



# Intelligent Perception and Situation Awareness for Automated vehicles

Christian Laugier, Julia Chartre

## ► To cite this version:

Christian Laugier, Julia Chartre. Intelligent Perception and Situation Awareness for Automated vehicles. Conference GTC Europe 2016, Sep 2016, Amsterdam, Netherlands. hal-01428547

**HAL Id: hal-01428547**

**<https://inria.hal.science/hal-01428547>**

Submitted on 15 Jan 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.

Copyright

# Intelligent Perception and Situation Awareness for Automated vehicles

**Christian LAUGIER**

*Research Director at Inria , Chroma team  
christian.laugier@inria.fr*

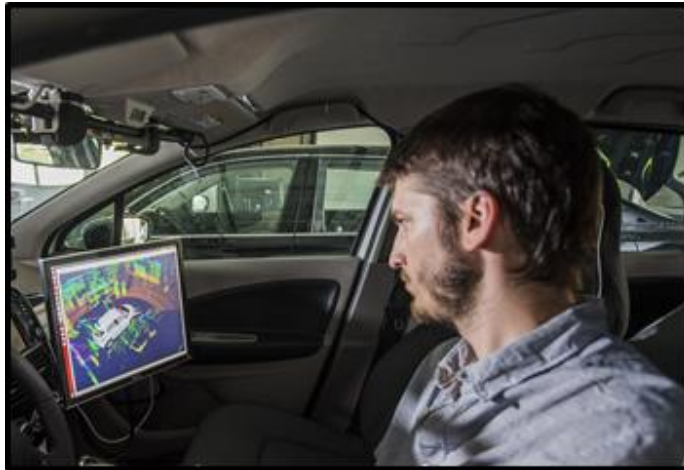
**Julia CHARTRE**

*R&D Engineer at Inria, Chroma team  
julia.chartre@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*

## **ADAS & Autonomous Driving**



**GTC Europe 2016, Autonomous Vehicle track  
Amsterdam, Sept. 28 – 29 2016**

# How to improve Robustness & Efficiency & Capabilities of Embedded Perception & Decision-making Systems ?

Complex Dynamic Scenes



**Situation Awareness  
& Decision-making**



Road Safety Campaign, France 2014



**Anticipation & Prediction  
for avoiding accidents**

## Main features

- ✓ Dynamic & Open Environments => *Real-time processing*
- ✓ Incompleteness & Uncertainty => *Appropriate Model & Algorithms*
- ✓ Human in the loop => *Interaction & Social Constraints (including traffic rules)*
- ✓ Hardware / Software integration => *Satisfying Embedded constraints*



# Industrial State of the Art & Today's Limitations

- ❑ **Perception** for Autonomous Vehicles: *New trend of automotive industry !*



Mercedes F015



Valeo's Cruise4U



Audi A7

CES 2015 & 2016  
(Las Vegas)  
+  
Large media coverage

But perception is still a **bottleneck for Motion Autonomy**,  
*... in spite of significant improvements (sensors & algorithms) during the last decade*

- ❑ **Robustness insufficient & High computational capabilities are required**  
*Still an obstacle to the full deployment !*



Inria / Toyota



Google Car



Audi A7

Trunk full of electronics & computers & processor units

Lack of  
Robustness &  
Efficiency

Lack of  
Integration into  
Embedded Sw/Hw

# Numerous real-life experiments ...but Safety is still insufficient => Some benign & serious accidents in the past few months (Google, Tesla ..)

**Autonomous Car:** Next generation technology & Expected market of 500 B€ in 2035



Tesla Autopilot based on Radar & Mobileye

- Partnership with Mobileye uncertain
- Commercial option : 3400 € in France



Costly 3D Lidar & Dense 3D mapping



Drive Me trials

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



Driverless Taxi testing in Pittsburgh (Uber) & Singapore (nuTonomy)

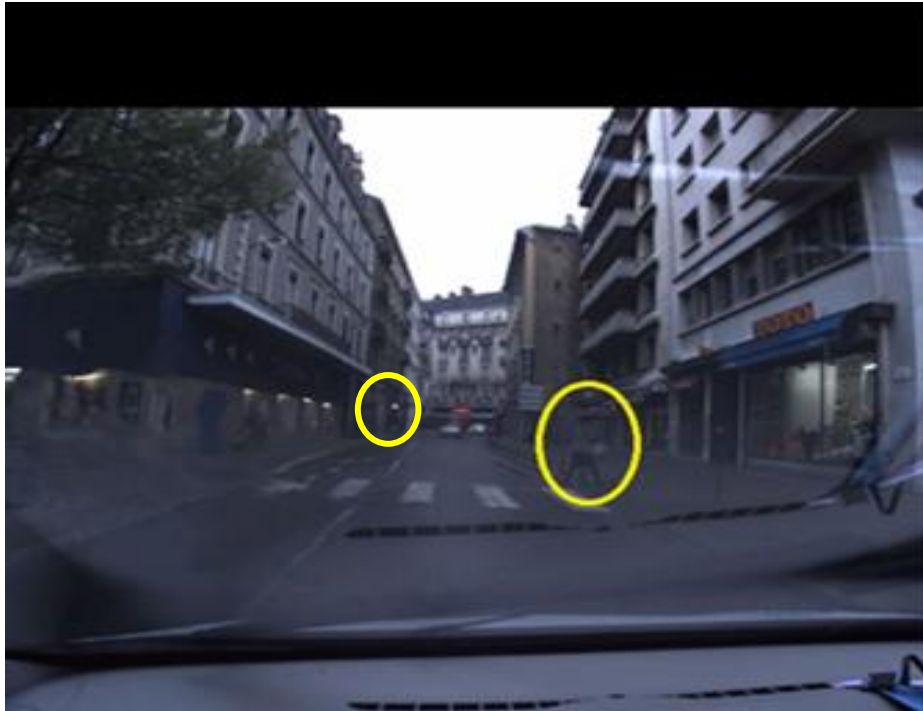
=> Numerous Sensors & Engineer in the car during testing





