J. Theoret. Neurobiol. **1**, 82–104 (1981)
Printed in Australia

COMPUTER SIMULATION IN FORTRAN OF LARGE NERVE NETWORKS. I. THE SYSTEM

RONALD J. MACGREGOR*
Department of Chemical Engineering, University of Colorado, Boulder, Colorado 80309, U.S.A.

(Received March 30, 1981)

Abstract

This paper describes a digital computer software system in FORTRAN for simulating the dynamic electrical activity of single nerve cells and of nerve networks (ranging up to 100,000 cells), and for displaying and analyzing global dynamic patterns in network activity. The production of computer-produced movies of network activity is described. A FORTRAN listing of a representative network simulation program is included for a 1700-cell network which learns with changing synaptic efficiency.

1. Introduction

Nerve networks are magnificent anatomical structures which mediate intricate dynamic patterns of electrical activity whose full range of diversity and significance has as yet been only glimpsed. Their full significance resides in the fact that these dynamic electrical patterns occupy a crucial position in the hierarchy of the organization of intelligent life. Specifically, the main dynamic variables of brain operation can be arranged in five strata as follows.

(5) Behavior, coordinated by the response of the muscle systems of the body to global activity of the brain.
(4) Mentation, representing global internal operations of the brain, coordinated by the interaction of various systems of nerve networks.
(3) Patterns of electrical activity coordinated by nerve network structure.
(2) Ionic current loops traversing nerve cell membranes, coordinated by cellular and molecular membrane mechanisms for modulating membrane conductance.
(1) Chemical secretions of neurohormones and transmitters, dependent on fundamental biochemistry and responsive to higher nervous system control.

* Supported by funds from the University of Colorado Computing Center and Grant No. ECS-7911794 from the National Science Foundation.

(Additional strata of physical chemistry and physics below and society, ecology, and cosmology above would in some sense complete this scale.)

The significant observation for the present purposes is that the coordination of electrical activity in nerve networks is the critical mediator between fundamental neurophysiological mechanisms on the one hand and the elemental building blocks of mentation and behavior on the other. As such, they are of fundamental significance in the worlds of biology and psychology, and have been studied from the 'bottom up' in the former and from the 'top down' in the latter. Nonetheless, the nature and intricacies of microdynamic neuroelectric patterns still remain essentially obscure. From this point of view, the main goals of nerve network research should be the elucidation of:

(1) the nature and character of global electrical patterns, *per se*;
(2) the relation of fundamental neurophysiological mechanisms (synaptic generation of ionic currents, excitability processes, etc.) to the genesis of pattern in the nerve nets; and
(3) the mapping between elements of mentation and behavior on the one hand and electrical patterns on the other.

It seems clear that computer systems such as the one to be described here and theoretical modeling of neural processes generally should be very helpful and perhaps even necessary in the achievement of each of these three classes of goals. This can be perhaps best illustrated by consideration of some of the main difficulties surrounding current experimental and theoretical research in this area.

First there is the extreme complexity and malleability of even the most basic neurophysiological mechanisms. Thus, in relatively simple forms (invertebrates) central nervous system complexity is at a relative minimum and the mapping of behavioral components through electrical patterns to neurophysiological mechanisms is, in principle, at least, often readily discernible. Examples are the reflex twitch mediated by the lateral line system and Mauthner cell in some fishes (Bullock and Horridge, 1965) and the description of locust flight control by Wilson and Waldron (1968). Even in these simple forms, however, the basic richness of cellular neurophysiology (synaptic chemical transmission, dendrodendritic synapses, excitability processes, accommodation, various forms of plasticity, idiosyncratic structures such as myelinated dendrites in the Mauthner cell, etc.), and of network configurational complexities (it appears impossible to conceive the interconnection patterns of networks with even 50 to 100 cells) renders satisfactory and complete understanding of the dynamic electrical properties of these networks very difficult to attain (Bullock and Horridge, 1965). Fundamental mathematical and simulation models of the conductance modulations and excitability processes generating electrical signals such as developed by Hodgkin and Huxley (1952), Harmon (1961), Lewis (1965), Rall (1962), MacGregor and Oliver (1974) and MacGregor and Lewis (1977) can be of a great deal of help in studying the generation of signals in single cells and relatively small networks in systems such as these. For example, it is easy with the computer system described here to develop a reasonable quantitative predictive model for an entire Mauthner cell to be used as a working tool in ongoing experimental research on the varied properties of that single cell.

Secondly there is the extreme refractoriness of global electrical potential patterns to experimental investigation. Nerve networks undoubtedly produce a wide range of patterns which we have not yet learned how to conceptualize, let alone measure. At least four levels worthy of exploration can be indicated. (a) *Simple reflexes.* Linear transmission of signals, involving many parallel fibers, through one to several synaptic linkages; i.e. a beginning-to-end pattern. Presumably much of the circuitry of the spinal cord and brain stem mediate such patterns as these. (b) *Switchboard patterns.* A network mediates between a family of inputs and a family of outputs, and the 'pattern' consists of the triggering of a subset of the outputs in an appropriate temporary cohesion on the basis of the input pattern. The cerebellum, and parts of the reticular formation, as well as various sensory and motor nuclei in the thalamus and elsewhere seem likely candidates as mediators of such patterns. (c) *Global microdynamic patterns.* More highly coalesced transient or standing patterns which correspond to elemental building blocks of mentation or behavior. The internal representations of external objects in perception, co-ordinated motor sequences in action, memories and thoughts in mentation, words in linguistics, and so on. The 'circularities' of Kubie (1930), the 'cell assemblies' of Hebb (1949), the 'trace systems' of Lashley (1960) and the 'statistical configurations' of John (1972, 1978) are candidate conceptualizations of these. Although the first two of these conceptions are essentially linear in the sense of being based on sequential chains or loops or transmitted spikes, it would seem that, at least in higher manifestations, such simple linear chains and loops will not do. Thus, in these cases the firing of a given individual cell is nearly always dependent on the approximately simultaneous firing of a large number of cells. Moreover, the firing of this particular cell often serves as an effective trigger only in conjunction with the approximately simultaneous firing of still other cells. Thus, one's concept of a global microdynamic pattern must be based on the concept of sets or clusters of cells firing at each state in the temporal evolution of the pattern. Such global microdynamic patterns might be thought of as emergent properties of nerve networks in the sense that their significance and character reside primarily in their total cohesion rather than in the participation of any single action potential, or perhaps of any particular single cell. The cerebral cortex certainly, and perhaps regions of the reticular formation, and limbic system as well may be thought to mediate meaningful global microdynamic patterns in this sense. (d) *Global fields.* The global collection of all ionic current loops in a particular volume of nervous system tissue—synaptic currents, action potential currents—as they course through intra- and extracellular fluid and across neuronal membranes, and the electromagnetic fields with which they are inextricably associated (Stratton, 1941). Such global current fields are the source of the potentials recorded commonly with macroelectrodes. Typically, for individual current loops, the magnetic fields are very small (Elul, 1972) but whether or not in some particular network structures and under some particular spatiotemporal activity pattern, the synaptic current loops from many cells may be momentarily in such an alignment as to produce a non-negligible magnetic field component remains an open question.

Experimental tools for investigating electrical patterns in nerve networks range from single microelectrodes which penetrate into or close to single neurons to recently developed techniques which measure and display global localization of blood flow as an indication of the general global distribution of electrical activity in different regions of the brain. Somewhere intermediate in this range is the EEG which measures the global extracellular aggregate of ionic currents at the electrode and thereby represents a distorted average of cell population activity. In point of fact, the activity pattern of a nervous network involves the intricate coordinated activity of thousands to millions of individual cells operating in concert, and the secrets of these intricacies have remained very largely hidden from experimental tools. Moore *et al.* (1966) have developed statistical techniques for analyzing single and simultaneously recorded spike trains in the hopes of generating inferences concerning their spatiotemporal patterns and these have indeed been useful in a wide variety of situations. Nonetheless, experimentally and mathematically, these techniques are generally restricted to dealing with two or three cells.

