

A cascade steering shared controller with dual-level dynamic authority

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Abstract: Advanced Driver Assistance Systems (ADAS) that consider the driver in the control loop (Shared Control ADAS) have the potential to influence upcoming functionalities in partially automated vehicles, improving the driving performance, reducing the workload, and increasing safety. According to the literature, two design parameters are relevant based on the cognitive level of the driving task. First, at the operational level, the steering controller must have a variable Level of Haptic Authority (LoHA), demanding more or less effort from the driver to override the system. Secondly, the tactical level needs an arbitration system to manage the transitions from manual-to-automated and automated-to-manual safely and progressively, with a variable Level of Shared Authority (LoSA). Based on these premises, this paper presents a cascade steering shared controller with a dual-level authority. The operational level consists of a hybrid MPC-PD controller, and the tactical level uses a Fuzzy Inference System (FIS). Results show the benefits of the system, assisting the driver in a collaborative overtaking maneuver.

Keywords: Shared control, arbitration, partially automated vehicles, driver-in-the-loop, authority transitions.

1. INTRODUCTION

Highly automated vehicles with non-compulsory human intervention are still under development, with a few more years ahead before being available for commercial users. In parallel, a research line on Advanced Driver Assistance Systems (ADAS) where driver and automation act jointly at the steering wheel (shared control systems (Abbink et al., 2018)) can have a high impact on future automated driving functionalities, adding cooperative continuous assistance to current ADAS which only provide momentary support (e.g., active lane-keeping). Also, these systems can support the driver during take-over maneuvers, which is an essential functionality in highly automated vehicles.

Motivations for shared control ADAS are many, e.g., recent crashes with the autopilot activated (Brown and Laurier, 2017), legal gaps regarding responsibilities in accidents, and drawbacks on driver resuming control (Saito et al., 2018). Conversely, considering the driver as an active control agent avoids these issues and can improve safety, comfort, and reduce workload in partially automated vehicles.

The development of these systems caught attention from different EU research projects such as HAVEit (Hoeger et al., 2008), the ABV Project (Sentouh et al., 2014), and recently, the PRYSTINE (Programmable Systems for

Intelligence in Automobiles) project (Druml et al., 2018). PRYSTINE main objective is the fusion of camera, radar, and LiDAR to provide a fail-operational perception of the external environment. Within this scope, different use cases are presented, including one based on shared control ADAS. PRYSTINE goes beyond the state-of-the-art by providing and implementing a framework that combines the control cooperation with additional modules that enhance the driver-automation interaction. The framework includes the following sub-systems:

- **Driver Monitoring System (DMS):** evaluates the state of the driver and his/her need for assistance.
- **Arbitration:** distributes the control authority between driver and automation.
- **Shared controller:** supports the driver with torque guidance-feedback at the control level.
- **Human-Machine Interface (HMI):** Informs the driver through visual, haptic, or audio signals, about the situation awareness of automation.

The focus of this paper is on the Shared Control System shown in Fig. 1, which comprehends two modules according to the cognitive level of the driving task (tactical and operational). These levels are part of the human-machine cooperation framework presented by Flemisch (Flemisch et al., 2019). This framework has been used previously in lane-keeping and obstacle avoidance systems (Benloucif et al., 2019; Sentouh et al., 2018; Guo et al., 2018). In these works, the operational level includes a lane-keeping

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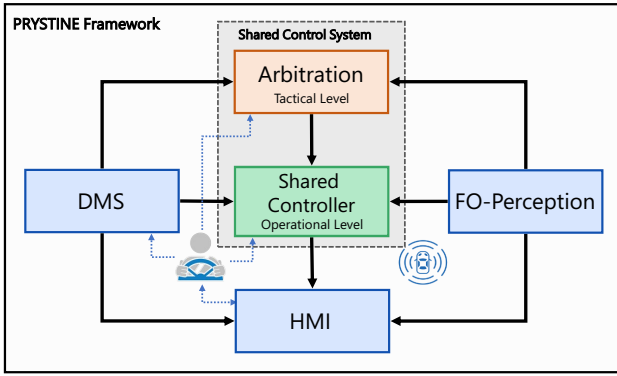


Fig. 1. PRYSTINE shared control framework

controller that uses optimization control techniques. On the other hand, the tactical level calculates the level of authority as a continuous value from 0 (manual) to 1 (automated) to activate and deactivate the controller. This work contributes to both cognitive levels as follows.

