PHASE TRANSITIONS IN NEURAL NETWORKS

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ABSTRACT

The behaviour of computer simulations of networks of neuron-like binary decision elements is studied. The models are discrete in time and deterministic , but the sequence of states of neurons in a net is not generally reversible in time because of the threshold nature of neurons. Self-organisation, or activity-dependent modification of interneuronal connection strengths, is used. Cyclic modes of activity which emerge spontaneously, underly possible mechanisms of short term memory and associative thinking. The transition from seemingly random activity patterns to cyclic activity is examined in isolated networks with pseudorandomly chosen connection matrices; and the transition is related to the gross properties of the network. Nets with inherent structure (from pseudorandom nature) and imposed structure are studied. When cycles of length greater than, say, 12 time units are considered separately from the less complex, shorter cycles; the aforementioned transitions appear to be consistently rapid, compared to the cycle length, unless architecture is imposed such that nearly independent groups of neurons exist in the same net.

CONTENTS

CHAPTER 1

INTRODUCTION

Artificially intelligent expert systems are becoming more and more sophisticated and the basic physiology and anatomy of the neural networks in the brain are better understood, but these two disciplines are not converging to promote an understanding of how the brain works. The number of interneuronal connections is vast (10^{14} in man) , making it practically impossible to map the connections in even a small section of the brain, yet it is these connections that cause the collective behaviour of neurons that allows complex functions of association memory, abstraction etc. By extensive computer simulations of neural networks, it is hoped that the fundamental conditions necessary for a system to be capable of higher functions will be better understood. This area of research must not be confused with "Artificial Intelligence" which deals with (useful) simulation of the performance characteristics of experts with "true" intelligence.

CHAPTER 1

In this chapter, the main reference is to the paper written by Clark, Rafelski and Winston, in which the authors describe a discrete time neural network model characterized by a matrix of connection strengths which are quasi-random and may be adapted in time. They studied the self-organisation (via plasticity algorithms) of the neural nets, which revealed the resilience against catastrophy and the richness of cyclic activity of brain-washed nets. These same nets will be studied here ,with the objective of understanding the nature of the transition to cycling.

To simulate the behaviour of a small network of neurons, a binary state vector was used to represent the on/off state of each neuron in the net at a particular time. The evolution of this state vector in time was determined step-by-step using a matrix of connection strengths between the neurons and firing threshold properties of each neuron. The state vector equals the threshold function acting on the input vector. The input vector is the product of the connection matrix and the previous state vector.

The behaviour of interest was repetitive patterns in the history of the state vector. The information in the net, that is, in the synaptic coupling and the thresholds, is transformed into the evolving pattern of the state matrix.

<u>Elements of Neurophysiology Pertinent to the Network Model</u>

The diversity and complexity of the structure of neurons, let alone that of small sections of cerebral cortex are such that it is necessary to make many simplifications to model the system, yet it is valid and rewarding to study the behaviour and capabilities of the model, with these constraints, at least as a large steppingstone to more complicated models.

(1) The neuron is the basic decision element. It can be in one of three states: on, off or in a refactory state (that is, its status is off until it has recovered from its previous firing and can once again be stimulated). In other words, the information transmitted by a neuron is binary only, not analogue. It is the firing patterns of the neurons, i.e. the history of their ON/OFF status that is of interest when characterising the behaviour of the net.

(2) The neuron has a certain stimulation threshold above which it fires and thereby takes the decision that it is sufficiently stimulated. A degree of stochastic behaviour (random 'incorrect' decisions) was introduced into the model via a noise parameter, to model the spontaneous firing of biological neurons. The threshold may vary from neuron to neuron, and as time progresses, according to function and activity of the neuron.

The nets were modelled with fixed thresholds, the same for all neurons, at first. Since threshold is a physiological property of the membrane of the cell body, it is not likely to differ much between neurons of the same type in the same area of the brain with the same hormonal levels. The short term time dependence was modelled simply as a refactory period, or the membrane potential recovery time, which marks the minimum separation of two successive activations of a neuron. Transmission across the synapse takes somewhat longer than transmission along the axon or dendrites of a small neuron (this is not a model of the sensory system), so the synaptic time was taken to be a unit in discrete time, and the neuron transmission time, zero.

(3) The stimulation of a neuron is the integrated effect of synapses with different neurons which have recently fired. The number and strength and polarity of synapses between neurons varies from neuron pair to neuron pair and may change in time during the learning process. The strength of stimulation decays exponentially in time. These features were modelled by a time dependent connection matrix linking N neurons to the same N neurons. The elements could be positive or negative (excitatory or inhibitory neurons) of any strength, and undirectional. The time evolution of these connection strengths depends on the activity of the neurons, and on whether selforganisation, learning, forgetting or association, etc., is being performed. These processes were modelled by plasticity algorithms which change the synaptic strengths in certain ways according to the algorithm chosen. The accumulation of exponentially decaying stimuli to a neuron was easily incorporated.

(4) Cycling, or periodic behaviour in a group of neurons, has been noticed in the cerebellum and is believed to underlie the mechanism of short-term memory, in the cerebrum. A dynamic mechanism of storage is suggested by the fact that electroshock applied to the cerebrum erases the preceeding few minutes of memory. Rhythmic fluctuations of electroencephalograms also suggests a large scale periodic structure. Hence the study of cyclic behaviour was of prime importance in the model.

(5) The cerebral cortex is made up not only of many layers of neurons, but is divided into cortical columns that extend vertically through these layers. The neurons (typically ten thousand) in a cortical column are highly interconnected (100 to 1000 synapses per neuron) and are more sparsely connected to neighbouring columns. The neural network model could resemble the collective behaviour of a very small, unlayered version of an element similar to a cortical column, although the purpose of this project was not to model a column. The network's behaviour in isolation needs to be better understood before inputs can

be applied meaningfully. A small measure of architecture was incorporated in the model in Chapters 4 and 5.

The Basic Model

Netsize N : Number of neurons.

Discrete time unit τ

State Variable : $$\Theta_i(t) = \begin{cases} +1 & \text{neuron active at } t \\ -1 & \text{neuron inactive at } t \end{cases} \quad i = 1 \text{ to } N \tag{1.1}$$

$$\text{or } L_i(t) = \frac{1}{2}(1 + \Theta_i(t)) = 1 \text{ or } 0 \tag{1.2}$$

Refactory period of a neuron : R_i , $R\tau$ is the time period after firing during which neuron cannot fire again.

Connection matrix $V_{ij}(t)$ = An assymetric matrix of coupling strengths of synapses from neuron j to i at time t

$$V_{ij} \quad \begin{cases} = 0 & \text{no coupling} \\ > 0 & j \text{ excitatory} \\ < 0 & j \text{ inhibitory} \end{cases} \tag{1.3}$$

Inhibition, a fraction of the neurons, h are chosen to be inhibitory, and all their output V_{ij} elements are negative.

Connectivity m is the fraction of other neurons connected to each neuron, that is, the average number of inputs to a neuron is Nm.

These factors N, m and h are incorporated into the properties of the connection matrix . Different types of nets have different algorithms for choosing the elements of the connection matrix to satisfy these properties (Clark Rafelski and Winston) The type of net used in this project is described later in this chapter.

Normalisation:

$$\sum_j V_{ij}(t) = \sum_j V_{ij}(0) \text{ and } \sum V_{ij}(t)|_{V_{ij}<0} = \sum_j V_{ij}(0)|_{V_{ij}<0} \tag{1.4}$$

Stimulation of a neuron i at time $t+\tau$:

$$u_i(t+\tau) = \sum_j V_{ij}(t)\, L_j(t) + e^{-\tau/t_{oi}(t)}\, u_i(t)\, L_i(t) \tag{1.5}$$

The first term is the sum of inputs from active synapses and the second term is the exponentially decaying signal accumulated if the neuron had not previously fired.

Accumulation t_{oi} is the characteristic decay time for input to neuron i. The stimulus is reduced by a factor ($e^{-\tau/t_{oi}}$) each step and is zeroed when the neuron fires. (1.6)

Dynamics

Firing decision : $L_i(t+\tau) = \theta_r\{u_i(t+\tau) - V_{oi}(t+\tau)\}$ (1.7)

where V_{oi} is the threshold of neuron i

$\theta_r(x)$ is the step function with a refactory condition

The refactory condition has been taken to be a step function $\theta(r_i)$ where

$$r_i(t+\tau) = \begin{cases} r_i(t) + 1 & L_i(t) = 0 \\ -R & L_i(t) = 1 \end{cases} \qquad (1.8)$$

A simplified version (provided a neuron is not in the refactory stage) is

$$L_i(t) = 1 \text{ iff } u_i(t) \geq V_o = \text{universal threshold.} \qquad (1.9)$$

Stochastic behaviour: To introduce noise, the threhold condition for a neuron to fire was replaced by a probability of the neuron firing

$$P_i = f_r^{\beta}[u_i(t) - V_{oi}(t)] \qquad (1.10)$$

where f is a smooth step distribution

$$f^{\beta}(x) = \frac{1}{e^{-\beta x}+1} \qquad (1.11)$$

where β is a suitable parameter to model noise

and where $f_r^{\beta\to\infty} = \theta_r$ = refactory step function (1.12)

This smoothed step allows for misfiring or spontaneous firing of neurons with stimulation close to the threshold level The decision to fire is if $P_i >$ random number (0,1).

As $\beta \to \infty$ (low noise) the previous deterministic behaviour is resumed. This condition was chosen for most studies.

The full state of information of a network at time t is the state vector $\sigma_i(t)$, the stimulation $u_i(t)$ and the refactory state $r_i(t)$. With no accumulation, i.e. Markovian nets and R = 1, state vector σ_i is sufficient. Initial conditions : full information about state at t = 0 must be specified to initiate the evolution of $\sigma_i(t)$.

External input $u_i'(t) = u_i(t) + e_i(t)$. (1.13)

$e_i(t)$ is an additional stimulus to neuron i at time t. External, time dependent input can thus be applied to the net.

Generating the Connection Matrix and Plasticity

Using the parameters N, m and h and a pseudorandom number generator, Nh inhibitory neurons were chosen by letting each neuron have a probability h of being inhibitory and comparing a random number between 0 and 1 with h, to make the decision, ie neuron is inhibitory iff the random number is less than h. Similarly, in the connection matrix, each element had equal probability m of being used, ie $V_{ij}=0$ iff the random number is greater than m. Unless otherwise specified, the elements used were assigned a value of unity (or -1 for inhibitory outputs). This means that all the synaptic strengths were initially equal, no more than one synapse was allowed from any neuron i to j, and neurons could synapse with themselves. Although the average number of inputs per neuron was Nm, there was a statistical spread on this number. This prescription for wiring must certainly have affected net behaviour to an extent.

A plasticity algorithm provides a recipe for altering the synaptic strengths, for instance, in the case of brainwashing, in order to discourage much used pathways. There are many plasticity tracks (Clark et al., page 241). One track to promote a selforganisation (brainwashing) is to seek out pairs of neurons, the first of which is active at time t and the second, at time t+1. If these neurons are linked, the link must be punished, if it is excitatory. If the link is inhibitory, it has failed to inhibit, but instead of increasing its negativity to change its effect on the second neuron, it too is reduced in magnitude.

In short, $|V_{ij}''| = |V_{ij}|(1-\delta)$ when $L_j(t) = L_i(t+1) = 1$. (1.14)

After each step, the connection matrix is normalised. The value of δ is an arbitarily chosen parameter, and it may vary with time, e.g. $\delta(t) = \delta_o(b)^t$ where b is less than one, that is the value of the brain-washing parameter fades during the process. Other plasticity tracks used occasionally in this project are learning and forgetting.

Summary Table of Some Plasticity Tracks: $o < \delta < 1$

$L_j(t-1)$	$L_i(t)$	Sign V_{ij}	V_{ij}/V''_{ij}		
1	1	+	$[1-\delta]$	}	Brainwashing
1	1	-	$[1-\delta]$	}	
1	1	+	$[1+\delta]$	}	
1	1	-	$[1-\delta]$	}	Learning
1	0	+	$[1-\delta]$	}	
1	0	-	$[1+\delta]$	}	
1	1	+	$1-\delta$	}	
1	1	-	$1+\delta$	}	Forgetting
1	0	+	$1+\delta$	}	
1	0	-	$1-\delta$	}	

Monitoring the Behaviour of the System

There are four possible types of behaviour: The activity can die out completely (death) or explode to the maximum possible activity with the given refactory period (epilepsy), or it can reach a stable state where $L_i(t+ k\tau) = L_i(t)$ (1.15) (cyclic state, length k) or it can keep evolving non-periodically during the time of observation (non-cyclic mode).

There are a finite number of possible states in Markovian net (no exponentially decaying stimuli) and there are a finite number of state vectors (2^N) in any net, thus even a "non-cyclic state" eventually cycles. Considering the possible states, the neural networks studied here repeat themselves remarkably easily. Death and epilepsy are to be avoided, by careful choice of threshold, by self-organisation or other methods that deflect catastrophic behaviour. Cyclic states can have multiple periodicities. The mininum period is K.

If K = R, all neurons are either perpetually inactive, or fire as often as allowed. Such neurons are termed ineligible. Neurons that are sometimes active and sometimes inactive without having to be in the refactory state, are termed eligible neurons.

The activity of a state vector at time t is the fraction of active neurons

$$\alpha(t) = \frac{1}{N} \sum_{i=1}^{N} L_i(t). \qquad (1.16)$$

The activity of a neuron is its average state of action : $\alpha_i = \frac{1}{T} \sum_{t=1}^{T} L_i(t)$. (1.17)

A neuron is eligible if $0 < \alpha_i < \frac{1}{R}$ or sometimes, more strictly, if

$$25\% \, \frac{1}{R} \leq \alpha_i \leq 75\% \, \frac{1}{R}. \qquad (1.18)$$

The eligibility of a cyclic state is the total number of eligible neurons.

The resilience of a net is its ability to recover from very high or low swings in activity, or its ability to survive under changing conditions of threshold or external stimulus.It is used here only qualitatively to distinguish resilient and non-resilient nets

The versatility of a net is the variation in behaviour that can be found in the net, depending on initial conditions, threshold, stimulus, etc.

The transient time of a net is the time after initialisation before it starts to cycle.

The transition time is the time it takes for the net to cycle, once parts of the net have started to cycle. Transition time depends on how you define the "almost cycling" condition. While cycling time is simply defined as an exact repetition of state vector,the approach to cycling could be defined as the similarity of states one period apart, or it could be the number of neurons with exactly cyclic activity.

Outline of the Development of the Aims of the Project

The original idea was to build a model with as many parameters and degrees of freedom as possible and then to set most of these to the simplest or trivial case and to find the requirements for survival before introducing complications one by one.

It was also necessary to define desirable behaviour in terms of cycling, eligibility, and versatility and to learn how to measure the performance of a net. Rhythmic activity is interesting because of the rhythmic variation of electroencephalograms and because of the cyclic modes' association with short term memory. Eligibility is desirable because more neurons participating allow more room for variations and complexity. It would be useful to know how to store as many cycles as possible on one connection matrix, and more eligible neurons would certainly help. A desirable net ought to be resilient to noise and fluctuations in activity and input and versatile in recognition of associated inputs and accessability of numerous cyclic modes.

How to achieve a degree of desirability through brainwashing was a major area of study(ch3, appendix 2). Other ideas pursued were window filters (appendix 2), topological structure of random matrices (ch 2), refactory period and accumulating stimuli (app 2), normal (individual) thresholds and effects of simplest architecture (ch 4 and 5). Ideas that were touched on were input to some neurons, forgetting algorithms, finite temperature effects, incomplete zeroing of potential after firing in response to a very large stimulus (frequency dependent on stimulus), a randomly chosen spread of connection strengths, learning and brainwashing controlled by feedback from net behaviour (aiming towards self-induced self-organisation and stimulus-induced learning and association.) These ideas will not be mentioned in later chapters.

After searching for a collective property that changes predictably with brainwashing, the search for an understanding of transitions to cycling was commenced. The relatively rapid phase transitions were investigated within a narrow, but hopefully realistic, range of parameters, and in the context of architecture and plasticity. Why are transitions so rapid? Why does cycling occur anyway? Does "phase" transition imply an intrinsic difference between a state destined to repeat itself, and another very similar state? What topology in a net leads to cyclic modes? (See Chapter 5).

A Few Problems Encountered En Route

- o The pseudorandom number generator used in this project was not as random as some of the more sophisticated random number generators. Therefore networks set up with the pseudorandom sequence had an uncertain amount of structure. The purpose of self organisation (brainwashing) is to reduce this structure inherent in any randomly generated network. For the purposes of the investigations of the thesis the given sequences sufficed. An analysis of an aspect of the structure of the random numbers (viz. the shortest route between pairs of neurons) is described in chapter 2. The linearlity of the distribution was also briefly examined. The most serious consequence was that the effective connectivity was larger than the parameter m - which should not qualitatively affect results.

- o Detection of the first inkling of cycling was not as simple as detecting cycling, although the transition region preceeding the cycle was examined in retrospect, once full details of the particular cycle were known. The first idea used was a correlation of the state vectors with a one period separation. The correlation ought to be one during cycling and should reduce to half in a chaotic region, thus defining a transition region as a region consistently more correlated temporally at k than the random region. The correlation was buried in so much 'noise' and coincidence at distances other than K, that other methods were prefered.

The second method was to examine the sequence of states of each neuron in search of sequences of length 6, identical to the latest sequence. Length 6 was chosen because ($6= \log_2(T)$) if T=64, which is the typical time span considered. The minimum separation of repeated sequences was taken to be the period if the interim states also matched up, ie the whole cycle followed exactly. This provided the first clue that the various neurons all start cycling within a short range of time. Finally, the length of the transition was found by tracinc the periodic sequence of states of each eligible neuron back in time until a mismatch occurred and the time elapsed from the moment the first neuron cycled to the moment all neurons cycled together , was called the transition. This can also provide a false impression, e.g. when a couple of neurons cycle early, with some simple cycle which becomes incorporated in a longer cycle later.

o The efficiency of the programme was essential to realise the maximum capability of the available computing power. Failure to optimise in any extreme way, limited the storage space to N = 200 for 500 steps (close to the maximum dimensions of the programme). See Appendix 1 for a version of the programme.

In some instances, important information is lost if only the total activity at each moment is monitored instead of the entire state vector; or if only the time average activity or complete cycling are monitored. To comment on neural networks, in a general way, is difficult because each net is so different. The programme must efficiently give all important information without recording vast amounts of detail, for instance, the role of apparently trivial dead neurons or active neurons may be important.

o Considering the difficulty in controlling self-organisation, the process of learning must be quite critical. There needs to be an input (of what nature and what strength?) and some kind of output which signals recognition of the input (cycle information?). The duration, sequence, and strength of plasticities (learning, consolidation and attention) all need to be right to successfully learn only one input, let alone optimising the amount of stored information in a net, which can be reasonably retrieved. Various attempts at learning were interesting but not in the main stream of the thesis .

o The nets dealt with were very small compared to elements of the brain. It is quite possible that there are drastic changes in behaviour when N is vastly increased, but hopefully these are only quantitative and not qualitative. The edge effects are reduced, in a way, by introducing normal thresholds.

o See chapter 2 for the outcome of a brief study on the topology of random matrices.

CHAPTER 2

Topology , distances and quasirandom numbers

Topology in terms of minimum distance between neurons

One of the first checks that can be done on a random number generator is to run a long sequence of random numbers and to ensure that the probability distribution is constant . More important for neural networks, however, is the possibility of sequential structure in the quasirandom sequence. A physically relevent measure of this structure is the distribution of the shortest distance between each pair of neurons, the distance being the number of synapses or connections en route from one to the other. The distribution of the distances for a given quasirandom network can be compared to theoretical expectations, obtained from an ensemble of perfectly random nets, and to results for nets with imposed topological structure.

THEORETICAL DISTRIBUTION OF DISTANCES BETWEEN NEURONS IN A RANDOM NET

Consider a net of N equivalent neurons, with Nm outputs (inputs) per neuron on average. N is very large and $0 < m < 1$. The trivial minimum distance of zero from a neuron to itself is not considered , so all distances are greater than zero.

Consider an average neuron ,'a' with Nm outputs . The distance from neuron 'a' to each of the N neurons in the net must be found:

Define $\nu(k)$ = number of neurons at distance k from neuron 'a'

$REM(k)$ = number of neurons at distance greater than k from neuron 'a'

$$= N - \sum_{r=1}^{k} \nu(r) \qquad (2.1)$$

Neuron 'a' has Nm outputs = netsize * connectivity ,

therefore $$\nu(1) = Nm \qquad (2.2)$$

The number of neurons left over is N-Nm therefore

$$REM(1) = N(1-m) \qquad (2.3)$$

One of these outputs ,neuron 'b', will have outputs to Nm neurons, some of which are reached after one step from neuron 'a',and the rest of which are thus at distance 2 from 'a', that is, a fraction m of the REM(1) neurons left = mN(1-m) new neurons reached via neuron 'b' leaving a smaller pool of unreached neurons numbering

$$REM(1)-mREM(1) = N(1-m)(1-m) \text{ neurons left over .}$$

Neuron 'a' has Nm outputs like neuron 'b', each of which reaches to a fraction m of the neurons left over, thus reducing the pool of left overs by a factor (1-m). All Nm of these outputs like 'b' will leave $REM(1)*(1-m)^{Nm} = N(1-m)^{Nm+1}$ neurons unreached after 1 or 2 steps

Therefore $$REM(2) = REM(1)*(1-m)^{Nm}. = REM(1)*(1-m)^{\nu(1)} \qquad (2.5)$$

The recursion relations for finding $\nu(k)$ and hence average distance are

$$\left.\begin{aligned} REM(k+1) &= REM(k)*(1-m)^{\nu(k)} \\ \nu(k+1) &= REM(k) - REM(k+1) \end{aligned}\right\} \qquad (2.6)$$

The probability of having distance k between any two neurons is $\nu(k)/N$ (2.7)

Average distance $$\bar{k} = \sum_{k=1}^{kmax} k*\nu(k)/N \qquad (2.8)$$

See figure 1 : theoretical distances as functions of N and M.

DISTANCES BETWEEN NEURONS IN QUASIRANDOM MATRICES

The inhibitory nature of a link is of no importance in this study, thus a V_{ij} matrix of mN^2 unit links is generated. If the distance from neuron i to neuron j is d, then the ij'th component of the d'th power of V_{ij} will be non-zero. Thus, by taking successive powers of V_{ij}, and counting the number of elements that change to non-zero at each power, the distribution and hence the average distance are found. The average number of outputs per neuron in a particular net is used to calculate the theoretical distance distribution.

COMPARISONS

Figure 1 shows the netsize and connectivity dependence of the average distance for theoretical random nets. An interesting insight and conclusion arises from studying Figure 1 - the distance properties of nets size 100-300 (typically used in this thesis) diverge from those of nets size 10^3 to 10^5 (the order of size of a cortical column and large enough to neglect 'edge effects') for m < .12 to .15 thus it is important to use <u>large</u> nets when looking at sparse connectivity. The average distance for quasirandom nets is slightly larger . I believe this is so because the inherent structure of quasirandom nets tends to weight links between certain neurons, causing the distance to other neurons to be larger than expected. To quantify the degree of this structure average distances and distributions for some architectured nets are shown in figures 2 and 3. The architecture is similar to that used in later chapters. By emphasising connectivity in diagonal blocks of the connection matrix, the net can be visualised as a number of netlets with sparser links between netlets than within netlets. The distribution of distances, figure 3, illustrates the way structure increases the distance between neurons, and how nets deviate less from theory for higher connectivity. Figure 2 shows the theoretical average distance as a function of m for N=100, to which quasirandom nets with or without architecture are compared. The degree of architecture which is indistinguishable from ordinary nets is local emphasis 5 within 4 netlets , that is, there are 5 internal to 3 external connections per neuron.

The distances in a net are differently distributed for various values of N and m in an interdependent fashion. Increasing N with constant m (figure 4) reduces the average distance, because there are more connections per neuron, M, however, increasing N with constant M increases the average distance because there are more neurons to be reached by the same number of outputs. Keeping N constant, average distance decreases with increasing M, as expected.

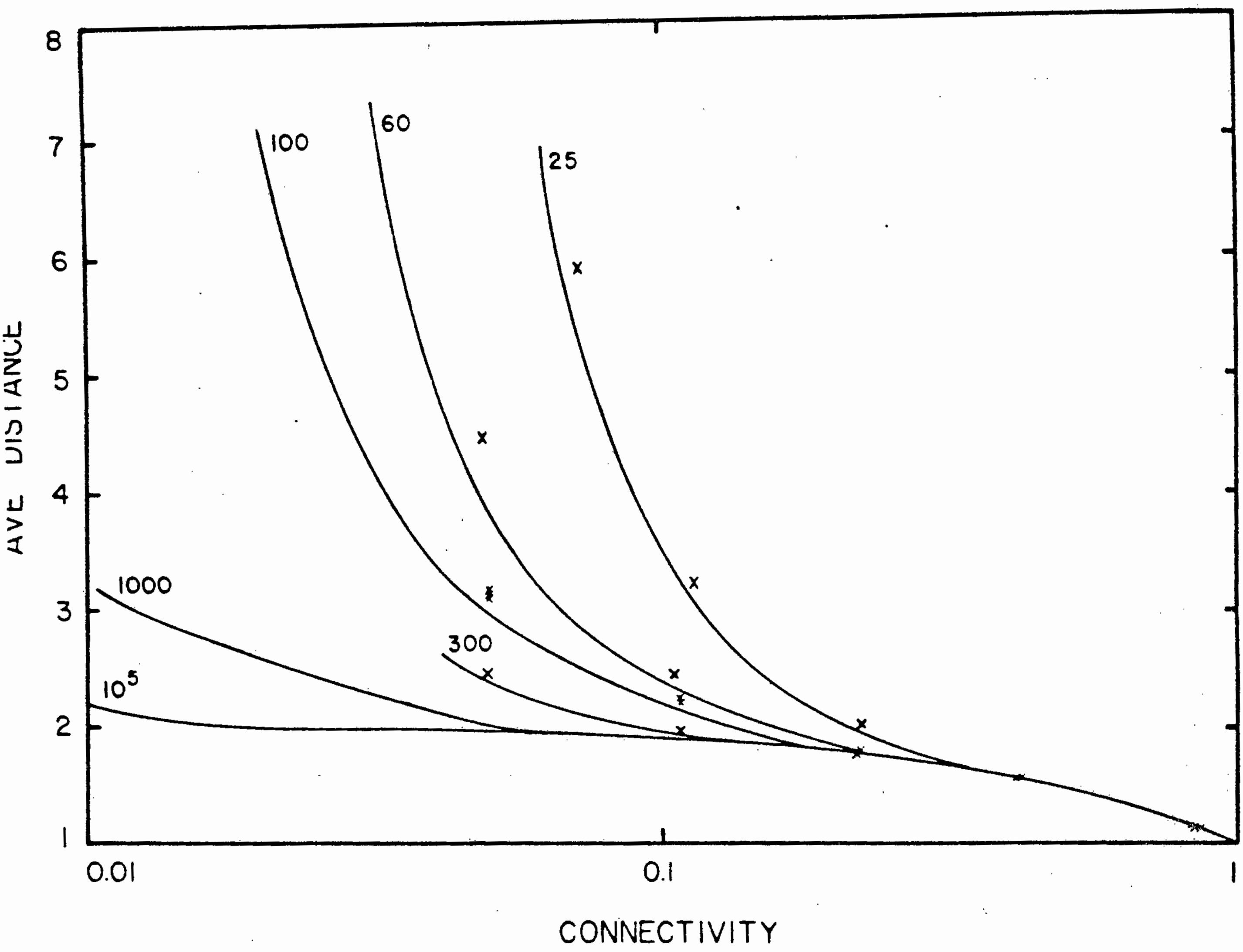


Figure 1 Average distance between neurons is plotted against connectivity m. Each line represents theoretical distances for the given net sizes. Crosses just above each line represent actual nets studied.

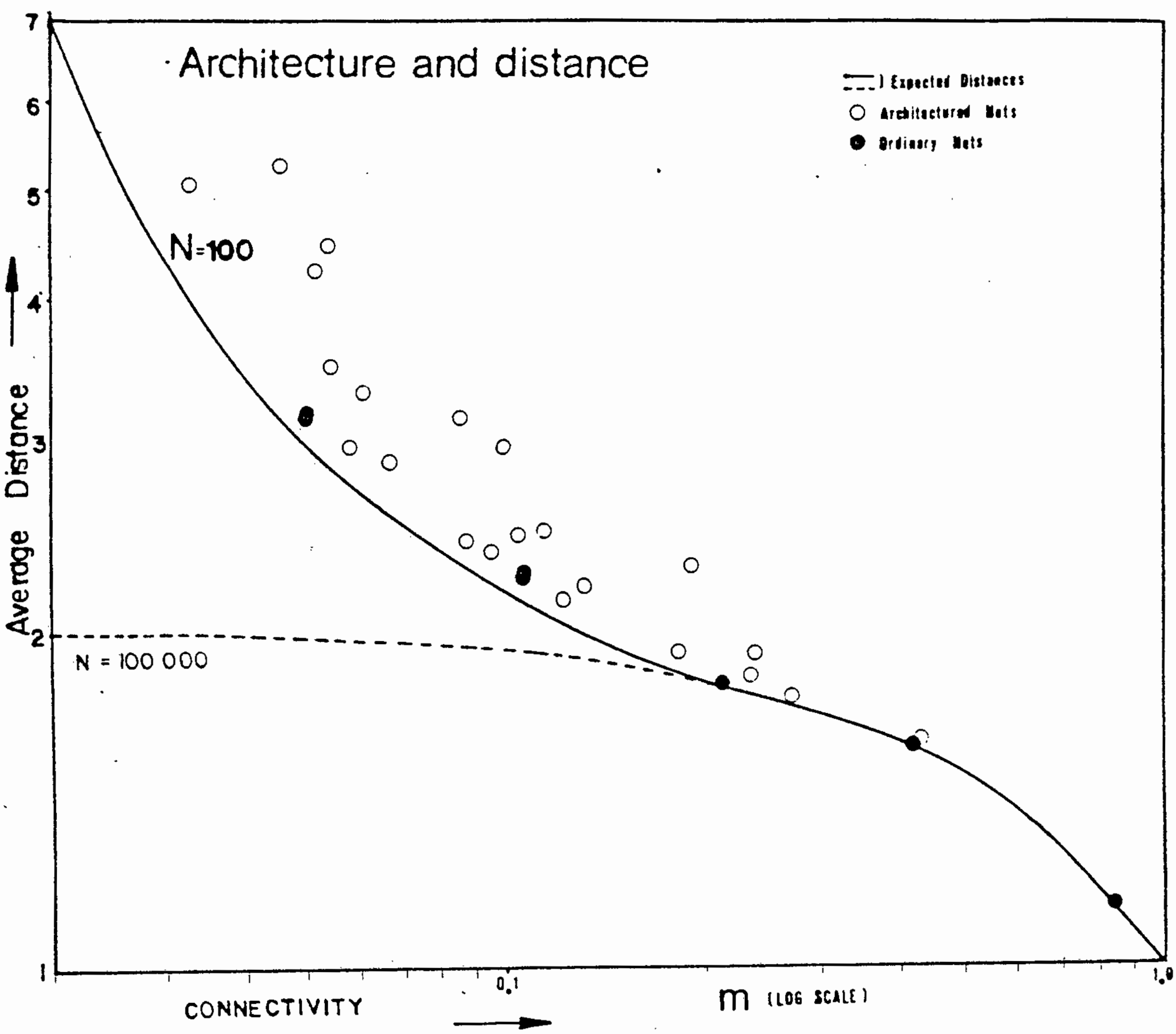
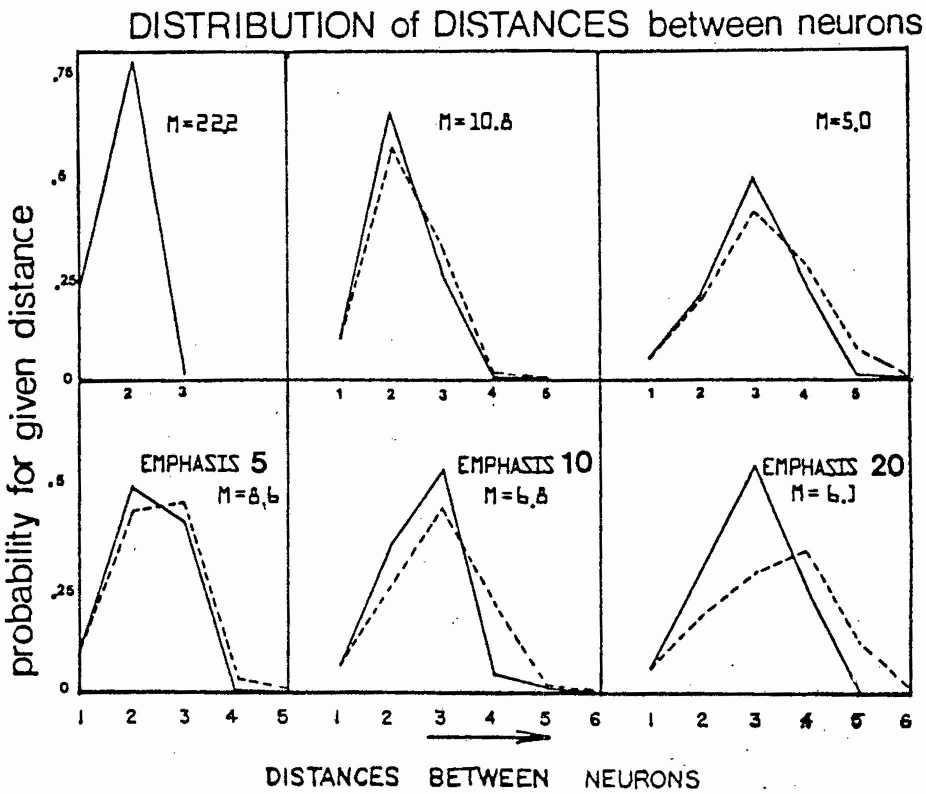


Figure 2 The average distances (number of synapses) between neurons is shown as a function of connectivity m, on a log scale. The lines represent theoretical values (solid for N=100 and dashed for N=100 000) The circles represent quasirandom nets (N=100) with varying degrees of architecture, with ordinary nets as solid circles. The points furthest above the line are for the most structured nets where each neuron is connected only to its nearest neighbours. The mildest architecture (nearest the line, is 4 netlets with emphasis 5 times on internal connections, (5 internal:3 external)

Figure 3   Each probability distribution shows the theoretical distances (solid line) compared to a quasirandom net (dashed line). The top three show decreasing connectivity and the lower three show increasing architecture. The emphasis is the ratio of internal to external connectivity for 4 netlets of a net sized 100. See the start of chapter 4.



