SEARCH MECHANISMS FOR ADAPTIVE RESONANCE THEORY (ART) ARCHITECTURES

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Abstract

A model to implement search in neural network hierarchies is outlined. The system models elementary properties of the chemical synapse, such as transmitter accumulation, depletion, and modulation. The search mechanism is embedded in an Adaptive Resonance Theory (ART) architecture.

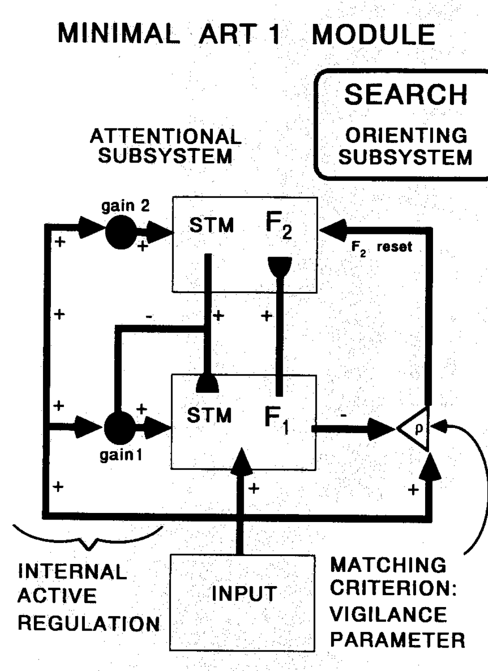
Introduction: ART

This paper outlines new search mechanisms for Adaptive Resonance Theory (ART) neural network architectures. These mechanisms were designed to implement the computational needs of ART systems embedded in neural network hierarchies, where there can, in general, be either fast or slow learning; and distributed, as well as very compressed, code representations [3].

Let us first review some of the main elements of Adaptive Resonance Theory. ART architectures are neural networks that carry out stable self-organization of recognition codes for arbitrary sequences of input patterns. Adaptive Resonance Theory was introduced by Stephen Grossberg [4]. More recent work has led to the development of two classes of ART neural network architectures, specified as systems of differential equations [1,2]. The first class, ART 1, has been shown to be capable of self-organizing recognition categories for arbitrary sequences of binary input patterns [1]

ART 1

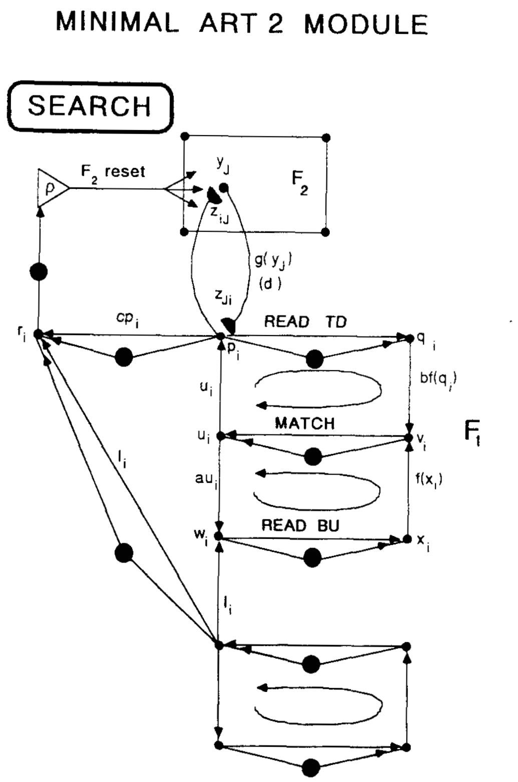
The main elements of a minimal ART 1 module are illustrated in Figure 1. F_1 and F_2 are the two principal fields of network nodes in the system. An input is initially represented as a pattern of activity across the field F_1, while the pattern of activity across F_2 corresponds to the category representation. The two fields are linked both bottom-up and top-down by adaptive filters. There is also an auxiliary subsystem, called the Orienting Subsystem, that becomes active during search. It is this search process that is the subject of the present article.



