

# **Nonconvergent Dynamics and Cognitive Systems**

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### **Abstract**

The conditions and mechanisms for producing general intelligent action in agents are the focus and proper study of cognitive science. Many such positions have been proposed, including symbolic and connectionist viewpoints. New points of view are beginning to emerge, including embodied and dynamical cognition, but have not yet been fully solidified into a single comprehensive position. In this article we present one such new viewpoint that emphasizes the importance of nonconvergent dynamics to the production of general intelligent behavior. This approach represents a fourth generation of connectionist thought, and is informed from new results in neuroscience and computational neurodynamics. We formulate the necessary and sufficient conditions for the production of intelligent behavior in this approach to cognition and introduce one such model capable of meeting these conditions.

### **Keywords**

computational neuroscience, cognitive architecture, nonlinear dynamical systems

## Nonconvergent Dynamics and Cognitive Systems

What are the mechanisms by which biological organisms, including human beings, produce general intelligent actions in order to survive, reproduce and thrive in their environment? This, in some form, is one of the basic questions that lies at the heart of cognitive science. Various ideas have been put forward as possible answers to this question. Metaphors of cognition have been inspired from the advanced technologies of the times, including hydraulic, phone switchboard and computer metaphors (Von Neumann, 1958). Inspiration has been sought from the realms of formal logic as the means of general intelligent action. Others have looked to abstracted models of how neural tissue functions as possibly holding the key insights to the production of intelligent behavior.

Historically the study of psychology has been focused on discovering the correlations and laws of human and animal intelligent behavior. Another way of saying this is that it has been focused on figuring out the *what* questions of intelligent behavior. *What* are the capacities of long and short term memory? *What* are the learning gains observed in different tutoring and lecturing strategies? Cognitive science, and especially the areas of AI and cognitive modeling, have on the other hand been studying the structures and mechanisms used by people and animals to support general intelligent behavior, and sometimes specifically what mechanisms could account for the properties observed by psychological studies. This approach to studying intelligent behavior can be thought of as asking the *how* questions. *How* can a collection of simple processors store, recognize and complete patterns? *How* does brain architecture result in emotion?

Alan Turing, with his famous and eponymous *Turing Test* suggested that intelligence is a matter of behavior or behavioral capacity (Haugeland, 1997; Turing, 1950). Whether a system has a mind, and how intelligent that mind is, is determined by what it can and cannot do. In the *Turing Test*, therefore, language ability and capacity is proposed as the behavior by which we can determine if a system has a general intelligent ability at or above the level of human beings.

Turing did not claim that a system would not be intelligent if it could not pass his test; only that it **would** be intelligent if it could. Therefore the *Turing Test* provides a sufficient condition for detecting the presence of general human level intelligence (though not a necessary one).

Intelligent behavior really lies on a continuum, from simple tropic behaviors of single celled organisms to tool and language use of human beings. We could imagine defining levels or categories of intelligence, each with an appropriate Turing-like behavioral test that could be used to determine inclusion of a system in a category. Such tests would necessarily not be of language use, but could test things like memory capacity (short, and long term), opportunistic vs. goal orientation and problem solving in unique situations. Such tests would give us the ability to state the necessary capacities and behaviors that need to be present to include a system in a certain level of intelligence.

Being able to define and detect levels of intelligence through outward behavioral characteristics is an important piece in the study of intelligent behavior. However, since the rejection of behaviorism and the rise of AI and cognitive science, we have not only been interested in the necessary behavioral characteristics that let us detect intelligence, but also in the types of internal mechanisms and processes that might be necessary and sufficient to produce such observed behaviors. The opening up of the study of intelligence to include internal mechanisms has allowed us to attack the problem both from the outside in, and from the inside out.

Once we begin studying the possible mechanisms of intelligence, it is natural to ask if there is any simplest set or category of mechanism that is both sufficient and necessary for the production of general intelligent behavior. Given that there are different levels of intelligence, are different mechanisms needed to achieve these different levels, or can the same mechanisms be used, only expanded to do more. Previous attempts to define such conditions have focused on things like the ability of formal logic like symbol manipulations to perform tasks we usually think of as intelligent, like playing chess or planning a sequence of tasks to perform a goal (Newell, 1980,

1990). Another major movement has focused on the power of simple non-linear processing units to remember, recognize and complete patterns (Werbos, 1974; Rumelhart, McClelland, & The PDP Research Group, 1986).

Another way of discovering the constraints of intelligence, besides psychological experimentation, is to directly observe the workings of the only known systems that are capable of general intelligent behavior, biological brains. These types of direct measuring of neurological functioning through such methods as EEG recordings and brain imaging techniques have provided us with valuable further constraints on the possible sufficient and necessary dynamics involved in cognition. Such understanding led directly to early connectionist modeling results, and is leading us even further in new directions.

Biological brains are awash in complex, nonconvergent dynamics. Such complex dynamics have usually been abstracted away in connectionist models, with the assumption that they are not necessary to the production of intelligent behavior. However, new ideas in nonlinear dynamical systems theories, both inside and outside of cognitive science, have begun to understand the possible important roles that aperiodic dynamics, such as chaos, may play in self-organizing systems.

Some researchers in dynamical cognition and neurodynamics have speculated on the possibilities that more complex, chaotic like dynamics may play in the role of adaptive behavior (Skarda & Freeman, 1987; Freeman, 1999; Freeman, Kozma, & Werbos, 2000; Kozma & Freeman, 1999, 2000, 2001). Chaotic dynamics have been observed in the formation of perceptual states of the olfactory sense in rabbits (Skarda & Freeman, 1987). Skarda and Freeman have speculated that chaos may play a fundamental role in the formation of perceptual meanings. Chaos provides the right blend of stability and flexibility needed by the system. Essentially, Skarda and Freeman believe that the normal background activity of neural systems is a chaotic state. In the perceptual systems, input from the sensors perturbs the neuronal ensembles from the

chaotic background, and the result is that the system transitions into a new attractor that represents the meaning of the sensory input, given the context of the state of the organism and its environment. But the normal chaotic background state is not like noise. Noise cannot be easily stopped and started, whereas chaos can essentially switch immediately from one attractor to another. This type of dynamics may be a key property in the flexible production of behavior in biological organisms.

The possible importance and uses of aperiodic dynamics to intelligence has not yet been fully explored in cognitive science. In this paper we demonstrate why aperiodic dynamics may be important to intelligent behavior, and define the necessary and sufficient conditions for general intelligent behavior if it is true that such dynamics play a crucial role in cognition. We will then present one such model capable of producing aperiodic dynamics for use in perceptual, memory and behavior producing systems.

### Theories and Conditions of Cognition

#### *Symbolic Systems*

The symbolic approach to cognition can best be seen in Newell and Simon's *physical-symbol system hypothesis* (Newell & Simon, 1972, 1976; Newell, 1980, 1990). A physical-symbol system is a physical device that contains a set of interpretable and combinable items (symbols) and a set of processes that can operate on the items (copying, conjoining, creating, and destroying them according to instructions) (Newell & Simon, 1976, p. 86). The physical-symbol system hypothesis states that a physical symbol system has the necessary and sufficient means for general intelligent action (Newell & Simon, 1976, p. 87). This is a strong empirical claim on the nature of intelligence. It states that any system that manipulates symbols is sufficient for producing intelligent behavior, and further that all intelligent systems are necessarily implementations of physical-symbol systems.

In practical terms, the types of syntactic manipulation of symbols found in formal logic and

formal linguistic systems typifies this view of cognition. In this viewpoint, external events and perceptions are transduced into inner symbols to represent the state of the world. This inner symbolic code stores and represents all of the system's long-term knowledge. Actions take place through the logical manipulation of these symbols to discover solutions for the current problems presented by the environment. Problem solving takes the form of a search through a problem space of symbols, and the search is performed by the logical manipulation of the symbols through stated operations (copying, conjoining, etc.). These solutions are implemented by forming plans and sending commands to the motor system to execute the plans in order to solve the problem. In the symbolic viewpoint, intelligence is typified by and resides at the level of deliberative thought. Modern examples of systems that fall within this paradigm include SOAR (Laird, Newell, & Rosenbloom, 1987) and ACT-R (Anderson, Silverstein, Ritz, & Jones, 1977).

Discrete symbolic systems do have a competitor within the symbolic paradigm. These models in general use probabilistic declarative structures and are often referred to as gradient models. They are motivated by psychological findings that membership in human categories is often not black and white. People have ideas on the degree to which a certain example belongs in a category, and they have notions of the prototypical member of a category. For example, a robin might be many peoples quintessential idea of a member of the 'bird' category, while a penguin has some decidedly unbirdlike characteristics (swims, doesn't fly) which makes it seem not 100% part of the category of 'bird'. Discrete symbolic systems have been criticized as unhumanlike in this regard when trying to form perceptual categories (though see (Miller & Laird, 1996), for attempt to allow discrete symbolic symbols to display graded responses).

Symbolic systems are often equated with the machine metaphor of mind. In this viewpoint of cognition, the brain is seen in some sense as a computer. The physical brain represents the hardware of the system, and the mind represents the software. The machine metaphor is a very attractive position for many reasons. It explains how the mind connects with and controls the

body, the old mind-body problem, in a way that does not resort to a form of dualism.

