Models of Self-Organizing Ontogenetic Development for Autonomous Adaptive Systems (SODAS)

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Abstract

Biological organisms show an amazing ability during their ontogenetic development to adaptively develop strategies and solutions to the various problems of survival that their environments present to them. Dynamical and embodied models of cognition are beginning to offer new insights into how the numerous, heterogeneous elements of neural structures may self-organize during the development of the organism in order to effectively form adaptive categories and increasingly sophisticated skills, strategies and goals (Kelso 1995; Thelen & Smith 1994; Port & Van Gelder 1995; Clark 1997; Hendriks-Jansen 1996; Freeman 1999a; Franklin 1995, 1997).   This development during the maturation of biological organisms, and the flexibility to adaptively modify behavior even in mature individuals in order to effectively survive in their environment, all without explicit instruction or prior representations of the world, represents a significant level of increased performance over the current best symbolic approaches to the development of artificial autonomous agents.

Intelligent behavior is characterized by flexible and creative pursuit of endogenously defined goals. It has emerged in humans through the stages of evolution that are manifested in the brains and behaviors of other animals. Intentionality is a key concept by which to link brain dynamics to goal-directed behavior. The archetypal form of intentional behavior is an act of observation through time and space, by which information is sought for the guidance of future action. Sequences of such acts constitute the key desired property of free-roving, semi-autonomous devices capable of exploring remote environments that are inhospitable for humans. 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 (reafference) by which to evaluate performance, and modification of the device by itself for learning from the consequences of its intended actions. These principles are well known among psychologists and philosophers. What is new is the development of nonlinear mesoscopic brain dynamics, by which using chaos theory to understand and simulate the construction of meaningful patterns of neural activity that implement the perceptual process of observation (Freeman & Kozma 2000). The prototypic hardware realization of intelligent behavior is already apparent in certain classes of robots. The chaotic neurodynamics of sensory cortices in pattern recognition is ready for hardware embodiments, which are needed to provide the eyes, noses and ears of devices for survival and autonomous operation in complex and unpredictable environments.

This research proposes to build on neurologically inspired, bottom-up, dynamic approaches to embodied category formation such as those done by Freeman (1975, 1999a), Kozma & Freeman (2000a, 2000b, 2000c) and Almassy, Edelman & Sporns (1998). We will expand such systems to function in real-time demanding task environments, to adaptively develop skills and react to changing situations all by simply interacting within the environment and extracting the temporally relevant patterns or embodied categories. We believe that building on such mechanisms from an embodied dynamical perspective will produce autonomous agents that display greatly increased flexibility in their behavior while also decreasing the amount of effort needed in order to program and train such agents to effectively perform the desired tasks. Such models will represent a better understanding of how the brains of biological organisms not only form perceptual categories of their environment during development, but also form patterns of behavior based on such environmental categories.

The behavior of the developed self-organizing agents will be illustrated on test scenarios, including software simulations, to show they display certain expected and unexpected behavioral patterns. In the last year of this project, possible links to research supported by ONR in the framework of Intelligent Distributed Agents (IDA) will be explored.

1. Research Objectives

The basic mechanism of survival for any biological organism appears to be the ability to adaptively form relevant categories from the flood of sensory data available to it, and to use such categories to guide its actions and behaviors in a useful and relevant manner for the given situation. How exactly biological organisms are able to perform this task is still only incompletely understood. The task is extremely difficult as it not only involves the formation of relatively static types of categories from environmental cues but also the recognition of relevant temporal patterns over extended and varying time scales. And even more amazing, such categories are not simply static information structures, but all past experiences seem always and instantly available to guide and afford patterns of behavior that are relevant to the current situation of the organism. How such past experience can seem to be instantly available when needed for a similar but new situation is unknown.

The research proposed here has four major objectives. Exploration of the phenomenon of fusion of sensory information into a coherent picture from multiple perceptual channels. The formation of embodied categories from chaotic neurodynamical mechanisms. The formation of action-oriented representations capable of affording opportunities for action for an autonomous agent. The self-organizing development of increasingly sophisticated skills, behaviors and goals in an autonomous agent.

1.1. Dynamical Models of Sensory Fusion

One goal of the proposed research is to explore new models of category formation in chaotic dynamical systems, and how such models may be similar to, and better models of, the category forming abilities of biological organisms. This research will attempt to build models of static and temporal category formation based on neurological theories of brain functions that organize sensory patterns using chaotic dynamics (Skarda & Freeman 1987, Kozma and Freeman 2000c, Freeman 1999a). In particular this research will be extending the current work being done to better understand how such models can fuse data from multiple sensory channels into a seamless and integrated whole and how the recurrent connections in such models allow the emergent formation of increasingly sophisticated embodied categories. The fusion of sensory modalities in such dynamic models represents a different approach to sensory fusion over classic symbolic models. Instead of a single integrating module that attempts to integrate all sensory modalities from preprocessing modules, in a dynamical perspective all separate sensory modalities continuously and concurrently inform one another through reentrant connections in order to form a sophisticated fusion of sensory data (Edelman & Tononi 2000). In such dynamical models there is no central integration unit yet, somehow, a coherent and integrated picture of the salient environmental factors is built up in real time from such decentralized interactions (Kozma et al. 2000).

Another goal of this research is to explore the ability of such models to recognize temporally relevant patterns within the environment of the organism. This research will build dynamical models of category formation that operate and form categories in real-time from the sensory data available without supervision of the learning process. This type of unsupervised learning in real-time of relevant categories is a necessary step in using such models in real-time autonomous agents.

1.2. Embodied Category Formation

Current theories of embodied cognition (Clark 1997, Hendriks-Jansen 1996) emphasize that embodied, situated categories represent the basis of cognition, from which affordances for action are identified and produced (Gibson 1979). Embodied category formation is adaptively significant to the development and survival of biological organisms. A goal of this research is to understand how such dynamical models of self-organizing categorization are related to and may be used as the mechanisms of theories of embodied representations. In particular, do such dynamical models represent a mechanism of embodied category formation as powerful as those of biological organisms.

