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Lead selection for SSVEP-based brain-computer interface

Yijun Wang, Zhiguang Zhang, Xiaorong Gao, Shangkai Gao, *Senior Member*, *IEEE*
Department of Biomedical Engineering, Tsinghua University, Beijing, China

Abstract—**SSVEP-based brain-computer interface (BCI) has potential advantage of high information transfer rate. However, individual difference greatly affects its practical applications. This paper presents a method of lead selection to improve the applicability of SSVEP-based BCI system. Independent component analysis (ICA) is employed to decompose EEGs over visual cortex into SSVEP signal and background noise. Optimal bipolar lead is selected by comparing signal correlation and noise correlation between different channels. The system with one optimal bipolar lead has reached an average transfer rate about 42bits/min for normal subjects. It has also been successfully applied to an environmental controller for the motion-disabled.**

Keywords—**Brain-computer interface, steady-state visual evoked potential, independent component analysis, lead selection**

I. Introduction

Visual evoked potentials (VEPs) recorded from scalp over visual cortex reflect the visual information processing mechanism in brain. Steady-state visual evoked potentials (SSVEPs) occur when stimulation repetition frequency is higher than 6Hz. SSVEP has been employed as an effective communication medium in BCI research. One of the examples is to determine gaze direction by SSVEP [1]-[3]. Several buttons flash at different rates. The user looks at a button and the system determines the frequency of the photic driving response over visual cortex. The button which matches the frequency is the target the user wants to select. The system designed by M. Cheng *et al*. reached a transfer rate greater than 50bits/min on some subjects, while the performance was unacceptable on some other subjects [1].

Obviously, the applicability of SSVEP-based system is limited due to individual difference. Amplitude, source location of VEP, and background noise are important factors which affect the performance of the system. Here, we propose a method of lead selection for the purpose of signal-to-noise ratio enhancement. First, independent component analysis (ICA) is applied to decompose EEGs into SSVEP signal and background noise. Then, spatial power distribution is displayed for comparing the correlation of decomposed signal and noise between different leads. Finally, one bipolar lead with higher correlation of noise and lower correlation of signal is selected as the optimal lead. The result of online tests showed the significant improvement of system performance.

II. Methodology

A. Data acquisition

32-channel EEGs (see Fig.1.(a)) were recorded with a BioSemi ActiveTwo system. 13 channels were located between Pz and Oz to record EEGs over visual cortex with a higher spatial resolution. A blinking light-emitting diode (LED) modulated by square wave was used as the stimulator. The integer repetition rate of stimulation covered the bandwidth from 9Hz to 17Hz. 60-second-long data were acquired in each test with different stimulation frequencies. Signals were sampled at 256Hz and preprocessed by a 50Hz notch filter and a 4-35Hz band-pass filter.

B. Lead consideration

Fig.1.(b) shows a typical example of temporal wave and amplitude spectrum of SSVEPs induced by 13Hz stimulation. The fundamental and second harmonics are identified clearly at 13Hz and 26Hz. The dominant background noise is α rhythm of spontaneous EEG. To detect the frequency of SSVEP accurately and conveniently, a proper bipolar lead should be selected.

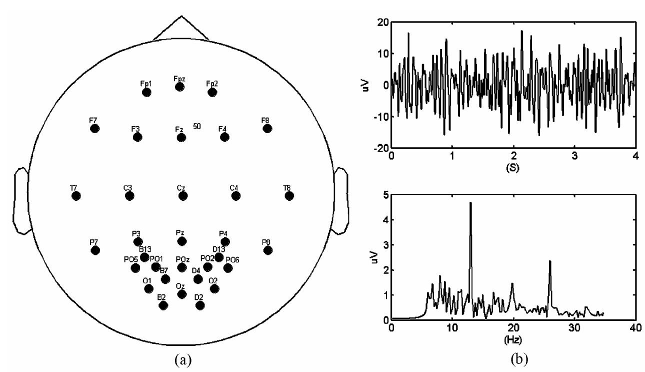

Fig.1. (a) Leads placement of 32-channel EEGs. (b) Temporal wave and amplitude spectrum of 13Hz SSVEPs.

In practice, channel with the most significant amplitude of SSVEP can be considered as the signal channel which commonly locates over visual cortex. The precise position can be determined with the study of EEG power map at stimulation frequency. The difficult problem is to select a proper reference channel for the bipolar lead. A correct choice of reference channel can enhance signal and reduce noise. Here, two factors for reference channel selection are under considerations: ①amplitude of SSVEP, ② distance from the signal channel. To retain SSVEP, the reference channel must have lower amplitude of SSVEP. To reduce background noise, it should have similar background activities with the signal channel. Therefore, the ones close to the signal channel, with low amplitude of SSVEP, could be the candidates of the reference channel. In general, the nearest channels around the signal channel have high noise correlation, whereas, they also have large correlation of SSVEP. On the contrary, the channels with low amplitudes of SSVEP are usually far away from the signal channel, and have less noise correlation. Therefore, a comprehensive consideration must be taken for optimal bipolar lead selection in order to get best signal-to-noise ratio.

