Evaluating the Performance of Non-Hair SSVEP-Based BCIs Featuring Template-Based Decoding Methods

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***Abstract*— Our previous study has demonstrated the feasibility of employing non-hair-bearing electrodes to build a Steady-state Visual Evoked Potential (SSVEP)-based Brain-Computer Interface (BCI) system, relaxing technical barriers in preparation time and offering an ease-of-use apparatus. The signal quality of the SSVEPs and the resultant performance of the non-hair BCI, however, did not close upon those reported in the state-of-the-art BCI studies based on the electroencephalogram (EEG) measured from the occipital regions. Recently, advanced decoding algorithms such as task-related component analysis have made a breakthrough in enhancing the signal quality of the occipital SSVEPs and the performance of SSVEP-based BCIs in a well-controlled laboratory environment. However, it remains unclear if the advanced decoding algorithms can extract high-fidelity SSVEPs from the non-hair EEG and enhance the practicality of non-hair BCIs in real-world environments. This study aims to quantitatively evaluate whether, and if so, to what extent the non-hair BCIs can leverage the state-of-art decoding algorithms. Eleven healthy individuals participated in a 5-target SSVEP BCI experiment. A high-density EEG cap recorded SSVEPs from both hair-covered and non-hair-bearing regions. By evaluating and demonstrating the accessibility of non-hair-bearing behind-ear signals, our assessment characterized constraints on data length, trial numbers, channels, and their relationships with the decoding algorithms, providing practical guidelines to optimize SSVEP-based BCI systems in real-life applications.**

I. Introduction

Steady-state visual evoked potentials (SSVEPs) are elicited when an individual gazes at one or more rapid and repetitive flickering visual stimulus [1], [2]. Tagging each command with a coded visual stimulus, SSVEP-based brain-computer interface (BCI) systems can translate users' intention to communicate with others or manipulate peripheral devices [3]. The low training time and high information transfer rate (ITR) have made SSVEP-based BCI systems gain more attention over other non-invasive BCI systems [4]. While recent studies have made considerable progress in improving BCI performance, SSVEP BCIs still face severe challenges in translating the laboratory-oriented SSVEP-BCI demonstrations to real-world environments.

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One of the obstacles of transitioning laboratory-oriented SSVEP-BCI systems to real-world applications is a long preparation time for scalp EEG recordings. In a common setting, accessing the EEG from the hair-covered regions requires skilled technicians to apply conduct gel and clean the hair after an experiment, which may be time-consuming and impractical in deploying SSVEP-based BCI paradigms to real-world situations. More recently, studies have shown that non-hair-bearing areas, such as the forehead and behind-ear areas, can be an alternative for accessing SSVEPs [5], [6]. Our previous study showed the SSVEPs obtained from behind-ear areas could extract informative data using the extended CCA decoding algorithm [7].

However, the online performance using non-hair-bearing EEG might not be comparable with that using the hair-covered occipital EEG [6]. This reveals another challenge, which should be, but not yet, addressed, on the extent to which the SSVEP-BCI performance is comparable between a well-controlled laboratory and a real-world environment.

In a well-controlled laboratory, decoding algorithms, such as task-related component analysis (TRCA) and canonical correlation analysis (CCA), using individual calibration data with spatial filtering techniques, have successfully demonstrated the ability of improving the signal-to-noise ratio (SNR) and ITR in a word-spelling task [8]–[10]. For example, our recent study, which applied a TRCA algorithm to decode SSVEPs, achieved a world-record ITR of 325.33 ± 38.17 bits/min (75 characters per minute) [10]. While studies using advanced coding algorithms have made a breakthrough in the SSVEP-BCI performances with the scalp EEG signals from the hair-covered occipital regions, it is not fully investigated whether, and if so, to what extent the advanced decoding algorithms can extract high-fidelity SSVEPs from the non-hair EEG and enhance the practicality of non-hair BCIs in real-world environments.

To this end, we conducted an off-line SSVEP experiment using a high-density (256-channel) EEG cap that covers regions from both hair-covered occipital and non-hair-bearing regions. This study aims to explore and evaluate SSVEP-decoding performance using two spatial filtering techniques, namely, TRCA and CCA, by analyzing EEG data from the hair-covered and non-hair-bearing areas. By merging state-of-art signal-processing algorithms and providing parametric assessments on empirical data, this study may shed light on developing and assessing the feasibility of SSVEP-based non-hair-bearing BCI systems. Furthermore, to evaluate the classification accuracy using TRCA- and CCA-based spatial

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filters, we applied parametric assessment over factors of interests, including data length, the number of training trials and channels. To the best of our knowledge, the performance of TRCA- versus CCA-based spatial filtering algorithms applied to non-hair-bearing EEGs has never been systematically assessed before. Of interest beyond the empirical functions of parameterization, the findings of this study will provide practical guidelines for developing real-world applications of SSVEP-based BCIs.

