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Enhanced CSP Spatial filtering for Improved Motor Imagery BCI Performance by Integrating the Sensation-induced Neurophysiological Prior

Lin Yao[1], Mei Lin Chen[1], Xinjun Sheng[2], Natalie Mrachacz-Kersting[3], Xiangyang Zhu[2], Dario Farina[4], Ning Jiang[1]

[1] Department of Systems Design Engineering, University of Waterloo, Waterloo, Canada
[2]State Key Lab of Mechanical System and Vibration, Shanghai Jiao Tong University, Shanghai, China
[3]Center for Sensory-Motor Interaction, the Faculty of Medicine, Aalborg University, Aalborg, Denmark
[4]Department of Bioengineering, Imperial College London, London, UK

E-mail: ning.jiang@uwaterloo.ca

ABSTRACT:
In this work, the idea of the sensation-induced neurophysiological prior was introduced to facilitate motor imagery (MI) classification. Covariance matrix of MI without Prior, with stimulus-induced Neurophysiological Prior, and with regularization, were separately constructed to extract spatial filter via Common Spatial Pattern (CSP). It has been shown that the MI BCI performance was significantly higher in MI with Neurophysiological Prior condition than other two with p<0.05, while there showed no significant difference between MI without Prior and MI with regularization. Integration of the externally induced neurophysiological prior has the benefit of helping CSP spatial filter extraction, and improve the classification performance of BCI users.

INTRODUCTION

Brain-computer Interface (BCI) provides a non-muscular communication and control channel between the user's thoughts and the external world, providing a promising channel for completely locked-in patient to re-interact interact with society [1]. Through mentally performing imagined movement of one's own limbs (e.g., left or right hand), their subjective motor intention can be decoded by translating the brain signals induced by the motor imagery (MI) [2], [3]. This is done without the need for external stimulus, such as visual stimuli in P300 and Steady-state visual evoked potential (SSVEP) based BCI system [4], [5]. MI based independent BCI has received enormous interest [6]–[9], and provided a new avenue for stroke neurorehabilitation [10], [11]. However, numerous experimental evidence has shown that a significant portion of individuals cannot successfully use MI-based BCI system. This phenomenon has been called "BCI-illiteracy" problem, where BCI control does not work for roughly 15%–30% of users [12]–[15].

There is extensive interest in further improving MI performance and reducing the number of BCI-illiterate users. Machine learning algorithms on MI detection has largely improved through several BCI competition, and the Common Spatial Pattern (CSP) is currently most widely used in MI detection [7], [8]. However, recent studies have reported gains in accuracy of approximately 5% when using CSP extensions and optimized spatial-spectrum filtering based on mutual information [9]. Some users still fail to reach the acceptable level of accuracy, which is often set to 70%, even with the state-of-the art algorithms [16], [17]. Other techniques shown to help subjects achieve greater BCI control include training the subject to modulate rhythmic activity [18], and coadaptating the subject with the machine [19] have all been shown to help more subjects to achieve BCI control. Recently, the idea of utilizing tactile stimulation for calibration and training subjects has shown to be a promising way to facilitate MI decoding [15]. Because of the similarity between vibration induced oscillatory activation and MI induced brain dynamics, and the fact that subjects were able to produce much more consistent brain acitivation patterns after receiving real tactile stimulation, we hypothesize that the neurophysiological prior induced by tactile sensation would help to improve MI decoding. In this study, the feasibility of this objectively induced neurophysilogical prior will be investigated.

MATERIALS AND METHODS

Subjects

Five healthy subjects participated in this experiment (two female, all right handed, average age 23.2±1.5 years). This study was approved by the Ethics Committee of the Shanghai Jiao Tong University, Shanghai, China. All participants signed an informed consent form before participation.

