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MACHINE LEARNING

Detection of epileptic seizures

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ACRONYMS

EEG Electroencephalogram

Ictal Physiologic state or event such as a seizure, stroke, or headache.

AF Activation Function

LF Learning Function

i.e. "*id est*", meaning "that is"

LN Linear Neuron

INTRODUCTION

1.1 EPILEPTIC SEIZURES IDENTIFICATION

Neuronal networks models will be developed for identifying the occurrence of epileptic seizures.

For that purpose, the neural networks will be classifying data from the brain's electric signals (in micro-volts), recorded mainly by Electroencephalogram (EEG).

Hence, the objective of the project is the identification of patterns that occur during an epileptic seizure.

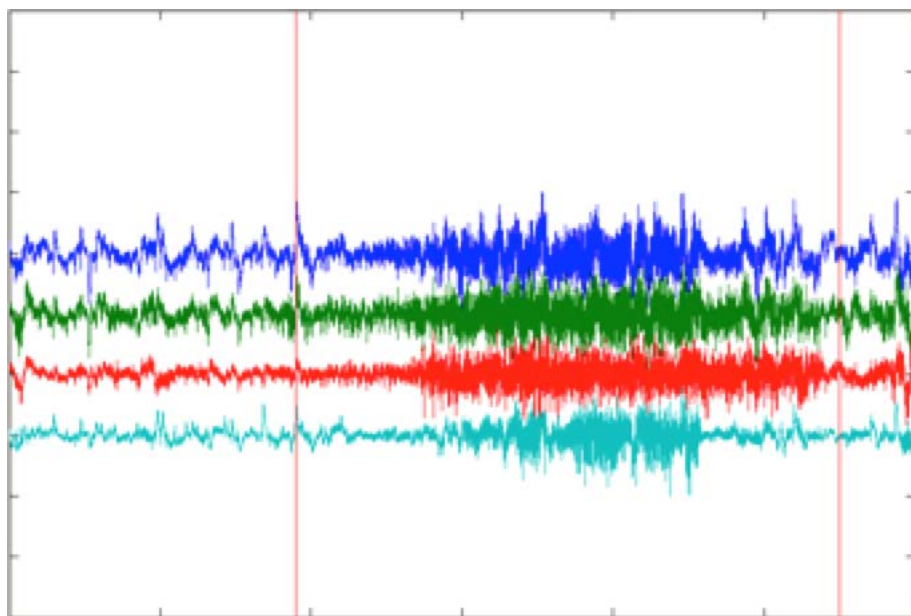


Figure 1: Sample from a EEG, during a seizure

We assume that the data can be classified in two different classes:

1. **Ictal** (seizure);
2. **Non-ictal** (normal state).

DATA SET

2.1 HOW IS THE DATA SET ORGANISED?

For using in this project, there is data formed by the EEG data from three patients (cod.63502, 92202 and 112502).

The indicated EEG data contains 29 characteristics of the EEG signal frequency. For each patient, there is also a *target vector* in which is recorded if a seizure occurred.

ID	Sex	Patient age (y)	Onset age (y)	Localization of seizures	Seizure type	Total EEG Recording (h)	No. of seizure	Seizure duration (s)		
								Mean	Min	Max
107702	F	29	10	RMT, RLT	CP(1), SP(7), UC(1)	183	9	82.3	13	172
109602	F	32	1	LMT	CP(8), UC(1)	162.6	9	121.9	74	157
112502	F	11	3	RMT	CP(4), SP(4), UC(6)	155	14	122.7	56	171
115002	F	32	8	RBF, RMT, LMT	CP(2), SP(2), UC(5)	151.6	9	122.5	38	210
132502	F	18	6	L-T, L-F	CP(13)	127.8	13	86.5	68	105
44202	M	21	5	RLT, RMT	CP(19), UC(3)	170.6	22	131.6	19	199
54802	M	17	1	LMT, LLT, L-T	SP(25), SG(6)	142	31	118.4	33	274
59002	M	18	11	LBT, LLT, RBT	CP(4), SP(4), SG(4), UC(1)	246.2	13	100.2	36	137
63502	F	63	30	LMT, R-T	CP(15), UC(4)	118.9	19	102.8	8	156
92202	M	39	8	L-F, L-C	CP(2), SP(3), UC(25)	110.6	30	15.4	6	43
95802	F	14	13	L-T, LLT	CP(6), SG(4), UC(4)	217.1	14	52.5	7	123
Sum	7F/4M	-	-	-	CP(74), SP(45), SG(14), UC(50)	1785.4	183	-	-	-
Mean	-	26.7	8.7	-	-	162.3	16.6	91.8	32.5	158.8

♦ Localization of seizures: ABC; A (R: right, L: left), B (-: none, B: basal, L: lateral, M: mesial), C (F: frontal, T: temporal, C: central).
E.g. RMT (right mesial temporal lobe), L-F (left frontal lobe), RBF (right basal frontal lobe).