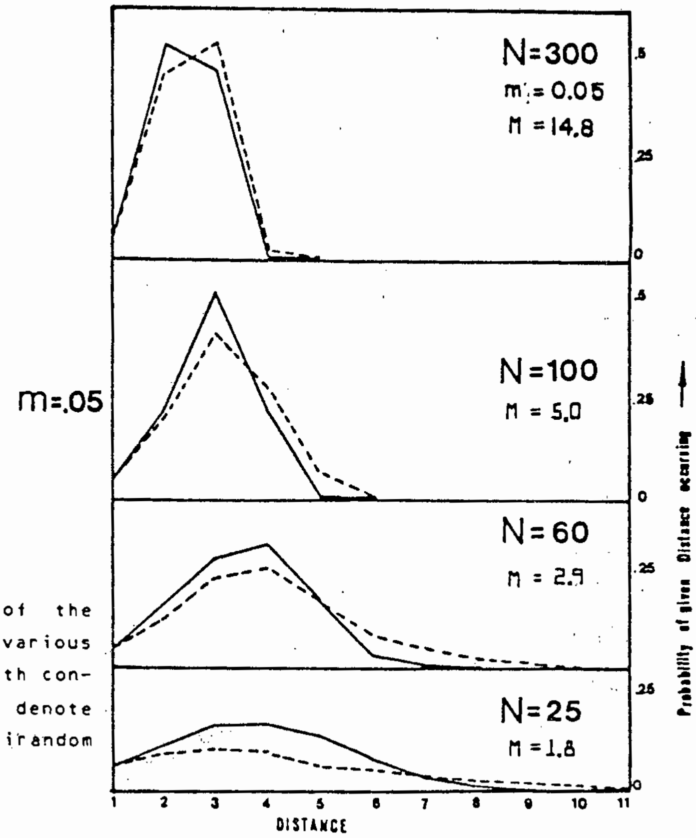


Figure 4   The probability distribution of the distance between two neurons is shown for various values of netsize (N=300,100,60,25) but with constant connectivity, m=.05 . Solid lines denote theoretical values and dashed lines, quasirandom nets.

Distribution of number of connections (in or out) per neuron

Since each element of the connection matrix is independently chosen to be 0 or 1 with constant probability (if no architecture), the distribution of inputs per neuron is binomial. Since m is not very small, the Poisson approximation is inapplicable. Figure 5 shows binomial distributions of inputs compared to actual distributions for various average M values. The average M in each net tends to be 0 to 10% larger than the expected value of Nm, since the random sequence is unevenly distributed. The variances of the distributions are larger than expected for certain values of m. This implies that choice of the connections is not entirely independent. The shift in average M only indirectly affects network behaviour, and can be accounted for, but the large variance affects the choice of threshold type, since some neurons have many more inputs than others, and different thresholds would be appropriate to make best use of each neuron.

BINOMIAL DISTRIBUTION.

For a given netsize, N, and connectivity, m, probability for a neuron to have r inputs is $P(r) = m^r (1-m)^{N-r} N! \,/[r!(N-r)!]$ (2.9)

average input $\langle r \rangle = Nm$ (2.10)

variance $\sigma^2 = \langle r^2 \rangle - \langle r \rangle^2 = Nm(1-m)$ (2.11)

COMMENTS ON CHAPTER 2

Studying the topology of nets via distances between neurons indicates even in the theoretical distance distributions, that 'edge effects' of small nets become noticeable in sparsely connected nets, in that the average distance between neurons increases sharply above 2. I imagine that the cyclic modes found in the dynamics of a net relate to the distance ,large distances being related to more complicated, longer cycles. Structure in nets is seen to raise the average distance slightly ,in the theoretical distance calculation and in the case of inherent structure in quasirandom nets. An interesting study of topology after brainwashing could involve extending the concept of distance to deal with non-unitary connection strengths. The study of the distributions of inputs per neuron shows an extent of non-randomness that must be used to qualify later conclusions.

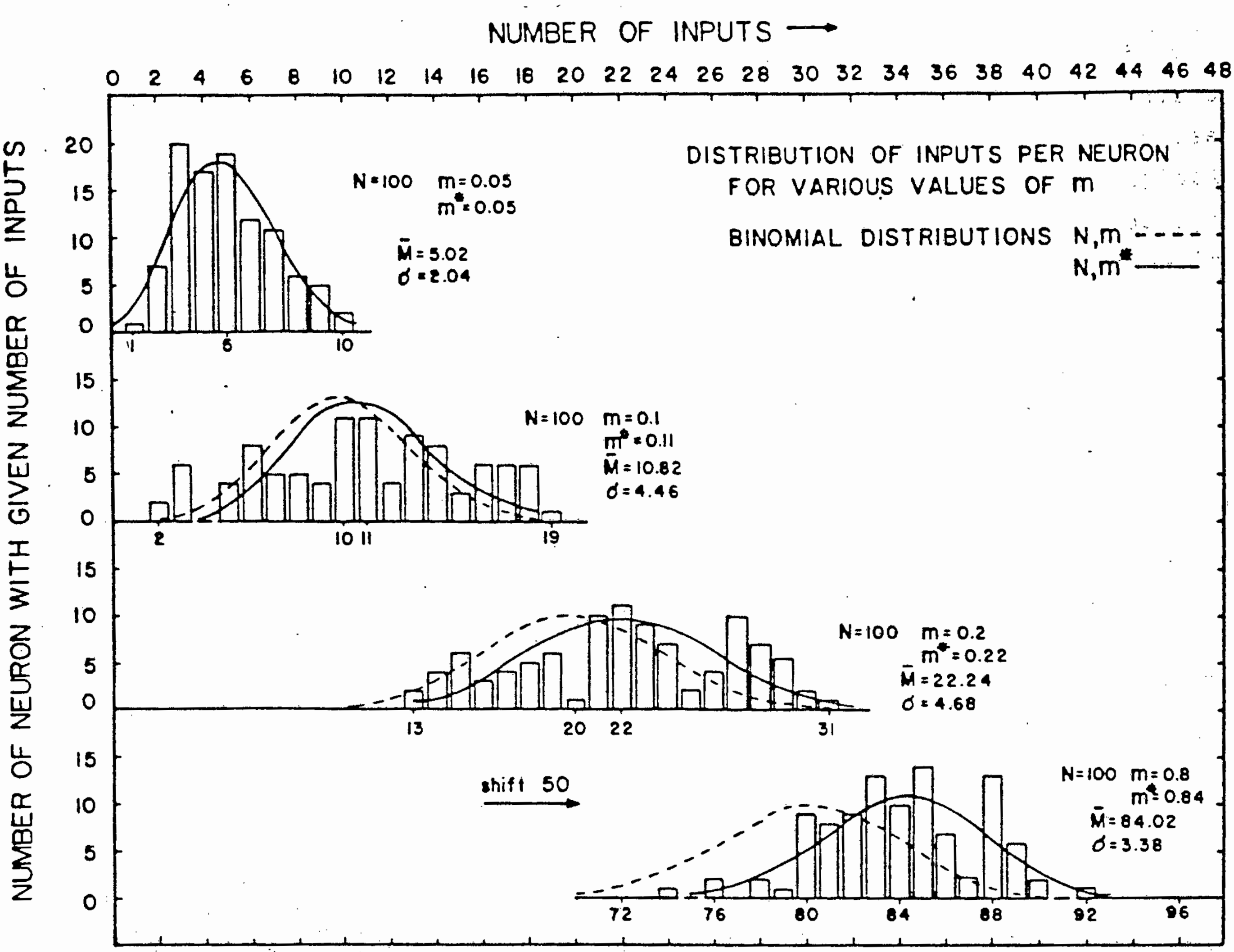


Figure 5 The distribution of connections per neuron is shown for various values of connectivity (N=100) The binomial distribution (lines) can be compared to the actual distributions found (histogram).

CHAPTER 3

The influence of hard-wired network parameters on cycling.

The behaviour of the net is studied for a variety of net sizes, connectivities, inhibitory fractions and brainwashing strengths. The occurrence of death, epilepsy, cycling and noncyclic states are studied, as well as aspects of cycling, including cycle length, transition time and eligibility. Accumulation, refactory conditions and probabilistic firing conditions are excluded from the study, and uniform thresholds and standard initial connection strengths of unity are used

Definitions

Transient time : From initialisation to onset of cycling

Transition time : From the time the first neuron cycles with period k to the onset of cycling of whole net.

Participation : The number of neurons in the cycle which are neither always on nor always off.

Non-cycling nets : Nets which (for initial conditions given) take relatively long to find a cycle. After searching for 500 steps, a run is deemed non-cycling.

Symbols used in this chapter

K	:	Period of cycling
Part	:	Number of neurons participating in cycle
Elg.	:	Number of eligible neurons i.e. 25% < $\bar{a}_i$ < 75% for transient and cycle
t_o	:	Transient time (To in tables)
Δt	:	Transition time (Tt in tables)
$\frac{\Delta t}{K}$	:	Relative transient time (w.r.t. cycling period)
#k > 2	:	Number of runs which lead to cycles longer than 2, expressed as a fraction of the number of runs in the set.
#k > 12	:	Fraction of runs in a set which lead to k > 12.
*	:	Typically used for runs which didn't cycle in 500 steps.
ε	:	Brainwashing's fractional change in connection strengths.
θ	:	Uniform threshold = half the average hardwired input per neuron.

Parameter Sets used in this Simulation

Code Number	5	7	10	11	12	13	14	15	16	17	18	20	11A	15A	18A
N=Net size	100	50	100	60	60	60	60	20	60	20	15	100	60	20	15
M=Connectiv.%	20	20	8	15	8	30	30	30	15	15	20	8	15	30	20
h=Inhibitory%	35	35	35	35	35	35	35	35	35	35	25	45	35	25	35
δ=BW fraction	10	10	10	10	10	10	5	10	5	10	10	10	10	10	10

The first brief examination of transition time of a net from unperiodic to complete cycling, indicated that the transition was shorter than the cycle length (typically $\frac{2}{3}k$) as if there were a conspiracy amongst participants in the cycle, rather than persuasion by certain neurons in a strong or stable cyclic mode for other neuron to join the cycle. The immediate questions were (1) does brainwashing change this (2) are there exceptions and when do they occur, and (3) what effect does changing N, m and h have?

Computer Study Outline (PNOV series)

A number of parameter sets (N, m, h, δ) were chosen (see above). For each parameter set, 3 or 4 different random nets were generated. Each net was run for a number of different thresholds ranging from .5 to 1.2 of the calculated threshold $\theta = \Sigma V_{ij}/2N$. The net was then brainwashed and run for a number of different brainwashing conditions (duration of and threshold during brainwashing). Firstly, averages of various measurements of the runs for each parameter set can be used to gain a rough idea of the effect of parameters on period, eligibility, success at finding cycles and the transition time.

Survival

Networks in the parameter ranges N = 15 to 100, m = 8 to 30%, h = 25% to 45% ie those under study, are fairly sensitive to threshold and are thus liable to die after a number of steps even when they have been brainwashed a little. For this reason a resuscitation loop for dead nets was used. When a net died, the threshold was reduced by ten percent and the activity reinitialised. Each net, washed or unwashed, was run and revived if necessary, until cycling occurred or until the 500 step limit was reached. The threshold at the start of each run was 1.2, 1.1, 1 or 0.9 times the expected threshold, θ. See appendix 2. Thus it was expected that thresholds of 1.2 θ and 1.1 θ would often cause a net to die. Observation shows that only marginally more of the above average threshold runs die out, but higher threshold nets tend to die more times in succession than lower threshold nets. There seems to be no useful pattern. The dependence on parameters of the likelyhood of death was studied by comparing what percentage of all runs of nets with the same N,m,h,δ parameters,with any threshold, end in death.

TABLE 1

N	m%	h%	δ %	death %
.20	30	25	10	81
.60	15	35	5	45
20	30	35	10	44
.15	20	25	10	44
.60	30	35	5	41
100	20	35	10	41
100	8	35	10	38
60	15	35	10	35
60	30	35	10	30
60	8	35	10	20
50	20	35	10	(14)
20	15	35	10	9
.100	8	45	10	0

Only two distinct effects are noticeable, but both have scanty evidence: (i) h = 25% has 44-81% deaths while h = 45% has no deaths. Increasing inhibitory fraction increases the resilience to change in threshold. (ii) Brainwashing with δ = 5 instead of 10%, increased deaths from 35 to 45 and 30 to 41% in the two cases seen. If this is generally the case, the possible reason is that since brainwashing makes nets more resilient, reducing BW parameter increases the occurrence of death.

Thresholds range from .9 to 1.1θ.

Absense of Easily Accessible Cyclic Modes

The search for cycling in each net was only pursued for 500 steps. Several nets had not yet cycled, because of a combination of long period, long transition and long transient. The non-cycling nets were found to be eligible, judging by the cycles found for other runs of the same net. Some nets cycled for none of the thresholds. The problem is that the unknown period and participation of the unfound cycle cannot be used to advertise

the nets as complicated. On the other hand, too eligible nets are not desirable if the cyclic modes are too inaccessible.
The occurrence of noncyclic nets seem to be parameter linked.

TABLE 2

N	m	h	BW δ	% Noncycling nets	
100	8	35	10	22%	Spread over all three nets
60	8	35	10	15%	1 net only out of 4
60	15	35	0;10	29%	2 nets out of 3
60	15	35	0;05	25%	Spread over all three nets
100	8	45	0;10	66%	2 nets out of 3
					Contributing factors seem to be high inhibition, large nets and low connectedness m. Most noncyclic nets are well brainwashed.

Effect of Parameters on Behaviour

Net size : see Table 3 N = 15 to 100
There are four groups of parameter sets with different m values. All nets have h = .35. Comparing average period to netsize within each set of constant m, shows that <K> is roughly proportional to netsize, and is also somewhat less than the average number of participating neurons, which is roughly proportional to N. <Part>/N varies between 18 and 37%. Note that the standard deviations in these averages are large because there can be a lot of variation in different nets with the same parameters. The average onset time and the fractions of cycles with periods greater than two and those with periods greater than twelve all increase with N, in demonstration of the increasing time taken for more neurons to approach cycling and to cycle. The relative transition time averages do not seem to depend on N. This is disregarding 1 and 2 cycles which grow less and less abundant with increasing N. It is noticeable that nets in which noncycling states occur have an average $<\frac{\Delta t}{K}>$ greater than one for those runs which do cycle. More on this later.

TABLE 3 (CH 3)

Effect of Netsize on k,part etc

N	m	$\bar{k}$	k>2 elg	k>2 elg%	elg%	$\bar{To}$	k>2 %run	k>12 %run	k>2 Tt/k	* %run
20	.3	3	8	(40)	21	9	36	2	.94	
60	.3	10	25	(42)	24	9	55	33	.86	
15	.2	3	9	(60)	18	4	22	0	.83	
50	.2	15	21	(42)	32	20	75	31	.68	
100	.2	25	25	(25)	20	56	78	56	1 ?	
20	.15	5	11	(55)	30	5	44	3	.89	
60	.15	27*	42*	(70)	37*	61*	65	50	1.04	29
60	.08	14*	23*	(38)	25*	37*	66	27	1.37	10
100	.08	29*	47*	(47)	33*	56*	73	48	1.34	15

TABLE 4 (CH 3)

Effect of Connectivity on k,part etc

N	m	M	$\bar{k}$	k>2 elg	k>2 elg%	elg%	$\bar{To}$	k>2 %run	k>12 %run	k>2 Tt/k	* %run
20	.3	6	3	8	(40)	21	9	36	2	.94	
20	.15	3	5	11	(55)	30	5	44	3	.89	
60	.3	18	10	25	(42)	24	9	55	33	.86	
60	.15	9	27*	42*	(70)	37*	61*	65	50	1.04	29
60	.08	5	14*	23*	(38)	25*	37*	66	27	1.37	10
100	.2	20	25	25	(25)	20	56	78	56	1 ?	
100	.08	8	29*	47*	(47)	33*	56*	73	48	1.34	15

M = Nm
k>12 are long cycles
k>2 are not trivial
* %run = % runs finding no cycling

$\bar{To}$ = onset time ,transient
Tt = transition time
Tt/k = relative transition

Connectivity m   m = 8% to 30%

The effect of m is compared for three cases of N in Table 4. The average period is not consistently affected by m, but it does seem that m = .3 causes less eligible nets with shorter periods, and yet m shouldn't be too low, for smaller nets.

Similarly, slightly more of longer cycles were recorded for m = 15-20% than were recorded for m = 30%. The distance between neurons increases as m is reduced (chapter 2),hence the above phenomenon is consistent with topological predictions.

In retrospect, the parameter sets should have been chosen for easier comparison by varying only one parameter at a time.

Inhibitory fraction   h : 25-45%

There is insufficient evidence for easy comparison because h = .25% vs .35% were recorded for small N and h = 35% vs 45% for large N and this screens the effect of h. Comparing 15 to 15A (N = 20 M = 30%) and 18A to 18 (N = 15 M = 20) shows that the behaviour is remarkably similar, even after brainwashing, except that h = .25 increased the incidence of death. Comparing 10 to 20 (N = 100 M = .08), i.e. h = .35 vs .45 shows that increased h results in more non-cyclic states (60% instead of 15%). The most remarkable effect of higher h is the improved eligibility of unwashed nets. The effect on transition time cannot be gauged with so many of the nets non-cyclic.

Brainwashing

When brainwashing is successful, the eligibility of a net should increase and the period and onset times correspondingly. With longer, more complicated cycles, transitions may possibly increase in length, but will the increase be greater than the increase in period, or will the relative transition rate actually drop with very long cycles?

Brainwashing is not always successful. Taking period, K, as an example, there are several occasions on which a net is overbrainwashed and very short cycles occur, or on which brainwashing fails to improve the eligibility of a boring net. On average, brainwashing increases cycling period by a factor of 3, but there are cases for which the cycling period is much reduced by brainwashing and cases for which it improves by a factor of 12 on average for a set of nets (See Table 6). For average cycle periods of individual nets, improvements of between 0.04 and 74 have been recorded in only 50 examples studied.

The brainwashing fraction δ, by which the relevant synaptic strengths are reduced in each step was set up at 5% and 10%. The latter δ would cause more brainwashing or would change the net in less time. Brainwashing times of 20 and 50 were used. Comparing similar nets Eqs.(13) and (14) (N = 60, M = 30% and h = 35%) first and (11) and (16) (N = 60, M = 15% and h = 35%) later:

Effect of increased BW time on 4 sets of nets - see figure 6

There was much variety in behaviour from net to net and for various degrees of brainwashing but <K> and <part> are correlated and δ = 5% lags δ = 10%. Which would be the best brainwashing rule to apply? This differs from net to net : no brainwashing for net 1, δ = 10% for longest time for net 2, δ = 5% for 20 steps for net 3 and δ = 10% for 20 steps for net 4. This seems to depend on the initial net - whether it be highly eligible or not or over-brainwashed or not. δ = 5% and δ = 10% have much the same effect on relative transition time.

In the first and third cases of (11) vs (16), comparison is somewhat difficult, since brainwashing doesn't change the behaviour of the nets. The second case is successfully brainwashed but δ = 5 is less effective than δ = 10. It seems that δ = 10 is best to use if overbrainwashing can be prevented, possibly by monitoring the eligibility of neurons during brainwashing and making sure it doesn't decrease.

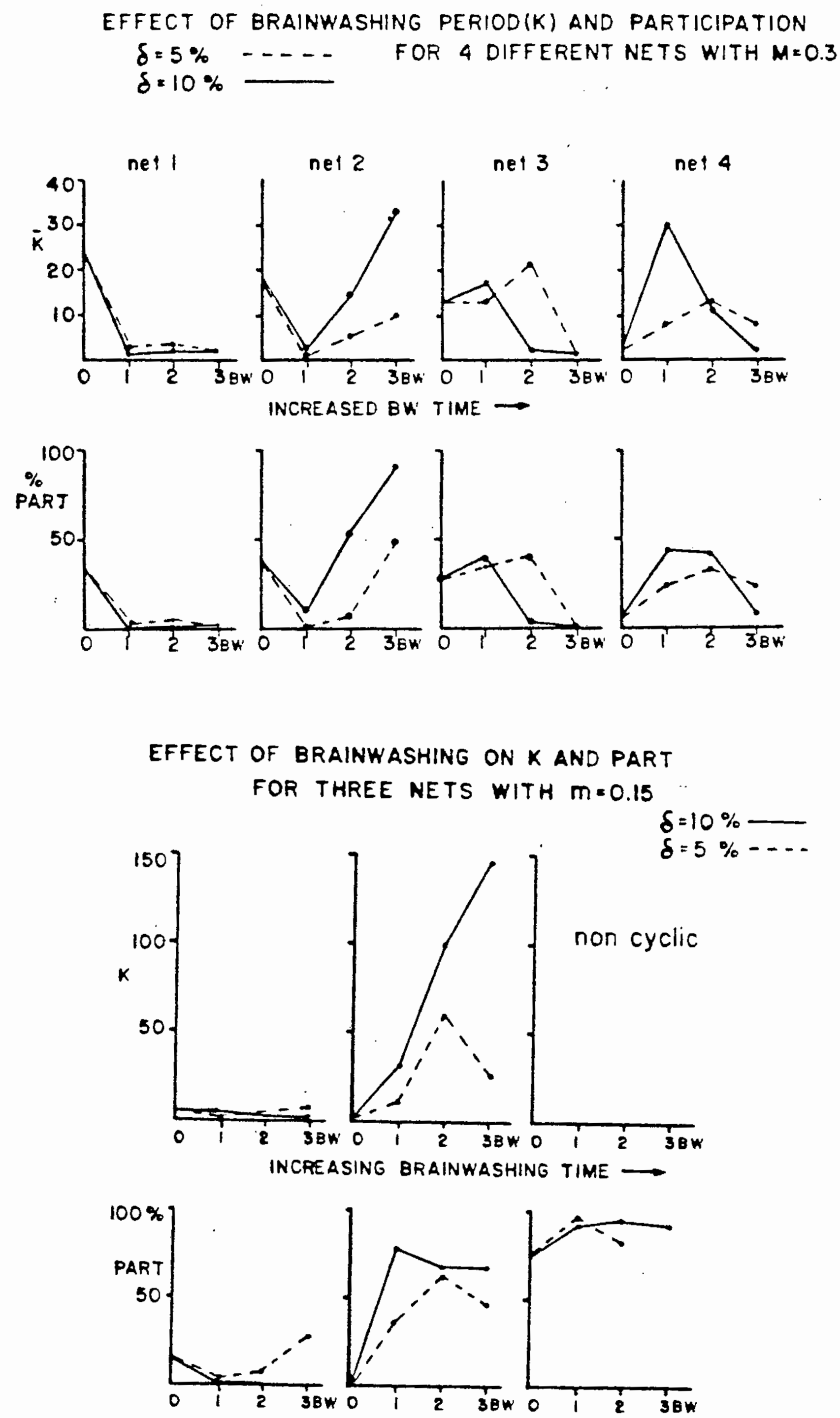


Figure 6 Cycle period and % of neurons participating in the cycle are plotted as a function of brainwashing time for 0 to 30 steps of brainwashing. Brainwashing factors δ=5% and 10% are compared for each net. N=60, h=.35, m=.3 and .15

Occurrence of Long Cycles   See Table 5

Out of a total of about 200 runs, 91 cycles with K > 15 were found, 11 for unwashed nets and 80 for brainwashed nets. Since 3 times more runs were made on brainwashed nets, this implies a 2.4 fold improvement for brainwashed nets.

However, for very long cycles (K > 100) only 1 of the 13 was for an unwashed net, and that was for h = .45. All the rest were found in BW versions of nets with parameter sets (10) (4 found) (11) (4 found) (12) (2 found) and (16) and (7) produced only one very long cycle each. Common features here are h = .35, N = 50-100, Nm = 8,9,5,9,10, respectively, that is, the higher N and lower m values were found most suitable for very long cycles. The higher M valued nets (M = 18,20 i.e. codes 5,13 and 14) had no k>100 cycles, but most of the 15<k<100 cycles, each set having 24, 13 and 10 such cycles respectively. The very long cycles are closely associated with the "non-cycling" states.

It seems, therefore, that taking the average of cycle lengths for sets of nets with the same parameters hides the fact that m does distinctly affect the occurrence of long cycles (which only occur in nets larger than 50). For m ranging from 8 to 30%, lower m-valued nets had numerous very long or unfound cycles while higher m-valued nets had more cycles, but shorter and easier to find, or in terms of topology, large distances between neurons. corresponds to an increased occurrence of long complicated cycles.See ch 2.

	Run #	(5)	(13)	(14)	(11)	(10)	(12)	(16)	(7)
	N	100	60	60	60	100	60	60	20
	M	18	20	20	9	8	5	9	10
Number of	100>K>15	29	13	10	8	8	5	8	5
Cycles	K>100	0	0	0	5	5	2	1	1
	Non-cycling				19	5	6		

TABLE 5 (CH 3)

PERIODS of long cycles or cycles with long transitions

Run code	BW	k>=12 Tt>=k	Tt>=2k	no cycle	k>100	15<k<100
12.1	0					35
	1		7,5,3			21,25
12.2	0		4			
	1		4			
12.3	1					16
12.4	1			******	220,146	28
13.1	0					38,46
13.2	0					18
	1					16,20,23,44,47,18
13.3	1					30,32
13.4	0		3			
	1	12				17,42
11.1	0		6			
	1		3			
11.2	1			***	131,137,267	49,58
11.3	0			****		
	1			*******	109	22,26,31,36
14.1	0					38,46
14.2	0					18
	1					16
14.3	1					35,23,21,24,17
14.4	0		3			
	1		4,4			23
15.4	1		4,7			25
16.1	0		6			
16.1	1		3			
16.2	1	32			104	16,88,46,32,31,41
17.2	0		6			
	1		4			16
18.2	1		4			
10.1	1	12	12,8,6,8		136,135	40
10.2	1	12		*		34
10.3	1	19	6,5	***	176,260	48,34,38,19
5.1	0					36,28
	1					65,28,23,45,40,33,52,79
5.2	0					25
	1					44,45,48,49,27,19
5.3	1					38,86,65,22,17,20,54
7.1	1	13				36,29,24,34
7.2	1				164	22
20	0			**	124	
	1		5	**		
15a	1		4			17

<u>The Occurrence of the Longest Transitions</u> (See Table 5)

Only 6 cases (that is 3%) were found with $k \geq 12$ and transition time greater than K. None of these cycles were very long, 32 being highest, and only a few neurons were found to be cycling by one cycle length before onset of cycling. The K = 19 cycle in net 10.3 is interesting because there is a large participation (51%) and the cycle is very similar to K=38 cycles found for different brainwashing conditions. These long transitions are not bunched in any particular parameter set, but do occur only in brainwashed nets with a rich variety of longish cycles.

Transitions longer than 2K were found for short cycles $K \leq 12$. 27 cases were found, 6 of which were in unbrainwashed nets. In spite of short cycle lengths, some of these cycles had many participating neurons (note net (10.1)) with a substantial fraction of them, participating more than a cycle length before onset. Net 10.1 has the most and the longest of these transitions. Net 12 also has many (both have parameter m = .08). Why is net 10.1 so exceptional? 4 seems to be a common factor of cycle lengths. K = 4 appears before brainwashing the net, but K = 12 and K = 8 appearing in brainwashed nets have long transitions (28 and 27 respectively) and high eligibility. Other cycle lengths are 136 and 40 which do not have slow relative transitions, but the actual times 91 and 27 respectively are comparable with the other transition times. Perhaps it is the closeness of the cycles and the high number of neuron participation in short cycles which allows such slow transitions.

Note that the distance between neurons (chapter 2) is between 2 and 3 for runs 12; 10; 20 and is smaller for other runs. Run 11 has distance about 1.8 and runs 13; 14; 15 have distances less than 1.8 . The larger distances invoke very long periods or non-cyclic states, but does not seem to be the only influence on cycle complexity.

<u>Average Relative Transition Time for Different Parameters</u> (See Table 6)

There is not much variation in the average values of $\langle \frac{\Delta t}{K} \rangle$ (for $K > 2$), which ranges from .65 to 1.38, in comparison with the variation in individual $\frac{\Delta t}{K}$ values which range from 3.3 for some shorter cycles to less than .1 for some of the longer cycles. There is a noticeable coincidence of $\langle \frac{\Delta t}{K} \rangle$ greater than unity with the occurrence of noncyclic states. This is in spite of the fact that the average period is generally higher in these nets. Supposedly, in very eligible nets, the shorter cycles have long enough transitions to increase the average, balancing the shorter transitions common in very long cycles. This is reflected in the average (non-relative) transition $\langle \Delta t \rangle$, which are less than $\langle K \rangle$, table 6. In other words $\frac{\langle \Delta t \rangle}{\langle K \rangle} \ll \langle \frac{\Delta t}{K} \rangle$ if $\Delta t / k$ decreases with increasing k , See figure 9

<u>TABLE 6</u> : <u>Averages of Relative Transition Times</u>

Run Code	N	m	h	δ	Number runs	Number K>2	Number Noncyclg.	$\langle K \rangle$ K>2	$\langle \Delta t \rangle$	$\langle \frac{\Delta t}{K} \rangle$ k>2	$\frac{K_{BW}}{K_o}$
15	20	.3	.35	10	64	23		7.2	5.7	0.94	2.0
15A	20	.3	.25	10	64	27		6.2	5.4	0.94	1.75
17		.15			64	28		8.6	6.3	0.86	0.96
18	15	.2	.25		64	13		4.6	3.4	0.69	1.17
7	50	.2	.35		36	27		20	8.5	0.65	2.42
12	60	.08			62	35	6	22	16	1.38	1.40
11		.15			48	17	14	53	34	1.06	11.5
16				5	44	19	11	28	20	1.16	4.6
13		.3		10	64	35		18	11	.86	.74
14				5	64	44		12	9	.96	0.65
10	100	.08	.35	10	40	23	6	34	31	1.34	6.5
20			.45		5	2	3	65	13	1.35	0.04
5		.2	.35		54	42		31	*	*	2.09

* this is information was not recorded in earlier programs.

Summary

The existence of rapid transitions to cycling, that is, where all the neurons enter the cycle within less than a cycle length, is fairly general, especially amongst longer cycles where even half a cycle length represent a large number of steps to make the transitions. Some shorter cycles have a long relative transition time with many neurons entering the cycle more than a cycle length before onset, which might, however, only be several steps from onset if the cycle is very short. There are a few exceptions for which cycles longer than 12 have long transitions.

There are correlations between nets with many eligible neurons and long cycles, and longer transitions and failure to find cycles and good responses to brainwashing. Larger nets (e.g. 100) with high inhibition (e.g. 35) and with m-values around 10-20% are good places to look, but each net varies widely from another with the same parameter set. Logically, increasing net size increases the number of eligible neurons, the cycle length and the onset times, whereas increasing the negative feedback seems to increase complexity and eligibility of cycles. Brainwashing needs to be strongly applied to some nets, provided overwashing can be avoided. The cycle lengths and relative transition times and eligibility creep up for most brainwashing algorithms, but the changes are not dramatic. The clue to longer cycles is in the topology of the connection matrix.

CHAPTER 4

Cycles, transitions and simple architecture - local emphasis on m.

Neurons are grouped into highly connected netlets with sparser connections between netlets. The onset of cycling and subcycling and the changes in relative transition times are studied for increasing local emphasis. The number and size of netlets is varied, but the brainwashing strength is kept at 10% for 20 steps and inhibition is h=.35 throughout.
Normal thresholds are used.

