Classifying Seizures in Electroencephalogram Data using Spectral and Fractal features

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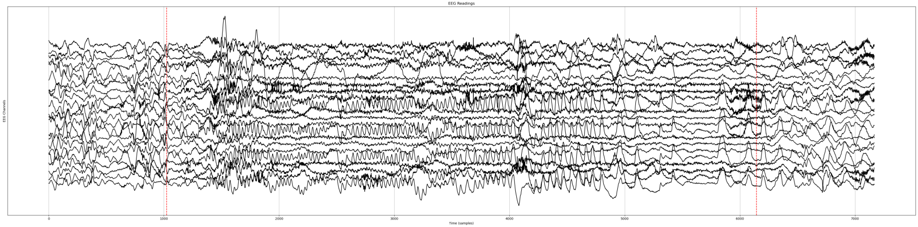

FIGURE: Raw data from a seizure period in the CHB-MIT Database

Seizures

- Sustained abnormal electrical activity ($\geqslant$ 7 seconds)
- Pediatric epilepsy affects 1 in 100 children.
- Diagnosed by visual inspection of brain waves by a clinician
- Automating seizure classification: area of ongoing research

Difficulties of detecting seizures in EEG data

- Seizures are rare (limited training data)
- Size of raw EEG data
  - EEG sampling rate: $f_s = \mathbf{256}$ samples per second
  - EEG electrode count: $d = \mathbf{23}$ electrodes
  - Result: 1 minute of data is in $\mathbb{R}^{d \times n}$, $n = 60 * f_s = \mathbf{15360}$ samples.

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Key question: How can we exploit the distinct mathematical structure of seizure brainwaves to perform dimension reduction on EEG data?

Past approaches to Seizure Classification in the Literature

Gotman et. al. (1982)[1] and Shoeb et. al. (2010)[2]

- Classifying seizures using limited bandwidth of **0** - **30** Hz Fourier components of EEG data
  - Earliest seizure detecion algorithms
  - Focus on only biologically relevant frequencies

Past Work on Seizure Detection

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Namazi et. al. (2015)[3]

- Classifying seizures using the Hurst exponent
  - EEG data might have **higher** fractal dimension during seizures

Definition

The **discrete s-energy** *of a finite dataset* $\{x_k\}_{k=1}^n \subset \mathbb{R}^d$ *for parameter* $s > 0$ *is defined by*

$$I_s\left(\{x_k\}_{k=1}^n\right) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j\neq i}|x_i - x_j|^{-s}$$

where $|.|$ *denotes the Euclidean norm on* $\mathbb{R}^d$*.*

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- Discrete energy → estimate EEG fractal dimension
- Feedforward neural network trained on discrete energy differences: **86.79%** test accuracy

Compare three approaches to classifying seizures from EEG data in pediatric epilepsy patients using models trained on:

- Full raw EEG recording ($\mathbb{R}^{23 \times n}$)
- Biologically relevant (0-30Hz) frequency component time series
  - Compress further using Principal Components Analysis
- Discrete energy time series ($\mathbb{R}^{\frac{n}{256}}$)

Children's Hospital Boston MIT Scalp Electroencephalogram Data (CHB-MIT) Database

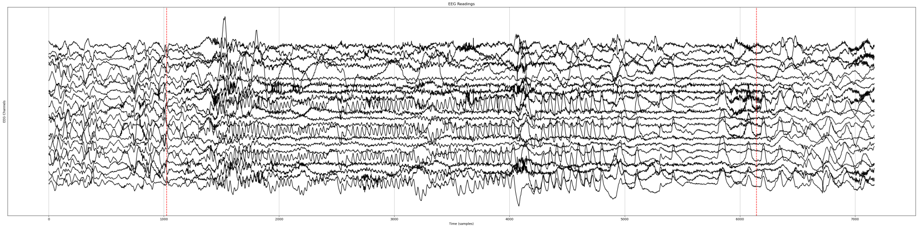
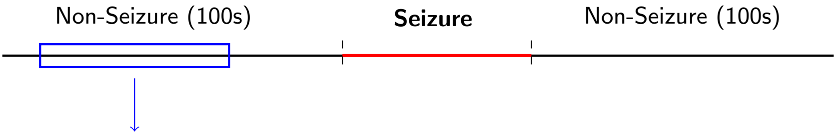


