

Embedded Perception & Risk Assessment for next Cars Generation

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Contributions from

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Asprom – UIMM – Cap’Tronic

Socio-economic & Scientific 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
- ✓ A Huge ADAS market: *\$16 billions in 2012 & Expected \$261 billions in 2020* ^(f)




CES 2015 & 2016
(Las Vegas)

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



Lack of Robustness & Efficiency 

Lack of Integration into Embedded Sw/Hw 

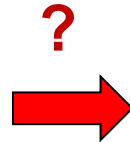
^(f) Forecasted US\$ 260 Billion Global Market for ADAS Systems by 2020. ABI Research. 2013.

Socio-economic & Scientific Context

⇒ Perception Technologies are *pushed forward* by Automotive industry



*Ownership & Affective behaviors
Driving pleasure*



*Technologies for Safety & Comfort
Driving Assistance v/s Autonomous Driving*

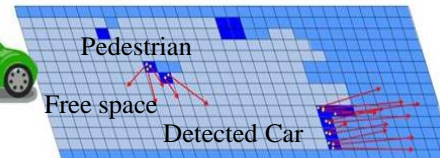
⇒ **Main Issues:** Robustness, Efficiency (*real time processing*), Dynamicity constraints
... and also Miniaturization (*Reducing Size / Cost / Energy consumption*)



Models & Algorithms for
Dynamic environments



Embedded
Sw/Hw integration



Appropriate world model

Embedded implementation



Addressed Problem & Challenges

Robust Embedded Perception & Risk Assessment for Safe & Socially Compliant Navigation in Open & Dynamic Human Environments

Complex Dynamic Scenes



**Situation Awareness
& Decision-making**



ADAS & Autonomous Driving



Road Safety campaign, France 2014



Anticipation & Prediction

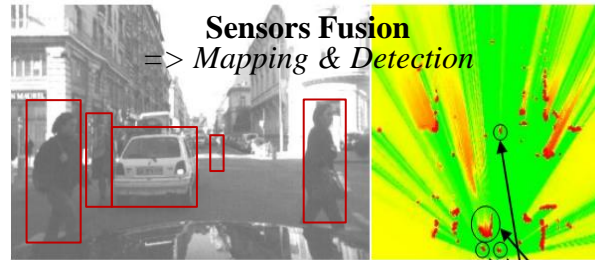
Main features

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

Key Technology 1: Bayesian Perception



Embedded Multi-Sensors Perception
=> *Continuous monitoring the dynamic environment*



❑ Main difficulties

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

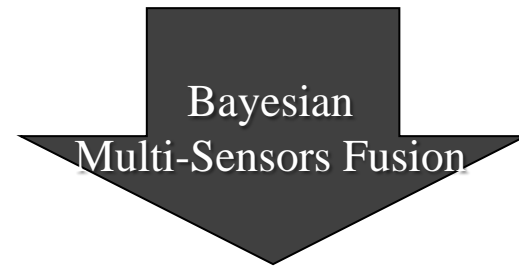
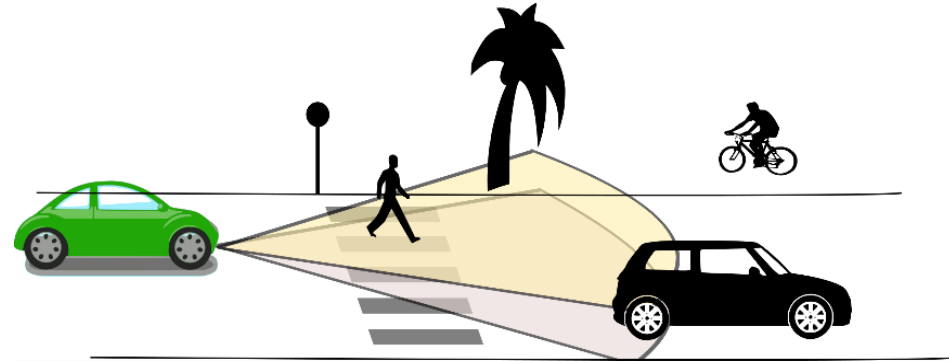
❑ Approach: Bayesian Perception

- *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


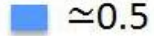

Multi-Sensors Observations

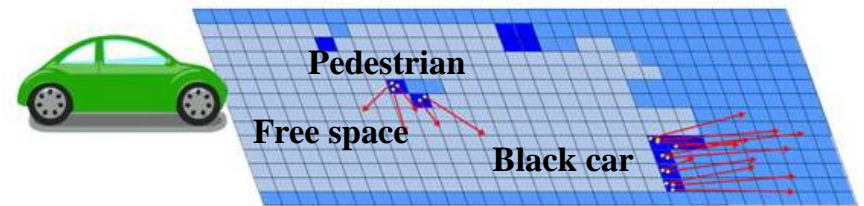
Lidar, Radar, Stereo camera, IMU ...



