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Monitoring driver fatigue using a single-channel electroencephalographic device: A validation study by gaze-based, driving performance, and subjective data



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ABSTRACT

Driver fatigue can impair performance as much as alcohol does. It is the most important road safety concern, causing thousands of accidents and fatalities every year. Thanks to technological developments, wearable, single-channel EEG devices are now getting considerable attention as fatigue monitors, as they could help drivers to assess their own levels of fatigue and, therefore, prevent the deterioration of performance. However, the few studies that have used single-channel EEG devices to investigate the physiological effects of driver fatigue have had inconsistent results, and the question of whether we can monitor driver fatigue reliably with these EEG devices remains open. Here, we assessed the validity of a single-channel EEG device (TGAM-based chip) to monitor changes in mental state (from alertness to fatigue). Fifteen drivers performed a 2-h simulated driving task while we recorded, simultaneously, their prefrontal brain activity and saccadic velocity. We used saccadic velocity as the reference index of fatigue. We also collected subjective ratings of alertness and fatigue, as well as driving performance. We found that the power spectra of the delta EEG band showed an inverted U-shaped quadratic trend (EEG power spectra increased for the first hour and half, and decreased during the last thirty minutes), while the power spectra of the beta band linearly increased as the driving session progressed. Coherently, saccadic velocity linearly decreased and speeding time increased, suggesting a clear effect of fatigue. Subjective data corroborated these conclusions. Overall, our results suggest that the TGAM-based chip EEG device is able to detect changes in mental state while performing a complex and dynamic everyday task as driving.

1. Introduction

Electroencephalography (EEG)-metrics are among the most reliable contemporary methods to assess cognitive states (Di Stasi et al., 2015a). EEG recording devices have dramatically developed in the last ten years thanks to technological progress (Minguillon et al., 2017), making ubiquitous acquisition of brain activity not only possible, but inexpensive (Borghini et al., 2014; Picot et al., 2008; Wang et al., 2015). These new devices, which are user-friendly, portable, and low-cost, have increased the use of EEG-metrics in daily-life situations (for a review, see Minguillon et al., 2017).

The EEG recording device “TGAM headset” (ThinkGear ASIC module, NeuroSky Inc., San Jose, CA, USA) is a single-channel, dry electrode, wireless signal transfer system (see Fig. 1B) that has received considerable attention from the general public (Dance, 2012; Bilton, 2013) and the neuroscientific community (e.g. Johnstone et al., 2012; Rogers et al., 2016) because of its set of features that make it an ideal wearable EEG system: the low intrusiveness of the equipment, the robustness of the sensor technology, and the wireless measurement solution (Gramann et al., 2011). Furthermore, since it has been validated for scientific use for assessing variations in the cognitive state (Johnstone et al., 2012), neural-engineering researchers have started

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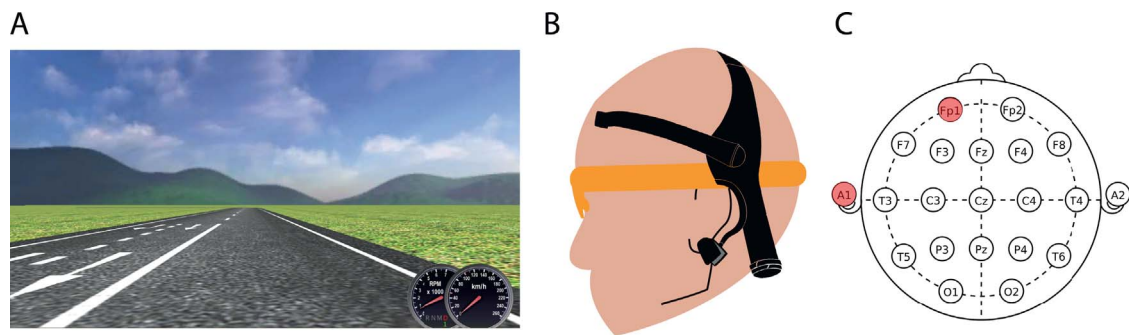


Fig. 1. A) A screenshot taken from the driving simulator. The speedometer gauges were displayed during the simulation. B) The configuration used to record EEG (black headset) and eye movements (orange element). C) The EEG device uses a monopolar montage with a single frontal dry electrode placed at Fp1, and uses the left ear-lobe as the reference/ground. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

developing EEG-based applications for daily-life (Minguillon et al., 2017), including for road safety (Morales et al., 2015).

