THE KIV MODEL – NONLINEAR SPATIO-TEMPORAL DYNAMICS OF THE CORTICAL-HIPPOCAMPAL SYSTEM

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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. KIII can account for the fast and robust classification and pattern recognition in cortices. In order to describe spatial planning and orientation functions, in this paper we expand KIII into the KIV model, which approximates the operation of the cortical-hippocampal system. KIV consists of several KII and KIII components, including sensory and cortical systems, as well as CA1, CA3, and dentate gyrus. Detailed description of the KIV model and its operation is given in the paper.

Summary

The discovery that brain dynamics exhibits chaotic features has profound implications for the study of higher brain function (Skarda & Freeman,1987; Schiff, 1994). A chaotic system has the capacity to create novel and unexpected patterns of activity. It can jump instantly from one mode of behavior to another, which manifests the fact that it has a collection of attractors, each with its basin, and that it can move from one to another in an itinerant trajectory. It retains in its pathway across its basins a history, which fades into its past, just as its predictability into its future decreases. Phase transitions between chaotic states constitute the dynamics that we need to understand how brains perform such remarkable feats as abstraction of the essentials of figures from complex, unknown and unpredictable backgrounds, generalization over examples of recurring objects, reliable assignment to classes that lead to appropriate actions, planning future actions based on past experience, and constant up-dating by learning.

The KIII model is a working example of the implementation of these chaotic principles in a computer environment, which exhibit several of the experimentally observed behaviors of brains, like robust pattern recognition and classification of input stimuli, and fast transitions between brain states (Chang and Freeman, 1996; Freeman, 2000; Kozma & Freeman, 2001; Kozma et al., 2001). KIII consists of various sub-units; i.e., the KO, KI, and KII sets. The KO set is a basic processing unit and its dynamics is described by a 2nd order ordinary differential equation. By coupling a number of excitatory and inhibitory KO sets, KI_e and KI_i sets are formed. Interaction of interconnected KI_e and KI_i sets forms the KII unit. Examples of KII sets in the olfactory system are the olfactory bulb, anterior olfactory nucleus and prepyriform cortex. Coupling KII sets with feed-forward and delayed feedback connections, one arrives at the KIII system. KIII shows very good performance in learning 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. This wing is usually of much smaller dimension than the 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 (Barrie et al., 1996). A memory pattern is defined therefore as a spatio-temporal process represented by the sequence of spatial AM patterns during a burst. The performance of the dynamic system when used to classify linearly non-separable patterns is evaluated. Our results are compared with evaluations using statistical classification methods and multi-layer feed-forward neural network-based classifications. KIII compares favorably with these methods especially regarding robustness and noise-tolerance of the pattern recognition.

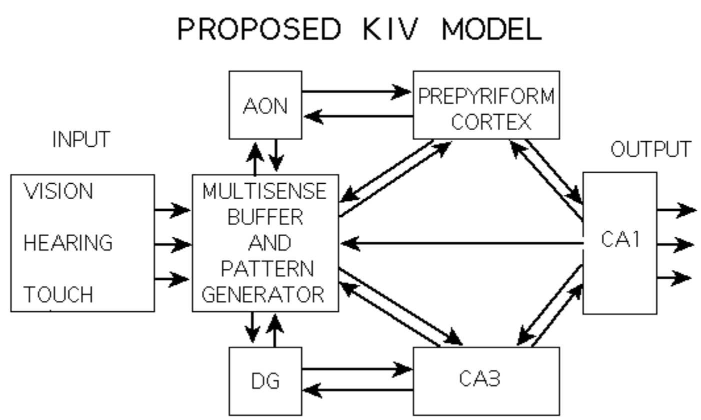

Figure 1: Components of the KIV system. Each of he active units of KIV are modeled as layers of excitatory and inhibitory neural populations, respectively.

The highest level of the K sets is the KIV model. As in the case of all other K sets, KIV's architecture and functionality is strongly biologically motivated. In this work we extend the KIII model into KIV that models the interaction in the cortical-hippocampal system; see, Fig. 1. KIV has the functionality of planning and action selection, in addition to classification and pattern recognition represented by single KIII units. KIV consists of several KIII sets, which model the cortical and hippocampal areas. The hippocampus is strongly involved in such cognitive processes as learning and memory. Long term potentiation, the likely cellular basis for memory formation (Bliss and Lomo 1973; Amaral and Witter, 1989; Kiss and Erdi, 2002). LTP is assumed to occur in different excitatory synapses in the hippocampus, as in the recurrent collateral systems of the CA3, between pyramidal cells of he CA3 and CA1regions, and also in the mossy fibers connecting the granule cells of the dentate gyrus to CA3 pyramidal cells. In the model, several types of learning rules have been used simultaneously, including habituation, Hebbian learning, and global stability control. All these learning methods exist in a subtle balance and their relative importance changes at various stages of the memory process.

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.

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