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Embedded Bayesian Perception and Collision Risk Assessment (invited talk)

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► **To cite this version:**

Christian Laugier. Embedded Bayesian Perception and Collision Risk Assessment (invited talk). ICRA 2017 - IEEE International Conference on Robotics and Automation, Workshop on Robotics and Vehicular Technologies for Self-Driving Cars, Jun 2017, Singapore, Singapore. pp.1-26. hal-01672240

HAL Id: hal-01672240

<https://inria.hal.science/hal-01672240>

Submitted on 23 Dec 2017

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Embedded Bayesian Perception and Collision Risk Assessment

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Invited Talk

IEEE ICRA 2017 Workshop on Robotics and Vehicular Technologies for Self-driving cars
Sands Expo and Convention Center, Marina Bay Sands, Singapore June 2nd 2017

Autonomous Cars & Driverless Vehicles

- Strong involvement of Car Industry & Large media coverage
- An expected market of 500 B€ in 2035
- Technologies Validation => Numerous recent & on-going real-life experiments (in addition to simulation & formal methods)



Tesla Autopilot based on Radar & Mobileye



3D Lidar & Dense 3D mapping
Numerous vehicles & miles covered



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



Drive Me trials

- 100 Test Vehicles in Göteborg, 80 km, 70km/h
- No pedestrians & Plenty of separations between lanes



Robot Taxi testing in Pittsburgh (Uber) & Singapore (nuTonomy)
+ Google / Lyft ?

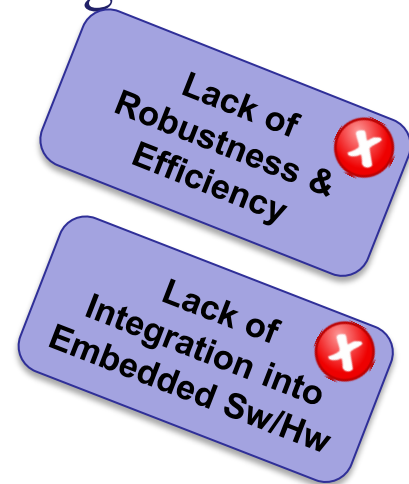
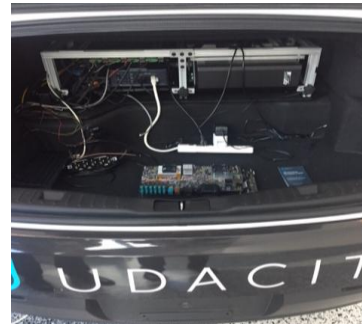


=> **Mobility Service**, Numerous Sensors ... Engineer in the car during testing

Several benign & serious accidents in past few months (Tesla, Google, Uber...)
Safety is still not guaranteed!

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



Trunk most of the time full of electronics & computers & processor units
=> High computational capabilities are still required

Focus of the talk

Complex Dynamic Scenes
understanding



**Situation Awareness
& Decision-making**



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



Anticipation & Prediction
for avoiding upcoming accidents

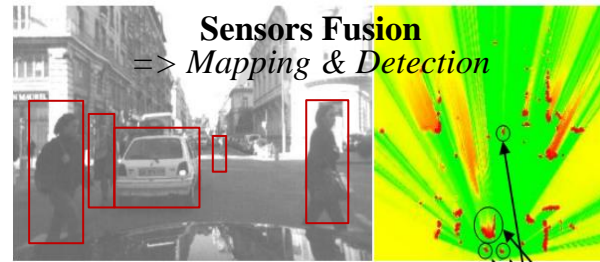
Main features

- ✓ 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*

Key Technology 1: Embedded Bayesian Perception



Embedded Multi-Sensors Perception
⇒ Continuous monitoring of the dynamic environment



❑ Main challenges

- ✓ Noisy data, Incompleteness, Dynamicity, Discrete measurements
- ✓ Strong Embedded & Real time constraints

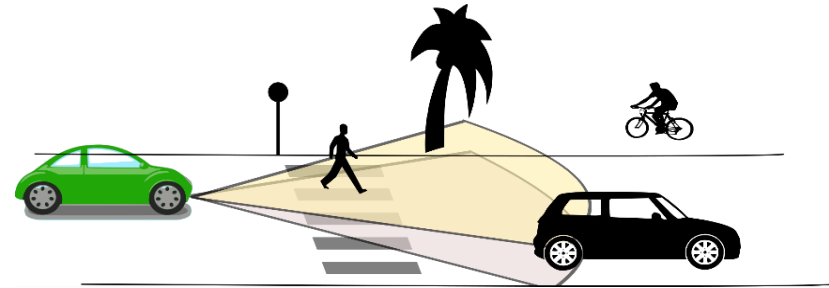
❑ Approach: Embedded Bayesian Perception

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

Bayesian Perception : Basic idea




□ Multi-Sensors Observations

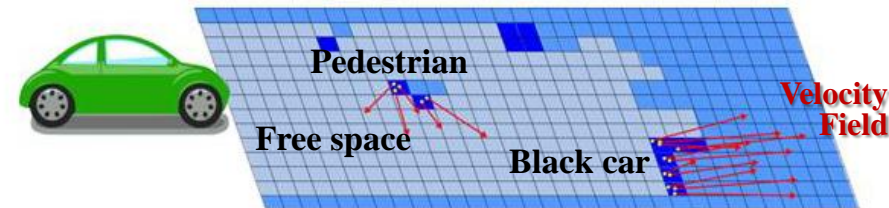
Lidar, Radar, Stereo camera, IMU ...