1.3. Action-Oriented Representations

Embodied and situated categories are inherently action-oriented mechanisms that not only represent information about the species typical environment, but also afford opportunities for action for the organism. A goal of this research is to extend the work done on chaotic dynamical systems as models of category representation, into using such models to also implement action selection mechanisms that can afford opportunities for relevant behavior in an autonomously behaving artifact.

1.4. Ontogenetic Development

A further goal of this research is to explore the ability of action selection mechanisms to self-organize increasingly sophisticated patterns of behavior, similar to how categories self-organize as a result of the dynamics of the system. In particular, can such an action selection mechanism self-organize behavior patterns in ways similar to the ontogenetic development of skills and strategies that many organisms experience during the developmental process. Can we produce action selection mechanisms that self-organize behaviors hierarchically, where simpler behavior patterns combine to perform more complex tasks, and heterarchically, where previously unrelated situations and behaviors are recognized as similar and are related to one another? The same sorts of interactive emergence that enable the formation of embodied categories may also be capable of developing emergent patterns of behavior that self-organize into increasingly effective skills, strategies and goals for coping with the environmental niche. A major goal of this research is to demonstrate the ability of such mechanisms to emulate this phenomenon of biological development to self-organize effective behavioral strategies during their ontogenetic development. Such a system would answer the questions of ethologists of how the brains of biological organisms manage to organize their behavior into complex and effective hierarchies of behavioral patterns during maturation and yet manage to exhibit amazing flexibility in dealing with environmental challenges. Such an action selection mechanism would be capable of learning the niche relevant categories and skills simply by interacting within the environment in real-time.

Ultimately we aim to develop new, more powerful models of category formation and action selection for autonomous agents inspired from bottom-up neurological theories of cognition. Such theories are dynamical and embodied views of cognition and represent new directions of thought from those of classical symbolic and connectionist approaches. We believe that autonomous agents developed from such a perspective will demonstrate a capacity for learning and an ability for the self-organization of complex and flexible patterns of behavior that represent significant improvements over the performance of existing approaches to building autonomous agents.

2. Scientific Relevance

2.1. Dynamical Brain Models

Biological organisms are constantly faced with a dynamic and changing environment. Survival under such conditions often requires the organism to react to quickly changing situations. Under such conditions, complex representations of the situation become computationally intractable. It seems unfeasible to attempt to trace every detail of the complex situation. Waiting for more information or to discover optimal solutions does the organism little good if solutions cannot be produced in time to react to the immediate problem. Classical symbolic models of cognition ignore, or at least minimize, the importance of the constraints imposed on the cognitive system by real time embedded interaction with the environment. Symbolic models view cognition as the discrete sequential manipulation of static representational structures. The evolution of the cognitive system, in the symbolic approach, passes through a defined sequence of states. However, such models do not speak to the timing of the states. A dynamical approach to cognition emphasizes many differing aspects over classical symbolic and connectionist approaches. Port and Van Gelder (1995) emphasize the importance of taking into account the dimension of time when thinking about and modeling cognitive processes:

> "The heart of the problem is time. Cognitive processes and their context unfold continuously and simultaneously in real time." (Port & Van Gelder 1995, pg. 2).

This basic insistence on the importance of real time interaction provides a new viewpoint of the cognitive processes. Now, rather than a disembodied, sequential manipulation of symbols, cognition is seen as a continual process of mutually influencing change. Real time constraints always impose limitations on the types and forms of computation that can be performed. But rather than being a hindrance, these constraints often force the cognitive system to use specialized solutions, that are computationally cheap but get the job done.

Another basic concept of the dynamical approach is the ability of such systems to spontaneously manifest ordered structure or behavior. The ability of such systems to self-organize represents a major conceptual tool that allows us to explain how intelligence and consciousness may arise from the interaction of elements that are themselves unintelligent and unconscious. Kelso (1995) describes the human brain as:

> "… *fundamentally* a pattern-forming self-organized system governed by nonlinear dynamical laws. Rather than compute, our brain 'dwells' (at least for short times) in metastable states: it is poised on the brink of instability where it can switch flexibly and quickly. By living near criticality, the brain is able to anticipate the future, not simply react to the present. (Kelso 1995, pg. 26)"

A few basic conditions are required in order to induce self-organizing phenomenon (Kelso 1995, Kauffman 1993). A large number of interacting components must be present. The components must massively interact with one another to generate nonlinear behavior. The system is open with respect to energy, it consumes energy and dissipates heat or waste in order to maintain its structure far from thermo-dynamical equilibrium (e.g. death). Such conditions are known to be necessary in order to induce self-organizing phenomenon in physical systems. However, using such principles to build systems that are capable of the self-organization of behavioral patterns is still not well understood. This research hopes to explore the question of how behavior patterns can self-organize into more complex forms that are adaptive and aid in the survival of the organism.

We will also address the question of information coding in aperiodic (chaotic) attractors. This goes beyond the safe and thoroughly explored territory of equilibrium and bifurcational schemes that use fixed point-based encoding. Fixed point-based encoding is the basic principle of today's computing paradigm and is still the basic explanatory mechanism used for current top down dynamical models of cognition. Our proposal is a great leap into the non-equilibrium dynamics of unstable periodic orbits. The complexity of the problems seems overwhelming, if not intractable and the intellectual challenge is indeed enormous. There is, however, hope that we can meet this challenge because we know existing systems working on this principle: brains. In the seminal paper by Skarda & Freeman (1987), the authors give a comprehensive account of spatio-temporal effects in brains using methods of dynamic system theory and chaos. Studies in various laboratories have been conducted to harness the principle of chaotic encoding for understanding brain dynamics, see Babloyantz and Destexhe (1986), Tsuda (1992, 1994), Schiff et al. (1994), Aradi et al. (1995).

Motivated strongly by neurophysiological observations, intensive research has been conducted in the field of computational neural networks utilizing chaotic encodings in software and hardware embodiments (Andreyev et al 1996; Aihara et al. 1990; Perrone & Basti 1995; Wang 1996; Schuster & Stemmler 1997; Borisyuk & Borisyuk 1997; Nakagawa 1998; Minai & Anand 1998). In a separate development Freeman's KIII nets have been established as revolutionary new dynamic memory devices based on encoding in aperiodic (chaotic) attractors (Freeman 1994; Freeman, Chang, et al. 1997; Chang et al. 1998; Kozma & Freeman 2000b).

