

A Novel Framework for the Assessment of the Impact of Affective UI Sounds in a Driving Situation Through Virtual Reality and Physiological Signals

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Abstract

The objective of this study was to develop an experimental framework that allows research on whether the combined use of a virtual reality (VR) driving simulator, electroencephalography signals collected during driving tests and designed attentional paradigms could be applied to assess the performance of affective warning sounds for re-channelling driver's attention in certain driving situations. Three VR driving scenarios with different stimuli and two driving tasks were designed and implemented. Acquisition of driver's physiological data and behavioural metrics were integrated to be gathered synchronously. In addition, an experimental protocol was designed for the assessment of the impact of affective warning sounds. The technical feasibility of the framework was evaluated with the results showing that the proposed framework enables the data acquisition and analysis for a variety of warning stimuli. After successful technical deployment, a study with experimental subjects will follow to evaluate the effectiveness of affective warning sounds.

Keywords: Driving simulator, attention, mental workload, sound, physiologic sensors, electroencephalogram, virtual reality

1 Introduction

Driving a car is a cognitively demanding task that engages a considerable continuous set of cognitive functions [1][2], such as perception, working memory, and attention. Perception involves recognizing and interpreting environmental information, such as road signs, traffic signals, and other vehicles.

Depth perception is critical for making accurate spatial judgments. Working memory supports remembering and following road signs, navigating complex routes, and responding to unexpected events. In addition to perception and working memory, attention plays a critical role in driving safety. It is viewed as a multiply dynamic cognitive schema that is triggered by and anticipates the

task context. Drivers' inattention, due to diverted attention caused by outer stimuli like navigation systems, mobile phones, or passengers can limit fast reactions and contributes significantly to traffic accidents.

In recent years, the development of multisensory driver assistance systems has been an active area of research. Studies conducted in this field have proven that visual and auditory warning signals can effectively alert drivers to potential hazards and quickly direct their attention to the desired location or direction in the environment. However, despite research to date, there is no consensus on the best way to design to capture the attention of drivers, increase alertness, and thus, respond to warning notifications in risk scenarios. To this end, the use of single or multimodal visual warnings such as head-up display (HUD) icons, auditory verbal/nonverbal warnings or even haptic information like vibrating steering wheels or seats has been recently explored [3].

The combination of visual, auditory, and tactile interfaces has been proven to be effective in understanding information, supporting effective attention and interruption management [4] [5]. Importantly, auditory cues have been shown to be advantageous in cognitive response in most cases, for triggering a driver's reaction to a target event [6]. Research on these auditory warnings has covered simple tones, earcons, auditory icons and speech messages [7]. While the meaning of auditory icons is considered to be easily understood by the driver, earcons are considered to be less obtrusive [8].

Our approach is based on the new concept of synthetic-generated affective sounds, that applies the envelope of naturally occurring sounds of which the emotional reactions are known [9] to amplitude modulate a synthetic-generated warning tone. Nevertheless, in spite of the assumed potential of using these synthetic affective sounds as little intrusive, but intuitive, warning signals in cars to influence the driver's attention, research on this subject is still very limited.

To monitor and evaluate attention on the primary driving task in driving simulators and as part of advanced driving assistance systems, classical methods such as self-reports, reaction time to specific driving tasks and videotaping drivers' gaze using camera-based solutions along with image processing techniques has been conventionally



Fig. 1: The experimental setup consists of a virtual driving simulation, attention-capturing primary driving tasks, recording of driving performance metrics and EEG capture of the subject.

applied. However, these strategies have evolved to more accurate and reliable approaches [10] like the exploration of driver's physiological information [11] to estimate the mental attention state of individuals driving in a simulated environment.

It was the goal of this study to develop a framework to allow research on whether the combined use of a custom immersive virtual driving simulation (see Figure 1), physiological signals collected during driving tests, and different attentional paradigms could be applied to evaluate how novel affective earcons can affect positively the driving performance, re-channelling driver's attention. The acquisition and processing of electroencephalography (EEG) signals [12] [13] [2], as well as the procedure for the estimation of driving performance metrics, were integrated into the virtual driving simulator to compare the influence of auditory warnings to visual in-vehicle warnings while the driver completed a series of highly attention-capturing primary tasks.

