CYBERNETIC INTELLIGENCE: A RETURN TO COMPLEX

QUALITATIVE FEEDBACK THEORY

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DEDICATION

To Lillian and others upon whose shoulders I have stood.

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ABSTRACT

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This thesis addresses the manner in which intelligence may act to steer an agent toward adaptive success when constrained by only the heuristics of phenocopy and the need to reduce basal drives. The theory associated with this work will be referred to as Cybernetic Intelligence.

Intelligence cannot be emulated as a computable function. Rather, it is believed that intelligence is a property of adaptive systems. It is further believed that, as a property, intelligence might be modeled in electronic hardware by a complex, stochastic processing engine. Such an engine would begin each learning cycle by accommodating an infinite input language of environmental stimuli taken over a finite input alphabet of exteroceptive modalities. Next, the engine would actively seek to assimilate a set of

scalable and potentially adaptive output behavior sequences from the delta between actual and expected input results. The output behaviors, induced over a finite alphabet of phenotypic motor outputs, would be agent-specific and tend toward supporting the host agent's adaptive success. In a mathematical sense, this suggests an emergent yet deterministic structure to an engine of intelligence.

In this research, the hypothesis was tested through two parallel experiments involving similar, untethered, vehicular agents. In the first experiment the agent, the proposed engine, and a suitable environment were simulated in computational software. The second experiment went one step further, embodying the agent and the engine in an electromechanical, hardware device. In both cases the agents were required to achieve nutritional homeostasis (maintain their own real or simulated DC power sources) while roaming freely within an experimental enclosure. Both agents had no benefit of pre-coded program instruction and were constrained only by a set of prototypical, basal heuristics that included motor taxes, an orienting response, and simulated chemotaxis. The experimental findings are reported as both an empirical record and in a logico-mathematic framework.

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INTRODUCTION

What is mind? Do infrahuman species have minds? Do invertebrates have minds or does that phenomenon belong only to the vertebrates? Do all of the vertebrates have minds? Do all mammals experience, to some degree or another, a version of mind and consciousness or is that a singular privilege available only to the primate central nervous system (CNS) (Morris, 1967)? Given the complex, stochastic noise inherent in an electrochemical, bio-mechanical physiology (Hobson, 1994; Longtin, Bulsara, & Moss, 1991), is mind just a particular, random link in the long chain of biological evolution?

If, in fact, a mind does exist within the neuro-anatomy of a particular organism and it is serviced by the respective host organism's vehicular physiology, then might there not be a mathematically precise way to account for the organism's cognitive processes of accommodation and assimilation as the organism encounters various environmental stimuli? Are the neuronal activities of the CNS so complex that no mathematical generalization can be made about its functioning (consider McCulloch & Pitts, 1943)? Is mind, then, just an emergent property of the CNS? Or, cautiously, is it the reverse?

Is cognition a disembodied activity of mind or is it the response that an organism's CNS makes to any stimulus in its host's environment: being done so by synaptic reorganization and observable vehicular behavior (Hebb, 1949)? Considering the binary nature of neuronal postsynaptic threshold activity in the CNS, are the activities of mind subject to the laws of probability? If we could depersonalize the equilibration of cognitive structures, would we see a simple, quantitative, cybernetic engine of intelligence manifesting measurable possession of both the capacities and faculties of knowledge,

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understanding, and apprehension? All of the foregoing are very interesting questions.

Perhaps one can agree with David Suzuki when he says, "The mind tends to defy definition." Or, as he suggests, "It helps if we can name some of its attributes" (Cowling, 1994). However, unlike the difficulties that we experience when we attempt to define the phenomenology of mind, there does exist an attribute and property of the CNS that is equally well known but that is instead readily identifiable, measurable, and predictable. In fact, so ubiquitous and fundamental is this property that, to one degree or another, it is common to all natural life possessing a CNS. The property is intelligence, and the degree to which it is possessed by a given species and its individual members will tend to differentiate and stratify the phyla just as absolutely as do fur and feathers.

Contrasted with the foregoing questions regarding mind, intelligence is an empirically evident behavioral artifact, a property, as it were, of certain organic systems that expresses itself as a cybernetic[1] process from within the organism's physiology. Simply, intelligence is a property of a particular class of neurosynaptic-driven organic systems that facilitates such systems to acquire necessary and sufficient knowledge of their environments so as to originate and sustain both homeostatic and species-specific adaptive survival behaviors. This thesis addresses the manner in which intelligence may act to

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[1] When defined for an autonomous agent, Cybernetic Theory is that theoretic paradigm which states that, given an environmental system and an agent in that system, the feedback returned to that agent from that environment as that agent seeks to act on that environment will, at least in part, influence the selection of action or action series that the agent will next seek to accomplish.

steer an agent toward adaptive success when constrained by only the heuristics of phenocopy and the need to reduce basal drives.

However, before discussing the manner in which the property of intelligence may act to steer an agent, we must bring together ideas from the study of biology, psychology, mathematics, and computational theory. It will be requisite to engage in at least some gentle discussion of these topics before examining how intelligence might be modeled as a complex, stochastic processing engine in electronic hardware. If we can arrive at an understanding of the mechanisms of a biogenic psychology, then we can begin to seek a candidate structure for the engine of intelligence that is both emergent and deterministic. However, even then, we will presume a great deal.

This discussion will be based in cybernetic theory. We will discuss the cybernetic influence of environment on the teleology of neuron and synapse and its implications in the development of precognitive and cognitive synaptic structures within the neural tube. We will look at the role that the body of the organism plays as both vehicle and host to the nervous systems that themselves direct the behavior of the organism. We will discuss the integration of stochastically occurring stimulus events into cognitive equilibria and what mathematic form that integral may take. Then, and only then, will we discuss the question of into which particular Turing architecture that biogenic model might be best embedded. Only then will we ask what experiments might lead to a better understanding of the implications of a theory of Cybernetic Intelligence.

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CHAPTER 1

THE CYBERNETIC PERSPECTIVE

Regarding the CNS, Norbert Wiener said that "its most characteristic activities are explicable only as circular processes, emerging from the nervous system into the muscles, and re-entering the nervous system through the sense organs, whether they be proprioceptors or organs of the special senses" (Wiener, 1957, p. 15). Wiener coined the expression "cybernetic" from a Greek word meaning "steersman," or one who steers, and his comment should need no further explanation. However, even though cybernetic's "central idea had entered biology in 1866 with the work of C. Bernard" (Boden, 1979, p. 131), it is imperative to allow Wiener to remind us of the obvious.

Our sensory mechanisms help us choose our way through the world and how we then act to modify the world, in turn, as a consequence of how the world has changed us (consider social learning theory, Bandura, 1976). If Wiener's circular process includes the world and all of its agents, it is possible that it cannot be described with absolute determinism or stochastic certainty. If the goal is to model the behavior of an organism's neural and muscular processes in the world but the model of the world is unknown, then the behavior of the organism in the world cannot be modeled absolutely. The best to be hoped for is to model the cybernetic properties of the organism and place that model in the world. In fact, it turns out that this is the paradigm that is used here to model the mathematic properties of the engine of intelligence and to validate the incorporation of Piaget's equilibratory theory as a principle cybernetic thread in that model.

Jean Piaget's equilibratory theory describes that process by which *Homo sapiens* coordinates ongoing experience into subsequent intelligent and adaptive behaviors. Margaret Boden of the University of Sussex has suggested that "for Piaget, cybernetics provides the dialectical area of a general theory of equilibration" (Boden, 1979, p. 134). Professor Boden's words imply a teleology to the process of equilibration as it occurs relative to the formation of cognitive structures within the CNS. However, while Wiener could only describe the cybernetic quality of the mechanisms in which cognitive structures actually form (i.e., the CNS) Wiener and Piaget together are able to suggest that it is through the natural, cybernetic functioning of the CNS that cognitive structures are equilibrated.

Since the equilibratory process is fundamentally a cybernetic one and is based on the accommodation and assimilation of experience into subsequent behavior, it is easy to see how Piaget saw that intelligence itself would help to serve in the formation of cognitive structures by using information taken from the organism's immediate circle of sensory and intellectual stimuli.

Piaget also believed that, because of the cybernetic nature of the equilibratory process within the CNS, the biological mechanisms that are the basis for an agent's intelligence functioned like "a system developed by the genome that expanded the genome's function" (Piaget, 1985, p. viii) itself. Here Piaget is describing intelligence as a system, or property, that not only aids the nervous system in the acquisition of equilibria but itself expands the functionality of its genetic host by the self-same acquisition of the derived equilibria. We believe that we may compare this favorably, if not easily, to a convolution integral of the psychological sort.

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In another, quite remarkably Lamarckian observation, Piaget claimed, that "biological (and epistemological) structure is an indestructible, though progressively modifiable, feature of the organism (and of its knowledge)" (cited in Boden, 1979, p. 2). Clearly, at least according to Professor Boden, Piaget would have agreed that knowledge gained by the organism's native capacity to utilize the property of its own intelligence would act to steer behavior and adaptive choice.

Late in his life Piaget added that no "a priori or innate cognitive structures exist in man" (cited in Piattelli-Palmarini, 1981, p. 23). He also "held that conduct was intelligent only when there was recombination of the behavioral or cogitative means employed to reach a goal" (Piaget, 1985, p. viii). These statements show that Piaget believed that equilibration cannot possibly take place using only synaptic structures formed as a consequence of zygotic morphogenesis. It also suggests that an engine of intelligence will require nothing less than a full circle of the processes suggested earlier by Norbert Wiener.

In summary, we have discussed how many of the characteristic activities and properties of the CNS can be explained only as circular processes, are cybernetic in nature, and are obvious through the emergent and teleologic behavior of the organism. The apparent dichotomy of emergence coinciding with teleology could be dismissed as symmetry breaking, bifurcation, or an increasing return (Nicolis & Prigogine, 1989; Waldrop, 1992). However, spontaneous behavioral output from the CNS is simply the behavior of a system first accommodating and later assimilating its experiences along with spurious noise in its feedback loop (Longtin et al., 1991; Peterson, 1993). Either way,

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whether through emergent phenocopy[1] or through behaviors driven by pheno-typic, synaptic structures, it is the brain and its synaptic mechanisms that suggest an epigenetic paradigm for intelligence. It is the brain, with its soft tissues, synaptic clefts, and incredible plasticity, that will provide the inspira-tion for our model.

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[1] For clarity's sake, consider what was said of the role of the pheno-copy in genetics as it was defined by Antoine Danchin during a debate that took place between Jean Piaget and Noam Chomsky. Danchin said, "A phenocopy is in no way a construction but simply a particular realization of a given program according to a strict determinism: there is neither preformation nor acquisition, but only a diachronic expression" (cited in Piattelli-Palmarini, 1981, p. 360).

CHAPTER 2

THE NEURON AND SYNAPSE

The soft tissue of the human brain has a texture and consistency roughly equivalent to that of soft jelly. It is an enigma of numberless, infinitesimally small, discrete nerve cells in a complex network of interconnecting nerve fibers (Crick, 1994). Although the *Homo sapien* encephalon appears as a gelatinous mass weighing from 1.0 to 1.5 kg and having a reasonably consistent texture, there are in fact a half dozen or so major substructures. Further, it is estimated there are well over one hundred billion individual nerve cells in the *Homo sapien* brain, or encephalon, and none of them is associated with proprioceptive sensation.

The working parts of the brain are the nerve cells, the neurons themselves. They are similar to most other living cells, having "several characteristic structural features; a plasma membrane, a nucleus, and a full range of other cytoplasmic organelles" (Camhi, 1984, p. 32). A typical neuron cell body, or soma, may be 10-20 μm (in cross section), have one long axon (millimeters to "more than a meter" in length) perhaps covered in a fatty myelin sheath, and have dozens of short dendrite tentacles (Restak, 1994, p. 18).

In general, a neuron can originate, relay, stop, or receive nervous impulses. However, some neurons seem to be in a curious state of continual, self-induced activity. Acting in self-oscillatory fashion, these neurons appear to use the summed effects of their autoreceptors as well as the excitatory presynaptic potentials (EPSP) and inhibitory presynaptic potentials (IPSP)

of incoming signals from connecting neurons to maintain the required depolarization action potential threshold necessary to fire (Kalat, 1995).

Neurons make contact with one another by means of minute, "almost-touching" mechanisms called synapses, or clefts. The synaptic clefts are something like naturally occurring "one-way" valves that send neural impulses along to the next neuron via the exchange of neurotransmitter and neuro-modulator molecules (Hobson, 1994). Although the lengthy axon portion of a nerve cell can be forced, experimentally, to propagate a signal in either direction along its length, in the living organism the path of propagation is fixed by the presence or absence of transmitter or receptor gates on either side of the cleft, respectively. The dendrites facilitate the reception of incoming impulses by providing additional surface area beyond the soma's compact structure by extensive and complex arboreal branching, not unlike those of their axonal counterparts. The synaptic cleft, or synapse, is that point at which an axon attaches itself to another neuron's soma or dendrite, but the synapse is very special. It is special in that it defines a particular relationship between the several neurons that may ultimately join each other in a 3-D web-like pattern. "Other parts of neurons frequently contact one another but, if the surface membranes are unspecialized, there is no synapse and hence no interaction" (Gray, 1974, p. 3).

