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Neurophysiological Predictors and Spectro-Spatial Discriminative Features for Enhancing SMR-BCI

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Abstract

Neural engineering research is actively engaged in optimizing the robustness of Sensorimotor Rhythms (SMR) –Brain Computer Interface (BCI) to boost its potential real-world use. This paper investigates two vital factors in efficient and robust SMR-BCI design – algorithms that address subject-variability of optimal features and neurophysiological factors that correlate with BCI performance. Existing SMR-BCI research using Electroencephalogram (EEG) to classify bilateral motor imagery (MI) focus on identifying subject-specific frequency bands with most discriminative motor patterns localized to sensorimotor region. A novel strategy to further optimize BCI performance by taking into account the variability of discriminative spectral regions across various EEG channels is proposed in this paper. The proposed technique results in a significant ($p < 0.007$) increase in average ($N = 10$) classification accuracy by 5.96 % accompanied by a considerable reduction in number of channels and bands. The session-to-session transfer variation in spectro-spatial patterns using proposed algorithm is investigated offline and classification performance of the optimized BCI model is successfully evaluated in an online SMR-BCI. Further, the effective prediction of SMR-BCI performance with physiological indicators derived from multi-channel resting-state EEG is demonstrated. The results indicate that the resting state activation patterns such as entropy and gamma power from pre-motor (fronto-central) and posterior (parietal and centro-parietal) areas, and beta power from posterior (centro-parietal) areas estimate BCI performance with minimum error. These patterns, strongly related to BCI performance, may represent certain cognitive states during rest. Findings reported in this paper imply the need for subject-specific modelling of BCI and the prediction of BCI performance using multi-channel rest-state parameters, to ensure enhanced BCI performance.

Keywords: Brain-Computer Interfaces, Electroencephalography, Discriminative spectro-spatial patterns, Neurophysiological predictors

1. Introduction

Brain-Computer Interface (BCI) is an augmented technology establishing a new mode of communication and control between brain and machines, bypassing the normal

pathway of nerves and muscles [1, 2]. During the last two decades, BCI has been extensively explored and has been found beneficial in medical [3-5] and non-medical applications [6-8]. Electroencephalogram (EEG) is a popular technique to acquire neurophysiological activity with high

temporal resolution and it has been used to decipher human thoughts and actions by accurately identifying their neural correlates [9]. A prominent type of BCI, namely sensorimotor rhythm (SMR)-BCI, uses mental rehearsal of movement or motor imagery (MI) to generate control signals. SMR-BCI studying activations in EEG has identified event related desynchronization/ synchronization (ERD/ERS) as the fundamental indicator of MI. ERD/ERS are the neural synchrony variations in contralateral and ipsilateral sensorimotor regions [12], and their presence is found to vary in temporal, spectral and spatial domains [13]. On account of this subject-specific nature of EEG patterns, robust signal processing and machine learning techniques are essential for accurate interpretation of signals which in turn create stable and reliable SMR-BCI. Additionally the investigation into how the physiological and psychological states affect SMR-BCI performance has garnered significant attention recently, since inconsistency among subject's performance is one of the major reasons that limits its practical use. Hence, it is necessary to investigate these challenging aspects of BCI – inadequacies in BCI algorithms and lack of user's skill or ability to generate stable patterns [14, 22].

EEG signal is nonstationary and has poor signal-to-noise ratio, with distinct subject-dependent parameters which makes optimized processing tool a necessity to achieve enhanced performance. Algorithms and technologies adopted in the BCI systems should be able to track the variabilities of the signals and robustly transform the identified tasks into intended outputs for successful BCI operation. One of the most cited methods is Filter Bank Common Spatial Pattern (FBCSP) which uses a set of band-pass filtered multi-channel EEG followed by its spatial transformation using Common Spatial Pattern (CSP) technique [16]. CSP is a spatial filtering approach which effectively addresses the low spatial resolution of EEG [17]. Various modifications to FBCSP are reported in literature [18-21] that focus on selection of time-frequency and spatial features which offers maximum discrimination between different limb movements. Discriminative FBCSP [13, 19] is a modified approach to FBCSP which identifies subject-specific discriminative bands, as opposed to use of fixed bands in FBCSP. This method selects spectral regions in central electrodes based on their discriminative power, which are then applied to all channels for further spectral and spatial filtering. Incorporating the selection of subject-specific frequency bands which are more discriminative to a set of channels may help to remove irrelevant information and will reduce the complexity in online processing.

Literature shows significance of central channels, C3 and C4 in classification of MI [26]. However, MI which is the covert simulation of movements, involves visual and cognitive processing along with motor processing which activates other cortical areas. Hence, contributions of other channels towards the discriminability of MI patterns must be taken into account. Motivated by this, to optimize spectro-

spatial information without compromising on performance, we propose a novel method that successively identifies subject-specific discriminative bands and channels. Preselection of either spectral or spatial information, followed by CSP spatial filtering has been reported in SMR studies [19]. However, an integrated approach that optimally selects both the subject-specific bands and channels, verified by inter-session and online performance, has hardly been reported.

