

International Journal of Technology 13(2) 286-296 (2022) Received March 2021 / Revised April 2021 / Accepted August 2021

International Journal of Technology

http://ijtech.eng.ui.ac.id

# Fatigue during Prolonged Simulated Driving: An Electroencephalogram Study

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**Abstract.** Fatigue resulting from driving has been the subject of interest in many studies, particularly due to its pertinent role in road traffic crashes. Fatigue can be evaluated by certain indicators, such as changes in neural activity. The objective of this study was to characterize fatigue associated with prolonged simulated driving by employing electroencephalography. Fourteen male participants were recruited and asked to drive a simulator for five hours in the morning. All participants had two resting conditions the night prior to the experiment (sufficient sleep or partial sleep deprivation). Subjective responses clearly demonstrated an increase in fatigue as a function of driving duration. Data from brain wave activities, however, did not present clear, consistent changes as fatigue progressed. These findings suggest that theta waves can be used as manifestations of fatigue and temporal waves as the selected cortical area of concern.

Keywords: Electroencephalography; Fatigue; Prolonged driving

# 1. Introduction

Road traffic accidents are a growing issue that has received greater attention among key stakeholders in Indonesia. The government has acknowledged this issue by establishing a National Road Safety Plan 2011-2035 (RUNK, 2011). Staggering statistics show that roughly four individuals are killed per hour due to road accidents (Indonesian Central Statistics Agency, 2019). More than 100,000 cases of road crashes were reported annually between 2016 and 2018, resulting in a total of about 91,400 deaths in those three years. Nearly 70% of the victims were within the productive age group, while productivity loss was estimated to amount to more than 3% of the Indonesian' national GDP. Human aspects are believed to be a significant contributing factor to these accidents, with driver fatigue cited as a recurrent issue in many crashes involving motorized vehicles.

The relationship between fatigue and road accidents has been addressed in the literature (see, e.g., Dawson et al., 2018; Wedagama & Wishart, 2018; Williamson et al., 2011), but how fatigue progresses throughout a task remains an interesting challenge. Fatigue is a construct that is relatively easy to perceive, but a widely accepted operational definition of fatigue is probably far more difficult to establish (Phillips, 2015). Williamson

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et al. (2011) defined fatigue as "a biological drive for recuperative rest," implying the need for rests (from whatever tasks) as signs of fatigue. These researchers further noted that fatigue is caused by three different factors: sleep homeostasis, the circadian clock, and the nature of the tasks.

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May and Baldwin (2009) proposed that fatigue can be classified as either task-related or sleep-related. Since fatigue can be viewed as a feeling of 'tiredness' experienced by an individual, subjective methods have been employed in measuring the manifestations of fatigue (Ahsberg et al., 2000; Kar et al., 2010; Powell et al., 2011). Fatigue can also be described by looking at performance decrements during a task, although Phillips (2015) stated concerns about the consistency of such measures across different task contexts. It can be summarized that fatigue measurement is related to at least three aspects: physiological, objective, and subjective. The physiological aspects are those related to the body, muscles, central nervous system, hormones, and blood condition (Philips, 2015), while the objective aspects are those related to performance decrement and subjective factors related to how a person perceives the fatigue situation (Toomingas et al., 2012). The use of physiological changes, including electrooculography (EOG), electroencephalography (EEG), and ocular indicators, to characterize fatigue has gained more attention in the past decade.

Often labeled as the gold standard, EEG has been used in many investigations to understand the progressions of fatigue associated with prolonged driving (Craig et al., 2012; Jap et al., 2009; Ma et al., 2018; Wang et al., 2018). A report by Jap et al. (2009) described the various EEG parameters used to characterize fatigue, including the EEG waves  $(\delta, \theta, \alpha, \text{ or } \beta)$  and their corresponding power ratio parameters. Note that additional issues need to be carefully considered, such as which cortical areas should be the source of signal collection, the number of channels used to acquire the signals, experimental settings (laboratory vs. field), and the kind of task factors manipulated in the study. Jap et al. (2011) suggested the use of EEG ratios (particularly  $\alpha/\beta$  and  $(\theta+\alpha)/(\alpha+\beta)$ ) from the temporal area. while Hu (2017) recommended EEG waves obtained from the central parietal area of the brain. Except for the investigation by Wang et al. (2018), most of these studies were conducted in laboratory settings. The number of electrodes varied from a couple of channels to up to 32 channels. A variety of task factors influencing fatigue have been examined in the literature, including driving duration, the quantity and quality of sleep obtained before the experiment, time of day, whether the task involves monotony, and a host of other task factors (Gharagozlou et al., 2015; Kee et al., 2010; Perrier et al., 2016).

