

Chapter 10

Learning and Recalling Canonical Visual Patterns

Various aspects of the proposed brain model have been simulated to provide initial assessments of the basic competence and operating characteristics of the component mechanisms. The tests described in this chapter involve the synaptic matrix, either in isolation or working together with some of the accessory circuits and the retinoid system. All of the stimuli used in these tests were visual objects with nonvarying shapes. They were projected to a simulated retina not only in pristine form but also presented as multiple objects in superposition, degraded by visual noise, or rotated away from the angular orientation at which they had been learned.

Pattern Recognition and Associative Sequential Recall

One of the more intriguing aspects of human cognitive activity is that of associative sequential recall. The stream of passive thought is often not constrained by the principles of deduction or the application of rules of inference; the succession of conscious impression seems to proceed rather along analogical and metaphorical links. A given situation may evoke a wide variety of imaginal recollections. Some may be obviously similar to the immediate stimuli; other recalled images may be so dissimilar to the initial perception as to be surprising and seemingly completely fortuitous. Useful insights and creative ideas often occur without our awareness of logical precession (see Shepard 1978 for an extended treatment of this topic). The following simulation yielded results suggesting that the synaptic matrix can generate associative relationships rich enough to provide a biological mechanism for such phenomena.

In an early test of the model (Trehub 1979), a synaptic matrix that received visual input from a 6×6 -cell retina was simulated. Two different modes of recall were examined. The stimuli consisted of 25 scenes, each composed of a combination drawn randomly from a set of four objects (patterns) or an empty space and randomly assigned to each quadrant of the scene (figure 10.1). Filled regions designated

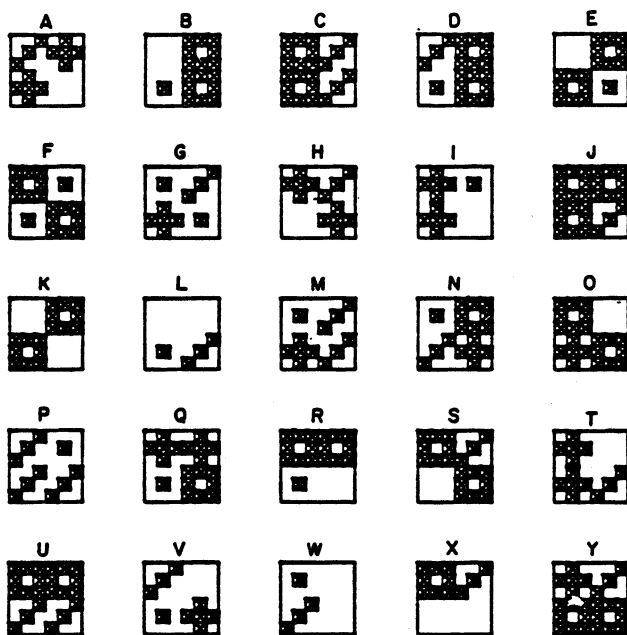


Figure 10.1

Scenes presented for learning and subsequent recall. Letters A–Y represent associated class designations. Source: Trehub 1979. Copyright Academic Press (London) Ltd. Reproduced by permission.

points of stimulation to the retina and thence through the afferent channel to their coordinate mosaic cells in the synaptic matrix. Each scene was arbitrarily centered on the normal foveal axis. Scenes were learned in accordance with equation 2.3 but without assuming a dendrodendritic spread of excitation in the mosaic cell layer. In this simulation, the learning parameters were arbitrarily set as follows: $b = 1$ (although it is not necessary to assign b in a simulation because b is assumed to be uniform over all adaptive cells); $c = 2$; $k = 100$. The products of active stimulus points (pixels constituting an afferent scene) and their coordinate synaptic transfer weights were summed for each scene on each of the 25 output classes (Ω_i) and ordered in terms of descending magnitude. This procedure yielded a table of associative rank, or hierarchy of recall, which is reflected in the relative latency of class cell discharge (figure 10.2).

For a given stimulus, if a class cell (Ω_i) remains inhibited immediately after it fires, the Ω that is next highest in the associative hierarchy will have an opportunity to fire. Thus, sequences of associative

