AttentivU: Designing EEG and EOG Compatible Glasses for Physiological Sensing and Feedback in the Car

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Figure 1. Side and front views of AttentivU glasses, showing the silver electrodes and frame as well as a user wearing them.

ABSTRACT

Several research projects have recently explored the use of physiological sensors such as electroencephalography (EEG) or electrooculography (EOG) to measure the engagement and vigilance of a user in context of car driving. However, these systems still suffer from limitations such as an absence of a socially acceptable form-factor and use of impractical, gel-based electrodes. We present AttentivU, a device using both EEG and EOG for real-time monitoring of physiological data. The device is designed as a socially acceptable pair of glasses and employs silver electrodes. It also supports real-time delivery of feedback in the form of an auditory signal via a bone conduction speaker embedded in the glasses. A detailed description of the hardware design and proof of concept prototype is provided, as well as preliminary data collected from 20 users performing a driving task in a simulator in order to evaluate the signal quality of the physiological data.

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Human-centered computing → Interaction devices;
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INTRODUCTION

Our everyday life and work have become increasingly complex and cognitively demanding. Our level of attention, engagement and vigilance influences how effectively our brain prepares itself for action, and how much effort we devote to each task. In some of these contexts, a decrease of vigilance or a momentary lapse of attention might even endanger the individual or other people's lives [24, 11, 58]. This is particularly relevant in the context of driving a car [54].

Several technologies exist for monitoring user attention, engagement and vigilance in a car, including gaze and eye-tracking systems [32] as well as video recording cameras [62, 63]. These prior solutions are prone to errors and limitations as cameras are particularly sensitive to the changing luminosity of the environment and pose privacy problems. Other measures include sensing physiological signals such as heart-rate variability [5], electrodermal activity [8], brain activity signals – Electroencephalography (EEG) [79], Electromyography (EMG) [21], and Electrooculography (EOG) [48]. Of these various modalities, EEG and EOG

have been reported to be promising and widely used in different contexts.

On the one hand, EEG is based on measuring electrical activity of the brain. This signal has been used as a neurophysiological indicator of the transition between wakefulness and sleep [2, 37, 70], and has been tested in different environments, where attention and vigilance are required. For instance, Shi *et al.* proposed several vigilance estimation models based on EEG [71, 72]. In a separate work, Eoh *et al.* found that there were significant differences in EEG between different driving periods of fatigued drivers [18]. Finally, Lin *et al.* developed a drowsiness-estimation system based on EEG [46]. EEG signals are also used to identify subtle shifts in user alertness, attention, perception, and workload in both laboratory and real-life contexts [20, 44]. Two major limitations of EEG-based systems are motion artifacts and form-factor: the electrodes are usually embedded in either a cap or a headband. While there has been a recent shift from expensive multiple electrode systems towards lower-cost 1-5 electrode setups, even a compact headband is not always considered to be compelling and socially acceptable for daily-life use.

On the other hand, EOG is based on measuring the biopotential signals that are induced due to cornea-retina dipole characteristics during eye movement. Researchers have shown that eye movements correlate with the type of memory access required to perform certain tasks, and are good measures of visual engagement and drowsiness [73, 74]. For instance, Bulling *et al.* investigated eye movement analysis as a promising sensing modality for activity recognition [7]. Many other studies report relations between features extracted from EOG and fatigue, drowsiness or vigilance [48, 52]. However, current EOG systems face similar issues to EEG headbands: they are either embedded in headbands and head caps like [23, 26] or attached to frames of glasses with wires and are not convenient or comfortable for daily-life use [6].

Various studies have indicated that signals from different modalities can represent different aspects of covert mental states [9, 15, 68]. In particular, EEG and EOG can represent internal cognitive states and external subconscious behaviors, respectively. These two modalities contain complementary information and can be used to construct more robust estimation models of vigilance, attention and engagement based on state-of-the-art methods. In the context of driving, such methods could provide novel ways to monitor drivers' attention and performance, as well as life-saving interventions that sustain drivers' attention whenever needed. Thus, we propose *AttentivU* which is a vigilance sensing device incorporated in the form-factor of a socially acceptable pair of glasses that supports real-time delivery of feedback in the form of an auditory signal via a bone conduction speaker (Figure 1). In this paper, we first discuss the feasibility of incorporating EEG and EOG in one, portable form-factor, as well as the potential advantages and

drawbacks of such system. We then evaluate the obtained EEG and EOG signals in a driving simulator scenario with 20 participants.

TERMINOLOGY

In this paper we use the terms vigilance, attention and engagement interchangeably. Vigilance is a term with varied definitions but the most common usage is sustained attention or tonic alertness. This usage of vigilance implies both the degree of arousal on the sleep–wake axis and cognitive performance. This paper defines vigilance and sustained attention as the ability to focus on one specific task for a continuous amount of time without being distracted. For a more detailed discussion of the different terms, we refer the readers to the review by Oken *et al.* [55].

This paper also uses the term cognitive fatigue, which is defined as the unwillingness to continue performance of mental work in alert and motivated participants [51]. Cognitive fatigue can also be defined as a phenomenon characterized by reduction of performance after continuous workload accompanied by subjective experience of exhaustion. It affects different cognitive functions including alertness, working memory, long-term memory recall, situation awareness, judgment, and executive control.

