



**HAL**  
open science

# Embedded Bayesian Perception and Collision Risk Assessment (invited talk)

Christian Laugier

► **To cite this version:**

Christian Laugier. Embedded Bayesian Perception and Collision Risk Assessment (invited talk). ICRA 2017 - IEEE International Conference on Robotics and Automation, Workshop on Robotics and Vehicular Technologies for Self-Driving Cars, Jun 2017, Singapore, Singapore. pp.1-26. hal-01672240

**HAL Id: hal-01672240**

**<https://inria.hal.science/hal-01672240>**

Submitted on 23 Dec 2017

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Embedded Bayesian Perception and Collision Risk Assessment

**Christian LAUGIER, Research Director at Inria**  
*Inria Chroma team & IRT nanoelec & Scientific Advisor for Probayes SA*  
[christian.laugier@inria.fr](mailto:christian.laugier@inria.fr)

*Contributions from*

*Mathias Perrollaz, Procópio Silveira Stein, Christopher Tay Meng Keat, Stephanie Lefevre, Javier-Ibanez Guzman, Amaury Negre, Lukas Rummelhard, Nicolas Turro, Jean-Alix David, Jérôme Lussereau, Tiana Rakotovao*



**Invited Talk**

*IEEE ICRA 2017 Workshop on Robotics and Vehicular Technologies for Self-driving cars*  
*Sands Expo and Convention Center, Marina Bay Sands, Singapore June 2<sup>nd</sup> 2017*

# Autonomous Cars & Driverless Vehicles

- Strong involvement of Car Industry & Large media coverage
- An expected market of 500 B€ in 2035
- Technologies Validation => Numerous recent & on-going real-life experiments (in addition to simulation & formal methods)



Tesla Autopilot based on Radar & Mobileye



3D Lidar & Dense 3D mapping  
Numerous vehicles & miles covered



Cybus experiment, La Rochelle 2012  
=> CityMobil Project & Inria



Drive Me trials

100 Test Vehicles in Göteborg, 80 km, 70km/h  
• No pedestrians & Plenty of separations between lanes



Robot Taxi testing in Pittsburgh (Uber) & Singapore (nuTonomy)  
+ Google / Lyft ?

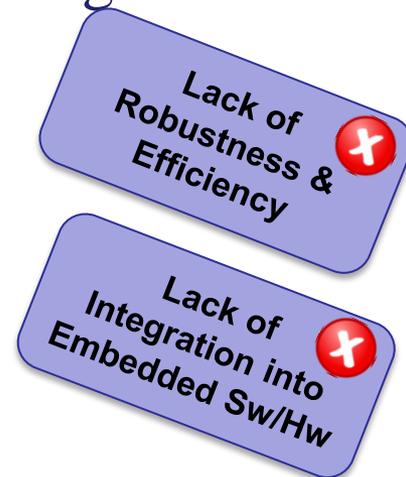
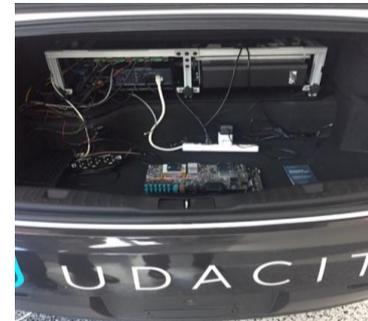


=> **Mobility Service**, Numerous Sensors ... Engineer in the car during testing

*Several benign & serious accidents in past few months (Tesla, Google, Uber...)*  
**Safety is still not guaranteed!**

# Perception: State of the Art & Today's Limitations

- ❑ Despite significant improvements during the last decade of both Sensors & Algorithms, **Embedded Perception** is still one of the major bottleneck for Motion Autonomy  
*=> Obstacles detection & classification errors, incomplete processing of mobile obstacles, collision risk weakly address, scene understanding partly solved...*
- ❑ **Lack of Robustness & Efficiency & Embedded integration** is still a significant obstacle to a full deployment of these technologies



Trunk most of the time full of electronics & computers & processor units  
*=> High computational capabilities are still required*

# Focus of the talk

Complex Dynamic Scenes  
understanding



**Situation Awareness  
& Decision-making**



Dealing with unexpected events  
e.g. Road Safety Campaign, France 2014



**Anticipation & Prediction**  
for avoiding upcoming accidents

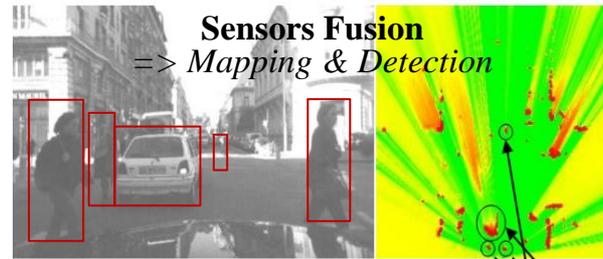
## Main features

- ✓ Dynamic & Open Environments => *Real-time processing*
- ✓ 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*

# Key Technology 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*

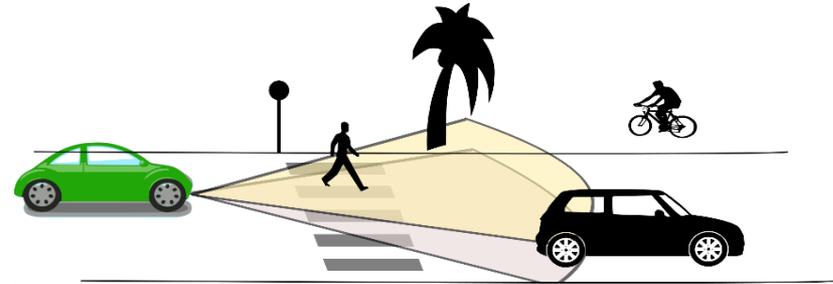
## ❑ Approach: Embedded Bayesian Perception

- ✓ *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

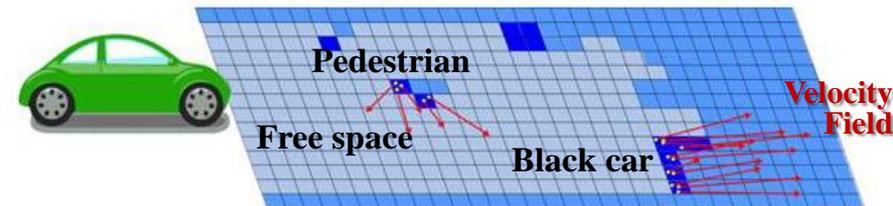
*Lidar, Radar, Stereo camera, IMU ...*



## □ Probabilistic Environment Model

- ✓ *Sensor Fusion*
- ✓ *Occupancy grid integrating uncertainty*
- ✓ *Probabilistic representation of Velocities*
- ✓ *Prediction models*