FIGURE: Raw data from a seizure period in the CHB-MIT Database

Patient Demographics

- 23 pediatric patients
- Ages 1.5 - 22 years
  - 4 patients had age $\leqslant 3$
  - Neonatal seizures were excluded

- Model: Long Short-Term Memory (LSTM)
- Dataset: 1 EEG file (23 channels) from each patient
- Excluding: patients under 4 years old, and seizures shorter than 7 seconds



Sliding windows for collecting training dataset

- Test accuracy: **87%**
- Limitation: only 1 EEG file from each patient is used for training due to limitation of computers, so it might not be generalizable to other EEG files.

- Applied Fourier Transform to convert raw EEG data from the time domain to the **frequency** domain.
- Observation: For both seizure and non-seizure plots, most of the signal power is concentrated in the **0–30 Hz** range.
- Conclusion: Focus on low frequencies.

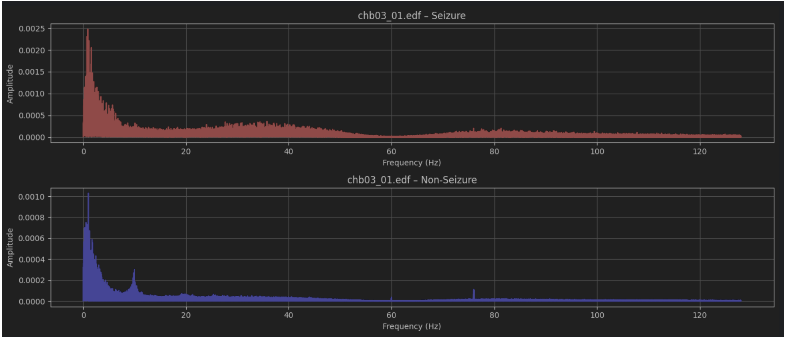


FIGURE: FFT magnitude spectrum for seizure (red) and non-seizure (blue) EEG segments

- Applied Fourier Transform to EEGs using a **1-second sliding window**, aligned with seizure onset time.
- Observation: In some patients, there is a clear **rise** of normalized Fourier transform data during the seizure.

Figure: Normalized low-frequency Fourier transform over time.

- **Goal**: Use Fourier Transform features (0–30 Hz) to classify seizure vs. non-seizure EEG segments.
- **Features**: Low-frequency Fourier data across common channels, reduced by PCA ($n = 7$).
- **Classifier**: Random Forest with balanced class weights.
- **Results**:
  - Accuracy: **86.8%**
  - Seizure class F1-score: **0.69**
  - Non-seizure class F1-score: **0.92**

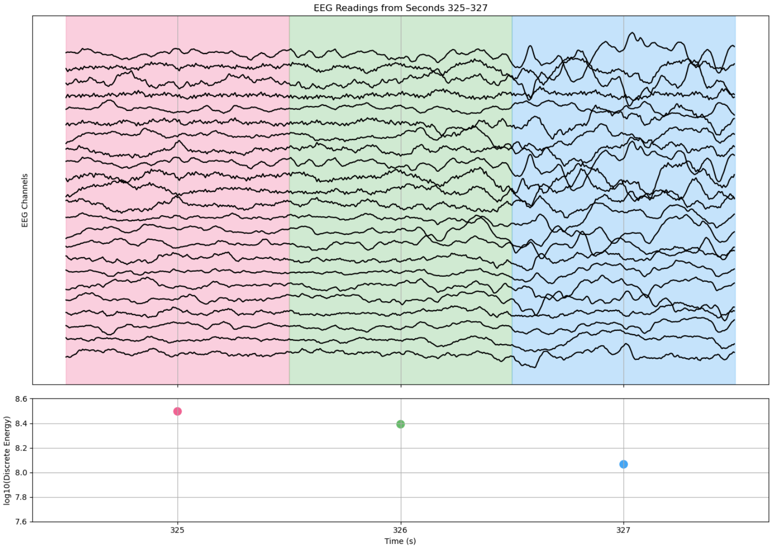


Figure: Finding the discrete energy for each second of EEG readings. This process reduces the dimension of the data by a great degree, since each data point produced will be the result of 256 time steps, each with 23 features

