

### Combining Bayesian and AI approaches for Autonomous Driving

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# Combining Bayesian & AI approaches for Autonomous Driving

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#### **Keynote Speech**

Workshop on "Perception & Navigation for Autonomous Robotics in Unstructured and Dynamic Environments" IROS 2021, Prague, September 27<sup>th</sup> 2021



The research work presented in this talk includes contributions from several Chroma team members:

- Postdocs & Researchers: D. Sierra-Gonzalez, O. Erkent
- Research engineers: L. Rummelhard, A. Negre, N. Turro, J.A. David, J. Lussereau, T. Genevois, A. Paigwar
- Also some former PhD students & Postdocs

=> I warmly thank each of them





## Brief overview of Technologies & Ongoing challenges for Autonomous Driving



- Due to both Road nuisances (pollution, traffic jams, accident...) & Current technological advances, Technologies & Services for <u>Human Mobility</u> are evolving rapidly => Reduce road Nuisances & Costs + Increase Efficiency & Safety
- Last decade: A Technological breakthrough (Sensors, GPU, DL...) & Numerous AV experiments in real traffic conditions





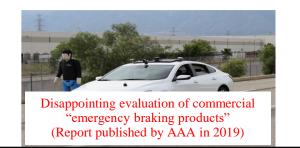




- Millions of miles have been covered in last decade, but SAFETY is still not guaranteed! (as evidenced by several accidents)
  - => Additional R&D work is still mandatory on 2 main research lines:
    - > Improving "Perception & Decision-making" technologies (in particular for Robustness & Scalability issues)
    - ➤ Developing "Validation & Certification" approaches for future deployment (in addition to traditional testing approaches)
    - => Develop a **new Framework** including **Realistic simulators**, **Augmented reality** capabilities, Integration of **Formal methods**This subject is addressed by **Inria & IRT Nanoelec** (several EU & National projects) ... **But not presented in this talk!**











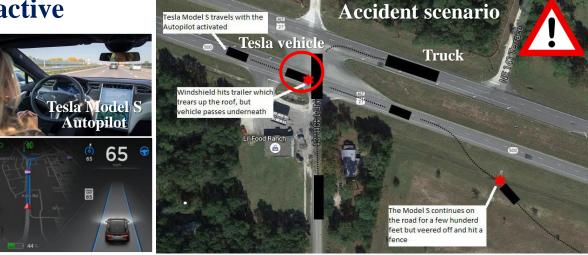
### Fatal accidents involving AVs – Perception failure



☐ Tesla: Driver was killed in a crash with Autopilot L2 active

*May 2016* 

- ✓ A truck turned left and blocked the route of the Tesla vehicle
- ✓ The Autopilot <u>failed to detect</u> the white moving truck, with a brightly lit sky (Camera Mobileye + Radar)
- ✓ The human driver was <u>not vigilant & didn't took over</u>



□ Uber: Pedestrian killed by Self-driving L3 vehicle => First fatal crash involving a pedestrian, see video bellow

Temple, Arizona, March 2018

✓ Despite the presence of multiple sensors (lidars, cameras ...), the perception system failed to detect the pedestrian & didn't disengaged

✓ In addition, the "Safety Driver" reacted too lately (1s before the crash)







### Improving Safety: AVs have to face two main challenges

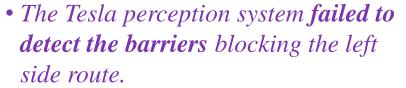


1st Challenge: The need for Robust, Self-diagnosing & Explainable Embedded Perception



Video source: AutoPilot Review @ youtube.com

Video Scenario (Tesla vehicle with Autopilot active):



• The human driver has to take over and steer the vehicle away from the blocked route.



## Improving Safety: AVs have to face two main challenges



#### 2<sup>nd</sup> Challenge: The need for Understandable Driving Decisions (Sharing the road with human drivers)

Unfortunately, Human drivers actions are determined by a complex set of interdependent factors which are very hard to model (e.g. intentions, perception, emotions ...)

