HYSTERETIC ARTIFICIAL NEURAL NETWORK FOR EEG DATA REPRESENTATION

Carmen Grigoaş[*, **] and Anca Lazăr[*]

[*]University of Medicine and Pharmacy "Gr. T. Popa" Iaşi, Romania
Faculty of Medical Bioengineering, Dpt. of Informatics and Medical Electronic
[**]Romanian Academy-Iasi Branch, Inst. for Theoretical Informatics, Iaşi, Romania

crmn_g@yahoo.com, ancam_2002@yahoo.com

Abstract: This paper aims to present a tool to express biosignals through patterns. To accomplish this we propose a hysteretic neural network architecture to extract knowledge from EEG time-series, useful in EEG signals representation for classification and decision. This approach may be interesting for brain computer interfaces, as a technique for data preprocessing for real time response tasks. The proposed architecture and training strategy is described in detail. This new architecture allows the use of a relatively small nonlinear network to produce similar performances as other larger ones cited in literature to be used for the same purposes. Simulation results reflect the applicability to brain computer interface of this type of artificial neural network signal processing tool.

Introduction

Real-time brain-computer interface (BCI) systems involve analysis of bio-signals to drive the activities of a computer, most of the tasks being mainly related to the classification problem. This problem is, in turn, linked to that of pattern extraction from raw electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), galvanic skin response (GSR), electrocardiogram (ECG) data, eventually integrated with functional magnetic resonance imagery (fMRI), in order to represent specific mental activities or to locate targets.

Some approaches concern mu waves of the EEG analysis. These recordings are usually associated with the motor cortex. They are diminished in amplitude with movement or the intention to move. An approach to identify an attempt to move may explore the characteristics of this rhythm. Some linear methods were devoted to analyze them ([18]). The open problem is that of discriminating between different movement tendencies.

Other approaches involve pattern recognition algorithms in the attempt to detect signature patterns of EEG activity which correspond to volitional behaviors. The eventual aim is to develop a vocabulary of EEG signals that are recognizable by the computer. The correlation of EEG with EMG or EOG offers the possibility of the creation of a thought pattern vocabulary. The implementation of this attempt with artificial neural networks is a promising technique, but the training period may be laborious in order to obtain a high percentage of accuracy in matching particular thoughts with brain wave patterns.

Different artificial neural network (ANN) architectures may be involved in extracting patterns from biological signals (J. Principe group [14], G. Pfurtscheller group [9], C. Anderson [8], S.J. Roberts [11], [12]).

This paper focuses on the EEG data representation with hysteretic ANN. There are two main types of hysteretic ANN-s: those which develop hysteresis in their behavior, although they are not compound of processing elements with explicit hysteretic nonlinearity, and those called "hysteresis neural networks" by some authors, including K. Jin'no [6], made up of processing elements with explicit hysteretic nonlinearity, usually binary hysteresis. We address to both of these types of networks in the present paper, using the generic name of "hysteretic artificial neural networks" (HANNs). The main contribution of the paper is to make a connection between three items:

- the concept of pattern language,
- recurrent hysteretic ANN dynamics representation capacities,
- solving the problem of expressing thoughts through EEG data readings means.

In the following section of this paper we summarize the concept of pattern language, in the attempt to link it with our contribution, hysteretic neural networks representations. The third section is dedicated to the presentation of the conceptual framework of our approach. In the forth section of the paper the current realization of the hysteretic network is described. This article closes in the fifth section with conclusion and outlook to further work.

Pattern language

One of the definitions of the pattern language ([7]) states that it is a structured collection of patterns that build on each other to transform reality into pattern architecture. The patterns are related through rules to

 ISSN: 1727-1983

problems solutions. Rules may be encoded in circuit connections which rand a particular sequence of patterns. This can be done with artificial neural network type systems, for instance. The goal of a pattern language is to use pattern forms to capture the essential insight of a problem embedded in a specific environment, so that others may make use of it in similar situations.

