Motion planning and control for intelligent vehicles in urban environments

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Centre for Automation and Robotics (CSIC-UPM)

Workshop Robocity, 2030, 11/06/2021

Outline

AUTOPIA: Who are we?

Our vision: Current challenges

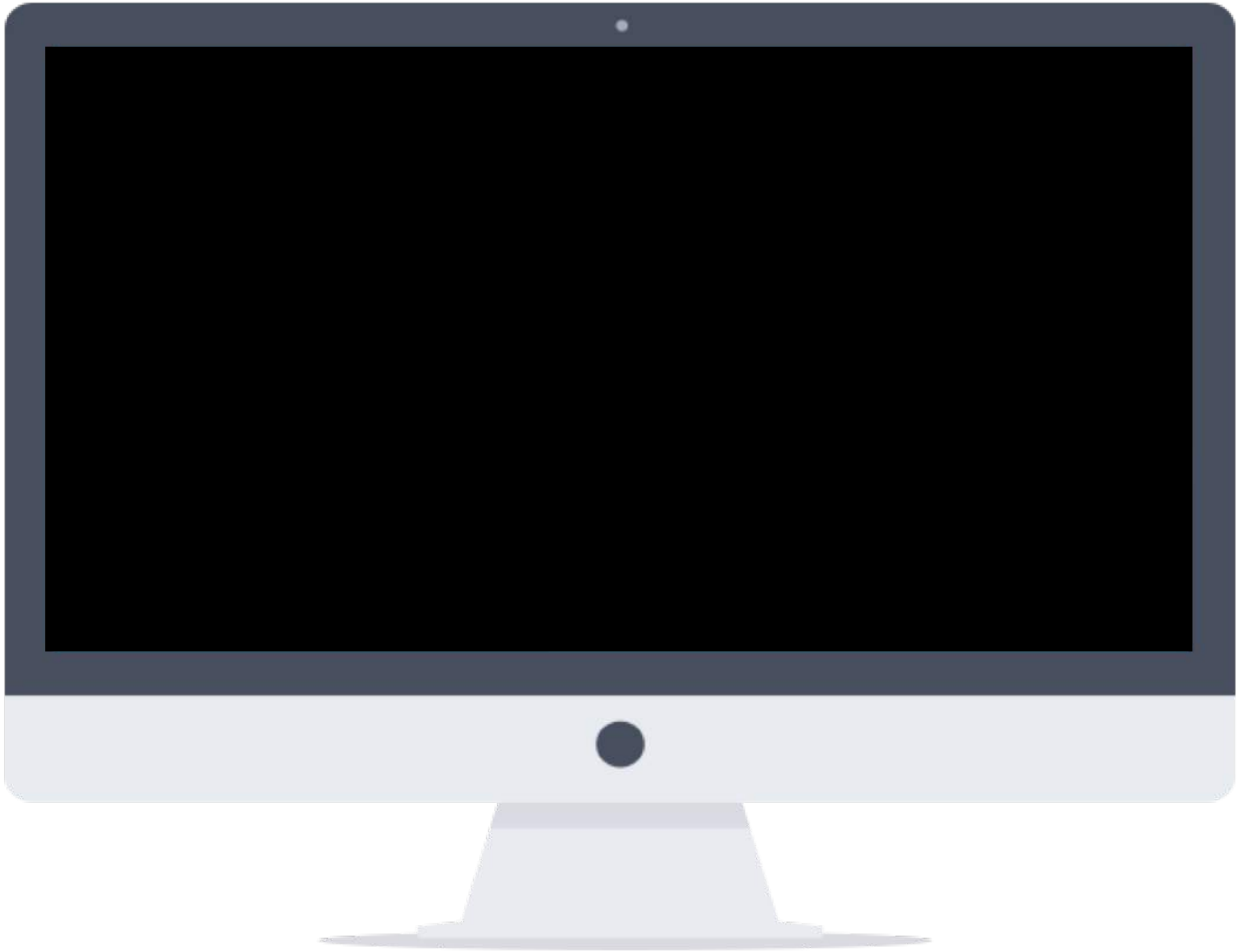
Research directions

- Supervisor
- World modelling & situation understanding
- Motion prediction
- Motion planning
- Control

Who are we?

Autopia Program

Who are we?



Vision

Who are we?

AUTOPIA explores techniques that can contribute to meet the big **challenges of Intelligent Vehicles in urban environments:**

- To develop **navigation, guidance & control** solutions for **intelligent vehicles** in specific situations where communication and interaction abilities may permit to solve understanding-decision dilemmas of isolated self-driving cars.
- Interest in **decision-making architectures** where **driver intentions and skills** can be adopted at different assistance levels (from SAE L2 to L4).
- To analyse the influence of **world modelling, localization and mapping uncertainty** in decision-making and **road interactions**
- Given the **strong segmentation** of the upcoming solutions and the long **transition period** where manual and automated vehicles will have to coexist, 4 design principles are at the core of our research:

Adaptability to driving scenarios and personalization to passengers' preferences

Dependability in the identified operational domain

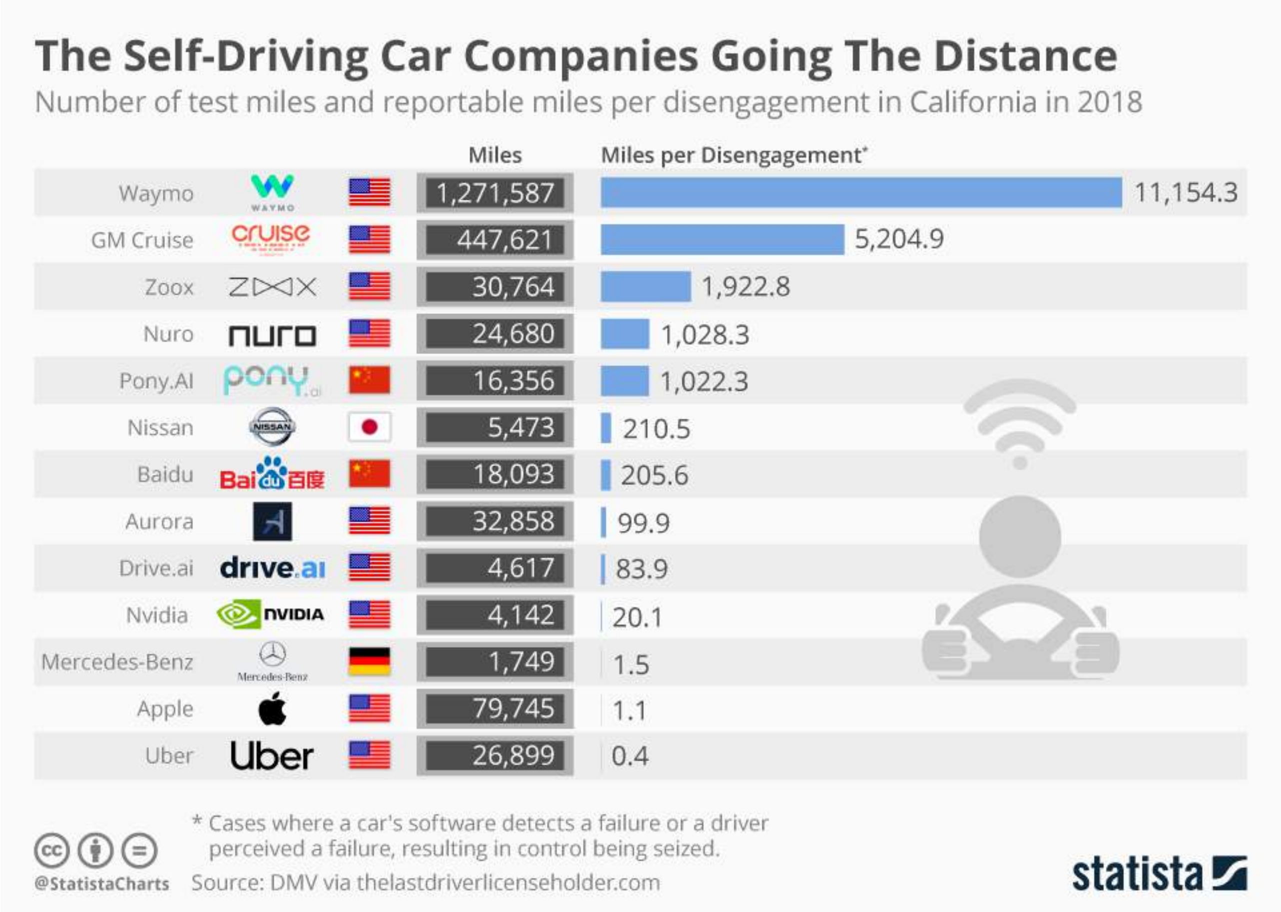
Safety by design through interpretable mechanisms

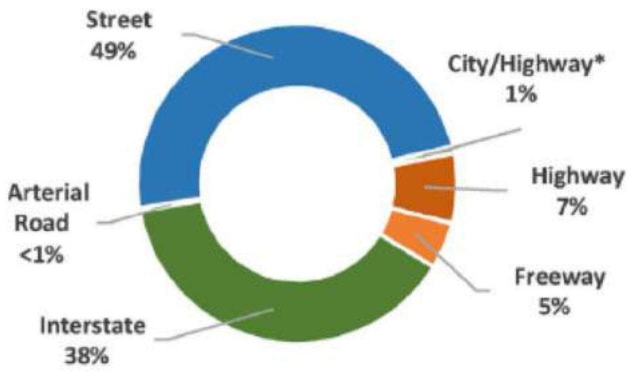
Developments relying on **open-source data**

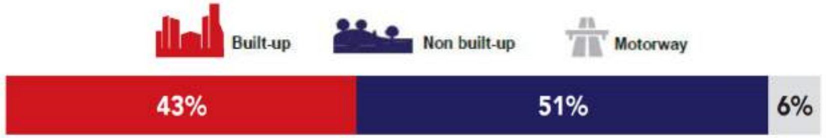
Current challenges

The numbers speak for themselves…

Current challenges





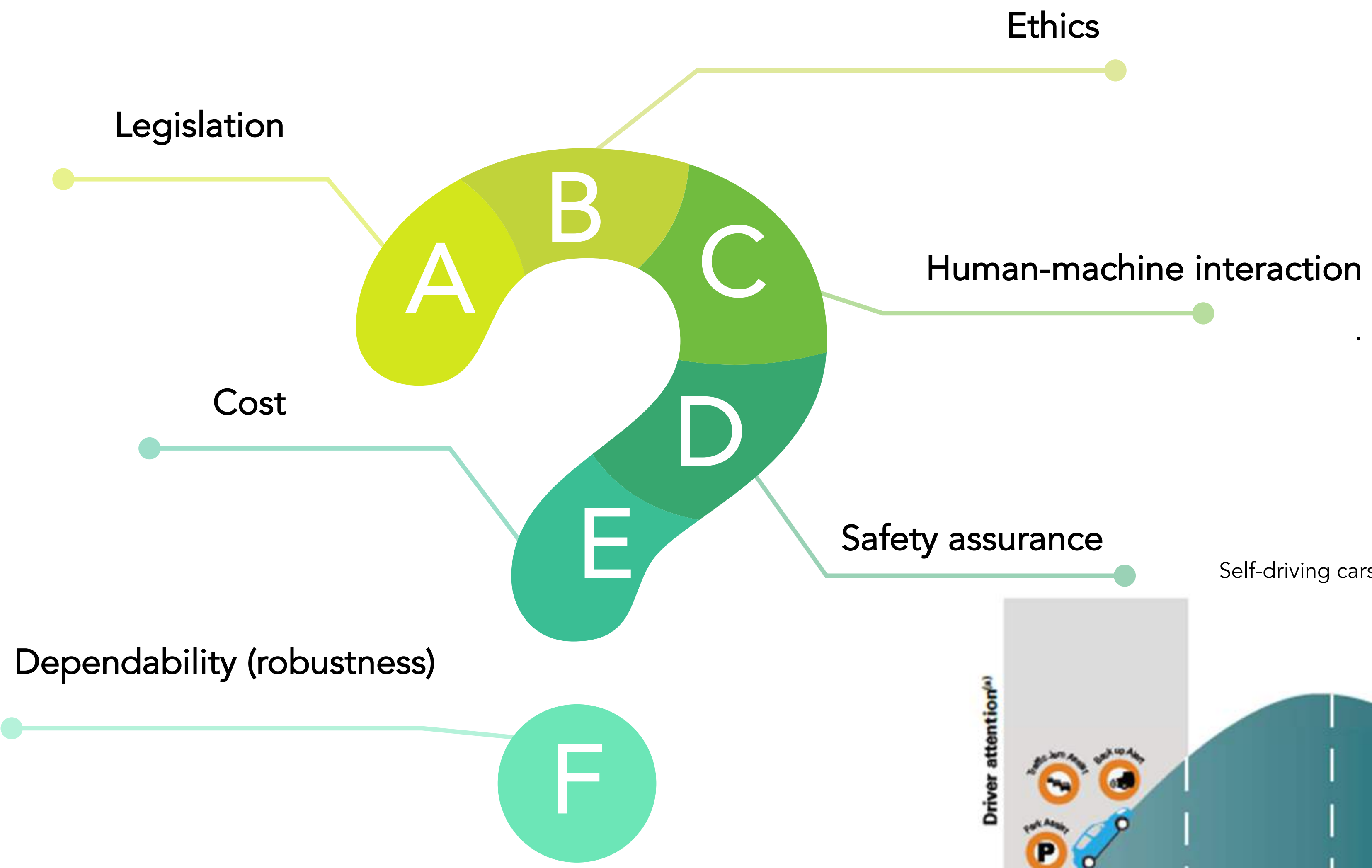


Fatalities by road type (UK)

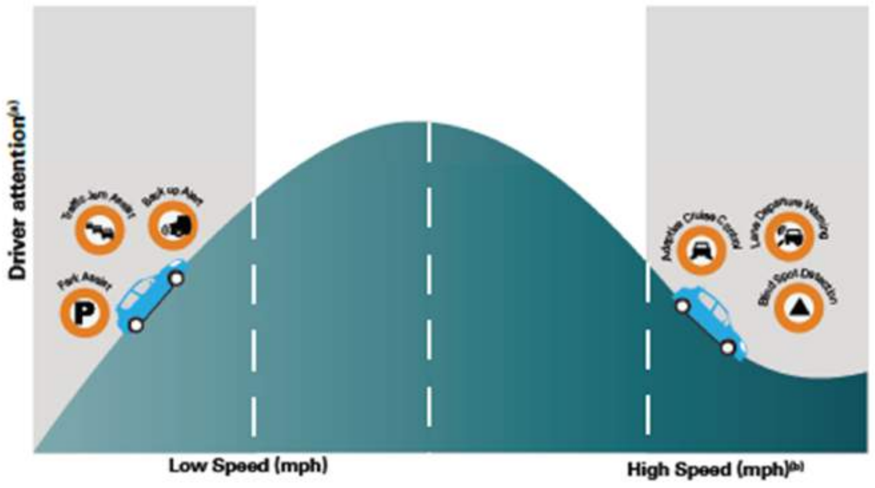
- **Average:** 27 miles/disengagement
- **Best case:** 11154 miles/disangagement (Google/Waymo)

Which are the barriers for a massive deployment?

Current challenges

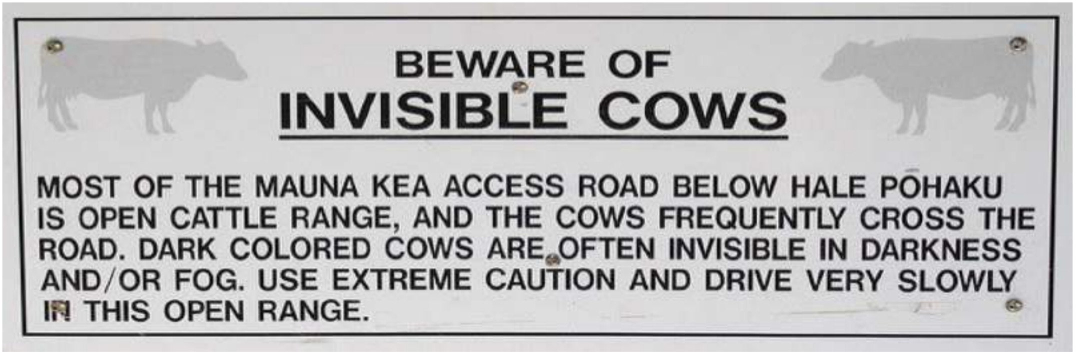


Self-driving cars: the next revolution, KPMG, 2013



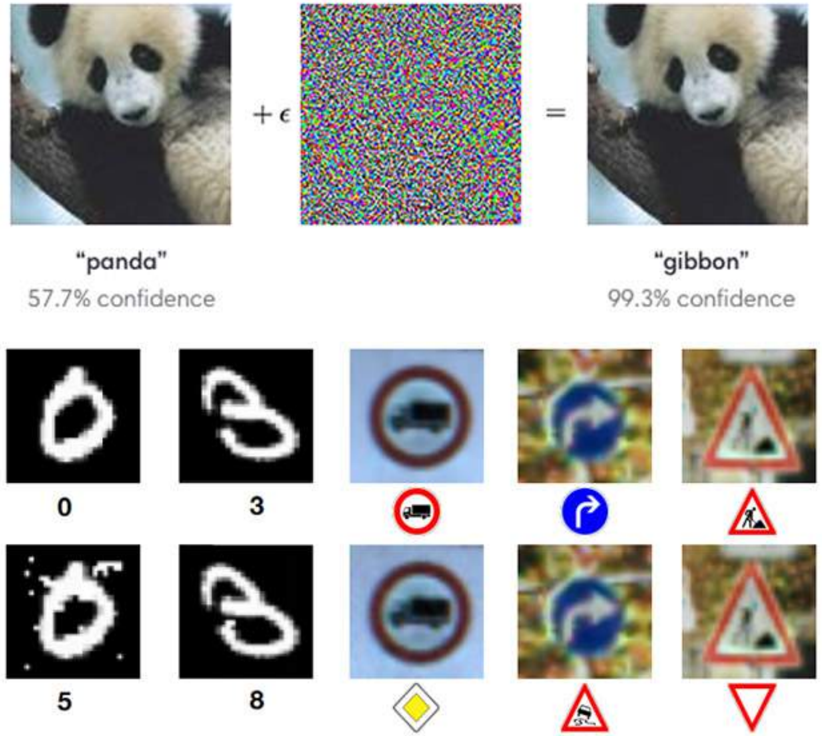
Dependability

Current challenges



Safety assurance: explainable AI?

Current challenges



Evtimov, I., Eykholt, K., Fernandes, E., Kohno, T., Li, B., Prakash, A., ... & Song, D. (2017). **Robust physical-world attacks on machine learning model**s. *arXiv preprint arXiv:1707.08945*, *2*(3), 4.

