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Preface

This volume documents the proceedings of the Annual International Conference on Biologically Inspired Cognitive Architectures (BICA) 2012, which is the Third Annual Meeting of the BICA Society and the fifth annual BICA meeting. The series of BICA conferences started in 2008 under the umbrella of the Association for the Advancement of Artificial Intelligence (AAAI). In 2010, the BICA Society was eventually incorporated as a nonprofit organization - a scientific society with headquarters in the United States, with the mission of promoting and facilitating the transdisciplinary study of BICA. Aims of the BICA Society include creating a world-wide scientific infrastructure that supports multidisciplinary researches in addressing the challenge of creating a computational equivalent of the human mind (known as the BICA Challenge). The list of Founding Members of the BICA Society is too long to be included here, and includes many eminent scholars and scientists.

As outlined in the manifesto of the BICA Society published in the Proceedings of BICA 2010, we can reasonably predict that in the coming years robots and artifacts with general-purpose human-level intelligence will become available. It is therefore vital for scientists from different disciplines to join their efforts and share results in addressing this important goal, and to analyze the scientific and technological aspects of the challenge, including ethical and moral problems. The BICA Challenge calls for an integrated understanding of artificial and natural intelligent systems, including their biological functions, cognition and learning. The BICA paradigm is a new approach that integrates different disciplines, from neuroscience to cognitive science, artificial intelligence and robotics. This approach will allow us, on the one hand, to better understand the complex operation of the brain in order to suggest new horizons for research in neuroscience and psychology, and on the other hand, to use inspirations from these fields for modern robotics and intelligent agent design.

The BICA Challenge can be compared to greatest human challenges of the past (the Human Genome Program, the Apollo Moon Expedition, etc.). It is unlikely that a single laboratory, no matter how big and full of resources it may be, can succeed in this fantastic effort. This huge challenge can only be tackled by unified efforts of many laboratories, scientists, institutions, and research facilities around the world that continuously exchange their ideas, knowledge and results.

Cognitive Integration through Goal-Generation in a Robotic Setup

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Abstract. What brings together multiple sensory, cognitive, and motor skills? Experimental evidences show that the interaction among thalamus, cortex and amygdala is involved in the generation of elementary cognitive behaviours that are used to achieve complex goals and to integrate the agent skills. Furthremore, the interplay among these structure is likely to be responsible of a middle level of cognition that could fill the gap between high-level cognitive reasoning and low-level sensory processing. In this paper, we address this issue and we outline a goal-generating architecture implemented on a NAO robot.

Keywords: Thalamo-Cortex, ICA, Hebbian Learning, Development, Goals.

1 Introduction

What brings together different skills and modules in a biological agents? In simpler animals like insects the integration is likely either the result of a genetic blueprint or embodiment [1]. Yet, in more complex cognitive agents, there seems to be some yet-to-be-understood architectural principle that encourages a seamless integration of different sensory capabilities and cognitive skills. It is long well-known, from both psychological and neuroscientific data, that severe anatomical damage does not prevent the brain from achieving a working unity [2]. Somewhat suprisingly, to a large extent, the unity of the mind is still one of the most puzzling and unresolved aspects of cognition and – although many models have been proposed[3-5] [6] – there are no universally accepted model for sensory-cognitive-motor integration.

This paper addresses the issue of integration through a goal-generating architecture targeted to that middle level of cognition investigated by Jackendoffion [7]. He suggests that there is a cognitive bridge that fills the gap between a high-level reasoning (e.g. task planning, etc.) and low-level sensorimotor control. It is tempting to wonder whether this intermediate level could be the key to cognitive integration in mammals-like cognitive systems. In fact, it is fair to maintain that most human actions are neither the result of sensorimotor contingencies nor the output of logical reasoning.

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The cortex shows an almost universal capability to adapt to different kind of stimuli, taking into consideration the particular input statistics [6,8]; so it makes sense to look at a general approach. Moreover, experimental evidences show each brain area can potentially develop any cognitive or computational skill [9,10]. On the other hand, it is well know that the mammal brain is able both to learn how to achieve goals and what goals have to pursued [11]. Putting together goal generation and generality leads to the idea the goal-generation arise by means of interplay between thalamus and cortex [12]. In fact, the thalamus is closely coupled with the cortex and each partition of the thalamus seems to provide control information to the corresponding cortical areas [13]. A further evidence of this fact is the massive neural connections from the cortex to the thalamus whereas the backward connections are less data intensive [14]. As working hypothesis it may be assumed that the cortex provides memory storage and input stimuli classification whereas the thalamus evaluates to what extent the current stimuli are related with previous data. The hypothesis is consistent with the experimental evidence showing that the brain bootstraps the generation of new goals taking advantage of hardwire criteria likely located in the amygdala [15,16].

In the robotic fields, many of the robotic setups focus either on the sensorimotor level or on the high-level reasoning. A lot of them are designed for very specific goal, since designer aim to solve specific sensorimotor, relational or logic issues. Of course, there are also cognitive agents able to develop new skills and to adapt to novel environments, such as those exploiting embodiment [17-19].

