Frequency Recognition for SSVEP–BCI Using Reference Signals With Dominant Stimulus Frequency

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***Abstract*—Detection of frequency for steady–state visual evoked potentials (SSVEP) is addressed. We propose to use the combination of CCA and training data–based template matching between two level of data adaptive reference signals that can deal with the dominant frequency. On the basis of magnitude of stimulus frequency components, the dominant channels are selected. The recognition accuracy as well as the information transfer rate (ITR) of the proposed method are examined compared to the state-of-the-art recognition method.**

***Index Terms*—brain computer interface, canonical correlation analysis, adaptive reference signal, spatial filtering**

I. Introduction

In recent years, the brain computer interface (BCI) has received increasing attention from researchers in signal processing, machine learning, neuroscience, and clinical rehabilation. Such interfaces capture brain activities associated with mental tasks and external stimuli, and enable non-muscular communication and control channel to convey messages or commands from human brain activities to the external world without peripheral nerves and muscles activities. Various types of responses such as event related potential (ERP) and evoked potential (EP) have been exploited in recent research. In particular, SSVEP based BCI has become one of the promising BCI systems due to its advantages of little user training, ease of system configuration, as well as high information transfer rate (ITR) [1]. SSVEP is a periodic EEG signal response elicited by repetitive visual stimulus with a flickering frequency higher than 6 Hz [2], [3].

In SSVEP-based BCI, users are asked to focus attention on one of the multiple repetitive visual stimuli at different frequencies. The target stimulus can be identified through a frequency analysis such as the Fourier transform [3] at which the user is focusing. Moreover, it has been reported that the canonical correlation analysis (CCA) between SSVEPs and sinusoidal templates is very powerful in frequency detection of SSVEP and has aroused more interests of researchers. The problem in these methods is a limitation due to the effect of background EEG signals reported in [4]. Therefore, an effective algorithm to recognize the SSVEP frequency with a high accuracy and a short time window length (TW) is considerably important for implementing of an SSVEP based BCI with high performance. Recently, multiway CCA and multi-set CCA has been proposed to optimize the reference signals by combining SSVEP training data in CCA for frequency recognition [5], [6]. Such process is time consuming and difficult to implement in practice. Nakanishi et al. has been proposed to integrate the interference frequency components to enhance the frequency detection of SSVEPs elicited by monitor refresh rate [7]. Therefore, the interference frequencies could provide additional information for frequency detection of the SSVEPs. Recently the same authors also developed a high speed brain speller by combining the CCA-based spatial filtering and correlation coefficient between single-trial SSVEPs, training reference signals obtained by averaging training set and artificial signals consists of sin-cosine waves [8]. However, such types of pre-constructed sine-cosine wave or artificial reference signals do not guarantee all frequency information in the real world signal of SSVEP. Islam et al. generated two levels of data adaptive reference signals to improve frequency recognition accuracy [9]. The first level of reference signals is obtained by averaging the training trials of the same stimulus frequency and the second level of reference signals is derived from the training trials of a specific target frequency are rearranged according to their maximum CCA value with the first level reference [9].

In SSVEP based BCI, it is limited that the number of useful channels of the first and second level reference signals in which dominant frequency of SSVEPs are clearly contained over full dimension of channel data. It is possible to reduce the number of non-dominent channels necessary for the classification without losing substantial classification performance. With fewer electrodes the detection accuracy is improved via a channel selection approaches such as Support Vector Mechine (SVM) [10] and Recursive Channel Elimination (RCE) [11] which are time consuming and training based. It is reported in [9], the averaging technique removes the noise of reference signals as well as makes the peak at the desired fundamental frequency higher than the harmonics. Therefore, SSVEP signals are stronger over channels than other background EEG. By the consideration of this contract, the maximum value of Fourier coefficient of an artificial reference signal at a frequency is used as index to consistently extract magnitude of dominant channels of SSVEP signal. The first level reference signal as well as training trials can be calculated as the highest values of the obtained maximum magnitude of the Fourier coefficient of several channel SSVEP signals at the derived index to dominant the target. Both types of reference signals are employed in classification of test trials to make effective decision of frequency recognition for SSVEP.

