FINAL SUMMARY OF RESEARCH

NASA Intelligent Systems Grant #NCC2-1244

SODAS: Self-Organizing Ontogenetic Development for Autonomous Adaptive Systems

Volume I:
Summary Report and Appendices I - IV

Grant Period: 03-01-2001 – 09-30-2004

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Volume I

I. Research Personnel

Principal Investigator (PI):
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Amaury Lendasse (University of Memphis; presently Helsinki University)
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Collaborators:
Peter Erdi (Kalamazoo College, Henry R.Luce Prof. of Complex Systems)
Mark D Holmes (Harborview Medical Center, University of Washington)
Jose Principe (University of Florida, Gainesville)
Toshio Fukuda (Nagoya University, Japan)
Ichiro Tsuda (Hokkaido University, Japan)
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Student Research Assistants (All University of Memphis):
Madhava Challa - 2001
Shahidul Pramanik – 2001-2002
Srinivas Achunala – 2001-2003
Derek Harter – 2001-2004 (Dissertation)
Prashant Ankaraju – 2001 -2002 (Thesis)
Nivedita Majumdar – 2002
Asha Kalindidi – 2002 – 2003 (Thesis)
Haizhon Li – 2003
Zhesheng Ziang – 2003
Sangeeta Muthu – 2002-2004 (Thesis)
Sai Sudha Ganti – 2003-2004 (Thesis)
Derek Wong – 2002-2004 (Thesis)

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II. Achievement Statements

Budget Accomplishments:

We have progressed with the budget plan as projected during the project period. We have received a no-cost extension for 6 months beyond the 3 year project period awarded originally. By the end of the extended project period we have completed the project budget in the amount of $695,064.00 according to the plans. Detailed budget data are attached.

Research Accomplishments:

We have completed the planned research goals in year 3 of the project. At the end of the extended project period of 3.5 years, we have completed and, in some areas, exceeded the milestones, which have been outlined at the start of the project in 2001. Our accomplishments and future plans are summarized in the Milestones document attached to this report. The project produced the following results:

- 33 journal articles,
- 33 conference proceedings,
- 1 PhD dissertation and 5 MS Theses,
- 1 Software Tool (Matlab Neurodynamics Toolbox),
- 9 Workshops and symposia,
- 4 Special Issues Edited or Co-Edited by senior personnel.

The reprints of research reports and articles produced with the support of this grant during the reporting period are available of the Computational Neurodynamics Lab web site http://cnd.memphis.edu. Detailed description of project results and achievements are given there as well.

Technical Conditions:

The Computational NeuroDynamics Laboratory (CND) at the Division of Computer Science, Dept. Mathematical Sciences, The University of Memphis has been the host organization of the project. Lab space for the project has been in the CND lab at two locations. Office space for graduate students is in 310 Dunn Hall (300 sqft), which also hosts the CND lab computer cluster with 16 parallel processors. CND Laboratory experimental facility hosting the mobile robot navigation environment for 2 Sony Aibo robots and supporting facilities are housed in 326 FIT (400 sqft), at the Fedex Institute of Technology building on the U of Memphis Campus site. Research in the CND Lab includes this NASA project, a related NSF-funded project, and a couple of collaborative research initiatives.

<u>Encl.:</u> Report document
Presentation handout (powerpoint)
Reprints of research publications & relevant documents

Budget Performance of SODAS

UoM Financial Records System Report printout is enclosed

III. Background of SODAS Project

The discovery that brain dynamics exhibits chaotic features has profound implications on the study of higher brain function. 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. It retains in its pathway across its basins a history, which fades into its past, just as its predictability into its future decreases. Phase 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, reliable assignment to classes that lead to appropriate actions, planning future actions based on past experience, and constant up-dating by learning.

The KIII model is a working example of the implementation of these chaotic principles in a computer software environment. KIII exhibits several of the experimentally observed behaviors of brains, like robust pattern recognition and classification of input stimuli, and fast transitions between brain states. KIII 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 feeding into an asymmetric sigmoid function. By coupling a number of excitatory and inhibitory KO sets, KI_e (excitatory) and KI_i (inhibitory) sets are formed. Interaction of interconnected KI_e and KI_i sets forms the KII unit. Examples of KI sets are PG and DG. Examples of KII sets in the olfactory system are the olfactory bulb, anterior olfactory nucleus and prepyriform cortex. In the hippocampus we have CA1, CA2, and CA3 as KII sets. By coupling KII sets with feed-forward and delayed feedback connections, one arrives at the KIII system. KIII shows rapid performance in learning new classes of training input data and it can generalize efficiently the classification of new test data.

