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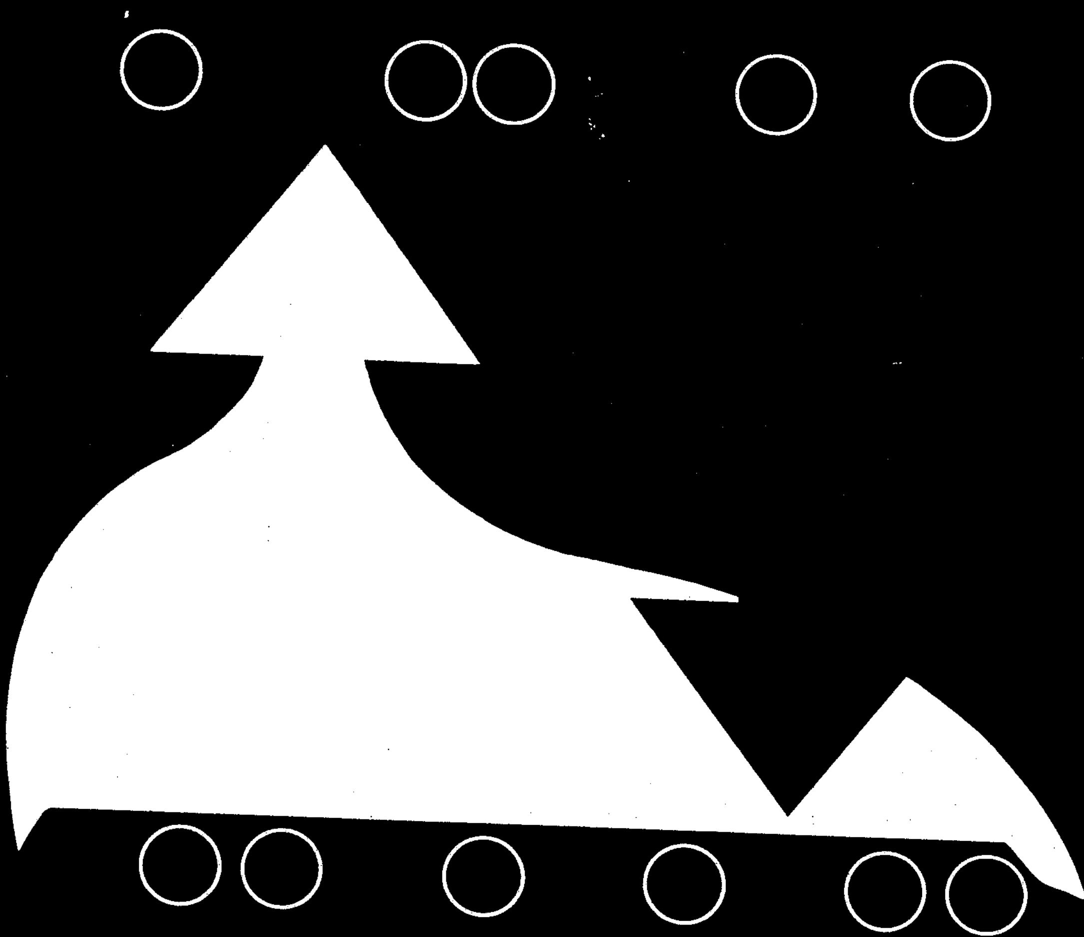

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A MULTILAYER NEURAL NETWORK MODELLING THE PERCEPTUAL REVERSAL OF AMBIGUOUS PATTERNS

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The capability of a multilayer neural network (based on a modified BSB model) for reproducing the stochastic dynamics of the perceptual reversal of ambiguous figures is assessed. Computer simulation results, as well as experimental data, are well fitted by a Gamma distribution.

1. Introduction

When an ambiguous pattern, such as the Necker cube or the Mach pyramid (Fig.1), is observed, the same visual input can elicit two different interpretations, giving rise to a cyclic perceptual alternation of such competitive interpretations. This repetitive cognitive behaviour can be regarded as the basic feature of the perceptual alternation phenomenon.

Mach Pyramid Necker Cube
Fig. 1

During a prolonged observation of an ambiguous drawing [1,2] , a stationary phase is reached in which both percepts appear with some regularity, and the perceptual durations of the competitive interpretations are well represented by a Gamma distribution, with a mean time normally ranging from few to about ten seconds . The analytic form of a Gamma distribution is:

$$p(t)\,dt = \frac{b^n\, t^{n-1}\ \exp(-bt)}{\Gamma(n)}\,dt \tag{1}$$

where $\Gamma(n)$ is the Euler-Gamma function.