Neurobiological observations provide a clue for the future direction of research. What distinguishes brain chaos from other kinds is the filamentous texture of neural tissue called neuropil, which is unlike any other substance in the known universe (Freeman 1995). Neural populations stem ontogenetically in embryos from aggregates of neurons that grow axons and dendrites and form synaptic connections of steadily increasing density. At some threshold the density allows neurons to transmit more pulses than they receive, so that an aggregate undergoes a state transition from a zero point attractor to a non-zero point attractor, thereby becoming a population. Mathematically such a property has been described in random graphs, where the connectivity density is an order parameter that can induce state transitions (Erdos & Renyi 1960). Accordingly, state transitions in neuronal populations can be interpreted as a kind of percolation phenomenon in the neuropil medium. The dendritic currents of single neurons that govern pulse frequencies sum their potential fields in passing across the extracellular resistance, giving rise to extraneuronal potential differences manifested in the EEG, which correspond to the local mean fields of pulse densities in neighborhoods of neurons contributing to the local field potentials. In early stages of development these fields appear as direct current "d.c." fields with erratic fluctuations in the so-called "delta" range < 1 Hz. The neurons are excitatory, and their mutual excitation provides the sustained aperiodic activity that neurons require to stay alive and grow. Unlike transistors, neurons have a short shelf life if they are isolated and left inactive. The activity of an excitatory population is self-stabilized by a non-zero point attractor (Freeman 1975), giving rise to a field of nearly white noise, up to a frequency limit determined by the duration of the action potentials. The feedback can be modeled as a one-dimensional diffusion process, which randomizes the input of each neuron with respect to others' output and its own output. At some later stage, typically in humans after birth, cortical inhibitory neurons develop or transform from excitatory neurons, which contribute negative feedback, leading to the appearance of oscillations in the gamma spectrum of the EEG. The mutual excitation persists, and, in fact, is essential for the maintenance of the near-linear range of cortical oscillations through a depolarizing bias.

2.2. Embodied Cognition

Clark (1997) also emphasizes the importance of real time interaction of the organism with the environment. For Clark: "the first moral of embodied cognition is thus to avoid excessive world modeling, and to gear such modeling as is required to the demands of real-time, behavior-producing systems." (Clark 1997). A second important concept in embodied cognition is the idea that perception and action are not separate and isolated systems, where perceptual information is passively gathered and then eventually acted upon once it is transformed by cognition. Instead perception and action are fundamentally linked, right down to the neural structures and representations formed.

According to Clark, solutions for organisms are softly assembled out of multiple, largely independent components. Such interactive emergence of solutions yields both robustness and variability of the solutions to the problem. The solutions that emerge are tailored to the idiosyncrasies of context, yet they satisfy some general goal of the organism.

As we've seen before in the concepts of self-organization, solutions in embodied mechanisms are also conceived of as fundamentally decentralized. Representations in embodied cognition are believed to be fundamentally action-oriented. That is they simultaneously describe aspects of the world and prescribe possible actions. They walk a balance between the passive representations of classical models and pure control structures.

Cognitive processes can extend outside the head of the organism. The world becomes part of the model or representation for the organism, and manipulations of the world state may serve to explore possible opportunities for action. Such epistemic actions (Kirsch & Maglio 1994) are observable in biological organisms and are hard to explain under a strictly classical framework of cognition.

The world is its own best representation. This is a fundamental tenet of embodied cognition. One should avoid costly, detailed world models and representations, in favor of embodied, action-oriented models. Such representations discretize the perceptual input and only represent and act upon the information directly relevant to the action and goals of the organism (Von Uexkull 1934).

Brooks (Brooks 1990) argues for behavioral decomposition, rather than functional decomposition, as a way of building situated, embodied robots. While this is a step in the right direction, it lacks the flexibility and adaptability necessary to exhibit a true type of ontogenetic development. Brook's subsumption architecture does allow for a limited emergence of solutions from the interaction of many heterogeneous behaving elements. However, such emergence is limited and does not allow for the development of more sophisticated behavioral skills from the agents basic repertoire.

2.3. Neural Darwinism

Edelman's theory of Neural Darwinism (Edelman 1987; Edelman & Tononi 2000) represents a selectional theory of brain development. Selectional processes during the maturation of an organism's brain represent possible mechanisms for the ontogenetic development of behavior and skills by the organism. Some work has been done on implementing the mechanisms described by Edelman in real world behaving artifacts (Almassy, Edelman, Sporns 1998; Sporns, Almassy, Edelman 1999; Verschure et al. 1995).

Our research into the development of behavior will be informed by the principles of Neural Darwinism. Our mechanisms will have the basic elements of Edelman's approach, such as reentrant structure, degeneracy and developmental selection. But our approach will include the additional concepts of the developmental process as the evolution of a dynamical system. In particular, the principles of dynamical cognitive systems, as described by Freeman (Freeman 1999a), are further specifications on the mechanisms of the development of behavior.

3. Technical Approach

3.1. Principles of Cognitive Dynamics

Our method is consistent with a dynamical approach to the development of an embodied cognition (Thelen & Smith 1994, Thelen 1995, Iverson & Thelen 1999, Kelso 1995). In such a view of cognition, development is pictured as an ontogenetic landscape of evolving and dissolving attractors. The attractors represent the development of stabile solutions and skills by the developing organism. As time passes, the organism interacts with the environment and continuously solves and works out real time problems that confront it. The solutions that the individual discovers in this real time interaction continuously affects the solutions that evolve in ontogenetic time. Thus as stabile solutions to problems are discovered, they become the basis for the future development of further abilities based on previously discovered stable solutions. Similarly, as the organism develops, stable solutions discovered previously may become unstable (due to morphological or developmental changes) which can push the system into new areas of the phase space in search of new behavioral solutions.