RELATED WORK

Glasses that Capture Physiological Signals

To the best of our knowledge, there are only two pairs of glasses that use either EEG electrodes or EOG electrodes in a socially-acceptable form-factor that are currently available on the consumer market: Smith Lowdown Focus Eyewear Glasses [74] by Muse and JINS MEME glasses [35]. Smith Lowdown Focus Eyewear is a light-weight, dry-electrode pair of EEG glasses with two electrode sites TP9 and TP10 according to the 10–20 EEG positioning system. JINS MEME glasses have a three-point EOG sensor on the nose-pads, a three-axis accelerometer, and three-axis gyroscope. Both glasses require the use of a secondary device such as a phone to get feedback about person's state of attention (JINS) or during meditations (Smith glasses). Any feedback and data are presented via a visual interface on the phone or via earphones, thus limiting possible use cases and presenting potential privacy issues for users.

The EmotiGO glasses research prototype [67] was designed for unobtrusive acquisition of a set of physiological signals, i.e., electrodermal activity, photoplethysmography (PPG), and skin temperature, which can be used to infer the emotional states of the wearer. Other papers investigated the possibility of extracting physiological signals like heart rate and breathing rate from Google Glass and other research prototypes like [14, 27, 28].

There are several jet lag/sleep improving therapy glasses such as the Re-Timer glasses [65]. They target light therapy and feature green-blue light LEDs diffused by a prism to stimulate the human circadian system through the eyes.

Other examples based on the same technology and principle include Ayo [22], Propeaq [61] and others.

Another example, which is closer to the system we present in this paper, are the Optalert's glasses [57]. They work by measuring the velocity of the operator's eyelid by using an LED built into the frame of the glasses. The metric is then translated into a score measured on the Johns Drowsiness Scale, which the operator sees displayed on their indicator or processor positioned in the car. The website does not detail what the indicator or processor consist of (LED or image) but based on the initial description, the system aims to close the loop and provide the feedback to its user in real-time about his/her cognitive states.

Glasses that Provide Information to the User

On the other side of the spectrum of technology embedded in glasses, there exist several examples of peripheral displays embedded in glasses, mostly to provide information to users on the go. For instance, Eye-q [10] is a wearable peripheral display embedded in eyeglasses that delivers subtle, discreet and unobtrusive cues in the wearer's periphery. The 1D Eyewear [55] similarly uses a 1D array of LEDs and pre-recorded holographic symbols to enable minimal head-worn displays with the help of computer-generated holograms (CGHs). In addition, the Focals glasses [19] support holographic lenses to provide the user with relevant information about the weather, messaging, etc.

Other glasses explore the use of auditory feedback as a source of providing real-time information to a user (e.g., Bose Frame glasses [4], Vue glasses [17]). However, these glasses do not provide assessments of the users' cognitive states.

Incorporating EEG in a Glasses Form-Factor

As mentioned previously, there are limited possibilities for incorporating EEG in a glasses form-factor which looks exactly like normal glasses. While a high frame for placing electrodes on the forehead could be acceptable in some settings like sports, they may not be socially acceptable during other daily life activities. In contrast, bendable ear-hook form-factors such as those used in the around-ear EEGs could represent a more acceptable alternative option. The only possibility would be to position the electrodes on the TP9 and TP10 sites according to the 10–20 EEG positioning system, as EEG signals can be obtained from those positions. To the best of our knowledge, only the Smith Focus glasses currently incorporate EEG on these positions which offers several possibilities to observe interesting phenomena, particularly event-related potentials (ERPs).

Temporal EEG electrodes for vigilance assessment

In addition to detecting ERPs, several papers report using lateral posterior electrodes and entropy measures for vigilance assessment in driving. For example, Hu [30] used entropy measures for feature extraction from a single electroencephalogram (EEG) channel. In particular, sample entropy (SE), fuzzy entropy (FE), approximate entropy (AE),

and spectral entropy (PE) measurements were deployed for the analysis of EEG signals and compared by ten state-of-the-art classifiers. They reported that optimal performance of around 90% of single channel is achieved using a combination of single channel among T6, TP7, T5, TP8, T4, T3 at the combination of feature FE, and classifier Random Forest (RF). The above results demonstrate that it is feasible to use a single channel for driver fatigue detection. In a separate work, Mu *et al* [53] also used PE, AE, SE and FE for EEG signals collected in normal (resting) state and fatigue driving states in order to extract features. In this case, retrospective analysis of the EEG showed that the extracted features from electrodes T5, TP7, TP8 and FP1 yielded better performance. As T8 channel is a well-established region for detecting changes in the drowsiness/fatigue state [34, 37, 68], we believe that closely located electrodes like TP9 and TP10 are well positioned to possibly detect and replicate the aforementioned findings.

