

Background:

- Electroencephalography (EEG) is a temporally precise and inexpensive tool for studying brain activity in autism spectrum disorder (ASD)
- For statistical analysis, measures of event-related potential (ERP) peaks often utilize automated window-based peak picking (AWPP) to find peak activity during a specified time window
- Common AWPP-derived dependent variables (DVs), such as peak amplitude and latency to peak, rely on waveforms among individuals exhibiting similar morphology
- Manual peak picking (MPP), in which humans select peaks based on visual inspection, is much more robust but is significantly more time consuming and prone to human error
- Splines are smooth lines characterized by relatively few parameters
- Fitting splines to ERPs presents an alternative method to derive DVs (see Fig 1.), which may offer a middle ground of performance assessment and time efficiency
- Given significant interindividual variability in waveform shape, this would represent a significant advance, particularly in developmental and clinical populations

Objectives:

1. Develop an algorithm to fit splines to ERP data
2. Assess its performance in both ASD and Typical Development (TD) compared to AWPP
3. Identify avenues for further development as a tool for analyzing EEG data in ASD

Methods:

- Data were collected in 106 EEG sessions with adult participants clinically diagnosed with ASD or TD controls. Participants were shown dynamic faces displaying emotional expressions
- Data were processed with simple filtering and artifact detection and averaged across trials to create ERPs
- AWPP was used to find a positive peak within a window of 40-190ms relative to the event (P100) and a negative peak in the window of 120-250ms (N170), both in averaged channel groups over the left and right occipitotemporal scalp
- A grand average of all the ERPs was used to manually create a starting spline, which was then automatically fit to each ERP for the same channel groups by our algorithm using local error around each control point
- The parameters that defined the fit splines were used in analysis

Results:

- Based on simple ANOVAs using both AWPP values and corresponding spline control points values (SCPV), our algorithm was successful in extracting meaningful data from ERPs
- A statistically significant difference between groups was detected using both AWPP-derived N170 amplitude ($p < .015$) and the SCPV ($p < .001$). Both variables were more negative in the ASD group
- In addition to comparable performance in group discrimination, the SCPV offer goodness of fit statistics including R2 values and Root Mean Squared Error
- Further, some SCPVs without an AWPP equivalent show promise of discriminatory power, indicating that our method may be capturing additional information

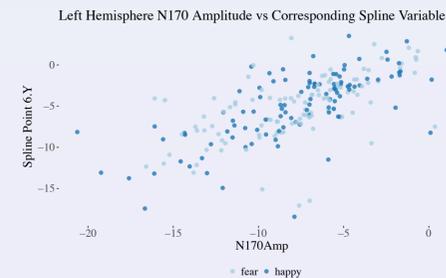


Figure 2. A plot comparing a DV derived from AWPP to the comparable variable derived by our spline algorithm (the Y coordinate for the 6th spline control point).

Splines offer automated analysis of ERP data that could empower researchers and save time.

What exactly are splines?
They are simply a handy way to represent smooth lines.

See Figure 1, below.

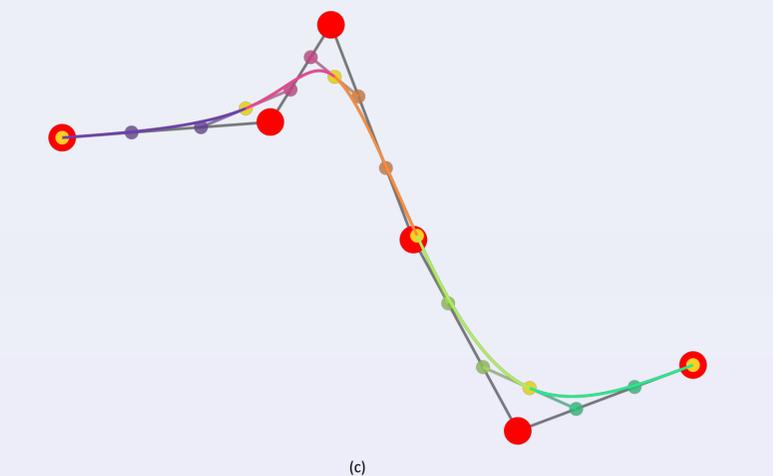
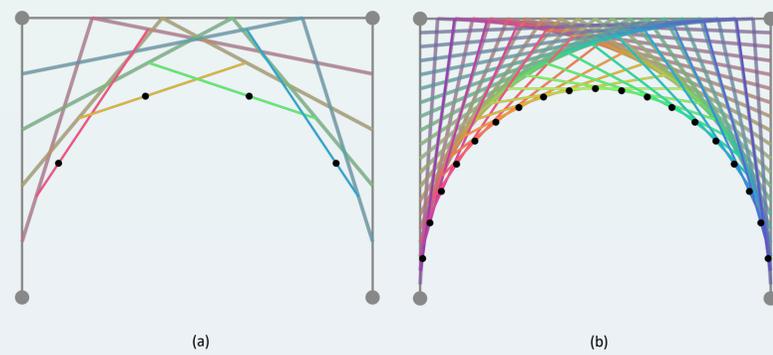


Figure 1. How Splines work. Cubic Bezier Curves are smooth lines defined by 4 points, seen in grey in (a) and (b). By interpolating between these points, points on a curve are calculated, seen in black in (a) and (b). Splines are smooth lines defined by a set of control points, as seen in red in (c). These control points are used to calculate Bezier curves that cleanly transition into one another, seen in various colors in (c). Our algorithm enforces constraints to keep certain control points at peaks in the ERPs as they are fit. These control points serve as our DVs, comparable to those derived by AWPP.