EEG Recording and Somatosensory Stimulation

EEG signals were recorded using a SynAmps2 system (Neuroscan, U.S.A.). A 64 channel quick-cap was used to collect 62 channel EEG signals, and the electrodes were placed according to the extended 10/20 system. The reference electrode was located on the vertex, and the ground electrode was located on the forehead. An analog bandwidth filter of 0.5 Hz to 70 Hz and a notch filter of 50 Hz were applied to the raw signals. Signals were digitally sampled at 250 Hz.

In this experiment, mechanical stimulation was applied to the wrist extensor tendons. The vibration motor (Pico Vibe 9mm Vibration Motor, Precision Microdrives Ltd., typical normalized amplitude 6 G) was

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used for wrist tendon stimulation. The vibrator was enclosed in a rubber case and sewn in an elastic band. This was done to isolate it from the skin on the subject's wrist to avoid any injection of leakage current to the hand. The vibration frequency was 110 Hz. The amplitude of vibration and stimulation positions were individually adjusted such that the subject could properly sense it.

Experimental Protocol

The experiment comprised of two sections. In the first section, the subject performed only left and right hand MI tasks, and in the second section vibration stimuli were applied to the subject's left and right wrist tendons and the subject's task was to passively feel the stimulation. In the first section, the subject's task was to perform MI according to a given cue. A total of 120 trials were performed by the subjects in 3 runs. At the beginning of each trial, a fixation '+' appeared in the center of the screen. At the 1st second, a vibration burst with the same intensity stimulated both hands to alert the user of the subsequent task. The vibration pulse lasted 200 ms. Then at the 3rd second, a red cue pointing either left (L-MI) or right (R-MI) was presented visually on the computer monitor. This cue was superimposed on the fixation '+' and lasted for 1.5 s. Subjects were instructed to perform the mental task after the appearance of the cue arrow. The mental task continued until the 8th second when the fixation '+' disappeared. Next there was a relaxation time period lasting for about 1.5 s, during which subjects relaxed and could blink. Finally a random time period of about 0 to 2 s was inserted after the relaxation period to further avoid subject's adaptation. In the second session, the subject's task was to feel the vibration sensation according to a given cue. A total of 120 trials were also performed by the subjects in 3 runs. The timing of the trial was the same, except that at 3.6 s, vibrations were only applied to the left or right tendon of the wrist until the 8th second when the fixation '+' disappeared.

Algorithm with Neurophysiological Prior

Spatial filter technology was adopted for reducing the high dimensional feature space and enhancing the feature discrimination between different mental tasks. The spatial filters were calculated based on the common spatial pattern (CSP), which has been extensively explored in MI-based BCI literature. Mathematically, it is realized by simultaneous diagonalization of the covariance matrices for the two classes. The bandpass filtered EEG signal is represented as X_k with dimensions M × N, where M is the number of recording electrodes, and N is the number of sample points, and k is the trial index. The spatial covariance of the EEG can be obtained from

$$C_k = \frac{X_k X_k^T}{trace(X_k X_k^T)} \tag{1}$$

where X_k^T denotes the transpose of the matrix X_k, and $trace(X_k X_k^T)$ is the sum of the diagonal elements of the matrix $X_k X_k^T$.

$$C_l = \sum_{k \in S_l} C_k \tag{2}$$

$$C_r = \sum_{k \in S_r} C_k \tag{3}$$

$$M_l = \sum_{k \in V_l} C_k \tag{4}$$

$$M_r = \sum_{k \in V_r} C_k \tag{5}$$

where S_l and S_r are the two index sets for left and right hand MI respectively, and V_l and V_r are the two index sets for left and right hand vibration stimulation respectively. C_l and C_r are the estimated covariance of left and right MI respectively, and M_l and M_r are the estimated covariance of the left and right hand vibration stimulation respectively.

$$C_l^P = (1-\beta)C_l + \beta M_l \tag{6}$$

$$C_r^P = (1-\beta)C_r + \beta M_r \tag{7}$$

$$C_l^N = (1-\beta)C_l + \beta I \tag{8}$$

$$C_l^N = (1-\beta)C_r + \beta I \tag{9}$$

The covariance with sensation-induced neurophysilogical prior will be C_l^P and C_r^P, for contrast, C_l^N and C_r^N will be regularized covariance, β is the parameter for the regulariztion, with the range between 0 to 1, and selected among {0:0.1:1}.

