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## A journey in the history of Automated Driving

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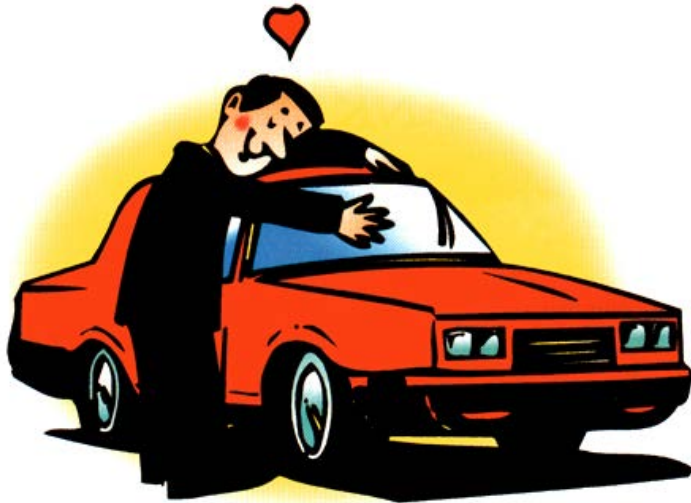
# A journey in the history of Automated Driving

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**Invited Pioneer's Talk**

*IROS 2019, Macau, China, November 6<sup>th</sup> 2019*



*Contributions: L. Rummelhard, A. Negre, N. Turro, J.A. David, J. Lussereau, T. Genevois, C. Tay Meng Keat, S. Lefevre, O. Erkent, D. Sierra-Gonzalez ... and also numerous former PhD students and Postdocs*

# Automobile & Human Mobility

## *A current Technological & Psychological breakthrough*



*On-going change of the role & concept of **private car** in human society !*



*Last century => Ownership & Feeling of Freedom  
Affective behaviors & Shown Social position  
Driving pleasure ... **but less and less true !***

*Next cars generation => Focus on **Technologies** for  
Safety & Comfort & Reduced Pollution  
**Driving Assistance v/s Autonomous Driving***

### Context of this recent evolution

- *Expected 3 Billions vehicles & 75% population in cities in 2050 => **Current model not scalable !***
- *Accidents: ~1.2 Million fatalities/Year in the world => **No more accepted by the human society !***
- *Driving safety & Nuisance issues (pollution, noise, traffic jam, parking ...) are becoming a **major issue for Human Society & Governments & Industry***
- *Technology & Internet & Ecology & Economic issues progressively change **mobility habits** of people => **Towards Less ownership & More shared mobility systems & Increased Autonomy ... e.g. Uber, BlaBlaCar, Tesla Autopilot, Waymo...***

# Early steps towards Autonomous Cars

## □ Early dream (1956):



*“Central Power & Light Company” predict Autonomous Cars  
.... on Electric super-highway*

*Advertorial: “ELECTRICITY MAY BE THE DRIVER. One day your car may speed along an electric super-highway, its speed and steering automatically controlled by electronic devices embedded in the road. Highways will be made safe – by electricity! No traffic jams ... no collisions ... no driver fatigue”*

## □ EU: Some milestones in the 80’s



VaMORs, Munchen Univ, 1986

- First autonomous vehicle on a road (mainly based on CV): VaMORs prototype, Dickmann, Munchen University, 1986
- EU project Prometheus (1987-95, ~750 M€), Largest R&D project on driverless cars (involving EU Industry & Universities)  
=> Large public demonstration in Paris in 1994

# EU: Some results in the 90's



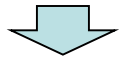
**Automatic parking, Inria, 1996**  
(low cost sensors, no map)



**City Platooning & Concept of shared cars**  
Inria, 1997



**Cycab concept (urban people mover)**  
Inria



[https://en.wikipedia.org/wiki/Automatic\\_parking](https://en.wikipedia.org/wiki/Automatic_parking)

- ⇒ *One of the world's first experimental prototypes of automatic parallel parking was developed on an electric car Ligier at INRIA in the mid-1990s<sup>[1][3]</sup>.*
- ⇒ *The underlying technology has been adopted by major automobile manufacturers offering an automatic parking option in their cars today.*
- ⇒ *First commercial version of the automatic parallel parking concept on Toyota Lexus in 2010.*



[1] I. Paromtchik & C. Laugier, « Autonomous Parallel Parking of a Nonholonomic Vehicle », IEEE Intelligent Vehicle Symposium 1996, Tokyo, Japan.

# International Events & Projects *(A great impact, 1<sup>st</sup> decade 21<sup>st</sup> century)*



**USA 2004 & 2006: Darpa Grand Challenges (High speed & Off-road)**  
*=> Significant step towards Motion Autonomy... But still some uncontrolled behaviors in 2004*



**USA 2007: Darpa Urban Challenge (97 km, 50 manned & unmanned vehicles, 35 teams)**  
*=> Impressive progress towards autonomous driving .... but still some collisions (Perception & Decision-making failures)*



**EU 2010: VIAC Intercontinental Autonomous Challenge (A. Broggi, Parma)**  
*=> 13 000 km covered, 3 months race, leader + followers*



**USA 2011: Google Car project (1<sup>st</sup> large Industrial project on AD)**  
*Fleet of 6 automated Toyota Prius, costly 3D lidar (dense mapping)  
140 000 miles covered on California roads with occasional human interventions*

# Technology status & Ongoing challenges for AVs

- Strong involvement of Car Industry & GAFA + Large media coverage + Increasing Governments supports
  - An expected market of 515 B€ at horizon 2035 (~17% world automobile market, Consulting agency AT Kearney, Dec 2017)
  - But Legal & Regulation issues are still unclear ... idem for Technologies Validation & Certification issues !
- => Numerous experiments in real traffic conditions since 2010 (Disengagement reports & Insights on system maturity)
- => But still insufficient ... Realistic Simulation & Formal methods are also under development (e.g. EU Enable-S3)



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



Numerous EU projects in last decades  
Cybus, 3 months experiment, low speed  
La Rochelle 2012 (France)



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



Drive Me trials (Volvo, 2017)

- 100 Test Vehicles in Göteborg, 80 km, 70km/h
- No pedestrians & Separations between lanes



“Self-Driving Taxi Service L3” testing in US (Uber, Waymo) & Singapore (nuTonomy)

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

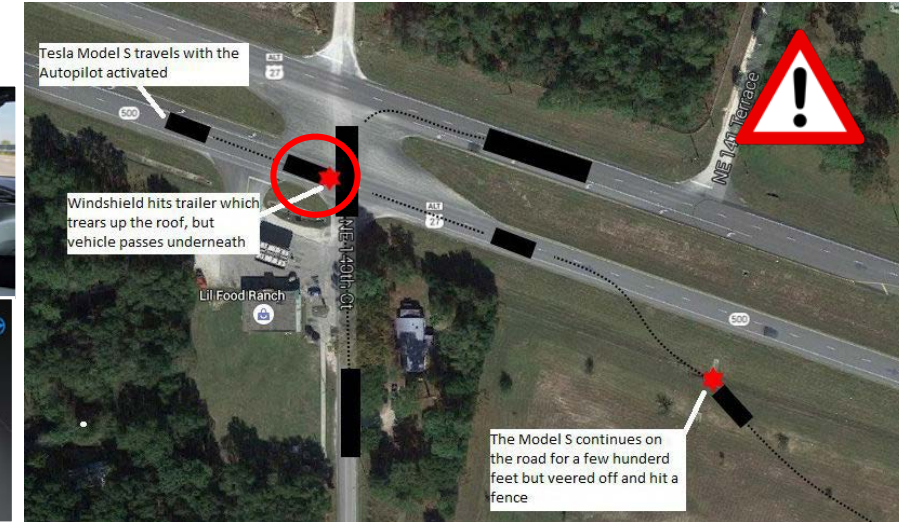


Millions of miles driven since 2010 (Google, Tesla, Waymo, Uber) Several benign & serious accidents in past few years Safety is still not guaranteed!