$P[o|Z,C]$  :     $\approx 0$      $\approx 0.5$      $\approx 1$



**Concept of Dynamic Probabilistic Grid**  
⇒ Occupancy & Velocity probabilities  
⇒ Embedded models for Motion Prediction

## □ Main philosophy

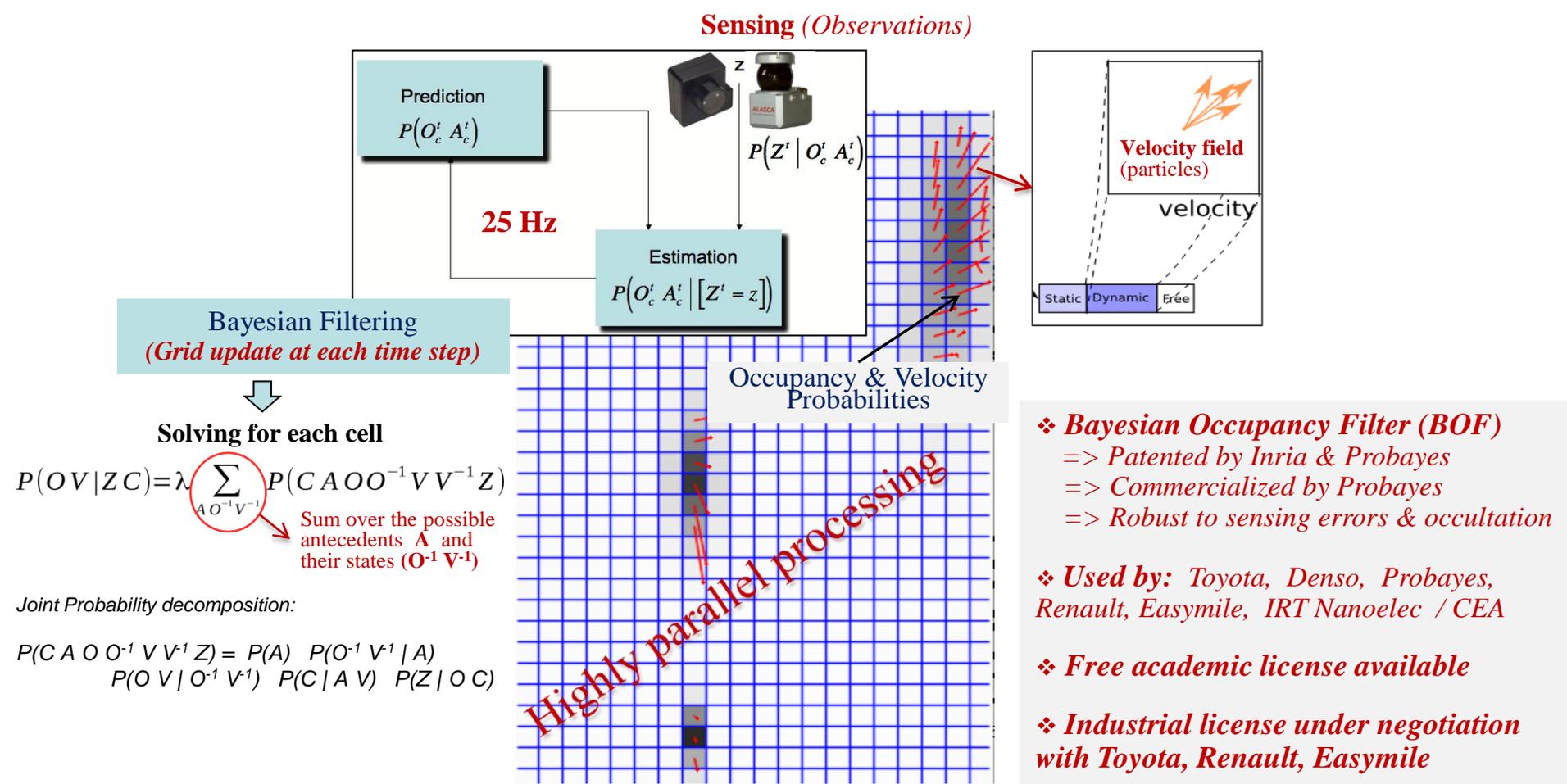
*Reasoning at the grid level as far as possible for both :*

- **Improving efficiency** (highly parallel processing)
- **Avoiding traditional object level processing problems** (e.g. detection errors, wrong data association...)

# A new framework: Dynamic Probabilistic Grids

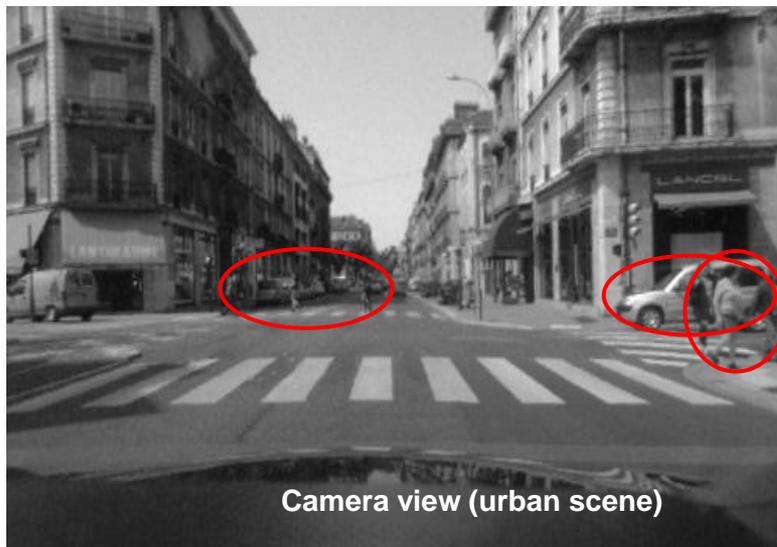
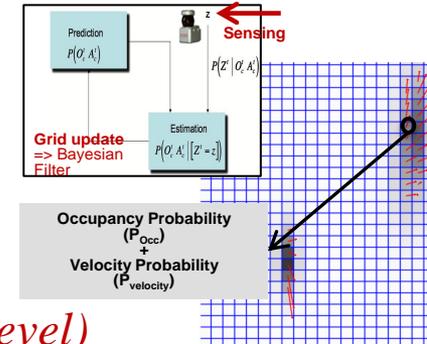
=> A clear distinction between Static & Dynamic & Free components

