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Intelligent Perception and Situation Awareness for Automated vehicles

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► **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

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Intelligent Perception and Situation Awareness for Automated vehicles

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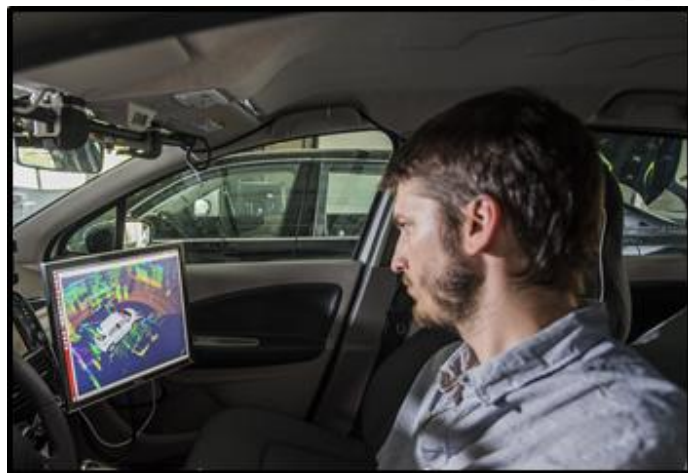
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ADAS & Autonomous Driving



**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



ADAS & Autonomous Driving

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

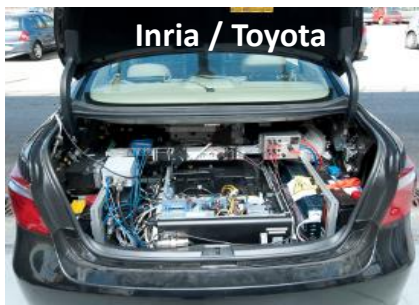
- ❑ Perception for Autonomous Vehicles: *New trend of automotive industry !*



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 !



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



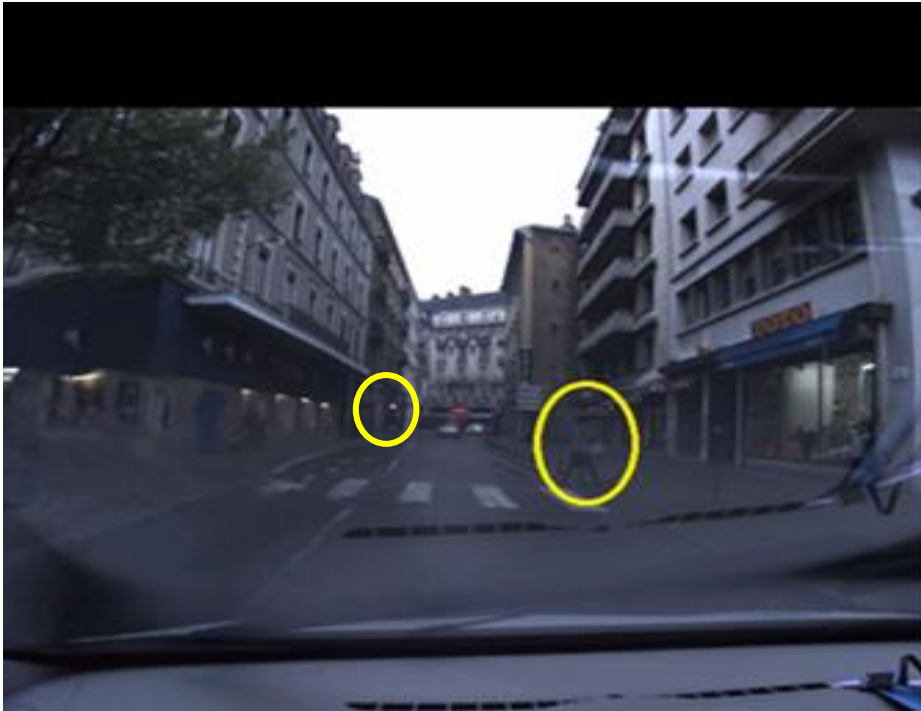
Driverless Taxi testing in Pittsburgh (Uber) & Singapore (nuTonomy)