Along with the system optimization techniques, the inherent physiological characteristics of users that attribute to SMR-BCI performance variation impacting its reliability are investigated in various studies [15, 22-25]. Literature reports the correlation of BCI performance with resting state alpha levels [22]. This denotes that the subject with higher alpha power, exhibits higher transition in SMR (μ) power relating to event related desynchronization with onset of movement imagination resulting in stronger features that can be accurately classified. Literature also reports resting state theta, alpha, beta and gamma rhythms to be neurophysiological indicators of BCI performance [23-25]. Correctness of prediction in terms of correlation coefficient between predictors and BCI performance reported in literature ranges from 0.4 to 0.7 [15]. The research reported in [15, 22-25] used resting-state EEG from individual channels or Laplacian filtered channels to define the predictors. There are indications in literature regarding the cognitive states that come into play during resting-state which are likely to influence BCI performance.

Literature reports that the modulations of spectral estimates of EEG in certain cortical areas indicates various cognitive states of user [27-29]. Theta activity in frontal midline areas and parietal areas are associated with focused internal attention and selective attention respectively [30-32], theta-beta ratio in frontal areas are negatively related to executive attentional control [30], synchronized alpha activity are observed during tasks requiring internal attention focus and short term memory retention tasks, and posterior gamma power modulated by cognitive coordination tasks [33]. Further, irregularity measure of EEG signal, such as Sample Entropy is employed to quantify the alertness of user during MI tasks. It is reported in [34-36] that higher sample entropy in EEG implies active engagement of the subject in the experimental task performed. The cognitive states during resting state can be considered to have characteristic cortical activations and hence a multi-channel approach might yield more relevant predictions as opposed to conventional methods. Hence, in this study we propose to compute multi-channel predictor models that offer minimum error of estimation of BCI performance. To the best of our knowledge, this approach has not yet been reported.

The remainder of this paper is organized as follows. Section 2 presents the experiment setup that is used to record EEG data. Section 3 introduces the details of the proposed algorithm Section 4 presents the results that demonstrate the performance of proposed algorithms. Section 5 discusses the

Fig. 1. Timeline for trials in calibration and feedback sessions.

results and reviews their significance. Finally, Section 6 summarizes the contributions of the paper.

2. Experiment and Analysis

2.1 Protocol and Timeline

An experiment that allows a subject to use a SMR-BCI system based on the bilateral hand movement was designed. The experiment included calibration and feedback sessions, designed to investigate SMR patterns of motor tasks, predictors of SMR-BCI performance and develop optimal BCI system for online SMR-based control. The calibration session was intended to record EEG signals to investigate the relevance of spectro-spatial optimization in SMR-BCI performance, thus creating an optimal BCI system that can be employed in feedback session. Ten subjects (3 females and 7 males, age 26.6 ± 5.5 years, all right-handed) participated in this study. This research was approved by the Institutional Review Board of Nanyang Technological University, Singapore (IRB-2016-07-019).

The calibration and feedback sessions were recorded on the same day from each subject, with 5-10 minutes interval between sessions. The participants were seated comfortably in a chair with arms placed on the armrest. EEG was recorded using BrainAmp actiCHamp amplifier from 31 electrodes placed on the scalp according to 10-20 system. The signals were sampled at 500Hz, and filtered with a band pass filter of 0.05 to 200 Hz. Twenty channels from the sensorimotor (SM) area were used in further analysis thereby excluding spurious interactions of physical limb/eye muscle artefacts in occipital and temporal electrodes. Each experiment started with a 20 seconds period in which subject was instructed to relax with eyes open. This was followed by the calibration session, which included 2 runs. For four subjects, the experiment proceeded with feedback session. The timeline for the sessions is indicated in Fig.1 and explained below.

The visual cues for the recording sessions displayed in Fig. 1 are as follows. Each trial started with a 2 second interval in which a white cross appeared in the center of the black screen. Subject was instructed to regard this as the visual fixation point. Following this, a green arrow pointing toward right or left appeared for one second and the subject was instructed to perform right or left hand movement task accordingly until the

cross disappears. The cross disappeared after 4 seconds, and the subject was instructed to relax. This rest period for 2 seconds marked the end of the trial, and this timeline is repeated for the entire run with task cues presented in random order. The calibration session consisted of two runs in which the subject was asked to imagine the motor task. The suggested actions were first hand imagination of clenching of right or left fist according to the cue received. The MI calibration runs had 50 trials each, resulting in 100 trials of bilateral MI tasks each. The data from MI calibration session was used to model BCI system for the feedback session. For the feedback session, the timeline was the same, except for the visual cue for feedback as indicated in Fig. 1. The feedback was given in the form of a horizontal blue directional progress bar that appeared once the arrow indicating task cue disappeared. The amplitude of bar was proportional to the confidence of prediction, and this amplitude variation is indicated by dotted white arrow in the figure. The online BCI system classified incoming data every 0.25 seconds and the predictions were accumulated to determine amplitude of bar at a given instance. The feedback session consisted of a single MI run with 50 trials.

