Seizure prediction: A Visual Approach

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***Abstract*—Activity preceding the onset of epileptic seizures has been an elusive subject for neuroscience research, without a clear grasp of what patterns might be responsible. In this work, we present an *out of the box* approach to this problem, trying to mimic the visual inspection process that a trained physician might do to locate the beginning of a pre-ictal state in an EEG plot. We explore different data labeling methods for the posterior training of a Convolutional Neural Network, taking into account only visual characteristics for classification. Ten second images (300x400 px) were synthesized from scalp EEG recordings belonging to 10 epileptic patients from the public Physionet CHB-MIT database. A tortuosity measure was taken for each one-second window, for each channel (23 channels in 10-20 bipolar configuration). Unsupervised clustering methods in conjunction with the mean and the standard deviation of the tortuosity sets were used to identify pre-ictal states; interictal states were selected according to the same proximity criteria used for the Kaggles Melbourne University AES/MathWorks/NIH Seizure Prediction Challenge. The proposed labelling method indentified 28 posible pre-ictal states across 10 patients. Data from pre-ictal states and interictal states was used to train , and test, a Convolutional Neural Network classifier for each of the 8 patients selected. A classification accuracy of 99.29% was achieved for the best patient; however, an accuracy of 46.93% was also obtained for the worst patient. Mean performance across patients was 76.03%, a 52.07% improvement over chance.**

***Index Terms*—CNN, Deep Learning, epilepsy, medical imaging.**

I. Introduction

EPILEPSY is a neurological disorder affecting 39 million people worldwide, from which at least two thirds are in an age superior to 60 years [1]. This condition is most noticeable due to the presence of abnormal electric discharges in specific regions of the brain, affecting the normal activity of nerve tissue in the organ, this episodes are called epileptic seizures. Different types of seizures can be identified according to the epileptic focus location and how many neurons are affected [2].

Nowadays, the common protocol of monitoring a person with this condition is the use of electroencephalography (EEG), which can vary according to the type of electrode or its distribution. Electrodes can either be invasive or not, non invasive electrodes are placed in the scalp of the patient. This instrumentation is capable of identifying electrical activity in the extracellular region of the nerve tissue, different electrodes collect electrical information unique for their channel, the brain location that its being measured by the electrode. Currently this procedure is used for the diagnosis and monitoring of epileptic patients, the activity registered by the different channels is examined posterior to the study, with the purpose to identify an epileptic event for the correct specific diagnosis of the patient [3]. Diagnosis consist in the visual examination of the EEG by a specialist that has to identify, not only the type of event that can occur, but also the starting times of the clinic condition, even when the patient is not showing physical symptoms (silent epileptic seizures). In general, the neurologist tries to search for zones with low amplitude and frequency in the signal followed by a progressive increase of those features, then finalizing in a new segment of the signal with a relative low amplitude and frequency signal again [3]; this behavior is synchronized in different channels of the EEG.

The clinical care of epileptic patients is a topic that has gathered attention of various professionals involved with the disease, new methods of diagnostic and care for those patients search the improvement of the way which the patients face their condition and also to mitigate the repercussion of the symptoms in their daily lives. The objective of this work is to look for new ways to identify activity preceding seizures, with the ultimate goal of alerting the patient of incoming episodes.

II. Materials and methods

A. Dataset

Scalp EEG data was obtained from Physionet's CHB-MIT Scalp EEG Database [4], it contains scalp EEG data from 23 subjects, ranging from ages 1.5 - 22, for 5 males and 17 females. We selected a subset of 10 patients for our work, 6 females and 4 males, again from ages 1.5 - 22. Records were converted to the same bipolar 10-20 format as that of subject chb01, records with missing channels were ignored. From the processed data, 300 x 400 px images were created, each one containing 10 seconds of EEG data from 23 channels, as can be seen in Fig.1, these images were used for posterior analysis.

