LEARNING INTENTIONAL BEHAVIOR IN THE K-MODEL

OF THE AMYGDALA AND THE CORTICO-HYPPOCAMPAL FORMATION

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Abstract

The interaction between the amygdala and the hippocampal and cortical areas in reptilian brains is studied using the dynamical K model approach. Special emphasis is given to the role of amygdala in decision making as part of the limbic system, 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 2-dimensional computational environment for multi-sensory control of the movement of a simulated animal. The results demonstrate efficient goal-oriented navigation and obstacle avoidance.

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 signals [2, 4], and they have been used successfully for pattern recognition and classification of various input data. 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.

Recently, the KIV model has been developed, which is the highest level in the hierarchy of K sets [5, 6]. KIV has the function of action selection, in addition to classification and pattern recognition represented by single KIII units. KIV consists of four major components, including cortex, hippocampal formation, the midline forebrain with the basal ganglia, and the amygdala with further parts of the limbic system. All components are involved with learning and memory. Previous studies aimed at analyzing the role of the cortico-hippocampal formation in learning and navigation [6, 9]. The present work investigates the amygdala and its interaction with other major parts of the KIV model.

Biological evidence indicates that the amygdala, together with the orbitofrontal cortex, is intimately involved in decision-making and emotion processing for goal-directed behavior [1]. Decision-making is made based on the motivational value that is expected after execution of the selected behavioral action sequences [10]. The amygdala is a subcortical region in the anterior part of the temporal lobe, which is the center of sensory emotional associations covering fear, danger, and satisfaction, and other motivational and emotional sensations. It receives information from the visual, auditory, olfactory, and somato-sensory

cortices and projects the outputs to subcortical sensorimotor areas [7]. The amygdala is hypothesized to encode the emotional and motivational significance of cues [8].

The present work starts with the description of the KII model of the amygdala and its relation to the cortical and the hippocampal KIII units. We analyze the effects of various model parameters influencing robust operation of the model. These parameters include the gains among the amygdala and the hippocampal and cortical units. We emphasize the significance of the sparseness of these connections. Reinforcement learning with positive and negative reinforcement signals is used in a 2-dimensional environment. It is demonstrated that a multi-sensory agent with long-range and short-range sensing is capable of effectively navigating in a challenging environment using a KIV-based controller.

The Role of 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 hippocampal formation as KIII units comprising KIV, without incorporating the Septum and the Basal Ganglia. For details of KIV; see [5]. The cortex and the hippocampus are connected through the coordinating activity of the amygdala (AMY) to the brain stem and the rest of the limbic system. Fig. 1 illustrates the connections between components of the simplified KIV. The connections are shown as generally bidirectional, but they are not reciprocal.

Figure 1

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 amygdala 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 amygdala receives only internal input and is privileged with higher connection density. A recommended starting parameter will be 20%. We use this value in further considerations.

The KIV level of function is established by the interactions among the CA1, PC, and Amygdala, which are modeled as KII sets. The effective formation of a KIV state variable is manifested in the emergence of a wave form that is a shared component of the variance of the carrier wave outputs of the component KII sets. This common wave form constitutes the input to the amygdala, which is the source of goal-oriented control of the motor system. This common component is the indication of the onset of a macroscopic attractor at the KIV level.

The emergence of chaotic behavior in KIII sets is the result of the competition between the 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 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.

The variance of the activity of each component at every level can be partitioned into fractions. The largest fraction is that belonging to the component itself. A much smaller fraction is covariant with activities in components at each higher level. Thus a neuron has a pulse train at the microscopic level with a certain variance in pulse intervals. A small fraction of its variance, of the order of 1%, is covariant with the mesoscopic KIII set within which it is embedded. A similar fraction is covariant with the global action of a KIV set at the macroscopic level. This macroscopic fraction of the total variance is crucial to brain function in behavior.

Computer Simulation Experiment

In computer simulation of the KIV model we use a 2D simulated Martian environment [9]. In this environment, the simulated 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. At the learning phase, the robot explores the environment using a predefined strategy. E.g., it moves in a given direction 5 steps or until it meets an obstacle, and it randomly turns afterwards. Learning based on experience is a key issue in navigation. For the hippocampal KIII inputs, not only the instantaneous readings of 6 inputs (3 distances and 3 angles from global landmarks) were used, but also the sequence of the most recent 9 vectors. This means that the input vector at the hippocampal KIII unit has 6x10=60 dimensions. The cortical KIII unit also remembers the previous steps and uses them together with current sensory readings. In the implementations of the cortex, the sequences of 14 most recent sensory readings are used. This means that the input vector to the cortical KIII unit has 8x15=120 dimensions. The size of the amygdala is an internal variable to the KIV model. We used 80 nodes in the present KII model of the amygdala, which resulted in very good goal-oriented navigation performance with the KIV model. Further studies are under way to optimize the size of the amygdala.

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 a negative reinforcement signal. This

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 amygdala. Four types of reference activation patterns are formed, corresponding to moving Forward, Backward, Right and Left. AT the control phase, these reference patterns are used to make decision on the direction of the next step.

