



## Detecting Driver Mental Fatigue Based on EEG Alpha Power Changes during Simulated Driving

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### Abstract

**Background:** Driver fatigue is one of the major implications in transportation safety and accounted for up to 40% of road accidents. This study aimed to analyze the EEG alpha power changes in partially sleep-deprived drivers while performing a simulated driving task.

**Methods:** Twelve healthy male car drivers participated in an overnight study. Continuous EEG and EOG records were taken during driving on a virtual reality simulator on a monotonous road. Simultaneously, video recordings from the driver face and behavior were performed in lateral and front views and rated by two trained observers. Moreover, the subjective self-assessment of fatigue was implemented in every 10-min interval during the driving using Fatigue Visual Analog Scale (F-VAS). Power spectrum density and fast Fourier transform (FFT) were used to determine the absolute and relative alpha powers in the initial and final 10 minutes of driving.

**Results:** The findings showed a significant increase in the absolute alpha power ( $P = 0.006$ ) as well as F-VAS scores during the final section of driving ( $P = 0.001$ ). Meanwhile, video ratings were consistent with subjective self-assessment of fatigue.

**Conclusion:** The increase in alpha power in the final section of driving indicates the decrease in the level of alertness and attention and the onset of fatigue, which was consistent with F-VAS and video ratings. The study suggested that variations in alpha power could be a good indicator for driver mental fatigue, but for using as a countermeasure device needed further investigations.

**Keywords:** Driver mental fatigue, F-VAS, Video rating, EEG alpha power

### Introduction

Fatigue is a transitional state between awake and sleep which manifests itself as lack of alertness and deteriorated mental or physical performance and often associated with drowsiness. Driver fa-

tigue is one of the major causes of accidents and casualties in roads. Road accidents due to fatigue are often much more severe than other crashes, since the driver reaction time increases (1).

Driver fatigue is deemed to account for up to 40% of road accidents (2). It is conjectured that 10-30% of road deaths are related to driver fatigue (3). Many studies have suggested that mental fatigue induces deterioration in cognitive abilities. Mental fatigue causes reactions become prolonged, more fluctuable, and more error tending (4, 5). Impairments in perceptual and cognitive functions after extended wakefulness are responsible for performance deteriorations. Grandjean defined fatigue as a state with decreased efficiency and lack of general willingness to work (6, 7).

There are different techniques and methodologies for mental fatigue measurement. These can be classified as subjective, psychological, performance and physiological methods. In subjective methods, standard questionnaires such as F-VAS and Karolinska sleepiness scale have been employed (8-13). Moreover, the use of behavioral and psychological techniques in mental fatigue investigation has been adopted in several preceding studies (14-17). Among these studies, a set of video recordings of facial expressions, mannerisms and personality traits questionnaires were common methodologies with high reliability and validity (17). In addition, some fatigue studies on driving simulator exploited performance features such as steering wheel angle and lane departure (18-20). Some other researchers have focused on driver's physiological changes, such as the measurement of eye activity, heart rate, skin electrical potential and specially EEG activity as a means to detect cognitive states (21, 22). Although several physiological indices available for assessing the alertness level, EEG signal may be one of the safest and most predictive, (23-25), since it immediately reflects brain activity. Driving involves several tasks such as motion, reasoning, visual and auditory processing, decision-making, perception and cognition. Driving is also under the influence of emotion, anxiety and many other psychological factors (24). All physical and mental activities associated with driving are reflected in EEG signals. The brain electrical activity rhythms are classified according to frequency bands including delta, theta, alpha and beta waves (26). Alpha rhythm has the frequency range from 8-13 Hz, which occurs

during wakefulness, especially in the occipital cortex area of the brain. It typically appears during eye closure and reduced when eyes open and attenuates severely during attention tasks (27).

In previous researches, EEG measurements have been used to detect performance variations. It is known that increase in delta power during internal processing is associated with mental task performance (28). Other researchers have reported that an increase in EEG theta power depends on decreased performance in monotonous tasks (29). Although some definite trends were observed in the delta, theta and alpha power frequency bands during fatigue, the results of different studies may be influenced by inter-individual and intra-individual variations in EEG data (30).