=> Numerous Sensors & Engineer in the car during testing

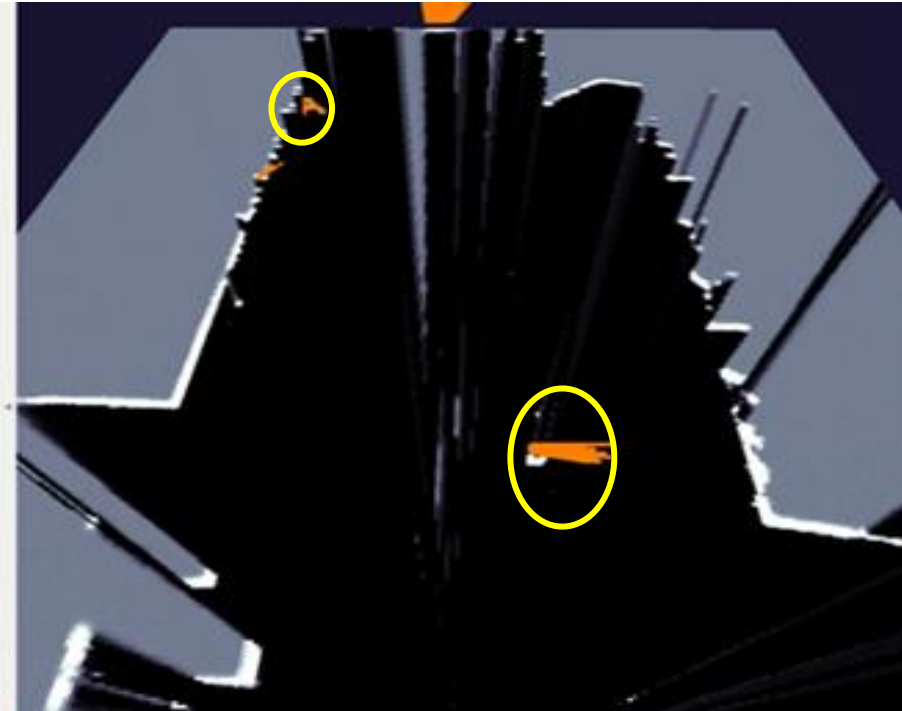


Improving robustness using Multi-modality sensing

Camera Image at Dusk (Pedestrians not detected)



Processed Lidar data (Pedestrians detected)



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

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

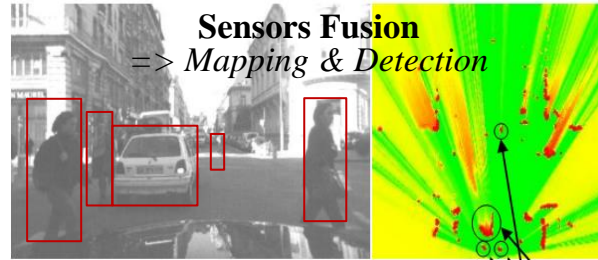
- Develop **Robust & Efficient Multi-Sensor Fusion** approaches using probabilistic models
- **Good news:** A new generation of **affordable “Solid State Lidars”** will arrive soon on the market !
 - => No mechanical component & Expected cost less than 1000 US\$
 - => Numerous announcements since Spring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

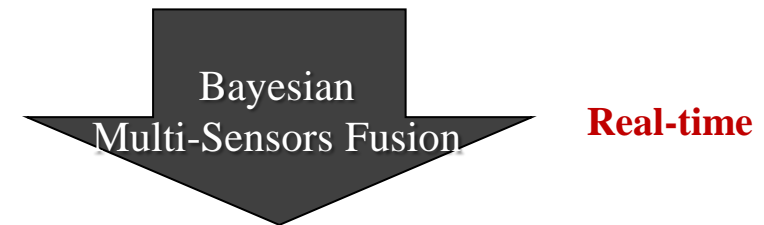
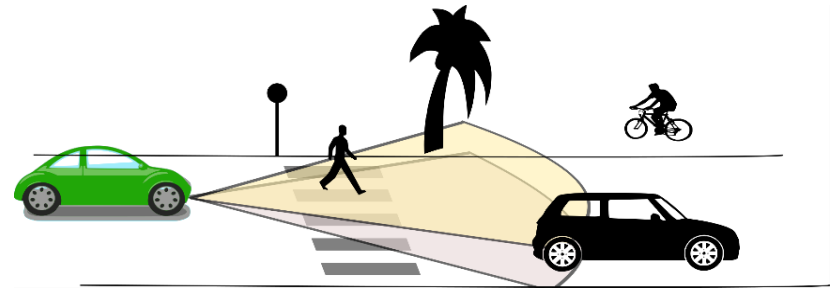
❑ Approach: Embedded Bayesian Perception

