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# Improving Autonomous Driving Safety through a better Understanding of Traffic Scenes and of Potential Upcoming Collisions: A Bayesian & Machine Learning Approach (Invited Plenary Speech)

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# Improving Autonomous Driving Safety through a better Understanding of Traffic Scenes and of Potential Upcoming Collisions : *A Bayesian & Machine Learning Approach*

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**ADAS & Autonomous Driving**

*Invited Plenary Speech*

*ICARCV 2018 – Plenary Forum on the “Impact of AI on Robotics and Computer Vision”  
Singapore, November 20th 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 Enable-3)*



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)*

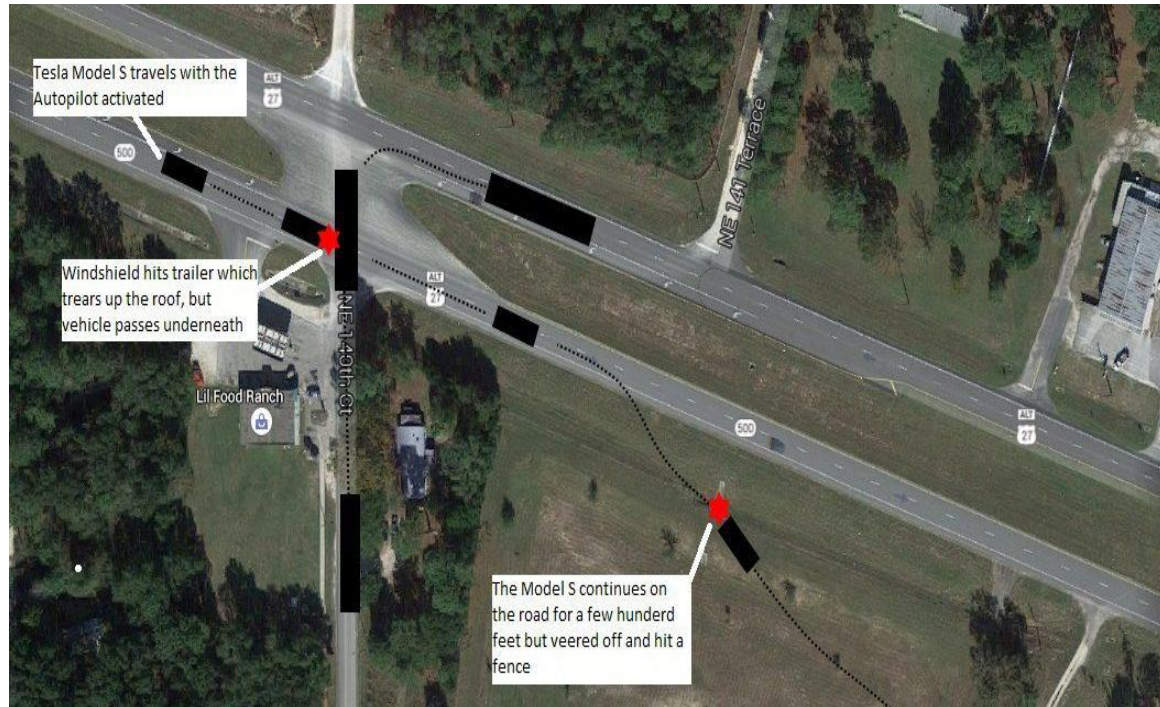
- ❑ **Tesla driver killed in a crash with Autopilot active** – Williston Florida, May 7<sup>th</sup> 2016
- ❑ **The Human driver was not vigilant** => *A false sense of Safety for the user ?*
- ❑ **The Autopilot didn't detected the trailer as an obstacle**
  - *Camera => White color against a brightly 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)*



