THE INVESTIGATION OF COMPLEX NEURAL NETWORK ON EPILEPTIFORM PATTERN CLASSIFICATION

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Abstract: This paper shows the behavior of the CMLP neural network, in recognition and classification of epileptiform patterns in EEG, in particular, dealing with spike and eye-blink patterns. Despite development of a number of approaches based on real neural networks to automatically detect epileptiform patterns [3], [9], [11], [12], these systems are still jeopardized by frequent false-positive detections, many times due to ocular movements [12]. The CMLP neural network presents interesting features in this application such as: (a) the learning speed is several times faster than in the RMLP [8]; (b) the space complexity is only about half of the real MLP [7];(c) comprehension of many mathematical objects is more substantial when they are considered in the complex plane, because part of its related information is fundamentally complex, such as the phase [6]. This work uses an EEG database, obtained at MNI (Montreal Neurological Institute). Three electroencephalographers marked the spike and blink events of the EEG signals. The approach has been validated with statistical parameters for sensitivity and specificity.

Introduction

Over the times, research has been carried out on the automatic detection of epileptogenic events with the object of helping in the diagnosis of epilepsy indicative patterns, in an attempt to diminish the revision times of the electroencephalogram registers (EEG) and facilitate visualization. The big difficulty is the complexity of the rhythms found in the EEG.

This work aims at contributing to this automation, verifying the validity of the complex networks in the recognition of epileptogenic patterns and supplying technology to the SIDAPE (Argoud [2]) project developed with the Biomedical Engineering Institute of the Universidade Federal de Santa Catarina (UFSC) [Federal University of Santa Catarina], which has as one of its main problems, the large number of FP (False-Positives) generated by ocular activity, especially eye-blinks.

We also intend, through this work, to minimize one of the critical aspects in the automatic detection of spikes which is that of the automatic differentiation between these epileptogenic patterns and ocular movement patterns.

Therefore, the main focus of this work is to implement the MLP network with complex backpropagation algorithm and confirm its efficiency in the recognition of epileptogenic patterns, that is to say, establish a complex more efficient than the real network in this task, Pereira[10].

Materials and methods

We utilized the complex MLP network in this work, where the complex backpropropagation algorithm was developed by Nitta [7] and is described by the equations (1) − (14).

$$Y_n = \sum_m W_{nm} X_m + V_n \qquad (1)$$

where, W_{nm} is the complex value of the weight of the neuron connection n and m. X_m is the complex value of the entry signal of the neuron m and V_n is the complex value of the threshold of the neuron n. To obtain the value of exit signal complex, one converts the activation value Y_m into real and imaginary parts, as in Equation (2):

$$Y_n = x + iy = z \qquad (2)$$

The exit function of each neuron is considered in Equation (3):

$$f_C(z) = f_R(x) + i f_R(y) \qquad (3)$$

The value of $f_R(u)$ is a sigmoidal function presented in Equation (4):

$$f_R(u) = \frac{1}{1+\exp(-u)} \qquad (4)$$

W_{ml} was used for the weight between the entry neuron l and the hidden layer m, $V_{nm,}$ for the weight between the hidden layer neuron m and the exit neuron

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n, θ_m, as the threshold of the hidden layer neuron m, and γ_n as the threshold of the exit neuron n, respectively. Being that I_l, H_m and O_n denote the value of the entry neuron l, of the hidden layer neuron m and of the exit neuron n, respectively. Being that, U_m and S_n also denote the potential inside of the hidden layer neuron m and of the exit neuron n, respectively. These terms are related in the Equations (5) to (8).

$$U_m = \sum\nolimits_l w_{mll} I_l + \theta_m \quad (5)$$

$$S_n = \sum\nolimits_m v_{nm} H_m + \gamma_n \quad (6)$$

$$H_m = f_C(U_m) \quad (7)$$

$$O_n = f_C(S_n) \quad (8)$$

The error between the actual pattern O_n and the target T_n of the exit neuron n is obtained by Equation (9).

$$\delta^n = T_n - O_n \quad (9)$$

One can define the quadratic error of a pattern p as per Equation (10):

$$E_p = \frac{1}{2}\sum\nolimits_{n-1}^{N} \left|T_n - O_n\right|^2 \quad (10)$$

where, N is the number of exit neurons.

