Situation Awareness & Decision-making for Autonomous Driving

Christian Laugier

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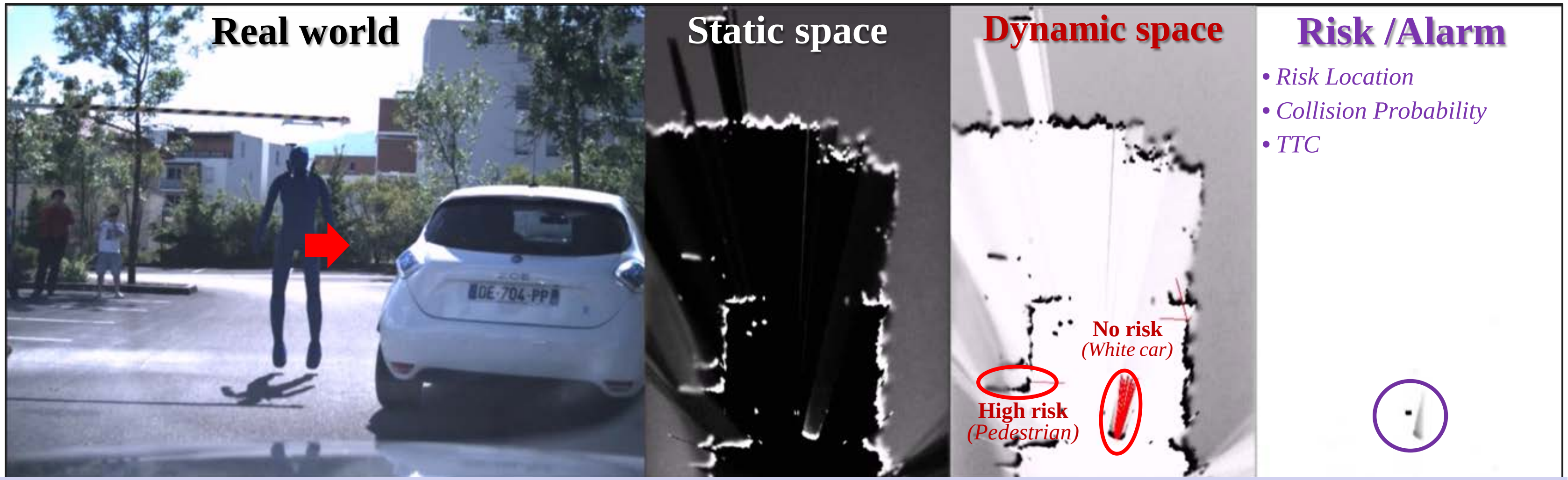
ADAS & Autonomous Driving



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 !

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, 50 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*

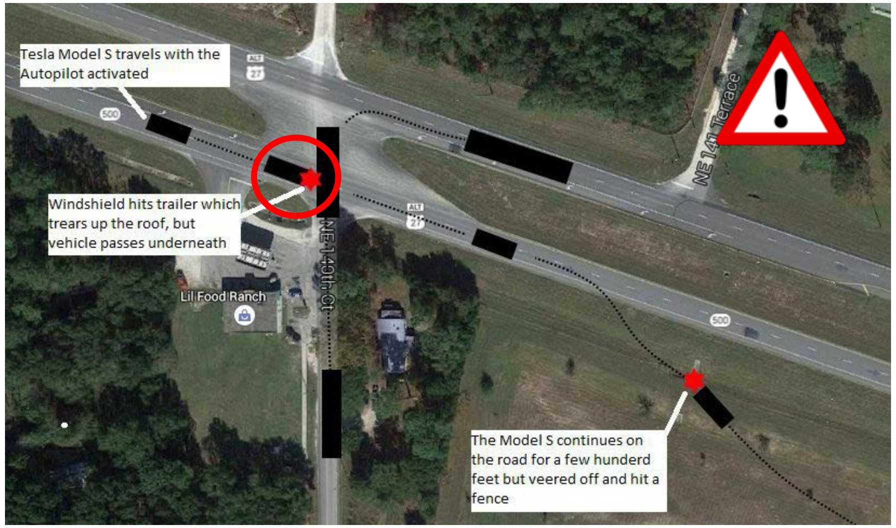
⇒ ***Uber:*** *System testing since 2017, Disengagement every 0.7 miles in 2017 (improved now)*

⇒ ***Waymo:*** *1st US Self Driving Taxi Service launched in Phoenix in Dec 2018*

⇒ ***Disengagement reports provide insights on the technology maturity***

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

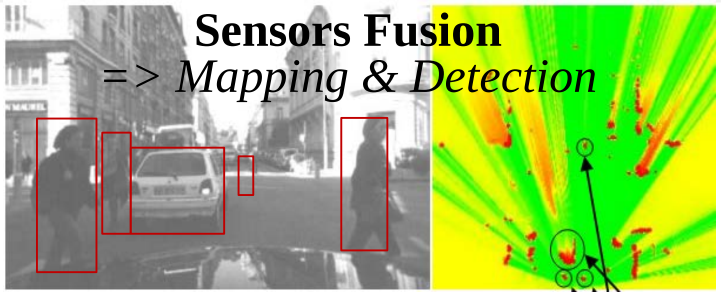
Anticipation & Risk Prediction required
for avoiding an upcoming collision with "something"
=> *High reactivity & reflexive actions*
=> *Focus of Attention & Sensing*
=> *Collision Risk estimation + Avoidance strategy*

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)

1^{st} 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

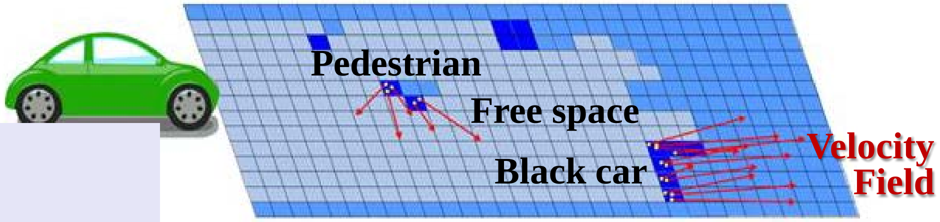
- **Multi-Sensors Observations**
  Lidar, Radar, Stereo camera, IMU …

Bayesian
Multi-Sensors Fusion

Real-time !

- **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]

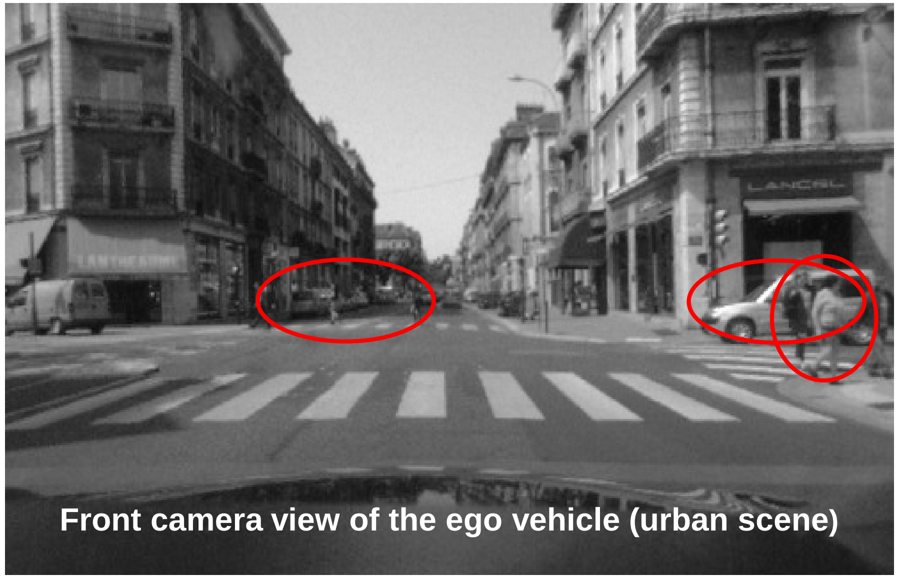
- **Main philosophy**

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…)*

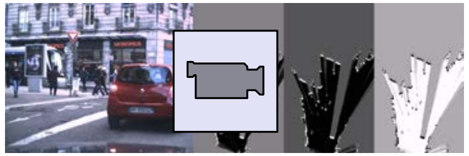
Dynamic Probabilistic Grid & Bayesian Filtering – *Main Features*

