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# Towards Fully Autonomous Driving? The Perception & Decision-making bottleneck (Plenary Talk)

Christian Laugier

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# Towards Fully Autonomous Driving ? The Perception & Decision-making bottleneck

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

## *Contributions from*

*Mathias Perrollaz, Christopher Tay Meng Keat, Stephanie Lefevre, Javier-Ibanez Guzman, Amaury Negre, Lukas Rummelhard, Nicolas Turro, Julia Chartre, Jean-Alix David, Tiana Rakotovao, Julien Mottin, Diego Puschini*



**ADAS & Autonomous Driving**



## Plenary Talk

*IEEE ARSO 2016, Shanghai, July 7-9 2016*

# Socio-economic context

- On-going change of the role & concept of private car in human society



*Ownership & Feeling of Freedom*  
*Affective behaviors & Social position*  
*Driving pleasure ... but less and less true !*

*Focus on **Technologies** for*  
*Safety & Comfort & Reduced Pollution*  
*Driving Assistance v/s Autonomous Driving*

- ❖ Technology & Internet progressively change de **mobility habits** of people  
=> *Shared mobility systems, more carpooling, more ADAS ...*  
*e.g. Uber, BlaBlaCar, Tesla Autopilot ...*
- ❖ A Huge ADAS market for Automotive Industry  
=> *\$16 billions in 2012 & Expected \$261 billions in 2020 <sup>(f)</sup>*

<sup>(f)</sup> Forecasted US\$ 260 Billion Global Market for ADAS Systems by 2020. ABI Research. 2013.

# Technological context

- ❑ **Perception** for Autonomous Vehicles: *New trend of automotive industry !*
  - ✓ Perception is a bottleneck for Motion Autonomy
  - ✓ Strong improvements (sensors & algorithms) during the last decade



CES 2015 & 2016  
(Las Vegas)

- ❑ *But... High Computational requirement & Insufficient Robustness are still an obstacle to the full deployment !*



Lack of Robustness & Efficiency +

Lack of Integration into Embedded Sw/Hw +



# What about Safety issue ?

## ❑ Safety is still insufficient (*a false sense of Safety*) !

=> *Still some Perception & Situation Awareness errors (even in commercial systems)*

=> *On May 7<sup>th</sup> 2016, Tesla driver killed in crash with Autopilot active (recently revealed by Tesla)*

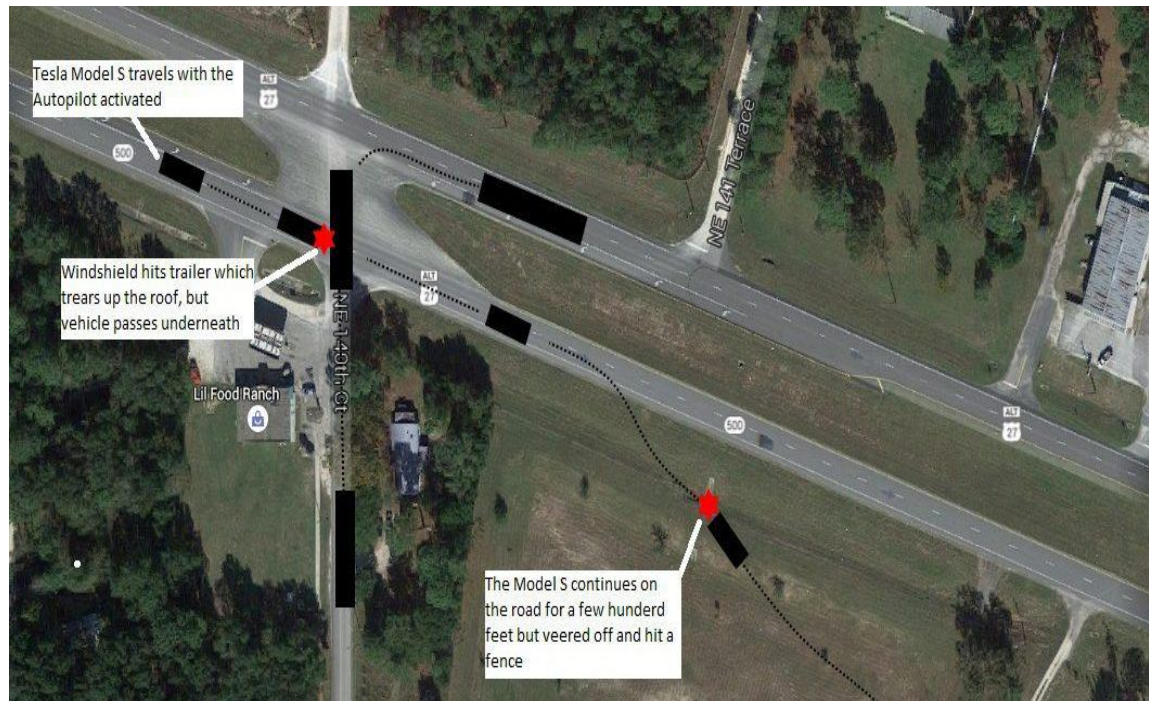


Displayed information

Tesla Model S – Autopilot

Front perception:

*Camera + Radar + US sensors*



**Autopilot didn't detected the trailer as an obstacle (NHTSA investigation + Tesla conjecture):**

❖ **Camera** => *White color against a brightly lit sky (+ High ride height ?) !*

❖ **Radar** => *High ride height of the trailer probably confused the radar into thinking it is an overhead road sign !*

# Focus of this talk: How to improve current Embedded Perception & Decision-making Systems ?

Complex Dynamic Scenes



**Situation Awareness  
& Decision-making**



Road Safety campaign, France 2014



**Anticipation & Prediction**

## Main features

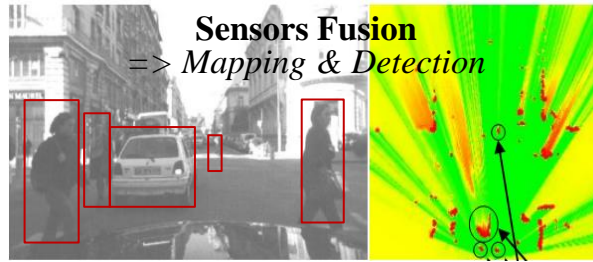
- ✓ Dynamic & Open Environments (*Real-time processing*)
- ✓ Incompleteness & Uncertainty (*Model & Perception*)
- ✓ Human in the loop (*Social & Interaction Constraints*)
- ✓ Hardware / Software integration (*Satisfying Embedded constraints*)



# Key Technology 1: Bayesian Perception



**Embedded Multi-Sensors Perception**  
⇒ *Continuous monitoring of the dynamic environment*



## ❑ Main difficulties

*Noisy data, Incompleteness, Dynamicity, Discrete measurements + Real time !*

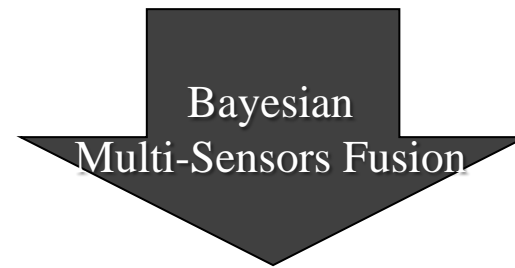
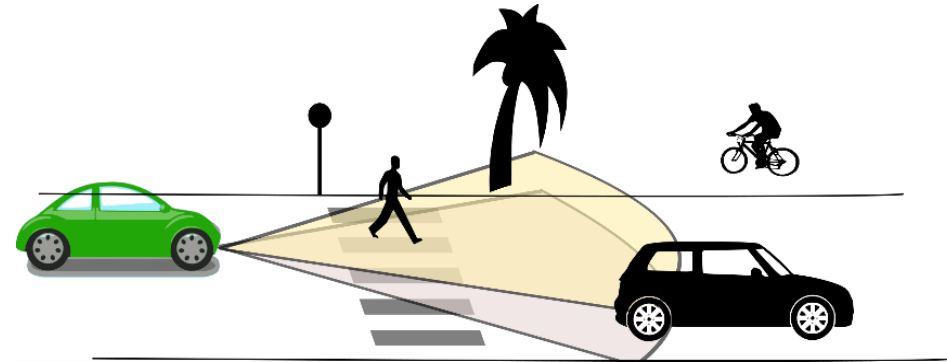
## ❑ Approach: Bayesian Perception

- *Reasoning about Uncertainty & Time window (Past & Future events)*
- *Improving robustness using Bayesian Sensors Fusion*
- *Interpreting the dynamic scene using Contextual & Semantic information*

