An Automatic Subject Specific Channel Selection Method for Enhancing Motor Imagery Classification in EEG-BCI using Correlation

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Abstract

A motor imagery (MI) based brain-computer interface (BCI) decodes the motor intention from the electroencephalogram (EEG) of a subject and translates this into a control signal. These intentions are hence classified as different cognitive tasks, e.g. left and right hand movements. A challenge in developing a BCI is handling the high dimensionality of the data recorded from multichannel EEG signals which are highly subject-specific. Designing a portable BCI whilst minimizing EEG channel number is a challenge. To this end, this paper presents a method to reduce the channel count with the goal of reducing computational complexity whilst maintaining a sufficient level of accuracy, by utilising an automatic subject-specific channel selection method created using the Pearson correlation coefficient. This method computes the correlation between EEG signals and helps to select highly correlated EEG channels for a particular subject without compromising classification accuracy (CA). Common spatial patterns (CSP) are used to analyse imagined left and right hand movements and the method is evaluated on both BCI Competition III Dataset IIIa and right hand and foot imagined tasks on BCI Competition III Dataset IVa. For both datasets, a minimum number of EEG channels are identified with an average channel reduction of 65.45% whilst demonstrating an increase of >5% in CA using channel Cz as a reference.

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1. Introduction

A brain-computer interface (BCI) aims to provide a communication pathway for severely motor impaired people whose natural neuromuscular pathways have become damaged [1] and translates neurophysiological signals into commands used to control external mechanisms [2]. One common example of a BCI system is based upon imagined movement or motor imagery (MI) and does not require actual body movement [3] instead using the recorded neurophysiological activity associated with imagined movement as control commands [4]. Some BCI systems record multichannel electroencephalography (EEG)/magnetoencephalography (MEG) data to achieve good performance but many of these recorded channels will contain irrelevant information and noise [5, 6, 7] which requires a preprocessing step to remove [8, 9, 10]. There is often little evidence that exists on the location and number of channels needed for a particular MI task to achieve optimal performance. Additionally, the number of channels and their location is also likely to vary between individuals meaning that even if an optimal subset of channels is found for one subject, this same subset is unlikely to produce the same performance for a different subject. Producing a subset of channels enables the rejection of noisy channels whilst allowing for a similar if not higher level of classification accuracy with the benefit of reduced processing time, equipment and computational cost. Thus, this paper presents an algorithm which can automatically select subject specific subsets of channels to enhance classification accuracy of MI tasks.

To date, there have been a number of channel selection methods discussed in the literature based with on either manual or automatic techniques. Channels are often simply manually selected based on prior neurophysiological knowledge. For instance, MI based BCI systems generally focus on the sensorimotor cortex and channels around C3, C4, and Cz of the 10-20 system where most movement-related activity tends to occur [8, 11, 12].

If channels are not selected manually, then they may be selected using a filter-based technique, wrapper-based technique, or a combination of these. In wrapper-based techniques, potentially useful subsets of channels are evaluated and subsequently selected using a specific classifier through training and testing. However, this technique does tend to overfit and is more expensive in terms of computation when compared against filter-based methods. He et al. [13] used Common Spatial Patterns (CSP) and a Bayes classifier to reduce their channel count from 59 to an average of 33 whilst reporting an accuracy of approximately 95%. Whereas Wang et al. [14] used a Fisher discriminant classifier and CSP to show accuracies above 90% for two subjects using just four channels.

Filter-based techniques, on the other hand, tend to be faster, do not require a classifier, and are scalable. However, these benefits come with the disadvantage of a generally lower accuracy than wrapper-based methods. Yang et al. [15] were able to reduce their channel count from 118 to 11 without significantly affecting accuracy, whilst Yang et al. [16] used a genetic algorithm in combination with an artificial neural network (ANN) to give an accuracy of 80% with 10 channels and 86% from just 6 channels using another dataset. Recently, Gaur et al. [10, 17] randomly selected fifteen channels from a dataset of twenty-two channels over the motor cortex region. This approach helped them to achieve a better classification accuracy than when using all twenty-two channels. In a more recent study, EEG signals were classified into left hand and right MI task using tangent space based transfer learning to enhance the generalized capability of BCI applications [18]. For a review of channel selection algorithms specific to EEG, readers can refer to [19] whilst [20] provides a more recent survey of MI specific filtering techniques.