The learning rule for the *backpropagation* algorithm with complex values and descriptions assuming a sufficiently small learning constant (learning speed) $\in > 0$ and the unitary matrix A. One demonstrated that the weights and the thresholds can be modified in accordance with the Equations (11) − (14).

$$\Delta v_{nm} = \bar{H}_m \, \Delta\gamma_n \quad (11)$$

$$\Delta\gamma_n = \varepsilon(\mathrm{Re}[\delta^n](1-\mathrm{Re}[O_n])\,\mathrm{Re}[O_n] + i\,\mathrm{Im}[\delta^n](1-\mathrm{Im}[O_n])\,\mathrm{Im}[O_n]) \quad (12)$$

$$\Delta w_{ml} = \bar{I}_l \Delta\theta_m \quad (13)$$

$$\begin{aligned}\Delta\theta_m &= \varepsilon[(1-\mathrm{Re}[H_m])\,\mathrm{Re}[H_m]\times \\ &\times\sum_n(\mathrm{Re}[\delta^n](1-\mathrm{Re}[O_n])\,\mathrm{Re}[O_n]\,\mathrm{Re}[v_{nm}]+ \\ &+\mathrm{Im}[\delta^n](1-\mathrm{Im}[O_n]\,\mathrm{Im}[O_n]\,\mathrm{Im}[v_{nm}])- \\ &-i(1-\mathrm{Im}[H_m])\,\mathrm{Im}[H_m]\times \\ &\times\sum_n(\mathrm{Re}[\delta^n](1-\mathrm{Re}[O_n])\,\mathrm{Re}[O_n]\,\mathrm{Im}[v_{nm}]- \\ &-\mathrm{Im}[\delta^n](1-\mathrm{Im}[O_n])\,\mathrm{Im}[O_n]\,\mathrm{Re}[v_{nm}])]\end{aligned} \quad (14)$$

The real MLP, utilized to compare the performances, was implemented through the backpropagation algorithm developed by Amari [1], which corresponds to the MLP which we know. This algorithm can be described following the rules for the up-dating of the *backpropagation real* algorithm, Equations (15)−(18).

$$\Delta v_{nm} = H_m \Delta\gamma_n \quad (15)$$

$$\Delta\gamma_n = \varepsilon(1-O_n)O_n\delta^n \quad (16)$$

$$\Delta w_{ml} = I_l \Delta\theta_m \quad (17)$$

$$\Delta\theta_m = (1-H_m)H_m \sum_n v_{nm}\Delta\gamma_n \quad (18)$$

where δ^n, I_l, H_m, O_n, v_{nm}, γ_n, w_{ml}, θ_m are all real numbers.

We utilize as an EEG data base, the data bank which was obtained in the MNI (Montreal Neurological Institute), of examinations of seven patients proven to be epileptics, on a long-term monitoring basis, where two of them underwent this same monitoring in two different moments. We can therefore consider that we have 9 groups of examinations, corresponding to seven patients.

The bank was sampled at 100Hz and was separated in files of 15s signals for each one. We made a random selection and separated 30 files of each patient in a total of 270 windows of 15s each. These files were submitted to evaluation by three electroencephalographers who carried out the reading of the events: spike and eye-blinks.

The topology utilized in the CMLP and RMLP networks was a three layer feedforward perceptron, (100-27-1).

We trained the networks with 120 signal epochs: 60 with spikes and 60 with eye-blinks. The tests were made with 600 signal epochs, different to the training signals, being that 300 were spike epochs and 300 eye-blinks.

For comparison reasons, the initial weights of the complex network, were saved for each training; in the training of the real networks, the real part of the complex weights was utilized, saved from the previous training.

The signals were pre-processed by FFT, in order to remove the sensibility of the network in relation to the position of the event in each signal extension.

To confirm the efficiency and effectiveness of the CMLP compared to RMLP, we applied the statistical sensitivity and specificity Equations (19) and (20).

Sensitivity = (PTx100)/(PT+FN) (19)

Specificity = (NTx100)/(NT+FP) (20)

where PT – positive truth ; NT – negative truth; FP – false positive; FN – false negative.

Results

The CMLP and RMLP networks were trained with values from the learning constant, varying from 0.1 to 0.6, with a stop criterion of 0.1 (Nitta [7]). The training signals were presented to the network in a random sequence, unlike those utilized in the tests.

Table 1 which shows the training behavior, confirms the convergence capacity and the learning speed of the complex network in relation the real one, Nitta[7]. In this table the training numbers 0-6 correspond to the CMLP network and 7-12 to the RMLP network. In the table, CP – corresponds to the (critério de para) (stop criterion) (average quadratic error), CT – (número de ciclos de treinamento) (number of training cycles), **ε** – learning constant and FA – (função de ativação) (activation function), NC – (não houve convergência) (no convergence).

Table 1: Behavior of the networks during the definite training. The training of 1 to 6 corresponds to the CMLP and 7 to 12, to RMLP

Training	CP	ε	CT	FA
1	0.1	0.1	28,541	Sigmoidal
2	0.1	0.2	5,944	Sigmoidal
3	0.1	0.3	3,388	Sigmoidal
4	0.1	0.4	3,869	Sigmoidal
5	0.1	0.5	NC	Sigmoidal
6	0.1	0.6	NC	Sigmoidal
7	0.1	0.1	36,231	Sigmoidal
8	0.1	0.2	15,873	Sigmoidal
9	0.1	0.3	10,582	Sigmoidal
10	0.1	0.4	7,838	Sigmoidal
11	0.1	0.5	6,509	Sigmoidal
12	0.1	0.6	5,525	Sigmoidal

Table 2 illustrates the results of the tests with the networks which converged during the training and shows the identification capacity of the presence or not of the determined event, spike or eye-blink, at entry, graphs 1 and 2, according to Nita (*apud* Pereira[10]).