□ Probabilistic Environment Model

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

$P[o|Z,C]$:  ≈ 0  ≈ 0.5  ≈ 1



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

□ Main philosophy

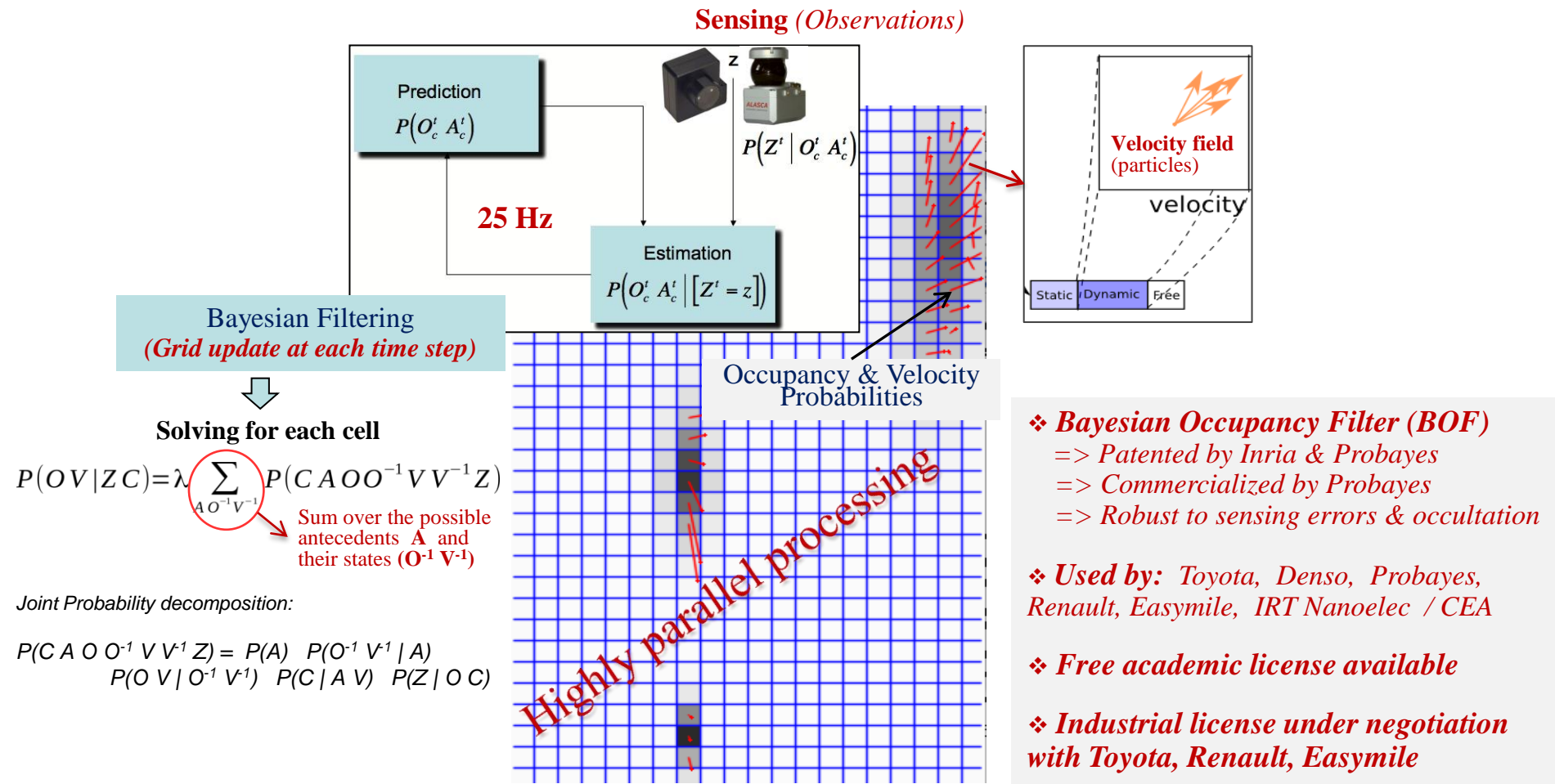
Reasoning at the grid level as far as possible for both :

- **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]



Solving for each cell

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

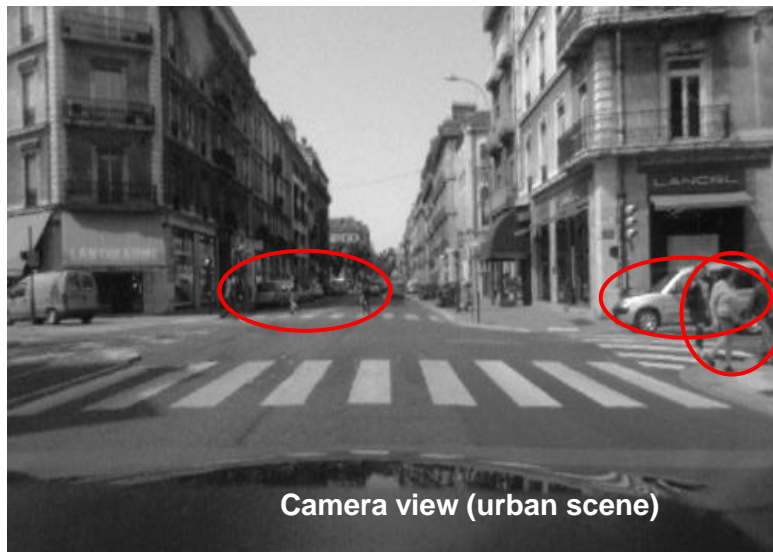
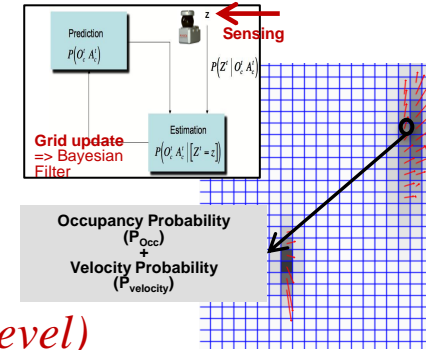
Sum over the possible antecedents **A** and their states (**O⁻¹ V⁻¹**)

Joint Probability decomposition:

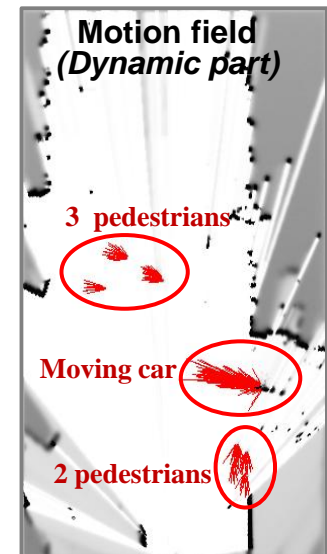
$$P(C A O O^{-1} V V^{-1} Z) = P(A) P(O^{-1} V^{-1} | A) P(O V | O^{-1} V^{-1}) P(C | A V) P(Z | O C)$$