Computer simulation programs for large networks of activity provide a means for generating ongoing dynamic activity in a model whose possible manifestations can then be sought for in unit records and in EEG's, thereby potentially linking these two domains of experimental investigation. Moreover, the intricate dynamic patterns evidenced in the computer simulation program can be displayed, explored, and analyzed by a wide variety of techniques including motion picture production, and again, the experimental unit and EEG recordings can be thought of as partial glimpses of these patterns. Although this very significant capability of computer systems has yet to be fully exploited in brain research, some such tools are described later in this paper.

Thirdly, the obscurity of even the outline of the representation of the intricacies of functional organization in higher forms. In higher forms such as mammals the increasing intervention of highly interconnected nervous system tissue and corresponding mentation between neurophysiological mechanism and behavior (Brown, 1977) masks all but the most rudimentary of mappings as was possible in principle in simpler forms. Research at this level has tended to be either primarily brain or biologically oriented and to proceed from the 'bottom up' in emphasizing the relationship between structural and physiological mechanism and electrical signal, or to be primarily psychological and to proceed from the 'top down' in emphasizing the relationship between behavior or mentation and electrical pattern. In either case, the farthest reaches of accomplishment generally tend to fall short on either side of satisfactory descriptions of large-scale coordinated electrical patterns in large nervous networks. Thus, for example, we have a highly satisfactory description of the peripheral aspects of visual perception leading up to a great deal of intricate knowledge concerning 'feature extraction' (Hubel and Wiesel, 1965). Nonetheless, the description falls short of elucidating how the various features are dynamically coalesced into the internal representation of objects. Also on the biological side, we have plausible concepts of changing synaptic efficiency and 'reverberating loops' as contributing to learning and memory traces (Mark, 1974) but we do not have delineations of what resulting dynamic forms might be produced by such processes. Computer simulation of nerve networks can serve a variety of important purposes in this context. For example, nerve network models such as that presented by Harth and his colleagues (Finette *et al.*, 1978) can be of a great deal of use in exploring the possible network configurations that produce feature extraction in sensory systems. On the other side, network models in artificial intelligence such as early 'perceptron' theories (Rosenblatt, 1962), 'bionics' (Gawronski, 1971), Grossberg's (1970) modeling, or the 'brain system theory' approach of Arbib (1972) can produce candidate dynamic models for the underpinings of various observed behavioral and psychological phenomena. The structure and operations of memory storage and recall provide examples. The central contribution of nerve network study, however, is the elucidation of the intricacy of global pattern as it relates to *both* biological mechanism and to psychological function and this has yet to be realized.

Fourthly, at the highest level, the extreme subtlety, sublimity, and apparent mystical-like nature of many of the highest of nervous system phenomena. The possibility of 'emergent'-like phenomena occurring perhaps a handful of times over a billion or so years of evolution (possibly involving, for example, the coordination of global microdynamic patterns in large nerve networks, the coherent organization and utilization of global current fields or their electric (or electromagnetic) counterparts in volumes of nervous system tissue, and consciousness) suggest that it may be necessary to study systems *in toto* to understand their true character. Computer simulation systems for the activity of large nerve networks can provide partial input into considerations of the ultimate questions regarding man's brain and mind.

Previous investigators have produced network computer simulation programs generally similar to the one described here. Examples are Farley and Clarke (1961), Smith and Davidson (1969), Perkel and Smith (1976) and Anninos (1972). The system described in this paper is in broad principle similar to those employed by those authors and includes the following refinements and extensions:

(1) Optionally high verisimilitude in basic cell dynamics, including a multimodular representation of cell morphology, nonlinear synaptic interaction, variable accommodation and refractory properties, etc.
(2) A wide range of possible network sizes and structures to be simulated at acceptable operating costs (ranging from single cells, to a standard program for up to 10,000 cells, and data-packed versions regularly operable at up to 50,000 and 100,000 cells, respectively, these limits being allowed by the 377,000 word storage capacity of the University of Colorado computing system).
(3) The ability to learn (dynamic patterns tend to imprint themselves on the model networks by changing synaptic efficiency).

(4) A wide variety of programs and capacities to display and analyze activity patterns (movies of microdynamic patterns, EEG's and spectral analysis, spatial distributions of firing rates, synaptic coupling coefficients for very large numbers of synapses, spike train analysis, interpretations of candidate global microdynamic patterns in terms of groupings of 'successful synapses', etc.).

The system is described here under the headings of 'The basic membrane module', 'The standard network simulation programs', and 'The activity display and analysis programs'. Representative results are presented in a companion paper (MacGregor and Gochis, 1981).

2. The basic membrane module

The basic membrane module represents our model of the relationships between alterations in membrane conductance, current influx and efflux, and the transmembrane electrical potential for a homogeneous patch of neuronal membrane. Since the former are the products of molecular and cellular gating processes and the latter is the unitary component of the overall dynamic pattern of the network, this module represents the basic causal link between those strata discussed in the Introduction.

Flexibility.—A central feature of the module is the flexibility with which it can be used. Thus the module can represent excitable or passive patches of membrane. The module can be used in multiple representation to piece together a multipatch representation of an entire cell. Alternatively, it can be used (as is done in most of the present work) to approximate the input–output behavior of an entire cell, wherein the module is purported to represent the dynamics of the triggering section, and an input stimulating current is conceived to represent all somadendritic currents funneling into that section, and the axon is considered to act merely as a delay line for the transmission of spike potentials. Networks of large numbers of neurons can then be simulated by using multiple realizations of individual cells which in turn may be represented by single modules or multiple modules. In all cases, one can include virtually any desired degree of verisimilitude (many patches for fine resolution of representation for a single cell; or, shaved verisimilitude for cost efficiency in very large-scale network simulations, etc.).

Circuit model and flow.—The standard circuit model for a membrane patch is shown in Fig. 1. In this model the upper node represents a point adjacent to the patch in the intracellular fluid and the lower node represents a point adjacent to the patch in the extracellular fluid. The capacitance represents the tendency of polarized molecules in the nerve cell membrane to rotate in a changing electric field and thereby comprise Maxwell's displacement current. The next three branches represent the permeability of the membrane to various ionic species. The batteries in these pathways represent the equilibrium potentials for these species derived from basic ionic equilibrium theory. The next two conductance pathways represent excitatory and inhibitory synapses, respectively, which act

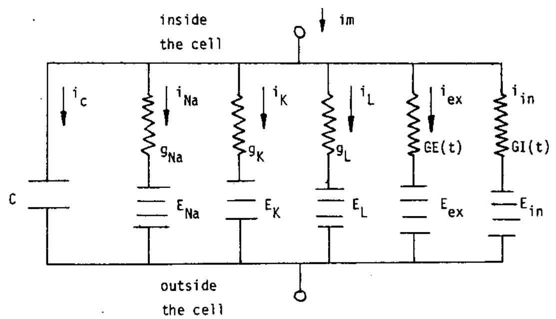

Fig. 1. Equivalent circuit model for electric potential across a unit area of membrane.

by changing membrane conductance selectivity to particular ionic species thereby defining equilibrium potentials for those processes. In terms of information flow, the module is activated by three input functions of time, *SC*, *GE*, and *GI*. In response to these input functions, it produces four state or output variables: the transmembrane potential *E*, the threshold θ, the spiking variable *S*, and the transmembrane post spike conductance variable g_k. The input functions *SC*, *GE*, and *GI* are used to represent current flowing into a patch or out of a patch from elsewhere in the neuron—for example, into a triggering section from dendritic regions, or between adjacent patches along a dendrite, current applied into a patch from an externally applied electrode, current or conductance changes effected on the membrane patch by input terminals from an afferent fiber tract, or by recurrent connections from other cells in the same network.

