ICA-based artifact removal in EEG

John J.B. Allen

http://jallen.faculty.arizona.edu/ICA_Workshop
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"Clinical" vs Actuarial Approaches

Clinical Versus Actuarial Judgment

ROBYN M. DAWES, DAVID FAUST, PAUL E. MEEHL

Professionals are frequently consulted to diagnose and predict human behavior; optimal treatment and planning often hinge on the consultant’s judgmental accuracy. The consultant may rely on one of two contrasting approaches to decision-making—the clinical and actuarial methods. Research comparing these two approaches shows the actuarial method to be superior. Factors underlying the greater accuracy of actuarial methods, sources of resistance to the scientific findings, and the benefits of increased reliance on actuarial approaches are discussed.

“Clinical” vs Actuarial Approaches

Human raters
- Good source of possible algorithms
- Lousy at reliably implementing them
  - Inter-rater
  - Intra-rater

Actuarial methods
- Always arrive at the same conclusion
- Weight variables according to actual predictive power

Algorithmic EEG Artifact Approaches

- **Amplitude criteria**
  - Too sudden: 100uV between samples

- **Activity criteria**
  - Too big: 250uV/2sec epoch
  - Too small: <0.5 uV range across 100ms

- **Regression-based EOG correction**

- **Can we make ICA-based correction algorithmic?**
ICA is a "blind source separation" technique.

ICA separates sources of activity that are mixed together at recording electrodes.
What is ICA?

For EEG data

Channel data (X) can be thought of as a weighted (W) combination of independent component activations (Wx), each of which has a scalp projection (W^{-1}).

You can think of ICs as putative sources of the scalp-recorded EEG.
ICA Decomposition

$\mathbf{x} \mathbf{W} \mathbf{W}^{-1}$

- ERP Data
- Activations
- Maps
- ICA Components
ADJUST: An automatic EEG artifact detector based on the joint use of spatial and temporal features

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Abstract

A successful method for removing artifacts from electroencephalogram (EEG) recordings is Independent Component Analysis (ICA), but its implementation remains largely user-dependent. Here, we propose a completely automatic algorithm (ADJUST) that identifies artifactual independent components by combining stereotyped artifact-specific spatial and temporal features. Features were optimized to capture blinks, eye movements, and generic discontinuities on a feature selection dataset. Validation on a totally different EEG dataset shows that (1) ADJUST’s classification of independent components largely matches a manual one by experts (agreement on 95.2% of the data variance), and (2) Removal of the artifactual components detected by ADJUST leads to near reconstruction of visual and auditory event-related potentials from heavily artifactual data. These results demonstrate that ADJUST provides a fast, efficient, and automatic way to use ICA for artifact removal.
Automatic Classification of Artifactual ICA-Components for Artifact Removal in EEG Signals

Irene Winkler*, Stefan Haufe and Michael Tangermann

Abstract

Background: Artifacts contained in EEG recordings hamper both, the visual interpretation by experts as well as the algorithmic processing and analysis (e.g. for Brain-Computer Interfaces (BCI) or for Mental State Monitoring). While hand-optimized selection of source components derived from Independent Component Analysis (ICA) to clean EEG data is widespread, the field could greatly profit from automated solutions based on Machine Learning methods. Existing ICA-based removal strategies depend on explicit recordings of an individual’s artifacts or have not been shown to reliably identify muscle artifacts.

Methods: We propose an automatic method for the classification of general artifactual source components. They are estimated by TDSEP, an ICA method that takes temporal correlations into account. The linear classifier is based on an optimized feature subset determined by a Linear Programming Machine (LPM). The subset is composed of features from the frequency-, the spatial- and temporal domain. A subject independent classifier was trained on 640 TDSEP components (reaction time (RT) study, n = 12) that were hand labeled by experts as artifactual or brain sources and tested on 1080 new components of RT data of the same study. Generalization was tested on new data from two studies (auditory Event Related Potential (ERP) paradigm, n = 18; motor imagery BCI paradigm, n = 80) that used data with different channel setups and from new subjects.

Results: Based on six features only, the optimized linear classifier performed on level with the inter-expert disagreement (<10% Mean Squared Error (MSE)) on the RT data. On data of the auditory ERP study, the same pre-calculated classifier generalized well and achieved 15% MSE. On data of the motor imagery paradigm, we demonstrate that the discriminant information used for BCI is preserved when removing up to 60% of the most artifactual source components.

Conclusions: We propose a universal and efficient classifier of ICA components for the subject independent removal of artifacts from EEG data. Based on linear methods, it is applicable for different electrode placements and supports the introspection of results. Trained on expert ratings of large data sets, it is not restricted to the detection of eye- and muscle artifacts. Its performance and generalization ability is demonstrated on data of different EEG studies.
Research article

A practical guide to the selection of independent components of the electroencephalogram for artifact correction

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ABSTRACT

Background: Electroencephalographic data are easily contaminated by signals of non-neural origin. Independent component analysis (ICA) can help correct EEG data for such artifacts. Artifact independent components (ICs) can be identified by experts via visual inspection. But artifact features are sometimes ambiguous or difficult to notice, and even experts may disagree about how to categorise a particular component. It is therefore important to inform users on artifact properties, and give them the opportunity to intervene.

