PhD student Nicola Albarella

Control Architectures for Advanced Driving Assistance Systems

Tutor: Prof. Stefania Santini

Cycle: XXXV Year: THIRD

Background information

- MSc degree: Automation Engineering
- Research group: Daisy Lab (Prof. Stefania Santini)
- PhD start date 01/11/2019 end date 31/10/2022

- Scholarship type: company-funded scholarship
- Partner company: Kineton S.r.l.

- Periods abroad: 10/01/2022 – 10/09/2022 at Autonomous Driving Lab, University of Tartu, Tartu, Estonia

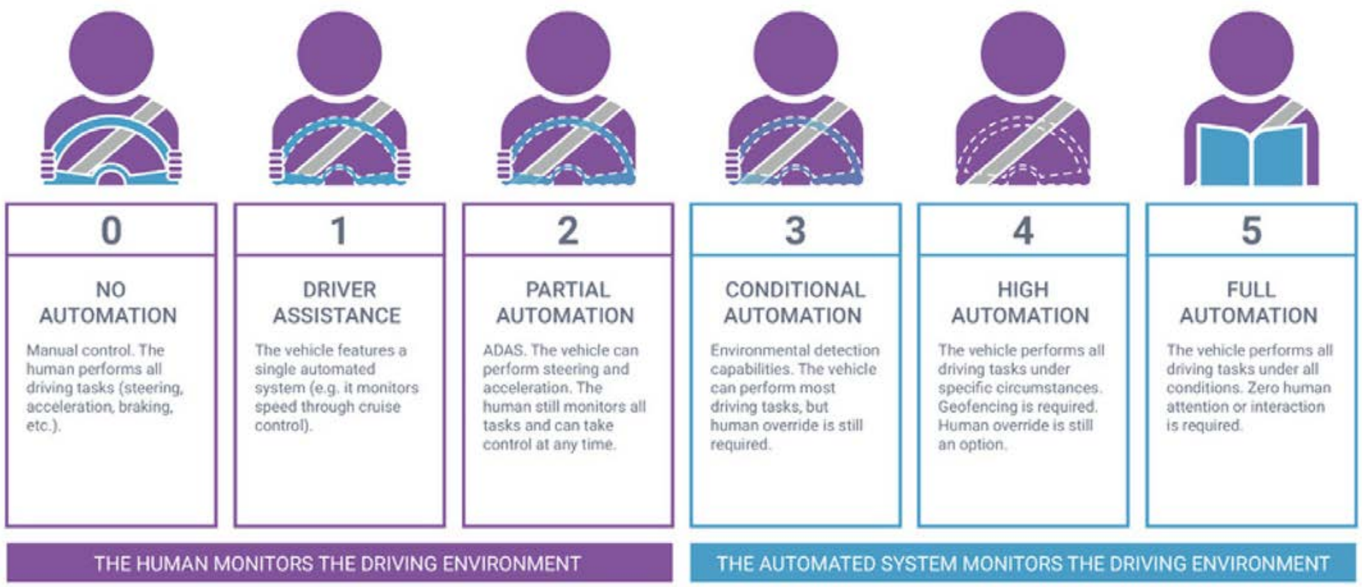
Summary of study activities

- **Ad hoc courses**: Safety Critical Systems for Railway Traffic Management, Strategic Orientation for STEM Research & Writing, Machine Learning.
- **M.Sc. courses**: Embedded Systems, Formal Methods, Big Data Analytics and Business Intelligence, Control Systems for Autonomous Ground Vehicles.
- **Seminars**: Patent searching best practices with IEEE Xplore; GDPR basics for computer scientists; At the Nexus of Big Data, Machine Intelligence, and Human Cognition; Exploiting Deep Learning and Probabilistic Modeling for Behavior Analytics; Approaches to Graph Machine Learning; Big Data and Computational Linguistics; Risk assessment in real life: experiences from the railway domain.

