Classification of Epileptoid Oscillations in EEG Using Shannon's Entropy Amplitude Probability Distribution

Ronald Broberg[1] and Rory Lewis[2]

[1] Department of Mathematics, University of Colorado at Colorado Springs, Colorado Springs, CO USA 80918, USA
[2] Department of Computer Science, University of Colorado at Colorado Springs, Colorado Springs, CO USA 80918, USA

Abstract. This paper presents an additional tool the authors have developed to continue merging the fields of computational neuroscience with medical based neurodiagnostic clinical research, particularly those associated with machine learning in Big Electroencephalogram (EEG) Data. The authors introduce a means to identify various types of epileptic pathologic oscillations using a parameter based on the Shannon entropy of the probability distribution of the amplitudes within EEG signals. Multiple entropy and entropy-like measures have been explored to aid in epileptic seizure classification including Kolmogorov-Sinai entropy, spectral entropy, Renyi entropy, approximate entropy, and equal frequency discretization. Here we propose a more computational efficient measure which calculates a discrete probability distribution directly from the recorded amplitudes of an EEG recording over a specified window and uses an entropy-like calculation to reduce dimensionality.

1 Introduction

In previous work the authors have studied the subjective nature of what constitutes a pathological oscillation [15], and the huge dimensionality of the human brain, which has approximately 100 billion neurons each having about 1,000 connections (synapses)[16]. Moreover, neurological pathological activity may manifest itself differently from animal to animal or individual to individual [17] [7]. In a healthy human brain there is a precise interaction of neural activities, but when one develops a neurological illness (pathology) this synchronization breaks down. These abnormal synchronization processes are found in the pathological oscillations associated with several neuropsychiatric disorders including epilepsy, acute brain injury, Alzheimer's, autism post-neurosurgery Intensive Care Units (ICU) seizures, stroke, schizophrenia, dementia and basal ganglia disorders such as Parkinson's disease. In this paper we present a novel tool using Shannon's entropy function to help convert Big EEG Data into a machine learning state that will improve the efficiency of detecting seizure associated with epilepsy. Kannathal[6] grouped entropy estimators into two classes: spectral and embedded. Spectral estimators include spectral entropy[5] such as those obtained from

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Fourier Transform and Renyi entropy[6] which differs from the spectral entropies in the weighting of the lower frequencies. Embedded entropies include state space reconstructions[1], Kolmogorov-Sinai entropy[6], approximate entropy[10], and sample entropy[12]. Orhan [8] used an entropy-like method *'Equal Frequency Distribution'* where the amplitudes of the EEG signal where discretized into 'N' bins of equal size and then applied Shannon's entropy function to the resulting discrete probability distribution. He then calculated the EFD over a range of differing 'N' values to create a set of entropy-like values that could be used for epileptic seizure classification. Accordingly, we present a more efficient embedded entropy derived from the amplitude of EEG recordings in the classification of epileptic seizure events.

We examine a simple entropy measure in three experiments using three distinct EEG data sets. First, the amplitude entropy measure is explained. The following sections apply the method to the three data sets. In the first data set, the measure is used to classify epileptic and non-epileptic EEG segments prepared by Andrzejak.[2] The second applies the measure to two tonic-clonic, grand mal, seizure events in a pair of EEG traces made available by Quiroga.[11] In the third, the measure is applied to the 800 hours of EEG data prepared by Shoeb[14] and made available through PhysioNet.[4] In 1948 Shannon [13] defined entropy in informational theory as $H = -\sum p_i log(p_i)$ .We have used this definition to measure the entropy in the amplitude of EEG recordings after discretizing data through the straight forward conversion of the amplitude signal from floating point values to integers. The entropy measure in a given EEG segment is calculated after creating a probability distribution for a particular EEG amplitude by summing the frequency of each amplitude within the segment and dividing by the total number of amplitude measurements within the segment. In the following, Y^* is the sum of the raw frequency count for each distinct amplitude y_i within a particular given EEG segment $Y^* = \sum y_i$ where by definition, Y^* sums to number of data points within a given segment. Traditionally, the sum is normalized by dividing each amplitude frequency by the total sum of data points which results in a discrete probability distribution from which an entropy can be calculated as in (1) $p_i = \frac{y_i}{Y^*}$.

