

AIM Networks : AutoIncurive Memory Networks for Anticipation Toward Learned Goals

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Abstract

The ability to anticipate future states is a key adaptive property of living systems (Glenberg, 1997). Robert Rosen (1985) suggested that an anticipatory system is characterized by finality, and “is a system containing a predictive model of itself and/or of its environment, which allows it to change state at an instant in accord with the model’s predictions pertaining to a later instant”. Daniel Dubois (Dubois & Resconi, 1992; Dubois, 1998a, 2000) defined the concept of incurive and hyperincurive anticipatory systems, able to generate respectively one or several anticipations influencing the computing of the next state of the system. In this article, the concept of autoincurion is proposed as the ability for a system to compute its successive internal states as a function of its past, present and anticipated states, to select among several anticipated states, and to autonomously change its own equation parameters by learning. Some fundamental properties of a neural network architecture and dynamics are proposed to define AutoIncurive Memory Networks. AIM Networks can learn and activate multiple attractors simultaneously, exhibiting synergic dynamics of attractors encoding external inputs. This allows them (1) to compute their successive states as a function of past, present, and multiple anticipated states, (2) to change the way they compute their successive states through symmetric or asymmetric modification of the synaptic structure during autonomous learning, and (3) to select sequences of anticipations oriented toward learned goals.

Keywords : anticipation, autoincurion, conditioning, goal direction, learning, neural networks.

1. Anticipations in Recursive, Incurive, Hyperincurive, and Autoincurive Systems

Anticipation of future internal states s_{t+n} by living systems at time t improves processing of these states at time $t+n$, such as perception speed and accuracy and motor planning and selection in human semantic processing (Glenberg, 1997; see Lavigne & Denis, 2001; Lavigne & Lavigne, 2000). Anticipatory processes are adaptive in giving living systems the ability to orient behavior away from negative states and toward positive goals, on the basis of stimuli occurring in the environment and internal anticipations (Rolls, 1986, 1990, 1999). Recursive,

incurative and hyperincurative systems have been formally defined to account for different types of anticipations computed as a function of past, current, and anticipated states (Rosen, 1985, 1991; Dubois, 1996, 1998a,b, 2000; Dubois & Resconi, 1992).

A recursive system is capable of simple anticipation by computing its successive states as a function of its past and present states as:

$$s_{t+1} = R(\dots, s_{t-2}, s_{t-1}, s_t; p) \quad (1.1)$$

where s_t are the vector states at time t , R is the recursive function and p is a set of function parameters. By knowing the function R , the values of the parameters p and the initial conditions $s(t-2)$, $s(t-1)$, $s(0)$ at time $t = 0$, the successive states $s(t+1)$, $s(t+2)$, ... where the interval of time $\Delta t = 1$ is a duration, can be recursively computed.

An incurative system computes its successive states as a function of future states. Dubois (2000) defines a strong incurative system as one that compute at time t its future successive states $s(t+1)$, $s(t+2)$, ... as a function of its states at past times ..., $t-3$, $t-2$, $t-1$, present time t , and at future times $t+1$, $t+2$, $t+3$, ...

$$s_{t+1} = I(\dots, s_{t-2}, s_{t-1}, s_t, s_{t+1}, s_{t+2}, \dots; p) \quad (1.2)$$

where the variable s at future times $t+1$, $t+2$, ... is computed by using the equation itself. Such an incurative system is self-referential because it computes its future states from itself and not from a model-based prediction (see Dubois, 2000, for a presentation and examples).

Living systems interacting with their environment are open systems which "cannot normally have true knowledge of future states", given that only a system "in a closed world and having a perfect world model would be able to have true knowledge of future states" (Davidsson, Astor & Ekdahl, 1994). Then the best an open living system can do is to compute its next actual state at time $t+1$ by using *predictions* of *possible* future states at time $t+2$, ... depending on stimuli processed in the environment. The actual state of the system can then be an anticipated state if the new input is a predicted one or an unpredicted state if another input is processed. Such models may be related to Robert Rosen's (1985) definition : "An anticipatory system is a system containing a predictive model of itself and/or of its environment, which allows it to change state at an instant in accord with the model's predictions pertaining to a later instant". Living systems in interaction with their environment would refer to weak anticipatory systems, which compute actual internal states as a function of possible anticipated internal states:

$$s_{t+1} = I(\dots, s_{t-2}, s_{t-1}, s_t, s_{t+1}^*, s_{t+2}^*, \dots; p) \quad (1.3)$$

where the variables s at times ... $t-2$, $t-1$, t , are actual states of the system, and the variables s^* at future times $t+1$, $t+2$, ... are the predicted values of possible future states computed using a predictive model of the system (Davidsson, Astor & Ekdahl, 1994; see Dubois, 2000, for a discussion). Such a system should then be able to compute past, current and anticipated future states in parallel at a same time t .

A hyperincursive anticipatory system is an incursive discrete anticipatory system generating multiple iterates at each time step (after Dubois & Resconi, 1992):

$$s_{t+1} = HI(\dots, s_{t-2}, s_{t-1}, s_t, s_{t+1}^{*1}, \dots, s_{t+1}^{*i}, s_{t+2}^{*1} \dots s_{t+2}^{*i} \dots ; p) \quad (1.4)$$

where each iterate s_t generates at each time step i different iterates s_{t+1}^{*i} of possible anticipated states. Hyperincursivity is a property of living cognitive systems able to anticipate several possible future states in parallel at a same time. Such systems are unpredictable in the sense that they don't compute their next actual state as a function of the initial conditions alone. As the system can only take one actual state at each time step, it is necessary to define a decision function making a choice for the next actual state s_{t+1} among the set of anticipated possible states $s_{t+1}^{*1}, \dots, s_{t+1}^{*i}$. "The decision process could be explicitly related to objectives to be reached by the state variable s of this system" (Dubois, 2000). Cognitive systems are hyperincursive given that they can compute their next state s_{t+1} as a function of their past states s_{t-2}, s_{t-1} , current state s_t , and several anticipated states $s_{t+1}^{*1}, \dots, s_{t+1}^{*i}, s_{t+2}^{*1} \dots s_{t+2}^{*i} \dots$. The decision process can then be based on a comparison process between the anticipated possible states $s_{t+1}^{*1}, \dots, s_{t+1}^{*i}$ and learned goals. Goals would be anticipated and allow decision among anticipated states as a function of their ability to predict the goal, and as a function of the goal's positive or negative valence parameter $s_{t+i}^{*+/-}$.

