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Spatiotemporal Source Tuning Filter Bank for Multiclass EEG based Brain Computer Interfaces

Soumyadipta Acharya, Mohsen Mollazadeh, Kartikeya Murari and Nitish Thakor

Abstract— **Non invasive brain-computer interfaces (BCI) allow people to communicate by modulating features of their electroencephalogram (EEG). Spatiotemporal filtering has a vital role in multi-class, EEG based BCI. In this study, we used a novel combination of Principle Component Analysis, Independent Component Analysis and Dipole Source Localization to design a Spatiotemporal Multiple Source Tuning (SPAMSORT) filter bank, each channel of which was tuned to the activity of an underlying dipole source. Changes in the Event-Related Spectral Perturbation (ERSP) were measured and used to train a linear Support Vector Machine to classify between four classes of motor imagery tasks (left hand, right hand, foot and tongue) for one subject. ERSP values were significantly ($p<0.01$) different across tasks and better ($p<0.01$) than conventional spatial filtering methods (Large Laplacian and Common Average Reference). Classification resulted in an average accuracy of 82.5%. This approach could lead to promising BCI applications such as control of a prosthesis with multiple degrees of freedom.**

I. INTRODUCTION

A brain-computer interface (BCI) provides a novel channel of communication and control for people with severe neuromuscular disabilities. In non-invasive BCIs, users learn to convey their intent by modulating certain features of their electroencephalogram (EEG). Current EEG based BCI systems have been developed using sensorimotor rhythms (μ and β) [1], [2], P300 potentials [3], slow cortical potentials [4], etc. In spite of the potential benefits to end users, EEG based communication has limited bandwidth and accuracy due to the inherently low signal-to-noise ratio of any feature of interest in the EEG. Furthermore, due to volume conduction of the brain and attenuating effects of the scalp, it is difficult to extract information pertaining to the activity of well localized cortical regions. Spatiotemporal filtering methods such as Laplacian, Large Laplacian (LL) and Common Average Reference (CAR) help in scalp localization of EEG features, and have been shown to have an important role in BCI [5]. However, these are largely heuristic and fail to take into account individual neurophysiological and anatomical differences, especially those relating to neural sources.

We present a novel method for designing a Spatiotemporal Multiple Source Tuning (SPAMSORT) filter bank. Our approach uses a combination of Principle Component Analysis (PCA), Independent Component Analysis (ICA), and Dipole Source localization, to design a subject specific filter bank, each 'channel' of which, is 'tuned' to the activity from an underlying dipole source in the cortex. We applied our method to data from a multi-class motor imagery task and tested the hypothesis that the SPAMSORT approach significantly improves feature extraction and thus could facilitate development of a BCI with multiple degrees of freedom.

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All the authors are with the Department of Biomedical Engineering, Johns Hopkins University, Baltimore, MD, USA. (e-mail: {acharya, mohsenm, kartik, nitish}@jhu.edu) Corresponding author Soumyadipta Acharya (Phone: 410-955-0077)

II. METHODS

A. Data description

Multi-class motor imagery data were obtained from the data set IIIa from the BCI competition III made available by the laboratory of Dr. Gert Pfurtscheller [6]. Sixty channels of event related potentials were recorded from a subject. The task consisted of performing motor imagery of the left hand, right hand, foot, or tongue in response to a cue. The order of the cues was random. The experiment consisted of 360 trials of 7 s each. As shown in Fig. 1, within a trial, the first 2 s were blank. At t=-1 s an acoustic stimulus indicated the beginning of the trial, and a fixation cross was displayed that stayed on till the end of the trial. From t=0 s an arrow to the left, right, up or down was displayed for 1 s and at the same time the subject was asked to imagine a left hand, right hand, foot or tongue movement, respectively, until the fixation cross disappeared at t=4 s. Trials were visually inspected for artifacts and the artifactual trials were labeled.

B. Preprocessing

The data contained discontinuities indicating saturation of the measuring equipment and breaks in recording. We performed linear interpolation of the data over individual discontinuities and filtered the interpolated data. We used an equiripple bandpass FIR filter in the 6-30 Hz band. Following this, trials which had been designated as artifacts were removed and the remaining trials were separated into four classes. Data not part of any trial were discarded. Finally, we were left with 298 trials with each class contributing either 74 or 75 trials.

