Learning intentional behavior in the K-model of the amygdala and entorhinal cortex with the cortico-hyppocampal formation

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Abstract

The interaction between entorhinal cortex (EC), amygdala, and hippocampal and cortical areas in vertebrate brains is studied using the dynamical K model approach. Special emphasis is given to the role of EC in decision making under the influence of sensory, orientation, and motivational clues. We introduce a simplified KIV model with positive and negative reinforcement learning in the hippocampus and the cortex. The developed model is implemented in a 2D computational environment for multi-sensory control of the movement of a simulated animal. Our results support the interpretation of recent EEG measurements with instantaneous macroscopic phase transitions.
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1. Introduction

Based on Freeman's decades-long studies into the dynamics of neural populations, a hierarchy of K-models has been developed, including KO, KI, KII, and KIII sets [3]. K-sets are strongly motivated by neurophysiological principles, and they are expressed as a lumped-parameter set of 2nd order ordinary differential equations. K sets reproduce major properties of measured EEG and unit (pulse) signals [2,5], and they have been used successfully for pattern recognition and classification. K models compare very well with other classification methods, especially in the case of difficult classification problems with strongly nonlinear class boundaries and with relatively few learning examples.

The KIV model is the highest level in the hierarchy of K sets [6,7]. KIV has the function of action selection, in addition to classification and pattern recognition represented by single KIII units. KIV consists of several major components, including cortex (COR), hippocampal formation (HF), the midline forebrain (MF) with the basal ganglia, entorhinal cortex (EC) and the amygdala (AMY). All components are involved with learning and memory. Previous studies aimed at analyzing the role of the cortico-HF in learning and navigation [7,10]. The present work investigates the EC and its interaction with AMY and other major parts of the KIV model. Biological evidence indicates that the AMY, together with the adjacent cortex, is intimately involved in decision-making and emotion processing for goal-directed behavior [1,8,9]. Decision-making is made based on the motivational value that is expected after execution of the selected behavioral action sequences [11].

Recent EEG experiments indicate the effective formation of a global state variable, which is manifested in the emergence of a wave form that is a shared component of the variance of the carrier wave inputs from various cortical areas.
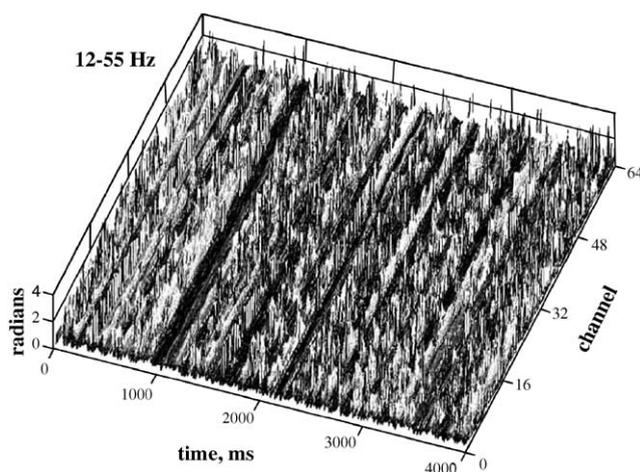

Fig. 1. Instantaneous phase differences of EEG of an array of 64 electrodes. Extended periods with small phase differences are interrupted by brief periods with increased phase differences [4].

The emergence of this common component is the indication of the onset access to a macroscopic attractor by phase transitions. An example of the observations is given in Fig. 1, where the instantaneous phase differences are plotted against temporal and spatial coordinates. The spatial coordinate is represented by the linear array of 64 EEG electrodes extending across the hemisphere [4]. Synchronized jumps in the instantaneous phase differences are clearly visible for large part of the hemisphere at alpha rates. This work aims at developing the KIV model of the brain, which can be used for the interpretation of EEG observations.

The present work starts with the description of the KII model of the EC and its relation to the cortical and the hippocampal KIII units. Reinforcement learning with positive and negative reinforcement signals is used in a 2D environment. Spatio-temporal oscillations in KIV have been used for the interpretation of state transitions identified in recent EEG measurements.

2. The role of entorhinal cortex and amygdala in the formation of the global KIV state

In this section, we employ a simplified version of the KIV model. We consider the cortex and the HF as KIII units comprising KIV, without incorporating the Septum and the Basal Ganglia. The cortex and the hippocampus are connected through the coordinating activity of the EC/AMY to the brain stem and the rest of the limbic system. Fig. 2 illustrates the connections between components of the simplified KIV. The connections are shown as generally bidirectional, but they are not reciprocal.