An autoincursive system is a hyperincursive system able to modify by learning (1) the way it computes its goal' parameter allowing the decision process, (2) the way it computes its anticipated possible states $s_{t+1}^{*1}, \dots, s_{t+1}^{*i}, s_{t+2}^{*1} \dots s_{t+2}^{*i} \dots$, and (3) the way it computes its own equation p parameters. An autoincursive system is then an hyperincursive system which computes its next state at time $t+1$, as a function of its states at past times $\dots, t-3, t-2, t-1$, present time t , and of its anticipated possible states at future times $t+1, t+2, t+3, \dots$

$$s_{t+1} = HI(\dots, s_{t-2}, s_{t-1}, s_t, s_{t+1}^{*1}, \dots, s_{t+1}^{*i}, s_{t+2}^{*1} \dots s_{t+2}^{*i} \dots ; p) \quad (1.4)$$

In an autoincursive system the anticipatory equation parameters p depend on the past, present, and anticipated internal states of the system (autoincursion):

$$s_{t+1} = AI(\dots, s_{t-2}, s_{t-1}, s_t, s_{t+1}^{*1}, \dots, s_{t+1}^{*i}, s_{t+2}^{*1} \dots s_{t+2}^{*i} \dots ; p; l) \quad (1.5)$$

where equation parameters p are computed at time $t+1$ as a function of the past, present, and anticipated internal states of the system, and of parameters p at time t . The AutoIncursive function accounts for learning in the system according to a set l of learning parameters.

2. AIM Networks (AutoIncursive Memory Networks)

Autoincursive systems compute their next state at time $t+1$ as a function of their past, present and anticipated states, according to an equation for which parameters themselves vary as a function of the states of the system. Autonomous anticipations and modifications of the anticipatory equations by learning both require cognitive abilities such as neural activation/inhibition and long term potentiation/depression exhibited in neural networks.

2.1 Network States and Anticipations

Neural network models have been proposed to account for anticipatory properties of cognitive systems, defined as automatic spreading of activation from a neuron or neuron population to associated neurons (Anderson, 1983; Becker, Moscovitch, Behrmann, & Joordens, 1997; Collins & Loftus, 1975; Gillund & Shiffrin, 1984; Hinton & Shallice, 1991; Kintsch, 1988; Lavigne & Denis, 2001, 2002; Masson, 1991, 1995; Plaut, 1995; Sharkey & Sharkey, 1992; Wang, 1996, 2000). To account for semantic activations between stimuli, neurons activated by a given input, after stimulus perception, can activate associated neurons encoding different stimuli, through the learned synaptic matrix.

Attractor networks dissociate fast dynamics of neurons (about 10-100 ms) and slower dynamics of inputs, of more cognitively realistic durations (about 1000 ms). Inputs correspond to activations received by neurons from stimulus perception or from other brain areas. They are encoded by attractors, which are populations of neurons encoding a same input (Amit, 1989; Amit & Brunel, 1997; Hebb, 1949; Hopfield, 1982; Hopfield & Tank, 1986). Attractor networks can account for dynamics of anticipations (Grossberg, Levine, & Schmajuk, 1992; Grossberg & Stone, 1986; Masson, 1991, 1995; Plaut, 1995; Sharkey & Sharkey, 1992) and more specifically for sequence processing (Howard & Kahana, 2001; Jones & Polk, 2001; Gross, Heinze, Seiler & Stephan, 1999).

Models of the cortical column have been developed (Amit & Brunel, 1997; Amit, Brunel & Tsodyks, 1994; Brunel, 2000; Brunel, Caruso & Fusi, 1998), which can account for the simultaneous activation of several attractors at a time. These rate models give a good understanding of the sustained reverberating activity of attractors through excitatory feedback in terms of mean spike rate of neuronal populations (short term memory) (Amit, 1996; Hebb, 1949; Miyashita, 1988), as well as of the dynamics of activations between two simultaneous attractors (Mongillo, Amit & Brunel, 2003). They can account for a ramping-up prospective activity of prefrontal neurons, specific to a not presented (then anticipated) stimulus, following the presentation of a cue stimulus, when both stimuli have previously been learned as associated (see Miller, Erikson & Desimone, 1998 for neurophysiological evidences in monkeys). Both populations of neurons encoding the actually presented cue stimulus and the anticipated target stimulus can be simultaneously activated in prefrontal cortex, allowing the activation of sequences of stimuli.

In addition, anticipations have to be goal oriented (Cruz, 1992; Levine, Leuven, & Prueitt, 1992; see Asensio, Montiel, & Montano, 1999; Milan, 1995; Tani & Kukumura, 1994). To do this, a connectionist model has been proposed to account for goal driven selection of possible actions (Polk, Simen, Lewis & Freedman, 2002). This model accounts for sequential selection of actions as a function of a current state and a given goal, encoded in the network as attractors. Goals, however, are encoded in a specific subpart of the network. Then, their status as goals is given by the *ad hoc* architecture of the network, and not by learned associations with other encoded representations in the network. Neurophysiological data, however, assess for the existence of reward-specific neurons in rat medial prefrontal cortex (Pratt & Mizumori, 2001). This suggest to define goals as neurons populations encoding rewards, which are associated to (by hebbian learning), and then activated by neurons encoding the positive valence of rewards. The neural basis of the encoding of inputs valence involve the amygdala (Cardinal, Parkinson, Hall & Everitt, 2002; Rolls, 1986, 1990, 1999).

An account for anticipatory processes toward learned goals requires an analysis of the synergic interactions between (1) prefrontal cortical prospective activity of sequences, and (2)

amygdala activation of cortical reward-specific neurons encoding goals. This article proposes a model of a cortical network in which attractors' activity can be modulated by amygdala neurons external activity. The cortical network itself is a rate model in which neurons transfer function converts input intensity into firing rate. This network exhibits synergic dynamics of multiple simultaneous attractors encoding input, anticipated associates, and goals. To account for goals encoded by reward-specific neurons in a biologically realistic neural network model, excitatory neurons of a prefrontal cortical network are connected to external excitatory neurons encoding the positive or negative valence of inputs (rewards, punishers, or none of them).