- ✓ *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

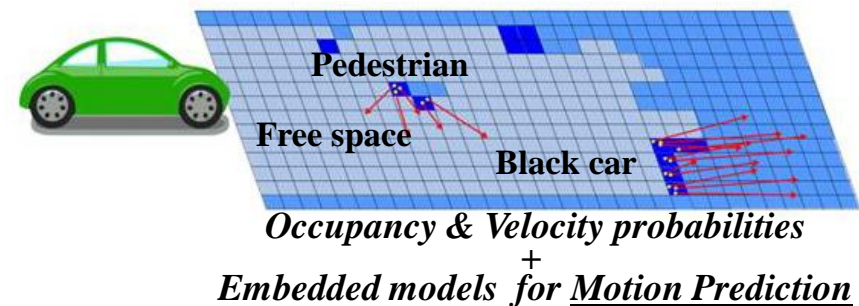
Lidar, Radar, Stereo camera, IMU ...



□ Probabilistic Environment Model

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

$P[o|Z,C]$:  ≈ 0  ≈ 0.5  ≈ 1



□ Main philosophy

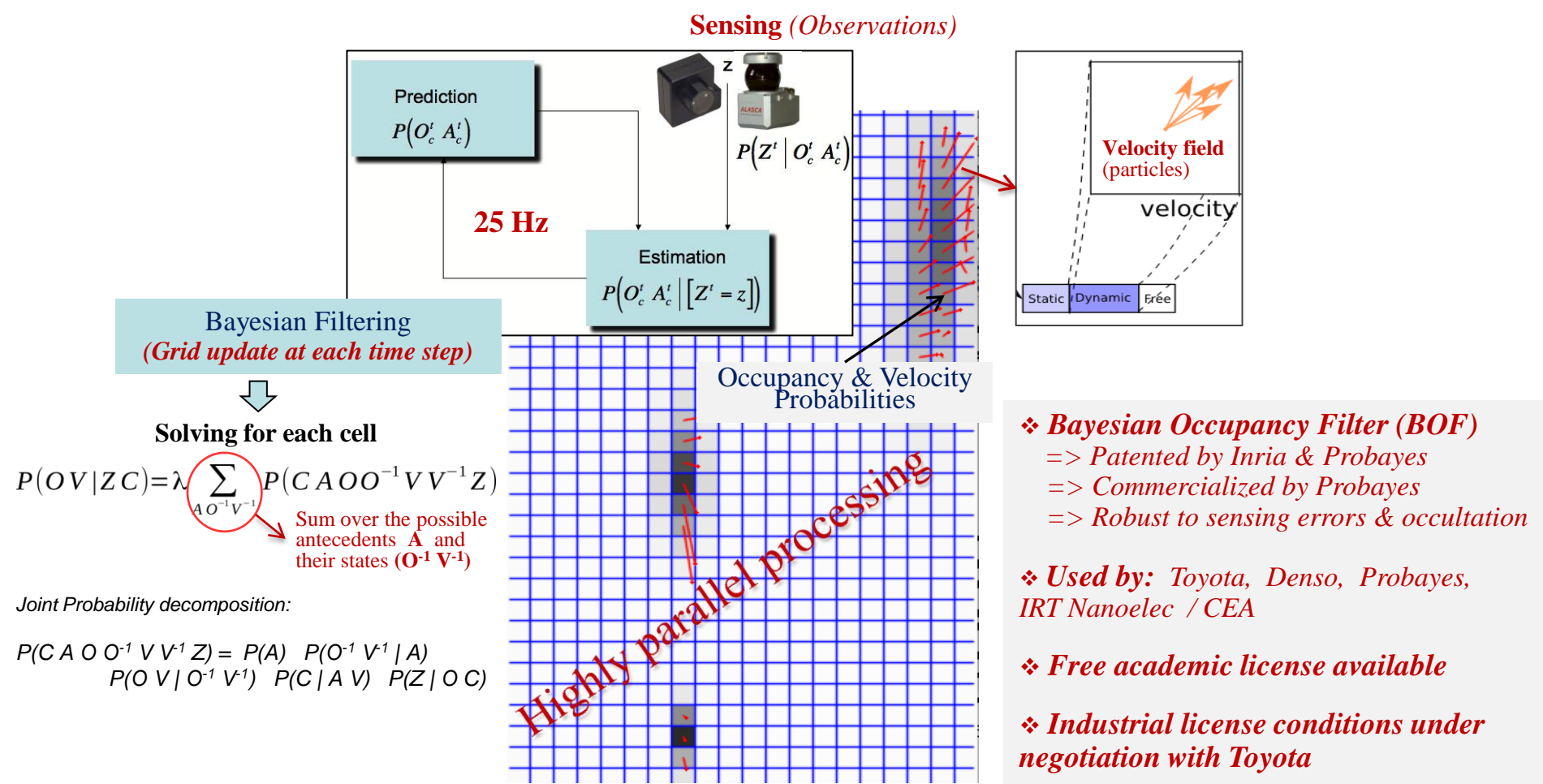
Reasoning at the grid level as far as possible for both :

