

and as tutors. I will show examples of this approach for different stages in the origins of symbolic intelligence grounded through sensory-motor intelligence: the discovery of symbol use, the big spurt in vocabulary, the origins of grammar, and the origins of the self.

## 4.20 Towards an Integrated Hierarchical Planner for Complex Robot Tasks

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Planning and execution is crucial for the performance of complex tasks in challenging environments with a mobile service robot. Furthermore, if we want the robot to adapt its behavior based on experiences of previous execution traces, task planning can be a point to apply the learned knowledge resulting in a changed behavior. The plans can also be part of the experience itself and be used afterwards for learning. For this, hierarchical planning has the benefit of providing additional levels of abstraction to the plan generation and the resulting plans itself. To change the robot's behavior only additional methods need to be added to the planning domain or preconditions of existing methods might be changed while the implementation of operators can be fixed.

In the first two years of the RACE project an off-the-shelf HTN planner has been used. Since this imposes several limitations, ongoing work will be presented of a hierarchical planning system which is closely integrated to execution monitoring and is able to use different kinds of knowledge.

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## 4.21 Robot Manipulation in Human Environments: Challenges for Learning Algorithms

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Manipulator robots are widening their range of activities in factories, as well as finding increased application in human-centered domains such as healthcare, education, entertainment and services. For robots to become handy co-workers and helpful assistants, quick and user-friendly ways to endow them with flexible manipulation skills are needed. At the Perception and Manipulation Lab of IRI (CSIC-UPC), we are addressing several of the learning challenges arising in this context [1]. Namely, manipulator robots should be easy to teach by non-experts [2] and acquire skills from demonstrations [3, 4], they need to be intrinsically safe [5] able

to appropriately deal with forces [6] and to perceive and manipulate deformable objects [7, 8, 9, 10], to, tolerant to noisy perceptions and inaccurate actions [11, 12], and they must exhibit a high adaptability [13, 14] to non-predefined and dynamic environments, as well as the capability of learning to plan [15]. The cited works will be showcased along the presentation and support for their development is acknowledged from the European projects PACO-PLUS, GARNICS and IntellAct, the Spanish projects PAU and PAU+, and the Catalan grant SGR-155.

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## 4.22 Skill Development through Affordance-based Bootstrapping

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Joint work of Sahin, Erol; Oztop, Erhan; Nagai, Yukie; Piater, Justus

In this talk, we introduce our robot learning framework which follows a similar timeline with human infant development. In the initial stages of the development, the robot organizes its action parameter space to form behavior primitives, and explore the environment with these primitives to learn basic object affordances such as graspability, pushability and rollability. After learning, the robot can emulate observed goals by making multi-step plans using the discovered behaviors and affordances.

The focus of this this talk will be on the next stages of development where the robot learns more complex behaviors and affordances in multi-object environments with the help of a demonstrator. Regarding to complex behavior learning, we studied how the robot can directly map demonstrated complex action trajectories to its own sensorimotor space. We proposed a mechanism that enables the robot to extract subgoals (with the help of demonstrator through motionese) and to imitate the observed complex behavior by satisfying these subgoals sequentially. The new complex behaviors that involve two or more objects should be further explored as before to learn multi-object affordances. At the end of this talk, we will discuss how multi-object affordance learning can be bootstrapped by utilizing basic affordances as additional properties of the objects.

## 4.23 Sensorimotor Memory: Representation, Learning and Inference

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An efficient representation of sensorimotor system is vital to robot control and its ability to learn new skills. While the increasing sensor accuracy and the speed of signal processing failed to bridge the gap between the performance of artificial and human sensorimotor systems, the motor memory architecture seems to remain neglected. Despite the advances in robot skill learning, the latter remains limited to predefined tasks and pre-specified embodiment. We propose a new motor memory architecture that enables information sharing between different skills, on-line learning and off-line memory consolidation. We develop an