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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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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-13)*



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)*

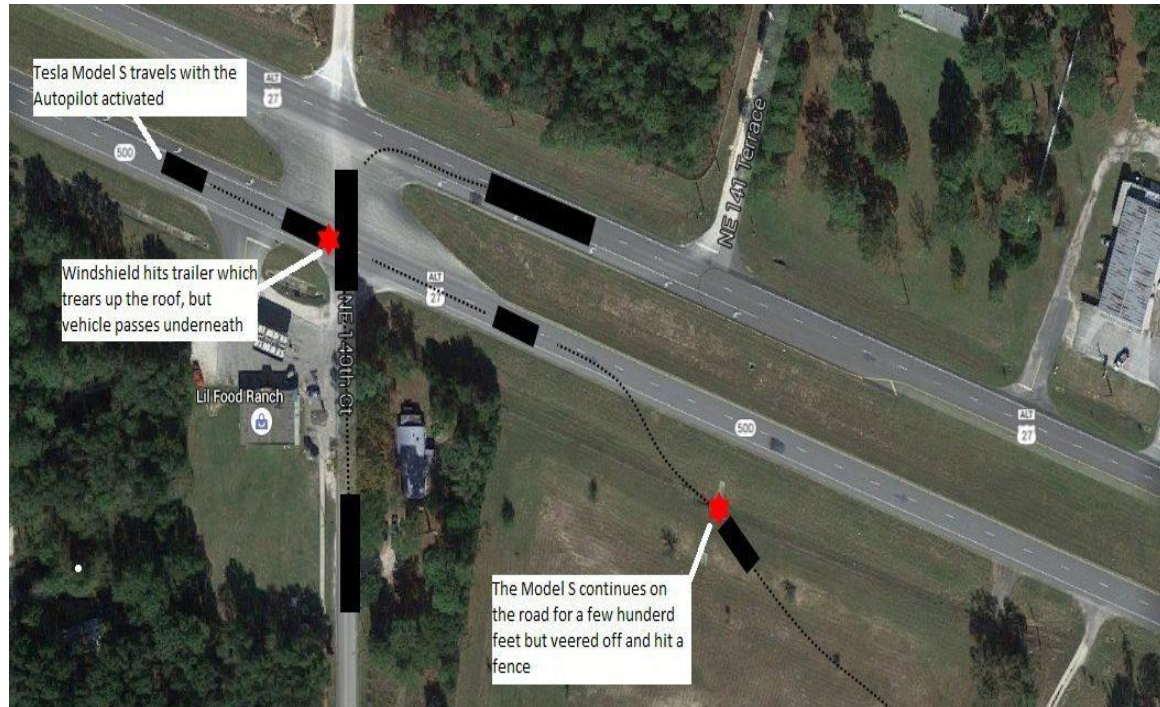
- ❑ **Tesla driver killed in a crash with Autopilot active** – Williston Florida, May 7th 2016
- ❑ **The Human driver was not vigilant** => *A false sense of Safety for the user ?*
- ❑ **The Autopilot didn't detected the trailer as an obstacle**
 - *Camera => White color against a brightly lit sky ?*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

