Navigation and Cognitive Map Formation Using Aperiodic Neurodynamics

Derek Harter **Robert Kozma**
Department of Computer Science
University of Memphis
Memphis, TN 38152 USA
{dharter|rkozma}@memphis.edu

Abstract

Biological brains are saturated with complex dynamics. Artificial neural network models abstract much of this complexity away and represent the computational process of neuronal groups in terms of simple point, and sometimes periodic attractors. But is this abstraction justified? Aperiodic dynamics are known to be essential in the formation of perceptual mechanisms and representations in biological organisms. Advances in neuroscience and computational neurodynamics are helping us to understand the properties of nonlinear systems that are fundamental in the self-organization of stable, complex patterns for perceptual, memory and other cognitive mechanisms in biological brains.

Much of this new understanding of the principles of self-organization in biological brains has yet to be used to improve the performance of animats and other biologically inspired models of behavior generation. In this paper we review some of the findings of how biological brains may use aperiodic dynamics in the formation of perceptual mechanisms. We discuss some models of this formation of chaotic attractors for perceptual categorization. And finally we present some work using these models to develop cognitive maps and navigation behavior in an autonomous agent.

1. Introduction

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

Nonlinear systems in critical states have many interesting properties. Phenomenon such as stochastic and chaotic resonance (Kozma and Freeman, 2001) are known which enable such systems to actually detect the presence of signals much better in noisy environments than nonlinear systems are capable of doing. Their greatest interest lies however in their fundamental relationship to self-organization and emergence of complex patterns and behaviors in complex environments. Complex, aperiodic dynamics are both an indication of and a mechanism for the emergence of such self-organizing properties.

Insights in nonlinear systems theory are beginning to be applied to understanding the dynamics of the brains, and how such processes produce cognition (Freeman, 1999, Tsuda, 2001, Freeman, 2003). Aperiodic dynamics are know to play a fundamental role in the mechanisms for the self-organization of meaning in mammalian perceptual systems (Skarda and Freeman, 1987, Freeman, 1991). Neurological evidence has shown that perceptual meanings (of recognized smells) are created through the formation and dissolution of chaotic attractors in the olfactory bulb. We will discuss this example of the self-organization of a perceptual pattern of meaning. We use this type of organization in aperiodic systems to model the formation of place cells in the simulated hippocampus of an autonomous agent. And we also show how these mechanisms may be used to produce goal-directed navigation in an autonomous agent.

2. K-Sets: A Neurodynamical Population Model of Brain Dynamics

3. Place Cell Formation using Aperiodic Neurodynamics

3.1 Experimental Architecture and Environment

Perceptual meanings are formed through aperiodic attractors in the spatio-temporal activation of neuronal groups in the perceptual cortex. The same basic mechanisms of aperiodic dynamic in perception are also used by the biological brain in other areas to form memory and behavior producing structures (Kozma et al., 2003). In this section we use the basic KIII architecture to demonstrate the formation of place cells in a simulated hippocampus of an autonomous agent.

In this experiment, we used the Khepera virtual environment simulator (Michel, 1996). Figure 1 (bottom left) shows the morphology of the Khepera agent. The Khepera robot is a simple agent that contains 8 infra-red and 8 light sensors. It has two independently controlled wheels that allow it to move forward, backward, and turn left and right in place. The environment for this experiment is shown in figure 1. In the environment we place 8 light sources, which will be used as salient environmental locations (i.e. they can be thought of as food sources for the agent in the environment). The light sources are detectable to the agent at a distance, and the range where the light source is detectable is indicated in Figure 1. In addition to the 8 salient environmental locations, there are 4 landmarks. The landmarks are always detectable to the agent, and it knows the distance and direction to each of the 4 landmarks as part of its sensory information.

The architecture of the simulated hippocampus is shown in Figure 2. The portions of the architecture that form the cognitive map of the environment are simulated by a KA-III. These are the CA1, CA2 and CA3 areas, and are based on biological evidence of the structure of the hippocampus. Each of the CA areas contains an 8x8 array of KA-II units (for a total of 64 units in each CA region). Each CA area is connected to the other 2. The interconnection of these 3 CA regions via inhibitory and excitatory feedback forms a KA-III unit. The connections between CA regions will be changed via Hebbian modification.