Basic module state variable equations.—The four equations,

(1A) $$\frac{dE}{dt} = -E(1 + g_k) + [SC + GE(E_{ex} - E) - GI(E - E_{in})],$$

(1B) $$\frac{d\theta}{dt} = \frac{-(\theta - 1) + cE}{\lambda},$$

(1C) $$S = \begin{cases} 1, & E \geqslant \theta, \\ 0, & E < \theta, \end{cases}$$

(1D) $$\frac{dg_k}{dt} = \frac{-g_k}{\tau} + b \, . \, S,$$

constitute a four-state variable description of the dynamic properties of the basic neuron patch (MacGregor and Oliver, 1974). This model of the excitable processes reduces the Hodgkin–Huxley description of spike generation on the basis of prescribed time courses for sodium and potassium conductances to a threshold

rule (the equation for theta) and the first-order dynamic equation for the post-spike potassium conductance. This substitution loses the precise description of the shape of the action potential and some verisimilitude regarding the spike production process. It does nonetheless give a good empirical match to repetitive firing characteristics including accommodation data (using an extension of Hill's model) and adaptation (using an extension of Kernell and Gustafson's models) (MacGregor and Oliver, 1974) including the accumulation of post-spike potassium conductance. The parameters c, λ, b and τ allow for the creation of individual model cells with wide flexibility in dynamic characteristics. For example, by setting $c = 0$, $\frac{1}{2}$ or 1, one produces cells with no accommodation, high ceiling type (after Bradley and Somjen) or maximum accommodation (MacGregor and Oliver, 1974). By setting b equal to low or high values, one creates bursting cells, or sluggish, highly refractory cells, respectively. Nonexcitable or passive membrane is represented by the system of equations simply by deleting the expressions for θ, S, and g_k and dealing with the current balance equation for E only.

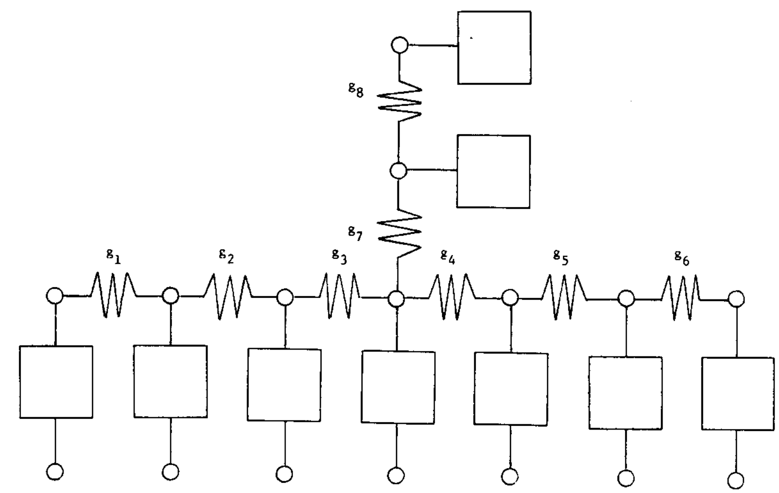

Fig. 2. Modular model for the dynamics of a Mauthner cell. (Each block module represents an electrical circuit model as shown in Fig. 1 for the corresponding spatial region. External input can be specified as appropriate for each region in terms of an applied current, *SC*, or excitatory or inhibitory conductance changes, *GE* or *GI*.)

Extension to multi-patch model of a single cell.—A representative multi-patch model for a single cell is shown in Figure 2. This model can be thought of as the outlines of a module for the Mauthner cell. For each of the patches included the following equation applies:

(2) $$\frac{dE}{dt} = -E(1 + g_k) + [SC + GE(E_{ex} - E_{in})] - GI(E - E_{in})] + + g_{i-1}(E_{i-1} - E) + g_{i+1}(E_{i+1} - E).$$

Thus, the main new idea is that current is allowed to flow Ohmically between adjacent patches in proportion to the potential difference in the two patches. The conductance parameters, g_i, represent the electrical conductance between the patches. SC represents externally applied input and is zero if appropriate. One can apply similar module clustering to represent virtually any neuron morphology.

Extension to include long lasting synaptic action.—On occasion it is desirable to represent the dynamic action of synapses whose post-synaptic conductance changes substantially outlast the duration of the action potential which triggered them. Examples are inhibitory psp's on cells of the thalamus presumably responsible for generating the alpha rhythm (Andersen and Andersson, 1968) and recurrently mediated inhibitory psp's on pyramidal cells of the hippocampus (Yokata *et al.*, 1970). A reasonable first approximation to this is accomplished by using the following equation,

$$\frac{dG}{dt} = \frac{-G}{\tau_g} + d \,.\, IN(t). \tag{3}$$

In this expression the function $IN(t)$ represents the pre-synaptic triggering element of the synapse, presumably a spike train. IN will be 1 for the time course of a spike, and 0 other times. τ_g is the time constant of decay of the synaptic conductance, and d scales its magnitude.

Difference form of the basic equations.—All of the differential equations used in this dynamic modeling are at most first order in time. To simulate these equations in FORTRAN on digital computers, it is reasonable to use the approximation shown in Equation (4). The approximation is written here for the four basic state variable equations for the basic module. The same procedure can be used for virtually any other equation that may be used in the system.

$$\text{(4A)} \quad E_t = E_{t-1} \exp[-(1 + g_k + GE + GI)/5] + \frac{(1 - \exp[-(1 + g_k + GE + GI)/5]) \,.\, (SC + 7GE - GI - g_k)}{(1 + g_k + GE + GI)},$$

$$\text{(4B)} \quad \theta_t = \theta_{t-1} e^{-1/\lambda} + (1 - e^{-1/\lambda}) \,.\, \lambda \,.\, (1 + cE_{t-1}),$$

$$\text{(4C)} \quad S_t = \begin{cases} 1, & E_t \geqslant \theta_t, \\ 0, & E_t < \theta_t, \end{cases}$$

$$\text{(4D)} \quad g_{k,t} = g_{k,t-1}\, e^{-1/\tau} + bS_{t-1}.$$

3. The standard network simulation programs

The standard network simulation programs are constructed by grouping together basic membrane and cellular models described above in various configurations and arrangements.

Flexibility.—A central feature of the network simulation programs is their flexibility. Thus, for example, one may simulate small networks (say, a dozen cells) with a great deal of fine-grained resolution and verisimilitude for single constituent cells (say, multiple patches, etc.) or very large interconnected networks of up to 100,000 interconnected cells. Input–output relations in convergent–divergent relay pathways may be simulated, or one may simulate internal reverberations within recurrently connected networks. Network parameters and properties may be fixed, or may be plastic and represent various models of learning effected by, for example, changing synaptic effectiveness.

Basic network module.—The basic network module used in our simulations is illustrated in Fig. 3. The total population is partitioned into a subset of excitatory

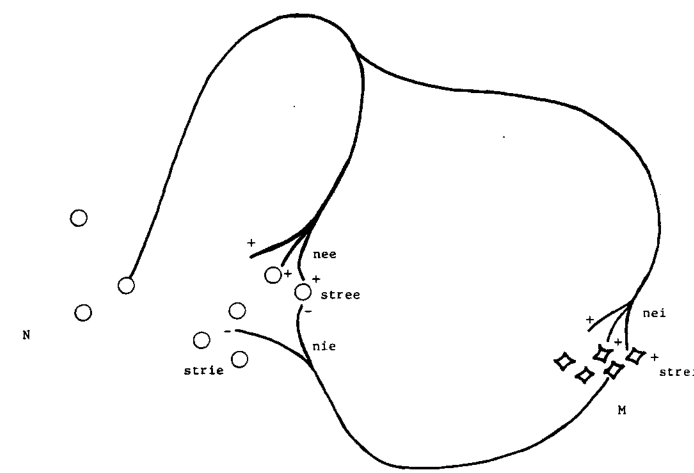

Fig. 3. Basic network module. (N excitatory cells characterized by parameters c_e, λ_e, b_e, τ_e and M inhibitory cells characterized by c_i, λ_i, b_i, τ_i. There is a recurrent excitatory loop mediated by the excitatory cell population onto itself through *nee* synapses from each excitatory cell, and a two-stage recurrent inhibitory loop mediated by the excitatory population onto itself by way of the intermediary inhibitory population. Further details are given in the text.)

cells and a subset of inhibitory cells, all of which are drawn from their same basic populations respectively. There is a basic recurrent excitatory loop (mediated by excitatory to excitatory connections) and a basic recurrent inhibitory loop (mediated by excitatory to inhibitory and inhibitory to excitatory connections). All cells or any subset of cells may be stimulated from the outside in any desired fashion. In the standard structure, excitatory cells are laid out at every grid point in a two-dimensional lattice NR by NC units in height and width, respectively. Inhibitory cells are placed at the intersections of every fourth line and fourth row. There are thus a total of $NR \times NC$ excitatory cells and $NR \times NC/16$ inhibitory cells (NR and NC are multiples of 4). The output connections of an excitatory or an inhibitory cell fall on cells uniformly distributed with a radius of RE or RI from the cell. An excitatory cell makes $NOCEE$ connections on excitatory cells and $NOCEI$ connections on inhibitory cells. An inhibitory cell makes $NOCIE$ connections on excitatory cells and no connections on inhibitory cells. Within the circular field, the individual cells connected to are chosen at random with uniform distributions on radial distance and angle. All such random choices are precisely duplicated on every firing of the sending cell. If a connection falls out of the boundaries of the network, that connection is placed at an appropriate position near the opposite boundary.