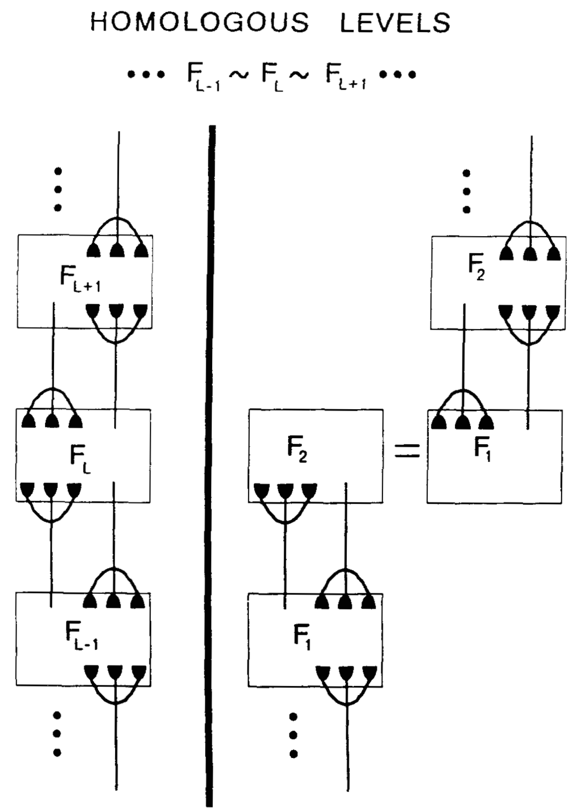
1. Minimal ART 1 neural network module [1].

ART 2: Three-layer levels

Figure 2 shows the principal elements of a minimal ART 2 module [2]. It shares many characteristics of the ART 1 module, having both an input representation field F_1 and a category representation field F_2, as well as Attentional and Orienting Subsystems. Figure 2 also illustrates one of the main differences between the examples of minimal ART 1 and ART 2 modules so far explicitly developed. Namely the ART 2 examples all have three processing layers within the F_1 field. These three processing layers allow the ART 2 system to stably categorize sequences of analog inputs that can, in general, be arbitrarily close to one another. This category learning is stable even in the fast learning situation. In Figure 2, one F_1 layer reads in the bottom-up input, one layer reads in the top-down filtered input from F_2, and a third layer brings together patterns from the top and bottom layers before sending a matched pattern back through a feedback loop



2. Minimal ART 2 neural network module, with three-layer F_1 level [2].



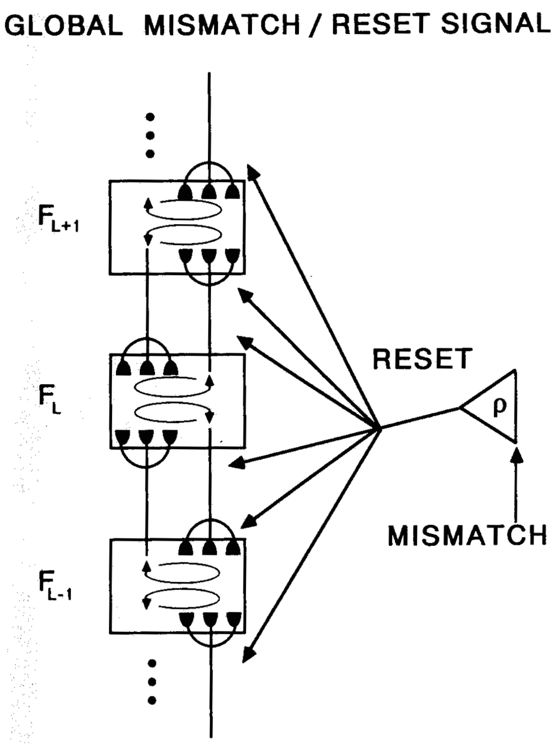
3. Homology of levels F_L in an ART hierarchy.

ART Hierarchies: Homology of levels

We will now consider the problem of embedding this minimal ART module in a neural network hierarchy. We first observe that it is no longer possible to make a sharp distinction between the characteristics of the input representation level F_1 and the category representation level F_2. As much as possible, the basic structures of all the network fields in a hierarchical ART system should be homologous (Figure 3). This constraint is, in fact, satisfied if all levels F_L of the hierarchy are endowed with the F_1 structure of the minimal ART 2 module. This design is appropriate for the F_2 level as well as the F_1 level because the principal property required of a category representation field, namely that input patterns be contrast-enhanced, is an inherent property of this three-layer field structure.

