AMI: Attention based Adaptative Feedback with Augmented Reality to Improve Takeover Performances in Highly Automated Vehicles

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Abstract: In the coming decade, the level 3 of semi-autonomous vehicles on the SAE scale is set to develop. However, the question of the transition of control between human and vehicle remains a widely debated question. From a cognitive point of view, this operation consists of placing the user back in a sensorimotor loop while limiting cognitive overload. In order to reduce this, several augmented reality / mixed reality approaches have been carried out. In this preliminary study, we propose an approach based on adaptive feedback. A naive adaptation model based on the work of Herzberger is introduced, studying the behavior of the user through his head behavior to determine an attention level.
We carried out an experiment in a driving simulator reproducing a highway in virtual reality and displaying AR feedback through the virtual environment. The experiment tends to show that users perform better when they are placed in front of adaptive feedback. In a future work, we plan to complicate this model.

1 INTRODUCTION

1.1 Transition of Control in Highly Automated Vehicle (HAV)

The vehicle automation scale defined by the SAE references five levels of automation. Level 3 vehicles on this scale alternate periods of autonomous driving with periods of manual driving. Several taxonomies of takeover have been proposed in the literature (Radlmayr et al., 2014). In our study, we will focus on the transition of control from the HAV to the driver when initiated by the automation system (Lu and de Winter, 2015).

While this transition appears in the literature in different cases, three of them require particular behaviors from the driver: the takeover due to roadwork (Hayashi et al., 2019), the one due to technical failure, and the one due to ambiguous marking (Sportillo et al., 2018). These processes involve notions of vehicle control and situation awareness. In order to allow the driver to quickly regain awareness of the situation, several interfaces have already been developed but the issue of interfaces design for the takeover is still a burning question. In this study, we focus ourselves within the framework of interfaces known as ”automation interfaces” based on K. Bengler (Bengler et al., 2020) theory. The driver's situation awareness is widely determined, in this theory, by his attention level. Getting a model of one's attention is therefore the first step to direct it to the salient points of a situation and to guarantee a sufficient level of awareness.

1.2 Mesuring Driver's Readiness to Takeover

Some studies assess a user's performance evaluating their behavior before regaining control. Indeed, the approaches aiming to study the behavior of the vehicle (Phan et al., 2014) cannot be used during the automation phase. Vehicle behaviors are therefore used in experiments to highlight user performance via a posteriori statistical analyzes (Gold et al., 2016). Therefore, we must concentrate on the action of the driver while it is engaged in a Non-Driving Related Task (NDRT). A majority of studies propose to focus on driver's gaze behavior to predict his performance in a takeover (Zeeb et al., 2015). Results show that the takeover success rate is linked with visual behavior. We also note that visual NDRT has more impact on performance than auditory NDRT (Merat et al., 2012) (Merat et al., 2014) An interesting model for evaluat-

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ing driver attention has been proposed by (Herzberger et al., 2018) Authors estimate that visual fixation time on the road is a good indicator of a driver's ability to takeover. Others suggest looking at the full body behavior of a user by studying not only his gaze, but also the position of his limbs and the attitude of his face. (Deo and Trivedi, 2020). It is therefore currently possible to determine the driver's attention level. That is why we propose to base our adaptive augmented reality feedback on this estimation.

1.3 Mesuring Performances of Takeover

The evaluation of a takeover of a vehicle is carried out on the basis of various factors such as the type of behavior (braking, cornering, no particular reaction), the fluidity of the trajectory (determined by the maximum angle and maximum acceleration). To measure the interest of devices of this kind we used standardized questionnaires like the NASA-TLX(Hart, 1998) to measure the mental load induced by a task and to detect cognitive overload (Eriksson et al., 2019)(Lindemann et al., 2019). In this study, we will seek to improve these indicators through the use of an adaptive system. The adaptive system, by avoiding overloading the user with unnecessary information, should reduce the mental load and improve performance.

