

# Intelligent Perception and Situation Awareness for Automated vehicles

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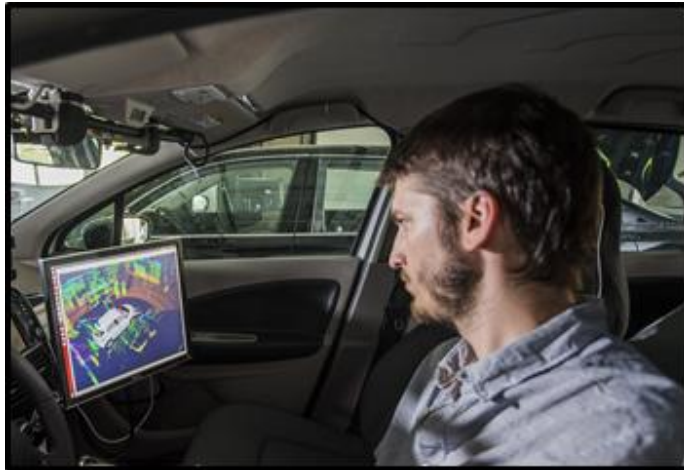
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## **ADAS & Autonomous Driving**



**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

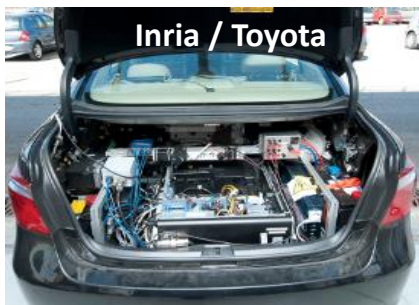


Audi A7

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



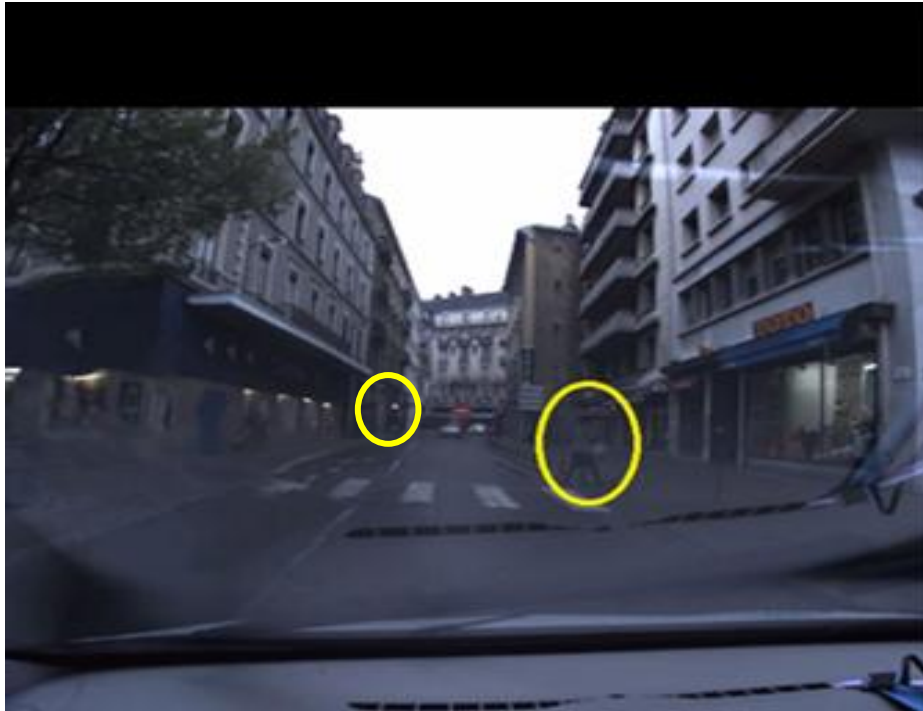
Driverless Taxi testing in Pittsburgh (Uber) & Singapore (nuTonomy)

