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# Tutorial on Autonomous Vehicles Technologies for Perception & Decision-Making

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Tutorial @ Institut d'Automne en IA 2018 (IA2 2018)  
Campus ISAE-Supaero, Oct 15-19 2018

# Autonomous Vehicles Technologies for Perception and Decision-Making

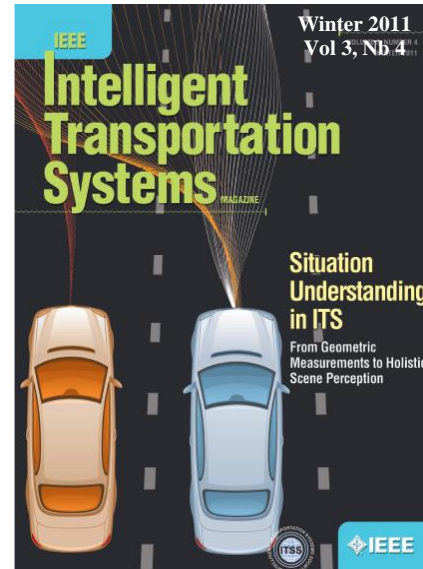
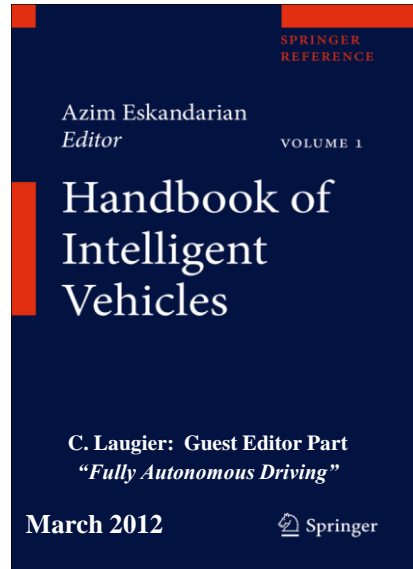
Dr HDR Christian LAUGIER

Research Director at Inria & Scientific Advisor for Probayes and for Baidu China

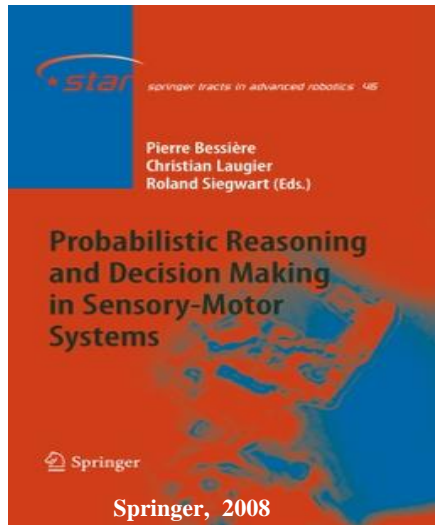
Inria Grenoble Rhône-Alpes, Chroma team

*Christian.laugier@inria.fr*

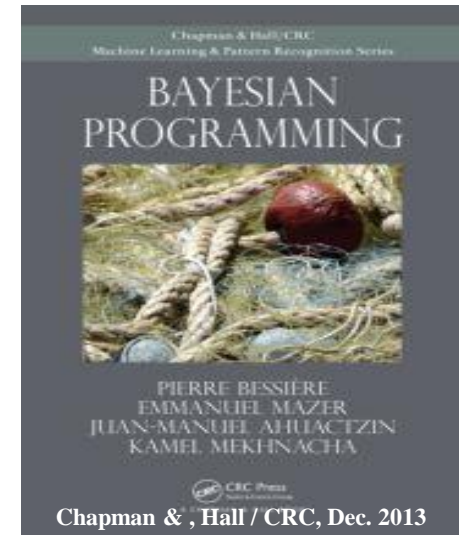




# Relevant Literature on Robotics & IV & ITS



**IEEE RAS Technical Committee on "AGV & ITS"**  
Chairs: Ph. Martinet, C. laugier, C. Stiller  
*Numerous Workshops & Journal Special issues since 2002*  
*=> Membership open*



# Content of the Tutorial

- ❑ **Socio-economic & Technological Context + State of the Art**
- ❑ Decisional & Control Architecture – Outline
- ❑ Bayesian Perception (*key Technology 1*)
- ❑ Embedded Bayesian Perception & Experimental results
- ❑ Bayesian Risk Assessment & Decision-making (*Key Technology 2*)



# Cars & Human Mobility

## *A current Psychological & Technological breakthrough*

A quick on-going change of the role & concept of **private car** in human society !



*Last century => Ownership & Feeling of Freedom  
Affective behaviors & Shown Social position  
Driving pleasure ... but less and less true !*

*Next cars generation => Focus on Technologies for  
Safety & Comfort & Reduced Pollution  
Driving Assistance v/s Autonomous Driving*

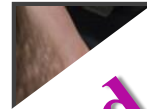
### ❖ Context

- *Expected 3 Billions vehicles & 75% population in cities in 2050 => Current model not scalable !*
- *Accidents: ~1.2 Million fatalities/Year in the world => No more accepted !*
- *Driving safety & Nuisance issues (pollution, noise, traffic jam, parking ...) are becoming a major issue for Human Society & Governments & Industry*

# Cars & Human Mobility

A current Psychological & Technological Evolution

A quick on-going change of the role & concept of **private car**



**Towards less ownership & More shared mobility systems**  
**Increased Autonomy**

*Last century => Ownership & Feelings  
Affective behaviors & Shown Status  
Driving pleasure ... but less*

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

- ❖ Technology will change the **mobility habits** of people
  - => *Shared mobility, carpooling, more ADAS & Autonomy (e.g. Tesla autopilot)*
  - => *Uber, BlaBlaCar, Robot Taxis (Uber, Nutonomy)...*

Market for Automotive Industry

*2012 & Expected \$261 billions in 2020 (f)*

(f) Forecast of the Global Market for ADAS Systems by 2020. ABI Research. 2013.

# Autonomous Cars – *State of the Art* (~ 30 years R&D)

## □ Some early results in Europe (80's & 90's)

### 1986 VaMors (Dickmann, Munich U)

=> First autonomous vehicle on a road (mainly based on CV)

=> Followed by EU project Prometheus



### Pioneer work at INRIA in the 90's

- ✓ *Autonomous parking*
- ✓ *Platooning in cities*
- ✓ *People mover (Cycab)*



PRAXITELE





# Autonomous Cars – *State of the Art (~ 30 years R&D)*

## □ Some international important Events & Results (*first decade 21<sup>st</sup> century*)



### 2004 & 2006 Darpa Grand Challenges *High speed & Off-road*

*Significant step towards Motion Autonomy  
... But still some uncontrolled behaviors in 2004 !!!*



### 2007 Darpa Urban Challenge

*97 km, 50 manned & unmanned vehicles, 35 teams  
... Impressive progress towards motion autonomy, but still some collisions  
(decision-making mainly based on automatom)*



### 2010 VIAC Intercontinental Autonomous Challenge

*13 000 km covered, 3 months race, leader + followers (A. Broggi)  
=> See Spring 2011 IEEE RAM issue for more details*



### 2011 Google Car project

*Fleet of 6 automated Toyota Prius, equipped with a costly 3D lidar (dense mapping)  
140 000 miles covered on California roads with occasional human interventions*

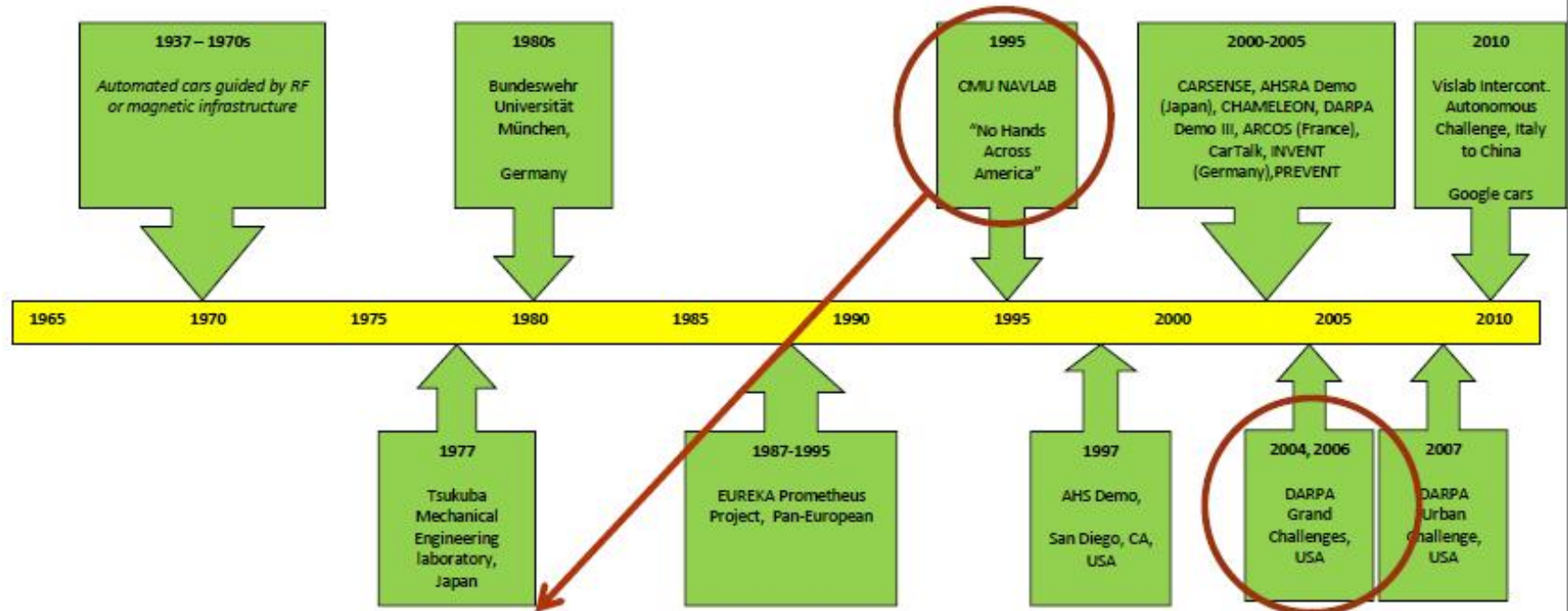


# Autonomous Cars – State of the Art (~ 30 years R&D)

Credit to Paul E. Rybski, CMU (2010)  
 The path to Commercial Autonomous Cars: The Darpa Urban Challenge and Beyond



## Brief Timeline of Autonomous Cars



NAVLAB No Hands Across America (2005) : Highway driving



<http://www.cs.cmu.edu/afs/cs/project/ahv/www/>



[http://www.youtube.com/watch?v=ubJVV1\\_4l8E](http://www.youtube.com/watch?v=ubJVV1_4l8E)

DARPA Grand Challenge (2004, 2006): High-speed offroad driving



<http://www.cs.cmu.edu/~red/Red/redteam.html>  
<http://cs.stanford.edu/group/roadrunner/old/announcements.html>

# Autonomous Cars & Driverless Vehicles

- Strong involvement of Car Industry & Large media coverage
- An expected market of 500 B€ in 2035
- Technologies Validation & Certification => Numerous recent & on-going real-life experiments + Simulation & Formal methods (e.g. EU Enable-33 2016-19)



Tesla Autopilot based on Radar & Mobileye  
*Commercial ADAS product*



3D Lidars & Dense 3D mapping  
 Numerous vehicles & Millions of miles driven



Cybus experiment, La Rochelle 2012  
 => CityMobil Project & Inria



Drive Me trials (volvo, 2017)  
 • 100 Test Vehicles in Göteborg, 80 km, 70km/h  
 • No pedestrians & Plenty of separations between lanes



Robot Taxi testing in US (Uber, Waymo) & Singapore (nuTonomy)  
 => **Mobility Service**, Numerous Sensors ... Safety driver in the car during testing



Millions of miles driven (Tesla, Waymo, Uber...) **Safety is still not guaranteed!**



# Safety issues: *Example of the Tesla accident (May 2016)*

## ❑ Safety is still insufficient (*a false sense of Safety for users ?*)

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

*=> On May 7<sup>th</sup> 2016, Tesla driver killed in a crash with Autopilot active (and driver not attentive)*

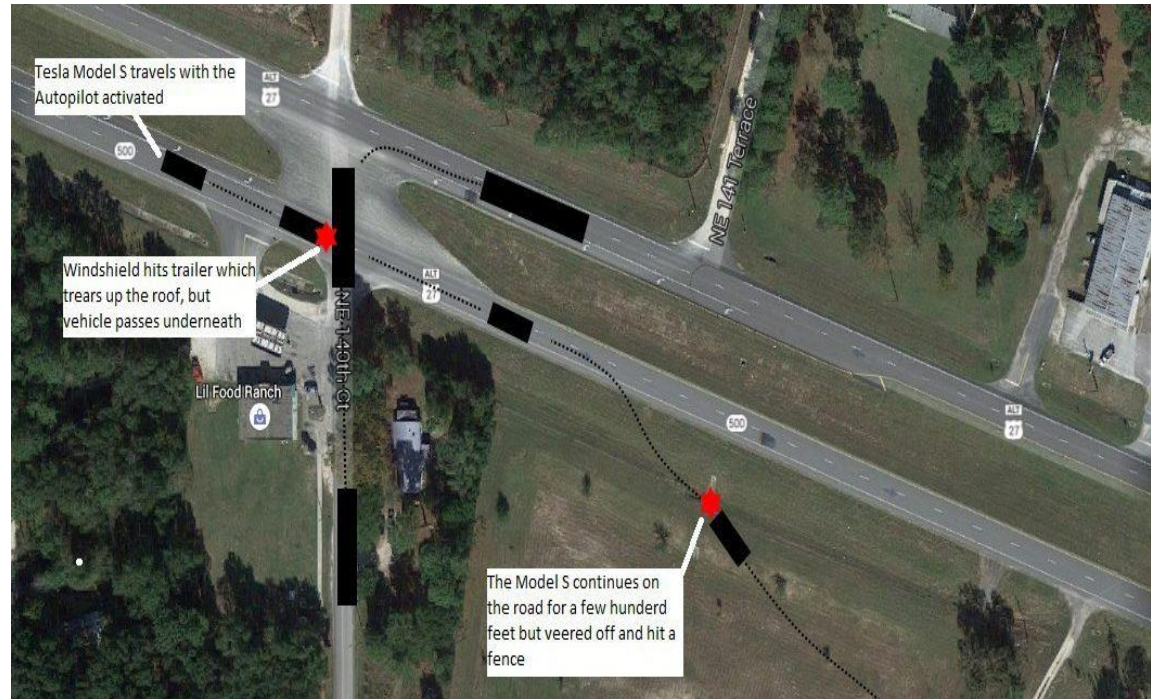


Displayed information

Tesla Model S – Autopilot

Front perception:

*Camera (Mobileye) + Radar + US sensors*



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

❖ **Camera** => *White color against a brightly lit sky ?*

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

# Safety issues: *Example of the Uber Accident (March 2018)*

- ❑ **Self-driving Uber kills a woman in first fatal crash involving pedestrian**  
*Tempe, Arizona, March 2018*
- ❑ **The vehicle was moving at 40 mph and didn't reduced its speed before the crash (collision risk not detected). The Safety Driver didn't reacted**
- ❑ **In spite of the presence of multiple onboard sensors (several lidars in particular), the perception system didn't predicted the collision !**



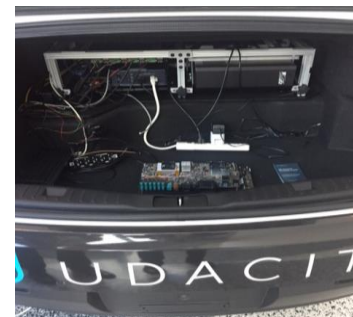


# Perception: State of the Art & Today's Limitations

- ❑ Despite significant improvements during the last decade of both Sensors & Algorithms, **Embedded Perception** is still one of the major bottleneck for Motion Autonomy

*=> Obstacles detection & classification errors, incomplete processing of mobile obstacles, collision risk weakly address, scene understanding partly solved...*

- ❑ **Lack of Robustness & Efficiency & Embedded integration** is still a significant obstacle to a full deployment of these technologies



Lack of Robustness & Efficiency ✘

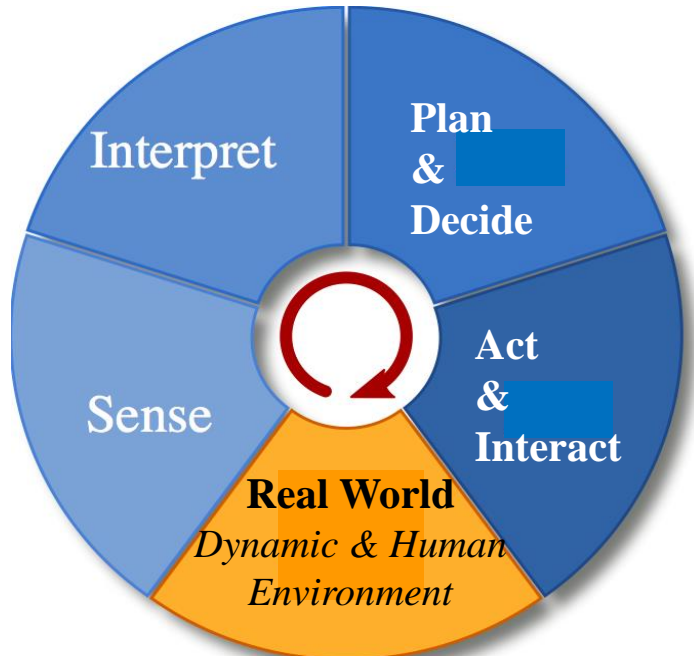
Lack of Integration into Embedded Sw/Hw ✘

- Until recently, car trunks was most of the time full of electronics & computers & processor units
- On-board high computational capabilities & dedicated softwares are still required, even if new products currently appear on the market (e.g. Nvidia Drive-PX, Ambarella embedded vision platform ..)