B. Pre-Processing

Given that the image is in binary format, relevant visual characteristics were constrained, as it has to be representative of the underlying signal but exploiting the generality and scale that visual representations give. A perfect candidate feature is the tortuosity, as has been used in multiple medical imaging applications for vessel characterization [5]. Although there are multiple ways to evaluate tortuosity, the most common is characterized as:

$$T = \frac{L}{D} \tag{1}$$

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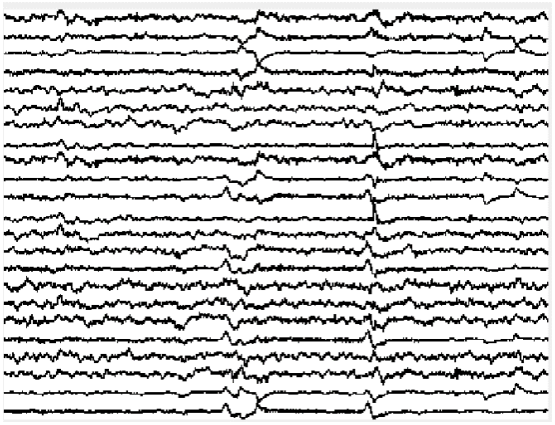


Fig. 1: Visual representation of EEG signal created for all data samples. 23 channels in 10/20 configuration

Where L denotes the total length of the segment and D its cord length (the distance between endpoints).

For each one second image snippet (13x40 px) tortuosity was calculated, producing a 230 dimensional feature vector for each image. To estimate the segment length, pixel counting was used, plots with steep ascends (amplitude) or with high frequencies are going to be 'larger', thus having greater tortuosity, than those that do not present much activity; cord length was fixed to be constant, 40 px, as the greatest possible value was 42.05 px. Using these constraints, tortuosity can be represented as a linear transformation of pixel density (number of white pixels), optimizing computation time:

$$T = 1 - \frac{\rho_{px}}{W * H} \tag{2}$$

III. Results

A. Features

Normalized tortuosity was used for clustering analysis, as a first approach, each of the 10 seconds snippets for the 23 channels were used as feature vectors (230 features). Despite its high dimensionality, there is clearly a pattern in centroid distribution after fitting a *K-means* model [6] (Fig. 3a), as each centroid corresponds to a combination of mean activity in spatial channels; furthermore, each channel combination contains channels with similar mean activity (Fig. 3b).

To account for changes in activity within and between channels, and reduce dimensionality of the problem, the mean tortuosity and its standard deviation were calculated for the 23 x 10 tortuosity matrix corresponding to a 10 second image. These two variables were highly correlated for all patients, as can be seen for subject 1 in Fig. 2, although its not entirely clear why. To validate this result and confirm that it is not biased by the method implemented, a set of images generated from random signals was evaluated, finding no correlation between variables in it.

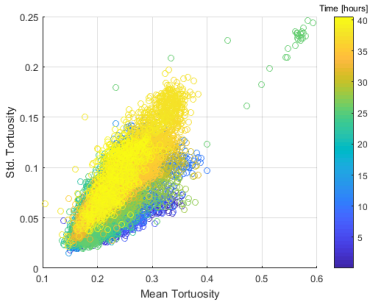


Fig. 2: Mean tortuosity and its standard deviation across time (Subject 1). Illustrating the high correlation between these two variables.

B. Labeling

Tortuosity deviation for each ten second image was calculated and used as a feature to fit a *K-means* model with 20 groups. After classification, it is possible to identify changes in grouping for activity preceding some of the seizures (Fig. 4). To quantify this, Shannon's Entropy was calculated for a moving window of the preceding 15 minutes (90 datapoints) across time. The difference of the resulting entropy signal was taken and smoothed with a moving mean of 15 minutes, using its squared value to find the mean change in entropy μ and its standard deviation σ. The changes in grouping activity can then be found thresholding the signal at value $\mu + \sigma$. Due to the nature of the data, all the positive values after thresholding were set to 0 if they were adjacent to discontinuities in the signal.

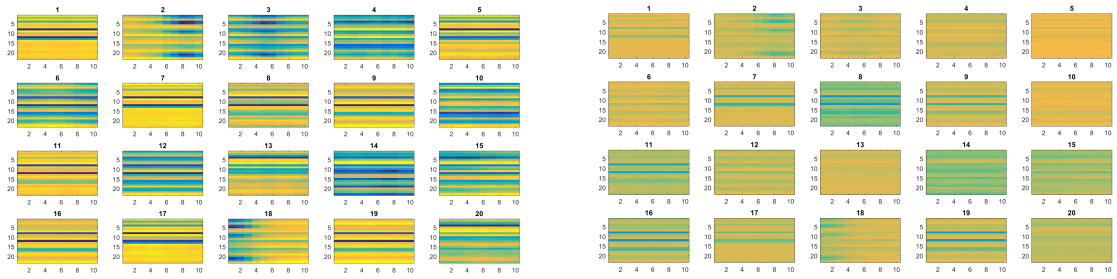
After filtering discontinuous data, a moving sum of 15 minutes was calculated to get an activation signal (avoiding multiple activations for the same pre-ictal state). This method also identified changes in waking activity and post-ictal states, as these are not of interest for labeling, signals less than an hour after a seizure or more than four hours away until the onset of one were ignored (invalid activations and adjacent values set to 0). Finally, data corresponding to the closest activation to the onset was used as a candidate of a pre-ictal state (Table I). Interictal states, however, were classified using the same criteria as Kaggle's Melbourne University AES/MathWorks/NIH Seizure Prediction Challenge [7]: multiple seizure clusters were identified, a cluster containing consecutive seizures less than 4 hours apart; interictal data must be more than 4 hours away from any cluster.