In this paper, we propose a multilayer neural network model that is able to describe the main characteristics of the perceptual alternation phenomenon [3] and, in particular, the stochastic distribution required.

2. A single layer model of perceptual alternation

In a previous work [3] we described a single-layer neural network (SLN) model of perceptual alternation that was based on the "Brain State in a Box" (BSB) model proposed by Anderson and coworkers [4,5] . The SLN is the basic building block of the multilayer model that we present in the next section. Here we summarize and discuss the principal characteristics of the single-layer network.

The recognition processes related to an ambiguous pattern can be modelled by an autoassociative neural network in which the features characterizing both alternative interpretations must be coded in the activities of the network "neurons". So the state vector $\vec{f}$ of the network can be seen as composed of two subvectors, $\vec{f_A}$ (the first l components of $\vec{f}$) and $\vec{f_B}$ (the last $m - l$ ones), associated with the features of the two alternative interpretations, A and B, of the ambiguous pattern. Furthermore, such interpretations exclude each other, and can never be present together; hence, it is important that the excitation of the subvector $\vec{f_A}$ should exert an inhibiting influence on the subvector $\vec{f_B}$, and vice versa.

The connection matrix, C, is obtained by learning, through some trials, the two competitive interpretations, A and B, using a generalized Hebb rule. The matrix contains two square blocks, E_{AA} and E_{BB}, representing the positive autoconnections of each subvector ($\vec{f_A}$ or $\vec{f_B}$) to itself, and two rectangular blocks, I_{AB} and I_{BA} ($I_{AB} = I_{BA}^T$), which are the inhibitory connections of $\vec{f_B}$ to $\vec{f_A}$, and vice versa, that is:

$$C = \begin{pmatrix} E_{AA} & -I_{AB} \\ -I_{BA} & E_{BB} \end{pmatrix} \tag{2}$$

In this way, the SLN is able to reinforce the features of only one interpretation, while the features of the other are weakened; hence, when a constant input, $\vec{G}$, representing a static ambiguous pattern is presented, the system can reach a stable state (i.e., a corner of the box in BSB model), corresponding to one of two alternative percepts , in which every neuron of the related subvector is firing at its maximum rate . At this point, in order that the system may simulate an experimental cyclic behaviour, we assume that, once the system has reached a corner, a habituation process becomes effective for a fixed time lag, giving rise to a continuous decrement in the components of that subvector, which leaves the corner. As a result, the subvector representing the alternative part of the state vector becomes dominant and further decreases the activity of the other subvector.

The dynamical evolution of the i-th component of the state vector (i.e. the activation value of the corresponding neuron), from time t to time $t + \tau$, can be expressed by the equation:

$$f_i(t+\tau) = LIMIT\left[\left(\sum_{j=1}^{m} C_{ij} f_j(t) + \beta G_i\right)\left(1 - \sigma_i(t)\right)\right] \tag{3}$$

where $LIMIT$ is a function limiting the values of the state vector components to those ranging between zero and one, C_{ij} is the element of the connectivity matrix and βG_i is the i-th component of the stimulus multiplied by a constant parameter β and $\sigma_i(t)$ stands for the habituation process. The effect of this process is to lower the input sensitivity of the neurons. Accordingly, $\sigma_i(t)$ is usually zero but when the $LIMIT$ function becomes active, it assumes the value $\sigma = \sigma_o$ ($\sigma_o \in (0,1)$) for a fixed time lag.

A plausible value of the unit time τ is about a tenth of a second. In fact, to use continuous values of the neurons' activation, that is their firing rate, one must integrate the instantaneous activity of neurons over a suitable time interval (τ).

Computer simulations of the network behaviour [3] have shown the existence of a stable limit cycle in which the two percepts, A and B, alternate periodically; furthermore, this network exhibits considerable robustness to noise. In fact, the addition of a biologically plausible synaptic noise does not change significantly the temporal evolution of the SLN.

3. The multilayer model and its stochastic dynamics.

In order that the system may exhibit a stochastic behaviour, we designed a multilayer neuronal network (MLN) with a single-layer network as basic element. Such improvement involves inserting in the model the probable redundancy of the neural assemblies acting as "recognizers" in the brain [6]; then, an ambiguous input stimulus, $\vec{G}$, can be shifted among such parallel recognizers, as a consequence, for instance, of eye movements.