# Bayesian Perception : Basic idea




## Multi-Sensors Observations

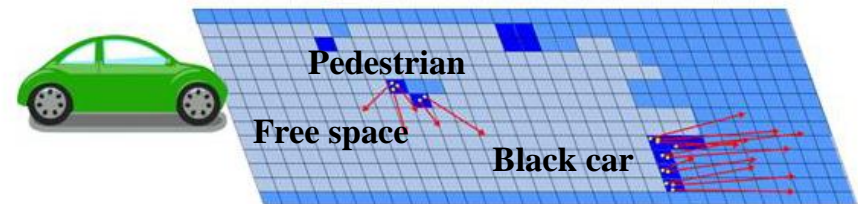
*Lidar, Radar, Stereo camera, IMU ...*



## Probabilistic Environment Model

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

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



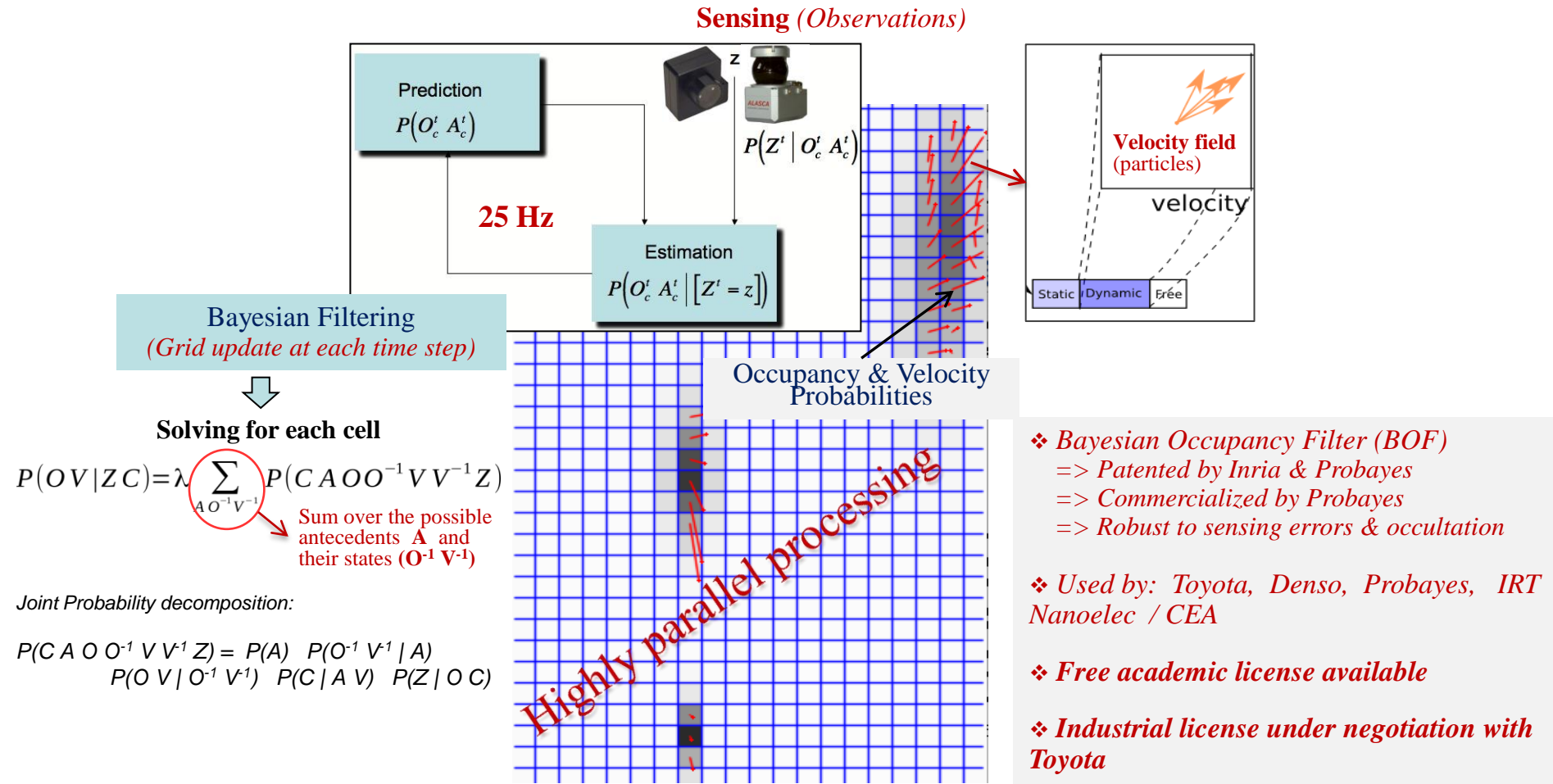
Occupancy probability + Velocity probability  
+ Motion prediction model



# A new framework: *Dynamic Probabilistic Grids*

## *A clear distinction between Static & Dynamic & Free components*

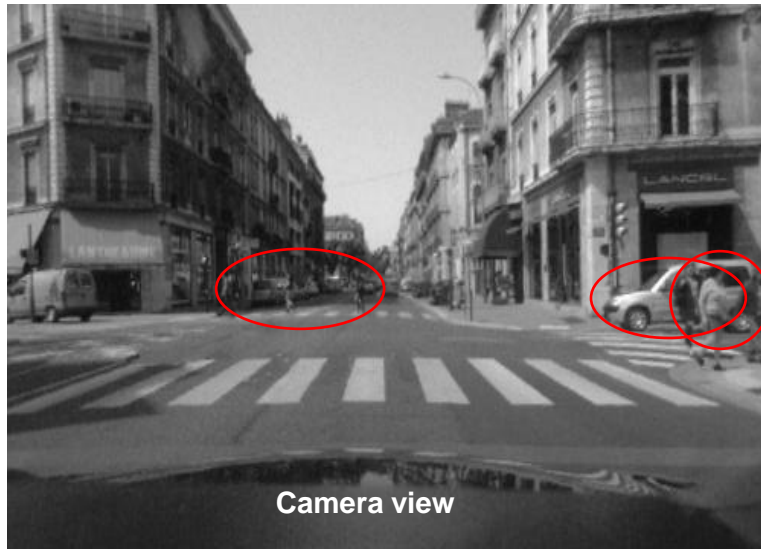
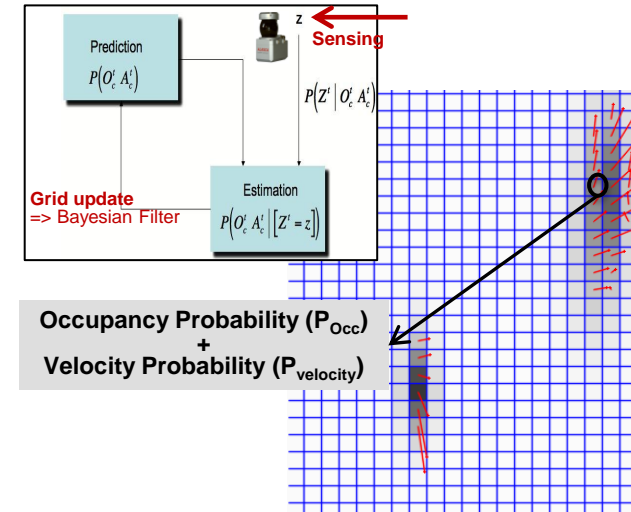
[Coué & Laugier IJRR 05] [Laugier et al ITSM 2011] [Laugier, Vasquez, Martinelli Mooc uTOP 2015]



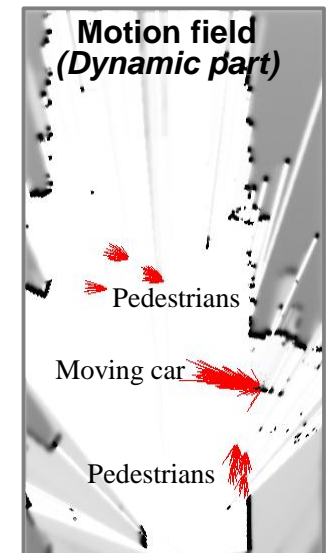
# Bayesian Occupancy Filter (BOF) – Outline

## Main features:

- Estimate **Spatial occupancy**
- Analyze **Motion Field** (*using Bayesian filtering*)
- Reason at the **Grid level** (*i.e. no object segmentation at this reasoning level*)

