# Situation Awareness & Decision-making for Autonomous Driving

Christian Laugier

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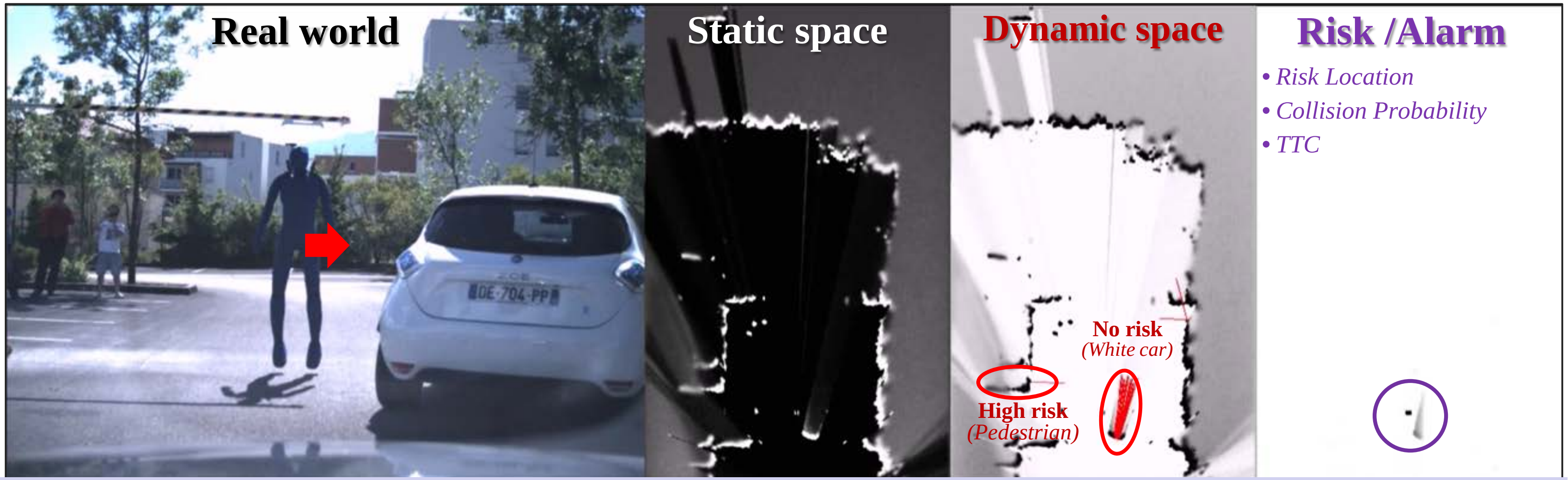



**Keynote talk, IROS 2019 Cutting Edge Forum on "Robotics, AI and ITS contributions to Autonomous Driving"**

***IROS 2019, Macau, China, November 5th 2019***

# 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:*** *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**

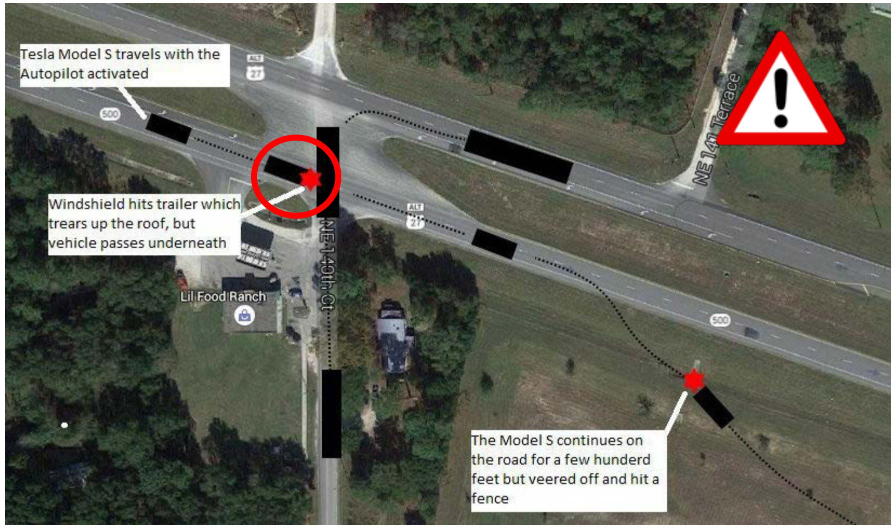
**Safety is still not guaranteed !**

# Fatal accidents involving AVs – *Perception failure*

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

✓ ***The Autopilot <u>failed to detect</u> 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*

*Temple, Arizona, March 2018*

✓ ***Despite the presence of multiple sensors (lidars, cameras …), the <u>perception system failed to detect the pedestrian & didn't disengaged</u>***

✓ ***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)*

**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***


*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*
- *The 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)*


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

**Dealing with unexpected events**


*Road Safety Campaign, France 2014*

**Anticipation & Risk Prediction required**

*for avoiding an upcoming collision with "something"*

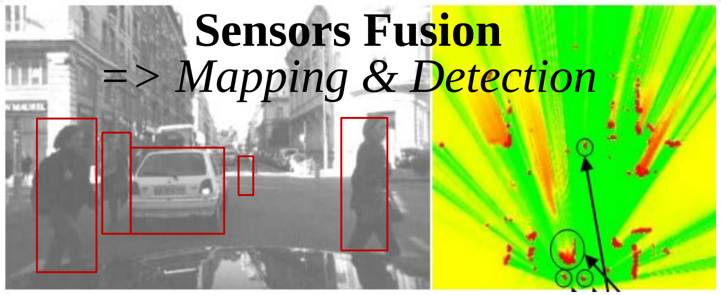
*=> High reactivity & reflexive actions*
*=> Focus of Attention & Sensing*
*=> Collision Risk estimation + Avoidance strategy*