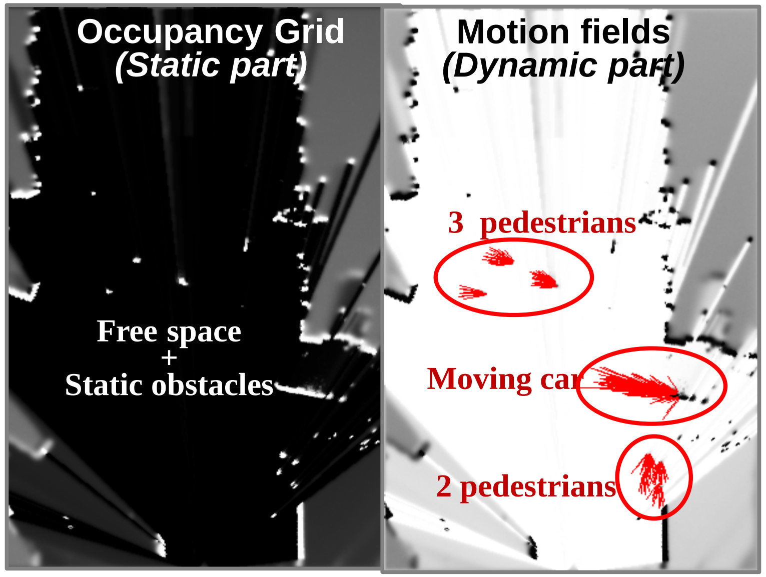
=> Exploiting the dynamic information for a better understanding of the scene


Front camera view of the ego vehicle (urban scene)

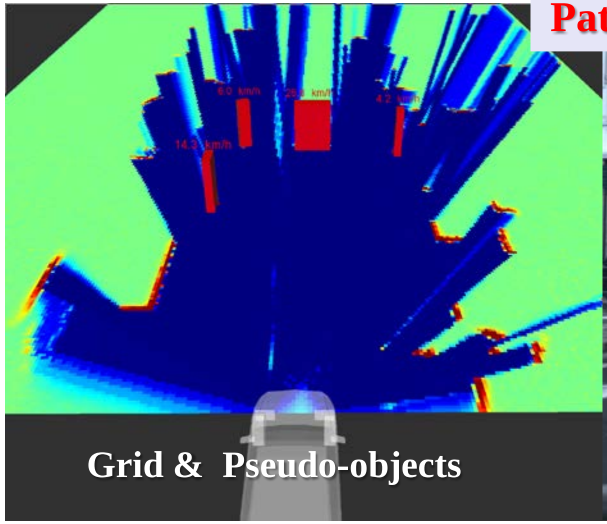
Sensors data fusion
+
Bayesian Filtering
+
Extracted Motion Fields

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



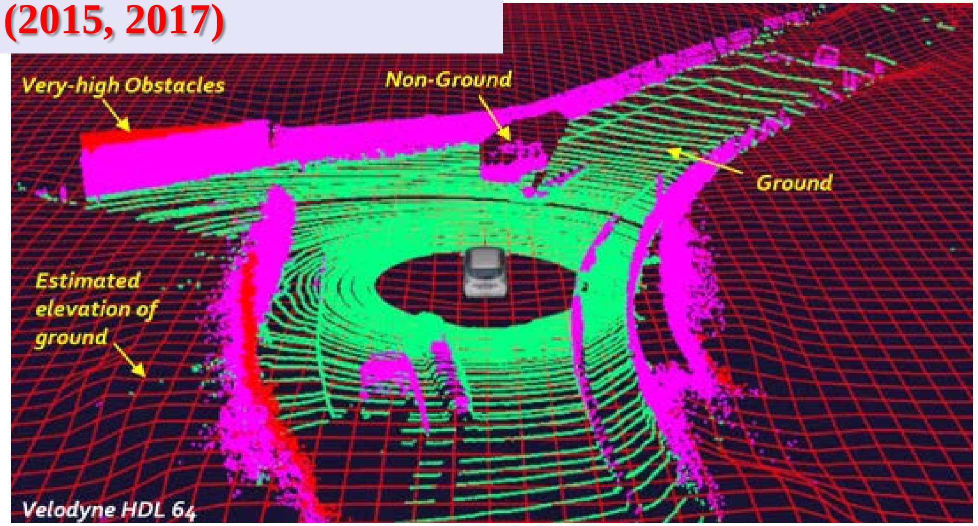


Patented Improvements & Implementations (2015, 2017)


Grid & Pseudo-objects

Classification *(using Deep Learning)*

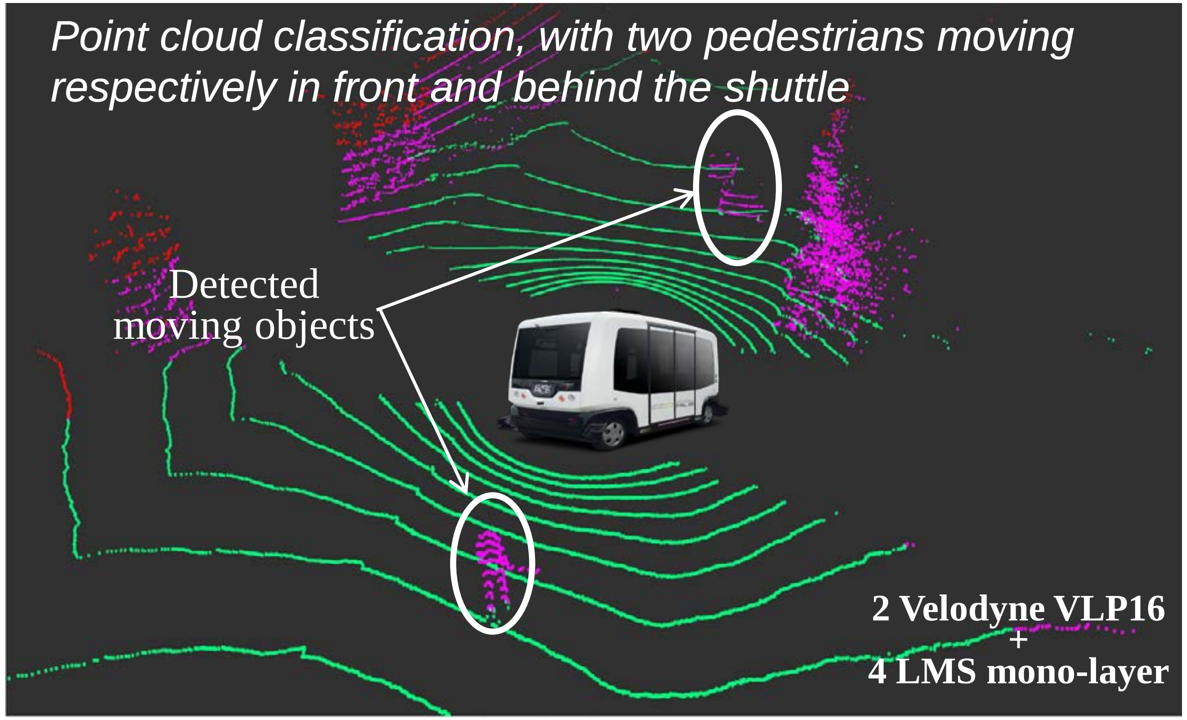
Detection & Tracking + Moving Objects Classification
=> CMCDOT 2015 (including a "Dense Occupancy Tracker")

