Traded Control Architecture for Automated Vehicles Enabled by the Scene Complexity Estimation

Juan Felipe Medina-Lee[a], Jorge Villagra[b] and Antonio Artuñedo[c]
Autopia Program, Centre for Automation and Robotics (CSIC), Ctra. M300 Campo Real, km 0.200, Arganda del Rey, Spain

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Abstract: A number of urban driving situations are still today too challenging to be handled by an autonomous driving system (ADS), and an intervention from humans inside the vehicle may be necessary. In this work, a novel traded control architecture is proposed to enhance the operational domain of the ADS under the premise that vehicles and humans may need to adapt their cooperation level depending on the context. To that end, a complexity level will be defined and computed in real time for each driving scene, and the role of the ADS and the human operator will be defined accordingly. With this information in hand, the system will alert the human operator when the involvement level will be lower than required or when a complex scene is detected.

1 INTRODUCTION

Different autonomous driving systems (ADS) have been introduced over the last years. Although these systems have shown benefits like safety or comfort, they still need intervention from the human operator to handle all possible situations. The trading of control is suitable for situations when the actor that has the authority over the vehicle (ADS or human operator) is not able to handle the situation anymore (Chao huang, fazel Naghdy, 2019). This responsibility shift may lead to wrong and even unsafe behaviors if the situation awareness of the human operator is not high enough during the handover situation (Drexler et al., 2020).

Contrarily to shared control, traded control refers to a scheme where a specific task is entirely performed by a unique agent, either human alone or automation alone (Inagaki, 2003). For trading of control to be implemented, it is necessary to decide when the control must be handed over and to which agent; who makes the decision on the authority arbitration is also important (Muslim and Itoh, 2019). This still remains one of the greatest challenges for assistive technologies in automobiles (Inagaki and Sheridan, 2018).

Mutual understanding is the essence of trading control systems. As a result, the ADS shall be able to perceive the driver status in order to perform different driving tasks and make safer decisions, and the human operator must easily understand the goals and capabilities of the ADS (Muslim and Itoh, 2019). This is addressed in (Lindemann et al., 2018) by implementing an augmented-reality windshield display to increase the situation awareness of the human operator by showing him/her the ADS status. In (Sonoda and Wada, 2017) the authors use vibro-tactile devices that enable the human operator to predict or perceive actions selected by the ADS, increasing also the situation awareness and the trust in the automated decisions.

Human-machine interaction has been addressed with a wider scope in some recent EU-funded research projects. (AutoMate-project, 2019) focuses on driver-automation interaction and communication with other vehicles for high levels of driving automation. In this context, different degrees of cooperation are introduced to achieve a successful human-machine interaction. In contrast, (Vi-DAS-project, 2019) focuses on the development of intuitive HMI to warn and assist the driver in anticipating potentially critical events by applying the latest advances in sensors, data fusion and machine learning. Moreover, (ADAS&ME-project, 2019) addresses the transition between different levels of driving automation, considering the driver state with regard to its attention, visual/cognitive distraction, stress, workload, emotions, sleepiness and fainting.

This work, framed in EU-funded PRYSTINE

[a] https://orcid.org/0000-0003-4489-4280
[b] https://orcid.org/0000-0002-3963-7952
[c] https://orcid.org/0000-0003-2161-9876

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project (Druml et al., 2019), explores an alternative view where vehicles and humans may need to adapt their cooperation level depending on the context. To that end, it defines and assigns a Complexity Level (CL) to each driving scene in real time and defines the role of the ADS and the human operator accordingly. The CL of the scene depends on the number and quality of the trajectory candidates generated by the ADS, which is significantly different when driving into a highly occupied roundabout than navigating on a highway at off-peak hours. When the CL decreases, the proposed ADS changes the level of driving automation accordingly, and can handle more driving tasks without human intervention. Nevertheless, the human operator must be prepared for an eventual system-to-human transition of control to avoid undesirable consequences (Biondi et al., 2019); for that reason, in this work, a driving monitoring system (DMS) is constantly estimating the involvement level of the human operator. With this information in hand the ADS may generate a warning when the involvement of the human is lower than recommended, so the situation awareness is kept in safe levels.

