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STOCHASTIC DYNAMICS AND INPUT DIMENSIONALITY IN A TWO-LAYER NEURONAL NETWORK FOR MODELLING MULTISTABLE PERCEPTION

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Abstract

A two-layer neuronal network model of the perceptual alternation of multistable figures is presented. Results of computer simulations have shown that the model makes it possible to obtain the stochastic Gamma distributions of the experimental perceptual durations of the alternating interpretations, as well as some other characteristics of the perceptual alternation phenomenon such as the dependency of reversal times on the complexities of pattern interpretations.

1. Introduction

The problem of "ambiguity" often arises from modelling the biological process of coding the external environment into its "inner" representation. In visual perception, an example of this kind of situations is the "perceptual alternation phenomenon" related to some visual patterns, called "ambiguous" or "multistable" figures. The visual input associated with an ambiguous figure can elicit two different interpretations, thus giving rise to a cyclic perceptual alternation of the two competitive interpretations. In Figure 1, three examples of this kind of figures are shown. The first is the Mach pyramid, which can be seen as a room or as a truncated pyramidal structure, (e.g. a roof); the second is the "Necker" cube, allowing two identical, though perspectively different, interpretations; and the third is a figure called "Rubin vase", which can be perceived as two faces on a white background or as a white vase on a black background.

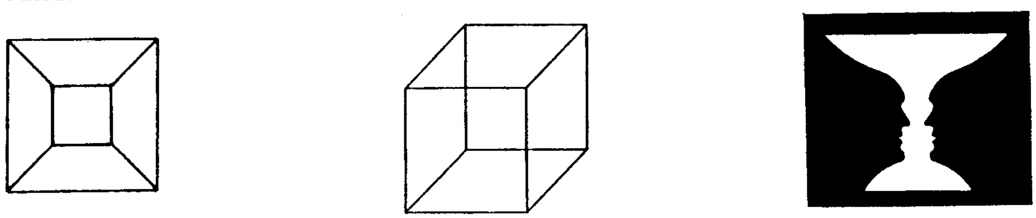

Fig. 1: Three Multistable Figures.

It should be stressed that if the observer is not aware of the existence of two different interpretations of the pattern, frequently the alternation process does not start, and the perceived configuration does not change [8]. Moreover, during a prolonged observation of an ambiguous drawing, 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, as pointed out by the extensive experimental work of our group [2),3),5)].

Different models of visual perception alternation that are based on artificial neuronal networks have been proposed in the last few years [6),9),11)]. In this paper, we propose a multilayer neuronal model that takes into account the main characteristics of the perceptual alternation phenomenon and, in particular, the stochastic distribution required.

Our model is based on a multilayer network (MLN) of redundant structures made up of identical single-layer neuronal nets (SLNs), working in parallel and independently of one another. The SLN was extensively discussed in [12)]. Here we briefly recall that the SLN is a simple recognizer, based on the properties of the "Brain State in a Box" [1)], in which the state vector $\vec{f}$ can be split into two parts: $\vec{f}_A$, associated with the first interpretation, A, of an ambiguous figure (e.g. the "faces" of the Rubin pattern) and $\vec{f}_B$, associated with the alternative interpretation, B, (the "vase" in the Rubin pattern); $\vec{f}_A$ and $\vec{f}_B$ consist, respectively, of n_A and n_B elements, which are "neurons" linked to the features of the two interpretations.

The connection matrix, C, is obtained by the Hebbian learning of both interpretations during different trials, and 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}, which are the inhibitory cross-connections of the subvectors:

$$C = \begin{pmatrix} E_{AA} & -I_{AB} \\ -I_{BA} & E_{BB} \end{pmatrix}. \tag{1}$$

The oscillating dynamics of the SLN is described by the following equations:

$$f_i(t+\tau) = LIMIT\left[\left(\sum_{j=1}^{n_A+n_B} C_{ij} f_j(t) + G_i\right)\left(1-\sigma_i(t)\right)\right]; \quad i = 1, ..., n_A + n_B, \tag{2}$$

where $LIMIT$ is a function restricting the values of the state vector components into the range $[0,1]$, to avoid non "physiological" levels of neuron activity; C_{ij} is the element of the connection matrix; G_i is the i-th component of the stimulus; and $\sigma_i(t)$ stands for the habituation process. The effect of this process is to lower the input sensitivity of the neurons when they are firing at their maximum rate: $\sigma_i(t)$ is usually zero but when the $LIMIT$ function becomes active, it assumes the value $\sigma = \sigma_o$ ($\sigma_o \in (0,1)$) over a fixed time interval (usually, .6-.7 for a period T equal to 30 τ). A biologically plausible noise can be added to the connection weight (i.e., the elements of C), without affecting the stability of the limit cycle.

2. Stochastic dynamics of the multilayer neural network

The MLN includes the probable redundancy [7)] of the neural assemblies acting as "recognizers" in the brain, and is composed of elementary blocks made up by single SLNs. The network consists of two layers: the lower one is made up of r redundant SLNs which work in parallel and independently of one another.

We assume that the visual input stimulus, $\vec{G}$, is shifted among such parallel recognizers, for instance, by eye movements. The input $\vec{G}$ is mapped on an SLN of the lower layer, with such a probability that the stimulus will be present, on average, in only one or two SLN(s) of the lower layer over each time interval.