Symbols introduced in this chapter

Γ	:	Threshold scaling factor ranges from 0-1 for normal to uniform thresholds
% V_{ij} left	:	After brainwashing $\frac{\Sigma V_{ij}(t)}{\Sigma V_{ij}(o)}$ leads to normalisation factor for $V_{ij}(t)$
Elg.	:	Eligibility (sometimes used for number of participating neurons)
*	:	K = * for "non-cycling" states
Nsub	:	Size of the subnets
m_{int}	:	Connectivity between neurons within the same netlet
m_{ext}	:	Connectivity between neurons in different netlets
Qsub	:	Emphasis on local connections ≡ 1 for smooth nets $= m_{int}/m_{ext}$
Reps	:	Repeated states in netlets See below and ch 5

Definitions

Normal thresholds : Each neuron has a threshold proportional to its wired input $V_{oi} = \sum_j V_{ji}$

Uniform thresholds : All neurons have the same threshold

$$\theta \equiv \frac{1}{N} \sum_i V_{oi} = \frac{1}{2N} \sum_{ij} V_{ij} \equiv \frac{Nm}{2}(1-2h)$$

Repeated state	: When the state of the neurons in a netlet repeats itself after an interval, and at least six successive states repeat themselves, the repeated state is recorded in that netlet.The chance of such a repeated state occurring in a random set of states is $(2^{-6})^{Nsub}$.
Trivial cycles	: K = 1 or K = 2
Homogeneous nets	: Each element in the connection matrix has an equal probability of being on when the net is set up ie a net without imposed architecture

This chapter describes a study of nets with very simple architecture. It seemed necessary at this point to examine whether a structure in the nets causes them to cycle easily, and the transition to be rapid. For one group of neurons to lead another to cycling, the leading group should be in close contact with one another, to fix the period of cycling. This grouping seems to be random, and remains undetected, since it presumably differs from cycle to cycle. However, an imposed structure could be examined to see its effect on the entrance to cyclic modes. It was not obvious what kind of architecture should be implemented. In a first attempt the net was divided into a number of equally sized smaller netlets, each with similar properties, and the netlets were connected together by neuron to neuron links pseudorandomly chosen in the usual way. This was achieved by weighting the probabilities used to generate the connection matrix in favour of selfconnectedness, that is, each neuron was more likely to be connected to other neurons in its group than to neurons in the rest of the netlets.

The size of the netlets needs to be small if there are to be a number of netlets. Some netlets would also have more inhibitory neurons than others. This led to the introduction of normal thresholds which partially alleviate the problems of variability of small nets.

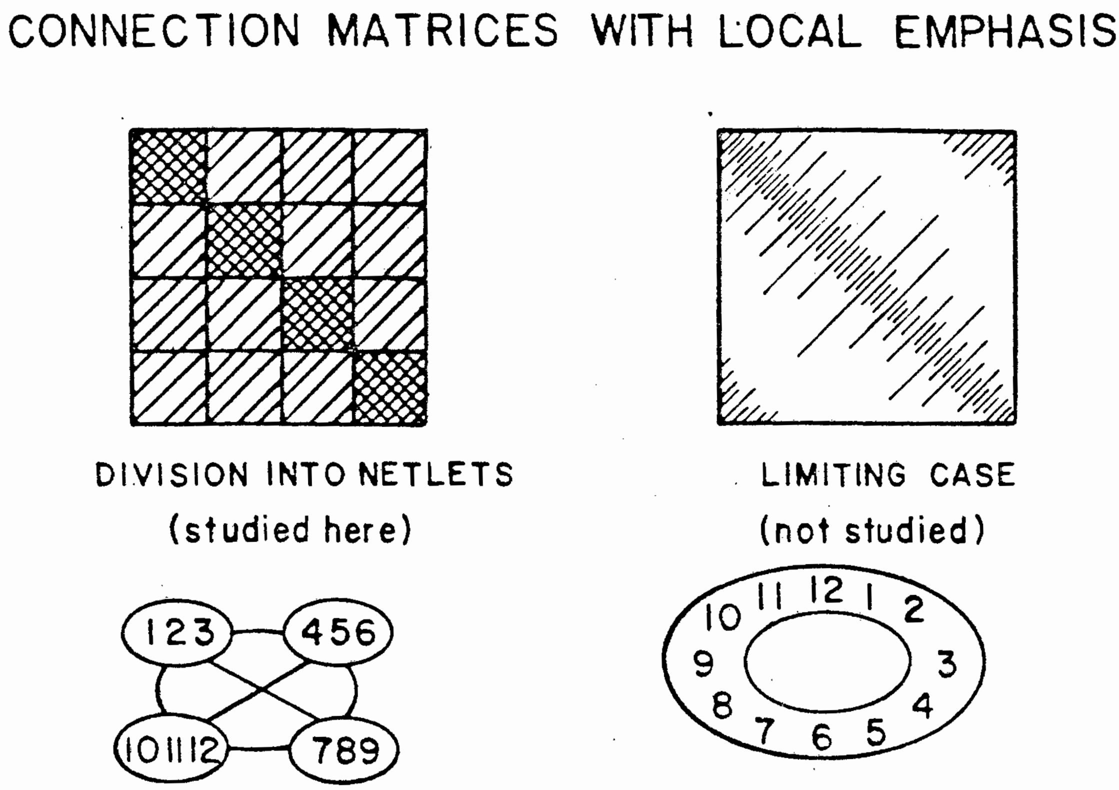


Figure 7 Schematic connection matrices show simple architecture imposed by weighting the connection probability (shading density) in the block diagonal region (left matrix) or near diagonal region (right matrix) The grouping of neurons is loosely cross linked netlets (for the left matrix) and a ring-like structure (for the other matrix)

TABLE 1

List of available parameter choices

EMPHASIS ON LOCAL CONNECTIONS

NUMBER OF NETS = 84
N = net size
Nsub = subnet size
m = connectivity
Qsub = m(int)/m(ext)
Mint = # internal links
Mext = # external links
BW = bw at 10%.
Y = threshold type : 0 normal to 1 uniform

MONITORS
k = cycle period
elg = eligibility
To = transient time onset to cycling
Tt = transition time
reps = repeated states
BW = extent of brainwashing = % Vij left
* = non-cycling
Vo = threshold
#d = number of deaths

N	Nsub	m	Qsub	Mext	Y	run code numbers
100	50	.15	5		0	24-28
		.2	1,100			64,65
	25	.2	1,5	15,7.5	0	) 66-72
			17,57	3,1	0	)
	25	.2	1,5	15,7.5	.3	) 77-84
			17,57	3,1	.3	)
		.15	12		0	48,49
		.3	3		0	56
150	30	.15	0		0	63
100	20	.15	5		0	4,5,29,30,50,51
			10		0	54,55
			20		0	57,58
	10	.15	1		1,3,0	7-23,39,40,47,61,62
			5,10		0	1-3,6,32-35,45,46,52,53
		.3	3		0	36-38,41,42
			1		0	59,60
		.1-.6		9	0	73-76

Thresholds

In most of this section and all subsequent studies, the firing threshold of each neuron is proportional to the number of inputs to that neuron. Brainwashing and other plasticity algorithms used in this project did not affect these thresholds. A short comparison between uniform thresholds, used for most previous studies, and proportional or normal thresholds can be found in appendix 4.

Nsub = Size of Netlets

Netlet size and the behaviour of nets with symmetrical inhomogeneous connectivity. The unwieldly heading above was chosen because "structured" seemed an inappropriate adjective for nets in which no netlet specifically feeds another, or has more inhibitory nature or any specific design in its connections, The connections are still randomly chosen and no part of the net has different properties from another part. An ideal extension would be to weight local connectivity and designate no boundaries of netlets. (See figure 7).

A problem here is that netlets are so small that they do not function properly in isolation, and so the effects of one netlet on another might be more difficult to quantify. Another problem is that one of the most useful monitors has proven to be the number of repeated states or repeated sequences of states within a netlet. However, if the number of states has anything to do with 2 to the power of the number of eligible neurons, then repetitions must be far more common in smaller netlets. Be that as it may, a comparison of the effect of Nsub in structured nets is interesting. As a control, a comparison can be made between a number of nets which, in fact, have no local emphasis and are homogeneous.

It is possible that the properties of structured nets described here will not be discovered in much larger simulations in which the netlet size is substantially larger, however , as was seen in chapter 2, presence of structure tends to increase the average topological distance between two neurons.

TABLE 2 (CH 4)

RUNS WITH LOCAL EMPHASIS 5

sub	m	Mint	Mext	code	#runs	Reps	k<=2 #run	noncyc #runs	Max Elg	k>2 Elg	_*_ Elg	Max K	_ K	To
0	.15	12.5	2.5	24-28	10	none	4	2	100	49	40	393	125	147
5	.2	12.5	7.5	68,69	4	none	0	3	52	52	88	43	43	383
)	.15	8.3	6.7	many	12	none-many	0	4	100	26	51	338	51	202
)	.15	5.3	9.7	many	16	none-many correlated	5	5	100	39	46	101	35	172

.igibility: maximum;
average (k>2);
average (all nets ,cycling or not)

·cling period: maximum;
average (k>2)

= average transient time

mber of runs: total #
with k<=2
without cycling

e table 1 for description of symbols.

Comparing Netlet Sizes for Homogeneous Nets with Normal Thresholds

Many more repeated states were recorded in netlets sized 10 than for bigger netlets, as expected. Since the nets are homogeneous, the choice of netlet boundaries is arbitrary and thus repetitions are not expected. The $N_{sub} = 10$ nets used had m = .15, which might account for the seemingly longer cycling or onset times which would allow time for more repeated states. The smaller the netlet, the less possible states there are and the more likely to have reps. Bearing this in mind, compare the effect of N_{sub} in nets with $Q_{sub} = 5$. (See Table 2). There are no marked tendencies in behaviour as N_{sub} changes. There is a stuttering decrease in cycling period as N_{sub} decreases. The number of runs used in the study is too small to compare too closely. If all the netlets were separated, then small netlets would have low eligibility and short cycles, but as the general cycle is reduced by small netlets, the number of netlets makes the common multiple of periods larger.

Effect of Division into Netlets

As an initial indicator, a 100 neuron net was divided in two with an emphasis 100 on internal connectivity. That implies about 10 inputs from net 1 and 1000 from net 2 as total net inputs to net 2. From the homogeneous net with medium cycle length and eligibility, a net was formed that did not cycle. This, in itself, was not unusual since many homogeneous nets failed to cycle, but it does suggest that a measure of architecture makes cycling more complicated. For interest sake, the opposite extreme is of this model is to have zero internal emphasis. A 150 neuron net was divided into three 50 neuron netlets. Each neuron was not connected to any other neuron in the same netlet, i.e. the V_{ij} matrix was off-diagonal. Since the net never cycled no 3-related symmetriescould be found. Rather curiously, repeated states were recorded in only one of the three netlets, but since it had only external input, there must have been periodic conditions in part of the other two netlets, for which no repeated states were recorded. Such nets also appear to be complicated. Often in physiology, one type of neuron connects to another type in another layer, but it is not the aim of this study to examine such complications.

Before conducting a study ot the influence of local emphasis on behaviour, it would aid the future analysis to outline what sort of outcome would be expected: Reducing the number of external connections ought to encourage each netlet to cycle independently, but the few existing inputs from other netlets should keep disrupting the attempts to cycle, unless all inputs are severed or all the netlets are in a common cyclic mode. This may be manifest as a profusion of repeated states, with different repetition rates, within the netlets, before the net, as a whole, begins to cycle. The number of repeated states should depend on the number of eligible neurons per netlet (fewer neurons can repeat their state more easily than many) and on the number of external inputs.

To allow a profusion of repeated states, the number of inputs must be critically balanced between allowing a sequence of six repetitions to form before interrupting, and yet supplying sufficient external stimulus for many different periodicities to occur. Amongst these repeated states may emerge the inkling of a slow transition, with correlated repetition lengths showing how one netlet leads the others to cycling, or how one netlet prevents the onset of cycling. The eligibility in netlets may be increased by the external prodding from other netlets in the net.

Some Results:

TABLE 3A

Increasing local emphasis Qsub for net N = 100 N_{sub} = 20 m = .15

Qsub	MExt	MInt	#	#K≤2	Elg	Elg_{max}	$\bar{K}$	K_{max}	#Repeated states
5	$6^2/_3$	$8^1/_3$	1	.	56	100	114	338	None, few, none
10	$4^2/_7$	$10^5/_7$	.	.	50	73	110	213	Few,- Several Some correlated
20	$2^1/_2$	$12^1/_2$	.	.	43	54	54	215	Varies, very many (100's)

Increasing Qsub, that is, increasing the inhomogeneity, is marked by a slight drop in the number of neurons in, and the length of, cyclic modes. The non-cycling state for Q=5 could effectively further raise the Elg and K averages of the set. Note the absence of trivial cycles and the scarcity of non-cyclic states. This table does not include the homogeneous case for comparison. (See Tables 3B and 3C).

In Table 3B a similar study is made with Nsub = 25. The data does not compare well with Table 3A, because the noncyclic and trivial states are more abundant. When these states are accounted for by conservatively setting K = 100, Elg = 90 for non-cycling states and K = 1 Elg = 0 for trivial cycles, the following numbers appear:

Adjusted	Q =	1	5	17	57	12
version of	Elg. =	12	81	68	26	51
Table 3	K =	15	86	75	35	74

Apparently the inhomogeneity at first improves Elg and K, but thereafter, as before, Elg. and K slowly decrease with increasing inhomogeneity, Qsub. Repeated states are more common when there are few external connections.

Table 3C shows the effect of Qsub when N = 10. For such small netlets, the effect of architecture is apparently detrimental, since eligibility and period drop off sharply.

The above comparisons are an illustration of drawing too many conclusions from a small data sample. Compare Qsub = 1 cases for tables 3b and 3c. They only differ in m = .2 and m = .15 respectively and yet the second set produce a higher elg. and period, enough to upset the conclusions drawn from these "spot tests". The studies that follow need to include more runs, but also need to examine the effect of architecture on the same basic net, instead of averaging over a set of very varied tendencies. This initial study has hinted that between Qsub = 1 and Qsub $\geq$ 5, there is an improvement which needs to be examined more closely to find whether there is a range of optimum inhomogeneity. The effect requires some minimum netlet size, as indicated by the failure for Nsub = 10. Before proceeding to the next study, however, there is data available to analyse the effects of connectivity, m, and to examine the occurrence of repeated states more closely and to search for slow phase transitions and the conditions under which they occur. There is also a correlation between cycling period, onset time and number of participating neurons. (See figures 8 and 9).

TABLE 3B : EFFECT OF CHANGING EMPHASIS , Qsub (for Nsub = 25)

ub	m	Mint	Mext	k<=2 #run	noncyc #runs	Max Elg	$\overline{Elg}$	Max K	$\bar{K}$	repeated states
	.2	5	15	2		47	23	63	28	none
		12.5	7.5		3	52	52	43	43	none
		17	3	1	3					none - few
		19	1			50	26	76	35	many, correlated
	.15	12	3			75	51	151	74	many, correlated

TABLE 3C : EFFECT OF CHANGING EMPHASIS , Qs (for Nsub = 10)

m	Mint	Mext	k<=2 #run	noncyc #runs	Max Elg	$\overline{Elg}$	Max K	$\bar{K}$	reps
.15	1.5	13.5	2/8	2	100	44	256	78	few - very many
	5	10	0/6	1	100	30	65	20	none - many
	8	7	0/2	0	5	4	2	2	none

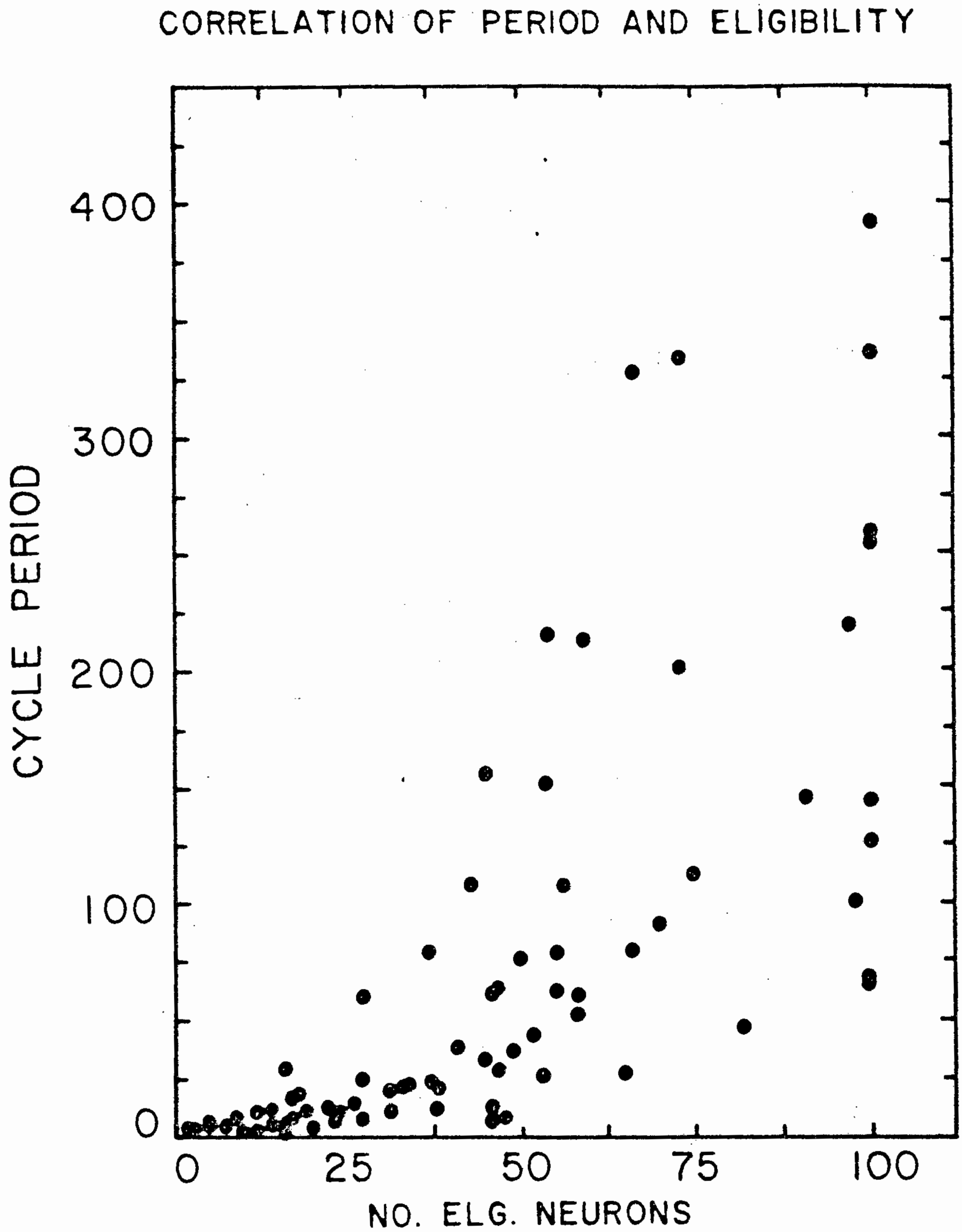


Figure 8 Period is plotted against % participating neurons (N=100). Each dot represents one run. The limit on period caused by shortage of eligible neurons is illustrated in this graph.

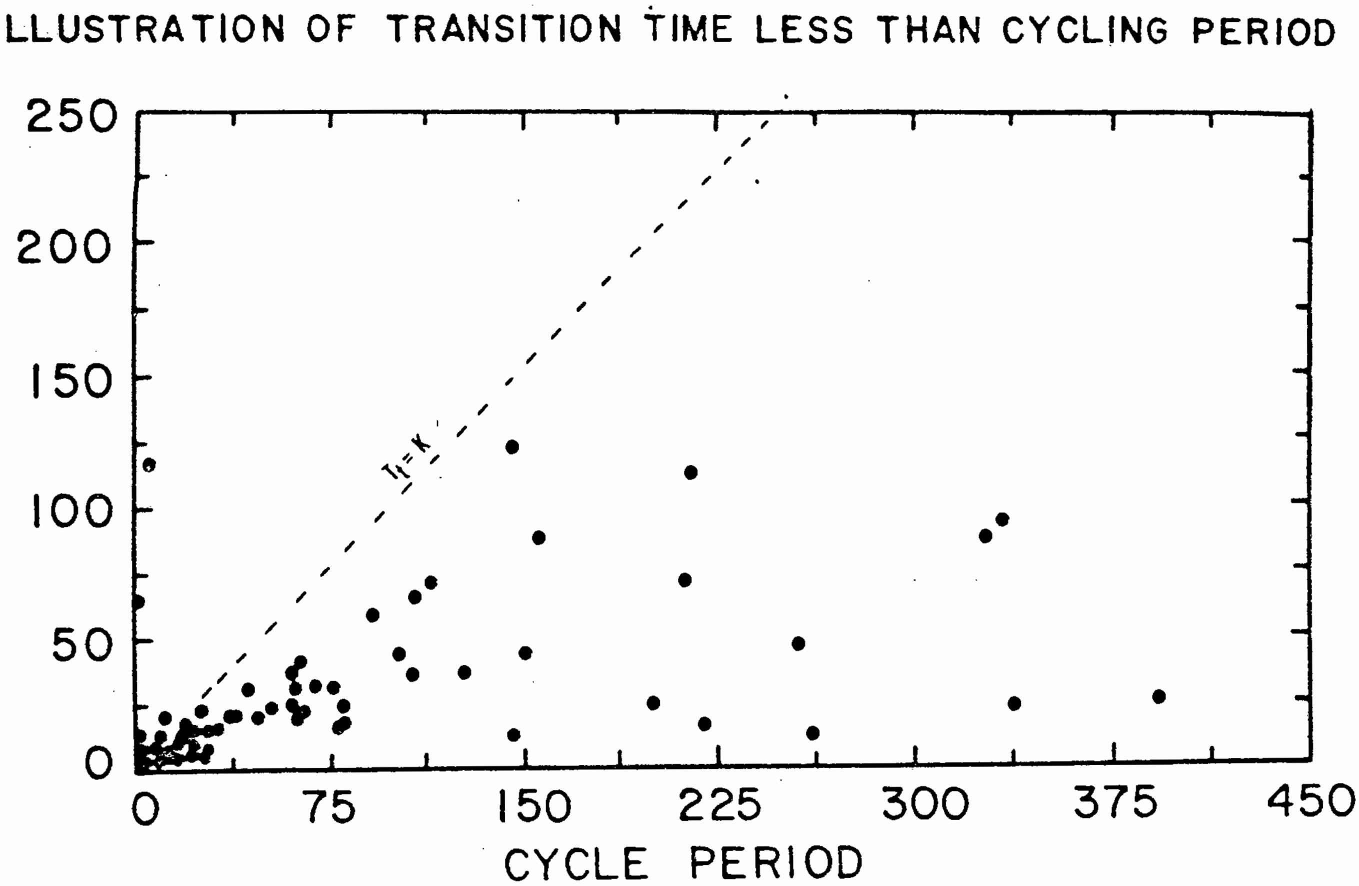


Figure 9 Transition time vs period (for a maximum runtime of 500 steps) An expanded version of the shorter periods is shown in the second graph. Each dot represents one run, thus the distribution of cycle lengths and transition times are also illustrated. Note that Tt (transition time) is less than k for k>12 and Tt < k/2 for k>160 , but the ratio Tt:k is extremely varied for individual cases.

9 TRANSITION TIME : CYCLING PERIOD FOR SHORTER CYCLES

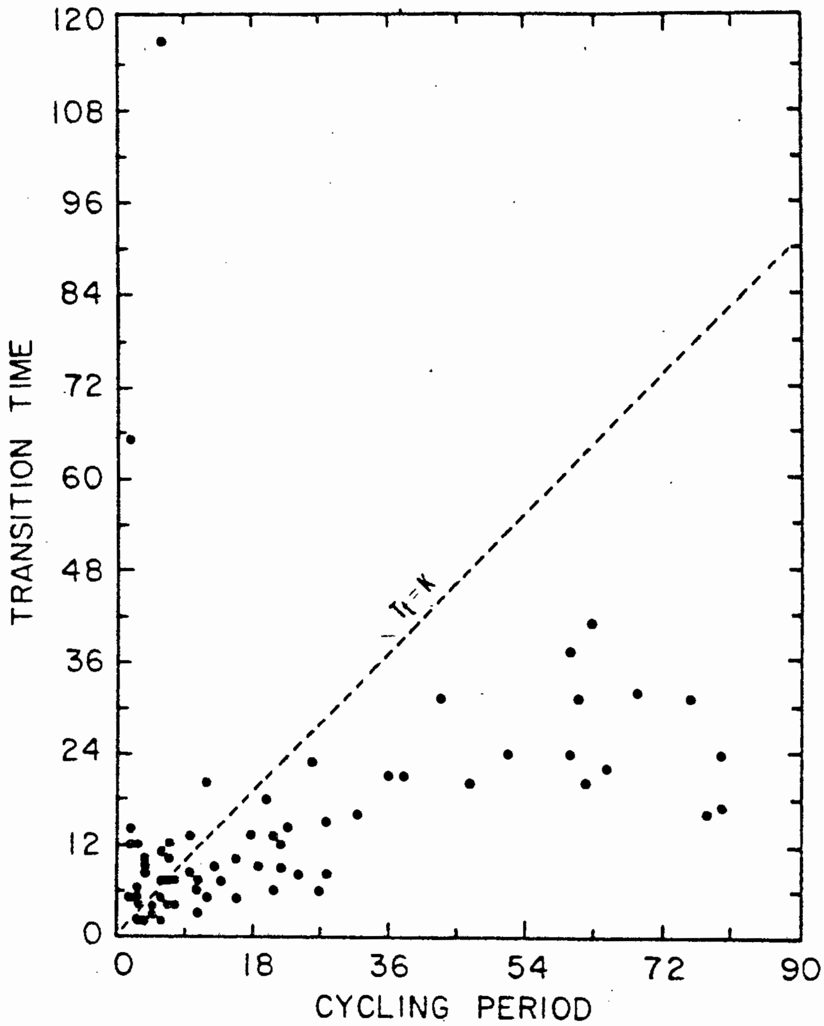


FIGURE 9b

Effect of Connectivity on Cycling

(See Table 4A and 4B)

Note that the data is rather limited, particularly for M = .2, Q = 5, of which three out of four nets were found not to cycle. This unusually high number is somewhat out of trend with the rest of the table, which shows increasing cycle length and eligibility with decreasing m. This is for normal threshold nets. Inhomogeneity does not change the range of optimal m depicted in the fig 10a

Nets of 100 neurons were used throughout and it would have required large computer efforts at that stage, to systematically study larger nets. It is thus difficult to distinguish whether the fraction of connectivity (m) or the average number of connection (Nm) is the more important variable influencing behaviour. With thresholds proportional to the effective

TABLE 4A+B : EFFECT OF M ON HOMOGENEOUS and INHOMOGENEOUS NETS

Nsub	#runs	k<=2 #run	noncyc #runs	Max Elg	K>2 Elg	___* Elg	Max K	K>2 <K>	___* K	
10	7	4	0	9	9	7*	7	6	3*	HOMOG.
50,25	2+5	2	0	82	35	25*	63	27	20*	
10	34	5	10	100	45	55*	256	55	61*	
10	4	0	4	.	.	100*	.	.	100*	
10,25	10+3	11	0	5	4	2*	6	5	2*	INHOMOG.
25	4	0	3	52	52	81*	43	43	86*	
10,20,50	42	11	11	100	35	43*	393	57	54*	
10	12	2	9	97	97	83*	220	220	94*	

verages Elg* and K* include all nets, taking (100) for noncyclic modes excitatory input connections to each neuron, it was expected that the net escapes the effects of M and N somewhat. However, this was not found to be true. One view point is that when a neuron with a few input connections is stimulated to fire, its activity is more dependent on which inputs are stimulating it, that is, its firing pattern depends directly on a few other neurons. Alternatively, a neuron with many inputs can be fired by a large number of combinations of input neurons, which somehow allows this neuron to cycle more easily and with a short cycle, i.e. it is in close communication with the rest of the net and behaves accordingly. When thinking about very much larger nets, with complicated structure, how should connectivity M be defined? Each neuron would be part of a set of netlets of neurons but in that set it has a wide variation of connectivity with respect to each net chosen. When a block of neurons is uniformly interconnected, it is obvious that $m = \frac{\text{Ave. No. input}}{\text{Net size}}$. If a block of nets is divided into netlets, $m = \frac{\text{Ave. No. input}}{\text{Netlet size}}$. But if there are a few external connections to each netlet m lies between the above mentioned values.

Note, in Table 3B $N_{sub} = 25$ $m = .2$ in data for the effect of Qsub, that the number of noncyclic states increased for $Q_{sub} = 5$. But that for $Q_{sub} = 1$ (homog) or Q_{sub} very high (almost divided into netlets) there were no non-cycling states. That is, in some sense, at $Q_{sub} = 5$, the effective m was reduced, yet m_{int} in the netlets would than have been higher than .2, in fact as high as .5, and when the netlets are nearly separated, $m_{int} = .8$; netlets should be epileptic?! This will be investigated further in the next chapter on cutting nets.

Ref. figure 10 : The graphs show the fraction of runs with no cycling, cycling and trivial cycling respectively, as a function of m. Ignoring m=.2 , inhomogeneous and homogeneous nets are similarly influenced by m. A non-cyclic net is a relative designation, because of 500 step limit. The graph is dependent on this limit. The trivial states are also fairly arbitrarily defined. Sometimes k=1 cycles are found rapidly, indicating that, either the net is ineligible, or that the threshold algorithm does not apply at higher m. On other occasions, an "unlucky" swing in activity results in a trivial cycle but this occurs after the net has been in random state for a considerable time, i.e. the state could have been designated non-cyclic, had the 500 step limit been different.

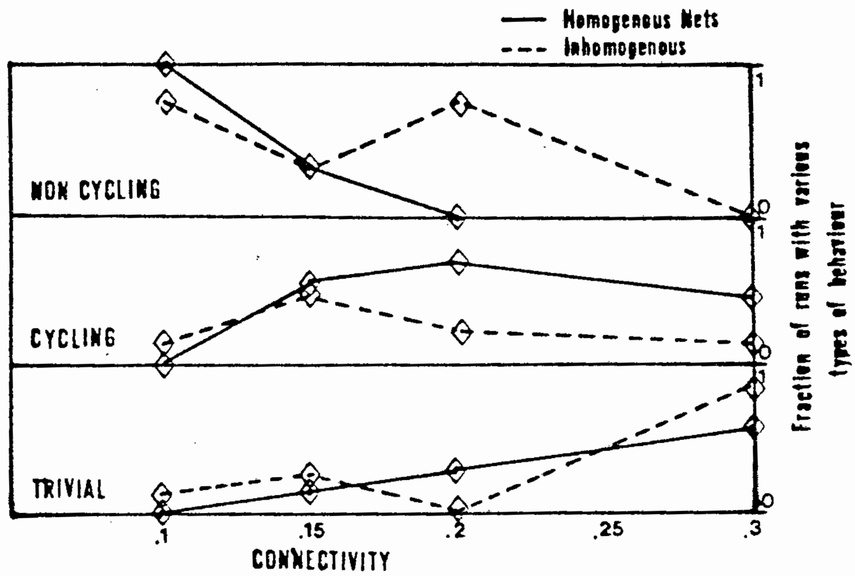


FIGURE 10 All network responses are catagorised into trivial, noncycling or cycling. The fractional abundance of each of these types of cycles is shown as a function of m. Solid lines representing homogenous nets can be compared to the dashed lines representing nets with imposed structure.

Repeated States : Their Absence or Profusion

TABLE 5 : Summary of Qualitative Information on Repeated States

No. repeated states	:	(a) All cases of Nsub = 50
		(b) All cases of m = .3
		(c) Most cases with K $\leq$ 2 (44/49)
		(d) Most cases with no cycling (39/53) and 8 of the remaining 14 cases have very few reps and are of netsize 10
		(e) Others: 10 cases for N = 25, m&Q={.15&12 { .2&1,5 5 of which had transient times less than period.
A few uncorrelated reps	:	(a) 8 Non-cycling cases with netsize = 10
		(b) A few caves with K $\leq$ 2 (3/49) in highly emphasized nets with netlet size = 10 and long transients.
		(c) 19 cases with transient $\leq$ 21
		(d) 2 cases with 100% participating
		(e) 4 cases with transient << period and highly inhomogeneous
		(f) 2 others with transients longer than period
Several repeated states	:	(a) Homogeneous Nsub = 10 nets (13 cases) 5 of which have correlated reps. 5 have K > 50 and have high eligibility and longish transient. 5 have low eligibility but short transients. 3 are inbetween.
		(b) Highly inhomogeneous nets, 3 cases : one an trivial cycle with long transient, the other two have typical values for transition approximately half the period which is approximately half the transient.

<u>Many repeated states</u> : (a) Very high Qsub, Nsub = 20, 25 (18 cases) either less than 20% eligible or highly eligible nets with very long transients.
(b) Qsub = 5 (8 cases) Nsub = 10 either low elg. or long transient.
(c) Homogeneous nets (9 cases) Nsub = 10 highish eligibility.

Certain conditions can account for most of the occurrences of repeated states:

(1) When Nsub = 50 N = 100 the two netlets are so large that no repeated states are likely to occur unless both nets cycle together or are disconnected.

