Multi-direction Hand Movement Classification Using EEG-based Source Space Analysis

Vikram Shenoy Handiru[1], A. P. Vinod[2] and Cuntai Guan[3]

Abstract— **Recent advances in the brain–computer interfaces (BCIs) have demonstrated the inference of movement related activity using non-invasive EEG. However, most of the sensor-space approaches that study sensorimotor rhythms using EEG do not reveal the underlying neurophysiological phenomenon while executing or imagining the movement with finer control. Therefore, there is a need to examine feature extraction techniques in the cortical source space which can provide more information about the task compared to sensor-space. In this study, we extend the traditional sensor-space feature extraction method, Common Spatial Pattern (CSP), to the source space, using various regularization approaches. We use Weighted Minimum Norm Estimate (wMNE) as a source localization technique. We show that for a multi-direction hand movement classification problem, the source space features can result in an increase of over 10% accuracy compared to sensor space features. Fisher's Linear Discriminant (FLD) classifier with the One-versus-rest approach is used for the classification.**

I. Introduction

Brain Computer Interface (BCI) technology has gained a lot of attention in the recent years owing to its wide applications, especially in the area of neurorehabilitation. BCI technology translates the neural signals into control commands to drive the external effectors. With the recent advances in signal processing, machine learning, and neurophysiology, researchers have demonstrated the successful decoding of hand movement in multiple directions and speed, thus opening up the possibilities of BCI control commands in higher dimensions with finer control [1],[2]. To obtain features corresponding to finer control commands, EEG source imaging (ESI) or source localization (ESL) is shown to be promising as it helps in localizing the cortical sources using the information obtained from sensor space [3],[4]. Since EEG sensor data is very noisy and lacks sufficient discriminative information at first look, it is transformed into different subspace using Common Spatial Pattern (CSP) to find the patterns that have high marginal maximization between two distinct tasks [5]. However, the conventional CSP approach is sensitive to outliers and not very robust to noisy trials. Thus, there are several variants of CSP, which include regularization [6], [7], Filter bank CSP [8], and many others. Although there have been several studies focussing on CSP modeling in the sensor space, hardly any study investigated the possibility of using the EEG-based discriminative cortical patterns to classify the challenging tasks such as multi-direction arm movement, to the best of our knowledge. It is necessary to have spatial information much more than just the scalp topography to achieve higher classification accuracy in multiclass movement related tasks. It is because the cortical activation regions corresponding to such complex tasks are often overlapping and located very close to each other inside the cortex [9]. Although fMRI can provide very high spatial resolution, it has poor temporal resolution, thus not suitable for real-time applications in BCI. As EEG in sensor space also does not provide much information regarding the cortical source responsible for a very particular task, inverse modeling can be useful to localize the active cortical sources from the obtained scalp EEG signal. Since the number of cortical sources outweighs the number of EEG channels, this inverse problem becomes ill-posed. Given this issue, apriori information about the number of dipoles, volume conductivity, region of interest (ROI) and other regularization parameters are used to minimize the unknown variables.

In this paper, we present the source space analysis to improve the performance of multi-direction hand movement classification using EEG. We extend the classical CSP technique in source space by examining different regularization approaches. With this, we extract the cortical features associated with hand movement in 4 directions. The remainder of this paper is as follows: Section II presents the Experimental setup and Data Acquisition; Section III describe the source space analysis and the feature extraction. Section IV presents the results and discussion. Section V concludes this paper with possible future directions.

II. Experimental setup and Data Acquisition

The experimental tasks involved 2-D center out reaching of the right hand in 4 orthogonal directions (North (N), South (S), East (E) and West (W)), using the MIT-MANUS robot. The experimental setup is same as the one presented in [2]. EEG data of 7 subjects are collected at the Brain Computer Interface lab at Institute for Infocomm Research, Singapore. Data recording is done using Neuroscan SynAmps 128 channel EEG amplifier at a sampling rate of 250 Hz. Electrooculography (EOG) is also recorded, to minimize the effect of eye movement-related artifacts. The continuous signal recording is bandpass filtered from 0.5Hz to 40Hz using 5th order zero-phase Butterworth filters covering frequency bands ranging from delta to low gamma. EEG trial segmentation is done based on the trial code and the time

[1]Vikram Shenoy Handiru is with the Nanyang Institute of Technology in Health and Medicine (NITHM), Interdisciplinary Graduate School, Nanyang Technological University, Singapore e-mail: vikram002@e.ntu.edu.sg). [2]A. P. Vinod is with the School of Computer Science and Engineering, Nanyang Technological University, Singapore. [3]Cuntai Guan is with the Institute for Infocomm Research, Agency for Science, Technology and Research (A*STAR), Singapore, and School of Computer Science and Engineering Nanyang Technological University, Singapore.