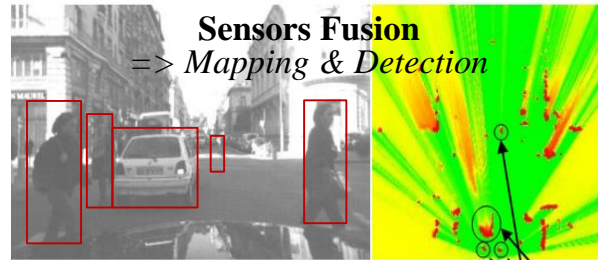
Main features

- ✓ 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...*

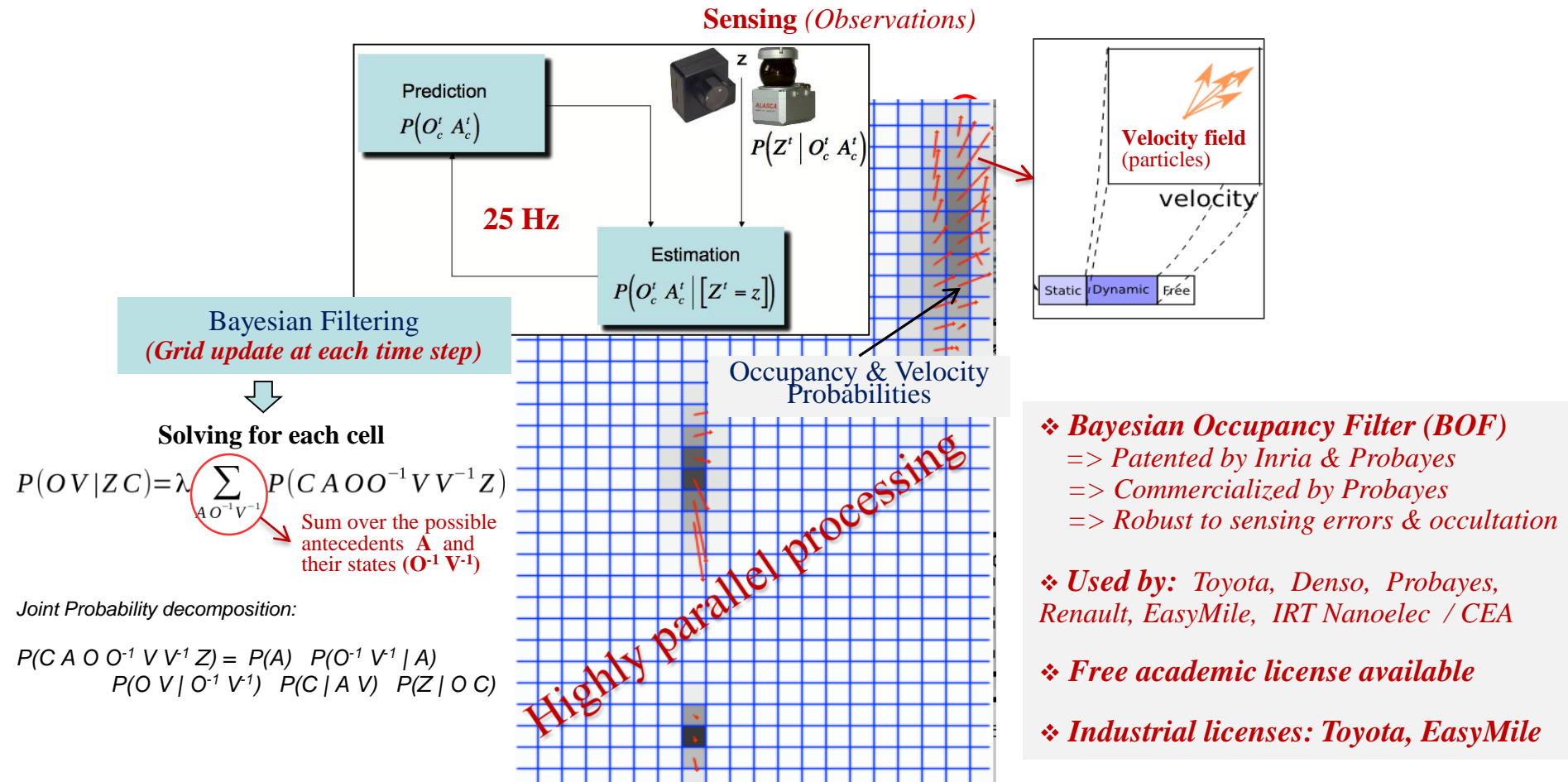
Concept of Dynamic Occupancy Grid

=> A more and more popular approach for Autonomous Vehicles

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

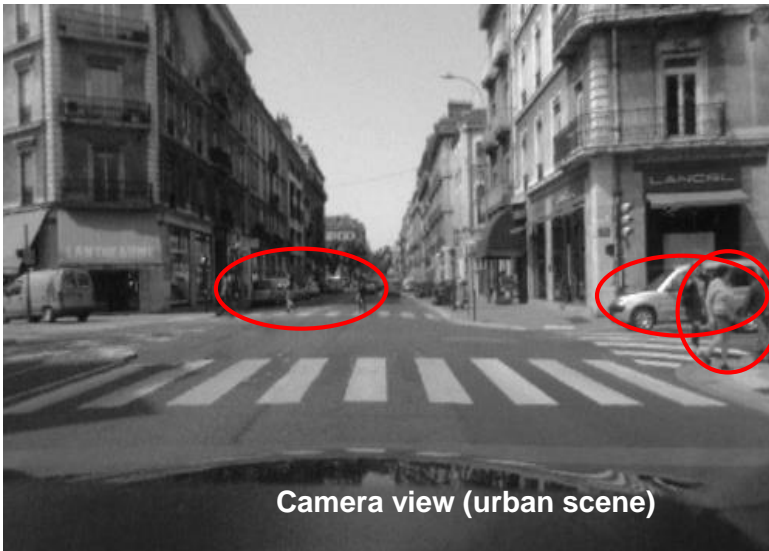
Concept of “Bayesian Occupancy Filter” (Inria)