# Content of the Tutorial

- Socio-economic & Technological Context + State of the Art
- **Decisional & Control Architecture – Outline**
- Bayesian Perception (*key Technology 1*)
- Embedded Bayesian Perception & Experimental results
- Bayesian Risk Assessment & Decision-making (*Key Technology 2*)

# Decisional & Control Architecture – *Outline*

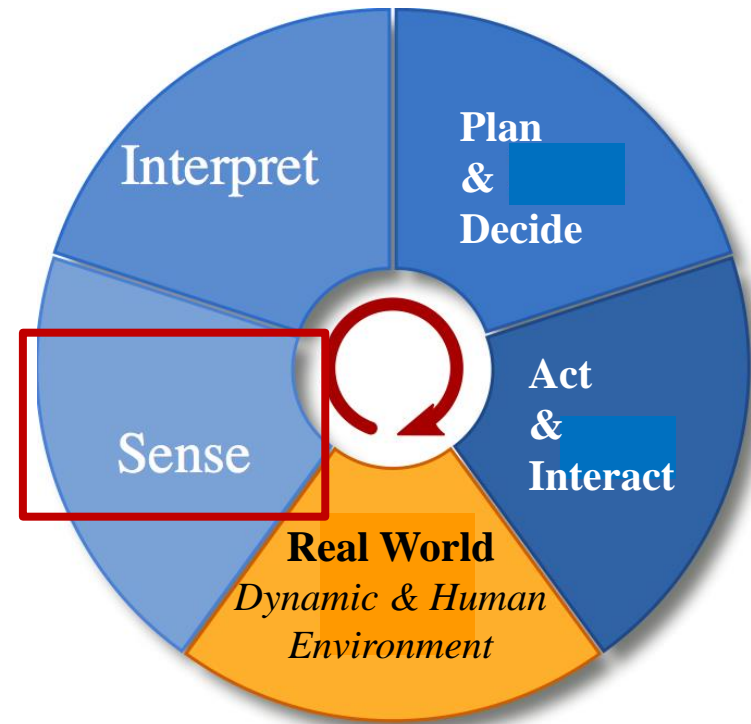


❑ **How to control Robot actions in a Dynamic world populated by Human Beings (under strong real-time constraints) ?**

❑ **Combining & Adapting interdependent functions for:**

- ✓ Sensing the environment using various sensors
- ✓ Interpreting the dynamic scene (using Semantics and Prior Knowledge)
- ✓ Planning Robot motions & Deciding of the most appropriate action to be executed
- ✓ Acting & Interacting in the real world (Safety & Acceptability)

# Decisional & Control Architecture – Sensing



## ❑ Objective

Perceive what is happening in the Dynamic Scene using various sensors

## ❑ Main Difficulty

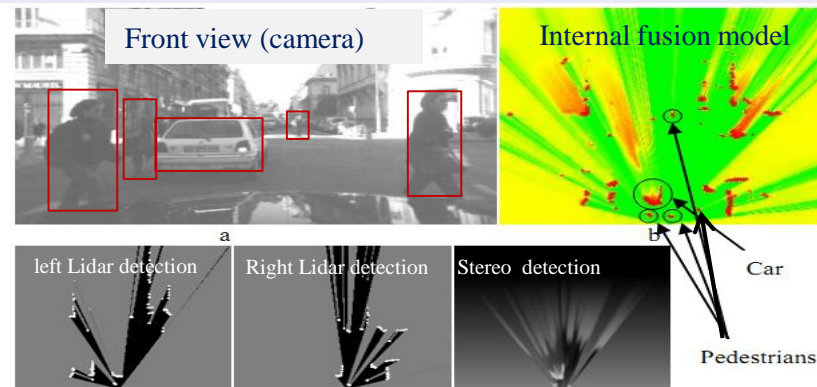
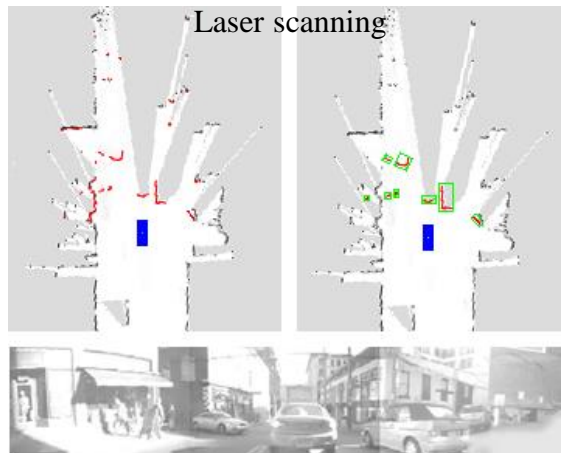
- ✓ Huge heterogeneous sensory data
- ✓ Sensing errors & Uncertainty
- ✓ Real-time processing

## ❑ Main Functions

- ✓ Localization & Mapping (SLAM)
- ✓ Static Obstacles + Mobile Objects Detection & Tracking

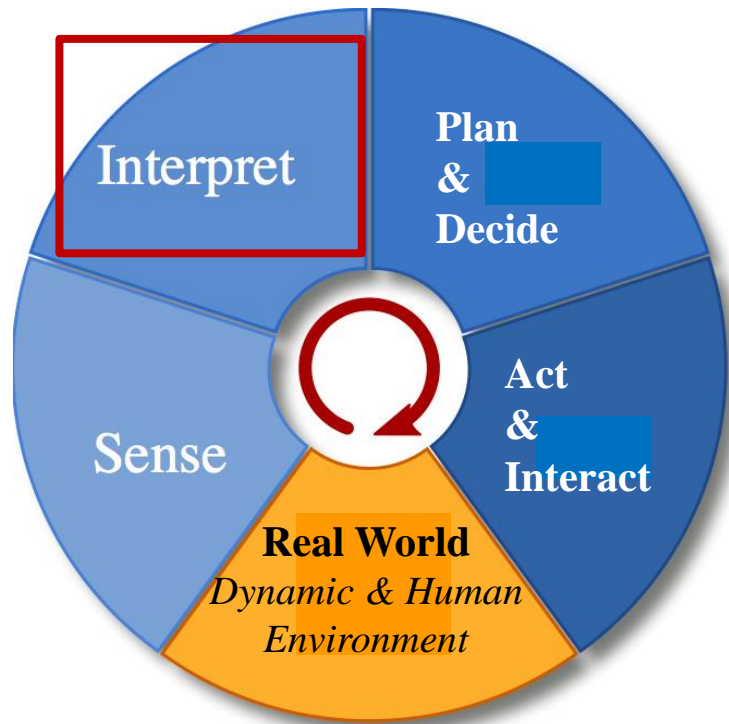
## ❑ Main Models & Algorithms

- ✓ Bayesian Filtering
- ✓ Feature based & Grid based approaches





# Decisional & Control Architecture – Scene Understanding

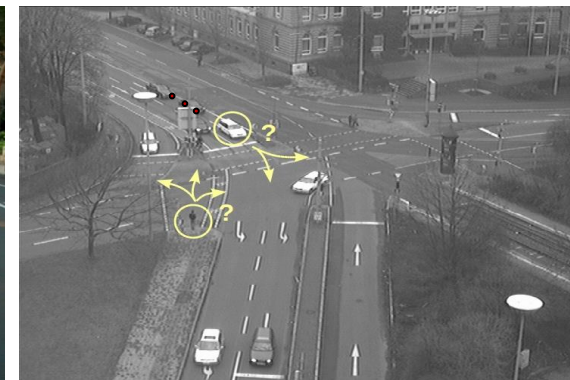
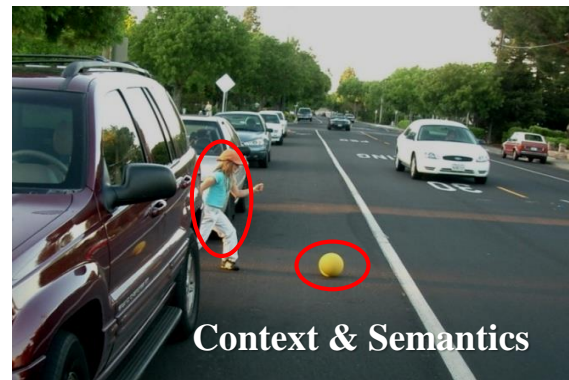
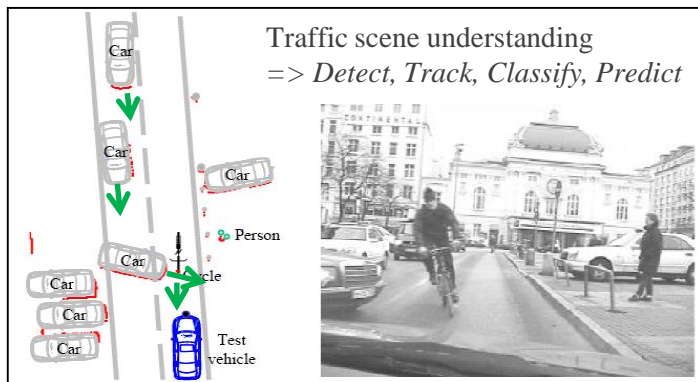


## ❑ Objective

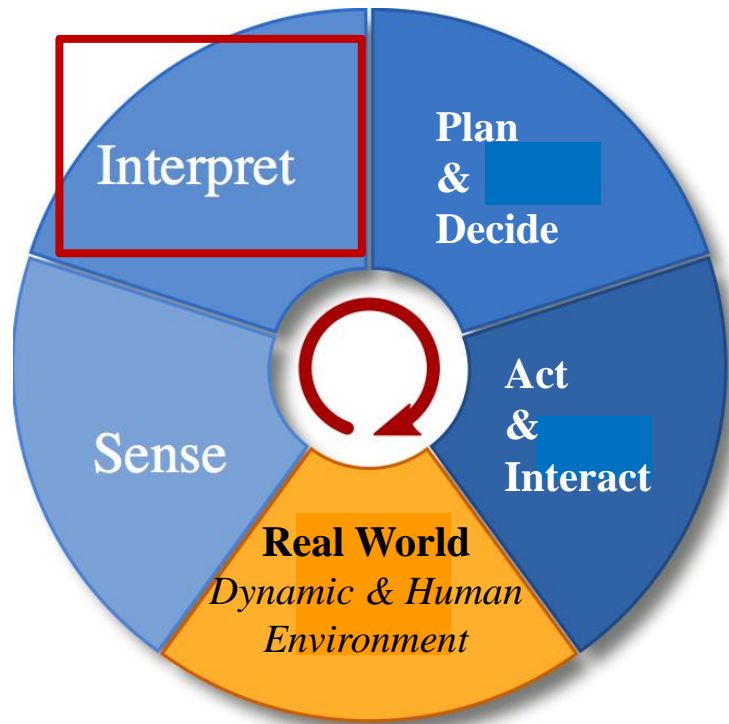
Understand the content of the Dynamic Scene using **Contextual & Semantic knowledge**

## ❑ Main Difficulty

- ✓ Uncertainty
- ✓ Real-time processing
- ✓ Reasoning about various type of knowledge (history, context, semantics, prediction)



# Decisional & Control Architecture – Scene Understanding

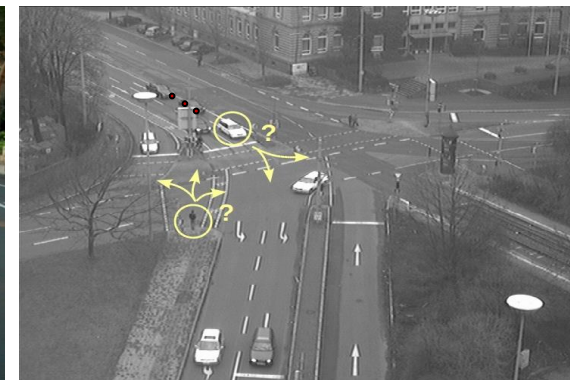
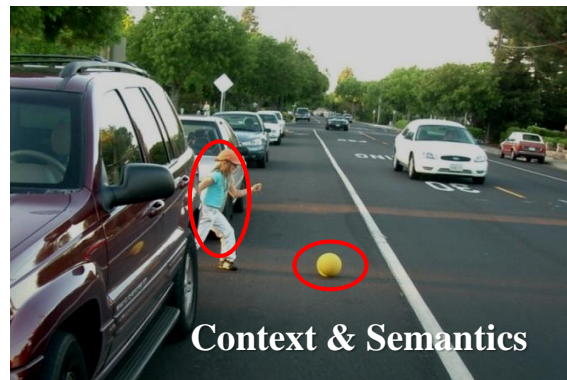
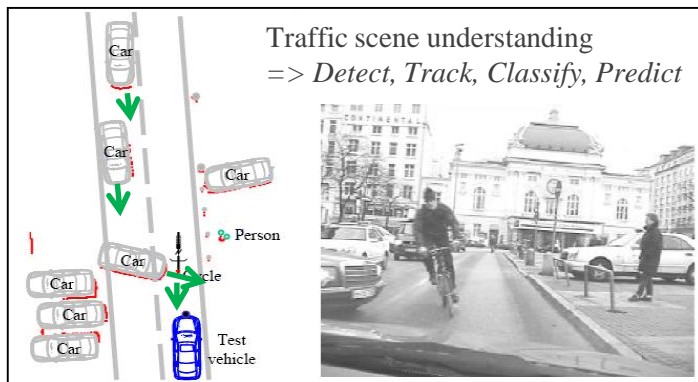


## □ Main Functions

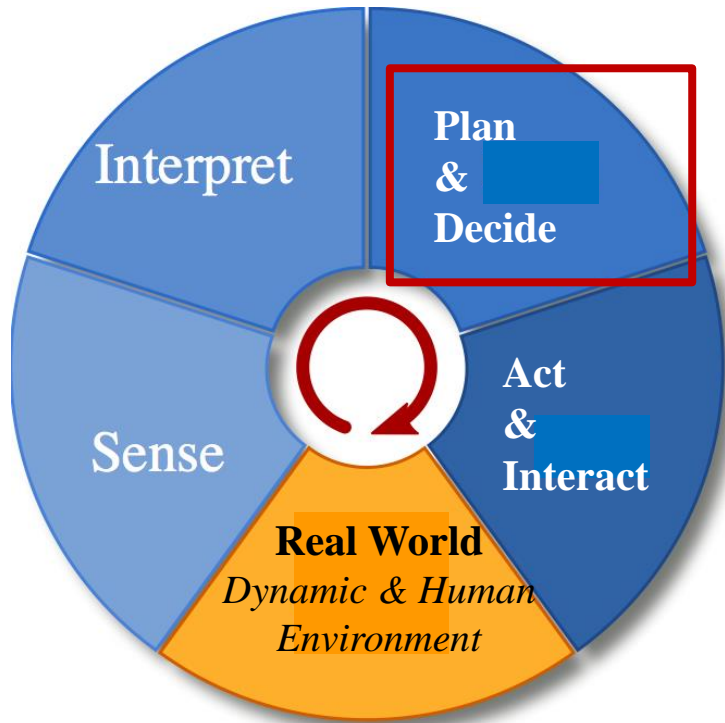
- ✓ Detection & Tracking of Mobile Objects (DATMO)
- ✓ Objects classification (recognition)
- ✓ Prediction & Risk Assessment (avoiding future collisions)

## □ Main Models & Algorithms

- ✓ Bayesian Perception Paradigm
- ✓ Behaviors modeling & learning
- ✓ Bayesian approaches for Prediction & Risk Assessment