The operation of the KIII model is described as follows. In the absence of stimuli the system is in a high dimensional state of spatially coherent basal activity, which is governed by an aperiodic, nonconvergent global attractor. In response to an external stimulus, the system activates a landscape of multiple attractors. It is kicked out of the basal state into a local basin of attraction, which is a memory wing. This wing is usually of much lower dimension than is the basal state. It shows coherent and spatially patterned amplitude-modulated (AM) fluctuations. The system resides in the localized wing for the duration of the stimulus then it returns to the basal state. This is a temporal burst process that lasts for about a hundred milliseconds. A memory pattern is defined therefore as a spatio-temporal process represented by the sequence of spatial AM patterns during a burst. KIII-based modeling of the olfactory system is used to classify linearly non-separable patterns. Its performance is compared with those of statistical classification methods and multi-layer feed-forward neural network-based classifications. KIII compares favorably with these methods regarding robustness and noise-tolerance of the pattern recognition, especially for classification of objects that are not linearly separable by any set of features.

The next highest level of the K sets is the KIV model. As in the case of all other K sets, the architecture and functionality of KIV is biologically motivated. In this work we extend multiple KIII sets into a KIV set that models the interactions in the cortical-hippocampal system. KIV is intended to have the functionality of planning and selection of action, in addition to classification and pattern recognition represented by single KIII units. KIV consists of three KIII sets, which model the cortical and hippocampal areas. All 3 are involved with learning and memory. The hippocampus is strongly involved in the cognitive processes of spatial and temporal orientation (cognitive mapping and short-term memory). In the KIII and KIV models several types of learning rules are used simultaneously, including habituation, Hebbian reinforcement learning, supervised learning, and global stability control through normalization. All these learning methods exist in a subtle balance and their relative importance changes at various stages of the memory process.

In the SODAS project, the principles of KIII and KIV sets are developed and implemented in the generation of self-organized development of autonomous adaptive systems. The systems under consideration have the tasks of recognition of sensory stimuli and make decisions regarding future actions, depending on the external inputs and internal motivations and goals of the autonomous agent. Our research activity is concentrated toward three major areas:

(1) Developing the theory of encoding sensory data in nonconvergent, chaotic memories (KIII), and also establishing tools for reading out relevant information from the spatially distributed dynamical activity patterns (KIV level);
(2) We apply the K models to describe sensation and perception for emergent goal-oriented behaviors. In particular, we establish the KIV model with 3 KIII components, each of which acts as interface with the external and internal environments, respectively, coordinated through the amygdala for generation of behavior and actions;
(3) Implement the above theoretical results in software and hardware domains, in order to demonstrate the operation of the dynamical principles. This leads us to enabling a novel technology of intelligent autonomous robots for remote missions with the capacity of on-site situation evaluation and decision-making, without requiring human presence and guidance.

IV. Milestones of SODAS Project

A. MODELING SPATIO-TEMPORAL DYNAMICS OF BRAINS

1. Development of the Computational KIV Model of Dynamic Memories

A major achievement of the research is the development of the mathematical/ computational model of the brain as a KIV set. The KIV entity is analogous to the cerebral hemisphere in the vertebrate brain at the evolutionary level of the salamander, which is the locus of goal-directed behavior. KIV works with 3 types of sensory signals:

- Exteroceptors are sensory receivers that are directed to the environment, terrain, sources of fuel, hazards, etc. It can represent visual, auditory, somatosensory, touch, etc signals.
- Interoceptors are directed to the state of the device itself, such as the remaining charge on its batteries, rate of depletion or re-charging, state of its drive and turn motors, actual movements, and discrepancies between motor speeds and actual motion.
- Orientation signals, e.g., gravity, visual flow, magnetic field. Orientation beacons describe the actual location of the animal with respect to a reference system, including “home”, and both positive (attractive) and negative (repellent) environmental cues other than “home”.