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

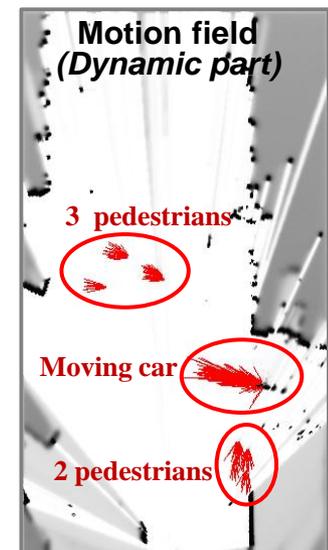


# Bayesian Occupancy Filter (BOF) – Main Features

- Estimate **Spatial occupancy** for each cell of the grid  $P(O | Z)$
- **Grid update** is performed in each cell in parallel (using *BOF equations*)
- **Extract Motion Field** (using *Bayesian filtering & Fused Sensor data*)
- **Reason at the Grid level** (i.e. *no object segmentation at this reasoning level*)



Sensors data fusion  
+  
Bayesian Filtering



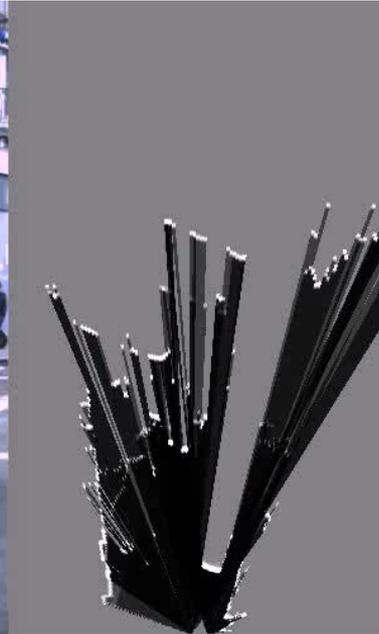
**Exploiting the Dynamic information for improving Scene Understanding !!**

# Experimental Results in dense Urban Environments

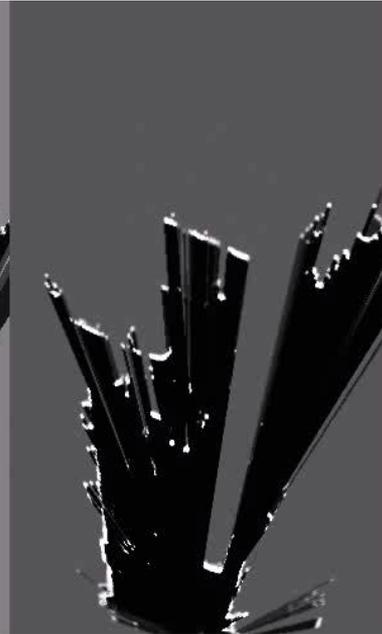
## Observed Urban Traffic scene



Ego Vehicle (not visible on the video)



OG Left Lidar



OG Right Lidar



OG Fusion  
+  
Velocity Fields

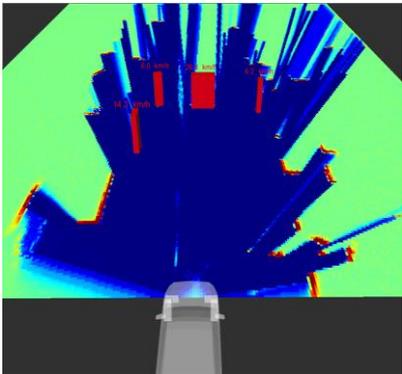


# Recent implementations & Improvements

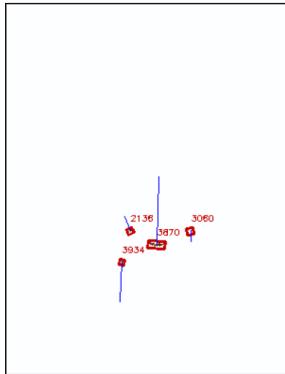


*Several implementations (models & algorithms) more and more adapted to **Embedded constraints & Scene complexity***

- ❖ Hybrid Sampling Bayesian Occupancy Filter (HSBOF, 2014) [Negre et al 14] [Rummelhard et al 14]  
=> **Drastic memory size reduction** (factor 100) + **Increased efficiency** (complex scenes)  
+ **More accurate Velocity estimation** (using Particles & Motion data from ego-vehicle)
- ❖ Conditional Monte-Carlo Dense Occupancy Tracker (CMCDOT, 2015) [Rummelhard et al 15]  
=> **Increased efficiency using “state data”** (Static, Dynamic, Empty, **Unknown**) + **Integration of a “Dense Occupancy Tracker”** (Object level, Using particles propagation & ID)
- ❖ CMCDOT + Ground Estimator (under Patenting, 2017) [Rummelhard et al 17]  
=> **Ground shape estimation & Improve obstacle detection** (avoid false detections on the ground)



Grid & Pseudo-objects



Tracked Objects

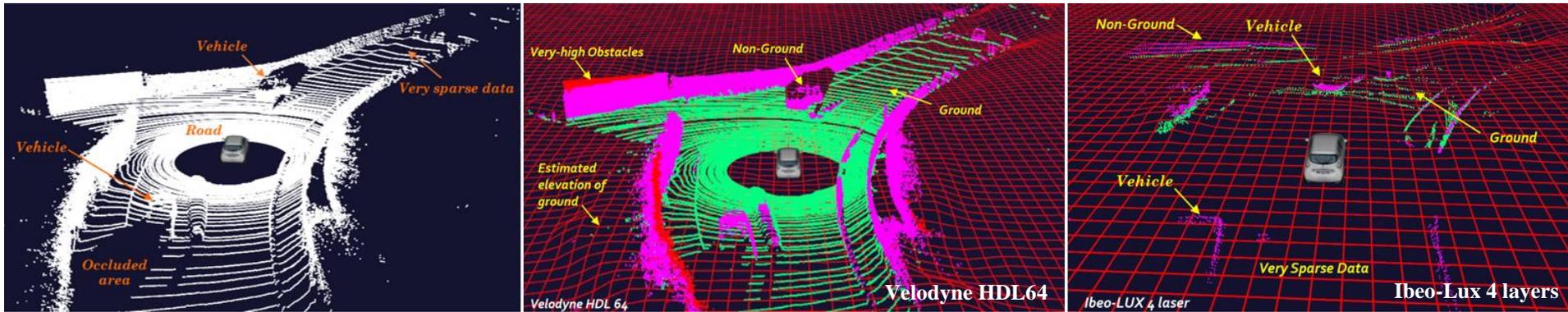


Classification (using Deep Learning)