The symbolic approach works well as a model of cognition, and is capable of modeling many impressive examples of intelligent behavior in AI. However, challenges to this viewpoint of cognition have appeared, both as practical criticisms of the performance of such systems and more philosophical challenges to the physical-symbol system hypothesis.

On the practical side, symbolic models are notoriously inflexible and difficult to scale up from small and constrained environments to real world problems. If symbolic systems are both necessary and sufficient for intelligent behavior, why do we seem to have such problems in producing the flexibility of behavior exhibited by biological organisms?

The inability of symbolic systems to cope with such problems has lead many to a new viewpoint of cognition. When one views cognition as mainly working on the level of deliberative thought, then the hard problems of intelligence appear to be those such as logic and language use. From this viewpoint, the abilities of organisms to orient themselves spatio-temporally, form perceptual categories and develop basic motor skills seem to be easy problems that can be immediately solved once basic systems exist to take care of the harder problems of deliberative thought. But if the physical-symbol system hypothesis does not hold and deliberative thought is not the basic level where intelligence resides, then this viewpoint may be exactly backwards. Those abilities that are so easily dismissed as simple because all children learn them with seeming effortless are instead seen as complex and essential to cognition. Perhaps it has taken most of the time of evolution to solve these basic features of intentional activity, and language and logic are phylogenetically more recent and comparatively easy to solve once the proper base of spatio-temporal skills is in place to support them.

### *Connectionist Systems*

A connectionist view of cognition provides an alternative theory of mind to the symbolic approach. The connectionist approach to cognition has existed for as long as the symbolic



approach. However, symbolic viewpoints of cognition have dominated the field of cognitive science until a resurgence of interest in connectionist models in the mid '80s.

The connectionist approach differs from the symbolic paradigm in almost all major dimensions. Connectionist models offer a subsymbolic paradigm, where representations are built from the changing contributions of processing units that represent features below the normal level of human symbolic features. Connectionist models emphasize parallel processing, while symbolic systems tend to process information in a serial fashion. Connectionist representations are distributed over many units, while cognitivist symbols are static localized structures. Connectionist models offer many attractive features when compared with standard symbolic approaches. They have a level of biological plausibility absent in symbolic models that allows for easier visualization of how brains might process information. Parallel distributed representations are robust, and flexible. They allow for pattern completion and generalization performance comparable to biological organisms. They are capable of adaptive learning. In short, connectionist models are an attractive alternative model of cognition.

The connectionist hypothesis might be stated as: large-scale parallelism of (relatively simple) non-linear processing units doing local processing and producing distributed representations are necessary and sufficient to the production of general intelligent behavior.

*First Generation* Clark (2001) categorizes modern connectionism into three generations. The first-generation of connectionism, that began with the perceptron and the work of the cyberneticists (Rosenblatt, 1958; McCulloch & Pitts, 1943), was revived in the mid '80s with the PDP research groups work (among others) on parallel distributed processing (Rumelhart et al., 1986). First-generation connectionist systems were typified by a multi-layer architecture (usually composed of two or three layers) with strictly feed-forward connections. Backpropagation learning rules have been especially successful in the proliferation of these models (Werbos,

1974). Such architectures are very familiar to practitioners of AI and Neural Network research. These connectionist models of cognition are very attractive and important for many reasons. They are biologically plausible models with some of the flexibility of pattern-recognition and generalization exhibited by biological organisms.

*Second Generation* Second-generation connectionism began to appear in the early '90s. Second-generation connectionism extends first-generation networks to begin to deal effectively with dynamic spatio-temporal events. First-generation networks displayed no real capacity to deal with time or order in the environment. Second-generation connectionist systems added recurrent connections to the networks in order to expand these capabilities (Elman, 1990, 1991). Recurrent connections are connections that connect later layers in the network with earlier layers. So second-generation connectionist networks are no longer strictly feed-forward, they contain recurrent connections. The addition of recurrent connections allows for previous states of the network to affect decisions about the current input. In essence, recurrent connections provide a type of short term memory that allows for the categorization of patterns extended in time across the inputs of the network. This ability to deal with spatio-temporally extended patterns in time is an important addition to the capabilities of connectionist systems.

*Third Generation* Third-generation connectionism is the most recent extension of the connectionist paradigm. This generation of models is typified by even more complex dynamic and time involving properties. These models use more complex, and biologically inspired architectures, along with various recurrent and hard-coded connections. So, for example, rather than the typical three layers of first and second generations, third-generation networks may have many areas that represent and reflect architectures and subsystems of biological brains. Because of the increasing emphasis on dynamic and time properties, third-generation connectionism has

also been called dynamic connectionism. See Figure 1 for a summary of Clark's classification of connectionist generations.

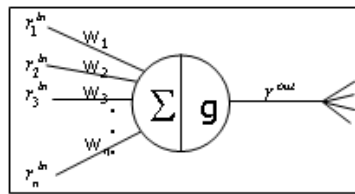
### Nonlinear Dynamics and Cognitive Systems: The Fourth Generation

Biological brains exhibit aperiodic oscillations with a much more rich dynamical behavior than fixed-point and limit-cycle approximation allows. Early connectionist systems captured some of the flavor of neuronal functioning, but abstracted away much of this rich dynamical behavior in favor of simple fixed-point dynamics (Hopfield, 1982; Grossberg, 1980; Kohonen, 1972; Anderson et al., 1977). Second and third generation systems recapture some of the more complex dynamics because of recurrent connections and specialized architectures, but many are still parameterized to ultimately settle down to fixed-point attractors. The question of what use, if any, aperiodic dynamics may play in cognition has largely been ignored, or its possible significance unrealized. The exploration of nonconvergent dynamics in cognitive processes may constitute the fourth generation of connectionist thought in its evolution towards capturing more of the dynamics and functioning of biological brains. In this section we will argue that, far from being unnecessary noise of no use in cognition, aperiodic dynamics are necessary for general intelligent behavior.

#### *Nonlinear Dynamics in Science*

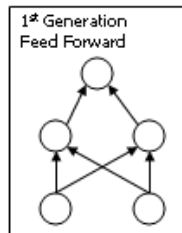
The study of nonlinear dynamics has blossomed in all areas of science in the past decades for many reasons. Nonlinear dynamics provide new conceptual and theoretical tools that allow us to understand and examine complex phenomena that we have never been able to tackle before. Nonlinear dynamics seem to show up everywhere, in physical systems like electrical circuits, lasers, optical and chemical systems. But we especially see its ubiquity all around us in the biological world, from fractal growth patterns in biological development and city formation to the self-organizing characteristics of population models, and the importance in regulating healthy biological rhythms such as the beating of the heart.

- **Generation 0**
  - McCulloch-Pitts Sigma Node, Perceptron



- **3<sup>rd</sup> Generation**
  - Dynamical connectionism
  - Neurobiological Realism
  - Multiple recurrent paths
  - Time delays
  - Noise

- **1<sup>st</sup> Generation**
  - Multi-Layer
  - Strictly feed-forward



- **2<sup>nd</sup> Generation**
  - Recurrent (Elman) nets
  - Temporal structure

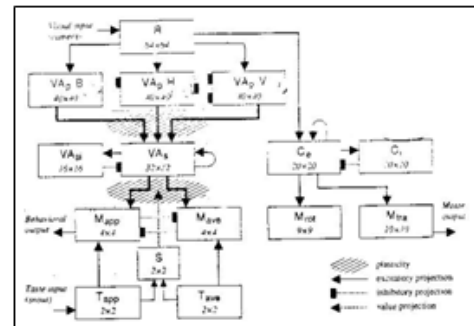
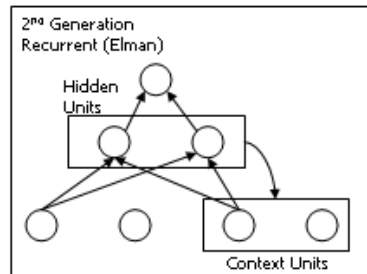


Figure 1: Clark’s (2001) classification of generations of connectionist systems. Connectionist models have been moving towards more biological architectures, recurrent connections and time-varying dynamics

The study of nonlinear dynamics is concerned with systems whose time evolution equations are nonlinear. But why is nonlinearity an important property of systems? Simply put, in a linear system if you change a parameter or perturb the system, the amplitude and frequency of the system may change, but the qualitative nature of the behavior will remain the same. For example, perturbing an oscillating pendulum does not change the fact that it continues to oscillate with a regular harmonic motion. In a nonlinear system, however, this fact does not hold. Perturbations of the system can cause a qualitative change in the behavior of the dynamics. A small perturbation can cause sudden and dramatic changes in both the qualitative and quantitative behavior of the system (Hilborn, 1994).

