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Perceptual alternation of ambiguous patterns:
a model based on an artificial neural network

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ABSTRACT

This work describes an artificial neural network modelling some peculiar aspects of human perception in the presence of so-called *ambiguous figures*. When one of such patterns is observed, the same visual input can elicit two different interpretations, *A* and *B*, giving rise to a cyclic perceptual alternation of the two competitive percepts.

The neural network used to model the phenomenon consists of two layers of identical subunits, which have been derived from the *Brain-State-in-a-Box (BSB)* model developed by Anderson and coworkers. Computer simulations have demonstrated that the model based on this two-layer neural network allows one to obtain the stochastic Gamma distributions of the experimental perceptual durations of the two alternative interpretations of an ambiguous pattern. Moreover, simulation results are in good agreement with some other characteristics of the perceptual alternation phenomenon.

1. INTRODUCTION

One of the basic procedures related to the interactions between a biological organism and the external world lies in the process of coding the external environment in an *inner representation* through which the organism extracts the structured and significant parts of an incoming message (i.e., signals or *figures*) from the unstructured and uninteresting ones (i.e., noise or *the ground*).

Modelling such a process is often affected by ambiguity, which constitutes a severe, yet intriguing, problem. Perceptual processes provide a large number of examples of ambiguity: the matching of the two bidimensional retinal images of a scene in their appropriate stereoscopic reconstruction exhibits a very high degree of ambiguity; at a higher level of abstraction, speech analysis is often affected by semantic ambiguity; etc..

Clearly, in the areas of artificial vision systems and automatic speech translators, ambiguity represents a major problem, whereas the human brain easily overcomes the difficulties associated with ambiguous situations. For instance, in word or pattern recognition, the brain focuses on extracting the most resembling representation of the object to be recognized among the many similar candidates previously stored.

To accomplish this task, the neural systems exploit their synergetic structure in connecting many concurrent hints. Selfridge gave an interesting example of such cooperation.

The example shows that the human perceptual system uses the identification of one item in an image to easily recognize other items for the solution of a case of ambiguity. In the following string

TAE CAT

of characters, the graphic sign A is immediately interpreted as an "H", or an "A", depending on the most likely meaning suggested by the context.

The above considerations lead to conclude that the study of *pathological* situations in which *ambiguity* is the main characteristic of the sensory input can aid in defining the perceptual processes associated with more usual unambiguous situations. Accordingly, the phenomenon of perceptual alternation of ambiguous visual patterns has been the subject of many investigations in the field of cognitive psychology^{2,6,7,11}.

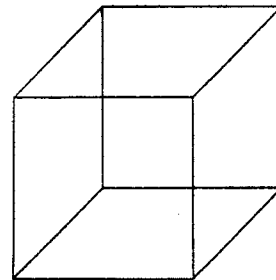
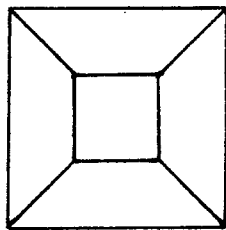


Figure 1: *Two ambiguous figures: the Mach Pyramid and the Necker Cube*

Observing one of such patterns (e.g., the Mach pyramid or the Necker cube, see Figure 1) can elicit two different interpretations of the same visual input, giving rise to a cyclic perceptual alternation of the two competitive percepts. Then it can be deduced that, in the presence of an ambiguous pattern, the cognitive aspects of pattern recognition also include a repetitive temporal behavior of the recognition process itself.

Such behavior may constitute the basis for an in-depth analysis of perceptual alternation. The *repetitive dynamics* of this phenomenon and the large amount of experimental data obtained under various conditions can be fully exploited to develop a phenomenological model that can be continuously tested and integrated by inserting new experimental data related to the various aspects of the phenomenon.

This strategy should allow one to prevent the usual drawback inherent in the modelling of perceptual processes: more precisely, it often occurs that the high complexity of the perceptive systems does not allow one to obtain experimental data on perception that are discriminating enough for the models available. In other words, the following situations may affect cognitive models: too simple models are likely to be in contrast with the results of further perceptual experiments, or, *similar* experimental results may often be incorporated into *conflicting* models, once that these models have been slightly modified in order to consider such results from different standpoints.