The remainder of the paper is as follows: section 2 presents a review of the ADS implemented by Autopia Program. Section 3 describes the traded control architecture proposed in this work. Finally, section 4 analyses the results in a simulated urban scenario.

2 AUTOMATED DRIVING ARCHITECTURE

The traded control system is embedded in the Autopia program's autonomous driving architecture (Artunedo, 2019). This chapter reviews the main components of that architecture in order to provide the reader the necessary background for the remainder of the paper. The functional diagram of Figure 1 depicts the main components of the autonomous driving architecture.

The ADS interacts with both the ego-vehicle and the human operator. The interaction with the ego-vehicle consists of reading the sensors and handling the actuators in order to conduct the driving process in a safely and comfortable way. The system interacts with the human operator using an on-board HMI and a Driving Monitoring System (DMS) that estimates its drowsiness level.

The *perception and motion prediction* module merges information from different ego-vehicle sensors like LiDARs, GPS and propioceptive sensors into a dynamic occupancy grid that stores occupied space and objects' dynamic information. This module also applies signal processing techniques to obtain a reliable localization estimation. Finally, it predicts the traffic agents motion by considering their inter-dependent behaviours in a probabilistic framework (Villagra et al., 2020).

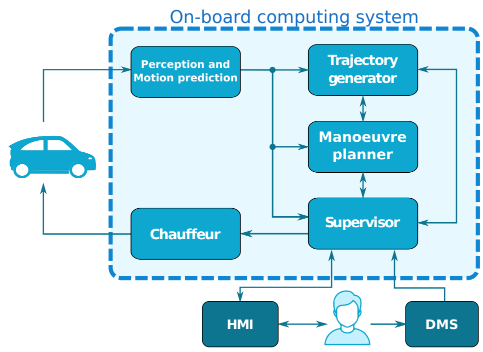


Figure 1: Autonomous driving architecture for Autopia Program.

The *trajectory generator* module creates a set of safe and comfort-optimized trajectories for the current traffic scene. The path candidates are generated using Bézier curves and the speed profiles are computed taking into account the reachable states of dynamic obstacles, the traffic regulations and comfort parameters. A complete description of the trajectory generation module is presented in (Medina-lee et al., 2020). The quality of each candidate is quantified using four decision variables: longitudinal comfort, lateral comfort, safety and utility. Each decision variable is obtained by combining a set of Trajectory Performance Indicators (TPI) like accelerations, jerks, closeness to obstacles, smoothness, among others. The TPI are normalized scalar values from 0 to 1, summarized in Table 1.

Each decision variable $DV_{(i,k)}, k \in [1,4]$ for a candidate i is computed by combining a number T_k of TPI, listed in Table (1), using a weighted geometric mean as follows

$$DV_{(i,k)} = \sqrt[T_k]{\prod_{j=1}^{T_k} f\left(TPI_{(i,j)}, \omega_j\right)}\ ,\ k = 1 \ldots 4 \qquad (1)$$

where ω_j are normalized values between 0 and 1.

The *Manoeuvre planner* module selects the best set of navigable corridors for the ego-vehicle (Medina-lee et al., 2020). It uses traffic information, obstacles on the scene and global route data to decide which of the available corridors are the most pertinent for the *trajectory generator* module. This hierarchical architecture allows the ADS to execute strategic manoeuvres like overtaking or adjusting the global route when a lane is blocked.

Table 1: Trajectory Performance indicators and Decision Variables of trajectory candidates.