This property of nonlinear systems is important in at least two ways. A nonlinear system exhibiting aperiodic dynamics is constantly generating and exploring unique areas of its possible behaviors. This generation of diversity can be a very important property in producing flexible, intelligent behavior. Also, random environmental perturbations can be handled by a nonlinear process, where they would be disastrous to a linear one. For example, a random perturbation to a portion of beating heart muscle fiber that was governed by a linear oscillation would cause the fiber to beat in a new period, possibly conflicting with other areas and leading to fibrillation. Nonlinear processes governed by an attractor can become entrained to one another, and even in the face of random perturbations they will eventually settle back down to beat in synchrony. Nonlinear processes are able to handle random environmental perturbations, but still maintain coherent dynamical state. Linear processes are destroyed by randomness.

Really, nonlinear dynamics are the rule not the exception in systems observed in nature. Almost all real systems are nonlinear at least to some extent. Classical physics and science has been surprisingly successful in using idealized linear approximations to model many physical processes. The range of phenomena that could not be handled successfully by linear approximation was however much greater. But some phenomena at least are beginning to be

understood through the application of nonlinear dynamics. To quote a famous mathematician Stanislaus Ulam, “Calling the subject nonlinear dynamics is like calling zoology ‘nonelephant studies’ ” (Gleick, 1987). The study of linear systems restricts science to only a very small portion of the vast range of possible dynamics. The complex behavior of the brain, we would argue, is one such phenomena where the application of nonlinear dynamical modeling can yield greater understanding.

In a sense, symbolic systems seem to belong in the classical vein of using a linear approximation to model a phenomenon. In this case the systematic application of formal logic to the tasks of problem solving and memory. But these systems suffer the same weaknesses that all linear approximations share. Unexpected situations or perturbations cannot be handled by such models. We will next look at some of the evidence for nonlinear dynamics in the functioning of perceptual neurological functioning.

#### *Nonconvergent Dynamics for Perception*

In their influential paper, Skarda and Freeman (1987) argued that chaos, as an emergent property of intrinsically unstable neural masses, is very important to brain dynamics. In experiments carried out on the olfactory system of trained rabbits, Freeman was able to demonstrate the presence of chaotic dynamics in EEG recordings and mathematical models. In these experiments, Freeman and his associates conditioned rabbits to recognize smells, and to respond with particular behaviors for particular smells (e.g. to lick or chew). They performed EEG recordings of the activity in the olfactory bulb, before and after training for the smells.

The EEG recordings revealed that in fact, chaotic dynamics (as shown by the observed strange attractors) represented the normal state when the animal was attentive, in the absence of a stimulus. These patterns underwent a dramatic (nonlinear) transition when a familiar stimulus was presented and the animal displayed recognition of a previously stored memory (through a behavioral response). The pattern of activity changed, very rapidly, in response to the stimulus in

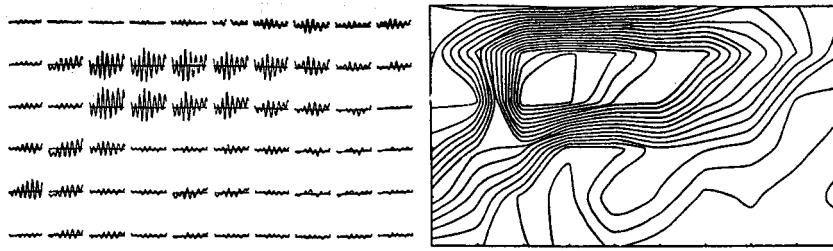


Figure 2: EEG carrier wave patterns (left) and contour map (right) of olfactory cortex activity in response to a recognized smell stimulus (from Freeman, 1991, p. 80)

both space and time. The new dynamical pattern was much more regular and ordered (very much like a limit cycle, though still chaotic of a low dimensional order). The spatial pattern of this activity represented a well defined structure that was unique for each type of odor that was perceptually significant to the animal (e.g. conditioned to recognize). Figure 2 shows an example of such a recorded pattern after recognition of a stimuli of the EEG signals and the associated contour map. In this figure after recognition, all of the EEG waves are firing in phase, with a common frequency (which Freeman called the carrier wave). The pattern of recognition is encoded in the heights (amplitude modulations) of the individual areas. The amplitude patterns, though regular, are not exact limit cycles and exhibit low dimensional chaos. In other words, different learned stimuli were stored as a spatio-temporal pattern of neural activity, and the strange attractor characteristic of the attention state (before recognition) was replaced by a new, more ordered attractor related to the recognition process. Each (strange) attractor was thus shown to be linked to the behavior the system settles into when it is under the influence of a particular familiar input odorant.

Figure 3 shows the effects on the spatial attractor pattern due to learning. Every time a new odor was learned by the animal, all of the existing attractor patterns changed. In this figure the contour pattern of activity for sawdust is shown (before learning the banana odor), for the banana

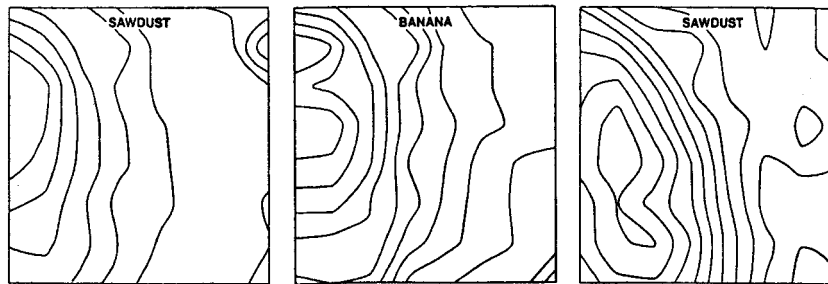


Figure 3: Change in contour maps of olfactory bulb activity with the introduction of a new smell stimulus (from Freeman, 1991, p. 81)

odor, and then again for sawdust. Notice that the spatial pattern for sawdust no longer resembles its previous pattern. Whenever an odor becomes meaningful in some way, changes in the synaptic connections between neurons in different parts of the olfactory cortex take place. Just as in the Hopfield model and other neural networks, these changes are able to create another attractor, and all other attractors are modified as a result of this learning. However, in real brains, the attractors of perceptual meaning are not simple point attractors, but are specific strange attractors.

Freeman suggests that “an act of perception consists of an explosive leap of the dynamic system from the basin of one (high dimensional, in the attentive state) chaotic attractor to another (low dimensional state of recognition) (Freeman, 1991). These results suggest that the brain maintains many chaotic attractors, one for each odorant an animal or human being can discriminate. Freeman and Skarda speculate on many reasons why these chaotic dynamics may be advantageous for perceptual categorization. For one, chaotic activity continually produces novel activity patterns which can provide a source of flexibility in the individual. But since chaos is a ordered state, such flexibility is under control. As Kelso remarks, such fluctuations continuously probe the system, allowing it to feel its stability and providing opportunities to discover new patterns (Kelso, 1995). Another advantage of chaos is that it allows for very rapid switching between attractors, which random activity is not able to do. Freeman also proposed that



such patterns are crucial to the development of nerve cell assemblies. For example high dimensional chaos may provide a neutral pattern of correlation activity so that learning does not occur during the attentive state. Only upon collapse of activity to more ordered regions do regular phase synchronizations occur between neural areas, which allow for hebbian synaptic changes to reliably occur.

*Necessary and Sufficient Conditions of Nonconvergent Dynamical Viewpoint*

Aperiodic dynamics play a significant role in the organization of perceptual mechanisms in biological organisms. The presence of self-organizing critical states have also been detected in other brain systems. These observations have led to the hypothesis that such dynamics are ubiquitous in brains, and are necessary to the flexible organization of biological behavior. Symbolic systems provide little insight into how they may be connected with an environment and generatively construct knowledge about the world they experience. Looking at symbolic systems as models of biological cognition, they are also silent on why such aperiodic dynamics appear in biological brains. Classical connectionist systems have yet to explore the uses of aperiodic dynamics in memory and action.

These observations of the possible significance of nonconvergent dynamics in brains has led us to speculate on the necessary and sufficient conditions they suggest. Specifically:

- Complex, nonconvergent dynamics are necessary to the production of general intelligent behavior.
- An embodied system with appropriate environmental/sensory coupling and internal structural systems for handling the “what”, “where”, “why” and “how” functions of the agent are necessary to the production of general intelligent behavior.
- The exploitation of nonconvergent dynamics by and within such an appropriately embodied system are necessary and sufficient for producing general intelligent behavior.

In essence we have proposed two conditions for the production of general intelligent behavior. Aperiodic dynamics characteristic of critical states are necessary for the flexible self-organization of memory and behavior. The dynamics of the brain are strongly coupled with their environment. The interaction of brain dynamics with the environmental system produces behavior. We will explore these issues further in the next section, where we describe one such model of cognition.

#### A Necessary and Sufficient Model for the Production of General Intelligent Behavior

The discovery that brain dynamics exhibit chaotic features, and further, that these dynamics may be necessary for the self-organization of intelligent behavior has a profound impact on the types of theories we should propose to explain cognition. In this section we present one such model that is capable of meeting the necessary conditions for the production of general intelligent behavior outlined above.

