USING ICA FOR REMOVAL OF OCULAR ARTIFACTS IN EEG RECORDED FROM BLIND SUBJECTS

Arthur Flexer[1], Herbert Bauer[2], Jürgen Pripfl[2], Georg Dorffner[1]
[1] The Austrian Research Institute for Artificial Intelligence
Schottengasse 3, A-1010 Vienna, Austria
[2] Department of Psychology, University of Vienna
Liebiggasse 5, A-1010 Vienna, Austria

Abstract. One of the standard applications of Independent Component Analysis (ICA) to EEG is removal of artifacts due to movements of the eye bulbs. Short blinks as well as slower saccadic movements are removed by subtracting respective independent components (ICs). EEG recorded from blind subjects poses special problems since it shows a higher quantity of eye movements which are also more irregular and very different across subjects. It is demonstrated that ICA can still be of use by comparing results from four blind subjects with results from one subject without eye bulbs who therefore does not show eye movement artifacts at all.

INTRODUCTION

Independent Component Analysis (ICA) [Comon 1994] is one of a group of algorithms to achieve blind separation of sources [Jutten & Herault 1991]. ICA has already been used successfully for blind source separation of EEG data. ICA finds an unmixing matrix which linearly decomposes the multichannel EEG data into a sum of maximally temporally independent and spatially fixed components. These Independent Components (ICs) account for artifacts, stimulus and response locked events and spontaneous EEG activity. One of the standard applications of ICA to EEG includes artifact detection and removal (see [Jung et al. 1998] and [Jung et al. 2000]). Selected components responsible for artifacts are set to zero and all other ICs can be projected back onto the scalp yielding EEG in true polarity and amplitudes.

EEG recorded from blind subjects poses special problems since it shows a higher quantity of eye movements which are also more irregular and very different across subjects. We present an application of ICA to removal of ocular artifacts in evoked potentials recorded from four blind subjects. We develop a semi-automatic procedure for detection of ICs responsible for ocular artifacts. We show empirically that ICA is still able to remove these ocular artifacts and compare results with those obtained from one subject without eye bulbs who therefore does not show eye movement artifacts at all.

DATA

We recorded evoked potentials (EP) from seven subjects who have been born blind. One subject (subject A) was born without eye bulbs and does therefore not show any ocular artifacts. EPs were recorded while subjects were performing a "tactile" version [Winkler 1998] of the 3DC cube rotation test [Gittler 1990]. "Tactile" meaning that instead of graphical presentation of cubes on a computer screen, actual material cubes could be manipulated by the subjects with their hands. The recordings of two subjects had to be dismissed from the data set since they showed consistent huge artifacts of unknown origin (possibly movements of the tongue and of the whole head) across all electrode channels and single trials. Therefore four subjects (hence B, C, D and E) remained besides subject A.

EEG was recorded with 22 (subject A) or 21 electrodes (all other subjects) positioned evenly across the head according to the international 10-20 system [1]. Eye movements were recorded as vertical and horizontal electrooculogram (VEOG and HEOG) using two electrodes in a bi-polar montage per EOG channel. Data was recorded with a sampling rate of $125Hz$ and FIR-filtered with a bandpass from 0 to $30Hz$. The subjects were allowed to solve the 3DC tasks at their own pace which resulted in big variation of the lengths of the single trials (subject A: $11.49sec \pm 5.28sd$, subjects BCDE: $45.08sec \pm 22.37sd$). The data set consists of 34 single trials from subject A and 35 from each of the subjects B,C,D and E. Item onset is one second after the start of the recordings. The mean of the first half second of data is subtracted as a baseline from all of the channels and single trials.

