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SELF-REGULATION OF LTM TRACE DECAY IN ADAPTIVE ART2 NEURAL NETWORKS

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The article introduces a modification of an adaptive ART2 neural network with an additional subsystem that is able to overcome a problem of the adaptive ART2 networks concerned with exhausting the long term memory (LTM) resources. This subsystem is sensible to the amount of the uncommitted resources and outputs an inhibitory activity during the learning time. Thus, network is able to control uncommitted resources, because of regulation the rate of forgetting in the adaptive ART2 model. The article considers networks behavior and submits the results from the carried out simulations of the network.

1. Introduction. In the context of developing systems that use neural network components, neural networks are often given some initial, perhaps well defined sample of instances that represent the domain the network is applied to. The network is expected to learn this training set and then perhaps by some constructive or deconstructive process to arrive at an optimal set of resources that offer a balance between the stability and generality of the system. This is not a trivial problem even where the domain is well known. Also, there are applications (possibly the majority) which are not well defined and for which such planning is more difficult or even impossible, because the network needs to learn about an unknown input space. In these circumstances the system's future inputs are unknown. Often such applications use unsupervised self-organising learning paradigms that have the ability to self-learn from the input space. In common with other networks these networks have limited resources. In a situation where the input space is huge, the net may not be able to learn all the details required for an adequate functioning of the system. For example if at some arbitrary level of vigilance an Adaptive Resonance Theory (ART) [1] network runs out of resources, the network will block, and either the granularity of the categories must be increased with an accompanying loss of detail, or more resources must be allocated. This situation may also arise when the input space is not huge, but continually changing. In this situation as learning continues, not only may more category nodes be required, but existing category exemplars may also shift and some may become unused as their inputs become assimilated to other similar categories.

One possible solution to this problem is to dynamically allocate more resources to the network. However, this is not very reasonable approach and ultimately in a large system it may be impractical as it implies underwriting a potentially unending expansion of the network's resources. A more satisfactory solution that would allow the network to work continuously without blockage, or unlimited expansion, would be to release those resources which contain inactive information. Such a solution is attractive because if implemented adequately within the dynamics of an ART network such forgetting of information should not be permanent. If patterns that were mapped to a forgotten node reappear in the environment, they can be relearned.

Several artificial neural networks applications include mechanisms that model different aspects of forgetting. The SPIN project [4] is concerned with the classification of data from a 3-D scanning device, using Self-Organising Feature Map (SOFM) of Kohonen. Fritzke [2] adapted the SOFM architecture to allow for growing or shrinking cell-structures. This kind of self-adapting structure erases unused information by dropping the nodes representing this knowledge. Fritzke's adaptation of the SOFM is efficient, but it is relatively complex and it uses additional node features and corresponding maintaining subsystems.

2. Self-regulation of *LTM* trace decay in adaptive *ART*2 model. The dynamics of the classic ART2 model [1] as well as its modification adaptive ART2 [7], [6] assume using of committed and uncommitted nodes in a F2 field. The network resonates in response of an input pattern, that is followed by a learning process and a change of both adaptive filters. Learning rules of the adaptive ART2 model carries out forgetting of seldom used categories and can be predicted by differential equations:

$$\frac{dz_{ji}}{dt} = \begin{cases} g(y_j)[p_i - z_{ji}] & \text{if } g(y_j) = d \\ -\lambda z_{ji} d & \text{if } g(y_j) = 0 \end{cases} \tag{1}$$

$$\frac{dz_{ij}}{dt} = \begin{cases} g(y_j)[p_i - z_{ij}] & \text{if } g(y_j) = d \\ -\lambda z_{ij} d & \text{if } g(y_j) = 0 \end{cases} \tag{2}$$

The choice of a category to be learned depends on the winning F2 node. Thus the neural network can learn either an existing category or creates a new one by using LTM traces of a uncommitted node. Regardless of a possible large amount of F2 nodes, it is limited, therefore insufficient sometimes to hold an endless in itself variety input space. Some tasks require using of many narrow categories that complicate the problem of limited network resources. When the network run out of the nodes amount, both classic and adaptive ART2 models cannot work. the adaptive ART2 model can release some committed nodes by weakening the LTM traces, but the rate of releasing is constant and does not depends on the uncommitted nodes amount. Such networks are convenient when applications are concerned with very noised or changeable input space. Nevertheless such mechanism could not overcome the problem of resource limitation.