II. Methods

A. Data Acquisition and Tasks

In this experiment, eight visual flickering stimuli (60×60 mm squares, 5.7 deg view angle and 60 mm distance from neighboring targets) were rendered on 23-inches liquid crystal display (LCD) with a refresh rate of 120 Hz and 1920×1080 screen resolution. Stimulation frequency of each target was 8, 9.2, 10.9, 12, 13.3, 15, 17.1, 20 Hz and developed under MATLAB (mathworks, Inc.) using the Psychophysics Toolbox extensions [12]. This study only focused on eight mention frequency detection.

Three males and one female (Subjects A, B, C, and D) aged 21-26 (mean 23.3 and S.D. 2.22) took part into our experiment. All subjects gave informed consent, and this study was approved by the research ethics committee of Tokyo University of Agriculture and Technology. During the whole experiments, each subject sat on a comfortable chair in front of the display screen at a distance of 60 cm and focused on a flickering target on the screen. They were asked to gazed at one of the visual stimuli was indicated in the order of 8 Hz, 9.2 Hz, $\ldots$, 20 Hz for 4 s. There is 0.5 s intervals between each trial. Subjects were asked to shift next target at the time. To evaluate the proposed method for recognizing 8 different stimulus frequency of SSVEP, We used the signals observed in electrodes P7, P3, Pz, P4, P8, O1, Oz and O2 for analysis using active electrodes g.LADYbird driven by g.GAMMAbox (Guger Technologies, Austria). The electrodes for GND and reference were AFz and A1, respectively. The signals were amplified by MEG-6116 (Nihon Kohden, Japan), which provides lowpass and highpass analog filters for each channel. In this experiment, we set the cut-off frequencies of the lowpass and highpass filters to 100 Hz and 0.5 Hz, respectively. The amplified signal was sampled by an A/D converter, AIO-163202F-PE (Contec, Japan) with a sampling rate of 1200 Hz. Figure 1 shows the screenshot of eight targets (left trace) and the location of the electrodes (right trace).

B. Frequency Recognization Methods

All data are band-pass filtered between 7–50 Hz with an infinite impulse response (IIR) filter. Zero-phase forward and reverse IIR filtering was implemented using the filtfilt() function in Matlab. A real time classifier analyze the multichannel EEG with time interval 4 s. We used the following newly proposed methods for determining the command.

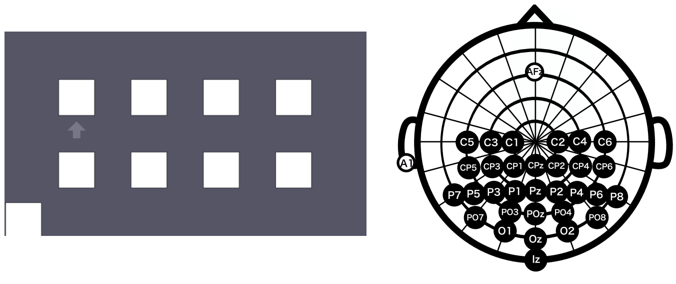

Fig. 1. Screenshot of eight targets on the screen (left trace) and the location (P7, P3, Pz, P4, P8, O1, Oz and O2) of the electrodes (right trace).

1) SSVEP Frequency Analysis with CCA: CCA is a classical method for measuring similarity between two multivariate signals. These signals do not necessarily have the same number of variables. This can be seen as an extension of the ordinary correlation between two random variables [13], [14], [15]. The underlying idea behind CCA is to find a pair of linear combinations, called canonical variables, for two sets, in such a way that the correlation between the two canonical variables is maximized. Given two sets of random variables X and Y, CCA finds w_x and w_y that maximize the folllowing criteria:

$$\rho(X, Y) = \max_{w_x, w_y} \frac{w_x^T C_{xy} w_y}{\sqrt{w_x^T C_{xx} w_x w_y^T C_{yy} w_y}} \quad (1)$$

where ρ is called the canonical correlation, C_{xx} and C_{yy} are the within-sets covariance matrices, and C_{xy} is the between-sets covariance matrix. The maximum value of ρ with respect to w_x and w_y represents the maximum canonical correlation. In the case of the SSVEP frequency recognition X refers to the set of multi-channel EEG signals representing the SSVEP and Y contains a set of reference signals of same length as X to be used in frequency recognition for SSVEP based brain computer interfacing (BCI). The frequency of the reference signals with the maximal correlation is selected as the stimulus of SSVEPs [14].