Reducing Dimensionality with Discrete Energy

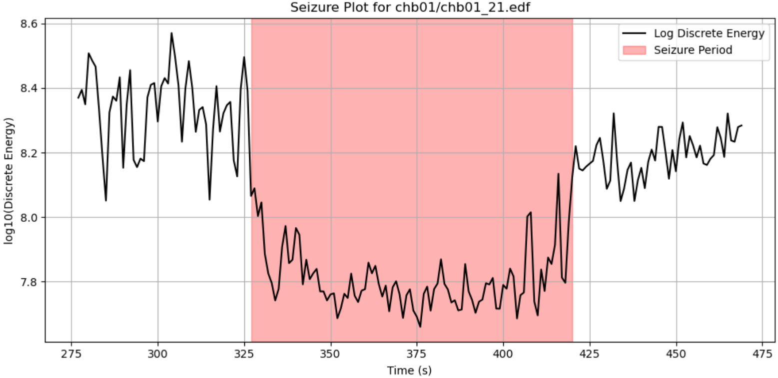
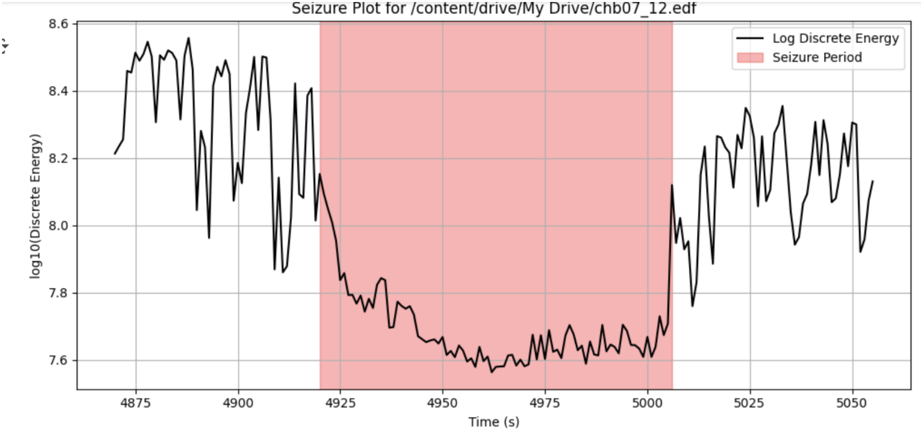


Figure: Discrete energy often drops during seizure periods (highlighted in red)

- **Training dataset**:
  - Datapoints in the **seizure group**: the discrete energy over time (calculated for each second) during each full seizure period as well as a random buffer of timesteps before and after the seizure
  - Datapoints in the **non-seizure group**: the discrete energy over time (calculated for each second) for random periods of time that were not during seizures
- **Goal**: to classify whether a given discrete energy time series contains a seizure period or not

- Model performance was tested with 5-fold cross validation
- **Classification performance**:
  - Overall accuracy of **87%**
  - Detected **90%** of discrete energy time series with seizures and misclassified **16%** of non-seizure time series
- **Conclusion**: despite the input data being reduced to a 1-dimensional time series with 256 times fewer timesteps, enough information was retained that a model was still able to predict the presence of seizures with relatively good accuracy

Computing integrals of the Seizure Discrete Energy Plots




```
Estimated seizure integral (area under curve): 661.3600926832951
Estimated preictal integral (area under curve): 713.6737973519548
Estimated postictal integral (area under curve): 694.7157979924451
```

FIGURE: The discrete energy integral from patient 7 when s=1. Note apparent differences in pre-ictal, post-ictal, and seizure integrals

