Validation of Automated Artifact Removal Procedures in Dense-Array EEG

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Introduction

The electroencephalogram (EEG; see Figure 1) records high temporal resolution human brain activity that is comprised of signal and noise which are intermingled with each other. The signals received are brain signals primarily from local field potentials that propagate to the scalp, while the noise received arise from various sources of artifacts of biological and non biological origin. One of the most prominent sources of noise that infects the brain activity collected are the ocular artifacts. These artifacts arise from electric potential differences caused by blinks and eye movements, which are collected at mostly frontal EEG electrodes. To properly analyze the data, one must remove ocular artifacts from the EEG data, and independent component analysis (ICA) offers an attractive approach to doing so. ICA decomposes preprocessed data into maximally independent components (ICs), which are organized into spatial topographies and time-courses (Bell & Sejnowski, 1995). ICs are usually classified as artifact or non-artifact via visual inspection of these topographies and time-courses. However, this can be time-consuming and error-prone, and automated approaches provide an easier and more principled way of removing artifactual ICs. This is especially true for recently developed “dense-array” EEG systems with 256 electrodes compared to standard electrode caps which contain 64 electrodes or less (given that ICA typically provides one component per electrode).

Figure 1. The figure above depicts the EEG equipment used to collect data.

Objectives

The objective of this research was to implement and validate an automated ICA approach by using a MATLAB script that correlated the IC time-courses with electrooculogram channel time-courses (EOG ; attached around the eye). The automated approach was validated by comparing the overlap between the automated classifications with classifications of the same ICA decompositions made manually by two humans. We also visualized the effects of automated removal on the signals of interest (sensory event-related potentials or ERPs).

Methods

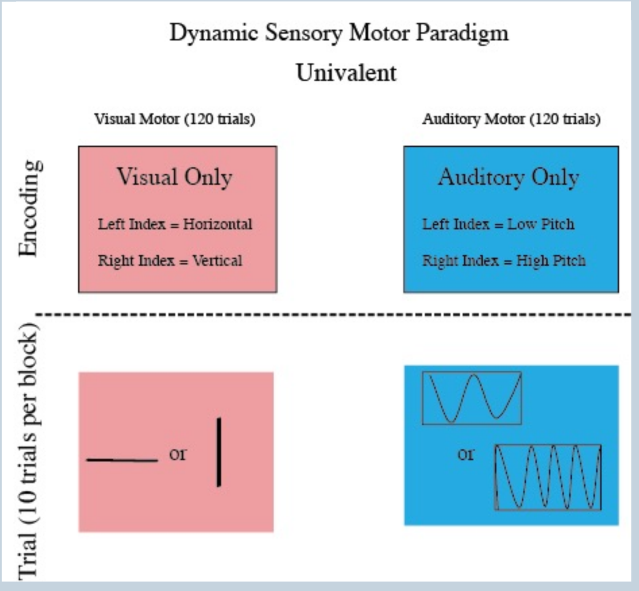

Figure 2. The figure above depicts the paradigm used for the experimental task.

Apparatus: The dense-array EEG equipment consists of an electrode cap with 256 electrodes that goes from the back of the neck to the front of the face, between the eyes and over the cheekbones, and the ears from left to right (see Figure 1). Our sample was 9 subjects (4 female; age range = 19-30 years).
Task design: While fitted with the EEG cap, subjects completed an experimental task that required subjects to categorize visual and auditory stimuli. The visual stimuli consisted of a straight line or horizontal line, and the auditory stimuli consisted of high-pitch or low-pitch sound, as shown in Figure 1.
Preprocessing: Before running the ICA, the EEG data was preprocessed by filtering the continuous data (high-pass filter 1Hz, line noise notch 60Hz) and then segmenting the data into trials (-200ms to 1500ms around stimulus onset). Next, we identified the noisy channels and trials (based on the absolute signal amplitude) and removed them because these can worsen the ICA decomposition.
ICA: The ICA was run using the RunICA implementation (Infomax) in Fieldtrip (Oostenveld, Fries, Maris & Schoffelen, 2011), to decompose the data into 256 components. Typically, we would then manually go through each component, visually identifying components as ocular artifacts and removing them. Eye blink artifacts are characterized by a frontal topography, as shown in Figure 3 (lower panel), with patterns of deflections or “dips” in the time-course. Figure 3 also shows an example eye movement IC (upper panel), characterized in its topography by opposite polarity around the eyes, and slower deflections in its time-course.
Automated approach: Our approach automates the identification of blink and eye-movement artifacts based on these visual features.
(1) A set of electrooculogram (EOG) electrodes placed around the eye to best capture the ocular artifact
(2) We extracted time-courses from these EOG channels and computed the Pearson’s correlation between them and each IC time-course, separately for blinks and eye movements.
(3) Correlations were standardized by converting absolute values to z-scores, to counteract variability in correlation strength between subjects (see Figure 4).