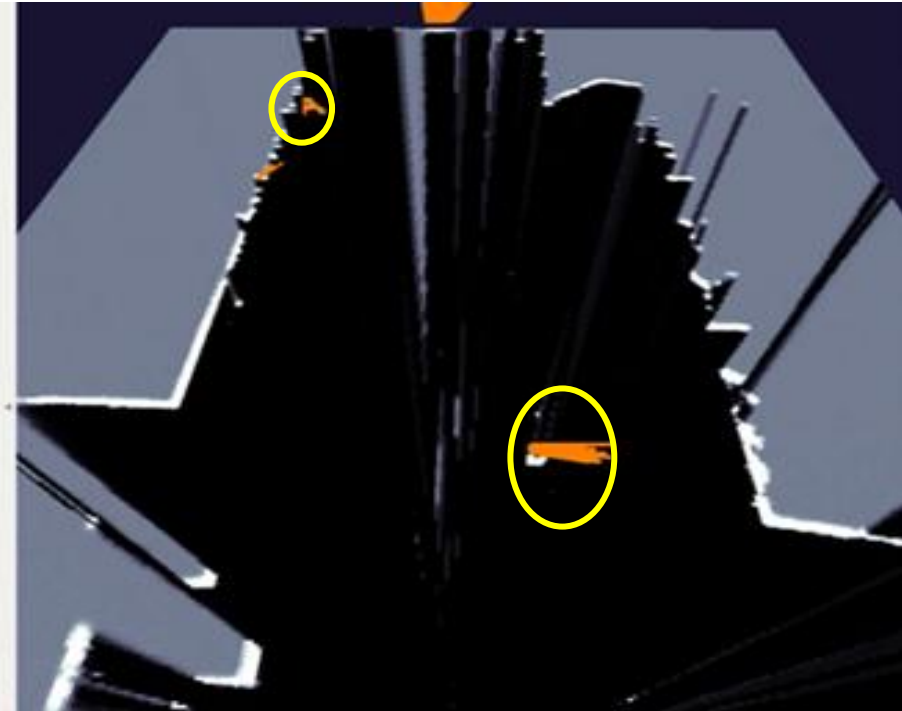
# Improving robustness using Multi-modality sensing

Camera Image at Dusk (Pedestrians not detected)



Camera output depends on lighting conditions  
Cheap & Rich information & Good for classification

Processed Lidar data (Pedestrians detected)



Lidar more accurate & can work at night  
Good for fine detection of objects ... but still Expensive

- Develop **Robust & Efficient Multi-Sensor Fusion** approaches using probabilistic models
- **Good news:** A new generation of **affordable “Solid State Lidars”** will arrive soon on the market !
  - => No mechanical component & Expected cost less than 1000 US\$
  - => Numerous announcements since Spring 2016

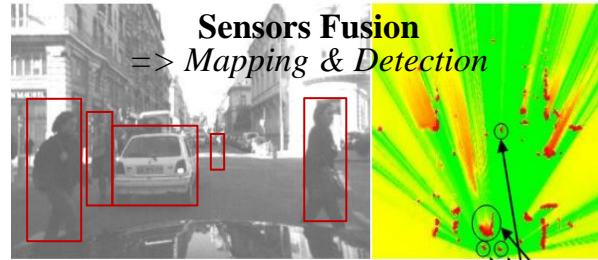


# Key Technology 1: Embedded Bayesian Perception



**Embedded Multi-Sensors Perception**

⇒ *Continuous monitoring of the dynamic environment*



## ❑ Main challenges

- ✓ *Noisy data, Incompleteness, Dynamicity, Discrete measurements*
- ✓ *Strong Embedded & Real time constraints*

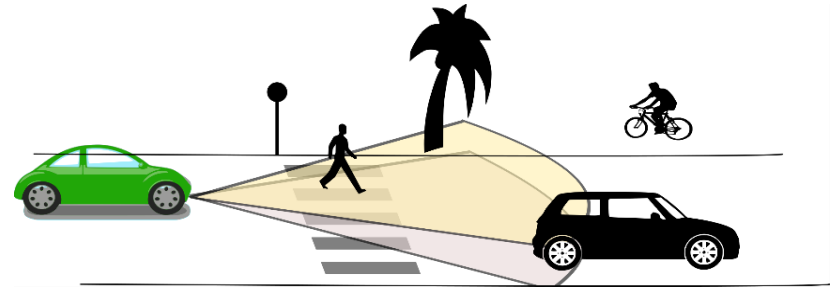
## ❑ Approach: Embedded Bayesian Perception