Decision Variable	TPI
Longit. Comfort	Long. Accel. Avg.
	Long. Accel. Max.
	Long. Jerk. Avg.
	Long. Jerk. Max.
Lateral Comfort	Lat. Accel. Avg.
	Lat. Accel. Max.
	Lat. Jerk. Avg.
	Lat. Jerk. Max.
	Smoothness
Safety	Free Ride
	Safe chase
	Closeness
	Lane Invasion
Utility	Avg. speed
	Path Length
	Obstacle Free

The *supervisor* module is in charge of three main tasks, as depicted in Figure 2. The selection of the best trajectory candidate is performed by selecting the candidate that maximizes a merit function that combines the four decision variables. The traded control task decides the CL of the current scene and establishes the Level of Driving Automation (LoDA) for the ADS and the Required Involvement Level (RIL) for the human operator in the driving process. The HMI is used to display the current trajectory, important warnings, the required and current involvement levels and the ego-vehicle status. The human operator can use it to change the driving mode (manual or automated), to select the destination point and to perform a safe-stop manoeuvre. The traded control task is described in detail in the next chapter.

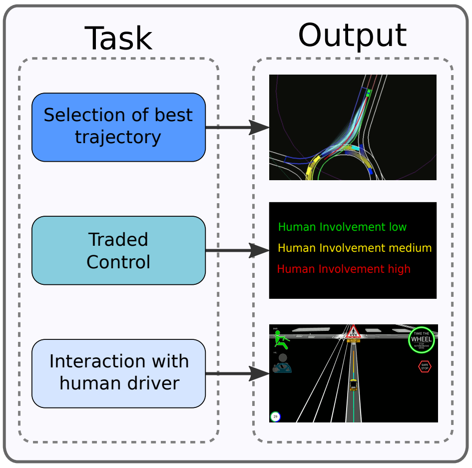


Figure 2: Supervisor functional diagram.

The *chauffeur* module is the low-level control for the vehicle. It receives the best trajectory from the supervisor and generates the necessary steering wheel, throttle and brake commands for the ego-vehicle to follow that trajectory. This control system has been already tested in a real car with good performances in (Artunedo et al., 2017).

3 TRADED CONTROL ARCHITECTURE

The traded control module determines the CL of the current driving scene, the LoDA and, ultimately, the proper RIL for the human operator. If the traffic scene is too complex, this module recommends the human operator to take over the wheel and pedals or it performs a safe-stop manoeuvre if the human is completely disengaged. The block diagram of Figure 3 depicts the different stages in this process, whose main components are detailed below.

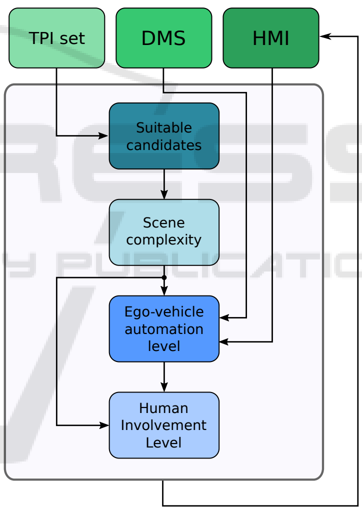


Figure 3: Traded control architecture.

3.1 Scene Complexity Level

The CL of the scene is estimated based on the quality of the candidate trajectory set. To that end, the concept of *candidate suitability* S_i is proposed in this work. A candidate is considered suitable if its decision variables are greater than predetermined thresholds, as shown below:

$$S_i = \begin{cases} 1 & if \;\; DV_{(i,k)} > thd_k \\ 0 & otherwhise \end{cases} \tag{2}$$

The percentage of suitable candidates is computed as the ratio between the number of *suitable* candidates and the number of *valid* candidates. A candidate is considered *valid* if it meets three requirements: the maximum curvature is feasible for the vehicle, it is collision-free and it fully remains inside the navigable space. This percentage of suitable candidates is used as an input of a finite state machine (FSM) to determine the CL of the scene (see Figure 4). In this work, four complexity levels are proposed: Complex, Medium, Simple and Basic. Once a CL state is reached, it is not possible to change to another state for a period of time, which is a configurable parameter of the ADS.

