Design of Automated Algorithm to Detect Artifacts in Intracranial EEG

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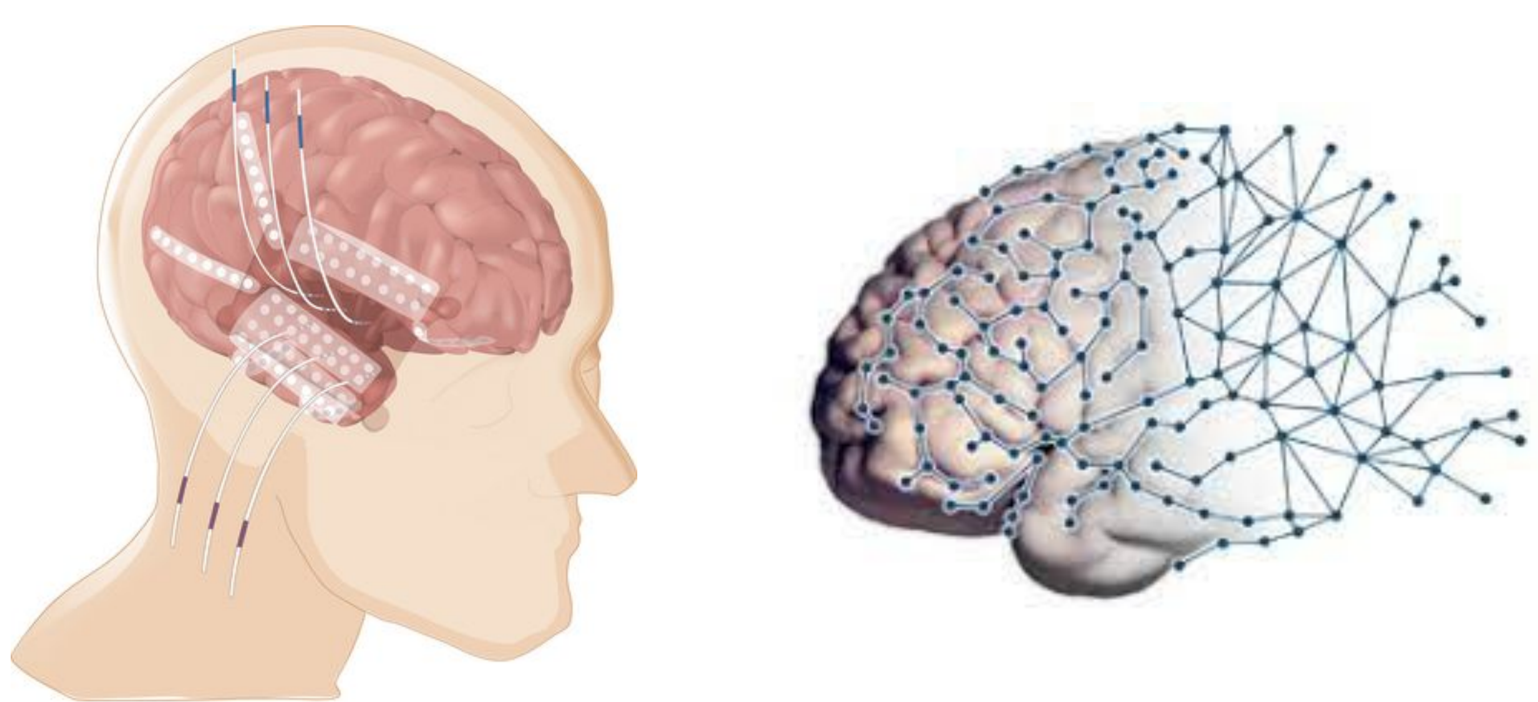
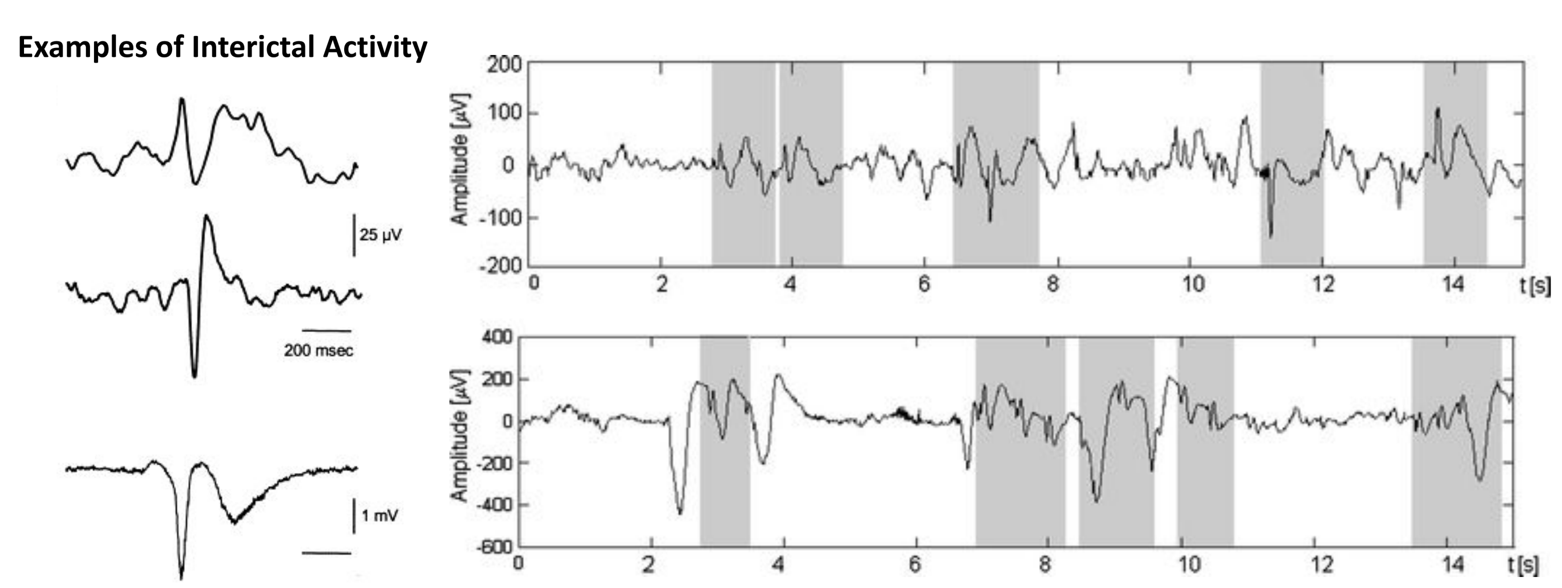
Background