Program flow: storage.—Time is partitioned into discrete intervals, typically taken as one millisecond. The program stores in central memory: values for the four-state variables for all cells at each instant, matrices which represent all the activity in transit at any given instant in time (it does this by keeping track of all activity due to arrive at cell i, j time units from now, where i represents the identity of any particular cell in the net and j takes on the values of 1 up to the maximum conduction time plus 1), and finally miscellaneous parameters for cells and records of activity. Typically, the program writes out on an external data file a permanent record of its ongoing dynamic activity as that activity is generated. Thus, the storage requirements for central memory can be minimized. Items 1 and 2, the state variables and the activity-in-transit matrix, are the primary space limiters of the program. With ordinary FORTRAN, one can simulate up to about 3,000 cells in typical representations. By means of data packing, one can extend this upper limit to 100,000 cells.

Program flow; computations.—The heart of the program computation is three do loops as indicated in Fig. 4. The two internal loops effect updating of the state variables of all the excitatory and inhibitory cells respectively. The do loop over the excitatory cells, for example, uses Equation (4) to update the four-state variables, E, θ, S, and g_k. To do this it uses the values at the previous time of these variables from the central memory and the present input functions SC, GE, and GI which in turn are obtained from the activity-in-transit matrix for this cell together with, if appropriate, externally applied input effected at this time. If a cell does not fire at this time, computation proceeds to the end of the do loop and hence to the next cell. If, on the other hand, the cell does fire at this particular time, computation then goes into the distribution of activities subpackage which distributes the output from cell i appropriately to the cells to which it connects. This is effected by placing the increments of activity in the activity-in-transit matrix so that these will arrive at the correct target cells with the correct time delays. Thus, synapses are brought into the computation only when they are active. In our simulations detailed connections are often made within general constraints by virtue of a random number generator. When this is done, each cell generates exactly the same random sequence of numbers and connections each time, so that the structure of the net, although chosen randomly at first, is fixed once chosen. Moreover, when this is done, a microstructure parameter, $IMICR$, is read into the program along with input data

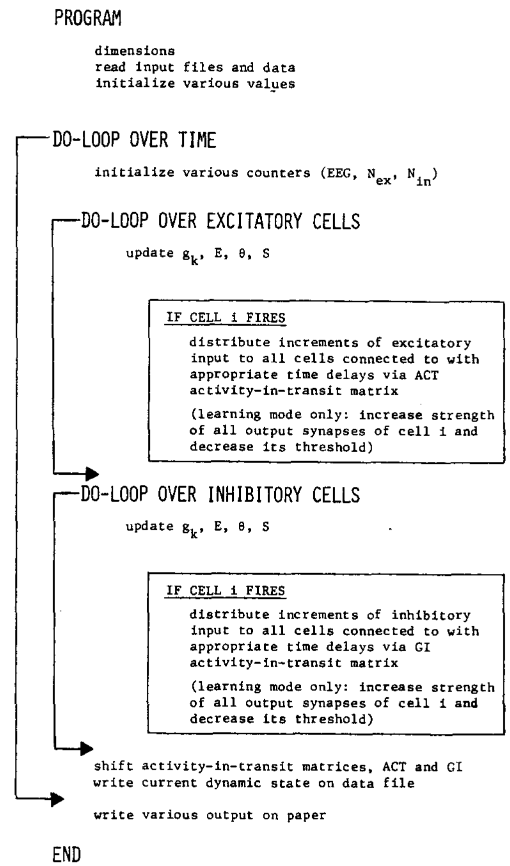

Fig. 4. Computational structure for main simulation programs.

in the form of a random number seed to uniquely determine the particular microstructure for this particular run. All such random choices are completely repeatable and can be resimulated and rechecked as many times as is desired. The do loop over the inhibitory cells is precisely parallel to that over the excitatory cells.

The first statements within the time do loop keep track of various functions of time such as the number of excitatory and inhibitory cells firing at any time, and the EEG which is here represented by the sum of all the generator potentials of the individual cells. The code before the time do loop incorporates various setup requirements including reading-in of parameters, initializing variables, setting up data files, etc. The coding after the time do loop effects various clean-up operations. For example, printing out on paper or on the data file various overall information such as, for example, the numbers of excitatory and inhibitory cells firing as a function of time, the standard mean and standard deviations of these quantities, or final synaptic strengths or thresholds as the embodiment of the structure of the network if this has been a learning run.

Main input parameters to program.—The main parameters specified for a particular simulation run include the number of excitatory and inhibitory cells, represented by N and M, respectively; the parameters, c, λ, b, and τ for the excitatory and for the inhibitory populations. Our current versions use the same values of these parameters for all cells in the individual populations although they have different values for the different populations. However, it is easy to alter the program so that the prescribed values are mean values and that values for individual cells are chosen with allowable fluctuations around these means. For all three types of connections, one reads in the numbers of connections and the strengths of connections (excitatory–excitatory, excitatory–inhibitory, and inhibitory–excitatory). The program is set up to simulate inhibitory–inhibitory connections also, but we have not used this option. In all our simulations so far we have used a maximum conduction time of five time units and chosen individual conduction times for every individual synapse independently from a uniform distribution between one and five. It is easy to alter this if so desired. If appropriate, a learned structure embodied in the set of all synaptic strengths and all thresholds is read into the program usually from a data file.

Specification of stimulation.—Stimulation to individual cells in addition to the recurrent reverberations within the net can be effected in several ways. First, there is a specific subroutine called STIMLS which allows one to specify virtually any specific temporal pattern of stimulation involving any subset of cells in the net. This subroutine requires specification of five parameters: the beginning and end times of the simulation, the interval between stimuli, the total number of cells stimulated, and the number of cells stimulated at any particular time unit. In addition, the individual identities of all the cells to be stimulated must be specified. With this subroutine we have prescribed external stimulation in the shape of pulsing columns or squares, or activity running around the edges of squares, for example. Secondly, one can simulate the ongoing random bombardment of a population in a general diffuse nondiscrete sense by simply incrementing the SC variable by a random amount for each cell at each time as desired in the ongoing updating of state variable loop. Thirdly, a stimulation device that we often use to trigger ongoing internally-sustained reverberations involves random selection of a given nominal percentage of cells to be triggered externally with the first X-time units.

Output data file.—We produce detailed output data files for the microdynamic activity of these simulations for virtually all simulation runs. These data files are called candidate microdynamic patterns (CMDP) and contain a statement of all the input parameters and other information that characterized the particular simulation, and a record for each time unit of activity that includes the time, the EEG value, the number of excitatory cells firing, the number of inhibitory cells firing, and, finally, the identity of all the specific individual cells that fired at that particular time. These data files then are kept in the computer system's storage for this project and may be drawn upon subsequently for detailed analysis and search for patterns. It is possible also to store on data files the values of the generator potentials for any subset of cells or all the cells over any desired time range.

