The Estimation of Occupants' Emotions in Connected and Automated Vehicles

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Keywords: Connected and Automated Vehicles, Emotion, Dimensional Model, Physiological Signals, Human Centered Artificial Intelligence.

Abstract: One critical factor of success and user acceptance in connected automated vehicles (CAVs) is trust in technology, being the main obstacle that remains from a customer's perspective. Trust in automated systems is based on feelings of safety and acceptance, being the emotional process the most influential aspect. One of the main ambitions of SUaaVE project (SUpporting acceptance of automated VEhicle) is to develop an emotional model to understand the passenger's state during the trip (in Real-Time), based on body biometrics, allowing to adapt the vehicle features to enhance the in-vehicle user experience, while increasing trust, and therefore acceptance. This research addressed a initial experiments to identify changes in the emotional state of the occupants in different driving experiences (in a driving simulator and in real conditions) by measuring and analysing the physiological signals of the participants, serving as a basis for the generation of the emotional model. The results showed that it is possible to estimate the level of Arousal and Valence of the participants during the journey from the analysis of ECG, EMG and GSR signals. These results have positive implications for the automobile industry facilitating a better integration of human factor in the deployment of CAV.

1 INTRODUCTION

Many researchers, experts and companies in the automobile industry (Sensum, 2020) coincide in stating that future automated vehicles will be entirely focused on the passenger experience and understanding the passenger requirements. Research on the introduction of emotional passenger state in the artificial intelligence (AI) of connected and automated vehicles (CAVs) to make every service empathic is needed. Yet, nowadays most of the development is being focusing on the technological feasibility of such vehicles without sufficiently considering the human factor, particularly in the context of the anticipated vehicle-user interactions considering the emotions of the occupants. However, both the science and technology of emotion are still in relatively youthful states (Sensum, 2020), being necessary to tackle this topic of research from the perspective of Human Centered Artificial Intelligence (HAI).

Emotion state could be obtained through questionnaires, behaviour analysis and physiological response. Questionnaires are the most used technique,

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Belda-Lois, J., Iranzo, S., Silva, J., Mateo, B., Palomares, N., Laparra-Hernández, J. and Solaz, J.
The Estimation of Occupants' Emotions in Connected and Automated Vehicles.
DOI: 10.5220/0010214802620267
In *Proceedings of the 4th International Conference on Computer-Human Interaction Research and Applications (CHIRA 2020)*, pages 262-267
ISBN: 978-989-758-480-0

because of their simplicity, but not adequate to real time interpretation (Harmon-Jones & Winkielman, 2007). Behavioural analysis, body posture, gaze and facial gesture can determine some emotions but other emotions, such as happiness, do not have a clear behavioural pattern or are recognised at late stages, such as drowsiness in fatigue.

The emotional response and many cognitive processes are partially processed unconsciously and the physiological response analysis allow to access to the unconscious response (galvanic skin response or skin conductivity, heart rate, electroencephalography, facial electromyography, breathing and blood pressure). The study conducted by Holzinger shows that physiological data can be used for stress recognition (Holzinger et al., 2013). In the case of automotive field, drivers stress has been detected with galvanic skin response, somnolence with breathing, fatigue with facial gesture and blinking or distraction with eye tracking (Tan & Zhang, 2006). Additionally, there have been great improvements recently resulting from the shrinking costs and growing accuracy of biometric sensors such as smart and wearable devices and non- intrusive (not necessary to attach sensors) solutions such as recording breathing with a camera (Laparra Hernández et al., 2019).

Existing work is focused on directly estimating human emotions based on a number of measures (Eyben et al., 2010). However, it is not an enough reliable approach to picture of a person's state.

Given this context, SUaaVE project (SUpporting acceptance of automated VEhicle), funded from the European Union's Horizon 2020 Research and Innovation Programme, aims to develop an emotional model to monitor and interpret the passenger state in CAVs based on the emotional response. In particular, this model will be based on the circumplex model of emotion (Russell, 1980). In his theory, the emotions are differentiated by their location on a bi-dimensional space created by the pleasantness-unpleasantness (Valence) and by the activation (Arousal). The variation among emotions is continuous and goes from negative to positive in the case of the Valence, and from passive to active in the case of the Arousal. Different emotions can be plotted in the two-dimensional space as shown in Figure 1. For example, happy has positive Valence and medium Arousal while sadness has negative Valence and low Arousal. Different studies have revealed that Valence and Arousal can be estimated with psycho physiologic methods, such as Skin Conductance Level (SCL), Heart Rate Variability (HRV) or Electroencephalography (EEG) (Chanel et al., 2007; Stickel et al., 2009).

