Paladyn, J. Behav. Robot. 2017; 8:100–111 DE GRUYTER OPEN

Research Article Open Access

François Ferland*, Aurélien Reveleau, Francis Leconte, Dominic Létourneau, and François Michaud

Coordination mechanism for integrated design of Human-Robot Interaction scenarios

https://doi.org/10.1515/pjbr-2017-0006
Received May 16, 2017; accepted December 4, 2017

Abstract: The ultimate long-term goal in Human-Robot Interaction (HRI) is to design robots that can act as a natural extension to humans. This requires the design of robot control architectures to provide structure for the integration of the necessary components into HRI. This paper describes how HBBA, a Hybrid Behavior-Based Architecture, can be used as a unifying framework for integrated design of HRI scenarios. More specifically, we focus here on HBBA's generic coordination mechanism of behavior-producing modules, which allows to address a wide range or cognitive capabilities ranging from assisted teleoperation to selective attention and episodic memory. Using IRL-1, a humanoid robot equipped with compliant actuators for motion and manipulation, proximity sensors, cameras and a microphone array, three interaction scenarios are implemented: multi-modal teleoperation with physical guidance interaction, fetching-and-delivering and tour-guiding.

Keywords: Robot control architecture, telepresence, attention mechanism, episodic memory

1 Introduction

Design of an interactive mobile robot is one of [1] if not the most challenging integration problem in robotics. It involves dealing with action (manipulation, mobility), perception (environment, people), interaction (information exchange modalities such as interpretation of perceptual cues, human-robot interfaces, etc.), and systems (mechatronics, control, software, cognition) [2] in relation to the application domain. These elements are all interdependent, as each one of them influences the others.

Robot control architectures define the interrelations between decision-making modules required for robots to behave 'intelligently' in their operating environments. There is an infinite number of ways to implement robot control architectures, whether they are biologically inspired by or related to human cognition (e.g., ACT-R/E [3], ICARUS [4], SOAR [5, 6]) or engineered to achieve specific requirements (e.g., DIARC [7]). This makes it difficult to compare them [2], since research on robot control architectures is conducted more as feasibility-type studies (e.g., "is it possible to use X to control the robot Y in task Z" [8, 9]). And although there is no consensus on a common architecture, how to engineer a system that effectively integrates the functionalities required is an open question of fundamental importance in robotics and human-robot interaction (HRI) [10]. Integration and coordination of different types of processing modules (perception, reasoning, behaviors) is one significant challenge, and there is currently no dominant solution [11]. However, with more advanced robot platforms continuously pushing technological limitations, new opportunities arise to work on the integrated design of interaction and intelligent capabilities on robots.

In our previous work [12], we outlined our plan to address the integration of physical, cognitive or evaluative dimensions associated with an interactive mobile robot. The robot control architecture we presented as the integration framework is HBBA, short for Hybrid Behavior-Based Architecture. According to Brachman [13], "versatility, purposeful perception and reasonableness are all exemplary characteristics of real, honest-to-goodness intelligent systems", and all seem to require the kind of integration intelligent architectures should provide. Nils Nilsson [14, 15] used the term 'habile' to refer to versatility. The field of Artificial General Intelligence is pursuing similar objectives based on symbolic, emergentist, hybrid or universalist design characteristics [16]. In our work, the main criterion is the integration and interaction of decisional mod-

***Corresponding Author: François Ferland:** Interdisciplinary Institute for Technological Innovation (3IT), Department of Electrical Engineering and Computer Engineering, Université de Sherbrooke, Québec, Canada, E-mail: francois.ferland@usherbrooke.ca
Aurélien Reveleau, Francis Leconte, Dominic Létourneau, François Michaud: Interdisciplinary Institute for Technological Innovation (3IT), Department of Electrical Engineering and Computer Engineering, Université de Sherbrooke, Québec, Canada, E-mail: {aurelien.reveleau, francis.leconte, dominic.letourneau, francois.michaud}@usherbrooke.ca

alities. To consider these key elements in HBBA, our goal is to implement generic mechanisms, i.e., mechanisms that are independent of the robot's physical/perceptual capabilities and intended usage as well as to coordinate the use of Behavior and Perception modules (which are associated with the robot's sensors and actuators) in relation to the intended tasks and applications. One source of our inspiration is selective attention observed in humans: based on the limited resources available, it selects what is important to focus on based on the intentions of the system. In psychology, two schools of thought exist [17]: Late Selection (LS) theory [18] considers that our perceptual analysis capabilities are actually unlimited and that selection occurs later based on the perceived importance of the stimuli; Early Selection (ES) theory [19] holds that human perceptual capabilities are limited and unimportant stimuli must be filtered before they overload our processing capabilities. In HBBA, selecting Behavior modules and filtering their outputs relate to LS, while filtering the inputs of Perception modules can be compared to ES. This paper therefore follows up on our previous work by presenting how such generic mechanism is used in HBBA to coordinate the activation and configuration of perception and behavior modules. We believe that such a mechanism is key to design robots with autonomous capabilities that can be changed or adapted easily to be used in different application contexts.

This paper is organized as follows. Section 2 presents a brief overview of HBBA, with a focus on its integration and coordination mechanism. Section 3 introduces IRL-1/TR, a robot platform used for experimenting with HBBA. Section 4 follows describing HBBA implementation for three interaction scenarios: 1) a telepresence application using a display of proximity, visual, audible and force data [20]; 2) a fetch-and-deliver task using an episodic-like spatio-temporal memory model [21]; and 3) a tour-guide task with perception filtering for selective attention [22]. Section 5 discusses design issues and expected challenges to be addressed with HBBA, followed by conclusions and suggestions for future work.

2 Hybrid Behavior-Based Architecture (HBBA)

HBBA basically blends two robot control paradigms [23]:

- **Behavior-based control.** Behavior-based control is based on a set of distributed modules, called behaviors, that receive inputs from sensors and/or other behaviors in the system, and provide outputs to the robot's actuators or to other behaviors. Through interaction with the environment and within themselves, they achieve and maintain an overall system-level behavior. The functionality of behavior-based systems is said to emerge from those interactions and is thus neither a property of the robot or the environment in isolation, but rather a result of the interplay between them [24].
- **Hybrid control.** Hybrid control aims to combine the real-time response of reactivity with the rationality and optimality of deliberation. It is also referred to as layered or tiered robot control architecture, with layers usually organized according to the principle of increasing precision with decreasing intelligence [25]. However, complex issues are involved in how to interface and partition these layers [24].

