Proceedings of the
7th Graz Brain-Computer Interface Conference 2017 DOI: 10.3217/978-3-85125-533-1-18

SPATIAL FILTERS SELECTION TOWARDS A REHABILITATION BCI

E. Colamarino[1,2], F. Pichiorri[2], D. Mattia[2], F. Cincotti[1,2]

[1] Department of Computer, Control, and Management Engineering Antonio Ruberti, Sapienza University of Rome, Rome, Italy

[2] Neuroelectrical Imaging and BCI Lab, Fondazione Santa Lucia IRCCS, Rome, Italy

E-mail: cincotti@dis.uniroma1.it

ABSTRACT: Introducing BCI technology in supporting motor imagery (MI) training has revealed the rehabilitative potential of MI, contributing to significantly better motor functional outcomes in stroke patients. To provide the most accurate and personalized feedback during the treatment, several stages of the electroencephalographic signal processing have to be optimized, including spatial filtering.
This study focuses on data-independent approaches to optimize spatial filtering step.
Specific aims were: i) assessment of spatial filters' performance in relation to the hand and foot scalp areas; ii) evaluation of simultaneous use of multiple spatial filters; iii) minimization of the number of electrodes needed for training.
Our findings indicate that different spatial filters showed different performance related to the scalp areas considered. The simultaneous use of EEG signals conditioned with different spatial filters could either improve classification performance or, at same level of performance could lead to a reduction of the number of electrodes needed for successive training, thus improving usability of BCIs in clinical rehabilitation context.

INTRODUCTION

Brain-computer interface (BCI) technology allows people with severe motor disabilities to use their brain activity (e.g. the electroencephalographic, EEG, signals) to control external devices, thereby bypassing their impaired neuromuscular system, or receive a feedback related with their cognitive processes [1]. One of the most recent and promising BCI applications regards post-stroke functional motor rehabilitation [2]. For instance, the introduction of BCI technology in assisting the motor imagery (MI) practice has been demonstrated to uncover the rehabilitative potential of MI, contributing to significantly better hand motor functional outcomes [3]. In order to facilitate the practice of voluntary covert and /or overt access to the affected hand, patients received a discrete feedback that should be the faithful representation of the brain activity (congruent with the affected hand).
To bridge the gap between research-oriented methodology in BCI design and the usability of a system in the clinical realm requires efforts towards BCI signal processing procedures (feature extraction and translation) that would optimize the balance between system accuracy and usability. This study focuses on the process of feature extraction and more specifically on its spatial filtering step.
Spatial filters are generally designed to enhance sensitivity to particular brain sources, improve source localization and/or suppress artifacts. Most commonly, spatial filters are a linear combination (i.e. weighted sums) of channels. There are several approaches for determining the set of spatial filter weights. These approaches fall into two major classes: data-independent and data-dependent spatial filters [4]. According to the review [5] of signal processing methods used in BCI studies, the surface Laplacian, the common spatial pattern, the common average reference and the independent component analysis are the most employed filters. For sensorimotor rhythms-based BCIs, the common average reference and Laplacian methods are superior to the ear reference method because they enhance the focal activity from the local sources and reduce the widely distributed activity [6]. Furthermore, concerning the two variations of the Laplacian filter, i.e. the large and the small Laplacian, it appears that they are the best filters in prediction and source identification, respectively [7].
This study approached the spatial filtering step by hypothesizing that filtering the EEG data with a different data-independent spatial filters would return a better rendering of the scalp areas of interest to allow for a more suitable *physiologically informed* feature extraction. As such, this procedure would best lead to a reinforcement of individual *correct* EEG patterns during BCI training [3] and, thus, maximize target prediction in the rehabilitation training.
In this view the specific study aims were: (a) to compare performances of different spatial filters as a function of the scalp areas relevant for hand or foot executed motor tasks (i.e. areas of interest), (b) to compare performances of gold standard filters, e.g. Laplacian filters, versus those obtained by pooling information (EEG features) coming from different spatial filters, (e.g. two kinds of bipolar filters), (c) to evaluate the impact of number of electrodes needed in those spatial filters which showed similar classification performance.
Confirming the main hypothesis, we might suggest that the a priori (defined one time, before starting the analysis) choice of just one spatial filter at the start of the