That tiny connection between neurons is important for yet another reason. The synaptic junction or cleft is actually a gap of minuscule proportions. The gap between axon, dendrite, or soma (at the synaptic junction) is usually from 20 to 50 nm. Certain activities in that gap can lead the post-synaptic neuron either to build towards or to suppress an action potential of

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approximately a 50 to 70 mV. All this occurs following synaptic neurotrans-mitter exchanges and any post-firing, refractory period rest required by the particular neuron. Also, the surface topology of presynaptic and postsynaptic surfaces are cell membrane jungles of tiny, voltage operated ion gates and molecular metabotropic receivers immersed in a constantly changing bath of potassium, chloride, calcium, sodium ions, and assorted brain chemicals.

The synapse can act functionally to permit one neuron to excite another neuron, but it can also act as an inhibitory stimulus to the receiving neuron (as the latter neuron is additionally stimulated by other incoming neuronal signals). Depending upon the level of concentration of any of several dozen neurotransmitter molecules in the cerebral blood supply or present in the presynaptic and autosynaptic terminals, the effective product of a synaptic exchange may be to increase or amplify the incoming neuronal impulses from any one (or all other) involved neuronal sources. However, although the process of activating a given neuron is a spatially or temporally summed, electro-chemically occurring event and is specifically analog in nature, there is a binary character to the firing or not firing of any given neuron at any given time. This point is critical to the model to be constructed here, and the bi-stable, or binary nature of this point, will be revisited in a later part of this chapter.

It may help to offer another perspective on the neuron by describing the electrical activities in which it must engage in the CNS. Although a neuron is not a computer circuit, it does act in much the same way as one might. The design requirements for a neuron follow.

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The proposed neuron will sum a parallel grouping of signals, process those signals, and return a pulse-width modulated output based on those signals. At the highest level, a multi-element system composed of several of the proposed neuron elements will be interconnected into a network. This narrative describes one such neuron unit or cell. A network of these cells could easily be constructed with the outputs from each individual neuron cell being assigned to the input of any single neuron or group of neuron's input circuitry. For simplicity, henceforth, the neuron units will be referred to as cell or cells. A single neuron cell is shown in Figure 1.
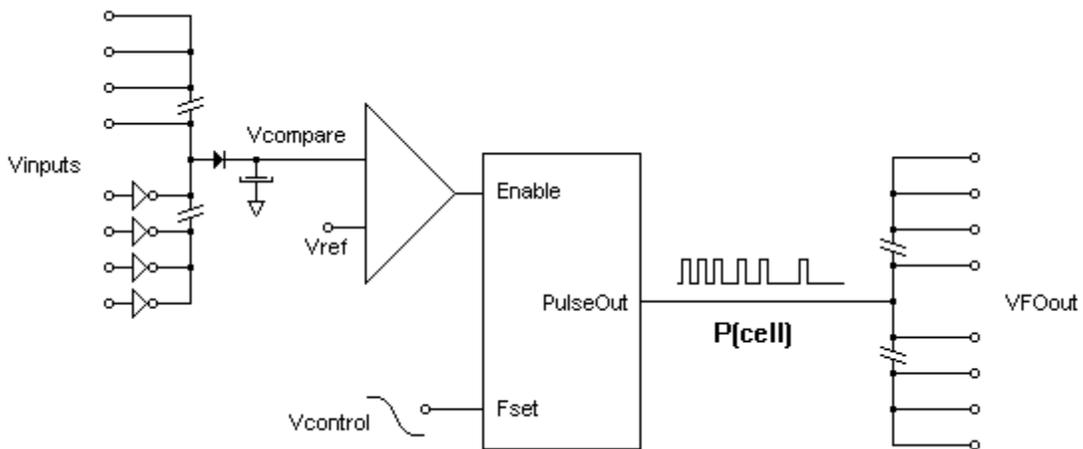

Figure 1. Example of a single cell

The input circuit to each cell will be based on the output of an analog comparator. The comparator's reference threshold input will be set according to need and its comparison input will be the summed result of all inputs to the respective cell passed over a complex active summing network and analog peak detector.

The central element of each cell will be a retriggerable, multivibrator configured as a variable frequency oscillator (VFO) which, when enabled by the comparator's output, will begin to oscillate. The output amplitude of all VFOs (cells) will be clamped to a common Vmax and, obviously, will be bi-stable in nature.

There are two additional time-dependent characteristics to each respective cell. A minimum refractory period must be observed between oscillator pulses (i.e., there is a maximum frequency defined for each respect-ive cell) and there will be a gradual decrease in maximum oscillator frequency that must occur after any nominal period of continual burst mode operation. Frequency roll-off and a minimum frequency limit will be determined uniquely for each respective cell.

Taken individually or in a large system, these circuits are not noiseless. Rather, they are subject to random triggering to some greater or lesser degree. In a large system the cell outputs of a finite number of VFOs can feed to points outside the system and a finite number of input lines can feed back into the system.

Returning to the biological model, it can be seen in nature that signals are propagated between neurons along axonal and dendritic fibers (Adrian, 1974). Of course, the physical properties of those propagations are com-pletely different from signals propagated along metallic conductors. However, the fundamental principle of information transfer is quite similar (Camhi, 1984) and there is a noticeable stochasticism as a result of spurious noise within the organic system that apparently leads to ambiguous neural reactions.

In fact, there is empirical evidence to suggest that a positive relationship may exist between systemic noise and the validity of sensory stimulus in the acquisition of intermodal, (i.e., motor, symbolic and associational), taxes, and cognition (Longtin et al., 1991; Peterson, 1993; Thelen, 1995). Further, since pathology is inherent and patently specific to any organic system, the contribution of all neural signal bandwidths, implied throughputs, and propagation delays likely serve to determine the nature and efficiency of the organism's environmental interaction (Rouly, 1994). Plainly then, it is in the context of the repetitive nature of an organic system's acquired behaviors that those behaviors, in turn, contribute directly to the scope of acquiring new habituations (Hebb, 1949). All of this is to say that nervous system activity occurs in such a way as to make statistical inference and deterministic calculation regarding the CNS possible, although after the manner of an intuitionist logic (consider Von Neumanns's words in Aspray & Burks, 1987, p. 564).

In a remarkable paper entitled "A Logical Calculus of the Ideas Immanent in Nervous Activity" Warren McCulloch and Walter Pitts thoroughly discussed the implications of exactly these binary and Boolean-valued neuron firings within the nervous activity of the CNS. Although at the time McCulloch and Pitts did not demonstrate empirically that the mathematic hypothesis that they described was accurate, we now know that "the activity of the neurons is an 'all-or-nothing' process" (McCulloch & Pitts, 1943, p. 118; compare Kalat, 1995, p. 46) as it relates to the information content of their communications with one another. This "all-or-nothing" process is equivalent to a binary scheme and can be dealt with accordingly.

In summary, we have created a general model of a neuron, a rather typical neuron in fact, and one that might be present in any of several member species of the sub-phylum chordate vertebrates. We realize that our visit to the neuron was absent mention of associable glial mass, explanation of hemologic support, or more thorough neuro-biological exposition. But we suggest that the mechanisms offered as substantive are sufficient for this work. Further, emerging from the general model was a concrete model of the neuron depicted as a circuit realizable in electronic hardware. Finally, we noted for future reference that the pertinent information content of all intra-neuron relations is strictly binary in nature, time dependent, and entirely stochastic.

We will now consider an application of this new understanding of "networkable" neurons in their prototypic setting, the neural tube. We will consider their beginnings, their development, and what, if any, teleology they portend for our model.

CHAPTER 3

THE NEURAL TUBE

The mechanism of the beginning of a *Homo sapien* is purely practical in nature: It requires the fertilization of an ovum. As the zygote develops, very early brain structures appear. In fact, during the first 2 weeks of *Homo sapien* gestation (during embryonic mitosis) the cells of the CNS and peripheral nervous system (PNS), respectively, begin to proliferate and migrate. These early CNS and PNS cells are initially referred to as the neural tube.

By the 3rd week of gestation, the neural tube will have started to form from out of the rapidly growing mass of cells (Encarta, 1994; Kalat, 1995). The encephalon, or brain, develops from the neural tube's head end outward. Original cerebral material proliferates and begins to migrate outward, producing in turn the structures of the hindbrain, the midbrain, and last, the forebrain.

First to form among the identifiable brain structures are those primarily concerned with involuntary autonomic organ activities. These structures include, among others, the brain stem, the medulla oblongata, and pons Variolii, for example. Shortly afterward, other groups of cells begin to form the complex structures of the cerebellum. As will be mentioned in the chapter on the vehicular host, the cerebellum is associated with ballistic motor control and motor programs, both conditioned and unconditioned.

As cerebral development continues, the midbrain structures start to form. Eventually, the seat of human sentient reasoning abilities, the forebrain and neocortex, are the last to migrate and begin differentiation. In fact, "The first signs of neocortical proliferative activity and migration are seen in the 2-month embryo" with cellular proliferative activity within the six layers of the

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neocortex being mostly complete by the eighth month of gestation (Cohen & Salapatek, 1975, p. 169). However, complete cellular "differentiation and migration [and myelination] of young neurons continues for several years after birth" (Cohen & Salapatek, p. 169). From this it is plain that it takes more than 40 weeks of gestation for *Homo sapiens* to develop the brain structures necessary to achieve the full neurologic capacity of the adult of the species. However, this fact does not necessarily preclude intrauterine cognition.

Immature cognitive function notwithstanding, there is a moment in *Homo sapien* embryonic neural development that is arguably the most important. For this discussion of the cybernetic properties of the biomechanism, that moment occurs at a slightly different point in each organism's individual development. That moment is a function of the unique genetic structure of each embryo's individual CNS and PNS physiologies. That moment occurs when the first spontaneous CNS and autonomic nervous system (ANS) activity begins. It occurs when some critical number of neural cells have completed their respective, nominal phase of morphogenesis and start rudimentary, independent, direct electro-chemical (i.e., neurogenic) control over their host organism.

For *Homo sapiens* that moment occurs at approximately the end of the 4th gestational week (*Encarta*, 1994). It is then that the organism[1] first begins to subtly react to, and thus can potentially interact with, its environment. At

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[1]At this point in the organism's development we must limit the discussion of cybernetic cause and effect to phrases regarding the neurology of the organism's CNS as the sole active agent. While this may be acceptable for a discussion of embryologic development, at least in a theoretical sense, it is imperative that it remain the *modus operandi* for all later discussions if the engine of cybernetic intelligence is to remain logically consistent.

that moment in the organism's metamorphosis, an emergent and teleologic property of the genome is first seen in its most primitive state and to its least degree of sophistication and activity. Mind is now present.[2] Innate and minimal, perhaps, but it is the psycho-biological substrata of an emergent, sentient consciousness yet to come.

As early as the 12th gestational week, taxes motor control in the fetus has progressed sufficiently to support the motor activity of defensive ocular (i.e., squinting) behaviors. Also at 12 weeks of gestation, some *Homo sapien* fetuses demonstrate characteristics of sentient self-awareness. Presumably to receive oral-tactile stimulation, these fetuses demonstrate the behavior of thumb sucking (Papalia & Olds, 1995). Other prenatal fetuses simply demonstrate the behaviors of sucking and swallowing (Semmler, 1989). However few these empiric fetal behaviors may be, they represent an incredible set of data that seems to support the conclusions of Wiener and Piaget on the cybernetic structure of the human cognito-sensory system.

Thus, we suggest that, while still in utero, these motor behaviors appear to be the end products of the combined cognito-sensory servo mechanisms of the brain, proprioceptive and exteroceptive senses, and complex taxes behaviors. They constitute a cybernetic process and they occur very early in the organism's development. Table 1 shows a selected group of these early fetal taxes. They help to demonstrate a precedent of cybernetic feedback innate to the organism occurring at a very early point in

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[2]By the same logical method or argument stated in Footnote 1.

