Feasibility Study of Drowsiness Detection Using Hybrid Brain-Computer Interface

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ABSTRACT

In this study, we developed a hybrid brain–computer interface for drowsiness detection using electroencephalography (EEG) and electrooculography (EOG). Measurement was done with a single-channel EEG amplifier. A simple responsive task performed in a drowsy environment was used to experimentally demonstrate the advantages of the proposed system. Additionally, we performed the first investigation of hybrid EEG/EOG indices for drowsiness detection. Pearson's correlation analysis revealed that hybrid EEG/EOG indices were better correlated with the Karolinska Sleepiness Scale—the standard subjective measure—than were conventional EEG or EOG indices. Our investigation could contribute to both sleep research and the development of real-time drowsiness detection in the near future.

Keywords

Drowsiness detection;EEG;EOG;hybrid BCI

1. INTRODUCTION

According to the National Highway Traffic Safety Administration, drowsy driving caused about 72,000 crashes, 800 fatalities, and 44,000 injuries in 2013. Drowsiness detection methods have been actively researched for more than a decade in an effort to reduce the rate of accidents caused by drowsy driving. Subjective questionnaires, measures of driving performance (such as rates of accidents and lane changing), and physical and biopotential measures have been proposed to identify driver drowsiness [3]. These methods all have advantages and disadvantages [14]. Questionnaires cannot be used in real time, but may still be useful for validating other measures; measurement of driving performance is nonintrusive, but could be unreliable in a real driving environment; physical measures such as driver motion and pupil tracking , especially camera-based techniques, are accurate but limited by light conditions and background; and biopotential measures are quite accurate and reliable, but require intrusive measurements. In this study, we focused on two biopotential measures: electroencephalography (EEG) and electrooculography (EOG).

Table 1: Karolinska sleepiness scale (KSS).

Score	Meaning
1	Extremely alert
2	Very alert
3	Alert
4	Rather alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, no effort to stay awake
8	Sleepy, some effort to stay awake
9	Very sleepy, great effort to keep awake, fighting sleep

Feasibility studies of driver drowsiness detection using EEG were conducted almost ten years ago [4]; later, one research group did similar experiments for driver fatigue detection [6]. Both investigations focused on the ratio of EEG signals in low-frequency and high-frequency bands. Another research group validated a common subjective measure, the Karolinska Sleepiness Scale (KSS), against EEG variables [7]. Many pioneering studies have demonstrated that EEG may be a reliable and accurate measure for drowsiness detection, attracting engineers to develop more applications of this technology [11][10][12]. To improve the accuracy of drowsiness detection, a few researchers have proposed multimodal biopotential measures, including EEG and EOG [8][9]. Although such multiple-channel recording systems can reach more than 90% accuracy, they are highly intrusive for drivers.

Numerous studies on driver drowsiness have been performed over more than a decade; however, most of these were based on complicated measurement systems. Hence, the development of a practical system and application is still a challenging issue. Recently, researchers have introduced hybrid brain–computer interfaces (BCIs) for patients who have severe motor disabilities but have residual motor abilities such as eye movement [2]. Hybrid BCIs serve as a direct commutation pathway from the human brain, through computers. Here, we propose a practical system for drowsiness detection using a hybrid BCI that records EEG and EOG simultaneously. This method is less intrusive than conventional methods because the measurement system is based on single-channel EEG/EOG recording. Moreover, we investigated for the first time a hybrid EEG/EOG signal-processing algorithm for drowsiness detection.

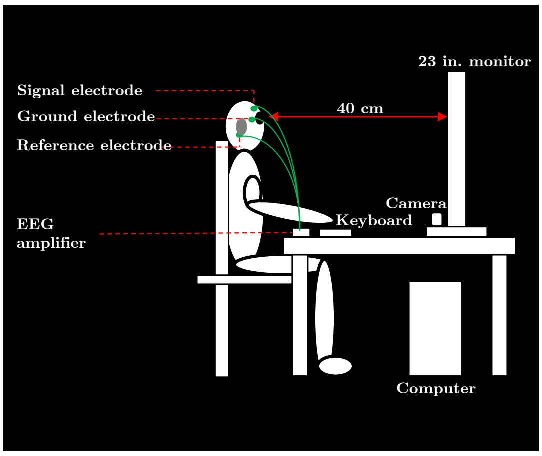

Figure 1: Illustration of the experimental setup used in this study.