Orientation beacons are fed into the hippocampal simulation through the DG region (Figure 2, left). The DG again contains an 8x8 matrix of KA-II units. Orientation signals from the 4 landmarks are fed into the DG units. Each of the 4 landmarks has 8 units associated with the direction to the landmark, and 8 units associated with the distance. Directions are broken into 8 cardinal units, North, NorthEast, East, SouthEast, South,

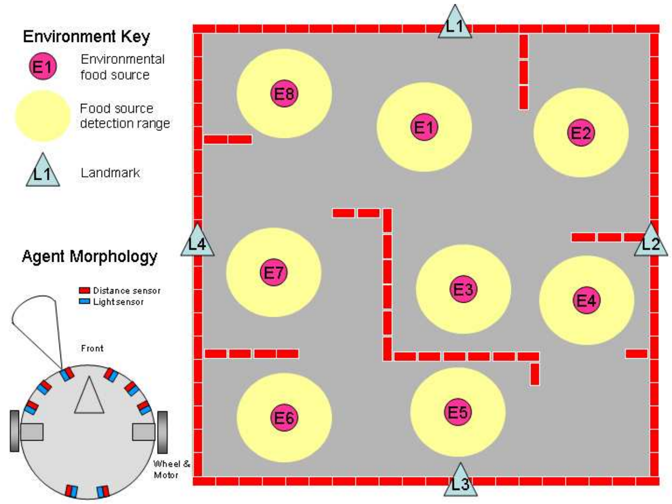

Figure 1: Agent morphology (bottom left) and environmental setup for hippocampal simulations. The environment contains landmarks, used as allocentric reference points by the agent, and salient environmental locations, such as food sources. The agent is only able to detect the presence of a food source when it is within a particular range of it.

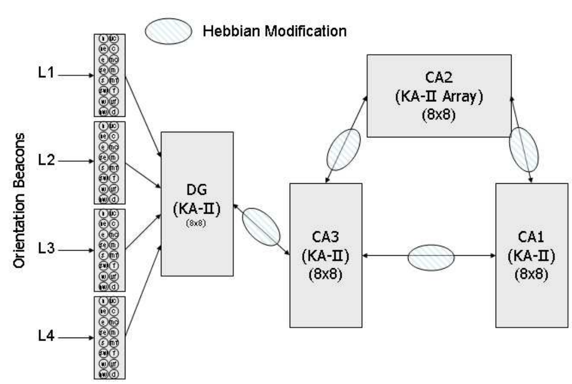

Figure 2: Architecture of KA-III hippocampal simulations

SouthWest, West and NorthWest. Units are sensitive to the direction of a particular landmark, though we use a graded response with a normal distribution which allows more than 1 unit to be active. Similarly there are 8 cardinal distance values VeryClose, Close, MediumClose, Medium, MediumFar, Far, VeryFar, Distant. Again a graded response with normal distribution is applied to the units. The DG area connects with the CA3 area, and the connections between these areas are also subject to Hebbian modification.

3.2 Method

We use two types of learning in the simulation, Hebbian modification and habituation. Hebbian modification only occurs when the robot is within a certain range of a light source. Therefore the light sources provide a certain valence signal that acts as a stimulus to learn environmentally salient locations. When the robot is not within proximity to a light source, no reinforcement signal is produced. During these times habituation of the stimulus occurs. This has the effect of lessening the response of the simulated hippocampus to unimportant regions in the environment (Kozma and Freeman, 2001).

The expected effect of this stimulation is to form 2 distinct types of dynamical patterns in the CA regions. When the agent is out of range of an environmentally salient location, the dynamics should be in the high-dimensional chaotic state, receptive to input but not indicative of recognizing a salient event. When in range of a light source, the system should transition to a low dimensional attractor, indicative of recognition of the important location. Further, the spatial amplitude modulation patterns in the CA regions upon such recognition should form 8 unique patterns, one for each of the recognized regions.

