0.1. Introduction

0.2. Channel selection

Channel selection is one of the solutions when it comes to reducing the amount of data we send from one transmitter to the other. Our objective is clearly to send as much informative data as possible, but that comes with a cost that we may not be able to deal with, depending on other critical points we have seen. Moreover not all signals carry useful information, some of them may just add noise and complicate our classification of neural data. Because of this, channel selection is not just a feat of data size optimization but of accuracy optimization as well. By removing noise we can increment our accuracy and by removing less informative channels we can send data effectively without having to worry about the critical point we have previously stated. [1]

0.2.1. Signal data

Here I describe the structure of data, saying the rationale behind the cuff electrode signals. Why radial and longitudinal etc... We cut to 10 channels more or less so we send the signal and we can handle that data size. The problem with the data is that since we apply electrode cuffs chirurgically there may be noise added and electrodes that straight up work poorly. Therefore we need to define a precise pipeline that can discard non informative signal or worse, noise from our channels. Ideally, if we would discard more than 16 channels and have less than 10, we could try to perform some sort of de-noise over the channels.

0.2.2. Requirements and Specifications

We have a setup time that includes many procedures. So we do not have a lot of time for training and processing. We receive our data in two different streams. A first stream composed of 8 channels that lasts 1 minute. A second stream with the remaining 8 channels that lasts again 1 minute. Also our setup is composed of small micro-controllers that can perform little to no calculation. We have to keep in mind a few things.

- We cannot train after having received the data cause it would take too much time
- We cannot train beforehand a specific model since the data we have is different from the one we will receive.
- Possibility is to train a very general auto encoder that can compress data and add some sort of de-noise by removing the wrong information.
- and like this.

However, there is a problem in the previous studies. The effect of the same algorithm on different subjects is quite different. Research on reducing the impact of differences between individuals on the classification performance is the core work of this paper. DWT and CNN based multi-class motor imagery electroencephalographic signal recognition

Because of these restrictions the best methodology is an online approach that can evaluate the channels either while we are receiving them or right after the transmission is over. Cross-Correlation Based Discriminant Criterion emerges as the best solution [Cross-Correlation Based Discriminant Criterion for Channel Selection in Motor Imagery BCI Systems], especially when paired with a CNN classifier such as the ENGNet we implemented based on [] as shown in this review at 1.2.[https://www.ncbi.nlm.nih.gov/pmc/articles/PMC977454

0.2.3. Pipeline of the work

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- Read data
- Analyze by metrics that depend only on the signal itself (variance etc...) if we can
- ASR
- Cross-correlate within channels
- CNN
- Pack the signal and send i

0.2.4. Cross-correlation and evidence

Wavelet Coherence Based Channel Selection for Classifying Single Trial Motor Imagery Cross-Correlation Based Discriminant Criterion for Channel Selection in Motor Imagery BCI Systems XCDC measures similarity between signals by cross-correlation, and emphasizes the electrodes that: 1) signals of the same class show larger similarity, and 2) signals of different classes differ more obviously. After ranking the channels according to XCDC, signals from the channels with highest discriminant criterion are chosen as the input of a convolutional neural network (CNN) classifier, which further evaluates the credibility of the chosen channels by classification accuracy. The performance of XCDC is evaluated and compared to CCS [26] and CSP-rank and is better than both (change this). The complexity of XCDC is quadratic. Deriving the discriminant score D of a channel involves the computation of cross-correlation between every pair of trials, resulting in a quadratic complexity.

0.2.5. Artifact subspace reconstruction (ASR)

Artifact subspace reconstruction (ASR) is an automatic, online-capable, component-based method that can effectively remove transient or large-amplitude artifacts contaminating electroencephalographic (EEG) data Evaluation of Artifact Subspace Reconstruction for Automatic Artifact Components Removal in Multi-Channel EEG Recordings

0.2.6. Genetic Algorithm why not (BPSO) and why not in general wrapper methods

Filtering techniques for channel selection in motor imagery EEG applications: a survey A review of channel selection algorithms for EEG signal processing EEG electrode selection method based on BPSO with channel impact factor for acquisition of significant brain signal

0.2.7. Evaluation of channel selection methods by building a classifier (CNN)

Why EEGNet...

0.2.8. Overall staple

EEG Channel Selection Techniques in Motor Imagery Applications: A Review and New Perspectives

0.2.9. Conferene notes 5/2/24

Bibliography

[1] Abdullah, I. Faye, and M. R. Islam. EEG Channel Selection Techniques in Motor Imagery Applications: A Review and New Perspectives. *Bioengineering*, 9(12):726, Nov. 2022. ISSN 2306-5354. doi: 10.3390/bioengineering9120726.