Human–Machine Interaction in Automated Vehicles: A Hierarchical Cooperative Control Framework

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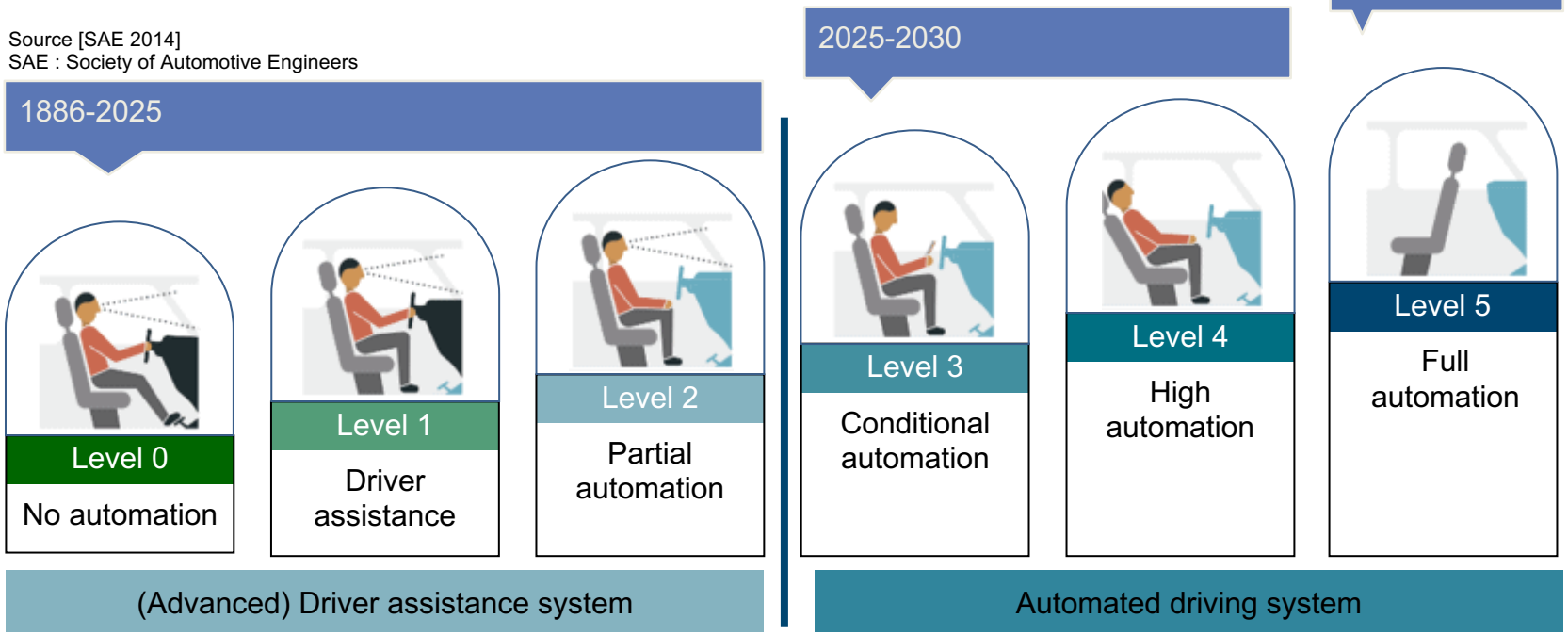
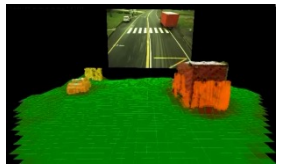
General Context & Challenges

- Automated driving has made considerable progress over the last decades
- Technological evolution towards automated driving
- Automated vehicles have already driven thousands of kilometers
  - Feasibility has been demonstrated … but there is still a long way to go!


(Tesla modèle S)


(Google autonomous car)




VisLab's 3DV sensing technology


(Vislab Braive from University of Parma, Italy)



- Increasing automation changes the role of the driver: **from control to supervision!**
- How will drivers interact with future automated driving systems?

Level 3 discontinued by BMW & Mercedes-Benz
→ focus on Level 2++ systems

Challenges related to driving automation

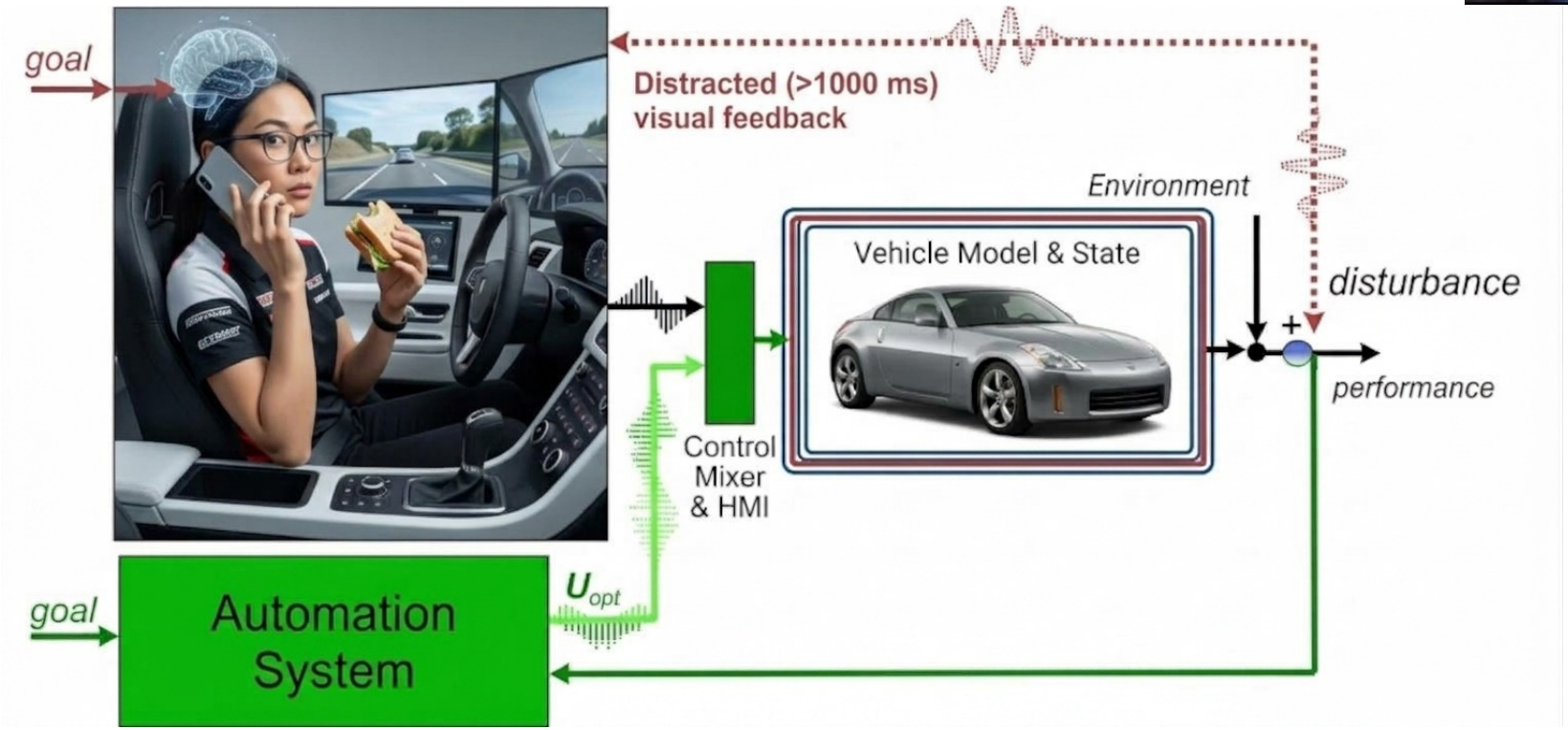
Main Challenges [Bainbridge L. 1983]

- Impact of automation on the driver
  - Loss of situation awareness [Kaber and Endsley 2004]
  - Over-trust [Lee and See 2004]
  - Skill degradation [Young and Stanton 2007]
  - Etc…









Bainbridge L. (1983). Ironies of automation. *Automatica*, vol. 19, no 6, p. 775-779.

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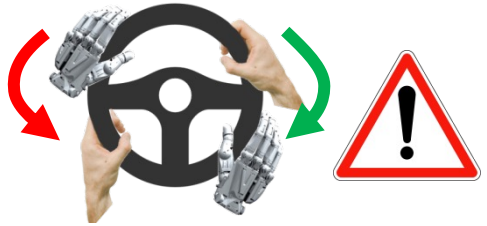
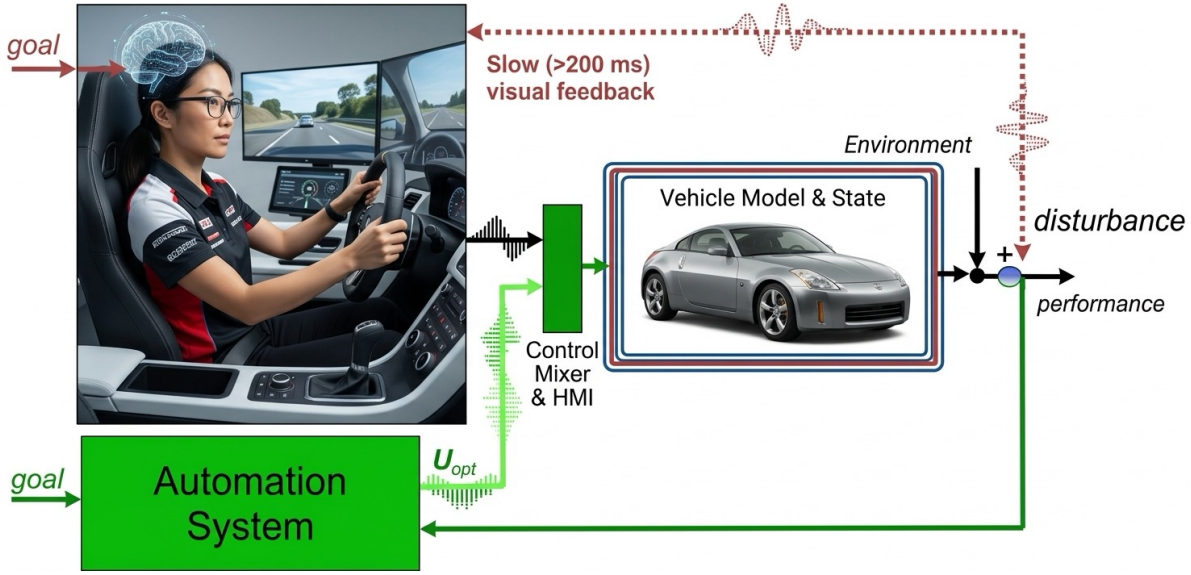
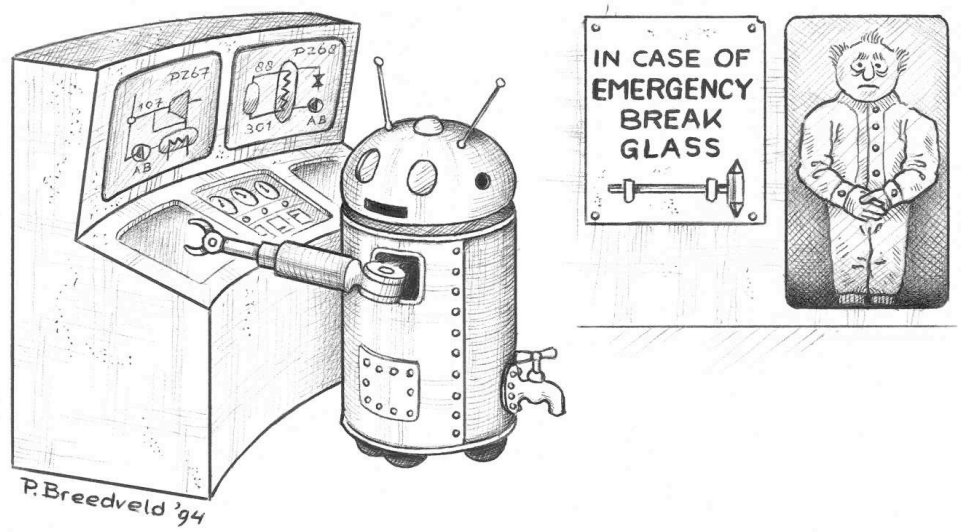
  - Shared control and control transition management
  - Arbitration and dynamic authority allocation
  - Understanding driver and system actions









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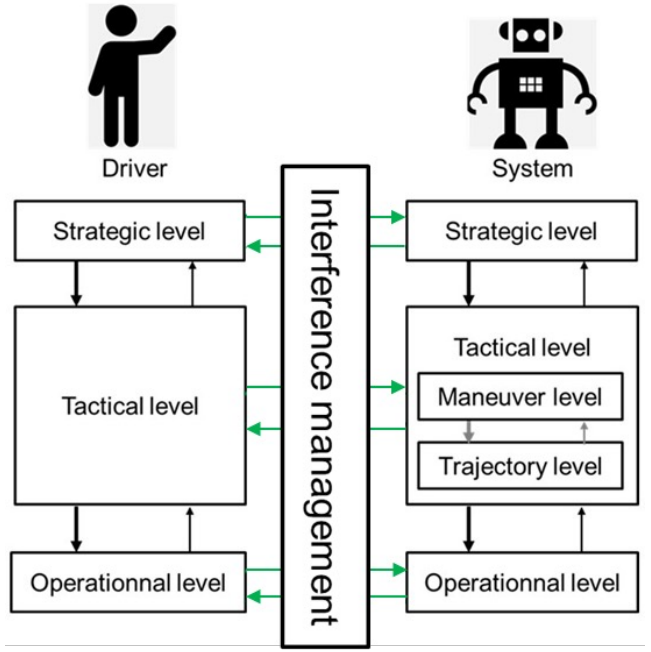
Scientific Challenges & Research Gaps

- How can **tactical decisions** and **driver intentions** be integrated into low-level control while ensuring **safe and coherent vehicle behavior**?
- How can **control authority be dynamically shared** between the driver and automation in case of **conflicting goals or intentions**?
- How can interaction **adapt to individual driver characteristics for personalization** while keeping the driver in the loop?

