Is EEG Really Better Left Alone for Developmental Datasets?

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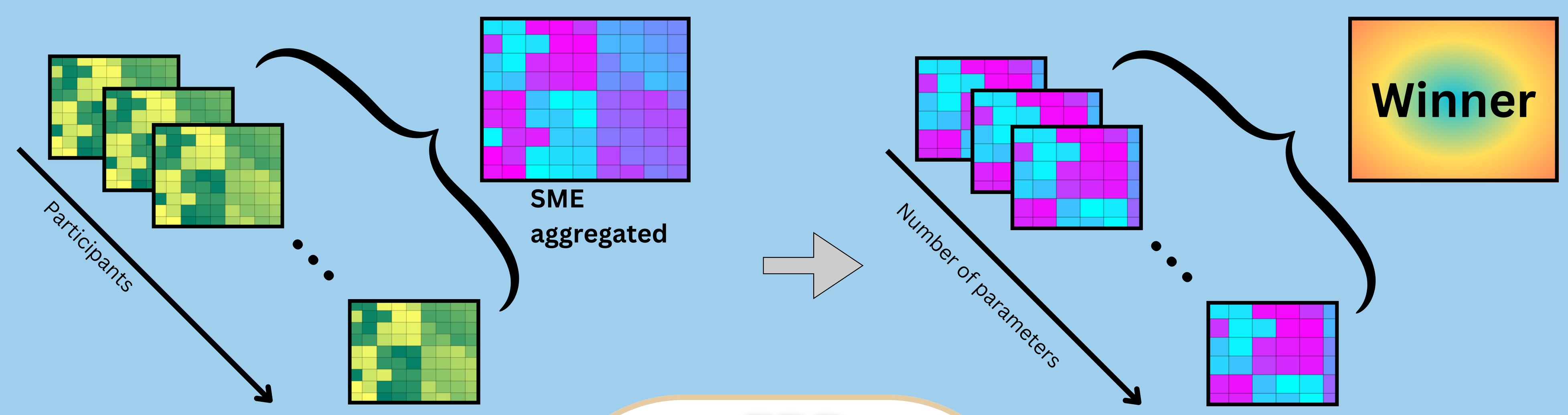
Background

- Noise is unavoidable in EEG/ERP data.
- Preprocessing operations aim to remove noise & isolate brain signal.
- Efforts to standardize different preprocessing methods suggest an automated approach is best for reproducibility and that standardized parameters can yield optimal results [2][3].
- However, preprocessing standardization has only been done using adult data [3].
- High variability in child EEG/ERP data makes it difficult to *truly* standardize denoising techniques[1][6][10][12].
- Little is known about which preprocessing methods are optimal for child EEG/ERP data.

Research Q's

- What are the optimal parameters for each preprocessing step of child EEG/ERP data?
  - Are these different in adults?
- Does child EEG/ERP data require full automaticity, manual completion, or a hybrid of the two?

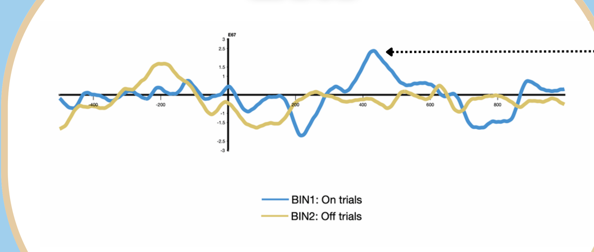
Results



SME calculated for each participant

Smallest difference in variance for each parameter and compared

ERP



Clear P3 component @ significant electrode as calculated by the t-max statistical test[5].

Winners

Filter → Line Noise → Bad Channel → ASR → ICLABEL

- Filter: 1.0Hz
- Line Noise: IIR Filter
- Bad Channel: 0.15 - .285
- ASR: 5
- ICLABEL: 0.5-1.0

The "winners" at each preprocessing step. Each parameter yielded the least variance in the data relative to other parameters within each preprocessing step.

Methods

Denoising [4][8]

Filter ★ → Line Noise ★ → Bad Channel ★ → ASR ★ → ICLABEL ★

Re-ref (Cz) — before Bad Channel

ICA (runica) — before ICLABEL

- Filter: 0.01Hz, 0.1Hz, 0.25Hz, 0.5Hz, 0.75Hz, 1.0Hz
- Line Noise: Notch linear filter, IIR filter, CleanLine Plugin[CITE]
- Bad Channel: correlation range of 0.15 - 0.975 in steps of 20
- ASR: standard deviation thresholds 5 to 100 in steps of 20
- ICLABEL: probabilities 0.5-0.9 in steps of 0.2

★ SME calculated; winner moves on

Data Quality Measure

Standardized Measurement Error (SME) [9]

Individual Single Trial SME score within a time window

$$SME = \frac{SD}{\sqrt{N}}$$

SD = Standard deviation of mean amplitude across trials within given time-window
N = Number of trials

Aggregating SME scores across participants

$$RMS(SME_{1:N}) = \sqrt{\frac{SME_1^2 + SME_2^2 + \ldots + SME_N^2}{N}}$$

N = Number of participants

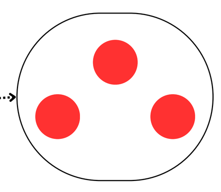
Choosing a winner

$$winner = \min_{i=1}^{n}\{|\max RMS(SME) - \min RMS(SME)|\}$$

n = Number of denoising parameters

Data & Task

- Data:[7]
  - 6-9 years old (n=24).
  - 128-channel EEG Geodesic Hydrogel system
    - 9 EOG channels and 9 face/scalp electrodes automatically removed before preprocessing.
  - Re-reference at Cz
  - Sampling rate: 500 Hz
- Task: sequence learning.
- ERP: P300 [11]



Discussion

- Evaluating child (developmental populations) EEG/ERP data quality is important because of vulnerability to noise and artifacts.
- Our findings suggest a liberal approach to data preprocessing with the exception of filtering and component removal.
- Filtering may serve as the most principle method for removing noise in developmental EEG data[3].
- Many of these parameters are deviations from the "default settings" in EEGLAB.
- Our pipeline resulted in multiple significant ERPs.
- There are many other preprocessing techniques; our findings only generalize to the specific ones chosen for this analysis.

Limitations

- Only used EEGLAB.
- Used one measure of variance.
- No control over recording conditions.

Future applications

- Testing different cognitive tasks and ERPs [13].
- Directly comparing to adult data.
- Examining manual versus automated channel rejection and artifact rejection.
- Experimenting with other toolboxes.
- Developing other methods to quantify noise in EEG/ERP data (e.g., [3]).

References

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Code and more...

I am applying to PhD programs this cycle...check out my website!

Recommended pipeline (under development)

The code for this project!