Automatic optimization of parameters for Ocular Artifact Correction in EEG

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Abstract

Here is the abstract.

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 results of classification algorithms. 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 several parameters to be tuned for obtaining the optimal results. Users of the BCI or medical professionals are usually knowledgeable about tuning some of the parameters but not all, hence it requires either an expert 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 (insert reference), in which the learning process is seen as a black-box function for which parameters can be optimized.

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 *Principal Component Analysis*, *Independent Component Analysis* or *Discrete Wavelet Transform*, in the signal processing world has had mixed results. Most of these techniques considers how to extract the information from the signals, instead of reducing the noise in the data. Other approaches such as (source) considers removing noise from a correction perspective. [ECG source] uses EOG signals measured by sensors on the subjects eyes, and estimates a propagation factor to determine the amount of the EOG signal to remove from the EEG signal, thus using the EOG signal as an artifact signal. Similarly, [OACL guys] have had positive results in estimating a pseudo-EOG signal for binary class EEG data, making it possible to obtain an artifact signal without using any secondary measurements.

*A thank you or further information

Optimization of hyperparameters for Ocular Artifact Correction

short overview, maybe show a figure describing the pipeline.

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 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.

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 $x(t)$:

$$\textbf{moving avg equation/pseudocode} \tag{1}$$

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:

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

Artifact Removal

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

Filter-bank CSP

Here we talk about FBSCP, what it is, how it works and why we use it.

Bayesian Optimization

Motor Imagery Classification

Experimental Results

Here we present how we tested/evaluated the pipeline, which data we evaluated on and the results we got from the our validation efforts.

Table 1: *Example table*

Name		
First name	Last Name	Grade
John	Doe	7.5
Richard	Miles	2

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

Discussion

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

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.