# Decisional & Control Architecture – *Decision-making*



## ❑ Objective

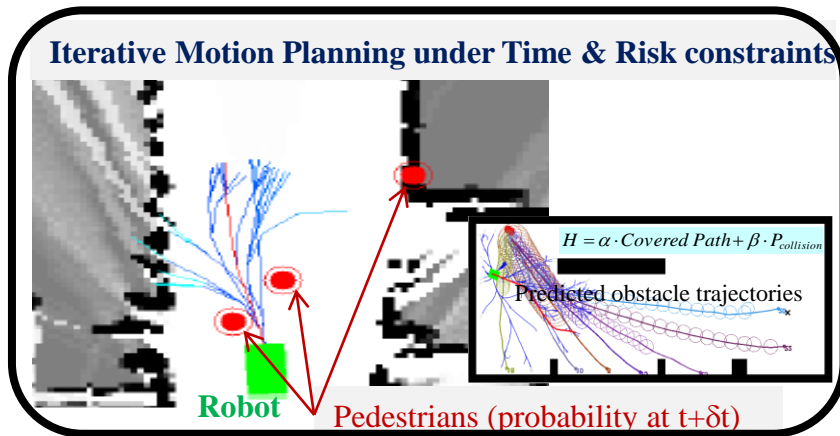
Planning robot motions & Deciding of the most appropriate action to be executed by the robot (Goal & Context & Risk)

## ❑ Main Difficulty & Functions

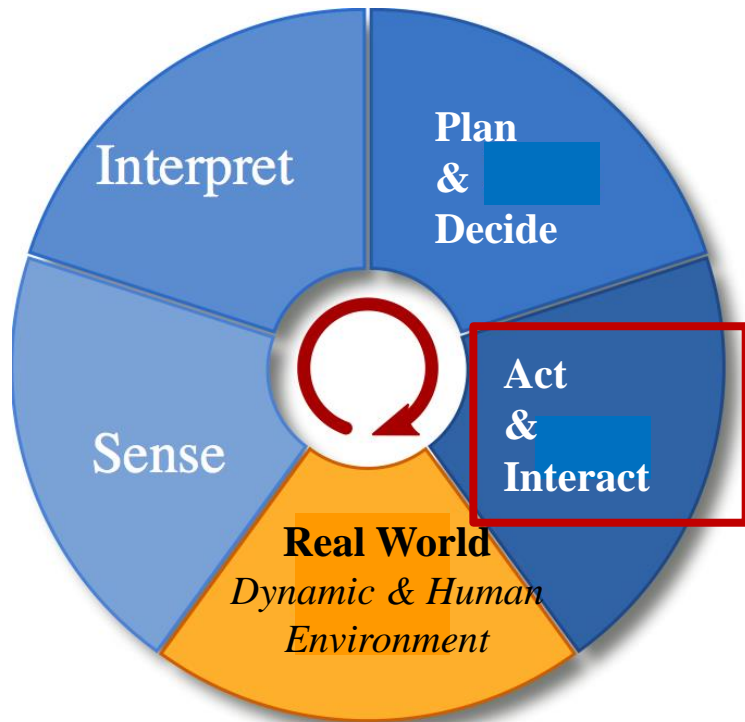
- ✓ On-line Motion Planning under various constraints (time, kinematic, dynamic, uncertainty, collision risk, social)
- ✓ Decision making under uncertainty using contextual data (history, semantics, prediction)

## ❑ Main Models & Algorithms

- ✓ Iterative Risk-based Motion Planning (e.g. Risk-RRT)
- ✓ Decision making using Contextual data & Bayesian networks







## ❑ Objective

Controlling the robot for executing **Safe & Socially Acceptable robot actions**, while taking into account the related **Human – Robot Interactions**

## ❑ Main Difficulty & Functions

- ✓ Robot navigation while taking into account both Safety & Social constraints
- ✓ **Human in the loop**

## ❑ Main Models & Algorithms

- ✓ Human-Aware Navigation paradigm (safety & social filters)
- ✓ Intuitive Human-Robot Interaction





# Content of the Tutorial

- Socio-economic & Technological Context + State of the Art
- Decisional & Control Architecture – Outline
- **Bayesian Perception (*key Technology 1*)**
- Embedded Bayesian Perception & Experimental results
- Bayesian Risk Assessment & Decision-making (*Key Technology 2*)

# Embedded Perception: Main features

Complex Dynamic Scenes  
understanding



**Situation Awareness  
& Decision-making**



ADAS & Autonomous Driving

Dealing with unexpected events  
e.g. Road Safety Campaign, France 2014



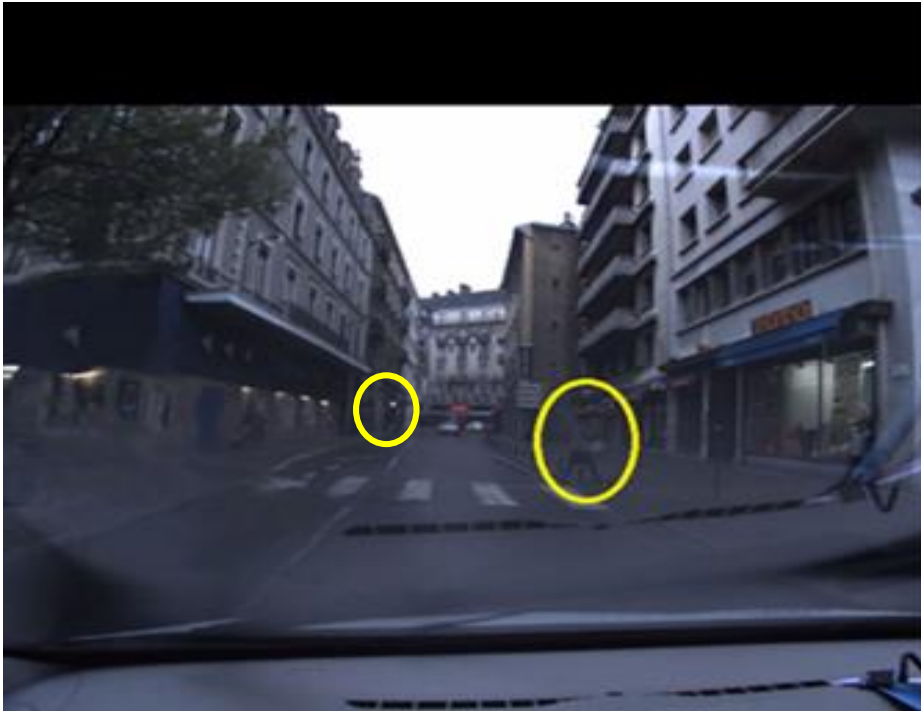
**Anticipation & Prediction**  
for avoiding upcoming accidents

## Main features

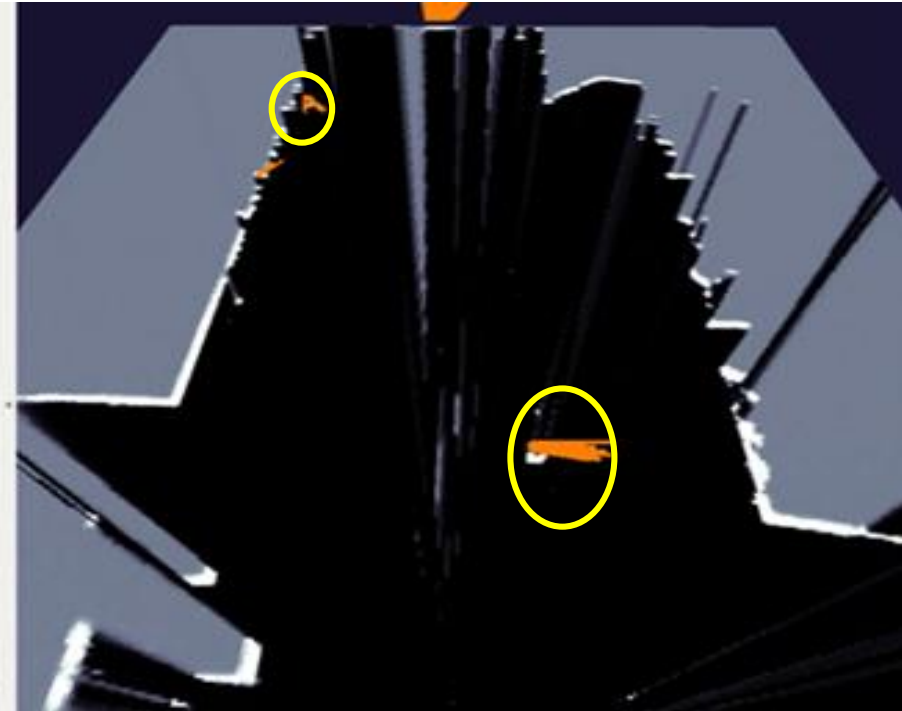
- ✓ Dynamic & Open Environments => *Real-time processing*
- ✓ Incompleteness & Uncertainty => *Appropriate Model & Algorithms (probabilistic approaches)*
- ✓ Sensors limitations => *Multi-Sensors Fusion*
- ✓ Human in the loop => *Interaction & Behaviors & Social Constraints (including traffic rules)*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

# Improving robustness using Multi-Sensors Fusion

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*

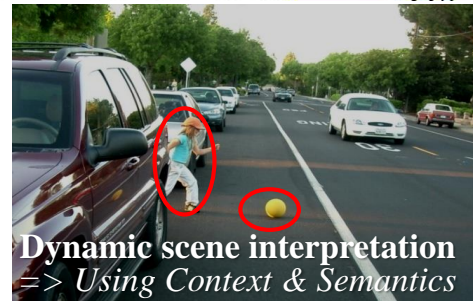
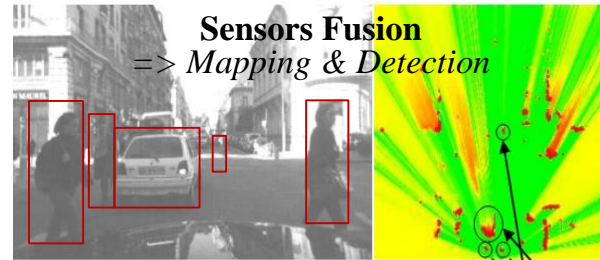
- *Any sensor may generate perception errors => It is mandatory to develop **Embedded Robust & Efficient “Multi-Sensors Fusion”** approaches (e.g. using probabilistic models & filtering)*
- *A new generation of **affordable “Solid State Lidars”** is supposed to shortly arrive on the market !*
  - => No mechanical component & Expected cost less than 1000 US\$ before mass production*
  - => Numerous announcements since Spring 2016 ... **but products not yet on the market !!***



# Key Technology: 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

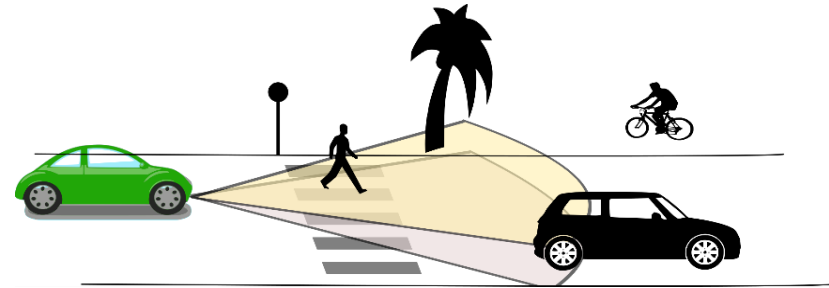
- ✓ *Reasoning about Uncertainty & Time window (Past & Future events)*
- ✓ *Improving robustness using Bayesian Sensors Fusion*
- ✓ *Interpreting the dynamic scene using Contextual & Semantic information*
- ✓ *Software & Hardware integration using GPU, Multicore, Microcontrollers...*



# Bayesian Perception : Basic idea




## □ Multi-Sensors Observations

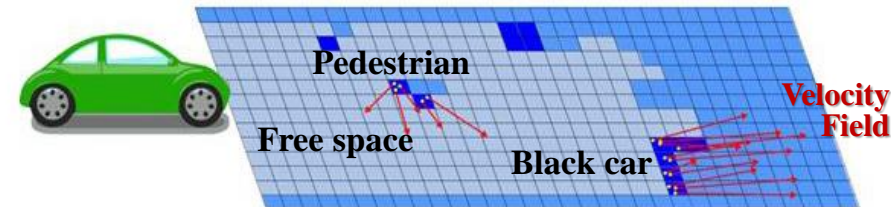
*Lidar, Radar, Stereo camera, IMU ...*



## □ Probabilistic Environment Model

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

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



*Concept of Dynamic Probabilistic Grid*  
⇒ *Occupancy & Velocity probabilities*  
⇒ *Embedded models for Motion Prediction*

## □ Main philosophy

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

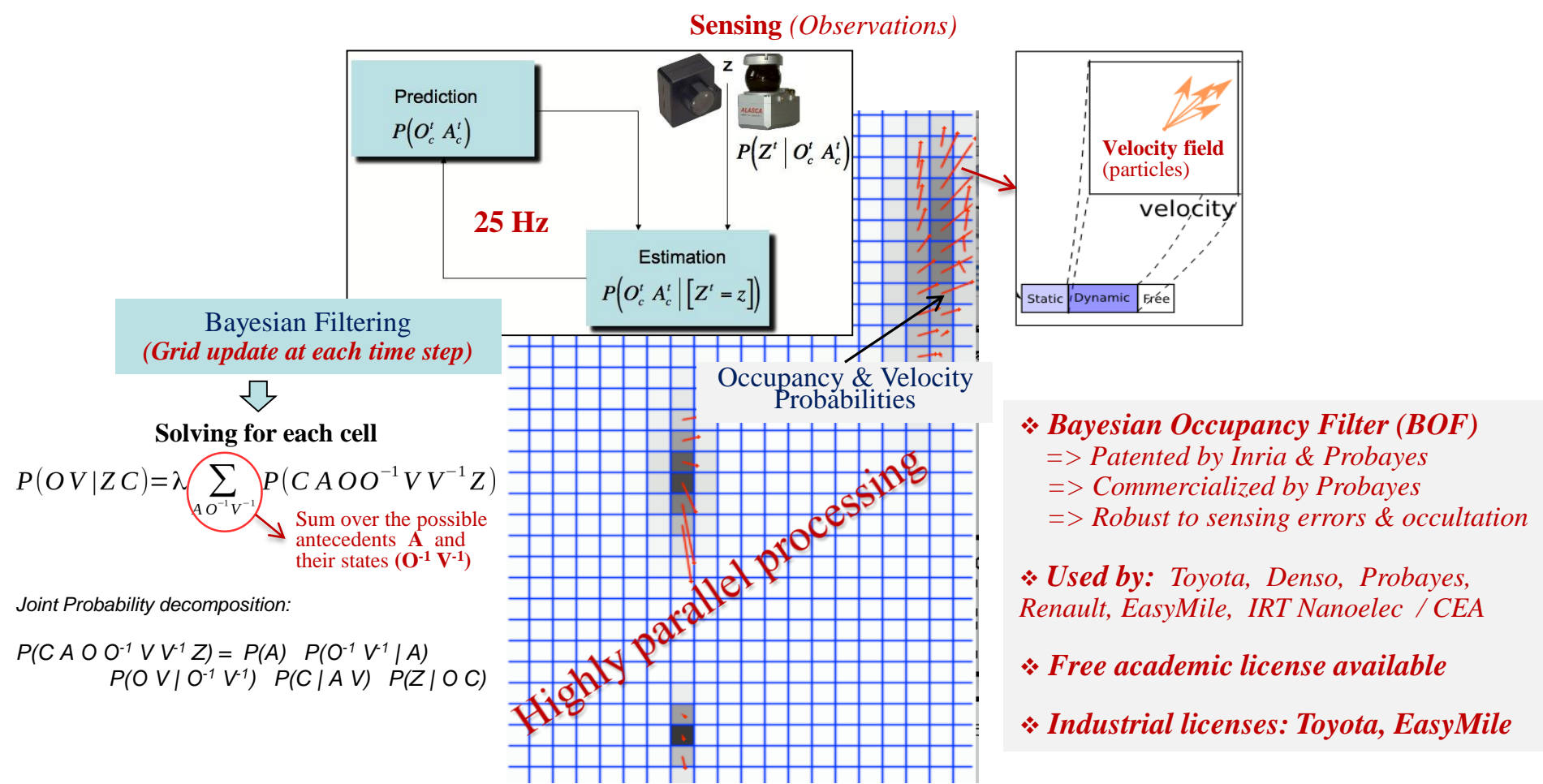
- *Improving efficiency (highly parallel processing)*
- *Avoiding traditional object level processing problems (e.g. detection errors, wrong data association...)*