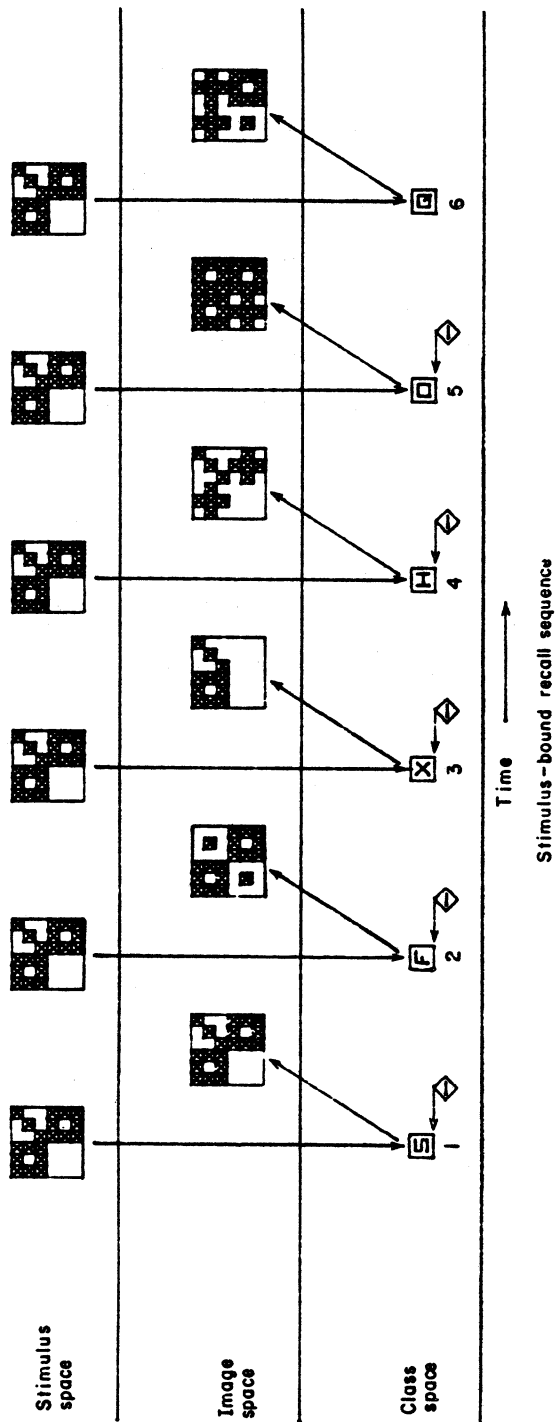
		Input scene																											
		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y			
Associative recall hierarchy	1	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y			
	2	G	D	X	B	K	S	M	S	T	U	E	P	L	G	W	R	W	F	X	F	I	R	P	P	S	H		
	3	I	N	J	N	J	Q	I	V	G	C	J	M	L	B	B	L	B	U	X	L	J	H	N	R	I			
	4	K	Q	T	V	N	X	T	X	M	E	N	T	T	D	D	V	D	O	H	M	X	D	L	C	S			
	5	K	O	Y	O	G	V	A	Y	A	K	A	W	I	V	S	M	H	J	O	G	L	N	V	H	C			
	6	E	L	M	Q	A	O	E	Q	Y	R	G	V	P	E	F	U	S	D	Q	C	O	H	G	F	T			
	7	P	S	I	S	M	H	W	F	C	O	U	U	A	K	J	C	O	S	Y	Y	C	L	I	U	M			
	8	O	U	U	R	U	Y	L	I	H	X	O	G	C	U	Q	T	Y	N	C	J	P	F	M	U	Q			
	9	T	R	P	U	C	L	C	N	X	T	C	B	Y	H	U	G	L	B	D	P	N	S	U	I	F			
	10	J	F	G	F	O	D	Y	G	W	Y	R	F	E	Q	Y	A	V	F	V	O	D	Q	Y	O	O			
	11	D	K	S	L	R	U	K	T	Q	A	B	Q	W	R	X	F	N	A	R	Q	S	B	T	Y	G			
	12	R	V	E	A	B	P	P	O	O	M	Y	D	J	O	T	D	T	Q	B	H	E	A	A	T	U			
	13	W	E	O	P	Y	C	H	C	J	I	M	C	O	J	A	N	I	K	U	A	B	O	K	Q	K			
	14	V	Y	F	Y	D	R	N	M	F	S	D	J	K	P	C	J	U	C	J	W	F	G	E	P	W			
	15	Q	H	K	J	W	B	J	D	R	N	W	O	H	G	N	Y	R	E	P	F	K	Y	Q	G	E			
	16	N	J	L	H	T	T	V	R	S	P	I	N	D	A	I	S	A	H	T	U	W	M	D	M	B			
	17	U	M	R	K	I	H	O	B	P	G	T	S	N	Y	K	Q	P	I	I	X	Q	T	C	A	X			
	18	C	A	H	E	P	J	X	U	U	D	Q	Y	B	L	H	X	J	T	L	S	T	U	J	D	D			
	19	B	P	A	M	Q	M	D	J	K	L	P	I	V	M	E	I	X	V	M	V	H	R	H	V	B			
	20	Y	G	W	H	N	U	P	E	B	X	H	U	S	M	H	W	Y	N	R	A	X	R	N	N				
	21	X	T	Q	G	L	A	R	W	L	F	H	A	S	F	V	O	M	P	G	E	Y	I	F	K	V			
	22	F	W	D	X	X	W	B	L	V	Q	S	R	Q	C	G	R	C	G	A	K	M	C	B	E	U			
	23	L	C	N	T	S	G	S	E	N	H	V	E	X	T	L	E	G	M	K	D	I	J	O	B	A			
	24	S	X	V	C	V	K	Q	A	D	W	L	X	F	X	P	B	K	W	E	N	V	E	X	H	L			
	25	H	I	B	I	F	E	F	K	B	V	F	K	R	I	W	K	E	L	W	B	G	K	S	L	R			

Figure 10.2

Hierarchical associative order of all scenes in response to each stimulus scene. Source: Ibid. Copyright Academic Press (London) Ltd. Reproduced by permission.

recall are produced by inhibiting for the duration of a recall sequence each Ω immediately after it has discharged and signaled the scene that it has detected and classified. If an initial retinal pattern is maintained as a continuing stimulus to the mosaic cells in a synaptic matrix while class cells are successively inhibited immediately after their activation, the sequence of associations is called a stimulus-bound recall sequence. If an initial pattern is not maintained as a stimulus and subsequent excitation of mosaic cells is provided only by the brief class cell collateral volleys back to the imaging matrix, the sequence of associations is called an image-bound recall sequence.

