# Learning EEG: Identification of novel electroencephalogram classifications and variability of baseline features in a large clinical dataset

David O. Nahmias[1,2,*], Kimberly L. Kontson[1], and Eugene F. Civillico[1]

[1]US Food and Drug Administration, Center for Devices and Radiological Health, Office of Science and Engineering Laboratories, Division of Biomedical Physics
[2]University of Maryland-College Park, Department of Electrical and Computer Engineering
*Corresponding author: David.Nahmias@fda.hhs.gov

FDA Center for Devices and Radiological Health

University of Maryland 1856 Department of Electrical & Computer Engineering

## Background & Motivation

**Background:**

❖ Medical devices that interface with the nervous system for diagnostic, therapeutic, or rehabilitative purposes are a major area of innovation in the medical products industry.
❖ Electroencephalography (EEG) is typically non-invasive, relatively inexpensive, and has been shown to contain biomarkers for neurological disorders and behavioral states.

**Motivation:**

❖ Despite the increasing use and public health importance, very little is known about the consistency and variability of baseline quantitative EEG measurements in healthy individuals and patient populations.
❖ EEG signals can be used for brain-machine interfaces to control external robotic devices, such as exoskeletons and prostheses.
❖ Understanding population variability in EEG could facilitate the evaluation of safety and efficacy of EEG-based medical devices.

## Methods

**Dataset:**

❖ The Neural Engineering Data Consortium EEG corpus with 10,535 subjects with 16,377 EEG recording sessions (~500GB). [1]
- Each session is accompanied by a clinical note containing clinical impressions and patient characteristics.
- Subset of 2,999 sessions labeled as 'Normal' (n=1509) or 'Abnormal' (n=1490).

**Extracting patient information:**

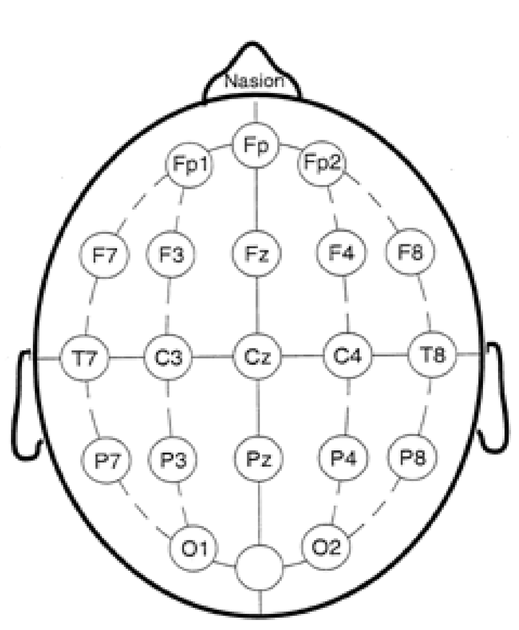
❖ Clinical notes are provided in the form of text files.
❖ Through custom Python code, the following patient information is extracted:
- Sex: Male (n=4,673), Female (n=5,039)
- Age: Mean=47.97, SD=22.08, IQR=32 (n=10,233)
- Medication Lists (e.g. Dilantin, Keppra)
- Neurological Disorders (e.g. Epilepsy, Seizures)
- Expanded 'Normal' (n=4,164), 'Abnormal' (n=9,912) labels

MEDICATIONS: Metoprolol, others.
CLINICAL HISTORY: A 60-year-old male with bilateral hand tremor. Patient reports that the tremor waxes and wanes. He had difficulty providing the history.
INTRODUCTION: Digital video EEG is performed in the lab using standard 10-20 system of electrode placement with one channel of EKG. Hyperventilation and photic stimulation were completed.
TECHNICAL: No significant issues.
DESCRIPTION OF THE RECORD: In wakefulness, the background includes a well organized pattern with a 9 Hz alpha rhythm and a small amount of low voltage, frontocentral beta. Drowsiness is characterized by slow rolling eye movements why deeper stages of sleep were not sustained. Photic stimulation did not significantly activate the record. Hyperventilation did not activate the record significantly. Heart rate 72 beats per minute.
IMPRESSION: Normal EEG in wakefulness and brief drowsiness.
CLINICAL CORRELATION: No focal or epileptiform features were identified in this EEG. A normal EEG does not exclude a diagnosis of epilepsy. If seizures are an important consideration, a follow up tracing capture in deeper stages of sleep is suggested.

*Sample EEG Clinical Report*

**Extracting common EEG channels:**

❖ Captured across a variety of systems in clinical settings, since 2002.




*19 channel 10-20 layout*

## Methods

**Goals:**

❖ Statistically identify EEG features that are consistent when measured on different time intervals (0.5, 1, 2, and 4 minutes) within a given recording; statistically measure intra-subject variability of EEG features across recordings.
❖ Determine if an EEG signal and features alone can correctly classify subjects according to specified characteristics.
- Analysis and experiments implemented in Python, Kernel Support Vector Machine (kSVM) via scikit-learn.
- Tested on EEG without event related information and based on extracted classifications/characteristics.

