ART NEURAL NETWORKS FOR BRAIN PATHOLOGY DIAGNOSIS

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Abstract: The present paper is devoted to the questions of the electroencephalograms (EEG) classification. The main objective of the work is ART Neural Network method as applied to the EEG clustering. The first section reviews the problem of epilepsy diagnostics. Then the algorithm based on the *ART* model is described. Adaptive Resonance Theory (*ART*1) Neural Networks for fast, stable learning and prediction have been applied in a variety of areas. Applications include automatic target recognition, medical diagnosis. The paper describes *ART*1 model for recognition EEG patterns while diagnosing brain diseases.
Keywords: ART1 Neural Network model, cluster algorithm, recognition, electroencephalograms, epilepsy.

INTRODUCTION

Epilepsy is a brain disease. According to Karlov [1], attributes of epilepsy can be divided into two initial groups - clinical and electroencephalogical ones. The paper covers exploring EEG patterns. Following Povorotinskii [2] neuron activity displayed on EEG records is caused by various reasons. That's why the analysis was limited to two general classes: "normal class" and "pathological one". There is no precise definition of healthy human EEG patterns. However, physicians use the parameters [2] in practical clinic activity. Frequency component is defined by rhythm index:

$$I_r = \frac{T_{r1}}{T_{EEG}} * 100\%, \quad (1)$$

where I_r - rhythm index, T_{r1} - time interval of certain rhythm, T_{EEG} - EEG recording time.

In the present study the *ART*1 Neural Network algorithm is proposed for EEG clustering [4]. The procedure of recognition is based on *ART*1 Neural Network with two neuron layers. They consist of fully connected units and classify α-rhythm and β-rhythm. The *ART*1 model takes binary (0/1) input. In medical diagnostic systems absence of syndrome is 0, and presence of syndrome is 1. The most often used descriptive parameters for α-rhythm are presented in Table 1 as binary vector.

ART NEURAL NETWORKS MODEL

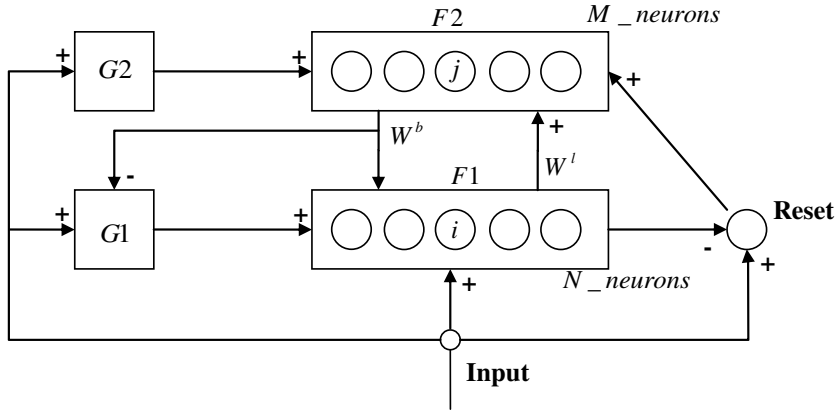

Fig. 1. The $ART1$ Neural Network Model.

The $ART1$ model consists of two neurons layers [4,5]. The neurons are binary ones (with values 1 and 0). The comparison layer is $F1$ and the recognition one is $F2$. Each $F1$ neuron is connected to all neurons in $F2$ via vector W^f and vice versa via the binary valued W^b. Gain $G2$ is the logical OR module.

The $ART1$ learning algorithm:

1. Initialization:

$$w_{ji}^b(0) = 1$$
$$w_{ji}^f(0) = \frac{1}{1+N}, \quad (2)\ 0 \le i < N; 0 \le j < M; 0 \le \rho \le 1$$

where N is the number of neurons in $F1$, M the number of neurons in $F2$, ρ - the vigilance threshold.

2. Apply the new input pattern X.

3. Compute the activation values Y' of the neurons in $F2$:

$$y_i' = \sum_{j=1}^{N} w_{ij}^f(t) x_i; (3)$$

4. Select the winning neuron $k, (0 \le k < M)$;

5. Vigilance test: if

$$\frac{W_k^b(t) \cdot X}{X \cdot X} > \rho, (4)$$

where multiplication denotes inner product, go to step 7, else go step 6. Note that $W_k^b \cdot X$ is essentially the inner product $X^* \cdot X$, which will be large if X^* and X are near to each other;

6. Neuron k is disabled from further activity. Go to step 3;

7. Set for all $l, 0 \le l < N$:

$$w_{kl}^{b}(t+1) = w_{kl}^{b}(t)x_l,$$
$$w_{kl}^{f}(t+1) = \frac{w_{kl}^{b}(t)x_l}{\frac{1}{2} + \sum_{i=1}^{N} w_{ki}^{b}(t)x_i}; \quad (5)$$

8. Re-enable all neurons in and go to step 2.

ALGORITHM FOR PATHOLOGY EEG RECORDS RECOGNITION

It is considered that the following algorithm can be applied for the initial EEG clustering. The initial data are shown in the Table 1 [3].

Table 1. Vectors X for learning procedure of $ART1$ neural network (α – rhythm).

i	Description of pattern ("yes" – 1, "no" - 0)	x_i	
		Normal	Pathological
1	α – rhythm predominates in the back of the head fields;	1	0
2	α – rhythm lowers by amplitude;	1	0
3	The α – rhythm is sinusoidal	1	0
4	Frequency oscillations – 0.5 Hz;	1	0
5	Amplitude between 30..40 μV (40..60 μV);	1	0
6	Index I_r - 75..95%	1	0
7	Stable α – rhythm ($I_r > 50\%$)	0	1
8	Amplitude asymmetry – more 30%;	0	1
9	Frequency asymmetry – more 1 Hz;	0	1
10	Frequency stable missed;	0	1
11	Lowering of amplitude less then 20 μV or increase more then 90 μV ;	0	1
12	Lowering of index I_r less than 50%.	0	1

Step 1: Describe dictionary of classes and their attributes (vector X). For example, cluster w_1 - "Normal electroencephalograph activity", w_2 -"additional diagnostics".

Step 2: Compose input learning vectors both for the α -rhythm and the β -rhythm.

Step 3: Learn $ART1$ Neural Network.

Step 4: Read patterns description from database and initialize input vector for clustering.

Step 5: Compare this vector to solving functions - formula (5).

Step 6: Save or print results of classification.

RESEARCH PERSPECTIVES AND RESULTS

This algorithm is supposed to be effective for the practical clinical use. In [1] the authors describe the most complete set of typical epilepsy attributes. The *ART*1 model can create new categories and reject an input pattern when the network reaches its capacity. However, the number of classes discovered in the input data by *ART*1 depends to the vigilance parameter.

The advantage of the *ART*1 model is its ability to create new classes from the input vector. The drawback of the model is that it can corrupt the weights for all previously learned patterns while teaching a new class.

The realization of the *ART*1 model may be a software system, its base class representing a neuron. The objects of the Neuron class will be included into the main *ART*1 Neural Network class. The set of pathological EEG patterns is limited. That's why the program will contain two objects of the *ART*1 class (in terms of the Object Oriented Programming - OOP). The first object will store α-rhythm pathological patterns and the second - β-rhythm ones. By means of such program architecture the stability/plasticity dilemma [4] will be solved.

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