Figure 10.3 shows a comparison of the two modes of recall in response to the presentation of scene S as the initiating stimulus. In both modes, the first pattern class and image recalled are those correctly matched to the initiating scene, as one would expect in an accurate perceptual system. The second response of the network is also the same for both modes: the class and image recalled are those



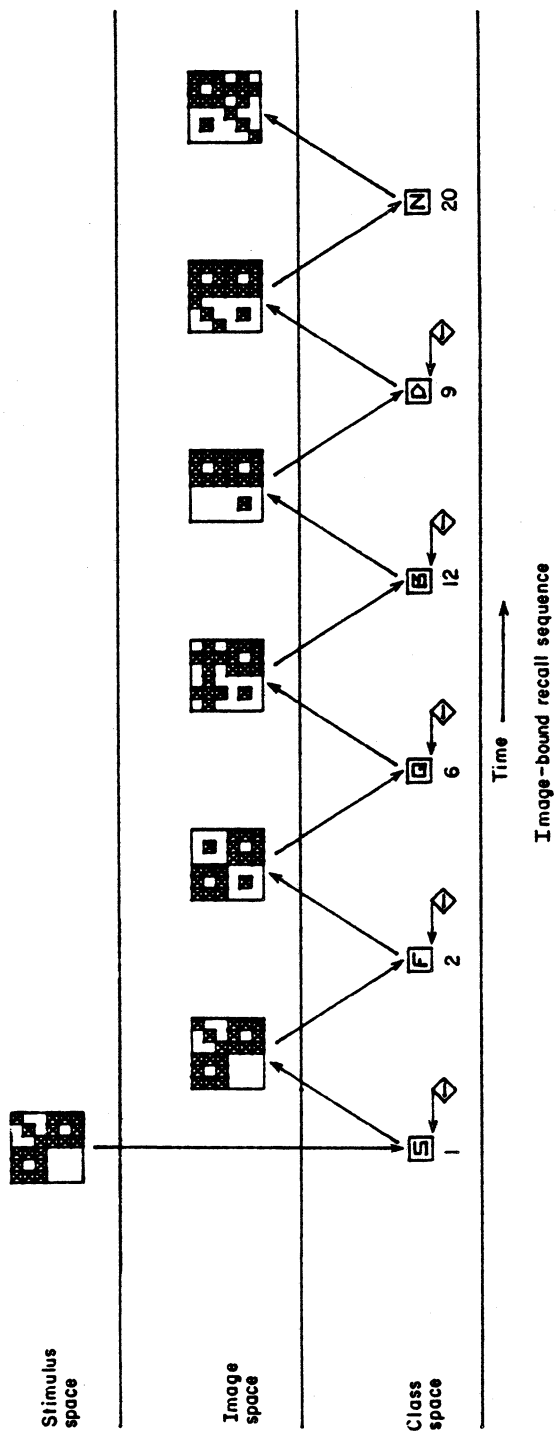


Figure 10.3
 Example of two modes of recall in response to scene S. Numbers below class designations represent associative rank relative to S. Source: Ibid. Copyright Academic Press (London) Ltd. Reproduced by permission.

standing at rank order 2 in associative strength with scene S. This outcome is also to be expected because the image that generates the second response (class F) in the image-bound sequence is identical to the external scene in the stimulus-bound sequence (see figure 10.1). Thereafter, however, the chain of association is distinctly different in the two modes of recall.

Whereas the stimulus-bound sequence proceeds monotonically down the associative hierarchy (orders 1, 2, 3, 4, 5, 6) with respect to the initial scene, the image-bound sequence defies monotonicity and ranges widely over the associative hierarchy of the initial scene (orders 1, 2, 6, 12, 9, 20). Yet despite its random appearance, this latter sequence of associative recall is systematically determined by the functional characteristics and learning history of the synaptic matrix.

The first six recollections of the synaptic matrix in response to each of the 25 scenes were examined, and the median and range of associative ranks were derived (figure 10.4). In the stimulus-bound recall mode, associative rank relative to the initial scene was always identical to the order of recall. For the image-bound recall mode, however, after the second recall, median associative rank departed markedly from recall order, and the range of associations within the first six recollections spanned almost the entire hierarchy.

These data show that sequential recall in a synaptic matrix can exhibit, on the basis of this module's intrinsic properties, characteristics of orderliness or looseness of association that appear to conform with human associative behavior.

Recognition under Noisy Conditions: I

In this simulation (Trehub 1987), a microworld was constructed in which three motivated characters moved about and interacted within an environment that had a number of objects and "natural" features relevant to a number of goals arbitrarily installed in each of the characters. The microworld consisted of David, Lisa, a dog named Wolf, David's house, Lisa's cottage, a restaurant, a pond, a pine tree forest, and a rabbit. Here we will consider only the visual-cognitive aspects of the simulation and ignore the motivations that shaped each character's travel route in the simulated environment.