=> Numerous Sensors & Engineer in the car during testing



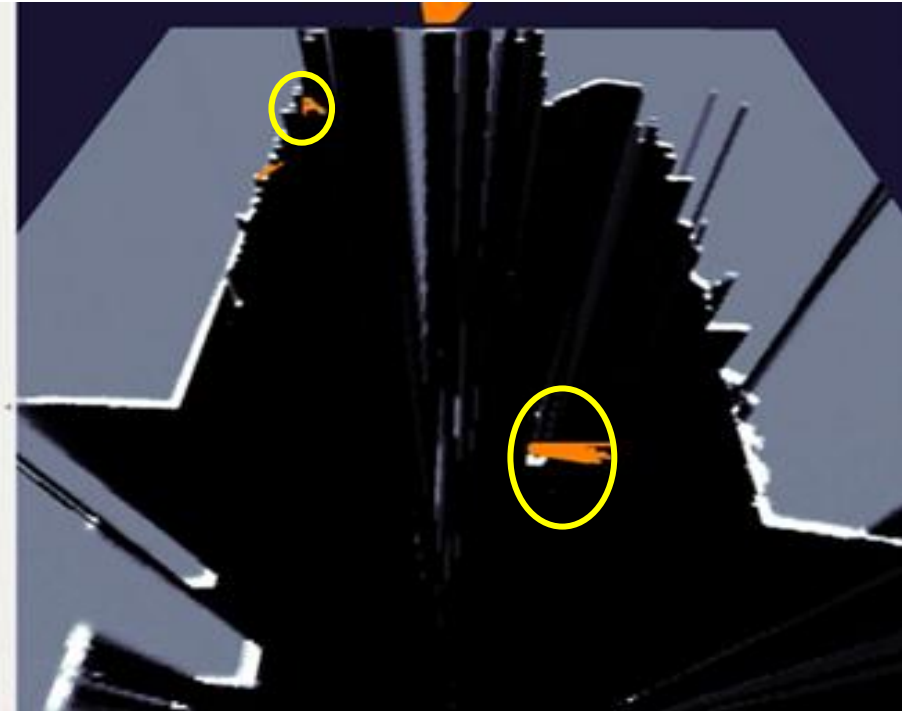
# Improving robustness using Multi-modality sensing

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



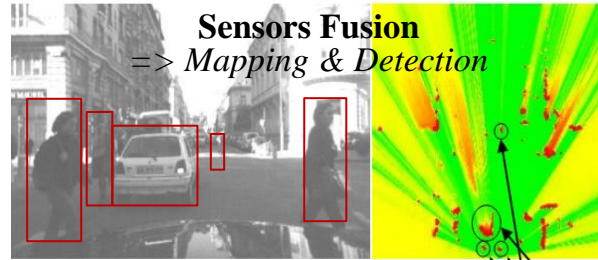


# Key Technology 1: Embedded Bayesian Perception



**Embedded Multi-Sensors Perception**

⇒ *Continuous monitoring of the dynamic environment*



## ❑ Main challenges

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

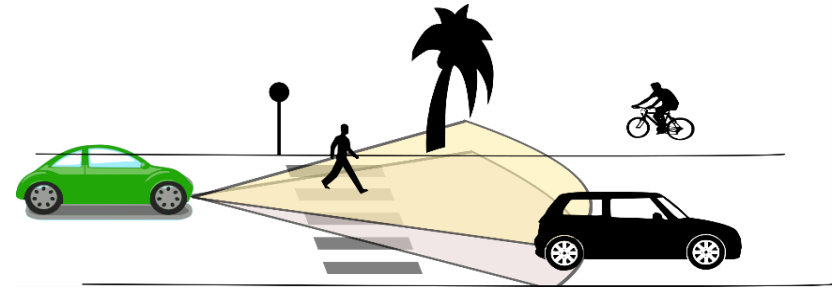
## ❑ Approach: Embedded Bayesian Perception