The agent is allowed to roam in the environment, using a low level mechanisms to produce efficient, but random wandering. The agent roams for a set time period (1000 seconds) during which sensory data is perceived and hebbian modification occurs as described previously.

3.3 Results

We first look at the amplitude modulation (AM) patterns produced by the hippocampal simulation characteristic of the 8 salient regions in the agents environment. In Figure 3 we show examples of the amplitude of the activity of the 8x8 units in the CA3, displayed as contour maps. We next explain these contour maps and how they were produced.

After the agent was allowed to wander in its environment, and hebbian modification was applied to the simulated hippocampus, we tested the response of the simulated hippocampus in the following manner. We randomly chose 4 points close to each of the 8 environmentally salient regions. We placed the agent at these points in the environment for 1 second where it received the appropriate perceptual inputs (e.g. distance and direction information to the 4 environmental landmarks). We captured the responses of the 8x8 units in the CA3 region during this 1 second of activity. We then calculated the standard deviation of the 8x8 CA3 units during the 1 second of activity to come up with a single matrix of 8x8 values characterizing the amplitude of the activity of each of the units. We plotted these amplitude patterns as contour maps and displayed the results in Figure 3.

The results in Figure 3 show visually the response of the simulated hippocampus after learning. The CA3 responds with a similar AM patterns for points close to a particular location; for example test points 1,2,3 and 4 at location 8 show 2 valleys to the left of the 8x8 CA3 and 3 or so peaks near the bottom of the CA3 region. However, the AM patterns formed at the different locations seem to be different and distinct from one another.

Although the contour maps give evidence of the formation of unique AM patterns in response to environmental locations, we can more clearly see the results by measuring the similarity of the AM patterns to one another. In Table 1 we show the results of measuring the Euclidean distance between the 4 points tested at the 8 environmental locations to each other. We show each of the target location/test patterns and which of the other AM patterns (excluding itself) the target was closest to. We treat the AM pattern as a 64 dimensional vector and use simple Euclidean distance to determine closeness of one AM pattern to another. As can be seen, the AM patterns formed in the CA3 region of the KA-III hippocampal simulation form fairly coherent patterns. Patterns around an environmentally salient location tend to be most similar to one another. The performance is not perfect, however. For example, location 2 test points 3 and 4 ended up being closest to AM patterns formed at location 7. The fairly unique formation of AM patterns around the environmental locations can be interpreted as the formation of "place cell" like patterns in the simulated hippocampus.

As another example of the aperiodic attractors formed by the hippocampal simulation, we show a state space plot of the activity of a single unit in the CA3 region. Figure 4 shows a state space representation of the activity of a unit (in column 3, row7) in the CA3 region. The state space plots are plotting the activity of the unit against itself with a 12ms time delay. Again we show the activity of the unit in response to 4 tests (rows in the figure) at the 8 environmental locations (columns in the figure).

This figure shows and example of how the KA-III may produce subsymbolic type representations of the input patterns. In this case, the unit seems to have formed at least 3 distinct aperiodic attractors. The unit activity at