Probabilistic Environment Model

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

$P[o|Z,C]$:  ≈ 0  ≈ 0.5  ≈ 1

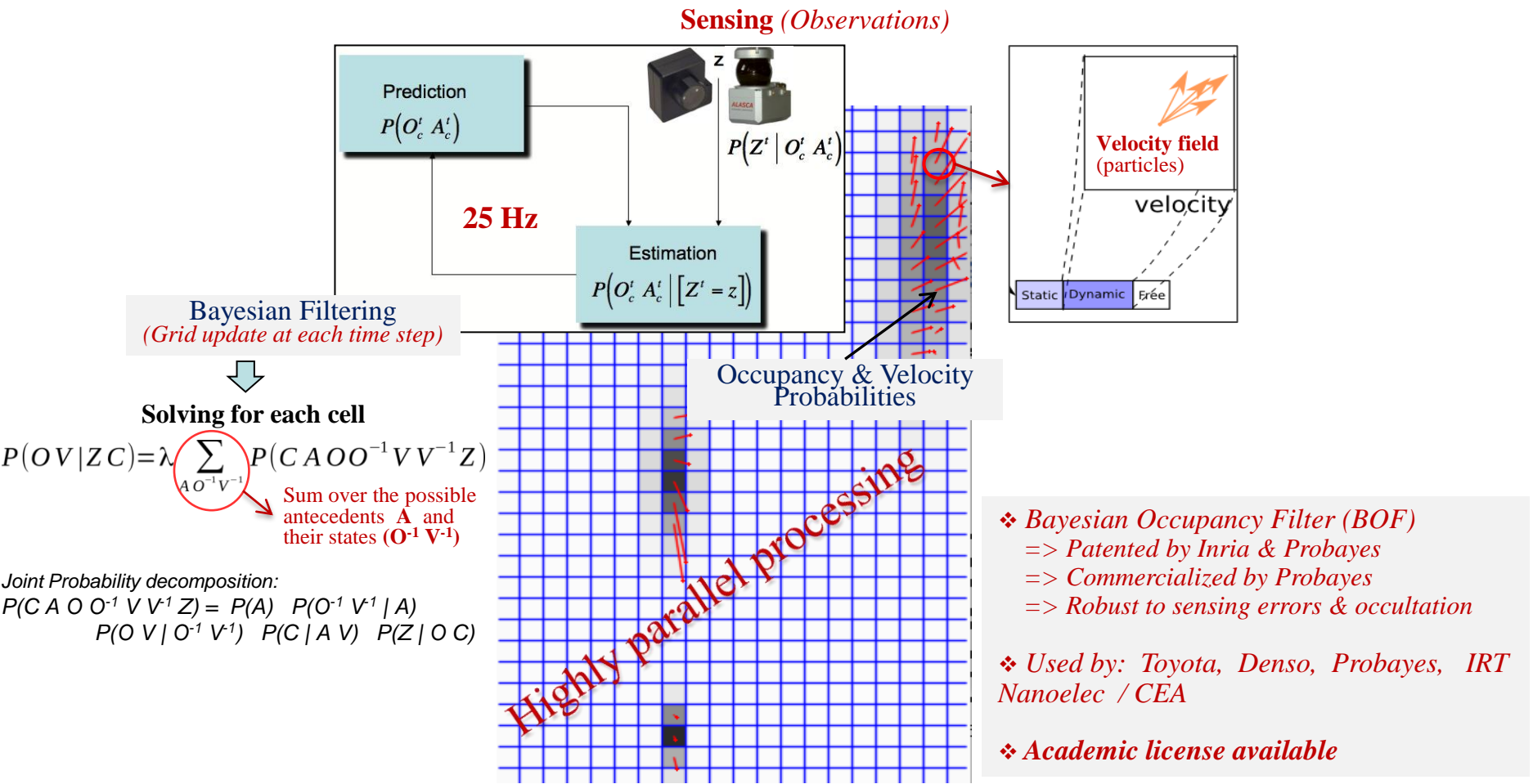


Occupancy probability + Velocity probability
+ Motion prediction model

A new framework: *Dynamic Probabilistic Grids*

A clear distinction between *Static & Dynamic & Free* parts

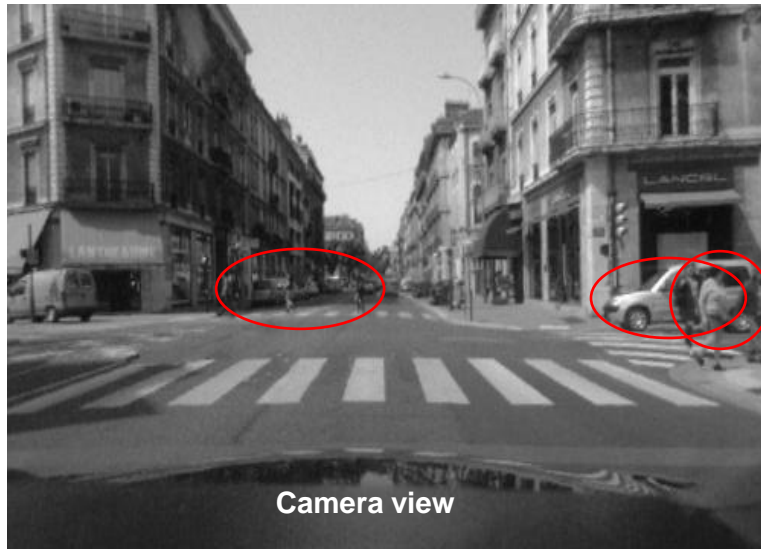
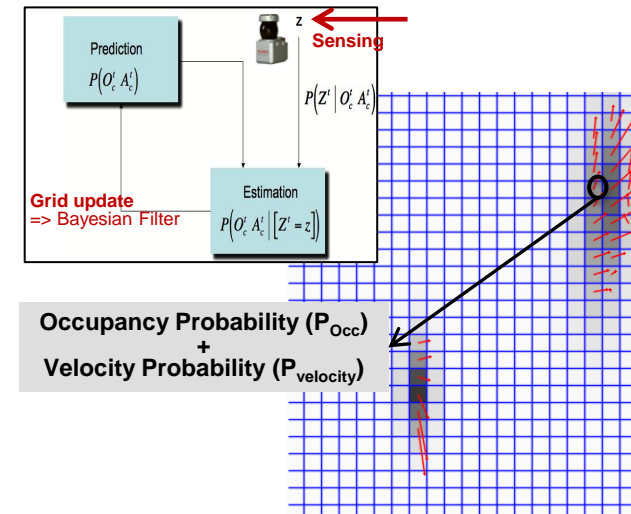
[Coué & Laugier IJRR 05] [Laugier et al ITSM 2011] [Laugier, Vasquez, Martinelli Mooc uTOP 2015]



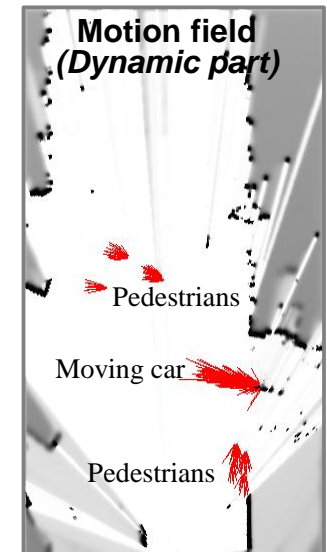
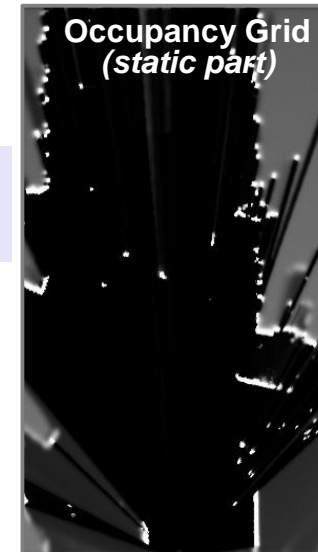
Bayesian Occupancy Filter (BOF) – Outline