##### *K Set Primer and History*

The K-set hierarchy, developed by Walter J. Freeman and associates (Freeman, 1975, 1999; Skarda & Freeman, 1987; Freeman, 1991), is both a model of neural population dynamics and a description of the architectures used by biological brains for various functional purposes. The lowest level of the hierarchy, the K0 set, provides a basic unit that models the dynamics of a local population of tens of thousands of neurons. The dynamics of the K0 set are described by a second order ordinary differential equation feeding into an asymmetric sigmoid function:

$$ab \frac{d^2 x(t)}{dt^2} + (a + b) \frac{dx(t)}{dt} + x(t) = f(t) \quad (1)$$

This equation was determined by measuring the electrical responses of isolated neural populations to stimulation and other conditions. The  $a$  and  $b$  parameters are time constants that were determined through such physiological experiments.  $x(t)$  is the pulse density of the modeled neural population, in other words the average number of neurons that are pulsing in the

population at any given point in time.  $f(t)$  is a nonlinear asymmetric sigmoid function describing the influence of incoming activation.

A K0 unit models the dynamics of an isolated neural population. From the basic K0 unit can be built up architectures that capture the observed dynamics of increasingly larger functional brain areas. The KI models excitatory-inhibitory feedback populations. KII models interacting excitatory-inhibitory populations and correspond to organized brain regions such as the olfactory bulb (OB) or the prepyriform cortex (PC). KIII combine 3 or more KII populations to model functional brain areas such as cortex or hippocampus, and are capable of aperiodic dynamics of the type observed in these regions to, for example, derive meaning from perceptual senses. KIV is a model of the basic limbic system, combining KIII sets, to model the "what" (perceptual), "where" (hippocampal orientation memory), "why" (forebrain value system) and "how" (motor control) of a basic embodied biological agent. The KIV level theoretically is sufficient for the production of general intelligent behavior such as that observed in reptiles and simple mammals. Table 1 summarizes the K-set hierarchy described above.

The KI set provides a form of positive feedback. In a KI set, two or more excitatory populations are connected to one another. Their mutual excitation allows for the populations to maintain their activation levels at a steady non-zero state. The KII set allows for a form of negative feedback to be used by neural populations. In a KII, inhibitory populations are connected with excitatory populations. As the excitatory population becomes more active it begins to more actively stimulate the inhibitory population. The inhibitory population, in turn, then inhibits the excitatory population and through a process of negative feedback maintains the dynamics of the system within certain bounds. Negative feedback is a well known process of homeostatic control and is used extensively in artificial systems such as a thermostat to maintain a constant room temperature. Negative feedback is characterized by damped oscillatory or cyclic behavior. Positive and negative feedback are well known properties of biological systems and were first

Table 1: Characterization of the hierarchy of K sets.

Type	Structure	Inherent dynamics	Examples in brain*
K0	Single unit	Nonlinear I/O function	All higher level K sets are composed of K0 units
KI	Populations of excitatory or inhibitory units	Fixed point convergence to zero or nonzero value	PG, DG, BG, BS
KII	Interacting populations of excitatory and inhibitory units	Periodic, limit cycle oscillations; frequency in the gamma band	OB, AON, PC, CA1, CA3, CA2, HT, BG, BS, Amygdala
KIII	Several interacting KII and KI sets	Aperiodic, chaotic oscillations	Cortex, Hippocampal Formation, Midline Forebrain
KIV	Interacting KIII sets	Spatio-temporal dynamics with global phase transitions (itinerancy)	Hemisphere-wide cooperation of cortical, HF and MF areas coordinated by the Amygdala

\* Notations: PG - periglomerular; OB - olfactory bulb; AON - anterior olfactory nucleus; PC - prepyriform cortex; HF - hippocampal formation; DG - dentate gyrus; CA1, CA2, CA3 - cornu ammonis sections of the hippocampus; MF - midline forebrain; BG - basal ganglia; HT - hypothalamus; DB - diagonal band; SP - septum

explored extensively for control of systems by cyberneticists (Wiener, 1965).

In the original K model, the purpose of the KIII set was to model the chaotic dynamics observed in rat and rabbit olfactory systems (Freeman, 1987; Shimoide, Greenspon, & Freeman, 1993; Freeman & Shimoide, 1994). KII are capable of oscillatory behavior, as described above. When three or more oscillating systems (KII) of different frequencies are connected through positive and negative feedback, the incommensurate frequencies can result in aperiodic dynamics. The dynamics of the KIII are produced in just this manner, by connecting three or more KII units of differing frequencies together. The KIII set was not only capable of producing time series similar to those observed in the olfactory systems under varying conditions of stimulation and arousal, but also of replicating power spectrum distributions characteristics of biological and natural systems in critical states (Solé & Goodwin, 2000; Bak, Tang, & Wiesenfeld, 1987).

The power spectrum is a measure of the power of a particular signal (or time series as for example that obtained from an EEG recording of a biological brain) at varying frequencies. The typical power spectrum of a rat EEG (see Figure 4, top) shows a central peak in the 20-80 Hz range, and a  $1/f^\alpha$  form of the slope. The measured slope of the power spectrum varies around  $\alpha = -2.0$ .  $1/f^\alpha$  type power spectra are abundant in nature and are characteristic of critical states, between order and randomness, at which chaotic processes operate. Power spectra of biological brains have been observed to vary from  $\alpha = -1.0$  to  $\alpha = -3.0$ . The atypical part of the experimental EEG spectra is the central peak, indicating stronger oscillatory behavior in the  $\gamma$  frequencies. This central peak in the 20-80 Hz range is known as the  $\gamma$  frequency band, and is associated with cognitive processes in biological brains. The K-models are capable of replicating the power spectra of biological EEG signals, as shown in Figure 4, bottom (Harter & Kozma, 2003; Freeman & Shimoide, 1994; Freeman, 1995).

The KIII sets have been shown to be capable of organizing perceptual categories in the fashion observed in biological perceptual systems. The KIII used as such a pattern classifier is

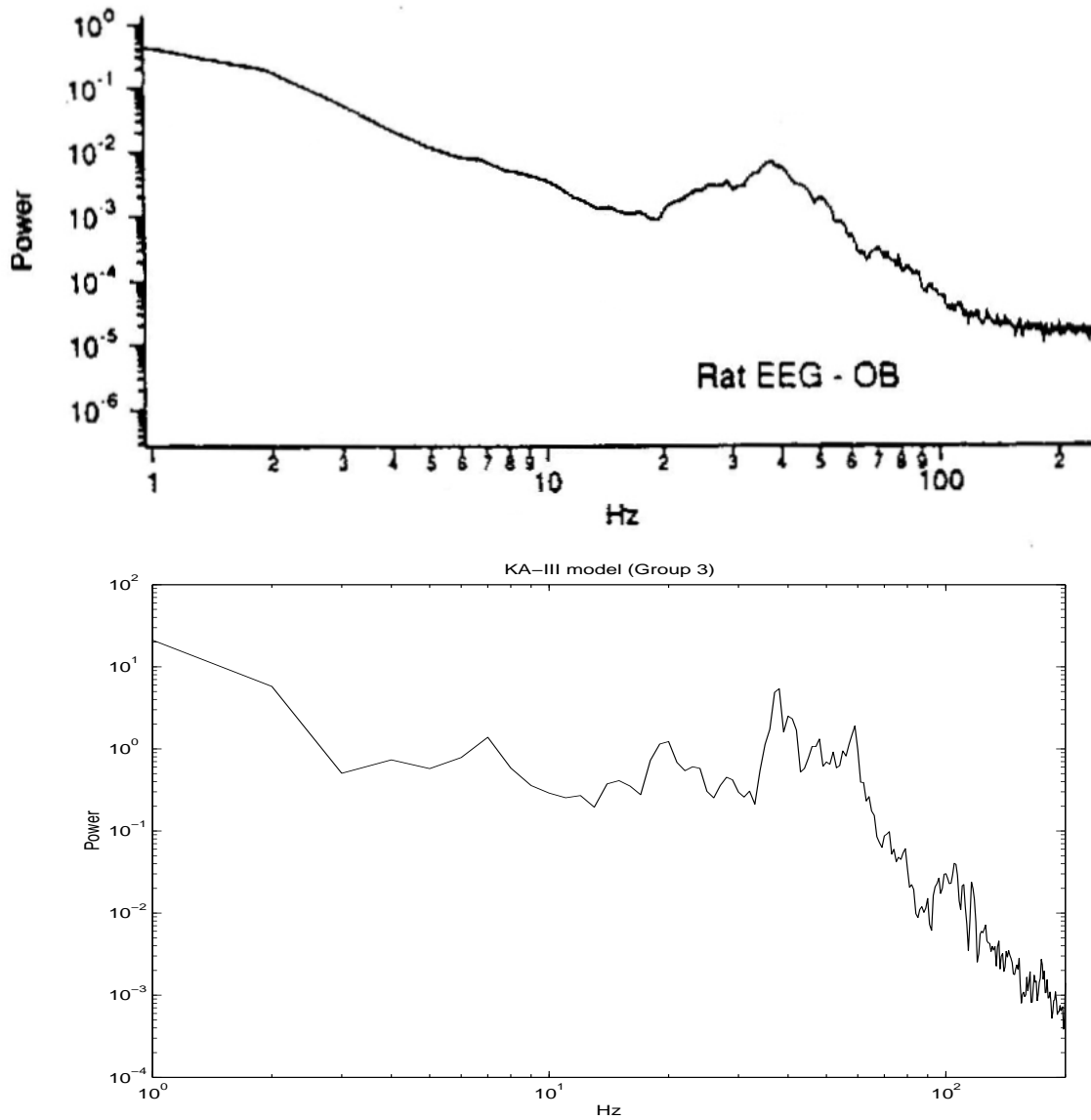


Figure 4: The power spectrum of a rat Olfactory Bulb EEG is simulated with the KA-III model. The calculated “ $1/f$ ” slope of the EEG and model is approximately -2.0. Rat OB data from (Kay et al., 1995), KA power spectrum from (Harter & Kozma, 2003)

very robust and compares well with more standard methods of pattern classification (Kozma & Freeman, 2001).