1.4 Augmented Reality for the Takeover in Autonomous Vehicle

Using Augmented reality with head up display interfaces (HUD) generally improve takeover performance compared to classical HUD (Langlois and Soualmi, 2016). But in some cases such as quick longitudinal reactions, it may not be relevant(Lindemann et al., 2019). Researchers have also determined the optimal locations for information on a HUD thanks to an approach based on the psychological theory of proxemics. Data should be displayed at different distances and angles depending on their nature (personal, automation...)(Haeuslschmid et al., 2016). Information should rather be displayed as explanation of actions allowed by the environment rather than highlighting the danger(Lorenz et al., 2014). It has also been shown that the interaction feedback for taking back control should allow the user to quickly envision possible scenarios in order to evaluate and implement them on their own (Eriksson et al., 2019) based on the taxonomy introduced by Endsley and Sheridan (Endsley, 1999) according to which any task can be divided into four processing levels: "Monitoring", "Generation", "Choice" and "Implementation". They suggest both feedback of the carpet and the red line (see figure 1), indicating to the user whether or he can overtake or not. In this study the control takeover interfaces seek to improve the driver's level of attention without trying to measure it. However, as far as we know, there are not any model allowing an augmented reality interface taking into account the driver's level of attention. In this study, we propose a new model of adaptation based on an attention estimation and a feedback displayed to the driver. This model is validated in a virtual reality simulator on a group of subjects. We will present in part 2 the model proposed to answer this, and in part 3, we will present the experiment lead to study this model. Then, in part 4 and 5 we will present the results and our conclusions.

2 PROPOSED MODEL

We first propose a simple adaptation model called AMI (Adaptive attention Model for human vehicle Interaction) in order to explore its effectiveness. This model is described in figure 2. It consists of an attention model, an adaptation model and visual feedback from the literature that we will describe individually in the following sub-parts.

2.1 Attention Model

Herzberger considers that attention is proportional to the staring time of an element of the road (Herzberger et al., 2018). We used his modeling named ARI for our adaptation model. ARI can be described as

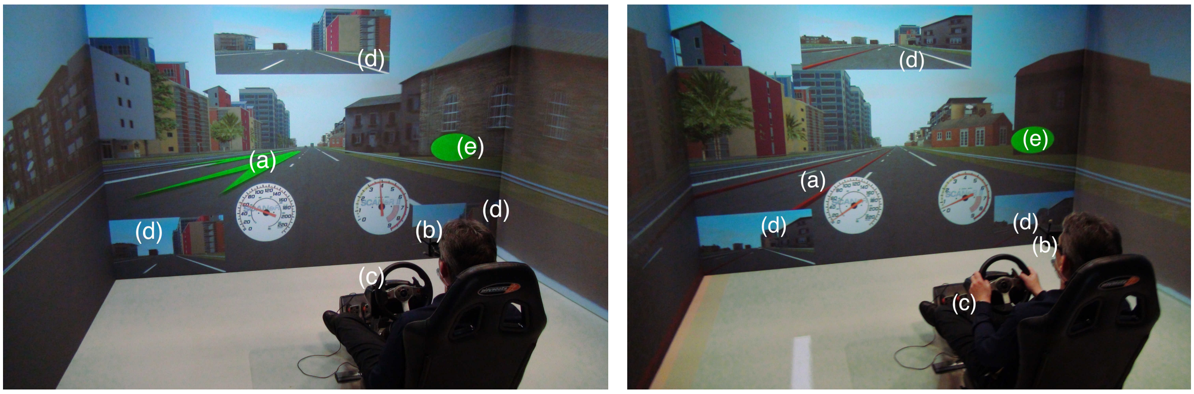
$$ARI(t) = \sum_{k=t-N}^{t} \mathbb{1}_f(k) \cdot \theta_1 + (1 - \mathbb{1}_f(k) \cdot \theta_2$$

θ_1 and θ_2 are the coefficients of contribution of the gaze and the absence of gaze of the road, $\mathbb{1}_f$ the indicator function of the set of points verifying the assertion "the user is looking at the road', and N the size of the sliding window.

Thus, we outlined the gaze's scope area corresponding to the situations in which the driver is looking at the road. In real time, the behavior of the head was recorded at a frequency of 10Hz on a sliding window of 10 seconds and we established the relation between the number of points corresponding to the zone and the others.

We have taken the parameters of Herzberger's experiment with $\theta_1 = -\theta_2 = 0.05$ and N = 200.

