JOINT SPATIAL-TEMPORAL FILTER DESIGN FOR ANALYSIS OF MOTOR IMAGERY EEG

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ABSTRACT

This paper addresses the key issue of discriminative feature extraction of electroencephalogram (EEG) signals in brain-computer interfaces. Recent advances in neuroscience indicate that multiple brain regions can be activated during motor imagery. The signal propagation among the regions can give rise to spurious effects in identifying event-related desynchronization/synchronization for discriminative motor imagery detection in conventional feature extraction methods. Particularly, we propose that computational models which account for both signal propagation and volume conduction effects of the source neuronal activities can more accurately describe EEG during the specific brain activities and lead to more effective feature extraction. To this end, we devise a unified model for joint learning of signal propagation and spatial patterns. The preliminary results obtained with real-world motor imagery EEG data sets confirm that the new methodology can improve classification accuracy with statistical significance.

Index Terms— Electroencephalograph, motor imagery, spatial filter design, brain computer interface

1. INTRODUCTION

Motor imagery is a dynamic state that can induce the same motor representation internally as the corresponding motor execution [1], and studies have shown that distinct brain signals such as event-related desynchronization (ERD) or event-related synchronization (ERS) are detectable from EEG during motor imagery [2, 3]. Therefore, motor imagery based brain-computer interface (BCI) has become a highly intensive research area [4, 5, 6]. Because EEG signals are dynamic, stochastic, non-linear and non-stationary [7], discriminative feature extraction is of great importance.

Due to the volume conduction effect, information related to motor imagery is mixed with unrelated brain activities and becomes very weak in EEG. This gives rise to the significance of spatial filter design for EEG feature extraction: to enhance the discrimination of the projected signal in the surrogate sensor space [8]. Take common spatial pattern (CSP) as an example. Based on the assumption that raw EEG signals are instant linear mixtures of several source signals, the desired spatial filters are designed to obtain sources with most prominent ERD/ERS by maximizing the variance of the projected signal under one condition while minimizing it under the other condition [9, 10].

Recently, brain activities of motor imagery more than ERD/ERS are found in multi-functional areas using functional magnetic resonance imaging (fMRI) or EEG [11, 12]. In particular, the analysis of neural connectivity is gaining importance in the neuroscience field because it describes the general functioning of the brain and communication between its different regions [13, 14]. For example, casual connectivity is found in motor related core regions such as the primary motor cortex (M1) and supplementary motor area (SMA) during motor imagery [12]. Such casual flow or time-lagged correlation is beyond volume conduction and is caused by possible neuronal propagation [15]. Therefore, rather than simply modeling EEG signals as instant mixtures of signals with or without ERD/ERS, advancing BCI calls for computational models that are able to depict such underlying process associated with the brain activity of interest and achieve better classification performance.

Based on the above analysis of EEG functional connectivity, it can be concluded that traditional spatial filter design methods address the volume conduction problem but ignore information propagation of EEG. This limitation results in incomplete separation of discriminative signals from the indiscriminating ones. Details of the necessity of taking the time-lagged propagation and weakness of conventional spatial filter design will be discussed in Section 2. Considering the shortcoming of existing spatial filter design methods, we aim to develop a novel computational model that is able to account for both information propagation and the volume conduction effect in EEG. Specifically, this work comprises the following contributions: firstly, spurious effects in identifying ERD/ERS in conventional feature extraction methods caused by signal propagation are discussed; and secondly, a unified model for the joint learning of signal propagation and spatial patterns is devised.

2. FEATURE EXTRACTION BASED ON JOINT SPATIAL-SPATIOTEMPORAL FILTER DESIGN

2.1. Problem Formulation

Let $X(t)$ be the multi-channel EEG signal at time t. To overcome the volume conduction effect, a spatial filter **w** is usually used to estimate the source signal

$$\hat{s}(t) = \mathbf{w}X(t) \tag{1}$$

where $\hat{s}(t)$ is the estimated source signal based on the spatial filter.

However, the existence of time-lagged axonal propagation of macroscopic neural behavior among source signal of different regions of the brain gives rise to mixing effects of time-lagged source signal $s(t)$, which follows an MVAR model

$$s'(t) = \sum_{\tau=1}^{p} B(\tau)s'(t-\tau) + s(t) \tag{2}$$

where coefficient matrices $B(\tau)$ describe the information propagation effects of the resulted mixed signal $s'(t)$.

