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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)

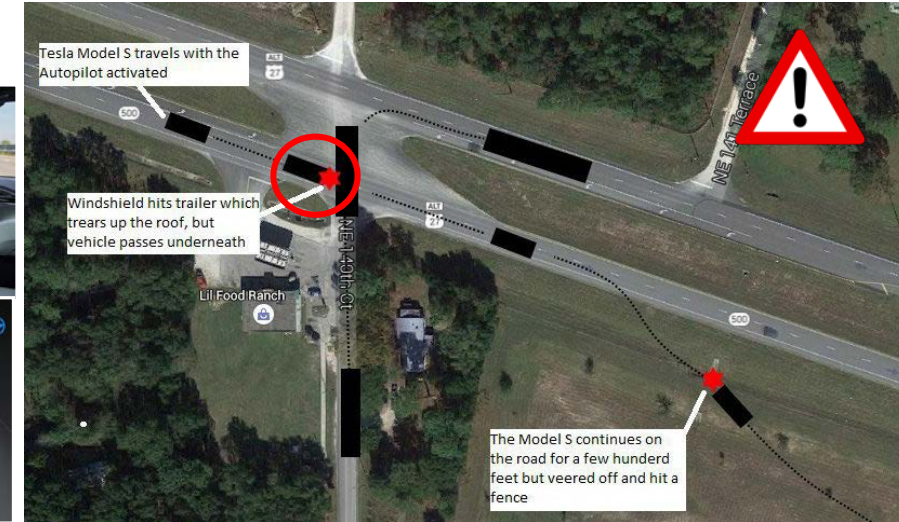


Millions of miles driven since 2010 (Google, Tesla, Waymo, Uber) Several benign & serious accidents in past few years Safety is still not guaranteed!

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

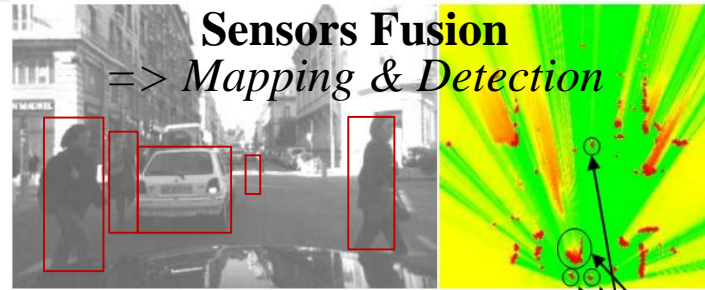
Main features

- ✓ 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*

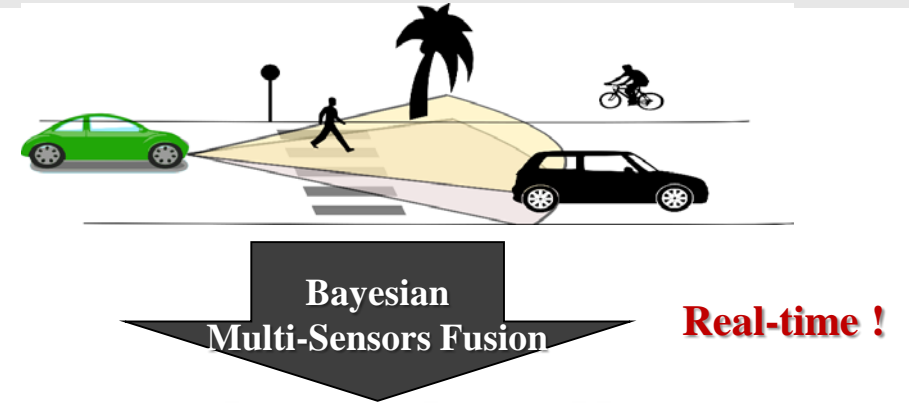
❑ Our Approach: Embedded Bayesian Perception

- ✓ *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

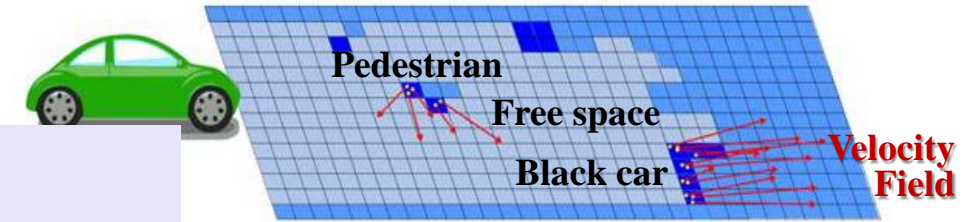
□ Multi-Sensors Observations

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”