On the basis of the above considerations, we shall now describe some properties of the phenomenon of perceptual alternation; they have been deduced from experiments carried out in our laboratory, or from previous works, and should be included in the model.

- If an observer knows that a stimulus can elicit two or more alternative interpretations, he spontaneously replaces the actually perceived configuration with the alternative one. In this way, he begins a sequence of *cyclic fluctuations* of the two competitive interpretations, which, however, are never elicited simultaneously^{2,4}. Instead, if the observer is unaware of the two possible interpretations of the pattern used as a stimulus, it often appears that the alternation process does not start¹¹, hence the perceived configuration remains the same.
- The rate of perceptual fluctuation rises in the first 2 - 3 minutes till it reaches a stable value. During the following period, called stationary phase, the experimental data are very reproducible^{2,4}.
- The durations of the two percepts in the stationary phase are stochastically distributed around their mean values according to a two-parameter Gamma distribution^{2,8}, and the mean times usually range between few and about ten seconds.
The Gamma distribution can be expressed in analytic form as follows:

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

where $\Gamma(n)$ is the Euler-Gamma function, and the values of the two parameters, b and n , can be derived from experimental data by using the method of moments:

$$b = \frac{\bar{t}}{\sigma^2}, \quad n = \frac{\bar{t}^2}{\sigma^2}, \quad (2)$$

where \bar{t} is the average and σ^2 is the variance.

The two parameters are individual characteristics which also depend on the stimulus considered.

- Some physical parameters, like the noise added to the stimulus or the absolute value of the stimulus luminance¹⁸, little affect the mean durations of the two percepts; by contrast, other parameters, like the visual angle subtended by the figure, can have a stronger effect³.
- The ratio between the perceptual durations of the two competitive interpretations constitute an *a posteriori* measure of the pattern ambiguity^{15,19}. The degree of ambiguity of a pattern can be derived from the *a posteriori* probabilities of the alternating percepts, A and B , namely, $p_A = \bar{t}_B / (\bar{t}_A + \bar{t}_B)$ and $p_B = \bar{t}_A / (\bar{t}_A + \bar{t}_B)$, as the p_B/p_A ratio between the two probabilities, which is obviously equal to the \bar{t}_B/\bar{t}_A ratio. This ratio ranges from 1, for a pattern with two equivalent alternative interpretations ($p_A = p_B = 1/2$), to 0, for an unambiguous pattern with only one accepted interpretation ($p_A=1, p_B=0$).
Experimental results show an analytic dependence of this ratio on the differences between the complexities of the two alternative interpretations¹⁵ according to Structural Information

Theory⁵.

In the past few years, different models of visual perception alternation have been devised, which are based on artificial neural networks^{9,12,20}. In the present paper, a multilayer network is proposed that describes all the aforesaid characteristics of the phenomenon and, in particular, the stochastic distributions of the durations of the two alternative interpretations.

2. THE NEURAL MODEL OF PERCEPTUAL ALTERNATION

Our model is based on a multilayer network (MLN) made up of complex subunits that simulate the probable redundancy of the neural assemblies acting as recognizers in the brain¹⁰. The MLN consists of two layers of identical elementary blocks, called Single Layer Networks (SLNs), which operate in parallel and independently of one another.

2.1. Single Layer Network

Each subunit (SLN): is an autoassociative network that uses continuous values (between 0 and 1) of the neuron activations and a discrete time variable; is based on the properties of the *Brain State in a Box* model¹; and represents a development of the Kawamoto-Anderson model of multistable perception¹².

To model this phenomenon, one can assume that the state vector \vec{f} of the SLN consists of two sets of neurons (named *subpopulations*): the first set, \vec{f}_A , is made up of n_A elements or neurons, and is associated with the *perceptual features* of the first interpretation, A , of a figure (e.g., the *room* in the Mach pyramid); the second set, \vec{f}_B , is made up of n_B elements, and is associated with the alternative interpretation B (i.e., the *pyramid* in the Mach figure). Hence the vector \vec{f} turns out to be composed of $n_A + n_B$ elements.

