

Aperiodic Dynamics and the Self-Organization of Cognitive Maps in Autonomous Agents

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Abstract

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 understand the properties of nonlinear systems that are fundamental in the self-organization of stable, complex patterns in many types of systems, from biological ecosystems to human economies and in biological brains. In this paper we introduce a neurological population model that is capable of replicating the important aperiodic dynamics observed in biological brains. We use the mechanism to self-organize cognitive maps in an autonomous agent.

Keywords: Self-Organization, Nonlinear Dynamics, Cognitive Maps

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 & 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,

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and how such processes produce cognition (Freeman 1999; Tsuda 2001; Freeman 2003). Aperiodic dynamics are known to play a fundamental role in the mechanisms for the self-organization of meaning in mammalian perceptual systems (Skarda & 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 cognitive maps in the hippocampus of biological organisms.

K-Sets: A Neurodynamical Population Model of Brain Dynamics

Aperiodic Dynamics in Olfactory Systems

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

The EEG recordings revealed that in fact, chaotic dynamics (as shown by the observed strange attractors) represented the normal state when the animal was attentive, in the absence of a stimulus. These patterns underwent a dramatic (nonlinear) transition when a familiar stimulus was presented and the animal displayed recognition of a previously stored memory (through a behavioral response). The pattern of activity changed, very rapidly, in response to the stimulus in both space and time. The new dynamical pattern was much more regular and ordered (very much like a limit cycle, though still chaotic of a low dimensional order). The spatial pattern of this activity represented a well defined structure that was unique for each type of odor that was perceptually significant to the animal (e.g. conditioned to recognize). Figure 1 shows an example of such a recorded pattern after recognition of a stimuli of the EEG signals and

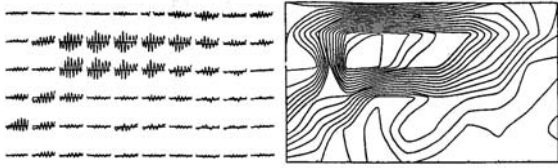


Figure 1: EEG carrier wave patterns (left) and contour map (right) of olfactory cortex activity in response to a recognized smell stimulus (from Freeman, 1991, p. 80)

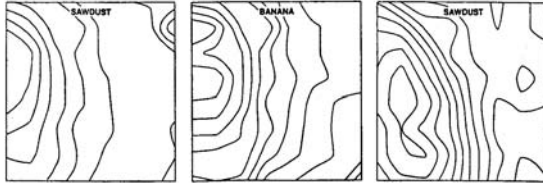


Figure 2: Change in contour maps of olfactory bulb activity with the introduction of a new smell stimulus (from Freeman, 1991, p. 81)

the associated contour map. In this figure after recognition, all of the EEG waves are firing in phase, with a common frequency (which Freeman called the carrier wave). The pattern of recognition is encoded in the heights (amplitude modulations) of the individual areas. The amplitude patterns, though regular, are not exact limit cycles and exhibit low dimensional chaos. In other words, different learned stimuli were stored as a spatio-temporal pattern of neural activity, and the strange attractor characteristic of the attention state (before recognition) was replaced by a new, more ordered attractor related to the recognition process. Each (strange) attractor was thus shown to be linked to the behavior the system settles into when it is under the influence of a particular familiar input odorant.

Figure 2 shows the effects on the spatial attractor pattern due to learning. Every time a new odor was learned by the animal, all of the existing attractor patterns changed. In this figure the contour pattern of activity for sawdust is shown (before learning the banana odor), for the banana odor, and then again for sawdust. Notice that the spatial pattern for sawdust no longer resembles its previous pattern. Whenever an odor becomes meaningful in some way, changes in the synaptic connections between neurons in different parts of the olfactory cortex take place. Just as in the Hopfield model and other neural networks, these changes are able to create another attractor, and all other attractors are modified as a result of this learning. However, in real brains, the attractors of perceptual meaning are not simple point attractors, but are specific strange attractors.

Freeman suggests that “an act of perception consists of an explosive leap of the dynamic system from the basin of one (high dimensional, in the attentive state) chaotic attractor to another (low dimensional state of recognition) (Freeman 1991). These results suggest that the brain maintains

many chaotic attractors, one for each odorant an animal or human being can discriminate. Freeman and Skarda speculate on many reasons why these chaotic dynamics may be advantageous for perceptual categorization. For one, chaotic activity continually produces novel activity patterns which can provide a source of flexibility in the individual. But since chaos is an ordered state, such flexibility is under control. As Kelso (1995) remarks, such fluctuations continuously probe the system, allowing it to feel its stability and providing opportunities to discover new patterns. Another advantage of chaos is that it allows for very rapid switching between attractors, which random activity is not able to do. Freeman also proposed that such patterns are crucial to the development of nerve cell assemblies. For example high dimensional chaos may provide a neutral pattern of correlation activity so that learning does not occur during the attentive state. Only upon collapse of activity to more ordered regions do regular phase synchronizations occur between neural areas, which allow for Hebbian synaptic changes to reliably occur.