The development of the K-set hierarchy from K0 to KIII is necessary for modeling and explaining the the dynamics observed in perceptual processes of biological brains. Not only does it involve positive and negative feedback mechanisms for homeostatic control, but also utilizes aperiodic dynamics for flexible generation and recognition of patterns. Though work through the KIII set have focused on perceptual category formation, there is evidence that the basic units of dynamics developed by the KIII for perception are also used in the organization of memory and behavior dynamics. The expansion of the KIII set to model a complete agent, involving the “What” “Where” “Why” and “How” systems of condition two will be described in the next section.

#### *Limbic System and Intentional Behavior*

Intentional behavior, in the words of Freeman (2000), is:

... an act of observation through time and space, by which information is sought for the guidance of future action. Sequences of such actions constitute the key desired property of free-roving, semi-autonomous devices... Intentionality consists of the neurodynamics by which images are created of future states as goals, of command sequences by which to act in pursuit of goals, of predicted changes in sensory input resulting from intended actions by which to evaluate performance, and modification of the device by itself for learning from the consequences of its intended actions.

Intentionality is a result of the endogenous (e.g. internally generated) construction and direction of behavior into the world. We see it in all biological organisms that select their own goals, balance their activities to satisfy multiple, and sometimes conflicting needs, and learn from experience statistical regularities of their environment that are exploitable for survival. Intentional behavior has very much to do with the coordination of all parts of the body, into focused activity. This type of perceptual awareness and coordination is consistent with the concepts of situated and embodied cognition. As noted before, the successful understanding of intentionality is believed by some to be a more fundamental way of understanding cognition as a

whole, and upon which more deliberative and logical reasoning skills of humans are built.

The concept of intentional behavior has to do with how the biological organism dynamically organizes and constructs goal states and generates behavior to approach, evaluate and satisfy those goals. In a more traditional autonomous agent view, this boils down to solving the action selection problem, but in a way that does not depend on hard-coding the goals and desires into the organism. Instead through normal developmental progressions, such goal states need to be discovered, constructed, and hierarchically organized. Baars, among others, has postulated a hierarchy of goal contexts that provide a focus for attention and action (Baars, 1988). However, little has been proposed on how such a goal hierarchy comes to develop in an organism. Thelen and Smith's concept of the ontogenetic landscape (Thelen & Smith, 1994) provides the beginnings of a metaphorical representation of how a goal hierarchy develops. They believe that skills are developed by the successive formation and dissolution of attractor dynamics. Development is seen, by them, as the hierarchical organization and construction of the ontogenetic landscape in the service of the needs and desires of the organism. This formation of behavioral sequence patterns are what are used to integrate and direct intentional behavior.

Brain scientists have known that the minimal nervous system that is capable of supporting the basics of intentional behavior is the limbic system. Phylogenetically, the development of the basic limbic system first appears in amphibians, such as the salamander. This system is comprised of the phylogenetically oldest parts of the forebrain (involved in interoception and goal formation), along with the paleocortex and the deeper lying motor nuclei, as well as some form of a primitive hippocampus. Figure 5 shows a schematic illustration of a prototypical vertebrate limbic system.

The model of the basic limbic system presented here provides a starting framework upon which to develop models of the formation of hierarchical goal-state dynamics. This basic architecture, along with principles of self-organization and chaotic neurodynamics, provides a framework for the development of intentional behavior in autonomous agents and a better understanding of such mechanisms in real brains.



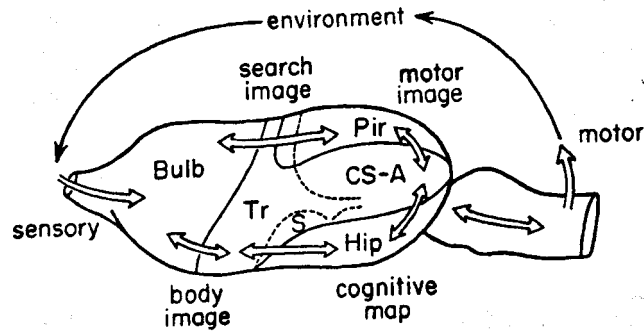


Figure 5: A schematic representation of the basic vertebrate limbic system. There are three major divisions, sensory areas, cortex, and motor areas, along with a hippocampus for cognitive maps and other types of long term memory (from Freeman, 2001)

Intentionality is a particular *level* of intelligent behavior. The category of intentional behavior can be recognized by such behaviors as: goal directed activity but not overly so; performing opportunistic behavior when such opportunities arise; orientation in the environment directed towards the salient goals; basic memory such as episodic and cognitive maps; and hierarchical balancing of multiple sometimes conflicting goals.

The architecture of the limbic system, with its four functional areas, is a necessary condition for achieving a basic level of intentional behavior. Intentional behavior is simpler than general human level intelligence, but it is a fundamental prerequisite for a system to have true intentionality before general human level intelligence can be achieved.

Some simple long-term memory is required for intentional behavior to occur. Without an episodic memory, systems can be stuck in a loop of repetitive, unproductive behaviors, such as observed with wasps and other insects that do not possess the full architecture needed for intentional behavior. Episodic memory allows the cognitive system to recognize such loops (as boredom) and break out of the unproductive behavior by trying something different.

*KIV Model*

As described previously, the purpose of the KIII set is to model the aperiodic dynamics observed in the sensory systems of biological brains, and to begin to understand how such dynamics may take part in the formation of meaning for the organism. While perception is an important component in the production of intelligent behavior, it is only a small part of the whole. One insight of the embodiment movement is that studying pieces of the cognitive puzzle (perception, memory, etc.) may in many cases miss important points on how behavior emerges from the pieces working together as a whole in a complete autonomous agent (Freeman, Burke, & Holmes, 2003).

The KIV architecture is a model of what biologists believe may be the simplest neurological structure capable of basic intentional behavior, the limbic system (Kozma, Freeman, & Erdi, 2003; Kozma & Freeman, 2003). The limbic system is composed of four basic functional areas: sensory/perceptual areas, memory and orientation, value system (needs and goals) and motor systems. These four areas can roughly be described as the “What” “Where” “Why” and “How” functions respectively. Figure 6 is a schematic representation of the KIV model of the limbic system.

The hypothesis captured in the KIV model is that the same types of aperiodic dynamics that have been shown to be crucial to the formation of meaning in perceptual systems are also necessary for the formation of memory and motor maps, as well as the hierarchical organization of competing goals. Therefore, at the heart of the sensory, memory and valence system lies a KIII set, which is capable of producing the requisite aperiodic dynamics. We will describe each of the four areas in detail next.

*What (Sensory/Perception)* As discussed previously, aperiodic dynamics have been observed in rabbit sensory systems, and are believed to play an important part in the formation of meanings. In the KIV architecture, external signals (exteroception) arrive from the environment (Figure 6 top). Each sensory channel is mapped into meanings of interest to the organism, through a