# Embedded Perception: Main features

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

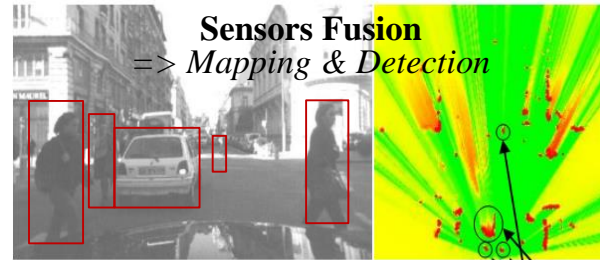
## Main features

- ✓ Dynamic & Open Environments => *Real-time processing & Reactivity*
- ✓ Incompleteness & Uncertainty => *Appropriate Model & Algorithms (probabilistic approaches)*
- ✓ Sensors limitations => *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*

## ❑ Embedded Bayesian Perception paradigm

- ✓ *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...*

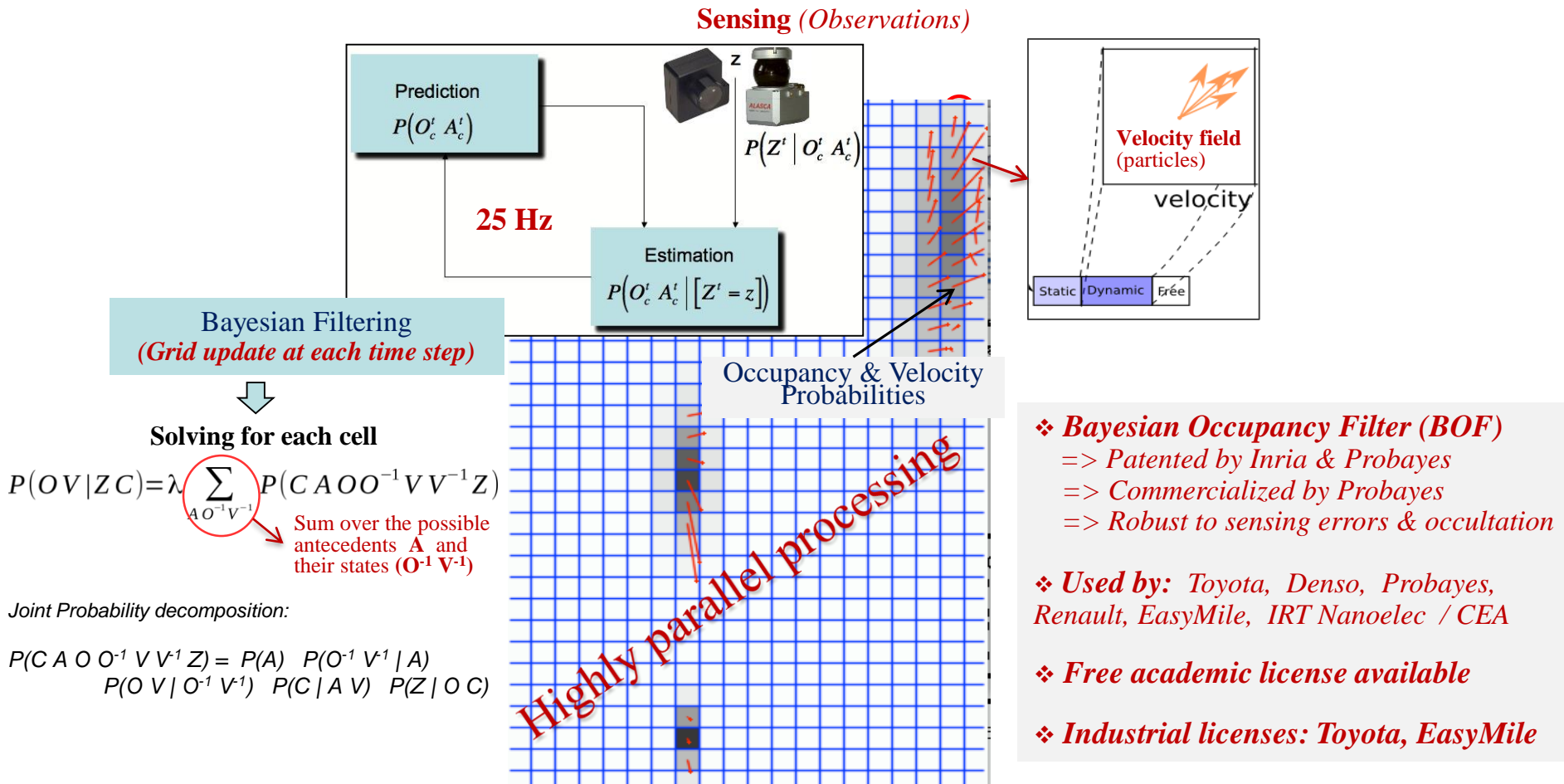
# Concept of Dynamic Occupancy Grid

=> A more and more popular approach for Autonomous Vehicles

=> A clear distinction between Static & Dynamic & Free components

## Concept of “Bayesian Occupancy Filter” (Inria)

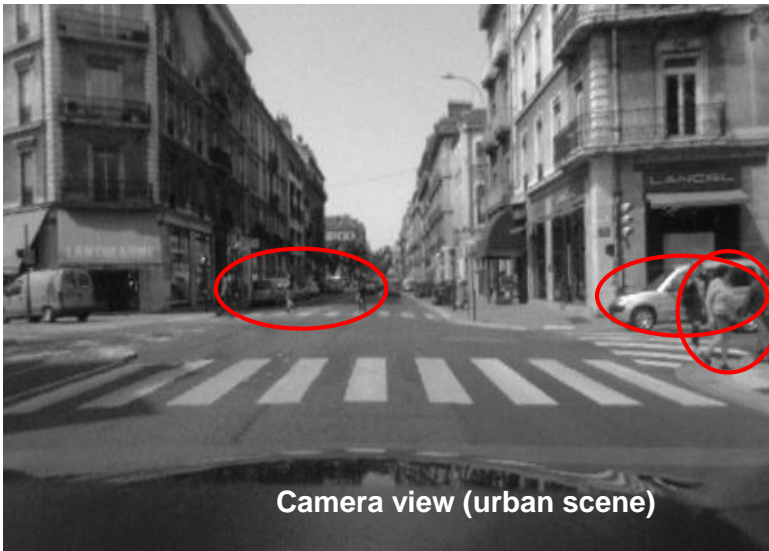
[Coué & Laugier IJRR 05] [Laugier et al ITSM 2011] [Laugier, Vasquez, Martinelli Mooc uTOP 2015]



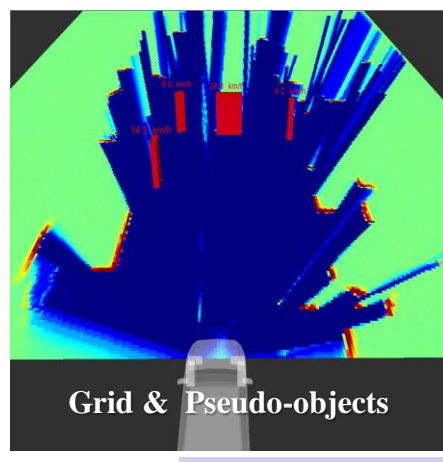
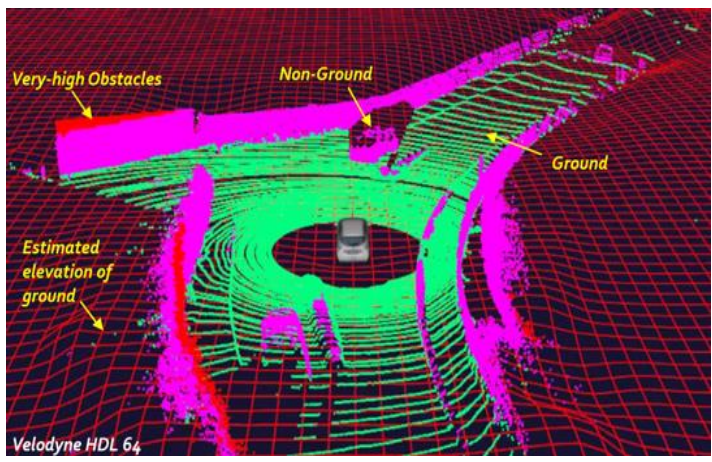