Driver fatigue (i.e., under-aroused) is the most critical issue for transportation safety (National Transportation Safety Board, 2017), representing the main cause of motor vehicle crashes and traffic-related deaths (Touryan et al., 2016). Wearable EEG-based fatigue monitors have the potential to help drivers to assess their own levels of fatigue (Ko et al., 2015) and, therefore, to prevent the deterioration of driving performance (Dawson et al., 2014). Given its features, the TGAM headset should be suitable for use as a driver fatigue monitor. Unfortunately, since the pioneer case study by Yasui (2009), the question of whether the TGAM headset can monitor driver fatigue remains open. The few reports that have investigated this issue have not obtained conclusive results (see below), due to the inconsistencies and/or limitations in their methods/research designs. Examples of these limitations include 1) the use of unfiltered/unprocessed EEG data (Wan et al., 2013; Lin et al., 2015; He et al., 2015; Hsiao et al., 2015; He et al., 2016; Abdel-Rahman et al., 2015; He et al., 2014; Lim et al., 2014), 2) the use of an imprecise operationalization of the construct of fatigue – often confused with postprandial somnolence – (He et al., 2014, 2015), and 3) the absence of (comparative) gold standard indices of fatigue (Lim et al., 2014). All these limitations have compromised the potential utility of this wearable single-channel EEG device as a fatigue monitor.

Here, we present the first conclusive evidence about the sensitivity and validity of a single electrode EEG device (TGAM-based) as a driver fatigue monitor. We investigated the effects of a 2-h driving time – a common inducer of fatigue at the wheel (Wijesuriya et al., 2007; Di Stasi et al., 2012, 2016) – while we continuously monitored drivers' brain activity as well as their saccadic velocity. As saccadic velocity is a well-known fatigue index (Schmidt et al., 1979; Galley and Andres, 1996; Schleicher et al., 2008; Hirvonen et al., 2010; Di Stasi et al., 2016), we used it as a standard reference measure for fatigue. We also collected driver performance and subjective ratings of alertness and fatigue. We hypothesized that, during the 2-h driving session, participants would gradually experience higher levels of fatigue. EEG activity, recorded at the prefrontal cortex, as well as saccadic velocity, would reflect this phenomenon. Furthermore, we expected that participants would show poorer driving performance (i.e., increased speeding behavior) as the driving session progressed.

2. Material and methods

2.1. Ethical approval

We conducted the study in conformity with the Code of Ethics of the World Medical Association (WMA, Declaration of Helsinki) (WMA, 1964). The experiment was carried out under the guidelines of the University of Granada's Institutional Review Board (IRB approval #24/CEIH/2015).

2.2. Participants

Seventeen active drivers (mean age [\pm standard deviation, SD] = 25 ± 3.45 years, range 22–34; 12 men) volunteered to participate in this study. All participants had normal or corrected-to-normal vision and held a valid driver license (average number years of driving experience [\pm SD] = 5.94 ± 2.74 years). We asked participants to abstain from alcohol and caffeine-based beverages 24 and 12 h, respectively, before the driving session. Additionally, they had to get at least 7 h of sleep the night prior to the study. Thus, for screening purposes, we measured subjective levels of arousal using the Stanford Sleepiness Scale before the driving session (Hoddes et al., 1972) (see below): no participants scored more than 3, had they done so they would have been excluded from further testing (Connor et al., 2002; Morad et al., 2009; Di Stasi, et al., 2015a). No participants were excluded based on this criterion. Two participants suffered from simulator sickness and did not finish the driving session. Therefore, we finally analyzed data from 15 out of 17 participants (mean age \pm SD = 24.33 ± 2.69 years, range 22–31; 10 men). From three of them, due to log system failures during the recording, we only analyzed performance and subjective data.

2.3. Experimental design

The study followed a within-subjects design with the Time-On-Driving (TOD) as the independent variable. Each experimental session consisted of four consecutive 30-min TOD blocks (TOD1[0–30 min], TOD2[30–60 min], TOD3[60–90 min], and TOD4[90–120 min]) (Di Stasi et al., 2012; Di Stasi, et al., 2015b). Participants did not rest between TOD blocks. We chose this temporal window to be close to the maximum TOD that professional drivers are allowed before a mandatory break (Vehicle and Operator Service Agency[VOSA], 2009). As dependent variables, we considered several psychophysiological (the EEG power spectra, as well as the saccadic peak velocity while driving), driving performance (the percentage of speeding time), and subjective indices (the perceived alertness and fatigue before and after the driving session).

