THE KIV MODEL – NONLINEAR SPATIO-TEMPORAL DYNAMICS OF THE PRIMORDIAL VERTEBRATE FOREBRAIN

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Abstract

EEG measurements indicate the presence of common-mode, coherent oscillations in various cortical areas. In previous studies the KIII model has been introduced, which interprets the experimental observation as nonlinear, spatially distributed dynamical oscillations of coupled neural populations. In this paper we combine multiple KIII sets into the KIV model, which approximates the operation of the basic vertebrate forebrain together with the basal ganglia and motor systems. This paper outlines a summary description of the essential components of the KIV model, as the basis for future modeling of their cooperative dynamics guided by analysis of multichannel EEG in animals and humans.

Keywords: Neurodynamics, Chaos, Cortex, Hippocampus, Spatio-temporal EEG

1. INTRODUCTION

The discovery that brain dynamics exhibits chaotic features has profound implications for the study of higher brain function [15], [14]. The KIII model is a working example of the implementation of these chaotic principles in a computer environment. KIII exhibits a number of experimentally observed behaviors of brains, like robust pattern recognition and classification of input stimuli, and fast transitions between brain states [4], [6], [12], [13]. KIII shows very good performance in the several kinds of learning needed to categorize input data, and it can generalize efficiently in various classification problems.

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. The system resides in the localized wing for some time, then it returns to the basal state. This is a temporal burst process of the duration of up to 200 milliseconds; see [16] for the olfactory bulb, and [2] for neocortex).

The next highest level of the K-sets is the KIV model. As in the case of all other K-sets (Freeman, 1975), the architecture and functionality of KIV is strongly biologically motivated. The data that are required for modeling neurodynamics at this level are derived by analysis of EEG recorded simultaneously from multiple electrodes in sensory and limbic structures [11], [7], [8], [9]. KIV provides the neuro-architecture that is needed to model the interactions of key neural populations in the primordial vertebrate forebrain. Among these parts are the sensory cortices, the motor cortices and nuclei, and the hippocampal formation, which is essential for cognitive processes such as orientation, learning and memory.

In this paper, the architecture of the KIV model is outlined, starting with a description of the internal organization of the hippocampus. There follows the functional description of the interaction of hippocampus with the sensory cortices and basal nuclei comprising the primitive forerunner of the limbic system at the level of the salamander [10]. Several types of essential learning processes in the basic vertebrate forebrain are described using illustrative examples.

2. OUTLINE OF THE KIV MODEL

Three types of sensory signals are considered in KIV: exteroceptors, interoceptors (including proprioception), and orientation signals; e.g., gravity, visual flow, magnetic fields. Each of these sensory signals provide stimuli towards the brain, namely the sensory cortices, midline forebrain (MF) unit, and the hippocampal formation (HF), respectively; see Fig. 1. The present model is motivated by the architecture and putative function at the level of the amphibian brain. It is not intended to mimic all the biological details; rather it is used to incorporate the main elements required for operation of brains at the KIV-level of functionality.

Figure 1

The hippocampus is the main focus of cognitive mapping that supports spatial navigation and temporal orientation (short term memory). There is a rich literature of hippocampal-based navigation models [3], [1]. In our model, the following parts of the hippocampus are modeled: Dentate Gyrus (DG), CA3, CA1, and CA2. We need CA2 in our model to generate the hippocampal KIII dynamical system, serving as its chaotic controller. CA1, CA2 and CA3 are modeled as KII units, while DG will be a KI unit. KII units are shown to generate point attractors, limit cycle attractors, and even chaotic attractors (though lacking robustness) in the gamma band.

We model both the sensory cortical (SC), midline forebrain (MF), and the hippocampal formation (HF) systems as KIII sets. Each KIII set has three KII units as components and exhibits robust aperiodic oscillations in the gamma range. Each shows spatial coherence in the form of a shared, spatially distributed, aperiodic wave form, with amplitude modulation patterns occurring in sequential frames over time, indicating the existence of landscapes of chaotic attractors corresponding to categories of sensory stimuli that have been learned. These AM patterns are manifestations of self-organizing dynamics that creates coherent activity in the form of "wave packets" [5] as vectors of information in perception. The gating of bursts of KIII activity is governed by a limit cycle attractor in the KII set modeling the septum, that is fixed at frequency in the theta band, here 5 Hz (analogous to a sniff or saccade).