In this paper we present an intermediate cognitive system able to generate new goals and process the incoming sensory information. The cognitive framework can be implemented using either bioinspired algorithms or not. The main contributions of this paper are: to extend a computational framework of the thalamus-cortex interaction and validate some preliminary results presented in [20].

2 Goal-Generating Architecture

In this section we sketch the Goal-generating Architecure (IA) which ought to help fleshing out a cognitive middleware. Specifically, the IA is composed of a set of Intentional Modules (IM) and a single Global Phylogenetic Module (GPM). To a certain extent, the IM ought to model the interaction between the thalamus and the cortex whereas the GPM models the amygdala, providing bootstrap innate criteria whose output is projected to each IM in the network. Such approximation is justified by neuroanatomical evidence showing that the amygdala and other parts of core affective circuitry modulate the attentional matrix in the brain. It is also worth to remember that the amygdala also projects to other areas notably the forebrain and the thalamus [15]. The input layer of the IA receives the sensory data whereas the output layer sends command to the actuators. Here, we focus on the internal details of the IM. The IM is the key module of the network and represents the basic computational unit that generates goal during the sensory acquisition. The IM receives two inputs: sensory information and a control signal. The control signal is the maximum between an external control signal $e_s(t-l)$ coming from another IM (if any) and a signal from the GPM. The GPM control signal is broadcasted to all IMs in the archtiecture. The IM has two symmetrical outputs: a category signal y and a new control signal r_s computed internally by the model. r_s is important since expresses the relevance of the sensory input at time t with respect to the previous history of the IM. Furthremore, r_s plays an important role during both the learning phase and the runtime activity.

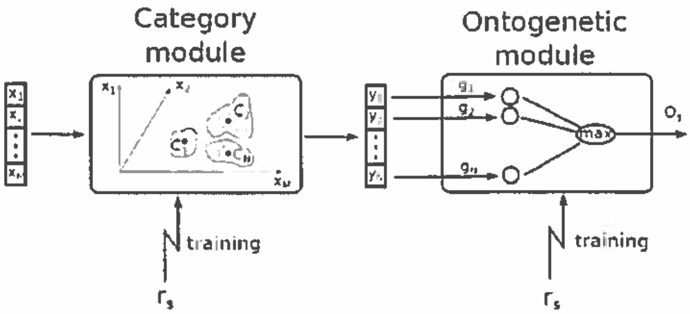

Fig. 1. (Left pane) The category module (Right pane) The ontogenetic module

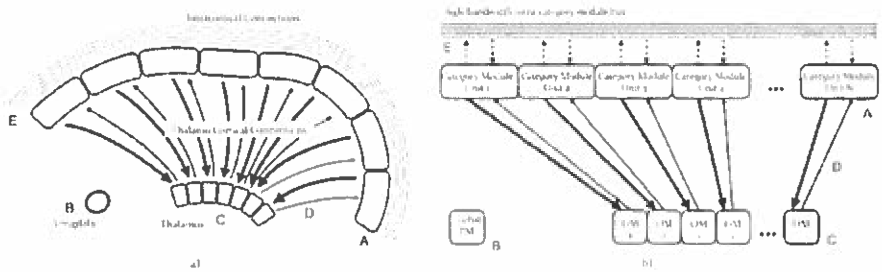

Fig. 2. A sketchy comparison between the thalamocorticalsystem and the presented architecture: A. Category Modules vs cortical areas. B. GPM vs. amygdala. C. Ontogenetic modules vs. thalamus. D. Control signals. E. high bandwidth data bus vs. intracortical connections

The IM is composed by two different submodules:the Category Module (CM) and the Ontogenetic Module (OM). The CM deals with the categorization of the sensory input, a sketchy aproximation of a cortical subarea. It is worth noting that the input vector could be generated by a single sensory source or could be a mix of different sensor modalities. The CM must be able to categorize the input, i.e. to *represent* the sensory input as correlation measure of a set of basis. On the other hand, the OM models a thalamus subareas and it must be able to associate the sensory information with the relevance of the sensory input itself. The relevance may be the result either of a natively phylogenetic signal (in the model this is GPM outcome) or of an internal association between the representation of the sensor values (e.g. the output of the CM) and a past experience with a *similar* input. The signal propagation through the IM can be summarized by the following steps:

1. Acquisition of the sensory input $\boldsymbol{x}$, and the global relevant signal g_s.
2. Given the input $\boldsymbol{x}$, the CM computes the category signal $\boldsymbol{y}$ (see below for details).
3. The OM models the associative memory by means of Hebbian Learning.
4. IM computes r_s representing the relevance of the incoming input $\boldsymbol{x}$ at time t.
5. Training phase: the IM adds new categories update the the OM.

