Using ICA for removal of ocular artifacts in EEG recorded from blind subjects

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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.

Key words: Independent Component Analysis, Electroencephalogram

1 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 electro encephalogram (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 [Vigario 1997], [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. Related approaches to magnetoencephalographic signals can be found in e.g. [Barbati et al. 2004] and [Jun & Pearlmutter 2005].

EEG recorded from blind subjects poses special problems since it shows a much higher quantity of eye movements which are also more irregular and very different across subjects. These ocular signals can be much larger in amplitude than EEG signals and therefore pose a serious problem for further analysis. We present an application of ICA to removal of ocular artifacts in event-related 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.

2 Data

The recording of the human electro encephalogram (EEG) is a non-invasive method to record electric brain potentials from the human scalp via a set of electrodes. An event-related potential (ERP) is the electro cortical potential measurable in the EEG before, during and after sensory, motor or mental events. We recorded event-related potentials (ERP) 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. ERPs 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.

Whereas most ERP studies focus on "pulse"-evoked short latency and short duration EEG events, "Slow Potential Topography" (SPT) (see [Bauer 1998] for a comprehensive review) concentrates on slow and long-lasting shifts in ERPs. Recording of SPT data requires careful consideration of some methodological prerequisites concerning a high stability of the technical baseline (amplifier and electrode-scalp interface, recording of true DC-EEG). SPT turned out to be a fairly direct measure of temporally extended cortical activity with negative-going slow potential shifts accompanying enhanced activity of a brain region (see e.g. [Vitouch et al. 1997], [Lamm et al. 1999] and

[Bauer et al. 2003]). The standard method to analyze SPT data is to average across all single trials of ERPS thereby losing all information about faster components and to analyze only positive and negative shifts of very slow potentials. Only these long-lasting DC-trends are time locked to the onset of the recording and still sufficiently similar across trials. It is common practice to analyze SPT averages at the single latency after stimulus onset when the topographical pattern corresponding to the investigated cognitive activity is most pronounced. The data in this study was recorded as true DC-EEG thereby enabling SPT analysis.

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 [3]. Eye movements were recorded as vertical and horizontal electro-oculogram (VEOG and HEOG) using two electrodes in a bi-polar montage per EOG channel. Data was recorded with a frequency range from DC to $30Hz$ and a sampling rate of $125Hz$. The recording system was a DC-amplifier BDS 3064 (Ing. Zickler Ges.m.b.H, 2511 Pfaffstätten, Austria). The recordings were then 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.

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

3 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. $u = Wx$).

Due to the Central Limit Theorem a linear mixture of independent random variables is necessarily more Gaussian than the original variables. Therefore maximizing the nongaussianity achieves the unmixing of the recorded signals x. This implies (i) that it is enough to assume that the source signals $s_i(t)$ are *statistically independent* at each time step t, though their mixtures $x_i(t)$ are not; (ii) that in ICA we must restrict ourselves to at most one Gaussian source signal. Since there exist numerous ways to measure nongaussianity (e.g. kurtosis, negentropy, mutual information, etc.) and different approaches towards maximization, ICA is a whole family of algorithms for solving the blind source separation problem (see e.g. [Lee 1998], [Hyvaerinen 1999], [Hyvaerinen & Oja] and [Roberts & Everson 2001] for an introduction and overview). ICA is a very general-purpose method of signal analysis and data analysis.

We used the "infomax" neural network algorithm [Bell & Sejnowski 1995] for ICA [4]. 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 non-linearity and $u = Wx$.

ICA has already been used successfully for blind source separation of EEG data. Application of ICA to ERPs include artifact detection and removal (see [Vigario 1997], [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 ERPs is more recent (see [Vigario 1997], [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

[4] All ICA related computations were done with the MATLAB toolbox EEGLAB [Delorme & Makeig 2004].

accounted for by the selected components can be obtained in true polarity and amplitudes.

4 ICA for removal of ocular artifacts

There are two main types of ocular artifacts, those due to blinks and those due to saccadic movements (see e.g. [Overton & Shagass 1969], [Jung et al. 2000] and [Joyce et al. 2004]). Blink artifacts are due to contact of the eyelid with the cornea which alters ocular conductance. The influence of blink artifacts on recording electrodes decreases rapidly with distance from the eyes. Saccade artifacts arise from changes in orientation of the retino-corneal dipole. The cornea of the eye is positively charged relative to the retina. Rotation of the retino-corneal axis results in changes in electrical potential. 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 question is how to decide which independent components (ICs) account for eye movements and should therefore be set to zero.

