Evaluating NeuroSky's Single-Channel EEG Sensor for Drowsiness Detection

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Abstract. NeuroSky's single-channel EEG sensor has drawn researchers' interest because the sensor offers higher usability at a significantly lower cost. The sensor is minimally obtrusive, measuring the brainwaves from a single location on the head. This is an excellent feature from a usability standpoint. Yet, the sensor needs to be evaluated for specific applications. This paper presents preliminary assessment of the sensor in detecting drowsiness. A simulated driving task was used as a testbed. A total of 14 participants participated in the study. The results reveal no statistically significant difference in brain activities between the drowsy and the attentive states, indicating that the brainwaves used in the analysis are unable to distinguish the two driving states.

Keywords: Driver's distraction · Brain-computer interface · Brainwaves · Single channel EEG Sensor · NeuroSky

1 Introduction

Traditionally, electroencephalography (EEG) sensors are multichannel (with as many as 256 channels in some cases), use wet electrodes, and transmit data through a set of wires [24]. Although the sensors precisely record brain activities with proper preparation, their usage is largely limited to the clinical and laboratory setups primarily because the sensors demand longer preparation time and offer lower usability.

Recent development of the single-channel, dry-electrode EEG sensor technology has drawn researchers' interest because the technology features higher usability at a significantly lower cost, offering possibility of conducting studies in informal environments such as schools and homes, and while mobile. One such widely used sensor is MindWave Mobile from NeuroSky which we used in this study [18]. iBrain Device from NeuroVigil is another single-channel EEG sensor [19]. However, it was not available for purchase during the time of our experimentation. Other commercial offerings are specific to certain applications

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including Zeo's sensor for sleep monitoring, EmBand Headset from EmSense for neuromarketing [8], and a seven-channel EEG sensor from Muse for meditation exercise [17]. Emotiv's EPOC+ is another off-the-shelf low-cost device, which records brainwaves from 14 channels [12]. We did not use the sensor in our study because the 14 channel configuration is not minimally obtrusive and hence, may bring discomfort to some drivers, especially when it is required to wear for a longer period.

The use of the NeuroSky sensor has been increasing for Human-Computer Interaction (HCI) and Brain-Computer Interface (BCI) research. Marchesi and Ricco proposed an e-learning system that customizes educational experience according to the attention and meditation signals captured via the NeuroSky sensor [16]. Al-Barrak and Kanjo used the same signals to distinguish relaxing outdoor places from boisterous places [3]. Yoh et al. developed a Brain-Computer Interface (BCI) game, called NueroWander, which uses the sensor's attention and meditation signals as game controllers [29]. Blondet et al. used the sensor in a prototype system for detecting the user's mental states in real-time [5]. Hal et al. proposed a real-time stage 1 sleep detection system that uses the sensor [26].

In this research we investigated the applicability of the sensor in detecting drowsiness. Specifically, we wanted to examine whether the NeuroSky's MindWave sensor can differentiate machine operator's attentive state from his/her drowsy state. If it can, then the sensor can be a viable low cost solution to multiple applications where an operator's drowsiness can potentially be harmful. A case in point is security guards who are required to monotonously monitor security video feeds. Other cases are operating airplanes or driving vehicles in which drowsiness can cost lives.

We used simulated driving as a testbed because it is a cost effective setup for a feasibility study such as this one. Driver's drowsiness can be detected in several ways. One approach focuses on monitoring of vehicle behaviors via lane and steering tracking [4,14]. This approach offers good practicality in sense that there is no need of attaching any sensors to the driver's body. However, this approach performs suboptimal in bad weather and for poor lane markings, and requires additional hardware attachments to the vehicle. Machine vision is another approach that is routinely explored for monitoring driver's face and eyes [15,20,27]. Yet, most vision-based methods are not very successful in handling real-life challenges such as monitoring in the low light environments, under facial occlusion, and for drivers with eyeglasses.

