SOME MECHANISMS FOR A THEORY OF THE RETICULAR FORMATION

by

W. L. Kilmer
W. S. McCulloch
J. Blum

Division of Engineering Research
Michigan State University
East Lansing, Michigan
February 28, 1967

SOME MECHANISMS FOR A THEORY OF THE RETICULAR FORMATION

by W. L. Kilmer,[1] W. S. McCulloch,[2] and J. Blum[3]

The major portion of this work was supported by the AFOSR, administered through Michigan State University. Support was also given by the following: Air Force Office of Scientific Research Grant AF-AFOSR-1023-66 through Michigan State University; DSR Project 55-257, sponsored by the Bioscience Division of ~~the National Aeronautic~~s and Sjpace Administration, Contract No. NSR 22-009-138 through the Massachusetts Institute of ~~Technology Instrumen~~tation Laboratory; the National Institutes of Health Grant NB-04985-03 through the Massachusetts Institute of Technology; U. S. Air Force (Research and Technology Division) Contract AF33(615)-1747 through the Massachusetts Institute of Technology; and the Teagle Foundation Inc., through the Massachusetts Institute of Technology.

[1] Associate Professor, Department of Electrical Engineering, Michigan State University, and Consultant, Massachusetts Institue of Technology Instrumentation Laboratory

[2] Research Associate, Research Laboratory of Electronics, Massachusetts Institute of Technology, and Consultant, Massachusetts Instrumentation Laboratory

[3] Massachusetts Institute of Technology Instrumentation Laboratory

TABLE OF CONTENTS

ABSTRACT

Throughout the life of the vertebrates, the core of the central nervous system, sometimes called the reticular formation, has retained the power to commit the whole animal to one mode of behavior rather than another. Its anatomy, or wiring diagram, is fairly well known, but to date no theory of its circuit action has been proposed that could possibly account for its known performance. Its basic structure is that of a string of similar modules, wide but shallow in computation everywhere, and connected not merely from module to adjacent module, but by long jumpers between distant modules. Analysis of its circuit actions heretofore proposed in terms of finite automata or coupled nonlinear oscillators has failed.

We propose a radical set of nonlinear, probabilistic hybrid computer concepts as guidelines for specifying the operational schemata of the above modules. Using the smallest numbers and greatest simplifications possible, we arrive at a reticular formation concept consisting of 12 anastomatically-coupled modules stacked in columnar array. A simulation test of its behavior shows that despite its 800-line complexity, it still behaves as an integral unit, rolling over from stable mode to stable mode according to abductive logical principles, and as directed by its succession of input 60-tuples.

Our concept employs the following design strategies: modular focusing of input information; modular decoupling under input changes; modular redundancy of potential command (modules having the most information have the most authority); and recruitment and inhibition around reverberatory loops. Presently we are augmenting these strategies to enable our model to condition, habituate, generalize, discriminate, predict, and generally follow a changing environment.

Our program is epistemological. We are trying to develop reticular formation concepts which are complex, precise, and valid enough to inspire reasonable experiments on the functional organization of this progenitor of all vertebrate central nervous tissues.

SOME MECHANISMS FOR A THEORY OF THE RETICULAR FORMATION

1. INTRODUCTION

Throughout the vertebrate phylum, the reticular formation (RF) is the nervous center which does most to integrate the complex of sensory-motor and autonomic-nervous signals, thereby permitting organisms to function as units instead of mere collections of organs. The RF consists generally of the nervous core of the spinal cord, with bulges in higher animals in the lower spinal (lumbar) region, and in regions corresponding to the neck and brain stem areas of man (see Figure 1). In the highest vertebrates it comprises about 1/1000th of the central nervous system. The RF receives relatively unrefined information from all sensory-motor systems which link the organism to its environment (visual, auditory, vestibular, etc.) and from all internal housekeeping systems which insure the organism's internal well-being (visceral, cardiovascular, respiratory, etc.). Its primary task, somewhat oversimplified, is to commit the organism to either one or another of 20 or so, but less than 30, gross modes of behavior -- e.g., run, fight, sleep, vomit -- as a function of the nerve impulses that have played in upon it during the last fraction of a second. It also sends out control directives to all other more specialized nerve centers so that they in turn can behave in an integrated, coherent manner.

In higher vertebrates, many variations on the central modal themes of behavior are mediated through a profusion of other brain regions. The RF interacts with the highest of these regions primarily through the thalamus, the information anteroom of the higher brain, by dictating what kind of functions the cerebrum is to compute on its input sensory, autonomic, and mnemonic information. We call this "function setting." The RF also tunes filters in sensory input pathways to rough-focus the organism's overall attention; it modulates motor output signals; it sets zero points in reflex servo and homeostatic feedback loops; it controls the organism's sleep-waking cycle and postural substratum; it participates with the hypothalamus in the regulation of vegetative activities; etc.

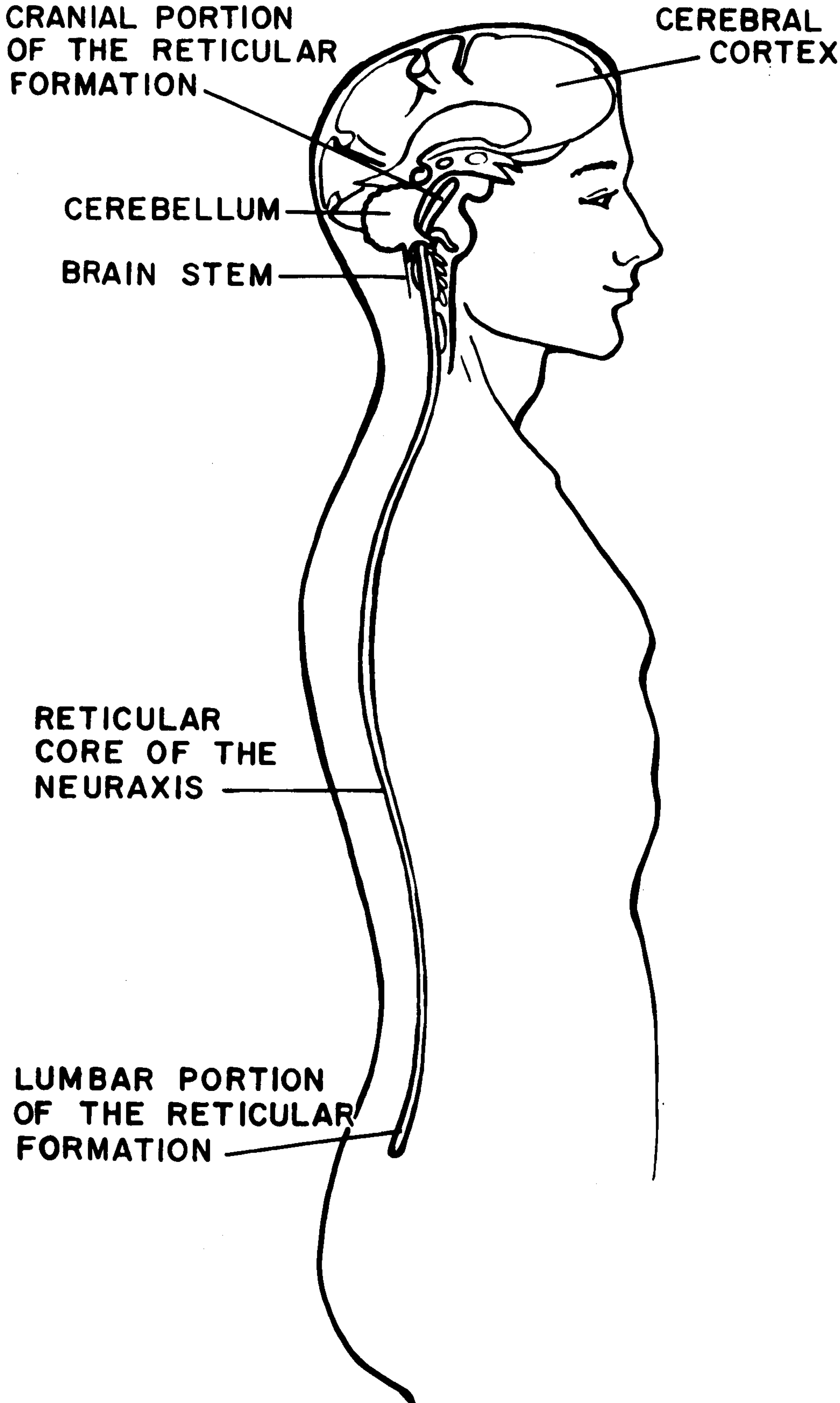


Figure 1. Location of the reticular formation in the cranium, brain stem, and spinal cord of man.

But the RF does not do everything. For we note that though decerebrate adult cats[8] can distinguish between tones, they cannot between tunes; and though they can see brightness and respond appropriately to simple moving forms, they apparently are devoid of all refined visual perception. Neither do they orient well to bodily touch, cold, pressure, or shock stimuli. Their movements are impoverished and highly stereotyped; they are modal. They lie, sit, stand, walk, run, fight, surrender, sleep, eat, drink, vomit, defecate, micturate, and mate. Their stalking, pouncing, directed cuffing, skillful playing, and other such activities, are essentially gone. They are stimulus bound with no capacity for long-range intentions or complex problem-solving. What they have left of their nervous system is too busy trying to keep them alive for that. They are able only to cope with the most urgent and important stimulus contingencies, because they must in their natural domain retain as much of their quick response capability as possible, and it takes all the neural circuitry they have left to do it.

If the behavior of decerebrate cats means what we think, the RF in its natural milieu is certainly not a refined, precise, articulate, or temporally-sophisticated mechanism by whole-brain standards. It is far more integrative than analytical, and far more comprehensive than apprehensive.[34] Yet one must not delude himself on this head. For even cockroach ganglia, consisting of only about 1000 primitive neurons, can adaptively sort out 29 from 30 pulse signal bursts[45] and the RF is by all measures a wizard compared to one cockroach ganglion.

P. Wall[121] has noted that RFs in experimental cats always seem to have a preferential set point instead of constantly and gradually passing from level to level. P. Dell[24] has discussed the functional stability of RFs in terms of their homeostatic tendency to eliminate input disturbances through corrective effector actions and by resetting input-filter operating points. Sometimes the corrective actions are neural load adjustments, such as bulbar RF elevation of arterial pressure through neurohumoral secretion,or reticulo-cortico-reticular depression of neural activity through feedback regulation. At other times the corrective actions involve CO_2 or O_2 induced changes in RF neural activity in both ongoing and recruitable (in emergencies) respiratory centers, or involve selective inhibition of some groups of interneurons (intermediate diagastric jaw-opening neurons, for example) with compensating facilitation of others (masseter jaw-closing motoneurons, for example). The latter often causes a drastic alteration of the cortical fractionation of reflex actions. It can also switch out one group or afferent pathways to a neural center and switch in another. Wall and Dell's homeostatic observations further corroborate our mode concept of RF function.

Let us try to develop our notion of what the RF does in another way. At the millipede state of evolution, the RF is essentially the entire central nervous system. By the pigeon stage, it has grown, or separated out, several comparatively specialized computers for making finer discriminations between sensory stimuli and for computing more precise motor control signals, than it could possibly produce by itself and still maintain its fast-acting overall command and control function. Chief among these specialized computers are the visual, vestibular, bodily-sensory, and auditory systems, and the cerebellum to compute precise auto-correlations for actions of the pigeon on the pigeon and the pigeon on its world (as required for pecking, control in flight, etc.). The pigeon RF has also evolved specialized basal ganglionic mechanisms for programming its associated bodily movements (required for running, fighting, feeding, mating, etc.); a set of well localized feedback paths, called simple reflexes; and a set of regenerative nerve loops for controlling various types of internal rhythms (cardiovascular, respiratory, digestive, etc.). But it is still clear, especially from the work of Lorenz and his school, that the pigeon, sea gull, goose, and other organisms of that evolutionary rank behave in a nearly modal fashion.

By the human stage of evolution, the RF has grown a cortical mantle over the rest of its phylogenetically older structures. These older structures, when left by themselves, are only concerned with the rather more immediate preservation of the individual and its species.[57, 58] But in humans, with their additional cortex, we find new and different types of functions, like language; we also find that the behavioral influences of many of the older functions, like anger, are greatly modified, and that an enlarged frontal lobe has mushroomed the development of long-range judgement, sophisticated attitudes, and deliberative purposes in the organism.[116] We find, too, that the visual, auditory, bodily-sensory, and motor outflow computers are larger and more intricate than ever. But, for all the RF's reliance on the discriminatory, associational, memory, abstractional, computing, and programming powers of the cortex, it apparently has never relinquished its central command function to the cortex. The evidence for this is both anatomical and physiological. Only the RF has a wealth of direct or monosynaptic connections to and from all other central nervous structures.[81, 89] Only the RF is able to arouse, put to sleep, and turn off (over-ride in a crisis) the rest of the entire forebrain.[70] And only the RF has the position and connectivity to possibly make computations wide enough (of sufficient scope) and shallow enough (in logical depth) to always arrive at good gross modal (integrative) decision within a fraction of a second, given the requisite information.[89]

*Our modal command concept of the RF is not incompatible with the amodal behavior of orchestra pianists, or active and learning cats that have almost completely ablated RFs, or incinerated martyr priests, or such things as the men of New Hebrides jumping head-first off 50-foot towers only to be stopped 3 inches from the ground by thongs tied around their ankles. It is true these things pose some problems for our development. The martyr-priests and tower jumpers operate under extreme cortical "control" of the RF. The violated cats dramatically demonstrate the neurological dictum that brains concentrate first, with whatever equipment they might have left, on staying alive. In this sense, no brain region is totally sacrasanct with respect to any major brain function. The pianists demonstrate just how nonmodal cortically modulated behavior can get. With this, let us delve a little more deeply into the relations between brain regions that these examples imply.

---

*This paragraph is mostly a rebuttal to comments made by engineers on an earlier version of this report.

Just as the commander of a fleet might have to plunge his ships into destruction in order to achieve a mission formulated by his mission control office, the RF might also have to act analogously in relation to some specialized brain agency it begot. For the RF must trust and listen to other brain centers just as a fleet commander must trust and listen to the fleet's radar, gunnery, engine room, combat, and navigational offices. After a modal command has been issued, both animal and fleet must carry it out according to a preprogrammed set of rules, with embellishments as contingencies demand. In the martyr-priest and tower-jumping examples, the RF's command to the rest of the central nervous system is the best reconciliation of a host of conflicting demands placed upon it. On the other hand, piano playing is a cortically-mediated activity requiring the fractionation of more primitive response patterns into a special blend of precise actions. The RF permits this kind of thing, but does not command or control it (except by default). In the cat case, we see that animals can survive massive RF lesions, animate, and even condition after them. This is because brain functions can migrate, given the necessity, time, and a decent anatomical chance, in order to get their primary jobs done. Similarly, if the conductor of an orchestra passes out, a front row instrumentalist can take charge, but usually only at considerable cost to the orchestra's quality of performance.

The RF is thus "general" -- or in classical Greek terminology, "first," -- in the brain. Its relation to other brain structures recalls the Biblical passage, "...but whoever would be great among you must be your servant, and whoever would be first among you must be your slave."

Now consider the RF, minus everything on its input side (generally speaking the dorsolateral regions), its output side (ventral-lateral RF, basal ganglia, etc.), all of its local reflexes, and all of its respiratory and other rhythmic operational aspects which are functionally separable from its main decisionary tasks. Denote what is left RF.* The task of RF* we take to be a blend of modal-commitment and function-setting activities; and the latter we take to be engendered by the former. <u>This is the fundamental assumption of our paper.</u> It has the greatest apparent validity at the medullary level of the RF. More rostrally, at the midbrain and thalamic levels, the RF decisionary functions grade off into predominantly nonspecific (function-setting) and associational-integrative activities. Let us denote by RF* a sharply modal idealization of RF*'s functions. RF* will be the object of our study from here on, and we will regard it as at least a promising theoretical progenitor of a realistic RF* concept.

We will next sketch the known RF neurophysiology and neuroanatomy, and then go on to propose a theoretical framework for RF* that we think stands a chance of being right enough and developmentally promising enough to eventually be of some use to us in understanding real RFs. What we are after first is a way to think about how RF* always arrives at an integrated modal decision in a dozen or so neural decision times instead of disagreeing among its several parts in the face of competitive or contradictory input signals. We believe that the highly characteristic RF anatomy is an indispensable clue to how this is done instead of an irksome or gratuitous constraint. Some would not agree with us. They must then advance along the lines of categorical philosophy or psychology, which is not our primary interest. We want to know, after Clerk Maxwell, not only the go of our mechanism, but the particular go of it.

The magnitude of our problem is signaled by some previous theoretical results. We know that logic nets organized along RF lines (linear arrays of finitely but unboundedly many identical descrete automata information-coupled in both directions) have probability 1 of not being able, after starting in equilibrium, to arrive at an equilibrium point in less than a bounded number of component-automaton decision times following a perturbation of inputs.[49, 50]

Other results on iterated logic nets [41, 47, 48] point up related difficulties in our problem. We recall the complete lack of methods to certify that coupled nonlinear oscillator manifolds would put us in any better stead on such accounts. It must be emphasized that our central difficulty hinges on the fact that we are concerned with transient or decisionary processes by which complex nonlinear decision-making systems roll over from stable mode to stable mode, and not the steady state effects in such systems (cf. Appendix 1).

2. NEUROPHYSIOLOGY AND NEUROANATOMY OF THE RF

The Scheibels have so far done what for us is the most definitive neuroanatomy available on the RF. In their milestone paper of 1958,[93] they caricatured the anatomical structure of the lower 2/3 of the RF in the brain stem by comparing it to a stack of poker chips. In each chip region the dendritic processes of RF neurons ramify in the plane of the chip face, often covering nearly half of the face area. The Scheibels and Nauta[81] describe the shape of RF neural dendrite arbors as primitive, neither tufted nor wavey, but consisting of long shaftlike processes whose branches are usually longer than the stem of their origin. Among dendrites of nearby neurons, there is a very large degree of overlap and intermingling, as shown schematically for the brain stem region in Figure 2. (This is very similar to Scheibels' Figure 1 in Reference 86.)

The dendritic organization of the nerve nuclei that furnish inputs to the RF is predominantly longitudinal, as seen in Figure 2b, or of a tufted or wavey character. The axons out of these nuclei, and the axonal collateralizations out of all of the longitudinal fibre tracts that feed into the RF, turn off sharply to reach into the RF in the planes of the RF's greatest dendritic ramification. Since in this process as many as a half dozen or more different input systems may synapse on a single RF neuron, and each RF input nucleus and fibre tract in general feeds very many RF cross-sectional levels, the Scheibels suggest that the RF might tolerate considerable puddling of information at each of its cross-sectional levels, but demand somewhat greater informational rigor between levels. Nauta similarly regards the RF dendritic anatomy as an isodendritic matrix which serves as the structural substrate for a near-continuum of signals.

The order of magnitude of the number of RF afferents, the number of RF neurons, and the number of RF efferents, is accepted as about the same from frog to man. RF dendrites generally appear to fan out about 60° ventrally from more ventral RF cell bodies, and about 180° dorsolaterally from more dorsal RF cell bodies. All processes of more laterally situated RF neurons are in general smaller than their more medial counterparts.[117,118] Smaller RF neurons are, of course, more concerned with local operations, and larger ones, with global functions. In general,

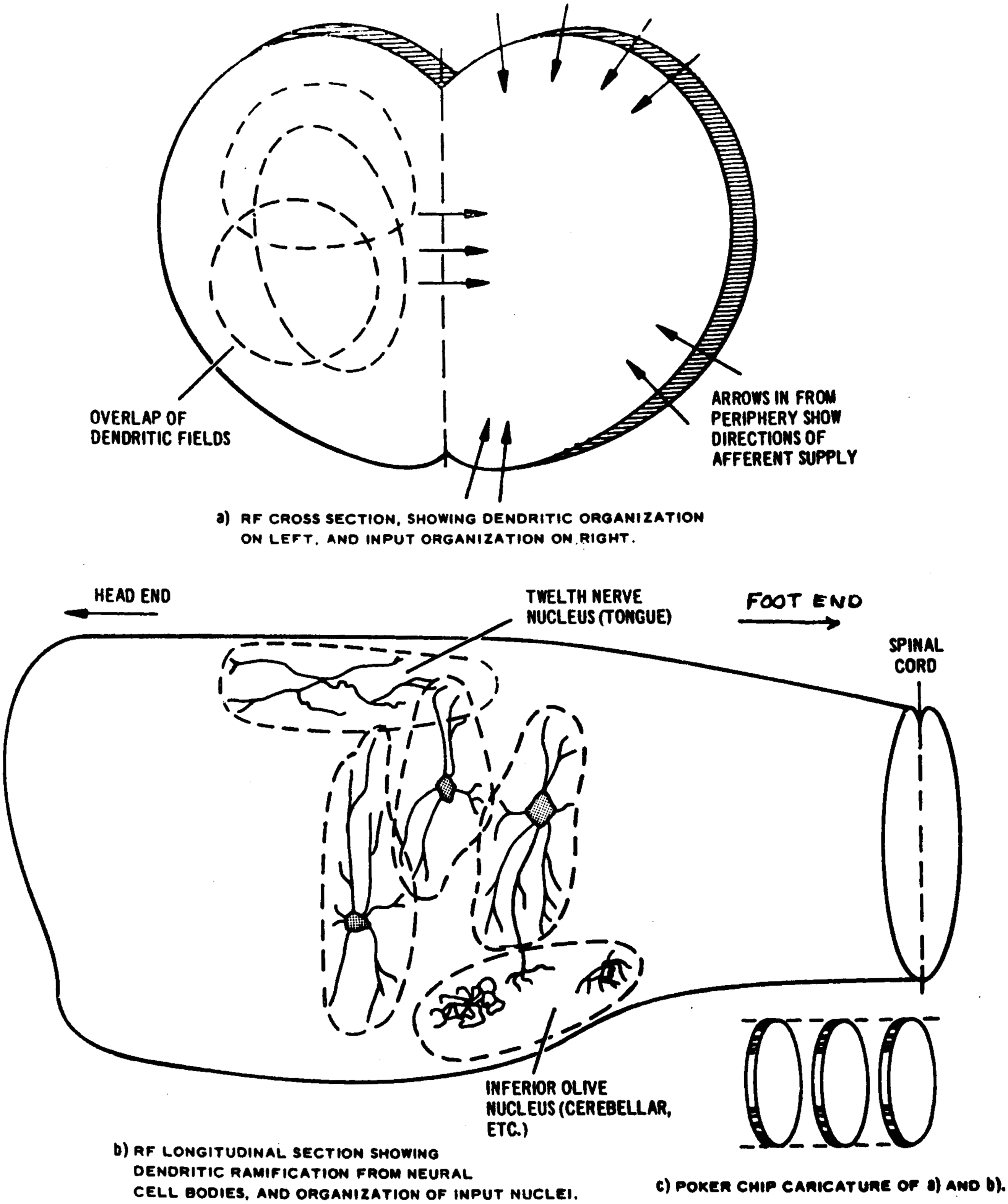


Fig. 2. Brain stem RF dendritic anatomy.

more ventral RF neurons participate more extensively in effector functions, more dorsal RF neurons in sensory functions, and more lateral RF neurons in vegetative functions.

The RF axonal anatomy corresponding to Figure 2b is shown in Figure 3. (This drawing is essentially Scheibels' Figure 4 of Ref. 86.) In Figure 3 a characteristic RF axonal process is seen coursing its way longitudinally over a major portion of the brain stem. Collaterals branch off into other RF levels and various RF input nuclei, as well as into both corticifugal (i. e., descending) and corticipetal (i. e., ascending) neural fibre tracts. A good many RF axons also project nonspecifically* into cerebral regions,[72-81] as well as directly out to the level of the first neuron in each of the sensory systems (e. g., to the retina of the eye, and to the muscles of the inner ear).[43] In short, the RF sits athwart all incoming and outgoing nervous transactions carried out over the entire neuraxis, and it both samples and modulates their spatio-temporal information sequences so as to command the gross modal operation of the organism.

Essentially all that is known about the Nissel architecture of the RF is that there is a full range of neural cell sizes. But neither neat circimscription of neural groups nor laminar nor other striking distributive organization is evident. This is quite opposite of those regions just outside the RF core (Nauta's definition of RF[81]).

Thus far no very helpful hypotheses have been developed relating the precise geometric forms and sizes of RF neurons to the type of functions they compute. In this sense, the RF is much more intractable than the frog's eye.[56]

Near any given RF neural cell body there may be tens of thousands of both fast conducting (100 meters/sec) insulated fibres and slow conducting (a few meters/sec) uninsulated fibres, but the functional significance of this has only been guessed at. We know that RF neurons characteristically

*"Nonspecific" projection tells cortex what functions to compute, but does not furnish the information for computation. The projection referred to mostly passes through at least one thalamic-level (i. e., diencephalic) synapse.

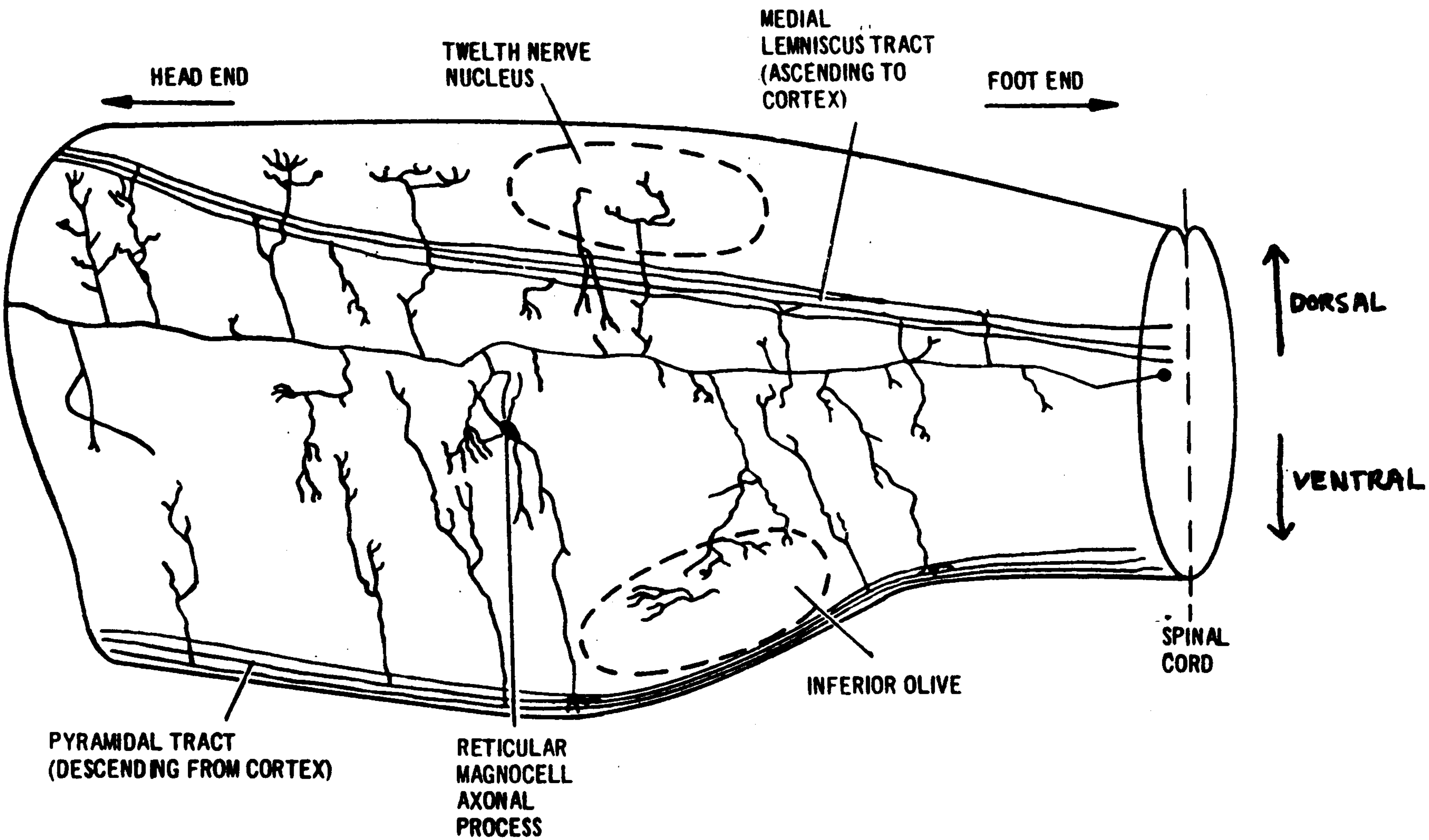


Figure 3. RF axonal anatomy corresponding to Figure 2 dendritic anatomy.

respond to exceptionally wide ranges of neural[10, 97] and chemical[23, 24] stimuli involving perhaps several sensory and vegetative modalities. For example, in cat there are RF neurons that increase their firing rates during asphyxia, tickling of hair cells in the nose, and postural unbalance. Other RF neurons respond to visceral disorders, crude body interface phenomena (touch, pressure, and cold), and certain phases of anti-gravity bodily kinetics; and still others to cerebral control signals, raw information from head-end distance receptors (eye and ear), and signals from neuro-endocrine receptors in the hypothalamus.