**Raw EEG:**
16 Minutes-19 Channels

**Preprocessing:**
- Re-sampled to 250Hz
- 0.5-50Hz filtering
- Re-referencing

**Feature Validation:**
- Frequency domain [Power Spectrum Density (PSD)]
- Time domain

**Statistical Measures:**
- Kruskal-Wallis (K-W) test on different time intervals.
- K-W test on same feature, time interval, and subject across recording sessions.
- Intraclass Correlation Coefficient (ICC) on band power ratios.

**Classification:**
**k-SVM**
Up to 418 features

| Characteristics | Classes |
|---|---|
| Sex | Male vs. Female |
| Age | Age group vs. Age group |
| Medication taken | One Med vs. None |
| Clinical Impressions | 'Normal' vs. 'Abnormal' |

Frequency domain features

1. (<1Hz) Lower/Total Power
2. (1 – 4Hz) Delta/Total Power
3. (4 – 8Hz) Theta/Total Power
4. (8 – 12Hz) Alpha/Total Power
5. (12 – 16Hz) Mu/Total Power
6. (16 - 25Hz) Beta/Total Power
7. (25 – 40Hz) Gamma/Total Power
8. Spectral Entropy

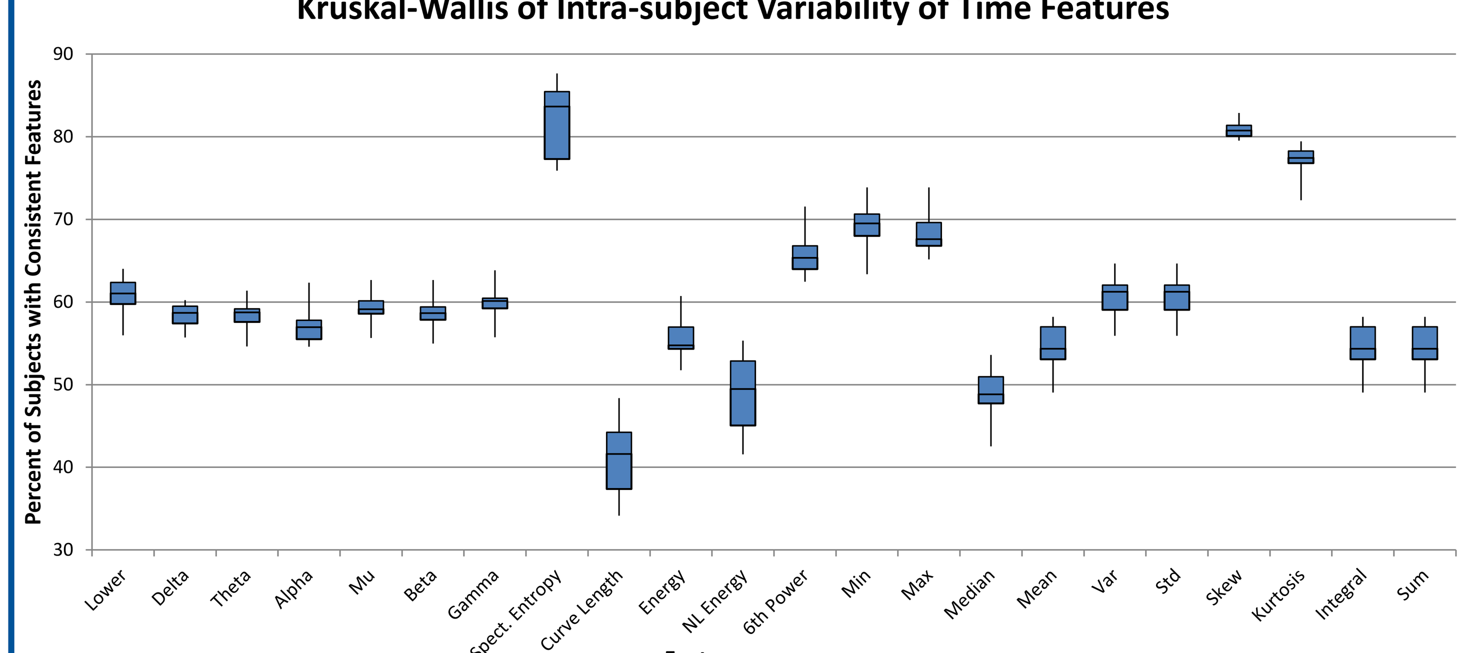
Time domain features

1. Curve Length
2. Energy
3. Non-linear Energy
4. Sixth Power
5. Minimum Value
6. Maximum Value
7. Median
8. Mean
9. Variance
10. Standard Deviation
11. Skew
12. Kurtosis
13. Integral
14. Summation