New Method: Here we first describe artifacts captured by ICA. We review current methods to automatically select artifactual components for rejection, and introduce the SASICA software, implementing several novel selection algorithms as well as two previously described automated methods (ADJUST, Mignon et al. Psychophysiology 2011; 48(2):229; and FASTER, Nolan et al. J Neurosci Methods 2010; 48(1):152).

Results: We evaluate these algorithms by comparing selections suggested by SASICA and other methods to manual rejections by experts. The results show that these methods can inform observers to improve rejections. However, no automated method can accurately isolate artifacts without supervision. The comprehensive and interactive plots produced by SASICA therefore constitute a helpful guide for human users for making final decisions.

Conclusions: Rejecting ICs before EEG data analysis unavoidably requires some level of supervision. SASICA offers observers detailed information to guide selection of artifact ICs. Because it uses quantitative parameters and thresholds, it improves objectivity and reproducibility in reporting pre-processing procedures. SASICA is also a didactic tool that allows users to quickly understand what signal features captured by ICs make them likely to reflect artifacts.
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Neural components

Expected properties

- Smooth/dipolar topography
- Large amplitude
- Strong evoked activity
- Power peak at physiological frequency
- Low artefact measures
Blink components

A

Expected properties

Frontal topography

Large amplitude

Opposite polarity below the eyes

No peak at physiological frequencies

High correlation with vertical EOGs

High eye movement related measures

Chaumon et al., 2015
Horizontal eye movement components

**Expected properties**

- Opposite sign bilateral frontal topography
- Step-like events
- Opposite polarity around the eyes
- No peak at physiological frequencies
- High correlation with vertical/horizontal EOGs
- High eye movement related measures

Chaumon et al., 2015
Non-artifact components may be mistaken for ocular components

**Expected properties**

- Inverse weight at posterior channels
- Noisy time course
- No opposite polarity around the eyes
- Weak correlation with EOGs

Chaumon et al., 2015
Muscle components

Expected properties

Focal topography
- Steady noisy time courses dissipating / building up across trials

Power at high frequencies
- High noise measures

Chaumon et al., 2015
Other types of artifacts may be mistaken for muscle components

### Expected properties

- Irregular/patchy topography
- Irregular / low frequency noise
- Stimulus evoked response

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Chaumon et al., 2015
Bad Channel components

Expected properties

- Focal (one channel) topography
- Noisy time course
- High correlation with marked bad channel
- High spatial / intertrial noise measures

Chaumon et al., 2015
Ambiguous mixture components

Expected properties

- More spread-out topography
- Stimulus evoked response
- Transient noise activity

Chaumon et al., 2015
Rare Events

Expected properties

Few high amplitude events in otherwise low amplitude time courses

High spatial / intertrial noise measures
What is ADJUST?

**ADJUST** = Automatic EEG artifact Detection based on the Joint Use of Spatial and Temporal features

- Automatic ICA-based algorithm that identifies artifact-related IC components
- Uses both spatial and temporal distributions
- Combines stereotyped features to efficiently and systematically reject an artifact

Mognon, Jovicich, Bruzzone, & Buiatti, 2010
How does it work?

- EEG is decomposed into ICs (done in EEGLab)
  - ICs defined only by statistical relationships.
  - It knows nothing about where electrodes are.
- Detectors are applied for 4 types of artifacts
  - Computes class-specific spatial and temporal features on all ICs.
  - Each feature has a threshold dividing artifacts from non-artifacts.
- For each detector, ICs identified as artifacts if features associated with the artifact exceed their respective threshold.

Mognon, Jovicich, Bruzzone, & Buiatti, 2010
**Artifacts**
- Eye blinks
- Vertical Eye Movement
- Horizontal Eye Movement
- Generic Discontinuity

**Features**
- Spatial Average Difference (SAD)
- Temporal Kurtosis (TK)
- Maximum Epoch Variance (MEV)
- Spatial Eye Difference (SED)
- Generic Discontinuities Spatial Feature (GDSF)
**MARA:** Six features derived from machine learning algorithm

1. **Current Density Norm:** ICA scalp maps can be interpreted as EEG potentials for which the location of the sources can be estimated. It is natural that artifactual signals originating outside the brain can only be modeled by rather complicated sources. Those are characterized by a large l2-norm, which MARA uses as a feature.

2. **Range Within Pattern:** The logarithm of the difference between the minimal and the maximal activation in a scalp map. Spatially localized scalp maps stemming from e.g muscle artifacts or loose electrodes are typically characterized by a high Range Within Pattern.

3. **Mean Local Skewness:** The mean absolute local skewness of time intervals of 15s duration. This feature aims to detect outliers in the time series.

4. **λ and Fit Error:** These two features describe the deviation of a component’s spectrum from a prototypical 1/f curve and its shape.

5. **8-13 Hz:** The average log band power of the α band (8-13Hz). This feature aims to detect the typical α peak in components of neural origin.