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



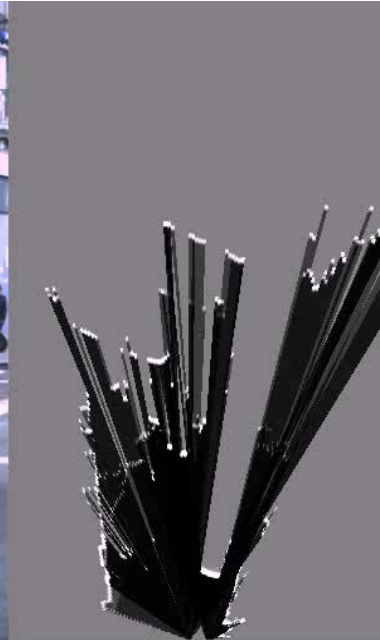
Exploiting the Dynamic information for improving Scene Understanding !!

Experimental Results in dense Urban Environments

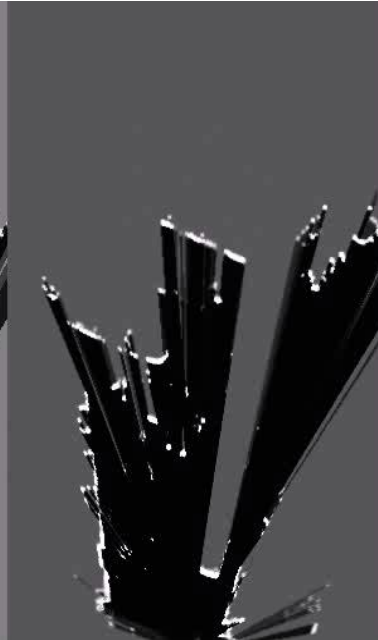
Observed Urban Traffic scene



Ego Vehicle (*not visible on the video*)



OG Left Lidar



OG Right Lidar



OG Fusion
+
Velocity Fields

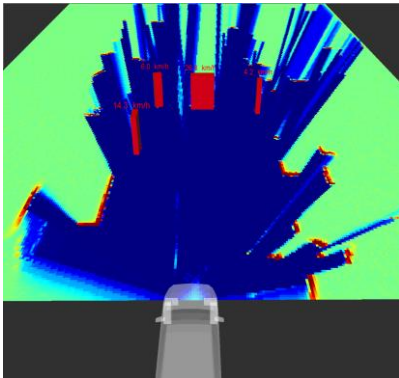


Recent implementations & Improvements

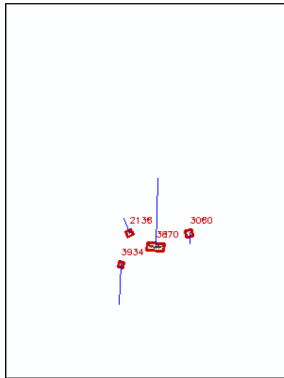


*Several implementations (models & algorithms) more and more adapted to **Embedded constraints & Scene complexity***

- ❖ 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 (under Patenting, 2017) [Rummelhard et al 17]
=> **Ground shape estimation & Improve obstacle detection** (avoid false detections on the ground)



Grid & Pseudo-objects



Tracked Objects

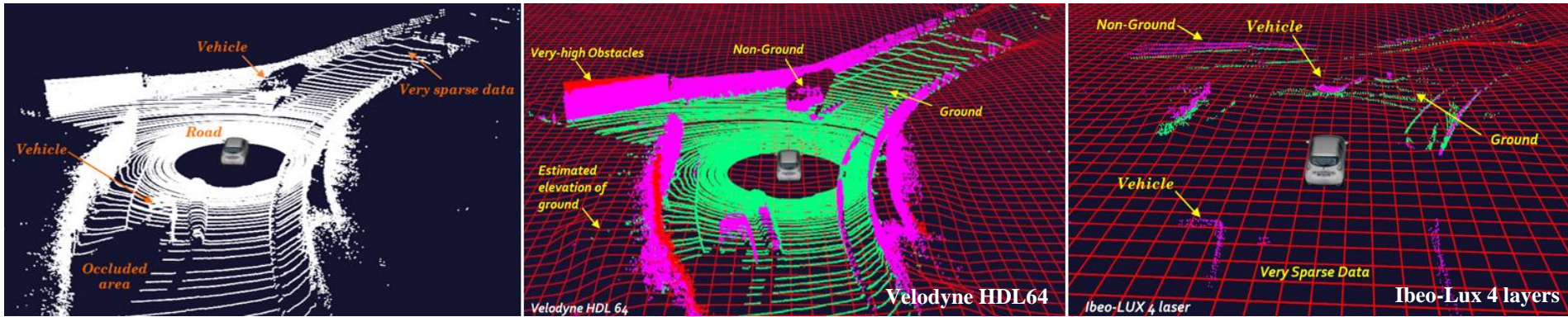


Classification (using Deep Learning)

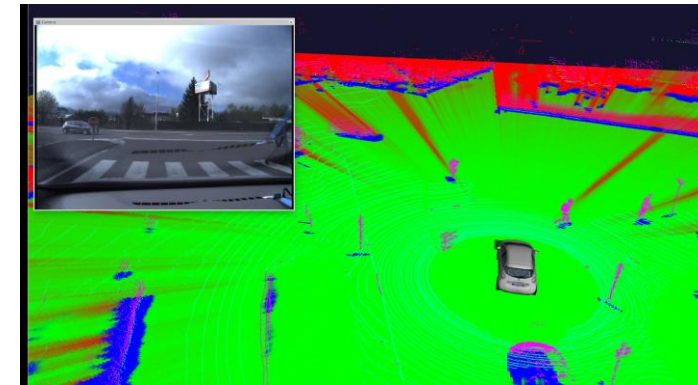
Detection & Tracking
& Classification

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



- ❖ Approach under patenting, to be soon published [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

