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COMPARISON OF METHODS FOR EEG CHANNEL SELECTION FOR MI TASK

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Abstract: Multi-channel EEG signal is mainly used in Brain signature categorization. Owing to the curse of dimensionality problem, the analysis and classification using several channels may lead to the undesired performance. Channel selection could be an effective way to improve EEG signal quality by removing those noisy, irrelevant channels. Selecting a lesser count of channels may lower down the system cost. Selecting the subject-specific, informative channels may help to identify the motor cortex that is correlated well with the performed motor imagery tasks. This paper provides the comparison of channel selection techniques for EEG signal. Two algorithms have been presented to identify subsets of channels which are capable of discriminating between samples of distinct classes. The CSP and Surface Laplacian algorithms are considered for channel selection. The performance of these methods in terms of accuracy is 82.9% and 76.24% respectively.

Index Terms – EEG, Channel selection, MI, Performance.

I. Introduction

Brain machine interface (BMI) systems are mainly employed in applications like communication and neuro-prosthetic for Divyanjans. A BMI system utilizes distinct inputs; however, EEG signals are widely employed as it is non-invasive, portable, and cost efficient. The signals produced by the brain while performing or imagining a motor related task i.e. MI signals are crucial inputs for BMI applications. Generally, the acquired EEG signals are multi-channel in nature. EEG data is mainly recorded from different locations across the brain. The full-channel EEG signals, initiates many complex features, and also introduces interference information from irrelevant channels, and reduces the system robustness. Therefore, effective channel selection algorithm is desired to lesson computation complexity and reduce the over-fitting problem that may be caused by the irrelevant channels, to enhance the performance of the system [1].

Source localization related to brain activities may be an important factor to identify the medical disorders, cognitive state, and a better understanding of the brain. Selecting appropriate channels in BMI applications helps to enhance the usability and the performance of the BMI as some channels are contaminated by noise or contain irrelevant information**.**
The motives of channel selection are: (i) to minimize computational complexity, by choosing the pertinent channels and obtaining the features of high relevance, (ii) to minimize the over fitting that may arise due to the utilization of unnecessary channels, and (iii) to minimize the setup time of particular applications [2].

The numerous algorithms have been presents to identify channel subsets which are capable of discriminating among samples of different classes. However, finding the subsets of related channels may not always be feasible. For certain applications lesser number of channels, may lessen the sufficient information. Efficient channel selection algorithms are of highly significant to get the optimal channels corresponding to a particular task. The main motive of utilizing channel selection is to reduce computational complexity, enhance classification accuracy by minimizing over-fitting, and decrease setup time[3].

This paper presents algorithms to minimize the channel count with the aim of minimizing computational complexity with good accuracy. Filter-based approaches are classifier independent and less computational intensive. This algorithm finds the correlation within EEG signals to select exceedingly correlated channels for specific user without disturbing classification accuracy. Common spatial patterns (CSP) and surface Laplacian are used mainly for this purpose. The spatial pattern coefficients in the Common Spatial Pattern (CSP)-based methods were used to select the channels[2-5].

The rest of the paper is organized as follows section II gives the details of algorithms available for channels selection. Section III describes the algorithms considered for the channel selection. Section IV discusses the results and paper is concluded in chapter V

II. Methods considered for channel selection

Many approaches have been presented for addressing the problem of channel selection. These methods are categorized as: wrapper method and filter method . In the first method, channel selection is wrapped with classification algorithm such as SVM , which recursively eliminates least significant channels for classification. Second method is independent of classifiers. Here channels ranking is done using criterion such as mutual information, CSP coefficients and fisher ratio.

Filtering techniques shows the advantage of scalability, the high speed and independence from the classifier. The methods taken into the consideration for channel selection are spatial filter methods[6].

A. Common Spatial Pattern coefficients (CSP)

The CSP algorithm makes spatial filters to learn with reducing the variance of one ctegory and increasing the variance of other . The aim of the algorithm is to enhance the categorization of two different signals. The spatial filters are designed to maximize the variance for first condition and minimize it for the second one. This can be applied for categorizing MI signals. (e.g. left versus right hand movement). 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. Here channels mainly contributing to the classification in terms of the signal power are selected. *Remarkable* channels depending on correlation coefficient are stipulated in the proposed method. The *peculiarity* of a channel is determined by the number of channels with which it produces high difference in values of correlation coefficient for MI tasks, compared to difference itself. For each *remarkable* channel, group of channels is created by using strongly correlated channels. After that fisher score is computed. Finally, the channel group with the highest fisher score is selected [7-10].