## 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)*

# *1st 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

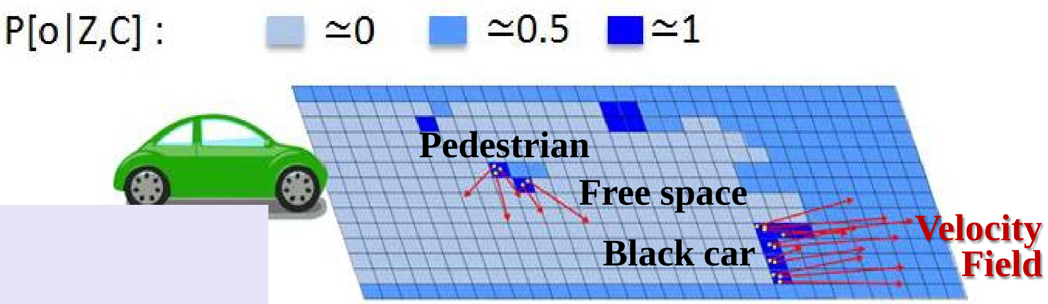
Bayesian
Multi-Sensors Fusion

**Real-time !**

- ❑ **Multi-Sensors Observations**

  *Lidar, Radar, Stereo camera, IMU …*

- ❑ **Probabilistic Environment Model including Dynamics**




***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]*

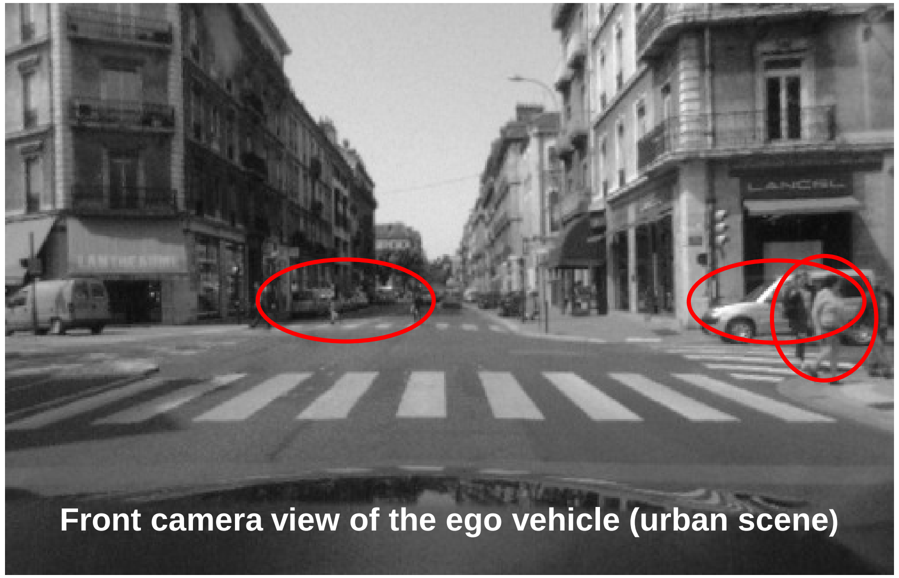
- ❑ **Main philosophy**

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

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

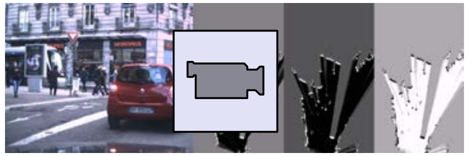
# Dynamic Probabilistic Grid & Bayesian Filtering – *Main Features*

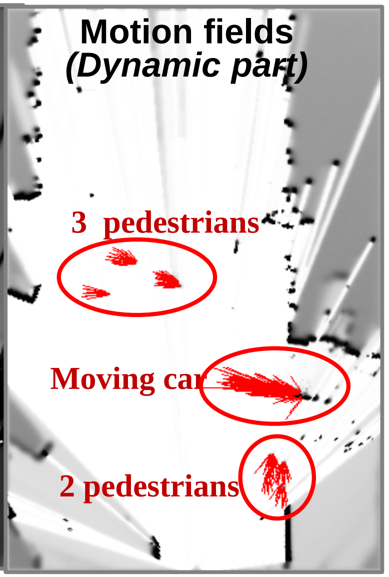
*=> Exploiting the dynamic information for a better understanding of the scene*



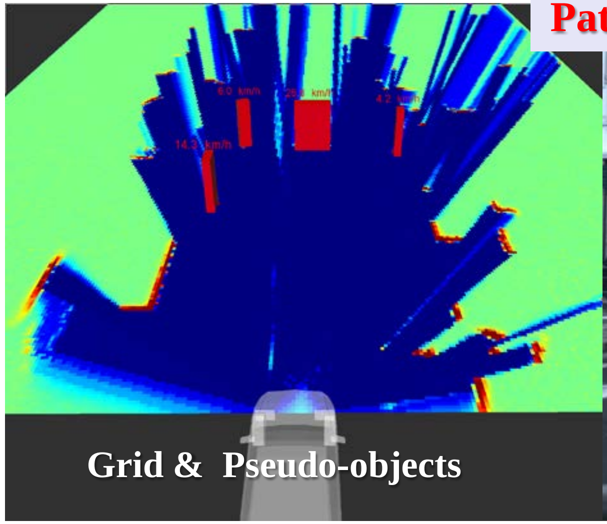

**Sensors data fusion**
**+**
**Bayesian Filtering**
**+**
**Extracted Motion Fields**

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

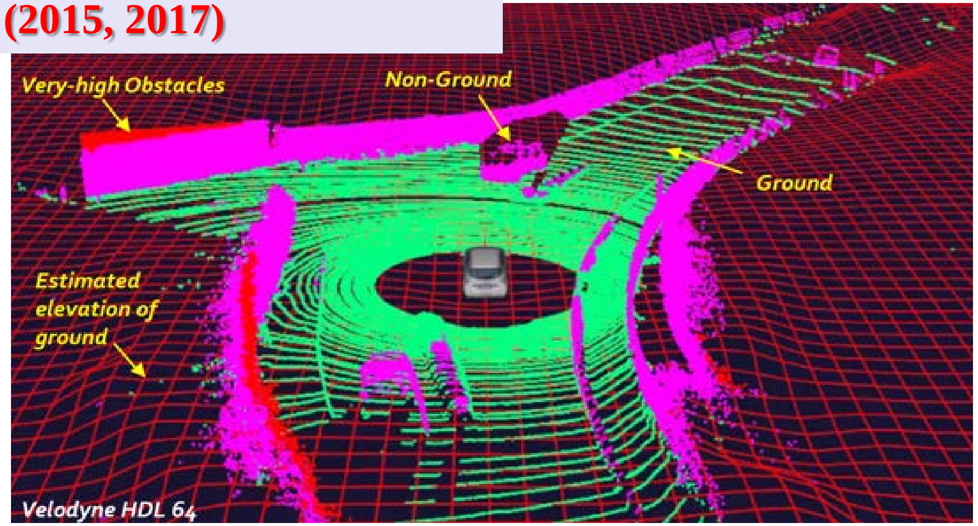



**Patented Improvements & Implementations (2015, 2017)**







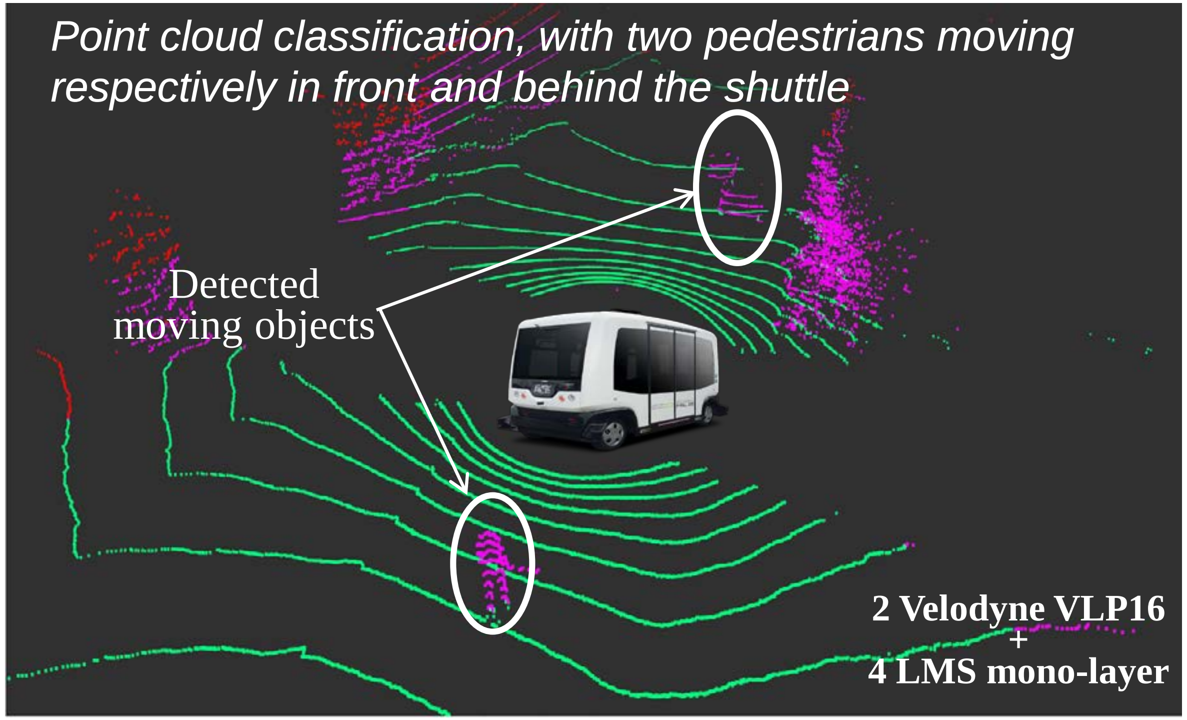

Detection & Tracking + Moving Objects Classification
=> CMCDOT 2015 (including a "Dense Occupancy Tracker")