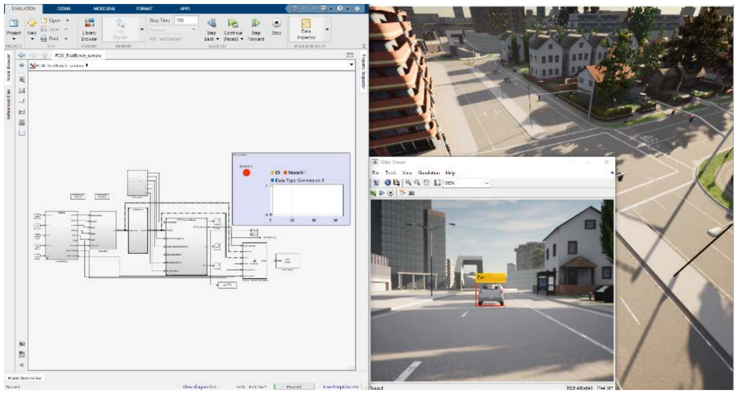
Research area

- Advanced Driving Assistance Systems (ADAS) and Autonomous driving

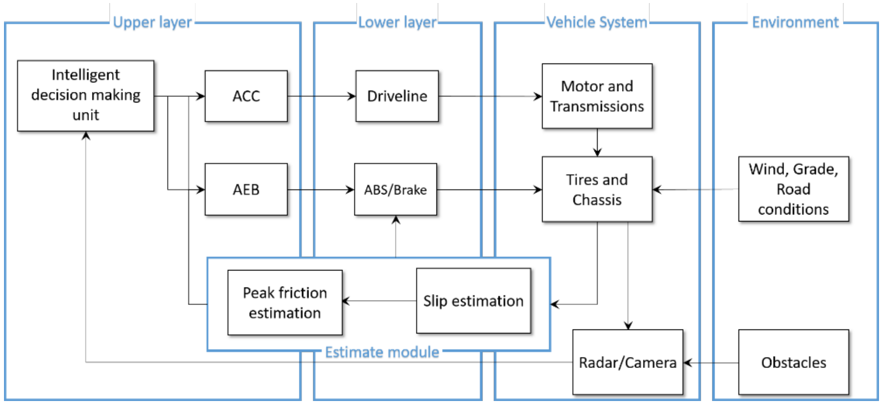
Design architectures to push assisted driving towards autonomous driving



Research results



Design and experimental validation of a camera based Forward Collision Warning [P2]



Embedding of road-tire grip data into longitudinal ADAS, resulting in improved safety over the state of the art [P1] [P3]

Design of a novel hierarchical motion planning architecture for autonomous driving

Research products

[P1]	S.Santini; N. Albarella; V.M. Arricale; R. Brancati; A. Sakhnevych; *On-Board Road Friction Estimation Technique for Autonomous Driving Vehicle-Following Maneuvers*, **Applied Sciences,** 2021,11,2197. doi: https://doi.org/10.3390/app11052197
[P2]	N. Albarella; F. Masuccio; L. Novella; M. Tufo; G. Fiengo; *A Forward-Collision Warning System for Electric Vehicles: Experimental Validation in Virtual and Real Environment*, **Energies,** 2021,14,4872. doi: https://doi.org/10.3390/en14164872
[P3]	N. Albarella; V.M. Arricale; A. Maiorano; L. Mosconi; G. Napolitano Dell’Annunziata; E. Rocca; *Improved Anti-Lock Braking System With Real-Time Friction Detection to Maximize Vehicle Performance*, **International Design Engineering Technical Conferences & Computers and Information in Engineering Conference,** Aug. 2021, doi: https://doi.org/10.1115/DETC2021-68431

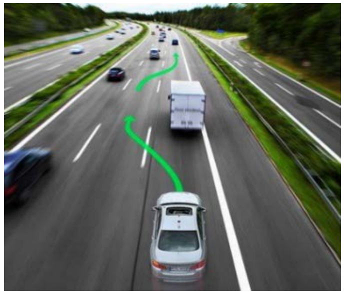
PhD thesis overview

Sensor data →

Sensing
- Localisation
- Obstacle Detection

→ Sensing state →

Planning
- Route
- Behaviour
- Motion



→ Reference motion →

Control
- Local Feedback

→ Actuator controls

Control — 2010 — 2012 — Sensing — 2016 — Planning...

