Dynamical Neural Network Algorithm for Autonomous Learning and Navigation Control [*]

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Abstract – *We present a model of spatial navigation based on the KIII dynamical model of perception developed by Walter Freeman in the 70's. We use a KIII model of the hippocampus that learns global orientation based on pre-defined landmarks and a KIII model of the sensory cortex that provides local sensory information about obstacles. We test the model using a task that requires the exploration of a previously unknown environment and the navigation towards a goal location. Computer simulations show that the simulated agent learns the position of the goal. The model provides a novel description of how navigation and way finding in the style of the brain.*

Keywords: Chaotic neural network, navigation, Hebbian learning, reinforcement.

1 Introduction

K sets represent a family of models of increasing complexity that describe various aspects of functioning in vertebrate brains [3]. A remarkable feature of the K models is that they allow a biologically plausible simulation of chaotic spatio-temporal neural processes at the mesoscopic and macroscopic scales. KO is an elementary building block that describes the dynamics of neural populations. Whereas KI is a layer of excitatory or inhibitory KO units, KII is a double layer of excitatory and inhibitory units. KIII is a set of 2 or more KII units connected by feed-forward and delayed feedback connections [4]. Due to the massive recurrent and delayed feedback connections, KIII exhibits aperiodic (chaotic) oscillations similar to those find in the brain (citation).

The K sets are modeled using 2nd order ordinary differential equations (ODEs). In a typical implementation of the KIII model, 64 2nd order units are found in a single layer, and the total number of ODE's in KIII is over 360. To solve the system of ODEs, a numerical solver is applied using the Runge-Kutta method with a discrete time step. Details of the mathematical equations, the solution algorithm, and the applied parameters of the model are given in [2, 5]. The existing K set of highest complexity is represented by the KIV model, which includes several KIII units. The KIV model incorporates the multi-modality of sensory processing in vertebrates [6].

In this work we study in detail two KIII components of the KIV model, which correspond to the hippocampal formation and the sensory cortex of the mammalian brain. As we discuss our new model and the simulated paradigms, we mention the similarities and differences between our approach and other models of navigation. For example, Mataric [9] presented a model that builds a cognitive map while the agent explores the environment and stores encountered landmarks. Planning a path to a goal is managed by spreading the activation from the goal landmark, a process that is equivalent to a graph search.

In the next section we outline the basics of the K sets, with special emphasis on the KIII components of KIV. Then, we describe the experimental setup used to test the model. We present computer simulations and discuss the results. We conclude with related work and perspectives of future research toward an integrated multi-sensory KIV model.

2 Modeling Navigation Using Hippocampal and Cortical KIII Sets

The operation of the KIII model can be described as follows. In the absence of stimuli the system is in a high dimensional state of spatially coherent basal activity, which is described by an aperiodic (chaotic) global attractor. In response to external stimuli, the system can be kicked-off the basal state into a local memory wing. This wing is usually of much smaller dimension than the

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basal state. It shows coherent and spatially patterned amplitude-modulated (AM) fluctuations. The system resides in the localized wing for the duration of the stimuli then it returns to the basal state. This is a temporal burst process that lasts for a few hundred milliseconds [4]. The system is able to store information in the sequence of AM patterns during a burst. When used to classify linearly non-separable patterns the system performs as good as multi-layer feed-forward neural network-based classifiers. KIII compares favorably with these methods especially regarding robustness and noise-tolerance of the pattern recognition.

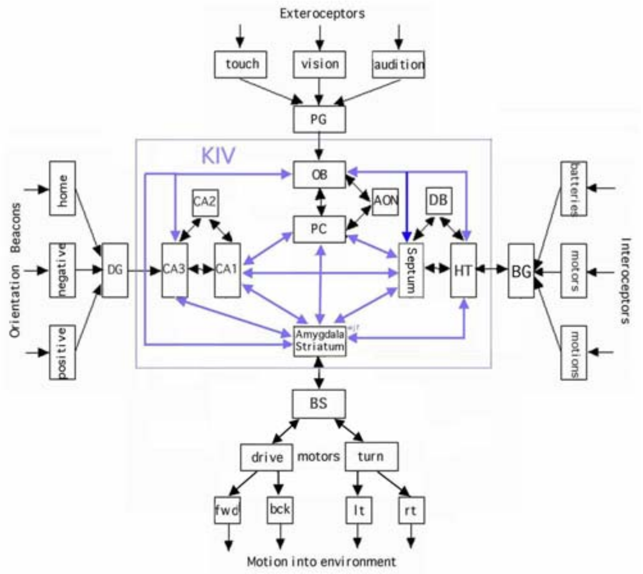

Figure 1. Components of the KIV model based on Kozma, Freeman, and Erdi (2003).