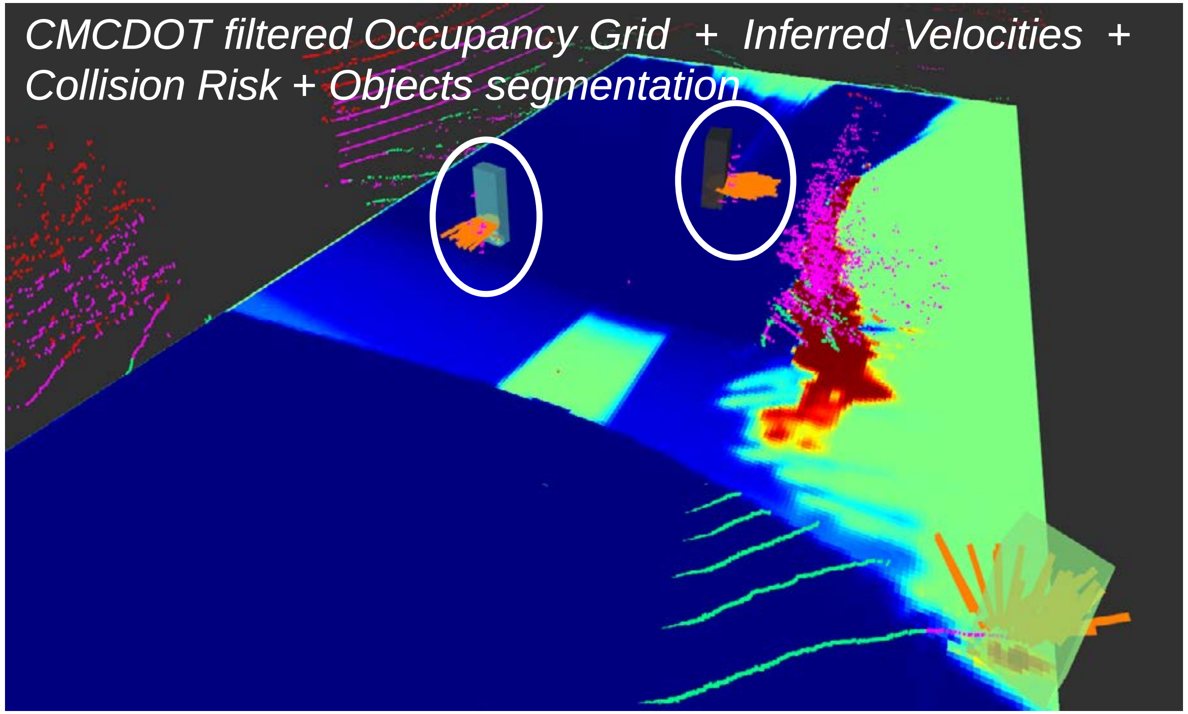
Ground Estimation & Point Cloud Classification
(patent 2017)

# 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)

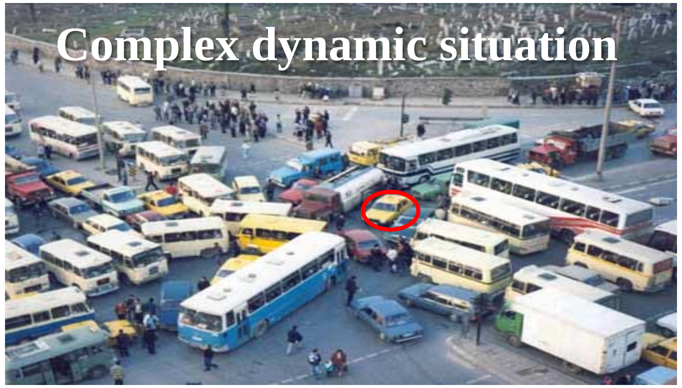
- **Shuttle sensors data** has been fused and processed in **real-time**, with a successful Detection & Characterization of the **Moving & Static Obstacles**
- **Full integration on a commercial product** under development with an industrial company (confidential)



# 2nd 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 ahead)*
- ✓ *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*
*δ= 0.5 s => Precrash*
*δ= 1 s => Collision mitigation*
*δ > 1.5s => 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 <u>Space & Time</u>** (under conservative motion hypotheses)*
- *Resulting information is used for choosing the most appropriate Collision **Avoidance Maneuvers***

## ❑ Experimental results

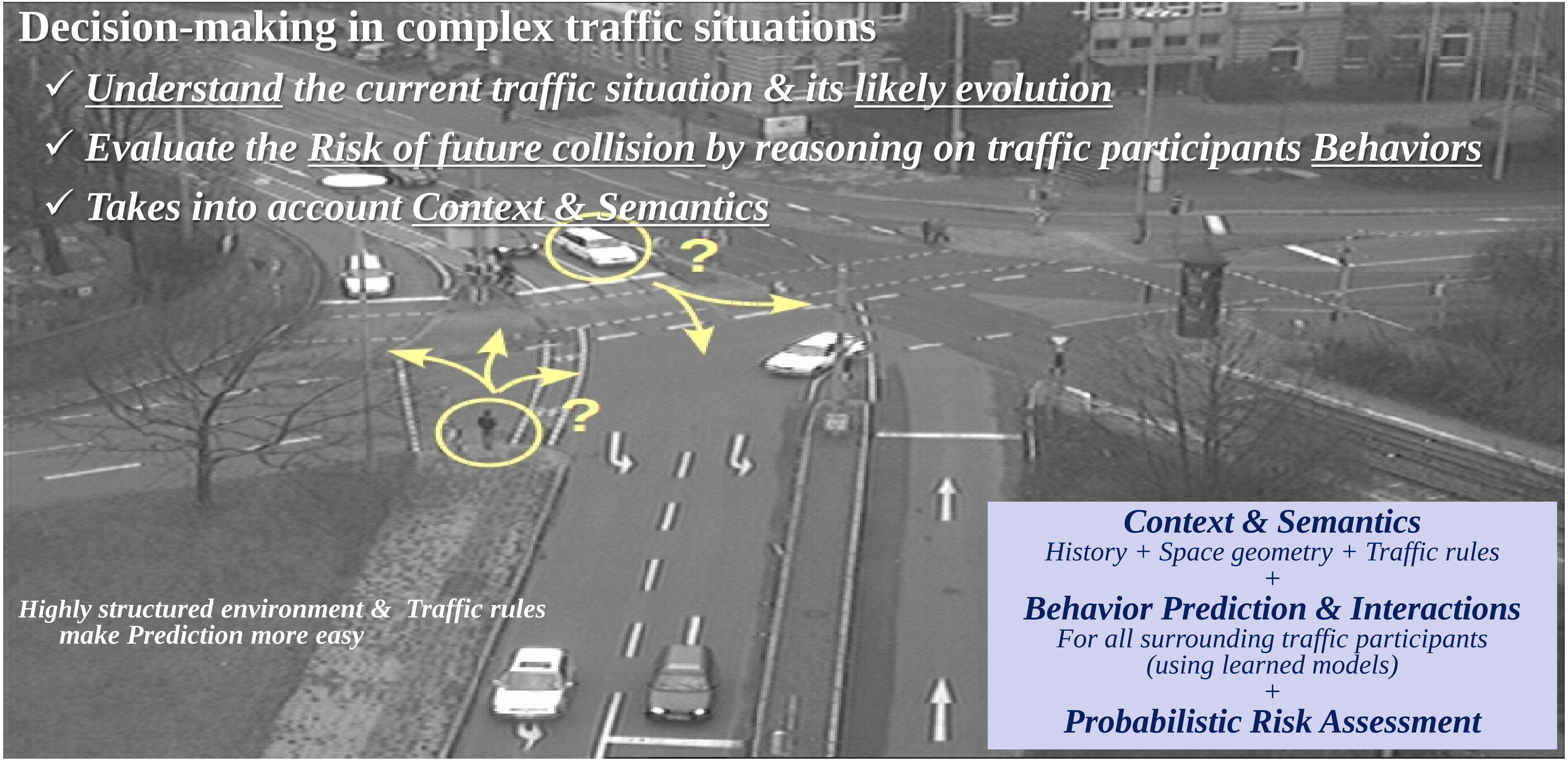


**Collision Risk Assessment** *(video 0:45)*
- **Yellow** => *time to collision: 3s*
- **Orange** => *time to collision: 2s*
- **Red** => *time to collision: 1s*

