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A Review on Spatial Pattern Methods for Brain-Computer Interface

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Abstract: **Brain-computer interface technology is the one in which the user's mental intentions are captured and used as control signals for external devices. BCI researches are becoming more popular as it can be used as a means of communication for people with severe disability. The efficiency of a BCI system depends on its signal processing stages. The signal processing stages include the signal acquisition, feature extraction and classification. In this paper, a brief review of one of the feature extraction methods called spatial pattern algorithms for BCI is provided.**

Index Terms- **brain computer interfaces, common spatial pattern, feature extraction.**

I. INTRODUCTION

Brain computer interfaces is also called as Brain machine interfaces (BMI). Researches focus on this technology in the hope that it will be helpful for people with motor disability. Wolpaw *et* al. [1] have defined BCI as "A BCI is a communication system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles". Wolpaw [2] describes that the proper objective of BCI development is to find the signals that the users can control, maximize that control, and translate it into action reliably and accurately. BCI technology has various applications other than assisting disabled people, like environment control [3], entertainment [4], etc. A BCI can be seen as a pattern recognition system.BCI system consists of various stages as signal acquisition, preprocessing, feature extraction and classification. The BCI technology can be classified into different types: according to nature of input signals used it can be classified into exogenous (external stimuli are used) and endogenous (based on the self regulation of brain signals without external stimuli); according to the data processing technique it can be classified into synchronous (brain signals are analyzed in a pre-defined window) and asynchronous (brain signals are analyzed continuously) [5]. Wolpaw *et al.* [1] have classified BCI into dependant (does not use brain's normal output pathways to carry the message but the activity in these pathways are used to generate brain activity that carries it) and independent (does not depend on any way on the normal output pathways).

II. BCI TECHNOLOGY

BCI has various stages mainly a signal acquisition part, preprocessing, feature extraction and the classification stage [6]. The brain activity can be measured using various recording methods like EEG, fMRI, ECoG, MEG, PET [7]. These methods are of two types namely, invasive (electrodes are implanted inside the brain) and noninvasive (include hap tic controllers and EEG scanners) [5]. In BCI applications the various brain signal types that are used includes the event-related potentials, mu and beta rhythms, event related synchronization/ desynchronization, visual evoked potentials and slow cortical potentials [8, 9]. Features need to be extracted from the brain signals and they need to be classified for controlling the external devices [10]. There are various methods for feature extraction as CSP, wavelet transform, autoregressive model [11], principal component analysis(PCA), and independent component analysis(ICA) [12]. Feature translation is the next important signal processing stage in BCI. Wolpaw *et* al. [13] have specified that the translation algorithm can be based on either on a classifier or a regression function. Regression analysis is a statistical tool for determining relationships between different variables. There are mainly five types of classifier algorithms: linear, nonlinear Bayesian, nearest neighbor, neural networks and a combination of classifiers [14, 15].

III. COMMON SPATIAL PATTERN

Brain computer interfaces can be seen as a pattern recognition system in which the brain activities are converted into control commands for external devices like computer [10]. In order to achieve this, certain features like band powers or power spectral density values need to be extracted from the acquired brain signal [10]. The amplitude modulations of sensorimotor rhythms can be obtained from time/frequency analysis of the EEG signals. The frequency based analysis is mostly done due to its simplicity and efficiency [16]. However frequency features does not provide any time domain information. Also because of the non-stationarity nature of EEG signal [17], time-frequency representations are mostly used [16]. Besides the temporal (time domain) and spectral (frequency domain) features, features related to spatial locations are also important for discriminant feature extraction [16, 18].

A. *Importance of Spatial Filtering*

The EEG signals recorded from electrodes have not only the neural voltage fluctuations but also have the voltages corresponding to the activities of distant current sources through volume conduction [18]. If EEG signal is represented as $x(t)$ which are generated by brain sources $s(t)$, then the EEG signal can be represented as [19],

$$\mathrm{x}(t) = \mathrm{A}\mathrm{s}(t) + \mathrm{n}(t),$$

where A is a matrix mapping the activity of each source to the electrode space. The sensory motor rhythms will be attenuated by the movement imagination in the corresponding cortical areas (e.g., left hand motor imagery affects the SMRs over the right motor cortex area) [18, 20]. Hence it becomes necessary to find the sources of the SMR modulation to discriminate between different motor imagery tasks and this can be achieved with spatial filtering as given below

$$\bar{s}(t) = W^T x(t)$$

where W=$[w_1, w_2, \ldots . w_d]$ projects the EEG signal to a lower dimension subspace[18] and $w_i$is a spatial filter which weights the electrode to get information about the sources.

