A biologically inspired computational model of the Block Copying Task

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Abstract

We present in this paper a biologically inspired model of the Basal Ganglia which deals with Block Copying as a sequence learning task. By breaking a relatively complex task into simpler operations with well-defined skills, an approach which is termed as a skill-based machine design is used in the device of computational models to complete such tasks. Basal Ganglia are critically involved in sensorimotor control. From the learning aspects, Actor-Critic architectures have been proposed to model the Basal Ganglia and Temporal Difference has been proposed as a learning algorithm. The model is implemented and simulation results are presented to shows the capability of our model to successfully complete the task.

1. Introduction

Robotics faces many sensorimotor control challenges when dealing with real world tasks, which require a series of coordination movements of the eyes, the head, and the hand(s) in both time and space (Pelz 2001). In this case, sequence learning plays a critical role in the design and operation of sensorimotor control architectures.

Sequential behavior is a fundamental part of machine learning. Complex behaviors are often proposed to be achieved by combining more primitive ones (Ballard 1992). The approach we are pursuing is termed as a skill-based machine design, in which we break a complex task into simpler operations requiring well-defined skills and set up a sensorimotor control framework which is based on sequence learning that make use of primitive skills.

Anatomic and physiologic studies suggest that Basal Ganglia are highly involved in sensorimotor control such as action selection, motor planning, decision making and sequential execution and learning (Houk 1995). It has been proposed that Dopamine Neurons in Substantia Nigra and Ventral Tegmental Area could be coding the error signal of predictive future rewards, suggesting that the Basal Ganglia implement a form of Reinforcement Learning, such as Temporal-Difference (TD) Learning (Houk 1995; Montague 1995). From the learning and structure aspects, the Basal Ganglia could be modeled using an Actor-Critic architecture in TD Reinforcement Learning.

2. Scenario and Experiment

The Block Copying Task (BCT) (Ballard 1992; Pelz 2001) has been chosen as our sensorimotor control research vehicle (figure 1).

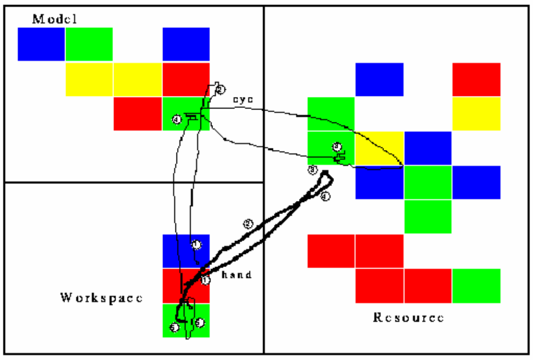

Figure 1: The display of Block Copying Task (Ballard 1997).

Although this task seems quite easy to humans, it is more difficult to be taught to animals. To build a biologically inspired machine that performs such task, it is helpful to think how a monkey could be trained to achieve it (Jabri 2002). In order to extract the basic action sequences, we have simplified the BCT to a one-dimensional scenario (figure 2), called Basic Scenario of BCT (BCTBS). Here, we assume the move-pick-drop (M-P-D) strategy (Ballard 1997) is used throughout the copying process and extract a 9-action sequence. Our desire is to simplify but yet to keep the framework basics sufficiently general as to allow for more sophistication of the skills and the experimentation scenarios, that is generalization and scalability.

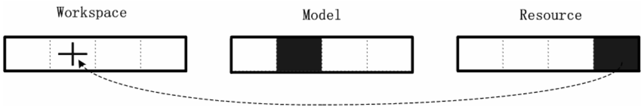

Figure 2: Block Copying Task Basic Scenario. In this Scenario, each area is identical one-dimension space. Both Model area and Resource Area contain only one block and they have the same color (black block). The goal is to move the black block from Resource Area to the "Cross" location in Workspace.

3. Architecture

The inputs in our model are the representations of sensory information which comes from both the environment and the other parts of the "brain" (the outside world for this specific model). The sensory inputs constitute a state space. The outputs are the representations of action selection results which correspond to the 9-action sequence.