INDEPENDENT COMPONENT ANALYSIS (ICA)

Independent Component Analysis (ICA) [Comon 1994] is one of a group of algorithms to achieve blind separation of sources [Jutten & Herault 1991]. To estimate the original sources from an observed mixture while knowing little about the mixing process and making only few assumptions about it and about the sources is called blind separation of sources. ICA allows to recover N independent source signals $s = \{s_1(t), s_2(t), \ldots, s_N(t)\}$ from N linear mixtures, $x = \{x_1(t), x_2(t), \ldots, x_N(t)\}$, modeled as the result of multiplying the matrix of source activity waveforms, s, by an unknown square matrix A (i.e. $x = As$). The task is to recover a version, u, of the original sources s, save for scaling and ordering. It is necessary to find a square matrix W specifying filters that linearly invert the mixing process (i.e. $u = Wx$).

[1] Positions for both groups of subjects were identical except that for subject A electrodes $Fp1$ and $Fp2$ were used instead of Fpz.

We used the "infomax" neural network algorithm [Bell & Sejnowski 1995] for ICA[2]. This approach uses the fact that maximizing the joint entropy, $H(y)$, of the output of a neural processor minimizes the mutual information among the output components, $y_I = g(u_i)$, where $g(u_i)$ is an inverted bounded nonlinearity and $u = Wx$.

ICA has already been used successfully for blind source separation of EEG data. Application of ICA to EPs include artifact detection and removal (see [Jung et al. 1998] and [Jung et al. 2000]) as well as analysis of event-related response averages (see [Makeig et al. 1996] and [Makeig et al. 1997]). Application of ICA to single-trial EPs is more recent (see [Jung et al. 1999] and [Jung et al. 2001]). In single-trial EEG analysis, the rows of the input matrix x are EEG and EOG signals recorded at different electrodes and the columns are measurements at different time points. ICA finds an unmixing matrix W which linearly decomposes the multichannel data into a sum of maximally temporally independent and spatially fixed components $u = Wx$. The rows of the output matrix u are courses of activation of the ICA components. These components account for artifacts, stimulus and response locked events and spontaneous EEG activity. The columns of the inverse matrix W^{-1} give the relative projection strengths of the respective components at each of the scalp sensors. These scalp maps of projection strengths provide evidence for the components' physiological origin (e.g. ocular activity projects mainly to frontal sites). Selected components can be projected back onto the scalp using the relation $x_0 = W^{-1}u_0$, where u_0 is the matrix u with irrelevant components set to zero. Thereby brain signals accounted for by the selected components can be obtained in true polarity and amplitudes.

ICA FOR REMOVAL OF OCULAR ARTIFACTS

There are two main types of ocular artifacts, those due to blinks and those due to saccadic movements. Saccade artifacts arise from changes in orientation of the retino-corneal dipole. Blinks artifacts are due to contact of the eyelid with the cornea which alters ocular conductance (see e.g. [Overton & Shagass 1969] and [Jung et al. 2000]). The influence of blink artifacts on recording electrodes decreases rapidly with distance from the eyes. The saccadic influence decreases much slower and shows a typical pattern of polarity difference between contra-lateral sites. If ICA is used for removal of ocular artifacts, the questions is how to decide which independent components (ICs) account for eye movements and should therefore be set to zero.

[Jung et al. 2000] apply ICA to three different data sets (numbers of electrodes range from 13 to 29) in order to remove ocular as well as other artifacts. ICA was done on 10 second epochs of the EEG data sets. The authors use visual inspection of ICs and scalp topographies (ocular activity projects mainly to frontal sites) to decide which ICs account for artifacts. Results

[2] All ICA related computations were done with the MATLAB toolbox EEGLAB [Makeig et al. 2002].

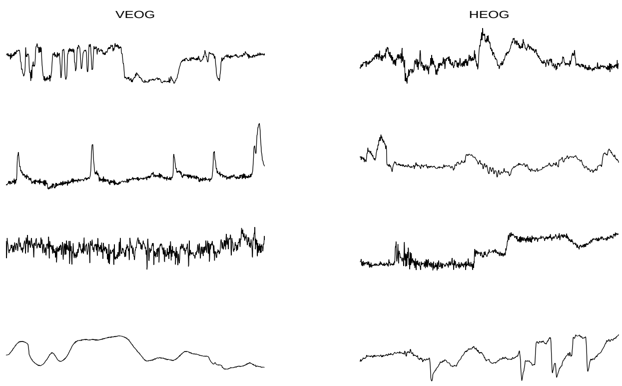

Figure 1: Illustrative examples of VEOG (left column) and HEOG (right column) from subjects B, C, D to E (top to bottom rows); x-axis is always ten seconds of recording; y-axis is amplitude (range differs between graphs for better visibility).

are compared to those obtained using Principal Component and Regression Analysis. Results are presented graphically, no quantification is given.