2) Proposed Algorithm: In different existing methods [6], [8] the reference signals are artificially generated with sine and cosine waves of all the stimulus frequencies and their harmonics. Indeed, the artificial reference signals exhibit frequency characteristics different from the real SSVEP. In [8], an extended CCA-based method is introduced to incorporate SSVEP training data, averaged reference signals and artificial sine-cosine wave to improve target identification accuracy. In real EEG signals the brain responses against visual stimuli do not exhibit the characteristics of pure sine-cosine waves. Hence, the potential problem is that the CCA with such artificial reference signals often do not result the optimal recognition accuracy due to their lack of features from the real EEG data. The reference signals are derived here from the training set of the real EEG.

Instead of using all the channels, selected channels with dominant target frequency are used as the data adaptive reference signals. The dominancy of the target frequency is determined in spectral domain. A C-channel EEG signal with stimulus frequency f_k at any trial is represented as $X_{f_k}(t) = \left[x_{f_k}^{(1)}(t), \ldots, x_{f_k}^{(C)}(t)\right]$; where $x_{f_k}^{(c)}(t)$ is the EEG signal of the c^{th} channel and C is the total number of channels. Let $S_{f_k}(f) = \left[s_{f_k}^{(1)}(f), \ldots, s_{f_k}^{(C)}(f)\right]$ be the spectrum of trial $X_{f_k}(t)$. Then, $\left|s_{f_k}^{(c)}(f_k)\right|$ represents the magnitude of the c^{th} channel at stimulus frequency f_k. The magnitude at stimulus frequency is used as quantitative measure of dominance of the corresponding channel over others. The channels of the trial X_{f_k} are rearranged as

$$X'_{f_k}(t) = \left[x_{f_k}^{\prime(1)}(t), \ldots, x_{f_k}^{\prime(c)}(t), \ldots, x_{f_k}^{\prime(C)}(t)\right] \tag{2}$$

such that $\left|s_{f_k}^{\prime(1)}(f_k)\right| > \left|s_{f_k}^{\prime(1)}(f_k)\right| > \cdots > \left|s_{f_k}^{\prime(C)}(f_k)\right|$, where $\left|s_{f_k}^{\prime(c)}(f_k)\right|$ is the spectrum of c^{th} channel $x_{f_k}^{\prime(c)}$. The trial with selected dominant channels can be represented as:

$$\widetilde{X}_{f_k} = \left[x_{f_k}^{\prime(1)}(t), \ldots, x_{f_k}^{\prime(G)}(t)\right] \quad \text{where } 1 \geq G \geq C \tag{3}$$

The channels are appeared in Eq. (3) according to their magnitude contribution at stimulus frequency f_k where G is the maximum number of channels are selected representing the dominant channels to enhance the frequency recognition. To generate first and second level reference signals, we use Eq. (3) as the training data set $\tilde{\mathcal{X}} = \left\{\widetilde{X}_{f_k}^{(n)}\right\}$, where n is the trial index $(n = 1, \ldots, N)$.

The underlying idea behind the first and second level reference signals is that the data adaptive reference signals are constructed by the common features more accurately with harmonic feature in test data to assist recognition performance of the SSVEP frequency. In recognition procedures, the number of pre-defined harmonics is the another factor in pre-constructed artificial reference signals [5]. Thus, the first level reference signal set $\mathcal{X}_1 = \{\bar{X}_{f_k}\}$, $k = 1, \ldots, K$, is calculated from the training data set $\tilde{\mathcal{X}}$ of the EEG signal as [9]:

$$\bar{X}_{f_k}(t) = \frac{1}{N}\sum_{n=1}^{N} \widetilde{X}_{f_k}^{(n)}(t) \tag{4}$$

where N is the total number of trials used in training set and $\bar{X}_{f_k}$ is the first level reference signal for the stimulus frequency f_k. Note that $\bar{X}_{f_k}(t)$ is an array of G time signals.

