

LEARNING ENVIRONMENTAL CLUES IN THE KIV MODEL OF THE CORTICO-HIPPOCAMPAL FORMATION

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Abstract

Previous studies on the KIV model outlined a general architecture of modeling sensory-perceptual-intentional action cycle in the primordial vertebrate forebrain using nonlinear dynamical principles. KIV consists of 3 KIII units representing aperiodic/chaotic dynamics in sensory cortex, hippocampal formation, and midline forebrain, respectively. The sensory cortex has demonstrated excellent performance as a pattern recognition and classification device. In this work, the behavior of the hippocampal formation is studied as part of the KIV system. We elaborate a reinforcement algorithm to learn goal-oriented behavior based on global orientation beacons, biased by local sensory information provided by visual or infra-red sensors. We illustrate the operation of the KIV model using the multiple T-maze navigation problem.

Introduction

K sets represent a family of models of increasing complexity that describe various aspects of functioning of vertebrate brains (Freeman, 1975). K models provide a biologically plausible simulation of chaotic spatio-temporal neural processes at the mesoscopic and macroscopic scales. KO is an elementary building

block of describing 2nd order dynamics of neural populations. KI is a layer of excitatory or inhibitory KO units, while KII is a double layer of excitatory and inhibitory units. KIII is a set of 2 or more KII units connected by feedforward and delayed feedback connections (Chang & Freeman, 1996; Kozma & Freeman, 2001). The hippocampal formation (HF) and the sensory cortex are examples of KIII sets. Finally, KIV consists of 2 or more KIII sets with additional KII and KI (Kozma, Freeman, Erdi, 2003).

KIII-based modeling of the olfactory system is applied to classify linearly non-separable patterns. The model's performance is compared with those of statistical classification methods and multi-layer feed-forward neural network-based classifications. KIII compares favorably with these methods regarding robustness and noise-tolerance of the pattern recognition, especially for classification of objects that are not linearly separable by any set of features (Kozma & Freeman, 2002).

In this work, the cortex and the hippocampal formation are modeled as KIII sets. This approach creates the basis of their integration at the KIV level, which allows a unified description of spatio-temporal neural dynamics during sensory processing and decision-making. Results obtained by a simplified KIV model for goal-oriented action are given in this work.

KIII Models of the Cortex and Hippocampal Formation

In a simplified KIV model, we incorporate two KIII systems. One is for sensory data in the sensory cortex, while the other KIII unit models the hippocampal formation. Figure 1 illustrates schematically the relationship between the sensory cortex and HF as KIII units. Figure 1 is a simplified version of the KIV structure (Kozma, Freeman, & Erdi, 2003), and it shows only 2 KIII sets. In our approach, the external data to HF originate from orientation beacons, while sensory cortices receive visual, infra, etc. signals from the environment. The 2 dotted circles mark the dynamical KIII sets in HF (CA1-CA2-CA3) and cortex (OB-AON-PC).

Figure 1

It is important to mention that our model is strongly biologically motivated, nevertheless, we do not intend to reflect every detail of the neural circuitry. The connection between the KIII sets is realized in the present model via interaction between CA1 and PC. These connections are sparse and they can be viewed as tools to produce an effective bias acting upon the operation of each KIII sets.

In the work introduced in this paper, we concentrate on the HF KIII, and consider the modulating effect of the signals coming from the sensory cortex KIII. According to the KIII methodology, HF and Cortex are modeled using a set of 2nd order ordinary differential equations. In a typical implementation, we have 60 2nd order unit in a single layer, and the total number of ODE's is over 360. We solve the system of ODEs with a discrete time step Runge-Kutta method. Details of the mathematical equations, the solution algorithm, and the applied parameters of the model are given in (Cheng & Freeman, 1996; Kozma & Freeman, 2001, Ankaraju, 2002).

Learning in the Hippocampal and Cortical KIII Models

The hippocampus is strongly involved in navigation. It has two behavioral modes, one is characterized with periodic, and one with aperiodic dynamics. A hippocampus-related navigating algorithm based on reinforcement learning was suggested by Foster et al (2000). However, their algorithm does not incorporate aperiodic dynamics. Periodic-aperiodic transitions appear in hippocampal place cells. The activity of a place cell is maximum only when the animal is visiting a particular location of its environment and does not depend on local sensory information. Spatial orientation and navigation seems to be supported by double coding: both 'rate codes' and more specific 'temporal codes' are present. Recently it was demonstrated that dynamically detuned oscillations account for the coupled rate and temporal code of place cell firing (Lengyel et al., 2003).