Table 1. Developmental Taxes by Syndrome, Onset, and Observed Completion

Taxes	Description	
Syndrome	Preliminary	Intact
I. Babkin	12 wks.; hand to face	24 wks.; observed intact
II. Suck & Swallow	12 wks.; sucking	20 wks.; observed intact
	12 wks.; swallowing	20 wks.; observed intact
	<observed together>	32 wks.; observed intact
III. Rooting	22 wks.; rooting	30 wks.; observed intact
	28 wks.; rooting by lips only	32 wks.; observed intact
IV. Eyes	30 wks.; pupillary dilation	32 wks.; observed intact
	30 wks.; visual fixation	36 wks.; observed intact
V. Somatosensory	08 wks.; tactile differentiation	28 wks.; observed intact
	12 wks.; defensive squinting	28 wks.; observed intact
	28 wks.; Moro response	32 wks.; observed intact

Note. From *Human Development* (pp. 71, 96), by D. E. Papalia and S. W. Olds, 1995, New York: McGraw-Hill, and *A Guide to Care and Management of Very Low Birth Weight Infants: A Team Approach* (pp. 221-225), by C. Semmler (Ed.), 1989, Tucson, AZ: Therapy Skill Builders.

the organism's maturational development. The table is organized by syndrome and chronology. Sources are cited along with the table.

Life is a phenomenologic property of which I am neither the sole proprietor nor the best interpreter. Therefore, the relevance of these ideas is not intended to interpolate life into the early organism's list of teleologies or

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properties. Rather, the relevance is simply to establish a basis for a model of an innate cybernetic engine of intelligence within a natural host.

That said, consider how, after just a few of the cerebral structures have formed from the neural tube, several predictable taxes patterns start to become apparent in a *Homo sapien* fetus. Figure 2 is a rough approximation correlating the significant onset of structural development in three major encephalic areas (i.e., medulla, cerebellum, and neocortex) with a selection of innate taxes behaviors based in synaptic structures. Figure 2 includes selected taxes taken from both pre-term and neonatal sources. "Term" is defined to be the 40-week interval after conception. The chronological scale is absolute, starting at conception, and makes no deference to whether birth occurred at "term." The earliest motor behaviors (those of fetuses 0-40 weeks gestational age) either were observed contemporaneous to gestation or were taken from pre-term deliveries. The postnatal behaviors (those of infants 40-80 weeks chronological age) are from more traditional sources of observation (Caplan, 1973).

The complex taxes behaviors shown in Figure 2 appear across diverse ethnic and genetic stock. They are behavioral phenocopy occurring, in part, because of innate synaptic structures within the brain. These behaviors begin early in the gestational period and are built from combinations of innate fixed action patterns, ballistic movements, and voluntary muscle movements. Figure 2 is not exact; it is a composite. However, as it is drawn from the several sources listed in the reference list, it may prove useful for comparative purposes.
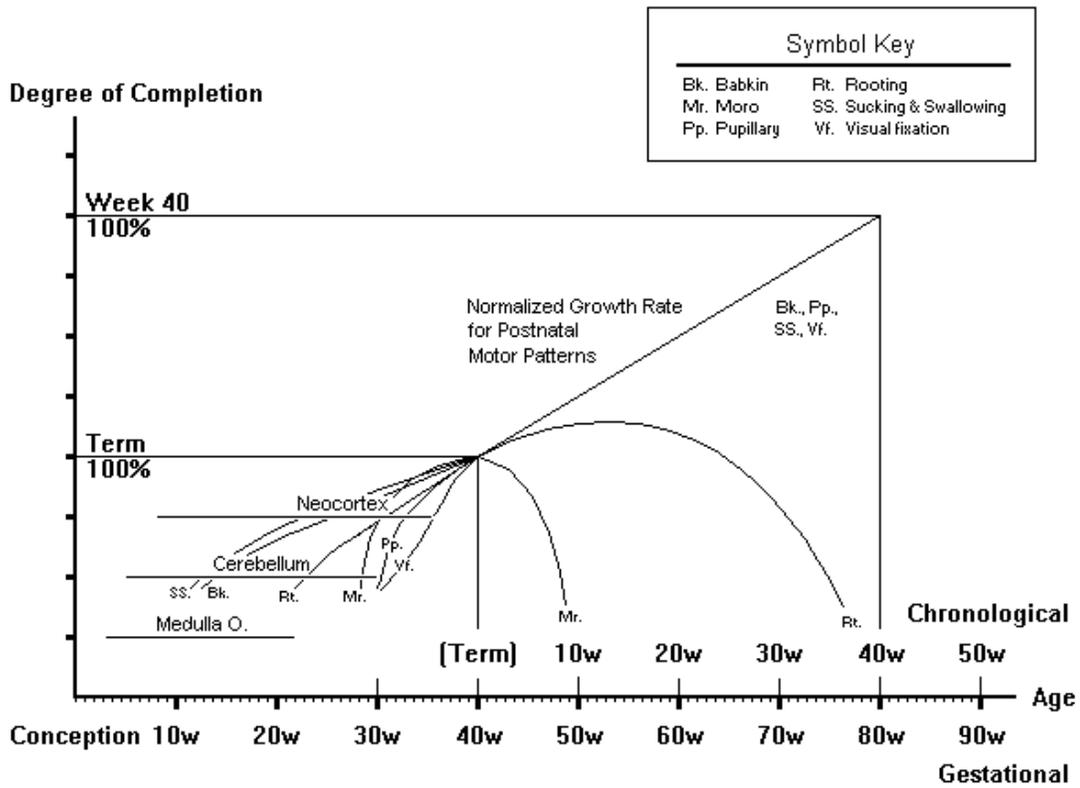
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Figure 2. Structural onset of innate taxes

Regardless of how futile the attempt to control its environment or how immature its perception of that environment might be, the complex taxes and voluntary behaviors demonstrated by a 12-week-old fetus cannot be ignored. The teleology of the organism's adaptive nature is a consequence of its apparent ability to exercise dominance over its environment and it is its cybernetic engine which permits the acquisition of that dominance. Said plainly, at some point after the individual neurons in the neural tube begin to fire, the organism becomes capable of limited equilibration. Why the neural tube begins to fire is not of interest. Perhaps its basis rests, in part, with the meaning of life, a topic better left to philosophers and theologians. For now,

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though, we must go back and reflect very carefully on Piaget's words and re-discover what they mean.

Consider Piaget's statement that no "a priori or innate cognitive structures exist in man" (cited in Piattelli-Palmarini, 1981, p. 23). Piaget's statement does not simply mean that "man" is not "born" with an innate set of competencies based on learned experience. For example, no "man" is "born" with the skills of a master carpenter. Rather, it means that a fetus's CNS must wait until there are no longer only innate structures (i.e., innate synaptic structures) among its rapidly developing cerebral tissues in order to begin the process of equilibrating cognitive structures as they were later defined by Piaget. This point is restated because it is possibly what Piaget is not saying that is of greater importance here than what he is saying. An example of a proof by the excluded middle, as it were, is offered.

Piaget has suggested that there are no learned behaviors, or regulations, present in the genome of *Homo sapiens*. That is, no one's zygote is created with an intact set of those regulations or adaptive competencies based on memory and experience. However, since the adult of the species obviously does possess fully formed equilibria, it must be that, at some point between conception and death, those equilibria were equilibrated. When does that process begin? The answer is simply that the process apparently starts spontaneously after some critical number of suitable neural cells[3] have become available out of the neural tube's development to participate in the equilibratory process (Piaget, 1985).

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[3]Obviously, neuronal material appropriate to the growth of Hebbian synapses.

We are not aware of Piaget making an exact specification of when that moment occurs or when the process begins. No man could do so, of course, although he did predict it. Logically, the equilibration of cognitive structures must begin in utero and that is all that is relevant here. After some nominal period of gestation has taken place and the brain has sufficiently differenti-ated and myelinated to produce sufficient suitable and available neurons supporting synaptic reorganization, equilibration begins.

Figure 3 is an illustration of the kind of neurogenic mechanisms described above. We call it the synaptic bridge. It is Lamarckian. It is also an abstract picture of the mechanisms and relationships present in neurogenic behaviors grounded in synaptic physiology. It shows the mechanism of the synapse serving as a bridge between the two physiological origins of synaptic structure and their respective neurogenic behaviors. Either or both of the two types of synaptic structures can use the bridge and result in behavioral phenocopy.
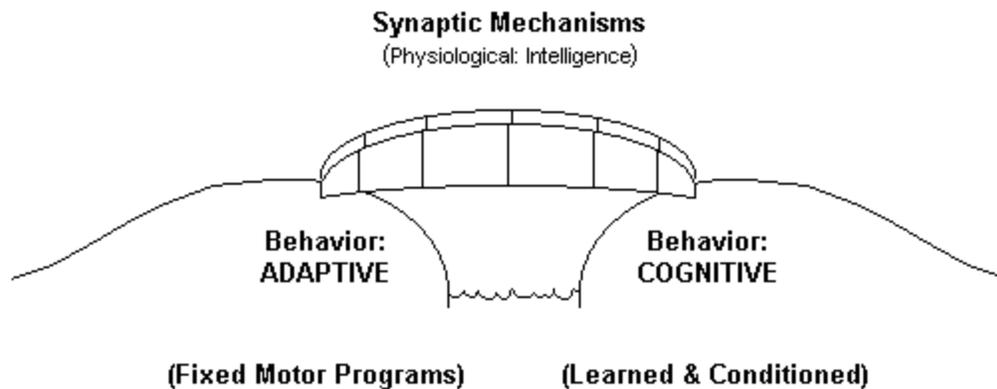

Figure 3. The synaptic bridge

Those behaviors that are innate to an organism's physiology (thus, pre-cognitive in the Piagetian sense) are based in synapses formed as a consequence of genomic expression and are on the left side of the bridge. Behaviors developed by the organism after exposure to any stimuli (cognitive or otherwise) are found in synaptic patterns represented to the right side of the synaptic bridge. In either case, "behaviors" are manifest only through the synaptic mechanisms of the bridge (i.e., they are neurogic) and are examples of phenocopy.

To summarize this chapter is to draw a startling conclusion. If we are correct in our assumptions and our analysis of the biological and psychological record, we must conclude that the phenomenology of "mind" exists solely within an embodied CNS, begins in utero as a consequence zygotic morphogenesis, and is built from the cybernetic property of synaptic reorganization. The precipitant object from this action is an agent capable of both proactive and reactive relations with its environment. This conclusion lays the framework for later development of a hardware model of the engine of intelligence.

CHAPTER 4

THE VEHICULAR HOST

The body as a vehicle, the nervous system as a mechanism, and the body as a vehicle for an adaptive intelligence were once pillars of a paradigm after which the art of artificial intelligence was fashioned (Kemeny, 1955). They are applied again in this thesis. We begin by identifying the biomechanism of the vehicular host and introduce to the discussion the concept of species-specific behavioral phenocopy, or basal heuristics.

Webster's Unabridged Dictionary defines a machine as "a structure or built-up fabric of any kind; specifically, the human or animal frame." Continuing, Webster states that a machine is also a "vehicle, as, formerly, a carriage, cart, etc." (McKehnie, 1983). In the *American Heritage Dictionary* a machine is defined as "a device consisting of fixed and moving parts that modifies mechanical energy and transmits it in a more useful form" (*American Heritage Dictionary*, 1992). Therefore, even based loosely on these simple definitions and their contemporary usage, "the entire material or physical structure of an organism" (i.e., its body) is an apparatus which may both semantically and legitimately be identified as a type of machine or, at the least, a biomechanism (*American Heritage Dictionary*).

Stated simply, an organism's corporeal structures provide a mechanism by which that organism gains the capacity to move within a given environment. For some organisms it is their cellular membrane that serves as an abstract motivator. For more complex organisms coordinated combination of muscle and appendage results in physical motion. In either case, the

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smallest, most discrete motor behavior is formally called "taxis," whether or not the behavior is proactive or reactive.

Controlled by the organism's nervous system (i.e., by neurogenesis) (Fentress, 1976), the teleology of all behavior appears to be purposive, although not necessarily intentional. We suggest that these behaviors fall on a short list. That list includes the behaviors of cognition, the behaviors of biological homeostasis, and those of overt motor behavior. From that list of purposive behaviors, telotaxis and homeostasis will become increasingly important to this discussion.

Telotaxis is "the orientation or movement of an organism toward or away from a particular stimulus" (*American Heritage Dictionary*, 1992). It is the most fundamental characteristic behavior of any organism. As a class descriptor for taxes behaviors in general, telotaxis presupposes nothing, is dynamic, and demands only that we acknowledge that it is a response to one or another stimulus. In fact, a single taxis behavior is so fundamental an atom of behavior stemming from identifiable and discrete neural sources that it can be represented symbolically by a predicate term in the predicate calculus (McCulloch & Pitts, 1943).

In multi-celled organisms, telotaxis is a common and vital behavioral characteristic. Consider, for example, the orienting response (Ornstein, 1972; Sutherland, 1989). Telotaxis behaviors are so ubiquitous that they cut cleanly across the phyla from such simple single-celled creatures as the amoeba all the way to *Homo sapiens*. At one extreme, the amoeba exhibits pseudopodic chemotaxis. At the other extreme, the primates exhibit complex, ballistic motor movements originating in the motor cortex and cerebellum (Fentress,

1976; Ornstein, 1991). We may even apply the term "instinctive to describe taxes and reflexes, as well as all complex innate activities generally made up of a cohesive number of movements that are invariable, completed at once, and peculiar to one given species" (Filloux, 1963, p. 41).