Multiple studies reported usefulness of EEG in drowsy driving detection. Most studies, however, used multichannel EEG sensors which limit their practicality [2,11,13]. Recently, Sarno et al. used Emotiv EPOC+ (14 channel sensor) for the detection of driver's fatigue [21]. A six-channel EEG-based drowsy detection system was demonstrated by Tsai et al. [25]. They placed the six electrodes approximately at the Fp1, Fp2, T5, T6, O1 and O2 locations (see Fig. 1), and reported 90% accuracy rate in drowsy state detection and 80% accuracy rate in attentive state detection. SmartCap is a commercially available EEG-based system for driver fatigue detection that uses only a few electrodes [23]. These systems demonstrate that reduction in the number of electrodes improves EEG's usability. In the current study, we focused our attention on a single-channel EEG sensor for drowsiness detection.

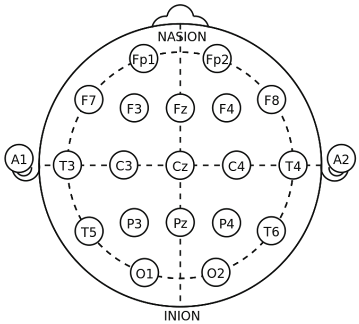


Fig. 1. EEG Electrode locations of International 10–20 system. The letter codes F, T, C, P and O stand for frontal, temporal, central, parietal, and occipital lobes, respectively. The letter codes A, and Fp identify the earlobes, and frontal polar sites respectively [28].

2 Experimental Design

2.1 Driving Simulator

We used simulated driving as a testbed. Specifically, we simulated monotonous driving through a pc-based software tool, City Car Driving v1.3 [9]. The simulator allowed us to stage a late evening highway driving scenario with medium to low traffic. To control the simulator, we used Logitech's G-27 controllers which included a steering wheel, and gas and brake pedals. The controllers' force feedback mechanism gives the feeling of actual driving.

2.2 Single-Channel EEG Sensor

We used a MindWave headset from NeuroSky to collect neuronal activities [18]. The headset consists of a single dry electrode which is attached to the driver's forehead at the Fp1 position and a ground electrode which is attached to an earlobe (see Fig. 1). The sensor samples neuronal activities with a frequency up to 512 Hz and outputs EEG power of brainwaves (delta, theta, alpha, beta, and gamma) at 1 Hz frequency. It also outputs proprietary eSense meters for attention and meditation. The sensor transmits the data wirelessly via a Bluetooth connection.

2.3 Experiment

The experiment has been approved by the Institute's Review Board. A group of seven participants (5 males and 2 females) volunteered for a 30 min driving session and another group of seven participants (5 males and 2 females) volunteered for a 60 min driving session. Their ages ranged from 18 to 40 years. After completing the consent form, the participants explored the driving simulator for about 10 min to acquaint themselves with the experimental setup. Next, they performed the driving task for either 30 min (short session) or 60 min (long session). The two driving sessions facilitated thorough evaluation of the sensor. Specifically, the initial study was conducted for 30 min driving only, but after observing indistinguishable brainwave patterns between the two driving states, we expanded the experiment for 60 min driving period to make sure that the driving period is not the affecting factor.

The lighting in the experiment room was dimed to make the driving environment conducive to drowsiness. Throughout the driving period, the participants' faces were recorded via a Logitech HD C270 webcam. The videos were later used to identify drowsy instances. In total, we collected 14 videos (14 participants $\times$ 1 recording per participant) and 14 sets of EEG signals (14 participants $\times$ 1 set per participant) during the experiment.

3 Data Analysis

3.1 Face Videos

The face videos were used to mark drowsy instances. Specifically, each 10 s driving period was annotated as *Drowsy Driving* if any facial clues of drossiness were observed including frequent eye blinking, heavy eyelids, rubbing eyes, constant yawning, and struggling to hold the head up. Otherwise, the period was annotated as *Attentive Driving*. The drowsy indictors were chosen based on Summala et al. research on detecting driver's drowsiness from video images [22]. The annotations were done independently by the two coders and then synthesized into a single binary signal of driving state per participant.

