A Computer Model for Learning Processes and the Role of the Cerebral Commissures

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Abstract. A computer model of the two brain hemispheres is constructed of discrete populations of neurons, and it is shown to exhibit the characteristics of the great cerebral commissures, as has been pointed out by Sperry and others. For the range of parameters used we find that such systems respond in a specific manner to specific stimuli, and furthermore, whatever memory is transferred to one simulated hemisphere is also transferred to the other. However, this behavior changes when the two hemispheres are separated. We find that memory is not transferred from one hemisphere to the other when the interconnecting commissures are severed. The above findings verify Sperry's experimental observation that the split brain behaves as if it were indeed two separate brains, each performing concurrently and simultaneously diametrically opposite tasks.

I Introduction

Anatomically speaking the brain consists of two hemispheres which are linked together by several bridges, and normally function as one organ. A rude schematic of the two hemispheres is shown in Fig. 1. The most prominent of these bridges is a great cable known as the great cerebral commisure, or more technically, the Corpus Callosum (CC). It has been suggested that the CC is the highest integrating organ of the brain, and also the bridge that transfers information from one hemisphere to the other [1, 2]. Surgeons in the thirties in some cases of severe epilepsy tried cutting the CC in order to prevent the spread of epileptic seizures from one hemisphere to the other. Efforts to pinpoint losses of function in such cases were unsuccessful [1]. By cutting the CC they did not notice any change in any function of the brain. It requires a specially designed test to show that the split brain is not, after all, entirely normal in its function.

The first convincing test was performed by Myers [2]. In his experiments he first noticed that what was learned by one side of the brain was not transferred to the other. In fact the two sides can learn diametrically opposite solutions to the same experimental problem so that the subject's response depends on which side of the brain was receiving the stimulus. Myers' experiment involved cutting the optic chiasma (OC). The OC is a structure in which half of the nerve fibers from each eye cross over to the brain hemisphere on the opposite side of the head (Fig. 1). When a stimulus
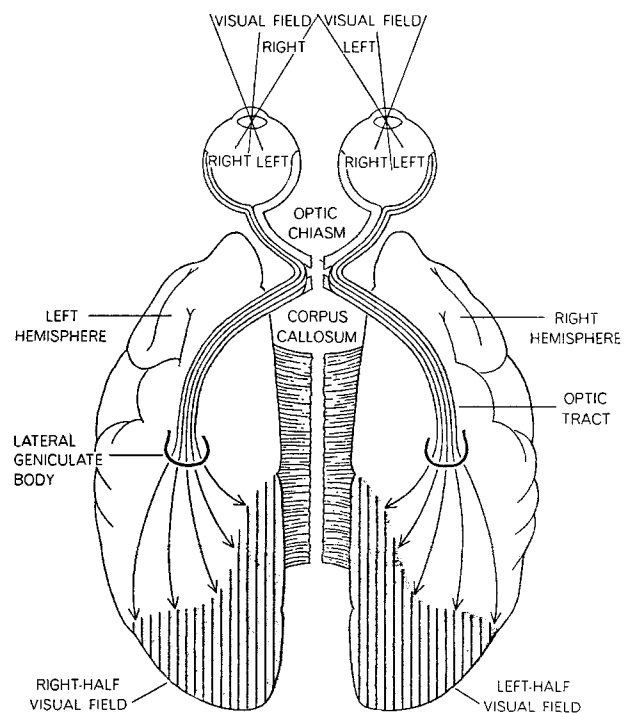

Fig. 1. The two hemispheres of the human brain. One can easily distinguish the connections that the two eyes make with the brain through the OC, as well as the connections between the two hemispheres through the CC. This figure was taken from Scientific American, January 1964, p. 244

is presented to an individual having one eye masked while the other eye remains open, then the learned memory pattern should be stored in the hemisphere corresponding to the open eye. Myers made the initial assumption that if the eye patch is shifted, so that the untrained eye is used, then the individual would not be able to recognize the same stimulus pattern, since the OC has been eliminated. But his experiments showed that this assumption was not correct. The subject's performance using the untrained eye was identical to that using the trained eye. This meant that whatever information was stored in memory from the training of the left eye was also available for comparison with the incoming information from the right eye. This result implied that the memory of the learned behavior pattern might have been stored in the brain stem rather that the cortex. But since the OC is not the only bridge between the two hemispheres it was still possible that the memory storage is actually located in the cortex. In fact, memory traces laid down in one hemisphere could transfer to the corresponding site in the other hemisphere by means of some other connections. Anatomy, as we stated above provides clear evidence for such system of interconnections which is the CC structure.