Consider that M1 and M2 are the signals corresponding to positive and negative class, respectively, with the dimension of m samples.

and
W: Filter matrix
lambda: Eigen values of each filter.
A: Demixing matrix.
Once the W is trained, the projection of new data X is computed as:
M_csp = W'*M;
The first two of spatial filters are utilized for spatially filtering of EEG signals in motor imagery based BCI system

B. Surface Laplacian

The surface laplacian approach calculates the second derivative of the instantaneous spatial voltage distribution for each electrode location. It intensify activity evolving from radial sources beneath the electrode. Hence it is a high-pass spatial filter which point out localized activity and minimizes scattered activity. Laplacian at each electrode location is obtained by combining the output of surrounding electrodes with the output at that location. The distances to the surrounding electrodes determine the spatial filtering properties of the Laplacian. As distance reduces, it becomes highly subtle to potentials of higher spatial frequencies and less suble to lower spatial frequencies. Laplacians can be acquired with two different sets of surrounding electrodes, i.e.nearest-neighbor electrodes called as small Laplacian and next-nearest neighbor electrodes called as a large Laplacian. If the control signals are exceedingly localized over time, then small Laplacian to give a higher signal-to-noise ratio. On the other hand, if the control signals are poorly localized the large Laplacian provide superior performance[7-10].

III. EXPERIMENTAL SETUP

In this work, CSP and SL are employed for EEG channel selection as a step to improve the performance of MI task classification. The proposed methods are tested based on the -- dataset. In the experiment, we use full channels and the selected channels of more importance, respectively, and the relationship between the recognition rate and the selected channels for selected channels is analyzed.

A. EEG DATASET

The datasets considered for experimentation consists of 14 records of motor imagination of left and right hand. “They include 11 channels: C3, C4, Nz, FC3, FC4, C5, C1, C2, C6, CP3 and CP4. The channels are recorded in common average mode and Nz can be used as a reference if needed. The signal is sampled at 512 Hz and was recorded with our Mindmedia NeXus32B amplifier. Each file consists in 40 trials where the subject was requested to imagine either left or right hand movements (20 each) [1]. This dataset can be accessed from: http://openvibe.inria.fr/datasets-downloads/ .

B. EXPERIMENTAL SETUP

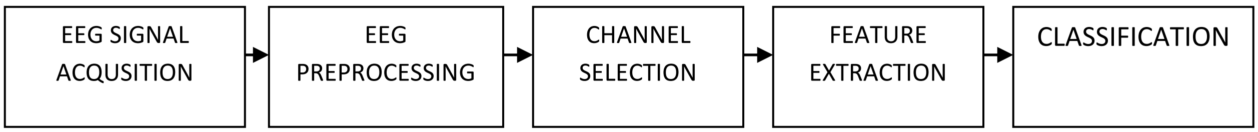

Fig. 1. Setup for EEG categorization with channel selector

As seen in the above figure channel selection block is added after the preprocessing of the EEG signal. The channel selection methods considered here are CSP and SL. It selects the particular set of the channels . This signal is then given to the feature extraction stage intead of giving the complete set of EEG channels. This works here as a dimentionality reduction tool. These features are then given to the classifier for categorizing the signal. The output of the different stages is given in the following section.

IV. RESULTS AND ANALYSIS

A. RESULTS OF CHANNEL SELECTION

The original EEG signal from the dataset mentioned is given below.