The highest level of the K sets is the KIV model (see Figure 1). As in the case of all other K sets, KIV's architecture and functionality is biologically motivated. In this work we extend the KIII model into KIV that models only the interaction in the cortical-hippocampal system and the sensory cortex (see Figure 2).

In the model, several types of learning rules have been used simultaneously, including habituation, Hebbian learning, and global stability control [5]. All these learning methods exist in a subtle balance and their relative importance changes at various stages of the memory process.

In our model, Hebbian learning is applied to modify the lateral connections between the excitatory nodes of the cortical and CA1 KII layers. We design the following learning cycle. Show a given pattern to the system for a duration of 100 ms, which corresponds to the drive period in animals, when sensory inputs are perceived. This is followed by a period of 100 ms without input pattern, corresponding to a resting part of the sensory cycle. After the 100 ms resting period, a new pattern is shown, and the whole cycle is repeated. We use Hebbian learning in combination with reinforcement. Namely, learning happens if the system receives a positive or negative reinforcement. This approach corresponds to rewarding or penalizing the animal depending on its response to the environmental information.

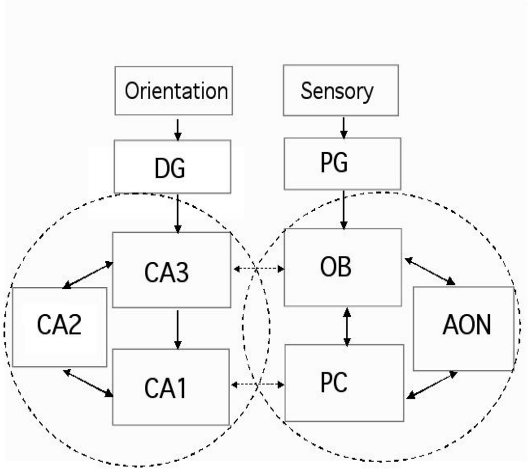

Figure 2. Schematic view of the simplified KIV model with the interacting hippocampal and cortical KIII units.

3 Description of the Navigation Problem

As a test bed we use a simple 2D grid. At any point in time, the robot can chose the next move from one of the 4 direct neighbors of the current grid position.

We consider two types of senses: (1) a long-range global orientation with respect to given landmarks, (2) sensing based on limited horizon (localized) in the neighborhood of the robot.

Consider an environment with given reference points/landmarks provided by orientation beacons. In a simple example we will consider 3 orientation beacons. These could be three point odor sources; three radio frequencies; three colors: red, green, blue; or three sound transmitters. One of these reference points is the base (home) location, the starting point for exploratory behavior. The others are learned environmental support cues. There is continuous sampling of the direction and range of the simulated animal to each of these 3 landmarks. As shown in Figure 3 we consider the past 9 time steps as inputs, in addition to the present time frame.

In the case of limited horizon the robot can perceive only a limited area that has the current position as its center.

Again, as shown in Figure 4 we consider the past 9 time steps as inputs, in addition to the present time frame.

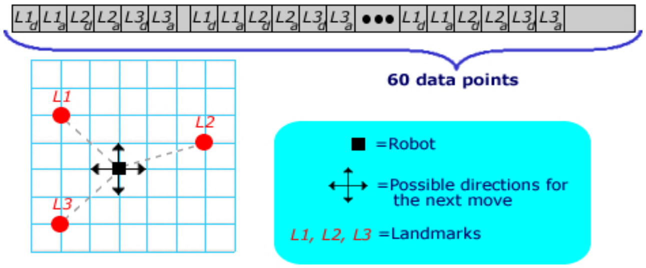

Figure 3. Outline of collecting orientation information with respects to 3 given landmarks located in the environment.