 DOI: 10.3217/978-3-85125-533-1-18

BCI signal processing is not optimal.
Common average reference (CAR), surface Laplacian (LAP) and bipolar filters, the latter commonly used in the EEG clinical field but not in sensorimotor rhythms-based BCI, were explored in this preliminary study on an EEG data set, acquired at IRCCS Fondazione Santa Lucia, that does not include stroke patients.

METHODS

Subjects: Forty subjects (seven of them with severe motor disabilities due to traumatic spinal cord lesion or progressive neurodegenerative disorders) participated in the study. Each subject gave written informed consent prior to inclusion. The study was approved by the Fondazione Santa Lucia (Rome) ethics committee.

Experimental protocol: The protocol consisted of two main parts: the screening session and some training (weekly) sessions. During the initial screening session, subjects were comfortably seated on a reclining chair (or, when necessary, on a wheelchair) in a dimly lit room. The session was divided in 12 runs (30 trials each one). Each trial began with a target appearing on a side of the screen (up/down, i.e., vertical, or left/right, i.e., horizontal). The trial lasted 5.8 seconds, with the inter trial interval of 1.8 seconds. Subjects were instructed to execute (first run) and imagine (second run) movements of their hands (opening and closing) or feet (flexion) upon the appearance on the screen of top or bottom target, respectively. When the targets appeared on the left or right side of the screen subjects were invited to move (third run) or to imagine (forth run) their left or right hand (opening and closing) upon the appearance of the target in the correspondent side. This sequence was repeated three times for a total of 12 runs. Subjects were instructed to minimize muscular, electrooculographic and blink activity. In the screening session, subjects were not provided with any feedback (any representation of their brain activity).

Experimental setup: Scalp EEG potentials were collected from 58, 59 or 61 positions assembled on an electrode cap (according to an extension of the 10-20 International System) and amplified by a commercial EEG system (BrainAmp, Brain Products GmbH, Germany) which sampled signals at 200 samples/s (per channels). Electrical reference has been provided by both ear lobes. The BCI system was realized using the BCI2000 [8] software system.

Signal processing and feature extraction: Using Matlab, EEG signals were band-pass filtered (0.1-70 Hz) with a forth order Butterworth filter and notch filtered at 50 Hz. The conventional ear reference, the common average reference (CAR), two different Laplacian derivations (small and large) [6] and two simple bipolar methods were considered in the study. In the bipolar methods (applied via software) each voltage difference was computed between two channels, longitudinally subtracting e.g. FCz from Fz and transversely subtracting e.g. Cz from C1.
EEG data recorded and filtered with each spatial filter considered were divided into epochs 1 second long. The spectral analysis was performed on EEG data epochs corresponding to task employing the Maximum Entropy method (16th order model) with a resolution of 2 Hz and considering no overlapped epochs. All possible features in a reasonable range (i.e., 0-36 Hz in 2 Hz bins) were extracted and analysed. A feature vector (spectral amplitude at each bin for each channel) was extracted from each epoch.

