34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

The Effect of Automatic Blink Correction on Auditory Evoked Potentials*

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Abstract— **The effects of blink correction on auditory event-related potential (ERP) waveforms is assessed. Two blink correction strategies are compared. ICA-SSP combines independent component analysis (ICA) with signal space projection (SSP) and ICA-EMD uses empirical mode decomposition (EMD) to improve the performance of the standard ICA method. Five voluntary subjects performed an auditory oddball task. The resulting ERPs are used to compare the two blink correction methods to each other and against blink rejection. The results suggest that both methods qualitatively preserve the ERP waveform but that they underestimate some of the peak amplitudes. ICA-EMD performs slightly better than ICA-SSP. In conclusion, the use of blink correction is justified, especially if blink rejection leads to severe data loss.**

I. INTRODUCTION

Electro-oculographic (EOG) activity, mainly blinks and saccadic eye movements, constitute a major source of artefacts in electroencephalographic (EEG) recordings. All fields of EEG analysis from spectral analysis to event-related potential (ERP) analysis have to take EOG artefacts into account. This paper focuses on ERPs, where the characteristics of the experimental setting cause subjects to blink but saccadic movements are usually small. Hence the focus will be in handling the EOG blink artefact.

There are three common ways to deal with blinks: avoidance, rejection and correction. A natural start is to try to avoid blinking and thus reduce the number of blinks. However, as everyone needs to blink, this is not always very effective. Some of us blink more than others and certain groups of people (such as children or patients) might not be in the position to control their blinking.

The next step is usually to reject those parts of the signal that contain blinks and try to manage with what is left. This might work in some applications but sometimes, as in ERP studies, blinks tend to overlap with the data of interest. In such cases blink rejection often leads to unacceptable data loss. The engineering approach is to make the best out of the available data and try to correct for blinks, while carefully estimating how this might bias the results.

There are several approaches to blink correction of which the most frequently used can be classified into regression based methods and component based methods. In regression based methods a linear model is created to model the distribution of blink artefacts across the scalp [1], [2]. Regression based methods require several EOG reference channels to get a source signal for the EOG and possibly calibration measurements to construct a blink model.

Component based methods first divide the EEG activity into a set of source components and then construct a blink-free data set by reconstructing the data without the blink related components. Examples of such methods include principal component analysis (PCA) [3], signal space projection (SSP) [4] and blind source separation (BSS) [5], [6], [7]. Of these the BSS methods seem to be the most popular. There are several BSS methods available, of which independent component analysis (ICA) using the FastICA algorithm is used here [8], [9].

In this paper two component based, automatic blink correction algorithms are compared against each other and to blink rejection (BR). The selected algorithms are blink correction using combined ICA and signal space projection (ICA-SSP) and blink correction using combined ICA and empirical mode decomposition (ICA-EMD). Of these ICA-SSP is a non-published combination of ICA and SSP, where ICA is used to define the field pattern of blinks and SSP to correct the data using spatial filtering. ICA-EMD is the Lindsen's combined ICA-EMD approach [3] with visual inspection of ICs replaced with automatic detection. The template matching approach by Li et al. is used to automatically classify ICs as blink related [6]. The rejection of blinks serves as a standard procedure to which the blink correction methods can be compared. The main goal is to quantitatively demonstrate the feasibility of ICA as a standard tool for blink correction.

II. MATERIALS AND METHODS

Five voluntary adults participated in a pilot study. Data collected from a 12 min auditory oddball task was used for the testing of blink correction methods. The standard tone in the oddball paradigm was a 1000 Hz sinusoid and the deviant tone a 1250 Hz sinusoid. The 75 ms tones were presented using a 1000 ms stimulus onset asynchrony (SOA) and there were in total 582 standard and 101 deviant tones.

