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# USEFULNESS OF EEG DATA SIGNAL PROCESSING EMPLOYING WAVELET TRANSFORM IN DATA SIGNAL PROCESSING OF BIO MEDICALS

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## 1 INTRODUCTION

In this study, adaptive resonance theory (ART 2) neural networks are investigated for on-line unsupervised recognition (spikes for epilepsy monitoring) and also epileptical seizures are generated from output nodes of the network. ART 2 networks are self-organizing systems that cluster data into different classes. Learning is completed when these categories are labeled by an expert and are saved in a look-up table. Recognition of new data is accomplished by finding the class assigned by ART 2 and searching through the table to get the proper labels. Unrecognized inputs are put into a new class for future labeling. In this study, an ART 2 neural network with 32 inputs was developed and trained using EEG data containing spike and non-spike waveforms. For comparison, a 32 input multilayer perceptron is also constructed and evaluated.Evaluation with three sets of EEG patterns indicates that the ART 2 Neural Network's performance is better than that of multilayer perceptron showing its high potential. Considering that ART 2 can be trained with one or few iteration (compared to thousands required for back propagation networks). Hence, this can be used for online training. Such systems are necessary for long-term EEG monitoring due to significant variations of spike waveforms that occur among individual patients during long recording time periods.

Many researchers' tasks include the recognition and generation of abnormal electrical wave patterns. Traditional algorithmic methods are insufficient to characterize epilepsy seizure. Medical diagnosis is one of the prime examples of this problem. Although many expert systems or so-called “intelligent" devices have been developed using traditional Artificial Intelligence (AI) approaches. Intelligent systems are developed using symbol and rule-based AI techniques. In essence, traditional AI requires the existence of a domain expert who knows the answer to many questions and can specify the rules to a knowledge engineer. This is, however, hardly the case in medicine since most of our knowledge is incomplete. This research focuses on the problem of epileptical EEG spike detection for the diagnosis and to construct an ART memory to evaluate epilepsy. Although many rules are proposed for the detection of spikes (e.g. width, amplitude, sharpness, etc.), they are not up to the satisfaction. Many EEG technicians are not aware of these rules consciously, yet they can identify spikes in ongoing EEG easily and accurately. Humans learn to recognize EEG spikes by seeing a number of such waveforms and generalizing their characteristics. Better results can be expected if a natural learning strategy is used by humans and adapted to machines. Multilayer perceptron trained with back propagation (BP) are the best known and most utilized NN models. Pattern recognition and classification by neural networks have several major advantages over traditional methods. Neural networks use massively parallel, non-algorithmic processing which is in some ways similar to those employed by the human brain. As a result, many competing hypotheses have been explored simultaneously. Neural networks store the patterns presented to them by modifying their states. Pattern elements are not memorized individually. Hence,scores of complex patterns may be retained. Neural networks have other advantages over current traditional systems that they are fault-tolerant and relatively insensitive to the underlying statistical distributions of patterns to be recognized. Neural network applications in EEG have been primarily focused on sleep staging, anesthesia monitoring and transient event detections such as spikes and K-complexes. All these studies used multilayer perceptron to train various EEG waveforms. These studies have shown that transient EEG events such as spikes and K-complexes can be successfully recognized [68]. These networks are formed offline with a fixed set of labeled data using the back propagation algorithm and do not adapt to new conditions during monitoring. Retraining with new patterns generally degrades the performance of the network in recognizing previously learned patterns. This property of the multilayer perceptron results in a rigid, non-adaptive system that cannot be modified or customized. To solve this problem, a new neural network architecture, which adapts to new circumstances is needed.

 

Once the pattern recognition task has been completed, then the network behavior can be modified by new information. As new patterns are added to the knowledge base (e.g., as data become available from more patients), the network may adapt itself to improve its recognition rate. Adaptive Resonance Theory (ART) architecture was originally developed by Grossberg and Carpenter [69]. The main thrust of this research is to develop online adaptive methods for the detection of EEG spikes using ART neural networks. A brief description of ART neural networks is presented in this section. We have developed techniques for the detection of EEG spikes. These techniques can be used for long-term monitoring of seizure patients by continuously training the system to recognize new waveforms online. After the development of these technologies, this can be employed for the detection of other transient EEG waveforms and biomedical signals.