In using dynamics we approach the problem by defining three kinds of stable state, each with its type of attractor. The simplest is the point attractor. The system is at rest unless perturbed, and it returns to rest when allowed to do so. As it relaxes to rest, it has the history of what happened, but that history is lost after convergence to rest.

A system that gives periodic behavior is said to have a limit cycle attractor. The classic example is the clock. When it is viewed in terms of its ceaseless motion, it is regarded as unstable until it winds down, runs out of power, and goes to a point attractor. If it resumes its regular beat after it is re-set or otherwise perturbed, it is stable as long as its power lasts. Its history is limited to one cycle, after which there is no retention of its transient approach in its basin to its attractor. Neurons in populations rarely fire periodically, and when they appear to do so, close inspection shows that the activities are in fact irregular and unpredictable in detail, and when periodic activity does occur, it is either intentional, as in rhythmic drumming, clapping and dancing, or it is pathological, as in the periodic oscillations of the eyes in nystagmus, or of the limbs during Parkinsonian tremor, or of the cortex during the hypersynchrony of partial complex seizures that are revealed by near-periodic spike trains.

The third type of attractor gives aperiodic oscillation of the kind that is observed in recordings of EEGs. There is no one or small number of frequencies at which the system oscillates. The system behavior is therefore unpredictable, because performance can only be projected far into the future for periodic behavior. This type is now widely known as "chaotic". The existence of this type of oscillation was known to Poincaré a century ago, but systematic study was possible only recently after the full development of digital computers. The best known systems with chaotic attractors have a small number of components and a few degrees of freedom, as for example, the double-hinged pendulum, the dripping faucet, and the Lorenz, Chua, and Rössler attractors (Freeman 1999b). These simple models are stationary, autonomous, and noise-free, forming the class of "deterministic chaos". Large and complex real-world systems, which include neurons and neural populations are noisy, infinite-dimensional, nonstationary, non-autonomous, yet capable of chaotic behavior which has been called "stochastic chaos" (Freeman 2000). The source is postulated to be the synaptic interaction of millions of neurons, which create fields of microscopic noise in cortex, but which are constrained by their own interactions to generate mesoscopic order parameters that regulate the spatiotemporal patterns of cortical activity revealed by the EEG. These spatiotemporal patterns are revealed by spatial patterns of amplitude modulation ("AM patterns") of a spatially coherent aperiodic carrier wave in the gamma range of the EEG. They appear in time series as bursts of oscillation, and their spatial patterning indicates the existence of an attractor landscape.

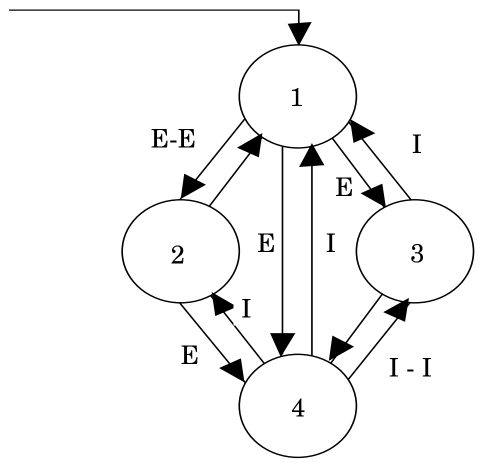

Figure 1 - KII scheme

Figure 1. KII scheme with four interconnected KII nodes. Each node performs a nonlinear transformation according to a physiologically plausible asymmetric sigmoid function (Freeman 1975). Nodes 1 and 2 are excitatory, while nodes 3 and 4 are inhibitory. The system has 4 gain parameters; W_EE is the gain between the excitatory nodes, W_II is the gain between inhibitory nodes. Gains W_IE and W_EI are for gains from E to I and I to E, respectively. In the text, the response of the KII set to a given impulse is analyzed. The impulse is coming through the Input channel.

The discovery that brain dynamics operate in chaotic domains has profound implications for the study of higher brain function (Skarda & Freeman 1987). A chaotic system has the capacity to create novel and unexpected patterns of activity. It can jump instantly from one mode of behavior to another, which manifests the fact that it has a collection of attractors, each with its basin, and that it can move from one to another in an itinerant trajectory (Tsuda 1996). It retains in its pathway across its basins its history, which fades into its past, just as its predictability into its future decreases. Transitions between chaotic states constitute the dynamics that we need to understand how brains perform such remarkable feats as abstraction of the essentials of figures from complex, unknown and unpredictable backgrounds, generalization over examples of recurring objects never twice appearing the same, reliable assignment to classes that lead to appropriate actions, and constant up-dating by learning.

The applied dynamic brain model will use principles of KIII sets. The KIII model consists of various sub-units; i.e., the KO, KI, and KII sets. The KO set is a basic processing unit, and its dynamics is described by a 2^{nd} order ordinary differential equation. By coupling a number of excitatory and inhibitory KO sets, KI(e) and KI(i) sets are formed. Interaction of interconnected KI(e) and KI(i) sets forms the KII unit (Figure 1). Examples of KII sets in the olfactory system are the olfactory bulb, anterior olfactory nucleus, prepyriform cortex. Coupling KII sets with feed-forward and feedback connections, one arrives at the KIII system (Figure 2).

Although the principles contributing to the KIII model have be known for a long time, certain stability issues represented serious obstacles in the practical use of KIII-based simulations. Applying advanced optimization techniques, the model could learn given input patterns but the performance of the system has been very sensitive to small changes in the model parameters (Chang, Freeman & Burke 1998). The reason for the problems has been identified as attractor crowding caused by the fragmentation of basins of attractors in the high-dimensional state space of KIII. Recently, a robust and stable operation of KIII has been achieved based on the concept of overlapping attractor basins (Kozma & Freeman 1999). KIII shows very good performance in learning input data and it can generalize efficiently in various classification problems. These results will be extended to include intentional action in agents' behavior via the plasticity of the underlying chaotic attractor basins.

