Functional Connectivity for Channel Selection in Brain-Computer Interface

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Abstract – In this paper, we present a channel selection method to improve common spatial patterns (CSP) for motor imagery (MI) classification. While traditional channel selection methods extract spectral power, coherence, or event-related potentials from the signals, this paper introduces a novel correlation-based channel selection method to identify channels that reflect the brain's functional connectivity during MI tasks. It is known that regions of the brain related to MI share a temporal coherence in their neural activity. Hence, the proposed method aims to leverage on the idea of functional connectivity by selecting channels that contain more correlated and discriminative information over others. Each channel is assigned a connectivity score and grouped with channels that it is strongly correlated with. For each group of channels, those that are most representative of the group are selected. Channels are further distilled by computing the Fischer score from the spectro-spatial features of the Filter Bank Common Spatial Pattern (FBCSP) to identify the most discriminative channels for classification. When evaluated against PhysioNet's motor imagery dataset (N=109), results showed that the proposed algorithm obtained superior classification accuracies across all 4 MI paradigms all while reducing the average number of channels by 83%. Correlation analysis also reveal interesting results that are congruent with neurophysiological principles, indicating a robust ability for feature selection, enabling the design of more efficient and accurate BCI systems.

Index Terms – Brain Computer Interface, Motor Imagery Classification, Machine Learning.

1. Introduction

The field of Brain-Computer Interface (BCI) is an emerging technology that offers an alternative pathway for the human brain to communicate with the external world. It involves the reception, analysis and translation of neural signals from the brain to enable various applications and functions including gaming [23], rehabilitation [31], emotion recognition [18], diagnosis of epilepsy [20] and many more, opening up brand new possibilities for communication and independence.

One notable application is Motor Imagery Electroencephalography (MI-EEG), which has gained widespread attention for its ability to decode motor intention [8] through capturing changes in the power of EEG signals in response to MI tasks also known as event-related synchronizations (ERS) and event-related desynchronizations (ERD).

Amongst different methods of extracting ERD/ERS-related features, the common spatial pattern (CSP) has proven to be highly effective for feature extraction [7] by obtaining spatial filters to maximize the differences in the covariance matrices that separates different classes. However, the CSP faces a frequency band dependency problem as different MI tasks affect the power across different frequency bands differently [8,19]. Hence, the CSP performs poorly on unfiltered data as the patterns of activity that are most informative become obscured by other sources of variability in the EEG signal. To address this problem, various extensions of the CSP have been proposed, such as the filter-bank CSP (FBCSP) [15], Sparse CSP [16], sparse filter band CSP (SFBCSP) [29], sub-band regularized CSP (SBRCSP) [22], and filter bank combined with Tikhonov regularization CSP (FB-TRCSP) [30], to improve the performance for MI classification.

As cognitive processes involve complex interactions between multiple brain areas, channel selection plays a large part in CSP analysis. In order to improve performance, EEG-based BCIs collect signals from multiple sites of the scalp (channels) [3]. However, this does not necessarily yield higher accuracies in MI classification [10], as acquired EEG signals are attenuated by various artefacts [2,9], inducing low spatial resolution and a low signal-to-noise ratio (SNR). Hence, it is crucial to streamline the process by identifying a minimal yet highly informative set of channels to capture the relevant information and eliminate interference from those task-irrelevant channels. Various channel selection algorithms have been proposed in the past [11,13,14,16,25,26], and while they have been highly effective in classifying regionally well-separated ERS/ERD features, subtle ERS/ERD patterns are generally harder to discriminate.