Whereas the first paper applying ICA to averaged EEG in general is by [Makeig et al. 1996], the first work reporting about application of ICA to single trial ERPs for artifact removal seems to be by [Vigario 1997]. The study reports about removal of ocular artifacts from five minutes of 22 channel recordings obtained from children lying with eyes closed. 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 are presented graphically, no quantification is given.

[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 also use visual inspection of ICs and scalp topographies to decide which ICs account for artifacts. Results 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 ERPs (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 ERPs. 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 ERPs 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 de-noised single trials deviates little from the average of the original single trials. De-noising of single trials via ICA also allows them to analyze the considerable variation of CNV amplitude and latency which is hidden by conventional averaging.

[Joyce et al. 2004] report about an extensive study on removal of ocular artifacts discussing and comparing different EOG electrode placement strategies as well as different algorithms for blind source separation. They present an automatic approach for extracting and removing ocular components after computation of ICA. Independent components are removed if (i) their activation is inverted in an ICA solution for EEG plus EOG channels relative to an ICA solution for EEG plus *inverted* EOG channels (inversion of component indicating relation to EOG channels), (ii) they correlate with EOG channels above a certain threshold, (iii) they show high power in low frequency bands. Although the authors claim that their approach is fully automatic the setting of thresholds for steps (ii) and (iii) make them semi-automatic at best. Results are presented graphically and in addition averages of artifact free trials are shown to be similar to averages of the same trials after removal of ocular artifacts. The latter is provided as a proof that the removal of ocular artifacts does not subtract any EEG related parts of the signals.

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, subjects who are born blind cannot even control their eye movements at all. Therefore blind subjects show (i) almost permanent 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 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 ERPs 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 ($\mid \rho^i_{veog} \mid > 0.4$ and $\mid \rho^i_{heog} \mid > 0.4$) 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 [5] to corroborate or dismiss decisions based on correlations alone.

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

5 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 proved successful. Visual inspection of results showed that the correlation threshold of 0.4 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 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 column).

As already discussed in Sec. 4, evaluation of artifact removal is difficult since the true EEG signals without influence from ocular artifacts are not known. Therefore no direct quantification of success can be given. Most authors present their results graphically like we did in Figs. 2 and 3. [Joyce et al. 2004] compare averages of artifact free trials to averages of the same trials after removal of ocular artifacts to give a quantitative measure of success. This is

provided as a proof that the removal of ocular artifacts does not subtract any EEG related parts of the signals. Unfortunately blind subjects show eye movements throughout the whole recordings which makes the extraction of artifact free periods impossible. Instead we took the following approach to providing an indirect yet quantitative proof of success.

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 ERPs recorded from subjects B, C, D and E more similar to ERPs recorded from subject A. To test this hypothesis we compared 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). This is because the data has been recorded as true DC-EEG to enable analysis of slow cortical potential shifts (see Sec. 2). 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. Pearson 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 $\rho_{before} = 0.068$ to $\rho_{after} = 0.526$ due to removal of ocular artifacts. Using Fisher's z' transformation to convert the correlations to the normally distributed variables z' we can see that the

difference between correlations is statistically significant at the 5% error level:

$$z = \frac{z'_{after} - z'_{before}}{\sigma_{z'}} = \frac{0.5846 - 0.0681}{\frac{1}{\sqrt{21-3}}} = 2.1913 > z_{95} = 1.96$$

The values for the three topographies used computing these correlations 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).

6 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. Event-related 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 event-related potentials recorded from subjects who did show eye movements more similar to event-related potentials recorded from the subject without eye bulbs.

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Fig. 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 in μV (range differs between graphs for better visibility).

Fig. 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 in μV (range differs between rows for better visibility); y-range is always the same within a row (before vs. after removal).

