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Aperiodic Dynamics for Appetitive/Aversive Behavior in Autonomous Agents

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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 modeled or used to improve the performance of autonomous robotic and virtual agents. In this paper we present a model of an autonomous agent learning appetitive/aversive behaviors using a neuronal group model capable of such aperiodic dynamics. We demonstrate how such dynamics are useful in the self-organization of perception and behavior, and discuss the use of aperiodic dynamics in the self-organization of cognitive mechanisms in autonomous agents.**

I. 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 [1] 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 [2]–[4]. Aperiodic dynamics are know to play a fundamental role in the mechanisms for the self-organization of meaning in mammalian perceptual systems [5], [6]. 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 learning of appetitive/aversive behaviors in an autonomous agent.

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

A. Aperiodic Dynamics in Olfactory Systems

In their influential paper, Skarda and Freeman [5] 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

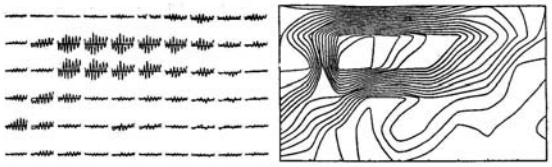

Fig. 1. EEG carrier wave patterns (left) and contour map (right) of olfactory cortex activity in response to a recognized smell stimulus (from Freeman, 1991, p. 80)

EEG signals and the associated contour map. In this figure after recognition, all of the EEG waves are firing in phase, with a common frequency (which Freeman called the carrier wave). The pattern of recognition is encoded in the heights (amplitude modulations) of the individual areas. The amplitude patterns, though regular, are not exact limit cycles and exhibit low dimensional chaos. In other words, different learned stimuli were stored as a spatio-temporal pattern of neural activity, and the strange attractor characteristic of the attention state (before recognition) was replace 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.

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) [6]. These results suggest that the brain maintains many chaotic attractors, one for each odorant an animal or human being can discriminate. Freeman and Skarda speculate on many reasons why these chaotic dynamics may be advantageous for perceptual categorization. For one, chaotic activity continually produces novel activity patterns which can provide a source of flexibility in the individual. But since chaos is a ordered state, such flexibility is under control. As Kelso [7] 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.

B. K-Set Model of Aperiodic Dynamics

The K-set hierarchy, developed by Freeman and associates [2], [5], [6], [8], 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:

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

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.

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

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 [9], [10]) 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 [11]–[13]. 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 [14], [15].

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 2, 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

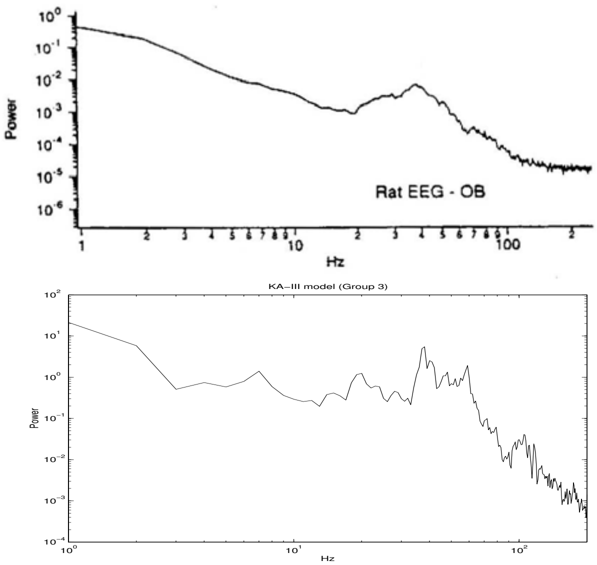

Fig. 2. The power spectrum of a rat Olfactory Bulb EEG is simulated with the KA-III model. The calculated "1/f" slope of the EEG and model is approximately -2.0. Rat OB data from [16], KA power spectrum from [9]

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 2, bottom [6], [9].

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 [1].

III. Appetitive/Aversive Behavior Using Aperiodic Dynamics

A. Experimental Architecture and Environment

In this experiment, we used the Khepera virtual environment simulator [17]. Figure 3 (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 3. In the environment we place 8 simulated food sources, 4 of which are good tasting and edible by the agent, and 4 of which are poisonous and have a correspondingly bad taste. We use light sources, and the Khepera agents light sensors, to simulate the production of an environmental gradient which may be followed by the agent to locate a food source. This gradient following is similar to simple tropic behaviors, such as following a chemical gradient (chemotropism, of which smell is an example), or following a light gradient (phototropism).