In this regard, emotion recognition has been investigated to characterize the emotional state of subjects through the analysis of heartbeat dynamics estimating four possible emotional states based on the circumplex model (Valenza et al., 2014).

Under this approach, the ambition of SUaaVE is to build an emotion prediction framework for the automated vehicle based on the estimation of the occupants' state (their values of Arousal and Valence) through monitoring their physiological responses on board, by measuring cardiovascular signals, as well as electrodermal and respiratory activity. All these biometrics have been identified as capable to recognize emotions (Shu et al., 2018).

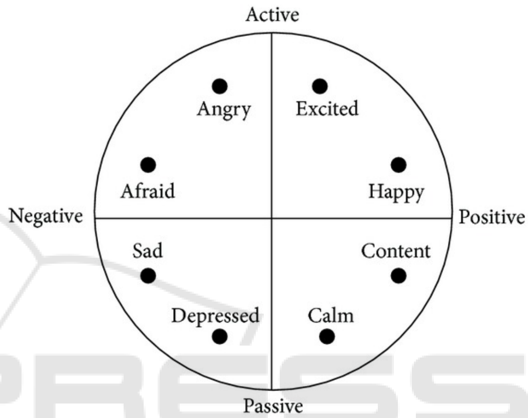

Figure 1: Two-dimensional emotion model based on Arousal-Valence space and basic emotions (Jirayucharoensak et al., 2014).

The aim of the article is to identify changes in the state of the occupants to different driving conditions, events and traffic environment (through the analysis of the physiological signal measured), interaciton with HMI devices and CAV as well as obtaining and estimation of the values of Arousal and Valence.This paper presents the results of the initial two experiments carried out in SUaaVE in a driving simulator and in a manual car in real conditions.

2 METHODS

2.1 Experiment 1: Measures in a Driving Simulator

The measurement of the physiological signals in a driving simulator was conducted in the dynamic simulator of IDIADA (DiM250 from VI-Grade), which generates longitudinal, transversal and rotational acceleration forces up to 2.5 g, characterised by low latency and high-frequency, replicating a wide range of vehicle dynamics manoeuvres. The scenario reproduced on the screens was a circuit around a big city, with fluent traffic, as observed in Figure 2. The participant was a male in the range of 30-35 years old, and with no cardiovascular pathologies. The participant performed manual driving control during the whole experiment. During the test, a codriver was also in the simulator to annotate the timing of the scenario events.

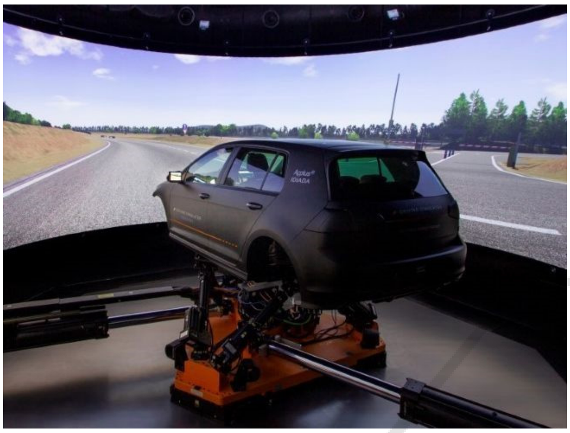

Figure 2: Dynamic simulator of IDIADA where the experiment 1 was performed.

The participant was instrumented with the equipment Biosignals Plux© for the acquisition of the following physiological signals:

- Electrocardiogram (ECG).
- Electromyography (EMG) of the facial muscles: Zygomatic and corrugator.
- Galvanic skin response (GSR).