Experiment 1: Entropy Measure of the Distribution of Amplitude in Fixed Segments with Data Set 1: Andrzejak / Bonn. This canonical data set was prepared by Andrzejak et.al. and made publicly available.[3] It has been used in multiple seizure studies including Kannathal, Orhan, and Acharya. Data samples are collected at 173.6Hz and are divided into 5 labeled sets of 100 files each. The time series have an effective spectral bandwith of 0.5 Hz to 85 Hz. Each file consists of 4097 data points representing a continuous 23.6 second interval. Sets A and B are extracranial with set A comprised of recordings with eyes open and B of records with the eyes closed. Sets C, D, and E are intracranial recordings made of epileptic patients following surgical hemispheric division. Set C comes from the non-epileptic hemisphere while sets D and E are from the epileptic hemisphere. Set D consists of recordings free from seizure while set E consists of recordings with seizure. To study the entropy within each set the authors

calculated the amplitude entropy of each 23.6 second segment in each 100 segment set. In the next step we aggregate the entropies in each set and test for normality using SciPy's *normaltest* which is based on D'Agostino and Pearson's test that combines skew and kurtosis to produce an omnibus test of normality. Low p-values reject hypothesis that the set is normal. Note that the aggregate of entropy of the segments within each set *in general* is not distributed normally about the mean, although the 'extra-cranial eyes open' and the 'intra-cranial seizure' both have values suggesting normal distributions. For future work the authors will study whether this could be due to artifact noise in the first case and an actual stochastic element in the latter. The statistical parameters of all 4 sets are illustrated in Table 3.

Entropy Between Each Set and EEG Classification. A training set is selected randomly from each of the sets A-E. An entropy H_j is calculated for each segment in each of the training sets. Boundary points are defined as follows: $D_{min} = min(D_{train})$, $D_{max} = max(D_{train})$, $E_{min} = min(E_{train})$ and $E_{max} = max(E_{train})$. The calculated boundary points are used to classify the test segments into the nonseizure/seizure state set as follows: no seizure(W), possible seizure (X), probable seizure(Y), seizure(Z).

$$W{:=}\{H_j|H_j{\in}[0,E_{min}]\} \quad (1) \qquad X{:=}\{H_j|H_j{\in}(E_{min},E_{min}+\tfrac{D_{max}-E_{min}}{2}]\} \quad (2)$$

$$Y{:=}\{H_j|H_j{\in}(E_{min}+\tfrac{D_{max}-E_{min}}{2},D_{max}]\} \quad (3) \qquad X{:=}\{H_j|H_j{\in}(E_{min},E_{min}+\tfrac{D_{max}-E_{min}}{2}]\} \quad (4)$$

The 2-fold cross-validation was repeated 100000 times. We find that this classification which includes the two indeterminate states has high precision. For the non-seizure class W, the precision is assessed as the number of non-seizures segments classified as such divided by the total number of segments assigned to the class. For the possible-, probable- and definite- seizure classes, the accuracy is assessed as the number of seizures segments assigned to the class divided by the total number of segments assigned to the class. The possible-seizure class is the least accurate by design and indicates the most mixed classification of seizure and non-seizure. As we move from class X to classes Y and Z, the confidence in the seizure classification increases. Allowing for indeterminate states X and Y, our confidence in the classification of the definite states W and Z increases. The rough set classification provides a more sensitive tool than a binary classification into seizure/non-seizure binary states with the seizure state composed of $X \cup Y \cup Z$ and the non-seizure state W.

Experiment 2: Evolution of Entropy in Time Seriesusing data Set 2: Quiroga & Caltech. Two longer EEG traces with seizure states have been made publicly available by Quiroga [11]. These files show tonic-clonic seizures of two subjects recorded with a scalp rigth central (C4) electrode (linked earlobes reference). They each contain a total of 3 minutes of data with an approximate 1 minute of pre-seizure recording followed by a seizure and some post-seizure activity. Each

Table 1. Classification with rough sets W,X,Y,Z

Set	C/E	D/E
W	98.1	97.9
X	86.3	70.1
Y	98.6	89.3
Z	99.9	97.8

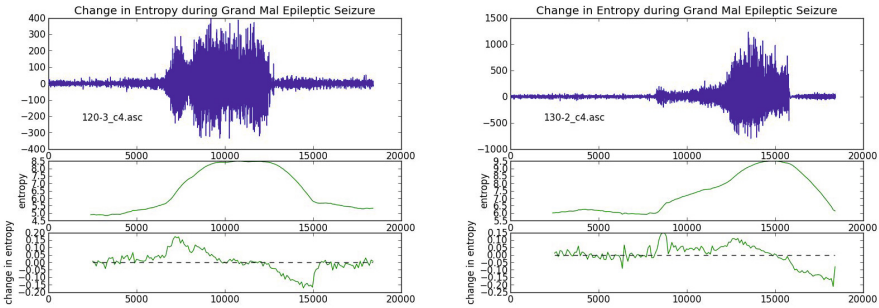
Table 2. Classification with binary W+X,Y+Z

