## **Embedded Bayesian Perception & Risk Assessment** for ADAS & Autonomous Cars

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

**Contributions from** 

Mathias Perrollaz, Christopher Tay Meng Keat, Stephanie Lefevre, Javier-Ibanez Guzman Amaury Negre, Lukas Rummerlhard





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C. LAUGIER – "Embedded Bayesian Perception & Risk Assessment for ADAS & Autonomous Cars"



## Content of the talk

- □ Socio-economic context & Addressed problem
- □ Bayesian Perception (*Key Technology 1*)
- Bayesian Risk Assessment & Decision-making (Key Technology 2)
- □ Conclusion & Perspectives



## **Automobile plays a big role in our human society** A Social & Industrial revolution in the 20<sup>th</sup> century

#### The car ?

A technological machine designed for enhancing individual Mobility ?



#### For most of cars owners it's more than that !

✓ Synonymous to **motion freedom** 

✓ Often considered as a Precious Personal
Goods & showing a particular Social position

✓ Often synonymous to **Driving Pleasure** (including speed feeling)... but this is progressively changing because of rules enforcements

✓ Look / Performances & Comfort / Safety are more and more considered as important criteria ....



# **But the reality is somewhat different !** in particular in cities











## Intelligent Mobility & Next Cars Generation A drastic change of the Societal & Economic context

- □ Huge expected growth of the number of Vehicles (~3 billions in 2050) & of People in cities (~75% of population in 2050)
- □ Human Society is **no more accepting** all the **nuisances** & the incredible socio-economic cost of traffic accidents => 50 millions injuries & 1.3 million fatalities/Year in the world [1] ... 93% of road accidents are caused by human errors !
- **Driving Safety & Efficiency** are now becoming **major issues** for both **governments** (regulations & supporting plans) and the **automotive industry** (technology & commercial issues)
- Growth of ADAS market: \$16 billions at the end of 2012 ... \$261 billions by 2020 [2]

□ New Technologies can strongly help for (e.g. for ADAS & Autonomous Driving)

- ✓ Constructing Cleaner & more Intelligent cars => Next cars generation
- ✓ Developing Sustainable Mobility solutions for smart cities => Cybercars

[1] G.Yeomans. Autonomous Vehicles, Handling Over Control: Opportunities and Risks for Insurance. Lloyd's 2014 [2] ABI Research on Intelligent Transportation Systems and Automotive Technologies Research Services



C. LAUGIER – "Embedded Bavesian Perception & Risk Assessment for ADAS & Autonomous Cars" Keynote talk, PPNIV 7Workshop, IEEE/RSJ IROS 2015, Hamburg, September 28<sup>h</sup> 2015

## The good news

□ Thanks to the last decades advances in the fields of *ICT & Robotics*, *Smart Cars & ITS* are gradually becoming a reality

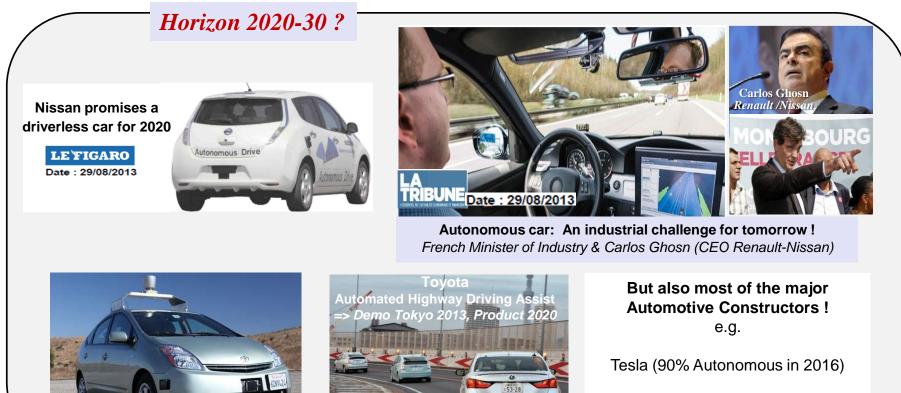
=> Driving assistance & Autonomous driving, Passive & Active Safety systems, V2X communications, Green technologies for reducing fuel consumption & pollution ... and also significant advances in **Embedded Perception & Decision-making systems** 