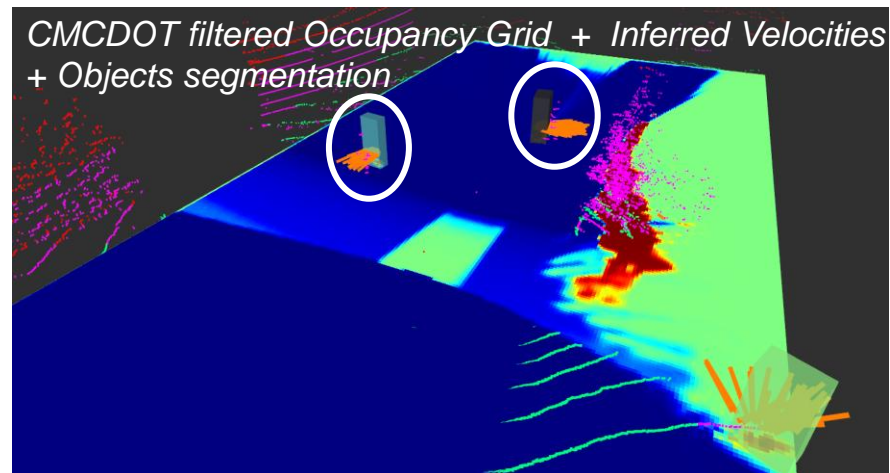
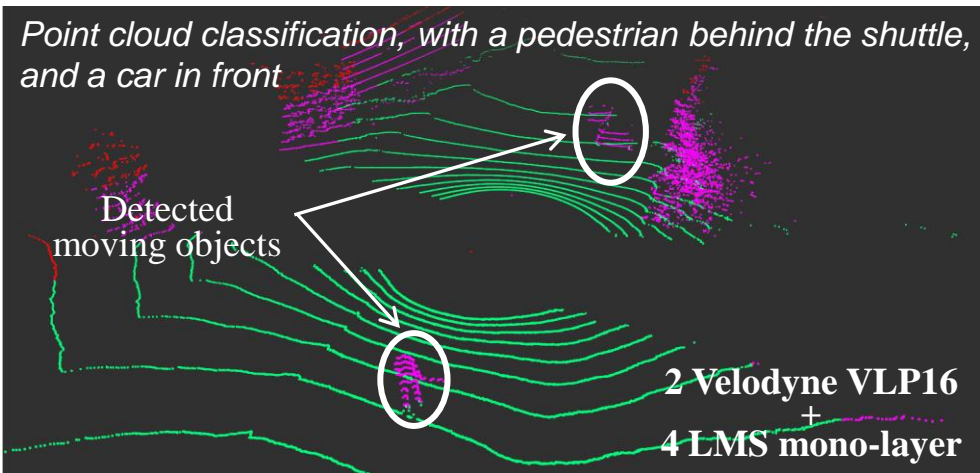
Integration of CMCDOT on a commercial vehicle

(cooperation EasyMile)



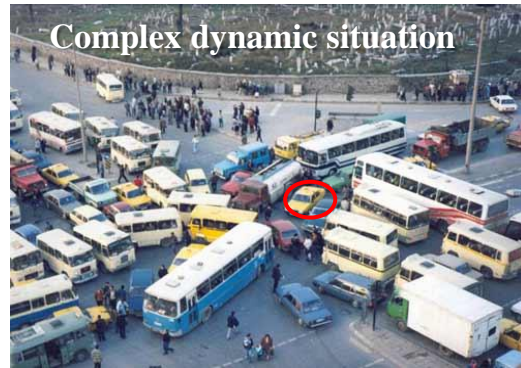
- Founded in 2014, EasyMile is a high-tech startup specialized in providing both software powering autonomous vehicles and the last mile smart mobility solutions
- The company (70 employees) is headquartered in Toulouse (France), with offices in Singapore and Denver (USA). It also operates through value added resellers, notably in Japan and the Middle East

- First tests of integration of the CMCDOT framework system on a commercial automated vehicle
- **The full system is implemented on a Nvidia TX1**, and has directly (and easily) been connected to the shuttle system network (using ROS)
- Sensor data is fused and processed, results are computed and provided in **real-time**
- Further full integration for the commercial product under discussion



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

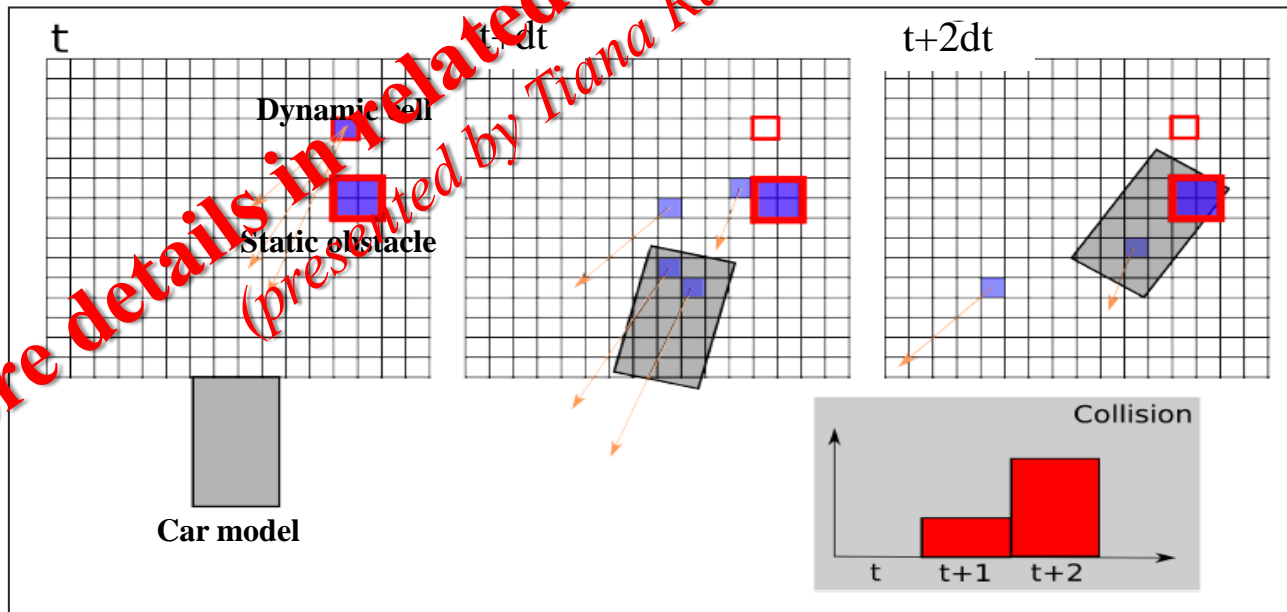
Proximity perception: $d < 100m$ and $t < 5s$