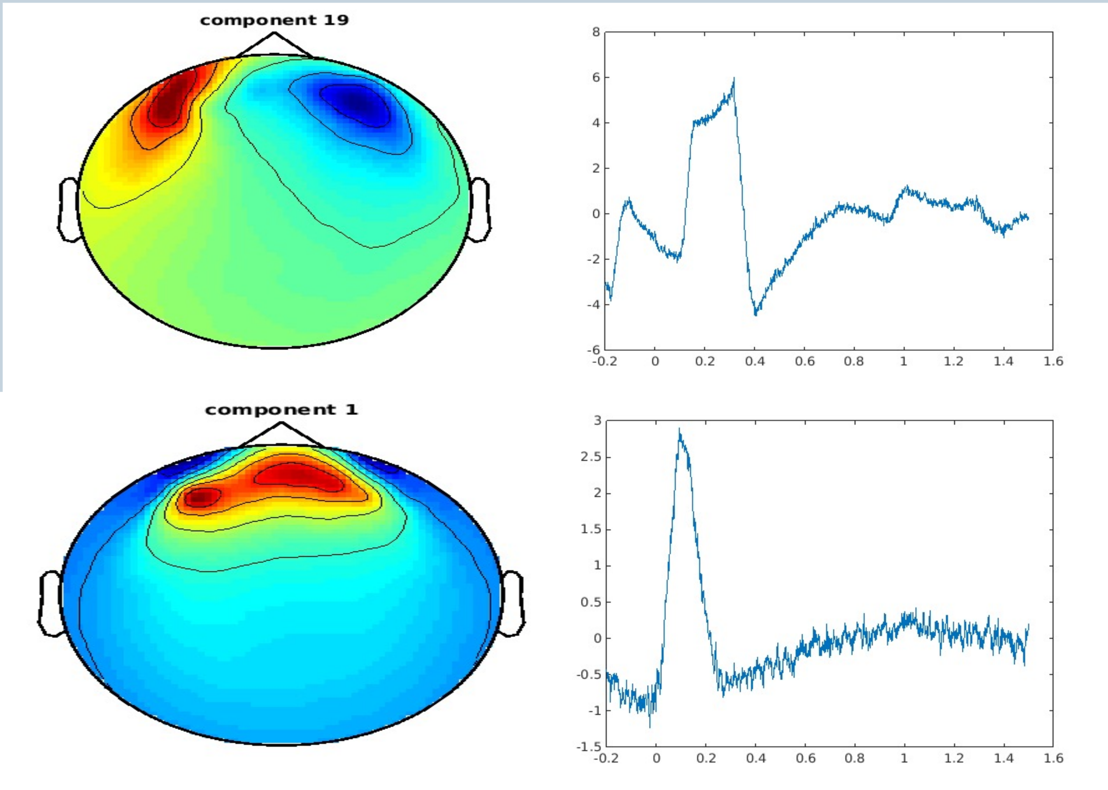

Figure 3. The figure above depicts topographies and timecourses of a representative eye movement (upper) and an blink (right) artifact, taken from one subject.

(4) We varied the threshold for artifact identification between z-score=3 (more liberal artifact identification; ICA_z3), and z-score=4 (more conservative, ICA_z4).
Validation: We adapted the approach of Pontifex et al (2017). We recruited two human observers, one intermediate (1-2 years experience) and one novice (0 years experience), who identified ocular artifacts based on the guidelines in Chaumon et al (2015). We compared the human classification results with the automated results, treating the ratings provided by an expert observer (4-5 years experience) as the “ground truth”.
We also validated the automated approach by visualizing the effect of applying it versus not applying it on resulting sensory ERPs. These ERPs were computed by averaging “Visual Only” and “Auditory Only” trials across subjects (see Figure 1), resulting in Visual ERPs, Auditory ERPs and their difference wave (Visual - Auditory ERP), across variations in preprocessing: raw (filtering only), noisy channels + trials removal only, auto ICA approach (ICA_z3 and ICA_z4) and auto ICA z3 + final visual inspection.