Within the model presented, network states correspond to combinations of attractors, encoding actual and anticipated inputs (including goals), activated simultaneously and at different levels. When a new input is presented to the network (previously anticipated or not), and according to the interactions between multiple attractors, network dynamics correspond to state shifts, which are changes in the levels of activations of attractors encoding actual and anticipated inputs.

To summarize, the AIM Network presented is a biologically realistic neural architecture able (1) to compute its successive states as a function of past, present, and multiple anticipated states, (2) to change the way it computes its successive states through modification of the synaptic structure during autonomous learning, and (3) to select sequences of anticipations oriented toward positive goals and away of negative goals, the learned goals influencing in turn the way the network anticipate future states.

2.2. Network Architecture

The model is a fully connected cortical column network of N_E excitatory (E) neurons and N_I inhibitory (I) neurons (Figure 1), with probabilities of having a hetero-synapse on any other neuron: P_{EE} from excitatory to excitatory neuron, $P_{IE} = P_{EI}$ from excitatory to inhibitory and from inhibitory to excitatory synapses, and P_{II} from inhibitory to inhibitory synapses. All neurons have auto-synapses set as the same values than their efferent hetero-synapses.

Within the network, neurons are connected through four types of pre-synaptic (j) to post-synaptic (i) synapses: S_{EE} excitatory to excitatory synapses, $S_{IE} = S_{EI}$ excitatory to inhibitory and inhibitory to excitatory synapses, and S_{II} inhibitory to inhibitory synapses. Synaptic efficacies correspond to excitatory ($J \geq 0$) or inhibitory ($J \leq 0$) post-synaptic potentials (mV) provoked by a spike. They are defined as J_{EE} and J_{IE} (respectively excitatory to excitatory and excitatory to inhibitory), and J_{EI} and J_{II} (respectively inhibitory to excitatory and inhibitory to inhibitory).

A low fraction f of excitatory neurons encode N_μ inputs μ processed by the network (sparse coding), defining attractors in which neurons encoding a given input have higher synaptic efficacies than with other excitatory neurons. Inhibitory interneurons are activated by excitatory neurons to prevent runaway propagation of activation throughout all the excitatory neurons and regulate dynamics of attractors in the network.

Excitatory and inhibitory neurons also receive noisy random activation from external excitatory neurons, with P_{En} and P_{In} , respectively. In addition, two types of external excitatory neurons of the amygdala, encoding the positive or negative valence of inputs, are connected to specific excitatory attractor neurons, as a function of their valence, by excitatory synapses J_{ijPV} and J_{ijNV} , with P_{EPV} , S_{EPV} and P_{EPN} , S_{EPN} .

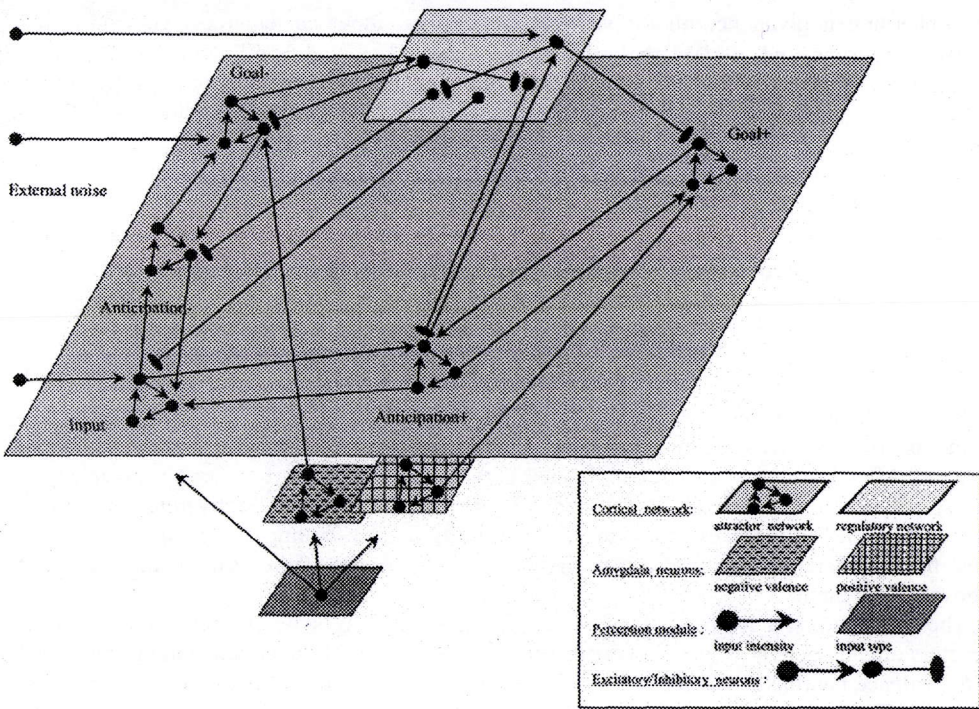


Figure 1: Structure of the AIM Network

2.3. Neurons Dynamics

All neurons in the network are leaky integrate-and-fire neurons converting input currents I_i (mV) into firing rates v_i (spikes.s-1 in Hz), according to a sigmoid transfer function approximating cortical neurons transfer function (Brunel, 1994, 1996):

$$\tau \frac{dv_i}{dt} = -v_i + \Phi(I_i) \quad (2.1)$$

with τ the neurons time constant: τ_E and τ_I for excitatory and inhibitory neurons respectively, and $\Phi(I_{i(t)})$ the transfer function :

$$\Phi(I_i) = \frac{v_{max}}{1 + e^{-\alpha(I_i - I_0)}} \quad (2.2)$$

with, for all excitatory and inhibitory neurons, the same values of v_{max} , the maximum spike rate, α the rate of activation, and I_0 the neurons spontaneous firing rate.

$I_{i(t)}$ is the total input intensity for neuron i (at time t):

$$I_i = I_{i(n)} + I_{i(\mu)} + \sum_{i,j} v_{jE} J_{iE} + \sum_{i,j} v_{jI} J_{iI} + \sum_{i,j} v_{jPV} J_{iPV} + \sum_{i,j} v_{jNV} J_{iNV} \quad (2.3)$$

Concerning a given neuron i , $\sum v_{jE} J_{jE}$ is the internal input current received from other excitatory neurons, and $\sum v_{jI} J_{jI}$ is the internal input current received from inhibitory neurons, v_j the spike rate of neuron j , and $J_{jE} \geq 0$ and $J_{jI} \leq 0$ the synaptic efficacies from, excitatory neuron j_E, j_{PV} , and j_{NV} and inhibitory neurons j_I , to neuron i . $I_{i\mu}$ is the external input current applied to neuron i if i encodes input μ and when input μ is presented to the network.