2.2 Data Extraction and Analysis

As indicated earlier, EEG data from 20 channels are used in the study, namely {F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, C3, C4, CP5, CP1, CP2, CP6, P7, P3, Pz, P4 and P8}. A 2.5 second segment of data corresponding to motor task is extracted from each trial starting from the onset of task indicated by the appearance of arrow (time $t=0$) in Fig.1. This segment is further used in SMR classification. To study the neurophysiological predictors, literature reports the use of the data corresponding to 'relax with eyes open' task. In our study, we use the data from concatenated segments of relax state of tasks (-2 to 0 seconds of each trial) during the calibration runs to derive predictors. The choice of this predictor can guide towards future investigations of inter-trial variations of BCI performance, and identification of robust predictors.

The data is baseline corrected and band pass filtered from 2-40 Hz. Baseline correction removes the dc shift in the EEG, by subtracting the average pre-stimulus (1 second) data from it. Subsequent band pass filtering removes the various data artefacts such as powerline frequency and activity other than

motor cortical sources resulting in low frequency drift and high frequency contaminations. The following section explains the major contributions reported in this paper. The data used in each study are mentioned here for clarity. Section 3.1 reports the proposed algorithm to determine discriminative spectro-spatial features, and optimized subject-specific model for online BCI system. This study uses the data from MI calibration runs to validate the proposed algorithm and to create optimized BCI model used in feedback session conducted on 4 subjects. Section 3.2 reports the proposed approaches to BCI performance prediction. The analysis used all MI runs of calibration session, to study correlations between neurophysiological predictors and SMR-BCI performance for imagined tasks.

3. Methodology

In this section, we discuss the proposed methodology to create robust SMR-BCI system by optimizing it with subject-specific discriminative spectro-spatial patterns. Further, we discuss the proposed approach to investigate variation in SMR-BCI performance among subjects and its correlates with their neurophysiology.

3.1 Investigating discriminative spectro-spatial patterns in EEG specific to SMR

SMR-BCI research using EEG signals rely on data-driven optimization techniques to extract characteristic ERD/ERS activations associated with MI. The objective of such techniques is to isolate information that discriminates bilateral MI which is spread across multiple EEG channels and distinct frequency ranges masked by rhythms unrelated to MI task. Among these techniques, FBCSP which employs frequency band optimization, is found to be an effective methodology in most studies [16], and is used as a baseline method in our analysis. The objective of similar studies is to determine the subject-specific frequency ranges that offer discrimination between bilateral motor tasks specific to motor cortical regions [37]. Fisher's ratio (J) is a parameter that quantify the

discriminative quality of spectral regions and is defined as the ratio of between-class to within-class variance [13]. In J -based methods, the approach is to identify frequency bands with higher J values, which in turn corresponds to better discrimination between two classes, from relevant channels such as C3 or C4 [13, 19]. In the proposed method, bands that are optimal for a subset of channels, that consolidates the scattered information in spectro-spatial distribution of J to further enhance the discrimination, are determined. Here, retaining the information from channels C3 and C4, and mu (8-12 Hz) band, additional subject-specific discriminative spatio-spectral patterns are identified. Subsequently, the method eliminates less informative bands and channels from the data, thereby reducing the feature dimension to be used in the online feedback sessions. The steps involved in optimal BCI model generation are shown in Fig. 2 and explained below.

As shown in Fig. 2, EEG data recorded from each subject, is pre-processed initially. After pre-processing, spectro-spatial distribution of J is determined. The proposed Parameter Search algorithm then determines a subset of discriminative bands (n_f) and channels (n_c) based on J , as explained below:

The pre-processed EEG from C channels is obtained in the form of $\mathbb{R}^{S \times C \times T}$, where S is the number of samples per trial and T is the total number of trials in the data. We define 9 frequency bands ($F = 9$) in the range 4-8, 8-12, 12-16, 16-20, 20-24, 24-28, 28-32, 32-36 and 36-40 Hz, each denoted by $f, i \in [1 F]$.

- For a single-channel EEG, determine the spectral power in F bands for the class-specific trials, E_1 and E_2 (both $\in \mathbb{R}^{F \times T}$). E_1 and E_2 represent EEG signals during left hand and right hand MI respectively.
- Fisher's Ratio for each band in each channel was then calculated by, $J = \frac{T}{2} \cdot \frac{(\mu - \mu_1)^2 + (\mu - \mu_2)^2}{\sigma_1^2 + \sigma_2^2}$, where $\mu_{1/2}$ and $\sigma_{1/2}$ are mean and standard deviation of E_1 and E_2 across trials respectively and $\mu = (\mu_1 + \mu_2)/2$.
- Repeat the same steps for all the channels to determine Fisher's ratio denoted as, $\{J_{fc} \in \mathbb{R}^{F \times C}\}$.
- For each channel, identify bands corresponding to two high J values, other than mu band ($f = 2$).