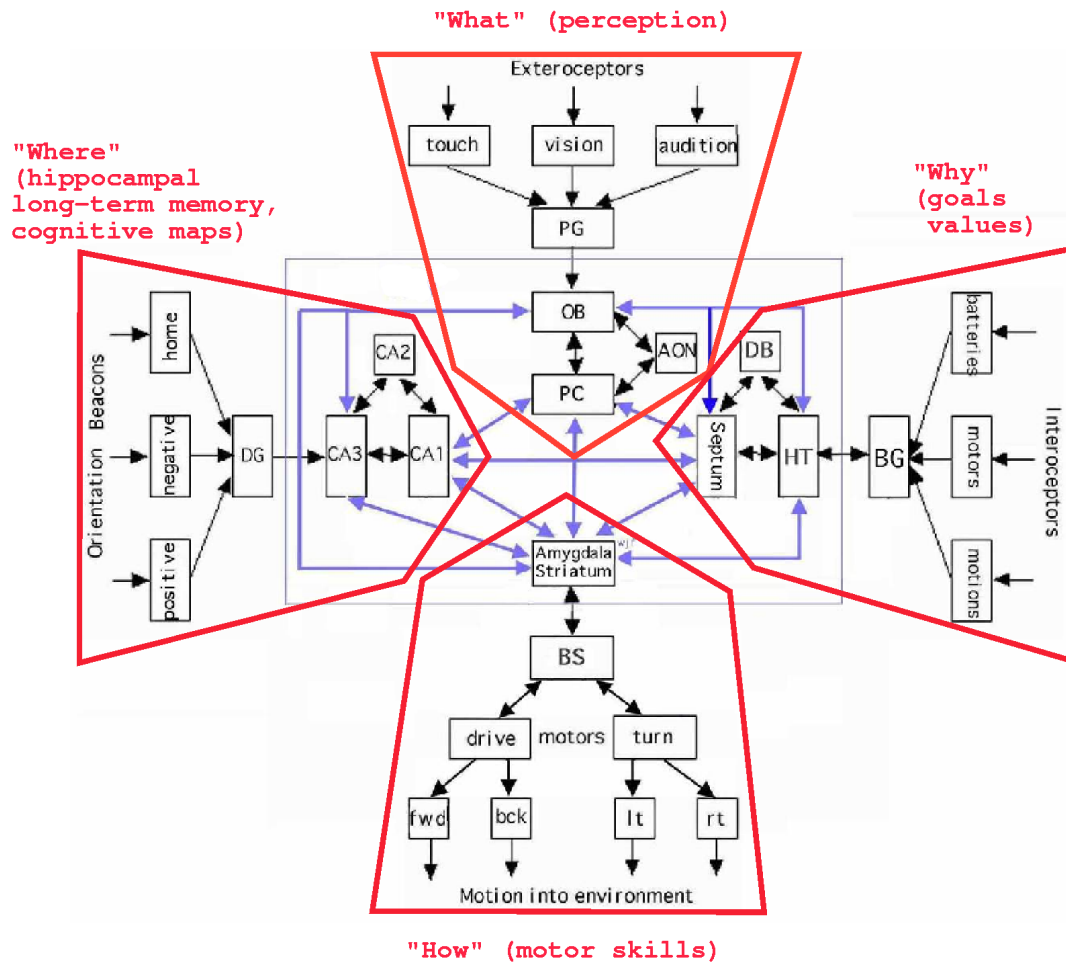


Figure 6: The KIV architecture, an embodied (biologically inspired) model that is capable of the hypothesized necessary conditions of aperiodic computational neurodynamics. See Table 1 for a description of the brain area labels. Based on figure from (Kozma & Freeman, 2003)

process of the formation of chaotic attractors due to learning. In the figure, the OB (olfactory bulb), PC (prepyriform cortex) and AON (anterior olfactory nucleus) are three groups of KII sets that form a sensory KIII. In a full model, each sense would be handled by one or more KIII groups of its own (not shown in figure). The formation and recognition of salient meanings in the environment provide the animal with a sense of “What” important things are in its immediate environment that can or should be dealt with.

*Where (Orientation, Memory)* A primitive hippocampus is the center of more long term memory and orientation functions in simple limbic systems. In the KIV architecture, the formation of cognitive maps of the environment, and the determination of the orientation of the organism in its environment (both locally and globally) is taken care of in the hippocampus. The orientation function of the hippocampus is depicted in the KIV model (Figure 6 left) as receiving orientation signals from the environment. The three CA regions (CA1, CA2 and CA3) form a KIII set that is responsible for the formation of memories of the environment of the organism. The formation of cognitive maps, and so called place cells, in the hippocampus, is performed in the CA KIII set, and takes advantage of the flexibility of aperiodic dynamics to form such representations.

*Why (Goals, Drives, Value Systems)* Figure 6 on the right composes the value system of the KIV architecture, and mediates the production of behavior to guide the organism in completing goals and tasks to satisfy its needs. This system keeps track of the reasons “Why” the organism is doing what it is doing. In the valence system, internal signals that monitor basic needs (such as food, or avoiding damage) are fed into the system (Figure 6 right). Another KII forms the heart of the system for forming and balancing a goal landscape of the organism (HT, DB and septum).

*How (Motor Actions)* The motor system (Figure 6 bottom) is responsible for directing actual effectors for “How” the organism will carry out behaviors in pursuit of its goals. The amygdala provides the goal-oriented direction for the motor system, that is superimposed on local tactile and other protective reflexes.

#### *Learning Mechanisms*

Four types of learning are used in the KIII components to form perceptual categories and other dynamics (Kozma & Freeman, 2001). These types of learning include hebbian type reinforcement, among others. Though not indicated in our necessary and sufficient conditions, these mechanisms are important pieces in the puzzle in how such complex aperiodic dynamics come to represent meanings for a biological organism. The four types of learning are:

- Continual short-term learning of environmental cues at high rates during exploration.
- Intermediate-term habituation to ambiguous, irrelevant, noisy inputs.
- Long-term reinforcement learning at critical situations (aversive or appetitive) using hebbian mechanisms.
- Renormalization as needed to maintain homeostatic stability in all units.

Continual short-term learning provides snapshots of actual sensory states at any given time instant. It provides the information for not only snapshots of actual sensory states, but also sequences of learning such present states and the recent past. This represents the short-term memory function of the organism, and provides a buffer of events that have recently occurred. These events can be passed to more permanent storage when salient events occur to the organism or in the environment to trigger such processes.

Habituation is a diminished response to sensory input. If a sensory signal is repeatedly encountered but it is never associated with any meaningful event to the organism, it gradually

becomes detuned by the short-term sensors and essentially ignored. This is the process by which we, for example, tune out such things as environmental noise like the air conditioner.

Hebbian learning is the process by which salient perceptual events become meaningfully associated with internal goals of the valence system. This type of learning is episodic, not continuous, and it produces more long-term effects. Hebbian learning is a well known mechanism that involves the strengthening of associations between units that tend to become active together. Through this type of reinforcement, environmental cues, such as a ringing bell or a particular smell, can come to be associated with salient events, such as the appearance of a food reward.

The above learning methods implement incremental changes in the KIII components. As KIIs are highly nonlinear units, learning effects may result in undesirable destabilization of the dynamics. Homeostatic regulation is a way of achieving stability by maintaining local balances using renormalization.

### Computational Neurodynamics in Practice

#### *Learning Object Avoidance*

The original K sets are good models of olfactory cortical dynamics. They can replicate the complex dynamics and spectra of biological cortical recordings. Also, not discussed here, the K sets can learn and thereby replicate some of the behavior of rabbits when learning new olfactory sensory stimuli. The K sets have also been extended to more abstract tasks to demonstrate their use in standard pattern recognition tasks (Shimoide et al., 1993; Kozma & Freeman, 2000, 2001).

We are currently extending the K model to not only perform perceptual tasks, but to also model the complete behavior of an organism, from perception to action and the steps needed in between (Kozma et al., 2003). One of the purposes of producing the KA model was to provide a simplified and efficient system that was still capable of producing the types of dynamics deemed important to biological organisms in producing general intelligent behavior. The KA model is a discrete version of the original K sets and is used to experiment with autonomous agents to

replicate and explain the dynamics of cortical systems in organizing and producing behavior (Harter & Kozma, 2003, 2002).

*Agent and Environment Setup* In this section we show an example of using KA units to produce simple behavior in an autonomous agent. We use a set up and task in the Khepera environment that has been explored in the original Distributed Adaptive Control models of Verschure and Pfeifer (Verschure, Kröse, & Pfeifer, 1992). Figure 7 shows the morphology of the Khepera robot and the internal architecture used to perform the experiment. The Khepera robot is a simple robot that contains 8 infra-red (labeled  $IR_{1-8}$  in the figure) and 8 light sensors (not used in this experiment). In this task, the simulated Khepera robot is originally designed with a set of basic reflexive behaviors that allow it to wander around in its environment, bumping into obstacles and moving away from them. For example, if the robot bumps into an object on the left side of its body, it backs up a little and turns away to the right and then attempts to continue forward. We used a virtual simulation of the physical Khepera robot to perform these experiments (Michel, 1996). The Khepera robot is equipped with two independent motors attached to wheels, that allow the robot to move forward, backward and turn.

*Learning Object Avoidance Behavior* In Figure 7B. we show the architecture used to perform the experiment. We hardwire a set of four reflexive behaviors to perform appropriate action sequences to allow the robot to wander in the environment. Three of the behaviors (bump right, bump left, bump front) respond to the robot running into an obstacle (touch) and trigger appropriate behavior sequences to escape from the obstacle (e.g. backup, turn away, then continue forward). The fourth behavior causes the robot to instinctively move forward (wander) whenever there are no obstacles obstructing it. In the experiment, we also have a set of units that are connected to the long range infra-red