$I_{i(n)}$ is the external noise received by excitatory an inhibitory neurons from external excitatory neurons.

The two types of positive PV or negative NV valence neurons transmit activation ($\sum v_{jPV} J_{jPV}$ and $\sum v_{jNV} J_{jNV}$) to attractors encoding inputs of positive or negative valence, respectively.

2.4. Attractors Dynamics

Each cycle in the network consists of a random updating of the spike rates of the neurons as a function of the intensities they receive. Prior to learning, the network has no structured attractor. After learning sequences of inputs, each learned attractor, encoding a given input, correspond to strongly associated neurons activated by the input and activating each other. When processing an input, excitatory neurons in the attractor encoding this input activate each other, the reverberating sustained activation progressively reach a stable level of spike rate after removal of the input.

The anticipatory activation of an attractor depends on its synergic activation by other attractors already activated in the network, by the presentation of the corresponding input, and by the valence neurons encoding the input valence associated to the attractor neurons encoding the input. To orient anticipations toward goals, the AIM Network has to code in memory internal representations of dynamic sequences of asymmetrically associated inputs. A simple way to perform a spatial asymmetric associative coding in memory of temporal sequences of inputs is through an asymmetric learning rule (see Mongillo et al, 2003).

2.5. Synaptic Learning

Synapses connecting excitatory neurons (J_{EE}) are plastic and sensitive to hebbian learning. Synaptic dynamics incorporate both associative long term potentiation (LTP) and depression (LTD) defining modifications of the synaptic efficacies J_{ij} from neuron j to neuron i (Amit & Brunel, 1997; Brunel, 1996; Lavigne & Denis, 2001, 2002):

$$\tau_c \frac{dJ_{ij}}{dt} = -J_{ij} + C_{ij} + J_{0/1} \quad (2.4)$$

Synaptic efficacy J varies according to the time constant τ_c . $J_{0/1}$ takes the minimum or maximum values when J crosses (getting respectively lower or upper) a threshold w , which stochastically varies between $J_0 + \theta$ and $J_1 - \theta$, with steps of ϵ .

Potentiation or depression of the synapse is given by the values of $C_{ij(t)}$. The asymmetric learning rule was derived from the covariance Hebb learning rule used by Brunel (1996). This asymmetric learning rule simulates spike timing dependent synaptic plasticity (STDP) (see

Song, Miller, & Abbott, 2000) or temporally asymmetric Hebbian learning (TAH) (Abbott & Song, 1999), on the basis of input order:

$$C_{ij(t)} = \lambda_+ v_{i(t)}(v_{j(t)} + k) - \lambda_-(v_{i(t)} + v_{j(t)}) \quad (2.5)$$

The left term refers to LTP and the right term refers to LTD. $v_{i(t)}$ and $v_{j(t)}$ are the spike rates of neurons i and j respectively, and λ_+ and λ_- are the potentiation and depression parameters respectively. k is an asymmetry parameter inducing asymmetric synaptic potentiation between pre- and post-synaptic neurons j and i (asymmetric synaptic depression is not presented in this study).

This implies that when inputs μ_1 and μ_2 are presented to the network in a sequence, encoded by neurons i and j respectively, neurons i and j are activated in this order and neuron i begins to be deactivated (when input μ_1 is not presented to the excitatory neurons anymore) when neuron j is fully activated (when input μ_2 is still presented).

Synaptic potentiation occurs between two (attractor) neurons when both are still activated, with $v_{i(t)} < v_{j(t)}$. Then, according to the learning eq. 2.5, $C_{ji} > C_{ij}$, inducing greater LTP from neuron i to j (J_{ji}) than from neuron j to i (J_{ij}). This allows neurons i encoding input μ_1 to activate more neurons j encoding input μ_2 than the reciprocal.

When an input is presented that has a given valence, associative learning can also occur between excitatory neurons of the attractor encoding the input and valence excitatory neurons. This allows the network to access the valence of anticipated inputs, and to spontaneously activate attractors associated with positive valence neurons (i.e., goals).

2.6. Autoincursion by learning of hyperincursive parameters

Depending on the different sources of activation of a given attractor, the multiple states arising in the network at a given time can be (1) past states which were previously the most activated states going toward decreasing activation, (2) the current output state being the most activated attractor, and (3) anticipated states encoding inputs not (yet) presented to the network and that could become the next most activated output state of the network.

The computation of network states depends on (1) parameters of the neuron transduction functions, which are defined prior to the simulation and do not evolve with learning: τ_E , τ_I in eq. 2.1, and v_{max} , α , and I_0 in eq. 2.2; (2) the p parameters of the synaptic matrix at a given time, which are modified online by learning as a function of network states. New values of p parameters are calculated at every cycle by the network itself: J_{ij} in eq. 2.4, and C_{ij} in eq. 2.5; and (3) the l parameters, defining learning of the p parameters at each time step, are chosen prior to the simulation: τ_c in eq. 2.4, λ_+ , λ_- , and k in eq. 2.5.

2.7. Model parameters used for simulations

The cortical column of the model was set to respect known physiological data on the respective proportion of excitatory pyramidal neurons and inhibitory interneurons (see Brunel & Wang, 2001). For computational reasons due to the limited memory capacity of the computer, the number of neurons in the model is limited to 10% of the number in an actual cortical column, that is to 4400000 synapses (with $dt = 0.2 \text{ ms} \ll \tau$, the neurons time constant,

a 300 ms run corresponds to 1500 network cycles. On a 3 GHz PIV computer, a 300 ms run was computed in around 45 mn at 7 ms per mn).

Connectivity and neurons properties were set close to known properties of the cortical column:

$N_E = 8000$ excitatory neurons (80%) ; $N_I = 2000$ inhibitory neurons (20%).

$P_{EE} = P_{IE} = P_{EI} = P_{II} = 0.05$. $P_{En} = P_{In} = 1$, with mean noise intensity of 10 (4) and standard deviation of 10 (4), for excitatory and inhibitory neurons, respectively.