$\delta = 0.5s$ => Precrash

$\delta = 1s$ => Collision mitigation

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

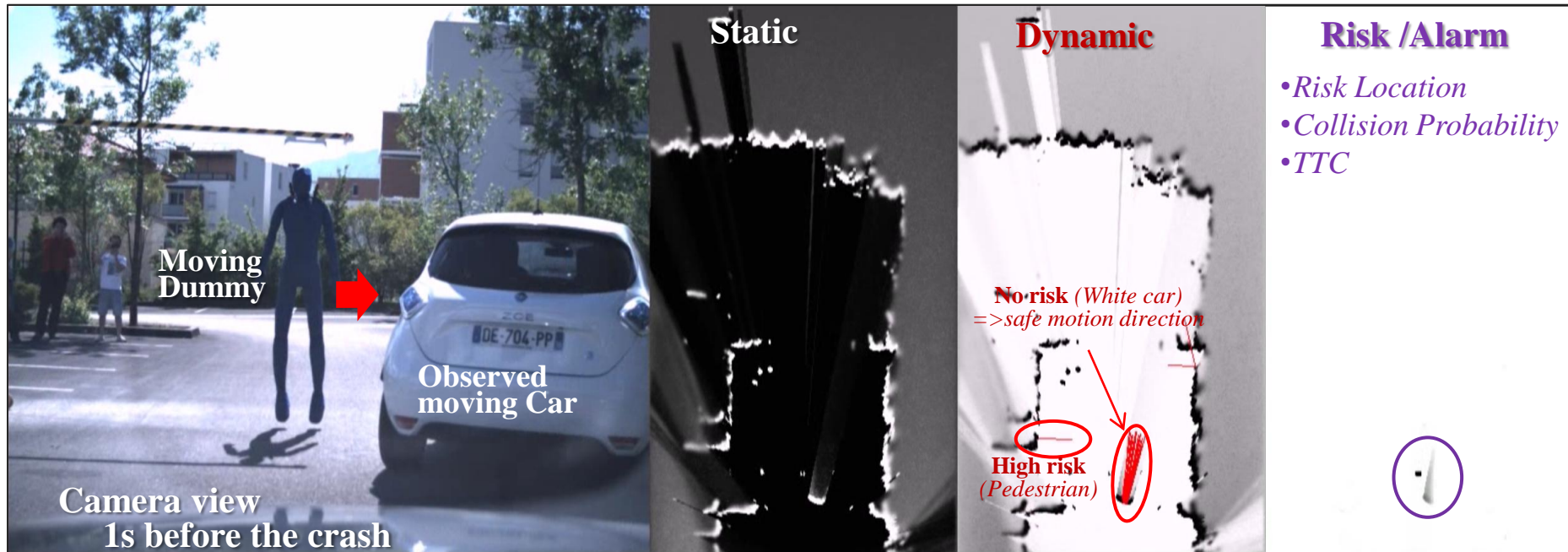
- Collision Risk Estimation: Integration of risk over a time range $[t, t + \delta]$
 - => Projecting over time the estimated Scene changes (DP-Grid) & Car Model (Shape + Motion)



More details in Related Interactive Session
(presented by Tiana Rakotonao)

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

=> *Static & Dynamic grids + Risk assessment*



More details in related Interactive Session
(presented by Tiana Rakotovao)