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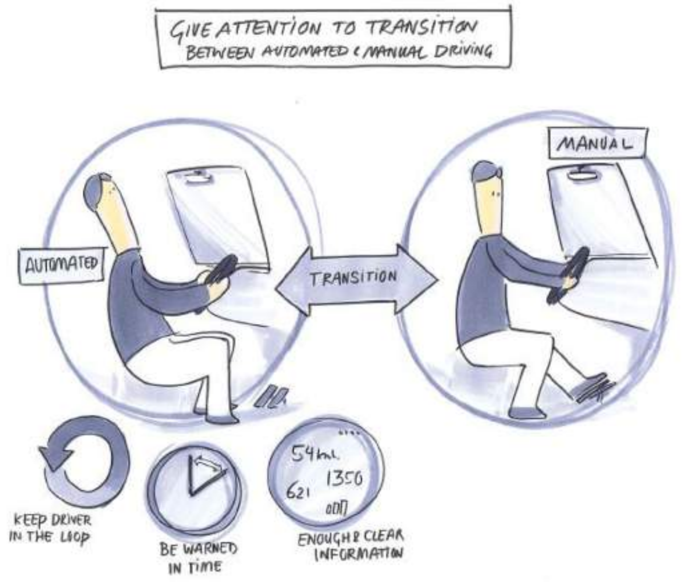
"Stop sign"
99%
confidence

"45 Speed limit sign"
100% confidence

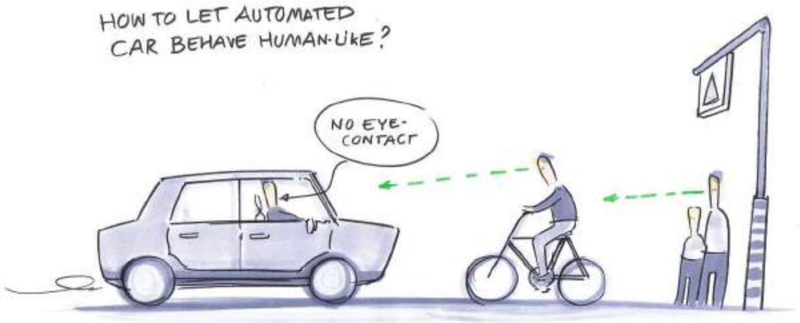
?

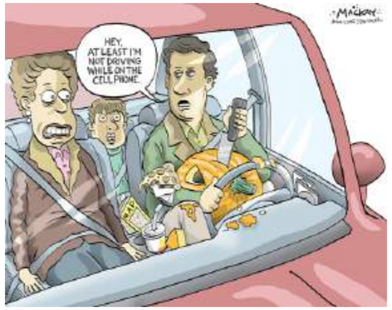
Human-machine “integration”

Current challenges



- Situation awareness
- Mode (automated-manual) confusion
- Usability
- Loss of skill associated with workload
- Trust

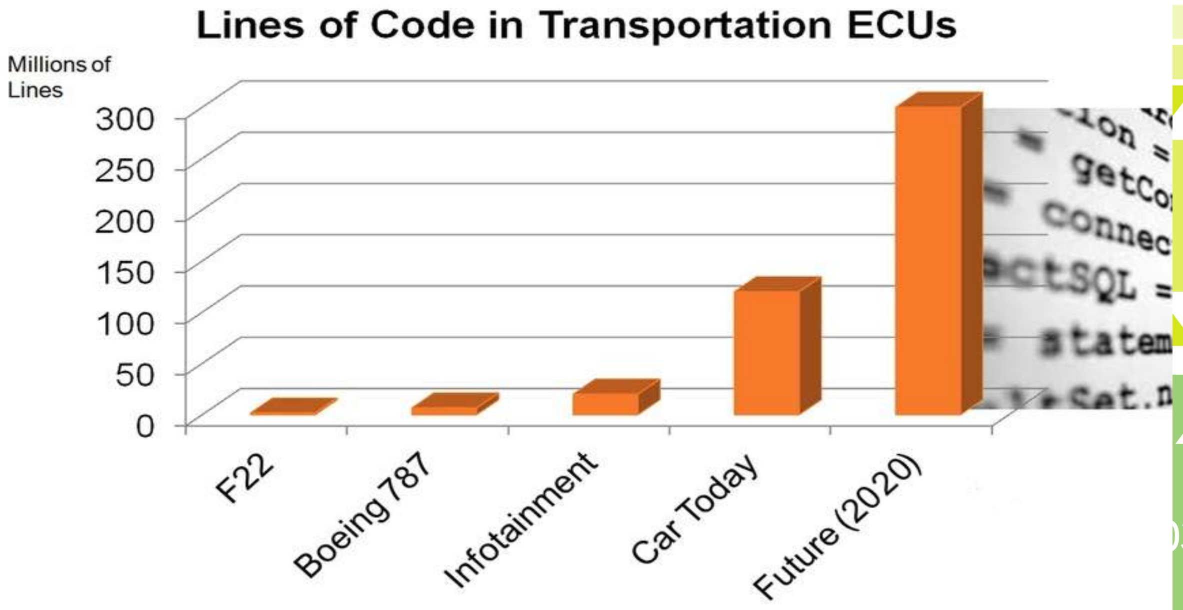


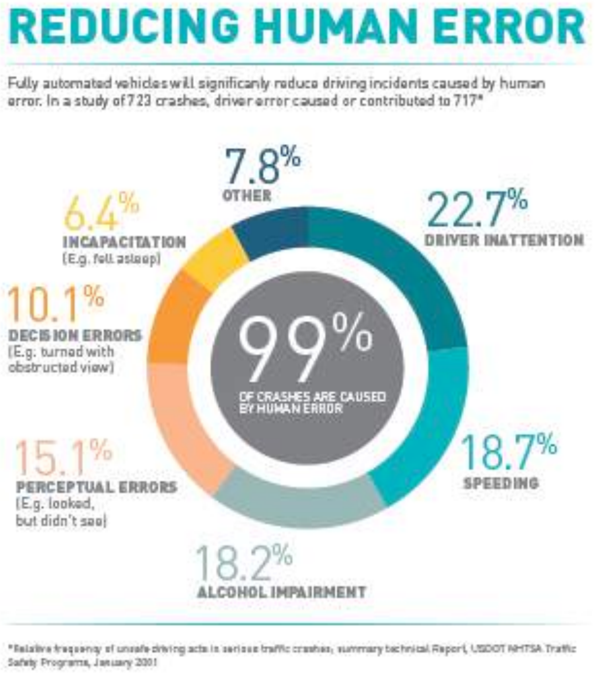


Major challenges…that often clash

Current challenges

- **Extreme external conditions** may appear suddenly (failure of another car, load falling on the road, lighting, …)
- There might be **new accidents** caused by automation for several reasons
- The human being has difficulty acting as a **safety fall-back**



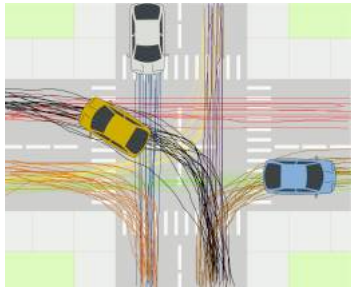


Research directions

Supervisor
World modelling & situation understanding
Motion prediction
Motion planning
Control

How do we contribute to (partially) remove the existing barriers?

Current challenges

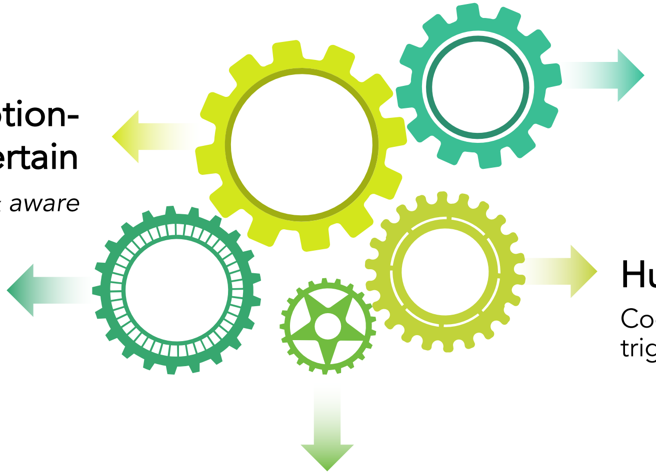


Adaptive motion-planning in the uncertain

Human-like & aware

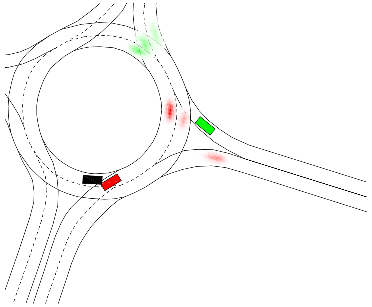
Situation understanding

Risk prioritization and intention estimation



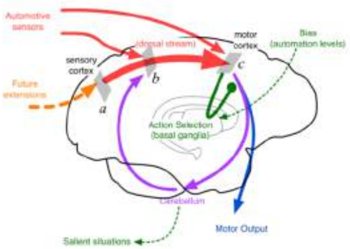
Motion prediction

Interaction-aware reachable sets



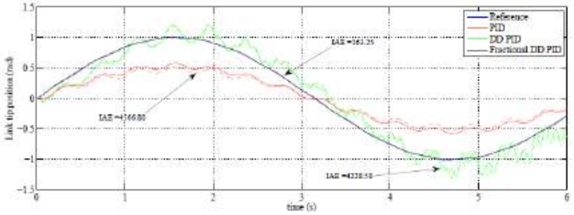
Human-machine integration

Cognition-inspired architecture for self-triggered automation-level



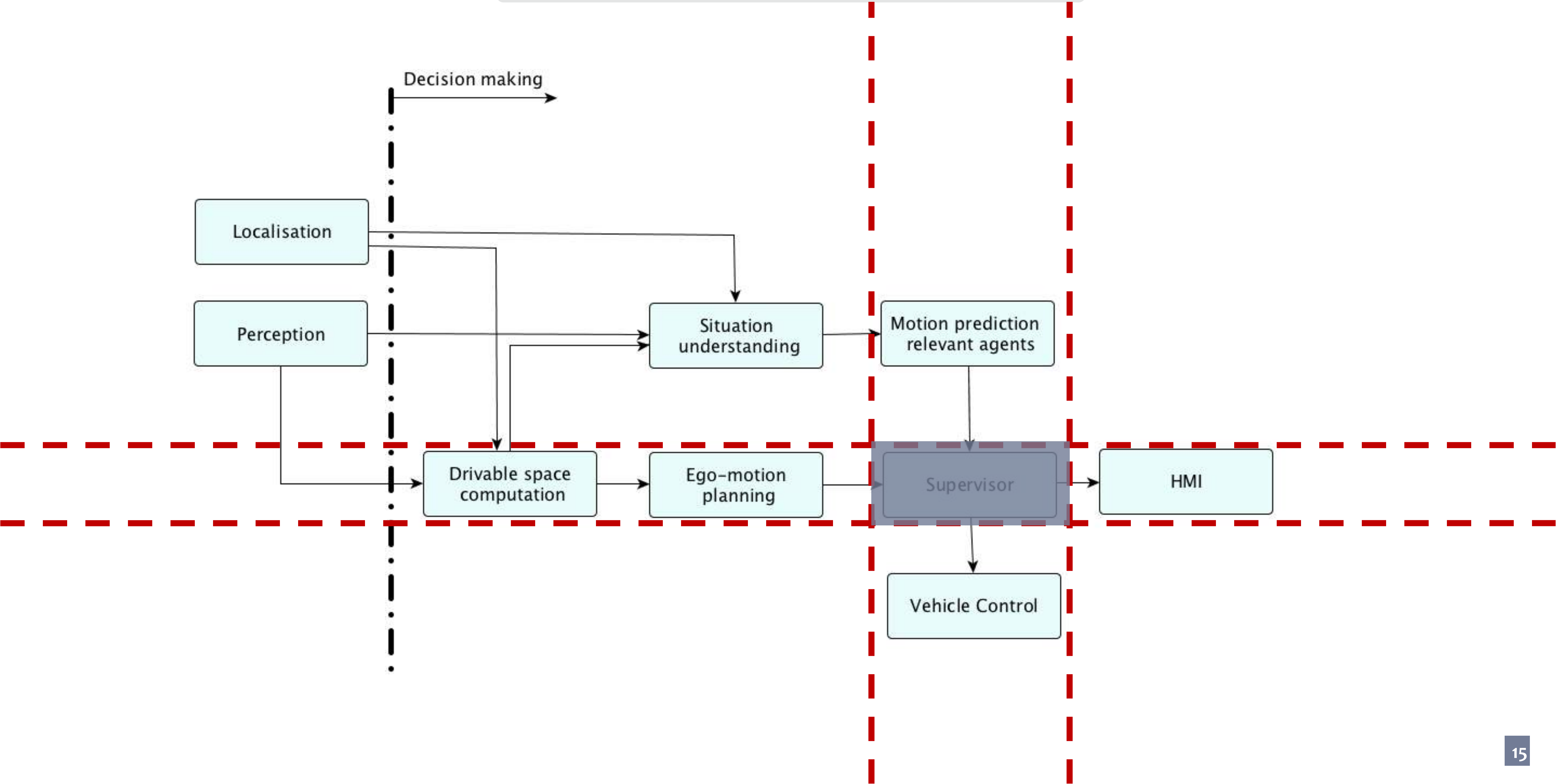
Interpretable "intelligence"

Model-free control



Decision-making process

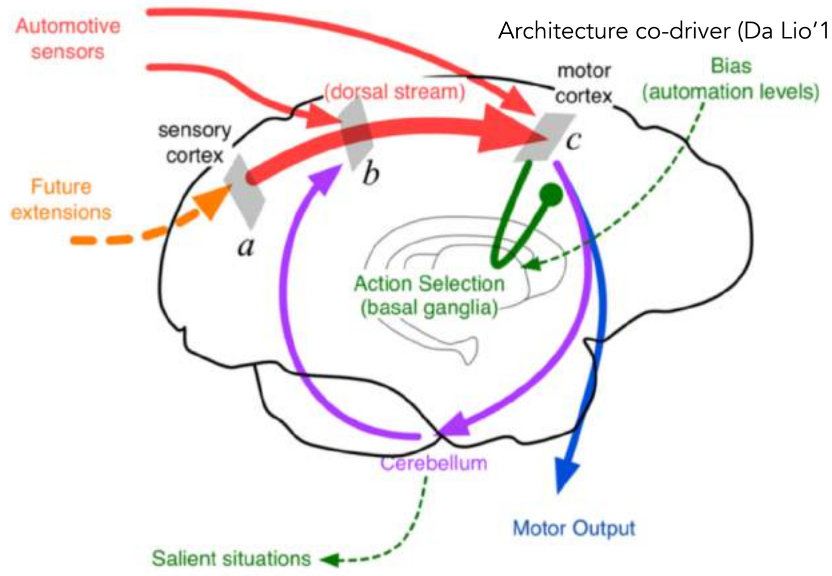
Research directions

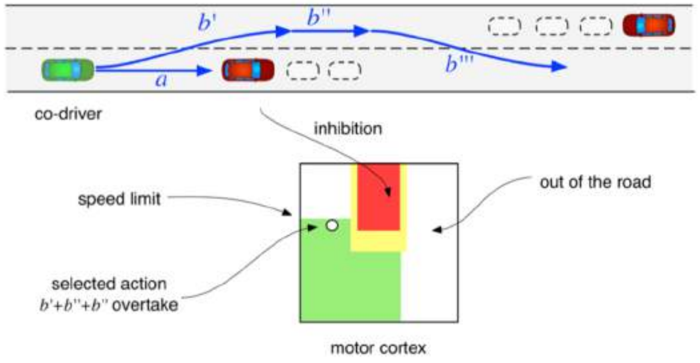


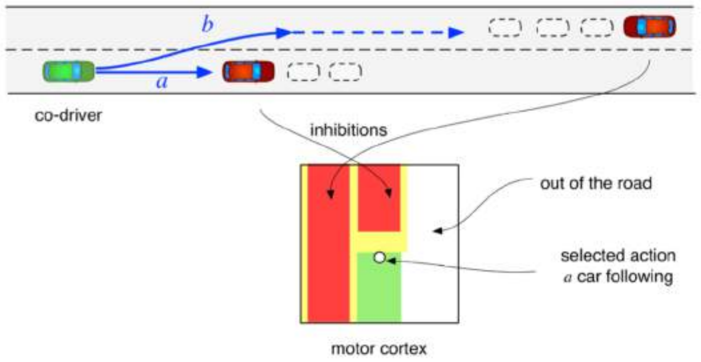
Towards an intuitive and safe decision-making: *data-driven co-driver* (1/3)

Research directions

Architecture co-driver (Da Lio'15)







Take advantage of the **Theory of simulation of cognition**, according to which thinking is essentially simulating perceptions and actions, structured around covert sensorimotor activities

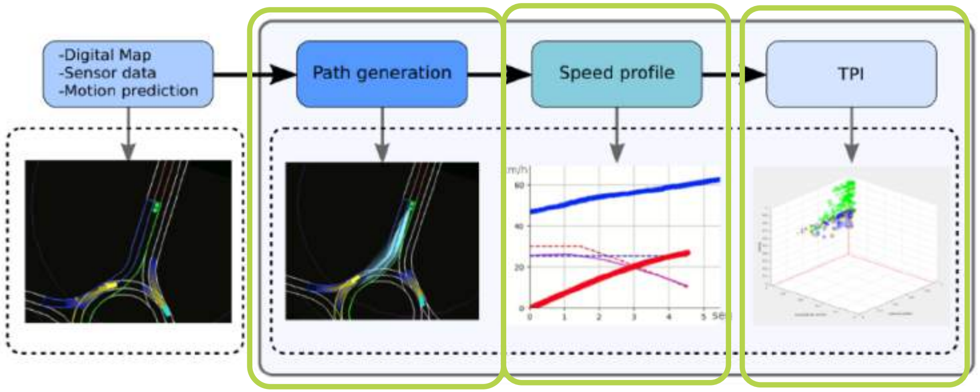
Based on agents capable of emulating a "**like me**" empathic framework, capable of using sensory-motor activities that **mirror human behavior** to infer intent and interaction

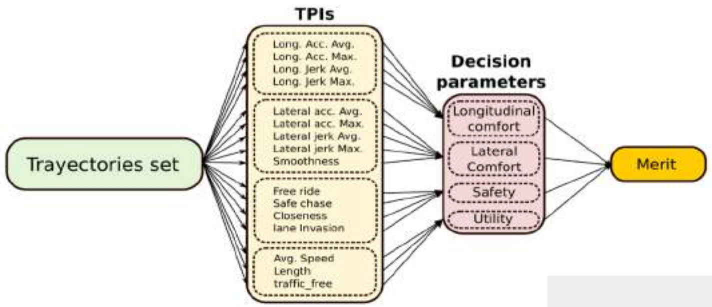
Architecture with 3 loops:

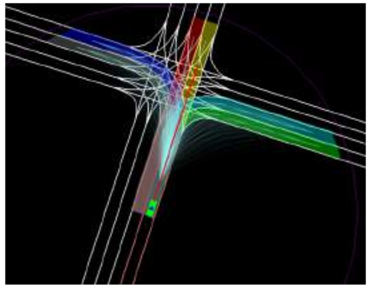
- A "**dorsal stream**", which represents inverse models nested in layers that generate "possibilities" from the sensory input.
- A mechanism of selection of actions **("basal ganglia")** that operates in several levels of the hierarchy.
- A "**cerebellum**" that learns advanced models.