K-Set Model of Aperiodic Dynamics

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

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

This equation was determined by measuring the electrical responses of isolated neural populations to stimulation and other conditions. The a and b parameters are time constants that were determined through such physiological experiments. $x(t)$ is the pulse density of the modeled neural population, in other words the average number of neurons that are pulsing in the population at any given point in time. $f(t)$ is a nonlinear asymmetric sigmoid function describing the influence of incoming activation, and is given in equation 2.

$$f(t) = k \left[1 - \exp\left(-\frac{e^{v-1}}{k}\right) \right] \quad (2)$$

A K0 unit models the dynamics of an isolated neural population. From the basic K0 unit can be built up architectures that capture the observed dynamics of increasingly larger functional brain areas. The KI models excitatory-inhibitory feedback populations. KII models interacting excitatory-inhibitory populations and correspond to organized brain regions such as the olfactory bulb (OB) or the prepyriform cortex (PC). KIII combine 3 or more KII populations to model functional brain areas such as perceptual

cortex or hippocampus, and are capable of aperiodic dynamics of the type observed in these regions to, for example, derive meaning from perceptual senses. In the simulations presented in this paper, we use a discretized version of the K-model (described in (Harter & Kozma 2003; 2002)) developed for use in large-scale autonomous agent simulations.

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

The power spectrum is a measure of the power of a particular signal (or time series as for example that obtained from an EEG recording of a biological brain) at varying frequencies. The typical power spectrum of a rat EEG (see Figure 3, top) shows a central peak in the 20-80 Hz range, and a $1/f^\alpha$ form of the slope. The measured slope of the power spectrum varies around $\alpha = -2.0$. $1/f^\alpha$ type power spectra are abundant in nature and are characteristic of critical states, between order and randomness, at which chaotic processes operate. Power spectra of biological brains have been observed to vary from $\alpha = -1.0$ to $\alpha = -3.0$. The atypical part of the experimental EEG spectra is the central peak, indicating stronger oscillatory behavior in the γ frequencies. This central peak in the 20-80 Hz range is known as the γ frequency band, and is associated with cognitive processes in biological brains. The K-models are capable of replicating the power spectra of biological EEG signals, as shown in Figure 3, bottom (Harter & Kozma 2003; Freeman 1991).

The KIII sets are capable of organizing perceptual categories in the fashion observed in biological perceptual systems. The KIII used as such a pattern classifier is very robust and compares well with more standard methods of pattern classification (Kozma & Freeman 2001).

Hippocampal Simulation

Experimental Architecture

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, Freeman, & Erdi 2003). We use the basic KIII architecture to simulate formation of cognitive maps in the hippocampus of an autonomous agent.

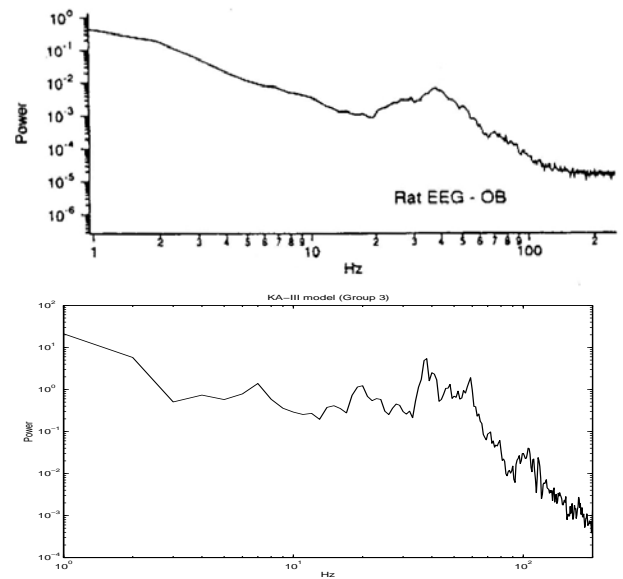


Figure 3: The power spectrum of a rat Olfactory Bulb EEG is simulated with the KA-III model. The calculated “ $1/f$ ” slope of the EEG and model is approximately -2.0 . Rat OB data from (Kay, Shimoide, & Freeman 1995), KA power spectrum from (Harter & Kozma 2003)