Behavior-based systems have proved to be best suited for environments with significant dynamic changes involving fast responses and adaptivity, while hybrid control is appropriate in environments and tasks involving internal models and planning. HRI implementations can certainly benefit from both. HBBA, illustrated by Fig. 1, unifies both paradigms by adding layers on top of a Behavioral Layer, which allows Behaviors to be configured and activated according to what is referred to as the Intentions of the robot. Intentions are data structures providing configuration and activation of Behaviors (i.e., the behavioral strategy) as well as modulation of Perception modules. They are therefore the basic components of HBBA's integration and coordination mechanism. Furthermore, while hybrid architectures usually impose a specific deliberative structure, for instance a task planner, to coordinate the lower-level Behaviors HBBA allows multiple concurrent independent modules at its highest level without constraining those modules to a specific decisional scheme. For instance, the RAPP framework proposes a reconfigurable control architecture for exploratory robots [26] where agents, programmed as finite state machines, can be dynamically loaded from a cloud-based repository depending on the task at hand. Even though this provides long-term flexibility, only one dynamic agent can control the robot at a time, which is not a limitation in the case of HBBA. Reinforcement learning has also been used to coordinate execution of lower-level behaviors [27] using a topological map as a task-relevant state space instead of using the sensory space of the robot. DAC-h3 [28], based on the Distributed Adaptive Control (DAC) architecture [29, 30], proposes a principled organization of various functional modules into a biologically grounded, multi-layered cognitive architecture, with behaviors which take care of motor control and regulate the internal drives or needs of the robot. HAMMER [31] is a computational architecture that provides top-down control of visual attention for computing resource allocation in the specific application for observing action demonstrations while learning skills. AKIRA [32] is a framework that uses the concept of energy pools for which different processes compete to manage computing resources consumption via thread priorities within a cognitive architecture. Similarly, AERA [33] manages computing resources through job scheduling for perception and learning. However, none of these architectures include computing resource management through attention (or any other mechanism) as part of a behavior coordination mechanism for a robot, as addressed by HBBA. Furthermore, while frameworks such as IDEA [34] perform task planning within computing execution time constraints, HBBA relies on the emergence of higher-level functionalities through the execution of individual behaviors, monitoring the exploitation of these behaviors over time in accordance with the produced Desires to perform task sequencing.

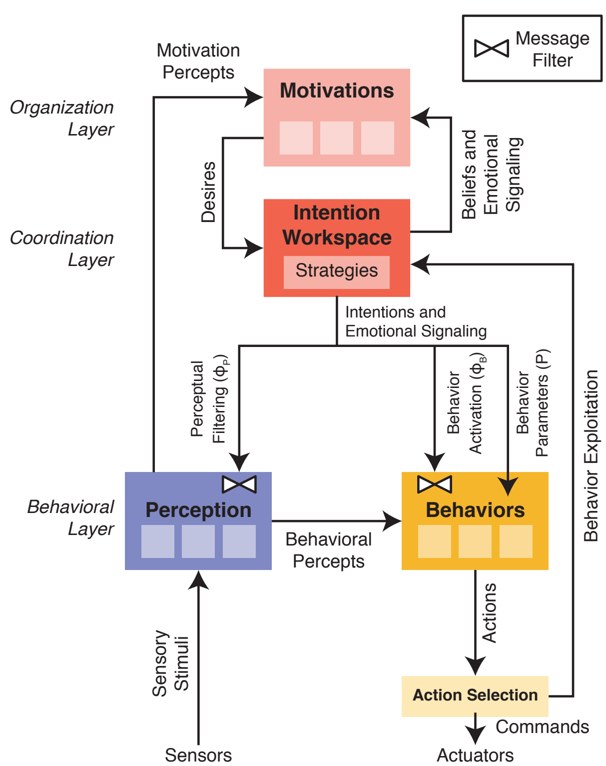

Figure 1: Hybrid Behavior-Based Architecture (HBBA).

Compared to other robot control architectures, what is particular to HBBA is how Intentions are generated and how they influence the behavioral strategy:

- Motivation modules in the Organization Layer act as distributed processes (just like Behaviors), generating Desires which are data structures representing satisfaction or inhibition of Intentions. Motivations can be driven directly by perceived data using simple rules, or involve more high-level reasoning capabilities such as task planning and scheduling, path planning, finite-state automata, etc.
- The Intention Workspace processes Desires to issue Intentions according to a policy inspired from the hedonic axiom, i.e., that organisms direct their behaviors to minimize aversions and maximize desirable outcomes [35]. The Intention Workspace therefore gathers all Desires (according to classes, e.g., *People Detection*, *Person Engagement*, *Room Wandering*, or *External Forces Reaction*) to infer the Intentions of the robot. A Desire has an intensity value that is used as an indication of its priority in relation to other Desires competing for the same resources. Within a same class, the Desire with the highest intensity is chosen. When multiple Motivations are present, the Intention Workspace can generate Beliefs. Beliefs can be internal feedback data structures to Motivations, provide knowledge about the internal and external interaction dynamics of the robot, and also identify conflicts between Desires and their satisfaction. The Intention Workspace also includes an Intention Translator, which transforms the selected set of non-conflicting Desires into Intentions based on a database of Strategies. Each Strategy describes how a specific class of Desire can be fulfilled on a particular robot platform, which includes activation of Behavior and Perception modules and transfer of Behavior configuration parameters to these modules.
- HBBA also observes Behavior Exploitation, i.e., how Behaviors are used over time as influenced by the events occurring in the environment and the Action Selection mechanism (which selects the commands sent to the robot's actuators, for instance according to priorities between Behaviors). Such observations can lead to Emotional Signaling (detecting situations based on models of how Behaviors are exploited over time [36–39]). Emotional signaling can also be used to modulate behavior parameters [40]. Behaviors are therefore used as an abstract representation from which to derive self-observable metrics (as opposed to application-defined metrics), making the robot learn from the dynamics of its interaction in the world based on its own perspective (grounded on its decision-making modules) [41, 42].

Overall, HBBA is a behavior-based architecture with no central representation that still provides the possibility of high-level modeling as well as reasoning and planning capabilities through Motivations or Perception modules. As the number and complexity of Perception, Behavior and Motivation modules increase to address more sophisticated interaction scenarios, the Intention Workspace becomes critical: it serves a role similar to that of a coordination layer in a hybrid architecture, or Action Selection in a behavior-based architecture. Compared to more formal planning approaches such as [27], HBBA is a robot control architecture presenting design guidelines and working principles for the different processing modules, without imposing a formal coding structure for their implementation. It is a multi-paradigm architecture that does not force a specific paradigm for implementing both upper-level reasoning modules and lower-level perception and behavior modules. HBBA is designed to combine various approaches for maximum versatility.

2.1 Integration and coordination mechanism of the intention workspace

To coordinate the execution of Perception and Behavior modules, HBBA employs a set of filters that modulate the message flow between these modules [22]. For each of these filters, represented by $\bowtie$ symbols in Fig. 1, message flow modulation is achieved with time-based decimation by discarding messages at a configurable rate. This rate is defined with ϕ_h, were filter h lets 1 message go through for ϕ_h messages received. The configuration for all filters of the system is captured in the $\Phi_{H\times1}$ vector, which includes filter rates for both Perception (Φ_P) and Behavior activation (Φ_B). For instance, $\phi_h = 2$ corresponds to a 50% reduction in data flow, while $\phi_h = 1$ lets all messages pass. Furthermore, $\phi_h = \infty$ discards all messages, completely stopping them from reaching a module. Thus, a filter can control the amount of information a Perception module has to process and the computing resources it consumes. Similarly, commands from Behavior modules can be completely stopped from reaching Action Selection. Consequently, module activation in HBBA is achieved by letting some or all messages flow in and out of it, and deactivation by completely forbidding it.