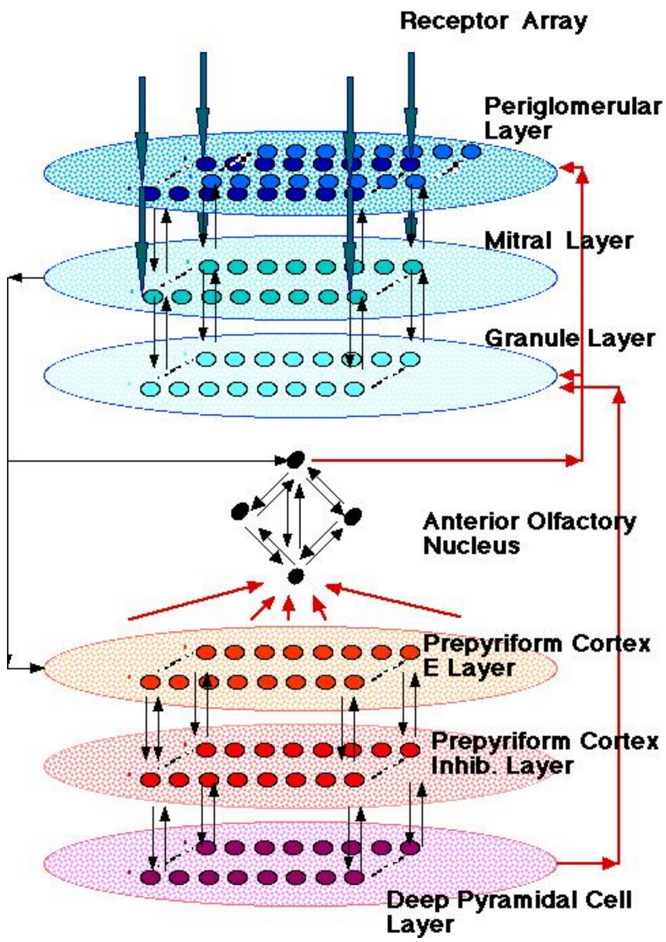

Figure 2 - KIII model

Figure 2. Schematic view of the multi-layer KIII model; the layers are: receptors, periglomerular cells, olfactory bulb with mitral and granule layers, anterior olfactory nucleus (AON), prepyriform cortex with excitatory and inhibitory layers, and deep pyramidal cells.

3.2. The Limbic System Model of Intentional Behavior

Brain scientists have known for over a century that the necessary and sufficient part of the vertebrate brain to sustain minimal intentional behavior is the ventral forebrain, including those components that comprise the external shell of the phylogenetically oldest part of the forebrain, the paleocortex, and the deeper lying nuclei with which the cortex is connected. These components suffice to support remarkably adept patterns of intentional behavior, in dogs after all the newer parts of the forebrain have been surgically removed, and in rats with neocortex chemically inactivated by spreading depression. Intentional behavior is severely altered or absent after major damage to the medial temporal lobe of the basal forebrain, as manifested most widely in Alzheimer's disease.

Phylogenetic evidence comes from observing intentional behavior in salamanders, which have the simplest of the existing vertebrate forebrains (Herrick 1948; Roth 1987). The three main parts are sensory (which, as in small mammals, is predominantly olfactory), motor, and associational (Figure 3). These parts can be judged to comprise the limbic system in all vertebrates, but in the salamander they have virtually none of the "add-ons" found in brains of higher vertebrates, hence the simplicity. The associational part contains the primordial hippocampus with its interconnected septum and amygdaloid nuclei, striatal nuclei, which are identified in higher vertebrates as the locus of the functions of spatial orientation (the "cognitive map") and temporal integration in learning (the organization of long and short term memory). These processes are essential, inasmuch as intentional action takes place into the world, and even the simplest action, such as searching for food or evading predators, requires an animal to know where it is with respect to its world, where its prey or refuge is, and what its spatial and temporal progress is during sequences of attack or escape. The feedback loops that support the flow of neural activity in the neurodynamics of intentionality are schematized in Figure 4.

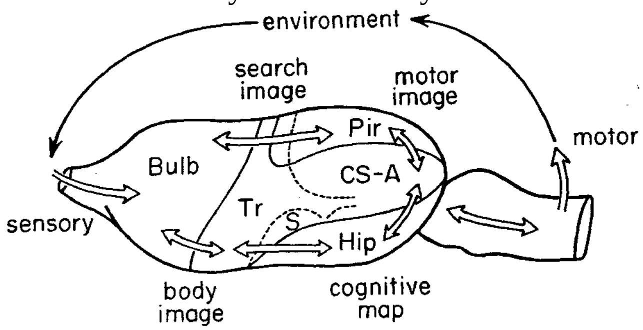

Figure 3 - Limbic System

Figure 3. This schematic illustrates the sensory, motor, and associational components of the right hemisphere (seen from above) of the simplest extant vertebrate brain in the salamander. The bidirectional connections between these 3 major subdivisions of the forebrain provide for the macroscopic interactions that support the neurodynamics of the process of intentionality: goal formation, action, perception, and learning from the sensory consequences of the action taken into the environment. These components form the prototype of the limbic system, which is found in all vertebrate brains, typically buried within exuberant growth of other "add-on" structures that operate in concert with the limbic system.

3.3. Selectional Mechanisms

We will be building on neurologically inspired, bottom-up, dynamical models of populations of neurons that self-organize to form embodied categories and adaptive behavior. The major predecessors of this line of research include those of Edelman (1987), Edelman & Tononi (2000), Freeman (1999a, 1995) and Skarda & Freeman (1987). Specifically we will be building on research done by Kozma & Freeman (2000a, 2000b, 2000c) on the formation of embodied categories from a chaotic spatiotemporal sensory environment and from Sporns, Almassy & Edelman (1999) and Almassy, Edelman & Sporns (1998) on the implementation of Edelman's theory of Neural Darwinism in an embodied autonomous agent. Our approach will extend such models to the realm of action selection in autonomous agents. We will create models of action selection that identify opportunities for action from the embodied representations formed by the agents through their interaction with the environment. Such models, we believe, will be capable of self-organizing increasingly sophisticated skills and behaviors in response to the demands of their task environment.