We determined the area of interest by asking a subject to stare at road and mirrors and collection the corresponding directions.



(a) Green carpet implementation
(b) Red line feedback implementation

Figure 1: Eriksson's feedback as implemented in our simulator. (a) carpet/red line feedback, (b) tracking glasses, (c) steering and pedals, (d) mirrors, (e) automation system state indicator.

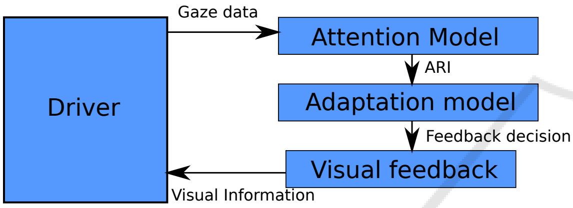


Figure 2: The AMI model.

2.2 3D Feedback

To allow the transfer of information through 3D interactions, we have implemented in our simulator feedback similar to those of Eriksson(Eriksson et al., 2019), the feedback of the carpet and the red line as described in figure 1.

2.3 Adaptation Model

The authors of the ARI study considered that a road sign could be missed as soon as the ARI was less than 0.33. So in this naive model, when the ARI was less than 0.33 we were using augmented reality feedback, otherwise the user wasn't helped.

3 EXPERIMENTAL PROTOCOL

To test the effectiveness of this protocol in a driving situation on the road, we imagined an experiment using the three scenarios described in figures 4c, 4a, 4b.

3.1 Research Question

We state the following research question
RQ : Can a simple adaptation model, based on a rudimentary attention model, improve the performance of takeover on autonomous vehicle?

3.2 Theoretical Hypothesis

We formulate the following hypothesis:
As part of a takeover initiated by the automated system, the objective and subjective performance of the driver is improved by taking his state into account.

3.3 Driving Scenarios

Two scenarios are regularly studied in the literature: the takeover at high velocity (Hayashi et al., 2019) (Zeeb et al., 2015) (Eriksson et al., 2019) on a highway and the takeover in town (Langlois and Soualmi, 2016). In this study, we focus on high speed takeover.

In order to diversify the driving situations, we have proposed three different driving scenarios:

3.3.1 Accident

The expected behavior requires precise actions on the part of the driver. It is depicted in figure 4a.

3.3.2 Sensors Failure

No specific action is necessary but the automated system is no longer able to drive. It is depicted in figure 4b.

3.3.3 Ambiguous Marking

Due to roadworks, the lane marking doesn't allow the automated system to define a safe behaviour and the driver must choose between two scenarios. This

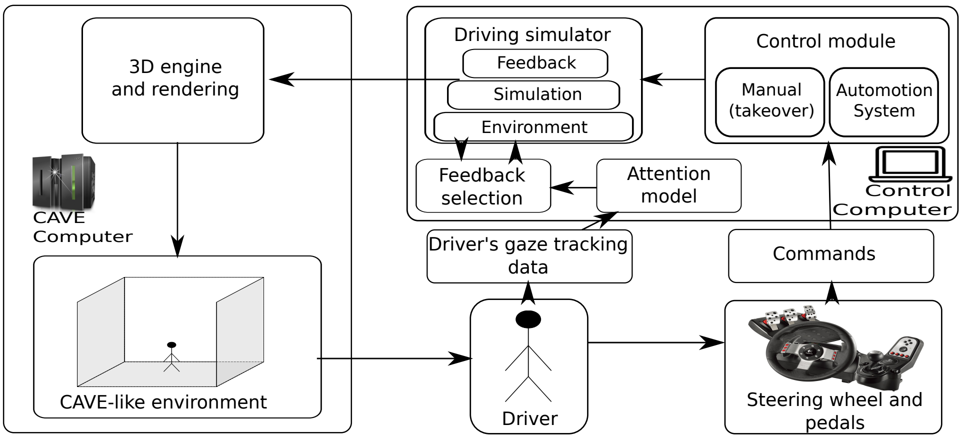


Figure 3: Implementation of the AMI model.

takeover is more complex than the previous ones because the traffic is denser and the obstacles are less visible. It is depicted in figure 4c.