Fig. 2. EEG signal processing schematic to create optimal BCI model comprising subject-specific spectro-spatial parameters, discriminative filters and classifier model.

Fig. 3. EEG signal processing pipeline in online-BCI system.

$$\hat{f}_c = \{f | J(f, c) = \max_{k=1 \text{ to } F, k \neq 2} J(k, c); J_{*,c} = J_{*,c} \cup f_{*,c}\}$$

until $|\hat{f}_c| = 2$.

- Repeat this for all channels, resulting in $2 \cdot C$ bands, $\hat{f} = \{\hat{f}_c, \forall c\}$. Determine $n_f - 1$ bands that appear most frequently in $\hat{f}$. These $n_f - 1$ bands and mu band constitute the most discriminative n_f bands.
- The average Fisher's ratio values in the n_f bands are calculated for each channel and denoted by $\hat{f}(c)$. We identify $n_c - 2$ channels with highest Fisher's ratio values by, repeating this,
$$\hat{c} = \{c | \hat{f}(c) = \max_{k=1 \text{ to } C, k \neq \{C3, C4\}} \hat{f}(k)\}, \hat{f} = \hat{f} \setminus \hat{f}(c), \text{ until, } |\hat{c}| = n_c.$$
 These $n_c - 2$ selected channels along with C3 and C4 constitute the most discriminative subject-specific n_c channels.
- This combination of n_f bands and n_c channels provides the most discriminative spatio-spectral pattern for this set of data.

In the proposed scheme, we fix the values of $n_f \in [2 \ 7]$ and $n_c \in [4 \ 16]$. For each combination of n_f and n_c , EEG signal from the corresponding bands and channels are extracted in the Data Extraction stage. An n_f -band filter bank is used to filter the n_c -channel EEG and the filtered signal serves as input to the CSP filter. The CSP algorithm [17] is then implemented and spatial filters corresponding to each band was obtained. For single-trial EEG, the features are derived in form of log-variance of spatially filtered signal, resulting in feature vector of dimension $4 \cdot n_f$ (4 is the parameter fixed in CSP algorithm). These features are further sent for classification using a linear Support Vector Machine (SVM) classifier [38]. We determine the classification performance for all combinations of n_f and n_c , from which the optimal subject-specific combination is selected.

The EEG from calibration session is used to validate the proposed approach. The proposed algorithm is validated by applying 5 runs of 5 fold cross validation. In each run, (i) dataset is divided into five groups ($k=1$ to 5) with equal number of trials and equally distributed labels, with no overlap between groups, (ii) for k^{th} fold, data from all groups except the k^{th} (training data), are used to train the BCI model –

{spectro-spatial parameters, n_f CSP filters each of length n_c and SVM classifier}, (iii) the model is then evaluated on the data from k^{th} group (test data), (iv) the procedure is repeated 5 times, such that all groups are evaluated. In the next run, the data is reshuffled and grouped again. This procedure is repeated till 5 runs are completed. The average classification performance in test data, over all the 5×5 folds is then computed and reported as the performance metric of our algorithm.

From the above approach, the variation in classification performance with changing n_f and n_c , is obtained. An optimal subset of spectro-spatial information, corresponding to peak classification accuracy can thus be determined, which can then be evaluated on an online BCI. The processing steps involved in online feedback session are displayed in Fig. 3. The data from calibration session, as mentioned earlier, is used to determine subject-specific BCI model that includes optimal number of bands and channels, spatial filters and classifier corresponding to the highest BCI performance. The relevant time segment (0 to 2.5 second) is extracted from the incoming data during the feedback session. The data extracted from selected frequency and channels are used to calculate features every 250 ms and is then applied to the classifier. The output of classifier, in terms of distance from classifier's hyperplane is accumulated and is translated into visual feedback as the amplitude of progress bar.

Considering, the non-stationarity of EEG signals, we performed an offline analysis to investigate the session-to-session transfer variation in spectro-spatial patterns and the performance of proposed algorithm. The EEG data from calibration session with two sessions of MI tasks, is used in this analysis. We investigate the transfer by calibrating the BCI using data from MI session 1 and evaluating this on data from session 2 and vice versa.

3.2 Analysis of Predictors

Associating BCI performance of users with their neurophysiological parameters quantifying motor skills and mental state of user, is a novel approach to understand BCI performance variation [15, 22]. The cognitive states of user during rest can be identified by parameters of EEG and their

modulation in certain cortical areas [27-31]. Here, we investigate the correlates of such neurophysiological parameters derived from multi-channel EEG with BCI performance and identify their relevance.