A total of 5000000 synapses: $S_{EE} = 3200000$ excitatory to excitatory synapses (400 per neuron), $S_{IE} = S_{EI} = 800\ 000$ excitatory to inhibitory and inhibitory to excitatory synapses, and $S_{II} = 200000$ inhibitory to inhibitory synapses.

Coding level: $f = 0.25$.

Transfer function parameters: $v_{max} = 80$; $\alpha = 0.20$; $I_0 = 20$.

Neurons time constants: $\tau_E = \tau_I = 1$ ms.

External noise: $I_{E(n)} = 8$ pA and $I_{I(n)} = 4$ pA.

Synaptic structure between excitatory and inhibitory neurons of the cortical column was set to obtain physiologically realistic values of mean neurons activity: 3 Hz for excitatory neurons and 9 Hz for inhibitory interneurons. $J_{IE} = 0.009$ mV from excitatory to inhibitory neurons; $J_{EI} = J_{II} = -0.0095$ mV from inhibitory to excitatory neurons, and from inhibitory to inhibitory neurons, respectively.

Within and between attractor synapses were set to ensure fundamental processes reported in cognitive psychology: sustained activity (short term memory), priming (anticipatory activation), and valence activation such as involved in goal activation. For a given excitatory/inhibitory balance, too weak synapses allow neither sustained reverberation of attractors nor anticipatory activation, and too strong synapses allow neither stable low rates of activity in absence of input nor the possibility of inhibition of activated attractors (See legends of Figures).

Auto-synaptic potentiation: $J_{II} = J_{A+A+} = J_{A-A-} = J_{G+G+} = J_{G-G-} = 0.02$ mV.

Hetero-synaptic potentiation: J_{A+I} ; J_{IA+} ; J_{A-I} ; J_{IA-} ; J_{A+A-} ; J_{A-A+} ; J_{A+G+} ; J_{A-G-} are the studied parameters which determine attractors dynamics (Figures & Insets), with the maximum hetero-synaptic potentiation $J_I = 0.0054$ mV.

Auto-synaptic basic level: $J_{EE} = 0.001$ mV.

Hetero-synaptic basic level: $J_{A+E} = J_{EA+} = J_{A-E} = J_{EA-} = J_{G+E} = J_{EG+} = J_{G-E} = J_{EG-} = 0.001$ mV.

Hetero-synaptic depression: $J_{G+I} = J_{IG+} = J_{G-I} = J_{IG-} = J_{A+G-} = J_{G-A+} = J_{A-G+} = J_{G+A-} = J_{I} = 0.0004$ mV.

The valence neurons were set with the same properties as excitatory neurons of the column.

Connectivity and neurons properties:

$N_{PV} = N_{PV} = 500$ positive and negative (excitatory) valence neurons.

$P_{EPV} = P_{EPN} = 0.08$.

A total of 425000 synapses: $S_{PVPV} = S_{PNPN} = 12500$ positive to positive and negative to negative valence neurons, and $S_{EPV} = S_{EPN} = 200000$ positive to excitatory and negative to excitatory synapses.

Transfer function parameters: $v_{max} = 80$; $\alpha = 0.20$; $I_0 = 20$.

Neurons time constants: $\tau_E = 1$ ms for positive and negative valence neurons.

Synaptic structure: Auto-synapses between neurons of a same valence group were set as within-attractor auto-synapses: $J_{PVPV} = J_{ijNV} = 0.02$ mV.

Synapses between valence neurons and goal attractor neurons were set to ensure enough goal attractor activation to orient anticipations, and not too much goal attractor activations so that the network was not fixed in the goal attractor state. Between positive valence neurons and goal attractor neurons: $J_{EPV} = 0.0016$ mV; between positive valence neurons and non-goal attractor neurons, and between negative valence group and excitatory neurons: $J_{ENV} = J_{ENV} = 0$ mV.

Simulations were run on a quenched version of the network (fixed synaptic structure) for two reasons: First, to analyze attractor dynamics in terms of a stable and well defined synaptic structure; Second, to allocate a maximum of computer memory to the computing of attractor dynamics, rather than to the computing of synaptic changes.

3. AutoIncurative Memory Processes as Synergic Dynamics of Attractors

The autoincurative abilities of AIM Networks are given by (1) a biologically realistic architecture of excitatory and inhibitory interneurons connections in a cortical column connected to valence neurons, and (2) adequate functional parameters of neuron transfer function and synaptic learning equations. An application of AIM Networks concerns cognitive processes of living systems, such as learning and goal orienting of anticipations.

3.1. Anticipatory Recursive, Incurative, Hyperincurative Processes

Recursive processes refer to anticipations based on associations learned by classical conditioning (association between a CS and an US) and pavlovian associative conditioning (between two stimuli). In multiple simultaneous attractor networks, two successive inputs are associated in memory when they are frequently co-occurrent in the environment (covariance Hebb rule) (see Brunel, 1996, Mongillo et al., 2003). Here, the asymmetric rule allows associative learning of temporally ordered sequences of attractor and guarantees that the network activates attractors in the order the encoded inputs were learned (Mongillo et al, 2003; Matsumoto & Okada; 2002). Within the AIM Network, recursive processes refer to the anticipatory activation, by an attractor encoding an actual input I (state s^1_i), of an associated attractor encoding an anticipated input A (s^*_i).