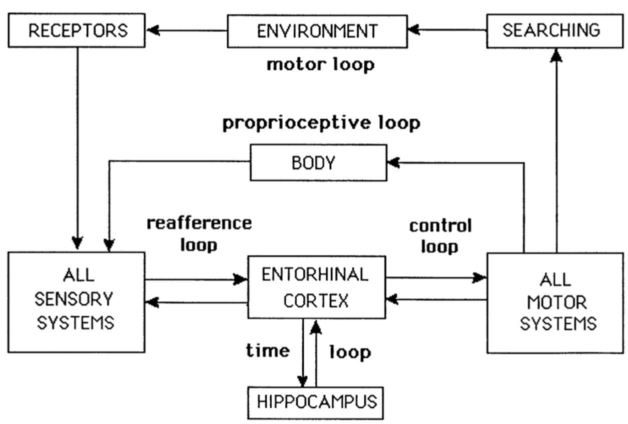

Figure 4 - Brain State Schematic

Figure 4. This diagram of brain state space maps the multiple feedback loops that support the intentional arc. Flow of neural activity inside the brain is in two directions. Forward flow from the sensory systems to the entorhinal cortex and on to the motor systems is by spatial AM patterns of action potentials at the **microscopic** level, by which transmitting cortices drive the neurons in their targets. Feedback flow from the motor systems to the entorhinal cortex by control loops, and from the entorhinal cortex to the sensory systems inside the brain, is by spatial AM patterns of action potentials at the **mesoscopic** level. This feedback constrains and modulates the microscopic activity in the forwardly transmitting populations. The mesoscopic feedback messages are order parameters that bias the attractor landscapes of the sensory cortices in preafference. Forward flow supports motor output and provides the content of percepts. Feedback flow supports integrative processes in learning that lead to the wholeness of intentionality. They enable the formation of a **macroscopic** AM pattern that reflects the integration of the activity of an entire hemisphere.

Our approach represents a selectional viewpoint of neurological function. Selectional mechanisms are believed to aid in learning on the mesoscopic and macroscopic time scales. Edelman & Tononi (2000) stress three main tenets of the theory of Neural Darwinism: developmental and experiential selection and reentry. Developmental selection generates extensive variability in the physical structures of the neural circuits which provides an immense and diverse repertoire of connectivity. Experiential selection selectively strengthens or weakens connections between neurons based on experience and performance. A diffusely projecting value or valence system guides and drives the selectional processes towards desired patterns of behavior. Developmental and experiential selection represent the variability and differentiation upon which selectional mechanisms can occur. The third tenet, reentry, correlates spatiotemporal events among neuronal group maps. This process provides for the integration of spatiotemporal information and is a crucial property that allows for the formation of embodied representations and categories in an unlabeled and chaotic world (Edelman 1987, Edelman & Tononi 2000, Damasio & Damasio 1994).

Selectional systems of sufficient diversity and variation display the property of degeneracy, which means that typically they contain many different structures that can perform a particular function or task and these varying structures are not necessarily identical. This property of degeneracy is important as the system develops towards more discriminating and sophisticated modes of behavior. What were at first many different structures for handling similar general events become specialized at recognizing and handling specific environmental contingencies Or put another way, variations of general events seen before can be handled better by some equivalent degenerate structures than others. Therefore degeneracy provides for a flexibility of behavior in coping with an infinitely varying task environment.

3.4. Value Systems, Plasticity and Homeostatic Regulation

Another important piece of the neuronal model is the presence of a diffusely projecting valence system. The valence system provides constraints on the selectional mechanisms and drives the system towards behavior patterns that increase survivability and satisfy general requirements. In biological organisms the valence system is a result of evolution by natural selection and represents a long history of experience of the species typical environment. Although valence systems are typically thought of as fixed aspects of the biological organism, there is evidence that one of the key aspects in the power of the developmental processes of mammals is a modifiable valence system that can participate in the somatic selectional process (Sporns, Almassy & Edelman 1999). We will be developing models with modifiable valence systems.

One view of a valence system is that it maintains a number of critical physical properties within certain viability zones. Organisms are unable to live if they are not able to continually maintain these critical levels of intrinsic need for sustenance, regulation of body temperature, etc. From a dynamical perspective, the properties can be thought of as state variables of the system. The behavior of the organism must always be geared towards meeting these basic survival criteria. Adaptive behavior is the ability to learn patterns of behavior that are better able to maintain this homeostatic balance of the essential variables of survival. Homeostatic regulation represents an important guiding principle of the autonomous systems we are constructing. The implementation of homeostatic regulation is a key to utilize the plasticity of the agents. In addition to homeostasis, long-term habituation and almost instantaneous associative hebbian learning is used to achieve the desired robust performance (Kozma & Freeman 2000b).

3.5. Computational Approach

Our computational approach is to develop a software architecture that is targeted for a general parallel distributed hardware environment and that can be realized on different physical systems and parallel architectures. The SODAS system will be broken into 2 layers: a logical layer that realizes an idealized simulated neurological model, and a physical layer that handles the realization of the idealized neurological model in some physical hardware environment. The logical layer will implement an idealized neurological model based on the principles outlined above. This layer will remain independent of the target hardware environment, and should not need modifications when transporting or implementing agents in new environments. The physical layer will be responsible for realizing the logical neurological model in a particular hardware environment. It will provide an abstract interface for the logical layer that hides the details of communication and hardware architecture. A physical layer will need to be developed for each differing hardware target upon which we wish to implement an agent. Our first target physical hardware platform will be a parallel cluster machine.

4. Expected Results

The major result of our research will be to demonstrate the ability of our models to develop sophisticated and flexible behavioral patterns simply through the real-time interaction of the agent with its environment due to a process of ontogenetic development. We will be expanding current models of the formation of embodied categories through dynamical processes to also self-organize an appropriate behavioral repertoire. Our system will represent the first concrete implementation of the ideas of dynamic embodied cognition and ontogenetic development in a complete autonomous agent. We will demonstrate the ability of such dynamical neurological models to form embodied category representations and to produce affordances or opportunities for behavior from such representations. Further we hope to demonstrate a process of artificial ontogenetic development of skills, strategies and goals. During the course of this research we will be developing various cognitive models of perceptual and motor tasks. We will then use the results of such cognitive models to develop more complete autonomous agents for simulated environments.

