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A Mobile SSVEP-based Brain-computer Interface for Freely Moving Humans: The Robustness of Canonical Correlation Analysis to Motion Artifacts

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Abstract— **Recently, translating a steady-state visual-evoked potential (SSVEP)-based brain-computer interface (BCI) from laboratory settings to real-life applications has gained increasing attention. This study systematically tests the signal quality of SSVEP acquired by a mobile electroencephalogram (EEG) system, which features dry electrodes and wireless telemetry, under challenging (*e.g.* walking) recording conditions. Empirical results of this study demonstrated the robustness of canonical correlation analysis (CCA) to movement artifacts for SSVEP detection. This demonstration considerably improves the practicality of real-life applications of mobile and wireless BCI systems for users actively behaving in and interacting with their environments.**

I. INTRODUCTION

Steady-state visual-evoked potential (SSVEP) is a frequency-coded brain response modulated by the frequency of periodic visual stimuli higher than 6 Hz [1]. SSVEP is known to be most prominent at the parieto-occipital scalp locations over the visual cortex [1, 2]. SSVEP provides high signal-to-noise ratio (SNR), high information transfer rate (ITR) and minimal user training, and thus has been widely adopted in a brain-computer interface (BCI) [1, 2]. By means of determining the frequencies of stimuli from a user's non-invasively recorded electroencephalogram (EEG), SSVEP becomes a promising medium signal in current BCI applications.

BCI researchers recently have more interests in bridging the SSVEP-based BCI to novel mobile EEG systems featuring dry electrodes and wireless telemetry [3]. Previous studies showed that dry EEG sensors could be employed to reliably acquire SSVEP signals [3]. Furthermore, it is feasible to implement an online SSVEP-based BCI on a mobile platform such as a cell-phone [4]. These progresses have greatly facilitated the translation of a BCI system from a laboratory-orientated research to a practical mobile BCI system. However, although these studies have reported promising results of using a mobile EEG/BCI system, the evaluation of the quality of SSVEP was often performed within the confines of well-controlled research laboratories. Because of the perceived difficulty of separating brain EEG data from non-brain artifacts, participants in such BCI experiments have been asked to sit still, suppressing or minimizing natural eye and head movements, waiting for and gazing at SSVEP stimuli. Neuroscience studies often assume that brain activity including SSVEP measured in well-controlled conditions and environments reflects a general principle of brain dynamics during cognitive processing in naturalistic environments. However, until recently only scattered studies explicitly investigated whether the brain switches to a different method of operation while humans actively behave, adapt to and interact with ever-changing environments.

To our knowledge, the signal quality of SSVEP under hostile recording conditions, *e.g.* freely moving humans, has not been fully explored. Our recent study [5] addressed the feasibility of using a mobile BCI system to detect SSVEPs during natural walking on a treadmill. The results showed that the SSVEP detectability, using canonical correlation analysis (CCA), progressively decreased as walking speed increased. The decreased accuracy might be attributed to the fact that fast walking swayed the EEG headset and thus involved large head-movement artifacts, which inevitably contaminated the EEG signals.

Nowadays, independent component analysis (ICA) has been widely applied to multichannel EEG to separate non-cortical artifacts and cortical signals (*i.e.* task-relevant responses) from scalp-recorded signal mixtures resulting from volume conduction [6]. Wang *et al.* [1] has reported that ICA was efficient to extract SSVEP and reduce the background noise. This study extends our previous work [5] to explore the effectiveness of ICA for enhancing the SSVEP quality and thereby improving the CCA-based SSVEP detectability in freely moving humans. It is worth noting that fully testing the capability and limitations of the mobile EEG/BCI technology is crucial not only for the practicality of the SSVEP-based BCI, but also for any applications that involve monitoring neural activities of unconstrained, freely-moving participants performing ordinary tasks in natural head/body positions and situations.

II. MATERIAL AND METHOD

A. Experiment setup

To explore the effects of human movement on the EEG, this study instructed participants to walk on a treadmill with adjustable speeds at 1, 2, and 3 mile (s) per hour (MPH). Participants were asked to intentionally gaze at a black/white flickering stimulus of 11 Hz or 12 Hz for 60 seconds during walking on the treadmill. The conditions of standing still (0 MPH) and/or gazing at the screen with a black background (0 Hz) were also included for comparison. Each participant underwent an experiment comprising 12 conditions (four

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treadmill speeds x three visual stimuli). A variable time interval of 10~20 seconds was inserted between two consecutive conditions to prevent visual and/or motion fatigue. The visual flickering (7.5 cm x 6.0 cm) was developed under Microsoft Visual C++ using the Microsoft DirectX 7.0 [7] and presented at the center of an LCD monitor with a 60 Hz refresh rate.