2.4. Driving simulation and performance

We used the OpenDS 2.5 software (Math et al., 2013, OpenDS, Saarbrücken, Germany) to create the virtual environment. We developed a two-lane, rounded rectangle (curvature angle of $\pi/2$ rad) road scenario. The road was ~ 1.5 km long with a width of 8 m, and it was surrounded by an empty and monotonous grassy meadow (see Fig. 1A). Participants drove a middle-sized car for 2 h without breaks (i.e. without stopping the vehicle or restarting the engine) around the same road in sunny conditions and without any other traffic present (average number of laps \pm SD = 62.2 ± 2.39). A speed limit of 60 km/h was

set up (average speed \pm SD = 53.37 \pm 2.25 km/h).

The interaction with the virtual car took place via devices typically present in an automatic transmission vehicle; accordingly, the primary controls of the simulator were physical. To control the car, participants used a Logitech G27 steering wheel (steering wheel, gas and brake pedals; Logitech International S.A., Lausanne, Switzerland) while seating on an adjustable car seat (PlaySeat®, Doetinchem, The Netherlands). Speedometer and tachometer gauges were shown in the bottom right of the screen. Six loudspeakers located around the driver, about the ground level, provided the simulated surround sound of the engine.

We used a video projector (EB-410W, EPSON Pty Ltd., Australia) to display the virtual circuit on a 1.32 \times 1.63 m screen, about 2.5 m from the driver's eyes (resulting in a view angle of \sim 26° vertically and \sim 33° horizontally). The experiment took place in a dimly lit laboratory. Similar experimental settings have been successfully used to investigate drowsy driving (Isnainiyah et al., 2014; Lawoyin et al., 2015).

During the entire experimental session, we controlled for room illumination and temperature, as well as for background noise (\sim 24 lx [Illuminance meter T-10, Konica Minolta, Inc., Japan], \sim 25 °C [Arduino controlled LM35 wire Digital Thermometer], and \sim 52 dB [Sound Level Meter DSL-330, Tecpel Co Ltd., Australia]).

The driving simulator recorded the car speed automatically (sample rate 20 Hz). We calculated the time spent speeding for each participant and TOD block, defined as the amount of time driving at a speed 10% or more above the speed limit.

2.5. EEG recordings and analyses

We collected EEG activity (at 512 Hz) using the TGAM headset (ThinkGear ASIC module TGAM1_R2V2.4A, NeuroSky Inc., San Jose, CA, USA). The device uses a monopolar montage with a single frontal dry stainless steel electrode (TGAM) placed at (approximately) Fp1 (contact area 12 \times 16 mm), according to the International 10/20 system (Jasper, 1958) (see Fig. 1B, C). The ear clip (left ear-lobe) acts as both ground and reference, which allows the TGAM chip to filter out the electrical noise from the body and the ambient environment. Before electrode placement, the pertinent areas of the skin were cleaned with a slightly abrasive paste and alcohol. Then, the dry electrode/ear clip were placed and secured with surgical tape.

The TGAM headset sends EEG raw data to a recorder unit via a Bluetooth connection. We collected the raw EEG data into EDF+ files using an ad-hoc LabVIEW software script (National Instruments Co., USA). Then, we imported the EDF+ files, preprocessed and analyzed them using Matlab (Mathworks Inc., USA). To remove physiological artifacts from eye activity, we filtered the signal using an order 10 Chebyshev type II filter, with a flat pass band between 0.1 Hz and 45 Hz, and an independent customized algorithm to remove blinks.

We segmented the whole EEG 2-h recording in four consecutive non-overlapped epochs of 30 min each (one for each TOD): TOD1, TOD2, TOD3, and TOD4. We divided data from each TOD into segments of 2 s in length. We considered artifacts and discarded segments with amplitudes out of the (-100 , 100 μ V) range. Then, we used the fast Fourier transform (window size of 512 samples and overlapping of 256 samples) – implemented in the EEGLAB Matlab toolbox – to perform spectral analysis and to calculate power spectra for the bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) frequency bands (Di Stasi et al., 2015a,b). Finally, we computed the average power for each frequency band and TOD. The power spectra were expressed as μ V²/Hz. We used the 10 logarithmic scale (\log_{10}) transformation to improve normality of data.

2.6. Eye movement recordings and analyses

We sampled eye movements binocularly at 1 KHz using infrared oculography (JAZZ-novo, Ober Consulting, Poznan, Poland). The JAZZ-

novo is a portable and lightweight, head-mounted system (see Fig. 1B). The eye-tracker uses a radio frequency connection to send raw data to a recorder platform. We collected the raw eye-movements data into EDF+ files using an ad hoc LabVIEW software script (National Instruments Co., USA).