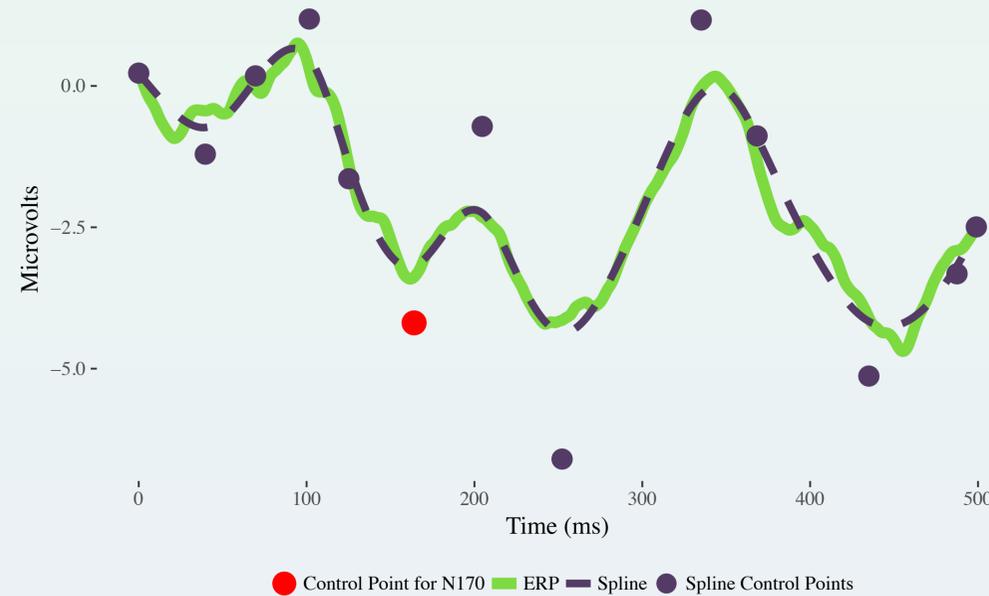


Figure 3. An assortment of splines that our algorithm fit ERP data, alongside that same data. All ERPs were fit starting with the same spline that was created manually to fit a Grand Average waveform. Despite the considerable variability between individual ERPs, our algorithm succeeds in fitting them well while maintaining comparability by enforcing which spline control points correspond to which features of the ERP. For example, in all the waveforms the 4th spline control point corresponds to a positive peak around 150ms, while the 6th spline control point corresponds to the subsequent negative peak.

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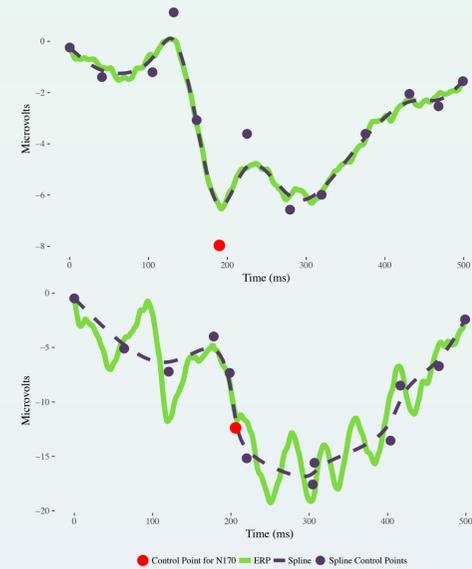


Figure 4. A comparison between two ERPs and their splines, one with low error (above, $R^2=0.99$) and one with high error (below, $R^2=0.82$).

Conclusions:

- Given the same data, novel methods were able to extract equivalent meaningful information from the ERPs when compared to AWPP
- Enhanced flexibility with regard to waveform shape, goodness of fit estimation, and novel values with possible discriminatory power offer advantages over the traditional method
- While our methods were not compared with MPP, the vastly lower cost in human effort highlights the value of this approach in quantifying individual difference in an automated and unbiased fashion
- Ongoing analyses of classification performance between groups could allow us to detect differential patterns of artifact by risk status
- Automated detection paired with a human reviewer via a visual check system could dramatically increase the accuracy and speed of the human while preserving input from human judgement
- Future directions include a more targeted measurement of error and further refinement of the fitting algorithm

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