Modeling the Driving Behavior of Electric Vehicles Using Smartphones and Neural Networks

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Abstract

Human drivers in autonomous vehicles will monitor the system and be ready to resume control in ambiguous or emergency situations. As a driver's reaction time to intervene after having realized a problem has occurred can be critical, we present the Interactive Automation Control System (IACS) to assist the driver when their takeover is required. The system displays manual or automated mode in an unobstrusive location in the vehicle, signaling when a Take Over Request (TOR) is necessary. We evaluate the system's performance during a situation in which the automation has not been defined to operate and study its impact on the overall driving performance, specifically the driver's reaction time to a TOR. Results showed significant improvements in driving performance with the proposed system. Both the response time to the TOR and the number of collisions decreased when the IACS was activated. Subjective ratings of the system regarding its performance showed high satisfaction levels.

1 Introduction

The upward trend of automation in the automotive industry has been enormous in the last decade. Many renowned companies and car manufacturers have already produced vehicles that are equipped with conditional automation (level 3) according to the Society of Automotive Engineers (SAE) definition: "Driving mode-specific performance by an Automated Driving System (ADS) of all aspects of the dynamic driving task with the expectation that the human driver will respond appropriately to a request to intervene" [1].

Depending on the level of automation of the vehicle, the role of the driver includes monitoring the performance of the automation for potential failures, and remaining alert for conditions where intervention in the control of the vehicle is required, i.e., in situations that have not previously been considered in the algorithms and that the automation might not be able to handle [2]. Autonomous vehicles represent an opportunity to continue working towards the ultimate goal of increased road safety through automation in which driver intervention in the control of the vehicle is unnecessary [3]. Until this moment, the transition of control from autonomous to manual in conditional automation is a pressing issue that needs to be investigated. As described in [4] when acting as monitor of an automated system, a driver's response time and intervention after having realized a problem has occurred can be critical. Studies have confirmed that driver reaction time (RT) to visual stimuli did not return to its baseline performance level immediately after a period of distraction [5, 6]. Therefore, RT depends on whether the driver has been engaged in secondary tasks as well as the type of these tasks. Specifically, more time is required to assess the system state, understand what has occurred and react in an appropriate manner. Drivers need to be available for occasional control with a comfortable transition time [7] as a vehicle with conditional automation can ask the driver to take over the control at any time. The way of conveying the information related to the control transfer can add further complexity to the problem of reaction time. In order to assist the driver when control is relayed back to them, an emergency Take Over Request (TOR) can be triggered. To improve the driver's situational awareness while driving in automated mode, we describe and evaluate an Interactive Automation Control System (IACS). The system displays manual or automated mode in an unobstrusive location in the vehicle and signals when a TOR is required. We evaluate the system during the most common situations in which the vehicle is leaving its Operational Design Domain (ODD) [8, 9, 10], i.e., the conditions and scenarios in which the automation has been defined to operate. We aimed at studying its impact on the overall driving performance and driver reaction time to a TOR. To this end we defined and tested the following hypotheses:

H0 The use of the IACS does not affect driving performance andlor driver reaction time to a TOR.

H1 The use of the IACS improves driving performance andlor driver reaction time to a TOR.

The next section considers related work with similar approaches. Section 2 describes the development of the system and simulation platform. Sections 3 and 4 describe the set up of the performed experiments and the procedure to acquire the data. Section 5 reports on the evaluation results of the developed system. Finally, Section 6 concludes the paper.

2 Related Work

The transition of vehicle control from automated to manual driving modus, the so-called handover phase, is critical as a sufficiently comfortable transition time is necessary [10]. Results based on auditory warnings showed, for example, a slower vehicle control and events anticipation time in automated as opposed to manual conditions [7]. A variety of simulator studies have investigated driving performance parameters such as braking time or lateral longitudinal lane positions after a handover. According to [11] Take Over Reaction Time (TOrt) is the time taken by the driver to take back control of the vehicle. Research has been pursued in several works to explore the effect of TOR in different critical system boundaries. Results show that the time needed in advance to notify drivers with visual and auditory signal messages about the transition initiation had an effect on the TOrt [12], the TOrt range with and without control transition being between 2.06 and 3.65 seconds [13].