# Fatal accidents involving AVs – *Perception failure*

## ❑ Tesla driver killed in a crash with Autopilot “level 2” active (*ADAS mode*) – May 2016

- ✓ *The Autopilot failed to detect a white moving truck, with a brightly lit sky (Camera Mobileye + Radar)*
- ✓ *The human driver was not vigilant & didn't took over*



## ❑ Self-driving Uber L3 vehicle killed a woman => *First fatal crash involving a pedestrian* Tempe, Arizona, March 2018

- ✓ *Despite the presence of multiple sensors (lidars, cameras ...), the perception system failed to detect the pedestrian & didn't disengaged*
- ✓ *The Safety Driver reacted too lately (1s before the crash)*





# AVs have to face two main challenges

## Challenge 1: The need for **Robust, Self-diagnosing & Explainable Embedded Perception**



*Video source: AutoPilot Review @ youtube.com*

### **Video Scenario:**

- The Tesla perception system failed to detect the barriers blocking the left side route.*
- The driver has to take over and steer the vehicle away from the blocked route (for avoiding the collision).*

# AVs have to face two main challenges

**Challenge 2:** The need for Understandable **Driving Decisions** (*share the road with human drivers*)

Unfortunately **Human drivers actions** are determined by a complex set of interdependent factors difficult to model  
(*e.g. intentions, perception, emotions ...*)

⇒ Predicting **human driver behaviors is inherently uncertain**

⇒ AV have to reason about **uncertain intentions** of the surrounding vehicles



The Lexus SUV, fitted with special sensors, struck the public bus on February 14 in Mountain View, California

*Video source: The Telegraph*

**Video scenario** (*Scene observed by the dash cam of a bus moving behind the Waymo AV*)

- *Waymo AV is blocked by an obstacle and it decides to execute a left lane change*
- *The bus driver misunderstood the Tesla's intention and didn't yield*
- *he two vehicles collided*

# Perception & Decision-making requirements for AVs

## Dynamic Scene Understanding & Navigation Decisions



### Situation Awareness & Decision-making

- ⇒ Sensing + Prior knowledge + Interpretation
- ⇒ Selecting appropriate Navigation strategy (planning & control)

## ADAS & Autonomous Driving



### Embedded Perception & Decision-making for Safe Intentional Navigation

## Dealing with unexpected events



### Anticipation & Risk Prediction technologies for avoiding upcoming collisions with "something"

- ⇒ High reactivity & reflexive actions
- ⇒ Focus of Attention & Sensing
- ⇒ Collision Risk estimation + Avoidance strategy

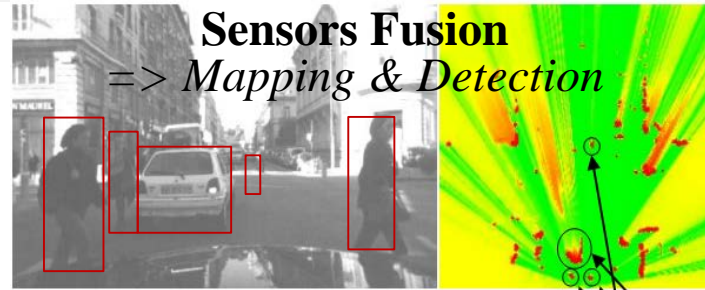
## Main features

- ✓ Dynamic & Open Environments ⇒ *Real-time processing & Reactivity (several reasoning levels are required)*
- ✓ 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 process (AI based technologies)*  
*Taking into account Interactions + Behaviors + Social rules (including traffic rules)*

# 1<sup>st</sup> Paradigm : 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*

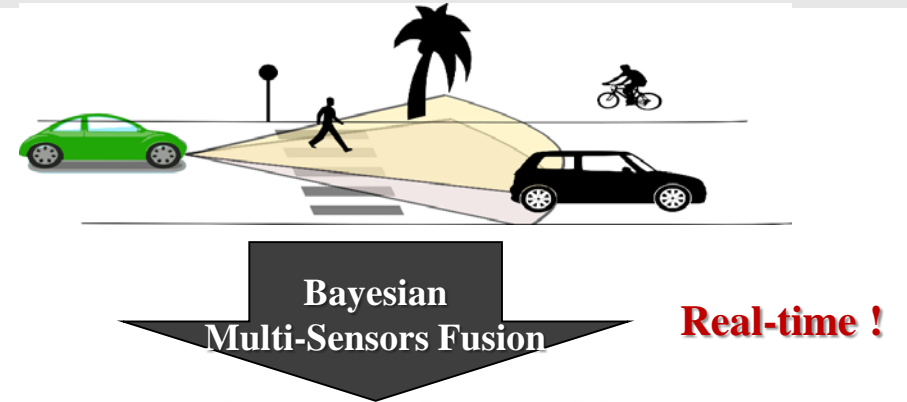
## ❑ Our Approach: Embedded Bayesian Perception

- ✓ *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

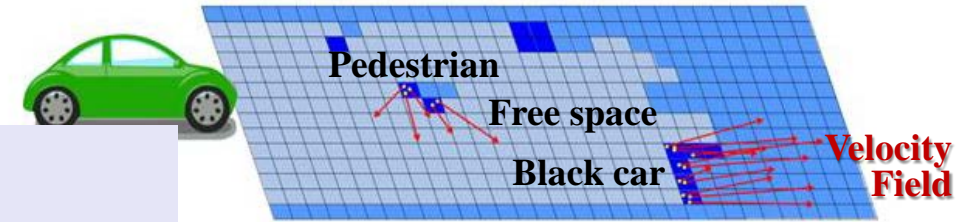
## □ Multi-Sensors Observations

*Lidar, Radar, Stereo camera, IMU ...*



## □ Probabilistic Environment Model including Dynamics

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



### *Concept of “Dynamic Probabilistic Grid + Bayesian Filtering”*

- ⇒ Clear distinction between Static & Dynamic & Free components*
- ⇒ Occupancy & Velocity probabilities*
- ⇒ Designed for Highly Parallel Processing (to satisfy real-time constraints)*
- ⇒ Includes Embedded Models for Motion Prediction & Collision Risk Assessment*
- ⇒ Patented technology & Industrial licenses 2018 (Toyota, Easymile)*

*[PhD Thesis Coué 2005]*  
*[Coué & Laugier IJRR 2005]*  
*[Laugier et al ITSM 2011]*  
*[Rummelhard et al ITSC 2015]*  
*[Mooc uTOP 2015]*