How can hierarchical cooperation between the driver and an automated driving system be implemented?



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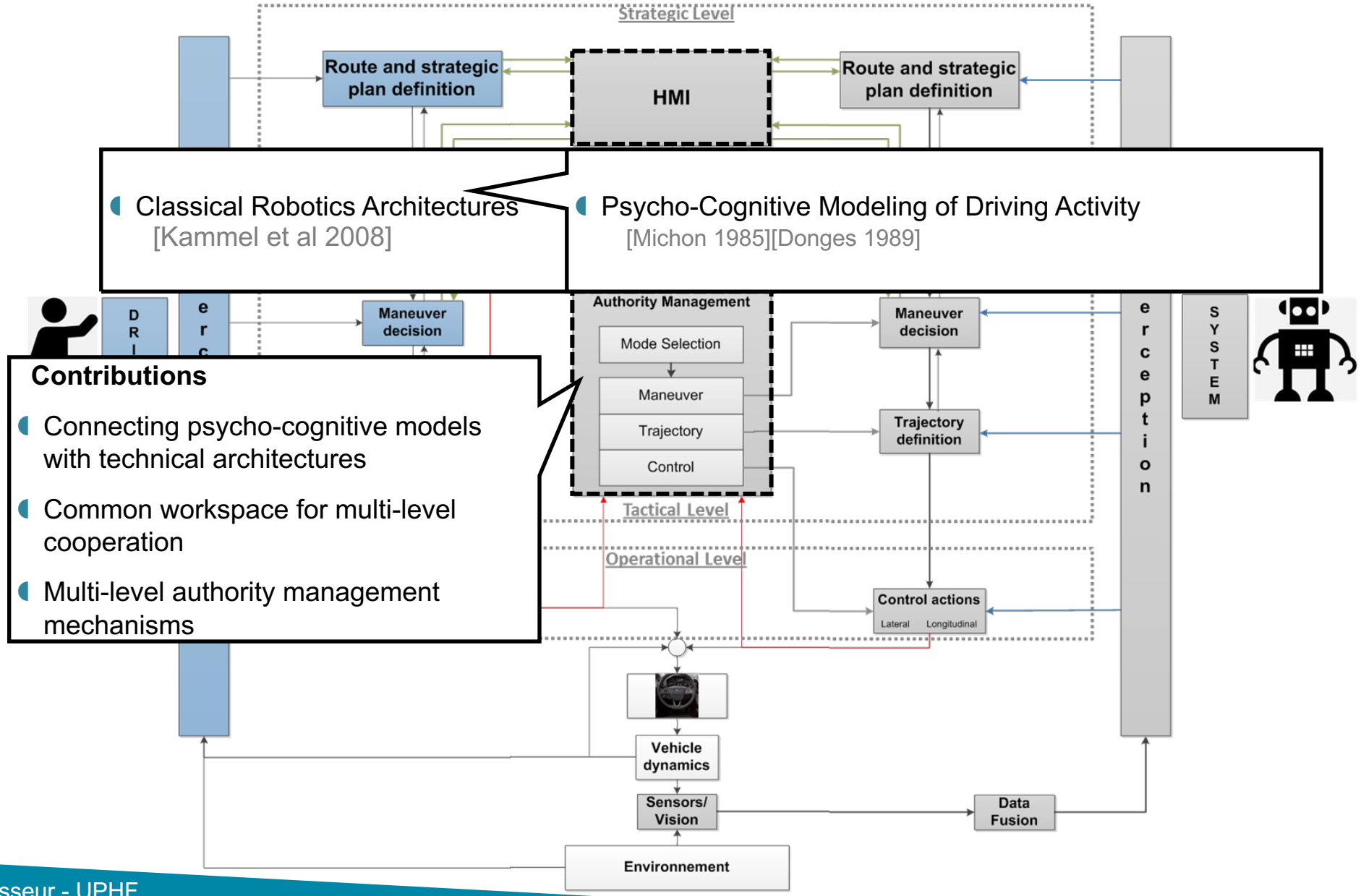
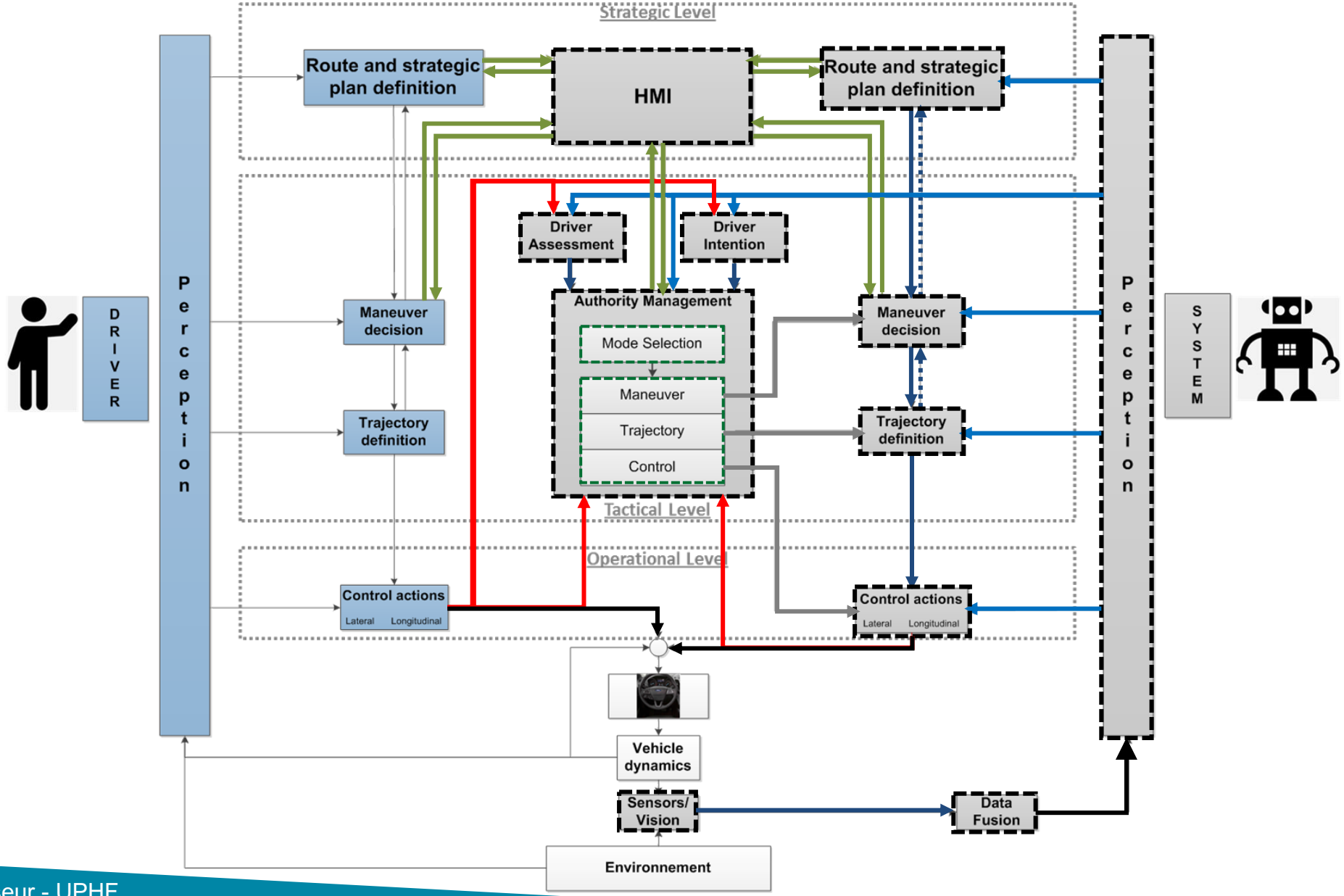
Which model for hierarchical human–machine cooperation?



Multi-level human–machine cooperation architecture



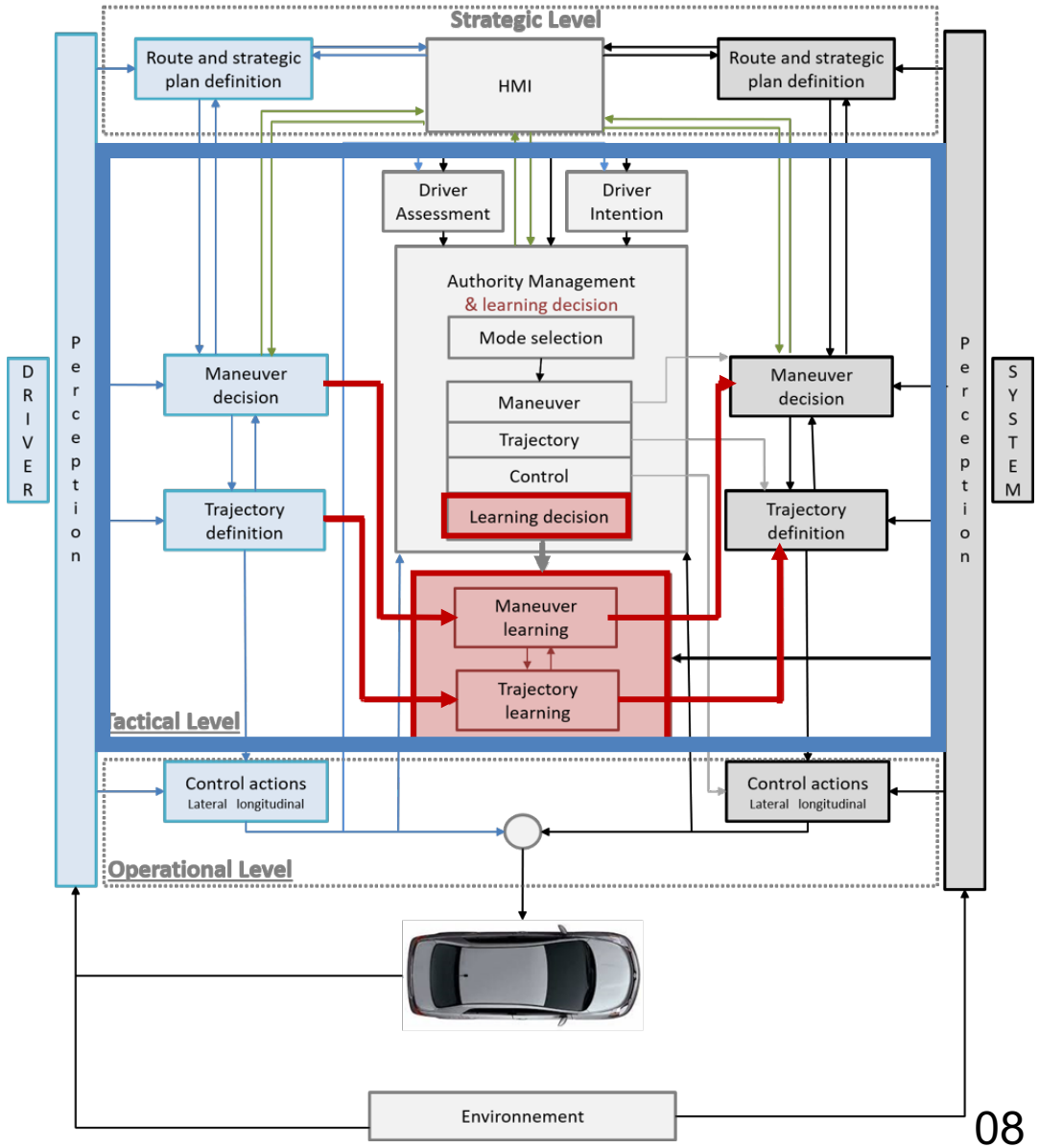
Self-learning capabilities for driver personalization

Objectives at the tactical level

- Personalize the operation of automated functions according to each driver's preferences
- Resolve potential conflicts between the automated system and the driver
- Improve drivers' trust in the automated vehicle

- Machine learning capabilities to enable continuous adaptation and driver personalization
- Adaptive authority management mechanisms to resolve conflicts at each level of interaction

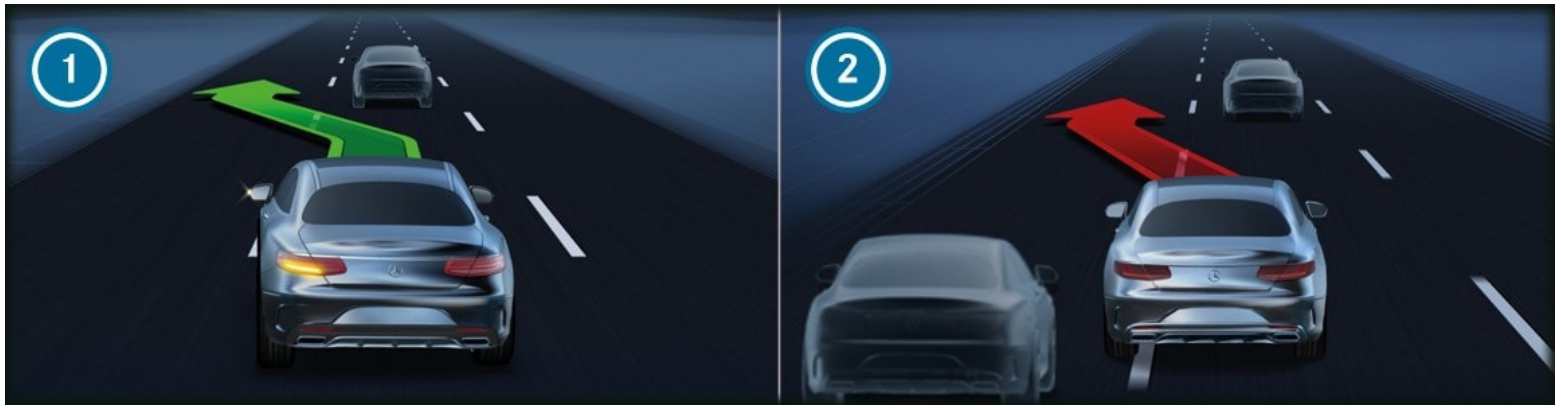
→ A **Self-Adaptive** multi-level human–machine cooperation architecture