# Bayesian Occupancy Filter Approach – *Main Features*

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



Sensors data fusion  
+  
Bayesian Filtering  
+  
Extracted Motion Fields



Ground Estimation & Point Cloud Classification

Detection & Tracking & Classification

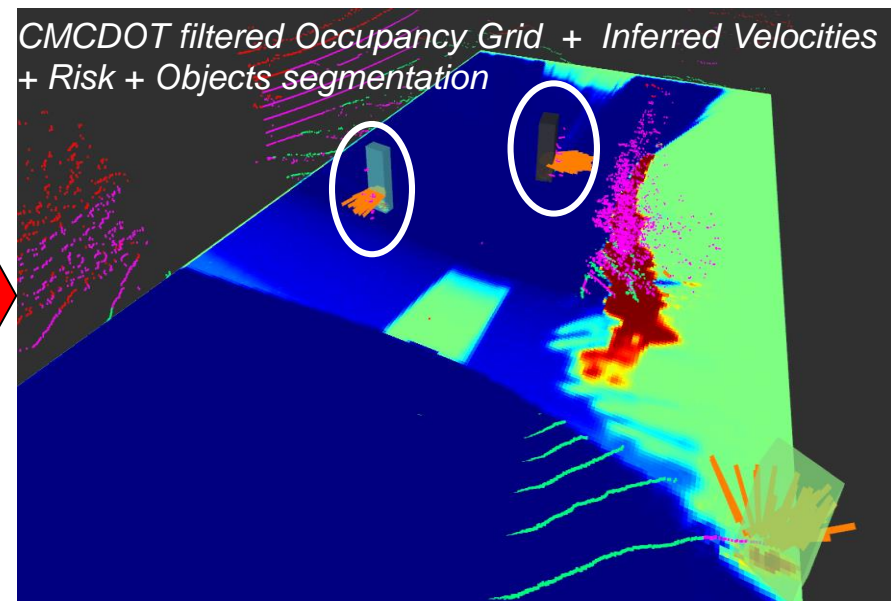
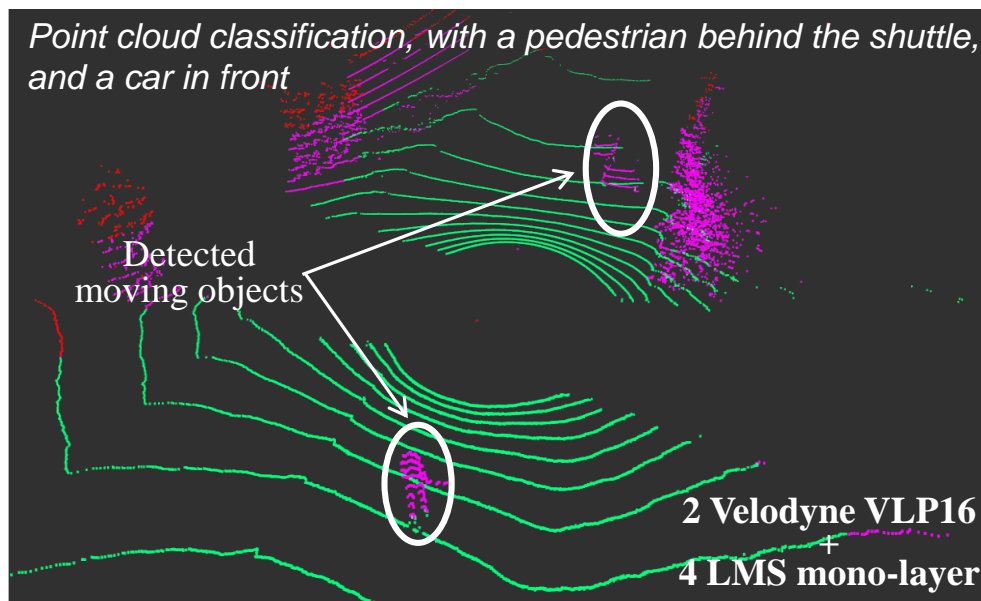
# Integration on a commercial vehicle