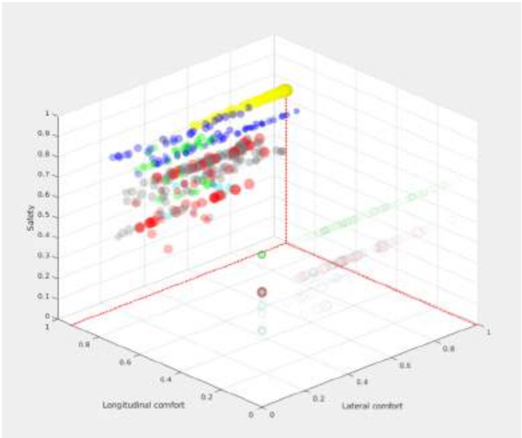
Towards an intuitive and safe decision-making : *data-driven co-driver* (2/3)

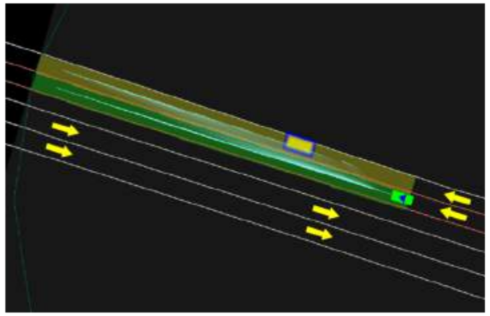
Research directions

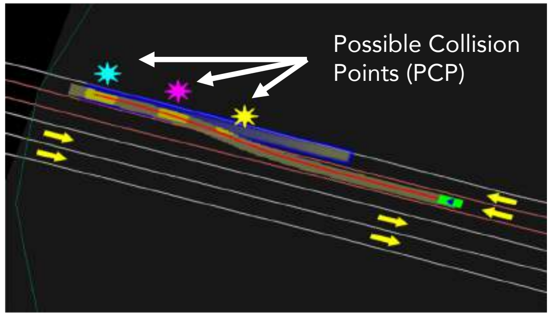


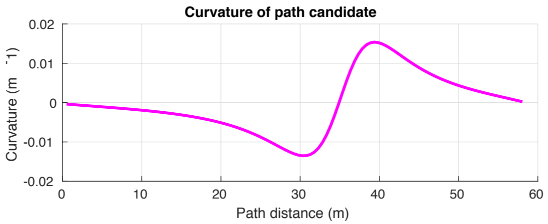


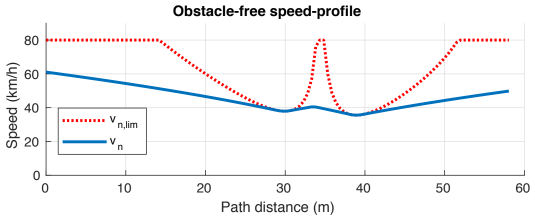


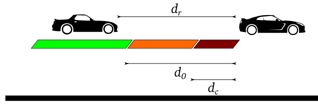




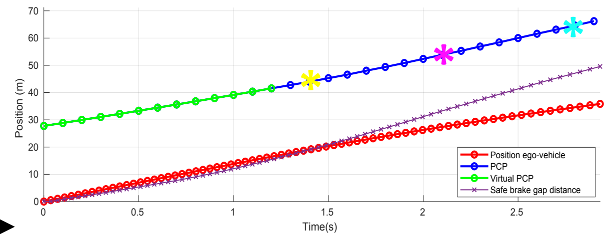


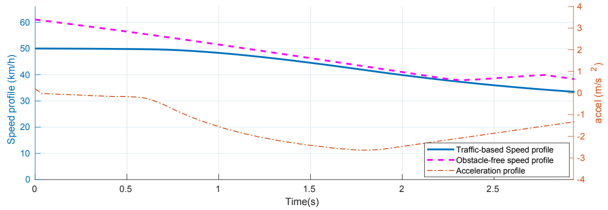


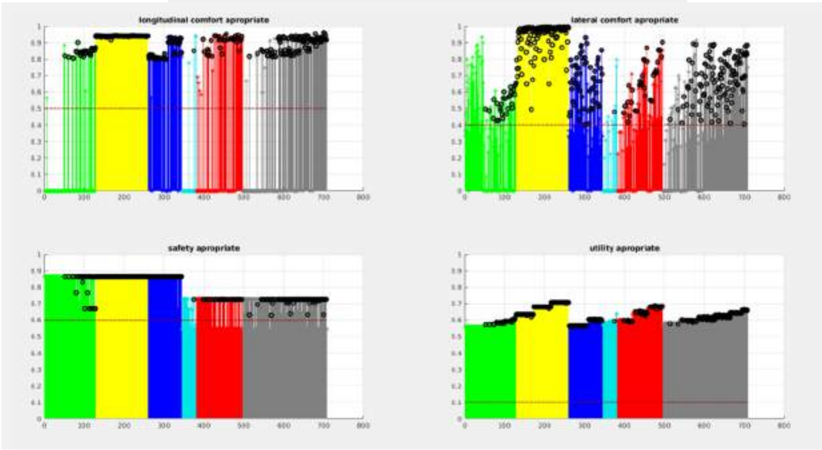




$$\ddot{x}_f^r = -c|\tilde{d}(t)|\left[-\frac{c}{2}\tilde{d}(t)^2 + \beta - \hat{\ddot{x}}_l(t)\right]$$



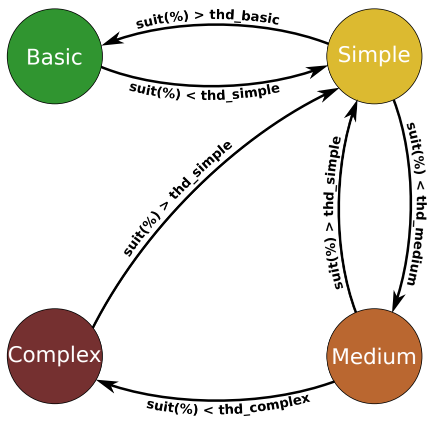


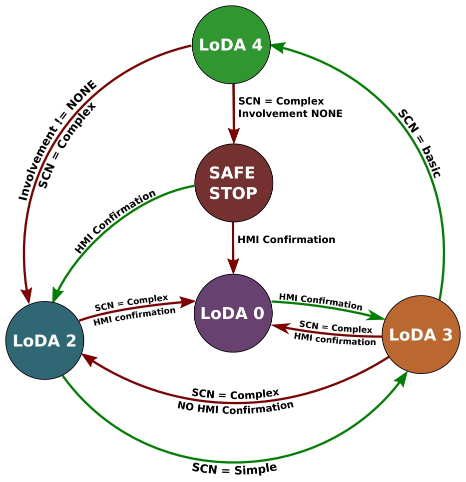


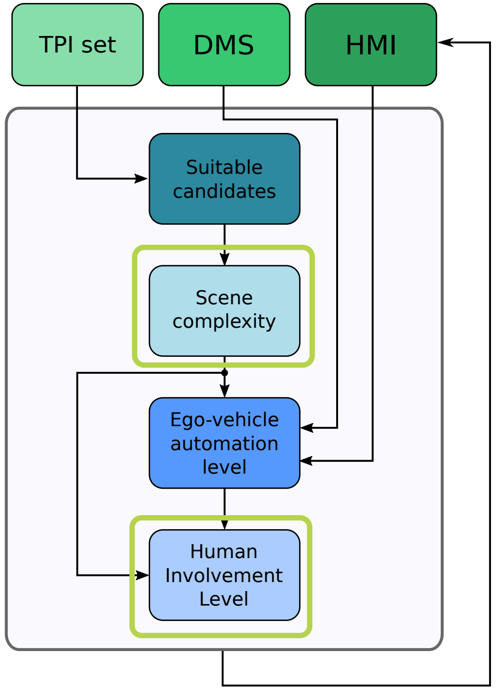
J. F. Medina-Lee, A. Artuñedo, J. Godoy, and J. Villagra, **Reachability Estimation in Dynamic Driving Scenes for Autonomous Vehicles**, in 2020 IEEE Intelligent Vehicles Symposium, 2020.
J.F. Medina-Lee, A. Artuñedo, A., J. Godoy and J. Villagra, **Merit-Based Motion Planning for Autonomous Vehicles in Urban Scenarios**. Sensors, 21(11), pp. 3755, 2021

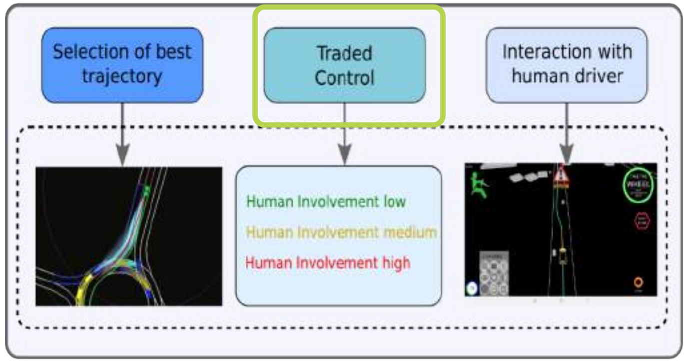
Towards an intuitive and safe decision-making : *data-driven co-driver* (3/3)

Research directions





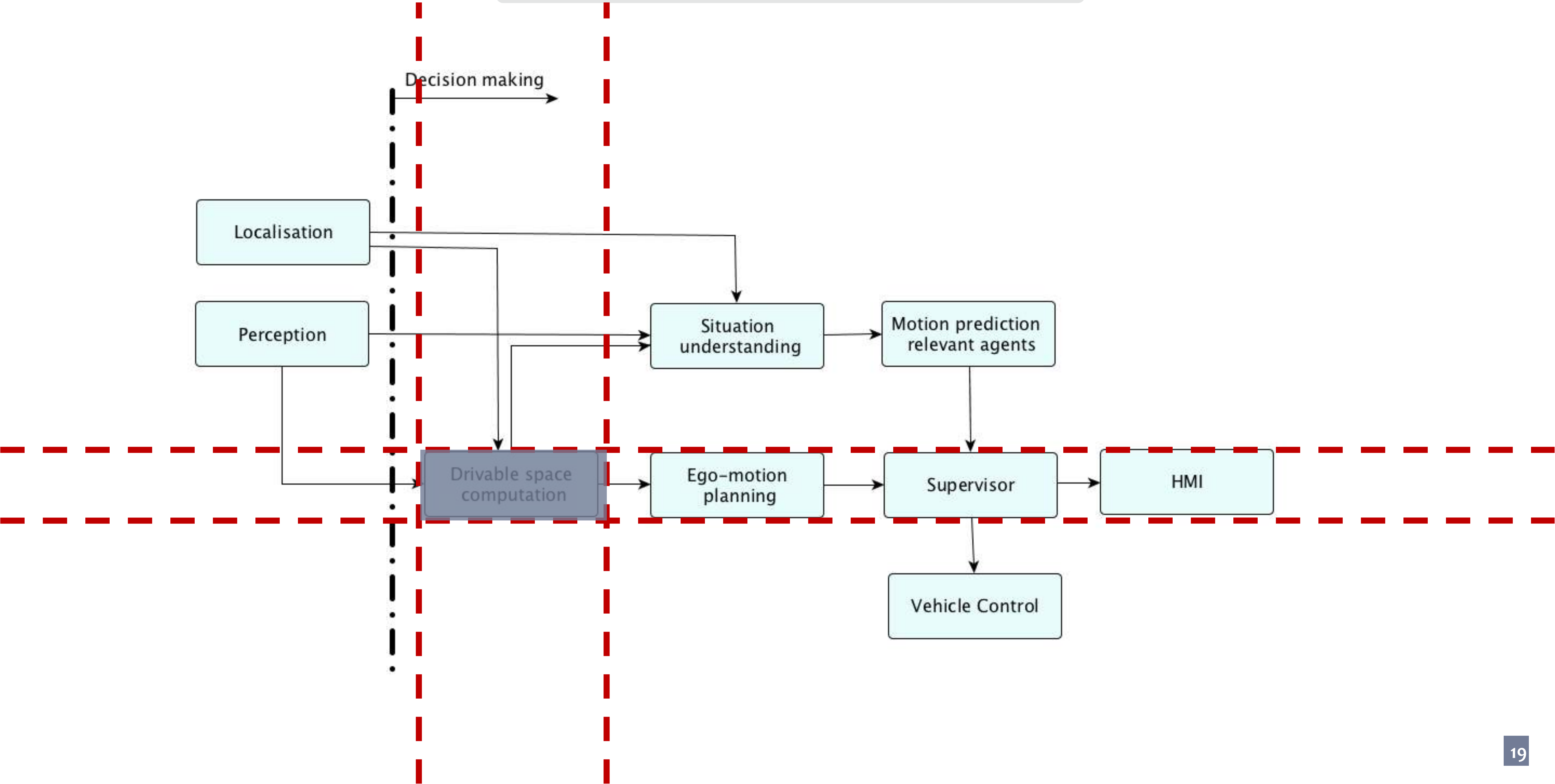




J. F. Medina-Lee, J. Villagra, and A. Artuñedo, **Traded control architecture for automated vehicles enabled by the scene complexity estimation**, in *4th International Conference on Computer-Human Interaction Research and* Applications, 2020

Decision-making process

Research directions

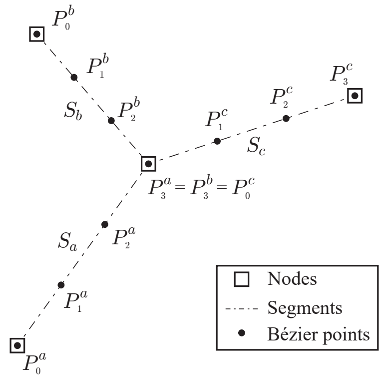


World modelling (1/2): self-generated corridors

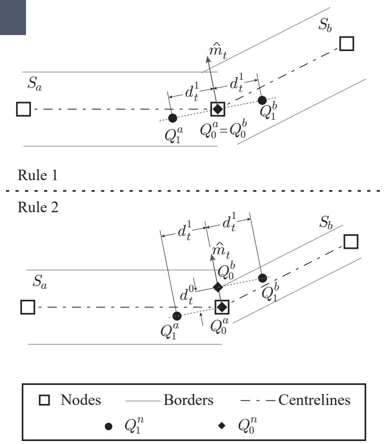
Research directions

Automatic generation of navigable corridors from Open Street Maps

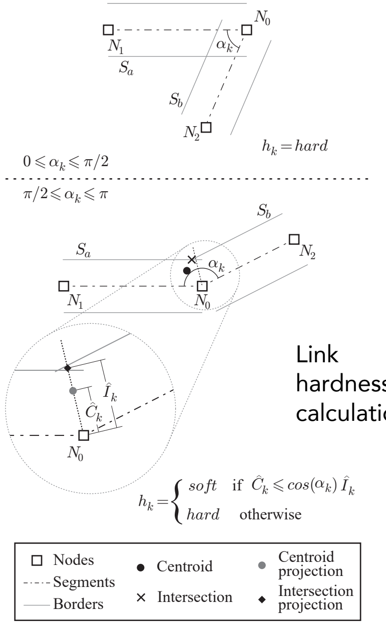
- Topology and attributes richness
- Smoothness
- Lane-level
- Real-time
- Precise (lOSMl)



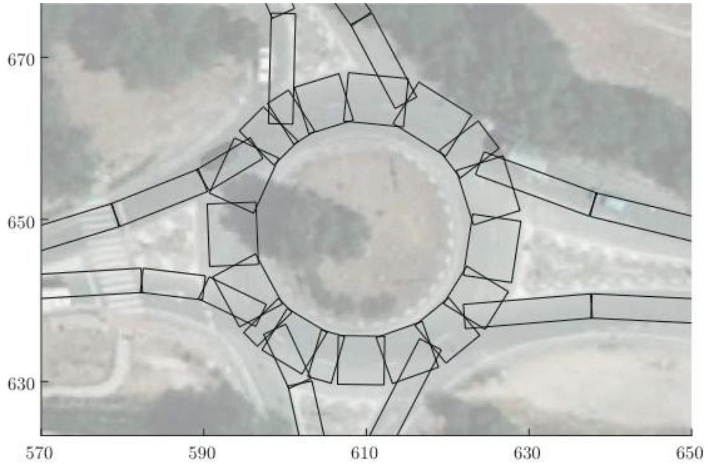
Example of Segments with Bézier control points

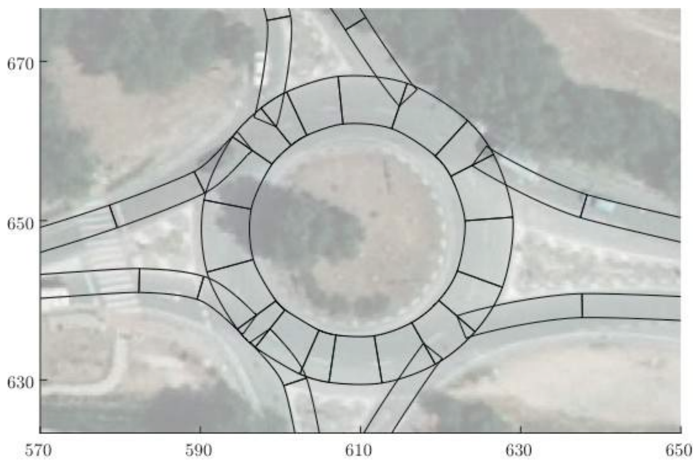


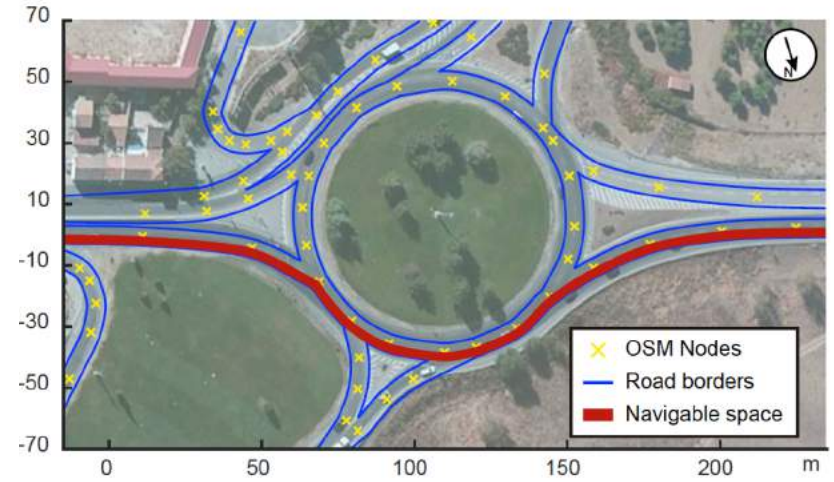
Bézier adjustment: Rules 1 & 2.



