Feature Extraction Methods for Resting EEG: Proposed Approaches and their Relation to Clinical Measures in Adults

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Background

- Electroencephalography (EEG) is a widely used technique to measure neural activity for purposes including biometric verification, identification of aberrant brain activity, and disease diagnosis.
- Features extracted from EEG data for analysis often differ among, as well as within, research domains.
- Previous work in the field shows that differences between developmentally disordered and typically developing brains can be measured in a features extracted from EEG data collected while at rest.
- People with Autism Spectrum Disorder (ASD), people with schizophrenia (SZ), and the typically developing (TD) population vary in sensory experience and sensitivity. This variability is captured by clinical measures such as the Glasgow Sensory Questionnaire, but may also be latent within resting EEG data.

Objective: To investigate feature extraction algorithms for resting EEG that (1) maximally discriminate between individuals with ASD, with SZ, and TD controls, as well as (2) predict clinically measured sensory sensitivity.

Methods

Group	N (N males)	Mean Age	Min. Age	Max. Age
ASD	38 (31)	25	18.02	43
SZ	10 (9)	22.91	18.57	28.95
TD	38 (21)	27	20.45	39

Table 1. Participant Demographics

Behavioral Assessment

- To quantify sensory sensitivity and responsivity, participants were administered the Glasgow Sensory Questionnaire (GSQ), a 42-question self-report instrument that quantifies visual, auditory, gustatory, olfactory, tactile, vestibular, and proprioceptive hypo- and hypersensitivity.

EEG acquisition and pre-processing

- EEG was recorded at 500 Hz with 128-channel Hydrocel Geodesic Sensor net as participants sat with their eyes closed.
- Data were filtered to remove line frequencies at 60 Hz and 120 Hz and re-referenced to the average of all channels.
- Data were then detrended and subject to a 1 Hz high pass filter.
- For cleaning and artifact removal, the Harvard Automated Processing Pipeline for EEG (HAPPE) was used. Files that retained less than 70% original variance were rejected post-HAPPE.

Feature Extraction Procedures

1. Cheong et. al (2015)[3]
   - Discrete Wavelet Transform > Standard Deviation
   - Features are standard deviations of detail coefficients at levels that correspond to canonical frequency bands alpha, beta, and gamma
   - Proposed for Autism diagnosis
2. Ahmadlou et. al (2011)[1]
   - Discrete Wavelet Transform > Katz Fractal Dimension of Detail Coefficients
   - Features are the Katz Fractal Dimension of detail coefficients at levels that correspond to canonical frequency bands alpha, beta, and gamma
   - Proposed for Alzheimer Disease diagnosis
3. Aydın et. al (2009)[2]
   - Wavelet Packet Decomposition > Log Energy Entropy
   - Features are the Log Energy Entropy of level 2 and 3 wavelet packet coefficients
   - Proposed for seizure detection
4. Yang et. al (2019)[4],
   - Wavelet Packet Decomposition > Log > Discrete Cosine Transform (DCT)
   - Features are the first two DCT coefficients of level 2 and 3 wavelet packet coefficients
   - Proposed for biometric recognition

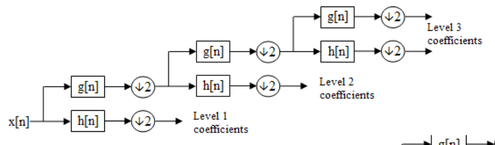

Figure 1. Diagram of 3-level Discrete Wavelet Transform

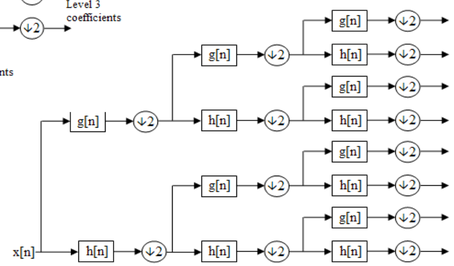

Figure 2. Diagram of 3-level Wavelet Packet Decomposition

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Analysis

Linear Discriminate Analysis (LDA)

- LDA was used to derive two linear models per extracted feature set.
- For discrimination of diagnosis, groups were ASD, SZ, and TD.
- For discrimination of GSQ scales, each scale was discretized to 3 levels, and each participant was assigned to one of 3 levels (low score, moderate score, high score).
- All features were scaled to have a mean of 0 and a standard deviation of 1 before LDA.
- During prediction of clinical measures, the LDA model was generated by a training set and prediction accuracy was derived from a test set that was unseen by the LDA model during training.
- 10-fold cross-validation ensured that prediction metrics were stable across subsampling of the data.

Randomly Sampled Feature Set

- A fifth set of features tested alongside the other extracted feature sets
- Generated by randomly sampling from an equal distribution between 0 and 1
- Values in Table 2 report difference in prediction accuracy between the random feature set and a given feature set proposed by previous literature.