- ✓ *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

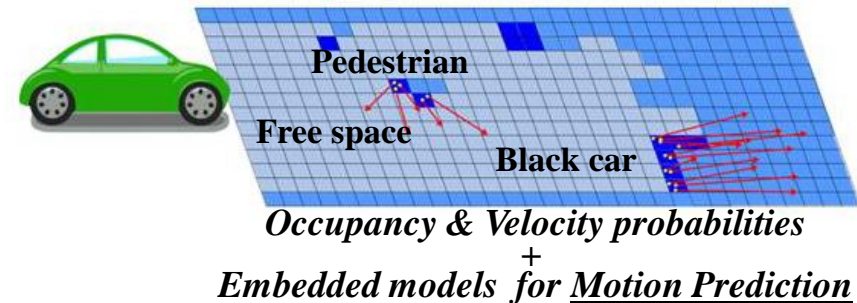
**Real-time**

## □ Probabilistic Environment Model

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

$P[o|Z,C] :$

■  $\approx 0$  ■  $\approx 0.5$  ■  $\approx 1$



## □ Main philosophy

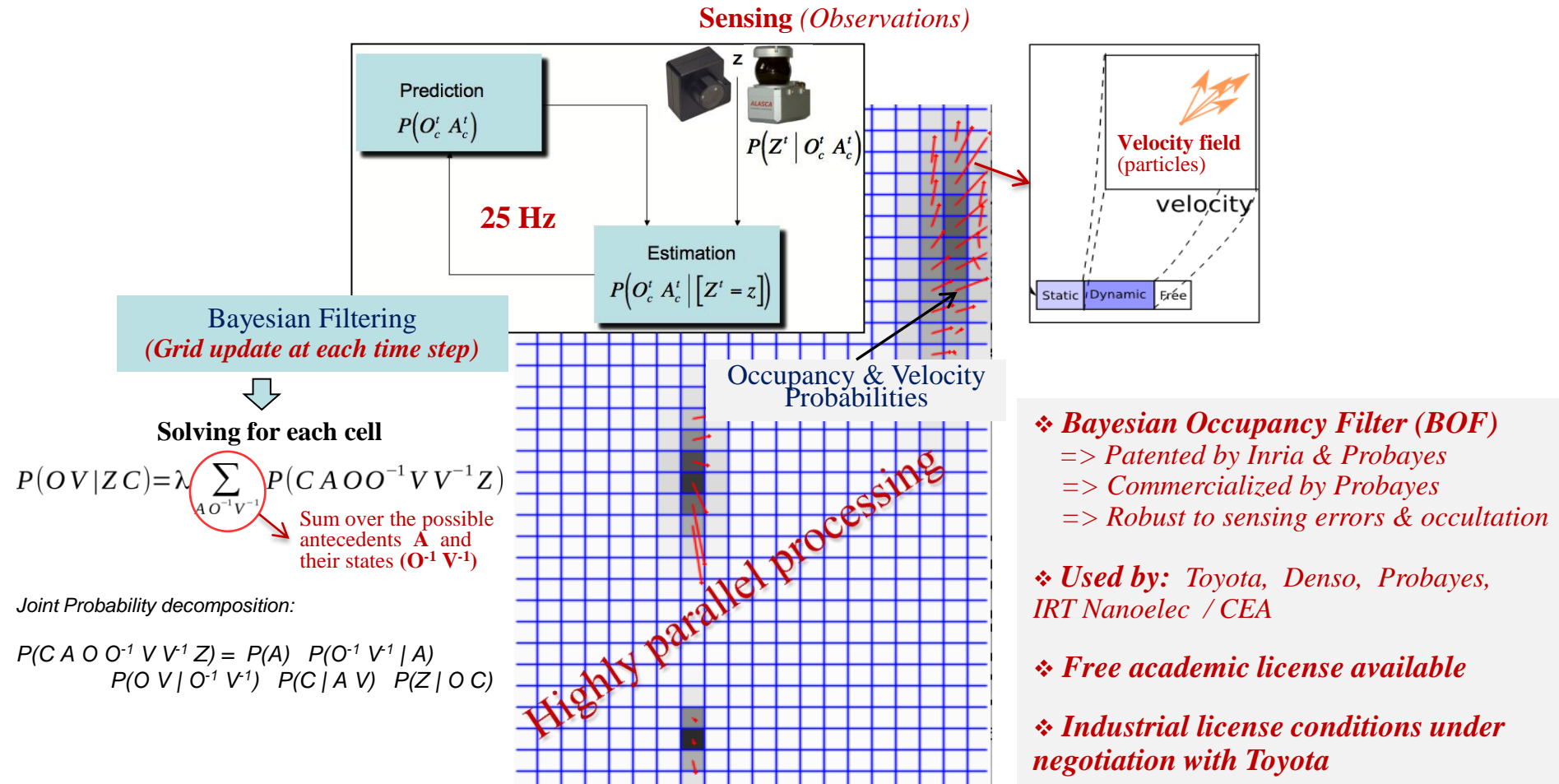
*Reasoning at the grid level as far as possible for both :*