ART Search Chemical Synapse Model

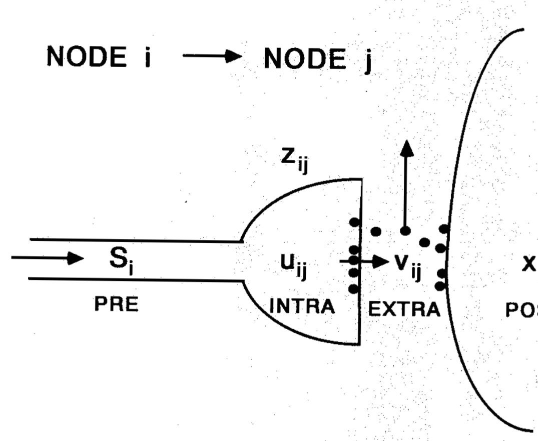
We now turn to the problem of implementing search in a hierarchical ART system. Assume that a mismatch has occurred somewhere in the system. How can a search signal reset the hierarchy in such a way that a new category can be selected? The schematic search systems for ART 1 and ART 2 imply a manifest asymmetry between F_1 and F_2. The ART search model resolves that asymmetry. A key observation pointing to a general solution of the search problem is that a global reset signal can reach the entire hierarchy by acting *between* the levels F_L (Figure 4). Locating the site of action of the reset signal between the levels allows each individual level to carry out its pattern processing function without having the reset signal introduce pattern bias into its internal feedback loops. The interfield locality of the mismatch/reset signal action is determined by a functional analysis of the signalling properties of the hierarchical ART system. We now outline a neural network model that implements such a system. The mechanism employs familiar properties of the chemical synapse [5], embedded in a particular class of models. The ART search model incorporates the dynamics of production and release of a chemical transmitter substance; the removal of transmitter from the extracellular space; and the modulation of these processes via nonspecific external signals. The net effect of these transmitter processes is to alter the ionic permeability at the postsynaptic membrane site, thus effecting excitation or inhibition of the postsynaptic cell.



4. Interlevel global mismatch / reset signal in an ART hierarchy.

Equations

The notation of the ART chemical synapse search model is illustrated in Figure 5, for a synapse between the presynaptic i^{th} node to the postsynaptic j^{th} node. The presynaptic signal (action potential) S_i arrives at a synapse whose weight is denoted z_{ij}. In the ART search model, the path weight z_{ij} is identified with the maximum amount of available transmitter. When the transmitter at this synapse is fully accumulated, the amount of transmitter u_{ij} available for release is equal to the path weight z_{ij}. When a signal S_i arrives, transmitter is typically released. The variable v_{ij} denotes the amount of transmitter in the extracellular space. Finally, x_j denotes the activity, or membrane potential, of the postsynaptic membrane.



5. ART chemical synapse model notation.

Equations (1)-(3) indicate the form of the equations for the variables u_{ij}, v_{ij}, and x_j in the ART search model:

INTRACELLULAR TRANSMITTER

$$\frac{du_{ij}}{dt} = (z_{ij} - u_{ij})\left[\begin{matrix}\text{PRODUCTION/}\\ \text{MOBILIZATION}\\ \text{RATE}\end{matrix}\right] - u_{ij}\left[\begin{matrix}\text{RELEASE}\\ \text{RATE}\end{matrix}\right] \quad (1)$$

EXTRACELLULAR TRANSMITTER

$$\frac{dv_{ij}}{dt} = -v_{ij}\left[\begin{matrix}\text{REMOVAL}\\ \text{RATE}\end{matrix}\right] + u_{ij}\left[\begin{matrix}\text{RELEASE}\\ \text{RATE}\end{matrix}\right] \quad (2)$$

POSTSYNAPTIC ACTIVATION

$$\begin{aligned}\varepsilon\frac{dx_j}{dt} &= -x_j + (A - x_j)\left[\begin{matrix}\text{EXCITATORY}\\ \text{INPUTS}\end{matrix}\right] - (B + x_j)\left[\begin{matrix}\text{INHIBITORY}\\ \text{INPUTS}\end{matrix}\right]\\ &= -x_j + (A - x_j)\left[\sum_i v_{ij} + \left\{\begin{matrix}F_L\\ \text{FEEDBACK}\end{matrix}\right\}\right] - (B + x_j)\left[\left\{\begin{matrix}F_L\\ \text{FEEDBACK}\end{matrix}\right\}\right]\end{aligned} \quad (3)$$

Observe that Equations (1)-(3) represent a highly simplified model of the chemical synapse. Equation (1) says that intracellular transmitter is produced and/or mobilized at some rate, driving the amount u_{ij} of transmitter available for release up toward some maximum level z_{ij}. The available intracellular transmitter u_{ij} is released at some rate, specified below.