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*)

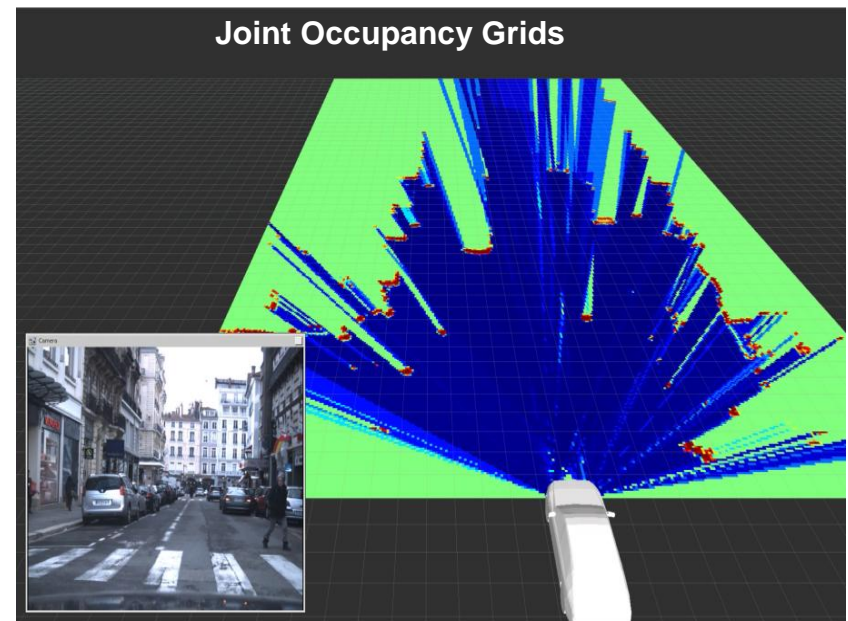
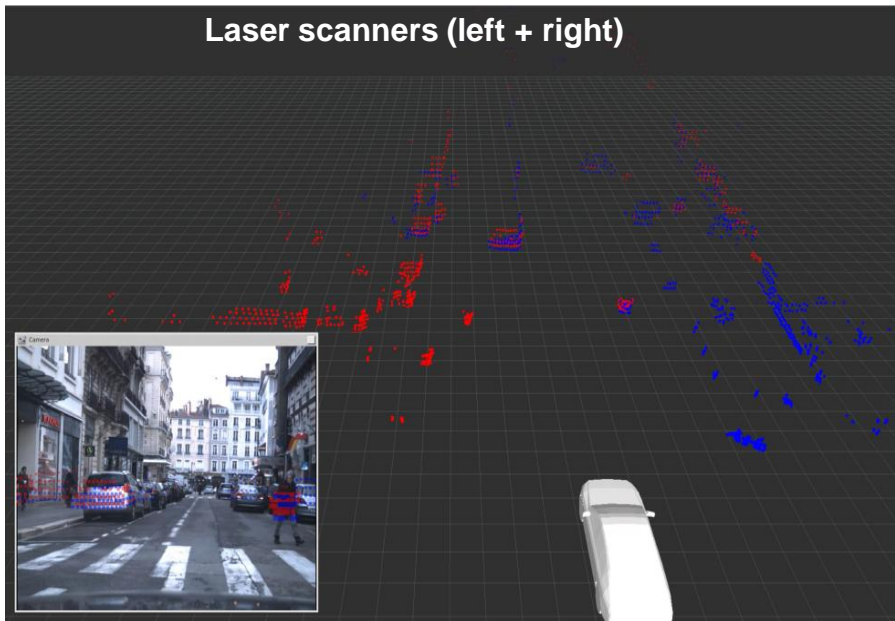


Sensors data fusion
+
Bayesian Filtering



Data fusion: *The joint Occupancy Grid*

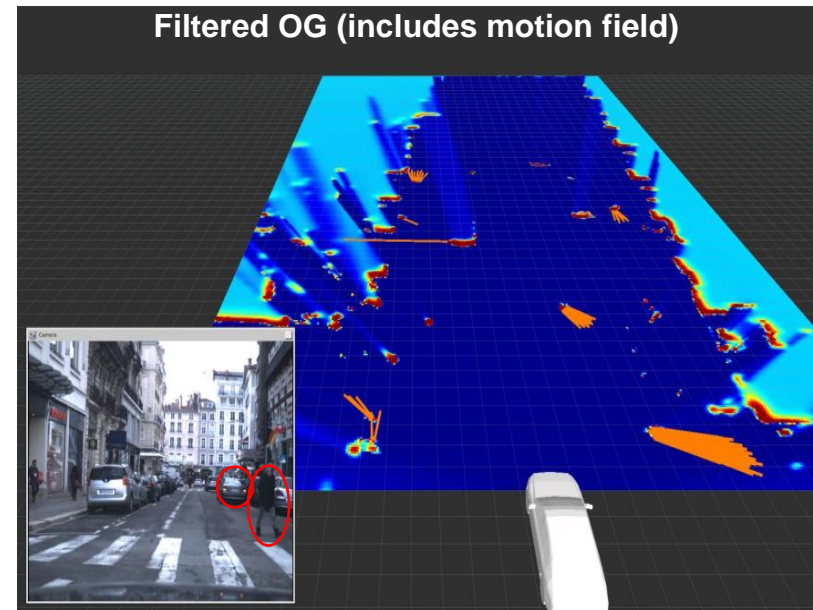
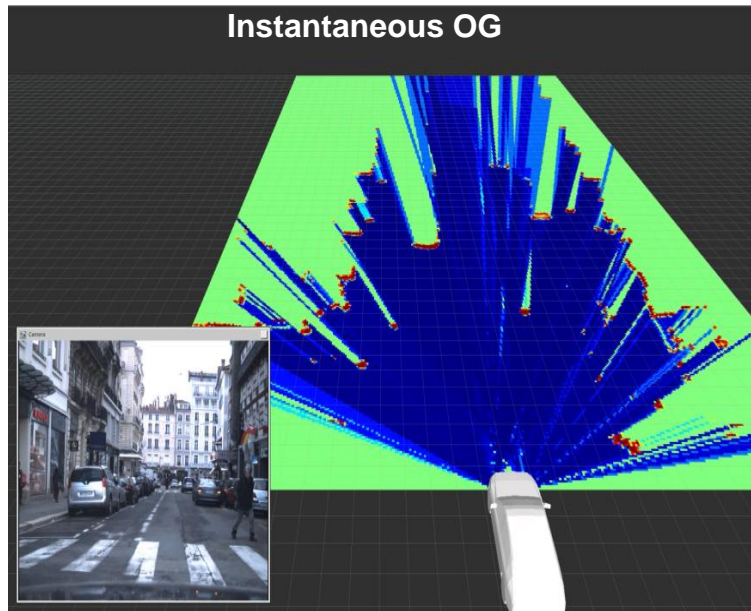
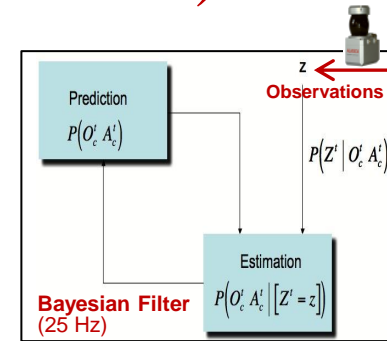
- Observations Z_i are given by each sensor i (*Lidars, cameras, etc*)
- For each set of observation Z_i , Occupancy Grids are computed: $P(O | Z_i)$
- Individual grids are merged into a single one: $P(O | Z)$