# *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*

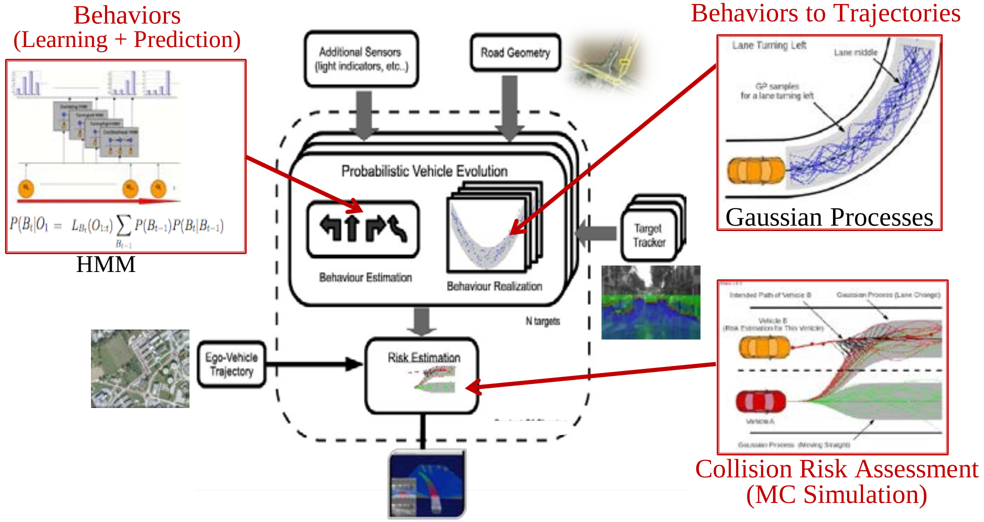
*Highly structured environment & Traffic rules make Prediction more easy*

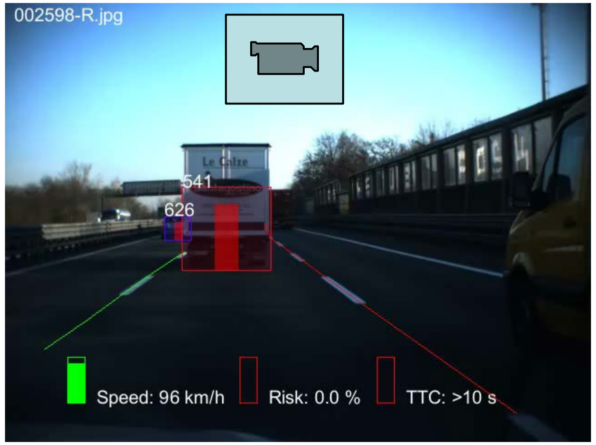
***Context & Semantics***
*History + Space geometry + Traffic rules*
+
***Behavior Prediction & Interactions***
*For all surrounding traffic participants (using learned models)*
+
***Probabilistic Risk Assessment***

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

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

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

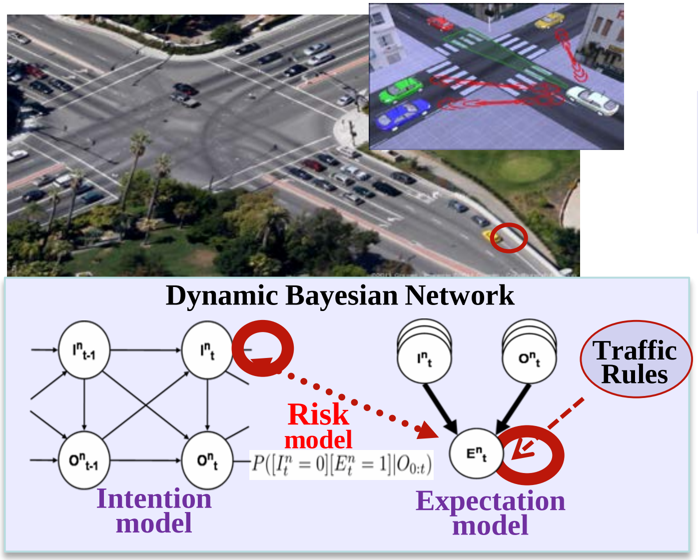



*Cooperation still on-going (R&D contracts + PhD)*

Courtesy Probayes

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

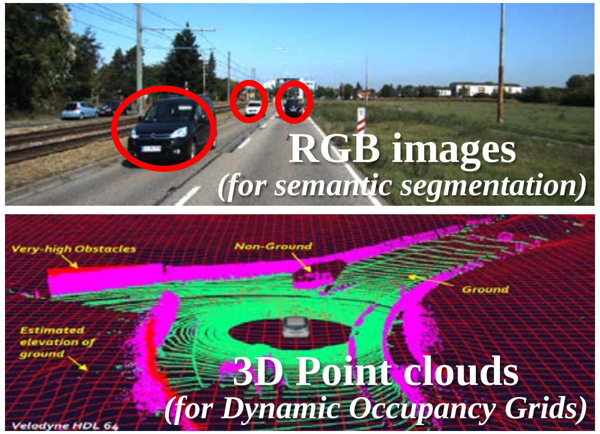


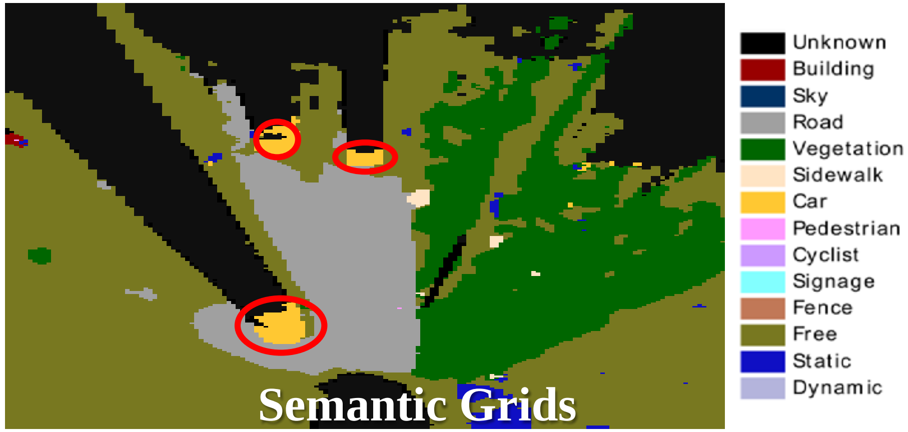

**Human-like reasoning**

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

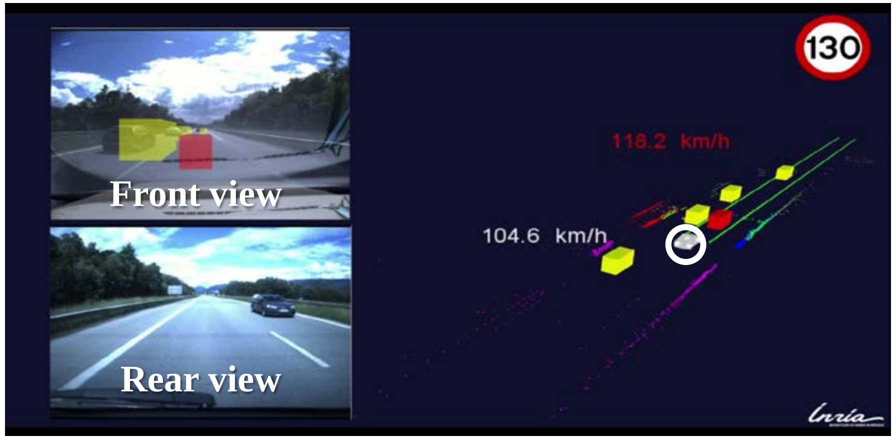
# $3^{rd}$ *Paradigm:* Models improvements using Machine Learning