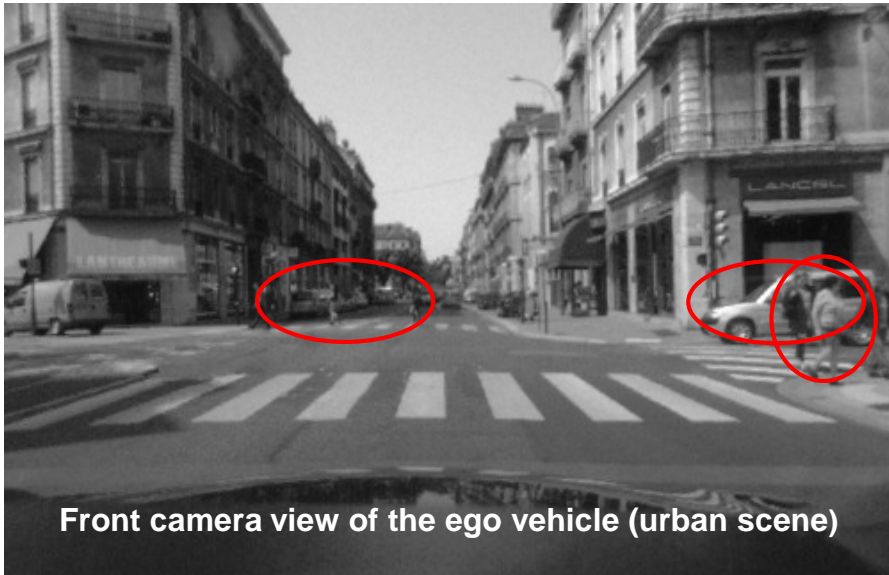
## □ Main philosophy

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

- Improving Efficiency & Reactivity to unexpected events => Highly parallel processing & High frequency !*
- Avoiding most of traditional object level processing problems (e.g. detection errors, wrong data association...)*

# Dynamic Probabilistic Grid & Bayesian Filtering – *Main Features*

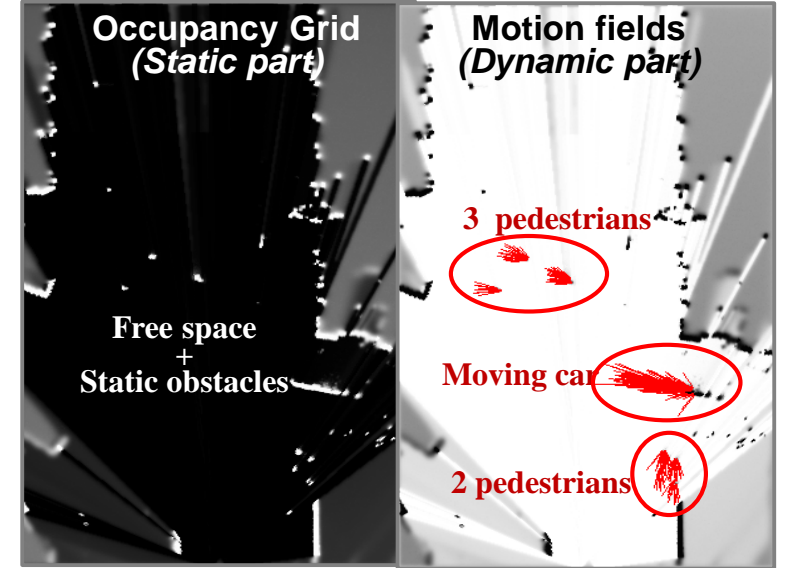
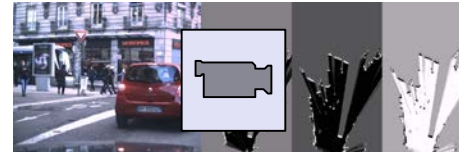
=> Exploiting the dynamic information for a better understanding of the scene



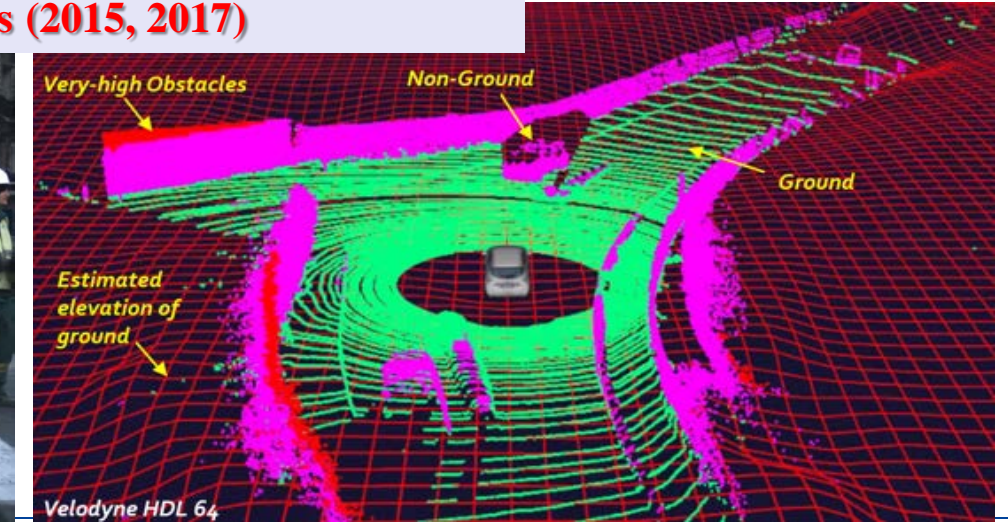
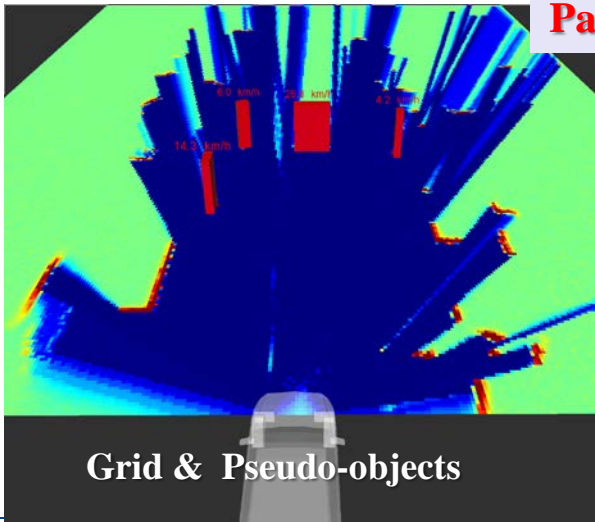
Sensors data fusion  
+  
Bayesian Filtering  
+  
Extracted Motion Fields



1<sup>st</sup> Embedded & Optimized version  
(HSBOF, patent 2014)