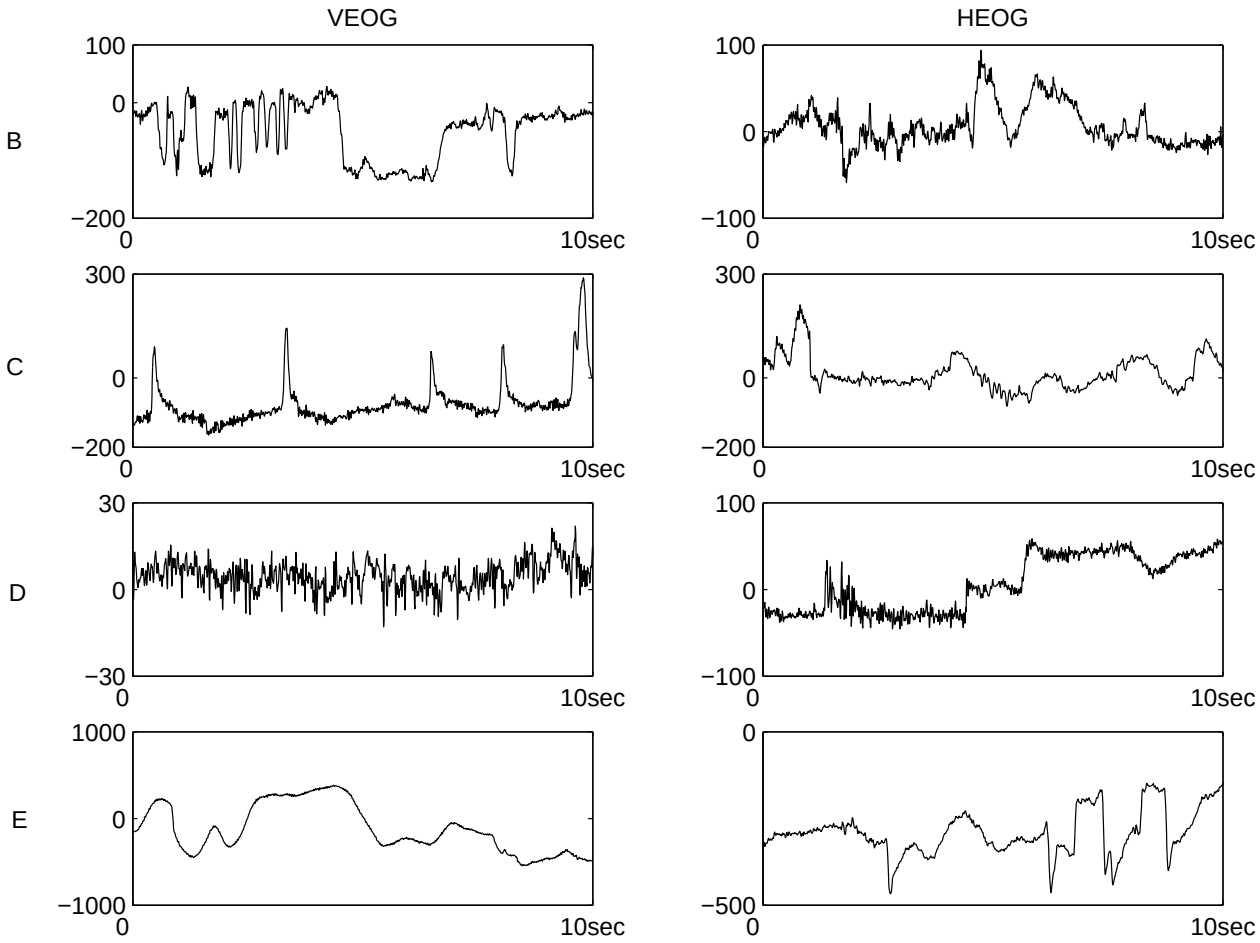
Fig. 3. Illustrative examples of signals (VEOG, HEOG, Fz, Oz; top to bottom rows) before (left column) and after (right column) removal of ocular artifacts for **subject E**; x-axis is always ten seconds of recording; y-axis is amplitude in μV (range differs between rows for better visibility); y-range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

Fig. 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 in μV.