It is worth noting that there has been equivocal consensus on how the EEG parameters should behave as a function of time on task (driving duration) or differences in task factors. Perrier et al. (2016) demonstrated fairly consistent increasing–decreasing trends of EEG power across the frontal, central, and parieto-occipital areas. The patterns, however, did not indicate linear changes in EEG power as the driving task progressed. Their work further showed the utility of EEG power in distinguishing sleep-deprived participants from those

who received an adequate amount of sleep. Craig et al. (2012) investigated which EEG signals were recorded and analyzed from different brain regions during fatiguing driving tasks. Their study demonstrated marked differences in EEG, particularly in the alpha and theta waves. Although manifestations of fatigue by subjective and ocular measures are typically evident in many studies, changes in driving performance and (particularly) EEG have often been less clear.

This study aimed to examine changes in EEG signals during prolonged (5-hour) simulated driving activity. The objective was motivated by the fact that a driving duration of more than 4 hours is a fairly common phenomenon, experienced by bus drivers, taxis, and travel vehicle drivers in Indonesia (Belia & Handayani, 2020; Prastuti & Martiana, 2017). Driving durations of more than 3–4 hours have been continuously observed among commercial drivers in Indonesia (Puspasari et al., 2017). The majority of previous investigations typically studied driving tasks that lasted for less than 3 hours (Craig et al., 2012; Wang et al., 2018; Bose et al., 2020). Moreover, previous reports have generally demonstrated mixed findings concerning patterns of EEG changes during short-duration driving. It is of interest to determine whether changes in EEG signals are consistent throughout longer driving durations. Lastly, only a handful of studies have examined EEG signals recorded from several brain regions and have simultaneously employed more EEG parameters. We expect this study to provide a more complete understanding of brain activities during long-duration driving. Valuable information could be derived and utilized from our results, particularly within the context of fatigue management strategies, which could ultimately help alleviate road traffic crashes.

### 2. Methods

### 2.1. Participants

Fourteen male participants (mean  $\pm$  SD of age 26.36  $\pm$  4.59 years, height 168.56  $\pm$  2.52 cm, and weight 71.69  $\pm$  15.35 kg, BMI 20.1–30.1) took part in this study. All participants were right-handed, and all had normal vision. Male participants were recruited, considering that most commercial drivers were male. The inclusion criteria of this study included having a valid driving license, having at least two years of driving experience, and being familiar with long-duration driving conditions. The participants were reimbursed after they participated in the experiment. The calculated statistical power (1- $\beta$ ) for a sample of 14 participants was 0.8016, which is higher than the suggested minimum statistical power of 0.8, indicating that the number of samples was sufficient.

### 2.2. Experiment Protocol

Experimental protocols complied with the Helsinki Declaration guidelines for human subject research. Participants were briefed about the experimental procedures, and all participants provided written informed consent. They were then trained to use the driving simulator until they could drive with minor driving mistakes. The training and familiarization session lasted approximately 1 h, based on the ability to drive on a simulator.

Participants took part in two driving simulation sessions. One session was performed after the participants had 7–8 h of sleep (normal sleep condition). The other session was performed following a partially sleep-deprived condition (sleep duration of about 3–4 h) (Chen et al., 2016; Di Millia & Kecklund, 2013; Philip et al., 2005). The simulation sessions were conducted on separate days and in a random order to minimize learning effects and biases. During the entire experimental day, participants were advised to refrain from consuming alcoholic or caffeinated beverages and in-between naps. Participants were

provided with a heavy meal (450–550 Cal) 1 h before the driving simulation task on arrival at the experimental laboratory. A brief interview and blood pressure measurements were then administered to ensure that the participants were physically and mentally ready to attend the driving simulation session. The participants' systolic and diastolic blood pressures did not exceed 120/80 mmHg during the experiment session.