Equation (2) says that intracellular transmitter becomes extracellular transmitter once it is released, and that this extracellular transmitter is removed from the extracellular space at some rate.

Equation (3) for the postsynaptic activity x_j is a shunting membrane equation, with the excitatory inputs driving x_j up toward a maximum, or depolarized, level equal to A; with the inhibitory inputs driving x_j down toward a minimum, or hyperpolarized, level equal to -B; and with activity decaying to a resting level (0) in the absence of inputs. Moreover, the net effect of extracellular transmitter from all the synapses converging on the j^{th} node is assumed to be excitatory, via the term

$$\sum_i v_{ij} \quad . \tag{4}$$

Internal feedback from within the target level F_L (Figure 2) can have both excitatory and inhibitory effects on x_j.

ART Search Hypotheses

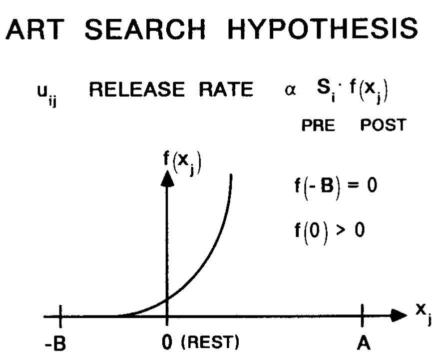
The ART search model is specified by the transmitter production, release, and removal rates in Equations (1) and (2). These implement the three ART Search Hypotheses listed below

ART SEARCH HYPOTHESIS 1: Intracellular transmitter u_{ij} is released at a rate jointly proportional to the presynaptic signal S_i and a function of the postsynaptic activity x_j.

The function $f(x_j)$ is assumed to have the qualitative properties illustrated in Figure 6. Equation (2) and the ART Search Hypothesis 1 imply that the amount of transmitter in the extracellular space is determined by the equation

$$\frac{dv_{ij}}{dt} = u_{ij} S_i f(x_j) - v_{ij}\alpha \tag{5}$$

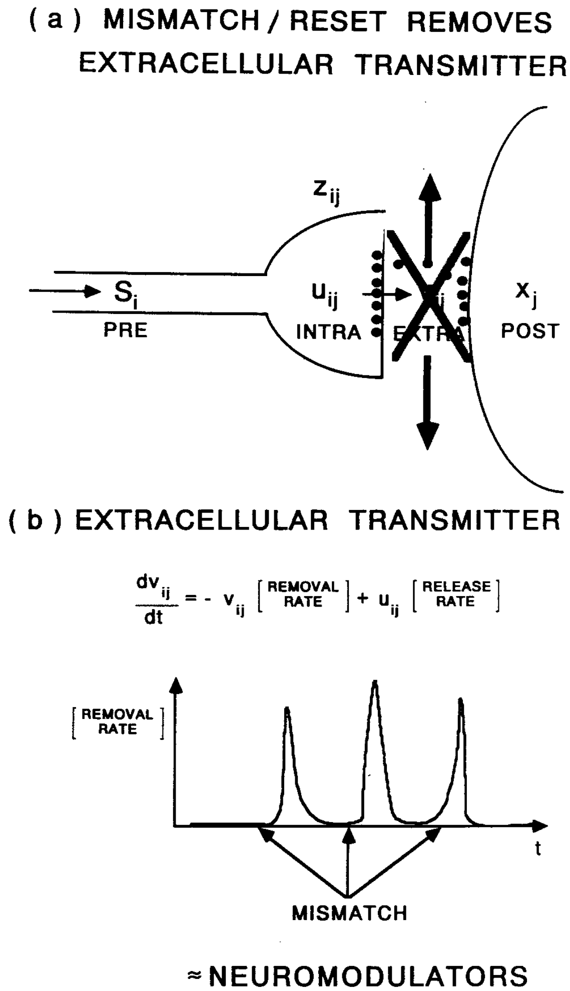
where α is a small constant.