In this experiment, we used the Khepera virtual environment simulator (Michel 1996). Figure 4 (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 4. In the environment we place 8 light sources, which will be used as salient environmental locations (i.e. they can be thought of as good food sources for the agent in the environment). The light sources are detectable to the agent at a distance, and the range where the food source is detectable is indicated in Figure 4. 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 5. 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 biological hippocampus. Each of the CA areas contains an 8×8 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 5, left). The DG again contains an 8×8 matrix of KA-II units. Orientation signals

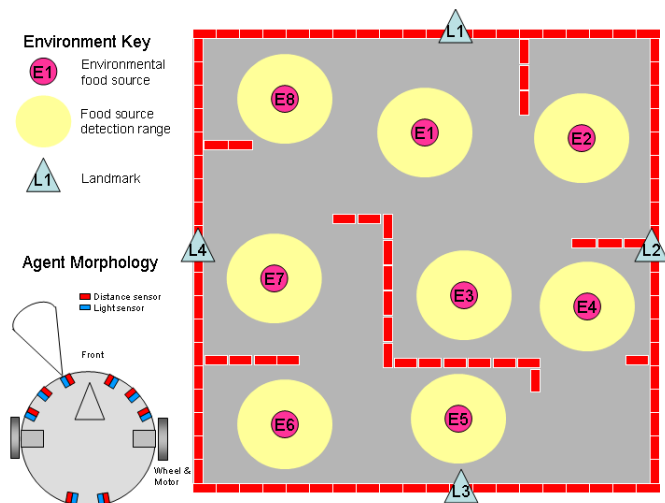


Figure 4: Agent morphology (bottom left) and environmental setup for hippocampal simulations. The environment contains landmarks, used as allocentric reference points by the agent, and salient environmental locations, such as food sources. The agent is only able to detect the presence of a food source when it is within a particular range of it.

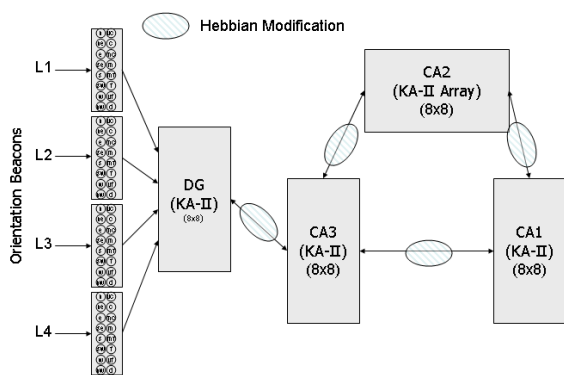


Figure 5: Architecture of KA-III hippocampal simulations

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, SouthWest, West and NorthWest. Units are sensitive to the direction of a particular landmark, though we use a graded response with a normal distribution, instead of a simple 1 unit is active and the others being inactive (0). 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.

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 & 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 mechanism to produce efficient, but random wandering. The agent roams for some time, 10,000 time steps in our simulations. In our simulation 10 time steps approximates 1 second of real world running time, therefore the total simulated time of an experiment is 1000 seconds.

Results

We first give examples of the time series produced in the CA regions. Two broad classes of activity patterns organize themselves as a result of the Hebbian and habituation weight modifications. The spatial-temporal patterns stay in a relatively high-dimensional background state when the agent is in an uninteresting location. This pattern changes to a more regular (e.g. cyclic) pattern when the agent is close to a food containing area. The differences in these patterns come about as a direct result of Hebbian modifications being contingent on being within a meaningful area.

Evidence of this shift, between high dimensional background state and low dimensional recognition state, can be seen in Figures 6. In this figure, we show a return plot of one

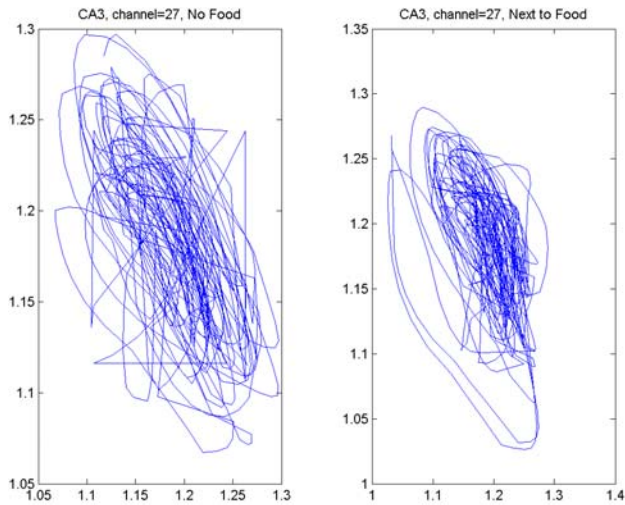


Figure 6: State space plots of unit 27 in the CA3 hippocampal region. Top we show the plot when the agent is outside of an important region. Bottom is the plot when the agent is within an environmentally salient region. Most units develop similar responses, which can be interpreted as a recognition of being in an environmentally salient area.

of the units from the CA3 area (unit 27) when it is outside of a food area (left) and when it is within (right). Notice that the dynamics for the unit are much more cyclic and regular when the agent is in a recognized area. The patterns of most of the units in the modeled hippocampus show similar transitions in their patterns from unrecognized to important areas.