The second level reference signal set $\mathcal{X}_2 = \left\{\hat{X}_{f_k}\right\}$, $k = 1, \ldots, K$, defined as [9]:

$$\hat{X}_{f_k}(t) = [\widetilde{X}_{f_k}^{(\lambda(1))}(t), \ldots, \widetilde{X}_{f_K}^{(\lambda(M))}(t)] \tag{5}$$

such that $\rho_{f_k}^{(\lambda(1))} \geq \rho_{f_k}^{(\lambda(2))} \geq \cdots \geq \rho_{f_k}^{(\lambda(M))} \geq \cdots \geq \rho_{f_k}^{(\lambda(N))}$, $\rho_{f_k}^{(n)}$ is the maximum CCA between the first level reference and n^{th} training trial and $\lambda(m)$ is a permutation function. M (where $1 \leq M \leq N$) is the maximum number of training trial to be included in the second level reference signals. Note that $\hat{X}_{f_k}(t)$ is an array of GM time signals.

With the two types of reference signals, three correlation coefficients based spatial filters are implemented to enhance the frequency recognition performance. Let us use a sample X is a test signal. The three coefficients could be defined as: (i) $H_{X\mathcal{X}_1}$; between the test signal X and the first level reference signal $\bar{X}_{f_k}$ in $\mathcal{X}_1$, (ii) $H_{X\mathcal{X}_2}$; between test signal X and second level reference $\hat{X}_{f_k}$ in $\mathcal{X}_2$ and (iii) $H_{\mathcal{X}_1\mathcal{X}_2}$; between first and second level reference signals $\mathcal{X}_1$ and $\mathcal{X}_2$ respectively. The derived correlation vector ρ_{f_k} corresponding to f_k is defined as [8]:

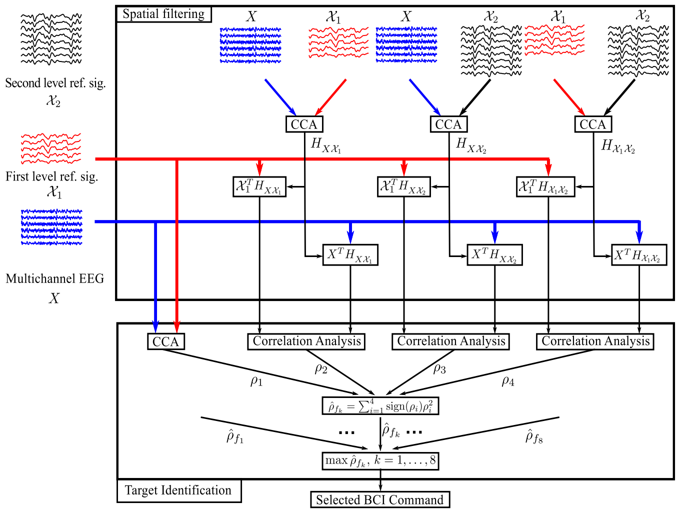

Fig. 2. Illustration of the proposed algorithm with different components for frequency recognition in SSVEP based BCI.

$$\rho_{f_k} = \begin{bmatrix} \rho_1 \\ \rho_2 \\ \rho_3 \\ \rho_4 \end{bmatrix} = \begin{bmatrix} \rho_1 \\ \rho(X^T H_{X\mathcal{X}_1}, \mathcal{X}_1^T H_{X\mathcal{X}_1}) \\ \rho(X^T H_{X\mathcal{X}_2}, \mathcal{X}_1^T H_{X\mathcal{X}_2}) \\ \rho(X^T H_{\mathcal{X}_1\mathcal{X}_2}, \mathcal{X}_1^T H_{\mathcal{X}_1\mathcal{X}_2}) \end{bmatrix} \tag{6}$$

In the same way as [8], the weighted version of correlation coefficient ρ_{f_k} was used to identify the target frequency as:

$$\hat{\rho}_{f_k} = \sum_{i=1}^{4} \text{sign}(\rho_i) \cdot \rho_i^2 \tag{7}$$

III. Results

To evaluate the average recognition accuracy, leave-one-out cross-validation is implemented to estimate simulated BCI performance. Classification accuracy and information transfer rate (ITR) were calculated for the proposed method, DARS [9] and hSbS [8] separately. To estimate the optimal BCI performance, this study also calculated accuracy and ITR using different short time window length (TW). The length of SSVEP signal is considerable important for frequency classification. The maximum number of channels in Eq. (4) as well as with second level reference signal, the maximum number of trail in Eq. (6) was set to 5 ($G = 5$) and 3 ($M = 3$) respectively. Fig. 3 shows averaged SSVEP recognition accuracy to understand the effects of dominant channels using CCA, Avg-CCA and AvgCCA-DF. For dominant channels, the proposed method derived better frequency recognition accuracies than CCA and AvgCCA. Fig. 4 shows the recognition accuracy of the three recently developed methods for different subjects as a function of signal length. For different subjects, while