In a further study, it was concluded that an 8.8 second-transition time for the presentation of TOR to the system boundary to safely react to a TOR was sufficient even for extremely distracted drivers [14]. The transition time needed in a highway scenario was 8 seconds according to [12].

The results of several studies ranged between 1.14–15 seconds for TOrt [8]. They depended on the lead-time from a TOR to a critical event (TORlt), the secondary tasks in which the probands were engaged during driving and the resulting levels of attention and cognitive load demand.

The Human Machine Interface (HMI) used in the referenced literature included visual information and/or acoustic warnings. For example, the engine speed dial was used in [8] to convey the TOR, it being hidden when a manual transition was issued and shown in its default configuration. Control resumption occurred through an acoustic message in combination with a TOR icon shown on the instrument cluster. To activate the automation an acoustic message was generated together with a symbol.

In the study in [15] a visual warning was provided in the vehicle in an interface along with an acoustic signal in a variety of take over strategies. Several locations in the vehicle were used with and without the integration of mobile phones. Evaluation results showed that the driver's performance improved when a multimodal stimuli (visual and audible) was used. However, the modality used to request the transition had no effect if sufficient time was established for transition.

Automated systems that classify driver take-over readiness and derive the expected take-over quality have been presented in several works. For example, in the collision probability estimator in [16] an emergency TOR that considers driver reaction time and driver state was developed for inclusion in driver assistance systems. The architecture of the system captured the driver's state and behavior inside the vehicle, which was then used to predict the collision probability in situation that required a Keep Lane Maneuver (KLM) and braking to avoid the collision. The results were then used to determine the level of safety of a potential vehicle control transfer.

A further study classified the driver's takeover readiness with 79% accuracy based on the complexity of the traffic situation, the current secondary task of the driver, and their gaze on the road [17].

Systems to keep the drivers informed have been developed and tested in order to maintain their situational awareness at an adequate level and facilitate the handover. One example uses a continuous, in-vehicle visual stimulus to reduce driver reaction time after a period of hypovigilance [2]. The authors in this study relied on subconsciously processed peripheral vision to implement an unobtrusive method based on luminescence and showed a tendency among drivers to respond faster to a TOR when their peripheral vision detected the stimulus.

In the proposed approach in this paper we rely on an unobstrusive method and contribute to the state of the art with a system to improve the driver's situational awareness while driving in conditional automation. The system indicates manual or automated mode depending on the road situation via a peripheral vision location in the vehicle, additionally signaling an acoustic warning when a TOR is required.

3 Simulation Platform Implementation

3.1 Scenario

Recreating the same simulation platform implementation as described in [18, 19, 20, 21] a vehicle was created with conditional automation capabilities (SAE level 3) that was able to sense the environment through a LiDAR installed on the roof. A path based on waypoints was created in order to give the vehicle a predefined route. The vehicle was equipped with a guidance system to follow the waypoints and complete the path. The speed along the route was 50km/h.

A signboard barrier with the caution message "area under construction" was introduced in the scenario at different locations for each experiment before a roundabout. When the barrier was visible, the TOR was triggered.

3.2 Interactive Automation Control System

The interaction with the automation control system involves a continuous transfer of information in both directions between the driver and the IACS. To implement the IACS, a display embedded in the vehicle's dashboard conveys the level of warning known as cautionary crash warning (CCW) [22]. Figure 1 depicts the modes conveyed by the IACS. The warning messages were transmitted through warning icons that contained additional text labels for a fast understanding and intuitive use. The warnings switched and were not shown simultaneously. The urgency coding was expressed via colors and blinking as follows:

1. **Manual driving**. Indicated with a constant non-blinking green indicator.

2. **TOR**. Represented with a blinking red indicator with acoustic sound.

3. **Automated driving**. Represented by a constant non-blinking blue indicator.

In-vehicle location of the IACS display to convey the driving modus information. The graphic shows all the warnings to provide the reader with a better overview of the system. However in the experiment they switched and were not shown simultaneously.

Figure 1: In-vehicle location of the IACS display to convey the driving modus information. The graphic shows all the warnings to provide the reader with a better overview of the system. However in the experiment they switched and were not shown simultaneously.