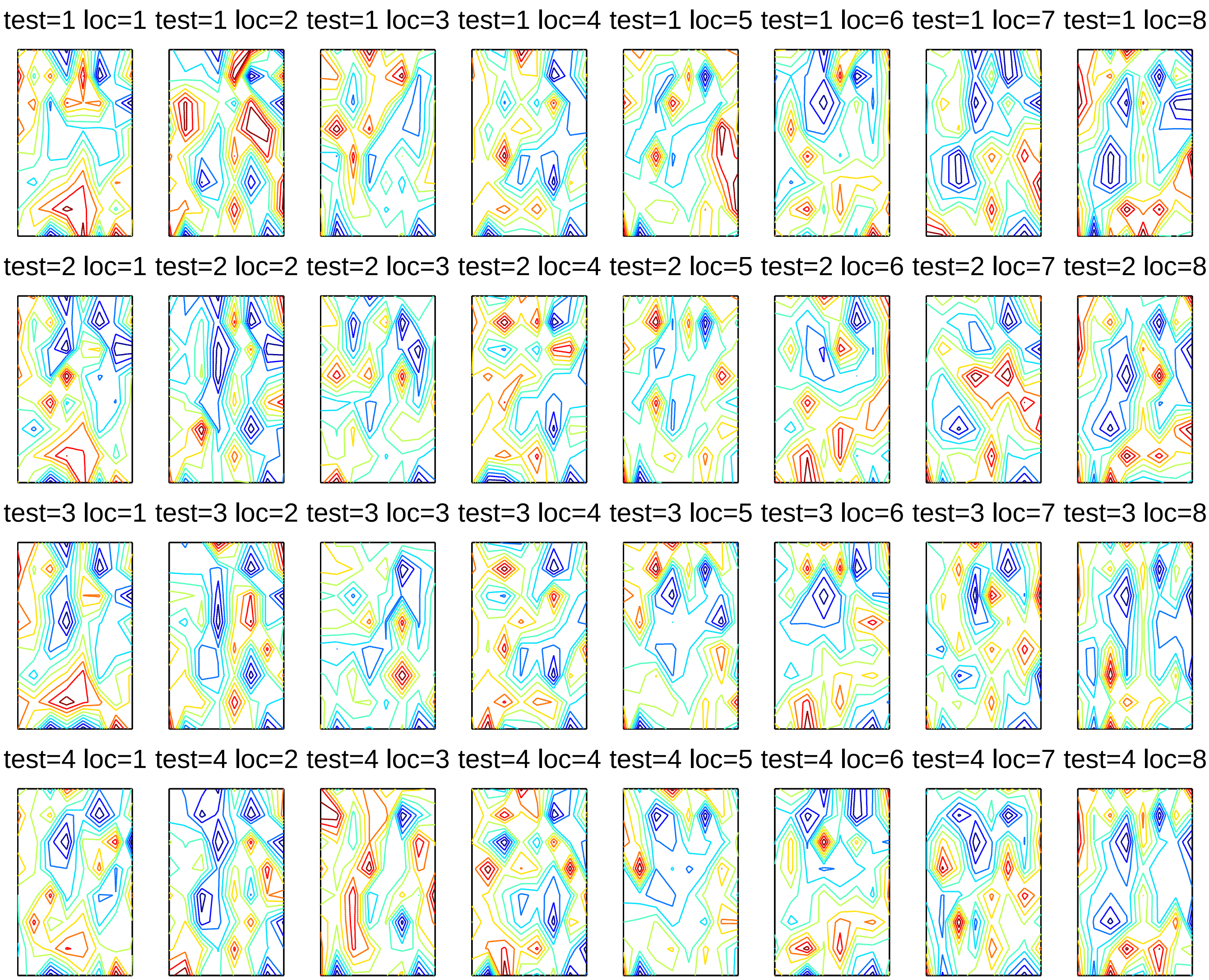

Figure 3: Example of AM patterns formed in the CA3 hippocampal region. In this figure we show contour maps of amplitudes of the activity in the 8x8 units in the CA3 region. We show the AM patterns for 4 test cases around each of the 8 salient locations in the environment.

locations 1 and 4 seem to be similar, and similarly attractors for locations 2,3,7,8 and also attractors for locations 4 and 5. Although the attractors produced are not perfectly consistent, they may be capturing some kind of similarity in a portion of the perceptual input between these 3 groups of locations. They therefore are dividing the environment into 3 subsymbolic patterns. Each of the 64 units in the CA3 region, when you observe the state space plots, performs a similar but different partitioning of the input stimuli. The resulting attractors in the 8x8 CA3 region produce the unique AM patterns observed at each of the locations in the environment.