At the *operational level*, as a complement to the lane-keeping controller (that minimizes the tracking errors), a second controller increases the stiffness around the optimal steering wheel angle, demanding more driver effort to override automation. This additional authority is known as the Level of Haptic Authority (LoHA) (Scholtens et al., 2018). Increasing the LoHA is beneficial when the automation intervenes to preserve safety (e.g., preventing a lane change when a vehicle is in the blind spot). Previously, the LoHA as a complementary controller has been used along with model-free controllers (van Paassen et al., 2017), with a fixed value, and with no considerations on stability issues. We enrich the operational level considering the LoHA together with a model-based controller using the optimization framework of Model Predictive Control (MPC), with a variable value, and considering control stability.

At the *tactical level*, an arbitration module negotiates the vehicle control authority between driver and automation. Previous works use conditional rules (Guo et al., 2018), and mathematical formulas (Nguyen et al., 2018) to change the authority. However, these strategies present limitations when adding more than two variables, but the authority decision can depend upon multiple aspects (e.g., driver status, vehicle state, risk of collision, driving environment, and others). The present work contributes to the tactical level with an arbitration module based on Fuzzy-Inference-Systems (FIS), which allows for a more practical way to design a multi-variable decision system while including human knowledge into the design rules. For its validation, the fuzzy logic system is compared against conditional on/off switching methods (with and without delay) evaluating comfort and conflict at the steering wheel.

This paper has the following structure: Section II presents the design of the cascade shared controller framework; Section III describes the operational level controller; Section IV explains the arbitration module for authority transition; Section V presents the use case of collaborative overtaking; Section VI shows the performance of the shared control system; Section VII presents the conclusions and the future work in shared control ADAS.

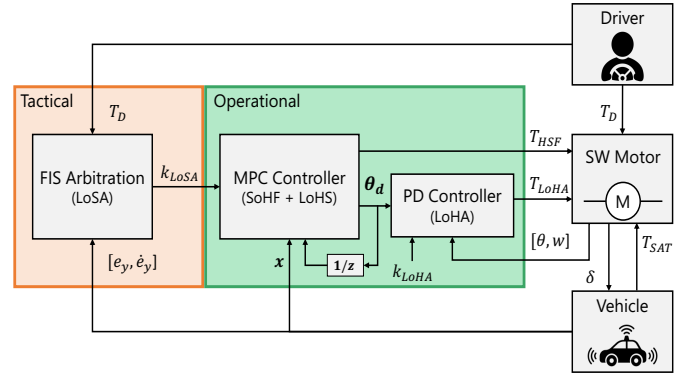


Fig. 2. Cascade shared control framework (dual-authority)

2. CASCADE SHARED CONTROL FRAMEWORK

Fig. 2 presents the shared control system, with emphasis on the operational and tactical level of the driving task (Flemisch et al., 2019). Additionally, it includes concepts from the haptic shared control framework developed in (van Paassen et al., 2017), which not only considers the feedback controller but recognizes four design choices for the shared control driving mode. The first is to design a trajectory based on human driving patterns. The other three refer to the following control-related concepts:

- **Level of Haptic Support (LoHS):** The torque feed-forward contribution against future disturbances.
- **Strength of Haptic Feedback (SoHF):** The torque feedback contribution to minimize the tracking errors.
- **Level of Haptic Authority (LoHA):** The torque required to deviate from the optimal control set point.

In our framework, the LoHS and the SoHF relate to the MPC control torque of Section III.1, which will herein be referred to as Haptic Support-Torque (T_{HSF}). The LoHA is given by a Proportional-Derivative (PD) controller, implemented in cascade architecture with the MPC. At the tactical level, a FIS-based arbitration module, which considers driver intention, handles the transitions of authority in an overtaking scenario, from manual-to-automated and automated-to-manual. In this sense, we define a second authority (at the tactical level).