To set these filters, the Intention Workspace implements the Intention Translation process shown in Fig. 2. First, it performs intensity-based selection using the list of current Desires to resolve conflicts between Desires of the same class. The selected set of behavior parameters for these Desires is noted as $P'_{K\times1}$. Similarly, the minimum required utility vector, noted as $U'_{K\times1}$, constitutes the requirements for a Constraint Satisfaction Programming (CSP) problem which aims at maximizing the fulfillment of Desires while respecting the limited resources of the platform. The CSP solver aims at fulfilling as many Desires as possible, prioritizing resources to Desires with higher intensity values. To specify how a particular Desire class can be translated into Intentions, a set of Strategies describes filtering rates as subsets of Φ for one or more Perception and Behavior modules, along with $v_{s,k}$, namely the utility produced by Strategy s for Desire class k, and resource costs, which are used by the CSP solver. Furthermore, high Φ values can be associated with lower resources costs, as a lower number of messages sent to a module will require less CPU time to process. The output of the CSP solver is the activation vector A', that indicates which Strategies have been selected. The solving process consists in maximizing Ω, which is defined as:

$$\Omega = I \cdot F + \sum_k \sum_s f_k a_s v_{s,k} \tag{1}$$

while respecting the resource constraint below:

$$\sum_s a_s c_{s,j} \leq m_j \tag{2}$$

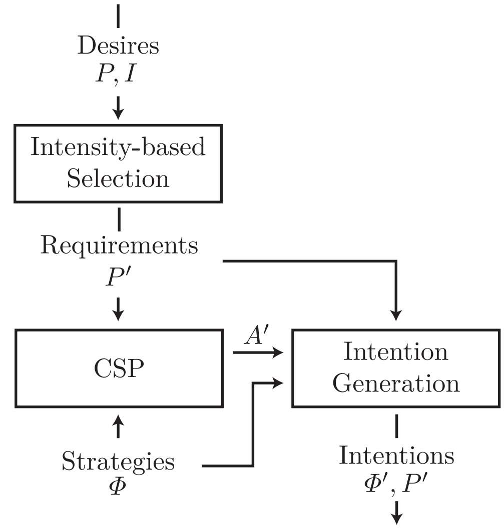

Figure 2: The Intention Translation process. Desires produced by Motivation modules are described by their behavior parameters (P) and intensity (I). Requirements represent the set of Desires that are selected on an intensity-based priority basis. Strategies indicate how a specific Desire can be fulfilled by Perception and Behavior modules by defining filtering rates Φ. Constraint Satisfaction Programming (CSP) selects proper strategies to activate (A') according to the resources available to the robot. Intention Generation relays the final parameters (P') and filtering rates (Φ) to the proper Perception and Behavior filters and modules.

where $c_{s,j}$ is the cost of activating Strategy s for resource j, and m_j the maximum that can be allocated for resource j. For instance, CPU load can be defined as $m_1 = 100$, and $c_{s,1}$ would represent the average CPU load of activating Strategy s. The left part of the summation in Ω aims to maximize the Intensity of the Desires to fulfil, and the right part aims to maximize the Utility of the Desires to fulfil. Finally, the Intention Generation module gathers the filtering rates from selected Strategies in Φ' to configure all of the filters of the platform, and relays behavior parameters P' to the proper modules.

Glossary

The following summarizes the concepts present in HBBA:

Sensor A sensor of the robot hardware and its related low-level driver. These modules produce raw stimuli for the Perception modules.

Actuator An actuator of the robot hardware and its related low-level driver. It accepts motor commands that were selected in the Action Selection module.

Perception Module Transforms stimuli (raw sensor data) into behavioral and motivational percepts (higher-level information such as face positions or maps of the environment).

Behavior Module Produces actions as motor commands for one or more actuators. Can be configured by parameters (P), for instance to specify a location to reach.

Motivation Module Manages high-level and long term goals for a robot. Multi-paradigm: can be implemented by simple state machines or advanced task planning algorithms.

Desire Produced by Motivation modules, a high-level description of a goal to achieve an action (ex. a location to reach) or information to gather (ex. detecting voices). It does not describe how such goals have to be achieved.

Intensity Represents the importance of fulfillment of a Desire. Used to determine priorities in case of conflicting Desires or lack of resources to fulfill all of them.

Beliefs Shared information between Motivation modules about internal and external interaction dynamics of the robot, such as Desire fulfillment and conflicts.

Intentions The set of module activations and configurations to achieve the current Desires of the robot.

Strategy Specifies how a Desire class can be fulfilled through Perception and Behavior modules activation and at what computational costs. Robot platform-specific.

Intention Translation The CSP-based process through which Strategies are selected to produce the Intentions of the robot.

Intention Workspace Where Desires and Beliefs are shared between Motivation Modules, Strategies are stored, and the Intention Translation process occurs.

Action Selection Performs priority-based command selection for each actuator. Commands from higher priority behaviors override lower priority ones.

Emotional Signaling Artificial emotions generated from behavior exploitation monitoring. Used by Motivations for task planning and by expressive behaviors.

3 Implementing HBBA on a robot platform

Evaluating versatility, purposeful perception and reasonableness [13] of a interactive and intelligent robot requires a platform equipped with broad range of capabilities used in various application contexts. The robot platform used is IRL-1/TR [22, 43]. IRL-1 is a humanoid platform with an expressive face, an orientable head, a 8-microphone array located around its torso, a color USB camera with a panoramic lens from Immervision (IMV), a Microsoft Kinect sensor, a Hokuyo UTM-30LX laser range finder on top of its mobile base, a wireless gamepad from Logitech, two compliant arms with four degrees of freedom (DOF) each and grippers. Differential Elastic Actuators (DEAs) [44] are used to provide force control and feedback to its manipulators. ManyEars [45] is the sound source localization, tracking and separation algorithm used with the 8-microphone array on IRL-1. IRL-1 can be installed on an omnidirectional, non-holonomic and compliant mobile platform [43] or on a differential-drive mobile base (referred to as TR for Telerobot) [46], as shown in Fig. 3. The TR base can translate the robot forward and backward, and rotate in place using two triplets of wheels (one on the left and one on the right) and a rear rocker arm. IRL-1/TR is 1.45 m in height and 0.60 m in both width and depth. It has two onboard computers: a 2.67 GHz second generation Intel Core i7 dual core processor to control the mobile base and a 2.10 GHz third generation Intel Core i7 quad core processor for the torso controllers (arms, head expression and orientation), sensor processing, and the coordination of the robot control architecture.