We detected and analyzed saccadic movements as in Di Stasi, McCamy, and colleagues (Di Stasi, et al., 2013b). Briefly, we identified saccades with a modified version of the algorithm developed by Engbert and Kliegl (2003). This algorithm bases saccade identification on a velocity threshold that adapts to the level of noise in the data (see Engbert and Kliegl (2003) for a detailed description). Here, we used $\lambda = 10$ (to obtain the velocity threshold) and a minimum saccadic duration of 10 ms. To reduce the amount of potential noise, we imposed a minimum intersaccadic interval of 20 ms so that potential overshoot corrections are not categorized as new saccades (Møller et al., 2002). Because the magnitude of a saccade is related to both the velocity and the duration of the movements (Gruart et al., 1995), we studied the effects of TOD on the saccadic peak velocity/magnitude relationship (Becker and Fuchs, 1969; Evinger et al., 1991). We assumed a power fit relationship between saccadic magnitude and peak velocity (Di Stasi, et al., 2013b). Thus, we performed robust linear regressions (using the robust fit function in MATLAB [Mathworks Inc., USA]) on the raw data for each participant for each TOD block. We did a robust linear regression on $\ln(PV) = m \ln(MAG) + b$, which assumes the power-law $PV = e^b MAG^m$. Here, b is the y -intercept and m is the slope. Thus, for each participant, we obtained four slope values of the saccadic peak velocity/magnitude relationship – one for each TOD – (hereafter, saccadic peak velocity).

2.7. Questionnaires

To evaluate the effectiveness of the fatigue-inducing manipulation, we asked participants to fill in the Stanford Sleepiness Scale (SSS) and an adapted version of the Borg rating of perceived exertion (BORG) (Borg, 1998). The SSS provides a global measure of how alert a person is feeling, ranging between 1 and 7 (Hoddes et al., 1973). It contains seven statements ranging from “Feeling active, vital, alert, or wide awake” (score 1) to “No longer fighting sleep, sleep onset soon, having dream-like thoughts” (score 7). The BORG indicated the level of fatigue (i.e., the level of perceived exertion associated with a task). It consists of a numerical scale (ranging from 6 to 20) anchored by “not exertion at all” (score 6) to “maximal exertion” (score 20). Participants filled in the questionnaires – in the same order – in two separate measuring sessions: at the beginning (i.e. Pre-driving), and at the end (i.e. Post-driving) of the driving session. Finally, at the end of the driving session, participants filled in the NASA-Task Load Index (NASA-TLX) (Hart and Staveland, 1988) as a global index of the perceived degree of task complexity (Di Stasi et al., 2009). The NASA-TLX values range between 0 and 100, with higher values indicating higher task complexity.

2.8. Procedure

After signing the consent form, participants filled in the SSS and BORG scales. Then, after a five-minute familiarization session, we calibrated the eye tracker and the driving simulation started. We instructed participants to follow the usual traffic rules and to keep the car mostly in the right lane. The speed limit was set up at 60 km/h. During the entire simulation, the experimenter did not communicate with participants, although they were constantly monitored through an observation window behind the car seat. After the simulation, participants filled in the same scales. In order to avoid diurnal fluctuations that affect arousal levels (Del Río-Bermudez et al., 2014), we carried out all experimental sessions between 9 a.m. and noon. Thus, we ran only one participant per day. Finally, to avoid an end-spurt effect-reactivation – that occurs when people know they are approaching the end of a task (Bergum and Lehr, 1963) – participants were blind about the duration

of the driving simulation.

2.9. Statistical analysis

To analyze the effect of TOD (i.e. fatigue), we performed separate repeated-measures ANOVAs on the dependent variables. For the *EEG power spectra*, we performed a two-factor, 4 (TOD) \times 4 (Frequency Band), repeated-measures ANOVA. For the *saccadic peak velocity* and the *speeding time*, we performed two one-factor repeated-measures ANOVAs, with TOD as the repeated-measures factor. Effect size was calculated using the partial η^2 statistic. We also performed separate trend analyses (one for each dependent variable) to identify the existence of significant trends in our data over the four TOD blocks. We used the Bonferroni adjustment to correct for multiple comparisons. If more than one trend was significant, we focused on the trend having the highest effect size. For all dependent variables, we compared each participant to him/herself across the TODs, and, therefore, variability between participants was part of the error terms. For the BORG and SSS scales, we used two separate paired *t*-tests with the two measuring sessions (i.e., Pre vs. Post-driving) as the repeated-measures factor. For all dependent variables, we used the Kolmogorov-Smirnov test and a graphical assessment to verify that both data and residuals were normally distributed. Both assumptions were always confirmed. Significance levels were always set at $\alpha \leq 0.05$.