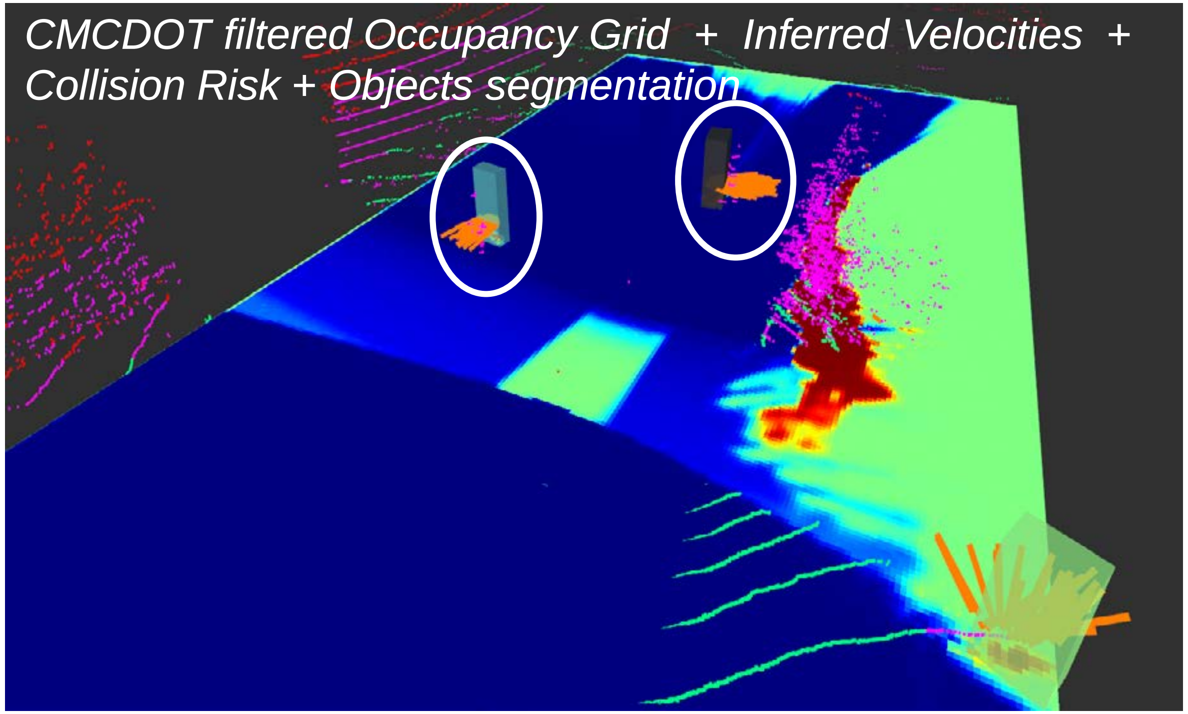


Ground Estimation & Point Cloud Classification
(patent 2017)

System Integration on a commercial vehicle

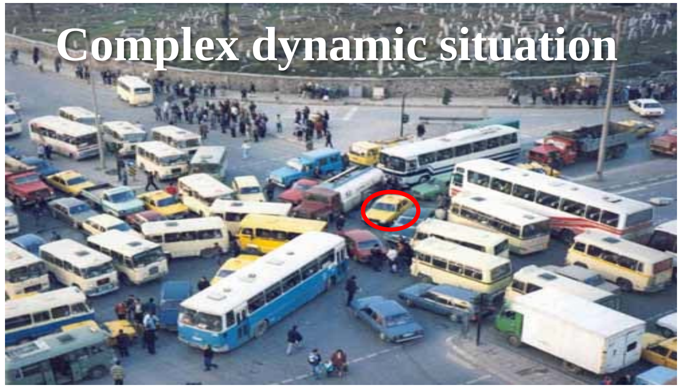
- **POC 2019: Complete system implemented on Nvidia TX1**, and easily connected to the shuttle system network *in a few days* (using ROS)
- **Shuttle sensors data** has been fused and processed in **real-time**, with a successful Detection & Characterization of the **Moving & Static Obstacles**
- **Full integration on a commercial product** under development with an industrial company (confidential)





2^{nd} 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+δ** (δ = 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 <u>unexpected & unclassified</u> events (i.e. "something" is moving ahead) ?

=> Exploit previous observations for anticipating <u>future objects motions</u> & related <u>potential future collision</u>