Link hardness calculation





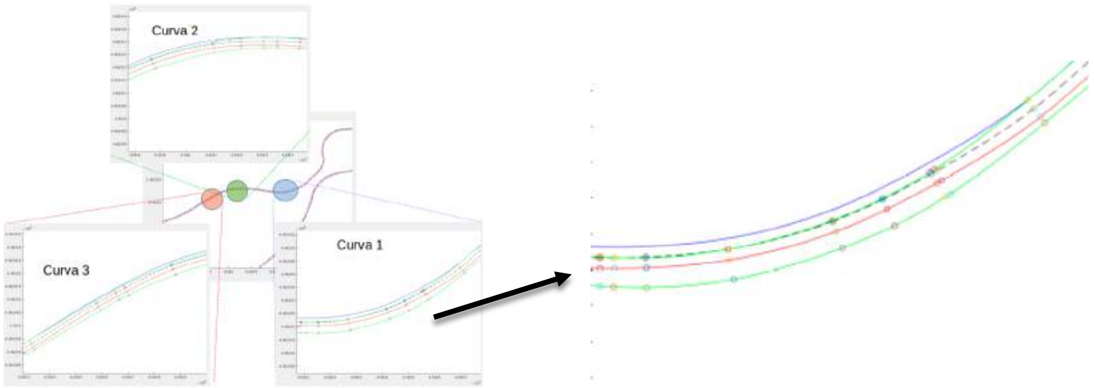


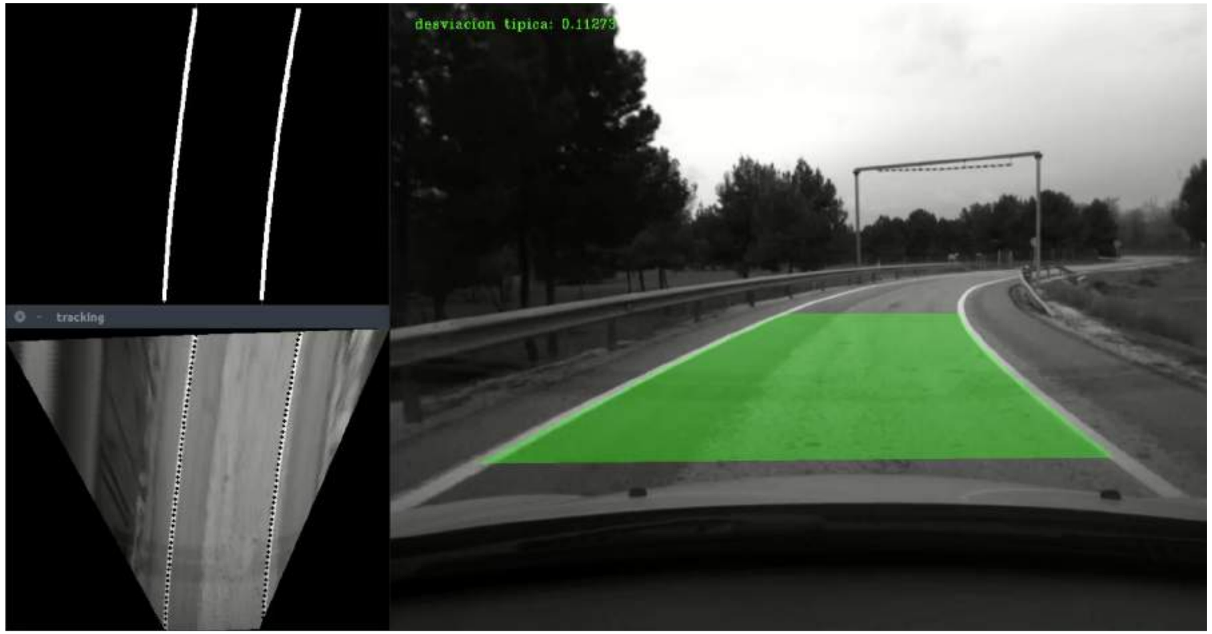
Godoy, J.; Artuñedo, A.. & Villagra, J. **Self-generated OSM-based driving corridors,**IEEE Access, 2019

World modelling (2/2): handling uncertainty

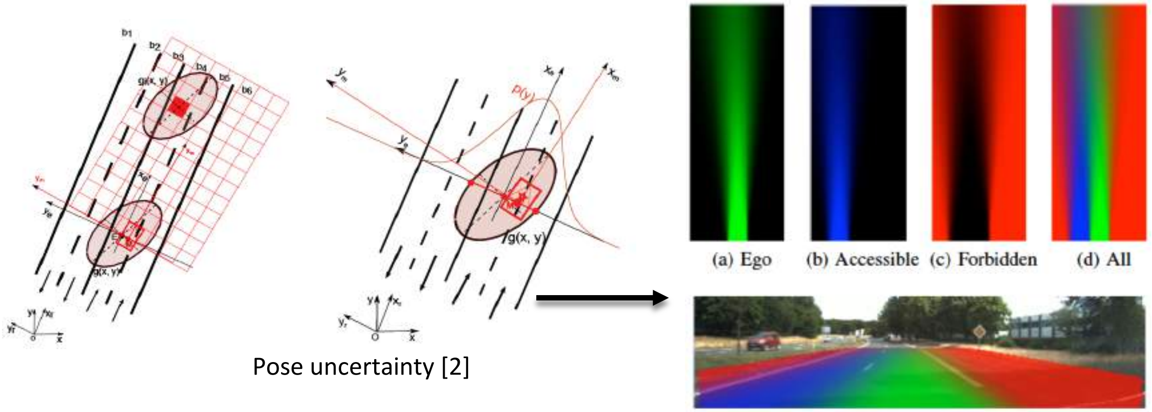
Research directions

Real-time OSM adaptation using corridors and computer-vision

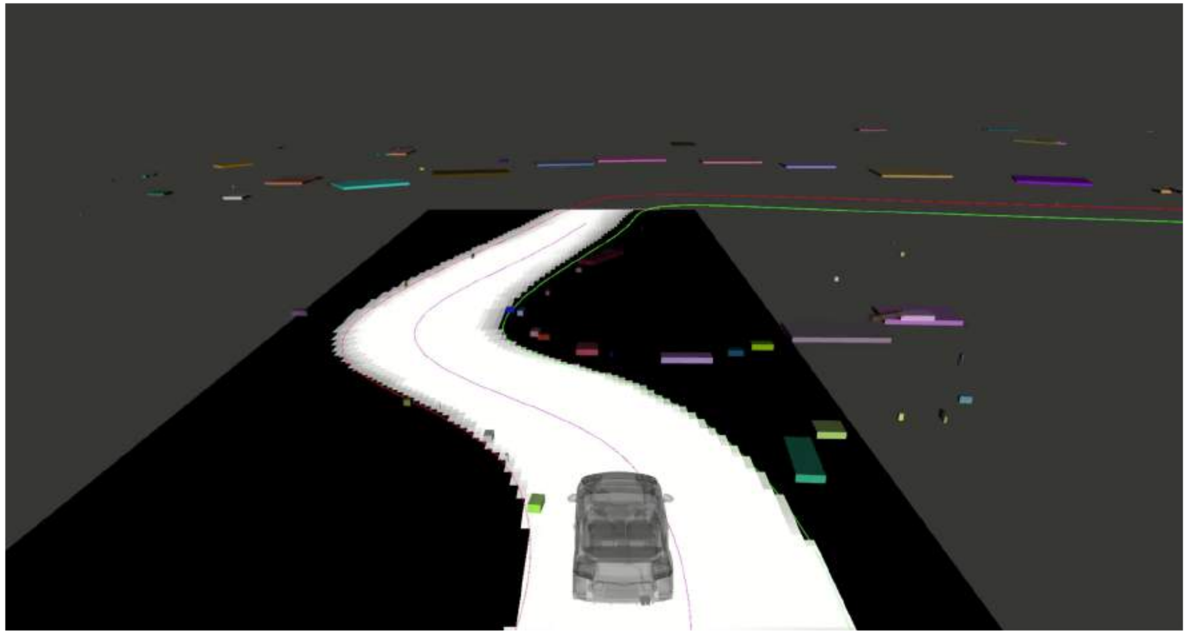




Probabilistic grid considering maps and measurements uncertainty



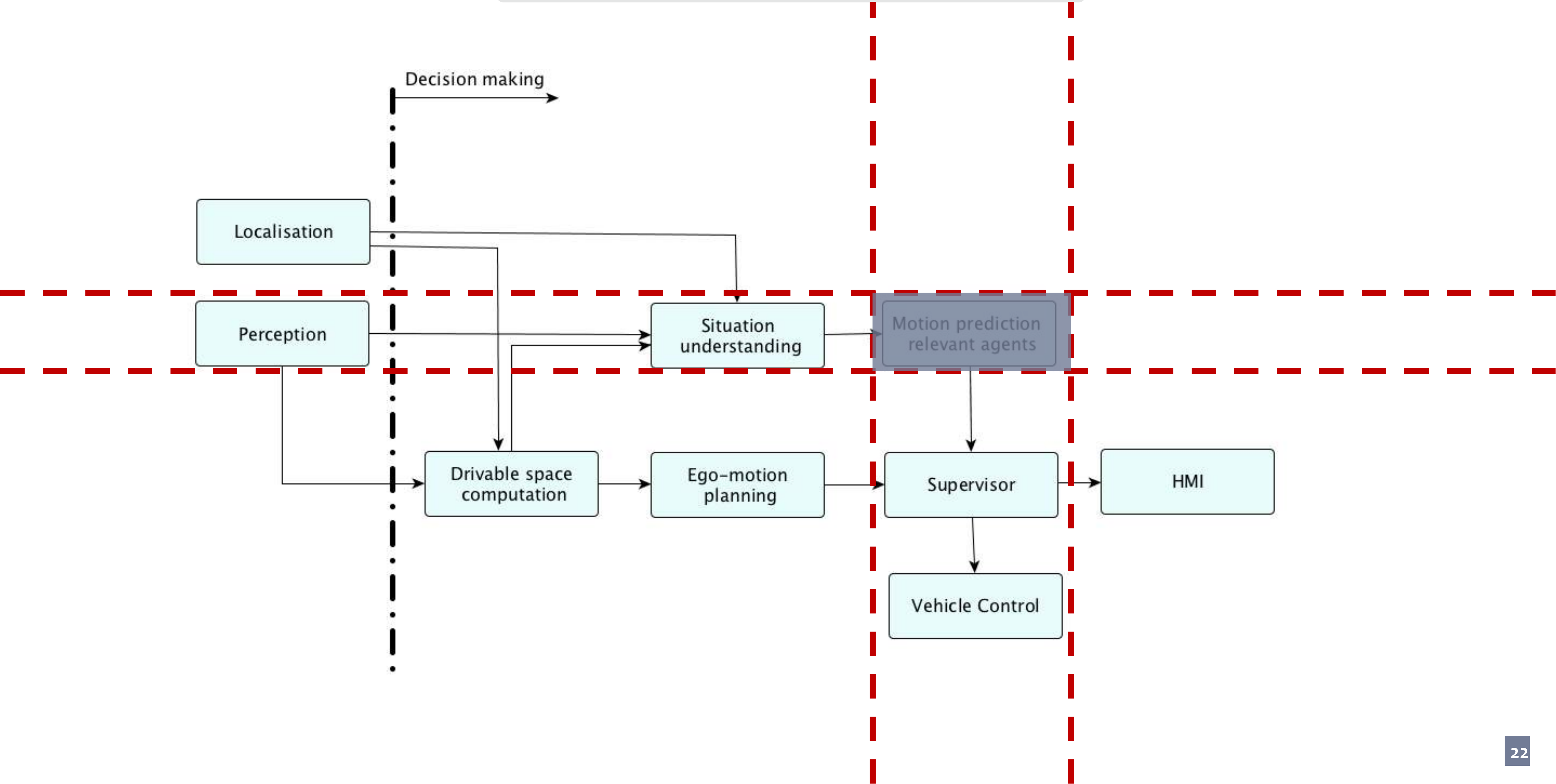
Pose uncertainty [2]



A. Artuñedo, J. Villagra, J. Godoy, and M. D. D. Castillo, **Motion Planning Approach Considering Localization Uncertainty**, *IEEE Transactions on Vehicular Technology*, vol. 69, iss. 6, p. 5983–5994, 2020.

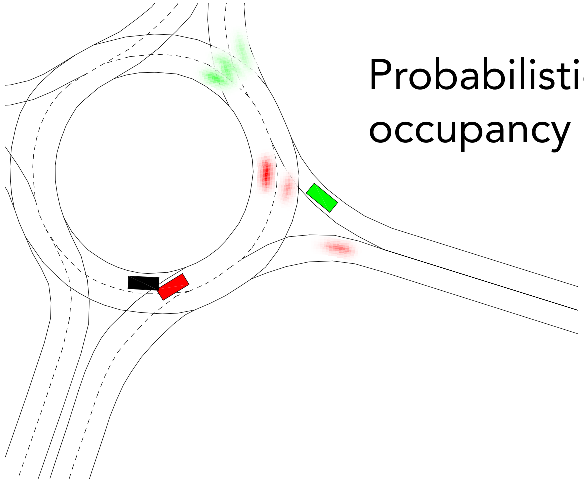
Decision-making process

Research directions

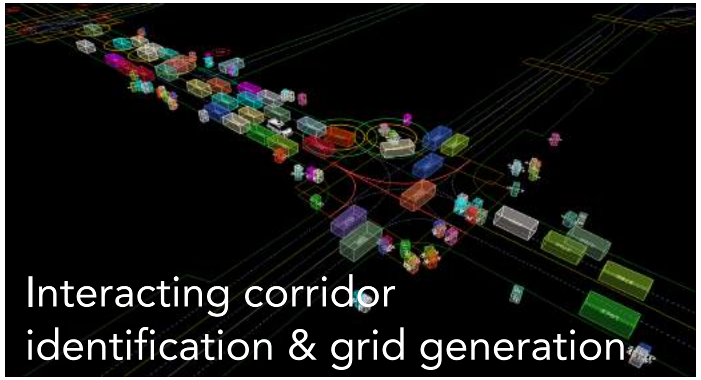


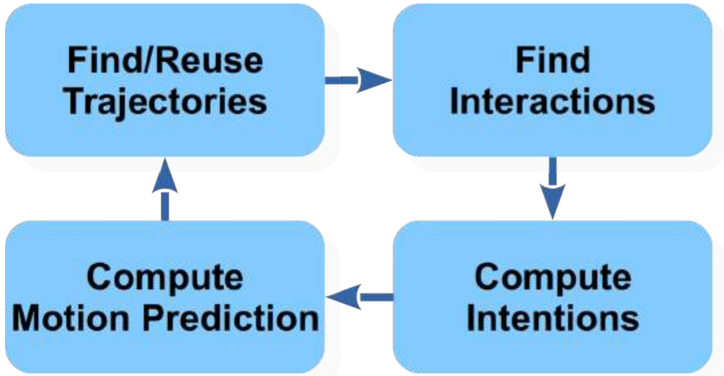
Motion prediction (1/2)

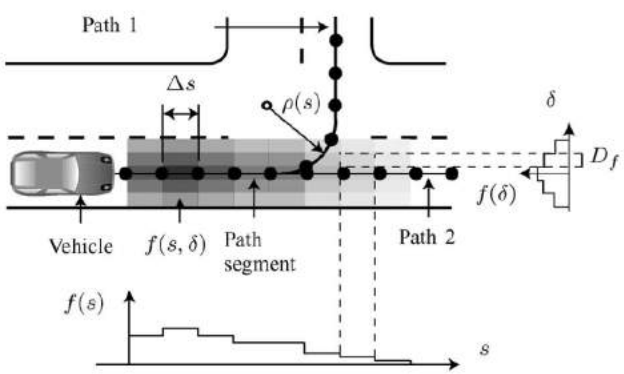
Research directions



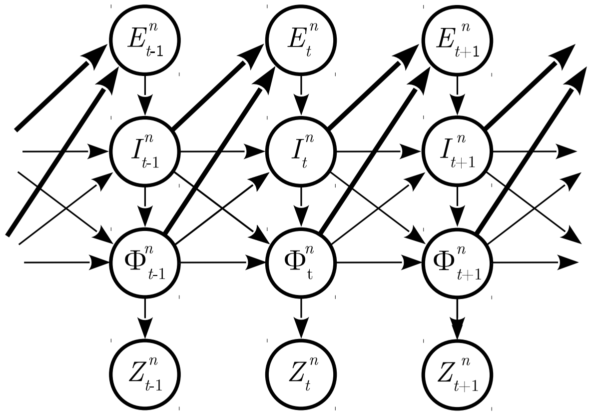
Probabilistic spatio-temporal occupancy grid







Learning-based probabilistic reachable sets



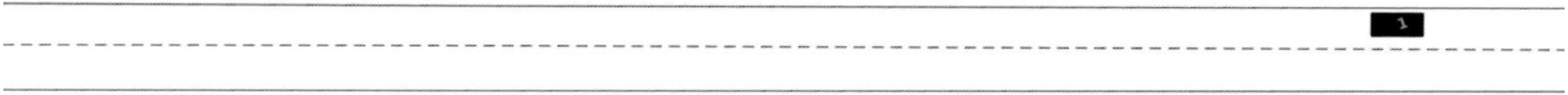
Interaction-aware intention & risk estimation

M. Althoff, D. Heß and F. Gambert, **Road occupancy prediction of traffic participants**, ITSC 2013, The Hague, 2013, pp. 99-105.

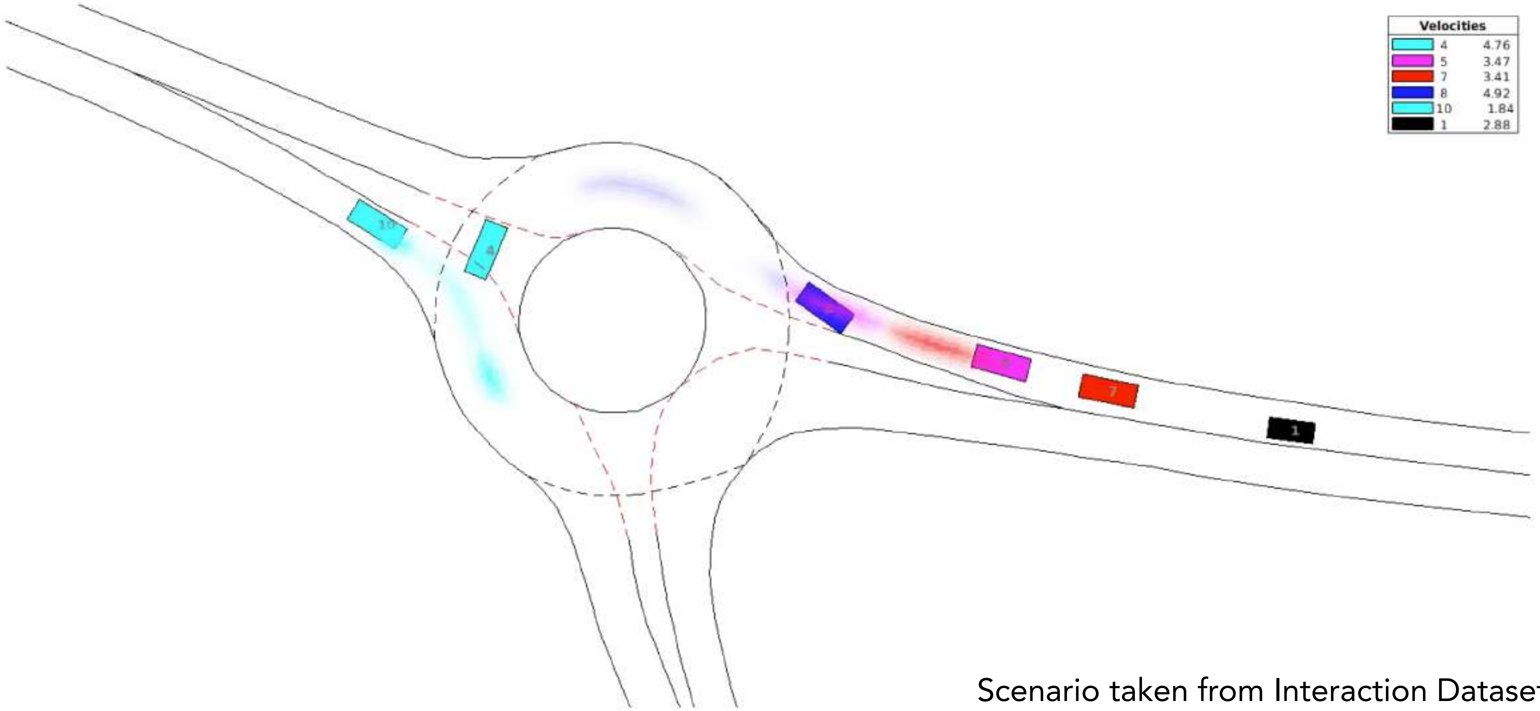
J. Villagra, A. Artunedo, V. Trentin, and J. Godoy, **Interaction-aware risk assessment: focus on the lateral intention**, in *2020 IEEE 3rd Connected and Automated Vehicles Symposium (CAVS)*, 2020