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

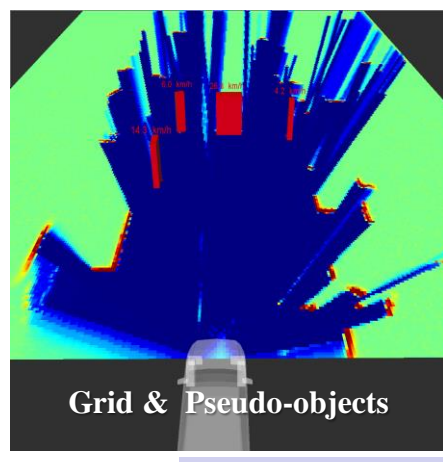
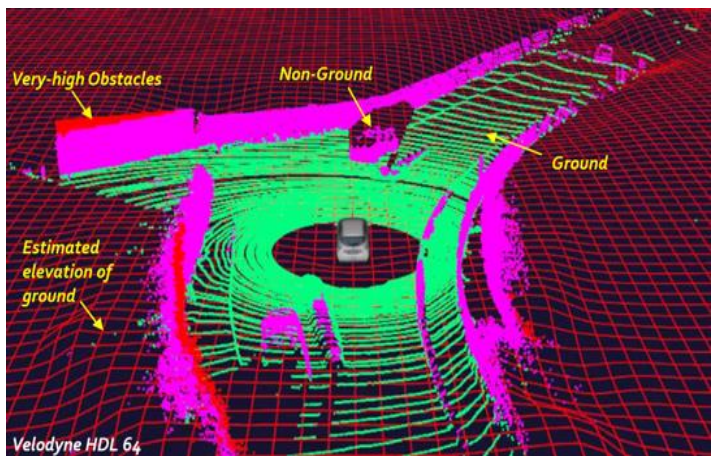
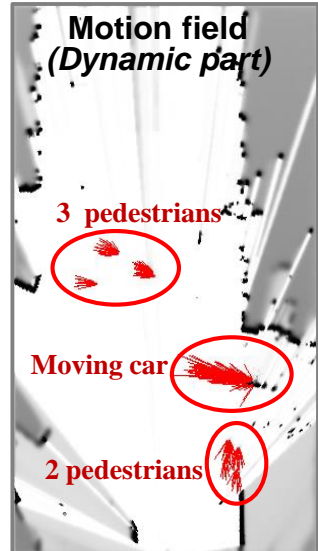