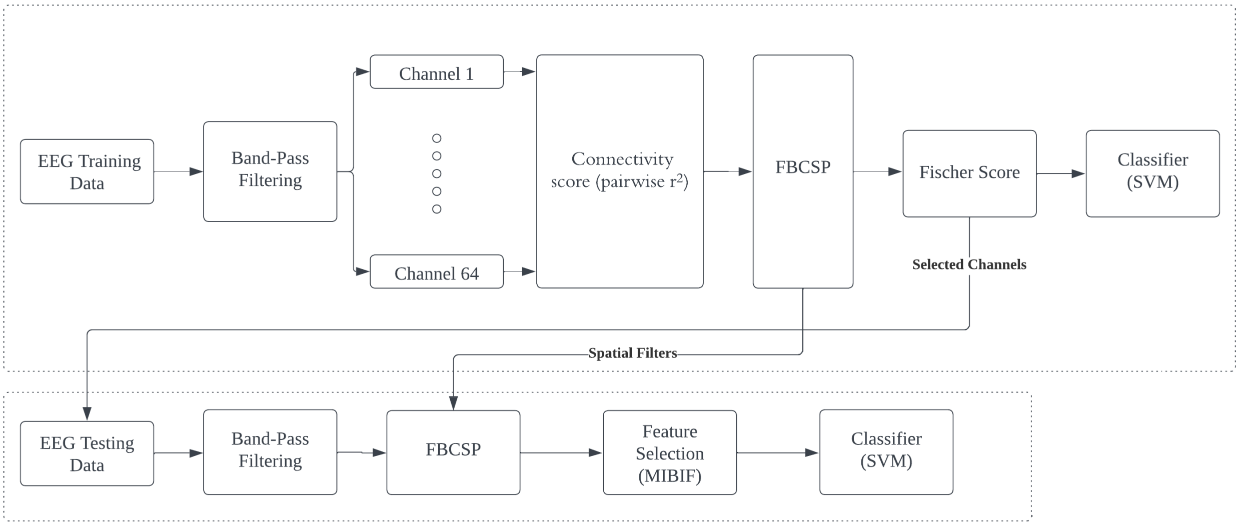

Figure 1: Method Framework

In recent years, however, features based on functional connectivity have attracted considerable attention. Brain regions that are functionally related tend to show similar patterns of activity over time and the strength and pattern between different regions can provide insight to the neural mechanisms of the brain [1,6,17]. Growing bodies of research suggest that the correlation coefficients between EEG channels can be informative for MI classification. Recently, a correlation-based channel selection regularized CSP (CCS-RCSP) approach identifies distinct channels using the mean correlation coefficient value with other channels [12]. Another approach uses correlation-based measures to identify the most distinctive channel and their correlated supporting channels [28]. However, these methods exhibit limitations in extensibility as MI tasks tend to involve groups of EEG channels that are weakly correlated because of cognitive processes that are mediated by different brain networks. Hence, nuanced spatial patterns between these channels may be omitted. In such cases, it may be challenging to identify the most informative channels for MI classification.

In order to address the above, this paper aims to achieve the following:

1. Propose a novel channel filter approach based on correlation analysis to select highly correlated and distinctive channels;
2. Train a support vector machine (SVM) classifier for the classification;
3. Conduct a set of experiments to evaluate the validity of the proposed method.

The paper is organized as follows. Section 2 explains the proposed channel selection method. Section 3 explains the experimental study. Section 4 evaluates the findings and Section 5 summarizes the paper.

2. Methodology

Figure 1 shows a block diagram of the proposed channel selection method. First, we compute the ‘Connectivity score’ derived from the strength of correlation between different channel signals. Then, the Fisher score of FBCSP features is calculated to further distil the set of channels to select ones that yield the greatest discriminative power. The final FBCSP features are then used during the testing phase of the experiment. In the following subsections, each step of the channel selection process is described in detail.

2.1 Determination Matrix

Correlation-based methods are useful for detection of task-related activations in the brain. In this initial step, we aim to reduce the number of candidate EEG channels in our dataset by comparing the similarity between different channels to estimate the functional connectivity between different brain regions. We assume that vital channels related to the MI task contain similar features across all trials for the same MI task, while irrelevant channels are likely to be more erratic. Based on this hypothesis, we can use the correlation coefficient to measure the similarity between channels as well as group channels into relevant networks.

The EEG signal, X, is initially z-score normalized and band-pass filtered to standardise the distribution of the signal across all channels, to ensure that the correlation coefficient is interpretable and comparison between channels is fair and unbiased. For any channel, the normalised EEG signal is defined as:

$$X_{Normal} = (X_{raw} - \bar{X}_{baseline})/S_{baseline}$$

From each class, EEG signals are then ensemble averaged with respect to each channel to reduce the effect of noise and identify common features.

