Proceedings of the Fifth International Brain-Computer Interface Meeting 2013 DOI:10.3217/978-3-85125-260-6-123

Strategy for Reducing Calibration Time With Invariant Common Spatio-Spectral Patterns

H. Cho[1], M. Ahn[1], S. Ahn[1], S. C. Jun[1,2]

[1]*Gwangju Institute of Science & Technology, South Korea;* [2]*Wadsworth Center, Albany, USA*

Correspondence: S. C. Jun, Gwangju Institute of Science & Technology, Gwangju, South Korea 500-712. E-mail: scjun@gist.ac.kr

Abstract. Most variability in neural signals is dominated by the variability of background noise. Thus, whenever BCI online feedback is conducted, the performance heavily depends on how readily classifier is generated reflecting the variability of user's brain state. For this, it is common practice to have a calibration phase (generally time-consuming) every online feedback session. In this work, a new concept for reducing calibration time is proposed with invariant CSSP treating noise effect as follows: 1) collect training data after a few early calibration phases according to common practice, and 2) apply iCSSP to online feedback with this pre-collected training data and ongoing acquired background noise. This strategy requires the collection of reasonable training data during early calibration phases, but does not require a calibration phase for every online feedback, and zero-calibration can eventually be achieved in some sense. We tested our idea with a total of 4 subjects. Each subject participated in the same motor imagery experiment on multiple days and we thus acquired data from two or three sessions for each participant. Our proposed concept and the conventional online paradigm are tested with iCSSP. For compasion, conventional CSSP was applied in the same manner. The results show that our proposed concept using iCSSP had comparable performance over all sessions/subjects to conventional one, while CSSP had a notable loss in performance. It is evident that our concept using iCSSP is quite robust to session-to-session variability. Thus, zero calibration can be achieved with iCSSP and pre-existing training data.

Keywords: EEG, Motor Imagery, Invariant Feature Extraction, Session-to-Session Variability, Zero Training

1. Introduction

Brain computer interface (BCI) can be achieved by modulating a user's neuronal signals accordingly. A neuronal signal that implicitly expresses brain activity is too dynamic and rapidly changing to control in a steady manner, and this variability yields low BCI performance, which is a big obstacle for BCI development. In practice, a time-consuming calibration phase is essential for collecting newly changing neural activity and regenerating a classifier with new information for each online feedback session. This calibration phase is generally time-consuming (tens of minutes) and may cause early fatigue for users, decreasing user's performance. Various ideas for reducing the calibration time have been presented using classifier adaptation [Vidaurre et al., 2011] and source imaging [Ahn et al., 2011].

It is believed that most variability in neural signals results from variability in background noise, or signals that are not associated with the control signal. This motivates us to design a strategy in which zero calibration is achievable if a classifier properly dealing with the session-to-session changes in noise exists. That is, when a classifier is simply updated with pre-existing training data (e.g., acquired from early calibration sessions or different subjects) and session-related noise in each session, the calibration phase is no longer needed and short-time noise acquisition immediately prior to the online feedback is sufficient. Our recently proposed invariant common spatio-spectral patterns (iCSSP) method [Cho et al., 2012] is an extractor that incorporates the background noise effect in the conventional CSSP framework, and can diminish the noise effect. In this work, we tested our proposed concept by applying iCSSP with Fisher linear discriminant analysis (FLDA) to a total of 4 subjects, where each subject takes part in multiple sessions.

2. Materials and Methods

Invariant Common Spatio-Spectral Patterns (iCSSP) estimates the spatio-spectral filters that maximize variance for one class and simultaneously minimize variance for non-stationary noise and the variance of another class [Cho et al., 2012]. iCSSP can be formulated as follows: Let $S(\tau)_i$ be τ-delayed S_i denoting the EEG signal [representing the (#channel) by (#sample) matrix', Σ be the spatio-spectral noise covariance or the covariance matrix of $\hat{N} = \left(N^T \quad N(\tau)^T\right)^T$, which is expressed by N (#channel) by (#sample) representing noise signal, and $N(\tau)$ be τ-delayed N . For class i (i = 1 or 2) and $\hat{C}_i$ (representing the covariance matrix of $\hat{S}_i = \left(S_i^T \quad S(\tau)_i^T\right)^T$),

$$\max_{w_1}\left(\frac{w_1^T \hat{C}_1 w_1}{w_1^T \hat{A}_2 w_1}\right),\quad \max_{w_2}\left(\frac{w_2^T \hat{C}_2 w_2}{w_2^T \hat{A}_1 w_2}\right),\quad \text{where}\quad \hat{A}_i = (1-\xi)\hat{C}_i + \xi\Sigma,\ \ \xi \in [0,1]. \tag{1}$$

Since Σ correctly estimates the various noise structures, iCSSP can be robust to noise. In the present study, ξ was confined to values $\geq$ 0.05. τ was determined by 10-fold cross validation.