For example when "an amoeba is subjected to some mechanical, chemical or light stimulus, it responds by forming a pseudopod (false foot) that enables it to move either toward or away from the source of the stimulus" (Filloux, 1963, p. 9). This particular example of telotaxis behavior is obviously quite species specific. That is, its overall description is dependent upon one particular organism's unique physiology and sensitivity in order to be mean-ingfully described. While all creatures having neurogenic physiologies exhibit telotaxis, the amoeba provides an instance of an unusual, species-specific, behavioral, basal heuristic.

Unfortunately, *Homo sapiens* has historically chosen to dissociate itself from the idea of possessing taxis behaviors. However, taxonomically speak-ing, these motor behaviors are as much in the *Homo sapiens* behavioral domain as they are in that of a laboratory rat. We are, after all, biological organisms (Coghill, 1964).

A summary of this chapter presents little that was not already known. However, it may have been said in an unexpected way. In this chapter we showed that the body of an organism is a vehicle. In an abstract sense a vehicle is "a device consisting of fixed and moving parts that modifies mechanical energy and transmits it in a more useful form" (*American Heritage Dictionary*, 1992) but, in a more concrete sense, it is that mechanism that facilitates telotaxis, which is "the orientation or movement of an organism

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toward or away from a particular stimulus" (*American Heritage Dictionary*).
Taxis behaviors, such as chemotaxis, are the primitive atoms of all other,
more complicated behaviors. We confirmed that behavior begins in the
nervous system, or is neurogenic in nature, and that the discrete source of a
taxis behavior can be represented symbolically by a propositional function, or
predicate term, in the predicate calculus (see Chapter 2 and the label P(cell)
in Figure 1). Finally, there exist fundamental, species-specific telotaxis that
often help in identifying a given species according to the natural heuristics of
that species' particular and peculiar phenocopy physiology and behavior.

CHAPTER 5

THE EQUILIBRATORY INTEGRAL

The Piagetian function of equilibration acts to create cognitive structures. "They begin when the nervous connections mature that make reciprocal assimilations possible" (Piaget, 1985, p. 73). This can begin to occur at any time in the development of the neural tube after which an adequate number of neurons have differentiated that are available to, and capable of, supporting the growth of Hebbian synapses. Hebbian synapses, of course, are the consequence of sufficiently repetitive, inter-neuronal activities which apparently act to precipitate the growth of, or enhancement of, synaptic junctions (compare Hebb, 1949, p. 174; Kalat, 1995, pp. 472, 535). "Any stimulus that acts repeatedly at the same time as a response will form a connection between the cortical cells involved. . . . All behavior is determined by such connections, innate or conditioned" (Hebb, p. 174). But what is the equilibratory act and what are the cognitive structures that it equilibrates, and what role does intelligence play in the equilibration of cognitive structures?

Equilibration is the process by which the CNS acts to assimilate sufficient phenocopy behaviors (while still accommodating current stimulus events) as may ultimately prove to be adaptively successful. Equilibration produces a quasi-Lamarckian result. Further, intelligence is that property of the CNS which represents a quantifiable aspect of the equilibratory engine serving as both an abstract and species specific indicator of the potential rate of equilibria acquisition and the adaptive quality of the equilibria equilibrated. Acting alone, intelligence is not capable of steering an agent toward adaptive success. However, as a property of an adaptive system, the relative qualities

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and quantity of the intelligence possessed by the agent have a direct relation-ship on whether and how adaptive success will be achieved. This point should be obvious from both the foregoing and by intuition.

The mathematics of equilibration, as described by Piaget (1985), is complex and is concerned with the behavior of an agent in the world. Piaget's equilibratory theory is an algebraic system consisting of a set of elements W and an operation E closed over the set. The set W decomposes into three subsets, A, S, and R, inclusively. Although defined as independent mathematical structures below, the three subsets A, S, and R comprise the objects, properties, and events in an agent's world. Viewed together as a set, the elements in W provide a dialectic area for a general theory of equilibration (Boden, 1979) and a cybernetic basis for the behaviors of an agent in the world (Wiener, 1957), and they suggest the quantifiers which follow. Figure 4 illustrates the composition of set W.

$$W = \{ A, S, R \}$$
$$A = \{ a, \bar{a} \}$$
$$S = \{ s_1, s_2, s_3, \ldots, \infty \}$$
$$R = \{ r_1, r_2, r_3, \ldots, r_m \}$$

Figure 4. The composition of set W

The set A is a finite set of Boolean-valued symbols. The set elements are used to ascribe relative value to the agent's most recently completed behavior by evaluating that behavior's adaptive success in the context of ongoing environmental events. According to drive reduction theory:

> a condition of need in organisms not only is an important factor in habit formation, through the need reduction and reinforcement relationship; it also plays an important role in determining the occasions when habits shall function in the evocations of action, the vigor of such evocations and their persistence in the absence of reinforcement. (Hull, 1943, p. 390)

Simply, if an evoked behavior satisfies an organism's phenocopy needs and if the satisfaction of those needs is penultimate to achieving adaptive success then, a relative true value is selected from set A. Otherwise, its compliment is selected.

The set S is an infinite set of all possible stimulus perceptions available to the agent, whether or not those perceptions are immediately or ultimately recognized by the agent. In those species demonstrating neurogenic behavior, at any given instant there are a finite number of sensory neurons and non-sensory neurons synapsing upon any subsequent neuron. Since the nature of neuronal firings is binary in character, there is an alphabet enumerated by the set of all neurons just described (McCulloch & Pitts, 1943). The cardinality of that alphabetic set is 2 raised to the power of the number of those neurons. The language constructed from groupings of concatenated letters out of that alphabet (i.e., words equatable to perceivable events occurring sequentially) is driven by an agent's experiences in the world and is not constrained by the cardinality of the input alphabet. Thus, the set S (the language of perceivables taken over the set of available neurons) is an infinite set.

The set R is an infinite but denumerable set of all possible response behaviors available to the agent. In those organisms whose behavior is neurogenic, at any given instant there are a finite number of neurons in the nervous system synapsing upon subsequent neurons or neuromuscular

junctions. Although the alphabetic set of possible, simultaneous firings in those neurons has the cardinality of 2 raised to the power of the number of those neurons, the language of constructable taxes words made from concatenated groupings of letters taken from that alphabet is infinite. Therefore, since the total count of neurons and inter-neuron synaptic junctions changes as synaptic tissue is made available, the count of words in the language (the set R of response behaviors) adjusts accordingly and, thus, is denumerable.

Figure 5 deals in more depth with the details of the composition of sets S and R, specifically, their respective elements S_p and R_q. Consider, if given a finite set of Boolean-valued elements whose cardinality is n, the operator shown in Figure 5 will enumerate an unambiguous subset of the Cartesian product of that set in lexicographic order and in disjunctive normal form. The subset enumerated is an ordered alphabet of symbols immanent in the original set of elements. A similar alphabet of symbols may be derived from the neural structures of some organisms.

At any given moment, in organisms whose behaviors are neurogenic, there will exist a finite set of neurons of cardinality *n*. The instantaneous and bi-stable excitatory or refractory state of those neurons will delimit one particular, active "true" symbol from the emergent neural alphabet. For example, if we select a sufficiently small time slice and meet minimum neural duration and intensity thresholds, the presentation of some particular antecedent stimuli to the organism at time *t* will result in a deterministic selection of an active neural symbol from within the organism's neural alphabet at time *t + 1*. Further, if we consider a time-sequenced ordering of those instantaneous symbols, there will emerge from within the organism's neurology a language

$$S = \{\, s_1, s_2, s_3, \ldots, \infty \,\}; s_p \in N^S$$

$$R = \{\, r_1, r_2, r_3, \ldots, r_m \,\}; r_q \in N^R$$

$$N = \left\{ \bigvee_{\substack{J=0 \\ k=j}}^{2^n-1} \bigwedge_{i=1}^{n} \left(X_i^{i_k}; \left\{ k \,\middle|\, \begin{array}{l} k \geq 2^{n-i} \Rightarrow k \leftarrow k - 2^{n-i} \\ k < 2^{n-i} \Rightarrow k \leftarrow k \end{array} \right\} \right. \right.$$

$$\text{where } n \geq 1 \qquad \left\{ X_i^{i_k} \,\middle|\, \begin{array}{l} k \geq 2^{n-i} \Rightarrow x_i \\ k < 2^{n-i} \Rightarrow \bar{x}_i \end{array} \right\}$$

Example: If $n = 5$ then, $N(X) = \{\, (\bar{x}\bar{x}\bar{x}\bar{x}\bar{x}), (\bar{x}\bar{x}\bar{x}\bar{x}x), \ldots, (xxxxx) \,\};$

Figure 5. Detail of the composition of sets S and R

of arbitrarily long concatenations of symbols (i.e., words) as the organism interacts with its environment.

Therefore, the operator shown above merely provides a means by which to examine the agent's entire "neural alphabet" in propositional form such that we may select a single, active "true" propositional subject element in N that is momentarily true at time t. The mechanism for generating an alphabet of neural propositions is identical for both the world stimulus to neural system input relationship or the neural system to behavioral response output relationship. Thus, we arrive at the sets S and R.

The equilibratory operator shown in Figure 6 is a convolution integral that is constrained only by species specific, basal constraints (i.e., the cardinality of the set of available neurons, the CNS bandwidth, sensory and motor neural pathways, locomotion system, etc.). The integral is a relation that acts to enumerate a scalable series of mappings the purpose of which is to facilitate neurogenic behavior. Each term e_i is an ordered triple composed of

$$E = \left\{ \sum_{i=1}^{m} e_i \right\} + e_{i-1} \; ; \; \begin{array}{l} \text{where } i \geq 1, \\ e_0 = \text{Null Set} \end{array} \; ; \; \begin{array}{l} s_p \in N^S \\ r_q \in N^R \end{array}$$

$$\text{and } ((a \wedge s_p), r_q) \Rightarrow (s_p, r_q)$$

$$\text{we find if } e_1 = \{(s_1, r_1), (s_2, r_2)\} + \{\phi\}$$

$$\text{and } e_2 = \{(s_3, r_1), (s_4, r_2), (s_5, r_3), (s_6, r_3)\} + e_1$$

$$\vdots$$

$$\text{then } e_m = \{(s_p, r_q)\} + e_{m-1}$$

Figure 6. The equilibratory integral

elements from set W. Each ordered triple contains two domain elements: one a proposition from set S and one Boolean element from set A. The range is taken from set R. Each mapping is an unambiguous subset taken from the Cartesian product of the set W.

By the definition of equilibration stated previously, only those behaviors proven to be adaptively successful will be assimilated. This means that, when the domain elements *a* and *s* are meeted, a relative true *a* need not appear in the resultant n-tuple by means of explicit representation. Conversely, for those behaviors which are not adaptively successful, an element *s* meeted with a relative false *a* is, by definition, nulled and is not a valid equilibria, or mapping.

Indeed, this is a peculiar algebra but one that is consistent with the cybernetic character of the process of equilibration as Piaget described it. Perhaps, what is more important is that it satisfies Piaget's call for "a

quantifier . . . whose domain of variation is the set of propositions" (Piaget, 1985 p. 13).

Two artificial agents were created to test the theory associated with this work, the theory of Cybernetic Intelligence. Evidence of the functioning of these agents' engines of intelligence is only a constructive proof that the foregoing theory can be modeled in both software and electronic hardware. However, their engines were complex, stochastic processing devices whose intelligence acted only to steer the agents toward adaptive success in their respective environments with no benefit of pre-coded program instruction.

In summary, this chapter presents for the first time a concise definition of the meaning of the word "equilibration" and a clear explanation of, and quantifiable role for, the neural artifact of intelligence. We constructed a formal algebraic system to help in understanding the biogenic processes that we are attempting to model. However, in spite of all this, we may still be unable to see the forest for all of the trees.

Clearly, we can recall our earlier lesson in cybernetic theory, the brief primer in neurobiology, our grounding in events emergent from within the neural tube of the prototype, and even our inquiry into the machine-like taxes of the vehicular hosts of our intelligence. But our biogenic model is only founded upon these properties of the prototypes of natural intelligence. It is the implementation of the paradigm that is of interest now. In Chapter 6 we will deal with the question of into which particular Turing architecture this hard-won biogenic model might be best embedded. Perhaps, as the threads are all spun together, we may even be able to suggest an experiment to test the fabric of this theory—this theory of Cybernetic Intelligence.