Scenarios for takeover shouldn't concentrate on short time budgets (TB)(de Winter et al., 2021) since the nature and the location of perturbations use to be known in advance. All of these scenarios were low emergency takeovers and the time budget was 15 seconds. The task at hand was relatively straightforward and required a slight deceleration each time. In scenarios 1 and 3 the user had to swing to the left to avoid obstacles.

3.4 Settings

We implemented the model as depicted in figure 3. The driver is placed in a CAVE-like environment and can interact with the driving simulator through the steering wheel and pedals. A control module encapsulates the manual and autonomous mode and allows the driver to switch between modes. The control module sends commands to the driving simulator which determines the behaviour of all simulated vehicles and the whole feedback. The AMI model selects the appropriated feedback using our attention model. Once all elements of the simulation have been calculated, a render engine providing a 3D representation of the simulation in the CAVE-like environment.

We used the driving simulator SCANeR Studio to model different scenarios. This software allows definition of precise scenarios, vehicle behaviors as well as a specific environment. We used a CAVE-like environment – an immersive virtual environment – with a Logitech G29 driving device. The inputs were captured by a simulink module allowing to switch between manual mode and a rudimentary autonomous driving mode. Driver was wearing AR glasses on which constellations where placed so that the position and orientation of the head were captured by an Optitrack device whose information was retrieved by a python3 module responsible for determining the driver's level of attention.

3.5 Independant Variables

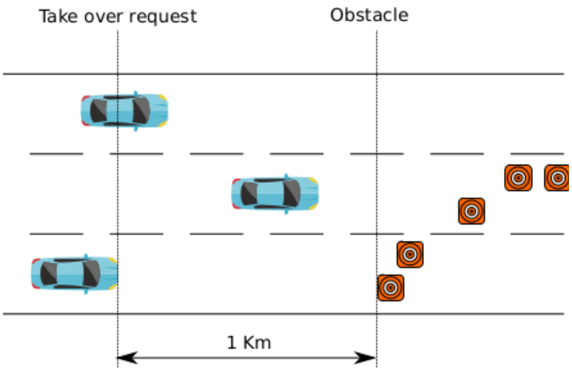
The independent variable was the lack or use of the AMI model. Groups that did not have access to an adaptation model saw the feedback all the time while those who did have access to the adaptation model only saw it when the ARI fell below the threshold of 0.33.

3.6 Experiment Design

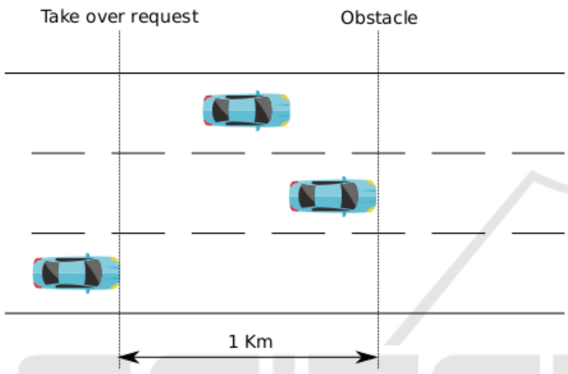
A between subject design was used for the independent variable. Each subject was welcomed and briefly presented with the task. They had five minutes to familiarize themselves with the simulator. Then, they had to carry out three takeover on a single road in order to learn the takeover task specifically. The subject was offered four ways to regain control of the vehicle: by accelerating or braking more than the automated system, by steering or pressing a button to deactivate the automated system. The takeover request (TOR) was performed by a recorded male voice asking in french to take over the control of the vehicle.

Then, they had to accomplish three scenarios depicted in figure 4. These three human interventions took place on a highway at 100 km/h, each lasting one to three minutes and separated by automation time lasting 4 minutes during which the user was invited to immerse themselves in a Non Driving Related Task (NDRT).