Data analysis: Consistently with the aims of the study two analysis were planned.
For the aim (a) just vertical runs, corresponding to the movement execution of hands or feet, were analysed. Hands opening/closing and feet flexion engage separate areas of the sensorimotor strip, different about anatomical and functional point of view.
Basing on the sensorimotor rhythms, the analysis was constrained to features belonging to the sensorimotor strip (FC, C and CP channels) in the range from 7 Hz to 31 Hz. The hands area was defined as the area containing derivations coming from FC, C and CP electrodes in all their even and odd positions (bilateral area); the feet area was defined as the area containing derivations coming from electrodes placed on the mid-line, e.g. FCz, according to the 10-20 International System.
Features belonging to those areas, first separately considered, i.e., hands area, feet area, and then in the combined manner, hands and feet areas, were the input for the stepwise regression which identifies the optimal subset of predictor variables (i.e. the features in this case) and assigns weights to them in order to build an effective regression model to evaluate the relationship between the predictors and the dependent variable (here equivalent to subject's movement intention). The maximum number of features to be selected by the stepwise regression algorithm was set, for all feature domain, to 8 because of results obtained in a preliminary study. The latter aimed to compute the optimal number of features from which the mean (among tasks and subjects) classification performance does not grow in a significant way. We concluded that increasing the number of features, from eight to largest values, does not significantly increase the performance values.
In order to compare performances of the six spatial filters considered, after the features translation step in which a linear classifier is used to predict if the epoch examined belonged to hands movement trials or feet movement trials, the Area Under Curve (AUC) of Receiver Operating Characteristic (ROC) curve was assessed using a 15-fold cross-validation design.
For the aim (b) both vertical and horizontal runs were analysed, allowing selection algorithm (stepwise) to choose features from both areas, hands and feet areas in combined manner for vertical runs and left and right hand areas in combined manner for horizontal runs. This analysis included six feature domains each one extracted from EEG signals pre-processed with one of six filters earlier defined and a new feature domain containing all (in sensorimotor strip and frequencies) features computed from EEG signals pre-processed by

 DOI: 10.3217/978-3-85125-533-1-18

longitudinal and transversal bipolar filters. The feature dimensionality reduction (stepwise regression), the classification (linear classifier) and the computation of performance index (AUC of ROC curve) followed the stages as proposed for (a).
For the aim (c) three representative subjects for which different spatial filters showed (for each subject) in (b) the same classification performances were identified. The number of electrodes needed to realize the hardware montage containing the eight (as earlier defined) optimal features was computed for each spatial filters.
Statistical analysis: To investigate the performances of different spatial filters in relation to the scalp areas, AUC values (in movement execution runs) were analysed by repeated measures two factors analysis of variance (ANOVA). The filter factor had six levels (the six filters earlier listed), the area factor had three levels (hands area, feet area, hand &feet area).
To the aim (b), for each task (vertical and horizontal task) AUC values were analysed by repeated measures two factors ANOVA in which filter factor had seven levels (6 filters listed earlier and the new filter obtained combining longitudinal and transversal bipolar filters) and modality factor two levels, the movement execution and imagination. Horizontal and vertical runs were studied separately.
The Tukey HSF post hoc analysis was conducted to assess pairwise differences. If not indicated otherwise, all results are presented as mean ± SE (standard error). For all statistical analysis, threshold for statistical significance was set to $p < 0.05$.

RESULTS

Spatial filters and scalp areas relation: The repeated measures two factors ANOVA of the AUC values revealed a significant effect of both filter ($F=28.72$, $p < 0.01$) and area ($F=52.43$, $p < 0.01$) factors and a significant area –filter interaction ($F=9.59$, $p < 0.01$). Figure 1 shows statistical analysis output and post-hoc tests result. The results are consistent with the findings in [6]: common average reference and large Laplacian methods are significantly superior to the ear-reference method.