# A new framework: Dynamic Probabilistic Grids

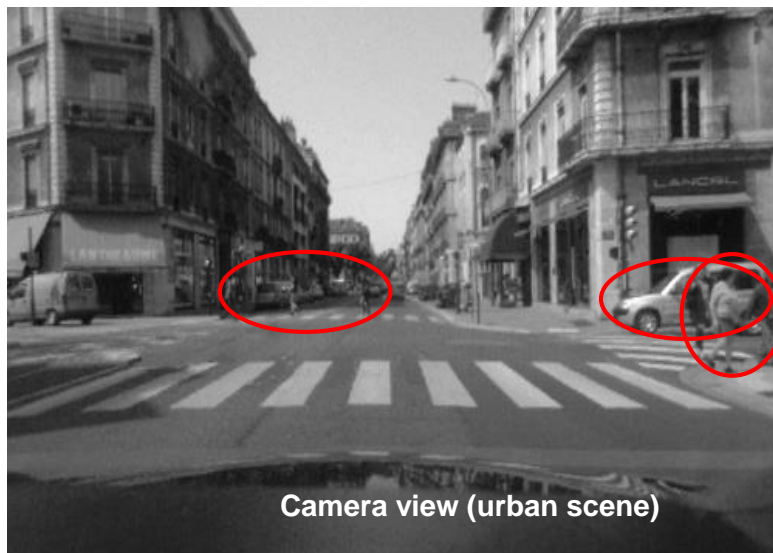
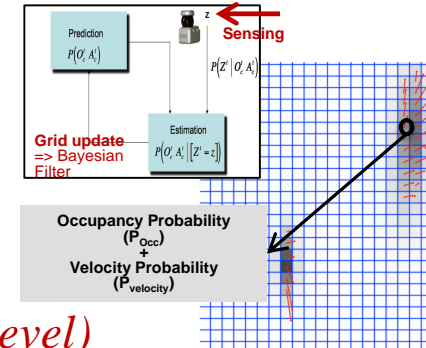
=> A clear distinction between Static & Dynamic & Free components

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

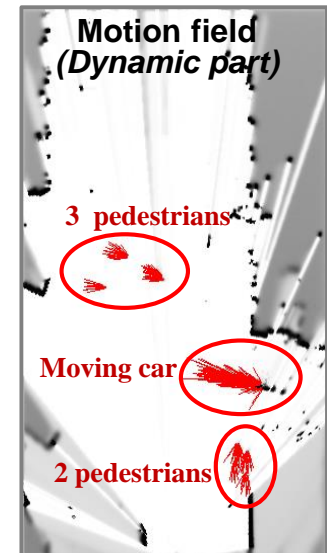


# Bayesian Occupancy Filter (BOF) – Main Features

- 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



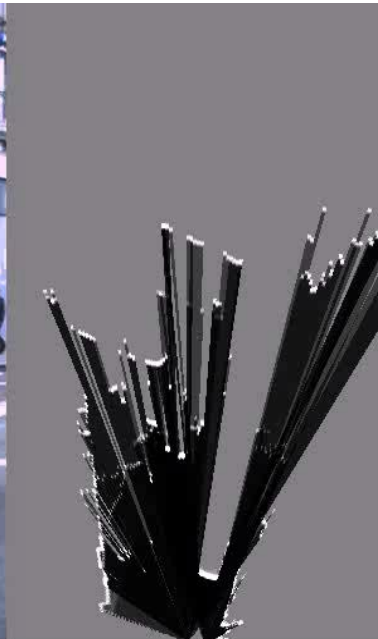
**Exploiting the Dynamic information for a better Understanding of the Scene !!**

# Concept illustration in a dense Urban Environment

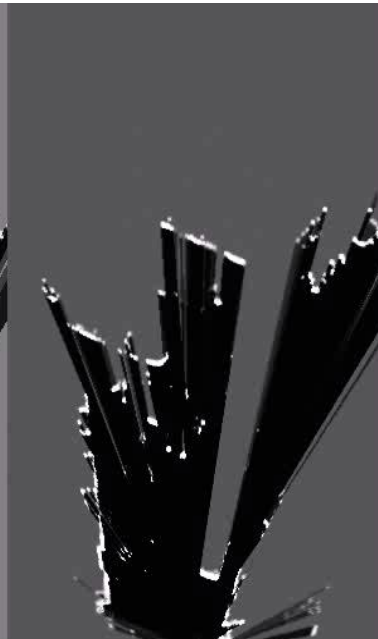
## Observed Urban Traffic scene



**Ego Vehicle** (*not visible on the video*)



OG Left Lidar



OG Right Lidar

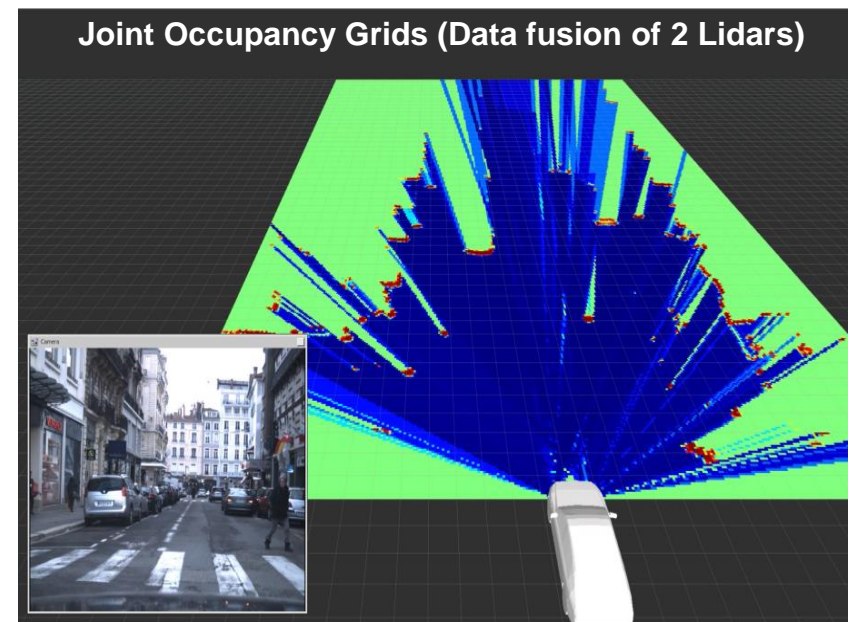
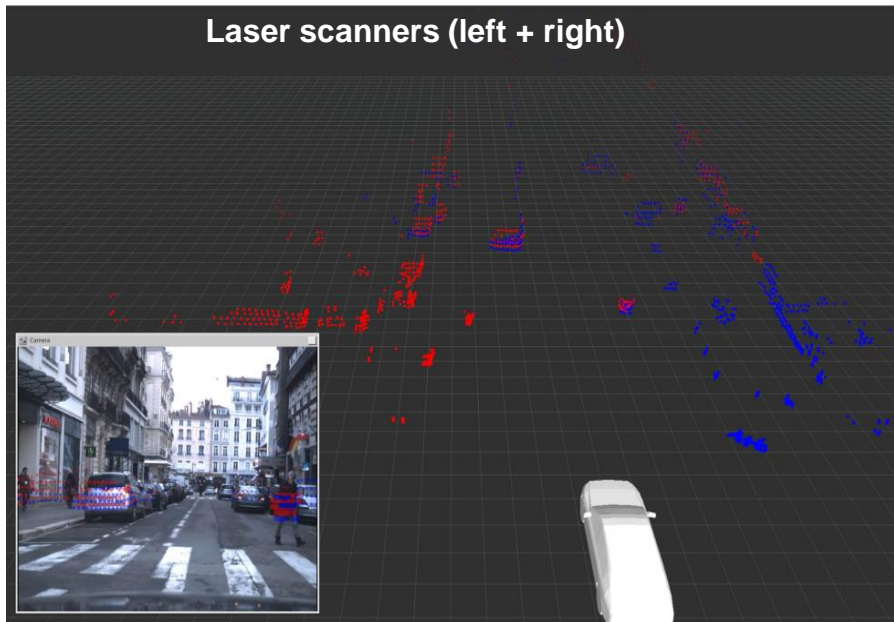


OG Fusion  
+  
Velocity Fields



# 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:  $P(O | Z)$

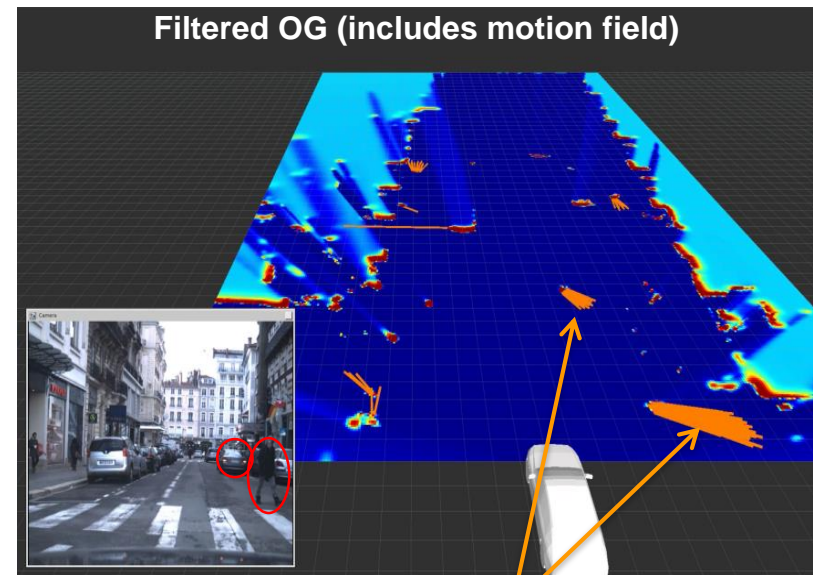
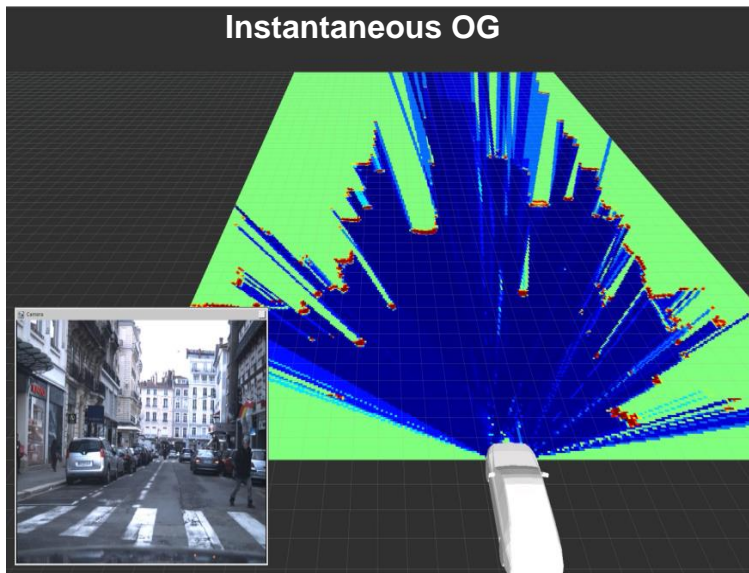
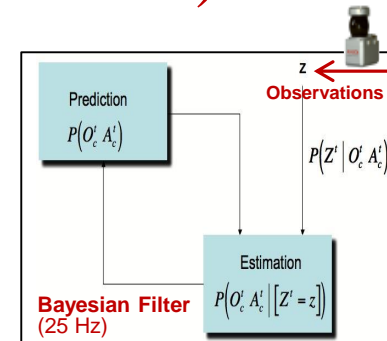




# Taking into account dynamicity

=> *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

# Bayesian Occupancy Filter – How it works ?

## Formalism

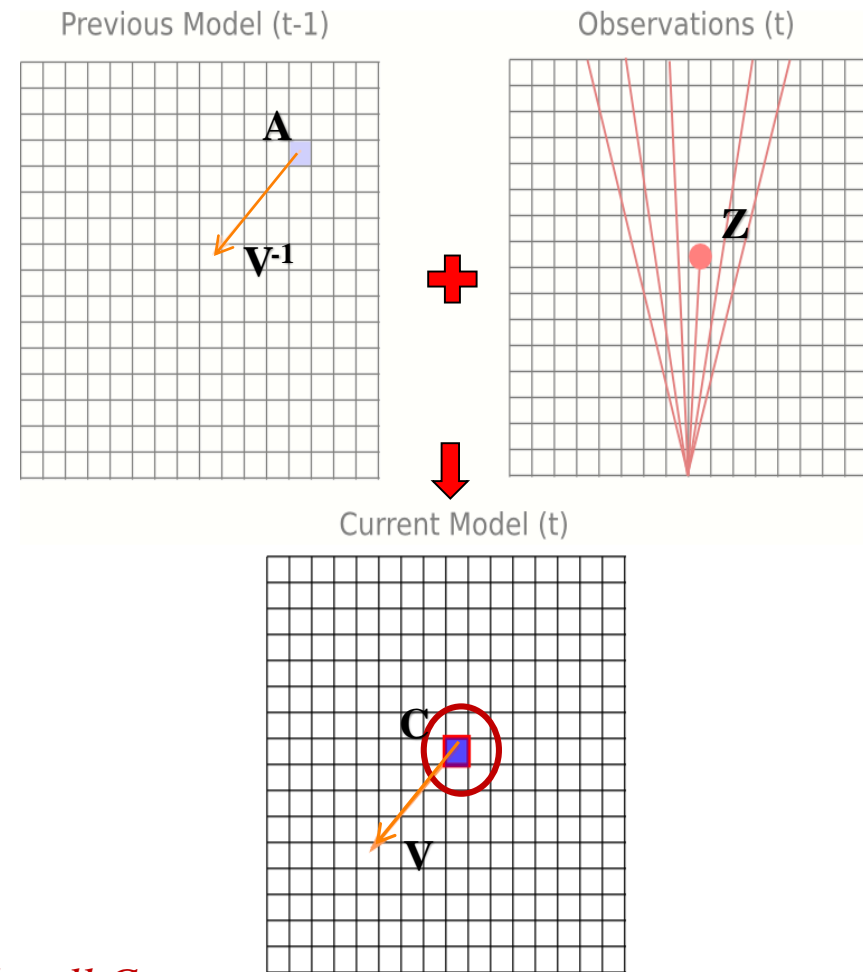
### ○ Variables:

- $C$  : current cell
- $A$  : antecedent cell, i.e. the cell from which the occupancy of the current cell comes from
- $O$  : occupancy of the current cell  $C$
- $O^{-1}$  : previous occupancy in the antecedent cell
- $V$  : current velocity
- $V^{-1}$  : previous velocity in the antecedent
- $Z$  : observations (sensor data)

### ○ Objective:

**Evaluate  $P(O \mid V \mid Z \mid C)$**

*=> Probability of Occupancy & Velocity for each cell  $C$ ,  
Knowing the **observations  $Z$**  & the **cell location  $C$**  in the grid*



# Bayesian Occupancy Filter – How it works ?

*How to theoretically compute  $P(O V | Z C)$  ?*

$$P(O V | Z C) = \lambda \sum_{A O^{-1} V^{-1}} P(C A O O^{-1} V V^{-1} Z)$$

Sum over the possible antecedents **A** and their states (**O**<sup>-1</sup> **V**<sup>-1</sup>) at time t-1

The joint probability term can be re-written as follows:

$$P(C A O O^{-1} V V^{-1} Z) = P(A) P(O^{-1} V^{-1} | A) P(O V | O^{-1} V^{-1}) P(C | A V) P(Z | O C)$$

**Joint probability** => used for the update of  $P(O V | Z C)$

**$P(A)$**  : Selected as **uniform** (every cell can a priori be an antecedent)

**$P(O^{-1} V^{-1} | A)$**  : Result from the previous iteration

**$P(O V | O^{-1} V^{-1})$**  : **Dynamic model**

**$P(C | A V)$**  : **Indicator function** of the cell **C** corresponding to the “**projection**” in the grid of the antecedent **A** at a given velocity **V**

**$P(Z | O C)$**  : **Inverse sensor model**



# Bayesian Occupancy Filter – How it works ?

*How to theoretically compute  $P(O V | Z C)$  ?*

$$P(O V | Z C) = \lambda \sum_{A O^{-1} V^{-1}} P(C A O O^{-1} V V^{-1} Z)$$

Sum over the possible antecedents **A** and their states (**O<sup>-1</sup> V<sup>-1</sup>**) at time t-1

The joint probability term can be re-written as follows:

$$P(C A O O^{-1} V V^{-1} Z) = P(A) P(O^{-1} V^{-1} | A) P(O V | O^{-1} V^{-1}) \\ P(C | A V) P(Z | O C)$$

But, computing this expression is difficult in practice

=> Huge range of possible antecedents

=> Strongly depends on Grid size & Velocity range

# Step 1: Occupancy Grid Construction

## *The Sensor Model*

### □ Sensors data

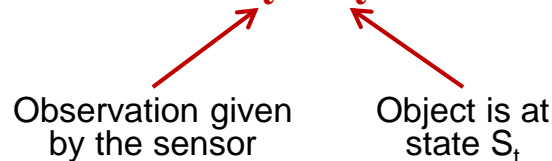
- Incomplete (objects states are only partially measurable)
- Uncertain (measures are noisy)

### □ The sensor model

=> Modeling the relationship between **Objects true states** and the **corresponding Observations** made by sensors

### □ Probabilistic representation (Thrun 2005 [1] )

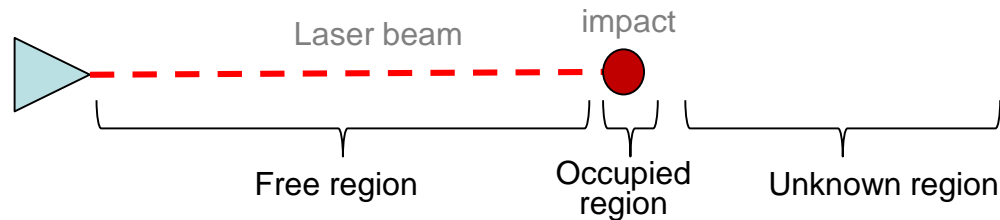
=> Inverse sensor model:  $P(Z_t | S_t)$