CHAPTER 6

THE TURING ARCHITECTURE

A fundamental principle of this thesis is that any architecture that presumes to model the property of intelligence found in the prototypes of natural intelligence must rely upon a mechanism that accounts for the cybernetic character of the engine being modeled. Plainly, the engines of natural intelligence are adaptive systems that exist within a feedback loop consisting of the world, exteroceptive input from the world, and output from the engine both back into the engine itself and into the world. These engines are knowledge acquisition systems—systems that use their acquired knowledge to gain adaptive success.

Any architecture to be selected must also account for the temporal ordering of the prototype's neural activities to some extent. One way to do this is to imply momentary, static values to the pair-wise ordering of the agent's efferent activity and subsequent afferent results. Indeed, if one considers the momentary, all-or-nothing character of the information flow between the neurons of the prototype, then one can easily interpret the instantaneous static value of natural neural activity in this manner. In fact, in the Chapter 5 we derived an entire algebra that supported a state-based learning engine and easily supported temporal ordering.

Another required aspect of the architecture is that it demonstrate an emergent yet deterministic learning algorithm similar to that occurring in several of the prototype species subsequent to neural tube development. For example, we require that an engine be capable of beginning each learning cycle by accommodating an infinite input language of experiential stimuli

taken over a finite input alphabet of exteroceptive modalities and, by means of step-wise transition and repetition, assimilate a set, or language, of scalable and potentially adaptive output behavior sequences from the delta between expected and actual afferent stimuli. Created in this way, an infinite language of behaviors will be induced over a finite alphabet of phenotypic behavioral output atoms, the language will be agent-specific, and it will be capable of supporting adaptive success to some greater or lesser degree. This aspect of the model is consistent with the aforementioned algebraic system, is consistent with post-neural tube behavioral neurogenesis in several prototype species, and even suggests a potential for Lamarkian results.

The selected architecture must have a learning cycle driven by the difference between expected and actually encountered afferent stimuli. Recall that the concept of the prototype's engine being causally driven to equilibrate new, corrective neurogenic structures is not a new one. As was mentioned earlier in regard to drive reduction theory, living systems involuntarily gener-ate behaviors that act to realign actual afferents with expected afferents by means of internal perturbation. This drive reduction theory was attributed to Clark Hull.

Finally, if the principles of cognitive equilibration and the definition of the property of intelligence in the prototype are accurate, then we may expect that a well-chosen Turing architecture should be dissociable from any "species-specific" harness or locomotive vehicle into which it may be installed. In fact, the engine designed and instantiated for this research was just such a "disembodied artificial intelligence" and conceivably could have been installed

into any suitable IO harness without loss of generality. That is, the engine about to be described would have performed equally well as the "brain" for an artificial rodent or as the "controller" for an autonomous vehicle.

It may be interesting to consider what might occur if this result were generalized back across the phyla. It could have potentially controversial implications. If equilibration occurs in all species and the property of intelligence is of genetic ontogenesis, then the only real differences between species are those of outward physiology. This result is of no significant value here but it remains interesting to consider in light of the foregoing discussions.

The engine of intelligence described in this chapter presents a unique experimental opportunity. For example, consider one possible experiment. In autonomous and untethered artificial agent applications, behaviors resulting in the location and utilization of a reliable power source is equatable to a complex set of taxes similar to chemotaxis and to nutritional homeostasis in the prototype. If an artificial agent were created and provided with a limited set of exteroceptive afferent modalities and a finite set of behavioral atoms based on some subset of the basal phenocopy of the prototype, then we could provide the agent with access to an experimental engine and test the hypothesis. In fact, this is what was done.

Finally, to answer the question of into which particular Turing architecture this hard won biogenic model might be best embedded: "The A-type unorganized machines are of interest as being about the simplest model of a nervous system with a random arrangement of neurons. It would therefore be of very great interest to find out something about their behaviour" (Turing, 1948, p. 36).

Turing explained the reasoning process behind that comment. He was comparing a "picture of the cortex as an unorganized [computing] machine" (Turing, 1948, p. 43) and contrasting the unorganized computing machine to the machine which has now become the standard computational engine of the 20th century, the Universal Practical Computing Machine[1]. He speculated on the role that such an engine might play in terms of genomic epigenesis and, more interesting, how an unorganized machine might "be organized by suitable interfering training" (p. 43).[2] Continuing, he said, "The organizing might result in the modification of the machine into a universal machine or something like it" (p. 43). It is to these ends that we introduce the following specific Turing unorganized machine architecture: the P-type machine.

A P-type Turing device is fundamentally an algorithm in itself which, as it runs, modifies its data store so as to acquire both time-sequenced knowledge and those behaviors that have proven to be "acceptable to its operator." In a sense, the algorithm acts as a recorder of both output efferents and associable input afferents. But, judging by the name that Turing gave the machine, there is a deeper, less obvious character to the device. Turing gave the machine the name P-type for the first letter of the words Pleasure and Pain.

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[1]Better known as the "Von Neumann architecture."

[2]By the phrase "interfering training" Turing was referring to a technique of modifying a machine's output by the use of a technique not unlike that of S/R conditioning. For example, if the machine were stuck in a loop producing all 1's, then by "interfering" (i.e., by appropriate antecedent stimulus intervention), a new, more appropriate behavioral response of, say all 0's, might be returned.

According to Turing (1948), a P-type machine is a Finite State Machine (FSM) with the unusual characteristic that the machine's transition table is not completely defined until after the machine is instantiated. Specifically, the choice of which input and output characters are to be associated with any particular transition table entry is to be left in an undefined condition until run-time events take place and the table is specified by means of Turing's algorithm. In the specific case of the experiment that will be described in Chapter 7, the following logicomathematic description is that of an operational P-type machine. Figure 7 shows one possible logico-mathematic definition of a P-type machine.

The P-type machine's purpose is to adapt to and learn from an environment about which it has absolutely no information. That is, the P-type's FSM kernel contains no embedded knowledge about any particular problem space and its "silicon" paper-tape is blank. Further, the character of the P-type TM is such that the designer of a P-type engine may arbitrarily implement such input sensors as may best emulate a particular prototype host's physiological Pleasure or Pain centers.

From the propositional mappings discussed in Chapter 5, recall that the equilibratory integral produced an ordered triple which, when logically reduced, resulted in an order pair. Also, the first element in the pair produced by the integral was an element member of the set S (the set of all possible perceivable stimuli) and the second element was from the set R (the set of all possible response behaviors).

The P-type machine uses this ordered pair directly, first as an output efferent and then as an expected input. When the actual afferent arrives, a

$M = \{Q, I, O, D\}$

$Q = \{q_0, ..., q_{(2^n-1)}\}$; a finite set of states.

$I = \{Dr, Db, T, D, Ex, In\}$; a finite set of input characters, an alphabet.

$O = \{LW, RW, Tng\}$; a finite set of output characters, an alphabet.

$D = \{Q \times I\}$; a finite set of transitions described by Turing(1948).

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where, n = a finite number, an integer.

Dr = Drive reduced, a chemotropic, basal heuristic, such that $Dr \in \{0, 1\}$.

$Db = \{db \mid db \in 0, 1\}$; a finite set.

T = tentative, the digits certainty value, such that $T \in \{0, 1\}$.

D = definite, the digits certainty value, such that $T \in \{0, 1\}$.

$Ex = \{e \mid e \in H0, H1, ..., H5, S, G, H\}$; a prototype inspired, but finite set of anticipated exteroceptive stimuli.

$In = \{i \mid i \in h0, h1, ..., h5, s, g, h\}$; a finite set of exteroceptive stimuli.

$LW = \{lw \mid lw \in 0, 1, 2, ..., 7\}$; a prototype inspired, but finite set of motor behaviors.

$RW = \{rw \mid rw \in 0, 1, 2, ..., 7\}$; a prototype inspired, but finite set of motor behaviors.

$H0 - H5$ = Haptic bits 0 - 5, such that $Hm \in \{0, 1\}$ and are $P(Hm)$, respectively.

$h0 - h5$ = Haptic bits 0 - 5, such that $hm \in \{0, 1\}$ and are $P(hm)$, respectively.

$S, s = P(S), P(s)$; sated, a proposition such that $P \in (0, 1)$.

$G, g = P(G), P(g)$; greater odor, a proposition such that $P \in (0, 1)$.

$H, h = P(H), P(h)$; hunger, a proposition such that $P \in (0, 1)$.

Tng = Tongue, a prototype inspired, but finite motor behavior, such that $Tng \in \{0, 1\}$.

$D : (Q \times I) \rightarrow Q$ and $\begin{cases} \text{remainder of:} \\ q \leftarrow (2 * q) / n, & \text{if } db = 0; \\ q \leftarrow ((2 * q) + 1) / n, & \text{if } db = 1. \end{cases}$

Note: Db are selected at random before instantiation and remain constant throughout the life of the experiment. (Turing, 1948)

Figure 7. P-type machine as M

meet is made of the expected and actual results and the relative adaptive quality of that event is ascertained. Relative trues result in either a new expectation/behavior pair being committed to memory or a new expectation/ behavior pair being generated at random if no previous memory of the stimulus event exists. Relative false results are discarded and either previously learned knowledge is next executed or, again, a new expectation/behavior

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pair is generated at random. (Compare the works of M. L. Tsetlin as cited in Narendra & Thathachar, 1989.)

To summarize: In this chapter we decided into which Turing architecture we could best embed our biogenic model. We defined the constraints required for a cybernetics-based, temporally ordered, binary-valued, stepwise scalable, species-independent engine of intelligence and then recalled that, in 1948, Alan Turing suggested a variant of the A-type unorganized machines as being "about the simplest model of a nervous system with a random arrangement of neurons" (Turing, 1948, p. 36). We took his suggestion to investigate their performance empirically. Finally, we selected a P-type unorganized machine and identified ideas for a possible hypothesis. In Chapter 7 we state that hypothesis explicitly and discuss some of the experimental results from the experiment that followed.

CHAPTER 7

EMPIRICAL TESTS

In Chapter 6 we suggested an experiment wherein an autonomous, untethered artificial agent could be required to first locate and then utilize a reliable power source. We stated that this task might be favorably compared to a complex set of prototype taxes similar to chemotaxis and to nutritional homeostasis. We suggested that, if an artificial agent were created and provided with a limited set of exteroceptive afferent modalities, a finite set of behavioral atoms based on some subset of the basal phenocopy of the prototype, and access to a P-type engine, then we could test our biogenic model to the best extent possible.

This is our hypothesis, and in this chapter we examine the record of two separate experimental efforts intended to empirically identify the character and performance of the theory of Cybernetic Intelligence as just such an embodied and adaptive control paradigm. We first describe an experiment that was a simulation run completely in software. Next, we describe a second experiment that, although still in active evaluation, was built completely of electronic circuits and mechanical components.

Created entirely within the environment of compiled computer code, the first experiment investigated the results of providing an artificial agent with access to a P-type unorganized machine as an adaptive controller. The P-type unorganized Turing machine was tasked with locating a simulated olfactory stimulus by means of simulated chemotaxes and then maintaining an arbitrary minimum level of simulated nutritional homeostasis. The movement of the artificial agent was accomplished by means of simulating a small

set of basal locomotive behaviors easily identifiable and available in the proto-

type. The behaviors associable with nutritional homeostasis required the

agent to develop a set of strategies involving sufficiently repetitive but minim-

ally proximal access to a simulated food source. Each of the machines that

were instantiated utilized a pseudo-random number generator to approximate

"random" choices where appropriate. The simulated experimental enclosure

was identical in each trial.

The second experiment is an investigation of an embedded and

situated, P-type engine of intelligence hosted by an autonomous, vehicular

agent. The agent emulates the heuristics of basal phenocopy by simulating a

nominal degree of haptic and olfactory exteroception like that of a natural

prototype. The robotic agent, an artificial rodent, has a tricycle-type, dual DC

motor locomotion system, an RF Radio Signal Strength (RSS) olfactory

stimulus receptor, and mechanical displacement haptic inputs. The agent is

tasked with seeking nutritional homeostasis. That is, the agent is tasked with

maintaining its onboard DC power source. It must achieve this first through

trial and error and then from habituated, acquired knowledge. The experi-

mental enclosure for this experiment closely resembles the one simulated in

the preceding software trial and is unchanged between individual trials.

The Software Experiment

In the case of the software experiment, a mixed procedural and

functional coding paradigm was selected to create a single, stand-alone,

executable program. The first step in the process was to code a set of

routines that together constituted a simulated world (see set W in Chapter 5).