A use case for driver personalization: Overtaking maneuver

→ **Use case : Overtaking/Undertaking maneuver**

Driving situation where the driver's preferences can influence both the decision and the way the maneuver is performed

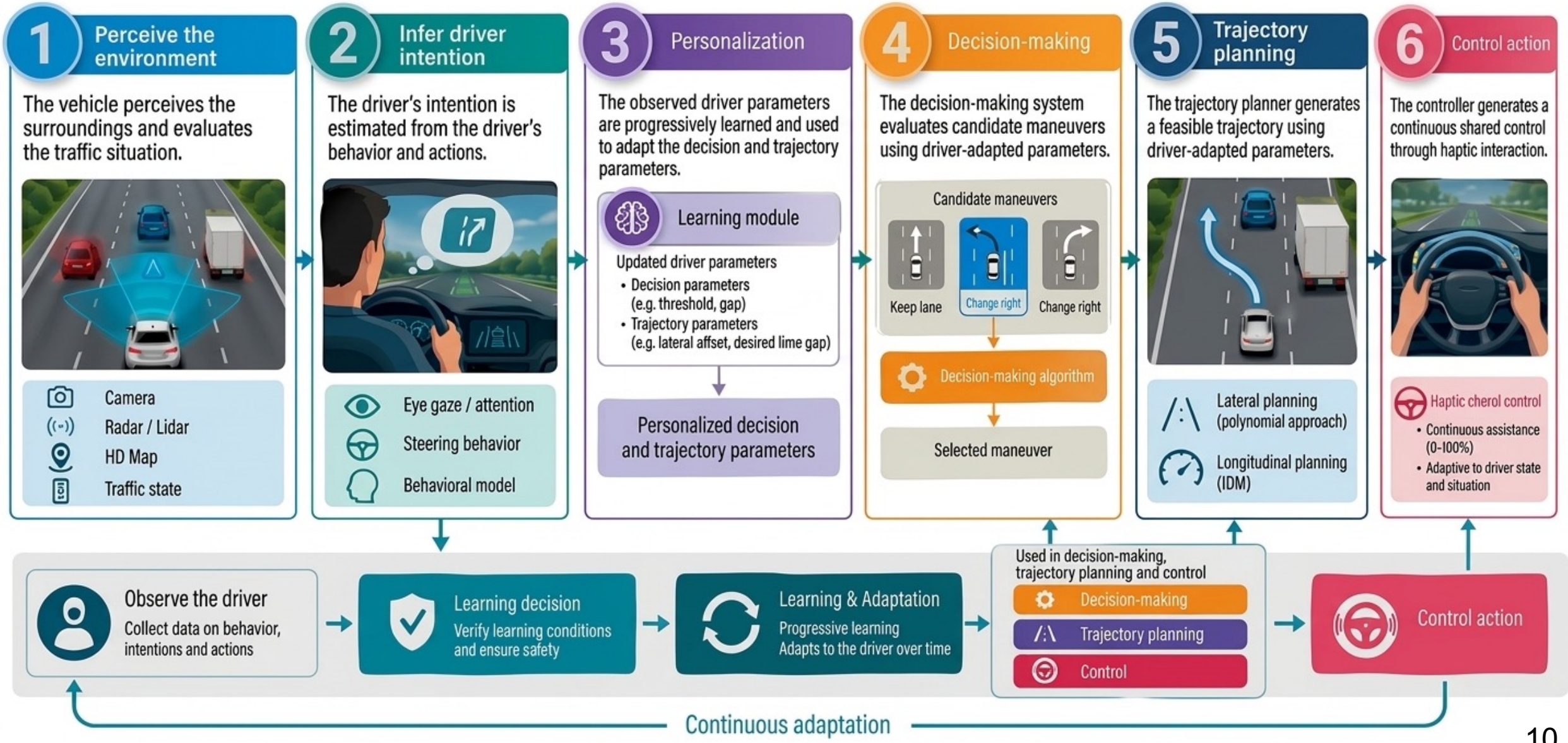


Active Lane Change System (ALCS)

This use case allows us to address two complementary questions:

- When should the vehicle overtake?
- How should the overtaking maneuver be performed according to the driver's preferences?

Personalized decision-making, planning & control process

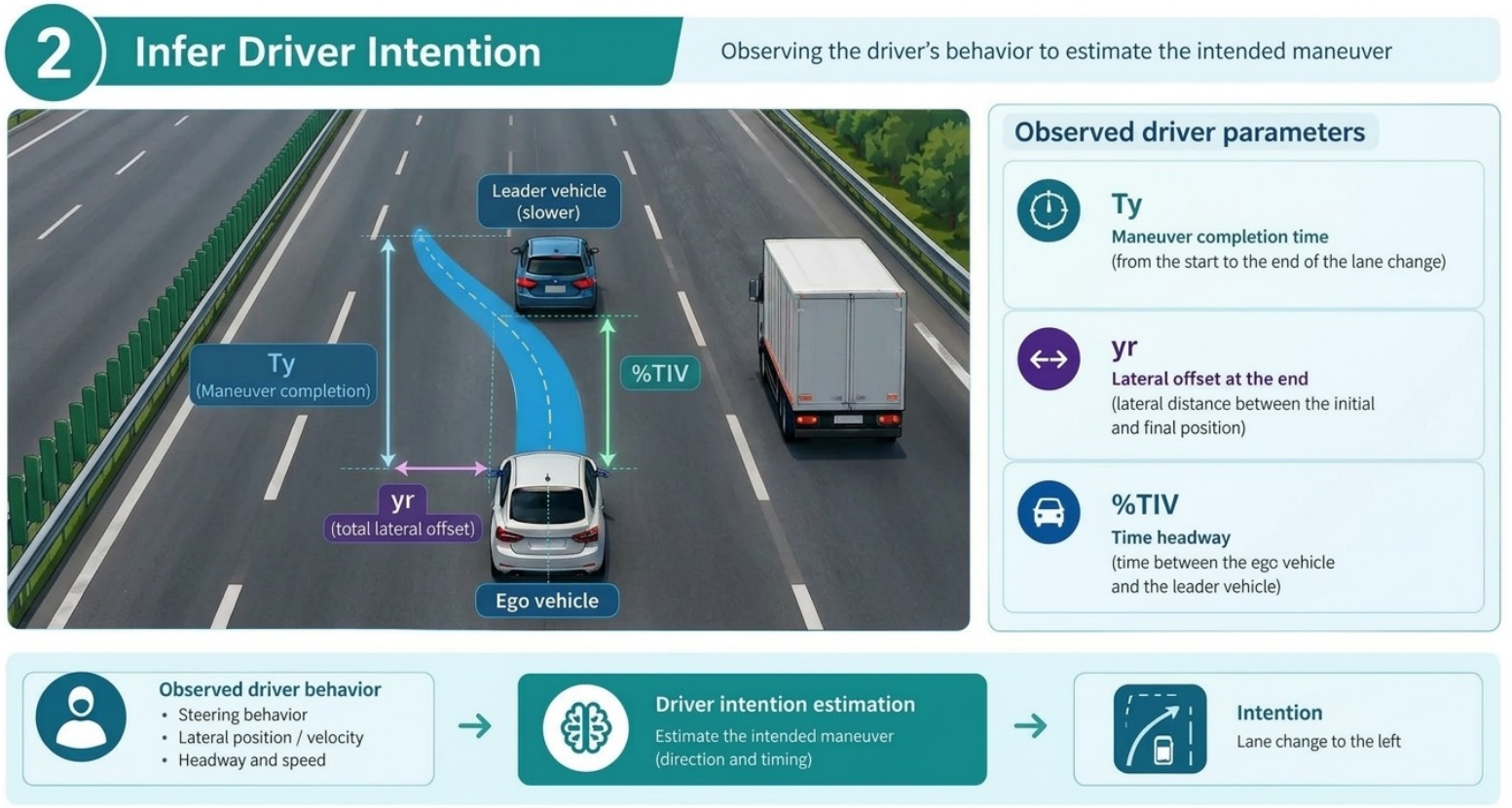


Driver intention detection

Objective: Infer the driver's intention

- Identification of the driver's LC decision-making and trajectory planning parameters for personalization



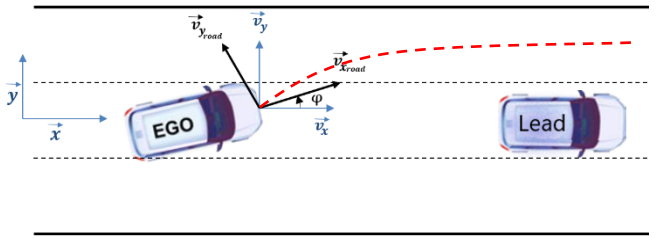


Understanding what the driver wants to do

- Observe the driver's lateral behavior
- Detect the driver's intention to change lane
- Estimate the parameters of the driver LC maneuver to be learned to the system

$$\begin{cases} DLCL_{int} = \left(v_{y_{road}} > \alpha_{v_y}\right) \wedge \left(y_c > \beta_{y_c}\right) \\ DLCR_{int} = \left(-v_{y_{road}} > \alpha_{v_y}\right) \wedge \left(-y_c > \beta_{y_c}\right) \end{cases}$$

$$v_{y_{road}} = v_x \sin(\varphi) + v_y \cos(\varphi)$$



Driver state monitoring

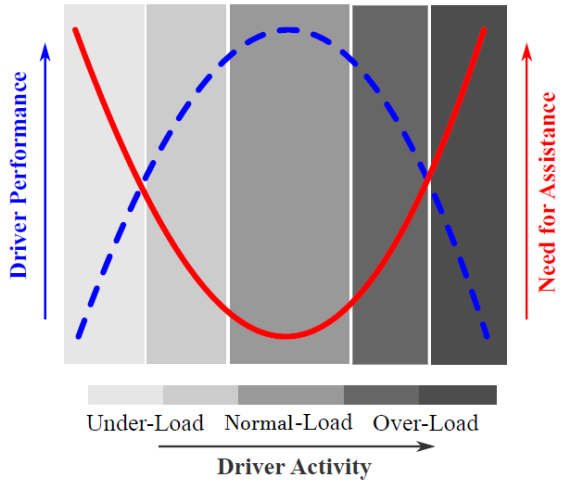
Objective: Determine the driver's vigilance and visual attention

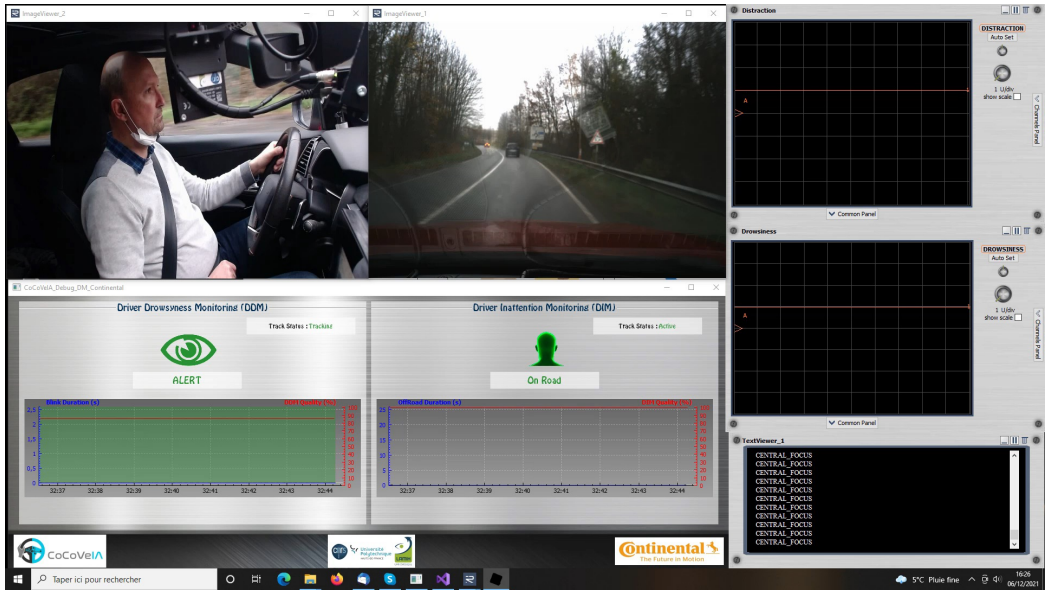
- Evaluate the driver's driving capabilities for
  - → authority management
  - → decision-making for learning

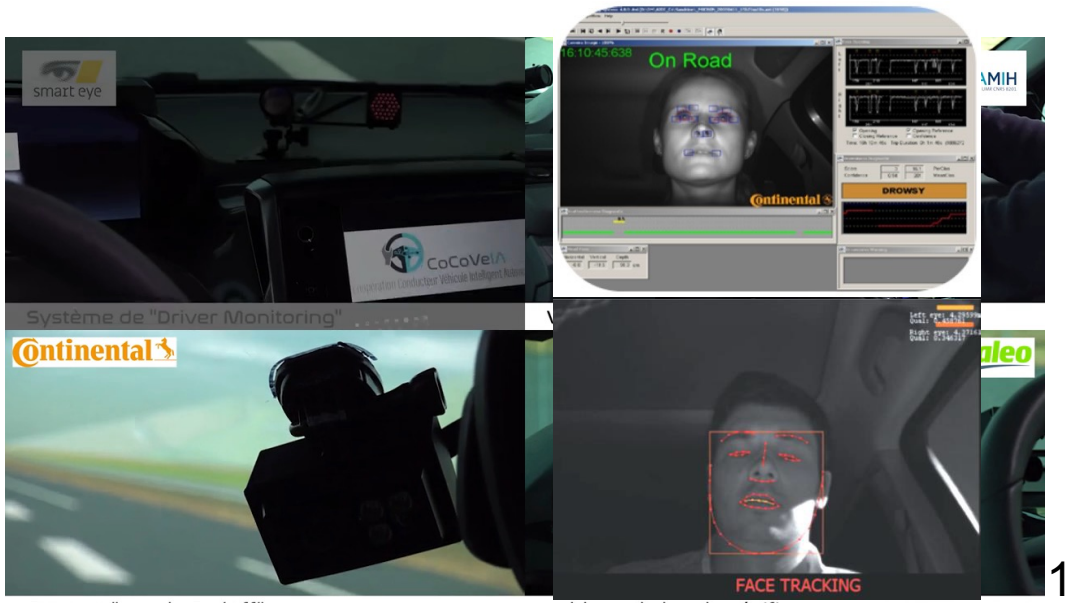
- Integration of an image-based Driver Monitoring System