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 field is represented in orange color

Underlying Conservative Prediction Capability

=> Application to Conservative Collision Anticipation

Autonomous
Vehicle (Cycab)



Parked Vehicle
(occultation)

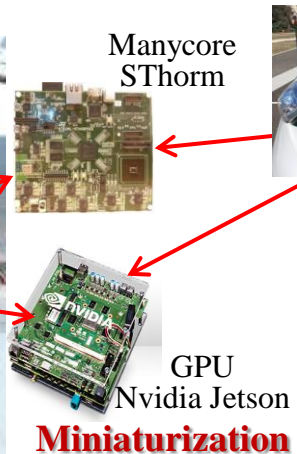
Thanks to the prediction capability of the BOF technology, the Autonomous Vehicle “anticipates” the behavior of the pedestrian and brakes (*even if the pedestrian is temporarily hidden by the parked vehicle*)

Implementation & Experiments (Vehicles)

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



Toyota Lexus



Renault Zoé



Integrated Perception Box
Movable & Connected

Implementation & Experiments (Infrastructure)

IRT Nanoelec experimental platform (*connected infrastructure + 2 Twizy*)



Equipped Renault Zoé



Connected Perception Box



Equipment for pedestrian crash test



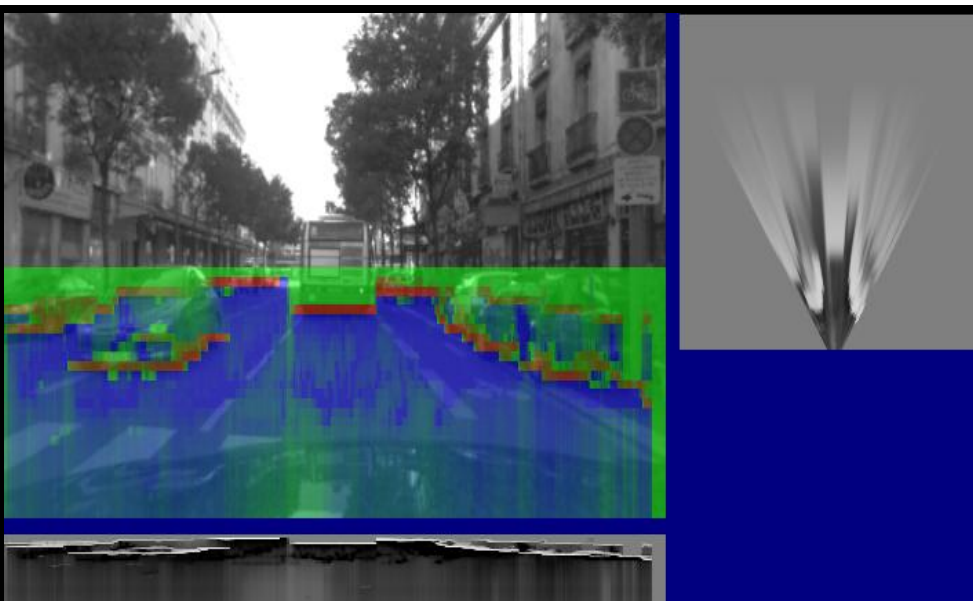
Towards a connected infrastructure

Experimental Results

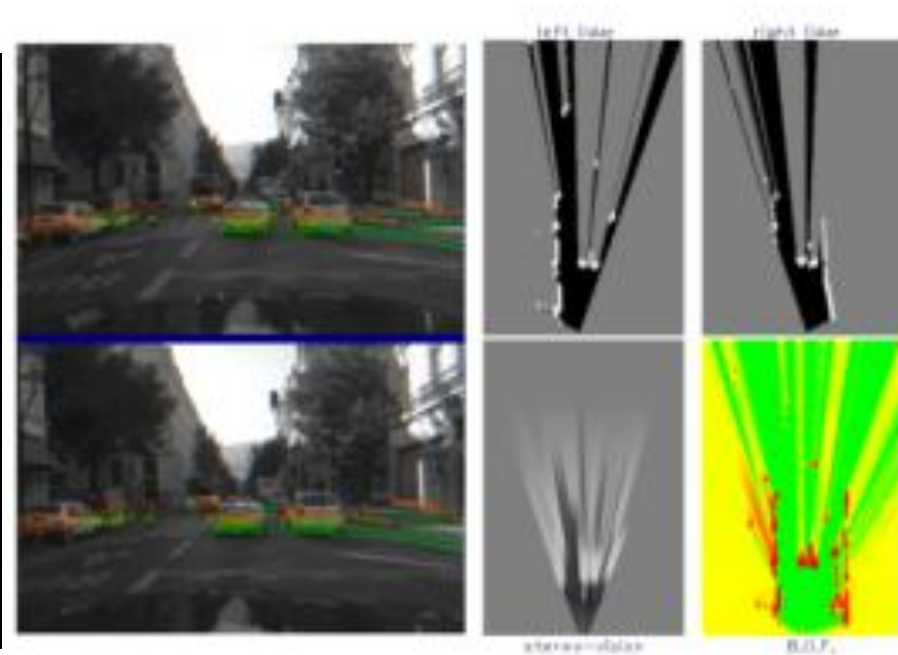
Stereo vision & Lidars Fusion (Inria / Toyota Lexus)