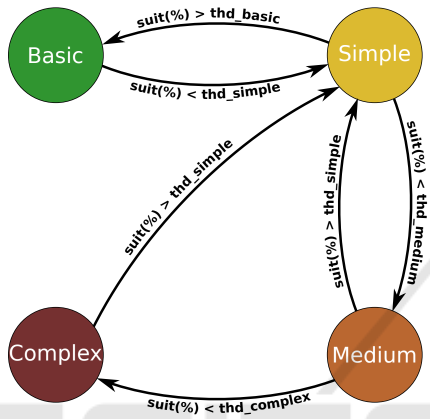


Figure 4: FSM for scene complexity level.

Note that if Complex state is reached, this state is maintained until the scene is considered Simple, so the behaviour of the FSM is more stable on complex scenarios.

3.2 Levels of Driving Automation

In this work, the Society for Automotive Engineers (SAE) J3016 standard (SAE International, 2016) is used as a starting point to define the levels of driving automation (LoDA). The LoDA 1 of the standard was not implemented because a driver assistance system is out of the scope of this project. Table 2 presents a description of the LoDA implemented in this architecture.

The proper LoDA for the ego-vehicle is automatically determined by the system using the FSM depicted in Figure 5. The transitions between states depend on the CL, on the reactivity of the human operator to the HMI requests and on the involvement level measured by the DMS system. A state named *safe-stop* is proposed to handle critical situations when the human operator is not involved at all, this state can only be reached from LoDA 4. Once the *safe-stop* state is reached, the speed profiles for the trajectories apply a constant deceleration until the ego-vehicle gets to 0 km/h. This state is maintained until the human operator uses the HMI to resume the autonomous driving or take over the wheel.

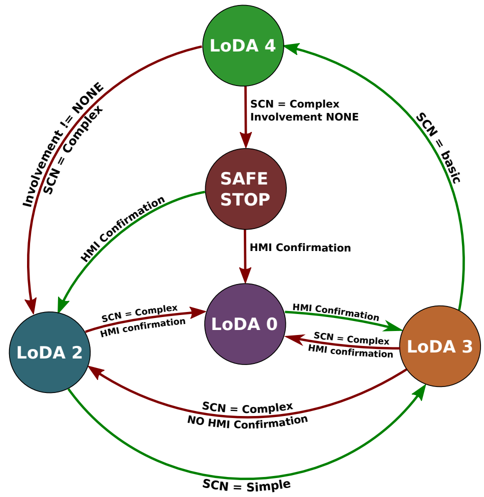


Figure 5: FSM for automation level.

3.3 Required Involvement Level

Once the CL and the LoDA are established, both variables are combined to propose an involvement level to the human operator, which can take 3 different values (none, medium, high). To that end, the correspondence matrix presented in Table 3is used.

Note that the higher the LoDA, the lower is the requested involvement from the human operator. In LoDA 4, no involvement is required from the human operator at all.

Finally, if the involvement level estimated by the DMS is lower than the one requested, an alarm will be prompted in the HMI.

4 EXPERIMENTAL RESULTS

The performance of the ADS was evaluated in an urban scenario with roundabouts and crossings in a realistic simulation environment using SCANeR Studio 1.9 software (AVSimulation, 2019).

4.1 Experiment Description

In the setup of the experiment, the ego-vehicle will first encounter a four-way intersection with two incoming and two outgoing vehicles (Figure 6(a)); it will then find a roundabout with two vehicles inside (Figure 6(b)) and, at the end, it will face a traffic-free

Table 2: LoDA implemented for the traded control task.

Automation level	Description
LoDA 0	Manual mode. The human operator is in charge of everything. The ADS only displays warnings on the HMI.
LoDA 2	Automated mode with conservative driving parameters. Safer candidates are chosen rather than risky ones. The ADS suggests the human operator to take over the wheel if the scene becomes complex. The RIL is high.
LoDA 3	Automated mode with normal-driving parameters. The ADS may suggest the human operator to take over the wheel if the scene becomes complex, but also can change to the highest LoDA if the scene has a basic complexity level. The RIL is medium.
LoDA 4	Automated mode with normal-driving parameters. The ADS may suggest the human operator to take over the wheel if the scene becomes complex, but if the driver is unable to take over the wheel, a safe-stop manoeuvre is performed. There is no RIL from the human operator to handle any situation.