The BCI performance for this analysis, is calculated using the baseline FBCSP algorithm, as average classification accuracy over 5×5 cross-validation folds and denoted by $Y \in \mathbb{R}^{N \times 1}$. Here N is the number of subjects (samples). The set of multi-channel predictors is denoted by, $X \in \mathbb{R}^{N \times C}$, where X is calculated by the relative band powers and sample entropy from resting state data. We adopt a two-fold approach in which, the first fold uses resting state data from MI session 1 to calculate X and Y is BCI performance of MI session 2, and vice-versa for the second fold. For each rest data segment, theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), gamma (30-40 Hz) band power values and total power estimate of the EEG signal are computed. The relative power of each band is then estimated as ratio of the band power to total power and averaged over all segments to obtain, X . Similarly, sample entropy is calculated for single-channel EEG time series from each rest segment and averaged over all segments. It is the negative natural algorithm of the probability that two sequences for a fixed number of data points in a time series remain similar at the next point, where self matches are not included [35].

For each predictor, we quantify its linear relationship with the BCI performance using correlation coefficient. To validate the prediction accuracy on a small sample set ($N = 10$), a leave-one-out cross validation is performed. For each left-out sample (subject), a linear model is created using the $N - 1$ samples, and the error of prediction is reported as root mean square value of error ($RMSE$). Assuming that accuracy of prediction can be increased by using multi-channel information, a sequential channel selection approach is proposed. The objective function presented here is to minimize the error of prediction by sequentially including channels until a fixed number of channels are selected or there is no further reduction in error upon appending channels.

The multi-channel predictors in X are defined as $X = \{x_i \in \mathbb{R}^{N \times 1}, i \in [1 C]\}$. The sequential approach is as follows: The initial step is to calculate the error of estimating Y using each x_i using linear regression. Using leave-one-out method, error of estimating left-out sample in Y is calculated in each fold and the average error over all the cross-validation folds is determined. The predictor index that corresponds to minimum error is selected in this step. The next step repeats the error estimation by appending the selected predictor with each of the remaining predictors. This results in two predictors which estimates Y using multiple linear regression. The average error over all cross-validation folds is determined, and the predictor set with least error is determined again. This process is repeated until K predictors are selected. The algorithm is summarized below:

- Initialize set of predictors, $\hat{x} = \{x_i\}$, set of selected predictors, $\hat{x}_c = \emptyset$.
- Estimate of Y : For $\forall i$, using leave-one-out approach, perform linear regression between Y and $\hat{x}$, calculating error of estimation for the left-out sample. The estimate of linear model $b_i = (x_i^T x_i)^{-1} x_i^T Y$ is calculated using the training set. The estimated value of left-out sample in Y is determined as $\hat{Y} = b_i \cdot x_i$.
- Average error of estimation over all folds, ε_i is determined for $\forall i$.
- Select the predictor with minimum error, $\hat{x}_c = \{x_i | \varepsilon_i = \min_{j=\forall i} \varepsilon_j\}$ and update the set of predictors as $\hat{x} = \{\hat{x}_c, x_i\}$.
- The process is repeated till $|\hat{x}| = K$.

The method essentially determines K channels whose resting state feature can create a linear model that estimates BCI performance. This method of estimation is repeated for the different type of predictors - multi-channel relative band powers of beta, gamma, theta and alpha bands and sample entropy and for two folds.

4. Experimental Results

The results of our analysis are reported in the following sub-sections.

4.1 Demonstrating Fisher's ratio based selection of spectro-spatial features

The proposed approach to identify subject-specific spectro-spatial features is based on Fisher's ratio J_{fc} , wherein the bands optimal for most of the channels are selected. As mentioned earlier, this is a significant modification over the existing approach of selecting frequency range based on Fisher values only in C3 or C4 [13]. We demonstrate the selection of discriminative features in both approaches using calibration data from subject S3. The DFBCSP method [19], selects 4 bands having higher Fisher's ratio value in channel C4, in order to perform band pass filtering of the multi-channel EEG. In Figure 4 (a), the black dashed plot shows Fisher values of 9 bands in channel C4 and red square markers denote these 4 optimal bands. The range of Fisher's ratio values in each band over all the channels is indicated as blue line bars. The bands corresponding to peaks are usually selected and applied to all channels. But it can be observed that for the selected four bands using existing approach (f_2, f_3, f_7, f_6), not all channels exhibit high J . Also, in bands not selected using this approach (for instance f_1), J indicates high discriminative quality of channels other than C4.

4.2 Subject variability in selection of spectro-spatial information

Several studies have reported the subject specificity of SMR-based information that discriminates bilateral motor imagery [14, 19]. This is the basis of many spatial and spectral

Fig. 4. (a) Fisher ratio (J) values in various bands for channel C4 alongwith the range of multi-channel J values in each band. (b) Spatial distribution of J in each band. Both figures are obtained using calibration data of subject S3.

localization algorithms aiming to obtain optimal features. The proposed algorithm for identifying discriminative spectro-spatial pattern selects a subset of n_c channels and n_f bands, out of the original 20 channels and 9 bands respectively for each subject. Fig. 5 displays this selection in ten subjects validated using the calibration data. In the spatial plots, black dots indicate all the 20 channels used and square markers represent the ones found to be most discriminative. The horizontal grid indicates 9 bands and the selected bands are highlighted. The proposed algorithm identifies this combination of channels and bands for which highest BCI performance can be achieved using the calibration data for each subject. This selection is further used in BCI evaluation session.