[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 more and more adapted to **Embedded constraints & Scene complexity** :

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

❖ Hybrid Sampling Bayesian Occupancy Filter (HSBOF, 2014)

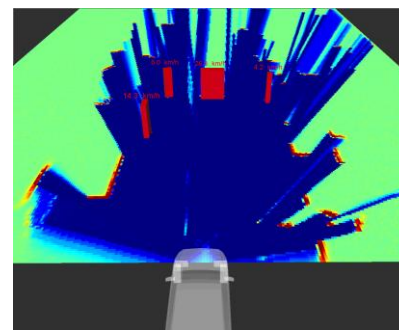
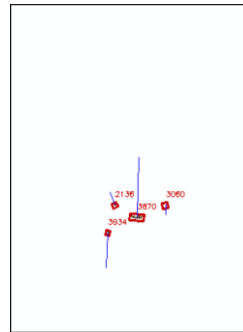
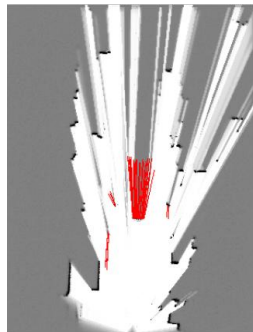
- ✓ *Reducing memory size by a factor 100*
- ✓ *More efficient in complex environments*
- ✓ *Velocities estimation more accurate (using particles & motion data)*



[Rummelhard et al 15]

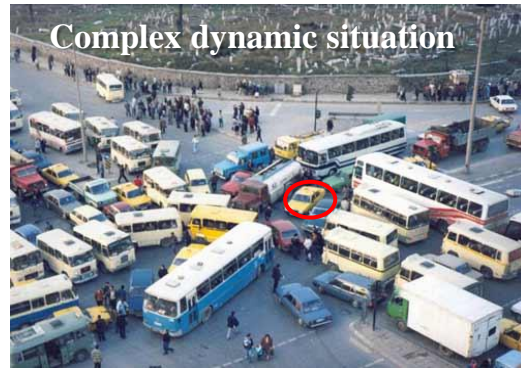
❖ Conditional Monte-Carlo Dense Occupancy Tracker (CMCDOT, 2015)

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



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 ...) & the **Social / Traffic rules**

Step 1: Short-term collision risk – Outline

=> *Grid level & Conservative motion hypotheses*

Objective:

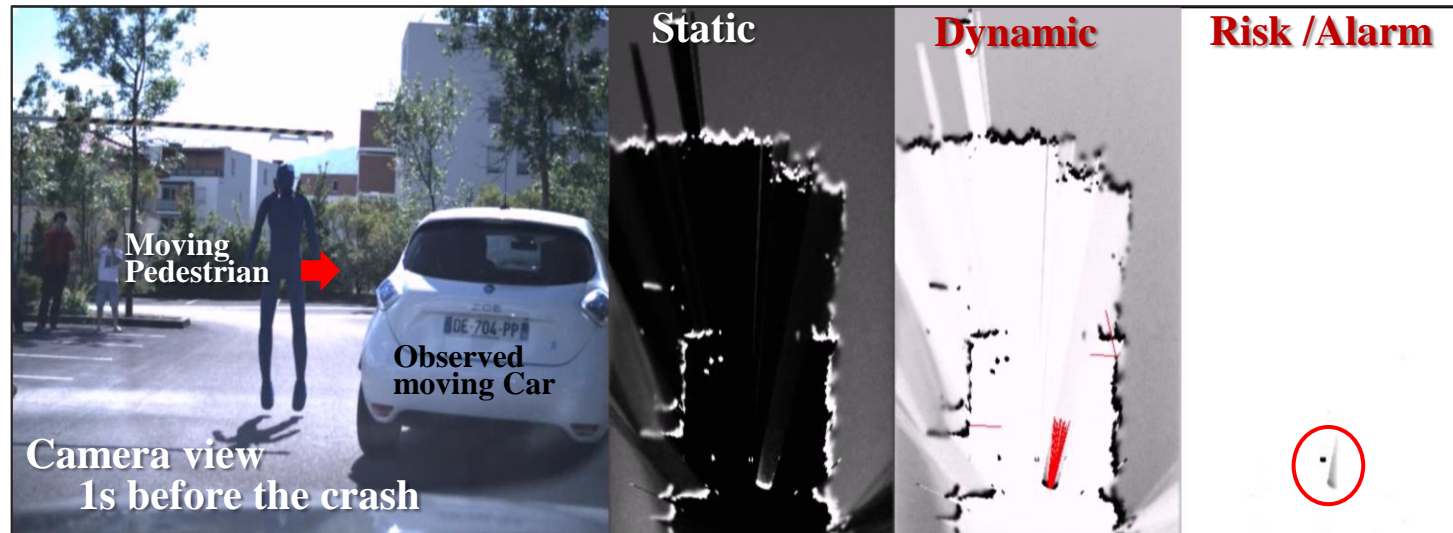
- *Detect “Risky Situations” a few seconds ahead (0.5 – 3 s)*
- *Risky situations are localized in Space & Time*
- *Conservative motion prediction in the grid (Particles & Occupancy)*
- *Collision checking with Car model (shape & velocity) for every future time steps (horizon $t + \delta$)*

