Emotion State Induction for the Optimization of Immersion and User Experience in Automated Vehicle Simulator

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Abstract: Users' acceptance is one of the predominant barriers of connected and automated vehicles (CAVS), which should be addressed at the highest priority. Loss of control, perceived safety and therefore lack of trust are some of the main aspects that lead to scepticism about the adoption of this technology. Addressing this issue, the H2020 project SUaaVE seeks to enhance the acceptance of CAVS through understanding the passengers' state and managing corrective actions in vehicle for enhancing trip experience. The research to understand passenger emotions is mainly based on experimental tests consisting in immersive experiences with subject's participation in a simulated CAV, specifically adapted to SUaaVE research purposes. This paper present different strategies to obtain realistic simulations with high levels of immensity in these tests using a dynamic platform with the objective of studying the emotional reaction of the subjects in representative scenarios and events within the framework of CAVs.

1 INTRODUCTION

The automation of driving is changing the role of humans so that SAE levels L4 and L5 of automated vehicles (SAE International, 2021) will take over all control and monitoring tasks for specific applications performed by humans in conventional motor vehicles (Drewitz et al., 2020). However, the lack of control can lead to lack of trust among users of fully automated vehicles (Lee & See, 2004), identified as a key issue in the acceptance and adoption of this emerging technology (Bazilinskyy et al., 2015). In this regard, trust in automation is strictly related to "emotions on human-technology interaction, which is a key factor for acceptance, but is also important for safety and performance" (Lee & See, 2004). For this reason, it should be a factor considered when designing complex, high-consequenced systems like Connected Automated Vehicles (CAVs) (Paddeu et al., 2020).

With this situation, H2020 SUaaVE project (SUpporting acceptance of automated VEhicle), aims to enhance the acceptance of CAVs through the formulation of ALFRED: A human centred artificial intelligence to humanize the vehicle actions of the CAV by understanding the passengers' state and managing corrective actions in vehicle for optimizing trip experience. One of the main challenges in SUaaVE, and in line with recent studies regarding empathic vehicles (Braun et al., 2020), is the emotion recognition of the vehicle occupants. It is also important to consider mental stress in the identification of these emotions in perception and cognition in drivers above all due to the possible affection of burn-out syndromes (Cuzzocrea et al.,

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2013). The measurement of these emotions is based on the obtention of arousal (level of intensity) and valence (level of pleasantness). These values can be estimated from physiological signals: Electrocardiogram (ECG), heart rate (HR), galvanic skin response (GSR), skin temperature (T) and facial electromyogram (EMG) from the corrugator and zygomatic muscles (Shu et al., 2018). Other approaches could also include additional behavioral parameters (facial expression according to landmarks, blinking, etc.) (Suja et al., 2014).

In order to understand the passenger emotions, the research is mainly based on experimental tests consisting in immersive experiences with subject's participation in a simulated CAV, specifically adapted to SUaaVE research purposes. This enables to monitor the subjects' reactions in different situations and contexts within the framework of automated vehicles.

This paper describes the experimental design for the first test of the project in a driving simulator. The aim is to provide and immersive experience to the participants with the objective of eliciting relevant and characteristic emotions in the framework of automated vehicles while gathering their physiological reaction.

2 METHODS

2.1 Experimental Design

The main objective of the experimental tests was to analyse the subject's response to different on-board situations and circumstances on an automated vehicle.

According to that purpose, we defined a set of scenarios required to validate the emotional model. These scenarios were designed to elicit the most representative emotions that passengers can feel in the framework of automated vehicles, thus can be represented by different values of arousal and valence. These emotions are: Fear, hope, pity, satisfaction, distress, anger, relief and joy. The elaboration of these relevant and critical scenarios was defined in a previous study within SUaaVE using people-oriented innovation techniques and with the participation of 592 subjects from different EU countries by means of online qualitative research tools and surveys (Belda et al., 2021).