Other Methods for Vigilance Estimation of Drivers Using EEG

One of the most cited and used indices in the vigilance estimation literature in driving scenarios is the EEG ratio index $(\alpha+\theta)/\beta$, where α (7–11Hz), β (11–20Hz), and θ (4–7Hz) are brain activity frequency bands. θ waves are usually associated with a variety of states including low levels of alertness during drowsiness and sleep and as such have been associated with decreased information processing. In contrast, α waves occur during relaxed conditions, at decreased attention levels and in a drowsy but wakeful state. Finally, β waves are related to alertness levels, and as the activity of β band increases, performance of a vigilance task also increases [38]. In Zhang *et al.* [80] the mean value of $(\alpha+\theta)/\beta$ increases significantly after the switch task where cognitive fatigue was measured, which was replicated by Eoh *et al.* [18]. As they explain, the index $(\alpha+\theta)/\beta$, combines the power of θ and α together “*during the repetitive phase transition between wakefulness and micro sleep,*” hence, mutual addition of θ and α shows a more significant effect compared to each of the components alone. Finally, Jap *et al.* [34] similarly found that a greater increase of $(\alpha+\theta)/\beta$ at the end of monotonous driving than other indices like θ/β or α/β . This work uses $(\alpha+\theta)/\beta$ and calls it the “*fatigue index.*”

Drawbacks and Limitations

Several issues should be kept in mind when using EEG. EEG has low signal to noise ratio (SNR). The artifacts including electrooculogram (EOG), electromyogram (EMG) and so on could hinder the signal quality of the EEG signal. That might be a paramount issue when working with low-cost, low-density number of electrodes.

Incorporating EOG in a Glasses Form-Factor

EOG signals provide information on various eye movements, which are often used to estimate vigilance because of an easy setup and high SNR [48, 60]. Many studies found relations between features extracted from EOG and fatigue, drowsiness or vigilance. Ma *et al.* extracted EOG features, mainly slow eye movements (SEM), to detect participants'

vigilance level during a monotonous task [48]. Morris *et al.* extracted specific components of eye and eyelid movement from EOG and found that blink rate was the best predictor of performance decrements resulting from pilot fatigue [52].

In comparison with EEG, the amplitude of EOG is significantly higher, which makes EOG more robust to noise than EEG. One critical issue with EOG-based methods for real-life applications is the electrode placement to record EOG.

In most state-of-the-art work, EOG is measured using four electrodes. Two electrodes are placed at the outer edges of the right and left eye to measure horizontal EOG, and vertical EOG is measured by two electrodes placed on the top and bottom parts of one of the eyes. However, this placement is not yet adapted for daily use as one would need to use glasses that touch the skin around the eyes and these glasses right now are mostly used in sports or environments, where risk for eye injury is high (factories, chemical labs), or VR headsets. Several works like [81] suggest using forehead EOG but in this case we run into the “headband” form-factor which is also used for low-cost, mobile EEG solutions and discussed in previous section.

To enable acceptable wireless EOG setup, compatible with daily life usage and extensive periods of wearing the glasses, we follow the method proposed by Kanoh *et al.* [36] for the placement of only three electrodes for EOG measurement. In their approach, three electrodes are used to measure EOG. One electrode is located on the nose bridge, and the other two electrodes are placed on the left and right nose pad, respectively. JINS MEME glasses [35] have these three EOG sensors placed on the nose-pads, and several works confirm the reliability of this placement to obtain data on number of blinks, etc. Moreover, the glasses look socially acceptable and were tested in in-the-wild settings.

Fusion of EEG and EOG using Small Number of Sensors

Having two physiological modalities naturally leads to a question of feasibility of fusing both of them to gain into improved classification outcomes. In Khushaba *et al.* [37], for example, a feature-extraction algorithm was developed to extract the most relevant features required to identify the driver drowsiness and fatigue states by analyzing the corresponding physiological signals from the 3 EEG and 1 EOG channel as well as electrocardiogram (ECG). Using EEG channels alone or a combination of EEG + ECG or EEG + EOG were shown to achieve highly accurate classification results when using nonlinear feature-projection methods.

Huo *et al.* [31] have shown that fusing forehead EOG data from 4 electrodes and EEG data from 12 electrodes can effectively improve the performance of driving fatigue detection. The authors also report that modality fusion of EEG and EOG yielded models of higher prediction correlation coefficient and lower root mean square error (RMSE) value in comparison with signal modality (EEG or EOG).

Additional Feedback Options

For use in driving tasks we rule out the use of visual feedback via an app, as our glasses are meant to be used in a visually charged environment, and we do not want users to get even more distracted by checking their phones or any other device to view their engagement level or fatigue level. Audio feedback may be a viable option in the case of bone conduction or other non-ear covering set-up, which is compatible with state-of-the-art glasses mentioned previously, like Bose AR Frame or Vue. For the current prototype of the glasses we choose auditory feedback which is built into the glasses, as well as a vibro-tactile feedback in a form of a pin clipped externally, on the body of the person, but other options and form-factors should be properly investigated.

Though to the best of our knowledge, there is no portable, closed-loop pair of glasses that deliver on-device, real-time feedback of any modality type based on physiological signals in the context of driving, the idea of having such a system is not new. Spence and Driver [76] proposed the use of auditory warning signals to maintain drivers' attention. Other modalities, like visual [47], tactile [29] or mixed [47] were also suggested. All the studies report that arousing warning signals (feedback) significantly improve task performance. Furthermore, using feedback might reduce the number of lapses of attention and thereby prevent potentially very dangerous driving episodes. Lin *et al.* [43] have demonstrated that an arousing tone-burst with a frequency of 1750 Hz can help users to maintain optimal driving performance. Same authors also investigated EEG dynamics and behavioral changes in response to arousing auditory signals that were presented to participants who were experiencing momentary cognitive lapses in a sustained-attention task [44].