- **Level of Shared Authority (LoSA):** The degree of operational authority given to the whole system, varying from 0 (manual) to 1 (automated)

The shared authority system is described in the next sections with the design and implementation of the shared controller and the arbitration system.

3. SHARED CONTROLLER OPERATIONAL LEVEL

This section describes the design of the operational level of the shared controller. First, the SoHF and LoHS are considered within the design of the MPC lane-keeping controller, as this control technique presents both feedback and feed-forward behaviors. Additionally, the LoHA is included in the control framework using a PD controller.

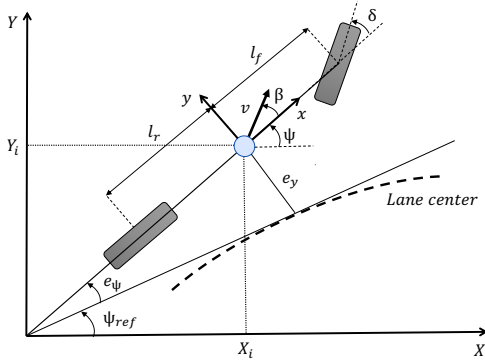


Fig. 3. Vehicle kinematic and lane keeping model

3.1 MPC Controller (SoHF and LoHS)

MPC is a common tool in autonomous driving controllers (Matute et al., 2019), and specifically to shared control applications, it appears in relevant works (Guo et al., 2018; Ercan et al., 2017). It is a model-based method that iterates to minimize an objective function in a finite-horizon, considering states and control inputs constraints. Its design comprehends two main considerations: the system model and the optimization problem formulation.

System model: The representation of the system is done through differential equations of three sub-models (vehicle, lane-keeping, and steering motor) that results in the single road-vehicle model illustrated in Fig. 3.

The *vehicle model* is represented with the bicycle kinematic equations (Kong et al., 2015) considering side-slip angle (β) as an algebraic state of the system (1). The position of the vehicle in the global coordinate frame is (X, Y) , with the respective heading angle (Ψ). The velocity of the vehicle center of gravity (v) has its longitudinal and lateral components (v_x, v_y) in the relative frame, considered as system states dependent upon the forward and lateral accelerations (a_x, a_y). The vehicle length (L) and the distance from the center of gravity to the rear axle (l_r) are part of the equations:

$$\begin{aligned} \dot{X} &= v \cos(\Psi + \beta) \\ \dot{Y} &= v \sin(\Psi + \beta) \\ \dot{\Psi} &= (v/l_r) \sin(\beta) \\ \dot{v}_x &= a_x \\ \dot{v}_y &= a_y \\ \beta &= \tan^{-1}((l_r/L) \tan(\delta)) \end{aligned} \quad (1)$$

The *lane-keeping model* (Rajamani, 2011) is described using derivatives of lateral (e_y) and angular (e_Ψ) errors, as in (2). It requires the use of the road curvature (k), which is obtained from the reference trajectory calculated offline using splines curves. Considering tracking errors reduces the number of optimization states of the MPC related to the lane-keeping task, using the tracking vector $[e_y, e_\Psi]$ instead of $[X, Y, \Psi]$. It also facilitates the inclusion of the road boundaries as state constraint ($e_{min} < e_y < e_{max}$).

$$\begin{aligned} \dot{e}_y &= v_x \sin(e_\Psi) + v_y \cos(e_\Psi) \\ \dot{e}_\Psi &= \dot{\Psi} - \frac{k}{1 - k e_y} (v_x \cos(e_\Psi) - v_y \sin(e_\Psi)) \end{aligned} \quad (2)$$

The *steering model* allows adding the steering torque as the control signal instead of the steering angle (δ). This is beneficial for shared control applications, as steering angle controllers perceive the driver intervention as a disturbance to the system (Nagai et al., 2002). The inertia (J) and damping (b) second-order model is used as in equation (3), where w is the steering wheel angular velocity, and $\theta = n_s \delta$ is the steering wheel angle, with n_s being the constant steering ratio. It also considers a linear approximation of the self-aligning torque $T_{sa} = k\theta$, and includes the torque of control $T = T_{HFS}$ as part of the model.