Next, Pearson's correlation analysis is used to construct a coefficient matrix. Pearson's correlation coefficient quantifies the linear dependence between two or more random variables. For a given set of sample points (x_1, y_1), (x_2, y_2), …, (x_{n-1}, y_{n-1}), (x_n, y_n), from channels x and y, the coefficient is defined as:

$$r = \frac{1}{n-1}\sum_{i=1}^{n}(\frac{x_i - \bar{x}}{S_x})(\frac{y_i - \bar{y}}{S_y})$$

where $\bar{k}$ is the sample mean and S_k is the sample variance and $k \in \{x, y\}$.

$$\bar{k} = \frac{1}{n}\sum_{i=1}^{n} k_i \,, S_k^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(k_i - \bar{k}\right)^2$$

Hence, the correlation of determination, r^2 helps gauge the strength of correlation between two random variables. The correlation of determination is computed between every pair of channels (N) for each class to reflect any connectivity patterns between them. Thus, for each trial, the calculation yields an N x N x 2 coefficient matrix C, where row *i* denotes the correlation between the *i*th channel and every other channel.

Next, we compute the mean correlation along row *i* of those channels that are strongly correlated with channel *i* and yield an value above a predetermined threshold. In the proposed method, this threshold is set to 0.9 via cross-validation. Hence, the connectivity score, S, of the kth channel is given as:

$$S^{(k)} = \frac{1}{M}\sum_{j=1}^{M} C_{kj} \; if \; C_{kj} > 0.9$$

Where there are M channels along row *i* that satisfy the above condition. Those said channels are then grouped to form an undirected graph composed of many disconnected subgraphs that would represent various functionally connected regions of the brain.

From every disconnected subgraph, channels with connectivity scores greater than the average are selected to represent the group. Those channels are high correlated with other channels in the group, that is to say, those channels are highly informative of the group. Hence the selected *k* channels from a particular subgraph of size N are:

$$C^{(k)} = \{k \in \{1,2, \ldots, K\} | S^{(k)} > \frac{1}{N}\sum_{k=1}^{N} S_k$$

To address the issue where there could be very little channels selected, C3, C4 and Cz were appended to the list of selected channels.

The pseudocode for the proposed method can be seen in Figure 2.

Algorithm

Convert EEG to the shape: *Trials* x *Channels* x *Sample Points*

```
For j = 1 : C do
    Normalise the data s.t. S_jt = (V_jt – mean_j (baseline))/std_j (baseline)
End
For i = 1 : T do
    For j = 1 : C do
        Compute the pair wise weighted correlations of determination
        between channel j and every other channel  k (s.t. k>j)  given by
        corrcoef(S_jt,S_kt)^2
        If corrcoef(S_jt,S_kt)^2>0.9 do
            union(j,k)
        End
        Compute the connectivity score for channel j
    End
End
For every disconnected subgraph do
    Select channels that yield an MI score above the mean
End
```

S_{jt} = Normalised t^{th} sampling point of the j^{th} channel
V_{jt} = Raw t^{th} sampling point of the j^{th} channel
C = Number of channels
T = Number of Trials
Corrcoef() computes the Pearson Correlation Coefficient
Union() joins two vertices using the union-find algorithm

Figure 2: Correlation-based Channel Selection Algorithm

2.2 FBCSP Fisher Score

Amongst those selected channels, the Fischer score of FBCSP features is computed to select a subset of those channels that are most discriminative. FBCSP aims to extract frequency optimized log-variance features of spatial filtered signals to maximize separability of different classes. FBCSP can be decomposed into three key stages: Frequency bandpass filtering, spatial filtering using CSP, and frequency band selection based on mutual information. Figure 3 visualizes this method of feature extraction. [30]

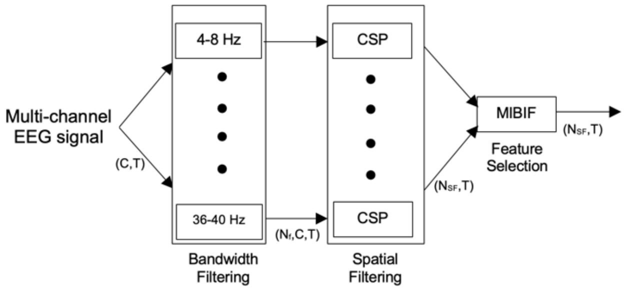

Figure 3: FBCSP architecture: (C: number of EEG Channels, T: Measurement samples per channel, N_f: Number of frequency bands, N_C: Number of classes)

Let the output of the m[th] filter bank of a channel group S in the i[th] trial be $X_{i,m}^{(S)}$ where there are M filter banks and I trials in total. The normalized sample covariance matrix $E_{i,m}^{(S)}$ is given as:

$$E_{i,m}^{(S)} = \frac{X_{i,m}^{(S)} X_{i,m}^{(S)^T}}{trace(X_{i,m}^{(S)} X_{i,m}^{(S)^T})}$$

