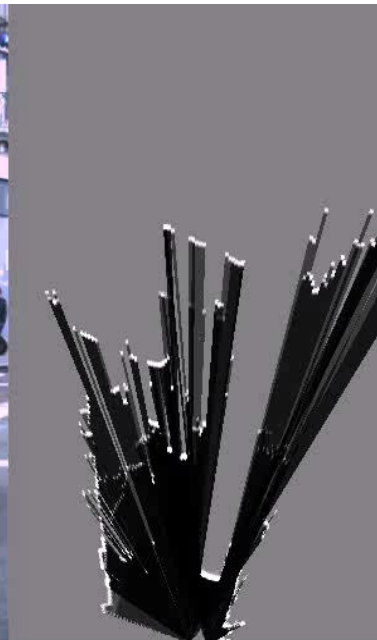
Experimental Results in dense Urban Environments

Observed Urban Traffic scene

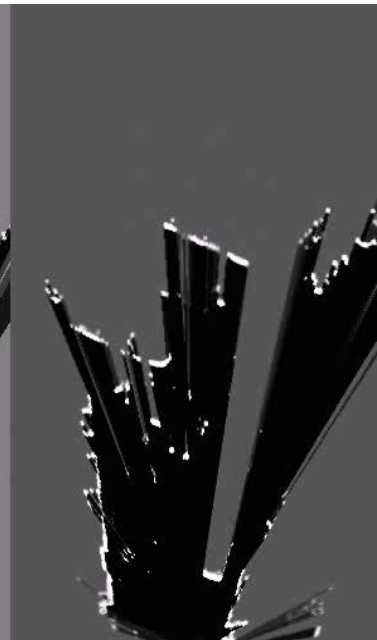


moving vehicle
ahead

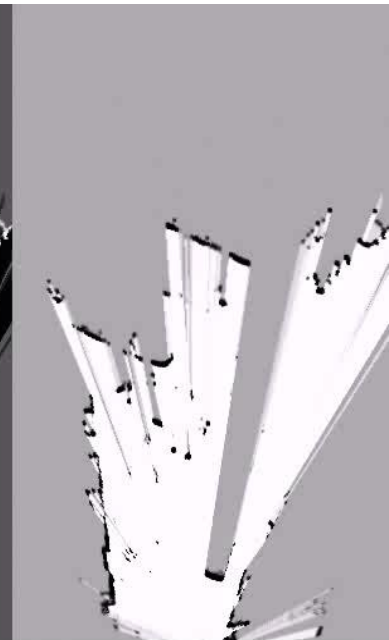
Ego Vehicle (*not visible on the video*)



OG Left Lidar



OG Right Lidar

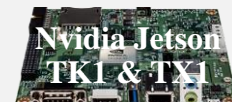


OG Fusion
+
Velocity Fields

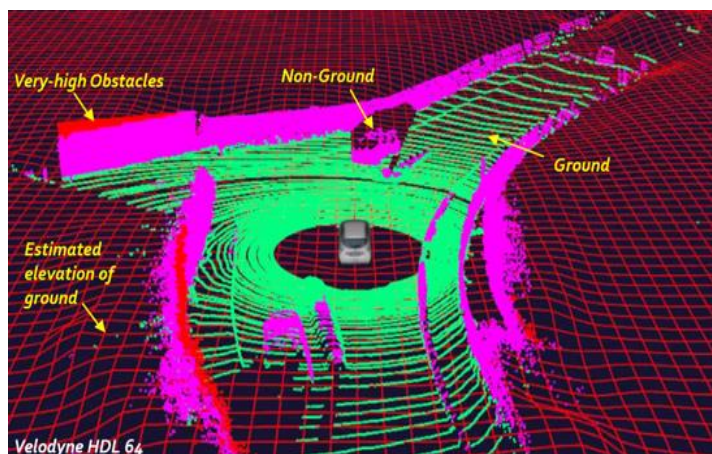


Patented Improvements & Implementations

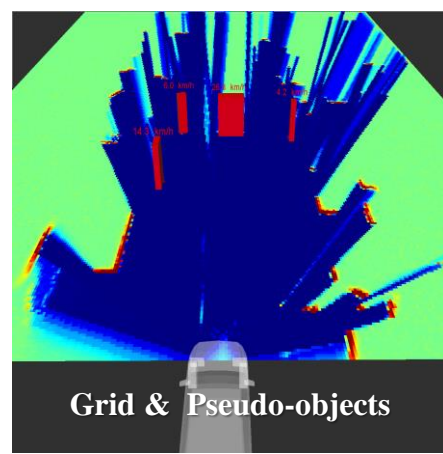
=> Several models & implementations more and more adapted to Embedded constraints & Scene complexity



- ❖ 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)



Ground Estimation & Point Cloud Classification



Moving Objects Detection & Tracking & Classification



Classification (using Deep Learning)