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

A new framework: *Dynamic Probabilistic Grids*

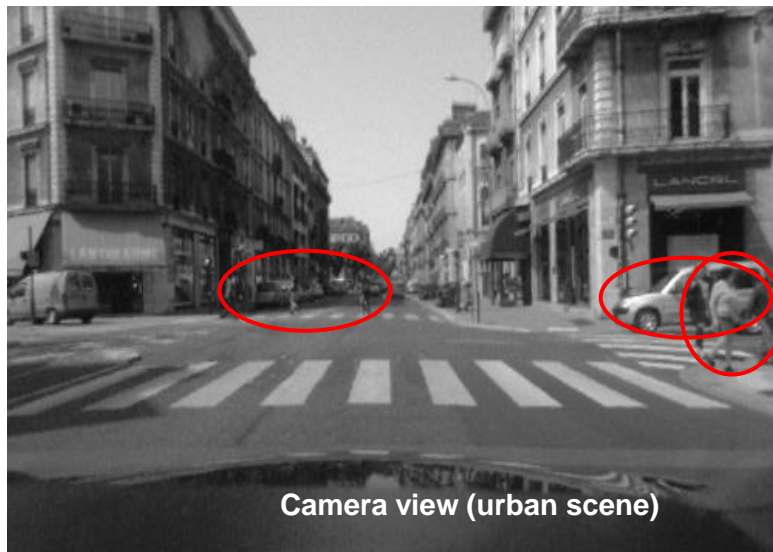
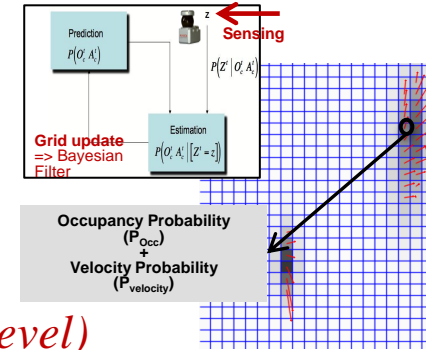
=> A clear distinction between Static & Dynamic & Free components

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

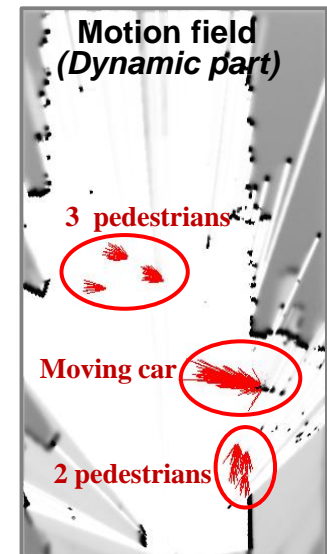


Bayesian Occupancy Filter (BOF) – Main Features

- 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 !

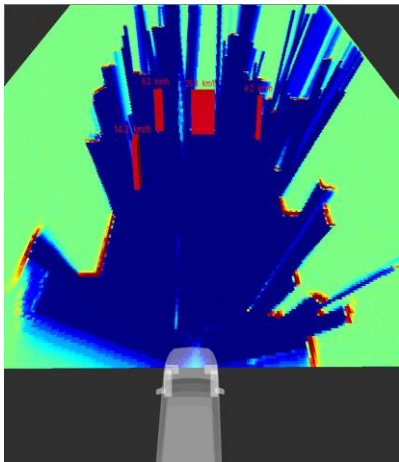


Recent implementations & Improvements

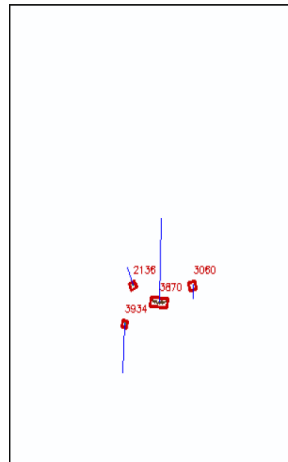


Several implementations (models & algorithms) more and more adapted to *Embedded constraints & Scene complexity*