Hence, the mean normalized sample covariance matrix for each class c is:

$$\overline{E_{c,m}^{(S)}} = \frac{1}{|I_c|} \sum_{i \in I_c} E_{i,m}^{(S)}, c \in \{1,2\}$$

When a spatial filter, $p^{(m)}$, is applied, the mean variance ratio between two classes is given as:

$$v(p^{(m)}) = \frac{p^{(m)^T} \overline{E_{1,m}^{(S)}} p^{(m)}}{p^{(m)^T} \overline{E_{2,m}^{(S)}} p^{(m)}}$$

The CSP algorithm finds the spatial filters that maximizes and minimizes the ratio between two classes where:

$$p_{max}^{(m)} = \arg\max_{p^{(m)}} v(p^{(m)}), p_{min}^{(m)} = \arg\min_{p^{(m)}} v(p^{(m)})\}$$

The CSP feature vector for a particular set of channels S in the m[th] frequency band is thus:

$$v_i = [v_{i,min}^{(m)}, v_{i,max}^{(m)}]$$

where:

$$v_{i,min}^{(m)} = \log(var\left(p_{min}^{(m)^T} X_{i,m}^{(S)}\right))$$

$$v_{i,max}^{(m)} = \log(var\left(p_{max}^{(m)^T} X_{i,m}^{(S)}\right))$$

The FBCSP algorithm uses the mutual information based individual feature (MIBIF) algorithm to compute the mutual information between feature vectors. The feature vectors of the two frequency bands that yield the most discriminative power are selected and fed to the SVM classifier along with the class labels.

$$u_i = [v_{i,min}^{m_1}, v_{i,max}^{m_1}, v_{i,min}^{m_2}, v_{i,max}^{m_2}]$$

Afterwards, we use the Fisher score to measure the distinguishable power of the FBCSP features of the k[th] channel set given by:

$$Z^{(k)} = \left(\frac{1}{|I_1|}\sum_{i \in I_1} u_i - \frac{1}{|I_2|}\sum_{i \in I_2} u_i\right)^2 / \sum_{c=1}^{2}\sum_{i \in I_c}(u_i - \frac{1}{|I_c|}\sum_{i \in I_c} u_i)^2$$

By comparing the differences between the mean values between two classes to the variability of the signals within each class, larger ratios indicate large differences in mean value between classes and lower variability within each class, indicating stronger discriminative power for classification from a channel set.

The channel set with the highest Fischer score, are selected as the optimal channel set for MI classification during the testing phase.

$$Z_K = \arg\max_{k \in \{1,\ldots,K\}} \{Z^{(k)}\}$$

3. Experimental Study

3.1 Dataset Description

To validate our proposed method, a series of subject-dependent classification experiments were conducted on PhysioNet's EEG Motor Movement and Imagery Dataset [21]. This data set consists of over 1500 recordings obtained from 109 volunteers and was the preferred dataset as it would effectively test the proposed method's ability to select channels based on nuances between subjects' activated brain regions. EEG signals with 64 channels (K=64) were recorded at a sampling rate of 160 Hz. Each subject performed 3 two-minute runs of each of the four following tasks:

I. A target appears on either the left or the right side of the screen. The subject opens and closes the corresponding fist until the target disappears.
II. The subject imagines performing the motor tasks in Task 1
III. A target appears on either the top or the bottom of the screen. The subject opens either both fists or both feet until the target disappears.
IV. The subject imagines performing the motor tasks in Task 3.

3.2 Experiment Framework

In the experiment, the EEG signals between 0s and 4.1s after each visual cue is used for the first 80 subjects. The EEG data from each trial is filtered between 4 and 40 Hz evenly in intervals of 4Hz using third-order Butterworth filters for FBCSP analysis. Lastly, the LIBSVM is used for classification with the Radial Basis Function (RBF) selected as the kernel function. Altogether, 5 x 1 cross-validation is performed to evaluate the performance of the proposed method.

