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Measuring Steady-State Visual Evoked Potentials from Non-hair-bearing Areas

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Abstract— Steady-State Visual Evoked Potential (SSVEP)-based Brain-Computer Interface (BCI) applications have been widely applied in laboratories around the world in the recent years. Many studies have shown that the best locations to acquire SSVEPs were from the occipital areas of the scalp. However, for some BCI users such as quadriparetic patients lying face up during ventilation, it is difficult to access the occipital sites. Even for the healthy BCI users, acquiring good-quality EEG signals from the hair-covered occipital sites is inevitably more difficult because it requires skin preparation by a skilled technician and conductive gel usage. Therefore, finding an alternative approach to effectively extract high-quality SSVEPs for BCI practice is highly desirable. Since the non-hair-bearing scalp regions are more accessible by all different types of EEG sensors, this study systematically and quantitatively investigated the feasibility of measuring SSVEPs from non-hair-bearing regions, compared to those measured from the occipital areas. Empirical results showed that the signal quality of the SSVEPs from non-hair-bearing areas was comparable with, if not better than, that measured from hair-covered occipital areas. These results may significantly improve the practicality of a BCI system in real-life applications; especially used in conjunction with newly available dry EEG sensors.

I. INTRODUCTION

Steady-State Visual Evoked Potential (SSVEP) is the electrical response of the brain to flickering visual stimuli. SSVEP-based brain-computer Interface (BCI) recently has been widely used in many applications due to its advantages such as little user training and high information transfer rate [1]-[9]. For example, Gao et al. [8] applied the SSVEP to the control of electric apparatus that featured noninvasive signal recording, little training requirement, and a high information transfer rate. As a result, more studies have explored applications of this technology.

As SSVEPs are pre-dominantly originated from the visual cortex, it seems natural to collect the signals by placing electrodes over the occipital regions. Some studies even performed an off-line pilot experiment to obtain the optimal electrode locations prior to on-line BCI practices. However, no matter how people perform the EEG recording from hair-covered areas, they suffered from the complications of recording such as long preparation time and insufficient skin-electrode contact area due to hair. These complications make BCI impractical for routine use in daily life. To overcome these problems, dry contact- and non-contact-type EEG sensors have been developed to enable user-friendly EEG measurements to improve the usability of BCIs [10]-[13]. However, a major concern over the use of dry electrodes for EEG measurement is that the SNR of the acquired signals might not be as good as that from the gel based electrodes [10]-[13]. Furthermore, for some BCI users such as quadriparetic patients lying face up during ventilation, assessing the occipital sites would be undoubtedly more difficult either by wet or dry electrodes. Therefore, an alternative approach to easily extract high quality SSVEPs becomes a crucial issue in BCI community.

The topography of SSVEP often shows a widespread scalp distribution because the SSVEP mainly projected from the visual cortex to the occipital areas, neck, forehead or even the face areas. Therefore, it's reasonable to believe that one could measure the SSVEP over non-hair-bearing areas. To our best knowledge, no study has yet systematically and quantitatively compared SSVEPs from different scalp and face locations using high-density EEG data. This study aims to answer two main questions: (1) Can SSVEP be measured from non-hair-bearing areas? What is the quality of the signals compared against that from the hair-covered area? (2) How many channels of non-hair-bearing SSVEP data would be needed to archive the same SNR measured from the occipital areas in SSVEP experiments? If the proposed non-hair-bearing montage approves feasible, the practicality of an SSVEP BCI system can be significantly improved, especially used in conjunction with dry EEG sensors such as non-contact [11] or polymer based electrodes [12].

II. METHODS

A. Stimuli and Procedure

The visual stimulus was a 5×5 cm square coded and rendered at the center of a 21" CRT monitor with a 120Hz refresh rate. The stimulus frequencies ranged from 9Hz to 13Hz with an interval of 1Hz. In general, this cannot be implemented with a fixed rate of black/white flickering pattern due to a limited refresh rate of a LCD screen. Wang et al. [14] developed a method that approximates target frequencies of SSVEP BCI with variable black/white reversing intervals. Based on this approach, any stimulus frequency up to half of the refresh rate of the screen can be realized. The stimulus program was developed in Microsoft

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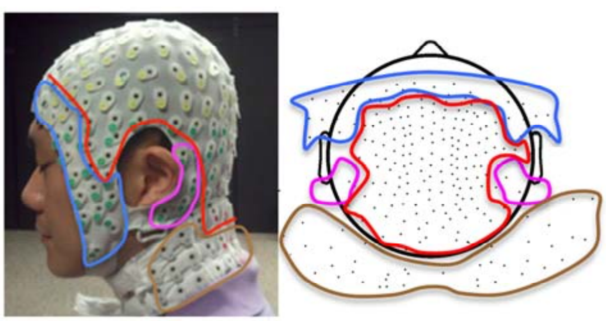
Visual C++ using the Microsoft DirectX 9.0 framework and rendered on Windows XP platform.