3.3 Experimental Setup

The sample of persons participating in the experiment included 24 participants, (mean age = 27.32, SD = 9.6), with a gender distribution of 64% male and 36% female. After being welcomed and having filled in a questionnaire with personal information and phone usage habits, participants were informed about the functioning of the simulation platform and the TOR. They were then asked to drive for 3 minutes to get familiar with the system. Afterwards, each of the subjects was asked to drive in the following 3 scenarios for a total time of 90 minutes:

- **Baseline**: No IACS system activated.
- **Scenario 1**: When the situation requires a TOR, the vehicle asks the driver to take over control by activating the TOR display. Only this button is activated, the remaining warnings for Automated and Manual driving are deactivated.
- **Scenario 2**: All the warnings available on the IACS display are enabled as described in subsection 3.2 during the entire experiment, switching depending on the current driving mode (i.e., conditional automation, TOR and manual).

Under conditional automation the participants were engaged in playing a certain smart phone game that was known to all of them. As already mentioned, during the journey an obstacle located on the road forced the drivers to take over the vehicle's control without warning (baseline) and with warning (scenario 1 and 2). The order of the scenarios was alternated for each driver to avoid bias. A button on the steering wheel activated the transition of control from automated to manual. Then the driver had to avoid the obstacle on the road. Afterwards, subjective ratings were collected from the participants. Figure 2 shows 2 participants in the experiment using their mobile phones during conditional automation driving condition.

4 Data Collection And Analysis

To study the effect of the system on driving performance, several metrics were selected considering that the drivers were engaged in other tasks while driving that kept them away from the main monitoring role expected in conditional automation. We assumed that the higher the reaction time, the higher the deceleration rate and higher steering wheel angle resulting from the effort to avoid a collision with the obstacle. The following driving performance metrics were logged as dependent variables and stored in a database linked to the simulator.

- **Reaction time** to the TOR, calculated from the time at which the drivers were alerted until they pressed a button on the steering wheel. Equation 1

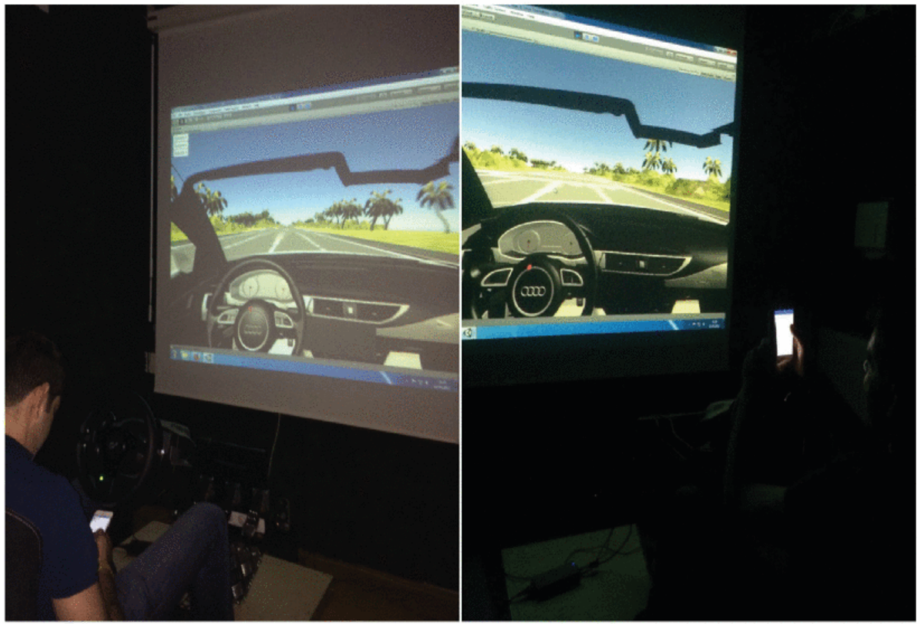

Figure 2: Participants in the experiment using their mobile phones during conditional automation.

reflects this, being t_a and t_p the instants of warning and pressing the button respectively.

$$r = t_p - t_a \tag{1}$$

- **Collision** against the obstacle, if any.