2. EXPERIMENT

Six healthy people aged 22–25 years participated in the experiment. To induce drowsiness, the experiment was conducted in a dark room as shown in Figure 1 and was performed after participants had eaten lunch or dinner. Participants were asked to wear hearing protection headphones to avoid auditory noise. This study was conducted in accordance with the Declaration of Helsinki as revised in 2000.

2.1 Hybrid brain-computer interface

The hybrid BCI used single-channel EEG recording with a 250-Hz sampling frequency (OpenBCI 8-bit Board Kit, Arduino-compatible). The signal electrode was at the Fp2 position of the standard 10/20 international system for EEG measurement. The reference was placed on the right mastoid, and the ground was placed between the right eye and the right ear as shown in Figure 1. In our preliminary measurements, we found that EEG and EOG signals could be recorded simultaneously at this position.

2.2 Experimental tasks

A typical personal computer was used in our experiment. Participants were requested to do a simple response task for 25 min as shown in Figure 2. At 1-s intervals, a white square randomly appeared in one of three positions on a black background. Participants were instructed to press the spacebar key as quickly as possible whenever the square appeared in the center position. Response time and error rate were recorded for further analysis. To assess drowsiness, the KSS questionnaire (Table 1) was performed every 5 min [3].

3. DATA ANALYSIS

EEG and EOG signals for each participant were recorded for 25 min and then equally divided into five segments. After accounting for the time required for KSS assessment, each segment had a final duration of 4.5 min. EEG and EOG indices were extracted from the segmented data for drowsiness detection.

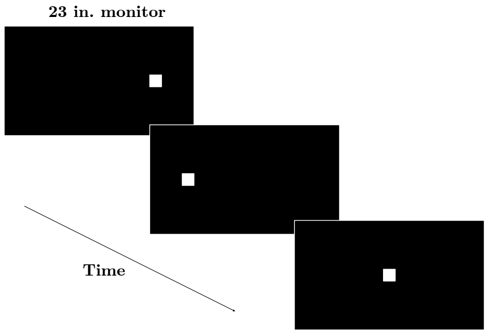

Figure 2: Depiction of the experimental task. At 1-s intervals, a white square randomly appeared in one of three positions on a black background. Participants were instructed to press the spacebar key as quickly as possible whenever the square appeared in the center position.

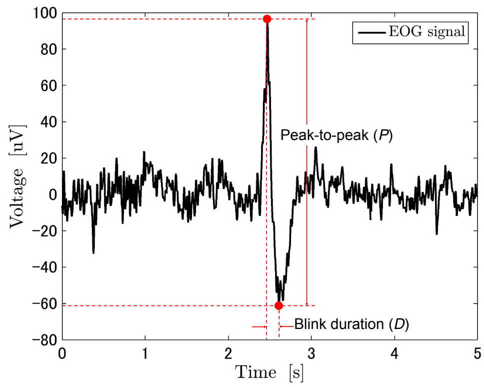

Figure 3: Demonstration of blink duration measurement.

3.1 EEG index

Each data segment was preprocessed by notch filtering at 50 Hz to cut electrical noise and band-pass filtering (4–25 Hz). In this study, we targeted three frequency bands: θ (4–8 Hz), α (8–13 Hz), and β (13–25 Hz). The δ band (0.5–4 Hz) was not included in the analysis because it was usually distorted by artifacts [4]. The relative powers of the three frequency bands (θ, α, and β) and three ratios among the three frequency bands (θ/β, α/β, and $(\theta+\alpha)/\beta$) were used as EEG indices. The relative power of θ was calculated using Equation 1. All indices have been used in previous studies [4, 6].

$$\text{Relative power of } \theta = \frac{\text{power of } \theta}{\text{power of } \theta + \text{power of } \alpha + \text{power of } \beta} \tag{1}$$

For the remainder of this paper, the relative powers of the three frequency bands are denoted by θ, α, and β.