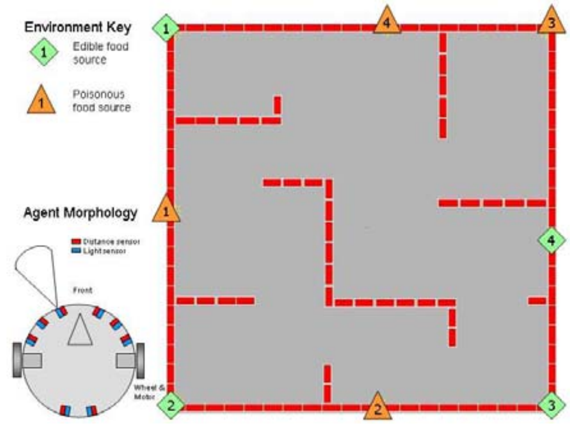

Fig. 3. Environment and agent used in the appetitive/aversive experiments. The agent (bottom left) is equipped with sensors spaced around its body and two independently controlled wheels for movement. The environment contains 8 food sources, 4 poisonous and 4 edible. Each food sources emits a property (perhaps like smell) which produces a gradient in the environment that is perceptible and followable by the agent.

The architecture used for learning appetitive/aversive behavior is shown in Figure 4, and is inspired by the Darwin series of robotic agents [18], [19]. The agent receives sensory information from four types of senses. A touch sense, a short-range sense that can detect the presence of obstacles (using the infra-red sensors), a sense of smell for following environmental gradients (using the light sensors), and a simulated sense of taste for detecting good/bad food sources. The touch sense (not shown in Figure 3 bottom left), and distance sense are used to allow the agent to wander in the environment and approach food sources. There are 5 touch sensors, that allow the agent to detect when it is touching an object in the front of its body, behind it, or to the left and right, or when it is not touching anything at all. There are also 8 short-range obstacle senses that allow the agent to detect the presence of obstacles at a short distance. When no food source gradient is detected, they are hardwired to cause the agent to produce a searching behavior behavior.

The smell sense (using light sources to detect environmental gradients), is hardwired, along with the touch and obstacle sense, to produce approach behavior to detected food sources. The agent simply follows the gradient (avoiding obstacles) to its source. There are 8 smell senses (light sensors) positioned around the body of the agent. Finally, a sense of taste is simulated for the agent using 2 sensors. When the agent touches an edible food source, this produces appetitive behavior (consumption) and pleasure signals in the value system of the agent. Poisonous sources produce avoidance behavior, which causes pain signals and behaviors that make the agent move away from the food source.

We use a KA-III to model the olfactory system and form perceptual categories of the smells in the environment. The olfactory KA-III is composed of three areas, the olfactory bulb (OB), anterior olfactory nucleus (AON) and prepyriform cortex (PC) (see Figure 4). These three areas are connected