Changes in EEG power spectra are associated with fluctuations in the alertness state (31). Monitoring physiological signals while driving can provide the possibility to detect and warn fatigue (32). Most investigations revealed that changes in delta and theta activity are related to the transition to fatigue. Therefore, EEG monitoring during driving may be a promising variable for using in fatigue countermeasure devices (24).

It has been suggested that during driving at night, delta band varies significantly with the degree of fatigue (33). Some researchers have presented an EEG-based cerebral workload index based on the increase of EEG power spectra in the theta band over prefrontal areas and the immediate decrease of EEG power spectra over parietal areas in alpha band during driving (34). While physiological mental fatigue level increases, the relative power of theta, alpha and beta rhythms decrease, but the relative power in delta rhythm increases (35). The relative power of alpha increased while the attention level of the driver decreased (36). However, research on the physiological links specially EEG frequency bands to driver fatigue is still exploratory and is an important area that needs further investigation.

Therefore, this study attempted to detect the driver mental fatigue through changes in EEG alpha power activity.

## Materials and Methods

### *Participant selection*

Twelve healthy male volunteer car drivers (ranging 20 to 30 years old) participated in an overnight study from 2 to 6 a.m. in Virtual Reality Laboratory of Khaje Nasir Toosi University of Technology in 2013. All the subjects held valid driving license with at least 2 years driving experience and had no history of prior brain injuries. The Epworth Sleepiness Scale was used to measure the participants for any trait sleepiness. After taking informed written consent, the subjects were requested to stay awake 18 h before the experiments and refrain from caffeinated drinks or any other stimulant as well as cigarette smoking for 12 h prior to the experiments. The drivers should have regular sleep pattern (i.e. sleeping not later than 1 a.m. and awaking not later than 9 a.m.) and not get used to daily napping which was studied through sleep diary for one week before the experiment.

### *Driving simulator preparation*

This research employed a fixed-based car driving virtual reality simulator (CI004 Semi) in a calm controlled room with fixed temperature and illumination conditions. Fig. 1 shows a snapshot of the car-driving simulator developed in mechatronics department of K.N. Toosi University of Technology.



**Fig. 1:** Snapshot of the car-driving simulator used for the implementation of the proposed protocol

A set of 110 km road sceneries had been designed and simulated. The first 90 km of the road was monotonous and straight with minimal side components to induce more fatigue and the last 20 km was winding mountainous road (see fig. 2).



**Fig. 2:** A scenery of the road captured from the car simulator LCD

The designed road was from the most dangerous parts of real road pattern of Iran, so called Haram to Haram road, photographed through Google maps using Autodesk AutoCAD Civil 3D (version 2013) and Autodesk 3Ds Max (version 2012) softwares.

### *EEG and EOG data acquisition:*

A portable g.USB amp bio-signal amplifier with 16 channels was used with 256 Hz sampling rate and 24 bit quantification with active electrodes for signal acquisition. During driving on the simulator, EEG and EOG signals were continuously recorded. The electrode positions on different areas of the scalp were based on the 10-20 international electrodes placement guideline. The main EEG signal channels were O1, O2, P3, P4, P7, P8, OZ, FP1, FP2, CZ, FZ, T7 and T8. In addition, two EOG channels were used horizontally for left and right eyes. The reference electrode was located at A2 and the ground electrode in FZ.

The EEG data analysis involved pre-processing, artifact removal, and features extraction. The EEG signal was first processed executing a band pass filter between 0.5 and 60 Hz. Then, the signal was notch filtered to remove the AC power fre-

quency. EEGlab (Version 10.2.5.6a) was utilized to remove muscular and ocular artifacts by visual inspection. All the signals were sequenced to epochs each lasting two seconds (1 epoch consisting of 512 samples = 2 seconds).

This research exploits power spectrum density and fast Fourier transform (FFT) analyzing technique to determine the absolute and relative powers of alpha frequency band. Relative alpha power was computed as the ratio between absolute alpha power and the total spectral power of the signal. We compared the absolute and relative alpha power variations in the first and last 10 minutes of driving with the F-VAS scores. For further certainty, this study employed the double check validity method by comparing the extracted features from EEG signals with the video rating scores.