Various MI related channel selection methods have been proposed [21, 22, 23, 24, 25]. In [21], the CSP-rank identifies the most relevant channels for each MI task in all frequency bands and features are only extracted from selected channels in those frequency bands utilizing the existing capability of the least absolute shrinkage and selection operator (LASSO) algorithm [22]. In another study, Park and Chung [23] performed channel selection using a frequency-optimized local region CSP approach using the variance ratio dispersion score (VRDS) and inter-class feature distance (ICFD) of small EEG channel groups. Another research group [24], applied class correlation, ReliefF, random forest feature ranking, and infinite latent feature selection (ILFS) in multiple frequency bands to identify relevant channels. Using a four-class MEG MI BCI dataset a channel group was formed based on strongly correlated channels whereas Park et al. [25], selected the group with the highest Fisher score as a channel subset using a filter-bank CSP technique.

This paper aims to implement channel reduction through subject-specific channel selection. The study aids in the selection of highly correlated EEG channels against a reference channel for each subject without compromising classification accuracy. A subject-specific subset of channels allows for a more performant classifier whilst allowing for a reduction in both computational complexity and hence time. Three variations of a novel channel selection technique are presented to automatically select these channels, taking as a reference channel C3, C4, or Cz for each subject.

The aims of the paper are thus:

1. To eliminate the non-discriminative information from discriminative information present in the EEG channels;
2. To implement subject-specific EEG channel selection where EEG channels are automatically selected based on the Pearson correlation coefficient method using a reference channel;
3. To evaluate the performance of the proposed methods on different MI tasks because in each task EEG signals are measured from the same cortical areas;
4. To find whether it is possible to achieve better classification accuracy using fewer monopolar EEG channels;
5. To report the classification accuracy when single trials are classified.

The paper is organized as follows: Section 2 describes the dataset, signal processing and feature extraction methods including correlation and CSP; Section 3 presents and discusses the results which includes a comparison of results reported in the literature using the same data-sets [26], whilst Section 4 concludes the study.

2. Methods

2.1. Dataset

The BCI Competition III Dataset IVa [22] was used for this study. The dataset contains multichannel EEG recorded from five healthy subjects seated in a comfortable chair with their arms on armrests. The dataset contains 118 EEG signals which were then band-pass filtered from 0.05 to 200 Hz then sampled at a frequency of 1000 Hz and further down-sampled to 100 Hz. Visual cues were shown to subjects to perform three different types of MI tasks for a duration of 3.5 s: (L) left hand, (R) right hand, or (F) foot. An inter-trial interval of approximately 2 s was allowed for participants to take

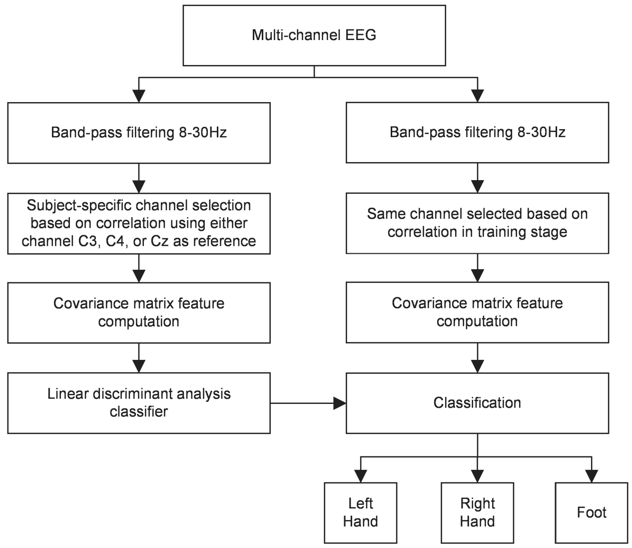

Figure 1: A block diagram detailing the signal processing pipeline from both a training and testing perspective.

a short break. For this study, classification of right hand and foot MI tasks was used to show the effectiveness of the proposed method compared to the results from a group [26] who studied the same classification problem.

Table 1: Trial information for BCI Competition III Dataset IVa.

Subject	Training trials	Testing trials
A01	168	112
A02	224	56
A03	84	196
A04	56	224
A05	28	252

A total of 280 trials were available for each of the five subjects with 118 EEG channels recorded. Table 1 displays the number of training trials (labelled) and test trials (unlabelled) for all five subjects. A detailed breakdown of the training and testing trials for each subject is given in Table 1.