- ✓ *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 ...*



Bayesian  
Multi-Sensors Fusion

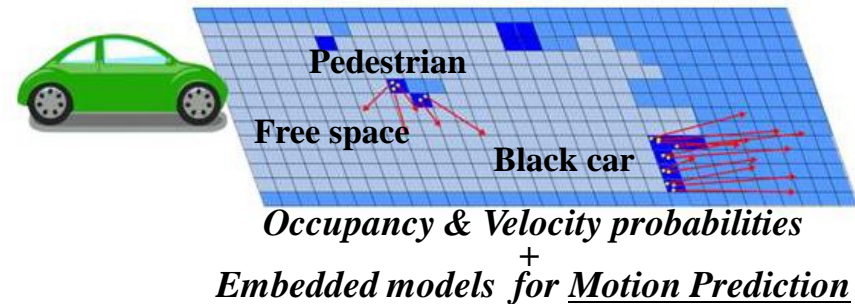
**Real-time**

## □ Probabilistic Environment Model

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

$P[o|Z,C] :$

■  $\simeq 0$  ■  $\simeq 0.5$  ■  $\simeq 1$



## □ Main philosophy

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

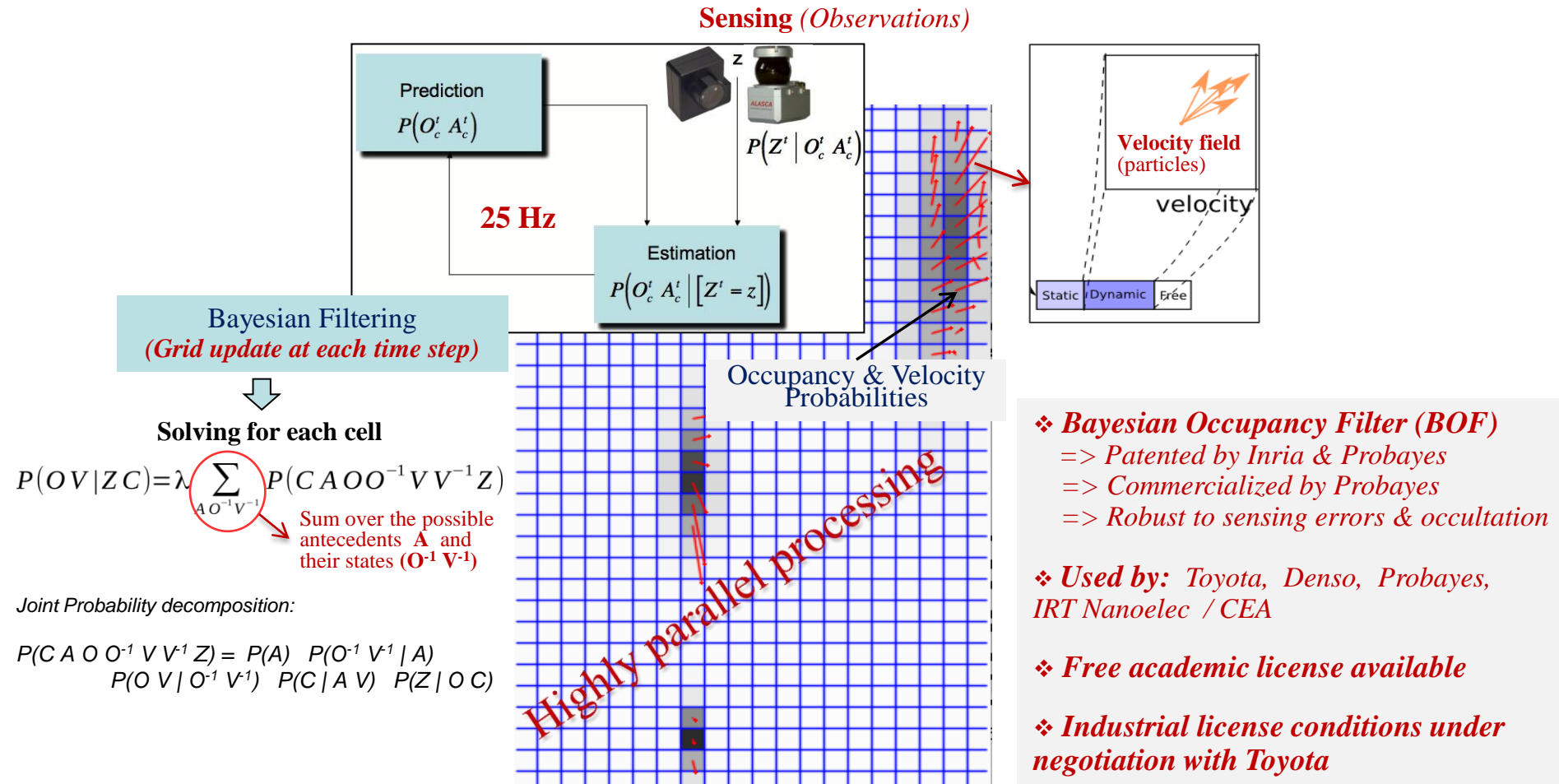
- **Improving efficiency** (highly parallel processing)
- **Avoiding traditional object level processing problems** (e.g. detection errors, wrong data association...)