The driving simulation task started at 7.00 a.m. The participants were required to drive on the driving simulator for 300 min (5 h) to induce sleepiness and fatigue caused by the prolonged driving task. In this study, how prolonged driving affects fatigue was simulated by setting a 5-h driving duration without a break between tasks. This situation is commonly experienced by truck drivers, long-distance bus drivers, and other public transport drivers in Indonesia. A 30-min rest after driving was provided to alleviate their fatigue after the driving task. During the driving task, participants were instructed to obey the traffic rules, to keep their vehicle in the left lane, and to maintain the driving speed within the range of 40 kph and 60 kph.

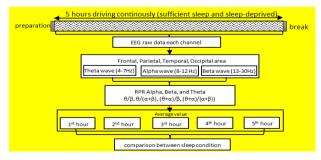
### 2.3. Apparatus

PC-based driving simulator software (City Car Driving v1.5.6, Forward Development, Russia) installed in a PC (Intel i7 processor, 4 GB of RAM, and 2 GB of VGA card) was used as the driving simulator in the present study. The dynamic simulation environment was displayed on a 32" LCD monitor (1366 × 768 pixels) positioned 40 cm in front of the participants. The simulator was equipped with a set of game controllers consisting of three pedals, manual transmission gear, a steering wheel system (Logitech G27, Logitech, China), and an external stereo speaker to generate the engine sound. The installed simulator was located inside a chamber with a pre-set air temperature of  $22^{\circ}$ C.

The driving simulator software provided a simulation loop track comprising highways and urban city roads with several intersections, traffic lights, road signs, and other vehicles and pedestrians. The vehicular traffic density of the driving simulation environment was set at 80% density, with moderate aggressiveness. The driving scenario consisted of several events, such as a pedestrian crossing, a leading vehicle with varying speeds, and a lane-changing event. The scenarios were similar for both experimental conditions.

### 2.4. Measurement and Analysis

Brain signals were recorded using a mobile EEG headset (Emotiv EPOC+, Emotiv, USA). This EEG headset quantified brain signals using 14 wet electrodes placed on 10–20 EEG systems and two reference channels to provide precise spatial resolution. The sampling rate of the EEG headset used in this study was 128 Hz (1 per 0.0078 s). The brain signals were transferred wirelessly to a laptop using a Bluetooth device and were recorded using Emotiv Bench software. Brain signals were recorded 5 min before and after the driving task and 30 min after the driving task.



## Figure 1 Data collection and analysis

Fast Fourier transform (FFT) was used to filter raw brain signal data. The raw data were stored in an edf file and then extracted using the EEGLAB toolbox in the MATLAB

environment to obtain filtered band-pass data. A power spectrum analysis (PSA) was then conducted to calculate the absolute power value for the following frequency waves:  $\theta$  wave (4–7 Hz),  $\alpha$  wave (8–13 Hz), and the  $\beta$  wave (13–30 Hz) to obtain the relative power ratio for each brainwave. From the brainwaves that were obtained, four ratios of brainwave ( $\theta/\beta$ ,  $\theta/(\alpha+\beta)$ , ( $\theta+\alpha$ )/ $\beta$ , and ( $\theta+\alpha$ )/( $\alpha+\beta$ )) were then calculated as the additional EEG parameters (Figure 1).

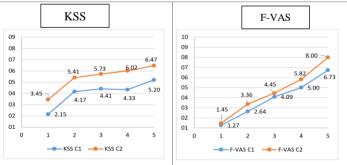
The subjective measurements of fatigue used in this study were assessed using the Karolinska Sleepiness Scale (KSS) (Kaida et al., 2006; Perrier et al., 2016) and the Subjective Fatigue Rating (Chuang et al., 2015; Gharagozlou et al., 2015). The KSS instrument consists of an explicit question about how sleepy or alert the participants had been feeling using a nine-point scale (1 = extremely alert and 9 = very sleepy, great effort to keep awake, fighting sleep). The subjective fatigue rating measures the participants' fatigue rating on a scale ranging from 0 (none) to 10 (worst possible fatigue). The subjective measurements were administered before and after the driving task, every 10 min for the KSS, and 30 min for the subjective fatigue score during driving. All participants were informed about the procedure of data collection during the interview and before the experiment started. To anticipate any effect on EEG data collection, the EEG data with a power value over 100  $\mu$ v<sup>2</sup> and below 0.5  $\mu$ V<sup>2</sup> was removed prior to data processing.