The exteroceptors and beacons give situation reports, and the septum organizes the valence from interoceptors. It is notable that the KIV level can be regarded as maintaining emotional states (desire, fear, frustration, hunger), but that it cannot be regarded as "conscious" in any meaningful sense. Goals are established by the human controller of the device, who can determine the specific location to which the device should move by establishing a beacon with a specific signal. The device may be familiarized with a significant signal by training to recognize the particular beacon (tone sound, light color, etc.) as signifying the location of a fuel depot. The device will approach it, choosing its path among known hazards and avoiding new hazards by learning about them.

The KIV model describes the crucial portions of the limbic system of brains that support intentional behavior such as orientation and operation in environments through acquisition of familiarity by exploration and learning. The 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.

> <u>*Achievement statement 1:* We have designed and built the KIV model. It is shown that KIV is sufficient for the production of general intelligent behavior such as that observed in simple mammals and reptiles. At the present stage of building the KIV model, we successfully tested the operation of the interacting hippocampal and cortical components, having motor action in a simplified implementation.</u>

2. Theory of Chaos in K sets

The KIII model has been extensively studied in the past years. After solving the problem of destabilization of chaotic trajectories based on local homeostatic balance conditions in KI and KII units, the model demonstrated excellent performance as a classifier. Additive noise plays an important role in achieving optimum operation of KIII. The emphasis of previous studies has been on analyzing the performance of the model as a practically useful dynamical memory device. We have analyzed the KIII attractors in the case of deterministic model (without noise), as well as with the introduction of noise. External or internal noise can initiate a transition between dynamical states of KIII. This effect has a resonance character and it can be used to enhance a weak periodic input signal, thus producing a high signal-to-noise ratio. It seems plausible to hypothesize that this creates a favorable conditions for itinerant oscillations among high- and low-dimensional attractors as they struggle for dominance without success. The addition of noise can enhance the signal-to-noise ratio, which is of great practical importance for signal processing applications.

> *Achievement statement 2:* We have identified a wide range of attractors, including fixed points, limit cycles, tori, and chaos. Itinerant behavior takes place at a given range of model parameters. A well-defined range of additive noise induces a resonance effect that creates especially favorable conditions for itinerant behavior. The identified parameters are used in the practical implementation of KIV.

3. Generating Biologically Plausible Intelligent Behavior by KIV

KIII and KIV models of dynamic memories operate in the region of self-sustained oscillations, which is achieved through appropriate tuning of the underlying KII Sets. A method for finding point attractors of KII sets is proposed. The numerical experiments confirm earlier hypotheses about KII sets having point attractors. The model has several fixed points or a combination of fixed points and limit cycle, depending on weight parameters. The behavior of the eigenvalues of the linearized KII system indicate that it becomes non-hyperbolic when approaching small amplitude limit cycle.

We have analyzed a discrete time model of K-sets. We have built a hierarchy of KA models, starting from the KA-I and KA-II units with fixed point and limit cycle dynamics, to the KA-III model with complex chaotic oscillations. For weak connection between KA-II sets, the leading Lyapunov exponents approach zero. The leading Lyapunov exponent incrementally increases with increasing scaling factor, until a certain level, where it drastically increases indicating the onset of a well-developed chaotic regime.

> *Achievement Statement 3:* We have demonstrated the presence of 1/f power spectrum distributions in the KA-III aperiodic dynamics, characteristic of critical states found in biological brains and also modeled by the original K-sets. The developed KA-III models are used to build an adaptive autonomous system that

explores the environment and generates optimal behavioral strategies in order to solve a given task.

B. SENSATION AND PERCEPTION IN INTENTIONAL NAVIGATION

4. Development of Sensory and Orientation Functions of KIV

The KIV model is used for the description of the interaction between the sensory and cortical systems, the hippocampus, the amygdala, and the septum. Neural activity patterns in KIV determine the emergence of global spatial encoding to implement the orientation function of a simulated animal. Our results embody the mechanisms, which we believe support the generation of cognitive maps in the hippocampus, based on the sensory input-based destabilization of cortical spatio-temporal patterns. In this research, the operation of two KIII sets that model the sensory cortex and the hippocampal formation (HF) are studied. The HF and cortex complete their functions by sampling the environment (external or internal) at a theta rate. To achieve this periodicity, KIV relies on the septum to generate the theta frame rate as a gating function. Temporal framing is done in all sensory systems. Examples of this sampling are the saccadic movement in visual system, sniffing in olfaction, perhaps something similar in the cochlea etc. Sensory signals to the cortex are the 6 short-range infrared signals as used in the case of simulated Khepera robot. For the sensory signals, we consider the past several time steps as inputs, in addition to the present time frame. The orientation signals are the distances and directions with respect to the landmarks, measured from the actual location of the robot.