# A new framework: *Dynamic Probabilistic Grids*

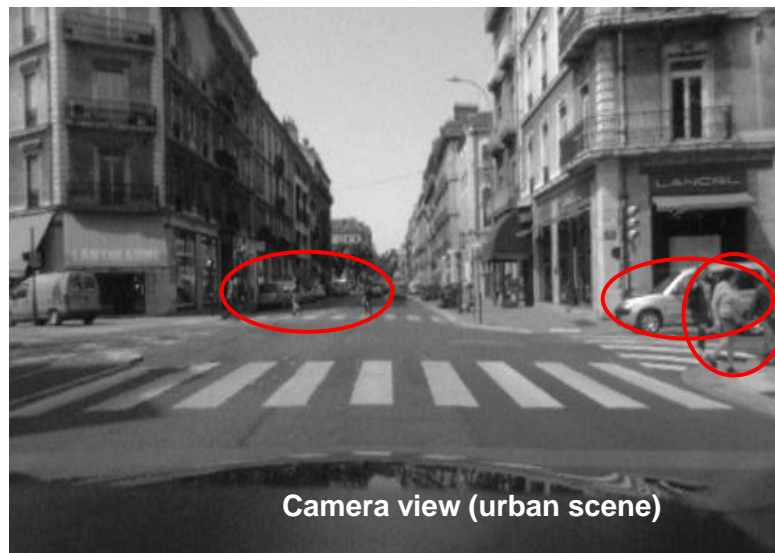
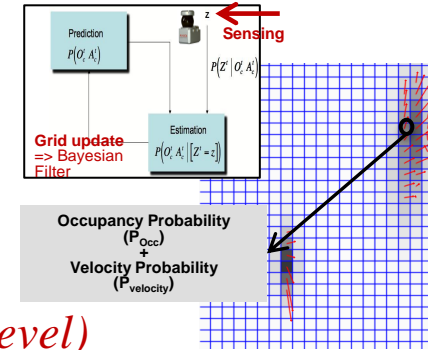
## => A clear distinction between Static & Dynamic & Free components

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

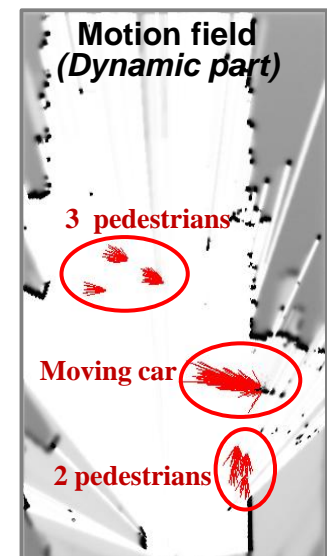


# Bayesian Occupancy Filter (BOF) – Main Features

- 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 Dynamic information !**

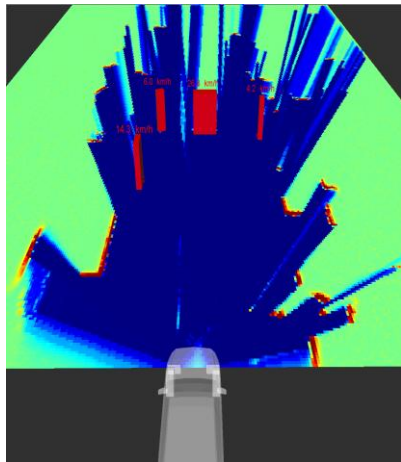


# Recent implementations & Improvements

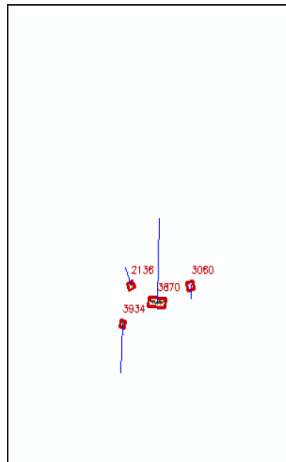


Several implementations (models & algorithms) more and more adapted to *Embedded constraints & Scene complexity*

- ❖ 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)