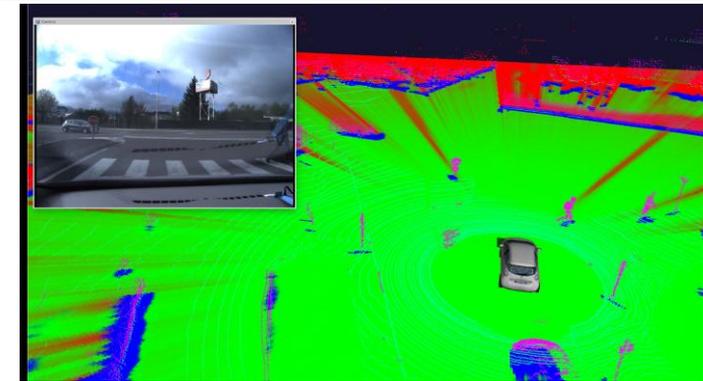
Detection & Tracking  
& Classification

# Ground Estimation & Point Cloud Classification

- ⇒ Smart OG generation taking into account the **ground shape & height of laser impacts**
- ⇒ Process properly sensors data (for OG & DATMO) & Avoid false detections on the road surface



- **Ground estimation** : 1m x 1m ground node resolution  
⇒ ground-points in green, obstacles in pink / red
- **Occupancy grid** : Images 0.1m x 0.1m occupancy grid resolution  
⇒ green for free space, blue occupied, red unknown



- ❖ Approach under patenting, to be soon published [1]
- ❖ Model accurate enough to represent rolling roads & Efficient enough for **real-time** performances on embedded devices
- ❖ The complete system (including CMCDOT) has been implemented on a Nvidia Tegra X1



[1] Ground estimation and point cloud segmentation using spatio-temporal conditional random field, Rummelhard et al, IV 2017, Redondo Beach, June 2017

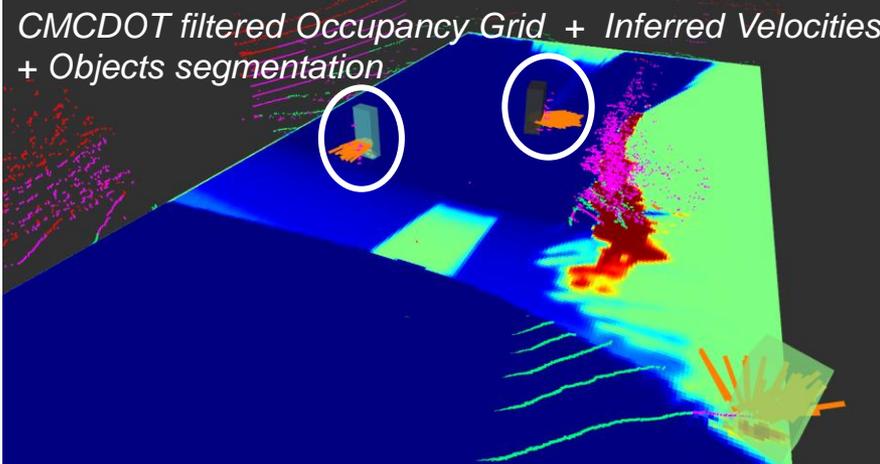
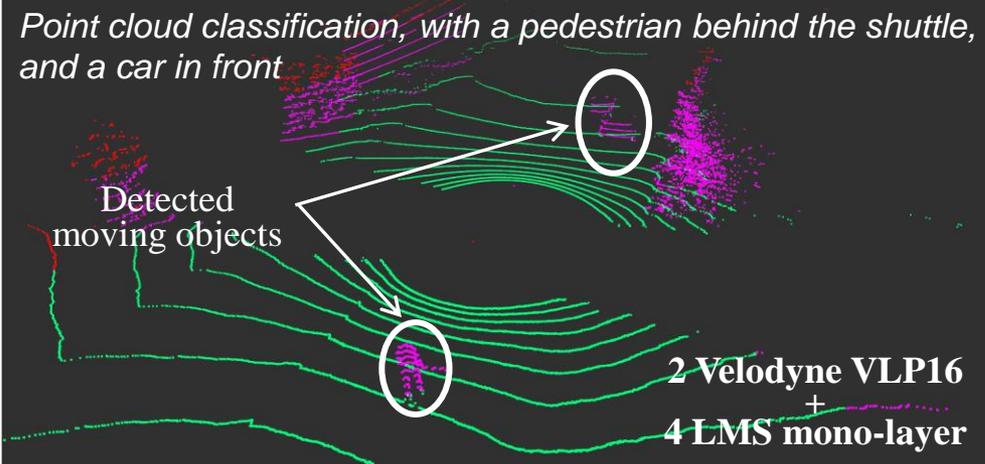
# Integration of CMCDOT on a commercial vehicle

(cooperation EasyMile)



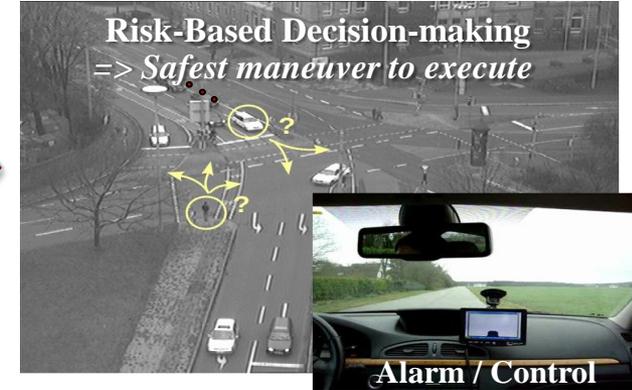
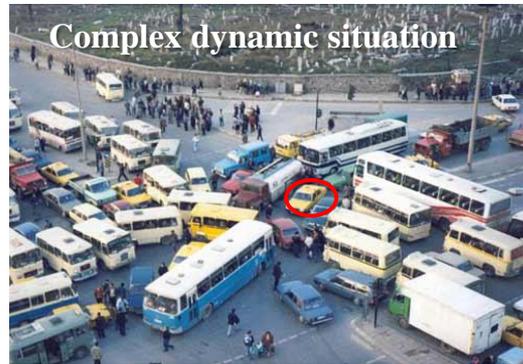
- Founded in 2014, EasyMile is a high-tech startup specialized in providing both software powering autonomous vehicles and the last mile smart mobility solutions
- The company (70 employees) is headquartered in Toulouse (France), with offices in Singapore and Denver (USA). It also operates through value added resellers, notably in Japan and the Middle East

- First tests of integration of the CMCDOT framework system on a commercial automated vehicle
- **The full system is implemented on a Nvidia TX1**, and has directly (and easily) been connected to the shuttle system network (using ROS)
- Sensor data is fused and processed, results are computed and provided in **real-time**
- Further full integration for the commercial product under discussion



# Key Technology 2: Risk Assessment & Decision

=> Decision-making for avoiding Pending & Future Collisions



## □ Main challenges

*Uncertainty, Partial Knowledge, World changes, Human in the loop + Real time*

## □ 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*

# Underlying Conservative Prediction Capability

=> *Application to Conservative Collision Anticipation*

[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)*

# Step 1: Short-term collision risk – Main features

=> Grid level & Conservative motion hypotheses (proximity perception)