## Patented Improvements & Implementations (2015, 2017)



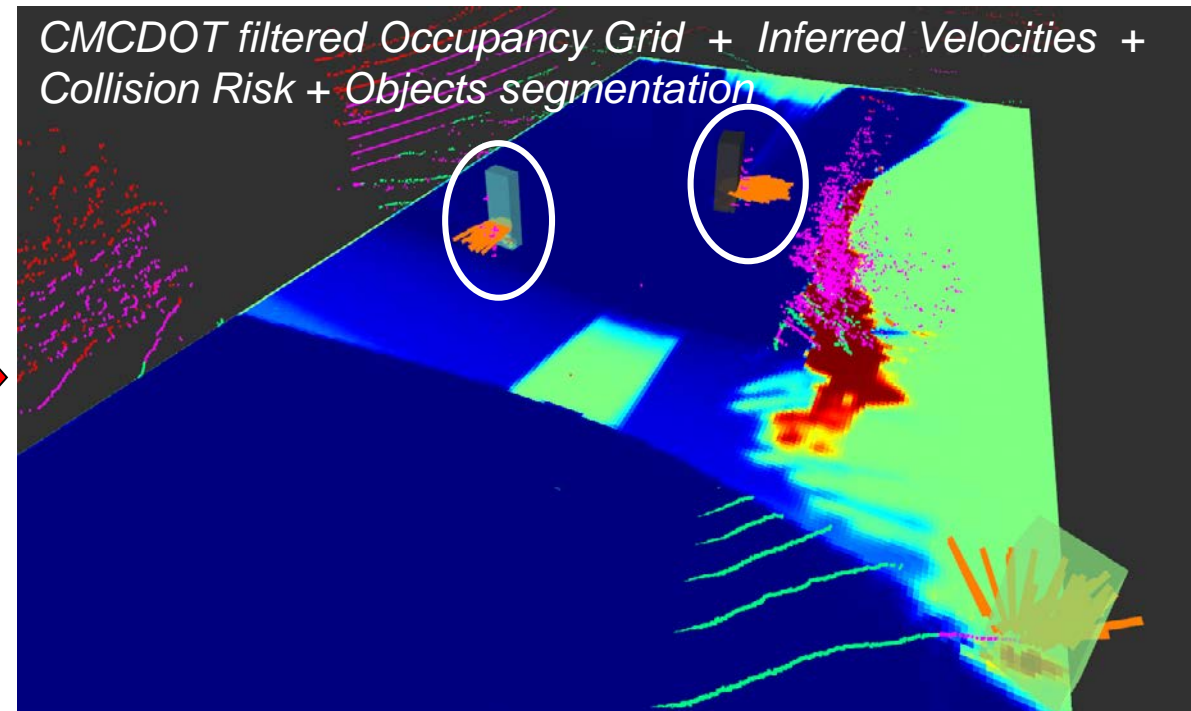
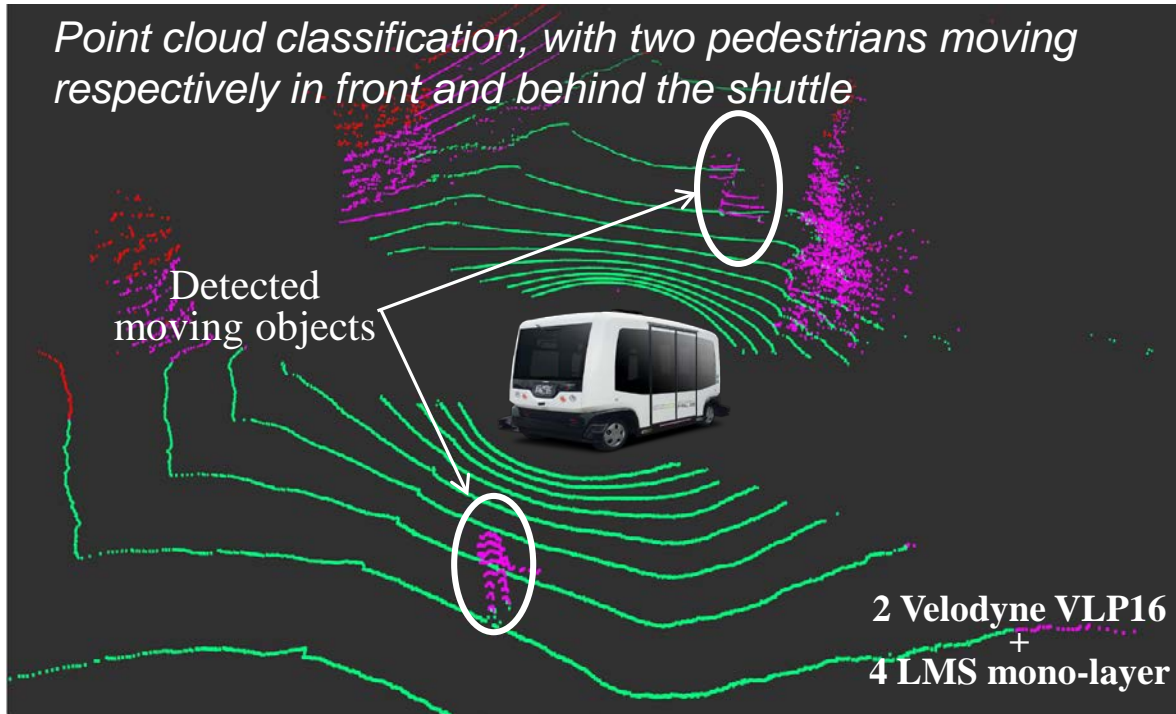
Detection & Tracking + Moving Objects Classification  
=> CMCDOT 2015 (including a “Dense Occupancy Tracker”)

Ground Estimation & Point Cloud Classification  
(patent 2017)

# System Integration on a Commercial Vehicle

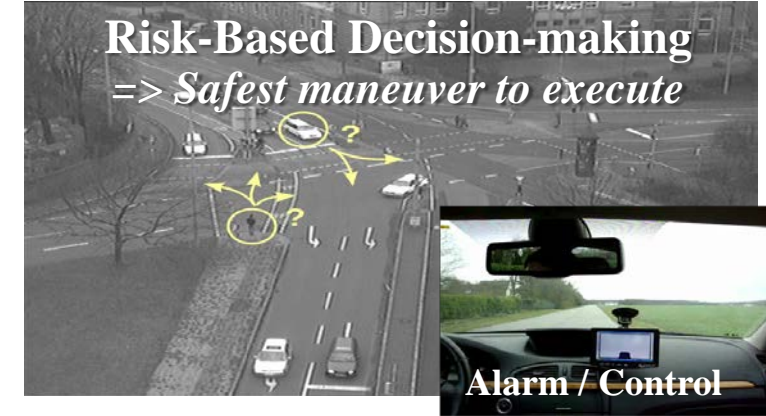
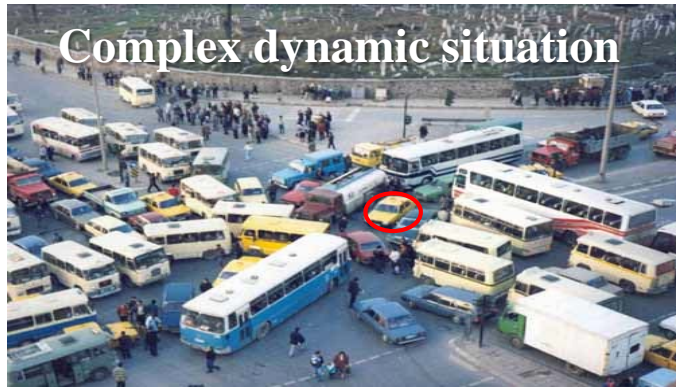


- **POC 2019: Complete system implemented on Nvidia TX1**, and easily connected to the shuttle system network *in a few days* (using ROS)
- **Shuttle sensors data** has been fused and processed in **real-time**, with a successful Detection & Characterization of the **Moving & Static Obstacles**
- **Full integration on a commercial product** under development with an industrial company (confidential)



# 2<sup>nd</sup> Paradigm: Collision 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 + Navigation Decision based on Perception & Prior Knowledge*

## □ 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*

## □ Decision-making: Two types of “collision risk” have to be considered

✓ *Short-term collision risk* => *Imminent collisions* with “something” (unclassified), time horizon  $<3s$ , conservative hypotheses

✓ *Long-term collision risk* => *Future potential collisions*, horizon  $>3s$ , Context + Semantics, Behavior models



# **Concept 1: Short-term collision risk** (*Basic idea*)

=> *How to deal with unexpected & unclassified events (i.e. “something” is moving ahead) ?*

=> *Exploit previous observations for anticipating future objects motions & related potential future collision*

Autonomous  
Vehicle (Cycab)



Parked Vehicle  
(occultation)

**Pioneer Results  
(2005)**

*[PhD Thesis C. Coué 2004]  
[Coué & Laugier & al 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 & Results*

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

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

*$\delta = 0.5s \Rightarrow$  Precrash*

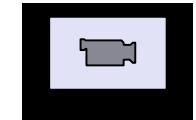
*$\delta = 1s \Rightarrow$  Collision mitigation*