Motion prediction (2/2)

Research directions



Scenario created with ScanerStudio

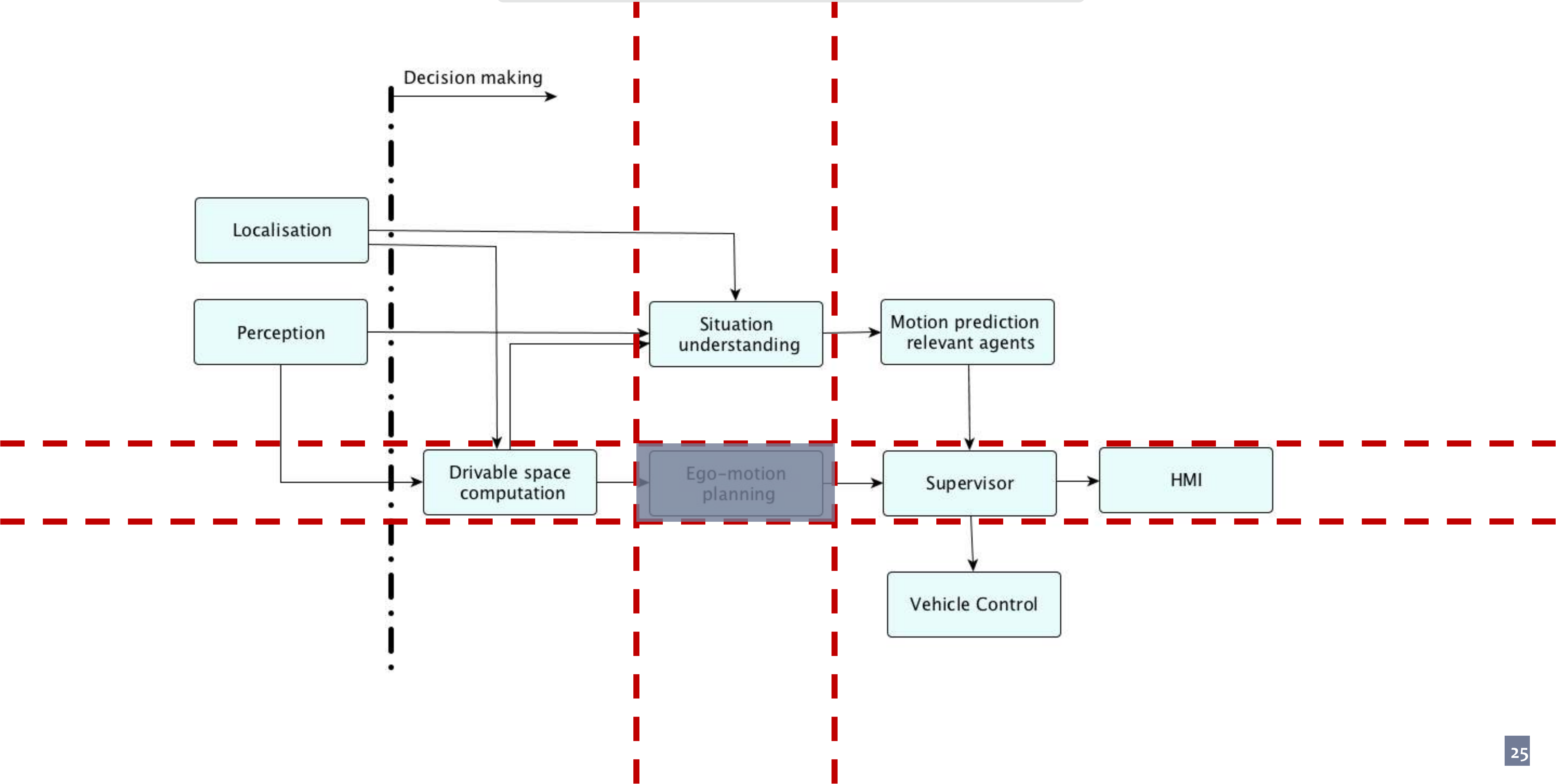


Scenario taken from Interaction Dataset

Trentin V., VIllagra, J. & Godoy, J. **Probabilistic interaction-aware motion prediction in roundabouts,** ICVES 2021

Decision-making process

Research directions

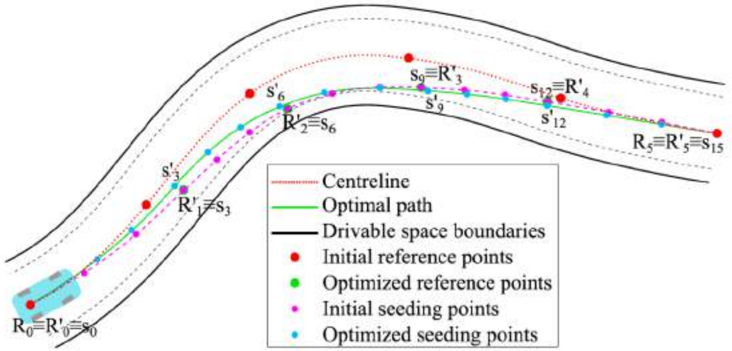


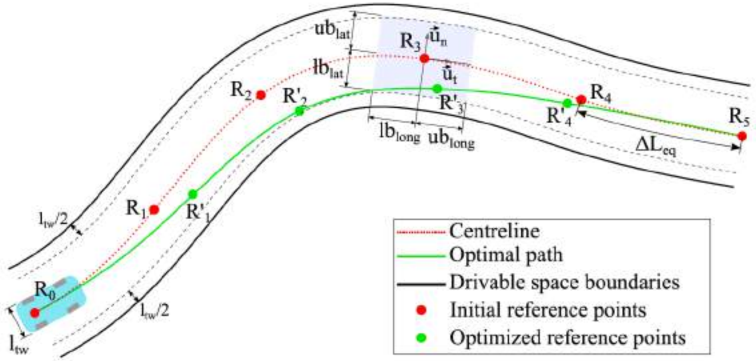
Human-like path planning (1/2)

Research directions

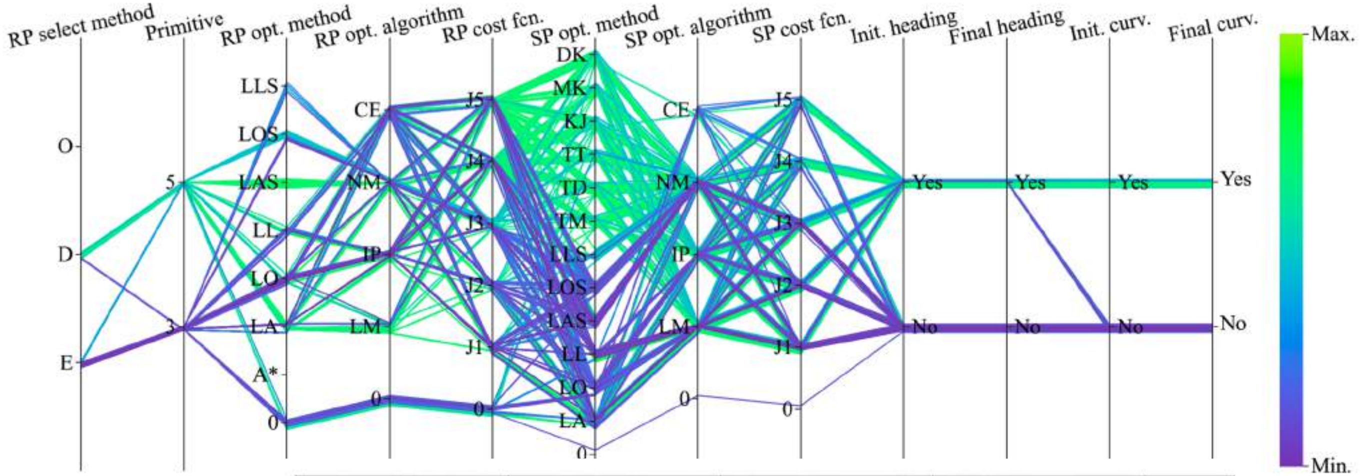
- **Mirroring** focuses on planning maneuvers with respect to the **human sensorimotor limits** (that is, maneuvers similar to human ones).
- Work on **primitives** with good tracking properties in any driving scene using variable samplings and auto-adaptive parameterization
- **90417 tests cases** have been evaluated per driving scenario, assessing 6 KPIs for up to 12 different parameter

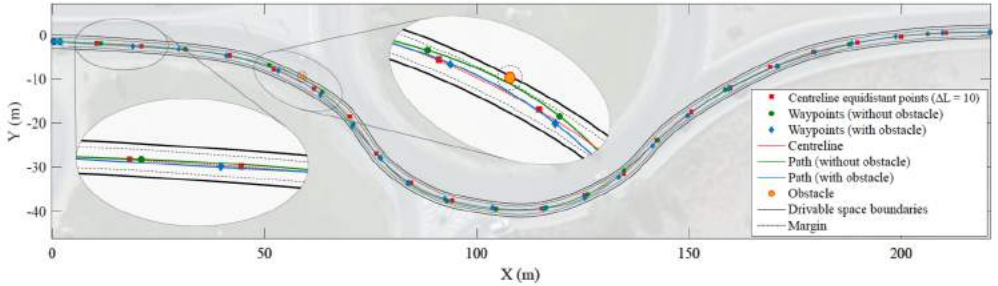
Seeding points optimization

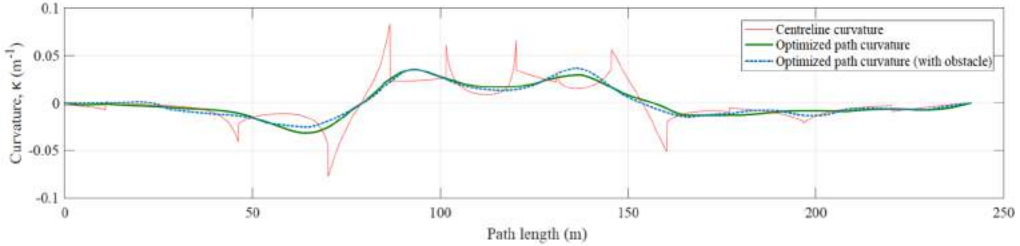




Reference points optimization based on longitudinal and lateral movements



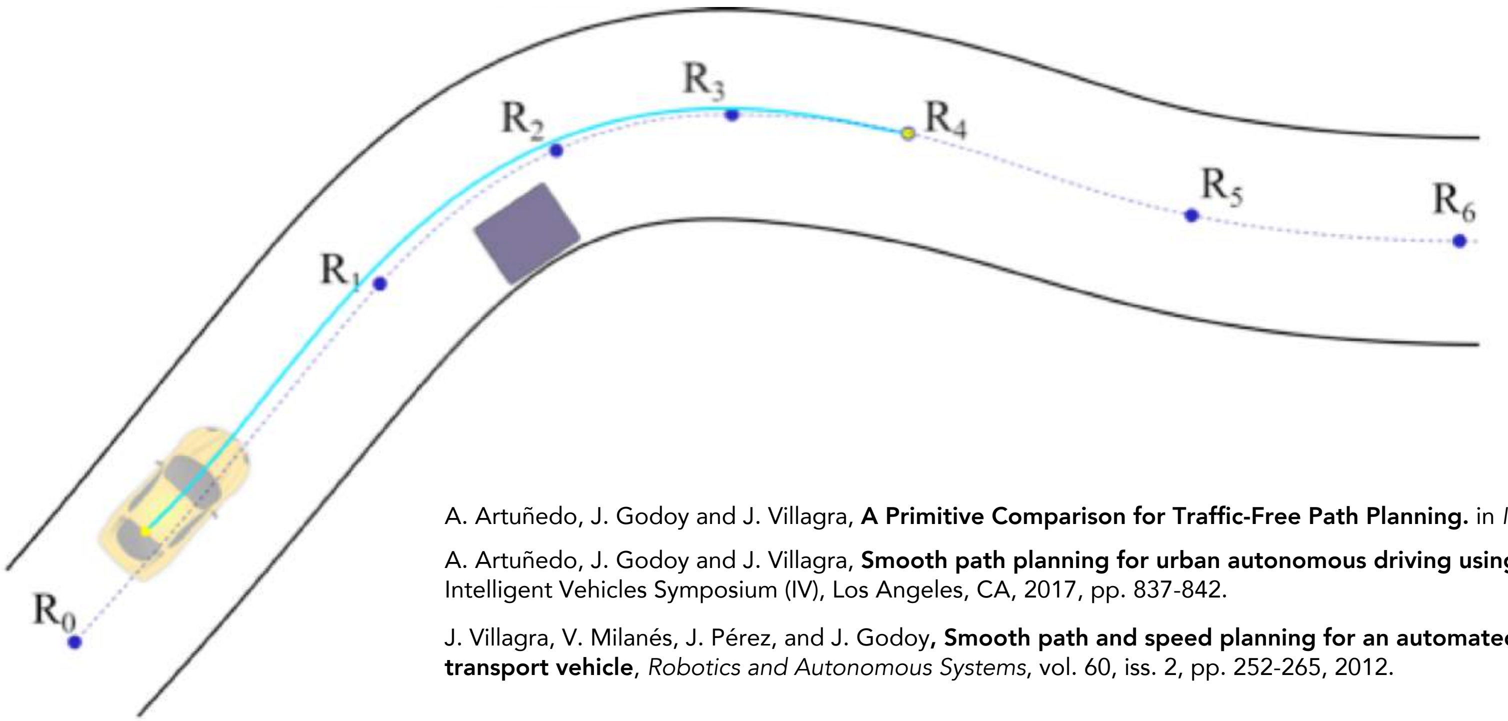




Human-like path planning (2/2)

Research directions

- **Reference points selection method**: Douglas-Peucker
- **Primitive**: quintic Bézier splines
- KPIs reflect a better overall performance when **two optimization stages** are carried out
- Higher impact of the cost function in the first optimization stage when compared with the second one
- **Real-time constraints** suggests to go for a **single optimization stage**



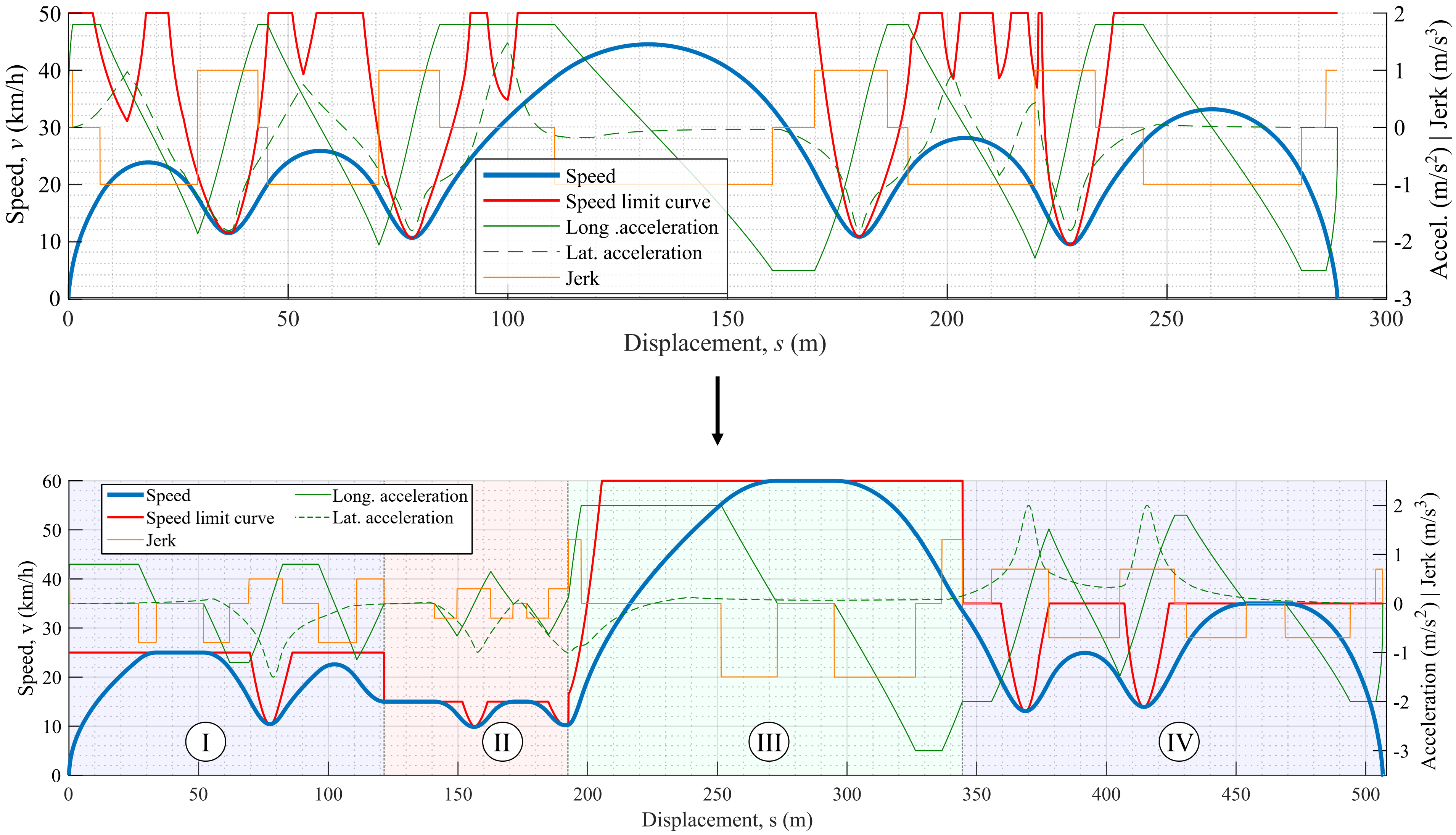
A. Artuñedo, J. Godoy and J. Villagra, **A Primitive Comparison for Traffic-Free Path Planning.** in *IEEE Access*, vol. 6, pp. 28801-28817, 2018.

A. Artuñedo, J. Godoy and J. Villagra, **Smooth path planning for urban autonomous driving using OpenStreetMaps**, 2017 IEEE Intelligent Vehicles Symposium (IV), Los Angeles, CA, 2017, pp. 837-842.

J. Villagra, V. Milanés, J. Pérez, and J. Godoy**, Smooth path and speed planning for an automated public transport vehicle**, *Robotics and Autonomous Systems*, vol. 60, iss. 2, pp. 252-265, 2012.

