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# Intelligent Perception and Situation Awareness for Automated vehicles

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# Intelligent Perception and Situation Awareness for Automated vehicles

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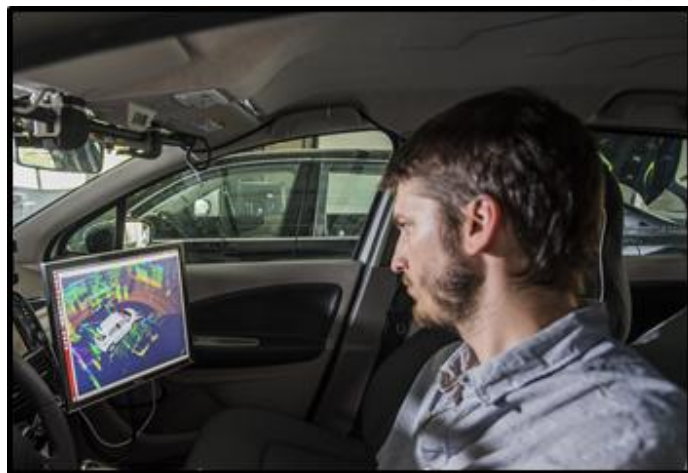
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## **ADAS & Autonomous Driving**



**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

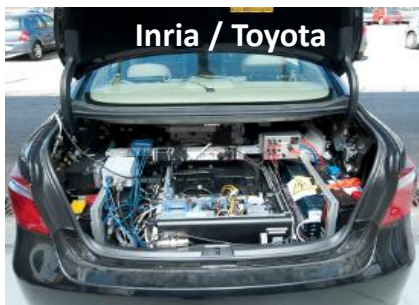
- ❑ Perception for Autonomous Vehicles: *New trend of automotive industry !*



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)

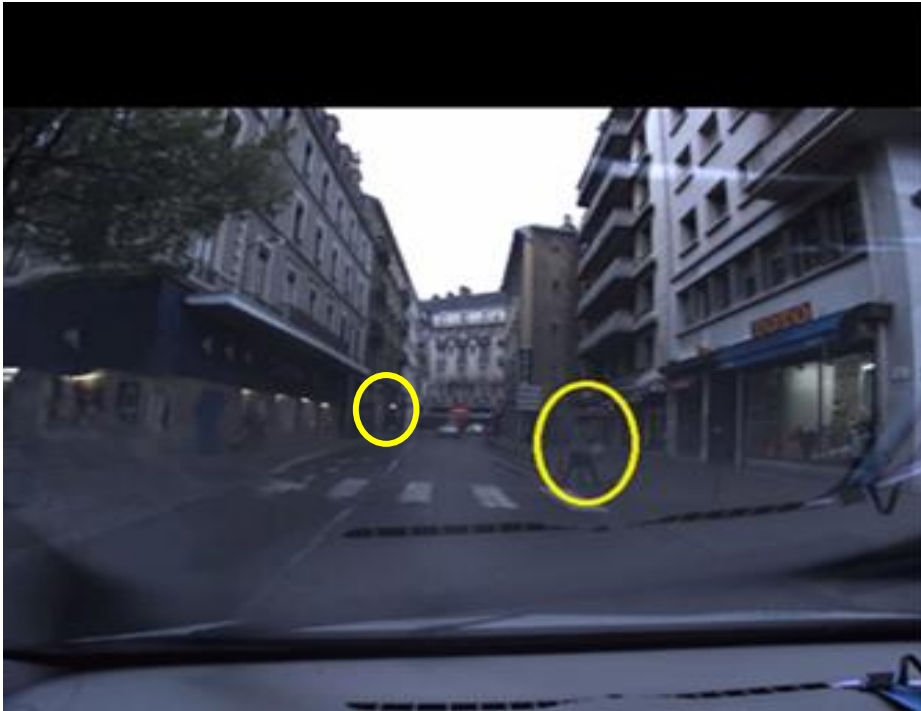
=> Numerous Sensors & Engineer in the car during testing