C. Network Training

For each subject, training and testing sets were selected from different seizure onsets for pre-ictal data, and between seizures for interictal data. All subjects training sets were class-balanced, also for most of the testing sets with the exception of subject 5 (Table II). A Convolutional Neural Network [8] was used to classify each image, the network's architecture was built from scratch (Fig. 5), given that existing ones might be biased for natural image recognition. Training was done with error backpropagation using Stochastic Gradient Descent

TABLE I: Results of Proposed Method in each patient

Subject	Seizures	Candidate Preictal States	Min Duration [min]	Max Duration [min]	Mean Duration [min]
1	7	5	39	212	74± 48.2
2	3	1	47	47	47± –
3	7	1	24	24	24± –
4	4	2	176	218	197± 29.7
5	5	2	79	80	79± 0.707
6	10	6	11	127	72± 44.5
7	3	2	57	277	167± 155.6
8	5	2	27	55	41± 19.8
9	4	3	4	205	134± 112.5
10	7	4	11	135	54± 57.3
Total	55	28	47.5	138	88.9± 7.6



(a) 'Centerwise' value visualization (b) Global value visualization

Fig. 3: Centroid results for 230 features (Subject 1). **a:** 20 centroids of 23 x 10 corresponding to 10 second information for each channel, color coded for minimum (blue) and maximum (yellow) values in each centroid. **b:** Centroid visualization color coded for minimum and maximum values across all centroids.

[9] with a decaying learning rate (0.99^n), momentum = 0.5 and weight decay = 0.01, with mixed patient-dependent results, as shown in Table II.

IV. Discussion

The EEG plotting gives a more general view of the signal, but at loss of local characteristics and, feature selection from it becomes a whole new problem as well. An almost linear relation was found between the mean of the tortuosity (proportional to high frequency/ high amplitude electrical activity) and its standard deviation, posing the question if variability within and between channels only occurs when high frequency/ high amplitude activity is present.

The first major hurdle for the development of a predictive algorithm is the correct classification of its training data, current methodology relies on a *one size fits all* time frame to separate preictal and interictal states, although we were able to identify some preictal states, the nature and variability of seizures makes it a difficult problem. Visual based classification with Convolutional Neural Networks gives promising results, although it varies between patients. Multiple factors might be responsible for this: some patients could present easily predictable brain activity while others do not; the labeling method misclassified some of the training data or simply there wasn't enough data for the network to learn global patterns.

Future work should focus on finding common ground between a time frame for classification and unbiased feature selection, Recurrent Convolutional Neural Networks and feature embedding might be a good fit for this problem, in order to find an accurate representation of the underlying distribution of brain activity and detect its abnormalities without assuming it (i.e. no need for a *K-means* model).

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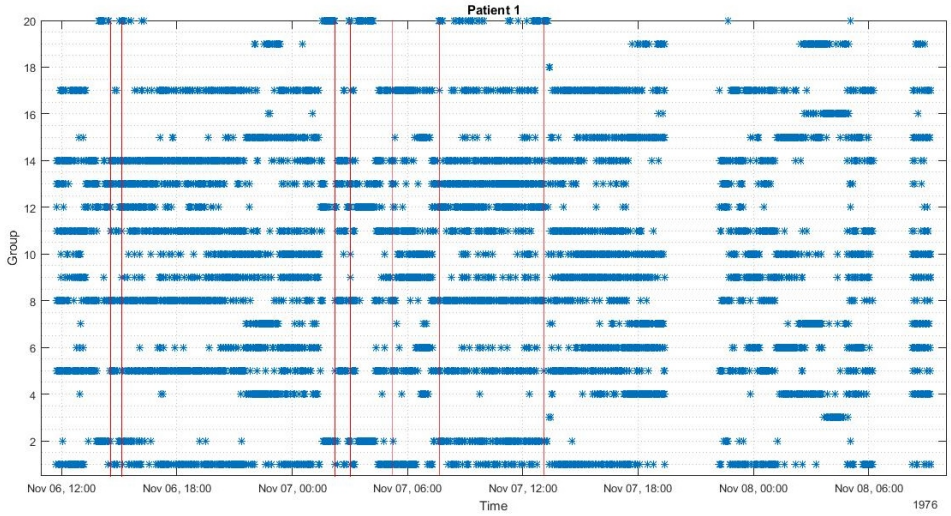


Fig. 4: K-means classification using tortuosity std. (Subject 1). Changes in group distribution are observed moments before seizure onset.