Subjects were seated in a comfortable chair in front of the monitor. A chin rest was used to fix the head 35 cm from the screen. The experiment consisted of four sessions, each including five 30s-long trials for the five different stimulus frequencies, which were randomly presented. Subjects were asked to gaze on the flickering stimulus for 30 seconds and then take a ~15s rest after each trial in order to avoid visual fatigue caused by flickering. There was a several-minute break between two sessions.

B. Data Acquisition

Five healthy male subjects with normal or corrected to normal vision participated in this experiment. All participants were asked to read and sign an informed consent form approved by the UCSD Human Research Protections Program before participating in the study.

EEG data were recorded using Ag/AgCl electrodes from 256 locations distributed over the entire head using a BioSemi ActiveTwo EEG system (Biosemi, Inc.). Fig. 1 shows the 256-channel cap that covers not only the brain areas, but also the non-hair-bearing areas including the forehead, face, behind-the-ear, and neck areas. Eye movements were monitored by additional bipolar horizontal and vertical EOG electrodes. Electrode locations were measured with a 3-D digitizer system (Polhemus, Inc.). All signals were amplified and digitized at a sample rate of 2,048 Hz. All electrodes were with reference to the nasion.



(a) (b)

Figure 1. Electrode placement for this study. (a) A subject wore a 256-channel electrode cap. The red line roughly delineates the boundaries between the hair and non-hair-bearing areas of the subject. Blue, magenta and brown circles represent the electrodes locates at the forehead/face, behind-the-ear, and neck areas, respectively. (b) Top view of the distribution of the scalp electrodes.

C. EEG Data Pre-processing

The 256-channel EEG data were first down-sampled to 256Hz. For each trial, six 4s-long EEG epochs were extracted according to event codes generated by the stimulus-presentation program [14]. For each stimulus frequency, the epochs from the four sessions were concatenated to form a dataset of 24 epochs. Epochs with severe artifacts (such as movement artifacts and eye blinks) were manually removed from the dataset. To remove the spontaneous EEG activities, the remaining epochs were averaged to obtain the multi-channel SSVEP signals.

D. EEG Data Analyzing

1) Signal-to-noise ratio (SNR)

This study used SNR to evaluate the quality of SSVEPs. Fast Fourier Transform (FFT) was used to calculate the amplitude spectrum of the 4s-long EEG data (i.e., y=|FFT(x)|). The frequency resolution of the resulting amplitude spectrum was 0.25Hz. The SNR was defined as the ratio of the amplitude of the SSVEP (at the stimulating frequency) to the mean amplitude of the background noise (within the frequency band of 8-15Hz, which includes 28 frequency bins)

$$SNR = \frac{28 \times y(f)}{\sum_{k=8}^{15} y(k) - y(f)} \quad \text{, where } k \neq f \tag{1}$$

2) Single-channel evaluation

Since this study aims to investigate the SNR of SSVEPs recorded at different locations, the SNR values for all electrodes were calculated, sorted, and categorized into four areas as indicated in Fig.1. In each of the four areas, the electrode with the highest SNR was selected for comparison. In the hair-covered area delineated by the red line, the electrode with the highest SNR was located in the occipital region. This procedure was applied to all stimulus frequencies.

3) Multi-channel evaluation

The spatial filtering technique has been widely used in EEG signal processing to improve the SNR of the EEG signals recorded from multiple scalp locations. In previous studies of SSVEP-based BCIs, the Canonical Correlation Analysis (CCA) algorithm has proved to be very efficient for improving the SNR of SSVEP signal [2]. CCA can calculate the canonical coefficients for the two different datasets (in this case, EEG dataset and a reference signal set) such that the correlation between the two canonical variables was maximized. The reference signal set is defined as

$$\begin{bmatrix} \sin(2\pi ft) \\ \cos(2\pi ft) \end{bmatrix} \tag{2}$$

where f is the stimulating frequency. In practice, the coefficients for the EEG dataset could be used as spatial filters to compute linear combinations of EEG data from all electrodes. For multi-channel data, the SNR of SSVEPs was calculated using the projection of the multi-channel data (i.e., the canonical variable).