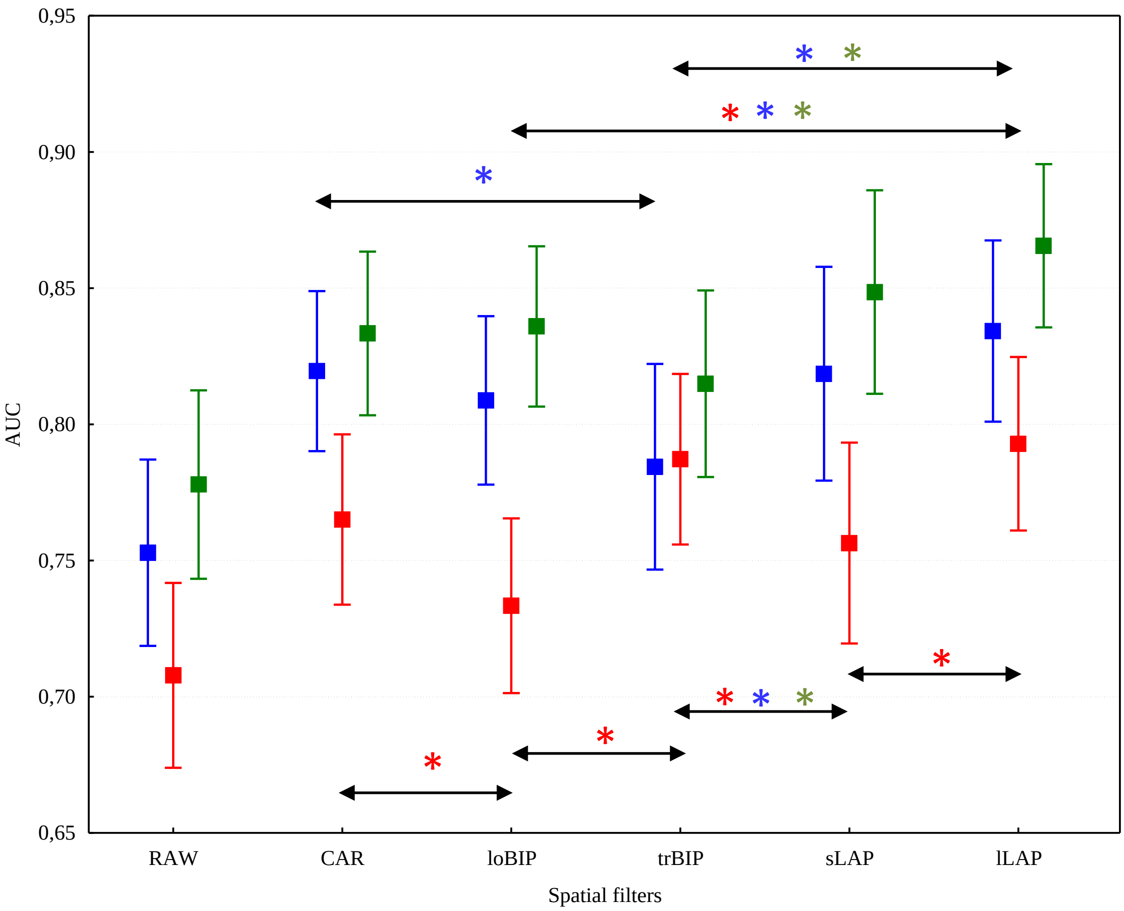

Fig. 1. Classification performance (AUC values of ROC curve) presented as mean ± SE (standard error) evaluated in movement execution vertical runs (hands opening/closing and feet flexion tasks) using features selected (by stepwise regression algorithm) from hands area (in blue), feet area (in red), both areas (in green) on EEG data no filtered (RAW), filtered with common average reference (CAR), longitudinal bipolar (loBIP) and transversal bipolar (trBIP) filters, surface Laplacian in its derivation small (sLAP) and large (lLAP). The symbol * shows the significant differences (p<0.05) pointed out by the Tukey HSF post hoc test. The colour of the symbol expresses the area in which this difference is significant. Although figure does not report the comparison between RAW and others filters, post-hoc tests confirm findings in McFarland et al., 1997.