4.1. Conceptual Design

The research would produce results on several levels. On the conceptual level we would expect to establish theories of pulsing dynamics of internal representations modulated by sensory inputs, leading to category generation and learning in cognitive agents. We would develop methods of shaping the attractor landscape of agents when needed, using learning methods at various time scales. For example prompt associative (Hebbian) learning for the microscopic level, and long-term habituation and stability using chaos control, adaptive critics and re-normalization tools for the intermediate and macroscopic levels. Further we would analyze various manifestations of mesoscopic organization using mathematical descriptions, and the role of this intermediate level in category formation. We would compare the mesoscopic organization of our cognitive models to that observed in actual biological systems.

In addition to the development of these conceptual tools for dynamical embodied category formation, we would also produce conceptual architectures of complete artificial limbic systems for intentionally behaving systems. Such architectures would be modeled after the properties of known simple biological limbic systems. We expect that agents built upon such principles would exhibit a flexibility of behavior and a capacity for learning that is beyond the capabilities of current agent architectures. In effect, we hope to build artifacts that display true intentionality and situated activity within their environment. The design of the components and architectures of these artificial limbic systems would form the basis for implementations and demonstrations in various autonomous agents.

4.2. Motor Coordination Tasks

Some of the first models we will build will be extensions of dynamical category formation. Our first models combining perception and action will be of simple motor coordination tasks, such as limb synchronization tasks and the production of oscillatory movements and their dynamic modification in response to environmental challenges. The Haken-Kelso-Bunz model (Kelso 1995, Haken, Kelso & Bunz 1985) is a top down dynamical model of the attractor states of a particular motor task performed by humans. In this task, people are asked to swing their index fingers back and forth (like car windshield wipers) to the beat of a metronome. People naturally exhibit one of 2 attractors, in-phase motion and anti-phase motion. This and other types of limb coordination tasks (Fuchs & Kelso 1994, Kelso 1995) provide a well studied domain of self-organizing behavior upon which to initially test our bottom-up neurological models. We expect to build models that emulate the types of phase transitions observed in these coordination tasks. This will provide alternative models of these self-organizing phenomenon to the traditional top-down models developed to explain such phenomenon. This will also provide some simple domains in which to integrate perceptual and motor activities and to test the ability of our artificial limbic systems to self-organize behavior in ways that are similar to biological organisms.

4.3. Real-Time Task Environments

An interesting domain studied by psychologists is in the development of skills while performing certain motor tasks in a real-time cognitively challenging game, such as Tetris (Kirsch & Maglio 1994). In this demanding environment, many behaviors are observed that can not be explained from a classical perspective (sense-act-plan). Many actions, called epistemic actions by Kirsch and Maglio, do not directly serve or bring the player closer to a goal. Some rotations and translations are performed simply to manipulate the perceptual environment. It is believed that these types of manipulations are performed because, contrary to a classical perspective, people do not build complete complex representations of the task domain. Such complex representations are too computationally expensive to be supported in the demanding real-time task environment. Instead people use the environment itself as its own representation, and simple physical manipulations of the "environment out there" are actually types of representational manipulations. The purpose of such epistemic actions are not directly relevant to a goal, but serve to change the perceptual environment in such a way that new affordances or opportunities for action may be directly observed from the situation. One objective of this research is to develop behavior producing systems that demonstrate these types of epistemic actions. Systems observed to display these types of behavior can be argued to be cognitively plausible models of action selection, and will indicate the validity of our embodied representational mechanisms as models of biological embodiment.

The Tetris environment, and other real-time demanding games, are also wonderful domains for studying the developmental process of skills from simple novice behaviors to advanced expert skills. Such development of skills can happen quickly in humans, in a matter of hours of interaction with the task environment. From simple motor skills and goals, players typically self-organize more complex and sophisticated patterns of behavior. Not only do the behavior patterns organize, but also the structure and type of goals pursued by the players evolve as they gain experience with the task environment. We expect to build models that will be able to display some of these characteristics, to organize increasingly sophisticated levels of behavior by interacting with the environment.

Such real-time demanding task domains also offer opportunities for the further study of the formation of embodied category representations. In particular, we will need to develop neurological models that can operate in real-time, using frequency based signaling rather than a simulated series of time steps (Verschure et. al 1995). In forming categorical and behavioral patterns in real-time, we will need to obey the dictate of embodied cognition to avoid excessive world modeling and gear that which is required to the demands of real-time, behavior-producing systems (Clark 1997).

4.4. Mobile Robotic Simulators

After the development of small models for isolated cognitive tasks, we will begin the development of more complex and complete autonomous agents. The goal of this phase of the research will be to develop models that could one day be used in real world robotic agents. We will begin by building agents for autonomous mobile robot simulators for various simple tasks. We expect to display the ontogenetic development of behavior in a more complex and realistic perceptual environment than that offered by the initial task domains of the research. Tasks will range from simple navigation and map building tasks, to the self-organization of higher level behaviors in the pursuit of endogenously defined goals. Our first environment will be the Khepera simulator environment.

4.5. Autonomous Agents

During the past five years the "Conscious" Software Research Group, under Franklin's direction, has designed and developed software agents that implement Global Workspace Theory, a psychological theory of consciousness and cognition. One of these "conscious" software agents, IDA (Franklin, Kelemen, and McCauley 1998), is intended to automate *all* the duties of a Navy "detailer" who assigns a sailor a new billet at the end of his or her current tour. This entails accessing personnel and job databases, choosing jobs via deliberation to offer the sailor while remaining within the Navy's policies, and negotiating with the sailor in natural language. IDA is a quite complex software system with many modules each typically inspired by some computational mechanism drawn from the "new AI." IDA can recognize and classify incoming sense objects (pieces of text). She cannot, however, learn to recognize and classify new sense objects. Nor would her current mechanisms allow her to recognize and classify within a much more complex and demanding sensory modality such as vision. This is a major weakness of IDA as a model of cognition.

