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Situation Awareness & Decision-making for Autonomous Driving

Christian Laugier

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Situation Awareness & Decision-making for Autonomous Driving

Christian LAUGIER, PhD & Dr Es Science

Research Director at Inria & Scientific Advisor for Probayes and for Baidu China

Inria Chroma team & IRT Nanoelec

christian.laugier@inria.fr

Contributions from

L. Rummelhard, A. Negre, N. Turro, J.A. David, J. Lussereau, T. Genevois, C. Tay Meng Keat, S. Lefevre, O. ErKent, D. Sierra-Gonzalez



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**

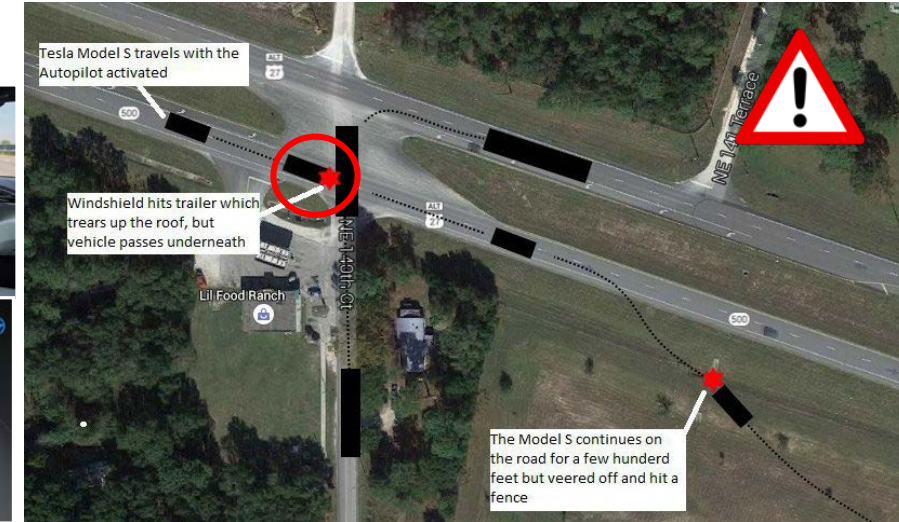


Millions of miles driven since 2010 (Google, Tesla, Waymo, Uber) Several benign & serious accidents in past few years Safety is still not guaranteed!

Fatal accidents involving AVs – *Perception failure*

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

- ✓ *The Autopilot 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*)

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
- 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)

ADAS & Autonomous Driving



Embedded Perception & Decision-making for Safe Intentional Navigation

Dealing with unexpected events



- ### Anticipation & Risk Prediction required for avoiding an upcoming collision with "something"
- ⇒ High reactivity & reflexive actions
 - ⇒ Focus of Attention & Sensing
 - ⇒ Collision Risk estimation + Avoidance strategy

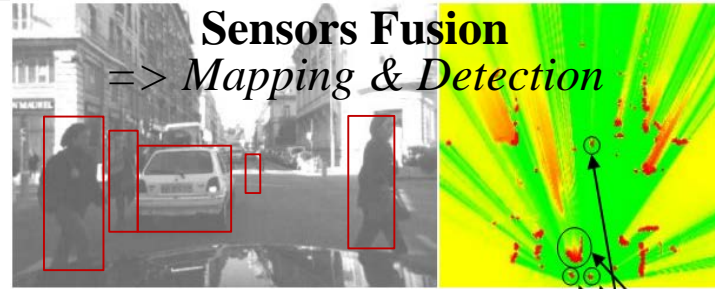
Main features

- ✓ 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*

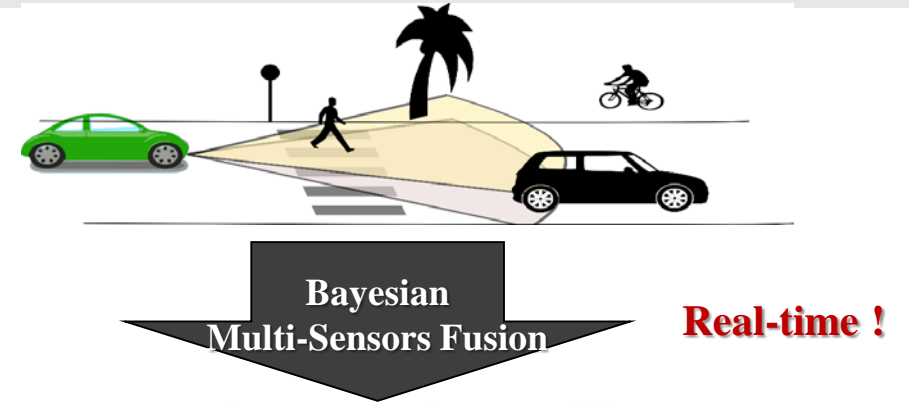
❑ Our Approach: Embedded Bayesian Perception

- ✓ *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

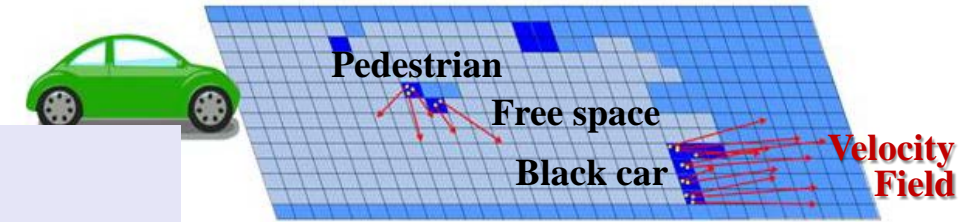
Multi-Sensors Observations

Lidar, Radar, Stereo camera, IMU ...