- ⇒ Predicting human driver behaviors is inherently <u>uncertain</u>
- $\Rightarrow$  AV have to reason about "<u>uncertain intentions" of the surrounding vehicles</u>



*Video source: The Telegraph* 

Video scenario involving a Waymo AV & a **Human Driven Bus.** 

The accident scenario was recorded by the dashcam of the Bus (bus not visible in the video)

- The Waymo AV was blocked by an obstacle and decided to make a left lane change
- The bus driver misunderstood the AV intention and didn't yield
- The two vehicles collided



#### Perception & Decision-making challenges – Outline



Dynamic scene analysis & Navigation Decisions





Embedded Perception & Decision-making for Safe Intentional Navigation

Detecting & Reacting in real-time to Unexpected Events



- ⇒Scene interpretation using Sensing & Prior knowledge
- ⇒Safe Navigation decisions (using semantics & context)

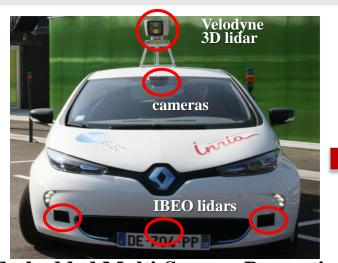
- ⇒ Detect & Predict imminent collision with "something" (unclassified unexpected event)
- ⇒Activate appropriate **reflexive avoidance strategy**
- □ **Main constraints:** Dynamic & Open Environments + Incompleteness & Uncertainty + Sensors limitations & Huge amount of data to process
- □ Implementation constraints: Real-time processing + Software / Hardware integration
- □ **Mixed traffic** (Human in the loop): A Human-Aware Decision-making process is required
  - => Taking into account Interactions + Behaviors + Social & Traffic rules
- □ Our Approach: Combining Probabilistic & IA approaches



Informatics mathematics

#### 1st Paradigm: Embedded Bayesian Perception

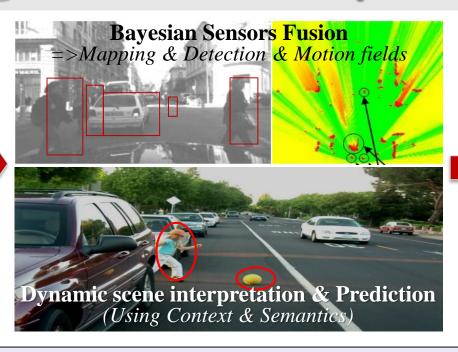




Embedded Multi-Sensors Perception

⇒ Continuous monitoring of the

⇒ Continuous monitoring of the surrounding dynamic environment





#### **Main Objective**

1st Leverage dynamic insights to better understand a complex traffic scene !!!

2<sup>nd</sup> Process Noisy data, Uncertainty, Dynamics ... while respecting strong Real-time constraints

#### Main Features of our approach

- ✓ Reasoning about Uncertainty & a Time window => Reasoning on Past & Future (predicted) events
- ✓ Improving robustness using Bayesian Sensors Fusion
- ✓ Interpreting the dynamic scene using Contextual & Semantic information
- ✓ Implementing the system using hardware accelerators (GPU, Multicores, Microcontrollers ...)

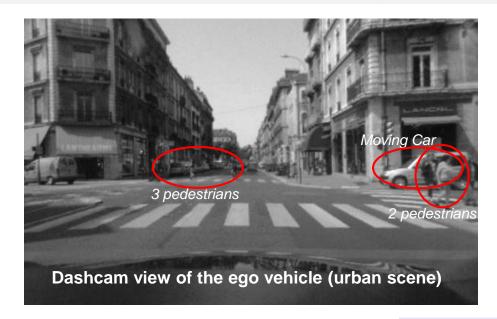


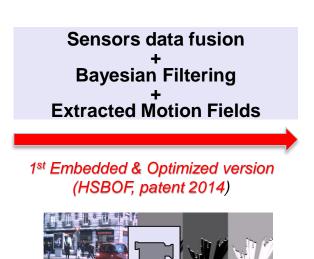


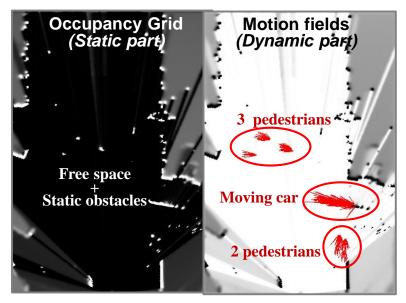
### Dynamic Occupancy Grid & Bayesian Filtering

