A Mobile Brain-Computer Interface for Freely Moving Humans

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Abstract. Recent advances in mobile electroencephalogram (EEG) systems featuring dry electrodes and wireless telemetry have promoted the applications of brain-computer interfaces (BCIs) in our daily life. In the field of neuroscience, understanding the underlying neural mechanisms of unconstrained human behaviors, *i.e.* freely moving humans, is accordingly in high demand. The empirical results of this study demonstrated the feasibility of using a mobile BCI system to detect steady-state visual-evoked potential (SSVEP) of the participants during natural human walking. This study considerably facilitates the process of bridging laboratory-oriented BCI demonstrations into mobile EEG-based systems for real-life environments.

Keywords: EEG, BCI, SSVEP, moving humans.

1 Introduction

A steady-state visual-evoked potential (SSVEP) is a frequency-modulated brain signal in response to a periodic visual flickering. Signals acquired from the parieto-occipital region over the visual cortex commonly provide the highest signal-to-noise ratio (SNR) than from other scalp locations. An SSVEP-based brain-computer Interface (BCI) has recently gained much attention since it requires minimal user training and provides high information transfer rate (ITR) [3]. The SSVEP BCI has thus become a promising modality for patients with severe motor disabilities to directly communicate with the environment through recognizing the frequencies of the acquired signals.

SSVEP has also been widely used in clinical diagnostic medicine. In 1959, Golla and Winter [4] first reported that migraineurs have distinct brain activities in response to photic stimulation, *i.e.* SSVEP, compared to healthy controls. Furthermore, Chen *et al.* [5] showed significantly different SSVEPs between interictal and peri-ictal periods in migraineurs. That is, SSVEP might be a useful tool for predicting the headache attacks. A mobile and wearable SSVEP-based BCI system is critical for continuously and robustly monitoring migraineurs' EEG activities in natural head/body positions and movements. Recently, rapid advances in mobile electroencephalogram (EEG) systems featuring dry and zero-prep electrodes, miniature electronics, wireless telemetry [1], and/or cell-phone-based platforms [2] have promoted the translation of a BCI system from a laboratory setting to real-world practices. Particularly, previous studies [1-2] have shown that a

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mobile and non-tethered EEG system can reliably detect SSVEP signals. However, the SSVEP studies were conducted in well-controlled laboratories, where participants were strictly instructed to restrict any body movements while gazing at the flickering visual targets – largely out of fear of introducing non-brain artifacts into the EEG data records. This restriction hinders the long-term, continuous and routine EEG monitoring in the workplace or at home. Until recently, Debener *et al.* [6] explored the feasibility of assessing BCI-related EEG tasks, *e.g.* P300 event-related potential (ERP), in walking humans. However, the feasibility of acquiring SSVEP signals in hostile recording conditions has not been fully explored.

This study systematically tests the feasibility of using a mobile and wireless BCI system to detect SSVEP of the participants during natural walking. A treadmill was adopted to create a speed-adjustable walking platform for eliciting different degrees of head/body movements, *i.e.* increasing the walking speed would accompany larger head and body sways. Canonical correlation analysis (CCA), which has been proved robust in detecting SSVEP frequencies [7-8], was used to explore the SSVEP detectability under different walking speeds.

2 Material and Method

2.1 Experiment Setup

To acquire EEG data during walking, this study employed an adjustable-speed treadmill to mimic natural human walking in daily life (Fig. 1(a)). Participants were instructed to gaze at a flickering stimulus of 11 Hz/12 Hz for 60 seconds while walking on the treadmill with three speeds of 1, 2 and 3 mile (s) per hour (MPH). The flickering stimuli (7.5cm x 6.0cm) were presented at the center of an LCD monitor with a 60Hz refresh rate. The stimulus program was developed under Microsoft Visual C++ using the Microsoft DirectX 7.0 framework [9]. For comparison, this study also acquired the EEG signals while participants were standing on the treadmill (0 MPH). A variable time interval of 10 to 20 seconds was interleaved with visual flickering stimuli to avoid visual and/or motion fatigue.

2.2 EEG Data Acquisition

Ten healthy participants (8 males and 2 females; 23-31 years of age; mean age: 27.5 years) with normal or corrected-to-normal vision participated in this experiment. Each participant signed an informed consent approved by the UCSD Human Research Protections Program before the experiment.