[Jung et al. 2001] apply ICA to single trial EPs (31 channels) recorded from 28 control subjects plus 22 neurological (autistic) patients performing a visual selective attention experiment. EEG records from the patient group were heavily contaminated by blinks and other eye movements. ICA decomposition was performed on one second epochs of single trial EPs. With the help of visual inspection of independent components and their scalp topographies plus, if necessary, source localization, artifacts caused by eye blinks were detected. Lateral saccadic eye movements are time locked to visual stimuli onset and are also systematically affected by differences in distance and direction of the stimuli relative to a fixation point. This systematic relationship as well as checking of the scalp topographies was used to detect independent components accounting for saccadic lateral movements. Power spectra of the independent components give further insight into their nature. With the help of ICA the authors were able to remove artifacts and contaminations without sacrificing neural signals at sites most affected by these artifacts. Results of this study go beyond artifact removal, but again no quantification of how successful artifact removal was is given.

[Britton & Jervis 2001] apply ICA to single trials of EPs recorded during a cued reaction time task which generates the so-called Contingent Negative Variation (CNV). The data set consisted of only 30 single trials recorded via 25 electrodes. ICA was computed separately on data from each of the single trials. ICs accounting for artifacts were detected via visual inspection. The authors are able to show that an average of the denoised single trials deviates little from the average of the original single trials. Denoising of single trials via ICA also allows them to analyze the considerable variation of CNV amplitude and latency which is hidden by conventional averaging.

Eye movements by blind subjects differ substantially from those of subjects with full eye sight. Blind subjects are not able to fixate on visual stimuli,

TABLE 1: CORRELATION OF VEOG AND HEOG WITH ICS. GIVEN ARE ONLY CORRELATIONS WITH ICS WHICH ARE RESPONSIBLE FOR OCULAR ARTIFACTS. NOTE THAT ALL BUT ONE (SUBJECT E) ARE GREATER THAN 0.40.

	ρ_{veog}	ρ_{heog}
subject B	-0.53 -0.49	-0.41 -0.66
subject C	0.86	0.74
subject D	0.56 -0.44	0.91
subject E	-0.63 **0.35**	0.60 -0.60

subjects who are born blind cannot even control their eye movements at all. Therefore blind subjects show (i) more eye movements, (ii) they are more irregular since not caused by visual stimuli and (iii) show very different patterns across subjects. See Fig. 1 for illustrative examples of eye movements from our subjects. Whereas e.g. subject C shows mainly blink activity in its VEOG (second row from top, left side of Fig. 1), subject E shows very strong and slow rolling behavior (bottom row, left side of Fig. 1). Note also the big differences in HEOG across subjects (right column in Fig. 1). In order to decide which ICs are due to eye movements we chose the following simple procedure:

- Compute infomax ICA for each of the subjects B, C, D and E separately. The respective input matrices x consists of all concatenated single trial EPs from one subject. An ICA outputs the ICs u and the square matrix W specifying the filters that invert the mixing process ($u = Wx$).

- Compute correlations $\rho^i_{veog} = cov(veog, u_i)/s_{veog}s_{u_i}$ and $\rho^i_{heog} = cov(heog, u_i)/s_{heog}s_{u_i}$ between VEOG and HEOG and all ICs from one subject (with cov and s being covariance and standard deviations, u_i the $i = 1, \ldots, 22$ ICs). Choose only ICs with high correlation ($\mid \rho^i_{veog} \mid > .4$ and $\mid \rho^i_{heog} \mid > .4$) as responsible for EOG artifacts.