*$\delta > 1.5s \Rightarrow$  Warning / Emergency Braking*

## □ Main Features

- Detect “*Upcoming potential Collisions*” a few seconds ahead (3-5s) in the *Dynamic Grid*
- Risky situations are *both localized in Space & Time* (under conservative motion hypotheses)
- Resulting information is used for choosing the most appropriate *Collision Avoidance Maneuvers*

## □ Experimental results



### 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 Collision Risk (*Object level*)

=> *Increasing time horizon & complexity using Context & Semantics*

=> *Key concepts: Behaviors Modeling & Prediction + Traffic Participants 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  
make Prediction more easy*

### **Context & Semantics**

*History + Space geometry + Traffic rules*

+

### **Behavior Prediction & Interactions**

*For all surrounding traffic participants  
(using learned models)*

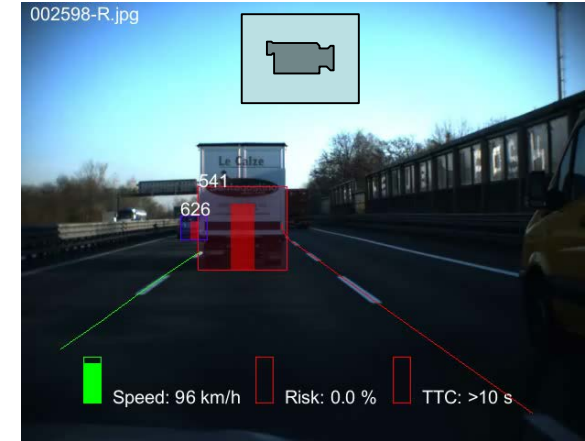
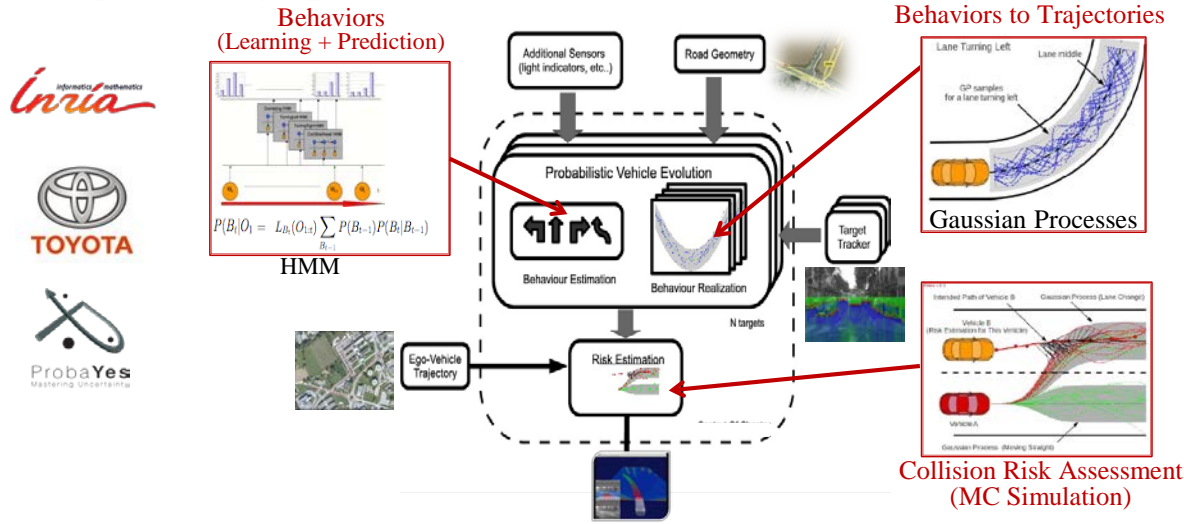
+

### **Probabilistic Risk Assessment**

# Behavior-based Collision risk – *Main approaches & Results*

=> *Increased time horizon & complexity + Reasoning on Behaviors & Interactions*

## □ Trajectory prediction & Collision Risk => *Patent 2010 (Inria, Toyota, Probayes)*

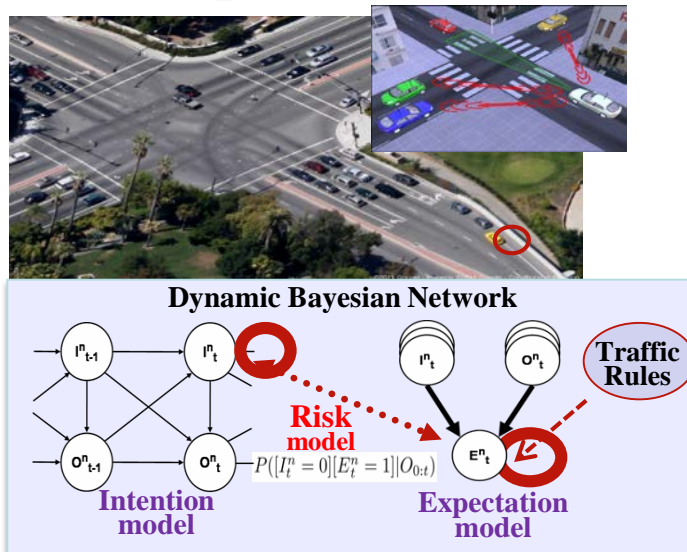


*Cooperation still on-going (R&D contracts + PhD)*

Courtesy Probayes



## □ Intention & Expectation (*Mixed Traffic & Interactions*) => *Patents 2012 (Inria - Renault) & 2013 (Inria - Berkeley)*



**Human-like reasoning**

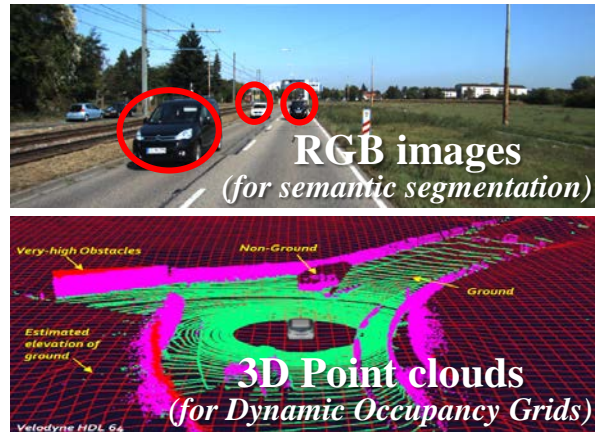


*Cooperation still on-going (R&D contracts + PhD)*



# 3<sup>rd</sup> Paradigm: Models improvements using Machine Learning

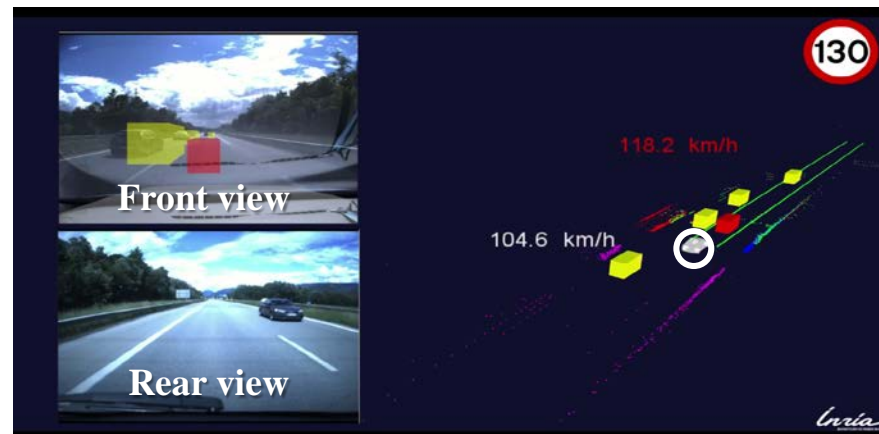
□ Perception level: *Construct “Semantic Grids” using Bayesian Perception & DL*