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***

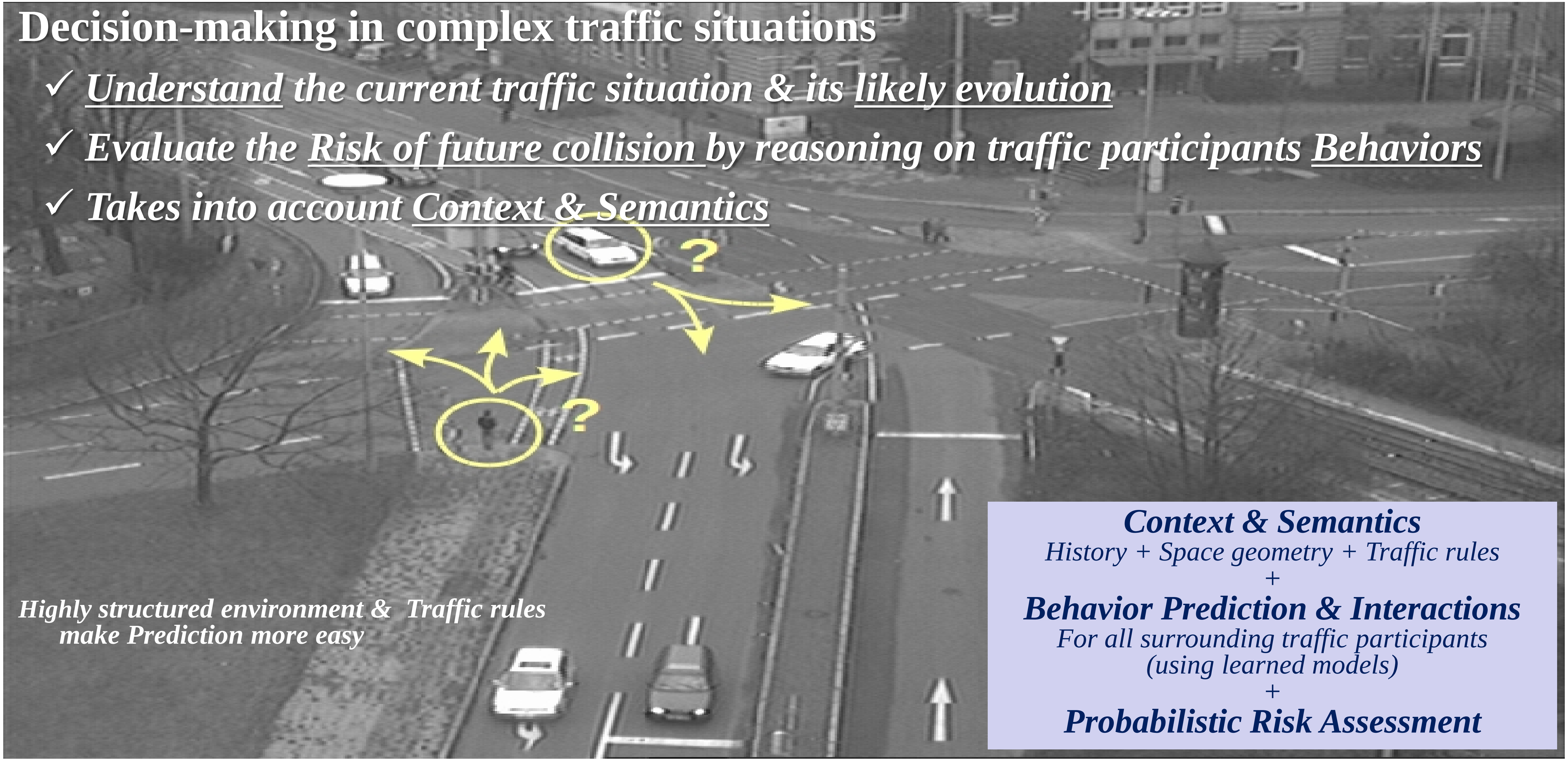
❑ Experimental results

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***

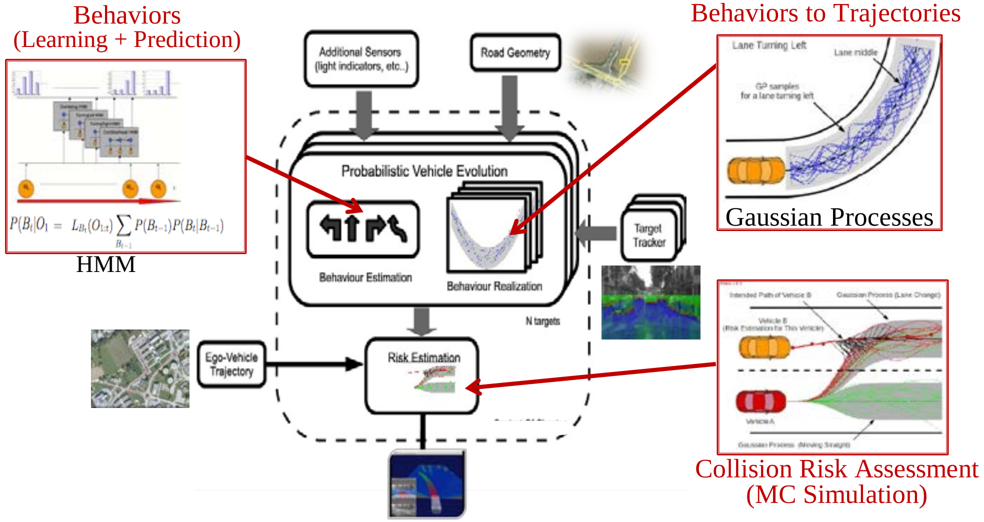
Highly structured environment & Traffic rules make Prediction more easy

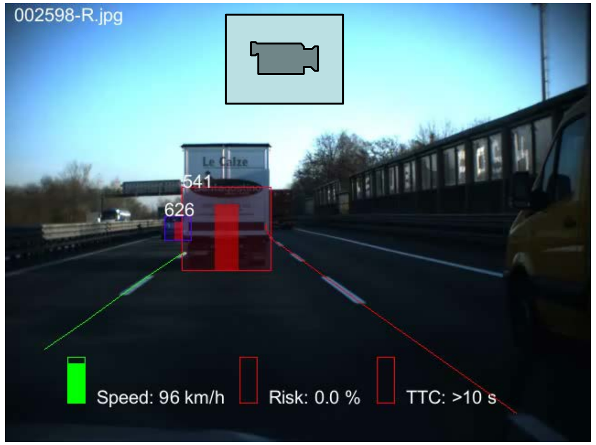
Context & Semantics
History + Space geometry + Traffic rules
+
Behavior Prediction & Interactions
For all surrounding traffic participants (using learned models)
+
Probabilistic Risk Assessment

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

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

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

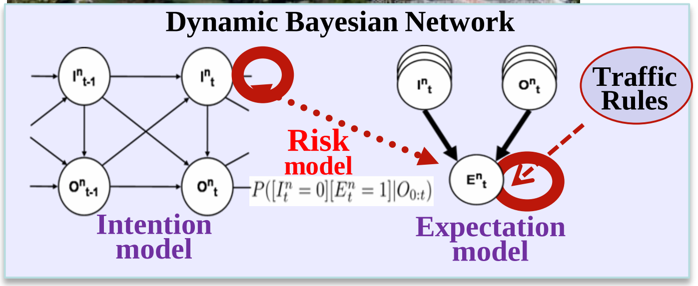




Courtesy Probayes

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

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

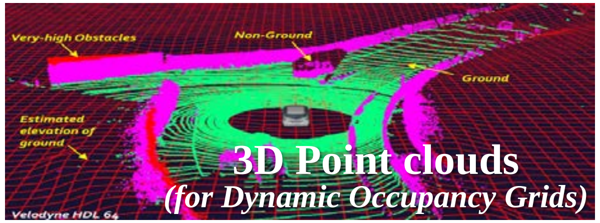


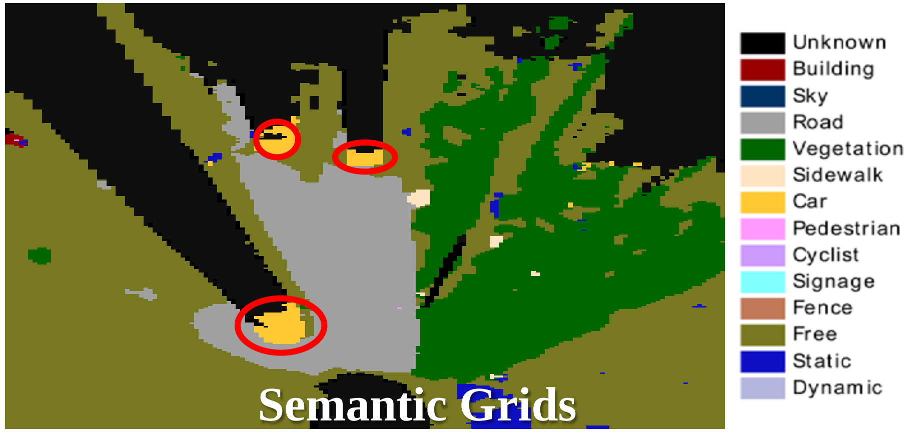
Human-like reasoning

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

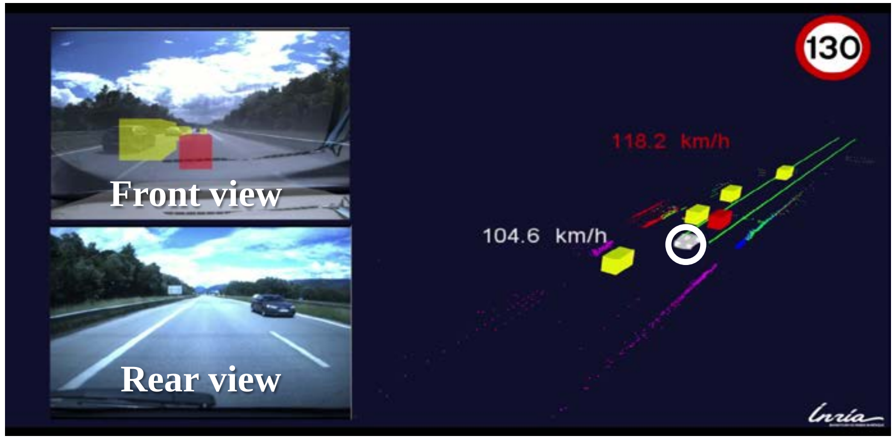
3rd *Paradigm:* Models improvements using Machine Learning

- **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)