(2) m = .3 leads to short cycles which are reached soon, allowing no time for repeated states.

(3) Trivial states (K = 1,2) are usually reached quickly, i.e. no repeated states occur. 10% of K = 1,2 states did have reps, but they had long transients.

(4) Non-cyclic states tend to have no repeated states in netlets, because the eligibility is so high that repetition is unlikely. Inability to cycle and lack of repeated states go hand in hand in spite of the long transient time available in which repetitions can occur.

(5) Highly inhomogeneous nets tend to have many repeated states, with either long transients (> 100) or low eligibility (< 20%) or both (see 6 and 7)

(6) Smaller netlets (N = 10) have more repeated states than larger netlets

(7) Long transients (> 100) allow time for many repeated states provided Elg. is not too high (< 50).

(8) The curious case of Q_{sub} = 0, non-cycling net, with repetitions in only one netlet, has been discussed.

Slow Transitions

The following rare cases with transition time greater than period of cycling are examined for a common cause of slow transitions . 20 cases out of more than 200 have long transitions and 16 of these have K $\leq$ 10, transient $\leq$ 15.

Run code	K	Δt	t_o	Elg.	Q_{sub}	N_{sub}	m	Comment
5	12	20	.	38	5	20	.15	An extended case of short K→ long transition
71	2	65	70	16	57	25	.2	Extraordinary long build up. Typical parameters for noncyclic nets
40	21	13	44	33	1	10	.15}	Δt<K, but K appears in reps,
54	13	9	58	46	10	20	.15}	disappears and reappears again.
58	6	117	118	46	20	20	.15	These parameters usually produce large K, t_o, Elg. but here K is short but Elg. and t_o still large.
						57	25	
.2		Γ = 0 } The Γ =.3 case has long						
					57	25	.2	Γ = .3} cycles and the Γ = 0 case has relatively slow transitions. Very many repeated states and subcycling occur indicating sparse interruption (1 external connection per neuron) which intuitively suggests long transients.

Transition = Δt

Transient = t_o

CHAPTER 5

Cutting connections to form netlets.

Once again (as in chapter 4) the transition time to cycling is scrutinised. Studies are made of eligibility, subcycling and occurrence and absense of interesting cycles and dominance between netlets is observed.

Symbols and definitions used in this chapter

Transient	:	Time from initialisation to onset of cycling
Transition	:	Time from first neuron cycling in its final mode to the whole net cycling
Relative transition time	:	Transition/cycling period (K)
After cut n	:	A net has been cut n times (see definition of cutting mechanism), that is, a net in which n neurons in each netlet are isolated from neurons in other netlets
Repeated states	:	semi-cycles in a netlet. There must be six successive states which are repeated a time T later. This periodicity is often referred to as: "Reps : T_1, T_2, T_3 ... " where T_1 is the periodicity of the first repeated state found
Participation	:	Number of Neurons that are neither on all through the cycle nor off all through the cycle ≡ Elg.

Description of the Cutting Mechanism

The search for slow transitions led to the use of nets with a degree of inhomogeneity in the connection matrix which was introduced subsequent to the establishment of a quasirandom net. The net was effectively divided into subregions or netlets with sparser connections between neurons in different netlets than between neurons in the same netlet. In an attempt to understand the effects piece by piece, a homogeneous net (that is, one in which the connection probability between any two neurons is the same- See chapter 2) was separated into netlets by severing links to and from certain neurons , one neuron (per netlet) at a time. The neurons' internal connections (to and from other neurons in the same netlet) were left untouched, but all external links (to and from neurons in other netlets) were cut, so that the particular neuron thus isolated could only affect, or be affected by other netlets indirectly, via the activity in its own netlet. See diagrams.

In contrast to the previous study, a particular net could be studied during the gradual metamorphasis from one net to many netlets , as links were cut. The behaviour of particular interest was long onset times or transients(often characterised by many repeated states) and slow transitions to cycling. Each time another group of connections were to be cut, the net was first allowed to reach a stable cyclic mode. Thus the severing of those particular links sometimes interrupted the cycle. Each new reduced connection matrix was tested with two or more randomly selected initial states.

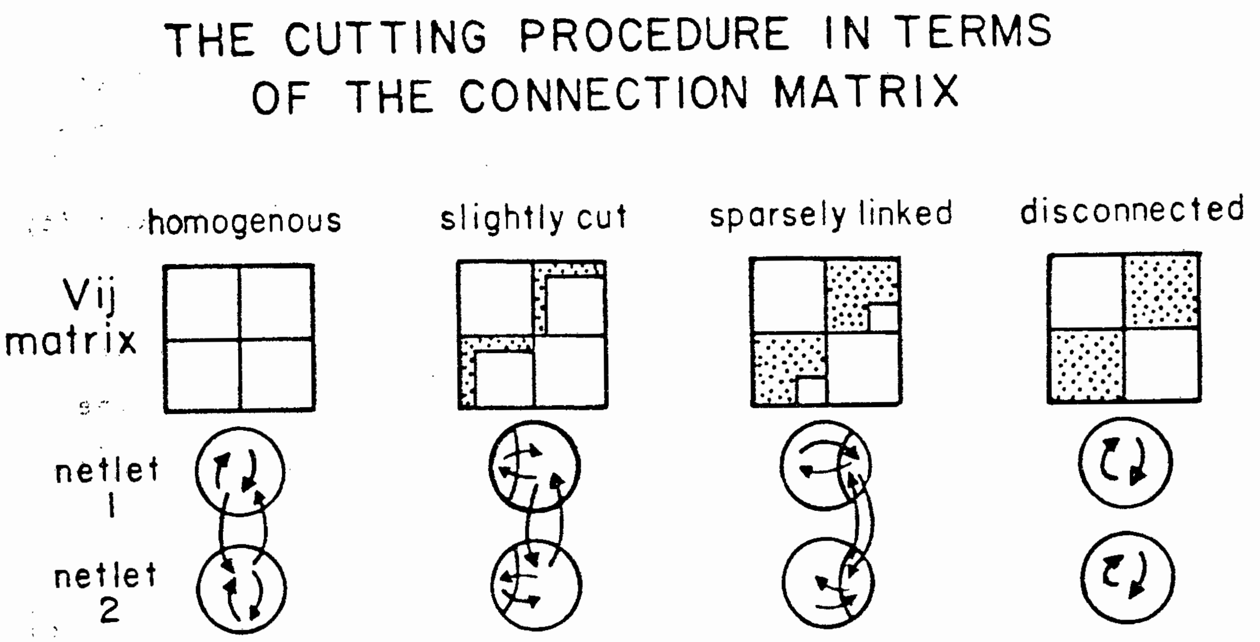


Figure 11 The connection matrix (with shaded regions set to zero) and the effective grouping of neurons caused by this cutting are shown. The diagonal blocks of the matrix (internal connections in the netlets) are unaltered, while the off-diagonal reions (netlet-netlet connections) are encroached by shading (severed links) as the netlets become progressively more disconnected. Arrows indicate full communication from set to set

Initial Description of the Effect of Cutting

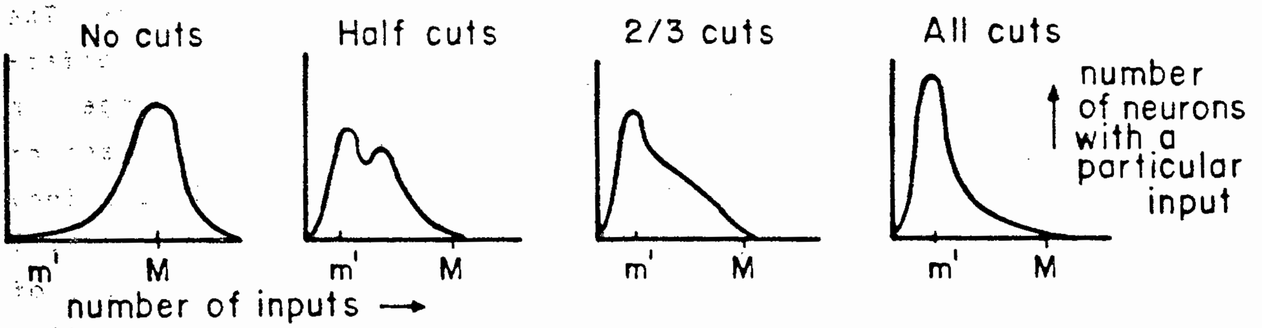
Results were expected to be similar to the previous study on nets with local emphasis, that is, eligibility should be higher after several cuts, but should subsequently decrease again, as the netlets became separated and finally independent, in correspondence with low and high emphasis on local connectivity of the previous study. Here, however, the changes in the matrix would be more gradual, so that the net could rapidly converge on a new but similar state after cutting. Similarities with the previous study would apply to the beginning and end of the procedure, but in between, although the average local emphasis would slowly increase, the distribution of external connections, being uneven, might affect the trends. See next section. In other words, the communication channels between netlets would depend on a few highly connected neurons.

The cyclic mode changed from net to net, even after minor changes in architecture, but the period of oscillation was not a very precise gauge of complexity of behaviour. Instead, eligibility, and the nature of onset of cycling had more consistent tendencies with alteration of parameters. The transition time tended to be longest shortly before the netlets were effectively independent. An unexpected feature was the abrupt change in eligibility that sometimes occurred as the result of a single set of disconnections. That is, nets changed from epileptic to chaotic (noncycling) or vice versa, as if some vital role had been played by those links just severed. However, this erratic behaviour was confined to the central part of the procedure, so that nearly homogeneous nets or nearly disconnected nets were more robust to changes in the connection matrix.

While tendencies in cycle period and eligibility depended on connectivity, netlet size, etc., the occurrence of blocks of repeated states within netlets showed consistent dependence on architecture and was linked to the rare occurrences of slow transitions.

A Note on Cutting

The distribution of inputs to neurons is related to the thresholds for each neuron (when inhibitory connections are considered). The graphs show that this distribution is affected strangely as the net is cut. (Inhibitory nature neglected for the graphs). If a net, size N, divided into n subnets, has connectivity m, then the average number of inputs per neuron is M = Nm, of which $\frac{Nm}{n}$ are internal to the netlets. The distribution of inputs is binomial (see ch 2) with N choices and chance m to have a link at each choice. As each neuron is severed from external connections, the input to that neuron drops by almost a factor, n, while a number of external neurons drop one in input. Therefore, after C cuts, the average number of inputs per neuron is $Nm*(1-[C/N]*[2n-2-Cn^2/N+Cn/N])$. The distribution of inputs after C cuts is the sum of two binomial distributions. The number of cut neurons is nC and they each have an input domain of N/n neurons in their respective netlets; while uncut neurons number N-nC each of which has an input domain of N-C(1-n) neurons. The chance of connection to any neuron in the input domain is still m. See sketches.



Distribution of the number of inputs per neuron as cutting is performed $\begin{cases} M = m * N \\ m' = m * N_{sub} \end{cases}$

Figure 12 The number of neurons vs the number of inputs per neuron is sketched for a net at various stages as it is disconnected. M is the average input before cutting and m' is the average input after cutting. Curious distributions of inputs per neuron occur en route. The exact width and shape of distributions depends on netsize, number of netlets and connectivity.

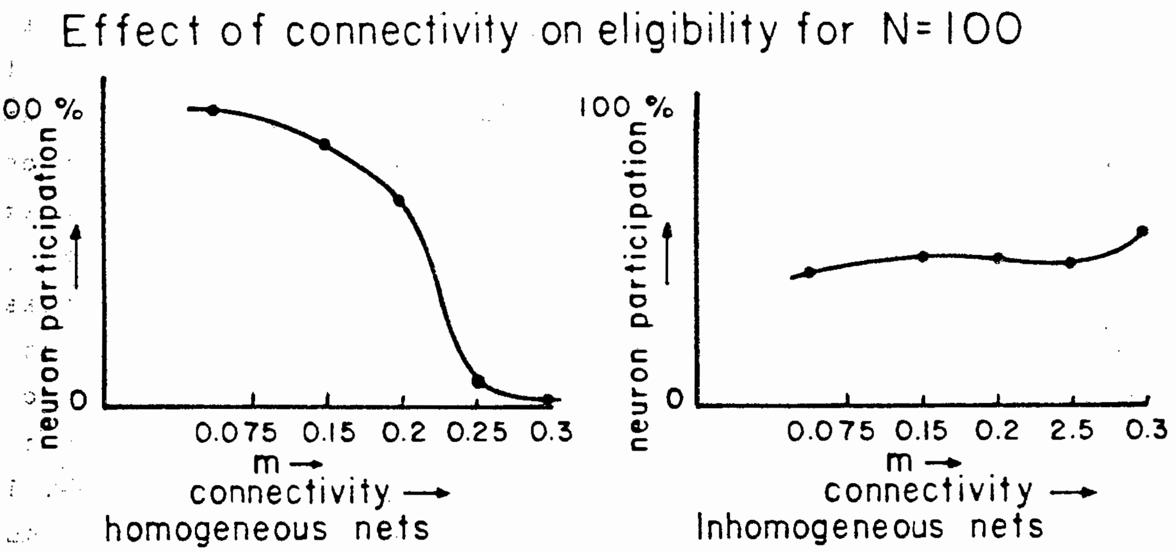
Participation of Neurons in Cyclic States as Netlets are Disconnected - Effects of m and Correlation of Participation with K

See figure 13 and 14

The participation is very m-dependent before cutting, but converges to the 50% region when the nets are nearly separated. This indicates that nets with N=100 are more m-dependent than nets with N=25 (+ a few external links). For various values of the connectivity, m, the effects of disconnection on eligibility differ. When m is as low as .075, the nets are at first chaotic and highly eligible until a few cuts have been made, and thereafter the eligibility decreases towards 50%, whereas for a high m of .3 the nets are epileptic until some cuts have been made and thereafter the eligibility increases towards 60%. The tendencies are hardly steady as the different m values have peaks at different levels of architecture. Taking an average of all runs (all m values) does, in fact, show a maximum participation at 15 cuts, i.e. the average local emphasis would be 6 (participation 66%), and then a steady decrease of participation as the emphasis increases. Participation tends to a value at high emphasis which is the same as the value of the average participation before any alterations are made to the nets. The first three cuts take the average to its minimum of 25% participation and thereafter there is an increase in participation towards 66%. This is not in disagreement with the previous study. However, this average curve does not describe typical behaviour for all values of m. If a net is fairly eligible to start with (m = .075, .15, .2), then cutting links will cause a reduction in eligibility, but after about 4 cuts the Elg. will peak again, and again after 10 or 12 cuts. The maximum Elg. (besides near initial state) occurs at 10, 21, 12 for m = o.75, 0.2, 0.25, respectively. Note 25 cuts are possible. If the net is initially too highly connected (m = .25,3) then cutting links provides the essential variation in number of inputs to neurons, and a much clearer maximum is reached later (after 15 cuts, average eligibility (m=.25) = 100%, after 18 and 20 cuts average eligibility (m=.3) = 66%).

The above considerations do not cast much light on the likely regime of slow phase transitions, but the graphs do show that since the Elg. vs m for homogeneous nets is decreasing, that cutting is necessary to allow cyclic states to occur in highly or slightly connected nets. Interesting transitions are likely to be found for highly eligible nets, with at least some minimum amount of architecture.

Please note from the graphs of period vs Elg, that for Elg less than a third periods are short (< 50) and that highly Elg. nets (over 80-90), are often non-cycling.



<u>Figure 13</u> The dependence of neuron participation in cycling on connectivity is shown for the two distinct cases of nets with uncut connection matrices and sparsely connected netlets. N=100 and there are 4 netlets Nsub=25, each with a few neurons externally linked. Inhibition is h=.35
Each point represents the average of eligibilities for three nets, and those particular nets, once cut, yield the right hand graph.

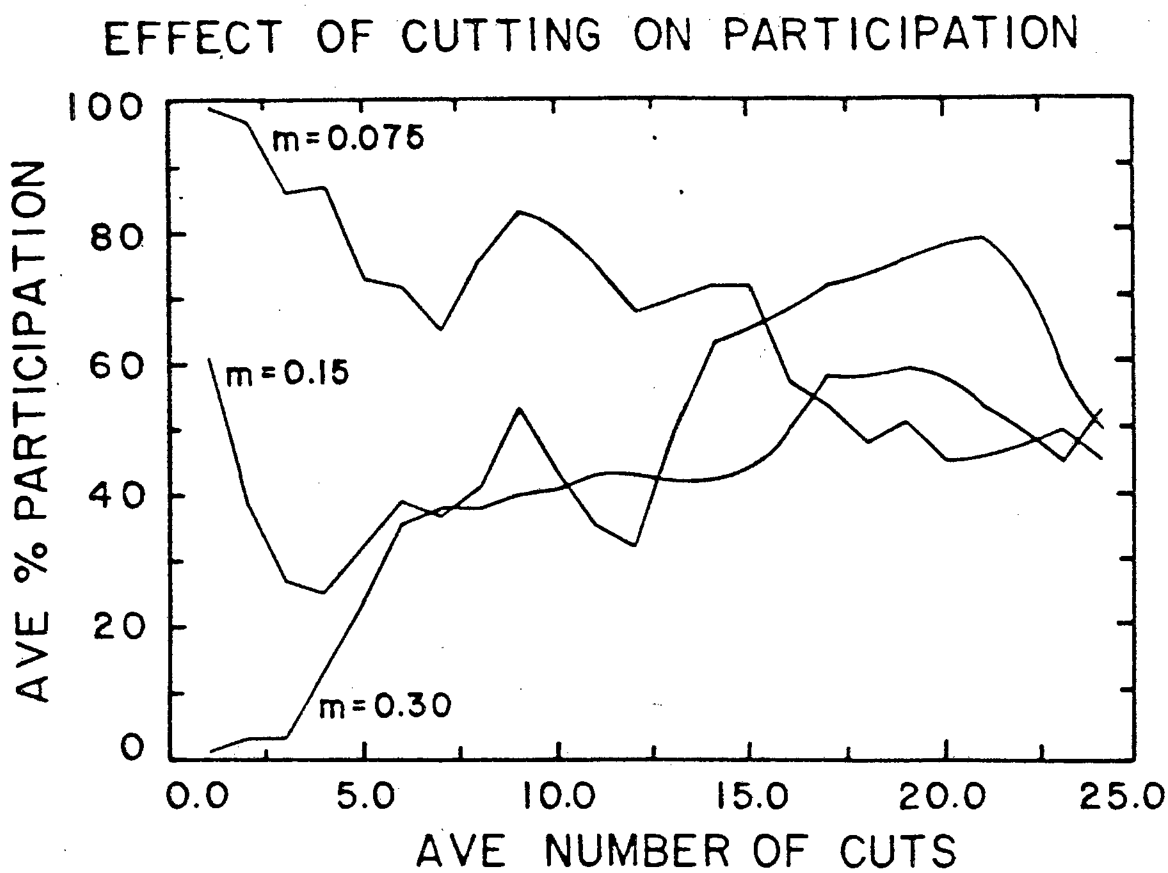


Figure 14 Number of participating neurons is plotted as a function of number of cuts made, or of disconnectedness. Each pseudorandom net (no cuts yet) is separated into four netlets by a process of 25 cuts. For each cut, one neuron in each netlet or quadrant of the net has all external links ,to and from other quadrants, severed. The is run after each cut to determine participation. Each line represents the average of several nets with the same parameters: N=100 h=.35 m=.075,.15 or .3

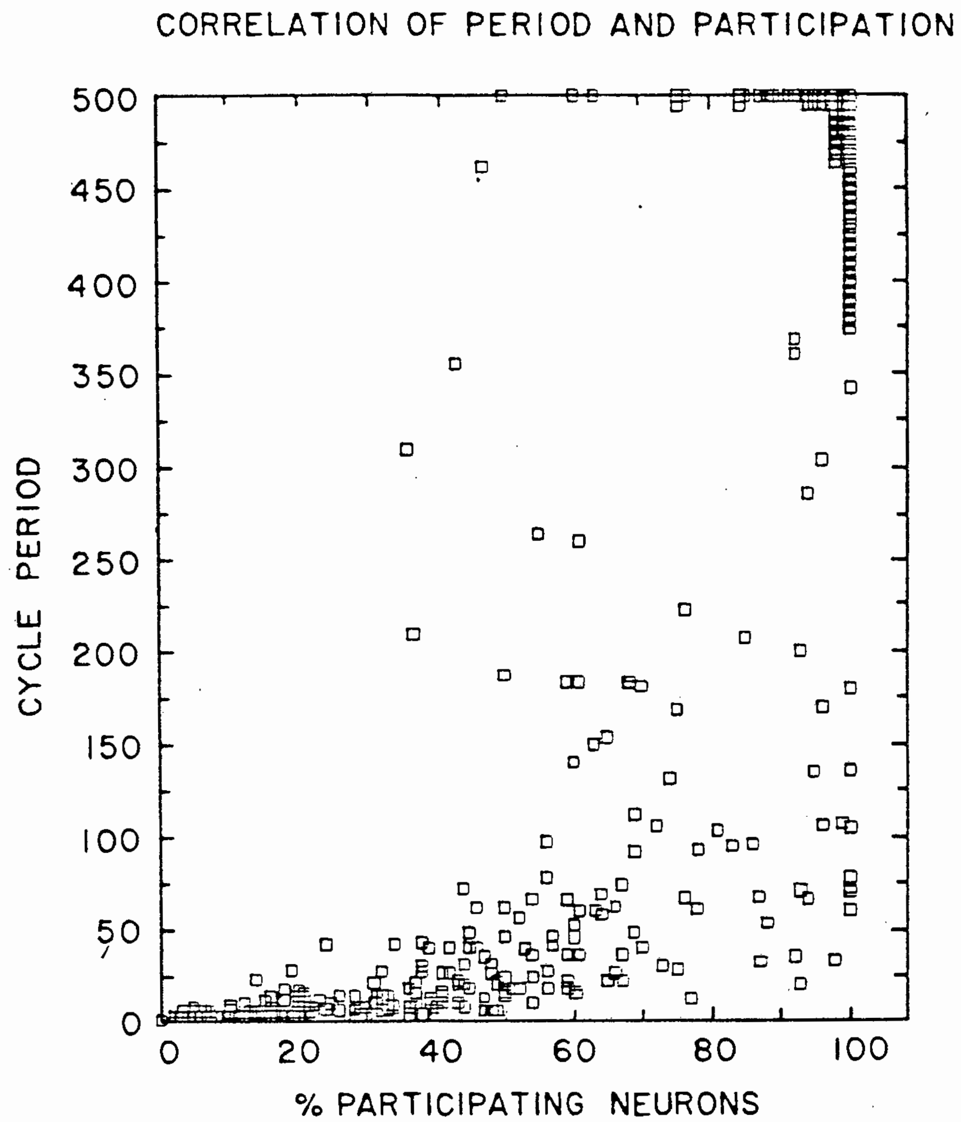
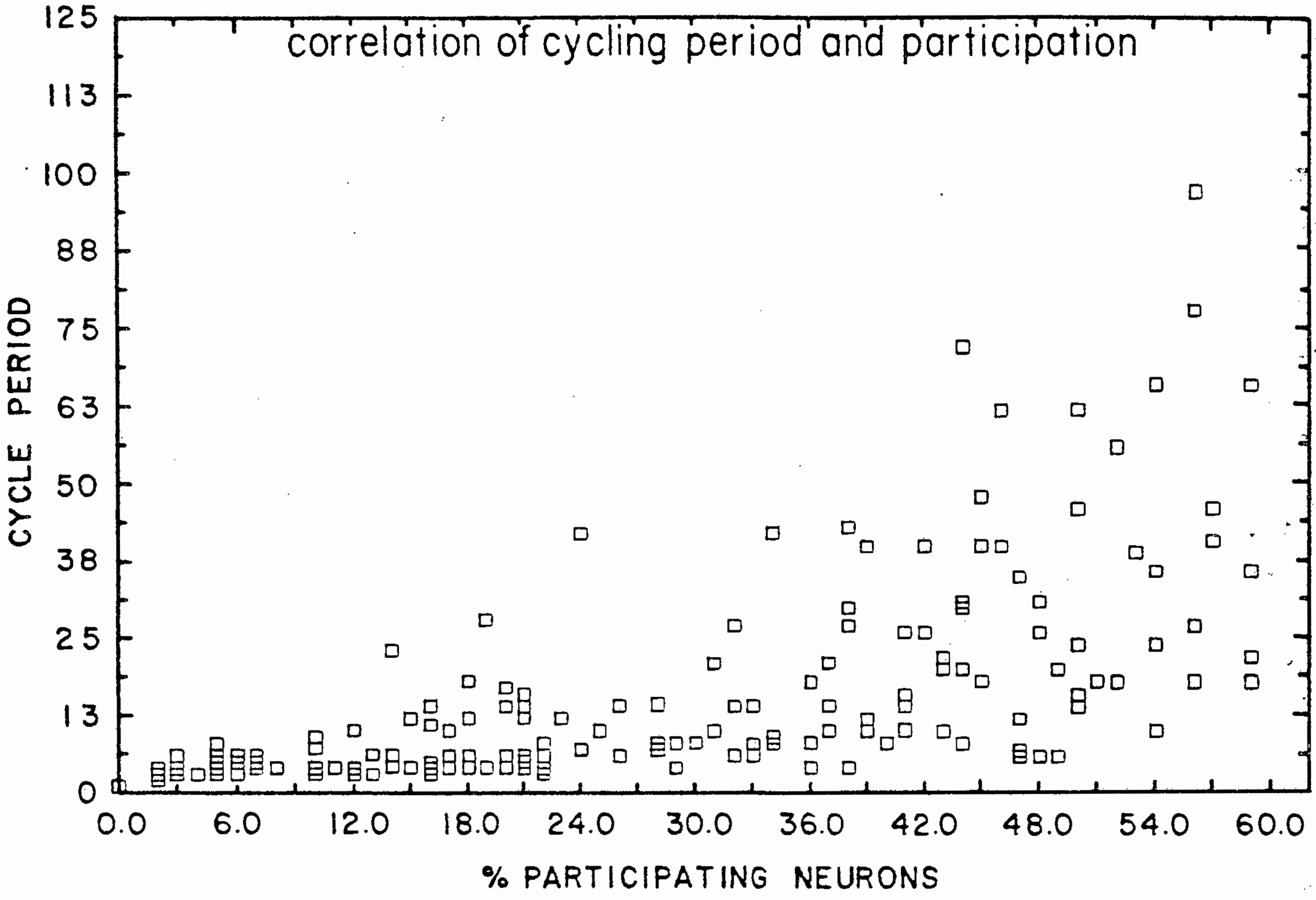


Figure 15 Cycling period is plotted against participation. Each square represents one or more occurrances of the same cycle. N=100. All combinations of other net conditions (m,h,cuts) are included. Noncyclic modes (for maximum runtime 500) are plotted as close to the top of the graph as possible.

Figure 15a Magnification of the lower k,lower participation region. Note that the long periods for cycles with participation less than 50% are a consequence of 4 independent netlets contributing to the common multiple of periods.

15A (SEE FIGURE **15**)



Repeated States

In the examination of cyclic modes of nets, two arbitrary time intervals are introduced for convenience. The first is the time spent looking for cyclic states. If no repetition is found by t = 500, the search is abandoned and the net assumed to be chaotic or non-cycling. The second time interval is involved in the search for subcycles in netlets. Because the state of the neurons in a netlet may often be repeated, it is only when a sequence of states reoccurs that a repeated state is recorded. The length of the sequence is conveniently chosen to be 6 successive states. In spite of this limitation, repeated sequences of six are a useful guide to how one netlet may be affecting another netlet.

Absence of Repeated States

Repeated states are rare in homogeneous or only partly isolated nets. If the communication is good between netlets, all tend to cycle together. The life time of repeated states in netlets is shortened when there are sufficient external links to interrupt the sequence of repeated states. If a repeated state is altered by input before 6 steps have passed, it is not recorded. Another way of saying this is that before significant architecture is imposed, the boundaries of the netlets are relatively arbitrarily chosen, and hence there is little reason why a single repeated state in a netlet should be followed by the same next state on separate occasions.

Repeated states are also rare in non-cycling nets with clearly defined netlets. This indicates that the few external links disrupt subcycles or that even the smaller netlets are non-cyclic. When a netlet has no changing inputs, it can not have more than one repeated state. This is common when there are very few or no connections between netlets left as the cutting procedure nears completion.

Generally, the longer the search for cycles, the more likely it is for Repeated states to appear, and the more likely there is to be a slow transition. When only a few neurons form the vital communication channels between netlets, repeated states can persist for some time in a particular netlet and possibly influence other netlets to follow the same period. Studies indicate that nets cut 18-22 times (out of 25) yield many repeated states. That is, when on average 3-7 out of 25 neurons per netlet have external links, i.e. 2-8% of the original external connections are left.

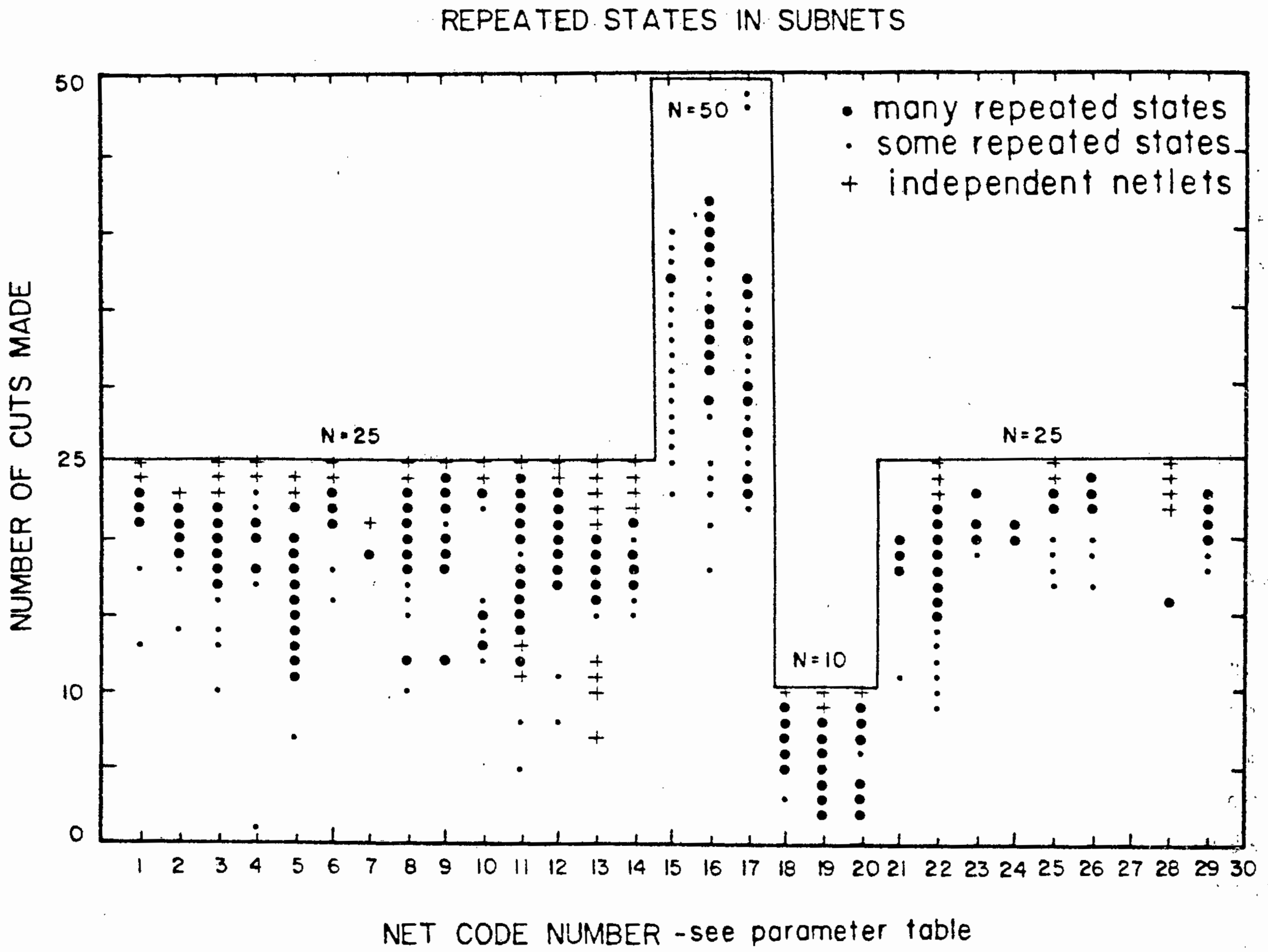


Figure 16 Repeated states. The various symbols depict the number of repeated states found in netlets. Each column represents one net. All nets are N=100, but the netlet sizes are 10 25 50 as shown. Netlet size is equal to the number of cuts necessary to completely sever the netlets. The vertical scale indicates increasing number of cuts. Big dots symbolise many repeated states > 50 and little dots about 15 to 50 repeated states. Crosses are for independent uninterrupted repeated states in each netlet. Code numbers indicate parameters m,h: (1-3):.075,.35 (4-6):.15,.35 (7-9):.2,.35 (10-11):.25,.35 (12-14):.3,.35 (15-17):.15,.35 (18-20):.3,.35 (21-29):.15,h=.2-.3

Origin of Cycling

It is all very well dividing a net into netlets and then showing that repetition occurs within the netlets, but how can one tell whether a so-called homogeneous net has natural divisions, little groups of neurons that closely affect one another? A much earlier study, in which cycling was detected by listing the periodic behaviour of each neuron, showed that often 2 to 3 out of 60 neurons had the same period (long before cycling onset). It is impossible to imagine 3 neurons with 12 external connections each, being unaffected by the rest of the net, and indeed, these neurons with common periodicity were not seen to precipitate a complete cycle. However it is unlikely that these pairs and triplets coincidentally had the same period and they could be necessary to seed cycling. Unfortunately, architecture was not under scrutiny at the time, so no correlation between periodicity pairs and triplets, and the connection matrix was sought. No study was made of inputs to epileptic neurons either. This relates to whether the origin of cycling is seeded, or stems from the restrictions introduced by the many to one algorithm for time evolution of the state of the network, or are both mechanisms the same mechanism?