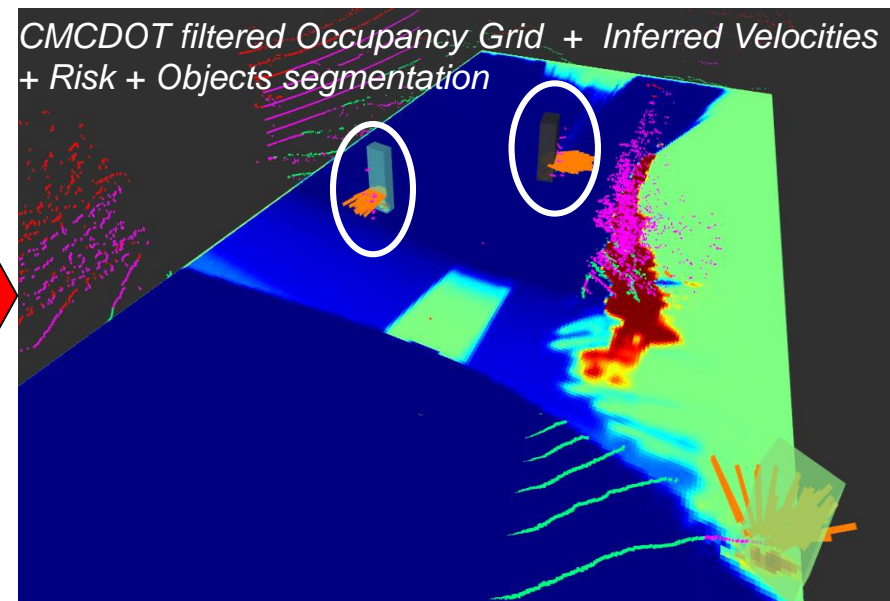
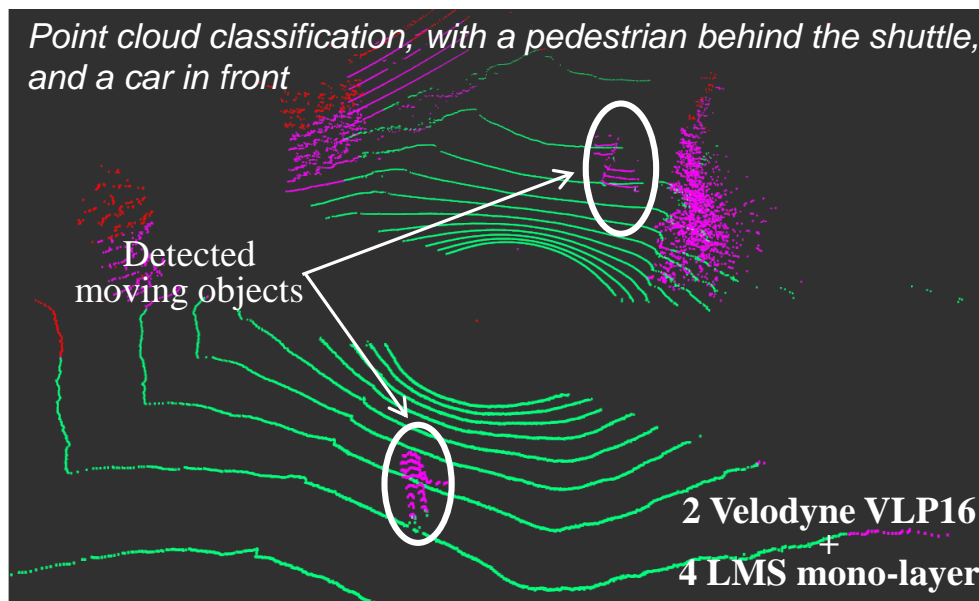
System Integration in a commercial vehicle



- **POC 2017: Complete system implemented on Nvidia TX1**, and easily connected to the shuttle system network *in a few days* (using ROS)

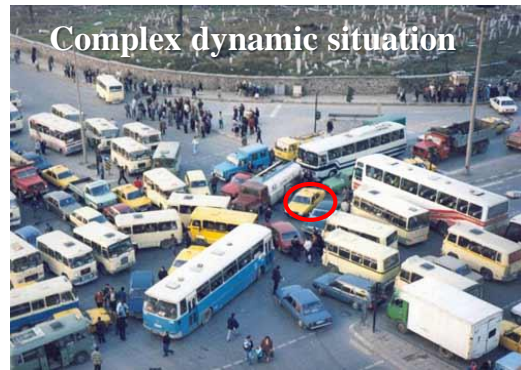


- **Shuttle sensor data** has been fused and processed in **real-time**, with a successful Detection & Characterization of the **Moving & Static Obstacles**
- **Full integration on a commercial product** under development with an industrial company (confidential)



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*

Concept 1: Short-term collision risk – Basic idea

⇒ How to deal with unexpected events ?