- **Steering wheel angle** resulting from trying to avoid the obstacle, calculated as denoted in equation 2. The value $t \in T$ represents the time elapsed between the alert and the completion of the simulation; $\theta^{\perp}$ stands for the maximum steering wheel angle in degrees and $in_t \in [-1, 1] \subset \mathbb{R}$ is the input value from the steering wheel sensor at time t.

$$\theta = max_{t \in T} |in_t \theta^{\perp}| \tag{2}$$

- **Deceleration rate**. The deceleration was calculated through the difference in seconds between the moment when the driver presses the brake pedal and the moment when the obstacle is avoided or a collision happens. The calculation is denoted in equation 3, where v_T and v_O are the speeds in the starting (when the driver starts braking) and the end (when the experiment ends) positions, and t_T and t_O their respective moments. When

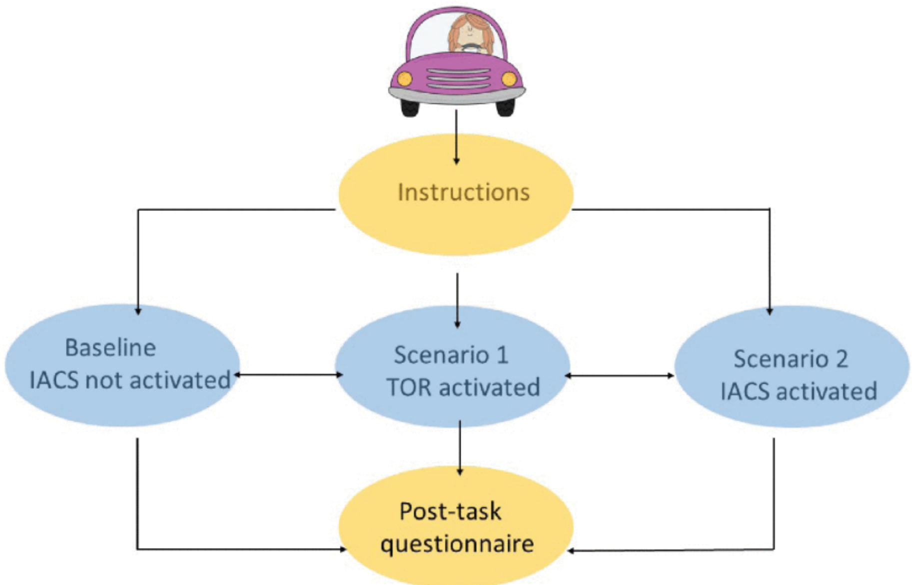

Figure 3: Flowchart of the procedure followed to implement the experiment.

the driver collides with the obstacle, v_T (hence t_T) values are recorded just one frame before to avoid a speed of $0ms^{-1}$.

$$d = \frac{v_T - v_O}{t_T - t_O} \tag{3}$$

After the experiment, the participants had to answer a questionnaire about the IACS that consisted of 13 questions categorized in 3 groups. A Likert rating scale varying from 1 to 5 was used. Figure 3 shows the flowchart of the experiment procedure.

For the analysis we first classified the collected data into 2 groups based on the frequency of in-vehicle phone usage. The un-paired sample t-test for means was applied to assess, using $\alpha = 0.05$, whether the mean of the measurements of reaction time, steering wheel angle and deceleration were statistically different from each other. To determine the independent or dependent relationship between the categorical variables collisions and scenario we applied the chi-square test for independence. For the comparison between scenarios the paired sample t-test for means was applied. Using $\alpha = 0.05$ it was assessed whether the mean of the measurements reaction time, steering wheel angle and deceleration were statistically different from each other. For the comparison between scenarios of number of collisions, a McNemar χ^2 two-tailed test for each of the variables was conducted. This test is perfectly suited to the kind of problem present in our research: a dichotomic variable extracted from the same subjects in different scenarios. Also, given the fact that we are using contingency tables with a low frequency numbers, we considered the potential for biased data and therefore applied the Yates correction.

5 Results

5.1 Phone usage habits

Out of 24 participants, 48% said that they used the phone frequently while driving, whereas the remaining 52% said that they used their phone while driving only in rare occasions. Figure 4 shows a graphical representation of the driving parameters distributed among the 2 groups. Regarding the number of collisions, there were no statistically significant differences between the two groups, the values for each scenario being as follows: $\chi^2(1, N = 24) = 0.10, p = 0.74$ for the baseline scenario, $\chi^2(1, N = 24) = 0.16, p = 0.68$ for scenario 1 and $\chi^2(1, N = 24) = 2, p = 0.15$ for scenario 2. The following subsections describe the results in detail for the rest of the parameters. The rest of the variables are evaluated applying an unpaired t-test with a significance level $\alpha = 0.05$ to see if phone usage habits affect to them.