The hippocampal formation and cortex complete their functions by sampling the environment at theta rate. To achieve this periodicity, KIV relies on the septum to generate the theta frame rate as a gating function. Temporal framing is done in all sensory systems. Examples of this sampling are the saccadic movement in visual system, sniffing in olfaction, and perhaps something similar in the cochlea. For the sensory signals, we consider the past several time steps as inputs, in addition to the present time frame. The orientation signals are the distances and directions with respect to the landmarks, measured from the actual location of the robot. If the robot has properly learned the environment, it will navigate efficiently and find a reasonably optimal path to the goal based on the combined use of the internally formed cognitive map, using only the home beacon and its classification landscape learned in the cortical areas. After learning, the length of the trajectory from 'Home' to 'Goal' is significantly reduced.

Multiple T-maze Simulations Using the Cortico-Hippocampal KIV set

Here we summarize results obtained by reinforcement learning implemented using Hebbian correlation rule in CA1 and PC. A key component of our approach is the introduction of a 5Hz periodicity in learning that simulates the theta rhythm. The theta rhythm will be introduced in the numerical experiments by providing the various KIII units with sensory stimuli periodically, at rates corresponding to the theta frequency. We can simulate the theta sampling in computer experiments with the KIV model by designing a learning cycle as follows. Show pattern A to the system for a duration, say, 100 ms, which corresponds to the drive period in the animal experiments. This is followed by a period of 100 ms without input pattern, corresponding to a resting part of the cycle. Afterward, a new pattern is shown, etc. This will generate a period of 5 Hz to approximate theta cycle. We have 3 major phases of the operation of the model: learning, validation, and control/testing phase. This is illustrated in Fig. 2, where we also show that the 5Hz cycle is present in all phases the operation of the KIII model.

Figure 2

As the test bed, we use a simple 2D multiple T-maze environment. In this environment, the movement can take place along a grid. Consequently, at any instance, the robot can chose the next move from one of the 4 direct neighbors of the given grid point. Consider an environment with given reference points/landmarks provided by orientation beacons. In a simple example we will consider 3 orientation beacons. 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. We consider the past 9 time steps as inputs, in addition to the present time frame.

Figure 3

At first, let the robot explores the environment and records the 6 sensory readings continuously. During the next phase with reinforcement learning phase, we apply the input orientation vectors continuously to the hippocampal 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.

Based on the orientation information only, it is very difficult to learn the goal location precisely. Therefore we add the cortex as system that biases the operation of the HF based on the local sensory information with respect to obstacles and the Goal. In the cortical KIII we conduct reinforcement learning similar to that of the HF. The difference is that in the cortex we use negative reinforcement (punishment) if the robot approaches an obstacle. The sensory information simulates an infra-red (IR) sensor of finite sensitivity of 2 grid points. The animal collects IR signals in 8 different locations (E, NE, N, NW, W, SW, S, SE). In the experiments introduced below we use a 15-step memory in the cortex, i.e., the robot remembers, in addition to the most recent step, also the 14 most recent sensory readings.

Once the exploration phase has been conducted extensively, we can test how well the robot has learnt the environment. We re-start it from home and give a goal location. If the robot is properly learned the environment, it will navigate efficiently and find a reasonably optimal path to the goal based on the use of the internally formed cognitive map using its classification landscape learned in the HF KIII.

The effect of learning is illustrated in Fig. 3a-c, where results of testing the KIV set navigation capabilities are given for 3 values of the cortical learning rate; 0, 0.4, and 1. Without cortical learning, the trajectory from the Start to the Goal is very long, 203; see Fig. 3a. By increasing the learning rate, the results are improving. Selecting a learning rate of 1, the length of the trajectory is reduced to 56; see Fig. 3c. The experiments had the following parameters: (1) learning rate in the hippocampus is 0,15; (2) connection matrix between the two KIII sets is uniform and all of its elements is $L=10^{-4}$. The value of the hippocampal learning rate has been optimized to give the best possible navigation performance. We have selected a small value of L , which allows a high degree of autonomy of the interacting KIII sets. The value of L , however, should be large enough, in order to provide sufficient influence of the cortex on the hippocampal dynamics.