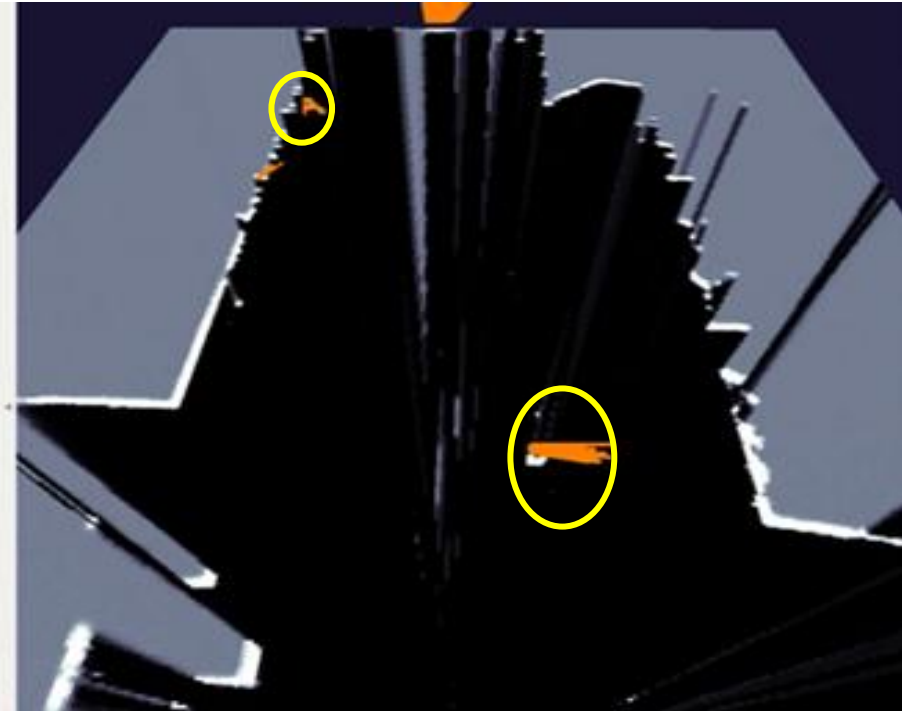
# Improving robustness using Multi-modality sensing

Camera Image at Dusk (Pedestrians not detected)



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

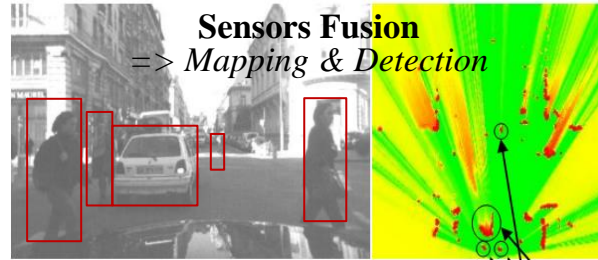
- Develop **Robust & Efficient Multi-Sensor Fusion** approaches using probabilistic models
- **Good news:** A new generation of **affordable “Solid State Lidars”** will arrive soon on the market !
  - => No mechanical component & Expected cost less than 1000 US\$
  - => Numerous announcements since Spring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

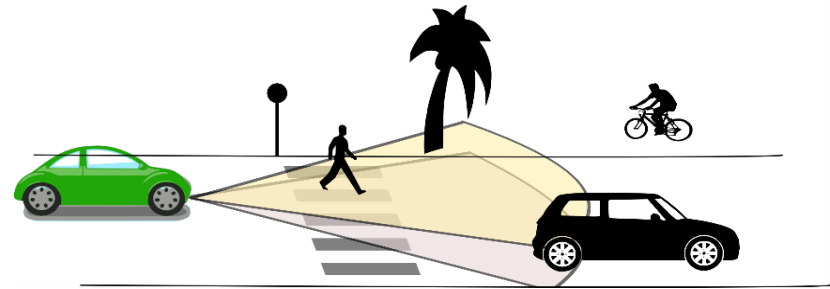
## ❑ Approach: Embedded Bayesian Perception

- ✓ *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 ...*



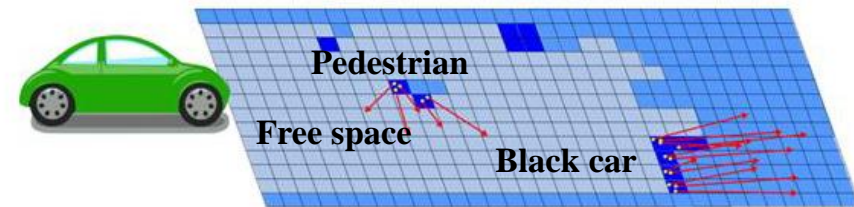
**Real-time**

## □ Probabilistic Environment Model

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

$P[o|Z,C]$  :