- ❖ 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

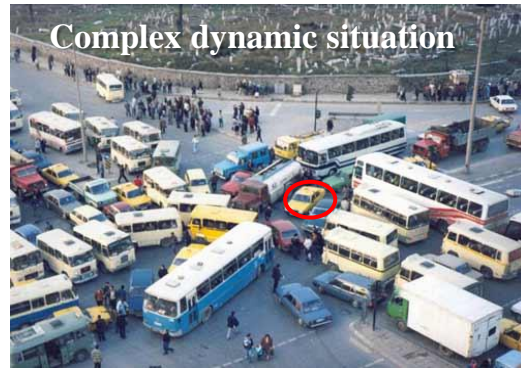


Classification (using Deep Learning)

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

$\delta = 0.5s$ => Precrash

$\delta = 1s$ => Collision mitigation

$\delta > 1.5s$ => 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



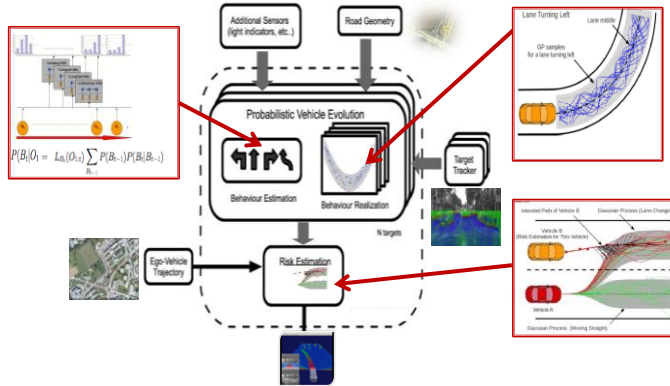
Highly structured environment + Traffic rules
=> Prediction more easy

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

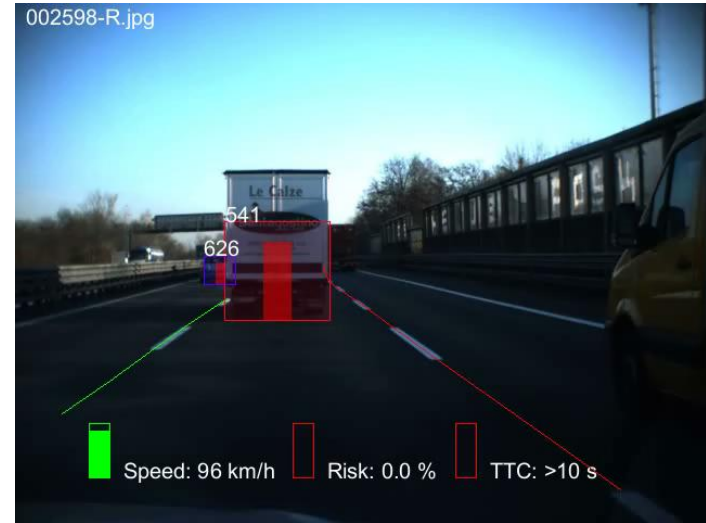
□ Trajectory prediction & Collision Risk => Patent Inria -Toyota - ProbaYes 2010