  - → Eyes and Face tracker system
  - → Body monitoring system
  - → Hands On/Off sensor

Data fusion algorithm to evaluate the driver state



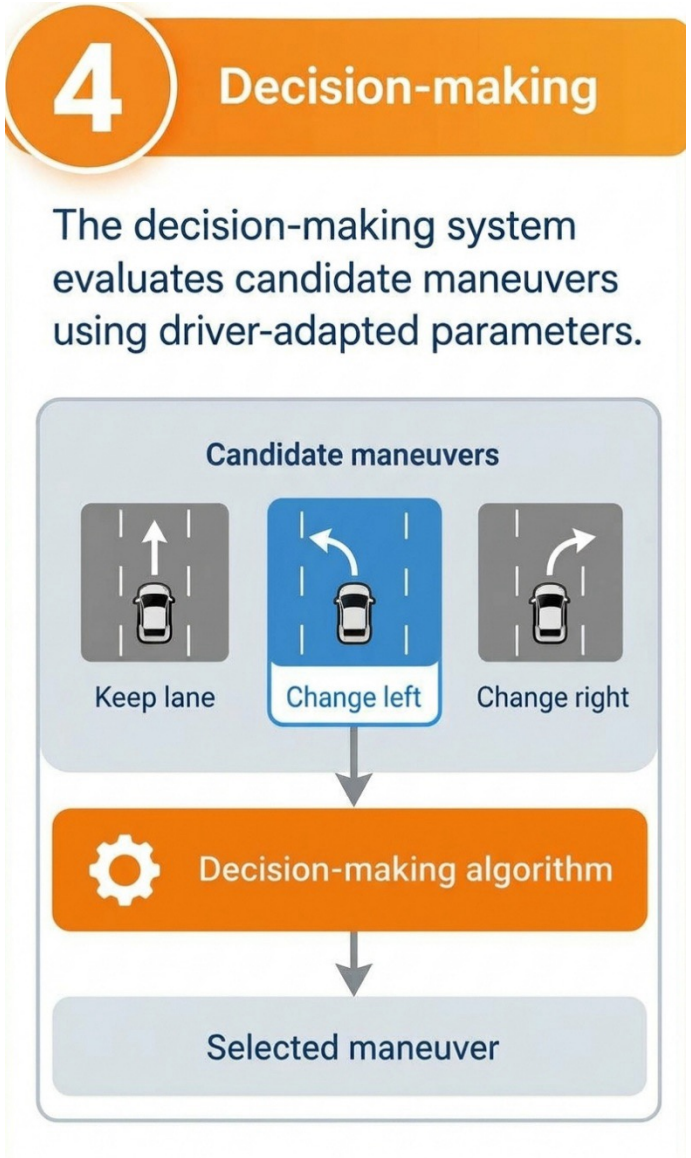




Capteur "Hands On/Off"

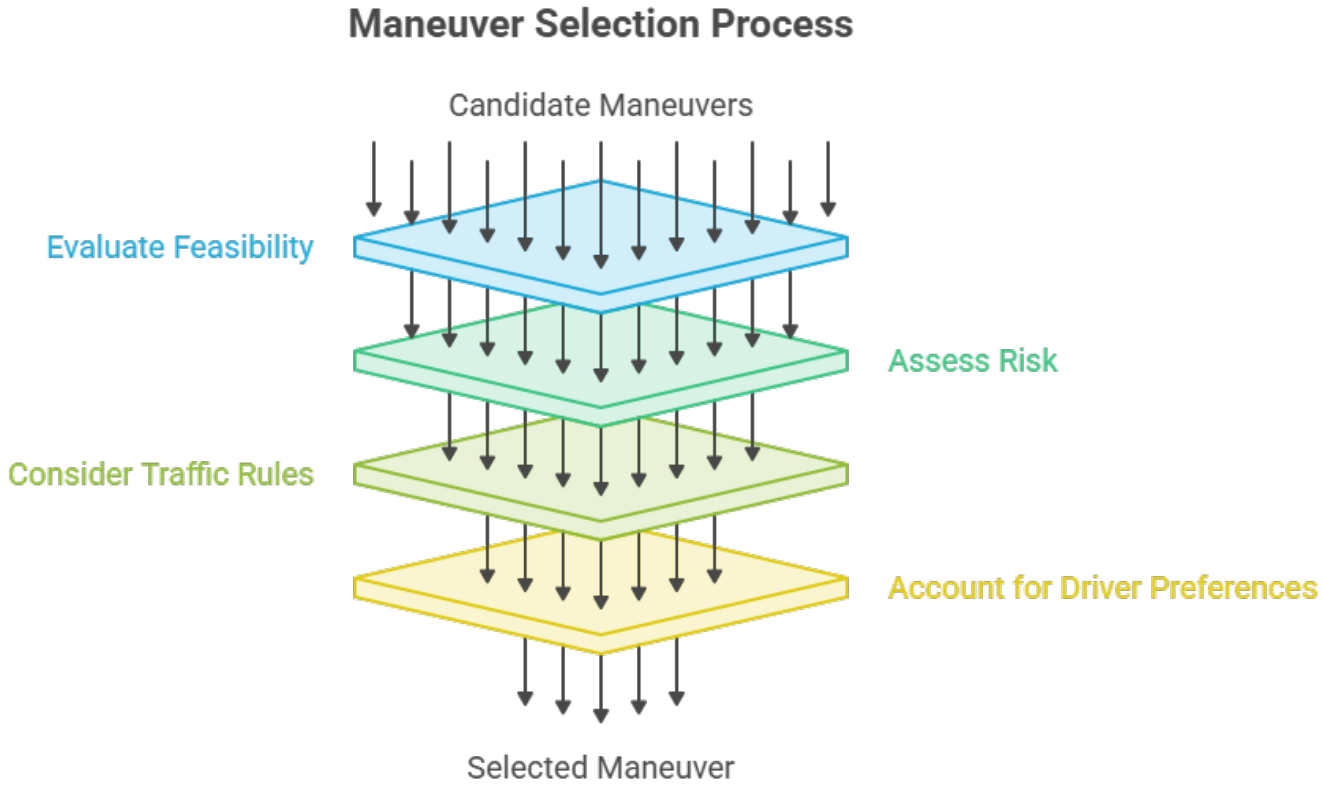
Tableau de bord spécifique

Tactical level: Personalized maneuver Decision-Making



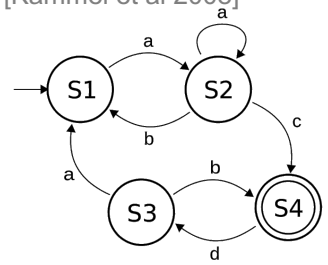
Objective : Choosing the appropriate and personalized maneuver

- Generate **candidate maneuvers**
- Evaluate their **feasibility and risk**
- Account for traffic rules and **driver-specific preferences learned** in step 3
- Select the most **appropriate maneuver**



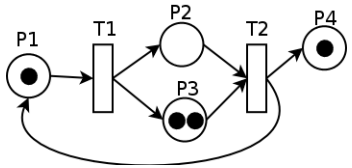
Decision-making strategy for LC maneuver

Finite-state machines
[Kammel et al 2008]

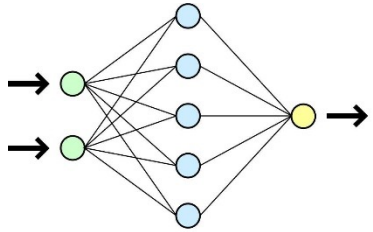


Procedural decision

Petri nets [Furda et al 2011]

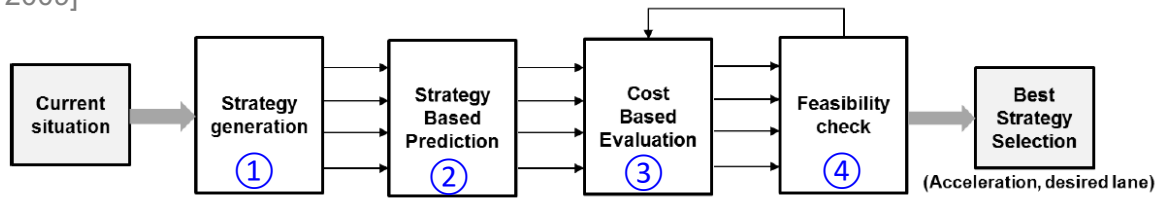


ANN [Pomerleau 1991]



Cost-function-based approach [Wei et al. 2009]

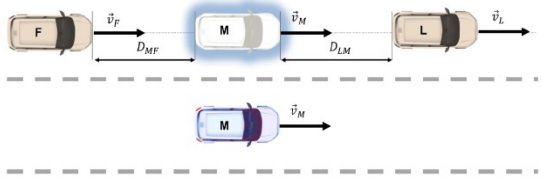
Evaluation of several alternatives

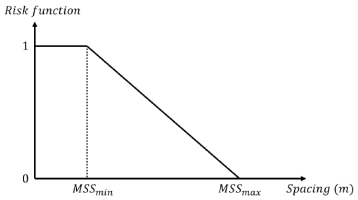


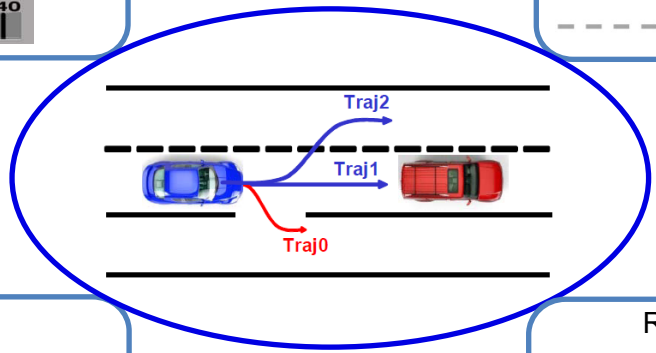
Generation of candidate strategies



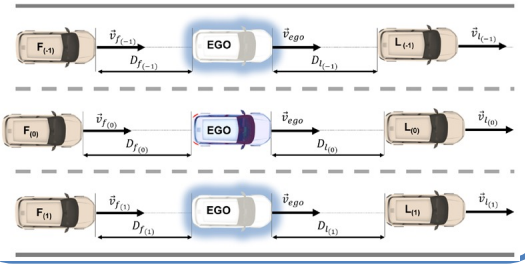
Feasibility check: assessment of lane-change risk



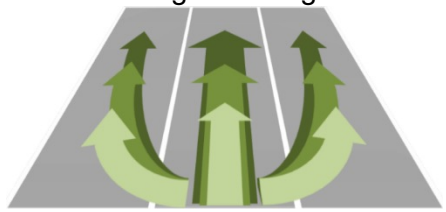




Traffic scene prediction (MPC principle)

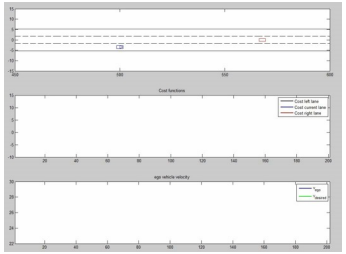


Ranking of strategies



$$C_i = w_{risk}C_{i,risk} + w_{legal}C_{i,legal} - w_{learn}C_{i,learn}$$

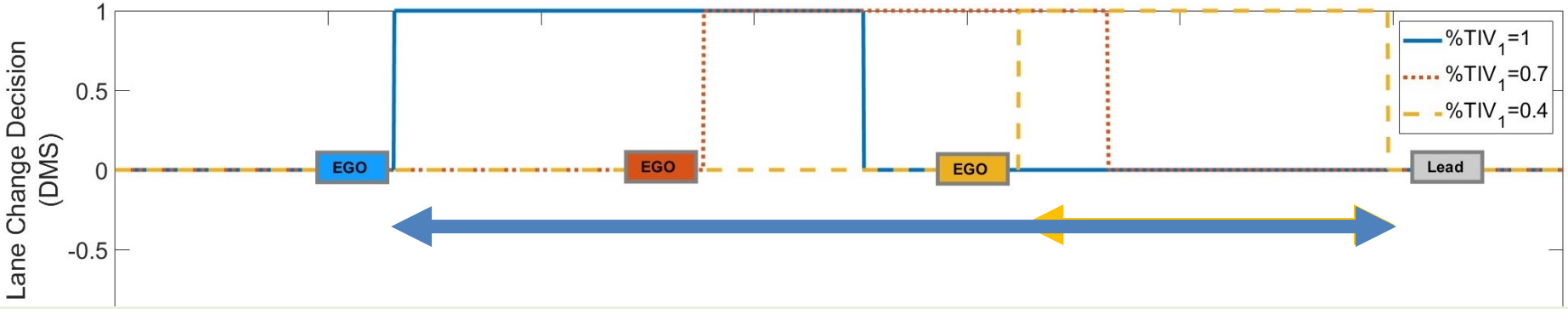
$$DMS = Index\{\min(C_i)\}$$



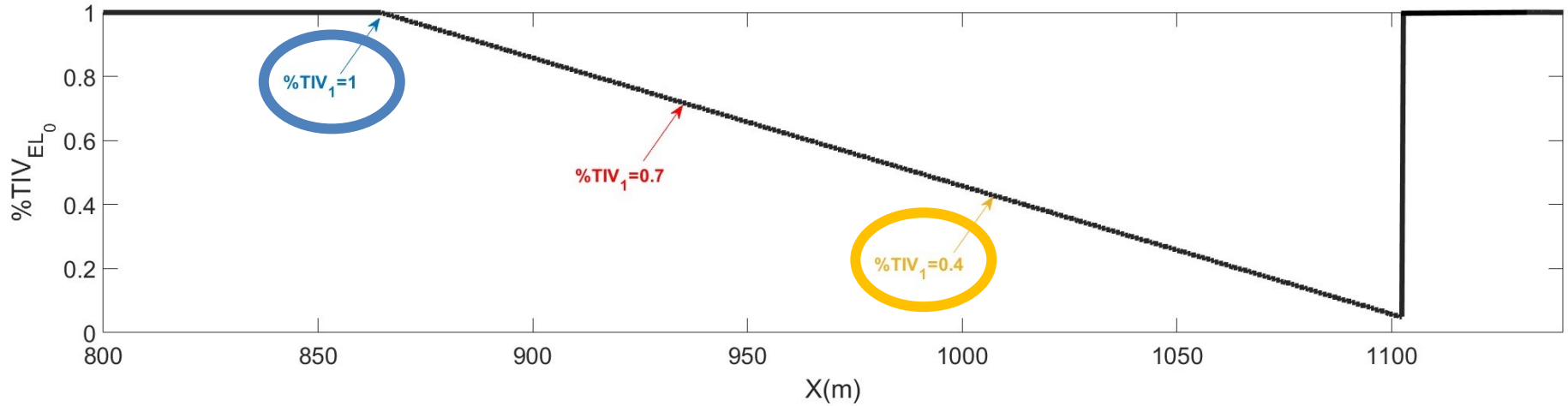
Decision-making strategy for LC maneuver