Figure 4

Figure 4 shows that the performance of the KIV navigation system deteriorates for cortical learning rates above 1. This behavior is interpreted as the result of the imbalance between the hippocampal and cortical KIII sets, due to the dominance of the latter. It is clear, that KIV can exhibit a favorable behavior by the multi-sensory fusion of the two types of signals available in these experiments.

Conclusions

In this work, we have introduced a novel method of navigation using the KIV set with hippocampal and cortical parts. We have shown the feasibility of the proposed methodology, and showed that K models are promising dynamic neural networks to address navigation tasks. Our results clearly demonstrate that the applied reinforcement learning algorithm in KIV produces significant learning gains, which are converted into improved navigation of the simulated robot through the environment.

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Figure Legends

Figure 1: Schematic view of the relationship between the hippocampal formation (HF) and sensory cortex KIII sets. Abbreviations: DG, dentate gyrus; CA1-CA3, Cornu Ammonis (hippocampal sections); PG, periglomerular; OB, olfactory bulb; AON, anterior olfactory nucleus; PC, prepyriform cortex.

Figure 2: Illustration of the theta periods thorough the learning, validation, and control phases by using the KIII model of the hippocampal formation.

Figure 3. Path of the robot during testing KIV; with cortical learning rate (a) 0; (b) 0.4; (c) 1.0.

Figure 4. Quantitative characterization of the dependence of the navigation performance on the learning parameters.

Biographies

Robert Kozma holds a Ph.D. in applied physics from Delft University of Technology (1992). Currently he is Professor of Computer Science at the University of Memphis. Previously, he has been with the faculty of Tohoku University, Sendai, Japan (1993-1996); Otago University, Dunedin, New Zealand (1996-1998); he held a joint appointment at the Division of Neuroscience and Department of EECS at UC Berkeley (1998-2000). His research focuses at spatio-temporal neurodynamics, multi-sensory fusion using chaotic neural nets, and self-organized development of intelligent behavior in animals and animats.

Walter J Freeman studied physics and mathematics at M.I.T., philosophy at the University of Chicago, medicine at Yale University (M.D. *cum laude* 1954), internal medicine at Johns Hopkins, and neurophysiology at UCLA. He has taught brain science in the University of California at Berkeley since 1959, where he is Professor of the Graduate School. He received the Pioneer Award from the Neural Networks Council of the IEEE, and he is IEEE Fellow. He is the author of >350 articles and four books: "Mass Action in the Nervous System" (1975), "Societies of Brains" (1995), "How Brains Make Up Their Minds" (1999), "Neurodynamics: An Exploration of Mesoscopic Brain Dynamics" (2000).

Péter Érdi is the Henry R. Luce Professor in Kalamazoo College. He also the head of Department of Biophysics, KFKI Research Institute for Particle and Nuclear Physics, Hungarian Academy of Sciences, and Széchenyi Professor at the Eötvös University. His main scientific interest is the computational

approach to the functional organization of the hippocampal formation. He is the co-author with Arbib and Szentagothai of the popular volume “Neural Organization – Structure, Function, and Dynamics” (1997).

Derek Wong completed his undergraduate studies in Computer Science in 2002, and currently he works on his M.Sc. degree at the Computer Science Division, The University of Memphis. He is a research assistant in the Computational Neurodynamics Lab directed by Dr. Kozma. He is also with the Cognitive and Linguistic Systems Lab at the Department of Psychology.

Robert Kozma



Walter J Freeman



Peter Erdi



Derek Wong (photo unavailable)