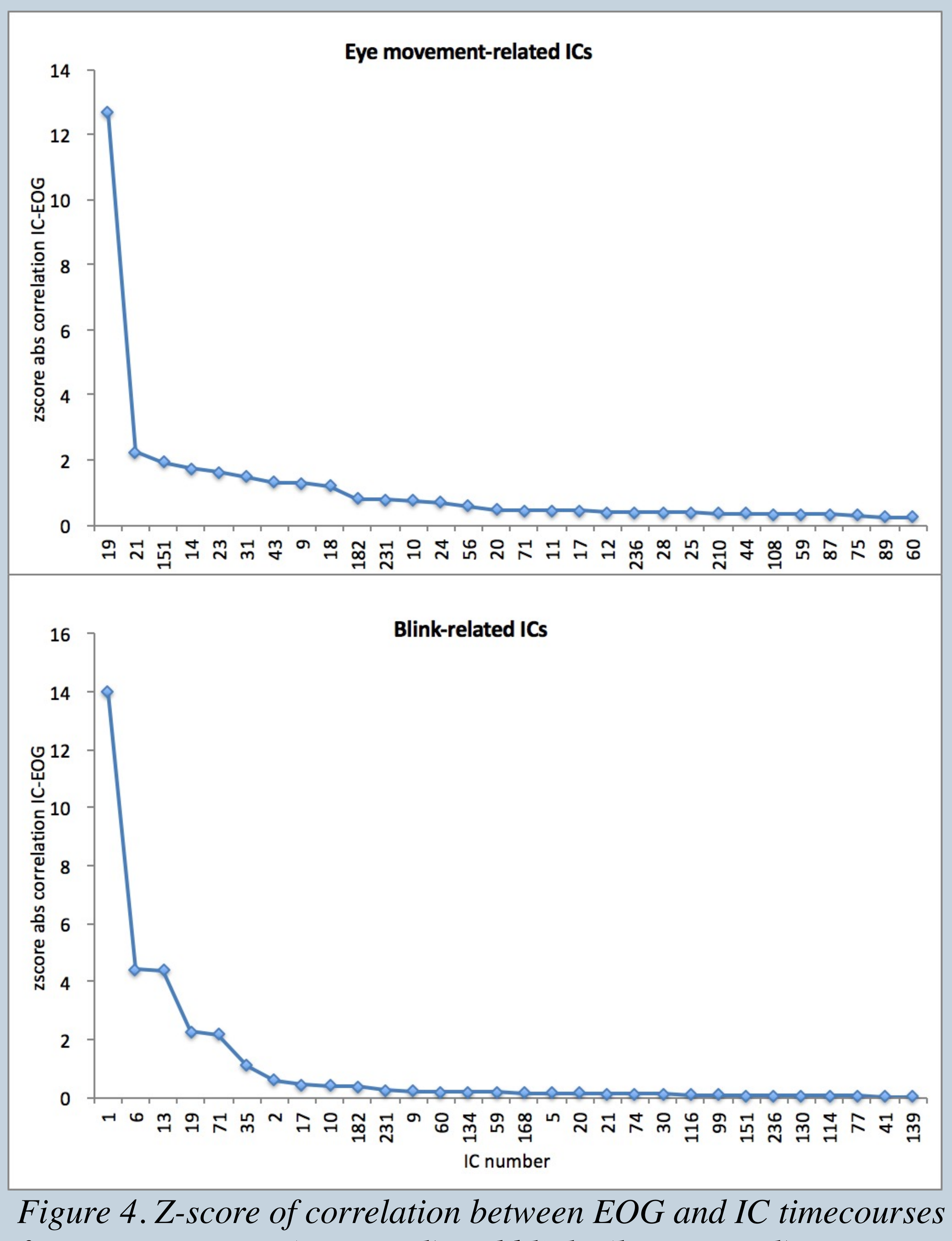

Figure 4. Z-score of correlation between EOG and IC timecourses for eye movements (top panel) and blinks (lower panel).