There are many definitions for patterns. One of them ([19]) states that “a pattern is the abstraction from a concrete form which keeps recurring in specific non-arbitrary contexts”. We may say that redundant data resulting from a specific environment, in a specific situation, embed a certain piece of information. We wish to extract it and encode it in an abstract form, dependant on the tool chosen for encoding. Such abstractions may serve to a better election of actions, following a certain classification process.

Relative to signal processing, we would like to have a special vocabulary for expressing common characteristics, and a language for relating them together. In the ANN’s world the language is related to the parameters of the network which perform a specific processing task. Codifying the solution of a problem with patterns and their relationships permits to capture the body of knowledge which defines our understanding of the appropriate tools to meet the needs of that problem. As an element of language, a pattern shows how this spatial configuration can be used, over and over again, to resolve the given system of forces, wherever the context makes it relevant.

Recurrent neural networks are synergetic devices, usually with a convergent behavior to a steady attractor. In this case it may be associated with a pattern or with a sequence of patterns.

Hysteretic neural network architecture

Many cooperative dynamical systems manifest hysteresis. Hysteretic behavior was observed at animals, as well as humans, being mostly related to the activity of the central nervous system [2], [20]. Transitions between movements, during locomotion, or cyclic lumbar flexion, exhibit hysteresis [1], [16]. Hysteretic behavior was also related to the selective attention, which, in turn, is linked with the input unsupervised preprocessing by the neural network and with the quality of the associative memory [6].

Hysteretic processing may be used to extract the increasing or decreasing parts of the input signals, for their independent processing [3]. Some second order recurrent artificial neural networks (RANNs) were proved to have intrinsic hysteretic behavior, if they have a sufficiently large positive feedback, independent of the monotony or non-monotony of their nonlinearity [17], [15]. A general form of the system of equations describing the dynamics of the recurrent neural structure with hysteretic behavior is given below:

$$\frac{dx}{dt} = -Dx(t) + Ey(t); \quad x \in \Re^n; D, E \in \Re^{n \times n} \qquad (1)$$

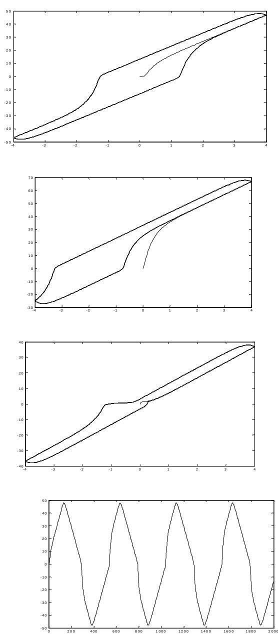
$$\frac{dy(t)}{dt} = Av(t) + Bu + I; \quad u \in \Re^p; I, y \in \Re^n$$
$$A \in \Re^{n \times n}, B \in \Re^{n \times p} \qquad (2)$$

$$(t) = f(z); \quad f : \Re^n \to \Re^n \qquad (3)$$

$$z(t) = Cx(t) + Hy(t); \quad C, H \in \Re^{n \times n} \qquad (4)$$

All the other forms of equations describing RANNs with hysteresis are special cases of these ones (see [6] and [20] for instance).

Matrix B is responsible of the link with the environment, weighting the external control and I is the offsets vector, while A is the interconnection matrix, reflecting the feedback in the network. No matter the form of f is, $z(t)$ will have a monotonic or non-monotonic variation, depending on the positive values of the elements of C and H. Variable $x(t)$ will develop hysteresis because of its dependence on $y(t)$, and so, on $v(t)$. An example can be seen in figure 1. Equation (4) models the linear restriction upon the feedback, also responsible for the hysteresis effect. The hysteresis is showing when the components containing reactions became positive. It is also connected to the existence of more then one equilibrium points, for which distinct branches of stabile state variation are identified, which may be controlled by changes in the values of different parameters of the system ([4]).