HBBA implementation in this paper is based on ROS. The Intention Workspace uses ROS' message passing structure, which is well-suited for message filtering. By adding an intermediary node between sensors and Perception modules, messages can be dynamically discarded to prevent data from reaching a module without having to alter the module's code, thus facilitating reuse of processing

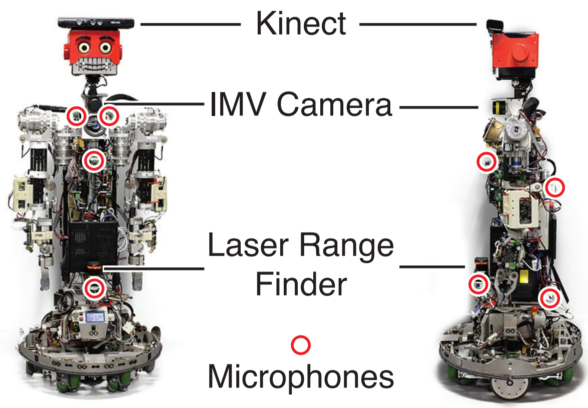

Figure 3: IRL-1/TR.

modules. These intermediary nodes are implemented using a modified version of the *throttle* Utility found in the *topic_tools* package, allowing the frequency divider ϕ to be modified by the Intention Workspace for each filter at runtime. The CSP implementation is based on Google's Operations Research Tools (http://code.google.com/p/or-tools/). The Intention Translator uses Google V8-based (http://code.google.com/p/v8) Javascript virtual machine to generate the Intentions of the robot. Each Strategy has a script that performs ROS service calls and topic publications to set message filters ϕ and behavior parameters P'. All possible connections are created but remain inactive by default (i.e., initializing $\phi_h = \infty$) unless a Strategy configures them differently. Tools have been developed to facilitate the definition of Strategies and behavior parameters, and to generate ROS-related files to combine modules and message filters together into a single launch script. The implementation of the Intention Translator module, message filters and related code is publicly available online (http://github.com/francoisferland/hbba). HBBA's coordination mechanisms are implemented as extra modules that manage communication between independently developed modules. This enables integration and resource consumption modulation of already existing modules that may or may not have been designed with HBBA in mind, without modifications. This is an advantage over implementation of architectures such as HAMMER [31], where the whole software of the robot has to be developed according to its computational model or the mechanism in [40] which requires adding a specific interface to each module to receive modulation signals from its coordination mechanism.

4 Design implementations and experimentations using HBBA

The following subsections present three design implementations following the HBBA framework with its integration and coordination mechanism of the Intention Workspace. Each design case has the robot work towards one specific goal and therefore only has one specific Motivation. The objective pursued with these experimentations is to examine if and how HBBA and the integration and coordination mechanism of the Intention Workspace can be used to implement HRI interaction scenarios of increasing complexity. Furthermore, they were meant to demonstrate HBBA's coordination mechanism in live settings to validate execution time, notably for filters and the CSP solving process.

4.1 Teleoperation using 3D display of proximity, visual, audible and force data

Teleoperation lies at the lower extreme in HRI levels of autonomy [1]. For mobile robots, it usually consists of a control station with a graphical user interface, allowing the operator to see, hear and move through the robot platform in a remote location. As the type and number of sensors and DOFs increase on the platform, additions need to be made to the operator interface with the objective of maximizing situation awareness [47–50] and minimizing cognitive load [50, 51]. IRL-1/TR is a great testbed to address such issues, and we used HBBA to design a telepresence system with a remote control interface that integrates proximity, vision, audible and force data in one 3D ecological [52] display. Illustrated by Fig. 4, the display consists of:

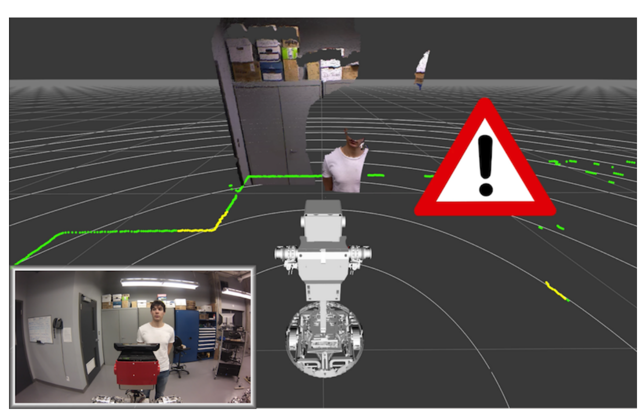

Figure 4: 3D display of proximity, visual, audible and force data.

– A 3D display constructed using color point clouds from the Kinect RGB-D images. IRL-1/TR rendering is shown to visualize the orientation of the head and the position of IRL-1's arms as well as steered wheels. The operator has full control over the viewpoints of this representation, which can range from egocentric to exocentric (top view, side views, upper views, at different zoom values).
– A representation of laser range finder proximity data. The laser range finder data are coloured from green to red to represent distance from obstacles. An exclamation point icon is displayed when something stands in IRL-1/TR's path.
– A representation of the forces perceived by the compliant actuators on IRL-1 arms and mobile base. Force direction and intensity can be displayed on IRL-1's rendering using three different ways: arrows oriented toward the force being sensed; force meter; change of the size and color of the structure sensing the force.
– A representation of the location of audible sources surrounding IRL-1/TR. This information is provided by superimposing a speech bubble or a blue ring icon to localize the sound source on the display. Icon opacity is set to decrease over time so as to provide the user with enough time to locate the sound source on the display.

Figure 5 presents the processing modules in HBBA for this application, oriented toward experimenting the use of colors, size, bar graphs and arrows for the visualization of forces, and the use of a speech bubble or a ring to position and identify the type of sounds [20]. The SLAM 3D module, based on [53], constructs a 3D model of the environment depending on the output of the Kinect RGB-D camera. Apply Gaze is used to orient the head of the robot according to the remote user's point of view. Avoid Obstacles is meant to prevent colliding with close obstacles detected by the laser range finder simply by making the robot stop moving. The Apply Velocity module relays velocity commands from the remote operator, and Plan & Follow Path performs path planning over long distances with the map produced by SLAM 3D. The Teleoperation Motivation acts as a bridge for the remote operators interface and translates their commands into Desires for the robot, while the output of Perception modules is transferred over the network.

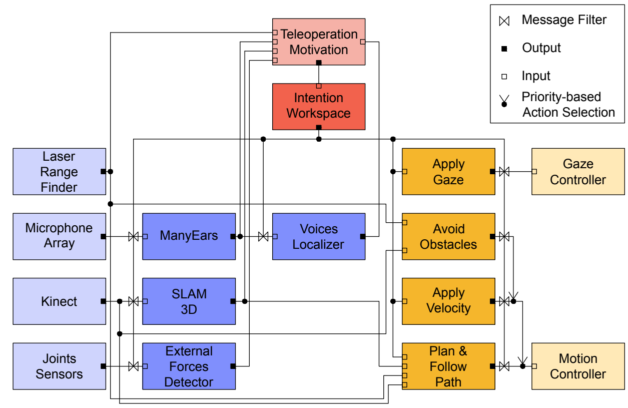

Figure 5: HBBA modules for the teleoperation application.

4.2 Fetch-and-deliver task using an episodic-like spatio-temporal memory model

Autonomous robots, especially if they operate in dynamic environments, require a mechanism for reasoning and learning, which rely on memory. However, memory is a multifaceted and complex phenomenon that remains poorly understood [54]. For instance, one type of memory associated with personal experiences is episodic memory. The episodic memory is responsible for collecting information about one's experiences over time and their relationships within a spatio-temporal context [55]. A common use of an episodic memory is the prediction of both future percepts and the consequences of planned actions. To do so, the episodic memory mechanism must be able to recall previously experienced events and episodes. In addition, based on evidence that emotions play a role in episodic memory mechanisms [56–58], similar type of influences should be considered in such memory models.