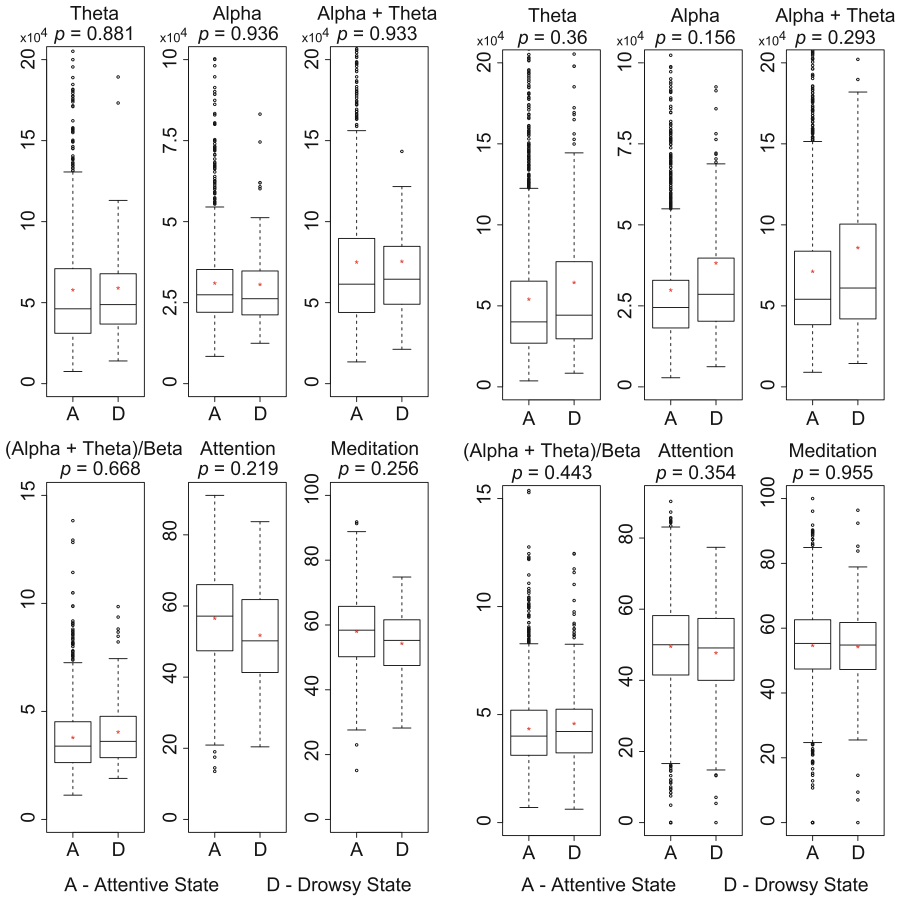
3.2 EEG Data

EEG data is typically divided into bands of frequency, including delta, theta, alpha, beta and gamma bands. Each band represents certain mental states. Specifically, the delta band (1–3 Hz) represents deep dreamless sleep, the theta band (4–7 Hz) represents sleepy mental state, the alpha band (8–12 Hz) represents relaxed mental state, and the beta band (13–30 Hz) represents active thinking.

Eoh et al. reported several EEG studies that showed a close correlation between the EEG power of the alpha and theta waves and drowsy driving [13]. Specifically, one study in their report showed that the EEG power of the alpha and theta waves was increased as the alertness level of the driver decreased [13]. Another study showed a decrease in the relative energy parameter (alpha+theta)/beta with drowsiness [11]. Craig et al. reported that the alpha and theta waves are most typically associated with fatigue or drowsiness

[10]. Therefore, in our analysis we decided to include the theta and alpha waves, and the (alpha+theta) and the (alpha+theta)/beta parameters. We also used the proprietary attention and mediation signals. In total, we utilized 6 signals from each participant's EEG data.