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



*Occupancy & Velocity probabilities*

*+ Embedded models for Motion Prediction*

## □ Main philosophy

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

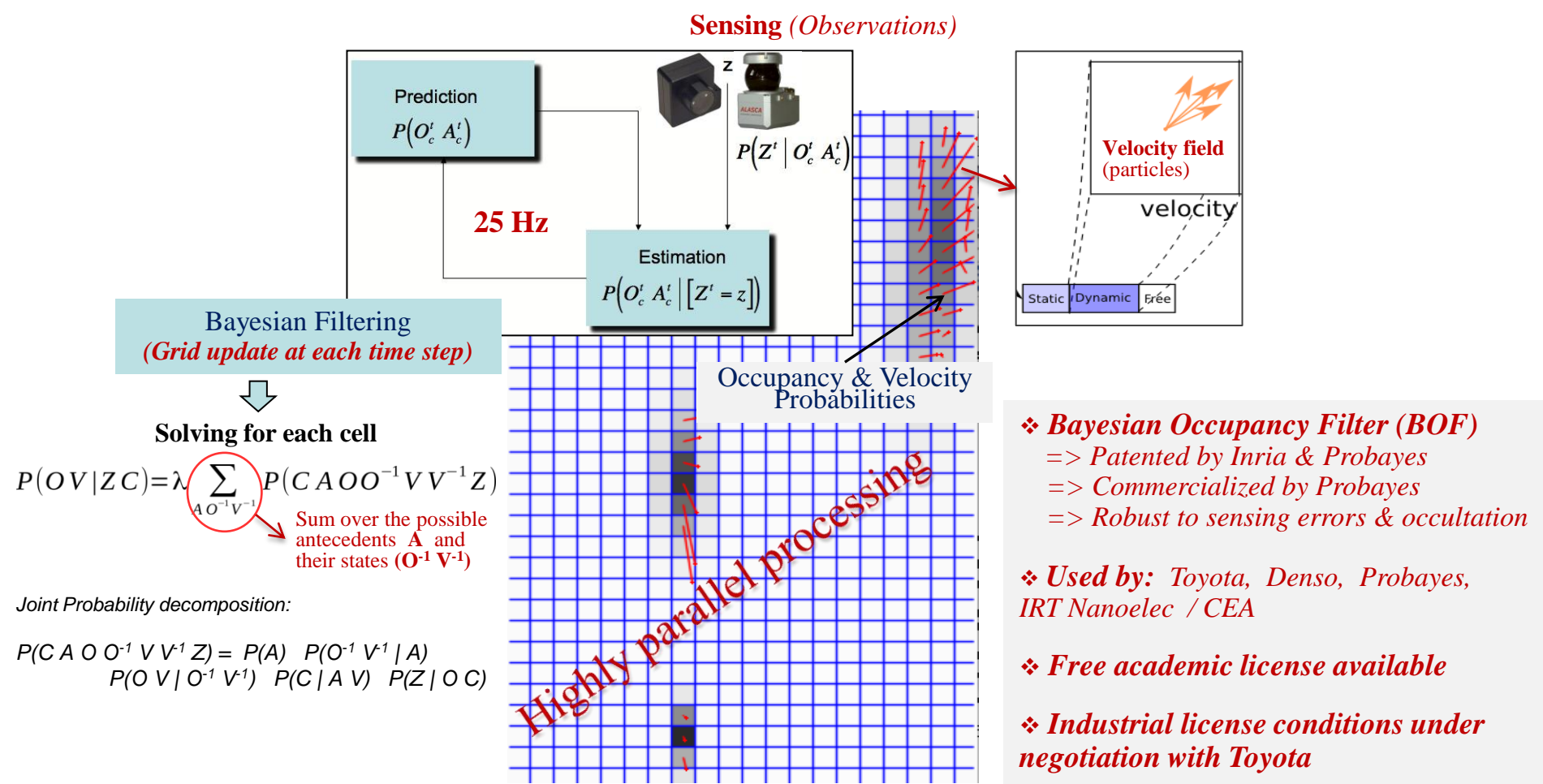
- **Improving efficiency** (highly parallel processing)
- **Avoiding traditional object level processing problems** (e.g. detection errors, wrong data association...)



# A new framework: *Dynamic Probabilistic Grids*

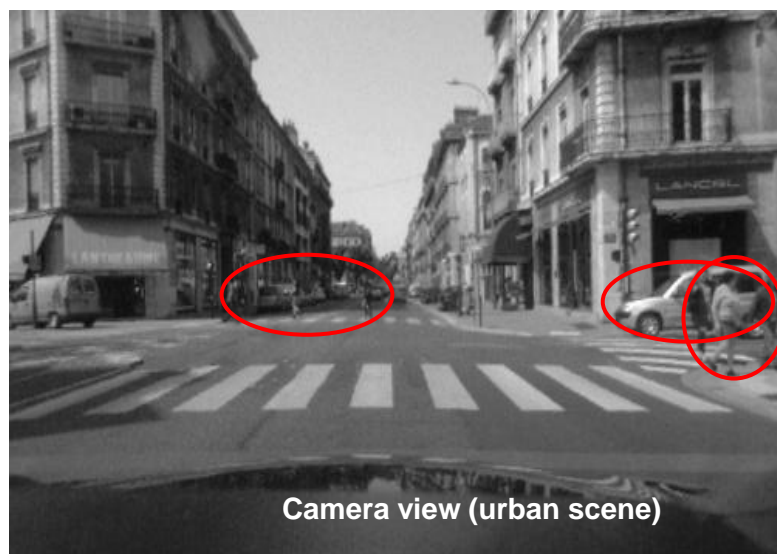
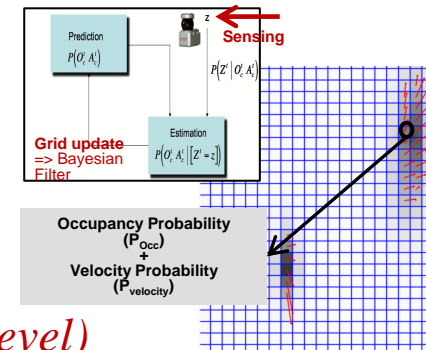
=> A clear distinction between Static & Dynamic & Free components