Next we look at the amplitude modulation (AM) patterns produced by the hippocampal simulation. Figure 7 shows examples of the AM patterns formed in the CA3 hippocampal matrix for 2 different locations within environmental regions 2, 4, 6 and 8 respectively. The AM patterns shown are from the CA3 hippocampal region. This region has 8x8 units, for a total of 64 time series. We measure the standard deviation of each of the 64 units for a 50ms time window, and plot the results as an 8x8 contour map of the deviations of each of the units in the area. The AM pattern contour plots, therefore, give you an idea of which units are more highly stimulated (higher amplitudes in their activity) and which are less so. As Figure 7 shows, the AM patterns are more similar to those produced from locations within the same environmental region.

As a more complete test of the formation of unique AM patterns, we feed robot with input from randomly selected locations, within the environmental food areas. AM patterns were collected for the randomly selected regions and compared to one another by calculating the euclidian distance between each pattern. This testing showed that, in fact, the patterns produced within a region are consistently more similar to one another, than those produced in another environmental region.

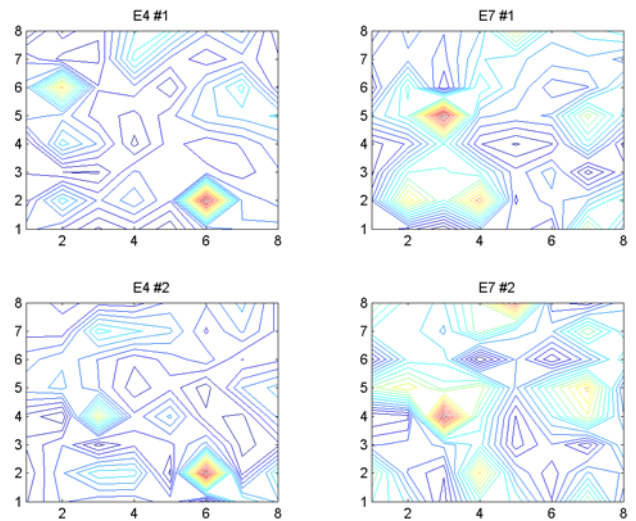


Figure 7: Example of AM Pattern formed in the CA3 hippocampal region. In this figure we show a pattern from two different locations within an environmentally salient region (Top and Bottom). We show AM patterns from environment regions E4 and E7. Similar AM patterns are organized and exhibited when the agent is in the same environmental region.

Discussion

The KA-III hippocampal simulation described here forms distinct AM patterns for the 8 salient environmental regions. These patterns are aperiodic spatio-temporal activity in the CA regions. The characteristic activity peaks in the AM patterns are examples of so called 'place cell' formation. Here we see high activity among certain regions correlated with being in a particular environmental location. For example, looking at the AM pattern for location 8 (Figure 7, right) you notice X peaks of activity among the units in the region. It is possible to interpret these peaks as being correlated with environmental locations, and therefore typical examples of the place cell.

The next step in this research is to begin to understand how such AM patterns might be used in the service of goal-directed navigation. It is known that if you measure the onset time of place cells in a biological brain, this time gradually shifts back in phase as the animal moves through the environment. This phase shift of the onset of the place cells may be evidence of the formation of navigation planning in the biological brain. One possible interpretation is that when the animal forms an intention to travel to a goal location, a sequence of AM patterns cycle through the hippocampus. This sequence can be interpreted as sequences of locations the animal intends to visit, from the current one to the next one, etc. in order to reach the goal. As the animal moves through the environment, its idea of the current location changes, and thus this whole sequence shifts back in phase in real-time to represent the next few intended steps the animal is planning to take. For this type of mechanism to be organized, the AM patterns must not simple form in an isolated way, but con-

nections between adjacent locations must be incorporated into the mechanism. If the agent learns which AM patterns are co-located to which others, it may be possible to set up such a mechanism to produce a goal-directed planning for navigating in the environment.

Conclusion

The self-organization of spatio-temporal patterns in nonlinear systems are essential to cognitive mechanisms in biological brains. We need to better understand how such mechanisms operate in order to build better models of cognition and smarter autonomous agents. This paper has demonstrated one such self-organizational mechanism for the creation of AM patterns in a cognitive map of an agents environment.

Acknowledgment

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