Results

	Average number of artifacts components (with SD)	Overall accuracy	TP count	TN count	FP count	FN count	Sensitivity (TP/(TP+FN))	Specificity (TN/(TN+FP))
Blinks								
Observer A (intermediate)	3.44 (1.67)	0.9943	22	2242	9	4	0.8462	0.9960
Observer B (novice)	2.22 (0.83)	0.9947	17	2248	3	9	0.6538	0.9987
ICA_z3	3.66 (1.22)	0.9969	26	2244	7	0	1.0000	0.9969
ICA_z4	2.89 (0.78)	0.9974	23	2248	3	3	0.8846	0.9987
Expert	2.89 (1.17)	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Eye movements								
Observer A (intermediate)	2.00 (0.87)	0.9943	8	2256	10	3	0.7273	0.9956
Observer B (novice)	2.67 (1.87)	0.9890	5	2247	19	6	0.4545	0.9916
ICA_z3	2.33 (1.94)	0.9930	8	2253	13	3	0.7273	0.9943
ICA_z4	1.89 (1.05)	0.9947	8	2257	9	3	0.7273	0.9960
Expert	1.22 (0.83)	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Collapsed Blinks + Eye movements								
Observer A (intermediate)	5.44 (2.19)	0.9886	30	2221	19	7	0.8108	0.9915
Observer B (novice)	4.89 (2.03)	0.9846	23	2219	21	14	0.6216	0.9906
ICA_z3	6.00 (1.80)	0.9921	36	2223	17	1	0.9730	0.9924
ICA_z4	4.78 (0.83	0.9930	32	2229	11	5	0.8649	0.9951
Expert	4.11 (1.27)	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Table 1. Classification overlap, depicted as the average number of artifact components identified, overall classification accuracy, true positive count, true negative count, false positive count, false negative count, sensitivity, and specificity.

Table 1 compares the performance of the two human observers, Observer A and Observer B, with the automated methods, ICA_z3 and ICA_z4. Both human observers and automated methods classified the same ICA components as artifact or non-artifact, separately for blinks and eye movements.
The overall accuracy defines how well each observer and automated method did relative to the expert’s ratings (irrespective of the “true” identity of the stimulus). We also computed sensitivity and specificity measures, which compute accuracies after splitting the data into true “artifacts” and true “non-artifacts” (see Figure 5). Sensitivity is how well the true artifacts were identified, whereas specificity is how well true non-artifacts were identified. These signal detection theory estimates enable a more detailed insight into data properties than overall accuracy alone. The results reveal that the automated methods outperformed the human observers in all categories, except for eye movements, for which Observer A did marginally better than ICA_z3, but not ICA_z4. However, the automated methods could not distinguish reliably between eye blinks and eye movements, so collapsing blinks and eye movements better represents how well the automated methods performed. To summarize:
1) Automated methods out-performed human observers in the collapsed data (for both sensitivity and specificity)
2) Automated methods are comparable to each other (ICA_z3 vs ICA_z4); ICA_z3 has better sensitivity, whereas ICA_z4 has better specificity.

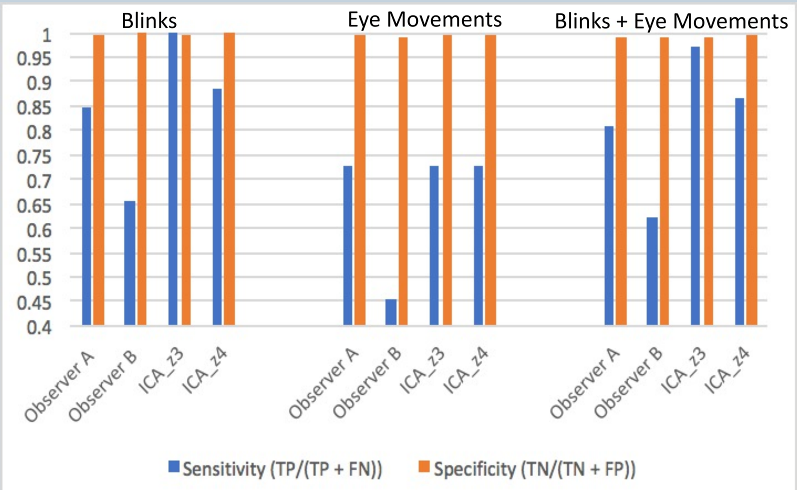

Figure 5. The figure above shows a bar graph of the sensitivity (blue) and the specificity (orange) of every observer and automated method in every category: blinks, eye movements, and collapsed blinks and eye movements.

Event-related potentials (ERPs) measure brain activity resulting from stimulus presentation. From the ERP time course of the visual and auditory ERPs, one can see the difference between ICA removal of ocular artifacts and no artifact removal at all (Figure 6). The blue and red waves are without ICA. In the auditory channel (upper panel), the non-ICA difference waves are contaminated by ocular artifacts around 600-800ms. The visual channel (lower panel) is also contaminated, but to a lesser degree because the auditory channel is more frontally located. This shows the extent to which ocular artifacts distort EEG and how essential it is to remove these artifacts before analyzing the data.