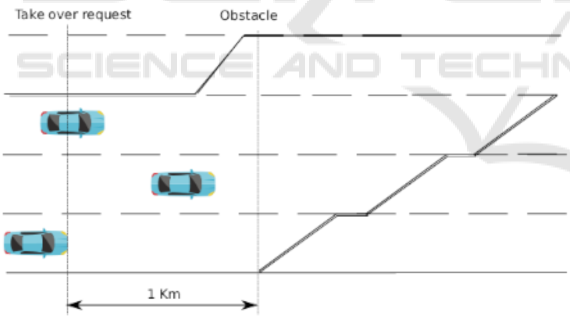
The NDRT was a twenty question task (Merat et al., 2014) whose answer was given orally by the experimenter. The user had to guess a living being in



(a) Scenario 1 : Takeover due to an accident.



(b) Scenario 2 : Takeover due to sensors failure



(c) Scenario 3 : Takeover due to ambiguous marking around roadworks

Figure 4: Studied scenarios.

a predefined list using only closed questions. When the user guessed right, it was invited to guess a new word. After the simulator phase, the subject had to answer a questionnaire consisting of the NASA-TLX and other questions specific to the experiment.

3.7 Data Collection

Several sets of data were collected to analyze the driver's performance.

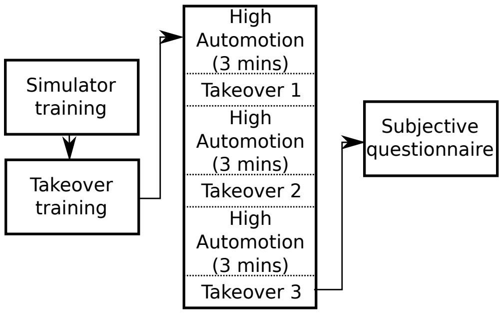


Figure 5: Experiment design.

3.7.1 Subjective Data

We focused on data collected from the NASA-TLX questionnaire to find out if the subject was more stressed by one mode or the other. These results were obtained by compiling subject's responses to post-test questionnaires. We are particularly interested in the **Temporal demand** and **Cognitive demand** variables which particularly reflect the variation of state that we seek to measure and which characterize cognitive overload.

3.7.2 Objective Data

Objective data were obtained by analyzing simulation data from the virtual environment including tracking data.
Reaction Time: Reaction time was calculated as the time difference between the moment the TOR occurred and the subject's inputs were registered by the system, whether driving or pressing the pedal. It indicated better situation awareness when coupled with other objective performance (Eriksson et al., 2019).
Type of First Reaction: The type of first reaction recorded the instant the user regained control. If a variation in the angle at the steering wheel has been recorded, it was a "turn" reaction, while braking results in a "braking" reaction. A turn-type first reaction was often considered abrupt.
Maximum Steering Wheel Angle: The maximum steering wheel angle was calculated as the maximum angle steering wheel during each of the scenarios. They testified to the fluidity of the path and therefore to a clear decision upstream.
Maximum Braking: Maximum braking was calculated as the maximum braking force value recorded by the acquisition system and indicates a panic reaction or lack of anticipation.
Maximum Acceleration: The maximum acceleration was calculated as the maximum pressure on the accelerator pedal recorded by the acquisition system. It varied between 0 (no pressure) and 1 (maximum

possible pressure). It was coupled with maximum braking to distinguish panic reactions from late reactions.

Critical ARI Duration: The critical ARI duration was calculated as the duration while the ARI was under 0.3, taking into account the tracking data and was related to the time during which the user had a reduced attention level. It was therefore used as a naive indicator of attention.

4 RESULTS

4.1 Sample Presentation

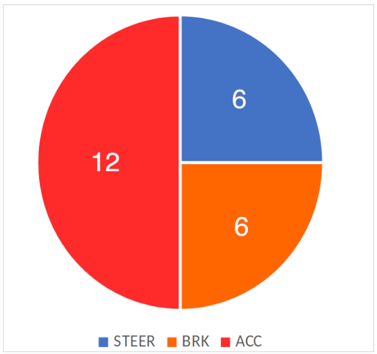
A total of 19 participants divided into two groups went through the three scenarios. Three of them could not go beyond the simulator training phase for reasons of simulator sickness and one had to be ruled out for technical problems during the experiment. The experiment was therefore actually carried out on 15 participants aged 23 to 44, including 13 men and two women, all possessing a driving license. Most of the subjects had never entered a CAVE-like environment and had never driven a vehicle in a simulator.