⇒ Exploiting previous observations + Conservative collision Prediction & Avoidance

Autonomous
Vehicle (Cycab)



Parked Vehicle
(occultation)

**Pioneer Results
(2005)**

[Coué & Laugier IJRR 05]

Thanks to the prediction capability of the BOF technology, the Autonomous Vehicle “anticipates” the behavior of the pedestrian 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 $t < 5s$

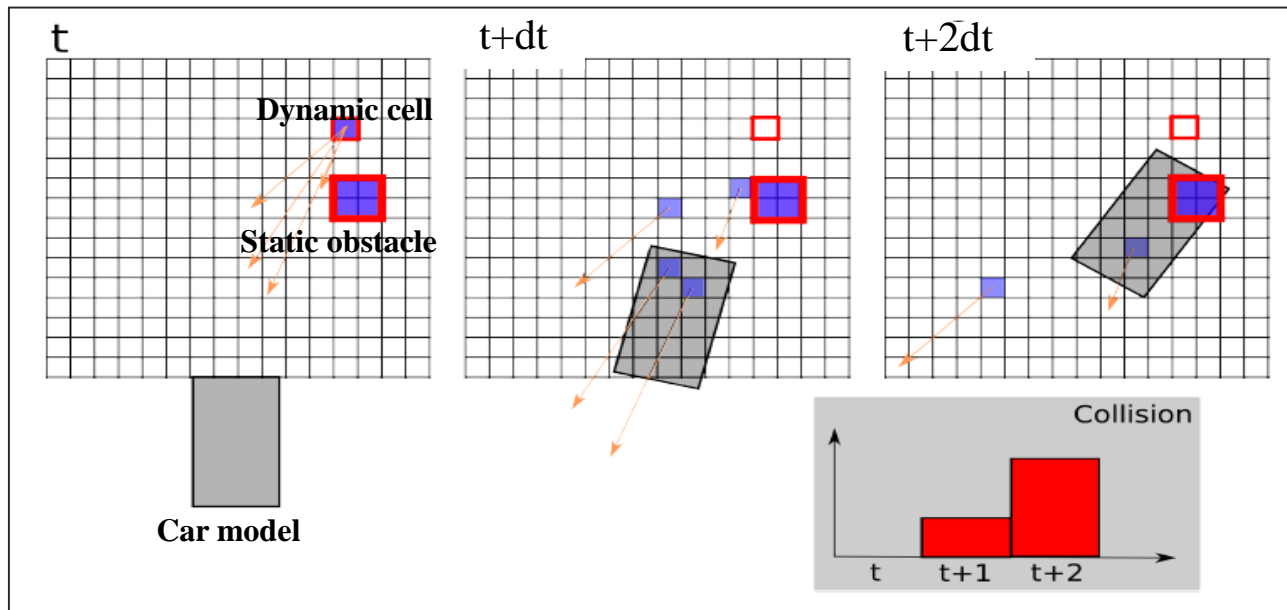
$\delta = 0.5s$ => Precrash

$\delta = 1s$ => Collision mitigation

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

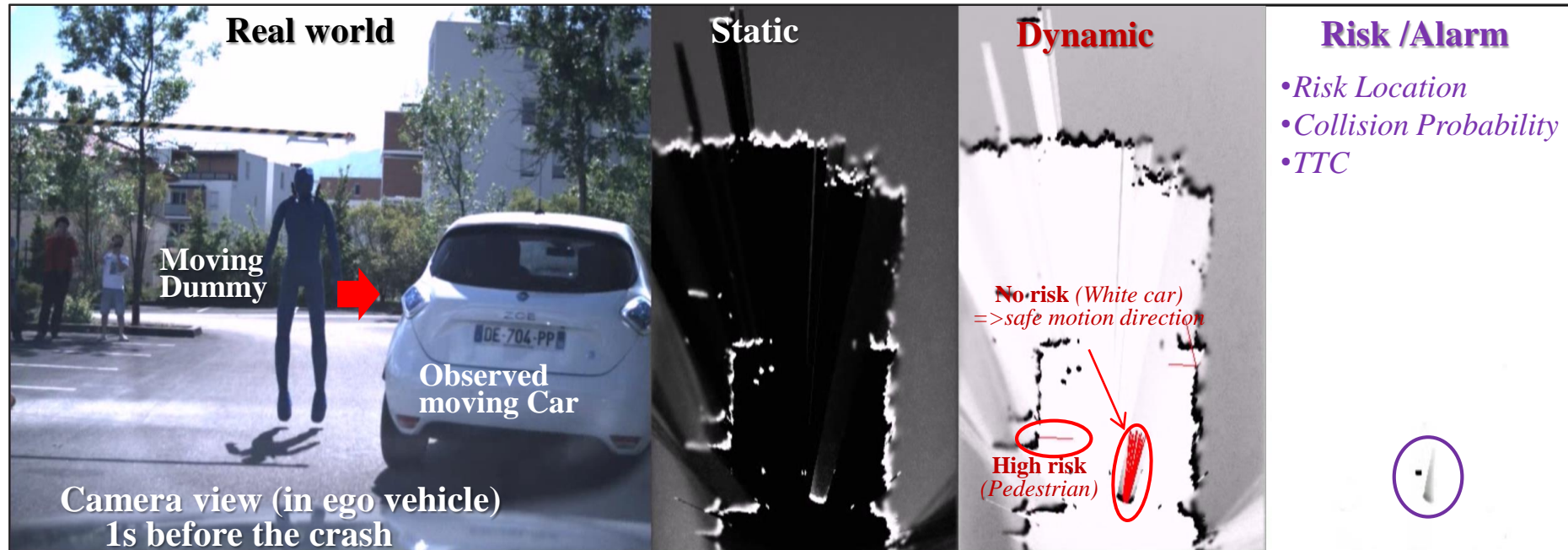
□ Collision Risk Estimation: *Integration of risk over a time range $[t \ t + \delta]$*