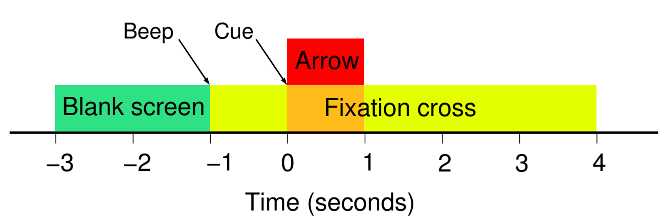

Fig. 1. Time course of the motor imagery task. The cue occurs from t=0 to t=1 s.

C. Independent Component Analysis

ICA is a statistical method that transforms observed multivariate data into components that are maximally independent [7]. It was first applied to EEG signals for blind separation of auditory event related potentials [8] and is now commonly used for removing noise and artifacts from the EEG signals [8]. Since the components are statistically independent, ICA is stronger than other classical methods such as PCA that just look for uncorrelatedness of transformed data. The goal is to recover independent sources from the observed sources,

$$\mathbf{x}(\mathbf{t}) = \mathbf{A}\mathbf{s}(\mathbf{t}) \tag{1}$$

where $\mathbf{x}(\mathbf{t})$ are the observed sources (recorded EEG signals), $\mathbf{A}$ is the mixing matrix and $\mathbf{s}(\mathbf{t})$ are the unknown source components. Solving the ICA problem using the infomax algorithm [9] finds a square matrix by gradient ascent that maximizes the joint entropy (or minimizes the mutual information) among the data projections,

$$\mathbf{s}(\mathbf{t}) = \mathbf{W}\mathbf{x}(\mathbf{t}) \tag{2}$$

where $\mathbf{W}$ is the unmixing matrix.

D. Filter Bank Design

The goal was to design a subject-specific, multi-channel spatial filter bank, such that each channel of the filter bank is tuned to the μ band activity emanating from the region of the motor cortex responsible for the corresponding motor task.

The data were separated into the 4 different types of motor imagery trials. For each category, the first step was to use PCA to separate the EEG into an optimal signal and noise subspace. This was followed by ICA decomposition of each class of data. The physiologically relevant component was selected by inspection, based on its scalp activation pattern and its corresponding equivalent dipole location. Usually, an independent component related to a motor area should have a dipole-like scalp map, i.e. the estimated dipole should have a reasonable position inside the motor cortex and the residual variance of estimation should not be high (10% threshold was set in our case) [10].

The selection was cross-validated by finding the component that contributed the maximum variance towards the relevant electrode of the raw data. To elaborate, in the right hand trials we expected to see activity around the C3 electrode. Fig. 2 shows the relative contributions of all the components at the 11 Hz frequency in the C3 electrode and the scalp activity maps for the three strongest components (1, 3, and 6) in this trial. As observed in the figure, component 6 is localized around the C3 area and accounts for 67% of variance at this electrode. The components chosen visually in all 4 classes had the maximum variance relative to the other components. The optimum number of principle components (PCs) were chosen to maximize the variance of the desired component in the related electrode (for the above case, component 6 at C3 electrode). An average of 16 components was generated for each class (12 for foot to 20 for left hand trials) and they accounted for an average of 55% of variance (45% for foot to 67% for right hand trials). From each of the 4 ICA decompositions, one component was chosen according to the previously described guidelines.

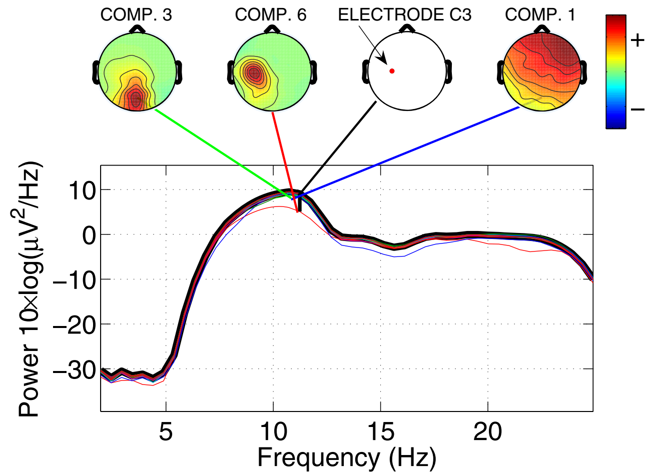

Fig. 2. Power contributions of all the independent components at 11 Hz (center of μ band) towards the C3 electrode from right hand motor-imagery trials. Scalp maps for the three strongest components are shown. Component 6 corresponds to the contralateral activation and accounts for 67% of the variance at C3.