Jerk-limited speed planning

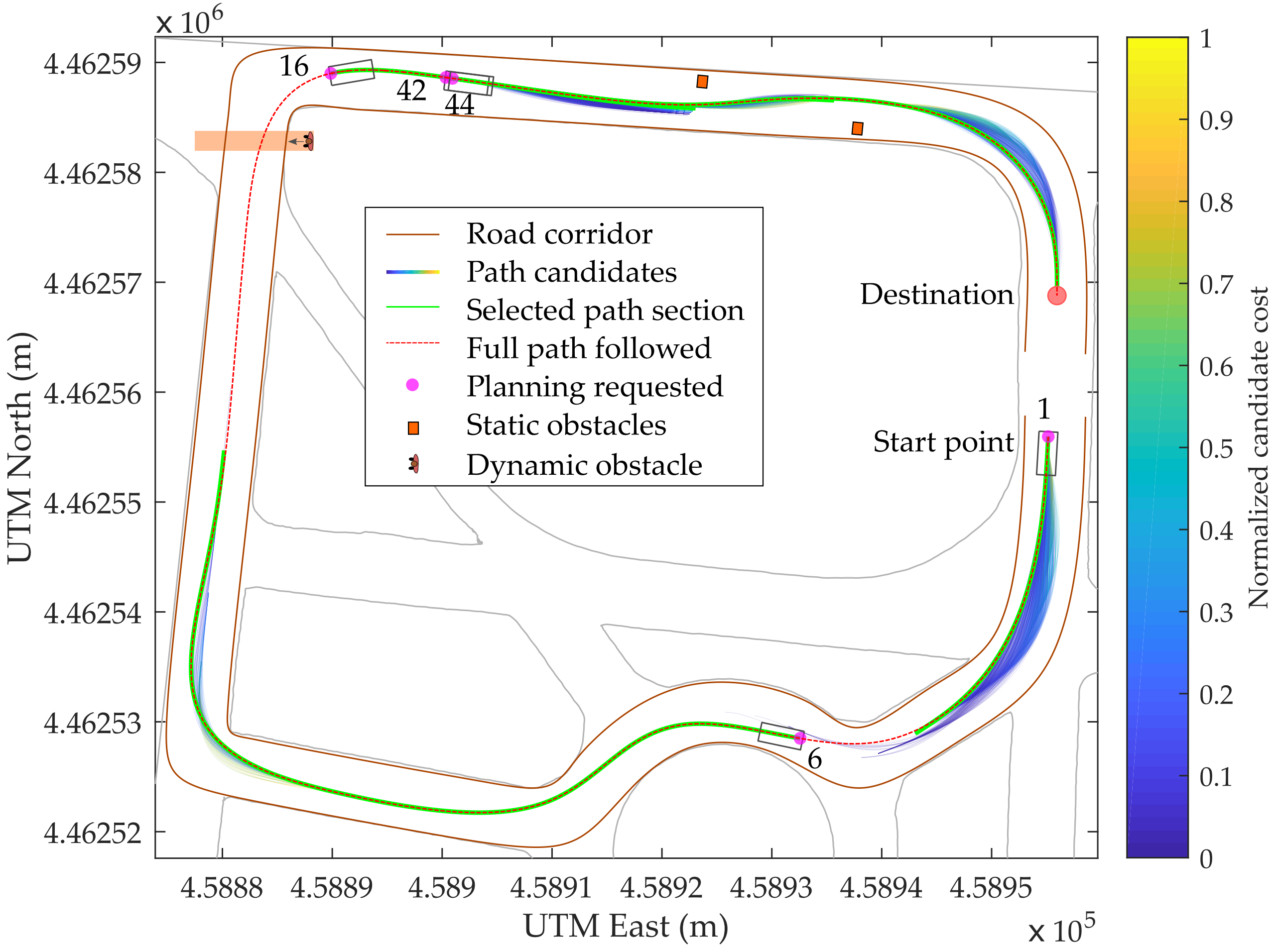
Research directions

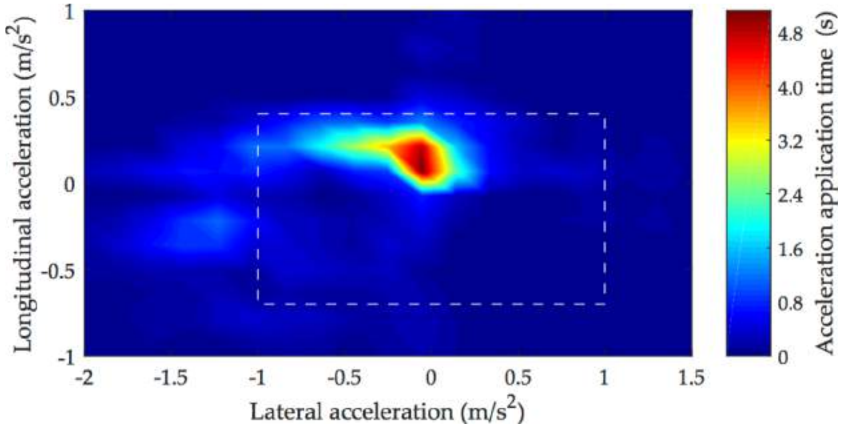


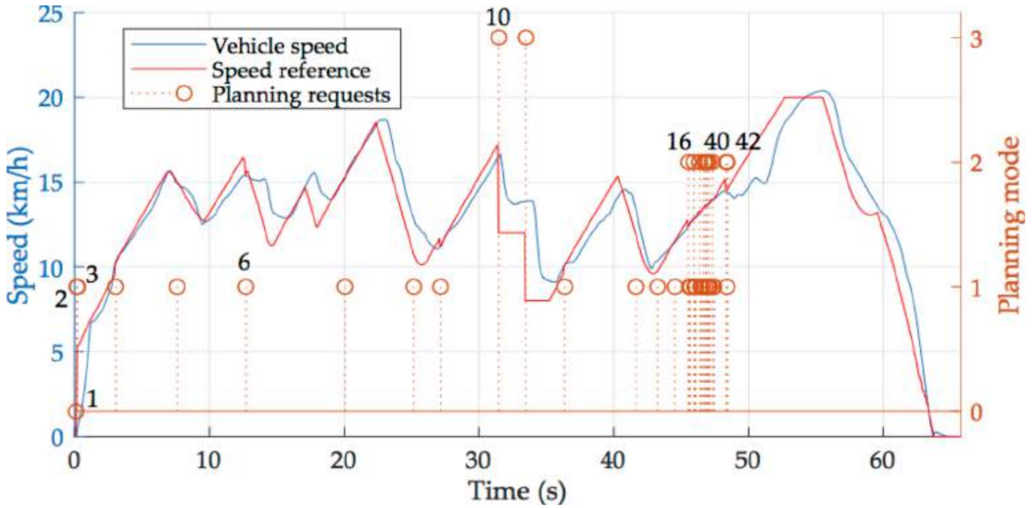
Artuñedo A., VIllagra, J. & Godoy, J. **Jerk-limited time-optimal speed planning for arbitrary paths,** IEEE Trans. on Intelligent Transportation Systems, 2021

Real-time experimental results

Research directions







A. Artuñedo, J. Villagra, and J. Godoy, **Real-Time Motion Planning Approach for Automated Driving in Urban Environments**, *IEEE Access*, vol. 7, p. 180039–180053, 2019

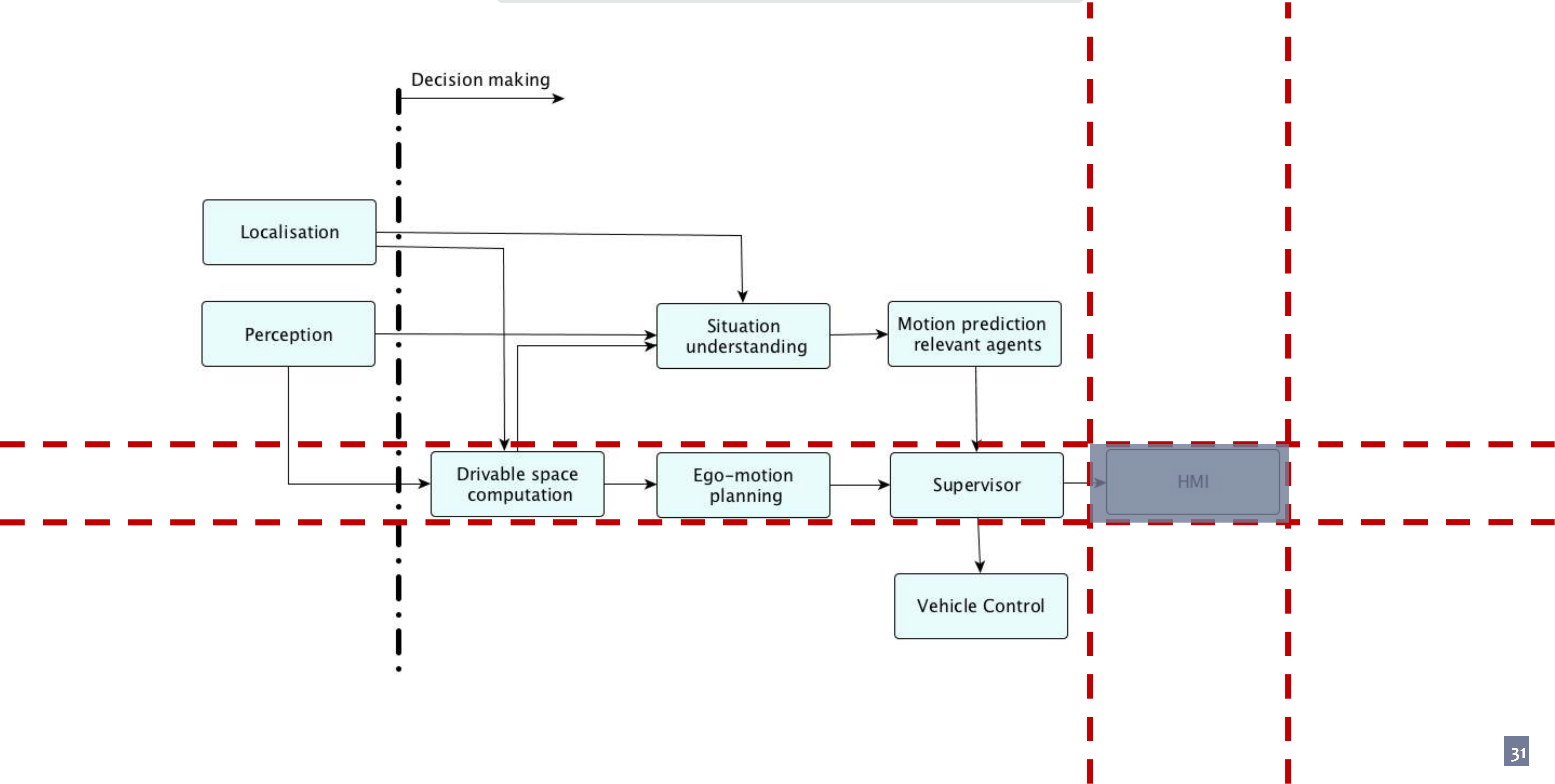
A. Artuñedo, G. Corrales, J. Villagra, and J. Godoy, **Machine learning based motion planning approach for intelligent vehicles**, in *2020 IEEE Intelligent Vehicles Symposium*, 2020.

Some experimental results (2/2)

A. Artuñedo, J. Villagra, J. Godoy, and M. D. D. Castillo, **Motion Planning Approach Considering Localization Uncertainty**, *IEEE Transactions on Vehicular Technology*, vol. 69, iss. 6, p. 5983–5994, 2020.

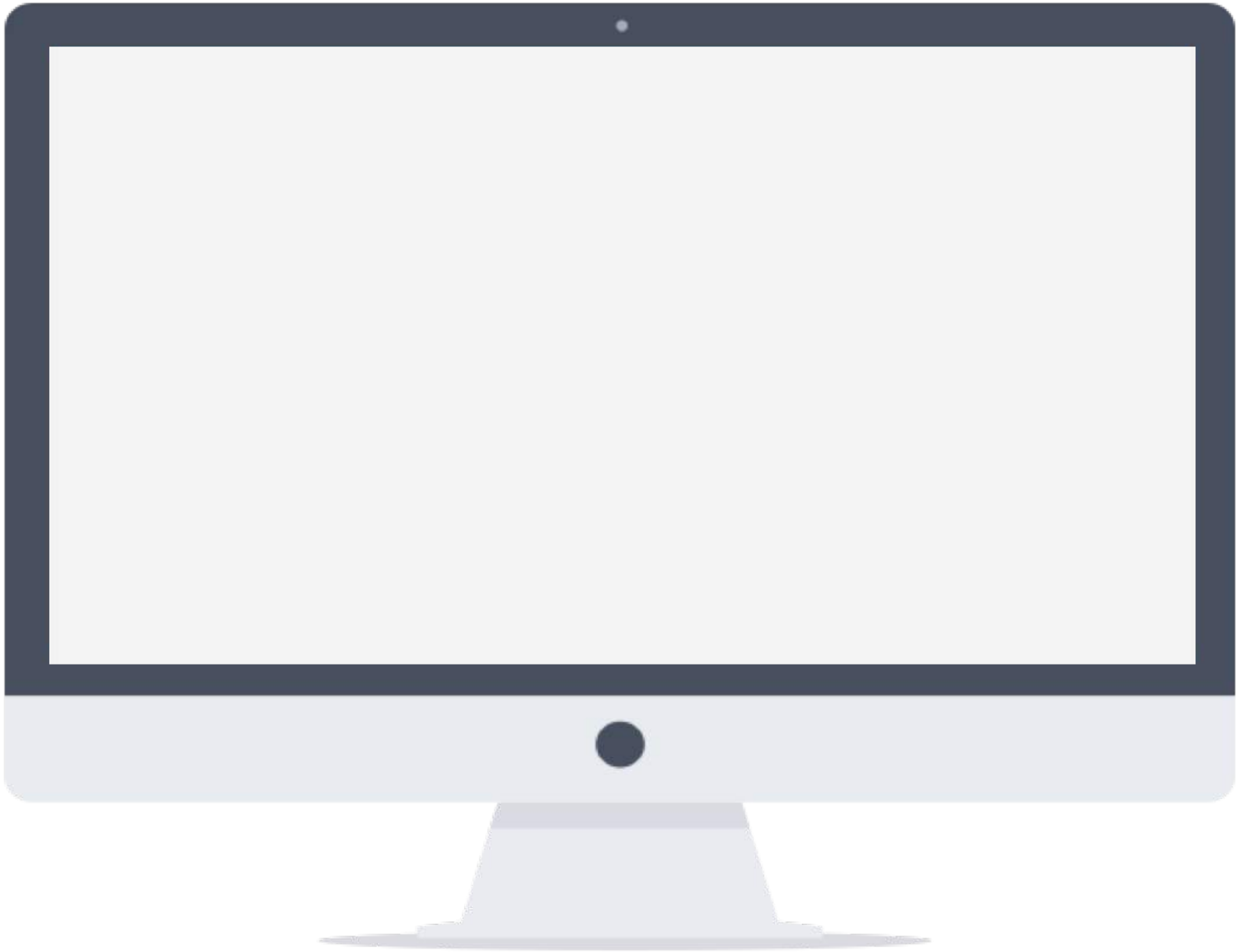
Decision-making process

Research directions



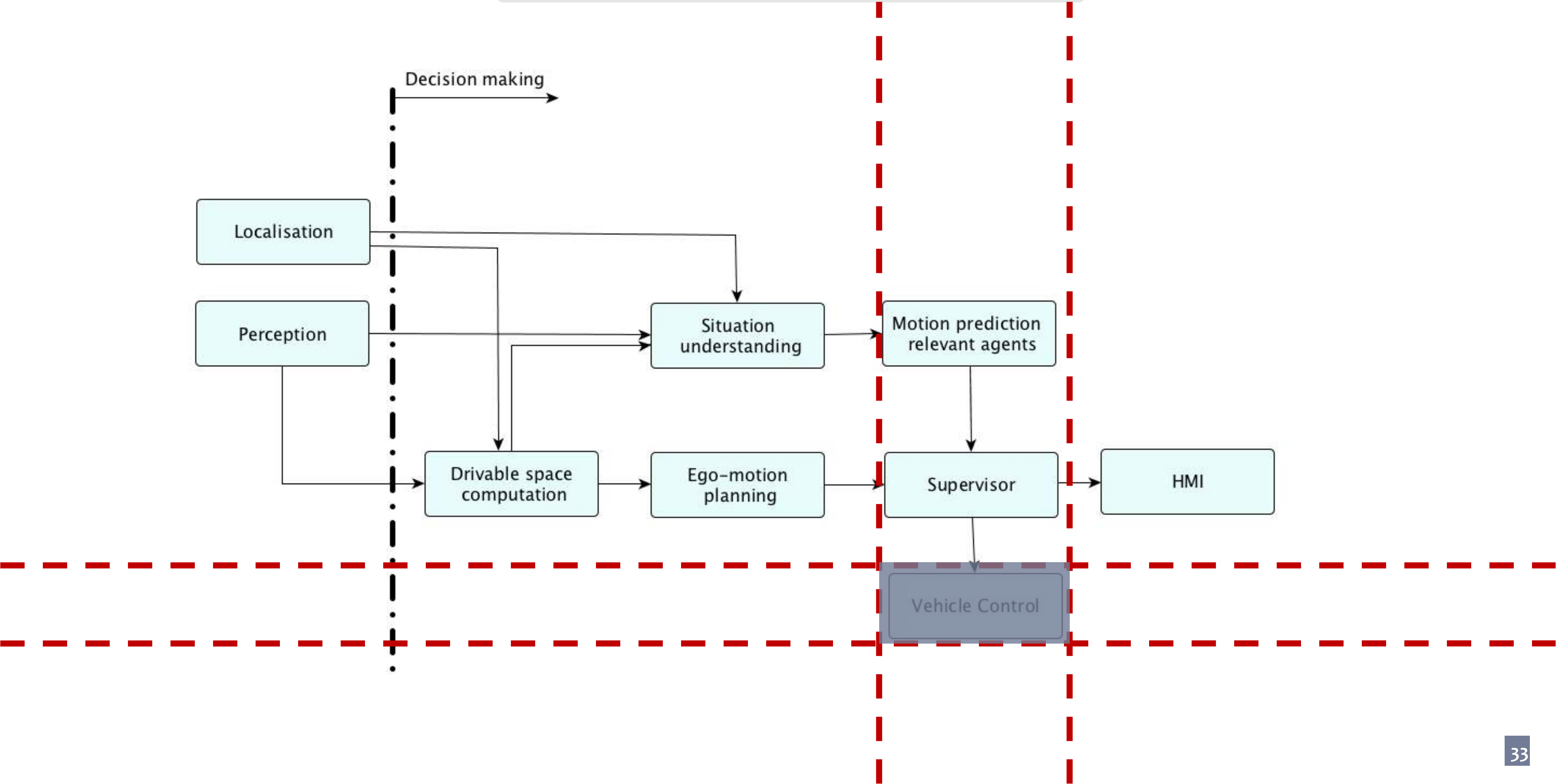
Driver monitoring system, HMI and traded control