> *Achievement Statement 4:* We have invented a novel method of learning spatial maps using a KIII hippocampal model, as part of KIV. We have demonstrated the feasibility of the learning methodology, and showed that K models can effectively solve navigation tasks. With this new advancement, we have expanded the potential application areas of the K sets from the classification task to a more complex decision making and behavioral generation domains.

5. Robust Multisensory Fusion in KIV

We have analyzed the KIII model in completing the task of spatial navigation. The system includes a hippocampal module that processes global spatial information and a cortical module that deals with local sensory information. The model of navigation that we propose describes the activity of the hippocampus and the cortex by using two, interacting KIII systems. The model has the following features:

- We used a localization system that uses high level and low-level sensory information to provide a robust representation of space.
- We used the chaotic dynamics of the KIII sets to implement pattern and place recognition systems.
- The place recognition system guides navigation based on global landmarks and the pattern recognition system performs obstacle avoidance based on local sensory information.
- The connectivities between nodes in the third layer of the KIII sets are updated using a Hebbian learning rule.

- The decision of which place to move next is based on the positive reinforcement the simulated animal receives while exploring the environment.

Although it accomplishes the same navigational tasks as other related models of spatial navigation, this novel approach is fundamentally different as it takes into consideration the chaotic dynamics observed at the EEG level. We test the model using several spatial navigation paradigms: goal finding, shortcutting and detouring.

> *Achievement Statement 5:* Computer simulations show that the performance of the agent qualitatively matches that of animals and related models. The advantage of our method compared to others lies in the way it manifests a natural fusion of multi-sensory information. This new approach provides a novel interpretation of how the brain accomplishes spatial navigation.

6. Phase Transitions in Brains and Brain Models

The goal of this research is to design advanced signal processing techniques to identify neural correlates of cognitive processing using EEG signals. A novel electrode array was designed and built for scalp recording: a curvilinear 1x64 row placed on the scalp with electrode intervals of 3 mm and length 19 cm, giving 10-fold increase over prior art in spatial resolution. The Hilbert transform was applied to get the instantaneous phase, giving 20-fold increase in temporal resolution.

The obtained data gave spatiotemporal patterns of unprecedented clarity and supported new theory with emphasis on four fundamental principles:

- Self-organized criticality (SOC): Brains maintain themselves at the edge of global instability by inducing a multitude of small and large adjustments. The time intervals and sizes of the changes have fractal distributions, as manifested in histograms and in 1/f forms of spatial and temporal power spectral densities.
- First order phase transitions: Each adjustment is a sudden and irreversible change in the state of a neural population that carries the population across a separatrix from one basin of attraction to another. The state changes are overlapping for populations of all sizes from less than a mm to an entire cerebral hemisphere.
- Chaotic itinerancy: The incremental changes by phase transitions at all levels tend to be recurrent at nearly periodic intervals and to repeat in the form of stereotypic behaviors and habits. Normally each attractor begins to dissolve as soon as it is accessed, allowing the brain to escape entrapment in a maladaptive behavior.
- Anomalous dispersion: The spread of each phase transition through the population is too rapid to be accounted for by serial synaptic transmission. Each population by virtue of long axons and small world effects has a group velocity at which information is transmitted and a much higher phase velocity at which a phase transition spreads. This ensures synchrony over domains ranging from less than a mm to over 20 cm.

To describe and explain background 'spontaneous 'cortical oscillations in the EEG, high-density 8x8 subdural arrays were fixed over sensory cortices of rabbits. EEG were spatially low pass filtered, temporally band pass filtered, and segmented in overlapping windows moved at 2 ms.