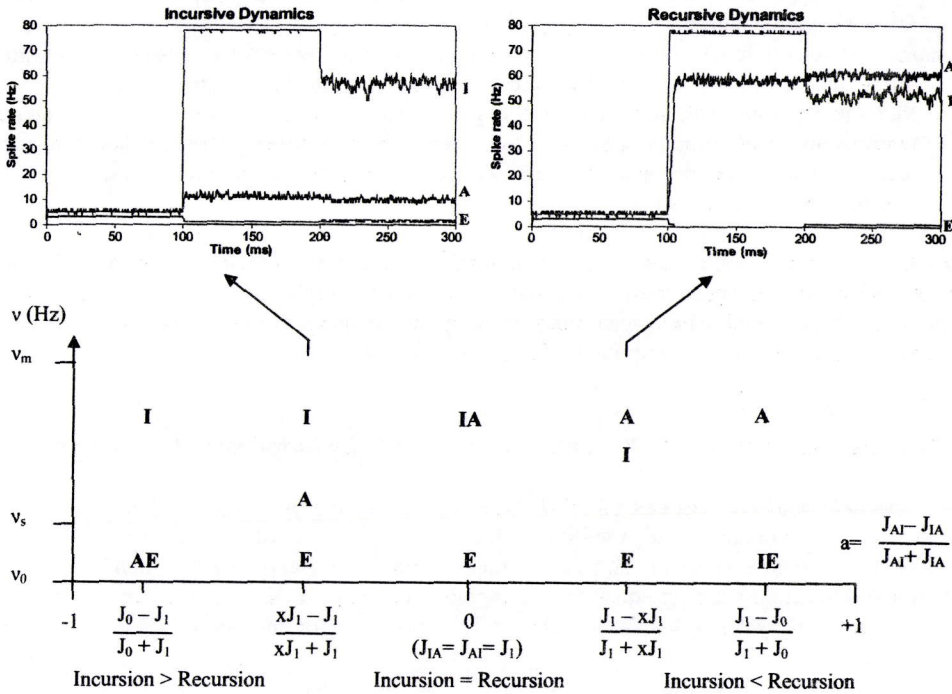


Figure 2: Recursive and Incursive Dynamics.

Network states (letter codes): Attractor spike rates (Hz) in stable network states, as a function of the asymmetric pair learning parameter a between input (I) and anticipated (A) attractors. $v_0 = 0$ is the minimum neuron activity, v_s , around 3 Hz, is the level of spontaneous activity of excitatory neurons, and v_m , slightly below 80 Hz, is the maximum neuron activity. Stable states correspond to different level of activity of attractors. A stable network state is a dynamic of opposite effects of excitation and inhibition: some attractors close to their maximum activation, some at various level above spontaneous activity, and some at lower rates than spontaneous activity, depending on their respective ratio of global excitation/inhibition (for better readability, the activities of valence neurons, inhibitory neurons, and neurons encoding no input are not displayed). States are presented for the synaptic structure described in the 'Model parameters' section, and for the following within attractors synaptic structure, with J_{ij} synapses from neuron j to neuron i : $J_0 = 0.0004$ mV; $J_{AI} = J_{IA} = J_I = 0.0054$ mV ($x=0.93$).

Network dynamics (insets): Attractor spike rates (Hz) in network dynamics as a function of time (ms). Two selected representative examples of recursive and incursive attractor dynamics are presented in insets. They correspond to the following protocol of inputs processing according to cognitively realistic time courses: 0-100ms: Stable state of the network without any input; 100-200ms: Processing of the actual input; 200-300ms: Attractor dynamics toward stable states.

For symmetric sets of synaptic parameters ($a=0$), input and anticipated attractors, I and A, are simultaneously activated at the same level. Left inset ($a < 0$) exhibits incursive processes in which the input attractor I (state at time t) remains the most activated at time $t+1$, due to asymmetric association stronger from anticipated attractor A to input attractor I. Right inset ($a > 0$) exhibits recursive processes in which the anticipated attractor A (state at time $t+1$) replaces the input attractor I (state at time t), due to asymmetric association stronger from input attractor I to anticipated attractor A. In all cases, other excitatory neurons E, encoding attractors not anticipated or no learned attractor, stay activated at sub-threshold activity; receiving more inhibition than activation.

The next state s_{t+1} can then shift to the anticipated input (A) or to a combination of the anticipated and actual inputs (A+I) as a function of the asymmetric synaptic strengths between attractors (Figure 2: right hand side letter codes and inset).

Incursive processes are accounted for by the computing of the networks' next state s_{t+1}^* as a function of an anticipated input (attractor encoding anticipated input A), having feedback effects on the activation of the attractor encoding the actual input I. The next state s_{t+1} can then stay the same (actual input I) or shift to a combination of inputs I and A, at respective levels depending on the asymmetric values of the synaptic weights (Figure 2: left hand side and inset).

Only for $a = -1$ and $a = +1$, the network exhibits 'pure' incursion or 'pure' recursion, respectively. For all other cases, both attractors I and A are associated in both directions (i. e., from I to A and from A to I), even through asymmetric synapses. Then, anticipations arise from a mix of simultaneous recursive and incursive processes, being equivalent for $a = 0$ (symmetric case). These simulation results replicate those from Mongillo et al (2003). They show that the respective levels of activation, as stable end-states of the networks' dynamics, are influenced by the asymmetry of synaptic potentiation between attractors encoding both inputs.

Hyperincursive processes are accounted for by the computing of the networks' next state s_{t+1}^* as a function of several anticipated inputs activated in parallel (attractors encoding anticipated inputs A_+ & A_- ; + and - signs are chosen to ease comparison with goal directed anticipations, but none of the anticipated inputs is associated to a goal). The anticipated inputs have feedback effects on the activation of the attractor encoding the actual input I. The next state s_{t+1} , as respective levels of activations of inputs I, A_+ and A_- , then depends on hyperincursive processes of activation between the anticipated inputs, depending on their mutual associations (Figure 3: left hand side letter codes and inset).

3.2. AutoIncursive Goal Direction as Selection of Anticipations toward Learned Goals

To account for goal direction as the selection of an actual state among several anticipated states, the network must be able to select anticipated states associated with positive goals. According to Dubois (2000), a decision process is required for the selection of one actual state among several anticipated ones, and "the decision process could be explicitly related to objectives to be reached by the state variable s of this system." This decision process can be accomplished by goals which orient anticipations as a function of their positive or negative valence (see Barnes & Thagard, 1996).