EEG was measured using a NeurOne amplifier (Mega Electronics, Kuopio, Finland) at a sampling rate of 500 Hz using a 125 Hz low-pass filter. A total of 26 EEG channels and four EOG channels were measured. EOG channels were positioned above and below the right eye (VEOG) and on the sides of the outer canthi of both eyes (HEOG). An average mastoid reference was used for all channels.

ERPs were analysed using the EEGLAB [10] framework combined with custom scripting in Matlab. Prior to epoching

*This work was supported by Tekes SalWe

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the data were two-way FIR band-pass filtered from 0.5 to 30 Hz. Epoching was done using a $-100\ldots700$ ms window around correctly identified deviant stimuli. Accurate stimulus onsets were measured using an audio stimulus detector [11]. Prior to averaging epoch baselines were corrected using $-100\ldots0$ ms as the epoch baseline. All epochs containing either manually identified artefacts or amplitudes exceeding ±65 µV were excluded from the analysis. Blinks were identified from the VEOGup-VEOGdown signal using a custom algorithm (article in preparation) that is partly inspired by Jammes et al. [12].

A. ICA-SSP

This method corrects blinks using a combination of ICA and orthogonal matrix projections. In this method ICA serves as a convenient tool for extracting blink related field patterns without manual intervention. The actual blink rejections do not utilise the ICA decomposition. The original uncorrected data is denoted $\mathbf{X} \in \Re^{d\times n}$, where d is the number of channels and n represents time (samples). The FastICA algorithm was first used to divide $\mathbf{X}$ (whole 12 min data set) into independent components (ICs) [8], [9]. The decomposition is

$$\mathbf{X} = \mathbf{A}\mathbf{S}, \quad (1)$$

$$\mathbf{A} = [\mathbf{a}_1 \ldots \mathbf{a}_k], \quad (2)$$

$$\mathbf{S} = \begin{bmatrix} \mathbf{s}_1^T \\ \vdots \\ \mathbf{s}_k^T \end{bmatrix}, \quad (3)$$

where $\mathbf{A} \in \Re^{d\times k}$ is the mixing matrix of the k ICs and $\mathbf{S} \in \Re^{k\times n}$ are the component time courses. Blink related ICs were then automatically identified using a template matching approach that selects the blink related components using the angle between $\mathbf{a}_k$ and the field pattern of an average blink [6]. The field patterns $\mathbf{a}_k$ of the blink related ICs were averaged and the result normalised to create a unit length, average field pattern vector $\mathbf{a_b}$ representing blink related activity. The SSP method was then used to divide the data into two orthogonal parts: one parallel and one orthogonal to $\mathbf{a_b}$ [4]. This was done using projections $\mathbf{P}_{||} = \mathbf{a_b}\mathbf{a_b}^T$ and $\mathbf{P}_{\perp} = \mathbf{I} - \mathbf{P}_{||}$. The orthogonal part $\mathbf{P}_{\perp}\mathbf{X}$ was taken as the corrected EEG signal. Thereafter, the ERP waveforms were calculated.

B. ICA-EMD

This method uses ICA combined with EMD in order to lose as little EEG signal as possible during reconstruction [3]. First the ICA decomposition of $\mathbf{X}$ was calculated and blink related ICs $\tilde{\mathbf{s}}_i$ were identified using template matching as before. To reconstruct $\mathbf{X}$ without blink activity, none of the ICs were removed but the blink related ICs $\tilde{\mathbf{s}}_i$ were corrected for blink activity using EMD filtering [3]. For EMD a Matlab/C code implementation by G. Rilling was used [13]. Reconstruction was done using the resulting modified $\mathbf{S}$ where ICs not related to blinks were left unchanged. However, due to the computational load of the EMD procedure, the whole data set $\mathbf{X}$ could not be processed at once. As a consequence the EMD filtering was integrated as part of the ERP analysis. This procedure has the following steps:

1) epoch data set $\mathbf{X}$ into l epochs
2) remove epoch baselines
3) for each epoch $\mathbf{X}_l$ do:
   a) calculate $\mathbf{S}_l = \mathbf{A}^{-1}\mathbf{X}_l$
   b) low pass filter each blink related IC $\tilde{\mathbf{s}}_{l,i}$ using EMD
   c) reconstruct $\mathbf{X}_l$ using modified $\mathbf{S}_l$
4) FIR 30 Hz low-pass filtering
5) remove epoch baselines and average epochs into ERPs

Note that the band-pass filter is replaced by a 30 Hz low-pass filter as the short epochs cannot be reliably 0.5 Hz high-pass filtered.