- ⇒ 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]*

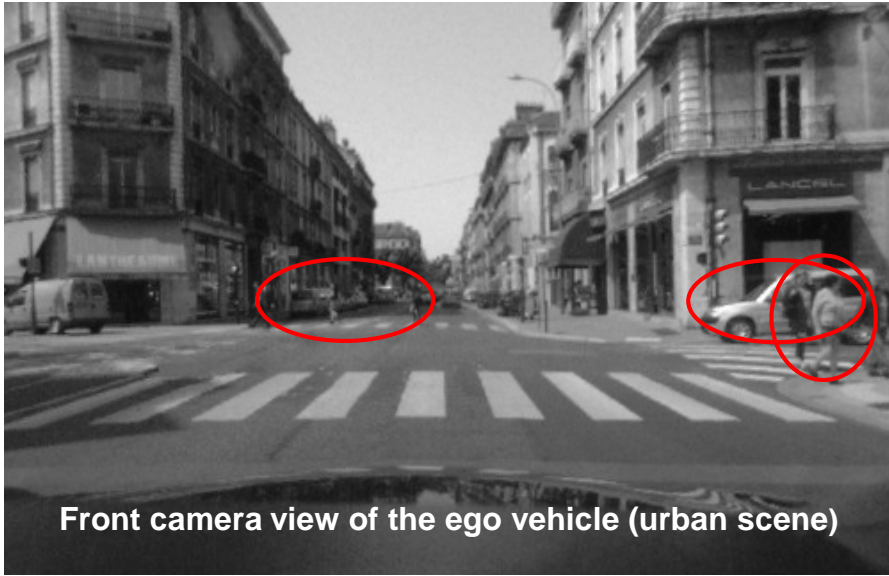
□ Main philosophy

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*

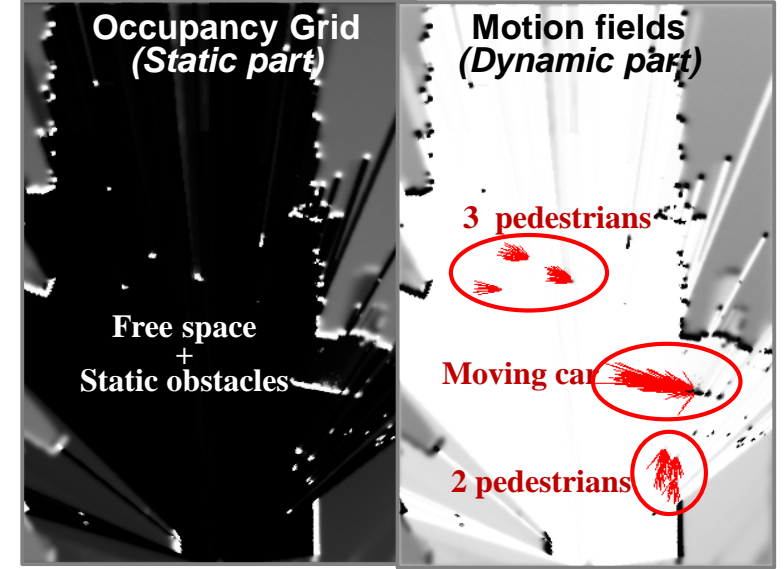
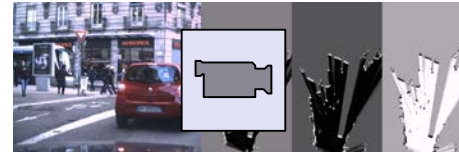
=> Exploiting the dynamic information for a better understanding of the scene



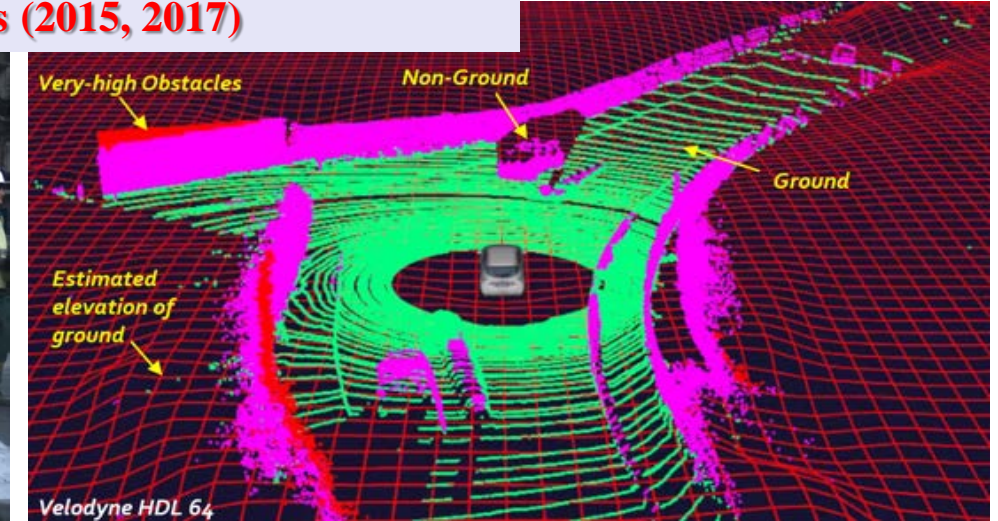
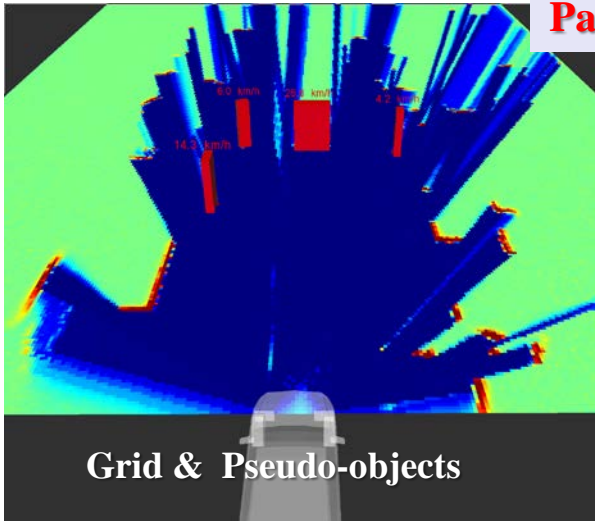
Sensors data fusion
+
Bayesian Filtering
+
Extracted Motion Fields



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



Patented Improvements & Implementations (2015, 2017)