The principal character, David, was endowed with a synaptic matrix so that he was able not only to move among the objects in his world, as the other characters could, but also to learn and later recognize the visual world about him. After David learned the individual elements of his world, the simulation program projected to his $21 \times$

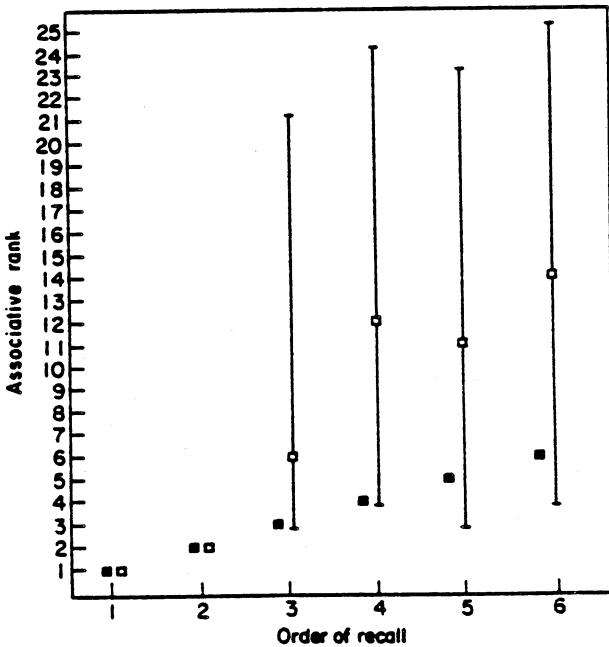


Figure 10.4

Median and range of associative rank of recalled scenes relative to initiating scenes through six sequential recollections. Filled squares designate stimulus-bound recall; open squares designate image-bound recall. Source: Ibid. Copyright Academic Press (London) Ltd. Reproduced by permission.

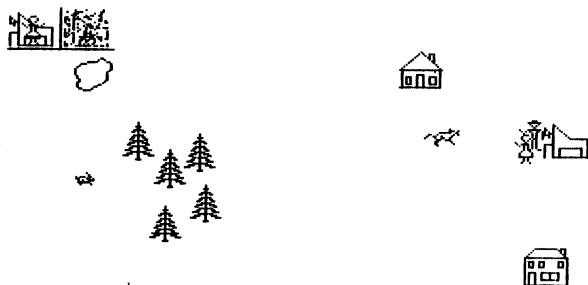
21-cell retina all objects that happened to be close to him (within an arbitrary distance) during the course of his activities. The visual stimuli were arbitrarily centered on the normal foveal axis, and he was programmed to make a "verbal" response appropriate to the objects encountered. If two or more objects happened to be close enough to be "seen," their patterns were arbitrarily superposed on the retina. When this occurred, the synaptic matrix had to disambiguate the complex image for each of the superposed objects to be correctly recognized. The network was able to respond to each of the constituent objects in succession because any class cell that signaled the presence of its associated object auto-inhibited immediately after its discharge. This released other class cells, enabling a different cell to fire and signal the presence of a different object (top, figure 10.3).

The program allowed the investigator to introduce controlled amounts of visual noise into the environment. Noise was both additive and subtractive; an active pixel (pixel = 1) in the visual field

would either be erased (pixel = 0) or remain unchanged, and an inactive pixel (pixel = 0) would be activated (pixel = 1) or remain unchanged. Pixels affected by noise were selected on a random basis, with the overall proportion of affected pixels determined by the percentage of noise introduced. Under the condition of 100 percent noise, each pixel in the visual field had a 50 percent chance of changing from *on* (active) to *off* (inactive) or from *off* to *on*.

Figure 10.5 shows a moment from the dynamic simulation in which David has encountered Lisa at the restaurant. The divided inset at the upper left shows the image of Lisa superposed on the image of the restaurant as they would appear on David's retina if there were no visual noise and as they actually appeared, degraded by the introduction of 40 percent noise. The verbal responses show that, under this condition of pattern superposition and visual noise, David correctly recognized both Lisa and the restaurant. Examination of records over extended periods of simulation indicate that, even with superposition of objects, errors in recognition are rarely made until the noise level exceeds approximately 70 percent. In the initial learn-

2(.4)LISA
2(.4)RESTAURANT



I HOPE THEY SERVE SEAFOOD CHOWDER TODAY.....
HI...LISA!.....

Figure 10.5

One frame of the microworld simulation copied directly from the CRT display. David has just encountered Lisa at the restaurant (far right). At the upper left of the display, the divided graphic inset shows, on the left, the image of Lisa superposed on that of the restaurant as it would appear to David if there were no visual noise. On the right side of the inset is the same image degraded by 40 percent random visual noise, which is the actual stimulus projected to David's retina. David's verbal responses at the bottom of the CRT display show that he has correctly identified both the restaurant and Lisa despite superposition and substantial image degradation.

ing situation, David was exposed to only one character or object at a time. Thus, the ability of the synaptic matrix to disambiguate and properly recognize later each superposed component of a complex of patterns, degraded by substantial levels of visual noise, represents a powerful generalization of the original learned response.

Recognition under Noisy Conditions: II

In the previous simulation, visual patterns were arbitrarily centered on the normal foveal axis. In the test described in this section, stimuli were presented in the visual field at locations eccentric to the initial point of fixation. Thus, the network had to initiate a visual saccade to each stimulus, and the stimulus pattern had to be adaptively shifted on a retinoid in order for its centroid to fall on the normal foveal axis.

The network was simulated with a 16×16 -cell retina. The learning parameters were arbitrarily set at $c = 1$; $k = 100$. A gradient coefficient of 0.6 was set for dendrodendritic transfer to neighboring cells in the mosaic array. Base error tolerance (ET) for centroid alignment on the normal foveal axis was set at three retinoid units.