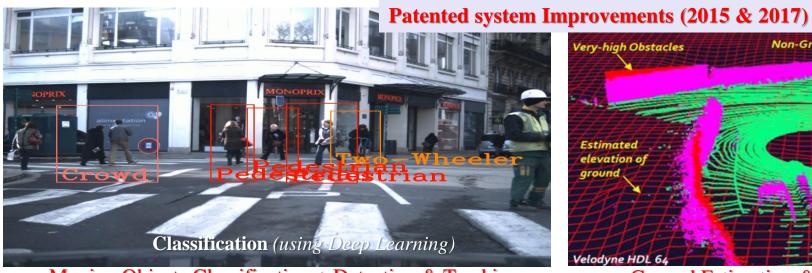


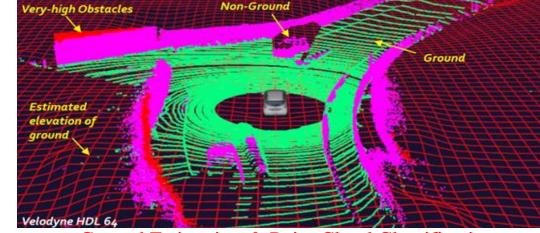
=> Use dynamic information for a better understanding of the observed scene











Ground Estimation & Point Cloud Classification (patent 2017)



### System Integration on a Commercial Vehicle

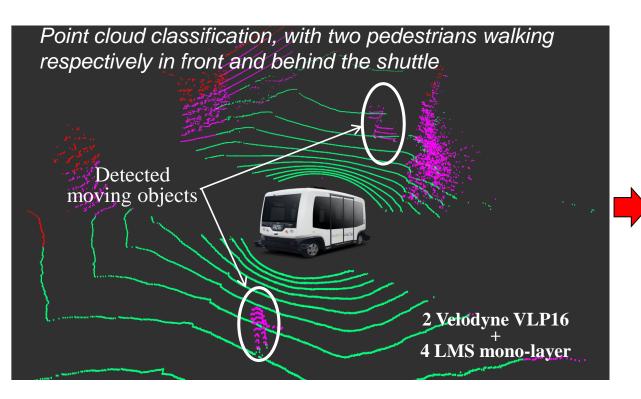


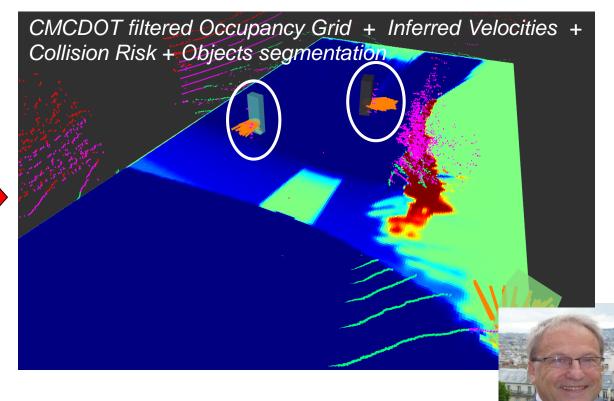


• POC 2019: Complete system implemented on Nvidia TX1, and easily connected to the shuttle system network *in a few days* (using ROS)



- Shuttle sensors 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 still under development with an industrial company (confidential)





### 2nd Paradigm: Collision Risk Assessment & Avoidance Strategies

=> Avoiding Pending & Future Collisions



Situation analysis + Prediction & Collision Risk Assessment + Safest Driving Decision