Probabilistic Environment Model including Dynamics

$P[o|Z,C]$: ≈ 0 ≈ 0.5 ≈ 1



Concept of “Dynamic Probabilistic Grid + Bayesian Filtering”

- \Rightarrow Clear distinction between *Static & Dynamic & Free* components
- \Rightarrow Occupancy & Velocity probabilities
- \Rightarrow Designed for Highly Parallel Processing (to satisfy real-time constraints)
- \Rightarrow Includes Embedded Models for Motion Prediction & Collision Risk Assessment
- \Rightarrow 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]*

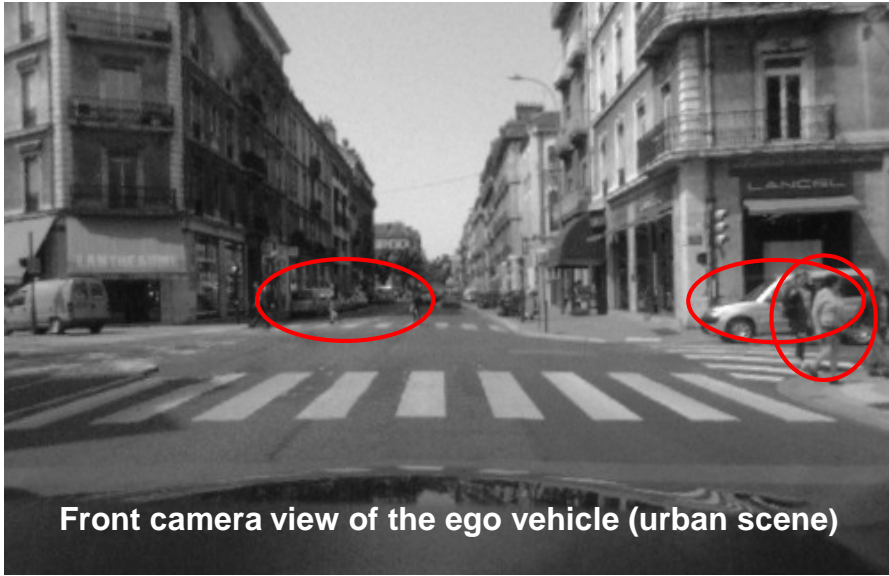
Main philosophy

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

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

Dynamic Probabilistic Grid & Bayesian Filtering – *Main Features*

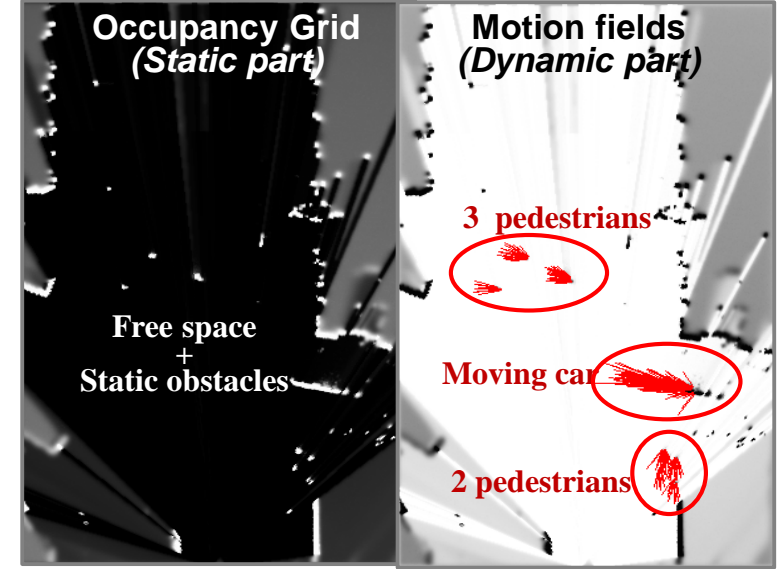
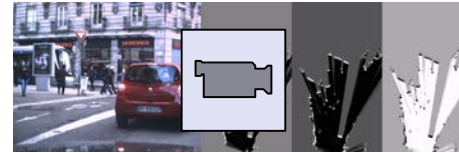
=> Exploiting the dynamic information for a better understanding of the scene



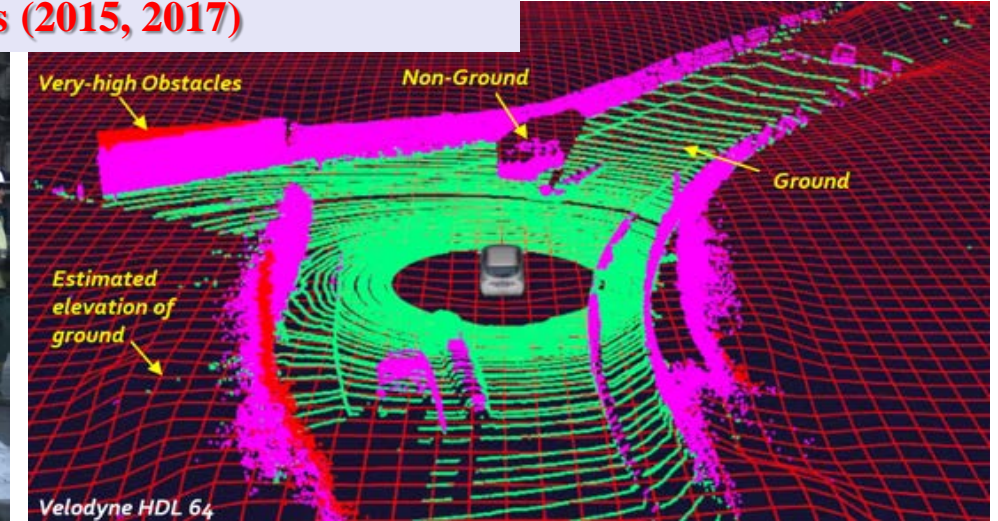
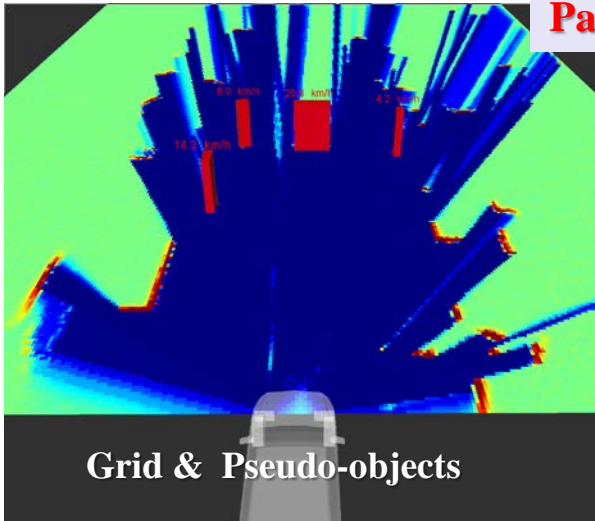
Sensors data fusion
+
Bayesian Filtering
+
Extracted Motion Fields



