Bachelor of Technology Project - I (ELD 431)

On

Does Specific Channels Matter in Channel Selection for MI EEG Decoding?

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Contents

Abstract

Brain-Computer Interface (BCI) technology offers a direct line of communication between the brain and a computer or other machine, bypassing the conventional pathway between nerves and muscles. The method of acquiring brain signals most frequently utilised in BCI systems is electroencephalography (EEG). It has been demonstrated that using motor imagery (MI) patterns in EEG-based BCI is an efficient way to convert user movement intentions into instructions for controlling external devices. A significant number of scalp electrodes are used in conventional EEG-based BCI to achieve excellent classification accuracy of MI. The clinical settings, where preparation time is crucial is a matter of problem with this, though. In order to increase classification accuracy, there is a suggested channel selection strategy that makes use of a priori information from the MI task and iteratively optimises the number of relevant channels, finally using only fewer relevant channels and thereby reducing number of channels significantly. Our report analyses whether these relevant channels really optimise the accuracy. We do this by selecting the channels using proposed algorithm with and without making the use of priori information of from MI task and then compareng the two results.

Keywords— Brain Computer Interface, Channel Selection, Motor Imagery, Event related Synchronization/ Desynchronization.

Chapter 1

Introduction

Because of its diverse application scenarios, the Brain-Computer Interface (BCI) system has attracted considerable interest from a number of research areas. Modern technology has made it possible for the BCI paradigm to translate human ideas into commands for actions, bypassing the traditional neuro-muscular circuit. Numerous topics, including as computational neuroscience, cognitive analysis, neuro-rehabilitation engineering, and neuro-gaming, are the focus of BCI research. Electroencephalography (EEG), magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS), and functional magnetic resonance imaging (fMRI) are some of the modalities used in BCI systems to gather brain signal (fMRI). EEG is the most popular data gathering method utilised in BCI systems due to its portability, affordability, and simplicity. The motor imagery (MI) patterns in an EEG-based BCI can be used to convert a user's intended movement into output commands for external device control. Because it has the potential to enhance the quality of life for ALS patients, motor imagery-based BCI, or MI-BCI, has attracted the interest of researchers. Studies conducted in the past on BCIs based on motor imagery reveal that the brain signals produced by actual movement and imagined movement over the sensorimotor cortex are identical. These patterns, known as Event Related Synchronization (ERS) and Event Related Desynchronization (ERD), result in a rise and reduction in the EEG signals' spectral power in specific frequency regions. These event-related potentials appear in the primary motor cortex areas oblique to the carried-out MI tasks.

To achieve good accuracy in the classification of MI tasks, placement of EEG electrodes in the motor cortex region is assumed to be as close as possible. According to some studies it is found that only two electrodes (channels), C3 and C4, which are in the left and right motor cortex of the brain respectively, are sufficient to obtain 80-90% MI classification accuracy after multiple sessions. We must cross-check whether this statement is mathematically true.

An increase in the number of electrodes raises various concerns, such as longer preparation times, more artifacts, and redundant signal information. So, if we can reduce the number of channels without tampering with the accuracy then it will be highly benificial. Although manual channel selection based on existing neurophysiological information might significantly shorten setup time, it does not always result in the highest classification rate. In order to find the most pertinent channels with the highest level of classification accuracy, we require a strong channel selection algorithm. We have a proposed channel selection algorithm [1]. We want to analyse whether this algorithm really provides us with most relevant channels.

Chapter 2

Methodology

From many papers that we studied, we found in most of the channel selection algorithms there are three main steps [2]. a) Use of priori information about the MI task to get the knowledge about target scalp region of interest(ROI) beforehand. b) Design the features using the EEG signals from those selected channels. c) Train a machine learning classifier on those features to predict the test samples.

We tried to investigate the effect of random channels on a state of art algorithm proposed in [1]. We replicated the results in this paper. The proposed algorithm in [1] can be summarised as follow:

2.1 IORCS: Iterative Optimization for Robust Channel Selection

IORCS [1] is a iterative optimization algorithm for robust channel selection for MI tasks. This algorithsm consist of following steps:

1. Segmentation of raw EEG data into trials by selecting the temporal region between 0.5 and 2.5 seconds after the cue is displyed.
2. Out of 118 channels from dataset, the 10 most pertinent channels are chosen in the channel selection stage using the proposed channel selection algorithm.
3. Nine overlapping filter bands 3-8 Hz, 7-12 Hz, 11-16 Hz....35-40 Hz are used to filter the EEG data for these channels. A Butterworth filter of order 4 is employed for this.
4. using the CSP algorithm, filtered signals are transformed into a new spatial subspace before being subjected to a feature selection process based on the minimum redundancy maximum relevancy (mRMR) algorithm.
5. The SVM classifier, powered by the LIBSVM library, is then used to train the chosen features.