A total of seven scenarios were generated through an open-source simulator for autonomous driving research (CARLA) with a duration between 3 and 5 minutes. The first scenario is a manual driving. The purpose of this one was to get to know the dynamics of the platform, the simulated dimensions of the car, visual perspective, sounds and in general to get familiarized to the simulation environment. Five more scenarios were designed in order to simulate full automated driving (L5), whereas one more scenario simulates automated driving (L4+) with a car failure, requiring to take over the vehicle (manual driving due to an electronic failure in the vehicle). Within this scenario, several options can be taken. For example, before a highway exit during autonomous mode from vehicle, the participant is requested to take over the car to drive inside an urban area. In case the participant does not take over, the vehicle stops safely after the new lane entrance. In Figure 1, a screenshot of one of these scenarios is depicted.

Figure 1: Example screenshots of some scenarios used in the test.

The experimental session has been designed in order not to exceed the duration of two hours.

2.2 Immersion Methods for Participants

The tests were performed in The Human Autonomous Vehicle (HAV) at IBV, shown in Figure 2, a complete dynamic driving simulator (six degrees of freedom) that allows to emulate the behaviour of a vehicle with different degrees of autonomy enabling fully immersive driving experience.

It is composed by 3 large screens to facilitate the immersion and includes steering wheel and pedals for simulating low levels of automation. The simulator provides surrounding sounds to the participants representing engine sounds (emulating the sound of an electric car), the road and other cars passing by. HAV includes an instrument panel that provides complete information of the vehicle to the participant, including speed, regenerative braking, battery level, information trip (expected time of arrival) and information failure. Both trip and failure information are also notified redundantly through audio messages.

Figure 2: Example of HAV simulating the behaviour of an autonomous vehicle in a highway.

In order to adjust and validate the procedure protocol for the test, a pre-pilot test with 6 participants was conducted. Participants were internal IBV staff and also external participants (to avoid potential bias in their results). According to the preliminary results obtained, we designed and implemented an extra set of strategies to optimize the user experience enhancing the realism to improve the participants' attention during the test. These strategies are defined next:

- Initial context: Imagination is one of the simplest emotion induction techniques, so in the beginning of each scenario, we needed the participants to imagine situations that elicit emotions. At first, the technician in charge of the tests informed the participants that they were in a hurry to reach the destination. We noticed that films, more than any other art forms, have a way of drawing viewers into a situation that helps people empathize and identify themselves with characters. After that, we recorded videos with professional actors reading a script that later were played before the scenario. With emotions and personality expressions hidden in the voice of the actor and a detailed storytelling we can elicit an initial cognitive load in the participant. Thus there are more examples in literature in which the formulation of methods to augment the construction of predictive models with domain knowledge can provide support for producing understandable explanations for prediction, as it is one of the future objectives of this experimentation (Holzinger & Kieseberg, 2020).
- Feedback during scenario: In each scenario, visual and audible information was provided through a Human-Machine Interface (HMI) in the HAV central console and audio messages were played as if it was an AI virtual assistant, providing time to destination, vehicle status and other trip information. A screenshot of the HMI is shown in Figure 3.
- This information lets the participant know the driving mode (sportive, eco, etc.) weather conditions that could affect the vehicle's roadmap (like cloudy, rainy or windy), status of traffic (like good fluency or jams in several locations on the way) and more pills that could affect the emotional state of the passenger of an autonomous vehicle circulating in both urban and intercity trips. Results of a metanalysis on 32 studies with a total of 2468 participants showed that the success-failure manipulation through real time feedback is a reliable induction technique to evoke both positive and negative affective reactions (Nummenmaa & Niemi, 2004).

Figure 3: Detail of the HMI.

- Embodiment: It can be a powerful tool to elicit cognitive emotion to participants. For instance, in one of the designed scenarios we force postural change in order to catch a smartphone ringing with a call that asks you to finish a certain office task (while making eye contact with the simulated road). This obliges the user to take a similar attitude than when there is a stressful situation at work.