=> *Projecting over time the estimated Scene changes (DP-Grid) & Car Model (Shape + Motion)*



Short-term collision risk – System outputs (real-time)

=> *Static & Dynamic Grids + Risk assessment*



- **FAQ :** What happen if some velocities change after that the collision risk for the next 3s has been evaluated ?
- **Answer:** The collision risk is recomputed at the next time step (i.e max 40ms after the change of dynamics).

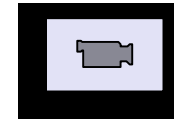
Short-term collision risk – *Experimental results*

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



Collision Risk Assessment (video)

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



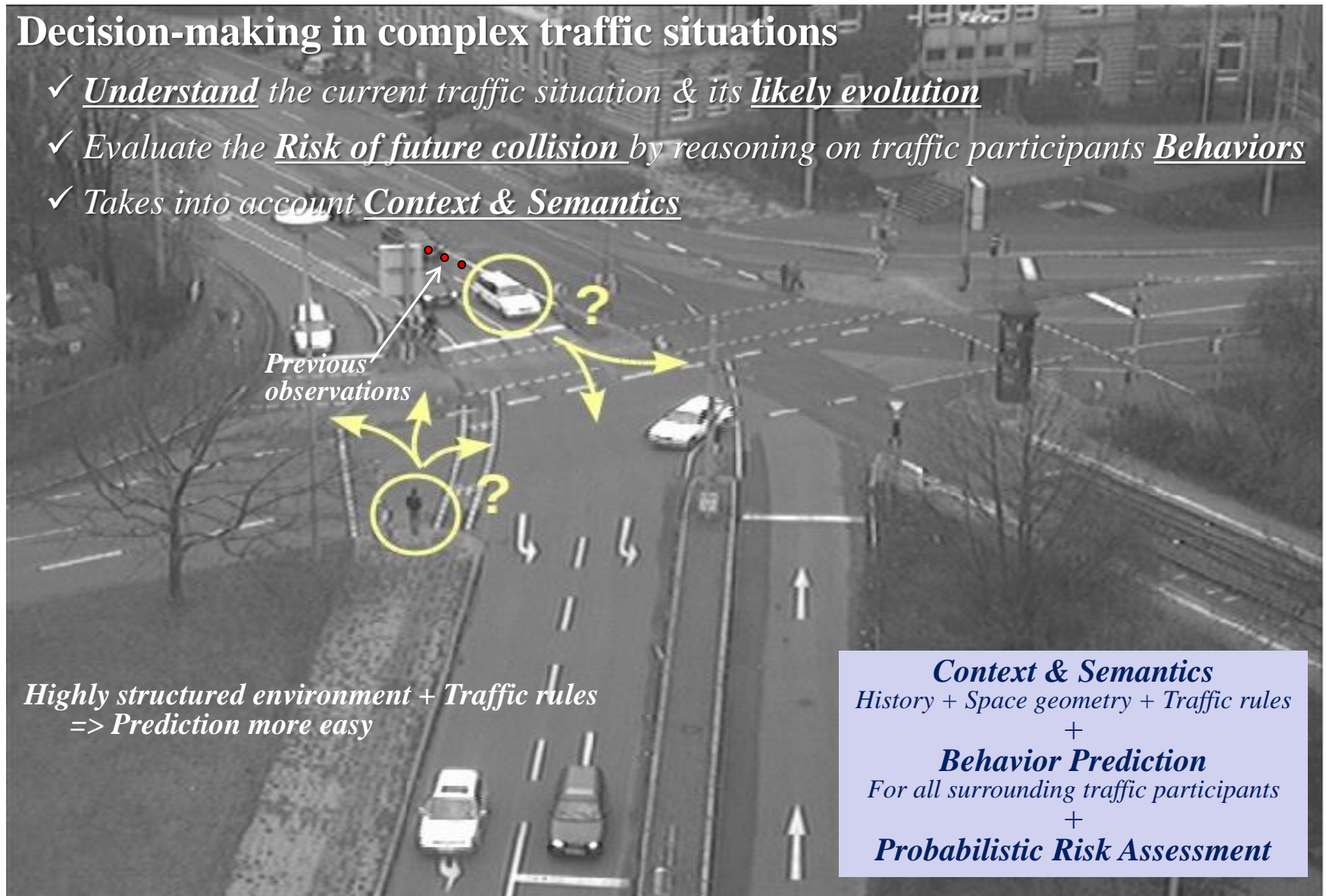
Concept 2: Long-term Risk Assessment (*Object level*)