- Electroencephalography (EEG) recordings measure voltage differences in the brain due to neuronal activity [1]
- Intracranial EEG (iEEG) is used in epilepsy patients to localize seizure onset in the hospital [2]
- Clinical iEEG recorded from epilepsy patients can be used to research brain connectivity



- Subjects can be participate in cognitive behavioral tasks (visual, auditory, and tactile) to elicit event-related responses [3]
- However, artifacts from noise or epileptic spikes can present in iEEG recordings [4]
- In particular, artifacts from interictal, or between seizure, activity confound event-related responses [4]



- The current gold standard for artifact and spike detection is visual inspection by an expert neurologist [5,6]
- However, an automated algorithm could significantly reduce the amount of time needed to manually look over hundreds of trials and provide consistency across different subjects
- Current automated approaches have been developed for clinical purposes to detect interictal spikes in EEG data and include time-based methods, frequency-based methods, and wavelet-domain methods [5]
- The goal of this project is to develop an automated algorithm to detect large interictal spikes and artifacts in iEEG data, as preprocessing for analysis

References

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[3] Miller KJ, Schalk G, Hermes D, Ojemann JG, Rao RPN (2016) Spontaneous Decoding of the Timing and Content of Human Object Perception from Cortical Surface Recordings Reveals Complementary Information in the Event-Related Potential and Broadband Spectral Change. PLOS Computational Biology.
[4] Fisher R.S., Scharfman H.E., deCurtis M. (2014) How Can We Identify Ictal and Interictal Abnormal Activity?. Issues in Clinical Epileptology: A View from the Bench.
[5] F. E. Abd El-Samie, T. N. Alotaiby, M. I. Khalid, S. A. Alshebeili and S. A. Aldosari. (2018) A Review of EEG and MEG Epileptic Spike Detection Algorithms. IEEE Access.
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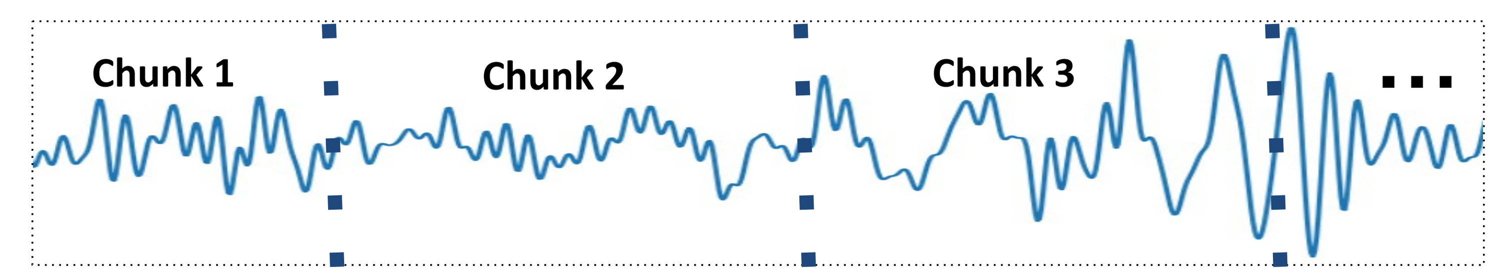
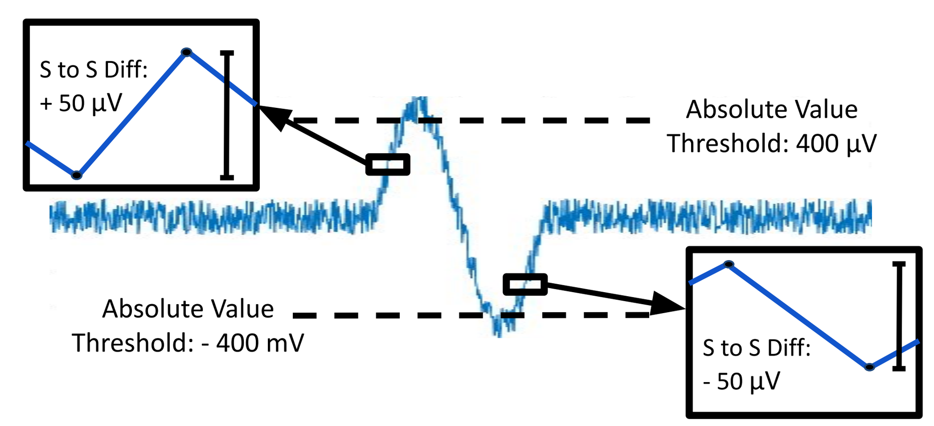
Methods for Artifact Detection