A simulated rodent "icon" physiology, with a discrete set of behavioral motor

atoms, and a simulated meter-sized octahedral enclosure with four floor-mounted and independent "feeding stations" make up the agent's world. These routines were then compiled into a linkable library which, when given a run-time command from an executive Mealy FSM, would generate the computational side effects of icon movement and associable haptic and olfactory feedback from the simulated enclosure. (Refer to Chapter 5 for a discussion of the sets R and S and the equilibratory integral.) Figure 8 shows the simulated enclosure and the icon rodent.

```
Feed Station 2 is Active.                    Rodent Model 3.1
```



```
Nutrient Level:  557              Touch a key to terminate.
```
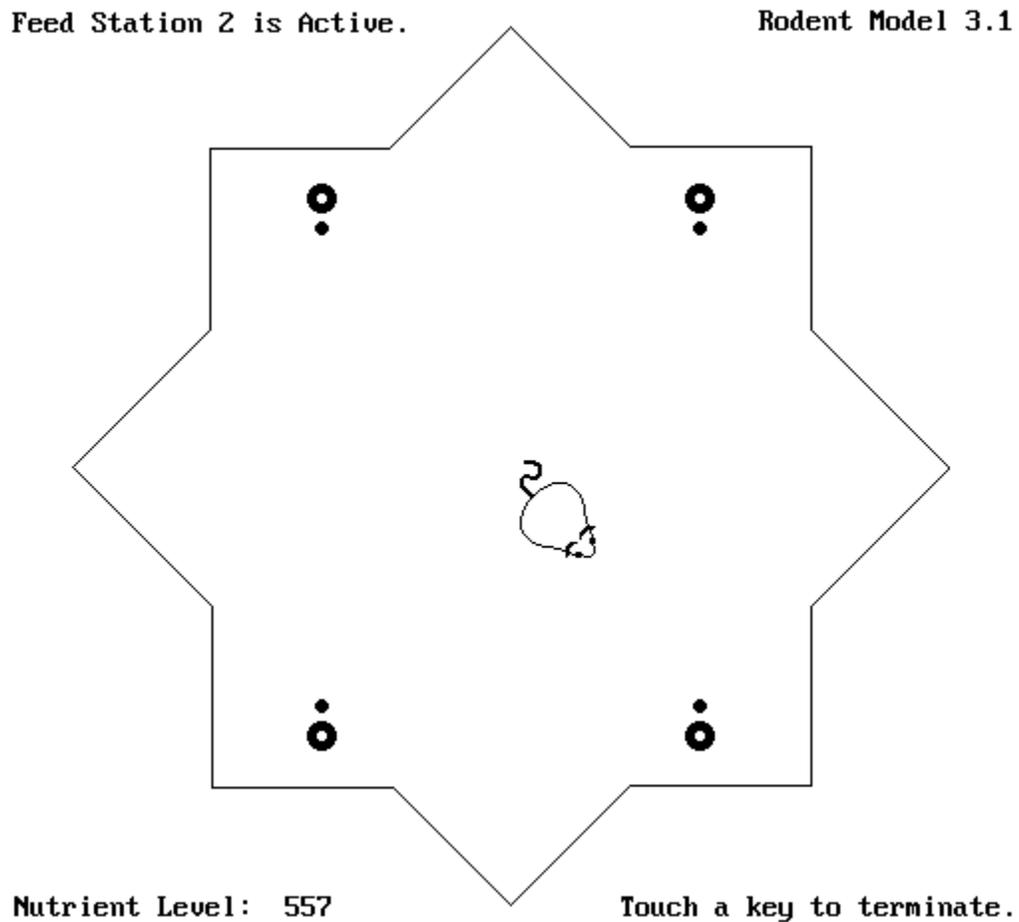
Figure 8. Simulated enclosure and the icon rodent

Obviously, if the rodent's motor behaviors caused a simulated collision with a simulated wall in its enclosure, then an appropriate haptic bit was set and that signal was returned from the library to the calling FSM executive. Also, the icon would appear to be confined to the inside of the enclosure. Figure 8 depicts the icon rodent and its simulated enclosure.

A Mealy FSM executive was the driving force behind each instantiated agent's P-type engine and was constructed in a manner similar to the algorithm described in Turing's 1948 paper (Turing, 1948). However, the P-type Turing machine in this experiment had access to a single track "paper" tape simulated in serial-access, mass storage and whose length was entirely scalable. The "scalability" of the mass storage device was different from the "finite" length tape used by Turing.

In Turing's case, the finite length of his tape supported an array-like indexing scheme of the tape's contents. The nature of the scheme's determinism and the P-type algorithm in general were based on the fact that the tape's contents represented a sequential recording of the behavioral atoms used to reduce some particular drive (in this case, hunger). By Turing's design, the algorithm recorded only those behaviors proving adaptively successful to the agent and stored in least incremental fashion backward as they related to the moment the particular drive was reduced (i.e., satiated, in our case). Thus, Turing's tape would have been written and could later be read as acquired, adaptive knowledge. However, Turing was not specific as to whether the read-back of the taped knowledge was to be a strictly enforced sequential process causing agent behavior to occur (until either blank tape or the death of the agent was encountered) or if an otherwise unspecified homunculus

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applied a priori knowledge to supersede the sequential process. In fact, it is this exact problem which appears to be a deficiency in the P-type engine's short-term memory capacity. This will be mentioned again later as its only shortcoming. But, for our purposes here, we would do well to remember that Clark Hull (1943) had much to suggest in regard to this problem in the prototype.

In our case, we enforced a strict sequential process that caused behavior to occur as a consequence of sequential reads from the tape when there were data on the tape or by random choice when there were no previously equilibrated structures on the tape. Otherwise, the overall intent of the P-type's FSM kernel (i.e., its equilibratory effect) was consistent with Turing's architectural design and purpose. (Refer to Chapters 5 and 6 for a review of the functionality of equilibration and the algebraic system we suggested that supports it.)

Two versions of the code were created. One version involved integrating a supervisory loop over the executable product, or R_Model program as it became known, for the purpose of collecting the results that follow. That version facilitated a mass-trials instantiation of the rodent model. However, another executable version that instantiated only a single agent was also created. They each produced interesting and differing results. In each version (mass trials or single-agent, respectively) the icon rodents had identical chances for adaptation and survival. Both used the same P-type engine and library.

In both versions, the icons were instantiated with an initial "nutrient" level of 600 units, or a condition of "just hungry." Each motor movement, or

transition of the P-type automata, caused the P-type machine either to execute the data on its tape or to solicit a new quasi-random afferent-efferent pair from the code library for execution. Each resulted in a cost of one "nutrient" unit. If the icon was successful at locating the single active feed station before its nutrient level reached zero, then it would acquire 100 nutrient units per feeding act. Feeding acts cost one unit of motor movement each. It is important to remember that, when each respective icon was instantiated, it began with a tape that was completely blank and that, over the duration of the experiment, the cells on an ever-enlarging tape had the chance to be filled with afferent-efferent pairs proven to be adaptively successful. A review of the underlying algebra of Chapter 5 will be helpful in understanding the theoretic basis for this system. However, in principle, each transition on the tape was an example of an equilibria, as was defined earlier.

Feeding acts began on proximity contact with the active feed station[1] but were not maintained by any innate behavioral atom. Rather, the behavior of successful feeding was an adaptive skill[2]. Once a meal in excess of 600 nutrient units was taken, the rodent icon was no longer driven by hunger (refer to earlier chapters regarding drive reduction theory) and could "choose" at "random" to wander off anywhere within the enclosure, at will. However, some icon mice gorged themselves with 1,000 or more "nutrient" units before

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[1] An emulation of the rooting reflex in the prototype.

[2] The accumulated knowledge of any icon instantiation could be captured and transferred to any subsequent icon in the form of a "tape." This taped knowledge would have the effect of acting as a Lamarckian-like inheritable change in the basal heuristics of the new icon's available phenocopy.

going off to "randomly explore" the enclosure. After an interval of random exploration, "hunger" was unavoidably encountered when the icon's nutrient level reached 600. When the level reached 600, the learning cycle began again and the icons were driven to find the feed station using their P-type engines and their learned "knowledge" on tape.

It was noticed early in the experiments that the rodent icons could be taught by means of a behavior modification technique called approximation. The technique involves presenting well-chosen but incremental antecedent stimuli to a subject. Then, when the subject responds in a manner consistent with expectation, a stimulus reinforcer is offered. In the case of the icon mouse, the antecedent stimuli was the presence of the simulated olfactory stimulus at some arbitrarily and initially near, appropriately angled distance. When the icon responded by approaching the food station and feeding itself, the program run was manually halted and a recording of the icon's behaviors was written to tape. Thereby, the effects of reinforcement were actualized, a learning cycle was completed, and the P-type engine had learned.

The technique was repeated a few more times. Each time, the antecedent stimuli were presented from slightly greater distances and from different angles. Ultimately, when it was thought that the rodent icon had accumulated sufficient knowledge about its environment to find the food station, training was terminated. Some icon instantiations trained in this manner ran unstopped for several days without further intervention. On the other hand, many more icon instantiations were never taught how to find the food station. In their case, they either halted after just a few meals or simply

never got near enough to the active feed station to take meal, and halted immediately. Similar results were produced in a mass-trials experiment.

Figure 9 shows the results of one set of 255 different instantiations of the P-type engine. The vertical axis shows the total number of transitions that each respective icon accumulated before halting. The horizontal axis reflects each one of 255 different icon instantiations. The most obvious result produced during these trials was that only 3 members of the 255 instantiated members of the icon population shown managed to survive up to an arbitrary 20,000 motor transition cut-off. In a comparison trial with the icon mice driven by only "random" inputs, none of those icon mice lasted beyond their initial nutrient level of 600 units.
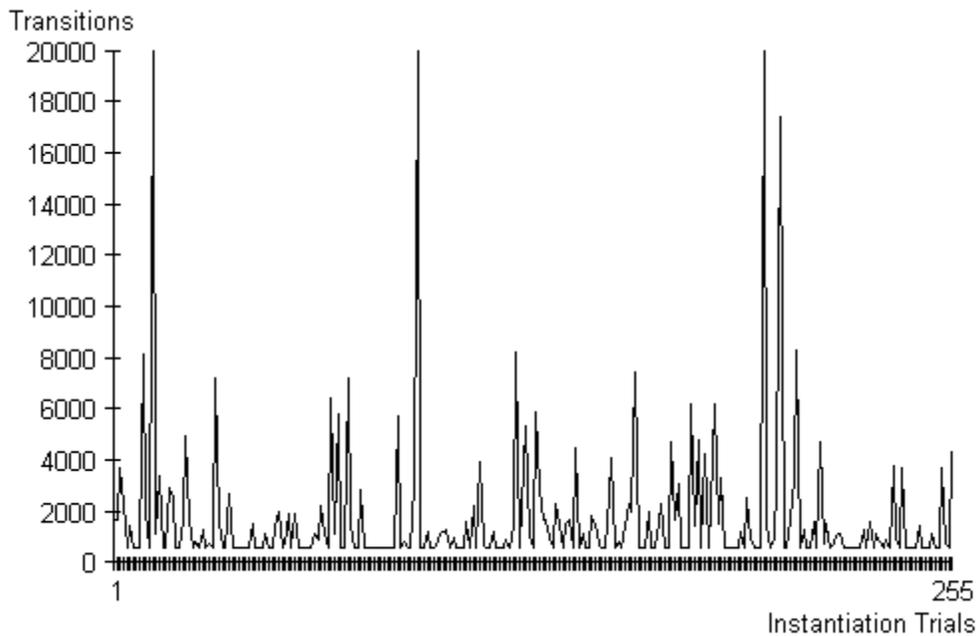
Figure 9. Mass-trials instantiation of a P-type machine

Another result of this experiment was that those icon mice that did acquire sufficient knowledge to repeatedly find the feed station during the experiment also learned how to feed themselves more effectively than did the rest of their "cousin" instantiations. For these mice, those surviving to the 20,000 motor transition cut-off, each icon accumulated an average meal intake level in excess of the hunger drive starting point of 600 nutrient units. Apparently, these engines not only adapted to their environments and learned how to find the food source[3] but they also acquired feeding behaviors superior to those of the mice achieving less than 20,000 motor transitions.

However, while these three machines did adapt, they also demonstrated one problem common to every population tested: They lacked any short-term memory. In *Homo sapiens* the expression "short-term memory" satisfies the need for an abstract term referring to the context- oriented switching that our engine of intelligence does between the immediate and superficial responses that our cognitive resources extend to temporally immediate stimuli and those which, though likewise often emerging from apparently "unreasoned" or even unconscious sources, are based in more complicated chemical changes in the brain referred to as long-term potentiation. The basic P-type algorithm offers no solution for this problem. However, a readily apparent variation to Turing's algorithm may result in significant experimental alternatives in this regard. For example, an entire branch of

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[3] In the mass-trials experiments one feed station, from among stations 0 through 3, was selected at random prior to the each particular icon's instantiation. The selected station remained active for the entire icon's run and was reselected as described for each subsequent icon.

mathematics dealing with multiple-prediction theory may yield useful suggestions if extended to a continuation of this work ("Automata," 2000).