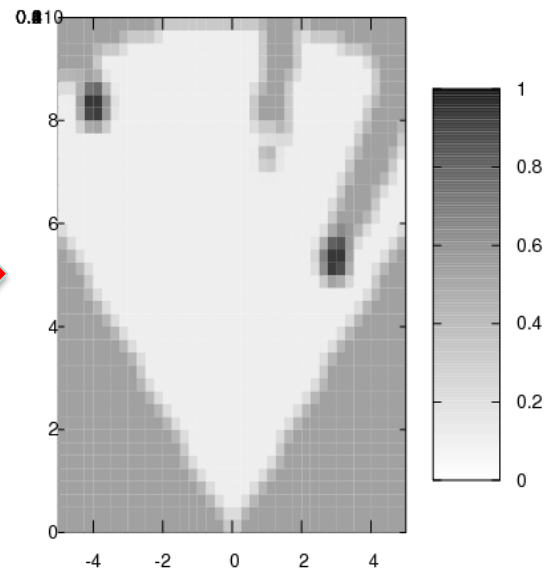
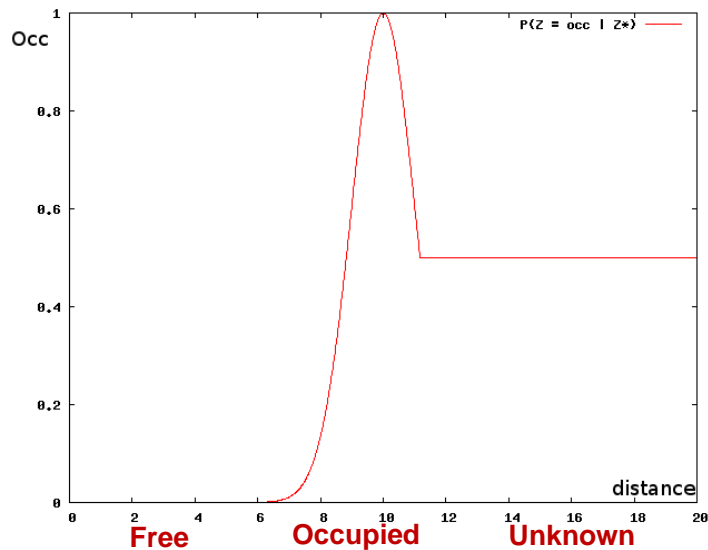
[1] Probabilistic Robotics, Thrun 2005

# Step 1: OG Construction – *The Lidar Sensor Model*

- **Basic idea:** A Laser beam split the space in 3 regions (Free, Occupied, unknown)



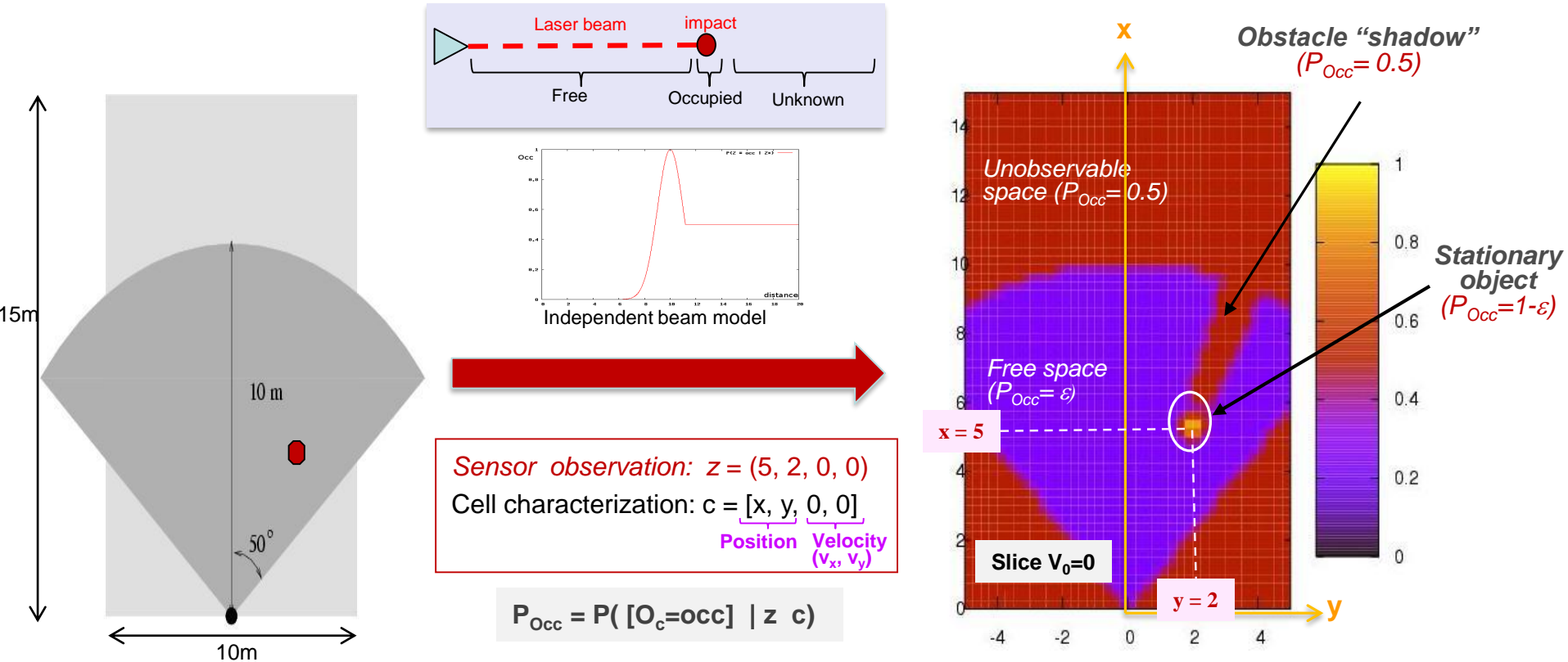
- **Probabilistic modeling:** The independent beam model



[1] Probabilistic Robotics, Thrun 2005

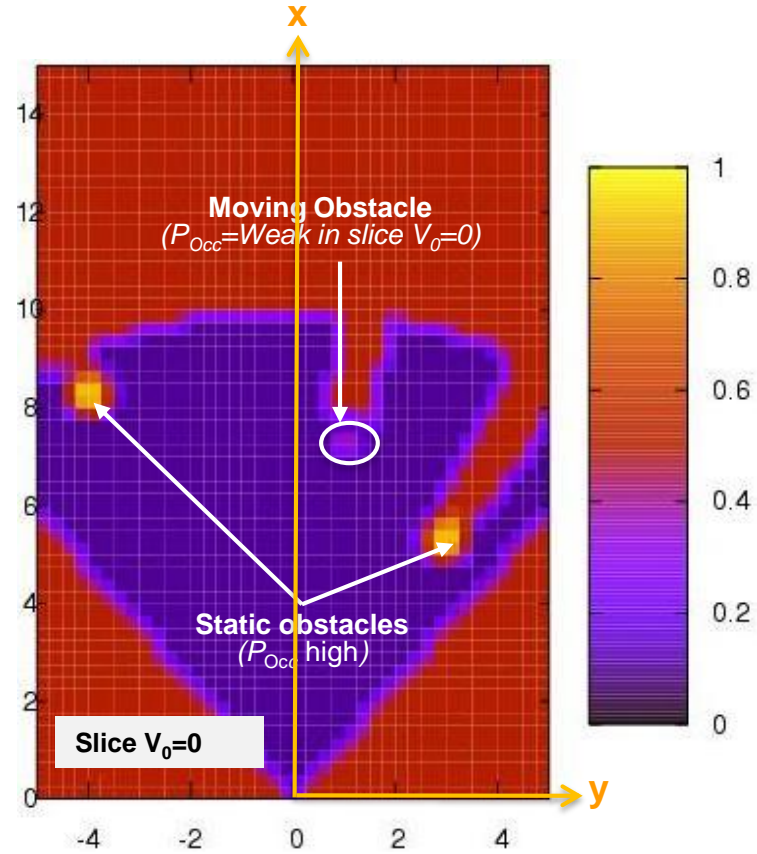
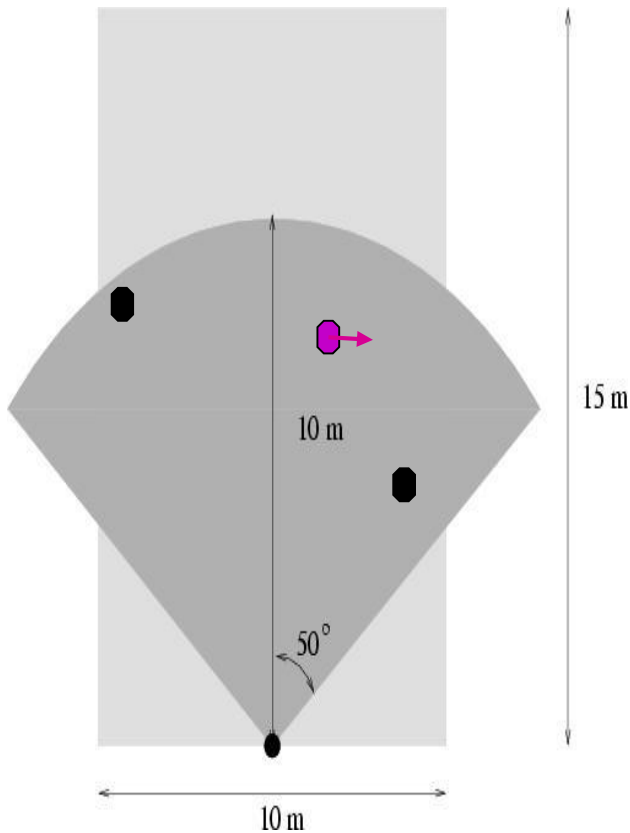


# Step 1: OG Construction – Example 1



- 1 Sensor (laser scanner)
- 1 Stationary object  $\Rightarrow$  Observation  $z$

# Step 1: OG Construction – Example 2



- 1 Sensor
- 2 Stationary objects => Observations ( $z_1, z_3$ )
- 1 Moving object => Observation  $z_2$

$$P_{Occ} = P([O_c=occ] \mid z_1 z_2 z_3 c)$$

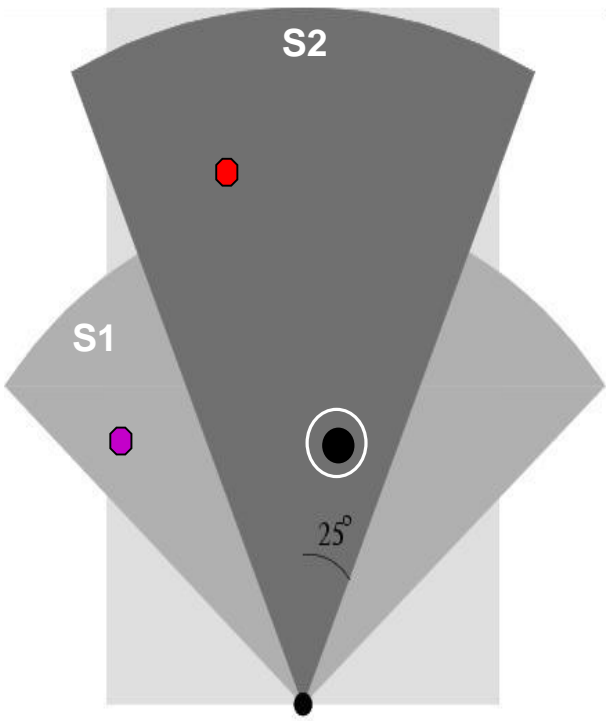
$$z_1 = (8.3, -4, 0, 0)$$

$$z_2 = (7.3, 1.9, 0, 0.8)$$

$$z_3 = (5, 3, 0, 0)$$

$$c = [x, y, 0, 0] \Rightarrow \text{in velocity slice } V_0=0$$

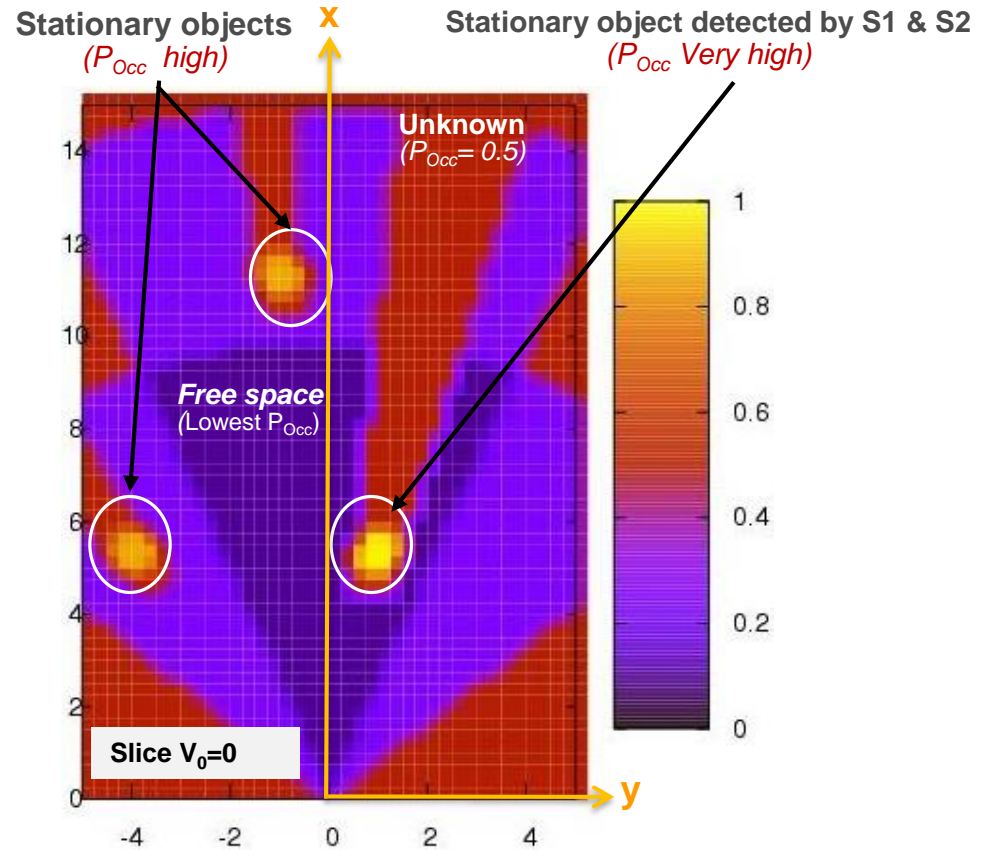
# Step 1: OG Construction – Example 3



2 Sensors (S1 & S2)

3 Stationary objects

- ⇒ Observations sensor S1:  $z_{1,1}$ ,  $z_{1,2}$
- ⇒ Observations sensor S2:  $z_{2,1}$ ,  $z_{2,2}$
- ⇒ **Black object detected by S1 & S2**



$$P_{Occ} = P([O_c = occ] | z_{1,1} \ z_{1,2} \ z_{2,1} \ z_{2,2} \ c)$$

$$z_{1,1} = (5.5, -4, 0, 0) \quad z_{1,2} = (5.5, 1, 0, 0)$$

$$z_{2,1} = (11, -1, 0, 0) \quad z_{2,2} = (5.4, 1.1, 0, 0)$$

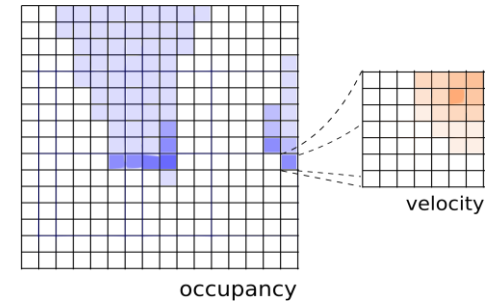
$$c = [x, y, 0, 0]$$

# Step 2: How to compute $P(OV | Z C)$ in practice?

*Initial approach: The classic BOF filtering process*

## Initial implementation:

- ✓ **Regular grid**
- ✓ **Transition histograms** for every cell (for representing velocities)