As indicated by (1) and (2), based on the assumption that $X(t)$ is instant linear mixture of source signals, estimated source signal $\hat{s}(t)$ based on the spatial filter **w** is actually estimate of $s'(t)$ rather than $s(t)$. In particular, in discriminating analysis, spatial filter **w** is designed to extract the most discriminative signal $\hat{s}(t)$. However, due to time-lagged correlation between $s(t)$, discriminative signals are still mixed with non-discriminative ones in $\hat{s}(t)$. This is the motivation to propose a joint learning function for demixing estimation of signal propagation and spatial patterns in this paper.

2.2. Proposed Method

As discussed before, it is necessary to take the casual flow into consideration together with spatial filter design in a unified model to have a better estimation of $s(t)$ rather than $s'(t)$. Substitute (1) into (2), then we have

$$\begin{aligned} s(t) &= s'(t) - \sum_{\tau=1}^{p} B(\tau)s'(t-\tau) \\ &= \mathbf{w}X(t) - \sum_{\tau=1}^{p} B(\tau)\mathbf{w}X(t-\tau) \\ &= \mathbf{w}(X(t) - \sum_{\tau=1}^{p} A(\tau)X(t-\tau)) \end{aligned} \tag{3}$$

where

$$A(\tau) = \mathbf{w}^{+}B(\tau)\mathbf{w} \tag{4}$$

are the propagation coefficient matrices after projection and it actually reveals the time-lagged correlation of different channels, and $\mathbf{w}^{+}$ is the pseudo-inverse of **w**. Let $\widetilde{X}$ be

$$\widetilde{X}(t) = X(t) - \sum_{\tau=1}^{p} A(\tau)X(t-\tau) \tag{5}$$

Thus we obtain

$$s(t) = \mathbf{w}\widetilde{X}(t) \tag{6}$$

Differently from the standard MVAR analysis where the process $s(t)$ is usually defined as temporally and spatially uncorrelated time sequence, here we assume $s(t)$ to be the source signal associated with the brain additivity of interest, i.e. motor imagery. Also we deal with the estimation of $s(t)$ using the objective in CSP to seek the desired projected signal $s(t)$ that has maximized power under one condition while minimized power under the other condition, expressed by the following optimization problem

$$\max \frac{1}{Q_c}\sum_{i\in Q_c} \mathrm{var}(s_i(t)) \;\; s.t. \;\; \sum_{c}\frac{1}{Q_c}\sum_{i\in Q_c}\mathrm{var}(s_i(t)) = 1 \tag{7}$$

where $c \in \{0,1\}$ indicates the class number and Q_c is the number of trials belonging to each class. Using the definition of the variance, (7) can be expressed by

$$\max_{\mathbf{w}} \mathbf{w}\widetilde{R}_1\mathbf{w}^T \;\; s.t. \;\; \mathbf{w}(\widetilde{R}_0 + \widetilde{R}_1)\mathbf{w}^T = 1 \tag{8}$$

where $\widetilde{R}_c$ is the estimate of the covariance matrices of the modulated EEG signal $\widetilde{X}$ under the two conditions as follows

$$\widetilde{R}_c = \frac{1}{Q_c}\sum_{i\in Q_c}\widetilde{X}_i\widetilde{X}_i^T \tag{9}$$

Let

$$\hat{A}(\tau) = \{ \begin{array}{cc} I, & \tau = 0 \\ -A(\tau), & \tau > 0 \end{array} \tag{10}$$

$\widetilde{X}(t)$ becomes

$$\widetilde{X}(t) = \sum_{\tau=0}^{p}\hat{A}(\tau)X(t-\tau) \tag{11}$$

Substituting (11) into (8) and (9), the optimization problem becomes

$$\begin{aligned} &\max_{\mathbf{w},\hat{A}(\tau)} \mathbf{w}(\sum_{\tau_i=0}^{p}\sum_{\tau_j=0}^{p}\hat{A}(\tau_i)R_1(\tau_{ij})\hat{A}(\tau_j))\mathbf{w}^T, \;\; s.t. \\ &\mathbf{w}(\sum_{\tau_i=0}^{p}\sum_{\tau_j=0}^{p}\hat{A}(\tau_i)(R_1(\tau_{ij}) + R_2(\tau_{ij}))\hat{A}(\tau_j))\mathbf{w}^T = 1 \end{aligned} \tag{12}$$

where

$$R_c(\tau_{ij}) = \frac{1}{Q_c}\sum_{i\in Q_c}X_i(t-\tau_i)X_i(t-\tau_j)^T \tag{13}$$