## □ Main Features

- Detect “Risky Situations” a few seconds ahead (3-5s)
- Risky situations are both localized in Space & Time
  - ⇒ Conservative Motion Prediction in the grid (Particles & Occupancy)
  - ⇒ Collision checking with Car model (shape & velocity) for every future time steps (horizon  $h$ )
- Resulting information can be used for choosing Avoidance Maneuvers

Proximity perception:  $d < 100m$  and  $t < 5s$

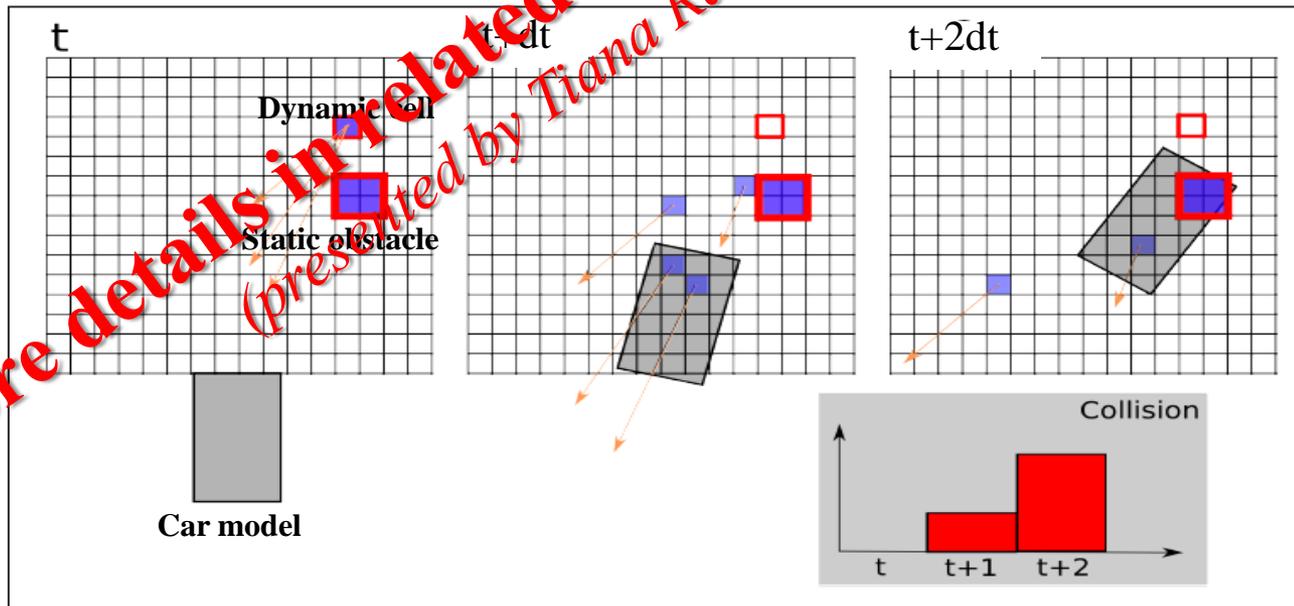
$\delta = 0.5s$  => Precrash

$\delta = 1s$  => Collision mitigation

$\delta > 1.5s$  => Warning / Emergency Braking

## □ Collision Risk Estimation: Integration of risk over a time range $[t, t + \delta]$

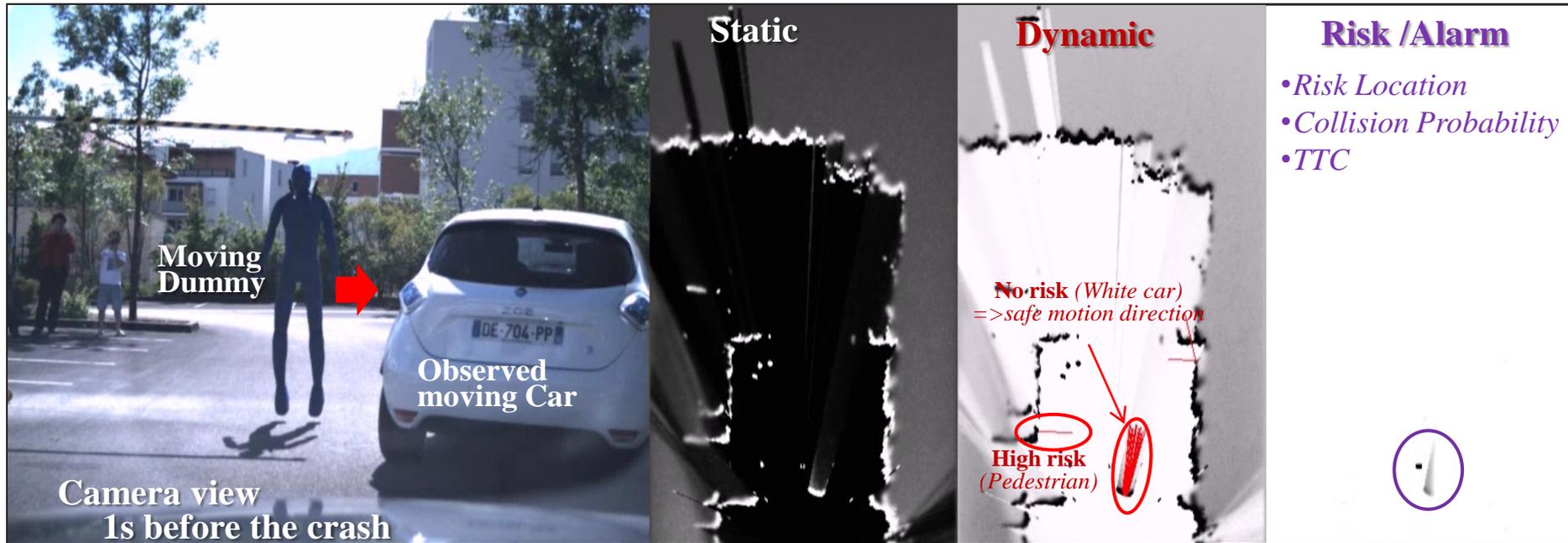
=> Projecting over time the estimated Scene changes (DP-Grid) & Car Model (Shape + Motion)



More details in Related Interactive Session  
(presented by Tiana Rakotonao)