Research directions



Decision-making process

Research directions

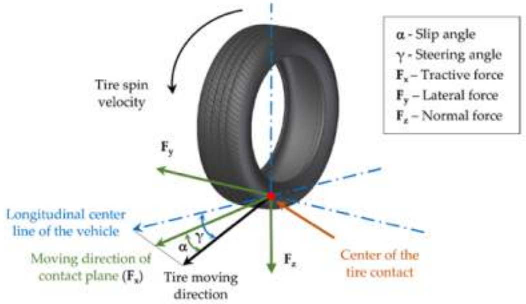


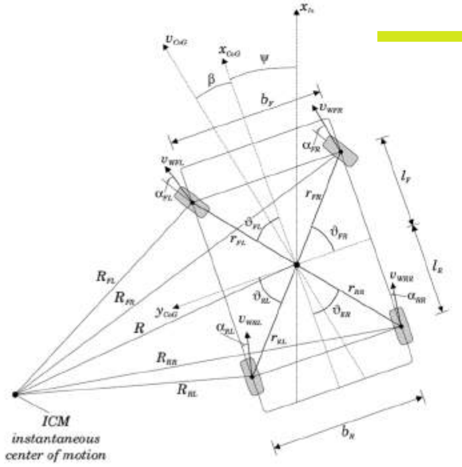
Challenges in control for autonomous driving

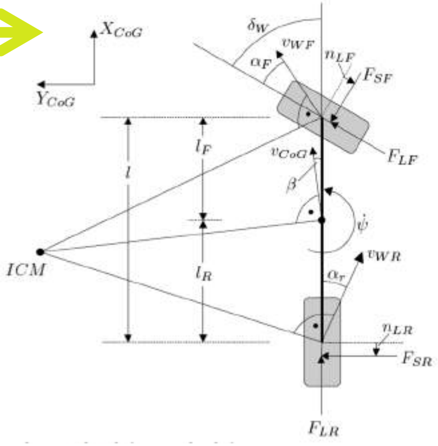
Research directions

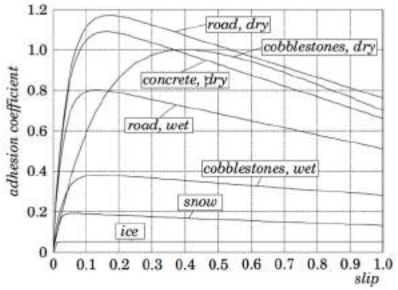
- Road and wind disturbances
- Parameter uncertainty: multi-plattfom applicability

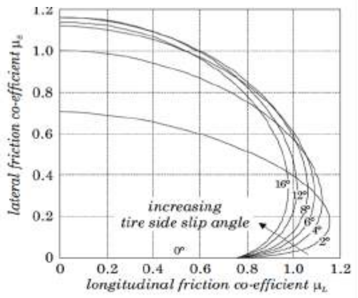
- Non-linearities: big slip angles, speed/wear-dependent tire modelling











Model-free control: from fuzzy logic…

Research directions


Low-Speed Longitudinal Controllers for Mass-Produced Cars: A Comparative Study


Comparing Fuzzy and Intelligent PI Controllers in Stop-and-Go Manoeuvres

Several model-based and model-free techniques evaluated

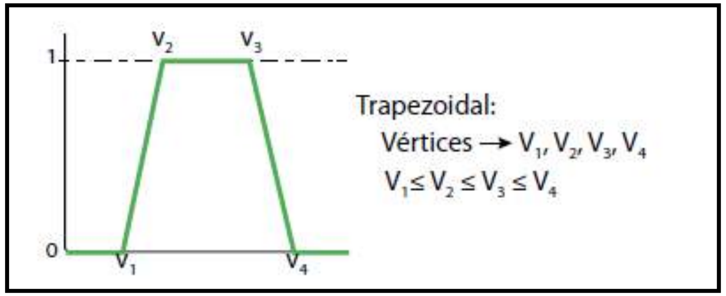
Fuzzy-based longitudinal and cascade lateral control

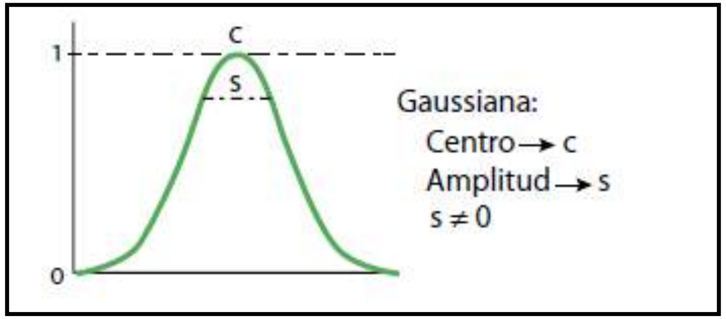
ORBEX: Ordenador Borroso Experimental (1996 and 2014)

- Mainly devoted to high level control
- Control strategies defined as a rule basis IF…THEN…
- Several membership functions for *fuzzyficación*

```
ErrorVelocidad -50 50 {
  MuyNegativo TRA -50 -50 -20 -10
  Negativo TRA -20 -10 -5 0
  Cero TRA -5 0 0 5
  Positivo TRA 0 5 10 20
  MuyPositivo TRA 10 20 50 50
  }
```

- Implemented as a class (2014)
- Modifiable at runtime





García, R. & de Pedro, T. **First Application of the ORBEX Coprocessor: Control of Unmanned Vehicles**
EUSFLAT-ESTYLF Joint Conference. Mathware and Soft Computing, 2000, Vol. 7(2-3), pp. 265-273

…to a unique data-driven approach…

- Some model-based approaches reveal **inadequacy** and **oversimplification** of the models describing the system.
- Alternative: use of a **model-free control paradigm**, to compensate for the uncertainties associated with non-linear, poorly known or highly variable models:
  - **Adaptive** approach without the need to structure the identification
  - **Versatile** technique (accepts to work without model or with gray-box models)
  - **Easy to tune** and without previous learning phase
  - **Real-time** implementable solution
  - Allows "**explainable" learning…**although safety assurance has not been reached yet

$$\mathbf{y}^{(\mu)} = \mathbf{F} + \alpha \mathbf{u}$$

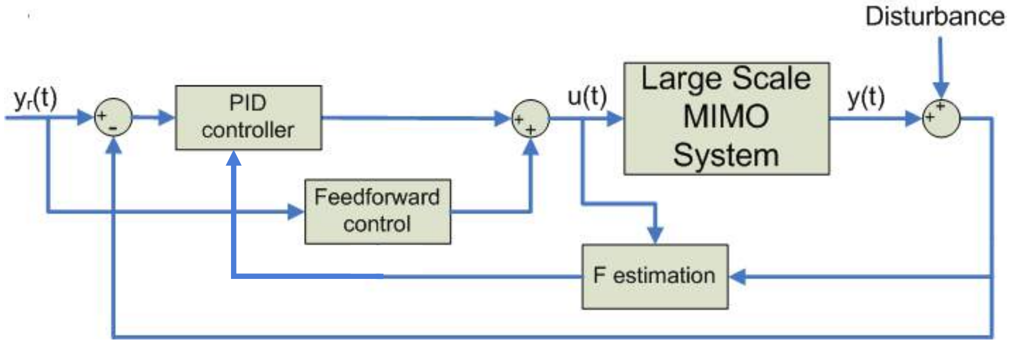
where

- y is the output of the system
- u is the input of the system
- $\mu \in \mathbb{N}$ (usually 1 o 2) : it may represent the system order, but not necessarily.
- $F(t)$: a sort of non-linear black box identifier. In discrete time :

$$F(t_k) = [y^{(\mu)}(t_k)]_e - \alpha u(t_{k-1})$$

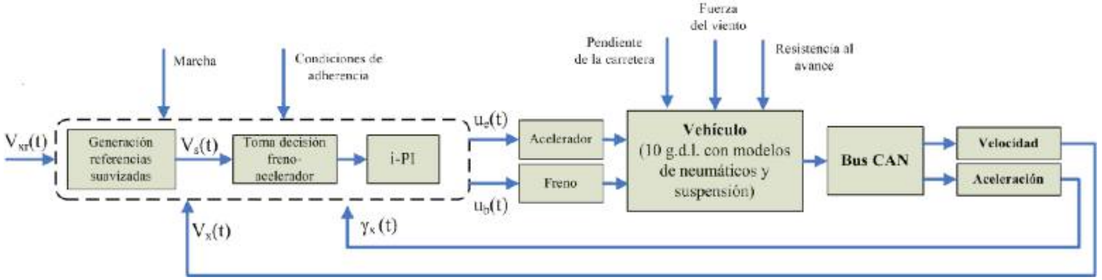
- $\alpha \in \mathbb{R}$: should allow F and αu to be of the same order of magnitude.

$$\boxed{u = \underbrace{\frac{1}{\alpha}\left(y^{r(\mu)} - \hat{F}\right) + \frac{K_p}{\alpha} e_y + \frac{K_d}{\alpha}\dot{e_y}}_{\text{feedback}} + \underbrace{f(x^r)}_{\text{feedforward}} \quad , \; e_y = y^r - y}$$



Fliess, M., & Join, C. (2013). **Model-free control.** International Journal of Control, 86(12), 2228-2252.

…with promising results: Cruise control…

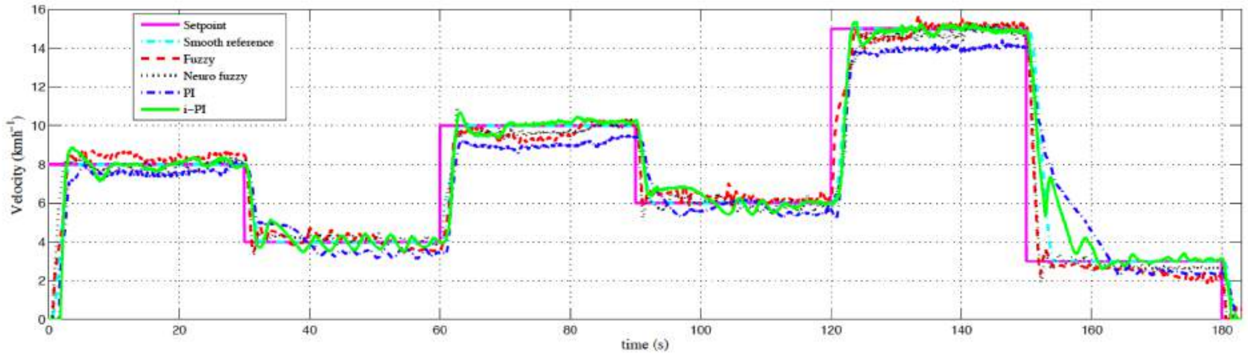


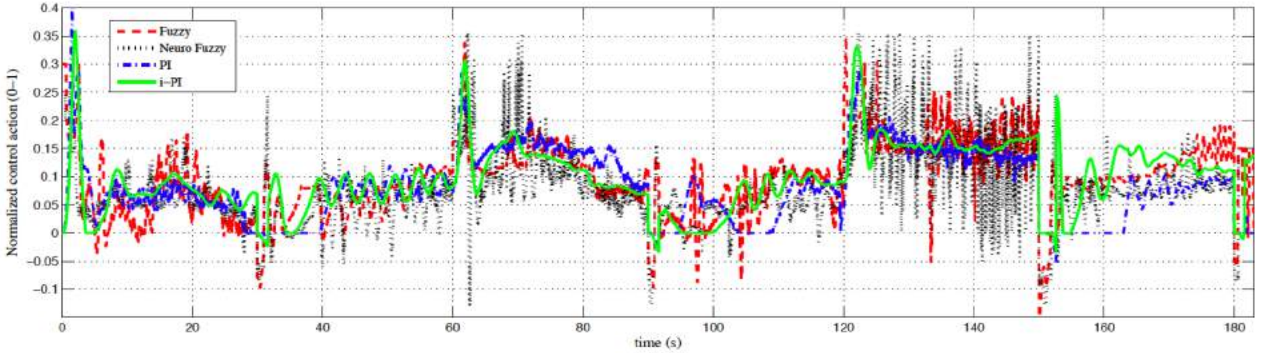
$$\dot{V}_x(t) = F(t) + \alpha u(t),\ \alpha = \{\alpha_e, \alpha_b\},\ u = \{u_e, u_b\}$$

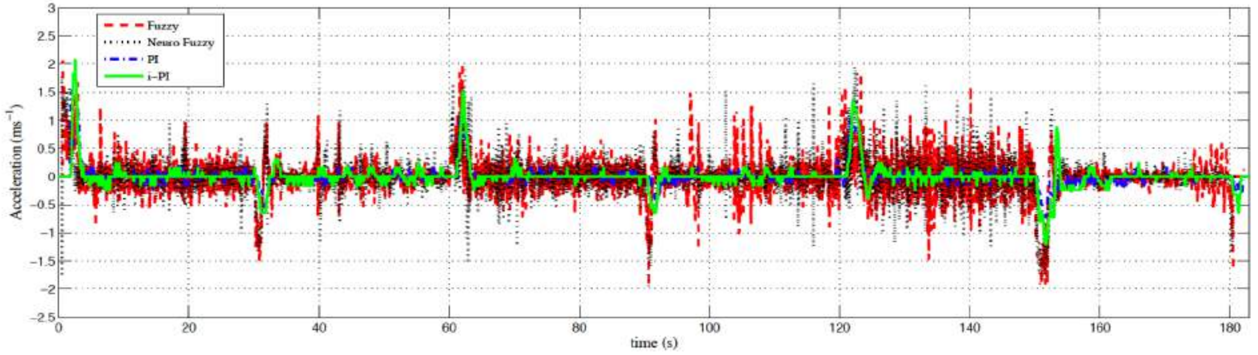
$$\begin{aligned} u_b(t_k) &= \frac{1}{\alpha_b}\left(\dot{V}_s(t_k) - F_b(t_k)\right) + K_{p_b} e(t_k) + K_{i_b} \int (e(t_k))\, dt \\ F_b(t_k) &= \gamma_x(t_k) - \alpha_b u_b(t_{k-1}),\ \alpha_b = \frac{1}{MrK_b} \end{aligned}$$

$$\begin{aligned} u_e(t_k) &= \frac{1}{\alpha_e}\left(\dot{V}_s(t_k) - F_e(t_k)\right) + K_{p_e} e(t_k) + K_{i_e} \int (e(t_k))\, dt \\ F_e(t_k) &= \gamma_x(t_k) - \alpha_e u_e(t_{k-1}),\ \alpha_e = \frac{1}{MrK_e} \end{aligned}$$

	IAE (km/h)	IAU
PI	0.66	1.20
Fuzzy	0.36	3.07
Neuro-fuzzy	0.25	6.89
MFC	**0.19**	0.291



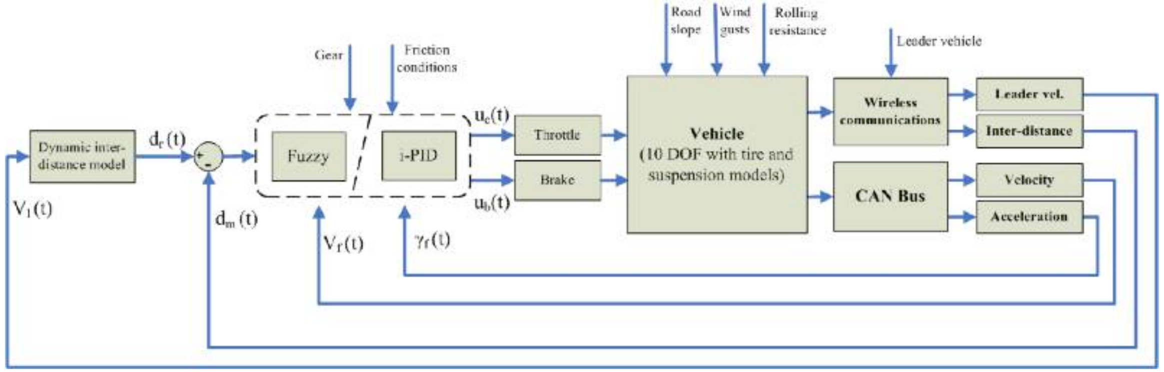




V. Milanés, J. Villagra, J. Pérez, and C. González, **Low-speed longitudinal controllers for mass-produced cars: A comparative study**, *IEEE Transactions on Industrial Electronics*, vol. 59, iss. 1, pp. 620-628, 2012.

… and Stop & Go

Research directions

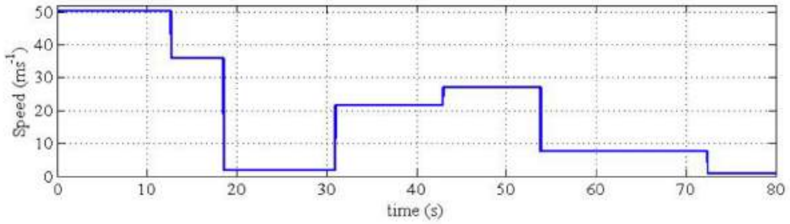


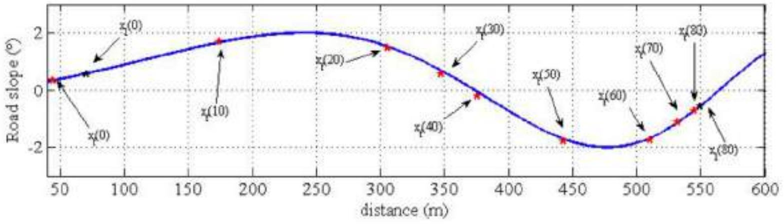
$\ddot{x}_f = F + \alpha u_e \longrightarrow$

$$\begin{aligned} u_e(t_k) &= \frac{1}{\alpha_e}\left(\ddot{x}_{f_r}(t_k) - F_e(t_k)\right) + K_{p_e} e(t_k) + K_{i_e} \int \left(e(t_k)\right) dt \\ F_e(t_k) &= \hat{\ddot{x}}_f(t_k) - \alpha_e u_e(t_{k-1}), \; e = \dot{d}_r - (\dot{x}_l - \dot{x}_f) \end{aligned}$$

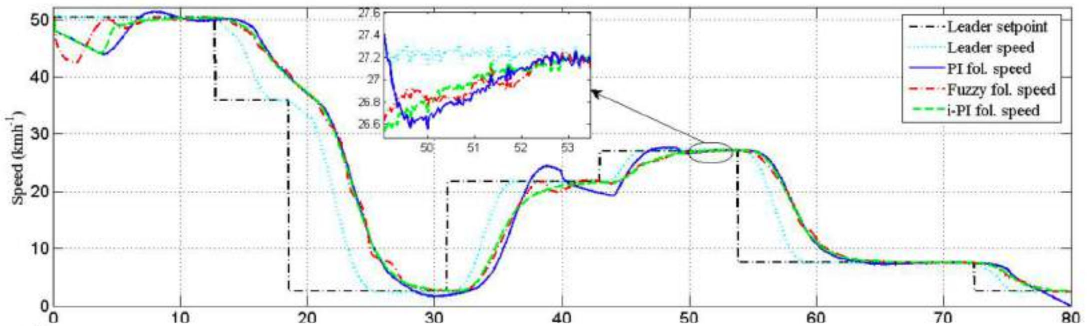
$\ddot{x}_f = F + \alpha u_b \longrightarrow$

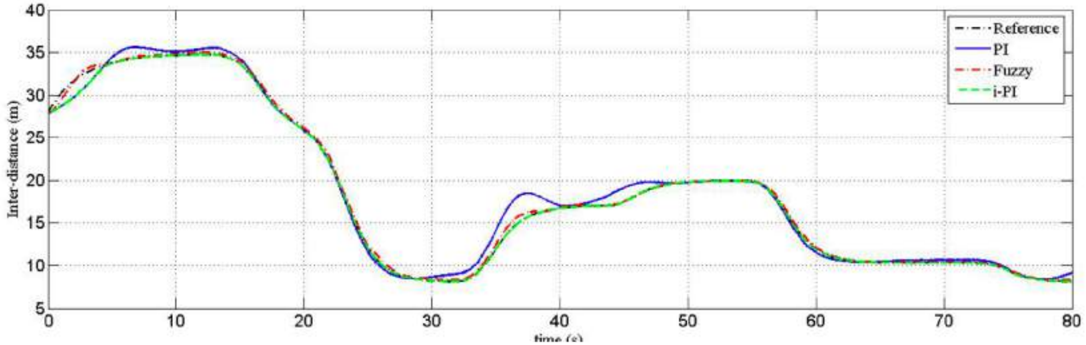
$$\begin{aligned} u_b(t_k) &= \frac{1}{\alpha_b}\left(\ddot{x}_{f_r}(t_k) - F_b(t_k)\right) + K_{p_b} e(t_k) + K_{i_b} \int \left(e(t_k)\right) dt \\ F_b(t_k) &= \hat{\ddot{x}}_f(t_k) - \alpha_b u_b(t_{k-1}), \; e = \dot{d}_r - (\dot{x}_l - \dot{x}_f) \end{aligned}$$

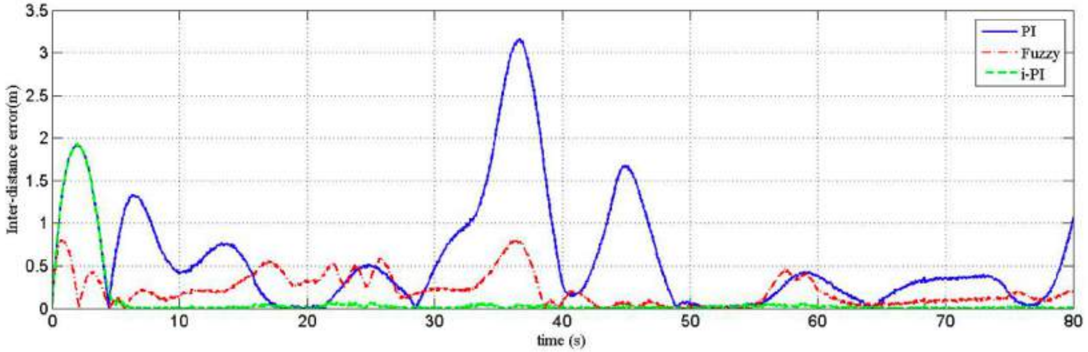




	IAE (m)	IAUD
PI	0.586	0.233
Fuzzy	0.208	0.589
MFC	**0.090**	0.291







V. Milanés, J. Villagra, J. Godoy, and C. González, "Comparing fuzzy and intelligent PI controllers in stop-and-go manoeuvres," *IEEE Transactions on Control Systems Technology*, vol. 20, iss. 3, pp. 770-778, 2012.