Test stimuli consisted of four different alphabetic characters in uppercase Geneva font: G, L, O, and Q. First, a quasi-random jumble of lines was presented as a separate stimulus and learned as "NO-LETTER." Then the model learned to recognize and identify each of the four letters in their pristine form (no noise degradation). Figure

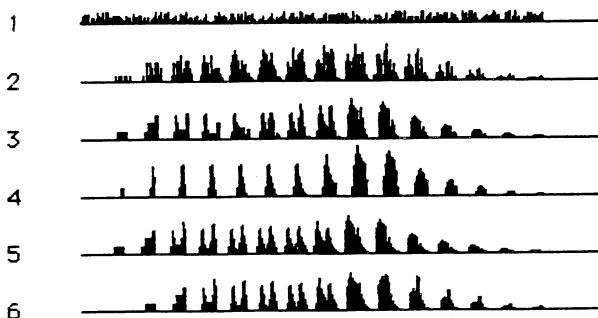


Figure 10.6

Distribution of synaptic transfer weights (ϕ) on the dendrites of filter cells following learning. Each point on the dendritic line represents the relative magnitude of transfer weight for that synapse. The stimuli that were learned in the examples shown are as follows: 1 = random visual pattern; 2 = quasi-random scribble (NOLETTER); 3 = G; 4 = L; 5 = O; 6 = Q.

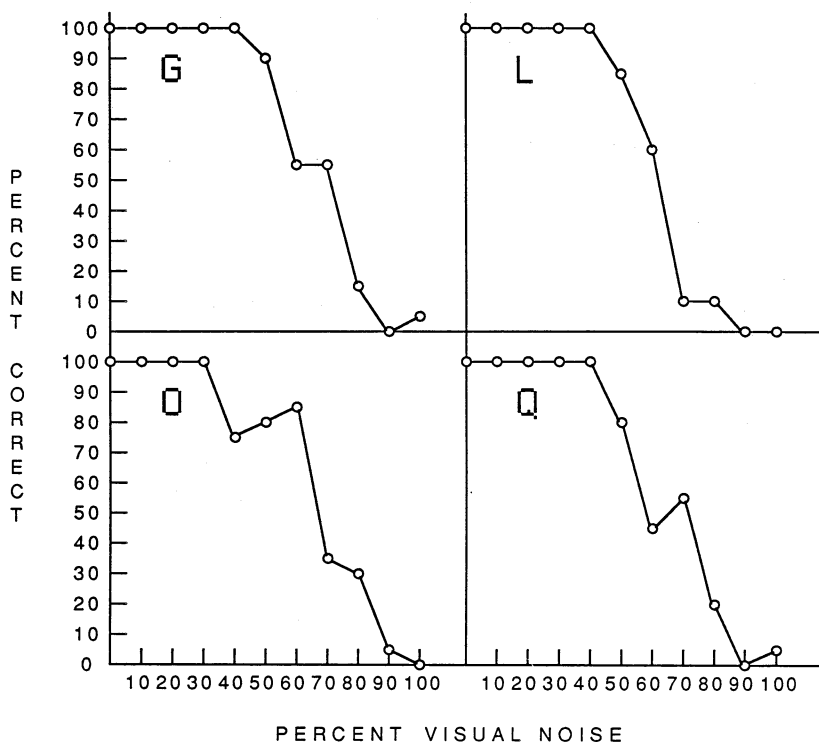


Figure 10.7

Recognition performance for each of four test stimuli as a function of level of visual noise.

10.6 shows the distribution of synaptic transfer weights (ϕ) on filter cells that had been modified in the course of learning the stimuli used in this simulation. Recognition tests were then performed in 10 blocks of 20 trials for each letter, with a different level of visual noise (additive and subtractive) introduced for each block of trials. Noise ranged from 10 to 100 percent, where the magnitude of noise indicates the proportion of stimulus pixels affected.

As each letter was presented, the model network was required to identify it. Response on each trial could be one of the following: G, L, O, Q, or NOLETTER. Because a letter was always presented, though it might be distorted by 100 percent noise, the response NOLETTER was always counted as an error. The four histograms in figure 10.7 show the percentage of correct responses for each of the four letters as the level of visual noise increased from 0 to 100 percent. In each case, there were no errors in recognition until visual noise

Table 10.1
Number of instances of false recognition under noisy condition

		Recognized As			
		G	L	O	Q
Letter Presented	G	-	0	4	5
	L	1	-	2	0
	O	2	0	-	5
	Q	3	0	15	-

exceeded at least 30 percent. Performance remained better than 50 percent correct until noise exceeded 60 percent.

The stimuli were deliberately selected to include three with substantially similar shapes (G, O, Q) and one with a shape unlike the others (L). Table 10.1 shows the number of false recognitions of each letter as a function of the letter presented. The pattern of confusion in recognition conforms in general with what one might intuitively expect. The greatest number of misidentifications occurred when the letter Q was presented. In the context of high levels of noise, it was incorrectly "seen" as the letter O 15 times. The specific vulnerability of the letter Q is apparently due to the fact that its discrimination from O depends on the presence of a tiny visual feature—the diagonal stroke at the bottom right of the figure. Interestingly, O was misidentified as Q only five times. (One wonders if the same task presented to humans would yield a similar asymmetry in confusions between O and Q.) The letter G was confused with O and Q in approximately equal measure. And the letter L exhibited the least number of misidentifications, a result that might be expected given its distinctive shape in the memory set.