The output of a node in a KII set is directed to nodes in another KII set, but it does not receive output from the same nodes but other nodes in the same KII set. Moreover, these connections are sparse; i.e., a given node in the EC is connected to a subset of the nodes in CA1 and PC. The sparseness can be expressed as a percentage of total connections for each node. In brains its value is estimated to be a few %. The
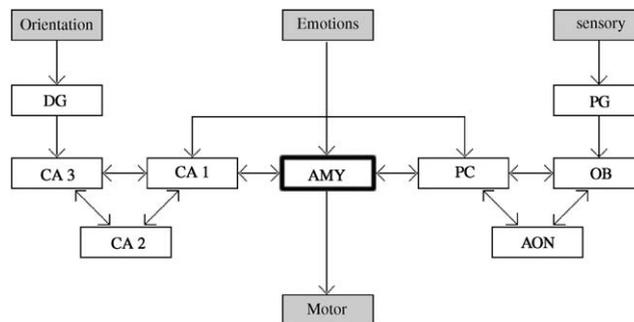

Fig. 2. Simplified KIV model illustrating the relationship between components of the HF, the sensory cortex and AMY. Abbreviations: DG, dentate gyrus; CA1–CA3, Cornu Ammonis (hippocampal sections); PG, periglomerular; OB, olfactory bulb; AON, anterior olfactory nucleus; PC, prepyriform cortex; EC, entorhinal cortex; AMY, amygdala.

KIV level of function is established by the interactions among the CA1, PC, EC, and AMY, which are modeled as KII sets. The AMY receives inputs from other KII sets (not from the environment), and it is privileged with full (100%) internal connection density. For the connection density of HF and PC KII to EC, the sparseness parameter 20% is used. The formation of a global KIV state variable is manifested in the emergence of a shared variance of the wave inputs from the component KII sets. This common wave form constitutes the global input to EC. The output of EC, through the AMY, is the source of goal-oriented control of the motor system.

Chaotic behavior in KIII sets is the result of the competition between 3 KII oscillators. In healthy brains, none of the KII components gain dominance above the others permanently. In KIV, the competing components are KIII sets, which maintain relative autonomy. At the same time, they do share common information to generate the KIV level of dynamics. The KIV dynamics is the access to the global macroscopic state. It is not the result of capture by any of the KIII or KII sets, the same way as the KIII level chaos is not the result of capture of the dynamics by any of the KII sets. In the next section we investigate the indications of the emergence of global collective state in KIV simulations.

3. Computer simulation experiment with KIV

In computer simulation of the KIV model we use a 2D simulated Martian environment [10]. In this environment, the robot moves along a grid. At any given grid point, the next move of the robot is chosen from one of the four directions, unless obstacles prevent movement to certain directions. The robot uses two sensory systems; namely global landmark detector and local infrared sensor (IR) with a finite sensitivity range of two grid points. The landmark detectors measure the distance and direction of three given landmarks, while the IR measures the distance between the location of the robot and any existing obstacles in eight directions (E, NE, N, NW, W, SW, S, SE).

The operation of the KIV model has three major phases: learning, labeling and control [7]. At the learning phase, the robot explores the environment using a predefined strategy. In the presence of positive reinforcement signal, learning occurs in the hippocampal KIII. We apply positive reinforcement in the hippocampus when the robot correctly moves towards the specified goal location. On the other hand, cortical KIII learning is based on negative reinforcement signal. Reinforcement is activated when the robot approaches an obstacle or if it gets trapped. Reinforcement learning is implemented using Hebbian correlation rule in CA1 and PC, respectively. During the labeling phase no learning takes place. Instead, the robot collects reference activation values from the AMY. Four types of reference activation patterns are formed, corresponding to moving forward or backward, and turning right or left. At the control phase, these reference patterns are used to make decision on the direction of the next step.

In the KIV model we have fixed the gains between the EC, CA1, and PC at the level of 0.0001. The coefficient of the Hebbian learning in the KIII sets is 0.85. The
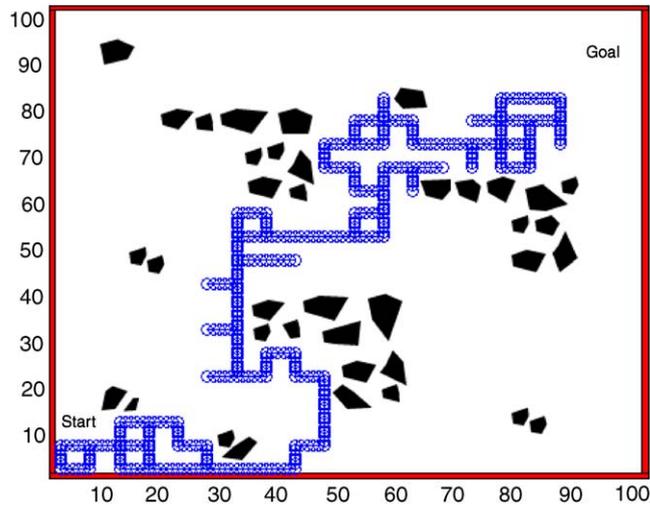
Fig. 3. Simulated path of the trained robot from the start (S) to the goal (G) using KIV model with multi-sensory inputs and AMY.