BCI Competition III Dataset IIIa [27] was also used which comprises EEG signals recorded from three subjects, wherein subjects perform right hand, left hand, tongue, and foot MI tasks. Sixty EEG signals were recorded for each subject. For this study, only EEG signals related to left and right hand MI tasks were considered. For each subject, a training (labelled) and testing (unlabelled) set were used for this classification problem.

Table 2: Trial information for BCI Competition III Dataset IIIa.

Subject	Training trials	Testing trials
B01	45	45
B02	30	30
B03	30	30

Each set consisted of 45 trials per set for subject B1 whilst subjects B2 and B3 contained 30 trials. A detailed breakdown of the training and testing sets for each subject may be obtained from Table 2.

2.2. Signal Processing

A BCI consists of several different signal processing stages as illustrated in Fig. 2. This paper will focus on the feature extraction stage by separating and eliminating non-discriminative information from discriminative information present in the EEG channels. This is performed by selecting appropriate EEG channels and hence performing dimensionality reduction, as a higher number of channels means a higher dimensional signal and therefore a higher subsequent number of potential features. As discussed earlier there have been several attempts to reduce this dimensionality as evidenced in the literature. This paper uses the Pearson correlation coefficient to reduce this dimensionality and hence the computational complexity with the aim of preserving or improving classification accuracy.

2.2.1. Feature Extraction

Pearson's Correlation Coefficient (CC) Features are extracted by taking of one of three channels, i.e. C3, C4, or Cz, as a reference and its correlation with the remaining channels is calculated. Channels with a correlation value of >0.5, >0.6, >0.7, or >0.8 are selected and the rest of the channels are discarded (Fig. 1). More details about the number of channels selected for each subject are reported in the results section.

The discrete classification of each evaluation trial is assigned a class. For each trial in the evaluation data for a particular subject, the features are extracted using a time segment between 0.5 s to 2.5 s following the cue having advised the subject to imagine a particular MI task (similar to the BCI Competition III Dataset IVa winner). With each CSP algorithm, 3 pairs

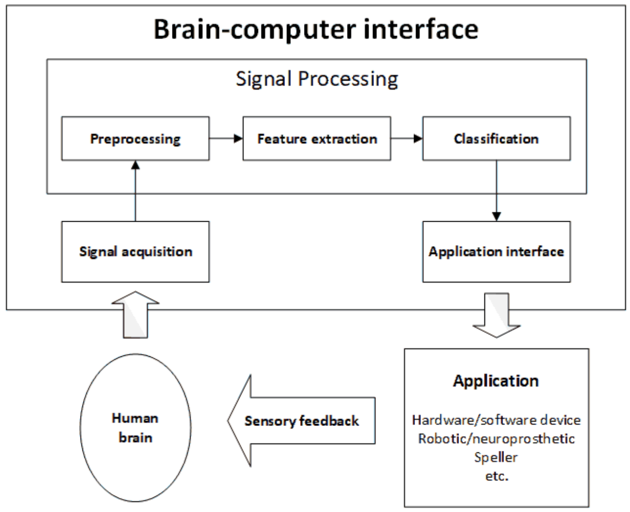

Figure 2: An overview of the brain-computer interface (BCI) closed loop.

of spatial filters (sf) are used to extract features (sf = 3), as recommended in [26, 28]. The extracted features are classified using a linear discriminant analysis (LDA) algorithm, more details of which may be obtained from [29].

The algorithm for the proposed method is found below:

Algorithm 1 Proposed subject specific channel selection algorithm

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Input: Let X denote the signal in time domain

Output: Subject specific channels selected based on correlation taking C3/C4/Cz as a reference channels separately

1: For each reference channel selected from C3/C4/Cz

2: For each subject in time domain

3: Using the selected as reference channel, compute correlation with all the remaining channels in training session

4: Select all channels with correlation > 0.7 in the training session and simultaneously select the same identified channels in evaluation session

5: **return** Channels selected for each subject with correlation > 0.7 in training session and evaluation session

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Common Spatial Pattern (CSP) The common spatial patterns (CSP) algorithm aims to learn spatial filters which minimise the variance of a class while maximising the variance of another. It is often helpful to bandpass filter the multichannel EEG signals [28, 12]. The band-power in any given frequency band gives the variance of the filtered EEG signals in the selected band. The CSP method obtains optimal discrimination for MI based BCI tasks based on band-power features [12]. The CSP method uses the spatial filters w by optimizing the function as follows:

$$Q(w) = \frac{w^T P_1^T P_1 w}{w^T P_2^T P_2 w} = \frac{w^T C_1 w}{w^T C_2 w} \tag{1}$$

where T signifies the transpose of the matrix. P_i gives the training data matrix with sample points as rows and channels as columns. The spatial covariance matrix for a particular class i is C_i.