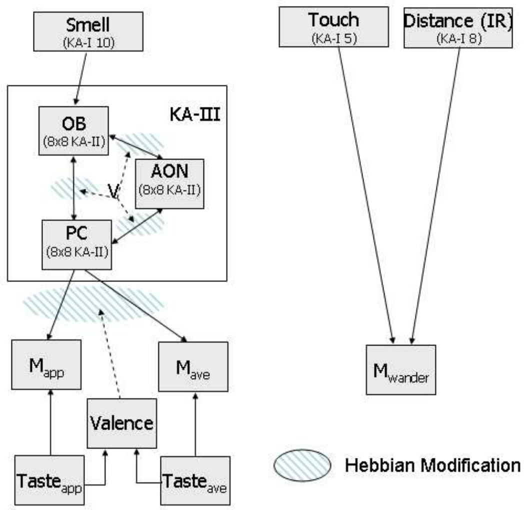

Fig. 4. Architecture of the neural model used for the appetitive/aversive task. There are four areas which receive direct stimulation from the agents sensors: Smell (using light-source gradients), Touch, Distance (short-distance obstacle sense using infra-red), and a simulated taste ($Taste_{app}$ and $Taste_{ave}$). Touch and distance senses are initially hardwired to produce search behavior if no food source is in range. When a food source is detected, the agent approaches and consumes it (approach and appetitive behavior M_{app}). Some food sources are edible, and some are poisonous. The agent is hardwired to trigger avoidance behavior when a poisonous food source is tasted (M_{ave}). The agent learns to identify poisonous food sources at a distance from smell and trigger avoidance behavior without having to first taste it. We use a simulated olfactory system to learn the good and bad smells. The olfactory simulation consists of an olfactory bulb (OB), anterior olfactory nucleus (AON) and prepyriform cortex (PC). Each of these areas is an 8x8 matrix of KA-II units. The three areas together form a KA-III capable of aperiodic dynamics and the formation of perceptual categories in the manner of biological brains. Weights between the 3 olfactory areas and from the PC to the M_{app} and M_{ave} are modified in response to pain and pleasure signals by Hebbian modification.

through positive and negative feedback to one another. The OB has projections from KA-I units that receive stimulation from the environmental smells.

B. Method

There are four areas which receive direct stimulation from the agents sensors: Smell (using light-source gradients), Touch, Distance (short-distance obstacle sense using infra-red), and a simulated taste ($Taste_{app}$ and $Taste_{ave}$). Touch and distance senses are initially hardwired to produce search behavior if no food source is in range. When a food source is detected, the agent approaches and consumes it (approach and appetitive behavior M_{app}). Some food sources are edible, and some are poisonous. The agent is hardwired to trigger avoidance behavior when a poisonous food source is tasted (M_{ave}). The agent learns to identify poisonous food sources at a distance from smell and trigger avoidance behavior without having to first taste it. We use a simulated olfactory system to learn the good and bad smells. The olfactory simulation is composed of the OB, AON and PC areas. Each of these areas is an 8x8 matrix of KA-II units. The three areas together form a KA-III capable of aperiodic dynamics and the formation of perceptual categories in the manner of biological brains.

The input to the olfactory system are the 12 KA-I units of the sense of smell. These units are stimulated from the 8 light sensors and from four additional signals which are invariant with regards to the type of smell being encountered, edible or poisonous. Simply put, each food source has a distinct and characteristic odor which is detectable by the agent. The light sensors give information on the direction of the smell, and the invariant stimuli provides information that lets the agent form appropriate categories.

The task of the simulated olfactory system is to learn to differentiate between the two basic types of smells in the environment and to trigger appropriate behaviors at a distance, before it actually has to taste the food source. Therefore, we want the olfactory system to become connected in an appropriate way to the appetitive and aversive behaviors, and to learn to override the instinctive approach behavior when it detects that the food source is poisonous.

We use two types of learning in the simulation, Hebbian modification and habituation. Hebbian modification is directed by the valence system (V), attached to the simulated sense of taste. Tasting good food sources causes pleasure signals to be generated, which strengthens the connections (e.g. via Hebbian modification) between active units. Poisonous foods sources cause pain, and a reversal of this effect by weakening connections between active units. The second learning mechanism is simple habituation. During times when the agent can not detects the presence of a salient smell, habituation of the stimulus occurs. This has the effect of lessening the response of the simulated olfactory system to unimportant stimuli [1].

The expected effect of this simulation is to form 2 distinct perceptual categories of the environmental smells. These should become strong enough to eventually activate appetitive or aversive motor actions at a distance, before the agent tastes the food source.

C. Results

In Figures 5 and 6 we give an example of the change in behavior that results from the agent being exposed to and forming perceptual categories of the smell sense. Figure 5 shows activity in the M_{app} and M_{ave} motor units as well as activity in the Taste units before learning has occurred. The agent first approaches and edible food source when it is detected in the environment. The $Taste_{app}$ becomes active when the agent reaches the food source since it is edible, which provides a pleasure signal for learning purposes. Next the agent approaches a poisonous food source. When the agent reaches this source, $Taste_{ave}$ becomes active and a pain signal is generated. This in turn causes aversive M_{ave} motor units to become active.