♦ Seizure type: type of the clinical seizures; CP: Complex Partial, SP: Simple Partial, SG: Secondarily Generalized, UC: Unclassified.
The numbers given in parentheses represent the number of seizures for each type.

♦ Seizure duration: mean, minimum, and maximum values of seizure durations, considering electrographic onsets and offsets of the seizures.

Figure 2: Patient information

In our analyses of the data, we assumed the data was normalised, *i.e.*, that the mean is zero and unitary variance.

2.2 HOW DOES THE DATA SET INFLUENCE THE PERFORMANCE OF THE CLASSIFICATION SYSTEM?

To analyse the influence of the data set in the performance, we started by pre-processing the data.

2.2 HOW DOES THE DATA SET INFLUENCE THE PERFORMANCE OF THE CLASSIFICATION SYSTEM?

Due to the difference in the number of negative samples in relation to the positive ones, we started by discarding some of the negative samples, in order to minimise the difference between the two classes.

Then, we proceed to the division into training and testing data set. We tested with several percentages, results that will be shown later.

Due to the large number of features, we have also done some tests while reducing the dimensionality of the problem, by analysing the primary components or by analysing the correlation between the features and the expected output.

NEURAL NETWORK ARCHITECTURE

The input of the neural network is the data-sets described earlier. Therefore, the size of the input is variable, depending of the user input.

The output, is binary exit, representing the existence of a seizure. As suggested, this binary exit was representing by two exits, instead of a simple true/false.

[1,0] : **Ictal** (seizure) ;

[0,1] : **Non-ictal** (normal state).

For the Neural Network Architecture, several models where used, such as:

1. **Feed forward networks**(feedforwardnet);
2. **Function fitting network**(fitnet);
3. **Cascade forward neural network**(cascadeforwardnet);
4. **Pattern recognition neural network**(patternnet);
5. **Layer recurrent networks**(layrecnet);
6. **Radial basis network**(newrb).

For this models, most parameters were set default, due to their complexity, or due to the time it was needed to train all the networks. But, to test the influence of different configurations, the influence of the size of the hidden layers was tested, and several training algorithms/functions where used:

1. **trainlm**;
2. **traingd**;
3. **trainbfg**;
4. **trainrp**.

RESULTS

4.1 NOTATION

For measuring the result of the tested neural networks, we calculated the Sensitivity and the Specificity of the classified samples:

$$\text{sensitivity} = \frac{\text{number of true positives}}{\text{number of true positives} + \text{number of false negatives}}$$

Figure 3: Sensitivity Definition

$$\text{specificity} = \frac{\text{number of true negatives}}{\text{number of true negatives} + \text{number of false positives}}$$

Figure 4: Specificity Definition

All the networks were evaluated using this metrics.

4.2 IS THE CLASSIFICATION SYSTEM ABLE TO ACHIEVE THE MAIN OBJECTIVE?

The table shown next contains the best 20 configurations, regarding the accuracy of the system.

	dataset	Function	Delay	#Hidden Layer	Hidden Layer Size	% for training	Classification Method	# Features	Accuracy
Radial Basis Function	63502			29	15	0.65	single point	15	0.8408
Feed Forward Net	63502	trainlm		1	5	0.65	single point	15	0.8394
Radial Basis Function	63502			29	1	0.75	single point	29	0.8370
Radial Basis Function	63502			29	8	0.75	single point	29	0.8300
Radial Basis Function	63502			15	15	0.75	10 consecutive ictals	15	0.8300
Radial Basis Function	63502			29	1	0.65	single point	29	0.8300
Radial Basis Function	63502			15	2	0.65	10 consecutive ictals	15	0.8300
Radial Basis Function	63502			15	2	0.7	10 consecutive ictals	29	0.8294
Radial Basis Function	63502			29	2	0.75	single point	15	0.8289
Radial Basis Function	63502			29	15	0.75	at least 5 of the last 10 are ictals	29	0.8289
Radial Basis Function	63502			29	15	0.75	10 consecutive ictals	15	0.8289
Radial Basis Function	63502			29	1	0.65	10 consecutive ictals	15	0.8285
Pattern Recognition Net	63502	trainlm		2	29	0.75	single point	15	0.8279
Pattern Recognition Net	63502	trainlm		2	29	0.75	at least 5 of the last 10 are ictals	29	0.8279
Pattern Recognition Net	63502	trainlm		2	29	0.75	10 consecutive ictals	29	0.8279
Radial Basis Function	63502			29	1	0.65	10 consecutive ictals	29	0.8271
Layer Recurrent Net	63502	trainlm	2	2	5	0.75	10 consecutive ictals	15	0.8269
Radial Basis Function	63502			15	15	0.65	single point	15	0.8263
Radial Basis Function	63502			29	8	0.7	at least 5 of the last 10 are ictals	15	0.8260
Pattern Recognition Net	63502	trainlm		2	29	0.7	single point	15	0.8260

