Muscle Artifact Removal in EEG using Canonical Correlation Analysis

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Introduction

Problem

The electroencephalogram (EEG) is frequently contaminated by electrophysiological potentials associated with muscle contraction due to biting, chewing and frowning. These muscle artifacts obscure the EEG and complicate the interpretation of the EEG or even make the interpretation unfeasible.

BSS-CCA method

The presented method [1] is based on the statistical Canonical Correlation Analysis (CCA) applied as a blind source separation (BSS) technique, taking advantage of the bigger correlation of brain activity compared to muscle artifacts.

Blind Source Separation (BSS)

Is a mathematical method to analyse the separation of a set of source signals $S[t]$ from a set of mixed signals $X[t]$, without the aid of information (or with very little information) about the source signals or the mixing process.

Mathematical representation

$$X[t] = AS[t] \tag{1}$$

With A, a mixing matrix. Then through the determination of an 'unmixing' matrix, $W = A^{-1}$, the sources can be 'recovered':

$$S'[t] = WX[t] \tag{2}$$

Autocorrelation

In discrete time autocorrelation is a statistical relationship between a signal $X[t]$ and its delayed version $X[t-k]$.

Mathematical representation

$$r_{xx} = \sum x[t]\, x[t-k] \tag{3}$$

Canonical Correlation Analysis (CCA)

CCA is used to identify and measure the associations among two sets of variables $X = [x_1(t), \ldots, x_n(t)]$ and $Y = [y_1(t), \ldots, y_m(t)]$, with $t = 1, \ldots, N$ (number of samples) and n and m the number of variables of each set.

Canonical variates (correlation coefficients)

CCA determines a set of canonical variates $U = [u_1(t), \ldots, u_k(t)]^t$ and $V = [v_1(t), \ldots, v_k(t)]^t$, with k, the number of canonical dimensions $k = min(n, m)$, Which are a linear combination of the variables within each set that:

- Maximize the correlation between the sets.
- Are uncorrelated with the variates of the other dimensions.

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Each variate of the i_{th} dimension is calculate as fallowed:

$$\begin{cases} u_i = w_{xi1}\, x_1 + w_{xi2}\, x_2 + \ldots + w_{xin}\, x_n = w_{xi}{}^t\, X \\ v_i = w_{yi1}\, y_1 + w_{yi2}\, y_2 + \ldots + w_{yin}\, y_m = w_{yi}{}^t\, Y \end{cases} \tag{4}$$

Weight vectors

$w_{xi} = [w_{x1}, \ldots, w_{xn}]^t$ and $w_{yi} = [w_{y1}, \ldots, w_{yn}]^t$ are weight vectors that maximize the correlation between the variates U and V. They are calculated with the following eigenvalue problem:

$$\begin{cases} C_{xx}^{-1}\, C_{xy}\, C_{yy}^{-1}\, C_{yx}\, W_x = \rho^2\, W_x \\ C_{yy}^{-1}\, C_{yx}\, C_{xx}^{-1}\, C_{xy}\, W_y = \rho^2\, W_y \end{cases} \tag{5}$$

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With the canonical correlation coefficient ρ_i as the square root of the i_{th} eigenvalue, and the weight vectors w_{xi} and w_{yi} as i_{th} eigenvector. The matrices $C_x x, C_y y, C_x y, C_y x$ are the covariance matrix between xx, yy, xy, and yx respectively.

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Canonical dimensions

Each pair of weight vector represents a canonical dimension. They are ordered in descending order by their respective correlation coefficient.

Theoretical basis of the algorithm

Let the observed EEG signals be $X[t] = [x_1(t), ..., x_k(t)]^t$, with $t = 1, ..., N$ with N the number of samples and k the number of electrodes. In the BSS analysis, it can be assumed that $X[t]$ consists of a mixture of signal sources:

$$X[t] = AS[t]$$

.