Legal issue is also progressively addressed by governmental authorities
 => June 22, 2011: Law Authorizing Driverless Cars on Nevada roads ... and this law has also been adopted later on by California and some other states in USA

=> Several other countries (including Europe, France, Japan ...) are also currently analyzing the way to adapt the legislation to this new generation of cars



## Automotive industry **Expected evolution from ADAS to Driverless Cars?**



=> 140 000 miles covered

Google Car 2011

Volvo, Mercedes Class S, BMW

Still some open questions: Why driverless cars? Intelligent co-Pilot v/s Full Autonomy? Acceptability ? Legal issue ? Driver / Co-Pilot Control transitions ?



## **Today talk: Addressed Problem & Challenges**

Safe & Socially Compliant Vehicle Navigation in Open & Dynamic Human Environments *Focus on Perception & Risk Assessment & Decision-making* 

Place Charles de Gaulle (Paris), every day





Road Safety campaign, France 2014



Situation Awareness & Decision-making in complex situations

### **Main features**

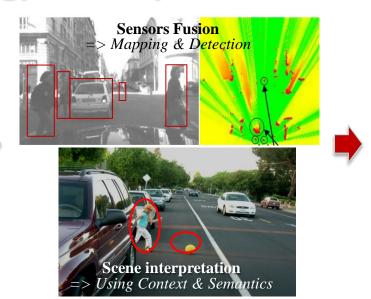
- ✓ Dynamic & Open Environments
- ✓ Incompleteness & Uncertainty (Model & Perception)

✓ Human in the loop (Social & Interaction Constraints)

## **Key Technology 1: Bayesian Perception**



Embedded Perception => Continuous monitoring the dynamic environment





### Main difficulties

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

### □ Approach: Bayesian Perception

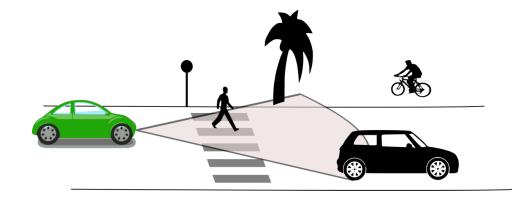
- > Reasoning about Uncertainty & Time window (Past & Future events)
- > Improving robustness using Bayesian Sensors Fusion
- > Interpreting the dynamic scene using Semantic & Contextual information



## **Bayesian Perception : Basic idea**

### Sensors Observations

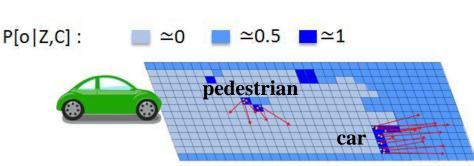
Lidar, Stereo camera, IMU ...