Impact of the decision threshold %TIV for a lane change (to the left) on the decision



Decision thresholds $(\%TIV_1 , \%TIV_{-1})$ can be tuned to personalize lane-change behavior to individual driver preference



Personalized lateral trajectory planning

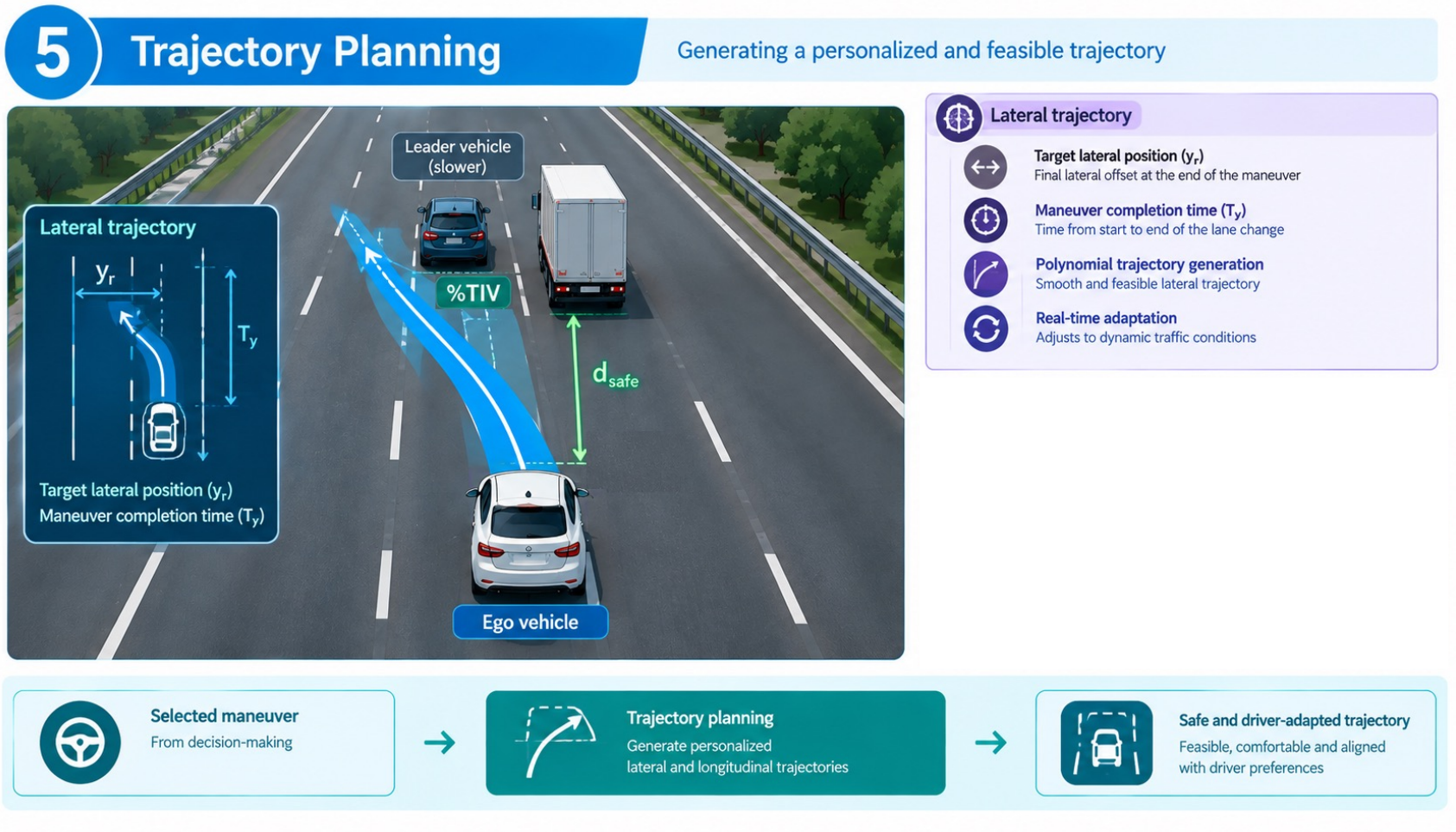
Lateral trajectory planning
→ Polynomial approach [Takahashi et al., 1989]

❑ Polynomial model

$$y_r(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 + a_5 t^5$$
$$\dot{y}_r(t) = a_1 + 2a_2 t + 3a_3 t^2 + 4a_4 t^3 + 5a_5 t^4$$
$$\ddot{y}_r(t) = 2a_2 + 6a_3 t + 12a_4 t^2 + 20a_5 t^3$$

❑ Advantages:

- Ease of understanding
- Real-time operation
- Real-time adaptation (y_r, T_y)



Impact of the **target position y_r** and the **LC maneuver duration T_y** of the lane-change maneuver on the planned trajectory

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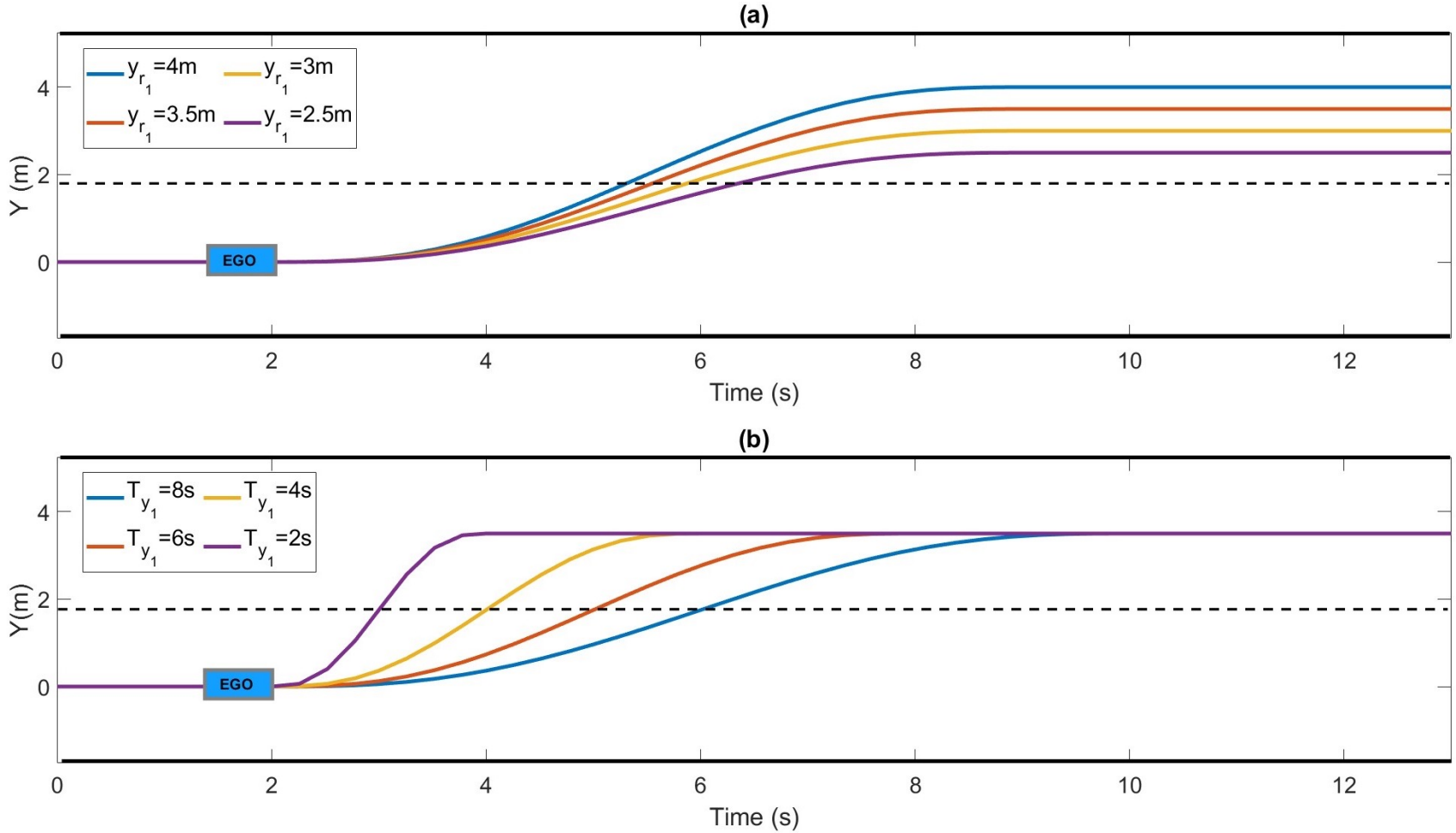


Impact of the **target position y_r** and the **LC maneuver duration T_y** of the lane-change maneuver on the planned trajectory

Longitudinal trajectory planning approach

Longitudinal trajectory planning
→ Intelligent Driver Model, IDM [Treiber et al., 2000]

❑ IDM for lane changing

$$a_{x_i} = a\left(1 - \left(\frac{v_{ego}}{v_d}\right)^2 - \left(\frac{D}{DIV_t}\right)^2\right) \quad i \in \{-1,0,1\}$$

- Desired safety distance

$$D = D_0 + Tv_{ego}$$

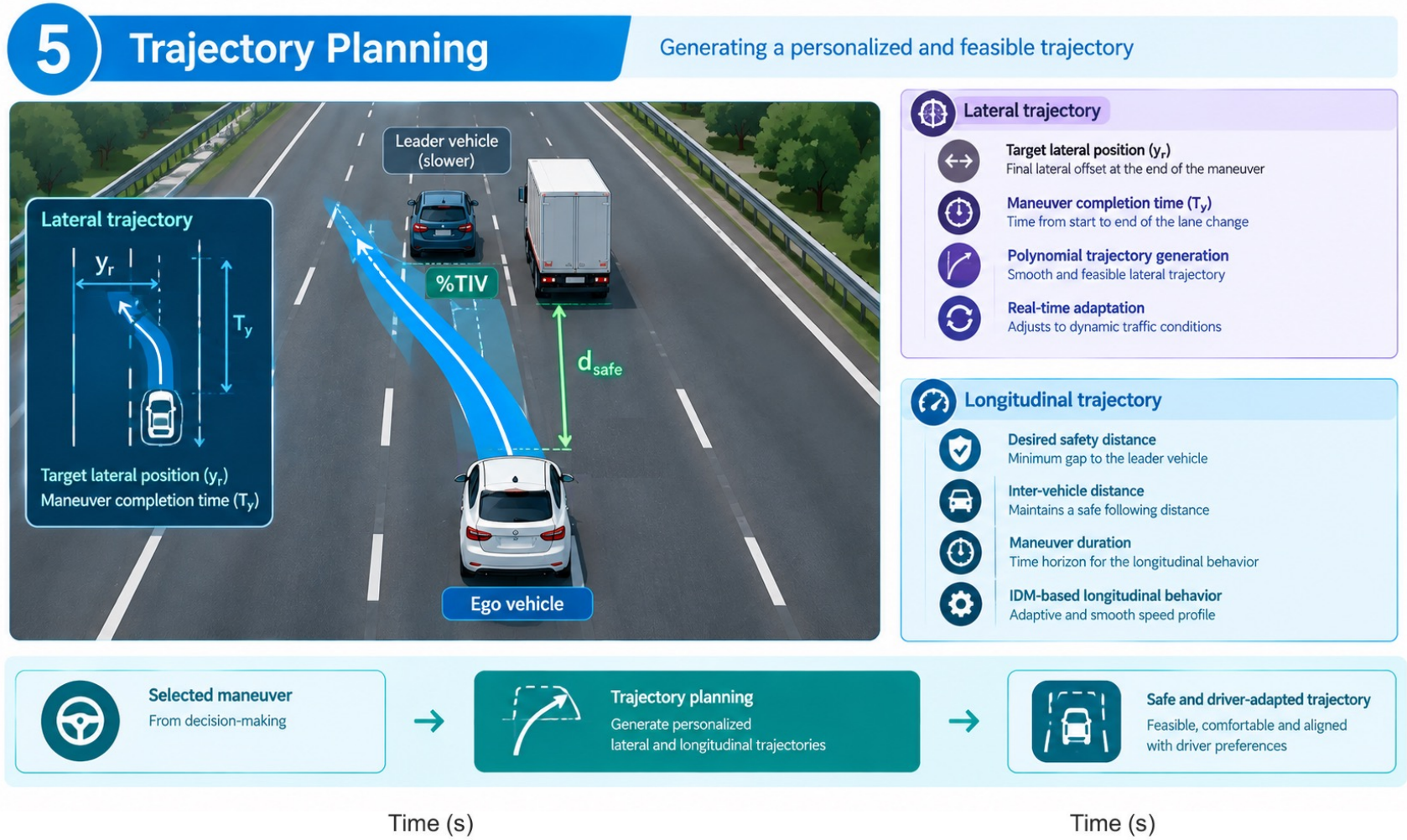
- Inter-vehicle transition distance

$$DIV_t(t) = DIV_{EL_0}(0) - \left(DIV_{EL_0}(0) - DIV_{EL_i}(t)\right)\left(1 - e^{\left(-\frac{t}{\tau}\right)}\right)$$

with : $t \in [0, \boldsymbol{T_{y_i}}]$

❑ Advantages

- Real-time operation
- Vehicle safety assurance
- Real-time adaptation $\boldsymbol{T_y}$