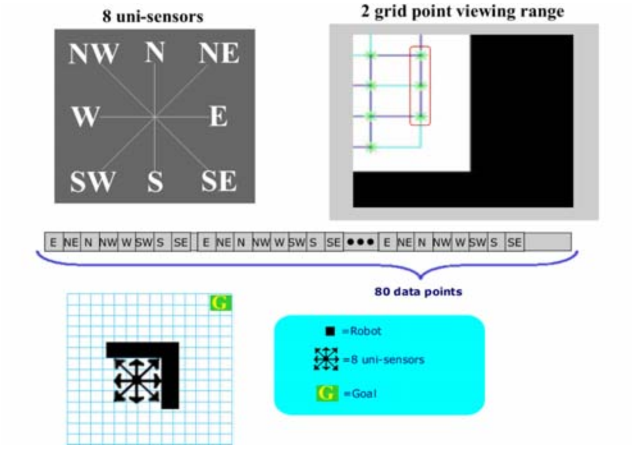

Figure 4. Outline of collecting sensory information using limited viewing range

The navigation problem is described as follows. First, we let the robot walk randomly in the environment and record the 6 sensory readings continuously. During the learning phase, we apply the input orientation vectors continuously to the KIII set for several hundred steps and perform reinforcement learning. If the system goes toward the specified goal location, we reward it by conducting a reinforcement learning loop. On the other hand, no learning takes place, if the randomly selected step was incorrect, i.e., it stepped away from the goal location, which is the central position in these experiments. In the case of the local sensing experiment , the reinforcement signal is negative. The robot is penalized if it goes to a corner location (see Figure 4) which simulates entrapment.

4 Navigation Results

4.1 Landmark-Based Navigation

Figure 5 shows the trajectory of the simulated robot when it performs random walk. The goal location is not reached after 70 steps. Figure 6 shows the trajectory when the robot uses its internal representation of space.

Once the exploration phase has been conducted extensively, we can test how well the robot has learned the environment. We restart it from home and give a goal location. If the robot has properly learned the environment with respect to the 3 environmental clues, it will navigate efficiently and find a reasonably optimal path to the goal. The model builds an internal representation of the environment by using the classification landscape of KIII. Figure 6 shows the trajectory of the robot after it has learned the position of the goal. The average length of the trajectory from start to goal is significantly reduced. Considering a path of length 20 steps from the origin, the leaned KIII hippocampal model produces a path with average distance of about 7 grid points from the goal. At the same time, the random walk results in an average distance of 14 grid points from the goal. As shown in Figure 7 landmark based navigation generates a trajectory that is always closer to the goal location than the trajectory produced by random walk.

It should be noted that based just on the orientation information, it is very difficult to learn the goal location precisely. Therefore, even a well-trained robot is unlikely to stop at the goal location. Rather, it will wander around in the neighborhood of the goal. Clearly, the robot should change its sensory modality to local sensing, once it reaches in the neighborhood of the goal.

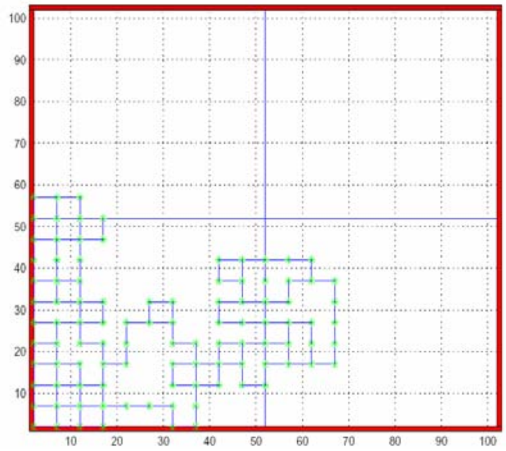

Figure 5. Random exploration of the environment in the hippocampal navigation model.

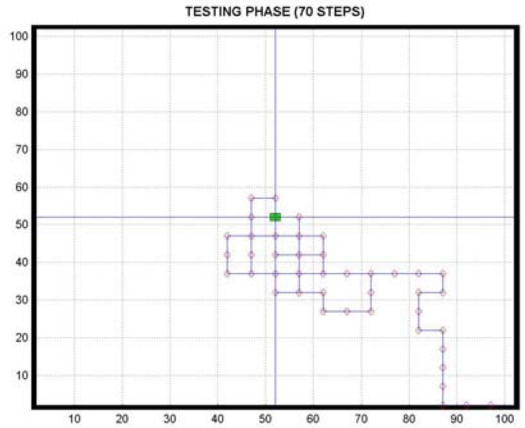

Figure 6. Goal oriented navigation using the hippocampal KIII model.