Slow Transitions

The phenomenon of slow phase transtions, for appreciable cycle lengths, is connected to the architecture of the net, according to my studies. That is, slow transitions occur most often when a group of netlets (each of which transits relatively rapidly to cycling) is weakly linked, allowing one netlet to seek dominance over another by "forced oscillation". If each netlet is eligible there may be a protracted time before one cycle length dominates all netlets and certain netlets may need to sacrifice eligibility in order to cycle at the dominant period.Hardware parameters, like inhibition, connectivity, net size and netlet size, affect the complexity, length and neuronal participation of a cycle, which indirectly governs the transient time and transition time, but the effects on these times are neither marked nor general. Architecture, on the other hand, is a reliable context for netlet subcycling and long, often highly eligible, transitions. (Note threshold is a frustrating parameter, as always. Normal thresholds seemed more reliable than other prescriptions, for this type of connection matrix.)

Parameters and Slow Transitions (See Table 1)

- Slow transitions for short cycles occur for a variety of architectural strengths, with increased likelihood after a net has been cut 5 times. Considering the number of cycles with $3 \leq K \leq 11$, there are not many such slow transitions. More were expected for such short cycles.

- Very slow transitions rarely occur before 21 cuts have been made and are usually for cycles shorter than 75. The longer periods, those greater than 100, are too long to have an even longer transition. In fact, but for the cases in Table 1, all transitions are less than 50 steps. Even those with longer transitions usually have even longer periods (see col.4), in fact, twice as long at least. The very long transitions have one or two netlets cycling completely ; well before the other netlets. This only happens when there are 4 or less input neurons per netlet. The relatively independent behaviour of netlets in these transitions can be seen in graphs of the asterisced transitions.

- Of the ordinary long transitions, only a quarter occur after 21 cuts. These transitions occur earlier than very long transitions do in the cutting process. Three quarters appear after about 12-20 cuts, or when at least half the neurons in each netlet are isolated. There is a wide range of period lengths which have ordinary slow transitions.

TABLE 1 (CH 5)

K(cuts) for LONG TRANSITIONS

This is a table of periods K ,with the number of cuts in brackets.

K<=10 transition > K for short periods k <= 10

net1 >K very long transitions,ie the first netlet to cycle with K starts cycling more than K steps before the rest of the net

Tt >K long transitions ,ie transitions longer than k ie the first neuron starts cycling > k steps before the net

Tt > 50 transitions shorter than K but longer than 50 steps

[cuts] number of cuts, 25 maximum, indicates the degree of structure

Run code	K <= 10	net1 > K	Tt > K	Tt > 50
1	6 [2-13]	22 [21]	36 [2-13]	150 [20]
	10 [16,17]		30 [16,17]	
2	10 [18]	12 [14]		
	10 [20]			
3	6 [18]	12 [22]	92 [17]	178 [14]
		66 [22]		
4		28 [22]*		107 [5]*
		31 [23]*		
5	6 [11-15,20]	36 [24]	112,74,40 [20]	208 [7],169[16]
	10 [18]		16 [21]	184 [23]
6	8 [24]		20 [18]	188 [23]
	4 [25]		16 [23]	
7	6 [12]			
8	11 [5-9]			260 [23]*
	4 [11-14]			
9	10 [18-21]	20 [18]		
	4 [18,20,21]			
10	6 [22]		141 [22]	108 [23]
	3 [5]			
11		56 [23]*	28 [19]	
13	6 [17]	15 [22]*	82 [11]	240 [19]
		130 [23]*		
14	6 [15]	30 [21-25]	80 [17]	
15	8 [20]	15,42 [21]	14 [14-19]	
	10 [20]	75,20 [25]	30 [25]	

Some Examples

E.g. net 4 - The 3 longest transitions in this net can be read from the table. Figure 17 shows in more detail how neurons in each netlet in each net are accumulated into the cycle. The first case is a relatively short transition of the form typically found in partially architectured nets (e.g. 57/25 cuts). However, because of the long cycle length, the absolute length of the transition is similar to the lower two transitions. (Compare 55 to 84 and 77). The latter cases are very slow transitions of the form typically found in highly architectured nets (e.g. 22/25 cuts). By typical form, is meant the successive recruitment of netlets in bursts lasting a third of K, but separated over the transition time of 2-3 cycle lengths. This gives a bumpy structure to the total accumulation of neurons in time (see the smaller graphs on the right) caused by a succession of rapid transitions in netlets. The first transition is not only relatively short, but is smooth, implying that there is no hidden grouping which causes groups of netlets to club together and enter the cycle. The concavity of the graph of participants in transition also indicates a sort of weak chain reaction, with more neurons being recruited per time step when there are more cycling ones to coax them in. Note how the dominance changes netlets with the 23rd cut, which perhaps severed more 3,4 to 1,2 links than vice versa. The lagging netlets also only submitted to the forced oscillation by excluding several neurons from participation.

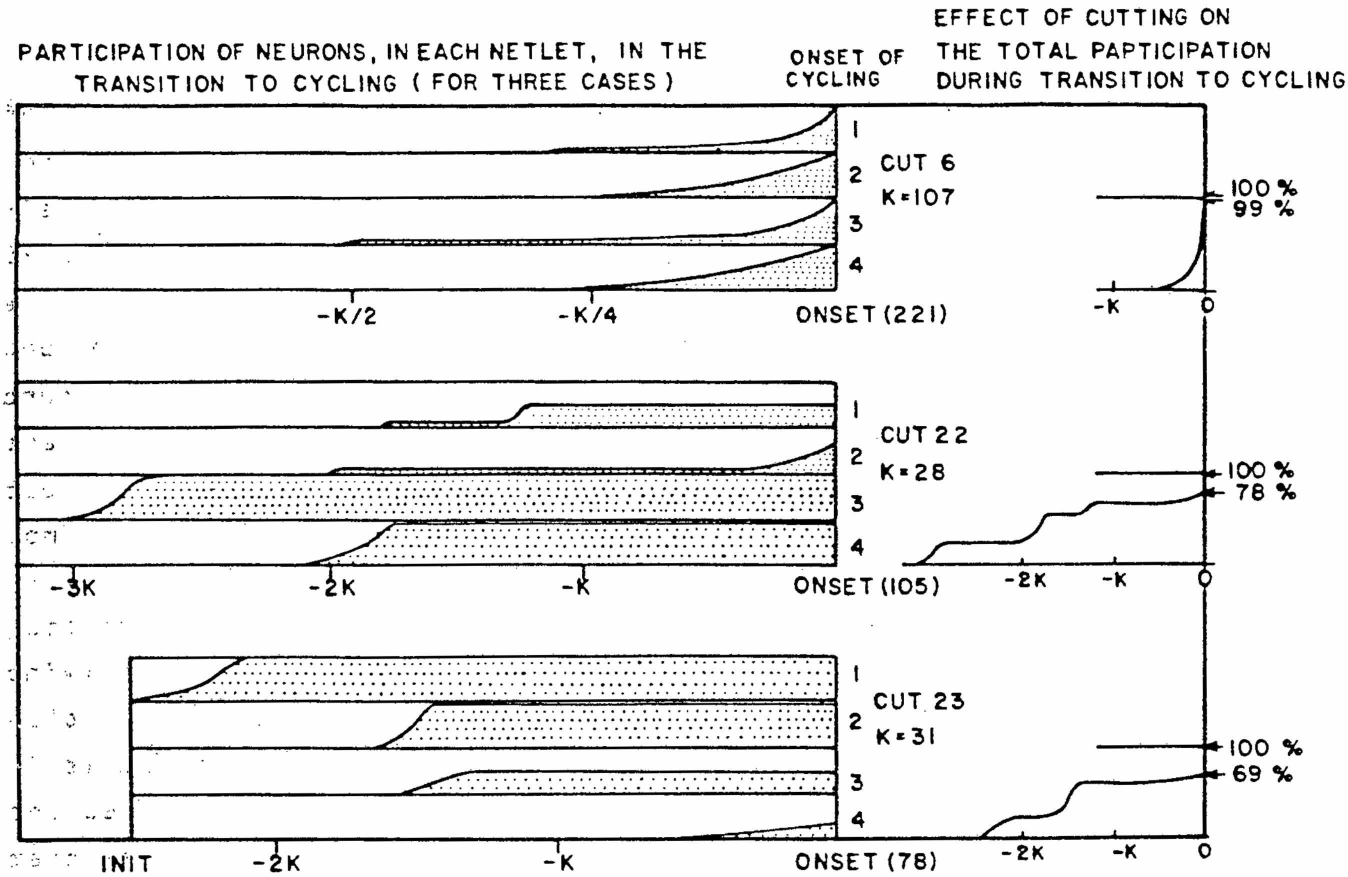


Figure 17 The number of neurons participating in the cyclic mode is plotted against time to show the transition phase. The three graphs represent a particular net at three different stages of cutting. Each net (N=100) is divided , by cutting, into four netlets . The participation in each netlet is depicted on the same time scale, from 90 steps before cycling till theonset of cycling. The onset time written at the onset of cycling, is the total transient time. The total participation vs units of cycle period are shown in the smaller graphs on the right, and the total participation during cycling is given for each net.

Other N Values

(Using subnets, N = 10 to 300 nets can be examined).

Smaller nets (10,25 and even 50) are more eligible than N = 100 for higher connectivity (.3, .25) and less eligible for lower connectivity (0.075, 0.15). For example, N = 25 is far less sensitive to m than N = 100. See figure 18a and table 2.

TABLE 2 : The M Dependence of Elg. in Various Netsizes

N	10	25	100	25	50	100	300	25	100	300	25	100	300	25	100	300
m	.3	.3	.3	.25	.25	.25	.25	.20	.2	.2	.15	.15	.1	.075	.075	.05
%Elg.	38	49	0	36	46	5	2	44	62	0	41	79	0	39	100	9

N = 10,25 data as gleaned from fully cut N = 100 nets.

Perhaps this N-m-dependence is a manifestation of a pseudorandom number generator that is not very random. See chapter 2.

Alternatively, larger nets (300, 100) may actually be more consistent than smaller nets, where the average numbers of inputs is so small that there is a large fluctuation from one neuron to another. In other words, when there are as many as thirty inputs to each neuron, the conditions to satisfy $\Theta(t+1) = \Theta(t)$ are more easily satisfied, resulting in stable K=1 states. The fewer connections there are, the more steps, on average, to communicate from one neuron to another (ch 2) resulting in larger timescales.

Even Larger Nets

A brief study of a few nets with N = 300 showed them to be surprisingly ineligible, even for lower than usual connectivity.table 2 and 3.

TABLE 3 N=300

m	5%	10%	15%	20%	5,25%*
Part	28≡9%	6=2%	0	0	7≡2%
K	11	6	1	1	2

*A net with emphasis on local connections was tried. The net was divided into 10 groups of 30 neurons, with 25% internal and 5% external connectivity.

No non-cycling modes were found, which was unexpected. Even with a limited amount of cutting, the maximum participation in any cycle was less than a half, and the longest cycle length was 131, with 134 participating neurons. A little cutting caused a noticeable abundance of repeated states in net-lets, for the particular case*, which started off with local emphasis before cutting:

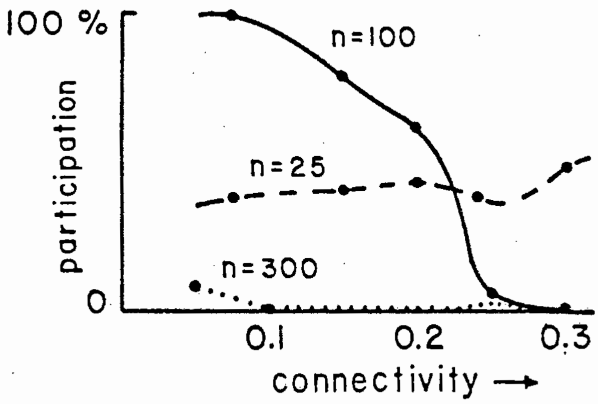
TABLE 4 effect of cutting on a particular N=300 net

Number of cuts/30	Period K	Transient	1st Neur. starts cycling	1st Netlet starts cycling	Part.%	Comment
4	4	33	11	8	18=6%	Slow transition, but short K, low part.
5	35	69	32	13	87=29%	Long transient, cycle & transition ~ K
6	131	13	12	3	103=34%	Rapid onset
7	131	99	98	23	134=45%	Long cycle & transient, transition < K
8	4	85	7	2	8=3%	Short K, low part., but long transient indicates higher ave Participation than 3%.

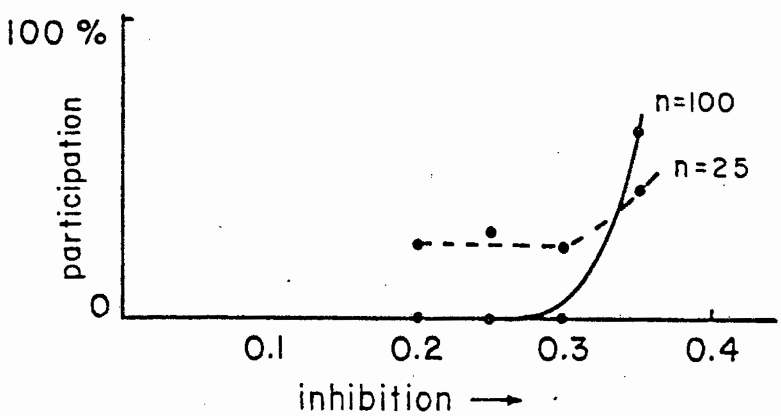
FIGURE 18 The effects of N, m, h on participation and long cycles.

18a : % participation as a function of connectivity m is shown for various net sizes. (N=25,100,300 m=.075-.3 h=.35)

18b : % participation as function of h is shown for various net sizes. (N=25,100 m=.2 h=.2-.35)



18 A
Effect of net-size on the connectivity dependence of eligibility



18 B
Effect of inhibition on various net-sizes

There are several examples here of long transitions and long transients which would be expected in highly inhomogeneous nets, yet the onset of cycling in netlets indicates that no netlet leads the others by far and the abundance of repeated states indicates that yet more links must be severed between netlets before very long transitions can be found.

Larger nets may need higher h to be more critically balanced.

Inhibitory Effects (See Table 5 and figure 18b)

Evidently, smaller nets (N = 25) are less susceptible to the changing inhibitory content than N = 100 nets are. The N = 100 nets are largely ineligible for h ≤ .3, and need more cutting than h=.35 nets before cyclic states are easily accessible. The higher the inhibitory fraction, the more complicated the cycles tend to be . The number of long cycles and non-cyclic modes rises sharply for inhibition increasing from .2 to .35 .

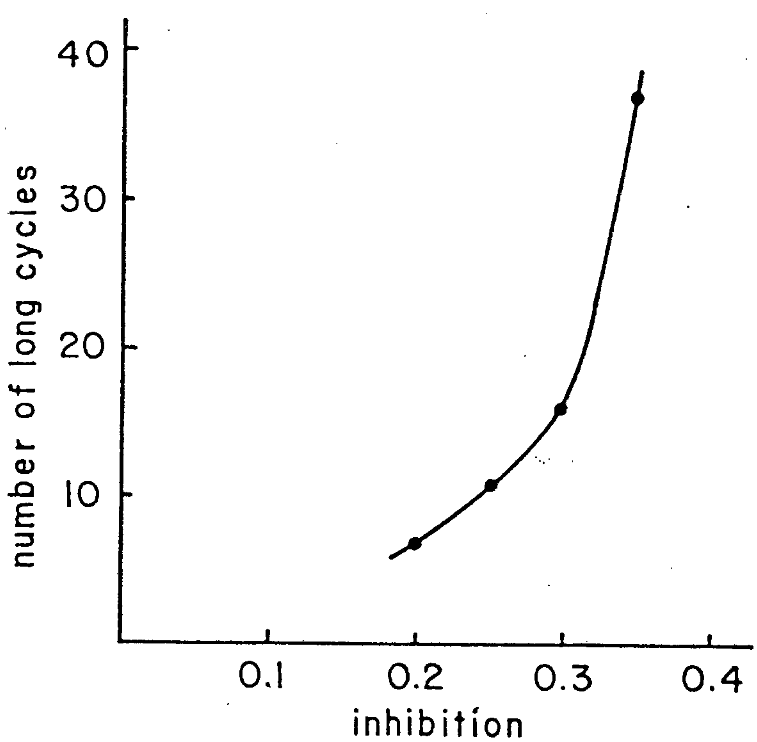


FIGURE 18C The total number of cycles longer than 15, for nets with different levels of inhibition. All stages of cutting are included in each net's count.

TABLE 5A INHIBITORY EFFECTS

N	m	h	k	part	number of cuts made in each of 3 cases before k>1 modes occur
100	.2	.2	1	0	8, 12, 13 / 25
		.25	1	0	10, 11, 13
		.3	1	0	3, 6, 6
		.35	33	62	0, 0, 0
25	.2	.2	5	25	
		25	4	29	
		.3	6	23	
		.35	17	44	

TABLE 5B ABUNDANCY OF LONG CYCLES >=20

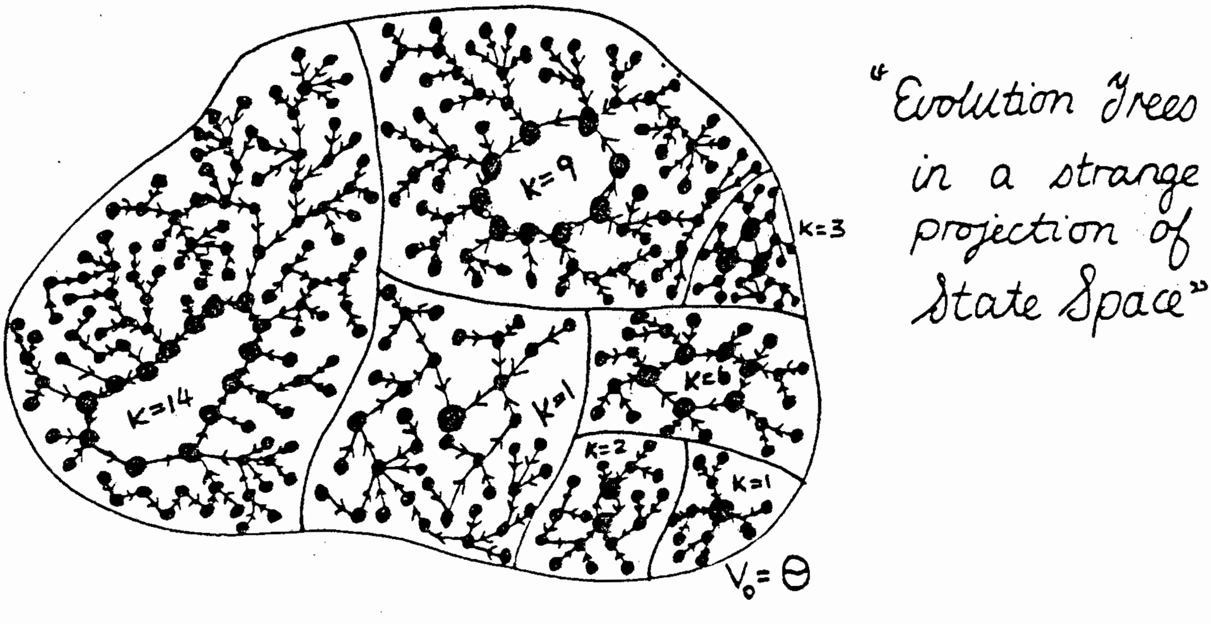
h	#[cuts]	#[long cycles]	range[K]	#[non cycling]	#[transient>50]
.2	. . . .	0		0	
	16,22,23	3	42 - 46	0	
	18 - 23	4	23 - 51	0	
		$\overline{7}$		$\overline{0}$	$\overline{3}$
.25		0		0	
	17,18,20-24	6	40 - 154	2	
	19 - 22	3	22 - 51	0	
		$\overline{9}$		$\overline{2}$	$\overline{7}$
.3	18 - 19	2	30 - 104	0	
	15 - 24	7	20 - 245	1	
	20 - 24	6	28 - 56	0	
		$\overline{15}$		$\overline{1}$	$\overline{10}$
.35	9,11-19	10	31 - 136	0	
	1,4,7,8,10, 12,15-23	9	20 - 260	9	
	0,12,19,22-24	6	20 - 356	3	
		$\overline{25}$		$\overline{12}$	$\overline{17}$

Origin of Cycling and State Space Visualisations

There are 2^N possible initial conditions for a net of size N. If there is no refactory period or accumulation of signal and if the connection matrix is constant and there are no perturbations, like noise or input, then the neuron state space resulting from a choice of threshold θ_i can be divided into non-overlapping regions, with all states in a particular region eventually leading to the same cycle or to death.

Because the algorithm for state evolution involves a binary decision based on several inputs, it is often many to one, that is, there are several possible states that could lead to the same following state, and each state has a unique next state. One of the above-mentioned regions would be a collection of states scattered in state space. If these states are represented as a patch on the state surface and arrows link states as in the evolutional sequence, then treelike structures can be imagined. (See diagram). Notice that there must be a perimeter of states with no previous states. For a net of N=100 the state surface would be a lot bigger than depicted in the sketch, there would be many more regions, or cycles and some of the regions would be much bigger, with much greater distance from the perimeter to the cycle. The accessibility of a particular cycle depends on the size of its region in state space, and the transient time is the distance from a point in the region to the cycle. The more branched the trees are at each node, the shorter the distance to the perimeter, or the larger the region occupied. Thus, intuitively, if connectivity increases the possible number of previous states, then the trees are very branched and the cycles are speedily reached. Inhibitory action may put stronger constraints on possible previous states and reduce the branching, allowing longer transients. When a net is structured, by division into netlets, the regions are teased out into longer cycles with longer transients. If the region is projected onto the state spaces of each of the netlets some of the branches would project as loops in the netlets (repeated states), but the projected tree would no longer have the unidirectional, single looped nature of the original, and there would be escape routes from most loops.

If the states in the cycle of a region are rolled out backwards along the branches towards a particular initial state, the continuous overlap of certain neurons' states will show the transition time. Note ,however, that the amount of overlap between a state in the cycle and a state in any of its branches may be less than the overlap with states in other regions!



<u>Figure 19</u> If time sequences of states of an evolving net are depicted as dots linked by directional arrows, then Markovian nets effectively divide state space into non-overlapping regions around each possible cyclic state. Many arrows may converge on one dot, if many states exist, all with the same following state, leaving a perimeter of states with no previous state. For example, death can be preceeded by very many states (h=.35)

Summary

Slow phase transitions (with respect to period) are readily found in sets of netlets interconnected by channels between the small communicating fraction of neurons in each netlet. A profusion of attempts to cycle in the various netlets is often coincident with the capability of slow transitions, where some netlets lead and others lag. The critical number of connections necessary was not pinpointed in any general way, but more sensitive changes in interconnection between larger and more consistent nets should yield a narrow region of optimal communication strength between netlets, for a particular parameter set.