$$\begin{aligned} \dot{\theta} &= w \\ \dot{w} &= \frac{-1}{J} (bw + k\theta - T) \end{aligned} \quad (3)$$

Optimization problem: It comprehends different objective functions related to tracking performance, driving comfort, and controller efficiency. The structure is shown in the equation (4):

$$\begin{aligned} \min_U & \sum_{i=1}^{N+1} z_i^T Q z_i + \sum_{i=1}^N [\Delta u_i^T R \Delta u_i + u_i^T S u_i] \\ \text{s.t.} & \quad \tilde{\mathbf{x}}_i = f(\mathbf{x}_i, \mathbf{u}_i, \mathbf{p}_i), \quad i = 1, \dots, N \\ & \quad \tilde{\mathbf{x}}_{min,i} \leq \tilde{\mathbf{x}}_i \leq \tilde{\mathbf{x}}_{max,i} \\ & \quad \mathbf{u}_{min,i} \leq \mathbf{u}_i \leq \mathbf{u}_{max,i} \\ & \quad \Delta \mathbf{u}_{min,i} \leq \Delta \mathbf{u}_i \leq \Delta \mathbf{u}_{max,i} \end{aligned} \quad (4)$$

The non-linear function f represents the road-vehicle model described from (1) to (3). The states vector of the system is $\mathbf{x} = [X, Y, \Psi, e_y, e_\Psi, \theta, w]$. The states optimization vector is $\mathbf{z} = [e_y, e_\Psi]$, which represent the trajectory tracking objective. In addition, the input vector $\mathbf{u} = T$ is optimized along with its change rate $\Delta \mathbf{u} = \Delta T$ for efficiency and comfort. All objective functions are minimized to 0. On the other hand, the states constraints vector $\tilde{\mathbf{x}} = [e_y, \theta, w]$ sets the physical limits of the steering wheel, in terms of position and velocity. Also, the lateral error equation allows adding the lane boundaries of the road as constraints. The optimization weight matrices correspond to the tracking performance $Q = \text{diag}(w_{e_y}, w_{e_\Psi})$, the control torque $S = w_T$, and the torque rate of change $R = w_{\Delta T}$. The use of $\mathbf{p} = [a_x, a_y, k_{LoHA}, k, \theta_d]$, the exogenous input vector, offers additional information to the controller. The first three components are constant vectors of dimension $N + 1$. The prediction of road curvature k is calculated using the reference trajectory and the MPC predictions of states $[X, Y]$. The desired steering angle vector at the next time step $\theta_d(t_{k+1})$ is the steering angle prediction of the MPC in the current time-step, as in (5).

$$\theta_d(t_{k+1}) = [\theta_2(t_k), \dots, \theta_N(t_k), \theta_{N+1}(t_k), \theta_{N+1}(t_k)] \quad (5)$$

3.2 PD-Controller (LoHA)

The LoHA is defined as the authority that the automation has over the control output (van Paassen et al., 2017;

Scholtens et al., 2018). Related to steering control, it refers to how rigid is the system around the desired steering angle. The higher the LoHA, the more difficult for the driver to deviate from the optimal control set point.

Some previous works include the LoHA proportional to the lateral error (Della Penna et al., 2010). In our approach, the MPC calculates the prediction of its states, providing a vector of predictions of optimal steering wheel angles, as shown in equation (5). From this vector, the current desired angle (θ_d) is taken as the first prediction ($\theta_d = \theta_2(t_k)$) which is the predicted angle value 50 ms ahead according to the MPC sample time configuration. Using this information the LoHA can be defined as follows:

$$T_{LoHA} = k_{LoHA}(\theta_d - \theta) \quad (6)$$

In this sense, the LoHA is effective when the driver acts over the steering deviating from the optimal steering position calculated by the MPC. Using this strategy, the HFS and the LoHA are congruent and related through the optimization of the MPC objectives. The LoHA is included in the model through the second-order equation of the steering system represented in (7a).