With $A_{k,k}$, the mixing matrix and $S[t] = [s_1[t], ..., s_k[t]]^t$ the source signals coming from brain activity and artifacts. Applying CCA between $X[t]$ and its delayed version $Y[t] = X[t-1]$ is potentially possible to recover these underlying sources $S[t]$ using the fallowing equation :

$$S[t] = U = W_x X[t]$$

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With U, the canonical variates of $X[t]$, and W_x the Weight vectors. By definition, U contains the less autocorrelated sources (muscle artifacts) in the last rows. Thus, by setting them equal to zero, and finding $A = Wx^{-1}$. The EEG signal without muscle artifacts can be reconstructed.

$$EEG_{corrected}[t] = \hat{X}[t] = AU_{zero}$$

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Method step by step

The following lines of code are written using MATLAB

1. **Obtaining the EEG signals**
2. **Obtaining X and its delayed version Y and removing the mean from each row**

```
X = [zeros(size(EEG, 1),1), EEG(:,2:end)];     X = X - mean(X,2);
Y = EEG;                                       Y = Y - mean(X,2);
```

3. **Applying CCA between X and Y**

```
[Wx,Wy,U,V] = CCA(X,Y);
```

4. **Finding 'unmixing' matrix (A) and setting to 0 artifact sources**

```
A = inv(Wx);
U(end – 2 :end, :) = 0;
```