□ Decision-making level: *Learn driving skills for Autonomous Driving*

❖ 1<sup>st</sup> Step: *Modeling Driver Behavior using Inverse Reinforcement Learning (IRL)*

❖ 2<sup>nd</sup> Step: *Predict motions of surrounding vehicles & Make Driving Decisions for Ego Vehicle*

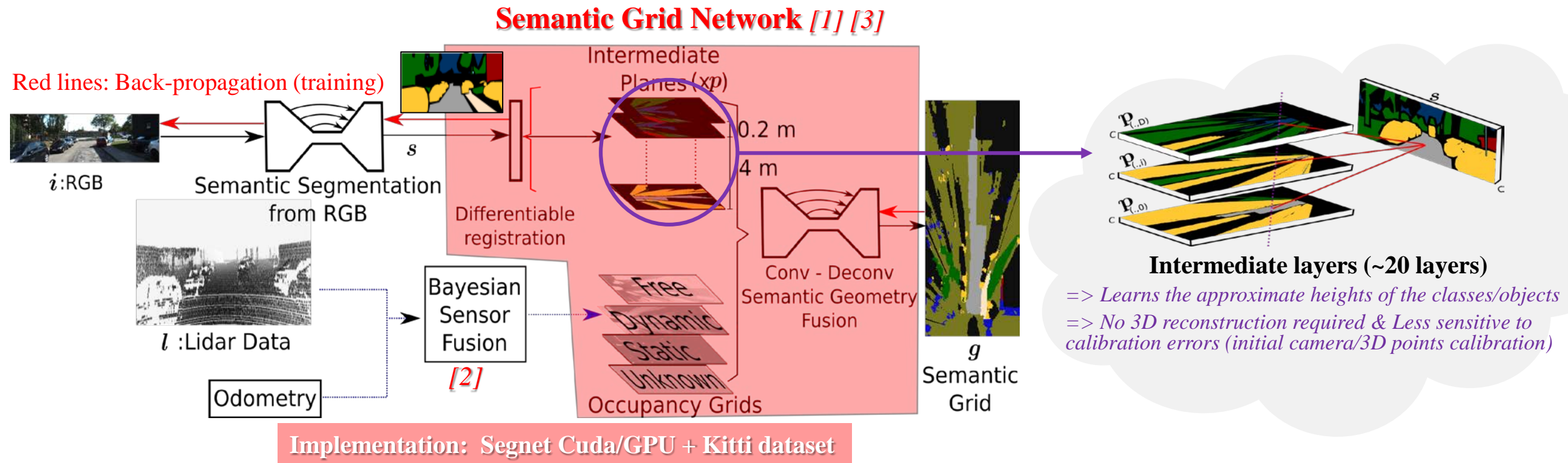


# Perception Level: Semantic Grids (Bayesian Perception + DL)

**Objective:** Add *Semantic information* (cars, pedestrians, roads, buildings...) in each cell of the Dynamic Occupancy Grid model, by exploiting *additional RGB inputs*

**Approach:** A new “*Hybrid Sensor Fusion approach*” combining *Bayesian Perception & Deep Learning*

[1] [2] + Patent 2019 (Inria, Toyota)

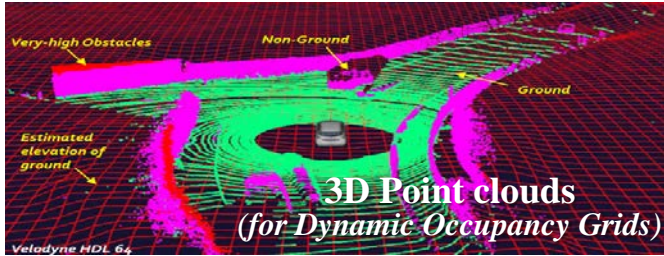


[1] Semantic grid estimation with a Hybrid Bayesian and Deep Neural Network approach, O. Erkent et al., IEEE IROS 2018

[2] Conditional Monte Carlo Dense Occupancy Tracker, Rummelhard et al., ITSC 2015

[3] Segnet: A deep convolutional encoder-decoder architecture for image segmentation, Badrinarayanan et al., IEEE PAMI 39(12) 2017

# Semantic Grids – *Experimental Evaluation Approach*



**Frontal View (RGB camera)**



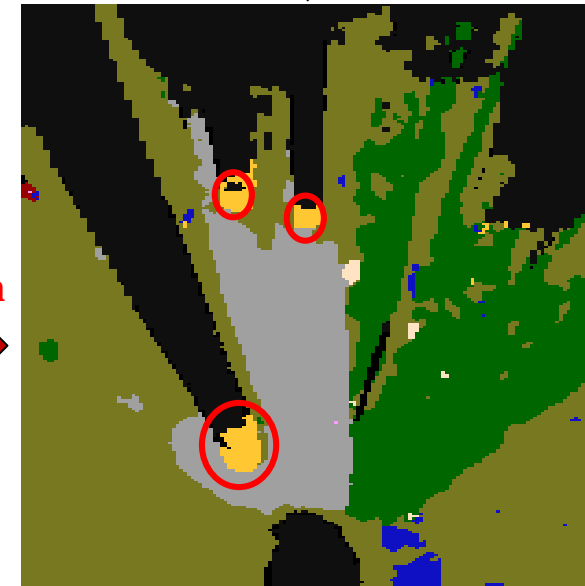
**Frontal View Ground-Truth**  
=> labelled by humans in training datasets

## Hybrid Sensor Fusion approach (Semantic Grid construction)



**Bird's Eye View Ground-Truth**  
=> Frontal View GT "projected" using Point-Cloud (Bayesian Perception)  
=> Densified by humans (point-clouds and images have different resolutions)

**Comparison**



**Semantic Grid Prediction**  
=> Dense structure obtained using hybrid integration

- |            |
|------------|
| Unknown    |
| Building   |
| Sky        |
| Road       |
| Vegetation |
| Sidewalk   |
| Car        |
| Pedestrian |
| Cyclist    |
| Signage    |
| Fence      |
| Free       |
| Static     |
| Dynamic    |

**Labels**

# Semantic Grids – *Experimental Results*

Ground Truth (GT)

GT Projection

Semantic Grid Estimation

2 cars finally recognized

Frontal View Estimation

2 cars not detected

Unknown  
Building  
Sky  
Road  
Vegetation  
Sidewalk  
Car  
Pedestrian  
Cyclist  
Signage  
Fence  
Free  
Static  
Dynamic

**2 cars not detected in frontal view estimation (semantic segmentation)**  
**... but recognized in semantic grid (with the help of Dynamic Occupancy Grid)**

Ground Truth (GT)

GT Projection

Semantic Grid Estimation

Truck finally recognized

Frontal View Estimation

Truck not detected

Fence not detected

Fence finally recognized

Unknown  
Building  
Sky  
Road  
Vegetation  
Sidewalk  
Car  
Pedestrian  
Cyclist  
Signage  
Fence  
Free  
Static  
Dynamic

**Fence not detected in frontal view estimation ... but recognized as an obstacle in semantic grid (with the help of Dynamic Occupancy Grid)**

**Truck not detected in frontal view estimation ... but recognized in semantic grid (with the help of Dynamic Occupancy Grid)**