Bayesian Occupancy Filter Approach – Main Features

=> 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

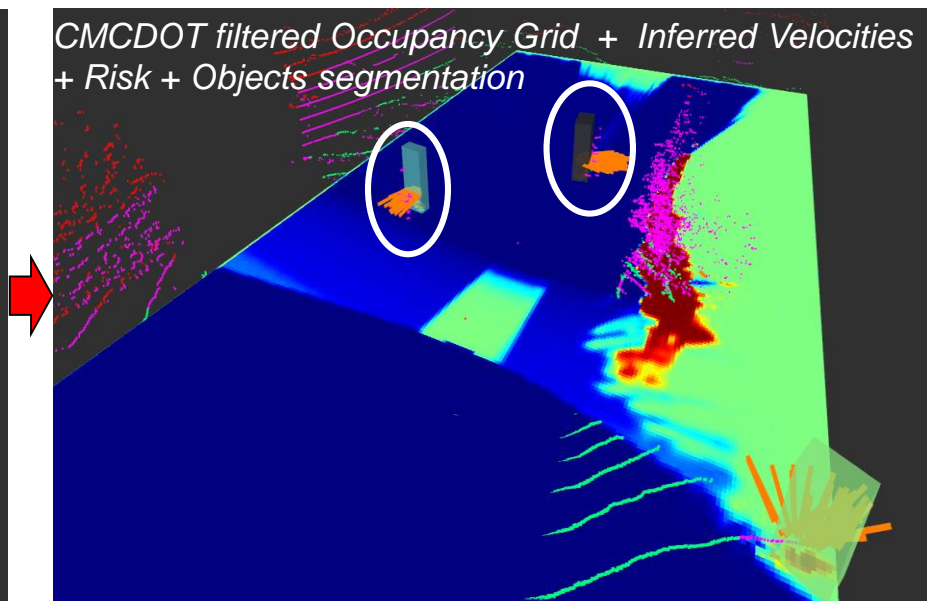
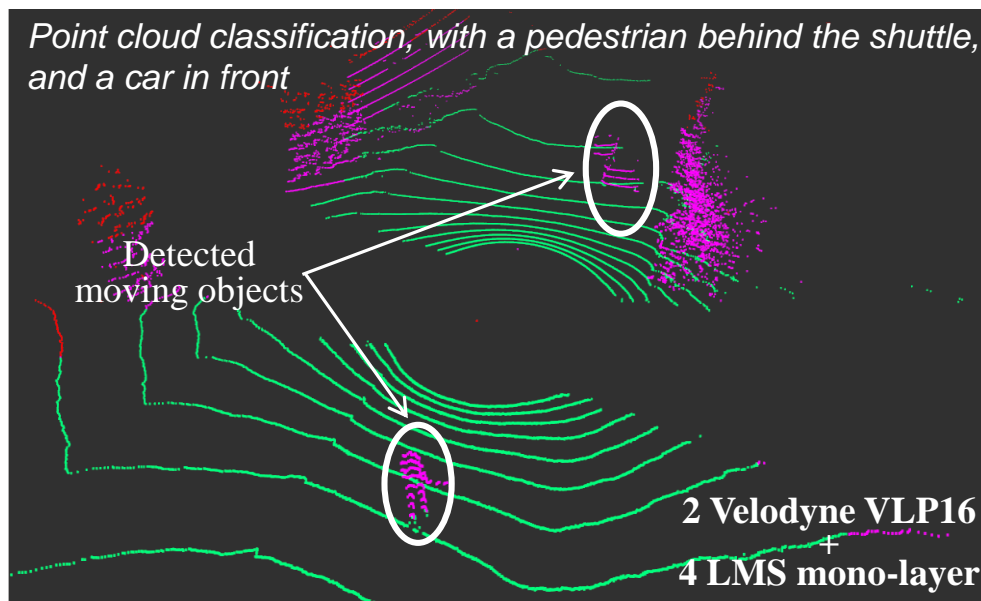
Integration on a commercial vehicle



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

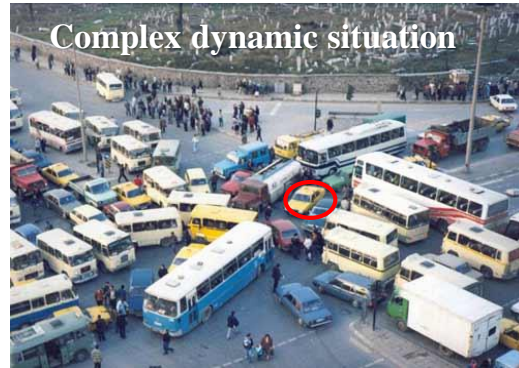


- **Shuttle sensor data** has been fused and processed in **real-time**, with a successful Detection & Characterization of the **Moving & Static Obstacles**
- **Full integration on a commercial product** under development with an industrial company (confidential)



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)*

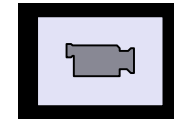
Short-term collision risk – *Experimental results*

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



Collision Risk Assessment (video)

