SPATIALLY CONSTRAINED INDEPENDENT COMPONENT ANALYSIS ALGORITHM FOR REAL-TIME EYE ARTIFACT REMOVAL FROM THE ELECTROENCEPHALOGRAM

M. De Vos[1], L. De Lathauwer[2], A. Vergult[1], W. De Clercq[1], W. Van Paesschen[3], S. Van Huffel[1]

[1] Katholieke Universiteit Leuven, Department of electrical engineering, ESAT-SCD, Belgium

[2] ETIS (CNRS, ENSEA, UCP), Cergy-Pontoise, France

[3] Katholieke Universiteit Leuven, University Hospital Gasthuisberg, Belgium

1 Introduction

Electroencephalography (EEG) is a non-invasive tool that offers millisecond temporal resolution for the study of neural mechanisms underlying mental activity. Eye blinks also produce electrical potentials creating significant electro-oculographic (EOG) artifacts in the EEG. EOG artifacts obscuring the EEG at the time of seizure onset may be problematic in the setting of a preoperative evaluation of patients with refractory epilepsy, since the ictal recordings are crucial for the localization of the epileptogenic zone. Also in an Event Related Potential (ERP) study, trials contaminated with eye artifacts are not useful. Furthermore, these artifacts are a source of false positives in automatic epileptic seizure detection systems.

Several EOG correction methods are already proposed based on different concepts. Each method has its own advantages and drawbacks. Traditionally, EOG artifacts have been corrected using regression-based techniques, which require the EOG signal. Later, also blind source separation methods have been introduced in order to blindly separate interesting brain signals from artifacts in EEG recordings [8]. These methods do not require the EOG reference signal and can be used in an Epilepsy Monitoring Unit (EMU). In EMU's, the EOG is not recorded simultaneously with the EEG since the EOG electrodes are cumbersome for the patient who is monitored for typically one week. Each method for artifact removal focuses on extra features that are important in a specific situation. E.g. using the artifact removal technique as a preprocessing method in a seizure detection system also requires a real-time algorithm. This has hardly been considered so far. We propose an automatic algorithm based on Spatially Constrained Independent Component Analysis (SCICA) for on-line eye artifact removal.
Temporally constrained ICA has been introduced by [6], in which a source is restricted in shape by a reference signal. We extract (and remove) one source with prior knowledge of a known mixing vector.

Attempts have been made to quantify in an objective way the performance of artifact removal techniques, e.g. in [9], but it should be emphasized that analysis of artifact removal is inherently difficult, since no true signal is known on which methods can be compared. Simulation studies can be and are often biased to the strong points of a newly proposed method. Our concept of SCICA is interesting in the sense that it is more generally useful. EEG measures the potentials on a limited number of scalp electrodes. When one is interested in brain activity generated from one specific region, SCICA can be used to compute the source signal from that region. SCICA can also be used for enhancing the selectivity of spike detection, as one can assume that epileptic spikes are originating in a specific brain area, the irritative zone. Another possible application of SCICA is situated in multimodal imaging. Nowadays, it is possible to record EEG simultaneously with functional Magnetic Resonance Imaging (fMRI) or SPECT. With SCICA, activated regions seen on fMRI or SPECT can be associated with the time-course of EEG.

2 Methods

2.1 Detection of artifacts

In order to provide a real-time algorithm, the artifacts have to be detected on-line. The human eye contains an electrical dipole caused by a positive cornea and negative retina. Eye blinks and movements change this dipole, which created the EOG signal. Eye-blinks are characterized by sharp spike-shaped positive deflections in the most anterior electrodes (Fp1 and Fp2 defined by the 10-20 system) with a rapid amplitude fall-off at more posterior located electrodes [5].

An artifact is detected when the EEG amplitude on Fp1 an Fp2 and the peak width exceed pre-defined thresholds. When a detection occurs, a time-window of 1.5 seconds of EEG around the artifact is extracted as input for SCICA.

2.2 Removal of artifacts: SCICA

2.2.1 The concept of ICA

Assume the basic linear statistical model

$$Y = \mathbf{M} \cdot X + N \tag{1}$$

where $Y \in \mathbb{R}^I$ is called the observation vector, $X \in \mathbb{R}^J$ the source vector and $N \in \mathbb{R}^I$ additive noise. $\mathbf{M} \in \mathbb{R}^{I \times J}$ is the mixing matrix.