$$J\ddot{\theta} + b\dot{\theta} + k\theta = T_{HFS} + T_{LoHA} \quad (7a)$$

$$J\ddot{\theta} + b_{eq}\dot{\theta} + (k + k_{LoHA})\theta = T_{HFS} + k_{LoHA}\theta_d \quad (7b)$$

The new equivalent stiffness value around the center position is $k_{eq} = k + k_{LoHA}$. However, the inclusion of the LoHA to increase the authority makes the system prone to become unstable. In this sense, it is useful to consider the damping ratio formula for the system in (3), to obtain the parameter $\xi = b/2\sqrt{Jk}$, which informs about the stability behavior. To avoid oscillations, we propose to keep the initial damping ratio which is now calculated as $\xi = b_{eq}/(2\sqrt{J(k + k_{LoHA})})$, using equation (7b), and results in the equivalent damping value of equation (8)

$$b_{eq} = b\sqrt{\frac{k + k_{LoHA}}{k}} \quad (8)$$

In this sense the designed LoHA will have the form of equation (9), where the second term is included in the system either via configuration of the steering wheel dynamic damping coefficient or by sending a complementary torque signal with the appropriate filtering process.

$$T_{LoHA} = k_{LoHA}(\theta_d - \theta) + (b_{eq} - b)w \quad (9)$$

4. ARBITRATION SYSTEM TACTICAL LEVEL

The strong cooperation between driver and automation in shared control requires a mediator that assigns the proper authority in each situation. Arbitration in the context of cooperative vehicle guidance is a time-critical structured negotiation between the human and the machine, that achieves, in good time, a clear and optimum goal for the overall system (Loper et al., 2008). It is necessary to harmonize the control actions of the driver and the vehicle controller at the tactical level (Gonzalez et al., 2017).

Table 1. Arbitration FIS rules (k_{LoSA})

e_y		<i>Low</i>			<i>Medium</i>			<i>High</i>			k_{LoSA}
		\downarrow	$-$	\uparrow	\downarrow	$-$	\uparrow	\downarrow	$-$	\uparrow	
T	$= 0$	A	A	A	A	T	M	M	M	M	k_{LoSA}
	> 0	T	T	T	T	M	M	M	M	M	

In the overtaking maneuver presented in this article, the arbitration module manages the authority transitions. First, from automated-to-manual mode, when departing to the left lane, and second, from manual-to-automated mode when the driver returns to the main lane. These transitions require a tactical level of shared control that cooperates with the operational level, through the k_{LoSA} .

The tactical level of shared control was previously used for the transition of authority considering lateral error and driver torque effort, evaluated through conditional rules or mathematical functions (Benloucif et al., 2019). The lateral error notifies the state of the vehicle regarding the lane objective, while the torque provides feedback on the driver's intention and effort. Our approach proposes the inclusion of the derivative of the lateral error as an indicator of the maneuver state (departing from/returning to the lane), using the fuzzy logic technique.

4.1 FIS Arbitration (LoSA)

Fuzzy Inference Systems (FIS) provides a solution for including human knowledge into the design of automated driving functionalities (Perez et al., 2011). It is done through a set of membership functions and linguistic if-then-rules that describe the behavior of the system. The arbitration module proposed in this section is composed of three inputs [e_y, \dot{e}_y, T_d] with three membership functions for the error states, and two for the driver torque. The output of the system is the LoSA gain (k_{LoSA}), a continuous value from 0 (manual mode) to 1 (automated mode) representing the authority given to the operational level. The design rules are shown in Table 1.

The lateral error (e_y) is defined by the set [*Low*, *Medium*, *High*], with *Low* being closer to the right lane, and *High* corresponds to left lane. The derivative of lateral error (\dot{e}_y) shows whether the vehicle is approximating to the right lane (\downarrow), parallel to it ($-$), or getting away from it (\uparrow). The driver torque indicates if there is conflict (> 0) or not ($= 0$). The output of the fuzzy system gives three options for k_{LoSA} , which represent an automation state [Manual (M), Transition (T), Automated (A)]. At this point, it is assumed that a high-level decision-making module, receives inputs from the external and in-cabin sensors to determine driver state and risk of collisions to indicate whether the transition is possible or not. Our assumption is that the overtaking is safe.