The lead selection patterns of two representative subjects are analyzed. The pattern of subject A focuses on correlation of signal and the pattern of subject B emphasizes correlation of noise. Independent component analysis (ICA) is used for decomposition of signal and noise from single channel EEG [4]. The detailed procedures are described as follows:

1) 13-channel EEGs X (with embedded SSVEP at 13Hz) between Pz and Oz are selected as the input. 13 independent components (ICs) are calculated as sources S through ICA, i.e. $S=W\cdot X$, where W is the demixing matrix.
2) Analyze the amplitude spectra of the ICs. The four with most significant power at stimulation frequency are supposed to be signal activities of SSVEP and the remaining are considered as noise activities. They are denoted as S_{Signal} and S_{Noise}. Then S can be expressed as $S= S_{\text{Signal}}+S_{\text{Noise}}$.
3) With the equation $X=W^{1}\cdot S= W^{1}\cdot(S_{\text{Signal}}+S_{\text{Noise}})$, X can be divided into two parts：
$$X_{\text{Signal}}=W^{1}\cdot S_{\text{Signal}}\ ,\quad X_{\text{Noise}}= W^{1}\cdot S_{\text{Noise}}$$
X_{Signal} and X_{Noise} are the reconstructions of SSVEP and noise activities over visual cortex respectively.
4) Calculate correlation coefficients for X_{Signal} and X_{Noise} between different channels. Denote $\mathrm{D}(X)$ as the variance of X , $\mathrm{cov}(X,Y)$ as the covariance of X and Y, correlation coefficients of channels i and j are expressed as:
$$\rho_{ij}^{\text{Signal}} = \frac{\mathrm{cov}(X_i^{\text{Signal}}, X_j^{\text{Signal}})}{\sqrt{D(X_i^{\text{Signal}})}\sqrt{D(X_j^{\text{Signal}})}}$$
$$\rho_{ij}^{\text{Noise}} = \frac{\mathrm{cov}(X_i^{\text{Noise}}, X_j^{\text{Noise}})}{\sqrt{D(X_i^{\text{Noise}})}\sqrt{D(X_j^{\text{Noise}})}}$$
5) Analyze amplitude spectra of X, X_{Signal} and X_{Noise} on all channels. Then map them (13 groups) to scalp (see Fig.2). For each group, the amplitude spectrum of X is in the bottom, the amplitude spectrum of X_{Signal} is on the top right corner and that of X_{Noise} is on the top left corner.

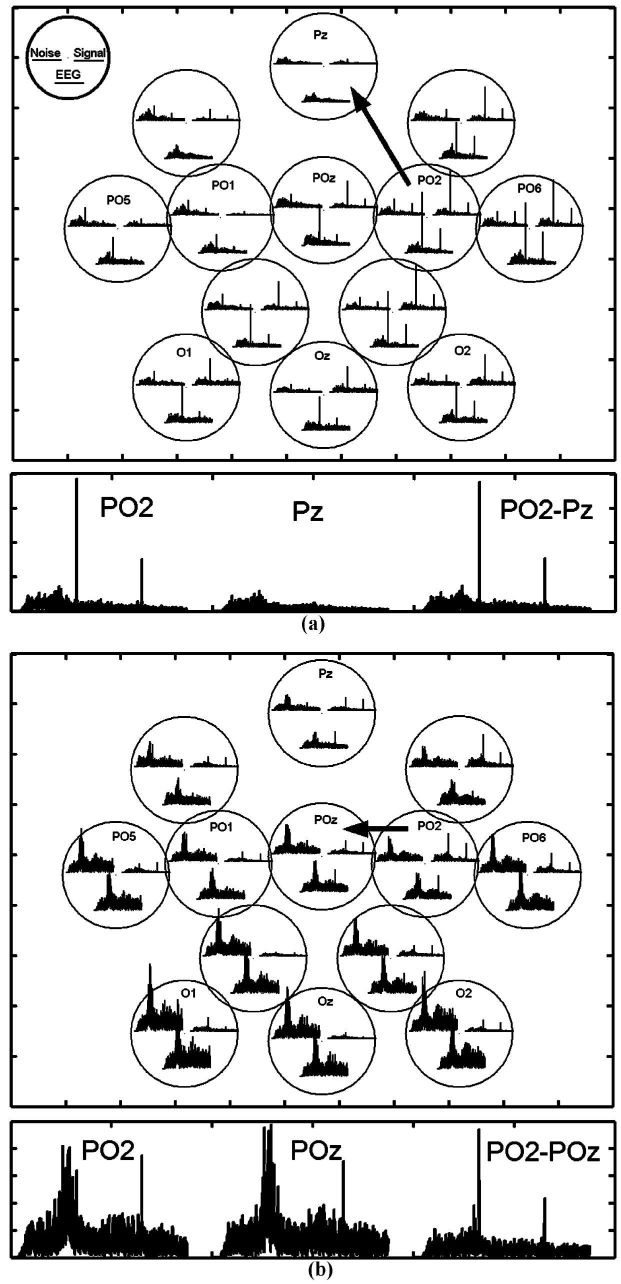

Fig.2. Spatial distributions of amplitude spectra on 13 channels over visual cortex ((a) subject A, (b) subject B). The parts down are the amplitude spectra of signal channel, reference channel, and bipolar channel.