Results

Measure	Cheong (2015)	Ahmadlou (2011)	Aydin (2009)	Yang (2019)
Age	-0.0241	-0.0291	**0.1021**	0.0674
Diagnosis	0.1021	0.0695	**0.1631**	0.1567
gsq_auditory_hyper	0.0644	0.0311	0.1076	**0.1106**
gsq_auditory_hypo	-0.0288	-0.0750	**0.0477**	0.0295
gsq_auditory_total	0.0424	0.0273	**0.1568**	0.0894
gsq_gustatory_hyper	-0.0061	-0.0402	**0.0106**	-0.0265
gsq_gustatory_hypo	-0.0053	0.0258	0.0394	**0.0894**
gsq_gustatory_total	0.0598	0.0167	**0.0727**	0.0621
gsq_olfactory_hyper	-0.0773	-0.0439	**0.0598**	-0.0348
gsq_olfactory_hypo	0.0523	0.0508	**0.1455**	0.0909
gsq_olfactory_total	0.0462	0.0508	**0.1538**	0.1477
gsq_proprioception_hyper	0.0697	0.0606	0.0962	**0.1561**
gsq_proprioception_hypo	0.0727	0.0462	**0.1197**	0.0758
gsq_proprioception_total	0.0720	0.0727	**0.1492**	0.1182
gsq_tactile_hyper	-0.0295	-0.0303	**0.1129**	0.0735
gsq_tactile_hypo	0.0455	0.0273	**0.0523**	0.0000
gsq_tactile_total	0.0697	0.0189	0.1364	**0.1432**
gsq_vestibular_hyper	-0.0667	-0.1341	**0.0341**	0.0311
gsq_vestibular_hypo	0.0136	-0.0015	**0.0591**	0.0288
gsq_vestibular_total	0.0227	0.0508	**0.1083**	0.1023
gsq_visual_hyper	-0.0788	-0.0614	0.0303	**0.0409**
gsq_visual_hypo	0.0220	0.0576	**0.1114**	0.0106
gsq_visual_total	0.0144	0.0227	0.1008	**0.1045**
gsq_hyper_total	0.0273	0.0280	**0.1689**	0.1121
gsq_hypo_total	0.0515	0.0333	**0.1470**	0.0932
gsq_total	0.0144	0.0114	0.1114	**0.1167**

Table 2. Percentage improvement in prediction compared to randomly sampled features. The best performing feature set for each measure is highlighted in orange.

Results, cont.

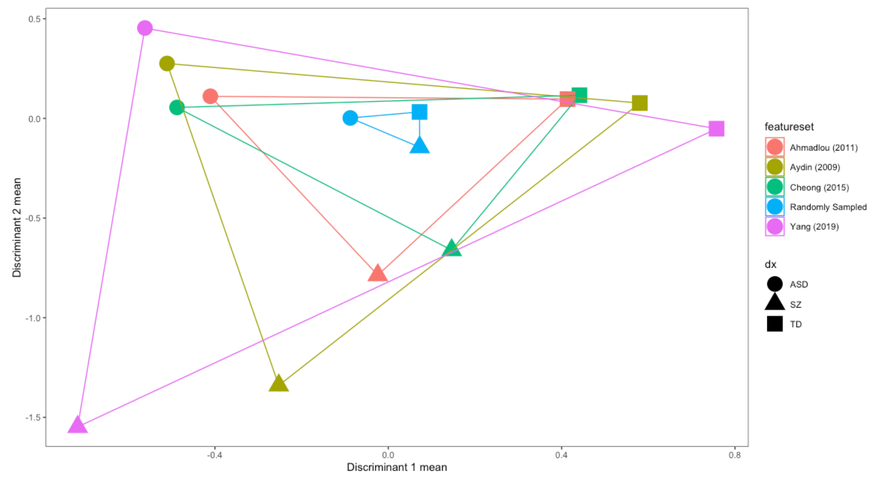

Figure 3. Linear discriminant means of ASD, TD, and SZ groups for each feature set

Discussion

- The best performing feature sets were Aydin (2009) and Yang (2019). These two models had the better predictive power in every clinical measure, with Aydin (2009) performing the best overall.
- As evident in Figure 3, Aydin (2009) and Yang (2019) are most able to separate their feature sets based on diagnostic group.
- Aydin (2009) and Yang (2019) both utilize the Wavelet Packet Decomposition during the feature extraction process, while Cheong (2015) and Ahmadlou (2011) only use the Discrete Wavelet Transform.
- Feature sets that are derived from the Wavelet Packet Decomposition may contain a greater amount of useful information than feature sets derived only from the Discrete Wavelet Transform, but this comes with the cost of a greater dimensionality of the feature set.
- Further work is required to determine if a classifier based on the Wavelet Packet Decomposition can be made robust enough to demonstrate good out-of-sample classification accuracy in autism diagnosis.
- Useful signal in resting EEG data may be specific to some brain region(s), such that noise is introduced when features derived from different brain regions are combined, leading to overall less descriptive features. A limitation of the current study is that the features are generated by EEG data that was collected at a variety of scalp locations and combined together.

References

[1]Ahmadlou, M., Adeli, H., and Adeli, A., (2011) Fractality and a Wavelet-chaos-Methodology for EEG-based Diagnosis of Alzheimer Disease. Alzheimer Disease & Associated Disorders: January-March 2011 - Volume 25 - Issue 1 - p 85-92 doi: 10.1097/WAD.0b013e3181ed1160

[2]Aydın, S., Saraoğlu, H.M. and Kara, S., (2009) Log Energy Entropy-Based EEG Classification with Multilayer Neural Networks in Seizure. Ann Biomed Eng 37, 2626 (2009). https://doi.org/10.1007/s10439-009-9795-x

[3]Cheong, LC, Sudirman, R. and Hussin, SS, (2015) Feature extraction of EEG signal using wavelet transform for autism classification. ARPN Journal of Engineering and Applied Sciences, vol. 10, pp. 8533-8540

[4]Yang, S., Hoque, S., and Deravi, F., (2019) Improved Time-Frequency Features and Electrode Placement for EEG-Based Biometric Person Recognition. EEE Access, vol. 7, pp. 49604-49613, 2019, doi: 10.1109/ACCESS.2019.2910752.

Funding Source: NIMH R01 MH107426 (McPartland, Srihari)