In (12), a $\mathbf{w}$ is the usual spatial filter aiming at the instant convolution of EEG caused by volume conduction effect, while $\hat{A}(\tau)$ can be regarded as estimates of time-lagged correlation after being projected to the scalp EEG.

The proposed discriminative learning algorithm of signal propagation and spatial patterns is illustrated in Figure 1. Briefly, we estimate $\mathbf{w}$ and $\hat{A}(\tau)$ separately using the expectation maximization (EM) algorithm in [16], because to solve the optimization problem in (12) to obtain $\mathbf{w}$ and $\hat{A}(\tau)$ simultaneously might lead to suboptimal solutions regarding the composite cost function. A spatial filter $\mathbf{w}$ can be obtained based on a fixed $\hat{A}(\tau)$ by solving (8). For $\hat{A}(\tau)$, we calculate $[\hat{a}_{1j}, \hat{a}_{2j}, \dots, \hat{a}_{Cj}]^T$ separately, which means that the information flow from different channels is optimized one by one. When $[\hat{a}_{1j}, \hat{a}_{2j}, \dots, \hat{a}_{Cj}]^T$ are calculated for all $j = 1, \dots, C$, we estimate new $\hat{A}(\tau)$ and $\mathbf{w}$ is updated accordingly. The loop will not stop until the convergence criteria is met. Note that during the optimization, only one $\mathbf{w}$ is used. After the optimization finishes we can obtain the projection matrix based on $\widetilde{X}$ and select more than one pair of filters as in the usual CSP procedure [6].

Input: Training EEG data that comprises N sample blocks of X, with each block having a specific class label;

Output: Spatial filter $\mathbf{w}$ and time-lagged correlation estimates $\hat{A}(\tau)$.

Step 1) Set the initial parameters of the spatiotemporal filters $\hat{A}(\tau)$ as zero matrices;

Step 2) Set the iteration count $k = 0$, and repeat the following steps until convergence whereby the criterion is defined as the change of the norm of $\mathbf{w}$ being less than a small threshold ζ:

a) Compute $\widetilde{X}$ based on $\hat{A}(\tau)$ using (11);

b) Compute the spatial filter $\mathbf{w}$ by solving the optimization problem in (8);

c) Compute the change in the norm of the spatial filter $\mathbf{w}$ by $\delta = \|\mathbf{w}^k\| - \|\mathbf{w}^{k-1}\|$; if $\delta > \zeta$ or the iteration count k is less than a preset number, continue to the next step; otherwise stop the computation;

d) For $j = 1 : C$, calculate $[\hat{a}_{1j}, \hat{a}_{2j}, \dots, \hat{a}_{Cj}]^T$ by solving the optimization problem in (12);

e) Update $\hat{A}(\tau)$.

Fig. 1. Pseudocode of the proposed method

3. EXPERIMENT

3.1. Data Description

16 subjects participated in the study with ethics approval and informed consent. All of them performed motor imagery and passive movement on the right hand. EEG from a total of 27 channels were obtained using Nuamps EEG acquisition hardware with unipolar Ag/AgCl electrodes channels. The sampling rate was 250 Hz with a resolution of 22 bits for voltage ranges of ± 130 mV. A bandpass filter of 0.05 to 40 Hz was set in the acquisition hardware.

In the experiment, the training and test sessions were recorded on different days from the subjects performing motor imagery. During the EEG recording process, the subjects were asked to avoid physical movement and eye blinking. Additionally, they were instructed to perform kinesthetic motor imagery of the chosen hand in the two runs. During the rest state, they did mental counting as instructed to make the EEG signals more constant. Each run lasted for approximately 16 minutes comprising 40 trials of motor imagery and 40 trials of rest state. Each training session consisted of 2 runs and the test session consisted of 2-3 runs of experiments.