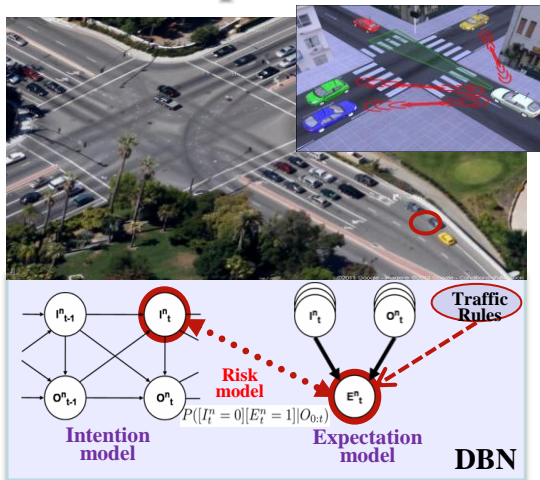
Inria

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



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
STM 32 Cortex M7@200 MHz



Nvidia Jetson Tk1



Nvidia Jetson TX1

GPU TECHNOLOGY CONFERENCE

GTC Europe 2016

BOF

2013

HSBOF

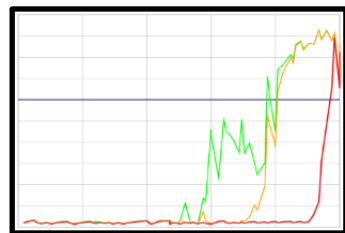
2014

CMCDOT

2015

CMCDOT *Cuda Optimization on Tegra*

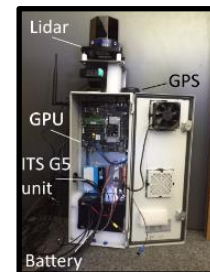
2016 - 17



Risk assessment system



Experimental Scenario



Perception Unit



Distributed Perception

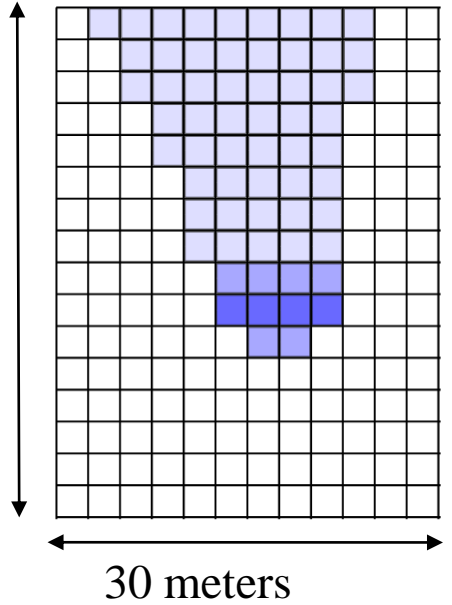


Zoe Autom. 1st Steps