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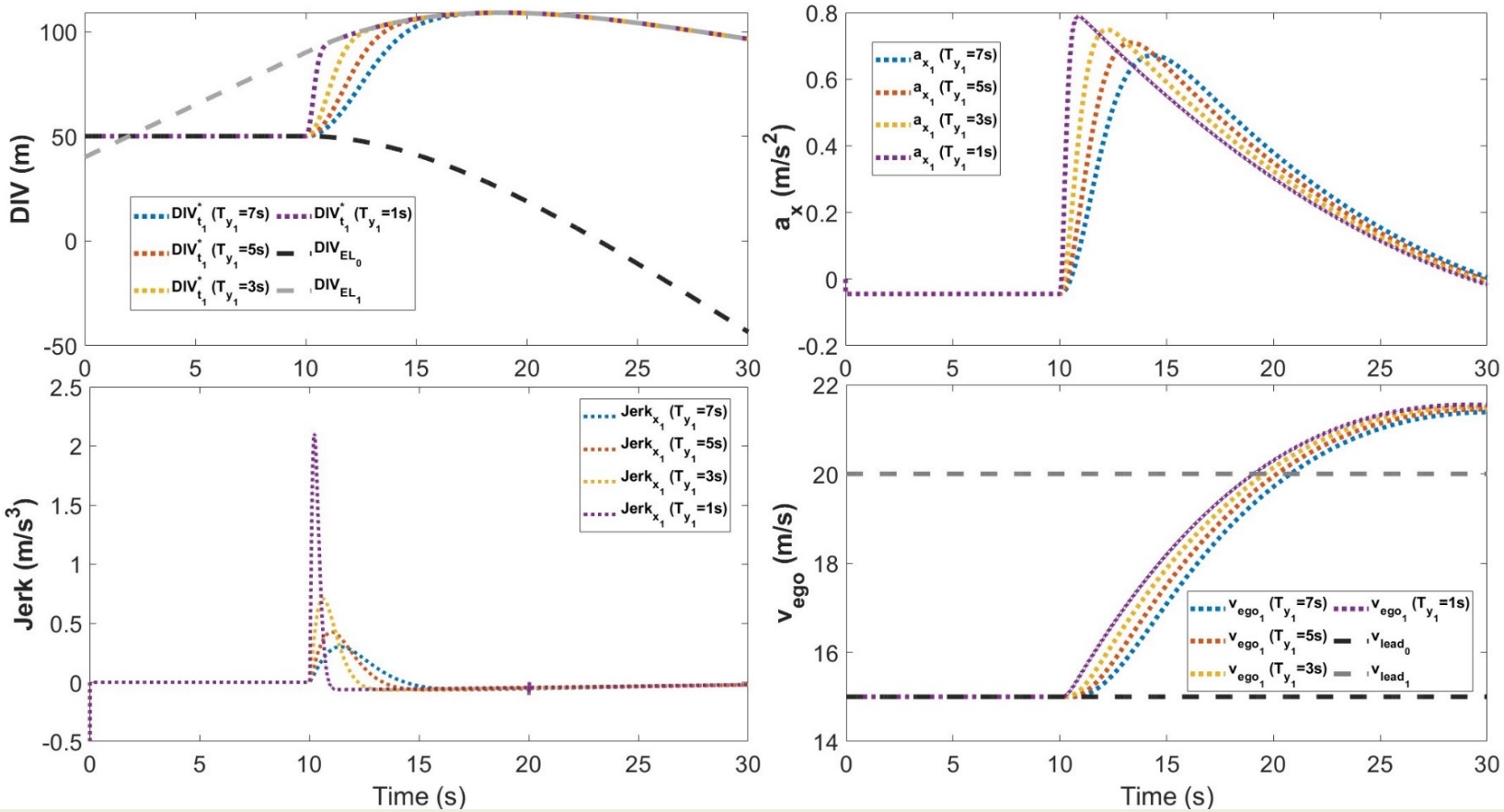
❑ Advantages

- Real-time operation
- Vehicle safety assurance
- Real-time adaptation $\boldsymbol{T_y}$

Impact of **LC maneuver duration T_y** on the longitudinal behavior of the ego vehicle



Trajectory planner parameters (y_{r_1}, T_{y_1}), $(y_{r_{-1}}, T_{y_{-1}})$ can be tuned to personalize lane-changing behavior to individual driver preferences

Learning-based personalization of decision-Making and Planning

3 Personalization

The observed driver parameters are progressively learned and used to adapt the decision and trajectory parameters.

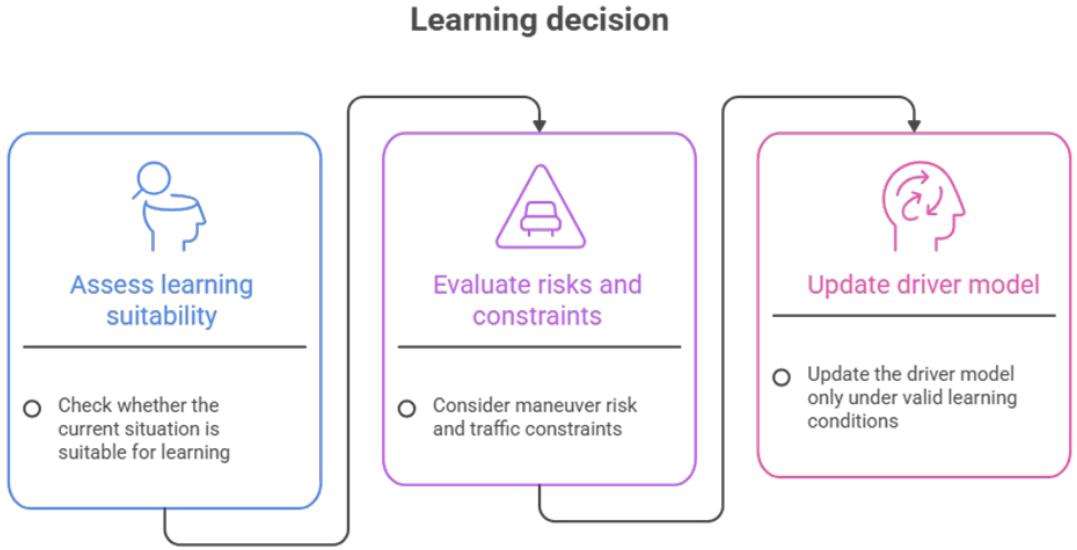
Learning module

Updated driver parameters

- Decision parameters (e.g., threshold, gap)
- Trajectory parameters (e.g., lateral offset, desired time gap)

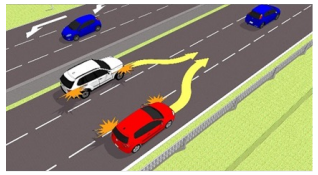
↓

Personalized decision and trajectory parameters



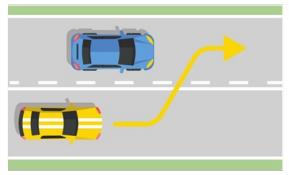
$$\rho_i = C_{P_{D_i}} \wedge C_{legal_i} \wedge C_{DS}$$

Risk of the maneuver



$P_D \in [\mathrm{P_{min}}, \mathrm{P_{max}}]$

Driving rules



- $v_x < v_{\mathrm{lim}}$
- Lane Markings

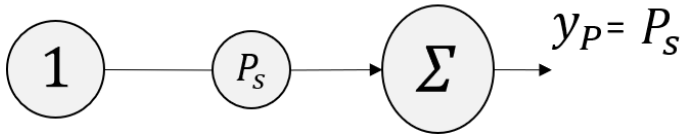
Driver state



- Driver inattention
- Driver drowsiness

Progressive Learning for personalization

Application of the ASGD (Adaptive Stochastic Gradient Descent) algorithm for LCAS personalization



Algorithm: ASGD for lane-change assistance system with learning decision

Input: P_D, i, ρ
Output: P_S, P_{D_m}
Initialization: P_{S_o}, P_{D_m}, α

For each new lane change i

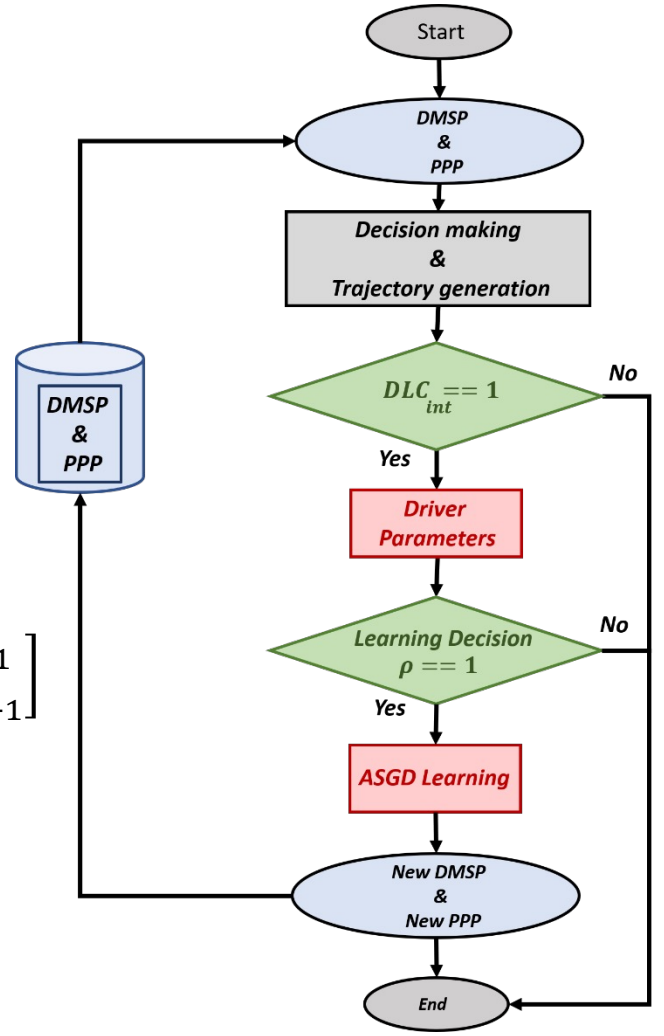
- The average driver parameters: $P_{D_m} \leftarrow \frac{1}{(1+\rho)}(P_{D_m} + \rho P_D)$
- The cost function: $\longrightarrow \quad \mathfrak{J}(P_S) \leftarrow \frac{1}{2}(P_S - P_{D_m})^2$
- The gradient: $\longrightarrow \quad \frac{\partial \mathfrak{J}(P_S)}{\partial P_S} \leftarrow (P_S - P_{D_m})$
- The adaptive learning rate: $\longrightarrow \quad \alpha(\rho) \leftarrow \alpha\rho$
- The ASGD algorithm: $\longrightarrow \quad P_S \leftarrow P_S - \alpha(\rho)\frac{\partial \mathfrak{J}(P_S)}{\partial P_S}$

End

$$P_s = \begin{bmatrix} DMSP \\ PPP \end{bmatrix}$$

$$DMSP = \begin{bmatrix} \%TIV_1 \\ \%TIV_{-1} \end{bmatrix}$$

$$PPP = \begin{bmatrix} T_{y_1} \\ T_{y_{-1}} \\ y_{r_1} \\ y_{r_{-1}} \end{bmatrix}$$