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markers. A total of 160 trials (4 class × 40 trials) per subject is epoched, except for the last subject where only 140 trials were recorded. The epoched filtered data is further spatially filtered using Surface Laplacian [10], followed by artifact removal using Independent Component Analysis.

III. Methodology

A. *Source space analysis*

EEG source space information is not directly observable from the scalp recordings. Therefore, it requires inverse modeling to find the cortical source activation. Prior to this, forward modeling is required wherein a particular head model is configured using the information from electrode location and subject-specific anatomy. A procedural block diagram of the proposed method is shown in Fig. 1.

1) *Forward Head modeling:*

3 layered (skull, scalp, and brain) spherical model is used for forward modeling with the conductivity values of 0.0125 S/m, 1 S/m, and 1 S/m respectively [11]. Symmetric Boundary Element method (sBEM) in OpenMEEG [12] is used to interpolate the triangular meshes. Formulation of EEG Source Localization is described by (1),

$$\phi = L_f X + \varepsilon \tag{1}$$

where, φ is the observed scalp EEG recordings of dimensions N (Channels) × t (time samples), L_f is the lead field matrix of dimension $N \times 3s$, where 's' is the dipole orientation in x, y and z-axes. L_f describes the relationship between the scalp surface potentials and the cortical activity. X gives us an estimation of surface potentials for unit source component activations with respect to the human head geometry and dipole electrical field propagation properties across different tissue types. ε is the noise perturbation term which can be modeled using trial-based noise covariance matrix. Since our study does not involve fMRI scans of the subjects, we use the Talairach human brain atlas as registered in ICBM 152 template [13], a nonlinear average of MRI scans of 152 healthy subjects. Brainstorm toolbox [14] is used to implement this source modeling with 15002 voxels (N_{source}).

2) *Inverse Source Modeling:*

We use the weighted minimum norm estimation (wMNE) for inverse modeling [15]. wMNE, a compensated form of minimum norm estimate also accounts for the activation of dipoles at the cortical surface in addition to the deeper ones. wMNE is mathematically represented as in (2):

$$D_{wMNE} = (L_f^{\,T} L_f + \alpha W^T W)^{-1} L_f^{\,T} \phi \tag{2}$$

where, L_f is lead field matrix, α is a regularization parameter, W is the weight matrix computed by taking the norm of columns of the lead field matrix L_f. Noise covariance matrix for each trial is used while estimating the source activation. Then the source kernel matrix D_{wMNE} is multiplied with the observed recordings to obtain the time-series information in the source space. Furthermore, dynamic Z-score normalization is performed on the baseline (pre-cue signal from -1 to 0s).

3) *Region of Interest (ROI) for functional modeling:*

Brodmann area BA6, which covers the dorsal premotor cortex in both the hemispheres, is chosen as the region of interest since it is shown to be associated with the direction of voluntary arm movement [16], [17]. Out of 15002 voxels resulted in the source kernel, only 296 voxels corresponding to the left and right premotor cortex are used for further feature extraction. These voxels can be considered analogous to the channels in the source space. Time series information from these voxels is further utilized in the feature extraction stage.

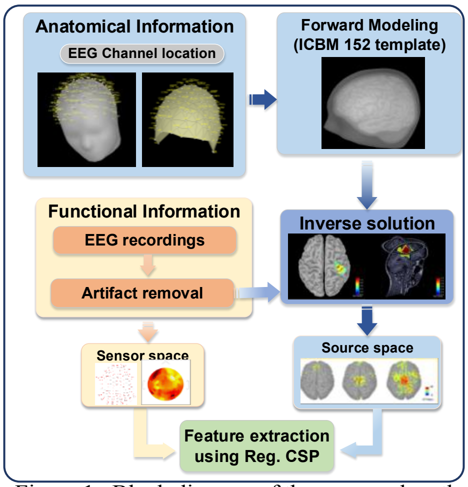

Figure 1. Block diagram of the proposed method.

