

Combining Bayesian and AI approaches for Autonomous Driving

Christian Laugier

▶ To cite this version:

Christian Laugier. Combining Bayesian and AI approaches for Autonomous Driving. IROS 2021 - IEEE/RSJ International Conference on Intelligent Robots and Systems - Workshop "Perception and Navigation for Autonomous Robotics in Unstructured and Dynamic Environments", Sep 2021, Prague, Czech Republic. hal-03518232

HAL Id: hal-03518232 https://inria.hal.science/hal-03518232v1

Submitted on 9 Jan 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.





Combining Bayesian & AI approaches for Autonomous Driving

Christian LAUGIER, PhD & Dr Es Science

Research Director at Inria & Scientific Advisor for Probayes Inria Chroma team & IRT Nanoelec – christian.laugier@inria.fr

Keynote Speech

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





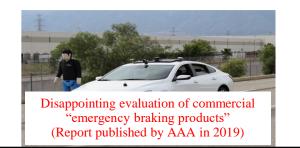




- Millions of miles have been covered in last decade, but SAFETY is still not guaranteed! (as evidenced by several accidents)
 - => Additional R&D work is still mandatory on 2 main research lines:
 - > Improving "Perception & Decision-making" technologies (in particular for Robustness & Scalability issues)
 - ➤ 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!**











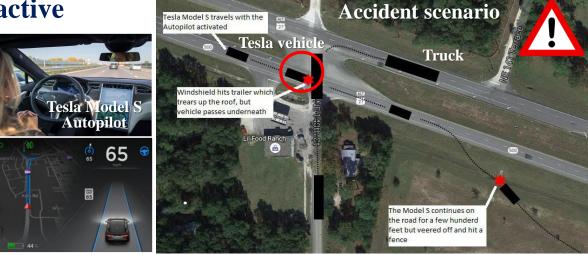
Fatal accidents involving AVs – Perception failure



☐ 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

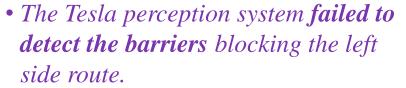


1st Challenge: The need for Robust, Self-diagnosing & Explainable Embedded Perception



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



2nd 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)

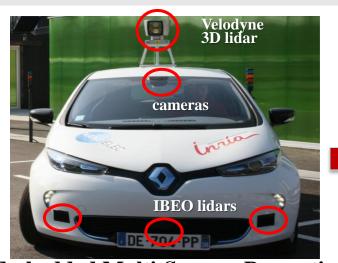
- ⇒ Detect & Predict imminent collision with "something" (unclassified unexpected event)
- ⇒Activate appropriate **reflexive avoidance strategy**
- □ **Main constraints:** Dynamic & Open Environments + Incompleteness & Uncertainty + Sensors limitations & Huge amount of data to process
- □ Implementation 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

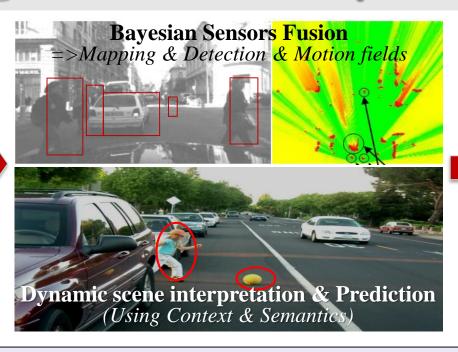




Embedded Multi-Sensors Perception

⇒ Continuous monitoring of the

⇒ Continuous monitoring of the surrounding dynamic environment





Main Objective

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

2nd 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 ...)

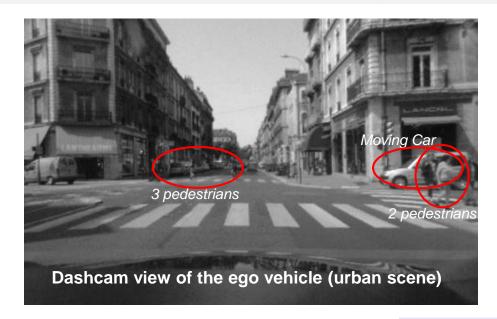


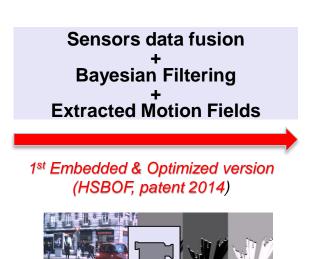


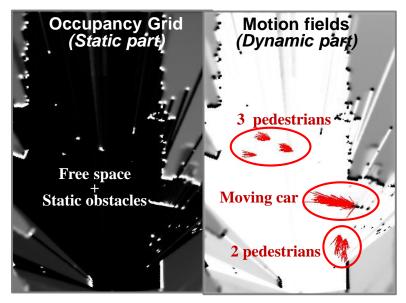
Dynamic Occupancy Grid & Bayesian Filtering