3.2. Data Processing

For each trial of data, time segments of 0.5 to 2.5s after the cue are used following most of the previous works, such as [17, 6]. The raw data is filtered using a bandpass filter with passband 8-35Hz for the same reason. The filtered training data is used to train the feature extraction model based on the proposed method as described in Section 2.2, and the obtained training features are used to train a support vector machine (SVM) classifier. During the optimization procedure, the maximum number of iteration is 30 and $\zeta = 0.02$. After the training step, test features can be obtained based on the feature extraction model and then classified by the SVM classifier.

3.3. Experiment Results

Table 1 summarizes the performance of the proposed feature extraction method in term of the classification accuracy of the test data, where we refer the proposed method as joint spatial-temporal filter design (JSTF). Figure 2 is used to show the comparison result in a more intuitive way.

It is revealed from the comparison that the proposed feature extraction method improves the performance of the classifier, with an average classification accuracy of 67.89% higher than that of CSP (65.56%). Moreover, a paired t-test is applied to the accuracy result, which is used to further evaluate the effectiveness of the proposed method. In particular, the significance of the improvement is validated at the 5% confidence level with $p = 0.014$. From the above results, we

Table 1. Session-to-session transfer test results

Method \ Subject	1	2	3	4	5	6	7	8
JSTF	**69.16**	**53.33**	**57.08**	**70.00**	**66.25**	**69.58**	75.83	92.08
CSP	65.00	51.25	55.00	66.67	54.58	67.08	77.08	94.16
Method \ Subject	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
JSTF	72.08	60.83	**50.83**	**82.00**	**52.08**	**76.25**	**67.08**	**71.66**
CSP	74.58	61.66	46.25	77.00	51.25	72.08	65.83	69.58

are able to confirm that the performance improvement of the classifier is achieved with the proposed method.

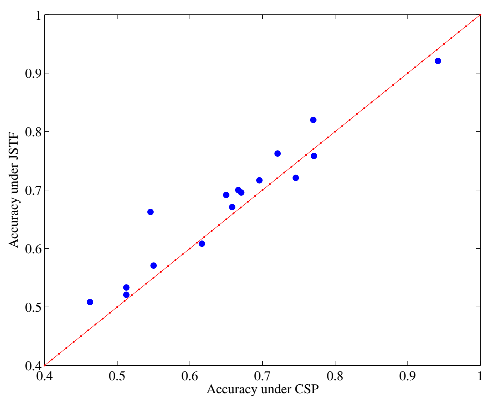

Fig. 2. Accuracy comparison between CSP and JSTF

4. DISCUSSION

The proposed computational model described in (12) links to the sparse connectivity analysis (SCSA) model in [16] and MVAR-ICA model in [15]. However, the aim of those two works is to estimate true connectivity between sources, therefore independence of the estimated source is the major concern in the calculation of both volume conduction demixing matrix and connectivity model. In our work, however, the objective is discriminating EEG data from two classes, so we identify the model using objective function based on the power of the projected signals to extract signals with most prominent ERD/ERS.

CSP is one of the most successful spatial filter design methods which seeks optimized spatial filters that maximize the variance of the spatially filtered signal under one condition while minimizing it under the other condition. However, as indicated in (1) and (2), merely linear spatial filters can not separate non-discriminative signals from discriminative ones effectively due to the existence of time-lagged correlation. Moreover, such information propagation could relate to non-stationarity of EEG. As (4) indicates, after projection time-lagged correlation exists in scalp EEG and it is possible that an electrode that actually contains no discriminative information could be given a high weight due to information flow from channels containing ERD/ERS. However, without the original discriminant power, these channels are not stable enough, as their dependence on other channels could be covered by noise when those sources are not sufficiently activated. The above analysis is the motivation to propose the unified model for discriminative learning of signal propagation and spatial patterns. By jointly estimating time-lagged correlation coefficient matrices and spatial filter, more efficient feature extraction can be achieved. The results in Table 1 validate that our computational model can improve the classification accuracy with statistical significance.

5. CONCLUSION

Co-existence of brain connectivity and volume conduction effect in EEG measurements can give rise to spurious effects in identifying activities associated with motor imagery best. In this paper, we have established a novel computational model that accounts for both time-lagged correlations between signals and the volume conduction effect. The model is identified via a joint signal propagation and spatial pattern learning algorithm in an EM manner. Based on the proposed oint spatial-temporal filter design method, underlying process of brain activity during motor imagery is better described and improvement in classification accuracy is achieved. As shown in the experiment results, the significance of this improvement has been validated with statistical significance.