In the above experiments when the CC was eliminated the following results were observed. If the subject was trained to discriminate between two optical patterns using the left eye while the right eye was masked, then shifting the eye patch it was as though there had been a change in subject and not just in eyes. There was no transfer of experience from one eye to the other. The matter went even deeper. The subjects with severed OC and CC sections could actually be trained in contradictory discriminations with two eyes. The learning time for either eye was the same. Thus, these experiments showed that the above hypothesis that some connections other than the OC and CC transfer the memory patterns was not correct, and indeed we have to focus our attention only on these two cables, the OC and the CC.

These experiments are just a sample from a large variety of studies with split brain that are being carried out by several groups in order to determine the role of cerebral commissures, and help to pinpoint various centers of specific brain functions. They have also suggested new concepts and possibilities for investigating the complexities of the brain by using neural models. However, it must be stressed at this point that any model has utility only insofar that it raises questions, suggests new relationships and serves to focus one's thoughts. This can be accomplished by using it to test a hypothesis or suggest useful experiments. In the present study we shall try to re-examine the experimental findings on split brain

research using a simplified computer model based on our previous simulation studies [3], in order to see how close our theoretical hypothesis can come to reality.

In Sect. II we present in detail the neural net model that we use for this study. We first describe all statistical parameters, and then we give the details of the method of our model. In Sect. III we describe the results of our observations of our computer simulations under several different sets of initial conditions, and in Sect. IV we compare our computer results with the experimental findings of several groups.

II Neural Net Model

(a) Structural Parameters of the Neural Model

τ Synaptic delay

A_l Total number of neurons in netlet l

h_l Fraction of inhibitory neurons in netlet l

μ_l^+ Average number of axon branches emanating from an excitatory neuron in netlet l

μ_l^- Average number of axon branches emanating from an inhibitory neuron in netlet l

K_l^+ Average excitatory post synaptic potential (EPSP) produced by an excitatory neuron, in arbitrary units of amplitude in netlet l (the so called coupling coefficient)

K_l^- Average inhibitory post synaptic potential (IPSP) produced by an inhibitory neuron, in arbitraty units of amplitude in netlet l (the so called coupling coefficient)

ϑ_l Firing threshold of neurons in netlet l

(b) Dynamic Parameters of the Model

n An integer giving the number of elapsed synaptic delays (i.e. elapsed time)

α_n The activity, i.e. the fraction of active neurons in the netlet at $t = n\tau$ (the actual number of active cells is given by $\alpha_n A$)

$\mathbf{a}_n = \{^i\alpha_n\}$ State vector of a single netlet at time $t = n\tau$ which specifies the particular set of neurons active at any given instance

(c) Model

A neural net simulating a brain netlet is constructed and kept in the computer memory. Each netlet l is made of A_l neurons which are interconnected with μ_l^+/μ_l^- neurons. All connectivities make up the so called connectivity matrix. Each neuron in the netlet is characterized at random as excitatory or inhibitory, according to the initially prescribed h_l, the fraction of inhibition. At time $t = 0$ an initial signal is assigned to the netlet by simply exciting a given fraction of the A_l

neurons. Then the system is allowed to relax and reach a stationary state in the following manner. When a neuron fires at time t it produces the appropriate PSP's after a fixed time interval which is called synaptic delay τ. All PSP's arriving at a neuron are summed instantly and if the sum exceeds the neuron threshold then the neuron fires. If it is less than the threshold then the neuron remains idle. After firing a neuron is insensitive to further stimulation for a period of time called the "refractory period". For our purposes we take the refractory period to be greater than τ, but less than 2τ. Temporal summation occurs without decrement but only for periods less than one synaptic delay. In other words, summation is limited to one synaptic delay and hence essentially it is spatial; the refractory period lasts only one synaptic delay but it is absolute.

In addition to the initially assigned excitation an external input can be introduced to a netlet at time $t=0$, representing the stimulus whose response to the brain we want to study. The particular neurons to which this stimulus goes to are also initially chosen at random at time $t=0$, but then the same neurons are selected for the duration of this stimulus.