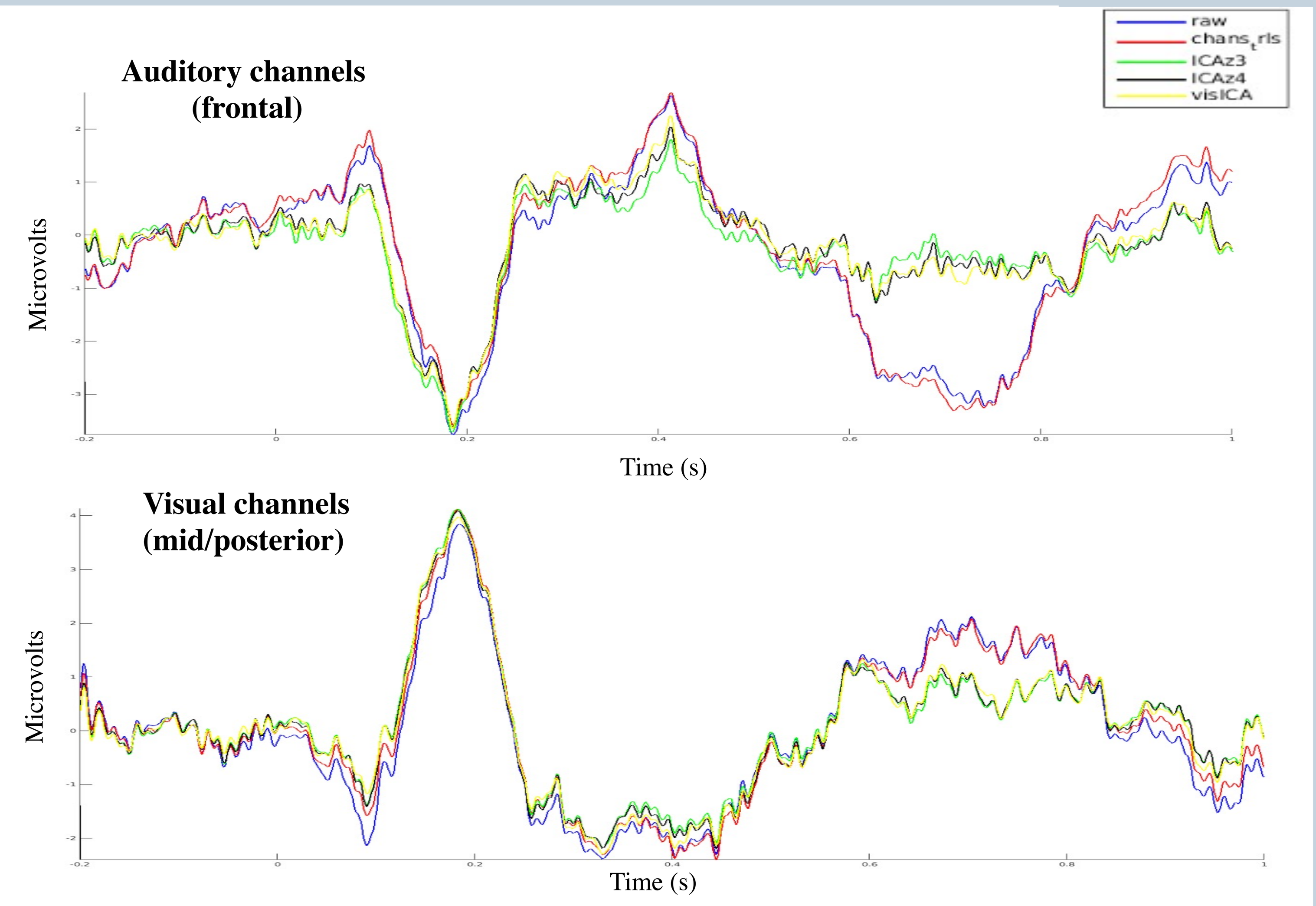

Figure 6. ERP difference waves (Aud - Vis condition) for auditory channels (upper panel) and visual channels (lower panel), across different types of artifact preprocessing (see legend).

Conclusions

- The automated method, ICA_z3 is the best approach in improving ocular artifact identification and removal, but only if it is combined with manual inspection. However, ICA_z4 performs well as a fully automated method which may be better for novice EEG analyzers.
- The time-courses from the ERPs showed the degree that the ocular artifacts affects EEG data, and the improvement in signal from our automated approach.

Acknowledgements

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