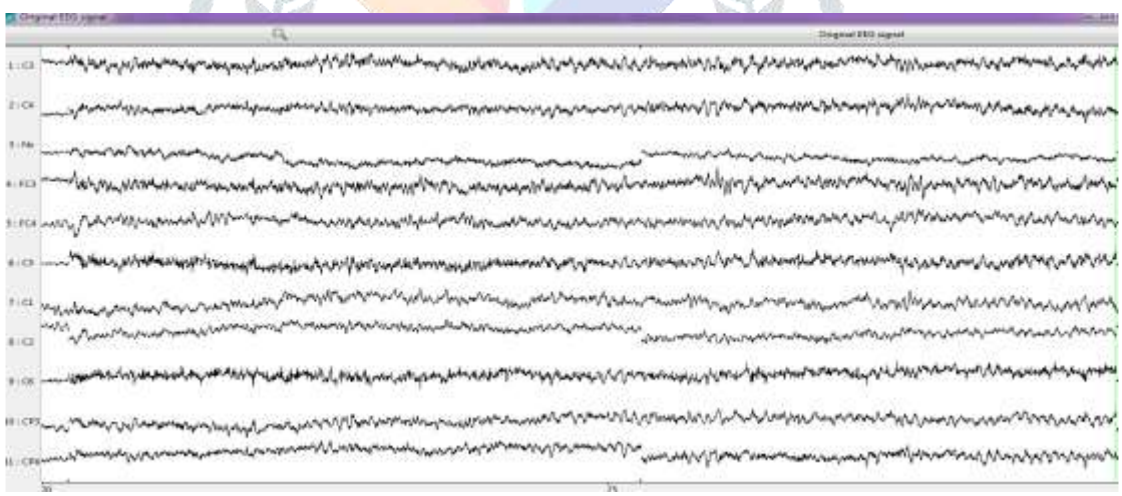

Fig. 2. Original EEG signal Window

It is having all ten channels along with the reference channel. The signal consist of some artifacts which may lead to misclassification. Hence artifacts has to be removed.

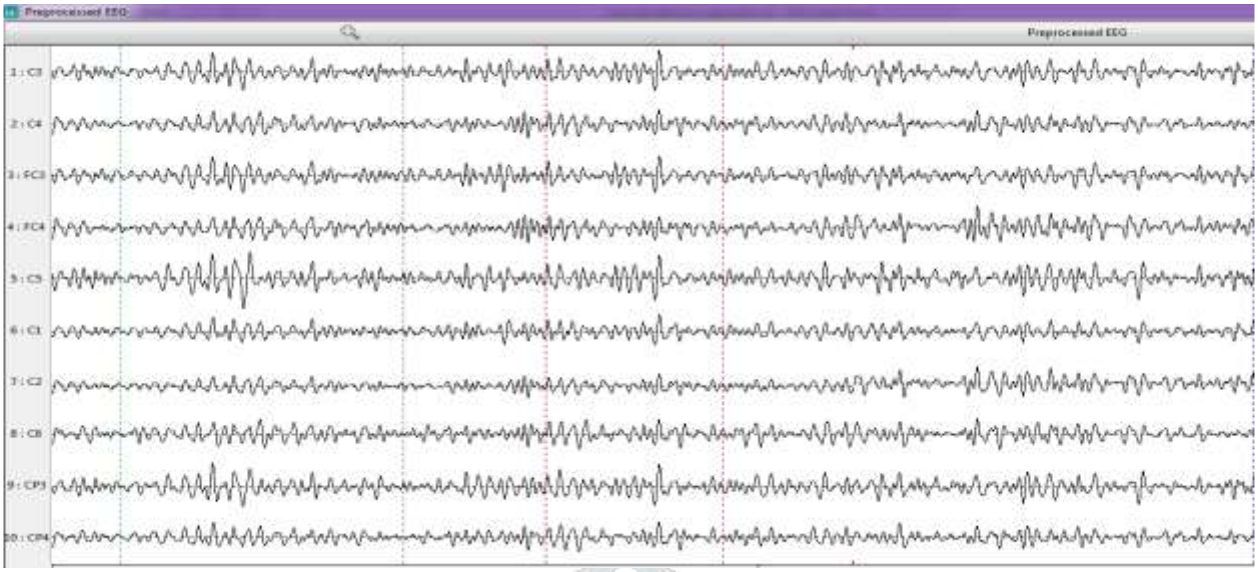

Fig. 3. Preprocessed EEG signal

This preprocessed output is given to the channel selector. The output of the two different channel selector is given below-