PhD thesis overview

Design **safe, effective** and **scalable** driving policies

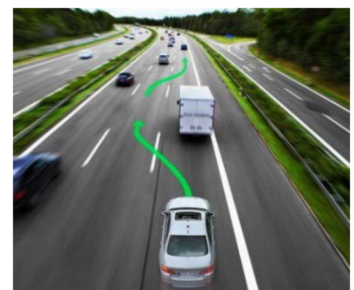
$$\pi: S \rightarrow A$$

$$s = [\xi_{ego}, \xi_{world}] \in S$$

known   unpredictable

Sensing state

Planning
- Route
- Behaviour
- Motion



Reference motion

State of the art planning:

- FSM, Petri Nets, Fuzzy Logic, RRT, A*, etc. → not scalable
- Mixed Integer Programming, Optimization based planning → prediction needed
- Game theory → prediction needed
- Machine Learning → unsafe

Hierarchical planning

Combine **machine learning** and **classical control**

$$\pi = \pi_D \circ \pi_C$$

Deep Reinforcement Learning

$$a = \pi_D(S)$$

Learning behaviours from data

Optimal Control

$$u = \pi_C(\xi_{ego}, a)$$

No need for prediction on ξ_{world}

Smaller search space

Better signal to noise ratio

π_C: Motion Planning

Mapping from discrete behaviours controls

– Nonlinear Model Predictive Controller (NMPC)

$$\dot{\sigma} = \frac{v\cos(e_\psi)}{1-\rho e_y}$$

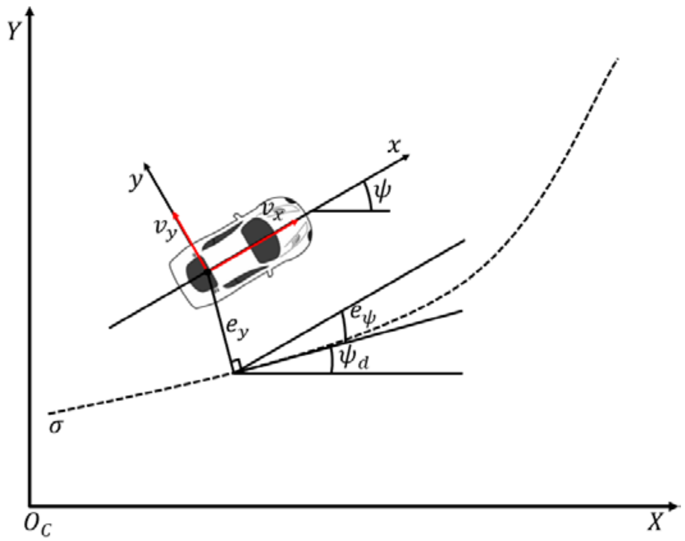
$$\dot{e}_y = v\ \sin(e_\psi)$$

$$\dot{e}_\psi = v\left(\frac{\tan(\delta)}{a+b} - \rho\frac{\cos(e_\psi)}{1-\rho e_y}\right)$$

$$\dot{v} = a$$

$$\dot{a} = \frac{a_{cmd} - a}{\tau}$$

$$\dot{\delta} = \delta_{cmd}$$



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$$\min_{\xi,U} \sum_{k=0}^{H_p-1} \left[\left(\xi_{k+1} - \xi_{ref}\right)^T Q\left(\xi_{k+1} - \xi_{ref}\right) + u_k^T R u_k\right]$$

$$\xi_{k+1} = f(\xi_k, u_k)$$

$${e_y}_{min} \le {e_y}_k \le {e_y}_{max}$$

$${e_\psi}_{min} \le {e_\psi}_k \le {e_\psi}_{max}$$

$$v_k \le v_{max}$$

$$a_{min} \le a_k \le a_{max}$$

$$\delta_{min} \le \delta_k \le \delta_{max}$$

$${a_{cmd}}_{min} \le {a_{cmd}}_k \le {a_{cmd}}_{max}$$

$${\delta_{cmd}}_{min} \le {\delta_{cmd}}_k \le {\delta_{cmd}}_{max}$$

π_D: Behaviour Planning

Mapping from state to discrete behaviours

- Need to separate effectiveness from safety
  - Effectiveness and comfort can be learned from data
  - Safety **cannot** be learned