From Fig. 5, it is evident that there exists subject specificity in the informative bands and channels. The proposed algorithm ensures that the channels C3 and C4 as well as band f_2 (mu band, 8-12 Hz) are included in every selection. Apart from this, the channels that are selected most frequently among all subjects are from parietal and centro-parietal areas. Further, the frequently selected bands include lower (12-16 Hz) and theta (4-8 Hz). On an average, among all subjects, reductions of 52.2% and 35% are achieved in number of bands and channels respectively required for the evaluation session respectively.

4.3 BCI Performance in terms of classification accuracy

BCI performance during calibration and evaluation sessions are displayed in Fig. 6. We report the performance of baseline method of conventional FBCSP [16] using all 20 channels and bands. Further, BCI performance using DFBCSP in which features are extracted from discriminative bands specific to C4 is provided. The average classification accuracy over ten subjects using FBCSP is $69.22 \pm 12.6\%$ and DFBCSP is $69.32 \pm 10.19\%$ with a reduction of 55.6% in number of bands used. The performance of the proposed algorithm is displayed using black bars in Fig. 6. It can be observed that in most of the subjects, the proposed method offers an enhancement in performance, resulting in an average performance of $75.18 \pm 9.91\%$. This is found to be significantly ($p < 0.007$) higher than the existing approaches.

The online BCI performance is displayed in blue bars for the four subjects who participated in the evaluation session. The average accuracy over 4 subjects is 72.50%. For subjects, S7 and S10, the performance is comparable or even higher than the calibration sessions. However, for the other two subjects, the performance falls. These subjects are found to have low/near-chance level performance even in the

Fig. 6. Comparison of BCI performance during calibration and feedback sessions.

Fig. 7. The combination of channels and bands that correspond to peak evaluation performance in Session 1 (red circle markers) and Session 2 (black square markers) for four representative subjects. The classification accuracy corresponding to the combination is also indicated.

calibration sessions, and hence the fall in their performance during evaluation session is not unexpected. The average online classification performance for four subjects using FBCSP is 70.5%. Hence, the proposed algorithm enhanced performance while reducing the number of bands and channels by 52.8% and 28.75% respectively on an average for 4 subjects.

The results of session-to-session transfer classification performance for few representative subjects are illustrated in Fig. 7. The combinations of channels and bands that correspond to peak evaluation performance are indicated in this scatterplot. In each plot, the nodes indicate combinations of channels (y-axis) and bands (x-axis). The markers in the node indicate selection – red circles for session1 and black squares for session 2. Using the proposed approach, average session-to-session transfer estimation classification accuracy

over all subjects for session 1 and session 2 are 79 and 76.8 % respectively. It can be noted that the non-stationarity in EEG has resulted in variation of optimal spectro-spatial parameters across subjects and sessions. However, it is worth noting that many channels and bands are found to be discriminative in both sessions.

4.4 Neurophysiological correlates of BCI performance

We study the relationship between BCI performance and specific spectro-spatial activations during rest state. The predictors that remain stable over the two folds can be identified as strong correlates of BCI performance. The BCI performance correlates with relative power in theta, alpha, beta, gamma and sample entropy obtained from rest-state EEG and the range of correlation obtained for each over two folds are [0.11 0.80], [0.02 0.71], [0.07 0.94], [0.30 0.80] and [0.16

Fig. 8. (a) Linear relationship between BCI performance (y-axis) and predictors (x-axis) obtained by linear regression. The multi-coloured markers denote each of the $N = 10$ subjects, circle and diamond markers indicate fold1 and fold 2 respectively. (b) Spatial distribution of correlation between predictors and BCI performance, $\times$ markers indicate significant predictors.

Fig. 9. (a) Average error of estimation over two folds as a function of dimension of predictor, K (b) Spatial map indicating frequency of selection of electrodes over two folds for predictors beta, gamma and entropy for $K = 8$.

0.90] respectively. Out of these, the relative alpha and theta power values from none of the channels are able to provide significant correlations ($p < 0.1$) in both folds. Fig. 8 (b) illustrates the correlation between baseline BCI performance during calibration session and three of the neurophysiological predictors, calculated in each channel, quantified in terms of correlation coefficient averaged over two folds. The correlations that are found to be statistically significant in both folds is marked using the black cross markers. An interesting observation is that this correlation is spatially localized and may provide meaningful information on the cognitive state of user during rest period. The beta power spread across fronto-central to parietal areas, entropy in fronto-central and parietal areas can clearly be seen, offering higher correlation. Further, gamma power is found to have significant correlation only in a parietal channel (P3).