#### **Environment Model**

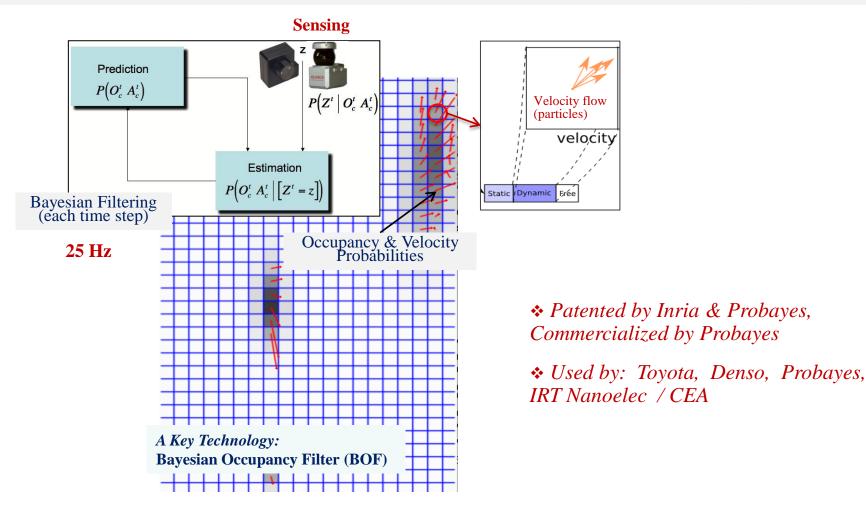
- Sensor Fusion
- Occupancy grid integrating uncertainty
- Velocities representations
- Prediction models



Occupancy probability + Velocity probability + Motion prediction model



## A new framework: Dynamic Probabilistic Grid A clear distinction between Static & Dynamic parts



Processing Dynamic Environments using **DP-Grids** (Occupation & Velocity Probabilities)

- Bayesian Inference + Probabilistic Sensor & Dynamic Models (Robust to sensing errors & occultation)
- Highly parallel processing (Hardware implementation : GPU, Many-core architecture, SoC)

## **Bayesian Occupancy Filter (BOF): Outline**

### Main features:

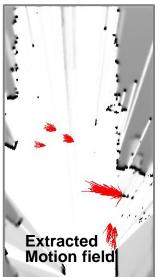
- Estimate Spatial occupancy
- Analyze Motion Field (using Bayesian filtering)
- Reason at the Grid level (i.e. no object segmentation at this level)

| Prediction $P(O_c^t A_c^t)$              | $P[Z^{t}   O_{c}^{t} A_{c}^{t}]$     |
|--|--------------------------------------|
| <b>Grid update</b><br>=> Bayesian Filter | Estimation $P(O'_c A'_c   [Z' = z])$ |
| Occupancy Pro<br>+<br>Velocity Proba     |                                      |
|  |                                      |



Sensors data fusion + Bayesian Filtering

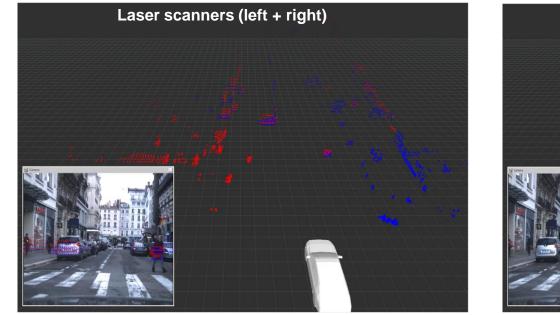


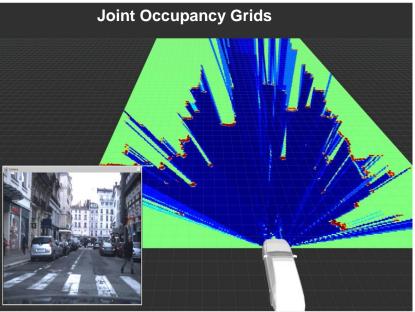




## Data fusion: The joint Occupancy Grid

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

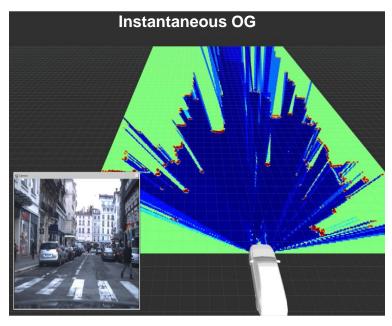


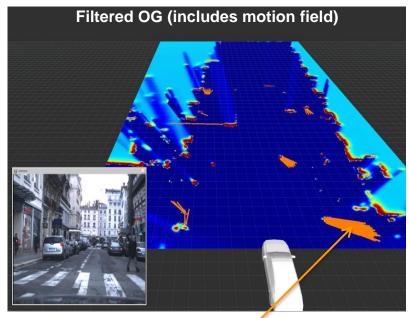




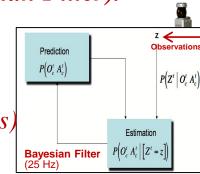
### Taking into account dynamicity: *Filtered Occupancy Grid (Bayesian filtering)*

