Cognitive Control and Adaptive Attentional Regulations for Robotic Task Execution

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***Abstract*—We propose a robotic cognitive control framework that exploits supervisory attention and contention scheduling for flexible and adaptive orchestration of structured tasks. Specifically, in the proposed system, top-down and bottom-up attentional processes are exploited to modulate the execution of hierarchical robotic behaviors conciliating goal-oriented and reactive behaviors. In this context, we propose a learning method that allows us to suitably adapt task-based attentional regulations during the execution of structured activities.**

I. Introduction

In this paper, we present a robotic cognitive control framework that permits flexible and adaptive orchestration of multiple structured tasks. Following a supervisory attentional system approach [12], [7], we propose an executive system that exploits top-down (task-based) and bottom-up (stimulus-based) attentional mechanisms to conciliate reactive and goal-oriented behaviors [4], [5]. In this paper, we describe adaptive mechanisms suitable for this framework. Specifically, we propose a learning method that allows us to regulate the top-down and bottom-up attentional influences according to the environmental state and the tasks to be accomplished. In contrast with typical task-learning approaches [11], [6], our aim here is to adapt and refine attentional parameters that affect the competition among active tasks and reactive processes. Learning methods for robotic supervisory attentional system have been proposed to enhance action execution automaticity and reduce the need of attentional control [8], instead here we are interested in flexible orchestration of hierarchical tasks.

In the following sections, we present the architecture of the executive system and briefly introduce the associated adaptive mechanisms.

II. System Architecture

The cognitive control framework presented in this paper is based on a supervisory attentional system that regulates the execution of hierarchical tasks and reactive behaviors. The system architecture is illustrated in Fig. 1. The attentional executive system is endowed with a long term memory (LTM) that contains the behavioral repertoire available to the system, including structured tasks and primitive actions; these tasks/behaviors are to be allocated and instantiated in the Working Memory (WM) for their actual execution. In particular, the cognitive control cycle is managed by the *alive* process that continuously updates the WM by allocating and deallocating hierarchical tasks/behaviors according to their denotations in the LTM. We assume a hierarchical organization for tasks and activities [9], [12], [7] and this hierarchy is represented in the WM as a tree data structure that collects all the tasks currently executed or ready for the execution (see Fig. 2). More specifically, each node of the tree stands for a behavior with the edges representing parental relations among sub-behaviors. In this context, *abstract* behaviors identify complex activities to be hierarchically decomposed into different sub-activities, instead *concrete* behaviors are for sensorimotor processes that compete for the access to sensors and actuators. The allocated concrete behaviors are collected into the attentional behavior-based system illustrated in Fig. 1.

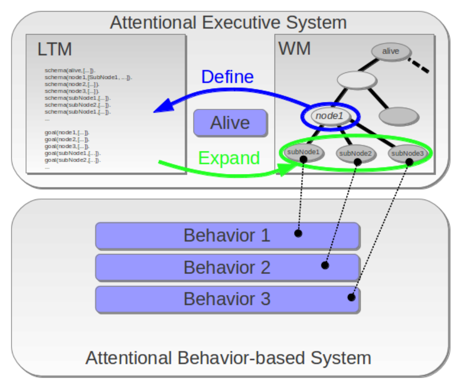

Fig. 1. System Architecture. The LTM provides the definitions of the available tasks, which can be allocated/deallocated in the WM by the *alive* behavior.