Experimental results have shown that the two alternative interpretations, A and B , exclude each other, and are never elicited together; consequently, the excitation of the subvector \vec{f}_A must exert an inhibiting influence on the subvector \vec{f}_B , and vice versa.

Moreover, as mentioned earlier, if an observer is unaware of the possible interpretations of an ambiguous pattern, it often occurs that the alternation process does not begin¹¹. Once the observer has been informed about the various interpretations of the stimulus, the alternation process starts and goes on automatically. In other words, such a process begins if the *inner representations* of both interpretations of the pattern are already present in the observer's *perceptual machine*.

Using the terms of the neural-network language, one can say that the connection matrix, C , should be obtained, during the learning phase, by teaching the neural network to recognize both interpretations in different trials. Hence matrix C is given by the weighted sum of two other matrices, C_A and C_B , that is:

$$C = c_A C_A + c_B C_B. \quad (3)$$

where C_A results from learning the interpretation A of the ambiguous pattern, and C_B is obtained by learning the interpretation B of the same pattern.

Both above-mentioned experimental conditions are satisfied if the matrix of synaptic weights, C , is obtained through learning both interpretations by following a Hebbian rule

$$C_{ij} = c_a \left((1 + \eta) f_i^{(a)} - \eta \right) \left((1 + \eta) f_j^{(a)} - \eta \right) + c_b \left((1 + \eta) f_i^{(b)} - \eta \right) \left((1 + \eta) f_j^{(b)} - \eta \right). \quad (4)$$

where $\vec{f}^{(a)}$ ($\vec{f}^{(b)}$) is the stimulus vector, representing the A (B) interpretation of the pattern, with the first n_A (the last n_B) elements equal to one and the remaining n_B (n_A) elements equal to zero. The above learning rule, parametrized by c_A , c_B and η , produces a symmetric weight matrix, C , made up of four parts: 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:

$$C = \begin{pmatrix} E_{AA} & -I_{AB} \\ -I_{BA} & E_{BB} \end{pmatrix}. \quad (5)$$

As a result, the SLN can reinforce the features of only one interpretation, while those of the other interpretation are weakened.

Once matrix C has been constructed, one can start the simulation process of the perceptual alternation in the stationary phase of the phenomenon. The system receives a constant input, \vec{g} , representing a static ambiguous pattern (i.e., a vector with positive values of the activations on all the $n_A + n_B$ components). Then the system reaches a stable state (i.e., a *corner* of the box in the BSB model), corresponding to one of the two alternative percepts. In such a state, every neuron of the related subvector is firing at its maximum rate. It is worth noting that this description of the network activity implies the use of continuous values of the neurons' activation. This requirement can be met by integrating the firing rate of the neurons over a suitable time interval, τ , covering the duration of some tens of spikes. Such a time can be regarded as the unit time of our network.

To allow the system to simulate the experimental cyclic behavior, we have modified the BSB equations and assumed that, once a neuron has reached its maximum firing rate, a habituation process becomes effective over a fixed time interval. Such a process lowers the input sensitivity of the neuron, thus causing a decrement in the components of the saturated subvector, which, as a consequence, may leave the *corner*.

The habituation phenomenon is evident in biological neural networks, such as the sensory-motor system of the *Aplysia* studied by Kandel and coworkers¹³. As an effect of habituation, the subvector representing the alternative part of the state vector \vec{f} may become dominant, hence the activity of the first vector is further decreased by the inhibitory effect of the connection matrix, C . The dynamical evolution of the i -th component of the state vector (i.e., the activation value of the related neuron) from time t to time $t + \tau$ can be expressed by:

$$f_i(t + \tau) = L \left[\left(\sum_{j=1}^{n_A + n_B} C_{ij} f_j(t) + g_i \right) \sigma_i(t) \right]; \quad i = 1, \dots, n_A + n_B, \quad (6)$$

where L is a limiting function that makes it possible to avoid “non-physiological” levels of neuron activity, and that can be defined as:

$$L(x) = \begin{cases} 1, & \text{if } x > 1, \\ x, & \text{if } 0 \leq x \leq 1, \\ 0, & \text{if } x < 0; \end{cases} \quad (7)$$