The table shown next contains the best 20 configurations, regarding the Specificity of the system.

4.3 GRAPHIC USER INTERFACE

	dataset	Function	Delay	#Hidden Layer	Hidden Layer Size	% for training	Classification Method	# Features	specificity
Layer Recurrent Net	92202	traingd	10	2	5	0.75	single point	15	0.9957
Feed Forward Net	63502	traingd		2	5	0.7	10 consecutive ictals	15	0.9919
Layer Recurrent Net	92202	traingd	5	2	29	0.7	10 consecutive ictals	29	0.9756
Feed Forward Net	63502	traingd		2	5	0.75	10 consecutive ictals	29	0.9637
Feed Forward Net	63502	traingd		1	5	0.65	single point	15	0.9527
Feed Forward Net	92202	trainlm		2	5	0.7	single point	29	0.9486
Layer Recurrent Net	63502	traingd	2	1	5	0.65	at least 5 of the last 10 are ictals	15	0.9436
Feed Forward Net	63502	traingd		2	5	0.7	10 consecutive ictals	29	0.915
Layer Recurrent Net	63502	traingd	2	1	5	0.7	single point	15	0.915
Layer Recurrent Net	63502	traingd	10	2	29	0.7	10 consecutive ictals	29	0.9079
Layer Recurrent Net	63502	traingd	2	2	5	0.75	single point	15	0.8987
Layer Recurrent Net	63502	traingd	2	2	5	0.75	10 consecutive ictals	15	0.8821
Layer Recurrent Net	92202	traingd	10	2	5	0.7	single point	15	0.8784
Layer Recurrent Net	63502	traingd	5	1	5	0.75	at least 5 of the last 10 are ictals	29	0.8776
Radial Basis Function	63502			29	15	0.65	single point	29	0.8725
Feed Forward Net	63502	trainlm		1	5	0.65	single point	29	0.8537
Layer Recurrent Net	92202	traingd	2	2	5	0.75	single point	15	0.8517
Radial Basis Function	63502			29	1	0.75	single point	15	0.8408
Feed Forward Net	92202	traingd		2	5	0.7	single point	15	0.8394
Radial Basis Function	63502			29	8	0.75	single point	15	0.837

The table shown next contains the best 20 configurations, regarding the Sensibility of the system.

	dataset	Function	Delay	#Hidden Layer	Hidden Layer Size	% for training	Classification Method	# Features	sensibility
Layer Recurrent Net	92202	traingd	10	2	5	0.75	single point	15	1
Feed Forward Net	63502	traingd		2	5	0.7	10 consecutive ictals	15	0.9932
Layer Recurrent Net	92202	traingd	5	2	29	0.7	10 consecutive ictals	29	0.983
Feed Forward Net	63502	traingd		2	5	0.75	10 consecutive ictals	29	0.9777
Feed Forward Net	63502	traingd		1	5	0.65	single point	15	0.9689
Feed Forward Net	92202	trainlm		2	5	0.7	single point	29	0.9592
Layer Recurrent Net	63502	traingd	2	1	5	0.65	at least 5 of the last 10 are ictals	15	0.9537
Feed Forward Net	63502	traingd		2	5	0.7	10 consecutive ictals	29	0.9383
Layer Recurrent Net	63502	traingd	2	1	5	0.7	single point	15	0.9071
Layer Recurrent Net	63502	traingd	10	2	29	0.7	10 consecutive ictals	29	0.9054
Layer Recurrent Net	63502	traingd	2	2	5	0.75	single point	15	0.8978
Layer Recurrent Net	63502	traingd	2	2	5	0.75	10 consecutive ictals	15	0.8917
Layer Recurrent Net	92202	traingd	10	2	5	0.7	single point	15	0.8878
Layer Recurrent Net	63502	traingd	5	1	5	0.75	at least 5 of the last 10 are ictals	29	0.8715
Radial Basis Function	63502			29	15	0.65	single point	29	0.8408
Feed Forward Net	63502	trainlm		1	5	0.65	single point	29	0.8394
Layer Recurrent Net	92202	traingd	2	2	5	0.75	single point	15	0.8374
Radial Basis Function	63502			29	1	0.75	single point	15	0.837
Feed Forward Net	92202	traingd		2	5	0.7	single point	15	0.8367
Radial Basis Function	63502			29	8	0.75	single point	15	0.83