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



Patented Improvements & Implementations (2015, 2017)



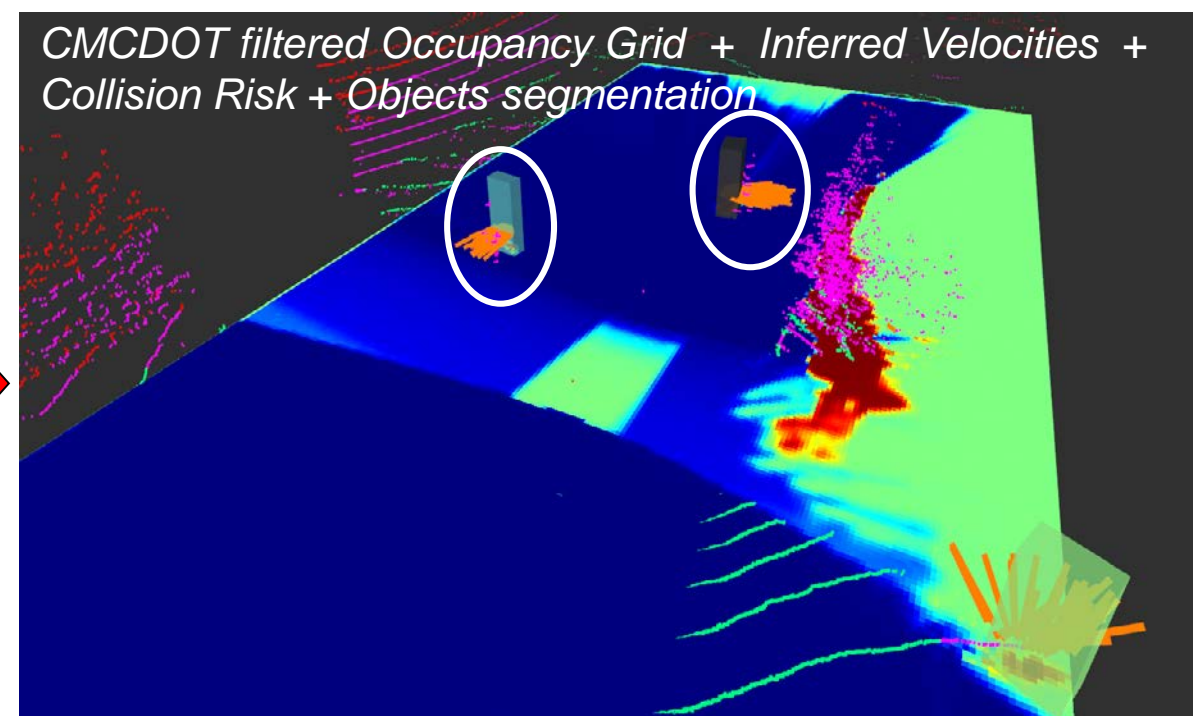
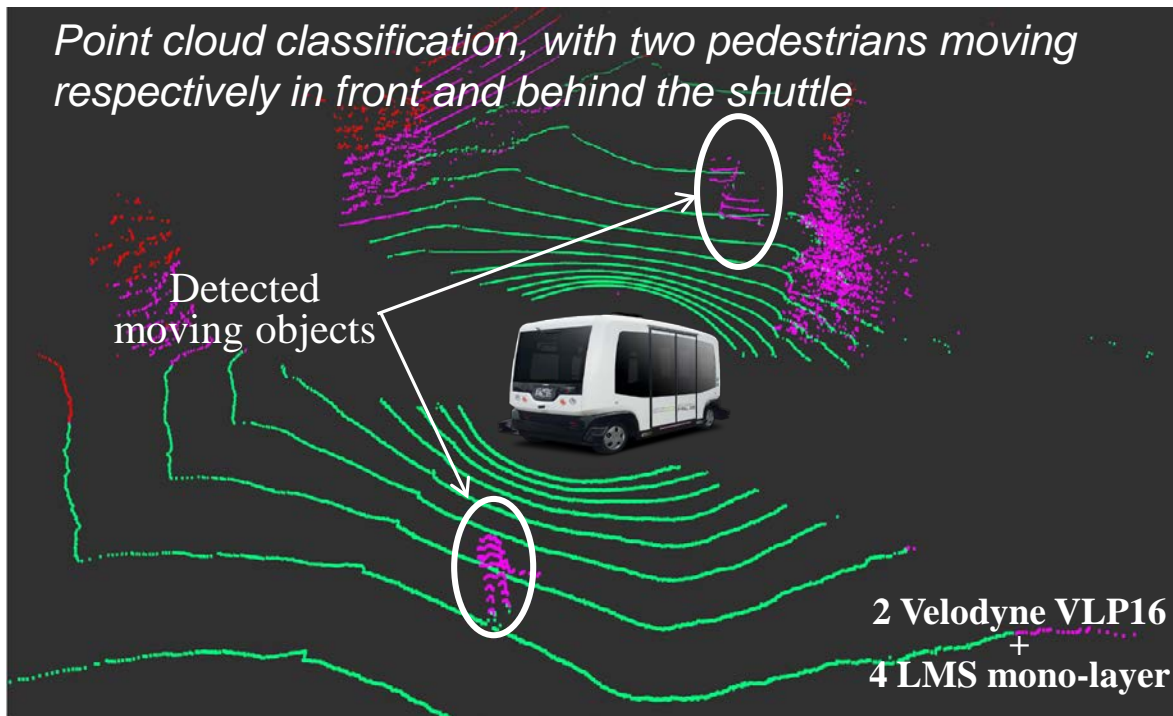
Detection & Tracking + Moving Objects Classification
=> CMCDOT 2015 (including a “Dense Occupancy Tracker”)