We know also that there is massive reticular involvement in motor outflow and attention-focusing affairs. For example, rats do not ordinarily distinguish yellow; but if they are hungry and small cheese, RF directed outflow sets up visual computations which enable them to. Also, Hernandez-Peon[43] has found cochlear nucleus (auditory pathway) neurons in anesthetized cat that respond well to clicks until odorous fish is placed under the cats' nose. Thus a modal decision might well be viewed as a very broad command to attend, e.g., to running, feeding, or fighting. P. Dell has developed this notion in terms of critical (in the sense of judgement) reactivity.[24]

In the plastic domain, RF neurons are the first to adapt out their responses to intense but meaningless stimuli (e.g., gunfire at a shooting range), and are generally the first to show signs of conditioning to sensory indications of imminent painful stimuli.[39, 59] But the RF does not learn very much on a long term basis. P. Shurrager's dog whose spinal cord had been transected as a pup, learned to walk, sit, lie, copulate, and void urine and excrement with nearly the right postures and motions. A soldier will sometimes hit the dirt on hearing any loud, sharp sound for years after a long battle experience. But these are extreme cases. The RF does not usually even retain conditioning for more than about 30 minutes.

There is strong evidence to suggest that the RF can change modal commitments at a steady rate of not more than about 3 times per second (spinal reflexes, some of whose paths can be traversed in about 20 milliseconds, notwithstanding), but must be driven with pulse repetition rates of the order of a few or a few hundred per second for this to occur.[124]

Most pulse rates at low power have very little overall effect inside RF tissue. If the RF is engaged in a significant overall decisionary activity, probably the focusing down affects following the crest of this activity persist for a minute or more.[5] We conjecture that cortical perceptions (is there a lion behind that bush or not?) are produced at the rate of about ten per second, and that this is the main limiting temporal factor in those cortico-reticular exchanges that primarily concern modal decisions. We note that humoral and hormonal rhythms, with periods of hours, days, months, and years, can have a great effect on the overall sensitivity and set of a RF.

We understand something of how vertebrate organisms take habits and conduct their neuronal affairs at the reticular level. It has remained the same from shark and lamprey to man.[81] But we know essentially nothing about the kinds of spatio-temporal information codes that RF employs to cope with its horrendous intrareticular communication and computation problem. Granted, there is some signal channeling as a function of pulse repetition rate that has often been noted experimentally.[32] And a good deal of recent spike interval histogram[119] and noise power work[120] has reinforced the old belief that much neural processing must be statistical. Also Lettvin, McCulloch, and co-workers have demonstrated how single neurons could compute any logical function of their inputs, indicating that the action potential's all-or-none character is not accidental. But RF spike waveshapes have been reported to often have very long trailing edges (up to 10 ms);[97] neural-glial field effects figure ever more prominently in RF operation;[2] and RF biophysico-biochemical parameters are continaully outcropping as possible distributed RF operating conditions.[2,23] So all is not combinatory logic, anatomical pathways, and statistical pulse frequency processing either. In a different vein, we can neither imagine how, nor whether, RF input information fractionates into small, coherent, more or less loosely coupled Hebbsian assemblies that intermingle to realize associative, cooperative, and intergrative decisionary behavior.

In the European newt, only the RF can regenerate the rest of the whole brain. Thus in some sense, it knows what it needs to help it run the organism in which it resides. In the newborn, the RF is mature whereas the rest of the forebrain is not. Apparently, give or take a few lesions, the RF is the sine qua non of viability whereas the other brain regions are not -- at least early in life. These facts shed light on reticular relations with other brain regions, but disappointingly little on intra-reticular operation.

In summary, a good deal is known about the RF' input and output systems, and something about its neurobiology, Much is lacking on the detailed connection patterns between the various neural types, and their counts with changes of position. Practically nothing is known about how RF inputs start appropriate computations racing up and down the net so as to always yield effectively unanimous decisions for modal command signals.

We are convinced that if the RF is ever to be really understood, we must have a theoretical model that will enable us to intuit from it logically sophisticated experiments of sufficient cybernetic dimensionality and complexity to take into account those differences which make a difference. N one-dimensional experiments can never take the place of one N-dimensional experiment in a thoroughly N-dimensional system.

3. LOGICAL REQUIREMENTS OF THE THEORY

First of all, we must understand what kind of logic the RF* described in our introduction performs. C. S. Pierce called it the logic of relations, but for its clearest statement we go straight to the father of modern biology, Aristotle. He described three kinds of logic: deductive, inductive, and abductive. RF* does the latter. Its scheme is to go from the facts and a rule to a case, i.e., the facts of sensory and internal perception as represented over the RF* input channels, and a rule for classifying these facts by an overall computational scheme; to a case of the form: the input is X and this implies action mode Y.

An organism's RF case structure is always the result of its evolutionary, developmental, and experiential heritage.

Computer theorists generally think of deductive, inductive, and abductive logic as follows:

deductive logic	~	execution of a given program
inductive logic	~	generation of a new program during a training period such that the new program can produce a proper output given any input closely related to one in the training set.
abductive logic	~	selection of the appropriate program from a repertoire in accordance with a rule for analyzing program requests. Since these program requests can be made in any form -- e.g., in natural language -- in general a calculus of n-adic intentional relations is needed for the analysis.

After each new modal decision, RF* keys the proper output program, and from then on as far as it is concerned everything follows in a completely deductive manner. (For example, the programmed output of the basal ganglia throws its keyed signal sequences for walking down over the interlocked entrainments of nerve centers in the arms and legs, and they in turn embellish the details of the orders given them as the contingencies of rough terrain, etc., demand; and so on out to the periphery, where the effector signals are transformed into smooth and complicated actions.)

Doubtless RF* never computes single modal decisions directly, but rather their half-center representations. To illustrate, Figure 4 shows the half-center dimensions for the lumbar enlargement of a dog. The advantage of such a representation is that for n dimensions, a single 2^n-valued function can be replaced by n two-(or sometimes more) valued functions.

Conditioning, habituation, and long-term learning in the RF require only inductive logic in principle, and quite probably at this stage are best studied in cortex.

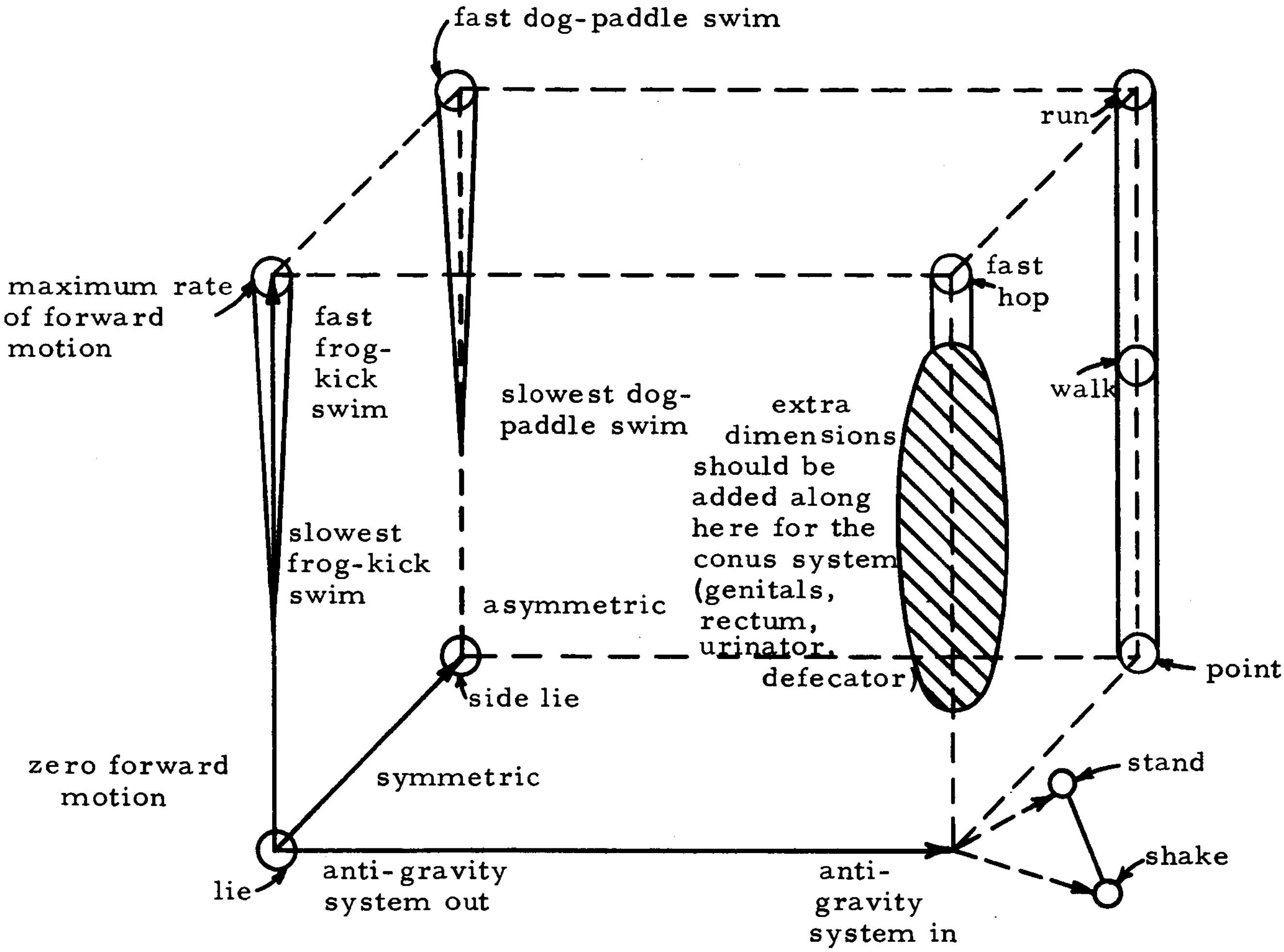


Figure 4. Half-center dimensions for lumbar RF of dog. (Note: Heavy lines show dimensions.)

4. THE PRESENT MODEL

This section describes our present RF* model, which we denote S-RETIC. It is a caricature of the poker chip analogy for the brain stem RF, and was constructed to be as simple as possible without violating our intuitive notion of what RF operation is like.

In the model we replace adjacent groups of the Scheibels' approximately 100-micra-thick poker chip regions by single modules which contain nonlinear, probabilistic hybrid computers. We require that all modules in the resulting columnar array be similar and operate on the same synchronous time scale. The modules are interconnected to a degree and in a way suggested by the known RF axonal anatomy. The anatomy is also the guide in specifying external S-RETIC inputs to each of the modules.

The plan is somewhat different on the S-RETIC output side. Since it is mainly the computational structure of single RF modal decisions that we are interested in, each of the S-RETIC modules is given only direct mode-indicator outputs. We assume that the effects of each S-RETIC mode change show up at some later time over S-RETIC's input lines. This departs from RF biology in that our S-RETIC outputs have no direct way of influencing the supposed organism's input and output systems which feed it. Such an overall-output approach seems justified by results like Doty's,[28] which show that even brain stem swallowing motoneurons "seem to have an unpredictable and random pattern from one swallow to the next, though the overall schedule of excitation and inhibition among the participating muscles in highly constant."

Figure 5 shows a reduced schematic of S-RETIC. All σ_i and γ_i lines are binary (an arbitrary but convenient basis of information coding); the M_i are S-RETIC's poker-chip logic modules; the S_i correspond to the various humoral, chemoreceptive, and exteroceptive and interoceptive sensory and internuncial systems that feed inputs directly into the RF; the Ω_i (only Ω_7 shown) are the modular mode-indicating output lines; and the upper and lower boundaries, T and B, correspond roughly to the midbrain and high cervical regions of the higher vertebrates, respectively. For clarity each type of connection appears in Figure 5 only once, whereas actually the connection types proximate to M_7 recur at all corresponding

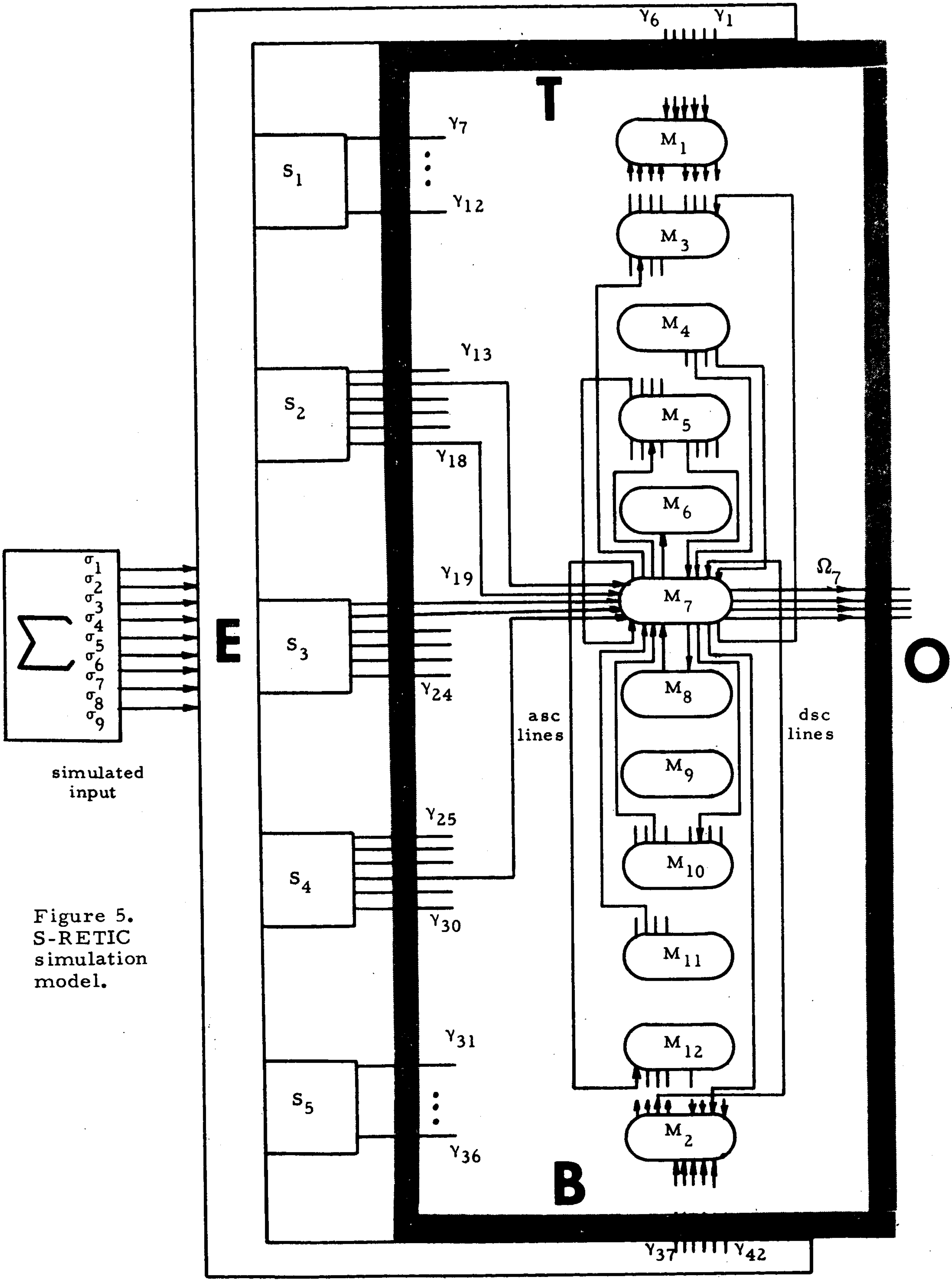


Figure 5.
S-RETIC
simulation
model.

similar locations over the entire figure. Thus, if a connection type diverges from or converges to one or a group of S_j or M_i in Figure 5, it does likewise at every corresponding similar location in S-RETIC. Each M_i, then, receives inputs from several but not all S_j, and each S_j feeds several but not all M_i. Each M_i feeds information directly to several but not all other M_i, and receives information directly from several but not all other M_j.

The M_i-to-M_j connections are arranged so that, in general, modules close together are information-coupled more closely than modules far apart. This is in line with the neuroanatomy. Similar restrictions are also all that govern the terminal distributions of the A and C bundles, though the anatomy of Nauta and Brodal suggests that somewhat more patterning and specificity than this exists in the real RF. The S_j output and M_i ascending and descending bundle sizes are delimited to 5, 4, and 4, respectively; and the degrees of S_j-to-M_i fan-in and fan-out are delimited as suggested by the RF input anatomy (involving nuclear regions, fibre tracts, and more localized lateral reticular structures). The precise nature of these delimitations is suggested in Figure 5, and is specified in detail in Appendix 4. The specification was made with the intention of imposing fairly even "use" distributions on the γ_i and σ_i. The corresponding γ_i connection relations are important because the information on these lines should be highly but nontrivially correlated, with the degree of correlation between each pair of γ_i determining their proximity in the $\gamma_{11}, \ldots, \gamma_{42}$ ordering. The γ_i are realizations of all 42 symmetric switching functions of the form $(\sigma_i \wedge \sigma_j) \vee (\sigma_j \wedge \sigma_k) \vee (\sigma_k \wedge \sigma_i)$, with i, j, and k pairwise different, i, j, ≤ 7, and k = 8 or 9.* (Cf. Appendix 2 for tabulation of functions.) This keeps the percentage of 1's on the γ_i's about the same as that on the σ_i's (cf. Appendix 3 for details), and preserves some useful distance properties in the passage from σ_i to γ_i signal sets. The M_i-to-M_j connections are made randomly so that the probability of a direct M_i-to M_j connection is inversely proportional to the absolute magnitude of the square root of (i-j). (Cf. Appendices 7 and 8 for connection table and details.) Σ and E in Figure 5 are thus included only to simulate an RF environment that engenders input signals from a covarying world. (For example, if a runaway car stops abruptly at a wall at the bottom of a hill, a witness is likely to hear a crash. His visual and auditory pathways then transmit correspondingly covariant signals into his reticular formation.)

Before discussing the details of the M_i in Figure 5, we note that RF biology recommends to our use the following M_i input design strategy, which not so incidentally is aligned with Leibnitz's notion of the diversified monad[55] (especially for $\{\sigma_i\}$, $\{\gamma_i\}$, $\{\gamma_{i_j}\}$, and $\{M_i\}$ set sizes of over 50, 1000, 50, and 100, respectively, which is more like what we are really thinking of anyway. We chose the small numbers 9, 42, 5, 12, because they were the smallest we thought we could get away with without completely violating our RF* concept). Each M_i of S-RETIC should receive a selection of γ_i inputs which just enables it to get a good picture, or relatively high resolution view, of the signal state in a certain small portion of the Σ bundle, but which only permits it a progressively poorer picture of the signal state in portions of the Σ bundle more outlying from its "area centralis." This makes each M_i both a generalist and a specialist. If each were only a generalist, S-RETIC would not be able to discriminate well enough. If each were only a specialist, S-RETIC would not be able to piece together a good global decision; in addition if any M_i should fail, the overall system would go totally blind in some Σ area, and that should never happen in an RF* system.

Figure 6 depicts the essentials of our notion. Over a cross-section of the Σ bundle, the M_i for which the figure was drawn derives from its γ_i inputs exactly k units of information on the signal states of all the σ lines within each marked off area of the cross-section (A or B, for example). Area A, then, belongs to the Figure 6 M_i's area centralis, and B its peripheral low-resolution area.

The idea is to have each M_i's area centralis displaced from each other M_i's area centralis, but such that each point in the $\{\sigma\}$ bundle's cross section is at least near the area centralis of some M_i. Then each M_i knows something about all of S-RETIC's input affairs, so is diversified, but is a specialist on only a subset of them. This admits the necessary

---

* "$\vee$" is logical inclusive or, "and"$\wedge$" is logical "and," with $(1 \wedge 0) = 0$ and $(1 \vee 0) = 1$.

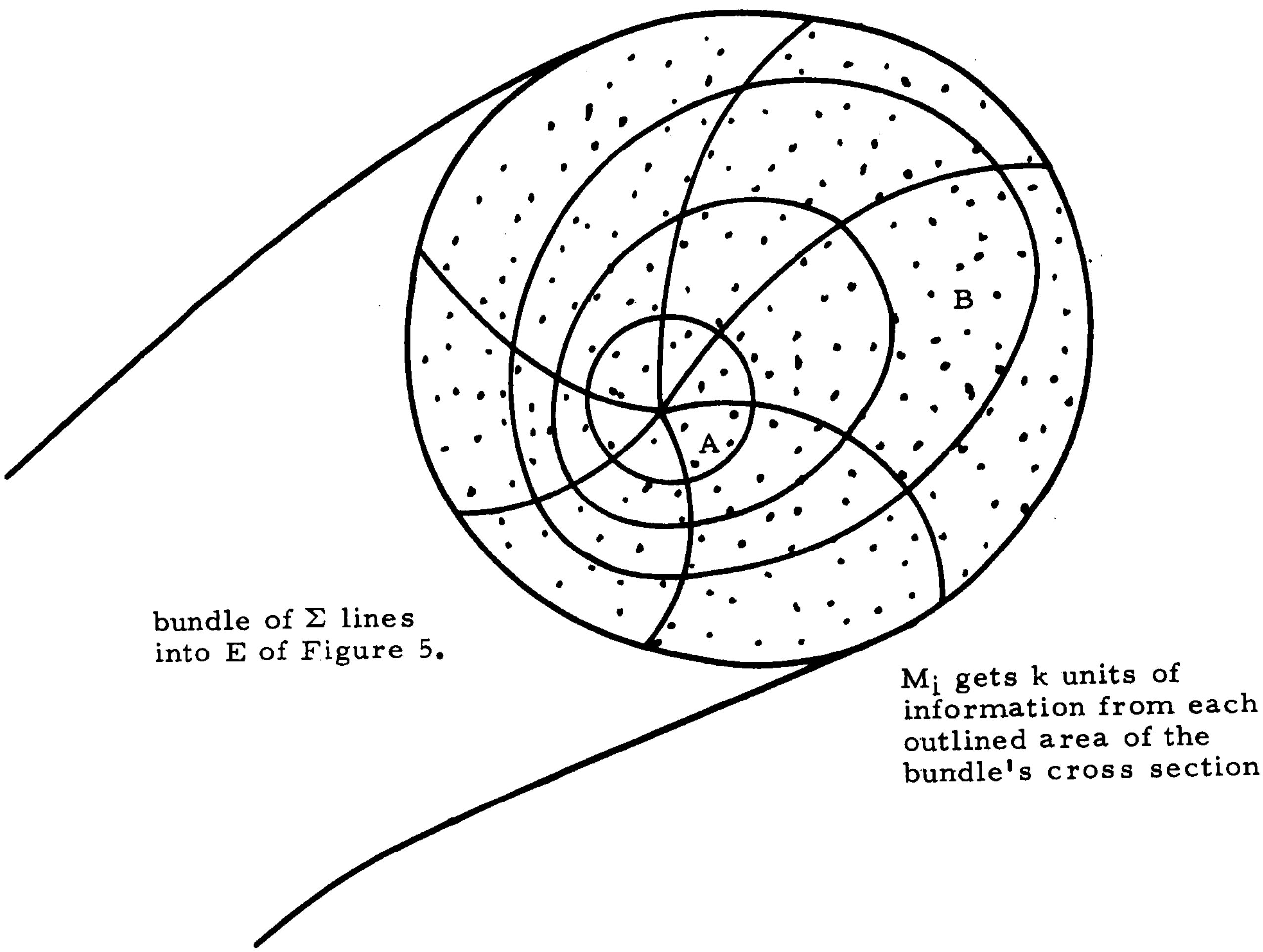


Figure 6. Basis of our module design philosophy.

S-RETIC acuity. Another important consequence of this strategy is that one can shoot holes through S-RETIC, and what's left performs with an overall decisionary acuity that is roughly proportional to the number of good M_i it has left. Careful checking will reveal that S-RETIC realizes the foregoing $\{\sigma_i\}$-to-$\{\gamma_i\}$-to-$\{M_i\}$ design strategy. (We are using a much more justifiable γ function specification than the one given here in our present work on trainable S-RETICs.)

Everywhere above, the Σ bundle does not correspond to any signal paths in the real world. But at the $\{\gamma_i\}$ level, there should be signal correlations of like character occurring in real world neurology over RF input pathways.

Figure 7, to be explained later, shows the scheme we chose for realizing our Figure 5 M_i. It was inspired by the desire to realize the logic, if not the mechanisms, of coupled nonlinear oscillator manifolds. This was because, to a reasonable approximation, that's what the RF is. The most ancient types of neural tissue always suggest this. (Appendix 1 tells why we did not actually use such manifolds in our model.) But we could also see that we would have to organize our logic along certain strategic lines in order to maintain some measure of control over our model's behavior.

We chose two major strategies in addition to the above area centralis M_i input strategy:

(a) Module recruitment according to a redundancy of potential command. This requires that those modules that apparently have the most information also have the most authority. It also requires that they be able to express their authority by recruiting other modules with less apparent information over to their modal persuasions.

(b) Module decoupling at times of S-RETIC input change. This enables modules to arrive at relative modal preferences following each overall input change mostly on the basis of their own direct γ inputs. They then gradually couple in with the rest of S-RETIC, interact with each other, and eventually converge on a single output modal consensus.

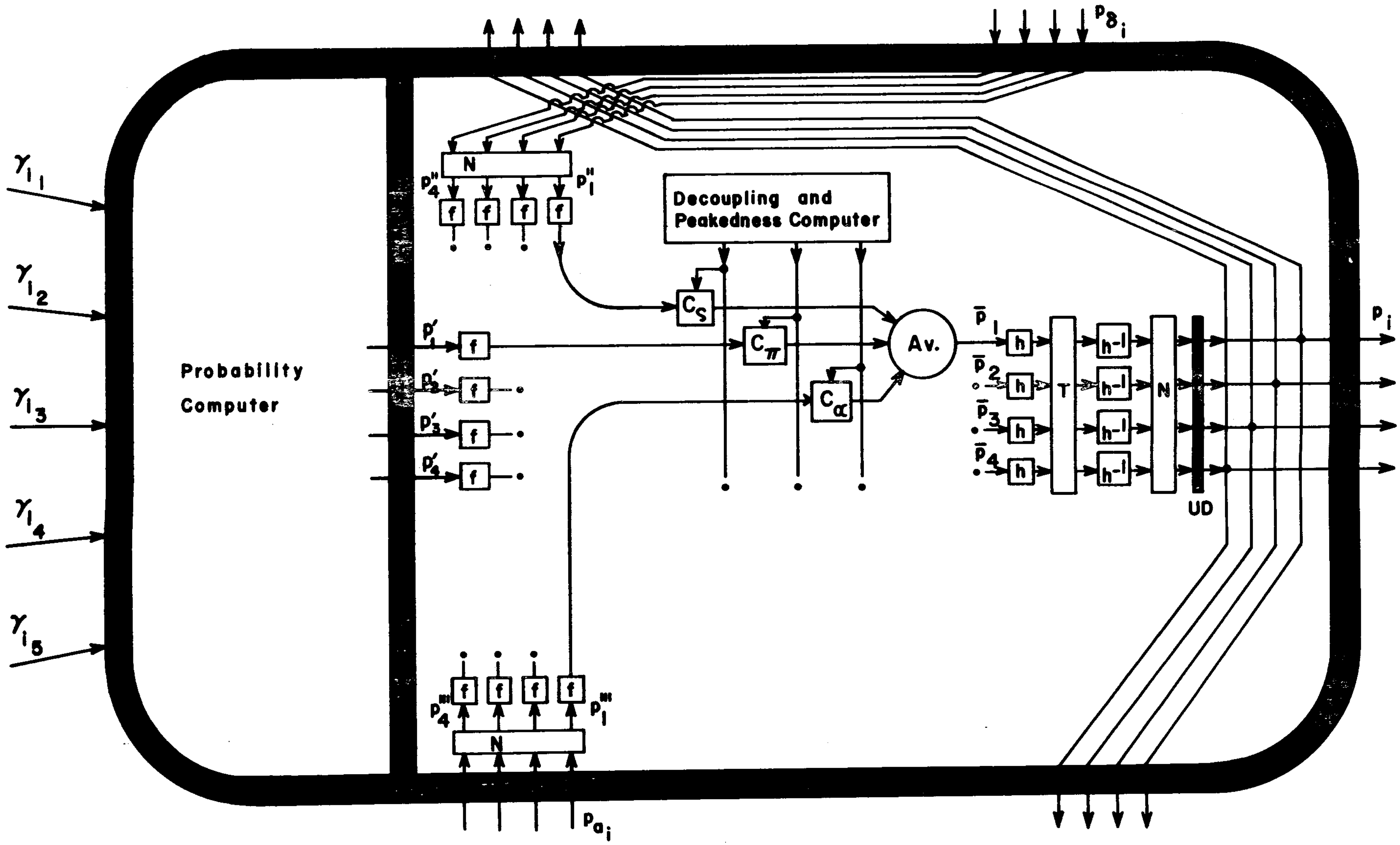


Figure 7. A typical M_i of Figure 5.

For a gross temporal picture of how S-RETIC does its computing, then, we can imagine that S-RETIC has just received a new overall input. Each M_i first computes its corresponding modal preferences, mostly on the basis of its new γ inputs. At the next time step, it exchanges modal preferences with selected other modules; concomitantly, it adjusts its own preferences to some degree as a function of those just received from other M_i. It continues to operate in this manner each time step thereafter, coupling in ever more tightly to the other M_i as it goes along (to a limit), until the next overall input change. Somewhere in this process, a consensus of modules is swung over to a single modal preference and is held there until the next overall input change occurs. At this point the whole sequence starts all over again.

Let us now take a coarse look at how each M_i works. Afterwards, we will go back and describe precisely how the foregoing strategies are implemented to achieve the desired S-RETIC behavior. In Figure 7, M_i's probability computer computes from its five present γ_{i_j} inputs the p' vector $(p'_1, \ldots, p'_4)$, where p'_j is the probability that the present overall $\{\gamma_i\}$ signal configuration properly corresponds to a jth mode output indication. This computation is actually only a table lookup, using tables as shown in Appendix 4. (Appendix 5 tells how Appendix 4 was derived. Summarily, Appendix 4 was computed from a random a priori assignment of each overall $\{\gamma_i\}$ signal configuration to one of our four modal categories. At present, however, we are trying to train in S-RETIC's Appendix 4 tables right from scratch, where all $p'_j = .25$, by reinforcement procedures.)