The significant correlations in each of these predictors and their linear relationship with the BCI performance is illustrated in Fig. 8 (a). The figure illustrates the relation as a scatter plot of the single-channel predictor corresponding to the significant peaks in Fig. 8 (b) versus BCI performance. The multi-coloured markers denote each of the $N = 10$ subjects and circle and diamond markers indicate fold 1 and fold 2 respectively. The linear relationship obtained using regression and the correlation value is indicated as well. For the small sample set in our study, each of these predictors can be found to provide robust prediction of performance over the two sessions.

4.5 Investigating multi-dimensional predictors of BCI performance

The results in Fig. 8 suggest that a spatial cluster can be identified which significantly correlates with BCI performance. We investigated whether multi-dimensional predictors obtained by grouping of informative channels can provide better estimation of BCI performance. For each physiological parameter, we identify K predictors (or

channels) using the sequential feature selection algorithm and the results of estimation are shown in Fig. 9. The combination of the predictors selected using this method offers minimum error of estimation. Fig. 9 (a) shows the average error in prediction ($RMSE$) over two folds for varying values of K , using each of the significant physiological parameters. It can be noticed that, if the dimension of predictors is increased, the error can be reduced. However, for a small sample set like the one in this study, the dimensionality is limited to maintain significance of results.

Due to the inherent variations between sessions, the group of K predictors (channels) that are selected may vary. Fig. 9 (b) displays the frequency at which each channel is selected over the two folds while $K = 8$. It can be observed that fronto-central and centro-parietal electrodes are often grouped in both folds denoting their contribution to prediction of BCI performance.

5. Discussion

The broad focus towards motor imagery in SMR-BCI is on account of the presence of explicit and distinguishable features of ERD/ERS patterns associated with motor control, over the sensorimotor cortex. This paper addresses the challenges in analysis of non-stationary and subject-specific bilateral motor patterns in EEG with the goal to improve SMR-BCI performance, with reduced feature dimensionality. Further, the paper investigates the neural correlates of SMR-BCI performance and establishes a causal relationship between one's resting-state multi-channel EEG parameters and BCI performance. Our results imply that motor skills and cognitive skills of user from relevant cortical areas contribute to one's MI skill, which in turn determines BCI performance.

Our first analysis aimed assessment of discriminative quality of defined spectral regions of EEG recorded from various spatial locations over SM area. Literature suggests that the channels in motor cortex according to 10-20 electrode placement namely, C3 and C4, provides significant motor-related patterns. However, researchers have reported [39] that other electrodes from pre-motor or supplementary motor areas may provide better discriminative patterns of bilateral MI that result in higher classification accuracy. We demonstrated in Fig. 4 how the discriminative quality of bands and channels selected by our proposed algorithm is higher than that in the conventional method of using reference channel (C3 or C4) for band selection. Further, it is interesting to note that, the collective discrimination power by including channels from other cortical areas along with central channels, as shown in Fig. 5, results in increased classification performance, as shown in Fig. 6. This is true for frequency bands as well, since addition of beta and theta bands to the informative mu band, the performance can be enhanced. Apart from significant increase in accuracy as reported in Fig. 6, the reduction of number of channels and bands offer various advantages. Primarily, this removal of redundant factors minimizes the feature dimension and optimizes its information content. In evaluation session, this reflects as reduction in complexity of

algorithms (due to lower dimensionality of features) and ease of set up (due to lesser number of channels). Further, literature has suggested that for a mental processing task such as MI, EEG changes are observed over premotor-parietal networks which activated by cognitive as well as motor aspects of MI [40]. The optimal spectro-spatial pattern obtained by the proposed method points out parietal and centro-parietal areas as the frequently selected ones over all subjects, in line with the reports in literature, and hence indicates neurophysiologically meaningful extraction of features. In the evaluation session, only four subjects participated in the neurofeedback experiment, and the average accuracy is 72.5 % as indicated in Fig. 6. The generalizability of the approach will need to be investigated using data from more number of subjects. However, in all subjects except S9, the evaluation results are comparable to the reported performance in literature [14]. An average accuracy of 77.9% in inter-session analysis demonstrates that the proposed spectro-spatial algorithm can potentially address the non-stationarities in EEG. Though the proposed technique is capable of tackling the inter-subject variability successfully, more effective adaptive tracking procedures are essential to fine-tune the intra-subject variabilities and enhance performance.

Researchers have studied the variation in SMR-BCI performance across subjects, suggesting that a standard generic protocol might not be suitable for all subjects. This performance variation is accounted to various inter-subject variabilities in user profile (age/gender/experience to perform task), psychology, neural anatomy and neuro physiology [15]. We investigated how an optimally selected set of multi-channel predictors can correlate with baseline BCI performance, as opposed to predictors from conventional single channel or sum of fixed set of channels. As seen in Fig. 8, a localized spatial cluster can be identified in beta, gamma and sample entropy which provides high and significant correlation with BCI performance. The performance of the proposed estimator that is created based on this finding is demonstrated in Fig. 9. The results indicate the relevance of using multi-channel (dimensional) predictors rather than single-dimensional predictors in literature.