6. REFERENCES

[1] M. Jeannerod, "Mental imagery in the motor context," *Neuropsychologia*, vol. 33, pp. 1419–1432, 1995.

[2] M. Stavrinou, L. Moraru, L. Cimponeriu, P. D. Stefania, and A. Bezerianos, "Evaluation of cortical connectivity during real and imagined rhythmic finger tapping," *Brain Topography*, vol. 19, no. 3, pp. 137–145, 2007.

[3] G. Pfurtscheller, C. Brunner, A. Schlogl, and F. H. Lopes da Silva, "Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks," *NeuroImage*, vol. 31, no. 1, pp. 153–159, 2006.

[4] C. L. Albert, G. R. Lorie, K. H. Jodie, F. W. George, and G. F. Daniel, "Robot-assisted therapy for long-term upper-limb impairment after stroke," *New England Journal of Medicine*, vol. 362, pp. 1772–1783, 2010.

[5] H. I. Krebs, J. J. Palazzolo, L. Dipietro, M. Ferraro, J. Krol, K. Rannekleiv, B.T. Volpe, and N. Hogan, "Rehabilitation robotics: Performance-based progressive robot-assisted therapy," *Autonomous Robots*, vol. 15, pp. 7–20, 2003.

[6] K. K. Ang, Z. Y. Chin, H. Zhang, and C. Guan, "Filter bank common spatial pattern (FBCSP) in brain-computer interface," *IEEE International Joint Conference on Neural Networks and Computational Intelligence*, pp. 2390–2397, 2008.

[7] I. Guler, M. K. Kiymik, M. Akin, and A. Alkan, "AR spectral analysis of EEG signals by using maximum likelihood estimation," *Computers in Biology and Medicine*, vol. 31, no. 6, pp. 441 – 450, 2001.

[8] B. Blankertz, R. Tomika, S. Lemm, M. Kawanabe, and K. R. Muller, "Optimizing spatial filters for robust EEG single trial-trial analysis," *IEEE Signal Processing Magazine*, vol. 25, no. 1, pp. 41–56, 2008.

[9] Z. J. Koles, "The quantitative extraction and toporraphic mapping of the abnormal components in the clinical EEG," *Electroencephalography and Clinical Neurophysiology*, vol. 79, pp. 440–447, 1991.

[10] J. M. Gerkinga, G. Pfurtscheller, and H. Flyvbjergc, "Designing optimal spatial filters for single-trial EEG classiffication in a movement task," *Clinical Neurophysiology*, vol. 110, pp. 787–798, 1999.

[11] E. Formaggio, S. F. Storti, R. Cerini, A. Fiaschi, and P. Manganotti, "Brain oscillatory activity during motor imagery in EEG-fMRI coregistration," *Magnetic Resonance Imaging*, vol. 28, no. 10, pp. 1403 – 1412, 2010.

[12] H. Chen, Q. Yang, W. Liao, Q. Gong, and S. Shen, "Evaluation of the effective connectivity of supplementary motor areas during motor imagery using granger causality mapping," *NeuroImage*, vol. 47, no. 4, pp. 1844–1853, 2009.

[13] ," .

[14] A. Ewald, L. Marzetti, F. Zappasodi, F. C. Meinecke, and G. Nolte, "Estimating true brain connectivity from EEG/MEG data invariant to linear and static transformations in sensor space," *NeuroImage*, vol. 60, no. 1, pp. 476 – 488, 2012.

[15] G. G.-Herrero, M. Atienza, K. Egiazarian, and J. L. Cantero, "Measuring directional coupling between EEG sources," *NeuroImage*, vol. 43, no. 3, pp. 497–508, 2008.

[16] S. Haufe, R. Tomioka, G. Nolte, K.-R. Muller, and M. Kawanabe, "Modeling sparse connectivity between underlying brain sources for EEG/MEG," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 8, pp. 1954 –1963, Aug. 2010.

[17] M. Arvaneh, C. Guan, K. K. Ang, and C. Quek, "Optimizing the channel selection and classification accuracy in EEG-based BCI," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 6, pp. 1865–1873, June 2011.