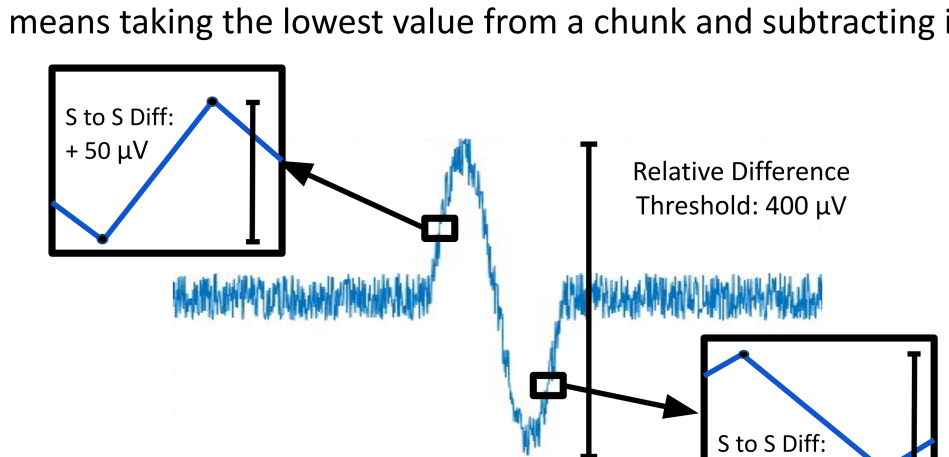
To better detect interictal spikes in large datasets, the samples are broken into separate chunks of equal size. Each chunk is then analyzed independently using one of the four following methods:



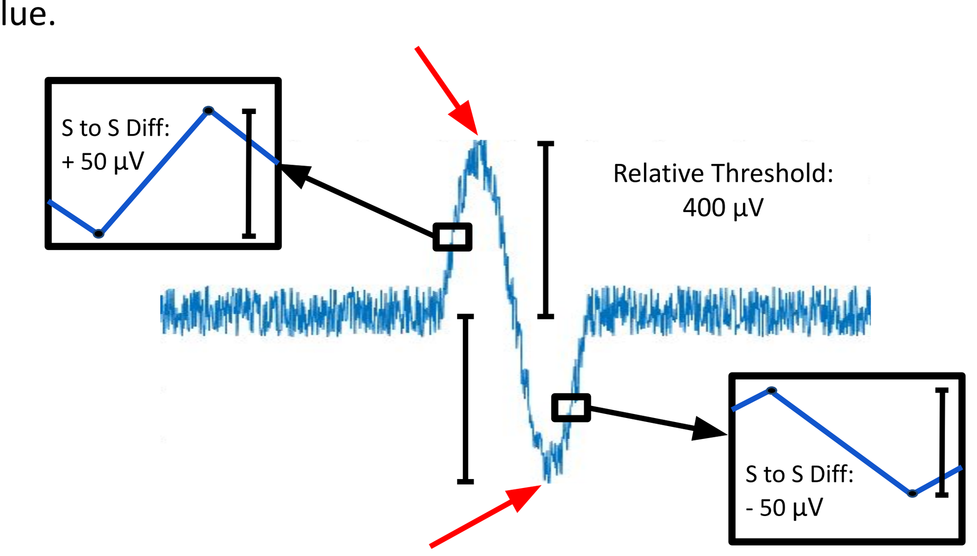
The first method involves using an absolute value threshold for each chunk and a sample-to-sample difference threshold in both positive and negative directions, to detect large deflections in each direction.



