LEARNING ENVIRONMENTAL CLUES IN THE KIII MODEL OF THE HIPPOCAMPAL FORMATION

Robert Kozma(1), Haizhon Li(1), and Walter J Freeman(2)

(1) Division of Computer Science
373 Dunn Hall, The University of Memphis, Memphis, TN 38152

(2) Division of Neurobiology
142 LSA, University of California at Berkeley, Berkeley, CA 94720-3200

Key words: Spatio-temporal Neurodynamics, Hippocampal Formation, Chaos, KIII and KIV models.

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 hippocampal formation is studied in details using KIII modeling techniques. We elaborate a reinforcement algorithm to learn goal-oriented behavior based on global orientation beacons. We illustrate the operation of the KIII hippocampal formation model using a simple 2D navigation problem.

SUMMARY

K sets represent a family of models of increasing complexity that describe various aspects of functioning of vertebrate brains (Freeman, 1975). 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 of describing 2^{nd} 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). Finally, KIV consists of 3 KIII sets with additional KII and KI support. Examples of KI sets are the Dentate Gyrus (DG) and Periglomerular cells (PG); examples of KII sets are the Olfactory bulb (OB), Anterior olfactory nucleus (AON), prepyriform cortex (PC), CA1, CA3, and CA2. The hippocampal formation (HF) and the sensory cortex are examples of KIII sets. The recently introduced KIV set describes the hemisphere-wide cooperation of sensory cortex, HF, and midline forbrain units, together with the amygdala, brain stem, and further parts of the limbic system (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, we give results obtained by using the KIII formalism for the description of the hippocampal formation. Intensive research is reported in the literature to describe the function of the hippocampus in cognitive map formation, spatio-temporal orientation, and navigation (Bliss & Lomo, 1973; Burgess, Recce, & O'Keefe, 1994; Arleo & Gerstner, 2000). In our approach, 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. Figure 1 illustrates schematically the relationship between the sensory cortex and HF as KIII units.

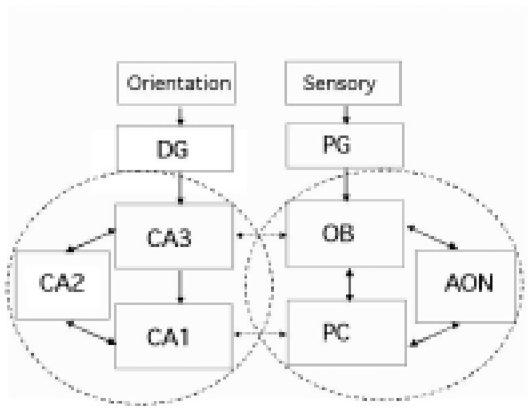

Fig. 1. Schematic view of the relationship between the hippocampal formation (HF) and sensory cortex KIII sets. Abbreviations: DG, dentate gyrus; CA1-CA3, Cornu Ammonis (hippocampal sections); PG, periglomerular; OB, olfactory bulb; AON, anterior olfactory nucleus; PC, prepyriform cortex.

Figure 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, auditory, somatosensory, etc. signals from the environment. The 2 dotted circles mark the dynamical KIII sets in HF (CA1-CA2-CA3) and cortex (OB-AON-PC). 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. Our emphasis is creating a working model that approximates the spatio-temporal dynamics of primordial vertebrate forebrains. Accordingly, the KIII sets maintain high dimensional chaotic dynamics autonomously. The connection between the KIII sets is realized in the present model via interaction between CA3 and OB, and CA1 and PC respectively. 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. In the framework of the KIII methodology, HF is 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 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). The hippocampus is strongly involved in the cognitive processes of spatial and temporal orientation (cognitive mapping and short-term memory). In our model several types of learning rules are used simultaneously, including habituation, Hebbian reinforcement learning, and global stability control through normalization. All these learning methods exist in a subtle balance and their relative importance changes at various stages of the memory process.

Here we summarize results obtained by reinforcement learning implemented using Hebbian correlation rule in CA1. 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.