(d) Method

In this model we consider the simulated intact brain consisting of two neural nets as described in the previous section. These are constructed with the same statistical parameters $(A, \vartheta, \mu^+, \mu^-, h, K^+, K^-)$ but different microscopic structures [3], and with their interconnections ($\mu_{12}^{\pm}$ and $\mu_{21}^{\pm}$) corresponding to the intact corpus callosum structure. See Fig. 2 for such a schematic. In addition to each neural net or simulated hemisphere we consider connections from each eye to both hemispheres in order to simulate the optic chiasma structure in the real brain. Such connections can be activated by the stimuli presented to the eye, carrying inputs to both hemispheres (what we described earlier as the external input). We establish the pattern of these connections also at random.

When all desired interconnections have been established and stored in the computer memory the netlet is activated by specifying the set of neurons which fire at $t=0$. One synaptic delay later all neurons which are linked to those initially active are found through reference to the connectivity matrix of the simulated brain. These neurons now receive excitatory or inhibitory inputs, as the case may be. The algebraic sum of the coupling coefficients ($K^{\pm}$) characterizing the active incoming connections represents the excitation level in any of these neurons. Whenever the sum exceeds the threshold the neuron fires and following one additional synaptic delay it becomes the source of excitation or inhibition for all neurons
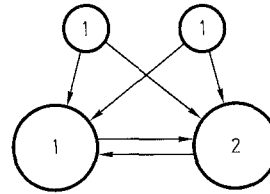

Fig. 2. The connections that the eyes make as given by Case (a), the normal case. The CC and OC structures are intact

connected to it. Otherwise all active incoming connections return to the initial value one additional synaptic delay later. When a neuron fires its threshold is raised to a very high value and remains at this level for the specified duration of the absolute refractory period, during which time the neuron may receive excitation but cannot fire due to its artificially high threshold. Finally, in order to incorporate the inputs from each eye to the corresponding simulated hemisphere and to the one in the opposite side we consider two bundles of afferent fibers from each eye to be attached to both hemispheres. Upon entering the netlets each of the afferent fibers splits and makes excitatory or inhibitory synaptic connections with μ_0^+ or μ_0^- different neurons if it comes from an excitatory or inhibitory neuron, respectively. Let K_0^+ or K_0^- be the average coupling coefficient of the synapses made by the afferent excitatory and inhibitory fibers, respectively. We thus introduce a stimulus either to both or to one eye. Let σ be the fraction of afferent fibers discharging at any instance of time. Then the number of active fibers will be $\sigma A_0 \mu_0$, where A_0 represents the number of cells outside the netlet. The recipient cells are chosen randomly at each time t from the total neuron population in the netlet.

The properties of nerve nets which simulate the two hemispheres are determined on one hand by their overall structural parameters, and on the other hand by their detailed or microscopic structure. The overall net parameters include the total number of neuronal elements in the net (A), the percentage of inhibitory elements (h), the average number of afferent connections made by each cell (μ^+ for excitatory elements and μ^- for inhibitory ones), the efficacy of these connections (K^+ and K^-, respectively) and the threshold for firing (ϑ). In addition to the overall (or "microscopic") net parameters an important role is also played by the "microscopic" patterns of connections, i.e. the detailed plan of connections made by each specific neuron. The objective of this work is to clarify the role of this "microscopic" structure in inducing changes in behavior in the simulated brain. It is clear that such changes can be determined only if a frame of reference is available for comparison of the behavior of different neural nets. Such frame of reference can be established using a number of criteria related to cycling activity, such as its presence or absence, its period, and the delay until its onset. In

Table 1. Statistical parameters of the simulated brain structures for several cases (the subscripts 1 and 2 refer to the two hemispheres)

Case	A_1	A_2	$\mu_{11}^{\pm}$ (min)	$\mu_{11}^{\pm}$ (max)	$\mu_{22}^{\pm}$ (min)	$\mu_{22}^{\pm}$ (max)	h_{11}	h_{22}	h_{12}	h_{21}	$\mu_{12}^{\pm}$ (min)	$\mu_{12}^{\pm}$ (max)	$\mu_{21}^{\pm}$ (min)	$\mu_{21}^{\pm}$ (max)	$K_{11}^{\pm}$	$K_{22}^{\pm}$	$K_{12}^{\pm}$	$K_{21}^{\pm}$
1	500	500	1	9	1	9	0.40	0.40	0.40	0.40	1	9	1	9	10	10	10	10
2	500	500	1	7	1	7	0.50	0.50	0.50	0.50	1	7	1	7	10	10	10	10
3	500	500	1	7	1	7	0.20	0.20	0.20	0.20	1	7	1	7	10	10	10	10
4	500	500	1	9	1	9	0.20	0.20	0.20	0.20	1	9	1	9	10	10	10	10
5	500	500	1	7	1	7	0.40	0.40	0.40	0.40	1	7	1	7	10	10	10	10
6	500	500	1	7	1	7	0.30	0.30	0.30	0.30	1	7	1	7	10	10	10	10