Lin *et al.* [45] also developed a system to detect an ineffective auditory feedback so that the system can trigger additional arousing signals, e.g. auditory warning signals or other stimulus modalities. They further combined lapse detection and feedback efficacy assessment for implementing a closed loop system. By monitoring the changes of EEG patterns, they were able to detect driving performance and estimate the efficacy of arousing warning feedback delivered to participants.

SYSTEM ARCHITECTURE AND FIRMWARE

The system architecture of the glasses is modular so as to facilitate easy integration of different input modalities and feedback options. Surface biopotentials for EEG and EOG are acquired with electrodes embedded in the glasses (see Figure 1). Given the low amplitudes and noise of EEG and EOG, the signals are processed in the analog domain before being converted to digital data as explained below.

Processing Module for EEG

The biopotentials are amplified with a micro-power precision instrumentation amplifier, with gain calibrated to ~10V/V, referenced to the EEG regulated by the power

management system discussed below. The rail-to-rail output is filtered through a cascade of first-order low-pass and first-order high-pass filters with cutoff frequencies around 50Hz and 0.5Hz, respectively. The filtered analog signal is amplified with a micro-power CMOS operational amplifier with gain calibrated to $\sim 100\text{V/V}$. This amplified signal is again passed through a copy of the cascade of first-order filters discussed above, and an operational amplifier with gain calibrated to $\sim 40\text{V/V}$. The amplifiers use low offset voltage, near-zero drift over time and temperature, and low noise and very high Common-Mode Rejection Ratio (CMRR). The entire preprocessing discussed above offers a gain of $\sim 40000\text{V/V}$, a bandwidth of around 0.5 to 50Hz, input impedance over 100GOhm, and CMRR over 100dB, while consuming merely $\sim 3\text{mA}$ of power regulated at 3.3V.

Processing Module for EOG

The biopotentials are fed to a low-power integrated signal conditioning block featuring a high signal gain of $\sim 100\text{V/V}$ and a high CMRR of 80dB (dc to 60Hz). The passive components around the AFE (analog front-end) further provide a gain of $\sim 10\text{V/V}$ and a first-order bandpass filter with cutoff frequencies around 0.5Hz and 40Hz. The entire preprocessing discussed above offers a gain of $\sim 1100\text{V/V}$, a bandwidth of around 0.5 to 40Hz, input impedance over 100GOhm, and CMRR over 110dB, while consuming merely $\sim 4\text{mA}$ of power regulated at 3.3V.

Microcontroller and Bluetooth

The processed EEG and EOG signals are fed to a high-performance, low-power (1.0mA idle / 3.9mA active supply current at 3.3V) 12MHz microcontroller featuring an 8-channel 10-bit Successive-approximation-register (SAR) Analog-to-Digital Converter (ADC). The digital data sampled at 1000Hz is sent over Universal asynchronous receiver-transmitter (UART) to a low-power, high-performance Bluetooth module featuring a 2.4GHz antenna, for transmission of data with maximum signal delay of $< 50\text{ms}$. While the Bluetooth module provides transmission of EEG and EOG, it can also receive feedback signals and send them to the microcontroller over UART. The microcontroller provides output options for visual, haptic or auditory feedback.

Power Management System

A dedicated power management system was designed primarily for voltage regulation of analog circuits, microcontroller and Bluetooth, and battery charging with LED indicators. A 3.7V 150mAh Lithium Polymer (LiPo) battery powers all the electronics for about 5 hours, given the current draw is $\sim 30\text{mA}$. An alternate LiPo battery measuring 29x36x4.75mm can be attached externally, improving a single-charge battery cycle to 15 hours. A micro USB slot has been provided for charging the battery.

Firmware

The source code is written in C and is modular for easy integration of other input modalities and feedback options. The main block of code configures pins and

EEPROM/memory variables, sets timers for output updates, and initializes the interrupt handler. Other firmware methods handle the ADC conversion central to the microcontroller for all analog - physiological (EEG and EOG) and battery voltage data and data transfer over Bluetooth.

FRAME AND ELECTRODE DESIGN

The frame of the glasses is designed to carry two PCBs, two EEG electrodes, two EOG electrodes, a reference electrode, and a LiPo battery (Figure 2).

Selected components of the glasses' frame are made from pure silver to serve as the electrodes for EEG and EOG. The temple tips of the glasses frame are the EEG electrodes. The nose pads are the EOG electrodes. At the nose bridge of the glasses, an extra silver plate is placed to serve as reference electrode. The total weight of the glasses including frame, electrodes, PCBs, and battery is 69.3 g.

Electrodes

We fabricated the electrodes in silver given its high conductivity ($\sim 63\text{m Siemens per meter}$) compared to other metals.

The EEG electrodes, designed to sit behind the ear on the temple tips of the glasses frame, were mechanically developed to attach with a pressure fit around the plastic frame of the glasses, removing any need for additional hardware and ensuring a smooth surface contact to the skin. The EEG electrodes were 3D printed in a 92.5% Sterling silver alloy, using a lost wax casting method. The earpieces are printed in nylon plastic with recessed imprints for the electrodes, allowing the electrodes to sit flush with the frame surface. The EOG electrodes sit at the nose pads of the glasses. They are also printed in 92.5% Sterling silver.

Figure 2. Exploded view of the glasses, showing EOG electrodes (1), reference electrode (2), EEG electrodes (3), PCBs (4), LiPo battery (5) and small open chamber for piezoelectric element to deliver bone conducted sound.