⇒ Increasing time horizon & complexity using *context & semantics*

⇒ Key concept: *Behaviors Modeling & Prediction*

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

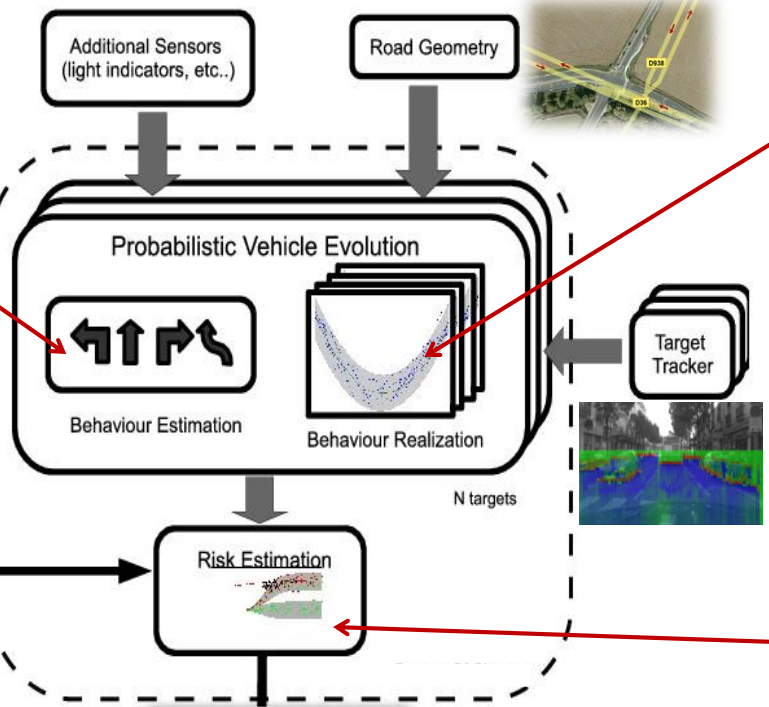
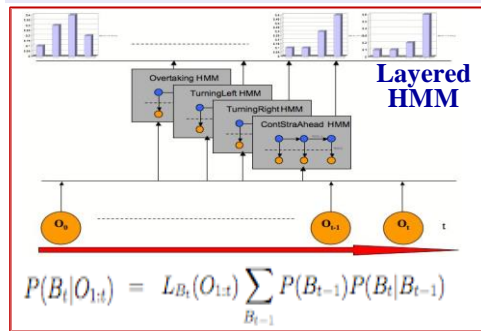
Context & Semantics
History + Space geometry + Traffic rules
+
Behavior Prediction
For all surrounding traffic participants
+
Probabilistic Risk Assessment

Behavior-based Collision risk (Object level)

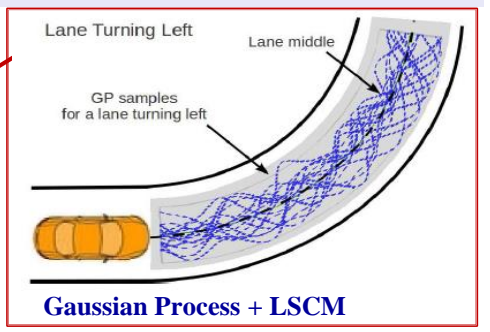
Approach 1: Trajectories Prediction & Collision Risk Estimation