Grid & Pseudo-objects



Tracked Objects



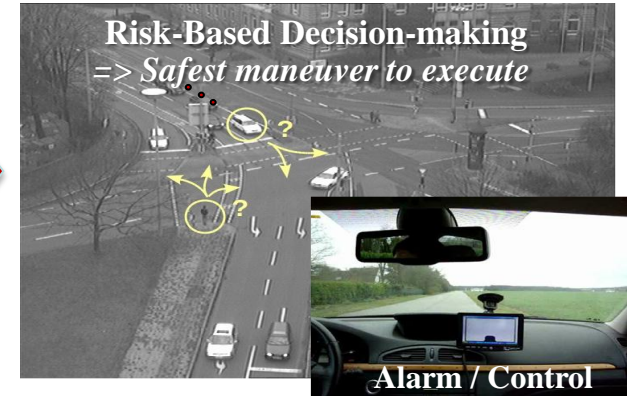
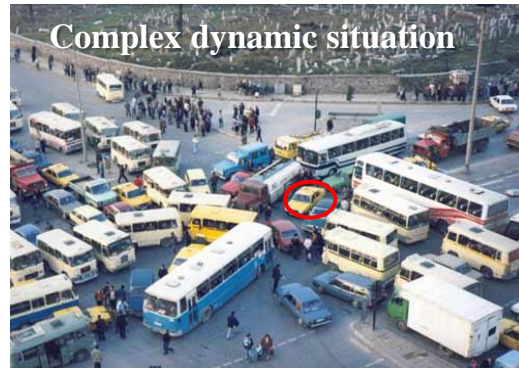
Classification (using Deep Learning)

Tracking & Classification  
=> See experimental results at the end of the talk (video)



# 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*

# Short-term collision risk – Main features

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

## Main Features

- Detect “**Risky Situations**” a few seconds ahead (0.5 to 3s)
- Risky situations are **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:  $d < 100\text{m}$  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

## System outputs





# Short-term collision risk – Experimental results

**Objective:** *Detect all dangerous situations & Avoid most of false alarms*



See video at the end of the talk



# Generalized Risk Assessment (Object level)

=> Increasing time horizon & complexity using context & semantics

## Decision-making in complex traffic situations

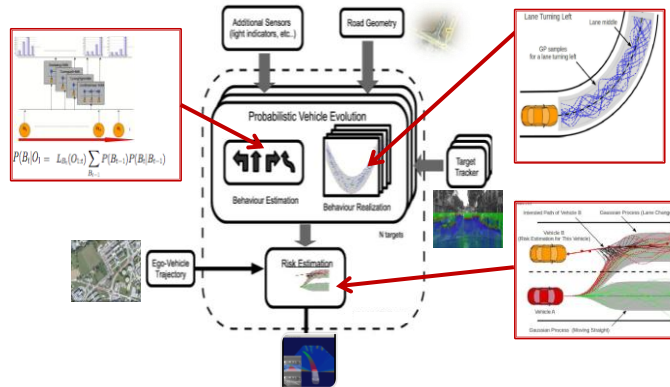
- ✓ Understand the current traffic situation & its likely evolution
- ✓ Evaluate the Risk of future collision by reasoning on traffic participants Behaviors
- ✓ Takes into account Context & Semantics



# Behavior-based Collision risk (Object level)

=> Increased time horizon & complexity + Reasoning on Behaviors

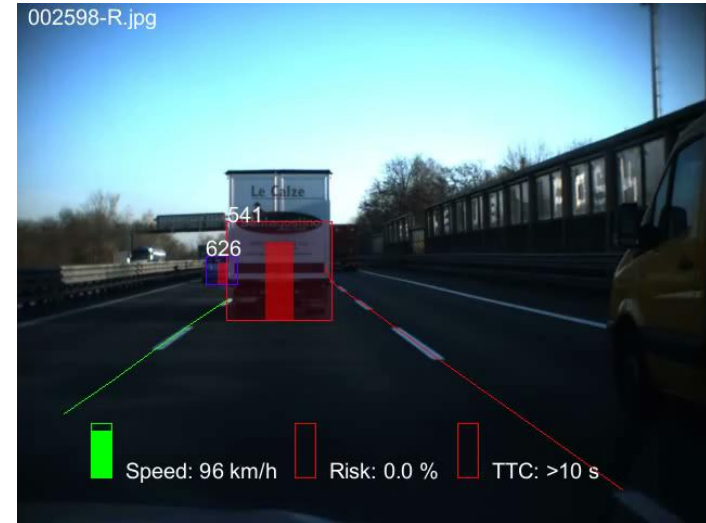
## □ Trajectory prediction & Collision Risk => Patent Inria -Toyota - ProbaYes 2010