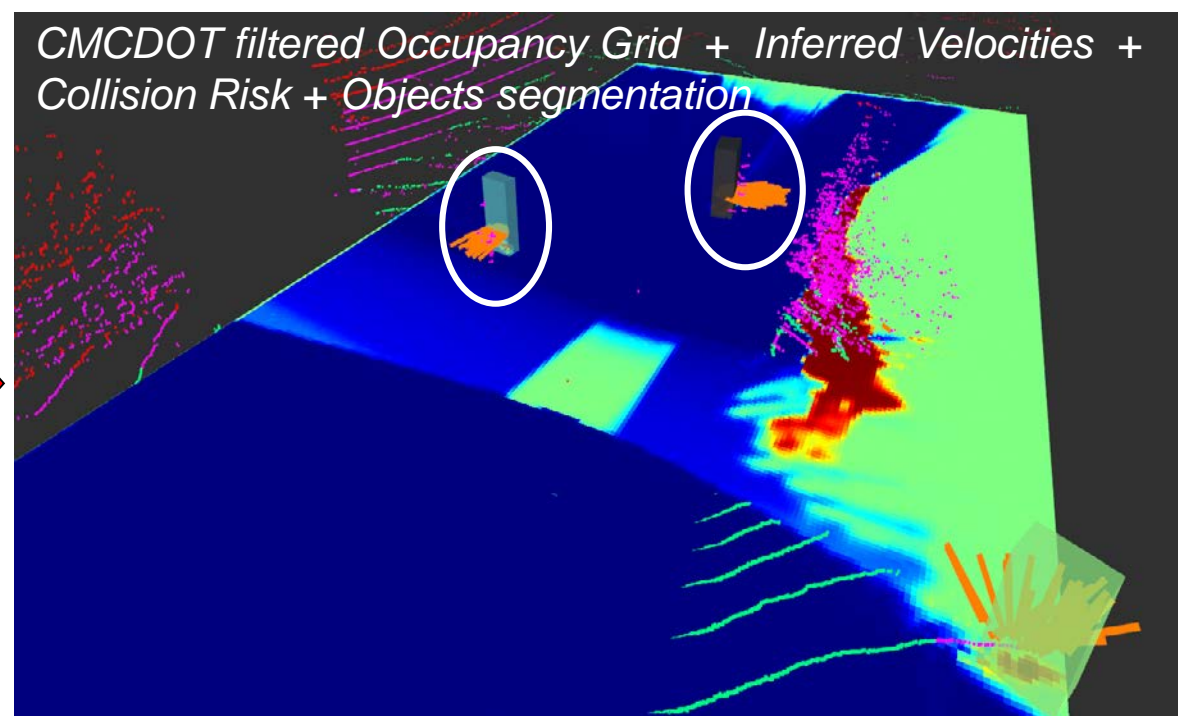
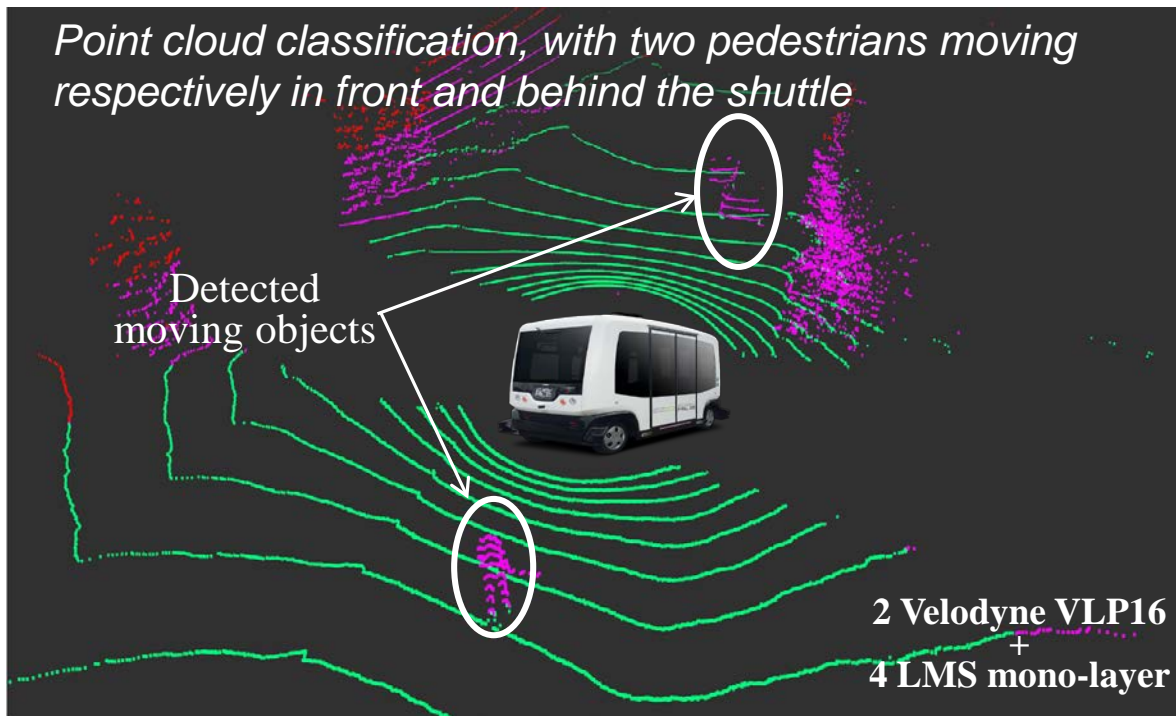
Detection & Tracking + Moving Objects Classification
=> CMCDOT 2015 (including a “Dense Occupancy Tracker”)

Ground Estimation & Point Cloud Classification
(patent 2017)

