An Architecture with Integrated Episodic Memory for Adaptive Robot Behavior

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Abstract

We propose a decisional architecture integrating an emotionally-influenced Adaptive Resonance Theory (ART) network as an episodic memory to adapt its expressive behavior in long-term interaction with people.

Introduction

For assistive robots, interacting efficiently with humans require the integration of multiple perception and action modalities. For instance, the use of a wide range of sensors can easily overload the computing resources of an autonomous robot. Components such as articulated facial expressions can provide non-vocal, meaningful communication channels, with no guarantee however that they will be perceived as natural or pleasant by all of its users in assistive tasks. In (Tapus, Ţăpuş, and Matarić 2008), participants in a physical therapy context interacted longer and preferred robots that matched their personality: coach-like and challenging for extroverts, and comforting and supportive for introverts. Similar observations were made in (Aly and Tapus 2013), where users preferred interacting with a Nao robot that matched its verbal and non-verbal behavior to the users' extrovert/introvert personality type. The robot behavior adaptation was made by analyzing the users' speech patterns. To enable a robot to adapt its behavior to a person's preferences on a long-term basis, we propose to integrate an episodic memory into a robot control framework named Hybrid Behavior-Based Architecture (HBBA) (Ferland et al. 2012). This paper presents HBBA and the episodic memory model, and describes how we intend to explore their integration as an adaptation mechanism for autonomous assistive robots.

HBBA

HBBA, shown in Figure 1, combines two robot control paradigms: behavior-based control ("Think the way you act"), and Hybrid control ("Think and act concurrently") (Matarić and Michaud 2008). HBBA unifies both paradigms by adding layers on top of a behavior-producing modules (referred to as Behaviors), allowing Perception and Behavior modules to be selected and configured according to the Intentions of the system. These Intentions are derived from Desires, which represent the satisfaction or inhibition of Intentions as generated by Motivations. Just like Behaviors, Motivations are distributed processes from which a decision can emerge at the Organization Layer. The Intention Workspace, situated at the Coordination Layer, gathers all Desires to infer the Intentions of the robot: this module determines which specific modules in the Behavioral Layer must be activated based on the Desires, by using a set of strategies that are related to the robot's capabilities. Like in the Behavioral Layer, conflicting Desires are selected on a priority basis according to their intensity.

Interaction performance can be affected by an unbalanced allocation of computing resources. For instance, acceptable delays in vocal interaction can be difficult to satisfy if computationally expensive modules are simply added to the architecture: it may result in a robot that can navigate efficiently, but may not perform well engaging and interacting with people, or *vice versa*. To solve this, human-inspired selective attention (Broadbent 1958) takes place in HBBA by perceptual filtering of Perception modules and by configuration and activation of Behaviors. Computing resources allocation can therefore be prioritized according to the current Intentions of the robot.

Episodic Memory Based on Adaptive Resonance Theory (ART) Networks

Collecting information about one's experiences over time and their relationships within a spatio-temporal context is a

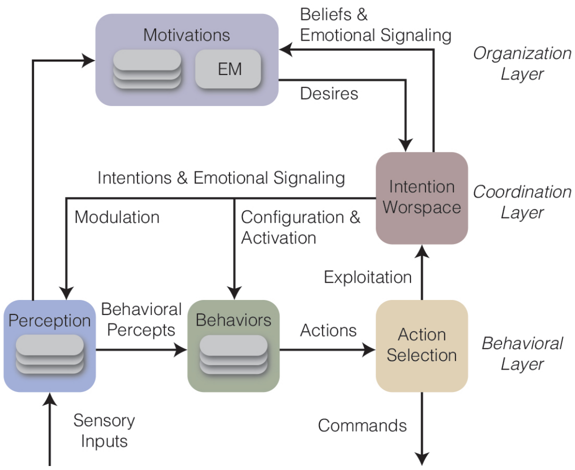

Figure 1: HBBA with integrated episodic memory (EM) as a Motivation module.

role associated to an episodic memory (EM) model (Tulving 1984). Adaptive Resonance Theory (ART) networks have been used to categorize patterns from contextual and state data (Carpenter and Grossberg 1987; Taylor et al. 2009). Wang et al. (2012) demonstrated the use of a cascade of two ART networks to create an EM-ART model: one ART encodes spacial events, and the other extract temporal episodes from the experienced events. A variant of EM-ART has been implemented and validated on IRL-1 (Ferland et al. 2012), a humanoid and compliant mobile robot. The input of the EM-ART network is made of channels synchronized by a short-term memory buffer that collects perception events such as people recognition or localization, and also actions such as the exploitation of Behaviors (which can then be used to validate the satisfaction of Desires). An artificial emotional module, influenced by the fulfillment of the Desires of the robot, is used to modulate learning rates and vigilance parameters of the EM-ART model, facilitating recall of episodes with high emotional intensity (e.g., an increase of Anger when someone is blocking the path of the robot). The implementation was validated in a series of trials involving a real, noisy environment with people (Leconte, Ferland, and Michaud 2014).

Learning From Emotionally-Significant Episodes

When the robot is interacting with a known person, the EM can be used to recall relevant episodes involving this person. If the robot also has the ability to perceive the emotional state of the person, the input layer of the EM-ART can be augmented to include this information into the episodes, either to characterize the episode or to change the response of the robot based on the emotional state of the person. This ability can be achieved by recognizing facial expressions through Action Units (AUs) (Ekman and Friesen 1978) or prosodic features of speech (Zeng et al. 2009). We plan to study three ways from which the detection of a person's emotional state might affect the episodic memory of the robot: 1) as an input to the short-term memory buffer; 2) as an input to the artificial emotions module; 3) as an input to both the short-term memory buffer and the artificial emotions module. Then, the expressive behaviors of the robot can be adapted through Emotional Signaling, for instance by altering joint acceleration in arm trajectories for gestures such as pointing or waving. This has been shown to have an impact on the perceived affective state of the robot (Saerbeck and Bartneck 2010). Work will be conducted on three platforms in two locations: Nao robots and a Meka humanoid robot at ENSTA-ParisTech, and IRL-1 at Université de Sherbrooke. We will be able to observe the impact of selective attention as performed by HBBA on both emotional state detection and episodic memory on robotic platforms with different capabilities, while using a common architecture with an identical Organization Layer.

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