Recognition under Rotation

The simulations just described demonstrate the robustness of the putative brain mechanisms when learned stimuli must be recognized despite degradation by visual noise. Now suppose that a visual stimulus is learned at a particular angular orientation in the frontal plane and is then presented at a different orientation. How robust will the network be in recognizing learned exemplars that undergo such rotational transformation? One way to ensure recognition under rotation is to transform input patterns covertly until they match the orientations of previously learned exemplars. Another way of dealing with recognition under rotation would not necessarily ensure successful recognition but might be ecologically efficient for many purposes:

to learn an object in enough different angular orientations so that exemplars of the object at intervening orientations would, with high probability, be more closely matched to their appropriate filter cells than to incorrect f cells. If this were the strategy, how would performance degrade as a stimulus departed from the angular orientation at which it was learned? How many different orientations would have to be learned to provide reasonably adequate performance with arbitrary stimulus rotations? The following simulation was run to provide some clues.

A 16×16 -cell retina provided input to the system. Parameters for learning were $c = 1$; $k = 100$. The gradient for dendrodendritic excitation was set at 0.6. Base error tolerance (ET) for automatically shifting pattern centroids to the normal foveal axis was set at three retinoid units. The uppercase letters L, O, and G (Geneva font) were the stimuli used in this test.

Each letter was learned at its normal vertical orientation (0 degree) and at a clockwise rotation of 22 degrees. Figure 10.8 shows the distribution of synaptic transfer weights on filter cells that were tuned to the stimuli at their standard orientation and at a clockwise rotation of 22 degrees. Because the letter L is an asymmetrical yet relatively simple stimulus, with a single vertical and horizontal stroke, it was used to see how a filter cell, having learned the pattern at its normal

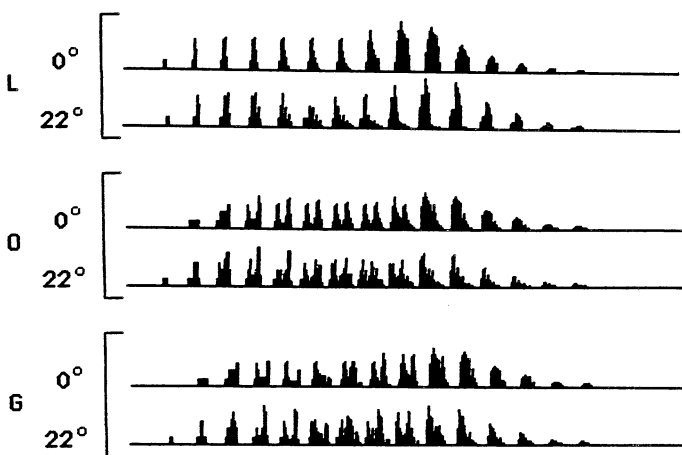


Figure 10.8

Comparison of synaptic transfer weight profiles on the dendrites of filter cells for each of three stimuli learned at normal (0 degrees) and rotated (22 degrees) orientation.

vertical orientation, would respond to exemplars of L at different angular orientations.

Figure 10.9 shows how the discharge of a filter cell that has learned a vertical L (0 degrees) changes when it is stimulated with the same letter at angular orientations ranging from -55 to $+55$ degrees. The responses of the cell over the range of stimulus orientations are plotted as an output proportional to its discharge when it is presented with the letter that it has learned. When the stimulus was rotated away from its normal representation, the filter cell response did not fall abruptly but rather exhibited a graded decrement analogous to the response of a band-pass filter in the frequency domain. Indeed, when the stimulus was tilted as much as 22 degrees in either the clockwise or counterclockwise direction, filter cell discharge declined to no less than 52 percent of its maximum.

In a test of recognition under rotation, each of the three letters was rotated clockwise from 0 to a maximum of 55 degrees in incre-

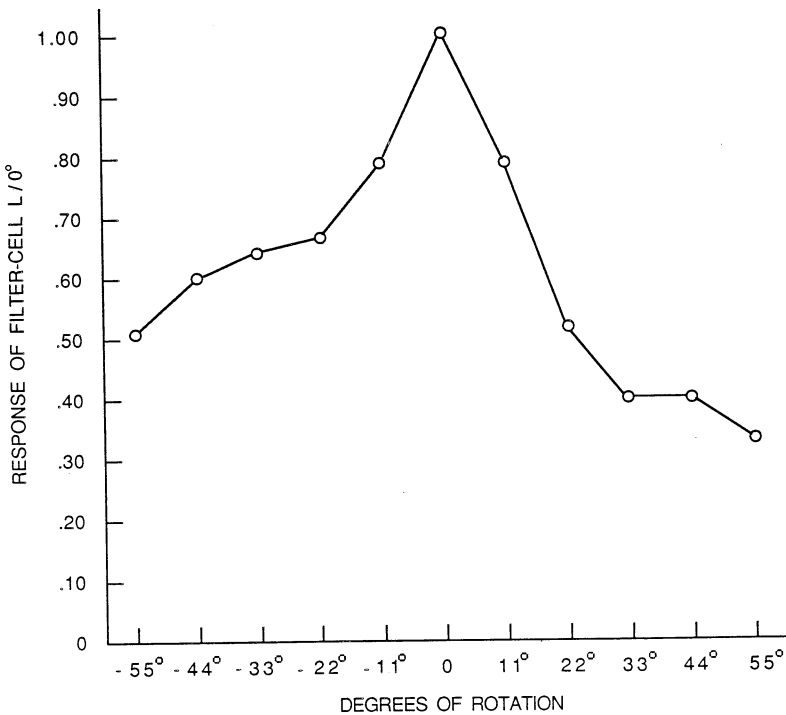


Figure 10.9
Response of a filter cell (L/0°) to rotation of its learned exemplar.

ments of approximately 11 degrees (figure 10.10). Each letter was presented for recognition in blocks of 20 trials for each of its angular orientations.