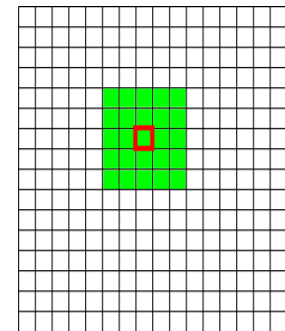
## Practical computation:

$$P(OV | ZC) = \lambda \sum_{A O^{-1} V^{-1}} P(C A O O^{-1} V V^{-1} Z)$$

Sum over the possible antecedents  $A$  and their states  $(O^{-1} V^{-1})$

=> Sum over the **neighborhood**, with a **single possible velocity per antecedent  $A$**  of equation:

$$P(C A O O^{-1} V V^{-1} Z) = P(A) P(O^{-1} V^{-1} | A) P(O V | O^{-1} V^{-1}) P(C | A V) P(Z | O C)$$



## Drawbacks:

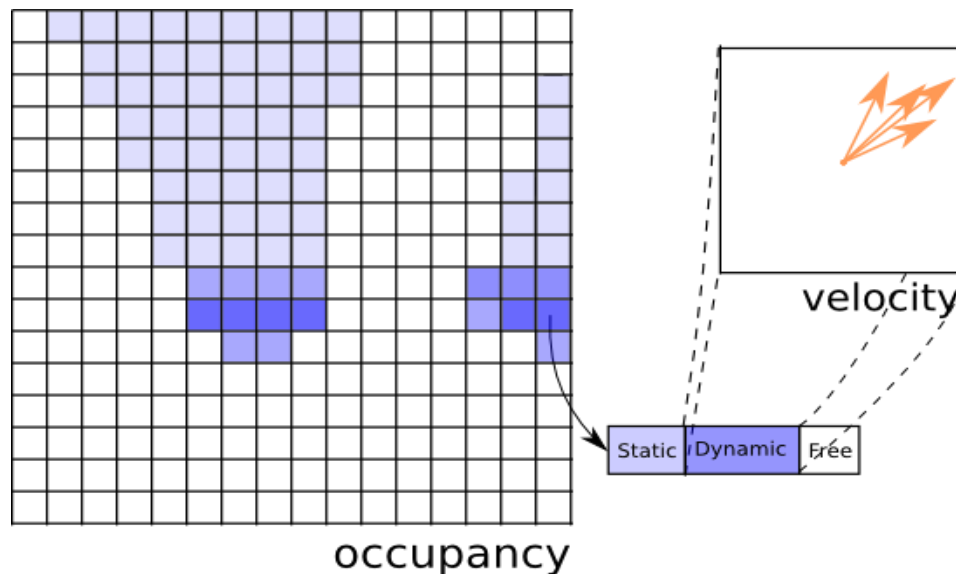
- => Large memory size required (velocity histograms large & almost empty)
- => Weak accuracy
- => Temporal & Spatial Aliasing problems



# Step 2: How to compute $P(OV | Z C)$ in practice?

*Improved approach: HSBOF updating process (principle)*

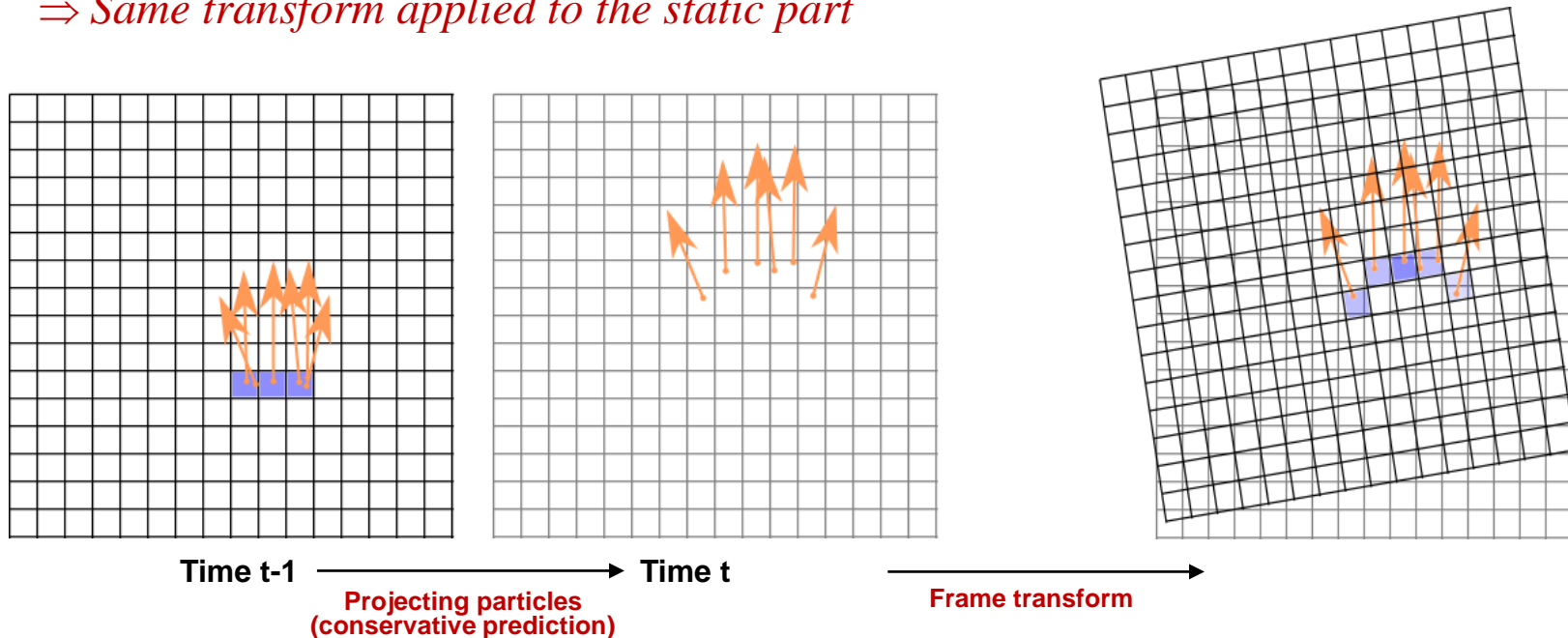
- **Basic idea:** *Modify the representation structure to avoid the previous computational problems*
  - ✓ Making a clear distinction between **Static & Dynamic & Free** components
  - ✓ Modeling velocity using **Particles** (*instead of histogram*)
  - ✓ Making an **adaptive repartition** of those particles in the grid



# Step 2: How to compute $P(OV | Z C)$ in practice?

*Improved approach: HSBOF updating process (principle)*

- Introducing a **Dynamic model** for “projecting” particles in the grid ( $S_{t-1} \rightarrow S_t$ )
  - ⇒ *Immediate antecedent association*
  - ⇒ *Simplified velocity prediction to the cells*
- **Updating Grid Reference Frame** (the car & sensors are in motion)
  - ⇒ *Translation & Rotation values **provided by sensors** (Odometry + IMU)*
  - ⇒ *Same transform applied to the static part*



# Step 2: How to compute $P(OV | Z C)$ in practice ?

*The HSBOF filtering calculation process*

$$P(OV | Z C) = \lambda \sum_{A O^{-1} V^{-1}} P(C A O O^{-1} V V^{-1} Z)$$

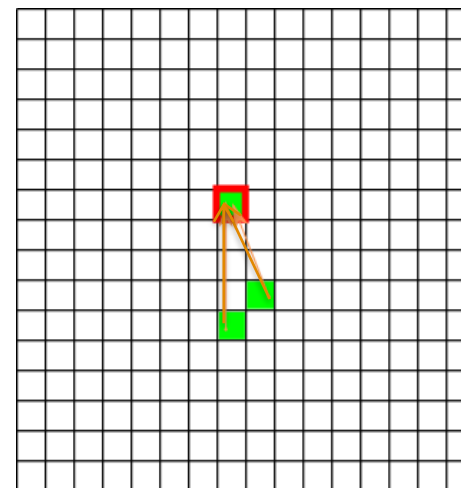
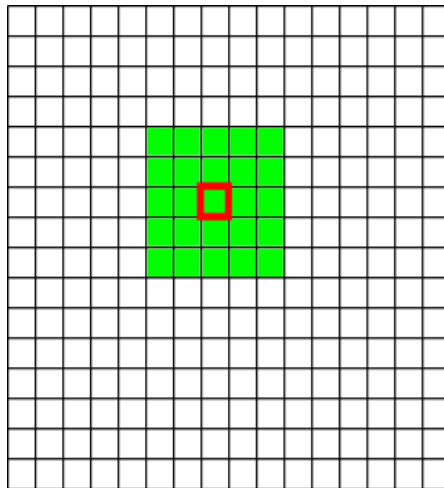
Sum over the neighborhood, with a single velocity per antecedent

**A more efficient computation approach :**

*=> Sum over the particles projected in the cell & their related static parts*

$$P(C A O O^{-1} V V^{-1} Z) = P(A) P(O^{-1} V^{-1} | A) P(O V | O^{-1} V^{-1}) \\ P(C | A V) P(Z | O C)$$

Previous  
computation approach  
(histograms)



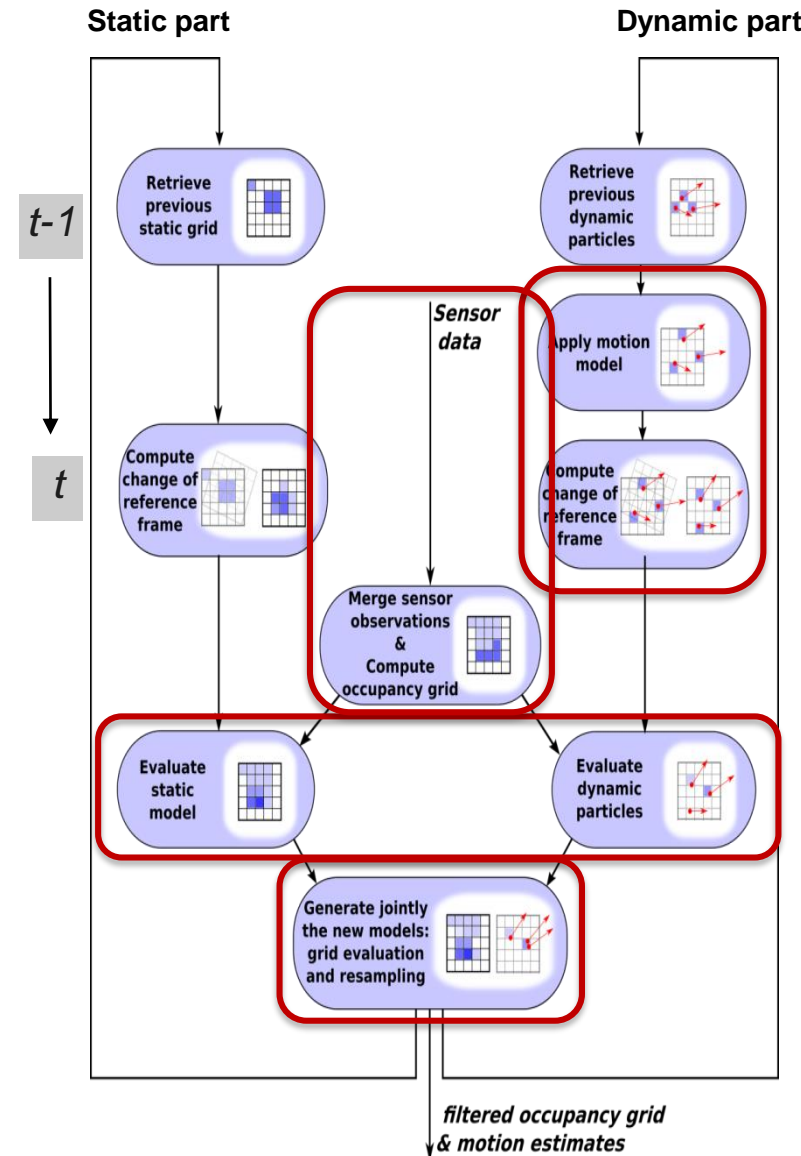
New  
computation approach  
(particles)

# Step 2: How to compute $P(OV | Z C)$ in practice?

## *HSBOF updating process (outline of the algorithm)*

### Main steps in the updating process

- Dynamic part (particles) is “**projected**” in the grid using motion model => *motion prediction*
- Both Dynamic & Static parts are expressed in the **new reference frame** => *moving vehicle frame*
- The two resulting representations are confronted to the **observations** => *estimation step*
- **New representations (static & dynamic)** are jointly evaluated and particles re-sampled





# Content of the Tutorial

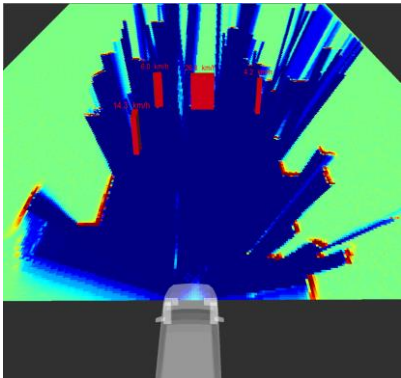
- Socio-economic & Technological Context + State of the Art
- Decisional & Control Architecture – Outline
- Bayesian Perception (*key Technology 1*)
- **Embedded Bayesian Perception & Experimental results**
- Bayesian Risk Assessment & Decision-making (*Key Technology 2*)

# Recent implementations & Improvements

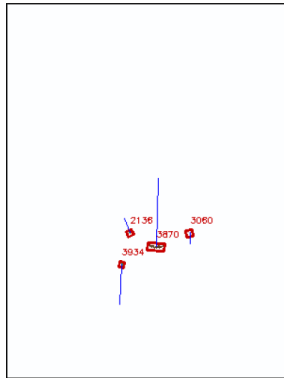


*Several implementations (models & algorithms) more and more adapted to **Embedded constraints & Scene complexity***

- ❖ 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)*
- ❖ CMCDOT + Ground Estimator (Patent 2017) [Rummelhard et al 17]  
=> *Ground shape estimation & Improve obstacle detection (avoid false detections on the ground)*



Grid & Pseudo-objects



Tracked Objects

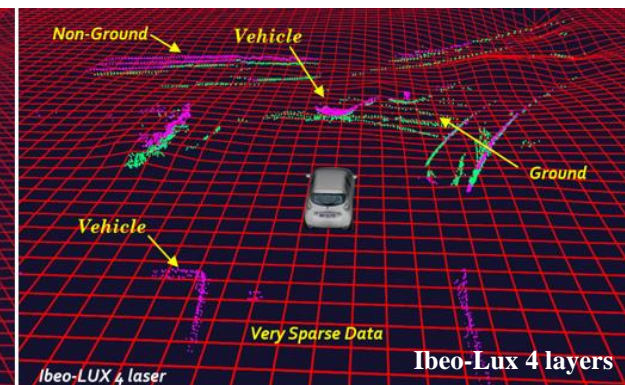
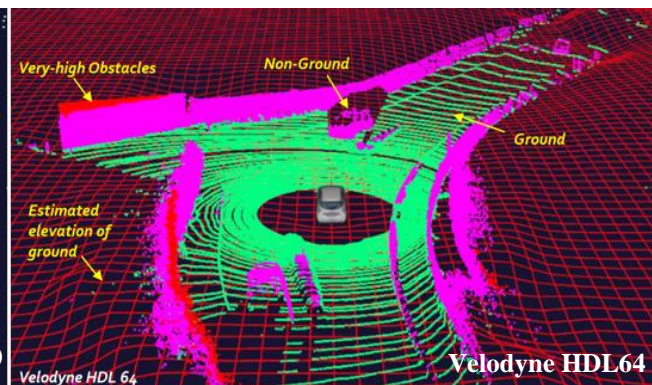
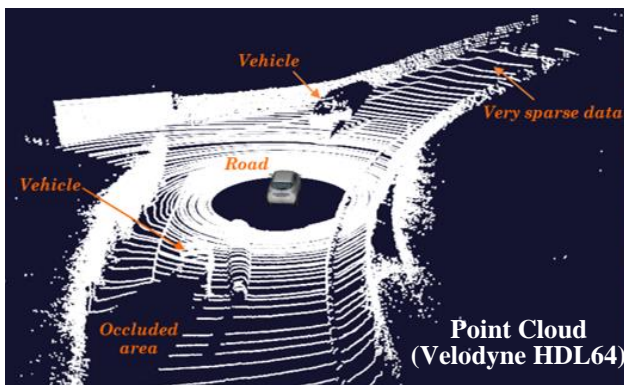


Classification (using Deep Learning)

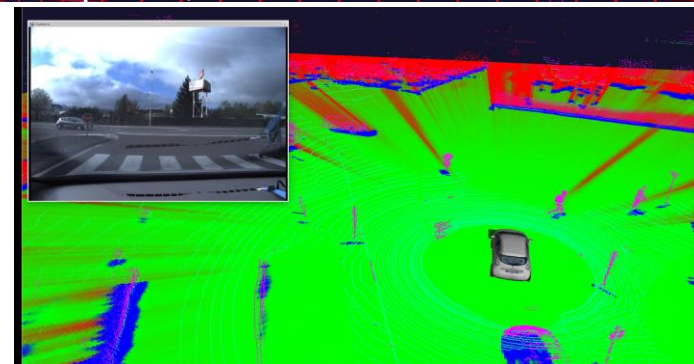
Detection & Tracking  
& Classification

# Ground Estimation & Point Cloud Classification

- ⇒ Smart OG generation taking into account the ground shape & height of laser impacts
- ⇒ Process properly sensors data (for OG & DATMO) & Avoid false detections on the road surface