The SNR of the multi-channel data was estimated by calculating the mean SNR of randomly selected combinations of electrodes from the 80 electrodes over the non-hair-bearing areas. The number of selected electrodes ranged from 1 to 80. For each number, the SNR calculation was repeated 1,000 times with different electrode combinations. The SNR and electrode positions of the combination with the highest SNR were saved for further comparison.

III. RESULTS

Fig.2 shows the SNR topography and the normalized amplitude spectrum on different head areas for Subject 1 and Subject 5. As expected, the occipital area has the highest SNR of SSVEP signals, indicating that the brain sources might locate in or near the visual cortex. The SNR depended on the distance between the electrode position and the occipital region. As shown in Fig.2 (a) and (b), the SNR decreased at other brain areas (e.g., the frontal area) and non-hair-bearing areas. Although the SNR of SSVEP signals recorded from the non-hair-bearing areas was lower than that recorded from the occipital region, signals acquired from the non-hair-bearing areas still showed a clear frequency response at the stimulating frequency (see Fig.2 (c) and (d)). This finding confirmed our hypothesis that the SSVEPs might be detectable from EEG signals measured from the non-hair-bearing areas on the head.

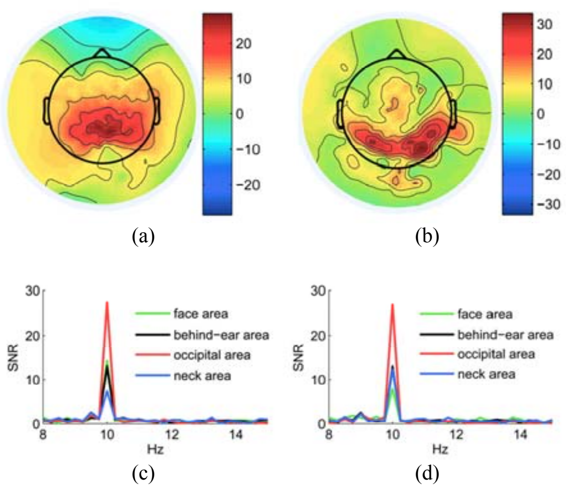


Figure 2. Scalp topography of the SNR's of SSVEPs at 10 Hz for (a) Subject 1, (b) Subject 5. Single-channel SNR from the occipital and non-hair-bearing areas for (c) Subject 1, (d) Subject 5.

Fig.3 illustrates the SNRs of SSVEP signals contributed by combinations of data from multiple electrodes placed at the non-hair-bearing areas for all subjects. For a single electrode, the occipital electrode has a much higher SNR than any electrode from the non-hair-bearing areas. In general, the SNR increased as the number of electrodes involved in the CCA processing increased (as indicated by the blue solid line in Fig. 3). For all the subjects, the best combination of multiple electrodes from the non-hair-bearing areas reached an SNR comparable to the occipital electrode. In particular, three subjects (Subjects 2, 3 and 5) had SNRs of non-hair SSVEPs even higher than those of the occipital electrode. All subjects reached comparable SNRs by using the optimal occipital electrode and a combination of 10 non-hair-bearing electrodes. For Subjects 2, 3, and 5, using as few as five non-hair-bearing electrodes could exceed the SNR of the occipital electrode.

Next, this study explores the optimal placements of multi-channel non-hair-bearing electrodes to realize a practical SSVEP-based BCI system. Fig. 4 shows the electrode placements with the highest SNR using 10 electrodes. For all the subjects, the 10 optimal electrodes covered multiple non-hair-bearing areas, all contributing to the improvement of the SNR of SSVEPs. This individualized electrode montage has the potential to result in many practical BCI applications.

