An Online SSVEP-Based Brain-Computer Interface for Freely Moving Humans

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Abstract. Most of current brain-computer interfaces (BCI) require users remain stationary during recordings because of the perceived difficulty of separating brain EEG data from non-brain artifacts. This study tests the feasibility of bridging an online steady-state visual-evoked potential (SSVEP)-based BCI to a low-cost consumer electroencephalogram (EEG) headset for freely-moving humans. This practice considerably facilitates real-life BCI applications using a mobile and non-tethered EEG system for humans actively behaving in and interacting with their environments.

Keywords: EEG, Low-cost Headset , SSVEP, BCI, Moving Humans

1. Introduction

Steady-state visual-evoked potential (SSVEP)-based brain-computer interface (BCI) has become a promising and direct channel allowing users to communicate with the environment due to its ease of use, minimal user training , large number of commands and high information transfer rate (ITR) [Wang et al., 2006; Müller-Putz et al., 2008; Bin et al., 2009]. SSVEP has also been used in clinical research and evaluation. For example, [Golla and Winter, 1959] first reported distinct electroencephalogram (EEG) in response to photic stimulation between migraine patients and normal. SSVEP might thus be used to predict migraine attacks. However, this BCI application requires continuous monitoring and evaluation of SSVEP of migraineurs in their natural head/body positions and movements. A natural next step is to translate laboratory-derived neuroscience concepts to performance in more real-world environments. Only few studies [Debener et al., 2012; Lin et al., 2013] have explored the feasibility of conducting BCI-related EEG tasks in natural movements, e.g. walking or running. This study extended our recent work [Lin et al., 2013] to construct an online SSVEP-based BCI based on a low-cost mobile EEG headset for freely moving humans.

2. Material and Methods

This study employed a 14-channel wireless EEG headset (Emotiv Systems Inc.) that sampled and filtered EEG signals at 128 Hz and within a band of 0.2-45 Hz, respectively. The electrodes are positioned at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. Three participants walked on a treadmill at speeds of 0, 2 and 4 mile (s) per hour (MPH) and intentionally gazed at one of the repetitive black/white flicker stimuli (of 9, 10, 11, and 12 Hz). An experiment comprised 3 sessions at different walking speeds. Each session repeated the following procedure 10 times: Verbal instructions guided participants to shift their attention on the visual target flickering at from 9 to 12 Hz sequentially. The participants needed to shift their gaze to the target stimulus within 1.5 second. Then, the 14-channel EEG data of 2 seconds were first submitted to canonical correlation analysis (CCA). This study adopted the procedure of self-regulating data [Wang et al., 2006] to sequentially append the acquired EEG signals for improving signal-to-noise ratio (SNR) and SSVEP detectability. That is, CCA used a 2-second moving window advancing at 0.25-second steps continuously. An SSVEP frequency was determined only if the same dominant frequency was detected by CCA in four consecutive windows. A trial was correctly performed if the SSVEP frequency matched the frequency of the target flicker. If an SSVEP frequency could not be detected within 8 seconds, the trial was terminated and labeled as an incorrect trial. This procedure took at least 17 seconds to correctly classify four visual flickers with an average response time of 4.25 seconds.

3. Results

Table 1 shows test results of the online SSVEP BCI in terms of accuracy (%), averaged detection time (sec), total experiment time (sec), and ITR (bits/min) at different walking speeds. On average, the system required less time (172.17 seconds) to complete the entire session and provided better performance (mean accuracy: 90%, mean averaged detection time: 4.31 sec, and mean ITR: 19.14 bits/min) under the standing condition, compared to that of the walking conditions. The performance significantly decreased as the walking speed increased from 2 MPH to 4 MPH (Accuracy: 75.83% vs. 47.50%, ITR: 11.25 bits/min vs. 2.59 bits/min).

Table 1. *Online SSVEP detection results under different walking speeds. Speeds: the speed of treadmill, Accuracy (%): the percentage of correctly detected SSVEP trials, Avg detection time (s): averaged time for detected SSVEP trials, Total time (s):the total time needed to complete a 10-repretition session, ITR (bits/min): information transfer rate.*

Subjects	*Speeds*	*Accuracy (%)*	*Avg. detection time (s)*	*Total time (s)*	*ITR (bits/min)*
S_L	Standing	90.00	4.37	174.75	18.85
	2 MPH	72.50	4.46	178.25	9.63
	4 MPH	40.00	4.34	173.50	1.08
S_S	Standing	90.00	4.26	170.25	19.35
	2 MPH	72.50	4.41	176.25	9.74
	4 MPH	60.00	4.53	181.00	5.24
S_W	Standing	90.00	4.29	171.50	19.21
	2 MPH	82.50	4.40	176.00	14.37
	4 MPH	42.50	4.38	175.25	1.44

4. Discussion

In general, the SSVEP detectability progressively decreased while participants switched from standing to walking, especially a significant drop in accuracy was found at 4 MPH (power walking). Since there were no trials terminated by the decision criterion of 8 seconds, the corresponding decision time did not increase as expected. In line with prolonged averaged time for detecting SSVEPs and completing a session, CCA tended to require longer duration of the EEG signals (and higher SNR) to correctly detect SSVEP frequencies as walking speed increased. The reason can be in part attributed to the fact that the SNR of the acquired SSVEP dramatically degraded and/or participants reported a loss of focus on the flickering target occasionally during fast walking. The decreased accuracy and increased time for SSVEP detection thus resulted in a lower online BCI performance (lower ITR) as walking speed increased.

Despite the poor detectability for fast walking, this study demonstrated the feasibility of bridging SSVEP-based BCI to a low-cost consumer EEG headset on unconstrained humans. The ITR at the standing and slow walking (2 MPH) can satisfy the performance requirement in practical BCI applications. Future work will focus on testing a larger number of users, quantifying the SNR fluctuations at different walking speeds, and optimizing the ITR for real-life applications.

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