System Integration on a commercial vehicle

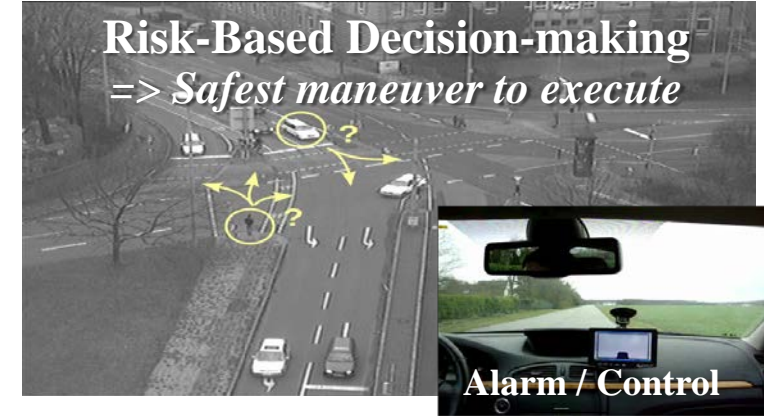
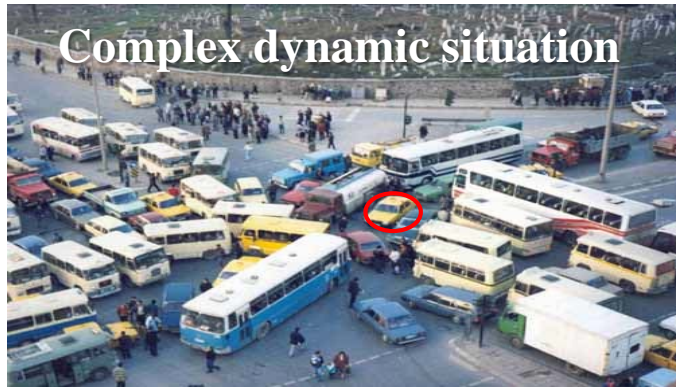


- **POC 2019: Complete system implemented on Nvidia TX1**, and easily connected to the shuttle system network *in a few days* (using ROS)
- **Shuttle sensors data** has been fused and processed in **real-time**, with a successful Detection & Characterization of the **Moving & Static Obstacles**
- **Full 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: $d < 100\text{m}$ and $t < 5\text{s}$

$\delta = 0.5\text{s}$ => Precrash

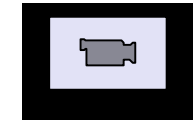
$\delta = 1\text{s}$ => Collision mitigation

$\delta > 1.5\text{s}$ => 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)*

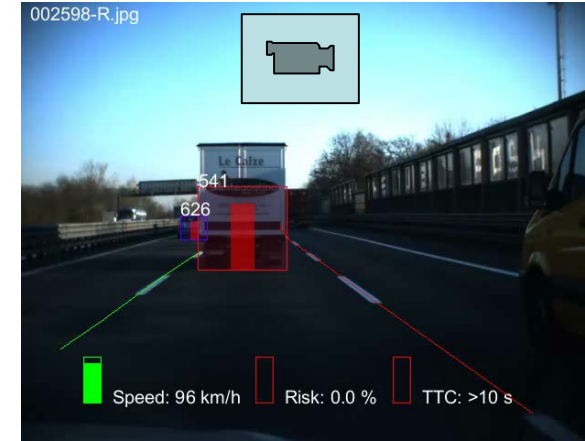
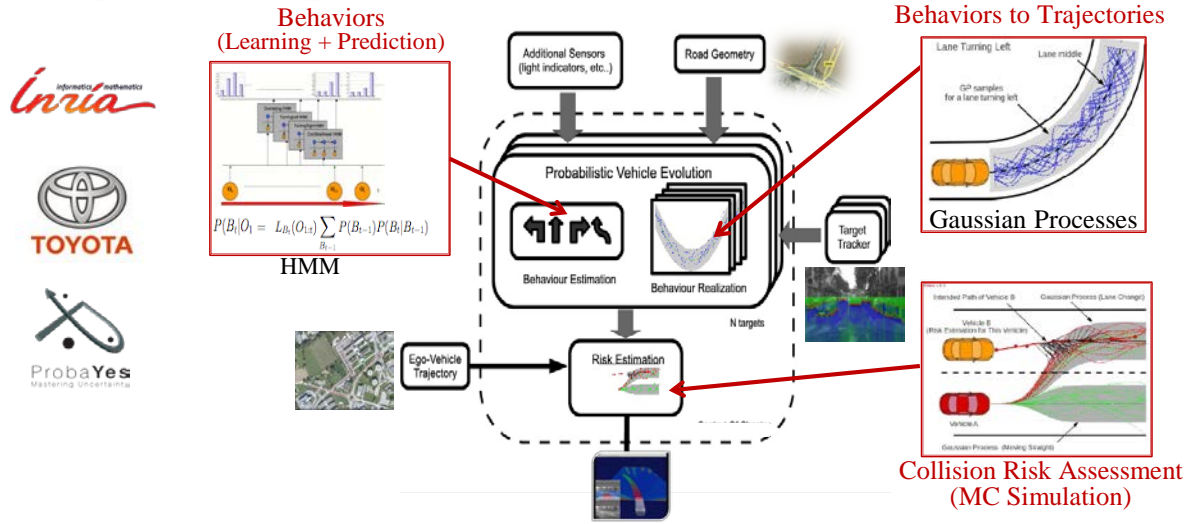
+

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)

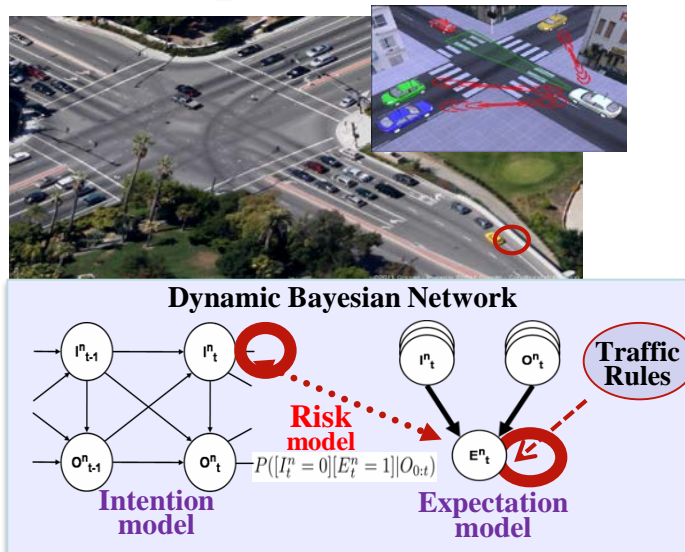


Cooperation still on-going
(R&D contracts + PhD)