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

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

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

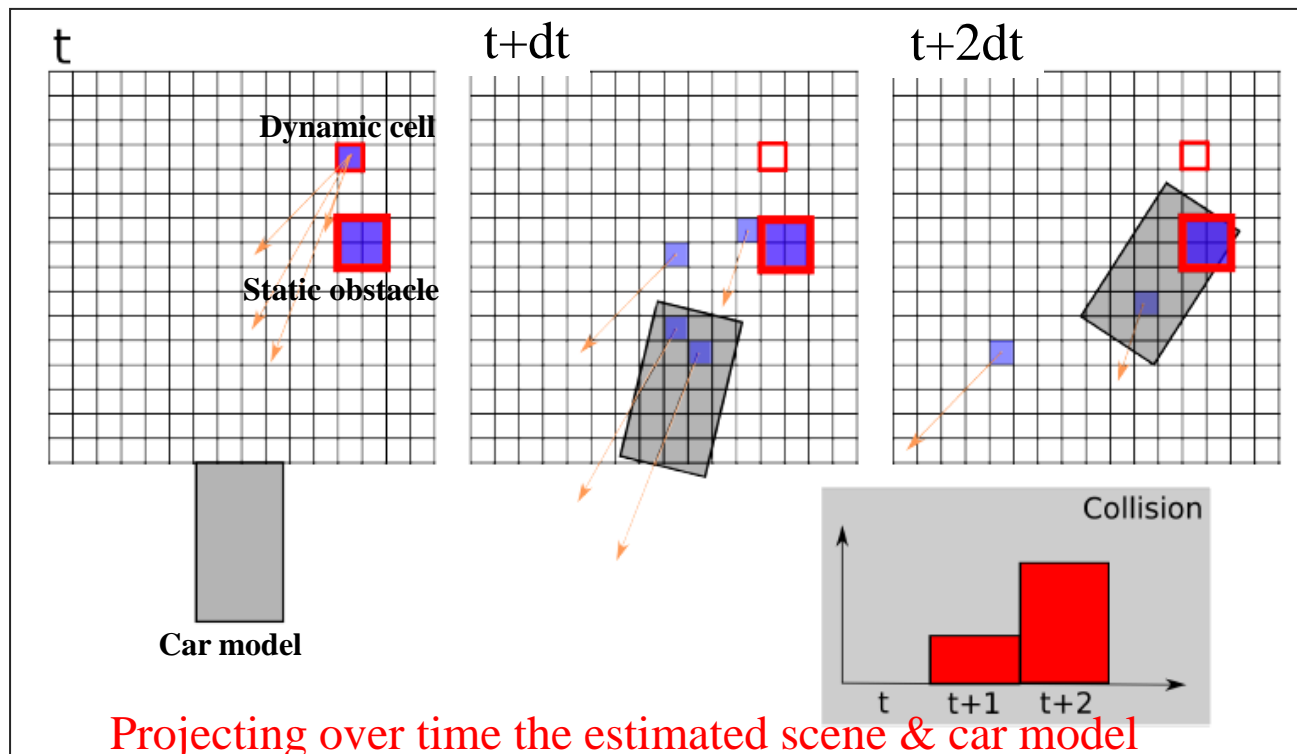
System outputs:



Step 1: Short-term collision risk – Prediction approach

Approach (using conservative prediction)

- ✓ Projecting over time the Estimated scene (*Particles & Occupancy*) & Car model (*Shape & Velocity*) => Apply a **conservative motion model** (using measured car motion data)
- ✓ Collision assessment for every next time step
- ✓ Integration of Risk over a time range $[t \ t+\delta]$



Step 1: Short-term collision risk – Experimental results



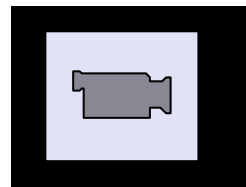
Urban street experiments

=> *Almost no false alarm (car, pedestrians...)*



Crash scenario on test tracks

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



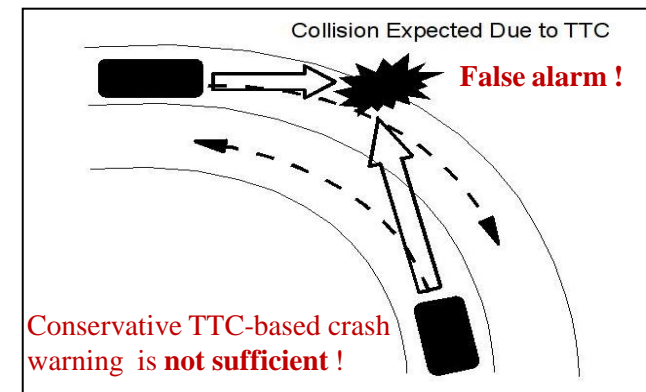
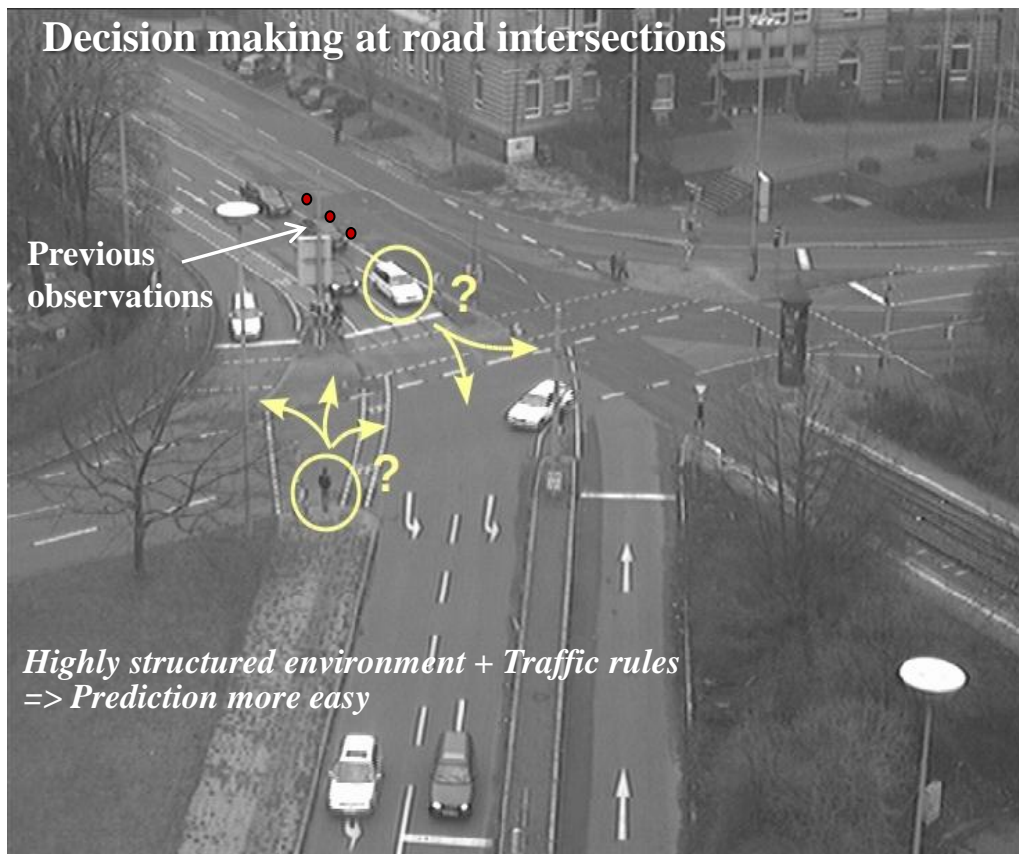
video