Extension to learning.—Various rules for learning can be incorporated into the system almost all of which are based on the idea that synaptic effectiveness changes with use. The most popular proposal is that the strengths of individual synapses increases when both pre- and post-synaptic cells fire approximately simultaneously. This kind of learning can be programmed in systems such as ours but puts somewhat of a strain on both space and time constraints of computation, first of all because the learning entails contingencies of firing in both pre- and post-synaptic cells and secondly because information must be stored for every single synapse in a net. This represents typically ten to a thousand times more pieces of information than the number of cells. These problems can be partially alleviated by the use of data packing. But since considerable space–time constraints remain and moreover and more importantly, since this kind of learning is not completely established physiologically and since other learning rules are both plausible and much easier to simulate, we have tried others. The one which we have found most useful to date is what might be called the 'exercise' learning rule. In this scheme, whenever a given cell fires, it both increases the strength of all its synapses by the same amount and decreases its threshold—that is, it becomes stronger and more sensitive. Computationally this requires the storage of only two-state variables for each cell (synaptic strength and threshold), one of which is already a state variable. It also allows in a primitive way for the emergence of particular pathways in the network because only those cells which fired in a particular learned pattern tend to become more sensitive and stronger and thus more likely to become activated. This kind of learning is readily incorporated in the state variable update do loop, described above, at the tail end of the subsection which distributes activity from firing cells. Thus, after a cell has fired and distributed its increments of activity into the activity-in-transit matrix, its synaptic strength is increased and its threshold decreased. These changes are exponential within a certain range and the final values and rates are parameters read into the program.

Data packed version for simulation of large networks.—Two version of programs exist for simulating networks of more than 10,000 cells. Both programs are virtually identical to the standard program described above but differ in that the main storage requirements for cell state variables and activity-in-transit matrices are data-packed to compress overall data storage requirements. Version A simulates up to 50,000 cells. In this program storage of state variables and activity in transit is stored by means of two FORTRAN words for each cell in the network. In this data packing, the variables, E, θ, GK and STR are allocated six bits apiece (each variable has 64 gradations) and the ACT and GI functions, excitatory and inhibitory activity on its way to i respectively, each are allocated 18 bits, representing three bits for each of six time units. Activity arriving at each time unit at the cell then is partitioned into two functions, excitatory current and inhibitory conductance change, each of which is scaled in eight grades.

Version B simulates up to 100,000 cells by data packing all the state variables and activity in transit into one FORTRAN word for each cell. In this data packing the state variables, E, θ, GK, and STR are allocated three bits each (allowing eight grades for each variable) and the activity due to arrive at i is stored in 18 bits, corresponding to three bits for each of six time units. Thus, for this case, the combined excitation and inhibition arriving at any time unit is scaled in one of eight grades. The input, program flow, and data files produced by these programs are virtually identical to those from the standard network program and can be analyzed by the same subroutines described below.

Operating costs.—The operating costs for these simulation programs on the University of Colorado computer system are remarkably reasonable. The simulation costs depend primarily on the number of cells in the network (storage requirements) and the average activity level in the network (computation time). At typical activity levels, say 20 of 2,000 cells firing at each unit, the standard operating cost at low priority rates is approximately $15 for one second (1,000 milliseconds). For 400 cells firing at each time unit in a network of 40,000 cells, this rate is approximately $300 for one simulated second. These approximate operating costs are for programs written entirely with FORTRAN. Further reductions in operating costs can be effected by utilizing partial assembly language programming of often used components.

4. Activity display and analysis programs

These programs for the analysis and display of electrical activity patterns operate on data files (CMDP) produced by the network simulation programs described above. The main variables characterizing the network dynamic pattern are the spike variable S and the generator potential E for all cells at each time. Also, a detailed listing of all internal synaptic connections is available, and of course, all other parameter values are available or reproducible as desired.

Flexibility.—Since all the programming is in FORTRAN (with the exception of some assembly language programming of often used components), it is easy to modify exisiting programs for individual cases, or to generate new analysis programs as ongoing research indicates.

Spatial.—(1) FIRRT. This program prints out in a spatiotopic two-dimensional grid, the average firing rate for every single cell in the system over some desired portion of the simulation. Thus, one can glance at this printout and see immediately where in space activity tended to be localized during the entirety of that particular run. A modification of this program is called ISORATE. This latter program traces on the same spatiotopic grid, interpolated lines of constant firing rates. This program essentially provides a sculptoring of the information contained in FIRRT. (This program is adapted from one published by Trappel (1971).) (2) MOVIES. The basic display in our computer-produced movies is a spatiotopic two-dimensional grid wherein the occurrence of an asterisk indicates the firing of a particularly-placed cell at a particular time. Thus, a set of asterisks corresponds to a set of action potentials in appropriately placed individual cells. The University of Colorado computer system produces microfilms of sequences of such individual displays directly. These are then processed locally by a film company (Alexander Films, Colorado Springs, Colorado) into conventional 16 mm movies.

The relative speed of the movies to model time is variable and can be fixed as desired. Typically, we use one frame per model millisecond so that one viewing second corresponds to 24 model milliseconds (or one model second takes about 42 viewing seconds). Moreover, the quality of the movement of the images across the network is adjustable by varying the lifetimes of the individual asterisks. That is, although in the simulations the individual cell action potentials last exactly one millisecond (although this also can be varied), one may artificially vary on the display grid the number of time units a particular asterisk will be fixed corresponding to one action potential. We have found that lifetimes of five time units for individual asterisks gives a nice fluid representation of movement through the network. At much lower lifetimes, the individual spikes are very fleeting whereas at longer lifetimes, the movement of patterns appears very viscous. We are currently in the process of producing movies of the motion of lines of constant generator potential across the same grid. These displays will be based on interpolated contour-lines of constant generator potential similar to that used in ISORATE. We cannot yet say which of these will be the better display, but the latter may be somewhat closer to the EEG signals that are measured with macroelectrodes.

Temporal.—(1) EEG. This program produces a graphic display of the temporal fluctuations of the sum of all the generator potentials of all the cells in the network. (This measure is a weak model of the EEG waves recorded with macroelectrodes. It is, however, a valid measure of the global activity of the nerve network. In one sense, it is the experimentally recorded EEG which is deficient rather than this global measure.) Our EEG functions are produced by graphic display packages on Tektronics interactive graphic terminals. Typically, they use a resolution of one model millisecond. (2) SPCTRA. Typically, a spectral analysis is performed on every EEG function by use of packaged fast Fourier transform programs. (3) DSPCTRA. Also for our simulations involving learning of particular patterns, we typically form a difference spectra obtained by subtracting bin for bin the spectrum for a particular learned stimulus from the spectrum for a pattern obtained in a network where all the synapses are of equal strength. (4) GENER. This program displays the time course of generator potentials in selected individual cells. Its operation is precisely analogous to that of EEG.

