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CORRECTION OF EYE-MOVEMENT ARTIFACTS OF DC-EEG SIGNALS

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Abstract: *For neurofeedback applications EEG frequencies below 0.5 Hz including DC-offset are essential. Since artifacts from eye movement can be found in the same frequency band of the so-called DC-EEG, these artifacts must be removed for proper DC-EEG analysis. To remove artifacts from eye movement, simultaneous electrooculograms (EOG) are recorded as an indicator. The clean EEG is then found by subtracting the EOG from the measured EEG. However, most approaches also remove the DC-part of the EEG in the process. We propose an adaptive algorithm to eliminate eye movement artifacts from an EEG in real-time while maintaining the DC-offset utilizing a recursive least squares approach.*

Keywords: *DC-EEG, neurofeedback, EEG signal processing*

Introduction

The method "slow cortical potentials" (SCP) is often applied for EEG-neurofeedback sessions. The principle is to detect slow changes of the EEG signal's baseline. Before analysis, pre-processing of the signal has to be conducted, especially to remove artifacts caused by eye movements. Most algorithms remove the DC-offset before signal processing. For example, methods for source separation like principal component analysis (PCA) or independent component analysis (ICA) need to subtract the mean of the signal.

Until now, as seen in [1], only the least squares (LS) approach has proven to sustain the offset if, during calibration, the ratio of EOG to EEG is high [4]. The obtained parameters $\beta_1, \beta_2, \beta_3$ (Eq. 1) are used for EOG elimination for the rest of the signal.

A measured EEG signal consists of the following components (see Eq. 1) [2].

$$s_m(n) = s_t(n) + \beta_1 \cdot r_v(n) + \beta_2 \cdot r_h(n) + \beta_0 \quad (1)$$

In this context, n is the current sample, $s_m(n)$ is the measured EEG for one channel, $s_t(n)$ is the true EEG without noise or offset, $r_v(n)$ is the vertically measured EOG and $r_h(n)$ is the horizontal EOG. These values can be measured directly, but β_1, β_2 as well as $s_t(n)$ and the DC-offset β_0 are unknown. A simple model for EOG and EEG interaction is as follows, with $s(n)$ the sought clean EEG with DC-offset (Eq. 2):

$$s(n) = s_t(n) + \beta_0 \quad (2)$$

The most common approach is to apply least squares estimation to the measured EEG in Eq. 1. Yet, the calculation of least squares has numerical problems due to several matrix inversions and cannot adapt after calculation.

Our idea is to implement a recursive least squares (RLS) methodology oriented on the approach in [2] in order to achieve real-time processing and adaptation.

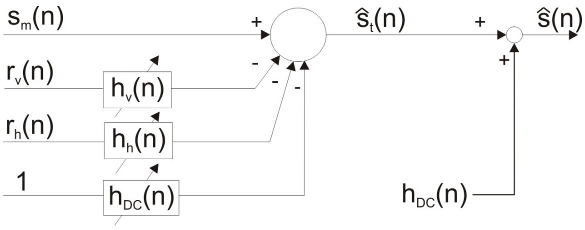

Figure 1: Adaptive filter structure

Methods

In [2] an RLS algorithm is introduced, which eliminates the influence of eye movements. The filters h_v and h_h of length M replace the parameters β_i. The described filter method is modified as can be seen in Fig. 1. The original filter structure is combined with an additional filter h_{DC}. In order to obtain the EEG with DC-offset, h_{DC} is later added to the true EEG.

For further analysis an EOG vector $r(n)$ and its filter vector $h(n)$ are introduced (see Eq. 3).

$$r(n) = \begin{pmatrix} r_v(n) \\ r_h(n) \\ 1 \end{pmatrix} \qquad h(n) = \begin{pmatrix} h_v(n) \\ h_h(n) \\ h_{DC}(n) \end{pmatrix} \quad (3)$$

The update is as follows (Eq. 4 - 7): $k(n)$ is the correction vector, $s_t(n)$ is the estimated true EEG, $R(n)^{-1}$ is the inverse of the correlation matrix.

$$k(n) = \frac{R(n-1)^{-1} \cdot r(n)}{1 + r(n)^T \cdot R(n-1)^{-1} \cdot r(n)} \quad (4)$$

$$\hat{s}_t(n) = s_m(n) - r(n)^T h(n-1) \quad (5)$$

$$h(n) = h(n-1) + k(n) \cdot \hat{s}_t(n) \quad (6)$$

$$R(n)^{-1} = R(n-1)^{-1} - k(n) r(n) R(n-1)^{-1} \quad (7)$$

The estimated EEG $\hat{s}(n)$ with DC-level (Eq. 8) is:

$$\hat{s}(n) = \hat{s}_t(n) + h_{DC}(n) \quad (8)$$

Initial values are $h(0) = 0$ and $R(0)^{-1} = \frac{1}{\sigma} I$.