- **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

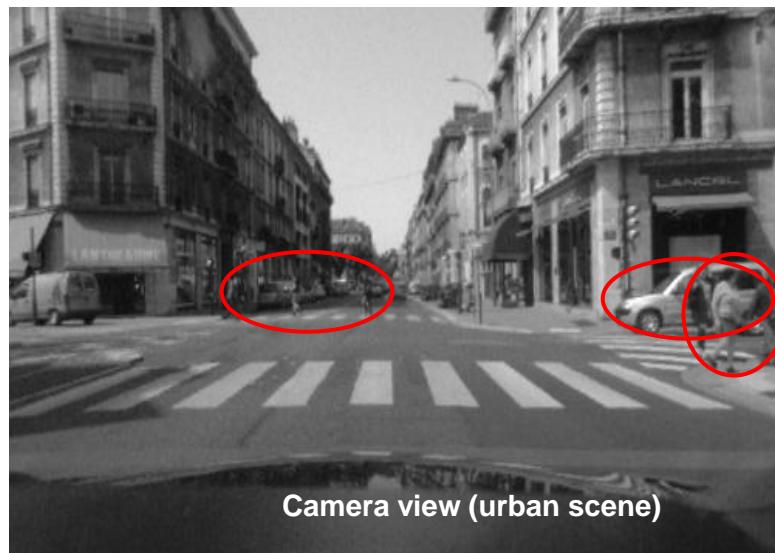
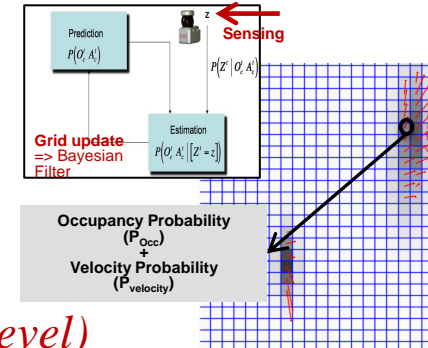
[Coué & Laugier IJRR 05] [Laugier et al ITSM 2011] [Laugier, Vasquez, Martinelli Mooc uTOP 2015]



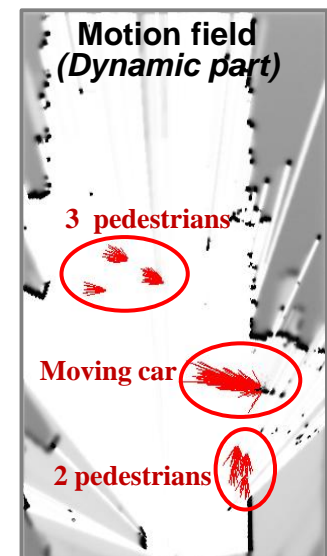


# Bayesian Occupancy Filter (BOF) – Main Features

- 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 !**

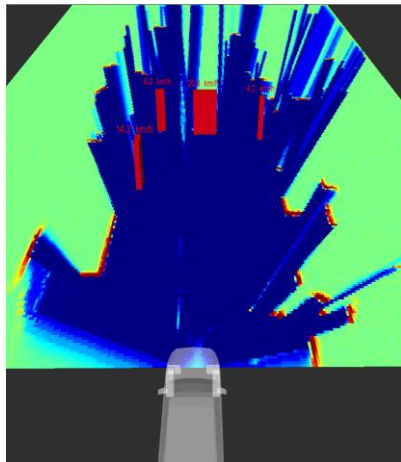


# Recent implementations & Improvements

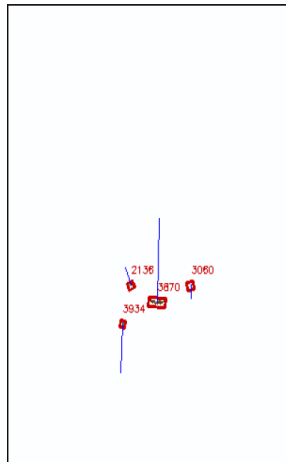


Several implementations (models & algorithms) more and more adapted to *Embedded constraints & Scene complexity*

- ❖ 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

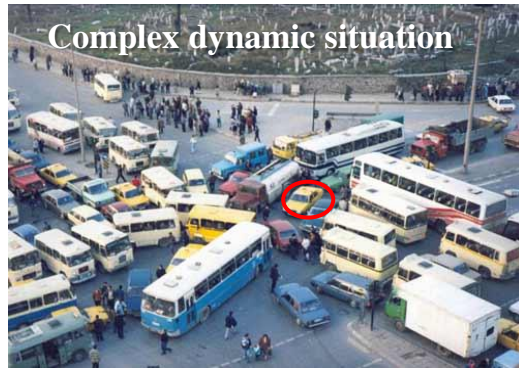


Classification (using Deep Learning)