Phase was measured by curve fitting using nonlinear regression with the cosine as the basis function. Analytic phase was measured with the Hilbert transform. Spatial phase patterns in 2-D were measured by fitting a cone as the basis function to the 8x8 phase surfaces. Measurement gave estimates of two fundamental state variables at each point in time: the rate of change in phase with time (the frequency), and the rate of change in phase with distance (the gradient). These 2 quantities enabled description of intermittent spatiotemporal patterns of phase. The diameters, durations, and phase velocities of these patterns varied with window duration and with interelectrode interval. The distributions of spatial wavelength and diameter were skewed, those of gradient and velocity were bimodal, and those of duration and interval were fractal. Recurrence rates of larger patterns were in the theta range.

> *Achievement Statement 6:* We have identified beta-gamma phase patterns in the ms-mm to m-s ranges, which evidence that neocortex maintains a scale-free state of self-organized criticality in each hemisphere as the basis for its rapid and repetitive integration of sensory input with experience. An act of perception is described as a widespread, almost instantaneous re-organization of neocortical background activity, which is induced by thalamic input acting as an order parameter.

To explain spatial patterns of phase in beta-gamma EEG activity of human neocortex, a high-density (10x10 mm) array of 8x8 electrodes (1.25 mm intervals) gave EEG signals from the inferior temporal gyrus of a neurosurgical patient awake and at rest. Frequency and phase were measured by the Hilbert method at each digitizing step and by the Fourier method in a moving window stepped along the filtered signals at the digitizing interval (5 ms). These measures enabled calculation of the location, size, time of onset, phase velocity, duration, and recurrence interval of radially symmetric spatial patterns denoted phase cones. Results: The apex of each cone showed the location and onset time of abrupt re-initialization of phase at a frequency in the beta-gamma range. Half power cone diameters were 5-50 mm or more. Durations had fractal distributions with means ranging from 6-300+ ms depending on window length. Recurrence rates of longer-lasting phase cones were in the theta-alpha range.

> *Achievement Statement 7:* It is concluded that phase cones reflect chaotic state transitions leading to new cortical patterns assimilating sensory input. The overlapping cones show that neocortex maintains a stable, scale-free state of self-organized criticality by homeostatic regulation of neural firing, through which it adapts instantly and globally to rapid environmental changes. The proposed mechanism for stabilization of hemispheric neurodynamics may open new avenues to study human cognition and dynamic brain diseases. The present results also suggest that phase structures in the human scalp EEG relating to cognition may be readily accessible with standard clinical EEG equipment.

C. SOFTWARE AND HARDWARE IMPLEMENTATION ENVIRONMENTS

7. Simple Software Simulation Environments for Action Selection: Tetris and Khepera

Our Tetris and Khepera computer simulations are aimed at the creation of action selection mechanisms that are capable of some of the flexibility of behavior displayed by biological brains on real-time tasks under difficult situations. We developed the Tetris Packing Task, which is a relatively simple task still rich in the possibilities for the emergence of skills, strategies and goals under conditions of time and resource constraints. This is a simple testbed for developing action selection mechanisms using principles of chaotic neurodynamics. The experience we have gained in creating the tetris environment is very useful in exploring emergent behavior in adaptive agents.

> *Achievement Statement 8:* We have used the simulated Khepera environment to generate cognitive maps for goal oriented task completion. In a basic operation, the robot is in a wall-following mode, with some random component added for more natural behavior. After sufficient amount of exploration, the robot develops the cognitive map. We have obtained these maps with various running conditions. The method is robust to moderate noise levels in the sensory signals.

8. Implementing KIII and KIV in simulated T maze and Martian environments

We simulated the multiple T-maze paradigm by placing the agent in the maze and giving it positive reinforcement in the hippocampal KIII, whenever it moved towards the goal location. On the other hand, we use negative reinforcement in the cortical KIII, if the robot finds an obstacle. The agent demonstrates a significant improvement after 5 trials compared to the first training trial and the performance can be further improved as the number of learning trials increases. A more challenging navigation problem is to find the location of the goal in a simulated Mars like rocky environment. We tested our navigation model in an environment that contains uniformly distributed obstacles of different sizes, which have exponential size distribution, approximating Martian terrain. The learning paradigm is the same as for the goal finding in the T-maze. We used Hebbian reinforcement learning in the KIV model having hippocampal and cortical KIII components.