In order to gather the subjective assessment of the subjects, after each scenario, the participants reported the emotions felt regarding every specific event of the journey conducted in the scenarios through the scales of Arousal and Valence from the Self-Assessment Manikin (SAM) (Bradley & Lang, 1994). The value of valence in a scale from 1 to 9 refers to the negative or positiveness of the emotion felt. In the same way, arousal refers to the intensity of the emotion in terms of calmness or excitation, as seen in Figure 4. A number of 30 events were evaluated including all scenarios.

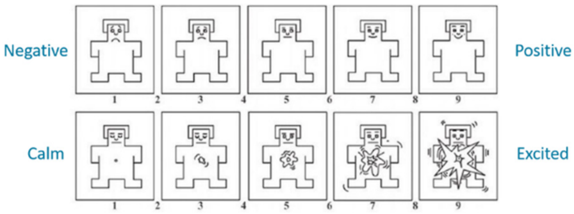

Figure 4: SAM questionnaire.

2.3 Participants

A total of 50 volunteers integrated the subject sample in the test. This sample is composed of car drivers between 25 and 55 years old, aged and BMI balanced. The sample has an equal distribution of males and females.

Exclusion conditions regarding the requirements of the participants were simple. They do not have to suffer visual & hearing impairment (wearing glasses was allowed) and generally not suffering motion sickness in transport. Thus, they had to come without drowsiness, alcohol or drug issues in previous hours.

The participants' physiological signals were continuously monitored and synchronized with the simulator. The synchronization is needed to associate the scenario events with the onset of the participants' emotional reactions.

The test was approved by the Ethical Committee of the Polytechnic University of Valencia (UPV).

2.4 Acquisition instrumentation

We used different equipment to gather biosignals and behaviour of the participants during the test. The equipment used to gather the biometrics, physiological data acquisition, were:

- Biosignalsplux©. This equipment, shown at left in Figure 5, allows high-quality physiological signals acquisition by placing electrodes over the skin with a high-resolution sample frequency. This device gives accurate measurements and it is very flexible for synchronizing with other devices, like, for instance, the software of the driving simulators.

- Empatica E4© wristband (see right part in Figure 5). A non-invasive equipment and the only wearable on the market to combine Electrodermal Activity (EDA) Photoplethysmography (PPG) and Temperature sensors, simultaneously enabling the measurement of the duality between sympathetic vs parasympathetic nervous system activity.

Figure 5: Left: biosignalsplux©. Right: Empatica E4© wristband.

The aim of measuring with both equipment is to have a more complete overview of physiological changes as a result of the fight between sympathetic and parasympathetic systems. On one hand, the Biosignals Plux allows a deeper analysis of the physiological reactions in a more accurate way. On the other hand, Empatica E4 allows to measure the signals in a much less invasive way, so it could be used in latter stages of tests (being easier to wear by the test subjects) once the signals are better characterized.

In general, the signals collected through these sensors are involuntary and subconscious, and then, they are hardly falsifying, so they can be used to assess emotional states in a continuous way and they are non-disruptive to the performance of the task. Through different processing and analysis we could obtain comparable outputs among them. The information about the physiological signals acquired is described in the following section.

Regarding the study of the participant's physical behaviour, a camera was placed in front of the driving simulator to gather the facial gestures and understand the participant's reactions. There are several software-based tools in the market able for analysing facial expression such as the Affectiva Affdex emotion recognition by iMotions© or Rekognition service by Amazon Web Services©. These software toolboxes detect changes in key face features (i.e., facial landmarks such as brows, eyes, and lips) and generates data representing the basic emotions of the recorded face. A photo of this sensor in the HAV and the image acquired is depicted in Figure 6. More information about the parameters calculated is described in the following section.

This experimental data (physiological signals, SAM questionnaires, labels with emotion type, arousal, valence and facial videos) are the input to generate the emotional model.