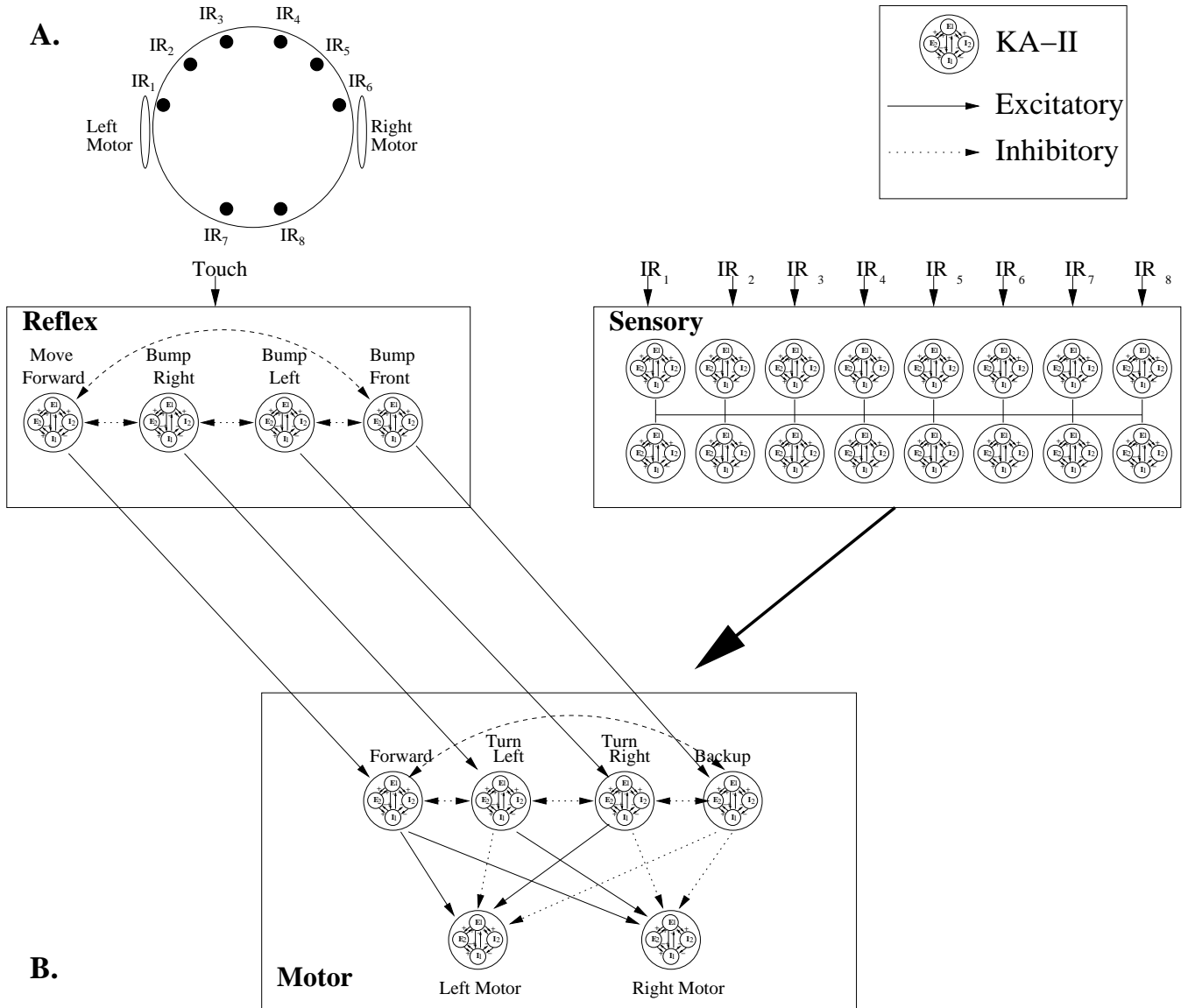


Figure 7: A. The morphology of the Khepera agent with 8 infra red sensors positioned around the body and 2 motors for movement. B. The internal architecture of the Khepera agent. Reflexes are hardcoded to produce exploration of the environment. Sensors gradually learn to produce behaviors to avoid objects at a distance.



sensors (labeled 'Sensory' in Figure 7B.). The infra-red sensors can sense obstacles at a distance from the robot. Initially these senses are connected with random weights to the four basic motor behaviors. All sensory units are fully connected to the four behaviors (not shown in figure). There are 16 KA-II units used in the sensory input, 8 of these units receive direct stimulation from the corresponding infra-red sense, while the other 8 receive the inverse of the infra-red sense. When a unit receives direct stimulation from an infra-red sensor, it becomes most increasingly activated as the sensor approaches an obstacle in the environment. Units that receive inverse stimulation become most highly activated when the obstacle is far away or no obstacle is detected by the sensor. This allows units to be sensitive to both the presence and absence of an obstacle in a particular direction from the robot.

We use Hebbian learning (Kozma & Freeman, 2001) on the connections between the 'Sensory' and the 'Motor' units. Since these connections are initially random, typically they do not affect the behavior of the robot in the beginning. The reflexes cause the robot to move around in the environment. Later on the robot may bump into something on its left. This will cause some of the Motor behaviors to be performed, such as turning right. Since the Sensory units that are connected to sensors on the left side of the body have become stimulated while approaching the obstacle, they remain highly active when the right turn behavior is activated. This allows the strength of the connection between the Sensory unit for detection of obstacles on the left and the right turn behavior to become strengthened due to learning. Similar strengthening takes place between units that sense the absence of obstacles on the right and right turn behavior as well. Eventually the link becomes strong enough to activate the right turn behavior when an object is sensed at a distance, before the robot actually bumps into it. Therefore we can say that the robot has learned a type of object avoidance behavior through coupling of the activity of its sensors with its motor behaviors.

In Figure 8 we show the results of learning object avoidance using the architecture and methods described above. In this figure we show the average performance of the robot over 50

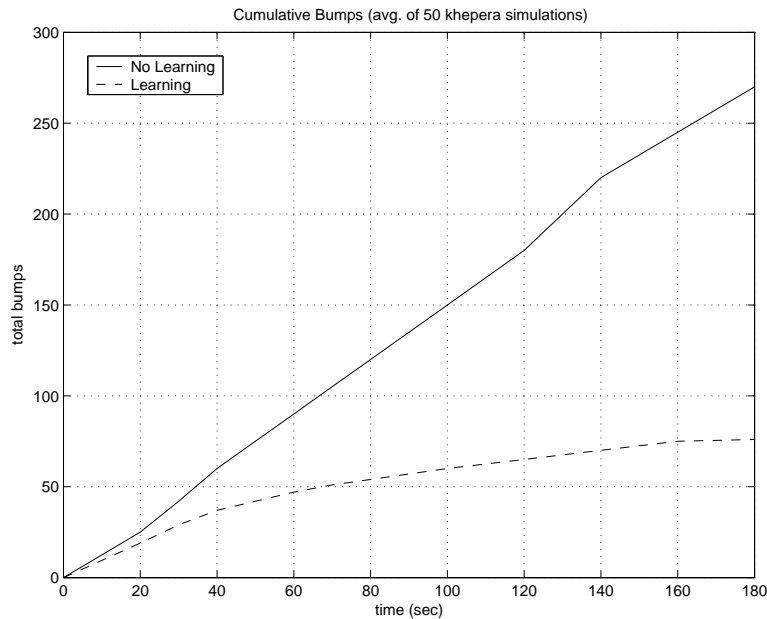


Figure 8: Results of Khepera simulation. As time goes by, the robot learns to bump into things less and less. This figure represents the cumulative results of 50 simulations. Time (in seconds) is along the X axis, and the cumulative bumps is plotted along the Y axis. We show the results without learning (only reflexive behavior) and with learning turned on.

independently conducted simulations. We plot both the results with only reflexive behavior (No Learning) and with the Sensory units connections being manipulated through Hebbian modification (Learning). Along the X axis we show the time (in seconds) that the simulation has been running. We plot the total number of times that the robot has bumped into an object in the environment. In the case of the 'No Learning' condition, the robot continues to move and bump into obstacles in the environment. In the Learning condition, the robot quickly begins to avoid objects, and will eventually learn to move through the environment without bumping into anything at all.

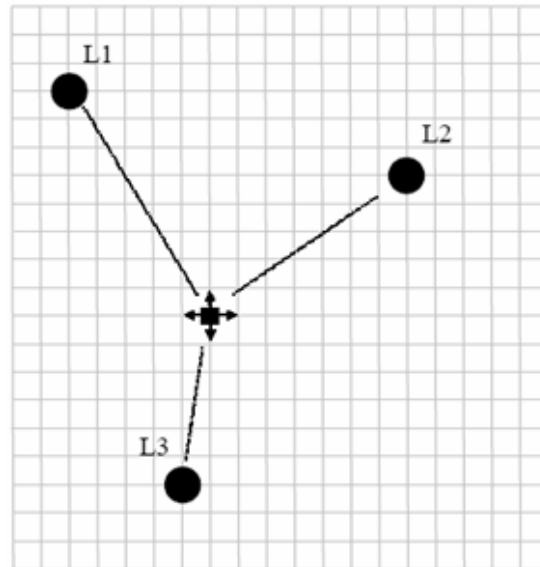


Figure 9: Illustration of the 2D exploration of the environment, which contains three reference points (landmarks): L1, L2, and L3. The orientation information includes the distances and direction toward the landmarks from the present position of the agent. (from (Kozma & Freeman, 2003))

#### *Navigation Using Reinforcement Learning in the Hippocampal KIII*

As another example we present a model of hippocampal cognitive map formation and navigation using a KIII. In this simulation we used a simple 2D environment, where the movement of the agent can take place along a grid. Consequently, at any instance, the agent can move in one of four directions to a neighboring point on the grid. Consider an environment with given reference points/landmarks provided by orientation beacons (Kozma & Freeman, 2003). In a simple example we will consider three orientation beacons; see Figure 9. These could be three point odor sources; three radio beacons, three visual landmarks of different shape or color, etc. One of these reference points is the base (home) location, the starting point for exploratory behavior. The others are learned environmental support cues. There is continuous sampling of the direction and range of the simulated agent to each of these three landmarks.