#### **Main Features of our approach:**

- ✓ Predict dynamic environment changes on a given "time horizon  $t+\delta$ " (using both History & Motion models)
- ✓ Estimate the Probabilistic Collision Risk at horizon  $t+\delta$  ( $\delta = a$  few seconds ahead). Two types of Collision-Risk (C-Risk) have to be considered, depending on both the <u>time horizon</u> & the <u>semantic information available</u>
- "Short-term C-Risk" characteristics: The Collision Risk is estimated at the Grid-level, the Moving obstacles are not classified, the time-horizon  $\delta = 3-5s$ , and the Prediction step is based on a "conservative motion hypothesis"
- ✓ "Mid-term C-Risk" characteristics: The Collision Risk is estimated at the Object level, the Involved entities are classified, and the Prediction step requires to reason about "Behavior models & Semantic information"
- ✓ <u>Driving Decisions</u> are taken on the basis of the <u>Predicted behaviors</u> of all the observed surrounding traffic participants (cars, cycles, pedestrians...), the <u>Social & Traffic rules</u>, and the <u>expected traffic participants Interactions</u>



#### Short-term C-Risk – Approach & Experimental results



#### **■** Experimental results (Urban streets & Test track)





#### □ Collision prediction in a crash scenario (in test track)



#### Video: Short-term C-Risk

- Yellow => 3s before collision
- Orange => 2s before collision
- Red => 1s before collision



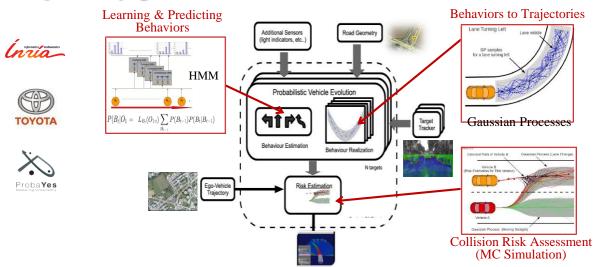


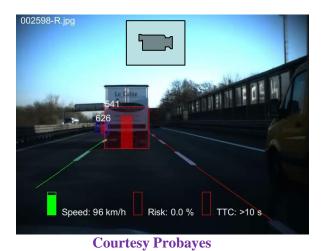


## **Mid-term C-Risk** – *Approach & Experimental results*=> Increased time horizon & complexity + Reasoning on Behaviors & Interactions



☐ Trajectory prediction & C-Risk assessment => Patent 2010 (Inria, Toyota, Probayes)



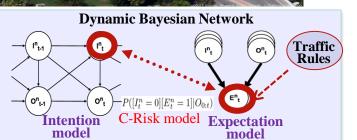


Cooperation still on-going  $(R\&D\ contracts + PhDs)$ 

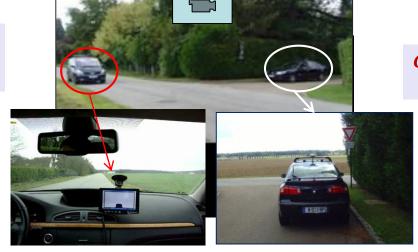
□ Intention & Expectation (Mixed Traffic & Interactions) => Patents 2012 (Inria - Renault) & 2013 (Inria - Berkeley)







**Human-like** reasoning



Cooperation still on-going  $(R\&D\ contracts + PhDs)$ 

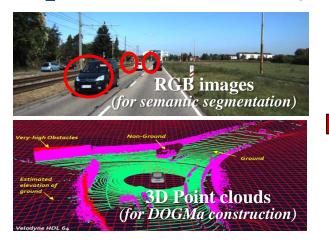


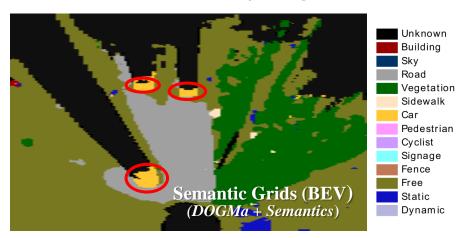
### 3rd Paradigm: Models improvements using Machine Learning



=> Exploit the complementarities of Bayesian Perception & DL based Computer Vision approaches (Richer semantics, Better understanding of 3D dynamic scenes, Mandatory for Decision-making step)