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

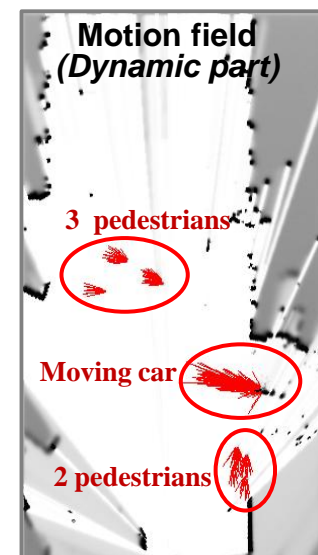


# Bayesian Occupancy Filter (BOF) – Main Features

- 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 Dynamic information !**

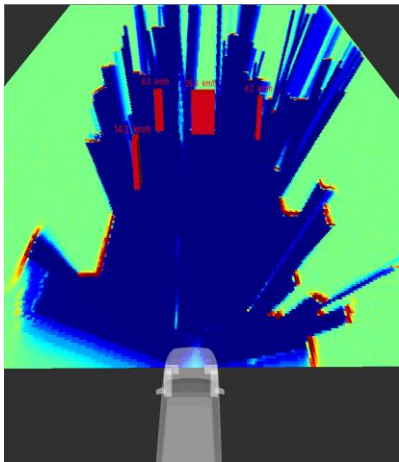


# Recent implementations & Improvements

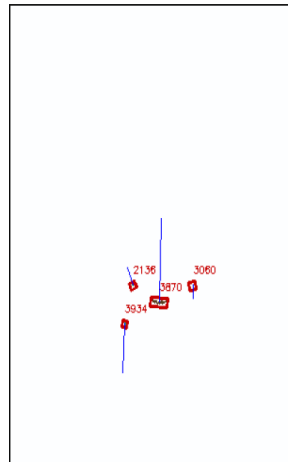


Several implementations (models & algorithms) more and more adapted to *Embedded constraints & Scene complexity*

- ❖ 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



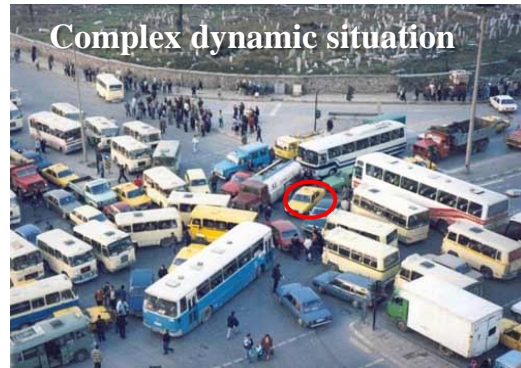
Classification (using Deep Learning)