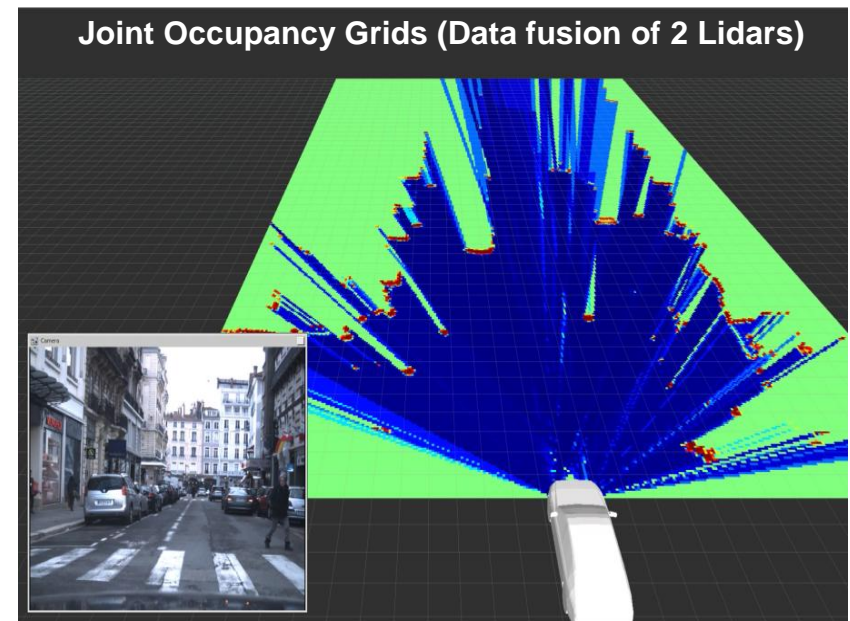
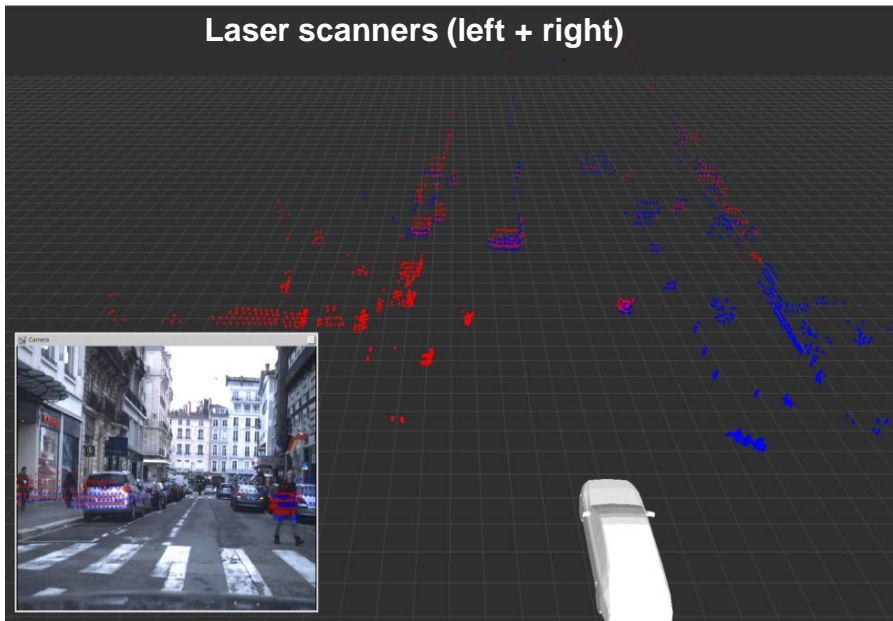


Sensors data fusion  
+  
Bayesian Filtering



# Data fusion: *The joint Occupancy Grid*

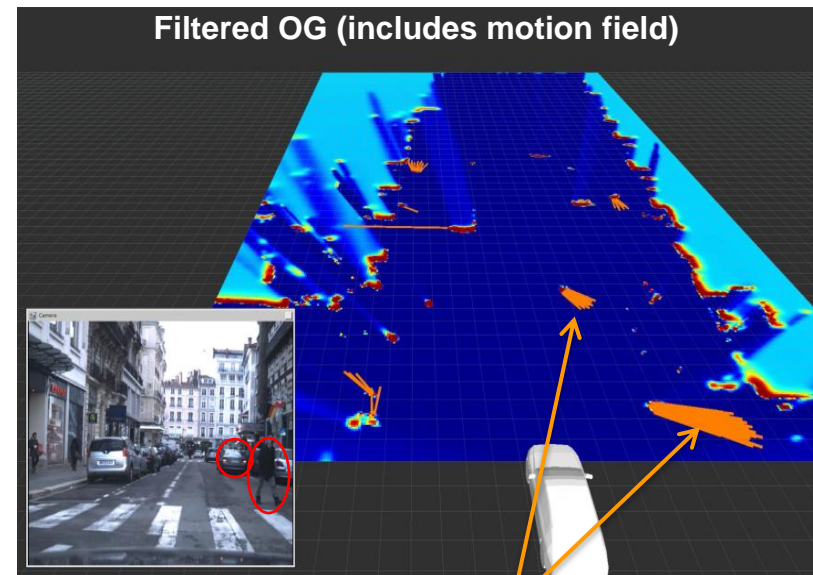
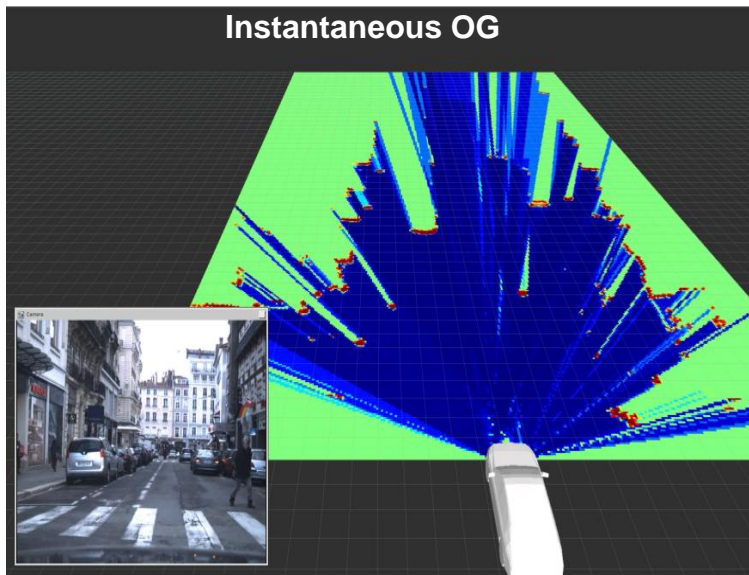
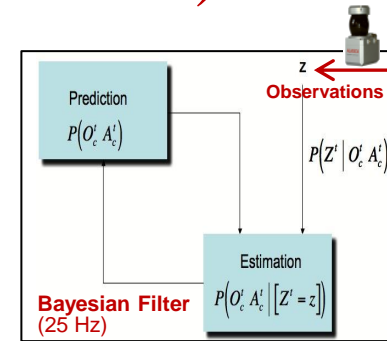
- Observations  $Z_i$  are given by each sensor  $i$  (*Lidars, cameras, etc*)
- For each set of observation  $Z_i$ , Occupancy Grids are computed:  $P(O | Z_i)$
- Individual grids are merged into a single one:  $P(O | Z)$





# Taking into account dynamicity: *Filtered Occupancy Grid (Bayesian filtering)*

- Filtering is achieved through the *prediction/correction loop (Bayesian Filter)*  
=> *It allows to take into account grid changes over time*
- Observations are used to update the environment model
- Update is performed in each cell in parallel (*using BOF equations*)
- **Motion field** is constructed from the resulting filtered data



Motion fields are displayed in orange color

# Underlying Conservative Prediction Capability

=> Application to Conservative Collision Anticipation

Autonomous  
Vehicle (Cycab)



Parked Vehicle  
(occultation)

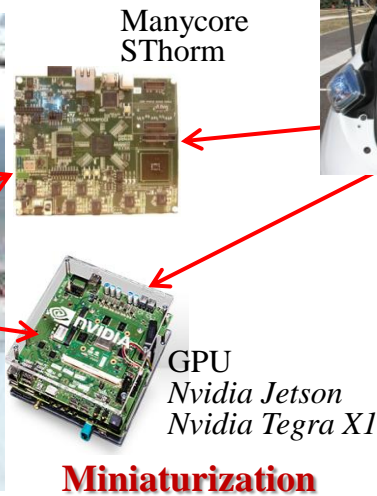
Thanks to the prediction capability of the BOF technology, the Autonomous Vehicle “anticipates” the behavior of the pedestrian and brakes (even if the pedestrian is temporarily hidden by the parked vehicle)