In this framework, each behavior is associated with an activation value, which is regulated by an adaptive clock [3], [2]. This clock represents a frequency-based attentional mechanism: the higher is the frequency, the higher is the resolution at which a process/behavior is monitored and controlled. The clock period is bottom-up and top-down regulated by a behavior-specific *monitoring function* $f(\sigma,\varepsilon)=\lambda$ according to the behavioral stimuli σ and the overall state of the WM ε. In particular, the bottom-up frequency $1/\lambda$ is directly affected by behavior-specific stimuli (e.g. distance of a target), while the top-down regulation is provided by a value μ that summarizes the overall top-down influences of the WM. In this context, bottom-up stimuli emphasize actions that are more accessible to the robot (e.g. object affordances), while top-down influences are affected by the task structures and facilitate the activations of goal-oriented behaviors. In this framework, multiple tasks can be executed at the same time and several behaviors can compete in the WM generating conflicts, impasses, and crosstalk interferences [10], [1]. Contentions among alternative behaviors competing for mutually exclusive state variables (representing resources, e.g. sensors, actuators, etc.) are solved exploiting the attentional activations: following a winner-takes-all approach, the behaviors associated with the higher activations are selected with the exclusive access to mutually exclusive resources.

III. Adaptive Regulations

In the proposed framework, action selection depends on the combined effect of top-down and bottom-up attentional regulations. In order to set these regulations, we associate each edge of the WM with a weight $w_{j,i}$ that regulates the intensity of the attentional influence from the behavior j to the sub-behavior i (bottom-up for $i = j$, top-down otherwise). This way, the overall activation value associated with each node is obtained as the weighted sum $\sum_j w_{i,j} c_{i,j}$ of the contributions from the top-down and bottom-up sources. These weights are to be suitably adapted with respect to the tasks and the environment. For this purpose, we propose to deploy a neural network approach. Specifically, during the execution the WM tree is associated with a multi-layered neural network, while the weights associated with the nodes are refined exploiting error backpropagation. In this setting, the system can be trained by a user that takes the control of the robot to correct the execution of a task. The training session is associated with an adaptive process: the difference between the system behavior and the human correction is interpreted as an error to be backpropagated through the task hierarchy in order to adapt the associated weights.

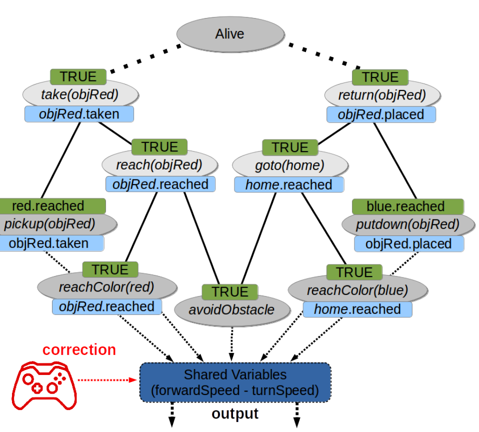

Fig. 2. WM configuration during the execution of a take-and-return task. The contending behaviors (leafs of the hierarchy) receive inputs from the upper nodes (black links) producing output values for the shared variables (dark blue box). The user can correct the execution (joypad) to train the system.

As an exemplification, we consider the instance of the WM illustrated in Fig. 2. In this case, a mobile robot has to take a colored object ($objRed$) and return it to the home position. Here, five concrete behaviors compete to acquire two contended variables ($forwardSpeed$ and $turnSpeed$) which are used to control the robots movements. For instance, the $avoidObstacle$ behavior is affected by two top-down influences ($reach(objRed)$ and $goto(home)$ subtasks), while the bottom-up influence is inversely proportional to the distance of the closest obstacle. During the execution of the task, the system selects the most emphasized behavior and produces a vector of values $\vec{v}$ representing motor patterns for the shared variables. The robot navigation is monitored by the human, which is ready to change the robot trajectory using a joypad when a correction is needed. The user interventions generate a new set of values for the shared variables $\vec{v}^*$ that dominate and override the ones produced by the other behaviors. As long as the user drives the robot, the difference between the systems output $\vec{v}$ and the suggested values $\vec{v}^*$ is exploited to estimate the total error of the task execution. This error is backpropagated from the concrete behaviors to the rest of the hierarchy, in so adjusting the weights associated with the behavior and sub-behaviors which are active in the WM.

IV. Conclusions

We presented an adaptive mechanism suitable for a cognitive control framework based on a supervisory attentional system approach. The proposed method permits adaptive and interactive adaptation of top-down and bottom-up attentional regulations in order to execute structured hierarchical tasks.

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