6. The ART Search Hypothesis 1 specifies transmitter release rate.

ART SEARCH HYPOTHESIS 2: The nonspecific mismatch/reset signal quickly removes transmitter v_{ij} from the extracellular space (Figure 7a).

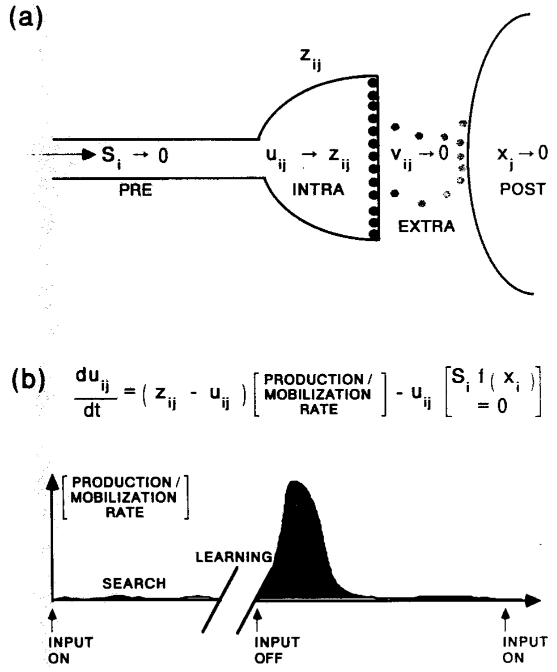
An elementary implementation of the mismatch/reset signal in the ART Search Hypothesis 2 can be constructed by assigning a transient large value to the v_{ij} removal rate (Equation (2)) (Figure 7). This implementation is then analogous to the dynamic of neuromodulators.



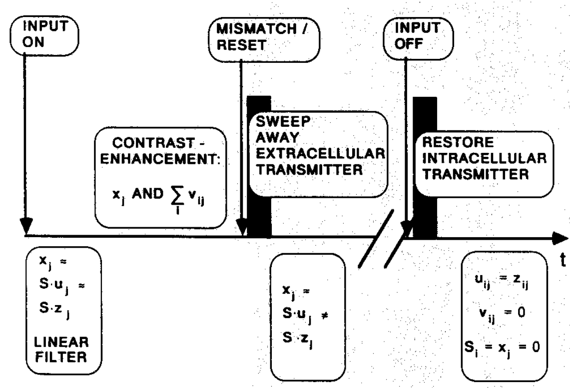
7. The ART Search Hypothesis 2 specifies rate of extracellular transmitter removal following a mismatch / reset signal.

ART SEARCH HYPOTHESIS 3: Offset of an input leads to a nonspecific signal that restores intracellular transmitter u_{ij} up to its maximal level z_{ij}.

The ART Search Hypothesis 3 allows the system to restore itself to its original, resting stated upon offset of the input (Figure 8).



8. The ART Search Hypothesis 3 specifies rates to effect system restoration upon offset of an input.



9. ART Search Hypotheses 1-3 implement computations that can carry out search in an ART system.

ART Search System Dynamics

Figure 9 summarizes system dynamics of this ART search model during a single input presentation. Initially the transmitted signal pattern $\mathbf{S} \cdot \mathbf{u}_j$, as well as the postsynaptic activity x_j, are proportional to the linear filter's weighted signal pattern $\mathbf{S} \cdot \mathbf{z}_j$. The postsynaptic activity pattern is then contrast-enhanced, due to the internal competitive dynamics of the target field F_L. The ART Search Hypothesis 1 implies that release of extracellular transmitter is greatly amplified in proportion to the level of postsynaptic activity. A subsequent mismatch/reset signal selectively removes transmitter from those pathways that caused the error. Following the reset wave, the new signal $\mathbf{S} \cdot \mathbf{u}_j$ is then no longer proportional to $\mathbf{S} \cdot \mathbf{z}_j$ but is, rather, biased against the prior category representation, due to removal of some of the available transmitter. A series of mismatch/reset events may ensue, until an adequate match is found. Learning occurs on a time scale that is long relative to that of the search process. Finally, offset of the input restores the system to its unbiased state and, in particular, restores the level of internal transmitter u_{ij} to its target level z_{ij}.

Acknowledgements

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