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

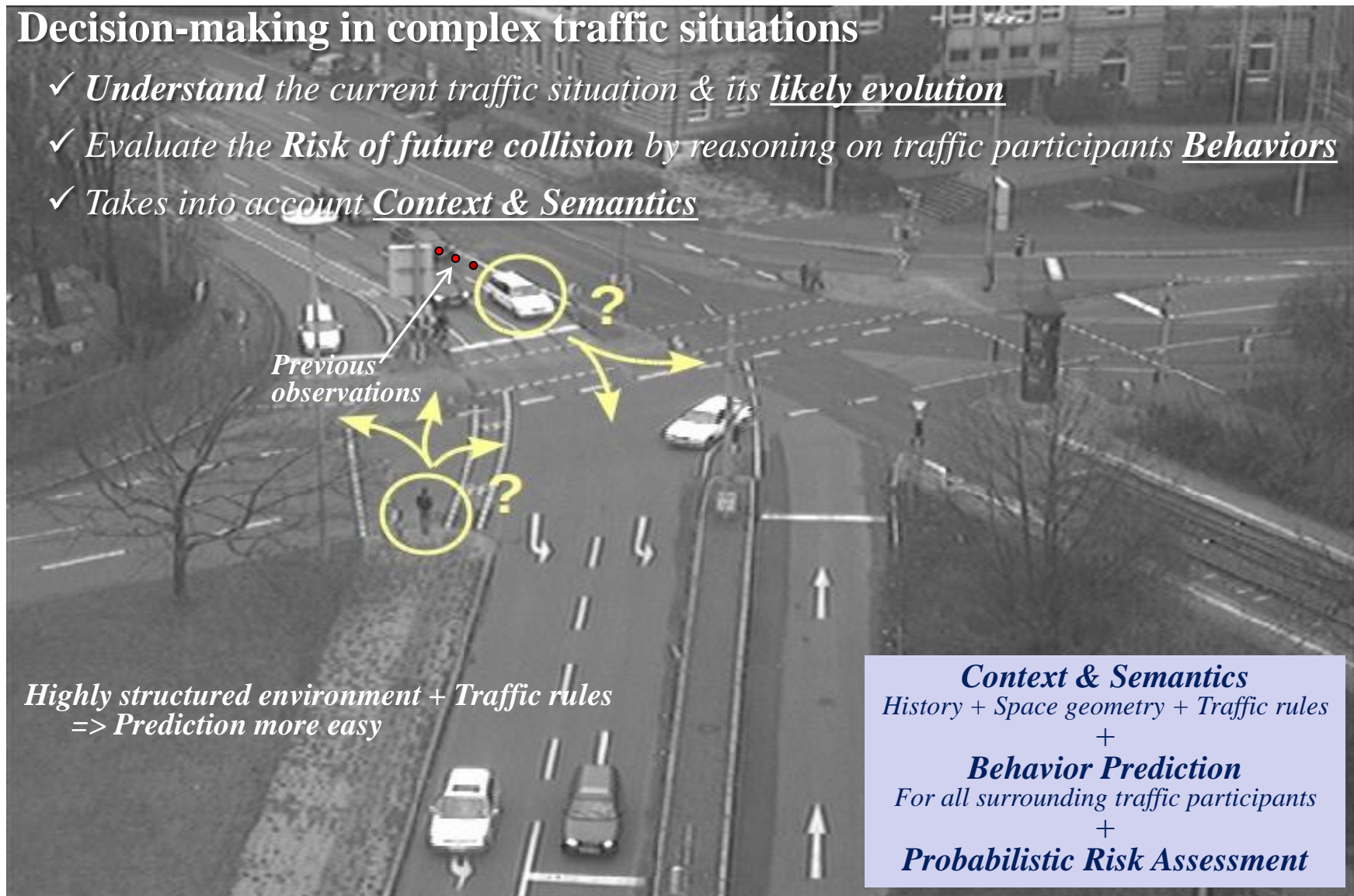


# Generalized Risk Assessment (Object level)

=> 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



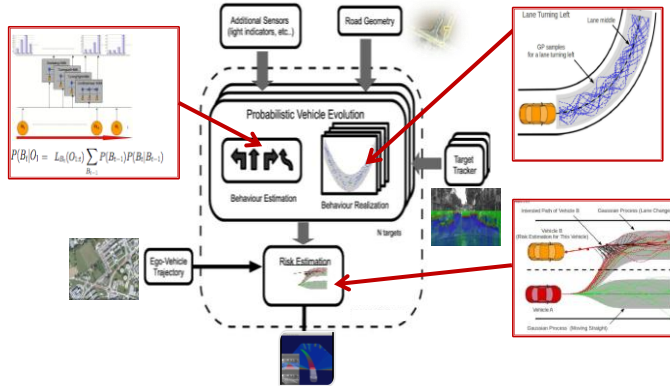
Highly structured environment + Traffic rules  
=> Prediction more easy

**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

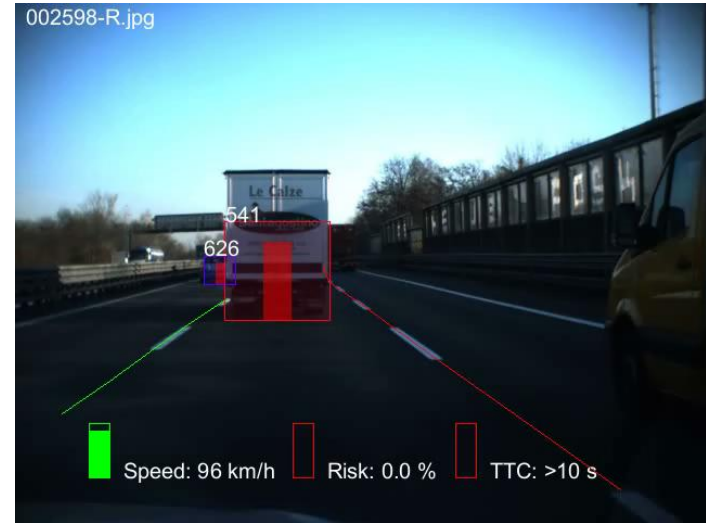
## □ Trajectory prediction & Collision Risk => Patent Inria -Toyota - ProbaYes 2010