B. 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. This study was approved by the UCSD Human Research Protections Program. Written informed consent was obtained from each participant.

This study adopted a 32-channel mobile EEG system (Cognionics, Inc.) featuring dry electrodes and wireless data transmission to record signals with a sampling rate of 250 Hz. Only twenty-two electrodes were used and placed over the frontal, parietal, and occipital areas, to record SSVEP signals.

C. EEG data processing

1) Pre-processing

This study was devoted to analyze the EEG from eight dry electrodes (P3, P1, P2, P4, PO3, PO1, PO2, PO4) placed over the parieto-occipital region, which has been reported most sensitive to SSVEP detection [2]. To remove the DC-drifts and high-frequency motion artifacts, the 8-channel EEG data were first filtered by a 1-50 Hz band-pass FIR filter with zero phase-shift. To yield better results of ICA, transient artifacts and noisy channels were sequentially removed by hand. The EEG data from a subject was removed from the further analysis because the remaining number of trials and channels after artifact rejection was too low.

2) Independent component analysis

ICA possesses the merit of estimating statistically independent components (ICs) from the signal mixtures. It has been widely applied to multichannel EEG signals to remove artifactual signals and thus improve the SNR of EEG signals. This study thus adopted the extended Infomax ICA algorithm, implemented in EEGLAB [8], to decompose the 8-channel EEG signals into components that distinctively modulate SSVEPs. The Infomax ICA finds an unmixing matrix, W, that linearly separates the time series data into an independent source matrix, U, by minimizing the mutual information among the output components, followed by the equation of $U=WX$. The rows of output data matrix, U, are the component activations. To remove artifactual components, only ICs (N = 1-4) with most prominent SSVEP-relevant spectral power (*i.e.* the magnitude of power difference between 11 Hz and 12 Hz) were selected and submitted to canonical correlation analysis (described below). After ICA decomposition, the activation of each 60-s IC was then segmented into one-second SSVEP trials.

3) Canonical correlation analysis

SSVEP-based BCIs have largely adopted CCA [2, 9] due to its ability to improve the SNR of SSVEPs. CCA is a multivariate statistical method to maximize the correlation between two multichannel signals (the EEG signal and the sinusoidal template signals associated to the flickering frequency in detecting SSVEP). It calculates the canonical correlation between multi-channel EEG signals and template signals at each stimulus frequency. The frequency of the template with the maximal correlation was selected as the SSVEP frequency. Accordingly, this study was to examine the robustness of applying CCA to SSVEP recorded under hostile conditions, *e.g.* walking on a treadmill. The CCA was separately applied to N-dimension IC activations and eight-channel EEG signals to classify the one-second SSVEP trials. Note that CCA calculation only relied on the fundamental frequency of template signals because the number of harmonics has been reported not a crucial parameter for the SSVEP detection [2]. SSVEP detection accuracy, *i.e.* the percentage of correctly recognized 1 s trials, was used for evaluating the performance.

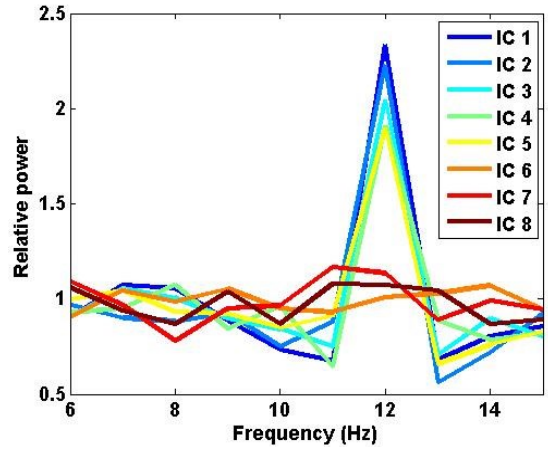

Fig. 1. Power spectrum density of SSVEP-sorted ICs from one representative subject gazing at 12 Hz flickering.