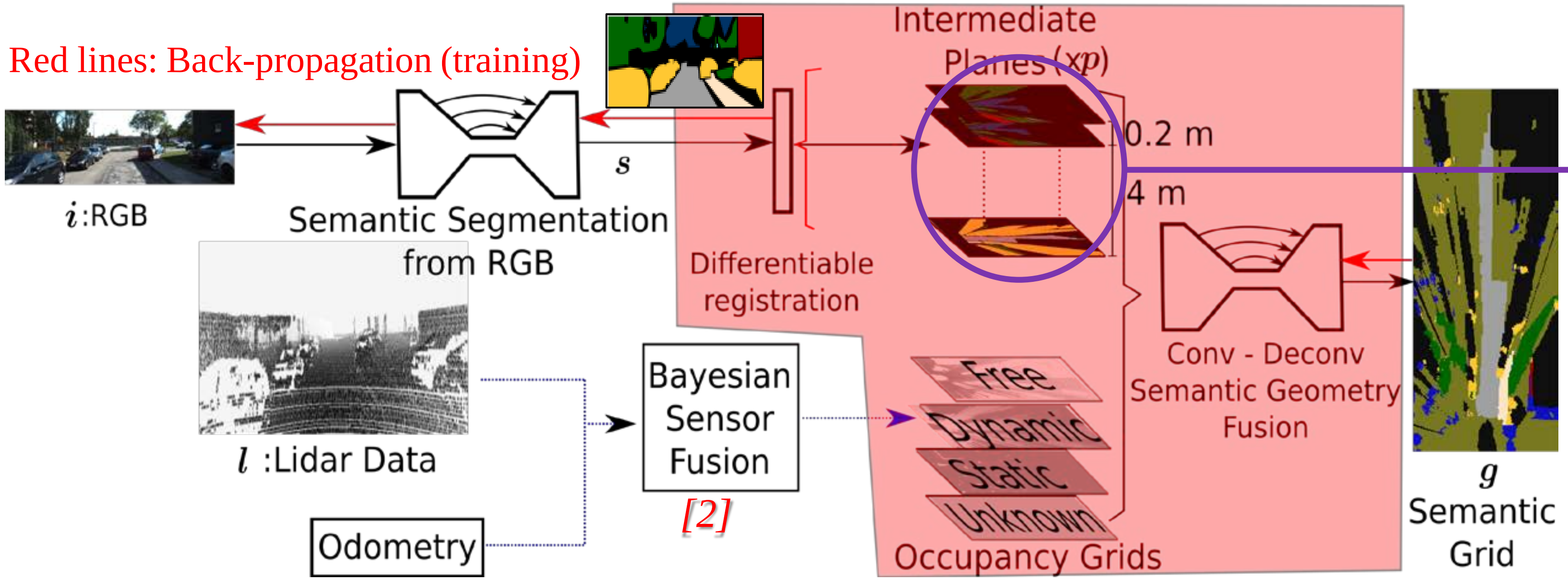
Objective: *Add **Semantic information** (cars, pedestrians, roads, buildings…) in each cell of the Dynamic Occupancy Grid model, by exploiting **additional RGB inputs***

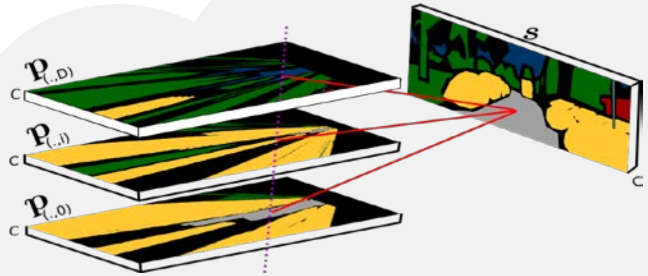
Approach: *A new **"Hybrid Sensor Fusion approach"** combining **Bayesian Perception & Deep Learning***

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

Semantic Grid Network *[1] [3]*

Red lines: Back-propagation (training)





Intermediate layers (~20 layers)

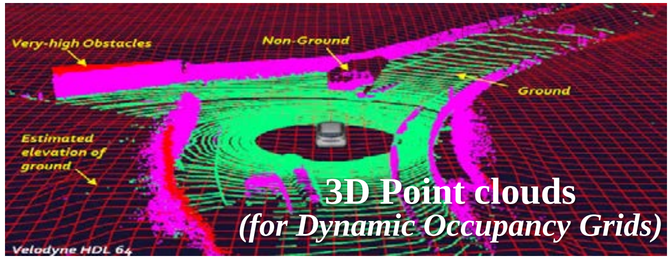
=> Learns the approximate heights of the classes/objects

=> 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*



3D Point clouds
(for Dynamic Occupancy Grids)

Frontal View *(RGB camera)*

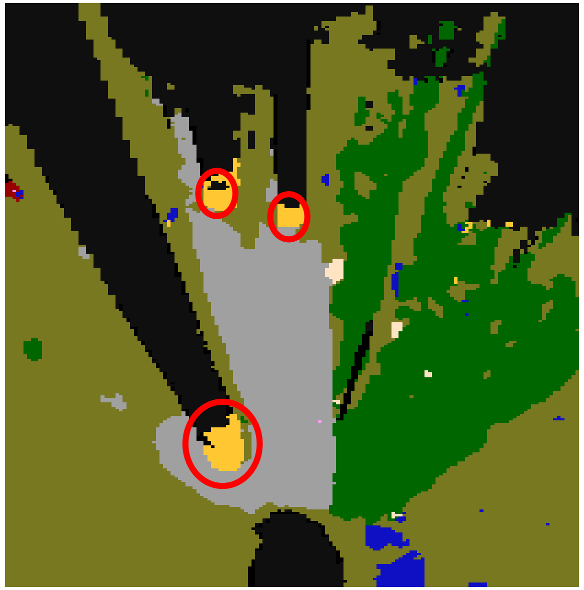
Hybrid Sensor Fusion approach (Semantic Grid construction)