- 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





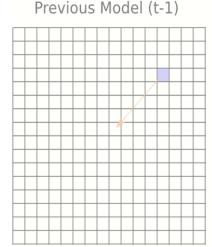
## **Bayesian Occupancy Filter – Formalism**

### Variables:

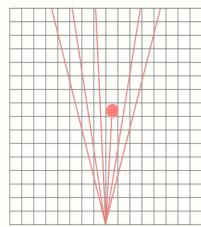
- C : current cell
- A : antecedent cell, i.e. the cell from which the occupancy of the current cell comes from
- O : occupancy of the current cell C
- O<sup>-1</sup> : previous occupancy in the antecedent cell
- V : current velocity
- V<sup>-1</sup> : previous velocity in the antecedent
- Z : observations (sensor data)

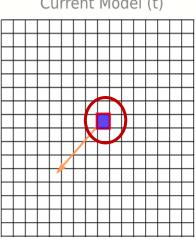
### **Objective**:

Evaluate P(O V | Z C) : Probability of **Occupancy & Velocity** for each cell C, Knowing the observations Z and the cell *location* C *in the grid* 



#### Observations (t)







Current Model (t)

### Bayesian Occupancy Filter How to theoretically compute P(O V | Z C)?

$$P(OV|ZC) = \lambda \sum_{A O^{-1}V^{-1}} P(CAOO^{-1}VV^{-1}Z)$$
  
Sum over the possible antecedents  
A and their states (O<sup>-1</sup>V<sup>-1</sup>)

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

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

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

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

P(O<sup>-1</sup> V<sup>-1</sup> | A) : Result from the previous iteration

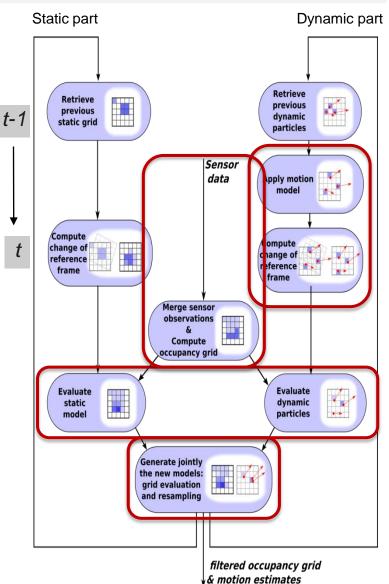
P(O V | O<sup>-1</sup> V<sup>-1</sup>) : Dynamic model

- 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) : Sensor model

### Bayesian Occupancy Filter How to compute P(O V | Z C) in practice (HSBOF process)

#### 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



### **Underlying Conservative** <u>Prediction</u> Capability => Application to Conservative Collision Anticipation

Autonomous Vehicle (Cycab)

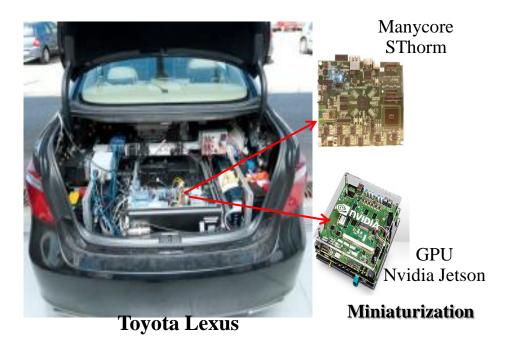


Parked Vehicle (occultation)