- Use both visual inspection of relative projection strengths (W^{-1}), of ICs u and of back-projections of single ICs [3] to corroborate or dismiss decisions based on correlations alone.

RESULTS

Applying the simple two step procedure (computing correlations plus visual inspection) described in the last section to data from subjects B, C, D and E proofed successful. Visual inspection of results showed that the correlation threshold of .4 enabled to identify all ICs responsible for eye artifacts. Only in one case (subjects E: $\rho_{veog} = 0.35$) it was necessary to relax the correlation criterium. Tab. 1 sums up all information related to the correlations between VEOG, HEOG and ICs. For all subjects, either one or two ICs are sufficient

[3]Using relation $x_0 = W^{-1}u_0$ with all but one component set to zero in u_0.

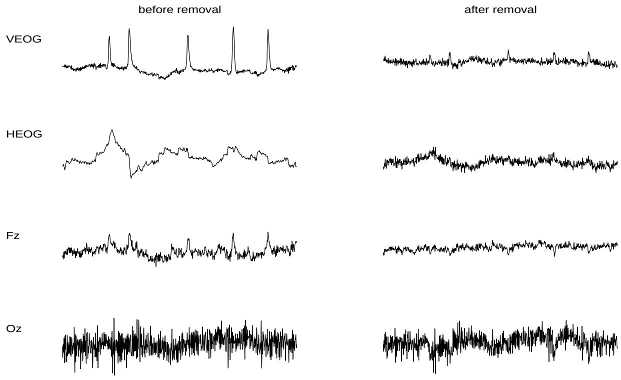

Figure 2: Illustrative examples of signals (VEOG, HEOG, Fz, Oz; top to bottom rows) before (left column) and after (right column) removal of ocular artifacts for **subject C**; x-axis is always ten seconds of recording; y-axis is amplitude (range differs between rows for better visibility); y-range is always the same within a row (before vs. after removal).

to account for VEOG or HEOG artifacts. Illustrative examples of successful artifact removal are given in Fig. 2 and Fig. 3. Note how blink artifacts for subject C which are clearly visible in the VEOG and at Fz (Fig. 2 top left and second from bottom at left) are almost completely removed (Fig. 2 top right and second from bottom at right). The signal at Oz is hardly affected at all by ocular artifacts and therefore left almost unchanged (Fig. 2 bottom left and right). Ocular artifacts due to slower rolling movements of eyes can be seen in recordings from subject E in Fig. 3. Artifacts clearly show in both VEOG and HEOG as well as Fz and Oz (Fig. 3 left column). These ocular artifacts seem to be removed quite well from all channels by ICA (Fig. 3 right

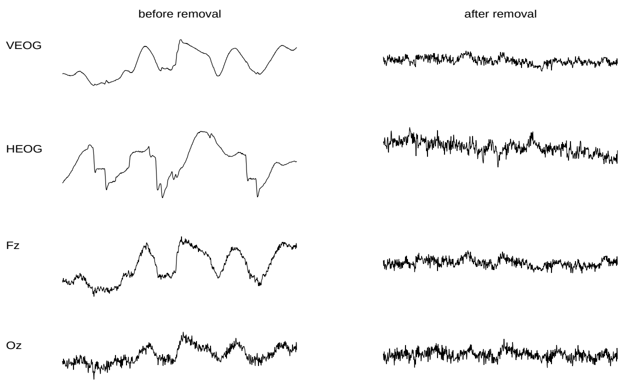

Figure 3: Illustrative examples of signals (VEOG, HEOG, Fz, Oz; top to bottom rows) before (left column) and after (right column) removal of ocular artifacts for **subject E**; x-axis is always ten seconds of recording; y-axis is amplitude (range differs between rows for better visibility); y-range is always the same within a row (before vs. after removal).