Table 2. Simulation studies with OC and CC intact, Case (a)

Case	ϑ	$\sigma A_0 \mu^{\pm}$ 1st hemisphere	$\sigma A_0 \mu^{\pm}$ 2nd hemisphere	Number of states in 1st hemisphere before cycling and learning	Number of states in 2nd hemisphere before cycling and learning	Number of states in 1st hemisphere before learning	Number of states in 2nd hemisphere before learning	Number of states in 1st hemisphere before cycling and after learning	Number of states in 2nd hemisphere before cycling and after learning	Number of states in 1st hemisphere after learning	Number of states in 2nd hemisphere after learning
1	10	2000	2000	16	16	4	4	12	12	2	2
2	10	2000	2000	10	10	2	2	14	14	2	2
3	10	2000	2000	4	6	2	2	4	4	2	2
4	20	2000	2000	8	8	2	2	8	10	2	2
5	10	2000	2000	12	12	2	2	10	10	2	2
6	10	2000	2000	26	28	2	2	20	22	2	2

earlier studies [3] it has been found that given certain overall parameters of the neural net, it will sustain cycling activity regardless of the "microscopic" structure, and the period of cycling will be approximately the same for nets having different detailed structures. On the other hand the delay until the onset of cycling depends on the "microscopic" structure. From a functional point of view cycling activity may be related to the "responsiveness" of the net to a given external stimulus. If a scheme of a recent memory involving cycling activity [8] is considered, then the delay for the onset of cycling may be directly related to some difficulty in recalling this experience. Thus, for the range of parameters that we used we find that these netlets may respond in specific manner to specific stimuli, and furthermore, whatever memory is transferred to one netlet is also transferred to the other. The response of the system is always monitored by the rise of cycling activity, as stated above, and also described in detail elsewhere [3].

III Computer Simulation Results

We report here our results of presenting a stimulus to the eyes under several sets of conditions, as described in detail below:

(a) Normal Case

As normal case we consider the one in which both the simulated CC and OC structures are intact. Table 1 summarizes several runs that we considered here. The first phase of the simulation consists of presenting a stimulus pattern to both eyes of the simulated brain. Each eye by virtue of its connections (see Fig. 2) to both hemispheres will activate certain number of neurons due to this external stimulus. This process is allowed to continue for approximately 200 synaptic delays until the system acquires cyclic sustained activity of certain frequency, which will be our bias for the modulation of the cyclic activity produced during learning.

The second phase of the simulation consists of presenting again the same stimulus to both eyes, but this time we allow the system to learn the external stimulus according to the following learning rule [4]: If the neurons $^i\alpha_n$ and $^j\alpha_{n-1}$ are active, i.e. $^i\alpha_n = {}^j\alpha_{n-1} = 1$ and $K_{ij} > 0$ then we increase the coupling coefficient K_{ij} by an amount δ_{ij}, so that the new coupling coefficient becomes $K_{ij} = K_{ij} + \delta_{ij}$; otherwise $\delta_{ij} = 0$.

The third phase of the learning process consists of examining again the system after learning, by presenting the stimulus pattern to both eyes. Here again we allow the system to run for approximately 200 synaptic delays by which time usually the system has acquired cyclic activity of a certain period. Thus, if

the system recognizes an external stimulus its response is monitored by the rise of cyclic activity. The response time is given by the number of states preceding cycling. The results for several runs with different statistical parameters are given in Table 2. Thus in all simulated brains used in this study in which all cerebral commissures are intact we see that the stimulus is recognized by both hemispheres. For example in case 1 of Table 2 we see that in the first hemisphere before learning we have a cyclic activity of period 4 (with response time of 16) while after learning the period is 2 (with response time 12). The second hemisphere has exactly the same response as the first hemisphere. This difference in cyclic activity before and after learning represents recognizing the signal. However we should clarify here the fact that in some cases the cyclic period after learning is the same with that before learning. This will be acceptable provided that the number of active neurons before and after learning are different, and may occur in any one of the present cases.