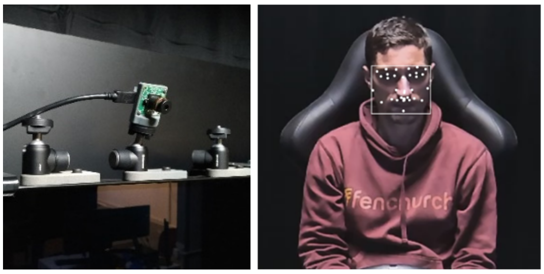

Figure 6: Left: camera placed in the driving simulator. Right: Example of facial landmarks of Affectiva.

2.5 Data Gathered

The set of physiological signals acquired and visualized in real time for each participant during the whole test are detailed next:

- Electrocardiogram (ECG) sensor (in case of biosignalplux) and Blood Volume Pulse (BVP) sensor (in case of Empatica) to obtain the heart rate (HR) and heart rate variability (HRV).
- Skin conductance sensor to record the electro dermal activity (EDA).
- Two facial electromyography (EMG) sensors to record recruitment activity of zygomaticus major and corrugator supercilia muscles.
- Infrared thermopile sensor to gather the peripheral skin temperature (only available in Empatica E4© wristband).

Regarding behavioural data, we are able to calculate the following parameters using facial landmarks analysis:

- Basic emotions: Calmness, Joy, Anger, Surprise, Fear, Sadness, Disgust and Contempt; with probability scores on a 0-100% scale.
- Valence (measure of how positive or negative the expression is).
- Engagement: A general measure of overall engagement or expressiveness.
- Attention. Measure of point of focus of the subject based on the head position.
- Interocular Distance: the distance between the two outer eye corners.
- Pitch, Yaw, & Roll: x, y, & z rotation of the head.

The physiological signals and the videos are synchronized with the time of each scenario using UNIX timestamps.

Besides objective measures, as mentioned before, the subjective opinion of participants was also collected.. It was gathered through:

- Socio-demographic profile form: Age, gender, driving experience and preferences.
- SAM questionnaire (Geethanjali et al., 2017). Appraisal of the emotional state of the participant (level of arousal and valence) with regards to different events on road.
- Survey to assess acceptability and acceptance from the perspective of automated vehicles and developed in SUaaVE by the University of Groningen (Post et al., 2020).

Since each physiological signal has its own representation, all of them requires to be set in the same proper scale. As we aim at having a continuous representation of the emotional state of the participants (in the domain of valence and arousal), physiological signals are calibrated with a self-reported emotional status at some specific times.

3 RESULTS

A preliminary analysis confirmed the hypothesis of providing a higher immersive user experience with the strategies aforementioned. This was observed by the comparison of the physiological signals of the participants performing the test with the strategies and without them (in the pre-pilot test). More concretely, it was noticed a more variable interval within heart and breathing rate and a higher quantity of responses generated by the sympathetic nervous system (shown by the number of peaks detected in the electrodermal activity signal of participants) in the test with the strategies.

The emotional reactions and their variation are also seen in the subjective assessment indicated by the subjects after the end of each scenario through SAM questionnaire. Figure 7 and Figure 8 show an example of the mean values of arousal and valence reported in two selected scenarios in the test with strategies. As it can be seen, there are different events in the scenarios where the interval relative to the range in Arousal and Valence is higher than 2.5 points in the scale, confirming the variation in the emotion felt by the subjects. This means high intensity with negative feeling of emotion load.

Regarding arousal, the mean values reached 7 points in events where the car gets closer to another vehicle circulating at high speeds in the highway (3rd event in scenario 2) and 6 points while raining and the participant witnesses an accident of other vehicle (3rd event in scenario 4). Having in mind the complete scale is from 1 to 9, these values in the upper third part of intensity of emotion proves a good immersion into the scenarios feeling the events with enhanced intensity.

We can observe the same behaviour in valence values reported in these events, where the values nearly reach 3.5 points in both cases. Furthermore, in the final event from scenario 4, participants agree in arriving with a low emotional load in terms of arousal with a positive feeling in terms of valence (around 7).