C. Comparison of results

Different comparisons were made to study the effects of blink correction. Firstly, the methods are compared using "clean epochs", i.e. epochs that did not overlap with manual rejections, whose amplitude remained within the preset limits and which did not contain blinks. Note that when using clean epochs, the blink correction algorithms operate on data that actually contains nothing to correct. This allows for the direct examination of the distortions introduced by the blink correction procedures.

Secondly, ERPs from "blink epochs", i.e. epochs containing no visible artefacts other than blinks, are compared against the BR ERP from clean epochs. This reveals how much ERP related activity the correction algorithms are able to extract from blink contaminated data.

Thirdly, the methods are compared using all available data for each method. For the blink correction methods this means both clean and blink epochs but for BR only the clean epochs. This shows what kind of ERPs each method would yield in a real analysis situation.

The epoched data sets were first averaged for each subject and the subject averages were further averaged to create a group average ERP.

III. RESULTS

A. Comparison using clean epochs

The comparison of group average ERPs using clean epoch data is shown in Fig. 1. The shape of the ERP is preserved well for both correction methods but the ERP amplitudes are underestimated, especially at Fz. It is seen that ICA-EMD follows the BR ERP time course more closely at Fz whereas ICA-SSP is more accurate at Pz. The largest differences between the correction methods are at Fz N100 and Pz P300.

B. Comparison using blink epochs

Figure 2 shows the comparison of group average ERPs using blink epoch data for the correction methods and clean data for BR. The shape of the ERP is again preserved but

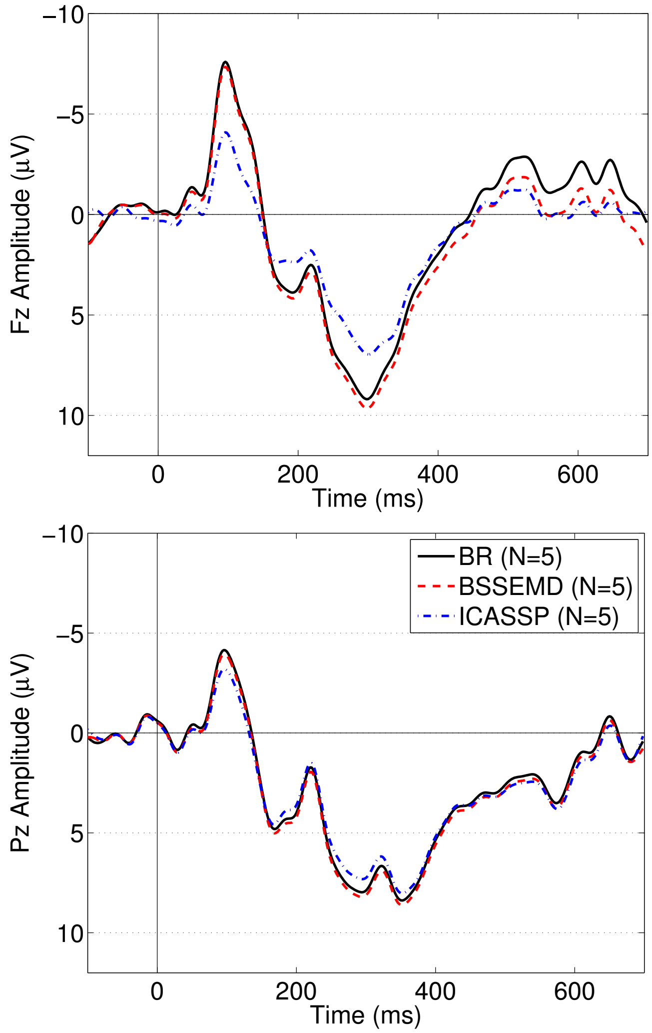

Fig. 1: Comparison of group average ERPs using data from clean epochs for channels Fz and Pz. The ERP is an auditive ERP triggered to correctly identified targets in an oddball paradigm. The numbers in parentheses are the number of subjects averaged.