Winkler et al., 2011
Pre-Processing Steps for ICA Artifact Rejection

1. **A rough pre-cleaning of the data** by e.g. channel rejection and trial rejection may be performed. This step is usually helpful for obtaining a good ICA decomposition.

2. **Filter:** As ICA decomposition is known to be sensitive to slow drifts, high pass filtering the data (at 0.5 Hz or even 2 Hz) can sometimes improve the quality of the decomposition. Note that MARA might lead to suboptimal results on narrow band-passed filtered data, because its spectrum features are calculated on the power spectrum between 2 Hz and 39 Hz.

3. **Run ICA!** Tools>Run ICA calculates ICA decomposition: The option ’pca’ can be set to perform a dimensionality reduction prior to IC computation. Such a step may be helpful, in order to reduces the noise level and avoid an unnatural splitting of sources. (It also makes IC computation faster and reduces and the number of components that have to be labeled.)

Winkler et al., 2011
The following slides were not used, but may be helpful, and derive from Laura Zambrano-Vazquez’s talk about ADJUST
Features

- **Spatial Average Difference (SAD)**
  - Spatial topography of blink ICs
  - Looks for higher amplitude in frontal vs. posterior areas

- **Temporal Kurtosis (TK)**
  - Kurtosis over the IC time course
    - Kurtosis is "peakedness" of the distribution (i.e. distribution of timepoints in the epoch)
  - Looks for outliers in amplitude distribution typical of blinks

Mognon, Jovicich, Bruzzone, & Buiatti, 2010
Features

- **Maximum Epoch Variance (MEV)**
  - Is a ratio of variance in epoch with most variance compared to mean variance over all epochs
  - Looks for slower fluctuations typical of vertical eye movement

- **Spatial Eye Difference (SED)**
  - Looks for large amplitudes in frontal areas in anti-phase typical of horizontal eye movement

- **Generic Discontinuities Spatial Feature (GDSF)**
  - Looks for local spatial discontinuities

Mognon, Jovicich, Bruzzone, & Buiatti, 2010
Where to begin?

- **Pre-processing**
  - Clean file for non-stereotyped “gross artifacts”
    - AKA Muscle activity and other external factors
    - Variable spatial distribution that could take up a lot of ICs
    - Low-Pass filtering, if appropriate for your data, can remove some artifacts and prevent so many ICs from capturing these higher-frequency noise artifacts

- **ICA**
  - From EEGLab or, if not performed already, can be called from ADJUST

- Run ICA’d files with ADJUST
  - Import dataset into EEGLab → Tools → ADJUST  OR
  - Use script and select file
ADJUST
Environment
Component Head Maps

# of channels in EEG data = # of components

Typically more true components than channels

Multiple true components combined into a single ICA component

We have 64 components because we had 64 channels

ADJUST will highlight in red the components it identified as artifacts
Looking at an individual IC

Head map
IC activity plotted against trial

Activity power spectrum

Features and thresholds
Component Data Scroll

Shows the activity of 64 components across epochs.
Artifact Detection

Things to look for
Eye blinks

- Features used
  - Spatial Average Difference (SAD)
  - Temporal Kurtosis (TK)

- Frontal distribution

- High power in delta frequency band

- In component data scroll high potentials with morphology of eye blink (like in EEG) can be observed
All have SAD and TK features over threshold

All have a frontal distribution

All have higher power in delta band

3 examples of eye blink artifacts
Look at Component Scroll for what IC 1 looks like

High potentials with these morphology further suggest the IC component is in fact eye blink related.
Vertical Eye Movement

- Features used
  - Spatial Average Difference (SAD)
  - Maximum Epoch Variance (MEV)

- Frontal distribution similar to that of an eye blink
It appears that the artifact is mostly driven by what is happening around trial 200.

SAD and MEV features are over threshold.
Horizontal Eye Movement

- Features used
  - Spatial Eye Difference (SED)
  - Maximum Epoch Variance (MEV)

- Frontal distribution in anti-phase (one positive and one negative)
SED and MEV features are over threshold.

Anti-phase, primarily frontal distribution.

In the IC Activity by trial, three sections stand out.

SED and MEV features are over threshold.
Generic Discontinuities

- Features used
  - Generic Discontinuities Spatial Feature (GDSF)
  - Maximum Epoch Variance (MEV)

- Variable distribution

- Sudden amplitude fluctuations with no spatial preference
  - Could be present in as little as one or 2 trials, and limited to 1 channel

- In component data scroll weird activity in the trial plotted on the IC activity
GDSF and MEV features over threshold

Variable distribution even at a single channel

IC activity shows a lot of variability across epochs and doesn’t show one as responsible
GDSF and MEV features over threshold

Variable distribution. In this case, present at a single channel

In the IC Activity by trial, one section stands out
Sample Files

Under L:\Projects\OC_Worry\Physiodata

- Few ICs
  - 714flankers.cnt.ICA.MAT

- A lot of ICs
  - 770flankers.cnt.ICA.MAT
  - 701pl.cnt.ICA.MAT