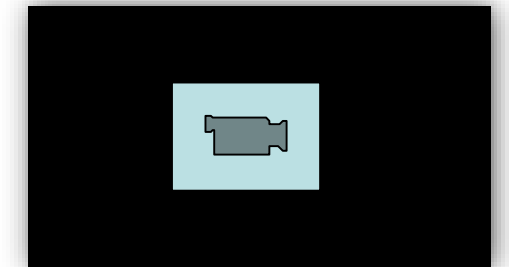
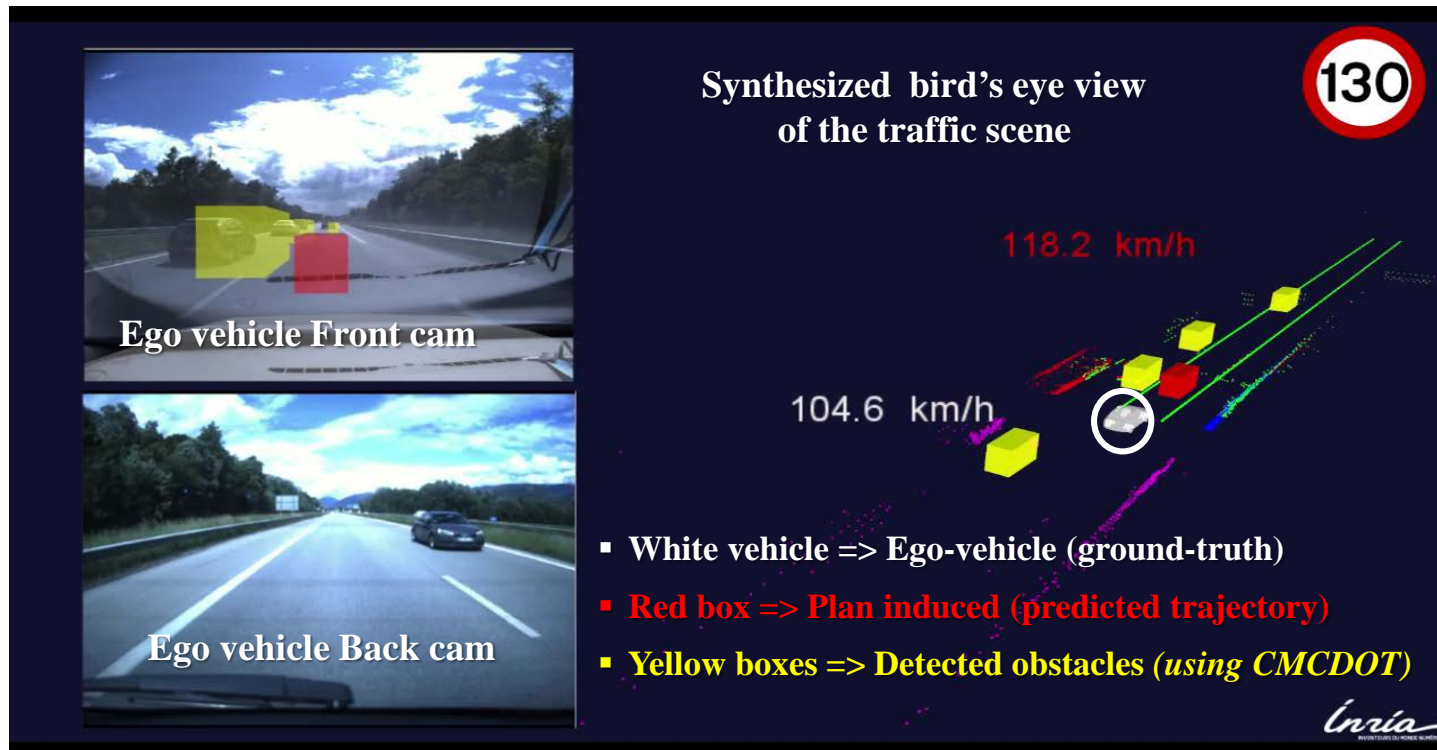


# Decision-making level: Learning Driving Skills for AD

## 1<sup>st</sup> Step: Driver behavior modeling

- Learn Model parameters from real driving demonstrations using *Inverse Reinforcement Learning (IRL)*
  - Driver behaviors are modelled using a **Cost function**  $C(s) = \sum_{i=1}^K w_i \cdot f_i(s)$  which is assumed linear on a set of **K hand-crafted features** (e.g. *Lane index preferences, Deviation from desired velocity, TTC to frontal targets, Time-gap to rear targets ...*)
  - A training set containing “interesting highway vehicle interactions” has been first constructed using our *Lexus vehicle*
- => Obtained models can be leverage to **Predict human driver behaviors & Generate human-like plans for the ego vehicle** (mandatory in mixed traffic)

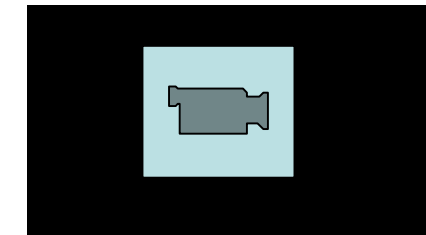
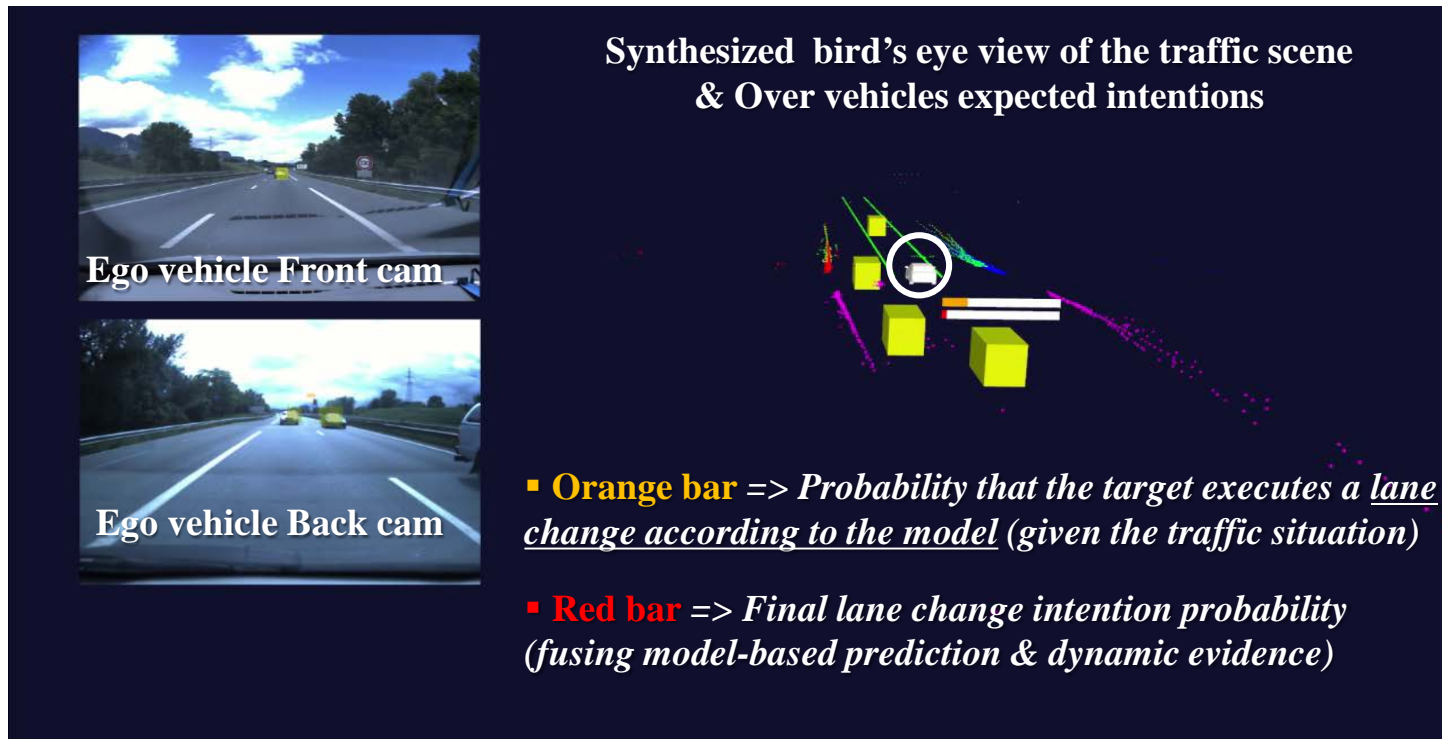
[Sierra Gonzalez et al, ICRA 2018]