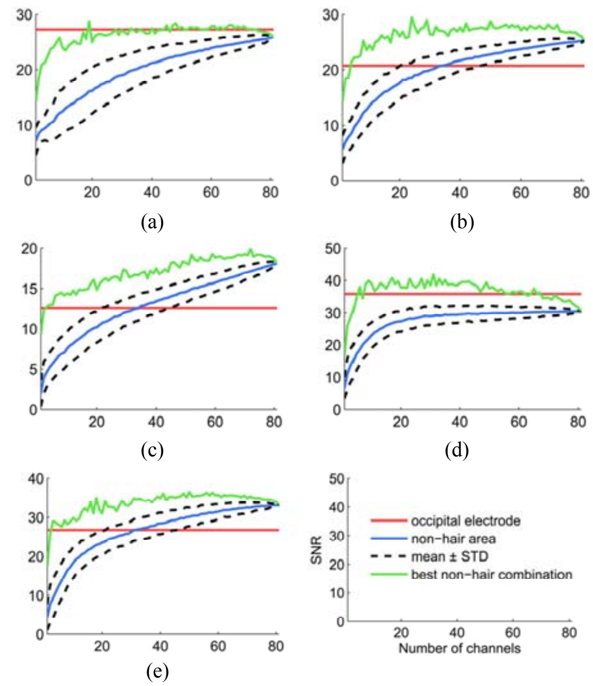


Figure 3. The relationship between the SNR and the number of electrodes used in the CCA processing. (a) - (e) correspond to Subject 1-5, respectively. The non-hair-bearing electrodes include those from the face, neck, and behind-the-ear areas. The signals measured from the occipital electrodes had the highest SNR.

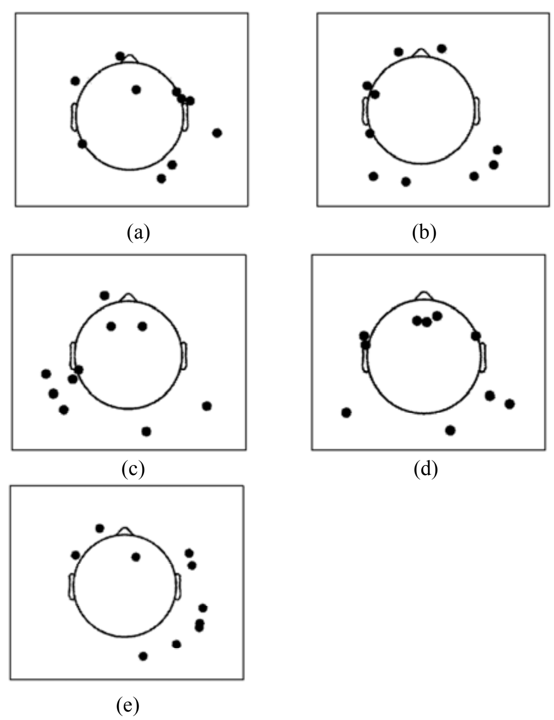


Figure 4. The 2-D projection for the placement of 10 electrodes that result in the highest SNR for each of the 5 subjects. (a) - (e) correspond to Subjects 1-5, respectively. The black dots indicate the electrode locations over the non-hair areas.

IV. CONCLUSION AND DISCUSSION

SSVEP-based BCI applications have attracted a lot of attention recently. However, to our best knowledge, no study has systematically compared the SNR of SSVEPs measured from hair-covered and non-hair-bearing areas. This study showed that, across the five subjects, EEG recordings from non-hair-bearing areas, including the face, neck, and behind the ear areas, could reliably measure SSVEPs. Generally speaking, the rank of the SNR was the occipital area > behind-the-ear > neck area ≈ face area. A lower SSVEP SNR obtained from the neck and face areas might be attributed to the contamination from the muscle activity to those areas.

The comparison between hair-covered and non-hair-bearing area showed that the quality of SNR depends on the electrodes selections. As shown in Fig. 3, the SNR of non-hair-bearing SSVEPs of Subject 3 matched well with that of the reference channel by using only two electrodes. The comparable results were found in Subjects 2 and 5. These results suggested that, if an optimal non-hair electrode combination could be known in advance, one could achieve comparable SNRs of SSVEP by using electrodes placed on the non-hair-bearing areas and the occipital area.

Using laboratory-oriented EEG setups for real-world SSVEP BCI applications is known to be impractical for routine use. An alternative approach to obtain informative EEG signals over no-hair-bearing sites is thus highly desirable. The results of this study demonstrated the feasibility of using a non-hair-bearing montage for measuring SSVEP, which we believe might significantly improve the practicality of BCI systems in real-life environments. If the proposed apparatus proves feasible in other BCI practices, a much wider range of applications of BCI will emerge.

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