Fişa suspiciunii de plagiat / Sheet of plagiarism's suspicion	Indexat la: 0131/01

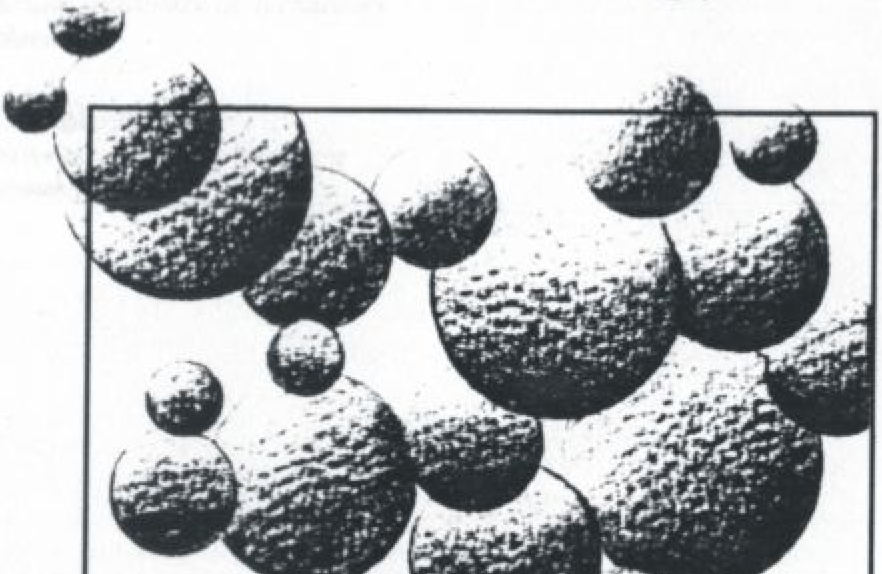
Opera suspicionată (OS)	Opera autentică (OA)
Suspicious work	Authentic work

OS	TRIFA, Viorel; GAURĂ, Elena Ioana. *Reţele neuronale artificiale. Arhitecturi fundamentale.* Cluj-Napoca: Mediamira. 1996.
OA	CICHOCKI, A.; UNBEHAUEN, R. *Neural networks for optimization and signal processing*. Chichester, New York: John Wiley & Sons. 1992.

Incidenţa minimă a suspiciunii / Minimum incidence of suspicion	
p.29: Fig.3.7	p.54: Fig.2.9
p.29:02-p.32:26	p.56:01-p.59:12
p.30: Fig.3.8	p.56: Fig.2.10
p.33:Fig.3.10	p.59:Fig.2.11
Fişa întocmită pentru includerea suspiciunii în Indexul Operelor Plagiate în România de la www.plagiate.ro	

Notă: p.72:00 semnifică textul de la pag.72 de la începutul până la finele paginii.

Neural Networks for Optimization and Signal Processing



A. Cichocki · R. Unbehauen

WILEY
Publishers Since 1807

2.2.5 The Hopfield Model of the Artificial Neuron

Today, the Hopfield model of the neuron is probably the most popular dynamic model of the artificial neuron cell [16-19]. Figs. 2.10a,b show the circuit structure of the neuron and its functional structure. The circuit consists of a capacitor C_j, resistors R_{ji} and a nonlinear amplifier with sigmoid transfer functions. It is assumed that the amplifier provides two symmetrical outputs (i.e. voltage signal v_j and its inverse $-v_j$) in order to ensure that all resistors simulating synaptic weights have positive values. This means that a positive synaptic weight is realized by connecting the resistor R_{ji} to $+v_i$ and a negative weight by connecting R_{ji} to the associated signal $-v_i$. The current I_j represents the bias (or the independent external input signal).

