EEG Ocular Artifact Correction with optimized parameters for OACL, CSP and classification

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Abstract

Here is the abstract.

1 Introduction

The field of Brain-Computer Interfaces (BCI) has in the recent years been under active research, especially with the popularity of machine learning techniques. The reason for the interest, is the many useful application of a well-working BCI, such as replacing lost motor function in disabled people, helping with analysis in brain imaging to diagnose brain conditions or novel applications in computer games.

The general idea of a BCI is to measure brain activity represented by electroencephalogram (EEG) signals, by putting sensors on the scalp, which can measure the electric impulses. However, the EEG data is noisy at best, and this problem can severely affect the classification results in a machine learning algorithm. Therefore, signal processing is an important step in any given BCI.

All in all, this leaves us with several steps in which several techniques may be applied to obtain the corrected EEG signal. Each technique applied may require any number of parameters to be tuned for obtaining the optimal results. Users of the BCI or medical professionals are usually not knowledgeable about tuning such parameters, hence requires either an export to help determine them or extensive training. Another, more useful approach would be to automatically infer the hyper-parameters from the training data. Recent work about algorithmically optimizing machine learning parameters has seen popularity by using Bayesian Optimization, in which the learning process is seen as a black-box function which parameters can be optimized.

1.1 Related Work

Much research effort has been put into developing or applying techniques for noise/artifact correction in EEG signals. Well-known methods, such as PCA, ICA or DWT, in the signal processing world has had mixed results.

2 Optimization of hyperparameters for Ocular Artifact Correction

short overview, maybe show a figure describing the pipeline.

2.1 Ocular Artifact Correction

We adapt the Ocular Artifact Correction (OACL) technique developed in (add reference) for multi-class datasets. The OACL method consists of two parts. First, we analyse the raw EEG signals to obtain the artifact signals, representing the parts of the raw signal that was determined to be noise. Then we find the

*A thank you or further information

filtering parameter of each the artifact signal, which determines "how much" of each signal that should be removed from the raw signal.

Let $x = \{s_0, ..., s_n\}$ where $s_i \in \mathbb{R}_{\geq 0}$ denote the raw EEG signal for some arbitrary channel. For simplicity, we can interpret x as a function $x : \mathbb{N}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$ where $x(t)$ denotes the amplitude of x at time t.

From $x(t)$ we perform all steps in artifact detection and removal.

2.1.1 Artifact Detection

The goal of artifact detection is to find some artifact signal $a(t)$ from $x(t)$ that represents which parts of $x(t)$ that are noise. Before finding the artifact signal $s(t)$, we first obtain a smoothed signal by applying a *moving average filter* to $x(t)$:

moving avg equation/pseudocode (1)

where m is the number of neighboring points, and n denotes the number of EEG samples in $x(t)$. From $s(t)$ we calculate the relative heights between samples as the maximal difference in amplitude between a sample and its neighboring samples.

$$\Delta(t) = max(|x(t) - x(t-1)|, |x(t+1) - x(t)|) \tag{2}$$

Now, we want to have some measure of what an artifact signal looks like. [OACL] found by inspection that ocular artifacts generally occur with sudden changes in amplitude (ΔA) between $[30\mu V - 50\mu V]$ and $[70\mu V - 150\mu V]$. For now, assume that we have some arbitrary ranges

$$h_r = [l, u] \quad l, u \in \mathbb{N}_{\geq 0} \tag{3}$$

then we can find the points in time where $\Delta(t)$ lies in the range h_r:

$$P = \{t \quad | \quad \frac{m}{2} < t < n - \frac{m}{2} \quad \text{and} \quad l < \Delta(t) < u\} \tag{4}$$

2.1.2 Artifact Removal

Explain how we use the artifact signals to remove artifacts from the eeg signal.

2.2 Filter-bank CSP

Filter-bank common spatial patterns *FBCSP*, is commonly known as a valid way of extracting relevant features from EEG data . The drawback of this method, is the limitation of CSP being a binary

2.3 Bayesian Optimization

2.4 Motor Imagery Classification

3 Experimental Results

3.1 Data Examination

$$e = mc^2 \tag{5}$$

3.2 Discussion

Here we discuss the results given in section 3, and talk more about what the results imply/how it could be improved.

4 Conclusion

Here we conclude on the paper by summarizing what we did and what our results was. Furthermore we address how the problem could be further improved/investigated.

References

[Figueredo and Wolf, 2009] Figueredo, A. J. and Wolf, P. S. A. (2009). Assortative pairing and life history strategy - a cross-cultural study. *Human Nature*, 20:317–330.