4.2 Parameter for transition

The basic form to link the operational and tactical levels is via multiplication $k_{LoSA}(T_{HFS} + T_{LoHA})$. Nonetheless, using the weight matrices of the MPC to make the authority transitions is more beneficial, as it does the work while keeping the constraints of the MPC active (e.g., the lane

borders limits). A previous work (Guo et al., 2018) uses the weight matrix of the optimized states ($\tilde{Q} = k_{LoSA}Q$), if $k_{LoSA} = 0$ the tracking objective has no effect and the torque is null (manual mode). However, this matrix involves more states than just tracking errors, which could lead to unknown system behavior. In this context, using the weight matrix of the control input ($\tilde{S} = k_{LoSA}S = k_{LoSA}w_T$) allows for control transitions under a controlled behavior, as it only modifies one variable. A high enough value of w_T minimize all torques of control to zero which corresponds to manual mode. After some experimental tests the following values are identified for $w_T = 10^z$. For $z = -0.5$ the system operates in automated mode ($k_{LoSA} = 1$), and with $z = 3$ the vehicle is in manual mode ($k_{LoSA} = 0$). It results in the following relation $z = f(k_{LoSA}) = -3.5k_{LoSA} + 3$.

5. USE CASE

This section presents the implementation of the shared controller with the configuration shown in Table 2. The performance is tested using the Driver in the Loop (DiL) automated driving platform of Fig. 4. The vehicle simulation software is Dynacar (Iglesias-Aguinaga et al., 2013), an integrated solution for the design of electric vehicles that features a vehicle physical model based on multi-body formulation. It is integrated with Matlab/Simulink for the development of the control/decision algorithms. The ACADO Toolkit (Houska et al., 2011) is the solver of the MPC optimization problem. The steering wheel used for the tests is part of the Augury H Kit, including a motor model 130ST with a nominal torque of 15 N.m, and with variable damping and inertia via software configuration.

One driver completed the experimental tests to validate the operational and tactical levels of the shared control framework. The first test evaluates the performance of the steering torque controller with different LoHA values. The second test evaluates the arbitration module, analyzing transitions from automated-to-manual, and manual-to-automated. All driving sessions had automatic longitu-

Table 2. Shared controller design parameters

System	Symbol	Name	Value
Vehicle	L	Length of vehicle	3.05 m
	l_r	Length CoG to rear	1.65 m
Steering	J	Motor inertial	0.075 Kg.m ²
	b	Motor damping	0.75 N/rad/s
	k	Self-aligning gain	3
	n_s	Steering ratio	8.45
MPC	N	Horizon length	30
	T_s	Sample time	0.05 s
	w_{e_y}	Position weight	5e3
	w_{e_ψ}	Heading weight	3e1
	w_T	Torque weight	1e(-0.5)
	$w_{\Delta T}$	Torque rate weight	1e(-2.5)
	θ_{lim}	Steering limit	± 7.854 rad
	w_{lim}	Speed limit	± 5.5 rad/s
	T_{lim}	Torque limit	± 10 N.m
	ΔT_{lim}	Torque rate limit	± 10 N.m/s
	e_{ylim}	Lateral error limit	$[-2, 6]$ m



Fig. 4. DiL automated driving simulator

dinal control at 10 [m/s], and the driver interacting with automation only at the steering wheel.

5.1 Overtaking maneuver

Fig. 5 shows the collaborative overtaking maneuver. It comprehends five stages and two modes of authority transition. First, the automated system is supporting the driver in the lane-keeping task (1). Secondly, the driver performs a lane change, and a gradual transition from automated-to-manual takes place (2). Once the vehicle is on the left lane, the driver has full control (3). Then, when it returns to the right lane, the authority is increased fluidly from manual-to-automated (4). Lastly, the driver-automation system returns to the initial state (5).

6. RESULTS

6.1 Operational Level Authority Test

Section III presented the design of an MPC shared controller with variable LoHA and considerations of stability. To test this controller, the driver performed an overtaking maneuver in automated mode with different LoHA. Initially, the driver starts with the hands on the wheel, until the distance to the front vehicle is 20 m. A vibration on the steering notifies the driver to start the overtaking. Then, the controller remains activated to measure the torque effort. Once the driver has overtaken the other vehicle by 10 m, a new vibration indicates to release the steering and let the automated system to return to the lane. It allows testing the stability of the controller.