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

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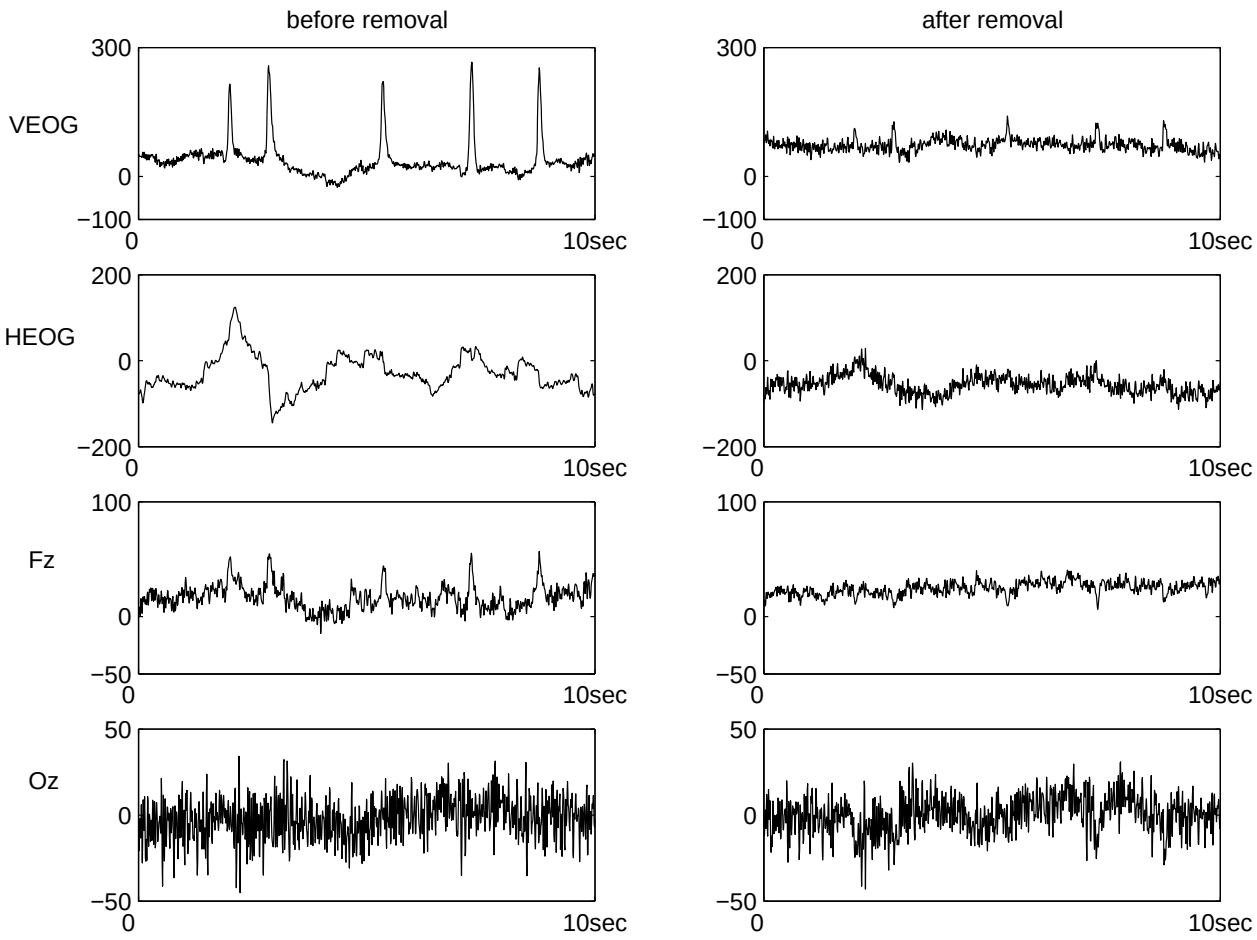
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