# Decision-making level: Learning Driving Skills for AD

## 2<sup>nd</sup> Step: Motion Prediction & Driving Decisions

- A realistic **Human-like Driver Model** can be exploited to **Predict the long-term evolution** (10s and beyond) of traffic scenes [*Sierra Gonzalez et al., ITSC 2016*]
  - For the **short/mid-term**, both the **Driver model** and the **Dynamics of the target** provide useful information to **determine future driving behaviors**
- => Our probabilistic model fuses **Model-based Predictions & Dynamic evidence** to produce robust **lane change intention estimations** in highway scenes [*Sierra Gonzalez et al., ICRA 2017*]



Comparison between demonstrated behaviors in test set & behaviors induced by the learned model & dynamics evidence

# Summary & On going work

## □ Autonomous Driving in various Traffic & Context situations (*cooperation with industry*)



Autonomous Shuttles  
(~15 km/h, Urban traffic)



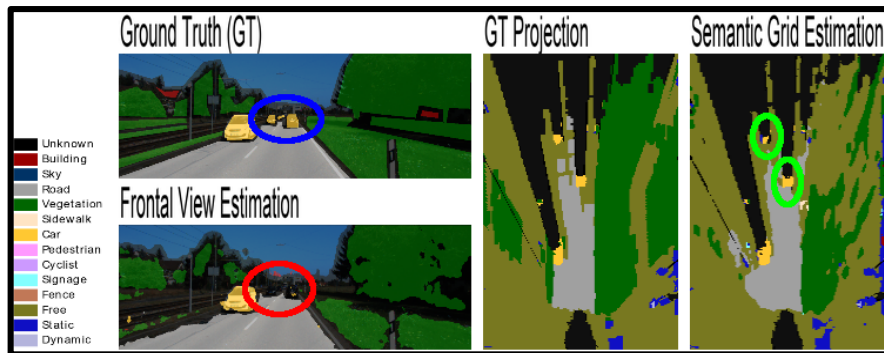
Autonomous Bus (Iveco)  
(up to 70 km/h, Urban traffic)



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 ...**

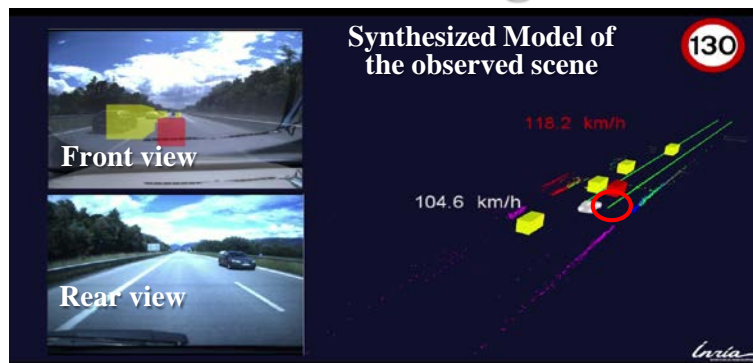
## □ Embedded & Extended “Semantic Grids” (*to improve scene understanding & decision-making*)



- Embedded “Semantic Grids” & “Panoptic Segmentation”
- Improved scene understanding (various weather conditions)
- **Cooperation Toyota**
- 1 Patent & 3 publications (IROS’18, ICARCV’18, Unmanned System journal 2019)

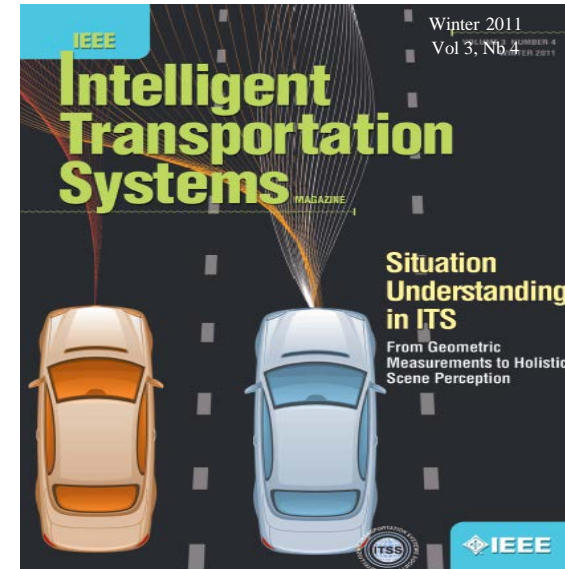
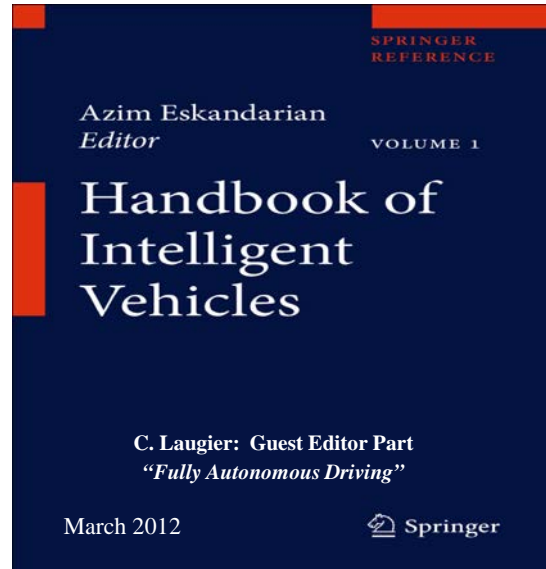
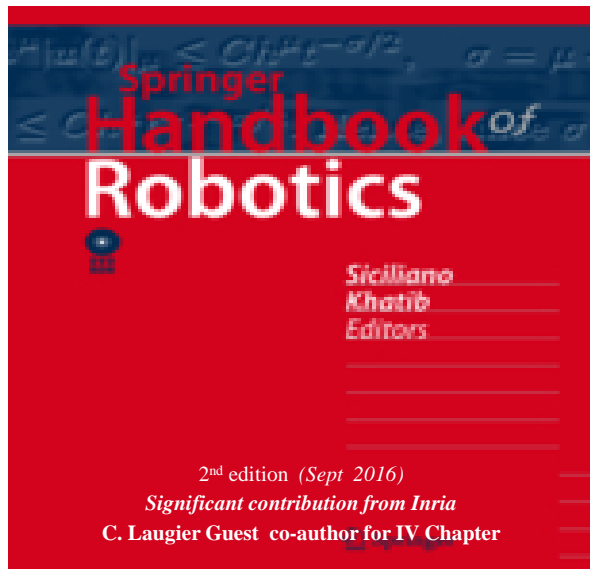


## □ Autonomous Driving in mixed traffic & Various traffic conditions (Prediction & Planning)



- **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





# Thank You