There are many ways to solve this optimisation problem but the optimisation technique used in this work is solved by initially visualising that the function $Q(w)$ is unchanged, if the filter w is rescaled. In fact $Q(kw) = Q(w)$, where k gives a real constant indicating the rescaling of filter w is arbitrary. Therefore, minimising $Q(w)$ is comparable to minimising $w^T C_1 w$ subject to the constraint $w^T C_2 w = 1$ as there is always a possible way to find a rescaling factor of w such that $w^T C_2 w = 1$. This constrained optimisation problem amounts to minimising the following function using the Lagrange multiplier method:

$$L(\beta, w) = w^T C_1 w - \beta(w^T C_2 w - 1) \tag{2}$$

The derivative of L with regard to w is 0 and the filters w minimising L are such that :

$$\frac{\partial L}{\partial w} = 2w^T C_1 - 2\beta w^T C_2 = 0 \Longleftrightarrow C_1 w = \beta C_2 w \Longleftrightarrow C_2^{-1} C_1 w = \beta w \tag{3}$$

Now, this is a standard eigenvalue problem. Hence, the eigenvectors of $Z = C_2^{-1} C_1$ are used to obtain the spatial filters minimising Eq. 1 corresponding to both the largest and the lowest eigenvalues. The features are extracted as the logarithm of EEG signal variance in the selected band after the projection of filters w using the CSP matrix [26].

3. Results and Discussion

Results are presented for classification of right hand and foot MI tasks and compared with those from another group [26] who studied the same classification problem.

The calculated feature set was obtained by taking sf=3 after channel selection using the above described method helping to attain highly separable features for all subjects. As an example, Fig. 4 shows the box plot of feature separability ($p < 0.05$) for subject 5 in the training session using a five-fold cross validation scheme for right hand and foot MI tasks.

It should be noted that the correlation of 0.7 was identified after an initial investigation by using one of the channels C3, C4, or Cz as a reference resulting in our three proposed methods: Proposed method 1 (PM1) using C3 as a reference, proposed method 2 (PM2) using C4 as a reference, and proposed method 3 (PM3) using Cz as a reference. Although the correlation coefficient was also computed between the range of 0.5 to 0.8, it was determined that the correlation value of 0.7 gave the best results without compromising the classification accuracy (CA). The results obtained in the training session with five-fold cross-validation with correlation coefficient(>0.7) started showing a decrease in CA except for one of the nine subjects with the proposed methods (PM1-C3 and PM2-C4) as shown in Table 3. For demonstration, the CA and channels selected have been shown in Table 3 and Table 4 respectively for correlation coefficients from 0.5 to 0.8. The bold values show the threshold of 0.7 which gives optimum results without compromising the classification ACC. See also Fig. 3 which shows cross-validation classification ACC plotted against total channel number (CH) for each correlation coefficient, i.e. 0.5, 0.6, 0.7, 0.8.

Table 3: Classification ACC in training session of proposed method with 5-fold cross validation. CC refers to correlation coefficient.

Subject	PM1-C3 (CC)				PM2-C4 (CC)				PM3-Cz (CC)			
	0.5	0.6	**0.7**	0.8	0.5	0.6	**0.7**	0.8	0.5	0.6	**0.7**	0.8
A01	90.45	90.52	**90.46**	89.3	92.25	92.28	**91.07**	89.29	89.88	89.93	**89.27**	89.29
A02	96.92	96.42	**96.42**	96.38	96.92	96.42	**96.41**	95.47	96.47	96.42	**95.07**	90.98
A03	71.22	73.09	68.1	69.9	81.15	78.64	**75.18**	70.17	69.15	68.17	**61.99**	54.71
A04	89.24	87.27	**91.06**	87.42	98.18	85.45	**94.55**	91.06	91.21	85.45	87.58	91.21
A05	100	100	**100**	96.67	96.67	92.67	**96.67**	79.33	100	100	**100**	88.67
B01	96.67	96.67	**96.67**	94.44	96.67	96.67	**97.78**	86.67	97.78	96.67	**97.78**	95.56
B02	100	96.67	**98.33**	98.33	100	98.33	**98.33**	98.33	100	98.33	**98.33**	96.67
B03	98.33	96.67	**98.33**	95	98.33	96.67	**95**	88.33	98.33	96.67	**98.33**	96.67
Average	92.85	92.16	**92.42**	90.93	95.02	92.14	**93.12**	87.33	92.85	91.46	**91.04**	87.97

Table 5 shows the accuracies of each subject A01-A05 and B01-B03 for the proposed methods PM1-PM3 along with the comparison method 4 with

Table 4: Channels selected with the proposed method in training session with 5-fold cross validation. CC refers to correlation coefficient.