C_{ij} is an element of the connection matrix; g_i is the i -th component of the stimulus; and $\sigma_i(t)$ stands for the habituation process, which lowers the input sensitivity of each neuron when it is firing at its maximum rate. Usually, $\sigma_i(t)$ is equal to 1, but when the function L saturates, $\sigma_i(t)$ assumes a constant value, $\sigma_o \in (0,1)$, over a fixed time interval (e.g., .3-.4 for a period of 30 times τ).

In this way, the SLN transforms the constant activations mapped from the ambiguous input stimulus into a succession of alternative waves of activation of \vec{f}_A and \vec{f}_B . Computer simulations of the SLN behavior²⁰ have pointed out that a stable limit cycle can be reached, in which the two competitive interpretations, A and B , alternate periodically. Moreover, the simulations have shown the considerable robustness of the neural network to noise: the temporal evolution of the SLN is not significantly affected by the addition of biologically plausible synaptic noise (see Figure 2)

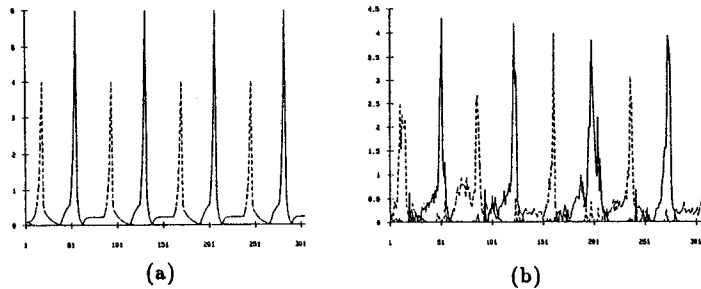


Figure 2: Two simulations of the SLN model: (a) noiseless, (b) with noise.

2.2. Multilayer network architecture

In the previous subsection, it has been shown that the periodic behavior of the SLN is not significantly modified by the addition of a biologically plausible quantity of synaptic noise. Therefore, in order that the neural system may exhibit a stochastic behavior similar to the one shown by the experimental data, we can increase the structure of the network by designing a multilayer neural network (MLN). The lower layer of the MLN is made up of a set of SLNs working in parallel, without any interconnections, and the upper layer is made up of only one SLN, identical to the lower ones.

We assume that the visual input stimulus, \vec{g} , is shifted among the parallel recognizers (SLNs) of the lower layer (e.g., by eye movements); over each time interval, the stimulus \vec{g} is mapped, and is likely to be present, on average, in only one or two SLNs of this layer^{16,17}. Concerning the input to the i -th neuron of the upper layer, $G_i^U(t)$, it is equal to the sum of the activities of the corresponding neurons in the lower layer:

$$G_i^U(t) = \sum_{k=1}^r f_i^k(t) \quad (8)$$

Under the above assumptions, the model exhibits a biologically plausible, ordered topology. The stimulus is connected, via a stochastic switch, to the neurons of one cell assembly of the lower layer (functional redundancy); the i -th neurons of all the SLNs of this layer are connected to the i -th neuron of the SLN constituting the upper layer (functional convergence).

3. COMPUTER SIMULATION RESULTS

We assume that the alternative perceptual interpretations, A and B , of the ambiguous pattern are strictly dependent on the temporal evolution of the upper layer of the MLN. More precisely, the system perceives A (or B) if the sum $\varphi_A(t)$ of the activities of the neurons of the subvector \vec{f}_A , normalized to one, is greater than the corresponding sum $\varphi_B(t)$ for the subvector \vec{f}_B (or, vice versa, if $\varphi_B(t) > \varphi_A(t)$).