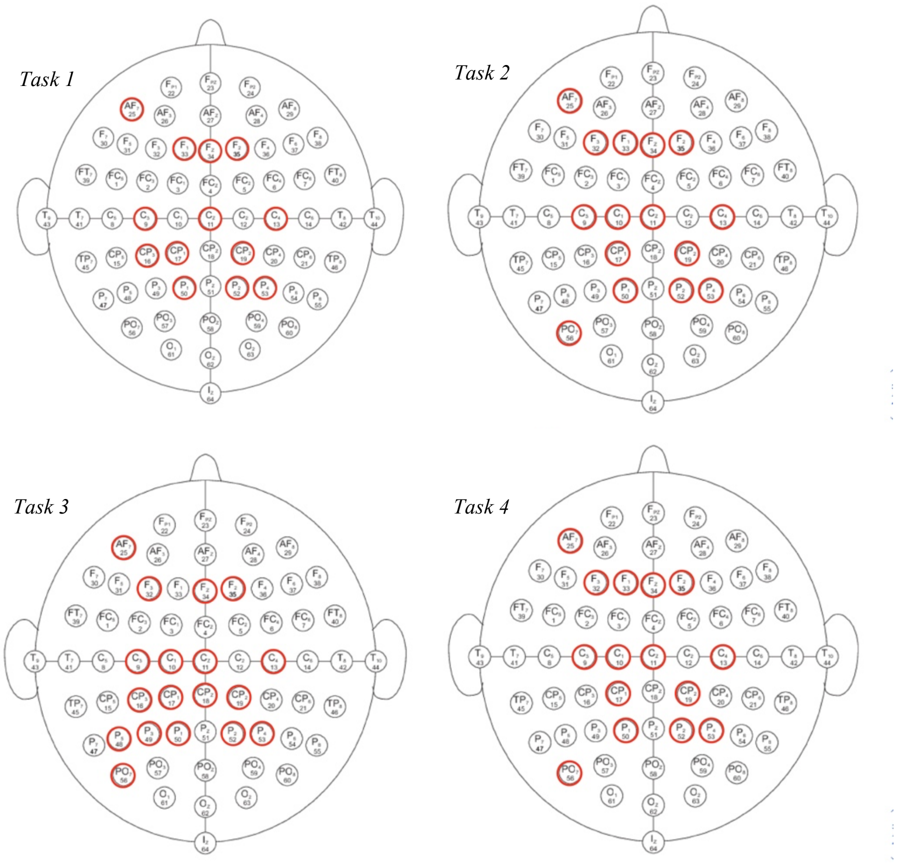

Figure 4: Selected Channels (red) of 4 motor imagery paradigms (Subject 1) [27]

4. Results and Discussion

4.1 Performance comparison and Channel Distributions

In Figure 5, the classification accuracies of the proposed channel selection method are compared against different fixed channel configurations. The results show that the proposed method achieved the highest mean classification accuracy across all four motor imagery (MI) tasks. Additionally, the proposed method outperformed the 64-channel configuration by 0.917% (task 1), 0.917% (task 2), 1.79% (task 3), and 2.45% (task 4) in mean classification accuracy. Moreover, the proposed method outperformed the 3-channel configuration by 4.12% (task 1), 4.12% (task 2), 8.20% (task 3), and 3.72% (task 4) in mean classification accuracy.

In Figure 4, the optimally selected channels for the first subject are circled in red. These selected channels show consistent patterns over areas of the brain that are involved in decision-making, sensorimotor integration, motor planning, execution, imagery, and voluntary movement control [5]. Specifically, channels over the

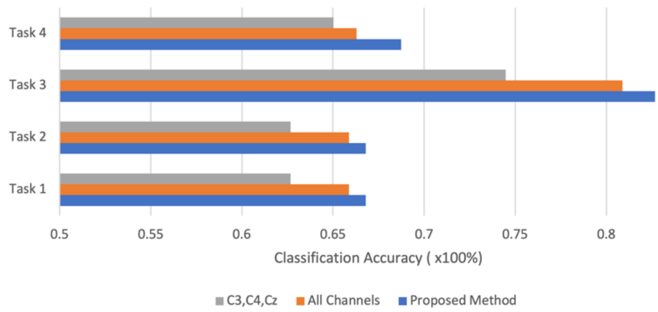

Figure 5: PhysioNet Motor Imagery Dataset Classification Accuracy

Prefrontal Cortex (PFC) (F3, Fz, F2, AF7), Parietal Cortex (PC) (Pz, P1, P4, CP1, CP2), and Primary Motor Cortex (PMC) (C3, C4) were repeatedly being chosen which are physio-neurologically meaningful and likely informative channels for classification.