The ratio of signal correlation to noise correlation between different channels is the basis of optimal lead selection. Besides the correlation coefficients, they can also be drawn out directly by observing the spatial distributions of amplitude spectra over scalp. As shown in Fig.2.(a), for subject A, EEGs have large amplitude of SSVEP and less background noise. Furthermore, amplitudes of SSVEPs change gradually over visual cortex. The key point of lead selection is to retain SSVEP component of the signal channel. PO2 is selected as the signal channel due to its strongest SSVEP. Then the channels with weak SSVEP, such as Pz, P4, and P8, can be considered as reference channel. The channels around PO2 are rejected because of large SSVEP. The arrow in Fig.2.(a) denotes that PO2-Pz can be considered as an optimal bipolar lead. The SSVEPs of subject B (Fig.2.(b)) are contaminated by strong spontaneous EEGs. We can not choose the signal channel from original EEGs. Through decomposition of EEGs by ICA, the spatial distribution of signal activities shows that PO2 has the most significant SSVEP and the SSVEPs of most channels around PO2 decrease sharply. The key point under this pattern is to reduce the background noise of PO2. Therefore, the channels close to PO2 and with weak SSVEP are preferable. As shown in Fig.2.(b), PO2-POz is a good choice to weaken the background activities.

C. Efficiency test

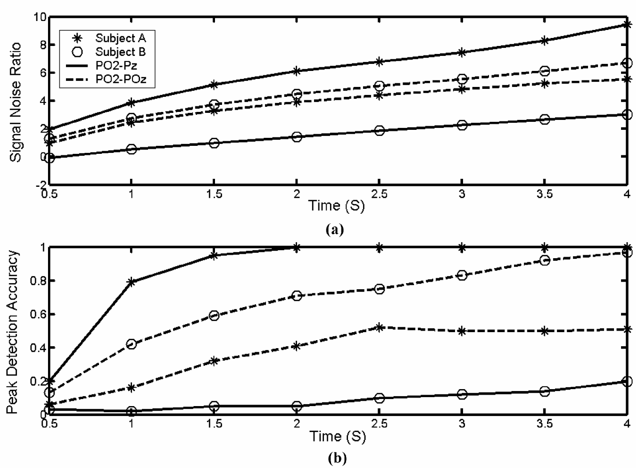

Fig.3. Signal-to-noise ratio and peak detection accuracy versus data length (from 0.5s to 4s) with different leads selected.

Two parameters, signal-to-noise ratio and peak detection accuracy, are used as the criterions to evaluate the efficiency of optimal lead selection through off-line analysis of the EEG data. The amplitude spectrum is calculated by $y=|\mathrm{FFT}(x)|$, where x is the temporal EEG data. FFT(x) is the 1024-point fast Fourier transform (FFT) of x. x is padded with zeros if it is shorter than 4s. The frequency corresponding to the maximum value of y is the stimulation frequency f if the result of frequency detection is accurate. Signal-to-noise ratio is defined as the ratio of y(f) to mean value of the 16 ajacent points:

$$SNR = \frac{16 \times y(f)}{\sum_{k=1}^{8} y(f+0.25\times k) + y(f-0.25\times k)]}$$

It approximately reflects the signal-to-noise ratio of SSVEPs. Fig.3.(a) shows the SNR versus data length (from 0.5s to 4s) on subjects A and B. Fig.3.(b) shows the corresponding frequency detection accuracy. According to above lead consideration, PO2-Pz is the optimal lead for subject A and PO2-POz is that for subject B. The results shown in Fig.3 demonstrate the efficiency of optimal lead selection. With the proper leads, the accuracy approaches to 100% when the data length is close to 4s.

III. RESULTS

The BCI system with optimal lead selection has been tested on 16 volunteers with normal vision (6 female and 10 male) in laboratory. The information transfer rate was estimated through an online phone call experiment. More details of the explanation can be found in [1]. The bit rate (B) of each selection can be expressed as

$$B = \log_2 N + P\log_2 P + (1-P)\log_2[(1-P)/(N-1)].$$

N is the number of targets and P is the accuracy of target selections. B multiplied by selecting speed is the transfer rate (bits per minute) [5]. All subjects fulfilled the task of 11-digit phone number input successfully. The highest rate is 57 bits/min and the lowest is 29 bits/min. The average number is 42 bits/min, which is much higher than the reported 27bits/min of the SSVEP-based BCI with conventional lead placement (ear reference) [1].

A BCI-based environmental controller [6] was tested in the Rehabilitation Center of China to help people with motion disability to control home appliances. 11 volunteers with spin cord injury (2 female and 9 male) participated in the experiments. Without any training, the average transfer rate is about 21 bits/min. This lower number may be caused by the noisy environment and big space between stimulator and subject set in the wheelchair.

The results demonstrate that optimal lead selection is an effective and reasonable method to improve the applicability of SSVEP-based BCI. The new system is applicable to >90% of the volunteers. This makes SSVEP-based BCI a more practical system.

ACKNOWLEDGMENT

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