II. Method

A. Experimental Procedure and EEG Data Description

Subjects were asked to fixate at the center of a 5 cm 5 cm squared coded visual stimulus with their chin on a chin rest. The distance of participants' head to a 21-inch CRT monitor was 35cm. The experiment was divided into 4 sessions, each consisted of presenting 5 individual visual stimuli (9-13 Hz in a random order) for 30 seconds, with participants taking a short rest between each 30-sec trial and each session. Eleven healthy male subjects, age 24.2±5.1 years old with normal or corrected-to-normal vision, participated in this experiment. All participants read and provided informed consent for the study, which was approved by the University of California, San Diego Institutional Review Board.

EEG data were recorded using a 256-channel AG/AgCl cap (Biosemi, Inc.). Three extra electrodes were manually placed behind the ear around 1 cm apart on each side. For each 30-sec trial, 6 to 7 epochs were extracted according to the event codes designed by the visual stimulus program [11]. The data were re-referenced offline to the forehead (electrode A3, roughly FPz in 10/20 system), with baseline correction performed by subtracting the mean amplitude over the 500 ms before epoch onset. All the epochs of individual frequency were concatenated together to form a dataset for further analysis. The evaluation of the accuracy and ITR was done by leave-one-trial-out, i.e. one trial was used as the testing data while others form the training dataset for preparing individual templates (see below). Parametric assessment of performance on various factors, including data length, number of training trials, and number of channels, was done by systematically reducing data length and randomly removing trials and/or channels, and this procedure was iterating through every subject independently. We used a linear mixed-effect model to assess these factors and their interactions that account for the performance using the template-based decoding with TRCA- and CCA-based spatial filters. Fixed effects included data length, number of trials and channels and their interactions, and were factors that were used in the assessment and random effects were intercept of subjects; Wald confidence of intervals at an alpha level of 0.05 was reported.

B. Target Identification algorithms

1) Framework of Template-Based Method: Training data and single-trial testing data are denoted as $\chi \in \mathbb{R}^{N_f \times N_c \times N_s \times N_t}$ and $X \in \mathbb{R}^{N_c \times N_s}$, respectively. Here, N_f is the number of stimuli; N_c is the number of channels; N_s is the number of sampling point, and N_t is the number of trials, respectively. The goal of the target identification is to take an input X and assign it to a target label C_n where $n = 1, 2, ..., N_f$. In both methods, feature values for n^{th} stimuli can be calculated as the correlation coefficients between the test data and the individual template signals $\bar{\chi} \in \mathbb{R}^{N_c \times N_s}$ obtained by averaging multiple training trials as feature values. The target class C_τ can be identified by the following rule:

$$\tau = \underset{n}{\operatorname{argmax}}\, \rho_n, n = 1, 2, ..., N_f$$

The discriminability of SSVEPs using the correlation features can be enhanced by applying spatial filters to the test data and individual templates.

2) Canonical Correlation Analysis: CCA is a statistical method to measure the underlying correlation between two sets of multidimensional variables. In the template-based decoding with CCA, three spatial filters are obtained by calculating CCAs between 1) test data X and individual templates $\bar{\chi}_n$, 2) test data X and computer-generated SSVEP models Y, and 3) individual templates $\bar{\chi}_n$ and computer-generated SSVEP models Y. The final feature value ρ_n can be obtained by combining three correlation coefficients between test data and individual templates after each spatial filter. The detail of this method can be found in [8], [9].

3) Task-Related Component Analysis: TRCA is the method that extracts task-related components efficiently by finding a linear coefficient that maximizes their reproducibility during task periods [10]. The problem can be solved by inter-trial covariance maximization. The covariance matrices $C_{i,j}$ between i^{th} and j^{th} trials of multichannel EEG data are first calculated, and then all possible combinations of trials are summed as $S = \sum_i \sum_j C_{i,j}$. The optimal coefficient $\hat{w}$ can be obtained by maximizing $w^T Sw$ with a constraint based on the variance of reconstructed signal to obtain a finite solution. In SSVEP-based BCIs, the spatial filters based on TRCA can be obtained using training data χ. In the test phase, pre-obtained spatial filters are used to enhance SNR of test data and individual templates, and the correlation coefficients between them are calculated as final features.

III. Results

We first demonstrated the classification performance and ITR as functions of data length and recording regions for the template-based decoding algorithms with spatial filtering, compared with the standard CCA. At a general level, all three classification algorithms performed better with data from the hair-covered occipital regions than from non-hair-bearing behind-ear regions. Notably, using two advanced algorithms, CCA and TRCA, the classification performance using the data from non-hair-bearing behind-ear regions was comparable with that applying the standard CCA to the data from the hair-covered occipital regions.