inria

TOYOTA

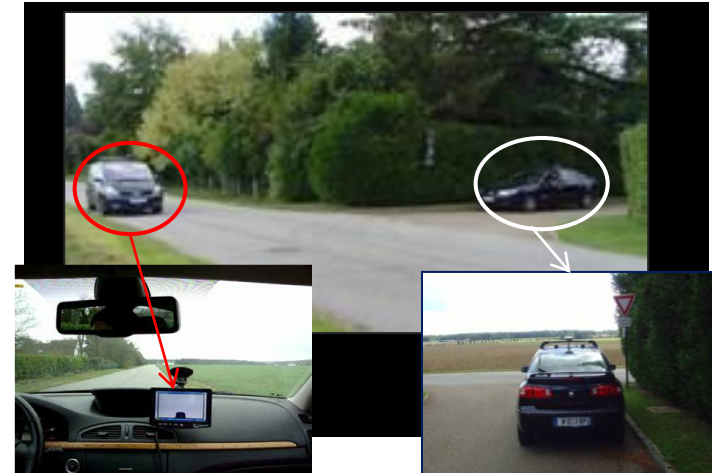
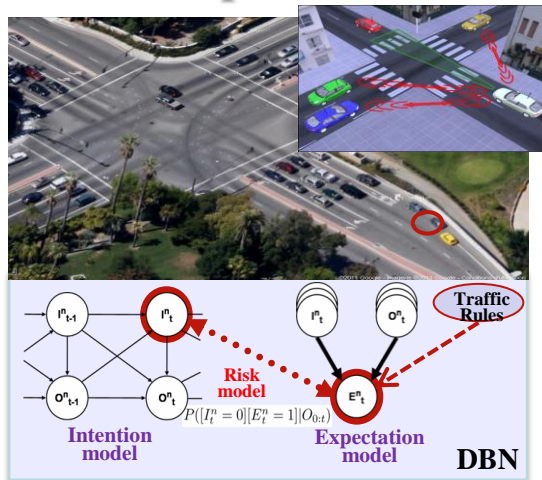
ProbaYes  
Mastering Uncertainty



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

inria

RENAULT



# Implementation & Experimental Results

Presented by Julia Chartre



# Experimental Vehicles and Perception Units

Toyota Lexus



Renault Zoé



ROS

Titan X



Jetson TK1



Jetson TX1



Perception Unit

# Objectives & Achievements 2013 -17

Embedded  
Hardware  
(STHORM)



Experimental Platform



Fusion on many core architecture



**Automotive Standard Multicore.**  
Dual cortex A9@ 800Mhz

microcontroller



**Microcontroller**  
STM 32 Cortex M7@200 MHz



**Nvidia Jetson Tk1**



**Nvidia Jetson TX1**

**GPU** TECHNOLOGY CONFERENCE

**GTC Europe 2016**

**BOF**

2013

**HSBOF**

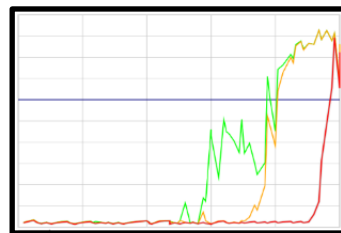
2014

**CMCDOT**

2015

**CMCDOT** *Cuda Optimization on Tegra*

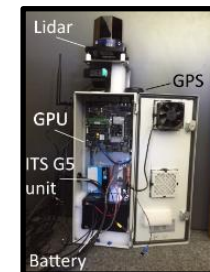
2016 - 17



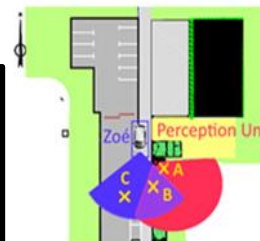
Risk assessment  
system



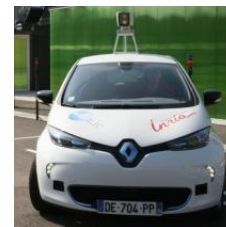
Experimental  
Scenario



Perception Unit



Distributed  
Perception



Zoe Autom.  
1<sup>st</sup> Steps

# GPU Implementation

- Highly parallelizable framework, **27 kernels** over cells and particles. (Resampling, sorting, predict, occupancy, speed estimation)
- **Real-time implementation** (processing 20 Hz sensor output), optimized using Nvidia profiling tools.
  - 700 x 300 Grids
  - 32768 velocity samples
  - Configuration with **8 to 12 Lidar layers** (2x4 to 3 x 4),
- Pushing the limits of the algorithm :
  - 1400 x 600 Grids
  - 65536 velocity samples



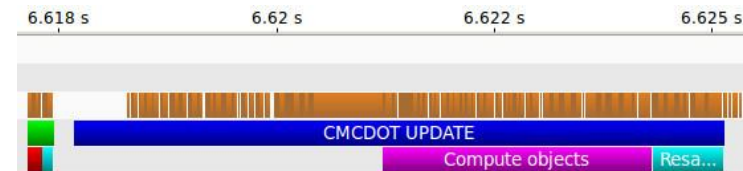
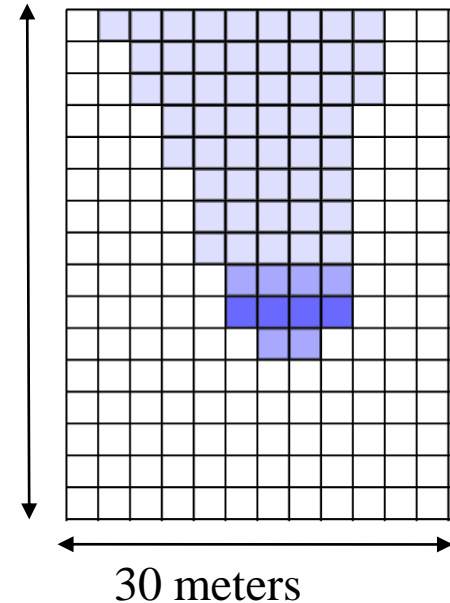
Jetson TK1: Grid Fusion 17ms, CMCDOT 70ms