The CM deals with the representations of the sensory input that can be generated by different sources or by a mixature of them. It implies that the internal algorithm can deal with different sensory modalities regardless the unity of measure. Using independent component analysis (ICA) each CM extracts the relevant basis given its input. The input is thus projected on the corresponding set of components and thus normalized and dimensionally simplified. It is interesting to observe that each IM has to shut down, from time to time, in order to improve or extend its set of ICA components. This activity is time-consuming and it presents, very speculatively, a strong resemblance with the memory consolidation role of sleep which, particularly in mammals, has a function not completely defined [21,22]. The outcome is then fed to a clustering function with an ad-hoc distance measure (Fig. 2, left pane). The sensory input can be defined as a vector $\boldsymbol{x} \in R^K$. This input is projected on the set of ICA M components. The projection $\mathbf{w} \in R^M$ is used to define a set of centers $C_1, C_2, \ldots, C_N$ in the M-dimensional space. Eventually, the vector $\boldsymbol{y} \in R^N$ may be computed as follows:

$$y_i = \rho(w, C_i) \tag{1}$$

where $\boldsymbol{y}=[y_1, y_2, \ldots, y_N]$ and $\rho(x, C_i)$ is the positive correlation index. Each element of $\boldsymbol{y}$ shows how the corresponding center well represents the input vector. It is worth noting that y is also the output of the overall IM. We consider the correlation measure y good enough to represent the sensory information. During the execution, the sensory inputs are grouped in few clusters, showing a certain statistics of the sensory information. However, one of the key features of the model is to dynamically generate the centers with respect to the relevance of the incoming sensory values.

The OM ideally represents the IM associative memory. It receives as input the category vector **y**, the relevant signal r_s during the training phase, and returns as ouput a signal $o_s \in R$ representing the relevance of the sensory input with respect to IM past history. To accomplish this task, the OM contains a set of internal state variables, called gates, ideally representing the weights of neurons with one input and one output (Fig. 2, right pane). The gates are grouped in a vector **g**= $[g_1, g_2, \ldots, g_N]$ where N is **y** dimension. The signal o_s is defined as:

$$o_s = max(y_i \cdot g_i) \tag{2}$$

where y_i is the element value of the CM output vector and g_i is the value of the single gate. o_s shows which y_i is associated with a past relevant information. During the training phase, to take into account the memory information within **g**, a stable Hebbian rule (Oja's version) is used:

$$g_i(t) = g_i(t-1) + \Delta\, g_i(t), \qquad (3)$$
$$\Delta g_i(t) = \eta[r_s(t) \cdot y_i(t) - g_i(t-1) y_i(t)^2]$$

where η is the learning rate, r_s is the relevant signal that acts as desidered output of the neurons i and y_i is the input of the gate. The training phase implements an associative learning between the relevant signal and the incoming inputs. The gates implicitly encode new generated goals.

3 Robotic Setup

The goal-generating architecture can potentially be applied to control any robot regardless of the kind of sensors and actuators. Moreover, the incoming sensory information can be either raw or filtered data since the CM generates categories using the sensory values without any a priori knowledge as the nature of incoming data. For the same reason, the cognitive agent may control any kind of actuator, after a development phase in which the categories and the gates are generated.

We tested our architecture on a NAO robot. It has 21 degrees of freedom (DOF). Given the rich endowment of sensors, only a few of them have been connected to the developing goal-generating architecture. The aim of the experiment is to verify wheter the robot is able to generate a new goal starting from a hardwired innate criterion. At the beginning, the robot generates a positive phylogenetic signal when it see a colored object regardless of its shape. The objective of the experiment, after the interaction with a structured environment, is the acquisition of a new criterion for a specific object shape regardless of its color.

The overall architecture is composed by a single IM. The IA receives colored logpolar image frames from the NAO camera and produces in output the pan and tilt commands where the angular amplitude of a movement is chosen randomly by a Gaussian distribution in such a way that the lower the relevant signal the greater the movement. It is worth noting that, in principle, the output signal of the IM could potentially drive directly the motors but in this first experiment we focused on the capability of the ontogenetic module to infer a new goal with respect to the category algorithm. The experiment is divided in three different steps:

1. a set of black geometrical objects are shown in front of the camera.
2. a single colored object with star shape is shown in front of the NAO.
3. the same set of black objects is shown (including a gray star-shaped object.

In the first step the robot does not focus on black objects, whereas in the second step the phylogenetic signal becomes immediatly high. After a while, also the ontogenetic signal becomes high due to the gates saturation. In the third step the agent shows interest, through the relevant signal, for star-shaped black objects.

Although this experiment may look very close to previous work [20], there are important differences. First, the system is now able to generalize to a whole network of IM (previously the system was limited to a single IM). Second, the system implements memory consolidation and invariant extraction by means of ICA in each IM. Third, a theoretically more satisfying version of Hebbian Learning has been used.

In the near future, some improvements are planned: first, the action-control model (based on action for perception paradigm) will be integrated in the intentional architecture; finally the dynamical generation of Intentional Modules will be implemented.

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