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

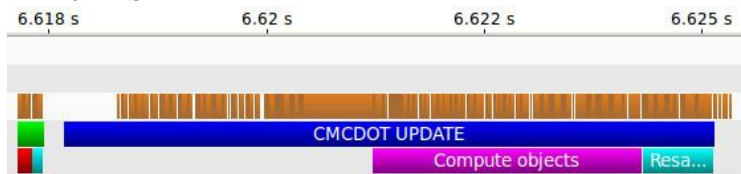
□ 1 px = 1 cell
= 10 x 10 cm



Jetson TK1: Grid Fusion 17ms, CMCDOT 70ms

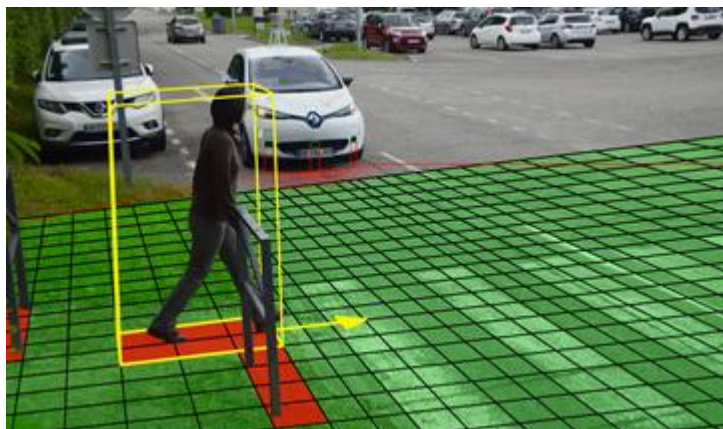


Jetson TX1: Grid Fusion 0.7ms, CMCDOT 17ms

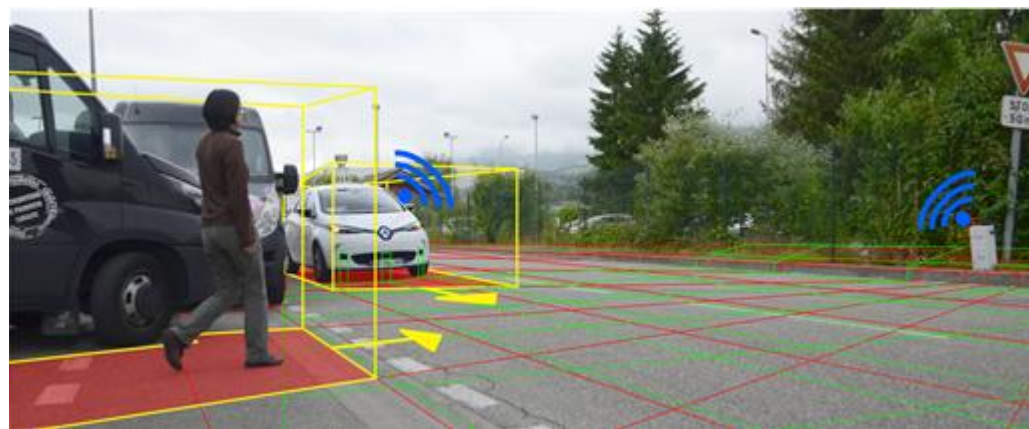


Experimental Platforms & Experiments

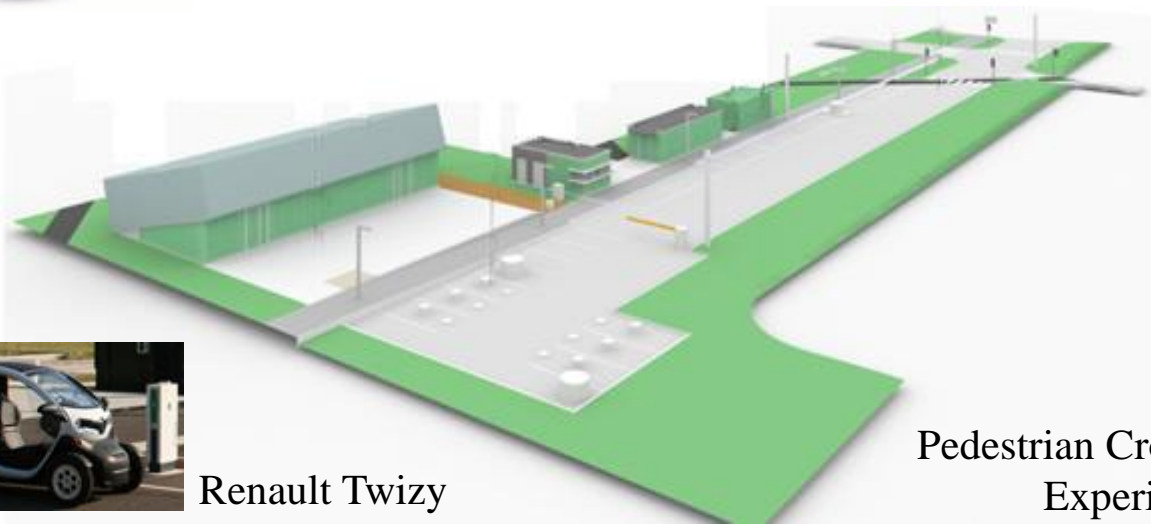
Embedded Perception



Distributed Perception



IRT Nanoelec Experimental Platform



Perception Unit



Connected Traffic Cone

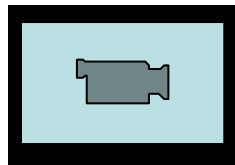
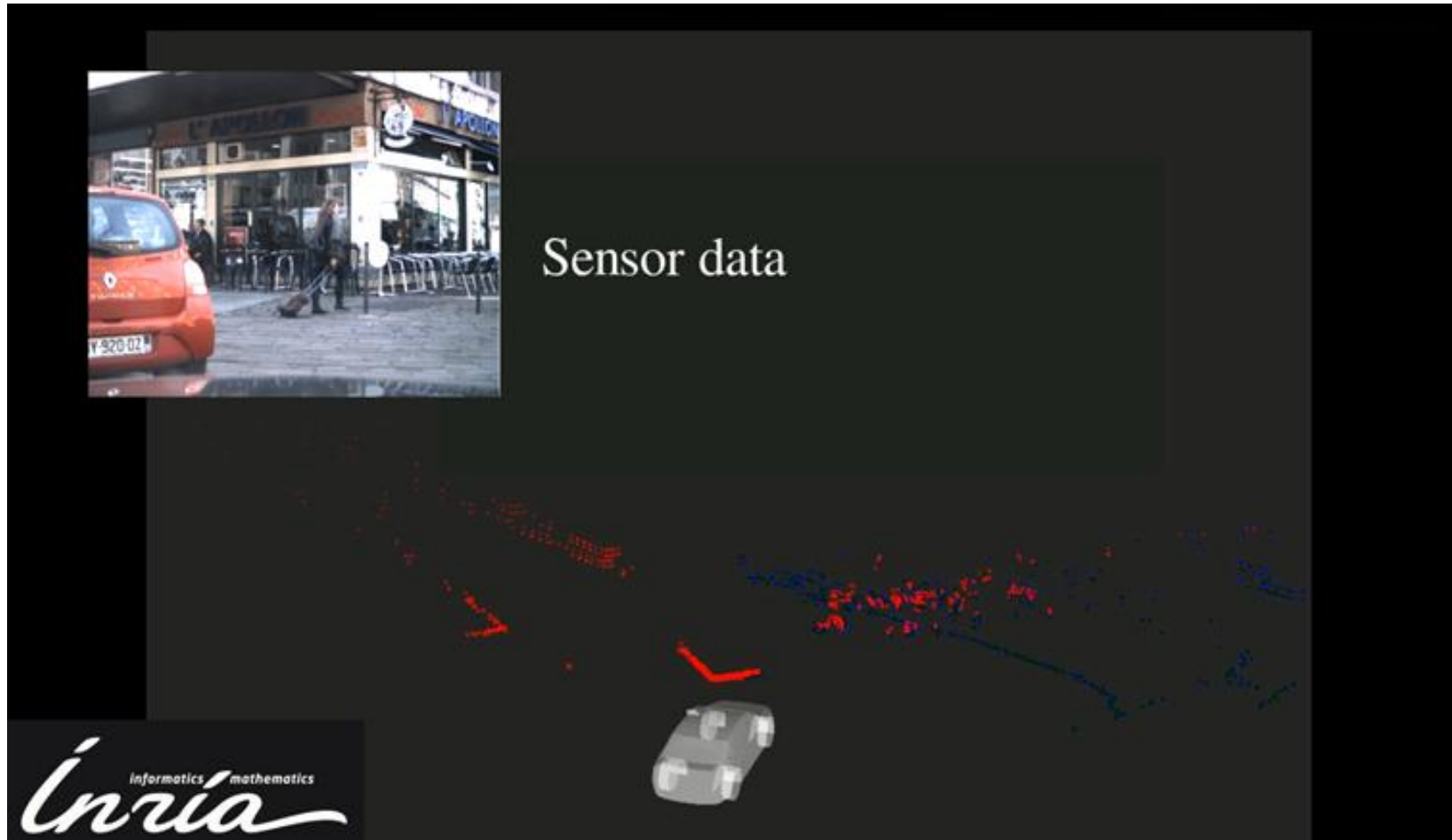