These four components were combined into a new 4×60 matrix, which decomposes the sixty channels of raw EEG into four channels.

$$\hat{\mathbf{s}}(\mathbf{t}) = [F_L\ F_R\ F_F\ F_T]^T\, \mathbf{x}(\mathbf{t}) \tag{3}$$

where $\hat{s}(t)$ denotes the activity emanating from the four different motor cortical regions corresponding to left hand, right hand, foot and tongue. F_L, F_R, F_F, F_T are the respective channels of the SPAMSORT filter bank which optimally extracts such activity.

E. Feature Extraction: Event Related Spectral Perturbation

Event Related Spectral Perturbation (ERSP) [11] of all trials was calculated using EEGLAB v4.515 toolbox [12] to measure the mean event related changes in the power spectrum of the desired component.

$$ERSP(f,t) = \frac{1}{n}\sum_{k=1}^{n} |F_k(f,t)|^2 \tag{4}$$

where for n trials, $F_k(f,t)$ is the spectral estimate of trial k at frequency f and time t. Frequency analysis was done with a Hanning window sinusoidal wavelet, 3 cycles in length at the lowest frequency (3 Hz), increasing linearly with frequency up to 9 cycles for the highest frequency plotted (35 Hz). To normalize the spectral estimate, the mean baseline spectrum calculated during the 1000 ms pre-stimulus was subtracted from each spectral estimate, resulting in the baseline normalized ERSP.

The features for our classification were the average values of the log transformed ERSP (in dB) calculated in a time-frequency window. The time window was from 1.2 to 2.8 s.

The frequency limits were 10.5 and 12.5 Hz, corresponding to the μ band of this subject.

F. Statistical Significance

Paired t-tests (p<0.01) were performed for all trials to detect significant differences in ERSPs generated (for individual trials) by the SPAMSORT, CAR and Large Laplacian filtering methods. Multiple t-tests were performed (p<0.01) to detect significant differences in the ERSP generated by a given channel in response to different types of trials.

G. Classifier

Support Vector Machines (SVM) are a new technique [13], [14] for data classification. An SVM maps training data into a higher dimensional space using the Kernel function. It then finds a linear separating hyperplane with the maximal margin in this higher dimensional space. We use a soft margin C-SVM [14] to classify the data. Given the training data $x_i, i = 1, 2...l$ where $x_i \in R^n$ and the training labels $y_i = \{1, -1\}^l$, training the SVM requires the solution to the following optimization problem.

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \tag{5}$$

subject to,

$$\begin{aligned} y_i \left(w^T \phi\left(x_i\right) + b \right) &\geq 1 - \xi_i, \\ \xi_i &> 0 \end{aligned}$$

where w and b define the hyperplane, ξ is the error term and $C > 0$ is the penalty for the error term. $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ is the kernel function with ϕ being the function that projects the data into the higher dimensional space. Our implementation of a four class SVM was based on the LIBSVM library [15]. We used a linear kernel $K(x_i, x_j) = x_i^T x_j$. Of the 298 total cases, we used 240 (60 from each of the four classes) for training and the remaining 58 for testing. The training data were randomized prior to training. Three SVMs were trained using the ERSP features that had been generated using the CAR, LL and SPAMSORT methods. The confusion matrices $\mathbf{C}$ of all the three SVMs were generated,

$$C(i, j) = P(\mathbf{x} \text{ in } j | \mathbf{x} \text{ in } i) \tag{6}$$

where $\mathbf{x}$ is a test case and i and j denote classes.

III. RESULTS

Fig. 3a compares the mean ERSPs generated by each channel of the SPAMSORT filter with those generated by similar channels of CAR and LL filters. The ERSP by SPAMSORT is significantly larger (p<0.01) for all types of trials except for tongue movement (p=0.87). Fig. 4 illustrates this effect on an average of 60 trials of left hand motor imagery. One can see the sharper localization of μ band ERSP by our method. Fig. 3b shows the mean ERSPs generated by each channel respectively, in response to the four different types of motor imagery tasks. The ERSP generated in the channel that is tuned to the corresponding motor imagery task is significantly different (p<0.01) from that generated by other tasks, except for the tongue channel with foot imagery (p=0.9). Fig. 5 illustrates an example of the ERSP generated by the four channels of the SPAMSORT filter bank in response to a single trial of left hand motor imagery task. The largest ERSP is generated in the channel tuned to left hand motor imagery, as can be seen clearly in the time frequency plots. Table I shows the confusion matrices generated by the three trained SVMs. Average classification accuracy for SPAMSORT, CAR and LL methods were 82.5%, 65.25% and 70.47% respectively.

