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A new SSVEP-based BCI utilizing frequency and space to encode visual targets

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Dear editor,

Brain-computer interfaces (BCIs) based on steady-state visual evoked potential (SSVEP) have attracted considerable attention from researchers owing to their improved performance, such as their higher recognition accuracy, more reliable relation to stimuli, and higher information transfer rate (ITR), compared with other types of BCIs.

A major challenge for SSVEP-based BCIs is the limited frequency band available for encoding visual targets. More visual targets potentially bring higher ITR. To address this, researchers are experimenting with designing new coding schemes, including presenting frequency stimuli in code form and taking advantage of joint phase and frequency information in the coding schemes [1–3]. These studies obtained remarkable results by applying frameworks of communication in BCIs.

Inspired by these studies, a novel coding method, which utilizes frequency and spatial information to encode visual targets, is proposed in this study. We extend the coding scheme of [4] by introducing frequency information into the original spatial coding scheme. We implement a BCI system that presents 16 visual targets by utilizing four different frequencies and four different positions relative to each frequency stimulus, according to our proposed coding scheme. Compared with the traditional BCI systems, which only utilize frequency information or spatial information in their coding schemes, our proposal stduy can further present more visual targets under limited frequency resources and limited spatial resources.

We extract a certain kind of feature (i.e., joint spatial features) related to the frequency and spatial properties of visual stimulation, i.e., the weight vector of signals measured from different electrodes and different reference signals in canonical correlation analysis (CCA). These features could be utilized to identify visual targets together with pattern recognition algorithms, such as the quadratic discriminant analysis (QDA) algorithm used herein. Moreover, the decoding method exploiting these features along with the QDA algorithm achieves a better performance. In previous studies [2,3], CCA was used for computing the correlation coefficients and the identification results were obtained by comparing values of the coefficients. We extract the joint features using CCA, which identifies visual targets by classifying the features and is different from previous studies.

Experimental design. The stimulus is presented on a 27-inch liquid crystal display (LCD) monitor, whose resolution and refresh rate are 1920 × 1080 pixels and 60 Hz, respectively. Three subjects (males, age: 23, 24, and 25) with normal or corrected-to-normal vision voluntarily participated in this study. Before the experiment starts, the subjects have been informed about and consented to the experimental contexts. The stimulus is shown in Figure 1(a), where the frequency stimulation is presented as flickering discs and the spa-

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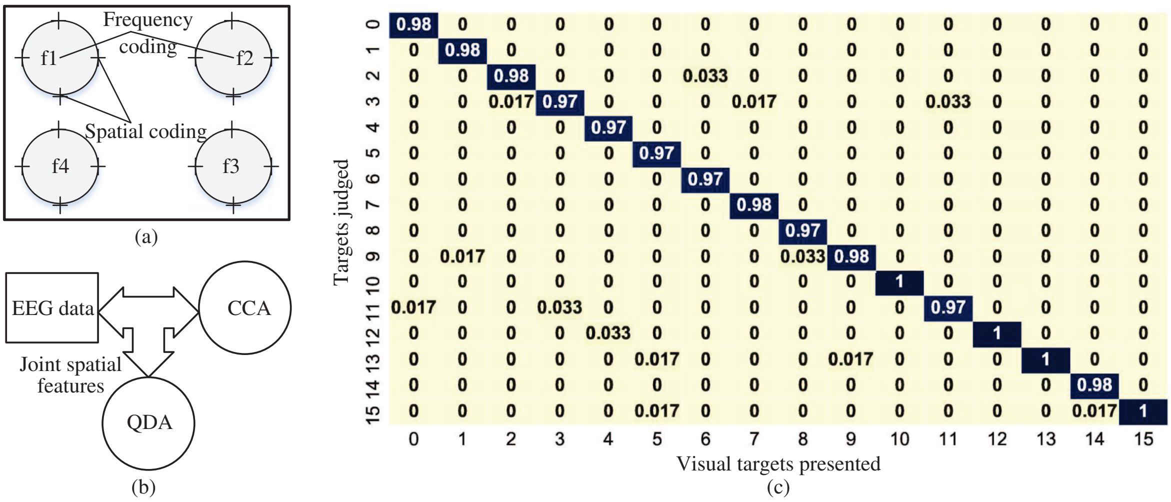