In this experiment, a spatio-temporal (ST) memory model consisting of a cascade of two Adaptive Resonance Theory (ART) networks [21] was developed to implement an episodic-like memory within HBBA. The first ART network is used to categorize spatial events, while the second one extracts temporal episodes from the robot's experiences. Learning and recall rates of the ART networks are dynamically modulated based on the robot's ability to carry out its task, using a simple model of artificial emotions. Once an episode is recalled, future events can be predicted, and the are used to influence the intentions of the robot.

Evaluation of our ST memory model had IRL-1/TR perceive its locations, objects and people in a fetch-and-deliver task, shown in Fig. 6. Figure 7 illustrates the implementation of HBBA for this fetch-and-deliver task. There-

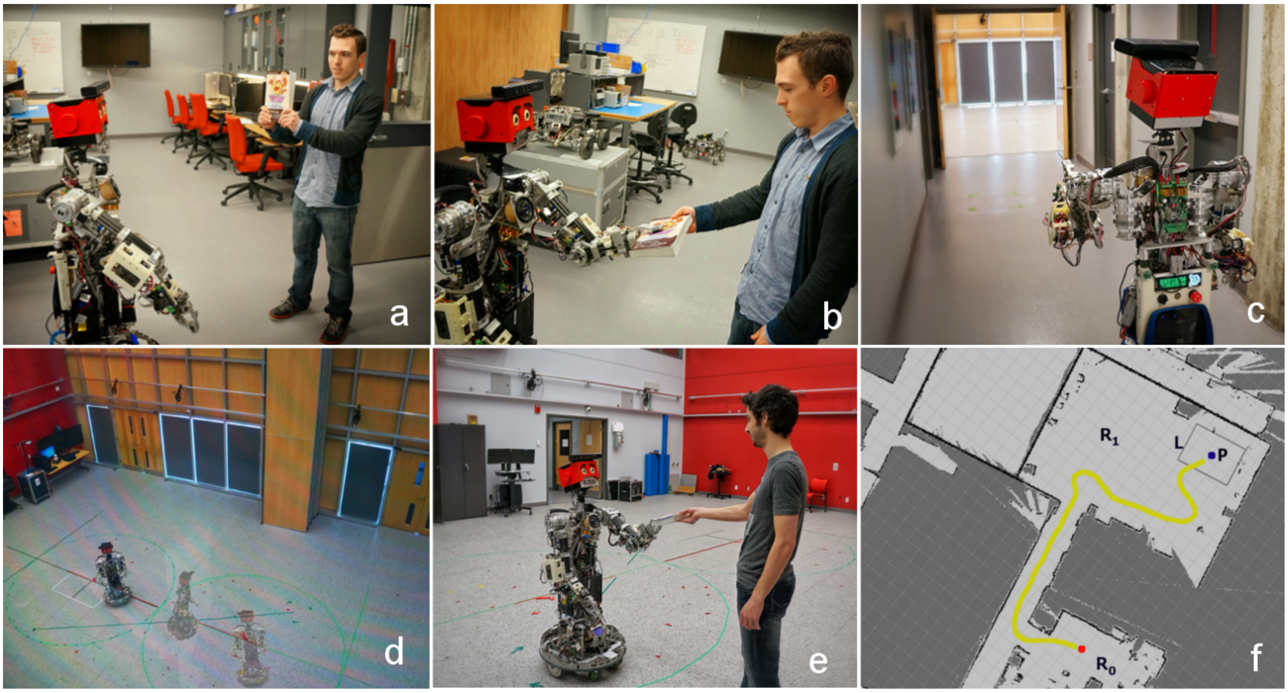

Figure 6: IRL-1/TR doing a fetch-and-deliver task: a) IRL-1/TR identifies a person and an object in a room; b) IRL-1/TR asks the person to give the object to its gripper; c) IRL-1/TR navigates autonomously to another room; d) IRL-1/TR wanders around, looking for somebody to deliver the object to; e) IRL-1/TR has found someone and gives the object; f) Top view illustration of the fetch-and-deliver task where the destination is a location in the second room.

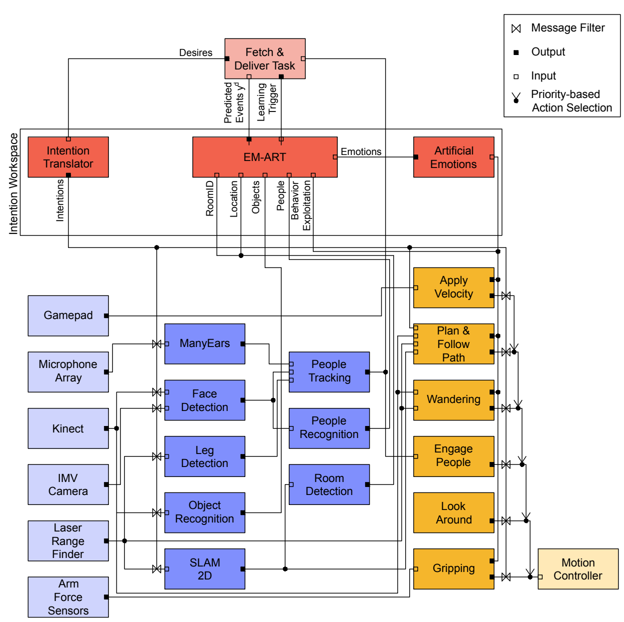

Figure 7: HBBA implementation for the fetch-and-deliver task.

fore, this experiment allowed us to test the integration and coordination mechanism of the Intention Workspace with a larger set of Perception modules with HBBA. For instance, the People Tracking module, which uses a particle-based filter to combine observations of multiple people detection modalities (Voice, Face, and Leg-based), is particularly well suited for the dynamic modulation of perception capabilities. All of those modules were developed outside of HBBA as independent modules for other projects, demonstrating the ability of HBBA's coordination mechanism to integrate additional elements without imposing a specific computational structure. Through the use of external filters to manage information going in and out of these modules, we can integrate them as-is in a more complete architecture that fully considers the constraints of the platform. Indeed, the on-board computer of IRL-1/TR cannot execute all the Perception modules shown in Fig. 7 at full capacity. Therefore, a subset of these capabilities can be activated or disabled ($\phi \in \{1, \infty\}$) dynamically, which enables the robot to still track the location of people while respecting its computing power limitations. Furthermore, the inclusion of the EM as an Intention Workspace module of HBBA to influence the Motivation module demonstrates the versatility of HBBA and its coordination mechanism of integrating a different paradigm (ART neural networks) in an already existing computational architecture.

4.3 Tour-guiding with perception filtering for selective attention

In this task, IRL-1/TR is used as a tour-guide of our facility and has to perform several tasks such as navigating the environment, interacting with visitors, providing spoken descriptions of various locations and pointing out interesting lab equipment, while behaving naturally in a robust manner. QR codes are used to associate specific locations visited in the tour, as shown in Fig. 8. The QR code provides a unique ID for an interaction to perform at a specific location. To memorize the tour to give, IRL-1/TR is operated with a remote control to map the environment and locate QR codes. When done, IRL-1/TR autonomously return to its starting location, while still being able to detect external events and interact with people. Figure 9 illustrates the robot control architecture implemented using HBBA, with the set of Perception modules using multiple sensing modalities (visual, audio and range finder-based) and two Behavior modules controlling the mobile base.