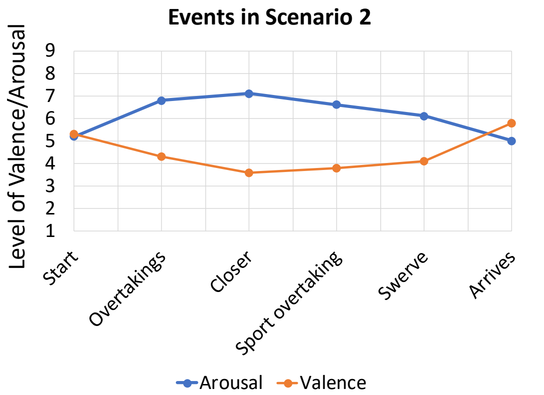

Figure 7: Mean SAM results in questionnaires from scenario 2 per event.

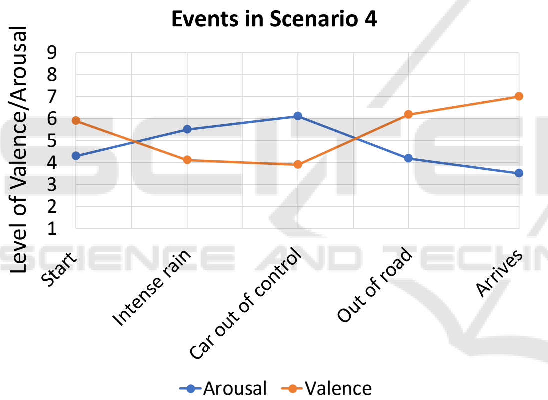

Figure 8: Mean SAM results in questionnaires from scenario 4 per event.

After a deep analysis of the data, the expected result is the database of physiological signals in the different autonomous driving situations and their self-appraisal of the emotion felt. This database is used to generate the dimensional emotional model. To this purpose, the most appropriate classificatory system is selected. These include: Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks such as the bidirectional Long Short Term Memory (BLSTM) or Transformers, Support Vector Machines (SVM), Relevance Vector Machine (RVM), Linear Discriminant Analysis (LDA) and others (Bong et al., 2013; Jang et al., 2012; Mohamad, 2005; Shu et al., 2018).

In these preliminary analyses, the initial results also show that the emotions felt varies from events according to the scenario and it is also gender dependent (variations in sentiment whether the participant was a female or a male). However, the emotion is independent of the achievement (on time or not) of the task of the different scenarios.

4 DISCUSSION

SUaaVE seeks to integrate the human component in CAVs through understanding the emotional state of the occupants. In this regard, the immersion strategies defined in this study are a key aspect for studying the occupants reactions in a realistic way in a driving simulator.

This study means the first step to generate a model so as to characterise drivers and passengers in L4+ CAVs from their physiological signals, to study the factors that might influence their emotional reactions during the trip. In fact, a better estimation of the occupants state can be used for the identification, together with vehicle sensors (cameras, radar, and LiDAR), of those factors that influence their emotional state, such as the vehicle dynamics (ride comfort), the environmental conditions (traffic density, behaviour other vehicles, presence of VRUs, etc.), or the interior ambient conditions & design. It also enables to consider the human factor in the development of advanced driver assistance systems (ADAS) as well as to support the artificial intelligence of the CAV by adjusting the decision-making algorithms of vehicles in terms of dynamics and itinerary for a comfortable and safe ride. In short, understand how we feel in a CAV and use such information to make system more empathic, responding to the occupant emotions in real time.

5 CONCLUSIONS

This paper addresses different strategies to enhance the immersivity and engagement of subjects while conducting tests in a driving simulator in the framework of automated vehicles.

The results of the test performed with these strategies showed that participants felt immerse in the simulation and that they could evaluate the events in the different scenarios as if they were real, with intense emotions noted both in objective and subjective feedback obtained from them, as it is the physiological signals, which were continuously monitored and by questionnaires respectively.

The following steps in SUaaVE, using as a basis the data base obtained from the tests with subjects (physiological signals and subjective assessment) is the generation of an emotional model aimed to estimate the passengers state from their physiological signals.

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