In Figure 6, we show activity after the agent has spent some time in the environment. Again, the agent first approaches an edible food source, and eventually reaches and consumes it, and therefore $Taste_{app}$ becomes active. Next the agent detects a poisonous food source. Now we see that instead of M_{app} appetitive approach behavior becoming active, instead

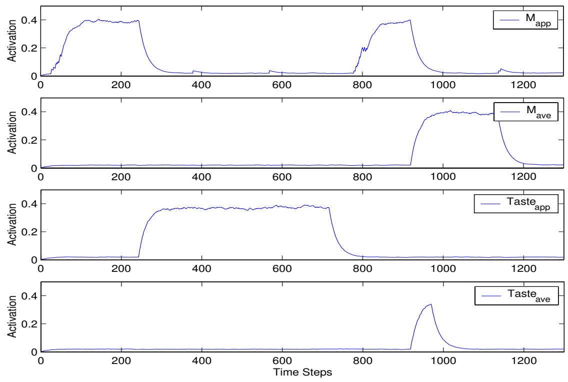

Fig. 5. Change in motor and taste unit activity before leanring. We show time series plots of the activity of a unit in the M_{app}, M_{ave}, $Taste_{app}$ and $Taste_{ave}$ areas. In this figure we show activity before learning has taken place. First the agent approaches and consumes an edible food source. Then the agent approaches and tastes a poisonous food source, causing $Taste_{ave}$ to become active.

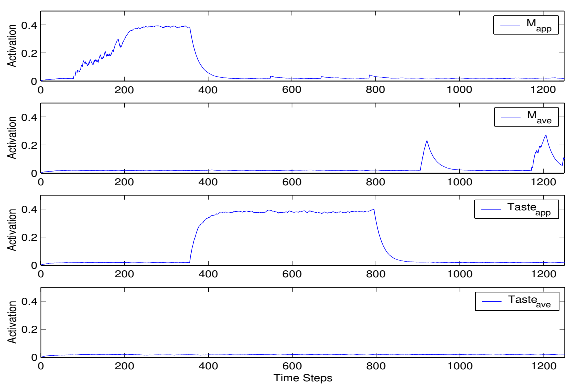

Fig. 6. Change in motor and taste unit activity in response to learning. We show time series plots of the activity of a unit in the M_{app}, M_{ave}, $Taste_{app}$ and $Taste_{ave}$ areas. In this figure, the same behavior still occurs for edible food sources, which happens first in these time series. But upon detecting a poisonous food source, M_{ave} becomes immediately active and the agent avoids the food source without tasting it.

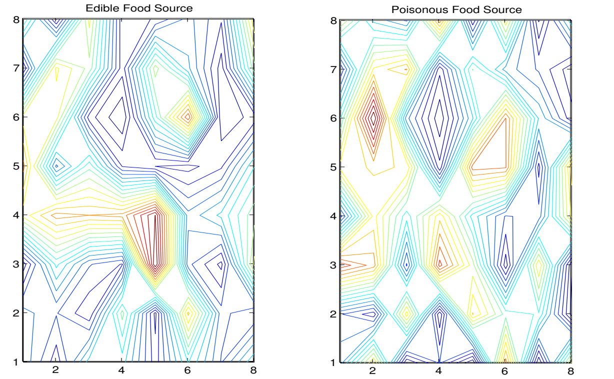

Fig. 7. Examples of AM patterns formed in response to edible (left) and poisonous (right) smell stimuli. AM patterns in response to like stimuli (e.g. to edible food sources) will be more similar to each other than to other stimuli as measured by euclidian distance.

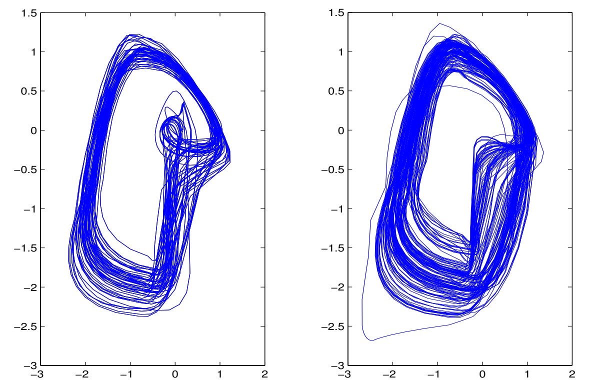

Fig. 8. State space plot of the activity of unit (row 7, col 3) in the PC area. We show the dynamics of the unit plotted against itself with a time delay of 7ms. for a 5 sec. period. Left plot is in response to stimulation by an edible food source, while right plot is in response to a poisonous food source.

the M_{ave} aversive behavior becomes activated. The agent avoids the poisonous food source, and never tastes it, thus we see no activity on $Taste_{ave}$.