#### □ Perception level: Fusing DOGMa & Semantically segmented RGB images





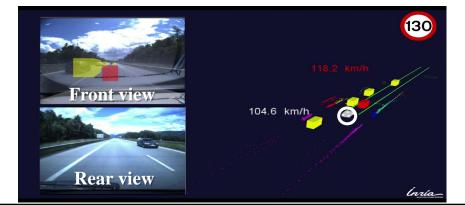
**DOGMa:** Dynamic Occupancy Grid Map

**BEV:** Bird's Eve View

#### □ Prediction & Decision-making level: *Learn driving skills for Autonomous Driving*

Step 1: Modeling Driver Behavior using Inverse Reinforcement Learning (IRL)

Step 2: **Predict motions** of surrounding vehicles & **Make Driving Decisions** for Ego Vehicle





#### Perception Level (1): Concept of "Semantic Grid"



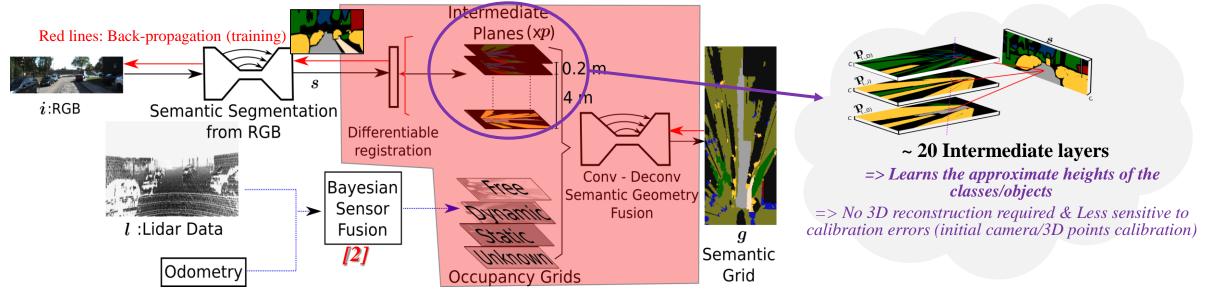
**Objective:** Add **Semantic information** (cars, pedestrians, roads, buildings...) in each cell of the Dynamic Occupancy Grid Map, by exploiting **additional RGB inputs** 

Approach: A new "Hybrid Sensor Fusion approach" combining DOGMa & Semantically Segmented
RGB images (using DL)

DOGMa: Dynamic Occupancy Grid Map



#### Semantic Grid Neural Network [1] [3] [Patent Inria & Toyota 2019]



Implementation / Testing: Segnet Cuda/GPU + Kitti dataset

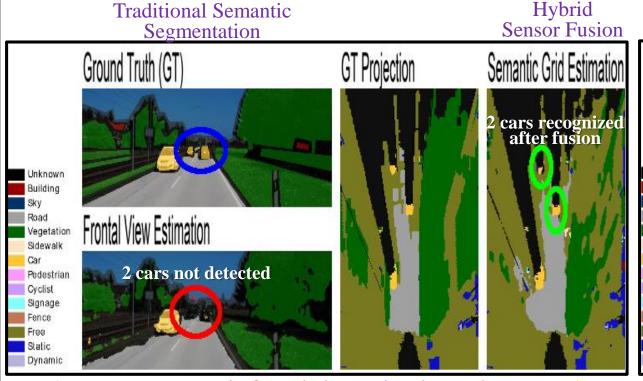
- [1] Semantic grid estimation with a Hybrid Bayesian and Deep Neural Network approach, 0. Erkent et al., IEEE IROS 2018
- [2] Conditional Monte Carlo Dense Occupancy Tracker, Rummelhard et al., ITSC 2015
- [3] Segnet: A deep convolutional encoder-decoder architecture for image segmentation, Badrinarayanan et al., IEEE PAMI 39(12) 2017





## Semantic Grids — Experimental Results [1] (Using Kitti dataset)





Hybrid **Traditional Semantic Sensor Fusion Segmentation** Semantic Grid Estimation after fusion Frontal View Estimation Sidewalk Pedestriai Truck not detected Cyclist Signage Fence recognized after fusion Fence not detected