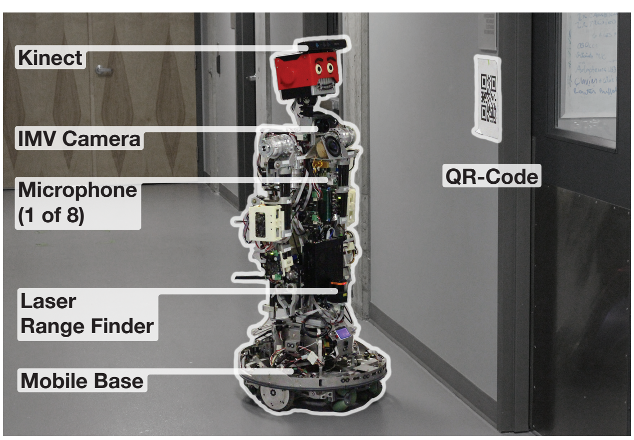

Figure 8: Tour-guiding with IRL-1/TR.

For this experiment, most of the modules and Strategies developed for the experiments described in Sec. 4.1 and Sec. 4.2 were directly transferred and extended for dynamic perceptual filtering, i.e., setting $\phi \in [1, \infty)$ to effectively reduce the computing power necessary depending on the Intentions of the robot. The goal was to emulate varying requirements in Perception capabilities over the course of its execution, and thus confirm that the Intention Workspace could correctly configure perceptual filtering based on internal and external events. One such event

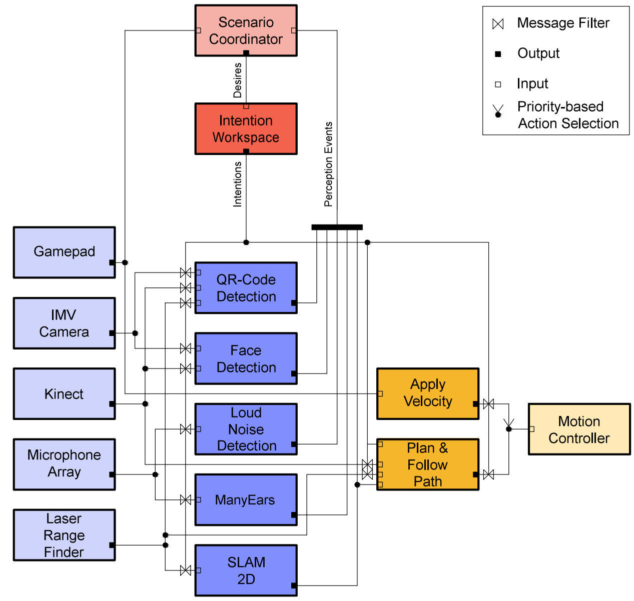

Figure 9: HBBA implementation for the tour-guide task.

is presence of a loud noise, which created the need for localizing a voice. Activation of the ManyEars module without reducing capabilities of other modules was not possible with the computing power available. In addition, when all modules were used at full capacity, the robot experienced multiple failures of the Kinect processing module, which resulted in corrupted depth data. Since the robot used this data to avoid obstacles not detected by the laser range finder, this could have had serious consequences for the robot and people interacting with it. Instead, perceptual filtering provided a higher filtering rate on Face Detection and deactivation of QR-Code Detection right after a loud noise was detected to allow more computing resources for ManyEars. Figure 10 shows the effect of perceptual filtering on detection rate [22]. While the detection rate decreases with perceptual filtering, detection could still be performed without showing signs of CPU overload. This experiment illustrates the integration of resource management as a coordination mechanism that can modulate CPU load of modules that were not specifically designed for HBBA. While resource management would be possible in formal planning architectures as in [31], it would have required a complete reimplementation of many modules we used in this experiment.

5 Discussion

Implementations of these interaction scenarios with IRL-1 illustrate how it is possible, by following the guidelines

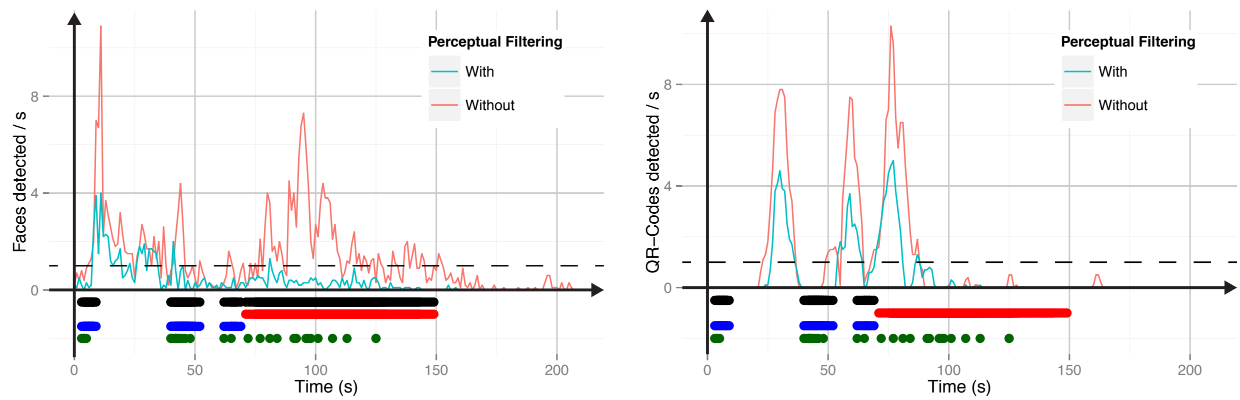

Figure 10: Examples of the effect of perceptual filtering from [22], which show the detection rate per second for faces (left) and QR-Codes (right) with the dash line marking 1 detection per second. The black bars indicate when filtering was applied on faces and QR-Codes. The red bar illustrates when a Strategy for path planning was selected. The blue bars indicate when a Strategy for voice localization was selected, which was triggered by loud noises (green dots).

of an architecture such as HBBA, to coherently integrate HRI capabilities and skills while moving towards higher level cognitive capabilities. The teleoperation application of Sec. 4.1 served as the base for the implementation of the others. Since Strategies are designed in relation to a specific robotic platform, they are thus shareable between instances of HBBA on IRL-1. For instance, the Strategies and implementations for modules such as ManyEars and Plan & Follow Path modules are identical for the three implementations presented. Moreover, while dynamic filtering was only used in the third experiment (in the first two $\phi \in \{1, \infty\}$ instead of $\phi \in [1, \infty)$), the integration and coordination mechanism allowed us to develop efficiently the Perception modules and to measure resource consumption in preparation for the third experiment. For instance, the Strategies designed for the fetch-and-deliver task were transferred to the tour-guiding task, where dynamic perceptual filtering was validated. We expect that most perception Strategies can be easily transferred between platforms with similar sensors, since it requires only a reassessment of their computing costs.