The p''_i and p'''_i signals into the M_i in Figure 7 give the momentary modal probabilities as evaluated by selected M_j above and below M_i. Each N box is a normalizer such that the sum of its four analog outputs equals 1. The twelve normalized p'_i, p''_i, p'''_i values are componentwise operated on by a nonlinear function, f, as shown in Figure 2. The $\overline{p}_i$ are computed through C_α, C_π, C_δ multiplier units and an Av averaging unit according to the formula

$$\overline{p}_i = \frac{C_\pi f(p'_i) + C_\delta f(p''_i) + C_\alpha f(p'''_i)}{C_\pi + C_\alpha + C_\delta} , \qquad (1)$$

where $C_\pi = C_{\pi_1} C_{\pi_2} Q$, C_δ, and C_α are determined as indicated below. The $\overline{p}_i$, then, are just weighted averages of p'_i, p''_i, p''' values after their trends have been appropriately exaggerated by f. Later we shall discuss f and the Cs as mechanisms for redundancy of potential command, and the Cs as mechanisms for decoupling. Figure 8 gives the f function.

Since $(\overline{p}_1, \overline{p}_2, \overline{p}_3, \overline{p}_4)$ is not in general a probability vector (all components ≥ 0, components sum to 1), we put $(\overline{p}_1, \overline{p}_2, \overline{p}_3, \overline{p}_4)$ through the h, T, h^{-1}, N blocks to make it so. These blocks also perform the indispensable function of nonlinearly interacting the four probability modalities so that S-RETIC is not just four single-mode probability computers in parallel. The output of h, T,h^{-1}, N is delayed one time unit in U D (for Unit Delay), and used as M_i's output to the ascending α stream, and the overall S-RETIC output bundle.

Since all of the M_i do not usually agree with probability 1 on which mode the overall $\{\gamma_i\}$ signal configuration properly corresponds to, we specify a general output modal decisionary scheme as follows: if 6 or more of the 10 complete modules indicate the jth mode with probability $\geq .5$, S-RETIC is said to converge on the jth mode. This output convergence criterion is most reasonable if one assumes that S-RETIC always predicates its modal computations on the present system mode, k. Then the probabilities out of M_j become transition probabilities from mode k. This reduces the equivocation in our output modal decisionary scheme considerably. As to its neurological versimilitude, motoneurons and internuncials on which RF outputs of the more modal type play probably have like decisionary character for go, no-go situations. But this is only a guess.

We now return to the details of formula (1), which reflects our M_i design strategies under the two headings: (a) redundancy of potential command, and (b) decoupling. Regarding (a), the f function serves to exaggerate the probabilistic modal indications of vector components which pass through them to a degree determined by the extent to which these indications depart from the neutral .25 point. Thus the f functions promote rapid overall computational convergence by amplifying the differences between the 1st, 2nd, 3rd, and 4th modal component gains around

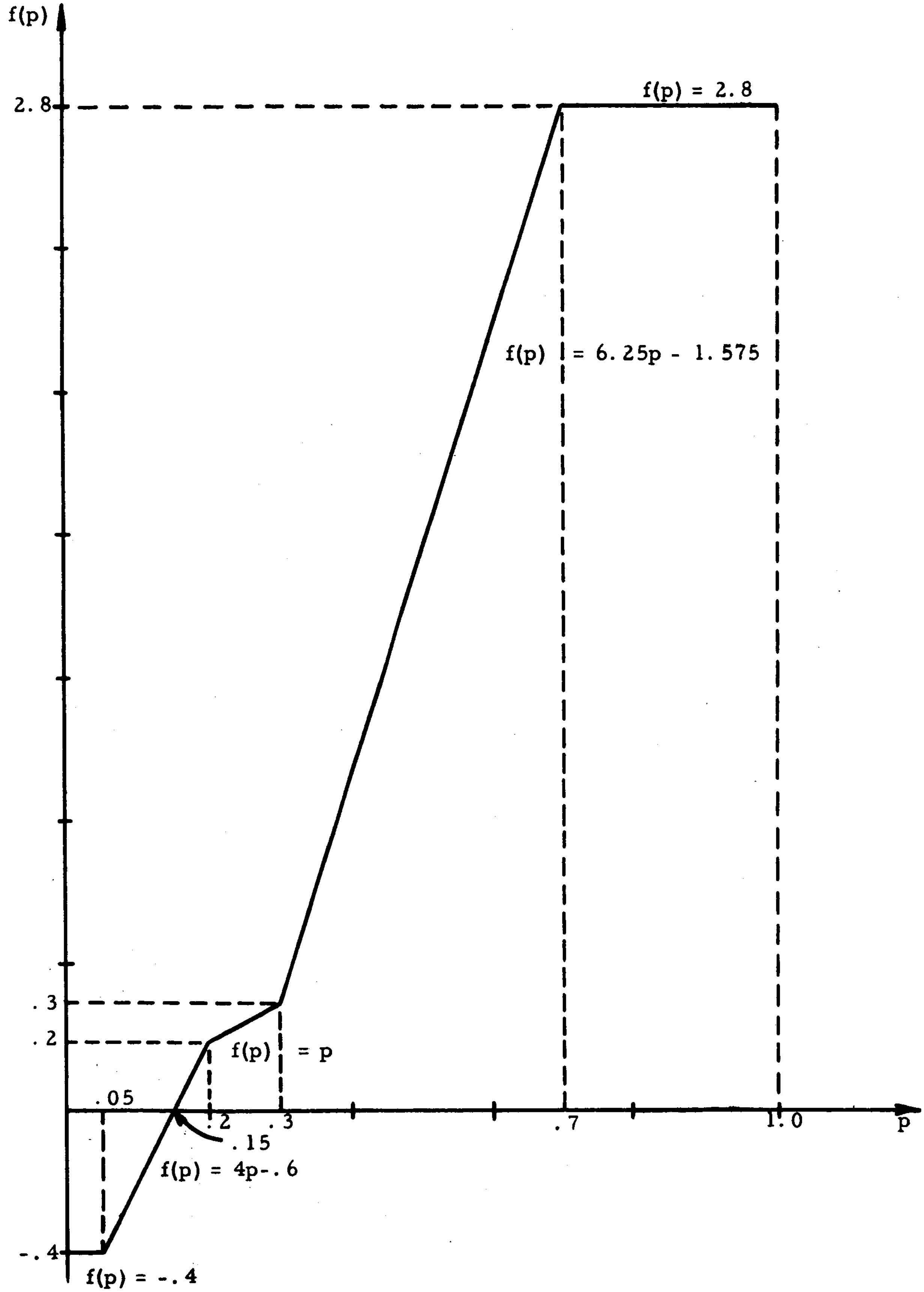


Figure 8. The f(p) function.

interconnected M_{i_1}, M_{i_2}, ..., M_{i_N}, M_{i_1} loops in accordance with the differences between the corresponding p_{α_i}, $p_{\delta_{i_j}}$ modal probability values. One consequence of this, as we shall see, is that some M_i tend to pick up, or recruit, other more equivocally indicating M_j over to their modal persuasion by a logic strikingly parallel to the frequency domain logic mediated by manifolds of coupled nonlinear oscillators. This is redundancy of potential command.

Also in connection with strategy, a), we identify the most crucial M_i as those whose output p_i vectors have components with values furthest from .25. We call such vectors "peaked." The C_{π_2}, C_α, and C_δ factors of each M_i are always 1, 1, and 1 if the corresponding p_{π_i}, p_{α_i} and p_{δ_i} are not peaked (do not have component values differing greatly from .25). But if at any time instant (i.e., computation clock time), any of the $f(p_{\pi_i})$, $f(p_{\alpha_i})$, or $f(p_{s_i})$ components are ≥ 1 or ≤ 0, C_{π_2}, C_α, or C_δ are set to 1.5, 2, or 2 respectively for that time instant (The asymmetry between C_{π_2}, C_α, and C_δ was necessary because of the two other factors in $C_\pi = C_{\pi_1} C_{\pi_2} Q$). Thus, for example, if any M_i have p_{π_i} and p_{α_i} vectors nearly equal to (.25, .25, .25, .25) and a $p_{\delta_i} = (.7, .1, .1, .1)$, p_{π_i} and p_{α_i} cannot overwhelm p_{δ_i}'s proper effect on M_i's output p_i vector. This again is redundancy of potential command.

The decoupling strategy, b) involves both a local M_i and global S-RETIC decoupling following overall $\{\gamma_i\}$ signal configuration changes. The purpose of this strategy is to prevent S-RETIC from being either too trigger-happy for new modal computations after slight and unimportant γ changes, or too prone to lock forever on output modal indications that get deeply intrenched at S-RETIC's output. (Monkeys and pigs have the most trigger-happy and sluggish RFs we know of among the higher vertebrates.) The idea is to quench α and δ signals after significant γ_i changes to sufficient degrees and for sufficient durations to allow injections of new γ_{i_j}-derived M_i output signals into the α and δ streams.

The b) strategy's global decoupling is expressed by the Q factor in C_π. If S-RETIC is converged on mode j at t - 1 and there are any $\{\gamma_i\}$

changes from t - 1 to t, Q is increased by an amount and for a duration that is roughly proportional to the degree of entrenchment of S-RETIC in mode j at t - 1. The values of Q at t are determined from the following table:

number of M_i for which the jth component of $p_i \geq .65$ at t - 1	value of Q at t Q at t
0 to 3	3.0
4 to 5	3.5
6 to 8	4.0
9 to 10	4.5

Q is decreased by 1 each time step after t until it reaches a minimum of 1, and then it remains at that value until the next overall $\{\gamma_i\}$ change. If at any time, on the basis of a new $\{\gamma_i\}$ change, a new Q is computed which exceeds the value Q has decayed to from the last Q computation, then, and only then, is Q set to its newly computed value. The same Q is used in the (1) formula of M_3, $M_4, \ldots,$ and M_{12}.

The b) strategy's local decoupling is expressed by C_{π_1}. It is determined separately for each M_i according to the following table:

Number of p'_i changes from t-1 to t that are > 1	C_{π_1} value at t
0	1
1	2
2	4
3	6
4	8

C_{π_1} is handled just like Q each time step after t, except that its minimum is 2 instead of 1 in order to keep M_i's output p_i normally about equally dependent on p'_i and (p''_i, p'''_i). An exception to the foregoing C_{π_1} rule occurs at t = 0, when an S-RETIC simulation run begins. Then $C_{\pi_1} = \infty$. At t = 1, the next time step, C_{π_1} is reset to 1.

Our concept of the strategic difference between local and global decoupling rests on the following analogy: Suppose a board of 12 medical doctors, each a generalist as well as a specialist in some different area of medicine, has to decide on which of 4 possible treatments each of a series of patients should receive. Each doctor corresponds to one S-RETIC module; each patient's medical record corresponds to one S-RETIC overall $\{\gamma_i\}$ input; and each treatment corresponds to one S-RETIC output mode. Every time the board looks at a new patient, the 12 doctors all decouple their decisionary ties to have a separate look at the records. After that, they begin their discussion, and in our terminology, information couple back in with each other in an attempt to shake sown a consensual decision (legal sense of consensual). This compares to global decoupling in S-RETIC.

Now suppose that the whole board, save one, in passing from the ith to the (i + 1)st patient is unable to see any significant differences in the records. The one that is able to should be left alone long enough to arrive at some preliminary conclusions of his own, and then he should be given a special opportunity to gainsay the rest of the board's tentative conclusions until they have heard him out. After that, he should submit to the full process of board discussion and play his regular role in shaping a total board decision. This corresponds to local decoupling in one S-RETIC module. The value of it, when contrasted to just additional global decoupling, is that it promotes greater overall decisionary speed because of its better organization and greater efficiency. The price of it is that overall decisions are not in general as soundly derived, because their startpoints are not neutral.

We now turn to the details of the h, T, and h^{-1} blocks in Figure 7. Their effect is to restore $\bar{p}$ to a probability vector such that the relative significance of $\bar{p}$'s components is not greatly distorted in the process. Since differences between small $\bar{p}$ probability components (e.g., between .25 and .05) are generally more significant then equal differences between large $\bar{p}$ probability components (e.g., between .65 and .85), we first pass $\bar{p}$ componentwise through an exponential h(x) of the form shown in Figure 9. We then add the absolute magnitude of the most negative resulting component to each result to get all components ≥ 0. We finally pass the results of this componentwise through a "translated inverse" of $h(x)$, denoted $h^{-1}(x)$, as shown in Figure 9. The equations for $h(x)$ and $h^{-1}(x)$ are derived as follows:

$$y' = y + .2$$

$$x' = x + .2$$

$$y'_{g*}(x') = e^{ax'} - 1 = 1.6 = e^{a1.6} - 1.$$

Therefore

$$a = \frac{\log_e 2.6}{1.6}$$

Therefore

$$y_{g*}(x) = e^{ax}e^{.2a} - 1.2$$

Therefore

$$y_g(x) = \boxed{e^{ax}e^{.2a} - 1 = h^{-1}(x)}$$

$$y'_h(x') = 1.6 - y'_{g*}(1.6 - x')$$

$$y'_h(x') = \left[1.6 - e^{a(1.6 - x')} - 1\right]$$

Therefore

$$y_h(x) = \boxed{2.4 - e^{1.4a}e^{-ax} = h(x)} \quad .$$

Note that in addition to h, T, h^{-1}, N's normalizing and mode-interacting effects, $h(x)$ limits the influence any given M_i can have. Thus, one pathological M_i cannot bully the rest of the net.

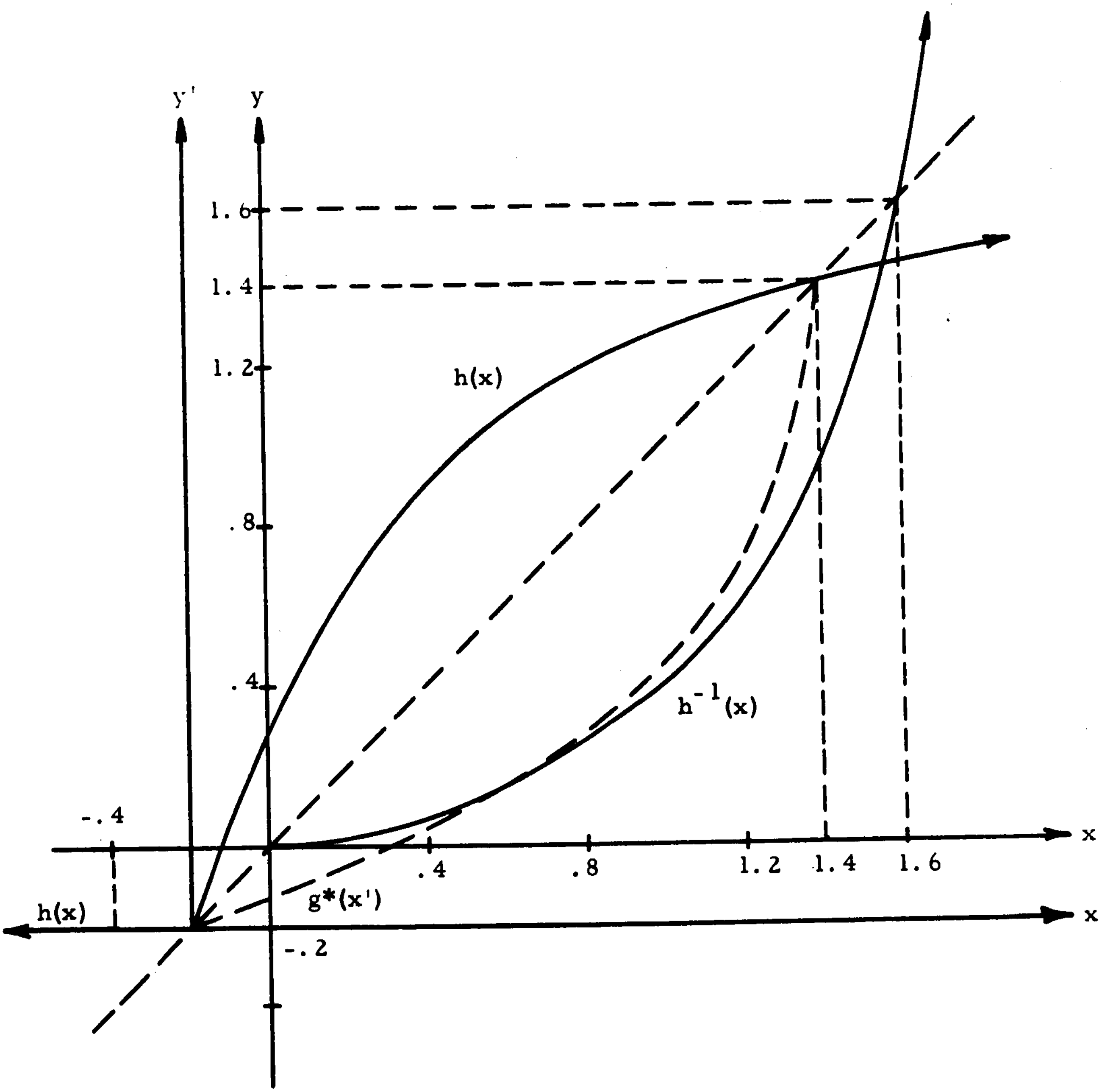


Figure 9. $h(x)$ and $h^{-1}(x)$ curves.

Our last M_i strategy is necessary only for speeding up convergences in certain clear cut cases, and for enabling convergences when there is no preferential p'_i vector provocation towards any one mode. In the latter case, a modal decision must be made in default of any determining input. The strategy is mechanized by adding in at the 15th nonconvergent cycle of each modal computation that gets that far without converging, the multiplication of each jth component f curve by

$$G_j = \frac{4 \sum_{i=3}^{12} (\text{jth component of } p_i)}{\sum_{i=3}^{12} (\Sigma \text{ of all components of } p_i)} \qquad j = 1, 2, 3, 4.$$

This could be analogous to the development of diffuse decisionary field strengths in real RFs.

Before describing our S-RETIC simulation results, we shall try to impart some intuition on what to look for in the following précis. Our RF* modeling problem is fundamentally one of appropriately matching: (1) the set of all possible correlated overall RF* model inputs; (2) the manner in which the RF* model's regional (i.e., M_i type) logic allows initial ascending and descending (i.e., α and δ type) signal sequences to evolve through it during a modal computation; and (3) the nature of the possible sequences of changes out of the correspondents to A, C, and the S_j in Figure 5, and also the nature of their associated sequences of modal specifications.

Beyond this, it is important to emphasize a few basic organizational and operational aspects any satisfactory S-RETIC model, denoted Retic below, must have. First, it must have sufficient input scope with respect to the overall central nervous system (CNS) model in which it resides so that it can receive the crucial S_i information in every eventuality; and it must have sufficient computational capacity so that it can arrive at the right modal decision, regardless of whether or not conflicting or competitive demands appear over different A, C, and S_j systems. For it is established that real reticular formations must be able to cope with virtually every possible sufficiently correlated barrage of input signals.

Second, a Retic must keep its flow of computation close enough to its input receiving areas so that all input changes can quickly exert their influence over its output and modal calculations; and the more important the input changes, the more quickly and profoundly must these influences be exerted. This is only reasonable in command and control systems for which momentary delays and wrong outputs can mean failure or annihilation. Thus, unlike some cortical systems, Retics must be pre-eminently interruptible, and not given to long periods of indecision because of excessive logical depth. Yet Retics must not be allowed to compute new modal commitments too quickly, for this would make them too vulnerable to noise and meaningless distractions (like "dreams," for example). Third, the logical design of a Retic must be extremely economical. Otherwise the heavy decisionary demands placed upon it would make it too large and too slow. Aside from a Retic's conditioning, habituation, long-term learning plasticity, and spatio-temporal coding of information, it is essentially a combinational logic circuit with very many highly correlated inputs and a small number of possible stable outputs. The main economy of any Retic organization of the general type suggested in Figure 6 stems from its repeated use of a fixed amount of modular logic throughout each modal computation. That is, logic signals are recirculated from combinations of M_i units to combinations of M_i units at successive time instants during each modal computation until an actual or approximate decisionary equilibrium is reached. Then the computation is said to be complete and the modal outputs are produced. In general, such a scheme enables the logic of each M_i to be used at nearly full capacity throughout each modal computation, and also enables each Retic input channel to be monitored continuously. This is vastly different from the way conventional one-way-flow combinational logic nets work in engineering systems.

To recapitulate, a Retic must be a wide, shallow, anastomotic logic net, consisting of a logical heterarchy of rather tightly coupled and similar computing modules, each the equivalent of about one neuron deep.

5. SIMULATION RESULTS

Appendix 9 contains selections from our S-RETIC simulation data. The "Run number i, cycle number j, sigma set number k" byline appearing at the top of each page refers respectively to which of three selected simulation runs the accompanying data were obtained from,* which Σ_i of the run is currently under test, and which computational pass through the $\{M_\ell\}$ since the introduction of the present Σ_i the data pertain to. This i, j, k triple will henceforth be denoted [i, k, j]. "Template" refers to the 5-tuple of γ values entering the M_i in question. The "normalized p-primes" are the present p' vectors passing from the first to the second part of each M_i. The "modal probabilities at end of present cycle" are the p_i vectors out of each M_i. On the first-cycle page of each Σ_i in the p' columns we have underlined the most significant high values and encircled the most significant low ones. Column sums for all p's and p_is are given as indications of column averages, and though never underlined or encircled, they are always important in the determination of modal decisions. We refer to the 10-tuple of p_i vectors on the first-cycle page of each Σ_i as the initial conditions for that Σ_i.

Since much of the meat of this report is contained in Appendix 9, the reader is encouraged to look at it for himself--it won't take him long if he follows only the most significant high and low values. The various design strategies all contribute to S-RETIC circuit actions as intended, so we shall not sort them out for separate discussion. Rather we shall summarize the most important features of S-RETIC behavior. They are:

(1) S-RETIC always converges, and always (so far) in less than 25 cycles. Every time modal gain factors were used, S-RETIC's overall modal preferences were clearly established in their relative degrees over the first 14 cycles of the Σ_i. See [1, 3, 14], [2, 7, 14], and [3, 1, 14]. The purpose of the gain factors is to speed up, and in rare cases enable, convergences from 14-cycle start points of approximate but inexact standoffs between 2 or more highest modes.

* In this paper we include the first run only. All three runs are included in the corresponding Michigan State University Division of Engineering Research Report.

(2) Once S-RETIC converges anew after at least one previous non-convergent cycle for a Σ_i, it stays converged. S-RETIC has at times maintained a previous convergence, though, for a few cycles after a Σ_i change, then deconverged, and finally reconverged to the same or a different mode a few cycles later. See [3, 4, 1-4]. Because S-RETIC always converges and then stays converged in this sense, we could redefine an S-RETIC mode to be that stable region of operation entered into at the final convergence of the overall input in question.

(3) After convergence, S-RETIC's p_i vectors always head for a limiting set which never contains any vector consisting of three 0 components and one 1 component. An exception to this would occur if all p' vectors had probability 1 in the same mode; but noise in the module T-circuits would cure even that. See run 1.

(4) S-RETIC rolls over from one mode to another easily and quickly under strong $\vec{p}'$ provocation. As this provocation becomes weaker and weaker, Σ_i initial conditions, and gratuitous S-RETIC circuit particularities, play a larger and larger role in the corresponding modal decisions. "Strong $\vec{p}'$ provocation" can mean high component values for one mode and low ones for the others; or it can mean a high $\vec{p}'$ column total on one mode and low ones on the others; or it can mean a blend of both. If high $\vec{p}'$ component values appear several times in each of several different modes, we have a dissociated (or disintegrated) situation, and the corresponding modal decision is often determined by the Σ_i initial conditions - and sometimes in a surprising way [1, 5, 1-9]. The logical complexity of a modal computation (as judged by us) is usually about proportional to the number of cycles before convergence unless $\vec{p}'$ provocation is weak or equivocal (see [2, 7, 1-20]). By "logical complexity" we mean the degree of $\vec{p}'$ competition and conflict, and the intricacy of the pattern of modal unbalances among the p_{α_i} and p_{δ_i} vectors at the start of a modal computation.

(5) Appendix 9 contains several specific decisionary effects that will now be discussed:

(a) In [1, 2, 107], we see a nice resolution of competition, or conflict, between module p' vectors. Here three mode 4 .5-components overcome a 1 and a .4 mode 3 component. This is as it should be; an M_i should hardly ever, if ever, be absolutely certain of an overall response mode just on the basis of its own γ input.

(b) In [2, 1, 1-5] we see M_5 recruiting other M_i over to its persuasion against the $\vec{p}'$ averages.

(c) In [1, 5, 1-16] we see three mode 1 .4s overcome a higher mode 4 $\vec{p}'$ average and initial condition bias (see column totals for the $\vec{p}_i$ in [1, 3, 1]).

(d) In [1, 5, 1-9] we see a higher mode 1 initial condition bias overcome a higher mode 3 $\vec{p}'$ average and an impressive list of mode 3 $\vec{p}'$ peak values. If it were not for the dissociation, or general scatter, of $\vec{p}'$ high component values here, we would be displeased by the convergence to mode 1. As it is, it seems pleasingly bio-logical. Note that it is difficult to discern any real computational progress in cycles 2 through 5, other than a slight reduction of variances among the mode j components of the $\vec{p}_i$, $j = 1, 2, 3, 4$. This prompts us to challenge anyone to write a set of decisionary motion equations for S-RETIC. The outcome for this Σ_i also convinced us that S-RETIC could still surprise us after hundreds of hours of studying its behavior. This is one justification for simulating S-RETIC.

(e) In [3, 1, 1-19] we see the $\vec{p}'$ mode averages swamping out two .7 mode 1 p' peaks. From (c), (d) and a case similar to the one just considered but not included in Appendix 9, we conclude that either $\vec{p}'$ peaks, or $\vec{p}'$ averages, or p_i initial conditions can carry an S-RETIC modal decision in opposition to the other two aligned against it. It can also happen that any two of these can carry a decision in opposition to the third. See [1, 6], [2, 3-5], and [2, 7-8].

(f) In [3, 1, 1-19] we see a contest between exactly matched modes 2, 3, and 4 decided by gratuitous circuit particularities (noise of a kind). In this case S-RETIC was little more than an elaborate 3-state flip-flop, started at a neutral point.

(g) In [2, 1, 1-10] we see a boundary M_i's (M_2's to be precise) mode 4 $\vec{p}'$ peak carry a modal decision against strong mode 1 initial conditions, a competing mode 1 $\vec{p}'$ peak, and a second highest mode 1 $\vec{p}'$ component average.

(6) We remark that anyone who carefully peruses a significant block of our simulation data will note many other interesting facets of S-RETIC decisionary behavior. For example: the <u>rate</u> of aggregate swelling of a modal component among the M_i determines to within a tolerance the regenerative gain of that component each cycle; the degree of "dissociation" (or the prevalence of apparently uncooperative phenomena, amenable to, say, a simple statistical description) among the $\vec{p}_i$ is <u>not</u> particularly related to the variances of their jth components; and M_i "recruitment" is <u>not</u> just the converse of $\vec{p}_i$ inhibition by other $\vec{p}_i$.

(7) Our simulations have proved that S-RETIC parameter settings can have wide tolerances. This is fortunate, for real RFs function all the way from coma to convulsion.

Appendix 10 gives a macro-level flow chart for our simulation program. It was written in a very transparent MAC language by J. Blum, and run on the MIT Instrumentation Laboratory Honeywell 1800 Computer.

6. FORM-FUNCTION RELATIONS FOR S-RETIC

S-RETIC computes an output modal function of the twelve p' vectors p'_1, $p'_2, \ldots, p'_{12}$, and a set of initial condition vectors, I_F. The I_F vectors are completely specified by the p'_1, p'_2, $p'_3, \ldots, p'_{12}$ vectors at the end of the previous Σ_i. We denote S-RETIC's output modal function $F(p'_1, \ldots, p'_{12}, I_F)$, and its possible values 1, 2, 3, and 4.

F has three symmetries that we shall rely on throughout the remainder of this Section:

I. For large numbers of modules, where the small number combinatorics of the M_i-to-M_j connections no longer appertain, F is invariant under all p'_i and corresponding I vector permutations, $i \neq 1, 2$. That is, simple exchanges of M_i positions within the net, each M_i's γ connections remaining intact, do not affect F.

II. F implies the same evaluation function on all four modes.

III. F sometimes converges on a mode different from the one with highest average over the p'_i vectors, or the I_F vectors, or both the p'_i and I_F vectors. See 5-(e) of the previous Section. More generally, our simulation data show that S-RETIC can converge to a mode favored by either the p'_i average, or the I_F average, or the p'_i peaks (as in .7, .1, .1, .1, e.g.), in opposition to the other two of these factors aligned against it. Any two of these factors aligned together can also overcome the third in opposition; and any one of them can overcome the other two when they are against it but not aligned on the same mode against it. There is thus a strength-of-effect symmetry over these three factors.