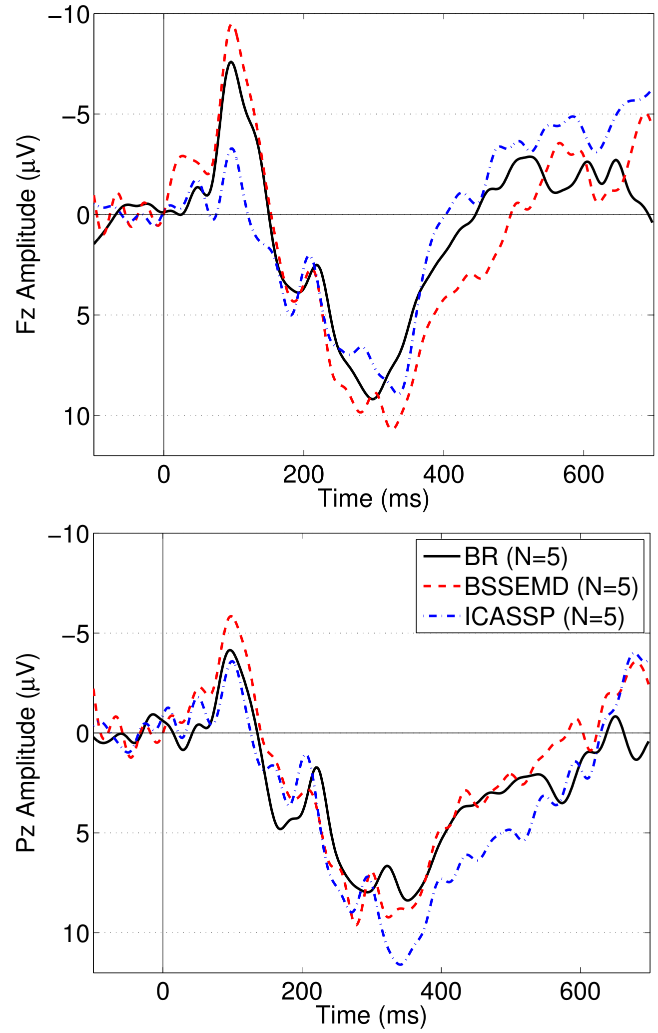

Fig. 2: Comparison of group average ERPs using blink epoch data for ICA-SSP and BSS-EMD but clean data for BR.

the estimates clearly contain more noise. At Fz BSS-EMD overestimates the N100 whereas ICA-SSP underestimates it. For Fz P300 both methods show an increase in peak latency. At Pz the N100 is well reproduced although BSS-EMD overestimates the amplitude. The Pz P300 is also overestimated, this time more by ICA-SSP.

C. *Comparison using all epochs*

The comparison of group average ERPs using all available data is shown in Fig. 3. It is seen that largest distortions in peak amplitudes occur at Fz where N100 and P300 amplitudes are underestimated by both methods. The largest error is made by ICA-SSP for the Fz N100 ERP amplitude.

Also at Pz the N100 ERP amplitude is equally underestimated by both methods. The Pz P300 ERP is well reproduced with only small differences between methods.

Note that the Pz P300 wave has two peaks indicating that there might exist some individual or other systematic differences in the data.

IV. DISCUSSION

Both blink correction methods yield similar results: peak amplitudes are underestimated and this effect is larger frontally. The P300 wave is better reproduced than the N100 wave. The largest difference between methods appears at the Fz N100 wave whose amplitude is severely underestimated by ICA-SSP.