3.1. Stochastic distribution of perceptual durations

If white noise is added to the elements C_{ij} of the connection matrix C and to the components g_i of the input vector \vec{g} , the MLN exhibits a stochastic dynamical behavior. The values N_{ij} of the matrix noise used for the simulations were at most 0.3-0.4 times the connection strengths C_{ij} , and the value N_i of the input noise was at most 0.4 times the corresponding input component g_i . The computer simulations of the dynamical network behavior showed that the activity of the upper layer of the MLN, after a short transient period (about two or three hundred time units τ), reaches a stationary phase. In this phase, the two subvectors, \vec{f}_A and \vec{f}_B , become alternately dominant (thus simulating the two percepts' alternation), and the durations of the percepts, t_A and t_B , (i.e., the time intervals over which $\varphi_A(t) > \varphi_B(t)$, or vice versa), are stochastically distributed around their respective mean values (see Figure 3).

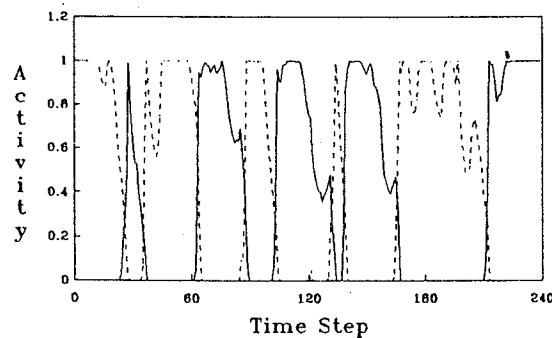


Figure 3: Temporal evolution of ϕ_A (continuous line) and ϕ_B (dashed line) of one run of the computer simulation.

Each computer simulation lasted from 10,000 to 20,000 time units τ ; this range made it possible to obtain a statistically significant amount of data. The simulated distributions were well fitted by the Gamma distribution, with a global efficiency ϵ of about 70 to 80 percent, at the one percent level of confidence.

Table 1 gives the values of the main parameters used in some simulations, together with the related values of the stochastic distributions, that is, the mean values of the durations of the two percepts, \bar{t}_A and \bar{t}_B , and with the results of the χ^2 goodness-of-fit test, i.e., the probabilities that χ^2 may be greater than the value observed.

Table 1

m	l	T_{hab}	\bar{t}_A	\bar{t}_B	$P(\Gamma_A)$	$P(\Gamma_B)$
20	10	30	16.4	16.2	.14	.09
20	13	30	24.2	37.3	.06	.41
20	11	30	10.5	24.7	.35	.06
18	9	30	15.3	15.4	.45	.45
10	5	30	15.3	15.7	.38	.14
10	5	35	20.4	20.0	.34	.32
10	6	35	20.2	40.5	.18	.26
10	6	30	24.3	39.2	.94	.07

Table. 1: The first 3 columns give, respectively: the dimension of the SLN (m), the dimension of subvector f_A (l) and the temporal duration (T_{hab}) of the habituation process, used for some computer-simulation runs of the MLN. The results related to such simulations are given in the last 4 columns; more precisely: the mean values of the perceptual durations of the two alternative interpretations (\bar{t}_A and \bar{t}_B) measured in τ units, and the probabilities of the χ^2 goodness-of-fit test ($P(\Gamma_A)$ and $P(\Gamma_B)$).

Figure 4 presents the results of the fitting procedure for a typical computer-simulation run.