5.1.1 Baseline scenario

Significant statistical differences were found in the steering wheel angle variable. There were no significant statistical differences for the other variables:

- **Reaction time**. Frequent usage = $(\mu = 1.89, \sigma = 0.47)$ vs. seldom usage = $(\mu = 2.12, \sigma = 0.49); t = 1.18, p = 0.2469$.
- **Steering wheel angle**. Frequent usage = $(\mu = 29.09, \sigma = 5.99)$ vs. seldom usage = $(\mu = 36.33, \sigma = 5.87); t = -2.99, p = 0.0068$.
- **Deceleration**. Frequent usage = $(\mu = 2.29, \sigma = 1.57) vs. seldom usage = (\mu = 1.13, \sigma = 2.08); t = 1.55, p = 0.1350$.

5.1.2 Scenario 1

No relevant differences between variables were found:

- **Reaction time**. Frequent usage = $(\mu = 1.76, \sigma = 0.47)$ vs. seldom usage = $(\mu = 1.75, \sigma = 0.4); t = 0.05, p = 0.9531$.
- **Steering wheel angle**. Frequent usage = $(\mu = 29.82, \sigma = 4.29)$ vs. seldom usage = $(\mu = 35.54, \sigma = 4.25); t = 1.56, p = 0.13$.
- **Deceleration**. Frequent usage = $(\mu = 2.34, \sigma = 1.39)$ vs. seldom usage = $(\mu = 2.00, \sigma = 2.23); t = 0.45, p = 0.6574$.

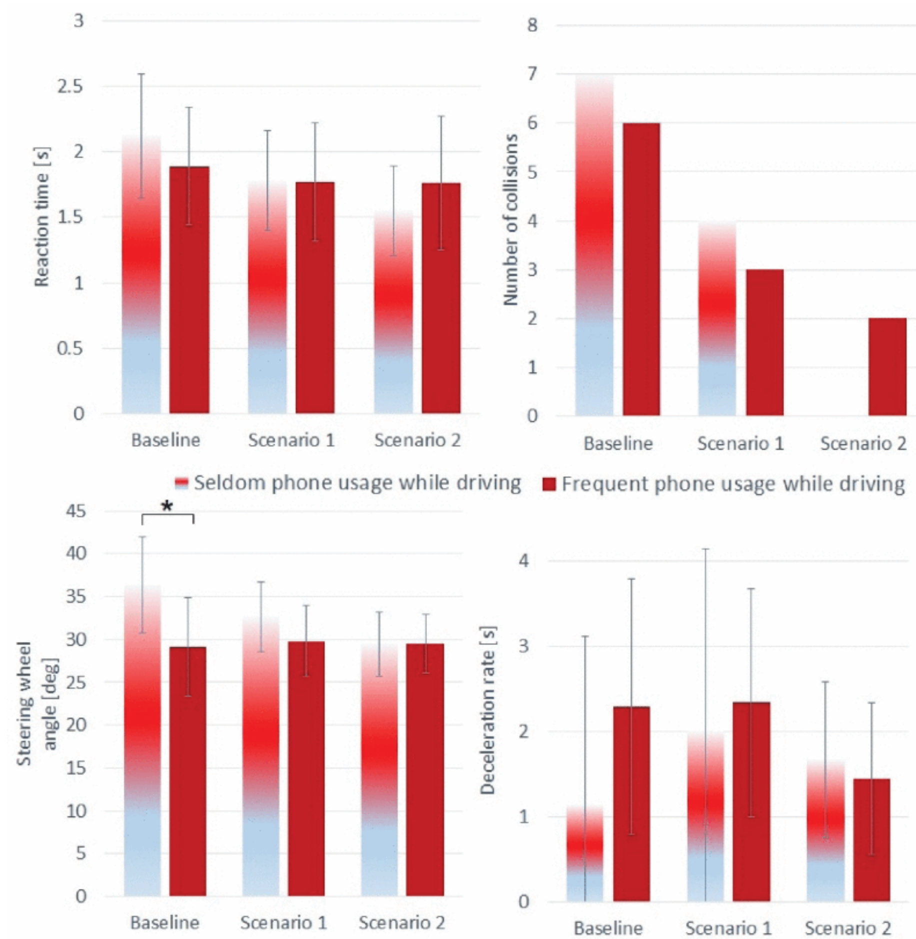

Figure 4: Average values and the standard deviation of the driving performance metrics logged during the experiment. Shows drivers who used their phone in a regular way while driving vs. drivers who did not.