We designed a two layers network. The lower layer is made up of r SLNs working in parallel, without any interconnections. The probability, $p(t)$, that the input $\vec{G}$ is present in the k-th SLN of the lower layer can be expressed as:

$$p(t) = p(ON/ON)p(t-\tau) + p(ON/OFF)(1-p(t-\tau)) \tag{4}$$

where $p(ON/ON)$ is the transition probability from the state ON (input present) to the state ON and $p(ON/OFF)$ is the transition probability from the state OFF (input absent) to the state ON . We chose such transition probabilities that, on average, the stimulus is present in only one SLN of the lower layer for every time step. When the stimulus is not present in the k-th SLN, the input vector is the null vector.

The upper layer consists of a single basic unit (SLN). The input to the i-th neuron, $G_i^U(t)$, is the sum of the activities of the corresponding neurons in the lower layer:

$$G_i^U(t) = \sum_{k=1}^{r} f_i^k(t) \tag{5}$$

We assumed that the perceptual interpretations, A and B of the ambiguous pattern resulting from this MLN are associated with the temporal evolution of the upper layer; then the system perceives A (or B) if the sum $\varphi_A(t)$ of the activities of the neurons of the subvector $\vec{f_A^U}$, normalized to one, is greater than the corresponding sum $\varphi_B(t)$ for the subvector $\vec{f_B^U}$ (or vice versa $\varphi_B(t) > \varphi_A(t)$).

A preliminary test of the MLN behaviour , was performed, via computer simulations, using the following parameter values : $m = 10$; $r = 10$; $\beta = 0.9$; $\sigma_o = 0.6$ or $\sigma_o = 0.65$ or $\sigma_o = 0.7$ (for a time lag of 30 times τ). The parameter l could assume two values: $l = 6$ and $l = 5$ (perfect symmetry between A and B). If $l = 6$, $G_i = 0.02$ for $i \leq 6$ and $G_i = 0.03$ for $i \geq 7$; if $l = 5$, $G_i = 0.02$ for every i value. The connection matrix C was symmetrical with $C_{ii} = 0$.

When white noise (of the order of 0.4 of the connection value) is added to the connection matrix C, the MLN exhibits a stochastic dynamical behaviour. After a short transient period, a stationary phase is reached in which the two percepts alternate (Fig 2a), and the durations of each percept, (i.e. the time interval in which $\varphi_A > \varphi_B$ or vice versa) are distributed around their mean values according to a stochastic distribution that is well fitted by a Gamma distribution (Fig. 2b).

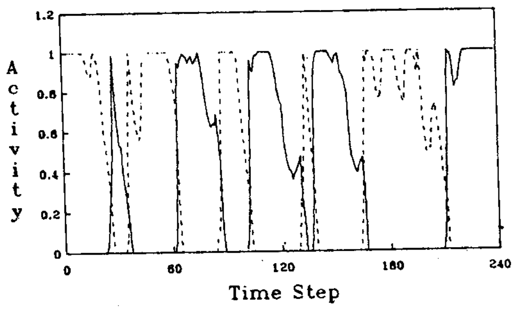

Fig. 2a

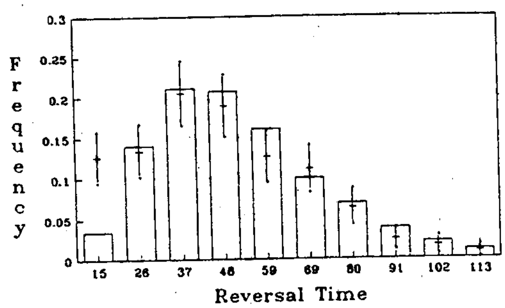

Fig. 2b

Fig. 2a Temporal evolutions of φ_A (continuous line) and φ_B (dashed line) during 240 iterations of one run of the computer simulation, for $l = 6$ and $\sigma_o = 0.6$.

Fig. 2b Comparison between the stochastic distribution of the reversal times of percept B, as obtained from the same run of the computer simulation as in fig. 2a, and the corresponding Gamma distribution histogram.

The values of the parameters b and n of the Gamma distributions, obtained by various computer-simulation runs, range from 0.01 to 0.1 τ^{-1} and from 2 to 5 respectively. In order to compare the simulation results with experimental ones [1,2], we point out that, if we choose the iteration time τ equal to 0.1 seconds, the mean duration times of computer simulations are of the order of a few seconds. This choices allows both the mean duration times and the values of the Gamma parameters to be very close to experimental ones [1,2].

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