Subject	PM1-C3 (CC)				PM2-C4 (CC)				PM3-Cz (CC)			
	0.5	0.6	**0.7**	0.8	0.5	0.6	**0.7**	0.8	0.5	0.6	**0.7**	0.8
A01	53	51	**48**	40	54	51	**50**	42	54	52	**49**	43
A02	52	50	**44**	42	55	50	**48**	43	52	35	**23**	9
A03	53	51	**47**	39	54	52	**52**	44	21	17	**12**	5
A04	29	23	**16**	11	84	61	**40**	17	58	37	**23**	12
A05	25	22	**13**	7	87	66	**34**	10	78	47	**28**	13
B01	55	49	**39**	20	59	46	**33**	19	60	53	**44**	25
B02	60	55	**45**	26	60	55	**48**	28	59	50	**44**	35
B03	53	44	**34**	21	51	35	**21**	13	54	49	**43**	28
Average	47.5	43.13	**35.75**	25.75	63	52	**40.75**	27	54.5	42.5	**33.25**	21.25

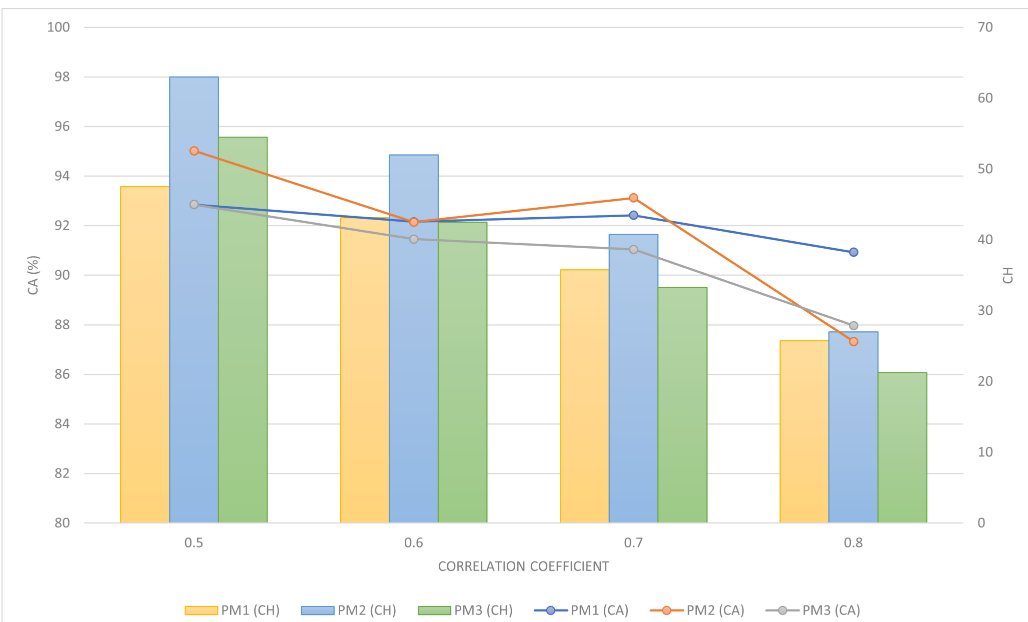

Figure 3: Cross-validation CA plotted against total CH for each correlation coefficient value in the training session.