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 (*for Safe Navigation Decision*)
- ⇒ **Prediction more easy** with highly structured environment & **Traffic rules**

Decision making at road intersections



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

+

Behavior Prediction
(For all surrounding traffic participants)

+

Probabilistic Risk Assessment

Behavior-based Collision risk (Object level)

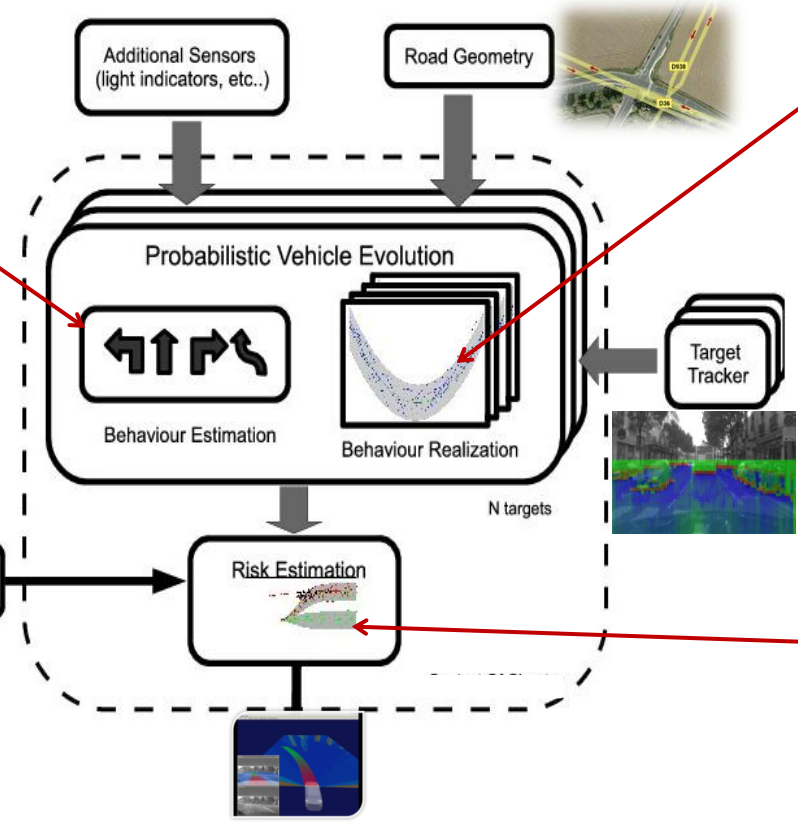
Approach 1: Trajectory prediction & Collision Risk Assessment

[Tay thesis 09] [Laugier et al 11]

Patent Inria & Toyota & Probayes 2010

Behavior modeling & learning
+
Behavior Prediction

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

Lane Turning Left

Lane middle

GP samples for a lane turning left

Gaussian Process + LSCM

Collision risk assessment (Probabilistic)

Intended Path of Vehicle B

Gaussian Process (Lane Change)

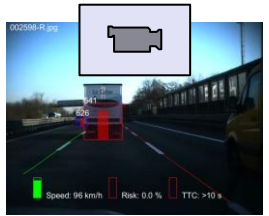
Vehicle B (Risk Estimation for This Vehicle)

Vehicle A

Gaussian Process (Moving Straight)

MC simulation

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 (*intersections*)

Patent Inria & Berkeley 2013 (*generalization*)

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

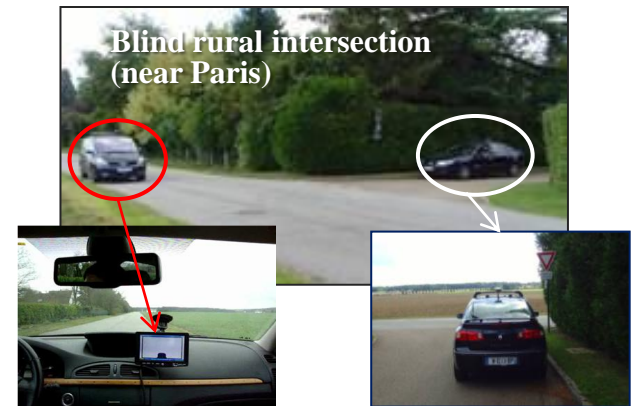
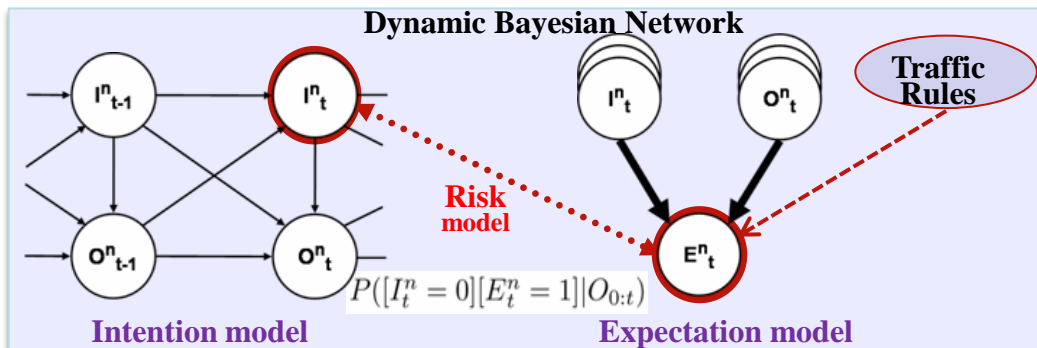
✓ Estimating “Drivers Intentions” from Vehicles States Observations ($X Y \theta S TS$) => Perception or V2V

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

✓ Risk = Comparing Maneuvers Intention & Expectation

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

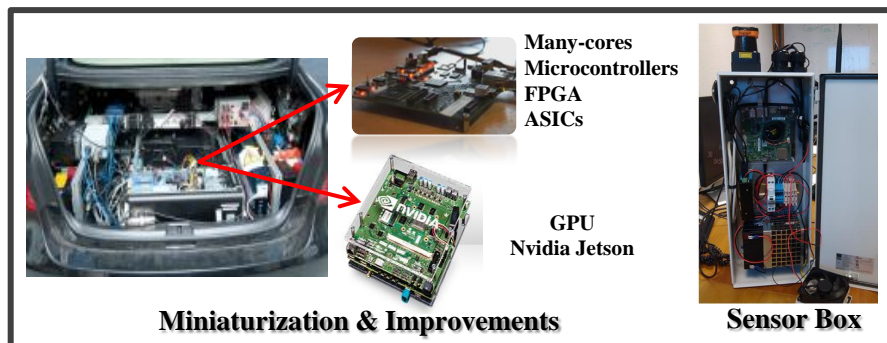
=> **Digital map** obtained using “Open Street Map”