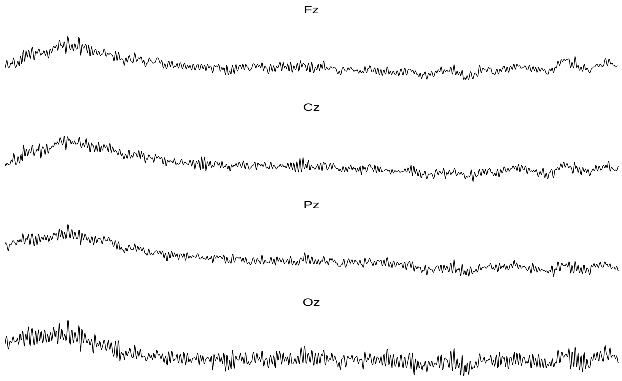

Figure 4: Grand averages across subjects BCDE after artifact removal at electrodes Fz (top), Cz, Pz and Oz (bottom); x-axis is eight seconds of recording starting one second before stimulus onset; y-axis is amplitude.

column). Since the true EEG signals without influence from ocular artifacts are not known no direct quantification of success can be given.

Given the fact that subject A performed the same tasks as all other subjects while not showing any ocular artifacts (because of not having eye bulbs), it could be argumented that removal of ocular artifacts should make EPs recorded from subjects B, C, D and E more similar to EPs recorded from subject A. To test this hypothesis we compared a grand averages computed from subjects B, C, D and E before and after ocular artifact removal with an average computed from subject A. All averages were computed across all respective single trials in all EEG channels. In Fig. 4 the grand averages across subjects B, C, D and E after removal of ocular artifacts are depicted at four selected electrodes. It can be seen that the main information in the averages is a DC-like trend (negativation). Temporal integration across a window from seven to eight seconds after stimulus onset further condensed information to a single topography per average. This one second window was chosen as being representative in time since the phenomenon under study is believed to be best visible after several seconds after stimulus onset. Correlation of the one-second temporal integration grand average from subjects B, C, D and E with the same information computed from subject A improved from .273 to .499 due to removal of ocular artifacts. The values for the three topographies used computing these correlation are depicted in Fig. 5. It can be seen that artifact removal made the topography of subjects B, C, D and E smaller in amplitude and more similar to the topography of subject A (note e.g. more negative values at posterior as compared to frontal electrodes in both topographies).

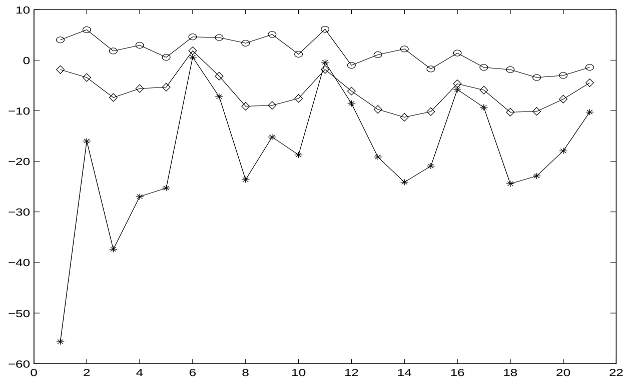

Figure 5: Comparing grand averages, x-axis electrode position (from frontal left F3 to occipital right O4), y-axis μV; subject A (top line, circles o), subjects BCDE (bottom line, stars *), subjects BCDE after artifact removal (middle line, diamonds $\diamond$).

CONCLUSION

We presented an application of Independent Component Analysis to the removal of ocular artifacts in EEG recorded from blind subjects. We could show empirically that application of ICA is successful although blind subjects cause more and more irregular ocular artifacts compared to subjects with full eye sight. We used a semi-automatic two step procedure for detection of ocular artifacts consisting of computation of correlations between VEOG, HEOG and Independent Components plus visual inspection of results. Since the true EEG signals without influence from ocular artifacts are not known no direct quantification of success could be given. Evoked potentials recorded from one of our subjects who was born without eye bulbs and did therefore not show any ocular artifacts allowed for an indirect proof of success. Removal of artifacts based on ICA made evoked potentials recorded from subjects who did show eye movements more similar to evoked potentials recorded from the subject without eye bulbs.

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