APPENDIX 1

Programme listing of the general version of the programme used for most studies. A pseudorandom net is set up in the main programme. Parameters are netsize, connectivity, inhibitory fraction, netlet size (optional) and local emphasis. Subroutine EVOLVE initialises the net and contains the algorithm for the evolution of the state vector in time. EVOLVE performs plasticity algorithms and applies external inputs as required. Cutting (architecture), resetting certain parameters and recovery after death are also dealt with. Subroutine PHASE detects aspects of cyclic behaviour and transitions to cycling.

```
C                    PROGRAMME
C                    NEURAL NETWORKS
C
C                 N   neurons - net size
C    PARAMETERS   Nsub netlet or subnet size
C                 QM average fraction efferents neurons
C                 Qsub emphasis on local connections in netlets
C                 QH fraction inhibitory neurons
C                 REF refractory period or delay
C                 T   decay ratio of stimulus
C                 B   inverse temperature
C                 IO max run time
C                 D   Increment to synapse Vij ]
C                 p   Decay of D per time step ] plasticity
C                 S   Sign of D for inhib Vij  ]
C                 AT attention                 ]
C    STATE        LO(J,I) neuron J at time I , 0 or 1
C    CONNECTIONS  LV(I,J) present connection I to J or Vji
C                 LV1(I,J) initial connection strength I to J
C                 LVM(J)  number incoming connections to J
C                 LE   sum of LV1 for all neurons at time 0
C                 LVM2 sum of LV for all neurons,at time I
C                 LVPOS sum of LV1>0 for all neurons at time 0
C                 LP sum of LV>0 for all neurons,at time I
C    ACTIVITY     QA initial probability of neuron firing
C                 A  initial number of active neurons
C                 LACT current number of active neurons
C                 LA(J) time average for neuron J
C                 LA1(J) activity of neuron J during transient
C                 AVE   time average for all neurons
C    THRESHOLDS   VMIN average threshold
C                 VMAX upper limit of window
C                 VO  window width
C                 VM(J) normal threshold for J
C                 GAMMA scales VMIN from normal(0) to uniform(1)
C                 GAD ratio of threshold to original value LE*N/2
C                 V2,V6,T6,RH  relate to BW normalisation
C    VARIABLES    F(J)  stimulus to neuron J
C                 RE(J) refactory state of J
C                 RH  ratio of fraction inhibitory links @ t=I:t=0
C                 R   random number
C                 NS  number of netlets
C                 D1  current value of D
C                 QMM,QMS values of QM ext,int to netlets
C                 LPQ  modified LE to include accumulated signals
C                 INP(),IPS(),IPT input controllers
C    TIMES        IO max run time
C                 TIMECH time elapsed during the previous run
C                 I8   time of onset of cycling of entire net
C                 I1   time of end of previous run
C                 I2   cycling period
C                 LA2(J)  (I8)-(time neuron J cycles)
C    COUNTERS     L3(J,I)  number cycling in netlet J,I before I8
C                 ELG  number of neurons with LA from 25 to 75%
C                 LX,LX1,LY,LY1  numbers of dead,epileptic neurons
C                 THCHC,X  counters of threshold changes
C                 LCUT  counts the number of cuts made in Vij
C                 H   number of inhibitory neurons
C
```

```
Declaration of variables , opening datafile and setting the formats

   COMMON /COM1/LV1(300,300),LVM(300),QH,VO,IO,A,LE,D,S,P,LP,T
   COMMON /COMO/I1,REF,LO(300,1000),N,LPQ,NSUB
   COMMON /COM2/LA(300),INP(10),AT,TIMECH,I8
   COMMON /COM3/LACT(1000)
   OPEN (UNIT=22,FILE='//UCT1/GWEN/DATA20')
   FORMAT(80I1)
   FORMAT(60I2)
   FORMAT(40I3)
   FORMAT(20I4)

Reading in the parameters

   PRINT*,'INPUT N ,<=300'
   PRINT*,'      CONNECTIVITY ,INHIBITION ,DECAY ,RANDOM SEED'
   PRINT*,'      SUBNETWORK SIZE AND CONNECTIVITY ENHANCEMENT'
   READ(22,*)N
2  READ(22,*)QM,QH,T,R
   READ(22,*)NSUB,QSUB
   PRINT*,' '
   PRINT*,'RANDOM= ',R

Setting up the connection matrix LV1(I,J)

   LE=0
   LP=0
   H=0
   DO 5 J=1,N
   LVM(J)=0
   QMM=QM/(1+(QSUB-1)*NSUB/N)
     neuron I links to neuron J
     DO 10 I=1,N
   R=RNDM(R)
   IF(R.LT.((QH*N-H)/(N+1-I))) THEN
   L1=-1
   neuron I is inhibitory
   H=H+1
   ELSE
   neuron I is excitatory
   L1=1
   ENDIF
     neuron J is synapsed from I
     DO 9 J=1,N
   R=RNDM(R)
   IF(R.LE.QM/QSUB) THEN
     LV1(I,J)=L1*1000
     integers used for efficiency
   ELSE IF(INT(J/NSUB).EQ.INT(I/NSUB))THEN
     neurons I,J are in the same netlet
     IF(R.LE.QM)THEN
     LV1(I,J)=L1*1000
     ELSE
     LV1(I,J)=0
     ENDIF
   ELSE
     LV1(I,J)=0
   ENDIF
```

```
c      number of input links to neuron J
       LVM(J)=LVM(J)+LV1(I,J)
       IF(L1.EQ.-1) GOTO 11
       LP=LP+LV1(I,J)
11     LE=LE+LV1(I,J)
9      CONTINUE
10     CONTINUE

c   more parameter inputs and some messages about parameters

       PRINT*,'input  ACTIVITY , REFACTORY PERIOD'
       READ(22,*)QA,REF
       A=QA*N
       D=0
       S=1
       P=1
       LPQ=LE/(N*(2.-T))
       QMS=QM*(N-NSUB)/QSUB
       PRINT*,'N(Subdivision) m(Ext)      h  t(decay ratio) Activity'
       PRINT*,N,'(',INT(N/NSUB),NSUB,')',QM,'(',QMS,')',QH,t,A
       PRINT*,' INPUTS TO EACH NEURON'
       DO 7 H=0,4
7      PRINT 4,(INT(LVM(I)),I=1+20*H,20+20*H)
97     CONTINUE
       READ(22,*)I0
       PRINT*,'Run time= ',I0

C        CALL THRES
c        subroutine for finding thresholds dynamically is excluded

       CALL EVOLVE

c   Options for further runs

25     PRINT*,'ENTER 0:new WINDOW  1:new START'
       PRINT*,'       2:new NETWORK 3:new PARAMETERS'
       READ(22,*)LG
       IF(LG.EQ.0) GOTO 97
       IF(LG.EQ.1) GOTO 8
       IF(LG.EQ.2) GOTO 6
       IF(LG.EQ.3) GOTO 12
98       end

C      *****************************************************************
       SUBROUTINE EVOLVE
       COMMON /COM0/I1,REF,L0(300,1000),N,LPQ,NSUB
       COMMON /COM1/LV1(300,300),LVM(300),QH,V0,I0,A,LE,D,S,P,LP,T
       COMMON /COM2/LA(300),INP(10),AT,TIMECH,I8
       COMMON /COM3/LACT(1000)
       DIMENSION RE(300),LV(300,300),F(300),MAD(300),CON(60),
     1 M2LA(300),MLA(300),VM(300),IPS(10)
3      FORMAT(I4,10(1X,10I1))
```

```
 Initial conditions

      state vector LO(J,t=0)
      LACT(1)=0
      DO 20 J=1,N
      R=RNDM(R)
      IF(R.GT.A/N) THEN
      LO(J,1)=0
      ELSE
      LO(J,1)=1
      LACT(1)=LACT(1)+1
      ENDIF
0     CONTINUE
      other variables to be initialised
      RH=1
      I1=1
      IPT=0
      DO 6 J=1,10
      IPS(J)=0
      LVPOS=LP
      LVM2=LE
      TIME1=1

  reentry point after resetting soft parameters

5     D1=-D/P
      choosing a threshold or window VMIN
      V2=A/(N-T*(N-A))
      GAMMA=0
      VMIN=V2*LE/N
      PRINT*,VMIN,'=VMIN   GAMMA=0'
      PRINT*,'NEW THRESHOLD,GAMMA WANTED ? 0=YES'
      READ(22,*)LLL
      IF(LLL.NE.0)THEN
      GAD=1
      ELSE
      PRINT*,'NEW VMIN,GAMMA'
      READ(22,*)VMIN,GAMMA
      GAD=VMIN*N/(V2*LE)
      print*,vmin,GAMMA,GAD
      V2=VMIN*N/LE
      ENDIF
      T6=T/LE
      V6=V2/LE
      individual thresholds VM(J) for each neuron
      DO 5 J=1,N
      VM(J)=(LE/N-LVM(J))*GAMMA+LVM(J)
      THCHC=0
      LCUT=0

 reentry point for continued run
0     continue
      AVE=0
      DO 2 J=1,N
!     LA(J)=0
```

```
c evolution of state of neurons to time I

      DO 15 I=1+I1,IO+I1
      V2=V6*LVM2
      IF(I.EQ.1) GOTO 30
      LACT(I)=0
      D1=D1*P

      DO 30 J=1,N
c     the state of neuron J at time I is LO(J,I)
C     the stimulus to neuron J is F(J)
      DO 25 K=1,N
      IF(I.GT.2)GOTO 25
      LV(K,J)=LV1(K,J)
25    F(J)=F(J)+LV(K,J)*LO(K,I-1)
C      external input stimulus
       IF(IPT.NE.0)THEN
       IF(J.LE.10)THEN
       F(J)=F(J)+IPS(J)
       ENDIF
       ENDIF
c    decision to fire
      IF(F(J).LT.V2*VM(J)) THEN
29    LO(J,I)=0
      ELSE IF(RE(J).GT.REF) THEN
      LO(J,I)=1
      LA(J)=LA(J)+1
      F(J)=0
      RE(J)=0
      ELSE
      LO(J,I)=0
      ENDIF
      F(J)=F(J)*T6*LVM2
      RE(J)=RE(J)+1

C   brainwashing
      IF(LO(J,I).EQ.0) GOTO 30
      LACT(I)=LACT(I)+1
      IF(I.EQ.1)GOTO 30
      IF(ABS(D1).LT.1) GOTO 30
        DO 16 K=1,N
      D2=D1
      IF(LO(K,I-1).EQ.1) GOTO 17
      IF(AT.EQ.0) GOTO 16
      D2=-D1
17    LU=LV(K,J)
      IF(ABS(LU).LT.ABS(D1)) GOTO 16
       IF(LU.GT.0.) THEN
       LU=INT(LU*(1+D2/100)*RH+.5)-LU
       LVPOS=LVPOS+LU
       ELSE
       LU=INT(-S*D2*LU/100-.5)
       ENDIF
      LVM2=LVM2+LU
      LV(K,J)=LV(K,J)+LU
16    CONTINUE
c     end of brainwashing inputs to J

30    CONTINUE
```

```
 next state known for all J

  PRINT*,I,' LACT',LACT(I)
  PRINT 3,I,(MAD(M1),M1=1,LACT(I))
 RH=((LVPOS-LVM2)/(2.*LVPOS-LVM2))*(2.*LP-LE)/(LP-LE)
 the separate normalisation of +,- done by RH
 AVE=AVE+LACT(I)

revival after death
 IF(LACT(I).EQ.0) THEN
 PRINT*,'DEATH @',I
 IO=IO+I1-I
 I1=I
 GAD=GAD*.9
 V6=V6*.9
 GOTO 455
 ENDIF

search for repetition or cycling
 IF(D.LT.0.1)THEN
 DO 80 I8=I-1,I1+1,-1
 IF(LACT(I).NE.LACT(I8))GOTO 80
 activity at t=I8 equals present activity
 DO 81 I9=1,N
 IF(LO(I9,I8).NE.LO(I9,I))GOTO 80
1    CONTINUE
 PRINT*,'State ,',I,' Equals State ',I1,'+',I8-I1,' PERIOD=',I-I8
 cycle period = I-I8
 start = I1+1  elapsed time = I-I1
 onset time = I8  transient = I8-I1
 TIMECH=I-I1
 I1=I

 CALL PHASE
 to calculate eligibility,transition times

 program rerun 5 times or until 20<=act<=80
2    IF(THCHC.GE.5.) GOTO 86
 IF(AVE/TIMECH.LT.20) THEN
 PRINT*,'THRESHOLD TOO HIGH -->',GAD*.9
 THCHC=THCHC+1
 IO=IO+I1-I
 I1=I
 TIME1=I1+1
 GAD=GAD*.9
 V6=V6*.9
 GOTO 455
  rerun with slightly lower thresholds
 ELSE IF(AVE/TIMECH.GT.80) THEN
 PRINT*,'THRESHOLD TOO LOW -->',GAD*1.1
 THCHC=THCHC+1
 IO=IO+I1-I
 I1=I
 TIME1=I1+1
 GAD=GAD*1.1
 V6=V6*1.1
 GOTO 455
  rerun with slightly higher thresholds
 ENDIF
```

```
C    CUTTING CONNECTION MATRIX:TOP LEFT 'L' OF NON-DIAGONAL BLOCKS

86      LCUT=LCUT+1
c       if completely cut end run
        IF(LCUT.GT.NSUB)GOTO 46
        PRINT*,' '
        PRINT*,'CUTTING ',LCUT
        DO 83 NS=1,1+INT((N-1)/NSUB)
c         netlet number NS
        J=(NS-1)*NSUB+LCUT
c         neuron J (1 from each netlet) to be internalised
        IF(J.GT.N)GOTO 83
c         cutting links to & from previous netlets
        DO 84 K=1,NSUB*(NS-1)
        VM(J)=VM(J)-LV(K,J)*(1-GAMMA)
        LV(K,J)=0
        VM(K)=VM(K)-LV(J,K)*(1-GAMMA)
c         cutting links to & from subsequent netlets
84      LV(J,K)=0
        DO 85 K=1+NSUB*NS,N
        VM(J)=VM(J)-LV(K,J)*(1-GAMMA)
        LV(K,J)=0
        VM(K)=VM(K)-LV(J,K)*(1-GAMMA)
85      LV(J,K)=0
83      CONTINUE
        THCHC=0
c         set initial state as element of latest cycle,rerun
        DO 87 JCUT=1,N
87      LO(JCUT,2)=LO(JCUT,I1)
        I1=2
        GOTO 40

80      CONTINUE
        ENDIF
15      CONTINUE
c   end of time step I

        IF(D.EQ.0) THEN
c        no cycle found in 500 steps
         PRINT*,'NO CYCLING YET'
         I8=I1+1
         TIMECH=IO
         I1=I-1

         CALL PHASE

c        next cut?
         IF(IO.EQ.500)GO TO 86
         GOTO 46
         interaction with user
        ELSE
c        brainwashing complete
         I1=I-1
         PRINT*,'BRAINWASHED FOR ',IO,INT(100*LVM2/LE),'% Vij left'
         GOTO 46
        ENDIF
98      I1=I-1

c   End of running and cutting .Iteract with user
```

```
c  End of running and cutting .Iteract with user

      PRINT*,'Normalisation factors SUMS Vij,Vij(t),Vpos,Vpos(t)'
      PRINT*,LE,LVM2,LP,LVPOS
      PRINT*,RH,'H',QH
      PRINT*,'YOU HAVE REACHED STEP',I1,' WITH',530-I1,' STEPS LEFT'
46    CONTINUE
      PRINT*,'TO CHANGE PARAMETERS , ENTER APPROPRIATE CODE :'
      PRINT*,'0  NO CHANGES                   5  CONTINUE RUN,WITH CHANGES'
      PRINT*,'1  NEW D S P (PLASTICITY)  2  EXTERNAL INPUT'
      PRINT*,'3  NEW REF,T(STIM DECAY)    4  NEW A VO  (WINDOW) '
      PRINT*,'6  ACCESS SYSTEM MONITORS   7  PARAMETER LIST'
      PRINT*,'9  EXIT EVOLUTION            55 RESTART &RUN FOR 500'
      READ(22,*)LL
78      IF(LL.EQ.0) GOTO 39
      IF(LL.EQ.1) GOTO 41
      IF(LL.EQ.2) GOTO 42
      IF(LL.EQ.3) GOTO 43
      IF(LL.EQ.4) GOTO 44
      IF(LL.EQ.5) GOTO 39
      IF(LL.EQ.6) GOTO 47
      IF(LL.EQ.7) GOTO 48
      IF(LL.EQ.9) GOTO 99
      IF(LL.EQ.55) GOTO 455
      IF(LL.EQ.551) GOTO 455
      GOTO 46

c  a continuation of the run has been requested
39    CONTINUE
      PRINT*,'YOU HAVE REACHED STEP',I1,' WITH',530-I1,' STEPS LEFT'
      READ(22,*)IO
      PRINT*,'HOW MUCH MORE TIME WOULD YOU LIKE ?',IO
      IF(IO.EQ.0) GOTO 99
c     99 is end of evolve
      I11=I1+1
      TIME1=I11
      I1=I11-1
      IF(LL.EQ.0) GOTO 40
      IF(LL.EQ.5) GOTO 45

c  Initialise 50% act run 500 steps
455   CONTINUE
      IF(LL.EQ.551)THEN
      I1=1
      LL=0
      ENDIF
c     PRINT*,'RESTART &RUN FOR 500'
      DO 452 J=1,N
      R=RNDM(R)
      IF(R.GT.0.5) THEN
      LO(J,I1)=0
      ELSE
      LO(J,I1)=1
      ENDIF
452    CONTINUE
      TIME1=I1+1
      IO=1000
      GOTO 40
```

```
c  new plasticity parameters requested
41    PRINT*,'PLASTICITY PARAMETERS'
C     PRINT*,'D=',D,'(',D1,') S=',S,'P=',P,' INHIBITION=',QH
C     PRINT*,'PLASTICITY MODE: 0;1=BW;2=LEARN;3=ALERT;4=FORGET'
      READ(22,*)LL
      IF(LL.EQ.0)THEN
       D=0
       S=1
       P=1
      ELSE
C      PRINT*,'0<P<1 FOR DECAY OF D (= % CHANGE OF LV)'
C      PRINT*,'INPUT D P'
       READ(22,*)D,P
       PRINT*,'INPUT D P',D,P
       AT=0
       S=1
       IF(LL.EQ.1)THEN
        S=-1
       ELSE IF(LL.EQ.2)THEN
        D=(-1)*D
       ELSE IF(LL.EQ.3)THEN
        AT=1
       ENDIF
      ENDIF
C      PRINT*,'D=',D,'(',D1,') S=',S,'P=',P,' INHIBITION=',QH
      GOTO 46

c  change in external stimulus requested
42    CONTINUE
      PRINT*,'STATUS OF INPUT NEURONS FOR PREVIOUS INPUT STAGE:'
      PRINT*,(IPS(JJ),JJ=1,10)
      PRINT*,' NEW STATUS ? 0=NO CHANGE'
      READ(22,*)JJ
      IF(JJ.NE.0) THEN
      READ(22,*)(IPS(JK),JK=1,10)
      PRINT*,(IPS(JJ),JJ=1,10)
      ENDIF
      READ(22,*)IPT
      PRINT*,'DURATION OF STIMULUS ?',IPT
      GOTO 46

c  new refactory time and stimulus decay factor requested
43    CONTINUE
      PRINT*,'REFACTORY PERIOD=',REF,' STIM ACCUMULATED=',T
      READ(22,*)REF,T
      PRINT*,'INPUT NEW REF,T',REF,T
      GOTO 46

c  monitoring requested
c  some of these monitors have been shifted to PHASE
c   and others were irrelevant and deleted
47    PRINT*,' '
      PRINT*,'ENTER CODE FOR DESIRED MONITOR'
C      PRINT*,'  0  NO DISPLAY          4  FOURIER TRANSFORM'
C      PRINT*,'  1  ELG AND ACT         5  CYCLING SCAN'
C      PRINT*,'  2  STATE MATRIX        6  AUTO CORRELATION'
C      PRINT*,'  3  ACTIVITY GRAPH      7  HISTOGRAM OF Vij'
```

```
c  new initial conditions
44      CONTINUE
        INITIAL CONDITIONS
        PRINT*,'INPUT NEW ACTIVITY , RANDOM SEED'
        PRINT*,'          START TIME'
        READ(22,*)A,R
        READ(22,*)I1
        DO 420 J=1,N
        R=RNDM(R)
        IF(R.GT.A) THEN
        LO(J,I1)=0
        ELSE
        LO(J,I1)=1
        ENDIF
420     CONTINUE
        A=A*N
        PRINT*,'INPUT NEW ACTIVITY , RANDOM SEED',A,R
        GOTO 46

48      CONTINUE
        PRINT*,'PARAMETERS N=',N
C       option never used
        GOTO 46

99      PRINT*,'END OF EVOLUTION'
        RETURN
        END
C       ***************************************************************
        SUBROUTINE PHASE
        COMMON /COMO/I1,REF,LO(300,1000),N,LPQ,NSUB
        COMMON /COM2/LA(300),INP(10),AT,TIMECH,I8
        DIMENSION LA1(300),K3(300),LA2(300),L3(300,30),LLS(1000)
        I3=INT(aLOG(real(TIMECH))/LOG(2.))
c       length of neurons history to be matched in periodicity search
c        PRINT*,n,' MONITORED NEURONS '

c     initialise
        IO=I1-TIMECH+1
c       start time =IO
c       period = I2
        I2=I1-I8
        DO 10 J=1,N
        LA1(J)=0
        LA2(J)=0
        DO 9 I=1,10
9       L3(J,I)=0
10      LA(J)=0

c    activity of each neuron J
        DO 20 J=1,N
        DO 30 I=IO,I8
c       LA1 = activity during transient
30      LA1(J)=LO(J,I)+LA1(J)
        DO 40 I=I8+1,I1
c       LA  = activity during cycling
40      LA(J)=LA(J)+LO(J,I)
20      CONTINUE
        IF(I8.EQ.IO)GOTO 81
```

```
c    neuron J starts cycling at LA2
       DO 50 J=1,N
       DO 60 I=I8,I0,-1
       IF(LO(J,I).NE.LO(J,I+I2)) THEN
       LA2(J)=I+1
       GOTO 50
       ENDIF
60     CONTINUE
       LA2(J)=I+1
50     CONTINUE

C      PRINT*,'CYCLE ENTRANCE TIMES'
c    grouping neurons

       LX=0
       LX1=0
       LY1=0
       LY=0
       DO 70 J=1,N
c      for each neuron J
        IF(LA(J).EQ.0)THEN
c         dead neurons
          IF(LA1(J).EQ.0)THEN
          LX1=LX1+1
          ENDIF
          LX=LX+1
        ELSE IF(LA(J).GE.(I2)/(REF+1)) THEN
c         epileptic neurons
          IF(LA1(J).GE.(I2)/(REF+1)) THEN
          LY1=LY1+1
          ENDIF
          LY=LY+1
        ELSE IF(LA2(J).LT.I8-N+1) THEN
c         very early cycling neurons
          PRINT*,'NEURON',J,' CYCLES AT T-',I8-LA2(J)
        ELSE IF(LA2(J).GT.I8) THEN
c         neuron can't start cycling after the net does
          PRINT*,'NEURON',J,' CYCLES AT T+',LA2(J)-I8,'!!!'
        ELSE
c         eligible neurons grouped according to cycle onset time
          NS=INT((J-1)/NSUB+1)
c         netlet number NS
c         time steps before onset of cycling = I
c         number neurons cycling in netlet NS,I before net,= L3
          DO 51 I=1,1+I8-LA2(J)
c         from a step before net cycles back to neuron J's onset
51        L3(I,NS)=L3(I,NS)+1
        ENDIF
70     CONTINUE

c    printing the transition details
```

```
c    printing the transition details
       NS=INT((N-1)/NSUB+1)
       L3MAX=0
      DO 80 J=1,N
       L3J=0
       DO 71 I=1,NS
71     L3J=L3J+L3(J,I)
        IF(L3J.NE.L3MAX)THEN
        PRINT*,(L3(J,I),I=1,NS),' IN ',I2,' CYCLE BY T-',J-1
        L3MAX=0
        DO 72 I=1,10
72      L3MAX=L3MAX+L3(J,I)
        ENDIF
      IF(L3MAX.EQ.0) GOTO 82
80    CONTINUE
82    CONTINUE
      PRINT*,LX1,' NEURONS DEAD ',LY1,' ON'
      PRINT*,LX,' NEURONS DEAD ',LY,' ON, IN CYCLE'

c    repeated states in netlets
      DO 100 NS=1,INT(N/NSUB)
      ASUB1=0
      ASUB=0
      II1=0
      DO 104 I=1,NSUB
      ASUB1=ASUB1+LA1((NS-1)*NSUB+I)+LA((NS-1)*NSUB+I)
104   ASUB=ASUB+LA((NS-1)*NSUB+I)
      PRINT*,'SUBNET',NS,ASUB1/(NSUB*TIMECH),ASUB/I2/NSUB
      DO 102 I=I1-TIMECH+1,I1
      LLSS=0
      DO 103 II=I+1,I1
       IF(II.EQ.I)GOTO 103
      DO 101 NNS=1,NSUB
      J=(NS-1)*NSUB+NNS
      IF(LO(J,II).NE.LO(J,I)) GOTO 103
      IF(LO(J,II+1).NE.LO(J,I+1)) GOTO 103
      IF(LO(J,II+2).NE.LO(J,I+2)) GOTO 103
      IF(LO(J,II+3).NE.LO(J,I+3)) GOTO 103
      IF(LO(J,II+4).NE.LO(J,I+4)) GOTO 103
      IF(LO(J,II+5).NE.LO(J,I+5)) GOTO 103
101   CONTINUE
      IF(II.EQ.I+1) THEN
      II1=II1+1
      GOTO 102
      ELSE IF(II1.NE.0)THEN
      PRINT*,'T=',I-1-II1,' REP TILL',I-1
      II1=0
      ENDIF
      LLSS=LLSS+1
      LLS(LLSS)=II
03    CONTINUE
      IF(LLSS.NE.0)THEN
      PRINT*,'T=',I,' REP ',LLS(1)-I,((LLS(J)-LLS(J-1)),J=2,LLSS)
      ENDIF
02    CONTINUE
00    CONTINUE

7     RETURN
      END
```

APPENDIX 2

Getting to know the model ; parameters , thresholds , brainwashing

Obstacles involved in setting up nets which can survive the variety of conditions found during studies are resolved. This development, although essential for simulation, has no direct bearing on the main thrust of the project.

Symbols:

δ = Brainwashing Fraction

t1 = decay ratio of δ in time $\delta(t) = \delta(t1)^t$

Ref = Refactory period

Elg = Eligibility

Act = Average activity

$<\theta>$ = Theoretically calculated threshold

T = Decay of stimulus = $\dfrac{u_i(t+\tau)}{u_i(t)}$
(without any new stimulation at $t+\tau$)

θ(Min)-θ(Max) = Lower and upper limits of window firing condition

Neural networks are very individualistic. What works for one net may not work for another. Many statistical results have large errors. For each particular computer model, it takes some experience and many dead ends before it is possible to design an experiment. The various parameters of hardware wiring, brainwashing and evolution of states of neurons, thresholds in particular, needed to have their convenient operating ranges found. A chronological description of this acclimatisation follows:

Firing thresholds for static nets

The parameters under consideration were m, h, α, β, R. Each net (typically N=80) was run for 20 steps only for this initial survey. Connectivity and inhibition were each varied from .3 to .4, initial activity from .2 to .8, noise parameter 10 or 100 and refactory period from 1 to 3. Note that the m values were chosen unusually high , through lack of experience. The aim was to find, by searching, a suitable threshold for each net, and to get a feeling for how this threshold varied from the expected threshold of $\frac{1}{2}Nm(1-2h)$ for various parameters. (A suitable range of threshold action allows the net to survive 20 steps without reaching a constant state, by dying, for instance). The most notable feature was the sensitivity to inhibitory fraction, so precautions were taken to ensure that the correct number of inhibitory neurons were chosen during the set-up proceedure. This was done by weighting the probability of being inhibitory according to how many inhibitors were still needed and how many neurons there were to choose from.

Thresholds actually cause an inherently unstable phenomenon. If the threshold is slightly too low, activity increases, stimulation increases and hence activity increases further. If the threshold is too high, the activity keeps decreasing to zero. This is where negative feedback or inhibition is so important. Initial conditions were also found to be important. Although most initial conditions led to the same outcome for the same threshold. Sometimes particular initial conditions led to quite unexpected outcomes.

TABLE 1

Thresholds θ and Survival

N	m	h	Rand	Act(o)	Ref	threshold θ	$\langle\theta\rangle$	avg Act(20)	Elg.	
80	.3	.3	.246753	37	1	3.3→3.8	4.8	33-44	37	
	.4	.3	.246753	37	1	4.5→4.8	6.4	58-60		$\theta \sim m \cdot \frac{2}{3}$
				37	1	4.9→5	6.4	death		
				32	2	3.7-3.9		32-36	(80-90% saturated)	
				32	2	4.0-4.2		death		
				24	3	.5-1.0		death,	preceeded by epilepsy (θ too low)	
80	.3	.4		37	1	1.9-2.4	2.4	30-44	25	
	.4	.4	.246753	37	1	2.5-2.9	3.2	35-39	28	
				37	1	3.0	3.2	death		
				32	2	1.7-2.2		21-30/ high elg. because of death	65	
				24	3	1.5-1.8		19-22	28 much higher θ than before	

- Thresholds unsatisfactorily unpredictable.

- The highest possible threshold that doesn't cause death yields the highest eligibility. See Figure A1

- Inhibitory fraction increase improves the consistency of behaviour and results in more resilient nets.

- Longer refactory periods need lower initial activity, or else the activity will be too low during the refactory period, leading towards death. The thresholds must also be lower, since the average activity must be less. Some accumulation of signal seems necessary to compensate for the refactory period.

- 20 steps is a relatively short time, thus the range of workable threshold was exaggerated

- The noise parameter was not seen to have a noticeable effect in this short time, so in subsequent studies noise was excluded for the sake of simplicity in detection of exact cycling.

EFFECT OF THRESHOLD LEVEL ON ACTIVITY AND ELIGIBILITY

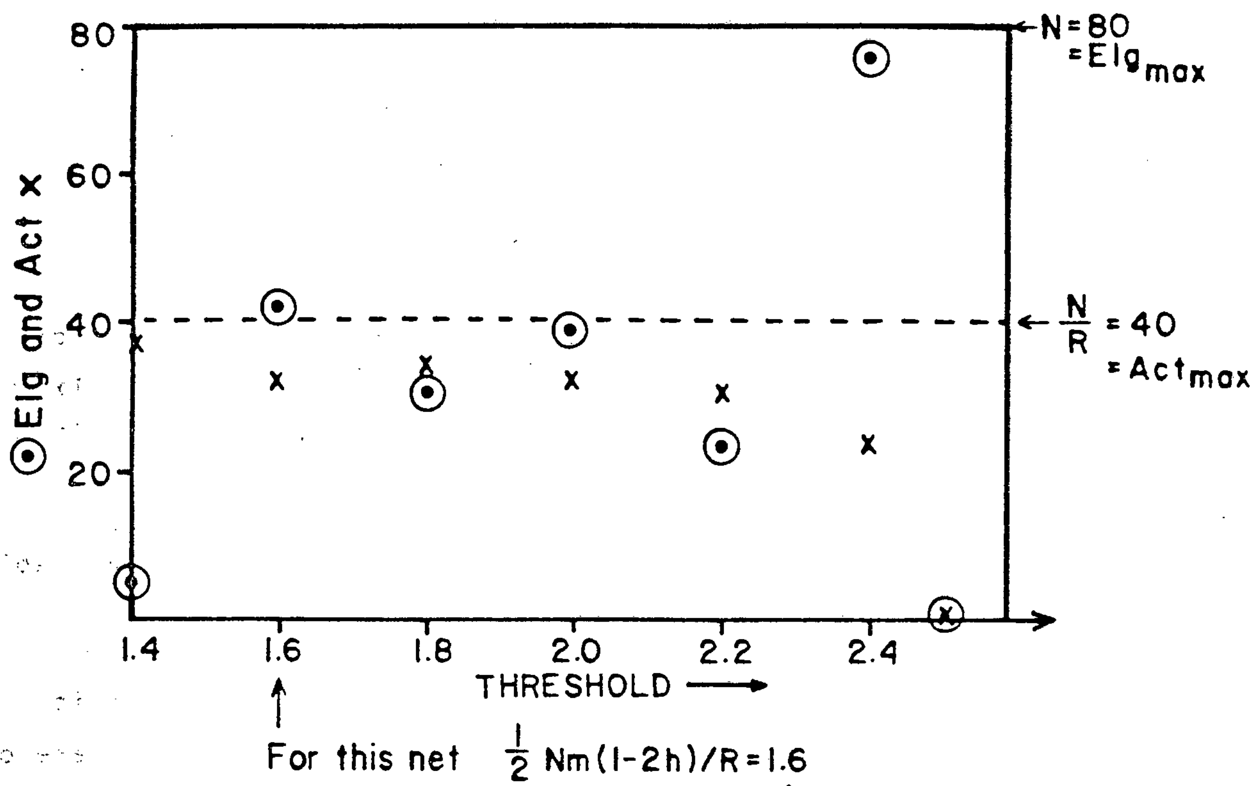


Figure A1 Crosses denote the mean number of active neurons as a function of the uniform threshold level. Circles denote the number of neurons participating in the evolution of the net. This graph is for a particular net of 80 neurons and with R=2 (a single refactory period) Results are representative of a significant fraction of brainwashed quasirandom nets. Note that the smallest activity and the largest eligibility occur for the highest tolerable threshold. The maximum eligibility possible is 80 and the saturated activity level is 40, since R=2.

Brainwashing

Some of the variables of this plasticity process are threshold, brainwashing strength and duration, and the growth or decay of the brainwashing strength. The aim of brainwashing was to show the variety and versatility of a brainwashed system, and to pinpoint the parameters.

Allowing:
N = 80, M = .3,.35,.4, h = .35,.3,.4, δ = .3,.2,.5, t1 = .5,.7,.83,.9,.95
Refs. = 1,2,3 (See table 2).

Note: Refractory periods of 3, without accumulation of stimulus, were largely ineligible. Eligibility and activity depended on threshold. For brainwashed nets, a range of thresholds was often possible, because the nets had improved resilience. Fluctuations between 7 and 93 percent activity were seen.

No cycling by individual neurons occurred during brainwashing - as expected. Brainwashing strengths that didn't decay too fast worked best, in terms of producing resilient, eligible nets. It is logical that brainwashing should be time consuming, allowing a net to respond to the structure in its connection matrix, and then weeding out the structure. Very sudden and large brainwashing corrections should be too dependent on initial conditions, or immediate neighbourhood of states which may not be general.

Once again, higher values of inhibitory fraction (h = .4) produced the most interesting nets. The highest eligibilities were found for h = .4 and m; $\delta(t)$; Ref = .4; .3 $(.9)^t$; 2 and .2; .2 $(.99)^t$; 1, respectively.

Note the slow decay rates of $\delta(t)$. Later studies used mostly δ = .1 with no decay. Refactory periods of 2 were much more favourable than Ref=1 or Ref=3 Time correlation functions for the state vector showed no marked maxima during brainwashing, indicating that brainwashing suppressed periodicity. What is the effectiveness of brainwashing a net with a large refactory time for the neurons? Brainwashing should be applied for much longer, to allow the connections that escape brainwashing during the refactory period to be corrected.

APPENDIX 2 TABLE 2

EFFECTS OF BRAINWASHING PARAMETERS N=80 ON RANGE OF THRESHOLD

m	h	d	t1	R	@	V0	<v0>	elg	act	
.3	.3	.5	.9	2	.3	2.0-2.6	2.4	8-40	26-28/40	.
.35	.35	.5	.9	2	.4	2.3-2.4	2.1	0	35-0	fluctuatn act but no survivl
.4	.4	.5	.9	2	.4	1.1-1.2	1.6			death & epilepsy
.4	.4	.5	.9	2		1.8-2.3	1.6	60	30	range of thresholds
.4	.4	.3	.9	1	.6	2.5	3.2	74	35/80	d & epi .act=3-72
.4	.4	.3	.9	1		3.2	3.2	0	49	
.4	.4	.3	.9	2		1.8-2.5	1.6	37-76	33-24/40	highly elg!,range of V0,the..
.4	.4	.3	.7	2		1.4-2.4	1.6	4-74	37-23	higher the better.(graphs)
.4	.4	.3	.7	3		1	1.1	7	24/27	death & epilepsy
.4	.4	.3	.5	2		2-2.7	1.6	32-64	23-32/40	
.4	.4	.2	.9	2		1.8-2.5	1.6	32-70	23-33	
.4	.4	.2	.9	1		3.3-3.7	3.2	25,64	59,45/80	
.4	.4	.3	.93	3	.2	1.0	1.1	4	23/27	recovers act=4,but mostly..
.4	.4	.3	.95	3	.3	1.0	1.1	5	24	saturated.Sensitive to V
.2	.4	.2	.99	1	.5	1-1.2	1.6	80!	48-36/80	low correln,big fluctuatns
.2	.4	.2	.9	1	.5	1.2-1.4	1.6	43-39	50-42	act flatter
.35	.35	.3	.9	1		3-3.5	4.2			hard to find V0
.35	.35	.3	.9	2		2.8,2.9	2.1	18-7	33-3/40	
.4	.3	.3	.9	1	.5	6	6.4			death & epilepsy all mixed
.35	.3	.3	.9	1			5.6			V0 not found
.35	.3	.3	.9	2		2.6-3.5	2.8	21-61	37-31	
.35	.3	.3	.9	3		1.6-2	1.9	3	25-23/27	close to saturation
control										
.35	.3	0	0	1			5.6			V0 not found,Unstable BW=0
.35	.3	0	0	2		2.6-3.6	2.8	0-21	38-34/40	
.35	.3	0	0	3			1.9			perpetually dying

m = connectivity h = inhibition
d = Bwash strength t1 = decay of d
R = refactory period @ = initial activity
V0 = thresholds <v0>= theoretical V0
elg = eligibility act = average activity

Windows

The idea of windows instead of thresholds as a firing condition for neurons was interesting, although of no physiological relevance. An upper threshold was introduced to prevent overstimulated neurons from firing, thus making epileptic states non-perpetuating. In conjunction, it was necessary to allow accumulation of signals. That is, if a neuron does not fire, a fraction, T, of its stimulus, is carried forward to the following time step. Thus, if T is not too small, an overstimulated neuron's stimulus will decay in time and sooner or later fall within upper and lower thresholds, allowing the neuron to fire. Death would be more easily avoidable, because accumulated signals would help revive a net with very low activity. Tunnelling past the window should be possible. It would be necessary for stimulus to be able to jump from below the window to above (or else overstimulation doesn't occur) and it would be satisfactory if the window were just jumpable from above, so that a slightly overstimulated neuron may possibly fail to fire if no additional stimulation occurs in the following time step. The average input per neuron, (ignoring refractory period) is:

$$\bar{u} = \alpha\, Nm(1-2h)\ (\mathrm{Ave}\,|Vij|)/(1-T(1-\alpha)) = (\sum_{ij} Vij)\alpha\ /\ N(1-T(1-\alpha)). \qquad (A2.1)$$

Initially the window limits were chosen symmetrically about this average stimulation. No brainwashing or refractory effects were used.

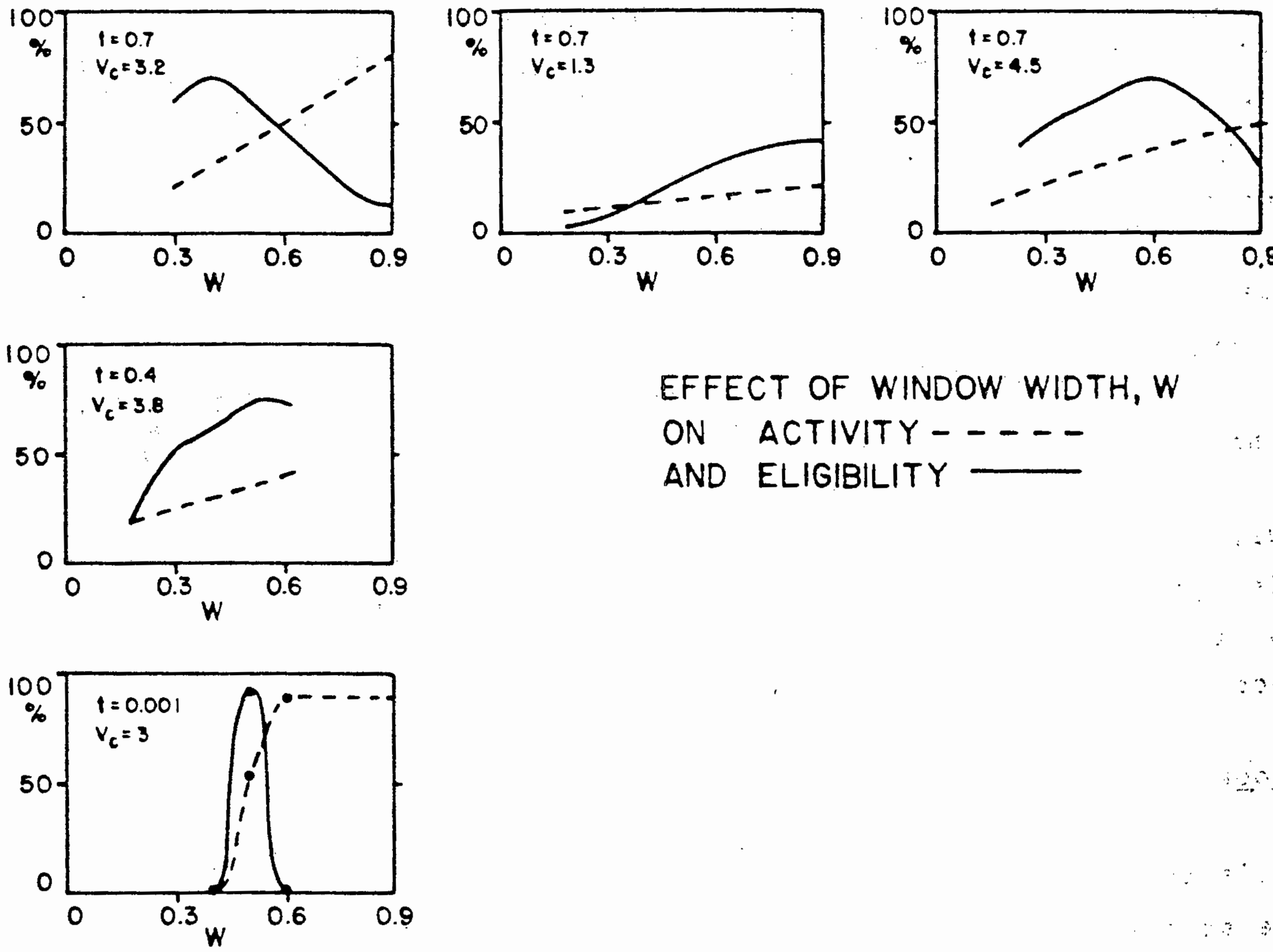
$$\theta(\mathrm{Min}) = \theta(1-\tfrac{w}{2}) \quad \theta(\mathrm{Max}) = (1+\tfrac{w}{2}) \text{ where } w \text{ is the width of the window } 0<w<2. \qquad (A2.2)$$

The aim was to find rythmic fluctuations controlled by the window and decay of stimulation. Monitors on overstimulated neurons were useful in understanding and controlling the behaviour. Cycling with windows and accumulating signals, is much more unlikely. Accumulated stimuli greatly extend the possible states of the net. With parameters:

N = 100, h = .3, m = .1 or .2, T = .001 or .4 or .7,

Width W = .1 to .9 Run for up to 500 steps.