# Implementation & Experiments (Vehicles)

*CPU+GPU+ROS / Stereo vision + Lidars + GPS + IMU + Odometry*



**Toyota Lexus**



**Renault Zoé**



# Implementation & Experiments (Infrastructure)

*IRT Nanoelec experimental platform => Connected infrastructure + 2 Twizy*



**Equipped Renault Zoé**



**Connected & Movable Perception Box**



**Equipment for pedestrian crash test**



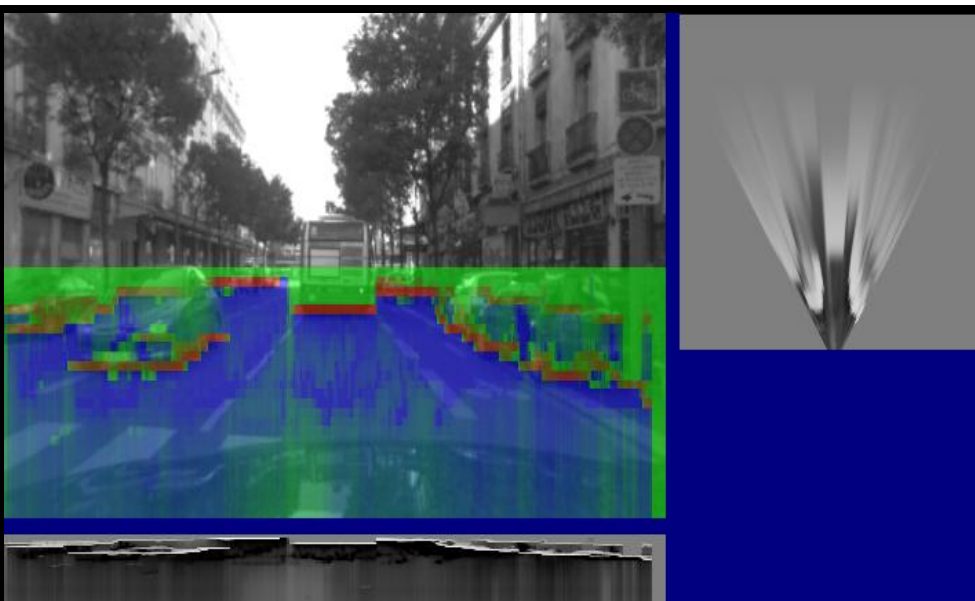
**Experimental connected infrastructure**

# Experimental Results (*Inria – Toyota Lexus*)

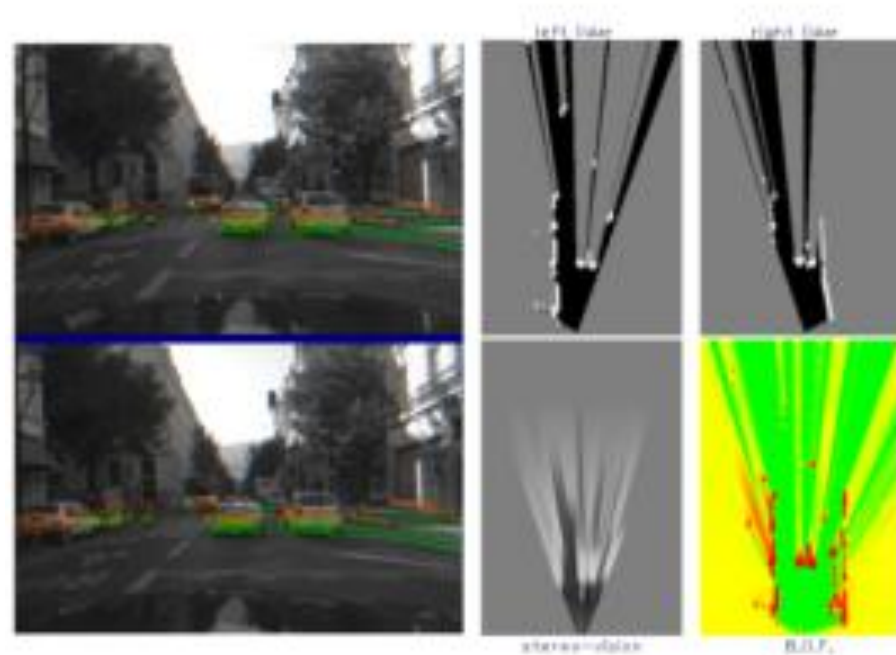
## *Multiple sensors Fusion (Stereo vision & Lidars)*



[Perrollaz et al 10] [Laugier et al ITSM 11]  
*IROS Harashima Award 2012*



*Stereo Vision*  
(*U-disparity OG + Road / Obstacles classification*)



*Bayesian Sensor Fusion (Stereo Vision + Lidars)*



# Recent implementations & Improvements

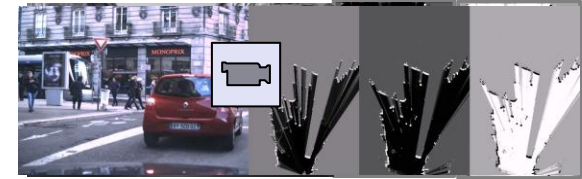
Several implementations (models & algorithms) more and more adapted to **Embedded constraints & Scene complexity** :

[Negre et al 14] [Rummelhard et al 14]

## ❖ Hybrid Sampling Bayesian Occupancy Filter (HSBOF, 2014)

- ✓ *Reducing memory size by a factor 100*
- ✓ *More efficient in complex environments*
- ✓ *Velocities estimation more accurate*

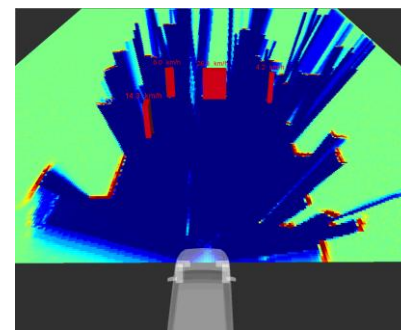
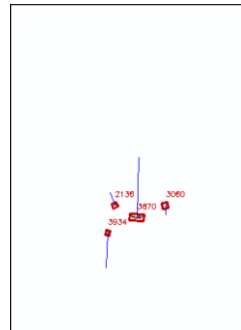
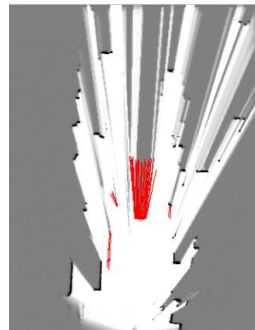
=> *using Particles & Motion data from vehicle (IMU + Odometry)*



[Rummelhard et al 15]

## ❖ Conditional Monte-Carlo Dense Occupancy Tracker (CMCDOT, 2015)

- ✓ *Increasing efficiency using “state data” (Static, Dynamic, Empty, Unknown)*
- ✓ *Incorporating a “Dense Occupancy Tracker” (using particles propagation & ID)*