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

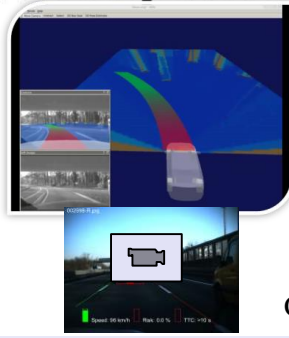
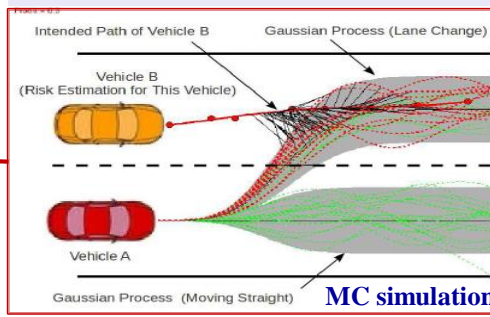
Behavior modeling & learning + Behavior Prediction



From behaviors to trajectories



Collision risk assessment (Probabilistic)



Courtesy Probayes

Experimental Results
Behavior Prediction & Risk Assessment on highway
Probayes & Inria & Toyota



Behavior-based Collision risk (*Object level*)

Approach 2: Intention & Expectation Comparison

=> *Complex scenarios with Interdependent Behaviors & Mixed Traffic*



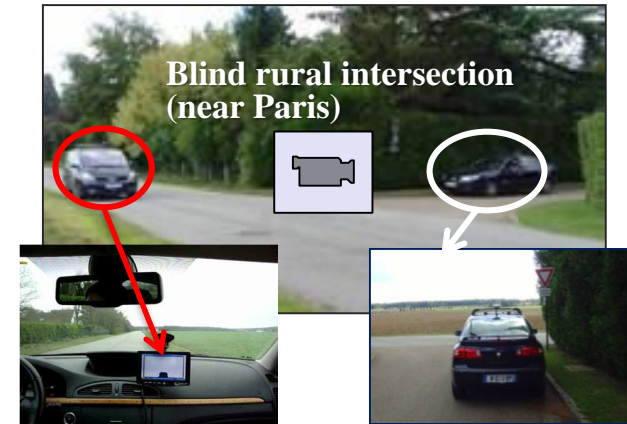
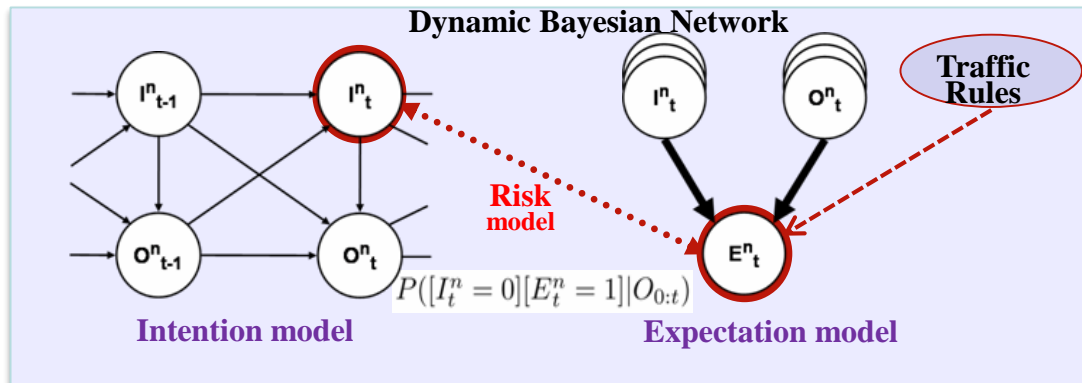
[Lefevre thesis 13] [Lefevre & Laugier IV'12, Best student paper]

Patent Inria & Renault 2012 (risk assessment at road intersection)
Patent Inria & Berkeley 2013 (postponing decisions for safer results)



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 Vehicles & Connected Perception Units