In Figure 7, the number of channels selected for each task is shown. The distribution across all 4 MI paradigms reveals a mean of 11, corresponding to an 83% reduction in the number of channels used for analysis, compared to the total number of

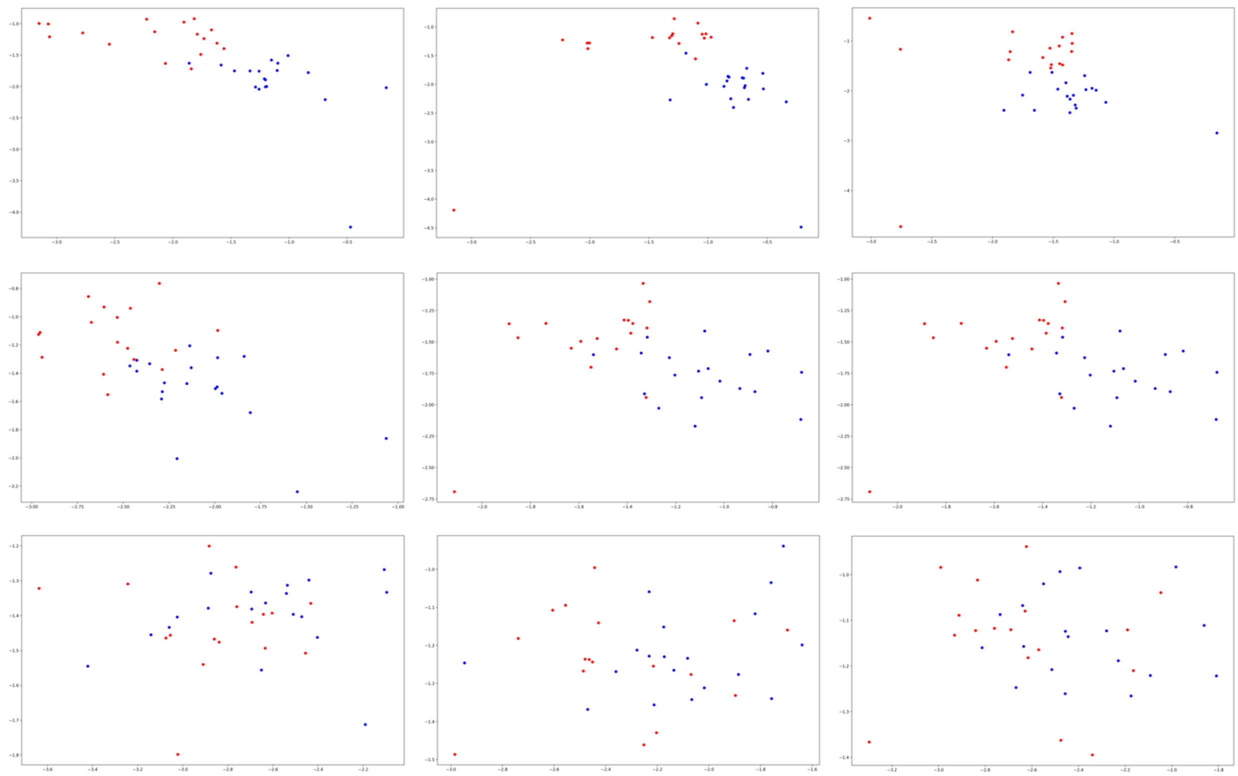

Figure 6: Distributions of the two best features (x-axis: value of feature 1, y-axis: value of feature 2) obtained by FBCSP (Task 1, Subject 1) with respect to different channel configurations (Top: 64 channels, Middle: 16 channels, Bottom: 3 channels)

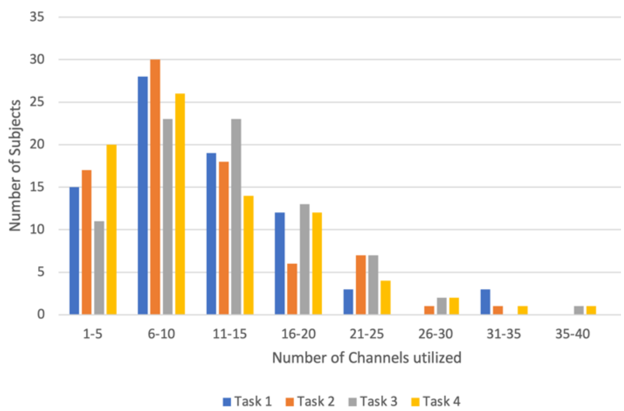

Figure 7: Number of Channels Utilized using the proposed method

available channels, as well as a standard deviation of 6.6. The standard deviation implies a confidence interval of approximately 68% that the number of utilized channels falls between 4 and 18. This suggests two things; while there is a source of variability in the brain's connectivity patterns across subjects causing more channels to be selected for some subjects than others, the proposed method is still able to consistently reduce the number of channels used for analysis significantly while capturing important information for classification across a large sample size. The complexity of the proposed method is:

$$O(K^2) + O\big(H^2(MN + H)\big) \in O\big(K^2(MN + K)\big)$$

where K is the number of channels, H is the number of selected channels, M is the number of trials, N is the number of sample points. While this has the same complexity as FBCSP [26], the proposed method demonstrates lower computational cost in practice.