# CMCDOT Detection & Tracking results



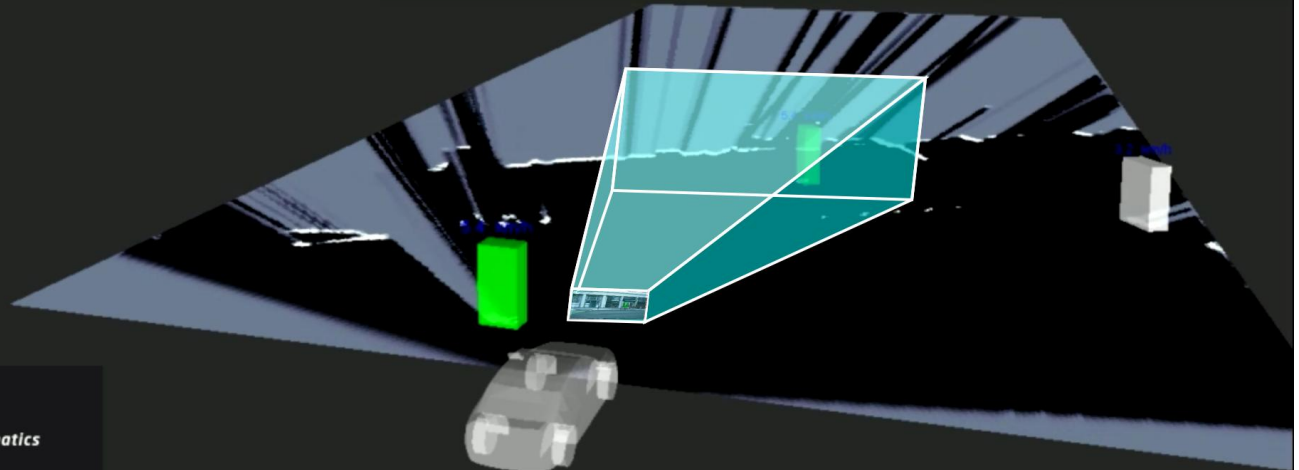
## Moving Object Classification

Pedestrian

Bicycle

Vehicle

Other

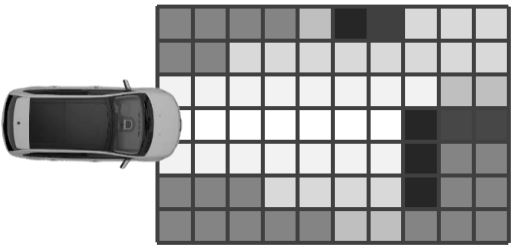
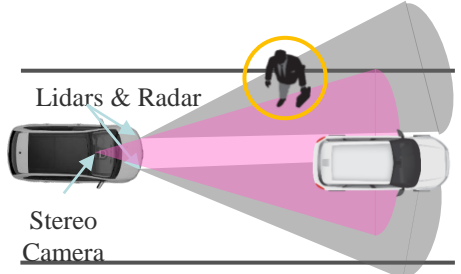


informatics mathematics  
*Inria*



# Software / Hardware Integration – Motivation

PhD Tiana Rakotova



~ Billions Floating-point operations per sec

- OGs in practice:
- High number of cells
  - Several sensors

Hardware accelerators

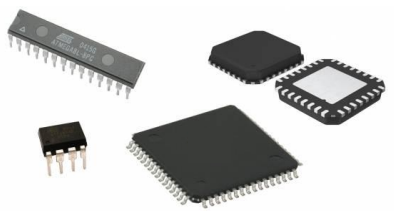


High-end GPUs & CPUs

Not adapted for automotive industry



Microcontroller, FPGA

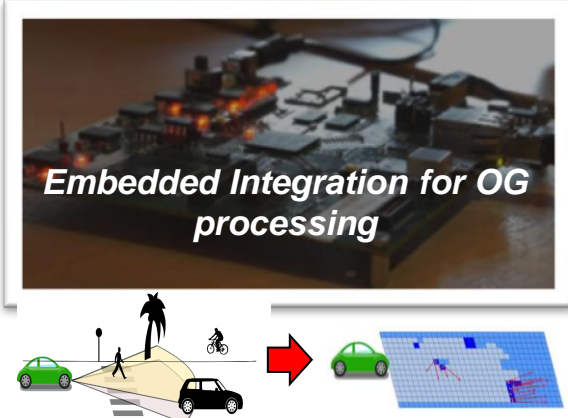


How to integrate computing requirements of OGs into embedded ECUs ?

# Software / Hardware Integration – Characteristics

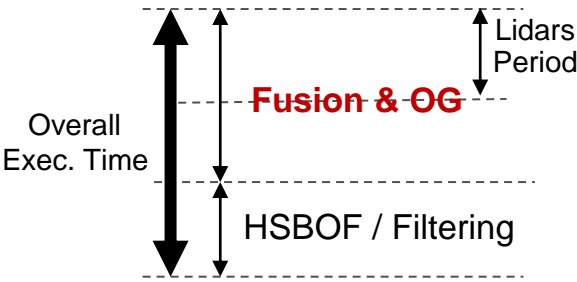
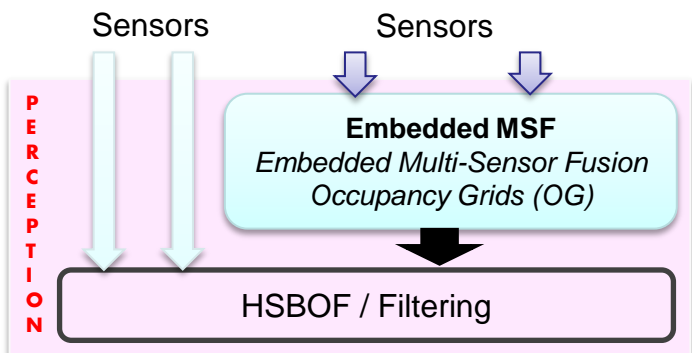
PhD Tiana Rakotova

**The challenge:** How to cope with contradictory requirements & constraints ?



- **Embedded characteristics:** *Low computing power, Low memory space, Low bandwidth*
- **Embedded constraints:** *Low purchase cost, Low energy consumption, Small physical size*
- **Algorithmic constraints:** *High computing requirement, High memory space & bandwidth requirement*

## Time Performance Analysis

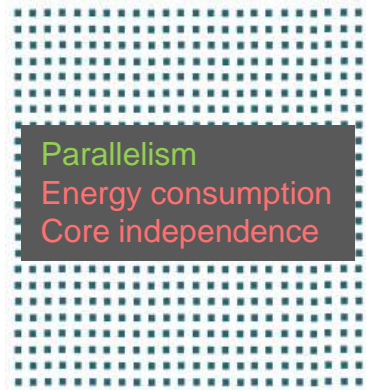
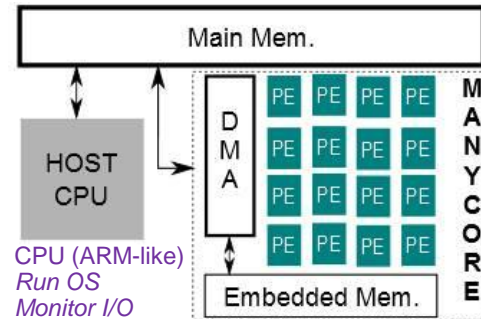


**HW Accelerator**  
=> Focus on Embedded Multi-Sensor Fusion



## Some Embedded Hardware characteristics

**Many-Core:** Hardware accelerator with several cores called Processing Elements (PE)



GPGPUs



Many-Core



CPUs

## MSF - HSBOF on Embedded Many-Core

=> Improvement factor 6 of “Energy consumption/performance ratio” [1]

Architecture	Performance	OG Rate	Energy consumption
GPGPU	94 ms	10.6 Hz ✓	12 W ✗
<b>Many-core</b>	<b>119 ms</b>	<b>8.4 Hz ✗</b>	<b>0,6 W ✓</b>
Multi-core	210 ms	4.7 Hz	2 W

First step toward an industrial solution



Inria /Toyota Lexus (2 Lidars @ 25Hz)

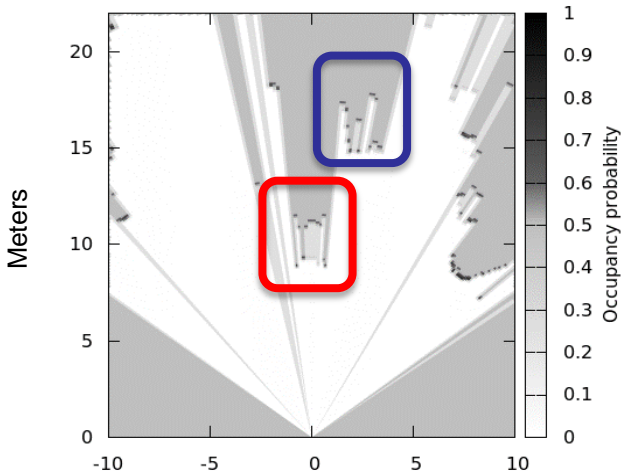
# Software / Hardware Integration – $\mu$ Controller

PhD Tiana Rakotovao

## MSF - HSBOF on $\mu$ Controller [2][3]

- ⇒ Low Cost / Energy / Size (widely used in Industrial product)
- ⇒ Implementation based on **Integer Arithmetic** (Quantized Occupancy Probability)
- ⇒ Time performance: **increase factor 5-10**
- ⇒ Energy Consumption: **decrease factor 100**
- ⇒ See details in [2]

Inria /Renault Zoé (4 Lidars @ 25Hz)



Multi-Sensor Fusion on  $\mu$ Controller

**ARM Cortex-M3 @48MHz**

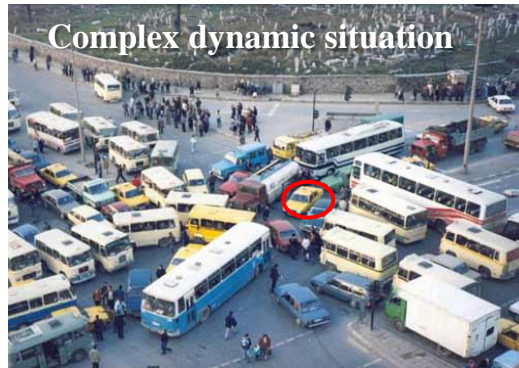
- No floating-point
- Power consumption < 1Watt
- Low-cost < 2 €



