Phase Information Enhanced SSVEP-BCI Using a Canonical Correlation Analysis Neural Network

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Abstract. This paper proposes to utilize the phase information to enhance steady-state visual evoked potential based brain-computer interface (SSVEP-BCI) based on a canonical correlation analysis neural network (CCA-NN). The preliminary offline results show that the proposed scheme can achieve a better classification accuracy than the standard CCA and the modified CCAs since it identifies the target by considering the flexible phase information.

Keywords: BCI, SSVEP, canonical correlation analysis (CCA), neural network (NN), phase information

1. Introduction

Recent years have witnessed a great success of steady-state visual evoked potential based brain-computer interfaces (SSVEP-BCIs) which can provide satisfactory performance with ease configuration and little user training [Bin et al., 2009; Wang et al., 2010; Volosyak, 2011]. Among the existing SSVEP-BCIs most utilize either the frequency information or phase information of SSVEPs for identification. More recently some work has been reported which make use of both frequency and phase information of SSVEPs simultaneously to improve the system performance [Jia et al., 2010; Pan et al., 2011; Shyu et al., 2012]. In particular, a modified canonical correlation analysis (CCA) called phase constrained CCA (p-CCA) is proposed in [Pan et al., 2011] to enhance the classification accuracy. If the phase information in p-CCA can be variable in a specified range rather than fixed at a value, it should be more suitable to practical applications. This study aims to use a CCA neural network (CCA-NN) with flexible phase information to improve the classification accuracy.

2. Phase Information in Canonical Correlation Analysis

Standard CCA (s-CCA) finds out the maximum correlation coefficient between two sets X and Y by finding two optimal projection matrices (W_X and W_Y). In general, SSVEP-BCIs using CCA detect the gazed-target by finding which reference signal (Y_k) has the maximum correlation with the multi-channel SSVEPs (X). Then the stimulus frequency (f_k) of reference signal (Y_k) is decided as the gazed-target. s-CCA only considers frequency information in reference signal (i.e., $Y_k=[\sin(2\pi f_k t),\cos(2\pi f_k t)]^T$), so it is possible to find an unreliable projection direction (W_X) which means that the combined signal ($X^T W_X$) has different phase from SSVEPs. It is unreasonable since SSVEP is phase-locked to stimulus.

In p-CCA the reference signal with additional phase information (i.e., $Y_k=[\cos(2\pi f_k t+\theta_k)]^T$) can make sure the combined signal with the similar phase as SSVEPs. However, the constant phase information does not conform to reality because SSVEP's phase usually has a large phase deviation around 20^o~40^o [Jia et al., 2011; Lee et al., 2010]. As a result, a CCA-NN is proposed to solve this issue.

2.1. Canonical Correlation Analysis Neural Network

In [Lai and Fyfe, 1999] artificial neural networks are adopted to implement CCA. Neural networks can find the weight vectors (W_X and W_Y) by optimizing a cost function. For example, the cost function shown in Eq. 1

$$J = E(xy) + \lambda_1(1 - x^2) + \lambda_2(1 - y^2) + \lambda_3(C_1 W_Y - \lambda_4^2) + \lambda_5(C_2 W_Y - \lambda_6^2)\,, \quad (1)$$

where $x=X^T W_X$, $y= Y^T W_Y$, C_1=[1 0], C_2=[1 0], and λ_j (j=1,2,3,4,5,6) are Lagrange multipliers, is proposed to find the maximum correlation coefficient while the variance of weights are constrained to 1 and the phase information can be constrained within (0,90^o) ($W_Y(1) \geq 0$ and $W_Y(2) \geq 0$). In fact, W_Y implies the phase information of the combined signal (i.e., $\arctan(W_y(2)/W_y(1))$). In this study, the flexible phase information within (θ_k-45^o, θ_k+45^o) is embedded in CCA-NN by means of constraining W_Y.

2.2. Offline Data Analysis

Six health subjects participated in the experiment where a visual stimulator presenting 6 frequency-tagged flickers (17.14 Hz, 15 Hz, 13.33 Hz, 12 Hz, 10 Hz and 7.5 Hz) was used. All subjects were indicated to gaze at one of 6 flickers in turn. Each dataset was divided into training set (for the phase information calibration) and testing set. s-CCA, p-CCA, and CCA-NN were applied in this offline data analysis respectively.

Table 1. *Offline classification accuracy and phase deviation of the combined signal.*

Subject	*Classification accuracy*			*Phase deviation*		
	s-CCA	*CCA-NN*	*p-CCA*	*s-CCA*	*CCA-NN*	*p-CCA*
S1	94.4%	99.1%	99.1%	77.1^o	34.9^o	0
S2	96.3%	98.2%	98.2%	76.2^o	33.0^o	0
S3	75.9%	79.6%	75.0%	75.6^o	40.4^o	0
S4	79.6%	89.0%	82.4%	76.3^o	34.0^o	0
S5	79.6%	82.4%	71.3%	75.5^o	34.8^o	0
S6	96.3%	95.4%	85.2%	75.3^o	60.4^o	0
Average	87.0%	90.6%	85.2%	76.0^o	39.6^o	0

3. Results and Discussion

In Table 1 it can be found that CCA-NN can achieve the best classification accuracy. The average phase deviation around 40^o indicates that the phase information of the combined signal can be constrained in a small range in CCA-NN. One interesting finding is that the large phase deviation seems to degrade the improvement (S6).

In summary, the phase constraint in s-CCA is too loose but in p-CCA it is too rigid. CCA-NN is the most generalized as it is able to constrain the phase in a selected range. The preliminary results show that CCA-NN can achieve the highest enhancements in terms of classification accuracy. Future work may include investigations on several problems. First, the convergence speed of CCA-NN is too low for an online application. Second, in the above experiment all the flexible phase information is constrained within (θ_k–45^o, θ_k+45^o) but this interval should actually be adapted to the measured SSVEPs.

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