4. Goal-Directed Navigation

4.1 Experimental Architecture and Environment

In this section we use the KA-III model to perform goal-oriented navigation in a simulated martian-like debris field that might be encountered by a martian planetary rover (Huntsberger, 2001, Tunstel, 2001). We use the Webots simulation environment (Michel, 2003), which is a physics based 3-d graphical simulation environment for real robotic platforms (see Figure 5).

The architecture of the agent for this simulation is shown in Figure 6. In this experiment the agent is hard-coded to instinctually move and avoid objects, using the agents touch and distance sensors (Figure 6, right). A

Table 1: Results of similarity (distance) measure of CA3 hippocampal AM patterns

Target		Closest		Target		Closest	
Loc	Test	Loc	Test	Loc	Test	Loc	Test
1	1	1	3	5	1	5	2
1	2	1	1	5	2	5	1
1	3	1	1	5	3	5	4
1	4	1	2	5	4	5	3
2	1	2	3	6	1	6	2
2	2	2	3	6	2	6	3
2	3	7	2	6	3	6	2
2	4	7	1	6	4	1	1
3	1	3	4	7	1	7	2
3	2	3	3	7	2	7	1
3	3	3	2	7	3	6	2
3	4	3	1	7	4	7	3
4	1	4	2	8	1	8	4
4	2	4	1	8	2	8	4
4	3	4	1	8	3	8	4
4	4	4	1	8	4	8	2

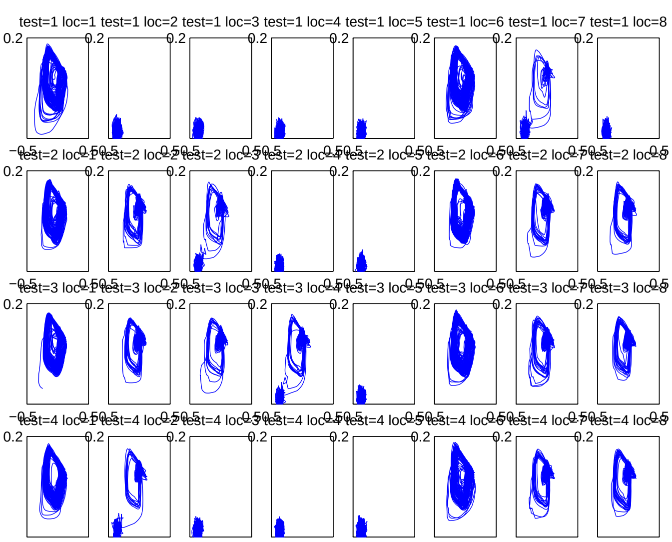

Figure 4: State space plot of activity of unit (column 3, row 7) in CA3 region during testing of KA-III hippocampal simulation.

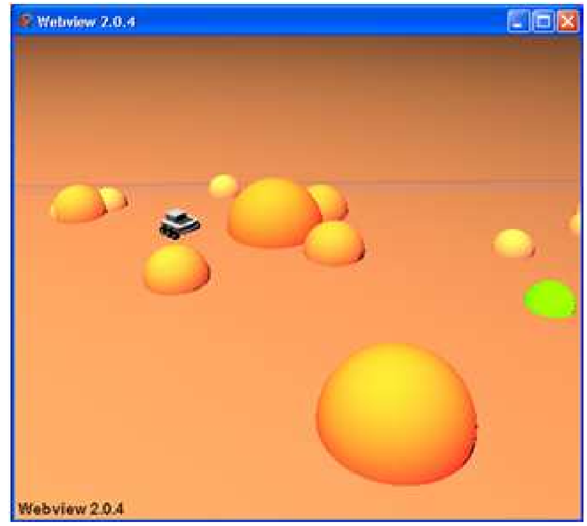

Figure 5: The Webots environment used for the goal-directed navigation demonstration.

goal location is selected in the environment, which emits a simulated gradient field that can be detected by the agents sensors. We think of the gradient field as a type of chemical gradient, such as might be followed by an animals olfactory system to locate a target. The gradient is invariant with respect to the obstacles in the environment, therefore the agent must combine local information about obstacles with the global information provided by the gradient to successfully navigate to the target.