 DOI: 10.3217/978-3-85125-533-1-18

Table 1: List of the eight features selected (by stepwise algorithm) in the features domains obtained from EEG data filtered with small surface Laplacian (sLAP) and using both longitudinal and transversal bipolar filter feature domains (long + trans BIP, simultaneous use of multiple spatial filters). No statistical differences for this pair of filters from the previous analysis. Three representative subjects (S01, S02, S03) were considered for the comparison (results in table from movement execution of vertical runs, hand opening/closing and feet flexion). The AUC values, for each subject, are the same for both filters (sLAP and long+trans BIP). Channels positions are conformed with 10-20 International System. Each channel indicated in sLAP is the central electrode of the difference (e.g., C3 is the central electrode: the surface Laplacian involved its neighbours C1, C5, FC3, CP3).

	S01				S02				S03			
	sLAP chan – freq (Hz)		long + trans BIP chan – freq (Hz)		sLAP chan – freq (Hz)		long + trans BIP chan – freq (Hz)		sLAP chan – freq (Hz)		long + trans BIP chan – freq (Hz)	
1	C3	11	FC3-C3	11	CP4	11	FC4-C4	11	C4	13	FC3-C3	13
2	Cz	27	Cz-C2	13	CPz	25	CP4-P4	25	CP3	13	C2-C4	13
3	C4	13	Cz-CPz	29	C4	25	CPz-Cz	25	Cz	25	F5-FC5	17
4	C4	21	CPz-Pz	21	C3	13	C1-Cz	11	C6	11	TP7-CP5	27
5	Cz	21	FC3-C3	17	C2	29	CP3-P3	27	FC5	29	FC6-C6	13
6	FC3	31	FC1-C1	11	FC3	15	CP1-CPz	25	C3	13	C1-Cz	25
7	FC2	25	FC4-C4	21	CP4	25	FC4-C4	25	CP3	15	FC4-FC6	31
8	CP6	13	C1-Cz	11	Cz	27	F5-FC5	19	C6	27	CPz-CP2	29
Number of electrodes need to realize this hardware montage	21		10		22		12		22		15	

Simultaneous use of multiple spatial filters: The repeated measures two factors ANOVA of the AUC values revealed a significant effect of both filter ($F=22.13$, $p < 0.01$) and modality ($F=46.72$, $p < 0.01$) factors and a significant modality –filter interaction ($F=2.79$, $p < 0.05$). The post-hoc Tukey HSF test confirms findings in [6] about differences existing between apply and not apply spatial filters on EEG data. The tests disclose pairwise differences ($p < 0.01$) between the common average reference (mean=0.83) and the large surface Laplacian (mean=0.87), the longitudinal bipolar filter (mean=0.83) and the large surface Laplacian (mean=0.87), the transversal bipolar filter (mean=0.81) and the small surface Laplacian (mean=0.85), the transversal bipolar filter (mean=0.81) and the large surface Laplacian (mean=0.87) and, above all, between the transversal bipolar filter (mean=0.81) and the simultaneous use of longitudinal and transversal bipolar filters (mean=0.87). No significant differences were seen between performances obtained using features extracted from the new domain and those from the two variations (small and large) of the surface Laplacian filter.

Minimization of number of electrodes: Table 1 shows the comparison between the features selected from the new domain (longitudinal and transversal bipolar filters) and the small surface Laplacian domain for three subjects for which classification performance is the same for both domains.

DISCUSSION

Feature extraction and feature selection are crucial steps to ensure an optimal BCI system performance. When applying BCI to support clinical rehabilitation it is mandatory to comply with quality of EEG patterns reinforced via BCI training to promote post-stroke (good) plasticity leading to a better motor outcome. Yet, deployment of BCI systems with high level of usability enables the actual transfer of this technology in routine clinical usage.

In this study the spatial filters commonly used in BCI control were compared with filters commonly used in EEG clinical application (e.g., bipolar filters) in order to allow for a *handy* feature selection but still taking into account the physiological requirements specific for this BCI application.

Here, the relation between performances shown by several (BCI and clinical gold standard) spatial filters and sensorimotor strip areas, engaged in different tasks, was investigated. Considering scalp areas separately (i.e., hands area and feet area) highlights interesting differences (e.g., from longitudinal and transversal bipolar in the feet area) that do not emerge considering features in the sensorimotor strip altogether.