5. **Applying BSS-CCA analysis**

```
EEG_corrected = A * U;
```

Results

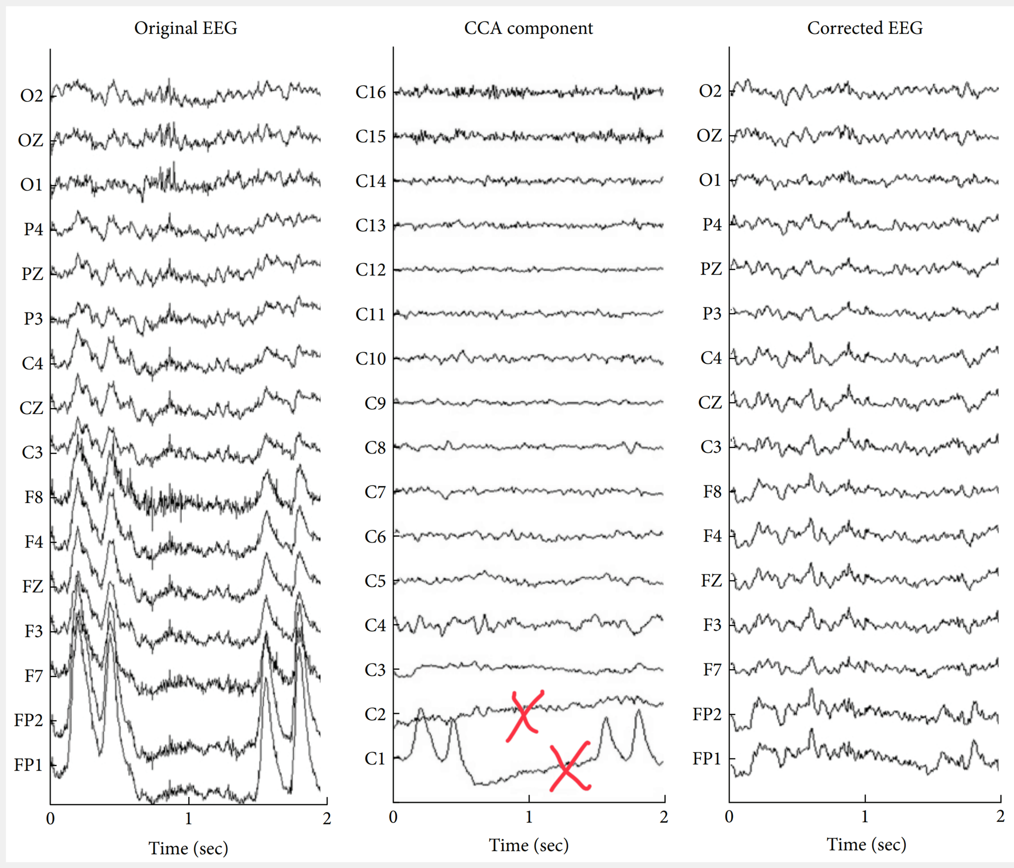

Figure 1. Demonstration of removal of EEG artifacts by BSS-CCA. The following results are from [2] since these show the CCA components (Canonical variates) Obtained. (a) A 2s portion of EEG time series that contains artifacts. (b) Corresponding CCA component activations. (c) EEG corrected by removing C1, C2 (muscle artifacts) from (b). *C15 and C16 where also removed for other purposes.*

Comparison with other methods

The present method was compared with other used techniques for muscle artifact removal:

- **Low-pass filter:** a low-pass Butterworth filter of order 8 was used with four different cutoff frequencies equal to 10, 15, 20, and 30 Hz
- **ICA algorithm:** Joint Approximate Diagonalization of Eigen-matrices (JADE) algorithm [3]

During the comparison, the average referenced muscle artifact signal M was superimposed on the average referenced signal B containing only brain activity

$$X(\lambda) = B + \lambda M \qquad \lambda = \text{contribution of muscle activity} \tag{6}$$

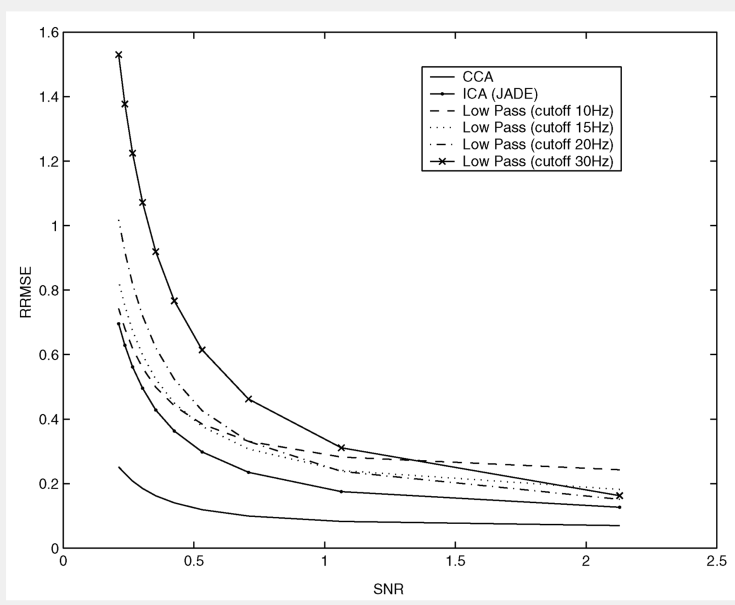

Figure 2. The RRMSE as a function of SNR on the EEG epoch B containing alpha (8–13 Hz) activity

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To compare the algorithms, The SNR and the performance expressed in terms of the relative root-mean-squared error (RRMSE) where used:

$$SNR(B) = \frac{RMS(B)}{RMS(\lambda \cdot M)} \tag{7}$$

$$RRMSE(B) = \frac{RMS(B - \hat{B})}{RMS(B)} \tag{8}$$

Where $\hat{B}$ is the signal after muscle artifact removal and the RMS is the Root Mean Squared. As can be seen in Figure 2, the BSS-CCA method outperformed all methods for all SNRs.

References

[1] De Clercq et al. "Canonical Correlation Analysis applied to remove muscle artifacts from the Electroencephalogram". In: *IEEE Trans Biomed Eng* (2006).

[2] Chin-Teng Lin et al. "Real-Time EEG Signal Enhancement Using Canonical Correlation Analysis and Gaussian Mixture Clustering". In: *J Healthc Eng* (2018).

[3] Jean-Francois Cardoso. "High-Order Contrasts for Independent Component Analysis". In: *Neural Computation* (1999).