### Research protocol

Before resuming the experiments, the car driver's sleepiness propensity was measured by the Epworth Sleepiness Scale. Then, EEG and EOG signals were recorded from the subjects in relaxed sitting posture for 3 minutes with closed eyes (imagining driving on a highway) and 3 minutes with open eyes (looking at a road picture on the screen) as a baseline for alertness. The subjects were asked to drive the monotonous road at a constant speed of 90 km/h. At the same time, a continuous EEG and EOG records were taken during the driving on the car simulator. Meanwhile, the drivers' faces and behaviors were monitored via video recordings in lateral and front views. These videos were used to rate the fatigue level of drivers on a four-point scale from 1(alert) to 4 (very tired) by two

trained observers. Moreover, the self-rating of fatigue was performed during the driving using F-VAS scored from 0 (no fatigue or energetic) to 10 (worst possible fatigue) in every 10 minute interval.

### Statistical data analysis

The descriptive statistics such as central and scattered indices were computed in order to describe the variables. Pearson and Spearman correlation coefficients were employed to explore the associations between F-VAS scores and video ratings, F-VAS and absolute and relative alpha powers. Paired-Sampled *t*-test was utilized to compare the means of F-VAS scores, video ratings, absolute and relative alpha powers in the initial and final 10 minutes of driving.

## Results

The drivers' mean age was 23.8 years (SD =1.44 years) with mean body mass index (BMI) of 21.57 (SD = 2.01). Other demographic characteristics and work-related information of the drivers were presented in Table 1.

As shown in Table 2 the self-report scale measured by means of F-VAS suggested that the participants had not been fatigued during the first 10 minutes of driving and moderately to extremely fatigue during the final section of driving. Compared with the initial section, the F-VAS scores increase significantly ( $P = 0.001$ ) during the final section of driving task, which demonstrates that continuous monotonous driving may predispose the subjects to cognitive fatigue.

**Table 1:** Drivers' demographic and background characteristics data

Parameter	Mean	Std. Deviation	Minimum	Maximum
Age (yr)	23.88	1.44	22	26
Height (cm)	176.30	3.74	172.00	184.00
Weight (kg)	65.63	7.00	52.00	76.00
BMI	21.57	2.01	17.37	23.24
Driving time in the experiment (min)	53.25	11.53	41.63	80.07
Sleeping hours in past 24hrs	5.29	1.14	1.50	7.00
Driving experience (yrs.)	3.95	1.03	3.00	6.00
Driving hours per week	10.58	2.81	7.00	15.00

**Table 2:** Different fatigue measures in I10D<sup>a</sup> and F10D<sup>b</sup>

Variables	I10D (Mean $\pm$ S.D.)	F10D (Mean $\pm$ S.D.)	Test <i>t</i>	<i>P</i>
F-VAS score	3.95 $\pm$ 1.22	7.53 $\pm$ 1.23	-27.33	0.001
Video rating score	2.73 $\pm$ 0.44	3.68 $\pm$ 0.46	-36.28	0.001
Absolute alpha power	0.0409 $\pm$ 0.0377	0.0450 $\pm$ 0.0378	-2.76	0.006
Relative alpha power	0.0417 $\pm$ 0.0413	0.0407 $\pm$ 0.0371	0.88	0.381

**a** I10D: The initial 10 min of driving; **b** F10D: The final 10 min of driving

Furthermore, table 2 presents the video scores rated by trained observers in the initial and final 10 minutes of driving. Paired-Sampled T Test suggests significant increase during the final 10 minutes of driving ( $P = 0.001$ ).

The results showed a mild, but significant correlation between F-VAS and video rating scores in the initial 10 minutes of driving ( $r = 0.404$ ,  $P = 0.001$ ). Meanwhile, Spearman's correlation test showed a relatively strong and significant association between F-VAS and video rating scores in the final 10 minutes of driving ( $r = 0.62$ ,  $P = 0.001$ ).

Table 2 also indicates the absolute and relative alpha powers in the initial and final 10 minutes of driving. There was a significant increase in the absolute alpha power during the final 10 minutes of driving ( $P=0.006$ ).