size of AMY is 80 nodes. We have conducted a series of experiments with the KIV set. An example of the observed trajectory of the simulated robot is shown in Fig. 3. It took the simulated robot 153 steps to get from the start to the goal using the KIV model. It is clear that the performance of the system is suboptimal. By further tuning the behavior of the KIV, the performance can be significantly improved. However, that has not been the main focus of the present work. Rather, we study the dynamics of the EC and its links to various KIII units.

4. Spatio-temporal dynamics of simulated EC with amygdala

We have evaluated the simulated KIV signals using the method proposed in [4]. The instantaneous phase differences of 64 EC channels in the KIV model are illustrated in Fig. 4 over a period of 500 time steps with sampling time of 1 ms. The activations of each EC channels have been filtered in the 15–75 Hz band. One can observe the sequence of quiet periods with smaller phase differences, interrupted by transitional periods with high variation of the phase differences. The observed effects are interpreted as indications of macroscopic phase transitions, as identified in actual EEG measurements [4].

Further details of the KIV simulations are depicted in Fig. 5, where the mean instantaneous phase differences are shown as the function of time. Extended periods with relatively low phase values are interrupted by short intervals with significantly increased phase differences. The observed period of 100–150 ms between phase jumps is in accordance with EEG experiments. Future studies will be conducted to
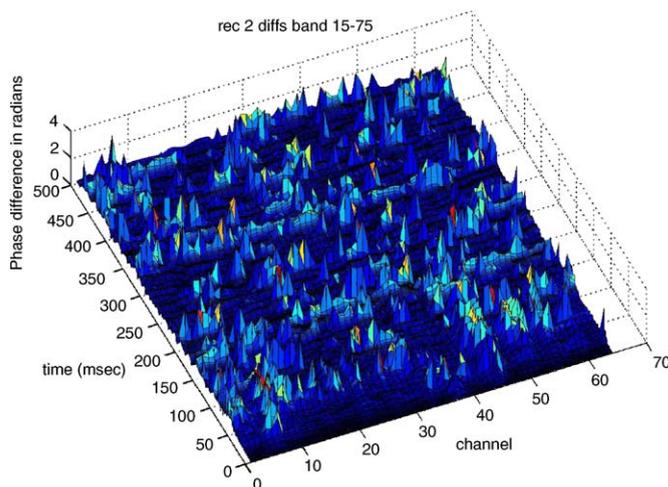
Fig. 4. Instantaneous phase differences of the simulated EC using the KIV model.
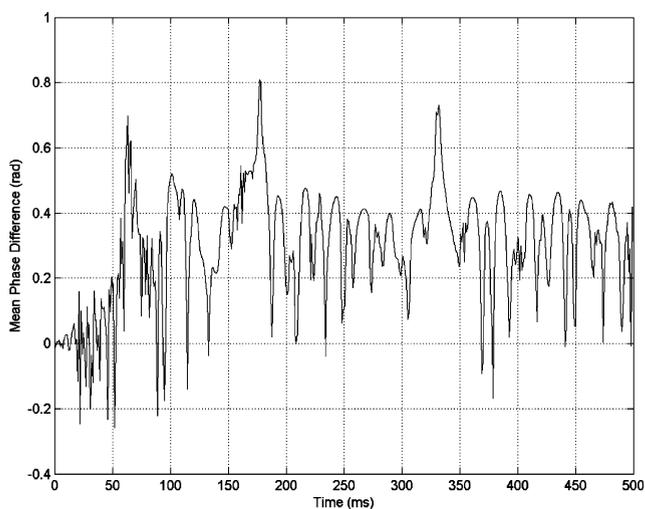

Fig. 5. Mean phase differences in the simulated EC as the function of time.

show how these results can be used for the interpretation of EEG behavior as global phase transitions in cognitive processing.

5. Conclusions

The main goal of the present study has been to investigate the role of the EC in coordinating the dynamics of the simplified KIV brain model. The developed KIV

model has been used in the computer simulation of multi-sensory navigation in a simple 2D Martian-like environment. The KIV model exhibited global phase transitions in the EC during goal-oriented navigation in the simulated environment. These results are used for the interpretation of actual EEG measurements. Future studies will be conducted to clarify the role of various parameters, such as sparseness and gain values among the KII components, and the optimum choice of learning parameters within the KIII units.

Acknowledgments

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