Frame

The frame is made from Nylon Plastic which is a flexible material. The frame's width is designed to be slightly smaller than an average person head, and coupled with the flexible plastic material, the frame can snugly grip onto a range of differently shaped heads. Additionally, the grip allows the user to maintain a normal range of head motion without degrading the electrodes' contact. A finite element analysis has been performed on all components under mechanical

load, particularly the hinges, to ensure that the frame can withstand typical use.

Auditory Feedback

Auditory feedback is delivered via bone conduction through a piezoelectric transducer, with maximum consumption 5mA for 65dB at 3V. The placement of the piezoelectric element was determined by testing for possible noise interference into the EEG signal. The final placement, on the mastoid behind the ear, was satisfactory both for lack of interference with the EEG signal and for quality of the bone conducted sound. The frame of the glasses has a small open chamber at the end of the ear hooks, allowing the piezo element to sit on a thin (0.9mm) plastic wall against the mastoid for direct vibrational transfer.

The audio output is triggered through PWM output from the Atmega328 microcontroller. Frequency of the output was calculated by dividing the prescaler value into the chip clock speed, and dividing the result by 256 to account for the wrapping of the PWM counter:

$\text{Clock (12MHz)} / \text{Prescaler (64)} / 256 \text{ (PWM bit wrapping)}$
 $= 732.4 \text{ Hz output (medium tone)}$

$\text{Clock (12MHz)} / \text{Prescaler (8)} / 256 \text{ (PWM bit wrapping)}$
 $= 5,859.3 \text{ Hz output (high tone, default setting for feedback in this paper)}$

Vibro-tactile Feedback

In this work, we used a feedback system in a form-factor of a pin which consists of a 3D printed case with removable electronics consisting of an Adafruit Feather 32u4 Bluefruit, 1 vibrating motor controlled by an Adafruit DRV2605L haptic motor controller, and a 105mAh LiPo battery. The vibration lasts for one second and is only provided when the fatigue level is medium and high (explained in Data Processing section). In order to design subtle haptic stimuli, we adjusted the voltage used to control the motors (pulse-width modulation), which changed the motor's vibration frequency and vibration amplitude. The low intensity of 0.3g (40Hz) was chosen to be considered appropriate and private.

VALIDATION OF ATTENTIVU

In order to study the potential utility of AttentivU, we run a user study with the following goals: 1) evaluate if the feedback stimulation triggered by the increase of fatigue of participants resulted in reduced fatigue levels, and 2) assess if both hardware and feedback components were positively rated by users.

Participants

Twenty participants between 21 and 35 years old (10 females, $M = 25.0$ years, $SD = 1.8$), participated in this study. All participants reported to be in good health. Informed consent was obtained from all participants prior to the study and the experimental protocol was approved by the ethics committee of the institution where the study took place. All participants reported being non-professional drivers with at

least 2 years of driving experience. All participants possessed normal or corrected to normal vision as one of the pre-requirements to participate in the study, as we wanted to make sure they could wear our glasses prototype.

Experimental Setup

The study was conducted using the SIMESCAR SILVER driving simulator (SIMUMAK) which was originally designed to teach novice drivers (Figure 3). The simulated environment is provided by three 32" monitors with a viewing angle of 135 degrees. In addition, there is a 10" control panel with the dashboard information situated behind the steering wheel. The cockpit is designed for one person and contains a steering wheel, three pedals (gas, brake, and clutch) as well as a gear level (5 gears + reverse). While the simulator allows for manual and automatic transmission, we focused on automatic transmission which deactivates the clutch pedal and the gear functionality is reduced to three main positions (forward, neutral, backward). The simulator also includes hardware switches for basic car features such as front lights, indicators, horn, and windshield wipers as well as safety belt. The simulator sits on top of a 2-degree of freedom moving platform with an inclination capability of ± 10 degrees, which transmits longitudinal and lateral accelerations when breaking, accelerating, and turning. Vehicle noise is provided with 5.1 surround speakers integrated in the headboard of the seat as well as the displays. During the driving test, the simulator captures telemetry information (e.g., speed, acceleration) as well as driving mistakes. To gain better insight into the driver's actions, we installed a Logitech HD Pro Webcam C900 webcam on top of the center screen which captured a frontal view of the drivers' face and upper body.

Figure 3. SIMESCAR SILVER driving simulator (SIMUMAK) used in the study.

At the beginning of the study, participants performed a 5-minute test drive, which would serve as a baseline measure as well as a way to acclimatize the participants with the driving simulator, as none of the participants had any prior experience using it. Subsequently, every participant completed 3 driving sessions in which participants were required to drive continuously between 60 and 80 km/h for 15-minute per session (Figure 4). These sessions involved

Figure 4. Participant 6 is performing a study. He is sitting in a simulator and wearing glasses as well as a pin (encircled in red).

the participants driving in night condition, with clear skies, on a highway and without traffic (Figure 5). We used the same settings for all the sessions to induce drowsiness and fatigue. The simulator was situated at a research lab and most of the experimental sessions took place at night between 8pm and 1am except for 3 participants who performed their sessions between noon and 6pm. The total duration of the study was 60 minutes and participants received \$30 check as a compensation.