- **Ground estimation** : 1m x 1m ground node resolution  
⇒ ground-points in green, obstacles in pink / red
- **Occupancy grid** : Images 0.1m x 0.1m occupancy grid resolution  
⇒ green for free space, blue occupied, red unknown



- ❖ Ground model constructed using a *Spatio-Temporal Conditional Random Field*, estimated through efficient parallelized process [1]
- ❖ Model accurate enough to represent rolling roads & Efficient enough for **real-time** performances on embedded devices
- ❖ The complete system (including CMCDOT) has been implemented on a Nvidia Tegra X1



[1] Ground estimation and point cloud segmentation using spatio-temporal conditional random field, Rummelhard et al, IV 2017, Redondo Beach, June 2017



# Integration on a commercial vehicle



- **POC 2017: Complete system implemented on Nvidia TX1**, and easily connected to the shuttle system network *in a few days* (using ROS)



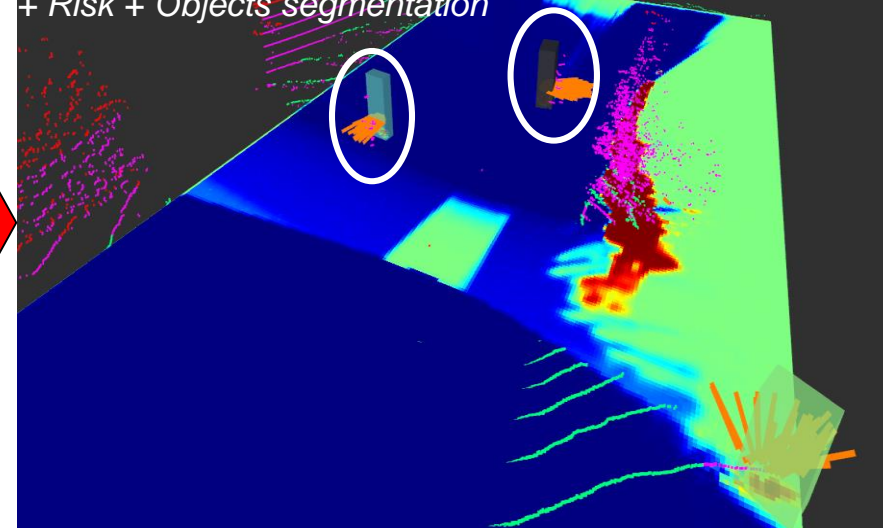
- **Shuttle sensor data** has been fused and processed in **real-time**, with a successful Detection & Characterization of the **Moving & Static Obstacles**
- **Full integration on a commercial product** under development with an industrial company (confidential)

Point cloud classification, with a pedestrian behind the shuttle, and a car in front

Detected moving objects

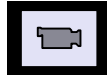
2 Velodyne VLP16  
+  
4 LMS mono-layer

CMCDOT filtered Occupancy Grid + Inferred Velocities + Risk + Objects segmentation





# CMCDOT – *Complete process illustration*



Sensor data



# Experimental Vehicles & Connected Perception Units

Toyota Lexus



ROS



Renault Zoé

Velodyne 3D lidar



cameras



IBEO lidars



## Connected Perception Unit

=> Same embedded perception systems than in vehicles

Nvidia GTX Titan X  
Generation Maxwell



Nvidia GTX Jetson TK1  
Generation Maxwell



Nvidia GTX Jetson TX1  
Generation Maxwell



# Software / Hardware Integration – GPU implementation



- Highly parallelizable framework, **27 kernels** over cells and particles  
=> Occupancy, speed estimation, re-sampling, sorting, prediction
- Real-time implementation (20 Hz), optimized using Nvidia profiling tools

## Results:

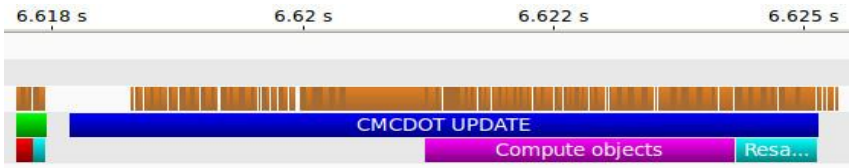
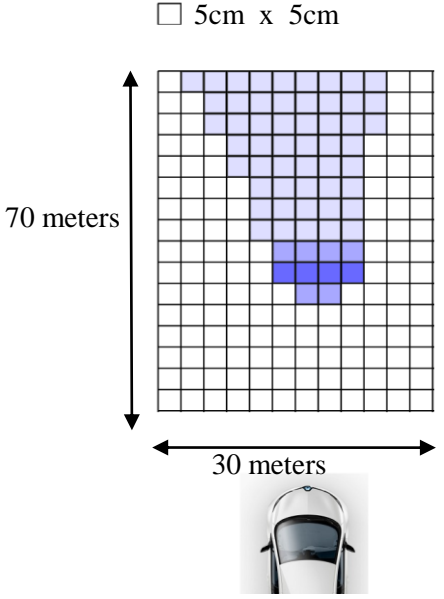
- Configuration with 8 Lidar layers (2x4)
- Grid: 1400 x 600 (840 000 cells) + Velocity samples: 65 536



=> Jetson TK1: *Grid Fusion 17ms, CMCDOT 70ms*



=> Jetson TX1: Grid Fusion 0.7ms, CMCDOT 17ms





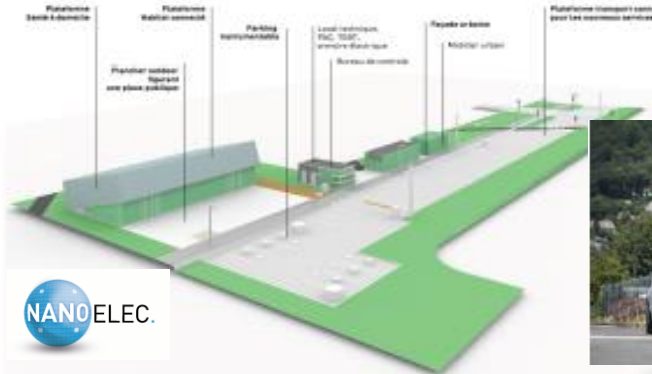
# Experimental Areas



Connected Perception Unit

## Protected experimental area

Un espace d'expérimentation : 3 plateformes

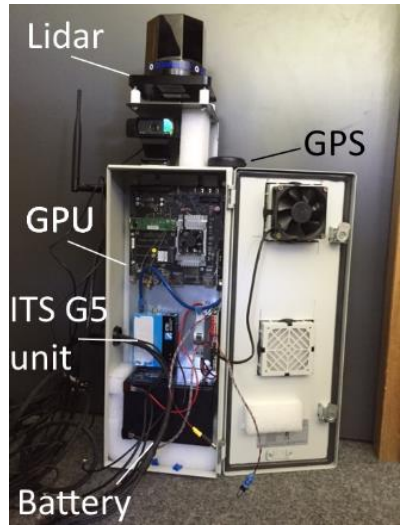
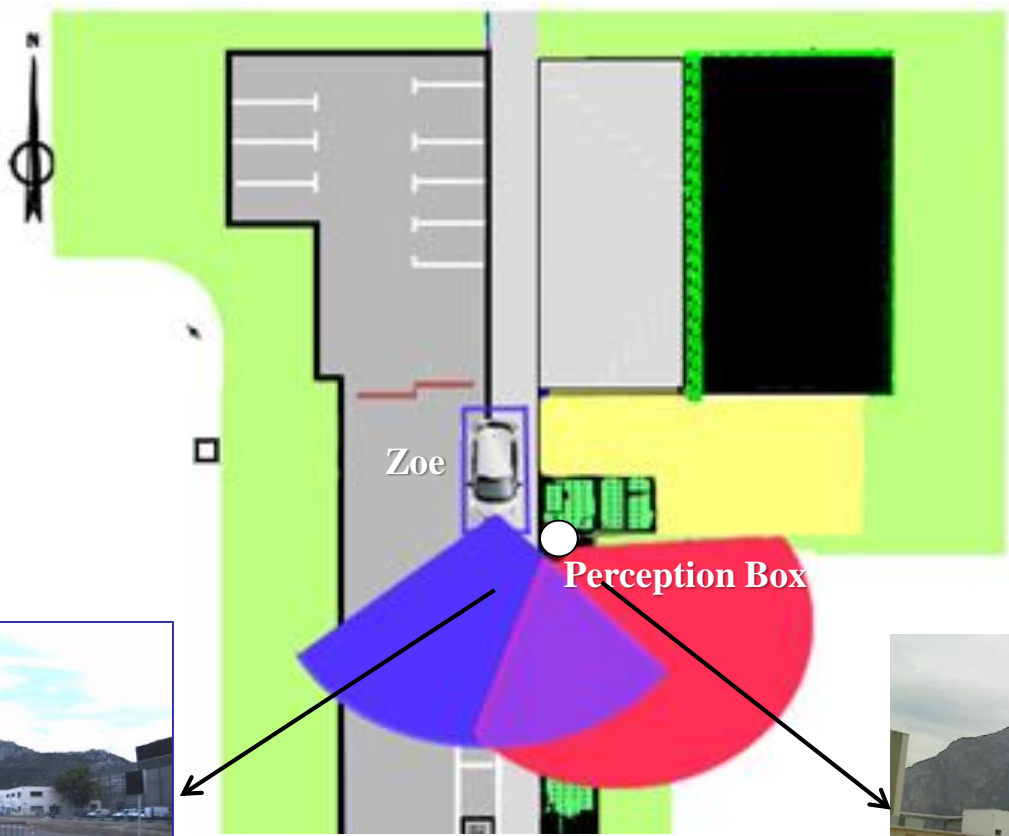


## Open real traffic (Urban & Highway)





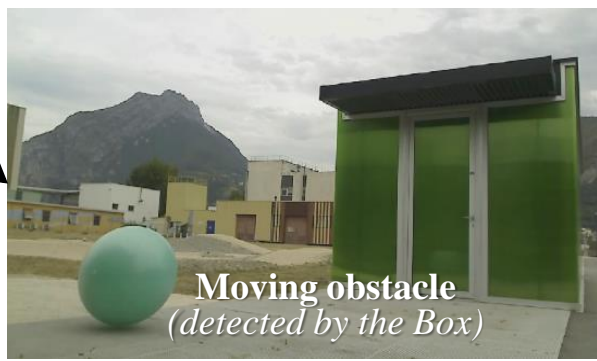
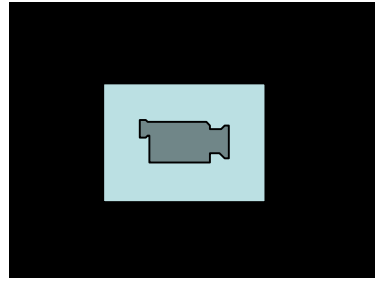
# V2X: Distributed Perception experiment using CMCDOT



Connected Perception Unit



Camera Image provided by the Zoe vehicle

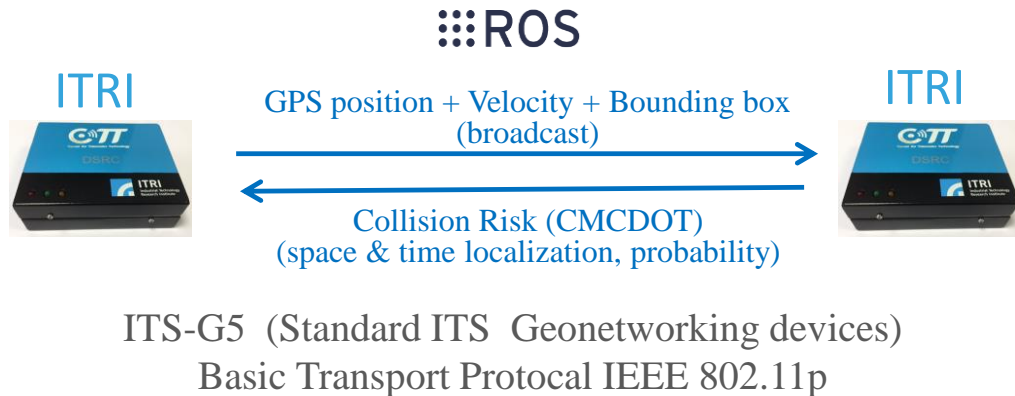


Moving obstacle (detected by the Box)

Camera Image provided by the Perception box

# V2X: Data exchange & Synchronization

## □ Data exchange



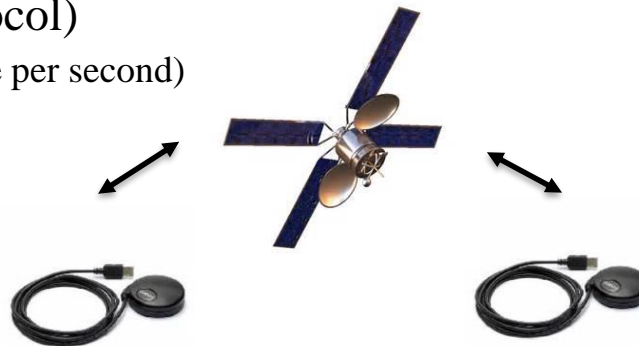
## □ Synchronization

### Chrony (Network Time Protocol)

GPS Garmin + PPS Signal (1 pulse per second)



Serial Port



GPIO + UART

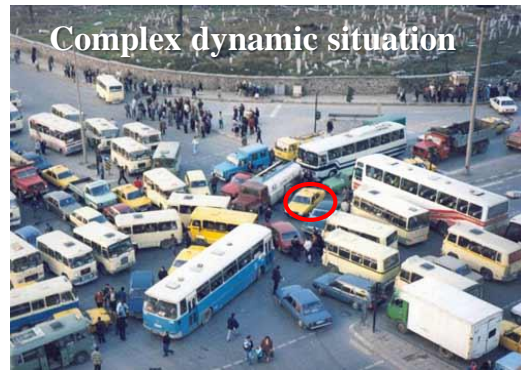


# Content of the Tutorial

- ❑ Socio-economic & Technological Context + State of the Art
- ❑ Decisional & Control Architecture – Outline => Not presented
- ❑ Bayesian Perception (*key Technology 1*)
- ❑ Embedded Bayesian Perception & Experimental results
- ❑ **Bayesian Risk Assessment & Decision-making (*Key Techno 2*)**

# 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*



# Underlying Conservative Prediction Capability

⇒ *Application to Conservative Collision Anticipation*

[Coué & Laugier IJRR 05]

Autonomous  
Vehicle (Cycab)



Parked Vehicle  
(occultation)

**Pioneer  
Results  
(2005)**

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)*

# Step 1: Short-term collision risk – *Main features*

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

## □ Main Features

- Detect “*Risky Situations*” a few seconds ahead (3-5s)
- Risky situations are *both 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  $t < 5s$*