## 2 ART MODEL

Adaptive resonance theory (ART) models are neural networks that perform clustering, and permit the number of clusters to vary the size of the problem. The major deviation between ART and previous clustering methods is that ART permit the user to manipulate the degree of similarity between members of the same cluster is defined as a user-defined constant called the vigilance parameter. ART networks can be used for many pattern recognition tasks, such as automatic target recognition and seismic signal processing.

### 2.1 Basic Architecture

The basic architecture of adaptive resonance neural network involves three groups of neurons.
1. Input processing field- F1 layer.
2. Cluster units – F2 layer.
3. Reset mechanism- That controls the degree of similarity of patterns placed on the same cluster.

### 2.2 Input Processing (F1 Layer)

It is divided into two portions. They are given as follows
(1) Input portion
(2) Interface portion
The Input part just represents the input vector given, but a lot of processing occurs in this partof ART2 network. The Interface portion aggregates the signal from the portion of entry with the use of F2 layer. That signal is used in comparing the similarity of the entry signal to the weight vector for the cluster unit which is chosen for learning. The F1 layer is connected to F2 layer through bottom-up weights $b_{ij}$ and theF2 layer is connected to F1 layer through top-down weights $t_{ij}$.

### 2.3 Cluster Units (F2 Layer)

This is acompetitive layer. The cluster unit that has the largest net input is selected to learn the input pattern. The activations of all distinct F2 units are set to zero. The interface units now aggregate information from the input and cluster units.The information from the input units is aggregated in the interface units. Depending on the similarity between the top-down weight and the input vector, the cluster unit may or may not be allowed to learn the pattern. It is done at the reset unit, based on the signals it receives from the input and interface portions of theF1 layer. If cluster unit is not permitted to learn, it is inhibited, and a new cluster unit is selected as the candidate.

### 2.4 Reset Mechanism States

There are three states
(1) Active- “ON”. The unit in F2 is on. Its activation is given by d, where d=0 for ART2.
(2) Inactive - “OFF”. The unit in F2 is off. Its activation =0, but it is available to participate in the next competition.
(3) Inhibit - “OFF”. The unit in F2 is off. Its activation =0and is prevented from participation in further competition during the presentation of the current input vector.

### 2.5 ART2 Network

ART2 accepts continuous valued vectors. ART2 has highly complex F1 units. The F1 units if ART2 posse’s combination of normalization and noise suppression, along with the comparison of weights needed for reset mechanism. ART2 has two types of continuous-valued inputs. One is called noisy binary signal and the other truly continuous. The first one can operate with the fast learning type data. The second type of data is more suitable for the slow learning mode.

### 2.6 Architecture of ART2

From the architecture, it is seen that the F1 layer has six types of units (W, X, U, P and Q). Between all the unitssay, W and X, P and Q, V and U there exists supplemental unit, which receives signals from distinct units, calculates its norms and sends to the different units. The architecture of ART2 network is shown below. The receiving unit receives both inhibitory and excitatory signals from the sending units through supplemental units. The X and Q units are connected to V units. The transformation occurring in the signal is indicated in connection. The P unit path is attached to the cluster units by bottom up and tops down weights. The arrow → indicates normalization. The units perform the operation of F1 layer and P units carry out the operation of F2 layer interface portion.

 

**2.7 ALGORITHM**

The ART2 algorithm involves few differential equations for training. Here $w_i$, $x_i$, $u_i$, $v_i$, $p_i$, $q_i$ and $y_i$ are called Short Term Memories (STM), and $b_{ij}$ and $t_{ji}$are referred to as Long Term Memories (LTM).