Ground Estimation & Point Cloud Classification
(patent 2017)

System Integration on a commercial vehicle

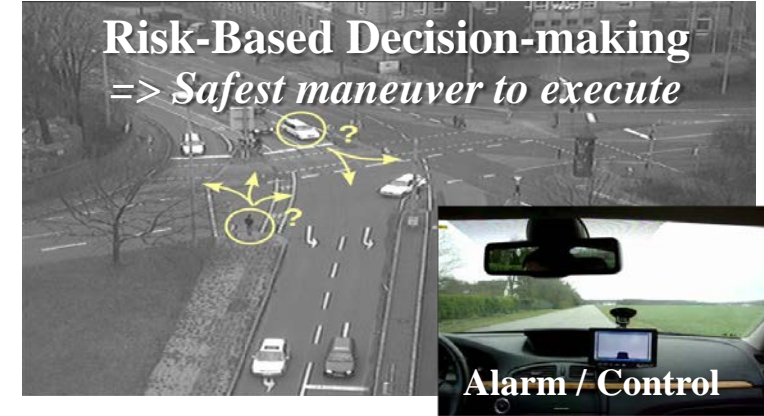
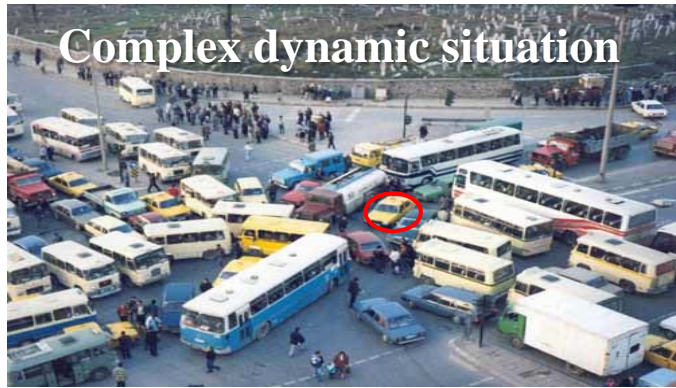


- **POC 2019: Complete system implemented on Nvidia TX1**, and easily connected to the shuttle system network *in a few days* (using ROS)
- **Shuttle sensors data** has been fused and processed in **real-time**, with a successful Detection & Characterization of the **Moving & Static Obstacles**
- **Full 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 $t < 5s$

$\delta = 0.5s$ => Precrash

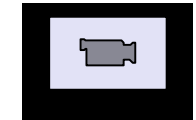
$\delta = 1s$ => Collision mitigation

$\delta > 1.5s$ => 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 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)*

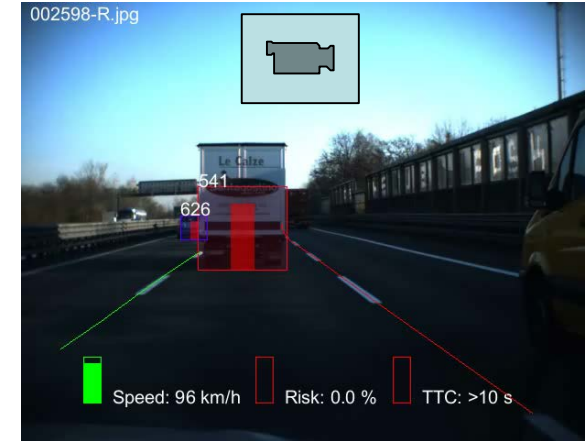
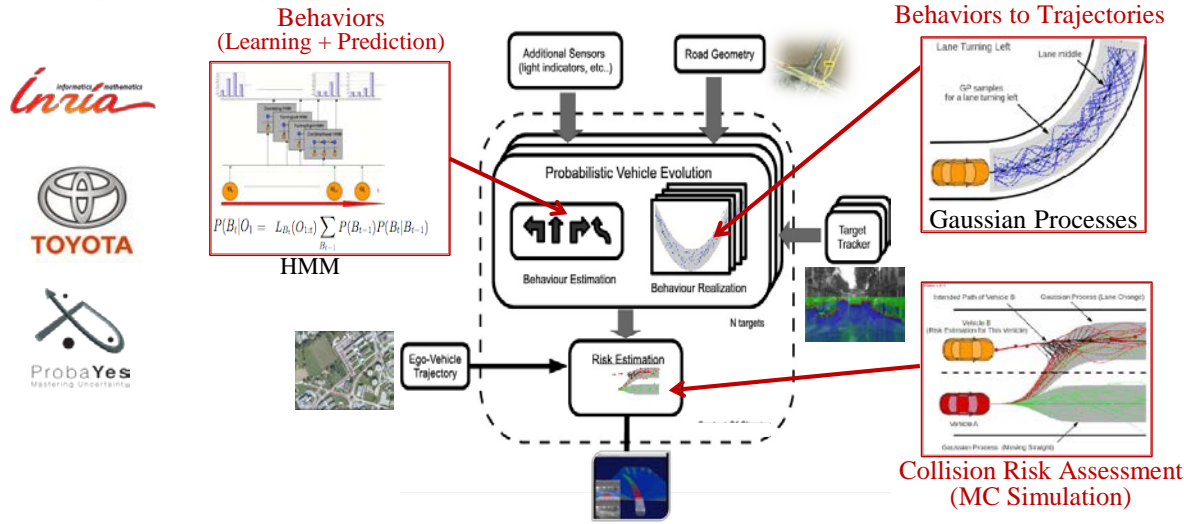
+

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)