The cortical KIII system initiates the function of pattern recognition by the agency of sensory input-induced destabilization of high-dimensional dynamics. This actualizes an attractor landscape formed by previous experience in the OB/PC, which in our model is the common sensorium for all distance receptors, as it is in the salamander [10]. The hippocampal KIII system, thereafter, uses the categorization embodied in the outputs of the OB and PC as its content-laden input, to which the DG contributes the temporal and spatial location of the environmental events.

Another KIII component of the integrated KIV system, the Midline Forebrain formation, receives the interoceptor signals through the basal ganglia, and processes them in the hypothalamus and the septum. MF provides the value system of the KIV, using information on the internal goals and conditions in the animal. It provides the "Why?" stream to the amygdala, which combines this with the "What?" and

"Where?" information coming from the cortex and the hippocampus to make a decision about the next step/action to be taken.

The motor part of the model limbic system is driven by the simulated amygdala. The direction of motion that it determines is based on the combined information from the three sensory systems, which collectively form the architecture of the global KIV. From EEG studies we infer that a cooperative state emerges from the collective interaction among the CA1, PC, Septum, and Amygdala, by which various behavioral patterns are formed and executed. The model given in Fig. 1 is designed to provide the platform with which to study by simulation this behavior formation and action selection mechanism. In a very simple approach, however, we define initially only three basic behaviors: wall following, object avoidance, and backup. Backup behavior is invoked if the robot is stuck or cannot execute a chosen action. A wide range of problems of intentional action can be solved with these three simple behaviors.

3. HIPPOCAMPAL MODEL OF NAVIGATION

A continuous inflow of information at a high sampling rate is stored in a short-term memory in the form of stack data storage/register containing up to 10,000 temporal frames. In this memory, always the oldest items are deleted if the memory capacity is exceeded. This is continuously updated and maintained in the HF without inducing phase transitions or reinforcements learning. DG plays a key role in preprocessing for the conversion of orientation information and environmental cues into location information that is contributed by in the CA1 and CA3 units of the hippocampus.

To illustrate the short-term learning mechanism, consider an environment with 3 reference points/landmarks provided by 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. Based on the distance and direction information for the landmarks, the present location of the robot is estimated. The estimation is performed by considering the DG as a feedforward NN, which learns the position by supervised learning, for example, backpropagation.

A practical example is for the robot to learn to identify its location using 3 landmarks. In the encoding use not only the instantaneous readings of the 6 inputs (3 distances and 3 angles) but the sequence

of the most recent 8 vectors. This means that the input vector will be 48=6x8 dimensional. Let the robot randomly walk in the environment and record the 6 sensory readings continuously. Apply these inputs continuously to the DG MLP for several thousand steps and perform continuous learning with BP, using the known location coordinates [x,y]. During the testing phase, we turn off the learning and check if the output of the MLP is, indeed, indicates the correct actual location of the robot. Examples of the generated place fields are given in Fig. 2a. The average localization error is illustrated in Fig. 2b.

Figure 2a & 2b

We apply reinforcement learning combined with non-Hebbian habituation for category formation. This learning is episodic, not continuous, long-term, and irreversible. It occurs when the device is moving into its environment and encounters important or unexpected changes in its sensory inflow. The KIII reinforcement learning [12] takes place in CA3/CA1 during the active periods provided by the theta rhythm, if reinforcement signal is present. In the numerical experiments, we use the same 2D environment, as in the previous section. The robot has 8 simulated near-field sensors. We use the most recent 8 time steps for learning. Reinforcement learning takes place during the 100 ms window defined by the theta rhythm.