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

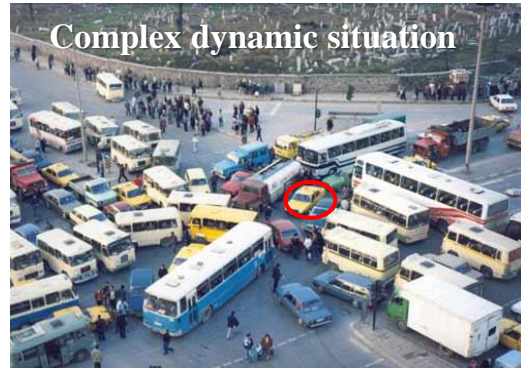


- **Shuttle sensor data** has been fused and processed in **real-time**, with a successful Detection & Characterization of the **Moving & Static Obstacles**
- **Full integration on a commercial product** under development with an industrial company (confidential)



# 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**  $t+\delta$*
- ✓ *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*

=> *Conservative collision Prediction & Avoidance*

[Coué & Laugier IJRR 05]

Autonomous  
Vehicle (Cycab)



Parked Vehicle  
(occultation)

**Pioneer  
Results  
(2005)**

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)*

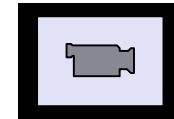
# Short-term collision risk – *Experimental results*

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



## Collision Risk Assessment (video)

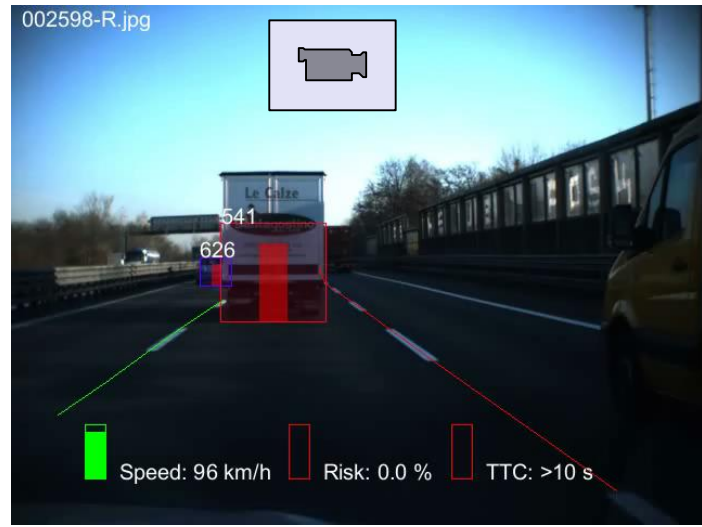
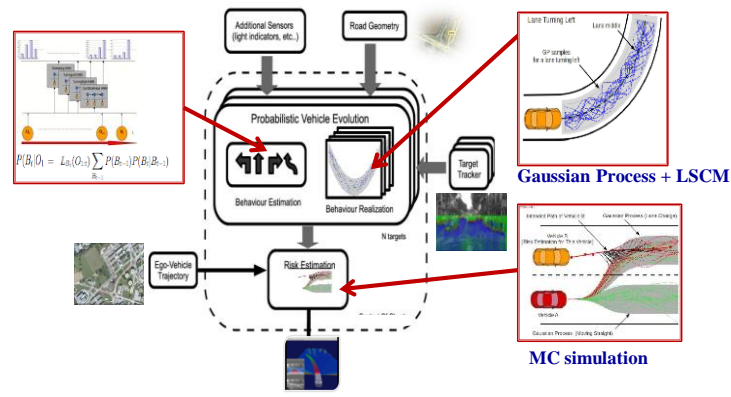
- **Yellow** => *time to collision: 3s*
- **Orange** => *time to collision: 2s*
- **Red** => *time to collision: 1s*