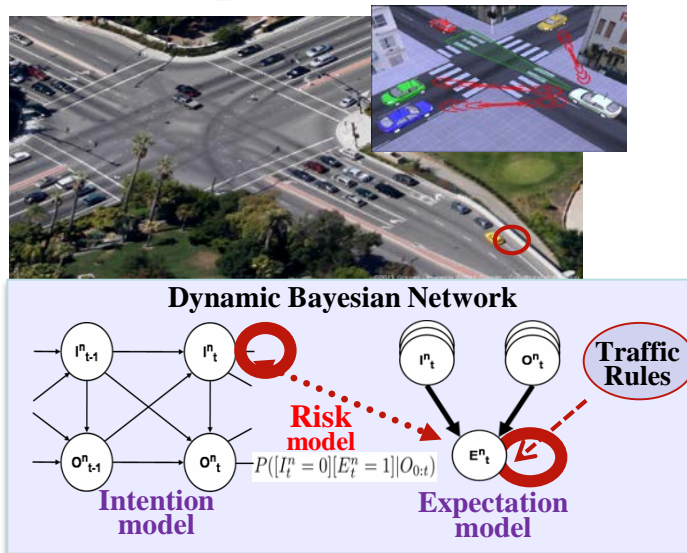


Cooperation still on-going
(R&D contracts + PhD)

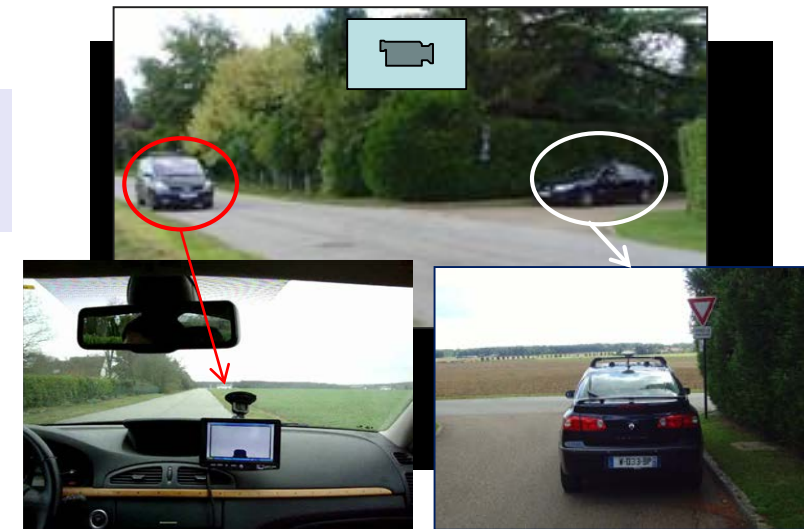
Courtesy Probayes



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



Human-like reasoning

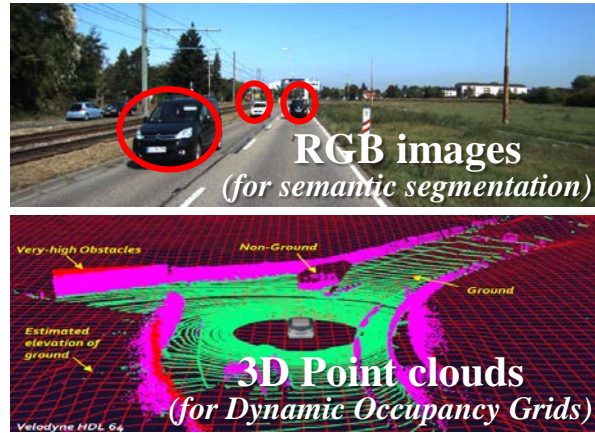


Cooperation still on-going
(R&D contracts + PhD)



3rd Paradigm: Models improvements using Machine Learning

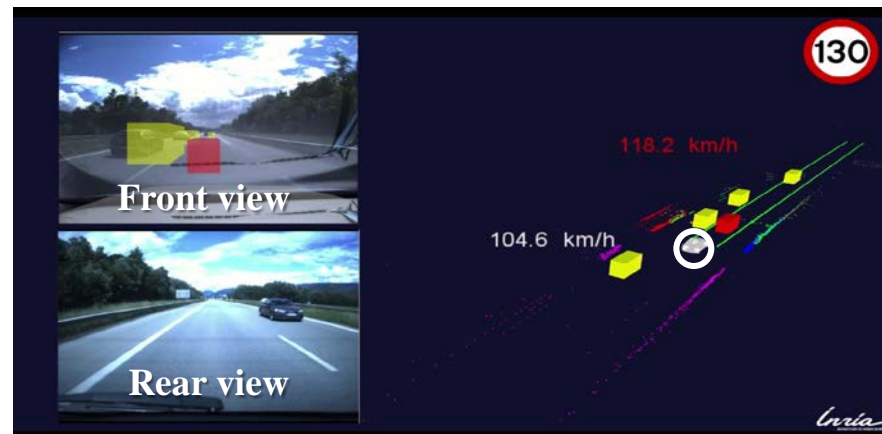
□ Perception level: *Construct “Semantic Grids” using Bayesian Perception & DL*