Altogether, the proposed method achieved superior classification accuracy while significantly reducing utilized channels, implying that correlation analysis can be a very useful feature for identifying functional connectivity of the brain.

4.2 Feature Distributions Analysis

Figure 6 displays the distributions of the two most discriminative CSP features across the first three folds for different channel configurations. The results show that the proposed channel selection method yields more separable features compared to the 3-channel configuration. However, it is slightly less separable and sparser than the 64-channel configuration, where the features are both denser and more separable.

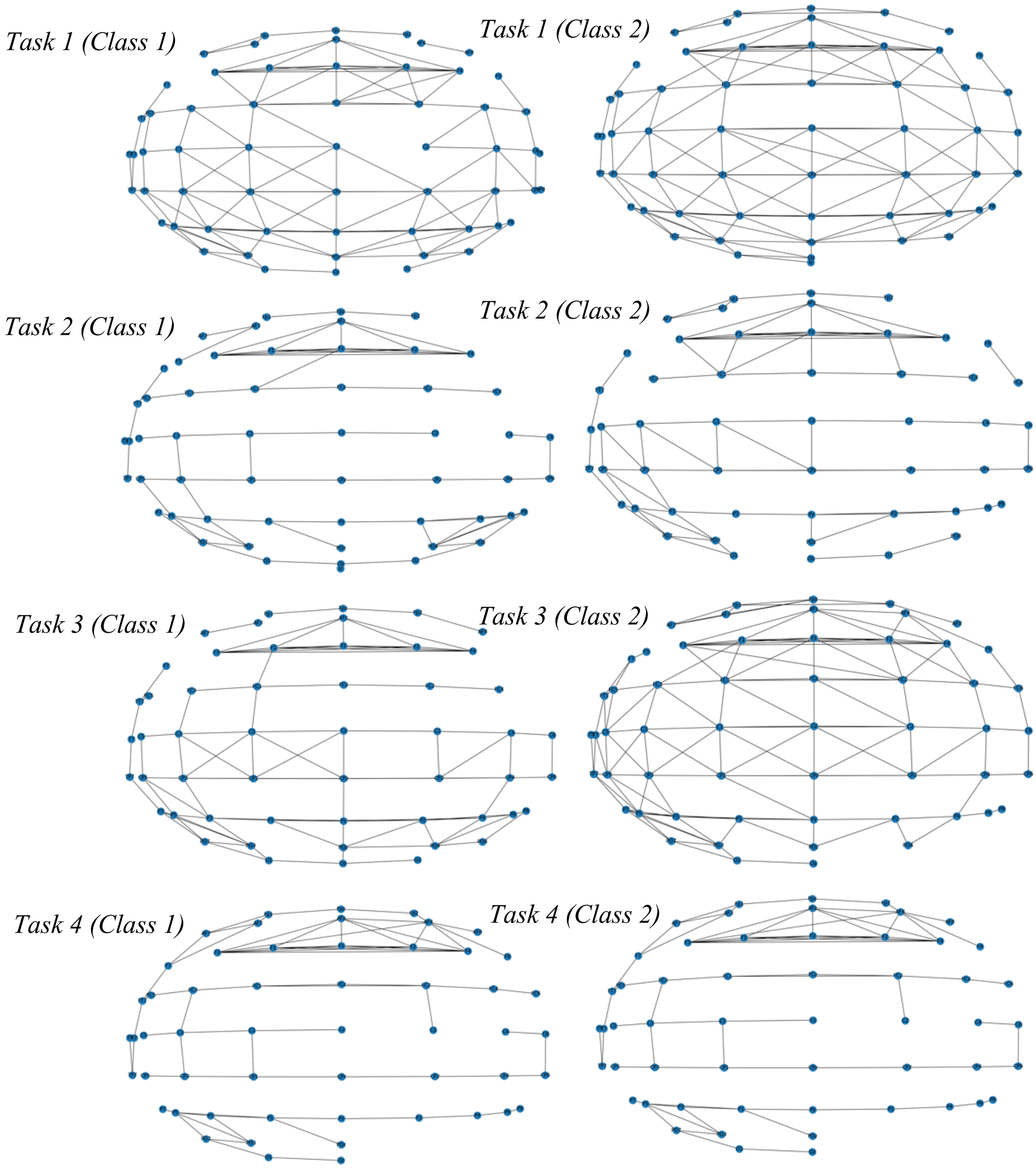

Figure 8: Cross-Channel Correlation analysis (subject 1) in the mu (8-12 Hz) frequency band visualized as a network with respect to each task

Interestingly, the testing accuracy using the optimized set of channels for this particular subject and task was 66.7% as supposed to 55.6% using all channels. Hence, this could be an indication of overfitting of the training data where the model has potentially fitted the noise from all 64-channels in the data, leading to an apparent improvement in performance accuracy of the training data. Hence, this shows that the proposed channel selection method also reduces noise by eliminating those from task-irrelevant channels.

4.3 Correlation Analysis

Figure 8 Is a graphical representation of the correlation matrix that aims to depict functionally connected regions of the brain through the use of vertices (channels) and edges, with adjacent vertices indicating a strong correlation between them . Hence, this helps to understand the interactions between different brain regions during MI tasks. It can be observed that signals tend to be far more interconnected when executing MI tasks (Task 1, Task 3) as compared to their imagined counterparts (Task 2, Task 4). For instance, Task 2 (Class 1) depicts the channels over the PFC region as an isolated subgraph, while Task 4 (Class 1 and 2) depicts channels over the PC as an isolated subgraph.

The PFC and PC regions are responsible for generating and maintaining the internal representation of the imagined movement, which is then transmitted to the PMC to generate corresponding motor commands [5]. However, since the motor commands generated during these MI tasks are not executed, they do not result in any sensory feedback, and the signals transmitted to the PMC from the PFC tend to be weaker and more erratic. This could explain why channels above the PFC are loosely connected with those above the PMC. On the other hand, Channels above the PFC are especially correlated likely due to the tight coupling with other regions, suggesting that these channels could be highly informative.