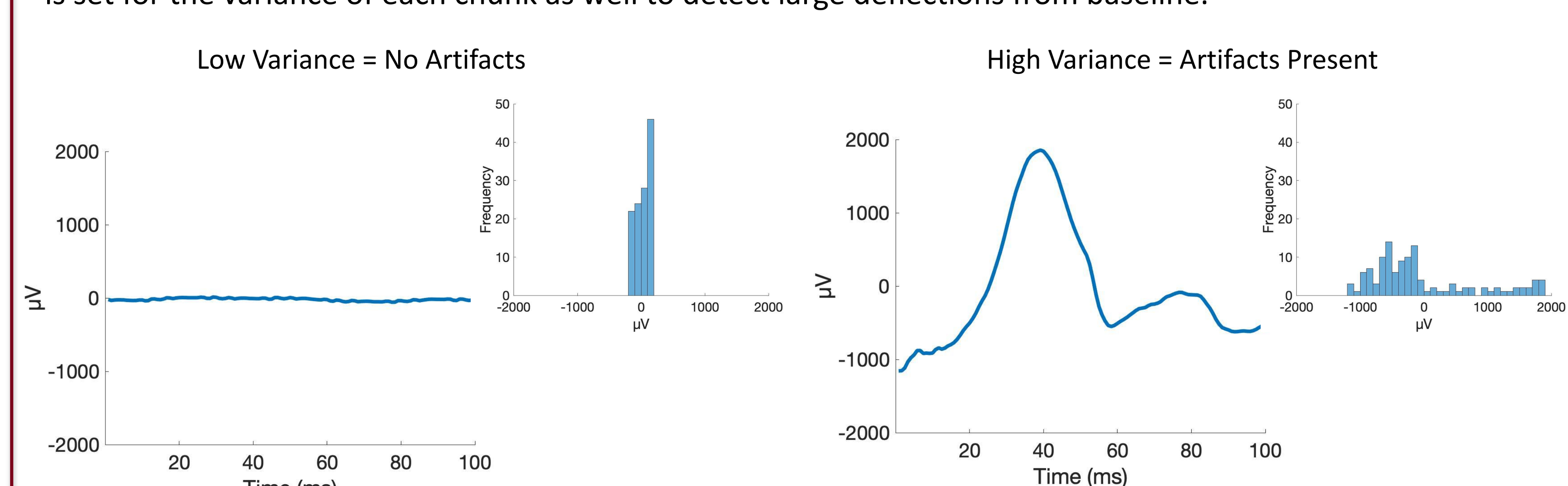
The second method has the same sample difference aspect but instead of an absolute value threshold, has a range threshold. This means taking the lowest value from a chunk and subtracting it from the highest.



The third method involves using a peakfinder function to find local minima or maxima in the data that are above a threshold value.



The last method involves using the sample variance in each chunk to identify large fluctuations. A threshold is set for the variance of each chunk as well to detect large deflections from baseline.



Results of Detection in Training Set

Method	Absolute Difference	Range	Peakfinder	Variance
Sensitivity	100%	100%	100%	100%
Specificity	100%	100%	100%	100%