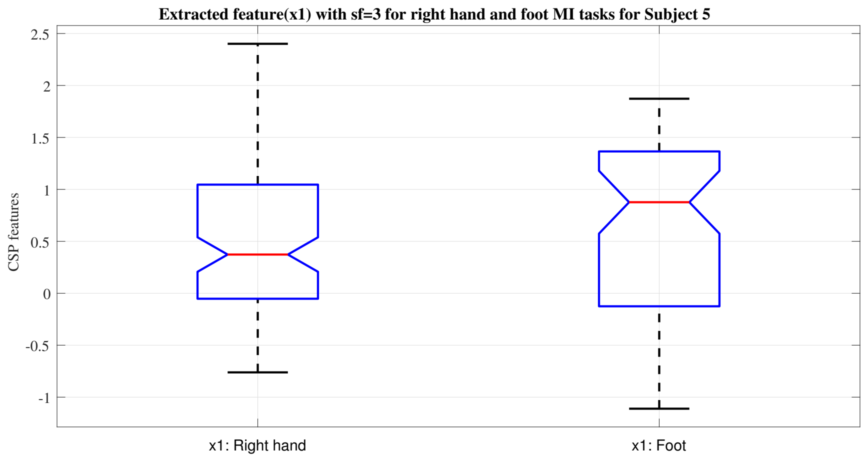

Figure 4: The box plot shows the extracted feature with sf=3 in the training session using five-fold cross validation for right hand and foot MI tasks.

Table 5: Classification ACC comparison of proposed methods (PM1, PM2, and PM3) with another research group for comparison (Comparison method 4 [26]) in the test session. Bold entries indicate highest classification ACC.

Subject	PM1-C3		PM2-C4		PM3-Cz		Comparison method 4	
	Accuracy(%)	Channels	Accuracy(%)	Channels	Accuracy(%)	Channels	Accuracy(%)	Channels
A01	75	48	65.18	50	**75.89**	49	66.07	118
A02	98.21	44	**98.21**	48	94.64	23	96.43	118
A03	48.47	47	**63.27**	52	57.14	12	47.45	118
A04	70.54	16	**77.23**	40	75.89	23	71.88	118
A05	**80.56**	13	65.48	34	72.22	28	49.60	118
B01	**96.67**	39	94.44	33	96.67	44	95.56	60
B02	61.67	45	61.67	48	61.67	44	61.67	60
B03	**98.34**	34	91.67	21	93.33	43	93.33	60
Average	78.68	35.75	77.14	40.75	78.43	33.25	72.75	96.25

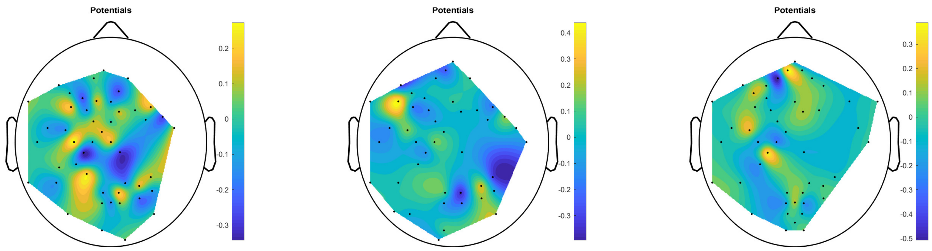

Figure 5: Channels selected for subject A01, subject A02 and subject A03 with channel C3 as a reference channel using PM1.

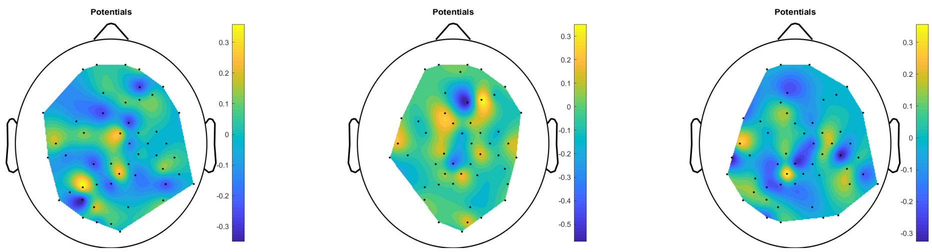

Figure 6: Channels selected for subject A01, subject A02 and subject A03 with channel C4 as a reference channel using PM2.

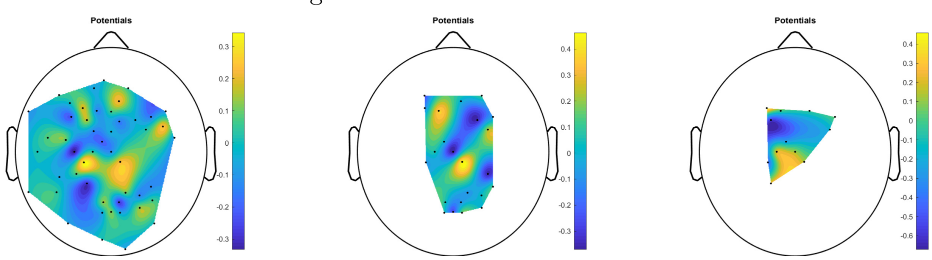

Figure 7: Channels selected for subject A01, subject A02 and subject A03 with channel Cz as a reference channel using PM3.