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

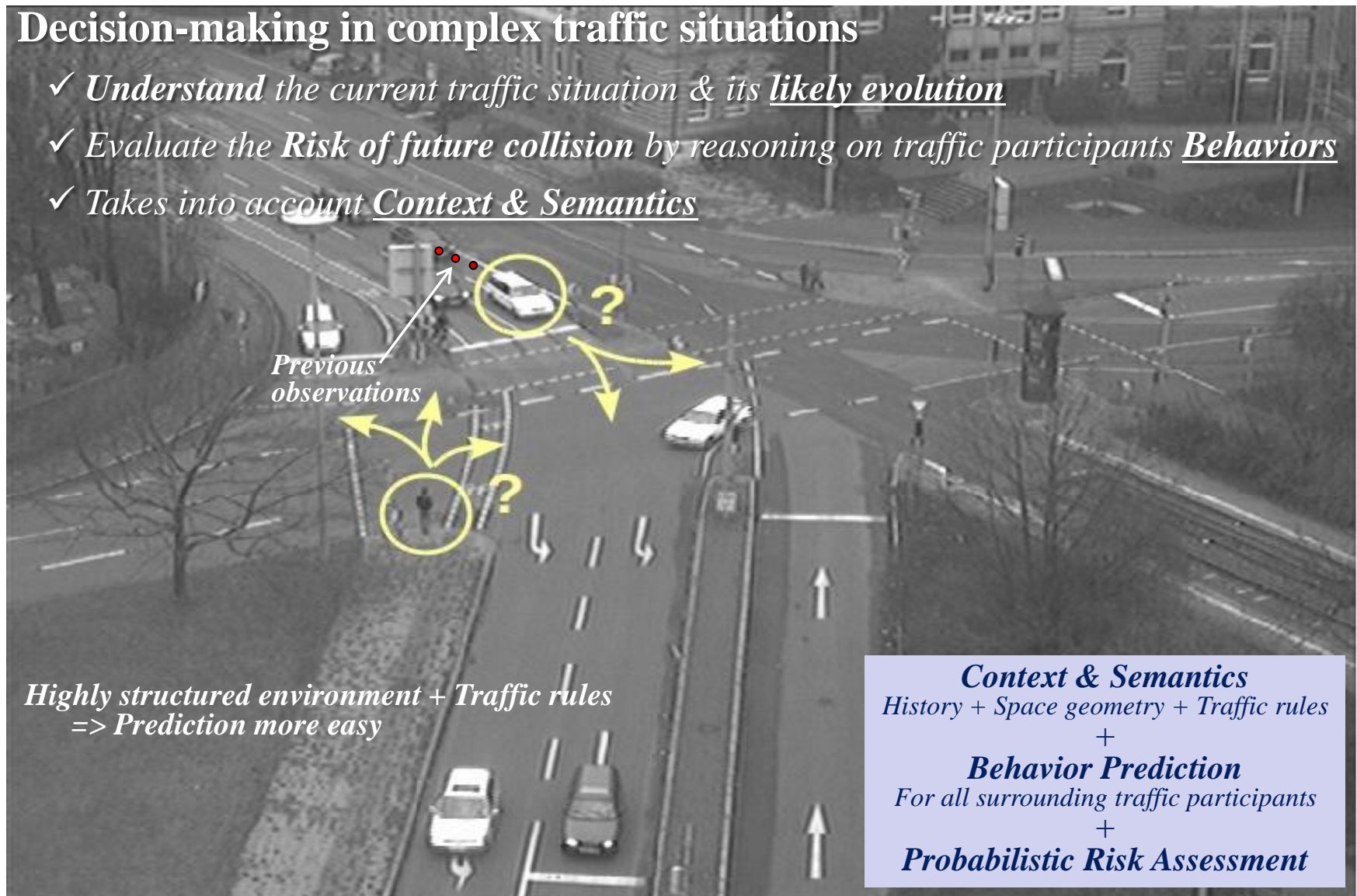


# *Generalized Risk Assessment (Object level)*

*=> 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*



*Highly structured environment + Traffic rules  
=> Prediction more easy*

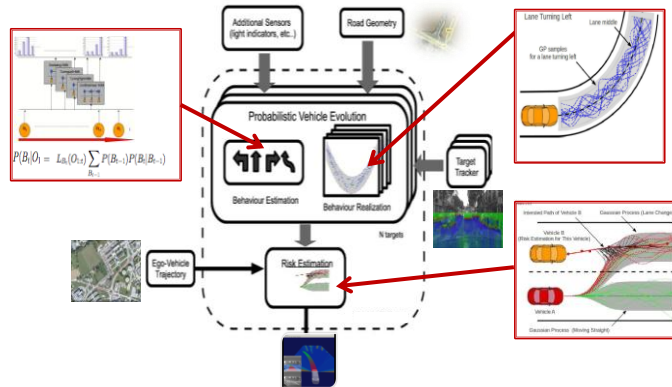
**Context & Semantics**  
History + Space geometry + Traffic rules  
+  
**Behavior Prediction**  
For all surrounding traffic participants  
+  
**Probabilistic Risk Assessment**