This algorithms have been well summarized in flowchart given in the paper, and it as below:

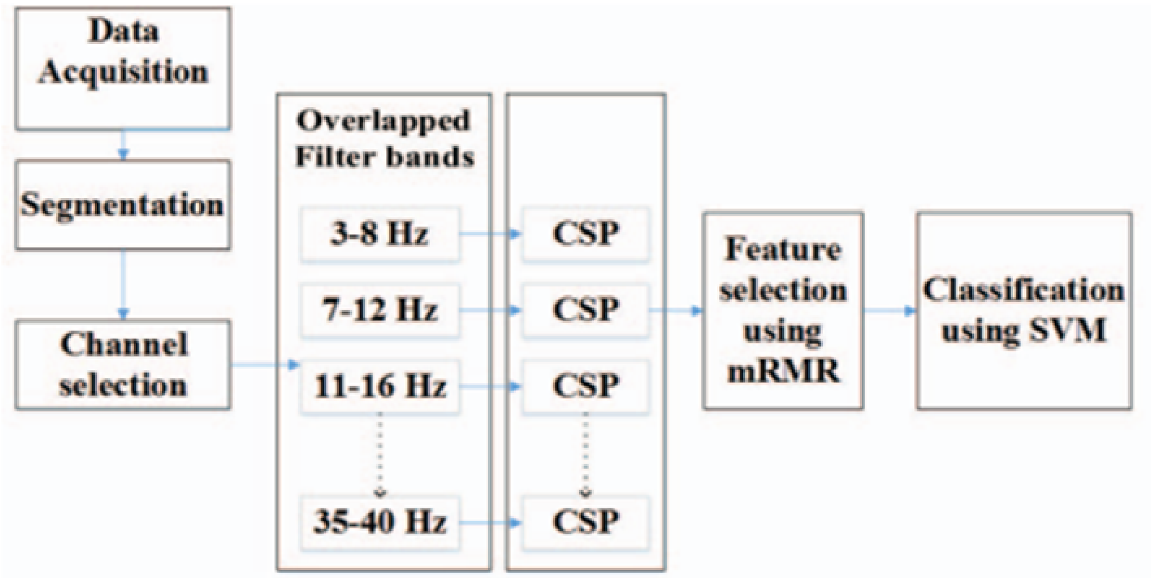


Figure 2.1: Flowchart of the proposed algorithm [1]

2.2 Randomly Selecting the Reference Channels in IORCS

We initialized with a randomly selected channel (without using the priori information about the MI task) as a seed to the channel selection algorithm given in the paper. We compare the results with the results obtained from IORCS replicated by us.

2.3 Randomly Selecting the Channels

We selected 10 random channels to get the results to compare whether the outcome was worse than outcome from IORCS.

Chapter 3

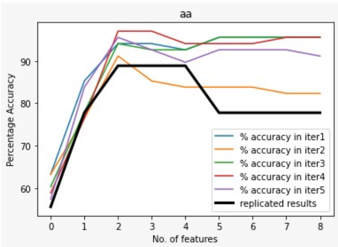
Data Description (Dataset IV a, BCI Competition III)

This dataset consists of 118 channel signal recordings from 5 participants collected in a single session. The left hand, right hand, or right foot were the three classifications of movement that the subjects were asked to visualise. The suggested method in this work intends to categorise right hand and foot trials because the competition dataset contained cues for the right hand and right foot imagery. There are 280 trials in the combined training and testing data. In this study, we have used data which was sampled at 1000Hz.

DatasetIV a, BCI Competition III Download Link

Chapter 4

Results



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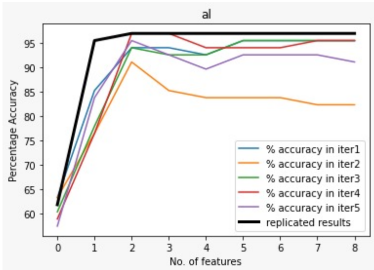

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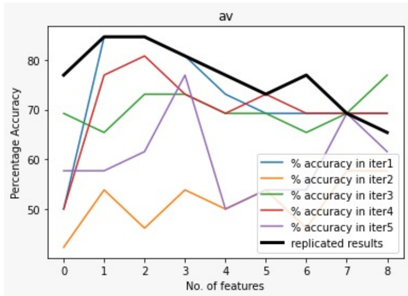