The results provide insights into causal relationship between resting state parameters and subject's BCI performance. The resting state parameters signify certain cognitive states of user during rest, and hence it can be presumed that these cognitive states determine the BCI skill of the subject. Literature reports various interpretations of EEG band power modulations, elicited from task-specific cortical areas that contribute to different aspects of cognitive processing. Also, the same rhythm might be synchronized and desynchronized at different electrodes at the same moment of time depending on the cognitive task being executed. In the current study, strong positive correlations are observed with resting state relative beta and gamma power and sample entropy, and weak positive correlations with alpha and theta power. The spatial map shown in Fig. 9 (b) displays the spatial clusters that predicts BCI performance with minimum error.

The entropy and gamma power from pre-motor (fronto-central) and posterior (parietal and centro-parietal) areas, and beta power from posterior (centro-parietal) areas are selected.

Literature reports increase in theta in frontal midline areas with increasing task demands [27] and focused internalized attention [29] and in frontal and parietal areas during selective attention [28]. Frontal theta/beta power is negatively related to executive attentional control [30] and focused attention elicits increase in beta power [31, 32]. Increase in gamma power is reported with cognitive processing [41-43], especially in posterior cortex during visual tasks [33] and cognitive coordination tasks [9]. Alpha activity indicates 'cortical idling', since it shows task-related decreases in various cognitive tasks and increases during rest and with eyes closed [44]. Task-related increases of alpha activity is reported for memory retention in short-term memory tasks or with increasing task load [45], with complex cognitive processes such as divergent thinking (creative idea generation) [46] and in tasks that require internal attention focus [47]. In a visuospatial attention task, alpha is modulated in sensory-specific regions, which in turn facilitates or suppresses sensory processing [48, 49]. Higher sample entropy is an indicators of high attention levels of user [36, 50]. Considering these research findings, the rest state activation patterns highly correlated with the BCI performance, represent the cognitive states associated with these are relaxed awareness to receive an expected sensory input (or task cue), internal attention (such as mental imagery), active attention and sensory processing to reject irrelevant stimuli. It is reasonable to state that MI skills during the task will benefit from these cognitive states during rest period. Further, investigations in this direction may pave ways to identify the ideal cognitive states to elicit good BCI performance in a subject. Similar observations are reported in [15, 51], that support the idea of neuromodulator to enhance such parameters. Hence, introduction of pre-training protocols in neurofeedback experiments to monitor the aforementioned parameters, can be interpreted as a means to augment SMR-BCI performance [15, 51, 52].

This paper discusses two challenging aspects of SMR-BCI research, namely the subject-specific optimization of data processing algorithms and prediction of a subject's ability to perform a BCI task, targeting towards a single ultimate objective: the enhancement of BCI classification performance. Extensive research has been reported in literature on developing robust algorithms to drive practical, reliable BCI systems. However, the ability of the user, his neurophysiology and underlying cognitive states indicating his BCI skill is equally relevant. We believe that both these concepts must be investigated concurrently. The study reported in this paper is a preliminary investigation towards this direction. Inspecting our two contributions, it is noteworthy that we identified the spectro-spatial features that discriminates bilateral MI as well as resting state neural parameters that estimate user's ability to elicit such features. The discriminative spectro-spatial

pattern based on fisher ratio has significantly improved the performance. Further investigations towards adapting the algorithm in real-time will certainly benefit the performance during evaluation session. This aspect will be studied in future. The proposed estimation analysis has facilitated a neurophysiological interpretation of SMR-BCI performance. We used a small sample ($N = 10$) set in this study similar to research in [23, 51]. Future work using a large sample dataset may help to attain better generalization of the estimator, since the number of predictors available as well as their spatial combinations are high. Literature has investigated such trial-to-trial variations in performance using gamma power [53]. Besides, the future research will incorporate a trial-wise performance estimation which may contribute to design of neurofeedback training protocols.

6. Conclusion

This paper proposes a novel method to choose the subject-specific discriminative EEG channels and bands that precisely separates spectro-spatial EEG features during ERD/ERS in order to accurately classify left and right hand MI tasks. Compared to the state of art method that employs fixed channels and bands, the proposed method provides statistically significant ($p < 0.007$) enhancement in classification accuracy by 5.96 %. The improved accuracy is obtained with 52.2 % and 35 % reductions in frequency bands and channels respectively, at the expense of the complexity incurred due to the proposed spectro-spatial feature optimization procedure. The algorithm is validated in online neurofeedback experiments for 4 subjects. Further, our paper investigates the neurophysiological correlates of SMR-BCI performance across subjects and proposes cluster based estimates of subject's MI skills using beta and gamma power and entropy. Our results indicate that the usage of EEG parameters from cluster of electrodes as multi-dimensional predictors provides more accurate and meaningful SMR-BCI performance estimations. In future, we will work towards developing more robust spectro-spatial feature selection and adaptation algorithms, and examining how the predictors can help to enhance the overall BCI performance in real time, for a larger group of subjects.

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