Trial length (s)		0.50	1.00	1.50	2.00	2.50	3.00	3.50	4.00	4.50	5.00
Accuracy (%)	(i) QDA with SF	63.77	79.69	88.17	90.58	92.25	95.92	96.65	97.38	97.70	98.15
	(ii) LDA with CC	48.59	67.43	78.64	85.03	90.68	90.99	95.50	94.97	93.82	96.75
	(iii) Frequency only	34.14	57.17	78.43	88.17	94.97	96.34	98.32	98.85	99.27	99.90
ITR (bits/min)	(i) QDA with SF	98.40	99.13	90.40	76.35	66.08	61.62	54.86	49.64	45.02	41.36
	(ii) LDA with CC	59.51	72.69	72.51	67.34	63.78	55.05	53.39	46.88	41.09	40.00
	(iii) Frequency only	28.87	37.99	38.64	33.60	29.67	28.96	26.03	23.78	21.66	20.02

(d)

Figure 1 (Color online) (a) The stimulation encoded by frequency and space; (b) the decoding method based on CCA and QDA; (c) the decoding accuracy of 16 visual targets, where the trial length is 5 s; (d) comparisons of BCI systems and decoding methods versus diverse trial lengths, where SF represents the joint spatial features and CC represents the correlation coefficients.

tial stimulation is presented by the different spatial targets tagged on the discs as crosses. In this study, the four frequencies we adopted are 15.00, 15.10, 15.20, and 15.30 Hz. The stimulus is developed using Psychophysics Toolbox (Version 3) [5] in Matlab (Version 2018b).

Data acquisition and preprocessing. The electroencephalogram (EEG) data are recorded by a Synamps2 EEG system (Neuroscan, Inc.) at a sampling rate of 1000 Hz. During the data collection stage, subjects wearing the electrodes-cap are seated in a reclining chair at a distance of 50 cm from the stimulus presentation screen. They are encouraged to maintain a comfortable posture to reduce fatigue. Because the SSVEP responses are related to the main visual regions of the brain, we use the corresponding 21 electrodes with a reference electrode placed at the vertex of the scalp. The electrodes, placed according to the international 10-5 system [6], are P_z, P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8, PO_z, $\mathrm{PO}3$, PO_4, PO_5, PO_6, PO_7, PO_8, O_z, O_1, O_2, CB_1, and CB_2. For every visual target, 60 trials with a trial length of 5 s, which means the gazing time of subjects for one visual target, are conducted to train our decoding method and evaluate the performance of the BCI proposed. The data are preprocessed by applying a notch filter of 50 Hz to remove the line noise and a bandpass filter of 13–78 Hz to extract the response signal from the stimuli. Moreover, a visual delay of 130 ms is considered herein.

Data analysis. As a pattern recognition algorithm, QDA considers different patterns as different joint Gaussian distributions in the multivariate features space. The features for classification are obtained by the CCA algorithm as shown in Figure 1(b). CCA is a method that measures the underlying correlation between two multi-dimension variables in statistics by applying linear weight vectors. In previous studies, CCA has normally been used to recognize frequency, while we take advantage of CCA to extract joint spatial features of diverse visual targets. We assume that the signal collected by the multi-electrode EEG acquisition device is X, and the reference signal is Y, which comprises the standard sine and cosine signals. For different stimuli, each with frequency f_i, the corresponding reference signal is noted as Y_i, where $i = 1, 2, 3, 4$ corresponding to the four frequencies of the stimuli. From CCA, the feature (noted as $\mathbb{F}$) extraction can be expressed as

$$\mathbb{F} = [\omega_X, \omega_Y],$$
$$\arg\max_{f_i} \left(\arg\max_{\omega_X, \omega_{Y_i}} \frac{\mathrm{cov}(X^{\mathrm{T}}\omega_X, {Y_i}^{\mathrm{T}}\omega_{Y_i})}{\sqrt{\mathrm{var}(X^{\mathrm{T}}\omega_X)}\sqrt{\mathrm{var}({Y_i}^{\mathrm{T}}\omega_{Y_i})}} \right), \tag{1}$$

where the cov() and var() are the functions of covariance and variance, respectively. ω_X and ω_{Y_i} are linear coefficients used to combine the multi-dimensional variable, i.e., the data measured and reference signals. Therefore, $\mathbb{F}$ represents the dependence of SSVEP responses and reference signals. $\mathbb{F}$ varies against diverse visual stimulation; thus, it could be used as an effective feature classifier.

