Convolutional Autoencoder for ERP Morphological Analysis

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Background:

- Electroencephalography (EEG) is a valuable tool for studying autism spectrum disorder (ASD) due to its high temporal resolution and direct measurement of cortical activity
- By repeatedly presenting stimuli to participants, researchers can derive event-related potentials (ERPs)
- The rich information present in ERP waveforms is typically reduced to a small number of measurements (e.g., peak amplitude), potentially discarding informative brain activity
- We propose the use of an autoencoder convolutional neural network (CNN) to automatically reduce the dimensionality of complex ERP waveforms while learning which features best distinguish among individuals
- Given the wide range of waveform morphologies commonly observed in neurodevelopmental disorders, such as ASD, our methods may shed new light onto neurophysiological differences not previously explored

Objectives:

1. Develop an autoencoder CNN to reduce the dimensionality of individual waveforms
2. Explore the relationships of the resulting dimensions with symptom measures
3. Identify avenues for further methodological development

Methods:

- Data were collected from with adult participants diagnosed with ASD (N=19) or schizophrenia (SZ; N=12), and typically developed controls (TD; N=32)
- Participants were shown a flashing black and white checkerboard (500ms phase reversals) to elicit a visual evoked potential (VEP)
- Resulting ERPs measured from occipitotemporal electrodes were normalized, split into training and test sets, and used to train our network (*Figure 1*)
- The encodings of all the ERPs, calculated after training, were analyzed
- This process was repeated 10 times with different training/test set splits to assess how robust the correlations were to changes in the training. This resulted in 10 different encoding and decoding models
- Encoding variables (EVs) primarily represent regions of time in a given ERP (*Figure 2*)

Results:

- Our CNN reduced the dimensionality of ERPs from 300 samples to an efficient encoding of 19 EVs
- Decoding the encodings of the test set reconstructed the ERPs with an average mean absolute error of 0.0411
- *Table 1* shows clinical correlates found consistently between the same EV and clinical variable across the 10 models. EV11 and Benton Facial Recognition Test Total showed a strong correlation, congruent with findings involving features in this time range in face-related tasks. EV13 correlated with the Sensory Gating Inventory Fatigue and Stress Vulnerability Subscale in all 10 models, among other pairings
- *Tables 2 and 3* show some clinical correlates found in specifically the TD group or ASD group, respectively. Of note, we find that the EV11 and Benton correlation appears driven by the ASD group. The ASD group has many more consistent clinical correlates than the TD group. This may be a result of greater homogeneity in the TD group on these clinical measures
- ANOVAs found no significant differences between groups in any one EV (all $p > 0.05$)

Autoencodings offer a new method of analyzing ERP morphology.

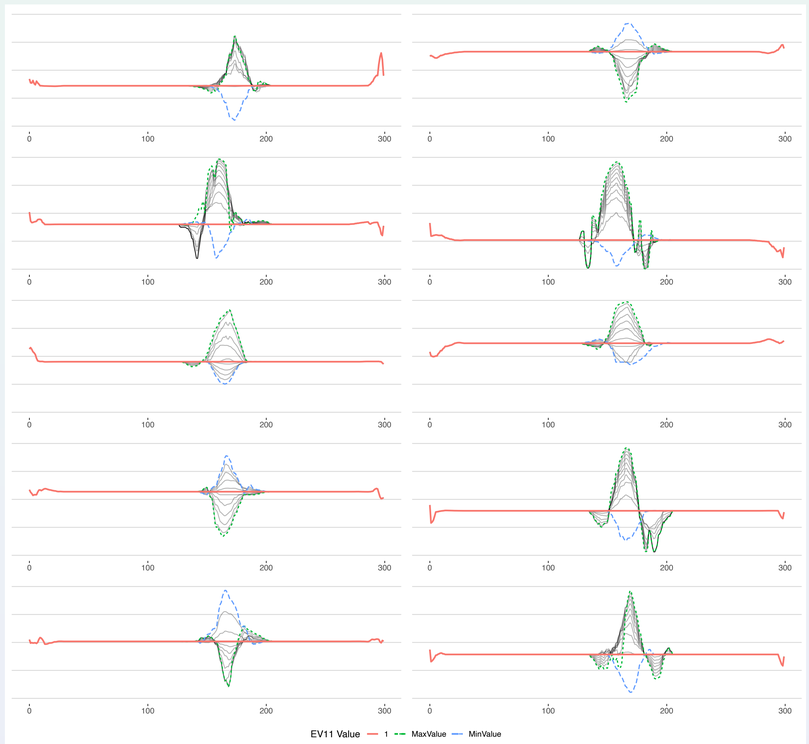

Figure 2 : Plot showing how the value of EV11 affects how an encoding is decoded for each of the 10 models. The red line shows the output when all EVs are set to 1, then decoded into an ERP. The green dashed line shows the output when EV11 is changed to the maximum value seen in that model, and the blue dashed line shows the same with the minimum value. Grey lines show values linearly spread between the maximum and minimum.