The goal of Independent Component Analysis is to estimate the mixing matrix **M**, and/or the source vector X, given only realizations of Y. In this study, we assume that $I \geqslant J$.
Blind identification of **M** in (1) is only possible when some assumptions about the sources are made. One assumption is that the sources are mutually statistically independent, as well as independent from the noise components and that at most one source is gaussian [3].

Another assumption is that the sources are mutually uncorrelated but individually correlated in time. Under these assumptions, the sources can be estimated with the SOBI algorithm [1]. This algorithm has shown to be useful in several biomedical applications. Furthermore, the SOBI algorithm is based on second order statistics. This reduces the need for having long measurements of the observation signal as it is the case when higher order statistics are computed (e.g. in [3]) before computing the source signals. This is necessary for the online application under investigation.

Most algorithms start with a pre-whitening step, in which the observation vector Y is transformed into another stochastic vector with unit variance. During this step, also a projection on the signal subspace can be carried out. For more details, we refer to [7].

2.2.2 SOBI

When the sources are individually correlated in time, but mutually uncorrelated, an ICA algorithm based on second order statistics can be derived [1].
Mathematically, this means that for all time lags τ the source correlation matrices are diagonal.

$$\mathbf{R}_y(\tau) = E\{Y(t)Y(t+\tau)^T\} \tag{2}$$

$$= \mathbf{A} \cdot \mathbf{R}_x(\tau) \cdot \mathbf{A}^T \qquad \forall \tau \tag{3}$$

where $\mathbf{R}_x$ is the correlation matrix of the source signals. Considering that this equation holds for all values of τ, the mixing matrix **M** is the matrix **A** that jointly diagonalizes all the correlation matrices.
This simultaneous diagonalization can be computed by a Jacobi iteration [3].

2.2.3 Jacobi angles for simultaneous diagonalization

In [3], it is shown that the optimal Jacobi angles for simultaneous diagonalization are derived from an eigenvalue problem. In order to maximise the diagonal elements of $\mathbf{J}^H\mathbf{R}_y(\tau)\mathbf{J}$ with **J** a unitary rotation matrix, we write the cost function as

$$f = \sum_p |\tilde{u}_{iip}|^2 \tag{4}$$

$$\text{where} \quad \tilde{u}_{iip} = \begin{pmatrix} c & -s \end{pmatrix} \begin{pmatrix} u_{iip} & u_{ijp} \\ u_{jip} & u_{jjp} \end{pmatrix} \begin{pmatrix} c \\ -s^* \end{pmatrix}. \tag{5}$$

u_{ijp} denotes the (i,j)th entry of the pth correlation matrix, $i \leqslant N < j$ and $c = cos(\theta), s = sin(\theta)\mathrm{e}^{j\alpha}$. Note that we write the equations for Jacobi angles for the general complex notation. The rotation angles θ and α can then be computed from the dominant eigenvector W of the following eigenvalue problem:

$$f = W^T \cdot \mathbf{G} \cdot W \tag{6}$$

$$\text{with} \quad W = (cos(2\theta) \quad sin(2\theta)cos(\alpha) \quad sin(2\theta)sin(\alpha))^T, \tag{7}$$

$$\mathbf{G} = \sum_p \mathrm{Re}(Z_p Z_p^H) \tag{8}$$

$$\text{and} \quad Z_p = \frac{1}{2} \begin{pmatrix} u_{iip} - u_{jjp} \\ -(u_{ijp} + u_{jip}) \\ i(u_{ijp} - u_{jip}) \end{pmatrix} \tag{9}$$

2.2.4 Introducing a spatial constraint

In order to introduce the constraint that one, say the last, mixing vector should be similar to a known vector $M = (m_1, m_2, \ldots, m_I)$, a second term is added to the cost function (6). This second term is the squared projection of the mixing vector $(\mathbf{V}_{new})_J$ at the current iteration onto M: $|M^T(\mathbf{V}_{new})_J|^2$. We have shown that the resulting cost function for a Jacobi iteration can be written as:

$$f = W^T \cdot \mathbf{G} \cdot W + w \cdot g^T W \ (+C) \tag{10}$$

where w is a scalar that allows one to weight the two terms in the cost function according to the confidence one has in M. C is an irrelevant constant.