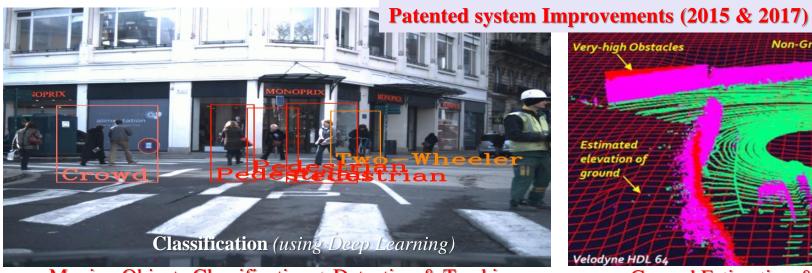


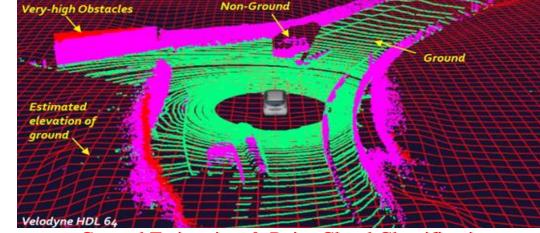
=> Use dynamic information for a better understanding of the observed scene











Ground Estimation & Point Cloud Classification (patent 2017)



System Integration on a Commercial Vehicle

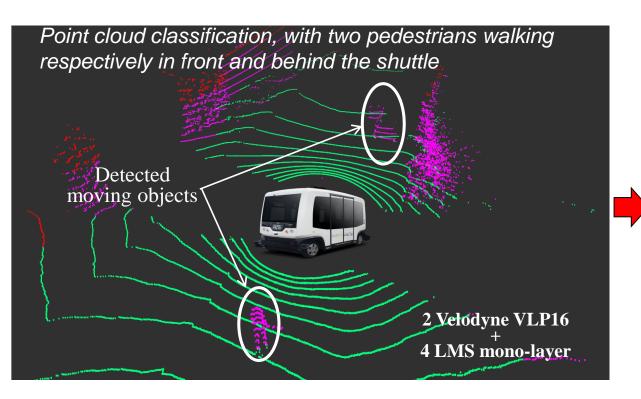


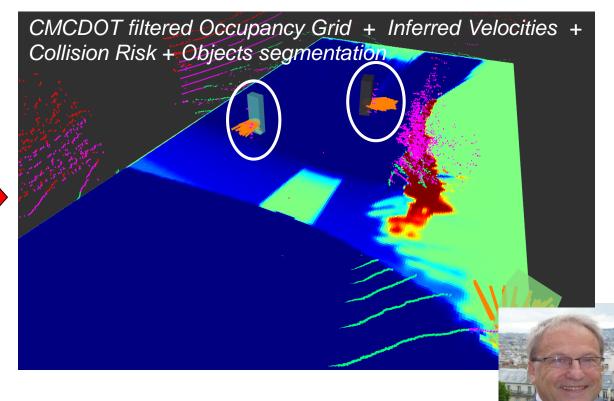


• POC 2019: Complete system implemented on Nvidia TX1, and easily connected to the shuttle system network *in a few days* (using ROS)



- 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



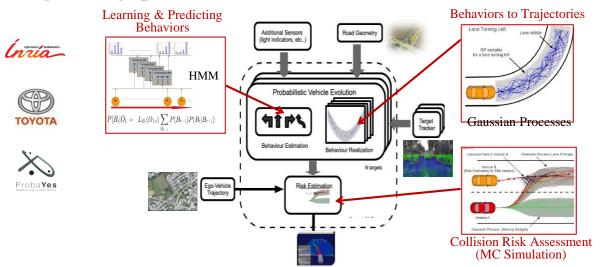


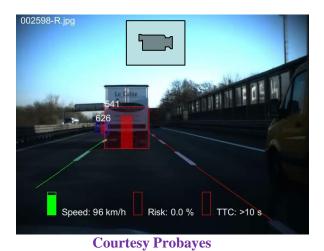


Mid-term C-Risk – *Approach & Experimental results*=> Increased time horizon & complexity + Reasoning on Behaviors & Interactions



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



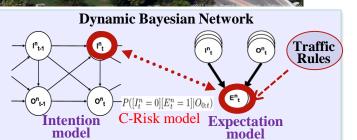


Cooperation still on-going $(R\&D\ contracts + PhDs)$

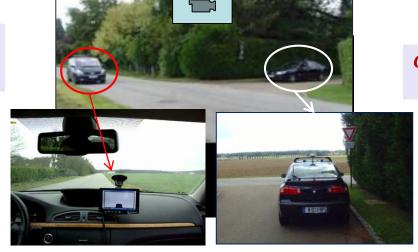
□ Intention & Expectation (Mixed Traffic & Interactions) => Patents 2012 (Inria - Renault) & 2013 (Inria - Berkeley)