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

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



CPU (2006) GPU (2010) Manycore & GPU low power (2015)

Improved Bayesian algorithms
Integration on Lightweight Hw (2017)

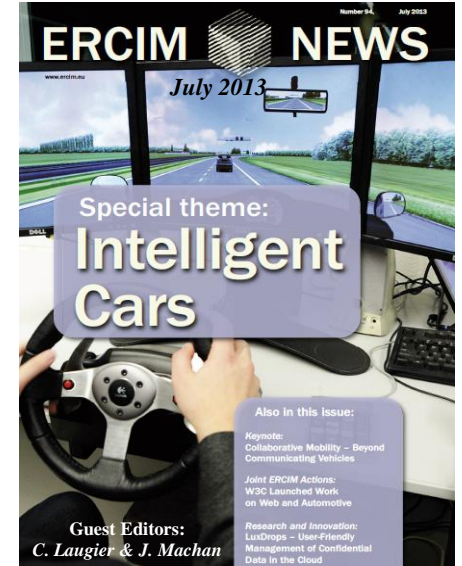
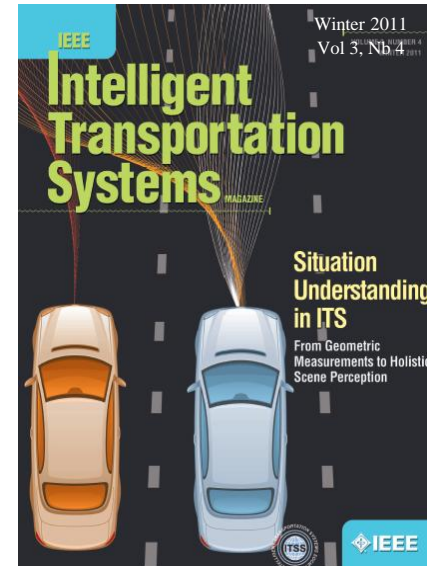
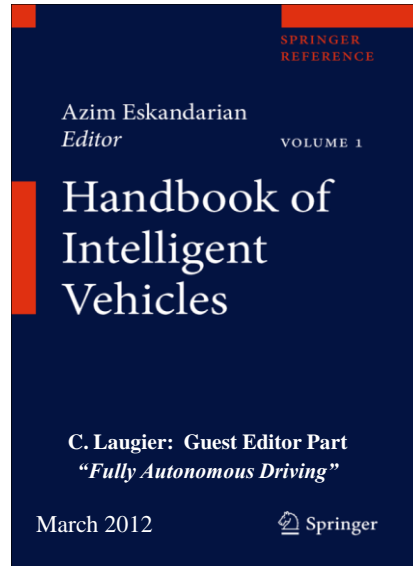
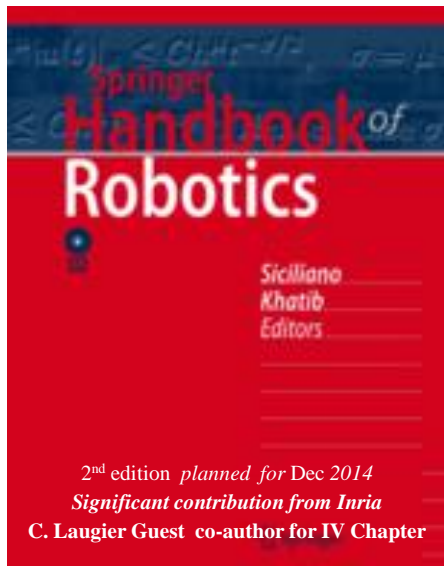
Dedicated Hw / Sw
integration (2018-20)

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

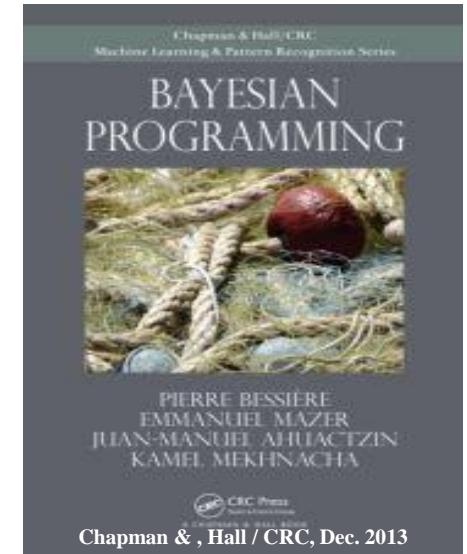
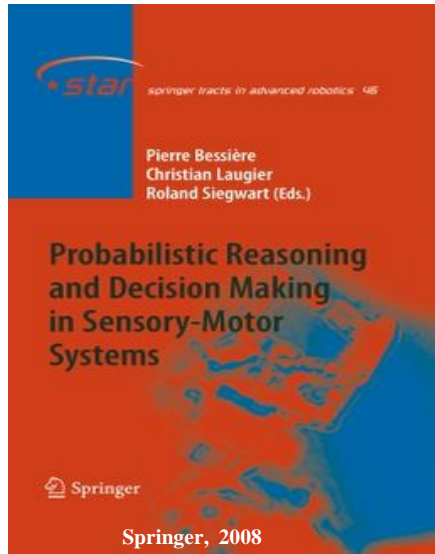
Technologies for Intelligent Mobility (*Perception + Decision + Control + Learning*)

- ✓ *Decisional Process for Autonomous Driving (PhD)* => *Berkeley & Renault (2015-17)*
- ✓ *Situation awareness & Learned driving behaviors (PhD)* => *Toyota (2015-17)*
- ✓ *Human-Aware mobility in crowded environments (PhD, A. Spalanzani)* => *ANR Valet + PIA Valeo ?(2016-18)*
- ✓ *Certification of Embedded Perception Systems (Postdoc + Engineer)* => *EU ENABLE-S3 (2016-19)*





Thank You  Any questions ?



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