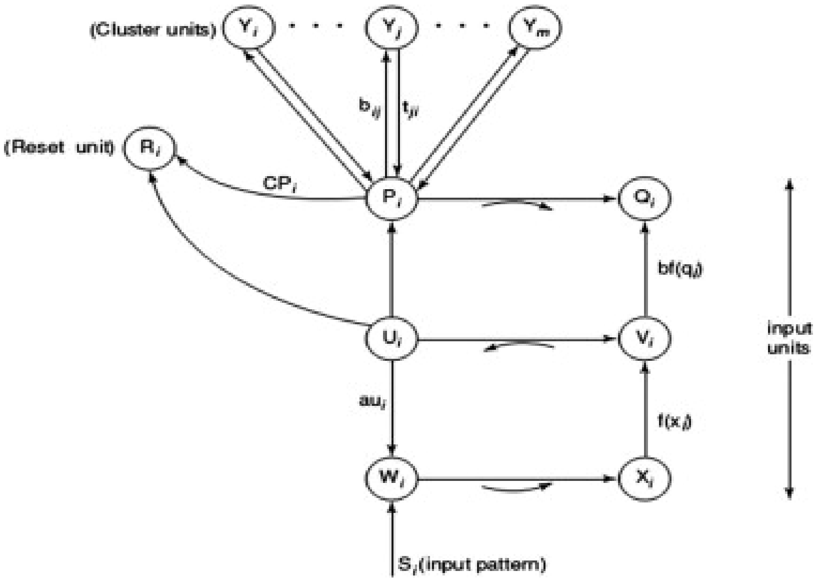


*Fig 4.1. ART 2 architecture*

**4.2.8 DESCRIPTION**

A learning trail consists of one presentation of one input pattern. When the learning trail starts, all activations are set to zero. The computation cycle starts with the calculation of activation of unit $U_i$. Then the signal is sent from $U_i$ to units $W_i$ and $P_i$. The activations of $W_i$ and $P_i$ are then computed. $W_i$ sums the signals from $U_i$ and $S_i$. $P_i$ sums the signals from $U_i$ and top-down signal. $X_i$ and $Q_i$ activations are the normalized forms of $W_i$ and $P_i$ respectively. Before the signal is sent to $V_i$, activation is calculated on each unit. Finally, $V_i$ sums the signals it receives from $X_i$ and $Q_i$. This entirely forms one cycle update of F1 layer. When the activations of F1 layer reaches equilibrium, P units send their signals to F2 layer, and winner unit is selected based on competition. The reset mechanism checks for reset whenever it receives a signal from P since the further computations are based on the value of that signal. This signal is going to be the most original signal the unit $R_i$ had received from $U_i$. After the check for reset is finished, the cluster unit may be rejected or accepted. Based on this, the learning process starts. ART2 perform slow learning and fast learning. In slow learning, only one iteration of the weight update equations occurs on each trail and in fast learning, the weight updates continue until the weights reach equilibrium on each trail. In fast learning, the placement of cluster stabilizes, but the weights will change for each pattern presented.

**2.9 CALCULATIONS OF F1 LAYER**

These calculations are necessary whenever “update F1 activations” occur in the algorithm. The normalization and noise suppression is based on these calculations. ‘J’ indicates the winning unit of the F2 layer based on the competition. If no winning unit is chosen, then d=0 for all units. The calculations of $w_i$ and $p_i$, $x_i$ and $q_i$ can be performed in parallel. The calculations involved are:

$$u_i = \frac{v_i}{e+v} \qquad (4.1)$$

$$w_i = s_i + au_i \qquad (4.2)$$

$$p_i = u_i + dt_{jt} \qquad (4.3)$$

$$x_i = \frac{w_i}{e+w} \qquad (4.4)$$

$$q_i = p_i \frac{p_i}{e+p} \qquad (4.5)$$

$$v_i = f(x_i) + bf(q_i) \qquad (4.6)$$

$$f(x) = \begin{cases} x \text{ if } x \geq \theta \\ 0 \text{ if } x \leq \theta \end{cases} \qquad (4.7)$$

**2.10 TRAINING ALGORITHM**

The training algorithm is as follows:

Step1: Initialize parameters a,b,θ,c,d,e, α and p.

Step2: Perform steps 3-13 up to specified the number of epochs of training.