The physiological signals were later processed to extract a set of key parameters that characterize their main features. After this, the values of Arousal have been estimated by a Principal Components Analysis (PCA) from the parameters of GSR and the HRV of the Low Frequency Band (0.04 – 0.15 Hz). GSR reflects the activity of the sweat glands, which respond to changes in the sympathetic nervous system. An increase in the level of emotional activation causes an increase in the level of GSR. HRV is inversely related to the intensity or emotional activation. When there is a high cognitive or emotional demand, the heart shows a steady rhythm to optimize performance, reducing heart variability. In contrast, when the person is in a state of relaxation or low activity, the heart rhythm is more variable, since it does not need to optimize the body's performance, thus increasing variability.

With regards to the estimation of the values of Valence, it was used the key parameter "normalised average value of activated frames" of EMG, taking into account that the zygomatic activation is mainly related to a positive Valence, whereas the corrugator activation corresponds to a negative Valence.

2.2 Experiment 2: Measures in Real Conditions

This experiment consisted on the measurement of the physiological signals of a co-driver, which is the most similar to a passenger traveling in a CAV. The participant was a female in the range of 30-35 years old, and with no cardiovascular pathologies. She performed an urban journey by car in the city of València (Spain) one morning of a weekday with variable weather.

In this case, the physiological signals were acquired by Empatica E4© wristband (allowing an unobtrusive monitoring of the driver), measuring the Blood Volume Pulse (BVP), from which heart rate variability can be derived (Figure 3).

Figure 3: Empatica E4© wristband.

During the experiment, the participant annotated the timing of any event on road. Furthermore, it was developed an online questionnaire (through Google Forms©) so that the co-driver pointed out, for each event, their emotional state through values of Valence and Arousal. The questionnaire follows the Self-Assessment Manikin (SAM) scale (Bradley & Lang, 1994), being the most appropriate to gather the emotional perception from subjects. The used scale consists of five pointers that relate directly to the Valence (positive or negative impact of the event) and the Arousal (level of excitement reached because of the event). Figure 4 shows the questionnaire used to assign values and characterize the emotion in each event.

The data acquired in real conditions were processed following the same methodology used for the data gathered in the experiment 1 with the dynamic simulator. The components of the HRV have been splitted by tree band-pass 3 order Butterworth filters in Very Low Frequency (VLF), Low Frequency (LF) and High Frequency (HF) with the common frequencies (0.04 Hz, 0.12 Hz and 0.40 Hz). Per each component 1 minute moving average of the square of the signal has been analysed.

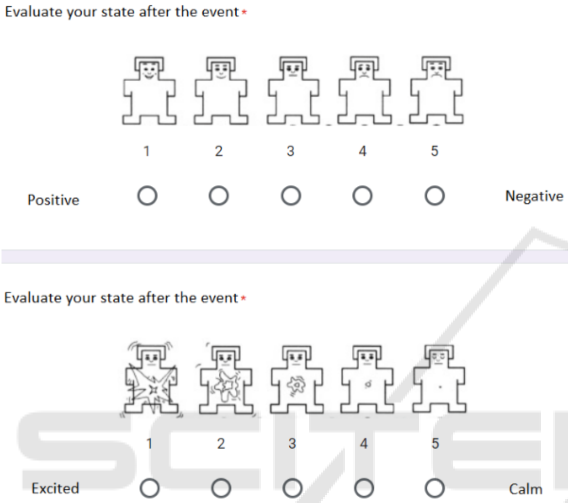

Figure 4: Google forms questionnaire (following SAM scale) used to evaluate the Valence and Arousal respectively of the co-driver in each event.

3 RESULTS

3.1 Experiment 1

The values of Arousal and Valence and their combination with respect to the events of the scenario simulated were observed. Figure 5 shows these results represented in the circumplex model. From the data it can be observed that different values of Arousal and Valence are obtained depending on the type of event on road.

In general, the Arousal levels are higher for negative Valence. This effect was expected because people are more reactive to negative stimulus in the virtual reality. Going into detail, the "Fog" event and the "Risky overtaking" were the ones eliciting the highest Arousal, whereas the event when the vehicle passed through a section of road with guardrails obtained the lowest values.