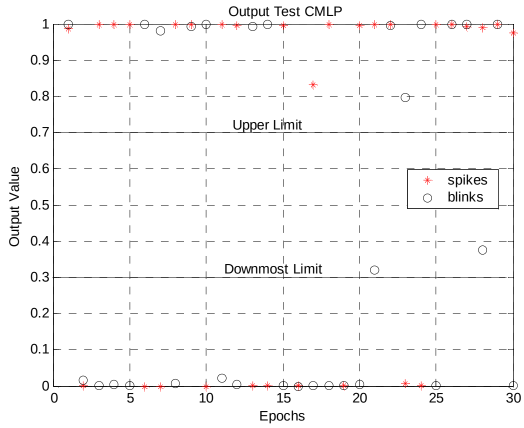
Abbreviations

MLP – Mulilayer Perceptron;
CMLP – Mulilayer Perceptron with complex backpropagation algorithm;
RMLP – Multilayer Perceptron with real backpropagation algorithm;
BP – Backpropagation;
EEG – Electroencephalogram;

Table 2: Performance of the complex and real networks for each training constant applied

Tests of 600 epochs	Sensitivity	Specificity	ε
CMLP	53.00%	60.00%	0.1
	51.00%	54.66%	0.2
	63.00%	46.00%	0.3
	66.00%	46.00%	0.4
	NC	NC	0.5
	NC	NC	0.6
RMLP	53.33%	53.33%	0.1
	53.33%	53.33%	0.2
	53.33%	53.33%	0.3
	53.33%	53.33%	0.4
	53.33%	53.33%	0.5
	53.33%	53.33%	0.6

Graph 1 represents one of the exits of the CMLP test and graph 2 represents one of the exits of the RMLP test. The lower and upper constant lines in each graph represent the positive detection thresholds for eye-blinks and spikes respectively. An eye-blink event which generates a test exit value larger than 0.7, characterizes a false positive detection. On the other hand, a spike event which produces a test exit value less than 0.3, characterizes the presence of a false negative.



Graph 1: CMLP test exit with 30 epochs containing spikes and 30 containing eye-blinks. Network exit values less than 0.3 represent eye-blinks and values above 0.7, spikes. The patterns in black are the eye-blinks and the red, spikes.

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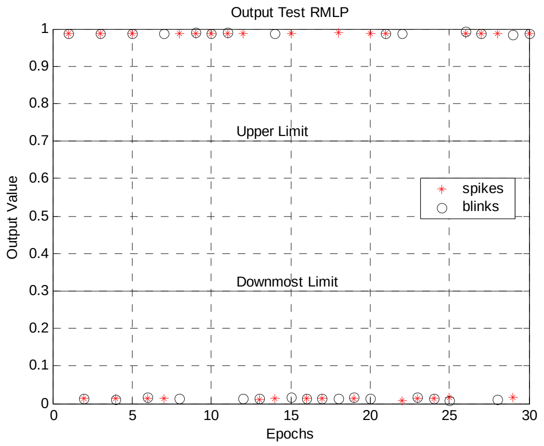

Graph 2: RMLP test exit with 30 epochs containing spikes and 30 containing eye-blinks. Network exit values less than 0.3 represent eye-blinks and values above, spikes. The patterns in black are the eye-blinks and the red, spikes.

Conclusions

By observing the results obtained for the definite training (Table 2) we were able to conclude that the complex networks are more effective and efficient with regard to the differentiation between spikes and eye-blinks, taking into consideration the training carried out with the learning constant **ε** of 0.1, which corresponds to the best performance obtained during the training. The graphs 1 and 2 also enable us to see the more efficient separation of the CMLP in relation to RMLP. Graph 1 (CMLP) shows a clearer separation between spikes and eye-blinks, according to Nitta (*apud* Pereira [10]), we could observe that 57% of the eye-blinks and 67% of the spikes were classified correctly, whilst 43% of the eye-blinks were classified as spikes and 33% of the spikes were classified as eye-blinks. In graph 2, the epileptiform events coincide with the eye-blinks more frequently, which proves the separation between the events, since they present the same exit value. We were able to observe in this graph that 53% of the eye-blinks and 53% of the spikes were correctly classified whilst 47% of the eye-blinks were classified as spikes and 47% of the spikes as eye-blinks.

We can deduce from the results obtained for CMLP in relation to RMLP, that the complex information which is usually not considered, makes the difference to produce more precise results (Hirose [4]).

We noted that the spikes and eye-blinks which are difficult automatic differentiation patterns in the domination of real numbers can be better separated using the CMLP, table 2, according to Nitta (*apud* Pereira [10]).

CMLP also needed a considerably lower number of training cycles during the learning (between 30% and 230% fewer cycles) when compared to RMLP (Nitta [7])

These results suggest that the introduction of complex information, that is to say, phase and amplitude of parameters which define a neural network, is appropriate and can improve the performance of same (Nitta [7]).

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