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)

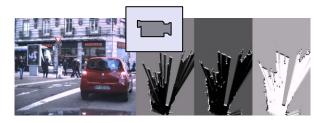


## **Implementation & Experimentation**





**Renault Zoé** 



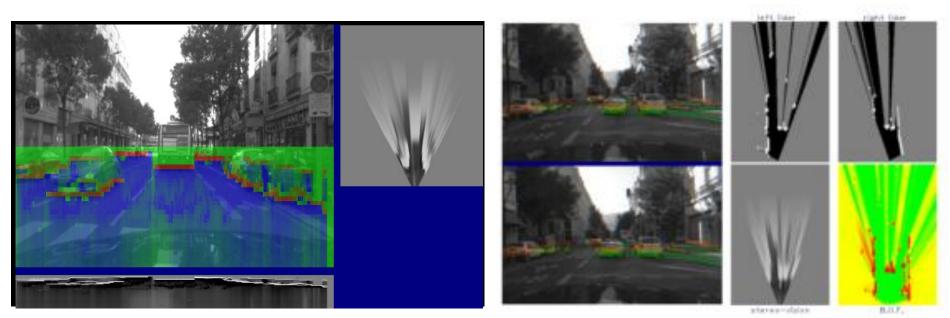
#### HSBOF & 2 Lidars



#### **Bayesian Sensor Fusion (Inria / Toyota Lexus)** CPU+GPU+ROS / Stereo + 2 Lidars + GPS + IMU



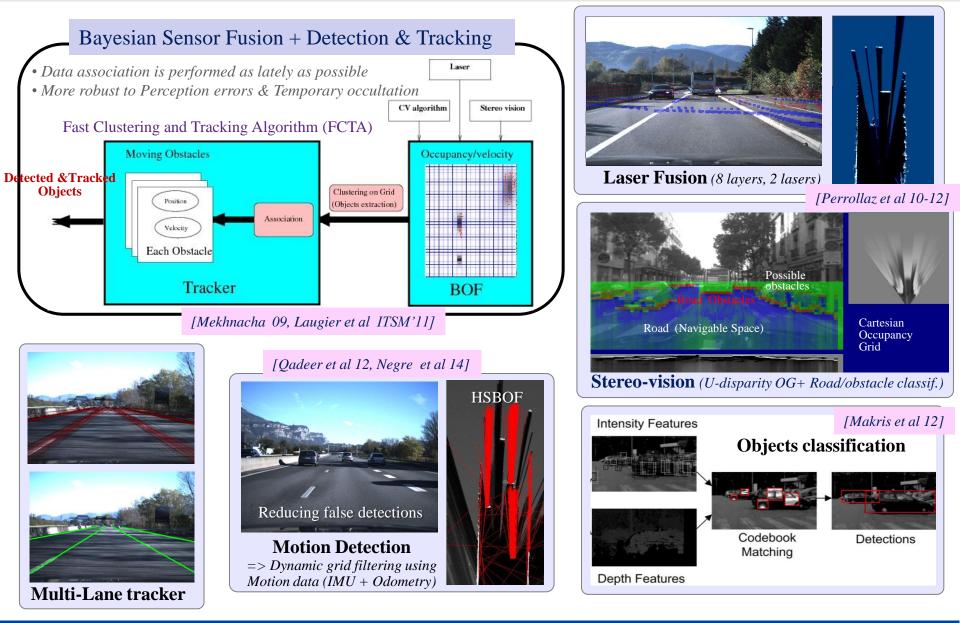
[Perrollaz et al 10] [Laugier et al ITSM 11] IROS Harashima Award 2012