(a)

(a’)

(b)

(c)

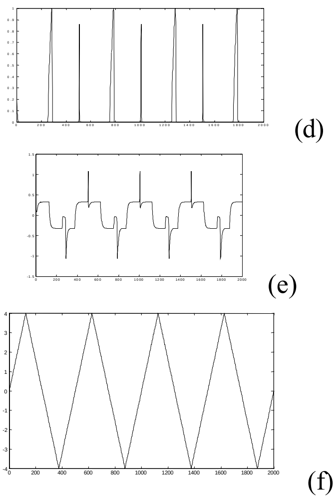


Figure 1: Hysteresis for x varying on behalf of v, resulted from equations (1), with (a) $f(z)$ = th(z) and (b) $f(z)$= exp(-z.*z); The input-output characteristics for I =0 (a), (a'), and for I = 2 (b); (c) x variation through time; (d) the coresponding y variation through time; (e) the derivative of one of the state variables for the (a') behavior; (f) excitation u

Figure 2 represents the block diagram for the implementation of equations (1)-(4). The nonlinearity f had been chosen to be a sigmoid of the type hyperbolic tangent, for the results depicted in figure 1.

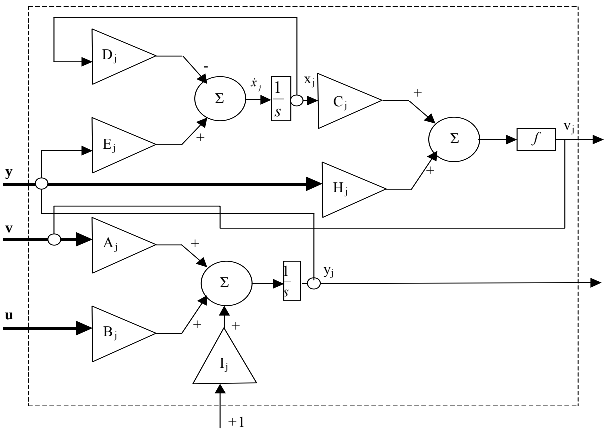


Figure 2: The block diagrame of a hysteretic oscilator

Recurrent networks perform associative memory, in form of stable states or stable limit cycles. This may be seen as an association between several forms presented at the input and a converging behavior resulted at the output of the network. When we have a network of hysterons (processing elements exhibiting hysteresis), the adaptation of the network can be done through the lateral connections (A in (2)) or through the control ones (B in (2)), or both.
The most frequent used models of artificial neural networks with hystertic behavior are the "hysteresis" ones. In this way the order of the network depicted in (1) – (4) is reduced to one, so the network is easily to design. A simple network with binary hysteresis, with only one variable parameter for each processing element was described in [6]. More general network equations are:

$$\begin{aligned} \frac{dx_j}{dt} &= -d_j x_j + \sum_{i=1}^{n} a_{ji} y_i + \sum_{k=1}^{p} b_{jk} u_k, \; j = \overline{1,n} \\ y_j &= f(x_j) = \begin{cases} 1, & x_j \geq L \\ 0, & x_j \leq R \end{cases} \end{aligned} \tag{5}$$

The parameters notation was conserved from the previous equations. In figure 3 a binary hysteresis neural network Simulink implementation is presented.

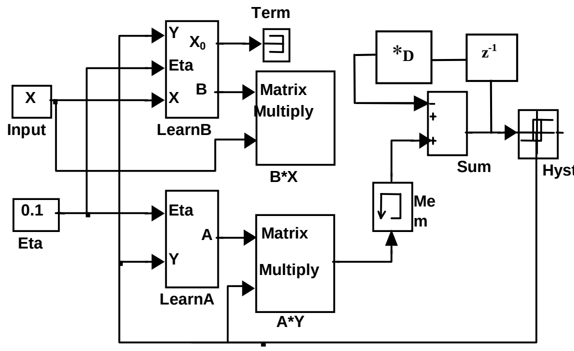


Figure 3: The hidden layer with binary hysteresis processing elements

Whatever the implementation of the hysteron is we are interested in the job it does in extracting features from EEG signals presented at its input. The adaptation algorithm is of Hebb type (Sanger algorithm) for principal component analysis (PCA), for the B weights:

$$b_j(t+1) = b_j(t) + \eta\left(y_j(t)x(t) - y_j^2(t)b_j(t)\right) \tag{6}$$

For the lateral connections of the hysteretic layer of the neural network an anti-Hebbian type of learning is considered:

$$\begin{aligned} a_j(t+1) &= a_j(t) - \eta(y_j(t)y_{j-1}(t) + y_j^2(t)a_j(t)) \\ y_{j-1}(t) &= \left[y_0(t) \quad y_1(t) \quad \cdots \quad y_{j-1}(t)\right]^T \\ y_j(t) &= f\left(b_j^T(t)x(t) + a_j^T(t)y_{j-1}(t)\right) \end{aligned} \tag{7}$$

The Simulink implementation of the learning algorithm (7) is presented in figure 7. Because of the nonlinearity considered, this layer tends to extract higher-order statistics of the input space. The $a_j(t)$ vectors shown a rapid convergence to 0 for proper choices of the learning parameters and initial conditions, as shown in figure 8. Moreover, the input projections obtained at the output of the hysteretic layer tend to be as uncorrelated with each other as possible, taking in consideration that the eigenvectors approximated by the hysteretic layer are not orthogonal, providing the basis for a better discrimination in an eventual following supervised classifier (figure 4). Only stable output vectors correspond to an important piece of information (solution of the nonlinear PCA problem). Stability of hysteretic neural networks was analyzed respectively in [17] and [6]. This paper aims to apply such kind of networks to EEG preprocessing.

Results

We have used EEG data from Purdue University, available from Internet, to test our particular methods of signal representation and classification. This approach allow us the verification of the method, comparing our results to those obtained at Purdue University and Colostate University [7], where these data were also used to test other representation algorithms. Data are presented to the Simulink implementation of the hysteresis ANN in the form of data sequences of 6x2500 dimension each. Data are labeled, so we are able to train the network to classify groups of signals, belonging to the same label. The hidden layer of the network depicted in figure 4 is a hysteretic one, with the parameters trained in an unsupervised manner, as mentioned in the previous section. The entire network has a hybrid training, which includes supervision on the output layer. The 6 rows of EEG data correspond to channels c3, c4, p3, p4, o1, o2, defined by the 10-20 system of electrode placement described in [8]. The 2500 samples of data correspond to a 10 seconds recording of 250 Hz sampling rate. The training strategy consisted in presenting packages of 10 fragments (corresponding to trials) per tested subjects, 5 subjects per epoch, two tasks to be classified and one rejection group of 10 fragments of 10s EEG recordings. There were 275 000 samples of 6 characteristics each of data per epoch, repeatedly presented to the network until convergence, which was reached after about $5x10^8$ samples, which seem to be a good result, compared to those presented in [7] and [8]. The network used to represent the EEG data is depicted in fig. 3 and 4. There were used two types of hysteretic processing element, one with rectangular type hysteresis nonlinearity and another with a functional hysteresis, as that depicted in figure 2. The representation layer of the network (hidden layer) consisted in 3 to 5 sub diagonal connected neurons. The output supervised layer may be added for classification purpose, the number of neurons being correlated with the number of classes to discriminate. Although the activity differs greatly from one patient to the next, and even within recordings from the same patient, all of them do seem to follow a general pattern that characterizes the particular activity. This is reflected in figure 6.

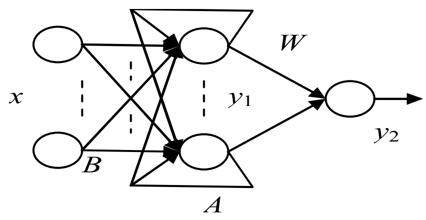


Figure 4: The block diagram of the classification network

$$
\begin{aligned}
y_1(t) &= f(Bx(t) + Ay_1(t) + I_1) \\
y_2(t) &= Wy_1(t) + I_2
\end{aligned}
\tag{8}
$$

In equations (8) f reflects the hysteretic behavior of elements y_1. The network is trained to produce a pattern to express the mental activity embedded in the corresponding fragments of EEG recordings. Such patterns may be used as vocabulary for EEG understanding by a specialized device in a classification task.

