Study of a Self-Learning Artifical Neuron Model

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Giving a large autonomy to each cell and using a statistical average of the entries as a self-learning mechanism are not new ideas [1,2]. But linking statistical and linear dependencies through algebric properties is an approach which leads to biological interpretations.

During the training phase, the incoming of the input vector $\vec{X}$ produce basis' vectors distortions in such a way that the length of $\vec{X}$ increase or decrease (depending on the sign of the neuron's potential : Hebbian effect) while the direction of $\vec{X}$ stay constant (fig. 1). So, the basis vectors of the input space are not orthogonal and normalized ; the metric $M = ((m_{ij}))$, where m_{ij} is the scalar product of the ith by the jth basis vectors, gives an algebric form of the anisotropic neuron "perception" of its input space. The learning rule (for more details see [3]) is written :

$$\Delta M = \mu \frac{\nu}{\|\vec{X}\|^2}\left(P - \frac{T_P}{T_M} M\right) \text{ with } \begin{array}{l} \|\vec{X}\|^2 = {}^tXMX \ , \quad P = MX\,{}^tXM \\ T_P = trace P, \ T_M = trace\, M \end{array} \text{ where}$$

μ is a positive constant, ν the neuron's potential and X the column matrix of the input vector

For the output calculation, the algebric addings involve cell potential calculation reconsiderations. The scalar product $\nu = \vec{X}.\vec{W}$ is given by ${}^tXMW$ and $\vec{W}$ is extracted from M. We need to underline that the main inertia axis of M point to a direction which is a sort of statistical average of the input's vectors. Instead of defining $\vec{W}$ as a eigenvector associated to the greatest eigenvalue, we prefered to choose it in the eigenvectors set at random by assigning each of them a probability proportional to its associated eigenvalue.

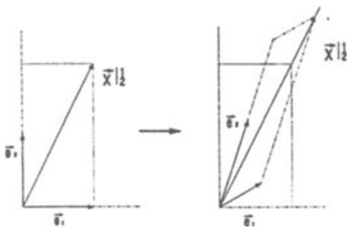

Fig.1 : Modification of M due the incoming of $\vec{X}$ (with $\nu>0$)

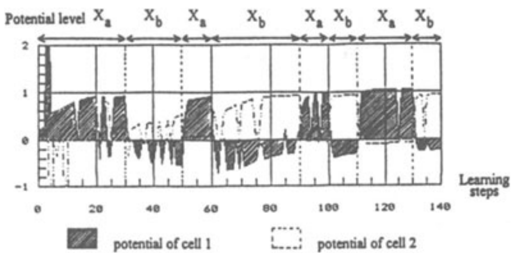

Fig.2 : Potential evolution of the two cells

Randomizing the potential calculation allows to have several neurons, connected to the same afferents, getting specialized in different directions of the input space due to lateral inhibitions (the specific treatment of the inhibition inputs is describe in [3]). As an example, let us consider two cells with the same two external inputs and inhibiting themselves mutually. The two following vectors are presented during the training phase : ${}^tX_a = (1,0)$ and ${}^tX_b = (0,1)$. For this type of algorithm, the good teacher always proposes the same vector until one of the cell has learned it and has forced the other cell to forget it (by inhibiting effect) ; then the other vector can be offered and be learned by the second cell (fig.2). At the end of the learning phase the system is leaded towards a stationary state ; statistically and with a great probability the cell 1 answers to X_a while the cell 2 reacts upon X_b.

As a discussion we would like to propose a biological interpretation. Introducing the metric M allows to take into account synaptic sensitivities (diagonal elements) but also inter-synaptic correlations (non-diagonal elements). So, thanks to M, it is possible to take into account some of the dentritic tree properties.

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[2] E. Oja, *A simplified neuron model as a Principal Components Analyser*, Journal of Mathematical Biology, 15, 267-273, 1982
[3] G. Vaucher, *Contribution à l'enrichissement du modèle formel d'un neurone*, Rapport d'étude, Supélec, R-SI-GV-TH-A1.1, France, June 1992.

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