# Behavior-based Collision risk (Object level)

=> Increased time horizon & complexity + Reasoning on Behaviors

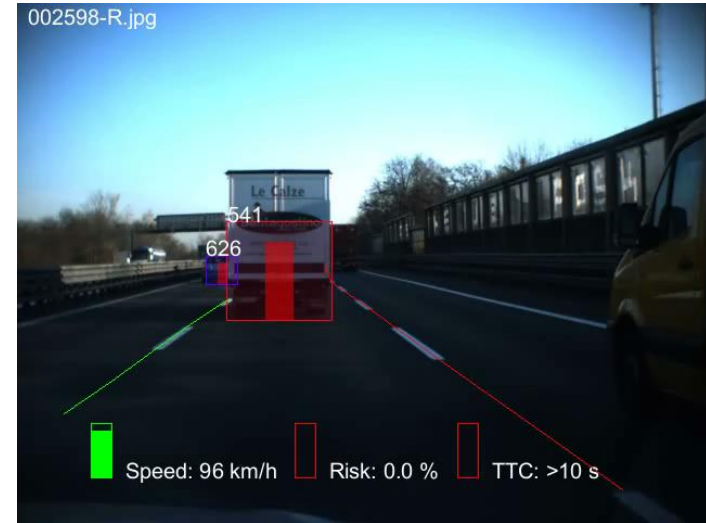
## □ Trajectory prediction & Collision Risk => Patent Inria -Toyota - ProbaYes 2010



inria

TOYOTA

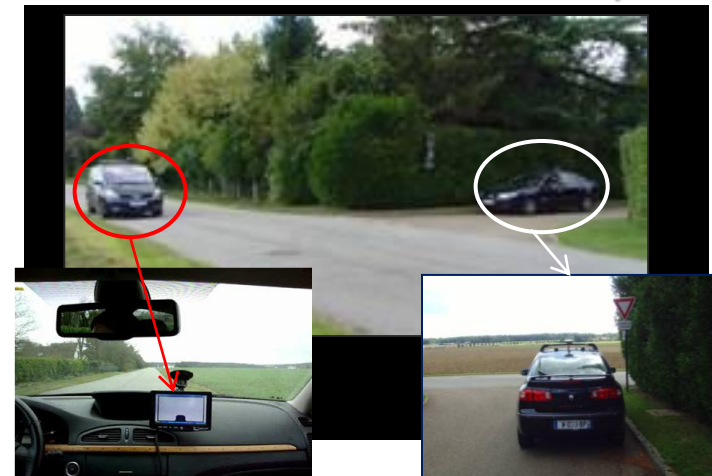
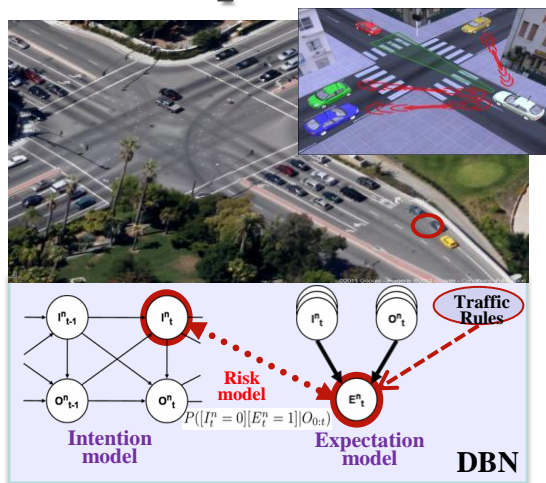
ProbaYes  
Mastering Uncertainty