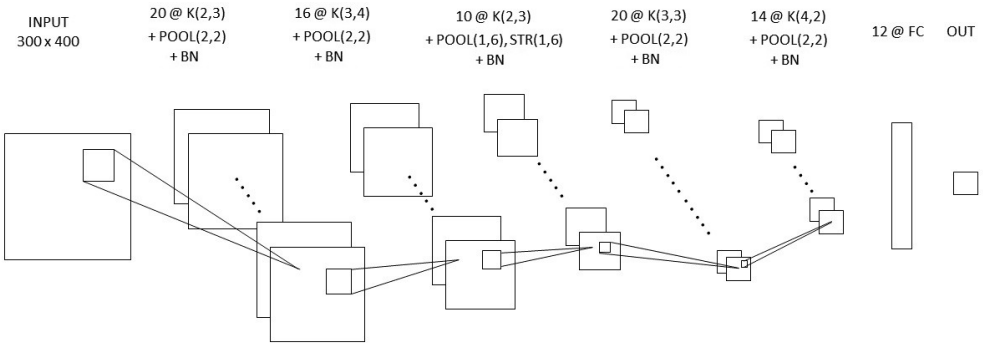
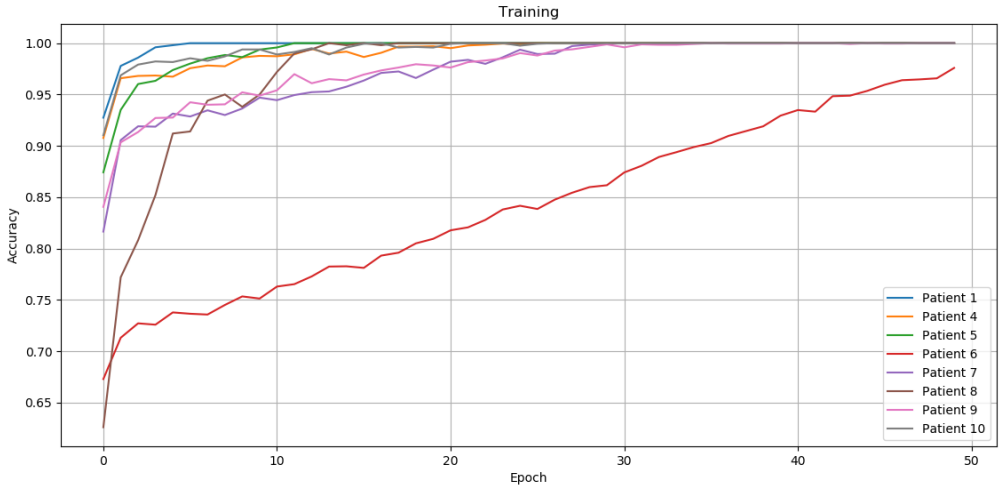


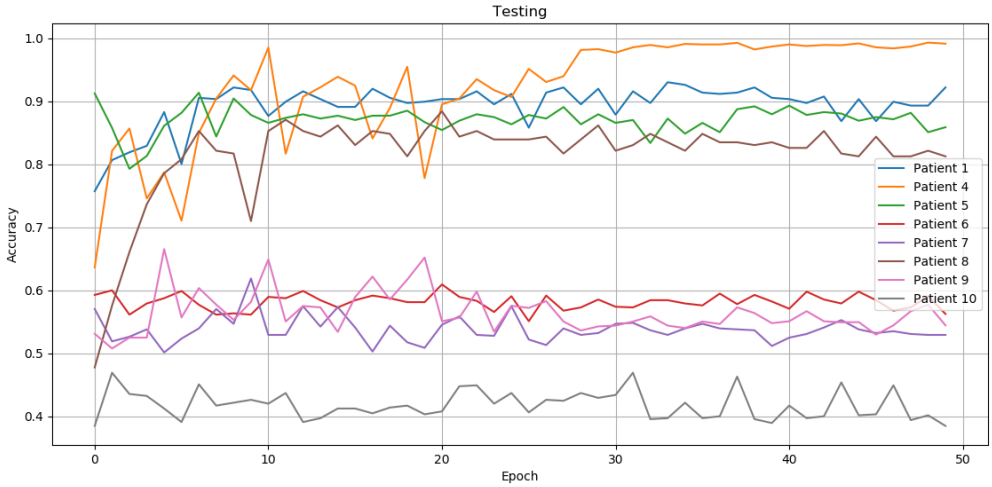
Fig. 5: Convolutional Neural Network architecture