Concerning the Valence, taking a curve was the one eliciting the highest Valence. This can be explained because the driver liked sport driving and the curve was taken appropriately. On the other hand, the lowest value of Valence corresponds to the "First breaking", possibly due to lack of experience of driving in a simulator at the beginning of the experiment.

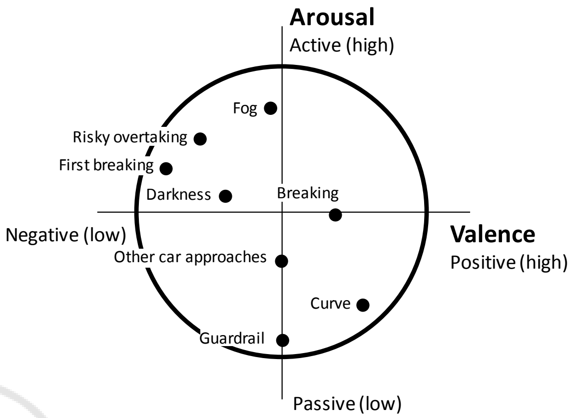

Figure 5: Values of Arousal and Valence obtained from the physiological signals acquired in the experiment 1 with the dynamic simulator.

3.2 Experiment 2

The Figure 6 shows the values of HRV for the whole trip. The first result is that there is noticeable variation of HRV for each event of the road. In general, it can be seen that HRV decreases (or the Arousal value decreases) as there is an event. This fact is especially remarkable with the events of low visibility, when there is heavy rain, or there is a risk of collision with another car, all with a decrease of Arousal values.

The moving average of 1 minute of each component of the HRV provides reliable measurements of the Arousal and the Valence declared by the user. In particular the VLF band is in good agreement with the Arousal (Figure 7) and the ration between the HF and LF band is in good agreement with the Valence (Figure 8).

As can be seen in SAM (Figure 4), the scale of Arousal moves from high Arousal (value 1) to low Arousal (value 5). Therefore, the relationship for the HRV is that the VLF decreases as the Arousal increases, as expected from previous results in the scientific literature.

The Valence scale in SAM (Figure 4) moves from positive Valence (value 1) to negative Valence (value 5). Therefore, the it is a direct relationship a higher ratio implies a more positive Valence (Figure 7).

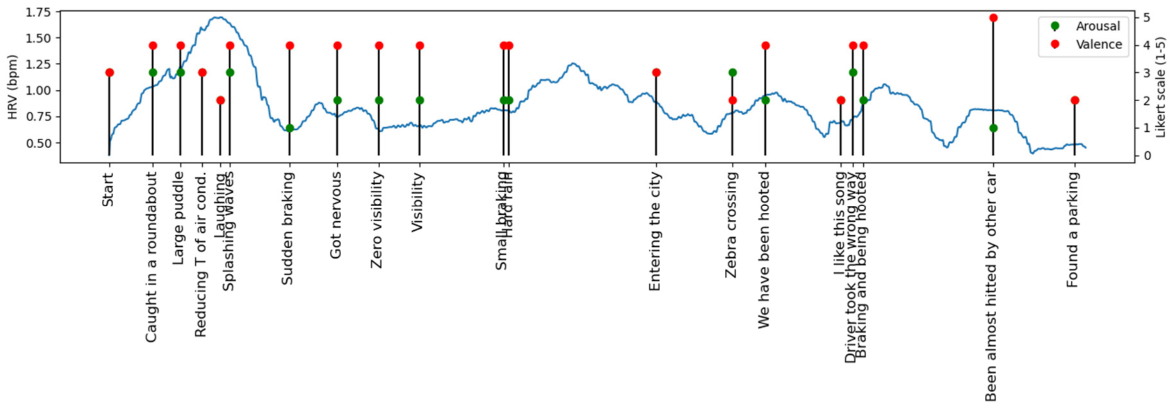

Figure 6: HRV along the experiment and emotional components (Arousal and Valence) declared by the user in each event.