In the rest of this Section, we outline an argument to show that S-RETIC computes a mode function, F, that no S-RETIC net without α and δ connections but with nonlinear summative output scheme could compute even though it be allowed more equipment. We denote such an alternative net, $\overline{N}$, and picture one in Figure 10. The $\overline{M}_i$ in Figure

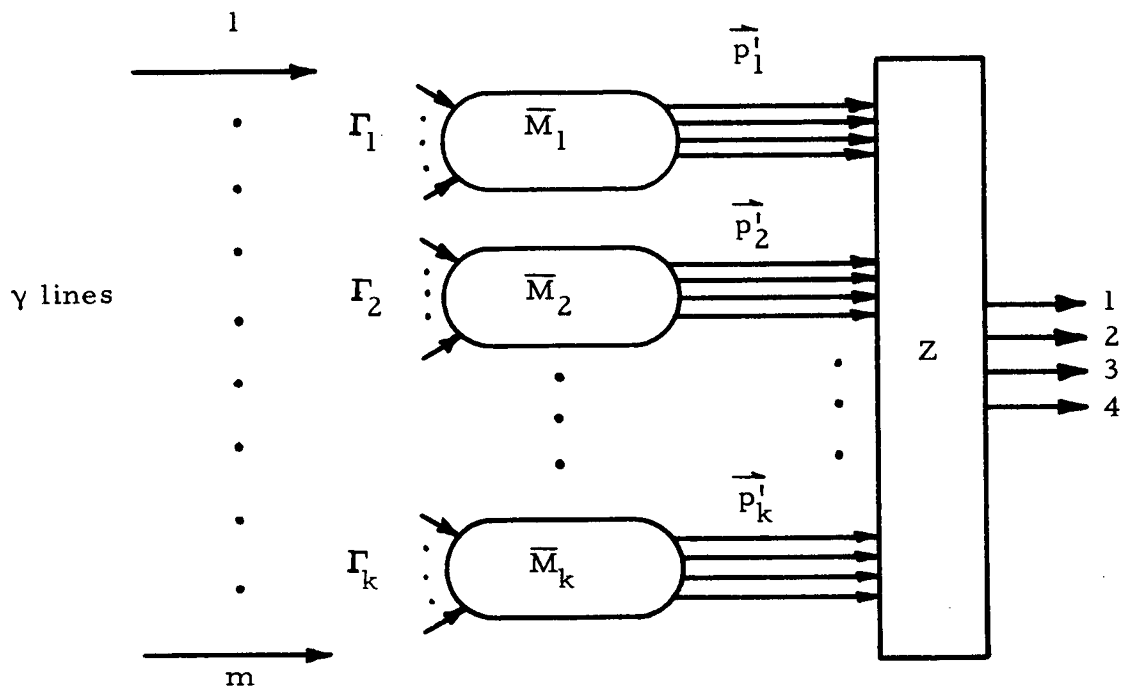


Figure 10. A modular net without intermodular coupling.

10 correspond exactly to the γ-to-$\vec{p}'_i$ part of each S-RETIC module, except that we allow each $\overline{M}_i$ to have more γ inputs and greater logical complexity than its M_i counterpart. We insist, though, that the $\overline{M}_i$ be simple enough so that at least two conflicting $\vec{p}'_i$ tendencies arise for each of several overall $\{\gamma\}$ inputs. (This condition cannot be made more precise until the end of the Section.) Obviously the larger S-RETIC is, the easier this condition is to satisfy.

We next suppose that Z computes a 4-valued modal function, Z, of its present and next-to-last $\vec{p}'_i$ input sets. We denote the latter set I_Z, and the function computed by Z, $Z(p'_1, \ldots, p'_k, I_Z)$. We require that k be less than or equal to the number of corresponding S-RETIC modules. Z, then, is defined to be 1, 2, 3, or 4 according as

$$S_1 = \sum_{i,j} f^1_{ij}(p'_{ij})$$

$$S_2 = \sum_{i,j} f^2_{ij}(p'_{ij}) \qquad 1 \le i \le k;\ i \text{ an } \overline{M}_i \text{ module number} \tag{2}$$

$$S_3 = \sum_{i,j} f^3_{ij}(p'_{ij}) \qquad 1 \le j \le 4;\ j \text{ a mode number}$$

or $$S_4 = \sum_{i,j} f^4_{ij}(p'_{ij})$$

has the highest value, where p'_{ij} is the jth component of $\vec{p}_i$, and the f^k_{ij} are arbitrary continuous functions of their arguments (proportional to log functions, perhaps).

If we had let our p'_{ij}s in Figure 10 be general degrees-of-presence of various properties in $\overline{N}$'s overall input stimulus, instead of specifying them as we did, Figure 10 could be reduced to a nonlearning Pandemonium Machine or to one of several popular Bayesian logic designs in the special case. We did not allow this because it would have prevented us from obtaining a rigorous comparison between $\overline{N}$ and S-RETIC. The results of such a comparison, though, would certainly have been similar to the one we are undertaking if it could have been made.

Let us now derive our underlined statement above. It is not a theorem because part of our argument for it stems from observations and extrapolations on our simulation data. Our method will be to try to equate F and Z in the special case where I_F is null (recall that for the first overall input of a simulation, $C_\pi = \infty$), the boundary $\vec{p}'_i$ of S-RETIC both equal .25, .25, .25, .25, k = 10, and the Z set of $\vec{p}'_i$ is identical to the F set of $\vec{p}'_i$ in every case. We will see that Z cannot equal F under such conditions and why, and then generalize to get our result.

Since Z must be invariant under all nonboundary $\vec{p}'_i$ permutations, $f^k_{ij} = f^k_{\ell j}$ in equations (2) for all (i, ℓ) pairs, $1 \leq i, \ \ell \leq 10$. Z must also employ the same evaluation function on each mode. Thus there must exist a cyclic permutation, Π, of the $\vec{p}'_i$ components such that

$$\Pi(p'_{i1}) = p'_{ij} \quad , \quad j \neq 1$$

$$\Pi(p'_{ij}) = p'_{ik} \quad , \quad k \neq j, 1$$

$$\Pi(p'_{ik}) = p'_{im} \quad , \quad m \neq 1, j\ k$$

and $$\Pi(p'_{im}) = p'_{i1}$$

the same for all $1 \leq i \leq 10$; and such that $f^\ell_{ij}(p'_{ij}) = f^m_{ik}(p'_{ik})$ for all i and for $\ell \neq m$ if and only if $\Pi(p'_{ij}) = p'_{ik}$ and $\Pi(p'_{i\ell}) = p'_{im}$. Dropping all unnecessary indices, equations (2) become

$$S_1 = \Sigma f_j(p'_{ij})$$

$$S_2 = \Sigma f_j(\Pi(p'_{ij})) \qquad 1 \leq i \leq 10$$

$$S_3 = \Sigma f_j(\Pi^2(p'_{ij})) \qquad 1 \leq j \leq 4 \qquad (3)$$

and $$S_4 = \Sigma f_j(\Pi^3(p'_{ij}))$$

Our S-RETIC simulation data requires that in each S_k sum of (3), f_k be monotonic increasing and f_j, $j \neq k$, be monotonic decreasing, f_k, though, cannot increase too fast as a function of p'_{ik}, because if it did the average $\vec{p}'_i$ could not determine Z's value as often as it does F's. Also the f_j cannot decrease too fast as a function of p_{ij} for the same reason. In other words, symmetry III gives us a severe set of constraints on the f_js. We denote the bounds on f_k and f_j for S_k by Sup f_k and Inf f_j (see Figure 11). These bounds must be established from simulation data.

Suppose now that we have a set of $\vec{p}'_i$ vectors all equal to $(.25+\epsilon, .25, .25, .25-\epsilon)$, a corresponding largest S_k in equations (3) equal to S_1, and a corresponding S-RETIC F value equal to 1. We want ϵ to be just large enough to make this true (in our S-RETIC simulation this was about .03). Next, consider a second $\vec{p}'_i$ vector set comprising $p'_1 = \cdots = p'_8 = (.1, .3, .3, .3)$ and $p'_9 = p'_{10} = (.7, .1, .1, .1)$. In equations (3), the difference between S_1 for the first and second $\vec{p}'_i$ sets is

$$\begin{aligned}
\Delta S_1 = \;& 8\,[f_1(.1) - f_1(.25+\epsilon)] + 2\,[f_1(.7) - f_1(.25+\epsilon)] \\
& + 8\,[f_2(.3) - f_2(.25)] \qquad + 2\,[f_2(.1) - f_2(.25)] \\
& + 8\,[f_3(.3) - f_3(.25)] \qquad + 2\,[f_3(.1) - f_3(.25)] \\
& + 8\,[f_4(.3) - f_4(.25-\epsilon)] + 2\,[f_4(.1) - f_4(.25-\epsilon)] \\
= \;& -\alpha^1_1 + \alpha^1_2 \\
& -\alpha^1_3 + \alpha^1_4 \\
& -\alpha^1_5 + \alpha^1_6 \\
& -\alpha^1_7 + \alpha^1_8 \quad ,
\end{aligned} \tag{4}$$

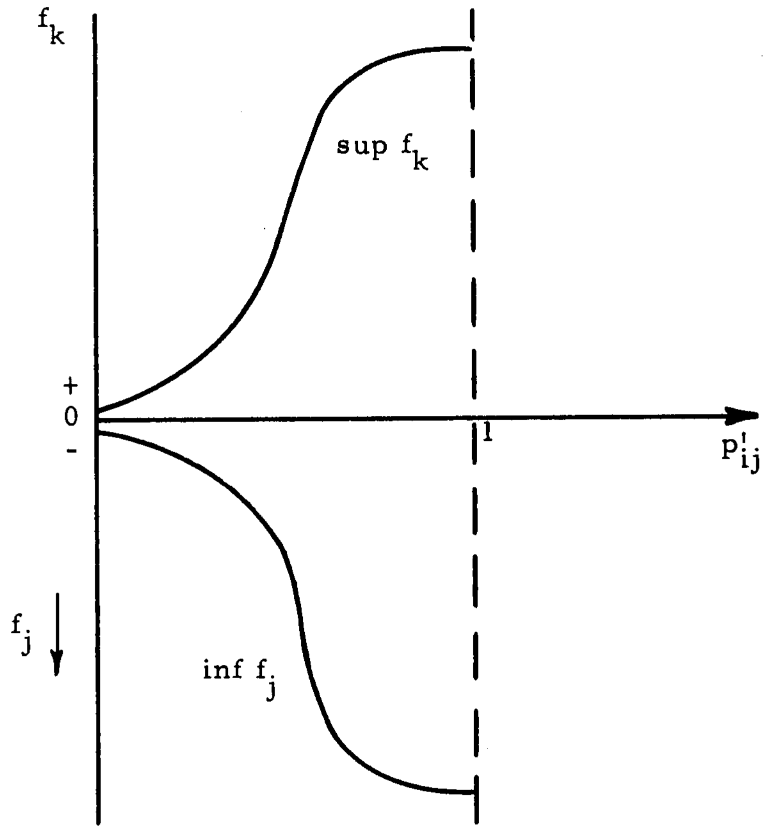


Figure 11. Bound curves on the f_k and f_j functions for S_k in equations (3).

where all $\alpha^{1}_{i} \geq 0$. Similarly,

$$\begin{aligned}\Delta S_k = &- \alpha^k_1 + \alpha^k_2 \\ &- \alpha^k_3 + \alpha^k_4 \quad , \qquad\qquad k = 2,\ 3,\ 4 \\ &- \alpha^k_5 + \alpha^k_6 \\ &- \alpha^k_7 + \alpha^k_8\end{aligned}$$

In our S-RETIC simulation, the F value for both sets of $\vec{p}'_i$ vectors above was 4. Suppose we have a set of f_j for equations (3) that enables Z to best approximate F -- indeed, perhaps equal it. Certainly $Z \neq F$ if all $\Delta S_k = 0$. Also, since the average of the second $\vec{p}'_i$ set above is (.22, .26, .26, .26), the f_j could not be such as to make each S_k equal to the average over i of the p'_{ik}. Furthermore, since each 4-tuple of S_k values has many $\vec{p}'_i$-set solutions for any selection of f_j functions, the question arises as to whether some second $\vec{p}'_i$ vector set other than the one given above exists such that either all ΔS_k for it are 0, or the highest S_k for it does not correspond to its F value. If so, $Z \neq F$.

We are certain there does not exists a set of f_j functions for equations (3) such that Z could be made equal to F. In fact, given any alleged set of such f_j, we could at least almost always find a second $\vec{p}'_i$ set such that all $\Delta S_k = 0$ for that set but F's value changed between that set and the first $\vec{p}'_i$ set (under the assumed null conditions on I_F and I_Z, of course). Anyone who studies our Appendix 9 should have no difficulty in seeing this. But if that should fail, we could always find a second $\vec{p}'_i$ set such that $F \neq Z$ for it by concentrating on a^k_j adjustments in (4), which because of the bounds and signs on the f_j would be unidirectional, smooth, and simple. This should be evident.

It now follows rather easily that removing our argument requirements that the number of $\overline{M}_i$ be 10 and that the Z $\vec{p}'_i$ set equal the F $\vec{p}'_i$ set would not change the character of our result at all. Nor can we see how it could be refuted using S-RETICs with more and more modules. They would seem only to demonstrate it even more spectacularly. Hence the underlined assertion early in this Section.

7. CONCLUSIONS AND FUTURE WORK

We can safely infer from our simulation results, the cooperative effect of our design strategies, and S-RETIC's specifications (Appendix 8), that proportionately increasing the numbers of everything but modes in S-RETIC would improve its performance in every important respect. Given a large number of M_i, we would put those with most similar area centrali farthest apart in the model. We would also want the set of M_i area centrali to form, at the $\{\gamma_i\}$ level, the equivalent of a highly overlapping cover of the complete $\{\sigma_i\}$ bundle. This would give us an S-RETIC of much greater decisionary acuity and competence, and vastly greater invulnerability to M_i failure, than the present test model enjoys. To a good approximation, such a structure would be slower than our test model according as the ratio:

$$\frac{\text{Number of splittings of each output line}}{\text{Number of } M_i} = \frac{N_1}{N_2}$$

is lower than 3/12, its value in our simulation. This assumes 4 modes. More than about 6 modes might slow the model down considerably, or make it unduly sensitive to noise.

How does the complexity of S-RETIC increase with larger $\{\sigma_i\}$ bundle sizes? First, let us assume an S-RETIC with k modules, ℓ γ_i inputs to each module, and a $\{\sigma_i\}$ set of m lines. In our simulated S-RETIC, $k\ell/m = (12 \times 5)/9 < 7$. We believe that $k\ell/m$ might satisfactorily remain less than 7m (constant) for increasing k, ℓ, and m. If so, N_1/N_2 above would increase linearly with m, giving us an overall S-RETIC complexity proportional to m. This compares favorably with the corresponding exponential relation in switching theory.

We have in the foregoing supplied one paradigm for getting a family or more than two information-coupled automata to work together in a slightly biological fashion. To the extent that our result was inspired by biology and is a good command and control computer for some purposes, we make a claim for bionics.

We especially emphasize that S-RETIC is not just a glorified pattern recognition net. It satisfies the additional temporal constraints of a real-time RF model. The previous Section indicates its functional peculiarities and strengths as compared to a large class of nonlinear, modular, Bayesian logic nets.

S-RETIC's compound virtue as a computer is that it is fast, economical, reliable according to the redundancy of potential command, and operational on all of its inputs at each time step.

We have recently augmented S-RETIC as shown in Figure 12 to begin our study of possible RF time-binding mechanisms. The ω_j lines there carry crude area centralis information from their modules of origin. There are 13 σ_i and 7 γ_{i_j} per M_i. We allow each M_i to remember its two previous inputs, outputs, Rpc reinforcements, Rac reinforcements, and modes of overall convergence. These combinations are then used to modify the p' vector response to future γ_{i_j}, ω_i inputs. This enables us to realize several types of cooperative conditioning, extinction, habituation, and long-term adaptation among the M_i. The problem is to get a group of M_i, each of which only partially appreciates the overall input-overall output correspondence problem, to learn in an integrated, harmonious fashion. The main obstacle seems to be interference due to local signal ambiguity on overall input-overall output relations. A major by-product of this work so far has been that we can now see how to engage and drop out RF operational parameters in a gradual manner. We are indebted to W. Brody for several insights on this.

We would like to note the Scheibels' suggestion that S-RETIC might be a more valid model if we regarded our M_i as instantaneous - functional instead of fixed-regional RF subcomputers. We are taking this remark seriously, for it implicates the legitimacy of our simplifications, the appropriateness of our outlook on RFs, and the propriety of our linguistic level.

Finally, we inquire as to the actual value of our simulation. Its main justification is that we can now think <u>with</u> our S-RETIC model, and not just <u>about</u> it. We hope his will help us to partially invent and partially derive some new insights into RF circuit actions. Another justification is that we now know the precise consequences of interlacing our simple set of strategies in a behavioral mechanism, and we can see that these consequences were much too complicated to apprehend beforehand. The simulation has strengthened our prejudice that classical mathematics, as symbol manipulation by logical rules, is good for steady state and microcosmic brain processes, but not yet global decisionary ones. We need a type of scientific poetry for that. Nothing else could possibly serve, we think, where each little cause can have such major effects, yet where each person is still able to make so much sense of it.

This takes us back to K. Craik's, "The Nature of Explanation." He would say, with K. Popper and others, and we would agree, that we do not yet have a theory of the RF. For there is no experiment that could invalidate our claims; our concept has not yet produced any risky predictions; it does not forbid any measurable RF event; and we have not yet proposed any real alternatives. In this sense, our results were though up, no out.

We wish to acknowledge Dr. Michael Arbib as a major consultant on the organization of this report. We also owe much of what clarity it might have to discussions with Drs. A. and M. Scheibel, Dr. L. Proctor, and Dr. W. McCrumb. D. Peterson and E. Craighill assisted greatly in programming the simulation, and R. Warren was a ready contributor of program organizational ideas.

The computer simulation was done at the Massachusetts Institute of Technology Instrumentation Laboratories under National Aeronautics and Space Administration Contract NSR-22-009-138. The theoretical work was done under Air Force Office of Scientific Research Contract AF-AFOSR-1023-66.

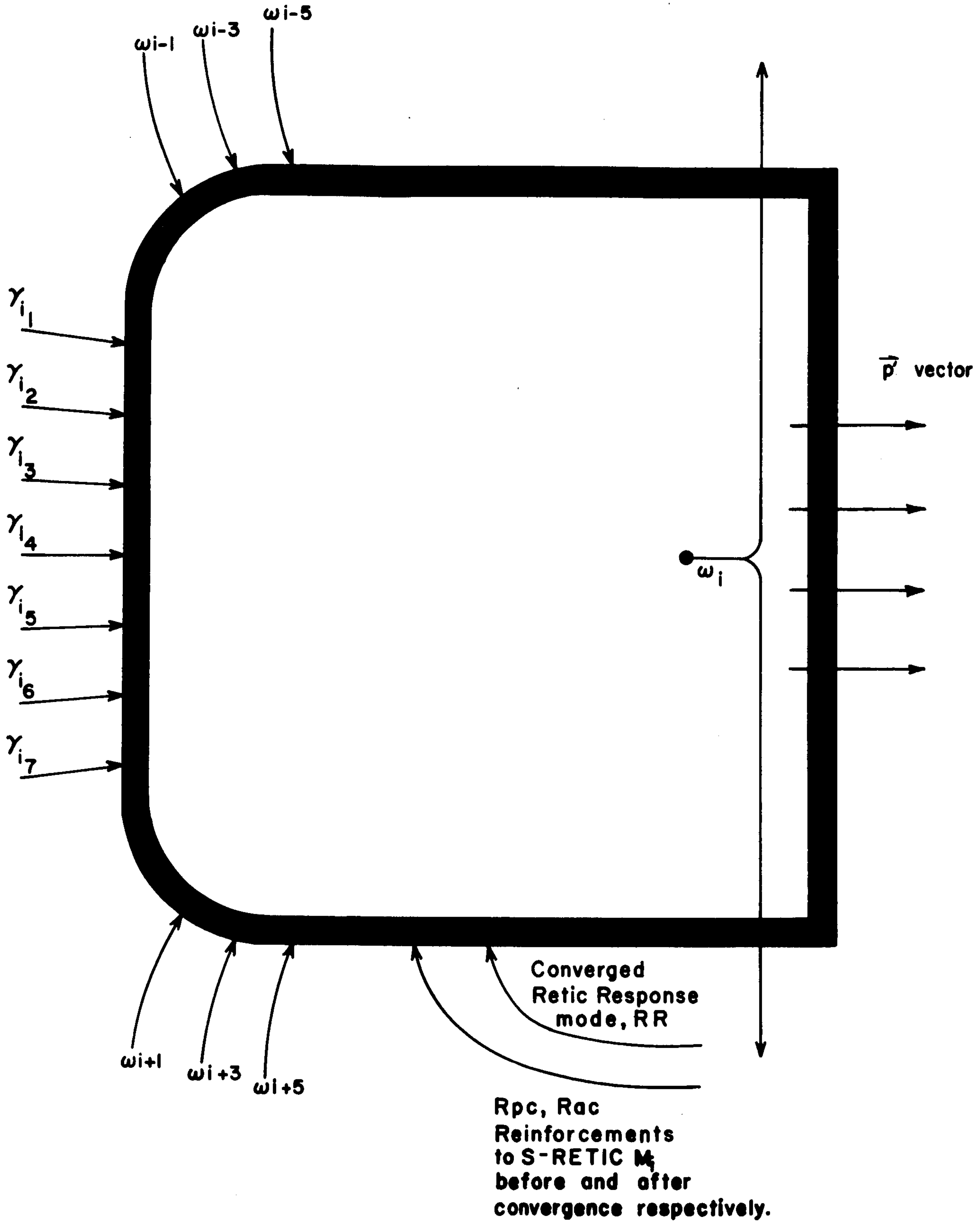


Figure 12. Augmented first part of typical S-RETIC M_i.

8. BIBLIOGRAPHY

1. Adametz, J. H., "Rate of recovery of functioning in cats with rostral reticular lesions," J. Neurosurg. 16, 185-197 (1959).

2. Adey, W. R., "Neurophysiological correlates of information transaction and storage in brain tissue," Brain Research Institute, University of California, Los Angeles.

3. Albe-Fessard, D., and Fessard, A., "Thalamic integrations and their consequences at the telencephalic level," Progr. Brain Res. 1, 115-148 (1963).

4. Altman, J., Organic Foundations of Animal Behavior. Holt, Rinehart and Winston, Inc. (1966).

5. Amassian, V., et al., "Patterns of activity of simultaneously recorded neurons in midbrain reticular formation," Annals New York Acad. Sci. 89, 883-895 (1961).

6. Arbib, M. A., "Automata theory the development," Electrical Engr. Dept., Stanford University (1966).

7. Arbib, M., Brains, Machines, and Mathematics. New York, (1964).

8. Bard, P., and Macht, M., "The behavior of chronically decerebrate cats," 55-70. *

9. Barlow, H. B., "Possible principles underlying the transformations of sensory messages," 217-234. **

10. Bell, C., Sierra, G., Buendia, N., and Segundro, J. P. "Sensory properties of neurons in the mesencephalic reticular formation," J. Neurophys. 961-985 (1964).

11. Beurle, R. L., "Properties of a mass of cells capable of regenerating pulses," Phil. Trans. Roy. Soc., 240, B:55-94 (1956).

12. Block, S. H., "A neural net for adaptive behavior," Rand Report RM-3638-PR, Rand Corp., Santa Monica, Calif. (1963).

13. Brodal, A., The Reticular Formation of the Brain Stem: Anatomical Aspects and Functional Correlations. Charles C. Thomas, Pub., Springfield, Ill.

14. Braitenberg, V., et al., "Observations on spike sequences, from spontaneously active purkinje calls in the frog," Kybernetik, (January 1965).

15. Brick, D. B., "Wiener's nonlinear expansion procedure applied to cybernetic problems," IEEE Trans. Systems Science and Cybernetics SSC1 (November 1965).

* Neurological Basis of Behavior, ed. G. Wolstenholme and C. O'Connor, Little, Brown, and Co., Boston (1958).

** Sensory Communication - Contributions to the Symposium on Principles of Sensory Communication, ed. W. A. Rosenblith, Massachusetts Inst. of Technology (July 19 to August 1, 1959).

16. Bullock, T. H., "The problem of recognition in an analyzer made of neurons," 717-724. **

17. Butenin, N. V., Elements of the Theory of Nonlinear Oscillations, Blaisdell Publ, New York (1965).

18. Caianiello, E. R., "Decision equations and reverberations," Kybernetik, (1966).

19. _____, "Decision equations for binary systems, application to neuronal behavior," Kynernetik (January 1966).

20. _____, "Nonlinear problems posed by decision equations," from Functional Analysis and Optimization, ed. Caianiello. University of Naples, Naples, Italy (December 1966).

21. Craik, K. J. W., The Nature of Explanation, Cambridge University Press, New York (1952).

22. _____, The Nature of Psychology, Selections From. ed. S. L. Sherwood, Cambridge University Press, New York (1966).

23. Dell, P., "Some basic mechanisms of the translation of bodily needs," 187-203. *

24. _____, "Reticular homeostatic and critical reactivity," Progress in Brain Research, Vol. I, Elsevier, Amsterdam (1963).

25. Doty, R. W., "Some neural facts relevant to attention, motivation and learning," from lecture at International Spring School of Physics "Cybernetics of Neural Processes," Naples, Italy (April 1962).

26. _____, "The role of subcortical structures in conditioned reflexes," Annals N. Y. Acad. Sci. 92, 939-945 (1961).

27. Doty, R. W., Beck, E. C., and Kooi, K. A., "Effect of brain-stem lesions on conditioned responses of cats," Exp. Neurol. 1, 360-385 (1959).

28. Doty, R. W., and Bosma, J., "An electromyographic analysis of reflex deglutition," J. Neurophysiol. 19, 44-60 (1956).

29. Drocchiolo, C., and Drago, A., "Linear separability and state reverberations," University of Naples, Naples, Italy (1965).

30. Droogleever Fortuyn, J., and Stefens, R., "On the anatomical relations of the intralaminar and midline cells of the thalamus," EEG and Clin. Neurophysiol. 3, 393-400.

31. Ebert, J. D., Interacting Systems in Development. Holt, Rinehart, and Winston, New York (1965).

32. Eccles, and Curtis, "On frequency specific pathways in vertebrate neural tissue," J. Physiol. 150, 374 (1960).

33. Fair, C. M., "The organization of memory functions in the vertebrate nervous system," Neurosciences Res. Prog. Bull. 3, 27-62 (April 7, 1965).

34. Fair, C., The Physical Foundations of the Psyche. Wesleyan University Press, Middletown, Conn. (1963).

35. Farley, B., Films on artificial neural net operation, shown at various cybernetics conferences. Films at MIT Lincoln Laboratories, Bedford, Massachusetts, 1963.

36. Fessard, A., "The role of neuronal networks in sensory communications within the brain," 585-606. **

37. Flexner and Flexner, "On puromyacin erosion in avoidance trained rats," in Proc. Nat. Acad. Sci. 52 (1964).

38. Gabor, D., "Hologram pattern recognition," Nature, (October 30, 1965).

39. Gastaut, H., "Some aspects of the neurophysiological basis of conditioned reflexes and behavior," 255-276. *

40. Handbook of Physiology, Sections 2, 3, Neurophysiology. ed. J. Field, H. W. Magoun, V. E. Hall, American Physiological Society, Washington, D. C. (1959-1960).

41. Hennie, F., Iterative Arrays of Logical Circuits. MIT Press, Cambridge, Mass., and Wiley, New York.

42. Harmon, L. D., and Lewis, E. R., "Neural modeling," Physiol. Rev. 46, 513-591 (1966).

43. Hernandez-Peon, R., "Reticular mechanisms of sensory control," 497-520. **

44. Herrick, C. J., The Brain of the Tiger Salamander, Amblystoma Tigrinum. University of Chicago Press (1948).

45. Humphry, and Rodin-Smith, "On the specificity of neural habituation in cockroach ganglia," Proc. Roy. Soc. London Series B 122, 106 (1937).

46. John, E. R., and Killam, K. F., "Electrophysiological correlates of avoidance conditioning in the cat," J. Pharmacology and Exp. Therap. 125, 252-274 (1959).

47. Kilmer, W. L., "Iterative switching networks composed of combinational cells," IRE Trans. Electron Computers EC-11, 123-131 (1962).

48. _____, "On Cycling Behavior in 1-Dimensional, Bilateral Iterative Networks," Research Report, Electronics Research Laboratory, Montana State College, August 1962.

49. _____, "On dynamic switching in 1-dimensional iterative logic networks," Information and Control 6, 399-415 (1963).

50. _____, "Topics in the theory of 1-dimensional iterative networks," Information and Control 7, (March 1964).

51. Kilmer, W. L., and McCulloch, W., "Towards a theory of the reticular formation," Proc. IEEE 5th National Symposium on Human Factors in Electronics, (May 1964).

52. Kilmer, W. L., et al., "On a cybernetic theory of the reticular formation," Proc. 1966 Bionics Symposium, Dayton, Ohio (May 1966). To be published.

53. Krieg, W. J. S., A Polychrome Atlas of the Brain Stem. Brain Books, Evanston, Illinois, (1963).

54. _____, Brain Mechanisms in Diachrome. Brain Books, Evanston, Illinois, (1963).

55. Leibnitz, Selections. ed. P. P. Wiener, Scribner's, New York (1951).

56. Lettvin, J. Y., Maturana, H. R., Pitts, W. H., and McCulloch, W. S., "Two remarks on the visual system of the frog," 757-776. **

57. Magoun, H. W., The Waking Brain. Charles C. Thomas, Pub., Springfield, Illinois, (1963).

58. McCulloch, W. S., Embodiments of Mind. MIT Press, Cambridge, Massachusetts, (1965).

59. McCulloch, W., and Kilmer, W. L., "Introduction to the problem of the reticular formation" in Automata Theory, Proc. of the 1964 International Summer School of Physics, Ravello, Italy, ed. E. Caianiello, Academic Press, (1966).