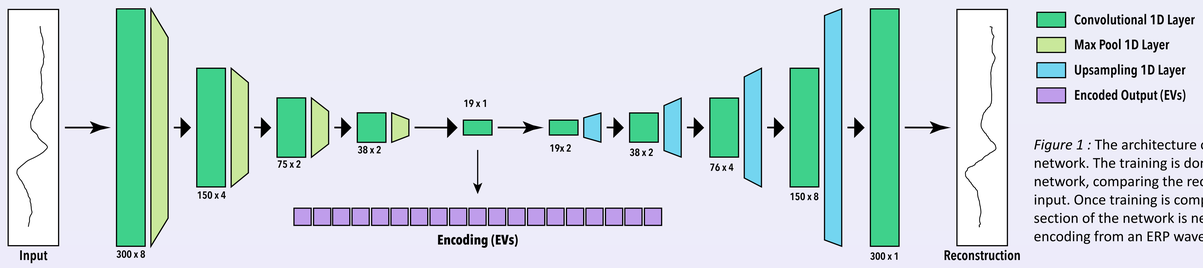

Figure 1 : The architecture of the autoencoder network. The training is done with the full network, comparing the reconstruction to the input. Once training is completed, only the first section of the network is needed to calculate an encoding from an ERP waveform.

ASD, SZ, & TD Groups

EV	Time Range (ms)	Clinical Variable	# of Models	Mean p value	Mean R value
EV6	48 - 125	Global Functioning: Role Scale Current	9	0.012	0.334
EV8	80 - 157	Sensory Gating Inventory Distractibility Subscale	8	0.019	0.298
EV11	128 - 205	Benton Facial Recognition Total Score	8	0.015	0.309
EV12	144 - 221	Glasgow Sensory Questionnaire Olfactory Subscale	10	0.009	0.344
EV12	144 - 221	Glasgow Sensory Questionnaire Auditory Subscale	8	0.020	0.297
EV13	160 - 237	Glasgow Sensory Questionnaire Auditory Subscale	10	0.034	0.271
EV13	160 - 237	Glasgow Sensory Questionnaire Olfactory Subscale	10	0.008	0.335
EV13	160 - 237	Sensory Gating Inventory Fatigue and Stress Vulnerability Subscale	10	0.011	0.326
EV14	176 - 253	Schizotypal Personality Questionnaire Excessive Social Anxiety Score	8	0.012	0.320
EV15	192 - 269	Schizotypal Personality Questionnaire Excessive Social Anxiety Score	10	0.006	0.347
EV16	208 - 298	Schizotypal Personality Questionnaire Excessive Social Anxiety Score	9	0.023	0.292

Table 1 : Clinical correlates with EVs in ASD, SZ, and TD groups.

ASD Group

EV	Time Range (ms)	Clinical Variable	# of Models	Mean p value	Mean R value
EV5	32 - 109	ADOS Mod 4 Communication Total	9	0.027	0.548
EV5	32 - 109	Scale for the Assessment of Negative Symptoms Total Score	9	0.026	0.517
EV8	80 - 157	Sensory Gating Inventory Distractibility Subscale	9	0.023	0.524
EV9	96 - 173	ADOS Mod 4 Communication in Social Interaction Total	10	0.011	0.609
EV9	96 - 173	ADOS Mod 4 Reciprocal Social Interaction Total	10	0.012	0.615
EV11	128 - 205	Benton Facial Recognition Total Score	10	0.003	0.658
EV17	224 - 300	Benton Facial Recognition Total Score	10	0.017	0.549

Table 2 : Clinical correlates with EVs in the ASD group.

TD Group

EV	Time Range (ms)	Clinical Variable	# of Models	Mean p value	Mean R value
EV7	64 - 141	Broad Autism Phenotype Questionnaire Aloof Personality Subscale	10	0.010	0.459
EV15	192 - 269	Reading the Mind in the Eyes Test Total Score	9	0.008	0.464
EV19	256 - 300	State-Trait Anxiety Inventory Total Score	9	0.018	0.428

Table 3 : Clinical correlates with EVs in the TD group.

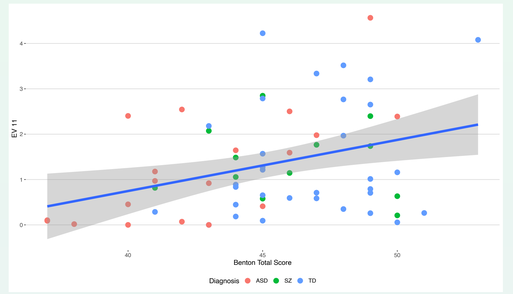

Figure 3 : Plot of EV11 vs the Benton Facial Recognition Total Score in both ASD and TD groups, with a linear fit line overlaid on top. These data are from a single model, in which the variables were significantly correlated ($r = 0.341$, $p = 0.006$).

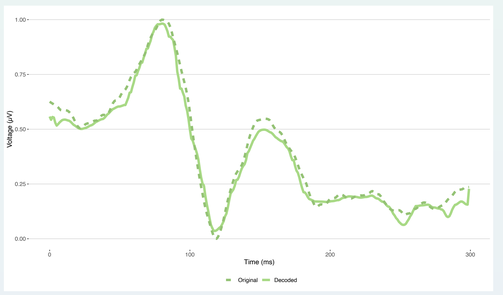

Figure 4 : Plot of an ERP compared with its reconstruction made by decoding its encoding using a single model.

Conclusions:

- We were able to successfully build and train an autoencoder CNN on our VEP ERPs to significantly reduce the dimensionality
- The EVs suggest that different time aspects of the ERP are associated with specific symptom domains
- Ongoing analyses include applications to additional experimental paradigms, assessing reliability of encodings, and novel visualization approaches for assessing data quality
- Our findings suggest that novel machine-learning techniques can automatically parse meaningful interindividual variability in the neural time course that can be linked with human-understandable features of the ERP
- Extensions of this work to differentiate clinical populations may reveal meaningful differences in brain activity that have been previously overlooked with traditional methods

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