Model-free Control for lateral dynamics (1/3)

Different strategies have been tested on real vehicles

- PID (e.g. Fiat Linea), Adaptive PID (e.g.Tiggo3), Youla Kucera (e.g. Renault ZOE), Feedforward+adaptive planning (e.g. Fiat Palio), Hinf LQR (e.g. HAVAL H7), Sliding mode (e.g. Renault ZOE), LQR (e.g. Hyundai Tucson), MPC (e.g. Volkswagen GTI)

Main limitations

- Tested in specific scenarios (low speeds or highways) or with well-known vehicle dynamics (robustness analysis is often omitted or somehow limited)

Ultra-local model

$$z_2^{(\mu)} = F + \alpha u \xrightarrow[\text{z}_2\text{: lateral error at GPS location}]{\text{Inspired on flatness relative degree for lateral dynamics (2)}} \ddot{z}_2 = F + \alpha u$$

Control law

$$u = \underbrace{\frac{1}{\alpha}\left(\ddot{z}_2^r - \hat{F}\right) + \frac{K_p}{\alpha} e_{z_2} + \frac{K_d}{\alpha}\dot{e}_{z_2}}_{\text{feedback}} + \underbrace{\arctan\left(Lp_r\right)}_{\text{feedforward}}, \quad e_{z_2} = z_2^r - z_2$$

F estimation

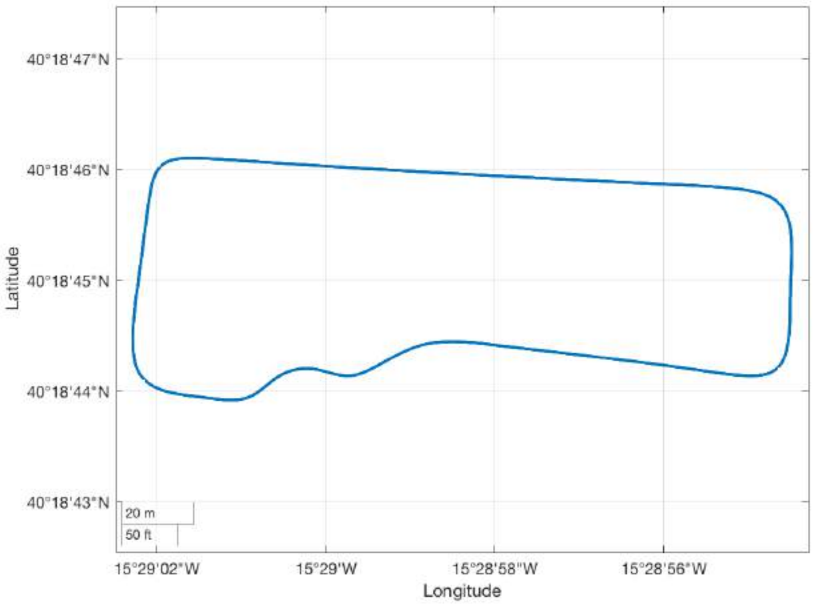
$$\hat{F}(t_k) = \hat{z}_2^{(\mu)}(t_k) - \alpha u(t_{k-1}) \xrightarrow{\mu=2} \hat{F}(t_k) = -\frac{30}{\tau^5}\int_{t-\tau}^{t} \left(2(\tau^2 + 6\sigma^2 - 6\tau\sigma) z_2(\sigma) + \alpha\sigma^2(\tau-\sigma)^2 u(\sigma)\right) d\sigma$$

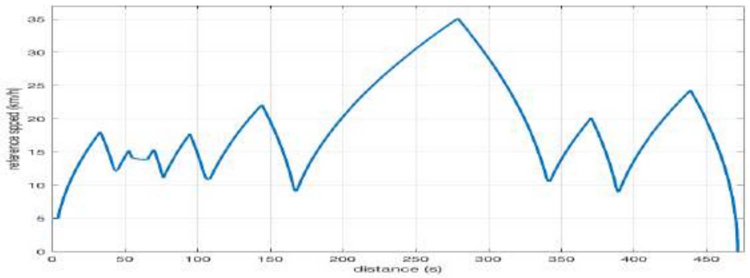
Error dynamics

$$\ddot{e}_{z_2} + K_d \dot{e}_{z_2} + K_p e_{z_2} = 0, \text{ if } \hat{F} = F$$

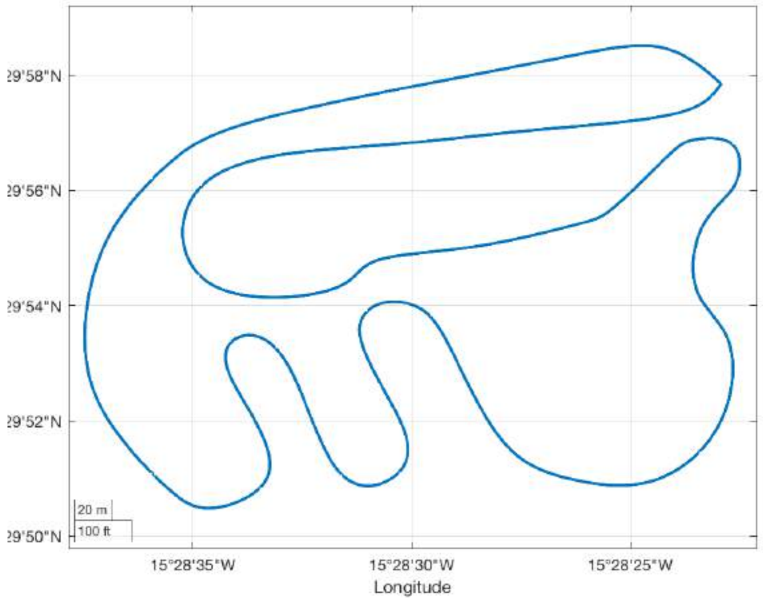
To be published soon

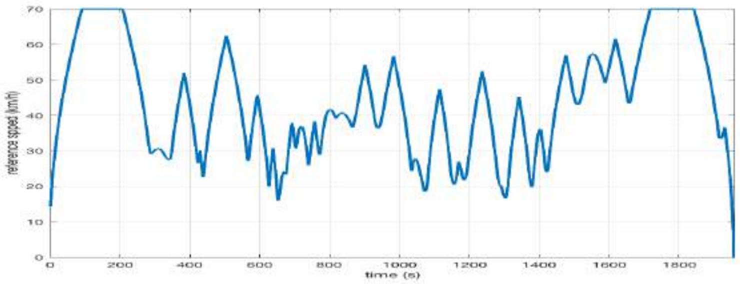
Model-free Control for lateral dynamics (2/3)



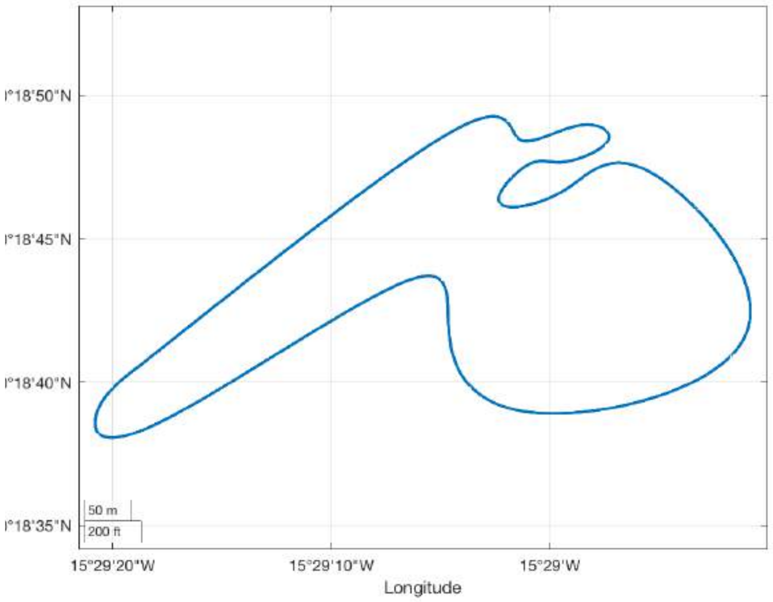


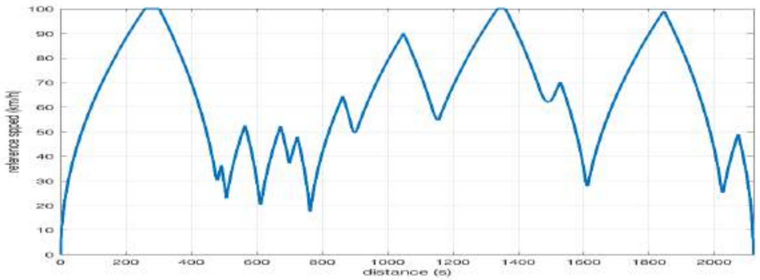
Vmax=50 km/h, a_{ymax}=1.75 m/s^2, a_{xmax}=0.4/(-0.7)m/s^2





Vmax=70 km/h, a_{ymax}=1.75 m/s^2, a_{xmax}=2/(-3)m/s^2



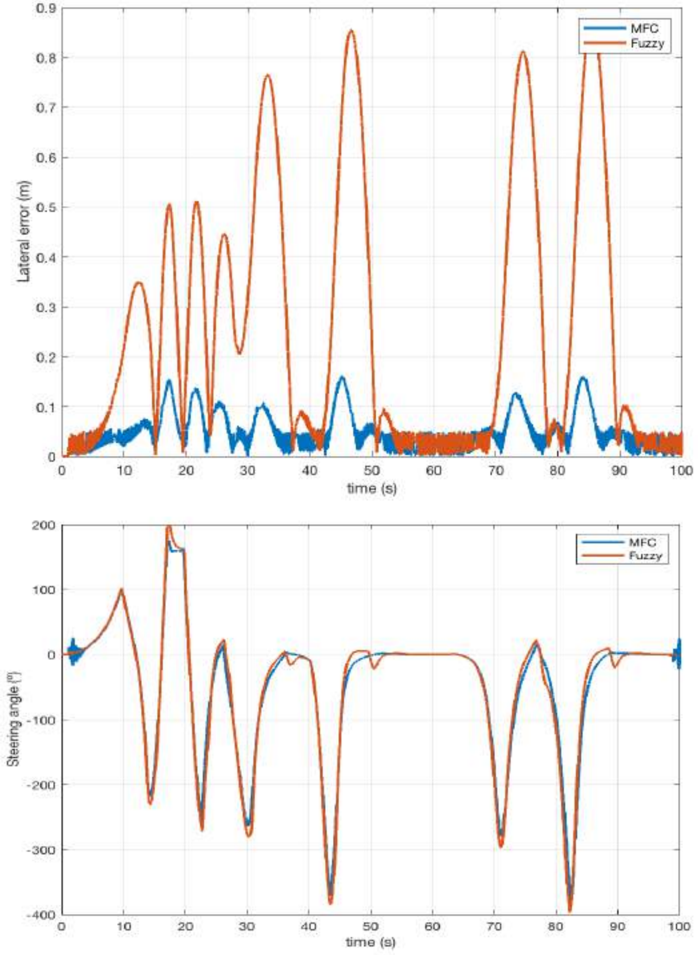


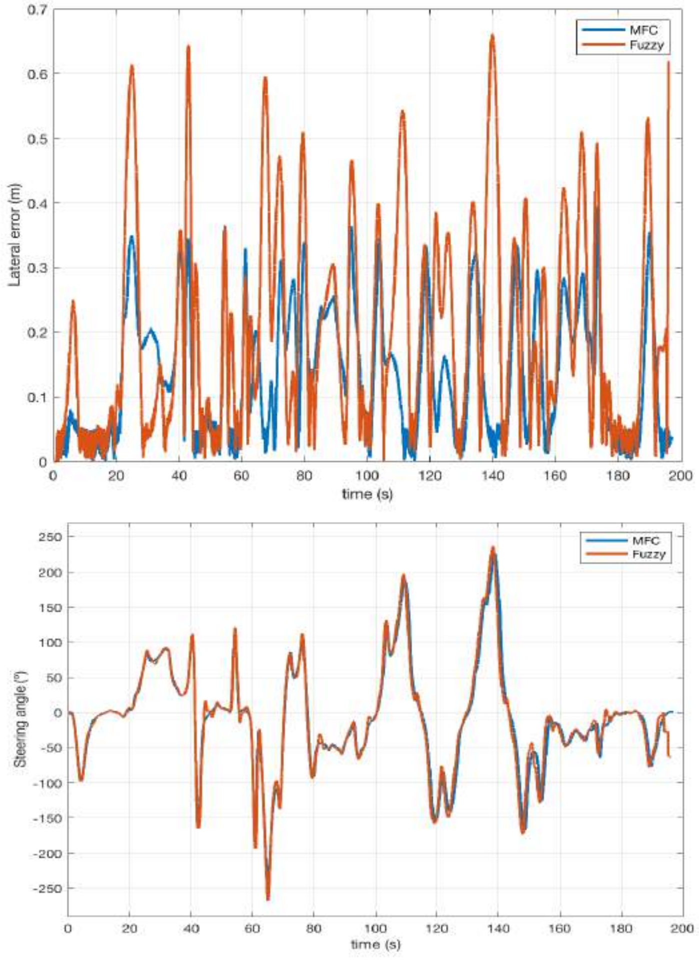
Vmax=100 km/h, a_{ymax}=4 m/s^2, a_{xmax}=2/(-3)m/s^2

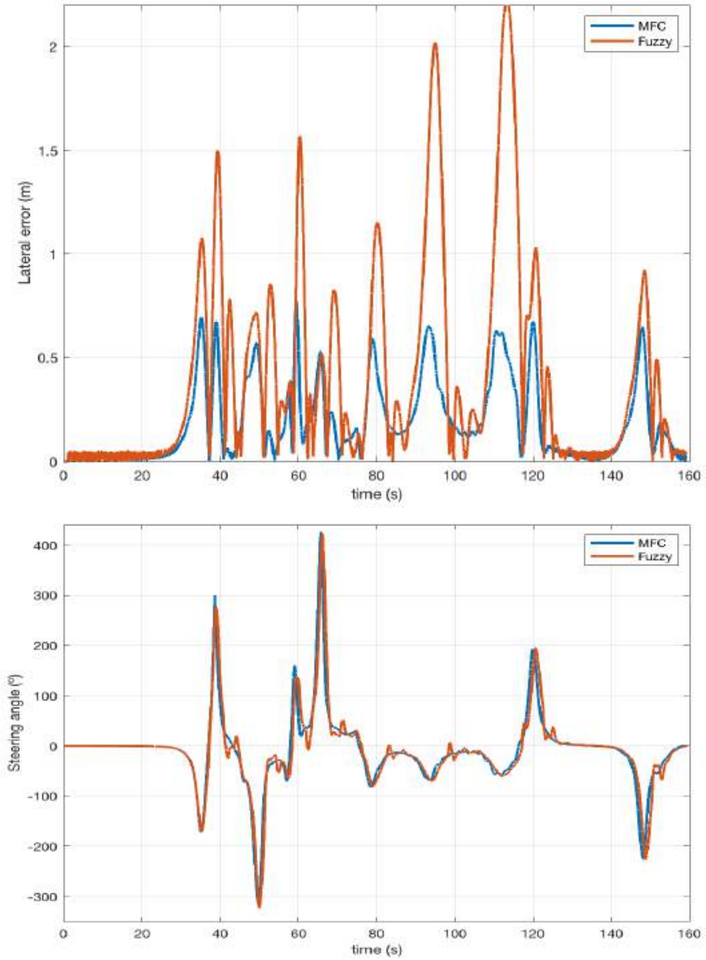
Trajectories generated using a tool for off-line smooth motion planning (to be soon released as open-source)

- Path relying on concatenated Bézier curves (C2 continuity)
- Maximum speed, longitudinal (des-)acceleration and lateral acceleration set by design

Model-free Control for lateral dynamics (3/3)







	IAE (m)	IAU
Fuzzy	0.257	67.85
MFC	**0.050**	65.29

	IAE (m)	IAU
Fuzzy	0.200	54.88
MFC	**0.136**	54.02

	IAE (m)	IAU
Fuzzy	0.413	42.94
MFC	**0.193**	41.97

Concluding remarks

- Full automation is not necessarily the best solution (at least in the short / medium term)
- The correct interaction between the machine, the driver and the other agents of the road becomes critical
- An “intuitive” decision system is necessary to make automated vehicles predictable
- Verifiable human-in-the-loop decision strategies are needed to achieve a safe and reliable behaviour
- Model-free control can be a powerful candidate both for a “universal” global chassis controller

Thank you for your attention


Jorge Godoy


Antonio Artuñedo


Juan Medina


Vinicius Trentin


Victor Jimenez


Juan Luis Hortleano


Miguel Beteta


Marcos Moreno