TABLE II: Data samples and accuracy

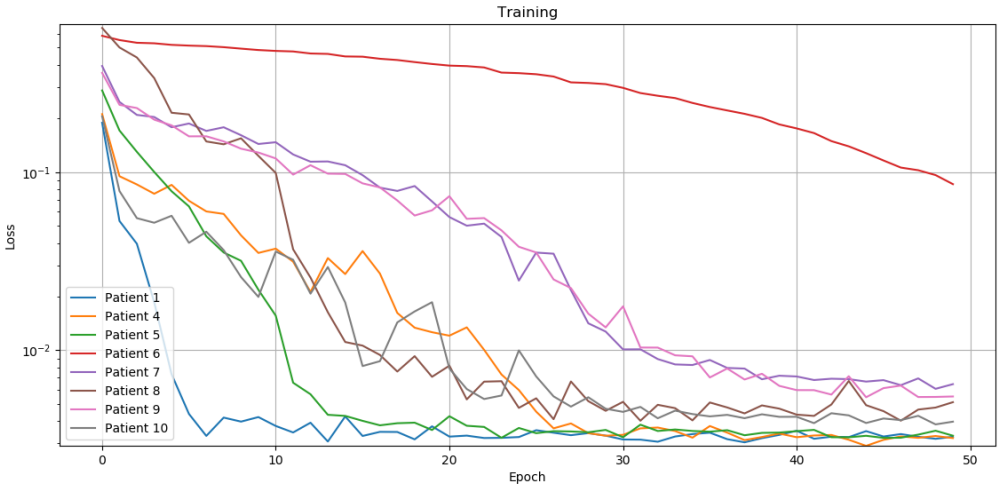
Subject	Training		Testing		Best Accuracy
	Preictal	Interictal	Preictal	Interictal	
4	1332	1332	1200	1200	99.29 %
1	248	248	243	243	93.00 %
5	477	477	404	474	91.34 %
8	250	250	112	112	88.39 %
9	1242	1242	1158	1158	66.53 %
7	1414	1414	341	341	61.88 %
6	1926	1926	480	480	60.93 %
10	814	814	326	326	46.93 %



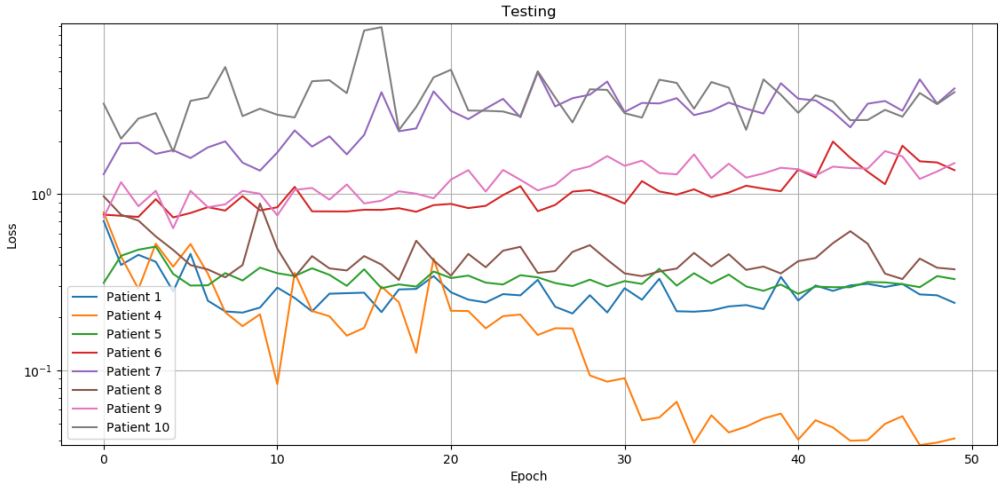
Supplementary Fig. 1: Training set Accuracy vs. Epoch



Supplementary Fig. 2: Testing set Accuracy vs. Epoch



Supplementary Fig. 3: Training set Cross-entropy vs. Epoch



Supplementary Fig. 4: Testing set Cross-entropy vs. Epoch