Table 3: RIL according to the CL and LoDA.

	LoDA 2	LoDA 3	LoDA 4
Basic	Medium	Medium	None
Simple	High	Medium	None
Medium	High	Medium	None
Complex	High	High	None

roundabout (Figure 6(c)). All scenarios will be handled using automated modes (LoDA 2-4). In the proposed experiment, the ego-vehicle will face complex scenarios in a shorter period of time than it would in real-life driving.

The upper section of Figure 6 depicts a bird's eye view of the relevant scenes which includes the motion prediction of the traffic agents. The lower section of the figure show the simulation environment for the same scenes.

4.2 Automated Driving Results

Figure 7 shows the path followed by the ego-vehicle after the experiment. The colors on the path indicate the RIL along the journey. Red color is assigned to high RIL, yellow is associated to medium RIL and green refers to no RIL at all. The figure also highlights the location of the stop-lines crossed by the ego-vehicle.

Figure 7 shows a high RIL when the ego-vehicle was approaching or crossing critical scenarios. Medium RIL during the road between the intersection and the first roundabout. Finally, in the last section of the journey, the RIL was lower because there was no traffic. At the end of the experiment, when the ego-vehicle reached a highway scene, the RIL was none.

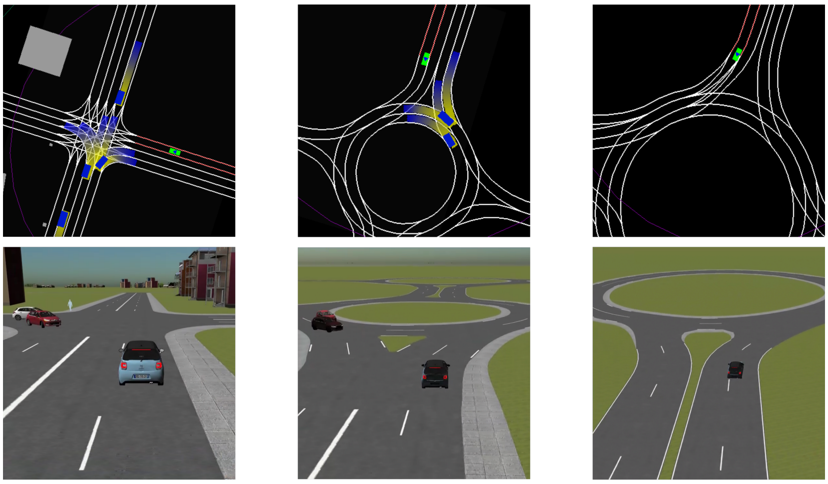
In the case of the four-way intersection, a complete involvement from the human operator was required 13,6s (t_{int} in Figure 8(a)) before reaching the stop-line; in the case of the first roundabout, this lead time was 12,29s (t_{rdt} in Figure 8(a)). According to (Naujoks and Neukum, 2013), the traded control had an acceptable performance, since the estimated time for average humans to take-over is between 6s and 10s.

Figure 8 plots the data of the traded control module during the experiment. This data includes: (a) Level of Driving Automation, (b) scene Complexity Level, (c) Requested Involvement Level and (d) measured involvement level of the human operator. The dotted vertical lines represent the stop-lines highlighted in Figure 6. Table 4 show the numeric equivalencies of Figure 8 for each traded control variable.

Table 4: Numeric equivalencies for the values of the traded control variables.