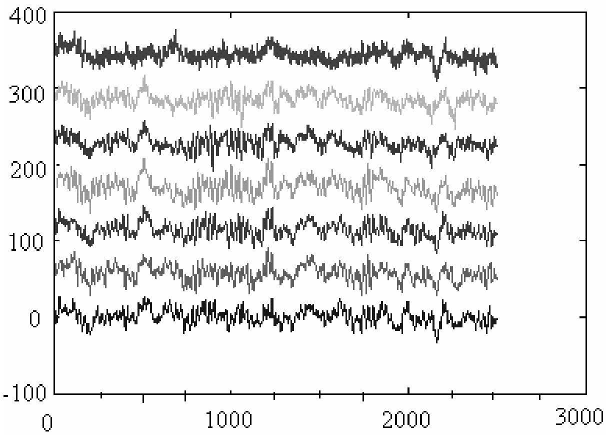


Figure 5: EEG waveforms from the 6 channels, from one subjects, performing a mental task

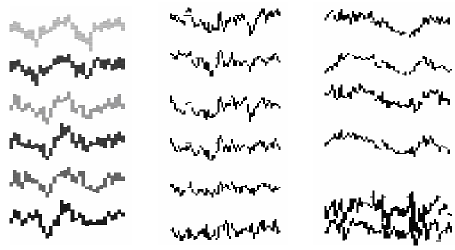


Figure 6: Fragments of ½ s correlated with different mental activities.

Discussion

The primary purpose of this experiment was to explore the possibility of a hysteresis neural network to extract pattern from fragmens of EEG recordings correlated with particular mental activities. Its usability is seen in the field of brain computer interface research, as well as in that of pattern language. The special

ISSN: 1727-1983 © 2005 IFMBE

nonlinearity used in the processing elements architecture presented a good performance for the task of pattern extraction, especially the one with smooth slope of nonlinearity. Further work is needed to evaluate the classification performance based on these patterns.

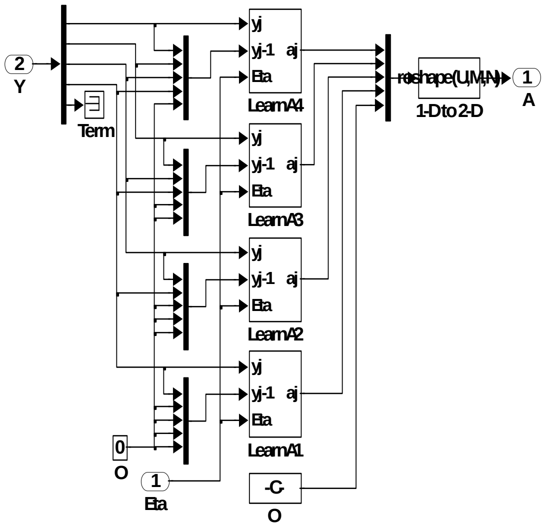


Figure 7: Block diagram of the learning algorithm for the lateral connections

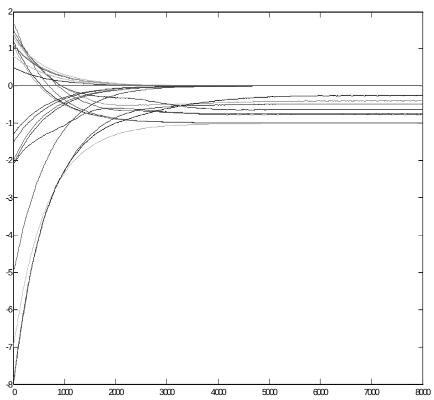


Figure 8: Dynamics of A weights

References

[1] ALEXANDER, R. M. (1989): 'Optimization and gaits in the locomotion of vertebrates", *Physics review*, **69**, pp.1199-1227.

[2] DIDDAY, R. L. (1976): 'A model of visuomotor mechanisms in the frog optic tectum', *Mathematical Biosciences*, **30**, pp. 169-180.