A possible approach to overcome the above mentioned problem in an adaptive ART2 model is to carry out an additional subsystem that varies the rate of the LTM trace weakening during the learning time.

This article considers an approach to complement learning by variable inhibition of the F2 activity during the learning, which introduces sn additional weakening of the LTM traces. The inhibition activity varies and depends on the relative part of the committed F2 nodes towards to uncommitted ones. When the system contains mostly uncommitted F2 nodes, the inhibition activity is weak, and vice versa, if the committed nodes predominate, then the inhibition activity is strong.

3. Adaptive *ART*2 neural network with inhibitory subsystem. To be able to count the relative part of committed F2 nodes in comparison with the amount of all F2 nodes, it is necessary an additional subsystem that carries out this function. The subsystem is noted here as **inhibitory** and is shown in Figure 1.

LTM traces in the top-down adaptive filter contain information about how many nodes in the F2 field are committed and how many are uncommitted. Each uncommitted node corresponds to a zero LTM vector that represents a learned category, and respectively each committed node represents a category with a nonzero LTM vector.

The inhibitory subsystem has an input layer of nodes k, which is fully connected to the F2 layer with no weights. In this way, all k nodes have activation always when a winner F2 node appears and no matter which one is a winner. The layer k is fully connected to the layer l by weighted connections, that form an adaptive filter $\tilde{z}_{ji}$, which is a copy of the top-down filter z_{ji}. Thus, the learning process changes the LTM traces of the third adaptive filter in the same manner as they are changed by the top-down filter. Therefore, the presented model has three learning rules.

The vector formed by the l activity is subjected to the normalization in the inhibitory subsystem, after that it activates the layer o, which is fully connected to another node – summator s. Its activity defines a ratio between committed and uncommitted F2 nodes and outputs an inhibitory signal to F2 during the learning.

The inhibitory subsystem activities can be presented by equations (3) - (6).

$$k_j = d \tag{3}$$

$$l_i = \sum_j \tilde{z}_{ji} k_j \tag{4}$$

$$o_i = \frac{l_i}{\varepsilon + \|l\|} \tag{5}$$

$$s = \sum_i o_i \tag{6}$$

An inhibitory subsystem outputs an activity s to F2 during the learning that inhibits learned categories by forgetting reinforcement.

The considered model carries out a LTM trace decay by two directions: both network parameter λ and variable F2 activity. In case of a small amount of committed F2 nodes, the s activity is weak as well as forgetting controlled by λ. However in the case of a large amount of committed nodes, s activity is strong and inhibits the F2 activity, measured by d. Thus a relative free LTM suffers weak forgetting in contrast to the occupied one, that suffers strong forgetting. This mechanism ensures the system with self-regulate coded LTM category amount.

A correct function of the neural network depends on the control of an inhibit subsystem activity that is carried out by a new networks parameter τ, $0 \leq \tau \leq 1$. A suitable value of this parameter can be found experimentally and depends on the F2 resource amount, featured of input space and the λ value. To be able to maintain a sufficient amount of LTM resources it should be guarantied overcoming the problem with a system blockage when the resources are exhausted.

Learning rules of the considered model can be presented by the next differential equations:

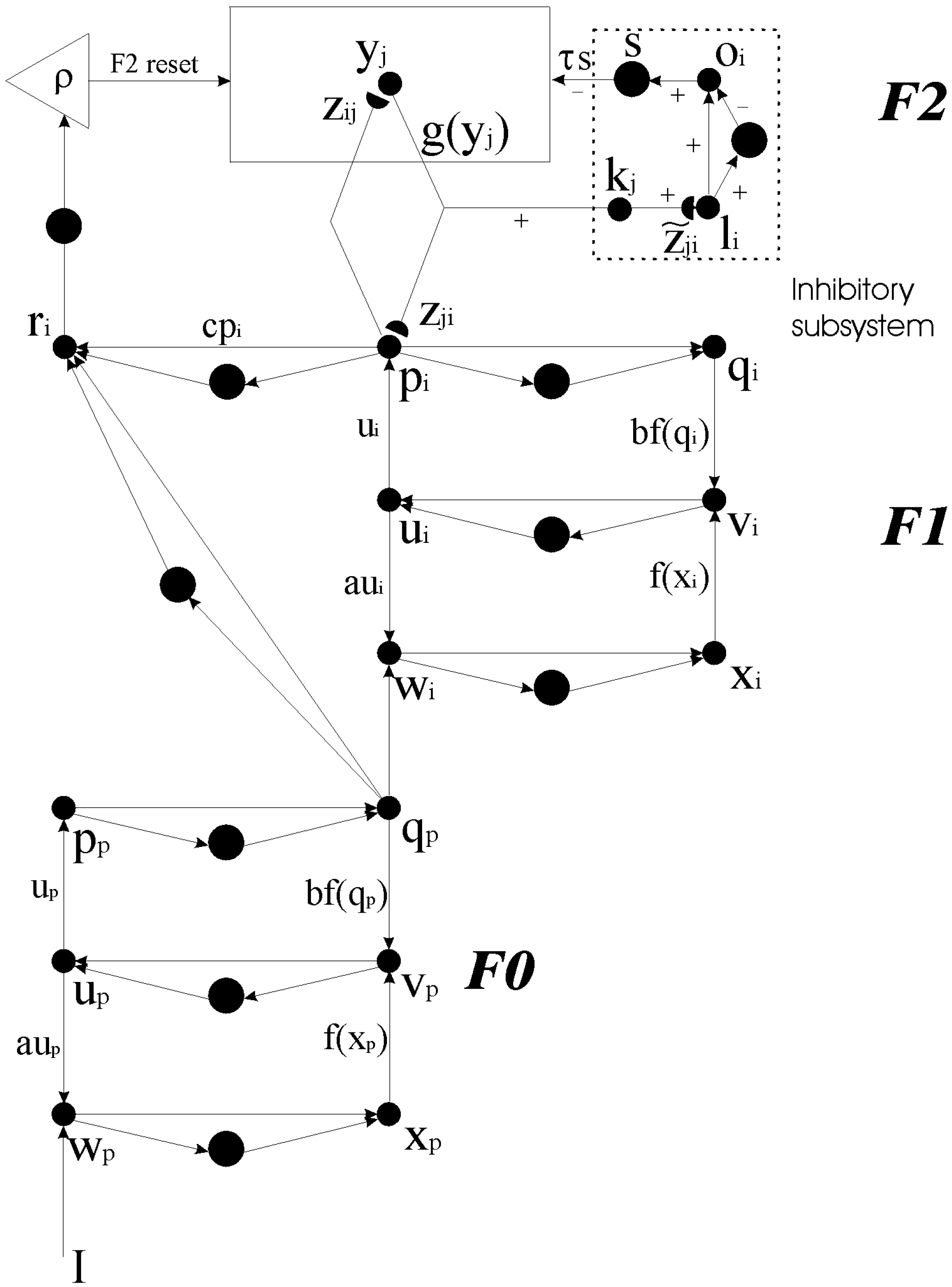

Fig. 1. Adaptive ART2 neural network with inhibitory subsystem

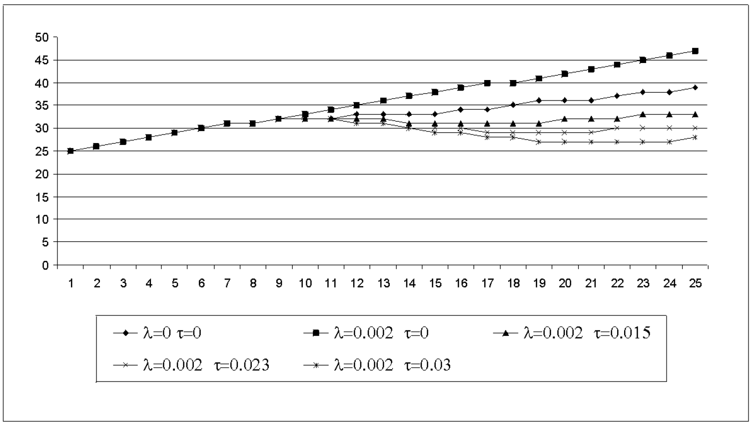

Fig 2. Experimental results for various parameter values

$$\frac{dz_{ji}}{dt} = \begin{cases} g(y_j)[p_i - z_{ji}] & \text{if } g(y_j) = d \\ -\lambda z_{ji}(d - \tau s) & \text{if } g(y_j) = 0 \end{cases} \tag{7}$$