 

Step3: For each input vector 's', do step 4-12.
Step4: Update F1 unit activations.
Step5: Compute signals to F2 units.
$y_i = \sum b_{ij} p_i$
Step6: While reset is true, perform Steps 7-8.
Step7: For F2 unit choose $Y_j$ with the largest signal.
Step8: Check for reset
$u_i = \frac{v_i}{e+v}$, $p_i = u_i + dt_{jt}$
$r_i = \frac{u_i + cp_i}{e+u+c+p}$
$if \|r\| < p - e$, then
$y_i = -1$ (inhibit j)
Since reset is true, go to step6
$if \|r\| \geq p - e$, then
$w_i = s_i + au_i$
$v_i = f(x_i) + bf(q_i)$
Reset is false, so go to step9.
Step9: Perform steps 10-12 up to specified thenumber of learning iterations.
Step10: Update weights for winning unit j.
$t_{ij(new)} = \alpha du_i + \{1 + \alpha d(d-1)\} t_{ij(old)}$
$b_{ij(new)} = \alpha du_i + \{1 + \alpha d(d-1)\} b_{ij(old)}$
Step11: Update F1 activations.
(Formulae mentioned in calculations of F1 layer are used)
Step12: Test stopping condition for weight updates.
Step13: Test stopping condition for a number of epochs.
In slow learning, a number of learning iterations are 1. In fast learning, for the first pattern learned by cluster use, will be parallel to t throughout training cycle and the equilibrium
weights are,
The stopping condition may be a number of epochs or the weight changes below a specified tolerance.
$t_{ij} = \frac{1}{1-d} u_i$
$b_{ij} = \frac{1}{1-d} u_i$
The parameters used in the algorithm can have following values.

TABLE 4.1 PARAMETERS USED IN ART2 ALGORITHM

| Parameters | Description |
|---|---|
| N | Number of input units |
| M | Number of output units |
| A | Fixed weight in F1 layer (10) |
| B | Fixed weight in F1 layer (10) |
| C | Fixed weight used in testing for reset (0.1) |
| D | Activation of winning F2 unit (0.9) |
| E | Parameter to prevent division by zero when norm of vector is zero (negligible value) |
| Θ | Noise suppression parameter (1/sqrt(n)) |
| Ά | Learning rate (small value) |
| P | Vigilance parameter (diminutive value) |
| $t_{ij}(0)$ | Initial top-down weight (0) |
| $b_{ij}(0)$ | Initial bottom up weight |

### 3 RESULTS AND DISCUSSION

The clustering of a set of EEG data containing 30 spike and 30 non-spike patterns is used for training the network.The spike and non-spike wave patterns generated by ART 2 at its output nodes are shown in Fig. 4.2.As seen, the network is iterated to produce 8 nodes for spikes and 15 nodes for non-spikes. As expected more nodes were generated for non-spikes since they can be of any shape observed in EEG. Surprisingly, it was alsonoted certain seizure waveforms at the output nodes of the constructed ART2 module iterated with long-term synaptic memory as illustrated in Fig. 4.3 and Fig. 4.4. The number of nodes and the accuracy of the network is strongly influenced by the vigilance factor (ρ) and to a lesser degree by the noise factor (θ). In this study, we have chosen a value for the vigilance factor by experimentally incrementing it in small steps and scanning through an estimated range.

 

The noise factor is recommended to be set at l/√n where n is the number of input nodes. Generally, for higher θ, more nodes are generated, and accuracy goes down. On the other hand, for lower θ, fewer nodes are generated, but accuracy goes down. Also, the network becomes unstable. We have determined θ = 0.223. The overall results comparing the supervised network (BP-NN) with the unsupervised network (ART2-NN) are shown in Table 4.2 and 4.3. ART 2 neural network generally produces lower accuracies since these networks are not trained under supervision. However, the ART 2-NN results were very close to the performances of the BP-NN nets indicating the high future potential of this approach.

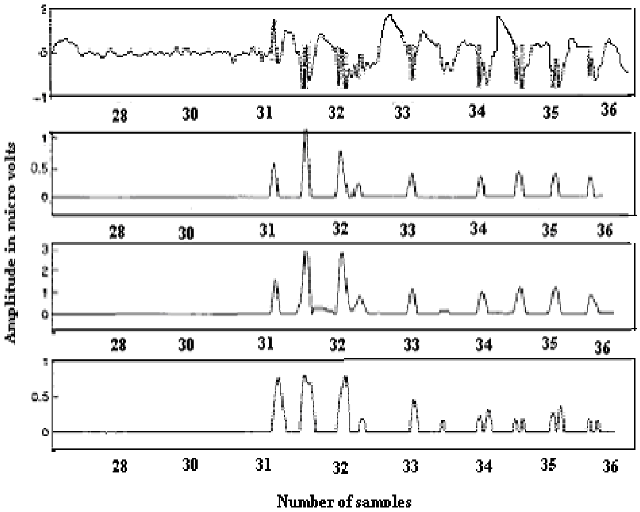


*Fig. 4.2 Spike and non-spike wave patterns generated by ART 2 at its output nodes*

