Automated Protocol for ERP Component Separation (APECS): Effects of Spatial Sampling on Blink Removal using Independent Components Analysis

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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 Automated Protocol for Electromagnetic Component Separation. 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.

Here we illustrate the use of APECS to evaluate effects of Channel Density and Number of Samples on the quality of blink removal, using the Infomax algorithm [3].

APECS FRAMEWORK

• ICA decomposition of data & extraction of blinks
  • Infomax algorithm
    • 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
  • Evaluation Metrics — cf. [2] for further details
    • Quantitative Metrics
    • Qualitative Metrics

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

EEG DATA

EEG Acquisition & Data Preprocessing
- 256 scalp sites; vertex reference (Geodesic Sensor Net).
- 0.1 Hz to 100 Hz analogue filter; 250 samples/sec.
- All trials with artifacts detected & eliminated.
- Digital 30 Hz bandpass filter applied offline.
- Data subsampled to create different channel densities & different #samples (see Experiment Design, upper right)

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

CURRENT RESEARCH QUESTIONS

- What are the effects of channel density on the efficacy of ICA for extraction of blink activity?
  - Evidence for blink splitting
  - Evidence for “false positives”
- How are these effects revealed through the use of multiple metrics for evaluation of data decomposition?
  - TEMPORAL: Correlation of each independent component with blink template (1)
  - SPATIAL: Blink–locked activity, averaged over 2 second and 400 milliseconds segments (BERPs)
  - STATISTICAL: Mean negentropy for each run

Figure 3. Mean negentropy for 111,000 dataset as a function of channel density.

EXPERIMENT DESIGN

Variations in Channel Density
- The original 256–channel data were downsampled:
  - 127 channel datasets
  - 60 channels datasets
  - 34 channels datasets
  - 22 channels datasets

Variations in #Samples/#Channels²
- The full dataset (111k samples) was downsampled to examine effects of different ratios of #Samples/Channel Density
- Creation of Blink Template
  - Blink events manually marked in the raw EEG.
  - Data segmented, timelocked to peak of blink.
  - Blink segments averaged to create a blink template.

Figure 4. Number of template matches and BERP correlations as a function of channel density and number of samples/channel² density.

QUANTITATIVE METRICS

Mean Negentropy as a function of Channel Density

Quantitative Metrics

BERP correlations and blink splitting as a function of channel density and number of samples/channel² density.

Figure 5. Relationships between number of template matches, BERP correlations and blink splitting as a function of channel density and number of samples/channel² density.

QUALITATIVE METRICS

Figure 6. Blink splitting illustration: L) Topography for IC #02. BERP template correlation = 0.965. R) BERP for IC#02.

Figure 7. Illustration of how reliance on spatial metric can lead to false positives: L) Topography for IC #27. Bink template correlation = 0.912. R) BERP for IC#27.

CONCLUSIONS

Multiple metrics provide both complementary & convergent information
  • Convergence of metrics provides increased confidence in component classification
  • Divergence of metrics provides additional information, to help avoid false positives. E.g., Correlations to blink template not always diagnostic (depends on channel density, samples)
  • ICA decomposition appears to be more reliable for dense–array datasets
  • As channel density increases, there is less evidence of blink splitting
  • As channel density increases, mean negentropy also increases, suggesting improved separation of linearly independent components.

REFERENCES

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