	Descriptive value	Numeric value
CL	Basic	0
	Simple	1
	Medium	2
	Complex	3
RIL	None	0
	Medium	1
	High	2

The ADS determines a LoDA 2 for crossing the intersection and the first roundabout. The second roundabout is handled with a LoDA 3 due to the absence of traffic. LoDA 4 is established in the final highway. The CL is increased in the difficult scenarios and decreased when no traffic or straight segments are faced, as expected. The RIL is high when approaching critical scenarios, so that the response time from the human operator can be reduced, if needed. The DMS data was artificially generated during the experiment in order to evaluate the system performance. The red shadows in 8(d) represent the moments where the HMI displayed an alarm because the



(a) *(b)* *(c)*

Figure 6: Experiment setup in simulation environment. Four-way intersection *(a)*. Roundabout with traffic *(b)*. And traffic-free roundabout *(c)*.

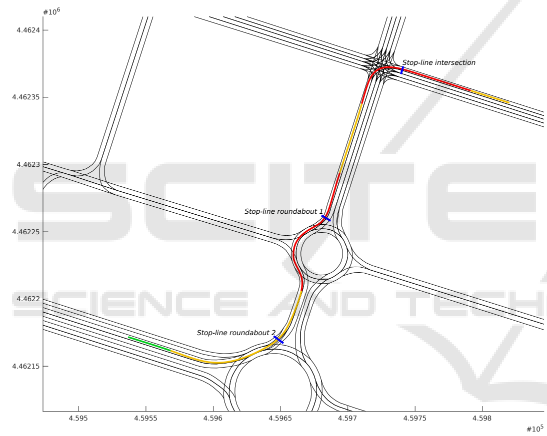


Figure 7: Complete trajectory followed by the autonomous vehicle.

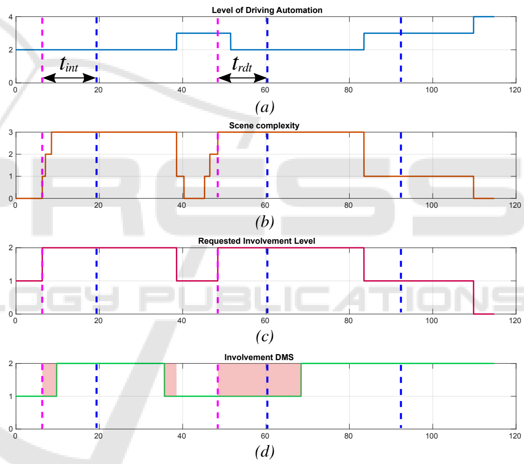


Figure 8: Traded control data for the proposed experiment.

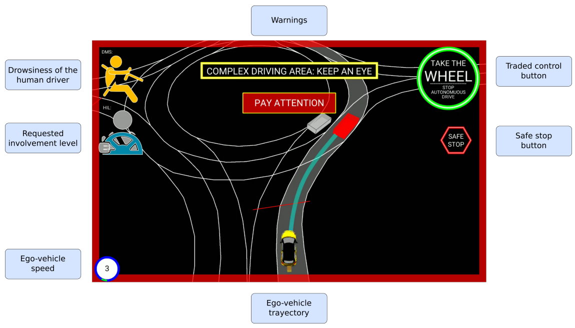


Figure 9: HMI warning due to low attention from the human operator.

involvement of the human operator was lower than the RIL. Figure 9 displays the HMI output in the entrance of the first roundabout of the simulation.

5 CONCLUSIONS

A novel traded control approach is presented, where the level of automation and the required involvement level of the driver is automatically determined from an estimation of the driving scene complexity level and the driver drowsiness estimation.

The proposed architecture interacts with the human operator using a HMI that displays warnings, RIL, and planning decisions. The human operator can also use the HMI to change the driving mode or to perform a safe-stop manoeuvre.

The implemented ADS was validated in an simulated urban scenario, where it was able to require higher involvement levels from the human when the scenes were more critical (approaching to an intersection or roundabout with traffic) with an average lead time of 13 sec.

Future work will focus on the evaluation of the approach on a real vehicle in open roads. To that end, the suitable candidates generation will be refined and adapted to the context, so that a higher number of operational domains can be handled and the user experience can be enhanced.

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