Performance is measured in percentage. Testing of BP-NN with ASC and ASA gave about 90% accuracy. This performance, however, dropped to about 80% when an inflexible set of data (ARA) containing waveforms from many new patients was tested. As previously described, the performance of the networks is generally lower when they are subjected to entirelycurrentwaveforms from new subjects. Overall, the test results indicate that it is possible to automate spike and seizure detection of epilepsy with ART2 network and accuracy level achieved are clinically acceptable and comparable to those of human oral observations.

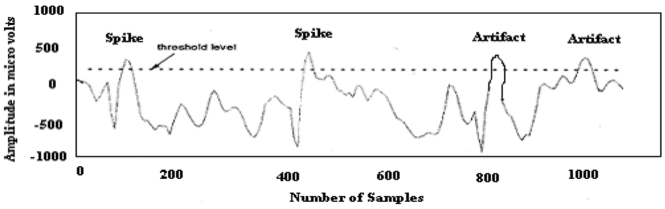


*Fig.4.3 Detection of spikes(S) and artifacts (A)*

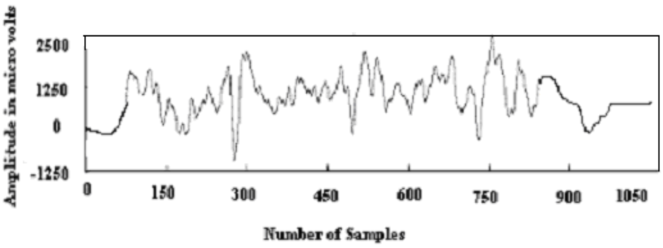


*Fig. 4.4 Linear combination for spike and wave detection*

TABLE 4.2 SPIKE AND WAVE DETECTION

| α | S & W | Aircraft | Sensitivity | Specificity | Average detection rate (%) |
|---|---|---|---|---|---|
| 1 | 25 | 5 | 100 | 91.66 | 95.83 |
| 2 | 25 | 4 | 100 | 93.33 | 96.66 |
| 3 | 24 | 3 | 96 | 95 | 95.5 |
| 4 | 24 | 2 | 96 | 96.66 | 96.33 |
| 5 | 22 | 1 | 88 | 98.33 | 93.16 |
| 6 | 21 | 0 | 84 | 100 | 92 |
| 7 | 19 | 0 | 76 | 100 | 88 |
| 8 | 17 | 0 | 68 | 100 | 84 |
| 9 | 16 | 0 | 64 | 100 | 82 |
| 10 | 15 | 0 | 60 | 100 | 80 |

TABLE 4.3 PERFORMANCE COMPARISONS OF SUPERVISED BP AND UNSUPERVISED ART 2 NN ARCHITECTURES USING THE TRAINING AND TESTING FILES

| Training Set #Files/#Sub | Training Set | | |
|---|---|---|---|
| | ASC 48/21 | ASA 100/21 | ARA 150/26 |
| ASC 48/21 | 100 | 98.78 Mean<br>99.67 Best | 90.33 Mean<br>92.00 Best |
| ASA 100/20 | 97.28 Mean<br>99.33 Best | 100 | 96.34 Mean<br>99.67 Best |

## CONCLUSION

It has been concluded that the ART 2 neural network model reproduces many of the observed activities of epileptical seizure. Epileptical seizure data can be recalled, and its characterization can be studied using ART 2 networks. We have outlined a systematic methodology, which reduces the construction of an iterative neural network, which closely models time series data from a given chaotic system, to a relativelyself-starting process. The dependence of the number of nodes and classification accuracy on the vigilance factor and threshold noise provides an opportunity for the user to optimize the network by minutetuning these parameters during online testing and thus ART 2 module can itself act as a memory to generate certain observed behaviors of epileptic disorders. The added stability and plasticity1 feature of ART 2 networks, and the speed at which network converges haveproven that this method of constructing working memory to characterize epileptical EEG seizure is best compared to other conventional neural network algorithms.

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