IV. DISCUSSION

We presented a general framework for designing a subject specific spatiotemporal filter bank to optimally extract multiple source activity from the EEG. This was demonstrated to be superior to existing heuristic spatial filtering methods,

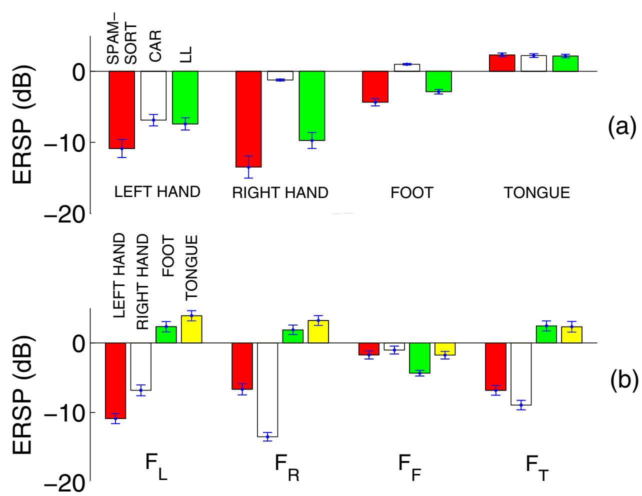

Fig. 3. (a) Mean ERSP values for the four different types of motor imagery trials obtained by SPAMSORT, CAR and LL. SPAMSORT significantly improves ERSP extraction. (b) Mean ERSP generated by the four channels of SPAMSORT in response to different types of trials. F_L, F_R, F_F, F_T refer to the SPAMSORT channels tuned to left, right, foot and tongue activity respectively. Significantly larger ERSP is generated by the filter channel tuned to the respective motor imagery task.

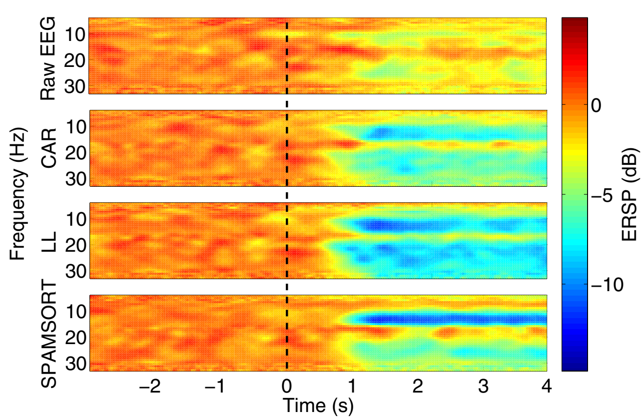

Fig. 4. Average time frequency plots of ERSP for the left hand motor imagery trials. Note the sharper μ band ERSP extracted by SPAMSORT.

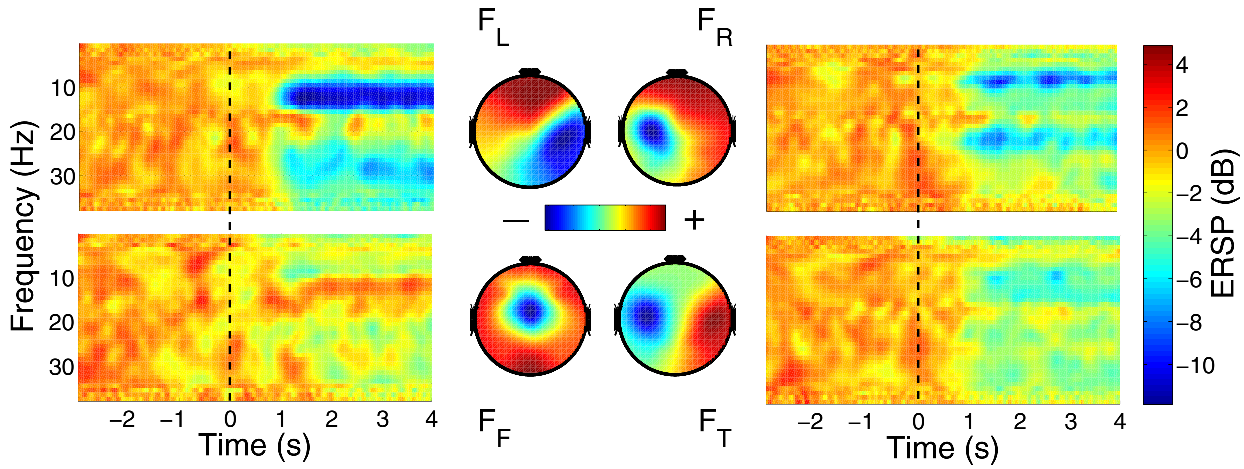

Fig. 5. Scalp maps of the four channels of SPAMSORT (F_L, F_R, F_F, F_T) depicting the scalp projections of the dipoles to which each filter channel is tuned. The corresponding time-frequency plots depict their activity in response to a single trial of left hand motor imagery. Note the strong μ band ERSP generated by F_L.