(b) The Stimulus is Presented to One Eye

The second case here is similar to the first with two differences: (i) Instead of presenting the stimulus to both eyes we allow only one eye to see the stimulus while the other eye is masked. (ii) After the learning process of the stimulus using one eye we shift the eye patch to the other eye and present the stimulus again to see if it recognizes it without learning. The results are shown in Table 3. Again we observe transfer of memory from one hemisphere to the other. For example in case 6 of Table 3 we see that in the first hemisphere before learning we have a cyclic activity of period 6 (response time 32) while after learning a period of 2 (response time 22). The second hemisphere has corresponding values of 6 (response time 36) before learning and 2 (response time 20) after learning.

(c) Elimination of the Optic Chiasma

In this case we cut the OC. This is done by leaving intact the connection of the eye to the directly corresponding hemisphere (left hemisphere in Fig. 3) and eliminating the connection to the opposite hemisphere (right hemisphere in Fig. 3). In order to investigate if there is transfer of memory of the learned stimulus from one hemisphere to the other, we present the stimulus to one eye as we did in (b) until learning. Then we shift the eye patch to the other eye and without learning we present the stimulus again to the unmasked eye. The results are given in Table 4. We see that in this case, too, the stimulus is still recognized. For example in case 2 of Table 4 we see that in the first hemisphere before learning we have a cyclic activity of period 6 (response time 34) while after learning a

Table 3. Simulation studies with one eye masked, Case (b). The two lines in each case represent the observations before and after shifting the eye patch, respectively

Case	θ	σA₀μ± 1st hemisphere	σA₀μ± 2nd hemisphere	Number of states in 1st hemisphere before cycling and learning	Number of states in 1st hemisphere before learning	Number of states in 2nd hemisphere before cycling and learning	Number of states in 2nd hemisphere before learning	Number of states in 1st hemisphere before cycling and after learning	Number of states in 1st hemisphere after learning	Number of states in 2nd hemisphere before cycling and after learning	Number of states in 2nd hemisphere after learning
1	10	400	1600	24	2	24	2	20	2	20	2
1	10	1600	400					20	2	20	2
2	10	1000	1000	40	2	42	2	20	2	20	2
2	10	1000	1000					20	2	20	2
3	10	400	1600	6	2	4	2	4	2	4	2
3	10	1600	400					8	2	8	2
4	20	400	1600	8	4	8	2	12	4	12	2
4	20	1600	400					10	2	10	2
5	10	400	1600	4	2	14	2	12	2	10	2
5	10	1600	400					14	2	15	2
6	10	80	100	32	6	36	6	22	2	20	2
6	10	100	80					24	2	24	2

Table 4. Simulation studies with the OC cut and one eye masked, Case (c). The two lines in each case represent the observations before and after shifting the eye patch, respectively

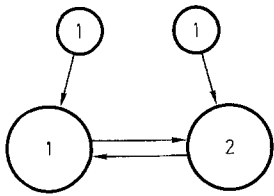| Case	θ	σA₀μ± 1st hemisphere	σA₀μ± 2nd hemisphere	Number of states in 1st hemisphere before cycling and learning	Number of states in 1st hemisphere before learning	Number of states in 2nd hemisphere before cycling and learning	Number of states in 2nd hemisphere before learning	Number of states in 1st hemisphere before cycling and after learning	Number of states in 1st hemisphere after learning	Number of states in 2nd hemisphere before cycling and after learning	Number of states in 2nd hemisphere after learning
1	10	400	0	47	2	46	2	72	12	68	12
1	10	0	400					52	4	52	4
2	10	1000	0	34	6	36	6	34	2	34	2
2	10	0	1000					32	2	32	2
3	10	400	0	10	2	10	2	6	2	6	2
3	10	0	400					10	2	10	2
4	20	400	0	18	2	0	0	74	2	72	2
4	20	0	400								
5	10	400	0	126	6	132	6	68	4	68	4
5	10	0	400					32	4	32	4
6	-10	80	0	24	2	30	2	30	6	30	6
6	10	0	80					22	2	22	2

Fig. 3. The connections that the eyes make as given by Case (c), where the OC is eliminated
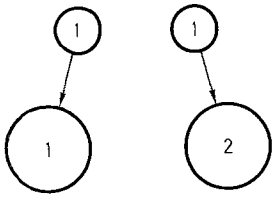

Fig. 4. The connections that the eyes make as given by Case (d), where both the OC and CC structures are eliminated

period of 2 (response time 34). By shifting the patch and presenting the stimulus which has already been learned we check to see if this stimulus is going to be recognized by the other eye without going through the learning process this time. We observe again a cyclic period of 2 (response time 32) which means that the stimulus memory is still available for comparison, and furthermore it is recognized. Similarly for the second hemisphere.