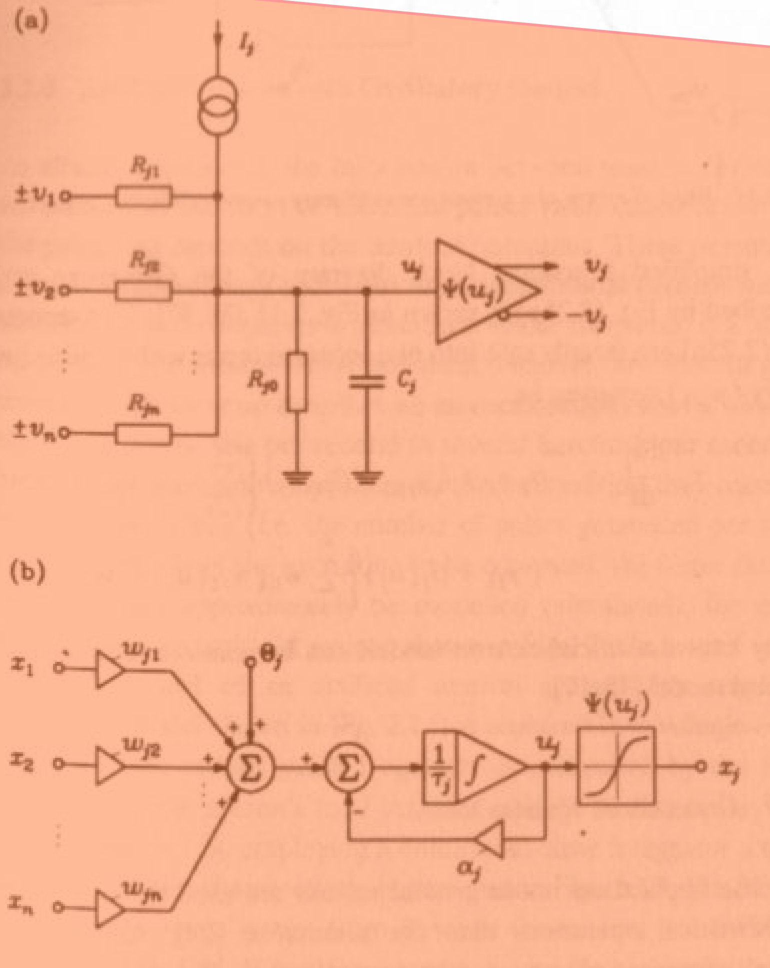


Fig. 2.10: (a) Hopfield model of a dynamic basic neuron cell
(b) Functional structure of the Hopfield neuron cell

By applying Ohm's Law and Kirchhoff's Current Law we obtain the following differential equation describing the neuron:

$$C_j \frac{du_j}{dt} = -\frac{u_j}{R_j} + \sum_{i=1}^{n} \frac{v_i}{R_{ji}} + I_j \,, \tag{2.22}$$

where

$$v_j = \Psi(u_j) \quad (j = 1, 2, \ldots, n)$$

and Ψ is the sigmoid activation function,

$$\frac{1}{R_j} = \frac{1}{R_{j0}} + \sum_{i=1}^{n} \frac{1}{R_{ji}} = G_{j0} + \sum_{i=1}^{n} G_{ji} \,,$$

in which G_{ji} denotes the conductances ($i = 0, 1, 2, \ldots, n$). The above set of equations can be written in the more general normalized form

$$\tau_j \frac{du_j}{dt} = -\alpha_j u_j + \left(\sum_{i=1}^{n} w_{ji} x_i + \Theta_j \right), \tag{2.23a}$$

$$x_j = \Psi(u_j) \,, \tag{2.23b}$$

where

$x_i = v_i$ ($i = 1, 2, \ldots, n$) are the input signals (voltages, potentials),
u_j is an internal signal called the internal potential, stimulus or action potential,
$\tau_j = r_j C_j$ is the integration time constant,
r_j is a scaling resistance,
$\alpha_j = r_j / R_j$ is a damping coefficient also called the decay, forgetting or leakage factor which makes the internal signal u_j zero for zero inputs,
$w_{ji} = \pm r_j / R_{ji} = \pm r_j G_{ji}$ are the synaptic weights (the plus-sign if R_{ji} is connected to $+x_i$ and the minus-sign if R_{ji} is connected to $-x_i$),
$\Theta_j = r_j I_j$ is the offset (an independent external signal).

A functional block diagram corresponding to Eqs. (2.23a,b) is shown in Fig. 2.10b. This block diagram consists of a summer with synaptic weights (w_{ji}), a damped (lossy) integrator and a nonlinear decision or limiting element (amplifier) with a sigmoid activation function. The amplifier used in the Hopfield model (with two symmetrical outputs $\pm x_j$) is characterized by a monotonic and differentiable function typically described by

$$\Psi(u_j) = \frac{1}{1 + e^{-\gamma u_j}} \quad \text{or} \quad \Psi(u_j) = \tanh(\gamma u_j), \tag{2.24}$$

where $\gamma > 0$ determines the slope or growth rate which is often not fixed, but can be varied during the computation process. The dynamic (time-constant) of the amplifier is assumed negligible. The dynamic of the whole neuron is determined by the capacitance C_j and the resistances R_{ji}. This dynamic can be adjusted by appropriate scaling. The synaptic weights are determined by the input conductances $G_{ji} = 1/R_{ji}$ connected to one of the output terminals ($+v_j$ or $-v_j$) of the j-th amplifier. Note that an excitatory synapse ($w_{ji} > 0$) requires that the resistor R_{ji} should be connected to the plus terminal while an inhibitory synapse ($w_{ji} < 0$) requires R_{ji} to be connected to the minus terminal of the j-th amplifier.