Jetson TX1: Grid Fusion 0.7ms, CMCDOT 17ms

□ 1 px = 1 cell  
= 10 x 10 cm

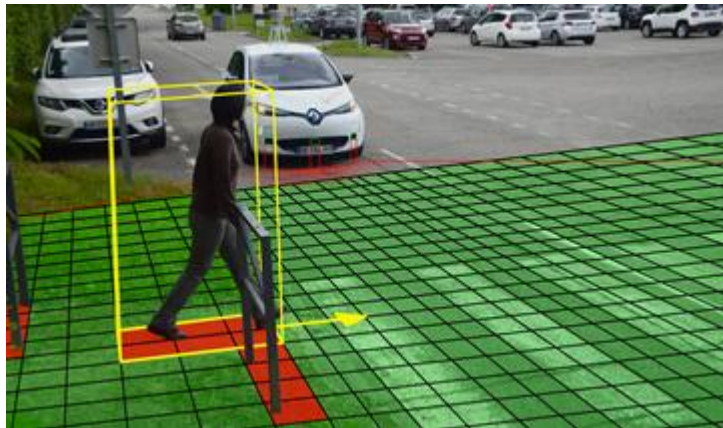
70 meters



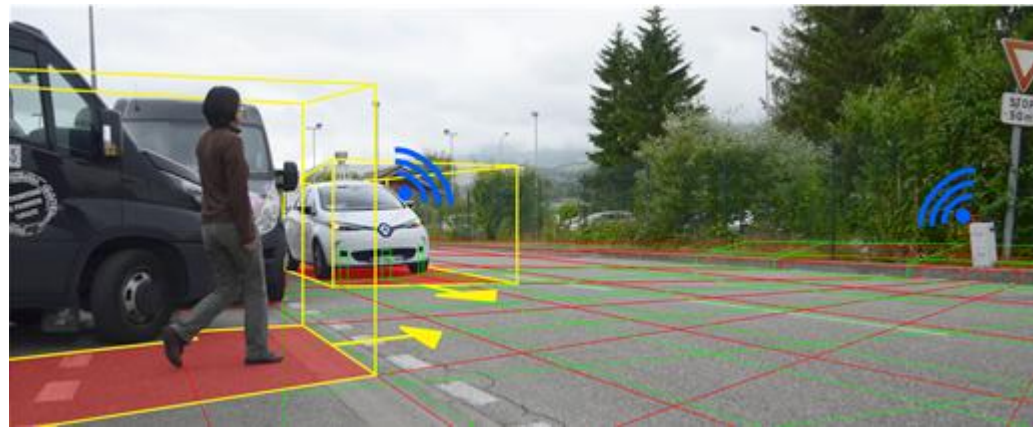


# Experimental Platforms & Experiments

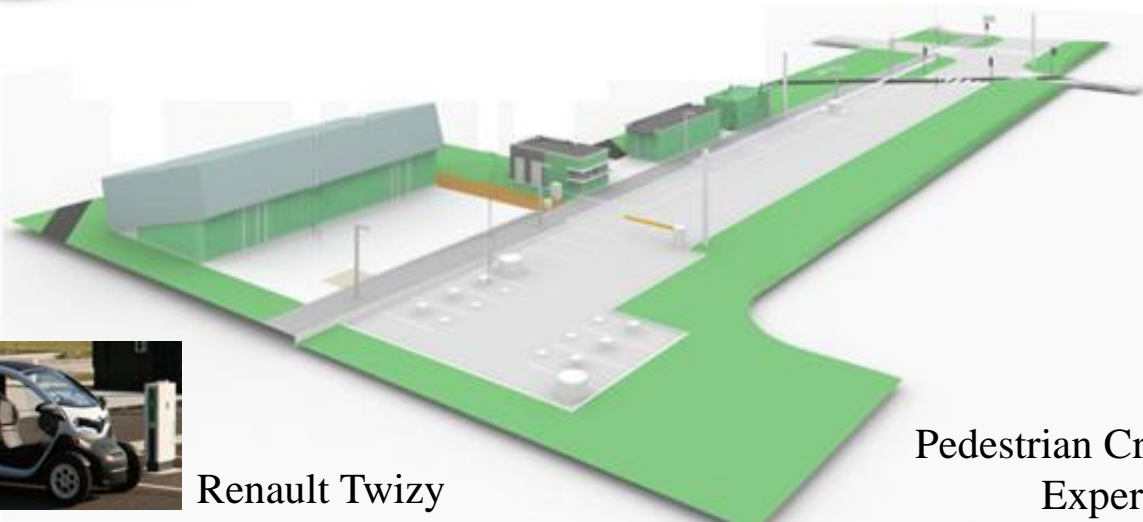
## Embedded Perception



## Distributed Perception



## IRT Nanoelec Experimental Platform



Perception Unit



Connected Traffic Cone