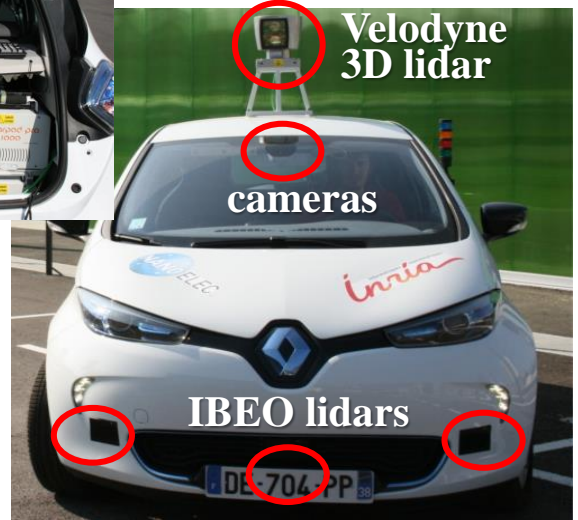
Toyota Lexus



ROS



Renault Zoé
Velodyne 3D lidar



Connected Perception Unit

=> Same embedded perception systems than in vehicles

Nvidia GTX Titan X
Generation Maxwell



Nvidia GTX Jetson TK1
Generation Maxwell



Nvidia GTX Jetson TX1
Generation Maxwell



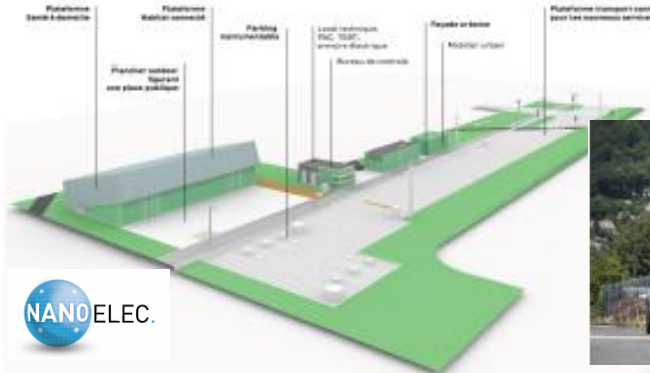
Experimental Areas



Connected Perception Unit

Protected experimental area

Un espace d'expérimentation : 3 plateformes

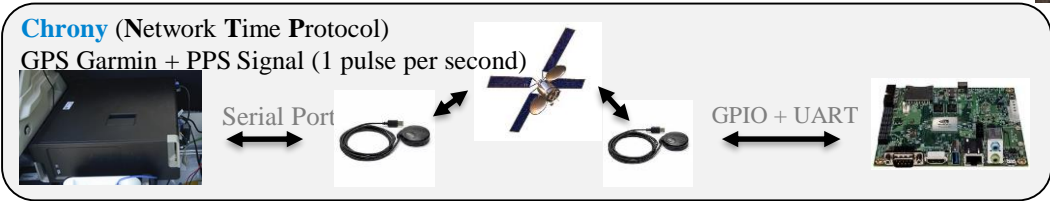
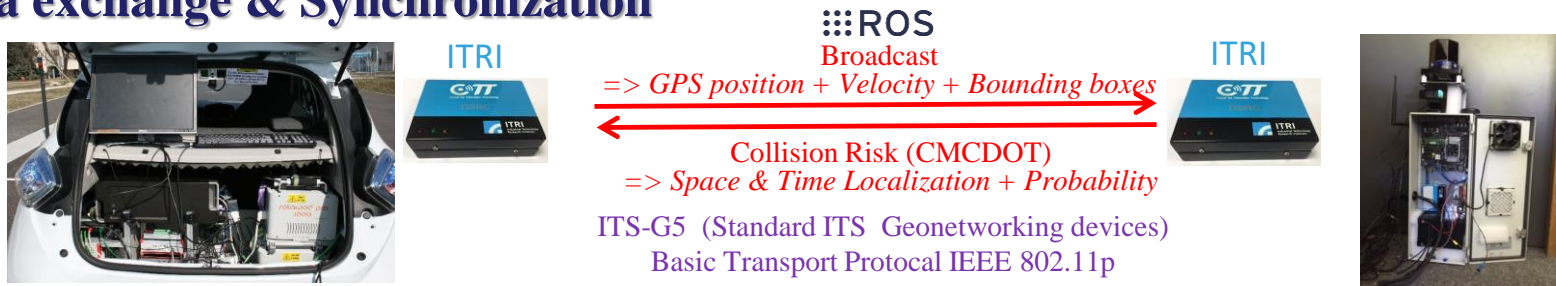


Open real traffic (Urban & Highway)



Paradigm 3: Distributed Bayesian Perception (using V2X)

Data exchange & Synchronization



Experimental results

Zoe vehicle
 View from the front camera

Connected Perception Box
 View from the box camera
 Moving obstacle (detected by the Box)

Lidar, GPS, GPU, ITS G5 unit, Battery

Perception Box

Paradigm 4: Improvements using Machine Learning

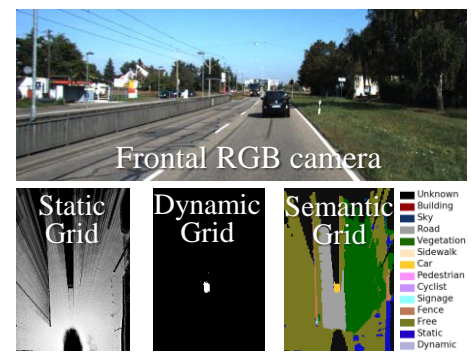
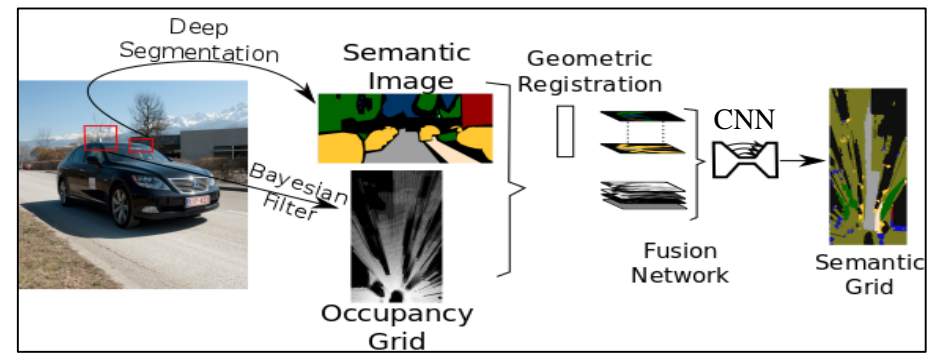
=> Current & Future work