Results of Simulated Navigation Using KIV with Amygdala

The goal of this section is to illustrate the operation of the amygdala using the example of goal-oriented navigation in a simulated 2D environment with obstacles. In the KIV model we have fixed the gains between the amygdala, CA1, and PC at the level of 0.0001. The coefficient of the Hebbian learning in the KIII sets is 0.85. The connections between the amygdala and CA1 and PC have a spareseness value of 20%, as it was discussed in the previous section. We have conducted a series of experiments with the KIV set. An example of the observed trajectory is shown in Fig. 2. 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 role of the amygdala and its links to various KIII units.

Figure 2

Accordingly, we have conducted 2 types of reference experiments. In the first case, the connection between the amygdala and the cortex has been cut. In this abnormal case of partially isolated cortex, we have observed that the simulated animal got stuck near an obstacle for a long time; for much longer than the 153 steps required by a regular system to reach the goal. Therefore, no efficient obstacle avoidance

takes place in the absence of the cortical KIII unit. In the second case, the connection between amygdala and hippocampus was eliminated, while the connection between amygdala and cortex remained intact. In this case the simulated robot did avoid the obstacles but it lacked global goal-directedness. As a result it needed much longer time to get to the goal, compared to experiments with intact hippocampal and cortical links.

Conclusions

The main goal of the present study has been to investigate the role of the amygdala in coordinating the dynamics of the simplified KIV brain model. It has been shown that the amygdala can contribute to decision-making in response to sensory, orientation, and motivational stimuli. The developed KIV model of the amygdala and the cortico-hippocampal system has been used in the computer simulation of multi-sensory navigation in a simple 2D Martian-like environment. The results demonstrate efficient goal-oriented navigation and obstacle avoidance. Sparse projections among the major brain areas are essential for the robust and reliable operation of the goal-oriented navigation system. 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.

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Brief Biographies

Robert Kozma holds a Ph.D. in applied physics from Delft University of Technology (1992). Presently he is professor of computer science and FedEx Fellow, FedEx Institute of Technology, and the Department of Mathematical Sciences, The University of Memphis. He is the Director of the Computational Neurodynamics Laboratory. Previously he has been on the faculty of the Department of Quantum Science and Engineering, Tohoku University, Sendai, Japan, the Information Science Department, Otago University, Dunedin, New Zealand, and he held joint appointment at the Division of Neuroscience and Department of EECS at UC Berkeley. His research interest includes spatio-temporal neurodynamics and the emergence of intelligent behavior in biological and computational systems.

Derek Wong currently working on his M.Sc. in Computer Science at the University of Memphis, where he has earned his undergraduate degree in 2002. He is research assistant the Computational

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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. 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).

Figure Legends

Figure 1: Simplified KIV model illustrating the relationship between components of the hippocampal formation, the sensory cortex and amygdala. Abbreviations: DG, dentate gyrus; CA1-CA3, Cornu Ammonis (hippocampal sections); PG, periglomerular; OB, olfactory bulb; AON, anterior olfactory nucleus; PC, prepyriform cortex; AMY - amygdala.

Figure 2: Simulated path of the trained robot using KIV model with amygdala. The total length of the successful path from Start to Goal is 153 steps.
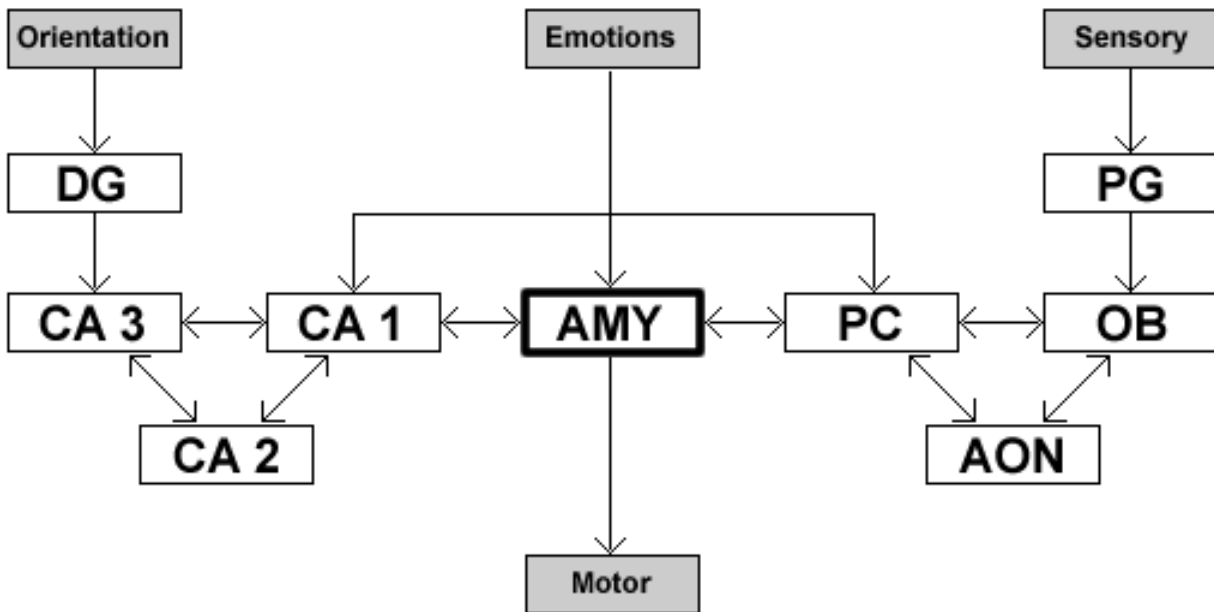
Figure 1

Figure 2