B. *Common Spatial Pattern*

CSP is an algorithm to develop the spatial filters for the motor imagery experiments [18]. Haixian *et al.* [21] has explained CSP in both geometrical and mathematical ways. The method can be explained in geometric basis that it is used to find directions in which the projected scatters between two EEGs are maximized. Mathematically this can be obtained by simultaneously diagonalizing two covariance matrices associated with two EEG populations (or classes) in order to maximize the difference between the two projected populations [21]. The spatial filtering is done by the CSP by linearly transforming the EEG measurements using the following equation,

$$\mathrm{Z} = \mathrm{W}^{\mathrm{T}}\mathrm{E}$$

where E is the EEG measurement, Z is the EEG measurement after spatial filtering and W is the CSP projection matrix [22]. The main function of the CSP algorithm is to find the projection matrix W, so that features that can discriminate two classes can be obtained [22]. The projection matrix is obtained by solving the eigenvalue decomposition problem

$$\Sigma_1 w_i = \lambda_i \Sigma_2 w_i$$

where Σ_1 and Σ_2 are the covariance matrices of EEG measurements corresponding to two classes and generalized eigenvalues λ_i measure the variance ratio between class 1 and class 2 [18]. In a nutshell, CSP finds spatial filters that maximize the variance for one class or population and simultaneously minimizing for the other [23]. CSP can also formulated as a Rayleigh quotient problem [24].

C. *Different CSP Variants*

Besides the CSP algorithm provides better discrimination it has limitations too. Some of the limitations are that the covariance estimation can be effected by the artificats in EEG, overfitting problem with the small training sets, the nonstationarity problem, etc. [18, 21]. In order to overcome various limitations of the standard CSP various methods have been developed by researchers.

The projection matrix W remains unchanged within or across sessions, on the other hand the EEG signal changes within time [25]. Hence the direction obtained from projection matrix may not be always optimal. Chen *et al*. [25] proposed an adaptive method to overcome this problem. Here the covariance matrices are adapted to the varying EEG signals and then the eigenvalue decomposition problem is solved with this adapted covariance matrices. The results they obtained for the adaptive CSP were slightly better than that for traditional CSP.

The standard CSP method is a supervised learning method (requires labeled EEG trials). It is difficult to get large number of labeled information at all the times and if small amount of trials is used then overfitting problem arises which leads to less efficient results [24]. On the other hand it is easy to get unlabeled information. Thus Wang *et al*. [24] proposed the comprehensive learning scheme of CSP (cCSP) that combines both the labeled and the unlabeled trials. The information from unlabeled trials was incorporated with the help of $\ell_1$graph. In the objective function of the comprehensive learning scheme of CSP a regularization term was also included to encode the knowledge of intrinsically temporal structure of the unlabeled EEG trials [24]. Wang *et al.* [24] obtained better performance of the proposed method for single-trial EEG classification.

The imagery classifications are done based on the changes in the mu and the beta rhythms and corresponding spatial distributions but these rhythmic changes will vary from subject to subject [26]. Hence fine tuning process will be required. Novi *et al.*[26] have proposed a method called sub-band common spatial pattern (SBCSP) to solve this problem. In this case they have decomposed the EEG signals into various sub-bands using a filter bank and CSP is performed on each sub-band [26]. Novi *et al.*[26] fused the scores from each sub-band and decision was made. They compared this method with the CSSP (common spatio-spectral pattern [27]) and CSSSP (common sparse spatio-spectral pattern [28]) method and found that the proposed method outperformed the two. The performance of CSP is dependent on the frequency band, hence setting up a broad frequency range or manual selection of subject specific frequency range [29]. The CSSP [27] and CSSSP [28] were proposed to solve the problem of manual selection of the frequency range. Ang *et al.*[29] proposed filter bank common spatial pattern, in which there are four stages as band pass filtering , feature extraction, feature selection and classification. FBCSP was compared with the SBCSP and the result outperformed that of SBCSP. In FBCSP fixed filter bank was used by all the subjects. Thomas *et al.* [30] proposed subject specific discriminative FB (DFBCSP), in which the parent FB filters the EEG from one channel (C3 or C4) and then fisher ratio of the filtered EEG signal was used to determine the subject specific discriminative frequency bands and they obtained successful results. In FBCSP there involves multiple spatial filtering which requires multiple estimations of the covariance matrices and thus this increases the sensitivity of the FBCSP to noise, artifacts and outliers. Ang *et al.* [31] proposed a method called composite FBCSP that employs a single spatial filter (computed from a weighted sum of covariance matrices) instead of multiple spatial filters. The results obtained had a better kappa values as compared to FBCSP [31]. Aghaei *et al*[32] proposed a novel method called separable common spatio-spectral patterns (SCSSP) where a heteroscedastic matrix-variate Gaussian model and was found to be computationally efficient and outperformed the FBCSP method.