Courtesy Probayes



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



Human-like reasoning

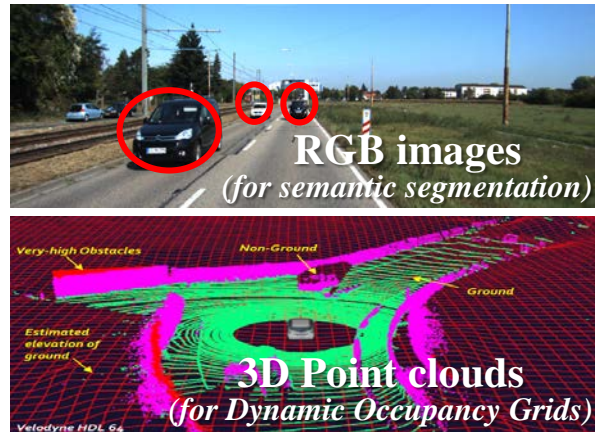


Cooperation still on-going
(R&D contracts + PhD)



3rd Paradigm: Models improvements using Machine Learning

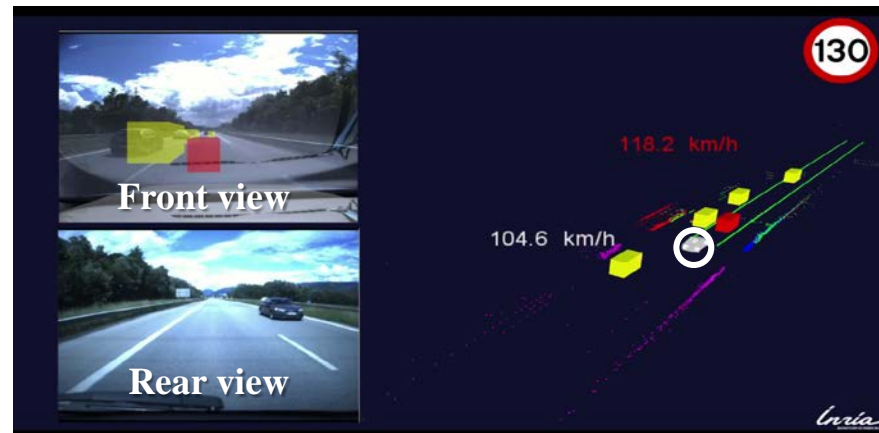
□ Perception level: *Construct “Semantic Grids” using Bayesian Perception & DL*



□ 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*

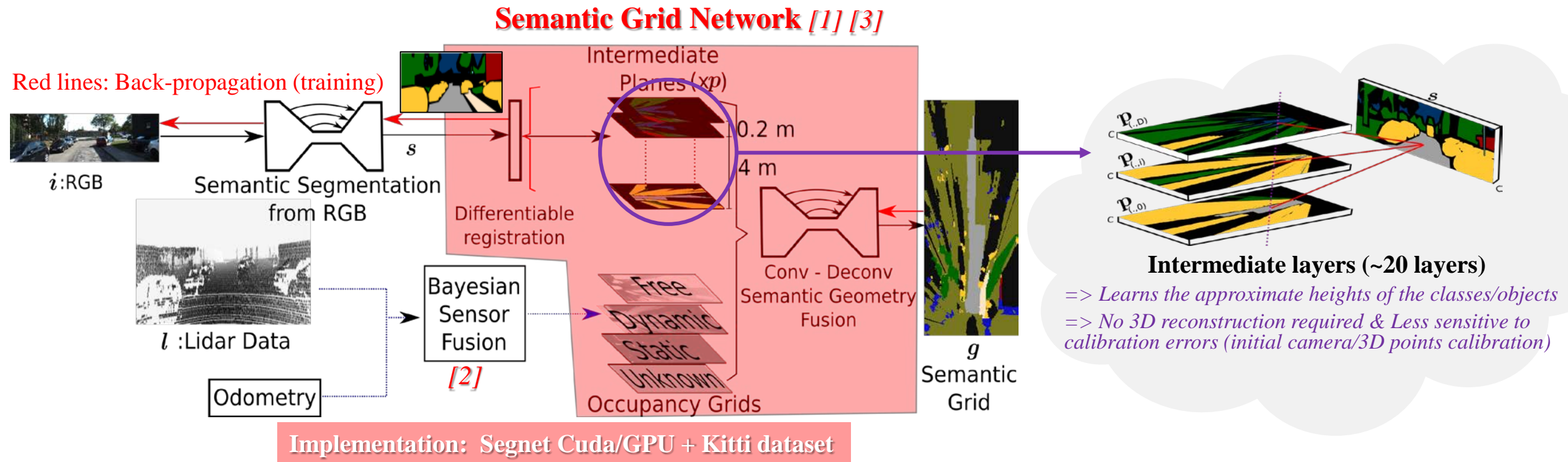


Perception Level: Semantic Grids (Bayesian Perception + DL)

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)

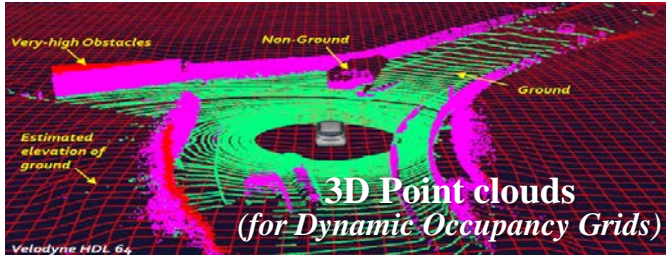


[1] Semantic grid estimation with a Hybrid Bayesian and Deep Neural Network approach, O. Erkent et al., IEEE IROS 2018