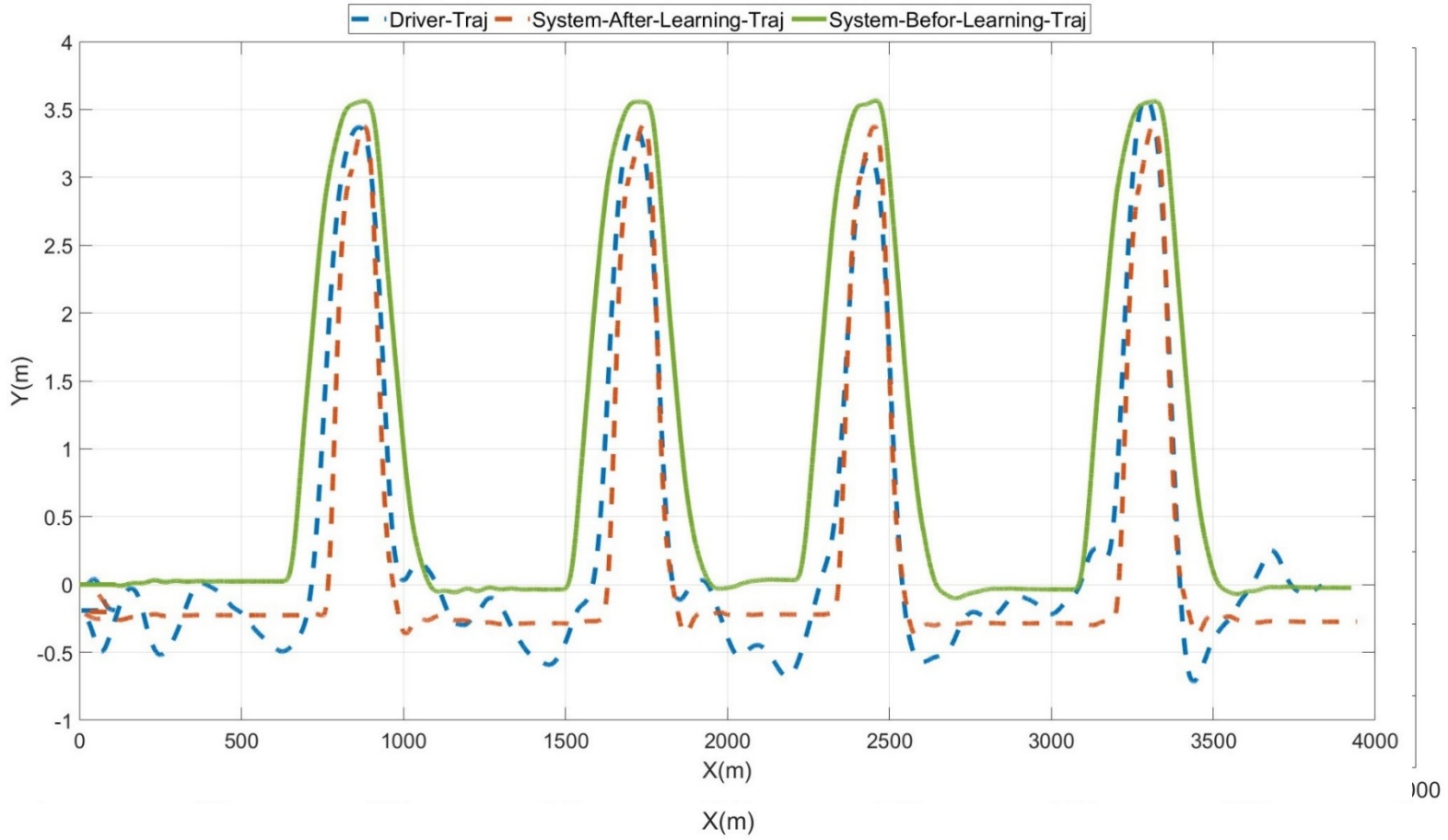
ASGD-Based Learning Method

Progressive learning: Results

The scenario: 4 overtaking maneuvers in automated driving mode without learning → highly anticipatory/conservative behavior
4 overtaking maneuvers in manual driving mode → the system observe and learns
4 overtaking maneuvers in automated driving mode with learning → test with updated driver parameters



SHERPA Full scale dynamic car simulator

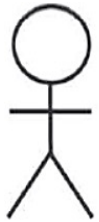


Experimental validation



Operational level : Personalized haptic shared control





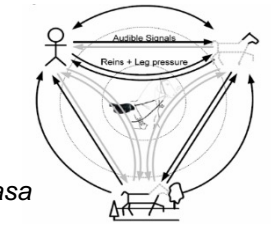


(Abbink et al 2012, adapted from Flemisch)





Flemisch et al. (2003). Nasa Report about the H-metaphor



Objective: To develop control strategies enabling direct intervention by the driver and the automated system in trajectory management via haptic feedback.

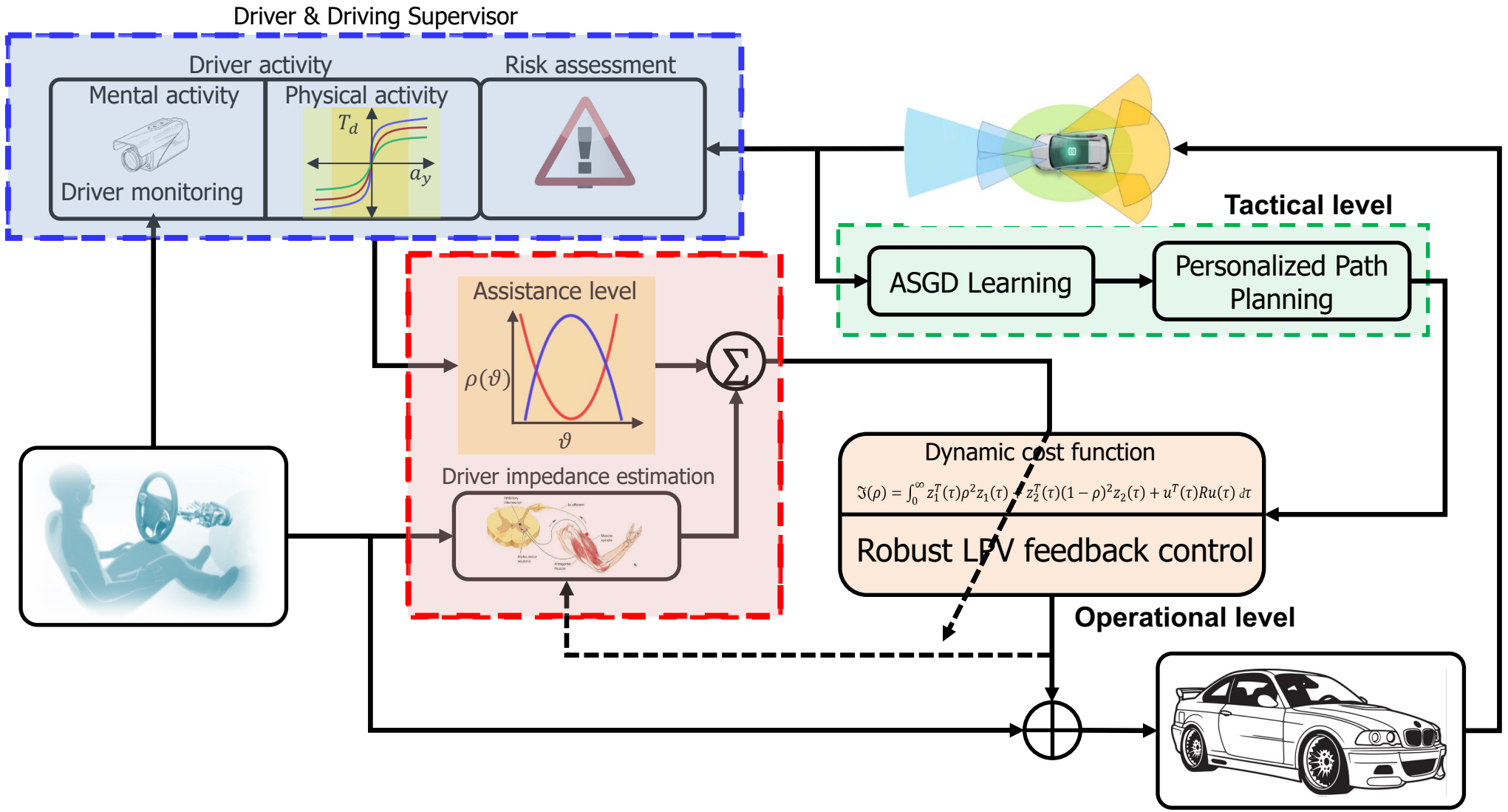
Smooth shared continuous control [Abbink et al., 2010]

- No "binary" activation or deactivation
- The driver participates in vehicle guidance at levels ranging from 0% to 100%

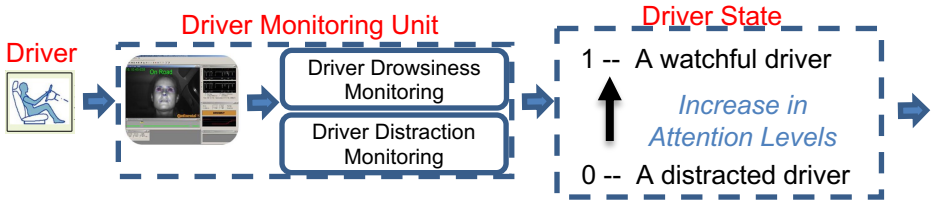
The control system must be designed to respect the driver's habits

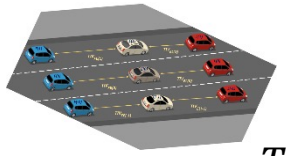
- Adaptive to driver state and the driving situation
- A driver model is integrated into the overall system model in the control design to take into account the physical interaction

Adaptive haptic shared control



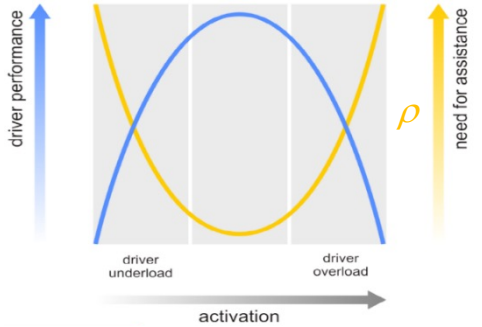
Adaptive haptic shared control: LPV-TS approach





$$Risk = 1 - \frac{TIV}{TIV_{max}}$$

Risk Assessment



U-shape function [Flemish and al., 2010]

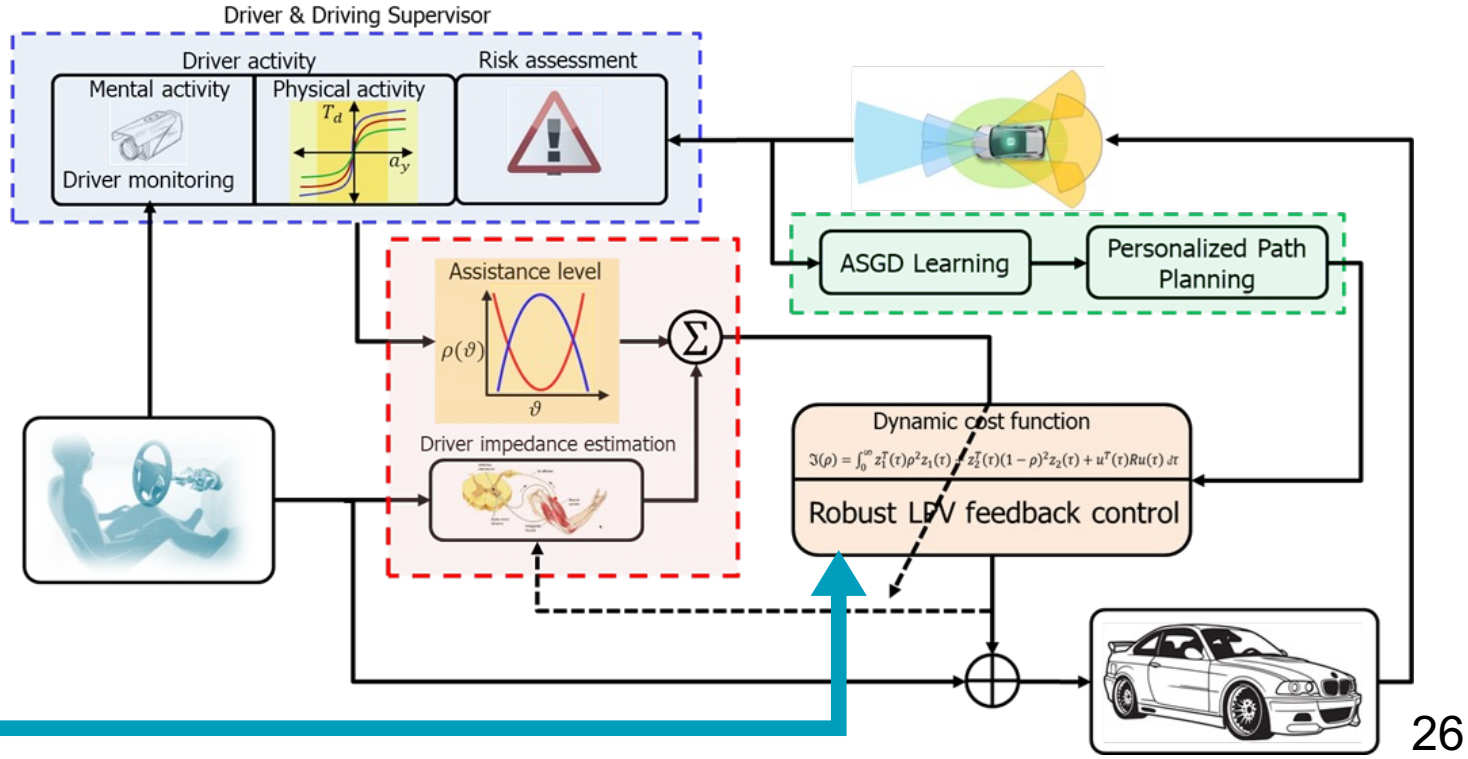
Varying parameters: $\theta = \{\Delta(v_x); \theta_s\}$ & ρ

$$\sum_{\theta} : \quad \dot{x} = \sum_{i=1}^{4} h_i(\theta)(A_i x + E_i d) + Bu$$

$$z(\rho) = \sum_{i=1}^{2} h_i(\rho)(C_i x + D_i u)$$

LMI formulation!