#### Stereo Vision

**Bayesian Sensor Fusion** 

## Grid & Object level processing architecture





### *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



## Short-term collision risk (Grid level, Conservative)

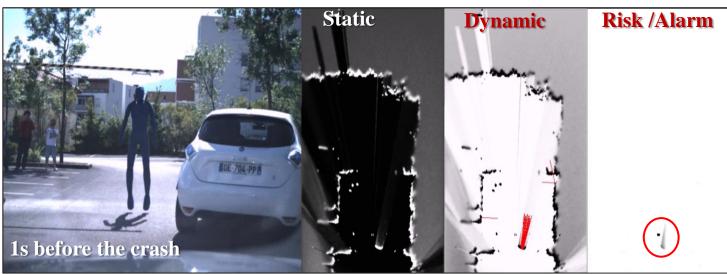
### **Objective:**

- > 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  $t+\delta$ )  $\delta=0.5 s => Precrash$ 

 $\delta = 1 s$  => Collision mitigation  $\delta = 1.5 s$  => Warning / Braking

### System outputs:

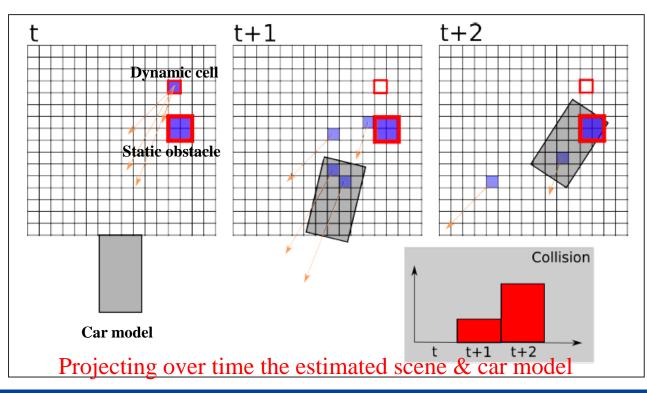




## Short-term collision risk (Grid level, Conservative)

### **Approach** (using conservative prediction)

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





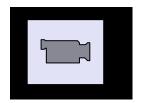
## **Short-term collision risk** – *Experimental results*



#### 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)

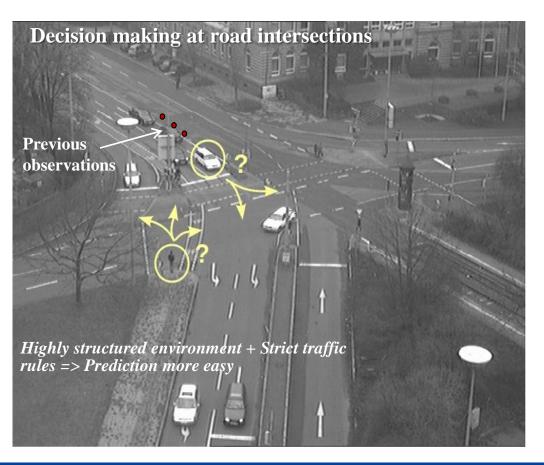


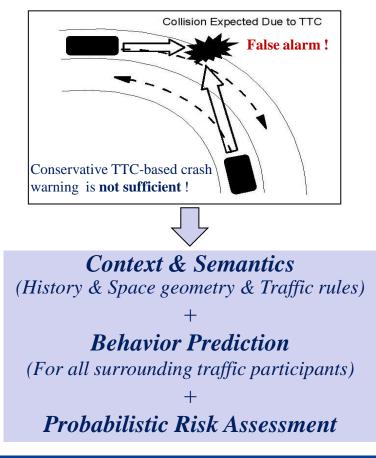
video



## **Generalized Risk Assessment (Object level)** => Increasing time horizon & complexity using semantics

- $\Rightarrow$  Understand the **Current Situation** & its **likely Evolution**  $\Rightarrow$  Evolute the **Bigly of future Colligion for Sofe Novigation Design**
- $\Rightarrow$  Evaluate the **Risk** of future Collision for **Safe Navigation Decision**
- $\Rightarrow$  Highly structured environment & Traffic rules make prediction more easy