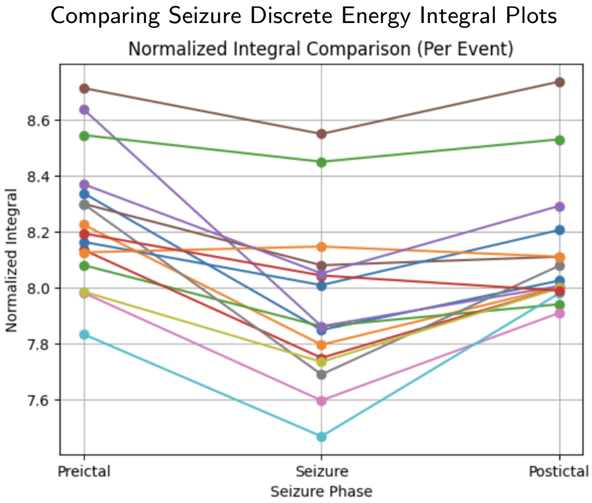


Figure: Discrete energy integrals of 16 patients during pre-ictal, post-ictal, and seizure periods. Note apparent decline in discrete energy during seizure periods.

Comparing the Discrete Energy of Non-Epileptic and Epileptic Patients

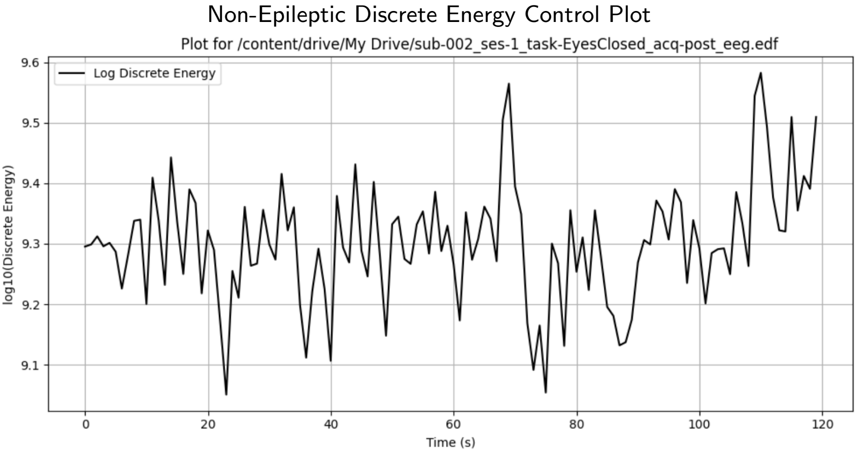


Figure: Discrete energy plot of healthy, non-epileptic patient. Note apparent difference in discrete energy range for healthy and epileptic patients.

This feedforward neural network (FNN) uses 9 ratio-based features derived from discrete energy integrals. The model was trained on standardized ratio features capturing relative energy shifts between seizure states, enabling it to learn discriminative patterns. It uses a simple 2-layer architecture trained with cross-entropy loss.

```
Total Test Accuracy: 0.8636
Class 0 Accuracy: 1.0000
Class 1 Accuracy: 0.6000
Class 2 Accuracy: 0.8333
Class 3 Accuracy: 1.0000

Predicted labels: [1, 0, 0, 3, 3, 2, 0, 0, 1, 1]
True labels:      [1, 0, 0, 3, 3, 2, 0, 1, 1, 1]
```

Figure: FNN accuracy and predicted classification. Class 0 is the seizure ratios, class 1 is the pre-ictal ratios, class 2 is the post-ictal ratios, and class 3 is the no seizure ratios.

Future Directions

- Identifying start time of seizure (sliding window): the first interval being classified as seizure is the start time
- Investigating why some patients' seizures do not show a decline in discrete energy when setting the s parameter to 1, but do for higher values of s.
- Creating a classification neural network that combines both discrete integrals and differences to detect seizures.
- Researching outliers such as neonatal seizure data further to see if we can draw similar patterns/comparisons as we did for the pediatric data.

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Thank you!

Questions?