TABLE 1. AVERAGED SSVEP ACCURACY (STANDARD DEVIATION) OBTAINED BY CCA WITH/WITHOUT ICA SELECTION

Methods	Standing	1 MPH	2 MPH	3 MPH
CCA	78.85 (9.09)	**67.20 (7.06)**	63.31 (4.67)	61.83 (7.44)
IC 1 + CCA	72.93 (12.46)	63.21 (11.28)	**64.16 (9.99)**	**62.76 (13.53)**
IC 2 + CCA	76.26 (12.21)	66.81 (9.40)	63.69 (8.82)	62.31 (13.42)
IC 3 + CCA	78.62 (10.11)	67.14 (10.62)	63.46 (9.30)	61.70 (12.23)
IC 4 + CCA	**79.18 (9.41)**	66.21 (9.68)	63.45 (7.17)	61.82 (9.34)

IC N + CCA: CCA calculation on N-dimension IC activations
Numbers in bold represent the best accuracy at each speed condition (no significant difference, p>0.05).

III. RESULTS

Fig. 1 illustrates the power spectrum density (PSD) of sorted ICs from one representative subject gazing at 12 Hz flickering. This result clearly showed that the criterion of power difference (between 11 Hz and 12 Hz) used in this study was capable of selecting SSVEP-relevant ICs for further analysis.

This study then evaluated the efficacy of CCA for detecting SSVEP based on EEG data with/without ICA pre-processing. Table 1 shows the averaged SSVEP detection accuracy based on 1 s EEG data or component activations at

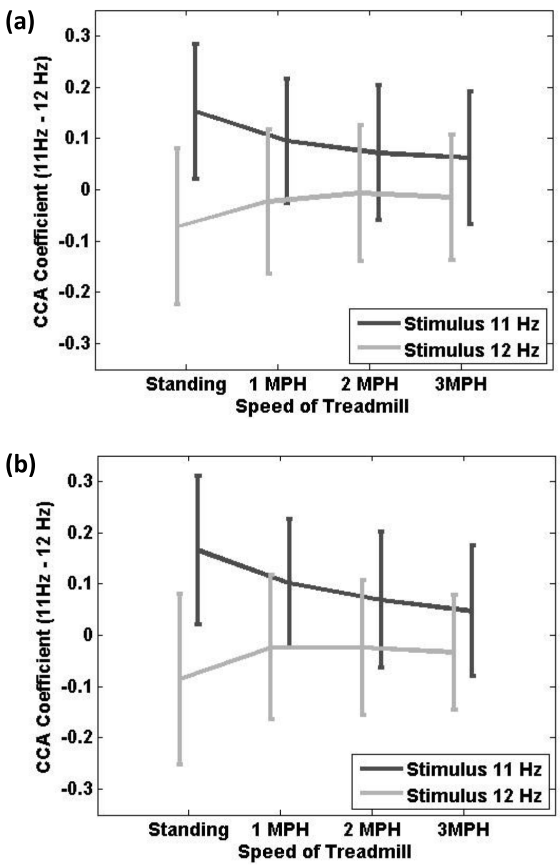

Fig. 2. Averaged difference of CCA correlation coefficient of SSVEP obtained (a) without and (b) with ICA selection (IC 4 + CCA) across different walking speeds. The black and gray lines correspond to visual stimulus of 11Hz and 12 Hz, respectively.

different walking speeds. First, when comparing the results obtained by CCA cooperated with a different number of ICs (*i.e.* IC *N* + CCA, using IC (s) with prominent differential power between 11 Hz and 12 Hz), the SSVEP detection accuracy tended to slightly increase under the conditions of standing and 1 MPH (the 2nd and 3rd columns of Table 1). However, the improvements were not statistical significant (p>0.05). The results for 2 MPH and 3 MPH were found insensitive to the number of selected ICs (p>0.05). Furthermore, CCA with/without ICA pre-processing provided comparable accuracy (p>0.05) at each walking speed. Lastly, all methods showed a decreasing trend as participants switched from standing to walking. A significant drop in accuracy (p<0.05) was found between standing and walking at 1 MPH using CCA and IC3/IC4 + CCA. No significant difference (p>0.05) existed in the comparisons of different walking speeds (*i.e.*, 1 MPH vs. 2 MPH, 2 MPH vs. 3 MPH or 1 MPH vs. 3 MPH).