As discussed in section II, what develops in the simulated olfactory regions are patterns of Amplitude Modulation (AM) which are indicative of meanings formed by the agent. In Figure 7 we show examples of the AM patterns formed in the PC region. The left contour map shows the AM pattern formed for edible smells, and the right map for poisonous smells. These contour maps were generated by recording the activity in the 8x8 array of the PC for 50ms, then calculating the amplitude of each of the 64 units for the 50ms (e.g. by using the standard deviation). We then plotted the results as a standard contour map.

The AM patterns thus formed are not static entities. Therefore, they will not be exactly the same between two presentations of the same type of stimuli. However, they do form two distinct categories, and the AM patterns for one type of stimuli (edible) exhibited will be closer to each other, than those formed for the other stimuli (poisonous), as measured by the euclidian distance between the AM patterns.

In Figure 8 we show an example of this type of variance. Here we generate a state space plot of the activity of one of the units (unit in row 7, col 3) in the PC area, with a 7ms time delay. This state space plot shows the activity over a 5 second time period. The left side is the activity in the unit when a edible smell is being presented, the right side is for a poisonous smell. In this figure, it is difficult to see any difference, and it appears that both stimuli produce similar dynamics.

However, if you look at where in the state space the activity occurs for each of the stimuli, you can detect the difference. In Figure 9 we show the same plots, but now we only plot the points in the space, and don't connect them with lines. Now you can see that, though the unit visits the same areas of the state space in both cases, it is more likely to be in one area of the state space for edible stimuli, and in another for poisonous stimuli. In essence what you see is that unit continues to visit all areas of its chaotic attractor no matter what type of stimuli is occurring. However, it will tend to more actively reside in

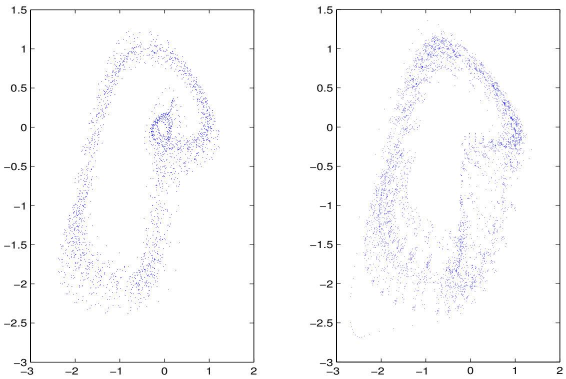

Fig. 9. The same state space plot as previous figure, except we only plot the points where the dynamics of the unit occurs. You can see the difference in density of the spaces visited by the unit in response to the different types of stimuli. Left is in response to edible stimuli, and right is in response to poisonous stimuli.

one part of the attractor in response to a particular stimuli. Different stimuli cause the unit to reside in different wings of the chaotic attractor. This can be seen as differences in the density of the activity of the dynamics in the state space plots.

IV. Discussion

The KA-III olfactory simulation described here forms distinct AM patterns for the two types of smells encountered in its environments. These patterns are aperiodic spatio-temporal activity in the olfactory regions (OB, AON and PC). The amplitude patterns are shaped through Hebbian modification and habituation to become sensitive to the environmental stimuli. The shaped patterns of activity are meaningfully connected to environmental stimuli, and become connected to appropriate behaviors, also through learning.

While our method is similar to other approaches using dynamical systems to build cognitive mechanisms for agents [20], it is unique in emphasizing the roles that aperiodic dynamics might play in such processes. This simulation is only an example of the use of aperiodic dynamics to organize perceptual categories, and the sensory environment is still very simple. However, the self-organization of categories using such aperiodic dynamics have distinct advantages as the basis for cognitive mechanisms of perception and action. Perceptual mechanisms based on aperiodic dynamics are potentially able to perform much better than other methods in noisy environments because of chaotic resonance [1]. Chaotic resonance, like stochastic resonance, helps nonlinear system detect the presence of faint signals in noisy environments much better than linear models. Perceptual mechanisms that display these types of aperiodic dynamics are capable of exhibiting chaotic resonance.

V. 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 the perceptual system of an autonomous agent for use in categorization and appetitive/aversive behavior generation.

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