Some inputs in the environment are unlearned reinforcers which lead to affective states genetically programmed to trigger automatic taxic behaviors. The input's affective valence triggers behavioral responses orienting the system toward positive-appetitive events (approaching behaviors) and away of negative-aversive events (avoiding behaviors) (Rolls, 1986, 1990, 1999). The positive or negative valence of unlearned reinforcers (e.g., 'food' or 'pain') can be associated with learned secondary reinforcers (e.g., 'places where there is food' or 'dangers which cause pain'), by classical conditioning when the two events are frequently temporally correlated. Experimental data show that anticipations in human memory are stronger when both inputs (a 'prime' and a 'target') share the same valence (Bargh, Chaiken, Govender & Pratto, 1992; De Houwer, Hermans & Spruyt, 2001; Fazio, 1995, 2000; Fazio, Sanbonmatsu,

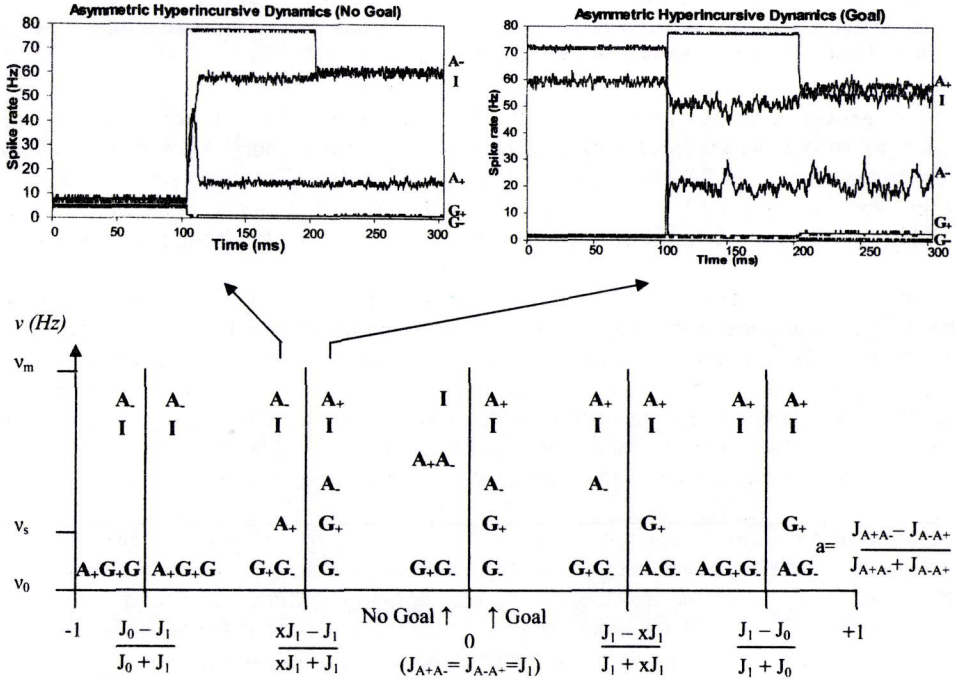


Figure 3: Hyperincursive and Goal directed Dynamics.

Network states (letter codes): Attractor spike rates (Hz) in stable network states, as a function of the asymmetric pair learning parameter a between anticipated attractors A_+ and A_- . $v_0 = 0$ is the minimum neuron activity, v_s , around 3 Hz, is the level of spontaneous activity of excitatory neurons, and v_m , slightly below 80 Hz, is the maximum neuron activity. Stable states correspond to different level of activity of attractors. A stable network state is a dynamic of opposite effects of excitation and inhibition: some attractors close to their maximum activation, some at various level above spontaneous activity, and some at lower rates than spontaneous activity, depending on their respective ratio of global excitation/inhibition (for better readability, the activities of valence neurons, inhibitory neurons, and neurons encoding no input are not displayed). States are presented for the synaptic structure described in the 'Model parameters' section, and for the following within attractors synapses, with J_{ij} synapses from neuron j to neuron i , and $J_{A^+} = J_{I^+} = J_{A^-} = J_{I^-} = J_{A^+A^+} = J_{A^+A^-} = J_{A^-A^+} = J_{A^-A^-} = J_{I^+} = J_{I^-} = J_{G^+} = J_{G^-} = J_I = 0.0054$ mV ($x=0.93$).

Network dynamics (insets): Attractor spike rates (Hz) in network dynamics as a function of time (ms). Two selected representative examples of multiple attractor dynamics are presented in insets. They correspond to the following protocol of inputs processing according to cognitively realistic time courses: 0-100ms: Stable state of the network with or without the external influence of valence neurons (activation or not of the goal attractor during the whole protocol); 100-200ms: Processing of the actual Input; 200-300ms: Dynamics toward stable states.

For symmetric sets of synaptic parameters between A_+ and A_- ($a=0$), and in absence of goal activation, both anticipated attractors, A_+ and A_- , are simultaneously activated at the same level. Goal activation, however, leads to the selection of the corresponding anticipated attractor. Left inset ($a<0$, no goal activation) exhibits anticipatory processes in which the anticipated attractor A_- is the most activated, due to asymmetric association stronger from anticipated attractor A_+ to attractor A_- . Right inset ($a<0$, goal activation of A_+) exhibits selection processes of the anticipated attractor A_+ ; despite asymmetric associations stronger from A_+ to A_- . Goal activation, by valence neurons, can then select anticipated attractors activated by an input, and lead to the activation of a sequence of attractors independently of the asymmetric synaptic parameters (case of $a=0$). From In all cases, other excitatory neurons E, encoding attractors not anticipated or no learned attractor, and goal attractors not activated G_- , stay activated at sub-threshold activity; receiving more inhibition than activation.

Powel & Kardes, 1986; Hermans, De Houwer & Eelen, 1994; see Fazio, 2001 for a review). Furthermore, anticipations are reported to be stronger when positive rather than negative inputs are processed, semantic anticipations being stronger in positive context than in neutral or negative context (Hänze & Hesse, 1993; Hänze & Meyer, 1998).

In the AIM Network, attractors encoding inputs are activated by valence neurons encoding the positive or negative valence of the inputs. A way to account for the differential activation of positive vs. negative inputs, positive valence neurons present a higher activity ($v_{j(PV)} > 0$ even if no input is processed) than negative valence neurons ($v_{j(NV)} \sim 0$ if no input is processed), these activities being influenced by mood states (Rolls, 1986, 1990, 1999). In positive states, positive valence neurons receive an input activation I_{ext} , which assures that attractors encoding positive inputs are the most activated and lead to stronger anticipations. Then positive goals can be spontaneously activated in the network and can (hyper)incursively activate attractors associated to them (goal direction).

Goal direction is accounted for by the network by recursive activation, by an attractor encoding an input l (state s_l^1), of several anticipated inputs (s_{l+n}^{*i}). They can be associated in turn to either positive goals (s_{l+n}^{*+}) or negative goals (s_{l+n}^{*-}). Valence neurons bias activation toward positive instead of negative goals. Through incursive processes, a positive goal can activate other anticipated attractors associated to the goal. The selection of the next network state is then biased toward attractors associated to the goal. A sequence, can then be activated in which successive attractors increase and then decrease their spike rates, until the 'goal' attractor becomes the next network state (Figure 3: right hand side letter codes and inset).