Furthermore, this HBBA implementation can also be applied to different development contexts. For instance, in the ENRICHME project [59], two HBBA configurations were used in the prototyping phase: one in a Gazebo-based simulation and the other on a Robosoft Kompaï 2 robot. The Plan & Follow Path implementation on this robot was not based on ROS, and therefore cannot be used in simulation. Thus two separate Strategies and Behavior modules are used, while the upper-level Motivation modules can stay identical to produce the same overall functionality of IRL-1 on the Kompaï 2 or any other robot. In fact, later on in the ENRICHME project the target robot was changed to a PAL Robotics TIAGo, and the upper-level Motivation modules were directly transferred to this new platform in both simulation and real settings. Since Motivation modules express goals as Desires, instead of using direct function calls or messages to a specific module, it becomes easier to change the lower level of the architecture while keeping the overall functionality of the robot intact. Using HBBA in this context means that the overall behavior can still be worked on without access to the robot. Furthermore, while the current implementation of HBBA relies on ROS, it is middleware independent and free of ROS-specific dependencies. A middleware package such as ROS, while useful in implementing robot infrastructures, does not enforce architecture design guidelines or provide any guidelines as to how decisional modules interact or are integrated, as one of its goal is precisely to be as application-agnostic as possible. Using finite-state machines to activate and configure Perception and Behavior modules such as the module for the navigation of the robot would require significant work to either re-write the finite state machine to the ROS-based navigation system used in simulation, or re-write a simulation of the original navigation subsystem. The use of HBBA and its integration and coordination mechanism, whether or not it is implemented on ROS or other middleware, facilitates such transfer, making HBBA a generic design framework.

6 Conclusion

Integration of specific interaction skills and capabilities in a mobile robot requires more than just putting pieces of hardware and software together: it calls for important coordination of the physical, sensing, processing and control capabilities. In order to do this efficiently, robot control architectures may be employed since they are powerful tools that support incremental and iterative design as well as evaluation of robotic platforms,what we made use of with HBBA. This paper presents the overall structure of HBBA along with its key integration and coordination mechanism, validated in three different interaction scenarios. Now that we have a stable implementation of HBBA on ROS, more research is being conducted while using HBBA to design mobile robots with higher level of cognition and capabilities. For instance, HBBA is currently adopted to implement a telepresence and assistance in daily living activities robot for homecare applications, which will allow us to validate the use of multiple Motivation modules. What is more, since the ability to transfer the implementation from one robot system to another is predicted to prove a considerable benefit [11], HBBA is currently being used in the Pal Robotics TIAGo robot as a service robot in care facilities for elderly people with mild cognitive impairment [59]. This implementation will reuse the AEM-ART spatio-temporal memory model, along with multiple motivations sources competing for the resources of the robot, to offer multiple cognitive, physical, and social stimulation activities to its users.

Acknowledgement: This work is supported by the Natural Sciences and Engineering Research Council of Canada (NSERC), the Canada Research Chair (CRC) in Mobile Robotics and Autonomous Intelligent Systems, and the Fonds de recherche Québec Nature et Technologies (FRQNT).

References

[1] M. A. Goodrich, A. C. Schultz, Human-Robot Interaction: A survey Foundation and Trends in Human-Computer Interaction. 2007, 1, 203-275, http://dx.doi.org/10.1561/1100000005

[2] T. W. Fong, I. Nourbakhsh, K. Dautenhahn, A survey of socially interactive robots Robotics and Autonomous Systems. 2003, 42, 143-166

[3] J. G. Trafton, L. M. Hiatt, A. M. Harrison, F. P. Tamborello, S. S. Khemlani, A. C. Schultz, ACT-R/E: An embodied cognitive architecture for human-robot interaction, Journal of Human-Robot Interaction, 2013, 2, 30-55

[4] P. Langley, J. E. Laird, S. Rogers, Cognitive architectures: Research issues and challenges, Cognitive Systems Research, 2009, 10, 141-160, http://dx.doi.org/10.1016/j.cogsys.2006.07.004

[5] J. E. Laird, A. Newell, P. S. Rosenbloom, Soar: An architecture for general intelligence Artificial intelligence, 1987, 33, 1-64

[6] J.-Y. Puigbo, A. Pumarola, C. Angulo,R. Tellez, Using a cognitive architecture for general purpose service robot control, Connection Science, 2015, 27, 105-117

[7] M. Scheutz, P. Schermerhorn, J. Kramer, D. Anderson, First steps toward natural humanlike HRI, Autonomous Robots, 2007, 22, 411-423, http://dx.doi.org/10.1007/s10514-006-9018-3

[8] M. Shaw, The coming-of-age of software architecture research, Proceedings International Conference on Software Engineering, 2001

[9] M. Shaw, What makes good research in software engineering?, Proceedings European Joint Conference on Theory and Practice of Software, 2002

[10] A Roadmap for U.S. Robotics – From Internet to Robotics tech. rep. Robotics in the United States of America, Robotics VO 2013

[11] Robotics 2020 Multi-Annual Roadmap, for Robotics in Europe, Release B SPARC, The Partnership for Robotics in Europe (2015), Robotics 2020 Multi-Annual Roadmap, For Robotics in Europe, Release B 2015

[12] F. Michaud, F. Ferland, D. Létourneau, M.-A. Legault, M. Lauria, Toward autonomous, compliant, omnidirectional humanoid robots for natural interaction in real-life settings, Paladyn. Journal of Behavioral Robotics, 2010, 1, 57-65, http://dx.doi.org/10.2478/s13230-010-0003-3

[13] R. J. Brachman, (AA)AI more than the sum of its parts, AI Magazine, 2006, 27, 19-34

[14] N. J. Nilsson, Eye On The Prize, AI Magazine, 1995, 16, 9-17

[15] N. J. Nilsson, Human-level Artificial Intelligence? Be serious!, AI Magazine, 2005, 26, 68-75

[16] B. Goertzel, Artificial General Intelligence: Concept, State of the Art, and Future Prospects, Journal of Artificial General Intelligence, 2014, 5, 1-48

[17] C. Bundesen, T. Habekost, Attention in Handbook of Cognition (K. Lamberts, R. L. Goldstone, R. Goldstone, eds.), 105-129SAGE Publications 2004

[18] J. A. Deutsch, D. Deutsch, Attention: Some theoretical considerations, Psychological Review, 1963, 70, 80-90

[19] D. E. Broadbent, Perception and Communication, London, UK, Pergamon Press, 1958

[20] A. Reveleau, F. Ferland, M. Labbé, D. Létourneau, F. Michaud, Visual representation of interaction force and sound source in a teleoperation user interface for a mobile robot, Journal of Human-Robot Interaction, 2015, 4, 1-23

[21] F. Leconte, F. Ferland, F. Michaud, Design and integration of a spatio-temporal memory with emotional influences to categorize and recall the experiences of an autonomous mobile robot, Autonomous Robots, 2016, 40, 831-848

[22] F. Ferland, F. Michaud, Selective attention by perceptual filtering in a robot control architecture, IEEE Transactions on Cognitive and Developmental Systems, 2016, 8, 256-270

[23] F. Michaud, M. Nicolescu, Behavior-based systems in Handbook of Robotics, ch. 13, Springer, 2016