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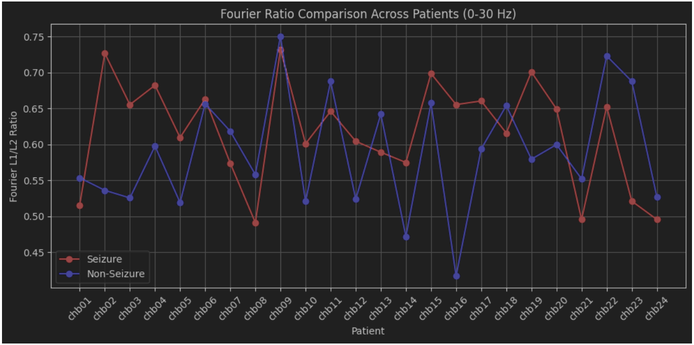
Appendix

- Computed the ratio of the L1 norm to the L2 norm of the fourier data (0–30 Hz).
- Observation: Although seizure and non-seizure ratios do not always show a large difference, the ratios range from **0.45 to 0.75** across patients.
- Conclusion: EEG time series are highly **nonforecastable**. Further there is no clear correlation between the relative degree of forecastability between seizure and non-seizure time series

$$\text{Fourier Ratio} = \frac{\frac{1}{n}\sum_{i=1}^{n}\left|\hat{f}_i\right|}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|\hat{f}_i\right|^2}}$$



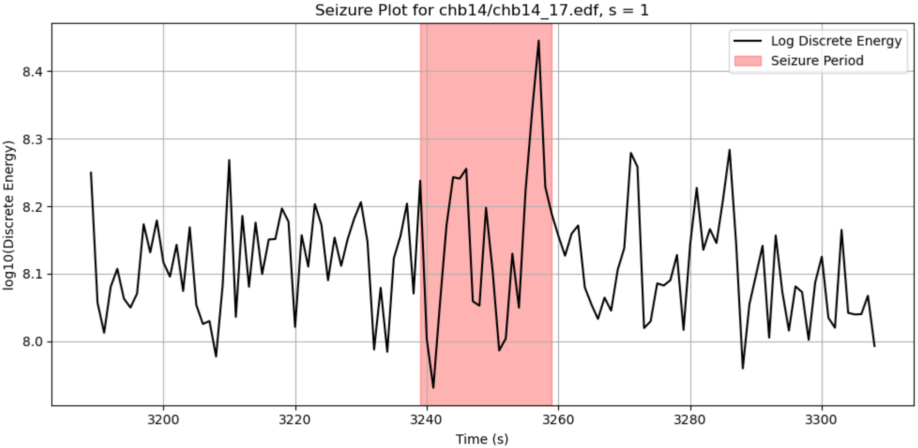


Figure: The discrete s-energy of EEG 17 from patient 14 when s=1. Note apparent lack of change during the seizure duration (highlighted in red)

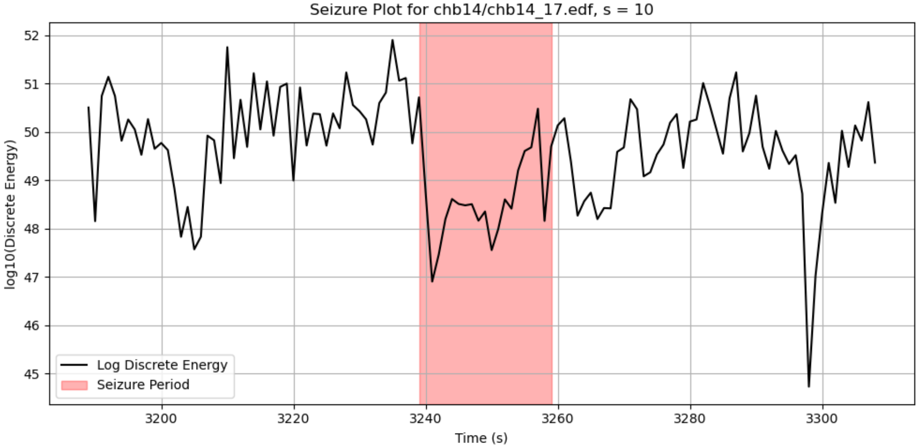


Figure: The discrete s-energy of EEG 17 from patient 14 when s=10. The sustained decrease in energy during the seizure duration (highlighted in red) is now visible