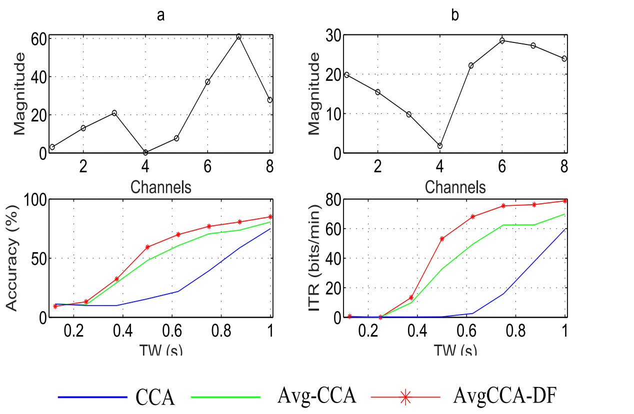

Fig. 3. The magnitude of channels obtained from averaged training signal (left trace a) and single trail (right trace b) at 8 Hz frequency and frequency recognition accuracies and ITR obtained by CCA, Avg-CCA and AvgCCA-DF.

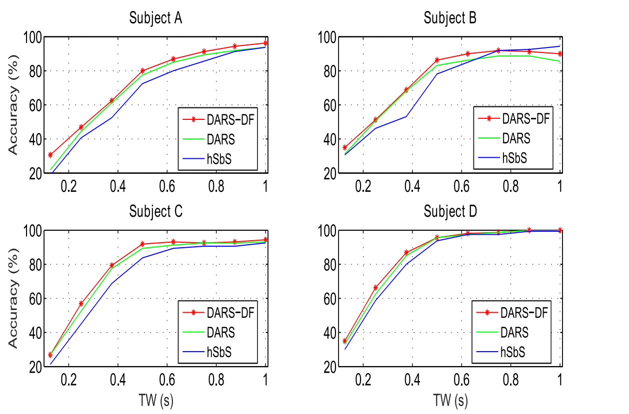

Fig. 4. Average frequency recognition accuracies obtained by hSbS, DARS and DARS–DF (proposed method).

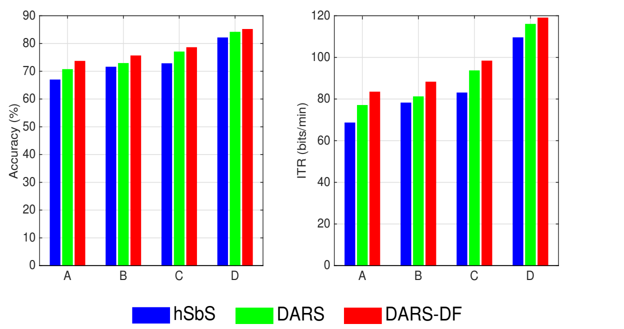

Fig. 5. Average frequency recognition accuracy (Left trace) and ITR (Right trace) obtained by hSbS, DARS and DARS-DF (proposed method) for individual subject A, B, C and D.

DSP performed better than the hSbS method, the proposed data–adaptive reference signals with dominant channels yields higher recognition accuracies than the resent developed DSP method for most time window (TW) lengths. Fig. 5 shows the averaged accuracy (left trace) and ITR (right trace) over the 8 stimulus frequencies for individual subjects A, B, C and D. The results show that the proposed method performs significantly better than other methods in all respects.

IV. Conclusions

This study proposed an effective frequency recognition method for SSVEP–based BCI . We designed two levels of data-adaptive reference signals with dominant frequency and evaluated the classification performance as well as ITR of the proposed method by the experiment. As a result, the proposed method showed higher recognition accuracies than recently reported methods in all four subjects.

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