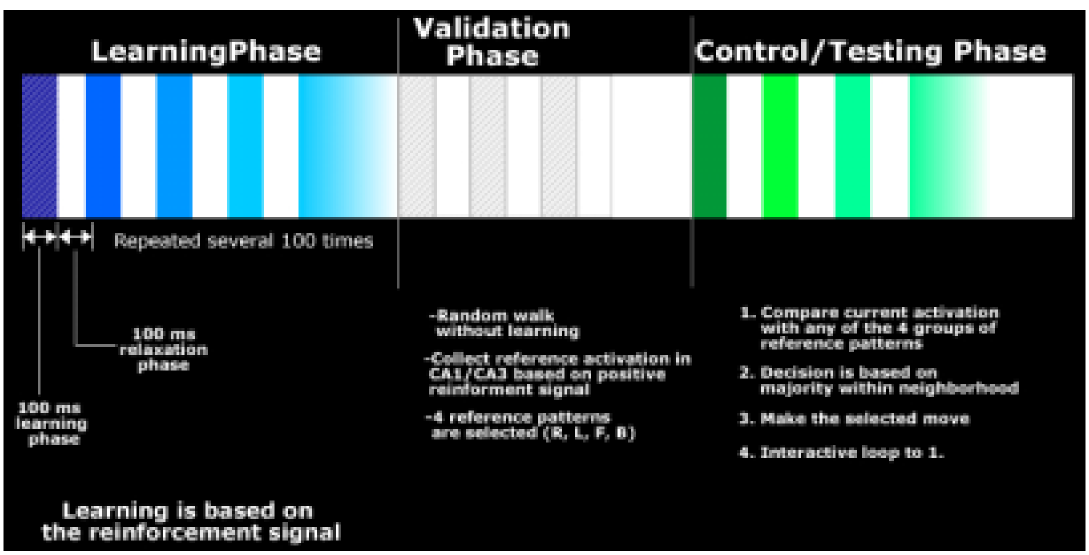

Figure 2: Illustration of the theta periods thorough the learning, validation, and control phases by using the KIII model of the hippocampal formation.

As the test bed, we use a simple 2D 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. 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. We consider the past 9 time steps as inputs, in addition to the present time frame.

At first, let the robot randomly walk in the environment and record the 6 sensory readings continuously. The path of the random exploration is shown in Fig. 3a.

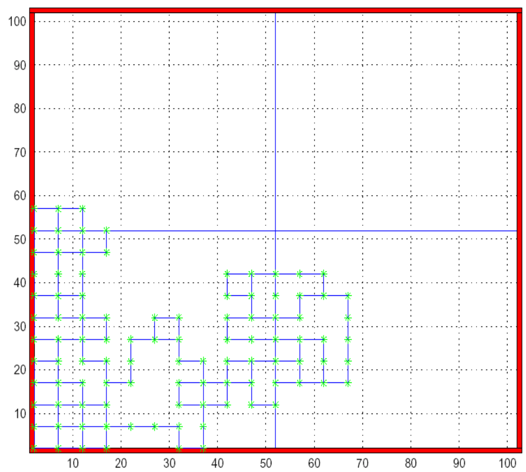

Figure 3a. Path of the robot during random walk.

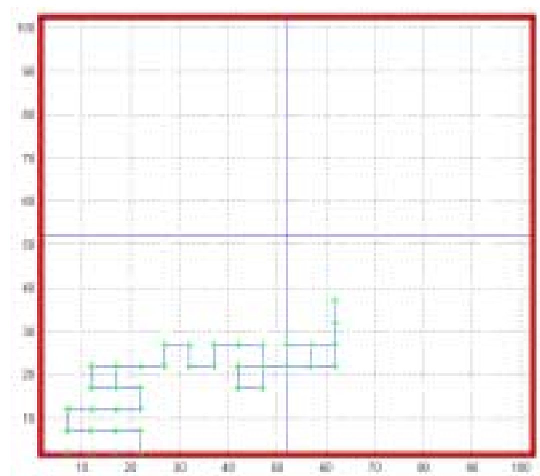

Figure 3b. Path after Hebbian learning; the Goal is at the central location [51,51].

During the 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.

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 with respect to the 3 environmental clues, 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. 3b. After learning, the average length of the trajectory from start to goal is reduced from 80 obtained for the random walk, to about 35 steps. It should be noted that based just on the orientation information, it is very difficult to learn the goal location precisely. Therefore, we terminate the run if the robot reaches the goal neighborhood within 2 steps. Further details of the learning, and thorough evaluation of the performance of the KIII HF model is given in the full paper.

In this work, we have introduced a novel method of navigation using the KIII hippocampal model, as part of the KIV set. 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, which are converted into improved navigation of the simulated robot through the environment.

References

Ankaraju, P. “The Hierarchy of K sets – From Pattern Recognition to Navigation,” *Masters’ Thesis*, The University of Memphis, 2002.

Arleo, A. and Gerstner, W. (2000) Spatial cognition and neuro-mimetic navigation: A model of hippocampal place cell activity. Biological Cybernetics, 83: 287-299.

Bliss, T.V.P., and Lomo, T. (1973) Long-lasting potentiation of synaptic transmission in the denate area of the anaesthetized rabbit following simulation of perforant path. *J. Physiol.* 232: 331-356.

Burgess, N., Recce, M., and O’Keefe, J. (1994) A model of hippocampal function. Neural Networks, 7 (6/7): 1065-1081.

Chang H.J. & Freeman W.J. (1996) Parameter optimization in models of the olfactory system, *Neural Networks*, Vol. 9, pp. 1-14.

Freeman, W.J. (1975) *Mass Action in the Nervous System.* Academic Press, 1975.

Kozma, R. & W.J., Freeman (2001) Chaotic resonance: Methods and applications for robust classification of noisy and variable patterns. *Int. J. Bifurcation and Chaos*, 11(6): 2307-2322 .

Kozma, R., Freeman, W.J. (2002) “Classification of EEG Patterns Using Nonlinear Neurodynamics and Chaos,” *Neurocomputing*, 44-46: 1107-1112.

Kozma, R., W.J. Freeman, P. Erdi (2003) “The KIV Model – Nonlinear spatio-temporal dynamics of the primordaial vertebrate forebrain,” *Neurocomputing (* in press).