Spatiotemporal.—(1) SYNCPCF. This program measures and stores the success level of all synapses in the network in a particular range of dynamic activity. It operates by counting the number of spikes in cell B which follow spikes in cell A within one to five time units. The program assigns both a synaptic transmission probability (based on simply dividing the number of spikes counted above by the number of spikes in A) and a T-statistic to every synapse. The T-statistic is computed on the basis of how many spikes from B should have occurred in this region on the basis of chance given both firing rates and assuming that all individual spikes are independent. The data file produced by the program then includes the firing rates for both the pre- and post-synaptic cells, the chance expected number of successful couplings, the actual number of successful couplings, the T-statistic, the number of standard deviations between the expected and observed rates, and finally the transmission probability. A modification of this program (COUPCOF) performs these computations for all possible pairs of any particular subset of cells one specifies. (2) NEBULAE. This program finds interrelated chains and loops of successful synapses. A nebula is a cluster of cells such that one may pass from any one cell in the nebula to any other along a path of successful synapses. The essence of this program is to produce circuit diagrams involving successful synapses as candidates for the substrata of global microdynamic patterns. It has a focus mechanism in the sense that the criterion for success (acceptable T-statistic or transmission probability) is variable. At each of several such criterion values, all the coupling coefficients produced by SYNCPCF are grouped into nebulae. (C) CLUSTERS. The nebulae program is very useful, but chains and loops appear to be not as significant as one might have naively thought. So another program which reads the output of SYNCPCF simply identifies, first, clusters of cells, firing in all of which precede firing in a cell to which they are synaptically coupled, and second, clusters of cells, the firing of all of which follow firing in a cell to which they are synaptically coupled. Both such groups then are candidates as clusters or groups of cells which fire approximately simultaneously and perhaps repeatedly approximately simultaneously throughout the simulation run. (4) PTSRCH. This program, pattern search, is also used to search for the repeated occurrence of approximately simultaneous firings in clusters of cells. It, however, is not restricted to cells which are related via synaptic connections but, rather, operates directly on the dynamic pattern only. It identifies a template of cells as those cells which fired over some small time range, then looks for the recurrence of that template of cells at each time unit for the duration of the run. (5) SPIKTRN. The above programs define subsets of cells which, for one reason or another, might be thought to be part of a coordinated global microdynamic pattern. This and the following program serve to analyze the detailed temporal patterns and interrelations of the individual cells in these groups. SPIKTRN simply lists and displays graphically the times of all spikes in a particular subset of cells at which one chooses to look. (6) AXCOR. This program produces autocorrelation histograms and cross-correlation histograms for any set of cells at which one wishes to look. These functions are essentially those produced and studied by Moore *et al.* (1966). (7) MULTICORE. This program produces multidimensional cross-correlation histograms for three or four simultaneous spike trains essentially along the lines described by Gerstein and Perkel (1969). We have found this program to be very useful for defining precise relationships among three or four simultaneously firing model cells. However, we have found it not very useful (at least as yet) with regard to the search for more global dynamic activity patterns, and moreover, somewhat limited because of the large number of spikes required to get meaningful statistics.

5. Discussion

Taken in total, the above-described programs represent but the first steps in a potentially unlimited capacity for simulation, display, and analysis of the intrinsic dynamic activity of model network activity. Virtually any network configuration of up to tens of thousands of cells can be simulated. Virtually any desired dynamic characteristics can be focused on, analyzed, and displayed. More important than the particular simulation, display, and analysis techniques, however, is the understanding to which they do or do not lead. What is really needed is correct and useful conceptualizations of dynamic activity patterns as they serve the purposes of the functioning brain. These programs, like experimental apparatus, are simply tools which are valuable or not to the extent that they further and enhance that level of conceptualization.

Acknowledgments

The author is indebted to many students, including Paul Gochis, Chris Steuri, Rob Vogel, Gary Berkowitz and Kurt Strein for their contribution to the computer programming involved in this work.

References

Andersen, P. and Andersson, S. A. (1968). *Physiological Basis of the Alpha Rhythm.* Appleton–Century–Crofts, New York.

Anninos, P. A. (1972). Cyclic modes in artificial neural nets. *Kybernetik* **11**, 5–14.

Arbib, M. A. (1972). *The Metaphorical Brain: An Introduction to Cybernetics as Artificial Intelligence and Brain Theory.* Wiley, New York.

Brown, J. (1977). *Mind, Brain, and Consciousness: The Neuropsychology of Cognition.* Academic Press, New York.

Bullock, T. H. and Horridge, G. A. (1965). *Structure and Function in the Nervous Systems of Invertebrates.* W. H. Freeman, San Francisco.

Elul, R. (1972). The genesis of the EEG. *Int. Rev. Neurobiol.* **15**, 227–272.

Farley, B. G. and Clarke, W. A. (1961). Activity in networks of neuron-like elements. *In: Information Theory (Fourth London Symposium)* (Cherry, C., Ed.). Butterworth Scientific Publications, London.

Finette, S., Harth, E. and Csermely, T. J. (1978). Anisotropic connectivity and cooperative phenomena as a basis for orientation sensitivity in the visual cortex. *Biol. Cybernetics* **30**, 231–240.

Gawronski, R. (Ed.) (1971). *Bionics, The Nervous System as a Control System.* Elsevier, Amsterdam.

Gerstein, G. L. and Perkel, D. H. (1969). Simultaneously recorded trains of action potentials: analysis and functional interpretation. *Science* **164**, 828–830.

Grossberg, S. (1970). Neural pattern discrimination. *J. Theor. Biol.* **27**, 291–337.

Harmon, L. D. (1961). Studies with artificial neurons. I. Properties and functions of an artificial neuron. *Kybernetik* **1**, 89–101.

Hebb, D. O. (1949). *The Organization of Behavior*. Wiley, New York.

Hodgkin, A. L. and Huxley, A. F. (1952). A quantitative description of membrane current and its application to conduction and excitation in nerve. *J. Physiol.* **117**, 500–544.

Hubel, D. H. and Wiesel, T. N. (1965). Receptive fields and functional architecture in two non-striate visual areas (18 and 19) of the cat. *J. Neurophysiol.* **28**, 229–289.

John, E. R. (1972). Switchboard versus statistical theories of learning and memory. *Science* **177**, 850–864.

John, E. R. and Schwartz, E. L. (1978). The neurophysiology of information processing and cognition. *Ann. Rev. Psychol.* **29**, 1–29.

Kubie, L. A. (1930). A theoretical application to some neurological problems of the properties of excitation waves which move in closed circuits. *Brain* **53**, 166–177.

Lashley, K. S. (1960). *The Neuropsychology of Lashley* (Beach, F. A., Hebb, D. O., Morgan, C. T. and Nissen, H. W., Eds.). McGraw–Hill, New York.

Lewis, E. R. (1965). Neuroelectric potentials derived from an extended version of the Hodgkin–Huxley model. *J. Theor. Biol* **10**, 125–158.

MacGregor, R. J. and Gochis, P. (1981). A computer software system in FORTRAN for simulating large nerve networks: II, some representative results. *J. Theoret. Neurobiol.* **1**, (to appear).

MacGregor, R. J. and Lewis, E. R. (1977). *Neural Modeling: Electrical Signal Processing in the Nervous System*. Plenum Press, New York.

MacGregor, R. J. and Oliver, R. M. (1974). Model for repetitive firing in neurons. *Kybernetik* **16**, 53–64.

Mark, R. (1974). *Memory and Nerve Cell Connections: Criticisms and Contributions from Developmental Neurophysiology*. Clarendon Press, Oxford.

Moore, G. P., Perkel, D. H. and Segundo, J. P. (1966). Statistical analysis and functional interpretation of neuronal spike data. *Ann. Rev. Physiol.* **28**, 493–522.

Perkel, D. H. and Smith M. H. (1976). A computer program for simulating a network of interacting neurons, I, II, & III. *Computers and Biomedical Research* **9**, 31–74.

Rall, W. (1962). Theory of physiological properties of dendrites. *Ann. N.Y. Acad. Sci.* **96**, 1071–1092.

Rosenblatt, F. (1962). *Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms*. Spartan Books, Washington, D.C.

Smith, D. R. and Davidson, C. H. (1969). Maintained activity in neural nets. *J. Assoc. Computing Machinery* **9**, 268–279.

Stratton, J. A. (1941). *Electromagnetic Theory*. McGraw–Hill, New York.

Trappel, R. (1970). Die näherungswiese graphische Darstellung von Isopotentiallinien aus EEG-Mehrkanalregiftrierungen mittels EDV-Anlage. *Experientia* **26**, 329–331.

Wilson, D. M. and Waldron, I. (1968). Models for the generation of the motor output pattern in flying locusts. *Proc. I.E.E.E.* **56**, 1058–1064.

Yokata, T., Reeves, A. G. and MacLean, P. D. (1970). Differential effects of septal and olfactory volleys on intracellular responses of hippocampal neurons in awake, sitting monkeys. *J. Neurophysiol.* **33**, 96–107.