Data Sets and Evaluation: Four subjects who provided written informed consent participated in the same motor imagery (right/left hand or foot) experiments on multiple days (two or three days). Two or three sessions were thus collected per subject. See Fig. 1b for details. Sixty-four EEG electrodes (Biosemi ActiveTwo) were attached to the scalp according to the 10-20 international system, and signals were digitized at a 512 Hz sampling rate. A total of 60 offline and 75 online trials per class were collected for each subject. This data was spectrally (8-30 Hz) and temporally (0-4 seconds after cue onset) filtered. Among the multiple sessions per subject, a single session that yielded good performance in online feedback was selected as the training data. Then iCSSP trained with this pre-chosen training data and session-related background noise (subjects looked at the arbitrary feedback without imagination) was applied to other sessions and the online and offline feedback performance was measured. For comparison, conventional CSSP was applied in the same manner.

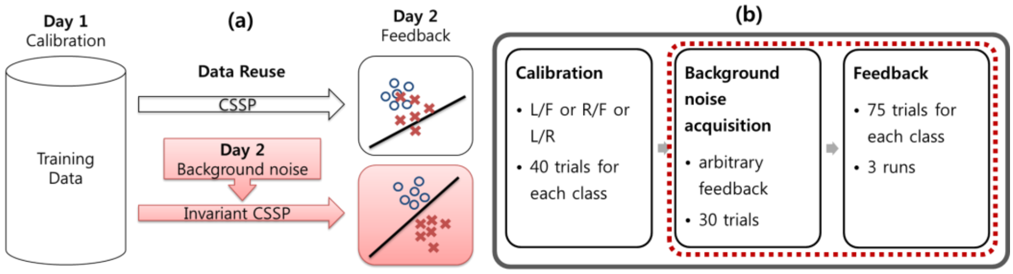

Figure 1. *(a) Illustration of our proposed concept. (b) Experimental paradigm (conventional: solid box; our proposed: dotted box) for online feedback.*

3. Results and Discussion

Table 1a shows the performance of CSSP and iCSSP in the conventional online feedback paradigm, which involved collecting calibration data and noise, generating the classifier with calibration data, and finally applying it to online feedback. Table 1b shows the performance of CSSP and iCSSP using our proposed concept. For our proposed concept, iCSSP is quite robust over sessions as compared with CSSP, and iCSSP is very comparable to the results for conventional iCSSP/CSSP. Session s3/2 in Table 1b shows interesting results, with remarkably higher performance for iCSSP. It is expected that the calibration and feedback phases had very different characteristics due to signal variability, indicating that the classifier trained with the same session calibration data strongly discriminated against the online data. In conclusion, this investigation shows that if reasonably informative training data are available in advance, then zero calibration is achievable with the acquisition of session-related noise data only (Fig. 1b).

Table 1. *Online and offline feedback performances (a) Conventional paradigm using the same session data only. (b) Our proposed method using the best-session calibration data (colored) and the session-related noise.*

Subjects/Sessions		***s3/1***	***s3/2***	***s5/1***	***s5/2***	***s6/1***	***s6/2***	***s6/3***	***s8/1***	***s8/2***	*Mean (standard deviation)*
Classes		LR	LR	RF	RF	RF	RF	RF	LF	LF	
(a) online	CSSP	86	64	83	91	87	78	55	92	97	74.4(±14.8) %
	iCSSP	83	62	83	87	89	78	53	92	97	**73.6(±15.5) %**
(b) offline	CSSP		**61**	**89**			**58**	**51**	**91**		70.0(±18.6) %
	iCSSP		**91**	**85**			**77**	**49**	**92**		**78.8(±17.7) %**

Acknowledgements

This work was supported MCST and KOCCA in the CT Research & Development Program 2012.

References

Cho H, Ahn M, Ahn S, Jun SC. Invariant Common Spatio-Spectral Patterns. *Proc. of TOBI 3rd Workshop*, 31-32, 2012.

Ahn M, Cho H, Jun SC. Calibraion Time Reduction through Source Imaging in BCI. *Proc of HCI Int Conf*, 174:269-273, 2011.

Vidaurre C, Sannelli C, Müller K-R, Blankertz B. Co-adaptive calibration to improve BCI efficiency. *J Neural Eng*, 8:025009, 2011.