This suggests that previous correlation-based methods of channel selection may be subject to limitations [12]. As functional connectivity between different brain regions can become obscured by the signal variability during imagined movements, this can result in channels over regions such as the PFC and PC being overlooked and not selected for analysis, especially when there is a small number of channels to represent these areas. That is to say, their mean correlation with all other channels could be low even though their correlation with channels above the PFC are high.

Hence, instead of immediately computing the mean correlation across all channels as in CCS-RCSP, the proposed method computes the mean correlation within different functionally connected regions of the brain, such that informative and representative channels from each region are selected. This wouldn't be the case in CCS-RCSP, especially since the number of channels that represent each region of the brain varies. Hence by identifying strongly correlated networks and selecting channels from each network that are highly representative of the group, we are able to select informative channels from each region even if signals between regions are weak.

4.4 Extensions

This study provides an effective way to select channels based on correlation analysis from a small dataset. Our proposed method has the potential to both improve the performance of MI-based BCIs and reduce the time needed for data acquisition, which is particularly beneficial for users with neurological impairments where neural pathways are weak. However, there are limitations to this study that could be addressed in future research. For instance, the proposed method was not compared to existing correlation-based channel selection methods, which affects the persuasiveness of the findings. Future studies could compare our proposed method against methods such as [12] and [28] on variety of datasets to further validate its effectiveness. Additionally, the use of channels C3, C4, and Cz in all experiments may introduce extra noise for subjects who do not exhibit informative signals at these channels. Therefore, it is recommended to use the proposed method in combination with existing channel selection methods, and this will be explored in future studies.

5. Conclusion

In this study, we introduced a novel channel selection algorithm for motor imagery (MI)-based brain-computer interfaces (BCIs). The algorithm utilizes correlation analysis to select highly correlated channels within each identified brain network, and then computes the Fischer score to identify the most discriminative channels among them. The selected channels are then used as features for classification. Experimental results demonstrate that our approach can effectively enhance the performance of MI-based BCI systems while significantly reduce channel utilisation, and can be used in conjunction with existing channel selection methods for further improvements. Overall, our proposed approach shows promise as a candidate for optimizing the performance of MI-based BCIs.

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