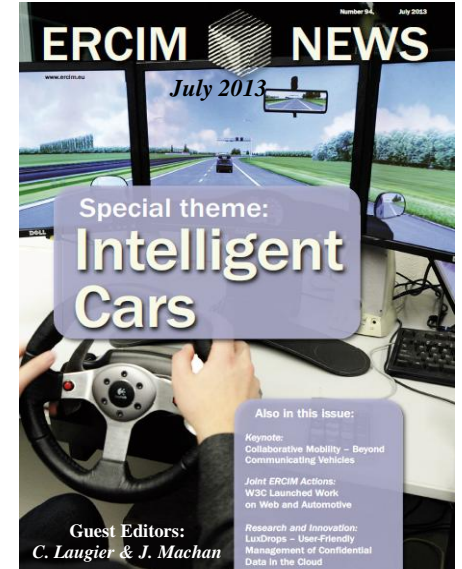
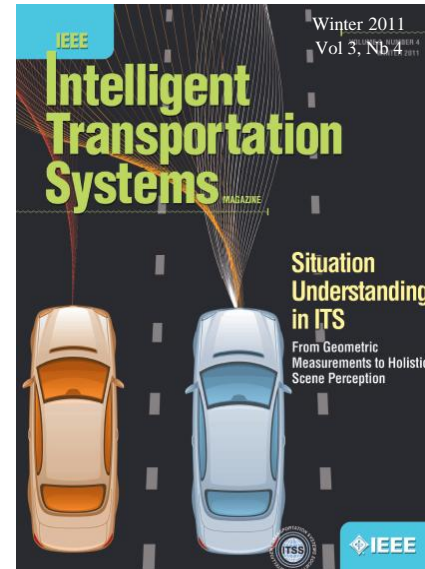
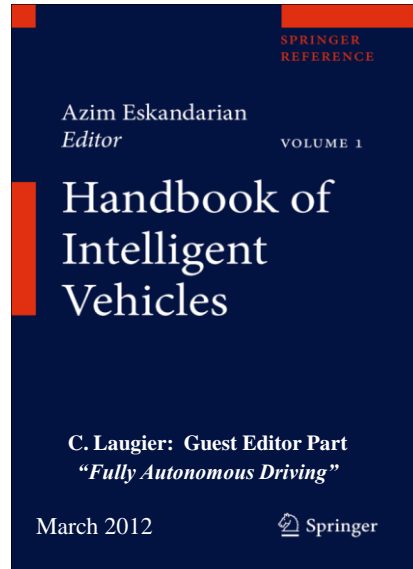
Renault Twizy

Pedestrian Crossing Experiments



Experimental results in urban environment





Thank You  Any questions ?