Fig. 2 illustrates the differential CCA coefficient values (*i.e.* the coefficient value of 12 Hz was subtracted from that of 11 Hz) obtained without/with ICA selection (IC 4 + CCA) across different walking speeds. If CCA correctly classified the SSVEP, a positive differential CCA coefficient represented that participants were gazing at the 11 Hz flickering, whereas a negative value corresponded to gazing at the 12 Hz stimulus. Both methods show that the differential

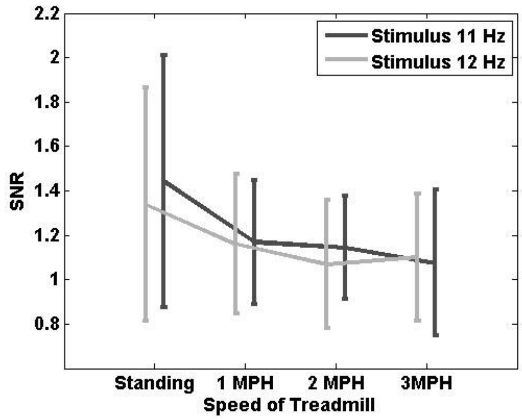

Fig. 3. Averaged SNR of SSVEP in response to visual flickering at 11 Hz (black line) and 12 Hz (gray line) along different walking speeds.

value gradually approached zero when participants walked faster on the treadmill. This was much pronounced while the subjects attended to the 12 Hz flickering. Specifically, the performance of CCA for 11 Hz-flickering outperformed that of 12 Hz by above 10% across different walking speeds (11 Hz vs. 12 Hz, standing: 86.12±5.63% vs. 71.13±19.45%, 1 MPH: 77.37±10.26% vs. 56.85±13.67% (p<0.05), 2 MPH: 70.98±10.46% vs. 54.87±10.44% (p<0.05), and 3 MPH: 67.34%±14.66% vs. 56.08±9.92%). IC 4 + CCA exhibited a similar trend, but with only 5 % difference in detection accuracy between 11- and 12-Hz stimuli.

Fig. 3 illustrates the averaged SNR in response to each visual flickering (11 Hz and 12 Hz) at different walking speeds. The SNR was defined as the ratio of the amplitude of the SSVEP to the mean power at adjacent frequencies, *e.g.* PSD(11 Hz) x 2 / (PSD(10 Hz) + PSD(12 Hz)). The SNR of SSVEP evidently degraded while participants started walking. The decline in SSVEP detection performance (Fig. 2) might be attributed to the lower SNR.

IV. Discussion

This study investigated the effectiveness of ICA-based artifact removal for improving CCA-based SSVEP detectability in freely-moving humans. To this end, a different number of SSVEP-related ICs was retained for CCA. As shown in Table 1, CCA with and without ICA pre-processing obtained comparable performance (p>0.05) at all walking speeds. This result could be attributed in part to the fact that the number of components separated by the ICA algorithm used in this study can only be smaller than or equal to the number of scalp channels (eight in this study). As the EEG data recorded from freely moving subjects were unavoidably very nosy. ICA, applied to eight-channel EEG data, might not be able to efficiently isolate SSVEPs from other competing sources and noise. Another possible explanation is CCA might be relatively robust to noise in the data. Huang *et al.* [10] recently applied empirical mode decomposition (EMD) to EEG data and reported that EMD pre-processing could improve the SSVEP detection accuracy of FFT, but had little effects on that of CCA. This study also applied CCA to the raw EEG data (without manually removing artifacts) for comparison, which interestingly yielded comparable results

(p>0.05). The robustness of CCA to movement artifacts can be in part attributed to the fact that it possesses the characteristics of both spatial filtering and feature selection [2]. In light of CCA's robustness to motion artifacts and low computational complexity, CCA might be a promising algorithm for SSVEP detection in hostile conditions in real-life applications.

The SSVEP detectability was found evidently decreased as walking speed increased (*c.f.* Table 1). It is very likely due to the fact that the SNR decreased as walking speed increased (*c.f.* Fig. 3).

Future efforts to detect SSVEP from freely moving humans could include (1) eliciting SSVEP at frequencies higher than the alpha band (8-13Hz) to minimize the SNR suppression caused by motion engagement, (2) assessing the effectiveness of other artifact-removal methods, and (3) constructing an online BCI for real-life applications.

V. Conclusion

This study assessed the limitations of using dry, non-prep EEG sensors with wireless telemetry in real-world environments by evaluating the SSVEP detectability under hostile recoding conditions. Although the SSVEP detectability degraded as the degree of motion increased, results of this study demonstrated the feasibility of assessing SSVEP collected from unconstrained subjects in natural head/body positions and movements. This sheds light on many new applications that involve monitoring neural activities of freely moving participants performing ordinary tasks within naturalistic environments.

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