□ 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*

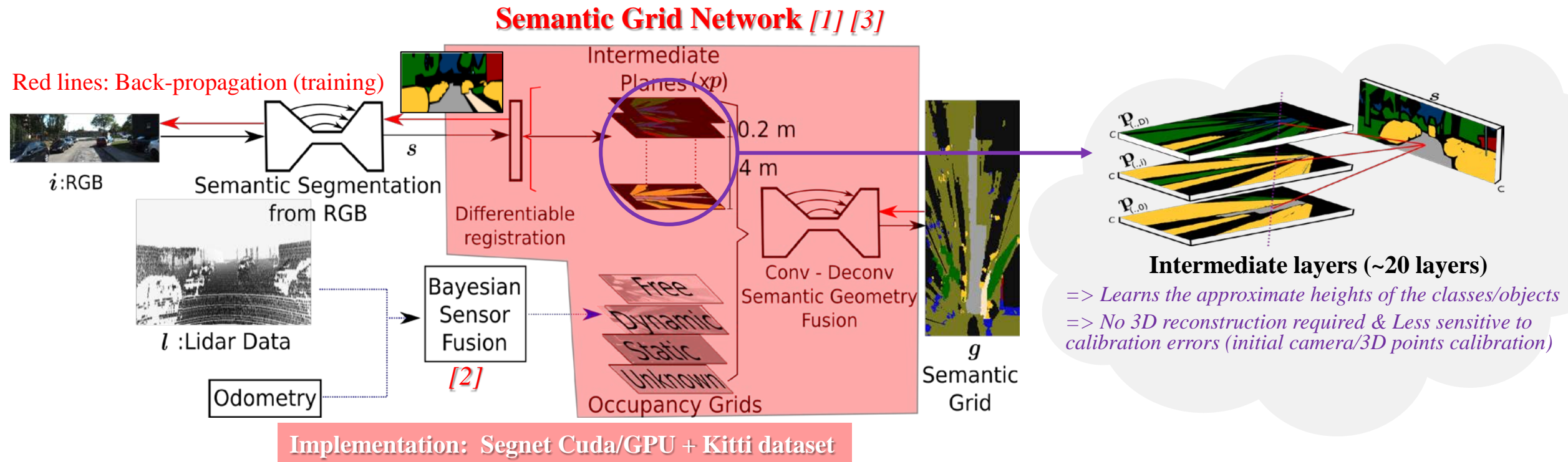


Perception Level: Semantic Grids (Bayesian Perception + DL)

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)

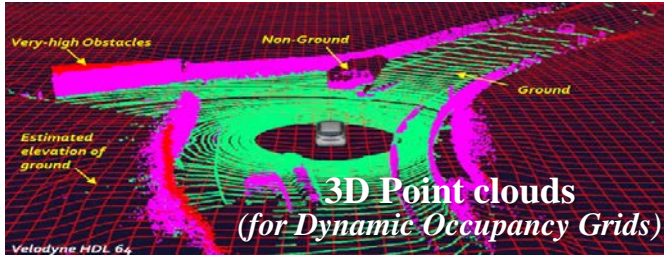


[1] Semantic grid estimation with a Hybrid Bayesian and Deep Neural Network approach, O. Erkent et al., IEEE IROS 2018

[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)



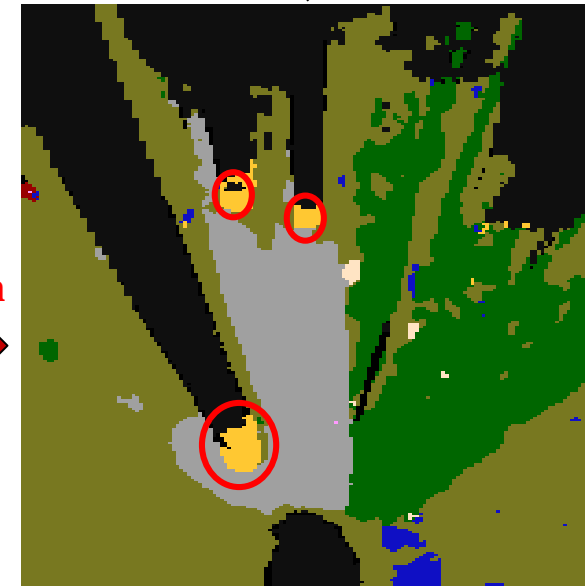
Frontal View Ground-Truth
=> labelled by humans in datasets

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 & Current work

Ground Truth (GT)



GT Projection



Semantic Grid Estimation



Frontal View Estimation



Ground Truth (GT)



GT Projection



Semantic Grid Estimation



Frontal View Estimation



○ **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)

2 cars not detected in frontal view estimation (semantic segmentation)
... 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



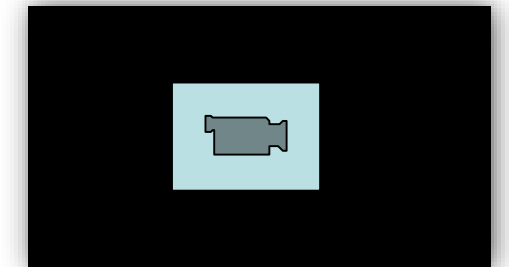
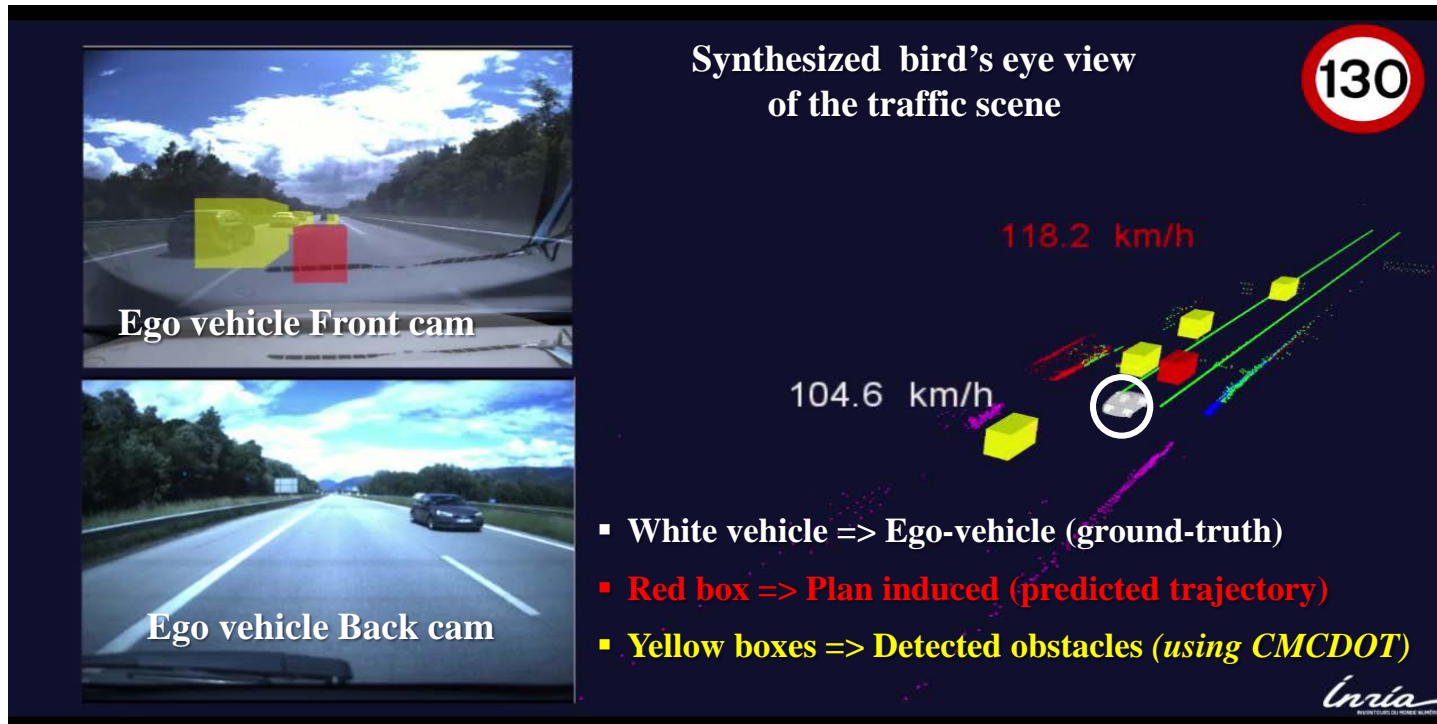
Decision-making level: Learning Driving Skills for AD