Short-term collision risk – *Experimental results*

- ⇒ Detect potential upcoming collisions
- ⇒ Reduce drastically false alarms



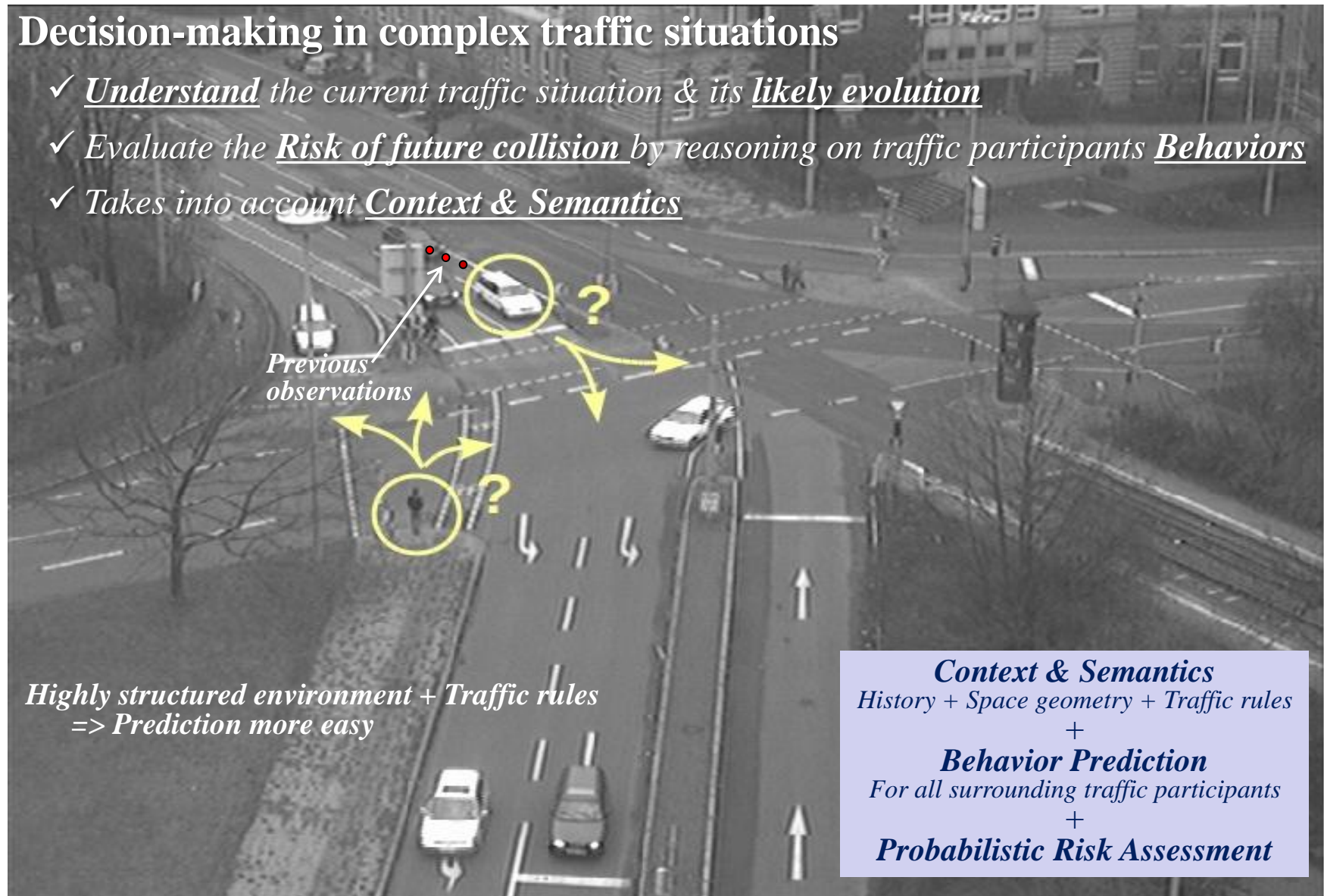
More details in related Interactive Session
(presented by Tiana Rakotovao)

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



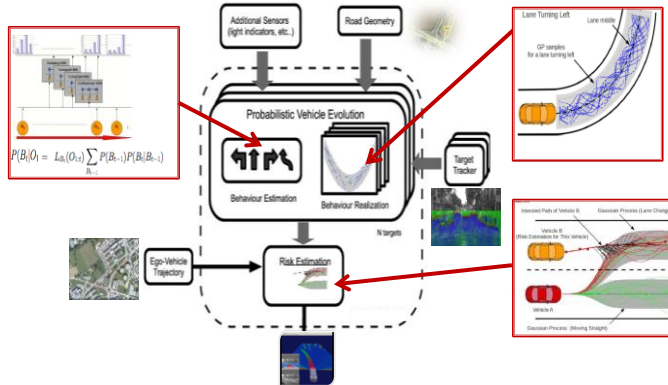
*Highly structured environment + Traffic rules
=> Prediction more easy*

Context & Semantics
History + Space geometry + Traffic rules
+
Behavior Prediction
For all surrounding traffic participants
+
Probabilistic Risk Assessment

Behavior-based Collision risk (Object level)

=> Increased time horizon & complexity + Reasoning on Behaviors

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

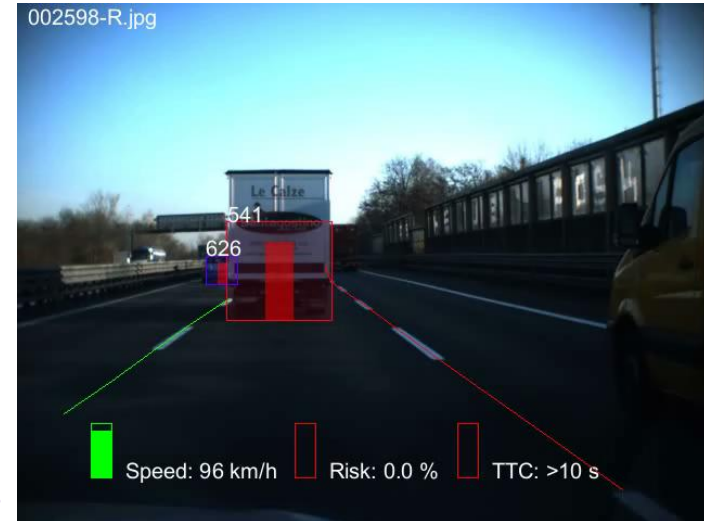


Inria

TOYOTA

ProbaYes
Mastering Uncertainty

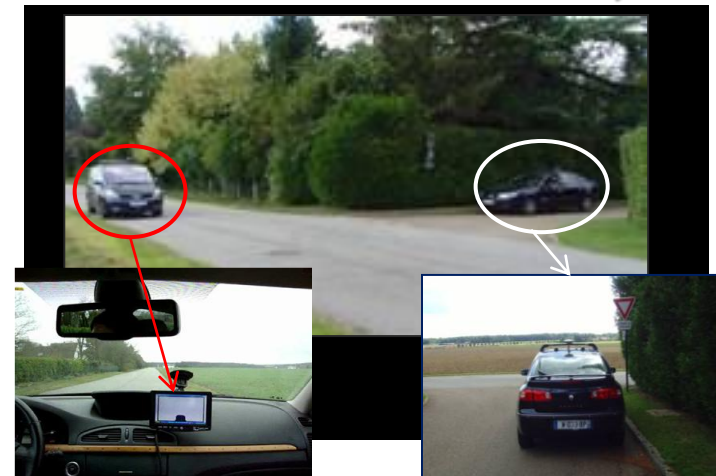
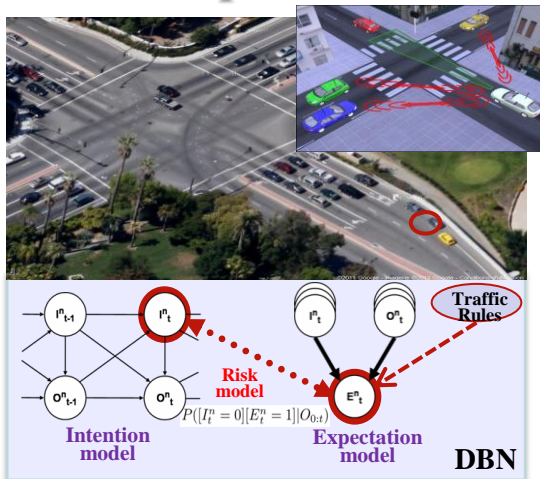
Courtesy
Probayes