APPENDIX

FORTRAN code listing for a representative simulation (1700-cell network)

```
MNF(Y)

      PROGRAM CRTXL04 (DATAOUT,INPUT,OUTPUT,TAPE7=DATAOUT,TAPE6=OUTPUT)
      DIMENSION THA(1700),STR(1700),LOCATN(200)
      COMMON E(1700),GK(1700),IS(1700),ACT(1700,6),GI(1700,6),
     1   ISUM(2000),ISUMI(2000),IEF(1000),IIF(100)
*     AUGUST, 1978.  THIS PROGRAM SIMULATES REVERBERATIONS IN A NETWORK
*     CONTAINING RECURRENT EXCITATION AND RECURRENT INHIBITION.  WE WILL
*     READ IN THE VARIOUS PARAMETERS AND SET THE INITIAL CONDITIONS,
*     REVISED:  JULY 1979.
*
*
      READ 500, N,M,NOCEE,NOCEI,NOCIE,NOCII,STREE,STREI.STRIE,STRII,
     1          MTSTOP,P
      READ 510, BEE,TADEE,BEI,TADEI
      READ 520, ISTST, IMICR
       READ 530, RE,RI,RS,NOCSA
      READ 505, DELTHET,THEF,DELTHIT,THIF
      READ 505, DELSTRE,STREMX,DELSTRI,STRIMX
      READ 805, LSTIM,INTERV,LSTOP,NSTIM,NSTIM1
      READ 810, (LOCATN(I),I=1,NSTIM)
      WRITE(7,900) N,M,NOCEE,NOCEI,NOCIE,NOCII,STREE,STREI,STRIE,
     1STRII,MTSTOP,P,BEE,TADEE,BEI,TADEI,ISTST,IMICR,RE,RI,RS,NOCSA
      WRITE(7,505) DELTHET,THEF,DELTHIT,THIF
      WRITE(7,505) DELSTRE,STREMX,DELSTRI,STRIMX
      WRITE(7,805) LSTIM,INTERV,LSTOP,NSTIM,NSTIM1
      WRITE(7,810) (LOCATN(I),I=1,NSTIM)
      NTL=(N+M)
      M1=N+1
      XN=FLOAT(N)
      AEDE=EXP(-1./TADEE)
      AEDI=EXP(-1./TADEI)
      MARKER=0
      LAST = 0
      IFE=0
      IFI=0
      IFES=0
      IFIS=0
      STE=STREE*NOCEE
      STI=STREI*STRIE*FLOAT(NOCEI*NOCIE)
*
*     HERE ARE THE PARAMETERS.
*
      WRITE (6,600) N,M,NOCEE,STREE,BEE,TADEE,NOCEI,STREI,BEI,TADEI,
     1 NOCIE,STRIE,NOCII,STRII,RE,RI,RS,NOCSA
      WRITE (6,610) MTSTOP
      WRITE (6,620)  IMICR
      WRITE(6,720) DELTHET,THEF,DELTHIT,THIF
      WRITE(6,730) DELSTRE,STREMX,DELSTRI,STRIMX
      WRITE (6,660) STE,STI
      WRITE(6,815) LSTIM,INTERV,LSTOP,NSTIM,NSTIM1
*
*     WE INITIALIZE THE MATRIX.
*
      DO 10  I = 1, NTL
      E(I)=0.$GK(I)=0. $IS(I)=0
      DO 10  J = 1, 6
      GI(I,J)=0.
   10 ACT(I,J) = 0.0
      DO 20  L = 1, MTSTOP
      ISUM(L) = 0
   20 ISUMI(L) = 0
      DO 23 I=1,NTL
   23 THA(I)=1.
      DO 21 I=1,N
   21 STR(I)=STREE
      DO 22 I=M1,NTL
   22 STR(I)=STRIE
*
*     NOW WE START THE NETWORK ACTIVITY AND MARCH IT THROUGH TIME.
*
      DO 180  L = 1, MTSTOP
      IF(L.EQ.LSTIM.AND.L.LE.LSTOP) CALL STIMULS(LSTIM,INTERV,NSTIM,
     1NSTIM1,MARKER,LOCATN)
      EEG=0.
      DELTHE=0.$DELTHI=0.
      DELTEX=0.$DELTIN=0.
      INI=0
```

```
      INE=0
*
*     THIS SECTION UPDATES THE N EXCITATORY CELLS.
*
      DO 80  I = 1, N
      S = FLOAT(IS(I))
      GK(I)=AEDE*GK(I)+BEE*S
      GTOT=1.+GK(I)+GI(I,1) $TRM=EXP(-GTOT/5.)
      E(I)=TRM*E(I)+(1.-TRM)*(-GK(I)-GI(I,1)+ACT(I,1))/GTOT
      EEG=EEG+E(I)
      IF (E(I).GE.THA(I)) GOTO 40
      IS(I) = 0
      GOTO 80
   40 IS(I) = 1
      INE=INE+1
      IEF(INE)=I
*
*     NOW THAT AN EXCITATORY CELL HAS FIRED,WE DISTRIBUTE ITS EXCITAT-
*     ION ACCORDING TO ITS CONNECTIONS AND TIME DELAYS.
*
      CALL RANSET (2.*FLOAT(I+IMICR)+1.)
      IF (NOCEE .EQ. 0) GOTO 60
      DO 50  J = 1, NOCEE
      NCT = INT(5.0*RANF(0.0))+2
      R=RE*RANF(0.)
      TH=6.28318*RANF(0.)
      NXR=I-40*((I-1)/40)+INT(R*(COS(TH)+SIGN(.5,COS(TH))))
      IF(NXR .GT. 40) NXR=NXR-40
      IF(NXR .LT. 1) NXR=40+NXR
      NYR=(I-1)/40+1+INT(R*(SIN(TH)+SIGN(.5,SIN(TH))))
      IF(NYR .GT. 40) NYR=NYR-40
      IF(NYR .LT. 1) NYR=40+NYR
      NREC=40*(NYR-1)+NXR
      ACT(NREC,NCT)=ACT(NREC,NCT)+STR(I)
   50 CONTINUE
   60 IF(NOCEI.EQ.0) GOTO 75
      DO 70 J=1,NOCEI
      NCT=INT(5.0*RANF(0.0))+2
      R=RE*RANF(0.)
     TH=6.28318*RANF(0.)
     NX=I-40*((I-1)/40)+INT(R*(COS(TH)+SIGN(.5,COS(TH))))
     NXR=2+4*((NX-1)/4)
     IF(NXR .GT. 40) NXR=NXR-40
     IF(NXR .LT. 1) NXR=40+NXR
     NY=(I-1)/40+1+INT(R*(SIN(TH)+SIGN(.5,SIN(TH))))
     NYR=2+4*((NY-1)/4)
     IF(NYR .GT. 40) NYR=NYR-40
     IF(NYR .LT. 1) NYR=40+NYR
     NREC=((NXR+2)/4+10*((NYR-2)/4))+1600
     ACT(NREC,NCT)=ACT(NREC,NCT)+STR(I)
  70 CONTINUE
  75 CONTINUE
     DELTH=DELTHET*(THA(I)-THEF)
     THA(I)=THA(I)-DELTHSDELTHE=DELTHE+DELTH
     DELE=DELSTRE*(STREMX-STR(I))
     STR(I)=STR(I)+DELE
     DELTEX=DELTEX+DELE
  80 CONTINUE
*
*    THIS SECTION UPDATES THE  M INHIBITORY CELLS.
*
     DO 130  I = M1, NTL
     S=FLOAT(IS(I))
     GK(I)=AEDI*GK(I)+BEI*S
     GTOT=1.+GK(I)+GI(I,1) $TRM=EXP(-GTOT/5.)
     E(I)=TRM*E(I)+(1.-TRM)*(-GK(I)-GI(I,1)+ACT(I,1))/GTOT
     IF (E(I).GE.THA(I)) GOTO 90
     IS(I) = 0
     GOTO 130
  90 IS(I) = 1
     INI=INI+1
     IIF(INI)=I
     CALL RANSET (2.*FLOAT(I+IMICR)+1.)
     IF (NOCIE .EQ. 0) GOTO 110
     DO 100  J = 1, NOCIE
     NCT=INT(5.0*RANF(0.0))+2
