APECS: A FRAMEWORK FOR EVALUATING ICA REMOVAL OF ARTIFACTS FROM MULTICHANNEL EEG

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INTRODUCTION

- ❑ Electrical activity resulting from eye blinks is a major source of contamination in EEG.
- ❑ There are multiple methods for coping with ocular artifacts, including various ICA and BSS algorithms (Infomax, FastICA, SOBI, etc.).
- ❑ APECS stands for ***A**utomated **P**rotocol for **E**lectromagnetic **C**omponent **S**eparation*. Together with a set of metrics for evaluation of decomposition results, APECS provides a framework for comparing the success of different methods for removing ocular artifacts from EEG.

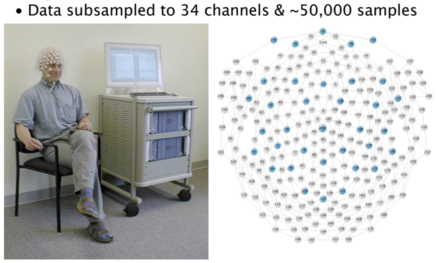
EEG DATA

EEG Acquisition:

- 256 scalp sites; vertex recording reference (Geodesic Sensor Net).
- .01 Hz to 100 Hz analogue filter; 250 samples/sec.

EEG Preprocessing:

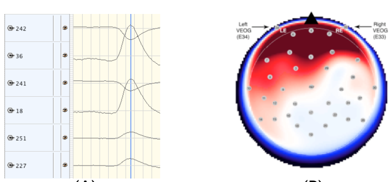
- All trials with artifacts detected & eliminated.
- Digital 30 Hz bandpass filter applied offline.
- Data subsampled to 34 channels & ~50,000 samples



(A) (B)

Figure 1. (A) EGI system; (B) Layout for 256-channel array

ANATOMY OF A BLINK



(A) (B)

Figure 2. (A) Timecourse of a blink (1sec); (B) Topography of an average blink (red = positive; blue = negative)

APECS FRAMEWORK

- ❑ Derivation of a blink-free EEG baseline from real EEG data
- ❑ Construction of test ***synthetic data*** (*see below*)
- ❑ ICA decomposition of data & extraction of simulated blinks
- ❑ Comparison of the cleaned EEG to baseline data (*see below*)
- ❑ Evaluation of decomposition & successful removal of blinks

❑ MATLAB implementations of FastICA and Infomax:

➢ **FastICA**

- Uses fixed-point iteration with 2nd order convergence to find directions (weights) that maximize non-gaussianity
- Maximizing non-gaussianity, as measured by negentropy, points weights in the directions of the independent components
- Implemented with tanh contrast function and random starting seed

➢ **Infomax**

- Trains the weights of a single layer forward feed network to maximize information transfer from input to output
- Maximizes entropy of and mutual information between output channels to generate independent components
- Implemented with default sigmoidal non-linearity and identity matrix seed

❑ Compute covariance between each ICA weight (spatial projector) and the blink template

❑ Flag each spatial projector whose covariance exceeds a threshold as projecting blink activity

❑ Compute projected eye blink activity:

$$x_{EyeBlink} = A_{EyeBlink} * s_{EyeBlink}$$

❑ Remove each projected blink activity by a matrix subtraction:

$$x_{BlinkFree} = x_{Original} - x_{EyeBlink}$$

SYNTHESIZED DATA

__Creation of Blink Template__

- Blink events manually marked in the raw EEG.
- Data segmented into 1sec epochs, timelocked to peak of blink.
- Blink segments averaged to create a blink template.

__Creation of Synthesized Data__

- A: "clean" data (34ch, ~50k time samples)
- B: "blink" data (created from template)
- C: The derived "blink" data were added to the clean data to created a synthesized dataset, consisting of 34 channels x 50,000 time samples

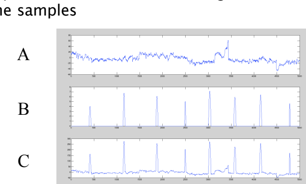


Figure 3. Input to ICA: Synthesized data, consisting of cleaned EEG plus artificial "blinks" created from blink template (Fig. 2).

EVALUATION METRICS

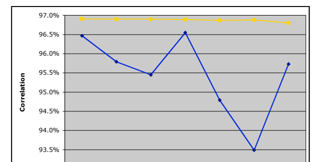
❑ Quantitative Metrics

➢ Covariance between ICA-filtered EEG and the baseline EEG at each channel for each of the 7 blink datasets

❑ Qualitative Metrics

➢ Segment EEG & average over segments, time-locked to the peaks of the simulated blinks. Visualize waveforms and topographic plots (Figs. 7-8).

QUANTITATIVE EVALUATION



	1	2	3	4	5	6	7
FastICA	96.47%	95.79%	95.45%	96.55%	94.79%	93.49%	95.73%
Infomax	96.91%	96.90%	96.90%	96.89%	96.87%	96.88%	96.80%

Figure 4. Correlation between "baseline" (blink-free) and ICA-filtered data across datasets. Yellow, Infomax; blue, FastICA.

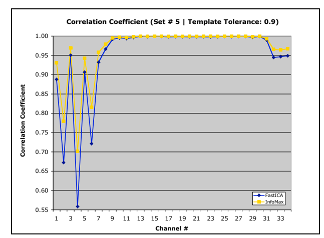


Figure 5. Correlation between "baseline" and ICA-filtered data for Dataset #5 across EEG channels (electrodes).

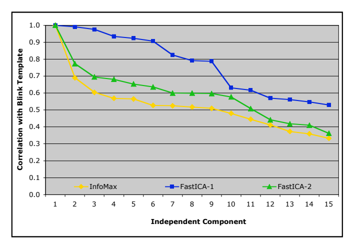


Figure 6. ICA decompositions most succcessful when only one spatial projector was strongly correlated with blink template.

QUALITATIVE EVALUATION

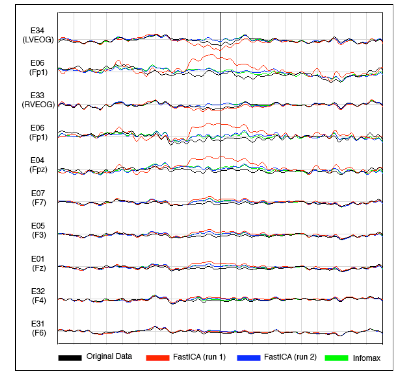


Figure 7. Average EEG time-locked to synthetic blinks.

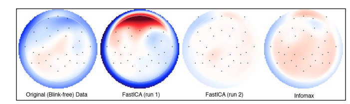


Figure 8. Topography of blink-averaged baseline and filtered EEG at peak of simulated blinks (midpoint of Fig. 7).

FUTURE DIRECTIONS

❑ Refinement of baseline generation procedures:

➢ Frequency / statistical filtering to extract slow wave activity related to amplifier recovery from original blinks

❑ Spatial sampling studies using high-density (128+ channel) EEG data

➢ Higher spatial sampling captures scalp electrical activity in greater detail, leads to more accurate and stable source localization

➢ Higher-dimensional space may affect how well ICA can determine directions that maximize independence

❑ Use of alternative blink templates, starting seeds

❑ High-performance C/C++ implementation

➢ Multiple processor versions of FastICA and Infomax

➢ Fast (Allows for virtually real-time ICA decomposition)

➢ Handles large datasets (128+ channels)

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