□ Intention & Expectation => Patents Inria - Renault 2012 & Inria - Berkeley 2013

Inria

RENAULT



Experimental Vehicles & Connected Perception Units

Toyota Lexus



ROS



Renault Zoé
Velodyne
3D lidar



2 Lidars IBEO Lux



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:

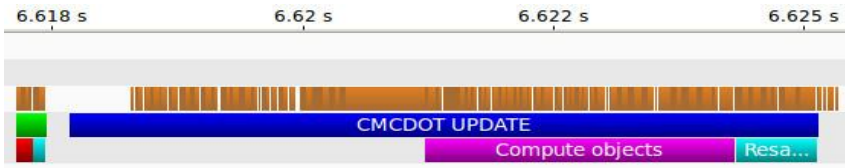
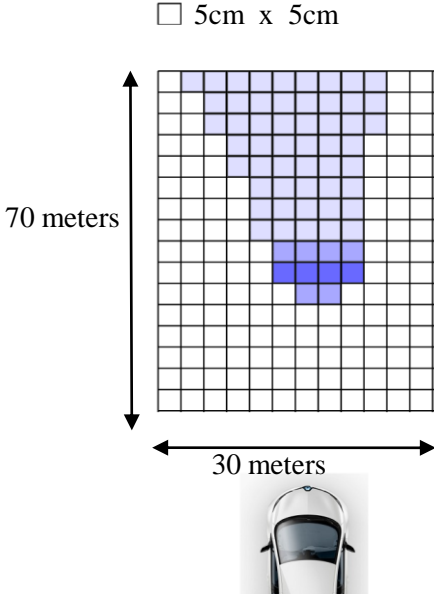
- Configuration with 8 Lidar layers (2x4)
- Grid: 1400 x 600 (840 000 cells) + Velocity samples: 65 536



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



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



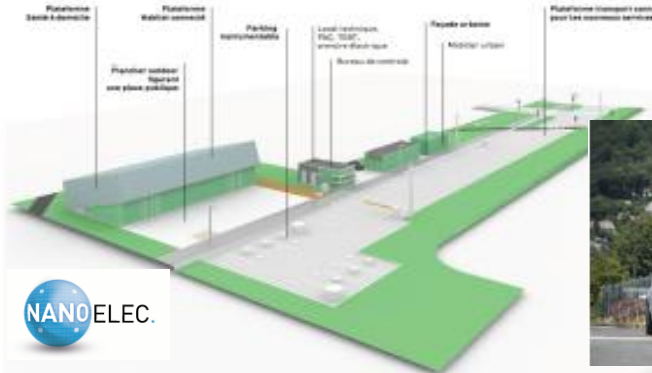
Experimental Areas



Connected Perception Unit

Protected experimental area

Un espace d'expérimentation : 3 plateformes



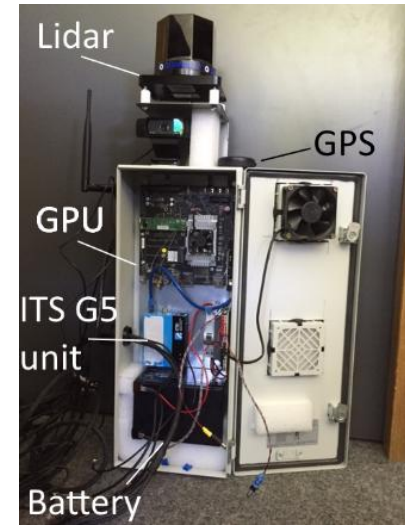
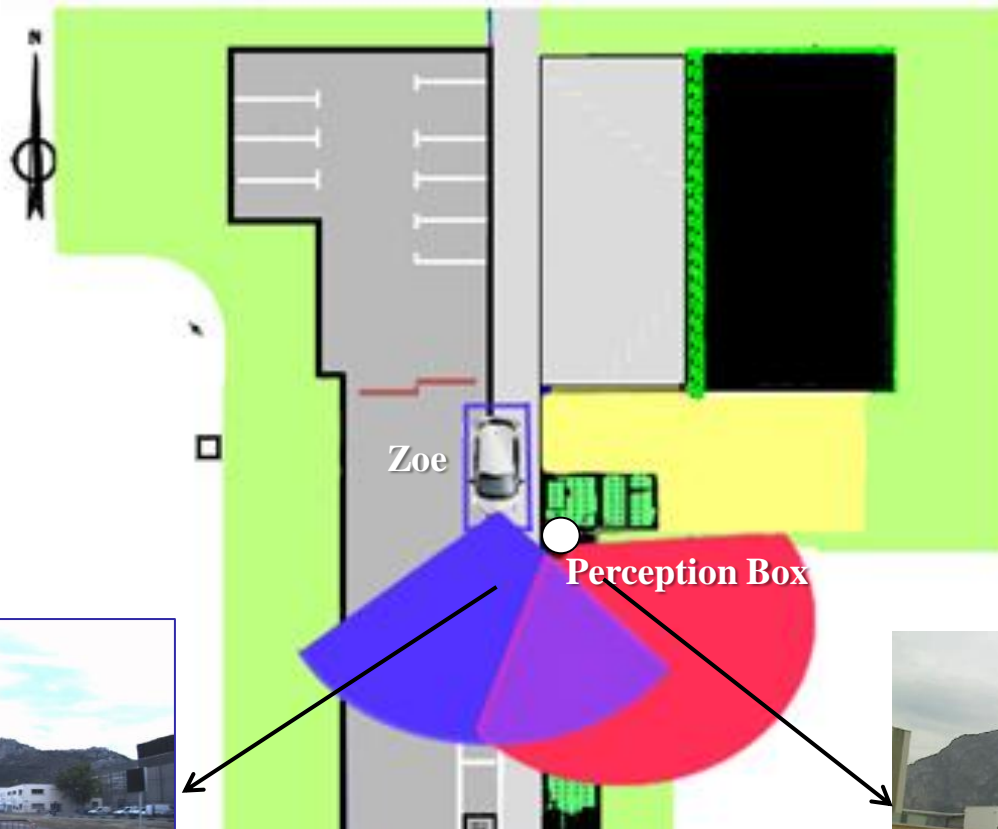
More details in related Interactive Session