(d) Elimination of Both the Optic Chiasma and Corpus Callosum

Finally, in the case of cutting off both OC and CC (Fig. 4), by presenting the stimulus pattern to one simulated hemisphere and allowing the system to learn the stimulus we observe that if we present the same stimulus to the untrained hemisphere it will respond by not recognizing the presented stimulus. The results are in Table 5. We compare the findings here with the results of Table 4 which gives the monitor bias cycling periods for the corresponding experiment. As an example consider the first microscopic structure of Table 4. Here we see that before learning the cyclic period is 2. After learning it is 12, which means that the stimulus is recognized. By shifting the stimulus to the other hemisphere we have a cyclic period of 4 without learning, which means that the stimulus is still recognized. On the other hand if one looks at the same microscopic structure of Table 5 we see that the stimulus is recognized only by the eye to which the hemisphere is connected to, in this case with a cyclic period of 4 (left hemisphere) and 2 (right hemisphere), and not by the other eye (cyclic period of 0).

IV Discussion

We have used a computer simulation model to investigate the circumstances under which a stimulus experience may be transferred from one brain hemisphere

Table 5. Simulation studies with the OC and CC eliminated and one eye masked, Case (d). The two lines in each case represent the observations before and after shifting the eye patch, respectively

Case	ϑ	$\sigma A_0 \mu^\pm$ 1st hemisphere	$\sigma A_0 \mu^\pm$ 2nd hemisphere	Number of states in 1st hemisphere before cycling and learning	Number of states in 1st hemisphere before learning	Number of states in 2nd hemisphere before cycling and learning	Number of states in 2nd hemisphere before learning	Number of states in 1st hemisphere before cycling and after learning	Number of states in 1st hemisphere after learning	Number of states in 2nd hemisphere before cycling and after learning	Number of states in 2nd hemisphere after learning
1	10	400	0	12	4	0	0	12	4	0	0
1	10	0	400					0	0	8	2
2	10	1000	0	16	2	0	0	10	2	0	0
2	10	0	1000					0	0	6	2
3	10	400	0	8	2	0	0	8	2	0	0
3	10	0	400					0	0	10	4
4	20	400	0	4	2	0	0	4	2	0	0
4	20	0	400					0	0	0	2
5	10	400	0	8	2	0	0	8	2	0	0
5	10	0	400					0	0	2	2
6	10	80	0			0	0	0	0	0	0
6	10	0	80					0	0	0	0

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to the other. We paid particular attention to experimental findings of split-brain investigations and used our model in a simulation to "mimic" the same situations as close as possible. Particularly, we refer to the experiments by Sperry [5], Gazzaniga et al. [6, 7], and Myers [1]. Our findings verify their experimental results that in a human brain indeed learning and memory are transferred through the OC and the CC. It is therefore now plausible to assume that in animals as well as in humans with intact CC and OC a copy of the visual world as seen in one hemisphere is sent over to the other, with the result that both hemispheres can learn together a discrimination presented to just one hemisphere. In the split-brain situation this extention of the visual pathway is cut-off. Experimentally this is attained by simply cutting the connecting OC and CC cables, as for example in Myers' experiments [1], and in our simulations it is attained by eliminating the relevant parts of the connectivity matrix (as explained in the previous sections) so that no potential may pass from one hemisphere to the other. Our results show that the visually isolated hemisphere is not able to learn the stimulus but rather has to go through the learning process from the beginning. These indications of doubling memory in the brain raise a number of new questions about the role played in the learning process by attention, perception and motivation. Thus new lines of thought and research can be suggested for investigating the mysteries of the mind.

The model used here is somewhat simplified. For instance, it does not allow for the gradual decay of synaptic potentials, and hence completely excludes temporal summation. However, this presentation is only a first approximation, and one should not forget that it is unrealistic to expect to reproduce in a model all the features of the nervous system. Starting from this point we plan to pursue further questions and build up in complexity our initial model.

In addition to the above verifications of the experimental findings some philosophical implications are also suggested. The separation of the hemispheres may create two independent spheres of consciousness within an individual organism. This conclusion is disturbing when we view consciousness as an indivisible property of the human brain. But for such concepts to be verified more sophisticated models and experiments have to be developed in order to relate the larger-scale characteristics of the nervous-system brain functions.

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