$$u = \sum_{i=1}^{4} \sum_{j=1}^{2} h_i(\theta) g_j(\rho) K_{ij}\, x,$$



Adaptive haptic shared control: LPV-TS approach

❑ **Adaptive multi-objective cost function :**

$$\Im(\boldsymbol{\rho}) = \int_0^{\infty} z_1^T(\tau)\boldsymbol{\rho}^2 Q_1 z_1(\tau) + z_2^T(\tau)(\mathbf{1}-\boldsymbol{\rho})^2 Q_2 z_2(\tau) + u^T(\tau) R u(\tau)\, d\tau$$

$$z_1 = Cx = [\beta\,; r\,; \psi_L\,; y_L\,; \dot{\delta}_d\,]$$

Lane-keeping performance

$$z_2 = C_2 x + D_2 u = [T_d - \sigma T_a\,]$$

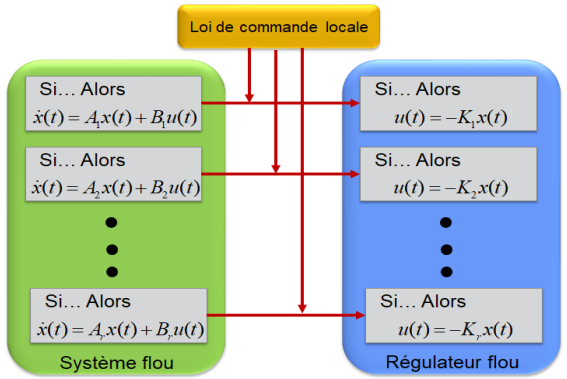
Steering assistance performance

- Control authority is assigned to the system $(\boldsymbol{\rho} = \mathbf{1})$

$$\Im(\boldsymbol{\rho}=\mathbf{1}) = \int_0^{\infty} z_1^T(\tau) Q_1 z_1(\tau) + u^T(\tau) R u(\tau)\, d\tau$$

- Control authority assigned to the driver $(\boldsymbol{\rho} = \mathbf{0})$

$$\Im(\boldsymbol{\rho}=\mathbf{0}) = \int_0^{\infty} z_2^T(\tau) Q_2 z_2(\tau) + u^T(\tau) R u(\tau)\, d\tau$$



PDC control

❑ **PDC control**

$$u = \sum_{i=1}^{4}\sum_{j=1}^{2} h_i(\theta) g_j(\rho) K_{ij}\, x,$$

$$K_{ij} = M_{ij}X^{-1}, (i \in \{1,2,3,4\}, j \in \{1,2\})$$

$$\begin{bmatrix} He\left(A_iX + BM_{ij}\right)^T & XC^TW_j^T & \left(C_2X + D_2M_{ij}\right)^T W_j' & M_{ij}^T & E_i \\ W_jCX & -I_{z_1} & 0 & 0 & 0 \\ W_j'\left(C_2X + D_2M_{ij}\right) & 0 & -I_{z_2} & 0 & 0 \\ M_{ij} & 0 & 0 & -R^{-1} & 0 \\ E_i^T & 0 & 0 & 0 & -\gamma I \end{bmatrix} < 0$$

Evaluation of the personalized haptic shared control

$$StD = \int_{T_{Ex}} T_d^2(\tau)\ d\tau, \quad StC = \int_{T_{Ex}} T_a^2(\tau)\ d\tau, \quad Conflict = \int_{T_{Ex}} |T_a(\tau) - T_d(\tau)|\ d\tau, \quad SW = \int_{T_{Ex}} |T_a(\tau) \cdot T_d(\tau) \cdot \dot{\delta}_d|\ d\tau$$

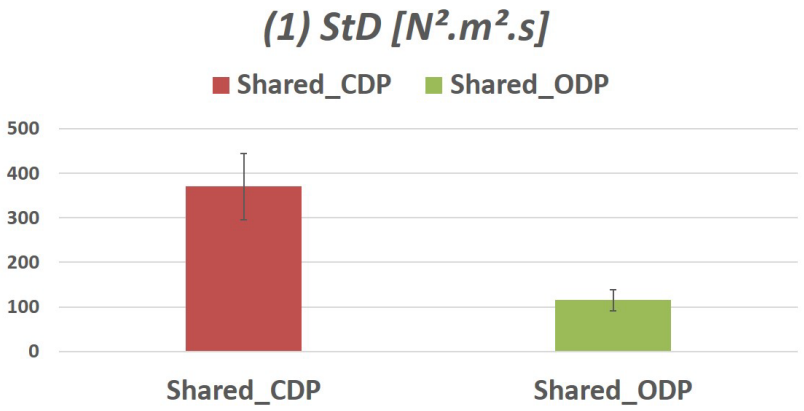


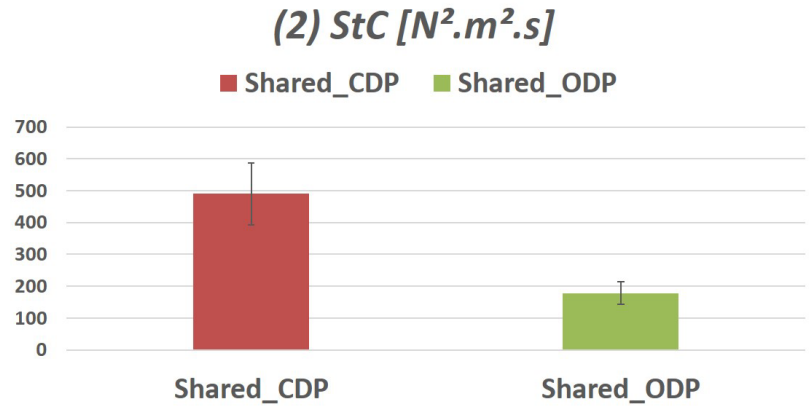
Simulation conditions

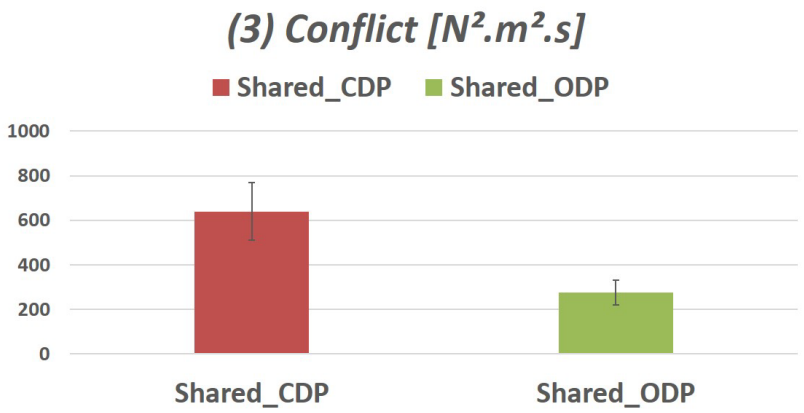
- SHERPA dynamic driving simulator
- 6 participants: 4 males, 2 females
- Obstacle avoidance scenario (no pre-generated lane-change trajectory)
- Shared-control mode: assessment of participants' lane-change capability

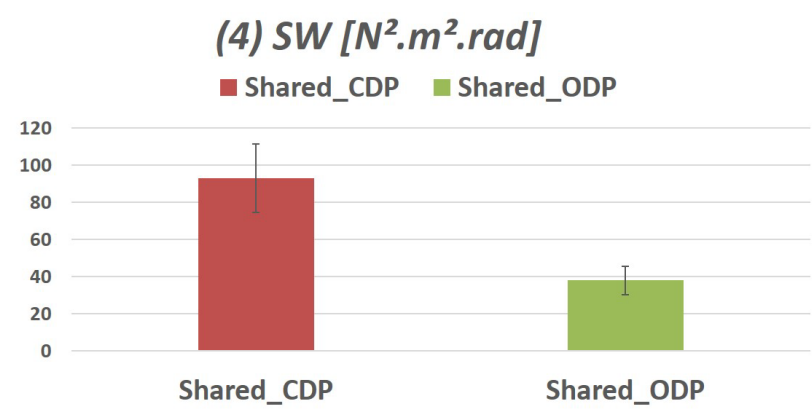
Constant driver parameters

Online driver parameters









Evaluation of the dynamic cost function approach

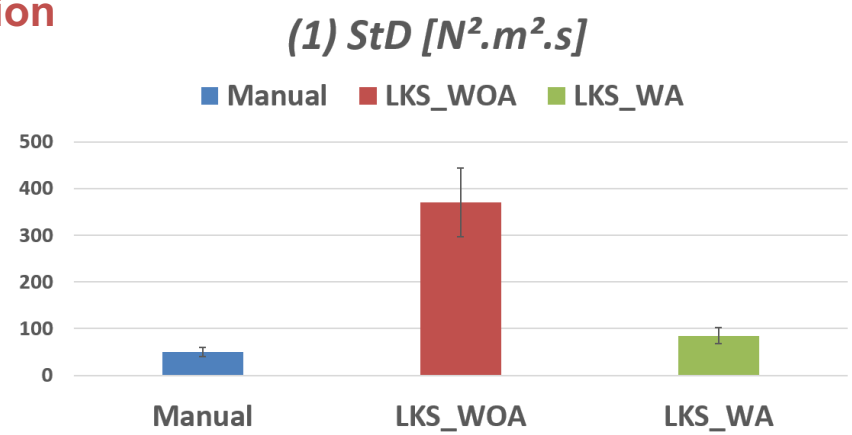
$$StD = \int_{T_{Ex}} T_d^2(\tau)\ d\tau, \quad StC = \int_{T_{Ex}} T_a^2(\tau)\ d\tau, \quad Conflict = \int_{T_{Ex}} |T_a(\tau) - T_d(\tau)|\ d\tau, \quad SW = \int_{T_{Ex}} |T_a(\tau) \cdot T_d(\tau) \cdot \dot{\delta}_d|\ d\tau$$

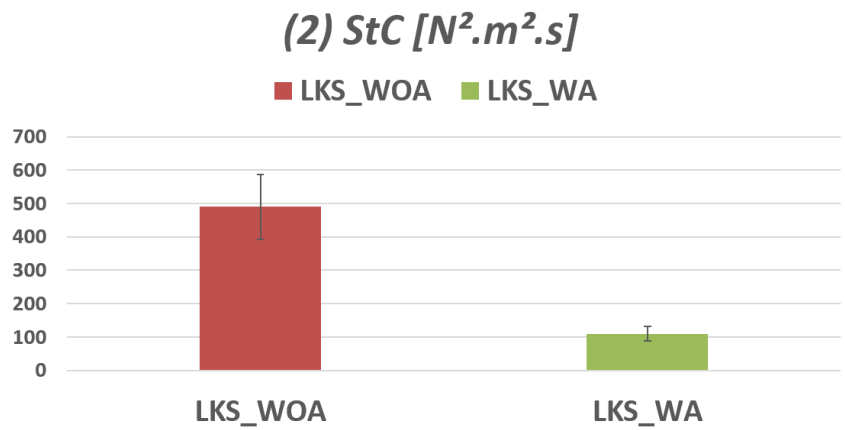
WOA : with adaptive cost function

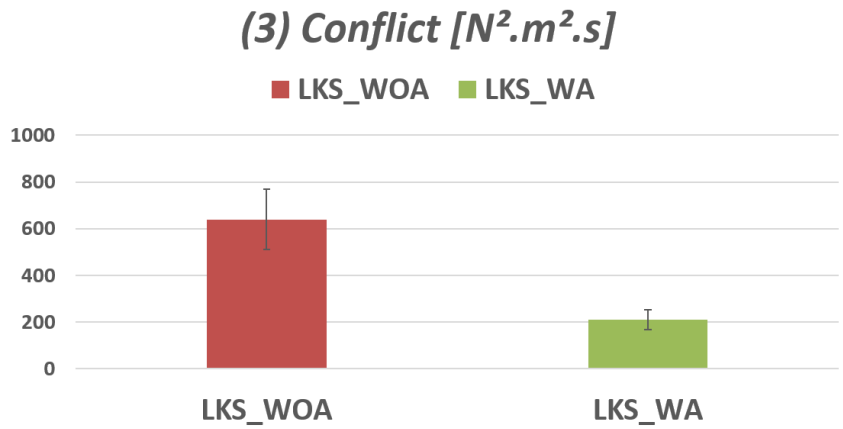
WA : without adaptive cost function

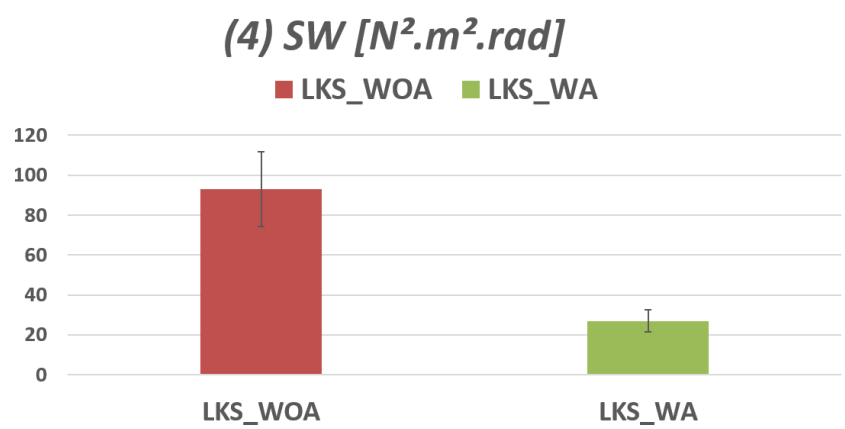
Objective evaluation results

Subjective evaluation results









Démonstrateur CoCoVeIA



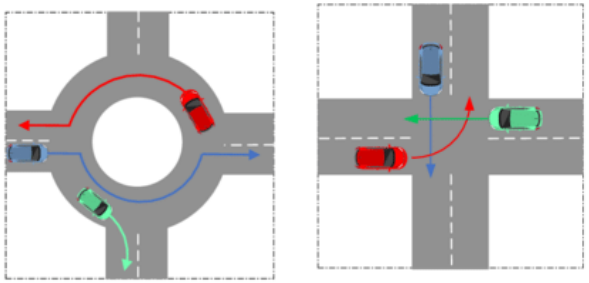
Conclusion

Personalizing an automated driving system involves:

- Integrating progressive self-learning capabilities to:
  - Personalize system decision-making
  - Personalize trajectory planning
  - Personalize haptic shared control
- Integrating high-level decisions into low-level control to ensure consistent and coherent vehicle behavior

Challenges currently being addressed

- Estimating driver capabilities and intentions remains an open challenge
  → *Driver diagnosis using set-based methods (parameter envelopes)*
- Extending the approach to more complex driving situations
  → *e.g., roundabouts, intersections, merging maneuvers*



- Developing fault-tolerant human-machine cooperation for safe and resilient automated driving
  → *Accounting for sensor uncertainties and actuator faults*


Merci...