Human-like reasoning



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

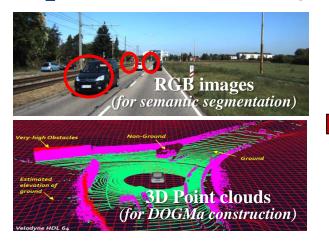


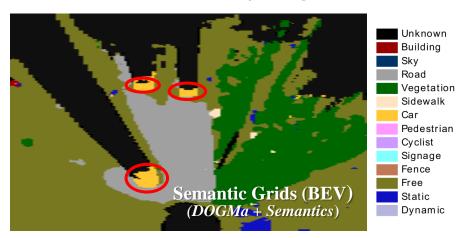
3rd Paradigm: Models improvements using Machine Learning



=> 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





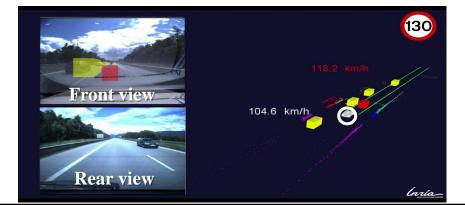
DOGMa: Dynamic Occupancy Grid Map

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"



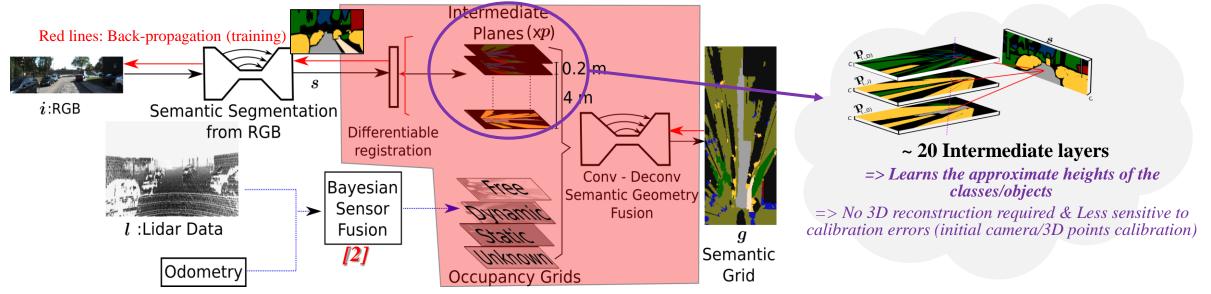
Objective: Add **Semantic information** (cars, pedestrians, roads, buildings...) in each cell of the Dynamic Occupancy Grid Map, by exploiting **additional RGB inputs**

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

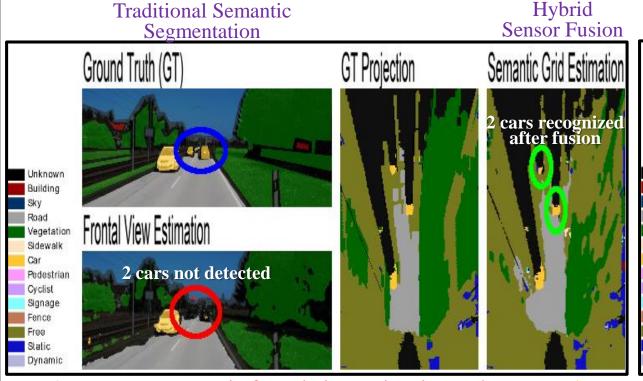
- [1] Semantic grid estimation with a Hybrid Bayesian and Deep Neural Network approach, 0. Erkent et al., IEEE IROS 2018
- [2] Conditional Monte Carlo Dense Occupancy Tracker, Rummelhard et al., ITSC 2015
- [3] Segnet: A deep convolutional encoder-decoder architecture for image segmentation, Badrinarayanan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

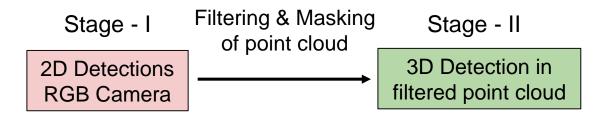
(Frustum PointPillars)

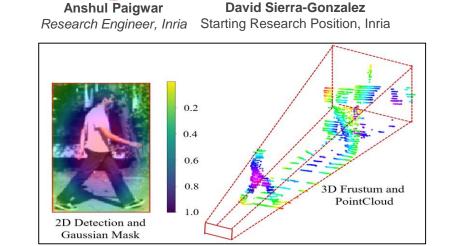
Objective: Realtime accurate detection & localization of small object like pedestrians in 3D point cloud of large-scale scenes