# Short-term collision risk – System outputs (real-time)

=> *Static & Dynamic grids + Risk assessment*



**More details in related Interactive Session**  
*(presented by Tiana Rakotovao)*

# Short-term collision risk – *Experimental results*

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



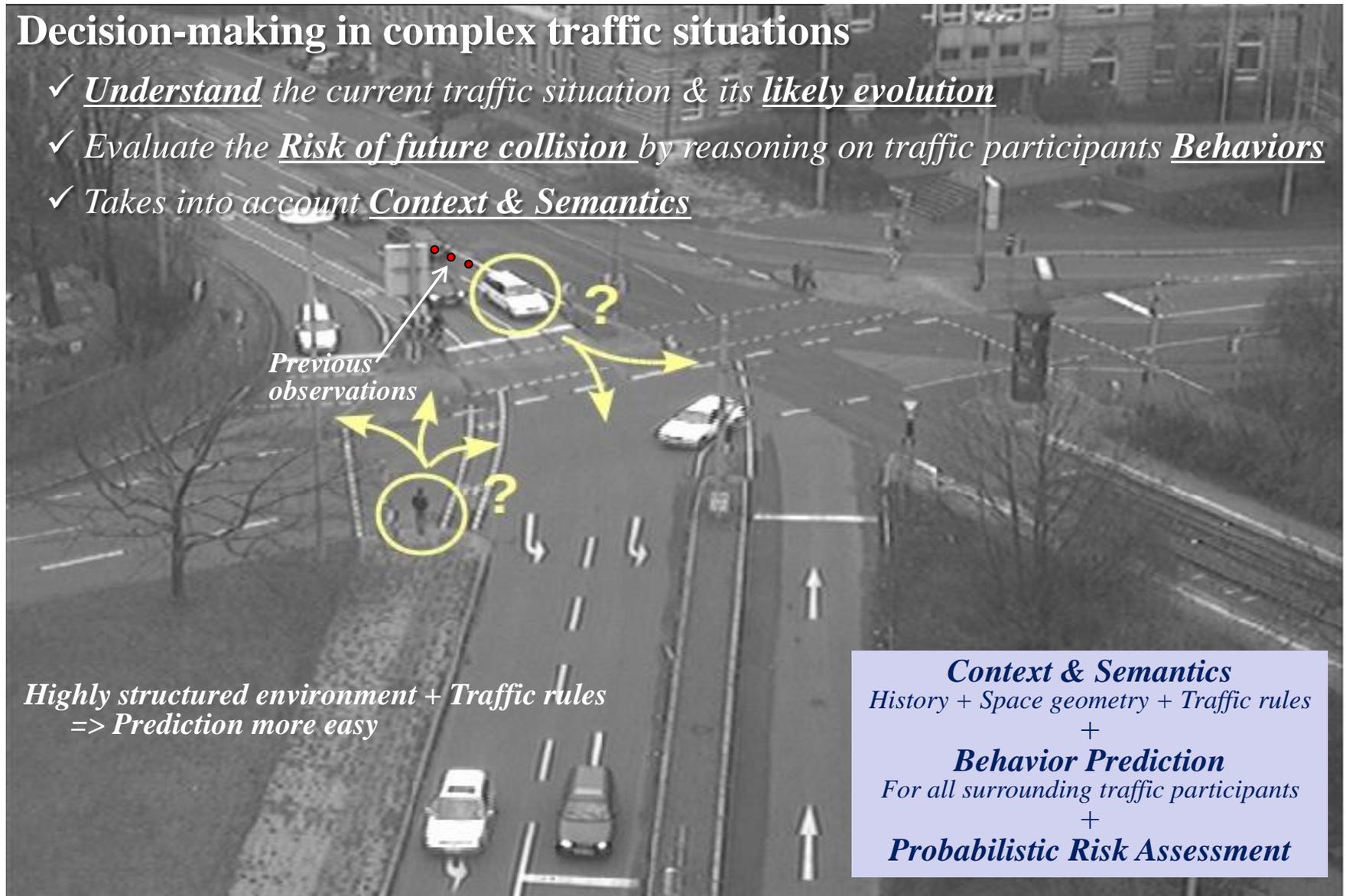
**More details in related Interactive Session**  
*(presented by Tiana Rakotovao)*

# Step 2: Generalized Risk Assessment (Object level)

- => Increasing time horizon & complexity using context & semantics
- => Key concept: **Behaviors Modeling & Prediction**

## 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



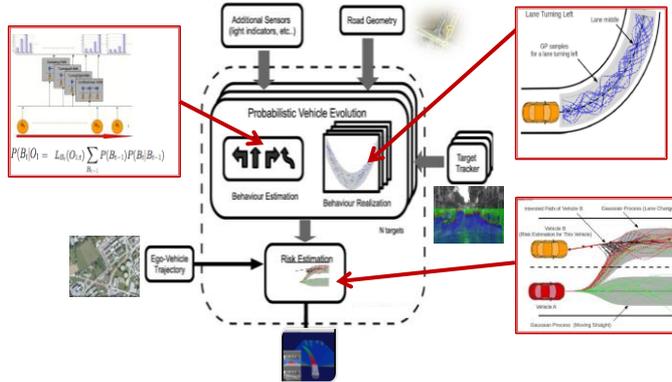
Highly structured environment + Traffic rules  
=> Prediction more easy

**Context & Semantics**  
History + Space geometry + Traffic rules  
+  
**Behavior Prediction**  
For all surrounding traffic participants  
+  
**Probabilistic Risk Assessment**

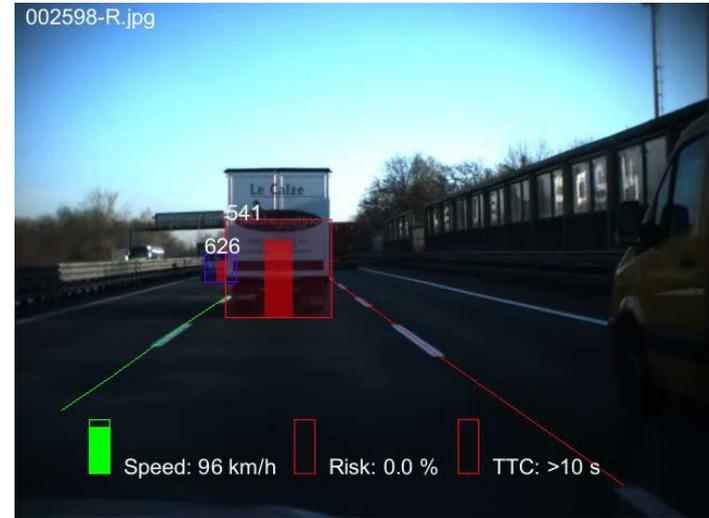
# Behavior-based Collision risk (Object level)

=> Increased time horizon & complexity + Reasoning on Behaviors

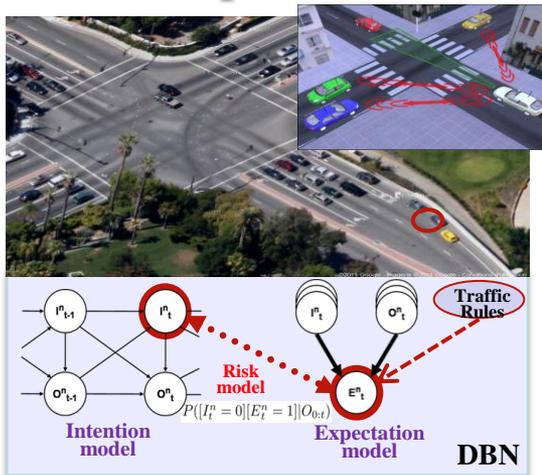
## □ Trajectory prediction & Collision Risk => Patent Inria -Toyota - Probayes 2010