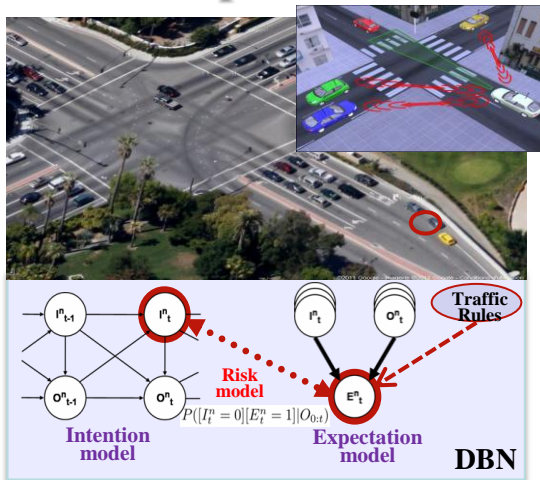
Inria

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



microcontroller



**Nvidia Jetson Tk1**



**Nvidia Jetson TX1**

**GPU TECHNOLOGY CONFERENCE**

**GTC Europe 2016**

**BOF**

2013

**HSBOF**

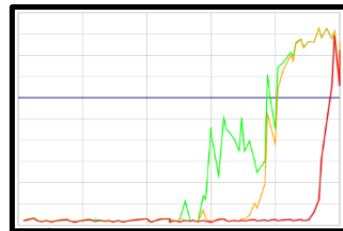
2014

**CMCDOT**

2015

**CMCDOT** *Cuda Optimization on Tegra*

2016 - 17



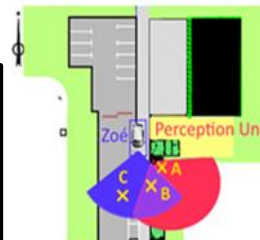
Risk assessment system



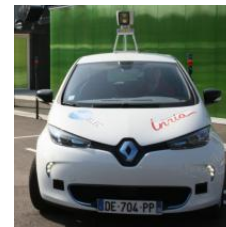
Experimental Scenario



Perception Unit



Distributed Perception

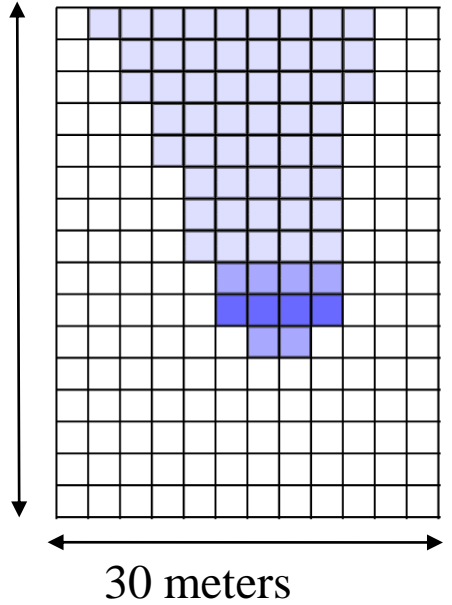


Zoe Autom. 1st Steps

# 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

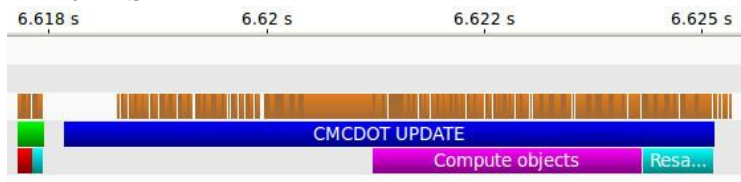
□ 1 px = 1 cell  
= 10 x 10 cm



Jetson TK1: Grid Fusion 17ms, CMCDOT 70ms



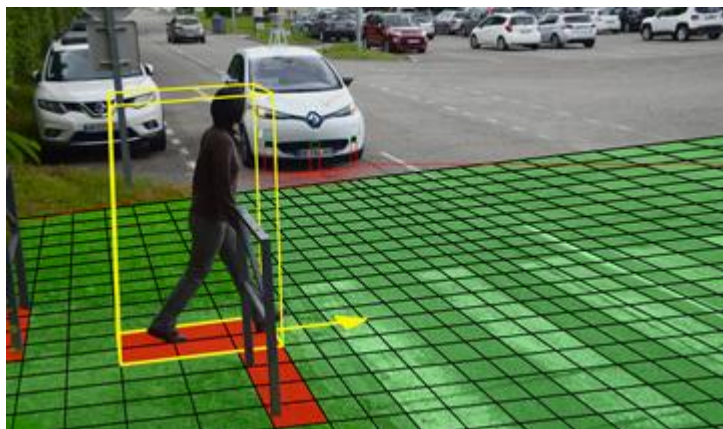
Jetson TX1: Grid Fusion 0.7ms, CMCDOT 17ms