We then evaluate the performance as a function of data length. Performance accuracy increased with data length (b = 9.78%, t = 13.58, CI = [0.08, 0.11]), and ITR marginally declined as data length increased (b = 0.89, t = 1.88, CI =

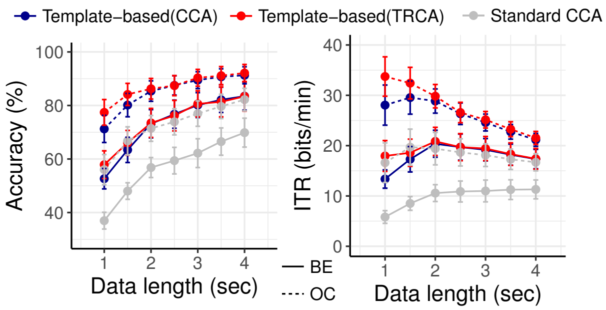

Fig. 1. The average accuracy (left panel) and ITRs (right panel) over 24 trials with data length 1 to 4 seconds across 11 subjects. BE: recordings from behind the ears; OC: recordings from the occipital regions.

[-0.04, 1.83]). We also verified that similar patterns over data length held for both data from the hair-covered occipital (b = 5.27%, t = 12.65, CI = [0.04, 0.06]) and non-hair-bearing behind-the-ear regions (b = 8.97%, t = 22.04, CI = [0.08, 0.10]). On the one hand, performance was better using the data from the hair-covered occipital regions than from the non-hair regions behind the ears (b = 23.05%, t = 7.16, CI = [0.17, 0.29]), especially with shorter data length (1s: b = 10.80%, t = 3.06, CI = [0.04, 0.18], 1.5s: b = 8.94%, t = 2.53, CI = [0.02, 0.16]). On the other hand, these patterns showed that the effect of data length was more drastic for data from the non-hair regions behind the ear than for the hair-covered occipital regions (b = 3.68%, t = 3.62, CI = [0.02, 0.06]). Performance was marginally superior with TRCA to CCA (b = 5.88%, t = 1.83, CI = [0, 0.12]), with no interaction with data length (CI = [-0.04, 0]) or regions (CI = [-0.08, 0.10]).

Because characterizing factors that may optimize the classification performance for data from the non-hair regions behind the ears was of particular importance in this study, we further examined performance as functions of the number of training trials, channels, and their interactions with data length.

A. Performance vs. Number of Training Trials

Generally, performance increased with the number of training trials. The average performance was relatively higher with CCA than those with TRCA when the number of training trials was limited (Figure 2(a), 2(d)). Additionally, the effect of training trial number interacted with data length for both TRCA- (b = 0.12%, t = 2.21, CI = [0, 0.002]) and CCA-based spatial filters (b = 0.10%, t = 2.23, CI = [0, 0.002]) (Figure 2(c), 2(f)). Performance increased more rapidly with the number of training trials for shorter than for longer data length. The slope of performance with data length, vice versa, was steeper when the number of training trials was smaller than when it was larger. By visual inspection of Figure 2(b) and 2(e), performance with CCA appeared to be relatively invariant to the number of training trials. However, once the number of training trials was large enough, n>14 for example in Figure 2(c) and 2(f), TRCA began to outperform CCA.

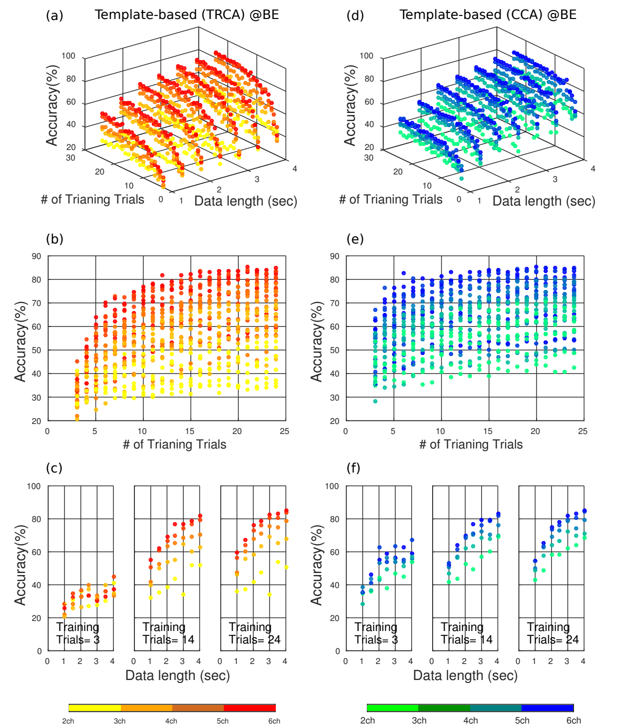

Fig. 2. The performance of target identification as a function of data length, number of training trials, and number of data channels, using TRCA (left panel) and CCA algorithms (right panel).