(See figure A2)



<u>Figure A2</u> In each graph, the percentage average activity (dashed line) and the percentage of eligible neurons (solid lines) are plotted as functions of window width W, with window centre V_c, chosen with consideration of network parameters (N=100 m=.1 to .2 h=.3) and accumulation, T. The column of three graphs illustrates the effect of changing accumulation, T, with T=.7,.4,.001 corresponding to halflives of stimuli equal to 1.94,.76,.001 steps respectively. The row of three graphs shows decreasing V_c causing a shift in the optimum eligibility with respect to window width.

Non-cyclic, dead and epileptic states were observed for cases with accumulation T = .4, .7. whereas , without accumulation (T=0) , but for one value of W (W=.5) , for which highly eligible nets were found, the rest of the runs ended in dead or epileptic states.

Wider windows resulted in higher activity, and maximum eligibility (70%) was observed for width about .6. See fig A2.
The highly eligible nets had large fluctuations in activity, but these rythmic fluctuations did not have constant period.

Thus, optimal window widths can be found for various values of t and α, at which the activity in the net oscillates widely, but cycling is absent (in 150 to 500 steps). Note that α affects the choice of the centre of the window, therefore low α needs a wider window.

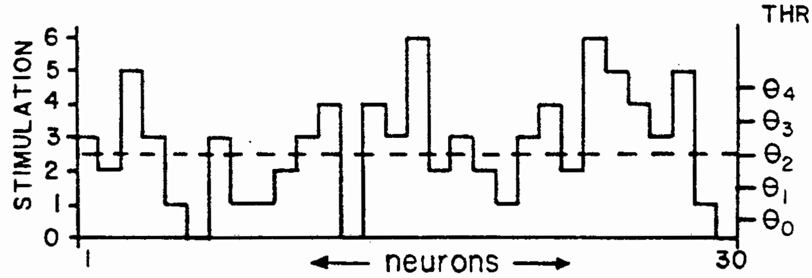
<u>Windows with independent upper and lower thresholds</u>

Initially, nets with no accumulation, refactory period, plasticity or noise were studied. The upper threshold was reduced from effectively infinite till the net died. The lower threshold was fixed during the process, at values less than or equal to the usual threshold. See appendices. Most nets cycled within 500 steps, and those that did not were very highly eligible. Typically, one integer value of lower threshold allowed a range of cycles, but an increase or decrease in this value caused death or epilepsy (higher threshold very high). Narrowing the window, whether from top or bottom, inevitably reduced the activity level. An interesting study to see just how low the upper limit can go, showed that reducing θ(max) slowly eventually causes interruption of the characteristic cycle, but on raising θ slightly again, the net restored its original cycle.

To illustrate this, consider the following diagrams of stimulation neurons 1 to N at time t_o. Shifting threshold or adding accumulated signa changes the states of only a fraction of the neurons, but the effect multiplied by the following step and a completely different region can b accessed. θ_4 and θ_0 would most likely cause death and epilepsy, respectively while θ_1; θ_2 and θ_3 would probably result in three different cycles, al though the difference in next states for these different thresholds small. If accumulation were included many more than 6 levels of stimulatio would be found, and hence many more possible thresholds between sure dea and sure epilepsy.

<u>Figure A4</u> Possible thresholds applicable to a given stimulation. A sample is shown of the stimulation to each neuron in a 30 neuron net, at one time. The upper graph shows the direct stimulation from the previous state of the net, and the lower graph includes accumulated signals from past states. Many possible thresholds can be applied to determine the next state of the net, each of which may generate different sequences of net activity. Few of these thresholds would allow long term perpetuation of activity. Accumulation is one means of allowing closer spacing of effectively distinct thresholds,as is brainwashing for example.

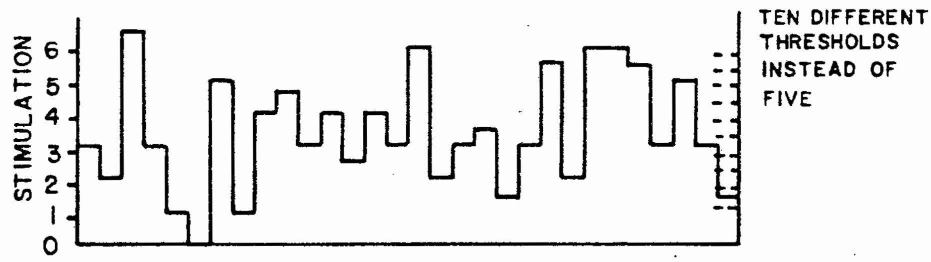
WITHOUT ACCUMULATION



NEXT STATE OF NEURONS

THRESHOLD		ACT	Δ ACT
θ_4	001000000000000100000001100100	5	
			4
θ_3	001000000001010100000101110100	9	
			8
θ_2	101100100011011101001101111100	17	
			5
θ_1	111100100111011111101111111100	22	
			5
θ_0	111110111111011111111111111110	27	

WITH ACCUMULATION



θ	1.2	1.7	2.2	2.7	3.2	3.7	4.2	4.7	5.2	5.7
ACT	27	25	22	21	13	12	9	8	6	4

ΔACT	2	(3)	1	8	1	(3)	1	(2)	2

FIGURE A4

Brainwashing and Windows

The window algorithm doesn't need brainwashed nets as much as others do because resilience to change in windows, and resilience to large fluctuations in activity are already there, but since the net is quasirandom, there will be some rut-like cycles that dominate, therefore brainwashing is of interest, but how is it to be implemented with, firstly, accumulated signal hiding the source of stimulating of a firing neuron, and, secondly, windows where overstimulated neurons don't have the inputs brainwashed.

Various amounts of brainwashing (δ = 3 - 10% for 25 to 100 steps were tried using high θ(max) so that the behaviour was very close to threshold nets. range of reactions and success rates of brainwashing were recorded. No substantial common differences in behaviour could be found.

Back to Thresholds

In an attempt to understand thresholds and develop general prescriptions for choosing suitable thresholds, the discrepancy between the useful threshold and the calculated thresholds was studied, with the aid of a feedback mechanism whereby activity (present, integrated or rate of change) was monitored and the threshold adjusted accordingly to maintain, as closely as possible, the prescribed activity. The average threshold ($\bar{\theta}(t)$) throughout the run and the average activity achieved ($\bar{\alpha}(t)$) were analysed. The feedback mechanism worked best when a reasonably close approximation to the correct threshold was used to start with, that is $\theta(0)$ chosen to be (average stimulus) x (fudge factor)

where average stimulus $= \frac{1}{2}$ Nm (1-2h) (A2.4)

and fudge factor $= (1-6(\alpha-\frac{1}{2})|\alpha-\frac{1}{2}|)$ to start with. (A2.5)

The aim, of course, was to find a better fudge factor prescription.

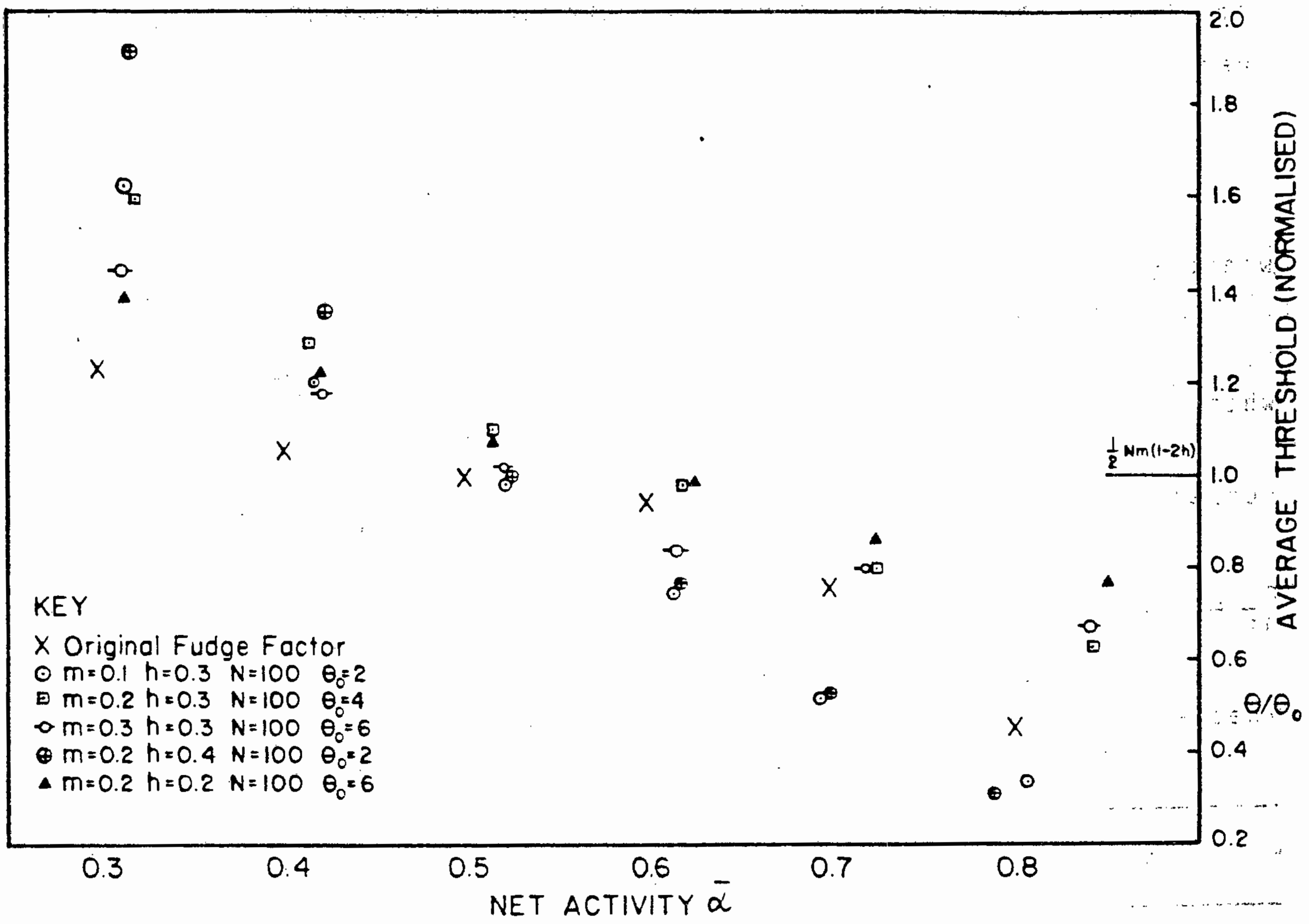
Parameters N = 20, 30, 40 ... 100 m = .1, .2, .3 h = .2, .3, .4

Desired activity: .2 .3 .4 .5 .6 .7 .8 .9

Initial fudge factor: 1.54 1.24 1.06 1 .94 .76 .46 .04

The study revealed that, individually, there is no static prescription for finding a functional threshold, that will apply for a large fraction of cases. Feedback, accumulation or other methods are more reliable escapes from instability. The general trends of the thresholds would be instructive to examine, in spite of lack of applicability. For each case studied, there was an expected activity . An average activity $\bar{\alpha}$, and expected threshold $\theta(\alpha_o)$ and an average threshold $\bar{\theta}$ (taken over 50 steps between 25 and 75). The average stimulation to each neuron should be α Nm (1-2h). If the desired activity α, is higher than a half, then the threshold must be lower than α Nm (1-2h). If the activity α is greater than α_o, then threshold must be increased, but by a smaller factor than $\Delta\alpha/\alpha_o$, or else $\bar{\theta}$ is just proportional to $\bar{\alpha}$. The outcome (see fig A5) shows that $\bar{\alpha}$ was greater than α_o, and that reflects on the imperfection of the feedback mechanism. The average thresholds were thus slightly too low. The points on the graphs were generated with negative feedback on the threshold, but that does not mean that choosing a constant threshold equal to the average threshold would result in the same activity. The most useful information that can be gleaned is the sensitivity to change in threshold as a function of parameters. The flatter the slope $\Delta(\theta_o)|\Delta\alpha$, the smaller the range of stability of θ. The steepest slopes were for h = .4 (high inhibitory fraction) and m = .1 (low connectivity) indicating that these conditions ought to increase stability.

FUDGE FACTORS FOR AVERAGE THRESHOLDS



<u>Figure A5</u> Average uniform threshold is plotted against average net activity. Different symbols are used for different net parameters, each point being the average of 6 nets. Each net was run for 75 steps while dynamical adjustments were made to the threshold at each step in order to maintain the prescribed activity. Average threshold for each run is normalised with respect to the expected uniform threshold for that net. Presribed activities ranged from .3 to .8 ; N=100 ; m=.1,.2,.3 and h=.2,.3,.4

This may arise from a more spread out distribution of inputs per neuron, that is

$$M : Nm(1-2h) \pm \sqrt{M} = M(1 \pm \frac{1}{\sqrt{M}}) \qquad (A2.6)$$

where smaller M has greater percentage deviation.

Comparing this to the experimental results, let $\sqrt{n} = \Delta\alpha/\Delta(\theta/\theta_o)$ at $\alpha = \frac{1}{2}$ where n and M should be proportional. (A2.7)

Comparing other parameter sets to the standard chosen to be m = .2 h = .3,

$$\frac{n}{n^*} = \left(\frac{\Delta\alpha/\Delta(\theta/\theta_o)}{(\Delta\alpha/\Delta(\theta/\theta_o))^*}\right)^2 = [\Delta(\theta/\theta_o)^*/\Delta(\theta/\theta_o)]^2 \text{ for same } \Delta\alpha. \qquad (A2.8)$$

Theoretically $n/n^* = M/M^*$

N	m	h	M	M/M*	n/n*
100	.2	.3	8	1	1
100	.2	.4	4	$\frac{1}{2}$	$\frac{1}{3}$
100	.2	.2	12	$\frac{3}{2}$	$\frac{9}{4}$
100	.3	.3	12	$\frac{3}{2}$	$\frac{3}{2}$
100	.1	.3	4	$\frac{1}{2}$	$\frac{1}{2}$

The agreement is good for changes in connectivity, but changes in inhibitory fraction cause exaggerated effects, so then inhibition effects stability more than by just altering the effective number of inputs.

Studies of various netsizes from 20 to 100 showed similar trends and similar spread of data.

The conclusion drawn from this section was that nets with static connections and constant thresholds and no accumulation or architecture were too inconsistent to be useful in the study of phase transitions. The next step was therefore to find out how to reliably and effectively brainwash nets.

Back to Brainwashing

The outcome of the previous attempts to brainwash showed that slow, gentl brainwashing most affected the quality of net behaviour (resilience eligibility).. That is, δ = .5 was too large and δ δ_o $(.5)^t$ decayed tc fast. The hardware parameters in this section were chosen and kept constar N = 50, m = .2, h = .3 (study 1) .35 (study 2), α = 50%, no accumulatior refactory effects or noise (temperature) effects.

The aim was, firstly, to find a criterion to measure brainwashing whic could be used to control the brainwashing algorithm. The standard deviatic of activity should increase when a net which tends to cycle with k=1 i- successfully brainwashed. Eligibility and resistance against death ar epilepsy should improve with brainwashing. Versatility and resilience t- threshold and hardware parameters should improve with brainwashing. The ide was to try various brainwashing strengths, brainwashing thresholds, duratic of brainwashing, for a number of different nets with the same parameters monitoring the distribution of synaptic strengths in the connection matrix and monitoring the cycling, eligibility and standard deviation of activity If a successful monitor or recipe for brainwashing were found, then brair washing in steps with accumulation, refactory period windows or othe hardware parameters would be investigated.

In the first study, three different nets were chosen. Each was run befor brainwashing, after bw with δ = 10% $(.9)^t$ and after bw with δ = 5% constant- Each brainwashing strength was used under 6 conditions of time and threshol for each net: (100 steps with θ = .9;1.0 and 50 & 100 steps with θ = .7;.8) Each net thus created was run with θ = .6, .7, .8, .9, 1, 1.1. (See tables)

The individuality of the pseudorandom sequence generating the connectic matrix had an overriding influence, even after brainwashing. The three net had good, fair and bad responses to brainwashing, respectively, with broac medium and narrow ranges of workable thresholds.

Case 1

The net was not ineligible before washing, and both brainwashing strengths and deviations resulted in several cyclic or non-cyclic states occurring after each brainwashing. The threshold was favourably from .7 to 1.

Case 2

Once again, the unwashed behaviour was slightly eligible. Some longer cycles were found after brainwashing, but not nearly as often or consistently as for case 1. Once again strength, duration and threshold of brainwashing made no discernible difference, except that lower thresholds were slightly better behaved. The net appears not to have been brainwashed.

Case 3

This net started only slightly eligible but after brainwashing was far less eligible or of interest. Brainwashing clearly failed. A further seven cases were tried, some successfully brainwashed, others not.
In successfully brainwashed nets , that is when bw favourable changes the quality of net behaviour, the improvement in eligibility is similar to the increase in standard deviation of the activity $\epsilon(\alpha(x))$. If ϵ is low during brainwashing (i.e. α nearly constant) then eligibility is low and the distribution of correction strengths in Vij remains bipolar (with a peaks for negative and positive correction strengths) instead of ranging into one smooth peak, although the net change in connection strengths may be great. Possibly by measurement of $\epsilon(\alpha)$ and eligibility, and feedback to θ, with a view to increasing both these quantities, could be a successful approach to brainwashing.

Following this, a summer student (Ref. Symons' report) studied the influence of brainwashing on period and transient time (acquisition time). He took averages over a larger number of runs and a larger number of nets. His conclusions (in brief) were: Acquisition time increases after brainwashing and the larger the net, the larger the improvement, for example, 10 times for N = 100. The cycling period also increases on average, but more eratically from net to net. He also observed this "individuality" phenomenon, in that averages for one net displayed different qualities to averages for another net, but averaging over nets with the same parameters produce visible tendencies. He showed brainwashing at δ = 10% for 10 steps to b slightly less effective than δ = 5% for 20 steps - favouring gentle washin - but δ = 1% was too small. He also noticed that after the initial burst o brainwashing, the increase was dramatic, but thereafter, more brainwashin produced oscillating effects in the improvement ratio, some nets eve being over brainwashed, causing a return to ineligibility. His results an conclusions were illustrated and supported by numerous graphs.

APPENDIX TO CHAPTER 2

EFFECT OF WINDOWS ON NETS WITHOUT ACCUMULATION

ref=0, accumulation=0, no brainwashing
N = 100 m = .15 h = .3 act = .5
maximum input < 25

Vmin	Vmax	Act	Elg	Cycle period	Transient	Comment
2.5	100			epileptic		RAND 1
2.5	60	44	95	none	500	Vo = 3.14
3-3.98	60	67	12-18	9,63,69,92,116	47-131	range of k's
	30	67	11-13	9	118-140	short k,long trans
3.33	30	44	93	none	600	interesting case
	60			death		
1	80			epileptic		RAND 2
1.0-1.98	80	81	10	10,6	< 20	Vo = 2.6
2	80			death	31	
1.985	80	58	43	4	64	NB large fluctuation
1-2	80	77-86	6-10	2,4	6-10	RAND 3
2-2.98	80	72-77		1,2,3,6	4-18	Vo = 2.8
3	80			death	14	
2.5	80	81	4	2	10	RAND 4
3-3.95	80	70-77	10-13	9,16,23	26-54	Vo = 3.1
3.96	80	64	5	4	24	
3.97				death		
3.2	60-15	76	13	23		RAND 5
3.2	12			messed		effect of lowering
3.2	14,15			23		Vo is noticed at 13.
3.2	13			14		Returning to high V
						restores original.

APPENDIX TO CHAPTER 2

EFFECTS OF DIFFERENT BRAINWASHING STRENGTHS AND THRESHOLDS

N=50 m=.2 h=.3 t=0 ref=0 temp=0 act=50% V=.6 to 1.1

Random	BW:d%	t1	T	V(BW)	V/Vo	cycle	elg	act
.3791428	0				.8-1.1	11	8	26
Vo=1.48								
	5	1	100	1.0	.8	1	0	
					.9,1	**		3-42
				.9	.6-.8	7-1	9-0	
				.8	.6-.8	10,20	15-23	
				.7	.6,.7	5,7	7,12	
			50	.8	.9,1	14,3	14,7	
				.7	.8	5	5	
	10	.99	100	1.0	.6-.7	6	7,12	
					.8-1	***		1-38
				.9	.6-.7	7,6	11,9	
					.8	*		1-42
				.8	.6	4	6	
					.7-.9	***		2-41
				.7	.6	1	0	
					.7	20	29	
					.9	*		3-38
					.8,1		0	0
			50	.8	.6-.8	6,20,23	12-24	
				.7	.7,.8,1	***		1-37
					.9,1.1		0	0

Random	BW:d%	t1	T	V(BW)	V/Vo	cycle	elg	act
.5487442	0				.8-1	3	6	30
Vo=2.74					1.1		0	0
	5	1	100	1.0	.6-.9	2-10	1-9	
				.9	.6-.8	2-8	1-7	
				.8	.6-.7	2	1	
				.7	1.1	8	6	39
			50	.8	.6,.7	2	1	
				.7	.6,.7	2,4	2,7	
	10	.99	100	1.0	.6-.9	2-5	1-5	32-39
					.8	*		31-44
				.9	.7	2	4	39
				.8	.6,.7	2	2	41
				.7	1,1.1	1	0	0
			50	.7	.6-1	1,2,5	1,12	45-35

Random	BW:d%	t1	T	V(BW)	V/Vo	cycle	elg	act
.6307110	0				.8,.9	3	3	36
Vo=3.25					1,1.1		0	0
	5	1	100	1,.9			0	0
				.8	.6,.7	10,1	17,0	36,0
				.7	.6,.7	1	0	36,0
			50	.8	.6,.7	5,1	9,0	
				.7	.8,.9	1	0	38,0
	10	.99	100	1-.7			0	0
				.8	.6,.7	4,1	3,0	,0
			50	.7	.6,.7	1	0	,0

APPENDIX TO CHAPTER 3

DIFFERENT SETS OF PARAMETERS N m h d . NETS B.WASHED & RUN
SOME EXAMPLES

N = net size
h = inhibition

k = cycle period
To = transient time
#run = number of runs made
elg = eligibility
k>2: average elg; 2<K<*
on = neurons always active in cycle
off = neurons always dead in cycle

m = connectivity
BW = brainwashed or not
d = brainwashing strength
Tt = transition time
Tt>K = number of long Tt; K>12
#* = number runs non-cycling
#d = number of deaths

NET 10 N=100 m=.08 h=.35 d=.1

BW	Kave	To	k>2 Tt/k	#runs	* #runs	#d #runs	k>2 #runs	k>2 elg	k > 2 off	on	k>12 Tt>K
0	2.5	6	1.33	4	0	10		9	22	69	0/0
1	35	152	1.86	12	2	2		59	19	22	0/3
0	14	14	1	4	0	3		32	26	42	0/3
1	17	248	1	4	1	0		51	26	23	0/1
0	1.5	17	0	4	0	4	0	0			0/0
1	65	159	1.24	12	3	11		66	5	37	1/6
AVE	29	123	1.34	40	6	30		47	17	34	1/13

NET 11 N=60 m=.15 h=.35 d=.1

BW	Kave	To	k>2 Tt/k	#runs	* #runs	#d #runs	k>2 #runs	k>2 elg	k > 2 off	on	k>12 Tt>K
0	4.5	31	1.67	4	0	0	2	17	14	29	0/0
1	2	7	1.56	12	0	0	3	8	5	47	0/0
0	1	14		4	0	8	0	0			
1	74	210	.81	12	3	41	7	53	2	6	0/5
0		500		4	4	0					
1	45	357	.8	12	7	6	5	56	1	3	0/5
AVE	27	189	1.04	48	14	55	17	42	4	18	0/10

APPENDIX TO CHAPTER 3

DIFFERENT SETS OF PARAMETERS N m h d . NETS B.WASHED & RUN
SOME EXAMPLES

N = net size
h = inhibition

k = cycle period
To = transient time
#run = number of runs made
elg = eligibility
k>2: average elg; 2<K<*
on = neurons always active in cycle
off = neurons always dead in cycle

m = connectivity
BW = brainwashed or not
d = brainwashing strength
Tt = transition time
Tt>K = number of long Tt; K>12
#* = number runs non-cycling
#d = number of deaths

NET 12 N=60 m=.08 h=.35 d=.1

BW	Kave	To	k>2 Tt/k	#runs	* #runs	#d #runs	k>2 #runs	k>2 elg	k > 2 off	on	k>12 Tt>K
0	35	50	1	4	0	0	4	38	8	14	0/4
1	9	14	1.47	12	0	0	12	18	6	35	0/2
0	10	84	1.33	4	0	0	4	28	21	11	0/0
1	2	10	2.44	12	0	0	3	12	15	33	0/0
0	5	12	1.56	4	0	0	3	12	9	36	0/0
1	4	7	.78	12	0	0	3	12	9	36	0/2
0	3	47	1.67	4	0	6	3	13	19	28	0/0
1	99	397	.56	10	6	23	3	57	3	0	0/3
AVE	14	82	1.37	62	6	29	35	23	10	26	0/11

NET 13 N=60 m=.3 h=.35 d=.1

BW	Kave	To	k>2 Tt/k	#runs	* #runs	#d #runs	k>2 #runs	k>2 elg	k > 2 off	on	k>12 Tt>K
0	23	13	.58	4	0	4	4	20	3	37	0/2
1	1.3	6		12	0	0	0				
0	14	12	.67	4	0	0	3	21	4	35	0/4
1	17	11	.70	12	0	12	9	40	0	20	0/6
0	13	11	.83	4	0	0	4	16	3	41	0/4
1	6	6	1	12	0	0	4	25	3	32	0/2
0	2	10	2.5	4	0	4	2	6	3	51	0/0
1	14	15	.81	12	0	17	9	23	0	36	0/4
AVE	10	9	.86	64	0	37	35	25	2	30	0/21

Appendix 4

Normal thresholds and list of computer simulations for chapter 4

Comparison between normal and uniform threshold types

Definitions of threshold types and Γ -See ch 4

The scaling factor, Γ, was introduced earlier, with the intention of findin how behaviour of nets changed as thresholds scaled from normal (Γ = 0) t uniform (Γ = 1)

$$V_{oi} = \{(1-\Gamma)\sum_j V_{ji}(t=o) + (\Gamma)\frac{1}{N}\sum_{ij} V_{ji}(t=o)\}\frac{GAD}{2} \; ; \qquad (A4.1)$$

GAD is a universal tuning parameter, adjusted for activity survival. GAD is unity to start with, and the calculated threshold is used; but if th net dies or goes epileptic, GAD can be used to adjust the threshold propor tionally so that the net's activity can perpetuate.

The behaviour of nets with netlets was explored in 84 runs . (See tables a the end of Appendices). In particular, runs 7-18 and 77-84 relate t threshold type. The effect of equal thresholds for all neurons, is to in crease instability over other cases in the sense that there is a narrowe range of thresholds that allows perpetuation of net activity. Therefore, i runs 7-18, a threshold factor was put in by hand, using previous experienc of those particular nets' operating ranges. In spite of this, four out o eight runs attempted at Γ = 1 (uniform thresholds) resulted in deaths eac time before the thresholds were reduced enough to allow the nets to survive Hence locally varying thresholds seemed an important improvement when con sidering small netlets.

Effectivness of Brainwashing for various Threshold Types

Runs 7-18 : See end of appendix 4 .Not only does this short table demonstrate no change in effectiveness of brainwashing for the different cases of threshold, but it shows that brainwashing doesn't generally increase cycle-length or number of participating neurons. (Notice that this is for uniform nets, that is, the connection probability between

TABLE A1

EFFECT OF Y (THRESHOLD TYPE) ON CYCLING AND ELIGIBILITY

Y	total # runs	K=1,2 # runs	K>2 Ave K	Max K	noncyc #runs	K>2 Ave Elg	Max Elg	
0	8	2	78	256	2	44	100	homogeneous
.3	8	2	35	146	1	33	100	nets
1	8	5	8	11	0	25	31	
.1	8	1	26	107	0	36	65	
0	16	4*	44	76	6	33	52	structured
.3	16	3	150	334	5	55	100	nets
0	8	4	14	20	2	43	48	automatic thresholds
0	8	2	78	256	2	44	100	adjusted thresholds (see text)

* these trivial states had very long transients

any two neurons is the same)

o Runs 77-84 : These eight runs have Γ = .3 and can be compared to sets 66-72 for which Γ = 0 but the nets are otherwise identical. The % V_{ij} left (see definitions ch 4) is similar for the two cases of Γ and period and Elg go up or down after brainwashing equally often for both types of threshold.

From these 24 runs, the sparse evidence indicates that brainwashing and its effects are independent of threshold type, except in as much as that k = 1 nets are not easily brainwashed, and such nets are more common for uniform thresholds.

Effect of Γ on Cycle Length and Number of Participating Neurons

(See Table 1)

Referring to the first three rows in Table 1 (i.e. homogeneous nets), Γ = has fewer trivial (k=1) states, longer periods, more "non-cyclic" states an a higher number of participating neurons. Γ = .3 case lies between Γ = 0 an Γ = 1 for these properties.

Note: Γ = 0, with unadjusted thresholds, (row 7 Table A1) show deteriorated behaviour almost as bad as Γ = 1 performance.

Γ = 1 case is much improved if nets are allowed to recover after death an try again.

Thus two features are highlighted : Firstly, proportional thresholds allo better performance than a uniform threshold, which seldom works on theoretically calculated scale, but must be tuned to allow even 40% of th nets to survive without death or epilepsy. Secondly, if the threshold leve is scaled according to performance of the net (i.e. reset at a lower valu after death of activity, or inserted initially after previous experienc with the nets concerned), then the cyclic states and eligibility of net with either type of threshold are improved.

In contrast, the data from structured nets, rows 5 and 6, Table 1, indicat that Γ = .3 is an improvement over Γ = 0, in other words, a degree o proportional threshold on a constant base allows longer, more eligibl cycles than completely normal (proportional) thresholds. This effect is fo very structured netlets, see chapter 4 for an explanation of the structure Starting from an average of 15 external connections per neuron (which i homogeneous for the given parameters N = 100 Nsub = 25 m = .2) the number i halved so that there are only 7.5 external connections on average, and 12. internal connections on average. This implies m internal = .5 and m externa = .1, and still the Γ = 0 is better than Γ = .3 case. But if external con- nections are 3 or 1 on average, internal connections are 17 and 1 respectively, so that $\frac{M_{int}}{M_{ext}}$ = 17 and 57 respectively, and normal threshold start to fade. This may be the cause of the high internal connectivity. Normal threshold nets are more prone to trivial cycles at high connectivity. The idea behind use of normal thresholds was to improve eligibility by giving neurons with very few or very many (exit-inhib) inputs more of a chance to be on or off, respectively. Yet, when there is an increased average number of connections the chances are more even anyway and the stimulus and normal threshold functions converge .