4.2 Objective Results

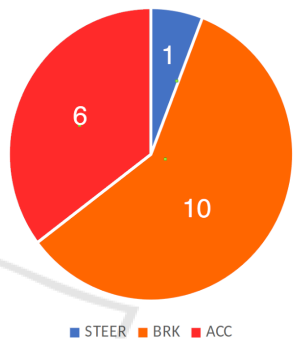
Only one collision was recorded, in the case of a fixed feedback in the third scenario. The average time during which the ARI was deemed critical by the system is approximately 15% of the time and no significant difference could be observed regarding maximum acceleration, maximum braking, and reaction time. descriptive statistics of the sample is shown in table 2. We found significant differences concerning the maximum angle recorded (alpha < 0.05). After running normality tests, we performed appropriate tests which can be seen on table 1. We can see a clear difference between the two modalities when the situation looks very complex (scenario 3). Indeed, users regained control by turning in 25% of cases (see figure 6), which shows a reaction of fear toward the approaching obstacle since steering is not the correct behaviour.

Table 1: T-tests performed on maximal angle distributions (mw stands for Mann Whitney, W for Welch's t-test).

Max Angle	Test	Stat	p-value	Effect Size
Scenario 1	MW	21.5	0.652	0.0964
Scenario 2	MW	19	0.27	0.4780
Scenario 3	W	2.43	0.017	1.3074



(a) Fixed feedback



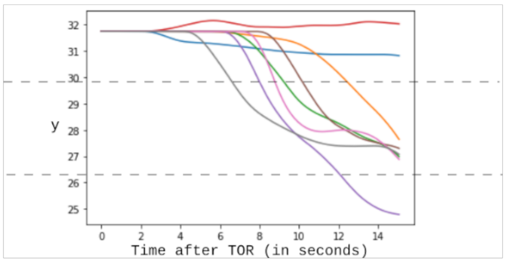
(b) Adaptive feedback using AMI model

Figure 6: Distribution of the types of takeover of control.

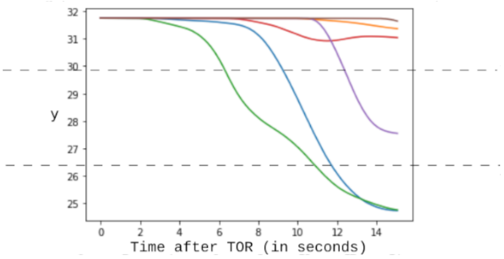
We performed Shapiro-Wilk normality tests which showed exits from normality in the first two scenarios, which is why we performed Mann-Whitney tests for the first two scenarios and a Welch's test for the third. Even if the results are not very significant in the other scenarios, the trend seems to be confirmed. To see the variations observed, we also printed in figure 7 the y position of the vehicle over time during the first 15 seconds of takeover. We can see that the path followed by the vehicle is smoother in case of Adaptive feedback rather than in case of fixed feedback. This figure shows that users react very fast to the takeover by turning the steering wheel without a proper situation awareness.

4.3 Subjective Results

Concerning the subjective results, the answers to the NASA-TLX questionnaire concerning Mental Demand (MD), Physical Demand (PD), Temporal Demand (TD), Success (Su), Effort (E) and Satisfaction (SA) are presented in table 3. A high average indicates a better score while a low average indicates a poorer score. We observe, as expected, that the men-



(a) Fixed feedback



(b) Feedback using AMI model

Figure 7: Variation of lateral position over time during the third scenario (staying at the lane after 15 seconds isn't related to failing at the task since driver decelerated in these cases). Y represents the y coordinate in the simulator and lines represents the position of the road lines on the road.

Table 2: Descriptive statistics for objective performances.

Variable	Group	N	Mean	SD
Reaction Time	Fixed	24	3.36	2.1410
	AMI	17	3.50	2.2285
Max. acc.	Fixed	24	0.77	0.2616
	AMI	17	0.71	0.2441
Max. brk	Fixed	24	78.85	108
	AMI	17	62.81	63.7703
Max. Angle	Fixed	24	0.107	0.0780
	AMI	17	0.077	0.0686

tal demand seems weaker when the subjects use the adaptive interface. Our normality tests were positive and therefore we proceeded to a Welch's Student test, whose results are presented in table 4. In general, subjective results appear to be slightly lower using the adaptive interface but the significance level is individually low.