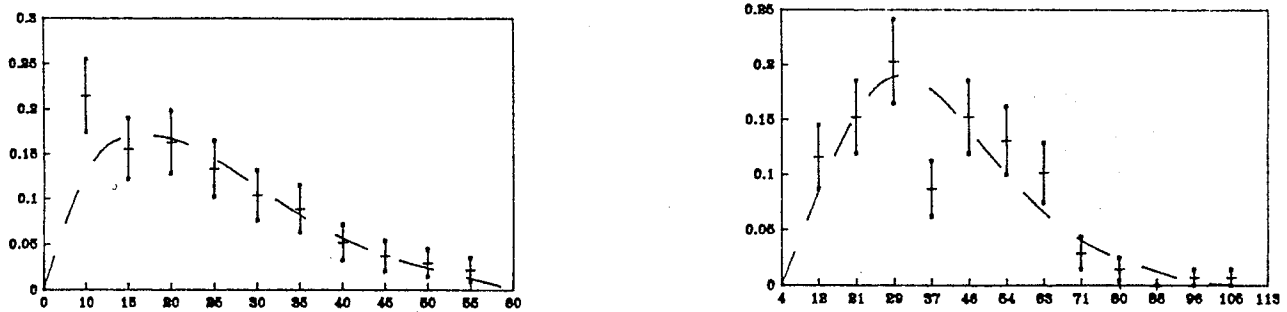


Figure 4: Comparison between the theoretical Gamma distributions (dashed line), and computer simulations of the reversal times of percepts, A and B, as given by the run corresponding to the last row of Table 1.

The values of the parameters b and n of the Gamma distributions, obtained by various

computer-simulation runs, range between 0.1 and 3.6 sec^{-1} and between 2 and 9, respectively. In order to compare the simulation results with experimental ones, it should be noted that, if the iteration time, τ , is taken equal to about 50 times a spike's duration, i.e., about 0.1 seconds, the mean duration times of the simulations are of the order of a few seconds. Such a τ value allows the mean duration times and the values of the Gamma parameters to be very close to experimental ones^{2,3}.

3.2. The role of percept complexities

A further phenomenological aspect of the perception of multistable patterns lies in the dependence of perceptual alternation on the complexities of the two alternative interpretations, *A* and *B*.

According to Structural Information Theory^{5,14}, the complexity of a pattern interpretation depends on the minimum number of rules required to obtain that interpretation. Experiments performed using ambiguous patterns characterized by interpretations of identical complexity (e.g., the Necker cube^{2,3}) prove that the mean duration times for the alternative interpretations of each pattern are nearly equal. Instead, when the two percepts of an ambiguous figure differ in complexity, the simplest interpretation prevails. Such results were deduced, for instance, from the study of a series of eight patterns based on the Mach pyramid¹⁵, which elicits two percepts (*roof* and *room*) of different complexities.

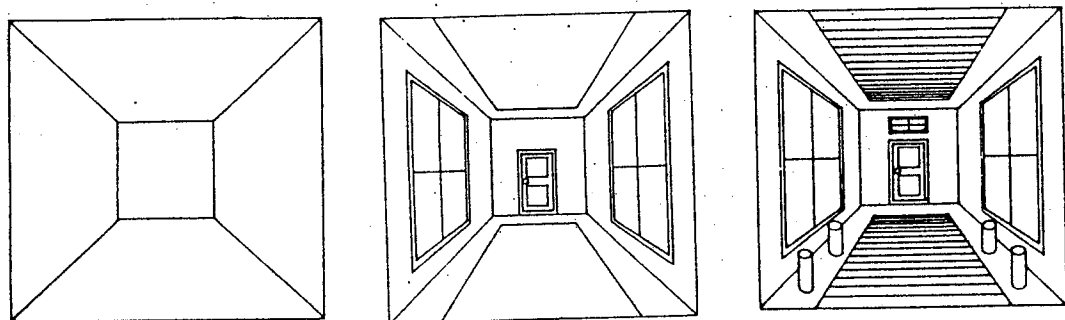


Figure 5: *Some patterns used in the experiment described in the text.*

The complete set of patterns was obtained by adding to the basic pattern some details, one by one, easily integrated into only one interpretation, thus favouring this interpretation. The difference in the interpretation complexities ranged from two to twenty information units. Figure 5 presents the first, fifth, and eighth patterns used in the quoted study.

Figure 6a gives the mean duration times, \bar{t}_A and \bar{t}_B , of the two alternative interpretations versus their interpretation complexities, I_A and I_B , for all the patterns of the series. One can notice that, when the difference in complexity between *A* and *B* increases, the interpretation *B* becomes more dominant.