Before the start of the experiment, the participants completed a demographic questionnaire (age, hours of sleep, driving experience, simulator experience, etc.), and we ensured that they understood the instructions. Additionally, we collected their subjective rating of fatigue using the Karolinska Sleepiness Scale, KSS. The goal of the study (measuring fatigue level) was explicitly explained to them and the devices were presented. Subsequently, before the test session started, the calibration session was performed as detailed in the subsequent session. The participants then performed the driving test session for 5 minutes on the chosen highway track. The same KSS rating of sleepiness was also carried out after each session ended. An additional questionnaire to collect feedback on the glasses and pin was also given to them immediately after each session. All the questions were typed in electronic form on a small 11" Macbook Air and were given to the participants while they were still sitting in the simulator. Once the three sessions were performed, the participants could leave the simulator and they were asked to fill out a final questionnaire with more general questions like *"Would you use such a system on a daily basis?"* *"Do you have any preference for any type of the feedback you experienced?"*, etc. At all times, a frontal view of the drivers' face and upper body, their EEG and EOG signals were recorded.

We decided to have three sessions but to only administer feedback in either haptic or auditory form during sessions one and three (random choice for a feedback modality). Participants were wearing both devices during all three sessions. This was done to ensure that all the participants would experience both types of feedback but that there was a "break" between each of the feedback types, a session where no feedback was administered. This helped us address

Figure 5. The highway road view that participants saw during the study.

the possible bias towards a type of feedback that was administered to the users as some users might have preferences towards one modality or another.

A pilot study with 3 male users was performed prior to the main study to determine the best setup, timing, check the data acquisition, and lights in the room. These three participants were not a part of a group of 20 users reported in this study. We additionally performed a study with 4 users in a real car, though we asked them to wear the glasses for a 15-20 minutes ride only and the device was not on, thus no feedback was administered. One of the experimenters was next to them at all times.

Signal Processing and Data Analysis

We built an online Brain-Computer Interface (BCI) system with minimal supervision that allows for the detection of user vigilance based on a multimodal combination of EEG and EOG features. The system itself is unsupervised, based on a fusion of a "fatigue index" we presented on page 4 and of blink detection in the EOG, but the determination of the various thresholds requires prior offline analysis to select the optimal thresholds. In particular, we acquired 2 minutes of blinks + eye movements, 2 minutes of data when the user was relaxed and had his/her eyes closed, and 2 minutes of data when the user was performing the test driving session (minutes 3-5 were taken from the test session) from 3 users. We applied the described method along with a grid-search across participants on EOG data for the detection of blinks and on actual task recordings for the upper and lower index values as well as for the fusion factor, as described below. We asked the users to perform the following eye movements: open eyes and keep them open without blinking, blink several times, close eyes and keep them closed, look left, look right, look up, and look down. We have also asked them to close their eyes and relax 4 times for 30 sec. These were the trials for our classification model. In total – 4 trials per person and per task were obtained.

We used a 1000ms sliding window with a 200ms step, to ensure that we had a chance of capturing blinks that are typically in the range of 500ms following the protocol suggested by Ma *et al.* [48]. Their blink detection algorithm is an improved version of the double thresholds method. Its key idea is to set two thresholds which represent the eyelid's closing speed and opening speed, respectively. The two thresholds can locate blink waveforms in EOG and be

executed in real time. We also identified an average B_{Nav} – number of blinks per person and per minute based on the 5-minute test driving session.

For the EEG, we calculated the fatigue index: $Y = (\alpha + \theta) / \beta$ as follows: we first computed the Power Spectral Density (PSD) over a 1-second sliding window and extracted the averaged power of alpha, beta, and theta frequency components to compute the index Y . We then smoothed the index using an Exponentially Weighted Moving Average (EWMA) to pick up general trends and further remove movement artifacts.

$$S(t) = \begin{cases} Y(t) & : t = 1 \\ a * Y(t-1) + (1-a) * S(t-1) & : t > 1 \end{cases}$$

where S corresponds to the smoothed index value produced using an EWMA, t is time, Y is the median-filtered index, and a is a regularization constant that is inversely proportional to the relative weighting of less recent events (a value of .3 was used in this study based on pre-test results). The output is a smoothed index per 15 seconds Y_{smooth} which is sent to our system. The smoothing duration was chosen empirically after pre-testing to identify a minimum timeframe that guarantees enough data to accurately make predictions.

We determined the distribution of Y from low (e.g., relaxation, Y_{min}) to high (e.g., driving in alertness state, Y_{max}) from the training session. Based on the minimum Y_{min} and maximum Y_{max} scores collected from the calibration for each participant, we calculated a normalized score for each participant between 0 and 100 as

$$Y_{norm} = \frac{Y_{smooth} - Y_{min}}{Y_{max} - Y_{min}} * 100$$

The fatigue range was divided into three different levels. A fatigue score of 0-30 was considered low, 31-70 as medium, and 71-100 as high. Feedback (regardless the modality, vibro-tactile or auditory) was only provided when the score was medium and high.

To perform the classification, we computed a factor on the basis of the average number of blinks compared to the average number of blinks at rest. In particular, if $B_{Ncurrent}$ was lower than B_{Nav} by 4 or more blinks for 4 consecutive epochs, we increased Y as follows: $Y = Y_{norm} * 1.25$. If $B_{Ncurrent}$ was higher by 4 or more blinks than B_{Nav} during 4 consecutive epochs, we lowered Y as follows: $Y = Y_{norm} * 0.75$. This classification decision was based on prior work showing a reduced number of eye blinks in fatigued drivers and pilots [50].