B. *Feature extraction*

Since traditional approaches use different variants of the CSP algorithm for feature extraction, we investigated CSP with and without regularization method in the sensor as well as source space. Overall, three different techniques namely CSP, Tikhonov regularized CSP (TRCSP) and Shrinkage Regularized CSP (SRCSP) are compared in both domains. CSP is a spatial filtering algorithm which learns the spatial filters by maximizing the variance of EEG signals from one class while minimizing the variance from other class. Formulation of CSP is as shown in (3) [18]:

$$J(w) = \frac{w^T C_1 w}{w^T C_2 w} \tag{3}$$

where, C_i is the covariance matrix of class 'i', and 'w' are the spatial filters. However, CSP is sensitive to overfitting, and thus, it requires some form of regularization. There are several approaches which add regularization term to an objective function $J(w)$ or the covariance matrix (C_i) as shown in (4) and (5) respectively [6]. For this purpose, we chose TRCSP and SRCSP.

$$\hat{J}(w) = \frac{w^T C_1 w}{w^T C_2 w + \alpha P(w)} \tag{4}$$

$$C_c = (1-\gamma) C_i + \gamma I \tag{5}$$

Here, α is the regularization parameter used in Tikhonov regularization and γ is a parameter employed in Shrinkage regularization which regularizes the covariance matrices. Tikhonov regularization is a classical approach to regularization problems in which the solution with larger weights is penalized. TRCSP regularizes the objective function $J(w)$ with quadratic penalties $P(w)$, and the results show that TRCSP is very efficient compared to CSP among in comparison with other regularization approaches [6]. In addition to this, we also consider Shrinkage regularized CSP, which regularizes class-wise covariance matrix, where the shrinkage parameter γ in (5) can be analytically solved using Ledoit and Wolf's method [19]. SRCSP approach is shown to perform better especially when the training sets are small [7]. For TRCSP, we chose the regularization parameter α to be 10e-4 instead of finding it using the cross-validation. Although it is a heuristic approach to choosing a regularization parameter, it saves a lot of computation time. However, there is no need to select a regularization parameter for SRCSP as it has a closed form solution for the shrinkage parameter. Wavelet CSP with feature selection (WCSP-FS), which is another variant of CSP used in [2], is also examined in our study. Wavelet CSP aims at maximizing the objective function $J(w_b)$ as in (6):

$$J(w_b) = \frac{w_b^T C_1 w_b}{w_b^T C_2 w_b} \tag{6}$$

Here, w_b corresponds to the spatial filter for a sub-band 'b' of the wavelet decomposition of the EEG signal. Since the traditional CSP can solve for the objective function by optimizing the Rayleigh quotient for only two classes (C_1 and C_2), we use one-versus-rest approach to extract the features from 4 classes. For each class i, covariance matrix C_1 is calculated for trials corresponding to class i, while C_2 is computed for trials corresponding to $j \neq i$. After solving the Eigendecomposition problem for W, features F_p (p = 1... $2m$) are calculated as (8):

$$Z = W \times E \tag{7}$$

$$F_p = \log\left(\left[\operatorname{var}(Z_p) / \sum_{i=1}^{2m} \operatorname{var}(Z_p) \right] \right) \tag{8}$$

where, E corresponds to the time series data (source space or sensor space), and Z is the resultant subspace obtained by projecting E using the spatial pattern matrix W. Only first, and last two spatial filters (m=2) of W are used for feature computation. For WCSP, we have used mutual information based feature selection in which the number of features selected (k) are based on cross-validation with the objective of highest classification accuracy for the training data. Subsequently, these multiclass features are classified using the Fisher's Linear Discriminant (FLD) classifier with the one-versus-rest (OVR) approach in 5×5 cross validation. FLD classifier aims at maximizing the between-class scatter matrix S_B and minimizing the in-class scatter S_W [2].

IV. Results and Discussion

The average classification accuracies of 4-direction (North, South, East, and West) classification for 7 subjects (S01, S02, S03, S04, S05, S06, and S07) using our proposed method are shown in Table I and compared with the existing methods in the sensor space. It can be observed that the classification accuracies are significant compared to the chance level accuracy of 25%. When we investigate the results across feature space (source and sensor), the classification accuracies are much higher compared to that of sensor space for a given feature extraction technique. The highest mean classification accuracy of 70.95% for seven subjects was obtained using WCSP features in the source domain. Overall, there was at least 10% improvement in the classification accuracy when source space features are used as compared to sensor space features. We believe that the increase in classification accuracy in source space is due to the additive information of underlying neuronal activity. It is in agreement with the findings reported in [4]. Also, paired t-tests revealed that the classification performance using the features of variants of CSP (with and without regularization) in source space is statistically significant compared to their sensor space counterparts ($p < 0.05$). However, when we use W-CSP with the cross-validated feature selection parameters as proposed in [2], we observe only a marginal improvement ($p > 0.05$) in the source space compared to sensor space. This could be due to the careful parameter selection (k) in the WCSP-FS in the sensor space. It is to be noted that the number of features responsible for highest training accuracy in sensor space may not be the same as in the source space.