Analysing this results, we are able to conclude that the system performs well, and that, in the overall, the Layer Recurrent Net is the top contender.

4.3 GRAPHIC USER INTERFACE

A Graphic User Interface was developed, and therefore, additional configurations, can be obtained.

In this interface, the user can select the Network type, the learning function, the size and number of the hidden layers, the number of features/characteristics and the classification method.

The user can also select the input method and the percentage used for training.

4.4 OTHER DATA

Figure 5: Graphic User Interface

4.4 OTHER DATA

We have tested hundred of configurations. Due to that fact, we were not able to include all in this report. The results can be obtained by running the *run.mat* script. The 2014a version of Matlab is recommended, due to graphic acceleration support.

CONCLUSIONS

Given enough training cases and desired target outputs, a neural network can successfully classify the existence (or not) of a seizure with a very high degree of accuracy.

We couldn't help but notice that the neural network with the best results was a network that uses delay, which was a surprise due to the fact that we partially remove the correlation between different instants of time (the usual focus of this type of networks). We also noticed that there were great fluctuation in the classification and that the value of the threshold is determinant.

We can now create all sorts of simple, relatively fast and relatively accurate Classification Networks for any problem that already has desired outputs, whose possibilities are, for all intents and purposes, infinite.

SIMULATIONS

Due to the high number of simulations performed we show here only the summary of each test:

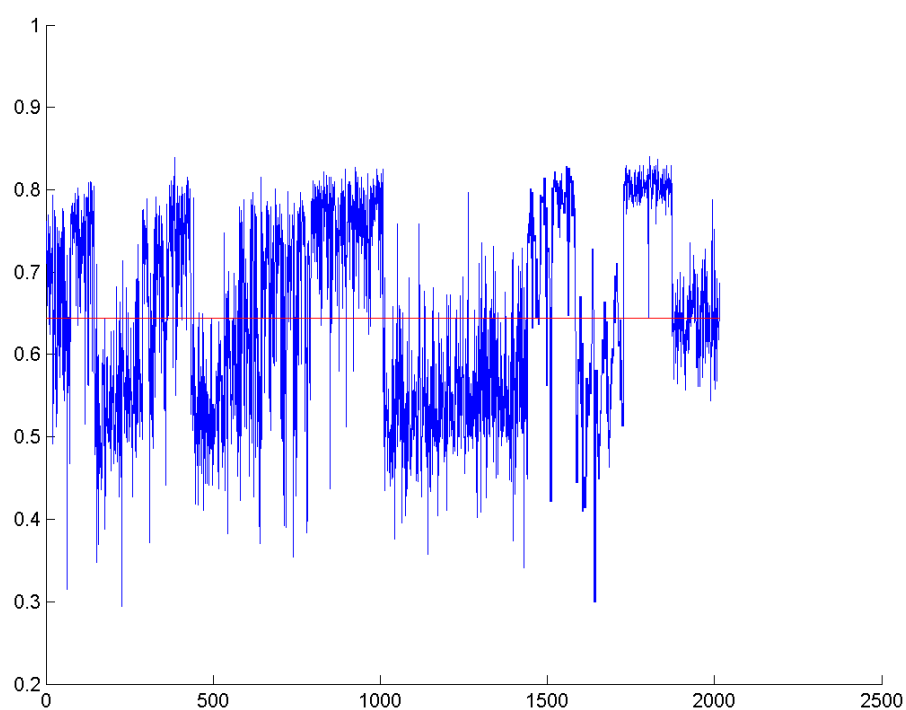


Figure 6: Accuracy/Run

SIMULATIONS

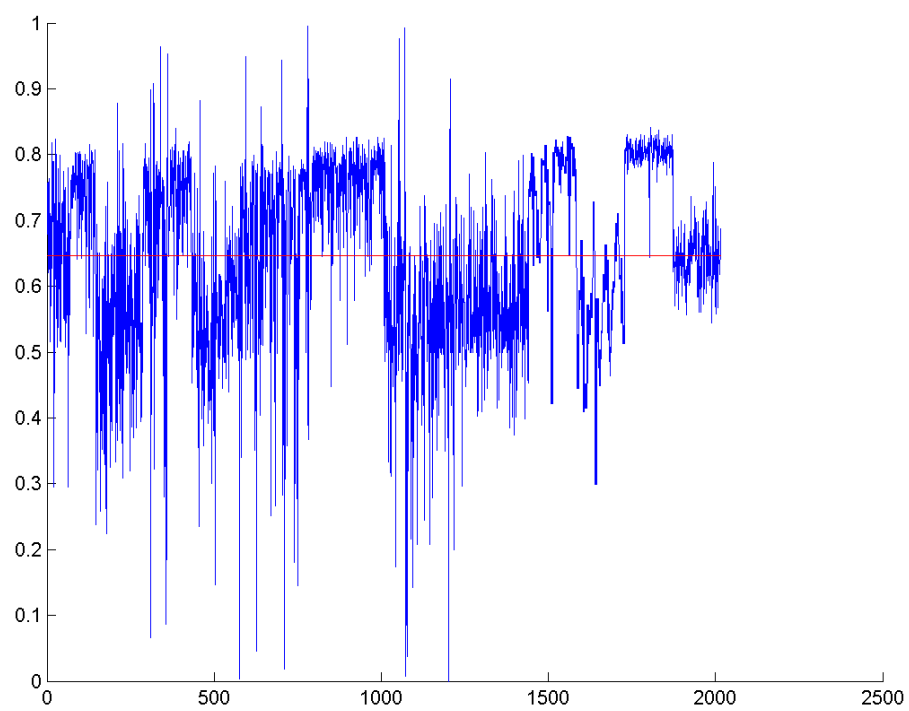


Figure 7: Specificity/Run

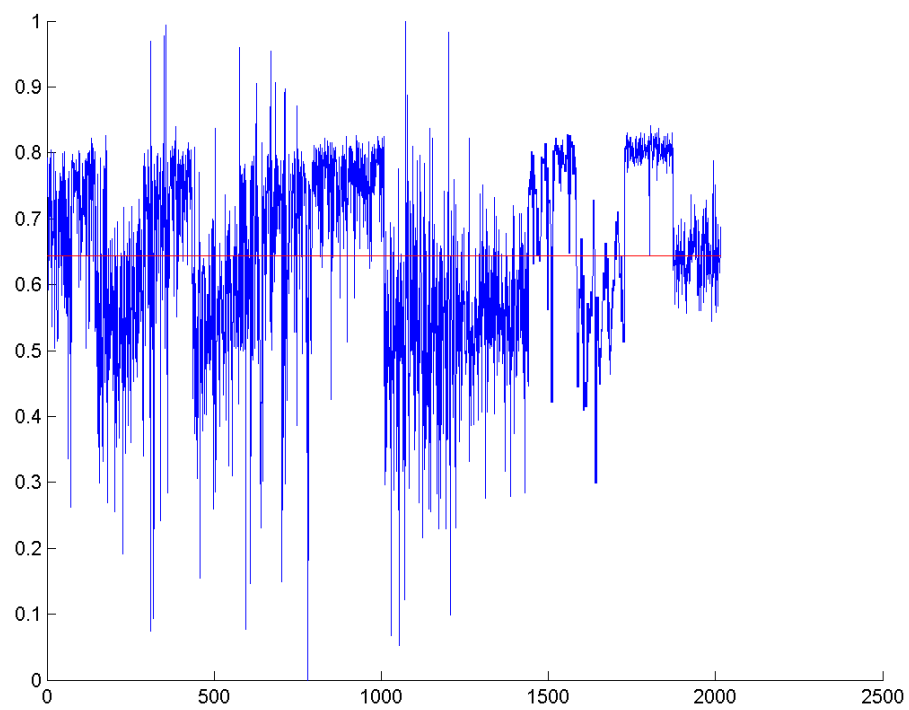


Figure 8: Sensitivity/Run