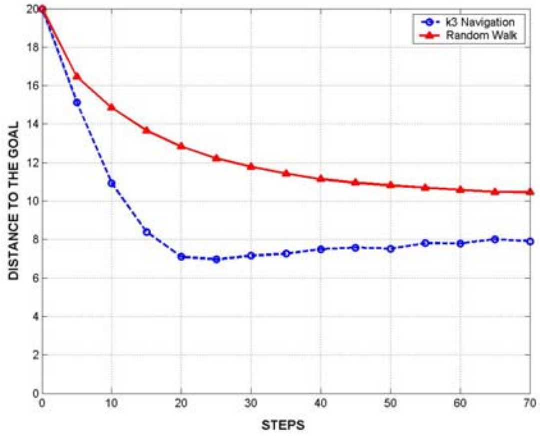

Figure 7. Distance to the goal for random walk and landmark based navigation.

4.2 Navigation Using Limited Sensory Horizon

Unlike the landmark-based navigation where the simulated robot explores an open environment, the navigation using a limited sensory horizon takes place in an environment that contains obstacles. As shown in Figure 9 , during random exploration the simulated robot does not reach the goal location. However, as shown in Figure 10, when the robot is trained to reach the goal it does so in an efficient manner by avoiding the obstacles in between the start and the goal location.

We measured the optimality of the trajectories generated during navigation by calculating the ratio of good and bad moves. Whereas a good move is defined as a step towards the goal, a bad move is defined as a step away from the goal. The good and bad moves are measured at two levels as shown in Figure 8. Table 1 presents the results for different sizes of the sensory horizon. As the size of the sensory horizon increases the ratio of good and bad moves also increases. This shows that the simulated animal is able to learn obstacle avoidance and reach the goal location.

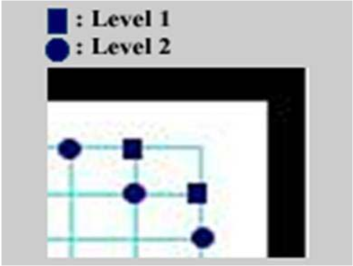

Figure 8. Two levels where good and bad moves are counted. Level 1: black squares, Level 2: black circles. Thin lines represent the grid and thick lines represent the obstacle.

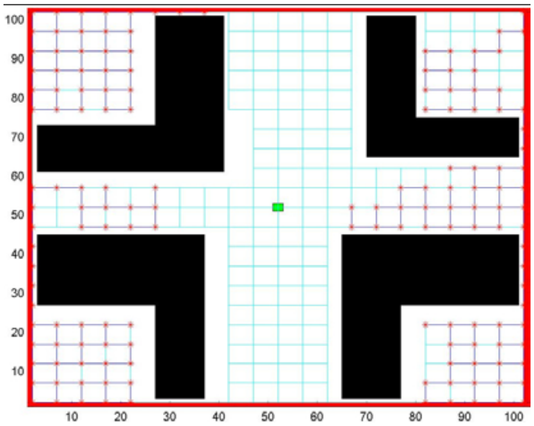

Figure 9. Random exploration of obstacles in the environment.

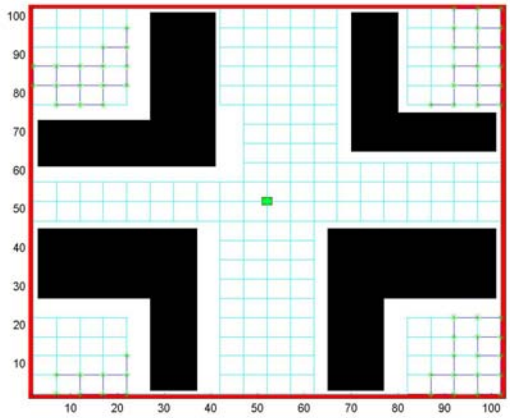

Figure 10. Trajectories after learning in cortical KIII of avoidance of being trapped in a corner position.

Table 1. Ratio of good and bad moves for different sizes of the sensory horizon.

$\frac{\text{Good Moves}}{\text{Bad Moves}}$	Random Walk	1 Grid Memory	2 Grids Memory	3 Grids Memory
Level 1:	2	2.56	3.09	3.50
Level 2:	1.5	1.56	1.58	1.63

5 Discussion

The paper presents a model of navigation based on chaotic spatio-temporal neural processes at the mesoscopic and macroscopic scales. The simulated robot is able to learn the position of goal location and to avoid obstacles. Other models of navigation that differ from our approach have been developed.