These simulation results exhibit a rich phenomenology of anticipatory processes. Asymmetric synaptic associations, between two attractors A+ and A- to be anticipated from an input I, determine which one becomes the next network state in absence of goal activation. However, the activation of a goal G+ selects the next network state A+ whatever the asymmetric association between A+ and A-. Then, in a given range of the asymmetric pair learning parameter a ; the processing of a sequence of anticipated attractors does not require asymmetric learning, given the assumption that a goal attractor activates an anticipated attractor.

As a function of the relative activations of the Input vs. Goal attractors, the model exhibits a goal anticipation mode, where the goal is the more activated and can influence the processing of new input, or an input anticipation mode, where the actually perceived input is more activated than the goal and can influence the activation of anticipated associates.

AutoIncursion corresponds to the computing of goal oriented anticipations depending on learned parameters (synaptic weights). Goal learning is the association between attractor neurons of the Pre-Frontal Cortex, encoding the 'goal' input, and neurons of the Baso-Lateral Amygdala, encoding the input's valence. Goal learning in cognitive systems is assured by synergistic classical (Pavlovian) and instrumental (Skinnerian) conditioning (see Cardinal et al., 2002). This allows the system to associate inputs to their valence, and to associate them together as a function of their valence. Positive reinforcers, or rewards, as well as negative reinforcers, or punishers, can elicit affective states influencing learning (Millenson, 1967; Weiskrantz, 1968; Gray, 1975; Rolls, 1986, 1990, 1999). Neuronal learning allows the system to vary the frequency of a behavior in order to obtain a reward and avoid a punisher, according to Thorndyke law of effects. To this aim, associations between two inputs are strengthened in

positive feedback (the second input is positive) and not in negative feedback (the second input is negative); by the way of increased neuronal activations in positive states compared to negative ones (Hänze & Hesse, 1993; see Rolls, 1999 about the neural basis of learning in positive and negative states). The spontaneous activity of positive valence neurons assures that positive inputs are more activated than negative inputs. This leads to stronger activations (eq. 2.1 & 2.2), and then to stronger associative learning (eq. 2.4 & 2.6), when a positive input (reward) is presented to the network than when a punisher is presented. Though this valence dependent learning has to be more deeply investigated in AIM Networks, when an input is presented, the network can activate more strongly attractors encoding associates leading to (i.e., associated themselves to) positive goals than attractors encoding associates leading to negative inputs.

4. AutoIncursion and Adaptation

On the basis of biologically realistic neuron properties and network architecture, the AIM Network presented can account for recursive, incursive, hyperincursive, and autoincursive properties of cognitive processes. In addition, synergic activation of neurons of the cortical module and of the amygdala can lead to goal direction of anticipations. Goal direction is an asymmetric processing of sequences of attractors, from input I to anticipated A+ attractors, that can occur on the structural basis of a symmetric set of synaptic parameters between the attractors. The AIM-Network presents the fundamental property of activating sequences of anticipations according to learned rules, such as reported in the prefrontal cortex (see Fuster, 2000). Interactions with the amygdala, encoding the valence of inputs, can account for goal directed sequences of anticipations. Future extensions of the model will have to take into account of several aspects out relative to the model itself and more generally to autoincursive systems.

First, recursion and incursion are assimilated as, respectively, forward activation by the input attractor of the anticipated attractor, and feedback activation by the anticipated attractor of the input attractor (Figure 2). Recursive and incursive processes have to be more deeply investigated as combinations of forward and feedback activation and inhibition. On the one hand, inhibition between attractors can be considered in a single column in the case of strong activation (of multiple attractors) leading to global inhibition of all the attractors (resetting mechanism) (Brunel & Wang, 2001). On the other hand, attractors are also embedded in different networks of different cortical areas (e.g., prefrontal and inferotemporal) involving neurons of variable dynamics (different integration time constants of NMDA and AMPA glutamatergic receptors). In addition to the data presented here with only fast neurons dynamics ($\tau=1$ ms), further investigation of the ratio of fast vs. slow neurons would be of importance to account for more precise time courses of activatory and inhibitory effects between attractors (Brunel, 2002).

Second, network's anticipated states are anticipated inputs which would change network states if presented to the network. They are not a full prediction of the actual next state reached when processing the anticipated input. The network do not anticipate future states of itself as a whole but states as a combination of activities of attractors, encoding external inputs in subparts of its neuron population. However, this property to "contain a predictive model [of itself and/or] of its environment" (Rosen, 1991) is necessary to the network to compute its next state autonomously and learn new anticipations. In addition, autoincursive properties are accounted for by the network as synaptic modifications leading to goal directed anticipations. Indeed, the

computing of new anticipations varies with learning given that synaptic weights are modifiable parameters of neuron transduction functions. However, not all the parameters of the transduction function and learning equation vary with learning.

Third, because of limited computing power, only a limited number of anticipated states can be computed in parallel at a time by the system. This limits its anticipatory power, given that the next state of the system is computed on the basis of a subset of all the possible anticipated inputs.

Forth, an AIM Network is an open system which internal states are not totally described by its internal equations. Internal states also depend on online interactions between the system and a deterministic but complex and then not fully predictable environment. Though this gives the system its autoincurive properties of modification of anticipations by goal learning, an open system can not completely compute its next state as a function of perfectly well known future states, and then do not fulfill the requirements for strong anticipatory systems (Dubois, 2000). Anticipated future states are predicted states with a variable probability to become actual states (see Davidsson, Astor & Ekdahl, 1994). This defines AIM Networks as weak or strong anticipatory systems, depending on their predictive power of future states, depending in turn on previous learning. The more accurately the matrix of synaptic weights encodes the temporal structure of inputs, the fittest are the anticipations in terms of adaptation to the environment. Then adaptation of anticipations to complex and changing environments is a function of learning of how and what to anticipate, that is of autoincurive properties of AIM Networks.

Acknowledgments

I am grateful to Nicolas Brunel for helpful discussions on asymmetric priming in cortical columns. I particularly thank Mickael Bieth for the implementation of the network and his help in testing the model, and Julien Chanois, Sylvain Denis, Benjamin Prevosto for their participation. I also thank Dirk Steiner for his reading of a previous version of the article.

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