Evaluating Mobile EEG Preprocessing: A Primer with Examples

Electroencephalography (EEG) data of moving participants is especially prone to noise and is often extensively preprocessed to obtain interpretable results. This primer suggests exemplary ways of assessing EEG data quality before and after processing helping to achieve reliable and valid results.

Practical Tips

- **Use several dimensions:** Make sure to evaluate your data quality on different dimensions, do not only try to estimate and attenuate noise on a single channel level but also assess its neurophysiological plausibility which is often reflected in spatial properties. You do not need to use all suggested measures of one dimension.
- **Optimize for data quality NOT statistical effects** [1]: Optimize your preprocessing to obtain neurophysiological plausible data and attenuate artifacts. Experimental effects are not suited to evaluate preprocessing and may introduce biased results if selection and testing are not strictly separated.
- **Effect Adaptation**: Tailor your preprocessing metrics to align with the expected experimental effects. For example, if studying fatigue over time (an effect with high within-person variance), ensure that preprocessing steps do not excessively reduce this variance.
- **Artifact vs. Signal**: Determine what constitutes an artifact versus a signal based on your study's aim. For instance, in studies involving motion or blink-related potentials, such activities may be considered signals rather than artifacts. Don't remove data that constitutes your signal of interest.
- **Preprocessing Pipeline Testing**: Test your preprocessing pipeline on multiple datasets or pilot data to ensure robustness across different conditions. Evaluate SNR on pilot data that will not be used in the main statistical analysis. This helps ensure the preprocessing pipeline is effective without biasing the results.
- **Iterative Refinement**: After initial preprocessing, check the data quality and iteratively refine your methods. For instance, if you notice residual muscle artifacts, apply a more aggressive artifact attenuation step and re-evaluate. If your lab has a standard pipeline, start from there.
- **Setup-Specific Adjustments**: Recognize that each dataset is unique due to variations in setup, hardware, tasks, and individuals. Assess data quality for each setup and tailor preprocessing accordingly.
- **Documentation**: Keep detailed and understandable records of your preprocessing steps and settings. This ensures transparency and reproducibility of your analysis. Keep a detailed log of the preprocessing. steps and settings used for each dataset. Note any deviations or special adjustments made for specific datasets, in particular if they require user interaction.

By following these tips and examples, you can systematically evaluate and refine your mobile EEG preprocessing, ensuring your data is clean, reliable, and well-suited to your experimental objectives.

1. Neurophysiological Plausibility Estimate
Rationale: Ensure that the EEG data reflects neural signals after preprocessing, not artifacts.

- **Consistency with Neuroanatomy**: Ensure that the observed topographic characteristics correspond to plausible generators of brain activity based on the task or stimulus being studied. Do not ignore the inverse problem!
  Example: For a motor task involving right-hand movement, verify that the preprocessed data shows increased activity over left sensorimotor areas (e.g., near C3 electrode location).
- **Spatio-Temporal Smoothness**: Check for smooth transitions in EEG signals over time and space.
  Example: Plot waveforms along with topographical maps. Ensure no abrupt changes or transients in the data.
- **Presence of Dipolar Sources**: Dipolar-source activity may contribute to the measured EEG. Identify brain-related independent components (ICs) and evaluate their dipolarity.
  Example [2], [3]: Run an Independent Component Analysis (ICA) and fit dipoles. A higher yield of dipoles with low residual variance (e.g., <15%) and an estimated location near the cortex may indicate neural activity. IClabel may help to classify components reflecting brain activity automatically.

2. Noise Estimate
Rationale: Quantify and minimize the impact of noise and artifacts in EEG data. Assess the noise before and after preprocessing.

- **Artifact Detection**: Identify and quantify common artifacts such as muscle movements, eye blinks, and environmental noise. Data decomposition tools like ICA can help separate these artifacts from neural signals.
  Example [3]: Use ICLabel to determine the average number of ICs labeled as eye or muscle artifacts.
  Tip: You can also use classifier confidence as a measure of decomposition performance. If the median probability for known eye blink ICs is low, sources may not have been separated well.
- **Power Spectral Density (PSD)**: Analyze the spectral characteristics (e.g., power spectral density) of your data to identify and quantify the presence of noise.
  Example: High-frequency noise or power spikes in certain frequency bands (e.g., at the frequency of an investigated rhythmic motion like walking) can indicate contamination by artifacts.
- **Standard Noise**: Use simulated data to evaluate preprocessing effectiveness.
  Example [4], [5]: Test preprocessing on data of a phantom head (e.g., "Hairy Gary") and compare noise levels before and after artifact removal.
- **Signal Noise (Prestimulus)**: Estimate noise during a pre-stimulus baseline period.
  Example [6]: For an oddball experiment, calculate the RMS of target trials during the −200 to 0 ms pre-stimulus period at Pz and average these values.
- **Calculation of RMS**: Objectively measure noise using RMS during defined epochs.
  Example [6]: Compute RMS of (noise) epochs to quantify noise levels.
- **Number of Rejected Samples/Epochs**: Count samples or epochs excluded due to artifacts.
  Example [7]: Use Adaptive Mixture Independent Component Analysis (AMICA) or Artifact Subspace Reconstruction (ASR) to quantify the number of rejected samples/epochs and report these.
- **Standard Deviation of Single Trials**: Measure within-person/between-trial variability.
  Example [7], [8]: Calculate the standard deviation of single-trial scores to ensure it is minimized.

3. Signal-to-Noise Ratio (SNR) Estimate
Rationale: Assess the quality of the EEG signal relative to background noise. A higher SNR indicates cleaner data with less noise interference.

- **Odd-Even Difference**: Measure SNR by comparing signal and noise within odd and even trials.
  Example [9]: Create two ERPs per subject, one for even-numbered and one for odd-numbered trials. Calculate SNR as the mean signal divided by the absolute noise difference within the P3 time window.
- **ERP and Baseline**: Compare ERP amplitudes to pre-stimulus baseline noise.
  Example [10]: Compute the mean ERP amplitude at the channel of interest and divide it by the standard deviation of the pre-stimulus baseline.
- **Tip** [11]: Evaluate whether pre-stimulus baseline correction is beneficial.

References

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