This study used a 32-channel EEG system (Cognionics, Inc.) featuring dry electrodes and wireless telemetry to record SSVEP signals with a sampling rate of 250 Hz. The headset is made from soft fabric and completely encloses the system's electronics (Fig. 1(b)). This study only used two four-electrode straps (eight electrodes: P3, P1, P2, P4, PO3, PO1, PO2 and PO4) over the parietal and occipital areas to record SSVEP signals (Fig. 1(c)). Dry electrodes at O1 and O2 were substituted by wets ones for performing a wet-dry comparison of the SSVEP performance (against adjacent dry electrodes: PO1 and PO2). For each participant, the dataset consisted of 8 60-s EEG segments (four walking speeds x two flickering frequencies).

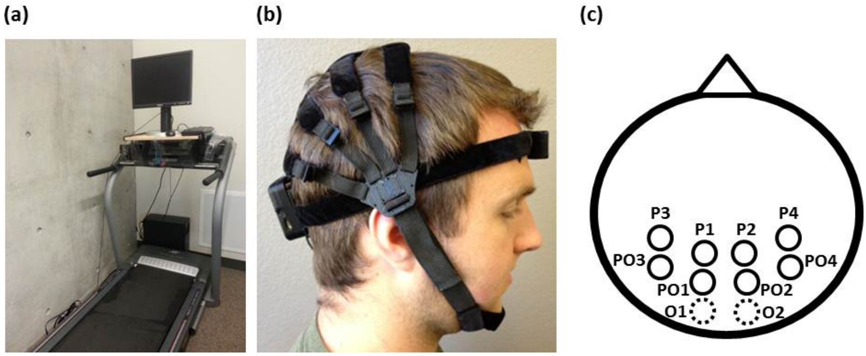

Fig. 1. (a) Experiment setup, (b) a 32-channel wireless EEG system, and (c) electrode locations used for extracting SSVEP signals

2.3 SSVEP Analysis

This study adopted CCA [7-8], a widely used algorithm in SSVEP-based BCIs, to detect frequencies of the SSVEP signals. CCA aims to maximize the correlation between the recorded EEG signals and the sinusoidal templates corresponding to the flickering frequencies. Applying the coefficients of CCA as spatial filters to multi-channel EEG time series returned SNR-enhanced SSVEP signals. Note that CCA calculation in this study only relied on the fundamental frequency of template signals.

In addition, this study systematically assessed two important parameters: (1) the length of an EEG epoch, and (2) the number of channels, from the recorded EEG signals to explore a better way for detecting SSVEP in freely moving humans. The 8-channel EEG data were first filtered by a 5-50 Hz band-pass Chebyshev Type I filter to remove low-frequency signal drifts and high-frequency motion artifacts. Each 60-s EEG time series was then segmented into *N*-s epochs (*N*=1-4). Epochs contaminated by severely transient motion artifacts were removed from further analysis. EEG data from one participant were excluded from the analysis because the remaining number of epochs was very limited after trial rejection.

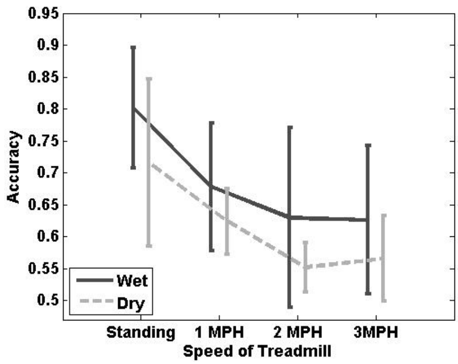

Fig. 2. Averaged SSVEP detection accuracy using two wet (O1 and O2) and dry (PO1 and PO2) electrodes across different walking speeds

This study performed three tests: (1) a comparison between the SSVEPs measured by dry versus wet electrodes; (2) the effect of the number of electrodes (four electrodes on the parieto-occipital strap versus eight electrodes on both the parieto-occipital and parietal straps in Fig. 1(b) and (c)) on the detectability of SSVEPs; and (3) the effect of the length of an epoch on the detectability of SSVEPs. This study evaluated the detectability of SSVEP by calculating the binary classification accuracy of single-epoch SSVEPs, *i.e.* the percentage of correctly recognized trials, at 11Hz and 12Hz under different walking conditions.