Data are presented as the mean  $\pm$  SD of the relative power ratio (RPR). Two-way (sleep condition × time of measurement) repeated ANOVA (RM-ANOVA) was employed to test the effect of sleep condition and time of measures (before and after the driving task and after 30 min of rest) on brain signals and subjective fatigue measurements. A post hoc test with Bonferroni correction was then applied when statistical significance was obtained. Statistical analysis was performed using statistical software. Statistical significance was set at *p* < 0.05 (two-tailed).

# 3. Results and Discussion

### 3.1. Results

As measured by subjective reports, fatigue shows a consistently increasing trend, although more linear patterns are shown for the F-VAS scores (Figure 2). At the beginning of the experiment, participants who received a normal amount of sleep reported a KSS score of "2" and a VAS score closer to "1," whereas those in the partially sleep-deprived condition reported a score of more than "3" and about "1," respectively. At the end of the experimental condition, the sleep-deprived group reported KSS and F-VAS scores of "6.5" and "8," respectively.



**Figure 2** Levels of subjective sleepiness and fatigue after five hours of driving. C2 denotes the partially sleep-deprived condition

It should be noted that taking a conservative KSS criterion of "5" as the limit for the driving duration, the participants with a reduced amount of sleep could only drive for about

1 h. By contrast, those with a sufficient amount of sleep may be able to continue for up to 5 h. All these differences were significant (p < 0.05). Changes in brain activities for each area are depicted in Figure 3. The blue line represents brain activities during sufficient sleep, and the orange line is during the sleep-deprived condition in the RPR. The RPR value is obtained by dividing the value of each band by the total power of all bands (Puspasari et al., 2017).

In general, lower alpha and beta power associated with reduced sleep was observed in all brain areas, whereas the opposite was true for theta waves (Figure 3). Beta wave activities were clearly noted in the temporal cortical area; mixed patterns were indicated for alpha and EEG signals from other brain areas. Clear theta wave patterns were shown in the temporal and occipital areas. Significant differences between the two sleep conditions (p < 0.05) were generally found for the theta waves, whereas such differences were observed only at the occipital area of the alpha wave.

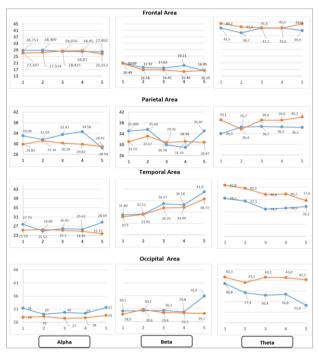


Figure 3 Changes in alpha, beta, and theta wave activities throughout the driving period

Apparent differences in theta activity between sufficient sleep and sleep-deprived conditions were observed in the temporal and occipital areas. We found that during sleep-deprived RPR, theta waves at the occipital relatively increased before the decline at the end of the driving session, whereas during sufficient sleep conditions, they decreased consistently. A slightly different pattern in the temporal area may indicate the behavior of theta waves related to prolonged driving—the theta waves showed a noticeable decreasing trend throughout the driving period.

## 3.2. Discussion

This study was primarily motivated by the fact that prolonged (more than 3 h) driving is relatively common among Indonesian commercial drivers, and we were curious to assess whether consistent changes in different EEG parameters could indeed manifest the resulting fatigue. As expected, the findings of this study clearly showed that prolonged driving was manifested by a linear increase in the perception of fatigue and sleepiness. Undue fatigue was recorded after 5 h of driving, particularly in the sleep-deprived group. Changes in feelings of drowsiness were somewhat non-linear, with greater levels of

sleepiness found among individuals in the sleep-deprived conditions. In a similar sleepiness level reported by Soares et al. (2020), fewer hours slept the night before driving corresponded to drivers who self-rated themselves as drowsier during driving. Fatigue induced by poor sleep quality and sleep deprivation is characterized by extreme sleepiness (Siswanto et al., 2017).

#### 3.2.1. Changes in EEG parameters

Unlike changes in subjective reports, consistent changes in brain wave activities were not clearly shown. Visual examinations tend to show inconsistent changes in many parameters, with a sudden increase/drop in the second hour of the task. A relatively consistent decrease in theta power was observed in the temporal and occipital regions, but the exact opposite occurred in the parietal regions. A consistent increase in beta power was found in the temporal region, whereas a slight decrease was observed in the frontal region. Two ratio parameters,  $(\theta+\alpha)/(\alpha+\beta)$  and  $(\theta / \alpha + \beta)$ , were found to decrease consistently in the temporal region. It is probably safe to suggest here that EEG activities (particularly theta and beta waves) from the temporal area can be used to describe fatigue associated with prolonged driving.