$$\frac{dz_{ij}}{dt} = \begin{cases} g(y_j)[p_i - z_{ij}] & \text{if } g(y_j) = d \\ -\lambda z_{ij}(d - \tau s) & \text{if } g(y_j) = 0 \end{cases} \tag{8}$$

$$\frac{d\tilde{z}_{ji}}{dt} = \begin{cases} g(y_j)[p_i - \tilde{z}_{ji}] & \text{if } g(y_j) = d \\ -\lambda \tilde{z}_{ji}(d - \tau s) & \text{if } g(y_j) = 0 \end{cases} \tag{9}$$

Equations (7) – (9) show that LTM trace weakening is regulated by two parameters: λ and τ.

4. Implementation and experiments. The architecture and learning rules described above have been tested using three simulators developed from the classic ART2 architecture with a preprosessing layer. They solve the differential equations of the learning rules using the fourth order Runge-Kutta method. The first simulator carries out the classic ART2 learning rules. The second one carries out the adaptive ART2. Third one carries out the adaptive ART2 architecture with an inhibitory subsystem, described in Figure 1. Programs were written in C++ programming language. The simulators have open interfaces that make them easy to utilize as a kernel of proper applications. The experiments use a testing set of input patterns, presented by Grossberg and Carpenter [1] and expanded with a set of 50 patterns. This additional set consists of 25 untypical patterns compared to the base set that form new categories; 13 patterns presenting redundant signals caused by noises and 12 patterns presenting a lack of signals.

The first group of simulations comprised 12000 presentations of arbitrary chosen patterns. This showed that the classic, adaptive ART2 model and adaptive ART2 with an inhibitory subsystem when $\tau = 0$ functioned identically and established 26 categories. This result indicates that all architectures work in the same way in the case where all patterns of the input space are presented with an approximately equal frequency.

The second group of simulations counts a number of committed F2 nodes when parameter τ accept different values. It was presented 50 series of 251 patterns to the simulators, both 250 randomly chosen from the base set and one from the additional set. The network parameters were: $\rho = 0.98, a = b = 10, c = 0.1, d = 0.9, \theta = 0.17, dif = 0.001, h = 0.1$

The results form the experiments are presented on Fig. 2. The choice of a proper value of the parameter τ is concerned with the limitation of F2 nodes, simultaneously keeping the system ability to work.

5. Biological plausibility of the model. This modification of the adaptive ART2 model can be concerned with some psychological processes in biological neural systems. For example the *interference theory of forgetting* [5] of cognitive psychology considers two active processes: proactive interference and retroactive interference. The most noticeable form of interference is the detrimental effect of new learning on the retention of older memories. This form of "backward" interference is referred to as *retroactive inhibition.* There is also an interference form prior learning on the retention of newer material. This "forward" acting interference is referred to as it proactive inference. While biologically distinct, both the interferences in the everyday forgetting from ordinarily two sides of the same process.

The adaptive ART2 model with an inhibitory subsystem can be considered in the context of the above mentioned theories. The particular mechanism of forgetting controlled by the parameter λ can be concerned with the retroactive interference, whereas forgetting controlled by an inhibitory subsystem and the parameter τ seems to be a model of proactive interference.

The considered model of neural networks can be associated to other psychological theories as the theory of access of memories [5].

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САМОРЕГУЛИРАНЕ НА ОТСЛАБВАНЕТО НА *LTM* СЛЕДИТЕ В АДАПТИВНИТЕ *ART*2 НЕВРОННИ МРЕЖИ

Анатоли Маринов Начев

Статията въвежда една модификация на адаптивна *ART2* невронна мрежа с допълнителна подсистема, която преодолява един проблем на адаптивните *ART2* невронни мрежи, свързан с изчерпване на ресурсите в дълговременната памет. Тази подсистема е чувствителна към обема на обвързаните възли като извежда потискаща активност по време на обучение. Така мрежата е способна да контролира неизползваните ресурси, регулирайки степента на забравяне в адаптивния *ART2* модел. Статията разглежда също мрежовото поведение и резултатите от проведените симулации на мрежата.