In the first tests the driver completed five overtaking maneuvers with different $k_{LoHA} = [0, 5, 10, 15, 20]$, with a constant damping coefficient (b), which is the default damping of the steering system. Fig. 6 (left side) shows the results of the tests. The first conclusion is that, as expected, increasing the LoHA requires a greater effort

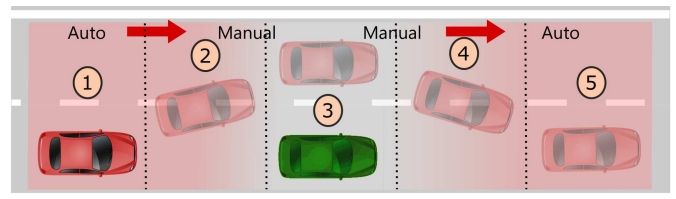


Fig. 5. Collaborative overtaking maneuver and transitions

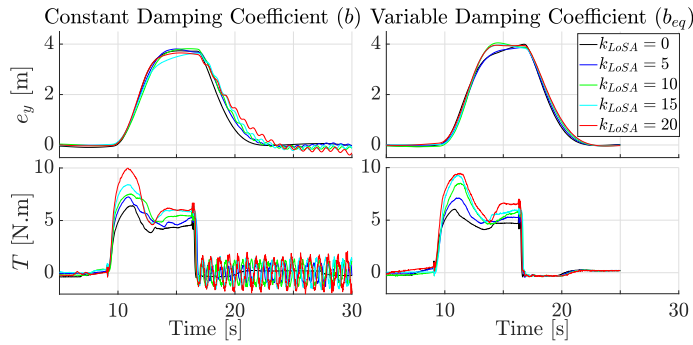


Fig. 6. LoHA tests with constant and variable damping

from the driver to do the maneuver. However, for higher authorities, when the driver releases the steering wheel, the system loses stability. It is important to notice that the original controller ($k_{LoHA} = 0$) is stable and the oscillations start when $k_{LoHA} > 0$.

The second set of tests included equation (9) to add stability to the system. The steering system damping coefficient is thus varied (b_{eq}) through the configuration of steering motor parameters. It allows keeping the damping ratio (ξ) of the original stable configuration when the stiffness increases by the LoHA. Fig. 6 (right side) shows that preserving the initial ξ eliminates oscillations and makes the vehicle lane-keeping stable for different k_{LoHA} .

6.2 Tactical Level Authority Test

The tests to evaluate authority transitions include four modalities to shift from manual-to-automated and automated-to-manual using the variable parameter k_{LoSA} calculated by the arbitration system. Those modalities are:

- (1) **No transition:** The controller is activated during all the overtaking maneuver.
- (2) **On/Off:** The controller is deactivated if $T_d > 4$ [N.m] when departing the lane, and activated if $\dot{e}_y < 0$ and $e_y < 2$, when returning to the lane.
- (3) **On/Off + filter:** The transitions are the same as on/off mode, with a first-order filter with $\tau = 2$ s.
- (4) **FIS:** The transition considers information of the triple input fuzzy system presented in Section IV.

The driver performs three tests with each mode of operation. Fig. 7 shows the representative results of the experiments to compare the authority transitions strategies. The test procedure is similar to Section VI.1. The vibration in the steering wheel notifies the driver when to make the lane change for the overtaking, but in this case, the driver never releases the hands from the steering wheel and guides the vehicle back to the lane.

The first mode of operation (No transition), demands the higher driver torque effort (T_D) as expected, however, in terms of comfort, it shows the best results based on the lateral acceleration and angular steering velocity. By contrast, the on/off modes demands less driver effort, but the sudden deactivation of the controller shows the largest peaks on steering wheel velocity and the lateral acceleration. Adding a 2 s filter does not reduce the peaks at the first transition, but it improves the comfort when the driver returns to the lane.