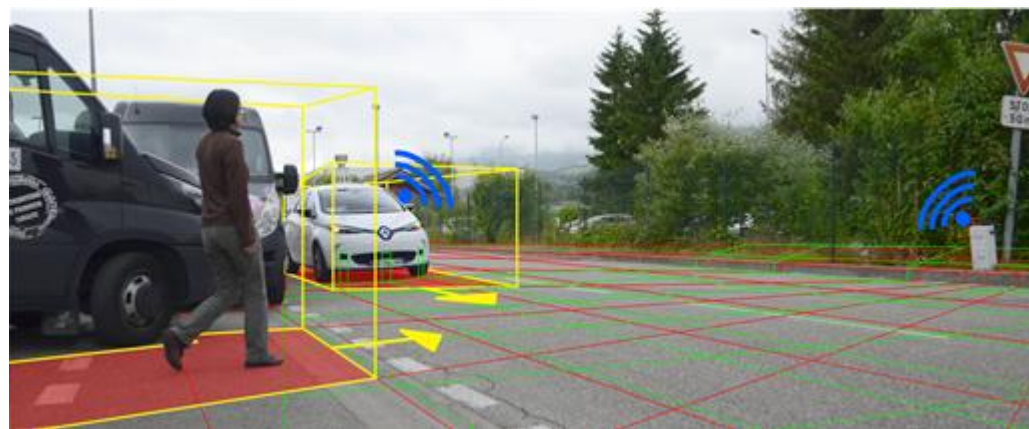


# Experimental Platforms & Experiments

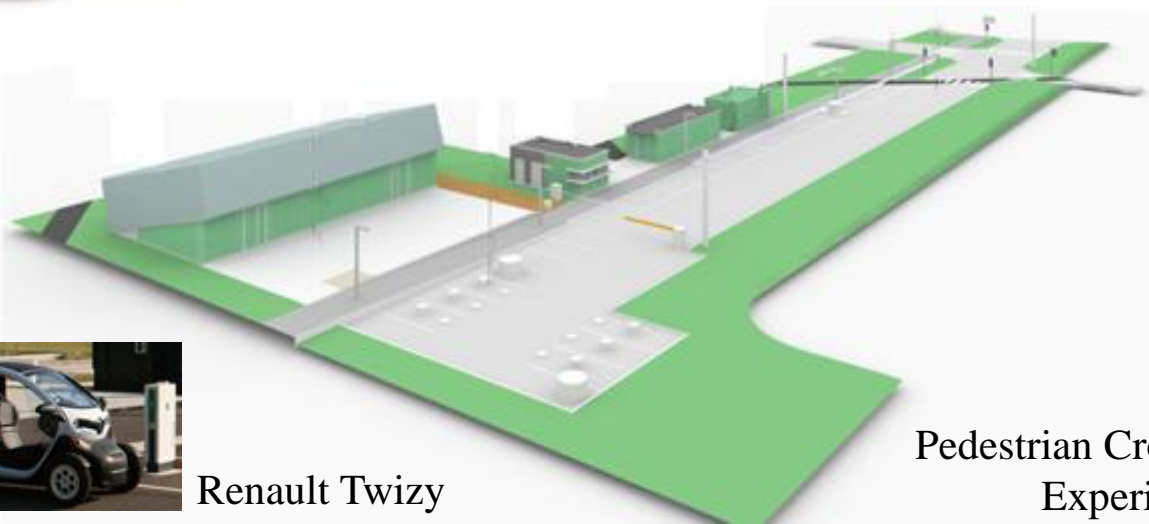
## Embedded Perception



## Distributed Perception



## IRT Nanoelec Experimental Platform



Perception Unit



Connected Traffic Cone