QDA follows Bayesian principles, and the criterion of judgment is based on the posterior probability, $\Pr(\mathrm{Tar} = t|\mathrm{Fea} = \mathbb{F})$, where Tar and Fea are the visual target and joint features, respectively. This assumes that there are k targets in total $(t = 1, 2, \ldots, k)$, whose prior probability are π_ts, conforming with $\sum_{t=1}^{k} \pi_t = 1$. In this study, all 16 visual targets exhibit equal probability, i.e., $\pi_1 = \pi_2 = \cdots = \pi_{16} = \frac{1}{16}$. Based on QDA, given the features $\mathrm{Fea} = \mathbb{F}$, the posterior probability of the t-th target is

$$\Pr(\mathrm{Tar} = t|\mathrm{Fea} = \mathbb{F}) = \frac{f_t(\mathbb{F})\pi_t}{\sum_{i=1}^{k} f_i(\mathbb{F})\pi_i}, \quad (2)$$

where $f_t(\mathbb{F})$ is the probability density function of the class t, which conforms to the multivariate joint Gaussian distribution as

$$f_t(\mathbb{F}) = \frac{1}{(2\pi)^{p/2}\,|\boldsymbol{\Sigma}_t|^{1/2}} \mathrm{e}^{-\frac{1}{2}(\mathbb{F}-\mu_t)^{\mathrm{T}}\boldsymbol{\Sigma}_t^{-1}(\mathbb{F}-\mu_t)}, \quad (3)$$

where p, $\boldsymbol{\Sigma}_t$, and μ_t are the dimension of the feature space, covariance metric, and mean vector of the features corresponding to the t-th target, respectively. Data collected in the offline experiment are divided into two parts, the training set and test set, to train the decoding method and evaluate the BCI's performance. Particularly, QDA is trained with the $\mathbb{F}$s and their labels from the training set to specialize parameters of its joint Gaussian distribution.

Results and discussion. Figure 1(c) illustrates the recognition accuracy of different visual targets by utilizing the decoding method we propose. The average decoding accuracy, which is beyond 98.15% (trial length of 5 s) with the chance-level of 6.25%, shows that the joint information of frequency and space is useful in encoding visual targets in BCIs. Moreover, it is demonstrated that the decoding method base on CCA and QDA is suitable for the BCI proposed herein.

Figure 1(d) provides comparisons between our BCI system and traditional BCI systems, with respect to their decoding accuracy and ITR, to demonstrate the effectiveness of the coding scheme and the decoding method. The ITR is calculated following the computation formula in [4]. Three BCI systems and decoding methods have been compared. They are (i) the BCI system encoded by frequency and spatial information, with the decoding method based on joint spatial features and QDA algorithm proposed herein; (ii) the BCI system encoded by frequency and spatial information with the decoding method based on correlation coefficients and a linear discriminant analysis (LDA) algorithm (the method in [4]); and (iii) the BCI system encoded by frequency information only, with the decoding method based on CCA algorithm (traditional BCI system and decoding method). In summary, (i) and (ii) have the same coding scheme but different decoding methods, whereas (iii) has different coding as well as decoding method.

According to our coding scheme, the number of visual targets in (i) and (ii) is four times that in (iii). Therefore, although the decoding accuracy of (iii) (four visual targets) is a little higher than (i) and (ii) (16 visual targets) when the trial length is longer than 2.50 s, (i) and (ii) achieve overwhelming advantages in terms of ITR for all trial length conditions. Moreover, it is clear that our BCI system and decoding method have achieved the best performance among the three different BCI systems and decoding methods.

Conclusion. In this study, a novel coding scheme for SSVEP-based BCI, which encodes visual targets with frequency and spatial information, is proposed. According to the coding scheme, a BCI system of 16 visual targets is designed and implemented. Additionally, to decode the information from the BCI system, we propose a decoding method based on joint CCA and QDA algorithms. We assess the performances of the BCI and the decoding method proposed herein in terms of their decoding accuracy and ITR. The accuracy can reach 98.15% (trial length of 5 s) and the ITR can reach 99.13 bits/min (trial length of 1 s), demonstrating the effectiveness of the BCI system together with the decoding method.

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