> *Achievement Statement 9:* The agent demonstrates skillful navigation in a complex environment. It is able to avoid obstacles and to reach the goal location using a suboptimal path. It learns goal-oriented behavior based on relatively few training examples. The average number of steps in the case of a trained KIV control system is much smaller (10 times less) than for random exploration. The experiment shows the power of the K-based navigation method in the case of limited and often contradictory sensory data.

9. Proof-of-principle of KIV Autonomous Control Using AIBO Mobile Robot Testbed

Intelligent autonomous agents are capable of independent action in open, dynamically changing environments. The agent used for this milestone is the SONY AIBO dog (ERS 220), called EMMA. EMMA is a wireless agent that communicates via a LAN to a PC. It has a small memory stick that stores the operations to be performed by the agent and it is battery-operated. We will use two types of sensors:

- Infra red IR sensors that detect the distance from obstacles (local sensing);

- CMOS camera sensor that can capture images and other visual information (long-range sensing).

The action selection mechanism is dependent on the sensory inputs from the robot. EMMA learns to navigate using colored balls as landmarks located in the environment (10ft x 14 ft). At present, we simplify the image processing task and use only color-detection mode of the CMOS cameras. We supplement AIBO's sensory system with an external camera located above the experimental area, which is used to give global positioning clues to EMMA. In the present implementation, we use Sony OPEN-R environment to communicate between Aibo and the PC, which runs KIV in Matlab. We have achieved a reasonably fast operation of EMMA with delay time between decisions is in the order of 1-2 seconds or less.

We have implemented a KIV-based control algorithm on EMMA mobile robot platform with two senses (vision and IR). In addition to the two KIII components, our system uses a model amygdala. The amygdala is responsible for coordinating the KIV operation and making a decision to be processed by the motor system. The amygdala is a complex system that self-organizes its operation using spatio-temporal chaotic principles. In the present implementation we use a simplified version of the amygdala, which uses a pre-defined rule to switch between operation modes dominated by the simulated cortex or the hippocampus.

> Achievement Statement 10: The autonomous robot EMMA has demonstrated her learning capabilities using a landmark system in open environment and in the presence of obstacles, as well. We have quantitatively characterized learning effects in the model hippocampus and sensory cortex, and also the role of short-term memory effects. The physical embodiment of the dynamical neural memory design was not part of our original milestones, therefore **these results indicate that we performed well beyond the prescribed project tasks by producing a proof-of-principle demonstration of dynamical memory and control in mobile robots.**

V. Broader Impact and Products

Educational:

Dissertations/Theses:

1. PhD Dissertation: Towards a model of basic intentional systems: Chaotic dynamics for perception and action in autonomous adaptive agents, Derek Harter (U of Memphis, 2004)

2. MS Thesis: Spatial navigation using KIV model in simulated environment, Derek Wong (U of Memphis, 2004)

3. MS Thesis: KIV model and navigation using AIBO, Sangeeta Muthu (U of Memphis, 2004)

4. MS Thesis: Automatic generation of cognitive maps using local and global orientation signals, Sai Sudha Ganti (U of Memphis, 2004)

5. MS Thesis: Building cognitive maps for navigation task in software agents, Asha Kalidindi (U of Memphis, 2003)

6. MS Thesis: The hierarchy of K sets: From pattern recognition to navigation, Prashant Ankaraju (U of Memphis, 2002)

Courses:
In the field of educational impact, there have been over 30 student class projects on research topics related to SODAS project in the following graduate courses at The University of Memphis with significant minority and women involvement:

1. COMP 8740/7740 Neural Networks (2001, 2003)
2. COMP 8745/7745 Computational Intelligence (2002, 2003, 2004)
3. COMP 8713/7713 Advanced Algorithms (2002)
4. COMP 8991/7991 Computational Neurodynamics (2003)
5. COMP 6470/4470 Soft Computing (2004)

Software Package:

- Neurodynamics Toolbox for Matlab, Test Version, http://cnd.memphis.edu/k/
  This version is under development; contains a package of Matlab .m files, to be used by students/researchers to build hierarchical K sets: KO, KI, KII, KIII, with demos and

worked out examples. This software is developed under an agreement with Mathworks Co.

Conference and Editing Products:

Journal Special Issues Edited:

1. Complex Nonlinear Neural Dynamics, Special Issue of *Journal of Integrative Neuroscience*, Eds. P. Andras, P. Erdi, R. Kozma, Imperial College Press, Vol. 2, No.1, pp. 1-147, 2003.