Hyohyeong *et al.* [33] provides modified CSP for subject to subject transfer (transfer useful information of subjects involving the same task to the subject with lower training samples). They exploited the composite covariance matrices determined by a linear combination of covariance matrices for all subjects in consideration. Two different methods were proposed to determine appropriate weights in evaluating composite covariance matrices: Method 1 de-emphasized covariance matrices involving fewer samples, while Method 2 emphasized covariance matrices for subjects with similar characteristics to the subject in consideration [33]. The method proposed by Hyohyeong *et al.*[33] worked well for subjects with a small number of samples, while the traditional methods worked better for subjects with a sufficient number of training samples.

One of the important objectives of the BCI research is to reduce the number of training trilas needed and at the same time conventional CSP algorithm is based on the sample-based covariance matrix estimation and the accuracy of estimation is badly affected if only small training set is available [34]. In order to tackle this problem Haiping *et al.* [34] proposed regularized CSP, to regularize the covariance estimation in CSP; two parameters have been employed, one to lower the estimation bias and the other to lower the estimation variance. Later Fabien *et al.* [35] reviewed several regularization techniques for CSP and also proposed four RCSP algorithms. They got the best results from the Tikhonov regularization method, which is a classical form of regularization generally used with regression problems [35].

In EEG based BCI technology, to get better performance signals from multiple sites of the scalp are required and at the same time large number of EEG channels may increase noise, redundant signals and long preparation time[36]. Therefore, there is a need to select least number of channels that yields best accuracy. Arvaneh *et al.* [36] proposed a novel sparse CSP (SCSP) for optimal EEG channel selection. The method outperformed the CSP in the case where the number of selected channels was small. Wang *et al.*[37] proposed L1 based CSP to make it less sensitive to outliers. In standard CSP the formulation is based on variance using L2 norm, and in the proposed method in [37] the formulation of variance is based on L1 norm. The spatial filters in this case are obtained through an iterative algorithm and Wang *et al.* [37] obtained better results compared to other CSP variants. Kam *et al.* [38] proposed time dependent CSP inorder to overcome the limitation of standard CSP that it does not consider the temporal information of EEG signals. The standard CSP is usually used for two-class problems, however its extension to multiclass problems are also studied [39]. Wentrup *et al.* [39] have mentioned various multiclass extensions of CSP and have proposed an information theoretic feature extraction method for multiclass.

IV. CONCLUSION

The common spatial pattern method had been widely used in brain-computer interface technology for feature extraction. Though it provides discrimination of EEG data, its performance are degraded by the artifacts in EEG data, the nonstationarity problem, overfitting problem that arises due to availability of small training data sets. Hence inorder to overcome these limitations of the basic CSP algorithm different variants have been developed by various researchers.

REFERENCES

[1]. Jonathan R. Wolpaw, Niels Birbaumer, Dennis J.McFarland, Gert Pfurtscheller, Theresa M. Vaughan, "Brain-computer interfaces for communication and control", Elsevier Science Ireland Ltd, Clinical Neurophysiology 113, pp. 767–791, 2002.

[2]. Jonathan R. Wolpaw, "Brain-Computer Interface Research Comes of Age: Traditional Assumptions Meet Emerging Realities", Journal of Motor Behavior, Vol. 42, No. 6, pp. 351-353, 2010.

[3]. Cincotti. F, Mattia. D, Aloise. F, Bufalari. S, Schalk. G, Oriolo. G, Cherubini. A, Marciani. M.G, Babiloni. F, "Non-invasive brain-computer interface system: Towards its application as assistive technology",

[4]. Roman. K, Benjamin. B, Gabriel. C, Klaus-Robert. M, "The Berlin Brain-Computer Interface (BBCI)-Towards a new communication channel for online control in gaming applications", Multimedia Tools and Applications 33, pp. 73–90, 2007.

[5]. Aboul Ella Hussanien, and Ahmed Taher Azar," Brain Computer Interface Current Trends and Applications", Intelligent Systems Reference Library, Vol. 74, Springer Interational Publishing, 2015.