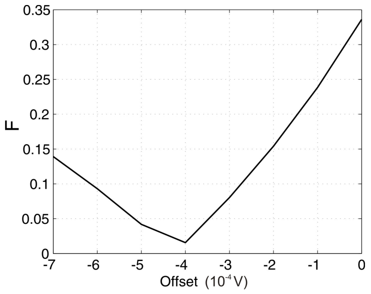

Figure 2: Estimation error for different initial DC-offsets using RLS (actual baseline $\beta_0 = -4$ x 10^{-4})

Correct parameterization of this RLS problem is crucial. In [2] a filter length of $M = 3$ and initial value $\sigma = 0.01$ are used. For our case, new parameterization was necessary. We assumed $\sigma = 10^{-5}$ with filter length $M >= 3$. This method is not sensitive to the size of M, unless M is smaller than 3 [2]. Since the estimation of the baseline showed an oscillating behaviour, a moving weighted average filter with fading memory was applied with $\epsilon = 10^{-3}$ as a forgetting factor (Eq. 9).

$$\hat{s}(n) = \hat{s}_t(n) + \epsilon \cdot h_{DC}(n) + (1-\epsilon) \cdot h_{DC}(n-1) \quad (9)$$

In order to determine an initial baseline, a combined approach was introduced. First, the initial value for the baseline was determined with LS (calibration) and then the EEG was estimated with RLS (see Fig. 1).
A relative error (F) measurement was conducted (see Eq. 10). Lower absolute values account for better estimation.

$$F = \frac{\sum_{n=1}^{N} |\hat{s}(n) - s(n)|}{\sum_{n=1}^{N} |s(n)|} \quad (10)$$

Results

The dataset was comprised of synthetic data. The dataset consisted of a sine wave with $f = 0.01$ Hz, superimposed with Gaussian noise and simulated EOG data with values from [1].
For the use of the RLS method the initial offset had to be estimated; without calibration the offset can only be guessed. The quality of estimation depends on this initial value as can be seen in Fig. 2.
In a subsequent test, RLS and LS were applied with a previous calibration (C) period. Three minutes were taken for calibration as at least 40 eye movements are necessary [3]. It is obvious that RLS with previous calibration through LS performs better than the LS method on its own (see Tab. 1). The RLS method with calibration estimates the DC-offset more correctly than the LS method (see Fig. 3). Artifacts from eye movements are removed by both approaches.

Table 1: Values for datasets with LS approximation and RLS with calibration (3 min.)

Method	F
C+LS	0.2303
C+RLS	0.0509

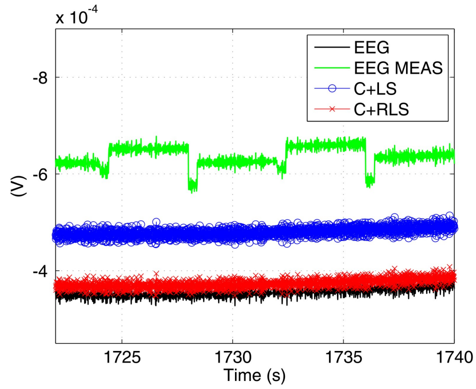

Figure 3: Comparison of LS and RLS with previous calibration (3 min.)

Discussion

The algorithm proposed in this paper offers real-time computation of eye-movement corrections sustaining the DC-offset. The RLS method performed better than LS in our simulation, but without the moving average filter it converges too slowly for practical use. Filtering of the baseline is therefore necessary. The approach with previous calibration is also promising because it can provide a more accurate initial value for the baseline.
As a result, this method can be applied for SCP recordings for neurofeedback in the future.
However, due to the limited data, further investigations have to be performed to prove this approach.

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