At first, the only landmark the animal is given is the 'home' beacon, which is set by the human controller. In an explorative mode, the home acts as a repeller with a monotonic gradient field centered at the home, that drives the animal away from home. Constrained by the obstacle, it continues its path along the steepest possible gradient. Soon or later it will not be able to move further, it stuck. That is a conflict, which generates a reinforcement signal for learning.

The above learning mechanisms are complemented with the following algorithm to form additional landmarks based on the experience during exploration. When the animal is stuck, the controller is notified about this event and its location. As a result, a new landmark is generated and its position is added to the existing ones. From now on, the animal gets orientation signals from all the beacons, including this new one. At each episode of being stuck, as behavioral response, we use is the 'back up' motion. At the same time, reinforcement learning has been initiated. An example of such exploration is shown in Fig. 3a. It took the system about 500 steps to get from 'Home' [0, 0] to the 'Goal' [80, 60].

Fig. 3a & 3b

In order to test the robot after training for about 500 steps, we re-start it from 'Home' and give a 'Goal' location. If the robot properly learned the environment, it will navigate efficiently and find a reasonably optimal path to the goal based on the internally formed cognitive map. This is illustrated in Fig. 3b. After learning, the length of the trajectory from 'Home' to 'Goal' is reduced to about 30 steps.

4. DISCUSSION AND FUTURE PERSPECTIVES

The KIV-set is intended to model the cerebral hemisphere in the vertebrate brain at the evolutionary level of the salamander, which is the locus of goal-directed behavior. The exteroceptors give situation reports, the beacons give space-time orientation, and the septum organizes the valence from interoceptors. Generic goals are established by the human controller of the device, which must determine the specific location to which it should move by using the beacons to locate itself in relation to specific exteroceptive signals. The device is to be familiarized with a significant signal by training to recognize them by categorization and association with particular beacons (tone sound, light color, etc.) as signifying their location, for example, that of a fuel depot or hazard. The device will approach its intended goal flexibly, choosing its path among known hazards and avoiding new hazards by learning about them.

The most critical unsolved problem that we face in development of the KIV model is the dynamics of association between classified exteroceptive signals in the context of value laden interoceptive signals and the cognitive space established with the help of the orientation beacons. The synthesis of these signals must lead to a decision that is to be conveyed to the motor systems for guidance of a sequence of steps. The synthesis implies the formation of a global state variable, that consists of a sequence of temporal frames, each of which is spatially patterned to express the necessary information on which to base a decision. To construct a model that supports the formation of the proposed KIV state variable, we need to study the global dynamics of vertebrate brains that are engaged the guidance of goal-directed behavior. The best available source of this kind of information is multi-channel EEG from high-density arrays of electrodes in multiple sensory and limbic structures [11], [8], [9]. At the present stage of building the KIV model, we have successfully tested the operation of the hippocampal components in a simplified implementation. We will concentrate our future efforts on defining, describing and modeling the macroscopic KIV state variable.

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FIGURE CAPTIONS:

Figure 1: Structure of the KIV model. Abbreviations: DG, dentate gyrus; CA1-CA3, Cornu Ammonis (hippocampal sections); PG, periglomerular; OB, olfactory bulb; AON, anterior olfactory nucleus; PC, prepyriform cortex; Spt, septum; DB, diagonal band; HT, hypothalamus; BC, basal ganglia, corpus striatum including thalamus; BS, brain stem. The sparse long connections that comprise the KIV set are shown as bi-directional, but they are not reciprocal. The entorhinal cortex is omitted, because that is a neocortical structure found only in mammals.

Figure 2a: Example of place fields generated in numerical simulations

Figure 2b: Average localization error. White color indicates high accuracy (within 1 lattice point); black denotes the largest error, i.e., d = 4 displacements in lattice geometry: $d = |\Delta x| + |\Delta y|$.

Figure 3a: Trajectory during exploration of the environment; starting from 'Home' at [0, 0], and the 'Goal' state is at [80, 60].