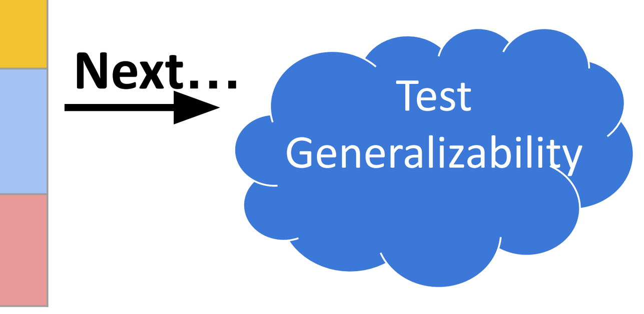
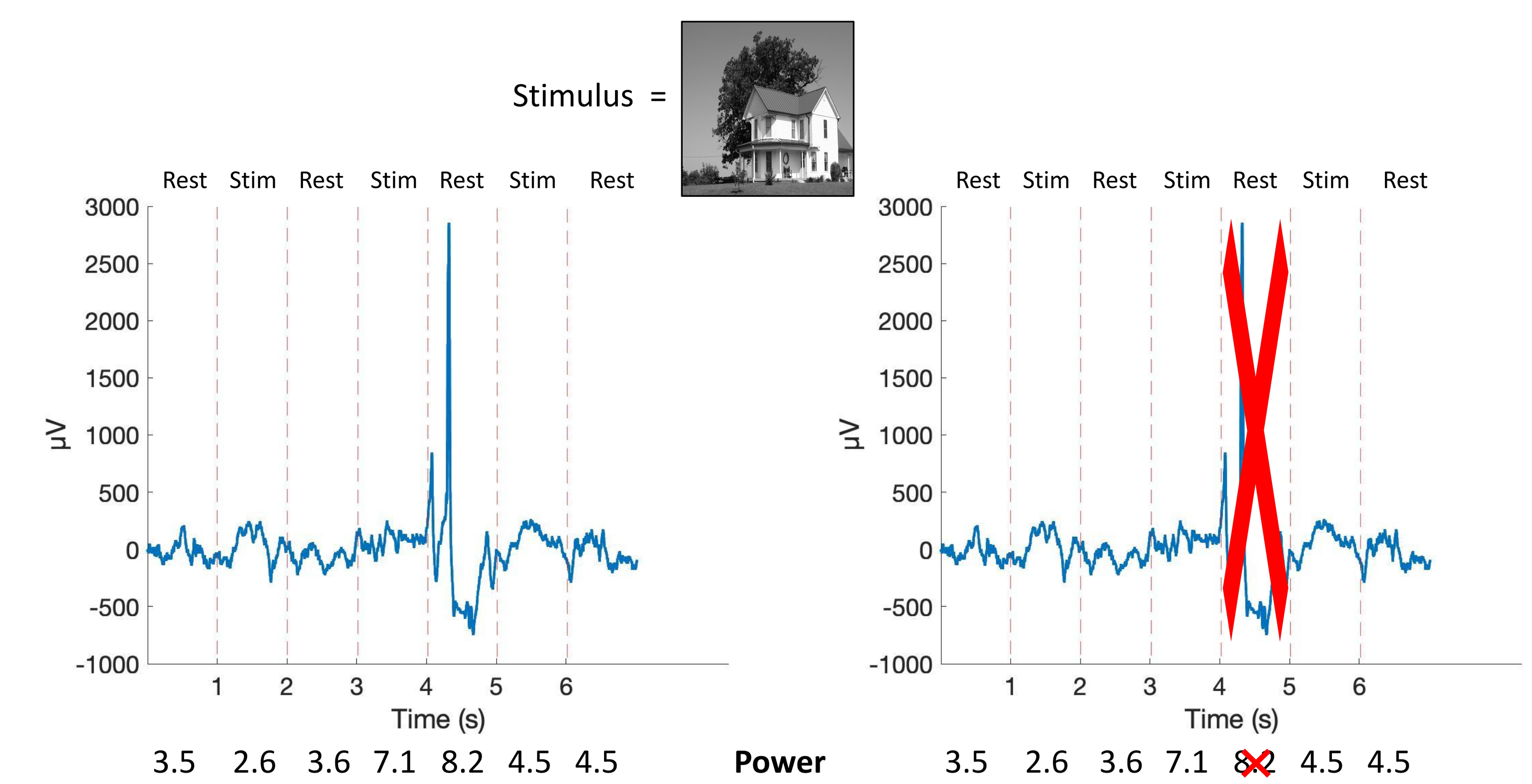


Figure 1. Shown is the accuracy of the algorithm across a training data set (consisting of 40 signals from individual channels across 31 trials in one subject) for identifying interictal activity when it is present (sensitivity) and identifying no interictal activity when it is absent (specificity). Gold standard compared against is visual inspection.



Difference Between Vision and Rest (R^2): -0.004 **Difference Between Vision and Rest (R^2): 0.09**

Figure 2. A signal with interictal activity is shown for a subject looking at a series of images (stimulus). Power and R^2 values are presented to show how a significantly larger percentage of the variation in the data can be explained by the visual stimulus when the interictal trial is excluded.

Discussion and Future Directions

All of the methods have been optimized for artifact detection on the training set as shown by perfect sensitivity and specificity scores (Fig. 1.). The next step is to test the algorithms on data from other runs and subjects with the goal of demonstrating generalizability. A successful automated, artifact detection algorithm will significantly reduce the number of trials that need to be visually inspected and ultimately help to increase the amount of variation in the data that can be explained by doing a cognitive task (Fig. 2.). Artifact detection and denoising has been a prominent issue in signal processing. We continue to search for appropriate, objective parameters for defining good and bad data.