60. McLardy, T., "Hippocampal formation of brain as detector-coder of temporal patterns of information," Perspective Biol. Med. 2, 443-452 (1959).

61. McLean, P. D., "Psychosomatic disease and the 'visceral brain:' recent developments bearing on the Papez theory of emotion," Psychomatic Medicine 11, 338-353 (1949).

62. _____, "The limbic system with respect to self-preservation and the preservation of the species," J. Nervous and Mental Disease 127, 1-11 (1958).

63. Melzack, R., and Wall, P. D., "Pain mechanisms: a new theory," Science 150, 971-979 (November 1965).

64. Minorsky, N., Nonlinear Oscillations. Van Nostrand, Princeton, New Jersey, (1963).

65. Minsky, M., "Matter, mind and models," Proc. IFIPS Congress, Spartan Books, Washington, D. C., (May 1965).

66. Minsky, M., and Selfridge, O., "Learning in random nets," Fourth London Symposium of Information Theory, Butterworths, London, 335-347, (1961).

67. Moore, G. P., Perkel, D. H., and Segundo, J. P., "Statistical analysis and functional interpretation of neuronal spike data," Annual Rev. of Physiol. 28, 493-522 (1966).

68. Moore, J., and Mahler, H. R., "Introduction to molecular psychology," Proc. California Association of Chem. Teachers, 42, 49-60 (January 1965).

69. Morrell, R., and Jasper, H. H., "Electrographic studies of the formation of temporary connections in the brain," Electroencephalog. Clin. Neurophysiol. 8, 201-215 (1956).

70. Moruzzi, G., "Reticular influences on the EEG," Electroencephalog. Clin. Neurophysiol. 16, 2-17 (1964).

71. Moruzzi, G., and Magoun, H. W., "Brain stem reticular formation and activation of the EEG," Electroencephalog. Clin. Neurology 1, 445-473 (1949).

72. Nauta, W. J. H., "Central nervous organization and the endocrine motor system," from Advances in Neuroendocrinology, University of Illinois, (1963).

73. _____, "Fibre degeneration following lesions of the amygdaloid complex in the monkey," J. Anatomy 95, 4(October 1961).

74. _____, "Hippocampal projections and related neural pathways to the mid-brain in the cat," from Brain 81:3, 319-340 (1958).

75. _____, "Some efferent connections of the prefrontal cortex in the monkey," from the Frontal Grannular Cortex and Behavior, McGraw-Hill, (1963).

76. Nauta, W. J. H., and Koella, W. P., "Sleep, wakefullness, dreams, and memory," Neurosciences Res. Prog. Bull. 4 (May 31, 1966).

77. Nauta, W. J. H., and Kuypers, H. G. J. M., "Some ascending pathways in the brain stem reticular formation," In Reticular Formation of the Brain, ed. H. H. Jasper et al. Little, Brown, Boston, 3-30 (1958).

78. Nauta, W. J. H., and Mehler, W. R., "Some efferent connections of the lentiform nucleus in monkey and cat," Anat. Record 139, 260 (1961).

79. Nauta, W. J. H., and Ramon-Moliner, E., "The isodendritic core of the brain stem," J. Comp. Neurology 126, 3 (March 1966).

80. Nauta, W. J. H., and Valenstein, E. S., "A comparison of the distribution of the fornix system in the rat, guinea pig, cat, and monkey," J. Comp. Neurology 113, 3 (December 1959).

81. Nauta, W. J. H., and Whitlock, D. G., "An anatomical analysis of the non-specific thalamic projection system," In Brain Mechanisms and Consciousness, ed. J. G. Delafresnaye, Illinois, 81-116 (1954).

82. Nilsson, N. J., "Adaptive Pattern Recognition: A Survey," Paper presented at the 1966 Bionics Symposium, Dayton, Ohio.

83. Olds, J., and Milner, P., "Positive reinforcement produced by electrical stimulation of septal area and other regions of rat brain," J. Comp. and Physiol. Psychology 47, 419-427 (1954).

84. Pask, G., An Approach to Cybernetics. Harper Bros., New York, (1961).

85. Pringle, J. W. S., "On the parallel between learning and evolution," Behavior 3:174, 90-110 (1951).

86. Scheibel, M. E., and Scheibel, A. B., "Hallucinations and the brain stem reticular core. Reprinted from Hallucinations, Grune and Stratton, 13-35 (1962).

87. _____, "Neurology of Learning," Reprinted from Childhood Education, (February 1966).

88. _____, "On neural mechanisms for self-knowledge and command," Mitre Report SS-3, First Congress on the Information Systems Sciences, Mitre Corp., Boston, Massachusetts.

89. _____, "Patterns of organization in specific and nonspecific thalamic fields," from The Thalamus, ed. Purpura and Yahr, New York (1966).

90. _____, "Periodic sensory nonresponsiveness in reticular neurons," Arch. Ital. Biol. 103, 300-316 (1965).

91. _____, "Some structuro-functional correlates of development in young cats," Reprinted from Electroenceph. Clin. Neurophysiol., Netherlands, (1963).

92. _____, "Structural substrates for integrative patterns in the brain stem reticular core," Reprinted from Reticular Formation of the Brain, Internation Symposium, Boston, 1958.

93. _____, "The adaptive response of individual reticular units to repeated stimuli," Vol. II-Recent Advances in Biological Psychiatry, Proc. Nineteenth Annual Conv. Soc. Biol. Psychiatry. Los Angeles, Calif. (May 1-3, 1964).

94. _____, "The response of reticular units to repetitive stimuli," Arch. Ital. Biol. 103, 279-299 (1965).

95. _____, "The brain stem reticular core - an integrative matrix," Proc. Approaches to Systems Theory in Biol., Case Tech. Symposium, Cleveland, Ohio (October 1966).

96. Scheibel, M. E., Scheibel, A. B., and Jasper, H. H., "A Symposium on Dendrites," Formal Discussion, No. 10 (November 1958).

97. Scheibel, M. E., Scheibel, A. B., Mollica, A., and Moruzzi, G., "Convergence and interaction of afferent impulses on single units of reticular formation," J. Neurophysio. 18, 309-331 (1955).

98. Scheibel, M. E., Scheibel, A. B., Walberg, F., and Brodal, A., "Areal distribution of axonal and dendritic patterns in inferior olive," J. Comp. Neur. 106, 121-150 (November 1956).

99. Scholl, D. A., The Organization of the Cerebral Cortex. Methuen and Co., Ltd., London, (1956).

100. Scott, J. P., "Critical periods in behavioral development," Science, 138, 949-958 (1962).

101. Sechenov, I. M., Reflexes of the Brain. MIT Press, Boston Mass., (1965).

102. Sharpless, and Jasper, "Habituation of the arousal reaction," Brain 79, 655 (1956).

103. Shurrager, P. S., and Culler, E., "Conditioning in the spinal dog," J. Exp. Psychol. 26, 133-159 (1940).

104. Shurrager, P. S., and Dykman, R. A., "Successive and maintained conditioning in spinal carnivores," J. Comp. Physiol. Psych. 49, 27-35 (February 1956).

105. Shurrager, P. S., and Dykman, R. A., "Walking spinal carnivores," J. Comp. Physiol. Psychol. 44, 252-262 (1951).

106. Skinner, B. E., "The phylogeny and ontogeny of behavior," Science, 9, (September 1966).

107. Smith, D. R., and Davidson, C. H., "Maintained activity in neural nets," J. Assoc. Comp. Mach. 9, 268-279 (1962).

108. Smythies, J. R., The Neurological Foundations of Psychiatry, Academic Press, New York, (1966).

109. Sperry, R. W., "Neurology and the mind-brain problem," American Scientist, 40, 291-312 (1952).

110. Sprague, J. M., and Chambers, W. W., "Control of posture by reticular formation and cerebellum in the intact, anesthetized and unanesthetized and in the decerebrated cat," J. Exper. Neurol. 170, 52-64 (January 1954).

111. Sprague, J. M., Chambers, W. W., and Stellar, E., "Attentive, affective, and adaptive behavior in the cat," Science 133, 165-173 (January 20, 1961).

112. Swanson, R. W., "Cybernetic in Europe and the U.S.S.R.---Activities, Plans, and Impressions," AFOSR 66-0579, U. S. Air Force, Washington, D. C. (March 1966).

113. Taub, A., "Local, segmental, and supraspinal interaction with a dorsolateral spinal cutaneous afferent system," Exper. Neurology 10, 357-374 (1964).

114. Tauc, L., "The activity of the Mollusc Neuron," On Integrative Actions in Single Neurons, Endeavour, (January 1966).

115. Ten Hoopen, M., "Multimodal interval distributions," Kybernetik, (January 1966).

116. Teuber, Hans-Lukas, "The riddle of frontal lobe function in man," 410-444.

117. Valverde, F., "A new type of cell in the lateral reticular formation of the brain stem," J. Comp. Neur. 117, 189-196 (October 1961).

118. Valverde, F., "Reticular formation of the pons and medulla oblongata, a Golgi study," J. Comp. Neurol. 116, 71-99 (1961).

119. Varju, D., "Central Organization of Neural Systems," Examples of the Quantitative Analysis of Central Nervous Processes A, 23-42.

120. Verveen, A. A., Derksen, H. E., "Fluctuations in membrane potential of axons and the problem of coding," Kybernetik, (February 1965).

121. Wall, P. D., Personal Communication.

122. Wall, P. D., "The laminar organization of dorsal horn and effects of descending impulses," Paper 850, Dept. of Biology and Center for Communication Sciences, Research Laboratory of Electronics, MIT, Cambridge, Mass., (1966).

123. Wall, P. D., "Two transmission systems for skin sensations," 475-520. **

124. Weir, B., "Spikes-wave from stimulation of reticular core," J. Exper. Neurol., 209-218 (August 1964).

125. Weiss, P. A., "Specificity in the neurosciences," Neurosciences Res. Prog. Bull. 3, (October 5, 1965).

126. Wiener, N., Nonlinear Problems in Random Theory. MIT Press, Cambridge, Mass., and John Wiley and Sons, New York.

127. Winograd, S., and Cowan, J., Reliable Computation in the Presence of Noise. MIT Press, Cambridge, Mass., (1963).

128. Young, J. Z., A Model of the Brain. Oxford, (1964).

APPENDIX 1

Convergence on a Model

To a certain extent, any chunk of nerve tissue that has to perform both an analyzer and an integrator function, as RF* does, can be viewed as an assembly of coupled nonlinear oscillators. (In a very rich sense, all neural tissue amounts to such an assembly, and certainly behaves nonlinearly overall.) In fact, the variety of abductive logic our RF* employs on its highly correlated input sequences strongly suggests a model of rather tightly-coupled multi-stable oscillator units cooperating probabilistically so as to admit at any given time only one of a small number of possible stable overall operating modes. Thus we turned to Weiner's work on correlation-coupled nonlinear oscillators, which shows that there are forbidden zones about each stable point, and suggests that generally such systems behave as required.[126] To illustrate, Figure A1-1 (Wiener's Figure 8.4 in reference 126) depicts for such a system the shape of the probability distribution of oscillator frequencies about a normalized stable point, as calculated by Wiener. The crucial thing about Figure A1-1 as far as our RF* model is concerned is that there is enough variability about the stable point to permit flexible system operation. Unfortunately, we found that a central defect of all such systems is that there is no reasonable analytical or experimental way of determining anything basic about the transient behavior between stable mode points following input changes. The same holds true for every sufficiently complex nonlinear artificial neural net theory we know of to data. (See, for example, references 11, 12, 18, 35, 107.) But to be able to follow such transients is central to our task, so we had to regard these systems as useless. Recalling that single nonlinear oscillators a la Minorsky[64] behave too rigidly, and that linear systems are unable to exhibit the necessary memory, cell assembly, and modal features,* we abandoned all coupled-oscillator and neural-net approaches to RF* theory construction as utterly hopeless.

---

* In other words, the long-term responses of linear systems are determined in a 1:1 manner from their input drives, whereas this is not true for nonlinear systems. So in this sense, linear systems are irredundant, whereas nonlinear ones have a chance of being redundant in the right way for modeling neural behavior.

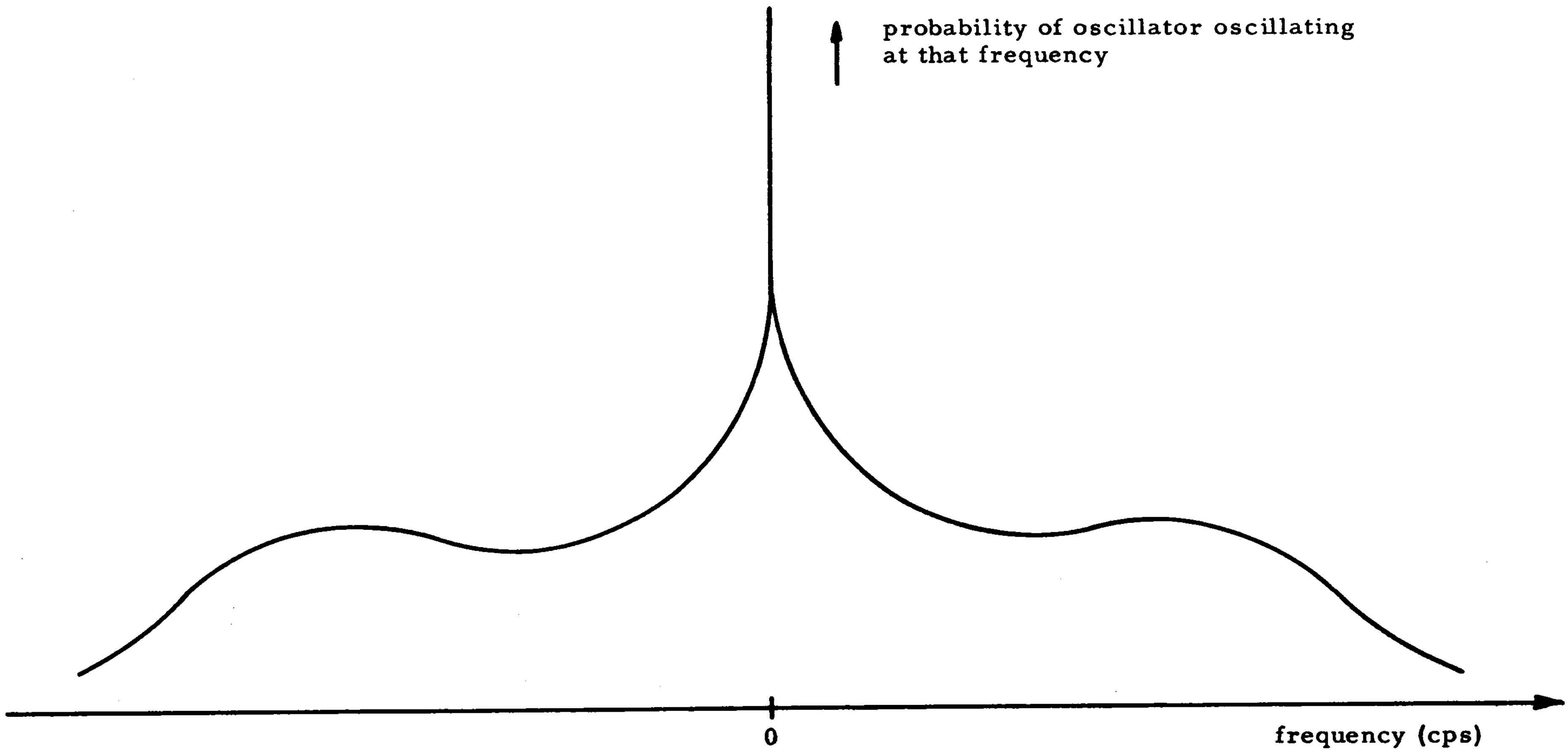


Figure A1-1. Wiener's Figure 8.4 in reference B-1.

Evidently we required considerably more initial structure than they would afford, i. e., we needed a well-developed set of strategies for designing a skeletal model of RF* behavior. Then we could revert to a computer-simulation and mathematics to investigate the complex behavioral consequences of varying these strategies. In order to pursue this plan without doing too much violence to the biology, we returned to the Scheibels' stack of poker chips analogy. The result is described in Section 4.

APPENDIX 2

γ_k Function Table

$$\gamma_k = (\sigma_i \wedge \sigma_j) \vee (\sigma_j \wedge \sigma_\ell) \vee (\sigma_\ell \wedge \sigma_i)$$

k	i	j	ℓ	k	i	j	ℓ
1	1	2	8	22	2	7	9
2	1	2	8	23	3	4	8
3	1	3	8	24	3	4	9
4	1	3	9	25	3	5	8
5	1	4	8	26	3	5	9
6	1	4	9	27	3	6	8
7	1	5	8	28	3	6	9
8	1	5	9	29	3	7	9
9	1	6	8	30	3	7	9
10	1	6	9	31	4	5	8
11	1	7	8	32	4	5	9
12	1	7	9	33	4	6	8
13	2	3	8	34	4	6	9
14	2	3	9	35	4	7	8
15	2	4	8	36	4	7	9
16	2	4	9	37	5	6	8
17	2	5	8	38	5	6	9
18	2	5	9	39	5	7	8
19	2	6	8	40	5	7	9
20	2	6	9	41	6	7	8
21	2	7	8	42	6	7	9

APPENDIX 3

Some σ_i; F, C, γ_i relationships for E, with only seven σ_i and the γ_i comprising the set of all 35 3-variable symmetric switching functions of the form $\gamma_i = (\sigma_j \wedge \sigma_k) \vee (\sigma_k \wedge \sigma_\ell) \vee (\sigma_\ell \wedge \sigma_j)$.

Number of the seven σ_i which equal 1	Number of $\sigma_1, \ldots, \sigma_7$ combinations for which this can happen	Number of the 35 γ_i which equal 1 in each of these combinations
1	7	0
2	21	5
3	35	13
4	35	22
5	21	30
6	7	35

APPENDIX 4

γ_j - to M_i Connection Table

i	j
	1
	14
1	23
	32
(M_u)	37
	13
	24
2	31
	38
(M_L)	41
	4
	11
3	15
	20
	40
	6
	17
4	28
	29
	33
	5
	8
5	21
	25
	34
	10
	16
6	26
	27
	39

i	j
	12
	18
7	23
	37
	42
	9
	13
8	18
	28
	36
	7
	10
9	19
	30
	35
	3
	15
10	22
	32
	39
	1
	12
11	26
	34
	41
	3
	6
12	7
	19
	30

APPENDIX 5

Exemplary $\{\gamma_i\}$, $\vec{p}'$ Table (6^{th} M_i)

ordered 5-tuple of γ_{i_j} inputs to M_6	$\vec{p}'$ vector corresponding to overall set of γ_{i_j} input signals			
$\gamma_{6_1}\gamma_{6_2}\gamma_{6_3}\gamma_{6_4}\gamma_{6_5}$	p'_1	p'_2	p'_3	p'_4
00000	0.273	0.152	0.333	0.242
10000	0.625	0.125	0.000	0.250
01000	0.563	0.375	0.000	0.063
11000	0.250	0.250	0.250	0.250
00100	0.250	0.350	0.150	0.250
10100	0.357	0.214	0.071	0.357
01100	0.833	0.167	0.000	0.000
11100	0.500	0.167	0.167	0.167
00010	0.000	0.308	0.385	0.308
10010	0.500	0.000	0.333	0.167
01010	0.692	0.154	0.077	0.077
11010	0.583	0.167	0.083	0.167
00110	0.125	0.333	0.292	0.250
10110	0.333	0.000	0.167	0.500
0110	0.444	0.222	0.111	0.222
11110	0.400	0.200	0.200	0.200
00001	0.000	0.040	0.440	0.520
10001	0.000	0.333	0.111	0.556
01001	0.333	0.222	0.333	0.111
11001	0.250	0.375	0.167	0.208
00101	0.083	0.083	0.417	0.417
10101	0.200	0.250	0.250	0.300
01101	0.500	0.167	0.333	0.000
11101	0.640	0.120	0.120	0.120

Appendix 5 (continued)

00011	0.000	0.000	0.750	0.250
10011	0.000	0.000	0.500	0.500
01011	0.214	0.143	0.357	0.286
11011	0.200	0.400	0.200	0.200
00111	0.333	0.000	0.333	0.333
10111	0.000	0.000	0.438	0.536
01111	0.000	0.750	0.125	0.125
11111	0.212	0.182	0.364	0.242

APPENDIX 6

THE PREPARATION SCHEME FOR APPENDIX 5

1. First of all we constructed a chart of the form:

$\Sigma_i \triangleq \sigma_1, \sigma_2, \ldots, \sigma_9$	Mode assignment of Σ_i point[1]	Values of $\gamma_1 \quad \gamma_2 \quad \ldots\ldots \quad \gamma_{42}$
0 0 ... 0	1	0 0 0
all 9-tuples	.	.
.	.	.
.	.	.
.		

using the γ-function chart of Appendix 1, and (actually, several different) assignments of Σ_i points that we found[1] yielded enough "interesting and reasonable"[2] sets of p_π vectors for enough Σ_i to enable us to perform a meaningful simulation.

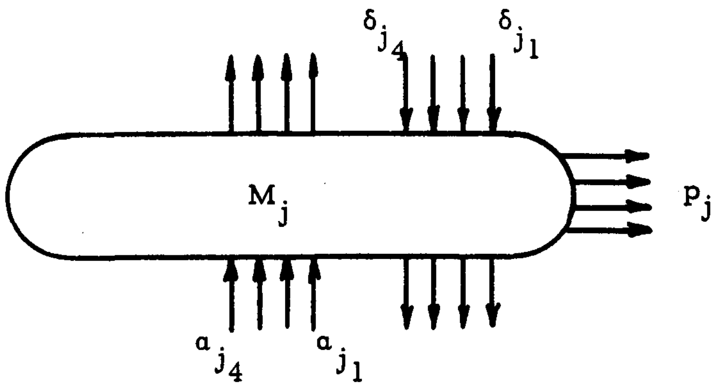
2. Then we constructed a chart of the form:

$\Sigma_i \triangleq \sigma_1, \sigma_2, \ldots, \sigma_9$	γ 5-tuple into M_1	M_2	....	M_{12}
0 0 . . . 0	00000	00000		00000
all 9 tuples			.	
.			.	
.			.	
.				

1. After much labor. This aspect of our simulation design is currently one of the most difficult and crucial.
2. Cf. the text Section on Simulation Results.

APPENDIX 7

M_i - to - M_j Connection Table



Connections into the j^{th} module, for j =	Let α_{j_k} or δ_{j_k} in the figure above come from the i^{th} module and go into the j^{th} module. It carries the k^{th} component of p_i, which we denote p_{i_k}. Below we list for each α_{j_k} and δ_{j_k} the i of the corresponding p_{i_k}. This gives the module of origin of the connection.						
	α_{j_1}	α_{j_2}	α_{j_3}	α_{j_4}	δ_{j_1}	δ_{j_2}	δ_{j_3}	δ_{j_4}
3	9	2	4	11	11	4	10	1
4	8	10	10	6	3	12	8	5
5	6	7	7	10	7	1	6	9
6	2	9	3	12	5	8	9	4
7	11	6	5	9	8	5	12	10
8	3	5	2	7	10	3	5	12
9	5	11	6	4	6	10	11	3
10	12	3	9	3	4	7	1	8
11	10	4	12	2	1	6	3	7
12	7	8	8	8	9	11	7	11

APPENDIX 8

Distribution of the $|i - j|$ in the M_i - to - M_j Connection Table

$\|i - j\|$	Number of M_i-to-M_j connections with this $\|i-j\|$	Ideal distribution to satisfy p_r (an M_i-to-M_j connection with $\|i-j\| = k) \triangleq p_k = \frac{C_o}{\sqrt{\|i - j\|}}$, where C_o is a connection constant such that $\sum_{k=1}^{10} 88\, p_k = 88$, with roundoff to the nearest integers.
1	18	18
2	16	15
3	12	12
4	11	10
5	9	8
6	7	7
7	6	6
8	5	5
9	3	4
10	2	3

88 = total = (8 x 10 from M_3 through M_{12}) +
(4 from M_1) + (4 from M_2)

APPENDIX 9.

SIMULATION RESULTS

TEST RETIC 483137 12.01.66

RUN NUMBER 3 CYCLE NUMBER 14 SIGMA SET NO. 1 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	0	0.070	0.310	0.310	0.310				
2	0	0.250	0.250	0.250	0.250				
3	0	0.070	0.310	0.310	0.310	0.046	0.334	0.178	0.440
4	0	0.700	0.100	0.100	0.100	0.671	0.158	0.058	0.111
5	0	0.070	0.310	0.310	0.310	0.049	0.276	0.407	0.266
6	0	0.070	0.310	0.310	0.310	0.046	0.240	0.475	0.237
7	0	0.070	0.310	0.310	0.310	0.207	0.246	0.331	0.213
8	0	0.700	0.100	0.100	0.100	0.635	0.163	0.126	0.074
9	0	0.070	0.310	0.310	0.310	0.044	0.235	0.399	0.320
10	0	0.250	0.250	0.250	0.250	0.403	0.206	0.227	0.163
11	0	0.070	0.310	0.310	0.310	0.098	0.316	0.297	0.287
12	0	0.250	0.250	0.250	0.250	0.175	0.246	0.332	0.245
	TOTALS	2.640	3.120	3.120	3.120	2.378	2.425	2.835	2.360

TEST RETIC 483137 12.01.66

RUN NUMBER 3 CYCLE NUMBER 1 SIGMA SET NO. 1 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	0	0.070	0.310	0.310	0.310				
2	0	0.250	0.250	0.250	0.250				
3	0	0.070	0.310	0.310	0.310	0.053	0.315	0.315	0.315
4	0	0.700	0.100	0.100	0.100	0.890	0.036	0.036	0.036
5	0	0.070	0.310	0.310	0.310	0.053	0.315	0.315	0.315
6	0	0.070	0.310	0.310	0.310	0.053	0.315	0.315	0.315
7	0	0.070	0.310	0.310	0.310	0.053	0.315	0.315	0.315
8	0	0.700	0.100	0.100	0.100	0.890	0.036	0.036	0.036
9	0	0.070	0.310	0.310	0.310	0.053	0.315	0.315	0.315
10	0	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250
11	0	0.070	0.310	0.310	0.310	0.053	0.315	0.315	0.315
12	0	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250
	TOTALS	2.640	3.120	3.120	3.120	2.600	2.466	2.466	2.466

Converge to mode 3 on cycle 19

RUN NUMBER 1 CYCLE NUMBER 21 SIGMA SET NO. 1 15TH CONVERGENT CYCLE. MODE = 1
WE ARE GOING BACK FOR A NEW SIGMA SET

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10101	0.200	0.250	0.250	0.300				
2	10101	0.556	0.111	0.333	0.000				
3	110	0.200	0.400	0.400	0.000	0.528	0.252	0.180	0.038
4	1001	0.083	0.500	0.250	0.167	0.570	0.307	0.085	0.036
5	10101	0.250	0.250	0.250	0.250	0.675	0.148	0.132	0.042
6	1010	0.692	0.154	0.077	0.077	0.845	0.061	0.053	0.039
7	110	0.000	0.333	0.667	0.000	0.471	0.113	0.384	0.030
8	11000	0.846	0.077	0.077	0.000	0.806	0.072	0.082	0.038
9	101	0.167	0.250	0.375	0.208	0.685	0.145	0.131	0.037
10	1000	0.461	0.230	0.076	0.230	0.731	0.148	0.073	0.046
11	10011	0.428	0.428	0.142	0.000	0.551	0.263	0.149	0.035
12	10	0.000	0.231	0.231	0.538	0.482	0.108	0.127	0.280
	TOTALS	3.684	3.215	3.129	1.790	6.348	1.622	1.401	0.627

90

RUN NUMBER 1 CYCLE NUMBER 1 SIGMA SET NO. 2

NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	0	0.081	0.189	0.351	0.378				
3	1001	0.000	0.000	1.000	0.000	0.041	0.038	0.881	0.038
4	1000	0.231	0.538	0.154	0.077	0.303	0.572	0.088	0.035
5	1100	0.200	0.250	0.250	0.300	0.543	0.176	0.164	0.114
6	1	0.000	0.040	0.440	0.520	0.032	0.032	0.403	0.531
7	11000	0.375	0.292	0.125	0.208	0.551	0.217	0.057	0.172
8	100	0.194	0.000	0.258	0.548	0.187	0.034	0.170	0.606
9	10000	0.280	0.480	0.080	0.160	0.281	0.571	0.039	0.107
10	101	0.200	0.250	0.250	0.300	0.357	0.218	0.222	0.200
11	11000	0.350	0.050	0.100	0.500	0.344	0.037	0.050	0.567
12	100	0.150	0.300	0.200	0.350	0.269	0.220	0.185	0.323
	TOTALS	2.311	2.539	3.458	3.591	2.913	2.121	2.265	2.698

Converge on cycle 7 to mode 4

TEST RETIC 483326 12.01.66

RUN NUMBER 1 CYCLE NUMBER 2 SIGMA SET NO. 2 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	0	0.081	0.189	0.351	0.378				
3	1001	0.000	0.000	1.000	0.000	0.038	0.038	0.884	0.038
4	1000	0.231	0.538	0.154	0.077	0.128	0.663	0.117	0.090
5	1100	0.200	0.250	0.250	0.300	0.234	0.310	0.197	0.257
6	1	0.000	0.040	0.440	0.520	0.034	0.033	0.416	0.515
7	11000	0.375	0.292	0.125	0.208	0.518	0.219	0.064	0.197
8	100	0.194	0.000	0.258	0.548	0.154	0.035	0.197	0.612
9	10000	0.280	0.480	0.080	0.160	0.234	0.616	0.041	0.107
10	101	0.200	0.250	0.250	0.300	0.364	0.178	0.185	0.271
11	11000	0.350	0.050	0.100	0.500	0.290	0.038	0.123	0.547
12	100	0.150	0.300	0.200	0.350	0.169	0.154	0.138	0.536
	TOTALS	2.311	2.539	3.458	3.591	2.169	2.288	2.367	3.174