Figure 1

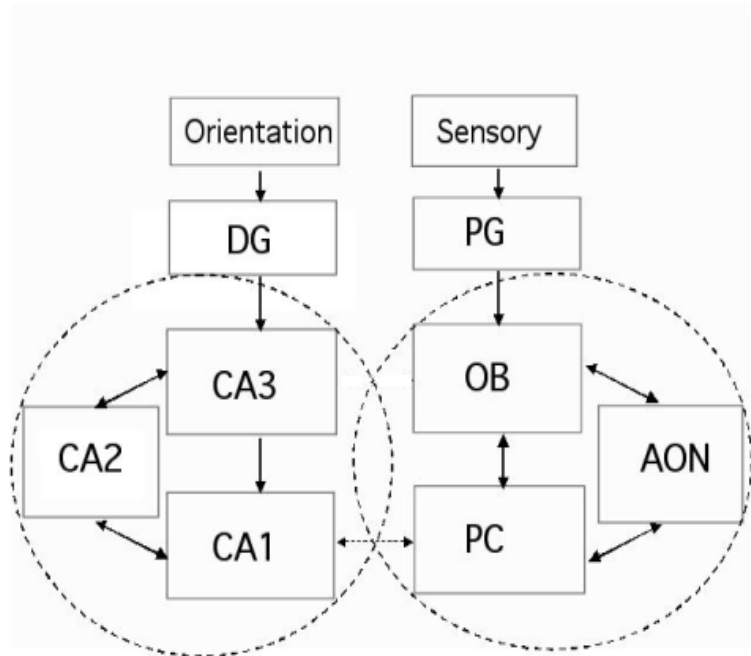


Figure 2

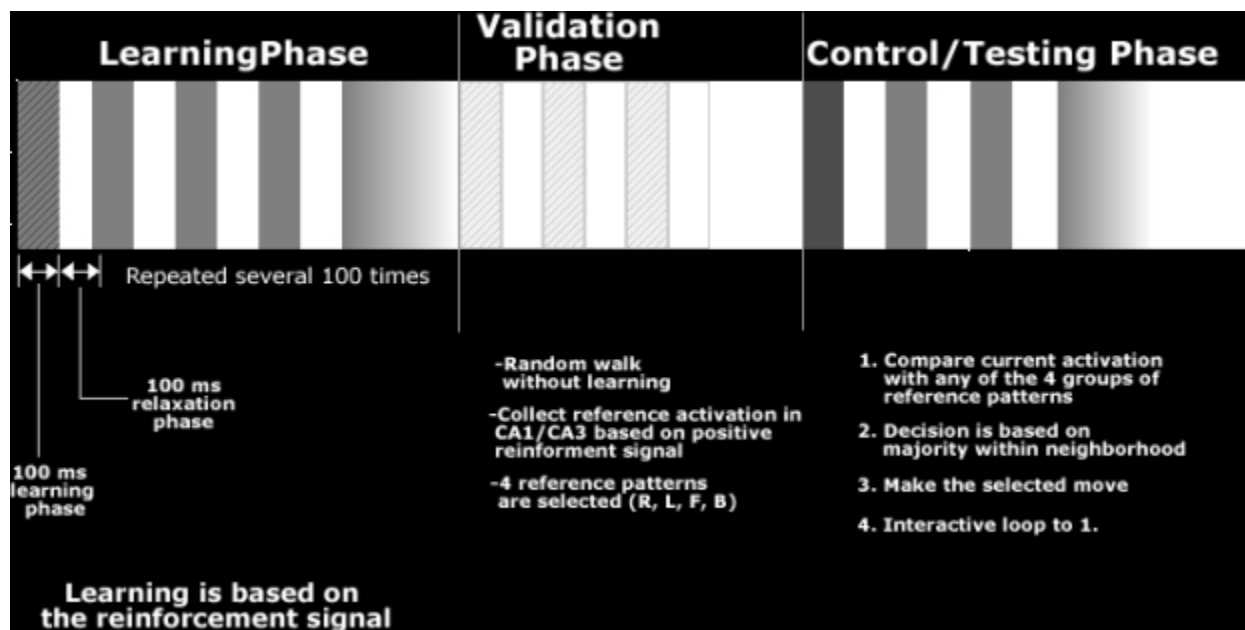
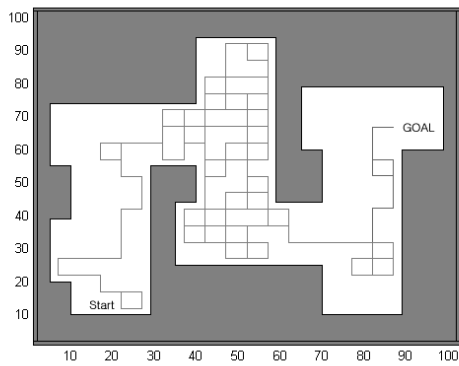
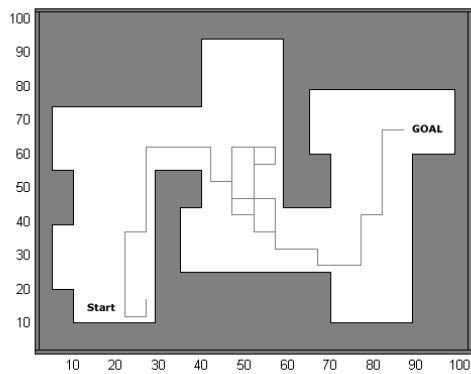


Figure 3aFigure 3bFigure 3cFigure 4