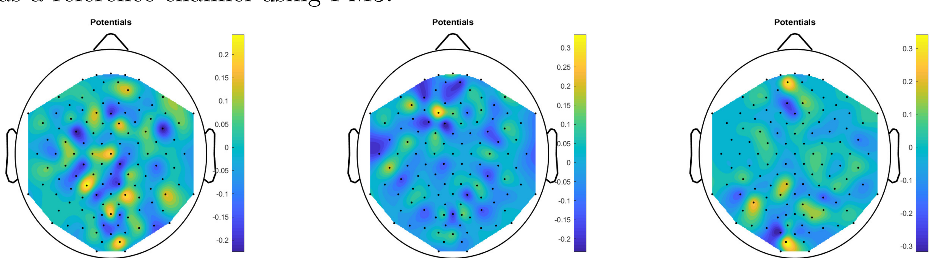

Figure 8: All 118 channels selected for subject A01, subject A02 and subject A03 using comparison method 4.

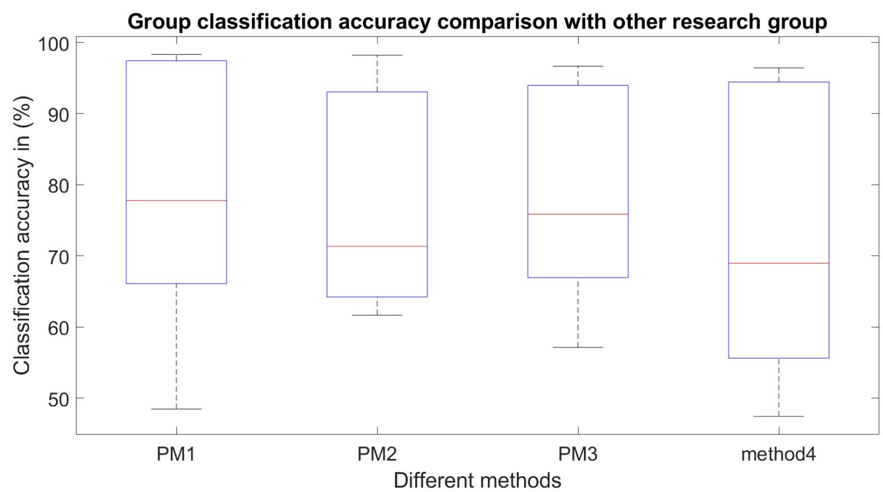

Figure 9: Group CA of proposed methods (PM1-C3, PM2-C4, PM3-Cz) with another research group's (Method 4) for comparison.

Fig. 9 displaying the average accuracy for each subject for comparison, a full description of which now follows.

Each of the three proposed methods, i.e. PM1, PM2, PM3, on average outperformed comparison method 4 whilst using a substantially reduced channel count. Across eight subjects PM1 shows an increased mean performance of >5% (p<0.08), with PM2 >4% (p<0.2), and PM3 >5% (p<0.09). The performance of each individual subject also improves on average over the three methods compared to the comparison method 4 [26].

Subject A01, although showing a slight drop in ACC with PM2 (reduced channels (RC) >50%) compared with Method 4, improved in accuracy in both PM1 (CA >8% and RC >59%) and PM3 (CA >9% and RC >58%). Subject A02 who scored highly in method 4 originally, improved marginally in both PM1 and PM2 (CA >1.5% and RC >62%) and (CA >1.5% and RC >53%), although dropped slightly in accuracy in PM3 (RC >80%). Subject A03 scored similarly to method 4 in PM1 improving by just over 1%, but improved in both PM2 (CA >15%) and PM3 (CA >9%) and an overall average in all three methods of CA >8%. Subject A04 improved in two of the three methods - PM1 (CA <1% and RC >86%), PM2 (CA >5% and RC >61%), and PM3 (CA >4% and RC >80%) with an average improvement of just over 2.6%. Although subject A02 showed little improvement on average over three methods (CA >0.5%), interestingly, subject A05 shows the most improvement with PM1 (CA >30%), PM2 (CA >15%), and PM3 (>22%) and an improvement on average over all three methods of >23%.