2 Materials and Methods

2.1 Driving Simulator and Experimental Tasks

A virtual driving route of 13910 meters was developed in Unity 3D, to be travelled at a speed of 80 km/h in 10 minutes. The Logitech G29 device is used as input device, and the HTC Vive Pro Eye VR headset displays the virtual reality driving simulation. Three driving scenarios

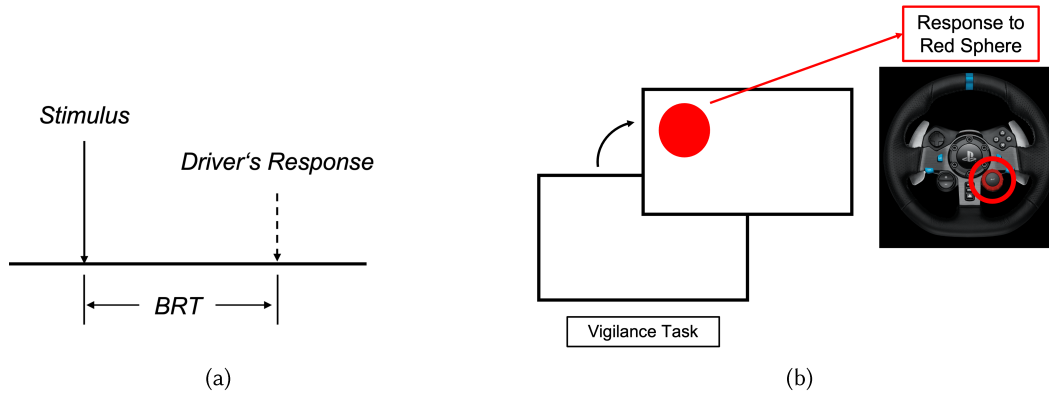


Fig. 2: Reaction time (RT) and task for eliciting attention.

were designed to gather neurophysiological measurements, enabling the measurement of reaction times (RT), driving positions and the response of drivers to events under different conditions.

- Scenario 1 contains no additional assistance, but the outright driving tasks. The driving scenario without any assistance was conceived to serve as a baseline and provide information about whether and which stimuli influenced the driver’s attention.
- Scenario 2 was developed to confront the driver with sounds used as a driving assistance mechanism. Two sound signals have been implemented to express warning and danger respectively.
- Scenario 3 implements visual warnings presented in the digital dashboard and triggered in situations that required the driver’s attentional resources.

In each scenario, simultaneous attention tasks (SAT), which required the ability to focus attention, have been developed and integrated into the Unity environment. Tasks are distributed with an interval of at least 20 seconds.

1. The first SAT includes an unexpected traffic jam scenario, which forced the driver to brake suddenly to avoid a collision with another vehicle. Artificial intelligence-based traffic was applied. To develop the interactive traffic scenarios, the *Simple Traffic System* asset was used [14]. This allowed the creation of waypoint-based routes that can be modularly connected to create traffic routes on roads

in selected scenes. The AI traffic logic was processed by a single AI traffic controller.

Auditory and visual stimuli are used to warn the driver at a suitable time.

2. The second SAT envisages a visual vigilance task to measure the attention state. A psychomotor vigilance task (PVT) has been adapted (Figure 2b) to determine sustained and behavioural attention using EEG signals and by measuring a subject’s reaction time to a specific visual stimulus. The driver should press a button on the steering wheel as quickly as possible when a red dot appeared on the driver’s windshield [15].

The reaction time (RT) measuring the difference between the reaction of the driver and stimulus time can be calculated as depicted in Figure 2a.

2.2 Procedure

The three above-mentioned scenarios allow us to gather neurophysiological measurements, reaction times, driving positions and the response of users to events.

To this end, the following experimental protocol has been defined and will be conducted with a study subject sample in a later phase of this research. Experiments must be conducted in a quiet and secluded room. After a briefing session (driving tasks, hardware, VR, EEG) EEG electrodes are attached to the participant. To reduce this risk of motion sickness, the driver is requested to start the experiment by practising for 5 minutes driving on the simulator. Participants are

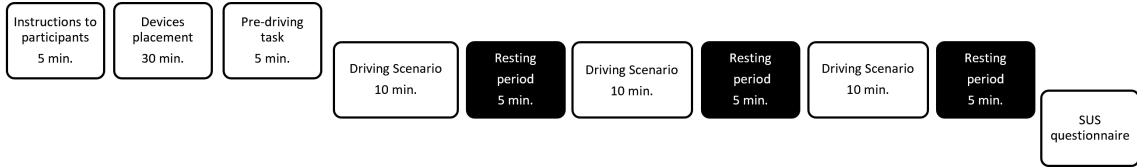


Fig. 3: Design of experimental protocol for the assessment of the impact of user interface (UI) sounds in driving situations.

instructed to drive through the three driving scenarios and may drop out of the experiment at any time.