- **Perception level:** ***Construct "Semantic Grids" using Bayesian Perception & DL***




- **Decision-making level:** ***Learn driving skills for Autonomous Driving***
  - *1st Step:* ***Modeling Driver Behavior*** *using Inverse Reinforcement Learning (IRL)*
  - *2nd Step:* ***Predict motions*** *of surrounding vehicles &* ***Make Driving Decisions*** *for Ego Vehicle*



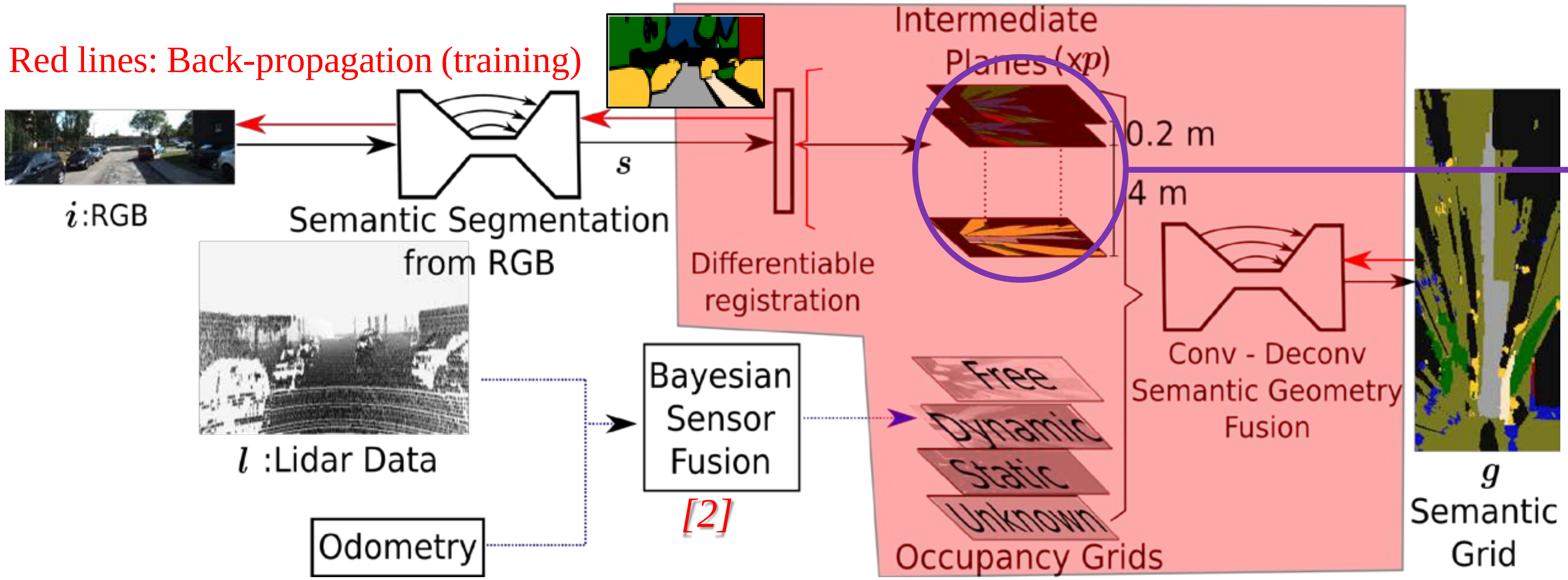
# *Perception Level:* Semantic Grids (Bayesian Perception + DL)

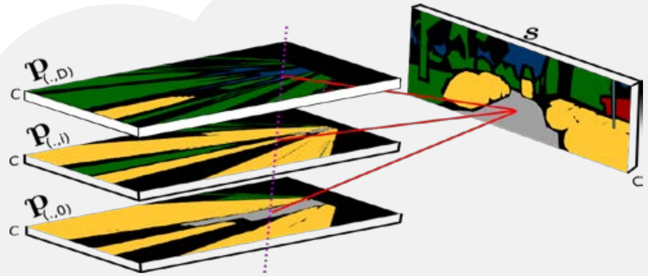
**Objective:** *Add **Semantic information** (cars, pedestrians, roads, buildings…) in each cell of the Dynamic Occupancy Grid model, by exploiting **additional RGB inputs***

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

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

**Semantic Grid Network** *[1] [3]*



**Intermediate layers (~20 layers)**

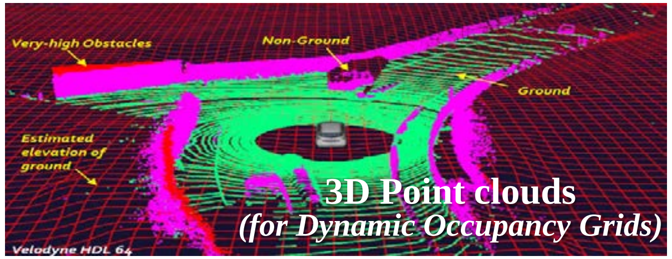
*=> Learns the approximate heights of the classes/objects*

*=> No 3D reconstruction required & Less sensitive to calibration errors (initial camera/3D points calibration)*

**Implementation: Segnet Cuda/GPU + Kitti dataset**


*[1] Semantic grid estimation with a Hybrid Bayesian and Deep Neural Network approach, 0. 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*