     R=RI*RANF(0.)
     TH=6.28318*RANF(0.)
     NYR=(4*((I-1601)/10)+2)+INT(R*(SIN(TH)+SIGN(.5,SIN(TH))))
     IF(NYR .LT. 1) NYR=40+NYR
     IF(NYR .GT. 40) NYR=NYR-40
     NXR=(((I-1600)*4-2)-40*((NYR/2-1)/2))+(INT(R*(COS(TH)+SIGN(.5,
    *   COS(TH)))))
     IF(NXR .LT. 1) NXR=40+NXR
```



```
      IF(NXR .GT. 40) NXR=NXR-40
      NREC=40*(NYR-1)+NXR
      GI(NREC,NCT)=GI(NREC,NCT)+STR(I)
  100 CONTINUE
  110 CONTINUE
      DELTH=DELTHIT*(THA(I)-THIF)
      THA(I)=THA(I)-DELTHSDELTHI=DELTHI+DELTH
      DELI=DELSTRI*(STRIMX-STR(I))
      STR(I)=STR(I)+DELI
      DELTIN=DELTIN+DELI
  130 CONTINUE
      DO 150  I = 1, NTL
      DO 140  J = 1, 5
      ACT(I,J)=ACT(I,J+1)
  140 GI(I,J)=GI(I,J+1)
      ACT(I,6)=0.
  150 GI(I,6)=0.
      IDUME=0
      IDUMI=0
      DO 160  I = 1, N
  160 IDUME=IDUME+IS(I)
      DO 170  I = M1, NTL
  170 IDUMI=IDUMI+IS(I)
      ISUM(L)=IDUME
      ISUMI(L)=IDUMI
      IFE=IFE+IDUME
      IFI=IFI+IDUMI
      IFES=IFES+IDUME*IDUME
      IFIS=IFIS+IDUMI*IDUMI
      IF (IDUME .NE. 0)  LAST = L
      DELE=DELTHE/FLOAT(N)
      DELI=DELTHI/FLOAT(M)
      DO 175 I=1,N
  175 THA(I)=THA(I)+DELE
      DO 176 I=M1,NTL
  176 THA(I)=THA(I)+DELI
      DO 177 I=1,N
      STR(I)=STR(I)-DELTEX/XN
      IF(STR(I).LT.0.) STR(I)=0.
  177 CONTINUE
      DO 178 I=M1,NTL
      STR(I)=STR(I)-DELTIN/FLOAT(M)
      IF(STR(I).LT.3.0) STR(I)=3.0
  178 CONTINUE
      IF (L-LAST .GE. 5) GOTO 190
  180 CONTINUE
  190 WRITE (6,630)
      WRITE (6,650) (ISUM(L), L = 1, LAST)
      WRITE (6,640)
      WRITE (6,650) (ISUMI(L), L = 1, LAST)
      WRITE (6,690)  LAST
      AFE=FLOAT(IFE)
      AFI=FLOAT(IFI)
      AFES=FLOAT(IFES)
      AFIS=FLOAT(IFIS)
      DUR=FLOAT(LAST)
      AFRE=AFE/DUR
      AFRI=AFI/DUR
      SDE=SQRT((AFES-AFE*AFRE)/DUR)
      SDI=SQRT((AFIS-AFI*AFRI)/DUR)
      WRITE (6,700)  AFRE,SDE
      WRITE (6,710)  AFRI,SDI
      WRITE (6,800)
      WRITE(6,930) (STR(I),I=1,NTL)
      WRITE (6,800)
      WRITE (6,930) (THA(I),I=1,NTL)
      WRITE(7,930) (STR(I),I=1,NTL)
      WRITE(7,930) (THA(I),I=1,NTL)
      STOP
*
  500 FORMAT(6I4,4F6.3,I4,F6.4)
  505 FORMAT (4F6.3)
  510 FORMAT(4F6.3)
  520 FORMAT (2I5)
  530 FORMAT(3F6.3,I4)
  600 FORMAT (*1OUTPUT TO NETWORK   (UPDATED VERSION: 79/07/11)*/* =====
     1=============*//* NUMBER OF EXCITATORY CELLS (N) = *,I4/* NUMBER OF
     2 INHIBITORY CELLS (M) = *,I4//* THE PARAMETERS ARE:*//* NOCEE = *,
     3I4,4X,*STREE = *,F6.3,4X,*BEE = *,F6.3,4X,*TADEE = *,F6.3/* NOCEI
     4= *,I4,4X,*STREI = *,F6.3,4X,*BEI = *,F6.3,4X,*TADEI = *,F6.3/* NO
     5CIE=*,I4,4X,*STRIE=*,F6.3/*NOCII=*,I4,4X,*STRII=*,F6.3/,*RE=*,F6.3
     6,5X,*RI=*,F6.3,2X,*RS=*,F6.3,2X,*NOCSA=*,I4,/)
  610 FORMAT (* MTSTOP = *,I4/)
  620 FORMAT (* IMICR = *,I5)
```

```
  630 FORMAT (1H1,*SUMMARY OF NUMBER OF EXCITATORY CELLS THAT FIRED*/)
  640 FORMAT (1H1,*SUMMARY OF NUMBER OF INHIBITORY CELLS THAT FIRED*/)
  650 FORMAT(30I4)
  660 FORMAT (*0 EXCITATORY STRENGTH =*,F9.3,9X,
     1           *INHIBITORY STRENGTH =*,F9.3)
  690 FORMAT (*1 DURATION =*,I6)
  700 FORMAT (*0 EXCITATORY:  MEAN =*,F9.3,9X,
     1           *S.D. =*,F9.3)
  710 FORMAT (*0 INHIBITORY:  MEAN =*,F9.3,9X,
     1           *S.D. =*,F9.3)
  720 FORMAT (/*DELTHET*,F6.3,4X,*THEF=*,F6.3,4X,*DELTHIT=*,F6.3,4X,
     1           *THIF=*,F6.3)
  730 FORMAT(/,2X,*DELSTRE=*,F6.3,4X,*STREMX=*,F6.3,4X,*DELSTRI=*,F6.3,
     1        4X,*STRIMX=*,F6.3)
  800 FORMAT(1H1)
  805 FORMAT(5I4)
  810 FORMAT(20I4)
  815 FORMAT(2X,*LSTIM = *I4,2X,*INTERV = *I4,2X,*LSTOP = *I4,2X,
     1*NSTIM = *I4,2X,*NSTIM1 = *I4)
  900 FORMAT(6I4,4F6.3,I4,F6.4,4F6.3,2I5,3F6.3,I4)
  930 FORMAT (25F5.2)
      END
```

```
      SUBROUTINE STIMULS (LSTIM,INTERV,NSTIM,NSTIM1,MARKER,LOCATN)
      DIMENSION LOCATN(200)
      COMMON E(1700)
      DO 10 I=1,NSTIM1
      J=I+MARKER
      E(LOCATN(J))=2.0
   10 CONTINUE
      MARKER=MARKER+NSTIM1
      IF(MARKER.GE.NSTIM) MARKER=0
      LSTIM=LSTIM+INTERV
      RETURN
      END
```

```
OUTPUT TO NETWORK    (UPDATED VERSION: 79/07/11)
================

NUMBER OF EXCITATORY CELLS (N) = 1600
NUMBER OF INHIBITORY CELLS (M) =  100

THE PARAMETERS ARE:

NOCEE =   10    STREE =  2.100    BEE =  4.000     TADEE =  5.000
NOCEI =    1    STREI =  3.200    BEI =  4.000     TADEI =  5.000
NOCIE=  16    STRIE= 3.000
OCII=   0    STRII=      0
E= 4.000       RI= 4.000  RS= 4.000  NOCSA=  10

MTSTOP =     1

IMICR =     0

ELTHET  .333    THEF=  .800    DELTHIT=  .333    THIF=  .800

 DELSTRE=  .333    STREMX= 3.500    DELSTRI=  .333    STRIMX=10.000

 EXCITATORY STRENGTH =   21.000          INHIBITORY STRENGTH =  153.600
 LSTIM =    1  INTERV =    1  LSTOP =  760  NSTIM =   76  NSTIM1 =    1
```