B. Performance vs. Number of Channels

Likewise, performance increased with the number of channels. Although this function seemed held for both algorithms, CCA showed a reliable increase in performance with channel number (b = 0.33%, t = 2.06, CI = [0, 0.002]). Moreover, CCA had better overall performance than TRCA when the channel number was limited. Furthermore, this channel-number effect interacted with data length for both TRCA (b = 0.11%, t = 5.72, CI = [0, 0.002]) and CCA (b = 0.16%, t = 3.05, CI = [0, 0.003]). The improvement of performance due to an increase in data length was more pronounced when the number of channels was small compared with it was large.

C. Performance vs. Number of Training Trials and Channels Interaction

When the number of training trials was small, an improvement of performance due to an increase of channel number was minimal. As the training trial number increased, an increase of channel number revealed the performance improvement. Critically, this interaction between the numbers of trials and channels was more pronounced with TRCA (b = 0.25%, t = 6.15, CI = [0.002, 0.003]) than with CCA (b = 0.01%, t = 2.37, CI = [0, 0.002]). As a result, with the number of channels increased, TRCA improved more significantly than CCA when there were adequate amounts of training trials.

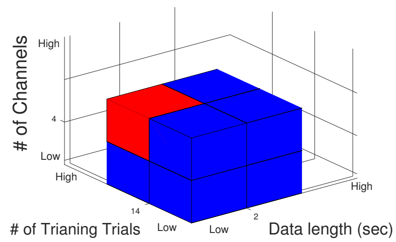

Fig. 3. Illustration of candidate algorithms that demonstrates relatively better performance given constraints of data length, number of trials, and channels. TRCA was highlighted in red and CCA was in blue.

IV. DISCUSSION

The goal of this study was to delineate the factors that may optimize classification performance of SSVEPs for real-life situations by (1) comparing performance between two state-of-art decoding algorithms applied to non-hair regions behind the ears and the hair-covered occipital regions, and (2) evaluating parameters of data factors and their relationships with empirical feasibility and accessibility of non-hair EEG signals.

In answer to the first attempt, we provided empirical comparisons of SSVEP-classification performance and ITRs obtained from the hair-covered occipital and the non-hair regions behind the ears, which were recorded from the same subjects, simultaneously, under the same experimental scenarios. Not surprisingly, recording from the occipital regions had overall better performance than that from behind-the-ear regions. Nonetheless, average accuracy using 4-s-length data achieved 81.36%±5.62%, which was comparable or better than when using 1/1.5-s-length data recorded from the occipital regions. The results showed similar patterns over data length between two recording regions, although a drop-off due to short data length was more for data obtained from the behind-the-ear than from the occipital regions. These observations were also true in comparisons between TRCA and CCA-based spatial filters, i.e., TRCA was superior to CCA for short data length.

Our second major contribution was characterizing factors and their relationships with classification performance for data from non-hair regions. The finding revealed relations between the number of trials and channels in a practical sense: the impact of the number of trials amplifies while data length is short, and reversely, data length has a larger impact when the number of trials is small. We also showed that CCA is more robust to the number of trials compared with TRCA; this makes CCA a better candidate when the available trial number is limited. By contrast, when training trials are adequate, TRCA seems to be benefited more with the accessibility of channel numbers. These findings may direct decisions while designing an SSVEP-based system according to its accessibility to recording durations and computation capacity on algorithms (see Figure 3 for a summary) given its ease-of-use paradigm and recording convenience. In the best scenarios, richness in data shall offer high classification performance. However, the applications in real-life situations almost always come together with constraints in recording accessibility and feasibility. Our assessments in data length, number of trials, channels, and their interactions provide practical guidelines to optimize the system in real-life applications.

V. CONCLUSION

SSVEP-based BCI systems have gained increasing attention due to their high efficiency, short training time and high ITR. As more and more studies make efforts in developing advanced algorithms to improve the SNR and classification accuracy, deploying SSVEP-based BCI applications to real-world environments still face practical challenges, including but not limited to long conductive contact, preparation time and an ease-of-use paradigm. This study tested and evaluated the possibility of combing the state-of-art decoding algorithms and non-hair SSVEPs to real-word environments. The results showed classification performance as a function of factors within hostile conditions, such as short training time, low channel selections, and short data length. This study also provides tentative directions for developing a dynamic learning model that compromises the training time, number of channel selections, and advanced algorithms.

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