## □ 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

Velodyne lidar

cameras

IBEO lidars



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**

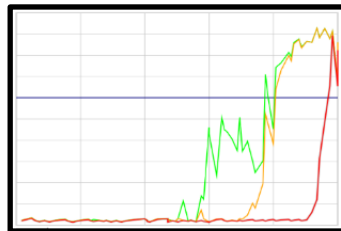
2014

**CMCDOT**

2015

**CMCDOT** *Cuda Optimization on Tegra*

2016 - 17



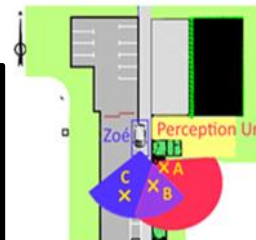
Risk assessment  
system



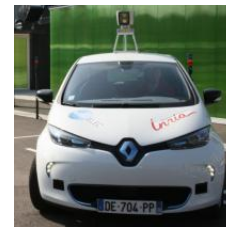
Experimental  
Scenario



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



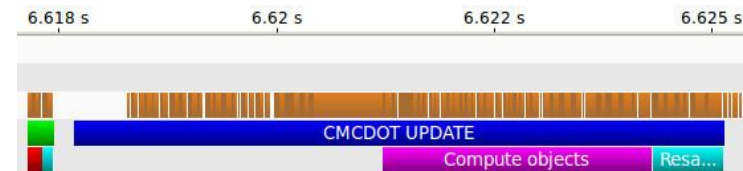
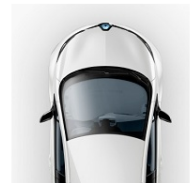
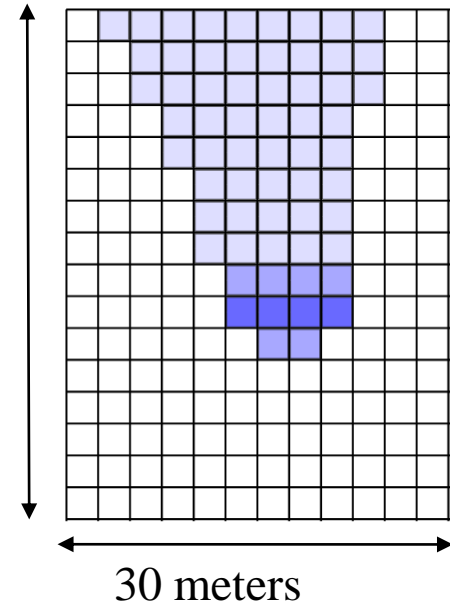
Jetson TK1: Grid Fusion 17ms, CMCDOT 70ms