APPENDIX TO CHAPTER 4
EMPHASIS ON LOCAL CONNECTIONS

NUMBER OF NETS = 84

N = net size
Nsub = subnet size
m = connectivity
Qs = m(sub)/m(ext)
Mint = # internal links
Mext = # external links
BW = extent of brainwashing
bw at 10%. BW=0 none
BW =% Vij left
Vo = threshold

k = cycle period
elg = eligibility
To = transient time
onset to cycling
Tt = transition time
reps = repeated states
Y = threshold type :
0 normal to 1 uniform
* = non-cycling
#d = number of deaths

Run	Nsub	Y	m	Qs	BW	#d	k	To	Tt	elg	reps	Vo
1	10	0	.15	5	0		22	12	9	34	few	2.33
					61		2	41				
2					0		65	230	2	100	many	2.34
					68		*	500		97	none	
3					0		2	8				2.15
					59		8	16	7	14	few	
4	20	0	.15	5	0		3	16	12	6	few	2.4 >k
					66		5	12	3	7	few	
5					0		28	13	8	16	few	2.44
					85		12	36	20	38	few	>>k
6	10	0	.15	10	0		2	11				2.22
					65		2	11				
7	10	1	.15	1	0	4	21	7	6	38	few	2.8(1.07)
					88	3	27	7	6	65	few	
8					0	3	4	19	10	20	few	2.5(.94)
					84	3	107	37	36	56	some	>k^
9					0		7	20	10	27	few	2.3(1.07)
					72		6	23	11	16	some	>k^
10					0		11	7	6	31	few	2.9(1)
					76		1	12				
11	10	.3	.15	1	0,99		1	4				2.8 ()
12					0		146	70	13	100	few	2.5 ()
					74		*					
13					0		6	15	5	14	few	2.3 ()
					65		4	7	2	2	few	
14					0		8	44	7	24	many	2.9 ()
					63		10	26	13	24	many	>k
15	10	0	.15	1	0		256	142	47	100	v.many	2.8 ()
					95		38	24	21	41	many	
16					0,67		**					2.5 ()
17					0,98		1					2.3 ()
18					0		10	13	8	19	v.few	2.9 ()
					68		8	18	4	17	some	
19	10	0	.15	1	0		20	30	18	28	some	2.6 m
					85		7	426	7	48	vv.many	k
20					0,65		**			99	none	
21					0,99		1					2.5()
22					0,54		2					2.9
23					0,79		**			99	none	2.36

Run	Nsub	Y=0	m	Qs	BW	k	To	Tt	elg	reps	Vo	
24	50		.15	5	0	393	30	25	100		2.32	
					87	*						
25					0	3	44	5	12		2.73	>k
					77	91	77	58	70			m
26					0,96	2					2.5()	
27					0	1	10				3.08	
					57	11	9	7	12			
28					0	2					2.2	
					72	*						
29	20				0	16	136	10	17	many	2.28	
					76	*						
30					0,72	**					2.48	
31					0,92 3	2	11				2.5	
32	10				0	19	32	9	31			
						4	101	9	7	many		>k
					89	2						
33					0	65	230	22	100	many,correlated		
34					0,68	2	15					
35					0,71	**				none		
36	10		.3	3	0,99	1					4.79	
37					0,42	2					5.1	
38					0,47	2					2.5(.57)	
39	10		.15	1	0	*				v.many		
						69	232	32	100	correlated		
					70	261	199	12	100	some		
					65	*				few		
40					0	1-5	8	3	8		1.1,1.2	
						21	44	13	33	some	1	
						16	6	5	17	some corr	.9	
					57	3-6			5			
						78	17	16	55	many corr		
41	10		.3	3	0,99	1,2						
42					0,42	1						
48	25		.15	12	0	36	88	21	49	few		
					89	62	21	20	55	few corr		
						151	48	44	54	vv.many		
49					0	6	31	7	23			>k
					89	114	267	71	75	many		
50	20		.15	5	0,bw	2	20	14	12	none		>k
51					0	338	124	23	100	few		
					85	*				none		
52	10		.15	5	0	101	73	44	48	many corr		
					94	4	34	9	15	few		>k
53					0,79	**				none		
54	20		.15	10	0	13	58	9	46	some k-k'-k !		
						213	73	71	59	many		
					73	80	18	17	66	several corr		
55					0	24	112	8	27	few		
					86	201	31	24	73			
56	25		.3	3	0,bw	1,5						
57	20		.15	20	0	22	57	12	38	few		
						215	167	113	54	many		
					85	61	107	31	46	some		
						28	169	15	47	many		
58					0	14	71	7	26	several corr		
						32	243	16	45	vv.many		
					79	6	118	117	46	many	>>k	

Run	Nsub	Y	m	Qs	BW #d	k	To	Tt	elg	reps	Vo
59	10	0	.3	1	0,55	1					
60					0	6,1	11	7,0	9,0	none	
					94	7-1	6	4-0	9,0		
61			.15	1	0	26	74	23	53	some	
						146	219	123	91	v.many	
					97	52	67	24	58	some corr	
62					0	12	19	5	22	few corr	
						* ,				some corr	
					76	23	23	14	37	some	
63	30	0	.15	0	0	*			1	net only N=150	
					87	*					
			m	Mext							
64	50	0	.2	10	0	3	101	2	4	none	
					96	47	44	20	82		
65				.2	0	*					
					86	*					
66	25	0	.2	15	0	3	42	2	4		
					95	18	14	13	18		
67					0	1	74				
						63	109	41	47	none	
					86	1	100				
68				7.5	0	43	34	31	52		
					76	*					
69					0,82	**					
70				3	0	*,1	278!			some	
					79	**					
71				1	0	2	148	12	10	many corr >k	
					80	2	70	65	16	many in 4 >>k	
72					0	76	103	31	56	many in 3	
					76	60	101	24	27	few	
			Mint	Mext							
73	10		1	9	0	*				several corr	
					64	***				none	
74	10		2	9	0	220	46	16	97	many corr	
					64	***				few	
75	10		3	9	0	2	36	5	2	few	
					72	***				few corr	
76	10		6	9	0	2	92	12	2	few	
					70	***				many corr	
		Y	m	Mext							
77	25	.3	.2	15	0	1					
					99	7	22	12	16	none	>k
78					0	1,3					
79				7.5	0	6	8	5	13		
						60	40	37	58		
					88	334	157	93	73		
80					0	127	350	37	100		
					70	*					
81				3	0,bw	**					
82					0,bw	**				few	
83				1	0	328	110	87	66	subcyc :k	
					49	156	89	88	45	vvvv.many	
84					0	80	60	24	37	subcyc	
					56	108	67	66	43	subcyc	

APPENDIX TO CHAPTER 5

EXAMPLES OF THE BEHAVIOUR OF NETS DURING CUTTING
TABLE OF ELIGIBILITIES
TABLE OF LONG TRANSITIONS (ONE PARTICULAR NET)
GRAPHS OF LONG TRANSITIONS
GRAPH OF TRANSITION TIME VS PERIOD

Some Individual Comments and a Description of the Effects of Cutting on each Net (mins 1 to 15)

Net 1 : $N = 100 \rightarrow 4*25$ $h = .35$ $m = .075$

Initially, as for all m = .075 nets, no cycling was found. Eligibility was high and there was no evidence of reps in netlets. After some nets a range of long cycles with rapid transitions were common. No reps were recorded until half the neurons had been restricted. Three types of cycles emerged: short ($K \leq 6$) mediumly eligible cycles with relatively long transitions and long transients; medium ($14 \leq K \leq 103$), highly eligible cycles with relatively short cycles, but for few exeptions; and long, very highly eligible nets with very rapid transitions and no repeated states.

The architectured stage (after 18 to 25 out of 25 cuts) is characterised by repeated states, which are particularly abundant after cuts 21 to 23, that is, with 2 to 4 neurons per netlet in communication. A variety of long cycles occurred. In one highly eligible net (cut 18), which didn't cycle, correlated reps in various netlets showed that the net nearly cycled on occasions, by that one or two netlets could not accept the period and the cycle didn't perpetuate.

A number of slow transitions occurred, e.g. cut 20: K = 150 transient = 95 transition = 72. No reps recorded!

Table of number of participating neurons in each netlet

Netlet	t = onset	t - k/4	t - k/2	
1	7	7	3	Netlet 4 is first to cycle,
2	22	22	0	followed by 1, 2 and 3.
3	23	0	0	
4	11	11	11	

Netlet	t = onset	t - 4K	t - $4\frac{1}{2}$K	Cut 21 : K 22 transient = 110
1	X	X	0	Transition = 102
2	0	0	0	Netlet 4 leads followed
3	X	0	0	by 1, 3 but not 2
4	X	X	X	

Net 2

Same parameters as net 1, but different net.

Initial behaviour - once again no cycling before architecture.

Cuts 0-5 and 9-12: highly eligible, non-cycling nets mostly, with no reps in 500 steps. Once again, repeated states occur only after 14 cuts, or more than half the neurons disconnected. Thus, the early behaviour of the net is characterised by a variety of very eligible, long cycles with rapid phase transitions and no reps in netlets and only occasionally a short cycle.

Later behaviour (after 14 cuts) differs from net 1 : a range of shortish cycles (K < 15) mediumly eligible with a few reps, but transitions are relatively slower. The scarcity of reps may mean that few cycles are easily attainable. Transitions are < 30. The differences between net 1 and 2 imply that parameters (how many neurons) are less important than pseudorandomness (which neurons).

Strong architecture → 1st netlet onset of cycling.

Net 3 (Same parameters as nets 1 and 2)

Again, the nets are highly eligible and don't easily cycle. Only, this time, no cycling or reps are seen for the first 16 cuts (with very few exceptions). Thereafter a host of short to medium length cycles with medium eligibility, several reps and a variety of transition times, occur. There are a couple of longer cycles (92, 178, 132) with rapid phase transitions and medium eligibility.

K = 178 occurs for cut 14, i.e. > $\frac{1}{2}$ neurons disconnected. Note that for this particular net, this is relatively early, eligibility is still high and reps scarce. Neuron one is the first neuron cycling, but netlet one is the last netlet to fall into cycling. That is, even this degree of architecture doesn't imply that neurons drive their own netlet to cycling ahead of others. Note that neuron 1 has no external outputs, that is, it influences other netlets to cycle via the other neurons in its netlet, yet the rest of the netlet may not yet be cycling fully. The few repeated states that occurred indicated that netlet 3 seemed to drive netlet 2 into reps with period 108 and 127.

The former occurred within the cycle 178, the latter before cycling commenced. Once the nets have found shorter cycles, transitions are still rapid, but the rep rate increases.

At cut 17 K = 92, an interesting exeption occurs. There is a very long transition starting at the outset (t.-329) but only 4 neurons in netlet 3 are involved until t_o - 78 which is within period length 92. The rest of transition is relatively rapid. In netlet one, a repetition length of 92 occurs, but disappears again briefly before onset of cycling. During this long transient time, many reps are recorded, and there is often a correlation of period between pairs or triplets of netlets, netlet 2 seems to interrupt these attempts to cycle. Most of the nets start the transition to cycle at, or soon after, the outset. After cut 17, K is a multiple of 6 and sometimes 11 and most reps are individual except after cut 22.

<u>Net 4</u> Parameters : N = 100 n = 4 (N_{sub}= 25) m = .15 (M = 15) h = .35

There is a notable difference in the behaviour of this more connected net, before much architecture is included. That is, for cuts 0 to 4 there are a range of shortish cycles with medium eligibility, rather different from the non-cycling nets found for m = .075. Rep and slow transitions are absent, as before, in unarchitectured nets. For the rest of the cutting, the period of cycling = K oscillates between short, long and not found, with the corresponding low and high participating of neurons. Only 20% nets have short cycles after cut 5. Remarkable changes in behaviour can occur for just one cut. Repeated states only occur later in the process, after 17 cuts. A rich profusion of reps is found after 18, 20, 21 cuts, which have very long or no cycles and very high elg. Thereafter, fewer, more independent, uninterrupted reps occur.

Cut	K	Nets 1	2	3	4
22	28	28	35,14	14	14
23	31,62	←	Few	→	→
24	310	5	1	31	2
25	42	6	1	14	2

These reps indicate that netlet 2 is uncertain and affected, then opts out when left alone. Netlet 2 is an originator of the 14 and 31 factors. It has the longest cycles amongst individual netlets.

Transitions : although the cycles are short at first, transitions are rapid, unlike previous occurrences of low K. Long transitions are found at cuts 22, 23. K is medium (28, 31, 62). There are only a few reps and good elg. 70-75%. The first neuron cycles soon after the start about 80 steps before onset. The first netlets are cycling by t.-2K → - very long transition.

<u>Net 5</u> (Same parameters as net 4)

This time the uncut net has a very long cycle (of 343) with 100% participation and rapid onset. This is agonisingly different to net 4. After the first cut, however, there follows a spate of shortish cycles with low to medium participation and rapid transitions. The transient times are relatively long, but no reps are recorded.

There is an exeption at cut 7, where a long cycle of 208 occurs. A few repeated states are recorded although the transient time is only 65. The first non-cycling net is at cut 10, which also, curiously, fell into a two cycle and for the same threshold, found no cycle in 500 steps, therefore the 2-cyle cannot be a very deep attractor. After cut 11, the number of repeated states increases to many by cut 17. From cut 10 onwards fluctuations between short, long and unfound cycles occur as the net is cut up or as thresholds are changed. The participation and cycle period are, as usual, correlated. No pattern emerges.

An interesting aspect of the occurrence of reps in non-cyclic nets is that after 10 cuts, there are none and after 18 + 19 cuts there are many, which is nothing new. But after 17 cuts, the eligibility is its usual high, but very many reps occur in netlets 3 and 4 and none in 1 and 2.

<u>Transitions in Net 5</u>

Cut 18 - The longest cycle 361 has a rapid transition and transient (T = 23) whereas the short cycle K = 10 has a very long transient t = 300, transition time 83 and the first cycling netlet is found at t = 80, i.e. 8K before onset, but this only includes 5 neurons, the rest undergoing a rapid transition to cycling.

<u>Cut 20</u>	Elg.	K	1st Neuron	1st Netlet	
	33	6	159 slow	24 slow}	
	70	40	85 slow	10 fast}	Many reps
	67	74	110 slow	29 fast}	pair-correlated
	72	106	20 fast	10 fast}	
	69	112	150 slow	21 fast}	

There is a richness in the number of available cycles. Most transitions are slow. This one cut averages as different from all the rest.

Net 6 : Early Behaviour

Once again, the net starts with a spark of long eligible cycles with very rapid transitions (cuts 0, 1, 2), followed by a long spate of extremely short cycles, till cut 12, which is followed by short cycles with medium elg. No reps occurred before cut 18. Non-cycling/long period highly eligible nets none several → many reps (cuts 19-23) with the last few nets short cycled, individual reps.

Slow transitions: Cut 23 K = 16 1st neuron (t-35) 1st Netlet (t-16)

Nets 7,8,9 m = 20% h = 35%

Early behaviour (general) : Cuts 0-7 short cycles with few exceptions. Cuts 9 to 17 (roughly) have a variety of cycles (if found) with moderately eligible neurons and fast transitions - except Net 7 which has short cycles. Some of the cycles in nets 8 and 9 are remarkably long. Later behaviour : Net 7 ends in a whimper (cuts 20-25). Net 8 has long to unfindable cycles and net 9 has some short and some long cycles. Repeated states are rare in net 7, with some at 19-21 cuts but nets 8 and 9 have many reps after 12, 15-23 or 18-24 cuts, reinforcing the previous occurrences of repeated states. Some very long transients occur 241 for K = 1 (net 8 cut 2) 360for K = 36 (cut 20). Long transitions occur for shortish cycles (K < 20) at medium stages of nets 7 and 8 and late stages of net 9. See graph of participation in the cycle K = 260 as during transition.

Nets 10, 11 m = 25% h = 35%

Early (before 12 cuts) both nets cycle easily, but usually with short periods and a few longer exeptions as cut 12 approaches. Thereafter most cycles are long, or not found. Net 10 has a variety of cycles and net 11 seldom cycles and then with long cycles. The individual netlets have quite long cycles for N = 25.

Repeated states are very common after 20-23 cuts as usual, even after 24 a few reps occur since interruption is still possible. Often reps are correlated in pairs or triplets, (especially before 19 cuts), but then some other periods later dominate.

Slow transitions for short cycles occur at a range of cuts. There are some examples of very long transitions at cuts 13, 19 and 23:

Examples of Slow Transitions in Nets 10 and 11

Net	Cut	K	Transition	Transient	
10	23	108	151	152	26 neurons cycle from onset. Net 2 has many reps and finally fully accepts 108 in the last 25 steps.
11	13	34	47	48	Repeated states 17, 2, 17, 17
11	19	28	28	33	few reps, low elg.
11	23	56	290	298	See graphs of participation in each netlet during transition period doubling? The first netlet to cycle actually has K = 4 and few neurons.

Nets 13, 14 and 15   m = .3

Early behaviour : short, ineligible cycles K < = 4, then K < = 12 after cuts 5, 10, 13 respectively. The first long cycles occur after cuts 6, 17, 20, respectively. Later, long cycles occur with reasonably eligible individual netlets. There are no short cycles after cuts 17, 16 and 20, respectively. Repeated states in netlets are shown for net 14:

Cuts	Netlets 7,	2,	3,	4	K
7	4	3	1	3	12
10	9	12	1	9	16
	7	X	1	7	16
	5	2	1	2	10
11	5	X	1	5	12
12	10	3	1	10	30
17	16	16	5	16+	80
19	48	48	5,10	+++	240
20	52+	52+	5	1	None
21-25	27	27	5	1	135
	42	7	5	1	210

Period is not always visible in in the reps, but after 12 cuts and especially after 21 cuts, K is the LCM of the 4 reps.

<u>Transitions in Nets 13, 14 and 15</u>

Net 13 : Fast transitions until cut 17

Cut 17 : K = 6 Tt = 16 Cuts 18-21 : no cycling
Cut 22 : K = 15 Tt = 28 See graphs of participation
Cut 23 : K = 130 Tt = 209 See graphs
Cut 24 : K = 13 x 23 x 2 x 1 > 500
Cut 25 : K = 11 x 8 x (2) x 1 = 88
K = 13 x 8 x (2) x 1 = 104
K = 13 x 8 x 2 x 11 > 500

Net 14 : At cuts 15, 17, K = 6, 80 have reasonably long transitions thereafter, cycle period is too long.

Net 15 : Cut 21 : K = 185, 42 short trans (relatively)
K = 10, 15 long transitions (30-45)

Cut 22 : K = 75 Tt = 162} transition > 2K
K = 20 Tt = 62}

APPENDIX TO CHAPTER 5

MAXIMUM ELIGIBILITIES FOUND IN CYCLES AS
NETS 1 TO 15 ARE CUT INTO 4 NETLETS EACH

	CODE NUMBERS OF THE NETS													
CUT	1	2	3	4	5	6	7	8	9	10	11	13	14	15
0	*	*	*	65	100	100	12	93	100	15	.	.	.	.
1	*	*	*	.	48	100	7	100	.	.	13	.	.	.
2	92	*	*	34	16	100	.	.	5	5	.	7	.	.
3	18	*	98	7	41	4	.	.	.	28	4	7	3	.
4	94	13	*	6	36	.	.	100	3	35	23	.	.	.
5	93	*	*	*	28	.	.	16	.	21	20	100	.	4
6	22	38	*	99	21	.	60	.	.	40	10	100	4	3
7	42	56	*	18	85	.	.	37	17	16	14	100	8	4
8	37	92	*	88	16	.	6	*	36	3	22	*	18	5
9	59	*	*	*	56	6	100	16	7	10	12	99	.	7
10	69	*	*	*	*	10	.	*	.	21	20	100	18	7
11	14	*	*	.	18	.	52	17	.	19	18	100	19	15
12	14	*	*	.	53	32	93	60	83	*	47	*	21	.
13	29	76	*	100	34	45	20	19	6	*	28	100	15	15
14	*	38	96	*	23	59	64	5	.	49	100	*	17	4
15	*	28	*	*	66	38	95	*	21	*	*	*	25	.
16	94	17	*	*	75	19	87	*	.	66	*	*	46	.
17	50	12	69	*	*	21	48	*	43	.	*	91	48	42
18	*	37	49	*	*	44	64	*	.	7	*	88	*	6
19	50	56	47	13	*	*	45	45	*	*	20	*	54	8
20	63	43	48	70	72	*	8	*	36	14	*	*	*	47
21	61	30	47	*	60	*	20	*	38	11	*	*	48	50
22	67	28	74	75	54	75*	7	65*	44	37	53*	36	40	48
23	65	21	56	71	68	50	7	61	76*	50*	97*	62	49	36
24	66*	21	52	36	59	40	7	60*	*	40	53*	47*	53	36
25	54	21	51	34	55	34	7	74	50*	34	51	*	48	49
M	8	8	8	15	15	15	20	20	20	25	25	30	30	30

* noncyclic modes occur . epileptic or K=1,2

APPENDIX TO CHAPTER 5

EXAMPLES OF SLOW TRANSITIONS IN ONE NET

N=100 M=15 H=35% Nsub=25

CUT	ELG	K	To	Tt	Tn	#REP	NETLETS ELG	NETLETS Tn / Tt
0	10	7	22	7	5	26	3 3 1 3	0 3 5 2 3 7 5 4
0	12	3	20	8	5	34	2 4 3 3	5 0 2 1 7 3 4 8
2	5	4	16	11	2	13	0 1 2 2	
* 6	99	107	231	54	1	338	25 24 25 25	0 1 0 0 28 28 54 27
7	18	18	36	20	4	25	4 2 9 3	1 4 0 2 5 10 20 5
7	16	3	19	9	3	15	3 1 6 6	3 3 2 0 5 3 9 5
8	88	53	50	29	0	72	23 22 23 20	0 0 0 0 27 29 29 26
*22	75	28	105	83	49	57	11 16 25 23	33 0 49 49 48 53 83 56
23	69	31	26	25	25	16	12 8 25 24	10 0 25 16 14 22 25 25
23	71	62	144	143	138	121	15 7 25 24	0 86 138 108 12 116 143 139
*23	69	31	78	77	64	51	12 8 25 24	0 42 64 45 19 46 77 52
23	71	62	102	101	98	80	15 7 25 24	0 65 98 74 12 75 101 84
23	71	62	18	17	3	21	15 7 25 24	3 0 2 2 17 5 15 11
24	36	310	5	4	4	3	9 0 25 2	0 0 4 3 4 0 4 4
24	36	310	18	17	11	3	9 0 25 2	6 0 0 11 17 0 9 12
25	34	42	13	12	12	3	9 0 23 2	11 0 0 12 12 0 6 12
25	34	42	16	15	5	3	9 0 23 2	0 0 5 5 3 0 15 6

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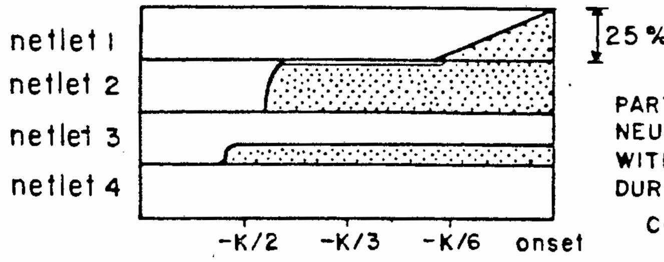
* see graphs

Transition Times

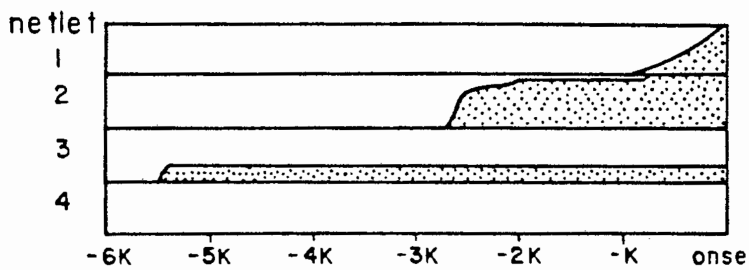
To = transient: start -> whole net cycle
Tt = transition: 1st neuron cycling -> whole net cycling
Tn = 1st netlet cycling -> whole net cycling
Tn / Tt in netlets: netlet cycling -> whole net cycling /
1st neuron in netlet cycling -> whole net cycling
=> Tt-Tn = transition time in netlet

NETLETS ELG = # eligible neurons in each of the 4 netlets

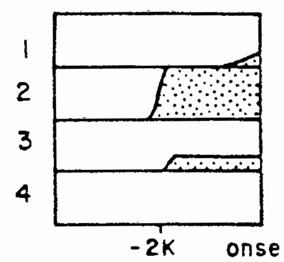


PARTICIPATION OF NEURONS IN CYCLE WITH K=260 DURING TRANSITION

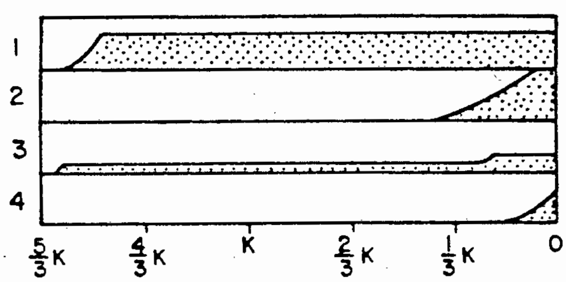
CUT 23



THE INCREASE IN NEURON PARTICIPATION DURING THE TRANSITION TO A CYCLE K=56 (CUT 23)



PARTICIPATION IN TRANSITION TO K=15 CUT 22



PARTICIPATION IN TRANSITION TO K=130 CUT 23

<u>FIGURE A6</u> Four transitions to cycling are depicted. Participation in each netlet is plotted against time, (shaded) so that the succession of netlets is visible.

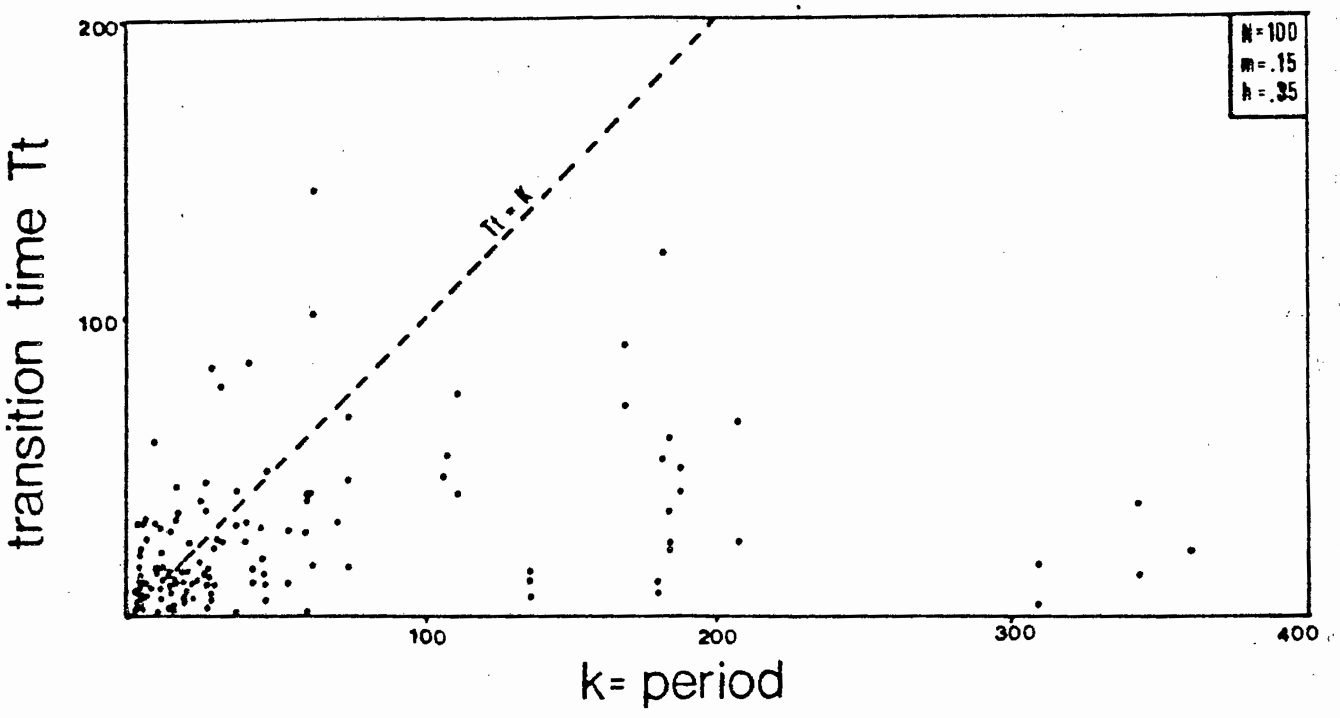


FIGURE A7 The relationship of transition time to period is shown. Each dot represents one run. The line k=Tt is a reminder that most transitions are relatively short, but that some, usually within structured nets, are longer.

SUMMARY

A computer model of a network of neurons used to study the phenomenon of cycling, was based on the on/off/refactory nature of the state of neurons ; the threshold nature of firing ; the inhibitory or excitatory nature of synapses and the activity-dependent changes in synaptic strengths that facilitate memory. The model operated in discrete time steps and a randomly generated connection matrix (conforming to certain gross features, N,m,h, structure) represented the synapses within a small ,closed set of neurons . The plasticity algorithm for self-organisation (activity-dependent alteration of synaptic strengths) was sometimes applied to nets before searching for cyclic behaviour. The activity sequence was recorded for the purpose of detecting cyclic behaviour and studying the length and accessability of a cycle, the number of neurons dynamically involved in the cycle and the time taken for the transition from no neurons cycling to all neurons cycling.

Each particular net was found to have a small number of different cycles easily accessable via different initial conditions. The occurrence of cycling ought to be rare, considering the possible number of states of the neurons (2 to the power N=netsize) and yet repetitions are easily found within 500 steps (and usually within 100 steps.) The next striking feature was that many initial conditions led to the same cycle or that there existed relatively few final states. The topological structure dictating these cycles differs between two nets with the same parameters, resulting in a wide variety of behaviour , but on average the complexity of cycling could be related to the topological quantity , distance , the average length of the shortest routes between pairs of neurons

(measured in number of synapses, regardless of polarity). For theoretically really random nets, distance is a function of netsize and connectivity only , and increases markedly at low connetivity , depending on the netsize. This clearly indicates the edge effect in smaller nets , which diverge from very,very large nets as m decreases , resulting in large distances between neurons (typically N=60 , m=8% nets would be in this catagory) which is consistent with the complicated cycling frequently observed for such parameters. In the low connectivity region, artificially high distances will prevail if nets as small as N=100 are used to model N=100000 systems.

The pseudorandom nets used in the model have slightly longer distances than their random counterparts and imposing structure increases the distances yet further. Inhibition and self organisation also affect topology, but were not studied in the context of distance .

On the practical side , the survival of nets tended to be critically dependent on threshold in an unpredictable way , which led eventually to the use of normal thresholds, so that each neuron had a threshold proportional to its hardwired input. (If the uniform threshold used is too high(low),activity will fall(rise), hence stimulation for the following step will fall, hence activity will fall further, in a positive feedback situation, unless a net is resilient to fluctuations in activity, via inhibitory action.) Sparsely connected nets and structured nets , with large topological distance, frequently failed to repeat any state for 500 steps and more highly connected nets showed a predominance of trivial cyclic states. Both these features were surprising after studying nets which easily found shortish cycles. The inhibitory fraction h=.35 was chosen from the suitable range .3 < h < .45 which allows several non-trivial modes to be found in a reasonable time. Higher h improved eligibility and allowed longer cycles.

The self-organisation algorithm, as used, was not found to be a reliable mechanism for improving the resilience , eligibility and variety of cycles of a net , although many instances of successful brainwashing (self-organisation) were observed, that is nets became more resilient to large fluctuations in activity/initial conditions and the inherent cycles were suppressed, allowing more neurons to participate eligibly.

The study of transitions to cyclic modes (from the time the first neuron cycled) revealed rapid transitions , shorter than one cycle period , for cycles the order of 10 or longer. Intuitively, longer transitions were expected - one neuron or group of neurons seeding a transition to cycling, rather than a more general condition leading to rapid transition. More eligible neurons were observed participating in the longer, more complicated cycles, and hence the transition time required to gather many eligible neurons into a cycle , increased , but very seldom exceeded one period. During the transition the number of participating neurons increased smoothly and at an increasing rate towards cycling , unless severe architecture was imposed on the net .

In chapters 4 and 5 structure was imposed on the connection matrix , causing partial division into netlets. Greater in-homogeneity in the distribution of connections led to greater distances between neurons and hence more complicated cycles. In very pronounced cases, the accumulation of cycling neurons took the form of a step-like succession of smooth transitions in each netlet. The behaviour was complicated by the fact that nearly independent netlets became less eligible because of the small size of each netlet. In the context of increasing inhomogeneity , transitions to cyclic modes were studied with the objective of understanding what sort of structure allows rapid transitions. A wide variety of parameters, application of self-organisation and the use of normal thresholds all yielded rapid transitions. In fact slow transitions were rare except when a net was divided into independent netlets with just sufficient internetlet connections for one netlet to disrupt the cyclic mode in another netlet. Eventually one of the cyclic modes would be sufficiently stable in one of the netlets to spread to other netlets by 'forced oscillation' resulting in a slow transition.

It would be useful, but difficult, to be able to quantify the degree of structure in a pseudorandomly generated net. The measure of distance between neurons was similar for pseudorandom nets and nets of 4 netlets with internetlet connections five times sparser than internal connections. The exclusion of synaptic strength and polarity in the distance calculation limits its usefulness.

This thesis has taught me a considerable amount about the 'state of art' of computer simulation in brain science. There is a relatively small group of scientists interested in neural networks, mostly physicists, scattered around the world. Reading their papers and books (some dating from the 50's, but most from the past 5 years) has been exciting , but also awe-inspiring because the unknowns in this field are vast and open. The mysteries of the mechanisms of higher functions of the brain are immediately interesting to most people, but the many-body problem of neural networks is especially tempting to physicists.

In doing the research for this project, I became sufficiently familiar with neural networks to sustain a long-term interest in the subject and to have a large number of ideas to pursue, since the subject is inherently open-ended. Many of the results obtained were unpredicted, hence in retrospect, the understanding of neural networks of this particular type has been expanded to be consistent with computer studies.