In each driving scenario, the two driving tasks are presented in a random order to avoid bias. A five minutes resting period is established between driving scenarios. The experimental and timing procedure is described in Figure 3.

After completing all driving tasks, the participant has to complete a questionnaire to evaluate the system’s usability. System usability scale (SUS)[16] is used as an instrument.

2.3 Data Collection

During the experiments, drivers’ EEG signals are collected using the OpenBCI Cyton hardware (OpenBCI, USA). Subjects wear a standard textile EEG cap with Ag/AgCl dry electrodes. Most of the frontal lobe electrodes and part of the parietal lobe electrodes have been used to discriminate between levels of attention [13][17]. In our study, electrodes are placed at Fp1, Fp2, FpZ, AF3, AF4, F7 and F8 positions in accordance with the 10–20 international system, and digitized at a 250 Hz. Electrode locations that collided with the VR headset were not used. OpenBCI-GUI software is used for real-time brain wave visualization, streaming and recording. Lab Streaming Layer [18] (LSL) open-source framework has been implemented to allow multimodal data to be synchronously collected, including EEG, eye-tracking data, and driving performance information captured from the VR simulation (i.e. triggers, the position of objects and RTs). For each experimental session, all synchronized data are recorded with LSL Lab Recorder tool in a single XDF file. Python and MATLAB software are used for signal processing and data analysis. Figure 4 shows the system architecture, including hardware and software components.

2.4 Data Analyses

Collisions, brake and pressing button reactions are recorded while driving through each driving scenario. Using this information, several behavioural measurements for each participant can be analyzed. Since lower reaction times are generally associated with a decrease in attention and alertness, the following metrics are estimated:

1. RTs of the occurring PVTs are defined as the duration between the onset of the deviation, the event and the onset of the response during the event.
2. RTs to the emergency braking situation.

EEG signals are particularly well suited to research how stimuli influence the driver’s attention and performance. EEG waves can be decomposed into different frequency bands in a range of 0.5-40 Hz. Band power [19] is correlated to the different states of attention [13][20], especially in the following frequency bands [21].

- Alpha (8-13Hz): Linked to sustained attention and to the level of attention [19]. Demanding and complex tasks decrease alpha activity [1].
- Beta (14-30Hz): When sustained attention to task completion steadily rises, EEG beta activity increases [10].
- Theta (4-7Hz): Theta waves are involved in higher brain functions including working memory and focused attention. An increase in the EEG power spectrum in the theta frequency band over the prefrontal cortex has been found related to increased focused attention during a task [20][1] [15].

3 Results

A virtual driving simulator was developed to obtain result data. Figure 5 shows a part of the generated road and the driver’s view (a). One component of the simulation includes an AI-generated