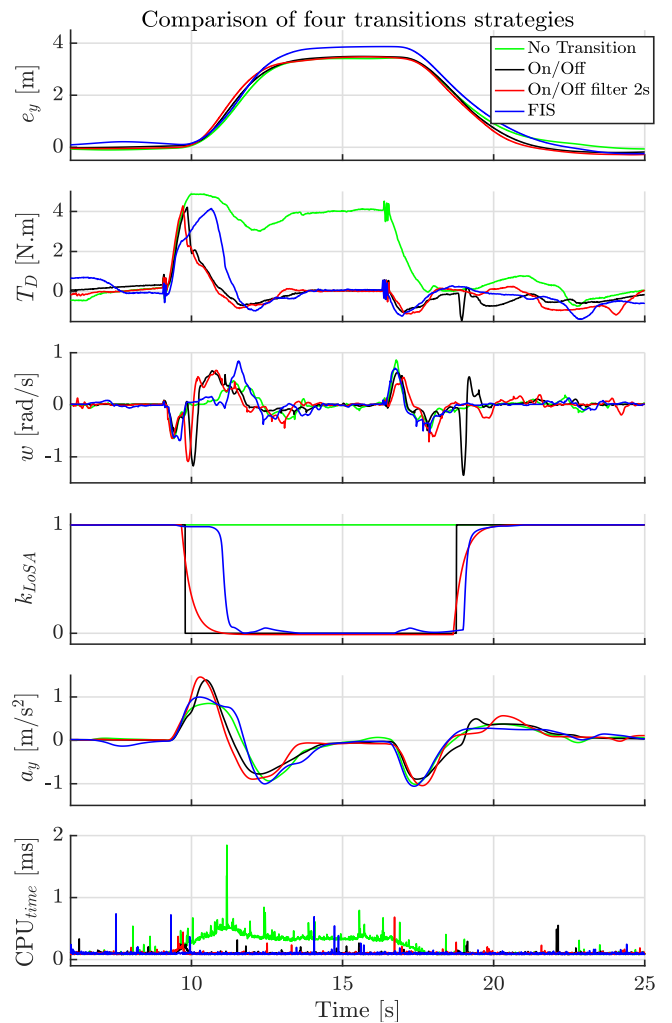


Fig. 7. LoSA tests with four transition strategies

The fuzzy arbitration system shows the best compromise between driver effort and comfort. The torque sensed at the steering wheel is lower than in automated mode, though slightly higher than the on/off strategy, which is a good indicator since it helps to avoid unintended transitions. Additionally, the comfort parameters are close to the automation mode that was optimal in this category, in both types of transitions (2nd and 4th stage of Fig. 5).

Fig. 7 shows that the change in w_T for the authority transitions does not impact the computational time (CPU_{time}) required to find the optimal MPC solution. However, in automated mode, this time increases because when the driver is on the left lane, the solver can not minimize the tracking objective function. Nonetheless, the $CPU_{time} < 1$ [ms] is suitable for a control loop of 10 [ms].

7. CONCLUSION

This paper presented a cascade steering shared controller with two levels of dynamic authority, developed under the framework of model-based optimization control. The tests assessed the performance of the LoHA at the operational level and the LoSA at the tactical level.

Implementing a proportional LoHA caused the system to lose stability. The solution was to modify the damping of

the steering wheel with the damping ratio formula. Results show that the controller with higher LoHA keeps the lane-keeping performance and stability, with a higher demand for driver effort. This controller is useful when the authority has to increase to correct driver maneuvers with a high risk of collision, for example, in a blind spot scenario. Additionally, a FIS-based arbitration module manages the authority transitions at the tactical level (LoSA) in a collaborative overtaking. The FIS design shown the best compromise between effort and comfort compared to full automation and binary switching strategies, in transitions from manual-to-automated, and automated-to-manual.

In future works, the framework will include a dynamic vehicle model to perform tests at higher speeds, and with different road curvatures. Including the longitudinal control of the vehicle in the optimization framework is a future improvement. Also, considering the driver state is a clear next step for the experimental validation of different use cases, which are of interest in the development of Shared Control ADAS for partial/conditional automation.

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