[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)



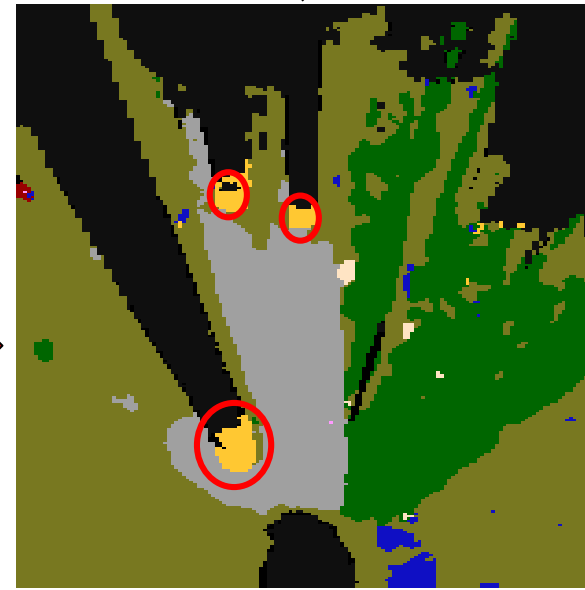
Frontal View Ground-Truth
=> labelled by humans in datasets

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



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



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)

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



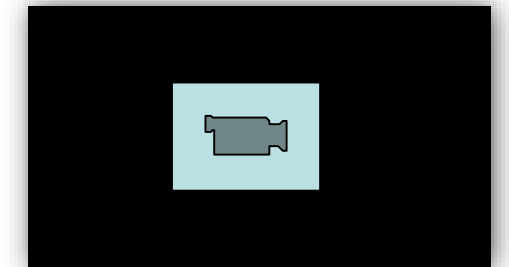
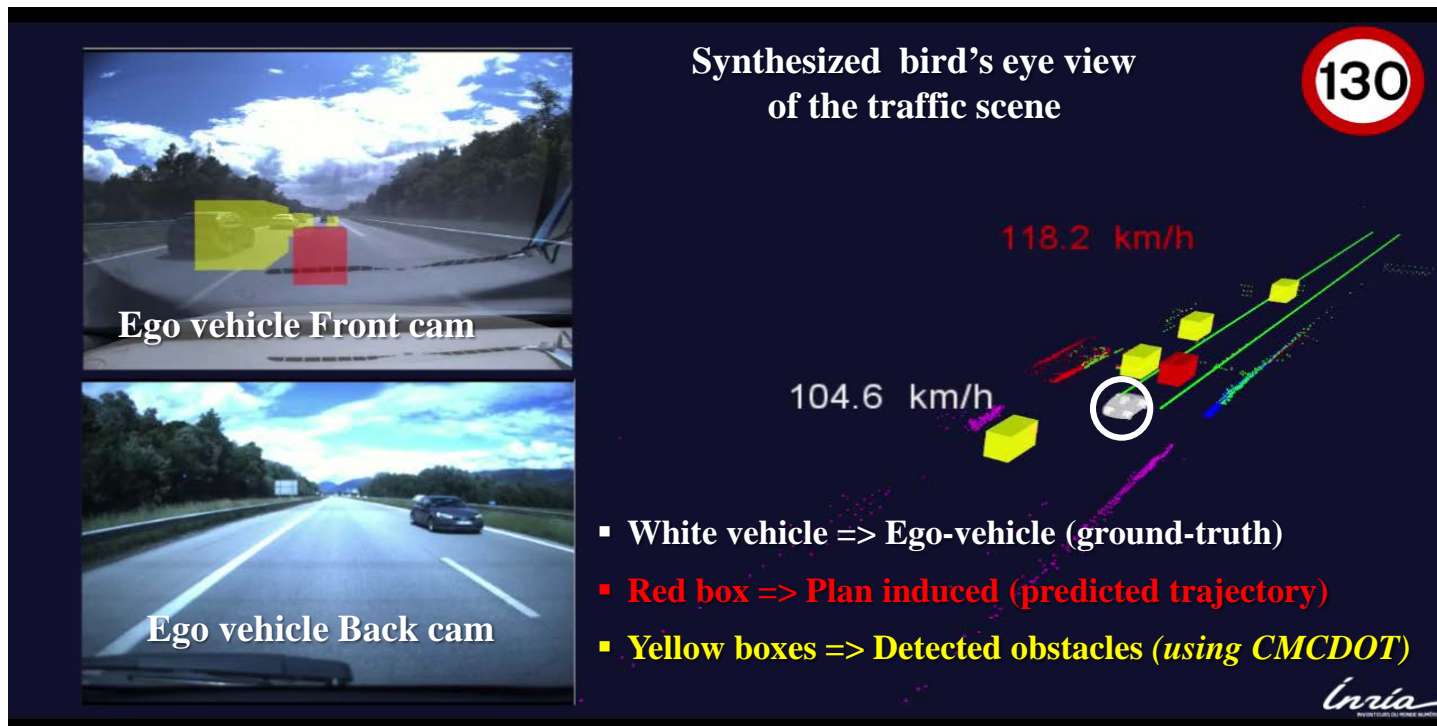
Decision-making level: Learning Driving Skills for AD

