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Detecting Drowsiness in RSVP Keyboard™ BCI Users with SSPI

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Introduction: EEG measures of vigilance have been studied in fields concerned with driver and pilot alertness, as well as for effect on performance during cognitive tasks [1,2]. Given the importance of alertness and motivation on the P300, it follows that detection of drowsiness is critical to ensure maximal response. The necessity of integrating these fields becomes most evident in populations such as those with severe speech and physical impairments (SSPI), where individuals may not be able to communicate drowsiness or entirely control an alert-drowsy transition. P300 communication devices, such as matrix speller or RSVP Keyboard™ [3] are directed to these populations because of the recognizable need for alternative communication. The RSVP Keyboard™ presents a sequence of rapidly flashing letters (200ms in duration), using the P300 and earlier sensory potentials as indications of target letter. The system requires a calibration phase, calculated using a machine learning algorithm, that is used to identify target letters based on the EEG evidence 500ms following each letter presentation. This study looked at measures of drowsiness as a possible indication why participants might score poorly on these calibration sessions after eliminating the possibility of noise or other interference.

Material, Methods and Results: Participants included four individuals with SSPI who were subjects in our RSVP Keyboard™ BCI studies. For each participant, study sessions with good and poor BCI performance (as measured by area under the curve [AUC] for calibration session) were selected, and EEG recordings analyzed for drowsiness. Participants self-rated for drowsiness on the Stanford Sleepiness Scale (SSS) [4]. EEG was recorded at 256Hz using a 16 channel g.tec system with standard 10-20 coordinates. Data were bandpass filtered from 2-60Hz with a 60Hz notch filter. Drowsiness detection was done using power measurements in the theta (4-8Hz) and alpha (8-13Hz) bands (using channels Fz, Cz, P1, and P2), and persistence of eye-blinks (using an average of Fp1 and Fp2) in the epochs. Power estimates were calculated prior to letter presentation, and epochs following this were screened for a 30% increase in both frequency bands, as well as a 50% increase in these bands' contribution to total power (power in band/total power). The epochs were formed by dividing the dataset into 4 second intervals, FFT applied, and resulting power calculated using MATLAB (v. 2015b). The power and eye-blink calculations were used to determine levels of drowsiness, outputting a score ranging from 0[not drowsy] -4[very drowsy] based on the percent of epochs that satisfied those drowsiness conditions (stepping from 20% to 100%). To eliminate the cause of noise on AUC, only files with more than 80% clean data (free from muscle or other high frequency activity above 6e-12uV) were included in the analysis. The drowsiness detection was more sensitive to within performance differences than the SSS (see Table 1), but neither score fully explained user performance.

	Best Perform. (AUC)	Drowsiness Est.	SSS	Worst Perform. (AUC)	Drowsiness Est.	SSS
Part. 1	0.8311	0	1	0.6845	0.5	1
Part. 2	0.9591	0	5	0.8032	2	1
Part. 3	0.8168	0.5	1	0.5354	1	3
Part. 4	0.6418	0.5	2	0.5925	2	2

Table 1: Best and Worst session performance for participants (part.'s) with SSS and Drowsiness Estimate

Discussion: While this study took a modest approach to the detection of drowsiness, we demonstrated possible drowsiness implications on performance in a P300 based BCI system. Further studies should incorporate lateralized eye movements and optimize channels for calculation of power measurements to make a more sensitive and accurate detector. While neither score was closely related to performance (AUC) in this small sample, automated drowsiness detection is more practical for BCI in this or any population, and further developments will likely result in improved sensitivity.

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Significance: The significance of this exploratory study is in creating potential avenues to improve performance on P300 based BCI systems by considering the impact of drowsiness on the underlying event-related potentials.

References:

[1] Koshino, Y., et al. "The influence of light drowsiness on the latency and amplitude of P300." Clinical EEG and Neurosci. 24.3 (1993): 110-113

[2] Oken BS, Salinsky MC, Elsas SM. Vigilance, alertness, or sustained attention: Physiological basis and measurement. Clinical Neurophysiology 2006, 117:1885-1901.

[3] Orhan, Umut, et al. "RSVP keyboard: An EEG based typing interface." Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on. IEEE, 2012.

[4] Hoddes, E., et al. "Quantification of sleepiness: a new approach." Psychophysiology 10.4 (1973): 431-436.