$$\pi_D = \pi_L \circ \pi_N$$

Deep Reinforcement Learning

$$a = \pi_L(S)$$

Learning effectiveness and comfort

Rule based monitor

$$a_{mask} = \pi_N(S)$$

Ensuring safety via formal validation

π_N: Responsibility Sensitive Safety

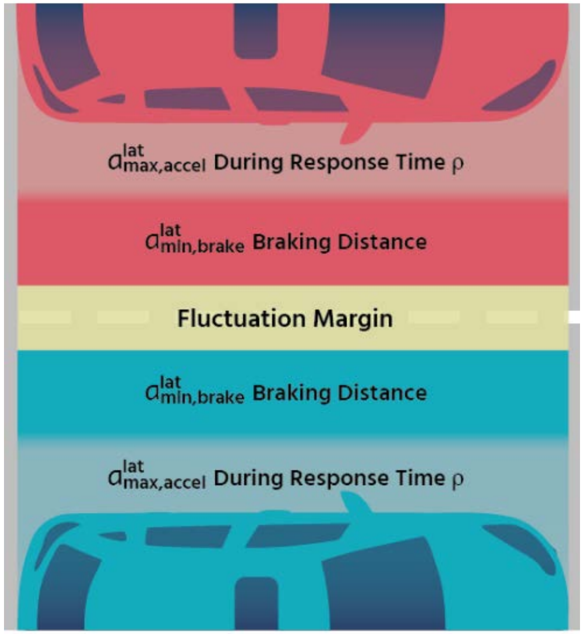
Formal model ensures safety under "*reasonable assumptions*"

$$d_{long_{min}} = \left[v_r \rho + \frac{1}{2} a^{long}_{max,accel} \rho^2 + \frac{\left(v_r + \rho a^{long}_{max,accel}\right)^2}{2 a^{long}_{min,brake}} - \frac{v_f^2}{2 a^{long}_{max,brake}} \right]_+$$

$$d_{lat_{min}} = \mu + \left[\frac{v_1 + v_{1,\rho}}{2} \rho + \frac{v_{1,\rho}^2}{2 a^{lat}_{min,brake}} - \left(\frac{v_2 + v_{2,\rho}}{2} \rho - \frac{v_{2,\rho}^2}{2 a^{lat}_{min,brake}} \right) \right]_+$$

$$v_{1,\rho} = v_1 + \rho a^{lat}_{max,accel}$$

$$v_{2,\rho} = v_2 - \rho a^{lat}_{max,accel}$$



Parameters ρ, μ, $\alpha^{long}_{max,accel}$, $a^{long}_{min,brake}$, $a^{long}_{max,brake}$, $a^{lat}_{max,accel}$ and $a^{lat}_{min,brake}$ can be tuned to change the cautiousness

[1] Shalev-Shwartz, S., Shammah, S., & Shashua, A. (2017). On a formal model of safe and scalable self-driving cars.

π_L: Behaviour Planning

– Deep Reinforcement Learning (DRL)

$$s_k = \begin{bmatrix} X^0 & Y^0 & v_X^0 & v_Y^0 & \psi^0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ X^N - X^0 & Y^N - Y^0 & v_X^N & v_Y^N & \psi^N \end{bmatrix}$$

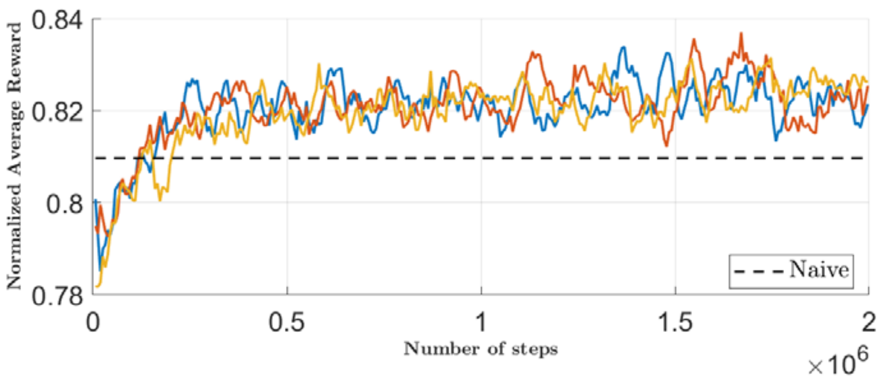
$$r_k = k_1 v$$

– Deep-Q Learning (DQN)
– Proximal Policy Optimization (PPO)