TEST RETIC 483326 12.01.66 61

RUN NUMBER 1 CYCLE NUMBER 3 SIGMA SET NO. 2 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	0	0.081	0.189	0.351	0.378				
3	1001	0.000	0.000	1.000	0.000	0.040	0.054	0.844	0.060
4	1000	0.231	0.538	0.154	0.077	0.114	0.593	0.115	0.176
5	1100	0.200	0.250	0.250	0.300	0.219	0.276	0.200	0.302
6	1	0.000	0.040	0.440	0.520	0.051	0.033	0.405	0.509
7	11000	0.375	0.292	0.125	0.208	0.507	0.216	0.077	0.199
8	100	0.194	0.000	0.258	0.548	0.144	0.036	0.197	0.621
9	10000	0.280	0.480	0.080	0.160	0.186	0.638	0.091	0.083
10	101	0.200	0.250	0.250	0.300	0.343	0.158	0.171	0.326
11	11000	0.350	0.050	0.100	0.500	0.270	0.044	0.190	0.494
12	100	0.150	0.300	0.200	0.320	0.197	0.082	0.105	0.614
	TOTALS	2.311	2.539	3.458	3.591	2.074	2.135	2.400	3.389

RUN NUMBER 1 CYCLE NUMBER 4 SIGMA SET NO. 2 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	0	0.081	0.189	0.351	0.378				
3	1001	0.000	0.000	1.000	0.000	0.042	0.121	0.696	0.140
4	1000	0.231	0.538	0.154	0.077	0.103	0.515	0.121	0.260
5	1100	0.200	0.250	0.250	0.300	0.234	0.242	0.201	0.320
6	1	0.000	0.040	0.440	0.520	0.065	0.037	0.403	0.494
7	11000	0.375	0.292	0.125	0.208	0.466	0.189	0.109	0.234
8	100	0.194	0.000	0.258	0.548	0.130	0.038	0.226	0.604
9	10000	0.280	0.480	0.080	0.160	0.169	0.493	0.228	0.108
10	101	0.200	0.250	0.250	0.300	0.286	0.154	0.199	0.359
11	11000	0.350	0.050	0.100	0.500	0.265	0.047	0.206	0.480
12	100	0.150	0.300	0.200	0.350	0.196	0.066	0.104	0.631
	TOTALS	2.311	2.539	3.458	3.591	1.961	1.906	2.497	3.634

RUN NUMBER 1 CYCLE NUMBER 5 SIGMA SET NO. 2 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	0	0.081	0.189	0.351	0.378				
3	1001	0.000	0.000	1.000	0.000	0.045	0.124	0.657	0.172
4	1000	0.231	0.538	0.154	0.077	0.087	0.450	0.154	0.308
5	1100	0.200	0.250	0.250	0.300	0.218	0.215	0.218	0.347
6	1	0.000	0.040	0.440	0.520	0.039	0.039	0.412	0.508
7	11000	0.375	0.292	0.125	0.208	0.435	0.161	0.111	0.290
8	100	0.194	0.000	0.258	0.548	0.122	0.039	0.235	0.602
9	10000	0.280	0.480	0.080	0.160	0.173	0.444	0.222	0.159
10	101	0.200	0.250	0.250	0.300	0.125	0.172	0.231	0.470
11	11000	0.350	0.050	0.100	0.500	0.262	0.051	0.209	0.476
12	100	0.150	0.300	0.200	0.350	0.190	0.053	0.129	0.626
	TOTALS	2.311	2.539	3.458	3.591	1.702	1.751	2.582	3.963

TEST RELIC 483326 12.01.66 64

RUN NUMBER 1 CYCLE NUMBER 6 SIGMA SET NO. 2 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	0	0.081	0.189	0.351	0.378				
3	1001	0.000	0.000	1.000	0.000	0.046	0.088	0.650	0.214
4	1000	0.231	0.538	0.154	0.077	0.064	0.368	0.173	0.393
5	1100	0.200	0.250	0.250	0.300	0.148	0.189	0.196	0.465
6	1	0.000	0.040	0.440	0.520	0.040	0.040	0.396	0.523
7	11000	0.375	0.292	0.125	0.208	0.359	0.131	0.122	0.385
8	100	0.194	0.000	0.258	0.548	0.066	0.043	0.247	0.642
9	10000	0.280	0.480	0.080	0.160	0.138	0.390	0.273	0.197
10	101	0.200	0.250	0.250	0.300	0.100	0.145	0.219	0.533
11	11000	0.350	0.050	0.100	0.500	0.200	0.083	0.242	0.473
12	100	0.150	0.300	0.200	0.350	0.194	0.045	0.135	0.624
	TOTALS	2.311	2.639	3.458	3.591	1.359	1.527	2.659	4.453

RUN NUMBER 1 CYCLE NUMBER 7 SIGMA SET NO. 2 1TH CONVERGENT CYCLE, MODE = 4

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	0	0.081	0.189	0.351	0.378				
3	1001	0.000	0.000	1.000	0.000	0.041	0.092	0.640	0.224
4	1000	0.231	0.538	0.154	0.077	0.046	0.340	0.147	0.465
5	1100	0.200	0.250	0.250	0.300	0.076	0.155	0.172	0.594
6	1	0.000	0.040	0.440	0.520	0.037	0.037	0.389	0.534
7	11000	0.375	0.292	0.125	0.208	0.267	0.133	0.119	0.479
8	100	0.194	0.000	0.258	0.548	0.068	0.038	0.222	0.670
9	10000	0.280	0.480	0.080	0.160	0.095	0.373	0.252	0.278
10	101	0.200	0.250	0.250	0.300	0.105	0.090	0.272	0.530
11	11000	0.350	0.050	0.100	0.500	0.194	0.055	0.227	0.523
12	100	0.150	0.300	0.200	0.350	0.138	0.051	0.140	0.670
	TOTALS	2.311	2.539	3.458	3.591	1.073	1.369	2.586	4.971

RUN NUMBER 1 CYCLE NUMBER 20 SIGMA SET NO. 2 14TH CONVERGENT CYCLE. MODE = 4

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	0	0.081	0.189	0.351	0.378				
3	1001	0.000	0.000	1.000	0.000	0.036	0.080	0.534	0.347
4	1000	0.231	0.538	0.154	0.077	0.041	0.285	0.083	0.588
5	1100	0.200	0.250	0.250	0.300	0.055	0.121	0.093	0.729
6	1	0.000	0.040	0.440	0.520	0.034	0.034	0.265	0.665
7	11000	0.375	0.292	0.125	0.208	0.191	0.097	0.039	0.670
8	100	0.194	0.000	0.258	0.548	0.051	0.037	0.140	0.770
9	10000	0.280	0.480	0.080	0.160	0.048	0.278	0.074	0.598
10	101	0.200	0.250	0.250	0.300	0.046	0.083	0.139	0.730
11	11000	0.350	0.050	0.100	0.500	0.159	0.052	0.094	0.693
12	100	0.150	0.300	0.200	0.350	0.062	0.044	0.061	0.831
	TOTALS	2.311	2.539	3.458	3.591	0.727	1.117	1.527	6.626

RUN NUMBER 1 CYCLE NUMBER 21 SIGMA SET NO. 2 15TH CONVERGENT CYCLE, MODE = 4
WE ARE GOING BACK FOR A NEW SIGMA SET

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	0	0.081	0.189	0.351	0.378				
3	1001	0.000	0.000	1.000	0.000	0.036	0.080	0.534	0.348
4	1000	0.231	0.538	0.154	0.077	0.041	0.286	0.083	0.589
5	1100	0.200	0.250	0.250	0.300	0.055	0.121	0.093	0.729
6	1	0.000	0.040	0.440	0.520	0.034	0.034	0.264	0.666
7	11000	0.375	0.292	0.125	0.208	0.191	0.097	0.039	0.670
8	100	0.194	0.000	0.258	0.548	0.051	0.037	0.140	0.770
9	10000	0.280	0.480	0.080	0.160	0.048	0.279	0.073	0.598
10	101	0.200	0.250	0.250	0.300	0.046	0.084	0.138	0.731
11	11000	0.350	0.050	0.100	0.500	0.159	0.053	0.093	0.694
12	100	0.150	0.300	0.200	0.350	0.062	0.044	0.061	0.831
	TOTALS	2.311	2.539	3.458	3.591	0.727	1.119	1.523	6.629

111

RUN NUMBER 1 CYCLE NUMBER 1 SIGMA SET NO. 3 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	11101	0.200	0.250	0.250	0.300				
2	11011	0.200	0.250	0.250	0.300				
3	11110	0.200	0.250	0.250	0.300	0.193	0.243	0.220	0.342
4	11111	0.200	0.250	0.250	0.300	0.158	0.185	0.209	0.446
5	11111	0.200	0.250	0.250	0.300	0.125	0.175	0.159	0.538
6	11110	0.400	0.200	0.200	0.200	0.432	0.149	0.160	0.257
7	11111	0.200	0.250	0.250	0.300	0.177	0.191	0.190	0.441
8	11110	0.400	0.200	0.200	0.200	0.418	0.145	0.155	0.279
9	11110	0.200	0.250	0.250	0.300	0.174	0.209	0.231	0.384
10	11100	0.400	0.200	0.200	0.200	0.401	0.142	0.155	0.300
11	11111	0.200	0.250	0.250	0.300	0.188	0.243	0.240	0.326
12	11111	0.200	0.250	0.250	0.300	0.130	0.110	0.129	0.628
	TOTALS	3.000	2.850	2.850	3.300	2.402	1.797	1.852	3.946

Converge on cycle 16 to mode 1

RUN NUMBER 1 CYCLE NUMBER 2 SIGMA SET NO. 3 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	11101	0.200	0.250	0.250	0.300				
2	11011	0.200	0.250	0.250	0.300				
3	11110	0.200	0.250	0.250	0.300	0.217	0.246	0.243	0.291
4	11111	0.200	0.250	0.250	0.300	0.257	0.191	0.205	0.345
5	11111	0.200	0.250	0.250	0.300	0.248	0.230	0.218	0.303
6	11110	0.400	0.200	0.200	0.200	0.421	0.156	0.165	0.256
7	11111	0.200	0.250	0.250	0.300	0.258	0.216	0.208	0.316
8	11110	0.400	0.200	0.200	0.200	0.444	0.161	0.159	0.234
9	11110	0.200	0.250	0.250	0.300	0.226	0.226	0.231	0.314
10	11100	0.400	0.200	0.200	0.200	0.435	0.178	0.179	0.206
11	11111	0.200	0.250	0.250	0.300	0.243	0.224	0.224	0.307
12	11111	0.200	0.250	0.250	0.300	0.212	0.236	0.235	0.315
	TOTALS	3.000	2.850	2.850	3.300	2.965	2.069	2.072	2.891

RUN NUMBER 1 CYCLE NUMBER 14 SIGMA SET NO. 3 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	11101	0.200	0.250	0.250	0.300				
2	11011	0.200	0.250	0.250	0.300				
3	11110	0.200	0.250	0.250	0.300	0.276	0.235	0.218	0.269
4	11111	0.200	0.250	0.250	0.300	0.403	0.192	0.191	0.212
5	11111	0.200	0.250	0.250	0.300	0.403	0.205	0.195	0.195
6	11110	0.400	0.200	0.200	0.200	0.429	0.183	0.192	0.194
7	11111	0.200	0.250	0.250	0.300	0.395	0.204	0.204	0.195
8	11110	0.400	0.200	0.200	0.200	0.450	0.186	0.180	0.182
9	11110	0.200	0.250	0.250	0.300	0.351	0.199	0.214	0.235
10	11100	0.400	0.200	0.200	0.200	0.454	0.183	0.185	0.176
11	11111	0.200	0.250	0.250	0.300	0.307	0.213	0.226	0.253
12	11111	0.200	0.250	0.250	0.300	0.345	0.213	0.211	0.229
TOTALS		3.000	2.850	2.850	3.300	3.818	2.016	2.021	2.143

TEST RETIC 483326 12.01.66

RUN NUMBER 1 CYCLE NUMBER 15 SIGMA SET NO. 3 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	11101	0.200	0.250	0.250	0.300				
2	11011	0.200	0.250	0.250	0.300				
3	11110	0.200	0.250	0.250	0.300	0.285	0.232	0.213	0.267
4	11111	0.200	0.250	0.250	0.300	0.415	0.189	0.188	0.206
5	11111	0.200	0.250	0.250	0.300	0.415	0.202	0.191	0.189
6	11110	0.400	0.200	0.200	0.200	0.443	0.177	0.189	0.190
7	11111	0.200	0.250	0.250	0.300	0.408	0.197	0.202	0.191
8	11110	0.400	0.200	0.200	0.200	0.456	0.184	0.176	0.182
9	11110	0.200	0.250	0.250	0.300	0.371	0.193	0.205	0.229
10	11100	0.400	0.200	0.200	0.200	0.459	0.180	0.184	0.174
11	11111	0.200	0.250	0.250	0.300	0.311	0.210	0.225	0.252
12	11111	0.200	0.250	0.250	0.300	0.397	0.198	0.193	0.210
	TOTALS	3.000	2.850	2.850	3.300	3.965	1.968	1.970	2.095

AVERAGES MODE I 0.396 MODE II 0.195 MODE III 0.197 MODE IV 0.209

GAIN FACTORS FOLLOW

132 1.566300319 00 7.672218369 -01 7.881571917 -01 8.383206490 -01

RUN NUMBER 1 CYCLE NUMBER 16 SIGMA SET NO. 3 1TH CONVERGENT CYCLE, MODE = 1

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	11101	0.200	0.250	0.250	0.300				
2	11011	0.200	0.250	0.250	0.300				
3	11110	0.200	0.250	0.250	0.300	0.399	0.193	0.178	0.228
4	11111	0.200	0.250	0.250	0.300	0.548	0.144	0.145	0.161
5	11111	0.200	0.250	0.250	0.300	0.559	0.151	0.139	0.149
6	11110	0.400	0.200	0.200	0.200	0.591	0.128	0.137	0.141
7	11111	0.200	0.250	0.250	0.300	0.545	0.151	0.149	0.153
8	11110	0.400	0.200	0.200	0.200	0.604	0.135	0.126	0.133
9	11110	0.200	0.250	0.250	0.300	0.551	0.135	0.145	0.167
10	11100	0.400	0.200	0.200	0.200	0.601	0.132	0.133	0.133
11	11111	0.200	0.250	0.250	0.300	0.483	0.155	0.160	0.200
12	11111	0.200	0.250	0.250	0.300	0.536	0.151	0.145	0.166
	TOTALS	3.000	2.850	2.850	3.300	5.421	1.480	1.461	1.636

RUN NUMBER 1 CYCLE NUMBER 29 SIGMA SET NO. 3 14TH CONVERGENT CYCLE, MODE = 1

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	11101	0.200	0.250	0.250	0.300				
2	11011	0.200	0.250	0.250	0.300				
3	11110	0.200	0.250	0.250	0.300	0.798	0.074	0.034	0.092
4	11111	0.200	0.250	0.250	0.300	0.872	0.036	0.052	0.039
5	11111	0.200	0.250	0.250	0.300	0.847	0.080	0.035	0.036
6	11110	0.400	0.200	0.200	0.200	0.859	0.043	0.041	0.055
7	11111	0.200	0.250	0.250	0.300	0.878	0.045	0.036	0.039
8	11110	0.400	0.200	0.200	0.200	0.839	0.048	0.076	0.035
9	11110	0.200	0.250	0.250	0.300	0.876	0.036	0.036	0.050
10	11100	0.400	0.200	0.200	0.200	0.852	0.036	0.071	0.039
11	11111	0.200	0.250	0.250	0.300	0.815	0.046	0.038	0.099
12	11111	0.200	0.250	0.250	0.300	0.869	0.036	0.043	0.051
	TOTALS	3.000	2.850	2.850	3.300	8.508	0.484	0.465	0.541

RUN NUMBER 1 CYCLE NUMBER 30 SIGMA SET NO. 3
WE ARE GOING BACK FOR A NEW SIGMA SET

15TH CONVERGENT CYCLE. MODE = 1

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	11101	0.200	0.250	0.250	0.300				
2	11011	0.200	0.250	0.250	0.300				
3	11110	0.200	0.250	0.250	0.300	0.798	0.074	0.034	0.092
4	11111	0.200	0.250	0.250	0.300	0.872	0.036	0.052	0.039
5	11111	0.200	0.250	0.250	0.300	0.847	0.080	0.035	0.036
6	11110	0.400	0.200	0.200	0.200	0.859	0.043	0.041	0.055
7	11111	0.200	0.250	0.250	0.300	0.878	0.045	0.036	0.039
8	11110	0.400	0.200	0.200	0.200	0.839	0.048	0.076	0.035
9	11110	0.200	0.250	0.250	0.300	0.876	0.036	0.036	0.050
10	11110	0.400	0.200	0.200	0.200	0.852	0.036	0.071	0.039
11	11111	0.200	0.250	0.250	0.300	0.815	0.046	0.038	0.099
12	11111	0.200	0.250	0.250	0.300	0.869	0.036	0.043	0.051
	TOTALS	3.000	2.850	2.850	3.300	8.508	0.484	0.465	0.541

TEST RETIC 483326 12.01.66

RUN NUMBER 1 CYCLE NUMBER 1 SIGMA SET NO. 4 1TH CONVERGENT CYCLE. MODE = 1

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	1	0.250	0.250	0.250	0.250				
3	1110	0.250	0.250	0.250	0.250	0.675	0.113	0.088	0.122
4	10001	0.250	0.250	0.250	0.250	0.716	0.090	0.100	0.092
5	10101	0.250	0.250	0.250	0.250	0.703	0.117	0.089	0.089
6	11000	0.250	0.250	0.250	0.250	0.583	0.136	0.135	0.145
7	10001	0.850	0.050	0.050	0.050	0.909	0.030	0.030	0.030
8	10001	0.250	0.250	0.250	0.250	0.584	0.134	0.148	0.132
9	1101	0.250	0.250	0.250	0.250	0.718	0.090	0.090	0.099
10	1100	0.100	0.100	0.100	0.700	0.100	0.040	0.045	0.813
11	11011	0.250	0.250	0.250	0.250	0.677	0.099	0.094	0.128
12	1010	0.200	0.250	0.250	0.300	0.700	0.091	0.095	0.112
	TOTALS	3.400	2.550	2.650	3.300	6.369	0.943	0.919	1.767

Stays converged on mode 1

RUN NUMBER 1 CYCLE NUMBER 2 SIGMA SET NO. 4 2TH CONVERGENT CYCLE. MODE = 1

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	1	0.250	0.250	0.250	0.250				
3	1110	0.250	0.250	0.250	0.250	0.652	0.123	0.091	0.132
4	10001	0.250	0.250	0.250	0.250	0.694	0.088	0.100	0.115
5	10101	0.250	0.250	0.250	0.250	0.560	0.115	0.097	0.226
6	11000	0.250	0.250	0.250	0.250	0.619	0.129	0.119	0.131
7	10001	0.850	0.050	0.050	0.050	0.908	0.030	0.030	0.030
8	10001	0.250	0.250	0.250	0.250	0.545	0.147	0.171	0.135
9	1101	0.250	0.250	0.250	0.250	0.693	0.089	0.108	0.108
10	1100	0.100	0.100	0.100	0.700	0.133	0.039	0.046	0.779
11	11011	0.250	0.250	0.250	0.250	0.434	0.174	0.166	0.223
12	1010	0.200	0.250	0.250	0.300	0.686	0.100	0.092	0.119
	TOTALS	3.400	2.550	2.650	3.300	5.930	1.039	1.026	2.003

RUN NUMBER 1 CYCLE NUMBER 3 SIGMA SET NO. 4 3TH CONVERGENT CYCLE. MODE = 1

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	1	0.250	0.250	0.250	0.250				
3	1110	0.250	0.250	0.250	0.250	0.615	0.131	0.091	0.161
4	10001	0.250	0.250	0.250	0.250	0.678	0.084	0.099	0.137
5	10101	0.250	0.250	0.250	0.250	0.587	0.108	0.087	0.217
6	11000	0.250	0.250	0.250	0.250	0.599	0.134	0.125	0.140
7	10001	0.850	0.050	0.050	0.050	0.901	0.030	0.030	0.036
8	10001	0.250	0.250	0.250	0.250	0.560	0.142	0.168	0.128
9	1101	0.250	0.250	0.250	0.250	0.661	0.105	0.119	0.113
10	1100	0.100	0.100	0.100	0.700	0.205	0.038	0.049	0.707
11	11011	0.250	0.250	0.250	0.250	0.479	0.175	0.167	0.178
12	1010	0.200	0.250	0.250	0.300	0.668	0.110	0.091	0.130
	TOTALS	3.400	2.550	2.650	3.300	5.957	1.060	1.030	1.951

RUN NUMBER 1 CYCLE NUMBER 14 SIGMA SET NO. 4 14TH CONVERGENT CYCLE. MODE = 1

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	1	0.250	0.250	0.250	0.250				
3	1110	0.250	0.250	0.250	0.250	0.806	0.075	0.033	0.084
4	10001	0.250	0.250	0.250	0.250	0.874	0.036	0.045	0.043
5	10101	0.250	0.250	0.250	0.250	0.810	0.076	0.033	0.079
6	11000	0.250	0.250	0.250	0.250	0.868	0.042	0.038	0.050
7	10001	0.850	0.050	0.050	0.050	0.905	0.030	0.030	0.034
8	10001	0.250	0.250	0.250	0.250	0.834	0.051	0.079	0.034
9	1101	0.250	0.250	0.250	0.250	0.882	0.036	0.036	0.044
10	1100	0.100	0.100	0.100	0.700	0.630	0.028	0.049	0.292
11	11011	0.250	0.250	0.250	0.250	0.827	0.044	0.037	0.090
12	1010	0.200	0.250	0.250	0.300	0.871	0.036	0.043	0.049
	TOTALS	3.400	2.550	2.650	3.300	8.312	0.457	0.425	0.804

RUN NUMBER 1 CYCLE NUMBER 15 SIGMA SET NO. 4 15TH CONVERGENT CYCLE. MODE = 1
WE ARE GOING BACK FOR A NEW SIGMA SET

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	1	0.250	0.250	0.250	0.250				
3	1110	0.250	0.250	0.250	0.250	0.806	0.075	0.033	0.084
4	10001	0.250	0.250	0.250	0.250	0.874	0.036	0.045	0.043
5	10101	0.250	0.250	0.250	0.250	0.810	0.076	0.033	0.079
6	11000	0.250	0.250	0.250	0.250	0.868	0.042	0.038	0.050
7	10001	0.850	0.050	0.050	0.050	0.905	0.030	0.030	0.034
8	10001	0.250	0.250	0.250	0.250	0.834	0.051	0.079	0.034
9	1101	0.250	0.250	0.250	0.250	0.882	0.036	0.036	0.044
10	1100	0.100	0.100	0.100	0.700	0.630	0.028	0.049	0.292
11	11011	0.250	0.250	0.250	0.250	0.827	0.044	0.037	0.090
12	1010	0.200	0.250	0.250	0.300	0.871	0.036	0.043	0.049
	TOTALS	3.400	2.650	2.650	3.300	8.312	0.457	0.425	0.603

RUN NUMBER 1 CYCLE NUMBER 1 SIGMA SET NO. 5 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	11	0.000	0.235	0.588	0.176				
2	1111	0.250	0.000	0.750	0.000				
3	11	0.294	0.412	0.176	0.118	0.447	0.388	0.113	0.051
4	10101	0.000	0.000	0.000	1.000	0.041	0.041	0.041	0.874
5	1001	0.200	0.250	0.250	0.300	0.669	0.113	0.087	0.130
6	11101	0.640	0.120	0.120	0.120	0.894	0.035	0.035	0.034
7	11011	0.125	0.500	0.375	0.000	0.157	0.503	0.299	0.039
8	111	0.499	0.165	0.166	0.165	0.785	0.064	0.087	0.062
9	1011	0.000	0.000	0.500	0.500	0.035	0.035	0.453	0.476
10	111	0.200	0.250	0.250	0.300	0.439	0.170	0.194	0.195
11	1111	0.000	0.250	0.542	0.208	0.041	0.185	0.601	0.171
12	1001	0.333	0.567	0.000	0.000	0.369	0.570	0.030	0.030
	TOTALS	2.541	2.851	3.718	2.889	3.883	2.108	1.942	2.065

Converge to mode 1 on cycle 9

RUN NUMBER 1 CYCLE NUMBER 2 SIGMA SET NO. 5 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	11	0.000	0.235	0.588	0.176				
2	1111	0.250	0.000	0.750	0.000				
3	11	0.294	0.412	0.176	0.118	0.275	0.412	0.159	0.152
4	10101	0.000	0.000	0.000	1.000	0.042	0.042	0.042	0.871
5	1001	0.200	0.250	0.250	0.300	0.393	0.191	0.133	0.281
6	11101	0.640	0.120	0.120	0.120	0.870	0.034	0.046	0.048
7	11011	0.125	0.500	0.375	0.000	0.127	0.520	0.309	0.043
8	111	0.499	0.165	0.166	0.166	0.727	0.096	0.126	0.048
9	1011	0.000	0.000	0.500	0.500	0.035	0.035	0.448	0.481
10	111	0.200	0.250	0.250	0.300	0.260	0.253	0.279	0.206
11	1111	0.000	0.250	0.542	0.208	0.042	0.174	0.617	0.165
12	1001	0.333	0.567	0.000	0.000	0.320	0.614	0.032	0.032
	TOTALS	2.541	2.351	3.718	2.889	3.095	2.374	2.196	2.332

RUN NUMBER 1 CYCLE NUMBER 3 SIGMA SET NO. 5 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	11	0.000	0.235	0.588	0.176				
2	1111	0.250	0.000	0.750	0.000				
3	11	0.294	0.412	0.176	0.118	0.222	0.334	0.212	0.229
4	10101	0.000	0.000	0.000	1.000	0.043	0.056	0.043	0.856
5	1001	0.200	0.250	0.250	0.300	0.376	0.193	0.131	0.298
6	11101	0.640	0.120	0.120	0.120	0.843	0.033	0.058	0.064
7	11011	0.125	0.500	0.375	0.000	0.136	0.514	0.296	0.051
8	111	0.499	0.165	0.166	0.165	0.670	0.129	0.154	0.046
9	1011	0.000	0.000	0.500	0.500	0.036	0.036	0.435	0.492
10	111	0.200	0.250	0.250	0.300	0.234	0.272	0.300	0.192
11	1111	0.000	0.250	0.542	0.208	0.108	0.135	0.635	0.120
12	1001	0.333	0.667	0.000	0.000	0.303	0.616	0.045	0.034
	TOTALS	2.541	2.351	3.718	2.889	2.977	2.322	2.313	2.386

7

RUN NUMBER 1 CYCLE NUMBER 4 SIGMA SET NO. 5 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	11	0.000	0.235	0.588	0.176				
2	1111	0.250	0.000	0.750	0.000				
3	11	0.294	0.412	0.176	0.118	0.268	0.316	0.208	0.206
4	10101	0.000	0.000	0.000	1.000	0.110	0.109	0.043	0.736
5	1001	0.200	0.250	0.250	0.300	0.386	0.190	0.126	0.296
6	11101	0.640	0.120	0.120	0.120	0.786	0.032	0.091	0.089
7	11011	0.125	0.500	0.375	0.000	0.248	0.406	0.230	0.114
8	111	0.499	0.165	0.166	0.166	0.656	0.127	0.172	0.042
9	1011	0.000	0.000	0.500	0.500	0.066	0.037	0.395	0.500
10	111	0.200	0.250	0.250	0.300	0.169	0.306	0.359	0.164
11	1111	0.000	0.250	0.542	0.208	0.136	0.129	0.623	0.110
12	1001	0.333	0.567	0.000	0.000	0.277	0.577	0.108	0.036
	TOTALS	2.541	2.851	3.718	2.889	3.107	2.234	2.359	2.298

RUN NUMBER 1 CYCLE NUMBER 5 SIGMA SET NO. 5 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	11	0.000	0.235	0.588	0.176				
2	1111	0.250	0.000	0.750	0.000				
3	11	0.294	0.412	0.176	0.118	0.291	0.311	0.214	0.162
4	10101	0.000	0.000	0.000	1.000	0.119	0.109	0.046	0.724
5	1001	0.200	0.250	0.250	0.300	0.458	0.175	0.114	0.250
6	11101	0.640	0.120	0.120	0.120	0.780	0.033	0.096	0.089
7	11011	0.125	0.500	0.375	0.000	0.274	0.378	0.223	0.123
8	111	0.499	0.166	0.166	0.166	0.635	0.142	0.175	0.046
9	1011	0.000	0.000	0.500	0.500	0.083	0.038	0.390	0.487
10	111	0.200	0.250	0.250	0.300	0.196	0.262	0.388	0.153
11	1111	0.000	0.250	0.542	0.208	0.044	0.171	0.618	0.165
12	1001	0.333	0.567	0.000	0.000	0.344	0.530	0.090	0.035
	TOTALS	2.541	2.551	3.718	2.889	3.228	2.154	2.359	2.257