Subject B01 and B03 have improved by only ca >1% and ca >5% with significant reduction of rc >35% and rc >43% in the channels selected using the PM1 and PM3. Moreover, the same classification was achieved with a reduced number of channels using PM1 (rc >25), PM2 (rc >52), and PM3 (rc >26).

With regards to channel reduction, PM2 uses <41 channels on average over all 8 subjects, representing <58% of the original 96.25 channels. PM1 gives a greater improvement with rc <36 channels, or <63% with PM2. PM3 demonstrates the greatest reduction in channel number on average over all subjects rc <65% of the original 96.25 channels.

Thus the PM1 and PM3 show comparable results in terms of average CA but with 35.75 and 33.25 average number of channels. Further analysis is required to determine why the reference taken from Cz produces the best outcomes in this case.

Figures 5 - 8 show the channels selected with PM1, PM2 and PM3, and comparison method 4 respectively in terms of electrode weights from a neurophysiological point of view. Fig. 5 depicts the different regions of the brain where subject-specific channels are selected for subject A01, subject A02 and subject A03 with channel C3 as a reference channel denoted by PM1 in terms of electrode weight. Similarly, Figs. 6 and 7 show the brain region selected in terms of electrode weight when subject-specific channels are selected for subject A01, subject A02 and subject A03 with channel C4 and channel Cz as a reference channel denoted by PM2 and PM3 respectively. For comparison, Figure 8 shows all 118 channels selected for subject A01, subject A02 and subject A03 denoted by method 4 [26]. Hence, it is possible to visually inspect the location of the automatically selected subject-specific channels when examined alongside comparison method 4 and it is evident from the figures that there is a substantial channel reduction using the proposed methods.

To contrast, another research group [25] identified correlated channels using the Fisher score to select the channel set for MI classification in the feature extraction step, and classified the selected features using the support vector machine (SVM) classifier [30]. In our study, channel selection was performed in the pre-processing stage where pairwise correlation was computed using the Pearson correlation method taking C3, C4, or Cz as a reference channel. This method is much simpler to understand and has the potential to be implemented for the online classification of MI tasks in BCI systems.

It is interesting to note that two out of our three proposed methods have shown a lower variance in CA than the comparison method 4 making our method more robust across multiple datasets.

This paper's findings demonstrate that it is possible to simultaneously reduce the number of channels whilst maintaining a sufficient (and in fact an increased) level of accuracy. The variation in the number and position of channels selected in each case highlights the inherent differences in the human brain and the subsequent difficulty involved in designing a MI BCI adding to the already challenging problem of non-stationarity present in the signals again highlighting the need for the technique presented within this paper.

It would be interesting to perform further analysis to ascertain whether correlation values to two decimal places would yield a higher CA whilst further reducing the number of necessary channels. Additionally, although on average a balance was struck between the correlation coefficient value and the number of channels rejected, this correlation value was fixed at 0.7 for all participants and it would be interesting to select a subject-specific correlation coefficient as there were certainly differences in CA between participants.

A future study could, for example, use a method to search all permutations of the correlation coefficient to a finer degree of resolution to find the optimal value whilst maintaining a set threshold CA level. Additionally, this dimensionality reduction has implications not only for the speed at which a dataset can be processed but also with regard the efficiency at which on online implementation of the system could be realised.

Ultimately, the techniques presented in this work could potentially lead to a fully automated and personalised BCI - one which is more adept at shaping to individual users' cortical physiology and hence to the highly individualised brainwaves produced therein.

4. Conclusion

In this study, an automatic subject specific channel selection technique was proposed to select channels for a MI-based BCI. These channels are selected automatically based on correlations computed between one of C3, C4, or Cz as a reference and other EEG channels. The results were presented using a correlation of 0.7, which demonstrates not only an improved overall CA but also a significant reduction in the number of channels, due to the well-documented association with the sensorimotor areas. This study offers two contributions to the research field. Firstly, the number of channels were significantly reduced using the proposed algorithms without compromising performance. This reduction in the number of channels makes it more suitable for the practical real-time application of BCI. Secondly, the idea of channel selection was introduced using the standard EEG channel distribution and an intelligent algorithm for automatic selection of channels for each subject. In future studies, a thorough analysis may reveal better selection criteria which should allow for a further reduction in channels whilst maintaining CA.

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