The distortions caused by ICA-SSP might be a consequence of the orthogonal projection used. It projects out EEG activity of all sources that have a blink-like scalp distribution leaving frontal EEG electrode sites most affected.

ICA-EMD performs slightly better, most likely due to the ICA decomposition that enables only the blink related signal components to be corrected. However, this comes with a computational price. Especially the EMD procedure is computationally very expensive, even more than the ICA, and therefore ICA-EMD cannot be directly applied to on-line

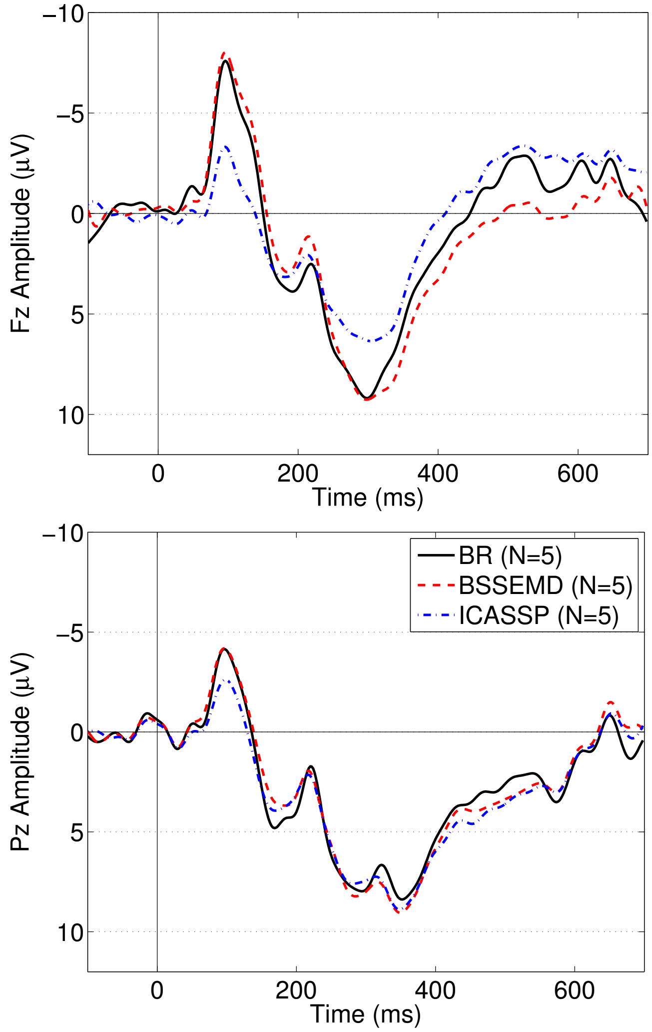

Fig. 3: Comparison of group average ERPs using all available data for each method.

analysis.

The results show that both blink correction methods can be used in ERP analyses. Especially when blink rejection leads to significant data loss and poor SNR in the ERPs, the use of blink correction is well justified. After all, a possibly slightly biased estimate of ERP is better than no estimate at all.

It is also worth emphasising that the blink correction methods used here do not require any calibration measurements, nor do they require any user intervention e.g. in detecting the blink related ICs. Hence it is easy to add them as a step in a larger automated analysis workflow.

This description of the effects of blink correction on the auditive ERPs is qualitative. More data, in the form of more subjects and longer measurements, is needed to establish quantitative measures for the size of the observed distortions. Another subject of future work would be the comparison of ICA-EMD to some commonly used regression method. This would provide insights into the differences between those methods and help data analysts select the most appropriate method for their application.

ACKNOWLEDGMENT

The authors wish to thank the SalWe research team at FIOH that made the data collection possible. The study was supported by the SalWe Research Program for Mind and Body (Tekes – the Finnish Funding Agency for Technology and Innovation grant 1104/10).

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