(presented by Tiana Rakotovao)

Open real traffic (Urban & Highway)



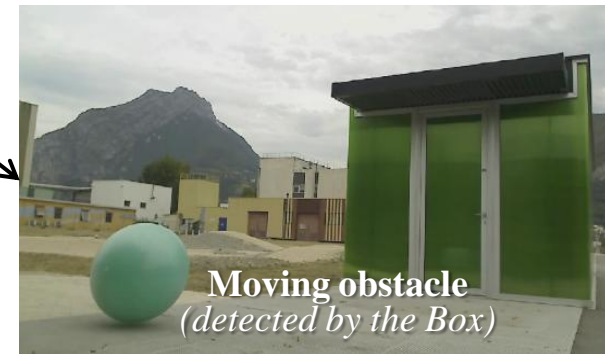
V2X: Distributed Perception Experiment



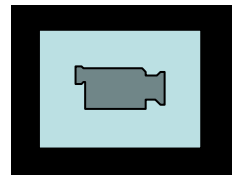
Connected Perception Unit



Camera Image provided by the Zoe vehicle

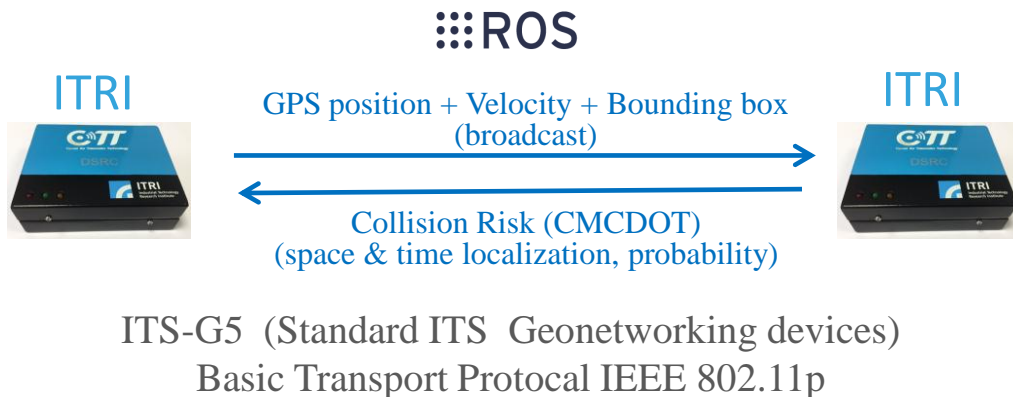


Camera Image provided by the Perception box



V2X: Data exchange & Synchronization

□ Data exchange



□ Synchronization

Chrony (Network Time Protocol)

GPS Garmin + PPS Signal (1 pulse per second)



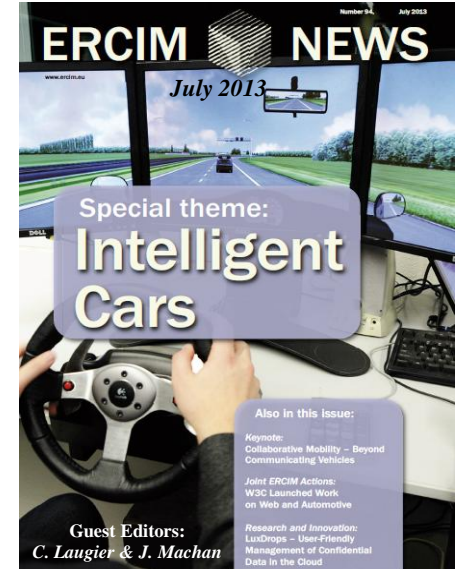
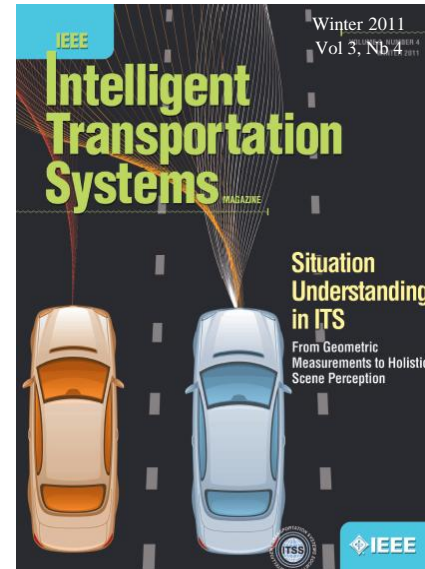
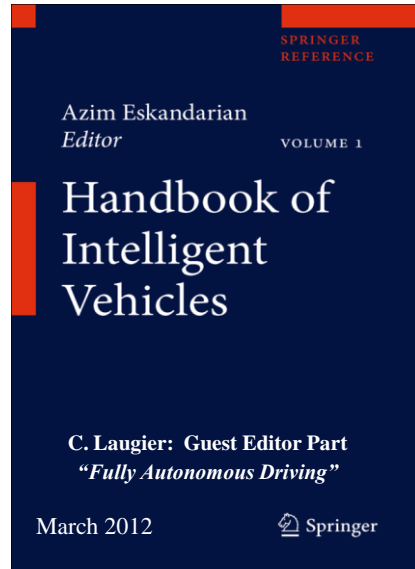
CMCDOT – Complete process illustration



Sensor data

Inria
informatics mathematics





Thank You  Any questions ?