RESULTS

Since we issued feedback to the participants when fatigue reached medium and high values, we expected that the distributions of fatigue indices before the feedback was provided to not be significantly different. In the after setting

Figure 6. Distributions of fatigue level of the users before the stimulation based on EEG and EOG signals. X-axis represents the type of feedback ((1) sound-accurate, and (2) vibration-accurate). Y-axis represents fatigue score of the participants.

(after the feedback was issued), if one of the two feedback modalities was more effective at reducing fatigue, then we expected to observe a lower average fatigue for that modality. Figures 6 and 7 show the before and after distributions of fatigue levels. We first compared before and after distribution between sound and vibration feedback. In the before setting, the distributions were not normally distributed (Shapiro-Wilk significant: $W = 0.97613$, $p = 0.001416$; $W = 0.92325$, $p = 6.846e-09$). We could not apply the standard linear model with a normal distribution and instead used a generalized linear model (from lmer in R) Analysis of variance with a Gamma distribution (suitable for strictly positive values, which was always the case here) and with the Participant ID (before: variance explained $<1e-5$; after v.e. $<2e-04$) and the Session number (before: v.e. 0; after v.e. 0) as random effects and the feedback type as the fixed effect. For the before distribution, we had $AIC = 1717.5$ and $BIC = 1734.2$ with a non-significant ANOVA ($Chisq = 0.2129785$, $df = q$, $p = 0.644$), which matched our expectation, since the experimental design guaranteed it. For the after distribution, we had $AIC = 1664.8$ and $BIC = 1681.5$ with a significant ANOVA ($Chisq = 10.67208$, $df = 1$, $p < 0.001$): On average the vibration modality reduced fatigue by 10 additional points compared to the sound modality. In absolute terms with the vibro-tactile modality the fatigue index value was halved.

We then examined the perceived subjective effect of the modalities on fatigue levels (KSS score on the administered self-evaluation scale). Figure 8 illustrates the results as boxplots. For the analysis, we applied a linear mixed model (lmer4 package in R) analysis of variance (ANOVA) to compare KSS fatigue scores across feedback types. We checked for normality with Shapiro-Wilk ($W = 0.87529$, $p\text{-value} = 0.01457$; $W = 0.89528$, $p\text{-value} = 0.04$) and for equality of variances with Fligner-Killeen test (med chi-squared = 0.53169, $df = 1$, $p\text{-value} = 0.4659$), the distributions are not normal and the variances are equal. We thus applied a generalized linear model with the same rationale as before. The fixed effect was the feedback type

Figure 7. Distributions of fatigue level based on EEG and EOG signals of the users after the stimulation.

and random effects included Participant ID (1.3% of variance explained, Std. 1.18) and Session (0% variance, Std. 0). There appear to be no significant confounding effects between the fixed effect and the random effects. We obtained

Figure 8. Perceived subjective effect of the two modalities on fatigue levels (KSS score on the administered self-evaluation scale).

an AIC of 152.7 and a BIC of 161.0, Chi squared 97.75, Df 1, $p(>Chisq) = 4.759522e-23$, Marginal $R^2 = 0.5538$, Conditional $R^2 = 0.7875$ and a significant ANOVA ($p < 2e-16$). The vibration feedback led to a perceived KSS score of 4/10, while sound feedback led to a higher perceived KSS score of 6/10 on average.

Design Insights from Questionnaires

As already mentioned, we administered questionnaires to gather insights from our participants about the form factor of our two hardware components. The glasses were appreciated by almost everyone (18/20 participants). 12/20 participants indicated that they wear glasses on a regular basis. Regarding the haptic feedback pin, all 20 participants liked it (Likert scale evaluation). Three users suggested embedding the pin inside of a car as a part of the feedback interface, particularly, the seat belt or the steering wheel. We also asked questions about the social acceptability of the system and how they perceived the use of both devices in real-life. The glasses form factor was reported as socially acceptable (4 points on a

scale of 1-5 for 16 users, 5 points for the remaining 4 users). 12 users actually commented that they did not expect the glasses to be “so comfortable as it is a research prototype.”

Regarding the overall size of the glasses, all participants evaluated the glasses as 4 points out of 5 mentioning that they are “still a bit bulky but they actually look not bad at all,” as one of the participants commented. Interestingly, everyone evaluated the weight of the glasses as 4 points out of 5. This goes in line with remarks from [49] who pointed out that participants rated the total weight of the pair of the glasses of 100 grams with an average score of 8 out of 10 points, where 10 indicated high wearing comfort. For eyeglasses that weighed 75g, the average score was 9/10 points. Ours currently weighing 69.3g, goes in line with these findings and suggestions. However, we acknowledge that our glasses are missing lenses which may add up to 10g depending on lens type.

Overall, these subjective reports should be taken with caution. While they are preliminary, they suggest that the device could be worn over extended periods of time. We further analyze the form factor challenges in the Discussion section.

Informal Interviews with Users

Users liked haptic and auditory feedback equally with a slight preference towards the haptic feedback (11/20 users). They all reported that they preferred haptic feedback over auditory as it brought them back to their driving task more efficiently. Most of the users (14/20) also commented that they would like to customize the sound of the feedback as well as its volume. Several participants commented that they would like to try visual feedback as well. It is also interesting to see some of their comments in more detail, as all the users except four of them drive a car on a regular basis.