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

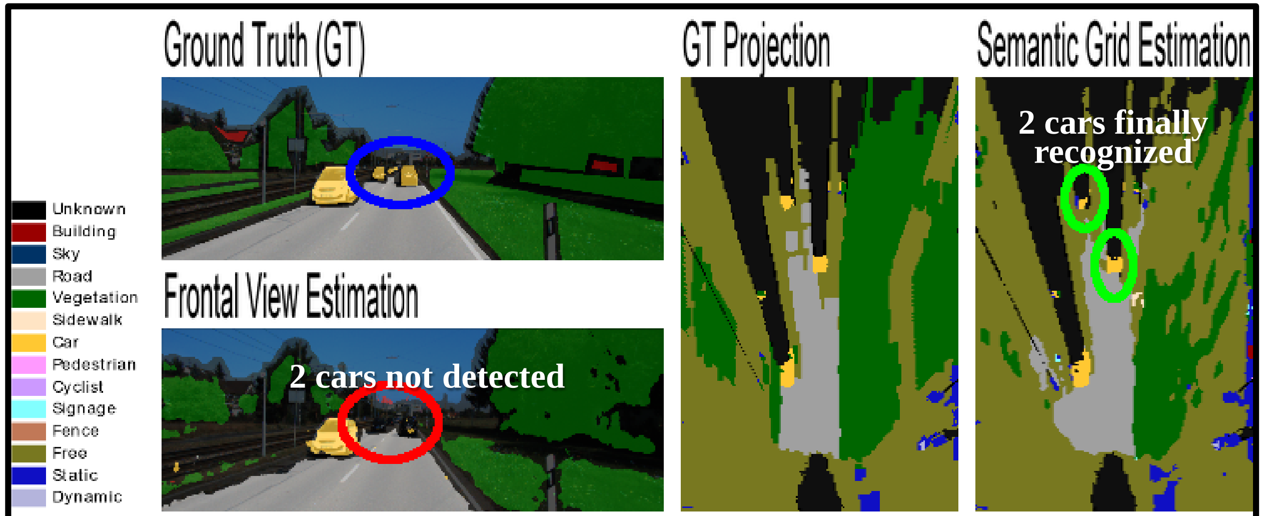


Semantic Grid Prediction
=> Dense structure obtained using hybrid integration

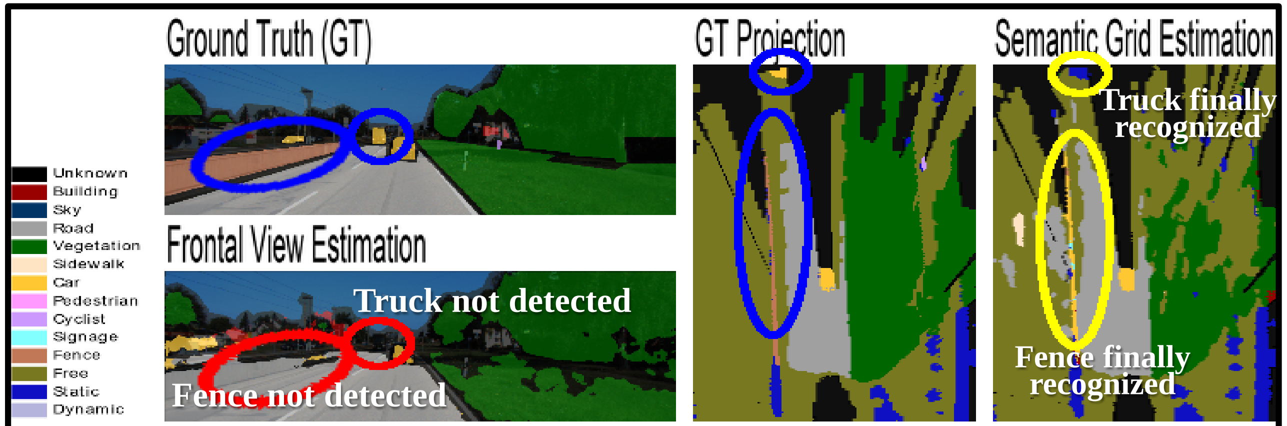
Unknown
Building
Sky
Road
Vegetation
Sidewalk
Car
Pedestrian
Cyclist
Signage
Fence
Free
Static
Dynamic

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

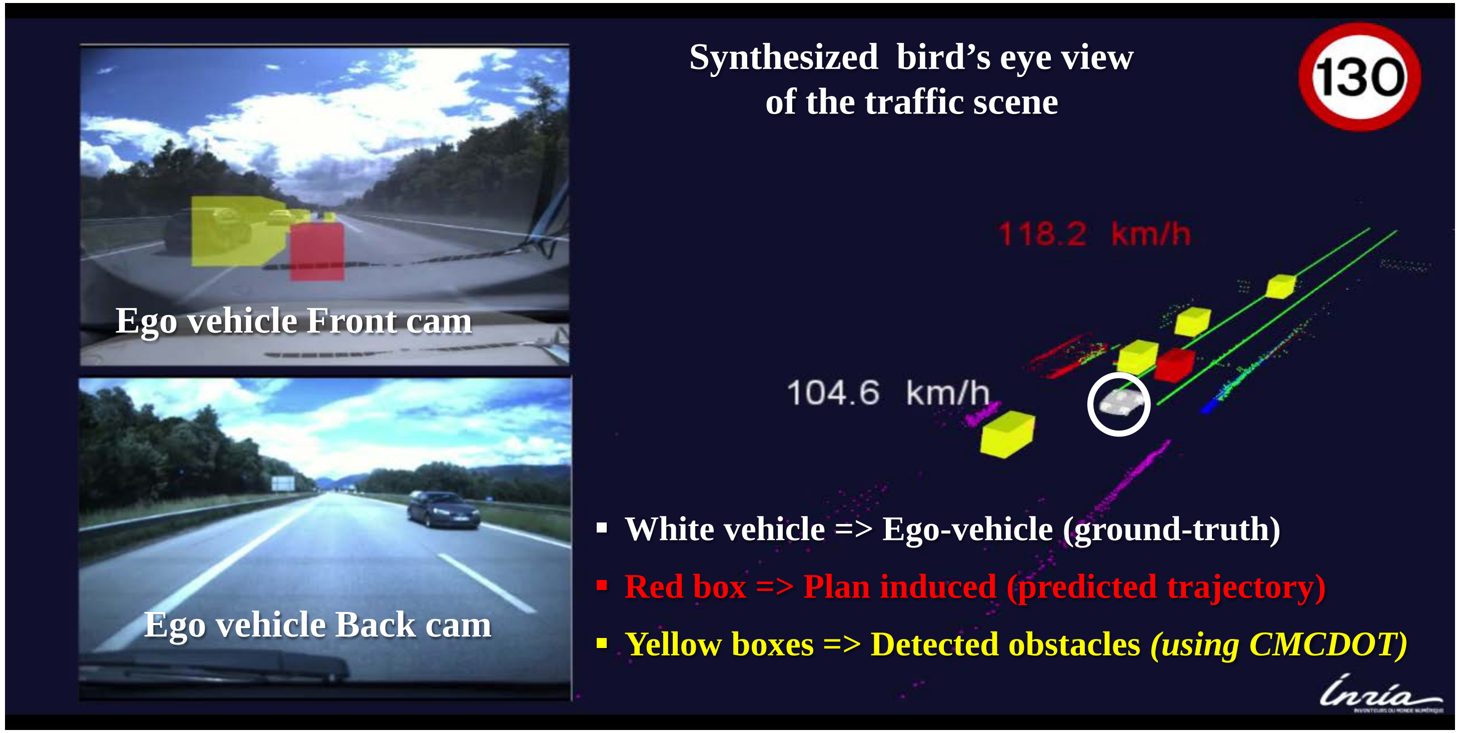
- Improve accuracy with more dense training datasets
- Implementation on embedded systems for real-time process
- Adaptation to bad weather conditions
- Panoptic segmentation & tracking

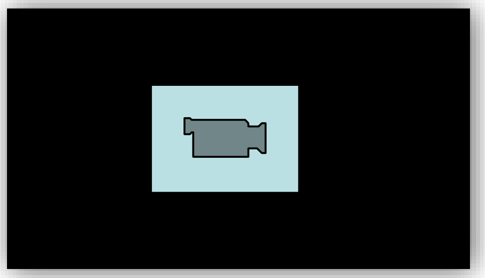
Decision-making level: Learning Driving Skills for AD
1st Step: Driver behavior modeling

[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** $C(s) = \sum_{i=1}^{K} w_i \cdot f_i(s)$ 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)*