Three sets of the spatial filter will be extracted based on the following augmented generalized decomposition problem:

$$(C_l + C_r)W = \lambda C_l W \tag{10}$$

$$(C_l^P + C_r^P)W = \lambda C_l^P W \tag{11}$$

$$(C_l^N + C_r^N)W = \lambda C_l^N W \tag{12}$$

The rows of W are called spatial filters; the columns of $W^{-1}$are spatial patterns. For the k-*th* trial, the filtered signal $Z_k = WX_k$ are uncorrelated. In this work, the log variance of the first three rows and last three rows of Z_k (corresponding to the three largest and three smallest eigenvalues), are chosen as feature vectors, and linear discriminative analysis (LDA) is selected as the classifier. The training set of LDA was only based on motor imagery dataset.

We attempted to give a view considering the nonstationary property of the data by performing a cross validation with a ten-fold chronological split. The 60 trials of each MI task were temporally sorted, and divided into ten partitions, each of which contained temporal information similar to actual BCI use. Difference Spatial filters were extracted from the above condition in the divided training set, i.e. without prior (equation 10), with neurophysiological prior (equation 11) and with regularization (equation 12).

RESULTS AND DISCUSSION

Fig. 1 compares the MI performance when the CSP spatial filters were extracted in different condition. One way ANOVA with repeated measure indicated that there was a significant difference among the three conditions ($F(2,8)=14.6$, $P<0.05$), and post-hoc comparison showed that the MI with Neurophysiological Prior was significant greater than other two conditions, and no significance difference was found between MI without Prior and MI with Regularization. It can be noted that two of the five subjects, the performance were around 60% with traditional method but it improved with the proposed method and surpassed the 70% accuracy level.

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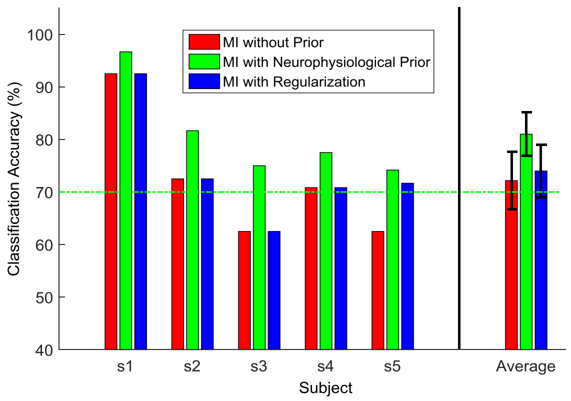

Figure 1. Classification accuracy across subjects. Red bar indicates the MI discrimination accuracy without Prior; the green bar indicates the MI with Neurophysiological Prior; the blue bar indicates the MI with regularization. Green line indicates the 70% accuracy.

The results have shown that the sensation-induced neurophysiological prior provides a way to help CSP spatial filters extraction, the induced prior has the characteristics of easy to induce, stable and less likely to be influenced by subject's internal state, such as attention, stress, which affect MI mental effort.

Through pre-experiment recording session of the real vibration sensation, it would also provide a way to evaluate the potential BCI performance of subjects [15] and provide guidance to subjects in order to better use MI based BCI system.

As the BCI performance is the result of a cumulation of BCI-specific and user-specific factors, this current offline analysis only focused on the algorithm part of CSP with stimulus-induced Neurophysiological Prior. This approach provided a potential way to further improve MI-based BCI performance.

CONCLUSION

Motor Imagery BCI performance can be further improved by integrating the stimulus sensation-induced neurophysiological prior. The stimulus-induced oscillatory dynamics facilitate the extraction of CSP spatial filters, which resulted an improved MI performance. This proposed method has the potential to further improve BCI performance.

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