3. Results

During a 2-h simulated driving session, we continuously recorded drivers' EEG power spectra, saccadic eye movements, and driving performance. For analysis purposes, we divided the driving time in four 30-min blocks: TOD 1, TOD 2, TOD 3 and TOD 4. We also collected subjective ratings of alertness and fatigue at the beginning and at the end of the driving session, and, at the end of the session, the perceived degree of task complexity.

3.1. Effectiveness of the TOD manipulation

To examine the effectiveness of the TOD manipulation, we analyzed changes in the saccadic peak velocity, and in the percentage of speeding time depending on the TOD, and in the SSS and BORG scores before and after the driving session.

Saccadic peak velocity changed across TOD blocks; $F(3, 33) = 10.62$, $p < 0.001$, partial $\eta^2 = 0.49$ (see Fig. 2A and Table 1). Trend analysis revealed a significant decreasing trend across the four TOD blocks; $F(1, 11) = 13.08$, corrected $p < 0.05$, partial $\eta^2 = 0.54$. These results confirm that TOD induced higher levels of fatigue as the experiment progressed (Di Stasi et al., 2012; Di Stasi, et al., 2015b; Hirvonen et al., 2010; Schmidt et al., 1979). In the same line, the driving performance and subjective results were also consistent with an effective fatigue-inducing manipulation. The speeding time changed across TOD blocks; $F(3, 42) = 6.95$, $p = 0.001$, partial $\eta^2 = 0.33$ (see Fig. 2B and Table 1). Trend analysis revealed a significant increasing trend across the four TOD blocks; $F(1, 14) = 7.84$, corrected $p < 0.05$, partial $\eta^2 = 0.36$. That is, participants exceeded the speed limits more often as the experiment progressed. Participants also experienced increased levels of sleepiness and fatigue at the end of the experiment (average $SSS_{pre} \pm SD = 2.0 \pm 0.7$ vs. $SSS_{post} \pm SD = 3.8 \pm 1.0$; $t(14) = 5.49$, $p < 0.001$; average $BORG_{pre} \pm SD = 7.7 \pm 1.4$ vs. $BORG_{post} \pm SD = 12.6 \pm 2.6$; $t(14) = 7.66$, $p < 0.001$). Finally, after the driving session, participants reported low levels of task complexity (average NASA-TLX $\pm SD = 44 \pm 8.5$), probably due to the monotony of the virtual scenario (Grier, 2015).

3.2. Effects of TOD on brain activity

The amplitude of the EEG power spectra was dependent on TOD and

the Frequency Band, $F(3,33) = 7.16$, $p = 0.001$, partial $\eta^2 = 0.39$; $F(3,33) = 28.755$, $p < 0.001$, partial $\eta^2 = 0.96$, respectively. The TOD \times Frequency Band interaction was also significant, $F(9,99) = 2.51$, $p = 0.013$, partial $\eta^2 = 0.19$ (see Fig. 3 and Table 1). We observed an overall inverted U-shaped quadratic trend across the experimental session for the power spectra of the delta, $F(1, 11) = 10.22$, corrected $p < 0.05$, partial $\eta^2 = 0.48$. That is, as the experiment progressed, delta EEG power spectra increased for the first hour and half, and, then, slightly decreased throughout the last TOD block (last 30-min). However, the power spectra of the beta band linearly increased across the experimental session, $F(1, 11) = 12.82$, $p = 0.004$, corrected $p < 0.05$, partial $\eta^2 = 0.54$. Finally, alpha and theta EEG power did not show a significant specific trend (corrected *p*-values > 0.05).

4. Discussion

We aimed to find conclusive evidence about the validity of using a single-channel, dry electrode, wearable TGAM-based chip EEG device to monitor driver fatigue. To obtain a much better understanding of how driver fatigue could be early detected while driving using wearable technologies, we combined this EEG device, for the first time, with high-speed eye tracking technology. Thus, we examined how EEG data (i.e. power spectra density) changed across a 2-h monotonous driving together with driver's saccadic peak velocity, a well-known index of fatigue (Diaz-Piedra et al., 2016). In addition, we analyzed the driving performance and subjective ratings of alertness and fatigue. We observed an inverted U-shaped quadratic trend for the delta EEG power spectra and an increasing linear trend for the beta EEG power spectra across the experimental session, which is coherent with saccadic eye movements and driving performance data. Thus, our combined results indicate that EEG-metrics recorded by this dry-electrode, single-channel EEG device can detect driver fatigue levels online.