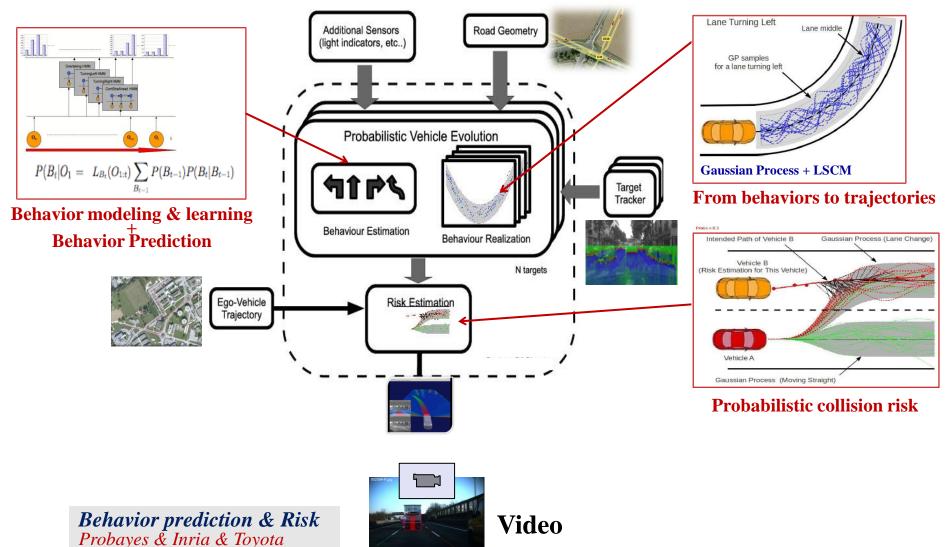




## **Behavior-based Collision risk (Object level)** Trajectory prediction & Collision Risk Assessment

[Tay thesis 09] [Laugier et al 11]

Patent Inria & Toyota & Probayes 2010



## **Behavior-based Collision risk** (Object level) Intention & Expectation approach



#### **Intersection:**

- ✓ Complex Geometry & Traffic context
- ✓ Large number of Vehicles & Possible Maneuvers
- ✓ Vehicle behaviors are Interdependent
- ✓ Human Drivers are in the loop !

### Human in the loop & Interdependent behaviors

- $\Rightarrow$  Detect drivers errors & Colliding behaviors
- $\Rightarrow$  **Risk** = Comparing maneuvers Intention & Expectations (using DBN)



## **Behavior-based Collision risk** (Object level) Intention & Expectation approach

Patent Inria & Renault 2012 (intersections) + Patent Inria & Berkeley 2013 (generalization)[Lefevre thesis 13] [Lefevre & Laugier IV'12, Best student paper]

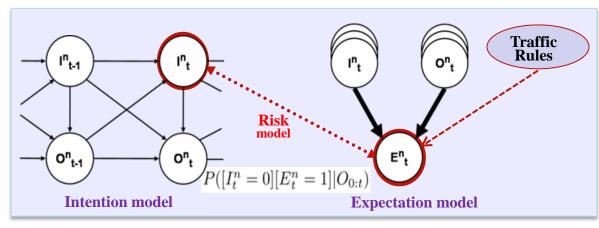
**A Human-like reasoning paradigm** => detect Drivers Errors & Colliding behaviors

- ✓ Estimating "Drivers Intentions" from Vehicles States Observations (X Y  $\theta$  S TS) => Perception or V2V communication
- ✓ Inferring "Behaviors Expectations" from Drivers Intentions & Traffic rules

✓ *Risk* = Comparing Maneuvers Intention & Expectation using a "Dynamic Bayesian Network"  $P([I_t^n = 0][E_t^n = 1]|O_{0:t})$ 

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

=> Digital map obtained using "Open Street Map"