5 DISCUSSION

5.1 Hypothesis Validation

The theoretical hypothesis according to which an adaptive model allows the improvement of mental load, and takeover performance seems to be confirmed, in particular in the case of the third scenario

Table 3: Descriptive statistics for subjective performances.

Variable	Group	N	Mean	SD
MD	Fixed	8	5.50	1.77
	AMI	7	3.71	1.60
PD	Fixed	8	1.88	1.13
	AMI	7	2.57	1.72
TD	Fixed	8	4.13	2.30
	AMI	7	3.43	2.37
Su	Fixed	8	4.75	3.15
	AMI	7	3.57	1.40
E	Fixed	8	5.50	2.33
	AMI	7	3.00	2.23
Sa	Fixed	8	2.50	2.67
	AMI	7	6	2.43

Table 4: T-tests performed on global performances.

Variable	p-value	Effect size	
MD	2.178	0.051	1.170
PD	-0.914	0.382	-0.479
TD	0.576	0.575	0.298
Su	0.956	0.362	0.484
E	1.213	0.247	0.627
Sa	-1.301	0.216	-0.671

which involves an obstacle which is not very easy to detect and requires greater concentration. Visual feedback, which is supposed to assist the driver, appear to be more effective when used sparingly, and subjects with naive feedback appear to have a slightly better situation awareness and higher performance. One could formulate the hypothesis that these performances are related to a better attention level. However, these results are still not heavily significant and should be confirmed in further studies.

5.2 Adaptation Model

Some subjects reported having been bothered by the rapid disappearance of interfaces, which they initially assimilated to a bug. This can be easily corrected by displaying the feedback a few seconds after the ARI comes back to a sufficient level.

5.3 Simulator Limitations

The low significance of the results can be explained by some bias in the simulator. In particular, the cognitive overload generated by the distracting task was not coupled with a level of stress or danger. Indeed, we can see that the temporal demand is rather low in both cases and this seems to imply that the subjects do not feel danger or particular emergency (Gemonet et al., 2021). In addition, simulators tend to increase the variability in driving performance (Gemonet et al., 2021).

In addition, our simulator did not inform the subject of his decisions and the choices of trajectories he took, which led subjects to have very little confidence in it and to remain very attentive to the road. Many subjects reported that they considered themselves to be fully attentive and that the distracting task had little impact on their performance.

5.4 Perspectives for the Attention Model

Our results are encouraging but the attention model is totally binary, meaning that one is considered by the system to be either completely attentive or completely inattentive, and eye-on-road type phenomena cannot be taken into account. It should be improved by integrating real knowledge of the situation in order to obtain noticeable differences in performance.

In particular, it would be necessary to add semantic elements of the situation and to make assumptions about elements of the scene. The ARI model proposes a study of the road staring time, but it would be necessary to give attention to the staring time of the important elements in the scene such as the vehicle in front, the obstacle or the other vehicles.

During the automation phase, numerous subjects express verbally of by moving their body their disagreement with the automated driving system decision (for example, slowing down). These visual and verbal behaviors should be integrated in our model.

6 CONCLUSION AND FUTURE WORKS

In this article, we present a new model of adaptive visual feedback for takeover in highly automated vehicle. This model is based on Herzberger's attention estimation. We developed a complete system in a virtual reality device (CAVE-like environment) with a driving simulator allowing the creation of specific scenarios and the data collection of the user's behavior. Adaptive feedback were displayed through the virtual environment (mixed reality).

Experiment were lead on around twenty participants of different ages. Results tend to show that user have slightly better performances using an adaptation model and feel less mental workload while taking over the vehicle. However, the results should be corroborated with future experiment on a more complex model. This experiment allowed us to collect data on driver's gaze behavior and gestures during takeover. We plan to improve this first model to obtain more detailed information on driver readiness and thus improve our adaptation model. Our work will aim at correlating particular behaviors with some poor performances recorded, in order to improve the feedback and simplify the interface by restricting the number of options displayed and then we will be able to test the effectiveness of a more complex adaptive model.

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