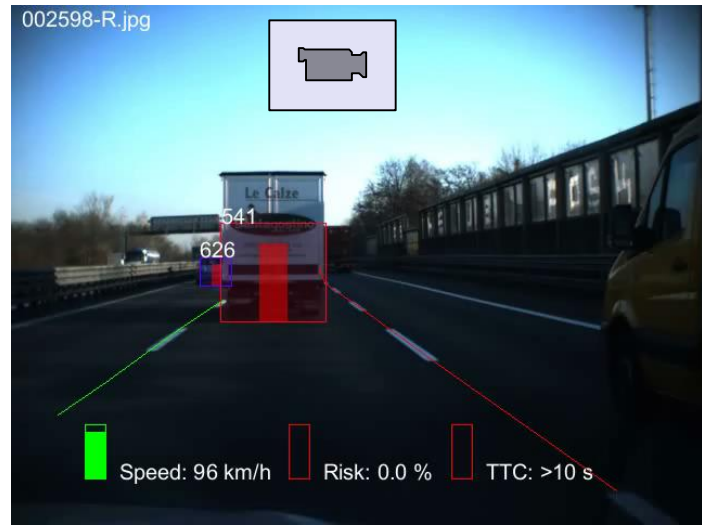
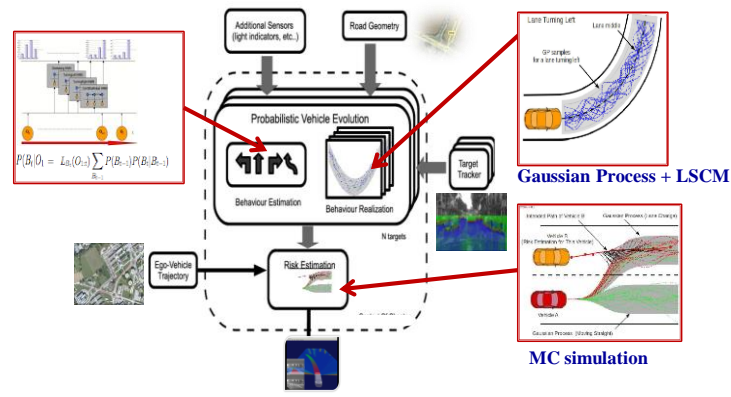
- **Yellow** => *time to collision: 3s*
- **Orange** => *time to collision: 2s*
- **Red** => *time to collision: 1s*



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

=> Increased time horizon & complexity + Reasoning on Behaviors

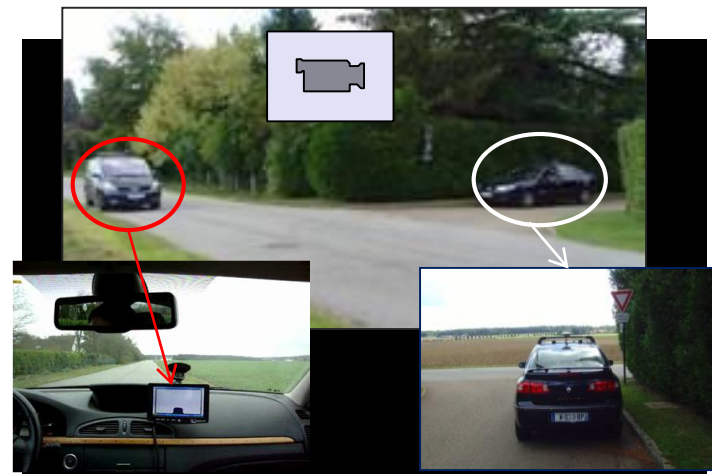
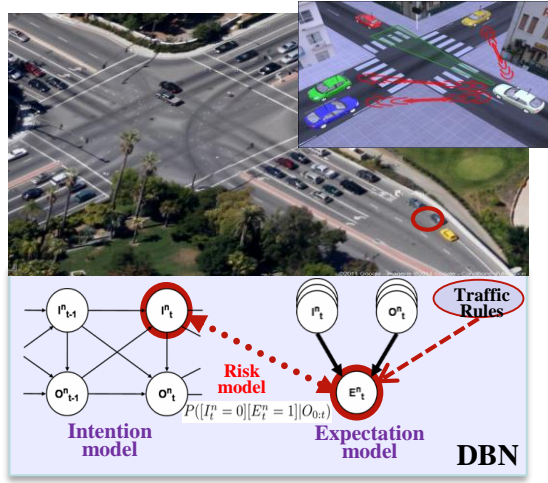
Trajectory prediction & Collision Risk => Patent Inria -Toyota - Probayes 2010