2. Temporal Coding for Neural Information Processing, Special Issue of *IEEE Transactions on Neural Networks*, Eds. DL Wang, WJ Freeman, A. Lozowski, R. Kozma, A. Minai, September 2004, Vol. 15, No. 5.

3. Intentional Systems – Biological Foundations, Modeling, and Robotic Implementations, Special Issue of International Journal of Intelligent System, Eds. R. Kozma, T. Fukuda, Wiley, forthcoming, 2005.

4. Nonlinear Spatio-temporal Neural Dynamics - Experiments and Theoretical Models, Special Issue of Biological Cybernetics, Eds. P. Erdi, R. Kozma, P. Andras, in press, 2005.

Workshops/Symposia/Tutorials Organized:

1. Workshop on "Nonlinear Neurodynamics," Organizer and Co-Chairs P. Andras, P. Erdi, R. Kozma, *Computational Neuroscience Conference CNS*2004*, Baltimore, July 2004

2. Symposium on "*Intentional Dynamic Systems*," Organized by R. Kozma, and D. Harter, April 23-25, 2004, FIT, Memphis, TN.

3. Tutorial on "*Dynamical Memory Neural Networks*" at IEEE IJCNN'03, July 20, 2003, Portland, OR

4. Symposium on the "*Dynamics of Perception and Cognition*," Organized by R. Kozma, February 27-March 1, 2003, Memphis, TN.

5. Workshop on "Non-linear spatio-temporal neural dynamics – Experiments and theoretical models," Organized by P. Andras, P. Erdi, R. Kozma, Alicante, *Computational Neuroscience Conference CNS*2003,* Spain, July 8, 2003.

6. Workshop on "Complex Nonlinear Neural Dynamics," Organizers P. Andras, A. Assadi, D. DeMaris, R. Kozma, *Computational Neuroscience Conference CNS*2002*, Chicago, July 25, 2002.

7. Symposium on "*Hippocampus: Structure, Function, and Dynamics*," Invited Series by P. Erdi, Organized by R. Kozma, May 23-26, 2002, Memphis, TN.

8. Workshop on "Complex Nonlinear Neural Dynamics," Organizers P. Andras, A. Assadi, D. DeMaris, R. Kozma, *Computational Neuroscience Conference CNS*2001*, Asilomar, July 5, 2001.

9. Symposium on "*Consciousness, Cognition, and Memory,"* Organized by S. Franklin, R. Kozma, April 6-7, 2001, Memphis, TN.

VI. Research Papers on SODAS (2001-2005)

Journal Papers - Computational

1. Harter, D., Kozma, R. (2005) "Chaotic Neurodynamics for Autonomous Agents," *IEEE Trans. Neural Networks,* 16(3) (in press, May, 2005)

2. Puljic, M., Kozma, R. (2005) "Activation Clustering in Neural and Social Networks," *Complexity,* (in press)

3. Kozma, R., Wong, D., Demirer, M., Freeman, W.J. (2005) "Learning intentional behavior in the K-model of the amygdala and enthorhinal cortex with the cortico-hippocampal formation," *Neurocomputing* (in press)

4. Kozma, R., Puljic, M., Bollobas, B., Balister, P., Freeman, W.J. (2005) "Phase Transitions in the Neuropercolation Model of Neural Populations with Mixed Local and Non-Local Interactions," *Biol. Cybernetics* (in press)

5. Harter, D., Kozma, R., (2005) "Aperiodic Dynamics and the Self-Organization of Cognitive Maps in Autonomous Agents," *Int. J. Intelligent Systems* (in press)

6. Beliaev, I., Kozma, R. (2004) "Time series prediction using chaotic neural networks: Case study of CATS Benchmark test" (submitted)

7. R. Kozma, M. Puljic, P. Balister, B. Bollobas, W.J. Freeman, (2004) "Neuropercolation: A Random Cellular Automata Approach to Spatio-Temporal Neurodynamics," *Lecture Notes in Computer Science*, vol. 3305, pp. 435-443.

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Appendix I

Extract from the SODAS Description accepted for funding by grant NCC2-1244

Technical Area : TA-4 Revolutionary Computing (Biology-Inspired Approaches)

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.

a. 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.

b. 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.

c. 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).

d. 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.