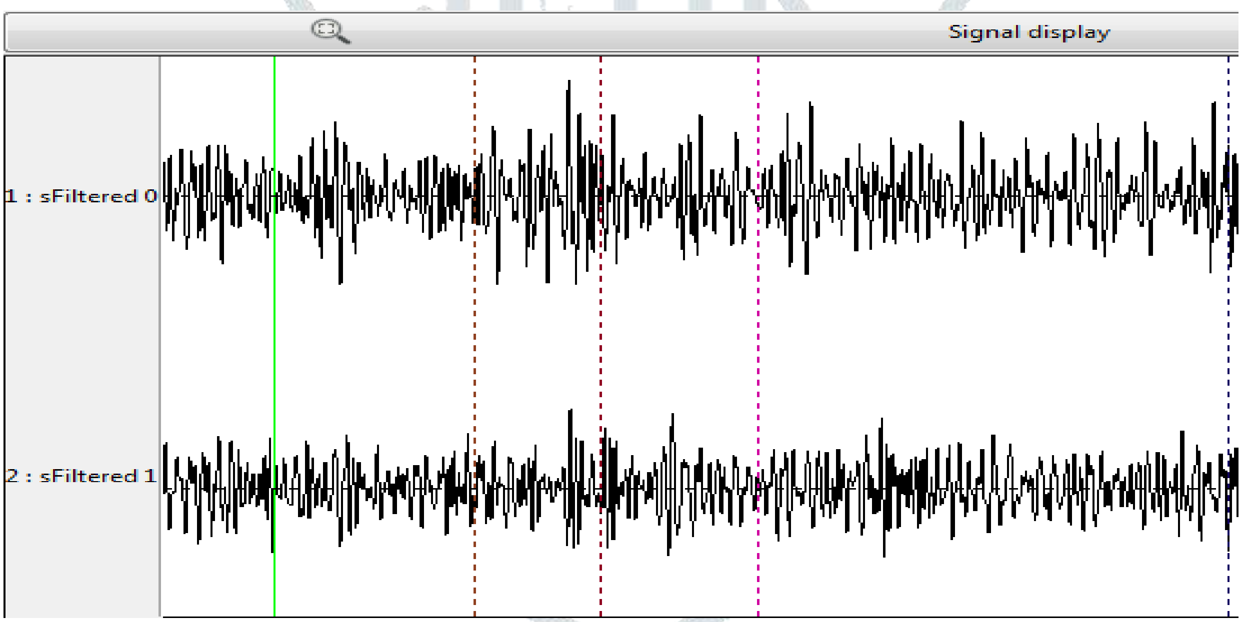

Fig. 4. EEG signal after channel selection using Surface Laplacian filter

Figure 4 shows the output of channel selector using the surface laplacian filter method.. only two channels are generated using this method. The output of CSP classifier is shown in the fig. 5. It has selected six channels. The classification accuracies corresponding to these methods are shown in fig 6 and fig 7 respectively.