Finally, given an arithmetic mean of 2,870 and a non-biased standard deviation of 1,819, it is clear that the performance of the three icon mice at the 20,000 life-time motor transitions level was well beyond the 6th deviation of all members of the population comprising their cohort. Simply put, the apparent success of their performance was significantly beyond any random sequence of events.

The Hardware Experiment

Unlike the safety of the foregoing computer simulations, a more complex test of the hypothesis has been devised. The test proposed involves the evaluation of the performance of another embodied P-type machine in a robotic agent. The experiment here described is ongoing and uses a hardware realization of the previous software agent. That is, we challenge an untethered, autonomous vehicular agent to establish and maintain nutritional homeostasis in an actual meter-sized octahedral enclosure. The small robotic agent is shown as Figure 10.

Consistent with the simulated enclosure depicted in Figure 10, the agent's physical enclosure has four feed stations embedded in the floor of the enclosure. During any particular trial, one feed station can be activated. Activation entails the powering of a center-loaded DC-voltage power source and starting a low-power Radio Frequency (RF) transmitter buried beneath the station.

It bears repeating that the electro-mechanical system comprising the octahedral enclosure, the robotic agent, and the agent's P-type controller
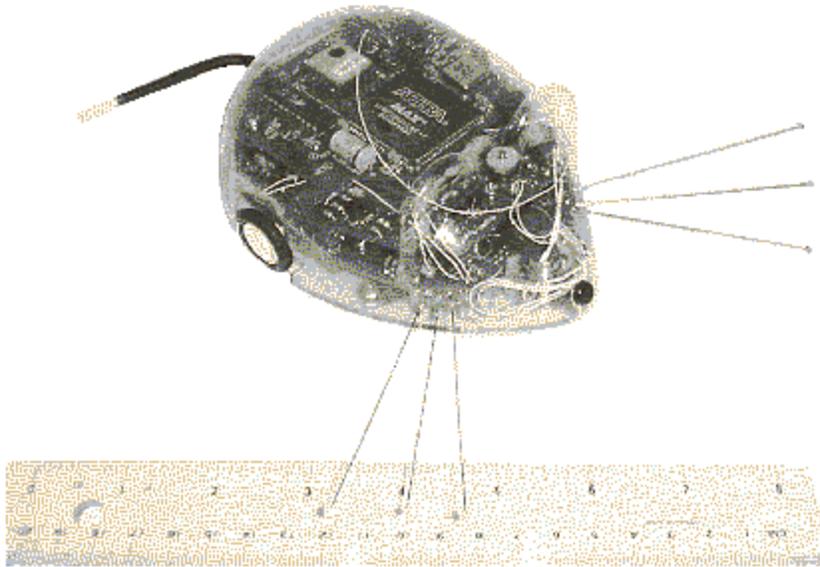
Figure 10. Autonomous and untethered robotic agent

contains no benefit of pre-coded program instruction. The agent is constrained only by a limited set of prototypical, basal heuristics derived in similar fashion to those of the software agent. We believe that this approach represents a unique solution to the problem of hard AI.

Due to the agent's small size and the complexity of mechanically integrating appropriate simulated haptic, olfactory, digestive, and gustatory sensors within the confines of an approximately 10x14x6 cm robotic mechanism, artificial ganglionic connections to the untethered agent are required. The neural ganglion servicing the agent are a 433 MHz RF afferent uplink and a 40 KHz Infra-Red (IR) efferent downlink. Although the artificial rodent's robotic mechanisms can be completely controlled via a standard desktop PC link, control of those mechanisms by the P-type engine precludes the use of that interface for all but check-out and diagnostic functions.

Identification of dependent and independent variables will require care. But, obviously, if the hardware-based artificial rodent can locate the active DC power source by means of amplitude-only RF homing, then the agent will have a better chance of replenishing its small built-in battery than if it cannot locate the RF source. Just to clarify, in the hardware agent olfactory stimulus, emulation occurs by means of Radio Signal Strength (RSS) homing and requires exceptional sensor and telemetry capability and data conversion capacity to match the performance available in the coded-only simulation environment. Preliminary testing suggests that this second empirical test will also be successful.

Overall, the empirical evidence that we collected and the experiments that we have proposed demonstrate the merit of Alan Turing's invention and the wisdom of a cybernetic paradigm for the engine of Cybernetic Intelligence. The capacity of the P-type Turing machine to acquire a functional knowledge of and adapt to its surroundings with sufficient alacrity that it can solve the complex problem of survival is impressive. However, it is by no means a proof. It only supports the contention of the hypothesis for these agents and their respective engines of intelligence. However, we tend to think that agents so equipped will likely be able to solve even more complex problems, given time and engineering resources.

Chapter 7 is the record of empirical testing that could easily be duplicated and expanded. However, the central theme of the chapter is an investigation of the utility of an embodied version of Turing's P-type engine. The functionality of the P-type engine was demonstrated to be powerful enough to direct simulated agents around a software world and to be flexible enough to

be embedded in a hardware-based robot. Although this simple model of Turing's engine demonstrated significant limitations in emulating the prototype's capacity for short-term memory function, it showed an equally remarkable, almost organic, capacity to learn and be taught.

Although Turing's efforts in 1948 were frustrated by the use of inefficient contemporary technologies, it was through his work and the works of men such as Norbert Wiener, Jean Piaget, Donald Hebb, and Clark Hull that we were able to identify the theory of Cybernetic Intelligence and to find success in the use of modern electronics.

Turing himself tried to implement such a machine on paper and was frustrated. But I believe that he was not defeated. He said, "I made a start on the latter [meaning an implementation of a P-Type machine] but found the work all too laborious at present" (Turing, 1948, p. 48). If only he had had the computational engines of today. He wanted them. In fact he said, "When some electronic machines are in actual operation, I hope that they will make this [a P-Type machine] more feasible" (p. 48).

CHAPTER 8

SUMMARY

In Chapter 1 we established a cybernetic paradigm for our biogenic model of intelligence. To do this, we selected a group of observers who described the cybernetic processes involving the CNS and who, in later chapters, helped to identify the artifacts of intelligence emergent within the prototypes of natural intelligence. Norbert Wiener, for example, pointed out that there was an apparent circle of influence associable between the characteristic activities of the CNS in an organism and the sensory stimuli returning to the organism from the habitat that it frequents. Albert Bandura confirmed Wiener's reflections that, as individuals restructure their habitats, their habitats in turn influence the individual restructurer. Margaret Boden shared the fact that even Jean Piaget saw cybernetic theory as a fundamental precept to his general theory of equilibration—a theory fundamental to this thesis.

Chapter 2 was concerned with a cursory overview of neuro-physiology. Several biologists and neuroethologists reported that neurons share their information by means of signals that are strictly bi-valued. Even though the input to a neuron is both a temporally and spatially summed analog value, the content of neural information output is actually a variable-frequency, binary-valued, pulse train. Although there is significant stochastic noise, or reson-ance, inherent in the CNS, it is really the repetitive nature of an organism's adaptive behavior that contributes to the ultimate acquisition of new behavior. The Boolean nature of information content immanent in neural activity was a key component in recognizing that it might be possible to create an artificial

engine of intelligence in electronic hardware. For this revelation we owe a debt of thanks to Warren McCulloch and Walter Pitts.

Using *Homo sapiens* as an example, Chapter 3 drew attention to a common chordate vertebrate pattern. The pattern is that of emergent, homeo-static, and phenotypic behavior occurring early in fetal neurophysiology but routinely developing into purposive and intentional neurogenic behavior in subsequent stages of life. We joined Jean Piaget and Donald Hebb in sug-gesting that, after sufficient neural material has migrated and differentiated, synaptic reformation might be possible. We wondered whether an artificial agent might be modeled that would be capable of an interactive relationship with its environment using a self-adaptive algorithm. Obviously, the nature of the self-adaptive process would have to involve a Boolean functioning mechanism.

Chapter 4 began by recounting the goals set by the founders of the discipline of AI and thinking that there would be safety in the definitions found in a dictionary. We ended Chapter 4 wishing that we had not searched the lexicon nor assumed that we wanted to remember anything. In Chapter 4 we were discretely stripped of muscle fiber and the skin of our "humanity" and deposited naked, a bundle of ganglion and proprioceptors within a species-specific harness serving both as sustaining host and locomotive vehicle to our electro-chemical, sentient consciousness.

Chapter 5 offered the first concise definition of equilibration theory and explained our view of the role of the property of intelligence in adaptive sys-tems. We constructed a formal algebraic system to explain our understanding of the foregoing biogenetic processes and reflected on the fitness of our

calculus to satisfy Jean Piaget's challenge of finding "a quantifier . . . whose domain of variation is the set of propositions" (Piaget, 1985, p. 13). Thus, we arrived with an unwieldy modeling problem that demanded a solution and we attempted to accumulate sufficient mathematic generalizations to code a solution. In Chapters 6 and 7 we learned that the code had, in fact, been written to test this thesis.

Chapter 6 focused on the material covered in the previous chapters and used that material to direct the selection of a particular computational engine first described by Alan Turing over 50 years ago. Chapter 6 began by reiterating the need for a cybernetic basis for the model. It reviewed the general understanding of the all-or-nothing character of neural activity and how the emergence of the autonomic nervous system from within the neural tube produces Lamarckian results. As we recognized the constraints that the heuristics of phenocopy expression pose to the prototype's need to reduce basal drives, we were reminded of Clark Hull's insight. However, we also realized that, if the principle of cognitive equilibration and our definition of intelligence were accurate, then they would likely cut across the phyla, with controversial consequences. Finally, given the binary nature of the information content immanent in nervous activity, we described a type of automata that could operate over a domain of variation consisting of propositions representing the momentary configuration of that nervous activity. From a manuscript written in 1948, we adopted the P-type Turing engine from among the A-type unorganized machines that Turing himself selected for our examination.

Chapter 7 is the record of two experiments. The first experiment involved a software-based agent and a simulated habitat as proof of concept for future investigations. The second experiment, although yet in its early stages, uses a hardware-based agent in a physical trial repeating the challenges of the first experiment. The experiments demonstrated the merit of Alan Turing's invention and the wisdom of using a cybernetic paradigm and biogenic model for the engine of intelligence. If the problems encountered in survival in completely unknown surroundings are NP-complete, then the experiments suggested that it is possible for a single track P-type Turing machine to evolve approximate solutions. Although Turing's efforts in 1948 were frustrated by the use of inefficient contemporary technologies, we found success in the use of modern electronics, replacing pencil, paper, vacuum tube, and relay with the silicon and GUI of a modern universal Turing machine.

CHAPTER 9

CONCLUSION

We challenge ourselves when we consider the meaning of the word "mind." What is it, what does it mean, and of what is it capable? For now, let us consider a simple question and ask ourselves to decide whether the mind—our individual mind—is the activity of flesh and blood or is somehow based in spirit and mystery.

Hypothetically, we are offered this choice, and we may choose only between the two options of flesh and blood or spirit and mystery. Without meaning to sound critical or philosophical, many of us are able to understand only those things with which we can associate ourselves either physically or intellectually. However, for those of us who insist that our individual minds, our engines of intelligence, exist as spirit and mystery, then this discussion is over. For the rest of us, though, if we conclude to the contrary that our minds are based in flesh and blood and housed in the space between our ears, then we must recognize unequivocally that a mind is an emergent phenomenon of the electro-chemical conditions present among the tissues of a healthy central nervous system—in this case, our own.

Like the sea squirt, the crawfish, the canines, and all of the primates, we are carriers of a prototypical ability to acquire and use knowledge about ourselves and our environments. Therefore, to some greater or lesser degree, these creatures, ourselves, and many others across the phyla are prototypes of an innate ability to acquire and use knowledge. We all possess engines of, and are the prototypes for, models of natural intelligence.

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The sea squirts, the primates, and many other species possess unique nervous system structures that directly act to cause behavior at the physiologic level. Their nervous systems, like ours, are neurogenic and act to facilitate every overt gesture and internal cognitive nuance. Their neurons, much like ours, must generate action potentials in reliable and predictable ways if they are, first, to demonstrate behavior and, second, to have that behavior become adaptively successful. Furthermore, their neurons, like ours, utilize minute inter-neural structures that serve either to excite or to inhibit the action potentials of adjacent neurons. Those neural structures are at the very root of what we all have in common. Those minuscule structures and their instantaneous, bi-valued outputs are at the heart of the theory of Cybernetic Intelligence.

This may have long since started to sound like a lesson in psychology, neurobiology, or cognitive science. However, we believe that a fluent under-standing of the materials brought out in this thesis are only the minimum of theoretic structure necessary to support any suggestion of an appropriate Turing architecture in which to embed our models of intelligence. This is important, to be sure. For it is our belief that the phenomenon of mind and its basis in the prototype engines of intelligence is the neurogenic consequence of the neuro-physiology of those same prototypes. We also believe that it is according to the phenotypic paradigm of the neuro-physiologies of those prototypes and their respective engines of intelligence that we should attempt to create our models of intelligence accurately, and not just by adopting the most convenient means available.