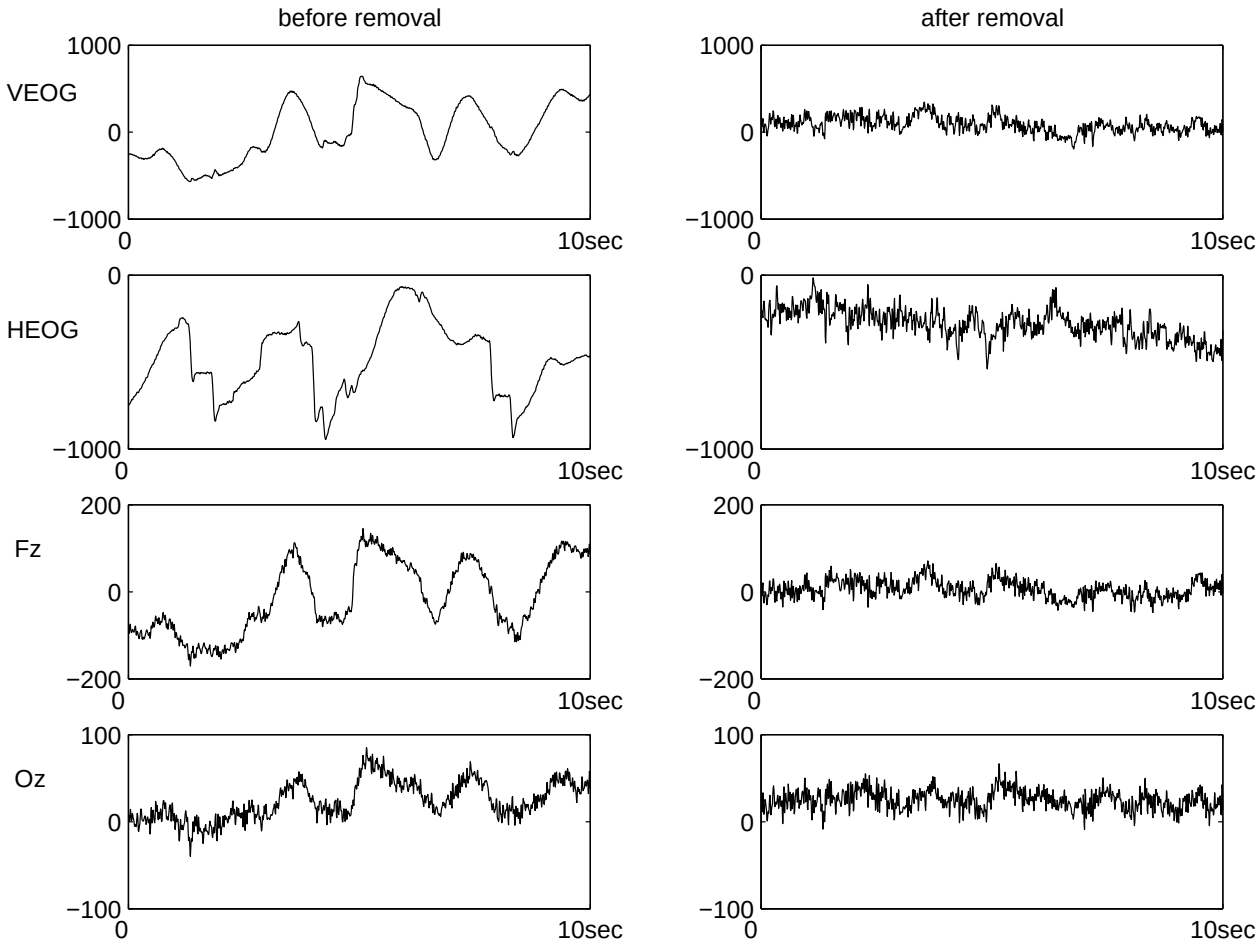
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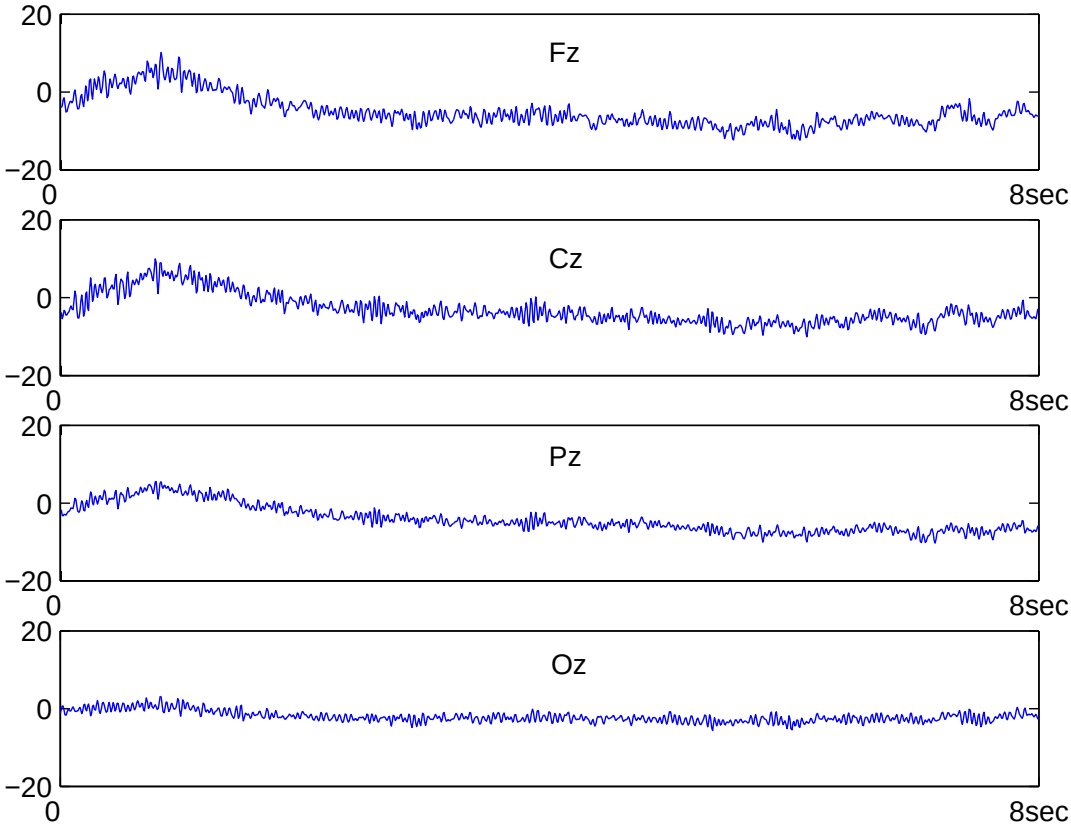
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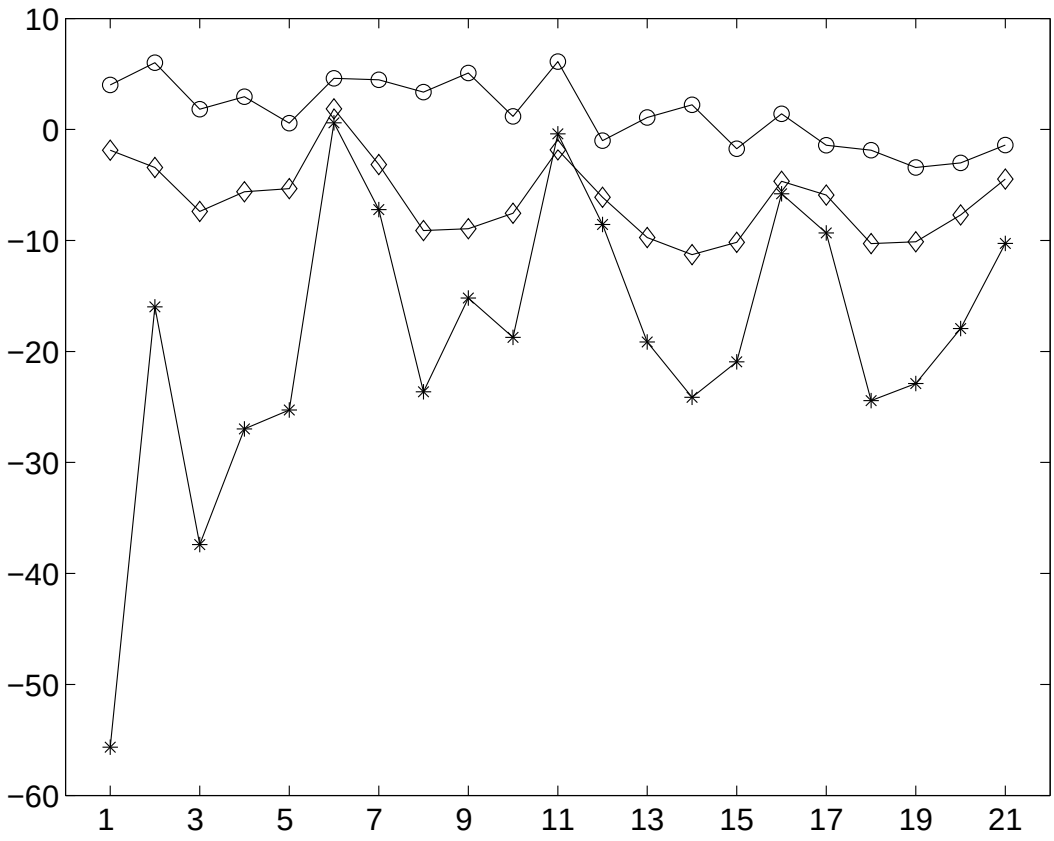
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	ρ_{veog}	ρ_{heog}
subject B	-0.53 -0.49	-0.41 -0.66
subject C	0.86	0.74
subject D	0.56 -0.44	0.91
subject E	-0.63 **0.35**	0.60 -0.60