=> 2 cars not detected in frontal view estimation.... but recognized as an obstacle in Semantic Grid (with the help of DOGMa)

=> Truck & Fence not detected in frontal view estimation.... but recognized as an obstacle in Semantic Grid (with the help of DOGMa)

[1] Semantic grid estimation with a Hybrid Bayesian and Deep Neural Network approach, 0. Erkent et al., IEEE IROS 2018

#### Perception Level (2): 3D Object Detection using Lidar & RGB camera Invia-

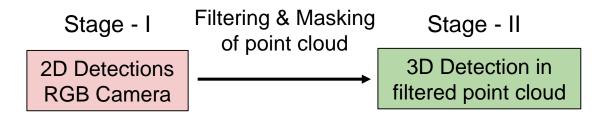
(Frustum PointPillars)

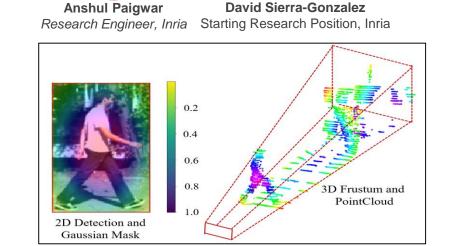
**Objective:** Realtime accurate detection & localization of small object like pedestrians in 3D point cloud of large-scale scenes

Challenge: LiDAR only approaches have poor accuracy as pedestrians have fewer data points and non rigid structure

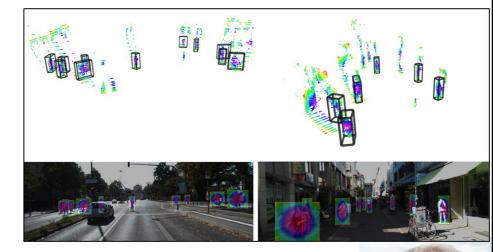
#### Proposed approach: Multi-stage sensor fusion approach [1]

- We outperform other multi-stage SOTA approaches for pedestrians BEV detection on the KITTI dataset
- Significantly faster runtime of 14 Hz.





**David Sierra-Gonzalez** 



[1] Frustrum-Pointpillars: A Multi-Stage Approach for 3D Object Detection using Lidar and RGB camera, A. Paigwar et al, ICCV 2021 Workshop on "Autonomous Vehicle Vision" (Oct 2021)

## Prediction & Decision-making level: Learning Driving Skills for AD (A) Step: Driver behavior modeling

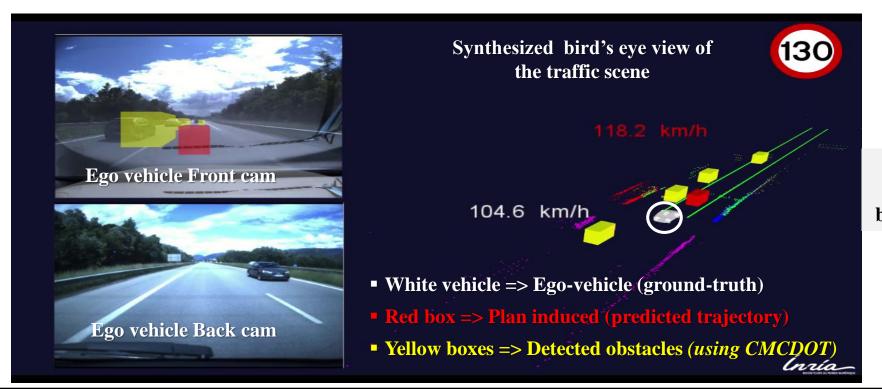


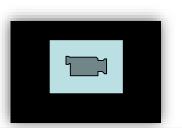


• Learn Model parameters from real driving demonstrations using *Inverse Reinforcement Learning (IRL)* 