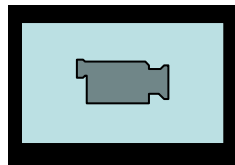
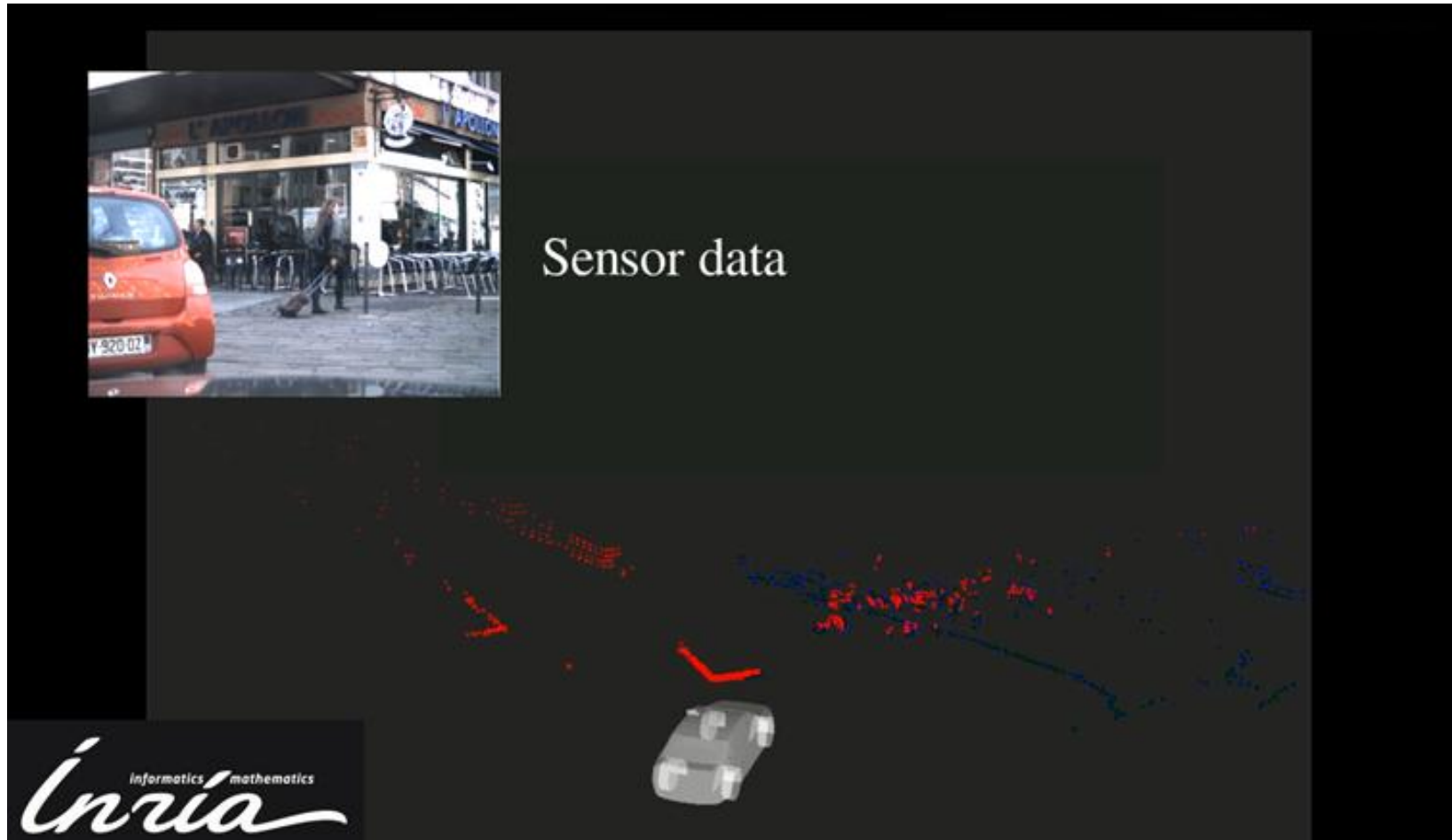


Renault Twizy

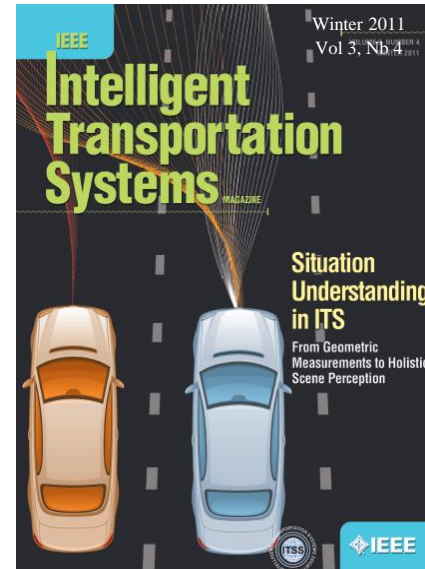
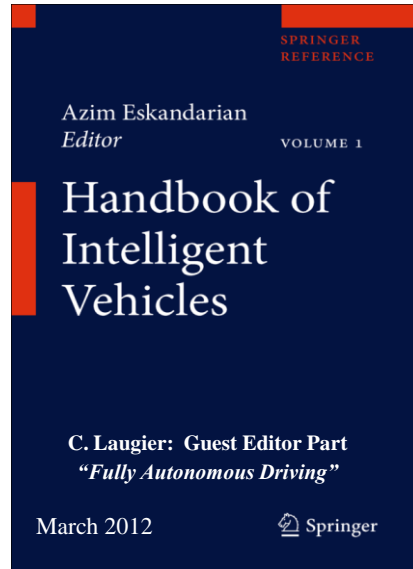
Pedestrian Crossing Experiments



# Experimental results in urban environment







**Thank You  Any questions ?**