Figure 3b: Trajectory from 'Home' to 'Goal' after completing a learning and exploration session.
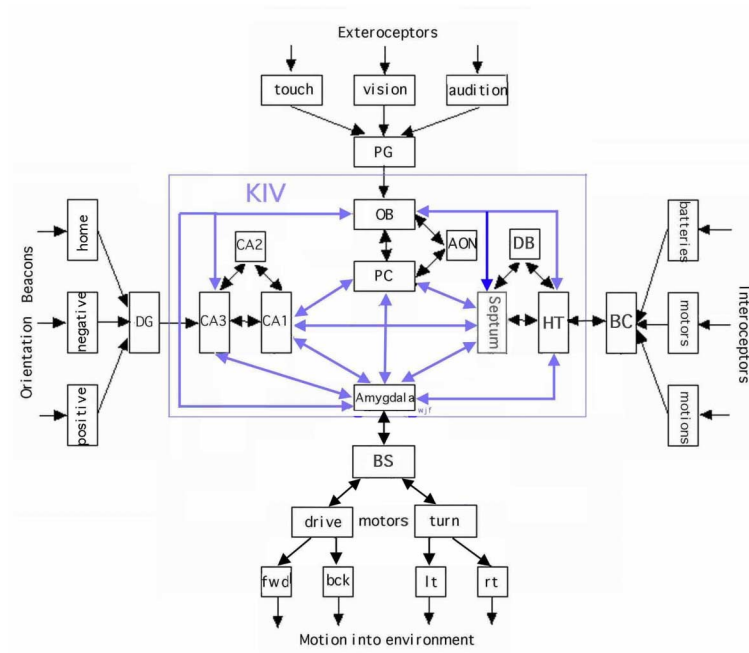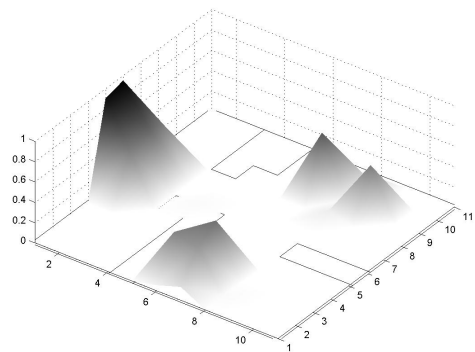
Figure 1 (Kozma et al)

Figure 2a (Kozma et al.)
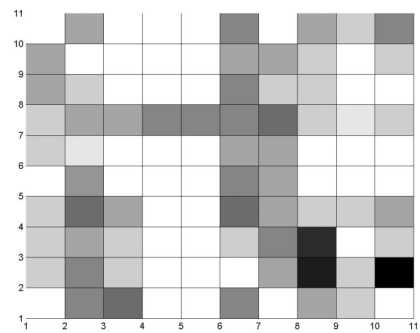

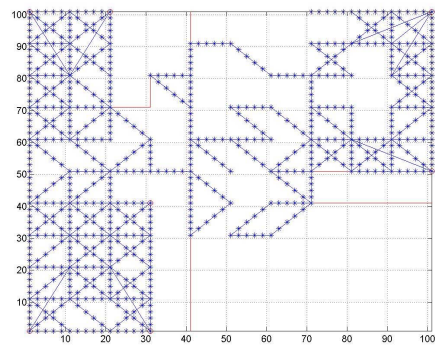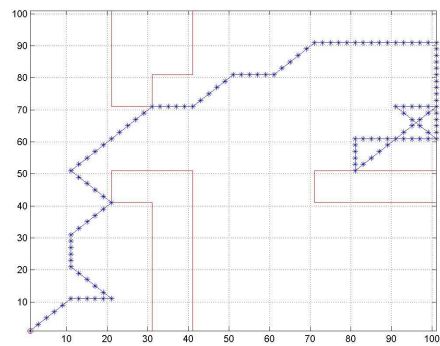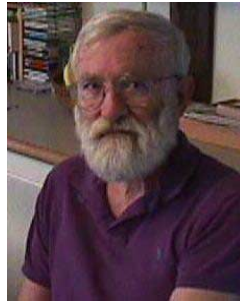Figure 2b (Kozma et al.)

Figure 3a (Kozma et al.)

Figure 3b (Kozma et al.)

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