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.*

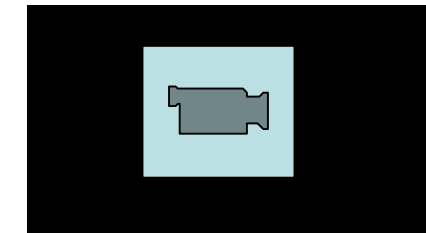
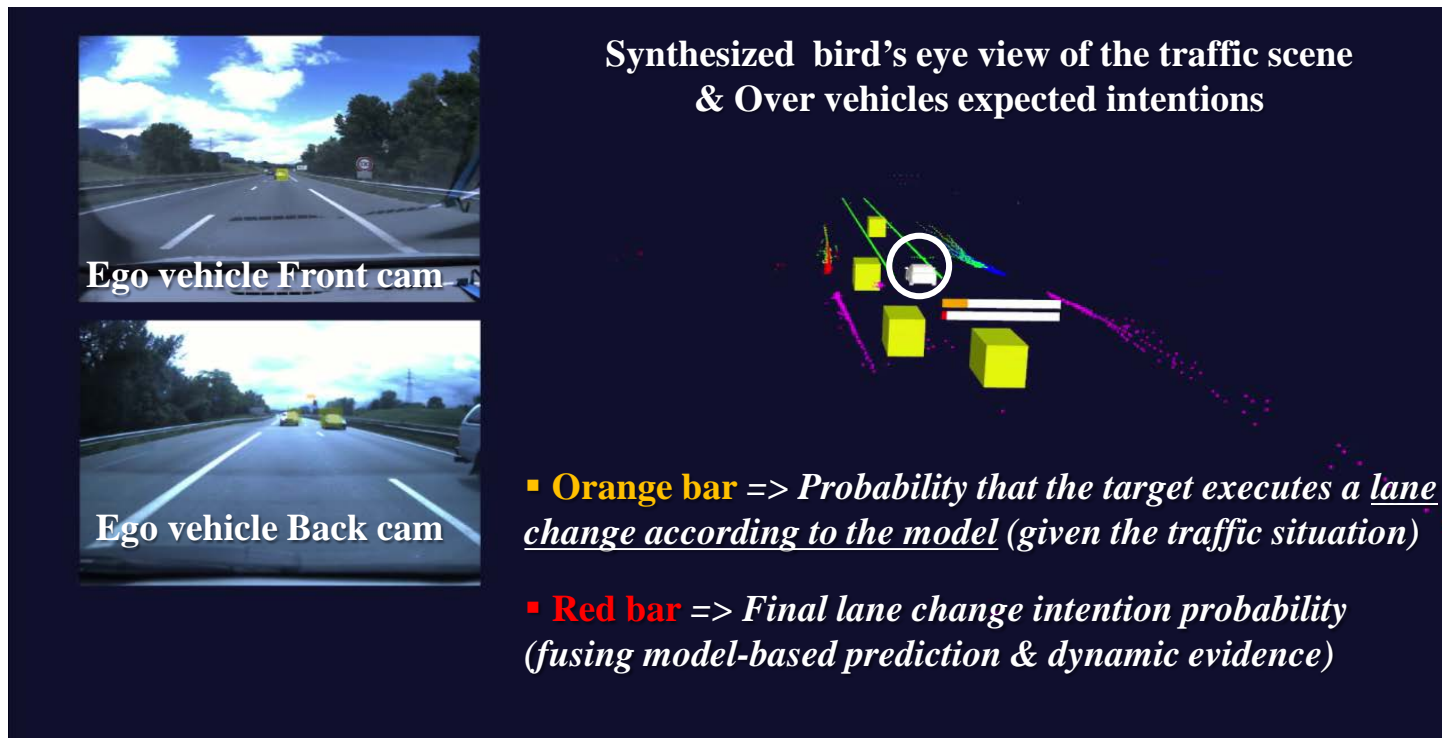
=> Obtained models can be leverage to **Predict human driver behaviors & Generate human-like plans for the ego vehicle** (mandatory in mixed traffic)



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]



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

Experimental Vehicles & Connected Perception Units

Toyota Lexus

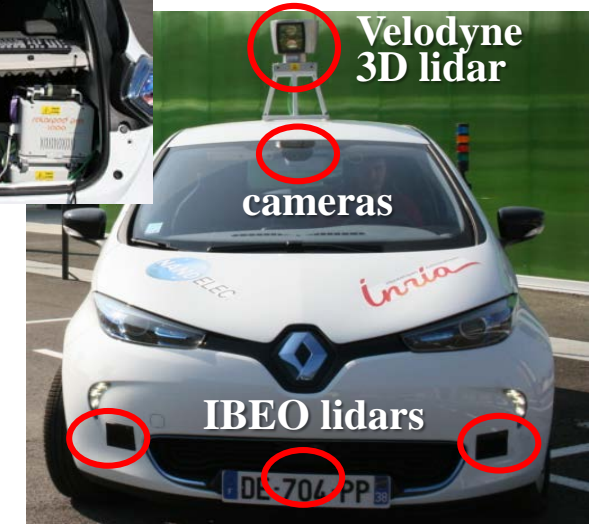


ROS

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)