4.2 Method

The simulated olfactory system receives sensory input on the strength of the smell signal from sensors positioned around the robots body. The task of the simulated olfactory system is to turn the agent towards the strongest direction of the gradient in order to follow the gradient to its source. The agent is trained by receiving positive reinforcement signals when it moves in a direction that reduces the distance from the agent to the goal. These signals are used to guide the hebbian modification of weights among units between the simulated perceptual system and from the perceptual to the motor systems. Reinforcement, however, is not received if the olfactory system is interfering with the object avoidance signals and causing the agent to run into an obstacle.

4.3 Results

In Figure 7 we show one result of the agents behavior after training. The agent starts in the lower left corner of the debris field and successfully finds a path to the goal location. In this example, the agent combines local information to perform object-avoidance, with global in-

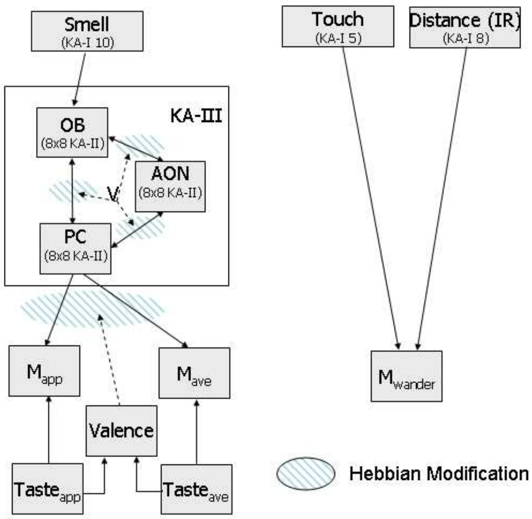

Figure 6: Architecture of the neural model used for the goal-directed demonstration. The agent is hardcoded to avoid obstacles and wander in its environment using touch and distance sensors (right side of figure). The agent receives sensory information from a simulated smell gradient produced at the goal location (left of figure). The agent is given reinforcement when it moves closer to its goal, which allows for hebbian modification to take place.

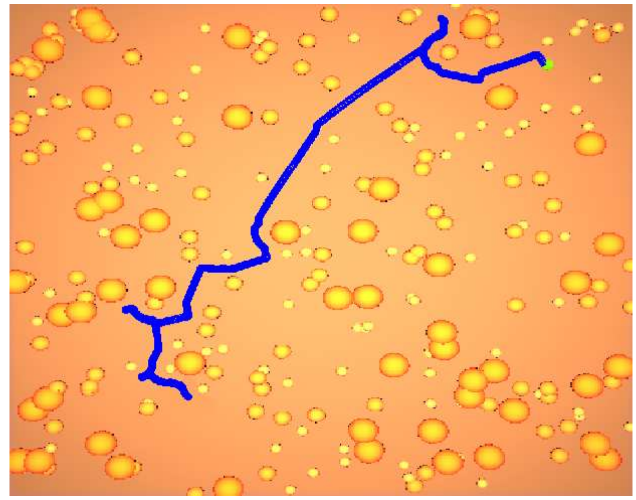

Figure 7: Results of a simulated run of the agent in navigating to its goal location (upper right, green rock). The agent avoids local obstacles while following the environmental gradient to the goal. The environment is a mars-like simulation of a debris field encountered in typical martian rover landing sites.

formation in order to follow the environmental gradient.

The figure showed one successful navigation of the agent to the goal location. It is necessary, however, to note that with this simple perception/action system the agent can easily get lost or fall into unproductive, repetitive behavior, depending on the starting/goal positions and obstacle placement. For example, sometimes the agent follows the gradient towards the goal only to find that it is blocked by obstacles. The object-avoidance behaviors can cause the agent to turn away and go back the way it came for a time. However the gradient-following may then kick back in and cause the agent to turn back in the direction it has already explored. This repetitive behavior represents a failure of the agent to remember its environment (or become bored), and will be discussed next.