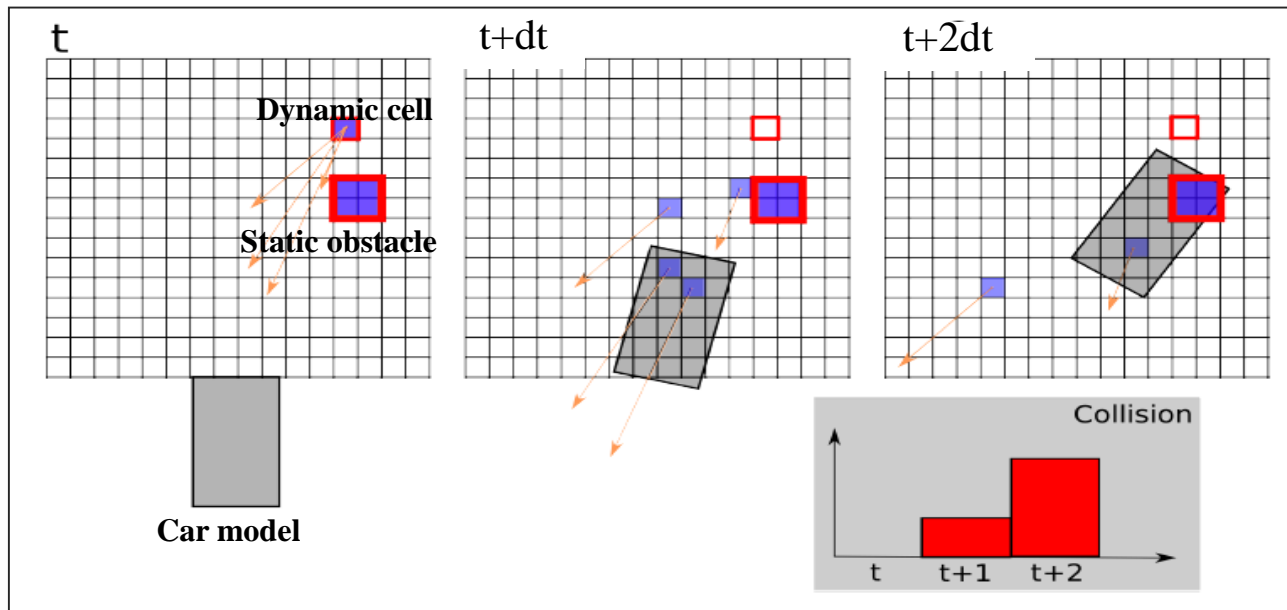
$\delta = 0.5s$  => *Pre-crash*

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

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

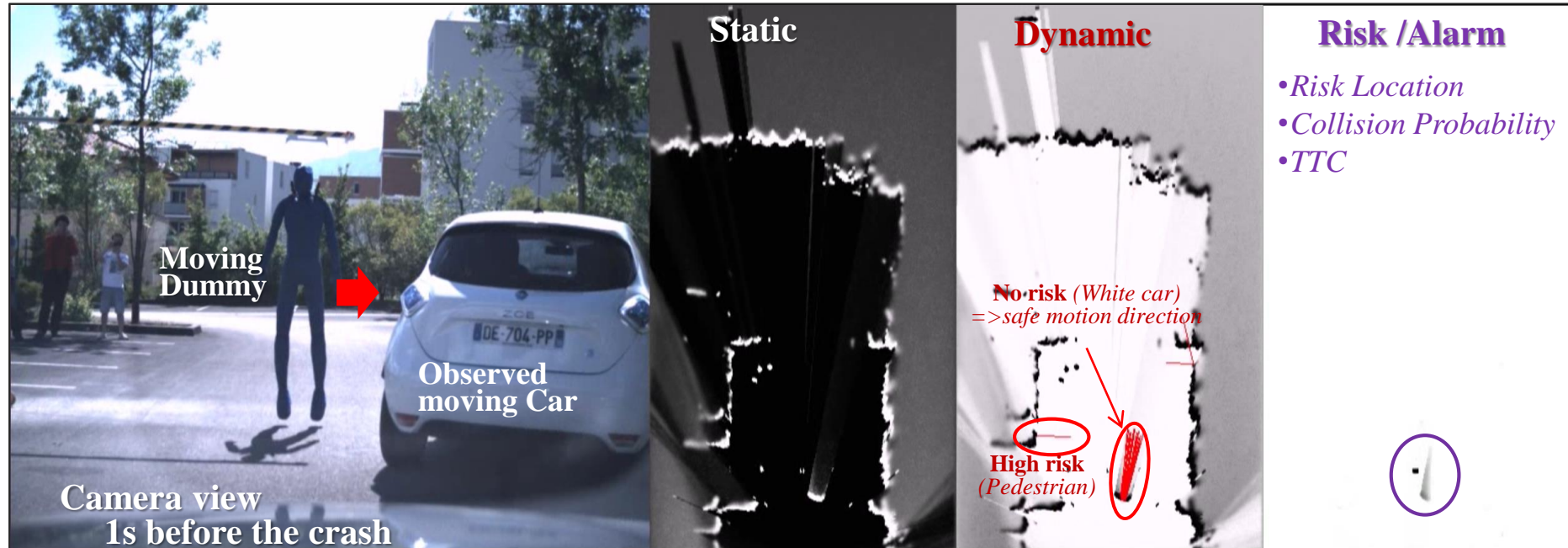
## □ Collision Risk Estimation: *Integration of risk over a time range $[t, t + \delta]$*

=> *Projecting over time the estimated Scene changes (DP-Grid) & Car Model (Shape + Motion)*



# Short-term collision risk – System outputs (real-time)

=> *Static & Dynamic grids + Risk assessment*



- **FAQ :** *What happen if some velocities change after that the collision risk for the next 3s has been evaluated ?*
- **Answer:** *The collision risk is recomputed at the next time step (i.e max 40ms after the change of dynamics).*



# Short-term collision risk – *Experimental results*

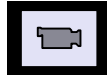
⇒ Detect potential upcoming collisions

⇒ Reduce drastically false alarms



Crash test with no automatic braking





Sensor data

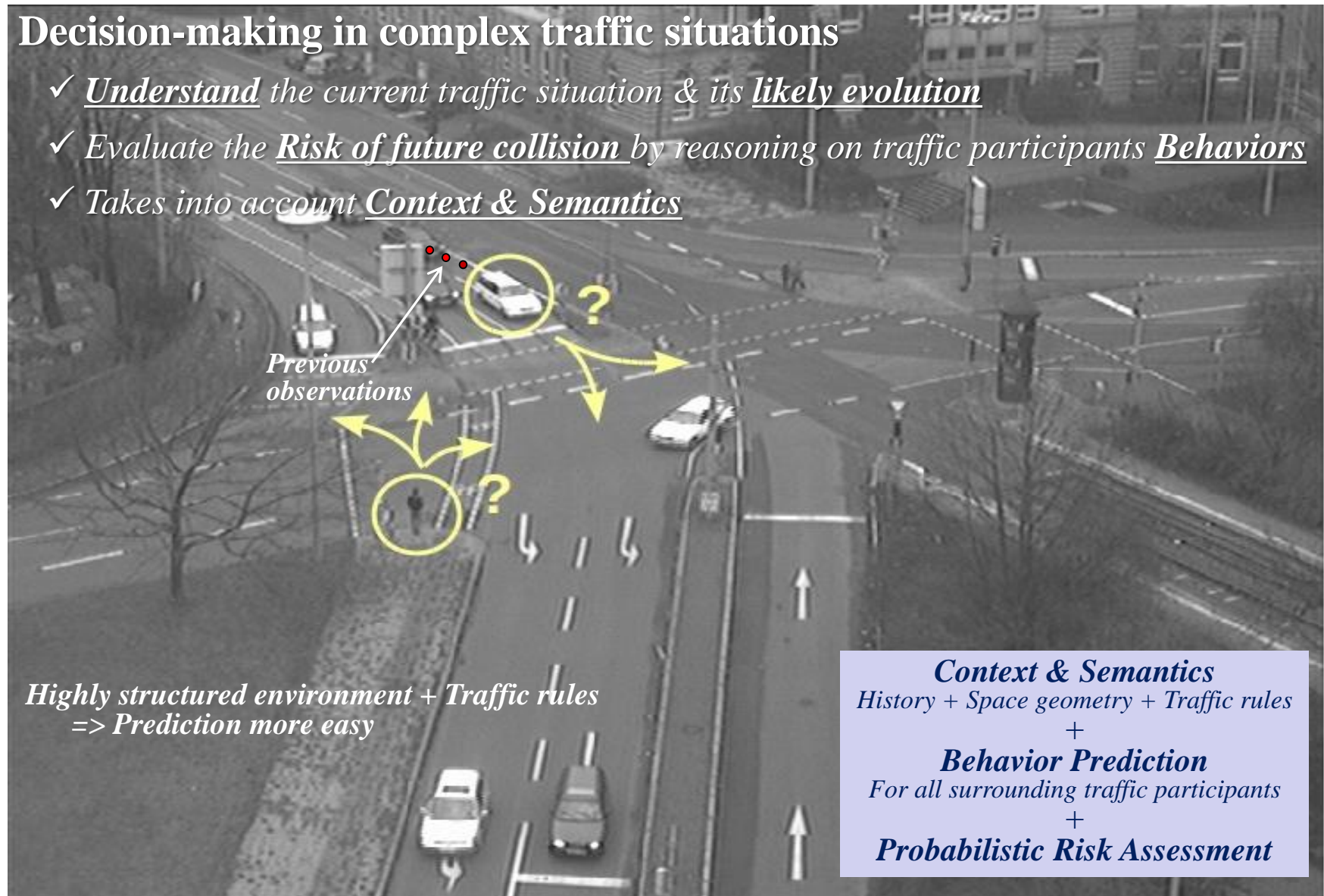


# Step 2: Generalized Risk Assessment (Object level)

- ⇒ Increasing time horizon & complexity using context & semantics
- ⇒ Key concept: **Behaviors Modeling & Prediction**

## 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)

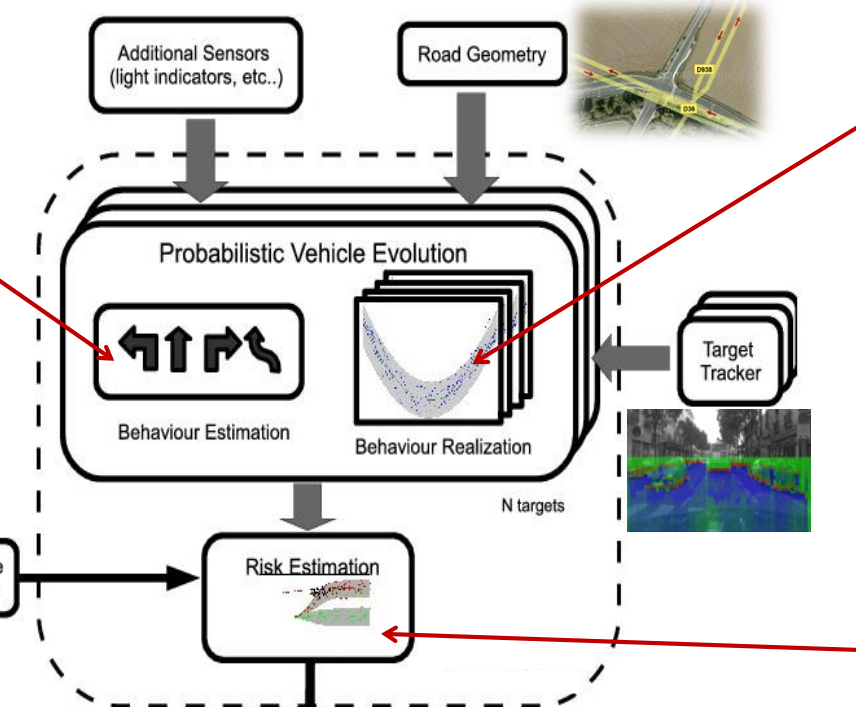
=> Increasing time horizon & complexity + Reasoning on Behaviors

## Approach 1: Trajectory prediction & Collision Risk Assessment

Patent Inria & Toyota & Probayes 2010 + [Tay thesis 09] [Laugier et al 11]

**Behavior modeling & learning**  
+  
**Behavior Prediction**

**Layered HMM**

$$P(B_t | O_{1:t}) = L_{B_t}(O_{1:t}) \sum_{B_{t-1}} P(B_{t-1}) P(B_t | B_{t-1})$$


**From behaviors to trajectories**

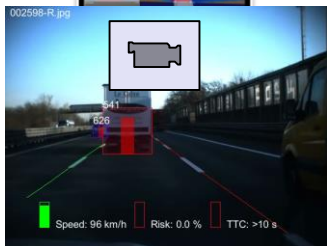
**Gaussian Process + LSCM**

**Collision risk assessment (Probabilistic)**

**MC simulation**



Courtesy Probayes



**Experimental Results**  
Behavior prediction & Risk Assessment on highway  
Probayes & Inria & Toyota



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

=> *Increasing time horizon & complexity + Reasoning on Behaviors*

## 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*

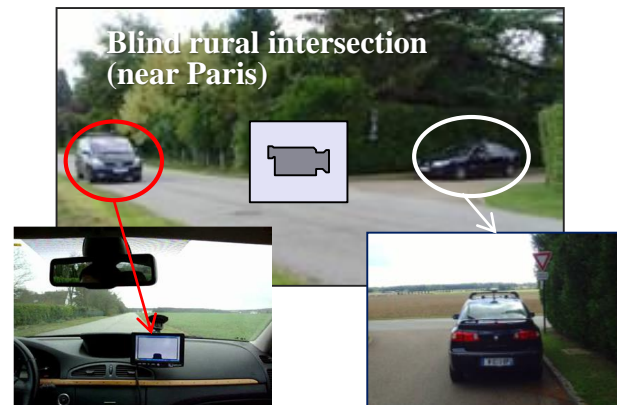
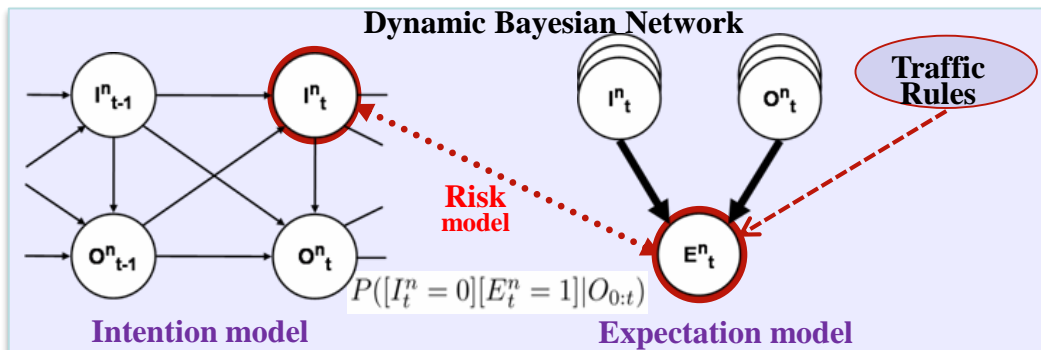
✓ Estimating “Drivers Intentions” from Vehicles States Observations ( $X Y \theta S TS$ ) => Perception or V2V

✓ 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”





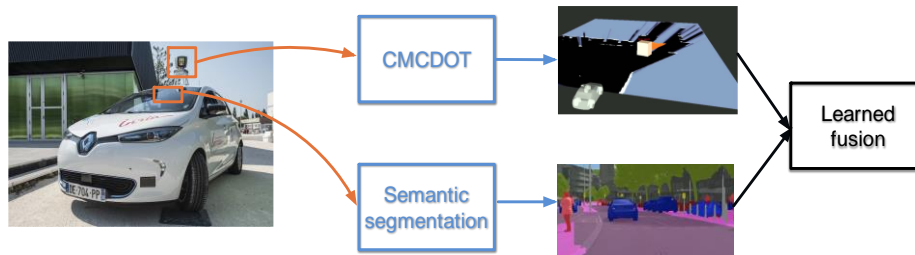
# Current & Future work

## □ New models/algos for integration in various platforms & dynamics

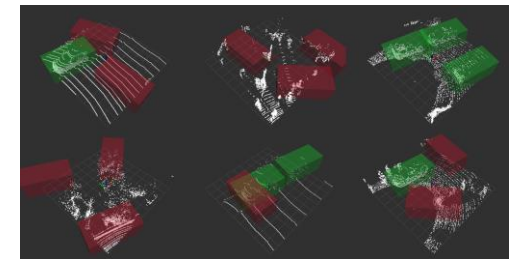


Integration within the Control Units of EasyMile EZ10 shuttle & Iveco bus & Renault Zoe

## □ News approaches & models for constructing “semantic grids” using CNN

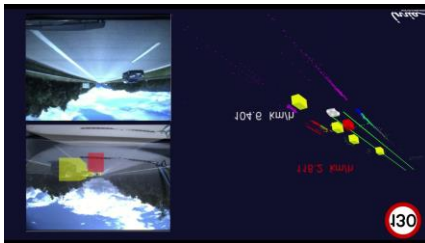


Fusing CMCDOT output (OG) with semantic output from RGB cameras (coop Toyota)  
=> *Patent application & Publications (IROS 2018 & ICARCV 2018)*

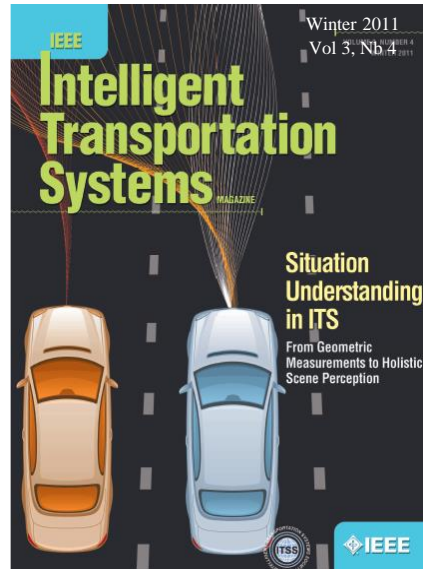
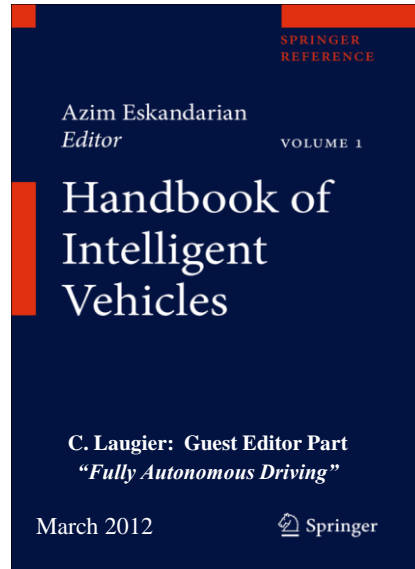


Semantic segmentation in a 3D point cloud  
=> *Master Thesis*

## □ Learning & Predicting driving Behaviors for Autonomous Driving



- Driver behavior modeling using Inverse Reinforcement Learning
  - Combining Model-based prediction with Dynamic evidence to estimate lane change intentions
- => *2 Patents application & publications (ITSC 2016, ICRA 2017, ICRA 2018)*



# Thank You Any questions ?