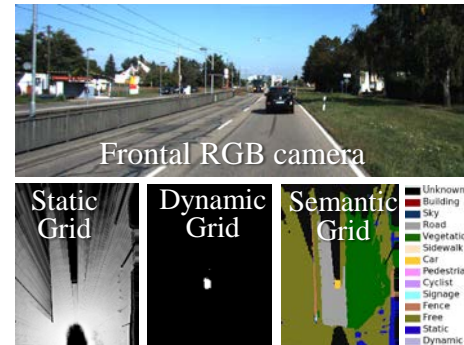
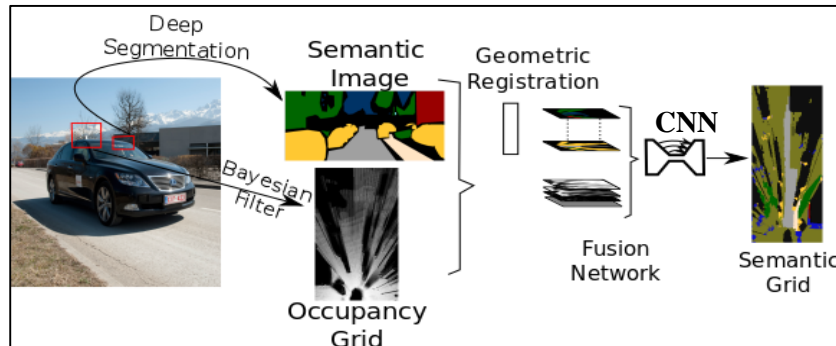
Autonomous Bus (Iveco)
(up to 70 km/h, Urban traffic)



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 ...**

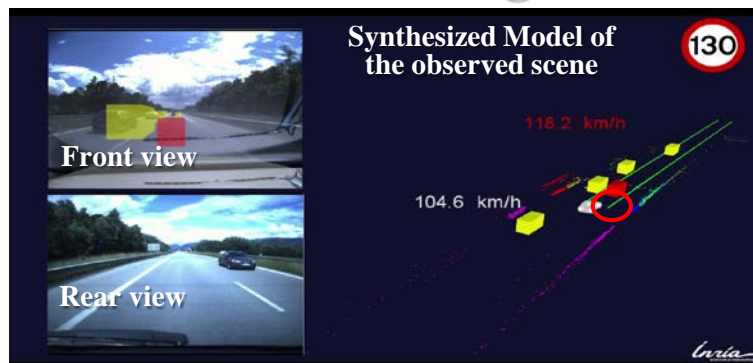
□ Embedded & Extended “Semantic Grids”



- 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)*

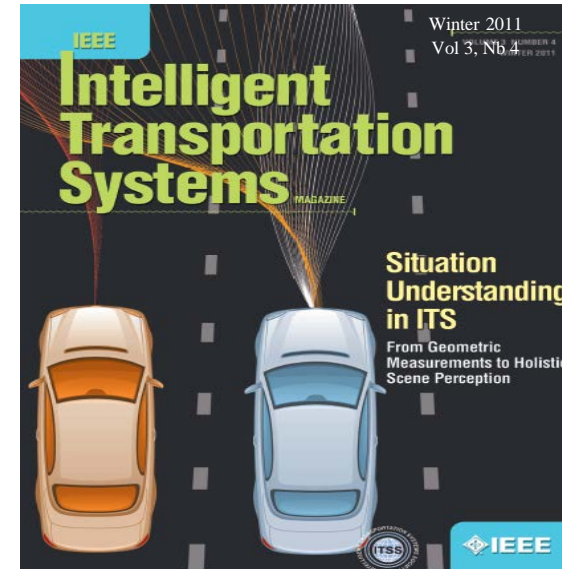
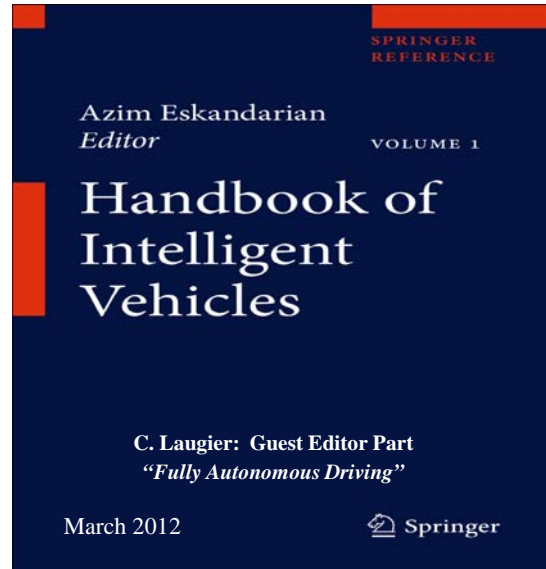
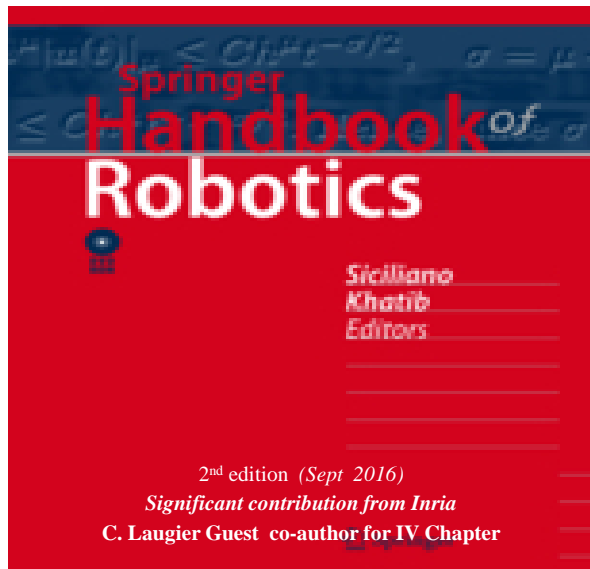


□ Autonomous Driving in mixed traffic (Prediction & Planning) using learned models



- **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*





Thank You