Maximization of this function under the constraint $\| W \| = 1$, using a Lagrange multiplier, leads to [2]

$$W = -\frac{1}{2}(\mathbf{G} + \lambda \mathbf{I})^{-1} g \quad (11)$$

where λ is a real scalar chosen in such a way that

$$\| W \| = 1 \Leftrightarrow \frac{1}{4} \sum_{i=1}^{3} \frac{(E_i^T g)^2}{(\lambda_i + \lambda)^2} = 1, \quad (12)$$

E_i and λ_i being the eigenvectors and -values of **G**. As can be seen from (12), the problem amounts to rooting a polynomial of degree 6 in the complex case and degree 4 in the real case and selecting the root of which the corresponding W maximizes f in (10).

2.2.5 Removal of artifacts

In order to remove eye artifacts from the EEG, SCICA is computed with as known mixing vector(s) M realistic distribution(s) of eye artifacts. The corresponding source signal is removed in order to clean the EEG.

3 Results

3.1 Results detection step: EEG data

In order to quantify the accuracy of the detection step of the method, 300 seconds of 21-channel scalp EEGs, sampled at 250 Hz, from epileptic patients were analyzed. The recordings contained eye blinks and epileptic spikes, which were marked by a neurophysiologist. The sensitivity of detection was 92.2 % and the specificity was 96 %. The method can be used on-line as a pre-processing step in a seizure detector as the computational delay was approximately 1.5 seconds.

3.2 Results separation step: simulation study

In order to quantify the accuracy of the artifact removal by SCICA, we selected 100 different signals with a time-length of 5 seconds containing background EEG without eye artifacts. On these signals, 1 eye blink artifact was at random time instances superimposed with a realistic distribution over the electrodes. The proposed algorithm was applied on these contaminated signals. As a comparison, we also remove the eye artifacts with an automatic SOBI based algorithm, where the artifactual component(s) are detected after the computation of the independent source signals by means of a fractal dimension criterium [4]. The accuracy of the methods was assessed by the Root Mean Squared (RMS) value of the difference between the cleaned EEG and the original EEG:

$$RMS = \sqrt{\frac{1}{S \cdot N} \sum_{s=1}^{S} \sum_{n=0}^{N-1} (cleaned(n,s) - original(n,s))^2} \quad (13)$$

with N the time-length and S the number of channels.

Table 1 shows the mean and median value of these computed RMS values. As can be seen from the table, the median RMS error is similar for both methods. However, the mean RMS error of SCICA is lower than the mean RMS of the SOBI-based method. This means that in most cases, similar results are found with both methods. In very few cases, the original EEG is severely affected by the SOBI-based method: also rhythmical seizure activity is removed. An example of the bad behavior is given in figures 1-3. The result of SCICA for this example was visually not distinguishable from figure 1.

	mean RMS	median RMS
SCICA	1.5	1.6
SOBI-based	98.3	1.9

Table 1: The mean and median RMS error ($\cdot 10^3$) of 2 eye artifact removal techniques in a simulation study. SCICA incorporates the knowledge of eye artifacts *a priori*, while the SOBI-based method blindly computes the sources and removes artifactual components afterwards

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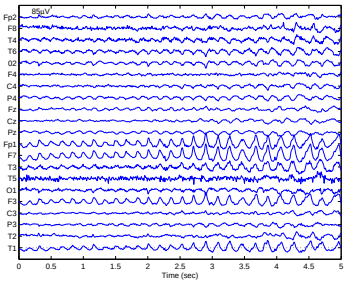

Figure 1: The original EEG.

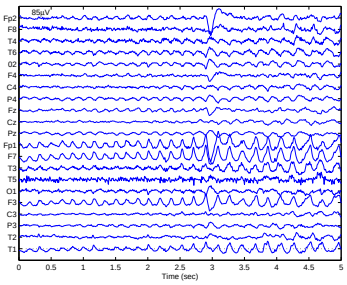

Figure 2: EEG contaminated with eye artifact at time = 3 sec.

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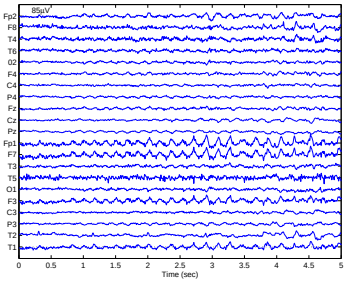

Figure 3: Corrected EEG with SOBI-based method.

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