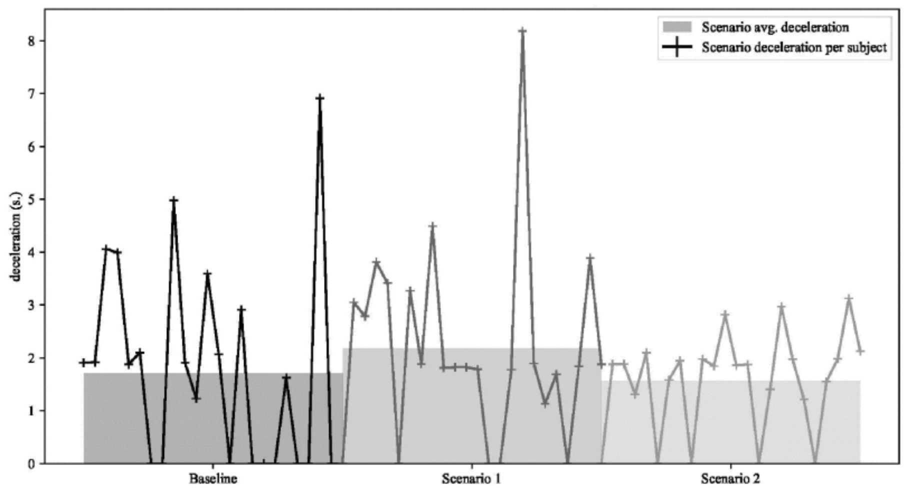

Figure 5: Deceleration rate over scenarios and subjects in all three scenarios.

5.1.3 Scenario 2

Similarly, there were no significant statistical differences in the parameters under scenario 2:

- **Reaction time**. Frequent usage = $(\mu = 1.77, \sigma = 0.53)$ vs. seldom usage = $(\mu = 1.55, \sigma = 0.36); t = 1.186, p = 0.2573$.
- **Steering wheel angle**. Frequent usage = $(\mu = 29.52, \sigma = 3.55)$ vs. seldom usage = $(\mu = 29.48, \sigma = 3.90); t = 0.02, p = 0.9811$.
- **Deceleration**. Frequent usage = $(\mu = 1.44, \sigma = 0.93)$ vs. seldom usage = $(\mu = 1.67, \sigma = 0.96); t = -0.59, p = 0.5616$.

5.2 Comparison depending on the scenario

Figures 5, 6 and 7 depict respectively the deceleration time, reaction time distribution and steering wheel angle over scenarios and subjects. Results regarding the reaction time, collision, steering wheel angle and deceleration in all scenarios are illustrated in Figure 8.

For the number of collisions variable, the results fell between the baseline and scenario 1 situation where $\chi^2(1, N = 24) = 2.083$.

The two-tailed p-value was 0.1489 and therefore, by conventional criteria, this difference was considered not statistically significant.

Similarly, for scenarios 1 and 2 no statistically significant differences applied, $\chi^2(1, N = 24) = 3.2$ with a p-value of 0.0736. However, the difference between baseline conditions (13) and scenario 2 (2) was highly significant, being $\chi^2(1, N = 24) = 7.692$, with a p-value of 0.0055.