# Concept 2: Behavior-based Collision risk (Object level)

=> Increased time horizon & complexity + Reasoning on Behaviors

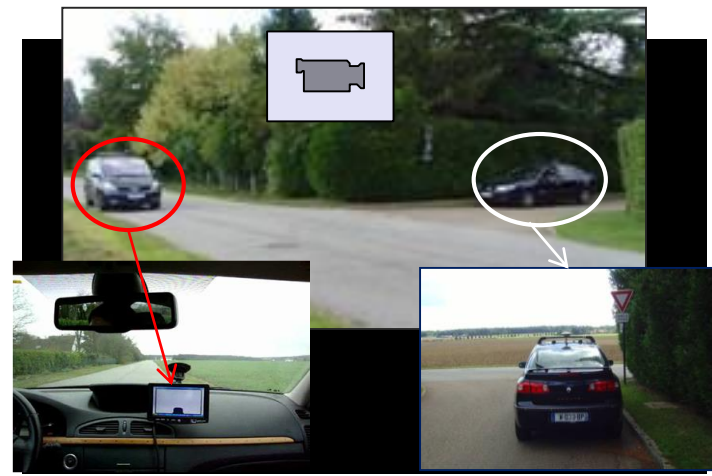
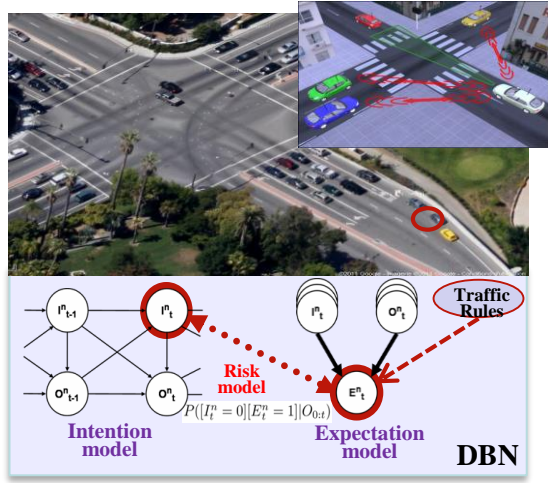
## Trajectory prediction & Collision Risk => Patent Inria -Toyota - Probayes 2010



Courtesy Probayes

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

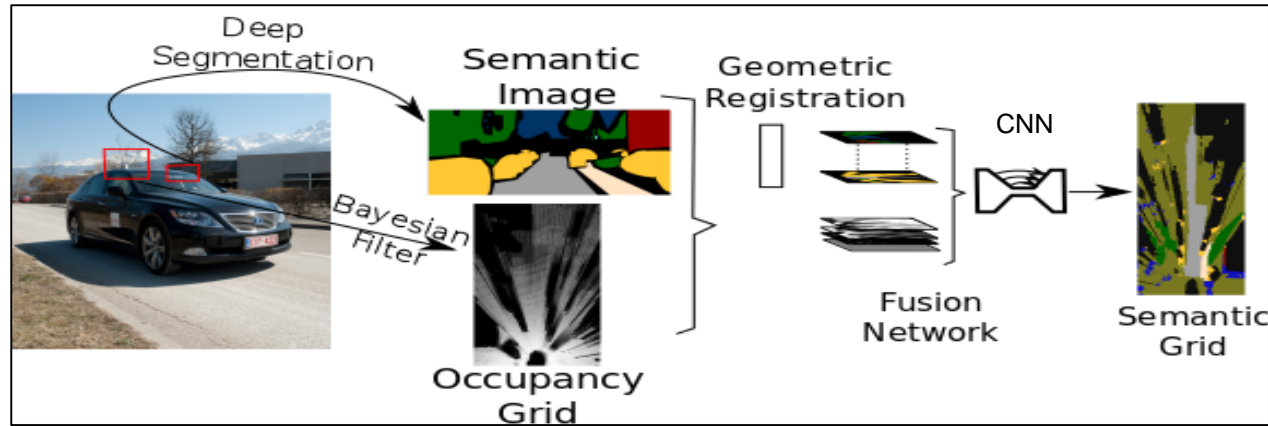
## Intention & Expectation => Patents Inria - Renault 2012 & Inria - Berkeley 2013