Set	C/E	D/E
W	98.1	97.9
$X \cup Y \cup Z$	97.3	89.8

Table 3. Classification with binary W+X,Y+Z

Set	C/E	D/E
W	98.1	97.9
$X \cup Y \cup Z$	97.3	89.8

signal was digitized at 409.6 Hz although after processing, the data set has an effective frequency of 102.4 Hz with an effective bandwidth of 1-50 Hz. Using windowed entropy the authors found that the longer EEG trace provides an opportunity to observe the evolution of entropy over the time series. An entropy measure of the amplitude distribution was calcuted as above for a frame of 23 seconds. This frame was moved 1 second and entropy recalculated over the length of the time series. The first deriviative of the entropy was also calcuated and is displayed in the bottom plot for each time series.

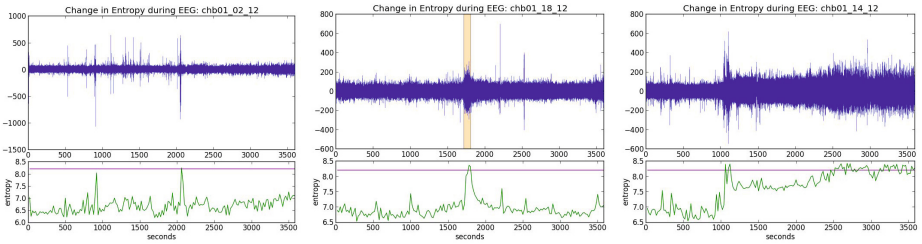


(a) (b)

Fig. 1. Evolution of Entropy on the Time Series: Original EEG comprising both a pathological oscillation and artifact **(a)**, Entropy Evolution on Caltech data series A **(b)**, Entropy Evolution on Caltech data series B

Experiment 3: Detection of Seizures in Extended Data Series using data from Shoeb at Boston Children's Hospital. This extracranial data was collected at the Boston Children's Hospital. The database is described in Shoeb 2004[14] and made available on PhysioNet.[4][9] From the public source, 664 EDF files totaling over 44 gigabytes of compressed data were downloaded. These files contain over 800 hours of EEG data. Most files contain 23 EEG signals and they all are sampled at 256 Hz. Meta data is included with seizure times labeled. The recordings are grouped into 23 cases and are collected from 22 pediatric patients with intractable seizures following withdrawal of anti-seziure medicine during

assement for surgical intervention. Using the Windowed Entropy method. we used tme evolving entropy series with non-overlapping 23 second windows are depicted in the figures below. Three exemplary plots from the CHB01 set are shown with a seizure free time series (a), a time series with a labeled seizure (b), and a non-seizure series with high noise (c). In Figure 3, an arbitrary entropy of classifier boundary of 8.2 is displayed. Additional study is being conducted to further improve this entropy analysis as a pre-processor into machine learning classifiers.



(a) (b) (c)

Fig. 2. Detection of Seizures in Real Data Series: Original EEG comprising both a pathological oscillation and artifact **(a)**, Entropy Evolution on PhysioNet a selected data series CHB01 without seizure **(b)**, with seizure. **(c)**, with noise and no seizure.

2 Conclusions and Future Work

These experiments show that in terms of adding a classification rule based system onto the original neuroClustering developed by the authors is a viable option so long as it will also be in a form conducive to domain adaptation. Utilizing perceptrons in the manner described in this paper to aid the neurosurgeons selecting what kind of pathological oscillations they are interested in and what they want the machine to deem as artifact, has shown to be a viable option that certainly renders the need to continue honing and refining the perceptron based method illustrated and defined in this paper and these experiments. For our future work we will test various thresholds in the perceptron algorithms against large sets of data and see where the strengths and weaknesses of timing and confidence levels pan out. Overall the results of these experiments are encouraging and are a source to drill down deeper into the methodologies presented in these experiments.

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