[24] R. C. Arkin, Behavior-Based Robotics, MIT Press, 1998

[25] G. N. Saridis, Intelligent robotic control, IEEE Transactions on Automatic Control, 1983, AC-28, 547-557, http://dx.doi.org/10.1109/TAC.1983.1103278

[26] C. Zielinski, W. Szynkiewicz, M. Figat, et al., Reconfigurable control architecture for exploratory robots, 10th International Workshop on Robot Motion and Control (RoMoCo), 2015, 130-135

[27] G. D. Konidaris, G. M. Hayes, An architecture for behavior-based reinforcement learning, Adaptive Behavior, 2005, 13, 5-32
[28] C. Moulin-Frier, T. Fischer, M. Petit, et al., DAC-h3: A Proactive Robot Cognitive Architecture to Acquire and Express Knowledge About the World and the Self, arXiv preprint arXiv:1706.03661, 2017
[29] P. F. M. J. Verschure, T. Voegtlin, R. J. Douglas, Environmentally mediated synergy between perception and behaviour in mobile robots, Nature, 2003, 425, 620–624
[30] M. Petit, S. Lallée, J.-D. Boucher, et al., The coordinating role of language in real-time multimodal learning of cooperative tasks, IEEE Transactions on Autonomous Mental Development, 2013, 5, 3-17
[31] Y. Demiris, B. Khadhouri, Hierarchical attentive multiple models for execution and recognition of actions, Robotics and Autonomous Systems, 2006, 54, 361-369
[32] G. Pezzulo, D. Ognibene, G. Calvi, D. Lalia, Fuzzy-based schema mechanisms in AKIRA, Proceedings of the 2005 International Conference on Computational Intelligence for Modelling, Control and Automation, and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC'05)
[33] E. Nivel, K. R. Thórisson, B. R. Steunebrink, et al., Bounded seed-AGI, International Conference on Artificial General Intelligence, Springer, 2014, 85-96
[34] N. Muscettola, G. A. Dorais, C. Fry, R. Levinson, C. Plaunt, IDEA: Planning at the core of autonomous reactive agents, Proceedings of the 3rd International NASA Workshop on Planning and Scheduling for Space, 2002
[35] R. C. Beck, Motivation, Theories and Principles, Prentice Hall, 1983
[36] D. O. Hebb, The Organization of Behavior: A Neuropsychological Theory, Wiley, New York, 1949
[37] G. Mandler, Mind and Body: Psychology of Emotion and Stress, W. W. Norton, New York and London, 1984
[38] J. E. Stets, Emotions and Sentiments, Handbook of Social Psychology, 2003
[39] C. Raievsky, F. Michaud, Improving situated agents adaptability using Interruption Theory of Emotions, Proceedings International Conference on Simulation of Adaptive Behavior, 2008, 301-310, http://dx.doi.org/10.1007/978-3-540-69134-1_30
[40] L. Hickton, M. Lewis, L. Cañamero, A flexible component-based robot control architecture for hormonal modulation of behaviour and affect, Conference Towards Autonomous Robotic Systems, 2017, 464-474
[41] F. Michaud, M. J. Mataric, Learning from history for behavior-based mobile robots in non-stationary environments, Machine Learning/Autonomous Robots, Special Issue on Learning in Autonomous Robots, 1998, 31/5, 141-167/335-354, http://dx.doi.org/10.1023/A:1007496725428
[42] F. Michaud, M. J. Mataric, Representation of behavioral history for learning in nonstationary conditions, Robotics and Autonomous Systems, 1999, 29, 187-200, http://dx.doi.org/10.1016/S0921-8890(99)00051-2
[43] F. Ferland, D. Létourneau, A. Aumont, et al., Natural interaction design of a humanoid robot, Journal of Human-Robot Interaction, Special Issue on HRI Perspectives and Projects from Around the Globe, 2012, 1, 14-29
[44] M. Lauria, M.-A. Legault, M.-A. Lavoie, F. Michaud, Differential Elastic Actuator for robotic interaction tasks, Proceedings of the IEEE International Conference on Robotics and Automation, 2008, 3606-3611
[45] F. Grondin, D. Létourneau, F. Ferland, V. Rousseau, F. Michaud, The many ears coordination mechanism for integrated design, open framework, Autonomous Robots, 2013, 34, 217-232, http://dx.doi.org/10.1007/s10514-012-9316-x
[46] F. Michaud, P. Boissy, D. Labonté, et al., Exploratory design and evaluation of a homecare teleassistive mobile robotic system, Mechatronics, Special Issue on Design and Control Methodologies in Telerobotics, 2010, 20, 751-766, http://dx.doi.org/10.1016/j.mechatronics.2010.01.010
[47] M. R. Endsley, Design and evaluation for situation awareness enhancement, Proceedings of the Human Factors Society, 32th Annual Meeting, 1988, 97-101
[48] J. C. Scholtz, B. Antonishek, J. D. Young, Implementation of a situation awareness assessment tool for evaluation of human-robot interfaces, IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 2005, 35, 450-459, http://dx.doi.org/10.1109/TSMCA.2005.850589
[49] H. A. Yanco, J. L. Drury, Where am I? Acquiring situation awareness using a remote robot platform, Proceedings IEEE Conference on Systems, Man and Cybernetics, 2004, 2835-2840, http://dx.doi.org/10.1109/ICSMC.2004.1400762
[50] D. Labonté, P. Boissy, F. Michaud, Comparative analysis of 3D robot teleoperation interfaces with novice users, IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics, 2010, 40, 1331-1342, http://dx.doi.org/10.1109/TSMCB.2009.2038357
[51] C. W. Nielsen, M. A. Goodrich, R. W. Ricks, Ecological interfaces for improving mobile robot teleoperation, IEEE Transactions on Robotics, 2007, 23, 927-941, http://dx.doi.org/10.1109/TRO.2007.907479
[52] B. Ricks, C. W. Nielsen, M. A. Goodrich, Ecological displays for robot interaction: A new perspective, Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, 2004, 3, 2855-2860, http://dx.doi.org/10.1109/IROS.2004.1389842
[53] M. Labbé, F. Michaud, Appearance-based loop closure detection for online large-scale and long-term operation, IEEE Transactions on Robotics, 2013, 29, 734-745, http://dx.doi.org/10.1109/TRO.2013.2242375
[54] R. Pfeifer, J. Bongard, How the body shapes the way we think: A new view of intelligence, MIT Press, 2007
[55] E. Tulving, Precis of elements of episodic memory, Behavioral and Brain Sciences, 1984, 7, 223-68
[56] L. R. Squire, Memory systems of the brain: A brief history and current perspective, Neurobiology of Learning and Memory, 2004, 82(3), 171-177
[57] E. A. Phelps, Human emotion and memory: Interactions of the amygdala and hippocampal complex, Current Opinion in Neurobiology, 2004, 14, 198-202
[58] J. L. McGaugh, B. Roozendaal, Role of adrenal stress hormones in forming lasting memories in the brain, Current Opinion in Neurobiology, 2002, 12, 205-10
[59] F. Ferland, A. Tapus, System integration for the ENRICHME project: A service robot for care facilities for the elderly, RO-MAN Workshop on Behavior Adaptation, Interaction and Learning for Assistive Robotics, 2016