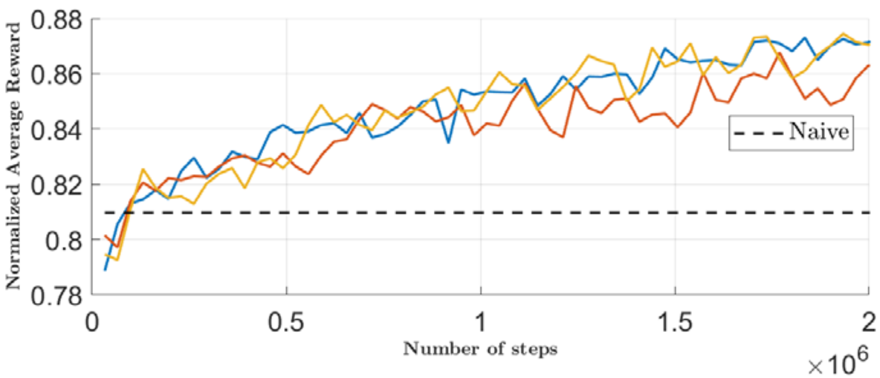
Behaviours a
Change lane to the left
Change half lane to the left
Keep same lane, same speed
Change half lane to the right
Change lane to the right
Slower
Faster

Highway driving results

DQN



PPO

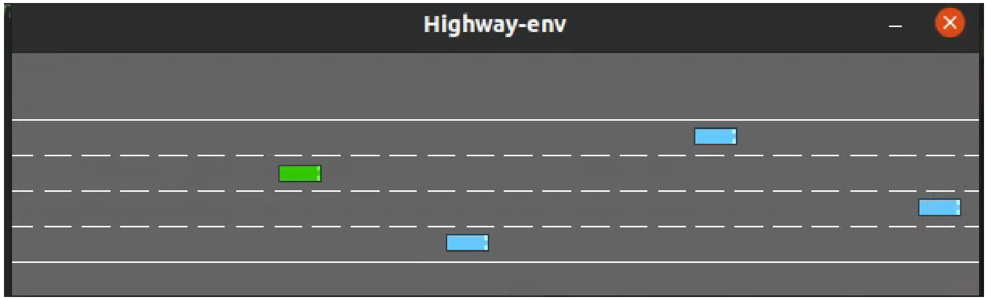


Algorithm	Average Reward	Average Length
DQN + mask	0.835 ± 0.037	40.0 ± 0.0
PPO + mask	0.881 ± 0.050	40.0 ± 0.0
DQN	0.826 ± 0.226	33.6 ± 10.2
PPO	0.647 ± 0.254	31.1 ± 12.5
Naive	0.809 ± 0.003	40.0 ± 0.0

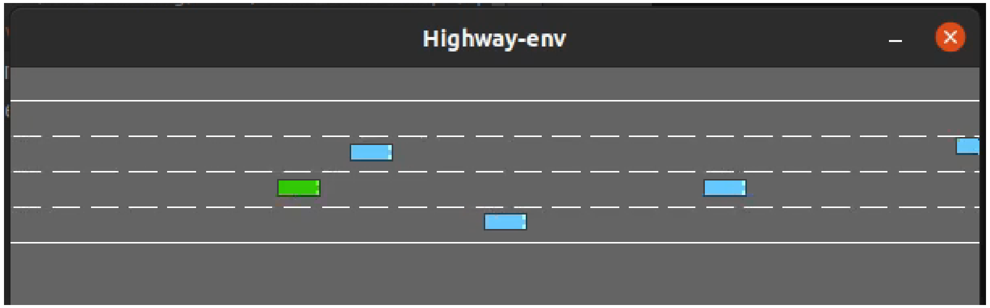
Highway driving results

OpenAI Gym based Highway Environment
4 lanes highway
Scenarios are randomly generated
Other road users are modelled through IDM and MOBIL

PPO + mask:



PPO:



Thanks for the attention!