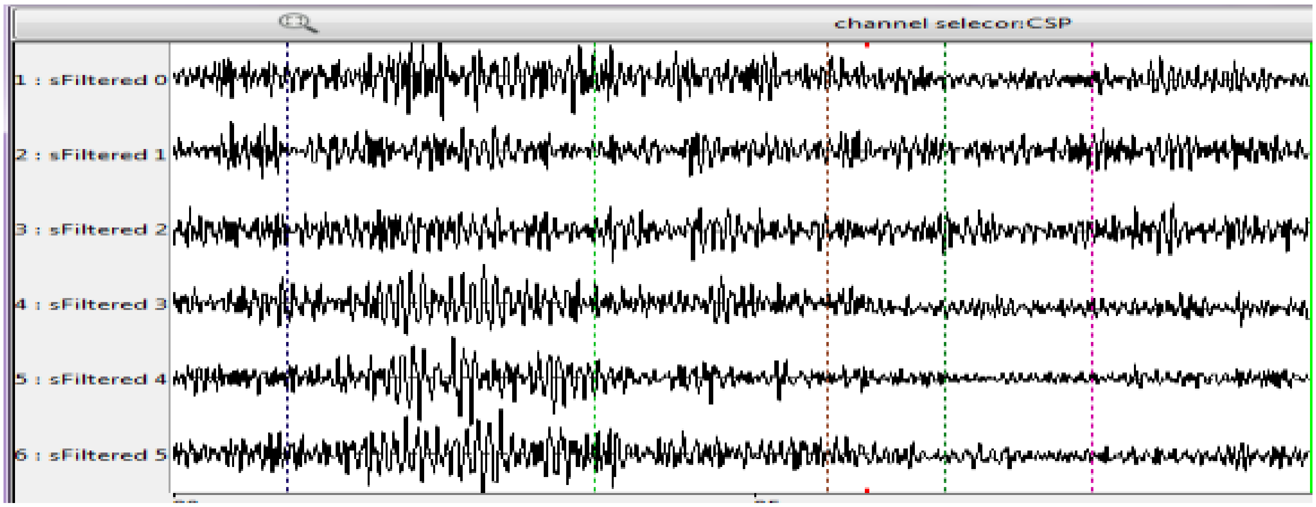

Fig. 5. EEG signal after channel selection using Common spatial pattern filter

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Classifier trainer> Finished with partition 1 / 7 (performance : 74.6032%)
Classifier trainer> Finished with partition 2 / 7 (performance : 73.4127%)
Classifier trainer> Finished with partition 3 / 7 (performance : 57.9365%)
Classifier trainer> Finished with partition 4 / 7 (performance : 86.5079%)
Classifier trainer> Finished with partition 5 / 7 (performance : 77.381%)
Classifier trainer> Finished with partition 6 / 7 (performance : 88.4921%)
Classifier trainer> Finished with partition 7 / 7 (performance : 75.3968%)
Classifier trainer> Cross-validation test accuracy is 76.2472% (sigma = 9.28322%)
Classifier trainer>   Cls vs cls      1     2
Classifier trainer>   Target  1:   81.2  18.8 %, 931 examples
Classifier trainer>   Target  2:   29.3  70.7 %, 833 examples
Classifier trainer> Training set accuracy is 79.195% (optimistic)
Classifier trainer>   Cls vs cls      1     2
Classifier trainer>   Target  1:   83.4  16.6 %, 931 examples
Classifier trainer>   Target  2:   25.5  74.5 %, 833 examples
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Fig.6 . Classifier performance of SL

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Classifier trainer> For information, we have 931 feature vector(s) for input 1
Classifier trainer> For information, we have 833 feature vector(s) for input 2
Classifier trainer> k-fold test could take quite a long time, be patient
Classifier trainer> Finished with partition 1 / 7 (performance : 85.3175%)
Classifier trainer> Finished with partition 2 / 7 (performance : 74.2063%)
Classifier trainer> Finished with partition 3 / 7 (performance : 67.8571%)
Classifier trainer> Finished with partition 4 / 7 (performance : 96.0317%)
Classifier trainer> Finished with partition 5 / 7 (performance : 92.8571%)
Classifier trainer> Finished with partition 6 / 7 (performance : 89.6825%)
Classifier trainer> Finished with partition 7 / 7 (performance : 75%)
Classifier trainer> Cross-validation test accuracy is 82.9932% (sigma = 9.9114%)
Classifier trainer>   Cls vs cls      1     2
Classifier trainer>   Target  1:   86.9  13.1 %, 931 examples
Classifier trainer>   Target  2:   21.4  78.6 %, 833 examples
```

Fig. 7. Classifier performance of CSP

Table: 1 Performance of channel selector algorithm

Channel selection method	Accuracy
Surface Laplacian method -SL	76.24%
Common Spatial Pattern filter-CSP	82.99%

From the above table it is found that the classification accuracy for SL is 76.24% and CSP is 82.99%. Hence with the CSP channel selector system performance can be enhanced.

V. CONCLUSION

For motor imagination recognition, traditional approaches based on full-channel EEG signals will lead to redundant data and hardware complexity. This paper presents a comparison of channel selection method to select optimal channels for EEG motor imaginary recognition. SVM classifier is used to classify imagination . The number of EEG channels can be reduced from 10 to 6 for CSP and from 10 to 2 for by using SL. In addition, we compared our methods. The results show the proposed method effectively improves the rate of MI recognition while reduces the channels sharply. Hence we can conclude that channel selection algorithms provide a possibility to work with fewer channels without affecting the classification accuracy

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