Pedestrian Crossing Experiments

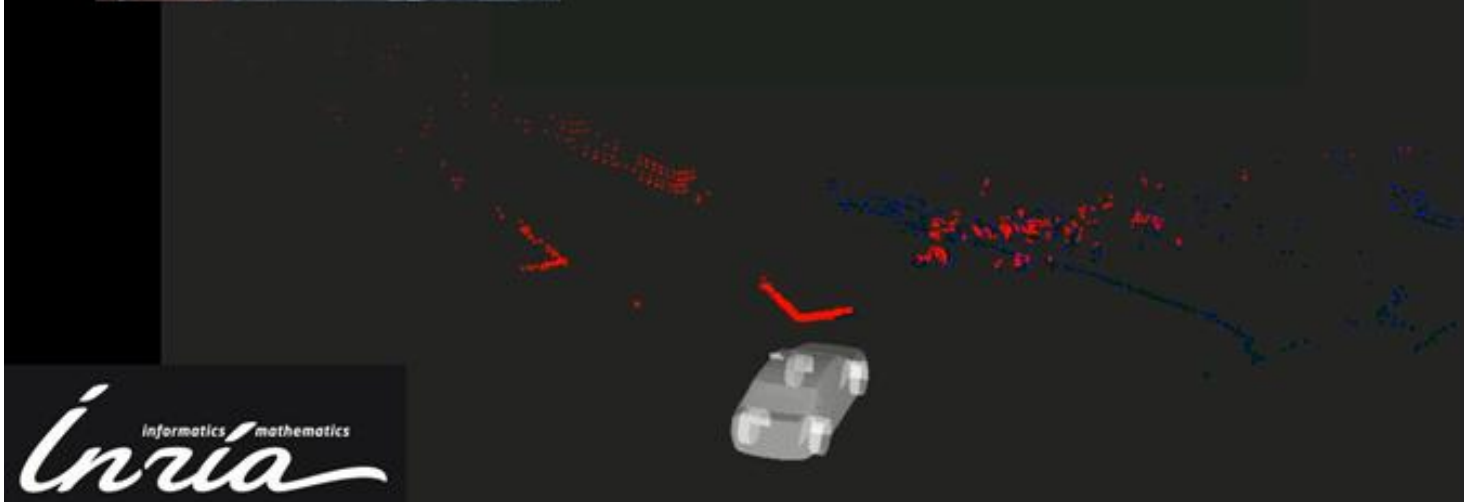
Renault Twizy



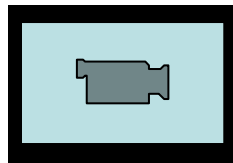
# Experimental results in urban environment



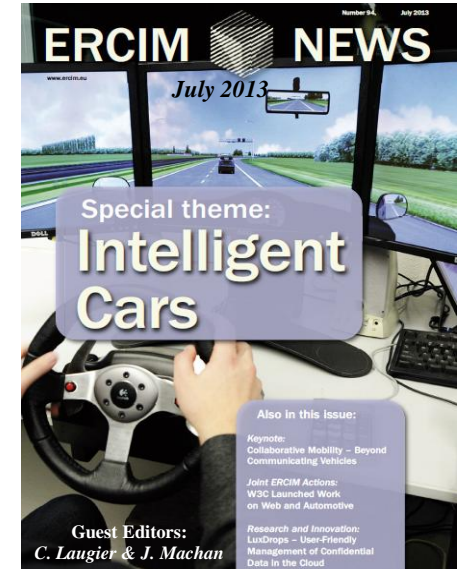
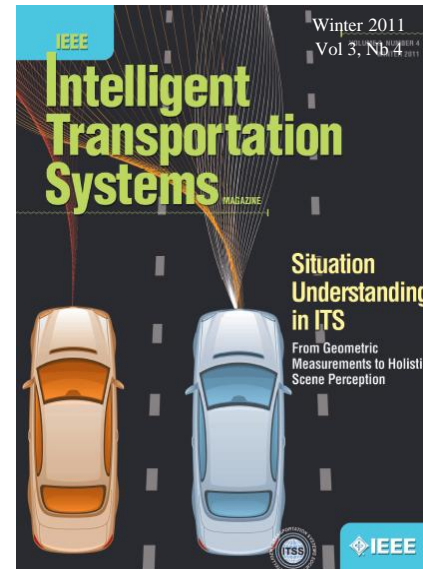
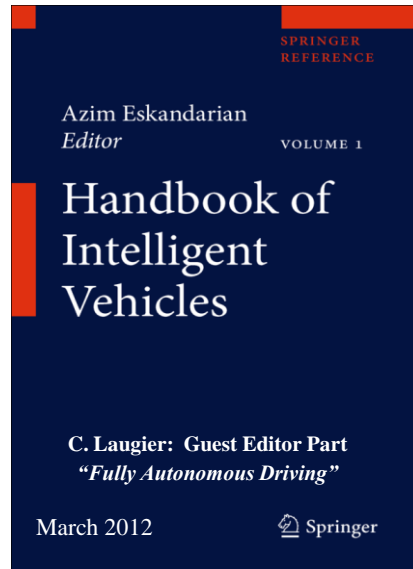
Sensor data



*Inria*  
informatics mathematics







**Thank You  Any questions ?**

