WEEK-2 REPORT : SAGNIK CHATTERJEE

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This is the weekly report for submission for my project work under Pooja Prabhu maam on the topic :- “Identification of Epileptic Abnormalities”.

Overview:

In this week ,I covered the remaining 2 papers that I referenced in the last report that was not covered i.e.
“Localizing epileptogenic regions using high-frequency oscillations and machine learning” and “Automatic detection and visualisation of MEG ripple oscillations in epilepsy”.

I have also attached another paper, “An Automated System for Epilepsy Detection using EEG Brain Signals based on Deep Learning Approach” that I have read in the extra-papers folder under Week2 folder.

Further started extracting the data points on the datasets provided. Currently I have only started working on only one dataset “ AB_1_SEI.edf”, and after I properly analyze this dataset would be able to quickly analyze the other datasets and would be able to start training the models.

For parsing the EDF file , I am using this tool https://github.com/holgern/pyedflib ,which reduces the work of not writing my parser from scratch.

Work Completed:

I have completely read the last 3 papers and also wrote a parser which converts the edf files into csv files which are included in the scripts file.

Also I have serialized the data from the first data set and what data points that I will consider.

Also wrote the analysis for the last 3 papers that I read and understood the use of pyedflib to use the edflib file.

Work To Be Completed:

To apply the data and serialize the data using pandas and numpy and convert the data into data points so that can start training the model on it.

Analysis of the Papers:

1. Localizing epileptogenic regions using high-frequency oscillations and machine learning

   Increased ripple and fast ripple rates in epileptogenic human brain electrode sites relative to electrode sites in healthy brain were first observed.These recording from mesasil temporal lobe structures demonstrated that ripple rates were elevated in epileptogenic atrophied tissue,where fast ripple rates were elevated in epilogenetic mesial temporal tissue irrespective of tether the tissue was atrophic.
   HFO's that occur on spike rates were noninferrior classifiers of the SOZ as compared with the rate of HFO's that were superimposed on spikes and HFO's alone.
   In patients in epilepsy ,some ripples that occur in certain brain regions serve not to consolidate memory but actually can disrupt memory, so a ML model to classify this would require to segment,co-register,normalize and then localize the electrode sites into MNI space.

   Coupling between the phae of theta oscillation in the neocortex and superimposed high gamma oscalliations is important during cognitive tasks and it has been the subject of speculation that PAC could occur in the epilepptonegic regions or during pathological events.

2. Automatic detection and visualisation of MEG ripple oscillations in epilepsy

   Visual analysis showed good concordance of the location of the ripples at the global level with the location of the MEG spikes in most patients.

   The concordance between of the MEG spike dipole locations and the restriction area.Out of the 16 patients ,8 patients with ripples who underwent surgery the spike and the ripple concordance were the same in

6 patients and the spikes performed better than the ripples in the other 2 patients.

All moments of a ripple were present in at least one channel was considered.This resulted in a large area hat seems involved in ripple generation.This is in contrast with the idea that ripples in intracranial ECoG are thought to have been generated in a small brain area.

The diameter of the ripple cluster seemed also larger than the spike clouds but dipole cloud were result of analysis of several selected spikes ,fitted over multiple latencies,while ripples were detected on each channel independently.

The best gold standard for identification of the epileptogenic zone is seizure freedom after respective surgery.
The restriction area was concordant with the MEG ripples in 2of them.

Also the chance of good localization if higher when the number of identified ripple is higher as seen in the case of patients with spikes in the unfiltered MEG.

3. An Automated System for Epilepsy Detection using EEG Brain Signals based on Deep Learning Approach

For classification , an input EEG signal is split into overlapping windows ,which are passed into different P-1D-CNN models in the ensemble i.e. different parts of the signal are assigned into the different parts for its local analysis.

The core component of the system if P-1D-CNN model.It is a deep model, consisting of convulational,batch normalization ,RELU ,fully connected and dropout layers.This is also an end-to-end model trainer and here rather than selecting all the features , a subset of the extracted features are selected and finally passed to a classifier for classification.

Performance Measure:

100 signals for each class is divided into 10 folds ,each fold(10%),in turn ,is kept for testing while the remaining 90% signals are used for learning the model.

The model is measure on well known basis of accuracy, specificity,sensitivity ,f-measure and g-mean .