The Actor-Critic architecture is used in this model (Sutton 1997). The network structure is shown in Figure 3.

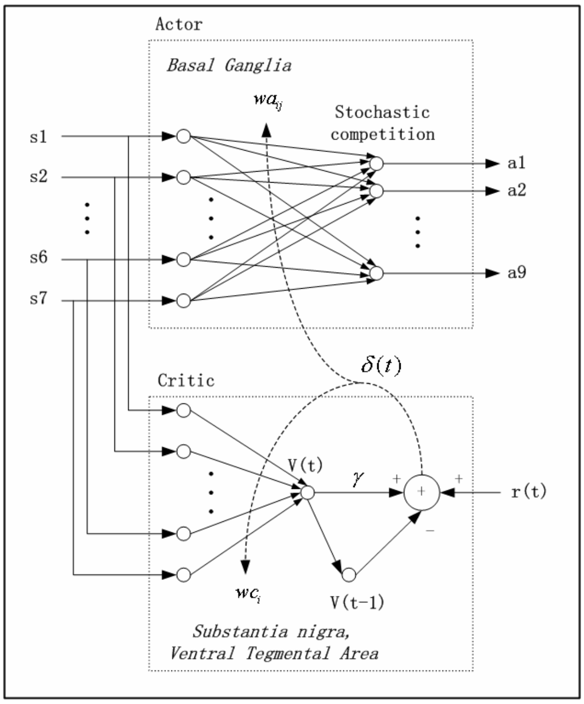

Figure 3: Basal Ganglia Model. The Actor-Critic architecture is used. Basal Ganglia corresponds to Actor, Substantia Nigra and Ventral Tegmental Area corresponds to Critic.

The sequence is learnt by associating each state to an action through trial and error method. The eligibility trace is also used to increase the capacity of the model (Sutton 1997).

4. Simulations and Results

The computational model (Figure 3) was simulated using MATLAB. The learning result is shown in Figure 4, from which we can see, the number of actions converge toward 9 after 2000 trials although not entirely equal to 9. The learning speed is fast at the beginning, but slows down after 300 trials. This is because the error of predictive future reward, which also determines learning speed, is larger at the beginning and becomes smaller after hundreds of trials, which lead the slower learning rate.

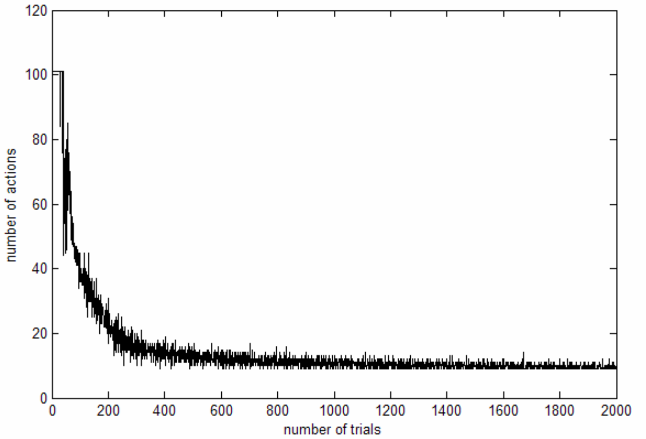

Figure 4: Learning curve.

5. Conclusion and Discussion

We have presented a biologically inspired computational model to BCTBS and a skill-based approach to decompose a complex task to some basic operations. The Actor-Critic architecture was used to model the Basal Ganglia and the TD reinforcement learning was used as the learning algorithm. The simulation results show that the algorithm converges to the expected solution.

Two limitations need to be mentioned here. Firstly, the model is restricted in the discrete input/output space and the maximum length of sequence is finite. Secondly, the model can only learn deterministic actions sequences which are already pre-defined. It has no ability to quit from an exceptional situation. Our future research will focus on overcoming the limitations discussed above, as well as other BCT scenarios.

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