For example, participant 7 commented “I liked the glasses a lot. I think that both vibration and audio were equal in terms of bringing my attention back to the driving, but I think in my car, auditory feedback would not work for me. I would not ignore the visual stimulation, something like a police or ambulance like, with flickering. It always makes me alert and vigilant.”

Participant 1 commented on his preference for the pin “I liked the pin much more. I wasn’t expecting it, when the vibration started but it was very, like awakening. I think that vibration and audio were equal in terms of bringing my attention back to the driving, but vibration kept me awake, for sure.”

Participant 8 who does not wear glasses mentioned that “both devices helped me to stay attentive to some extent. I do not wear glasses normally but I actually felt pretty confident with these [...]. I would love to have those actually, in the car, they might be really useful.”

Participant 4 enjoyed having auditory feedback *“I prefer auditory feedback and I found it accurate. Maybe it also worked for me because of the high pitch.”*

Participant 3 commented, *“I would need a customization of auditory feedback as I feel that on longer term that would be more like a white noise for me and I would not pay my attention to it.”*

Participant 5, 13 and 19 highlighted the importance of testing the system in a real setup, *“After the first vibration I was like, ‘ok, focus on the road.’ Vibrations worked for me and it was good. As for the auditory feedback, it was good as well but I think I would need to have it louder in my car, as I have a sports one and it is pretty noisy.”*

Two users additionally suggested to look for other use cases for the glasses, such as studying and office work.

DISCUSSION AND FUTURE WORK

Our experiment confirmed that both haptic and auditory feedback increased vigilance of the participants. As the results in Figure 7 show, the fatigue score of the users who received biofeedback was reduced significantly, regardless of the modality of the feedback. Moreover, participants positively perceived the system and both types of feedback when evaluating the system, as we can observe from the subjective questionnaires, informal interviews, and comments from the participants. They had, however, a slightly stronger preference for the vibro-tactile modality. On average the vibration modality reduced fatigue by 10 additional points compared to the sound modality.

Several challenges and limitations should be acknowledged and addressed in follow-up work.

Challenge 1: Design considerations and form factors. Although the pin received positive feedback, we will explore other ways of providing feedback, that might be even more compatible with the car environment, like having it embedded in a seat belt or a steering wheel, as a part of the car’s interface. We would like to further evaluate if form-factor and placement make a significant difference in the perception of feedback by the users and its effectiveness in driving scenarios. Another interesting design choice to try is incorporating visual feedback options within the same glasses. Thus, users might ultimately have an option to choose between auditory, visual or haptic feedback. We will further investigate the possibility of miniaturizing the glasses and making them even more light weight.

Challenge 2: Motion artifacts. This system, as many others before it, uses artifact reduction techniques. We kept the algorithm and signal processing pipeline as close to the previously published works as possible, to ensure reproducibility of the study. Moreover, several related papers [24, 38, 76] used similar signal processing in a mobile context, thus our results may remain valid even when there is movement. However, we plan to further investigate the fusion of EEG and EOG and adding more features to

improve the sensor data and algorithm outcomes, and reduce motion artifacts as well as perform studies with more users in real cars.

Challenge 3: Set-up. The actual experiment was pretty short and though we tried to address the novelty factor, it cannot be fully excluded as one of the possible confounding factors. We thus plan to test the system in actual cars, both with “typical” setup, where a driver performs a daily commute as well as in scenarios, where high vigilance is an actual requirement for safety reasons, like in the case of drivers who operate mining trucks.

Challenge 4: Fatigue detection. Though we performed a pilot study, as well as calibration for each participant prior to each experiment, and the vigilance index ratio used in this study is well documented and studied in prior work, we believe that additional work is needed and new algorithms could be proposed for detecting fatigue level. A more dynamic calibration protocol could be developed, which takes into consideration daily mood and other factors that might have an effect on fatigue. With such dynamic calibration, we might not need to calibrate the system each time it is being used. Additionally, including the EOG features other than number of blinks, e.g., blink duration, could be added to further improve the classification outcomes.

In future studies, we plan to test different adjustments of both haptic and auditory feedback (different locations and variations in patterns and intensity of vibrations; different sounds, frequencies and durations) with the goal of identifying a method that is most effective in helping the user to stay focused/get back to the “engaged” state while being minimally disruptive. We are also interested in verifying to what extent, if any, habituation may occur. Finally, we plan to extend our tests to the real car environment as well as challenges this environment brings (noise, a big number of stimuli around). Though we performed a small pilot study, the number of participants is too small to report any statistical analysis to be performed on the gathered data.

CONCLUSION

We demonstrated the feasibility of embedding silver EOG and EEG electrodes in a socially-acceptable form factor of a pair of eyeglasses. The signals can be processed in real time with the on-glasses processor or optionally sent to a separate computer. We tested the glasses on 20 adults in a lab setting where they were asked to perform a driving task in a simulator while experiencing auditory feedback provided by the glasses as well as haptic feedback in a form of a separate pin. The results show that both types of biofeedback redirect their vigilance to the task at hand. To the best of our knowledge, this is the first prototype of glasses that uses the same type of electrodes for bimodal setup. We hope that having access to both EOG and EEG data as well as a real-time feedback delivery mechanism will be a compelling platform for several applications including vigilance monitoring for improved safety and engagement.

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