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

# Paradigm 3: Improvements using Machine Learning

## Approach 1: Enrichment of traffic models using Semantic Segmentation

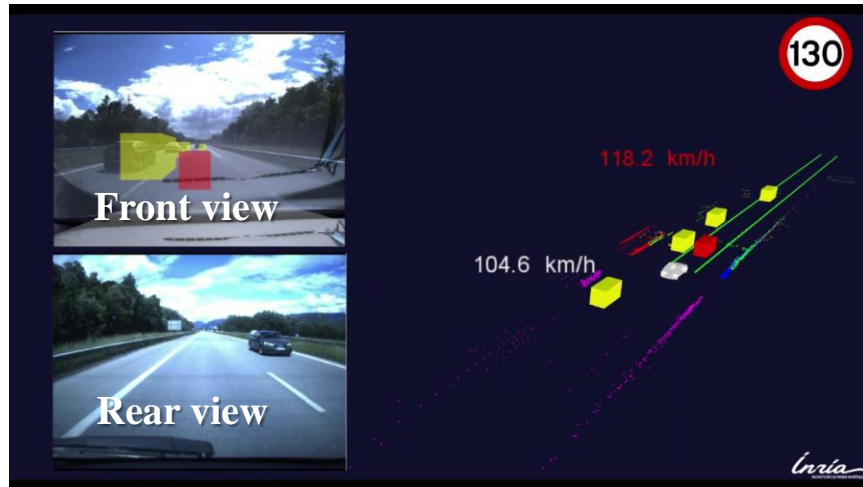


- Inputs: Occupancy Grid, RGB, Sensor Positions
- No need for 3D reconstruction
- **Output: Dense Semantic Grid**
- Patent Inria -Toyota & Publication ICARCV 2018 (session TuDT3 [1])

[1] Semantic Grid Estimation with Occupancy Grids and Semantic Segmentation Networks. O. Er kent, C. Wolf, C. Laugier, ICARCV 2018

# Paradigm 3: Improvements using Machine Learning

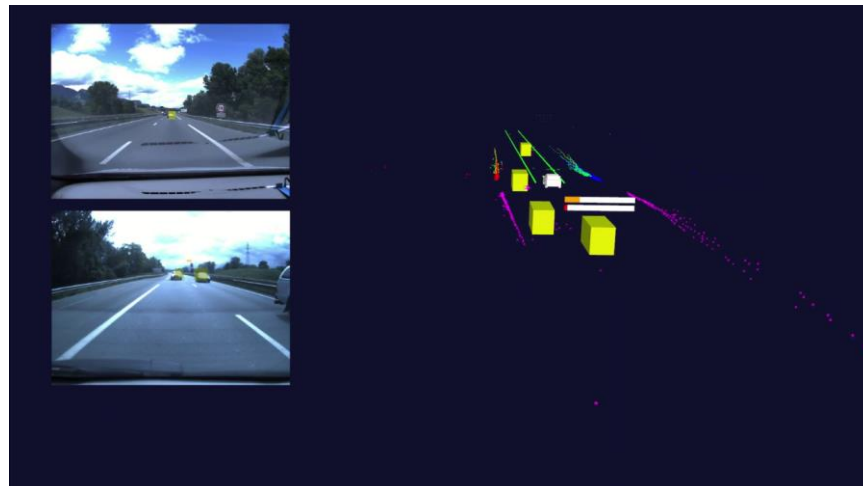
## Approach 2: Learning Driving Skills for AD (Behaviors & Prediction)



### Step 1: Driver behavior modeling

Learn the model parameters automatically from driving demonstrations (real driving data) using Inverse Reinforcement Learning (IRL)

[Sierra Gonzalez et al, ICRA 2018]



### Step 2: Motion prediction for Decision-making (AD)

- A realistic human-like driver model can be exploited to predict the long-term evolution of traffic scenes [Sierra Gonzalez et al., ITSC 2016]
- For the short/mid-term, both the dynamics of the target and the driver model provide useful information to determine future behaviors

[Sierra Gonzalez et al., ICRA 2017]