4.1. The effect of fatigue on ocular, driving performance, and subjective indices

We used ocular, driving performance, and subjective indices to validate EEG spectral changes associated with TOD (i.e. fatigue). These validation indices provide unambiguous evidence about our successful manipulation of fatigue (i.e., TOD): participants experienced higher levels of fatigue as the experiment progressed.

Saccadic peak velocity decreased with increased TOD, which is consistent with our previous findings during long driving sessions (Di Stasi et al., 2012; Di Stasi, et al., 2015b), simulated flying tasks (Di Stasi et al., 2016), and time-on-duty (Di Stasi et al., 2012; Diaz-Piedra et al., 2016), as well as with independent earlier reports (Galley and Andres, 1996; Hirvonen et al., 2010; Ahlstrom et al., 2013). Consistently, driving performance degraded with increased TOD, and perceived levels of alertness decreased and levels of fatigue increased after the two hours driving. Performance degradation and subjective results are in line with earlier studies using similar experimental procedures (e.g., Lal and Craig, 2002).

4.2. The effect of fatigue on (pre)frontal EEG spectra

Spectral measures have repeatedly been reported in the literature to be reliable correlated to mental fatigue (i.e. reduced arousal level) (Wascher et al., 2014). Here, we found that overall EEG power spectrum changed across the 2-h driving session. (Pre)frontal (in our study, Fp1) power spectra for the delta EEG band showed an inverted U-shaped quadratic trend (power increased during the first hour and half and decreased during the last half hour), while the power spectra of the beta band linearly increased as the driving session progressed. While numerous studies (e.g. Lal and Craig, 2002; Craig et al., 2012) have reported increased levels of all EEG-spectral power across the entire scalp due to arousal decrements – including frontal derivations (Kirov