Courtesy Probayes



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



# Experimental Vehicles & Connected Perception Units

Toyota Lexus



ROS



Renault Zoé

Velodyne 3D lidar



cameras



IBEO lidars



cameras

2 Lidars IBEO Lux



Connected Perception Unit

=> Same embedded perception systems than in vehicles

Nvidia GTX Titan X  
Generation Maxwell



Nvidia GTX Jetson TK1  
Generation Maxwell



Nvidia GTX Jetson TX1  
Generation Maxwell



# Software / Hardware Integration – GPU implementation



- Highly parallelizable framework, **27 kernels** over cells and particles  
=> Occupancy, speed estimation, re-sampling, sorting, prediction
- Real-time implementation (20 Hz), optimized using Nvidia profiling tools

## Results:

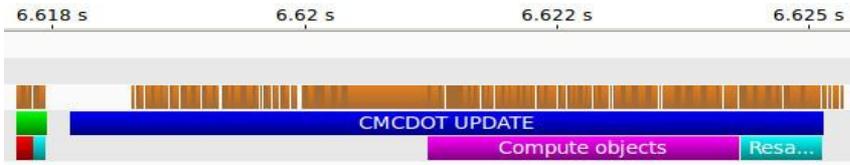
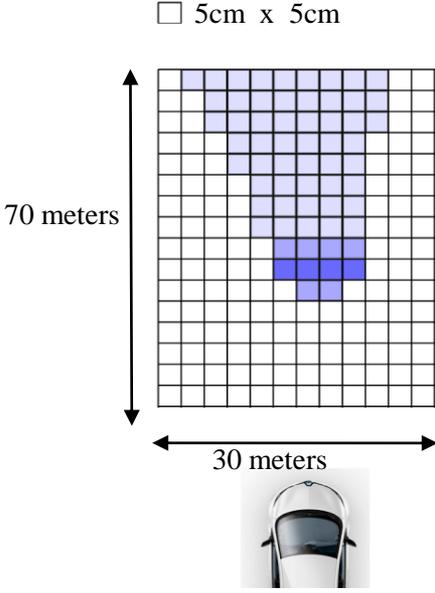
- Configuration with 8 Lidar layers (2x4)
- Grid: 1400 x 600 (840 000 cells) + Velocity samples: 65 536



=> Jetson TK1: *Grid Fusion 17ms, CMCDOT 70ms*



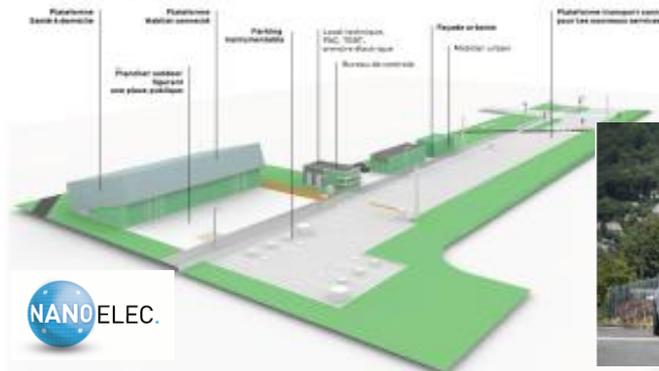
=> Jetson TX1: Grid Fusion 0.7ms, CMCDOT 17ms



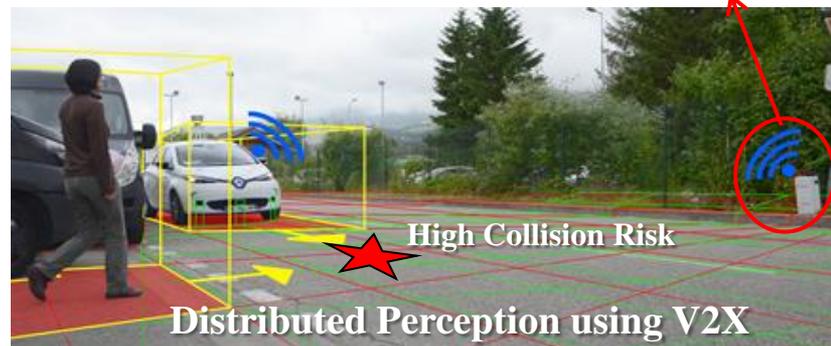
# Experimental Areas

## □ Protected experimental area

Un espace d'expérimentation : 3 plateformes



Connected Perception Unit



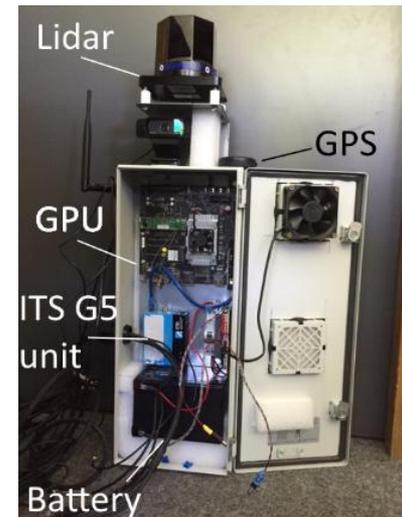
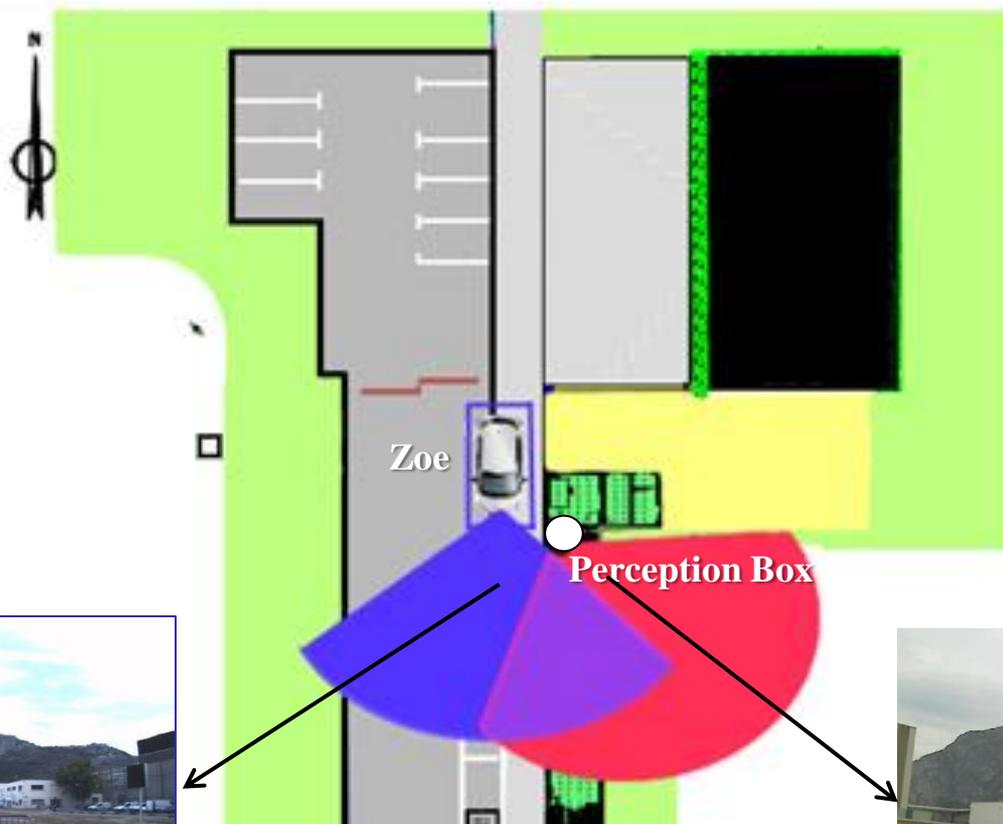
**More details in related Interactive Session**