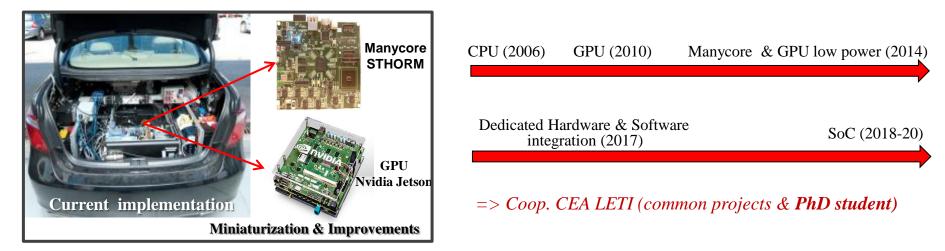


**Dynamic Bayesian Network** 

## **Current & Future work**

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

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



#### **Technologies for Autonomous Driving** (*Perception + Decision + Control + Learning*)

✓ PhD on "Driving Decisional Process" => Coop. Berkeley & Renault
 ✓ PhD on "Models & Algorithms for Autonomous Driving" => Toyota

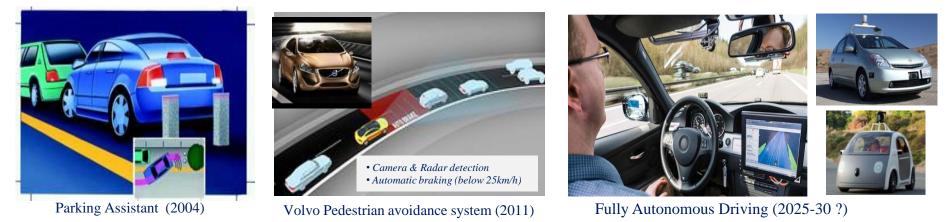






## **Conclusion & Perspectives**

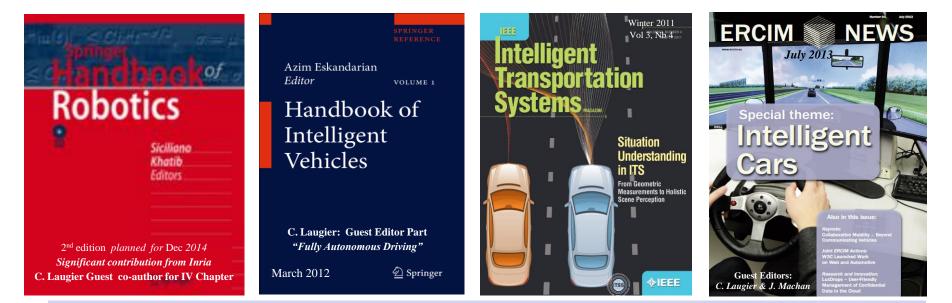
# □ Intelligent Cars (ADAS & Future Driverless Cars) are gradually becoming a reality



**Bayesian Perception & Situation Awareness & Bayesian Decision** are *key Technologies for dealing with uncertainty & addressing the Challenge of Autonomous Vehicles* 

Several implementations on commercial cars & Tests in realistic traffic situations have successfully been performed
 .... However system Robustness & Efficiency have still to be improved, in particular when human is in the loop (Share control & Interaction)





# **Thank You Any questions** ?

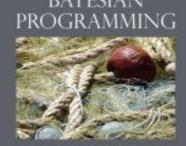
Pierre Bessière **Christian Laugier** Roland Siegwart (Eds.)

**Probabilistic Reasoning** and Decision Making in Sensory-Motor Systems Springer

Springer, 2008



**IEEE RAS Technical Committee on "AGV & ITS"** Numerous Workshops & Special issues since 2002



PIERRE BESSIÈRE EMMANUEL MAZER IUAN-MANUEL AHUACTZIN KAMEL MEKHNACHA

Chapman & , Hall / CRC, Dec. 2013

christian.laugier@inria.fr - http://emotion.inrialpes.fr/laugier