The percentage of correct responses for each of the six different orientations is given in table 10.2. Recall that the letters were learned at their standard orientation (0 degrees) and at a rotation angle of 22 degrees. It is not surprising that recognition performance was 100 percent correct for all letters at the two learned orientations. However, recognition was also at the 100 percent level for all letters at the intermediate orientation of 11 degrees, which had not been learned. Moreover, for the letters L and O, there were no errors at the novel orientation of 33 degrees. As clockwise rotation increased, recognition of the letter L decreased to 35 percent at the 55 degree orientation, while recognition of O remained at or near the 100 percent level. Recognition of the letter G was 75 percent correct at 33 degrees and declined to 55 percent at 55 degrees.

When we examine the nature of the errors made in this test (table 10.3), we see that L was confused with G 22 times but was never confused with O. There was only one confusion of the letter O, and that was with G. The letter G, on the other hand, was confused with

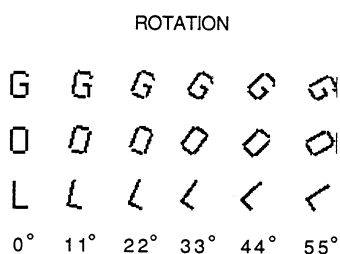


Figure 10.10

Stimuli used in test of recognition under rotation.

Table 10.2

Recognition under rotation

		DEGREES ROTATION					
		0°	11°	22°	33°	44°	55°
Letter Presented	L	100	100	100	100	55	35
	O	100	100	100	100	95	100
	G	100	100	100	75	70	55

Note: Cells indicate percentage of correct responses to test stimuli. Shaded cells show where exemplars were learned.

Table 10.3
Number of instances of false recognition under rotation

		Recognized As		
		L	O	G
Letter Presented	L	-	0	22
	O	0	-	1
	G	0	20	-

O 20 times but was never confused with L. The striking resistance of the letter O to confusion is most likely due to its relative symmetry under rotation, a property shared somewhat less by G and least by L. However, given the rough similarity in shape between G and O, it is impressive that recognition performance was 100 percent correct for these stimuli as well as for L when rotation was 11 degrees in angular distance from their bounding learned exemplars (0 degrees and 22 degrees).

More parametric work should be done to examine the performance of the model with rotated stimuli, but these results suggest that the proposed neuronal mechanism is robust under rotational transformation, as well as with visual noise. If, in fact, exemplars of a rotated object need only be learned at approximately 11 degree intervals to ensure adequate recognition with arbitrary rotation, then the issue of neuronal resource constraints becomes a less thorny one.

Episodic Learning and Recall

In chapter 5, a model neuronal mechanism was described that was able to control the timing, registration, and location of episodic learning in a synaptic matrix. It was also shown how this mechanism, composed of a clock circuit and a recall circuit, could serve to determine the temporal locus and sequence of recalled episodic experience. In the following simulation of episodic learning (Trehub 1983), the model was tested with some added assumptions concerning the effects of fluctuating levels of arousal and the time course of memory decay.

Learning proceeded according to the basic formula for synaptic modification (equation 2.3) in the matrices for stimulus detection and imagery, with the additional assumption of transfer weight (ϕ) modulation according to the momentary level of randomly fluctuating arousal. This assumption was made on the grounds that increased diffuse priming of filter cells (f) by higher levels of arousal would induce a more vigorous response in those cells that were undergoing

modification in the learning process and, as a result, the amount of free DTF (represented by the coefficient k) would increase. Thus,

$$\phi_0 = (b + S(c + kN^{-1}))L \quad (10.1)$$

$b \rightarrow \text{Lim}$

where L is a normal random variable with $\bar{x} = 1.0$ and $\sigma = 0.2$ (arbitrarily chosen) and represents a randomly fluctuating arousal context for each instance of learning.

A long-term decay function for synaptic transfer weights (ϕ) was chosen on the basis of Wickelgren's (1974) proposal for memory decay. Thus, for ϕ decay in episodic learning,

$$\phi_t = \phi_0 (1 - \beta t)^{-\psi} \quad (10.2)$$

where ϕ_0 = synaptic transfer weight immediately after learning; t = time elapsed since initial learning; β = first parameter for decay rate; and ψ = second parameter for decay rate. In this simulation, the two parameters were arbitrarily set with $\beta = 2.0$ and $\psi = 0.5$.

It was assumed that in order to recall any given component image in a contiguous sequence of learned stimuli (an episode), the sum of ϕ_t values (equation 10.2) supporting that image must exceed a concurrent threshold value. It was further assumed that recall threshold would change from moment to moment as an inverse function of the level of randomly fluctuating arousal (L). Thus,

$$\theta = L^{-1} + \tau \quad (10.3)$$

where θ = recall threshold; L = level of arousal; and τ = base threshold level. Note that L (which modulates recall threshold at each instance of recall) is taken as a normal random variable with $\bar{x} = 1.0$ and $\sigma = 0.2$.