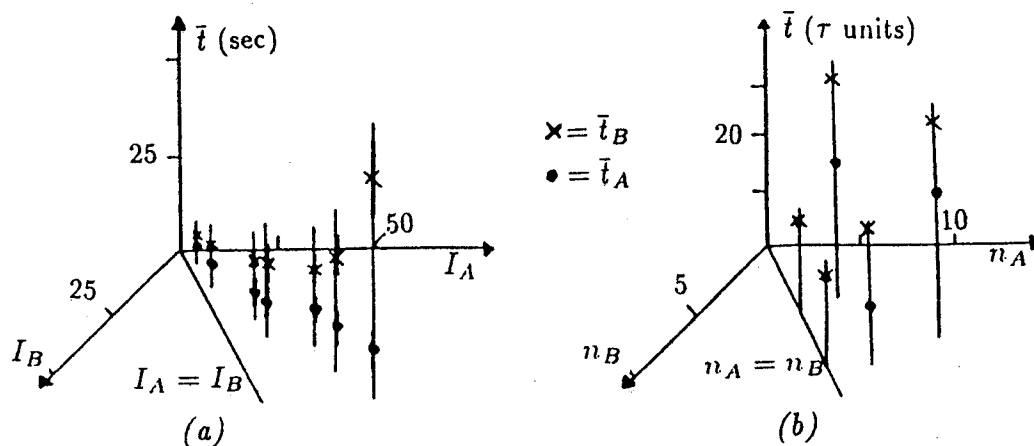


Figure 6: Comparison between experimental (a) and simulated (b) results.

Under the assumption of a relationship between the complexities I_A and I_B and the numbers of neurons of each SLN, n_A and n_B , associated with the two interpretations, A and B, the model points out a qualitative agreement between the computer-simulation results for the MLN (Figure 6b) and experimental results. The simulations gave almost identical \bar{t}_A and \bar{t}_B values for n_A equal to n_B , whereas, for $n_B < n_A$, \bar{t}_B was longer than \bar{t}_A .

4. CONCLUDING REMARKS

We conclude the description of the proposed approach to the perceptual alternation phenomenon by summarizing the results of computer simulations of our model, and by comparing such results with the phenomenological properties of the experimental data reported in the Introduction.

- The oscillating dynamics of the cell assemblies of the MLN can start only after the two competitive interpretations have been learned by the network by applying a Hebbian learning rule.
This fact is consistent with the experimental result showing that, if the observer is not aware of the possible two interpretations of the stimulus he is looking at, it often occurs that the alternation process does not start, and that the observer perceives only one of the two alternative interpretations.
- Computer simulations of the MLN have pointed out that, 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 with a stochastic behavior. Analogously, in real experimental situations, after an initial transient phase, the observer reaches a stationary phase in which the durations of the two interpretations keep constant

within statistical fluctuations, with high reliability^{2,3,4}.

- The experimental stochastic distributions of the alternative interpretations are well represented by the Gamma distribution, as demonstrated by the extensive experimental work carried out by our research group^{2,3,15,18}.

Also the simulated distributions of the perceptual durations obtained by the MLN model are well fitted by the Gamma distribution, with high efficiency^{16,17}. Moreover, the mean duration times and the values of the Gamma parameters derived from computer simulations are very close to the experimental ones, provided that the chosen time interval τ (i.e., the unit time of the MLN) is of the order of a tenth of a second.

- Concerning the perceptual alternations of ambiguous patterns eliciting alternative interpretations of different complexities, the assumption has been made about a relationship between the interpretation complexities, I_A and I_B , and the numbers of SLN neurons, n_A and n_B , associated with the two percepts A and B . As a result, the present model has evidenced a qualitative agreement between the computer-simulation results and experimental ones.

In conclusion, the multilayer model is able to provide a realistic enough description of the perceptual alternation phenomenon, under very different experimental conditions; in particular, it points out the quantitative fits of the stochastic distributions of the durations of the two alternative interpretations.

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