Jetson TX1: Grid Fusion 0.7ms, CMCDOT 17ms

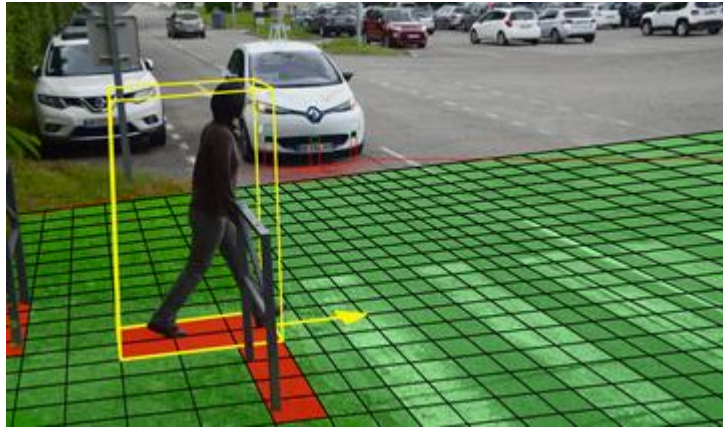
□ 1 px = 1 cell  
= 10 x 10 cm

70 meters

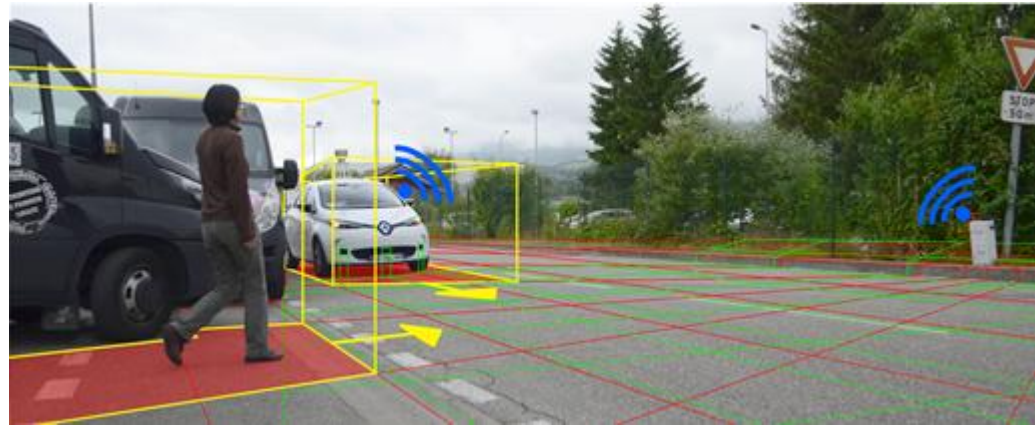


# Experimental Platforms & Experiments

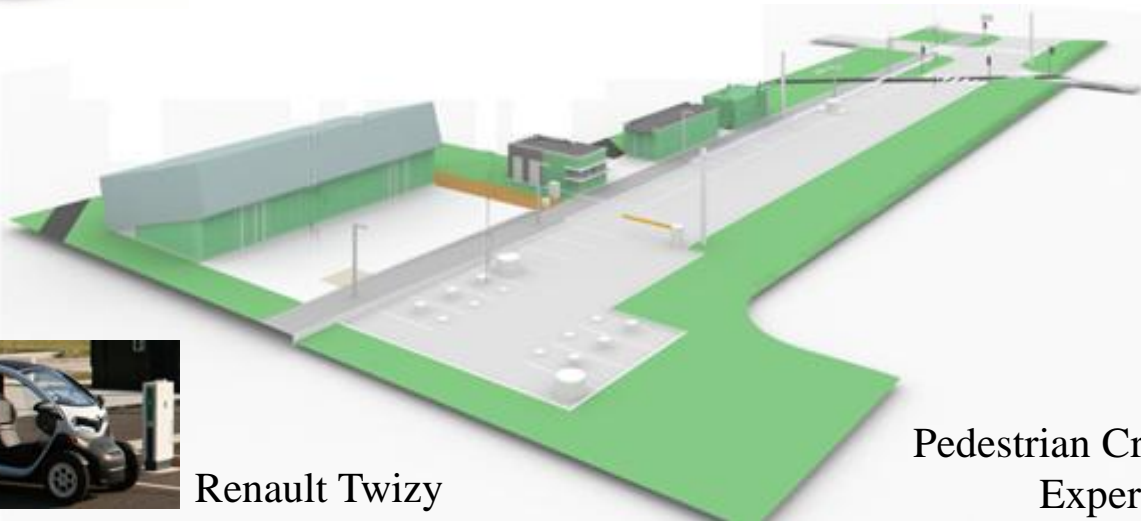
## Embedded Perception



## Distributed Perception



## IRT Nanoelec Experimental Platform



Renault Twizy

Pedestrian Crossing Experiments



Perception Unit



Connected Traffic Cone





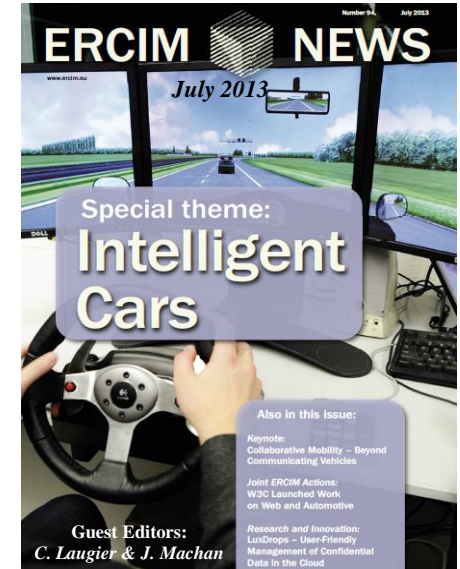
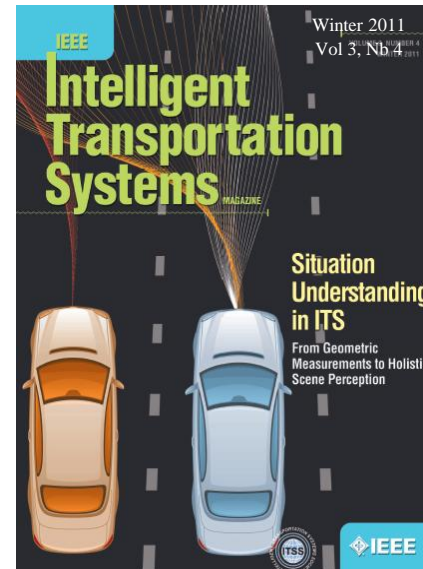
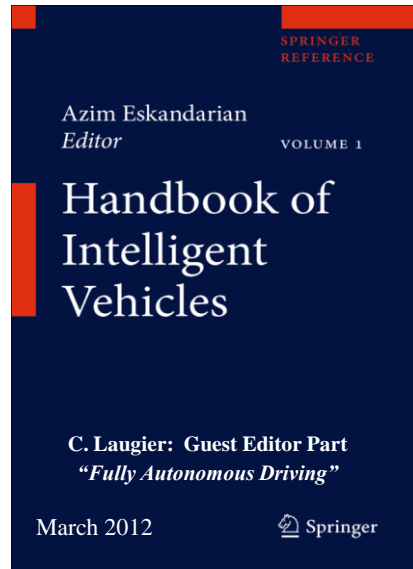
# Experimental results in urban environment



Sensor data

*Inria*  
informatics mathematics





**Thank You  Any questions ?**