[2] T. Rakotovao, et al. Multi-Sensor Fusion of Occupancy Grids based on Integer Arithmetic. IEEE ICRA 2016  
[3] Patent application

# Key Technology 2: Risk Assessment & Decision

=> Decision-making for avoiding Pending & Future Collisions



## □ Main difficulties

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

## □ Approach: Prediction + Risk Assessment + Bayesian Decision

- Reasoning about *Uncertainty & Contextual Knowledge (History & Prediction)*
- *Avoiding Pending & Future collisions (Probabilistic Collision Risk at  $t+\delta$ )*
- *Decision-making by taking into account the Predicted behavior of the observed mobile agents (cars, cycles, pedestrians ...) & Social / Traffic rules*



# Step 1: Short-term collision risk – Outline

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

## Objective:

- *Detect “Risky Situations” a few seconds ahead*
- *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  $t + \delta$ )*

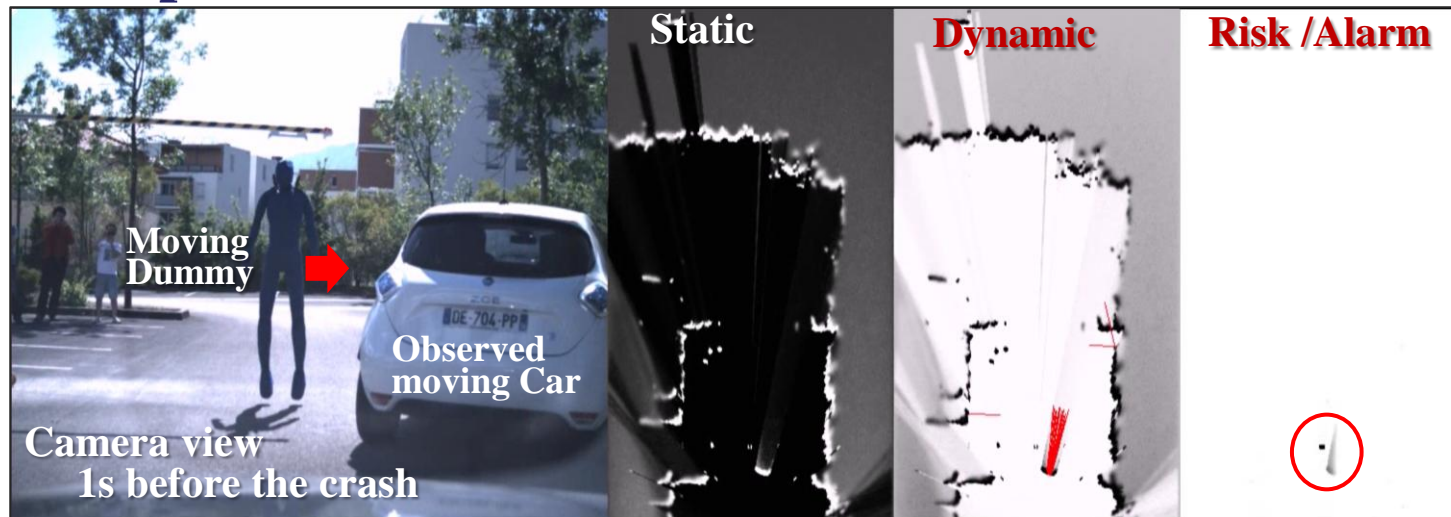
*Proximity perception:  $d < 100m$  and  $t < 5s$*

*$\delta = 0.5s$  => Precrash*

*$\delta = 1s$  => Collision mitigation*

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

## System outputs:



# Step 1: Short-term collision risk – Experimental results



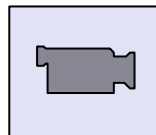
## Urban street experiments

=> *Almost no false alarm in complex dynamic scenes (car, pedestrians...)*



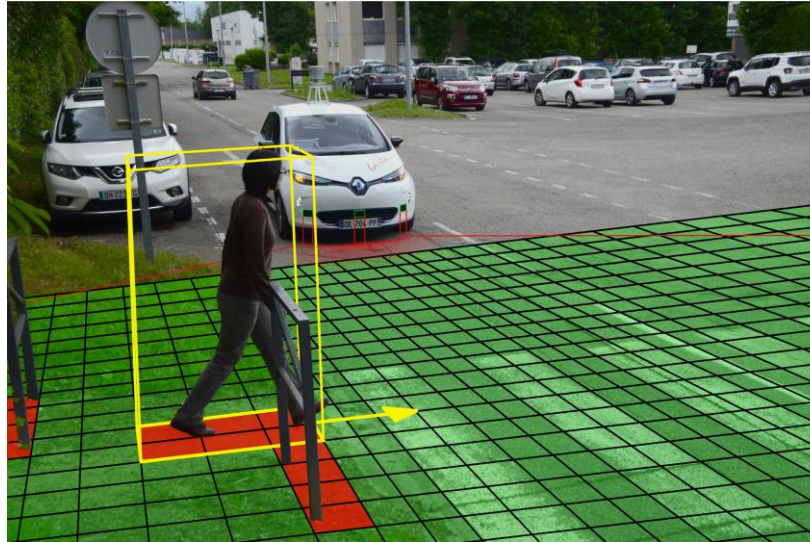
## Crash scenario on test tracks

=> *Almost all collisions predicted before the crash (0.5 – 2 s before)*

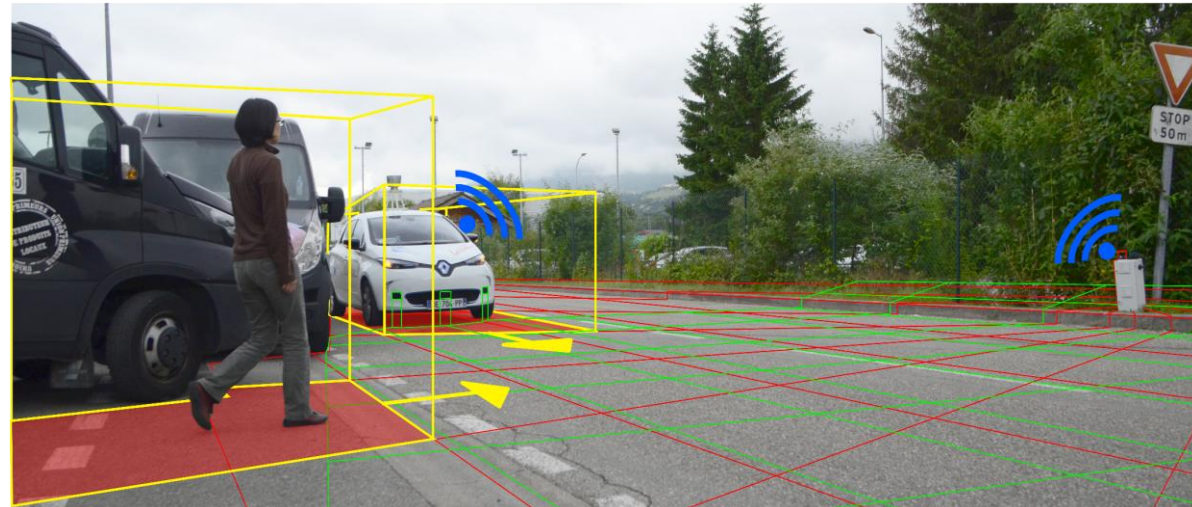
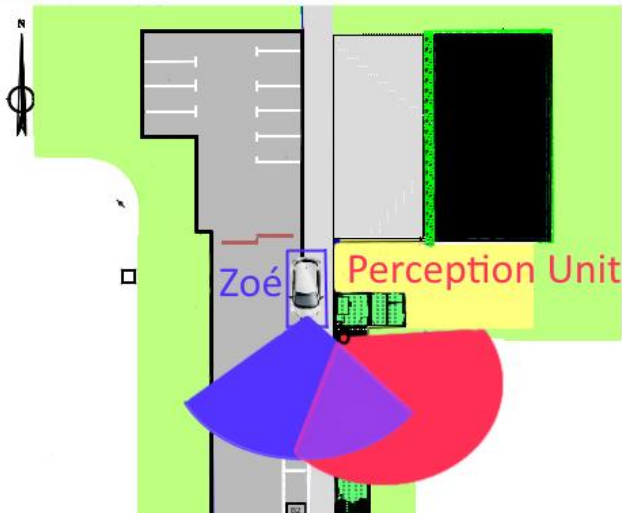