TABLE I

CONFUSION MATRICES GENERATED BY THE SVM FOR FEATURE SPACES GENERATED BY CAR, LL AND SPAMSORT.

	Percentages				
	Left	*Right*	*Foot*	*Tongue*	
Left	50.0	35.7	0.0	14.3	CAR
Right	6.7	93.3	0.0	0.0	
Foot	6.7	6.7	53.3	33.3	
Tongue	7.1	7.1	21.4	64.4	
Left	64.3	21.4	14.3	0.0	LL
Right	6.7	93.3	0.0	0.0	
Foot	13.3	0.0	60.0	26.7	
Tongue	14.3	0.0	21.4	64.3	
Left	78.5	7.2	0.0	14.3	SPAMSORT
Right	6.7	93.3	0.0	0.0	
Foot	6.7	6.6	86.7	0.0	
Tongue	7.1	0.0	21.4	71.5	

both in terms of feature extraction and classification accuracy. One of the possible drawbacks could be its purely data driven nature. Further studies with more subjects are needed to comment on the universal applicability.

The novelty of this method lies in the way ICA is used seperately for different classes of data and that equivalent dipole source localization and data variance is used to select an optimal component accounting for the neural source of interest. Solving the inverse problem of source localization is not feasible in real time (as is needed for a BCI application), but the SPAMSORT method allows for real-time tuning of individual source activity. This could facilitate the development of exciting BCI applications including control of prosthetic limbs with multiple degrees of freedom.

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REFERENCES

[1] J. R. Wolpaw, D. J. McFarland, G. W. Neat, and C. A. Forneris, "An EEG-based brain-computer interface for cursor control," *Electroenc. Clin. Neurophys.*, vol. 78, no. 3, pp. 252–59, 1991.

[2] G. Pfurtscheller, C. Neuper, A. Schlögl, and K. Lugger, "Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters," *IEEE Trans. Rehab. Eng.*, vol. 6, no. 3, pp. 316–25, 1998.

[3] E. Donchin et. al., "The mental prosthesis: Assessing the speed of a P300 based brain computer interface," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 174–79, 2000.

[4] N. Birbaumer et. al., "A thought translation device for the completely paralyzed," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 190–93, 2000.

[5] D. J. McFarland, L. M. McCane, S. V. David, and J. R. Wolpaw, "Spatial filter selection for EEG-based communication," *Electroenc. Clin. Neurophys.*, vol. 103, no. 3, pp. 386–94, 1997.

[6] A. Schlögl, F. Lee, H. Bischof, and G. Pfurtscheller, "Characterization of four-class motor imagery EEG data for the BCI-competition 2005," *Journal of Neural Engineering*, vol. 2, no. 4, pp. L14–L22, 2005.

[7] A. Hyvarinen and E. Oja, "A fast fixed point algorithm for independent component analysis," *Neural Comput.*, vol. 9, pp. 1483–93, 1997.

[8] S. Makeig, A. J. Bell, T. P. Jung, and T. J. Sejnowski, "Independent component analysis of electroencephalographic data," in *Adv. Neural Inf. Proc. Ss.* (D. Touretzky, M. Mozer, and M. Hasselmo, eds.), vol. 8, pp. 145–51, 1996.

[9] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural Comput.*, vol. 7, pp. 1129–59, 1995.

[10] S. Makeig and A. Delorme, "Electroencephalographic brain dynamics following manually responded visual targets," *PLoS Biology*, vol. 2, pp. 747–62, 2004.

[11] S. Makeig, "Auditory event-related dynamics of the EEG spectrum and effects of exposure to tones," *Electroen. Clin. Neurophysiol.*, vol. 96, pp. 283–93, 1993.

[12] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics," *J. Neurosci. Methods*, vol. 134, pp. 9–21, 2004.

[13] B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A training algorithm for optimal margin classifiers," in *COLT '92: Proceedings of the fifth annual workshop on Computational learning theory*, (New York, NY, USA), pp. 144–152, ACM Press, 1992.

[14] V. N. Vapnik, *The nature of statistical learning theory*. New York, NY, USA: Springer-Verlag New York, Inc., 1995.

[15] C.-C. Chang and C.-J. Lin, *LIBSVM: a library for support vector machines*, 2001. Software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`.