There are many modifications of the basic Hopfield model of the neuron described above. These modifications and extensions will be discussed in Section 2.3.

2.2.6 The Grossberg Model

The artificial neuron developed by Grossberg can mathematically be described by the following two equations:

the neuron's state equation

$$\tau_j \frac{du_j}{dt} = -\alpha_j u_j + (\gamma_j - \beta_j u_j)\left[\sum_{i=1}^{n} w_{ji} \Psi_i(u_i) + \Theta_j\right] \tag{2.25a}$$

and

the general purpose learning equation

$$\frac{dw_{ji}}{dt} = [-b_{ji} w_{ji} + d_{ji} \tilde{\Psi}_i(u_i)] h_i(u_i), \tag{2.25b}$$

where u_i is the internal activity of the j-th neuron; the neural output state y_j is related to the internal activity u_j by the equation $x_j = \Psi_j(u_j)$; $\alpha_j, \beta_j, \gamma_j$ are constants responsible for forgetting, the automatic gain control, and the total activity normalization; $\alpha_j u_j$ is called the self-term representing the passive exponential decay in the absence of the inputs (both the synaptic and the direct external input); and Θ_j is the direct external input. The function $x_i = \Psi_i(u_i)$ represents the nonlinear activation; different shapes of the nonlinear activation functions can be used in this model. The coefficients w_{ji} are the synaptic weights adjusted according to the learning equation. The coefficient b_{ji} is the forgetting term representing the passive low decay of the synaptic weights if b_{ji} is constant. The memory loss is modulated if b_{ji} is a time variable. The coefficient d_{ji} is the learning strength co trolling the speed of learning and representing the synaptic plasticity of th synapse w_{ji}. The function $\tilde{y}_i = \tilde{\Psi}_i(u_i)$ is the neural "learning signal" whic describes the state of the neuron i in the same way as $x_i = \Psi_i(u_i)$ although a lowance is made for different activation functions for output and learning pu poses. The function $h_i(u_i)$ is the activation representing the form of learning ar the memory process in the synapse w_{ji} stimulated by the incoming activity.

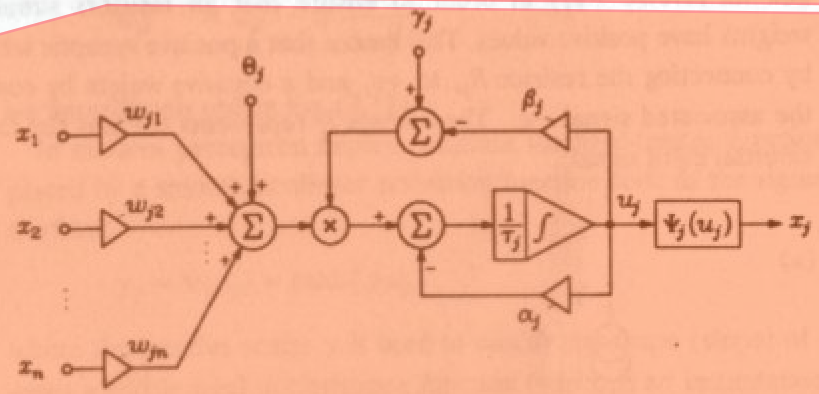


Fig. 2.11: Block diagram of a general nonoscillatory neuron cell based on the Grossberg model

A simplified functional block diagram of the Grossberg artificial neur described by Eq. (2.25a) is shown in Fig. 2.11 [36,37]. The summation terms Eq. (2.25a) are usually split into two separate terms with exciting (w_{jiE}) and inh bitory (w_{jiI}) synapses, i.e.

$$\tau_j \frac{du_j}{dt} = -\alpha_j u_j + (\gamma_{jE} - \beta_{jE} u_j)\left[\sum_{i=1}^{n_E} w_{jiE}\,\Psi_{iE}(u_i) + \Theta_{jE}\right] - (\gamma_{jI} + \beta_{jI} u_j)\left[\sum_{i=1}^{n_I} w_{jiI}\,\Psi_{iI}(u_i) + \Theta_{jI}\right]. \qquad (2.2$$

Many known artificial neuron models can be considered as special cases of th general model [13-17].

2.2.7 Generalized Neuron Model

In some applications more general models are used that involve more compl mathematical operations than the summation [24]. All the dynamic neur models discussed till now can be generalized to the set of nonlinear different equations