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

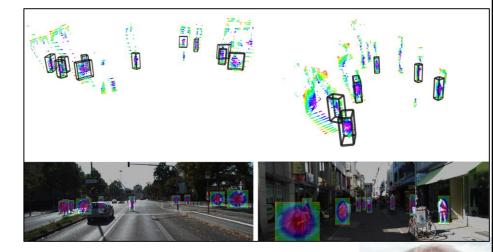
Proposed approach: Multi-stage sensor fusion approach [1]

- 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

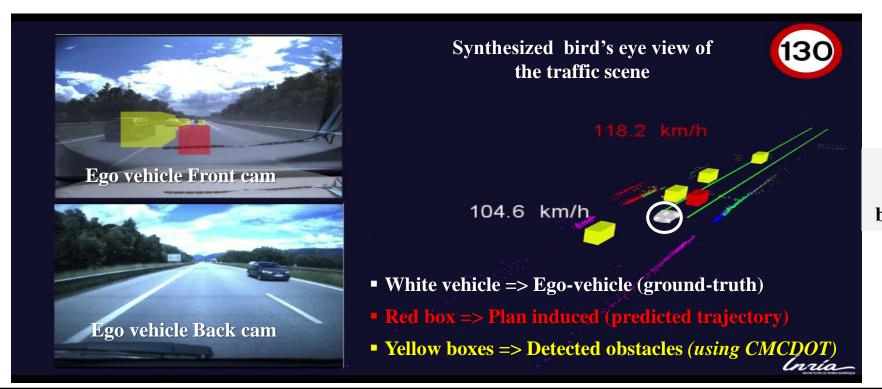


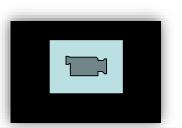


• Learn Model parameters from real driving demonstrations using *Inverse Reinforcement Learning (IRL)*

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

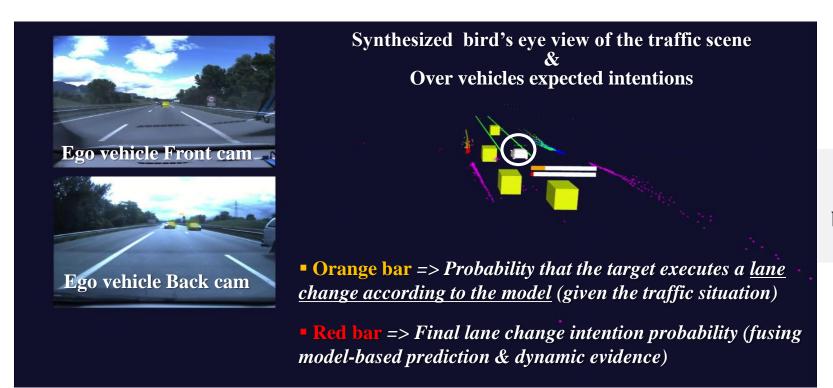








- **David Sierra-Gonzalez** • A realistic Human-like Driver Model can be exploited to Predict the long-term evolution (10s and beyond) of Starting Research Position Inria Chroma team traffic scenes [Sierra Gonzalez et al., ITSC 2016]
- For the **short/mid-term**, both the **Driver model** and the **Dynamics 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



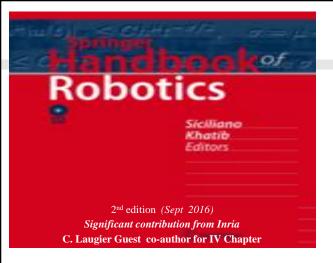
- Panoptic & Instance Segmentation + Domain adaptation (PhD student, Toyota & CPS4EU EU projects)
- Fusing RGB & Event cameras to improve objects detection in dynamic environments & adverse weather or lighting conditions (ES3CAP project)
- Detection & Tracking of Multiple Objects using DOGMa & Semantic 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)

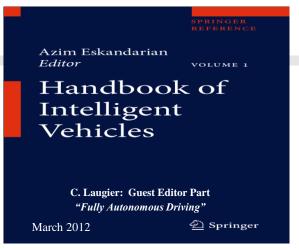


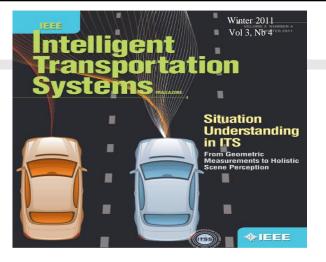








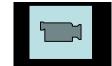






Thank You for attending my keynote speech

Any Questions or comments?



=> Please use IROS 2021 conference system