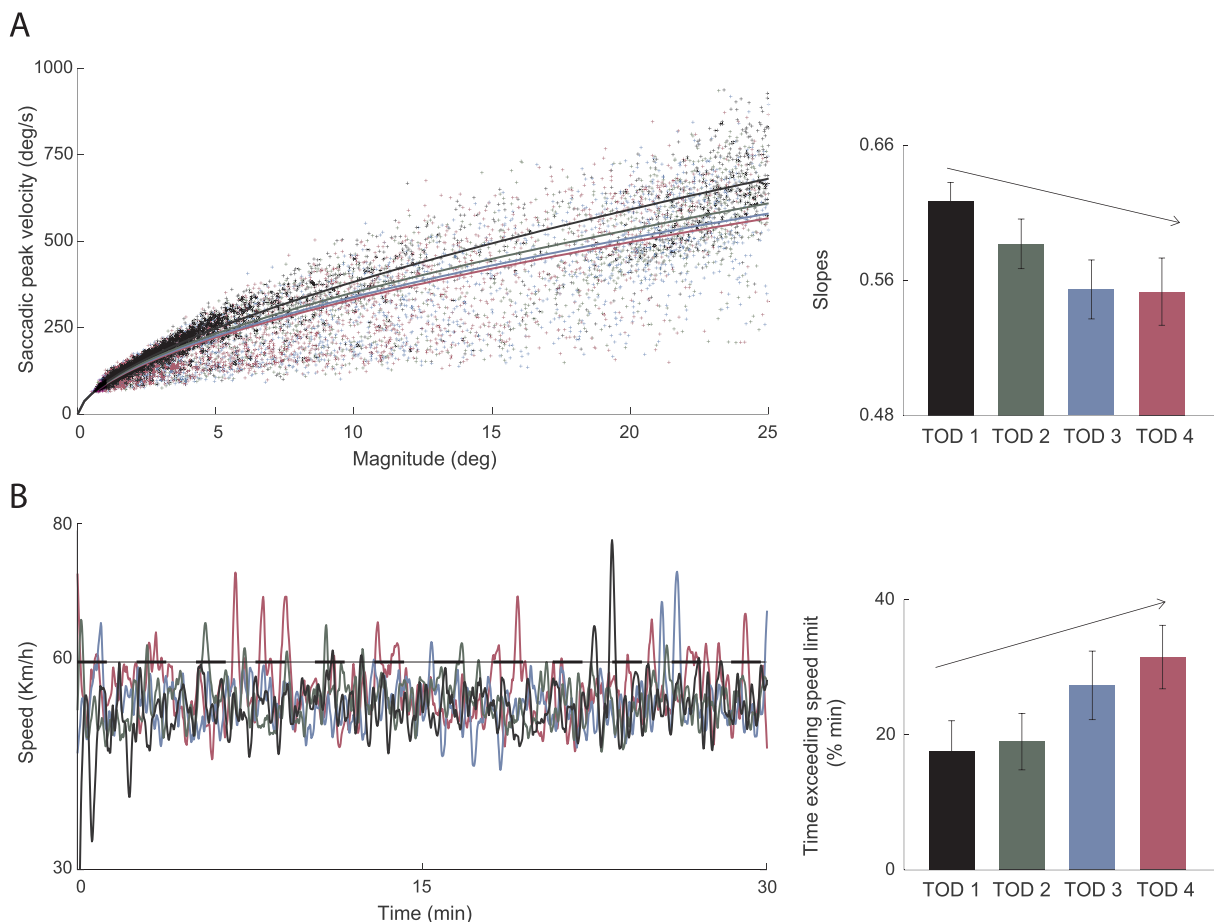


Fig. 2. Effect of Time-On-Driving (TOD) on the saccadic peak velocity and driving performance. A) Saccadic main sequence (peak velocity/magnitude relationship) for participant #14 across the four consecutive TOD blocks (1: black, 2: green, 3: light blue, 4: magenta; 30-min per block). Each dot represents a saccade. The curves are power-law fits to the data for each TOD block. Right panel: Average saccadic peak velocity across all participants for each TOD. The arrow indicates the significant linear trend of the saccadic velocity across TODs. Error bars represent the standard error of the mean across participants ($n = 12$). B) The speed profiles for participant #14 across the four consecutive TOD blocks (colors as in panel A). Right panel: Average number of times (%) of exceeding the speed limit (posted at 60 Km/h) across all participants for each TOD. The arrow indicates the significant linear trend of exceeding the speed limit across TODs. Error bars represent the SEM across participants ($n = 15$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

et al., 1996; Cajochen et al., 2002), this study, for the first time, replicated these differences using a single prefrontal channel. In line with earlier studies, as the cognitive state of the driver shifted from alertness to fatigue, we found an increase of frontal delta (e.g. Kong et al., 2017), theta (e.g. Wascher et al., 2014), and alpha (e.g. Simon et al., 2011) bands. Furthermore, as far as the fatigue arose (i.e. with the time-on-driving), there was an increase of frontal fast beta EEG activity, as found by previous studies (Dumont et al., 1999; Kiroy et al., 1996; Smit et al., 2005). It was suggested that the increase in beta power during sleep deprivation might result from the effort to stay awake (Corsi-

Cabrera et al., 1996; Lorenzo et al., 1995; Smit et al., 2005). Therefore, the increase in beta power in our study might reflect compensatory mechanisms to deal with the low arousal levels.

4.3. An arousal-based explanation

The results can be interpreted using an arousal-based theoretical approach (Andreassi, 2006): in a condition of a general cognitive deterioration, where the increase of delta EEG activity and the reduction of saccadic velocity occur as the driving session progresses, we

Table 1

Saccadic peak velocity (slope values of the saccadic peak velocity/magnitude relationship), speeding time, and power of each EEG frequency band for each one of the four Time-On-Driving (TOD) bins (30 min each).

	TOD1	TOD2	TOD3	TOD4
	M ± SD			
Saccadic peak velocity (deg/s)′	0.63 ± 0.04	0.60 ± 0.06	0.57 ± 0.07	0.56 ± 0.08
Speeding time (% time)′	17.55 ± 17.5	18.99 ± 16.14	27.32 ± 19.65	31.50 ± 18.22
Beta (μV ² /Hz)′	26.97 ± 0.82	27.57 ± 0.84	27.82 ± 0.88	27.78 ± 0.83
Alpha (μV ² /Hz)	29.28 ± 0.83	29.70 ± 0.93	29.84 ± 1.04	29.75 ± 1.12
Theta (μV ² /Hz)	31.79 ± 1.24	32.29 ± 1.20	32.48 ± 1.13	32.40 ± 1.36
Delta (μV ² /Hz) [†]	32.73 ± 1.39	33.53 ± 1.29	33.91 ± 1.19	33.86 ± 1.43

Note. Means and standard deviations (M ± SD) were calculated from the (mean) values of each participant. “/” denotes a statistically significant linear trend for the driving time manipulation. “†” denotes a statistically significant quadratic trend for the driving time manipulation.