RUN NUMBER 1 CYCLE NUMBER 6 SIGMA SET NO. 5 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	11	0.000	0.235	0.588	0.176				
2	1111	0.250	0.000	0.750	0.000				
3	11	0.294	0.412	0.176	0.118	0.215	0.291	0.255	0.237
4	10101	0.000	0.000	0.000	1.000	0.153	0.111	0.048	0.686
5	1001	0.200	0.250	0.250	0.300	0.490	0.168	0.105	0.235
6	11101	0.640	0.120	0.120	0.120	0.768	0.033	0.108	0.090
7	11011	0.125	0.500	0.375	0.000	0.269	0.345	0.206	0.178
8	111	0.499	0.166	0.166	0.166	0.621	0.148	0.187	0.043
9	1011	0.000	0.000	0.500	0.500	0.133	0.038	0.372	0.456
10	111	0.200	0.250	0.250	0.300	0.220	0.249	0.400	0.130
11	1111	0.000	0.250	0.542	0.208	0.075	0.141	0.642	0.140
12	1001	0.333	0.567	0.000	0.000	0.362	0.520	0.081	0.036
	TOTALS	2.541	2.551	3.718	2.889	3.310	2.047	2.407	2.234

RUN NUMBER 1 CYCLE NUMBER 7 SIGMA SET NO. 5 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	11	0.000	0.235	0.588	0.176				
2	1111	0.250	0.000	0.750	0.000				
3	11	0.294	0.412	0.176	0.118	0.332	0.238	0.247	0.181
4	10101	0.000	0.000	0.000	1.000	0.181	0.087	0.051	0.679
5	1001	0.200	0.250	0.250	0.300	0.530	0.160	0.095	0.214
6	11101	0.640	0.120	0.120	0.120	0.735	0.033	0.136	0.095
7	11011	0.125	0.500	0.375	0.000	0.341	0.290	0.172	0.195
8	111	0.499	0.165	0.166	0.165	0.593	0.149	0.209	0.047
9	1011	0.000	0.000	0.500	0.500	0.183	0.038	0.344	0.434
10	111	0.200	0.250	0.250	0.300	0.218	0.225	0.431	0.124
11	1111	0.000	0.250	0.542	0.208	0.153	0.121	0.570	0.154
12	1001	0.333	0.567	0.000	0.000	0.396	0.497	0.070	0.034
	TOTALS	2.541	2.551	3.718	2.889	3.668	1.842	2.328	2.161

RUN NUMBER 1 CYCLE NUMBER 22 SIGMA SET NO. 5 14TH CONVERGENT CYCLE, MODE = 1

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	11	0.000	0.235	0.588	0.176				
2	1111	0.250	0.000	0.750	0.000				
3	11	0.294	0.412	0.176	0.118	0.752	0.117	0.066	0.062
4	10101	0.000	0.000	0.000	1.000	0.616	0.033	0.036	0.313
5	1001	0.200	0.250	0.250	0.300	0.786	0.106	0.038	0.068
6	11101	0.640	0.120	0.120	0.120	0.831	0.029	0.076	0.062
7	11011	0.125	0.500	0.375	0.000	0.672	0.193	0.098	0.035
8	111	0.499	0.165	0.166	0.166	0.771	0.058	0.137	0.032
9	1011	0.000	0.000	0.500	0.500	0.532	0.029	0.218	0.219
10	111	0.200	0.250	0.250	0.300	0.678	0.081	0.202	0.038
11	1111	0.000	0.250	0.542	0.208	0.396	0.090	0.422	0.090
12	1001	0.333	0.567	0.000	0.000	0.669	0.265	0.037	0.027
	TOTALS	2.541	2.351	3.718	2.889	6.707	1.006	1.334	0.951

RUN NUMBER 1 CYCLE NUMBER 23 SIGMA SET NO. 5
WE ARE GOING BACK FOR A NEW SIGMA SET

15TH CONVERGENT CYCLE. MODE = 1

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	11	0.000	0.235	0.588	0.176				
2	1111	0.250	0.000	0.750	0.000				
3	11	0.294	0.412	0.176	0.118	0.752	0.117	0.066	0.062
4	10101	0.000	0.000	0.000	1.000	0.616	0.033	0.036	0.313
5	1001	0.200	0.250	0.250	0.300	0.786	0.106	0.038	0.068
6	11101	0.640	0.120	0.120	0.120	0.831	0.029	0.076	0.062
7	11011	0.125	0.500	0.375	0.000	0.672	0.193	0.098	0.035
8	111	0.499	0.165	0.166	0.166	0.771	0.058	0.137	0.032
9	1011	0.000	0.000	0.500	0.500	0.532	0.029	0.218	0.219
10	111	0.200	0.250	0.250	0.300	0.678	0.081	0.202	0.038
11	1111	0.000	0.250	0.542	0.208	0.396	0.090	0.422	0.090
12	1001	0.333	0.567	0.000	0.000	0.669	0.265	0.037	0.027
	TOTALS	2.541	2.551	3.718	2.889	6.707	1.006	1.334	0.951

RUN NUMBER 1 CYCLE NUMBER 1 SIGMA SET NO. 6 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	1011	0.200	0.250	0.250	0.300				
2	1110	0.200	0.250	0.250	0.300				
3	111	0.200	0.250	0.250	0.300	0.426	0.179	0.178	0.215
4	11101	0.200	0.250	0.250	0.300	0.457	0.177	0.179	0.186
5	1001	0.200	0.250	0.250	0.300	0.641	0.139	0.094	0.124
6	11100	0.499	0.166	0.166	0.166	0.785	0.062	0.077	0.073
7	1011	0.200	0.250	0.250	0.300	0.457	0.170	0.165	0.207
8	111	0.499	0.166	0.166	0.166	0.826	0.062	0.065	0.046
9	1100	0.200	0.250	0.250	0.300	0.442	0.168	0.183	0.205
10	1110	0.200	0.250	0.250	0.300	0.621	0.126	0.151	0.100
11	110	0.200	0.250	0.250	0.300	0.482	0.154	0.166	0.197
12	1010	0.200	0.250	0.250	0.300	0.467	0.167	0.175	0.189
	TOTALS	2.999	2.833	2.833	3.333	5.609	1.408	1.436	1.545

↑

Reconverges to mode 1 on cycle 3

RUN NUMBER 1 CYCLE NUMBER 2 SIGMA SET NO. 6 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	1011	0.200	0.250	0.250	0.300				
2	1110	0.200	0.250	0.250	0.300				
3	111	0.200	0.250	0.250	0.300	0.421	0.186	0.175	0.216
4	11101	0.200	0.250	0.250	0.300	0.498	0.167	0.155	0.178
5	1001	0.200	0.250	0.250	0.300	0.610	0.141	0.108	0.139
6	11100	0.499	0.166	0.166	0.166	0.771	0.064	0.080	0.083
7	1011	0.200	0.250	0.250	0.300	0.497	0.153	0.161	0.187
8	111	0.499	0.166	0.166	0.166	0.770	0.072	0.072	0.084
9	1100	0.200	0.250	0.250	0.300	0.489	0.160	0.155	0.194
10	1110	0.200	0.250	0.250	0.300	0.537	0.155	0.164	0.142
11	110	0.200	0.250	0.250	0.300	0.404	0.168	0.190	0.235
12	1010	0.200	0.250	0.250	0.300	0.477	0.165	0.167	0.189
	TOTALS	2.999	2.333	2.833	3.333	5.478	1.435	1.433	1.651

RUN NUMBER 1 CYCLE NUMBER 3 SIGMA SET NO. 6 1TH CONVERGENT CYCLE. MODE = 1

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	1011	0.200	0.250	0.250	0.300				
2	1110	0.200	0.250	0.250	0.300				
3	111	0.200	0.250	0.250	0.300	0.488	0.165	0.144	0.201
4	11101	0.200	0.250	0.250	0.300	0.559	0.151	0.134	0.153
5	1001	0.200	0.250	0.250	0.300	0.632	0.130	0.099	0.136
6	11100	0.499	0.165	0.166	0.165	0.772	0.064	0.078	0.084
7	1011	0.200	0.250	0.250	0.300	0.552	0.130	0.144	0.172
8	111	0.499	0.165	0.166	0.165	0.762	0.076	0.075	0.085
9	1100	0.200	0.250	0.250	0.300	0.552	0.143	0.133	0.171
10	1110	0.200	0.250	0.250	0.300	0.565	0.141	0.149	0.142
11	110	0.200	0.250	0.250	0.300	0.470	0.137	0.174	0.218
12	1010	0.200	0.250	0.250	0.300	0.547	0.141	0.140	0.170
	TOTALS	2.999	2.833	2.833	3.333	5.905	1.283	1.274	1.536

TEST RETIC 482541 11.30.66

RUN NUMBER 2 CYCLE NUMBER 1 SIGMA SET NO. 1 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10101	0.200	0.250	0.250	0.300				
2	101	0.200	0.250	0.250	0.300				
3	1100	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250
4	10011	0.200	0.250	0.250	0.300	0.221	0.249	0.249	0.278
5	10101	0.700	0.100	0.100	0.100	0.890	0.036	0.036	0.036
6	10011	0.200	0.250	0.250	0.300	0.221	0.249	0.249	0.278
7	10111	0.200	0.250	0.250	0.300	0.221	0.249	0.249	0.278
8	10001	0.200	0.250	0.250	0.300	0.221	0.249	0.249	0.278
9	11101	0.200	0.250	0.250	0.300	0.221	0.249	0.249	0.278
10	11001	0.200	0.250	0.250	0.300	0.221	0.249	0.249	0.278
11	11011	0.200	0.250	0.250	0.300	0.221	0.249	0.249	0.278
12	11110	0.200	0.250	0.250	0.300	0.221	0.249	0.249	0.278
	TOTALS	2.950	2.850	2.850	3.350	2.910	2.286	2.286	2.517

Converge to mode 1 on cycle 7

TEST RETIC 482541 11.30.66

RUN NUMBER 2 CYCLE NUMBER 3 SIGMA SET NO. 1 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10101	0.200	0.250	0.250	0.300				
2	101	0.200	0.250	0.250	0.300				
3	1100	0.250	0.250	0.250	0.250	0.302	0.228	0.232	0.236
4	10011	0.200	0.250	0.250	0.300	0.296	0.322	0.232	0.148
5	10101	0.700	0.100	0.100	0.100	0.804	0.058	0.050	0.087
6	10011	0.200	0.250	0.250	0.300	0.590	0.130	0.143	0.135
7	10111	0.200	0.250	0.250	0.300	0.355	0.156	0.185	0.302
8	10001	0.200	0.250	0.250	0.300	0.237	0.151	0.149	0.461
9	11101	0.200	0.250	0.250	0.300	0.585	0.174	0.126	0.114
10	11001	0.200	0.250	0.250	0.300	0.229	0.182	0.219	0.368
11	11011	0.200	0.250	0.250	0.300	0.206	0.208	0.231	0.352
12	11110	0.200	0.250	0.250	0.300	0.340	0.178	0.125	0.355
	TOTALS	2.950	2.850	2.850	3.350	3.949	1.792	1.696	2.561

RUN NUMBER 2 CYCLE NUMBER 5 SIGMA SET NO. 1 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10101	0.200	0.250	0.250	0.300				
2	101	0.200	0.250	0.250	0.300				
3	1100	0.250	0.250	0.250	0.250	0.415	0.188	0.161	0.234
4	10011	0.200	0.250	0.250	0.300	0.480	0.191	0.194	0.133
5	10101	0.700	0.100	0.100	0.100	0.774	0.083	0.041	0.100
6	10011	0.200	0.250	0.250	0.300	0.535	0.090	0.120	0.252
7	10111	0.200	0.250	0.250	0.300	0.415	0.124	0.094	0.366
8	10001	0.200	0.250	0.250	0.300	0.285	0.128	0.121	0.464
9	11101	0.200	0.250	0.250	0.300	0.647	0.144	0.079	0.129
10	11001	0.200	0.250	0.250	0.300	0.382	0.150	0.153	0.313
11	11011	0.200	0.250	0.250	0.300	0.243	0.166	0.160	0.429
12	11110	0.200	0.250	0.250	0.300	0.430	0.150	0.072	0.346
	TOTALS	2.950	2.850	2.850	3.350	4.611	1.417	1.199	2.771

RUN NUMBER 2 CYCLE NUMBER 21 SIGMA SET NO. 1 15TH CONVERGENT CYCLE, MODE = 1
WE ARE GOING BACK FOR A NEW SIGMA SET

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10101	0.200	0.250	0.250	0.300				
2	101	0.200	0.250	0.250	0.300				
3	1100	0.250	0.250	0.250	0.250	0.699	0.089	0.048	0.161
4	10011	0.200	0.250	0.250	0.300	0.773	0.040	0.091	0.094
5	10101	0.700	0.100	0.100	0.100	0.871	0.053	0.036	0.038
6	10011	0.200	0.250	0.250	0.300	0.726	0.051	0.060	0.160
7	10111	0.200	0.250	0.250	0.300	0.803	0.043	0.043	0.109
8	10001	0.200	0.250	0.250	0.300	0.756	0.045	0.102	0.095
9	11101	0.200	0.250	0.250	0.300	0.791	0.041	0.046	0.119
10	11001	0.200	0.250	0.250	0.300	0.758	0.043	0.100	0.097
11	11011	0.200	0.250	0.250	0.300	0.685	0.054	0.053	0.207
12	11110	0.200	0.250	0.250	0.300	0.767	0.040	0.062	0.129
	TOTALS	2.950	2.850	2.850	3.350	7.634	0.506	0.646	1.213

TEST RETIC 482541 11.30.66

RUN NUMBER 2 CYCLE NUMBER 1 SIGMA SET NO. 2 1TH CONVERGENT CYCLE. MODE = 1

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	1011	0.250	0.250	0.250	0.250				
2	1110	0.050	0.050	0.050	0.850				
3	111	0.250	0.250	0.250	0.250	0.555	0.113	0.134	0.197
4	11101	0.250	0.250	0.250	0.250	0.594	0.114	0.147	0.144
5	1001	0.250	0.250	0.250	0.250	0.368	0.217	0.201	0.212
6	11100	0.250	0.250	0.250	0.250	0.414	0.152	0.159	0.273
7	1011	0.400	0.200	0.200	0.200	0.584	0.134	0.134	0.147
8	111	0.250	0.250	0.250	0.250	0.596	0.128	0.116	0.158
9	1100	0.250	0.250	0.250	0.250	0.603	0.116	0.119	0.161
10	1110	0.250	0.250	0.250	0.250	0.569	0.122	0.157	0.151
11	110	0.250	0.250	0.250	0.250	0.413	0.136	0.134	0.315
12	1010	0.250	0.250	0.250	0.250	0.591	0.113	0.127	0.166
	TOTALS	2.950	2.750	2.750	3.550	5.291	1.349	1.431	1.927

Converge to mode 4 on cycle 10

TEST RETIC 482541 11.30.66 61

RUN NUMBER 2 CYCLE NUMBER 3 SIGMA SET NO. 2 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	1011	0.250	0.250	0.250	0.250				
2	1110	0.050	0.050	0.050	0.850				
3	111	0.250	0.250	0.250	0.250	0.336	0.158	0.212	0.292
4	11101	0.250	0.250	0.250	0.250	0.417	0.176	0.185	0.220
5	1001	0.250	0.250	0.250	0.250	0.315	0.232	0.225	0.225
6	11100	0.250	0.250	0.250	0.250	0.217	0.252	0.255	0.275
7	1011	0.400	0.200	0.200	0.200	0.509	0.174	0.153	0.163
8	111	0.250	0.250	0.250	0.250	0.450	0.191	0.159	0.198
9	1100	0.250	0.250	0.250	0.250	0.292	0.226	0.238	0.242
10	1110	0.250	0.250	0.250	0.250	0.416	0.169	0.211	0.202
11	110	0.250	0.250	0.250	0.250	0.247	0.184	0.182	0.386
12	1010	0.250	0.250	0.250	0.250	0.405	0.188	0.173	0.231
	TOTALS	2.950	2.750	2.750	3.550	3.608	1.954	1.997	2.438

RUN NUMBER 2 CYCLE NUMBER 5 SIGMA SET NO. 2 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	1011	0.250	0.250	0.250	0.250				
2	1110	0.050	0.050	0.050	0.850				
3	111	0.250	0.250	0.250	0.250	0.244	0.152	0.239	0.363
4	11101	0.250	0.250	0.250	0.250	0.283	0.233	0.234	0.248
5	1001	0.250	0.250	0.250	0.250	0.287	0.234	0.233	0.243
6	11100	0.250	0.250	0.250	0.250	0.174	0.269	0.270	0.285
7	1011	0.400	0.200	0.200	0.200	0.458	0.183	0.173	0.183
8	111	0.250	0.250	0.250	0.250	0.333	0.260	0.163	0.242
9	1100	0.250	0.250	0.250	0.250	0.243	0.232	0.239	0.284
10	1110	0.250	0.250	0.250	0.250	0.297	0.199	0.242	0.260
11	110	0.250	0.250	0.250	0.250	0.221	0.188	0.174	0.416
12	1010	0.250	0.250	0.250	0.250	0.348	0.211	0.177	0.262
	TOTALS	2.950	2.750	2.750	3.550	2.892	2.166	2.149	2.791

TEST RETIC 482541 11.30.66

RUN NUMBER 2 CYCLE NUMBER 7 SIGMA SET NO. 2 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	1011	0.250	0.250	0.250	0.250				
2	1110	0.050	0.050	0.050	0.850				
3	111	0.250	0.250	0.250	0.250	0.227	0.118	0.231	0.421
4	11101	0.250	0.250	0.250	0.250	0.261	0.239	0.236	0.263
5	1001	0.250	0.250	0.250	0.250	0.267	0.227	0.228	0.276
6	11100	0.250	0.250	0.250	0.250	0.142	0.266	0.265	0.326
7	1011	0.400	0.200	0.200	0.200	0.420	0.195	0.179	0.204
8	111	0.250	0.250	0.250	0.250	0.312	0.252	0.163	0.271
9	1100	0.250	0.250	0.250	0.250	0.204	0.211	0.206	0.377
10	1110	0.250	0.250	0.250	0.250	0.265	0.175	0.239	0.319
11	110	0.250	0.250	0.250	0.250	0.192	0.178	0.148	0.479
12	1010	0.250	0.250	0.250	0.250	0.307	0.198	0.153	0.340
	TOTALS	2.950	2.750	2.750	3.550	2.602	2.064	2.052	3.281

RUN NUMBER 2 CYCLE NUMBER 24 SIGMA SET NO. 2
WE ARE GOING BACK FOR A NEW SIGMA SET

15TH CONVERGENT CYCLE. MODE = 4

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	1011	0.250	0.250	0.250	0.250				
2	1110	0.050	0.050	0.050	0.850				
3	111	0.250	0.250	0.250	0.250	0.121	0.048	0.129	0.700
4	11101	0.250	0.250	0.250	0.250	0.090	0.042	0.071	0.796
5	1001	0.250	0.250	0.250	0.250	0.073	0.115	0.043	0.766
6	11100	0.250	0.250	0.250	0.250	0.046	0.045	0.083	0.825
7	1011	0.400	0.200	0.200	0.200	0.164	0.065	0.037	0.731
8	111	0.250	0.250	0.250	0.250	0.087	0.071	0.042	0.799
9	1100	0.250	0.250	0.250	0.250	0.056	0.043	0.075	0.824
10	1110	0.250	0.250	0.250	0.250	0.075	0.041	0.123	0.759
11	110	0.250	0.250	0.250	0.250	0.126	0.042	0.070	0.759
12	1010	0.250	0.250	0.250	0.250	0.097	0.050	0.042	0.809
	TOTALS	2.950	2.750	2.750	3.550	0.940	0.565	0.720	7.773

111

RUN NUMBER 2 CYCLE NUMBER 2 SIGMA SET NO. 3 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10	0.250	0.250	0.250	0.250				
2	1011	0.200	0.250	0.250	0.300				
3	11011	0.700	0.100	0.100	0.100	0.852	0.040	0.037	0.069
4	10101	0.200	0.250	0.250	0.300	0.291	0.140	0.166	0.401
5	11001	0.307	0.230	0.307	0.153	0.184	0.159	0.170	0.485
6	11000	0.250	0.250	0.250	0.250	0.189	0.150	0.130	0.529
7	10001	0.150	0.150	0.150	0.550	0.072	0.071	0.069	0.786
8	10011	0.200	0.250	0.250	0.300	0.232	0.118	0.170	0.478
9	1011	0.200	0.250	0.250	0.300	0.197	0.191	0.198	0.413
10	110	0.200	0.250	0.250	0.300	0.209	0.135	0.261	0.392
11	1011	0.200	0.250	0.250	0.300	0.183	0.163	0.148	0.505
12	1001	0.200	0.250	0.250	0.300	0.120	0.163	0.149	0.566
	TOTALS	3.057	2.730	2.807	3.403	2.534	1.334	1.502	4.628

Converges to mode 4 on cycle 10

TEST RETIC 482541 11.30.66

RUN NUMBER 2 CYCLE NUMBER 5 SIGMA SET NO. 3 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	10	0.250	0.250	0.250	0.250				
2	1011	0.200	0.250	0.250	0.300				
3	11011	0.700	0.100	0.100	0.100	0.822	0.041	0.059	0.076
4	10101	0.200	0.250	0.250	0.300	0.389	0.129	0.185	0.295
5	11001	0.307	0.230	0.307	0.153	0.243	0.224	0.222	0.310
6	11000	0.250	0.250	0.250	0.250	0.225	0.183	0.155	0.435
7	10001	0.150	0.150	0.150	0.550	0.100	0.096	0.092	0.710
8	10011	0.200	0.250	0.250	0.300	0.286	0.098	0.177	0.438
9	1011	0.200	0.250	0.250	0.300	0.263	0.233	0.228	0.274
10	110	0.200	0.250	0.250	0.300	0.251	0.109	0.337	0.302
11	1011	0.200	0.250	0.250	0.300	0.196	0.174	0.130	0.498
12	1001	0.200	0.250	0.250	0.300	0.161	0.162	0.155	0.520
	TOTALS	3.057	2.730	2.807	3.403	2.941	1.453	1.744	3.861

RUN NUMBER 2 CYCLE NUMBER 23 SIGMA SET NO. 3 15TH CONVERGENT CYCLE. MODE = 4
WE ARE GOING BACK FOR A NEW SIGMA SET

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10	0.250	0.250	0.250	0.250				
2	1011	0.200	0.250	0.250	0.300				
3	11011	0.700	0.100	0.100	0.100	0.546	0.043	0.042	0.368
4	10101	0.200	0.250	0.250	0.300	0.243	0.040	0.074	0.641
5	11001	0.307	0.230	0.307	0.153	0.130	0.102	0.043	0.723
6	11000	0.250	0.250	0.250	0.250	0.149	0.040	0.047	0.763
7	10001	0.150	0.150	0.150	0.550	0.131	0.045	0.036	0.786
8	10011	0.200	0.250	0.250	0.300	0.199	0.044	0.086	0.669
9	1011	0.200	0.250	0.250	0.300	0.156	0.044	0.057	0.742
10	110	0.200	0.250	0.250	0.300	0.176	0.043	0.128	0.651
11	1011	0.200	0.250	0.250	0.300	0.197	0.044	0.059	0.698
12	1001	0.200	0.250	0.250	0.300	0.130	0.040	0.059	0.770
	TOTALS	3.057	2.730	2.807	3.403	2.062	0.488	0.634	6.614

TEST RETIC 482541 11.30.66

RUN NUMBER 2 CYCLE NUMBER 1 SIGMA SET NO. 4 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	0	0.250	0.250	0.250	0.250				
2	0	0.250	0.250	0.250	0.250				
3	0	0.250	0.250	0.250	0.250	0.236	0.221	0.221	0.321
4	0	0.100	0.100	0.100	0.700	0.051	0.036	0.036	0.875
5	0	0.250	0.250	0.250	0.250	0.161	0.152	0.104	0.581
6	0	0.850	0.050	0.050	0.050	0.874	0.037	0.037	0.051
7	0	0.250	0.250	0.250	0.250	0.228	0.200	0.195	0.376
8	0	0.150	0.150	0.150	0.550	0.082	0.063	0.068	0.785
9	0	0.200	0.200	0.200	0.400	0.157	0.116	0.121	0.604
10	0	0.550	0.150	0.150	0.150	0.729	0.063	0.073	0.134
11	0	0.333	0.222	0.222	0.222	0.325	0.142	0.149	0.382
12	0	0.250	0.250	0.250	0.250	0.168	0.104	0.117	0.610
	TOTALS	3.683	2.372	2.372	3.572	3.014	1.137	1.124	4.723

Converge to mode 1 on cycle 10

RUN NUMBER 2 CYCLE NUMBER 3 SIGMA SET NO. 4 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	0	0.250	0.250	0.250	0.250				
2	0	0.250	0.250	0.250	0.250				
3	0	0.250	0.250	0.250	0.250	0.384	0.198	0.162	0.254
4	0	0.100	0.100	0.100	0.700	0.067	0.048	0.037	0.846
5	0	0.250	0.250	0.250	0.250	0.395	0.184	0.125	0.294
6	0	0.850	0.050	0.050	0.050	0.819	0.037	0.037	0.105
7	0	0.250	0.250	0.250	0.250	0.285	0.194	0.207	0.311
8	0	0.150	0.150	0.150	0.550	0.127	0.075	0.070	0.726
9	0	0.200	0.200	0.200	0.400	0.333	0.067	0.081	0.517
10	0	0.550	0.150	0.150	0.150	0.659	0.086	0.074	0.179
11	0	0.333	0.222	0.222	0.222	0.489	0.077	0.169	0.263
12	0	0.250	0.250	0.250	0.250	0.246	0.117	0.161	0.474
	TOTALS	3.683	2.372	2.372	3.572	3.811	1.087	1.126	3.974

RUN NUMBER 2 CYCLE NUMBER 7 SIGMA SET NO. 4 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	0	0.250	0.250	0.250	0.250				
2	0	0.250	0.250	0.250	0.250				
3	0	0.250	0.250	0.250	0.250	0.565	0.119	0.051	0.264
4	0	0.100	0.100	0.100	0.700	0.313	0.035	0.035	0.614
5	0	0.250	0.250	0.250	0.250	0.484	0.134	0.053	0.328
6	0	0.850	0.050	0.050	0.050	0.544	0.034	0.034	0.387
7	0	0.250	0.250	0.250	0.250	0.438	0.084	0.070	0.405
8	0	0.150	0.150	0.150	0.550	0.341	0.049	0.062	0.546
9	0	0.200	0.200	0.200	0.400	0.445	0.039	0.053	0.460
10	0	0.550	0.150	0.150	0.150	0.556	0.059	0.068	0.315
11	0	0.333	0.222	0.222	0.222	0.490	0.040	0.084	0.384
12	0	0.250	0.250	0.250	0.250	0.376	0.044	0.086	0.493
	TOTALS	3.683	2.372	2.372	3.572	4.556	0.641	0.601	4.200

RUN NUMBER 2 CYCLE NUMBER 24 SIGMA SET NO. 4 15TH CONVERGENT CYCLE. MODE = 1
WE ARE GOING BACK FOR A NEW SIGMA SET

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	0	0.250	0.250	0.250	0.250				
2	0	0.250	0.250	0.250	0.250				
3	0	0.250	0.250	0.250	0.250	0.663	0.107	0.043	0.186
4	0	0.100	0.100	0.100	0.700	0.476	0.031	0.031	0.459
5	0	0.250	0.250	0.250	0.250	0.673	0.123	0.040	0.161
6	0	0.850	0.050	0.050	0.050	0.726	0.035	0.035	0.202
7	0	0.250	0.250	0.250	0.250	0.689	0.085	0.041	0.183
8	0	0.150	0.150	0.150	0.550	0.515	0.041	0.061	0.381
9	0	0.200	0.200	0.200	0.400	0.622	0.036	0.036	0.304
10	0	0.550	0.150	0.150	0.150	0.734	0.043	0.072	0.149
11	0	0.333	0.222	0.222	0.222	0.669	0.042	0.049	0.239
12	0	0.250	0.250	0.250	0.250	0.691	0.041	0.042	0.224
	TOTALS	3.683	2.372	2.372	3.572	6.461	0.589	0.455	2.493

RUN NUMBER 3 CYCLE NUMBER 33 SIGMA SET NO. 1 15TH CONVERGENT CYCLE. MODE = 3
WE ARE GOING BACK FOR A NEW SIGMA SET

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	0	0.070	0.310	0.310	0.310				
2	0	0.250	0.250	0.250	0.250				
3	0	0.070	0.310	0.310	0.310	0.031	0.108	0.739	0.121
4	0	0.700	0.100	0.100	0.100	0.325	0.027	0.613	0.033
5	0	0.070	0.310	0.310	0.310	0.031	0.115	0.777	0.075
6	0	0.070	0.310	0.310	0.310	0.035	0.071	0.827	0.066
7	0	0.070	0.310	0.310	0.310	0.035	0.078	0.812	0.074
8	0	0.700	0.100	0.100	0.100	0.322	0.052	0.593	0.032
9	0	0.070	0.310	0.310	0.310	0.031	0.077	0.803	0.087
10	0	0.250	0.250	0.250	0.250	0.154	0.052	0.752	0.040
11	0	0.070	0.310	0.310	0.310	0.031	0.075	0.783	0.108
12	0	0.250	0.250	0.250	0.250	0.033	0.051	0.858	0.055
	TOTALS	2.640	3.120	3.120	3.140	1.032	0.711	7.561	0.694

RUN NUMBER 3 CYCLE NUMBER 1 SIGMA SET NO. 4 1TH CONVERGENT CYCLE. MODE = 3

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.100	0.300	0.300	0.300				
2	0	0.250	0.250	0.250	0.250				
3	1001	0.700	0.100	0.100	0.100	0.825	0.042	0.086	0.045
4	1000	0.100	0.300	0.300	0.300	0.041	0.156	0.652	0.149
5	1100	0.100	0.300	0.300	0.300	0.040	0.170	0.641	0.147
6	1	0.100	0.300	0.300	0.300	0.050	0.189	0.575	0.184
7	11000	0.700	0.100	0.100	0.100	0.817	0.041	0.097	0.043
8	100	0.100	0.300	0.300	0.300	0.048	0.209	0.541	0.200
9	10000	0.250	0.250	0.250	0.250	0.132	0.128	0.611	0.127
10	101	0.100	0.300	0.300	0.300	0.047	0.202	0.553	0.196
11	11000	0.250	0.250	0.250	0.250	0.135	0.125	0.599	0.139
12	100	0.100	0.300	0.300	0.300	0.041	0.154	0.650	0.153
	TOTALS	2.850	3.050	3.050	3.050	2.182	1.419	5.010	1.387

Stays converged on mode 3.