In the third year of the project being proposed here we plan to equip IDA with an additional sense (probably vision or audition) whose mechanism will be based on that developed during the first two years. This mechanism should be ideally suited to a sensory modality in which an individual object typically appears in a multitude of different presentations. IDA will provide a test bed for experimentation with such a sensory mechanism.

5. References

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6. Management Plan

The research personnel at the University of Memphis include Dr. Robert Kozma (PI) and Dr. Stanley P. Franklin and Derek Harter (co-PIs) and their graduate and undergraduate students. The project involves the Department of Mathematical and Computer Sciences, which is the administering unit.

The research personnel at the University of California Berkeley include Dr. Walter J. Freeman (co-PI) and his graduate and undergraduate students. The project involves the Department of Molecular and Cell Biology.

Dr Robert Kozma is the PI and the team leader of our project. He is responsible for running the project, coordinating his Lab's involvement in the research issues related to the fusion of sensory information in a dynamical embodiment and data processing, including the relationship of sensing and intentional action.

Dr. Stanley P. Franklin and his students will be responsible for the integration of various models of dynamical cognition developed into existing autonomous agents. He will coordinate collaborative activities between this research project and existing systems.

Dr. Walter J Feeman will work on how the biological principles of neurodynamics can be implemented in mathematical and computational models of intentionally behaving systems. His expertise in the neurodynamics of biological systems will be consulted as a guide in building such models. He will also coordinate collaborative activities and the broader impact of the project.

Derek Harter will help in developing the mathematical and computational models of intentionally behaving systems. He will be responsible for the implementation of the mathematical and computational models as various autonomous agent simulations.

We will use two basic ways to networking people, ideas, and data: personal meetings and electronic communications and networking.

On the personal level:

- Members at the Memphis campus will meet regularly in working discussions and also in the cognitive science and dynamical systems seminars;
- There will be a kick-off meeting at the start of the project, and annual meetings at the end of each project year. Team members from the University of Memphis will participate in the annual meetings;
- We will actively participate every year in national and international conferences to disseminate our results and to obtain feedback from the broad scientific community;
- A Workshop will be organized by our team members in the 3rd project year.

Electronic communication and networking:

- We will use electronic mails to everyday communications among team members. We will produce a newsletter on a monthly basis, to summarize research activities, achievements and possible problems. This channel is crucial to the continuous interaction with our collaborators.
- We will establish a web page of the project to display information on the project and the obtained results;
- Via the web page, we will provide an access to the Repository of our data, prototype autonomous agents, and to the available methodologies, like Matlab files and data processing algorithms.

7. Cost Plan

7.1. Year 1

7.2. Year 2

7.3. Year 3

7.4. Summary

7.5. Explanation

Personnel

1. We have 2 researchers as investigators in this project from the University of Memphis. Dr. Robert Kozma and Dr. Stan Franklin are faculty members at University of Memphis. Dr. Kozma will contribute 25% of his time to the project during the academic year, and full time during the summer months. Dr. Franklin will contribute 1 month of summer time to the project per year.

2. We have 1 researcher as investigator in this project from the University of California Berkeley. Dr. Walter Freeman is a faculty member at UC Berkeley and will contribute 22% of his time to the project.

3. Derek Harter is a Ph.D. student at the University of Memphis who will participate full time the first year as a programmer/analyst. In the second and third years he will participate full time as a post doctoral associate with the grant.

Equipment

Equipment expenditures for year 1 will be used to build a 8 node parallel cluster computer. This machine will provide a sufficiently powerful environment to build models of dynamical category formation and motor coordination tasks. Also in the year 1 equipment expenditures is budgeted for personal computers for 2 of the investigators upon which to develop mathematical models and other prototype simulations. The software budget for year 1 will buy licensing fees for various mathematical tools to be used throughout the project for model prototyping, and for the developmental and system software needed for the cluster computing environment. In year 2 we will be developing more complex neurodynamical models that will require the expansion of the cluster computer from 8 to 16 nodes, which will require the additional equipment expenditure to expand the cluster.

Travel

We have budgeted travel money for 2 domestic trips (or 1 international trip) for each of the Investigators per year to national or international conferences of interest to this research. This money is also for domestic travel of the investigators for the annual project review meetings. In year 3 we have budgeted extra travel expenses to pay for Workshop participants to travel to the University of Memphis.

Workshop

We will organize a Workshop in the last year of the project and invite the participation of scientists with interest in our research. Extra travel money has been allocate in year 3 to pay for travel expenses for some of the Workshop participants.

Agent Simulators

During years 2 and 3 we plan to explore various existing agent simulation environments upon which to test various aspects of our neurodynamical models. The money budgeted for this includes the tasks of buying and evaluating different simulation environments, and necessary programming modification to interface the environments with our neurodynamical models developed for the parallel cluster machine.

Consultants

We plan to invite speakers to the University of Memphis to consult with us, review our work and collaborate with various aspects of the project. The money budgeted for consultants includes paying for travel and speaking.

8. Resumes

Robert Kozma

Derek Harter

9. Declarations and Certifications

10. Appendix

10.1. Chaotic Resonance – Methods and Applications for Robust Classification of Noisy and Variable Patterns

Kozma, R. and Freeman, W.J. (2000b) Chaotic resonance - methods and applications for robust classification of noisy and variable patterns. *International Journal of Bifurcation and Chaos.* (in press).

10.2. Emergence of Un-Correlated Common-Mode Oscillations in the Sensory Cortex

Kozma, R., Alvarado, M., Rogers, L., Lau, B., Freeman, W. J. (2000) Emergence of un-correlated common-mode oscillations in the sensory cortex. *Proceedings Computational Neuroscience Conference*. CNS*2000 Special Issue of *Neurocomputing*. (in press).

10.3. *Local-Global Interactions and the Role of Mesoscopic (Intermediate-Range) Elements in Brain Dynamics*

Freeman, W. J. and Kozma, R. (2000) Local-global interactions and the role of mesoscopic (intermediate-range) elements in brain dynamics. *Behavioral and Brain Sciences* Vol. 23, No. 3, June, 2000. (in press).