3 Results

To compare the quality of SSVEP measured by dry versus wet electrodes, two wet electrodes were placed at O1 and O2, next to the dry electrodes at PO1 and PO2, to simultaneously measure the EEG signals during experiments. Figure 2 shows the detection accuracy of 1-s SSVEPs measured by wet and dry electrodes under different walking speeds. Using dry electrodes provided an averaged accuracy of 71.57±13.09% while participants gazed at the flickering in the standing condition, as compared to the wet electrodes (80.19±9.45%). The detection accuracy using either the dry or wet electrodes tended to degrade as the speed of the treadmill increased from 1 to 3 MPH (1 MPH: 62.41±5.14% vs. 67.78±9.97%, 2 MPH: 55.19±3.84% vs. 62.96±14.13%, 3 MPH: 56.57±6.62% vs. 62.59±11.61%), which were however all above the chance level (50%).

Figure 3 shows the effects of the epoch length and the number of channel on the detection accuracy of SSVEPs under different walking speeds. The results clearly showed that in general CCA returned better SSVEP detectability using longer epochs and more channels, *i.e.* the accuracy increased diagonally from the upper-left to the lower-right corner. Using 8-channel 4-s EEG data to detect SSVEP resulted in a maximal accuracy at any given walking speed, except for the condition of standing. Interestingly, EEG signals acquired from four channels placed on the parieto-occipital strap were able to detect SSVEP with a comparable accuracy of 91.85±8.35% against that of using 8 channels (91.11±8.35%). The accuracy declined as walking speed increased (1 MPH: 84.07±11.03%, 2 MPH: 75.56±18.09%, and 3 MPH: 74.81±16.25%).

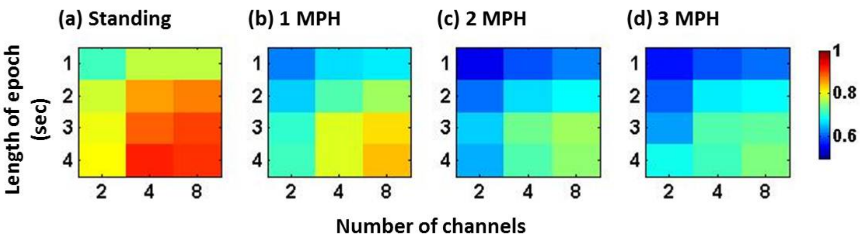

Fig. 3. Averaged SSVEP detection accuracy by CCA with different epoch lengths (1-4 sec) and numbers of channels across different walking speeds (a) standing, (b) 1 MPH, (c) 2 MPH, and (d) 3 MPH

4 Discussions and Conclusion

This study tested the feasibility of using a mobile and wireless BCI system featuring dry electrodes and wireless telemetry to detect SSVEP during natural human walking with emphasis on 1) evaluating the SSVEP quality acquired by the dry electrodes, 2) exploring an optimal set of parameters to detect SSVEP.

To evaluate the feasibility of using dry electrodes to acquire SSVEP, this study performed a wet-dry comparison (wet: O1 and O2, dry: PO1 and PO2). Using wet electrodes to acquire SSVEPs outperformed that of using dry ones by 9% in standing and ~6% in walking conditions (*c.f.* Fig. 2). This study further optimized SSVEP detectability by using progressively longer multi-channel EEG data. CCA tended to return better classification accuracy with longer data epochs from more channels. The accuracy was found improved by at least 13% across different walking speeds when CCA used 4-s EEG data from eight electrodes over the parietal and the occipital regions, compared to that of using only two electrodes at PO1 and PO2. This finding was consistent with previous works [7-8] that using longer epochs and more channels obtained better CCA-based SSVEP results in movement-restricted participants. The high detection accuracy could be attributed to the fact that CCA could improve SNR by using multivariate covariance information, the imported data with more channels and data points would be beneficial to the detection of the SSVEPs.

The SSVEP detectability was found monotonically decreased as walking speed increased (*c.f.* Fig. 3). It is very likely due to the fact that the fast walking involved large head/body sway movements, resulting in widespread motion artifacts over multiple sensors. A natural next step of this study is to apply the artifact removal approaches to enhance the SNR of SSVEP and thereby increase the reliability of the mobile and wireless BCI system for freely moving and unconstrained human subjects.

Conclusively, although the SSVEP detectability was found degraded as walking speed increased, this study demonstrated the feasibility of using a mobile EEG system (with dry, non-prep sensor and wireless telemetry) to monitor SSVEP under hostile recording conditions. This demonstration could greatly improve the practicability of SSVEP or BCI applications for continuous, long-term health care in the hospital and at home.

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