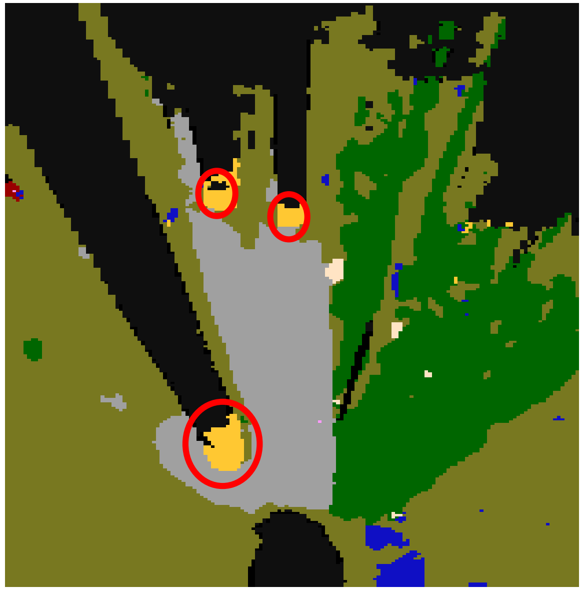

**Hybrid Sensor Fusion approach (Semantic Grid construction)**

**Frontal View** *(RGB camera)*

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

**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)*

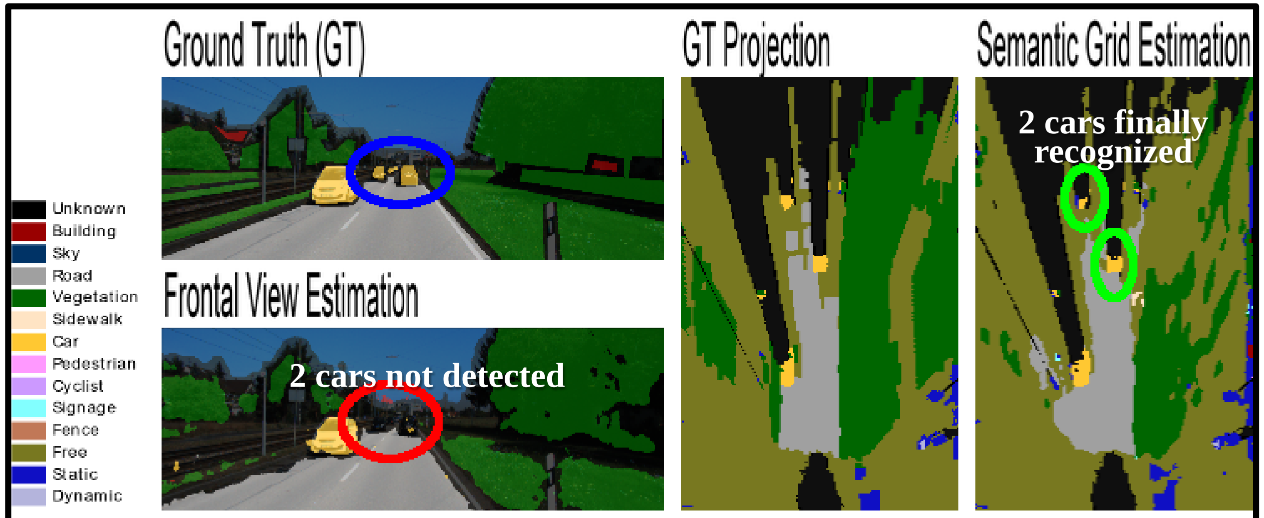
**Comparison**



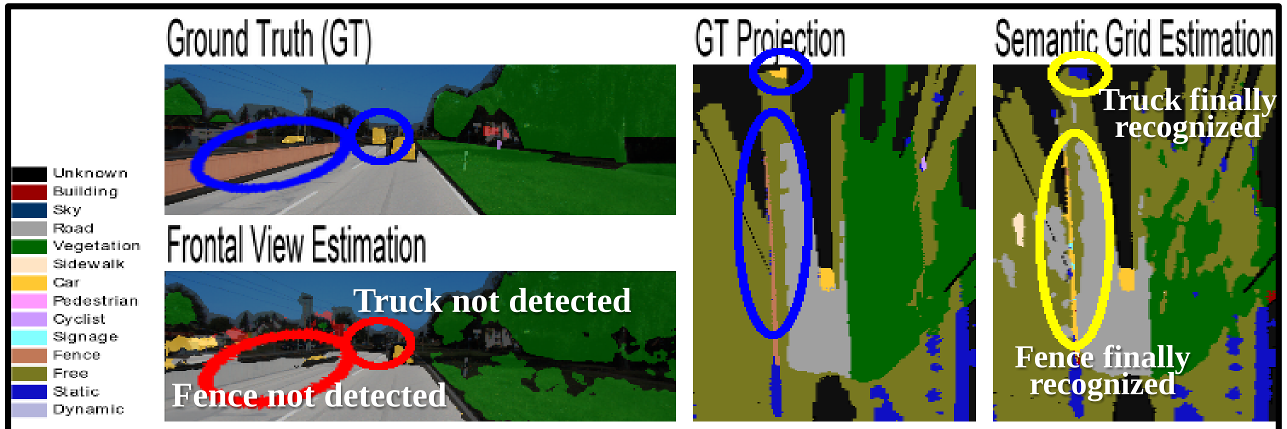
**Semantic Grid Prediction**
*=> Dense structure obtained using hybrid integration*


**Labels**

# Semantic Grids – *Experimental Results & Current work*




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




- **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)*

## Current Work

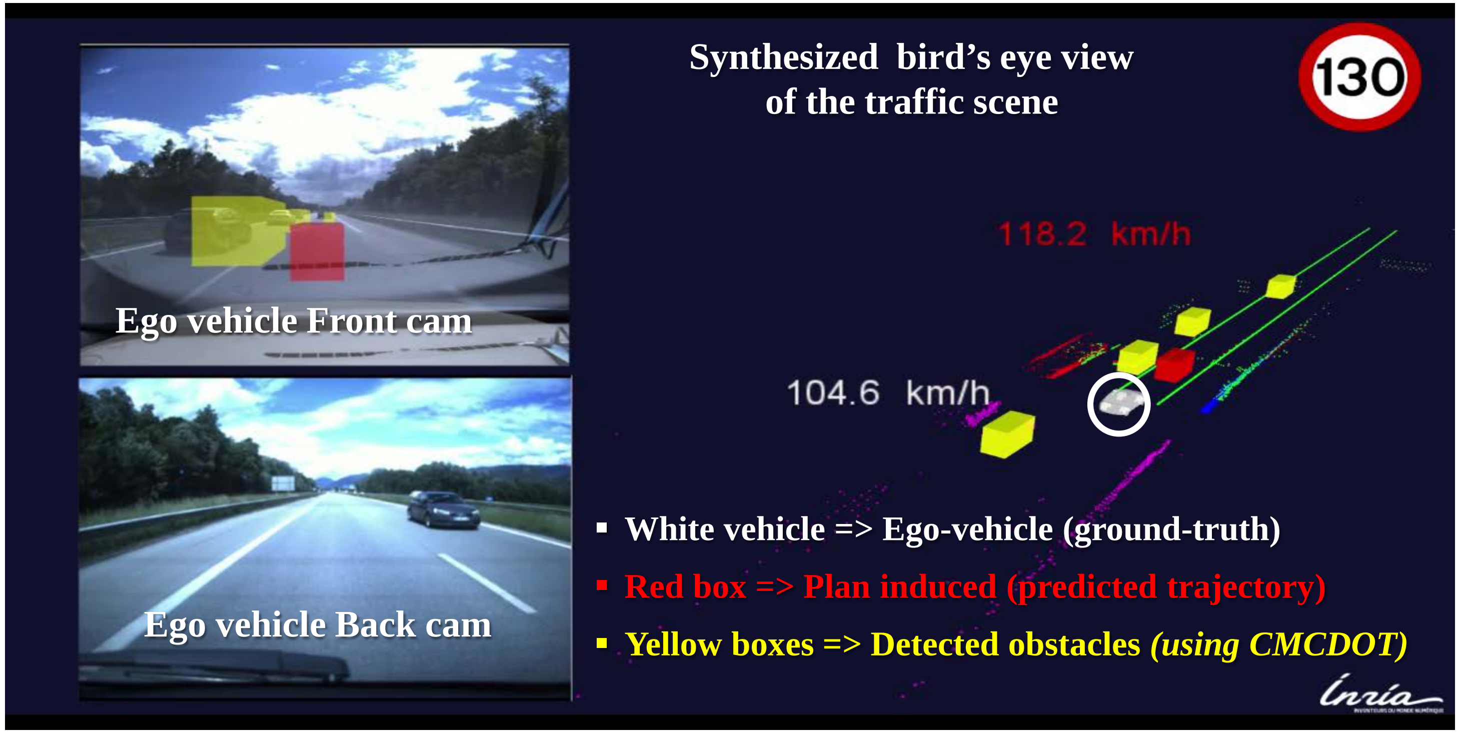
- Improve accuracy with more dense training datasets
- Implementation on embedded systems for real-time process
- Adaptation to bad weather conditions
- Panoptic segmentation & tracking

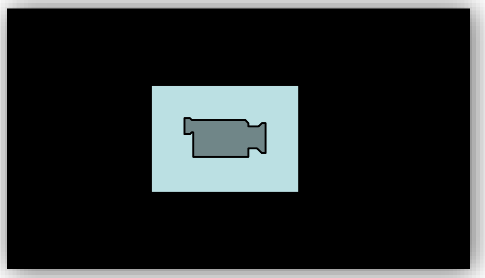
# *Decision-making level:* Learning Driving Skills for AD
## 1st Step: Driver behavior modeling