The EEG signals were averaged for a 10 s epoch, having 180 samples (6 samples per minute × 30 min) for each 30 min driving session and 360 samples



(a) (b)

Fig. 2. (a) Boxplot diagrams represent analysis of the EEG signals for the 30 min driving sessions. The ∗ symbols in the box-plots indicate the mean values of the distributions. $n = 1027$ (about 90% of the samples) for Attentive State (A). $n = 127$ (about 10% of the samples) for Drowsy State (D). (b) Boxplot diagrams represent analysis of the EEG signals for the 60 min driving sessions. The ∗ symbols in the box-plots indicate the mean values of the distributions. $n = 2215$ (about 90% of the samples) for Attentive State (A). $n = 253$ (about 10% of the samples) for Drowsy State (D). (Color figure online)

for each 60 min driving session. Although the 10 s period was heuristically chosen, the previous studies used similar sized periods [6,13,22].

4 Experimental Results

We observed an average drowsy driving period of 3 min for the short driving sessions (30 min) and about 6 min for the long driving sessions (60 min). Thus, the participants experienced episodes of drowsiness for about 10% of their driving time.

We performed statistical analysis to examine whether the EEG signals can reveal any statistically significant difference between the two driving states. For each of the six EEG signals, we grouped the signal values into *Drowsy Driving* and *Attentive Driving* according to the binary driving state signal. The distributions of the signals are shown in Fig. 2a for the 30 min driving sessions and in Fig. 2b for the 60 min driving sessions. Qualitatively speaking, the distributions of the two driving states are not much different in most cases.

Next, we performed a paired-T test on each pair of the EEG signals. Specifically, for every participant, we computed two mean values per EEG signal: One for *Drowsy Driving* and another for *Attentive Driving*. Finally, we performed a paired-T test on these values. These steps were repeated for each of the six EEG signals. The test results (p values) are shown at the top of the boxplots (see Fig. 2). The results reveal no statistically significant difference ($p > 0.05$) in EEG energy between the driving states for all the signals, indicating that the brainwaves used in the analysis are unable to distinguish the two driving states.

5 Conclusion

The preliminary assessment demonstrates that the brainwaves used in the analysis fail to detect drowsiness. The primary reason of the failure, we believe, is the location of the measurement site (Fp1 location). Typically, drowsy detection studies focus on the central (C) and parietal (P) measurement sites. For instance, Brown et al. analyzed the C3, C4, Pz, P3, and P4 sites for identifying drowsy driving periods [7]. Broughton et al. reported that theta activities of drowsiness were maximum at the Cz and Fz sites [6]. Thus, the Fp1 location alone was never used in the past drowsiness detection studies. The Fp1 location is typically examined in conjunction with the other sites. For instance, Tsai et al. for their six-channel EEG-based drowsy detection system used the Fp1 location in conjunction with the Fp2, T5, T6, O1 and O2 locations [25]. Similarly, Eoh et al. explored the Fp1 location along with the Fp2, T3, T4, P3, P4, O1, and O2 locations [13].

The other possible reason for the failure in detecting drowsiness could be the EEG data processing approach that we employed. We used only the mean values (per ever 10 s) of the EEG signals. A recent study by Abdel-Rahman et. al extracted multiple statistical features (max, min, mean, and standard deviation) and a frequency-based feature (power spectral density) from the MindWave's

EEG signals [1]. They reported 98.5% accuracy for the awake state and 96% accuracy for the sleepy state classifications.

Our future work includes exploration of other single-measurement sites, in particular the Cz and Fz sites as they are reported to be relevant for theta activities of drowsiness. We will also extract from our existing EEG signals the features reported in [1] and reevaluate the sensor.

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