RUN NUMBER 3 CYCLE NUMBER 2 SIGMA SET NO. 4 2TH CONVERGENT CYCLE. MODE = 3

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.100	0.300	0.300	0.300				
2	0	0.250	0.250	0.250	0.250				
3	1001	0.700	0.100	0.100	0.100	0.828	0.043	0.081	0.046
4	1000	0.100	0.300	0.300	0.300	0.092	0.180	0.554	0.171
5	1100	0.100	0.300	0.300	0.300	0.108	0.203	0.418	0.269
6	1	0.100	0.300	0.300	0.300	0.064	0.205	0.538	0.190
7	11000	0.700	0.100	0.100	0.100	0.804	0.042	0.109	0.044
8	100	0.100	0.300	0.300	0.300	0.130	0.147	0.571	0.150
9	10000	0.250	0.250	0.250	0.250	0.082	0.125	0.693	0.099
10	101	0.100	0.300	0.300	0.300	0.042	0.154	0.621	0.181
11	11000	0.250	0.250	0.250	0.250	0.138	0.210	0.512	0.139
12	100	0.100	0.300	0.300	0.300	0.132	0.224	0.425	0.216
	TOTALS	2.850	3.050	3.050	3.050	2.424	1.538	4.527	1.509

RUN NUMBER 3 CYCLE NUMBER 3 SIGMA SET NO. 4 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.100	0.300	0.300	0.300				
2	0	0.250	0.250	0.250	0.250				
3	1001	0.700	0.100	0.100	0.100	0.766	0.043	0.144	0.045
4	1000	0.100	0.300	0.300	0.300	0.095	0.169	0.559	0.175
5	1100	0.100	0.300	0.300	0.300	0.131	0.200	0.416	0.251
6	1	0.100	0.300	0.300	0.300	0.067	0.183	0.552	0.196
7	11000	0.700	0.100	0.100	0.100	0.789	0.050	0.115	0.044
8	100	0.100	0.300	0.300	0.300	0.145	0.155	0.535	0.163
9	10000	0.250	0.250	0.250	0.250	0.097	0.137	0.664	0.099
10	101	0.100	0.300	0.300	0.300	0.048	0.132	0.666	0.152
11	11000	0.250	0.250	0.250	0.250	0.142	0.254	0.453	0.149
12	100	0.100	0.300	0.300	0.300	0.137	0.223	0.441	0.197
	TOTALS	2.650	3.050	3.050	3.050	2.422	1.551	4.550	1.475

RUN NUMBER 2 CYCLE NUMBER 1 SIGMA SET NO. 5

NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	11111	0.250	0.250	0.250	0.250				
2	11111	0.250	0.250	0.250	0.250				
3	11111	0.250	0.250	0.250	0.250	0.524	0.155	0.113	0.206
4	11111	0.400	0.100	0.100	0.400	0.502	0.040	0.040	0.417
5	11111	0.250	0.250	0.250	0.250	0.542	0.163	0.106	0.188
6	11111	0.100	0.400	0.400	0.100	0.070	0.439	0.440	0.049
7	11111	0.100	0.400	0.400	0.100	0.103	0.429	0.423	0.043
8	11111	0.400	0.400	0.100	0.100	0.490	0.421	0.041	0.046
9	11111	0.250	0.250	0.250	0.250	0.441	0.156	0.156	0.245
10	11111	0.250	0.250	0.250	0.250	0.333	0.208	0.217	0.240
11	11111	0.250	0.250	0.250	0.250	0.521	0.113	0.118	0.245
12	11111	0.250	0.250	0.250	0.250	0.554	0.107	0.108	0.229
	TOTALS	3.000	3.300	3.000	2.700	4.084	2.235	1.765	1.913

Converge to mode 2 on cycle 8

RUN NUMBER 2 CYCLE NUMBER 2 SIGMA SET NO. 5 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	11111	0.250	0.250	0.250	0.250				
2	11111	0.250	0.250	0.250	0.250				
3	11111	0.250	0.250	0.250	0.250	0.449	0.164	0.160	0.224
4	11111	0.400	0.100	0.100	0.400	0.513	0.050	0.042	0.394
5	11111	0.250	0.250	0.250	0.250	0.131	0.280	0.360	0.228
6	11111	0.100	0.400	0.400	0.100	0.055	0.455	0.442	0.046
7	11111	0.100	0.400	0.400	0.100	0.087	0.444	0.421	0.045
8	11111	0.400	0.400	0.100	0.100	0.481	0.427	0.048	0.042
9	11111	0.250	0.250	0.250	0.250	0.249	0.224	0.244	0.281
10	11111	0.250	0.250	0.250	0.250	0.331	0.240	0.223	0.205
11	11111	0.250	0.250	0.250	0.250	0.329	0.302	0.172	0.195
12	11111	0.250	0.250	0.250	0.250	0.240	0.401	0.194	0.163
	TOTALS	3.000	3.300	3.000	2.700	2.870	2.992	2.310	1.826

RUN NUMBER 2 CYCLE NUMBER 21 SIGMA SET NO. 6 15TH CONVERGENT CYCLE. MODE = 4
WE ARE GOING BACK FOR A NEW SIGMA SET

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.250	0.250	0.250	0.250				
2	0	0.250	0.250	0.250	0.250				
3	1001	0.200	0.400	0.200	0.200	0.094	0.198	0.058	0.648
4	1000	0.250	0.250	0.250	0.250	0.055	0.046	0.057	0.841
5	1100	0.200	0.200	0.400	0.200	0.045	0.084	0.098	0.771
6	1	0.250	0.250	0.250	0.250	0.116	0.044	0.042	0.796
7	11000	0.250	0.250	0.250	0.250	0.063	0.047	0.047	0.841
8	100	0.100	0.100	0.100	0.700	0.035	0.050	0.063	0.850
9	10000	0.250	0.250	0.250	0.250	0.079	0.060	0.043	0.816
10	101	0.250	0.250	0.250	0.250	0.051	0.079	0.084	0.785
11	11000	0.250	0.250	0.250	0.250	0.132	0.049	0.047	0.769
12	100	0.400	0.200	0.200	0.200	0.143	0.040	0.044	0.771
	TOTALS	2.900	2.900	2.900	3.300	0.816	0.701	0.588	7.893

TEST RETIC 482541 11.30.66

RUN NUMBER 2 CYCLE NUMBER 3 SIGMA SET NO. 5 NO CONVERGENCE THIS CYCLE.

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	11111	0.250	0.250	0.250	0.250				
2	11111	0.250	0.250	0.250	0.250				
3	11111	0.250	0.250	0.250	0.250	0.351	0.212	0.179	0.255
4	11111	0.400	0.100	0.100	0.400	0.502	0.105	0.044	0.346
5	11111	0.250	0.250	0.250	0.250	0.108	0.299	0.371	0.220
6	11111	0.100	0.400	0.400	0.100	0.045	0.454	0.435	0.064
7	11111	0.100	0.400	0.400	0.100	0.079	0.441	0.432	0.046
8	11111	0.400	0.400	0.100	0.100	0.463	0.424	0.070	0.041
9	11111	0.250	0.250	0.250	0.250	0.139	0.286	0.289	0.284
10	11111	0.250	0.250	0.250	0.250	0.298	0.268	0.239	0.194
11	11111	0.250	0.250	0.250	0.250	0.308	0.306	0.215	0.169
12	11111	0.250	0.250	0.250	0.250	0.181	0.497	0.179	0.141
	TOTALS	3.000	3.300	3.000	2.700	2.479	3.297	2.456	1.766

RUN NUMBER 2 CYCLE NUMBER 14 SIGMA SET NO. 7 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10111	0.250	0.250	0.250	0.250				
2	10100	0.250	0.250	0.250	0.250				
3	100	0.250	0.250	0.250	0.250	0.248	0.259	0.241	0.250
4	1001	0.250	0.250	0.250	0.250	0.237	0.299	0.227	0.234
5	10110	0.250	0.250	0.300	0.200	0.253	0.251	0.266	0.228
6	1001	0.250	0.250	0.250	0.250	0.250	0.255	0.246	0.247
7	1110	0.300	0.250	0.250	0.200	0.264	0.252	0.254	0.228
8	1100	0.250	0.250	0.250	0.250	0.244	0.253	0.254	0.248
9	10101	0.250	0.250	0.250	0.250	0.238	0.287	0.237	0.236
10	1011	0.200	0.400	0.200	0.200	0.202	0.389	0.203	0.204
11	10000	0.250	0.250	0.250	0.250	0.244	0.258	0.249	0.247
12	110	0.250	0.250	0.250	0.250	0.249	0.251	0.250	0.248
	TOTALS	3.000	3.150	3.000	2.850	2.434	2.759	2.430	2.375

RUN NUMBER 2 CYCLE NUMBER 1 SIGMA SET NO. 7

NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10111	0.250	0.250	0.250	0.250				
2	10100	0.250	0.250	0.250	0.250				
3	100	0.250	0.250	0.250	0.250	0.202	0.204	0.189	0.403
4	1001	0.250	0.250	0.250	0.250	0.131	0.126	0.132	0.609
5	10110	0.250	0.250	0.300	0.200	0.176	0.192	0.184	0.445
6	1001	0.250	0.250	0.250	0.250	0.164	0.118	0.117	0.599
7	1110	0.300	0.250	0.250	0.200	0.154	0.128	0.128	0.588
8	1100	0.250	0.250	0.250	0.250	0.201	0.214	0.218	0.365
9	10101	0.250	0.250	0.250	0.250	0.141	0.129	0.118	0.610
10	1011	0.200	0.400	0.200	0.200	0.128	0.388	0.138	0.344
11	10000	0.250	0.250	0.250	0.250	0.180	0.132	0.131	0.556
12	110	0.250	0.250	0.250	0.250	0.177	0.169	0.171	0.482
	TOTALS	3.000	3.150	3.000	2.850	1.659	1.804	1.530	5.005

Converges to mode 2 on cycle 20

RUN NUMBER 2 CYCLE NUMBER 15 SIGMA SET NO. 7 NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10111	0.250	0.250	0.250	0.250				
2	10100	0.250	0.250	0.250	0.250				
3	100	0.250	0.250	0.250	0.250	0.248	0.259	0.241	0.250
4	1001	0.250	0.250	0.250	0.250	0.237	0.299	0.227	0.234
5	10110	0.250	0.250	0.300	0.200	0.253	0.251	0.266	0.228
6	1001	0.250	0.250	0.250	0.250	0.250	0.255	0.246	0.247
7	1110	0.300	0.250	0.250	0.200	0.264	0.252	0.254	0.228
8	1100	0.250	0.250	0.250	0.250	0.244	0.253	0.254	0.248
9	10101	0.250	0.250	0.250	0.250	0.238	0.287	0.237	0.236
10	1011	0.200	0.400	0.200	0.200	0.202	0.389	0.203	0.204
11	10000	0.250	0.250	0.250	0.250	0.244	0.258	0.249	0.247
12	110	0.250	0.250	0.250	0.250	0.249	0.251	0.250	0.248
	TOTALS	3.000	3.150	3.000	2.850	2.434	2.759	2.430	2.375

AVERAGES MODE I 0.243 MODE II 0.275 MODE III 0.243 MODE IV 0.237

GAIN FACTORS FOLLOW

216 9.738721423 -01 1.103862573 00 9.721914471 -01 9.500738367 -01

RUN NUMBER 2 CYCLE NUMBER 33 SIGMA SET NO. 7 14TH CONVERGENT CYCLE. MODE = 2

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	10111	0.250	0.250	0.250	0.250				
2	10100	0.250	0.250	0.250	0.250				
3	100	0.250	0.250	0.250	0.250	0.035	0.835	0.038	0.090
4	1001	0.250	0.250	0.250	0.250	0.034	0.886	0.043	0.035
5	10110	0.250	0.250	0.300	0.200	0.044	0.881	0.036	0.037
6	1001	0.250	0.250	0.250	0.250	0.070	0.862	0.033	0.034
7	1110	0.300	0.250	0.250	0.200	0.043	0.887	0.035	0.033
8	1100	0.250	0.250	0.250	0.250	0.033	0.861	0.071	0.034
9	10101	0.250	0.250	0.250	0.250	0.037	0.884	0.034	0.043
10	1011	0.200	0.400	0.200	0.200	0.033	0.856	0.066	0.043
11	10000	0.250	0.250	0.250	0.250	0.068	0.831	0.031	0.068
12	110	0.250	0.250	0.250	0.250	0.033	0.885	0.039	0.040
	TOTALS	3.000	3.150	3.000	2.850	0.434	8.672	0.431	0.461

RUN NUMBER 2 CYCLE NUMBER 34 SIGMA SET NO. 7 15TH CONVERGENT CYCLE. MODE = 2
WE ARE GOING BACK FOR A NEW SIGMA SET

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	10111	0.250	0.250	0.250	0.250				
2	10100	0.250	0.250	0.250	0.250				
3	100	0.250	0.250	0.250	0.250	0.035	0.835	0.038	0.090
4	1001	0.250	0.250	0.250	0.250	0.034	0.886	0.043	0.035
5	10110	0.250	0.250	0.300	0.200	0.044	0.881	0.036	0.037
6	1001	0.250	0.250	0.250	0.250	0.070	0.862	0.033	0.034
7	1110	0.300	0.250	0.250	0.200	0.043	0.887	0.035	0.033
8	1100	0.250	0.250	0.250	0.250	0.033	0.861	0.071	0.034
9	10101	0.250	0.250	0.250	0.250	0.037	0.884	0.034	0.043
10	1011	0.200	0.400	0.200	0.200	0.033	0.856	0.066	0.043
11	10000	0.250	0.250	0.250	0.250	0.068	0.831	0.031	0.068
12	110	0.250	0.250	0.250	0.250	0.033	0.885	0.039	0.040
	TOTALS	3.000	3.150	3.000	2.850	0.434	8.672	0.431	0.461

221

RUN NUMBER 2 CYCLE NUMBER 1 SIGMA SET NO. 8 1TH CONVERGENT CYCLE. MODE * 2

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10100	0.250	0.250	0.250	0.250				
2	10101	0.250	0.250	0.250	0.250				
3	1100	0.250	0.250	0.250	0.250	0.087	0.704	0.089	0.119
4	1011	0.250	0.250	0.250	0.250	0.081	0.752	0.086	0.080
5	10100	0.250	0.250	0.250	0.250	0.093	0.731	0.085	0.089
6	1001	0.250	0.250	0.250	0.250	0.102	0.738	0.079	0.079
7	100	0.250	0.250	0.250	0.250	0.084	0.754	0.081	0.080
8	1001	0.250	0.250	0.250	0.250	0.079	0.739	0.102	0.079
9	101	0.100	<u>0.700</u>	0.100	0.100	0.030	0.907	0.030	0.032
10	1101	0.250	0.250	0.250	0.250	0.115	0.637	0.130	0.117
11	10001	0.100	0.100	<u>0.700</u>	0.100	0.047	0.104	0.798	0.049
12	10	0.050	0.050	0.050	<u>0.850</u>	0.047	0.047	0.047	0.857
	TOTALS	2.500	3.100	3.100	3.300	0.768	6.116	1.530	1.584

↑

Stays converged on mode 2

RUN NUMBER 2 CYCLE NUMBER 2 SIGMA SET NO. 8 2TH CONVERGENT CYCLE. MODE = 2

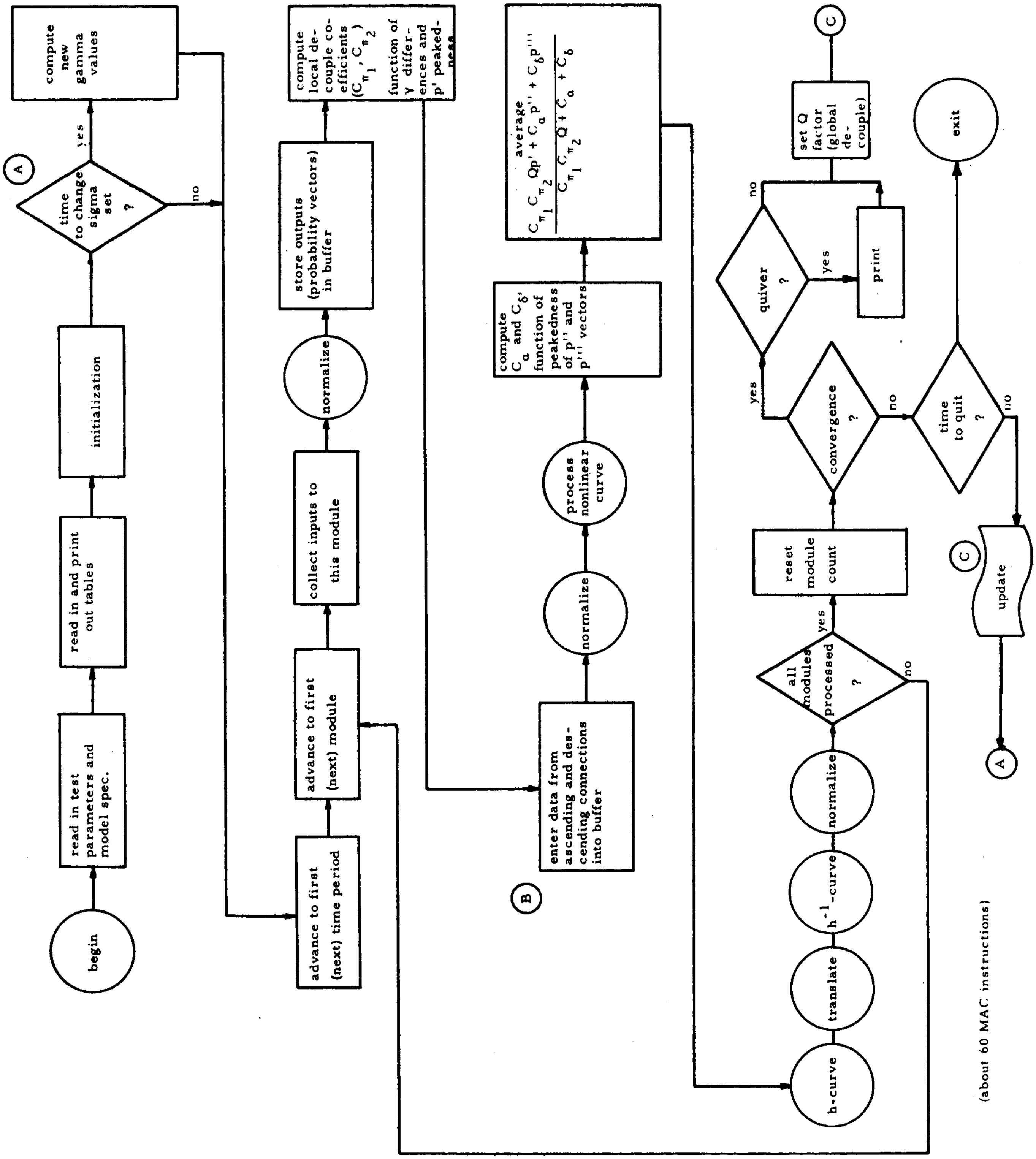
MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10100	0.250	0.250	0.250	0.250				
2	10101	0.250	0.250	0.250	0.250				
3	1100	0.250	0.250	0.250	0.250	0.080	0.695	0.111	0.112
4	1011	0.250	0.250	0.250	0.250	0.131	0.592	0.146	0.129
5	10100	0.250	0.250	0.250	0.250	0.107	0.702	0.101	0.089
6	1001	0.250	0.250	0.250	0.250	0.102	0.669	0.081	0.146
7	100	0.250	0.250	0.250	0.250	0.079	0.755	0.080	0.084
8	1001	0.250	0.250	0.250	0.250	0.092	0.623	0.112	0.171
9	101	0.100	0.700	0.100	0.100	0.030	0.890	0.046	0.032
10	1101	0.250	0.250	0.250	0.250	0.078	0.733	0.098	0.089
11	10001	0.100	0.100	0.700	0.100	0.047	0.142	0.762	0.047
12	10	0.050	0.050	0.050	0.850	0.048	0.048	0.048	0.854
	TOTALS	2.500	3.100	3.100	3.300	0.797	5.853	1.591	1.757

RUN NUMBER 2 CYCLE NUMBER 3 SIGMA SET NO. 8 3TH CONVERGENT CYCLE. MODE = 2

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	10100	0.250	0.250	0.250	0.250				
2	10101	0.250	0.250	0.250	0.250				
3	1100	0.250	0.250	0.250	0.250	0.077	0.687	0.120	0.114
4	1011	0.250	0.250	0.250	0.250	0.124	0.599	0.141	0.134
5	10100	0.250	0.250	0.250	0.250	0.101	0.721	0.097	0.079
6	1001	0.250	0.250	0.250	0.250	0.100	0.670	0.075	0.153
7	100	0.250	0.250	0.250	0.250	0.076	0.770	0.078	0.074
8	1001	0.250	0.250	0.250	0.250	0.081	0.635	0.109	0.173
9	101	0.100	0.700	0.100	0.100	0.030	0.884	0.052	0.032
10	1101	0.250	0.250	0.250	0.250	0.079	0.730	0.094	0.095
11	10001	0.100	0.100	0.700	0.100	0.045	0.223	0.684	0.047
12	10	0.050	0.050	0.050	0.850	0.047	0.100	0.047	0.803
	TOTALS	2.500	3.100	3.100	3.300	0.765	6.022	1.502	1.709

APPENDIX 10

FLOW CHART OF PROGRAM



RUN NUMBER 3 CYCLE NUMBER 15 SIGMA SET NO. 1

NO CONVERGENCE THIS CYCLE.

		NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
MODULE	TEMPLATE	MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	0	0.070	0.310	0.310	0.310				
2	0	0.250	0.250	0.250	0.250				
3	0	0.070	0.310	0.310	0.310	0.046	0.317	0.194	0.442
4	0	0.700	0.100	0.100	0.100	0.665	0.118	0.067	0.149
5	0	0.070	0.310	0.310	0.310	0.048	0.281	0.414	0.255
6	0	0.070	0.310	0.310	0.310	0.046	0.250	0.480	0.221
7	0	0.070	0.310	0.310	0.310	0.184	0.250	0.352	0.212
8	0	0.700	0.100	0.100	0.100	0.653	0.143	0.117	0.084
9	0	0.070	0.310	0.310	0.310	0.044	0.260	0.392	0.302
10	0	0.250	0.250	0.250	0.250	0.409	0.207	0.229	0.153
11	0	0.070	0.310	0.310	0.310	0.104	0.295	0.299	0.300
12	0	0.250	0.250	0.250	0.250	0.210	0.294	0.300	0.194
	TOTALS	2.640	3.120	3.120	3.120	2.413	2.419	2.849	2.317

AVERAGES MODE I 0.241 MODE II 0.241 MODE III 0.284 MODE IV 0.231

GAIN FACTORS FOLLOW

86 9.654229356 -01 9.677699255 -01 1.139633792 00 9.271733460 -01

TEST RETIC 483137 12.01.66

RUN NUMBER 3 CYCLE NUMBER 32 SIGMA SET NO. 1 14TH CONVERGENT CYCLE, MODE = 3

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET				MODAL PROBABILITIES AT END OF PRESENT CYCLE			
		MODE 1	MODE 2	MODE 3	MODE 4	MODE 1	MODE 2	MODE 3	MODE 4
1	0	0.070	0.310	0.310	0.310				
2	0	0.250	0.250	0.250	0.250				
3	0	0.070	0.310	0.310	0.310	0.031	0.108	0.739	0.121
4	0	0.700	0.100	0.100	0.100	0.325	0.027	0.613	0.033
5	0	0.070	0.310	0.310	0.310	0.031	0.115	0.777	0.075
6	0	0.070	0.310	0.310	0.310	0.035	0.071	0.827	0.066
7	0	0.070	0.310	0.310	0.310	0.035	0.078	0.812	0.074
8	0	0.700	0.100	0.100	0.100	0.322	0.052	0.593	0.032
9	0	0.070	0.310	0.310	0.310	0.031	0.077	0.803	0.087
10	0	0.250	0.250	0.250	0.250	0.154	0.052	0.752	0.040
11	0	0.070	0.310	0.310	0.310	0.031	0.075	0.783	0.108
12	0	0.250	0.250	0.250	0.250	0.033	0.051	0.858	0.055
	TOTALS	2.640	3.120	3.120	3.120	1.032	0.711	7.561	0.694

RUN NUMBER 3 CYCLE NUMBER 4 SIGMA SET NO. 4 3TH CONVERGENT CYCLE, MODE = 3

MODULE	TEMPLATE	NORMALIZED P-PRIMES FOR PRESENT SIGMA SET MODE 1	MODE 2	MODE 3	MODE 4	MODAL PROBABILITIES AT END OF PRESENT CYCLE MODE 1	MODE 2	MODE 3	MODE 4
1	10000	0.100	0.300	0.300	0.300				
2	0	0.250	0.250	0.250	0.250				
3	1001	0.700	0.100	0.100	0.100	0.612	0.042	0.299	0.045
4	1000	0.100	0.300	0.300	0.300	0.101	0.155	0.576	0.166
5	1100	0.100	0.300	0.300	0.300	0.144	0.201	0.426	0.227
6	1	0.100	0.300	0.300	0.300	0.056	0.183	0.575	0.184
7	11000	0.700	0.100	0.100	0.100	0.642	0.059	0.256	0.042
8	100	0.100	0.300	0.300	0.300	0.151	0.146	0.549	0.152
9	10000	0.250	0.250	0.250	0.250	0.097	0.135	0.672	0.094
10	101	0.100	0.300	0.300	0.300	0.048	0.123	0.683	0.144
11	11000	0.250	0.250	0.250	0.250	0.136	0.215	0.505	0.142
12	100	0.100	0.300	0.300	0.300	0.153	0.226	0.422	0.195
	TOTALS	2.850	3.050	3.050	3.050	2.144	1.490	4.968	1.396

Security Classification

DOCUMENT CONTROL DATA - R & D

(Security classification of title, body of abstract and indexing annotation must be entered when the overall report is classified)

1. ORIGINATING ACTIVITY (Corporate author)

Michigan State University
Dept of Electrical Engineering
East Lansing, Mich. 48823

2a. REPORT SECURITY CLASSIFICATION
UNCLASSIFIED

2b. GROUP

3. REPORT TITLE
SOME MECHANISMS FOR A THEORY OF THE RETICULAR FORMATION

4. DESCRIPTIVE NOTES (Type of report and inclusive dates)
Scientific final

5. AUTHOR(S) (First name, middle initial, last name)
William L. Kilmer, Warren S. McCulloch, and Jay Blum

6. REPORT DATE	7a. TOTAL NO. OF PAGES	7b. NO. OF REFS
Feb. 1967	110	128

8a. CONTRACT OR GRANT NO.	AF-AFOSR-1023-66
b. PROJECT NO.	9769-04
c.	61445014
d.	681304

9a. ORIGINATOR'S REPORT NUMBER(S)

9b. OTHER REPORT NO(S) (Any other numbers that may be assigned this report)
AFOSR 67-0928

10. DISTRIBUTION STATEMENT
Distribution of this document is unlimited.

11. SUPPLEMENTARY NOTES
TECH, OTHER

12. SPONSORING MILITARY ACTIVITY
Air Force Office of Scientific Research
Directorate of Information Sciences
Arlington, Virginia 22209

13. ABSTRACT

Throughout the life of the vertebrates, the core of the central nervous system, sometimes called the reticular formation, has retained the power to commit the whole animal to one mode of behavior rather than another. Its anatomy, or wiring diagram, is fairly well known, but to date no theory of its circuit action has been proposed that could possibly account for its known performance. Its basic structure is that of a string of similar modules, wide but shallow in computation everywhere, and connected not merely from module to adjacent module, but by long jumpers between distant modules. Analysis of its circuit actions heretofore proposed in terms of finite automata or coupled nonlinear oscillators has failed. We propose a radical set of nonlinear, probabilistic hybrid computer concepts as guidelines for specifying the operational schemata of the above modules. Using the smallest numbers and greatest simplifications possible, we arrive at a reticular formation concept consisting of 12 anastomatically-coupled modules stacked in columnar array. A simulation test of its behavior shows that despite its 800-line complexity, it still behaves as an integral unit, rolling over from stable mode to stable mode according to abductive logical principles, and as directed by its succession of input 60-tuples. Our concept employs the following design strategies: modular focusing of input information; modular decoupling under input changes; modular redundancy of potential command (modules having the most information have the most authority); and recruitment and inhibition around reverberatory loops. Presently we are augmenting these strategies to enable our model to condition, habituate, generalize, discriminate, predict, and generally follow a changing environment. Our program is epistemological. We are trying to develop reticular formation concepts which are complex, precise, and valid enough to inspire reasonable experiments on the functional organization of this progenitor of all vertebrate central nervous tissues.

DD FORM 1 NOV 65 1473

Security Classification