Craig et al. (2012) described changes in brain activities as their subject fatigued during a driving task involving nearly 50 participants and further explored which brain regions and EEG bands were affected. In general, their study showed that fatigue was associated with substantial changes in brain wave activities, particularly in the theta and alpha bands, but none for the delta band (below 4 Hz) in any brain region. An increase in beta wave activity was observed, but mainly from the frontal and mid-central sites.

Kee et al. (2010) reported increases in theta, alpha, and beta wave activities as a function of short driving duration, but the changes were not as substantial as changes in driving performance. A study examining fatigue during simulated driving (Golz et al., 2014) demonstrated significant alpha band increases. However, theta power did not present apparent changes throughout the driving task. In that study, EEG signals were obtained only from the occipital region. In their study, fatigue was characterized by clear and significant changes in driving performance and ocular indicators (microsleep percentage), which were somewhat different from patterns of EEG changes.

Pradep-Kumar et al. (2020) reported that alpha and theta were considered for analyzing the fatigue state of drivers. For high accuracy fatigue detection of an alpha wave during fatigue state, signals have been suggested to be taken from the occipital region (O1 electrode), temporal (T5), frontal (F3), and central (C4) regions, where signals for theta waves may be taken from the occipital (O2), temporal (T5), and frontal (F3, F8) regions.

#### 3.2.2. The effects of task factors

Data from this study demonstrated that marked differences in EEG were indeed present as manifestations of partial sleep deprivation. Theta power in the occipital and temporal regions of the sleep-deprived group was substantially more significant than in the participants who received adequate sleep. By contrast, the sleep-deprived condition was characterized by a marked reduction in theta wave activity, as indicated from the frontal, temporal, and parietal areas. Perrier et al. (2016) also studied the effects of sleep deprivation on EEG. Based on a one-hour driving task performed in the field, their study indicated marked changes in theta and alpha wave activities, coupled with a more moderate increase in beta activities. Greater activities in all bands manifested fatigue experienced by sleep-deprived drivers.

# 3.2.3. Research implications

From these and previous studies, we can conclude that fatigue (and drowsiness) from driving is often characterized by clear and consistent changes in driving performance and

ocular indicators. Lal and Craig's (2001) review described how EEG signals generally behave as fatigue sets in and progresses. Their findings suggest that each EEG wave can be profiled as induced by fatigue during driving tasks. This preference is probably to have widely accepted EEG patterns, as brain activities are influenced by driving fatigue. However, this is not the case. A large number of studies have demonstrated mixed results, which makes it difficult to employ EEG-based findings as foundations in determining different phases of fatigue. These difficulties are exacerbated by the fact that EEG signals can be recorded from different brain areas, analyzed using various procedures, and represented by different bands, both locally and globally. Many EEG parameters are available, but their correlations with subjective reports (KSS) vary substantially from one experimental case to another.

Although many other issues also need to be addressed, one that is particularly of interest here is the fact that many investigations have been conducted using a driving simulator as opposed to the more real field contexts. While driving continuously for more than three hours can be commonly observed in many settings, most research has involved only 1–2 h of driving. Fatigue associated with prolonged driving is undoubtedly an interesting issue. However, there are also task characteristics (monotony vs. dynamic tasks, secondary tasks, time of day, and demographic effects) that can significantly affect the relationships between fatigue and driving duration. Finally, it is imperative that we understand the cognitive processes during a driving task and how they relate to different brain areas. This will help to further understand why different driving tasks may have different profiles of EEG activities.

# 4. Conclusions

This study aimed to characterize fatigue during prolonged driving using an electroencephalography (EEG) perspective. We hypothesized that fatigue resulting from driving tasks could be manifested by well-defined changes in brain wave activities. Although apparent changes in subjective measures indicated fatigue and drowsiness, brain wave activities tended to be mixed. The signals varied considerably according to the parameters employed and the cortical areas from which the signals were obtained. Thus, we recommend that, although many have labeled EEG as the golden standard in evaluating fatigue, interpreting fatigue from EEG-based data should be done with caution. Different driving contexts may result in different patterns of brainwave activities. However, in this study, theta wave changes showed the most promising pattern in detecting fatigue induced by prolonged driving, whereas signals from temporal and occipital areas could be used for observation. To confirm the study results, further research should address fatigue from prolonged driving in the field instead of merely utilizing laboratory settings.

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