[6]. Obed Carrera-Leon, Juan Manuel Ramirez, Vicente Alarcon-Aquino, Mary Baker, David DCroz-Baron, Pilar Gomez-Gil, "A Motor Imagery BCI Experiment using Wavelet Analysis and Spatial Patterns Feature Extraction", IEEE Conference on Engineering Applications (WEA), 2012 Workshop on, 2012.

[7]. Katarzyna Blinowska, Piotr Durka, "Electroencephalography (EEG)", Wiley Encyclopedia of Biomedical Engineering, John Wiley & Sons, Inc., 2006.

[8]. Yijun Wang, Ruiping Wang, Xiaorong Gao, Bo Hong, and
Shangkai Gao, "A Practical VEP-Based Brain–Computer Interface", IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 14, No. 2, pp.234-239, June 2006.

[9]. Yijun Wang, Xiaorong Gao, Bo Hong, Chuan Jia, and Shangkai Gao, "Brain-Computer Interfaces Based on Visual Evoked Potentials Feasibility of Practical System Designs", IEEE Engineering in Medicine and Biology Magazine, pp.64-71, September/October, 2008.

[10]. Shiliang Sun and Jin Zhou, "A Review of Adaptive Feature Extraction and Classification Methods for EEG-Based Brain-Computer Interfaces", International Joint Conference on Neural Networks (IJCNN), pp. 1746-1753, July, 2014.

[11]. Sun-Yuge, Ye-Ning, Zhao-Lihong, Xu-Xinh, "Research on Feature Extraction Algorithms in BCI", IEEE, Chinese Control and Decision Conference (CCDC), pp.5874-587, 2009.

[12]. Zhisong Wang, Alexander Maier, Nikos K. Logothetis, and Hualou Liang, "Extraction of Bistable-Percept-Related Features from Local Field Potential by Integration of Local Regression and Common Spatial Patterns", IEEE Transactions on Biomedical Engineering, Vol. 56, No. 8, pp. 2095-2103, August 2009.

[13]. Dennis J. McFarland, Dean J. Krusienski and Jonathan R.Wolpaw, "Brain computer interface signal processing at the Wadsworth Center: mu and sensorimotor beta rhythms", Progress in Brain Research, Vol. 159, pp.411-419, February 2006.

[14]. Fabien Lotte, Marco Congedo, Anatole L´ecuyer, Fabrice Lamarche, Bruno Arnaldi, "A review of classification algorithms for EEG-based brain-computer interfaces", Journal of Neural Engineering, IOP Publishing, pp.24, March 2007.

[15]. Tarik Al-ani and Dalila Trad (2010). Signal Processing and Classification Approaches for Brain-Computer Interface, Intelligent and Biosensors, Vernon S. Somerset (Ed.), ISBN: 978-953-7619-58-9, InTech, DOI: 10.5772/7032. Available from:http://www.intechopen.com.scihub.io/books/intelligent-and-biosensors/signal-processing-and-classification-approaches-for-brain-computer-interface.

[16]. Han Yuan, and Bin He , "Brain–Computer Interfaces Using Sensorimotor Rhythms: Current State and Future Perspectives", IEEE Transactions on Biomedical Engineering, Vol. 61, No. 5, pp.1425-1435, May 2014.

[17]. Cedric Gouy-Pailler, Marco Congedo, Clemens Brunner, Christian Jutten, and Gert Pfurtscheller, "Nonstationary Brain Source Separation for Multiclass Motor Imagery", IEEE Transactions on Biomedical Engineering, Vol. 57, No. 2, pp.469-478, February 2010.

[18]. Wojciech Samek, Motoaki Kawanabe, and Klaus-Robert Muller , "Divergence-Based Framework for

Common Spatial Patterns Algorithms", IEEE Reviews in Biomedical Engineering, Vol. 7, pp.50-72, 2014.

[19]. Benjamin Blankertz, Steven Lemm, Matthias Treder, Stefan Haufe, Klaus-Robert Muller, "Single-trial Analysis and Classification of ERP Components –A tutorial", Neuroimage 56, pp.814-825, 2011.

[20]. Johannes Muller-Gerking, Gert Pfurtscheller, Henrik Flyvbjerg, "Designing optimal spatial filters for single-trial EEG classification in a movement task", Clinical Neurophysiology 110, pp.787-798, 1999

[21]. Haixian Wang and Wenming Zheng , "Local Temporal Common Spatial Patterns for Robust Single-Trial EEG Classification", IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 16, No. 2, pp.131-139, April 2008.

[22]. K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, "Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b," Frontal Neuroscience, Vol. 6, March 2012.