**David Sierra-Gonzalez** Starting Research Position Inria Chroma team

- Driver behaviors are modelled using a Cost function & Several hand-craft features (e.g. Lane index preferences, Deviation from desired velocity, TTC to frontal targets, Time-gap to rear targets, etc.)
- A training set containing "interesting highway vehicle interactions" has been constructed using our Lexus vehicle
- The obtained models can be leverage to both **Predict human-driver behaviors & Generate human-like plans for** the ego vehicle in mixed traffic. [Sierra-Gonzalez et al, ICRA 2018] [Sierra-Gonzalez PhD thesis 2019]





**Video:** Comparison between demonstrated behavior in test set & behavior induced by the learned model

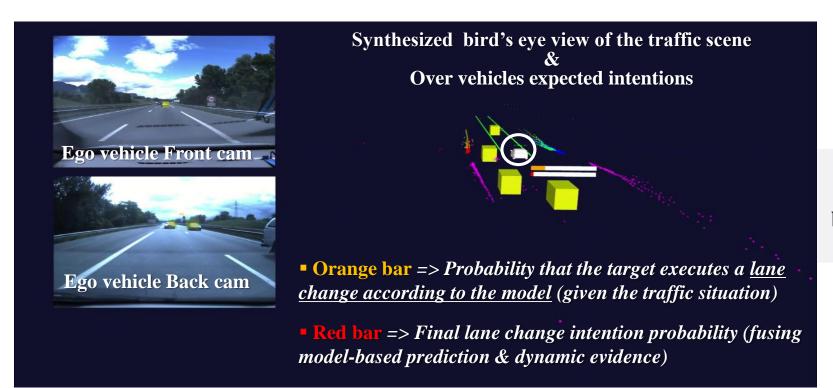








- **David Sierra-Gonzalez** • A realistic Human-like Driver Model can be exploited to Predict the long-term evolution (10s and beyond) of Starting Research Position Inria Chroma team traffic scenes [Sierra Gonzalez et al., ITSC 2016]
- For the **short/mid-term**, both the **Driver model** and the **Dynamics of the target** provide useful information to determine future driving behaviors
- Our probabilistic model fuses <u>Model-based Predictions & Dynamic evidence</u> to produce robust lane change intention estimations in highway scenes. [Sierra Gonzalez et al., ICRA 2017] [Sierra-Gonzalez PhD thesis 2019]





**Video:** Comparison between demonstrated behaviors in test set & **behaviors induced** by the both the *learned* model and the dynamics evidence





### Ongoing R&D work



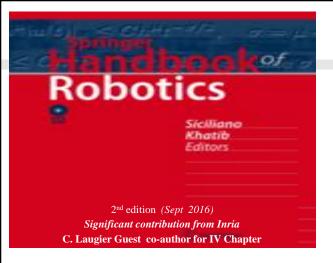
- Panoptic & Instance Segmentation + Domain adaptation (PhD student, Toyota & CPS4EU EU projects)
- Fusing RGB & Event cameras to improve objects detection in dynamic environments & adverse weather or lighting conditions (ES3CAP project)
- Detection & Tracking of Multiple Objects using DOGMa & Semantic Grids (Toyota project)
- Distributed Perception & Situation Awareness using Connected Vehicles & Road-Side-Units (PhD student, IRT Nanoelec & International industrial company, confidential)
- Real-time Planning & Control of Collision Avoidance or Mitigation Trajectories (PhD student, Renault)
- Validation & Certification framework combining Real Tests (in test-tracks), Realistic Simulation, Augmented Reality and Formal Methods (PhD student, IRT Nanoelec & Prissma project)

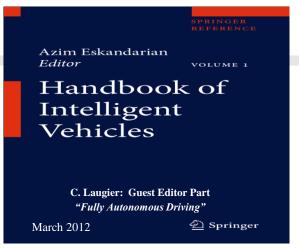


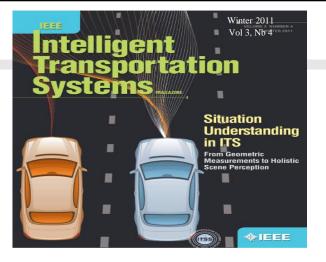














### Thank You for attending my keynote speech

Any Questions or comments?



=> Please use IROS 2021 conference system