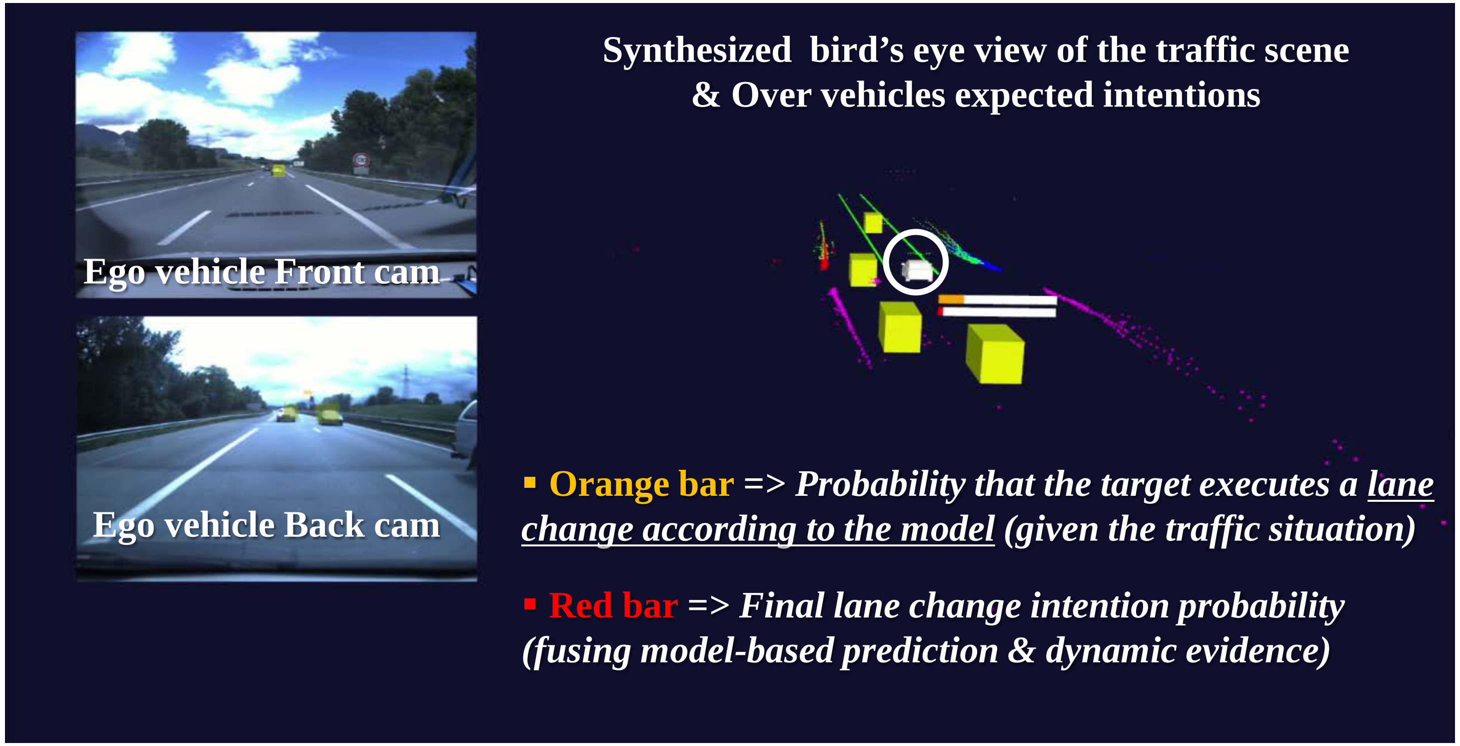


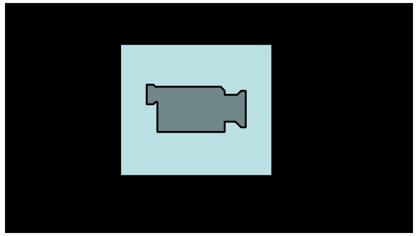
Comparison between demonstrated behavior in test set & behavior induced by the learned model

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]*





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

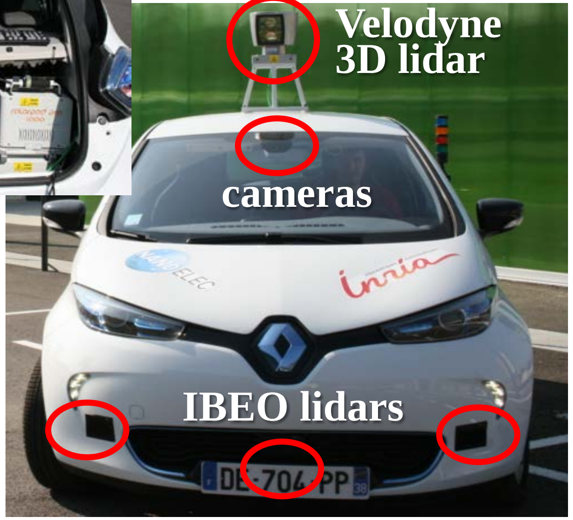
Experimental Vehicles & Connected Perception Units

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)

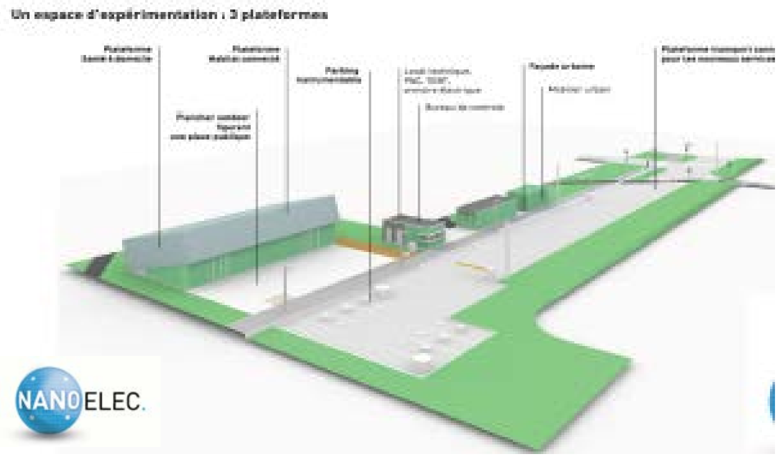
Nvidia GTX Titan X
Generation Maxwell

Nvidia GTX Jetson TK1
Generation Maxwell

Nvidia GTX Jetson TX1
Generation Maxwell

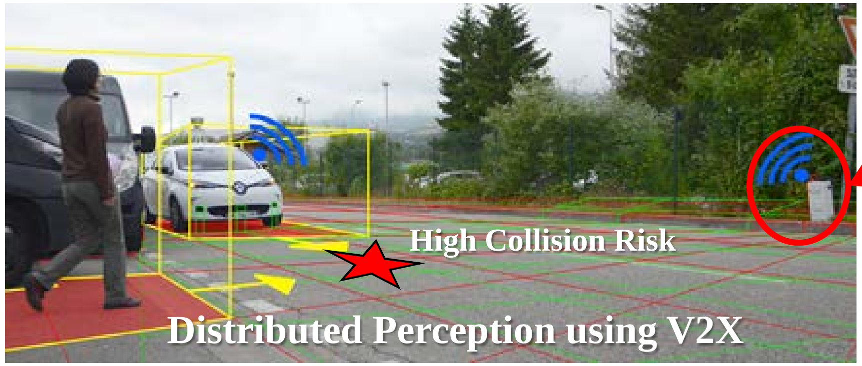
Experimental Areas

- **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)*

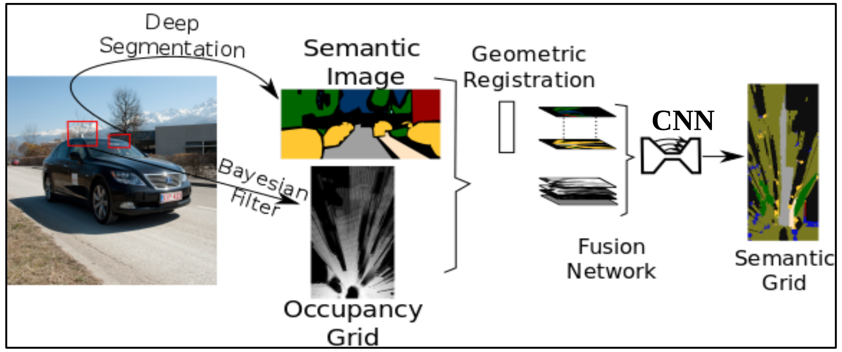
Autonomous Shuttles
(~15 km/h, Urban traffic)