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.*

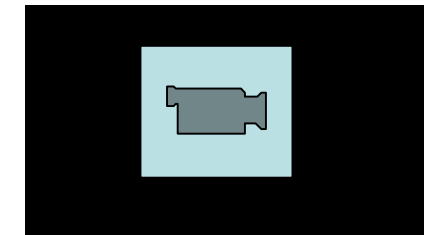
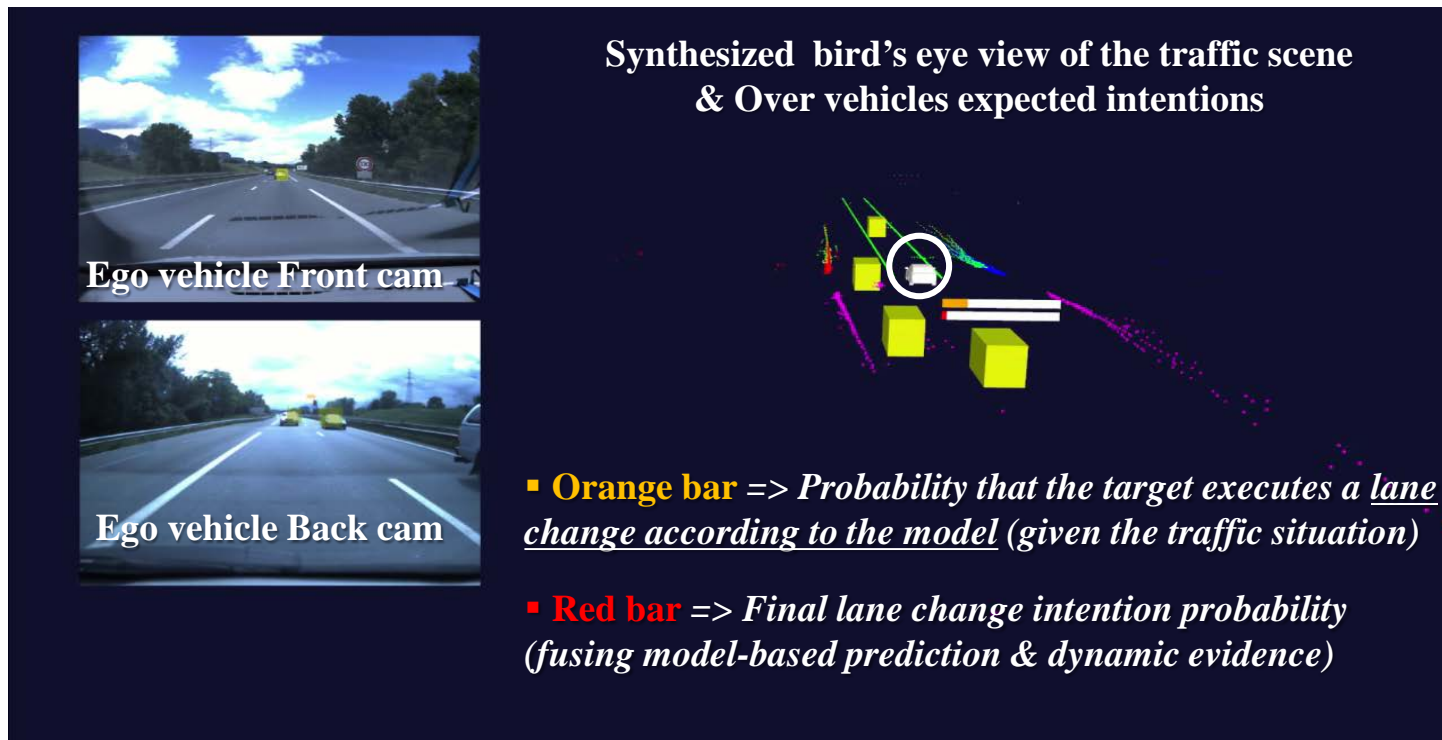
=> Obtained models can be leverage to **Predict human driver behaviors & Generate human-like plans for the ego vehicle** (mandatory in mixed traffic)



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

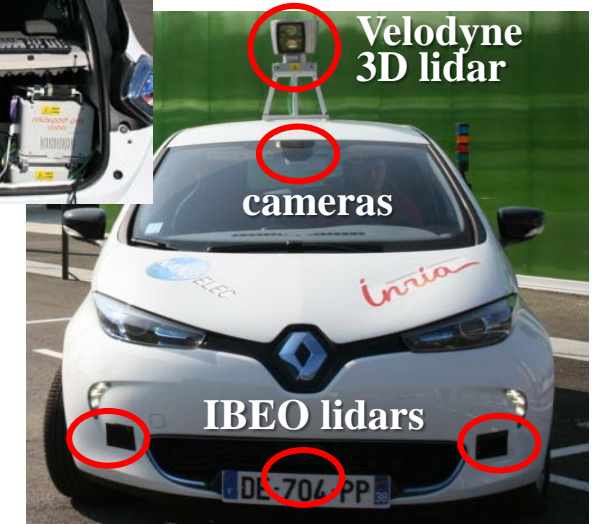


ROS

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

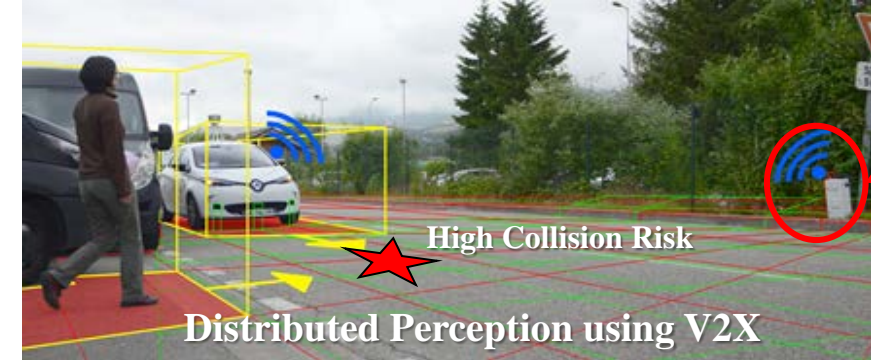
- ❑ Protected experimental area => *Testing Autonomous Driving L3 & L4*



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)