# Distributed Perception using V2X & Collision risk



Detection & Collision Risk  
using embedded Perception



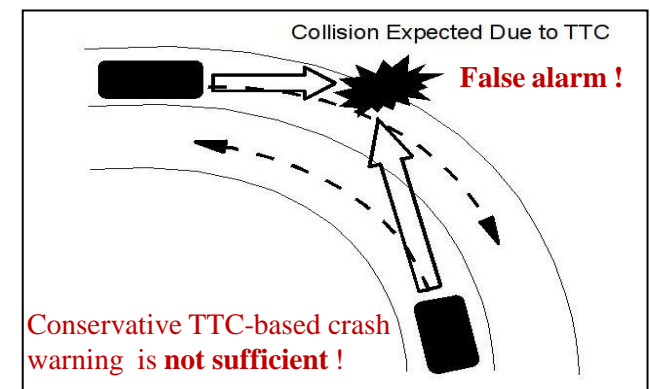
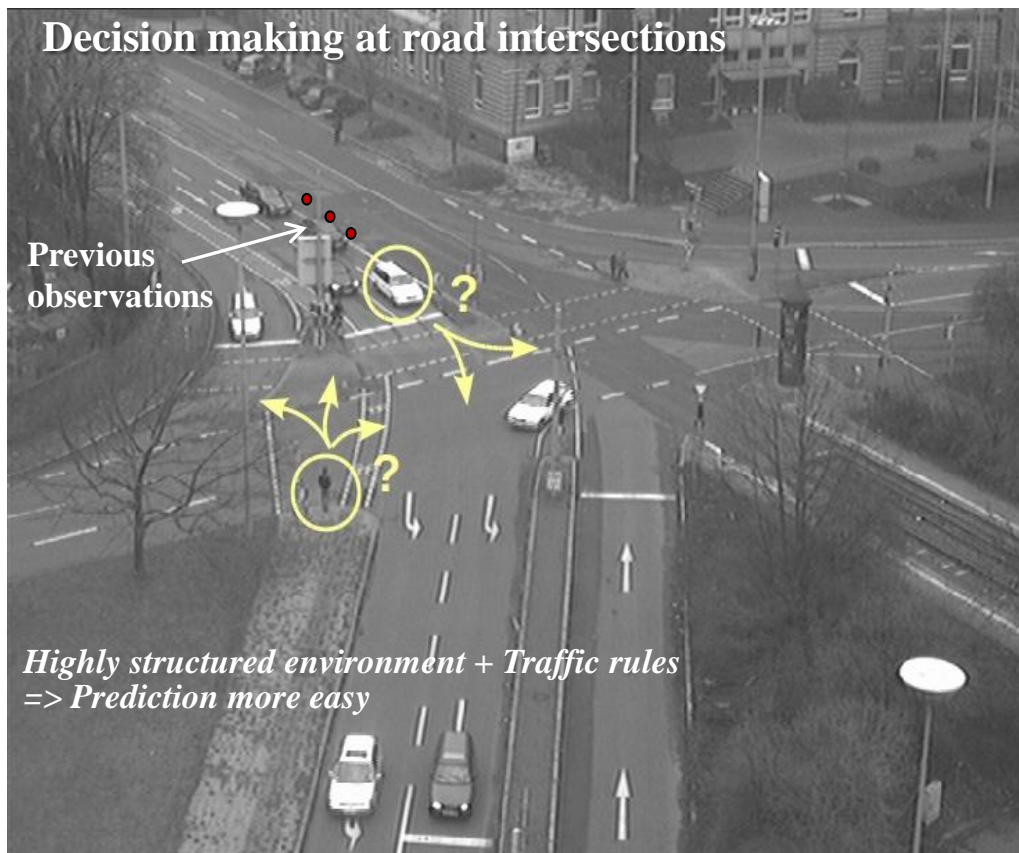
Detection & Collision Risk  
using Infrastructure Sensors & V2X



# Step 2: Generalized Risk Assessment (Object level)

=> Increasing time horizon & complexity using context & semantics

- => Understand the **Current Situation** & its **likely Evolution** (on a given time horizon)
- => Evaluate the **Risk** of future Collision (more complex maneuvers & trajectories)
- => Highly structured environment & Traffic rules make Prediction more easy



**Context & Semantics**  
(History + Space geometry + Traffic rules)

+

**Behavior Prediction**  
For all surrounding traffic participants

+

**Probabilistic Risk Assessment**

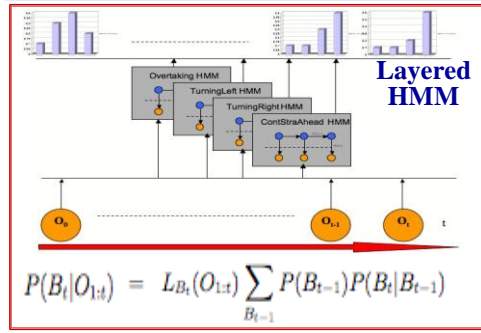
# Behavior-based Collision risk (Object level)

## Approach 1: Trajectory prediction & Collision Risk Assessment

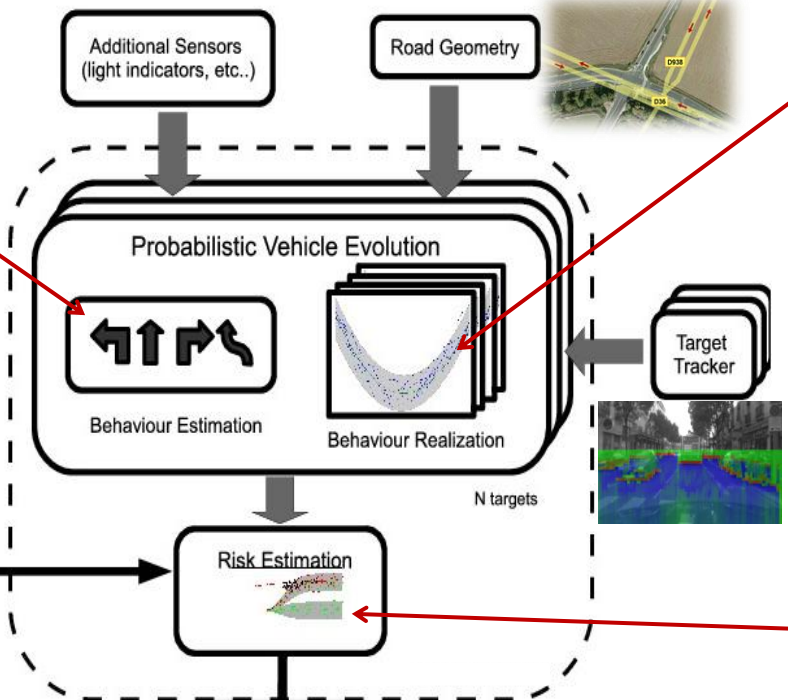
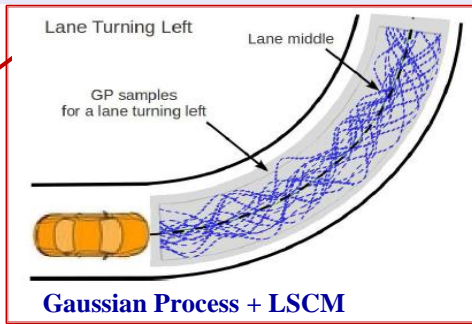
[Tay thesis 09] [Laugier et al 11]

Patent Inria & Toyota & Probayes 2010

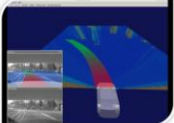
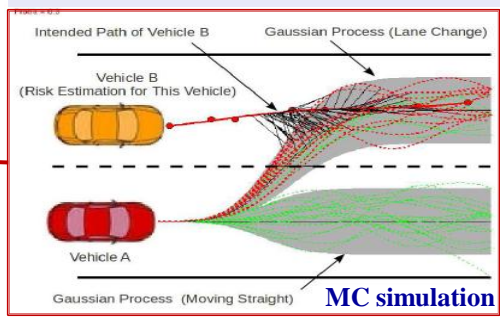
### Behavior modeling & learning Behavior Prediction



### From behaviors to trajectories



### Collision risk assessment (Probabilistic)



**Experimental results**  
**Behavior prediction & Risk Assessment on highways**  
 Probayes & Inria & Toyota

# Behavior-based Collision risk (*Object level*)

## Approach 2: Intention & Expectation comparison

=> Complex scenarios with *interdependent behaviors & human drivers*



[Lefevre thesis 13] [Lefevre & Laugier IV'12, Best student paper]

