Automated Interpretation of Abnormal Adult Electroencephalograms

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College of Engineering
Temple University

S. López, I. Obeid and J. Picone

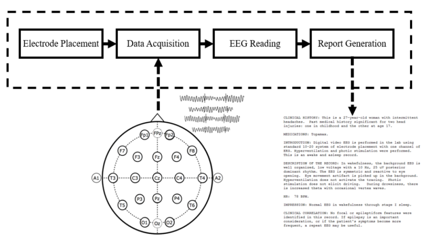
The Neural Engineering Data Consortium, Temple University

Abstract

- Interpretation of electroencephalograms (EEGs) is a process that is dependent on the subjective analysis of the examiner and has low interrater agreement.
- This study establishes a baseline for automated classification of abnormal adult EEGs using machine learning and a big data resource.
- 2,785 and 280 files from TUH EEG Abnormal were used for training and evaluation respectively. The first *T* seconds of data were used from a selected number of channels.
- The performance of three systems is evaluated:
  - hidden Markov Models (HMMs) (error rate: 26.1%)
  - HMM with a Stacked Denoising Autoencoder (HMM-SdA) (error rate: 24.6%)
  - a Convolutional Neural Network with a Multilayer Perceptron (CNN-MLP) (error rate: 21.2%).
- Even though these systems still lag human performance, we have established an experimental paradigm and demonstrated a promising baseline using deep learning technology for this task.

EEG Interpretation

- Manual interpretation of an EEG is performed by a board-certified neurologist. It takes several years to receive this certification. However, interrater agreement is low
- Increasing the interrater agreement for EEG interpretation is one of the advantages of an automated technique.



Characteristics of the Normal Adult EEG

- Reactivity: Response to certain physiological changes or provocations.
- Alpha Rhythm: Waves originate in the occipital lobe (predominantly) with frequencies that are typically between 8-13 Hz and voltage ranges of 15-45 µV.
- Mu Rhythm: Central rhythm of alpha activity commonly exhibiting frequencies between 8-10 Hz. This activity is visible in 17% to 19% of adults.
- Beta Activity: Faster activities in the frequency bands of 18-25 Hz, 14-16 Hz and 35-40 Hz.
- Theta Activity: Traces of 6-7 Hz activity present in the frontal or frontocentral regions of the brain.

The TUH EEG Abnormal Corpus

- This data source consists of a set of EEG sessions (signals and their reports) that are annotated as either normal (NRML) or Abnormal (ABNM).

Training

Description	Files		Patients		Hours
Abnormal	1398	50.20%	899	42.05%	546.43
Normal	1387	49.80%	1239	57.95%	518.29
Total	2785	100.00%	2138	100.00%	1064.72

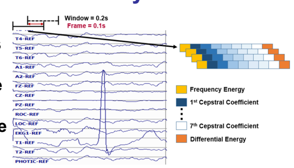
Evaluation

Description	Files		Patients		Hours
Abnormal	130	46.43%	105	41.50%	48.98
Normal	150	53.57%	148	58.50%	55.46
Total	280	100.00%	253	100.00%	104.44

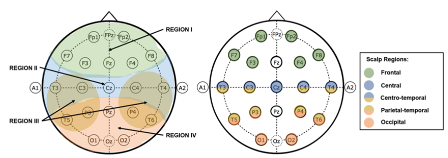
- The dataset was developed by selecting a subset of sessions from TUH EEG using natural language processing of the medical reports, and then performing manual review by a team of highly-trained undergraduate students.

Features and Dimensionality Reduction

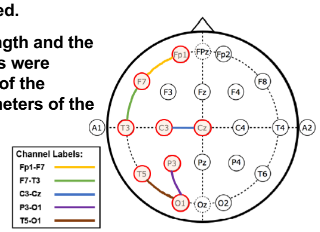
- A 26 dimensional feature vector was used as input. Of these, 9 were base features and the remaining were the first and second derivatives.



- HMM Experiments took one channel as an input, while the CNN took 4 channel groups.



- Only the first *T* seconds of a given channel of the signal were used.
- The window length and the channel regions were defined as two of the research parameters of the study.
- Channels were selected from different scalp regions.



GMM-HMM Systems

- To exploit the sequential nature of the data, Hidden Markov Models were utilized for EEG decoding.
- Note that initial experimentation led to setting *T=10s, HMM States=3 and Gaussian Mixtures=3.*
- The systems implemented are described as follows:
  1. HMM: sequentially analyzes windows of data and outputs a decision after the first *T* seconds.
  2. Epoch-Based HMM / Majority Vote: decodes one second epochs and generates a decision for each epoch. Majority voting is used to postprocess the epoch outputs for the final decision.
  3. Epoch-Based HMM / SdA: same as 2, but an SdA postprocesses the posterior probabilities with a deep learning system.

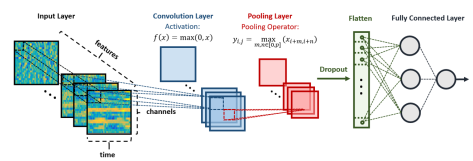
System Description	Error Rate (%)
GMM-HMM (#GM = 3 #HMM States = 3)	26.10%
Epoch-Based HMM/Majority Vote	24.55%
Epoch-Based HMM/SdA	**22.14%**

- All systems showed the best performance for channel T5-O1.

Ref/Hyp	Normal	Abnormal
Normal	90.00%	10.00%
Abnormal	37.70%	62.30%

CNN-MLP

- CNNs leverage sparse interactions and parameter sharing, which benefits the EEG decoding task:



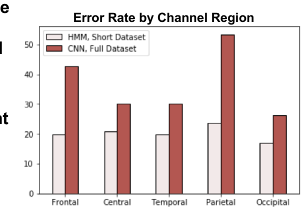
- The locality in the units of convolutional layers allows more robustness in the computation of feature maps for signals with many artifacts in selected frequency bands.
- Weight sharing, combined with pooling, minimizes the differences between input patterns when there are slight frequency shifts.
- In practice, the analysis of EEGs is conducted through the observation of 10 secs of data.
- For the decoding of EEGs through a CNN, the best temporal resolution was achieved by feeding the system 7 seconds of data at a time.
- Occipital channels showed the best performance.
- These results justify the use of deep networks for this task, but show that increasing the complexity of the model requires more training samples.

Configuration	# Convolutional Layers	Error (%)
$L_1 + F$	1	53.41%
$L_1 + L_2 + F$	2	22.94%
$\mathbf{L_1 + L_2 + L_3 + F}$	**3**	**21.15%**
$L_1 + L_2 + L_3 + L_4 + F$	4	25.81%

L_i is the convolutional layer, F is the fully connected layer

Locality Analysis

- Performance was investigated as a function of the location of the channels on the scalp to determine if the system was automatically learning similar information to that used by neurologists.
- Best performance was obtained by channels located in the occipital region.
- This is consistent with the way neurologists make this decision.



Conclusions and Future Work

- This study shows that it is possible to automatically classify abnormal adult EEGs considering only the background information with an error rate of 21%.
- CNN-MLP outperforms all hybrid HMM approaches for this task.
- The features that exhibited the most discriminative power for this task were the ones extracted from the occipital region of the scalp, which is consistent with the way in which neurologists classify EEGs.
- Since POSTS were one of the leading causes of confusion across models, identifying sleep state of the patient prior to classification would improve the overall performance.
- Example:

POSTS (benign variant)

Bifrontal Epileptiform Spikes

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