Of implementing neural epigenesis, reinforcement learning, and mental rehearsal in a mobile autonomous robot

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Abstract

One of the key implications of functionalism is that minds can, in principle, be implemented with any physical substratum provided that the right functional relations are preserved. In this paper we present an architecture that implements neural epigenesis, reinforcement learning, and mental rehearsal, some of the functional building blocks that may enable us to build an artificial brain. However, we conclude that a new kind of machines, where the learning algorithms would emerge from the dynamics of the interconnection between the processing elements, are necessary for the implementation of cognitive abilities that are irreducible to a mechanistic computing algorithm.

1 Introduction

Based on the hypothesis that the physical matter underlying the mind is not at all special, and that what is special is how it is organized (Edelman, 1992), one come to the idea of building or simulating systems with functional capacities similar to those observed in nervous systems and brains to try to understand the mind.

From a biological point of view, it has been determined that the genome contains the formation rules that specify the outline of the nervous system. Nevertheless, there is growing evidence that nervous systems follow an environmentally-guided neural circuit building (neural epigenesis) (Sipper et al., 1997) that increases their learning flexibility and eliminates the heavy burden that nativism places on genetic mechanisms (Quartz and Sejnowski, 1997). The seminal work of the Nobel laureates D.H. Hubel and T.N. Wiesel on the brain's mechanism of vision (Hubel and Wiesel, 1979) describes a prime example of the role of experience in the formation of the neuro-ocular pathways.

The nervous system of living organisms thus represents a mixture of the innate and the acquired: "... the model of the world emerging during ontogeny is governed by innate predispositions of the brain to categorize and integrate the sensory world in certain ways. [However], the particular computational world model derived by a given individual is a function of the sensory exposure he is subjected to..." (LLinas and Pare, 1991).

Categorization, i.e., the process by which distinct entities are treated as equivalent, is considered one of the most fundamental cognitive activities because categorization allows us to understand and make predictions about objects and events in our world. This is essential in humans, for instance, to be able to handle the constantly changing activation of around 10^8 photo-receptors in each eye. Computational models of adaptive categorization have been developed and tested with success, and have been used to explain some sensory and cognitive processes in the brain such as perception, recognition, attention, and working memory (Grossberg, 1998). However, other types of learning, such as reinforcement learning, seem to govern spatial and motor skill acquisition (Sutton and Barto, 1998).

While in the former case only resonant states can drive new learning (i.e., when the current inputs sufficiently match the system's expectations) (Grossberg, 1998), in the latter "learning is driven by changes in the expectations about future salient events such as rewards and punishments" (Schultz et al., 1997).

2 Our neurocontroller architecture

We have developed a neurocontroller architecture (Fig. 1 based on the above premises (environmen-tally-guided neural circuit building for unsupervised adaptive clustering and trial-and-error learning of behaviors) and tested it using an autonomous mobile robot in a navigation task. First, a learning algorithm called FAST for Flexible Adaptable-Size Topology (Pérez-Uribe, 1999) was developed to handle the problem of dynamic categorization of the robots' three 8-bit infra-red "eyes" (which correspond to 24 binary receptors). No external supervisor provides the desired outputs. Second, a trial-and-error learning process coupled with punishment and reward signals (Sutton and Barto, 1998) was considered to allow the robot gen-

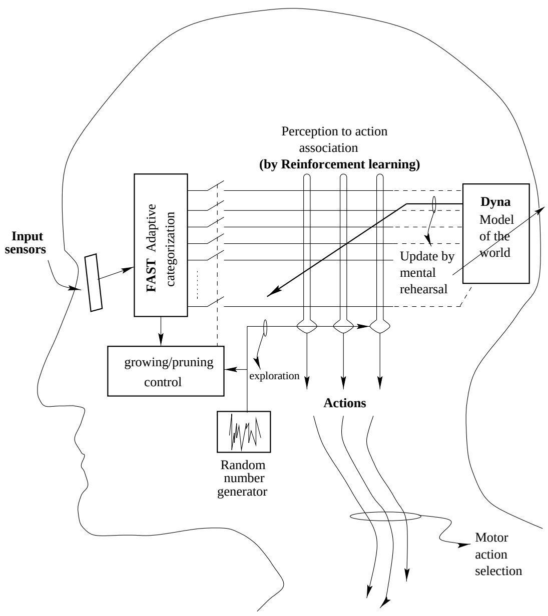

Figure 1: The neurocontroller architecture.

erate behavioral responses as a function of its sensations. Third, a model of the environment is dynamically created to improve the interaction with the actual environment (Sutton and Barto, 1998). The system alternately operates on the environment and on the learned model of the environment by a process of "mental rehearsal".

Finally, we have combined the capabilities of the incremental learning FAST neural architecture with reinforcement learning techniques and planning to learn an obstacle avoidance task with an autonomous mobile robot (Pérez-Uribe and Sanchez, 1999; Pérez-Uribe, 1999).

3 Concluding remarks

We have presented a neural architecture that implements neural epigenesis, reinforcement learning, and mental rehearsal. This architecture may be viewed as a first step towards the development of more complex neurocontrollers implementing many diverse cooperating brain-like structures. Indeed, the implementation of the learning paradigms presented above should enable us to think of a new kind of machines, where, effectively, learning by examples and interaction replace programming (without needing to emulate such principles using a programmable computing machine). In this kind of machines, the learning algorithms would emerge from the dynamics of the interconnection of the processing elements, which may be the key to realize a mind-like system endowed with "semantics" (i.e., a system that is capable of associating a meaning to the symbols it uses for computing) (Searle, 1980, 1990), and not merely with "syntax", as it is the case of our current computing machines.

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