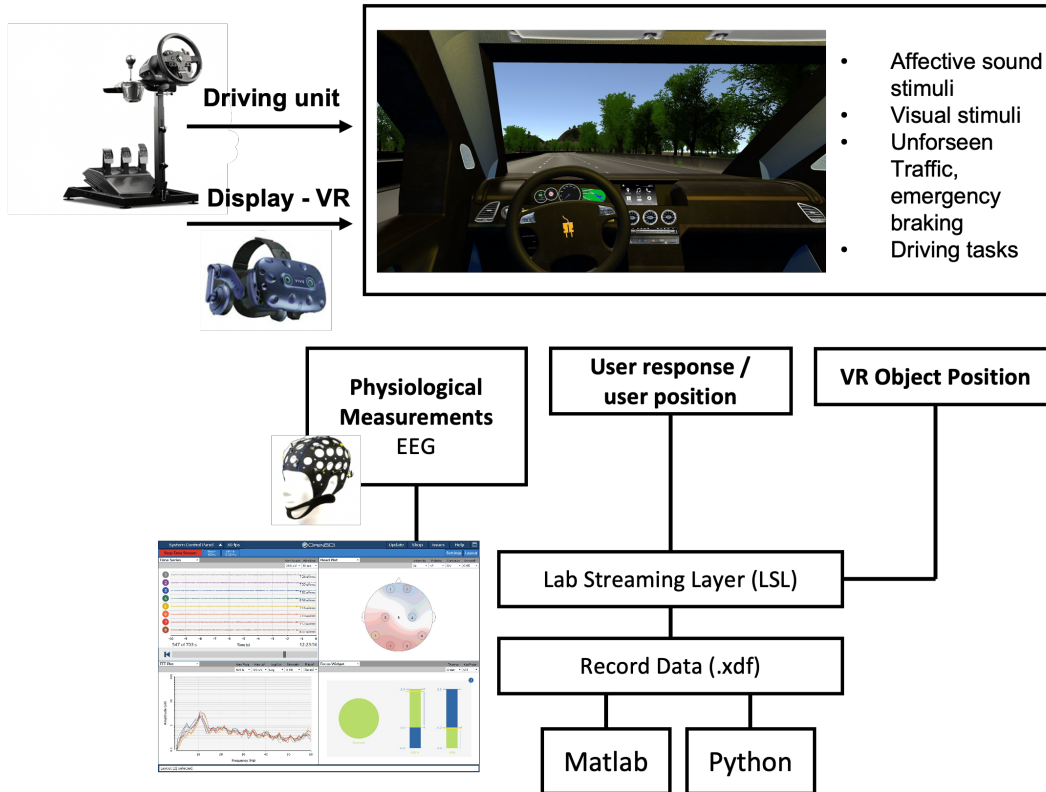


Fig. 4: System Architecture for the assessment of the impact of user interface (UI) sounds in a driving situation.

congestion situation (b) that the driver is confronted with while driving. Three different driving scenarios with different stimuli and two driving tasks in Unity 3D were set up.

The technical feasibility of the framework was assessed. The results showed that all the developed tools and the planned methodology were successfully integrated, enabling the experimental acquisition of the target data for the estimation of various driving performance indices for a variety of warning stimuli.

PVTs were integrated into the virtual driving scenario enabling the estimation of reaction times and, consequently, the driving performance and valuable information about the effectiveness of the stimuli used. EEG data using 8 electrodes and the OpenBCI hardware, eye-tracking data, as well as defined driver performance metrics can be synchronously acquired during VR experimental sessions using the LSL open-source framework.

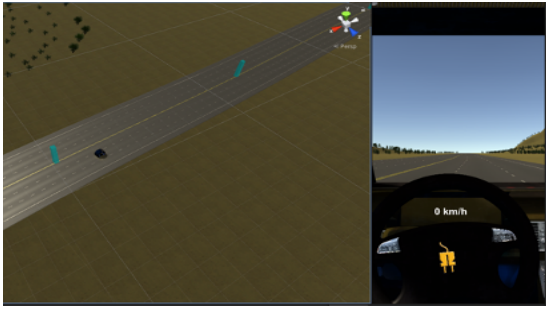
This way, changes in EEG alpha, beta, delta, gamma and theta power bands over time can be

quantified as well as other EEG features of interest for the evaluation of attention and emotional response while driving.

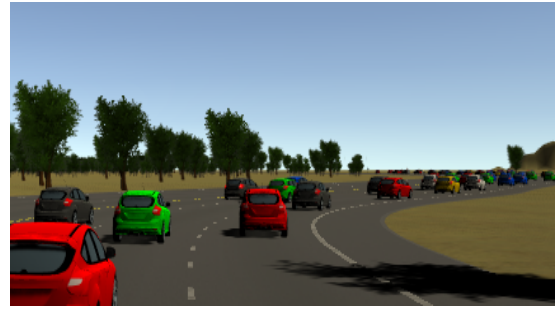
After successful technical deployment, which gives an outlook on the feasibility of a study and reinforces the effectiveness of the methods used based on current research literature, a study with experimental subjects will follow to evaluate the effectiveness of affective warning sounds. The study design has been submitted for approval by the ethics committee.

4 Conclusion and future research line

In this study, we have developed a framework that enabled us to explore whether affective warning sounds can be used in driving situations to improve attention and, therefore, driving performance. A virtual driving simulator was developed and different driving scenarios and tasks were implemented, to compare changes in drivers'



(a) Driving road



(b) Traffic jam

Fig. 5: nity driver route with driver's view and view of generated traffic jam situation

attentional status and reaction times when using visual, auditory and none assistance mechanisms. EEG power bands and driving performance metrics can be estimated during driving sessions.

The technical feasibility of the system was successfully tested, demonstrating the potential of our approach. The combination, of different metrics related to EEG brain measurements and reaction times, has the potential to assess the efficiency of driving support technologies, especially the use of affective sounds for driving assistance, under the experimental framework developed in this study.

The next steps in our research include conducting a study with a large and diverse sample of subjects to obtain statistically significant results and exploring new driving scenarios and unobtrusive sensors.

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