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Throughout this thesis we have focused on a single theoretic model of intelligence—one based in cybernetic, biogenic psychology. We discussed the cybernetic influence of the synapse on the genome. We discussed and explored how the synapse functions and its role in behavior. We derived a mathematic model to describe an agent in the world and explored some of that model's properties. Then, at last, we discussed into which Turing architecture our biogenic model might best be embedded.

If we had attempted to recount the facts and the story of a particular paradigm from the history of AI, then it would better have been done by a historian. Or if we had modeled our engine on a complex control system that sought only to converge upon a behavioral solution within a particular problem space, then we would be left with two questions. These imperative questions relate to morality and ethical principles and to the scrutiny upon which we base the paradigms of our research.

In the latter case, we must ask whether it is a more accurate approximation of the natural engines of intelligence to base our artificial engines upon ontogenetic paradigms or upon epigenetic ones. We must question whether it is more accurate to provide an artificial intelligence with both the rules with which to learn and the knowledge it will need throughout its lifetime or to create a cybernetic intelligence using only the principles of neuroethology as a template.

The answer to these questions will come in the form of a solution to the test left to us by Alan Turing[1]. That answer, if we can achieve it, may one day turn to us and ask, "Will I dream?" (the *HAL-9000*, in Hyams, 1984).

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[1]The test is one of a natural intelligence attempting to discern the difference between another natural intelligence and an artificial one. Successful completion of the test involves the natural intelligence finding no discernible difference between the tangible artifacts of either the artificial or the natural intelligence after some finite period of time.

SELECTED BIBLIOGRAPHY

Adrian, R. H. (1974). *The Nerve Impulse.* London: Oxford University Press.

American Heritage Dictionary of the American Language (3rd ed.). (1992). Princeton, NJ: Houghton Mifflin.

Aspray, W. (1990). *John Von Neumann and The Origins of Modern Computing.* Cambridge, MA: MIT Press.

Aspray, W., & Burks, A. (1987). *Papers of John Von Neuron on Computing and Computer Theory.* Cambridge, MA: The MIT Press.

Automata Theory: Multiple-prediction theory. (2000). *Encyclopaedia Britannica* [On-line]. Available: http://www.britannica.com/bcom/eb/article/8/0,5716,117178+10+109392,00.html

Bandura, A. (1976). *Social Learning Theory.* Englewood Cliffs, NJ: Prentice-Hall.

Bateman, G. (1972). *Steps to An Ecology of Mind.* Toronto, Canada: Chandler.

Bharucha-Reid, A. T. (1960). *Elements of the Theory of Markov Processes and Their Applications.* New York: McGraw-Hill.

Boden, M. (1977). *Artificial Intelligence and Man.* New York: Basic Books.

Boden, M. (1979). *Jean Piaget.* New York: The Viking Press.

Boden, M. (1989). *Artificial Intelligence in Psychology: Interdisciplinary Essays.* Cambridge, MA: MIT Press.

Boole, G. (1952). *Studies in Logic and Probability.* La Salle, IL: Open Court.

Brazier, M. A. B. (1960). *The Electrical Activity of the Nervous System.* New York: Macmillan.

Camhi, J. (1984). *Neuropathology.* Sunderland, MA: Sinauer Associates.

Caplan, F. (1973). *The First Twelve Months of Life.* New York: Perigee Books.

Coghill, G. E. (1964). *Anatomy and the Problem of Behaviour.* New York: Hafner Publishing Company. (Original work published 1929).

Cohen, L. B., & Salapatek. P. (1975). *Infant Perception: From Sensation to Cognition*. (Vols. 1-2). New York: Academic Press.

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Considine, D. M. (Ed.). (1976). *Van Nostrand's Scientific Encyclopedia* (5th ed.). New York: Van Nostrand Reinhold.

Cowling, T. (Executive Producer). (1994). *The Brain: Our Universe Within.* Bethesda, MD: Discovery Communications.

Craik, K. J. W. (1943). *The Nature of Explanation.* Cambridge: Cambridge University Press.

Craik, K. J. W. (1947). Theory of the Human Operator in Control Systems. In C. R. Evans & A. D. J. Robertson (Eds.), *Cybernetics* (pp. 120-139). Manchester, England: University Park Press.

Crevier, D. (1993). *AI: The Tumultuous History of the Search for Artificial Intelligence.* New York: Basic Books.

Crick, F. (1994). *The Astonishing Hypothesis.* New York: Charles Schribner's Sons.

Davis, M. (1982). *Computability and Unsolvability.* New York: Dover.

DeArmond, S. J., Fusco, M. M., & Dewey, M. M. (1989). *Structure of the Human Brain.* New York: Oxford University Press.

Empson, J. (1986). *Human Brainwaves.* New York: Stockton Press.

Encarta. (1994). *Developing Embryo's First Month* [CD-ROM]. Funk & Wagnalls.

Eysenck, H. J. (1967). *The Biological Basis of Personality.* Springfield, IL: Charles C. Thomas.

Fentress, J. C. (Ed.). (1976). *Simpler Networks and Behavior.* Sunderland, MA: Sinauer Associates.

Filloux, J. C. (1963). *The Psychology of Animals.* New York: Walker and Company. (Original work published 1950).

Franklin, S. P. (1995). *Artificial Minds.* Cambridge, MA: MIT Press.

Freeman, D. (1994). *Brainmakers: How Scientists are Moving Beyond Computers to Create a Rival to the Human Brain.* New York: Simon & Schuster.

Gardner, H. (1985). *The Mind's New Science: A History of the Cognitive Revolution.* New York: Basic Books.

Golton, M. A. (1983). *Your Brain at Work.* New York: Frank.

Gray, E. G. (1974). *The Synapse.* London: Oxford University Press.

Greenfield, S. (1995). *Journey to the Centers of the Mind: Toward a Science of Consciousness.* New York: Freeman.

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

Hobson, J. A. (1994). *The Chemistry of Conscious States: How the Brain Changes Its Mind.* Boston: Little, Brown.

Hull, C. L. (1943). *Principles of Behavior.* New York: Appleton-Century-Crofts.

Hyams, P. (1984). *2010.* Hollywood, CA: Metro-Goldwyn-Mayer/United Artists Entertainment Co.

James, W. (1950). *The Principles of Psychology.* New York: Dover.

Johnson-Laire, P. N. (1983). *Mental Models.* Cambridge, MA: Harvard University Press.

Kalat, J. W. (1995). *Biological Psychology.* Pacific Grove, CA: Brooks/Cole.

Kemeny, J. G. (1955). Man Viewed as a Machine. *Scientific American, 192*(4)*,* 58-67.

Lashley, K. S. (1950). In Search of the Engram. *Symposia of the Society for Experimental Biology, 4,* 454-482.

Longtin, A., Bulsara, A., & Moss, F. (1991). Time-Interval Sequences in Bistable Systems and the Noise-Induced Transmission of Information by Sensory Neurons. *Physical Review Letters, 67,* 656-659.

Mahowald, M. A., & Carver, M. (1991). The Silicon Retina. *Scientific American, 264*(5)*,* 76-82.

Mandler, G. (1975). *Mind and Emotions.* New York: Wiley.

Marciniak, J. J. (Ed.). (1994). Artificial Intelligence in Software Engineering. In *Encyclopedia of Software Engineering* (pp. 49-58). New York: Wiley.

McCulloch, W. S., & Pitts, W. (1943). A Logical Calculus of the Ideas Immanent in Nervous Activity. *Bulletin of Mathematical Biophysics, 5,* 115-133.

McKehnie, J. L. (Ed.). (1983). *Webster's New Unabridged Dictionary.* Cleveland, OH: Simon & Schuster.

Meister, M., Wong, R. O. L., Wong, D. A., & Shatz, C. J. (1991). Synchronous Bursts of Action Potentials in Ganglion Cells of the Developing Mammalian Retina. *Science, 252,* 939-943.

Morris, D. (1967). *The Naked Ape: A Zoologist's Study of the Human Animal.* New York: McGraw-Hill.

Muir, B. L. (1980). *Pathophysiology: An Introduction to the Mechanisms of Disease.* New York: Wiley.

Narendra, K. S., & Thathachar, M. A. L. (1989). *Learning Automata: An Introduction.* New Jersey: Prentice-Hall.

Nathan, P. (1982). *The Nervous System.* London: Oxford University Press.

Newell, A. (1990). *Unified Theories of Cognition.* Cambridge, MA: Harvard University Press.

Nicolis, G., & Prigogine, I. (1989). *Exploring Complexity: An Introduction.* New York: W. H. Freeman.

Ogden, T. H. (1983). The Concept of Internal Object Relations. *International Journal of Psycho-Analysis, 64,* 227-241.

Ornstein, R. (1972). *The Psychology of Consciousness.* New York: Viking Press.

Ornstein, R. (1991). *The Evolution of Consciousness.* New York: Prentice-Hall.

Papalia, D. E., & Olds, S. W. (1995). *Human Development.* New York: McGraw-Hill.

Peterson, I. (1993, October 23). Noisy messages for crayfish. *Science News,* p. 271.

Piaget, J. (1956). Equilibration Processes in the Psychobiological Development of the Child. In J. M. Tanner & B. Inhelder (Eds.), Equilibration Processes in the Psychobiological Development of the Child, Vol. 4. *The Proceedings of the World Health Organization Study Group on the Psychobiological Development of the Child.* Geneva: WHO.

Piaget, J. (1972). Intellectual Evolution From Adolescence to Adulthood. (Bliss, J. & Furth, H., Trans.). *Human Development, 15,* 1-12.

Piaget, J. (1975). Problems of Equilibration. (Duckworth, E. Trans.). In M. Appal (Ed.), *Topics in Cognitive Developments, Vol. I.* Philadelphia: Plenum Press.

Piaget, J. (1985). *The Equilibration of Cognitive Structures: The Central Problem of Intellectual Development.* (Brown, T. & Thampy, K. J., Trans.). Chicago: University of Chicago Press.

Piattelli-Palmarini, M. (Ed.). (1981). *Language and Learning: The Debate Between Jean Piaget and Noam Chomsky.* Cambridge, MA: Harvard University Press.

Posner, M. I. (1989). *Foundations of Cognitive Science.* Cambridge, MA: MIT Press.

Restak, R. M. (1994). *Receptors.* New York: Bantam Books.

Rosen, K. H., (1995). *Discrete Mathematics and Its Applications.* New York: McGraw-Hill.

Rouly, O. C. (1994). *The Biological Basis for Cognitive Heuristics.* Unpublished manuscript.

Semmler, C. (Ed.). (1989). *A Guide to Care and Management of Very Low Birth Weight Infants: A Team Approach.* Tucson, AZ: Therapy Skill Builders.

Singer, E. A. Jr. (1980). *Mind as Behavior and Studies in Empirical Idealism.* Columbus, OH: R. G. Adams.

Stein, D. G., & Rosen, J. J. (1974). *Neural Organization and Behavior: A Systems Analysis Approach to Brain Function.* New York: Macmillan.

Story, J. R., Harrison, H. J., & Reinhard, E. A. (1972, December). Optimum State Assignment for Synchronous Sequential Circuits. *IEEE Transactions on Computers, C-21*(12), 1365-1373.

Sue, D., Sue, D., Sue, S. (1994). *Understanding Abnormal Behavior.* Princeton, NJ: Houghton Mifflin.

Sutherland, S. (1989). *The International Dictionary of Psychology.* New York: Continuum.

Thelen, E. (1995). Motor Development: A New Synthesis. *American Psychologist, 50,* 79-95.

Turing, A. M. (1937). On Computable Numbers. *The Proceedings of the London Mathematical Society, 2,* 230-265.

Turing, A. M. (1948). Intelligent Machinery. *N. P. L. Report of the Controller.* (H.M.S.O. 1-20).

Turing, A. M. (1950). Computing Machinery and Intelligence. *Mind: A Quarterly Review of Psychology and Philosophy, 59,* 433-460.

Waldrop, M. M. (1988). Toward a Unified Theory of Cognition. *Science, 241,* 27-29, 296-298.

Waldrop, M. M. (1992). *Complexity: The Emerging Science at the Edge of Order and Chaos.* New York: Simon & Schuster

Wiener, N. (1954). *The Human Use of Human Beings: Cybernetics and Society.* New York: Doubleday Anchor.

Wiener, N. (1957). *Cybernetics: Or control and communication in the animal and the machine.* New York: Wiley.

Winston, P. H. (1992). *Artificial Intelligence.* Chicago: Addison-Wesley.