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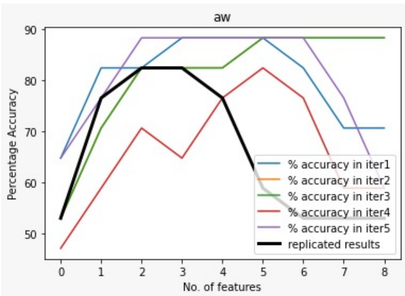

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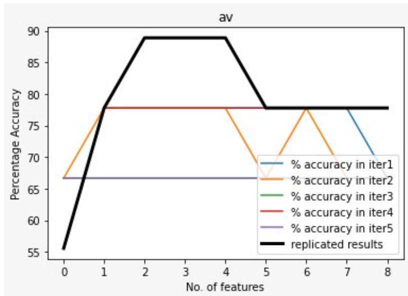
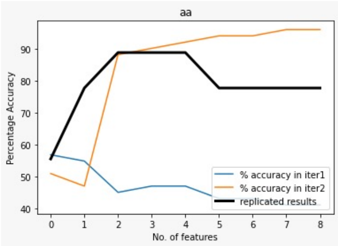


(e) Subject 5

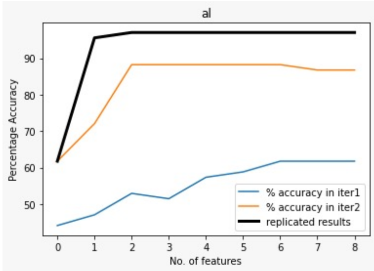
Figure 4.1

In the fig.3.1 we are comparing the results obtained from IORCS with results obtained from 10 randomly chosen channels done 5 times for 5 different subjects.

In the fig.3.2 we are comparing the results obtained from IORCS with results obtained from the same algorithm with randomly chosen reference channel done 2 times for 5 different subjects.



(a) Subject 1



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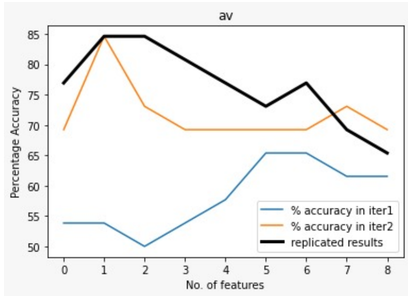

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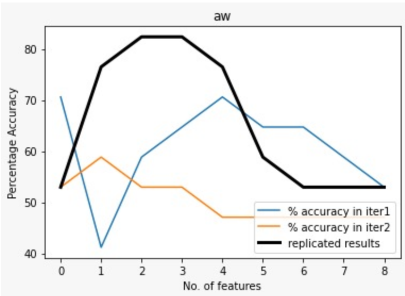

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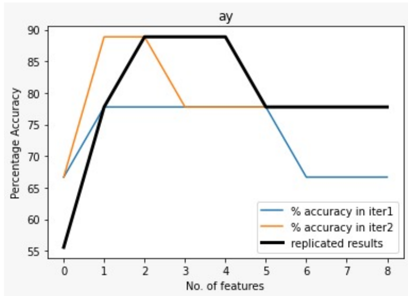

(e) Subject 5

Figure 4.2

Subject	Accuracy(%) with algorithmically selected channel (kernel centered at 'C3')	Accuracy(%) with randomly selected channels	Accuracy(%) With algorithmically selected channel(randomly selected reference)
aa	98.03	68.62	69.60
al	97.05	89.72	75.01
av	92.30	80.76	69.23
aw	82.35	88.23	61.76
ay	88.88	88.88	88.33
Mean	91.72	83.24	71.78

Table 4.1 : Individual accuracies and average accuracy of 5 subjects with and without algorithmically selected channels

Chapter 5

Conclusion

From the results obtained from a) selecting the given number of channels using the proposed state-of-art algorithm and selecting the reference channel using the priori information about the MI task b) selecting the given number of channels using the proposed state-of-art algorithm and selecting the reference channel randomly c) selecting the given number of channels randomly from all available channels, we can see that there is no severe deviation from the results obtained in (a), on the results obtained by selecting the reference channel randomly(b), or results obtained by selecting all the channels randomly(c).

From Table 4.1 we reached a conclusion that the proposed channel selection algorithm in IORCS might not give the most relevant channels since even if the channels are selected randomly then the results are comparable to the results obtained from IORCS.

The proposed state-of-art algorithm is based on some prior information about the MI task, but there have been issues with these priors and selections algorithms: a) Several research have shown that some of these priors are based on overinterpretation of EEG [3]. b) Overhyping the decodability of EEG and fMRI by over-tuning the hyperparameters of the optimization algorithms of decoding efficiency [4].

In IORCS, it is assumed that while performing the MI tasks the electrical signals are highly intense near motor cortex region but there is no scientific proof of this statement.

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