*(presented by Tiana Rakotovao)*

## □ Open real traffic (Urban & Highway)



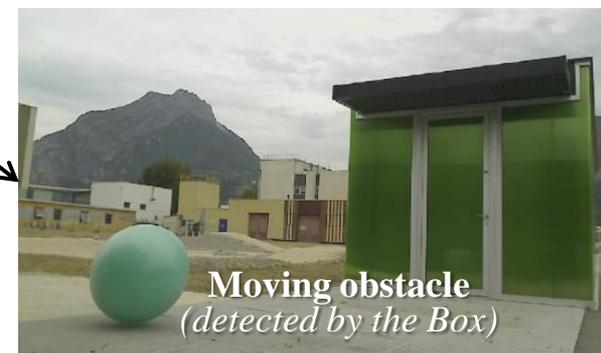
# V2X: Distributed Perception Experiment



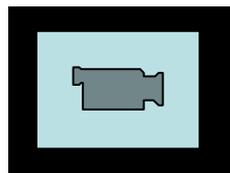
Connected Perception Unit



Camera Image provided by the Zoe vehicle

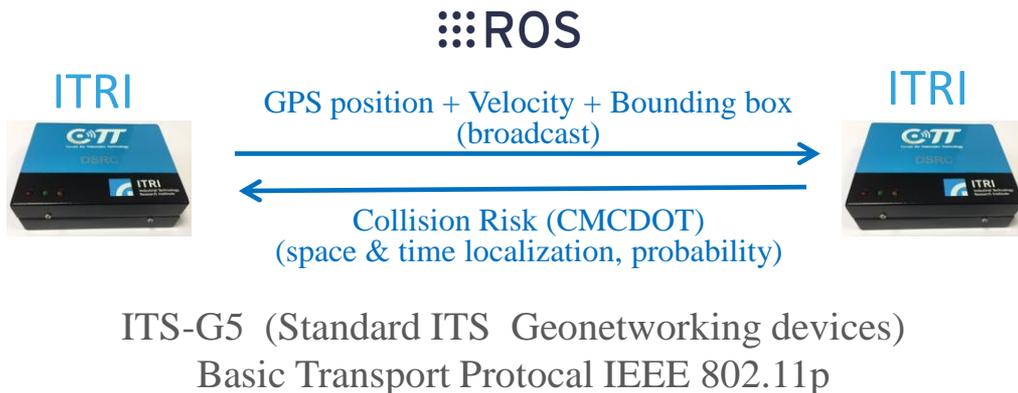


Camera Image provided by the Perception box



# V2X: Data exchange & Synchronization

## □ Data exchange



## □ Synchronization

### Chrony (Network Time Protocol)

GPS Garmin + PPS Signal (1 pulse per second)



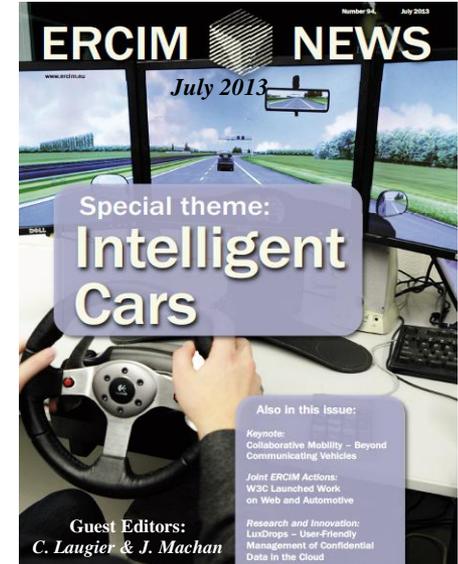
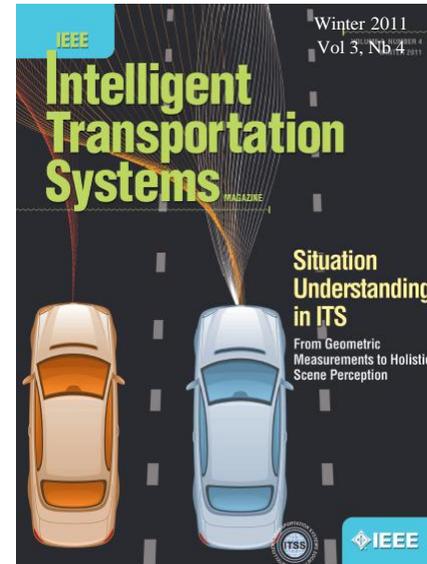
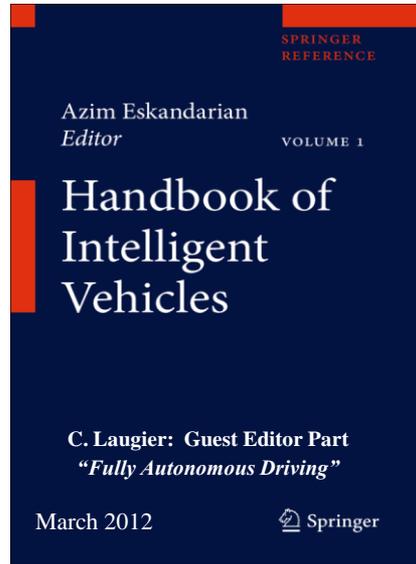
# CMCDOT – Complete process illustration

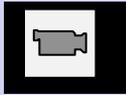


Sensor data

*Inria*  
informatics mathematics





**Thank You  Any questions ?**