Courtesy Probayes

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

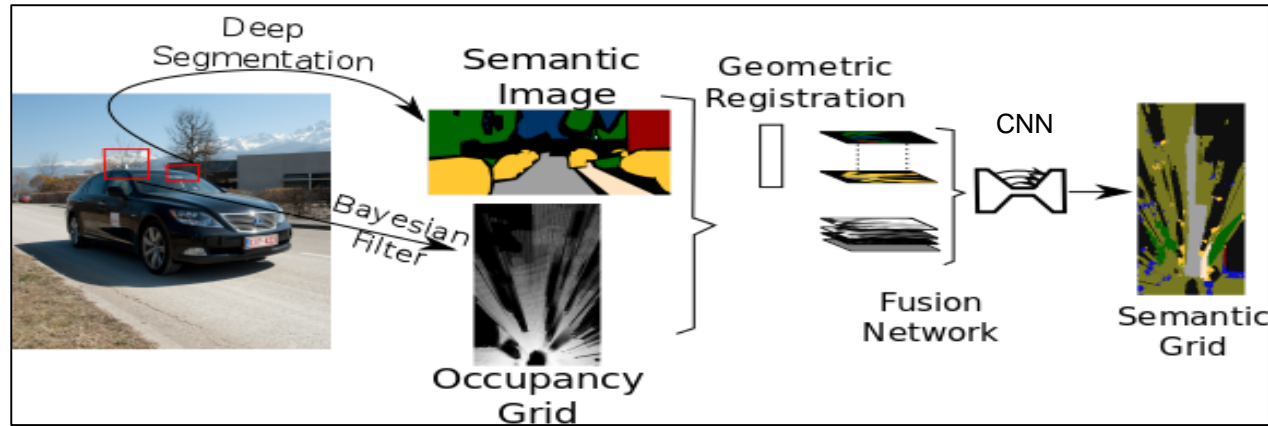
Intention & Expectation => Patents Inria - Renault 2012 & Inria - Berkeley 2013



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

Paradigm 3: Improvements using Machine Learning

Approach 1: Enrichment of traffic models using Semantic Segmentation

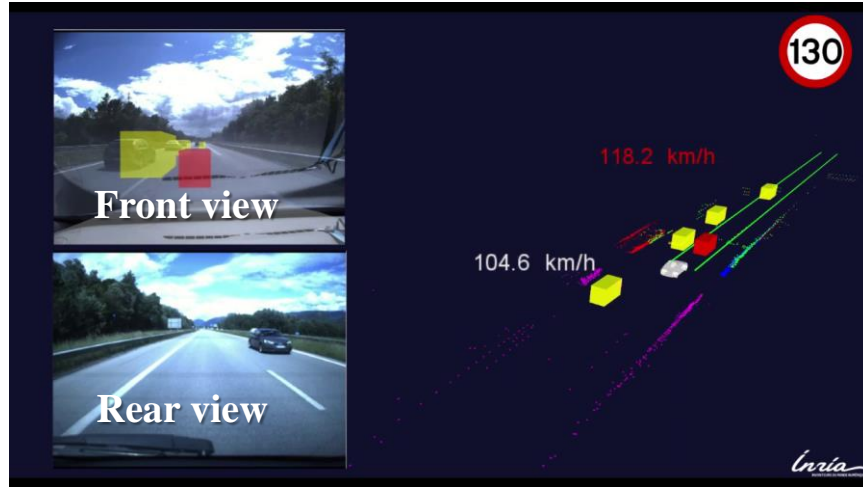


- Inputs: Occupancy Grid, RGB, Sensor Positions
- No need for 3D reconstruction
- **Output: Dense Semantic Grid**
- Patent Inria -Toyota & Publication ICARCV 2018 (session TuDT3 [1])

[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

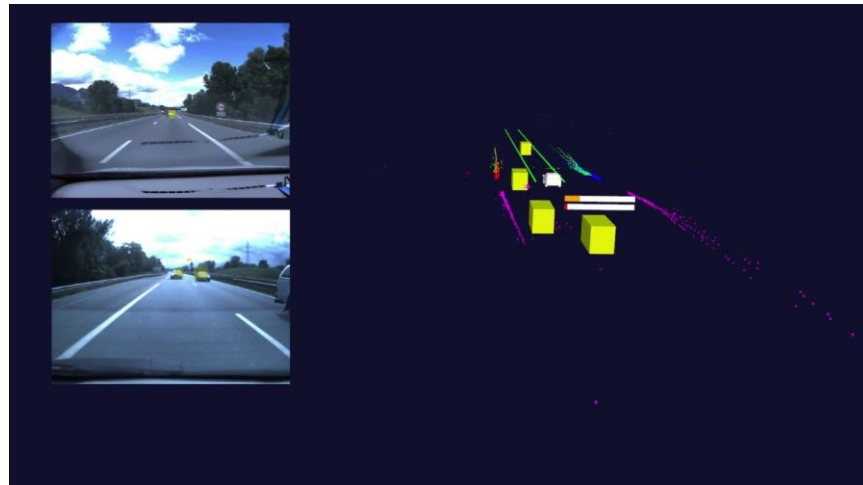
Approach 2: Learning Driving Skills for AD (Behaviors & Prediction)



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]