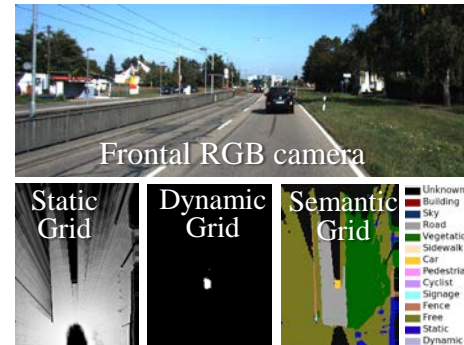
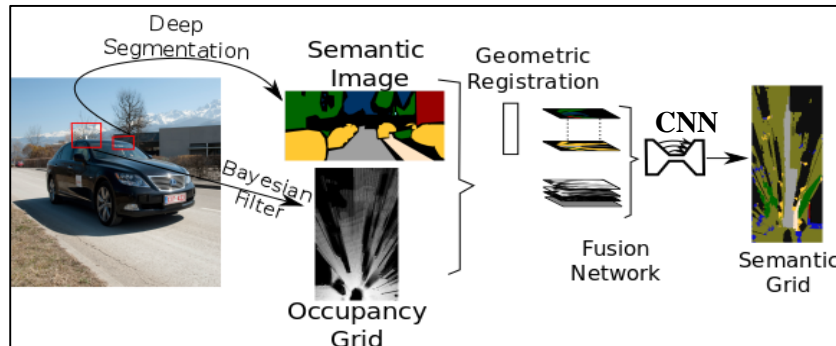
Autonomous Bus (Iveco)
(up to 70 km/h, Urban traffic)



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 ...**

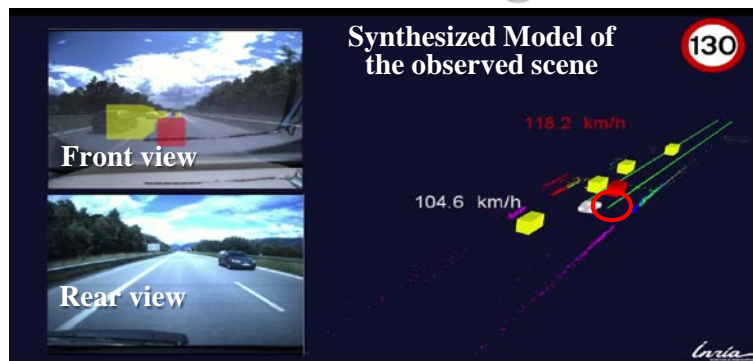
□ Embedded & Extended “Semantic Grids”



- 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)*

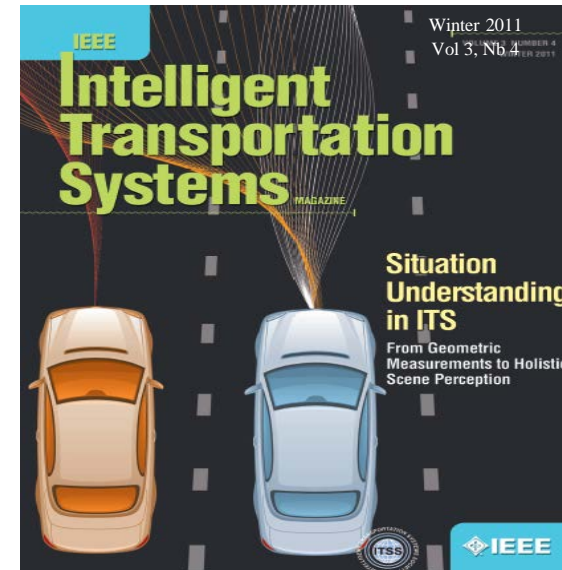
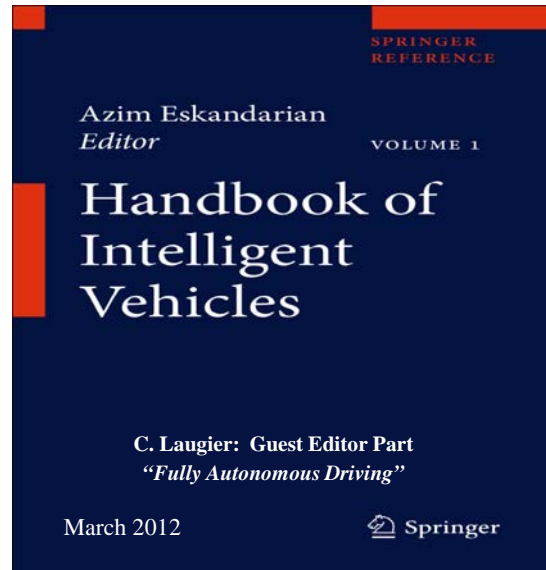
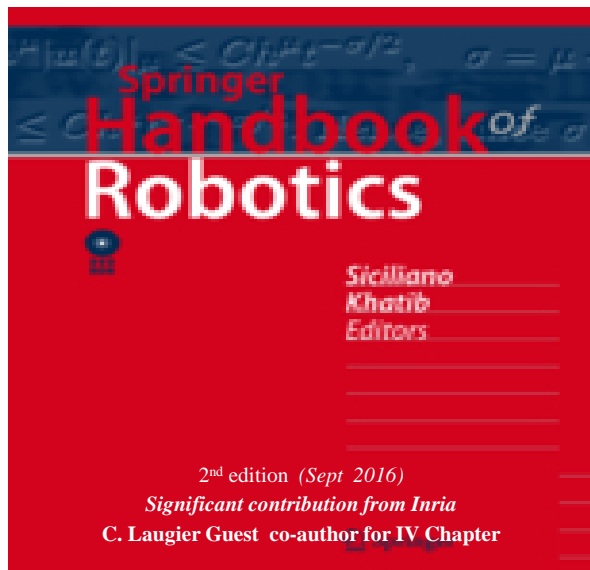


□ Autonomous Driving in mixed traffic (Prediction & Planning) using learned models



- **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