Orientation beacons describe the actual location of the animal with respect to a reference system that includes home, and both positive (attractive) and negative (repellent) environmental cues. The reference system is not given a priori, rather it develops as a result of the exploratory activity of the agent and its interaction with the environment. The orientation signals are the distances and directions with respect to the landmarks, measured from the actual location of the agent. For the signals, we consider the past several time steps as inputs, in addition to the present time frame.

*Reinforcement Learning in the Exploratory Mode* A practical example is to learn goal-oriented behavior by the agent using three landmarks. In this experiment, the locations of the landmarks are assumed as known. Formation of landmarks based on experience is a key issue in goal-oriented action; see e.g. Mataric and Brooks (1999). In the encoding, we use not only the instantaneous readings of the six inputs (three distances and three angles), but the sequence of the most recent 10 vectors. This means that the input vector to KIII is  $60 = 6 \times 10$  dimensional. Let the agent randomly walk in the environment and record the 6 sensory readings continuously. The path of a random exploration (200 steps) starting from the lower left corner of the rectangular 2D environment is shown in Figure 10.

Apply the continuously measured 60-dimensional input vectors to the hippocampal KIII set for several hundred steps and perform reinforcement learning. If the system moves toward the specified goal location, we reward it by conducting a reinforcement learning loop. On the other hand, no learning takes place, if the randomly selected step was incorrect, i.e., it stepped away from the goal location. Hebbian learning may take place during the window when positive reinforcement is applied (when the robot randomly moves closer to the goal). Hebbian learning is calculated based on the root mean square (RMS) intensity of the signals at each node, within a given time window of duration 128 ms. We use Hebbian learning on the excitatory lateral weights in CA1, following the rule:

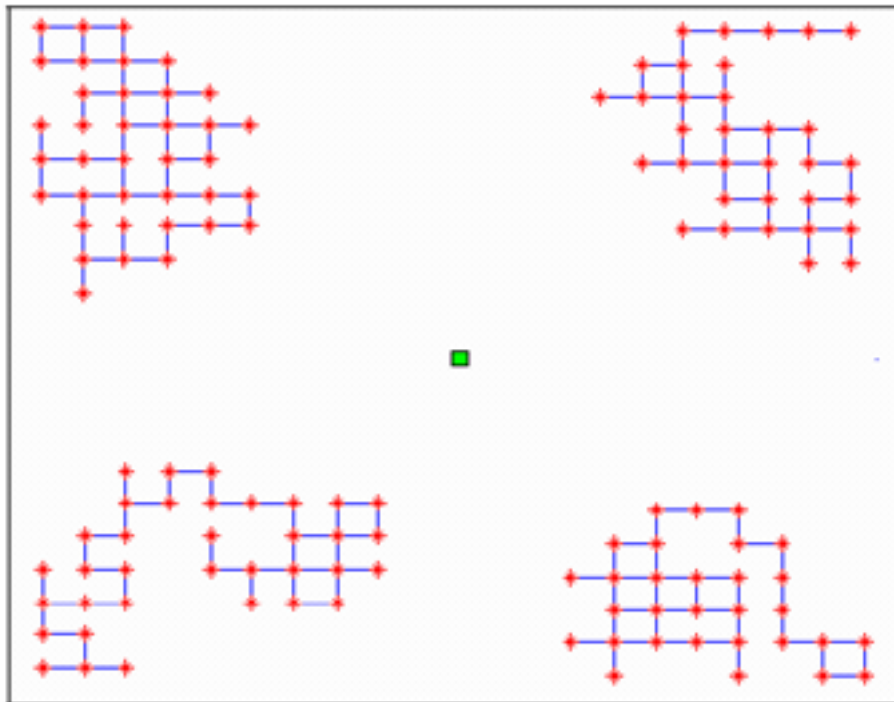


Figure 10: Random exploration of the environment in the hippocampal navigation model. The agent is put in the four corners and left to explore the environment. (from (Voicu et al., 2003)).

$$\Delta w_{ij} = \lambda(RMS_i - RMS_{SEA})(RMS_j - RMS_{SEA}) \quad (2)$$

Here  $\Delta w_{ij}$  is the Hebbian modification of the weight between nodes  $i$  and  $j$ ;  $\lambda$  is the Hebbian learning constant;  $RMS_i$  is the root mean square fluctuation intensity at node  $i$ ;  $RMS_{SEA}$  is the spatial ensemble average fluctuation intensity calculated across all excitatory nodes in CA1. The learning constant  $\lambda$  is experimentally tuned to have optimum performance in the hippocampal KIII set.

*Testing the Performance of Learning in Hippocampal KIII* Once the exploration phase has been conducted extensively, we can test how well the agent learned the environment. We re-start it from home and give a goal location to go to. If the agent has properly learned the environment with respect to the three environmental clues, it will navigate efficiently and find a reasonably optimal path to the goal based on the internally formed cognitive map using its classification landscape learned in the hippocampal KIII.

The effect of learning is illustrated in Figure 11. After learning, the length of the trajectory from home to the neighborhood of the goal (central location in Figure 11) is significantly reduced. It should be noted that, based on just the global orientation information, it is very difficult to learn navigating towards the goal location very precisely. We see in Figure 11 that the agent does not stop once it is in the neighborhood of the goal, rather it continues moving around the goal. Clearly, it should use another sensory modality, like vision or distance sensors, to identify the goal if it is nearby and move toward it. Animals use such a multi-modal sensing. The KIV model has the option of multi-modal sensory integration and the implementation of this strategy is in progress.

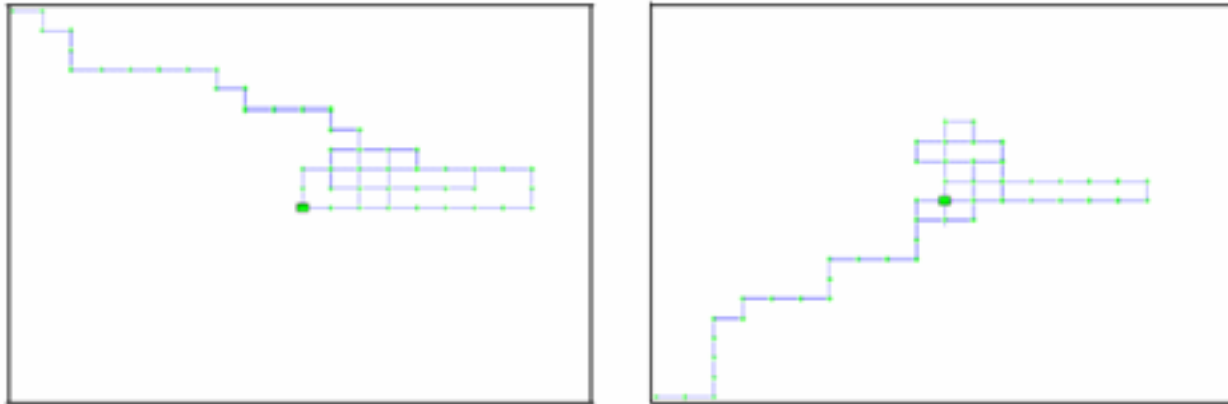


Figure 11: The path of the KIII navigation agent from start to goal, following a session with reinforcement learning. We show two different trials with the agent starting in the northwest corner (left) and the southwest corner (right). The goal location is in the center position. Note the significantly reduced path with respect to the case without learning. (from (Voicu et al., 2003))

### Conclusion

In this paper we have described some of the work on understanding why nonconvergent dynamics appear in biological brains, and how such dynamics might be necessary to the production of intelligent behavior and cognition. Aperiodic dynamics have been shown to be essential in critical brain states involved in the self-organization of meaning and memory. They have been detected in the organization of perceptual meanings in biological brains, and proved useful for pattern classification tasks. Some of the principles of nonconvergent dynamics that appear useful in the organization of neuronal dynamics have been known for awhile, such as homeostatic control through positive and negative feedback. Evidence has shown, however, that brains make use of self-organizing dynamics that go well beyond this simple mechanism.

Aperiodic dynamics, if necessary for perceptual mechanisms, are probably also necessary for the self-organization of memory, goal structure and resource allocation, behavior, and motor systems. The former have been studied for some time in neuro and cognitive science, but we are only beginning to form theories on how they might function in complete systems. Embodiment of

a cognitive system, being structurally coupled with the environment, is also necessary for such dynamics to self-organize.

Biological organisms evolved 4 basic functions in becoming intentional agents: “What”, “Where”, “Why” and “How”. These systems are involved in short and long term memory, and the formation of structures for tracking and realizing the goals and needs of the organism. KIV is a model that incorporates aperiodic dynamics to self-organize patterns of meaning and memory, along with a description of the architecture of the 4 necessary functions, and how phase transitions and attractors in one area influence and affect such attractors in others to produce behavior. We have begun to explore the formation of aperiodic dynamics to self-organize such behavior producing systems.

#### Acknowledgment

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