[23]. Zhisong Wang,, Alexander Maier, Nikos K. Logothetis, and Hualou Liang, "Extraction of Bistable-Percept-Related Features from Local Field Potential by Integration of Local Regression and Common Spatial Patterns", IEEE Transactions on Biomedical Engineering, Vol. 56, No. 8, pp.2095-2103, August 2009.

[24]. Haixian Wang and Dong Xu, "Comprehensive Common Spatial Patterns With Temporal Structure Information of EEG Data: Minimizing Nontask Related EEG Component", IEEE Transactions on Biomedical Engineering, Vol. 59, No.9, September 2012.

[25]. Cheng Chen, Wei Song, Jiacai Zhang , Zhiping Hu, He Xu, "An Adaptive Feature Extraction Method for Motor-Imagery BCI Systems", International Conference on Computational Intelligence and Security, pp. 275-279, 2010.

[26]. Quadrianto Novi, Cuntai Guan, Tran Huy Dat, and Ping Xue, "Sub-band Common Spatial Pattern (SBCSP) for Brain-Computer Interface", Proceedings of the 3rd International IEEE EMBS Conference on Neural Engineering, pp.204-207, May 2007.

[27]. S. Lemm, B. Blankertz, G. Curio and K.-R. Muller , "Spatio spectral filters for improving the classification of single trial EEG", IEEE Transactions on Biomedical Engineering, Vol. 52, pp. 1541-1548, 2005.

[28]. G. Dornhege, B. Blankertz, M. Krauledat, F. Losch, G. Curio and K.R. Muller, "Optimizing spatio-temporal filters for improving BCI", In Advances in Neural Information Processing System, Vol. 18, 2006.

[29]. K.K. Ang, Z. Y. Chin and C. Guan, "Filter Bank Common Spatial Pattern (FBCSP) in Brain Computer Interface", in Proceedings IJCNN, pp.2391-2398, 2008.

[30]. Kavitha P. Thomas, Cuntai Guan, Chiew Tong Lau, A. P. Vinod, and Kai Keng Ang, "A New Discriminative Common Spatial Pattern Method for Motor Imagery Brain–Computer Interfaces", IEEE Transactions on Biomedical Engineering, Vol. 56, No. 11, pp.2730-2733, November 2009.

[31]. K. K. Ang, Z. Y. Chin, H.Zhang and C.Guan, "Composite Filter Bank Common Spatial Pattern for Motor-Imagery Based Brain-Computer Interface", IEEE Symbosium on CCMB , pp.1-5, April 2011.

[32]. Amirhossein S. Aghaei, Mohammad Shahin Mahanta, and Konstantinos N. Plataniotis, "Separable Common Spatio-Spectral Patterns for Motor Imagery BCI Systems", IEEE Transactions on Biomedical Engineering, Vol. 63, No. 1, pp.15-29, January 2016.

[33]. Hyohyeong Kang, Yunjun Nam, and Seungjin Choi, "Composite Common Spatial Pattern for Subject-to-Subject Transfer", IEEE Signal Processing Letters, Vol. 16, No.8, pp.683-686, August 2009.

[34]. Haiping Lu, How-Lung Eng, Cuntai Guan, Konstantinos N. Plataniotis, and Anastasios N. Venetsanopoulos, "Regularized Common Spatial Pattern with Aggregation for EEG Classification in Small-Sample Setting", IEEE Transactions on Biomedical Engineering, Vol. 57, No. 12, pp.2936-2946, December 2010.

[35]. Fabien Lotte, and Cuntai Guan, "Regularizing Common Spatial Patterns to Improve BCI Designs: Unified Theory and New Algorithms", IEEE Transactions on Biomedical Engineering, Vol. 58, No. 2, pp.355-362, February 2011.

[36]. Mahnaz Arvaneh, Cuntai Guan, Kai Keng Ang, and Chai 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.

[37]. Haixian Wang, Qin Tang, and Wenming Zheng , "L1-Norm-Based Common Spatial Patterns", IEEE Transactions on Biomedical Engineering, Vol. 59, No. 3, pp.653-662, March 2012.

[38]. T. E. Kam and S. W. Lee, "Time-Dependent Common Spatial Patterns Optimization for EEG Signal Classification", Asian Conference on Pattern Recognition (ACPR), IEEE, pp.643-646, November 2011.

[39]. M. G. Wentrup, M. Buss, "Multi-Class Common Spatial Patterns and Information Theoretic Feature Extraction", IEEE Transactions on Biomedical Engineering, Vol.55, No.8, pp. 1991-2000, August 2008.