5. Discussion

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

The KIV architecture is a model of what biologists believe may be the simplest neurological structure capable of basic intentional behavior, the limbic system (Kozma et al., 2003, Kozma and Freeman, 2003). The limbic system is composed of four basic functional areas: sensory/perceptual areas, memory and orientation, value system (needs and goals) and motor systems. These four areas can roughly be described as the "What" "Where" "Why" and "How" functions respectively. Figure 8 is a schematic representation of the KIV model of the limbic system.

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

5.1 What (Sensory/Perception)

As discussed previously, aperiodic dynamics have been observed in rabbit sensory systems, and are believed to play an important part in the formation of meanings. In the KIV architecture, external signals (exteroception) arrive from the environment (Figure 8 top). Each sensory channel is mapped into meanings of interest to the

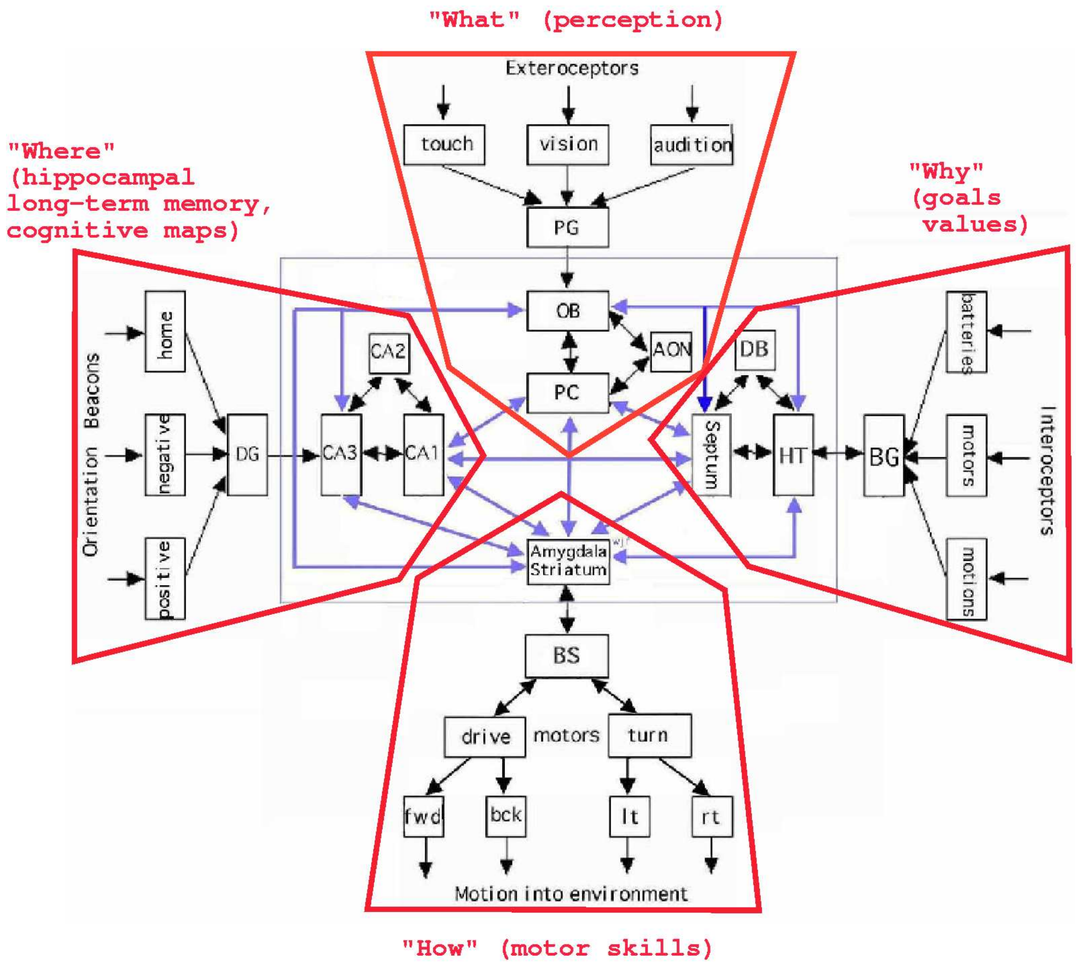

Figure 8: The KIV architecture. Based on figure from (Kozma and Freeman, 2003)