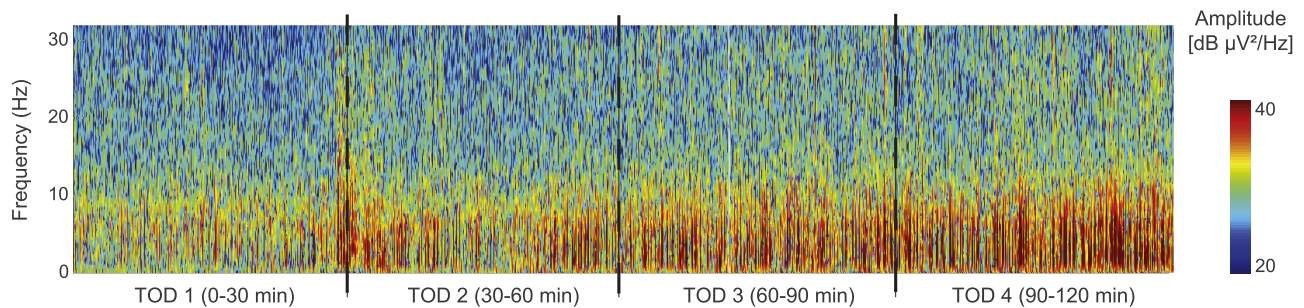


Fig. 3. Effect of Time-On-Driving (TOD) on the EEG power spectrum of one driver. The spectrogram (participant #14) shows the EEG power spectrum for the 2-h driving session. The dB scale is relative to $1 \mu\text{V}^2/\text{Hz}$.

observed the adaptive brain mechanisms to provide the proper arousal levels to perform the task (the increase of beta EEG activity) (Kirov et al., 1996; Craig et al., 2012). Arousal changes could also explain the decrease of delta EEG activity during the last TOD. Even when participants did not know the duration of the driving simulation, after more than 90 min of driving, they might have suspected that the session was ending, and the end-spurt effect (Bergum and Lehr, 1963) might have happened. Overall, this compensatory mechanism should, in part, arise at the level of prefrontal areas, which indicate sleep propensity during prolonged wakefulness and are also involved in the control of the saccadic movements (Burke and Coats, 2016; Marzano et al., 2007). In line with this hypothesis, the medial rostral prefrontal cortex (Fp1) has been recently associated with the saccadic programming, including the modulation of the saccadic peak velocity (Burke and Coats, 2016).

Note that we did not differentiate between fatigue and boredom (Lal and Craig, 2001). Thus, our results could be also interpreted as dependent on the reduction in motivation while performing a long monotonous task (for recent reviews on these topics, Borghini et al., 2013; Di Stasi et al., 2013a).

4.4. Implications

Our findings could help to bridge the gap between neural-engineering, basic neuroscience, and road safety by offering valid and conclusive evidence on the sensitivity of a wearable single electrode EEG device to monitor arousal variations while performing an ecological and complex task (i.e. driving). Furthermore, thanks to the possibility of simultaneously recording with other mobile peripheral sensors, this EEG device might make possible a multimodal approach to explore driving behavior. For example, the skin conductance response (SCR) has already been used to study driving behavior (Kinnear et al., 2013; Tagliabue and Sarlo, 2015; Tagliabue et al., 2017), and is also related to physiological arousal due to perceived mental effort (Howells et al., 2010). As the TGAM headset can be connected to a skin conductance sensor (e.g., (Abdur-Rahim et al., 2016)), the integration of both EEG and SCR would facilitate a more detailed assessment of driving behavior (Gianfranchi et al., 2017). Furthermore, the TGAM headset has a reduced cost and a simple setup. Therefore, this comprehensive assessment could be conducted outside a simulation laboratory. For example, the TGAM headset could be easily introduced in several “out of the laboratory” driving training programs (e.g., Tagliabue et al., 2013) to continuously monitor other arousal-related road safety factors, as for example (driver) mental effort (Di Stasi et al., 2009; Howells et al., 2010).

4.5. Conclusions

The EEG-based technology we tested accomplishes several neuroergonomics criteria to establish an ideal measure of the cognitive state in applied settings (Parasuraman and Rizzo, 2007). Briefly, two of the main requirements of such a measure of the cognitive state are

(Luximon and Goonetilleke, 2001): (i) sensitivity: it should detect significant variations in the cognitive state; and (ii) noninvasiveness: it should not interfere with the primary task. In our research, EEG-metrics were sufficiently sensitive to reveal significant differences between varied levels of mental fatigue and noninvasive, that is, the EEG recordings did not interfere with driving task performance. To sum up, our results suggest that the TGAM headset can provide a sensitive, real-time, non-invasive measure of variations of the cognitive state due to driver fatigue.

Conflict of interest

No conflicting relationship exists for any author.

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