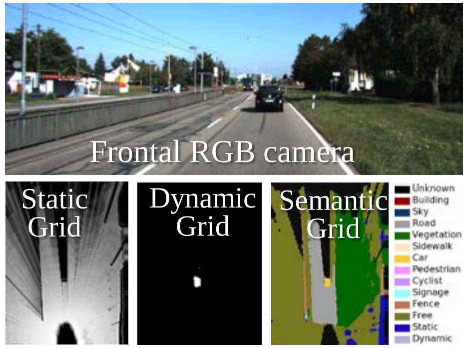
Autonomous Bus (Iveco)
(up to 70 km/h, Urban traffic)

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 …**

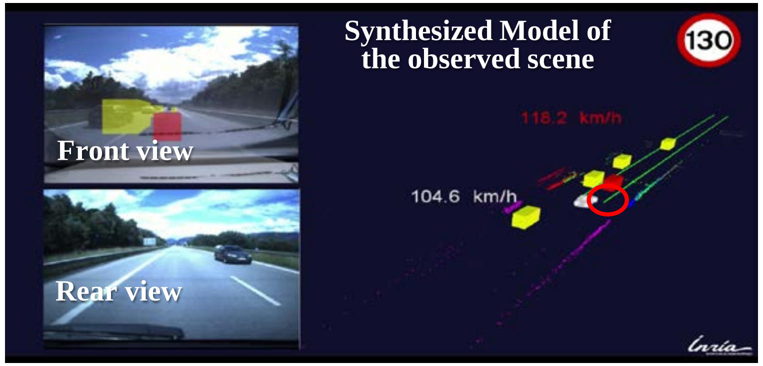
❑ Embedded & Extended “Semantic Grids”



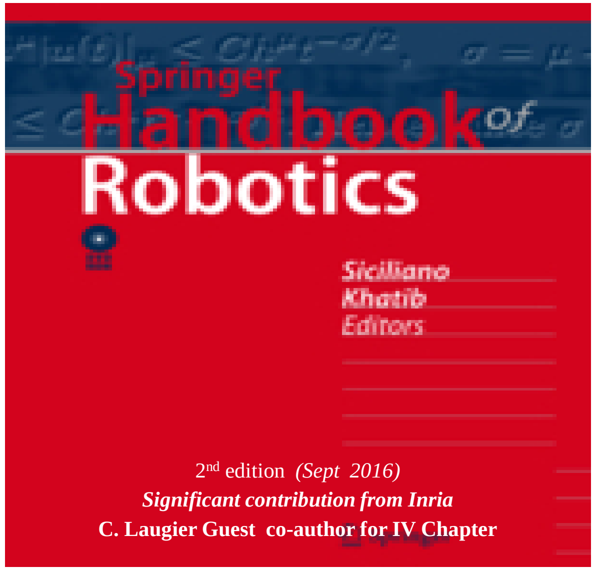


- Embedded “Semantic Grids” & “Panoptic Segmentation”
- Improved scene understanding (various weather conditions)
- **Cooperation Toyota**
- *1 Patent & 3 publications (IROS’18, ICARCV’18, Unmanned System journal 2019)*

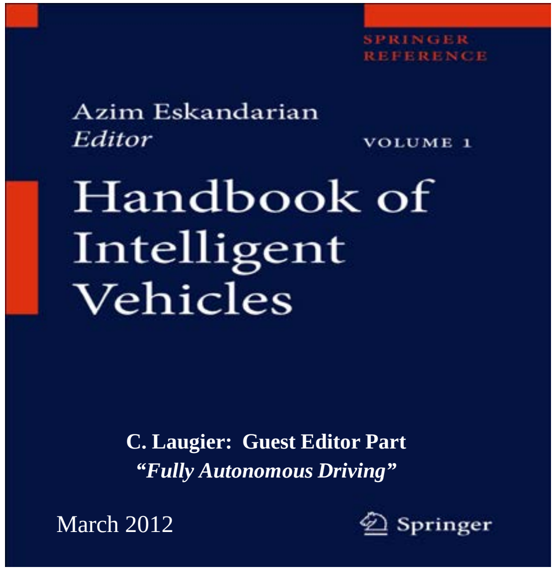
❑ Autonomous Driving in mixed traffic (Prediction & Planning) using learned models



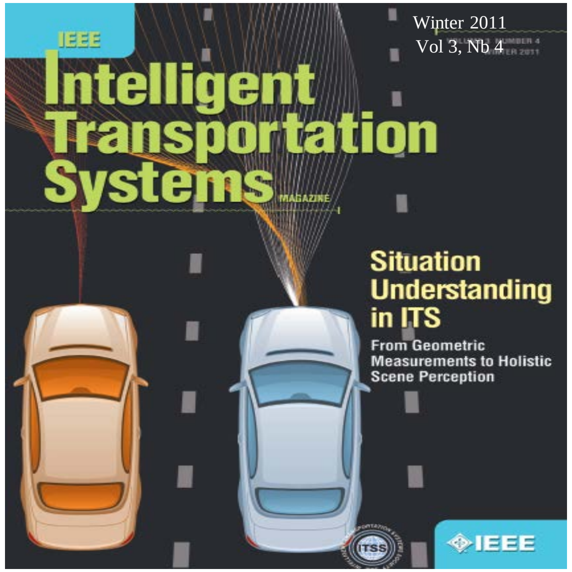
- **Driver Behavior modeling** using Driving dataset & Inverse Reinforcement Learning **=> *Human-like Driver Model*** *(for mixed traffic)*
- **Motion Prediction & Driving Decision-making for AD** performed *by combining “learned Driver models” & “Dynamic evidences”*
- **Cooperation Toyota**
- *2 Patents & 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



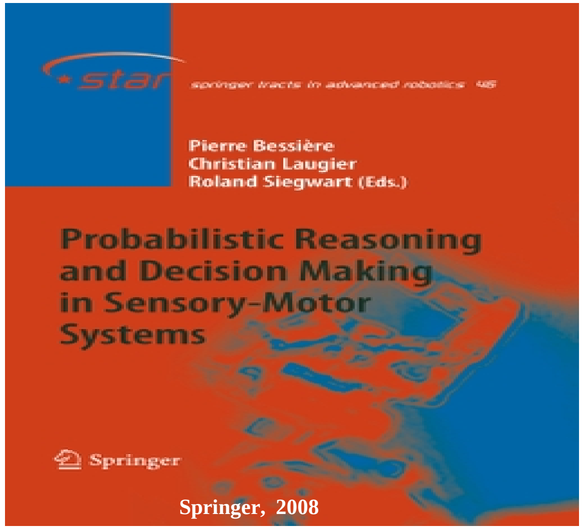
C. Laugier: Guest Editor Part
"Fully Autonomous Driving"
March 2012



Winter 2011
Vol 3, Nb 4

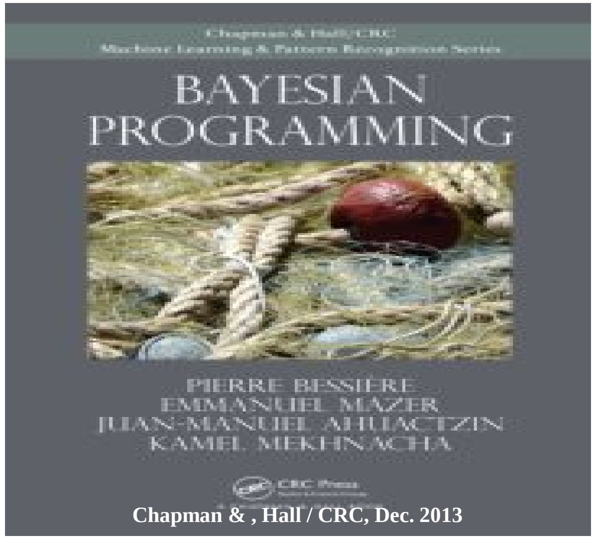
July 2013
Guest Editors:
C. Laugier & J. Machan

Thank You



Springer, 2008

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



Chapman & , Hall / CRC, Dec. 2013