*[Sierra Gonzalez et al, ICRA 2018]*

- **Learn Model parameters** from real driving demonstrations using ***Inverse Reinforcement Learning (IRL)***
- **Driver behaviors** are modelled using a **Cost function** $\mathcal{C}(s) = \sum_{i=1}^{K} w_i \cdot f_i(s)$ which is assumed linear on a **set of K hand-crafted features** *(e.g. Lane index preferences, Deviation from desired velocity, Time-to-collision to frontal targets, Time-gap to rear targets …)*
- A **training set containing "*interesting highway vehicle interactions*"** was constructed out of 20 minutes of highway driving data & used to automatically learn the balance between features. *We are extending the approach using larger datasets and various traffic conditions.*

=> Obtained models can be leverage to **Predict human driver behaviors & Generate human-like plans for the ego vehicle** *(mandatory in mixed traffic)*



Comparison between demonstrated behavior in test set & behavior induced by the learned model

# *Decision-making level:* Learning Driving Skills for AD
## 2nd 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]*

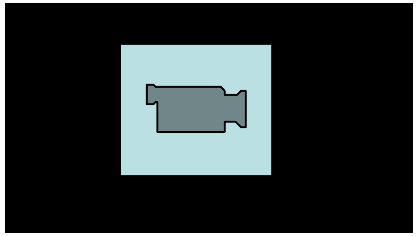
- For the **short/mid-term**, both the **Driver model** and the **Dynamics of the target** provide useful information to **determine future driving behaviors**

=> 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]*



**Synthesized bird's eye view of the traffic scene & Over vehicles expected intentions**

- **Orange bar** => *Probability that the target executes a lane change according to the model (given the traffic situation)*
- **Red bar** => *Final lane change intention probability (fusing model-based prediction & dynamic evidence)*



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

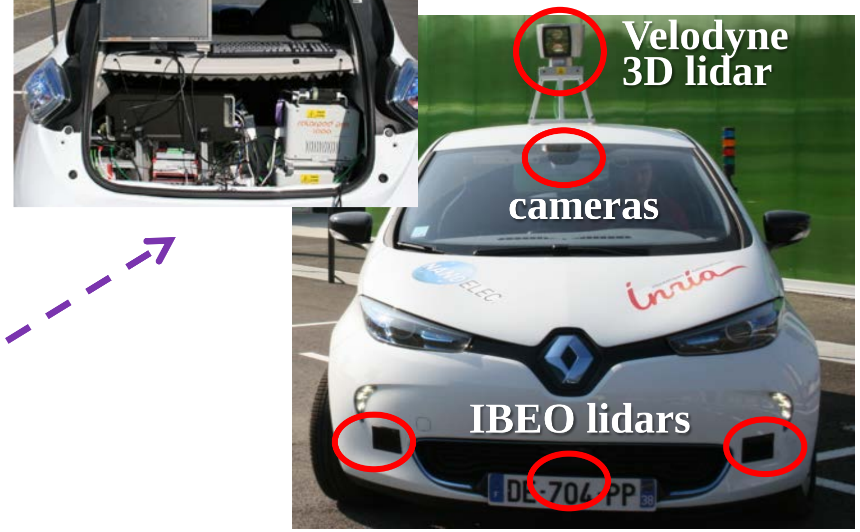
# Experimental Vehicles & Connected Perception Units

Toyota Lexus


ROS

**RT-Maps**
*under development*

Renault Zoé




**Connected Perception Unit (V2X communication)**

*Same embedded perception systems than in vehicles*
*=> Exchanging only relevant information (e.g. Risk parameters)*

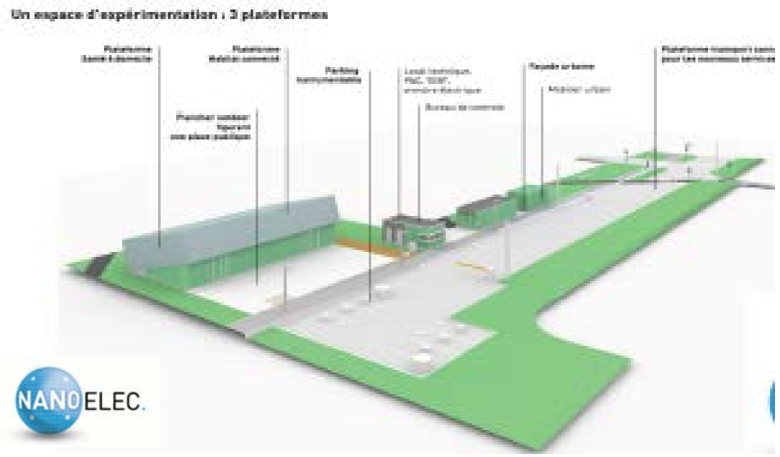
Nvidia GTX Titan X
Generation Maxwell

Nvidia GTX Jetson TK1
Generation Maxwell

Nvidia GTX Jetson TX1
Generation Maxwell

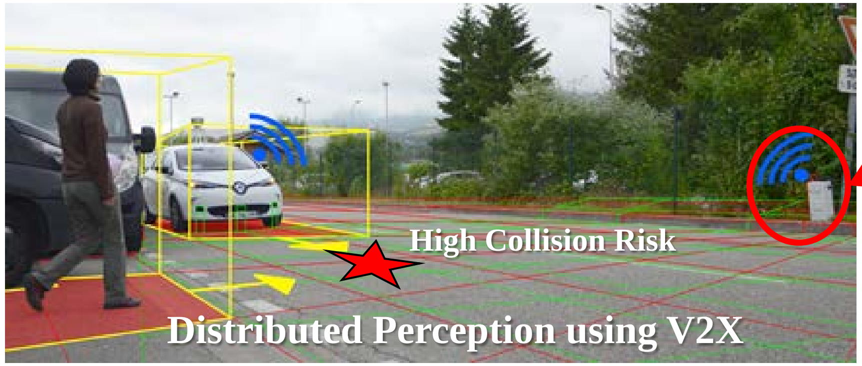
# Experimental Areas

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




Crash test track

Connected Perception Unit




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

# Summary & On going work

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

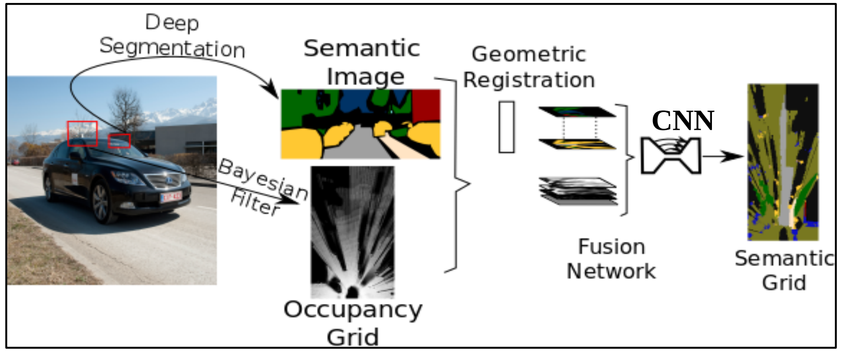
Autonomous Shuttles
(~15 km/h, Urban traffic)

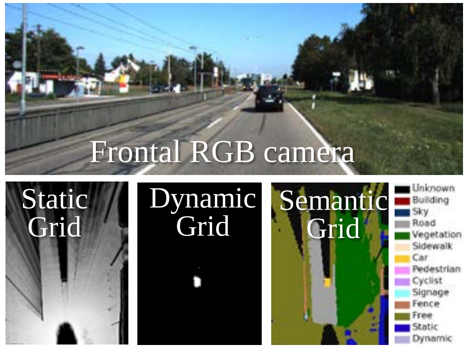
Autonomous Bus (Iveco)
(up to 70 km/h, Urban traffic)