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

5.2 Where (Orientation, Memory)

A primitive hippocampus is the center of more long term memory and orientation functions in simple limbic systems. In the KIV architecture, the formation of cognitive maps of the environment, and the determination of the orientation of the organism in its environment (both locally and globally) is taken care of in the hippocampus. The orientation function of the hippocampus is depicted in the KIV model (Figure 8 left) as receiving orientation signals from the environment. The three CA regions (CA1, CA2 and CA3) form a KIII set that is responsible for the formation of memories of the environment of the organism. The formation of cognitive maps, and so called place cells, in the hippocampus, is performed in the CA KIII set, and takes advantage of the flexibility of aperiodic dynamics to form such representations.

5.3 Why (Goals, Drives, Value Systems)

Figure 8 on the right composes the value system of the KIV architecture, and mediates the production of behavior to guide the organism in completing goals and tasks to satisfy its needs. This system keeps track of the reasons "Why" the organism is doing what it is doing. In the valence system, internal signals that monitor basic needs (such as food, or avoiding damage) are fed into the system (Figure 8 right). Another KIII forms the heart of the system for forming and balancing a goal landscape of the organism (HT, DB and septum).

5.4 How (Motor Actions)

The motor system (Figure 8 bottom) is responsible for directing actual effectors for "How" the organism will carry out behaviors in pursuit of its goals. The amygdala provides the goal-oriented direction for the motor system that is superimposed on local tactile and other protective reflexes.

6. Conclusion

Acknowledgment

This work was supported by NASA Intelligent Systems Research Grant NCC-2-1244.

References

Freeman, W. J. (1991). The physiology of perception. *Scientific American*, 264(2):78–85.

Freeman, W. J. (1999). *How Brains Make Up Their Minds*. Weidenfeld & Nicolson, London.

Freeman, W. J. (2003). The wave packet: An action potential for the 21st century. *Journal of Integrative Neuroscience*. in press.

Freeman, W. J., Burke, B. C., and Holmes, M. D. (2003). Aperiodic phase re-setting in scalp EEG of beta-gamma oscillations by state transitions at alpha-theta rates. *Human Brain Mapping*, 19:248–272.

Huntsberger, T. (2001). Biologically inspired autonomous rover control. *Autonomous Robots*, 11:341–346.

Kozma, R. and Freeman, W. J. (2001). Chaotic resonance - methods and applications for robust classification of noisy and variable patterns. *International Journal of Bifurcation and Chaos*, 11(6):1607–1629.

Kozma, R. and Freeman, W. J. (2003). Basic principles of the KIV model and its application to the navigation problem. *Journal of Integrative Neuroscience*, 2(1):125–145.

Kozma, R., Freeman, W. J., and Erdi, P. (2003). The KIV model - nonlinear spatio-temporal dynamics of the primordial vertebrate forebrain. *Neurocomputing*, 52-54:819–826.

Michel, O. (1996). Khepera simulator package version 2.0. Downloaded from WWW at http://wwwi3s.unice.fr/ om/khep-sim.html. Freeware mobile robot simulator written at the University of Nice Sophia-Antipolis.

Michel, O. (2003). Webots v4.0 3-d physics based mobile robot simulator. www.cyberbotics.com.

Skarda, C. A. and Freeman, W. J. (1987). How brains make chaos in order to make sense of the world. *Behavioral and Brain Sciences*, 10:161–195.

Tsuda, I. (2001). Towards an interpretation of dynamic neural activity in terms of chaotic dynamical systems. *Behavioral and Brain Sciences*, 24(4).

Tunstel, E. (2001). Ethology as an inspiration for adaptive behavior synthesis in autonomous planetary rovers. *Autonomous Robots*, 11:333–339.