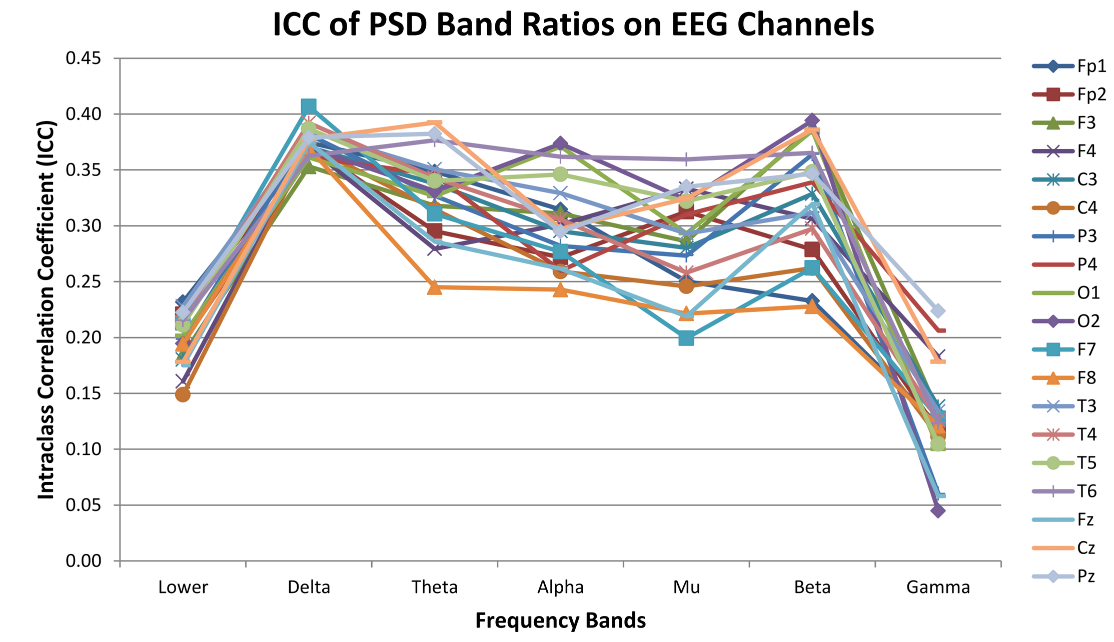
## Results & Conclusions

**Results:**

❖ For normalized features compared across different time intervals within a given recording, the K-W test failed to reject the null hypothesis (i.e. medians of all groups are equal) (n=13,970).




Spectral entropy, skew, and kurtosis were among the most consistent features across two sessions (n=2,257)




PSD ratios for bands in the 1-25Hz range were most consistent across three sessions (n=785)

❖ Significant classifications found between Clinical Impressions, Age, and Medications; None found for Sex.

| Age Groups | Samples | Test Accuracy |
|---|---|---|
| Age < 20 vs. Others | n=754 | 77.03% |
| 20 < Age < 50 vs. Others | n=9,220 | 64.75% |
| Age > 50 vs. Others | n=8,422 | 67.46% |
| Age < 10 vs. Age > 60 | n=738 | 86.11% |

| Clinical Impressions | Samples | Test Accuracy |
|---|---|---|
| NEDC 'Normal' vs. 'Abnormal' | n=2,920 | 74.35% |
| All 'Normal' vs. 'Abnormal' | n=7,681 | 71.62% |

| Medication Groups | Samples | Test Accuracy |
|---|---|---|
| Dilantin vs. None | n=982 | 66.32% |
| Keppra vs. None | n=802 | 72.50% |

**Conclusions:**

❖ Consistency metrics of EEG features developed through data-driven statistical measures.
❖ Significant classification results found on certain patient characteristics and clinical EEG impressions.

**Future Work:**

❖ Test feature variability on additional EEG features (e.g. Wavelets).
❖ Determine which features contribute most to different classifications; Apply deep learning models to EEG data.

## References

[1] Harati, Lopez, Obeid, Jacobs, Tobochink & Picone. "The TUH EEG CORPUS: A Big Data Resource for Automated EEG Interpretation." *Proceedings of the IEEE Signal Processing in Medicine and Biology Symposium*, pp. 1-5 (2014).

## Acknowledgements

This work was funded by CDRH OSEL Division of Biomedical Physics and DARPA-FDA IAA 224-14-6009, DARPA Biological Technology Office through the Hand Proprioception and Touch Interfaces (HAPTIX) program under Dr. Doug Weber, Program Manager.

**Disclaimer**: The mention of commercial products, their sources, or their use in connection with material reported herein is not to be construed as either an actual or implied endorsement of such products by the Department of Health and Human Services.