The model proposed by Samsonovich and McNaughton [8] uses CA3 as a memory capable of storing multiple charts. The concept of chart is equivalent to that of an attractor map. The activation of a certain map is determined by the initial sensory cues. The model of Samsonovich and McNaughton contains the following components: (1) a set of place units representing an attractor map identified as CA1, CA3 and the Dentate Gyrus, (2) an external sensory input array identified as sensory association cortex which provides high level representation of the sensory information to the hippocampus via entorhinal cortex and the perforant path. (3) an array of head direction units identified as cells in dorsal presubiculum, (4) an array encoding the angular velocity of the head, (5) an array representing the speed of motion, and (6) an array of integrator cells which are identified with some cells in the subiculum, the presubiculum and the parasubiculum which show spatial and orientation selectivity. The model was implemented using integrate and fire neurons and was simulated numerically using a simple Euler scheme. Unlike other models the simulated path integrator is able to show: doubling, stretching and vanishing of places.

An alternative representation to the multi-charts used by Samsonovich and McNaughton are the reference frames proposed by Redish and Touretzky [11]. In contrast to the assumption that the maps in the hippocampus emerge from the internal dynamics of the network, the reference frame hypothesis suggests that the hippocampal place cells are modulated by external information, such as path integration. In order to function well the multi-chart theory has to assume that there are prewired connections within the hippocampus. Taking into account the high level of brain plasticity such an assumption has a low likelihood of being valid. Redish and Touretzky offer an alternative explanation based on how an attractor network reacts to a slightly changed input. On one hand, if the current state of the attractor is stable and the input is not significantly changed then the same reference frame is used. On the other hand, if the input is offset by a large amount, the current position is encoded by a different cell.

One of the few hippocampal models that have been implemented on a mobile robot is presented by Burgess, Donnett, Jeffrey, and O'Keefe [10]. This model has an emphasis on the details of neural implementation and it takes into account part of the architecture found in the brain (see Figure 1.2). The first layer is the sensory information module, which contains an array of 60 neurons. Every neuron is tuned to fire whenever the animal is within a certain distance from a certain wall (the distance and the wall are specific for every sensory neuron). The next layer is the entorhinal cortex in which every neuron receives input from only two sensory cells associated with orthogonal walls. The next layer is formed by the place cells, which learn to discriminate regions of the environment by using competitive learning. At each time step the connections between the first 50 place cells that have the highest firing rate and the first 4 most active entorhinal cortex cells are validated. The fourth layer contains the goal cells. By moving away from a goal its corresponding place cell is activated less and less. By using this approach the animal is able to build for each goal a proximity gradient that can be used for approaching the location of the goal. In order to allow the animal to select short cuts towards the goal a more complex scheme must be utilized. A vector towards the goal is calculated by taking into account the information learned whenever the animal perceives the right goal location.

This model has been tested on a khepera robot with an on-board video camera and a ring of short-range detectors. The distance to the walls has been estimated by filtering the image received by the camera for horizontal lines and by providing information (e.g. the north wall can be identified by its dark upper half) that facilitates the processing of sensory information.

In sum, this model uses a very close architecture of the hippocampus. It takes into account most of the functional modules of the related brain regions. However, it makes several assumptions about the functions performed by the different layers of the system that could be different from reality and it does not consider the recurrent connections of CA3. One major drawback of the model is the fact that when the environment is contracted by a large enough factor, locations of peak firing of opposing cells cross over and the robot searches only at the edges of the environment.

Another model that uses an attractor network to simulate the hippocampus is proposed by Tsodyks [7]. It is assumed that the strength of the synapse between two places decreases with the distance between their fields. Particularly, the function used in the simulation is decreasing exponentially with distance. This assumption seems not to be realistic because while connections between adjacent places or even neighboring places can be driven by Hebbian learning the connections between distant places are very hard to form. Therefore, the proximity between places is not stored directly at the synapse level but can be inferred by using the recurrent connections in CA3.

6 Conclusions

We use the KIV model to help to understand how can the hippocampal neural circuitry and the whole cortical-hippocampal loop, supplemented with specific subcortical inputs implement different types of dynamic activity, and how these activity patterns contribute to the emergence of spatial encoding to aid orientation function of the animal. Our results describe the mechanisms, which facilitate the generation of cognitive maps in the hippocampus based on the sensory input-based destabilization of cortical spatio-temporal patterns.

In this work, we have introduced a novel method of navigation using the KIII hippocampal model. We have demonstrated the feasibility of the proposed methodology, and showed that K models are promising dynamic chaos neural networks to address navigation tasks. Our results clearly demonstrate that the applied Hebbian reinforcement learning algorithm in KIII produces significant learning gains. This efficient learning is converted into improved navigation control of the simulated robot through the environment. Future studies are directed toward integrating the present global navigation method into a multi-sensory KIV control system, in which global orientation information is combined with local sensory data, e.g. infra sensors and camera images.

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