Assuming an appropriate repertoire of language to characterize component images during an epoch of learning, figure 10.11 presents the set of primitive images and associated language that was used in the simulation. Figure 10.12 shows the results of testing the neuronal network for episodic learning and recall. A complete episode was learned via successive input on a 6×6 -cell retina. The sequence of stimuli is shown in figure 10.12 beside ELAPSED TIME 00. Episodic recall was tested at elapsed times corresponding to 1–14 days following the original learned experience. Failure to recall particular details of the episode increases as time passes. Occasional recovery of memory for forgotten details is also seen in figure 10.12.

<u>IMAGE</u>	<u>ASSOCIATED LANGUAGE</u>
	= me
	= a man
	= a woman
	= Ann's house
	= Forbes' store
	= a car
	= on Main Street (to)
	= my house
	= my car
	= me in my house
	= me in my car
	= me in Forbes' store
	= me in Ann's house
	= (somebody) meets (somebody)
	= me travelling (somewhere)
	= (somebody) together with (somebody)
	= (somebody) leaves (somebody)
	= (somebody) goes into (something)
	= (somebody) goes out of (something)
	= (something) collides with (something)

Figure 10.11

Primitive images and associated language. Source: Trehub 1983. Copyright Lawrence Erlbaum Associates, Inc. Reproduced by permission.

In order to convey the flavor of episodic learning and recall as exhibited by the model, a protocol of descriptive language appropriate to the original episode and to later "verbalized" recollections is presented below (figure 10.11). Oblique lines separate underlying component images (patterns evoked in the imaging matrix). Words bracketed by < and > indicate the absence of a specific image. Words in parentheses were arbitrarily added to improve the narrative flow of the protocols. Word tense was arbitrarily changed wherever it was grammatically appropriate.

Elapsed Time = 00

/I am in my house/. /I/ go out of/ my house/ (then) go into/ my

[illegible]

Figure 10.12

Simulation test. *Top row:* Complete sequence of learned images in the original episode. *Following rows:* Recalled episodic images at indicated elapsed times. Source: Ibid. Copyright Lawrence Erlbaum Associates, Inc. Reproduced by permission.

car/ (and) travel/ on Main Street to/ Ann's house/ (and) meet/
Ann/. /I/ together with/ Ann/ go out of/ Ann's house/ (and) go
into/ my car/ (and) travel/ on Main Street to/ Forbes' store/. /I/
together with/ Ann/ go out of/ my car/ (and) go into/ Forbes'
store/. (Then) I/ leave Ann/ (and) I/ go into/ my car/ (and) travel/
on Main Street/. /A car/ collides with/ my car/.

Elapsed Time = 01

/I was in my house/. /I/ went out of/ my house/ (and) got into/
my car/ (and) travelled/ on Main Street to/ Ann's house/ (then)
went into/ Ann's house/ (and) met/ Ann/. /Ann/ (and) I/ left
<somewhere>/ (and) went into/ my car/ (and) travelled/ on Main
Street to/ Forbes' store/. /Ann/ was with me/. /(I remember) my
car/ (and) going into/ Forbes' store/. /(Then) I/ left/ Ann/ (and) I/
got into/ my car/. /I/ travelled/ on Main Street/. /A car/ collided
with/ my car/.

Elapsed Time = 07

/I was in my house/. /I/ went out of/ my house/ (and) got into
 <something>. /I travelled/ <somewhere>. (Then I remember) /
 <somebody> met Ann/. /Ann/ (was) together with/ <somebody>. (I
 remember) /my car/ (and) going into/ <something>. (I remember) /
 leaving/ Ann/ (and) /getting into/ my car/ (and) travelling/ on
 Main Street/. (I remember) /another car/ (and) being in my car/.

Elapsed Time = 14

(I remember) <someone> /leaving/ my house/ (and) going into
 <something>. (Then) <someone> /met <somebody>/ (and) together/
 (they) got out of/ <something>. (I remember) /Main Street/.
 /<Somebody> was with/ me/. (I remember) /my car/ (and) <some-
 body> /going into/ <something>. (Then I remember) /I left/ Ann/
 (and) got into/ my car/ (and) travelled/ <somewhere>.

The behavior exhibited by this network can be elaborated in a number of interesting ways. For example, if the component images in an episode were to evoke different hedonic values linked to the magnitude of arousal (L), then the relative temporal density of particular episodically linked images and the individual probabilities of their recall would vary accordingly over an episode. Two different individuals experiencing the same episode might well give two quite different accounts depending on their personal emotional response during the experience. As an example of excessive arousal inducing psychopathological behavior, suppose an individual is in a heightened state of arousal for an extended period of time. Under this condition, the neuronal clock will run very fast for a long time due to arousal priming of the clock ring. Given a constant ϕ decay function (equation 10.2), ϕ changes in the filter cells (f) of the detection matrix might not have sufficient time to decay close to initial values before the f cells are recycled and primed for learning. If this happens, component episodic images would be confounded with earlier memories, and, if the confounding is extreme, one might characterize the individual as being in a pathologically confused state.

Not all episodic memories must be controlled by a single clock ring. It is more likely that there is a hierarchically structured system of clock rings and recall rings with short (high frequency) to long (low frequency) priming-pulse intervals for temporally organized learning. In such a network, we would assume that the high-frequency circuits would recycle over short periods of time, and low-frequency circuits would exhibit long recycle periods.