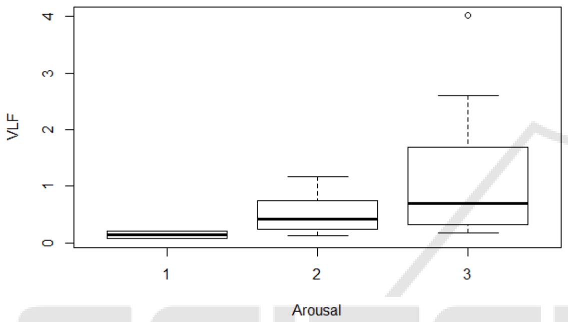

Figure 7: Relationship between the Very Low Frequency Component and the Arousal declared by the user.

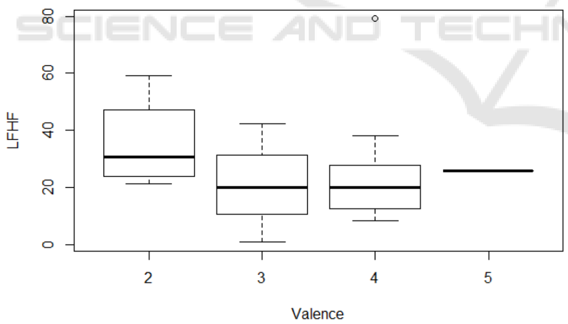

Figure 8: Relationship between Valence and the Ratio of HF and LF bands.

4 DISCUSSION

These experiments aimed to find out whether it is possible to identify changes in the state of driver to different driving conditions, events and traffic environment through the analysis of the physiological signals. The results obtained in both experiments showed that key parameters of ECG, EMG and GSR can to detect variations of the state of the driver and therefore estimate their emotional state by calculating the values of Arousal and Valence.

However, it is worth mentioning that these results are only preliminary and present certain limitations in samples and types of scenarios on road. A higher sample of participants, gender balance, driver experience and personal factors & preferences will be considered in the tests with subjects to be conducted in the next stage of SUaaVE in the Human Autonomous Vehicle (HAV) at IBV, a dynamic driving simulator, which offer high level immersive experiences on board. This will allow to obtain a reliable model capable to provide an accurate estimation of the values of Arousal and Valence.

The results of this initial experiments have positive implications for the automotive field, especially on CAV experience. By measuring and analysing the biometric data of the occupants, the emotional model will be able to estimate the emotion and reactions of the people in a vehicle, opening the possibility of analyzing travelers' emotions all along the journey in real time. In short, the approach set out will enable that the automated vehicles will understand how we feel and use such information to make system more empathic, responding to the occupant emotions in real time.

The development of the empathic module will provide OEMs and Tier 1 suppliers a detailed characterization of the passenger needs, enabling them the development of strategies to enhance the in-cabin experiences. This opens multiple possibilities to tailor the travel experience such as:

- Intelligent adjustment of vehicle movements.
- Offer services such as the personalization of entertainment content.

- Improve the interaction with interfaces and virtual assistants on-board.

Therefore, this empathic approach presented will revolutionize the transportation through the analysis of physiological (biometric) and contextual (environmental) data, fused together to improve the understanding the emotional state of the passenger. This will allow to respond to the user in an appropriate way, establishing trust between people and automated vehicles, as well as enhance the in-cabin and personalized experience. Furthermore, the empathic module can be applied, not only to cars but also to other means of transport such as buses, trucks, planes, ships, to understand the experience of the occupants and provide tailored services accordingly.

5 CONCLUSIONS

The results of the current experiment validate that it is possible to detect changes in the state of the occupants on board from physiological signals. The extraction and analysis of key parameters of ECG and EMG allows to obtain the values of Arousal and Valence and therefore estimate their emotional state.

These results have positive implications for the automobile industry enabling that CAVs will understand how we feel and use such information to make system more empathic, responding to the occupant emotions in real time, and therefore enhancing the CAV acceptance.

Future tests with subjects in the immersive Human Autonomous Vehicle (HAV) will allow to generate in SUaaVE project a reliable emotional model, being more sensitive to differences in gender perspective, driving experience and personal profile.

ACKNOWLEDGEMENTS

The paper presents the overall objective and the methodology of the project SUaaVE (SUpporting acceptance of automated VEhicle), funded from the European Union's Horizon 2020 Research and Innovation Programme under Grant Agreement No 814999.

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