Moreover, our findings showed no differences in absolute alpha power in different areas of the scalp in the initial and final 10 minutes of driving, except in the parietal area of the brain ( $P=0.005$ ). Paired-Sampled T Test suggests statistically significant difference in P4 site between absolute alpha powers in the initial and final 10 minutes of driving ( $P = 0.026$ ).

## Discussion

This study attempted to present a simple and reliable method for early detection of driver mental fatigue based on EEG alpha power in healthy sleep deprived drivers. In our experiment, different fatigue outcome measures including subjective self-report of fatigue (F-VAS), video ratings as well as EEG alpha powers were employed to evaluate the change in fatigue for drivers during the initial and final 10 minutes of driving.

The experimental results suggested a significant increase in the subjective self-report of fatigue (F-VAS scores) during the final 10 minutes of driving. The same results were obtained from Zhang (2008) study which found that the level of both subjective sleepiness and fatigue increase significantly from pre-task to post-task (37). They studied the impacts of visual display terminal (VDI) task on autonomic nervous system and central nervous system through subjective self-report of sleepiness and some physiological measures such as power spectral indices of HRV and wavelet packet parameters of EEG.

It should be regarded that our findings from F-VAS scores showed lowered variability (all participants reached the state of fatigue and extremely fatigue) in the final section of driving. This may be because a subject who is fatigue will be less likely to evaluate his/her state sufficiently. In other words, mental fatigue may impact the drivers' judgment of their existing state. Therefore, all participants had experienced fatigue and judged similar scores.

The findings of this preliminary research indicated a significant increase in absolute alpha power in the final section of driving. This is consistent with the known aspects of EEG alpha rhythm (38, 39). The increase in alpha rhythm in the final 10 minutes of driving depicted the decrease in the level of alertness and attention and the commencement of fatigue and drowsiness. The findings of the present study are well be in line with the findings of researchers in which they found significant difference between the alpha frequency band in the first and fifth section of driving (40). In another study, delta and theta activity increased in the final 3 hours of 7 truck drivers during night driving (41).

Nevertheless, our results revealed no significant difference between the relative alpha powers in the initial and final 10 minutes of driving. The reason for this may be due to the increase in delta and theta rhythms, which causes less relative alpha variability in the final section of driving.

In our study, most changes occurred in the right parietal region (P4) which was in contrast with the Schier (2000) study that showed the greatest changes in the right frontal region (F4) of the scalp (36). However, this is consistent with the reported role of the right hemisphere via blood flow measurement in attention demanding tasks (42).

This research holds a number of limitations, which should be addressed. Since the subjective self-report of fatigue was measured in the initial and final 10 minutes of driving, sudden variations cannot be detected using F-VAS technique. Another limitation to employing this scale is that drivers' verbal expression of their level of fatigue may alert them, thereby decreasing their fatigue level. Meanwhile, it is almost unfeasible to obtain fatigue feedback from a driver in real driving conditions unless significantly distracting the driver attention from the driving task. Our study benefited from using video rating of facial expressions and driver behaviors by trained observers that might not be able to see what goes on behind the facial behavior and expression. Placing the electrodes on the scalp to obtain signals is an intrusive technique that should be addressed as another limitation of researches using wired biological signals. Therefore, future projects should make the use of less-intrusive systems such as wireless electrodes and benefit the strengths of the various fatigue monitoring methodologies into a hybrid system to develop an efficient fatigue detection device in real driving situations.

The present study specifically deals with EEG alpha power in the initial and final section of driving in partially sleep-deprived drivers-a very prominent aspect of driver fatigue analysis. The results of this study may serve as a baseline for the development of an in-vehicle device preventing fatigue related crashes on monotonous roads and greatly improving the transport industry in terms of socio-economic benefits and safety.

## Conclusion

Driver mental fatigue is considered as one of the major implications for road safety. This study suggests that alpha brain wave rhythm can be a good indicator for early prediction of driver fatigue. Meanwhile, image processing of facial expressions may be a complementary method for road accident prevention. These indicators can be incorporated to develop a fatigue countermeasure device to prevent road accidents and reduce fatigue related costs.

## Ethical considerations

Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

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