[3] GORAS, L. et al. (1998): 'On the Posibilities of Using Hysteretic Elements in Signal Processing', *Proc. NDES'98*, Budapest, Hungary, pp. 234-238

[4] GRIGORAȘ, C. (2004): 'Hysteresis Neural Networks for Dynamic Representation in Mechanical Systems', *Buletinul Institutului Politehnic Iași, section I Mathematics-Theoretical Mechanics -Physic*, tom L(LIV), fasc.3-4, pp. 59-78

[5] INDIVIERI, G. (2001): ' A neuromorphic VLSI device for implementing 2-D selective attention systems', *IEEE Transactions on Neural Networks*, **12**(6), pp. 1455-1463.

[6] JIN'NO, K. AND SAITO, T. (1993): 'Analysis of a simple hystertesis network and its application for an effective associative memory', *IEEE Transactions on Neural Networks*, **4**, pp. 2172-2175

[7] KARHUNEN, J. AND JOUTSENSALO, J. (1995): 'Generalisation of PCA, optimisation problems and neural networks', *Neural Networks*, **8**(4)

[8] KIRBY, M. AND ANDERSON, C.W. (2003): 'Geometric Analysis for the Characterization of Nonstationary Time-Series'. In: E. Kaplan, J. Marsden and K.R. Sreenivasan (Eds.): *Springer Applied Mathematical Sciences Series Celebratory Volume for the Occasion of the 70th Birthday of Larry Sirovich*, Springer-Verlag, pp. 263-292.

[9] OBERMAIER, B. et al. (2001): 'Hidden Markov Models for online classification of single trial EEG Data'. *Pattern recognition letters*, **22**, pp. 1299-1309.

[10] OROSZ. E. (1994): 'Classification of EEG Signals Using a Sparse Polynomial Builder', Technical Report 94-111, *Computer Science*, Colorado State University

[11] PENNY, W. AND ROBERTS, S. (1997): 'Bayesian Neural Networks for Detection of Imagined Finger Movement from single-trial EEG', Technical report, Dept. of Electrical and Electronic Eng., Imperial College

[12] REZEK, I. AND ROBERTS, S. J. (2004): 'Ensemble Hidden Markov Models with Extended Observation Densities for Biosignal Analysis', In D. Husmeier, R. Dybowski, and S. Roberts (Eds.): *Probabilistic Modelling in Biomedicine and Medical Bioinformatics*, Springer Verlag, 2004.

[13] ROBERTS, S.J. et al. (1997): 'Temporal and Spatial Complexity Measures for EEG-based Brain-Computer Interfacing', *Medical and Biological Engineering and Computing*, 37[1], pp. 93-99

[14] SANCHEZ, J. C. et al. (2003): 'Ascertaining the Importance of Neurons to Develop Better Brain Machine Interfaces', *IEEE Transactions on Biomedical Engineering*, **61**, pp. 943-953.

[15] SLAVOVA, A. (1998): 'Generalisation of CNN with hysteresis nonlinearity', *Proc. of 5th Int. Workshop on CNNs and their Applications*, London, UK

[16] SOLOMONOW, M. et al. (2001): 'Neuromuscular neutral zones associated with viscoelastic hysteresis during cyclic lumbar flexion', *Spine E*, **26** (14), pp. 314-324.

[17] VISINTIN, A. (1994): 'Differential Models of Hysteresis', Springer-Verlag

[18] WOLPAW, J.R. et al. (2003): 'The Wadsworth Center Brain-Computer Interface (BCI) Research and Development Program', *IEEE Transactions on Neural Systems & Rehabilitation Engineering*, **11**, pp. 204-207.

[19] WALPAW, J.R. AND MCFARLAND, D.J. (1994): 'Multichannel EEG-based Brain–Computer Communication', *Electro-ecephalography and Clinical Neurophysiology*, **90**, pp. 444-449

[20] WANG, D. L. AND BROWN, G. J. (1999): 'Separation of speech from interfering sounds based on oscillatory correlation', *IEEE Transactions on Neural Networks*, **10**(3), pp. 684-697.

ISSN: 1727-1983