Patent Inria & Renault 2012 (*risk assessment at road intersection*)

Patent Inria & Berkeley 2013 (*postponing decisions for safer results*)



## A Human-like reasoning paradigm => Detect Drivers Errors & Colliding behaviors

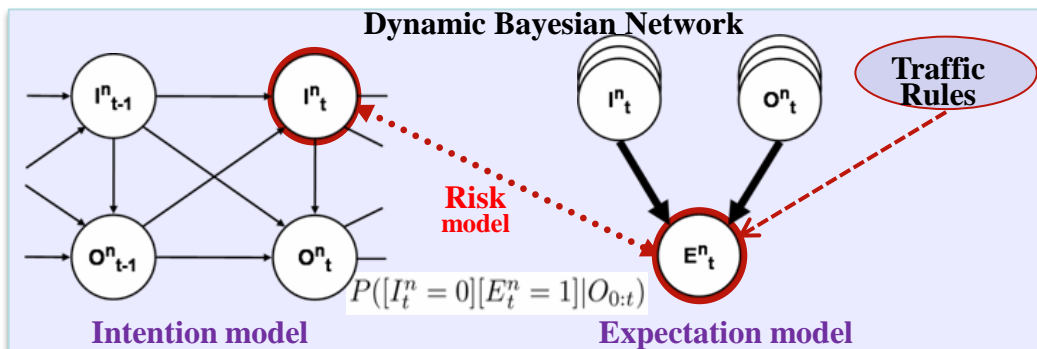
✓ Estimating “Drivers Intentions” from Vehicles States Observations ( $X Y \theta S TS$ ) => Perception or V2V

✓ Inferring “Behaviors Expectations” from Drivers Intentions & Traffic rules

✓ Risk = Comparing Maneuvers Intention & Expectation

=> Taking **traffic context** into account (Topology, Geometry, Priority rules, Vehicles states)

=> **Digital map** obtained using “Open Street Map”

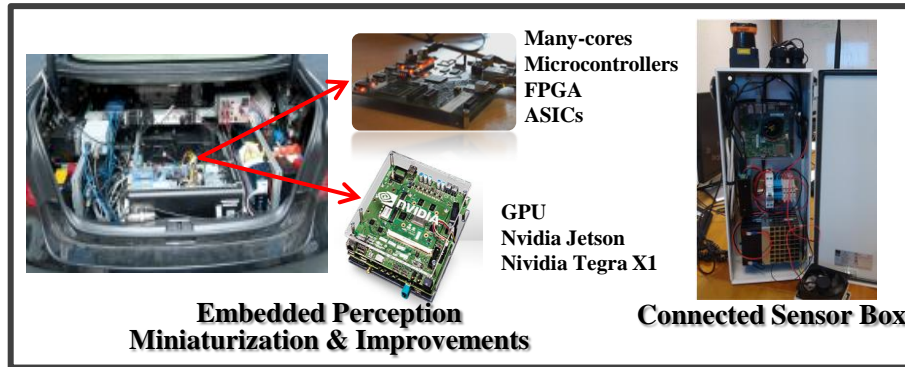




# Current & Future work

## Approaches for Software & Hardware integration (*Embedded Perception*)

=> Reduce drastically Size, Weight, Energy consumption, Cost ... while improving Efficiency



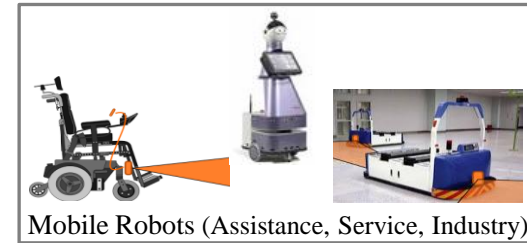
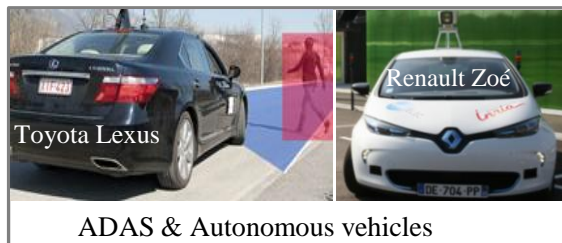
CPU (2006) GPU (2010) Many-cores & GPU low power (2015)

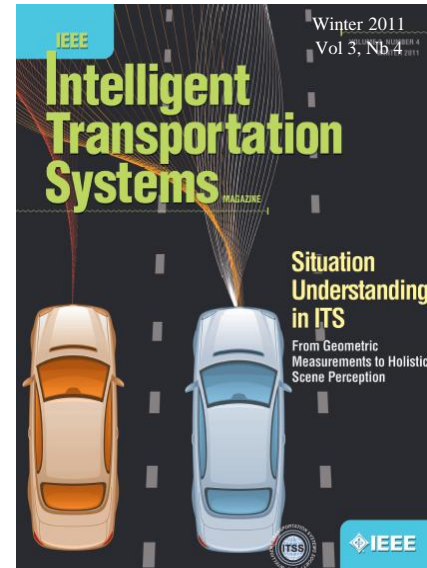
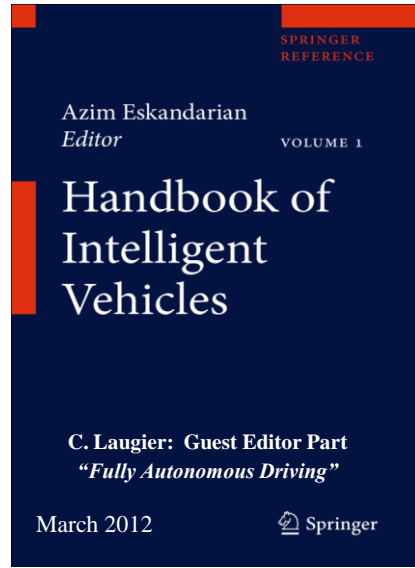
Improved Bayesian algorithms  
Integration on Lightweight Hw (2016-17) Dedicated Hw / Sw integration (2018-20)

*Coop. CEA & IRT Nanoelec (common projects & PhD student)*

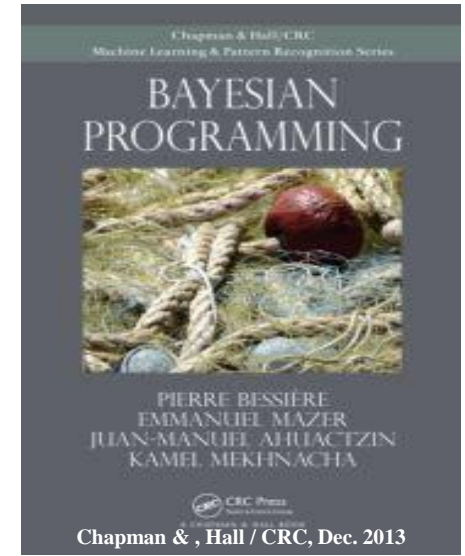
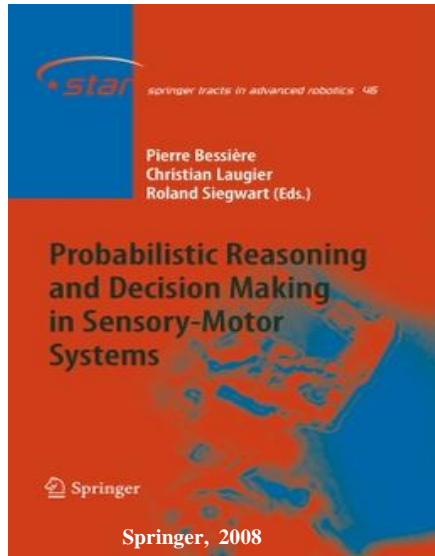
## Technologies for Intelligent Mobility (*Perception + Decision + Control + Learning*)

- ✓ Learning driving skills & Autonomous Driving (2 PhD) => *Berkeley & Renault + Toyota (2015-17)*
- ✓ Human-Aware mobility in crowded environments (PhD) => *ANR Valet + PIA Valeo (2016-18)*
- ✓ Certification of Embedded Perception Systems (Postdoc) => *EU ENABLE-S3 (2016-19)*
- ✓ Connected Sensors & Lightweight Hw for Mobile Systems (PhD + Postdoc) => *IRT nanoelec (2016-17)*





**Thank You  Any questions ?**



christian.laugier@inria.fr