□ Perception & Decision-making & Control integration in various contexts



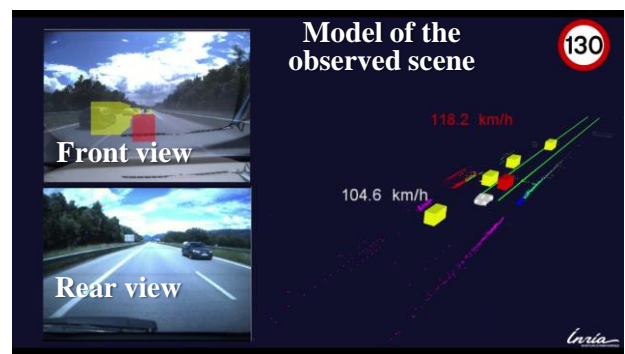
- Various Dynamics & Motion constraints
- Adapted Collision Risk Assessment & Collision avoidance maneuvers
- Cooperation IRT Nanoelec, Renault, Iveco ...

□ Models enrichment using Semantic Segmentation & Deep Learning

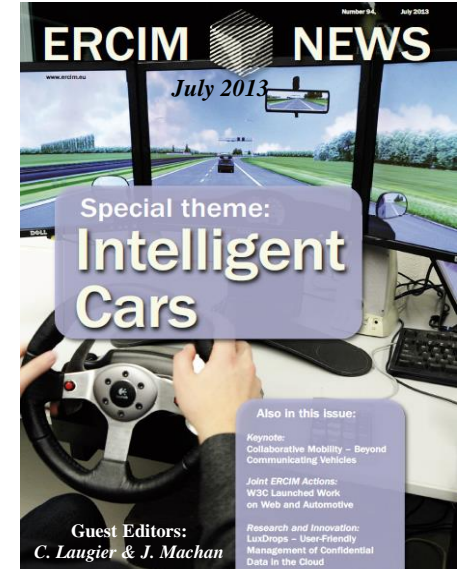
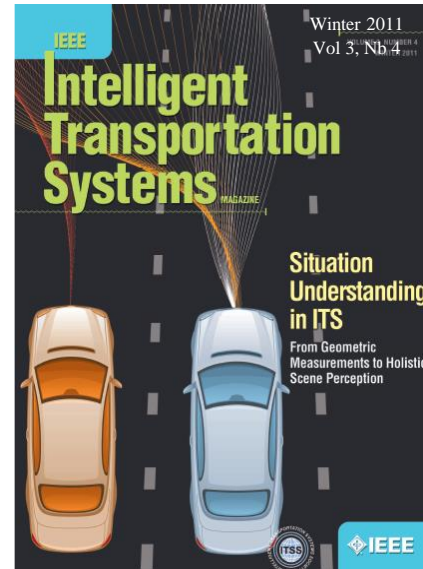
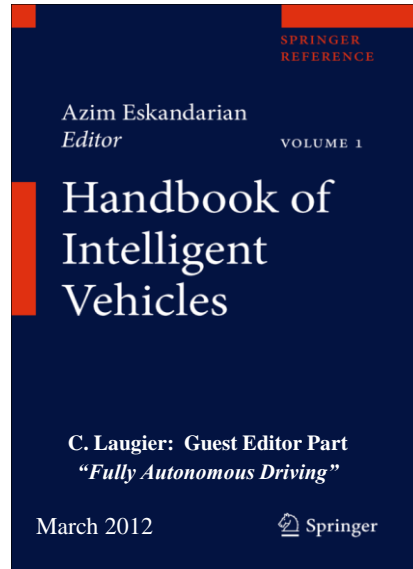


- Semantic Grids
- Cooperation Toyota & IRT Nanoelec
- Patent Inria-Toyota [IROS'18] [ICARCV'18]

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



- **Driver Behavior modeling** using Driving dataset & Inverse Reinforcement Learning => *Human-like Driver Model*
- **Motion Prediction & Driving Decision-making** by using learned Driver models & Dynamic evidences
- Cooperation Toyota
- 2 Patents & 3 publications (ITSC 2016, ICRA 2017, ICRA 2018)



Thank You Any questions ?