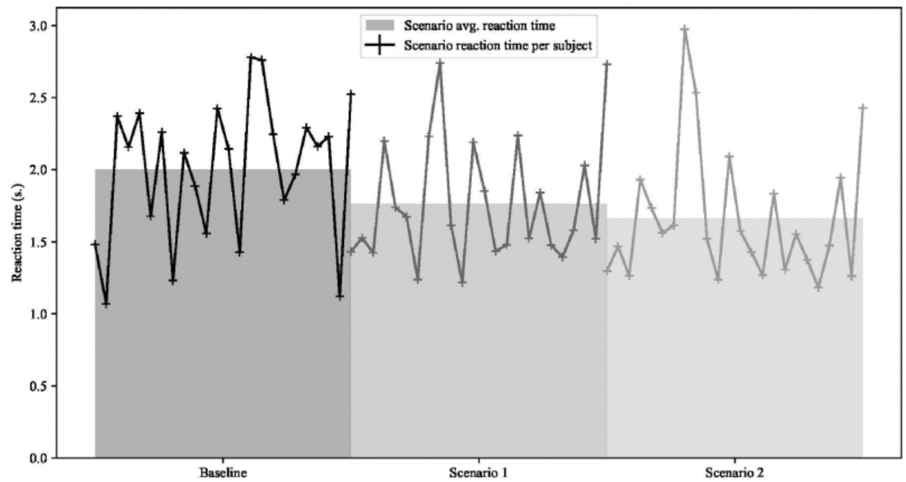

Figure 6: Reaction time distribution over scenarios and subjects in all three scenarios.

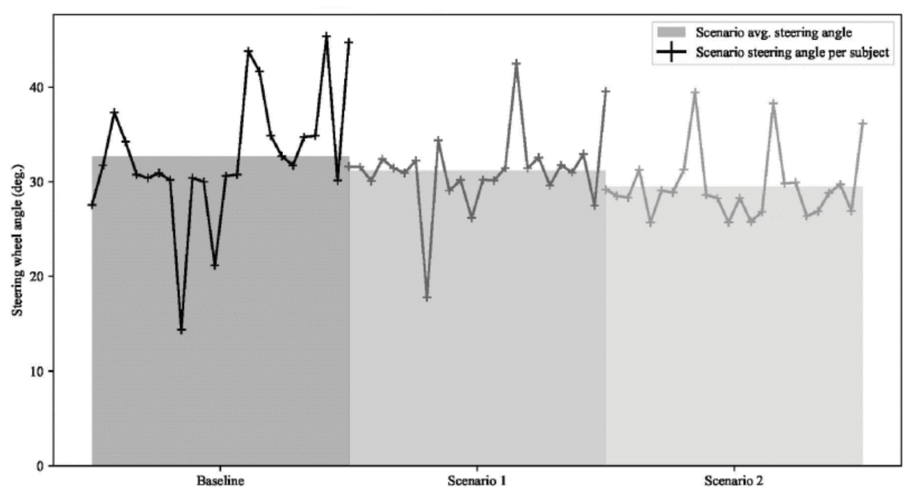

Figure 7: Steering wheel angle over scenarios and subjects in all three scenarios.