TABLE I. AVERAGE PERCENTAGE CLASSIFICATION ACCURACY OF 4-DIRECTION CLASSIFICATION USING FLD CLASSIFIER (5×5 CROSSVALIDATION)

Subjects	Sensor Space				Source Space			
	CSP	*TRCSP*	*SRCSP*	*WCSP-FS(k=13)*	*CSP*	*TRCSP*	*SRCSP*	*WCSP-FS(k=13)*
S01	36.87	56.12	54.37	87.87	67.87	70.87	53.5	91
S02	34.12	30.87	49.25	73.25	36	48.25	63.12	73.25
S03	35.75	51.37	57.37	68.25	56	59.5	67.62	67.5
S04	29	34.75	47	71.87	30.87	63	67.25	69.87
S05	33	35.75	47	60.87	38.12	51.5	56.5	61.37
S06	38.37	51.12	44	77.62	49	67.12	59.87	79.25
S07	37.25	45.28	66.42	55.85	51.71	62.71	71.28	54.43
Mean	34.9	43.61	52.20	70.80	47.8	60.42	64.98	70.95

In Fig. 2, amplitude variation of the left premotor cortex and the right premotor cortex averaged over trials corresponding to different arm movement directions is shown. It is to be noted that the pre-cue signal is attenuated because of the dynamic Z-score normalization which suppresses the baseline. It gives an indication of the post-cue signal relative to the baseline. Furthermore, the amplitude variation responses shown in Fig. 2 are the average response of all the voxels corresponding to scouts BA 6L (left premotor cortex) and BA 6R (right premotor cortex) respectively. Also, we investigated the wavelets features to find which frequency bands that provide the most discriminative information. Based on the cortical activation averaged over all the dipoles within the ROI, we found out that the delta band (< 4Hz) is discriminative, as shown in Fig. 3. It concurs with the findings reported in [1].

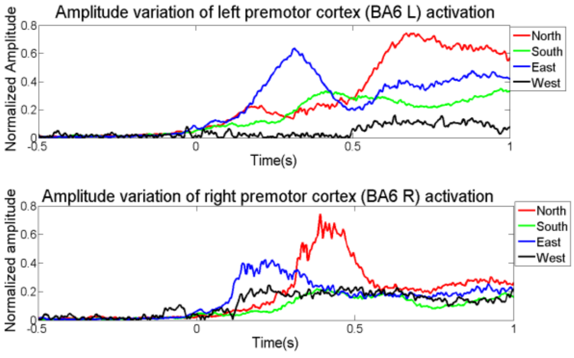

Figure 2. Mean amplitude variation response of Left and right premotor cortex for hand movement in 4 directions.

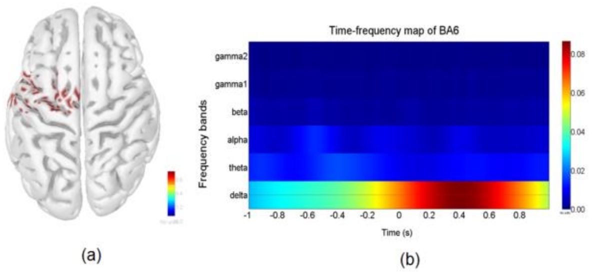

Figure 3. (a) Statistically significant activation ($p < 0.01$) shown at the cortical surface, (b) Morlet Wavelets decomposition corresponding to the averaged response in Brodmann Area 6.

V. CONCLUSION AND FUTURE WORK

In this study, we have presented the use of cortical source space features to analyze complex arm movement parameters like direction classification. We compared the traditional sensor space methods with corresponding features in the source space and we have shown that the source space features can provide better classification accuracy for the challenging classification tasks of hand movement in different directions. In addition to the better classification performance, we presented that the source space can make use of the underlying neurophysiological phenomenon as a priori for better data modeling. Instead of a data-driven approach to finding the ROI, we used the functional information of dorsal premotor cortex to guide us towards direction decoding. Different approaches involving regularization of an objective function and the covariance matrix are compared in this study in both feature space to evaluate the robustness of our proposed method. Certainly there is a scope for further improvement in the classification accuracy using robust feature selection techniques.

In future, we intend to examine the source space features for challenging motor imagery tasks like reach out, grasp and release action. It would be interesting to see how these source localization algorithms can help us in obtaining the discriminative features in online experiments. Successful decoding of complex motor imagery tasks will certainly help in neurorehabilitation setups.

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