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 …**

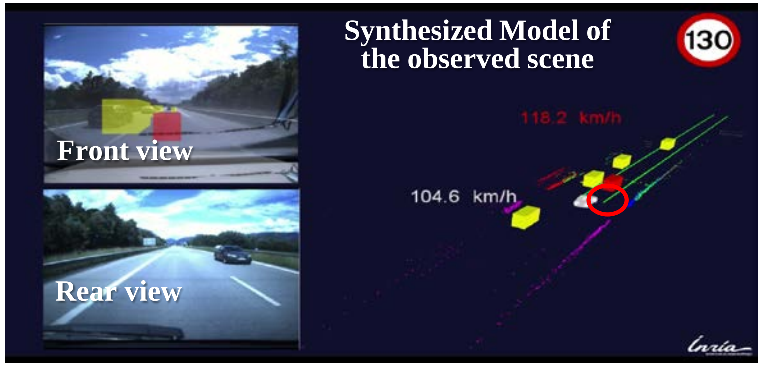
## ❑ Embedded & Extended "Semantic Grids"



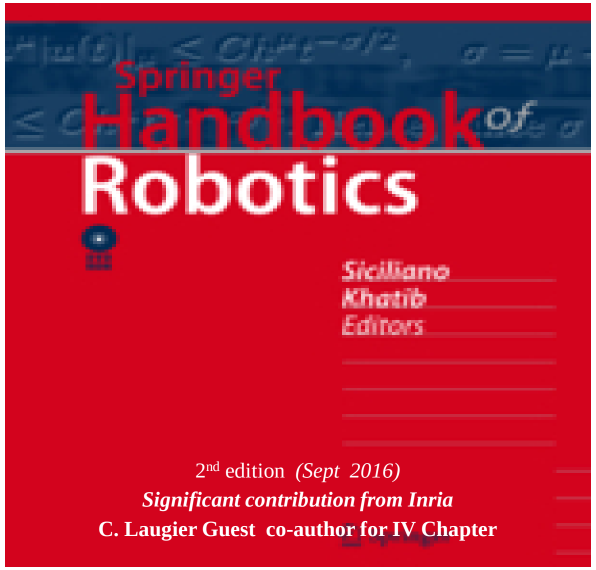




- Embedded "Semantic Grids" & "Panoptic Segmentation"
- Improved scene understanding (various weather conditions)
- **Cooperation Toyota**
- *1 Patent & 3 publications (IROS'18, ICARCV'18, Unmanned System journal 2019)*

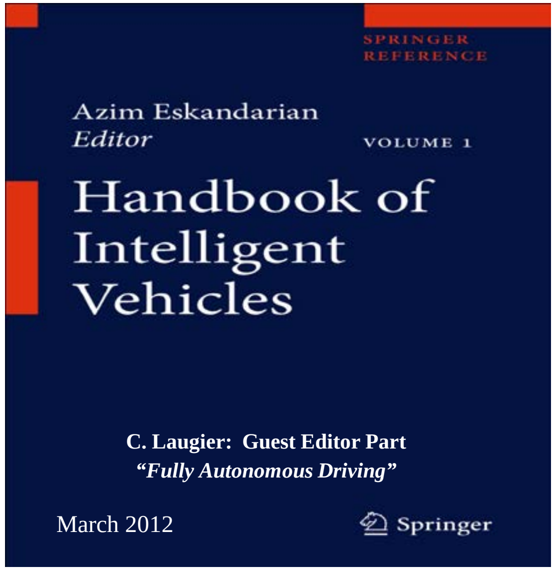
## ❑ Autonomous Driving in mixed traffic (Prediction & Planning) using learned models



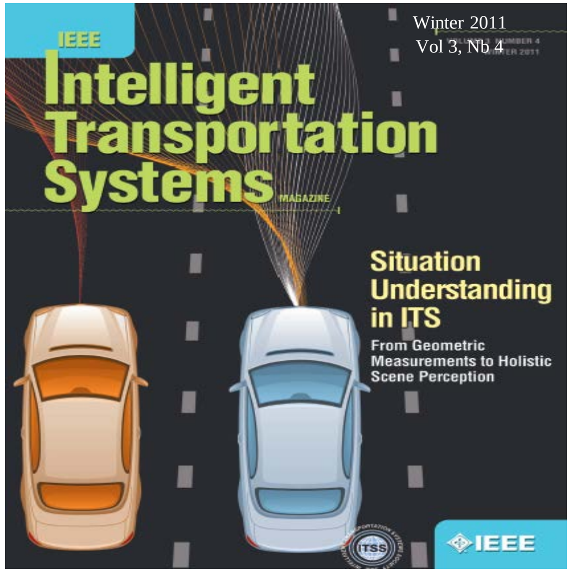

- **Driver Behavior modeling** using Driving dataset & Inverse Reinforcement Learning => ***Human-like Driver Model*** *(for mixed traffic)*
- **Motion Prediction & Driving Decision-making for AD** performed *by combining "learned Driver models" & "Dynamic evidences"*
- **Cooperation Toyota**
- *2 Patents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




2nd edition (Sept 2016)
*Significant contribution from Inria*
**C. Laugier Guest co-author for IV Chapter**



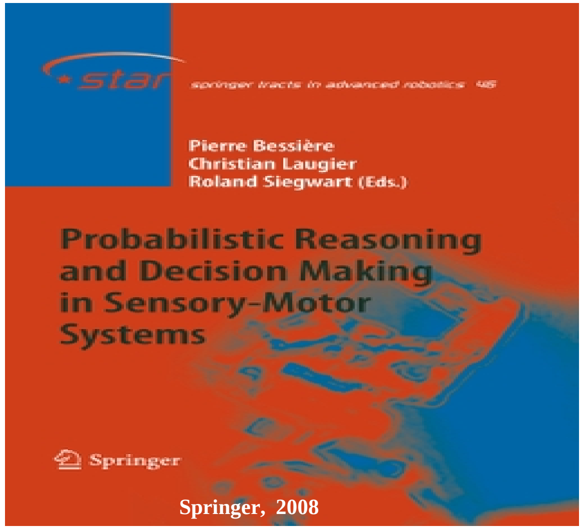

**C. Laugier: Guest Editor Part**
***"Fully Autonomous Driving"***
March 2012




Winter 2011
Vol 3, Nb 4

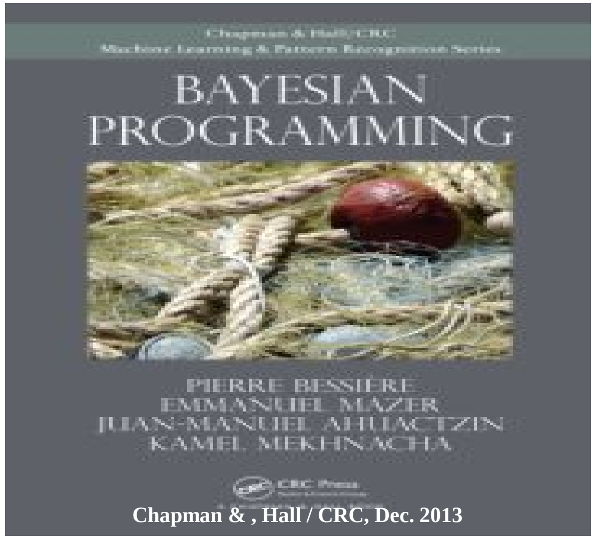

*July 2013*
**Guest Editors:**
***C. Laugier & J. Machan***

# Thank You




**Springer, 2008**


**IEEE RAS Technical Committee on "AGV & ITS"**
***Numerous Workshops & Special issues since 2002***
***=> Membership open !!***




**Chapman & , Hall / CRC, Dec. 2013**