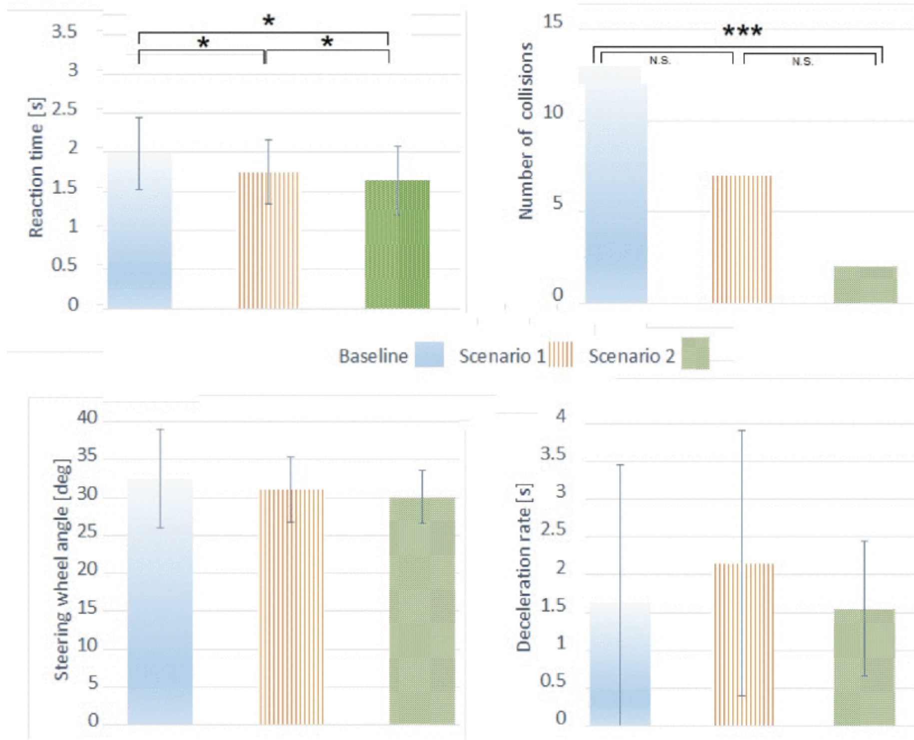

Figure 8: Average values and the standard deviation of the driving performance metrics logged during the experiment in all three scenarios.

Table 1: Results Regarding Driving Performance Depending On the Analyzed Scenario

Metric	Baseline		Scenario 1		Scenario 2	
	μ	σ	μ	σ	μ	σ
Reaction sime (s.)	1.99	0.46	1.75	0.43	1.64	0.44
Steer. angle (deg.)	32.56	6.5	31.03	4.28	30.07	3.52
Deceleration (s.)	1.64	1.82	2.14	1.76	1.55	0.89
T-Test ($\alpha = 0.05)						
Metric	**Baseline**		**Scenario 1**		**Scenario 2**	
	$t(19)$	p	$t(19)$	p	$t(19)$	p
Reaction sime (s.)	2.20	0.03*	2.73	0.01*	2.33	0.02*
Steer. angle (deg.)	1.19	0.24	1.75	0.09	1.38	0.17
Deceleration (s.)	-0.98	0.33	0.20	0.83	1.85	0.07

For the rest of the variables, the paired sample t -test for means was applied. The results are summarized in table 1. The only variable in which a statistically significant difference could be appreciated was the reaction time, for baseline vs. scenario 1, baseline vs. scenario 2 and scenario 1 vs. scenario 2.

5.3 Subjective Ratings

User ratings of the performance of the IACS showed a high satisfaction with the system, ($\mu = 2.64, \sigma = 0.88$) with 80% of the participants rating the system from good to excellent (8% excellent, 40% very good, 32% good). The remaining 20% rated the IACS as satisfactory. Regarding the comparative results of the systems used in scenario 2 and 3, the subjective ratings were very satisfactory ($\mu = 1.52, \sigma = 0.80$). 68% of the participants found the IACS to be more effective for the transition from conditional automation to manual driving while 20% of people were not sure about the assistance level and 12% did not consider the benefits to be higher. Finally, the question regarding the recommendation of the proposed system delivered a high score ($\mu = 1.16, \sigma = 0.46$) . 88% of participants would recommend the IACS proposed system, arguing that it increased their situational awareness regarding driving mode. 4% were not sure about recommending the system, and 8% said that they would not recommend it.

6 Conclusion And Future Work

We presented in this paper the IACS to improve the driver's situational awareness while driving in conditional automation mode and studied its impact on overall driving performance and driver reaction time for responding to a TOR. The use of the IACS affected the overall driving performance and driver reaction times differently depending on the scenario. Therefore the null **hypothesis H0**: The use of the IACS does not affect driving performance andlor driver reaction time to a TOR was rejected and the alternative **hypothesis H1** accepted. The response to the TOR was better in the group of people who used their phone more frequently. The good subjective results of the IACS were translated into the reduction in the number of accidents when taking over the control of the vehicle. The obtained results regarding reaction time when using the system are in the range between 1.55 and 2.34 seconds, depending on the scenario, staying fairly consistent with results obtained in related literature that also used visual and auditory handover messages (i.e., between 2.06 and 3.65 seconds in [13] or between 2 and 3.5 seconds in most control transitions in [8]). The deceleration values were smoother in scenario 2 in comparison with scenario 1. Most of the participants were satisfied with the system. The data collected during the experiment indicates differences in the number of collisions in different scenarios. This clearly indicates the difficulties of monitoring the surrounding while driving during conditional automation. This was particularly critical under baseline conditions with no warning regarding an object on the road. The presented system in this paper promoted a smoother transition from conditional automation mode to manual driving and consequently a reduced number of collisions in unexpected situations. Future work will address a more sophisticated system that will be evaluated in various scenarios with different periods of hypovigilance involving eyes or mind off road during limited self-driving automation.

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