3.2 EOG index

To extract the EOG index, the segmented data were subjected to band-pass filtering (1–40 Hz) and notch filtering (50 Hz). Blink duration was used as an EOG index, as it has been reported to increase significantly with drowsiness [5]. We used a novel technique to detect blinking and calculate blink duration from the EOG signal. Peak-to-peak magnitude (P) and the period of time between positive and negative peaks (D) were used to determine whether the incoming signal was a blink (Figure 3). P was an individual threshold calculated by averaging the values of the first five blinks for each participant; the P threshold was allowed to range up to 10% less than the average value. Blinks could be confirmed by video recordings of the experiment. Whenever the incoming signal was determined to be a blink, D was recorded as the blink duration. Average D was then calculated for each data segment. Blinking is conventionally defined as lasting for up to 1 s [13]. On the basis of our proposed technique and empirical study, however, D of more than 0.8 s was not identified as a blink signal.

3.3 Proposed hybrid EEG/EOG index

Our preliminary studies and empirical knowledge of EEG and EOG for drowsiness detection motivated us to propose a hybrid EEG/EOG ratio index. Three hybrid indices ($\theta/(\beta\times D)$, $\alpha/(\beta\times D)$, and $(\theta+\alpha)/(\beta\times D)$) were first introduced in this research.

3.4 Evaluation

KSS is widely used in sleep research as the standard drowsiness measure [7, 13]. To demonstrate superiority of the proposed hybrid indices over conventional EEG and EOG indices, we calculated Pearson's linear correlations between all indices and KSS. Moreover, we validated KSS against the percentage of errors made during the experimental task.

4. RESULTS AND DISCUSSION

Correlations between all indices and KSS are presented in Figure 5. Blink duration index (D) results were consistent with findings from previous research [5], and showed a trend toward longer duration when KSS drowsiness level was increased, especially in Participants A–D, and F. Of the EEG indices, the relative powers of θ and α were inconsistent among participants. The relative power of β had the same trend as D, and was quite consistent among participants. EEG ratio indices, which were focused on the ratio between the powers of the low- and high-frequency bands, were negatively correlated with KSS; this was particularly true for α/β. It could be concluded that an increase in high-frequency EEG power relative to low-frequency power was the result of drowsiness. Furthermore, the proposed hybrid indices ($\theta/(\beta\times D)$, $\alpha/(\beta\times D)$, and $(\theta+\alpha)/(\beta\times D)$) were better correlated with KSS than were EEG and EOG indices. In summary, $\alpha/(\beta\times D)$ had the highest significant negative correlation with KSS and performed the most consistently among participants; however, the results for Participant B were inconsistent with those of the other participants for most indices. This may have resulted from Participant B's low drowsiness level in terms of KSS, as shown in Figure 5 (b). One research group also has reported that EEG may be significantly different in individuals scoring 7 or higher on the KSS [1].

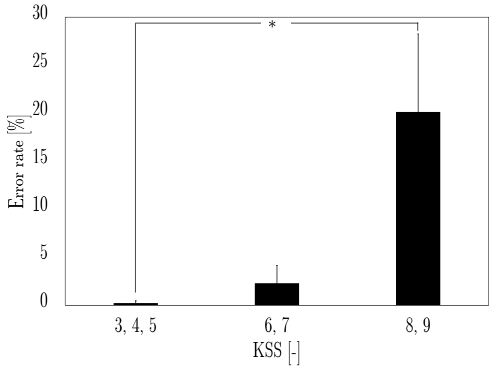

Figure 4: Validation of error rate on experimental task against KSS score. * denoted *p*<*0.05*