Our findings indicate that the comparison between the transversal bipolar and the small surface Laplacian filters showed different performances in the three scalp areas of interest analyzed. In particular, we found better performance for transversal bipolar filter in the foot area and for small surface Laplacian in the hand area. The identification of a best spatial filter is, therefore, related to the scalp area (its anatomical and functional properties) of interest and thus, improving performance can be pursued using specific filters for specific areas.

Further analysis will be oriented to investigate the reason why transversal bipolar filter shows better performance in the feet area.

In addition, these findings require a consolidation by exploring their use with other motor tasks (different from hand opening/closing and feet flexion, analyzed in this preliminary study) and/or imagined movements.

Furthermore, the integration of features information as in this case from longitudinal and transversal bipolar filters, led to an improvement of performance with respect to

 DOI: 10.3217/978-3-85125-533-1-18

considering each domain individually. Specifically, no differences were found between the performance obtained with the ***integration approach*** and those obtained with the surface Laplacian filters (i.e., the gold standard when scalp areas were considered all together). Moreover, comparing the number of electrodes needed to realize the hardware montage containing just the appropriate features for the rehabilitation (both in case of features selected from integrated approach and surface Laplacian filter), We suggest that the use of a new integrated approach for feature extraction and selection might enhance the usability of the BCI technology in the field of rehabilitation.
The next step to ultimately promote this approach to rehabilitation applications would be to analyze BCI data collected from stroke patients.

CONCLUSION

Different spatial filters show different performance in relation to the scalp areas of interest, suggesting that potentially useful information for optimal feature extraction in BCI contexts can be obtained taking into account neurophysiological aspects. This could be particularly relevant in the context of rehabilitation applications. Furthermore, to consider features from more than one feature domain improves classification performance and, comparing filters at same performance level, allows to reduce the number of electrodes, improving the usability of BCI technology. For these reasons, we suggest that the a priori choice of one spatial filter might not be optimal for BCI rehabilitation applications.

ACKNOWLEDGEMENTS

This work was funded in part by the Sapienza University of Rome - Progetti di Ateneo 2015 (C26A15N8LZ).

REFERENCES

[1] Daly JJ and Wolpaw JR. Brain-computer interfaces in neurological rehabilitation. The Lancet Neurology 2008; 7(11) pp. 1032-1043.

[2] Cincotti F, Pichiorri F, Arico P, Aloise F, Leotta F, de Vico Fallani F et al. EEG-Based Brain-Computer Interface to Support Post-Stroke Motor Rehabilitation of the Upper Limb. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2012, 4112–15.

[3] Pichiorri F, Morone G, Petti M, Toppi J, Pisotta I, Molinari M et al. Brain-computer interface boosts motor imagery practice during stroke recovery. Annals of Neurology 2015; 77 (5): 851–65.

[4] Wolpaw J and Wolpaw EW. Brain-Computer Interfaces: Principles and Practice. Oxford, 2012.

[5] Bashashati A, Fatourechi M, Ward RK, Birch GE. A survey of signal processing algorithms in brain-computer interfaces based on electrical brain signals. Journal of Neural Engineering 2007; 4(2): R32-R57.

[6] McFarland DJ, McCane LM, David SV and Wolpaw JR. Spatial Filter Selection for EEG-Based Communication. Electroencephalography and Clinical Neurophysiology 1997; 103 (3): 386–94.

[7] McFarland DJ. The advantages of the surface Laplacian in brain-computer interface research. International Journal of Psychophysiology 2015; 97: 271-276.

[8] Schalk G, McFarland DJ, Hinterberger T, Birbaumer N and Wolpaw JR. BCI2000: A General-Purpose Brain-Computer Interface (BCI) System. IEEE Transactions on Biomedical Engineering 2004; 51 (6): 1034–43.