The upper layer is constituted by a single SLN. The input to a neuron of the upper layer is equal to the sum of the activities of the corresponding neurons in the lower layer:

$$G_i^U(t) = \sum_{k=1}^{r} f_i^k(t) \tag{3}$$

After a short transient period, the activity of the upper layer of the MLN reaches a stationary phase in which the two subvectors, $\vec{f}_A$ and $\vec{f}_B$, become alternatively dominant, and in which the durations of the two percepts, t_A and t_B are stochastically distributed around their respective mean values. We found a range of parameter values for which the simulated distributions were well fitted by a Gamma distribution, with a good χ^2 [11].

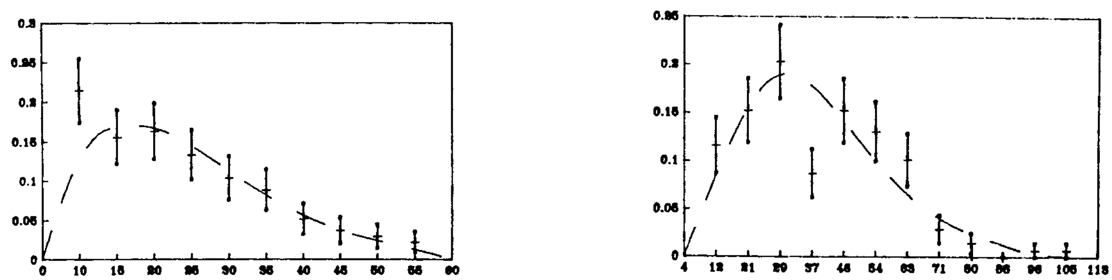

Fig. 2: Comparison between the theoretical Gamma distributions and computer simulations of the reversal times of percepts A and B.

Figure 2 shows a comparison between the stochastic distributions of the reversal times of the two percepts t_A and t_B (obtained via a computer simulation) and the corresponding theoretical Gamma distributions (dashed lines). It is worth noting that we use continuous values of the neurons' activation; this can be done by integrating the firing rate of the neurons over a suitable time interval, τ, covering the duration of some tens of spikes. A plausible value of the time τ, which can be regarded as the unit time for the MLN, is about a tenth of a second. This choice allows both the mean duration times (of the order of few seconds) and the values of the Gamma parameters to be very close to experimental ones.

3. Dependence of dynamics on the interpretations' complexities

An important phenomenological aspect of the perception of multistable figures is the dependence of perceptual alternation on the complexities of the two alternative interpretations. Following Structural Information Theory [4], the complexity of a pattern interpretation is linked to the minimum number of rules required to generate that interpretation.

Experiments on ambiguous patterns with interpretations of identical complexity, such as the Necker Cube [2),3], gave nearly equal mean duration times for the two interpretations; by contrast, when the two interpretations of an ambiguous pattern are different in complexity, the simplest interpretation becomes dominant. Such results were obtained, for instance, by studying a series of eight patterns based on the Mach pyramid [10]. The series started with the "classic" Mach pyramid (shown in Figure 1), where the two interpretations (roof and room) differed by 2 information units, and finished with an unbalance of 20 information units in the last drawing.

In Figure 3a, the mean duration times, $\bar{t}_A$ and $\bar{t}_B$ of the two interpretations versus the interpretation complexities, I_A and I_B, are shown. These data are reported in [10]. As one can see, when the difference in complexity between the interpretations A and B becomes greater, the interpretation B becomes more dominant.

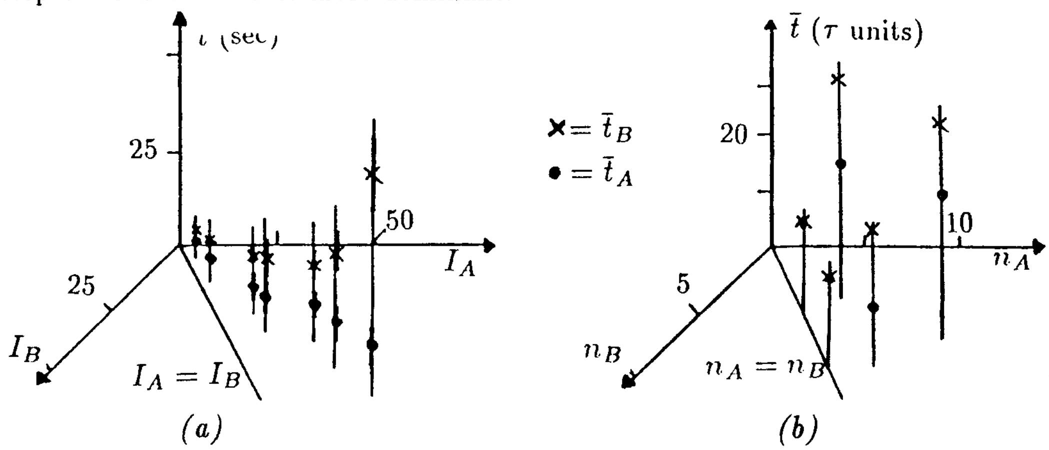

Fig. 3: See text.

If we assume a relationship between the interpretation complexities I_A and I_B and the number of SLN neurons, n_A and n_B, linked to the two interpretations A and B, the model shows a qualitative agreement between the results of computer simulations of the MLN (Figure 3b) and experimental results. In fact, the simulations give almost identical $\bar{t}_A$ and $\bar{t}_B$ values for n_A equal to n_B, whereas, when n_B is less than n_A, $\bar{t}_B$ becomes longer than $\bar{t}_A$.

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