Unfortunately, the experimental task may have been too simple in this study. Hence, we could not find significant correlations between response time and any other drowsiness indices. However, the average error rate of all participants during the experimental task was found to increase significantly with increasing KSS score, as shown in Figure 4. Error rates were calculated for three KSS score groups (3–5, 6–7, and 8–9) because no participant scored less than 3. Because of the small sample size, statistical testing was performed with a standard t test for unequal variance instead of the analysis of variance method. The error rate of the highest score group was significantly higher than that of the lowest score group ($t(13) = 2.44, p = 0.03$). Motivated by these results, we plan to perform studies using a more complicated experimental task, such as a driving stimulator, in the near future. In conclusion, the results of this study indicate that it is feasible to develop real-time drowsiness detection using our proposed hybrid BCI.

5. CONCLUSION

Here, we proposed a hybrid EEG/EOG-based BCI for drowsiness detection. EEG and EOG signals during performance of a simple response task in a drowsy environment were simultaneously recorded by a single-channel EEG amplifier. We report the first use of hybrid EEG/EOG indices to assess drowsiness. Our results reveal the superiority of our proposed indices compared with conventional indices. We expect that this paper will contribute to the development of real-time drowsiness detection and sleep research in the near future.

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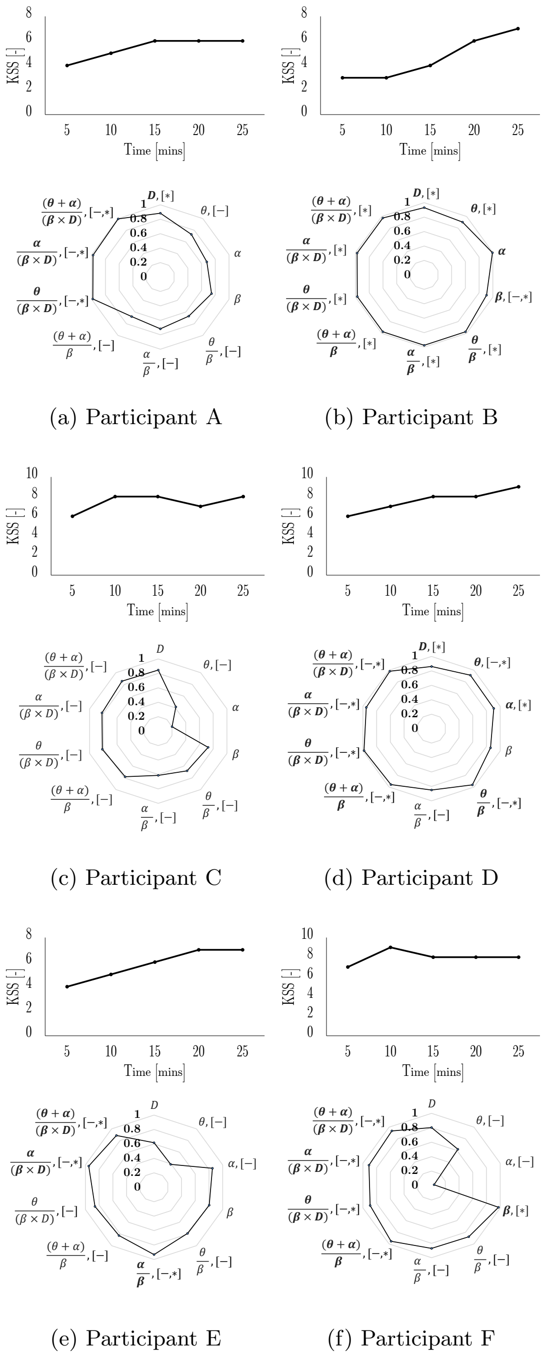

Figure 5: KSS results and comparison of Pearson's linear correlations between all drowsy indices and KSS among the seven participants. [−] indicates negative correlation, and significant correlation ($p < 0.05$) is denoted by [∗].

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